



Derrida–Retaux model: from discrete to continuous time

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Processes and Related Topics

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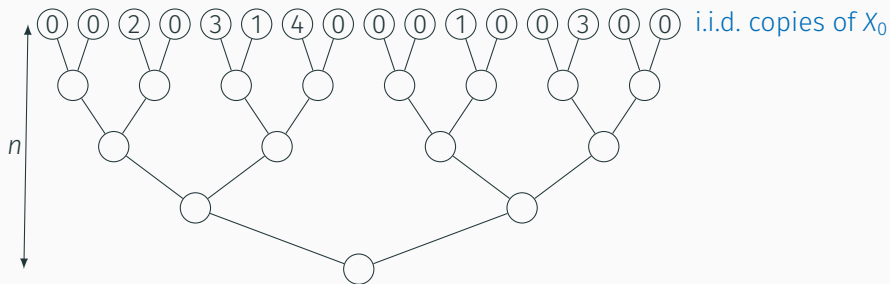
- ▷ Introduced by Collet–Eckmann–Glaser–Martin (1984), motivated by spin glass theory.
- ▷ Re-introduced by Derrida–Retaux (2014) for studying the depinning transition.
- ▷ **Definition:** Start with a nonnegative random variable X_0 and, for any $n \geq 0$,

$$X_{n+1} = \left(X_n + \tilde{X}_n - 1 \right)_+$$

where \tilde{X}_n is an independent copy of X_n .

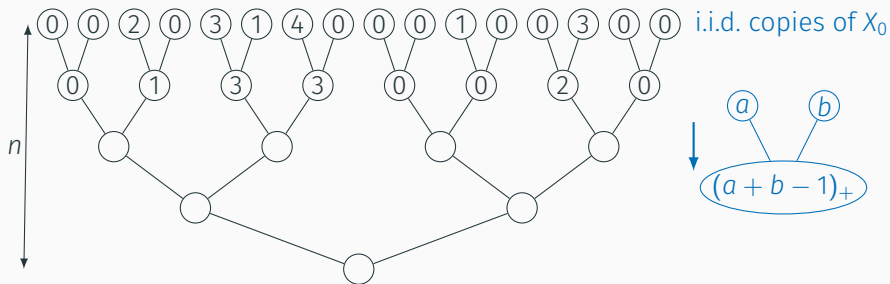
Definition on a tree

Construction of X_n on a binary tree:



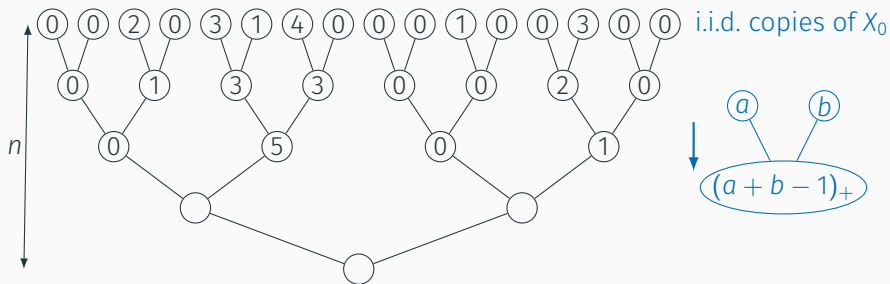
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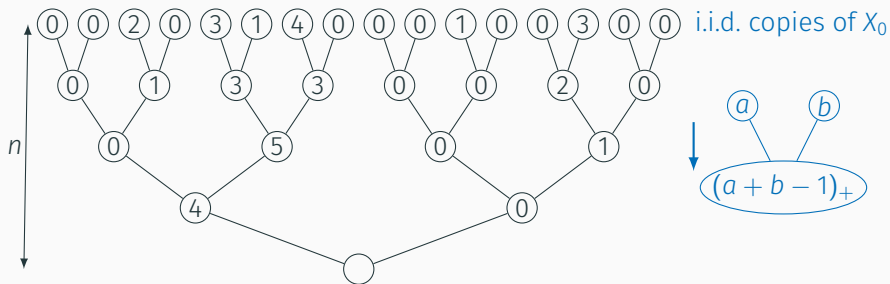
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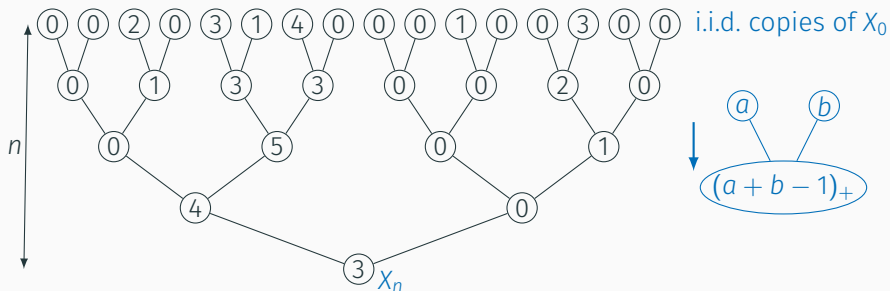
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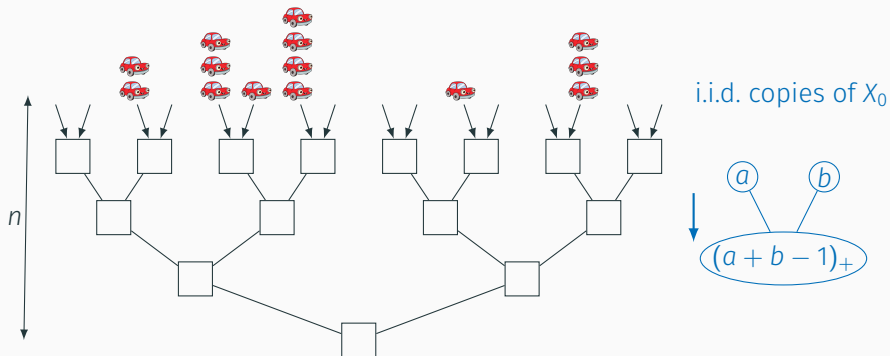
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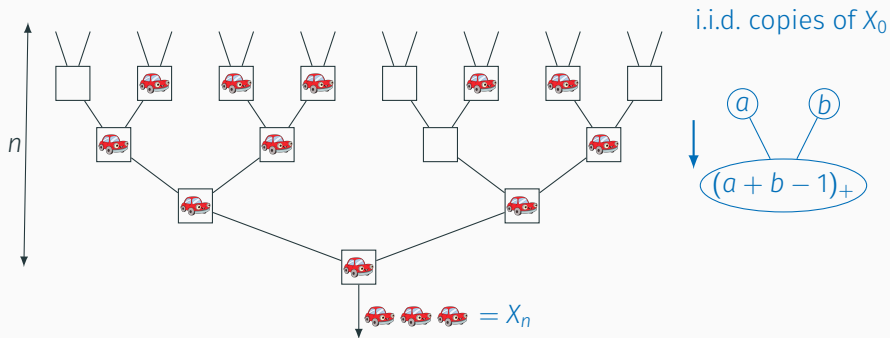
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Free energy: $F_\infty := \lim_{n \rightarrow \infty} \frac{\mathbb{E}[X_n]}{2^n} \in [0, \infty]$.

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Open question: Try to say something about the case where X_0 is not integer-valued.

Free energy near criticality

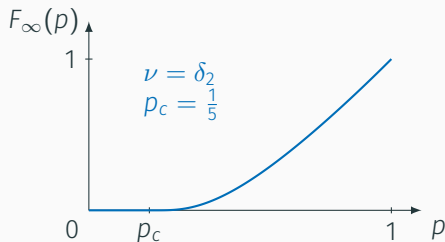
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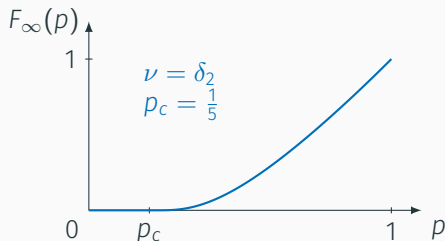
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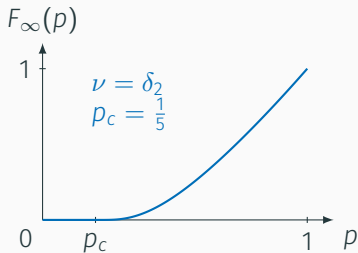
- ▷ If $X_0 \in \mathbb{N}$ a.s., then p_c is explicit by CEGM 1984.

Free energy near criticality

Conjecture (Derrida–Retaux 2014):

If $p_c > 0$, then as $p \downarrow p_c$

$$F_\infty(p) = \exp\left(-\frac{K + o(1)}{(p - p_c)^{1/2}}\right).$$

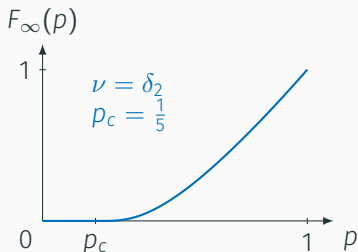


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Theorem (Chen–Dagard–Derrida–Hu–Lifshits–Shi 2019+): If ν is supported by \mathbb{N}^* and $\int_0^\infty x^3 2^x \nu(dx) < \infty$, then as $p \downarrow p_c$

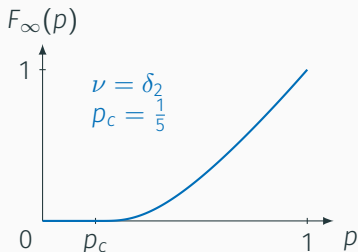
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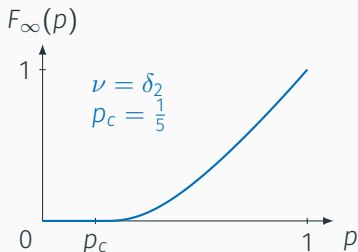
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- ▷ CDDFLS deal also with the case where $p_c > 0$ and $\int_0^\infty x^3 2^x \nu(dx) = \infty$.
- ▷ Hu–Shi 2018: case $p_c = 0$.

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- ▷ **Theorem (Chen–Derrida–Hu–Lifshits–Shi 2017)**: *If $\mathbb{E}[X_0^3 2^{X_0}] < \infty$, then*

$$\frac{C_1}{n} \leq \mathbb{E}[2^{X_n}] - 1 \leq \frac{C_2}{n}.$$

In particular, $\mathbb{P}(X_n > 0) \leq \frac{C_2}{n}$.

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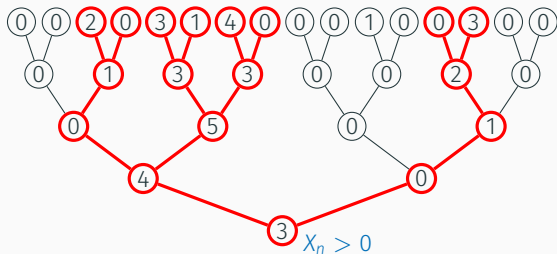
- ▷ **Conjecture (Chen–Derrida–Hu–Lifshits–Shi 2017)**: If $\mathbb{E}[X_0^3 2^{X_0}] < \infty$, then

$$\mathbb{P}(X_n > 0) \sim \frac{4}{n^2}.$$

Moreover, given $X_n > 0$, X_n converges in law to a geometric distribution with parameter $\frac{1}{2}$.

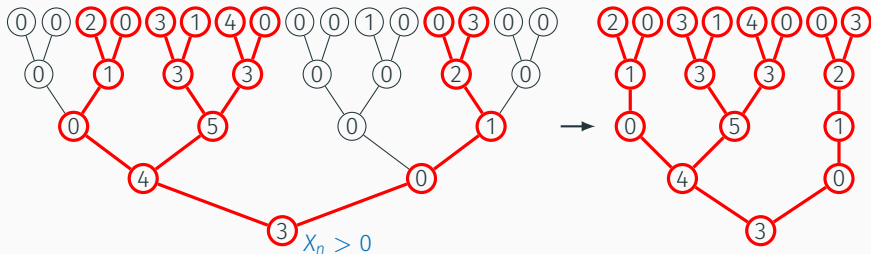
The red tree at criticality

Given that $X_n > 0$, we color in red the paths from a leaf to the root, where the operation “positive part” was not needed.



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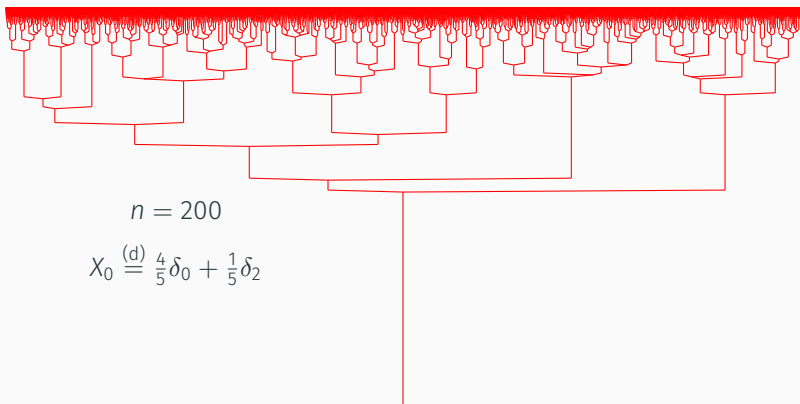
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The red vertices form a subtree, called the *red tree*.

Questions concerning the red tree

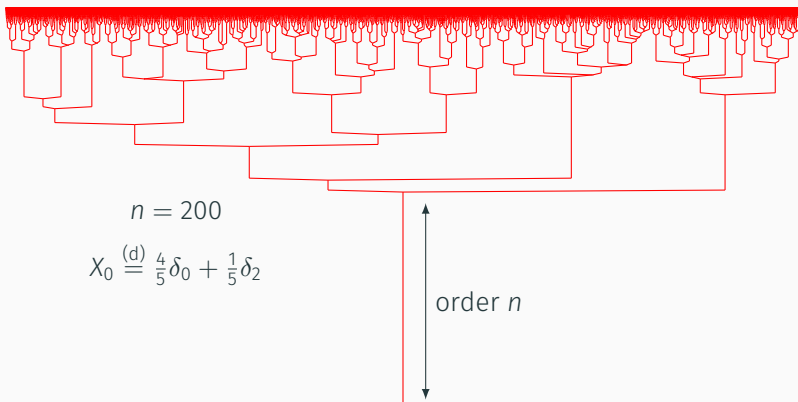
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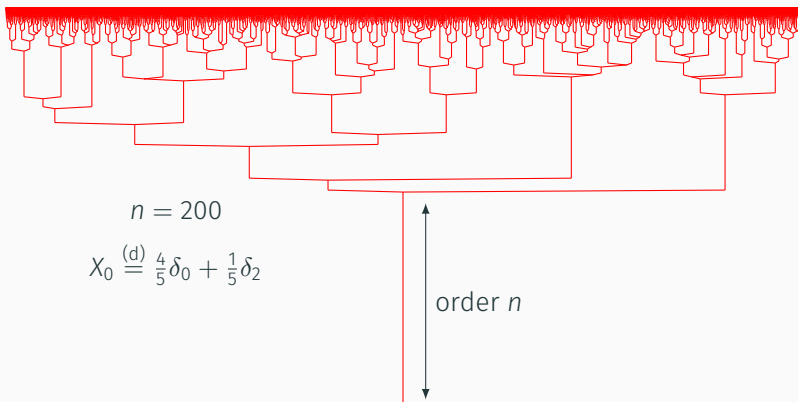
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- ▷ Scaling limit?
- ▷ Number of red leaves?



Continuous-time Derrida–Retaux model

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Initial condition: a nonnegative random variable X_0 .

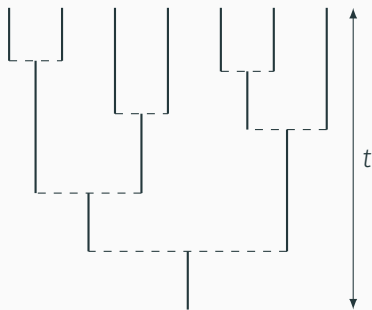
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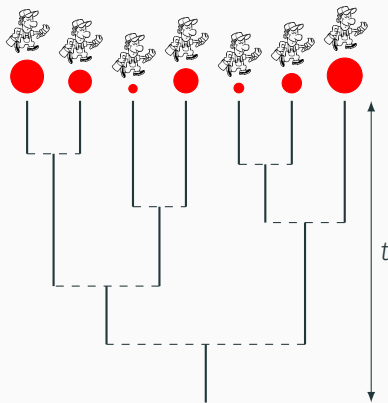


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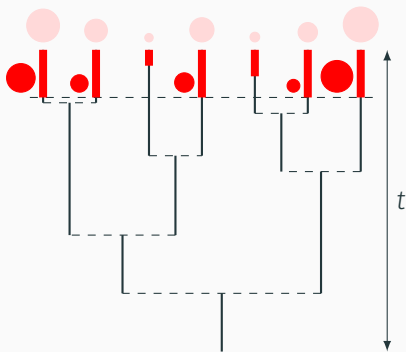


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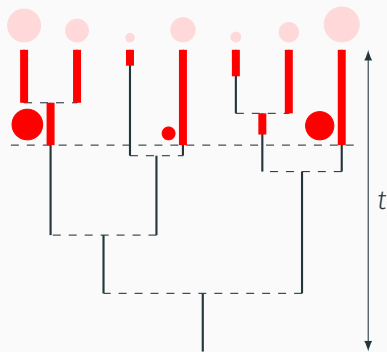


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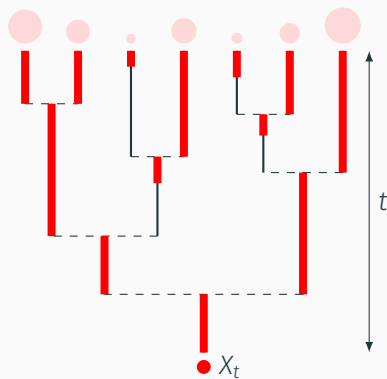


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- ▶ When two painters meet, they put their remaining paint in common.
- ▶ X_t is the remaining paint at the root.



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- ▷ **Open question:** If $F_\infty = 0$, then prove that $X_t \xrightarrow[t \rightarrow \infty]{\text{probability}} 0$.
- ▷ **Proposition:** Let μ_t denote the distribution of X_t for each $t \geq 0$. Then, $(\mu_t)_{t \geq 0}$ is the unique family of positive measures on \mathbb{R} solution (in the weak sense) of the PDE

$$\partial_t \mu_t = \partial_x (\mathbb{1}_{\{x > 0\}} \mu_t) + \mu_t * \mu_t - \mu_t,$$

with initial condition μ_0 .

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- ▷ **Proposition:** For any $t \geq 0$, $\mu_t = p(t) \delta_0(dx) + (1 - p(t)) \lambda(t) e^{-\lambda(t)x} dx$, where $p: \mathbb{R}_+ \rightarrow [0, 1]$ and $\lambda: \mathbb{R}_+ \rightarrow \mathbb{R}_+$ are the unique solutions of the ODE

$$\begin{cases} p' = (1 - p)(\lambda - p) \\ \lambda' = -\lambda(1 - p) \end{cases} \quad \text{with} \quad \begin{cases} p(0) = p_0 \\ \lambda(0) = \lambda_0. \end{cases}$$

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- ▷ $H := \frac{p(t)}{\lambda(t)} + \log \lambda(t)$ is an invariant of the dynamics.

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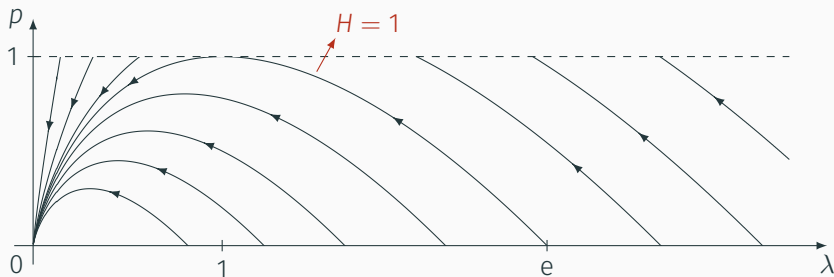
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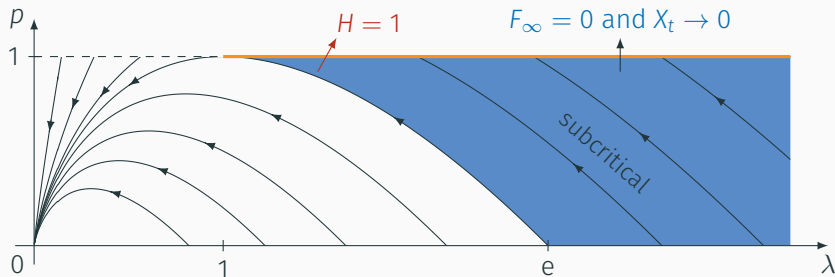
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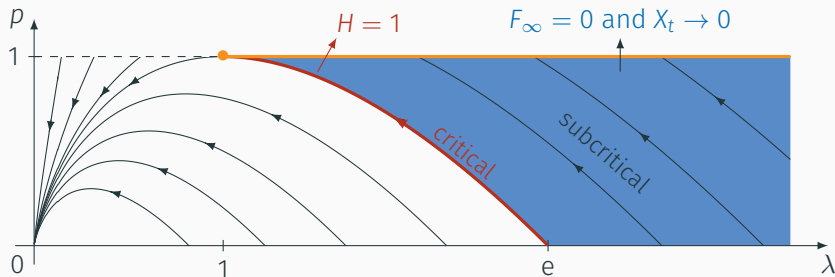
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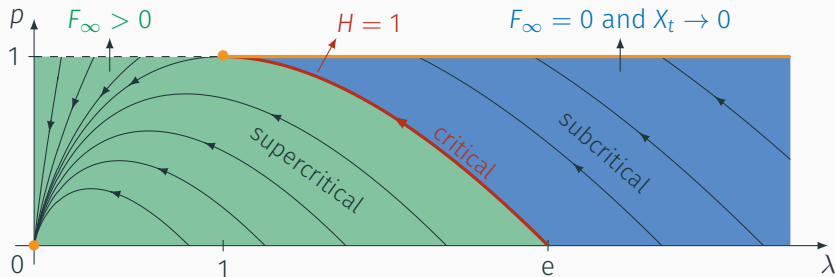
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$$X_t \stackrel{(d)}{=} \mu_t = p(t)\delta_0(dx) + (1 - p(t))\lambda(t)e^{-\lambda(t)x} dx$$

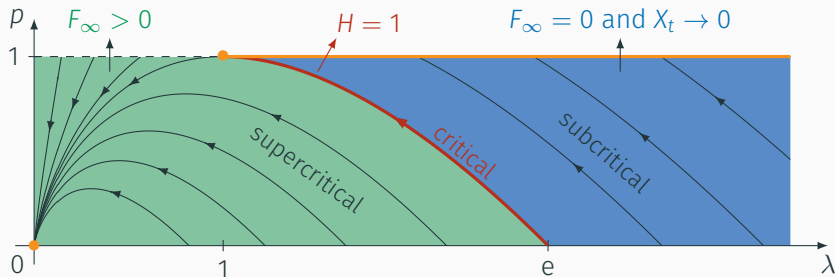
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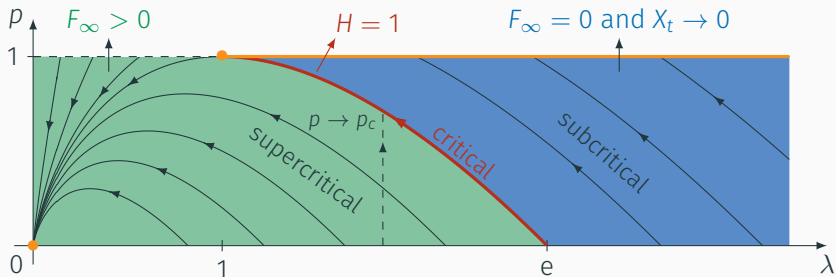


One can make explicit computations:

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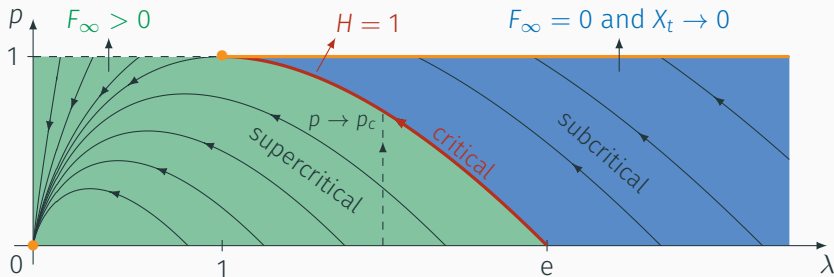
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One can make explicit computations:

- ▷ Infinite order transition for the free energy with exponent $\frac{1}{2}$.
- ▷ Precise asymptotic behavior of $p(t)$ and $\lambda(t)$ in each phase.

Theorem: *With a critical initial condition ($\lambda_0 > 1$ and $p_0 = \lambda_0 - \lambda_0 \log \lambda_0$),*

$$\mathbb{P}(X_t > 0) = 1 - p(t) = \frac{2}{t^2} + \frac{16 \log t}{3t^3} + o\left(\frac{\log t}{t^3}\right).$$

Moreover, given $X_t > 0$, X_t converges in law to $\text{Exp}(1)$.

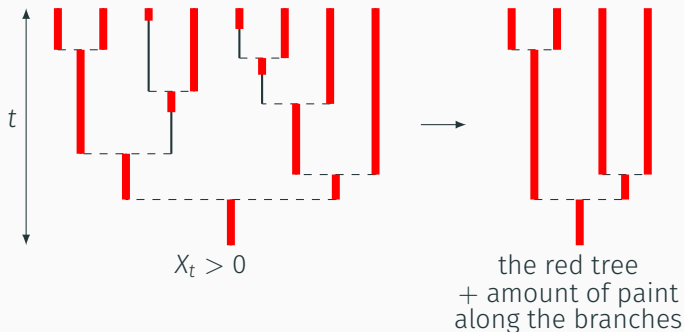
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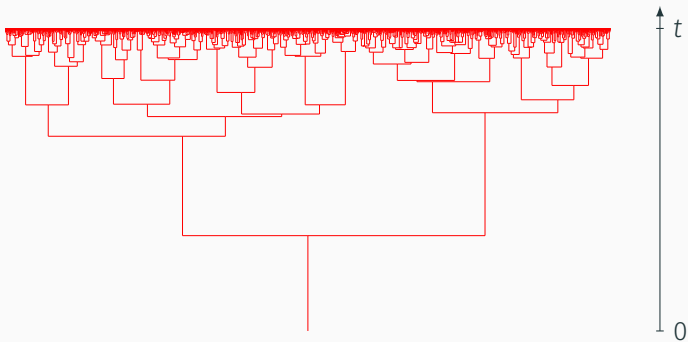
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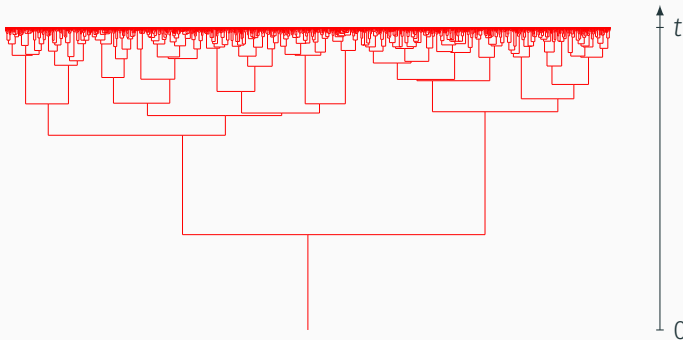
Our goal: Given $X_t > 0$, what does the subtree bringing paint to the root look like?



Description of the red tree

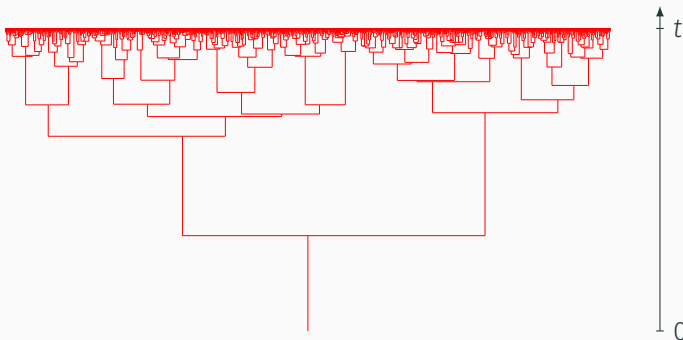


Description of the red tree



Given that $X_t = x$, the red tree of height t is a time-inhomogeneous branching Markov process defined on $[0, t]$ such that:

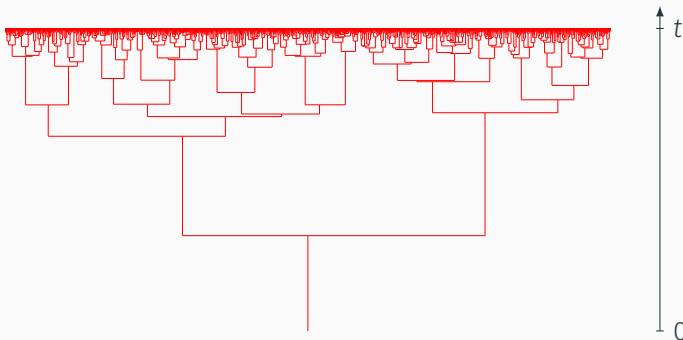
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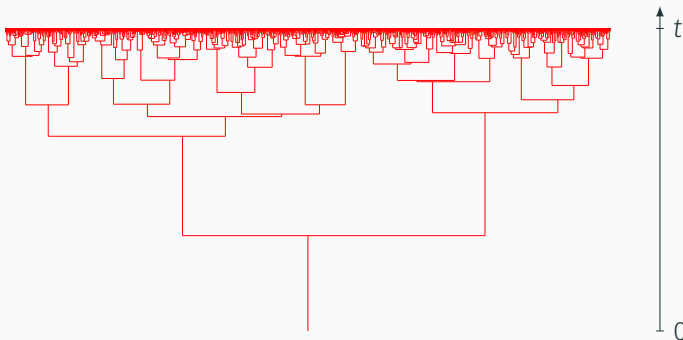
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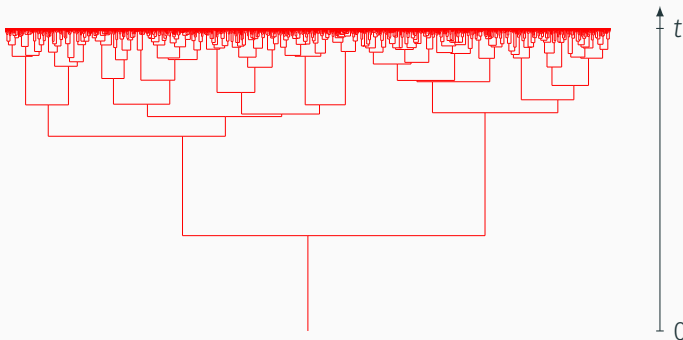
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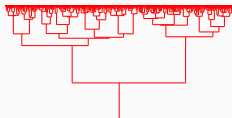


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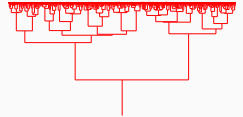
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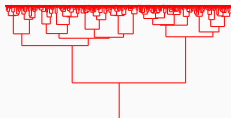


Theorem: Given that $X_t = x_t$, the red tree of height t , with time and masses rescaled by t , converges locally in distribution to a time-inhomogeneous branching Markov process defined on $[0, 1)$ such that:

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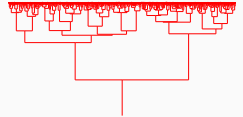
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Wide open question: universality among other hierarchical renormalization models?

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Last open question: What is the law of the mass of a typical red leaf?

Thanks for your attention!

