Conductance of a subdiffusive random weighted tree

Pierre Rousselin

LAGA Université Paris 13

William & Mary, GAG seminar September 16, 2020 How fast does this sequence vanish?

Assume

u_n \sqrsp 0;
u_n - u_{n+1} ≤ [resp. ≥] 1/f(u_n);
f: (0, a) → (0, ∞), \sqrsp, has an antiderivative (-F).

How fast does this sequence vanish?

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▶ $u_n \searrow 0;$ ▶ $u_n - u_{n+1} \leq \text{[resp.} \geq 1/f(u_n);$ ▶ $f: (0, a) \to (0, \infty), \searrow$, has an antiderivative (-F).

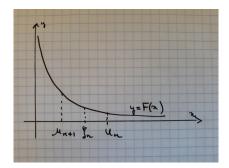
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 Use case 2
 - ▶ $u_n u_{n+1} \leq \text{[resp.} \geq C u_n^2 \log 1/u_n \text{ for some } 0 < C < \infty;$ ▶ $f(x) = 1/(Cx^2 \log(1/x));$ ▶ F(x) = ???

Mean value theorem

$$u_n - u_{n+1} \leq [\text{resp.} \geq] 1/f(u_n).$$



$$F(u_{n+1}) - F(u_n) = (u_n - u_{n+1})f(\xi_n)$$

$$\leq [\text{resp.} \geq] f(\xi_n)/f(u_n)$$

$$\leq f(u_{n+1})/f(u_n)$$

$$\geq 1$$

Cesàro's lemma

$F(u_{n+1}) - F(u_n) \leq f(u_{n+1})/f(u_n)$ ≥ 1

Cesàro's lemma

$$F(u_{n+1}) - F(u_n) \leq f(u_{n+1})/f(u_n)$$
$$\geq 1$$

$$\liminf \frac{1}{n}F(u_n) \ge 1$$

If $f(u_{n+1}) \sim f(u_n)$, then

 $\limsup \frac{1}{n} F(u_n) \le 1$

▶ $u_n - u_{n+1} \leq [\text{resp.} \geq] Cu_n^2 \log 1/u_n \text{ for some } 0 < C < \infty;$ ▶ $f(x) = 1/(Cx^2 \log(1/x));$ $F(x) = -C^{-1} \int^x \frac{\mathrm{d}s}{s^2 \log(1/s)} = C^{-1} \int^{1/x} \frac{\mathrm{d}s}{\log s}$

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However,

$$\frac{\mathrm{d}}{\mathrm{d}x}\frac{x}{\log x} = \frac{1}{\log x} - \frac{1}{(\log x)^2}.$$
So, li(y) $\sim_{y \to \infty} y/\log y$ and $F(x) \sim_{x \to 0} C^{-1}/(x \log 1/x).$

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So, $\lim(y) \sim_{y\to\infty} y/\log y$ and $F(x) \sim_{x\to0} C^{-1}/(x\log 1/x)$. (Some details later...)

 $\limsup(n \log n)u_n \le C^{-1}$ $\liminf(n \log n)u_n \ge C^{-1}$

Prologue

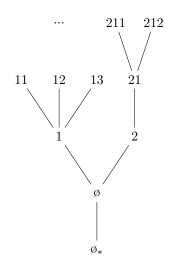
Conductance of a tree

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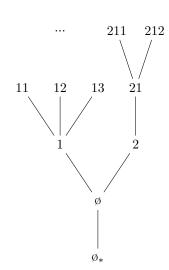
Planar trees, Neveu's formalism

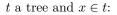


- ► tree t: subset of the set of finite words on N*;
- ▶ rooted at ø;
- artificial parent of the root: ϕ_* ;
- height in the tree: |212| = 3.
- ▶ parent: $(212)_* = 21;$
- number of children: $\nu_t(1) = 3;$
- t is infinite, without leaves (for simplicity) and locally finite:
 ν_t(x) ∈ [1,∞), for all x in t.

Reindexed Subtree

...

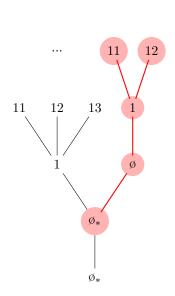




$$t[x] = \{ y \in t : xy \in t \}.$$

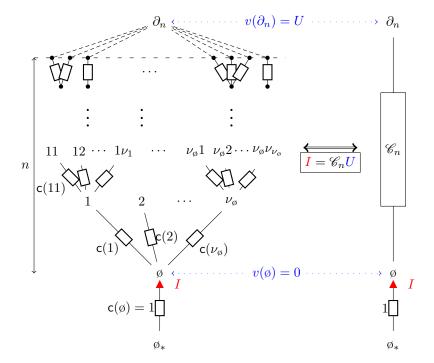
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t a tree and $x \in t$:

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Electrical networks on trees

Function
$$\mathbf{c}: t \setminus \{\phi_*\} \to (0, \infty);$$

- c(x): conductance of the edge $\{x_*, x\}$;
- \blacktriangleright (c(\emptyset) is always 1);

▶
$$\mathbf{r}(x) = 1/\mathbf{c}(x)$$
: its resistance.

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- $(c(\phi) \text{ is always } 1);$
- ▶ $\mathbf{r}(x) = 1/\mathbf{c}(x)$: its resistance.
- ▶ t_n : those vertices of t at height $\leq n \ (n \in \mathbb{Z}_+)$;
- For $x \in t_n$, $v(x) \in \mathbb{R}$: *potential* of the vertex x;
- For $\phi_* \neq x \in t_n$, $i(x) \in \mathbb{R}$: *current* flowing through the edge (x_*, x) ,
- Satisfying Ohm's law

$$\begin{split} v(x) - v(x_*) &= \mathsf{r}(x)i(x) \quad \text{or, equivalently,} \\ i(x) &= \mathsf{c}(x)(v(x) - v(x_*)). \end{split}$$

 \blacktriangleright Kirchhoff's current law at some vertex x:

$$i(x) = \sum_{j=1}^{\nu_x} i(xj);$$

▶ In term of potential (use Ohm's law):

$$c(x)(v(x) - v(x_*)) = \sum_{j=1}^{\nu_x} c(xj)(v(xj) - v(x))$$

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The potential at x is the c-weighted average of the potentials of its neighbors: v is *harmonic* at x.

Effective conductance

Fix the potential at some (sets of) vertices and harmonicity elsewhere:

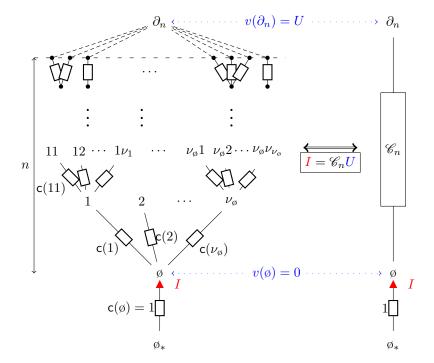
$$v(x) = \begin{cases} 0 & \text{if } x = \phi; \\ U & \text{if } |x| = n; \\ \frac{1}{\pi(x)} (\mathsf{c}(x)v(x_*) + \sum_{j=1}^{\nu_x} \mathsf{c}(xj)v(xj)) & \text{if } 1 \le |x| \le n-1. \end{cases}$$

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- Linear system, such a v exists and is unique;
- function $U \mapsto v$ clearly linear;
- ► $I = \sum_{j=1}^{\nu_{\emptyset}} i(j) = \sum_{j=1}^{\nu_{\emptyset}} c(j)v(j)$, total current entering the network;
- ▶ $U \mapsto I$ is also linear;
- ▶ define $\mathscr{C}_n(t) = I/U$ (and $\mathscr{R}_n(t) = U/I$): effective conductance and resistance between ø and the *n*-th level of *t*.



Series and parallel laws

Conductance of an m-ary tree

Conductance of a m-ary tree (2)

$$\mathscr{C}_n(t) = \frac{m}{\lambda} \beta_{n-1}(t) = \frac{m}{\lambda} \frac{\mathscr{C}_{n-1}(t)}{1 + \mathscr{C}_{n-1}(t)}.$$

In term of effective resistance:

$$\mathscr{R}_n(t) = \frac{\lambda}{m} (1 + \mathscr{R}_{n-1}(t)) = \cdots$$

Define the effective resistance of the infinite tree t as

$$\mathscr{R}(t) = \lim_{n \to \infty} \mathscr{R}_n(t) \in (0, \infty]$$
 (it exists, see later).

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Then $\mathscr{R}(t) < \infty \iff \lambda < m$. Phase transition:

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Random walk and transition kernels

- $\blacktriangleright P: t \times t \to [0,1];$
- ▶ P(x, y) is the probability that a random walker located at the vertex x will go to y (in one step).
- for any $x \in t$, $\sum_{y \in t} P(x, y) = 1$;

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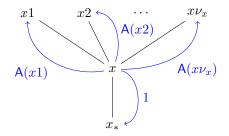
- ▶ P(x, y) is the probability that a random walker located at the vertex x will go to y (in one step).
- for any $x \in t$, $\sum_{y \in t} P(x, y) = 1$;
- nearest-neighbour random walk: P(x, y) > 0 if and only if y is a neighbour of x (its parent or one of its children);
- For $x \in t$, P_x : distribution of a path $(X_k)_{k\geq 0}$ in t, starting at x $(X_0 = x)$ with transition kernel P.

► Example:

$$P_{\emptyset}(X_1 = 1, X_2 = 12, X_3 = 1, X_4 = \emptyset)$$

= $P(\emptyset, 1)P(1, 12)P(12, 1)P(1, \emptyset).$

Random walk on a weighted tree



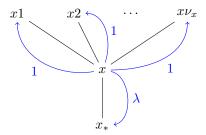
Transition kernel P:

$$P(x, x_*) = \frac{1}{1 + \sum_{j=1}^{\nu_x} A(x_j)};$$

$$P(x, x_i) = \frac{A(x_i)}{1 + \sum_{j=1}^{\nu_x} A(x_j)} \quad i = 1, \dots, \nu_x$$

Particular case: λ -biased RW ($A \equiv 1/\lambda$)

For some $\lambda > 0$,

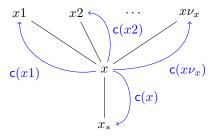


$$P(x, x_*) = \frac{\lambda}{\lambda + \nu_x};$$

$$P(x, xi) = \frac{1}{\lambda + \nu_x} \quad i = 1, \dots, \nu_x.$$

Simple RW if $\lambda = 1$.

Random walk on a tree with conductances



$$P(x, x_*) = \frac{\mathsf{c}(x)}{\pi(x)};$$

$$P(x, xi) = \frac{\mathsf{c}(xi)}{\pi(x)} \quad i = 1, \dots, \nu_x.$$

One can always associate conductances to a RW on t:

- ▶ λ -biased random walk: $c(x) = \lambda^{-|x|}$;
- ▶ in general, for weights A

$$\mathsf{c}(x) = \prod_{\emptyset \prec y \preceq x} \mathsf{A}(y).$$

Recurrence and transience

For $x \in t$, consider the times $(\min \emptyset = \infty)$:

 $\tau_x = \min\{k \ge 0 : X_k = x\}$ and $\tau_x^+ = \min\{k \ge 1 : X_k = x\}$

Two regimes:

- Recurrence Either for any x in t, $P_x(\tau_x^+ < \infty) = 1$: in this case, the walk almost surely visits every vertex infinitely many times;
- Transience Or, for any x in t, $P_x(\tau_x^+ < \infty) < 1$: in this case, almost surely, the number of visits at any vertex is finite (and can be zero).

$RW + EN = \heartsuit$

Recall that there is a unique solution $v: t_n \to \mathbb{R}$ to

$$v(x) = \begin{cases} 0 & \text{if } x = \phi; \\ 1 & \text{if } |x| = n; \\ (P(x, x_*)v(x_*) + \sum_{j=1}^{\nu_x} P(x, xj)v(xj)) & \text{if } 1 \le |x| \le n-1. \end{cases}$$

Now fix some height n > 0 in t and let

$$f(x) = P_x(\tau^{(n)} < \tau_{\phi}).$$

Then, $f(\phi) = 0$ and f(x) = 1 if |x| = n.

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Now fix some height n > 0 in t and let

$$f(x) = P_x(\tau^{(n)} < \tau_{\phi}).$$

Then, $f(\phi) = 0$ and f(x) = 1 if |x| = n. For 0 < |x| < n, decompose with respect to the value of X_1 :

$$f(x) = P_x(\tau^{(n)} < \tau_{\phi})$$

= $P_x(X_1 = x_*, \tau^{(n)} < \tau_{\phi}) + \sum_{j=1}^{\nu_x} P_x(X_1 = xj, \tau^{(n)} < \tau_{\phi})$
= $P(x, x_*)P_{x_*}(\tau^{(n)} < \tau_{\phi}) + \sum_{j=1}^{\nu_x} P(x, xj)P_{xj}(\tau^{(n)} < \tau_{\phi}).$

So
$$f(x) = v(x)$$
 for any $x \in t_n$.

$\mathrm{RW} + \mathrm{EN} = \heartsuit^2$

Finally, (recall that U = 1),

$$\begin{aligned} \mathscr{C}_n(t) &= I = \sum_{j=1}^{\nu_{\phi}} \mathsf{c}(x) P_j(\tau^{(n)} < \tau_{\phi}) \\ &= \pi(\phi) \sum_{j=1}^{\nu_{\phi}} P(\phi, j) P_j(\tau^{(n)} < \tau_{\phi}) \\ &= \pi(\phi) P_{\phi}(\tau^{(n)} < \tau_{\phi}^+) \\ &\searrow_{n \to \infty} \pi(\phi) P_{\phi}(\tau_{\phi}^+ = \infty) = \mathscr{C}(t). \end{aligned}$$

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Theorem

The random walk associated to the conductances $(c(x))_{x \in t}$ is transient on t iff $\mathscr{C}(t) > 0$ (i.e. $\mathscr{R}(t) < \infty$).

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Corollary

 λ -biased walk on an m-regular tree is transient iff $\lambda < m$.

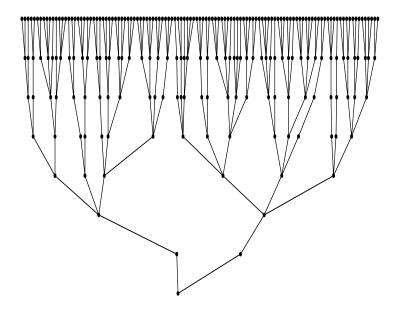
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Galton-Watson trees (branching processes)

- ▶ Reproduction law: $(p_i)_{i\geq 0}$, non-negative numbers adding up to 1;
- ▶ $p_i = \mathbb{P}(\nu = i)$: probability that an individual has *i* children;
- assume $p_0 = 0$ (for clarity) and $p_1 < 1$ (for non-silliness);
- ▶ key-value: $\mathbb{E}[\nu] = \sum_{i \ge 1} i p_i =: m$, average number of children.

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► key-value: $\mathbb{E}[\nu] = \sum_{i \ge 1} ip_i =: m$, average number of children. We build an infinite random tree T:

- the root has $\nu_{\phi} \sim \nu$ children;
- each of its children then reproduces *independently* in the same way;
- and so on...

Branching property: "Subtrees above any height k are independent trees distributed as T and are independent of what happens below k."

For $n \ge 0$, let $Z_n(T)$ be the number of individuals at generation n in T. Then,

$$W_n(T) \coloneqq \frac{Z_n(T)}{m^n} \to W(T).$$

Theorem (Kesten–Stigum, 1966) W(T) > 0 iff $\mathbb{E}[\nu \log \nu] < \infty$.

$\lambda\text{-}\mathrm{biased}$ walk on a Galton-Watson tree

Let's try to do this...

In the same way as before (Series/Parallel laws),

$$\mathscr{C}_n(T) = \sum_{i=1}^{\nu_o} \lambda^{-1} \frac{\mathscr{C}_{n-1}(T[i])}{1 + \mathscr{C}_{n-1}(T[i])}.$$

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By the branching property,

$$\mathbb{E}[\mathscr{C}_{n}(T)] = \mathbb{E}\Big[\sum_{i=1}^{\nu_{\varnothing}} \lambda^{-1}\Big] \mathbb{E}\Big[\frac{\mathscr{C}_{n-1}(T)}{1+\mathscr{C}_{n-1}(T)}\Big] = \frac{m}{\lambda} \mathbb{E}\Big[\frac{\mathscr{C}_{n-1}(T)}{1+\mathscr{C}_{n-1}(T)}\Big].$$
$$\leq \frac{m}{\lambda} \mathbb{E}[\mathscr{C}_{n-1}(T)]$$
$$\to_{n\to\infty} 0 \quad (\text{exponentially fast}) \quad \text{if } \lambda > m.$$

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$$\leq \frac{m}{\lambda} \mathbb{E}[\mathscr{C}_{n-1}(T)]$$
$$\to_{n \to \infty} 0 \quad (\text{exponentially fast}) \quad \text{if } \lambda > m.$$

Fatou's lemma implies (in case $\lambda > m$),

$$\mathbb{E}[\mathscr{C}(T)] = \mathbb{E}[\lim \mathscr{C}_n(T)] \le \liminf \mathbb{E}[\mathscr{C}_n(T)] = 0,$$

so $\mathscr{C}(T)=0,$ almost surely. Cases $\lambda=m$ and $\lambda>m$ are more difficult.

 λ -biased walk on a Galton-Watson tree (2)

Theorem (Russell Lyons, 1990)

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 $\mathscr{R}_n(T)/n \to 1/W$, a.s. and in L^1 .

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, a.s. and in L^1 .

- ▶ Perturbation around this critical case $(c(x) = m^{-|x|} \times \text{some r.v.})$ for an *m*-regular tree in Addario-Berry et al. and
- ▶ on a Galton-Watson tree (Chen-Hu–Lin 2018) with very precise asymptotics.

λ -biased walk on a Galton-Watson tree (3)

Open questions (as far as I know...):

- ► Does this result holds under the more reasonable assumption $\mathbb{E}[\nu \log \nu] < \infty$?
- ▶ What about the speed of the convergence $\mathscr{C}_n(T) \to \mathscr{C}(T)$ in the transient case?
- ▶ (Famous question:) In the transient case, does $\mathscr{C}(T)$ has a density (w.r.t. Lebesgue measure)?

Prologue

Conductance of a tree

Random walk on a tree

Galton-Watson trees

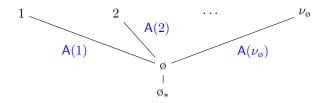
Conductance of a subdiffusive random weighted tree

Random finite sequence (whose length is also random):

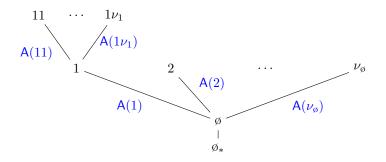
$$\mathbf{A} = (A(1), A(2), \dots, A(\nu)) \in \bigsqcup_{k>0} (0, \infty)^k.$$

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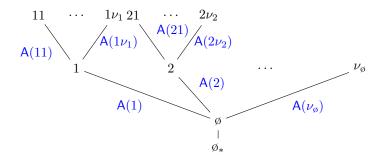
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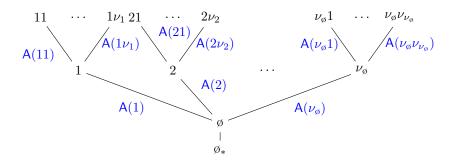
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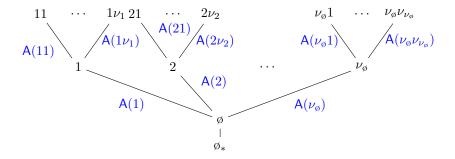


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 \rightarrow T, random tree with random weights.

Transience criterion

Theorem (Lyons–Pemantle 92, Faraud 11) Consider, for $s \ge 0$,

$$\psi(s) = \log \mathbf{E} \Big[\sum_{i=1}^{\nu} A(i)^s \Big].$$

Then, the random walk on the weighted tree T is transient iff

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Actually, many (4) "sub-regimes" in the recurrent case.
Very rich model of random walk, popular in the RWRE community.

Normalized case

From now on, we assume

$$\psi(1) = \log \mathbb{E} \sum_{i=1}^{\nu} A(i) = 0. \tag{H_{norm}}$$

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$$\mathscr{C}(T) = \sum_{i=1}^{\nu_{\phi}} \mathsf{A}(i) \frac{\mathscr{C}(T[i])}{1 + \mathscr{C}(T[i])}$$

and by the branching property,

$$\mathbb{E}[\mathscr{C}(T)] = \mathbb{E}\Big[\sum_{i=1}^{\nu_{\wp}} \mathsf{A}(i)\Big] \mathbb{E}\Big[\frac{\mathscr{C}(T)}{1 + \mathscr{C}(T)}\Big] = \mathbb{E}\Big[\frac{\mathscr{C}(T)}{1 + \mathscr{C}(T)}\Big],$$

hence

$$\mathbb{E}\Big[\frac{\mathscr{C}(T)^2}{1+\mathscr{C}(T)}\Big] = 0, \quad \text{thus} \quad \mathscr{C}(T) = 0 \quad \text{a.s.}$$

Biggin's theorem

Mandelbrot's martingale (1974):

$$M_n(T) = \sum_{|x|=n} \mathsf{c}(x) = \sum_{|x|=n} \prod_{\emptyset \prec y \preceq x} \mathsf{A}(x) \to M_\infty(T).$$

Theorem (Kahane–Peyrière 76, Biggins 77, Lyons 95) Under the hypotheses

$$\psi'(1) \coloneqq \mathbb{E}\left[\sum_{i=1}^{\nu} A(i) \log A(i)\right] \in [-\infty, 0); \qquad (H_{\text{derivative}})$$
$$\mathbb{E}\left[\left(\sum_{i=1}^{\nu} A(i)\right) \log^{+}\left(\sum_{i=1}^{\nu} A(i)\right)\right] < \infty, \qquad (H_{X \log X})$$

 $M_{\infty}(T) > 0$ a.s.

Recursive distributional equation

$$M_{n+1}(T) = \sum_{|x|=n+1} \prod_{\substack{\emptyset \prec y \preceq x}} \mathsf{A}(x)$$
$$= \sum_{i=1}^{\nu_{\emptyset}} \sum_{|x|=n+1, i \prec x} \mathsf{A}(i) \prod_{i \prec y \preceq x} \mathsf{A}(x)$$
$$= \sum_{i=1}^{\nu_{\emptyset}} \mathsf{A}(i) M_n(T[i]).$$

Therefore, M_{∞} has the same distribution as

$$A(1)M_{\infty}^{(1)} + A(2)M_{\infty}^{(2)} + \cdots + A(\nu)M_{\infty}^{(\nu)},$$

where $M_{\infty}^{(1)}$, $M_{\infty}^{(2)}$, ... are independent copies of M_{∞} , independent of the random vector $(A(1), \ldots, A(\nu))$.

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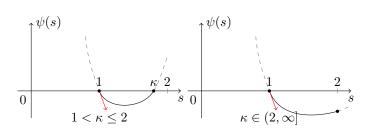
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where $M_{\infty}^{(1)}$, $M_{\infty}^{(2)}$, ... are independent copies of M_{∞} , independent of the random vector $(A(1), \ldots, A(\nu))$. This characterizes the distribution of M_{∞} among $\neq \delta_0$ probability measures (Quansheng Liu 97).

The "subdiffusive" regime Recall that $\psi(1) = 0$ and $\psi'(1) < 0$. Consider



 $\kappa = \inf\{s > 1 : \psi(s) = 0\} \in (1, \infty].$

Figure: Schematic behavior of ψ under our hypotheses

$$\mathbf{E}\Big[\Big(\sum_{i=1}^{\nu} A(i)\Big)^{\kappa}\Big] + \mathbf{E}\Big[\sum_{i=1}^{\nu} A(i)^{\kappa} \log^{+} A(i)\Big] < \infty, \quad \text{if } 1 < \kappa \le 2; \\
\mathbf{E}\Big[\Big(\sum_{i=1}^{\nu} A(i)\Big)^{2}\Big] < \infty, \quad \text{if } \kappa \in (2,\infty].$$
(H_{\kappa})

Heuristics

$$\mathscr{C}_n(T) = \sum_{i=1}^{\nu_o} \mathsf{A}(i) \frac{\mathscr{C}_{n-1}(T[i])}{1 + \mathscr{C}_{n-1}(T[i])} \quad \text{and} \quad \mathscr{C}_n(T) \to 0.$$

We expect that $\mathbb{E}[\mathscr{C}_n] \to 0$ "not too fast" so $u_n \coloneqq \mathbb{E}[\mathscr{C}_n] \sim \mathbb{E}[\mathscr{C}_{n-1}] = u_{n-1}$, then

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so if it converges, to some random positive function of T (say Y(T)), Y should satisfy

$$Y(T) = \sum_{i=1}^{\nu_{\phi}} \mathsf{A}(i) Y(T[i]),$$

so Y should be distributed as M_{∞} .

Our result

Theorem (R. 2020+)

Under the hypotheses (H_{norm}) , $(H_{\text{derivative}})$ and (H_{κ}) , as n goes to infinity,

$$\begin{split} \mathscr{C}_n/\mathbb{E}[\mathscr{C}_n] &\to M_\infty \quad a.s. \\ \mathbb{E}[\mathscr{C}_n] &\asymp \frac{1}{n^{1/(\kappa-1)}} \quad if \ 1 < \kappa < 2; \\ \mathbb{E}[\mathscr{C}_n] &\asymp \frac{1}{n \log n} \quad if \ \kappa = 2 \ and \\ \mathbb{E}[\mathscr{C}_n] &\sim \frac{1}{n \mathbb{E}[M_\infty^2]} \quad if \ \kappa > 2. \end{split}$$

Lower bound

$$\mathscr{C}_n(T) = \sum_{i=1}^{\nu_{\mathrm{s}}} \mathsf{A}(i) \frac{\mathscr{C}_{n-1}(T[i])}{1 + \mathscr{C}_{n-1}(T[i])}$$

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$$\mathbb{E}[\mathscr{C}_n] = \mathbb{E}\Big[\frac{\mathscr{C}_{n-1}}{1 + \mathscr{C}_{n-1}}\Big].$$

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Actually, \leq is rigorous (some very magic inequality involved).

Lower bound (2)

Some knowledge of M_{∞} (tail probability estimates) allow to compute, as a goes to infinity,

$$\mathbb{E}\Big[\frac{M_{\infty}^2}{1/a + M_{\infty}}\Big] \begin{cases} \asymp a^{1-\kappa} & \text{if } 1 < \kappa < 2; \\ \asymp a^{-1} \log a & \text{if } \kappa = 2; \\ \sim \mathbb{E}[M_{\infty}^2]/a & \text{if } \kappa > 2. \end{cases}$$

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so putting everything together, we obtain

$$u_{n-1} - u_n \le C \times \begin{cases} u_{n-1}^{\kappa} & \text{if } 1 < \kappa < 2; \\ u_{n-1}^2 \log 1/u_{n-1} & \text{if } \kappa = 2; \\ u_{n-1}^2 & \text{if } \kappa > 2, \end{cases}$$

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and we can use our mean-value theorem based inequalities to conclude.

Thank you slide

Thank you for your attention!

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Blank slide $7\,$