

Infinite branches of the Directed Spanning Forest in Euclidean and hyperbolic spaces

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- 1 Backgrounds
- 2 A motivating example: the Continuum Percolation model
- 3 The Directed Spanning Forest (DSF) in \mathbb{R}^d
- 4 The DSF in \mathbb{H}^d

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A 1st model of \mathbb{H}^d : the half-space model (H, ds_H^2)

The **hyperbolic space** \mathbb{H}^d is a d -Riemannian manifold that can be defined by several *isometric* models.

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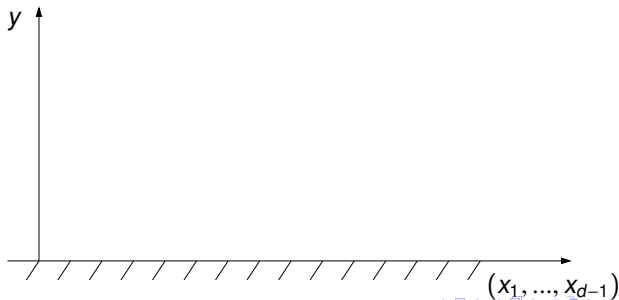
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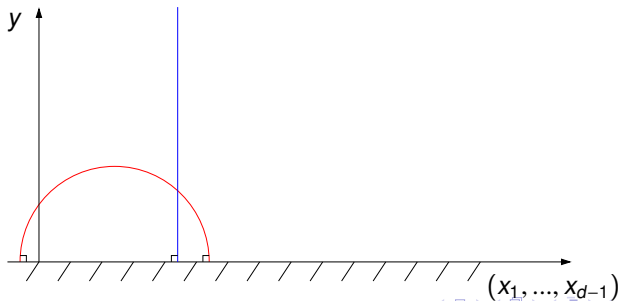


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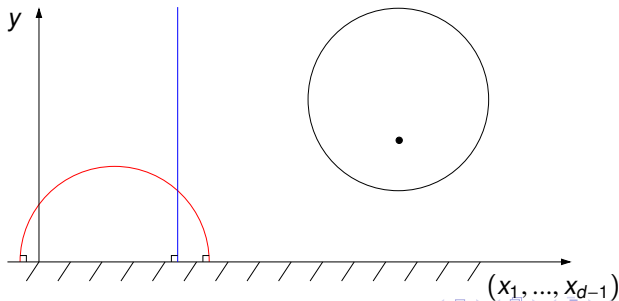


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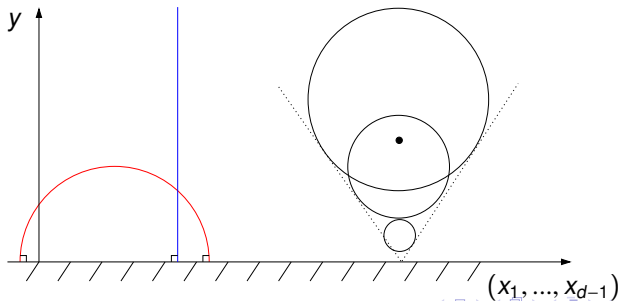


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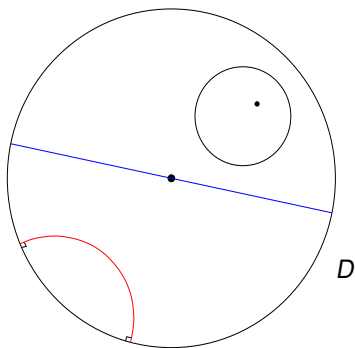
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A crucial difference between Euclidean & hyperbolic

Let $B_r := B(\cdot, r)$ be a ball with radius r .

$\text{Vol}(\cdot)$ and $\text{Surf}(\cdot)$ are relative to $\text{Leb}(\cdot)$ in \mathbb{R}^d and to $\mu(\cdot)$ in \mathbb{H}^d .

- In Euclidean space:

$$\lim_{r \rightarrow \infty} \frac{\text{Surf}(B_r)}{\text{Vol}(B_r)} = 0.$$

\mathbb{R}^d is said **amenable**.

- In hyperbolic space:

$$\lim_{r \rightarrow \infty} \frac{\text{Surf}(B_r)}{\text{Vol}(B_r)} > 0.$$

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Poisson Point Process

A homogeneous **Poisson point process** (PPP) \mathcal{N} with intensity $\lambda > 0$ in $E = \mathbb{R}^d$ or \mathbb{H}^d is a random point set such that:

- For any disjoint measurable sets $A, B \subset E$, the random variables $\#\mathcal{N} \cap A$ et $\#\mathcal{N} \cap B$ are independent.
- For any bounded measurable set $A \subset E$, $\#\mathcal{N} \cap A$ is distributed according to the Poisson law with parameter $\lambda \text{Vol}(A)$.

→ The most natural process to modelize a set of points without interaction.

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Simulation of the PPP \mathcal{N} in $[0; 10]^2$

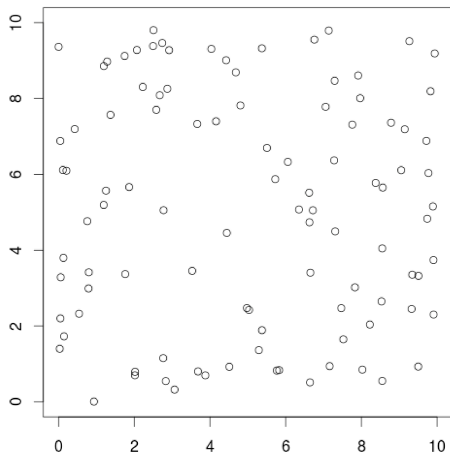


Figure: Simulation of the PPP \mathcal{N} in the (Euclidean) square $[0; 10]^2$, with intensity $\lambda = 1$.

Simulation of the PPP \mathcal{N} in H

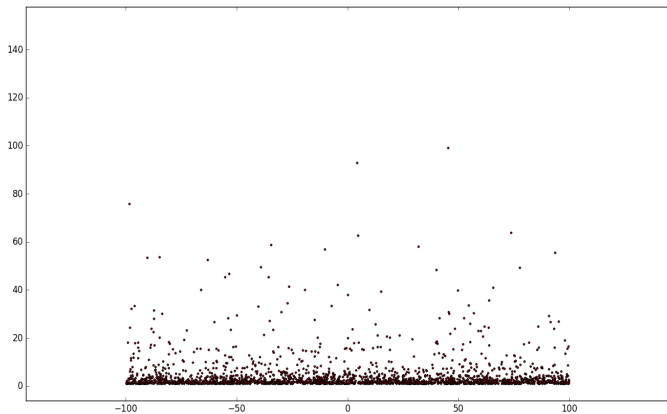


Figure: Simulation of the PPP \mathcal{N} in the half-plane H , with intensity $\lambda = 5$.

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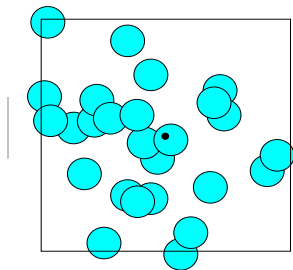
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$$\Sigma_\lambda := \cup_{x \in \mathcal{N}} B(x, 1).$$

→ Does Σ_λ contain (at least) one infinite c.c.?

When this is the case, there is **percolation**.



TH: For any $d \geq 2$, there exists a **critical intensity** $0 < \lambda_c(d) < \infty$ s.t.:

$\lambda < \lambda_c(d) \Rightarrow$ a.s. any c.c. of Σ_λ is finite.

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[Continuum Percolation, Meester, R. and Roy, R.]

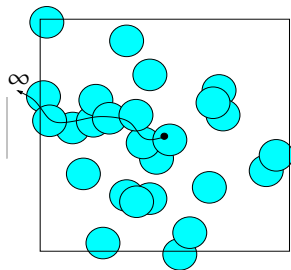
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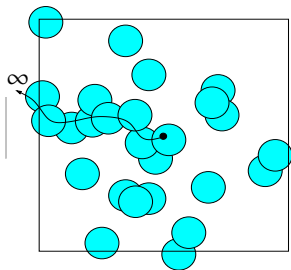
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- ① $\exists m = m(\lambda, d) \in \{0, 1, 2, 3, \dots\} \cup \{\infty\}$ such that

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GOAL: $m \in \{0, 1\}$.

- ② Excluding cases $m \in \{2, 3, \dots\}$: Easy.

- ③ Excluding case $m = \infty$: More difficult.

Based on the famous [Burton & Keane argument](#) using that

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- 2 A motivating example: the Continuum Percolation model
- 3 The Directed Spanning Forest (DSF) in \mathbb{R}^d
- 4 The DSF in \mathbb{H}^d

Joint works with [François Baccelli](#) (INRIA Paris), [Kumarjit Saha](#) (Ashoka Univ., India), [Anish Sarkar](#) (ISI Delhi, India), [Chi Tran](#) (Univ. Paris Est - MLV).

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Vertex set: the PPP \mathcal{N} in \mathbb{R}^2 ($\lambda = 1$).

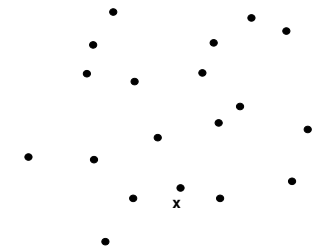
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Local rule: each $\mathbf{x} \in \mathcal{N}$ is linked to the closest vertex, say $A(\mathbf{x})$, in $\{z \in \mathbb{R}^2 : \langle z, \mathbf{x} + e_2 \rangle \geq 0\}$.

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\Rightarrow The **Directed Spanning Forest** with direction e_2 is the graph (\mathcal{N}, \vec{E}) .

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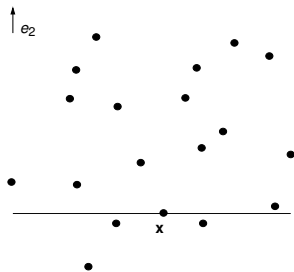
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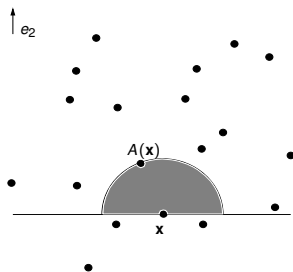
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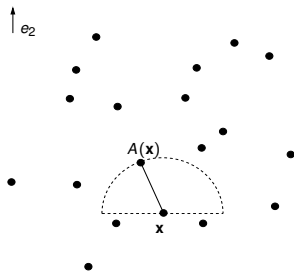
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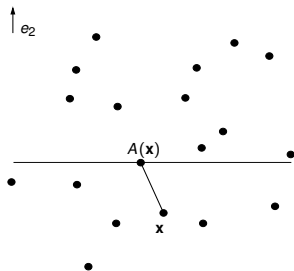
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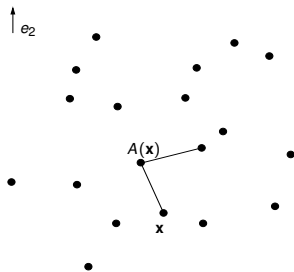
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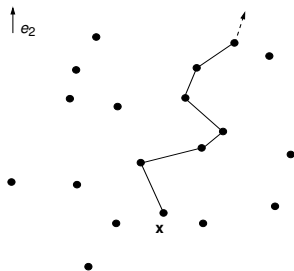
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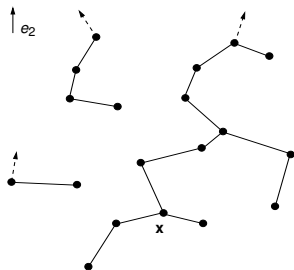
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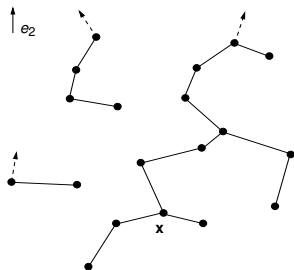
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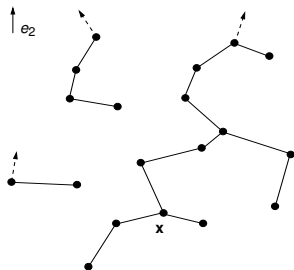
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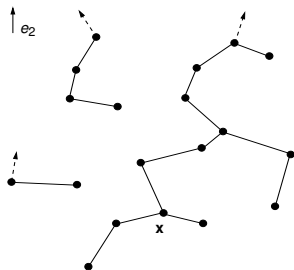
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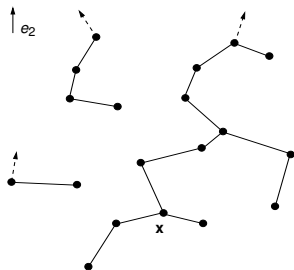
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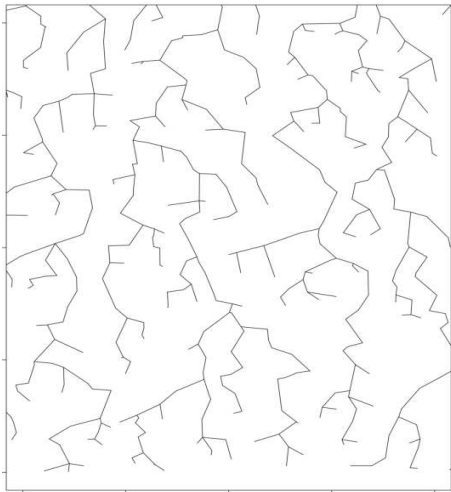
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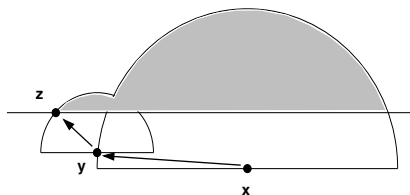
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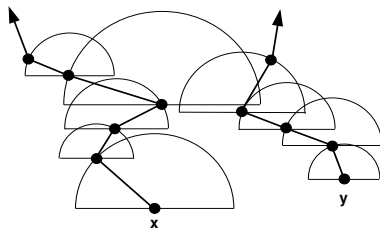
A simulation of the DSF



Dependence phenomena



(a)



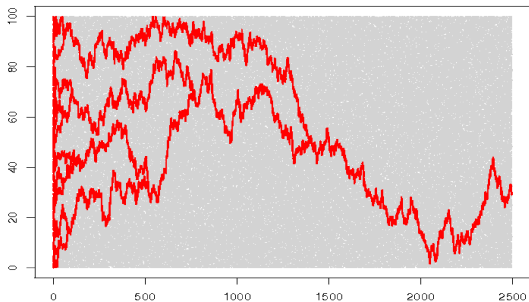
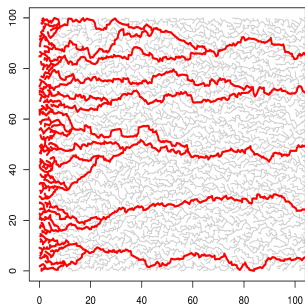
(b)

Figure: (a) Dependence phenomenon within a single branch: how the previous steps may influence the next steps. (b) Dependence phenomenon between two branches: the overlap locally acts as a repulsive effect.

Coalescence in \mathbb{R}^2

TH: [C. & Tran '12]

- (1) A.s. all the DSF branches eventually coalesce.
- (2) A.s. there is no bi-infinite branch in the DSF.



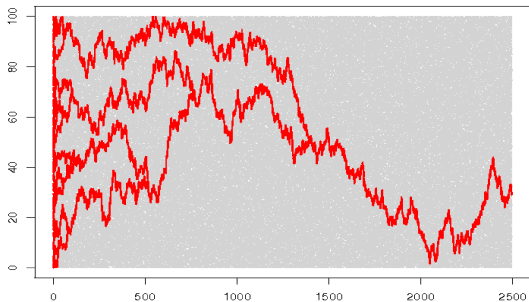
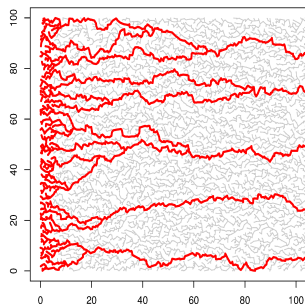
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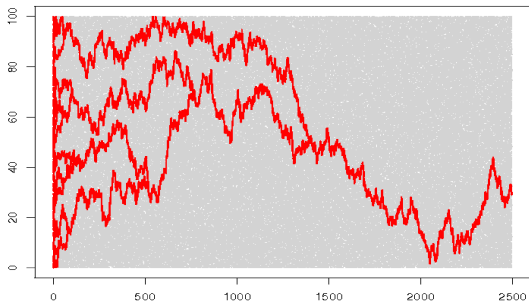
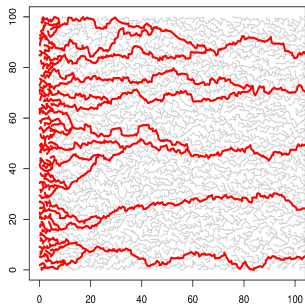
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With Saha, Sarkar & Tran ('18), we have proved:

The DSF in \mathbb{R}^2 , at a diffusive scale,
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In this work, new tools are developed...

- A new proof of coalescence and absence of bi-infinite path for the DSF in \mathbb{R}^2 *without* Burton & Keane argument.
- A generalization to $d \geq 3$.

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- (1) For $d \in \{2, 3\}$, a.s. DSF is a tree.
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PhD work of [Lucas Flammant](#) supervised by Chi Tran (Univ. Paris Est - MLV) and myself.

The Directed Spanning Forest in the Hyperbolic space,
Lucas Flammant, 67 pages, 2020. arXiv:1909.13731

The DSF in the half-space (H, ds_H^2)

Points at infinity: $(\mathbb{R}^{d-1} \times \{0\}) \cup \{\infty\}$.

Vertex set: the PPP \mathcal{N} in H (with $\lambda > 0$).

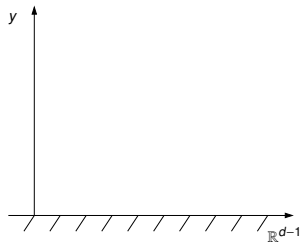
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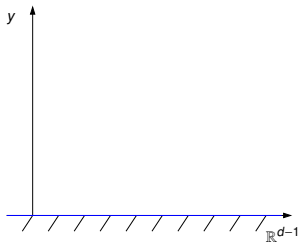
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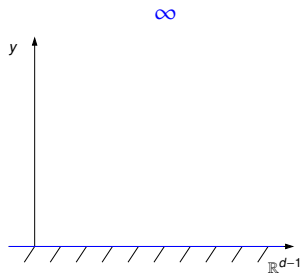
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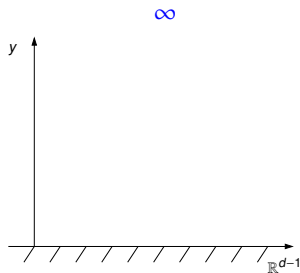
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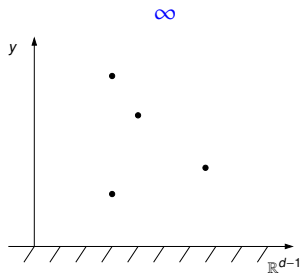
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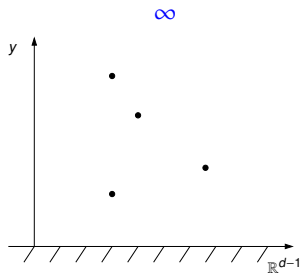
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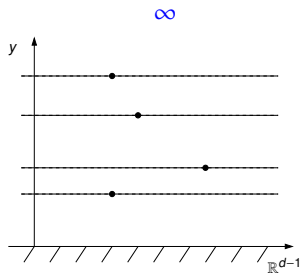
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Points at infinity: $(\mathbb{R}^{d-1} \times \{0\}) \cup \{\infty\}$.

Vertex set: the PPP \mathcal{N} in H (with $\lambda > 0$).

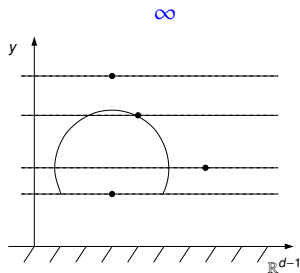
Horodistance: distance from a point to ∞ .

Horospheres: spheres centered at ∞ .

Local rule: each $\mathbf{x} \in \mathcal{N}$ is linked to the closest vertex (w.r.t. the metric ds_H^2), say $A(\mathbf{x})$, with higher ordinate y .

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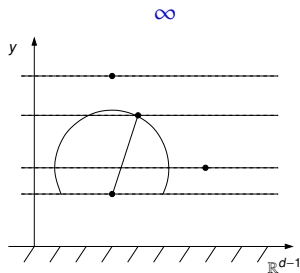
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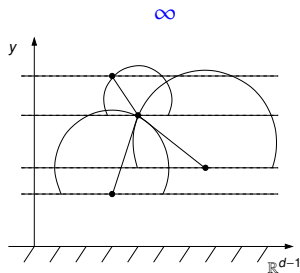
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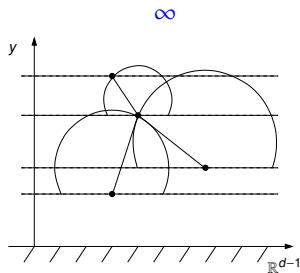
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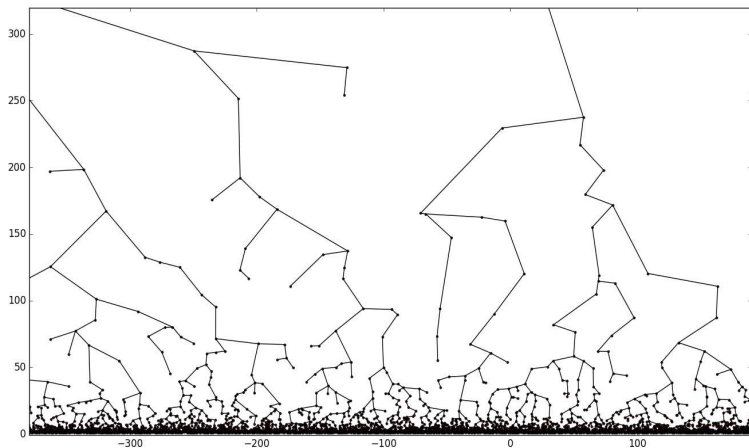
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Simulation of the hyperbolic DSF



Simulation of the DSF in \mathbb{H}^2 , represented in the half-plane model, with direction ∞ and intensity $\lambda = 10$.

Lucas's results about the hyperbolic DSF

TH: [L. Flammant ('20)]

For any $d \geq 2$ and any intensity $\lambda > 0$, the following happens:

- (1) A.s. the hyperbolic DSF is a tree.
- (2) A.s. the hyperbolic DSF contains infinitely many bi-infinite branches.
- (3) A.s. every bi-infinite branch admits an asymptotic direction in $\mathbb{R}^{d-1} \times \{0\}$.
- (4) A.s. for every asymptotic direction $(x, 0)$ in $\mathbb{R}^{d-1} \times \{0\}$, there exists a bi-infinite branch whose asymptotic direction is $(x, 0)$.
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Heuristic for coalescence

Let $\mathbf{x} = (\cdot, e^0)$.

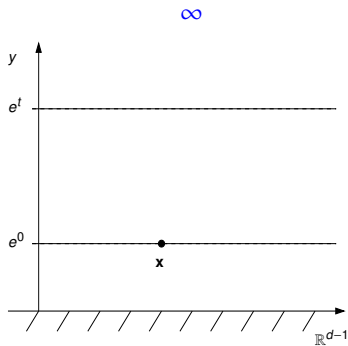
At level e^t , with proba $\rightarrow 1$ as $t \rightarrow \infty$,
the DSF path starting at \mathbf{x}
remains inside a cone.

Cone opening = $O(e^t)$ w.r.t. Euclidean dist.
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\Rightarrow Two DSF paths starting at \mathbf{x} and \mathbf{x}'
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\Rightarrow At each step, they have a proba > 0 to coalesce.

This eventually occurs!



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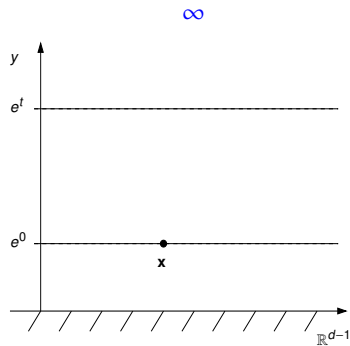
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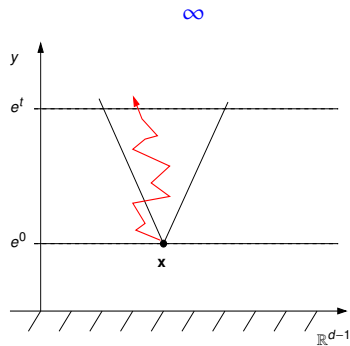
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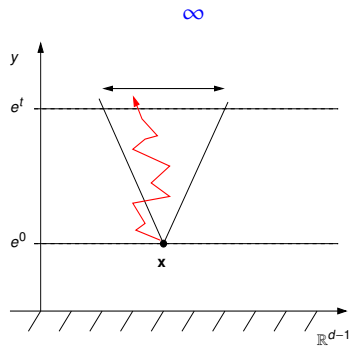
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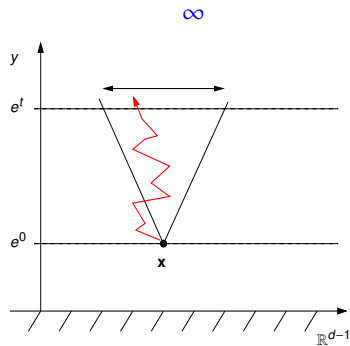
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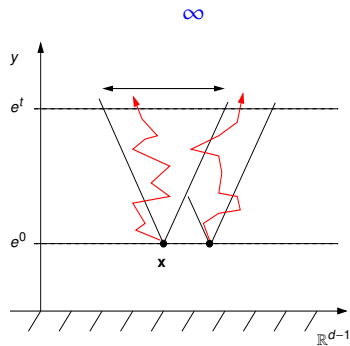
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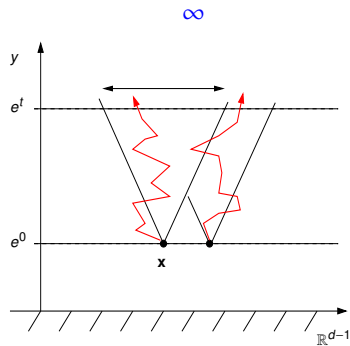
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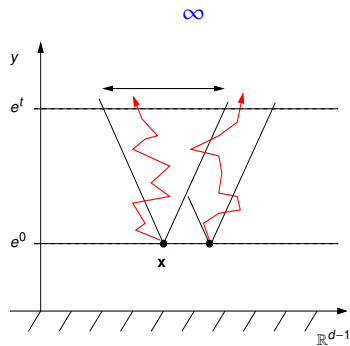
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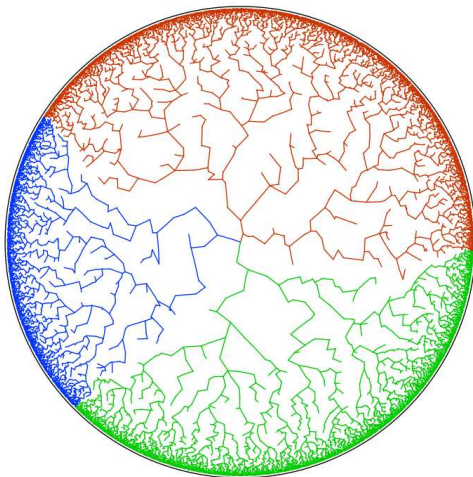
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Thank you for your attention!



Simulation of the **Radial Spanning Tree**,
represented in the Poincaré disk D , with colors.