

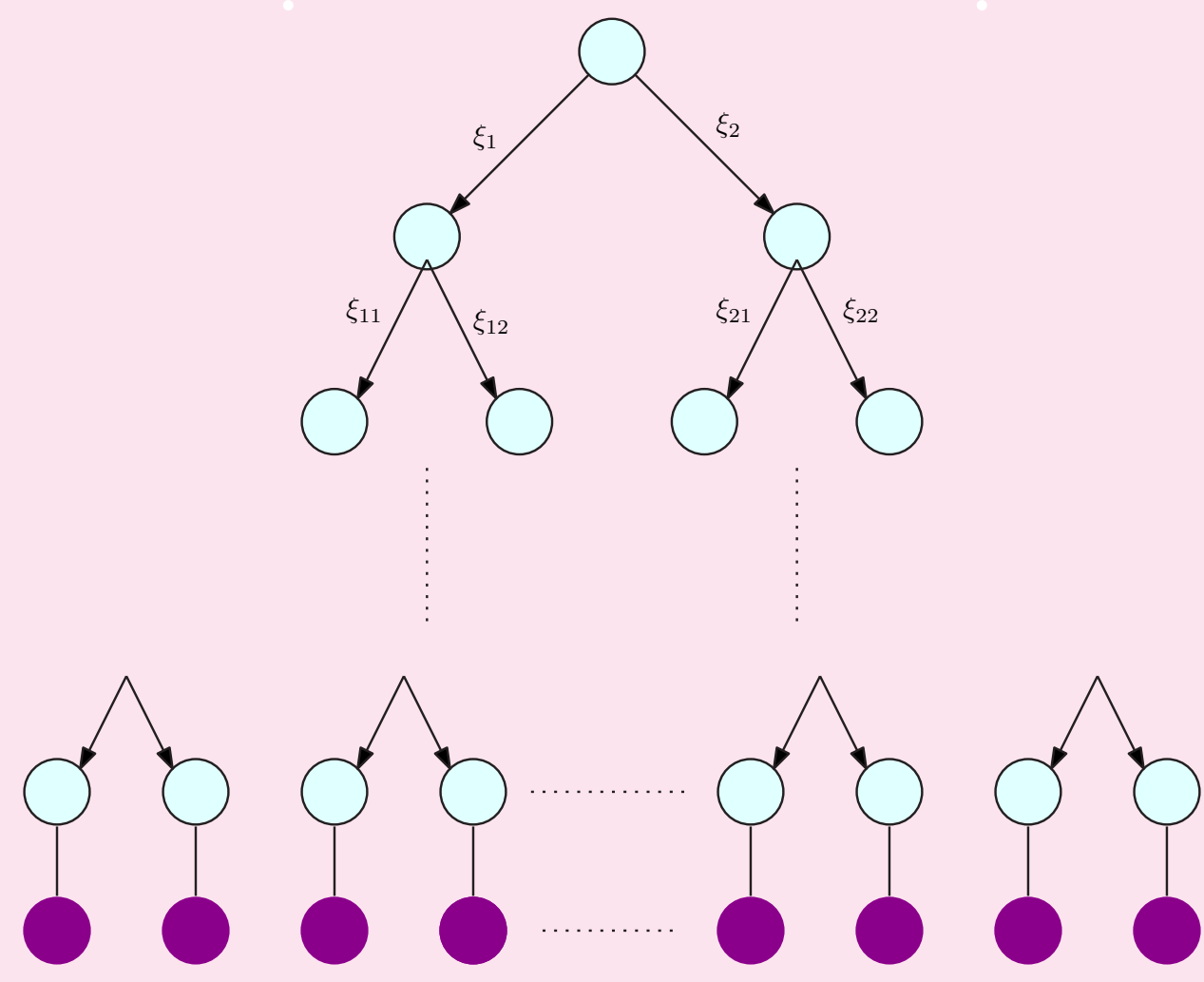
Right-Most Position of a Last Progeny Modified Branching Random Walk

Partha Pratim Ghosh, Technische Universität Braunschweig
(Joint work with Antar Bandyopadhyay, Indian Statistical Institute)



The Model

The time is discrete and starts at 0. At time $n = 0$, there is only one particle at the origin. At time $n = 1$, the particle dies and gives birth to some random number of offspring, which are then displaced according to a point process, say, \mathbf{Z} . Then, at each time $n \geq 2$, each particle at generation $n - 1$ dies and produces some random number of offspring, which are then given random displacements independently and according to a copy of the point process \mathbf{Z} .



Once this has been done, all particles at generation n are given further displacements by a set of i.i.d. random variables, of the form $(\frac{1}{\theta} A_v)_{|v|=n}$, which are independent of the process so far. The distribution of this displacement variables, namely A_v 's and the "scaling" constant $\theta > 0$ are two parameters of this model.

This new process will be called *Last Progeny Modified Branching Random Walk (LPM-BRW)*.

If we denote by S_v the position of an individual v , then the right-most position of the classical branching random walk

$$R_n := \max_{|v|=n} S_v,$$

and the right-most position of the modified branching random walk

$$R_n^* := \max_{|v|=n} \left(S_v + \frac{1}{\theta} A_v \right).$$

Question: How far the family may have spread in generation n for large n ? In other words, what is the asymptotic distribution of R_n^* ?

Transforming Relation

In our model, we take a specific type of distribution for the A_v 's. We take $A_v = \log \frac{Y_v}{E_v}$, where $(Y_v)_{|v|=n}$ are i.i.d. with some positively supported measure, say, μ and $(E_v)_{|v|=n}$ are i.i.d. Exponential(1) random variables and both sets of random variables are independent.

Theorem 1 (Basic Transforming Relation)

$$\max_{i \geq 1} \left(X_i + \log \frac{Y_i}{E_i} \right) \stackrel{d}{=} \log \left(\sum_{i \geq 1} e^{X_i} Y_i \right) - \log E,$$

where $\{Y_i\}_{i \geq 1}$ are i.i.d. positive and $E, \{E_i\}_{i \geq 1}$ are i.i.d. Exponential(1) and these sequences are independent of each other and also Independent of $\{X_i\}_{i \geq 1}$.

Theorem 2 (General Transforming Relation)

$$R_n^* \stackrel{d}{=} \frac{1}{\theta} \left(\log \left(\sum_{|v|=n} e^{\theta S_v} Y_v \right) - \log E \right).$$

Assumptions

Define

$$\nu(\theta) = \log \mathbb{E} \left[\int e^{\theta x} \mathbf{Z}(dx) \right]$$

We assume that $\nu(\theta) < \infty$ for all $\theta \in (-\vartheta, \infty)$ and $\nu(0) > 0$. Also, $\mathbb{E}[\mathbf{Z}(\mathbb{R})^{1+p}] < \infty$ for some $p > 0$.

Let θ_0 be such that the tangent to the graph of ν at the point $(\theta_0, \nu(\theta_0))$ passes through the origin.

SLLN for R_n^*

Theorem 3 For every non-negatively supported probability $\mu \neq \delta_0$ that admits a finite mean

$$\frac{R_n^*}{n} \xrightarrow{a.s.} \begin{cases} \frac{\nu(\theta)}{\theta} & \text{if } \theta < \theta_0; \\ \frac{\nu(\theta_0)}{\theta_0} & \text{if } \theta \geq \theta_0. \end{cases}$$

Comparison (Biggins[1976])

$$\frac{R_n}{n} \xrightarrow{a.s.} \frac{\nu(\theta_0)}{\theta_0}.$$

Centered asymptotic limits

Boundary Case ($\theta = \theta_0$):

Theorem 5 Assume that μ admits a finite mean, then there exists a random variable $H_{\theta_0}^\infty$ such that

$$R_n^* - \frac{\nu(\theta_0)}{\theta_0} n + \frac{1}{2\theta_0} \log n \xrightarrow{d} H_{\theta_0}^\infty + \frac{1}{\theta_0} \log \langle \mu \rangle,$$

where $H_{\theta_0}^\infty = \frac{1}{\theta_0} [\log D_\infty - \log E + \frac{1}{2} \log (\frac{2}{\pi \sigma^2})]$; D_∞ is the a.s. limit of the derivative martingale, $D_n = -\frac{1}{m(\theta_0)^n} \sum_{|v|=n} (\theta_0 S_v - n\nu(\theta_0)) e^{\theta_0 S_v}$; and $E \sim \text{Exponential}(1)$ is independent of D_∞ . Further, $\sigma^2 := \mathbb{E} \left[\frac{1}{m(\theta_0)^n} \sum_{|v|=n} (\theta_0 S_v - n\nu(\theta_0))^2 e^{\theta_0 S_v} \right]$.

Below the Boundary ($\theta < \theta_0$):

Theorem 6 Assume that μ admits finite mean, then

$$R_n^* - \frac{\nu(\theta)}{\theta} n \xrightarrow{d} H_\theta^\infty + \frac{1}{\theta} \log \langle \mu \rangle.$$

Above the Boundary ($\theta > \theta_0$):

Theorem 7 Suppose $\mu = \delta_1$, then

$$R_n^* - \frac{\nu(\theta_0)}{\theta_0} n + \frac{3}{2\theta_0} \log n \xrightarrow{d} H_{\theta_0}^\infty.$$

Comparison (Aïdékon [2013]) There exists a random variable H_∞ such that

$$R_n - \frac{\nu(\theta_0)}{\theta_0} n + \frac{3}{2\theta_0} \log n \xrightarrow{d} H_\infty,$$

where $H_\infty = \frac{1}{\theta_0} [\log D_\infty - \log E + C]$ and C is a constant.

References

1. A. Badyopadhyay and P. P. Ghosh. Right-most position of a last progeny modified branching random walk. *arXiv:2106.02880*, 2021.
2. A. Badyopadhyay and P. P. Ghosh. Right-most position of a last progeny modified time inhomogeneous branching random walk. *Statistics & Probability Letters*, 193: Paper No. 109697 (2023).
3. P. P. Ghosh. Large deviations for the right-most position of a last progeny modified branching random walk. *Electronic Communications in Probability*, 27: Paper No. 6 (2022).

Brunet-Derrida Type Results

Theorem 4 For any $\theta \leq \theta_0$,

$$\sum_{|v|=n} \delta_{\{\theta S(v) - \log E_v - \theta R_n^*\}} \xrightarrow{d} \bar{\mathcal{Y}},$$

where \mathcal{Y} is an inhomogeneous Poisson point process on \mathbb{R} with intensity $e^{-x} dx$ and $\bar{\mathcal{Y}}$ is the point process \mathcal{Y} seen from its right-most position.

Comparison (Madaule [2017])

$$\sum_{|v|=n} \delta_{\{\theta_0 S(v) - \theta_0 R_n\}} \xrightarrow{d} \bar{\mathcal{X}}$$

where \mathcal{X} is a decorated Poisson point process on \mathbb{R} and $\bar{\mathcal{X}}$ is the point process \mathcal{X} seen from its right-most position.

Proof of Transforming Relation

$$\begin{aligned} & \max_{i \geq 1} \left(X_i + \log \frac{Y_i}{E_i} \right) \\ &= \max_{i \geq 1} \left(\log \frac{e^{X_i} Y_i}{E_i} \right) \\ &= -\log \left(\min_{i \geq 1} \frac{E_i}{e^{X_i} Y_i} \right) \\ &\stackrel{d}{=} -\log \frac{E}{\sum_{i \geq 1} e^{X_i} Y_i} \\ &= \log \left(\sum_{i \geq 1} e^{X_i} Y_i \right) - \log E. \end{aligned}$$