

Early typical vertices in subcritical random graphs of preferential attachment type

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- In the classical models the power of a vertex is measured by its current degree.
- Here we introduce a simpler model with this idea.
- A new vertex n attaches to earlier vertices $m \in \{1, \dots, n-1\}$ with a probability proportional to m^α for a $0 < \alpha < 1$.
- Then the expected degree of n behaves like:

$$\sum_{m=1}^{n-1} m^\alpha \approx \frac{n^{\alpha+1}}{\alpha+1}$$

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- Let $V_n = \{1, \dots, n\}$ and choose the connection probability of two distinct vertices $i \neq j$ as

$$p_{ij} := (i-j)^{-\alpha} (i \wedge j)^{-\beta} ;$$

where $0 < \alpha < 1$ parameterizes the strength of the preferences of early vertices and $\beta > 0$ is an edge density parameter.

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- This is an inhomogeneous random graph with connection probabilities of preferential attachment type.

Inhomogeneous random graph of preferential attachment type

Theorem

In the inhomogeneous random graph of preferential attachment type there exists a giant component if and only if

$$\frac{1}{2} < c \text{ or } c > \frac{1}{2}.$$

This is a simplification of the main result in the Paper of Dereich and Mörters (2013).

We are working here in the *subcritical regime*, i.e. when $c < \frac{1}{2}$ and $0 < c < \frac{1}{2}$.

Main result

Main Theorem

Let $S_n(i)$ be the size of the connected component of vertex $i \in V_n$ in the inhomogeneous random graph of preferential attachment type in the subcritical regime. If $o_n \in V_n$ is such that $\frac{o_n}{n} \rightarrow u \in (0; 1]$, then

$$\lim_{u \neq 0} \lim_{n \rightarrow \infty} \mathbb{P}(S_n(o_n) \leq x) = \mathbb{P}(W \leq x);$$

for all $x > 0$, where

$$W = \frac{1}{2} \sqrt{\frac{2}{(2 - u)^2 + (2 - 1)}};$$

and W is a positive random variable satisfying

$$\mathbb{P}(W \leq x) = x^{(2-u)+o(1)} \text{ as } x \rightarrow 1.$$

For the inner limit we have

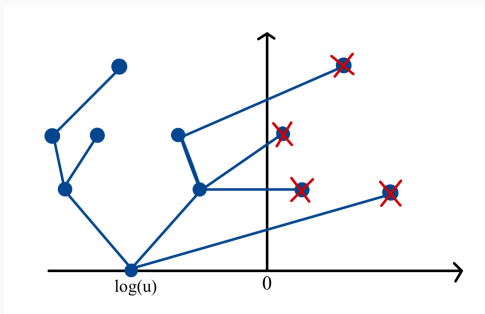
Proposition

If $o_n \in V_n$ is such that $\frac{o_n}{n} \rightarrow u \in (0;1]$ and $x > 0$, then

$$\lim_{n \rightarrow \infty} \mathbb{P} \{ S_n(o_n) \geq u + x \} = \mathbb{P} \{ T(u) \geq u + x \};$$

where $T(u)$ is the number of particles in a killed branching random walk.

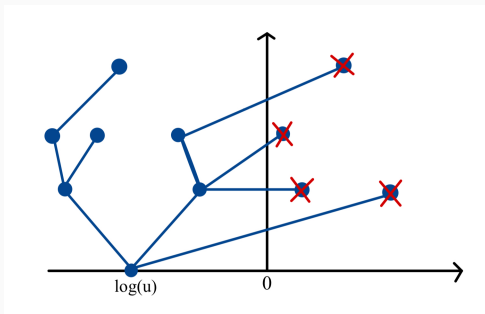
Branching random walk with killing



- The branching random walk is started in $\log u < 0$ and the displacements of the children of a vertex are given by an independent Poisson point process with intensity

$$(dy) = (e^{-y} \mathbb{1}_{y>0} + e^{-(1-y)} \mathbb{1}_{y<0}) dy :$$

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- The process becomes extinct after a finite number of generations in the subcritical phase.

Coupling to the killed branching random walk

- To couple the graph and the branching random walk, we map labels from $f_1; \dots; n_g$ to positions in $(-1; 0]$. We do this using the following map

$$n: f_1; \dots; n_g \mapsto (-1; 0] \quad ; \quad i \mapsto \prod_{j=i+1}^n \frac{1}{j} :$$

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- Note that the youngest vertex is mapped to the origin, and older vertices are placed to the left with decreasing intensity.

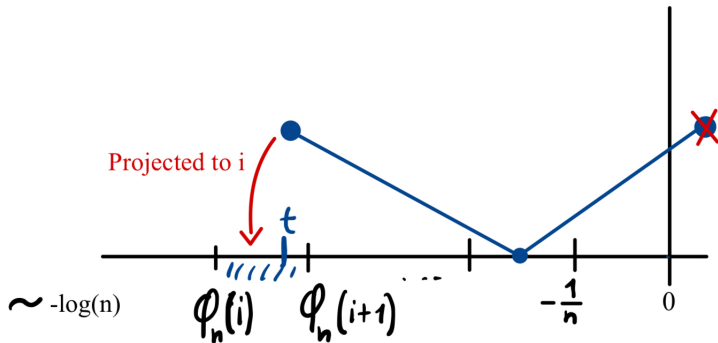
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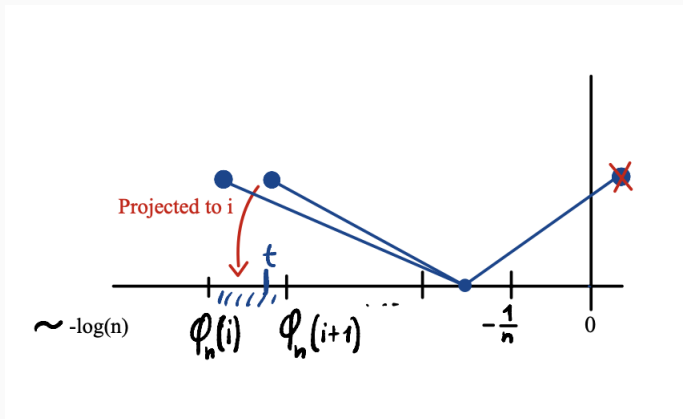
- Note that the youngest vertex is mapped to the origin, and older vertices are placed to the left with decreasing intensity.
- Observe that typical vertices are placed to the left and strong vertices are placed to the right.

Second step: Coupling to the killed branching random walk



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The coupling fails if



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- This effect allows to couple the Poisson offspring of the projected tree with the Bernoulli offspring of the (tree like) Graph.
-) There exists a coupling such that the projected tree coincides with the connected component of a typical vertex with high probability.

Convergence of the number of total particles

For the outer limit we have:

Proposition

Under the conditions of the main Theorem, for every $x > 0$,

$$\lim_{u \neq 0} \mathbb{P}(T(u) \leq xu) = \mathbb{P}(W \leq x);$$

where W is a positive random variable satisfying

$$\mathbb{P}(W \leq x) = x^{-(\alpha+1)+o(1)} \text{ as } x \rightarrow \infty.$$

The proof is based on the work of Aidekon et al

Thank you for your attention.

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- Our aim is to find the size of the largest component in the subcritical phase.
- In rank one models it is known that the size is of the order of the largest degree, in our language of order n
- We heuristically derive a conjecture: Suppose we were allowed to let $n \rightarrow \infty$ and $u \rightarrow 0$ simultaneously.
- At best we could be allowed $u \sim \frac{c}{n}$. Then our hypothetical result would give that the most powerful vertices would have a connected component of size n

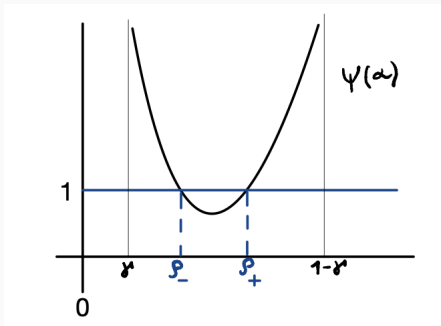
Branching random walks without killing

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- Define

$$\psi(\alpha) = E \prod_{x \in \Pi} e^{-\alpha x} :$$

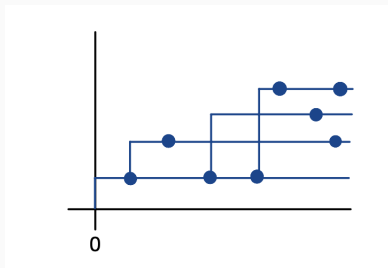


The Nerman Setup

- Let Φ be a point process on $[0; 1)$. We denote by $\mu = E[\cdot]$ the intensity measure of the point process.

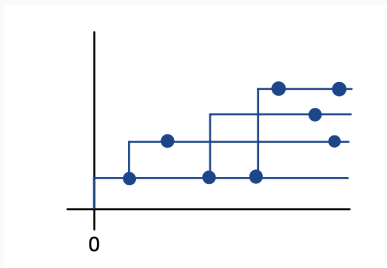
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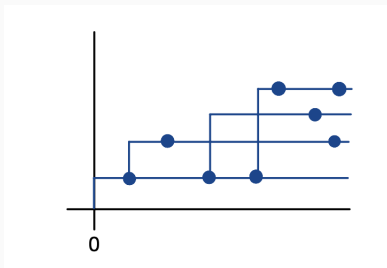
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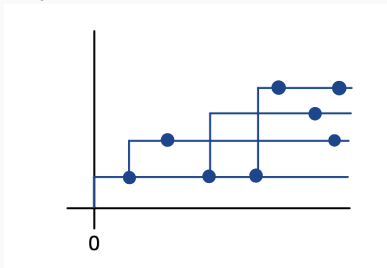
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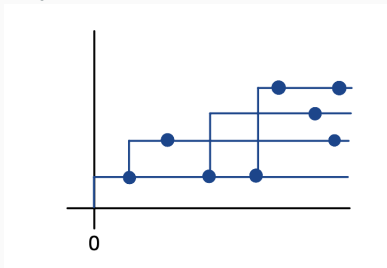
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 - μ is not concentrated on any lattice,
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The *Crump-Mode-Jagers* or *general branching process*.

Convergence of the total number of particles

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- The set-up of Nerman allows to also include a time dependent characteristic for each particle x .
- In our case it suffices to use a characteristic X_x , which may depend on x but is independent for each particle and distributed like some real valued X .
- We sum X_x over all particles born before time t ,

$$Z_t^X := \sum_{x: \tau_x < t} X_x$$

Convergence of the total number of particles

The following result is the work of Nerman formulated in our set-up.

Theorem

Suppose that $E[X] < 1$, then

$$e^{-t} Z_t^X \xrightarrow{P} W \text{ in probability, as } t \rightarrow \infty;$$

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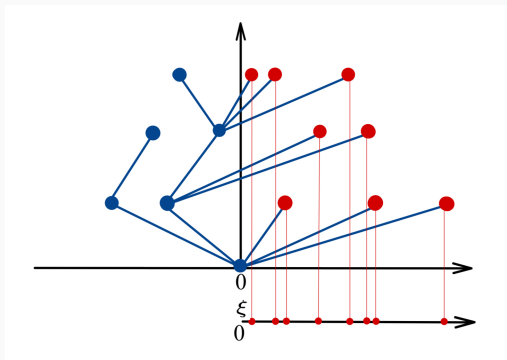
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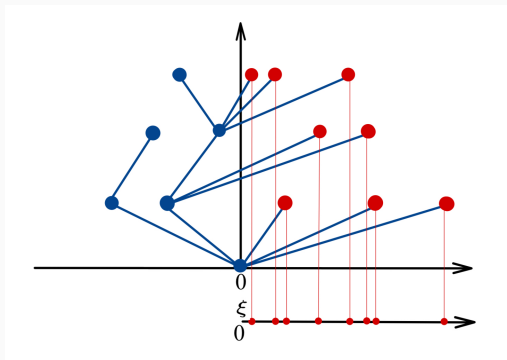
- In order to use this to prove our main result we have to derive a suitable Z_t^X and X from Z_t .

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Convergence of the total number of particles



- We let \mathcal{X} be the point process of locations of the frozen (non-branching) particles
- We let $X \geq 1$ be the total number of branching particles including the particle at the origin

Convergence of the total number of particles

This leads to the following Theorem:

Theorem

We have $E[X] < 1$ and λ satisfies the conditions above for the Malthusian parameter $\lambda = \lambda$. Moreover, for $t = \log u$, we have

$$Z_t^X \stackrel{d}{=} T(u):$$

Proof.

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$$Z_t^X \stackrel{d}{=} T(u):$$

Proof.

- Shifting all particle positions by $t = \log u$ the killed branching random walk $T(u)$ becomes a branching random walk $T^0(u)$ started at the origin, with displacements given by μ , with a killing barrier at $t = \log u$.

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- the number of branching particles is the characteristic X_x

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- It also holds that $\int_0^{\infty} e^{-t} dt = 1$.
- To complete the proof we have

$$\lim_{n \rightarrow \infty} \mathbb{P}(S_n(o_n) \leq u \mid X = x) = \mathbb{P}(T(u) \leq u \mid X = x) :$$

$$\lim_{u \neq 0} \mathbb{P}(T(u) \leq xu \mid X = u) = \mathbb{P}(W \leq x) ;$$

and therefore

$$\lim_{u \neq 0} \lim_{n \rightarrow \infty} \mathbb{P}(S_n(o_n) \leq u \mid X = x) = \mathbb{P}(Y \leq x) :$$

□

- Since $(\cdot) = 1$ we have that $W_n := \prod_{j=1}^n e^{x_j}$ is a Martingale.

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- Since $\sum_{j \in \mathbb{Z}^d} p_j = 1$ we have that $W_n := \sum_{|x|=n} p_x e^{-\langle x, \xi \rangle}$ is a Martingale.
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 - (i) $\log \left(\sum_{j \in \mathbb{Z}^d} p_j e^{-\langle j, \xi \rangle} \right) > 0$;
 - (ii) $E[W_1 \log W_1] < 1$;

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- By Biggins' theorem for branching random walks the martingale limit W is strictly positive if and only if the following two conditions hold,
 - (i) $\log(\sum_{|x|=1} p_x) - \sum_{|x|=1} p_x \log(p_x) > 0$;
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- The first one holds as $\sum_{|x|=1} p_x = 1$ and $\sum_{|x|=1} p_x \log(p_x) < 0$.
- For the second condition it suffices to check $E[W_1^\alpha] < 1$ for some $\alpha > 1$.