

# Limit theorems for critical branching processes

Emma Horton  
27 February 2024

## 1 Recap

## 2 Yaglom limit and Kolmogorov survival probability

## 3 Further results

- Many-to-few
- Genealogies
- Scaling limits

- The branching process is defined as

$$X_t := \sum_{i=1}^{N_t} \delta_{x_i(t)}.$$

- The law of  $(X_t)_{t \geq 0}$  is characterised via the non-linear semigroup

$$v_t[g](x) := \mathbb{E}_{\delta_x} \left[ \prod_{i=1}^{N_t} g(x_i(t)) \right],$$

where

$$X_t[g] = \int_E g(y) X_t(dy) = \sum_{i=1}^{N_t} g(x_i(t)).$$

- The mean semigroup is given by

$$\psi_t[g](x) := \mathbb{E}_{\delta_x} [X_t[g]].$$

- Recall the Perron Frobenius asymptotic

$$\psi_t[g](x) \sim e^{\lambda_* t} \varphi(x) \eta[g], \quad t \rightarrow \infty.$$

- When  $\lambda_* = 0$ , the expected population size remains constant but we have extinction almost surely.
- What happens to  $X_t$  if we condition on survival?

- Recall the Perron Frobenius asymptotic

$$\psi_t[g](x) \sim e^{\lambda_* t} \varphi(x) \eta[g], \quad t \rightarrow \infty.$$

- When  $\lambda_* = 0$ , the expected population size remains constant but we have extinction almost surely.
- What happens to  $X_t$  if we condition on survival?

- Recall the Perron Frobenius asymptotic

$$\psi_t[g](x) \sim e^{\lambda_* t} \varphi(x) \eta[g], \quad t \rightarrow \infty.$$

- When  $\lambda_* = 0$ , the expected population size remains constant but we have extinction almost surely.
- What happens to  $X_t$  if we condition on survival?

1 Recap

2 Yaglom limit and Kolmogorov survival probability

3 Further results

- Many-to-few
- Genealogies
- Scaling limits

# Yaglom limit for BGW processes

- Suppose  $(Z_n)_{n \geq 0}$  is a BGW process,

$$Z_{n+1} = \sum_{i=1}^{Z_n} \xi_i, \quad \xi_i \sim^{\text{iid}} \xi.$$

- Assume  $\mathbb{E}[\xi] = 1$  so that the process is critical.
- Further assume that  $\sigma^2 := \mathbb{E}[\xi^2] - \mathbb{E}[\xi] < \infty$ .
- Kolmogorow limit (Kolmogorov '38):

$$\lim_{n \rightarrow \infty} n \mathbb{P}(Z_n > 0) = \frac{2}{\sigma^2}$$

- Yaglom limit (Yaglom '48):

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[ \exp \left( -\theta \frac{Z_n}{n} \right) \mid Z_n > 0 \right] = \frac{1}{1 + \theta \sigma^2 / 2}.$$



# Yaglom limit for BGW processes

- Suppose  $(Z_n)_{n \geq 0}$  is a BGW process,

$$Z_{n+1} = \sum_{i=1}^{Z_n} \xi_i, \quad \xi_i \sim^{\text{iid}} \xi.$$

- Assume  $\mathbb{E}[\xi] = 1$  so that the process is critical.
- Further assume that  $\sigma^2 := \mathbb{E}[\xi^2] - \mathbb{E}[\xi] < \infty$ .
- Kolmogorow limit (Kolmogorov '38):

$$\lim_{n \rightarrow \infty} n \mathbb{P}(Z_n > 0) = \frac{2}{\sigma^2}$$

- Yaglom limit (Yaglom '48):

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[ \exp \left( -\theta \frac{Z_n}{n} \right) \mid Z_n > 0 \right] = \frac{1}{1 + \theta \sigma^2 / 2}.$$

# Yaglom limit for BGW processes

- Suppose  $(Z_n)_{n \geq 0}$  is a BGW process,

$$Z_{n+1} = \sum_{i=1}^{Z_n} \xi_i, \quad \xi_i \sim^{\text{iid}} \xi.$$

- Assume  $\mathbb{E}[\xi] = 1$  so that the process is critical.
- Further assume that  $\sigma^2 := \mathbb{E}[\xi^2] - \mathbb{E}[\xi] < \infty$ .
- Kolmogorow limit (Kolmogorov '38):

$$\lim_{n \rightarrow \infty} n \mathbb{P}(Z_n > 0) = \frac{2}{\sigma^2}$$

- Yaglom limit (Yaglom '48):

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[ \exp \left( -\theta \frac{Z_n}{n} \right) \mid Z_n > 0 \right] = \frac{1}{1 + \theta \sigma^2 / 2}.$$

# Yaglom limit for BBM on a compact domain

- Let  $D \subset \mathbb{R}^d$  be compact.
- Let  $(X_t)_{t \geq 0}$  denote a branching process where, given their point of creation, particles move independently according to a diffusion with generator  $L$ . Particles are killed on  $\partial D$  and at rate  $\beta > 0$ , they branch into a random number of particles with distribution  $A$ .
- Let  $\lambda$  denote the first eigenvalue of  $-L$  on  $D$ .
- Assume  $m := \mathbb{E}[A] > 1$ ,  $\mathbb{E}[A^2] < \infty$  and  $\lambda = \beta(m - 1)$ .
- Kolmogorov result (Powell '19):

$$\lim_{t \rightarrow \infty} t \mathbb{P}_x(N_t > 0) = C_1(x).$$

- Yaglom limit (Powell '19):

$$\lim_{t \rightarrow \infty} \mathbb{E}_x \left[ \exp \left( -\frac{\theta}{t} \sum_{i=1}^{N_t} f(X_t^i) \right) \mid N_t > 0 \right] = \frac{1}{1 + \theta C_2(f)}.$$

# Yaglom limit for BBM on a compact domain

- Let  $D \subset \mathbb{R}^d$  be compact.
- Let  $(X_t)_{t \geq 0}$  denote a branching process where, given their point of creation, particles move independently according to a diffusion with generator  $L$ . Particles are killed on  $\partial D$  and at rate  $\beta > 0$ , they branch into a random number of particles with distribution  $A$ .
- Let  $\lambda$  denote the first eigenvalue of  $-L$  on  $D$ .
- Assume  $m := \mathbb{E}[A] > 1$ ,  $\mathbb{E}[A^2] < \infty$  and  $\lambda = \beta(m - 1)$ .
- Kolmogorov result (Powell '19):

$$\lim_{t \rightarrow \infty} t \mathbb{P}_x(N_t > 0) = C_1(x).$$

- Yaglom limit (Powell '19):

$$\lim_{t \rightarrow \infty} \mathbb{E}_x \left[ \exp \left( -\frac{\theta}{t} \sum_{i=1}^{N_t} f(X_t^i) \right) \mid N_t > 0 \right] = \frac{1}{1 + \theta C_2(f)}.$$

# Yaglom limit for BBM on a compact domain

- Let  $D \subset \mathbb{R}^d$  be compact.
- Let  $(X_t)_{t \geq 0}$  denote a branching process where, given their point of creation, particles move independently according to a diffusion with generator  $L$ . Particles are killed on  $\partial D$  and at rate  $\beta > 0$ , they branch into a random number of particles with distribution  $A$ .
- Let  $\lambda$  denote the first eigenvalue of  $-L$  on  $D$ .
- Assume  $m := \mathbb{E}[A] > 1$ ,  $\mathbb{E}[A^2] < \infty$  and  $\lambda = \beta(m - 1)$ .
- Kolmogorov result (Powell '19):

$$\lim_{t \rightarrow \infty} t \mathbb{P}_x(N_t > 0) = C_1(x).$$

- Yaglom limit (Powell '19):

$$\lim_{t \rightarrow \infty} \mathbb{E}_x \left[ \exp \left( -\frac{\theta}{t} \sum_{i=1}^{N_t} f(X_t^i) \right) \mid N_t > 0 \right] = \frac{1}{1 + \theta C_2(f)}.$$

# General setting

Define

$$\mathcal{V}[g](x) := \mathcal{E}_x \left[ \sum_{\substack{i,j=1 \\ i \neq j}}^N g(y_i)g(y_j) \right], \quad x \in E, f \in B^+(E).$$

and

$$\Sigma = \eta[\beta\mathcal{V}[\varphi]].$$

## Theorem (Kolmogorov survival probability)

Under certain assumptions, we have

$$\lim_{t \rightarrow \infty} \sup_{x \in E} \left| \frac{t\mathbb{P}_{\delta_x}(N_t > 0)}{\varphi(x)} - \frac{2}{\Sigma} \right| = 0,$$

$$\text{i.e. } \mathbb{P}_{\delta_x}(N_t > 0) \sim \frac{C_1(x)}{t}.$$

## Theorem (Yaglom limit)

Under the same assumptions, for each  $f \in B^+(E)$ ,

$$\left( \frac{X_t[f]}{t} \mid N_t > 0 \right) \rightarrow Y, \quad \text{as } t \rightarrow \infty,$$

in distribution, where  $Y$  is an exponential random variable with mean  $\eta[f]\Sigma/2$ .

# Kolmogorov survival probability

- Note that

$$\mathbb{P}_{\delta_x}(N_t > 0) = 1 - \mathbb{P}_{\delta_x}(N_t = 0) = 1 - v_t[\mathbf{0}](x) = 1 - \mathbb{E}_{\delta_x} [0^{N_t}]$$

- Recall that

$$v_t[f](x) = \hat{P}_t[f](x) + \int_0^t P_s [G[v_{t-s}[f]]](x) ds,$$

where  $\hat{P}_t[f](x) = \mathbb{E}_x[f(\xi_{t \wedge \tau_\partial})]$ .

- However, this is not the right evolution equation to work with.



# Kolmogorov survival probability

- Note that

$$\mathbb{P}_{\delta_x}(N_t > 0) = 1 - \mathbb{P}_{\delta_x}(N_t = 0) = 1 - v_t[\mathbf{0}](x) = 1 - \mathbb{E}_{\delta_x} [0^{N_t}]$$

- Recall that

$$v_t[f](x) = \hat{P}_t[f](x) + \int_0^t P_s [G[v_{t-s}[f]]](x) ds,$$

where  $\hat{P}_t[f](x) = \mathbb{E}_x[f(\xi_{t \wedge \tau_\partial})]$ .

- However, this is not the right evolution equation to work with.

# Kolmogorov survival probability

- Note that

$$\mathbb{P}_{\delta_x}(N_t > 0) = 1 - \mathbb{P}_{\delta_x}(N_t = 0) = 1 - v_t[\mathbf{0}](x) = 1 - \mathbb{E}_{\delta_x} [0^{N_t}]$$

- Recall that

$$v_t[f](x) = \hat{P}_t[f](x) + \int_0^t P_s [G[v_{t-s}[f]]](x) ds,$$

where  $\hat{P}_t[f](x) = \mathbb{E}_x[f(\xi_{t \wedge \tau_\partial})]$ .

- However, this is not the right evolution equation to work with.

# Kolmogorov survival probability

For  $f \in B_1^+(E)$  and  $x \in E$ , set

$$u_t[f](x) = 1 - v_t[f](x), \quad t \geq 0$$

and

$$A[f](x) = \gamma(x) \mathcal{E}_x \left[ \prod_{i=1}^N (1 - f(x_i)) - 1 + \sum_{i=1}^N f(x_i) \right].$$

# Kolmogorov survival probability

For  $f \in B_1^+(E)$  and  $x \in E$ , set

$$u_t[f](x) = 1 - v_t[f](x), \quad t \geq 0$$

and

$$A[f](x) = \gamma(x) \mathcal{E}_x \left[ \prod_{i=1}^N (1 - f(x_i)) - 1 + \sum_{i=1}^N f(x_i) \right].$$

## Lemma

For all  $g \in B_1^+(E)$ ,  $x \in E$  and  $t \geq 0$ ,  $u_t[g](x)$  satisfies

$$u_t[g](x) = \psi_t[1 - g](x) - \int_0^t \psi_s [A[u_{t-s}[g]]](x) ds.$$

Three possible approaches:

- Spine decomposition
- Method of moments
- Laplace transforms/non-linear semigroup

- Know that exponential distribution is characterised by its moments.
- Let us consider the moments of  $t^{-1}X_t[f]$  under  $\mathbb{P}_{\delta_x}(\cdot | N_t > 0)$ :

$$\mathbb{E}_{\delta_x} \left[ \left( \frac{X_t[f]}{t} \right)^k \mid N_t > 0 \right] = \frac{\frac{1}{t^{k-1}} \mathbb{E}_{\delta_x} [X_t[f]^k \mathbf{1}_{N_t > 0}]}{t \mathbb{P}_{\delta_x}(N_t > 0)}$$

- Recall that

$$\mathbb{E}_{\delta_x} [X_t[f]^k] = (-1)^k \frac{\partial^k}{\partial \theta^k} \mathbb{E}_{\delta_x} [e^{-\theta X_t[f]}] \Big|_{\theta=0}$$

- Know that exponential distribution is characterised by its moments.
- Let us consider the moments of  $t^{-1}X_t[f]$  under  $\mathbb{P}_{\delta_x}(\cdot | N_t > 0)$ :

$$\mathbb{E}_{\delta_x} \left[ \left( \frac{X_t[f]}{t} \right)^k \mid N_t > 0 \right] = \frac{\frac{1}{t^{k-1}} \mathbb{E}_{\delta_x} [X_t[f]^k \mathbf{1}_{N_t > 0}]}{t \mathbb{P}_{\delta_x}(N_t > 0)}$$

- Recall that

$$\mathbb{E}_{\delta_x} [X_t[f]^k] = (-1)^k \frac{\partial^k}{\partial \theta^k} \mathbb{E}_{\delta_x} [e^{-\theta X_t[f]}] \Big|_{\theta=0}$$

- Know that exponential distribution is characterised by its moments.
- Let us consider the moments of  $t^{-1}X_t[f]$  under  $\mathbb{P}_{\delta_x}(\cdot | N_t > 0)$ :

$$\mathbb{E}_{\delta_x} \left[ \left( \frac{X_t[f]}{t} \right)^k \mid N_t > 0 \right] = \frac{\frac{1}{t^{k-1}} \mathbb{E}_{\delta_x} [X_t[f]^k \mathbf{1}_{N_t > 0}]}{t \mathbb{P}_{\delta_x}(N_t > 0)}$$

- Recall that

$$\mathbb{E}_{\delta_x} [X_t[f]^k] = (-1)^k \frac{\partial^k}{\partial \theta^k} \mathbb{E}_{\delta_x} [e^{-\theta X_t[f]}] \Big|_{\theta=0} = (-1)^{k+1} \frac{\partial^k}{\partial \theta^k} u_t[e^{-\theta f}] \Big|_{\theta=0}.$$



# Yaglom limit

Recall

$$u_t[g](x) = \psi_t[1 - g](x) - \int_0^t \psi_s [A[u_{t-s}[g]]](x) ds,$$

so that

$$u_t[e^{-\theta g}](x) = \psi_t[1 - e^{-\theta g}](x) - \int_0^t \psi_s [A[u_{t-s}[e^{-\theta g}]]](x) ds,$$

where

$$A[f](x) = \gamma(x) \mathcal{E}_x \left[ \prod_{i=1}^N (1 - f(x_i)) - 1 + \sum_{i=1}^N f(x_i) \right].$$

Differentiating  $k$  times with respect to  $\theta$  and setting  $\theta = 0$  gives

$$\psi_t^{(k)}[f](x) = \psi_t[f^k](x) + \int_0^t \psi_s \left[ \beta \eta_{t-s}^{(k-1)}[f] \right](x) ds, \quad t \geq 0, \quad (1)$$

where

$$\eta_{t-s}^{(k-1)}[f](x) = \mathcal{E}_x \left[ \sum_{[k_1, \dots, k_N]_k} \binom{k}{k_1, \dots, k_N} \prod_{j: k_j > 0} \psi_{t-s}^{(k_j)}[f](x_j) \right],$$

and  $[k_1, \dots, k_N]_k$  is the set of all non-negative  $N$ -tuples  $(k_1, \dots, k_N)$  such that

$\sum_{i=1}^N k_i = k$  and at least two of the  $k_i$  are strictly positive.

- Proceed by induction. Base case:  $\psi_t[f](x) \sim \varphi(x)\eta[f]$ .
- Inductive step:

$$\psi_t^{(k+1)}[f](x) = \psi_t[f^{k+1}](x) + \int_0^t \psi_s \left[ \beta \eta_{t-s}^{(k)}[f] \right](x) ds.$$

- Recall that from (H1),  $\psi_t[f](x) \rightarrow \varphi(x)\eta[f]$  so that, for  $k \geq 2$ ,

$$\lim_{t \rightarrow \infty} t^{-k} \psi_t[f^{k+1}](x) = 0.$$

Hence

$$\begin{aligned} & \lim_{t \rightarrow \infty} t^{-k} \psi_t^{(k+1)}[f](x) \\ &= \lim_{t \rightarrow \infty} t^{-k} \int_0^t \psi_s \left[ \mathcal{E} \cdot \left[ \sum_{[k_1, \dots, k_N]_{k+1}^2} \binom{k+1}{k_1, \dots, k_N} \prod_{j: k_j > 0} \psi_{t-s}^{(k_j)}[f](x_j) \right] \right] (x) ds \end{aligned}$$

Hence

$$\begin{aligned}
 & \lim_{t \rightarrow \infty} t^{-k} \psi_t^{(k+1)}[f](x) \\
 &= \lim_{t \rightarrow \infty} t^{-k} \int_0^t \psi_s \left[ \mathcal{E} \left[ \sum_{[k_1, \dots, k_N]_{k+1}^2} \binom{k+1}{k_1, \dots, k_N} \prod_{j: k_j > 0} \psi_{t-s}^{(k_j)}[f](x_j) \right] \right] (x) ds \\
 &= \frac{1}{t} \int_0^t \psi_s \left[ \mathcal{E} \left[ \sum_{[k_1, \dots, k_N]_{k+1}^2} \binom{k+1}{k_1, \dots, k_N} \frac{(t-s)^{k+1-\#\{j: k_j > 0\}}}{t^{k-1}} \prod_{j: k_j > 0} \frac{\psi_{t-s}^{(k_j)}[f](x_j)}{(t-s)^{k_j-1}} \right] \right] (x) ds
 \end{aligned}$$

- The inductive proof yields

$$\psi_t^{(k)} \sim t^{k-1} \varphi(x) k! \eta [f]^k (\Sigma/2)^{k-1}, \quad t \rightarrow \infty.$$

- Then, we have

$$\begin{aligned} \mathbb{E}_{\delta_x} \left[ \left( \frac{X_t[f]}{t} \right)^k \mid N_t > 0 \right] &= \frac{\frac{1}{t^{k-1}} \mathbb{E}_{\delta_x} [X_t[f]^k \mathbf{1}_{N_t > 0}]}{t \mathbb{P}_{\delta_x}(N_t > 0)} \\ &= \frac{\varphi(x) k! \eta [f]^k (\Sigma/2)^{k-1}}{\varphi(x) (2/\Sigma)} \\ &= k! \eta [f]^k (\Sigma/2)^k. \end{aligned}$$

# Why the 2nd moments?

**Probabilistic explanation:** asymptotically, two children of the MRCA, each with at least 1 descendant alive at time  $t$ .

Recall the operator

$$\begin{aligned} A[h](x) &= \gamma(x) \mathcal{E}_x \left[ 1 - \prod_{i=1}^N (1 - h(x_i)) - \sum_{i=1}^N h(x_i) \right] \\ &= \gamma(x) \mathcal{E}_x \left[ \sum_{i \neq j} h(x_i) h(x_j) - \dots \right] \\ &= \mathcal{V}[h](x) + h.o.t \end{aligned}$$

# Why the exponential distribution?

- There are asymptotically two children of the MRCA, each with at least 1 descendant alive at time  $t$ .
- Distribution of the time of the MRCA of the particles alive at time  $t$  is uniform.
- Therefore, under  $\mathbb{P}_{\delta_x}(\cdot | N_t > 0)$ ,

$$\frac{X_t}{t} \approx U \left( \frac{X_{Ut}^{(1)}}{Ut} + \frac{X_{Ut}^{(2)}}{Ut} \right).$$



1 Recap

2 Yaglom limit and Kolmogorov survival probability

3 Further results

- Many-to-few
- Genealogies
- Scaling limits

# Many-to-few

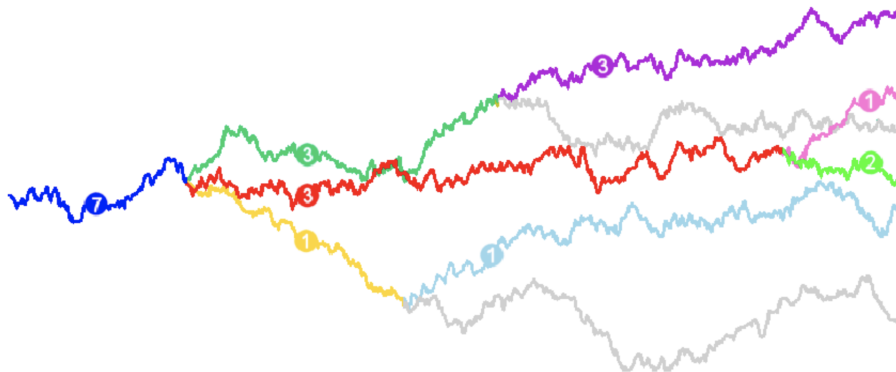
Recall the moment evolution equation:

$$\psi_t^{(k)}[f](x) = \psi_t[f^k](x) + \int_0^t \psi_s \left[ \beta \eta_{t-s}^{(k-1)}[f] \right](x) ds.$$

# Many-to-few

Recall the moment evolution equation:

$$\psi_t^{(k)}[f](x) = \psi_t[f^k](x) + \int_0^t \psi_s \left[ \beta \eta_{t-s}^{(k-1)}[f] \right](x) ds.$$



# Genealogical structure: ancestral trees

- Let  $(X, \mathbb{P})$  denote a Markov branching process.
- Let  $T > 0$ . On the event  $\{N_T \geq k\}$ , choose  $k$  distinct particles  $U_1, \dots, U_k$  uniformly from those alive at time  $T$ .
- What does the ancestral tree formed from these  $k$  particles look like?

# Genealogical structure: ancestral trees

- Let  $(X, \mathbb{P})$  denote a Markov branching process.
- Let  $T > 0$ . On the event  $\{N_T \geq k\}$ , choose  $k$  distinct particles  $U_1, \dots, U_k$  uniformly from those alive at time  $T$ .
- What does the ancestral tree formed from these  $k$  particles look like?

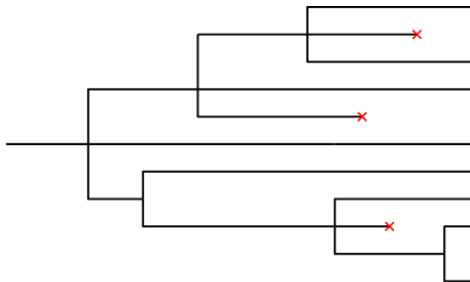
# Genealogical structure: ancestral trees

- Let  $(X, \mathbb{P})$  denote a Markov branching process.
- Let  $T > 0$ . On the event  $\{N_T \geq k\}$ , choose  $k$  distinct particles  $U_1, \dots, U_k$  uniformly from those alive at time  $T$ .
- What does the ancestral tree formed from these  $k$  particles look like?

# Genealogical structure: ancestral trees

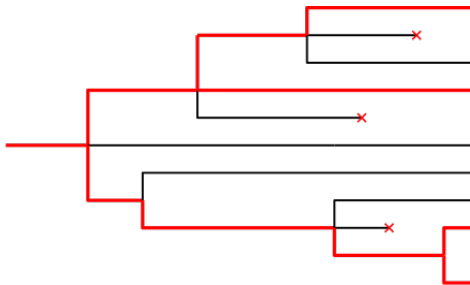
- Let  $(X, \mathbb{P})$  denote a Markov branching process.
- Let  $T > 0$ . On the event  $\{N_T \geq k\}$ , choose  $k$  distinct particles  $U_1, \dots, U_k$  uniformly from those alive at time  $T$ .
- What does the ancestral tree formed from these  $k$  particles look like?

# Ancestral trees

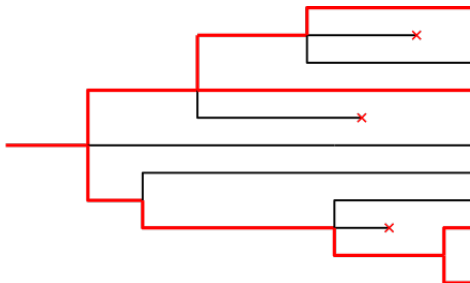




# Ancestral trees



# Ancestral trees

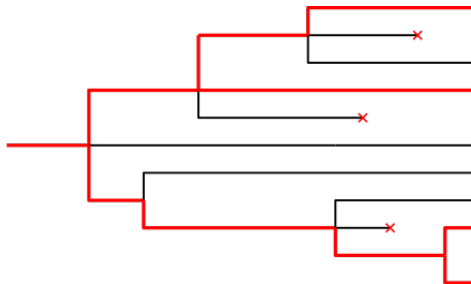


Equivalently, define the equivalence relation  $\sim_t$  on  $\{1, \dots, k\}$  by

$$i \sim_t j \iff U_i \text{ and } U_j \text{ share a common ancestor alive at time } t.$$

Let  $\pi_t^{k,T}$  denote the random partition of  $\{1, \dots, k\}$  corresponding to this equivalence relation.

# Ancestral trees



Equivalently, define the equivalence relation  $\sim_t$  on  $\{1, \dots, k\}$  by

$$i \sim_t j \iff U_i \text{ and } U_j \text{ share a common ancestor alive at time } t.$$

Let  $\pi_t^{k,T}$  denote the random partition of  $\{1, \dots, k\}$  corresponding to this equivalence relation.

What is the law of  $(\pi_t^{k,T})_{t \geq 0}$  conditional on  $N_T \geq k$ ?

- O'Connell, The genealogy of branching processes and the age of our most recent common ancestor.
- Lambert, Coalescence times for the branching process.
- Harris & Roberts, The many-to-few lemma and multiple spines.
- Harris, Johnston & Roberts, The coalescent structure of continuous-time Galton-Watson trees.
- Harris, Horton, Kyprianou & Powell, Many-to-few for non-local branching Markov process.
- Johnston, The genealogy of Galton-Watson trees.
- Zubkov, Limiting distributions of the distance to the closest common ancestor.
- Athreya, Boenkost, Durrett, Foutel-Rodier, Le, Palau, Pardo, Schertzer, Schweinsberg, Tourniaire, ...

# Genealogical structure: convergence to the BCRT

- Aim is to look at the scaling limit of the continuous planar tree associated with a MBP.

- Ulam Harris notation:

$$\Omega = \bigcup_{n=0}^{\infty} \mathbb{N}^n.$$

- The label  $\emptyset$  denotes the initial ancestor.
- Labels are of the form  $u = \emptyset u_1 u_2 \dots u_n$ , e.g. label  $\emptyset 215$  means the particle is the 5th child of the 1st child of the 2nd child of the initial ancestor.

# Genealogical structure: convergence to the BCRT

- Aim is to look at the scaling limit of the continuous planar tree associated with a MBP.

- Ulam Harris notation:

$$\Omega = \bigcup_{n=0}^{\infty} \mathbb{N}^n.$$

- The label  $\emptyset$  denotes the initial ancestor.
- Labels are of the form  $u = \emptyset u_1 u_2 \dots u_n$ , e.g. label  $\emptyset 215$  means the particle is the 5th child of the 1st child of the 2nd child of the initial ancestor.

# Genealogical structure: convergence to the BCRT

- Aim is to look at the scaling limit of the continuous planar tree associated with a MBP.

- Ulam Harris notation:

$$\Omega = \bigcup_{n=0}^{\infty} \mathbb{N}^n.$$

- The label  $\emptyset$  denotes the initial ancestor.
- Labels are of the form  $u = \emptyset u_1 u_2 \dots u_n$ , e.g. label  $\emptyset 215$  means the particle is the 5th child of the 1st child of the 2nd child of the initial ancestor.

# Genealogical structure: convergence to the BCRT

- Aim is to look at the scaling limit of the continuous planar tree associated with a MBP.

- Ulam Harris notation:

$$\Omega = \bigcup_{n=0}^{\infty} \mathbb{N}^n.$$

- The label  $\emptyset$  denotes the initial ancestor.
- Labels are of the form  $u = \emptyset u_1 u_2 \dots u_n$ , e.g. label  $\emptyset 215$  means the particle is the 5th child of the 1st child of the 2nd child of the initial ancestor.



# Genealogical structure: convergence to the BCRT

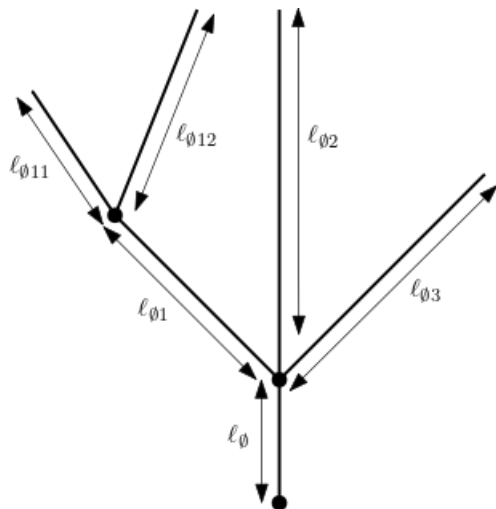
- Aim is to look at the scaling limit of the continuous planar tree associated with a MBP.

- Ulam Harris notation:

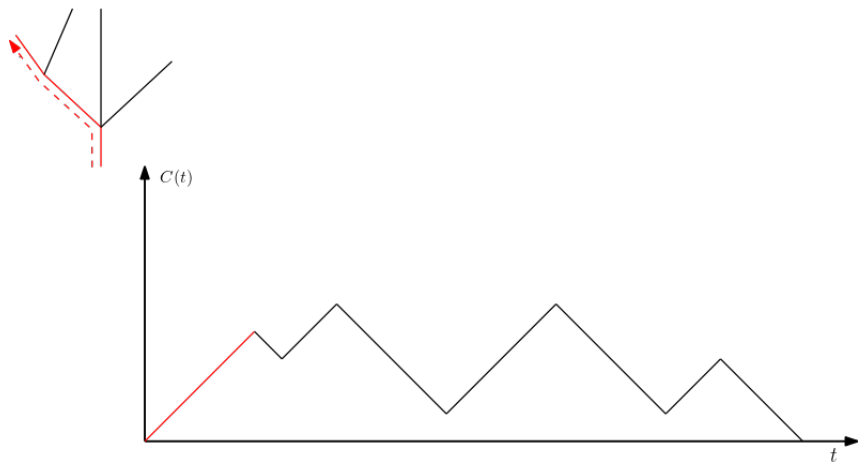
$$\Omega = \bigcup_{n=0}^{\infty} \mathbb{N}^n.$$

- The label  $\emptyset$  denotes the initial ancestor.
- Labels are of the form  $u = \emptyset u_1 u_2 \dots u_n$ , e.g. label  $\emptyset 215$  means the particle is the 5th child of the 1st child of the 2nd child of the initial ancestor.

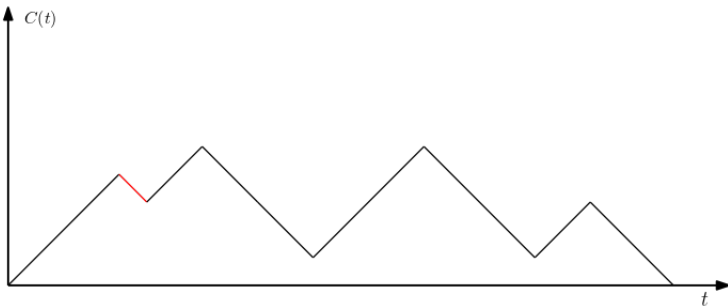
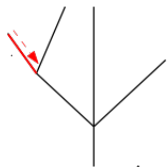
# Convergence to the Brownian CRT



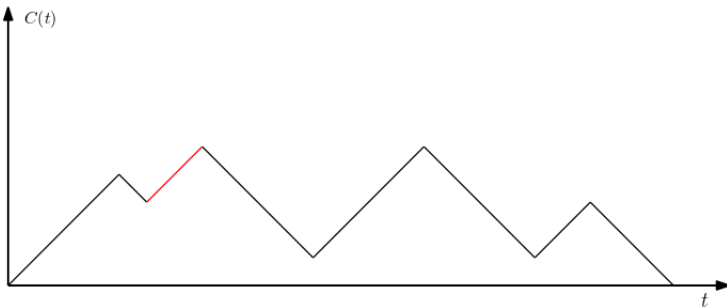
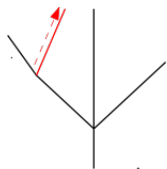
# Convergence to the Brownian CRT



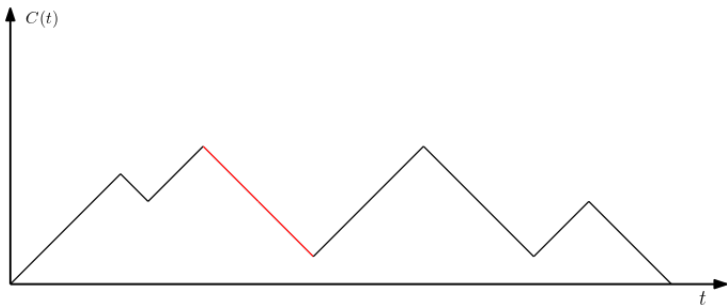
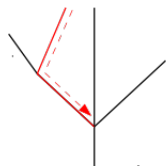
# Convergence to the Brownian CRT



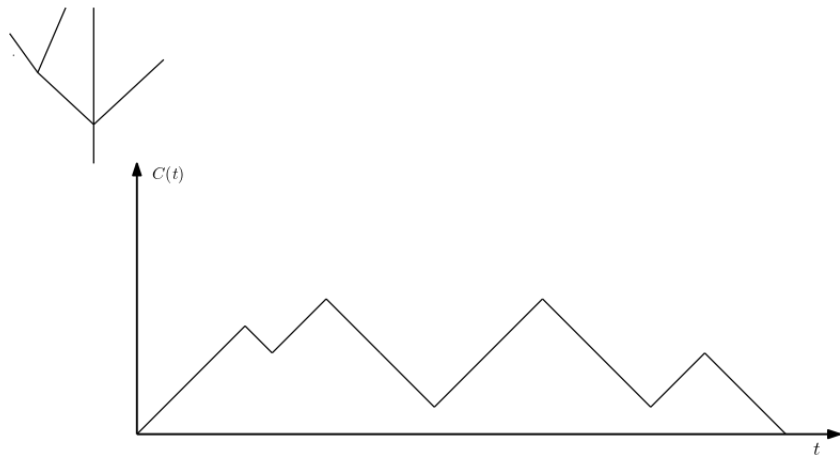
# Convergence to the Brownian CRT



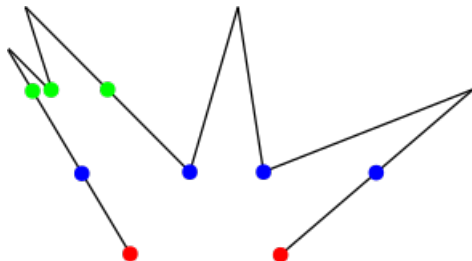
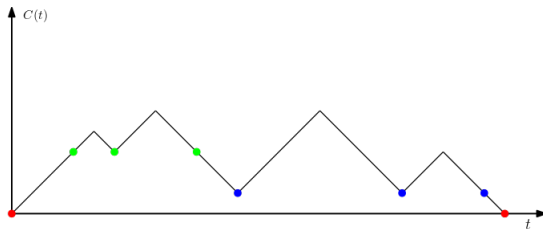
# Convergence to the Brownian CRT



# Convergence to the Brownian CRT

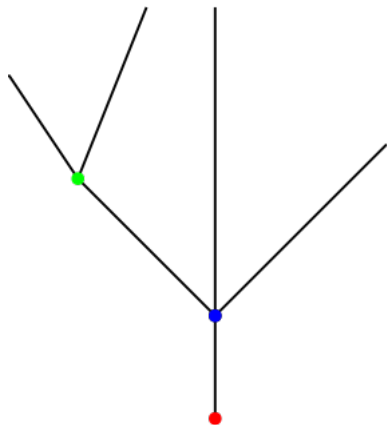
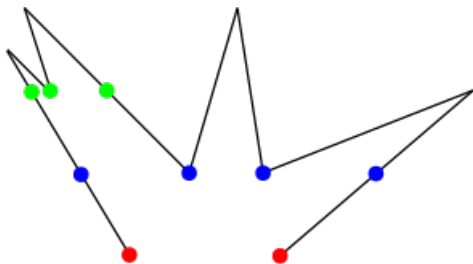


# Convergence to the CRT

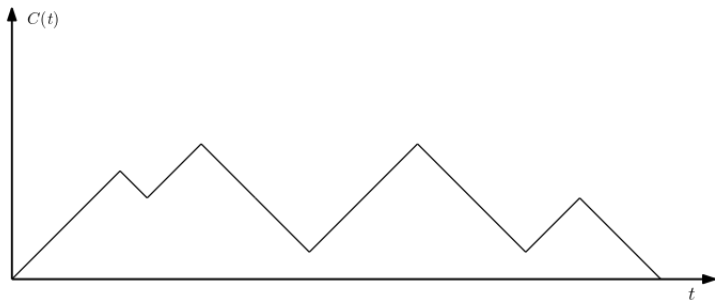
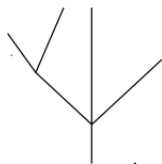




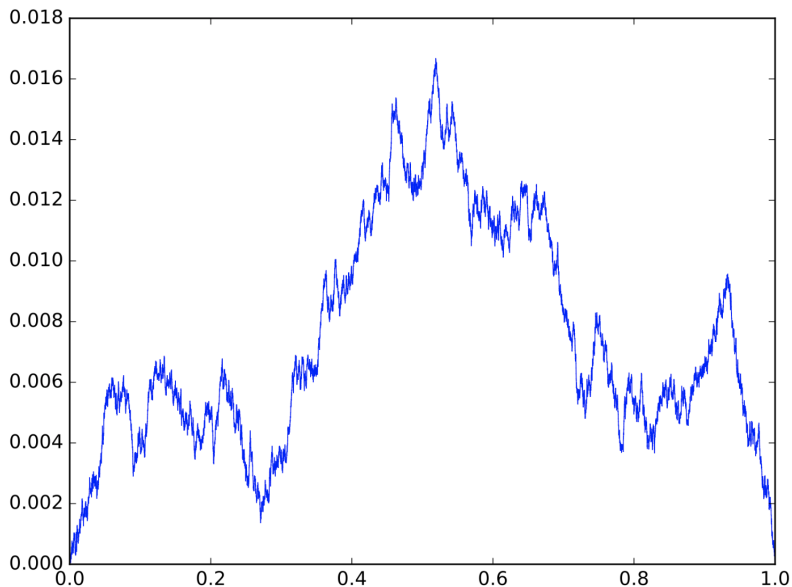
# Convergence to the CRT



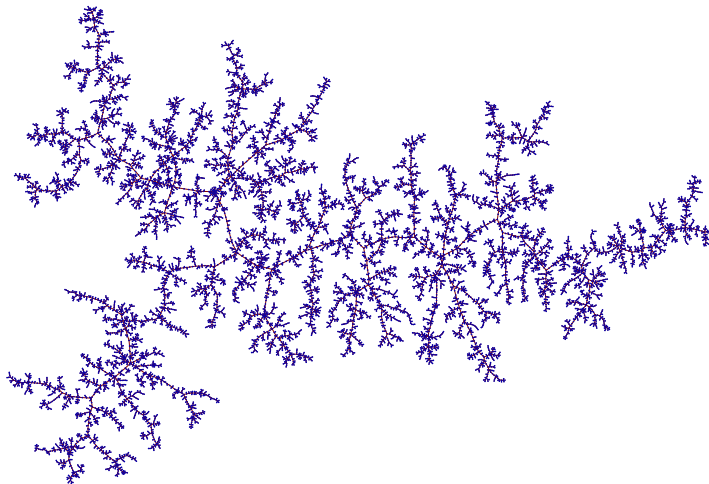
# Convergence to the Brownian CRT



# Convergence to the Brownian CRT



# Convergence to the Brownian CRT



Thank you!