

A line-breaking construction of the stable trees

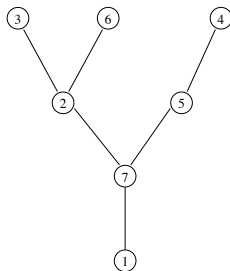


Christina Goldschmidt (Oxford)
Joint work with Bénédicte Haas (Paris-Dauphine)

Uniform random trees

Let \mathbb{T}_n be the set of unordered trees on n vertices labelled by $[n] := \{1, 2, \dots, n\}$.

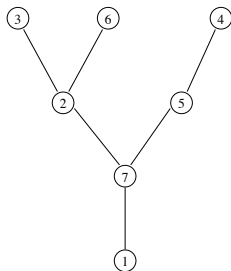
Write T_n for a tree chosen uniformly from \mathbb{T}_n .



Uniform random trees

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What happens as n grows?

An algorithm due to Aldous

In order to study T_n , it's useful to have a way of building it.

1. Start from the vertex labelled 1.
2. For $2 \leq i \leq n$, connect vertex i to vertex V_i such that

$$V_i = \begin{cases} i - 1 & \text{with probability } 1 - (i - 2)/(n - 1) \\ \text{uniform on } \{1, 2, \dots, i - 2\} & \text{otherwise.} \end{cases}$$

3. Take a uniform random permutation of the labels.

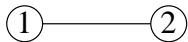
Aldous' algorithm

Consider $n = 10$.

①

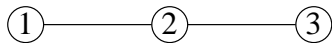
Aldous' algorithm

$V_2 = 1$ with probability 1



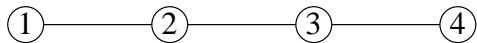
Aldous' algorithm

$$V_3 = \begin{cases} 1 & \text{with probability } 1/9 \\ 2 & \text{with probability } 8/9 \end{cases}$$



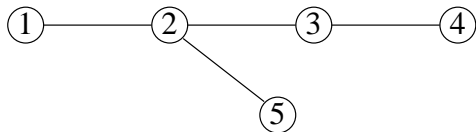
Aldous' algorithm

$$V_4 = \begin{cases} j & \text{with probability } 1/9, 1 \leq j \leq 2 \\ 3 & \text{with probability } 7/9 \end{cases}$$



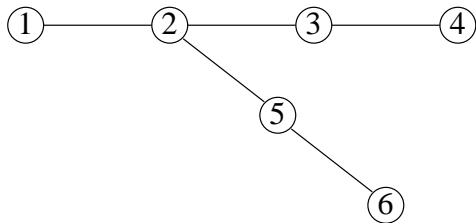
Aldous' algorithm

$$V_5 = \begin{cases} j & \text{with probability } 1/9, 1 \leq j \leq 3 \\ 4 & \text{with probability } 6/9 \end{cases}$$



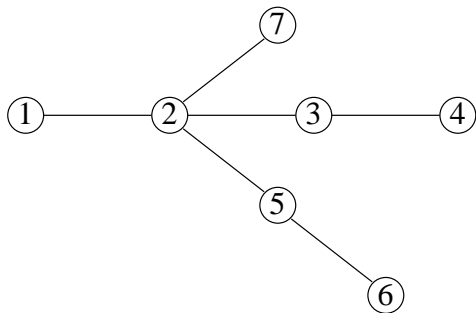
Aldous' algorithm

$$V_6 = \begin{cases} j & \text{with probability } 1/9, 1 \leq j \leq 4 \\ 5 & \text{with probability } 5/9 \end{cases}$$



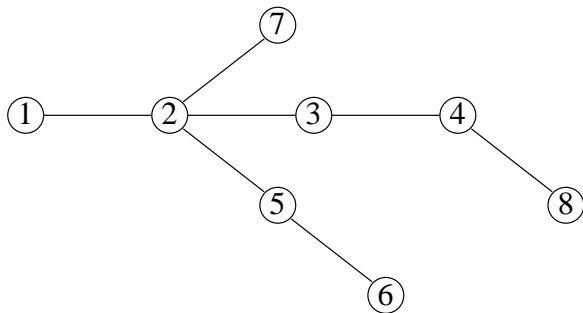
Aldous' algorithm

$$V_7 = \begin{cases} j & \text{with probability } 1/9, 1 \leq j \leq 5 \\ 6 & \text{with probability } 4/9 \end{cases}$$



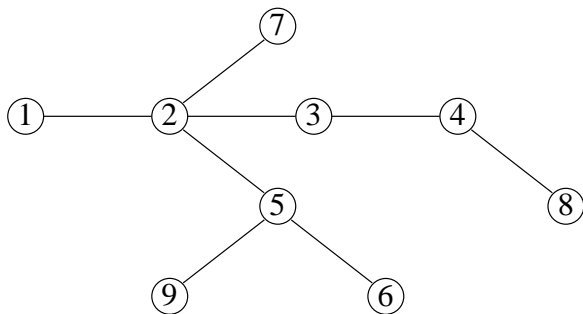
Aldous' algorithm

$$V_8 = \begin{cases} j & \text{with probability } 1/9, 1 \leq j \leq 6 \\ 7 & \text{with probability } 3/9 \end{cases}$$



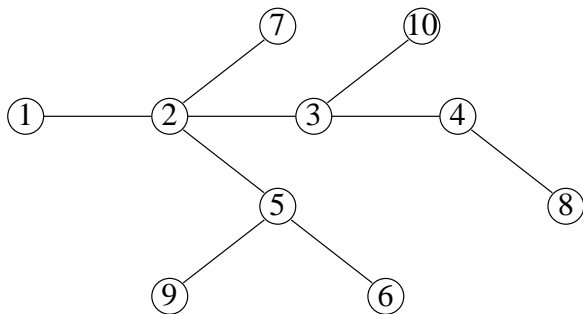
Aldous' algorithm

$$V_9 = \begin{cases} j & \text{with probability } 1/9, 1 \leq j \leq 7 \\ 8 & \text{with probability } 2/9 \end{cases}$$



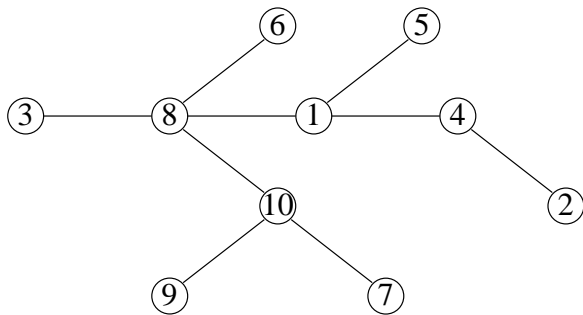
Aldous' algorithm

$$V_{10} = \begin{cases} j & \text{with probability } 1/9, 1 \leq j \leq 8 \\ 9 & \text{with probability } 1/9 \end{cases}$$



Aldous' algorithm

Permute.



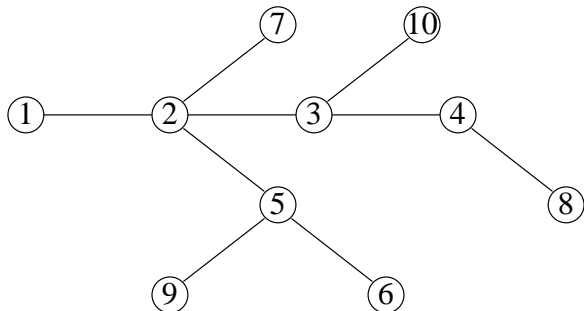
Typical distances

Consider the tree before we permute. Let

$$L_n = \inf\{i \geq 2 : V_{i+1} \neq i\}.$$

We can use L_n to give us an idea of typical distances in the tree.

In our example, $L_{10} = 4$:



Typical distances

For $2 \leq i \leq n$, connect vertex i to vertex V_i such that

$$V_i = \begin{cases} i-1 & \text{with probability } 1 - (i-2)/(n-1) \\ \text{uniform on } \{1, 2, \dots, i-2\} & \text{otherwise.} \end{cases}$$

$$L_n = \inf\{i \geq 2 : V_{i+1} \neq i\}$$

Proposition

As $n \rightarrow \infty$,

$$\mathbb{P}\left(n^{-1/2}L_n > x\right) \rightarrow \exp(-x^2/2).$$

Proof

$$\begin{aligned}\mathbb{P}\left(n^{-1/2}L_n > x\right) &= \mathbb{P}\left(L_n \geq \lfloor xn^{1/2} \rfloor + 1\right) \\ &= \mathbb{P}\left(2 \rightarrow 1, 3 \rightarrow 2, \dots, \lfloor xn^{1/2} \rfloor + 1 \rightarrow \lfloor xn^{1/2} \rfloor\right) \\ &= 1 \cdot \left(1 - \frac{1}{n-1}\right) \left(1 - \frac{2}{n-1}\right) \dots \left(1 - \frac{\lfloor xn^{1/2} \rfloor - 1}{n-1}\right).\end{aligned}$$

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So

$$\begin{aligned}-\log \mathbb{P}\left(n^{-1/2}L_n > x\right) &= -\sum_{i=1}^{\lfloor xn^{1/2} \rfloor - 1} \log\left(1 - \frac{i}{n-1}\right) \\ &\sim \sum_{i=1}^{\lfloor xn^{1/2} \rfloor - 1} \frac{i}{n} = \frac{\lfloor xn^{1/2} \rfloor (\lfloor xn^{1/2} \rfloor - 1)}{2n} \sim \frac{x^2}{2}.\end{aligned}$$

Typical distances

Once we have built this first stick of consecutive labels, we pick a uniform starting point along that stick and attach a new stick with a random length, and so on.

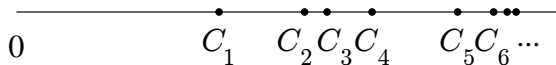
Typical distances

Once we have built this first stick of consecutive labels, we pick a uniform starting point along that stick and attach a new stick with a random length, and so on.

Imagine now that edges in the tree have length 1. The proposition suggests that rescaling edge-lengths by $n^{-1/2}$ will give some sort of limit for the whole tree. The limiting version of the algorithm is as follows.

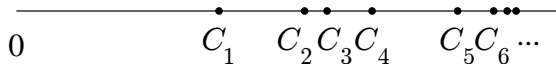
Line-breaking construction

Let E_1, E_2, \dots be independent Exponential(1/2) r.v.'s and set $C_k = \sqrt{\sum_{i=1}^k E_i}$. (Equivalently, let C_1, C_2, \dots be the points of an inhomogeneous Poisson process on \mathbb{R}_+ of intensity $t dt$.)



Line-breaking construction

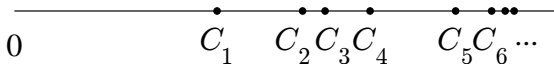
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(Note that $\mathbb{P}(C_1 > x) = \mathbb{P}(E_1 > x^2) = \exp(-x^2/2)$.)

Line-breaking construction

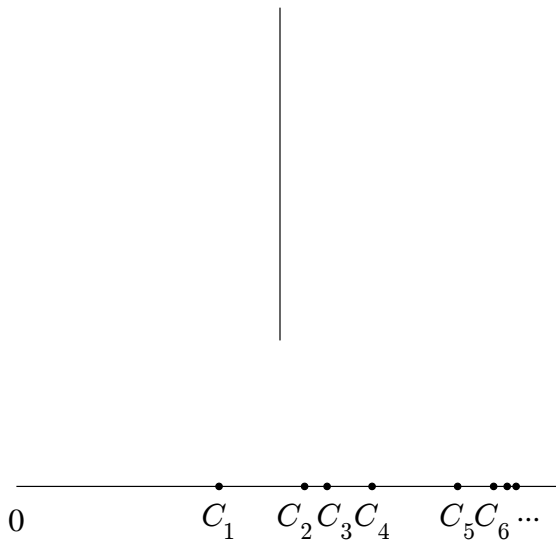
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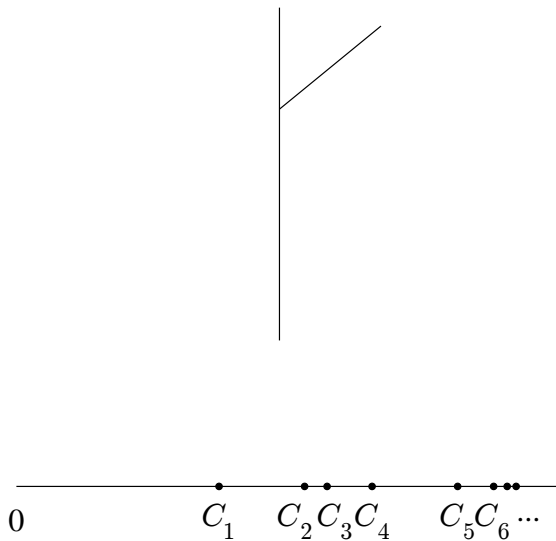
(Note that $\mathbb{P}(C_1 > x) = \mathbb{P}(E_1 > x^2) = \exp(-x^2/2)$.)

- ▶ Consider the line-segments $[0, C_1), [C_1, C_2), \dots$
- ▶ Start from $[0, C_1)$ and proceed inductively.
- ▶ For $i \geq 2$, attach $[C_{i-1}, C_i)$ at a random point chosen uniformly over the existing tree.

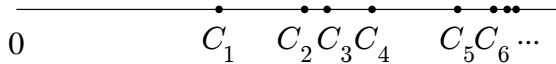
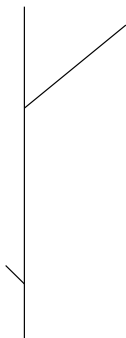
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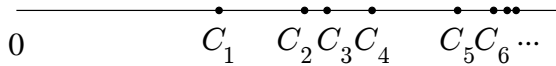
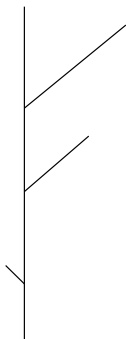
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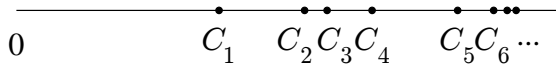
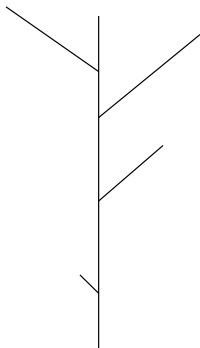
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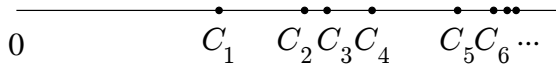
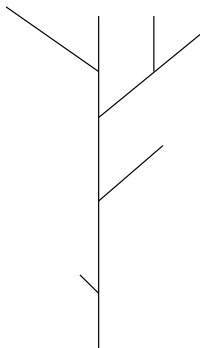
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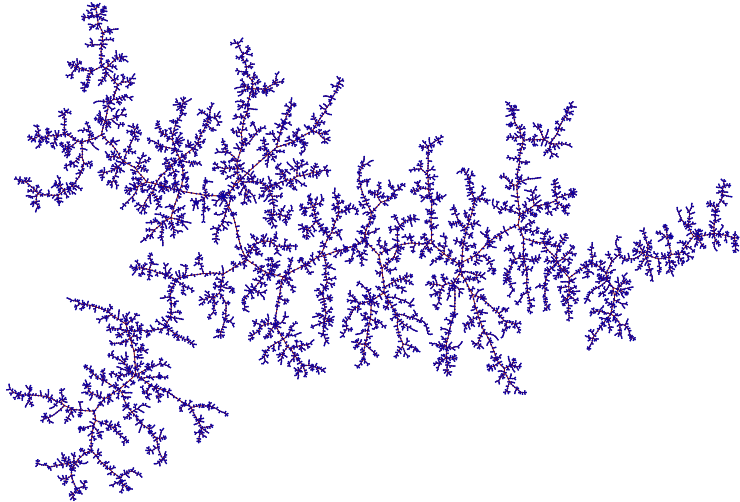
Line-breaking construction



Line-breaking construction



The Brownian continuum random tree



[Picture by Igor Kortchemski]

The scaling limit of the uniform random tree

Theorem (Aldous (1991); Le Gall (2005))

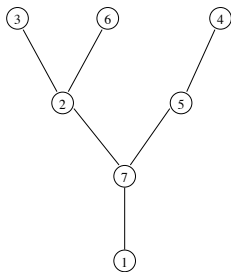
Then

$$\frac{1}{\sqrt{n}} T_n \xrightarrow{d} c\mathcal{T}_2 \quad \text{as } n \rightarrow \infty$$

where \mathcal{T}_2 is Aldous' *Brownian continuum random tree* and c is a non-negative constant. (The convergence is in the sense of the Gromov–Hausdorff distance.)

Trees as metric spaces

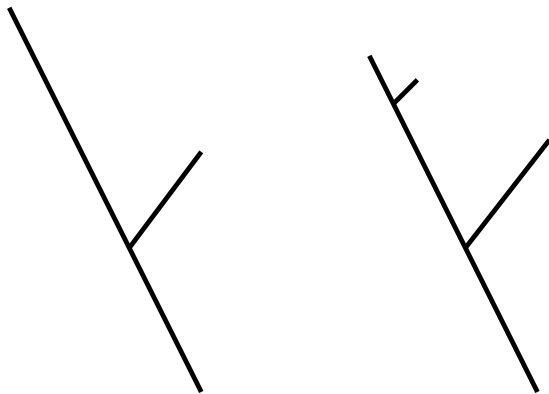
The vertices of T_n come equipped with a natural metric: the graph distance.



We write $\frac{1}{\sqrt{n}} T_n$ for the metric space given by the vertices of T_n with the graph distance divided by \sqrt{n} .

Measuring the distance between metric spaces

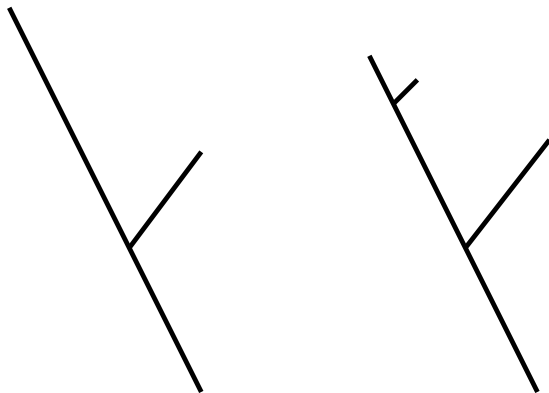
Suppose that (X, d) and (X', d') are compact metric spaces.



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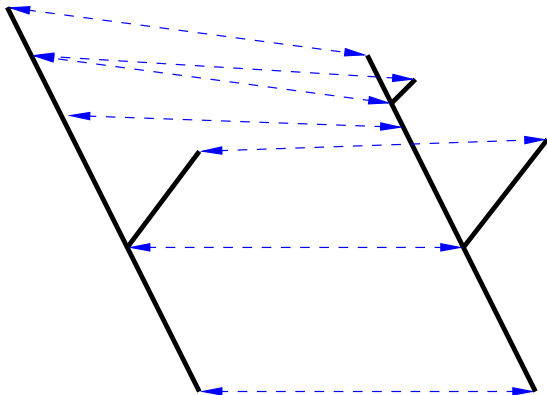
A **correspondence** R is a subset of $X \times X'$ such that for every $x \in X$, there exists $x' \in X'$ with $(x, x') \in R$ and vice versa.



Measuring the distance between metric spaces

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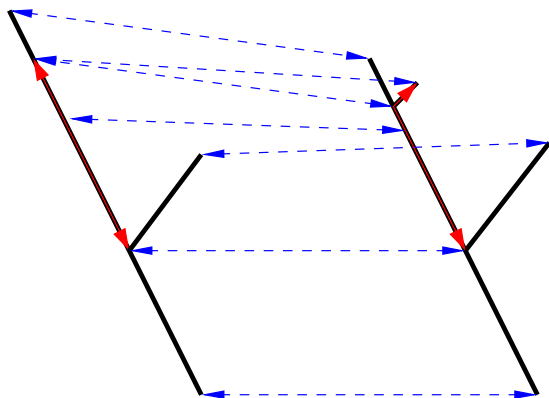
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Measuring the distance between metric spaces

The **distortion** of R is

$$\text{dis}(R) = \sup\{|d(x, y) - d'(x', y')| : (x, x'), (y, y') \in R\}.$$



Measuring the distance between metric spaces

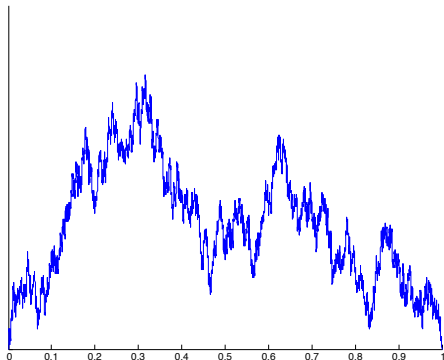
(X, d) and (X', d') are at **Gromov-Hausdorff distance** less than $\epsilon > 0$ if there exists a correspondence R between X and X' such that $\text{dis}(R) < 2\epsilon$. Write

$$d_{\text{GH}}((X, d), (X', d')) < \epsilon.$$

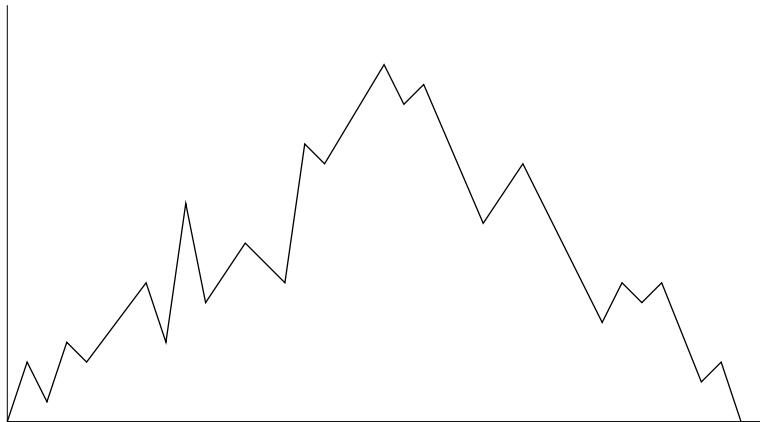
The Brownian CRT

Why **Brownian** continuum random tree?

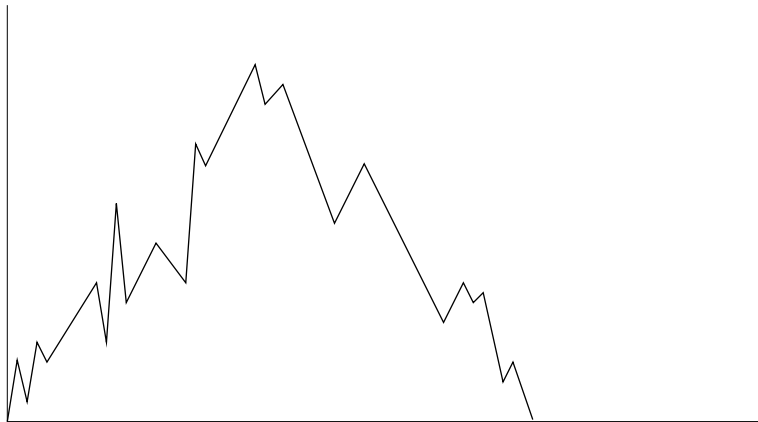
Because \mathcal{T}_2 can be obtained by a glueing operation performed on the standard Brownian excursion, $(e(t), 0 \leq t \leq 1)$.



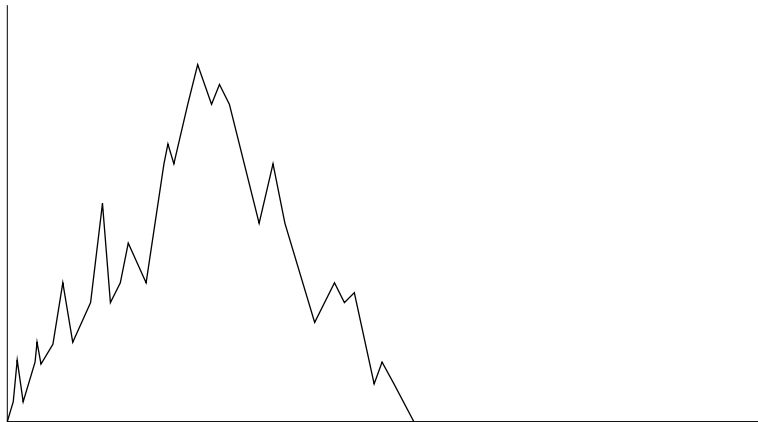
The Brownian CRT



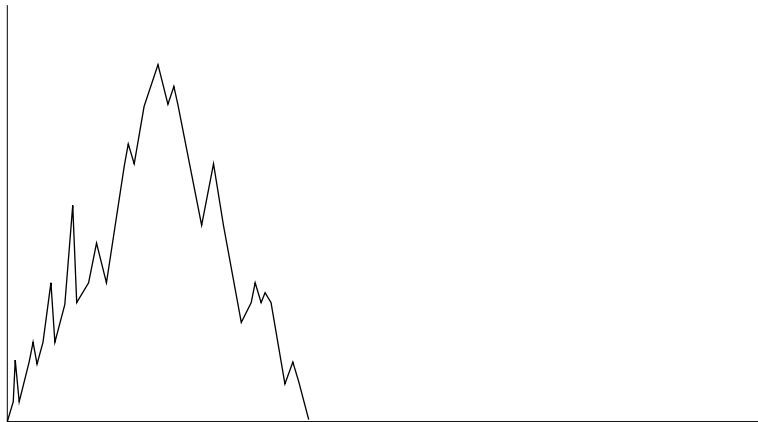
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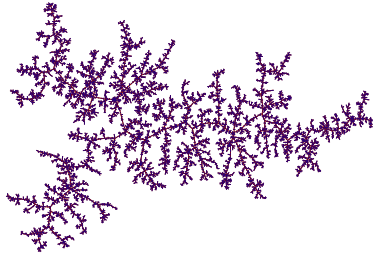
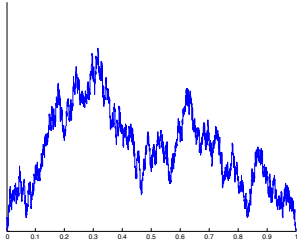
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The Brownian CRT



[Pictures by Igor Kortchemski]

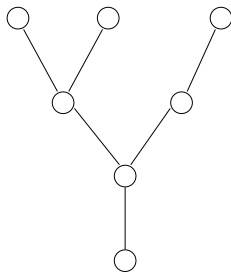
Critical Galton–Watson trees

Consider a Galton–Watson branching process with offspring distribution $(p_k)_{k \geq 0}$.

Suppose that the offspring distribution is **critical** i.e.

$\sum_{k=0}^{\infty} kp_k = 1$, and condition the tree to have **total progeny** n .

Let T_n^{GW} be the family tree associated with this process (thought of as a rooted plane tree with n vertices).



Combinatorial trees

By taking different offspring distributions, we can obtain various different natural combinatorial models:

- ▶ Poisson(1) corresponds to the uniform random tree (once we forget the planar order and give the tree a uniform labelling).
- ▶ Geometric(1/2) gives a uniform plane tree.
- ▶ $p_0 = 1/2, p_2 = 1/2$ gives a uniform (complete) binary tree (as long as n is odd).

The finite-variance case

Theorem (Aldous (1993); Le Gall (2005))

Suppose $\sigma^2 := \sum_{k=2}^{\infty} (k-1)^2 p_k < \infty$. Then

$$\frac{1}{\sqrt{n}} T_n^{GW} \xrightarrow{d} c_\sigma \mathcal{T}_2 \quad \text{as } n \rightarrow \infty$$

where \mathcal{T}_2 is Aldous' *Brownian continuum random tree* and c_σ is a non-negative constant. (The convergence is in the sense of the Gromov–Hausdorff distance.)

Infinite variance

What if the offspring distribution does not have finite variance? It is natural to consider offspring distributions such that $p_k \sim k^{-1-\alpha}$ for $\alpha \in (1, 2)$ (or, more generally, distributions in the domain of attraction of a stable law of parameter α).

The infinite-variance case

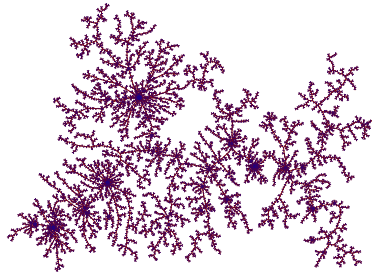
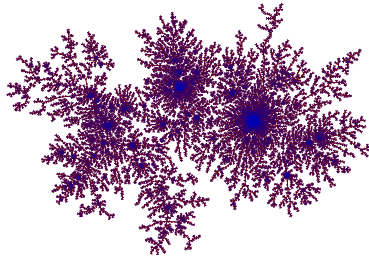
Theorem (Duquesne & Le Gall (2002); Duquesne (2003))

Suppose that $(p_k)_{k \geq 0}$ lies in the domain of attraction of a stable law of index $\alpha \in (1, 2)$. Then as $n \rightarrow \infty$,

$$\frac{1}{n^{1-1/\alpha}} T_n^{\text{GW}} \xrightarrow{d} c_\alpha \mathcal{T}_\alpha,$$

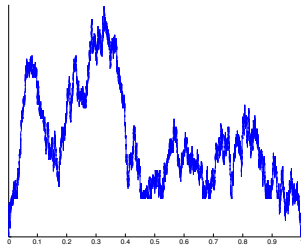
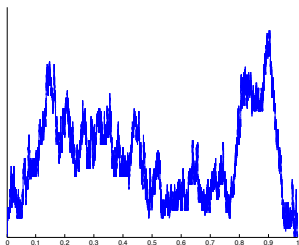
where \mathcal{T}_α is the *stable tree* of parameter α and c_α is a non-negative constant. (The convergence is in the sense of the Gromov–Hausdorff distance.)

The stable trees



The stable trees

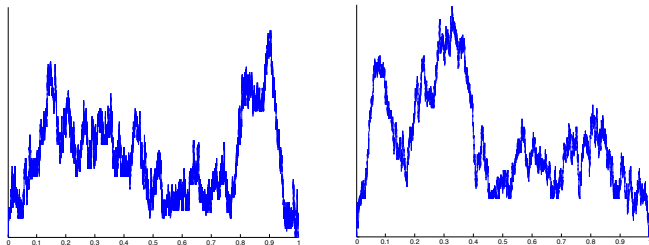
The stable trees also possess a functional encoding (although the excursions concerned are rather more involved to describe).



[Pictures by Igor Kortchemski]

The stable trees

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[Pictures by Igor Kortchemski]

An important difference between the stable trees for $\alpha \in (1, 2)$ and the Brownian CRT is that the Brownian CRT is **binary**. The stable trees, on the other hand, have only branch-points of **infinite degree**.

A uniform measure

The principal theme of the rest of this talk is how to give a (relatively) simple description of the stable trees (and how to use it to get at their distributional properties).

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For $\alpha \in (1, 2]$, the stable tree \mathcal{T}_α is naturally endowed with a “uniform” probability measure μ_α , which is the limit of the discrete uniform measure on T_n^{GW} . It turns out that μ_α is supported by the set of leaves of \mathcal{T}_α .

A uniform measure

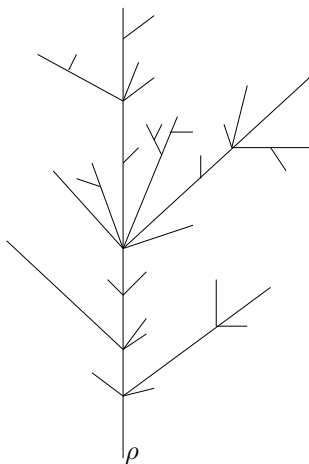
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Aldous’ theory of continuum random trees tells us that we can characterize the laws of such trees via **sampling**.

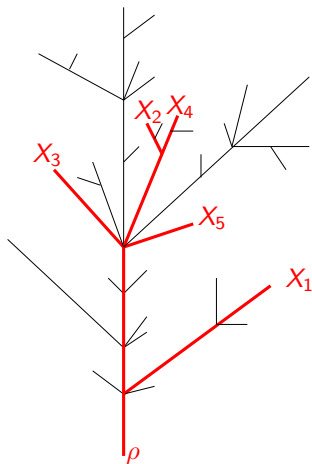
Reduced trees

Let X_1, X_2, \dots be leaves sampled independently from \mathcal{T}_α according to μ_α , and let $\mathcal{T}_{\alpha,n}$ be the subtree spanned by the root ρ and X_1, \dots, X_n :



Reduced trees

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Characterising the law of a stable tree

$\mathcal{T}_{\alpha,n}$ can be thought of in two parts: its **tree-shape** $T_{\alpha,n}$ (a rooted unordered tree with n labelled leaves) and its **edge-lengths**.

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The laws of $(\mathcal{T}_{\alpha,n}, n \geq 1)$ (the **random finite-dimensional distributions**) are sufficient to fully specify the law of \mathcal{T}_{α} .

Characterising the law of a stable tree

$\mathcal{T}_{\alpha,n}$ can be thought of in two parts: its **tree-shape** $T_{\alpha,n}$ (a rooted unordered tree with n labelled leaves) and its **edge-lengths**.

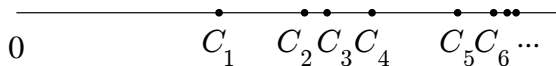
The laws of $(\mathcal{T}_{\alpha,n}, n \geq 1)$ (the **random finite-dimensional distributions**) are sufficient to fully specify the law of \mathcal{T}_{α} .

Moreover,

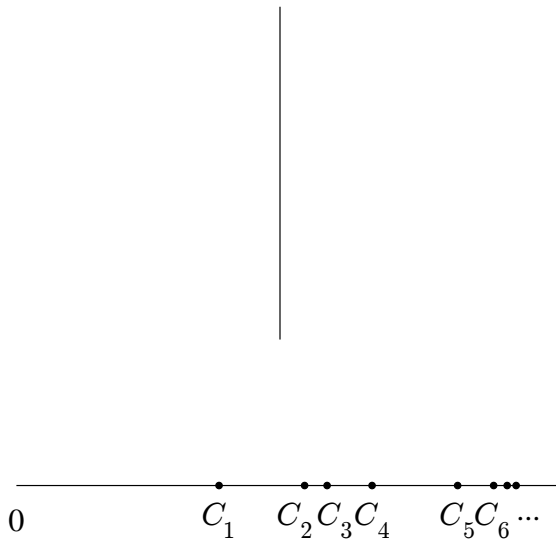
$$\mathcal{T}_{\alpha} = \overline{\bigcup_{n \geq 1} \mathcal{T}_{\alpha,n}}.$$

Reminder: Aldous' line-breaking construction of the Brownian CRT

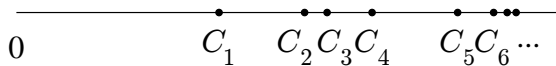
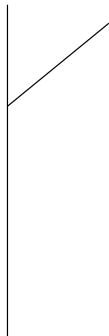
Let C_1, C_2, \dots be the points of an inhomogeneous Poisson process on \mathbb{R}_+ of intensity $t \, dt$.



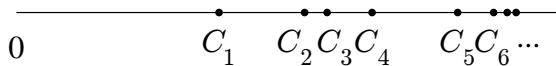
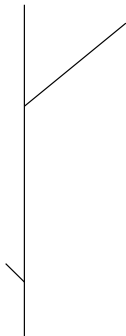
Line-breaking construction

 $\tilde{\tau}_1$ 

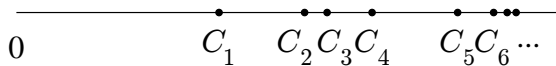
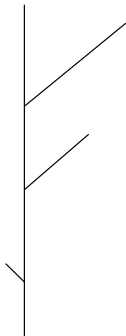
Line-breaking construction

 $\tilde{\mathcal{T}}_2$ 

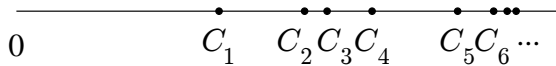
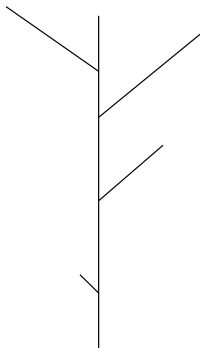
Line-breaking construction

 $\tilde{\mathcal{T}}_3$ 

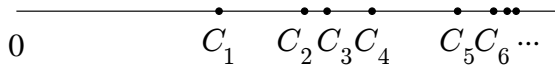
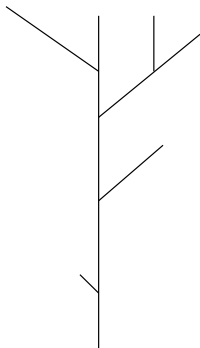
Line-breaking construction

 $\tilde{\mathcal{T}}_4$ 

Line-breaking construction

 $\tilde{\mathcal{T}}_5$ 

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 $\tilde{\mathcal{T}}_6$ 

Line-breaking construction

It turns out that the line-breaking construction precisely gives the random finite-dimensional distributions for the Brownian CRT, i.e.

$$(\tilde{\mathcal{T}}_n, n \geq 1) \stackrel{d}{=} \left(\frac{1}{\sqrt{2}} \mathcal{T}_{2,n}, n \geq 1 \right).$$

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Question: does there exist a similar line-breaking construction for the stable trees with $\alpha \in (1, 2)$?

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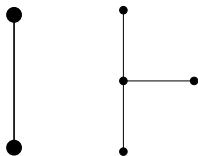
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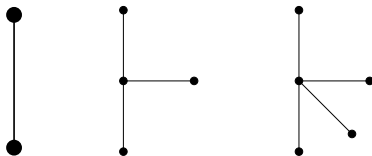
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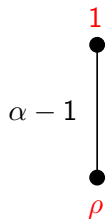
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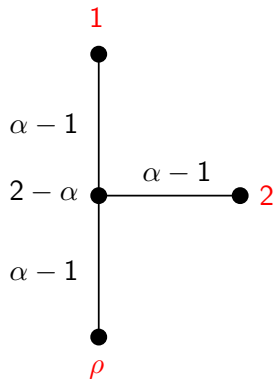
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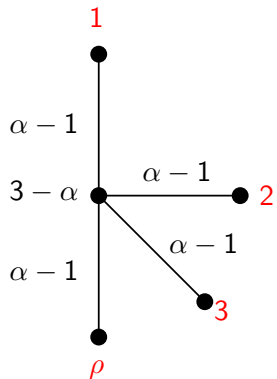
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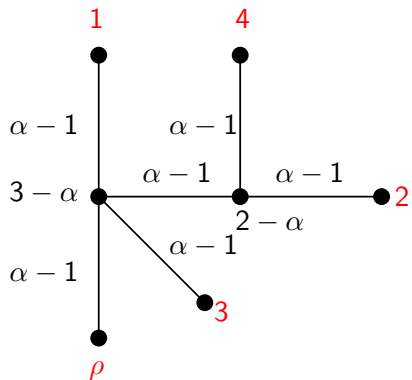
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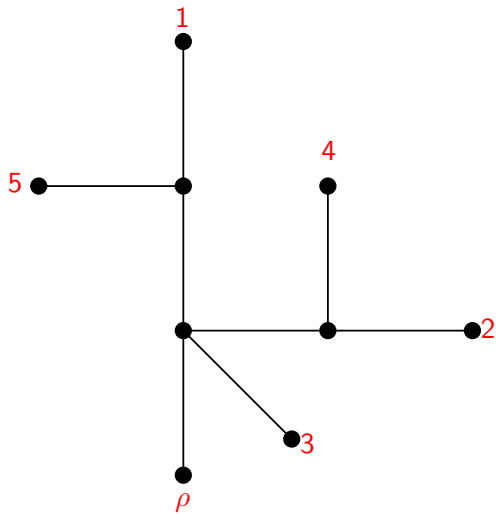
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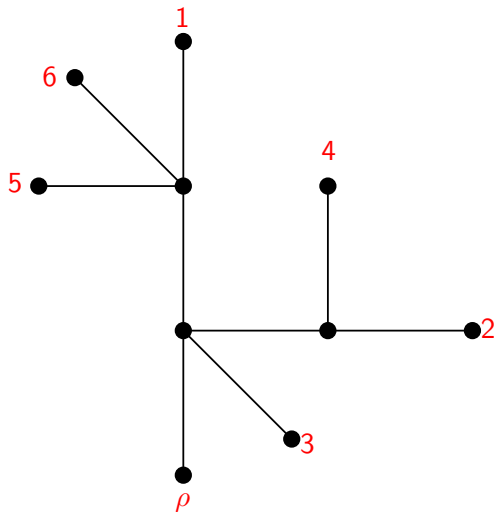
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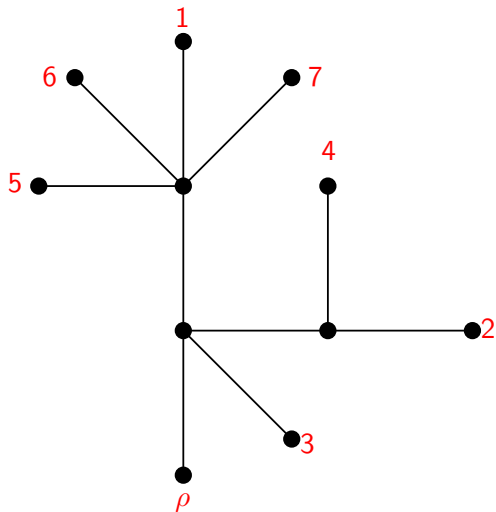
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Moreover,

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Our new line-breaking construction gives a nested sequence of continuous trees which converge a.s. to \mathcal{T}_α without any need for rescaling.

The generalized Mittag-Leffler distribution

For $\beta \in (0, 1)$, let σ_β be a stable random variable with Laplace transform

$$\mathbb{E}[\exp(-\lambda\sigma_\beta)] = \exp(-\lambda^\beta), \quad \lambda \geq 0.$$

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Say that a non-negative random variable M has the **generalized Mittag-Leffler distribution** with parameters $\beta \in (0, 1)$ and $\theta > -\beta$, and write $M \sim \text{ML}(\beta, \theta)$, if

$$\mathbb{E} [f(M)] = C_{\beta, \theta} \mathbb{E} \left[\sigma_\beta^{-\theta} f \left(\sigma_\beta^{-\beta} \right) \right].$$

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If $\beta = 1/2$ and $n \geq 1$, $\text{ML}(1/2, n - 1/2) = 2\sqrt{\text{Gamma}(n, 1)}$.

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- ▶ If black is picked, add $1/\beta$ to the black weight.
- ▶ If red is picked, add $1 - 1/\beta$ to the black weight and 1 to the red weight.

Let R_n be the weight of red at step n . Then [Janson (2006)],

$$n^{-\beta} R_n \xrightarrow{\text{a.s.}} W \sim ML(\beta, \theta).$$

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Then $(D_n, n \geq 1)$ behaves exactly as the red weight in the generalized Pólya urn with $\beta = \theta = 1 - 1/\alpha$. It follows that

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This suggests that the first stick in any line-breaking construction should have length distributed as $\text{ML}(1 - 1/\alpha, 1 - 1/\alpha)$.

A Markov chain

We define an increasing \mathbb{R}_+ -valued process which will play a role similar to that of the inhomogeneous Poisson process in the Brownian case.

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Let $(M_n, n \geq 1)$ be a Markov chain such that

- ▶ $M_n \sim \text{ML}(1 - 1/\alpha, n - 1/\alpha)$ for $n \geq 1$.
- ▶ The **backward** transition from M_{n+1} to M_n is given by

$$M_n = M_{n+1} \beta_n,$$

where β_n is independent of M_{n+1} and

$$\beta_n \sim \text{Beta} \left(\frac{(n+1)\alpha - 2}{\alpha - 1}, \frac{1}{\alpha - 1} \right).$$

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If $\alpha = 2$, $(M_n, n \geq 1)$ are the ordered points of an inhomogeneous Poisson process on \mathbb{R}_+ with intensity $\frac{t}{2} dt$.

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It suffices to show that $(M_n^2/4, n \geq 1)$ are the ordered points of a Poisson process of rate 1. But

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The relationship between successive points encoded in $M_n = \beta_n M_{n+1}$ where $\beta_n \sim \text{Beta}(2n, 1)$ gives exactly the right dependence structure. □

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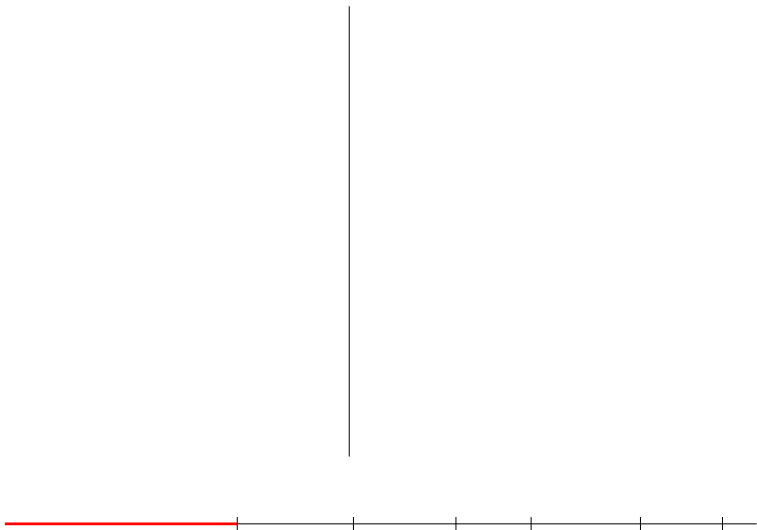
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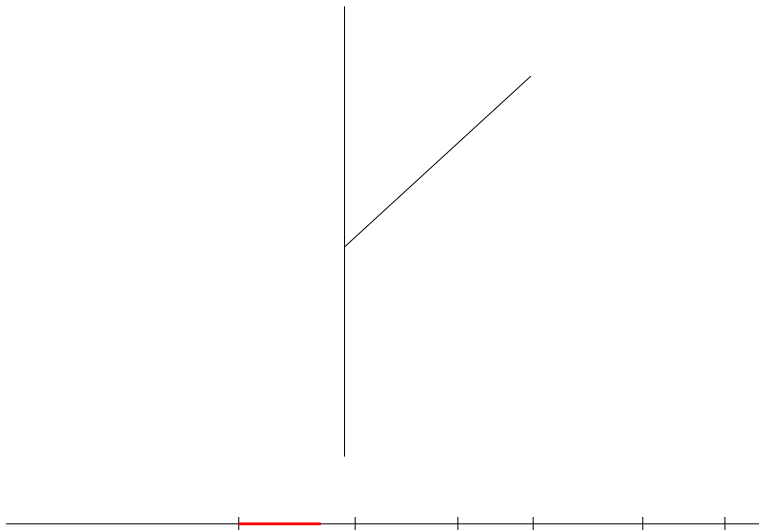
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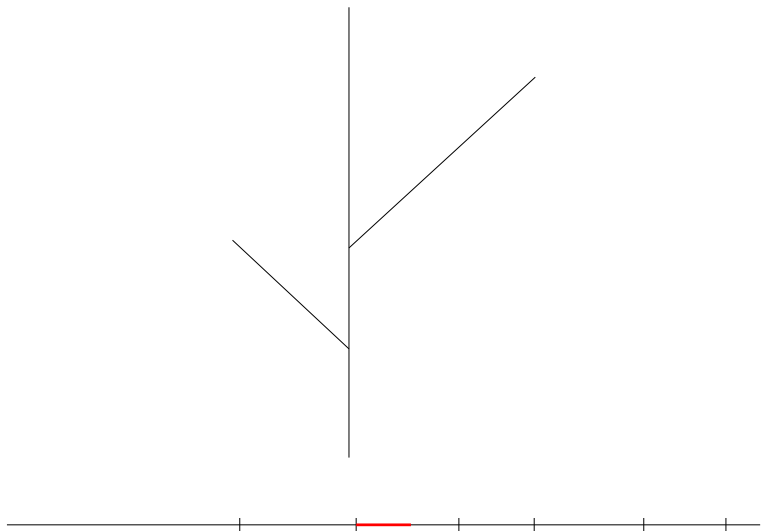
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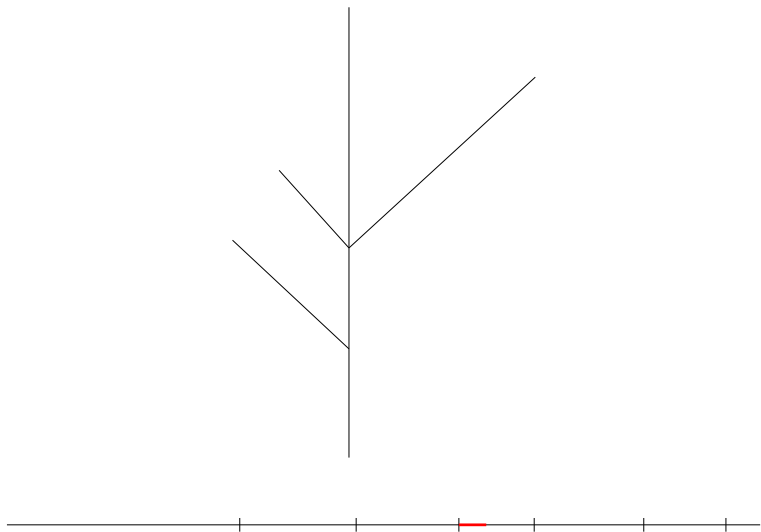
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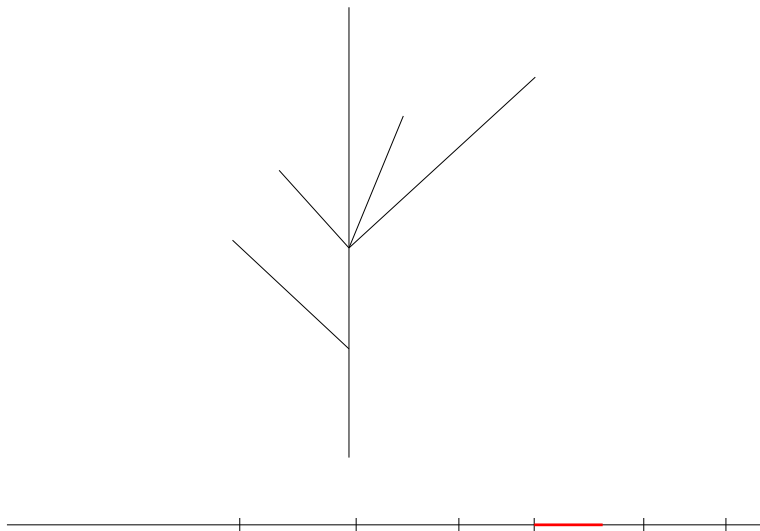
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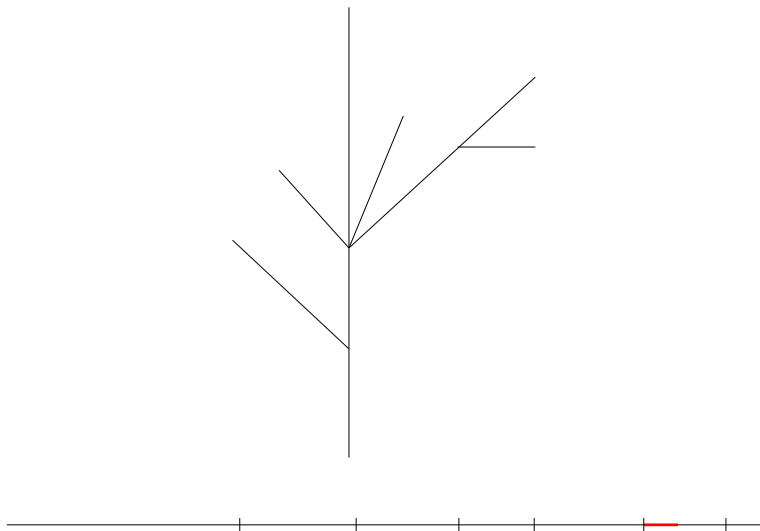


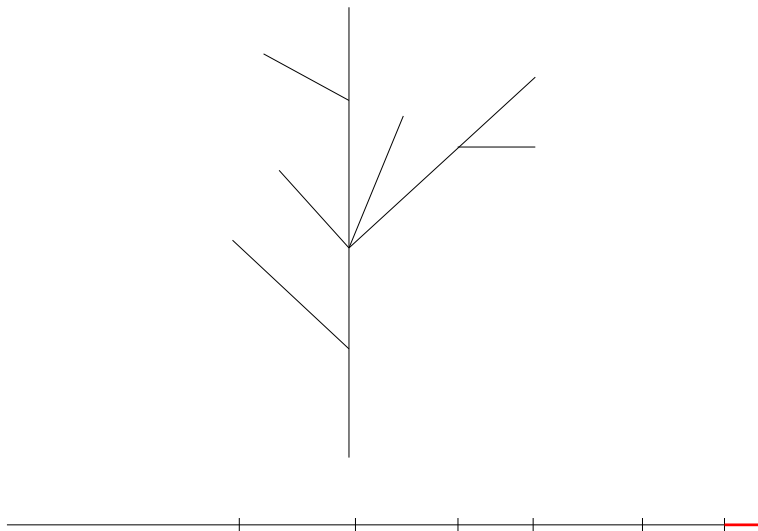


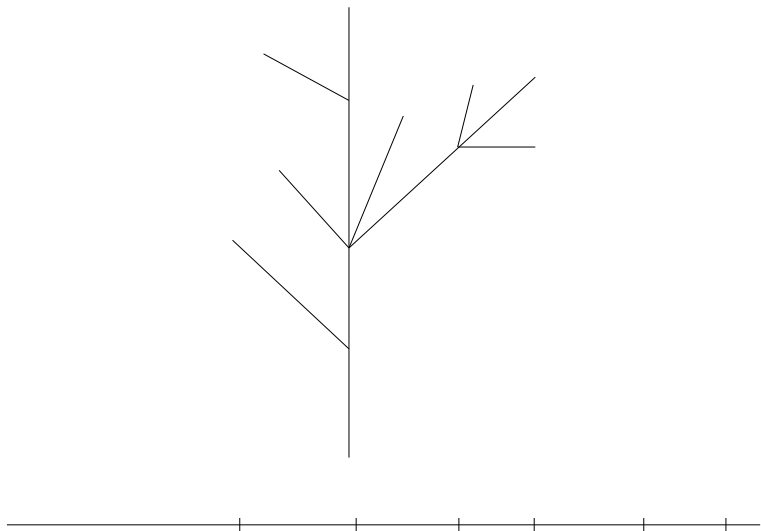


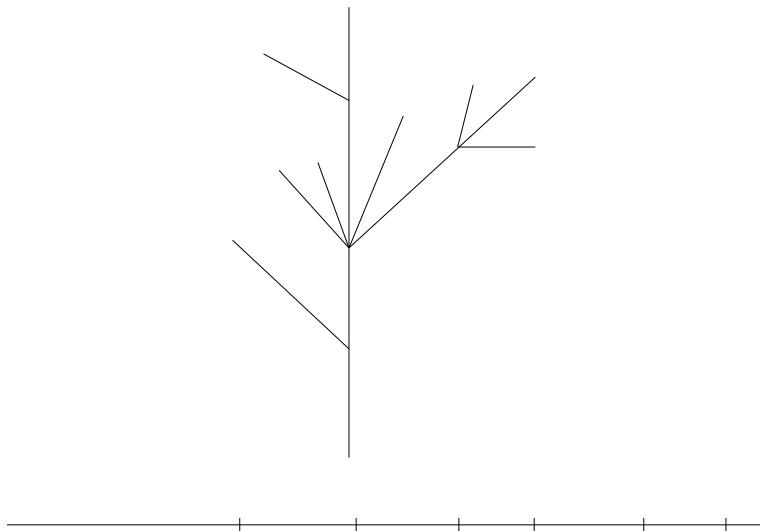


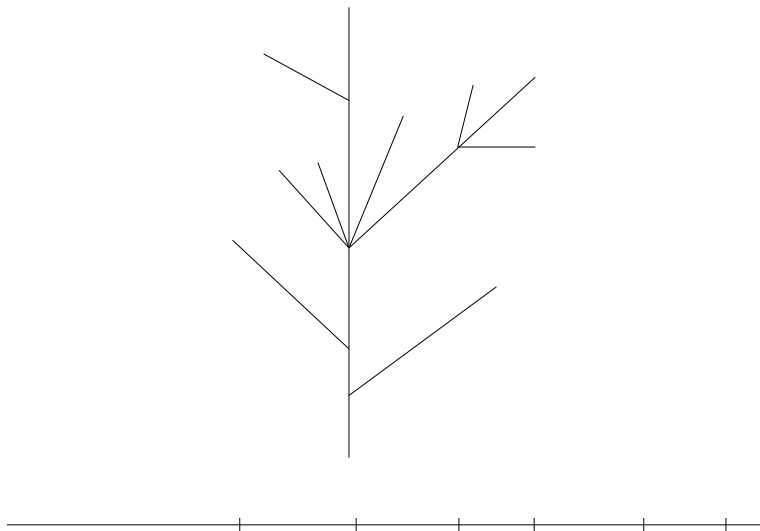


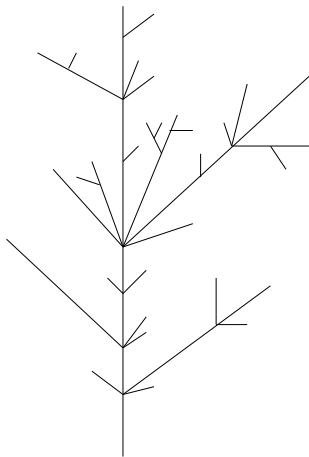












Line-breaking construction of the stable tree (II)

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Line-breaking constructions

Theorem (Haas & G.)

Let $(\tilde{\mathcal{T}}_n, n \geq 1)$ be the sequence of trees produced by either version of the construction. Then

$$(\tilde{\mathcal{T}}_n, n \geq 1) \stackrel{d}{=} (\mathcal{T}_{\alpha, n}, n \geq 1)$$

and, therefore,

$$\mathcal{T}_{\alpha} \stackrel{d}{=} \overline{\bigcup_{n \geq 1} \tilde{\mathcal{T}}_n}.$$

Remarks

In the case $\alpha = 2$, we have $\text{Beta}\left(1, \frac{2-\alpha}{\alpha-1}\right) = \text{Beta}(1, 0)$. We interpret this as $B_n = 1$ almost surely for all $n \geq 1$. Then we recover (a scaled version of) Aldous' Poisson line-breaking construction of the Brownian CRT.

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The tree-shapes $(\tilde{T}_n, n \geq 1)$ of $(\tilde{T}_n, n \geq 1)$ perform Marchal's algorithm.

Consequences: distributional results for $(\mathcal{T}_{\alpha,n}, n \geq 1)$

Edge-lengths:

Let t be a discrete rooted tree with $n \geq 2$ leaves and k edges. Then conditionally on $\mathcal{T}_{\alpha,n} = t$, the sequence of edge-lengths of $\mathcal{T}_{\alpha,n}$ has the same distribution as

$$M_n \cdot \beta_k \cdot (D_1, D_2, \dots, D_k),$$

where these random variables are independent and

$$M_n \sim \text{ML}(1 - 1/\alpha, n - 1/\alpha)$$

$$\beta_k \sim \text{Beta}\left(k, \frac{n\alpha - 1}{\alpha - 1}\right)$$

$$(D_1, D_2, \dots, D_k) \sim \text{Dir}(1, 1, \dots, 1).*$$

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*Dirichlet distribution: $\text{Dir}(a_1, \dots, a_n)$ has density

$$\frac{\Gamma(a_1 + \dots + a_n)}{\prod_{i=1}^n \Gamma(a_i)} x_1^{a_1-1} \dots x_n^{a_n-1}$$

with respect to Lebesgue measure on

$$\left\{ (x_1, \dots, x_n) \in [0, 1]^n : \sum_{i=1}^n x_i = 1 \right\}.$$

Consequences: distributional results for $(\mathcal{T}_{\alpha,n}, n \geq 1)$

Total length of the conditioned tree:

Conditionally on $\mathcal{T}_{\alpha,n}$ having k edges, the total length of the tree $\mathcal{T}_{\alpha,n}$ has the same distribution as

$$M_n \cdot \beta_k,$$

where these random variables are independent and $M_n \sim \text{ML}(1 - 1/\alpha, n - 1/\alpha)$ and $\beta_k \sim \text{Beta}(k, \frac{n\alpha-1}{\alpha-1})$.

Consequences: distributional results for $(\mathcal{T}_{\alpha,n}, n \geq 1)$

Total length of the unconditioned tree:

The total length of the tree $\mathcal{T}_{\alpha,n}$ has the same distribution as

$$M_n \cdot \left(\prod_{j=1}^{n-1} \beta_j + \sum_{i=1}^{n-1} B_i(1 - \beta_i) \prod_{j=i+1}^{n-1} \beta_j \right),$$

where the random variables on the right-hand side are mutually independent and such that

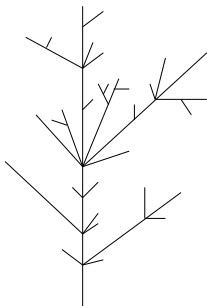
$$M_n \sim \text{ML}(1 - 1/\alpha, n - 1/\alpha)$$

$$\beta_i \sim \text{Beta} \left(\frac{(i+1)\alpha - 2}{\alpha - 1}, \frac{1}{\alpha - 1} \right), \quad i \geq 1$$

$$B_1, B_2, \dots, B_n \sim \text{Beta} \left(1, \frac{2 - \alpha}{\alpha - 1} \right).$$

Open problem

Does there exist a discrete version of our line-breaking construction (à la Aldous' construction of the uniform random tree)?



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Beta-Gamma algebra

The proof relies heavily on the following distributional facts.

- ▶ If $B \sim \text{Beta}(a, b)$ and $G \sim \text{Gamma}(a + b, 1)$ are independent then

$$G \times (B, 1 - B) \stackrel{d}{=} (G_1, G_2),$$

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$$\left(\frac{G_1}{G_1 + G_2}, \frac{G_2}{G_1 + G_2} \right) \stackrel{d}{=} (B, 1 - B)$$

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- ▶ Let $\mathbf{D} = (D_1, D_2, \dots, D_n) \sim \text{Dir}(a_1, a_2, \dots, a_n)$ and $\mathbb{P}(I = i | \mathbf{D}) = D_i$. Then, conditionally on the event $\{I = i\}$, we have

$$(D_1, \dots, D_i, \dots, D_n) \sim \text{Dir}(a_1, \dots, a_i + 1, \dots, a_n).$$

An idea of the proof (of version (II))

The key point is that, conditionally on the shapes $\tilde{T}_1, \tilde{T}_2, \dots, \tilde{T}_n$ (with \tilde{T}_n having k edges and ℓ internal vertices), the edge-lengths and vertex weights are such that

$$(L_1^{(n)}, \dots, L_k^{(n)}, W_1^{(n)}, \dots, W_\ell^{(n)}) \\ \stackrel{d}{=} \text{ML}(1 - 1/\alpha, n - 1/\alpha) \times \text{Dir}\left(1, \dots, 1, \frac{d_1 - 1 - \alpha}{\alpha - 1}, \dots, \frac{d_\ell - 1 - \alpha}{\alpha - 1}\right)$$

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This can be proved inductively.

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If we pick a co-ordinate which corresponded to an edge, it now has parameter 2. Splitting that co-ordinate with an independent uniform gives back 2 co-ordinates with parameter 1.

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$$\frac{d-1-\alpha}{\alpha-1} + 1 + \frac{2-\alpha}{\alpha-1} = \frac{(d+1)-1-\alpha}{\alpha-1}.$$

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This is the role of $(B_n, 1 - B_n) \sim \text{Beta}(1, \frac{2-\alpha}{\alpha-1})$.

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Recall that

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Recall that

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The β_n factor is precisely what is needed to rescale the Dirichlet vector in order to accommodate the extra co-ordinates we added.

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