

Random Surfaces and Quantum Loewner Evolution

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Overview

Part I: Picking surfaces at random

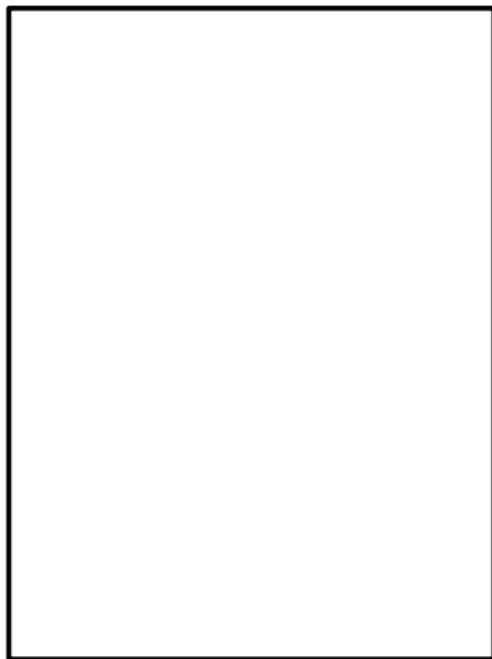
1. Discrete: random planar maps
2. Continuum: Liouville quantum gravity
3. Conjectured relationship

Part II: Quantum Loewner evolution

1. New universal family of growth processes
2. Tool to relate random planar maps to Liouville quantum gravity
3. Connected to many different topics in probability:
RPM, LQG, TBM, GFF, SLE, DLA, FPP, DBM, KPZ, KPZ

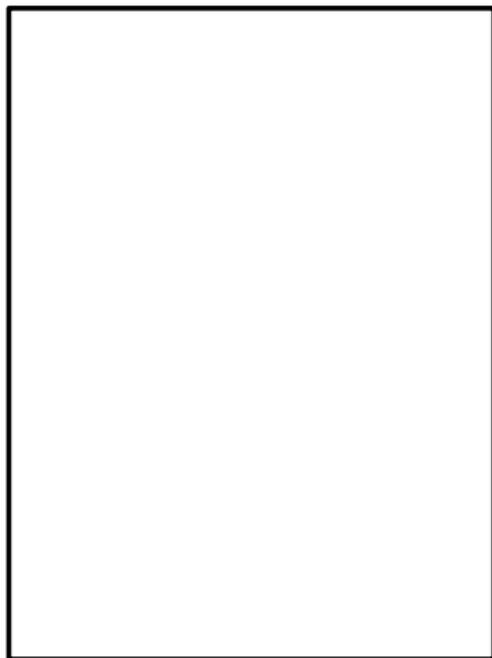
Part I: Picking surfaces at random

Quadrangulations



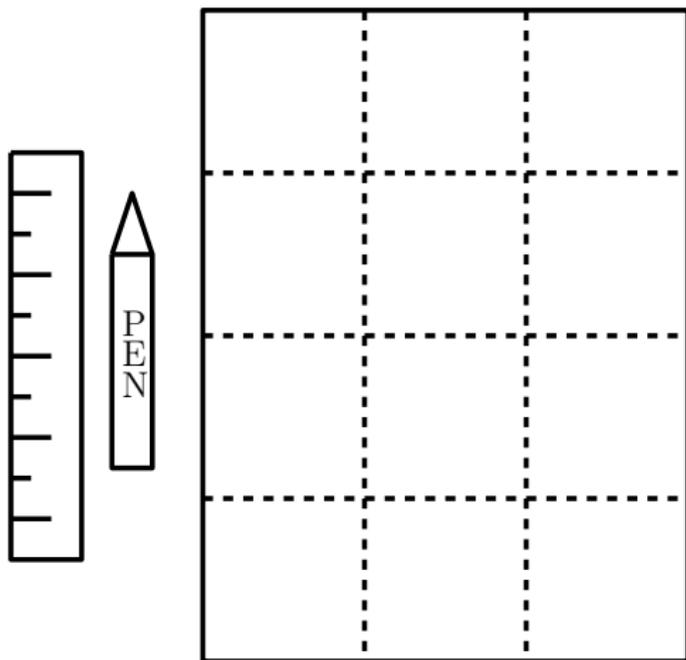
Start out with a sheet of paper

Quadrangulations



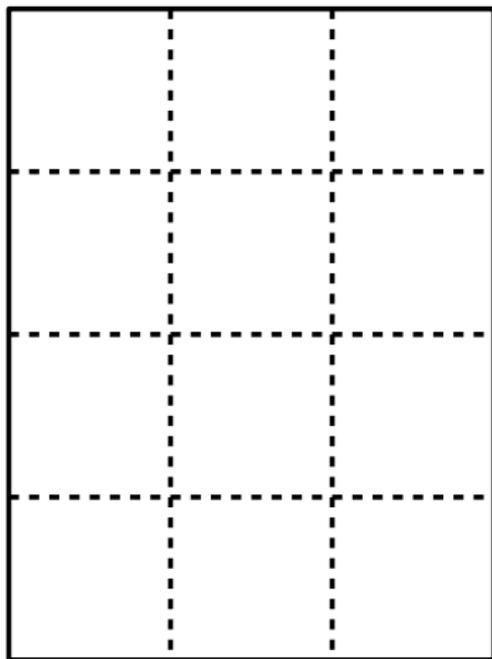
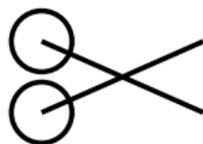
Get out pen and ruler

Quadrangulations



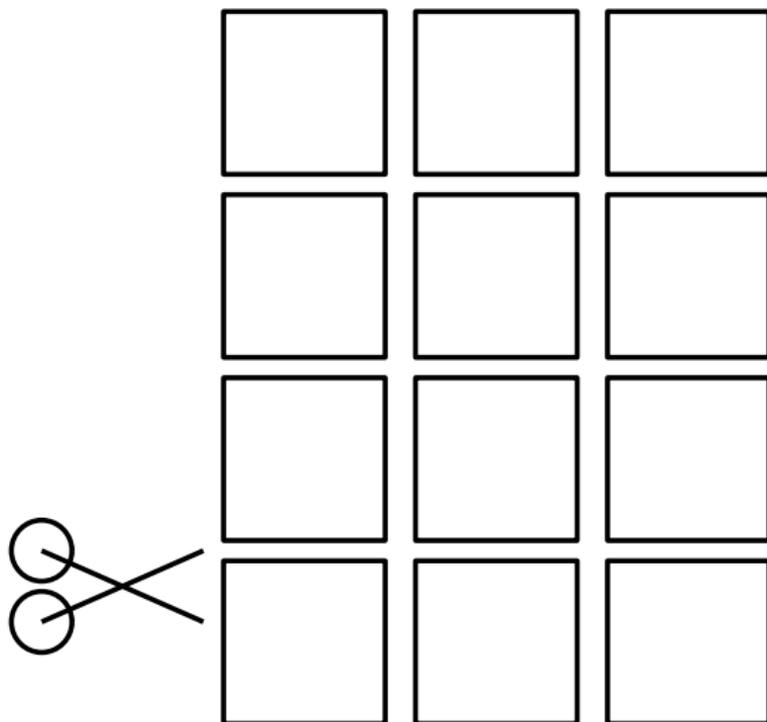
Measure and mark squares squares of equal size

Quadrangulations



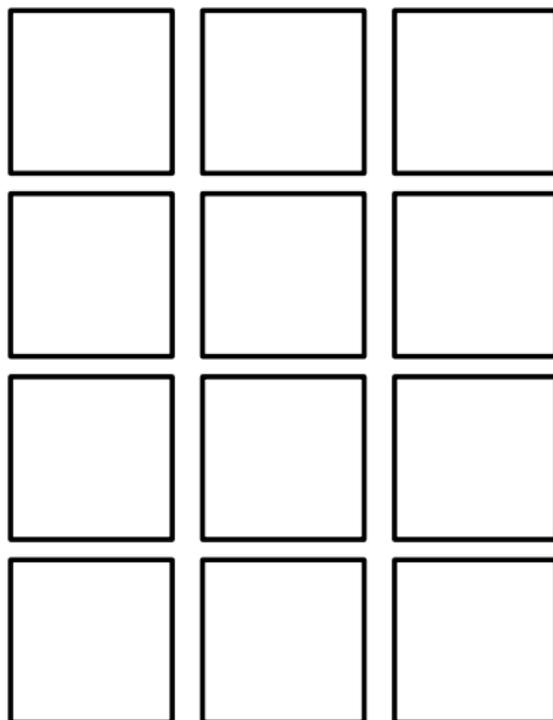
Get out scissors

Quadrangulations



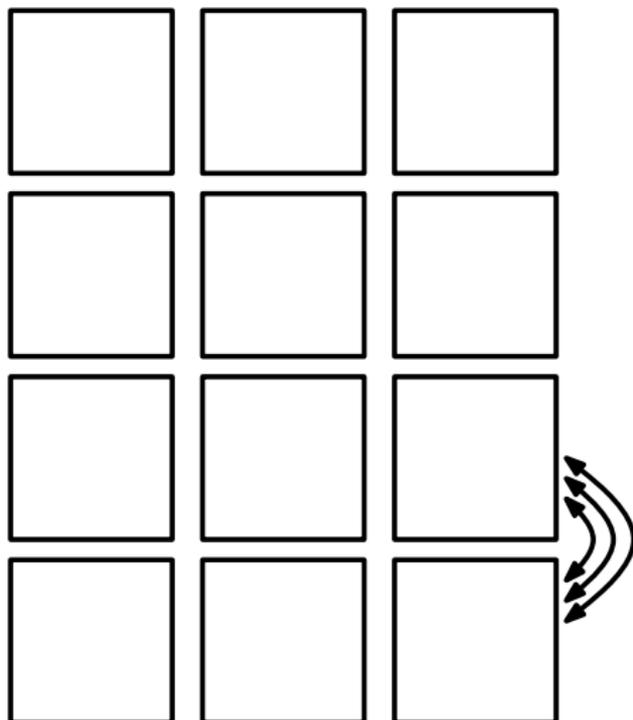
Cut into squares

Quadrangulations



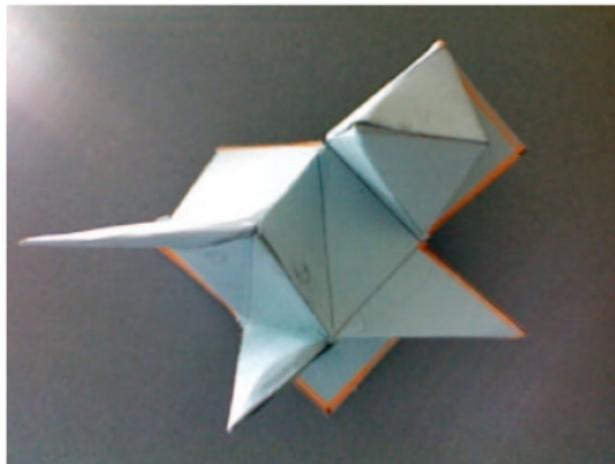
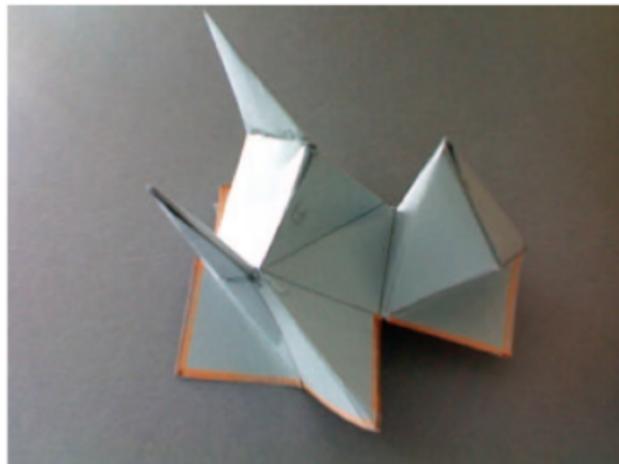
Get out bottle of glue

Quadrangulations

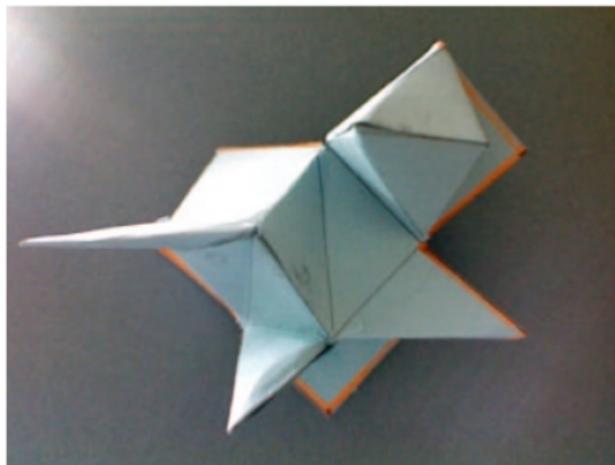
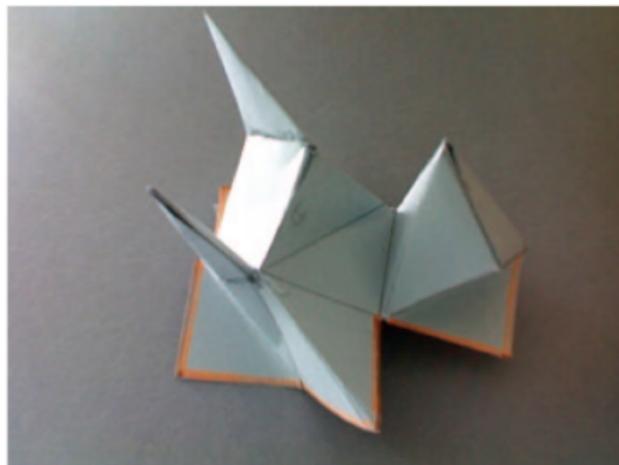


Attach squares along boundaries with glue to form a surface “without holes.”

Quadrangulations

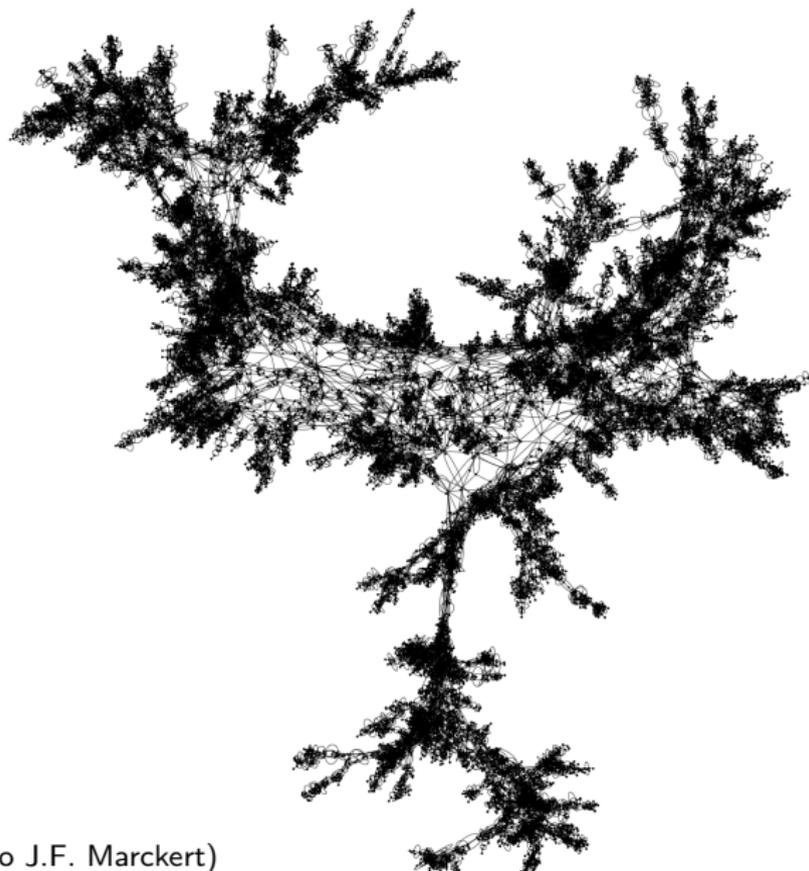


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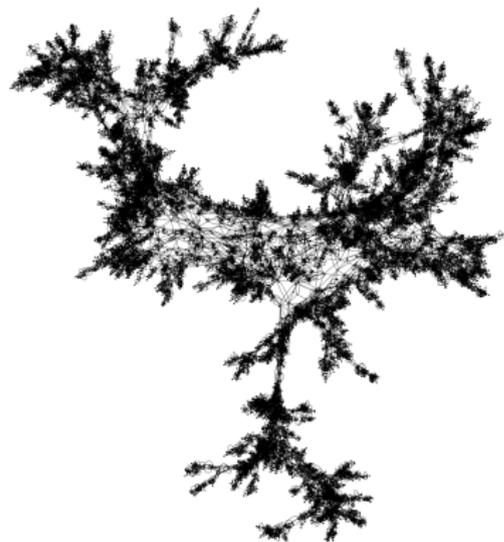
What is the structure of a typical quadrangulation when the number of faces is large?

Random quadrangulation with 25,000 faces



(Simulation due to J.F. Marckert)

Background



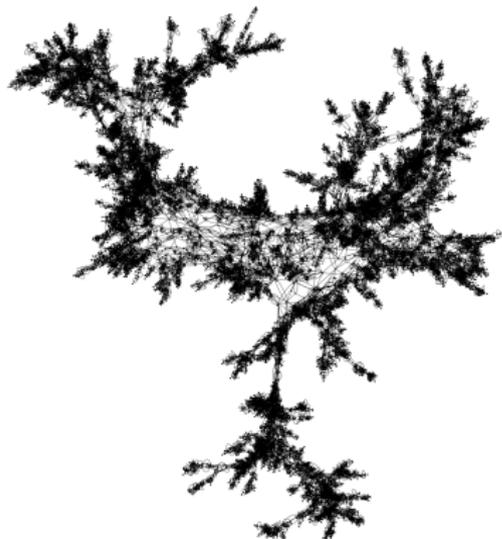
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First studied by Tutte in 1960s while working on the four color theorem

- ▶ **Combinatorics:** enumeration formulas
- ▶ **Probability:** “uniformly random surface,” Brownian surface
- ▶ **Physics:** statistical physics models: random walks, percolation, Ising model, uniform spanning tree, etc ...

Structure of large random planar maps

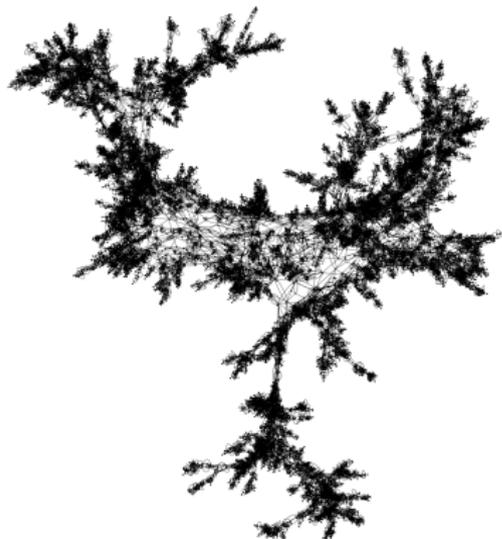
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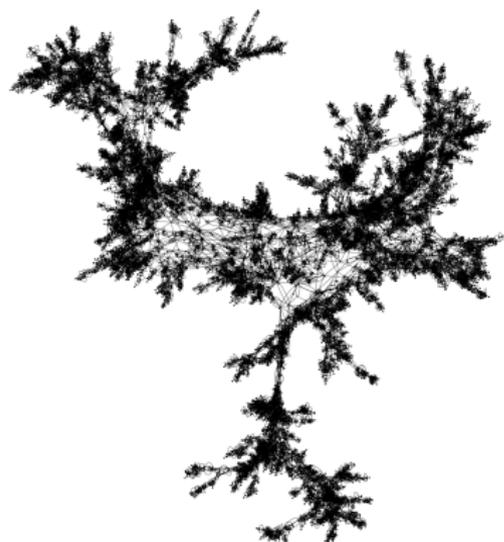
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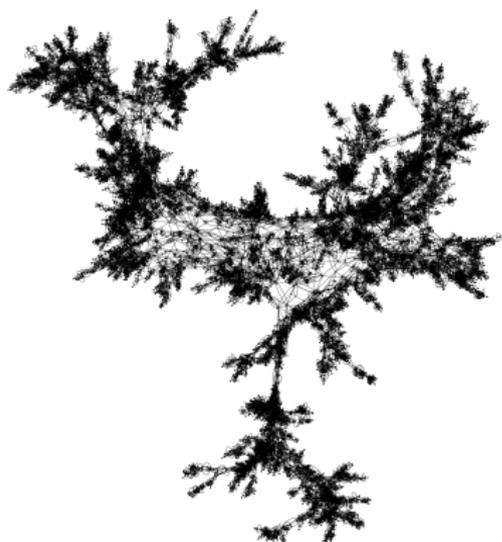
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 - ▶ 4-dimensional (Le Gall)
 - ▶ homeomorphic to the 2-sphere (Le Gall and Paulin, Miermont)

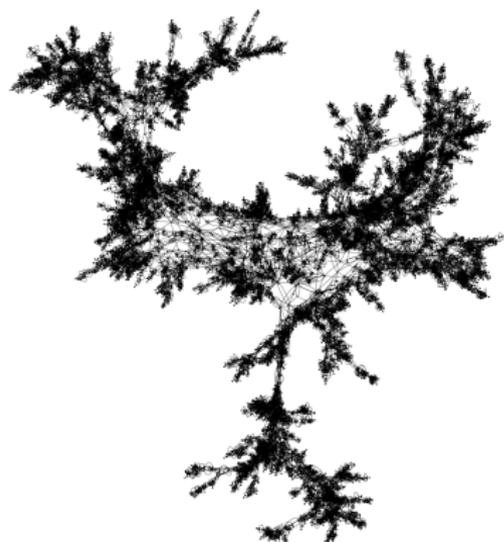
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Important tool: bijections which encode the surface using a gluing of a pair of trees

(Mullin, Schaeffer, Cori-Schaeffer-Vauquelin, Bouttier-Di Francesco-Guitter, S.,...)

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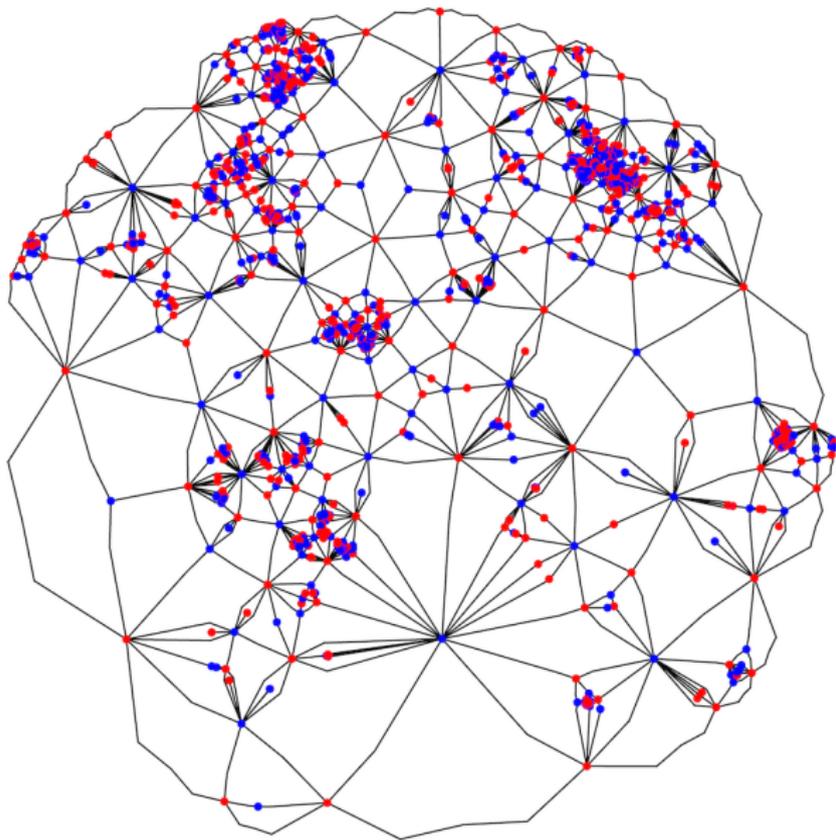
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Brownian map also described in terms of trees (CRT)

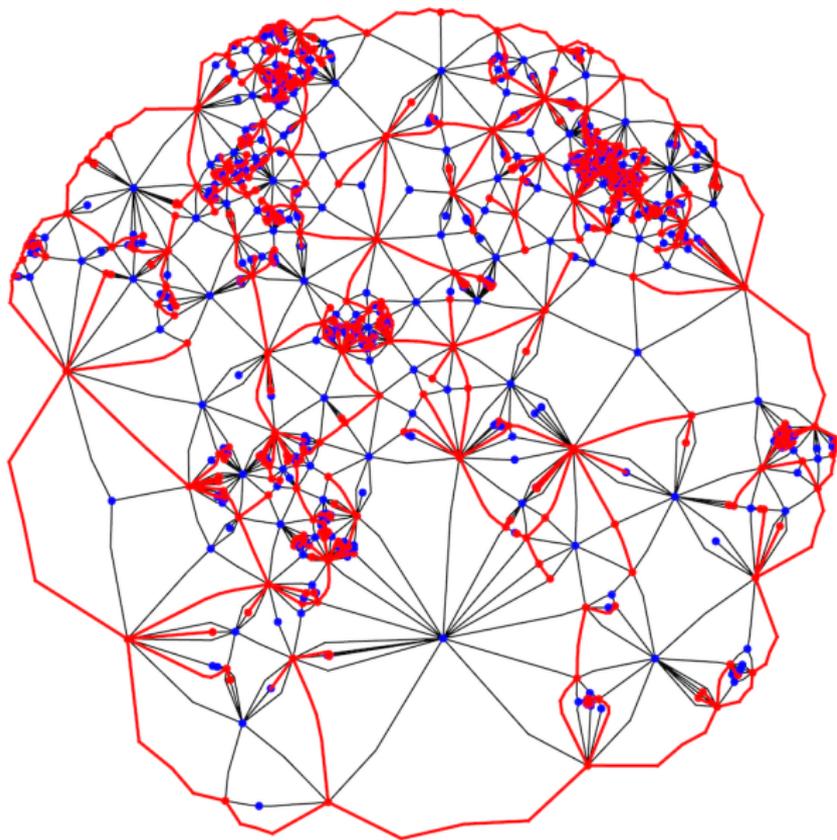
(Markert-Mokkadem)

Random quadrangulation



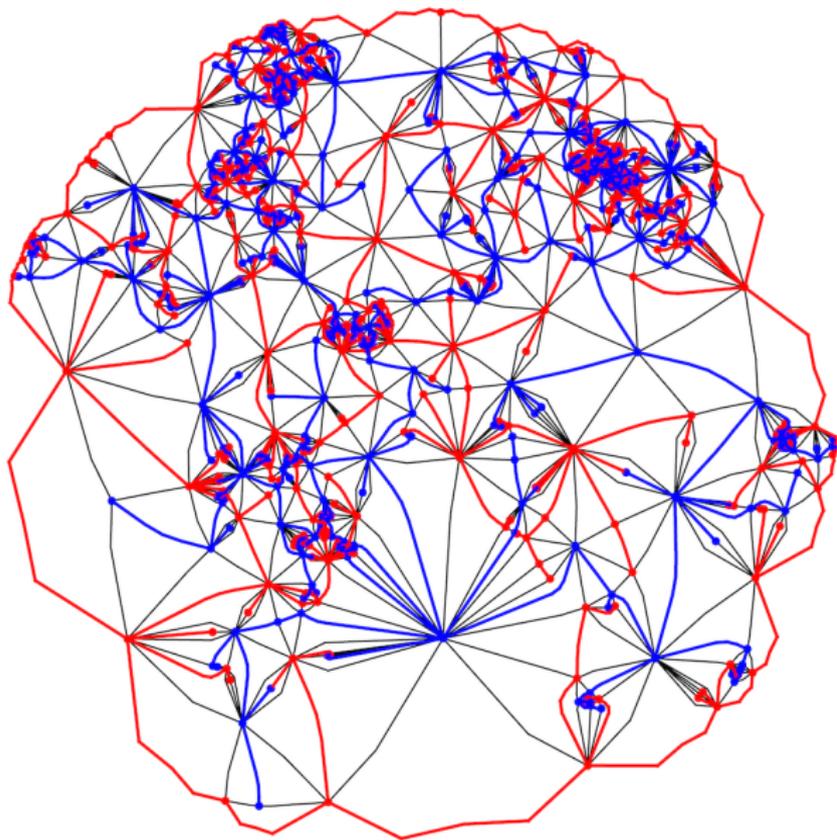
Sampled using H-C bijection.

Red tree



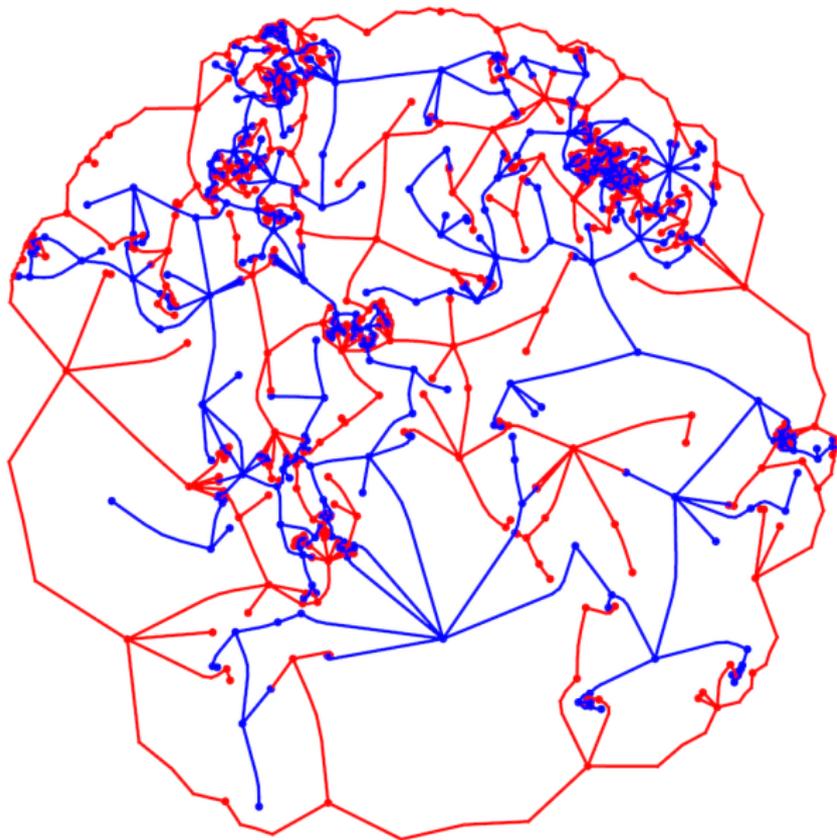
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Red and blue trees



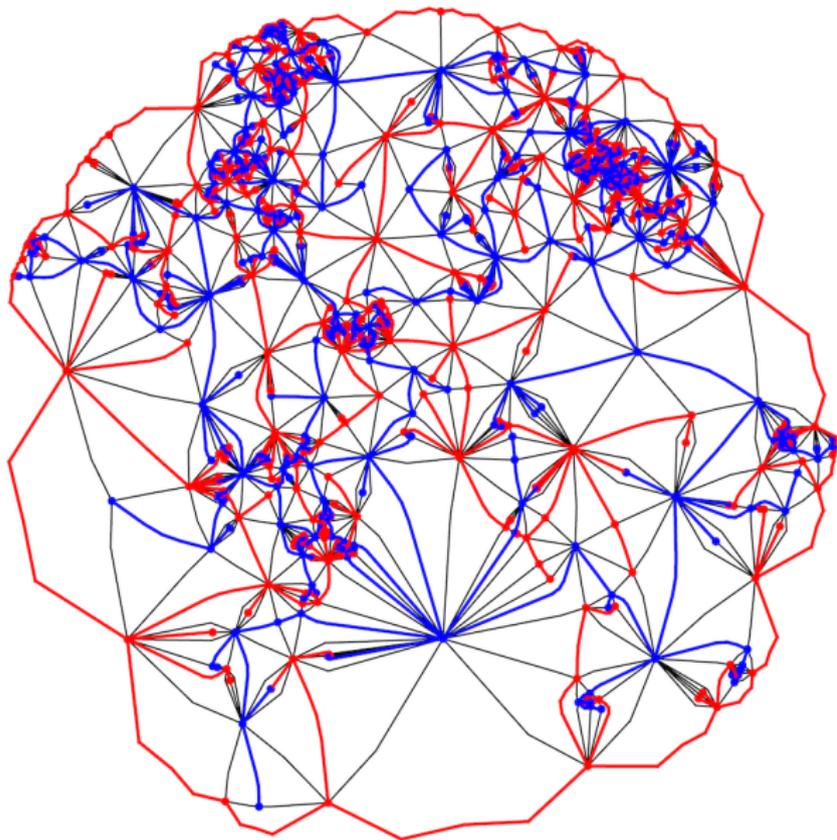
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Red and blue trees alone do not determine the map structure



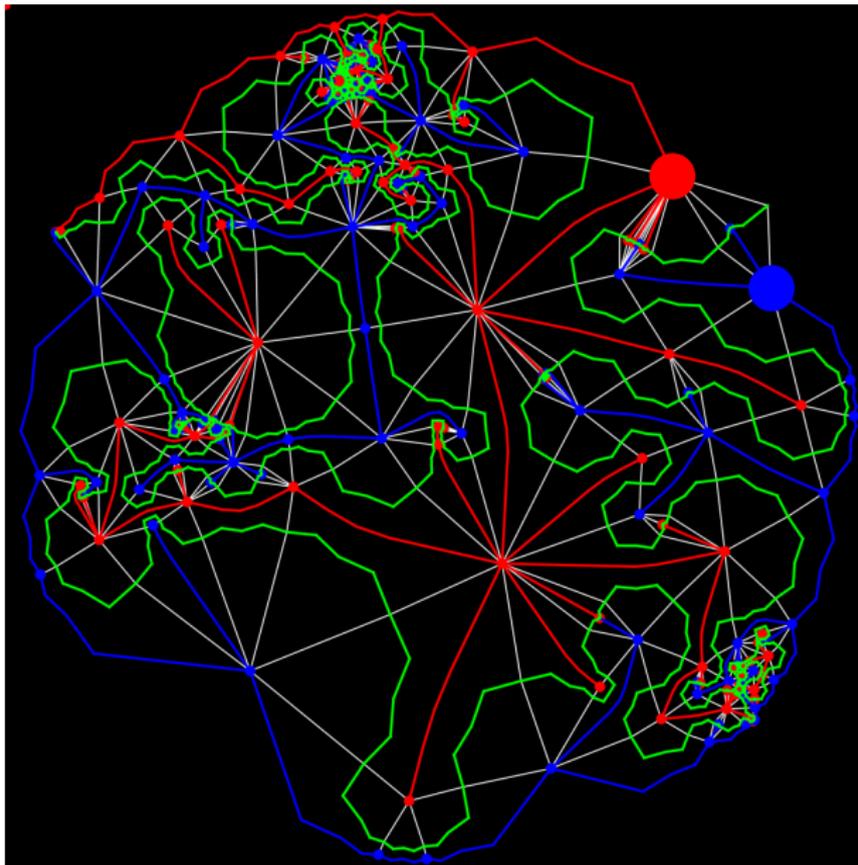
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Random quadrangulation with red and blue trees



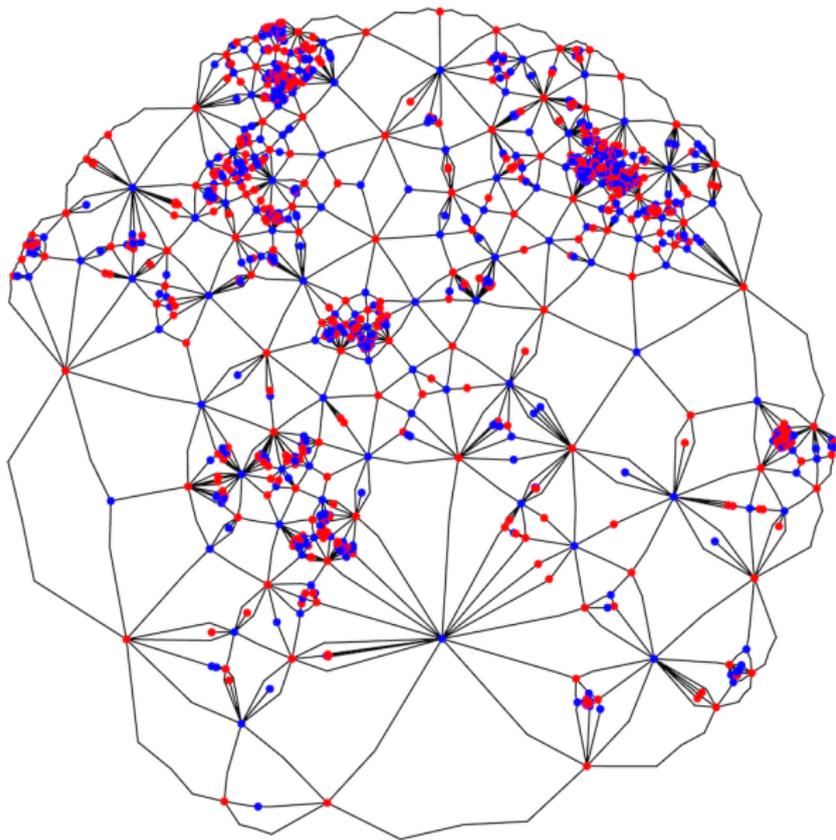
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Path snaking between the trees. Encodes the trees and how they are glued together.



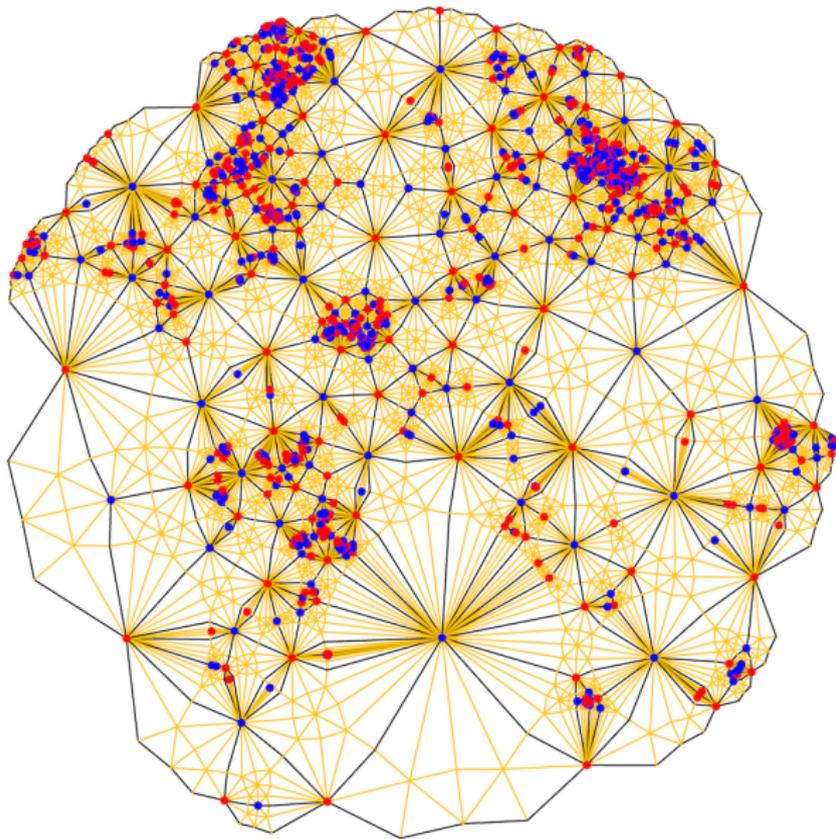
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How was the graph embedded into \mathbf{R}^2 ?



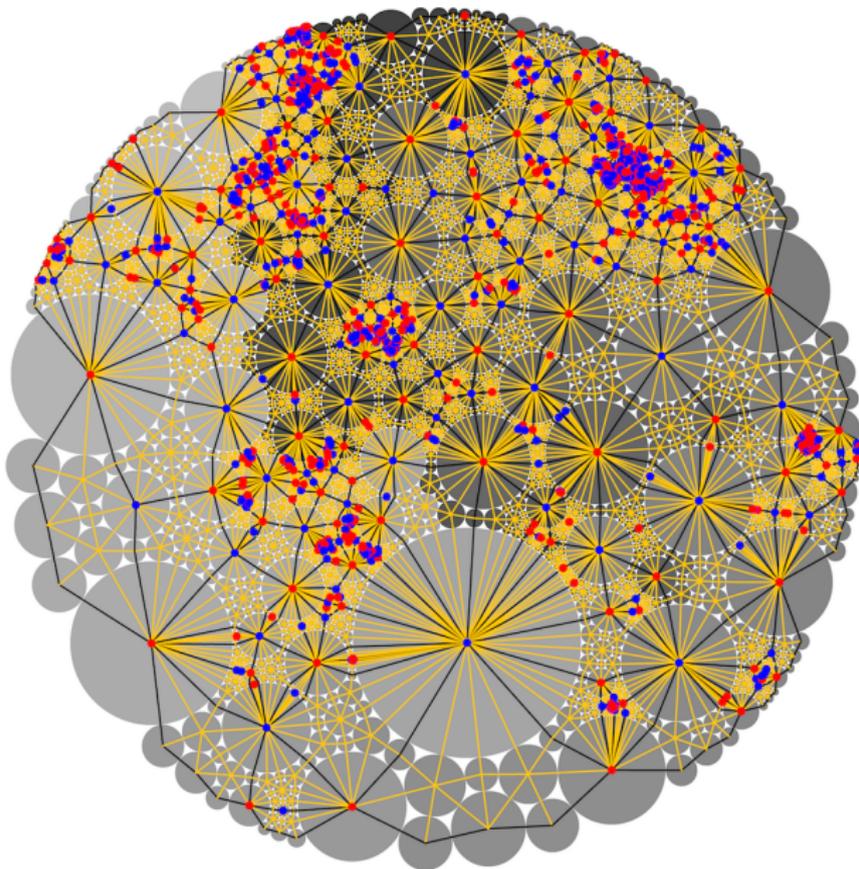
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Can subdivide each quadrilateral to obtain a triangulation without multiple edges.



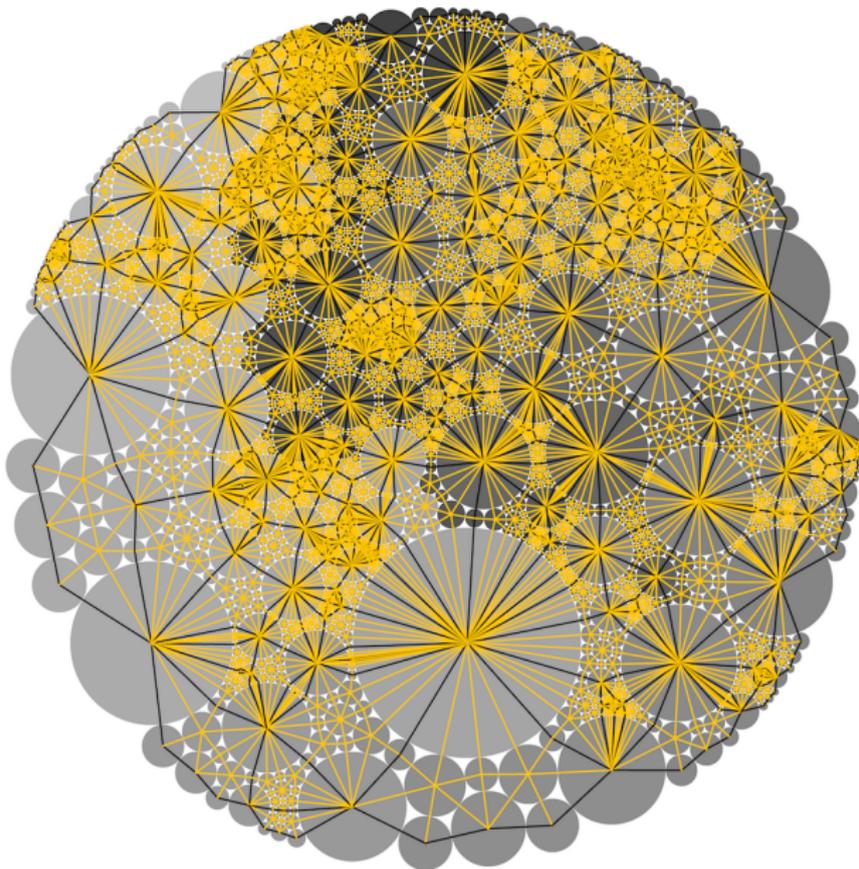
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Circle pack the resulting triangulation.



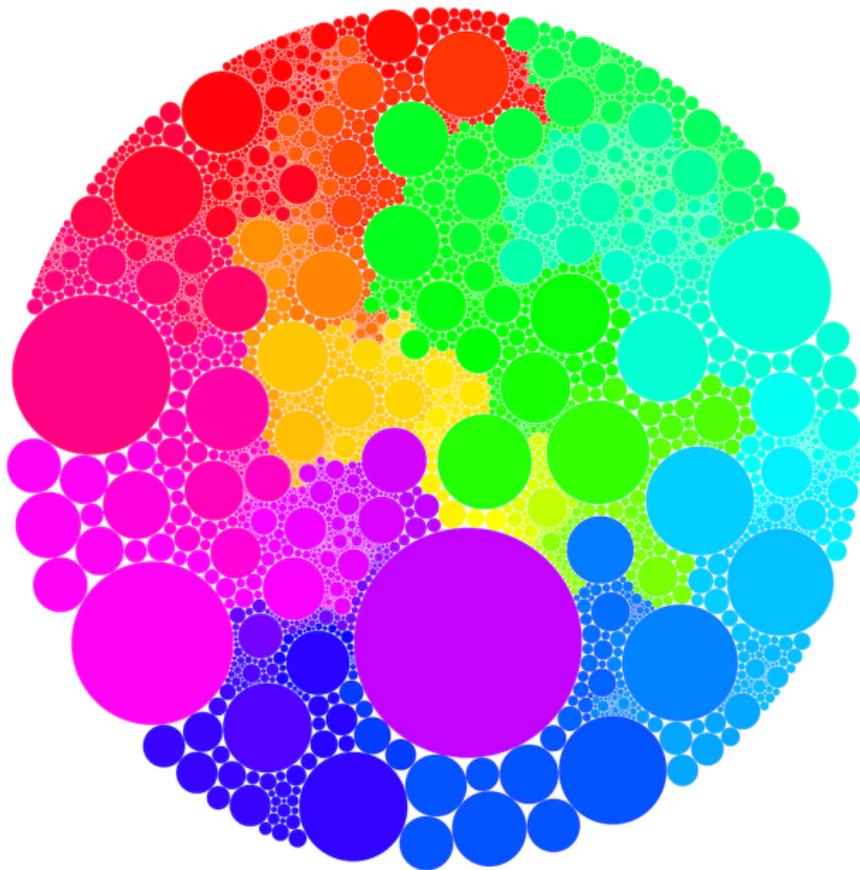
Sampled using H-C bijection. Packed with Stephenson's CirclePack.

Circle pack the resulting triangulation.



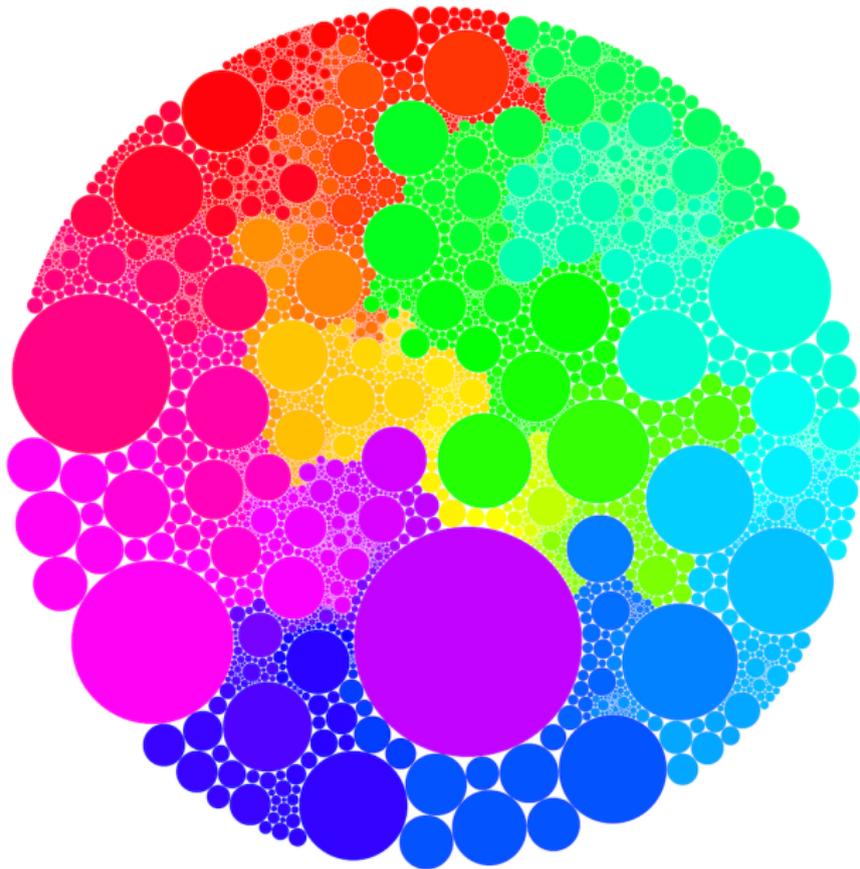
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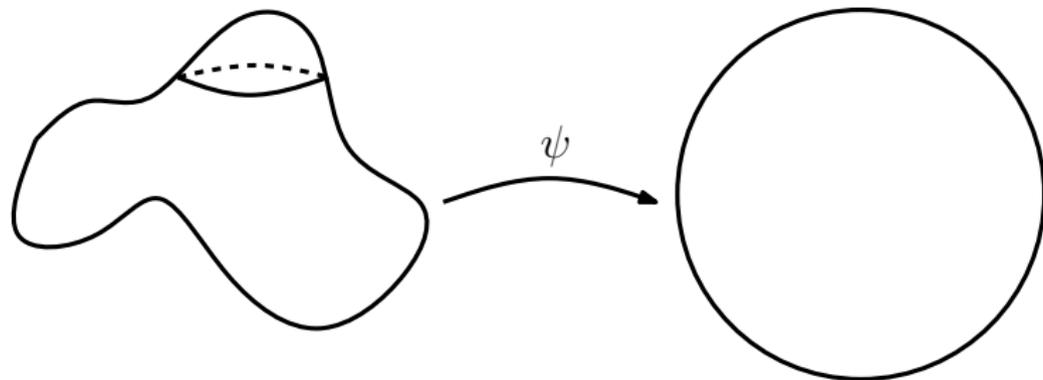
What is the “limit” of this embedding? Circle packings are related to conformal maps.



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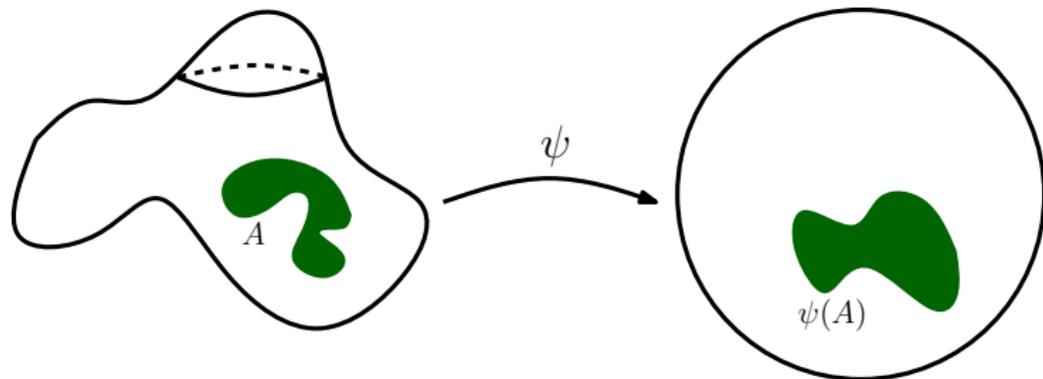
Picking a surface at random in the continuum

Uniformization theorem: every simply connected Riemannian surface can be conformally mapped to either the unit disk, the plane, or the sphere \mathbf{S}^2 in \mathbf{R}^3



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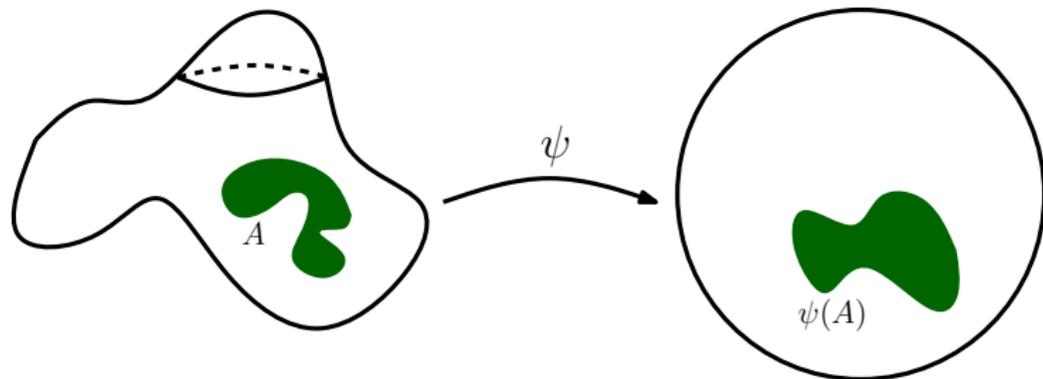
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Isothermal coordinates: Metric for the surface takes the form $e^{\rho(z)} dz$ for some smooth function ρ where dz is the Euclidean metric.

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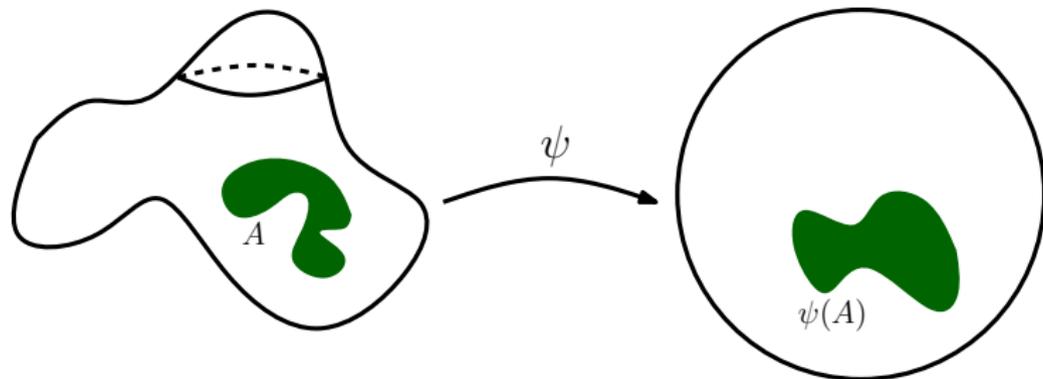
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⇒ Can parameterize the space of surfaces with smooth functions.

- ▶ If $\rho = 0$, get the same surface
- ▶ If $\Delta\rho = 0$, i.e. if ρ is harmonic, the surface described is flat

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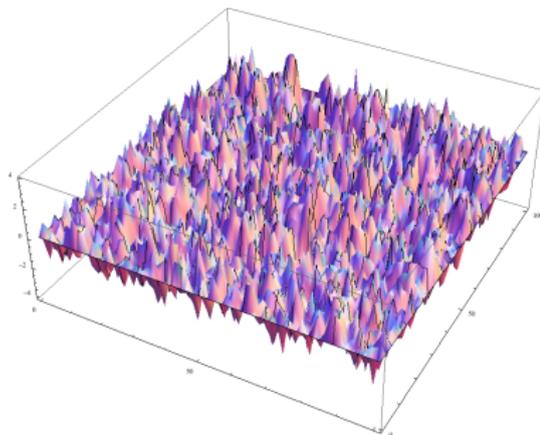
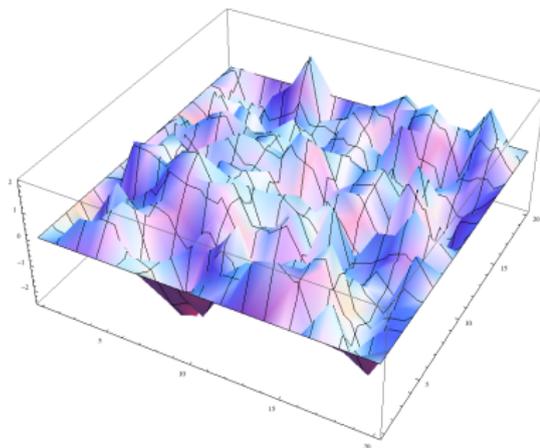
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Question: Which measure on ρ ? If we want our surface to be a perturbation of a flat metric, natural to choose ρ as the canonical perturbation of a harmonic function.

The Gaussian free field

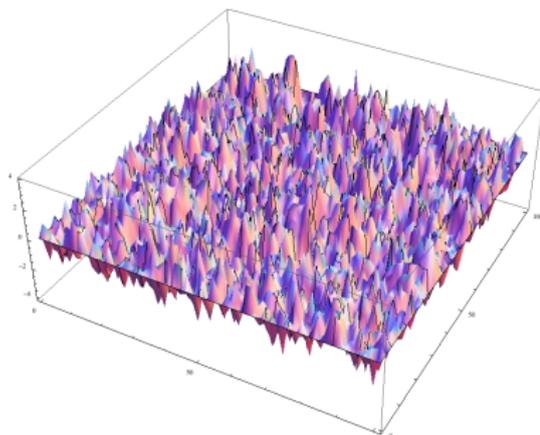
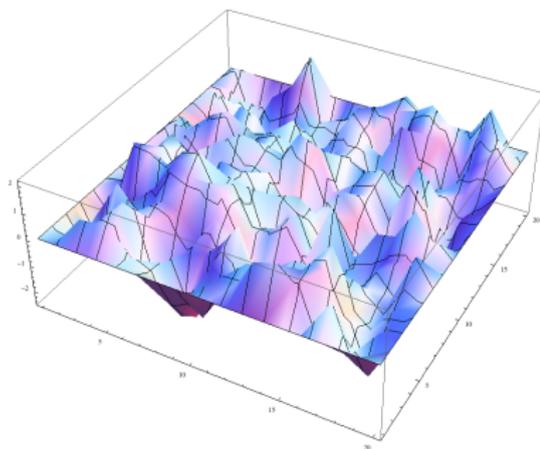
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- ▶ Measure on functions $h: D \rightarrow \mathbf{R}$ for $D \subseteq \mathbf{Z}^2$ and $h|_{\partial D} = \psi$ with density respect to Lebesgue measure on $\mathbf{R}^{|\mathcal{D}|}$:

$$\frac{1}{\mathcal{Z}} \exp \left(-\frac{1}{2} \sum_{x \sim y} (h(x) - h(y))^2 \right)$$

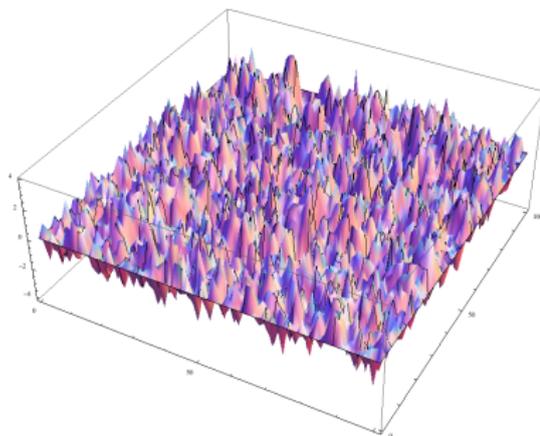
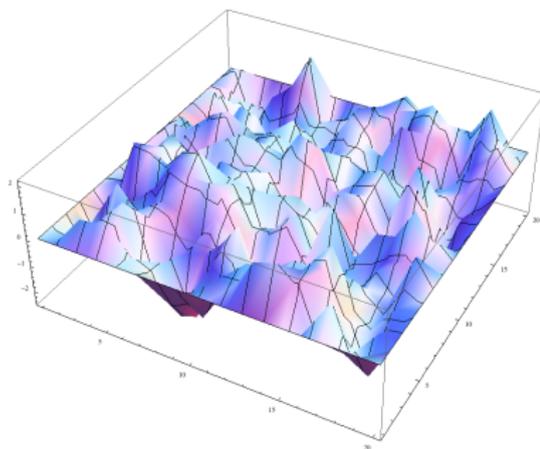


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- ▶ Natural perturbation of a harmonic function



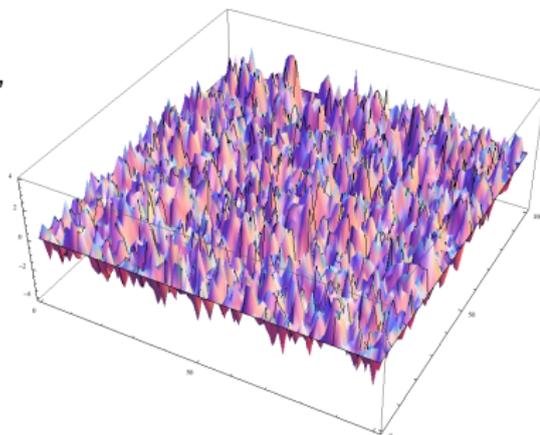
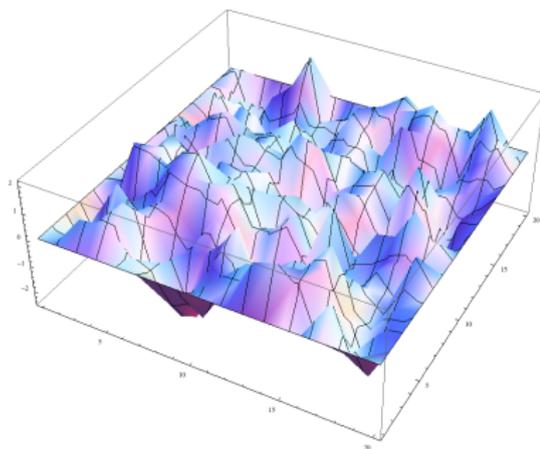
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- ▶ Fine mesh limit: converges to the continuum GFF, i.e. the standard Gaussian wrt the **Dirichlet inner product**

$$(f, g)_{\nabla} = \frac{1}{2\pi} \int \nabla f(x) \cdot \nabla g(x) dx.$$



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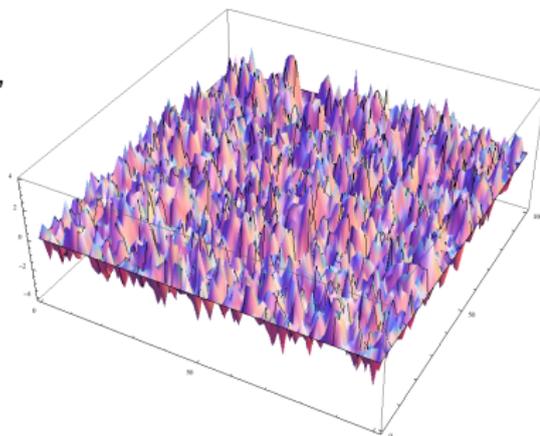
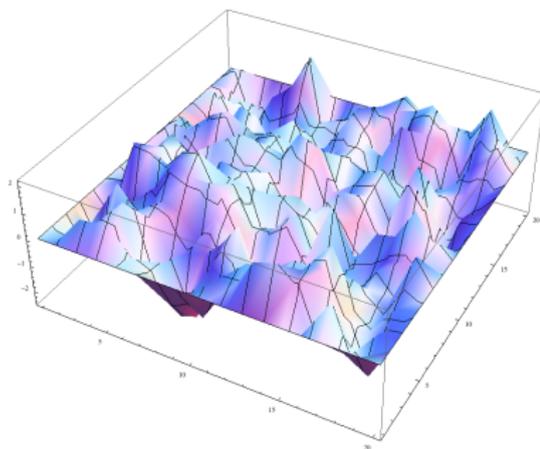
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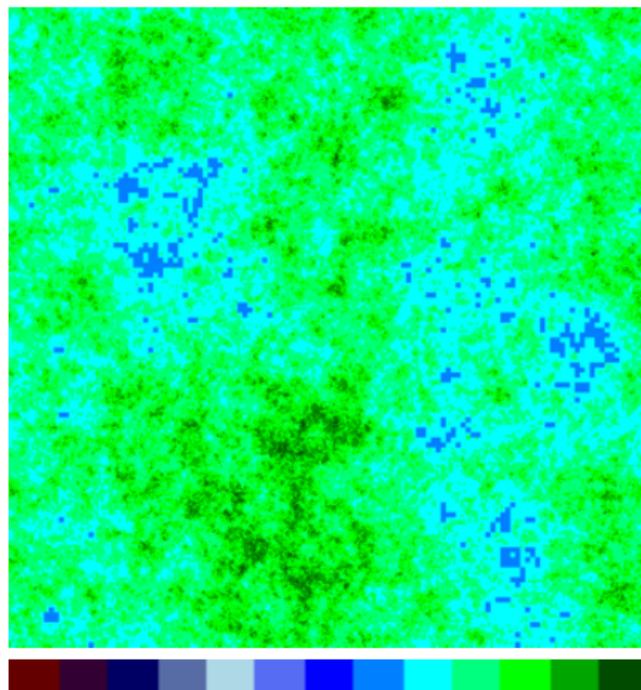
- ▶ Continuum GFF not a function — only a generalized function



Liouville quantum gravity

- ▶ Liouville quantum gravity: $e^{\gamma h(z)} dz$
where h is a GFF and $\gamma \in [0, 2)$

$$\gamma = 0.5$$

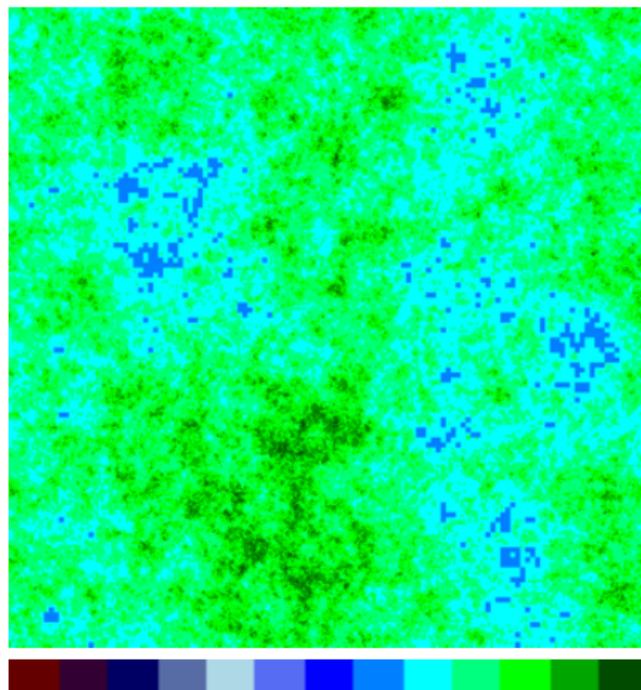


(Number of subdivisions)

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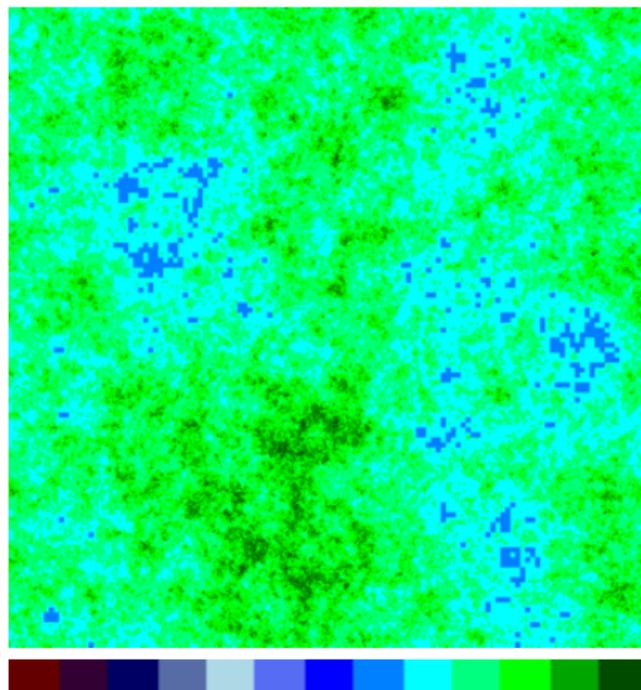


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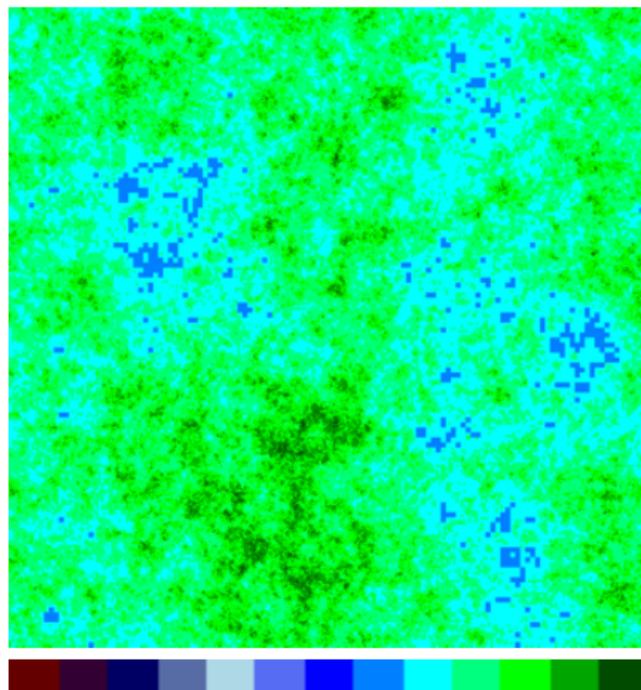


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 - ▶ Can compute areas of regions and lengths of curves

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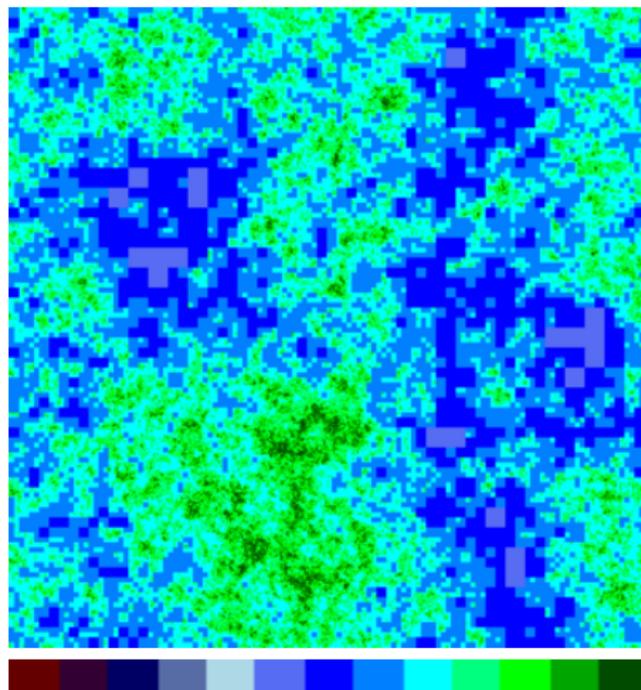


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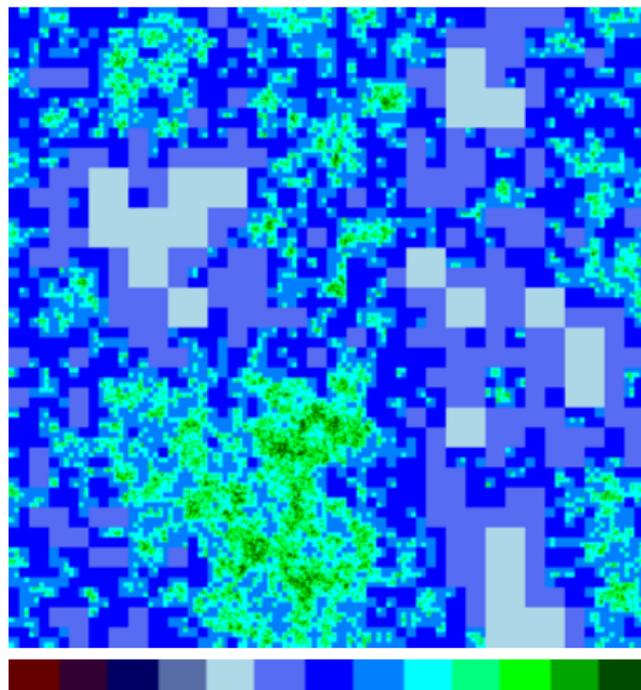


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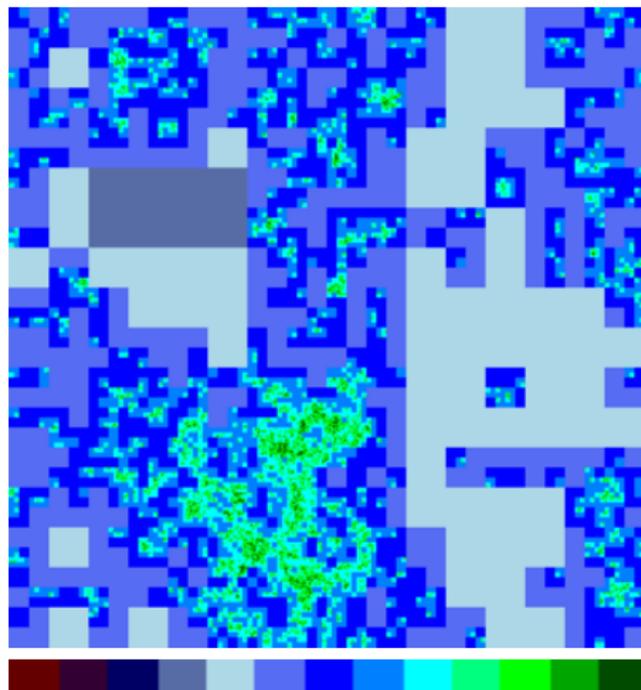


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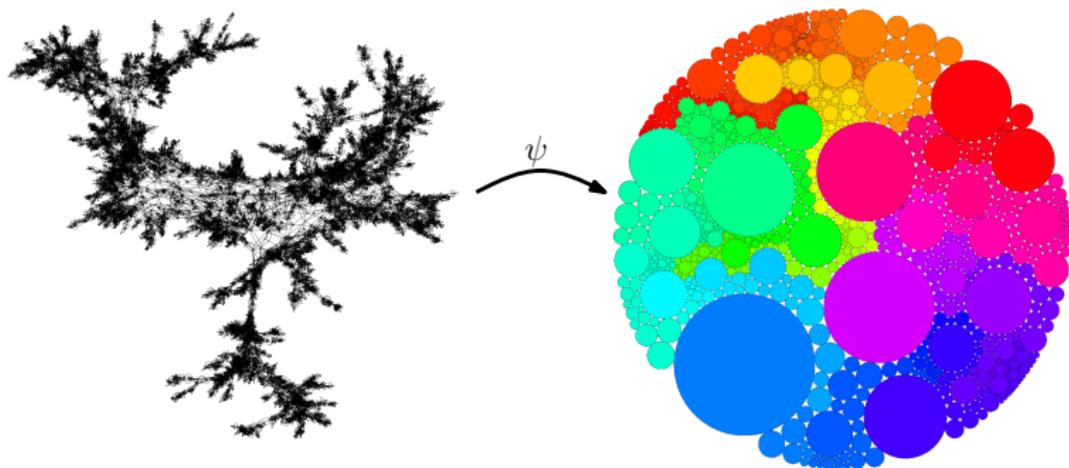
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 - ▶ Can compute areas of regions and lengths of curves

$$\gamma = 2.0$$

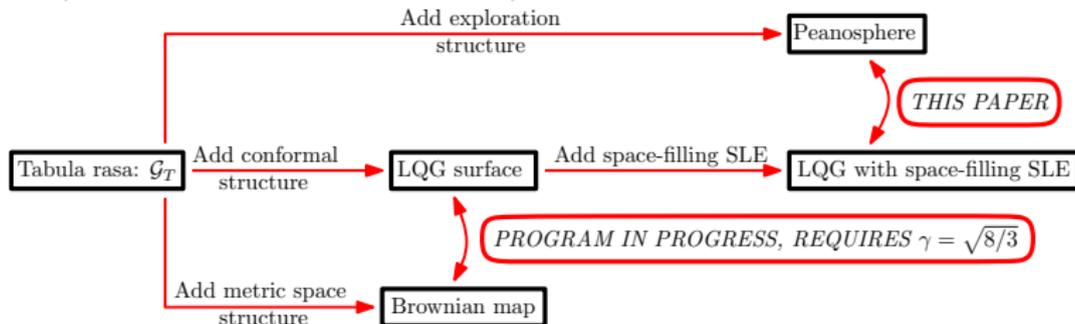


(Number of subdivisions)

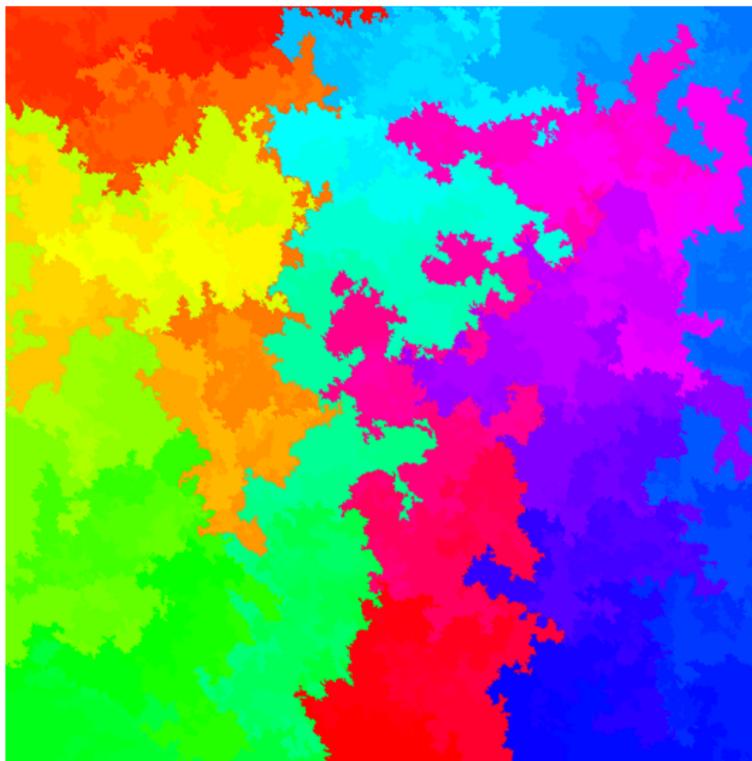
Paper with Duplantier/Miller gives form of convergence



(Simulation due to J.-F. Marckert)



Continuum space-filling path



Space-filling SLE_6 on a LQG surface. Random path which encodes the limit of a RPM.

Part II: Quantum Loewner Evolution

Recap

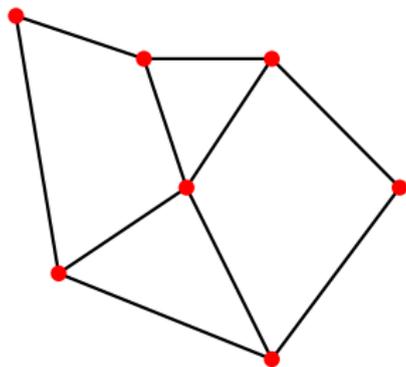
Two natural ways to pick surfaces at random

- ▶ **Discrete:** random planar maps
- ▶ **Continuum:** Liouville quantum gravity $e^{\gamma h(z)} dz$, h a GFF
- ▶ Conjectured to be the same for $\gamma = \sqrt{8/3}$
- ▶ LQG only made sense of so far as a **measure space**

Next part: describe new growth process which can be used to endow $\sqrt{8/3}$ -LQG with a metric space structure

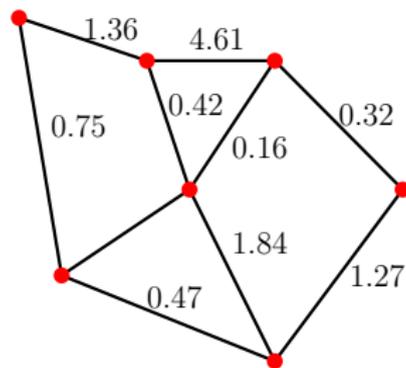
Detour: first passage percolation (FPP)

- ▶ Associate with a graph (V, E) i.i.d. $\text{exp}(1)$ edge weights



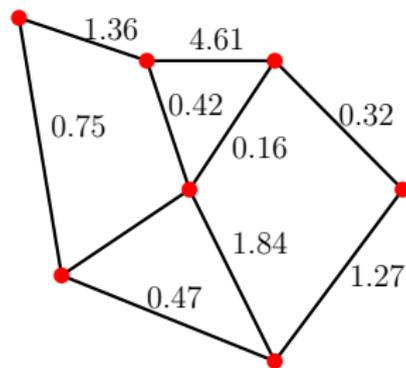
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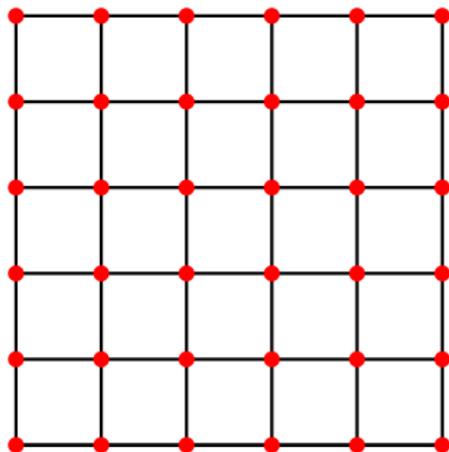
Detour: first passage percolation (FPP)

- ▶ Associate with a graph (V, E) i.i.d. $\text{exp}(1)$ edge weights
- ▶ Introduced by Eden (1961) and Hammersley and Welsh (1965)



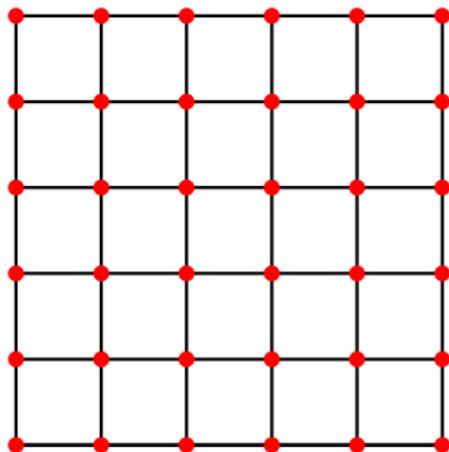
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- ▶ Associate with a graph (V, E) i.i.d. $\exp(1)$ edge weights
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- ▶ On \mathbf{Z}^2 ?



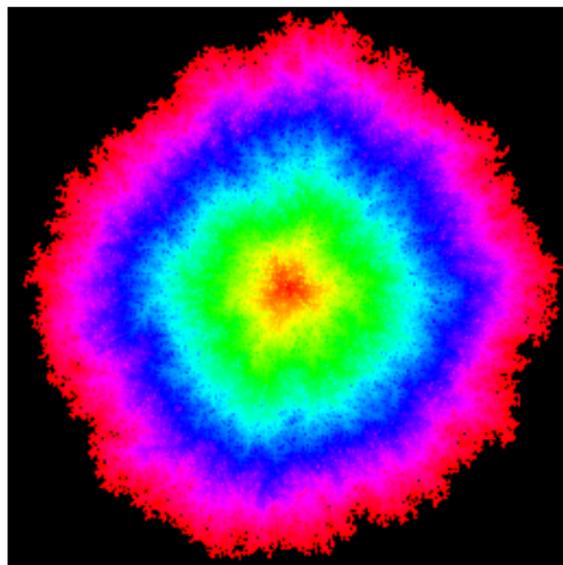
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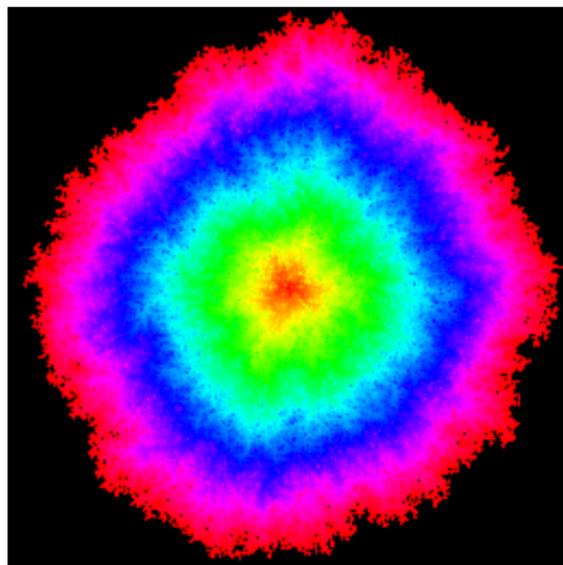
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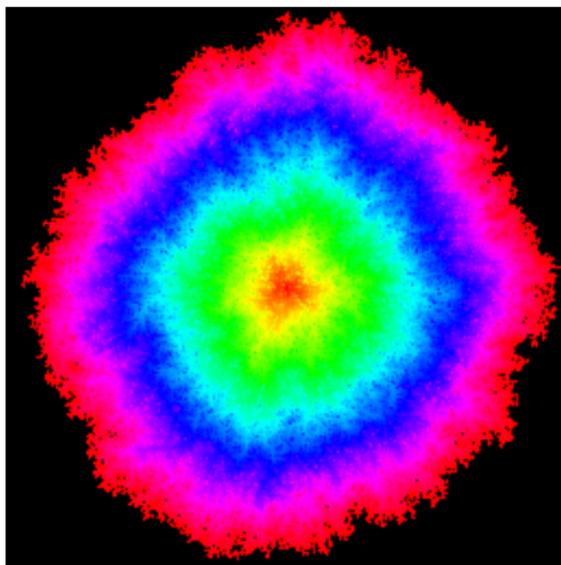
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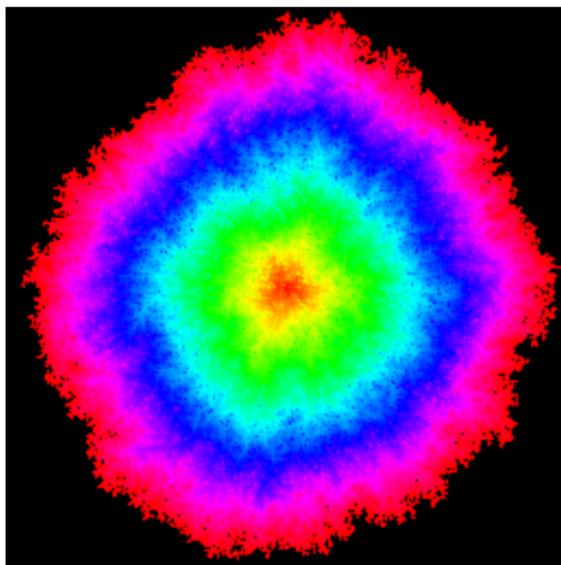
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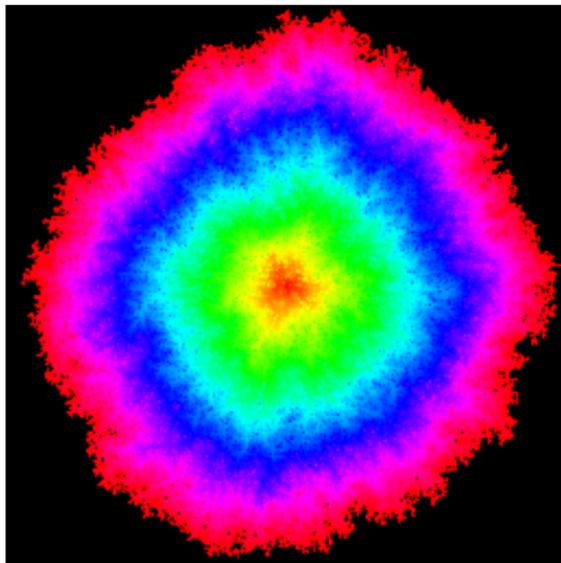
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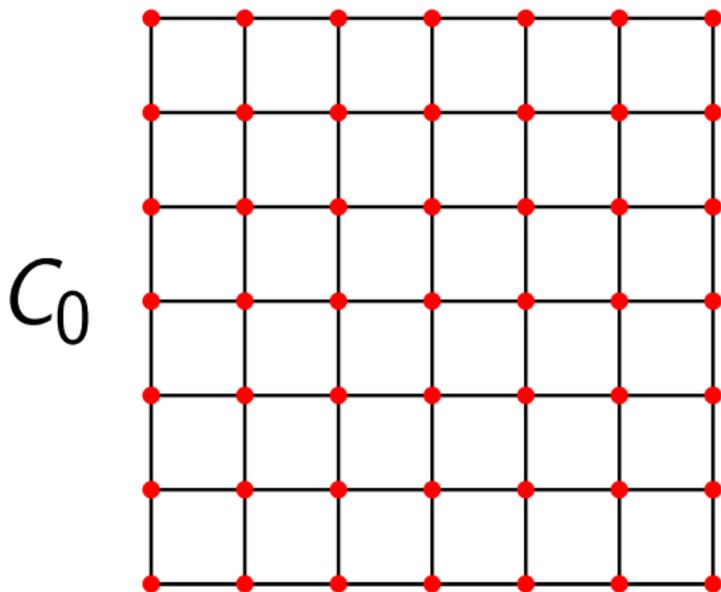
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- ▶ Cox and Durrett (1981) showed that the macroscopic shape is convex
- ▶ Computer simulations show that it is not a Euclidean disk
- ▶ \mathbf{Z}^2 is not isotropic enough
- ▶ Vahidi-Asl and Weirmann (1990) showed that the rescaled ball converges to a disk if \mathbf{Z}^2 is replaced by the Voronoi tessellation associated with a Poisson process



Markovian formulation

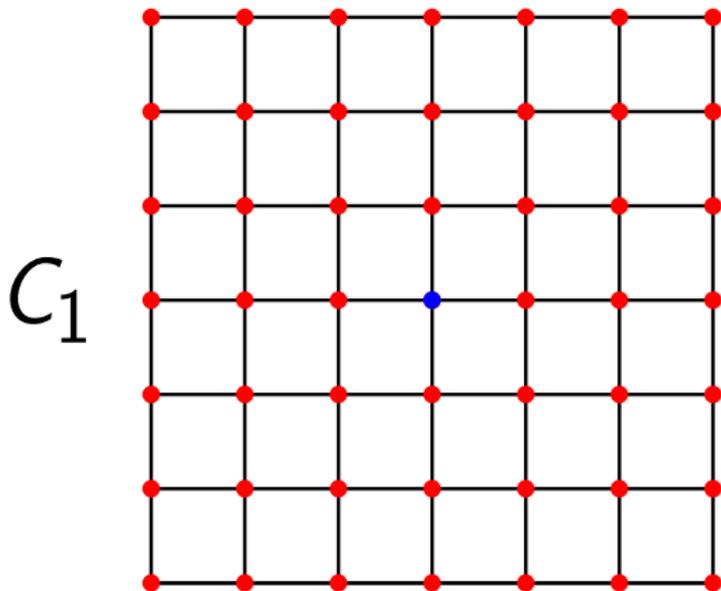
Rather than sampling all of the edge weights at once, can explore the FPP metric ball starting from a point in a Markovian way.



Due to the memoryless property of the exponential distribution, can sample the cluster C_{n+1} from C_n by selecting an edge uniformly at random on ∂C_n , and then adding the vertex which is attached to it.

Markovian formulation

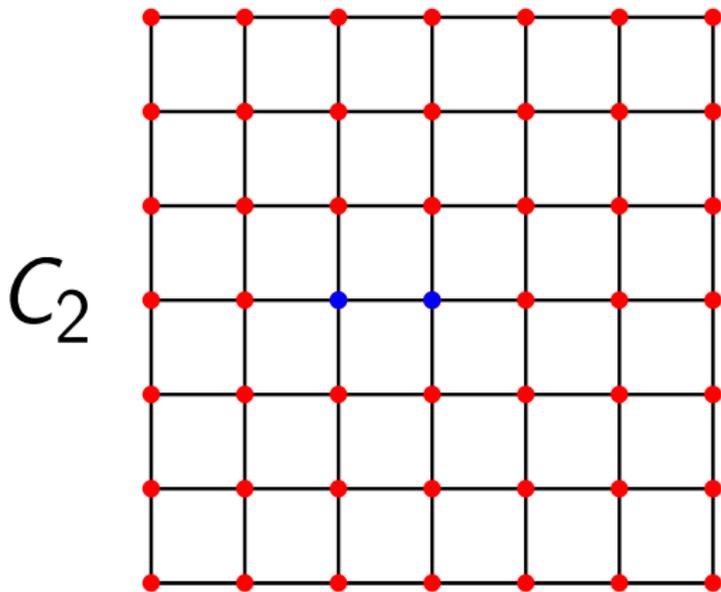
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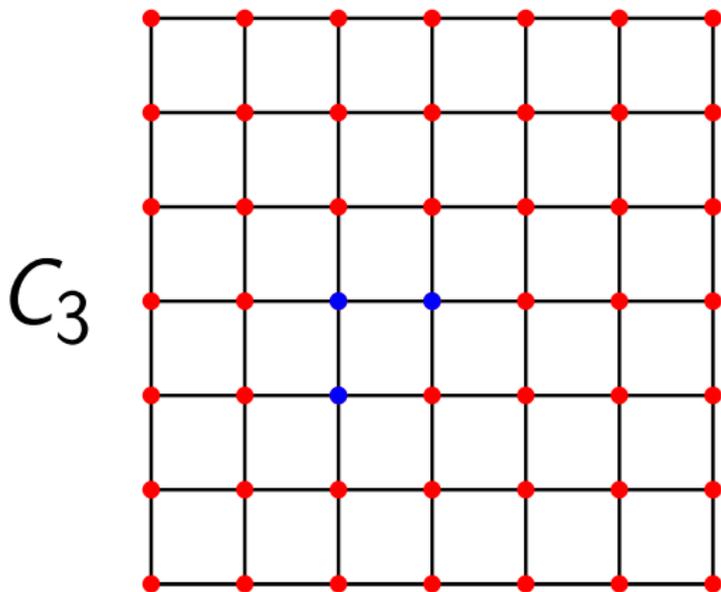
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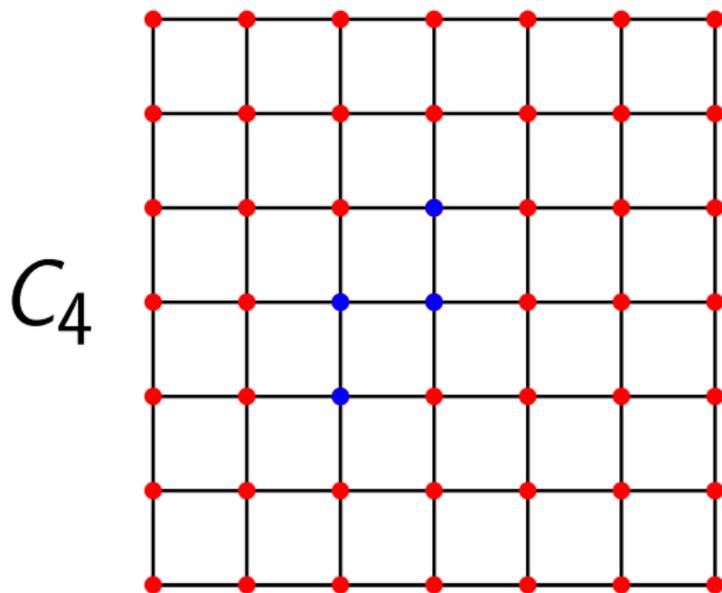
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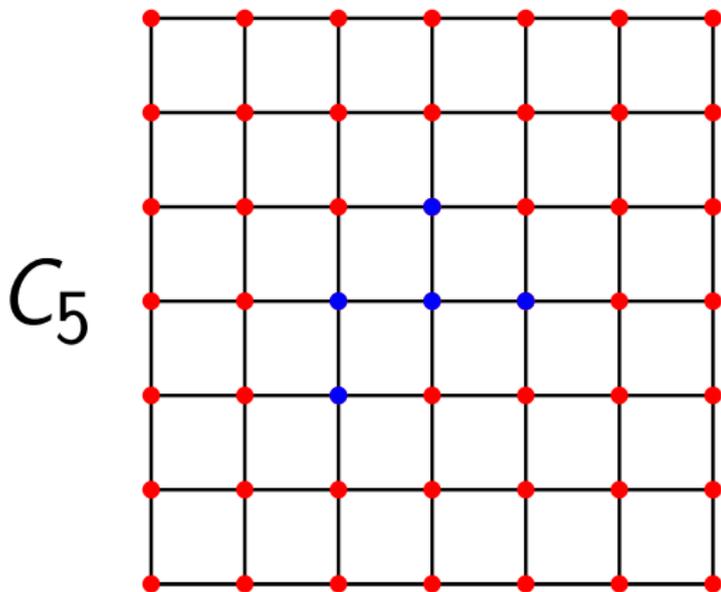
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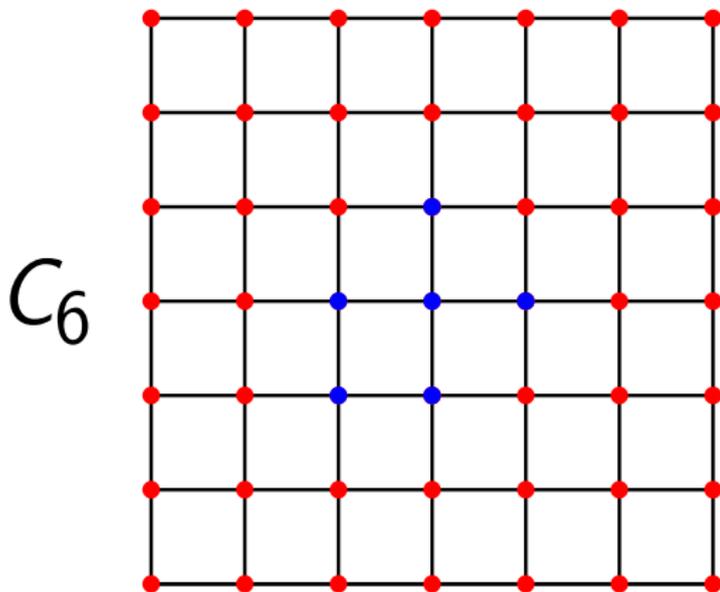
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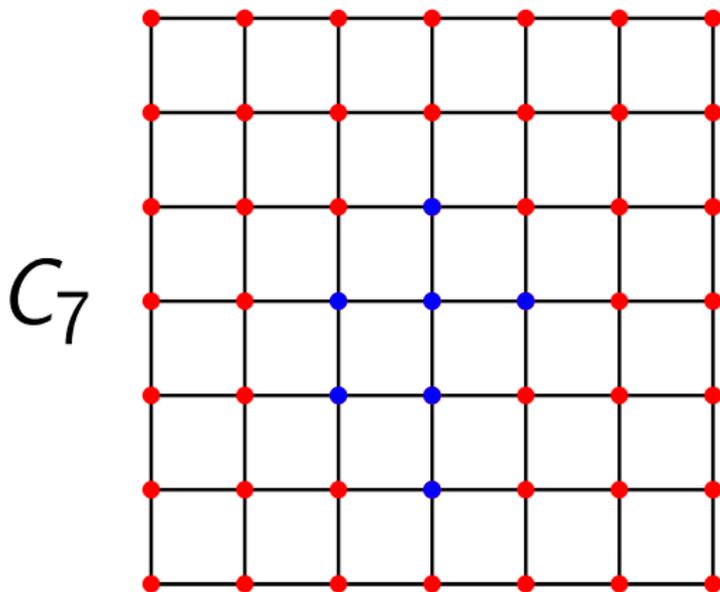
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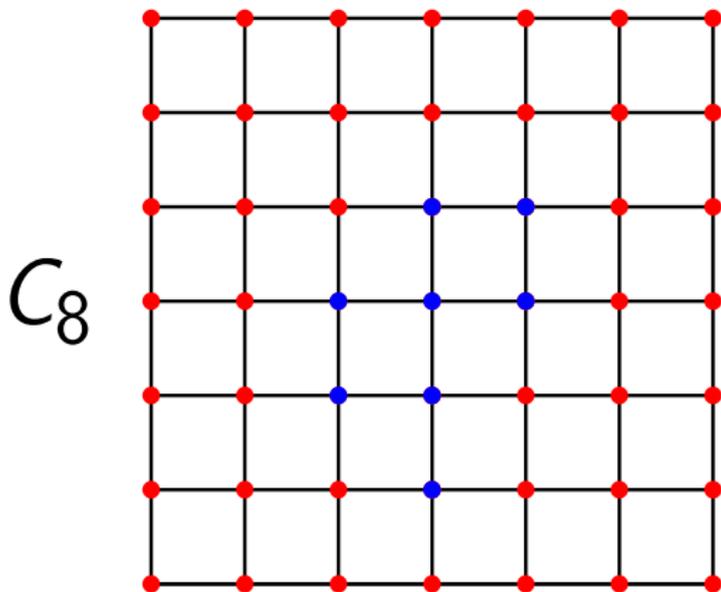
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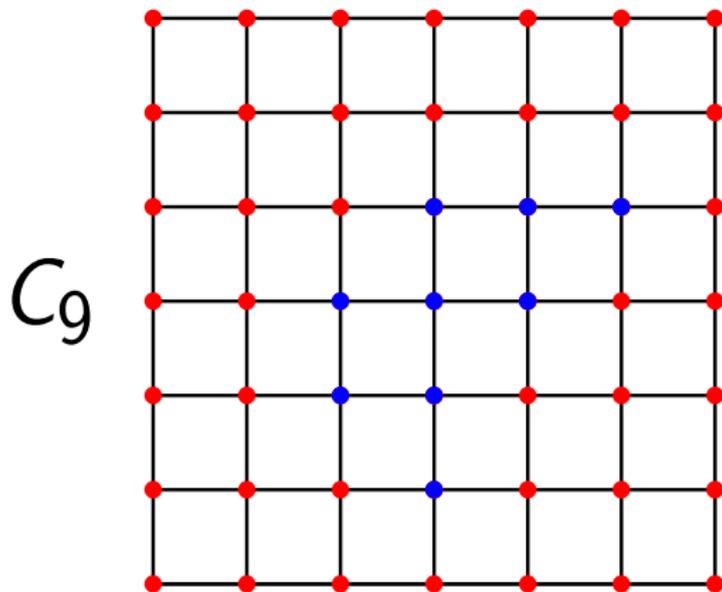
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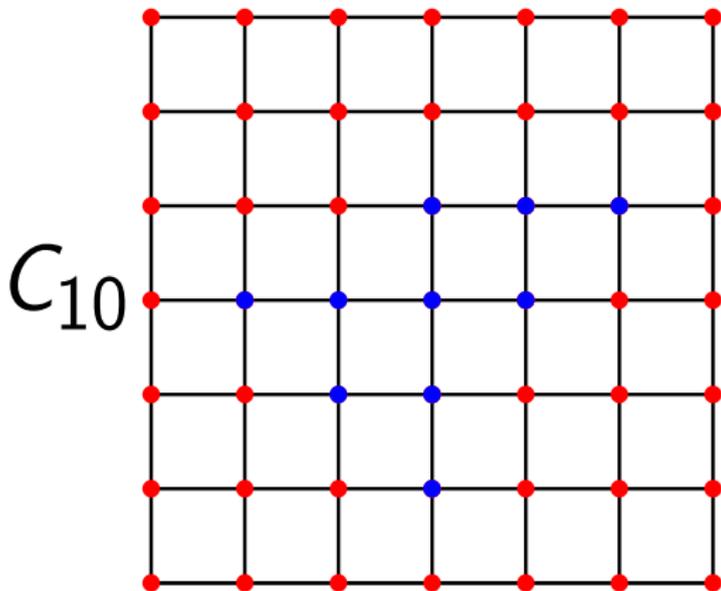
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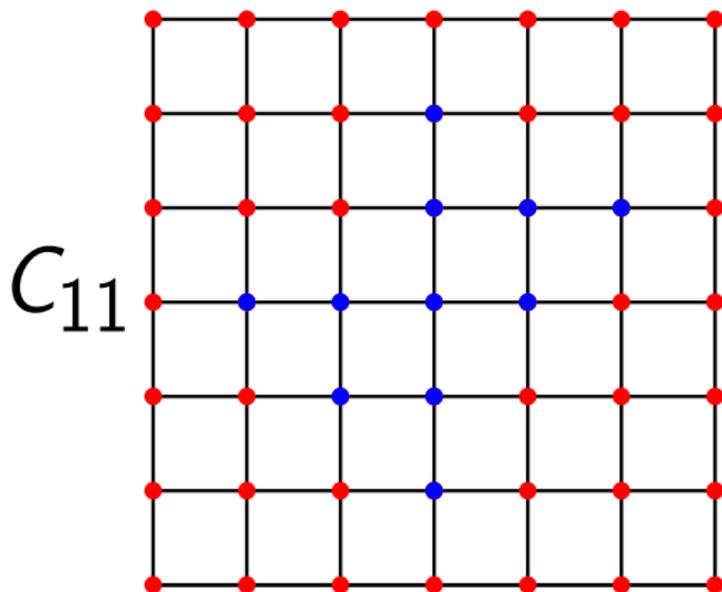
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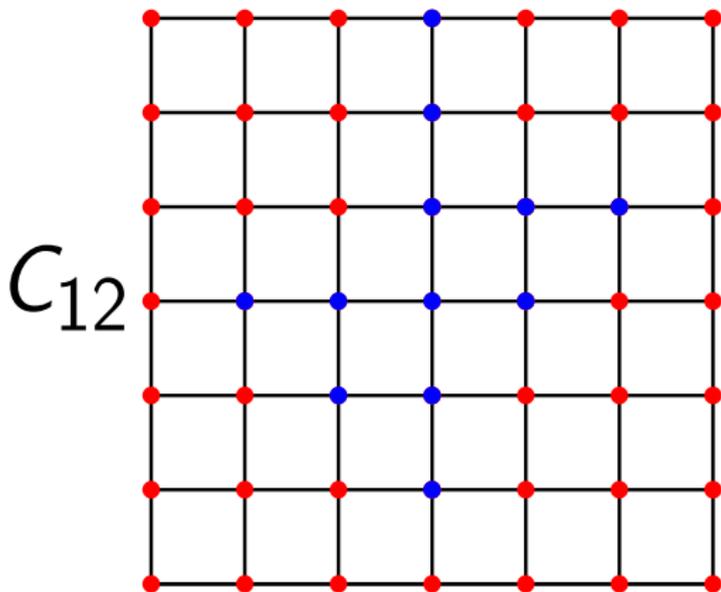
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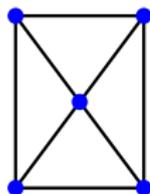
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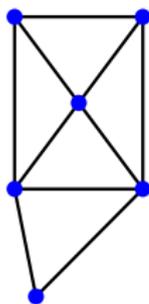
First passage percolation on random planar maps I

- ▶ Random planar map, random vertex x . Perform FPP from x .



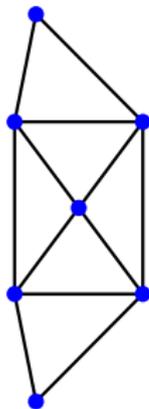
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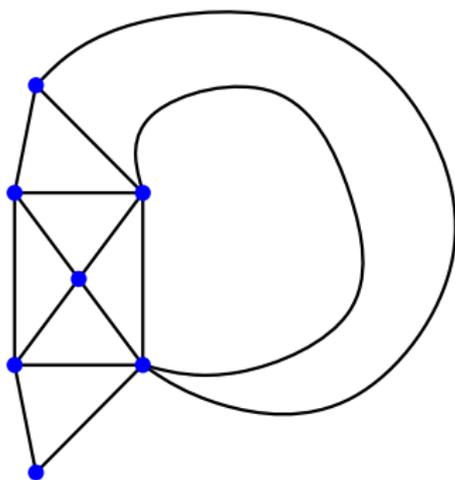
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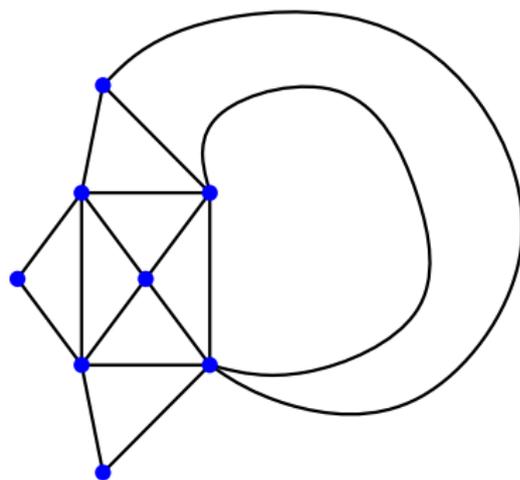
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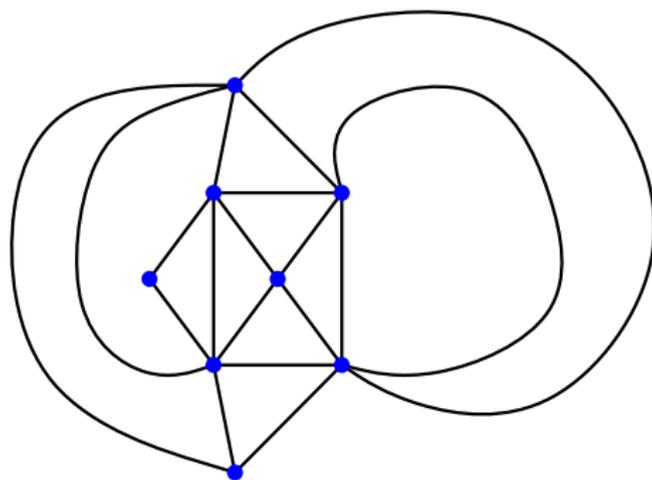
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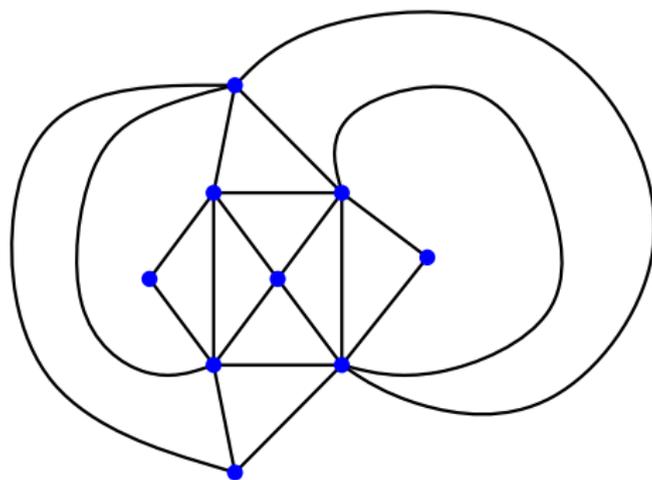
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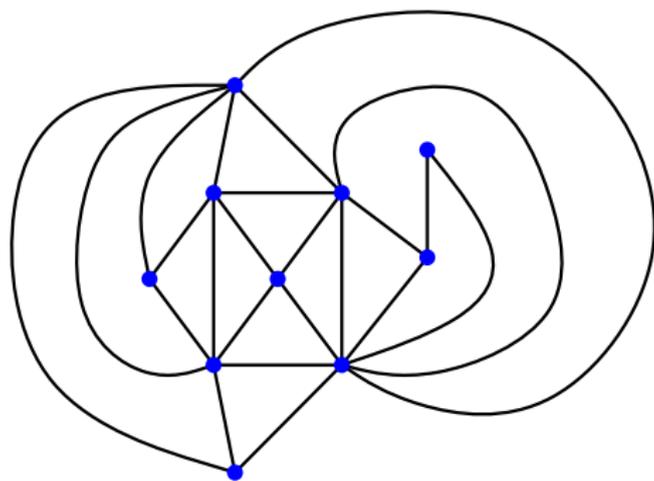
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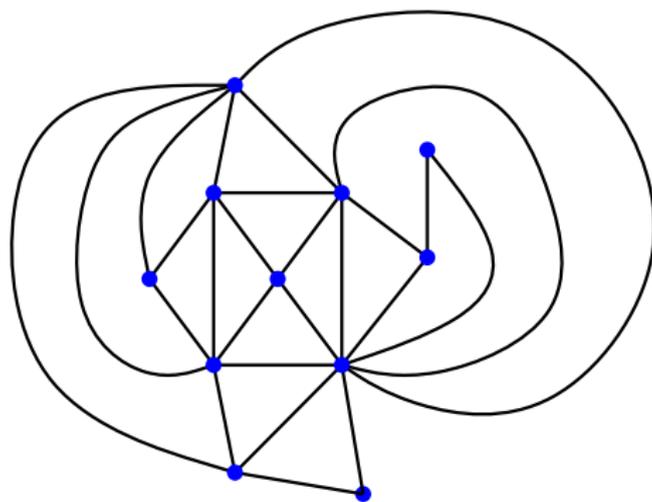
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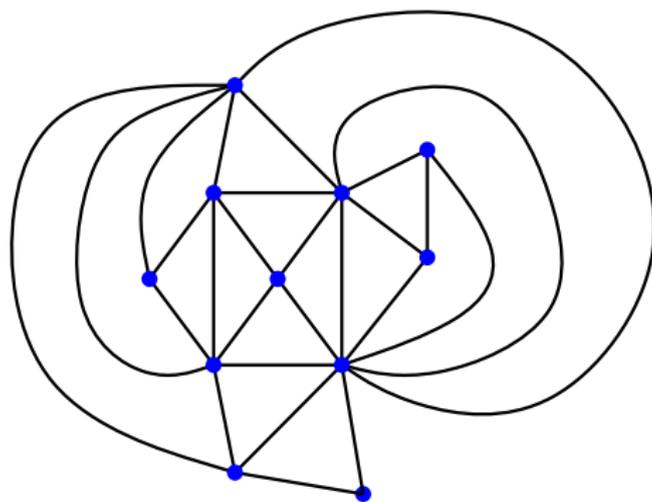
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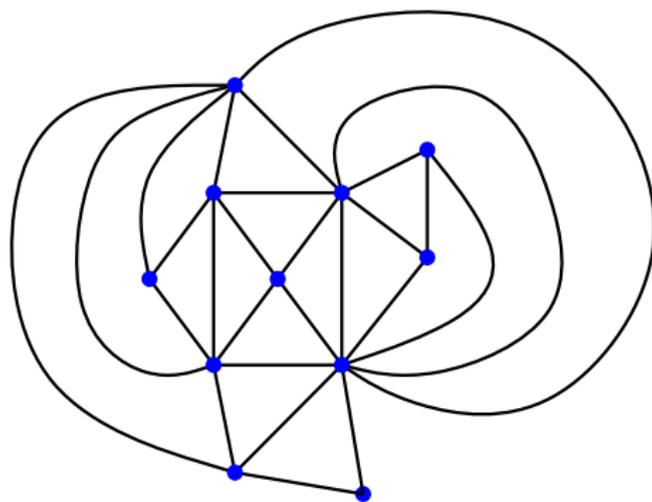
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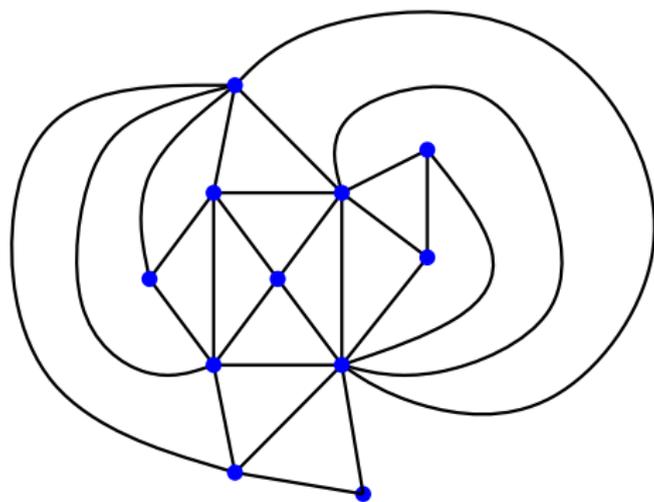


Important observations:

- ▶ Conditional law of map given ball at time n only depends on the boundary lengths of the outside components.

First passage percolation on random planar maps I

- ▶ Random planar map, random vertex x . Perform FPP from x .

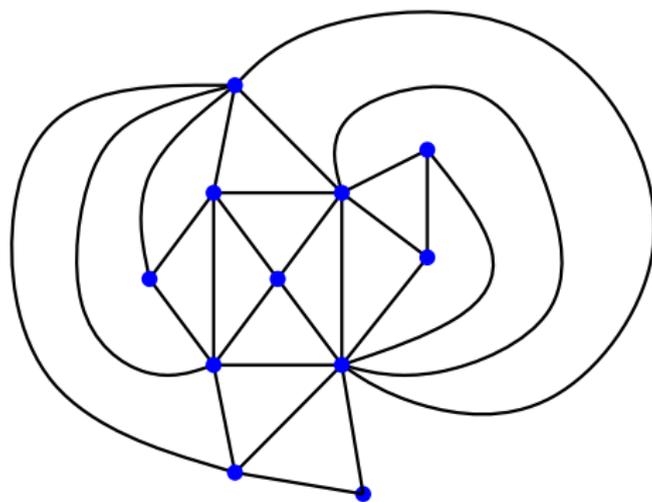


Important observations:

- ▶ Conditional law of map given ball at time n only depends on the boundary lengths of the outside components. *Exploration respects the Markovian structure of the map.*

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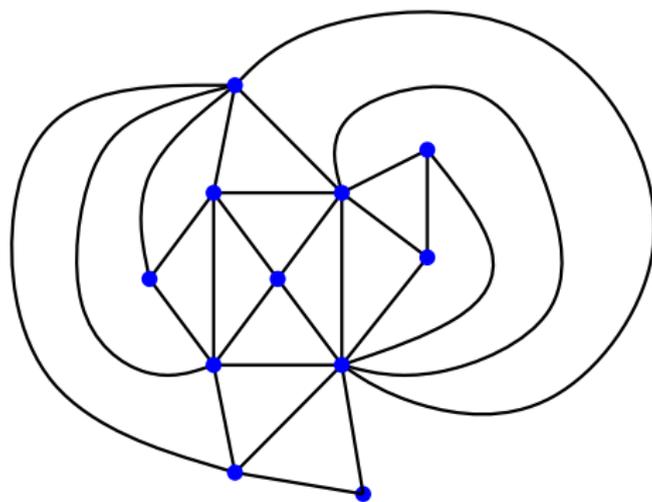


Important observations:

- ▶ Conditional law of map given ball at time n only depends on the boundary lengths of the outside components. *Exploration respects the Markovian structure of the map.*
- ▶ If we work on an “infinite” planar map, the conditional law of the map in the unbounded component only depends on the boundary length

First passage percolation on random planar maps I

- ▶ Random planar map, random vertex x . Perform FPP from x .



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Belief: Isotropic enough so that at large scales this is close to a ball in the graph metric

First passage percolation on random planar maps II

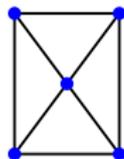
Goal: Make sense of FPP in the continuum on top of a LQG surface

- ▶ We do not know how to take a continuum limit of FPP on a random planar map and couple it directly with LQG
- ▶ Explain a discrete variant of FPP that involves two operations that we do know how to perform in the continuum:
 - ▶ Sample random points according to boundary length
 - ▶ Draw (scaling limits of) critical percolation interfaces (SLE_6)

First passage percolation on random planar maps III

Variant:

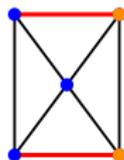
- ▶ Pick two **edges** on outer boundary of cluster



First passage percolation on random planar maps III

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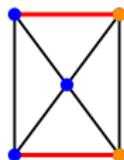
- ▶ Pick two **edges** on outer boundary of cluster
- ▶ Color vertices between edges blue and yellow



First passage percolation on random planar maps III

Variant:

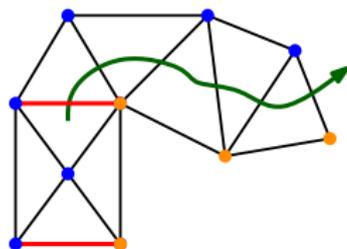
- ▶ Pick two **edges** on outer boundary of cluster
- ▶ Color vertices between edges blue and yellow
- ▶ Color vertices on rest of map blue or yellow with prob. $\frac{1}{2}$



First passage percolation on random planar maps III

Variant:

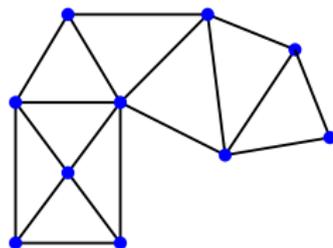
- ▶ Pick two **edges** on outer boundary of cluster
- ▶ Color vertices between edges blue and yellow
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- ▶ Explore percolation (blue/yellow) interface



First passage percolation on random planar maps III

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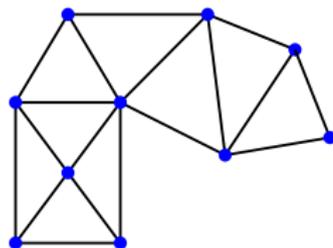
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- ▶ Forget colors



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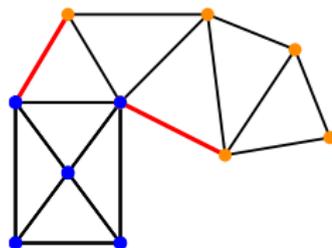
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First passage percolation on random planar maps III

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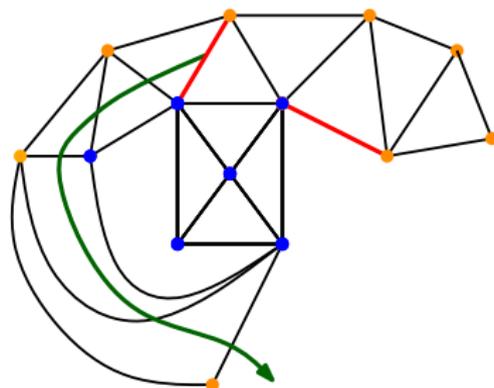
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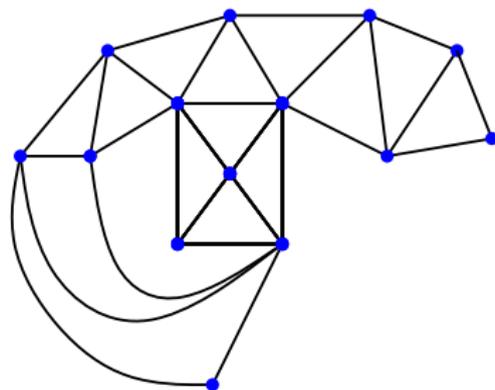
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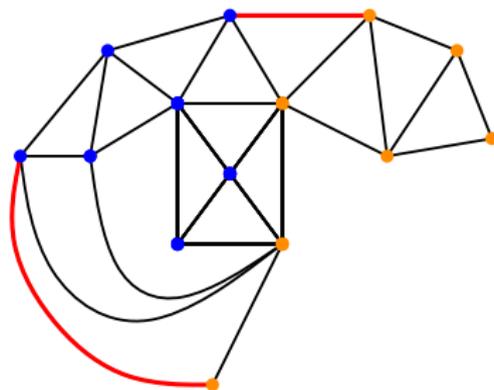
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First passage percolation on random planar maps III

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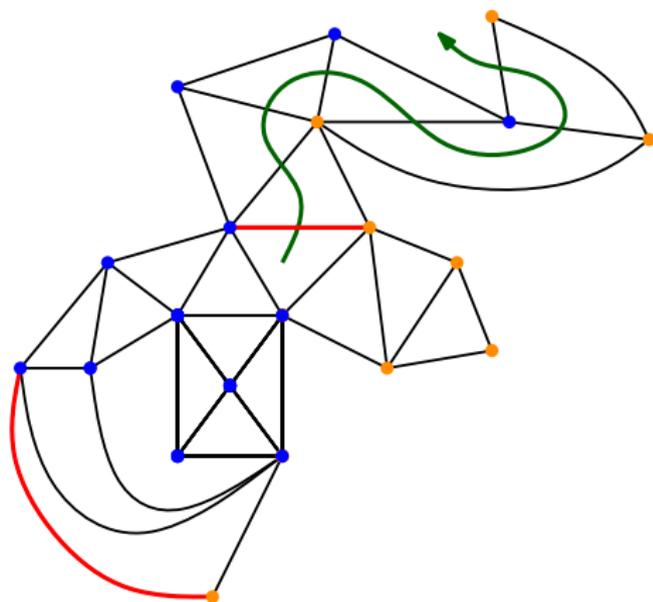
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First passage percolation on random planar maps III

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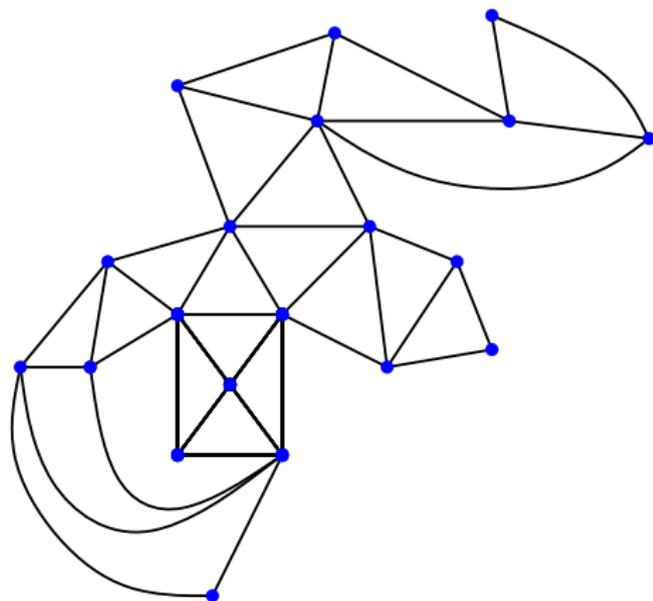
- ▶ Pick two **edges** on outer boundary of cluster
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- ▶ Explore percolation (blue/yellow) interface
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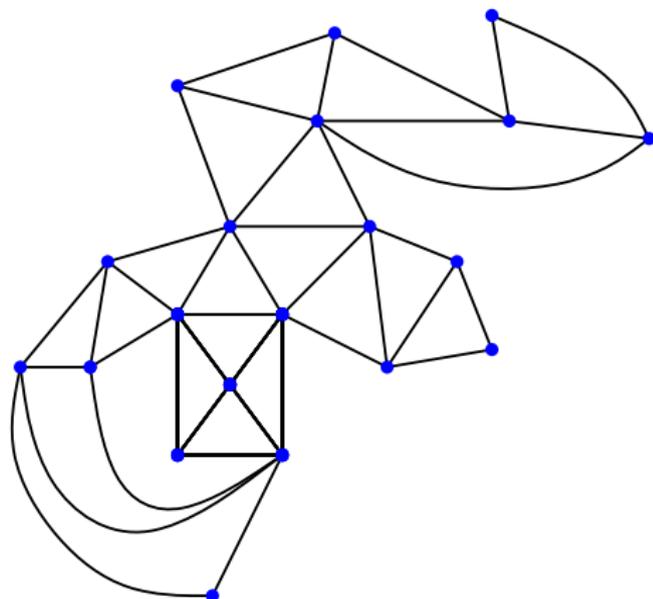
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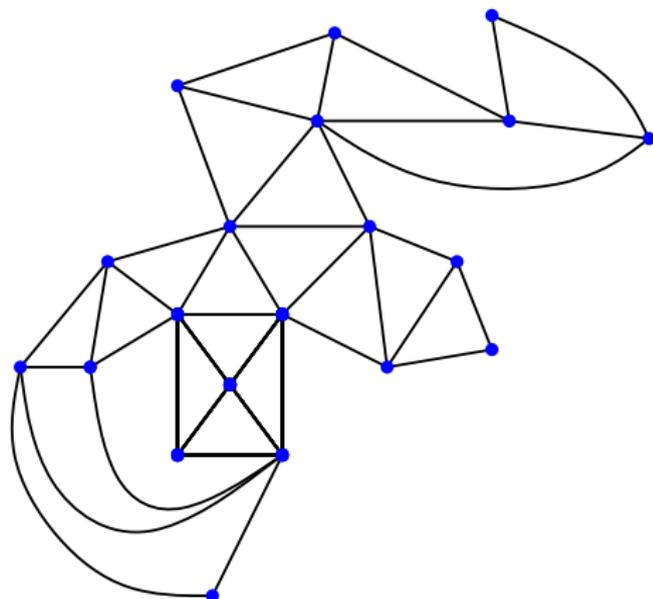
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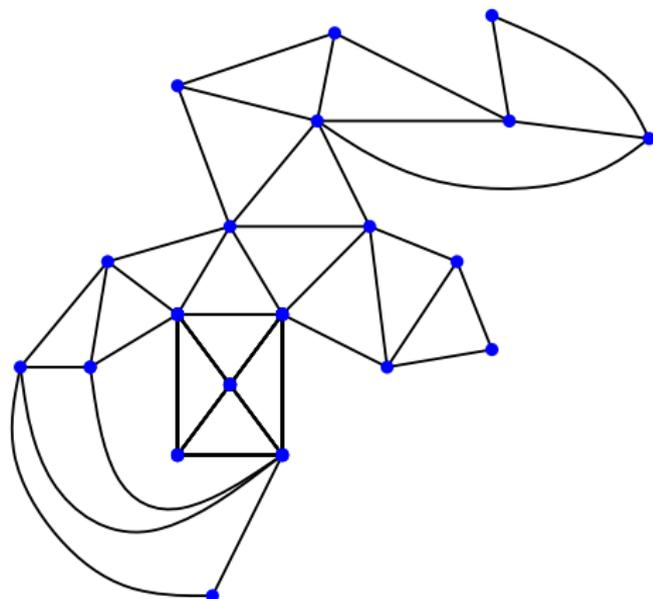
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- ▶ If we work on an “infinite” planar map, the conditional law of the map in the unbounded component only depends on the boundary length.



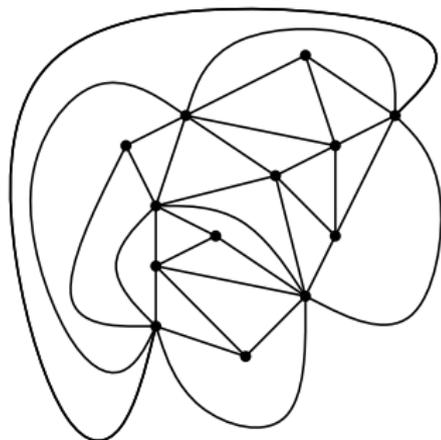
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- ▶ *This exploration also respects the Markovian structure of the map.*
- ▶ If we work on an “infinite” planar map, the conditional law of the map in the unbounded component only depends on the boundary length.
- ▶ Expect that at large scales this growth process looks the same as FPP, hence the same as the graph metric ball

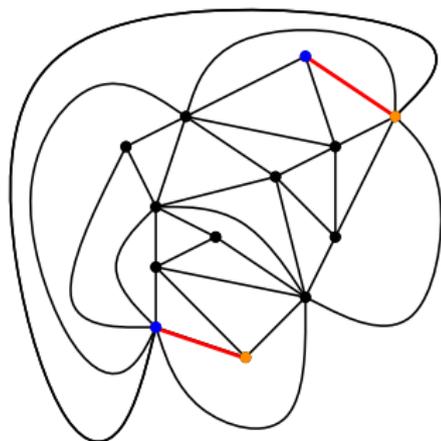


Continuum limit ansatz



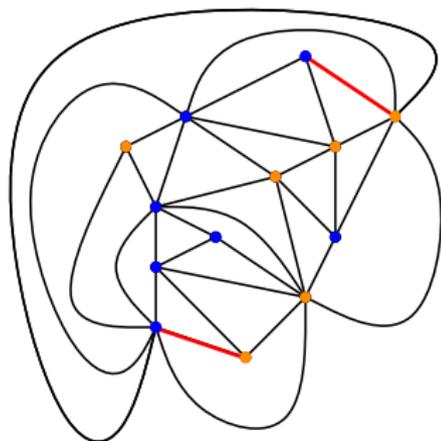
- ▶ Sample a random planar map

Continuum limit ansatz



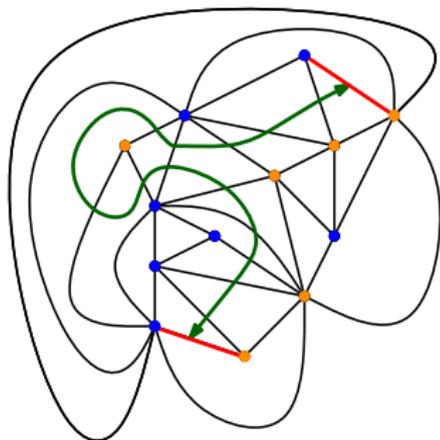
- ▶ Sample a random planar map and two edges uniformly at random

Continuum limit ansatz



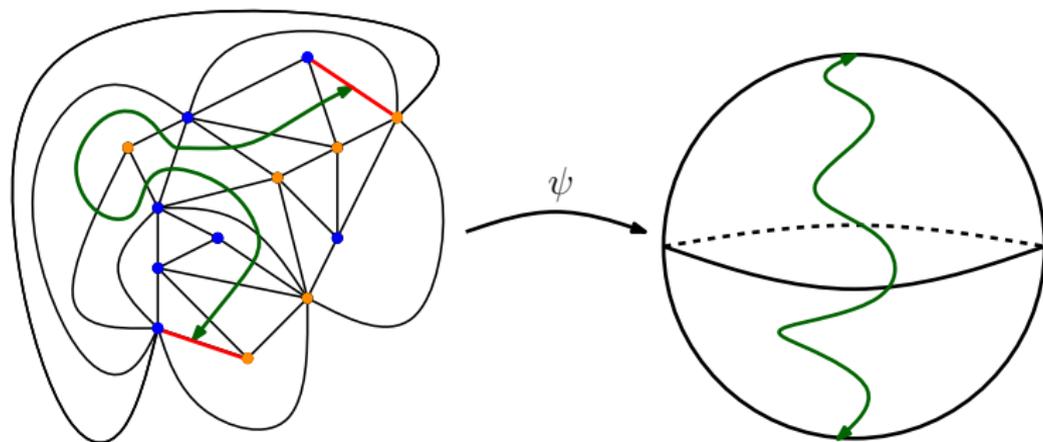
- ▶ Sample a random planar map and two edges uniformly at random
- ▶ Color vertices blue/yellow with probability $1/2$

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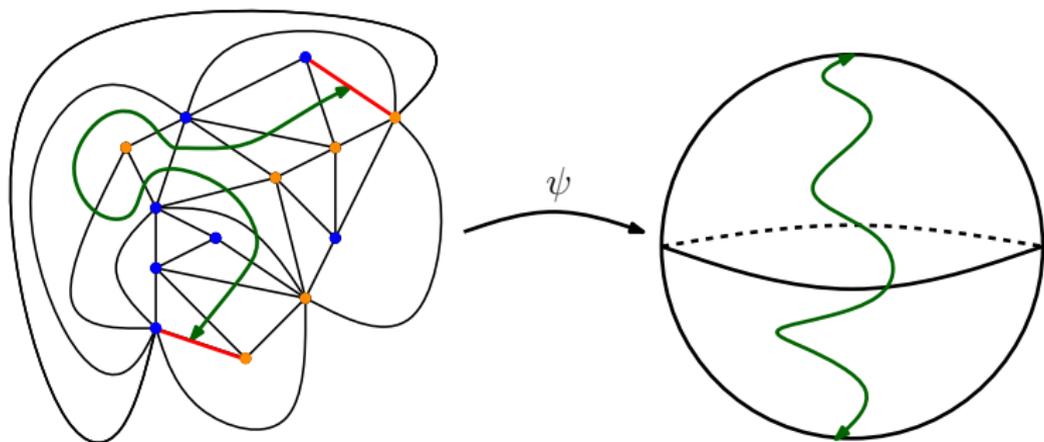
- ▶ Sample a random planar map and two edges uniformly at random
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Continuum limit ansatz



- ▶ Sample a random planar map and two edges uniformly at random
- ▶ Color vertices blue/yellow with probability $1/2$ and draw percolation interface
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Ansatz Image of random map converges to a $\sqrt{8/3}$ -LQG surface and the image of the interface converges to an independent SLE_6 .

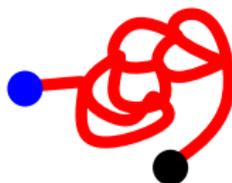
Continuum analog of first passage percolation on LQG

- ▶ Start off with $\sqrt{8/3}$ -LQG surface
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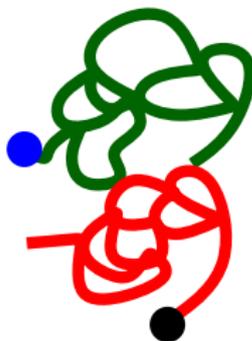
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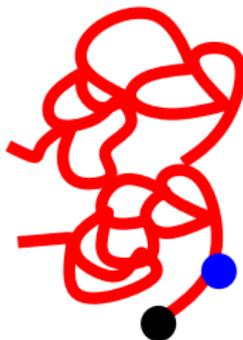
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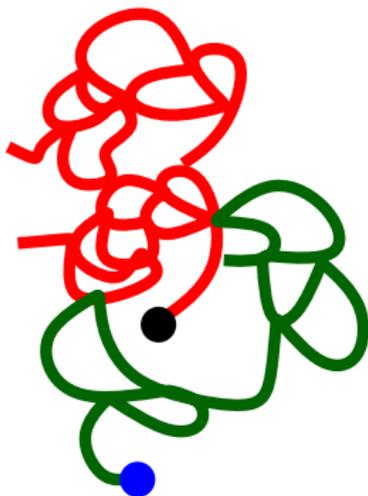
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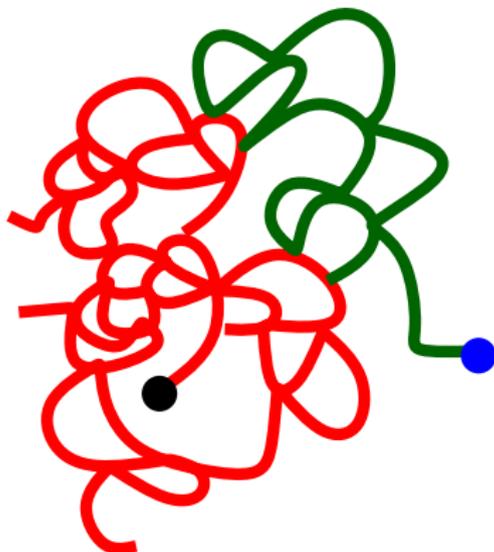
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$QLE(8/3, 0)$ is the limit as $\delta \rightarrow 0$ of this growth process. It is described in terms of a radial Loewner evolution which is driven by a measure valued diffusion.

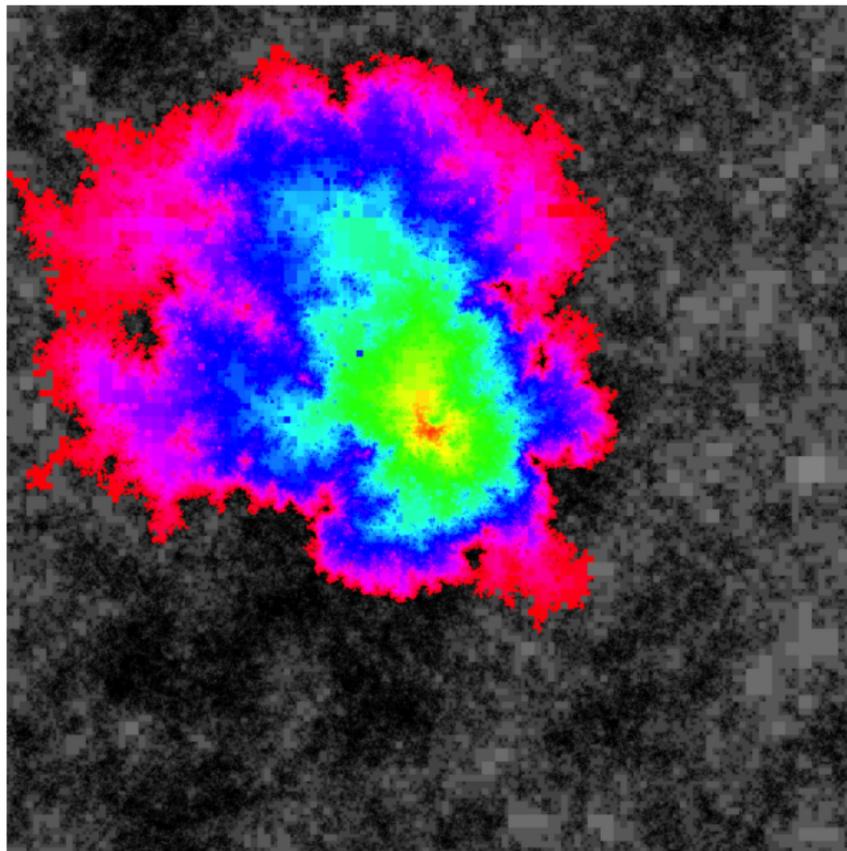
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$QLE(8/3, 0)$ is SLE_6 with **tip re-randomization**.



Discrete approximation of $QLE(8/3, 0)$. Metric ball on a $\sqrt{8/3}$ -LQG

What is $\text{QLE}(\gamma^2, \eta)$?

$\text{QLE}(8/3, 0)$ is a member of a two-parameter family of processes called $\text{QLE}(\gamma^2, \eta)$

- ▶ γ is the type of LQG surface on which the process grows
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Let μ_{HARM} (resp. μ_{LEN}) be harmonic (resp. length) measure on a γ -LQG surface. The rate of growth (i.e., rate at which microscopic particles are added) is proportional to

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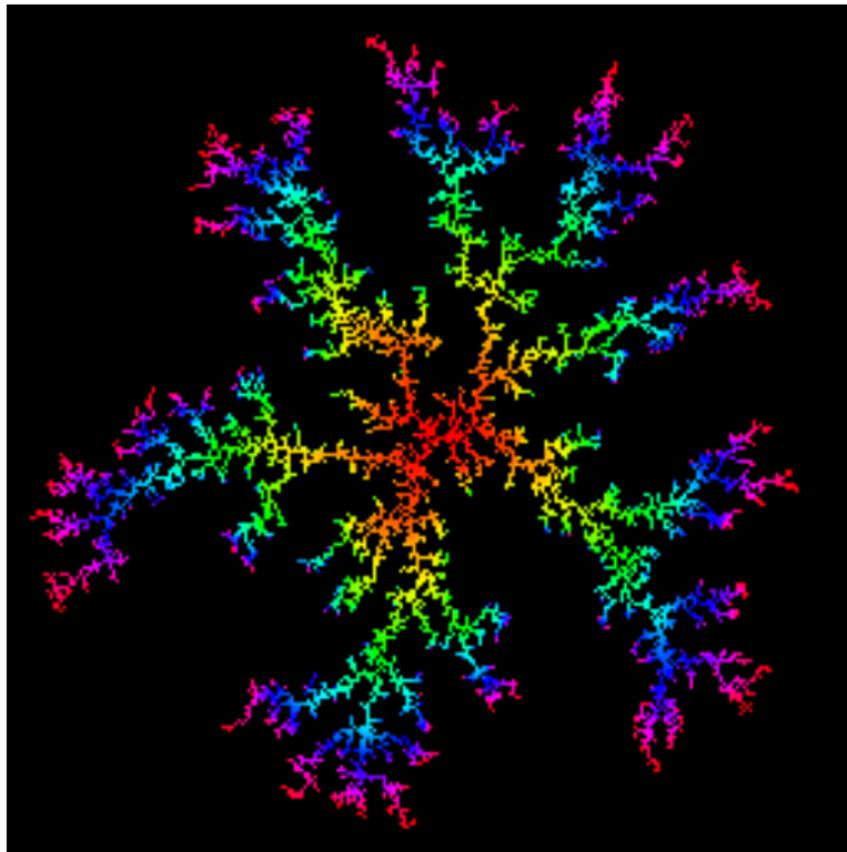
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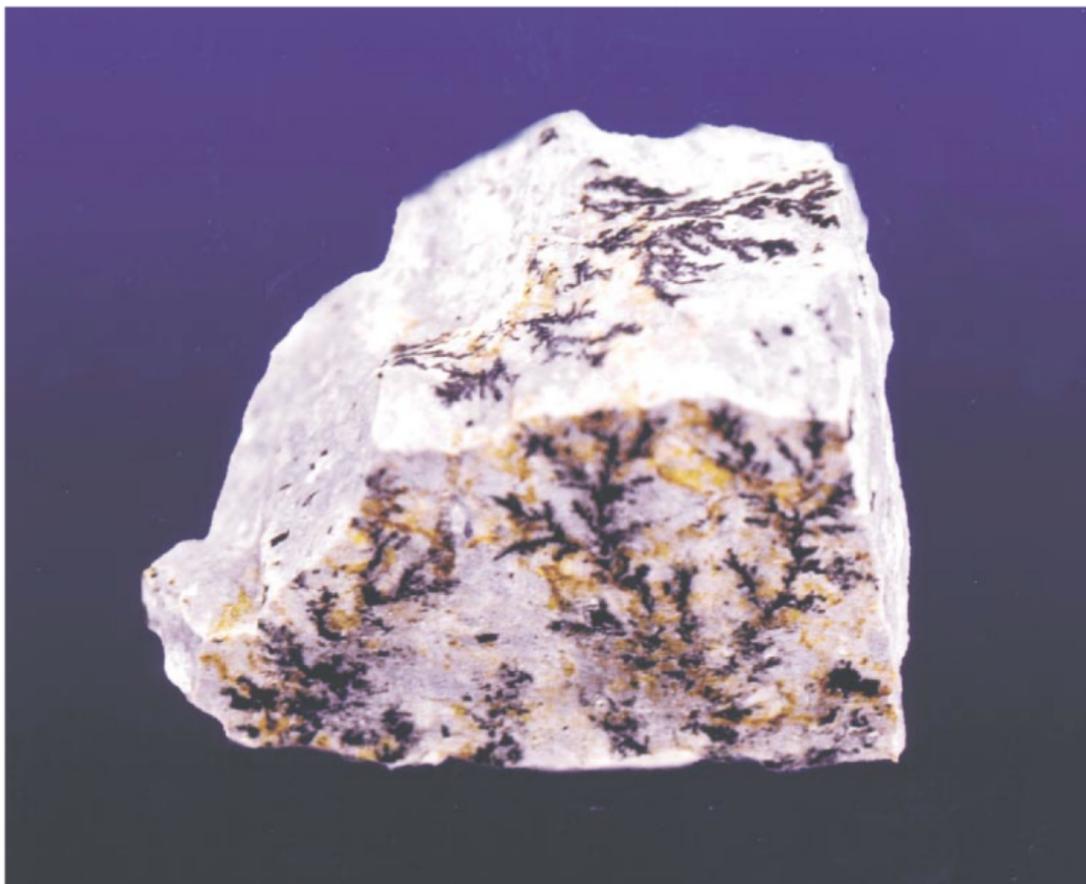
- ▶ **First passage percolation:** $\eta = 0$
- ▶ **Diffusion limited aggregation:** $\eta = 1$
- ▶ **η -dielectric breakdown model:** general values of η



Simulation of Euclidean DLA



DLA in nature: "A DLA cluster grown from a copper sulfate solution in an electrodeposition cell" (from Wikipedia)



DLA in nature: Magnese oxide patterns on the surface of a rock. (Halsey, Physics Today 2000)



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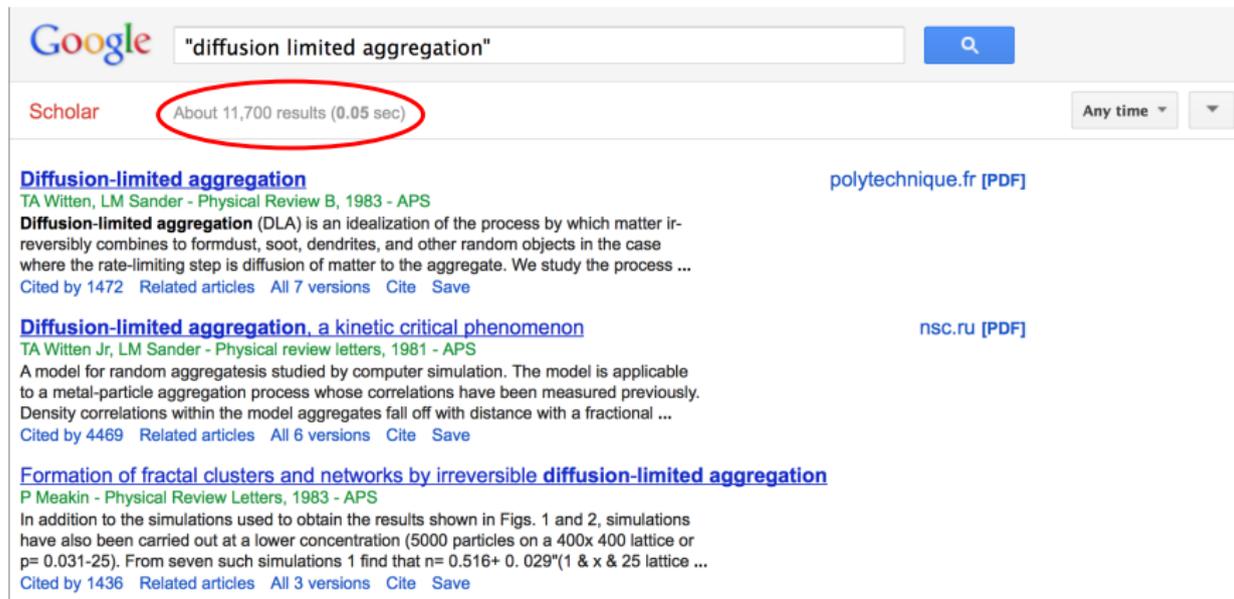


DLA in art: "High-voltage dielectric breakdown within a block of plexiglas" (from Wikipedia)

DLA in physics

Introduced by Witten and Sander in 1981 as a model for crystal growth

An active area of research in physics for the last 33 years:



Google "diffusion limited aggregation"

Scholar About 11,700 results (0.05 sec) Any time ▾ ▾

[Diffusion-limited aggregation](#) polytechnique.fr [PDF]
TA Witten, LM Sander - Physical Review B, 1983 - APS
Diffusion-limited aggregation (DLA) is an idealization of the process by which matter irreversibly combines to form dust, soot, dendrites, and other random objects in the case where the rate-limiting step is diffusion of matter to the aggregate. We study the process ...
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[Diffusion-limited aggregation, a kinetic critical phenomenon](#) nsc.ru [PDF]
TA Witten Jr, LM Sander - Physical review letters, 1981 - APS
A model for random aggregation studied by computer simulation. The model is applicable to a metal-particle aggregation process whose correlations have been measured previously. Density correlations within the model aggregates fall off with distance with a fractional ...
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[Formation of fractal clusters and networks by irreversible diffusion-limited aggregation](#)
P Meakin - Physical Review Letters, 1983 - APS
In addition to the simulations used to obtain the results shown in Figs. 1 and 2, simulations have also been carried out at a lower concentration (5000 particles on a 400x 400 lattice or $p = 0.031-25$). From seven such simulations 1 find that $n = 0.516 + 0.029(1 \& x \& 25 \text{ lattice ...}$
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Schramm 2006 ICM proceedings:

Given that the fractals produced by DLA are not conformally invariant, it is not too surprising that it is hard to faithfully model DLA using conformal maps. Harry Kesten [44] proved that the diameter of the planar DLA cluster after n steps grows asymptotically no faster than $n^{2/3}$, and this appears to be essentially the only theorem concerning two-dimensional DLA, though several very simplified variants of DLA have been successfully analysed.

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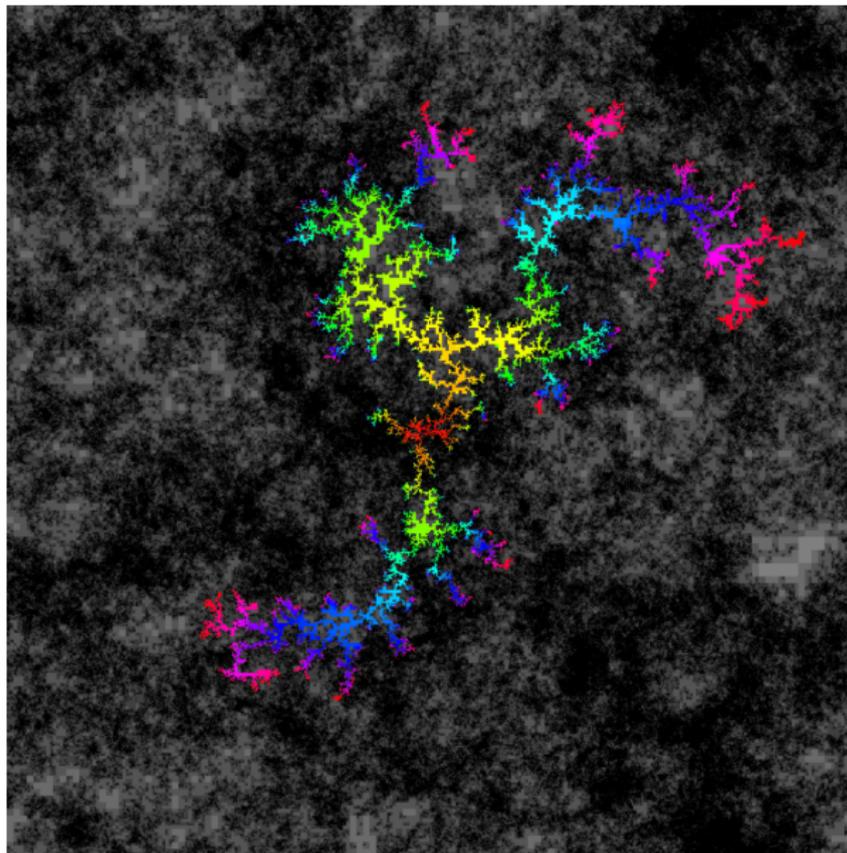
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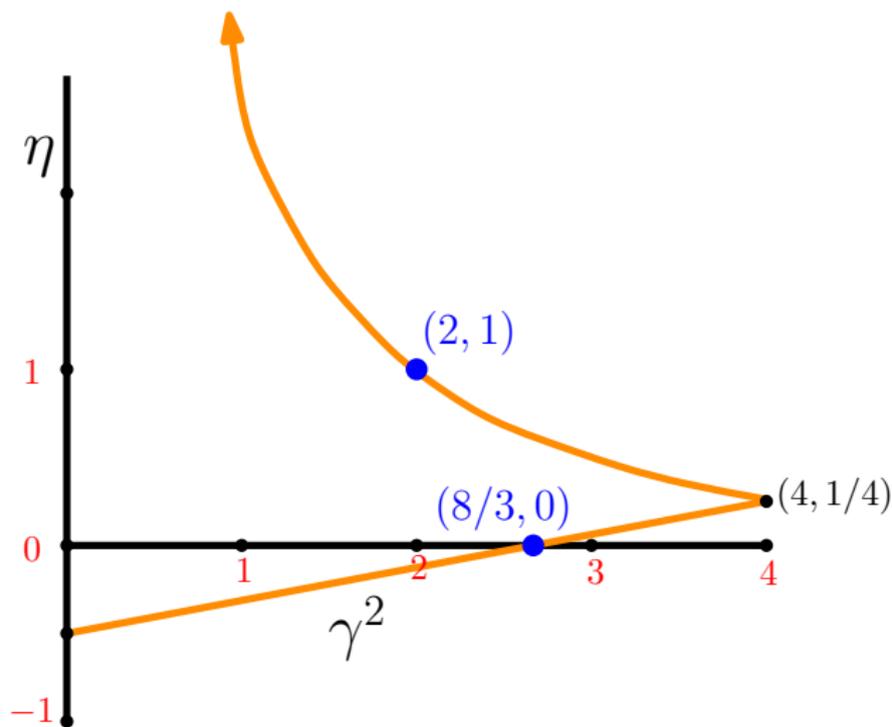
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What about DLA on random planar maps and Liouville quantum gravity surfaces?



Discrete approximation of $\text{QLE}(2, 1)$. DLA on a $\sqrt{2}$ -LQG

QLE(γ^2, η) processes we can construct



Each of the QLE(γ^2, η) processes with (γ^2, η) on the orange curves is built from an SLE $_{\kappa}$ process using tip re-randomization.

Results

What we can do:

- ▶ Existence of $\text{QLE}(\gamma^2, \eta)$ on the orange curves as a Markovian exploration of a γ -LQG surface.
- ▶ Derive an SPDE which the measure valued diffusion satisfies
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Work in progress:

- ▶ Show that $\text{QLE}(8/3, 0)$ endows $\sqrt{8/3}$ -LQG with a distance function
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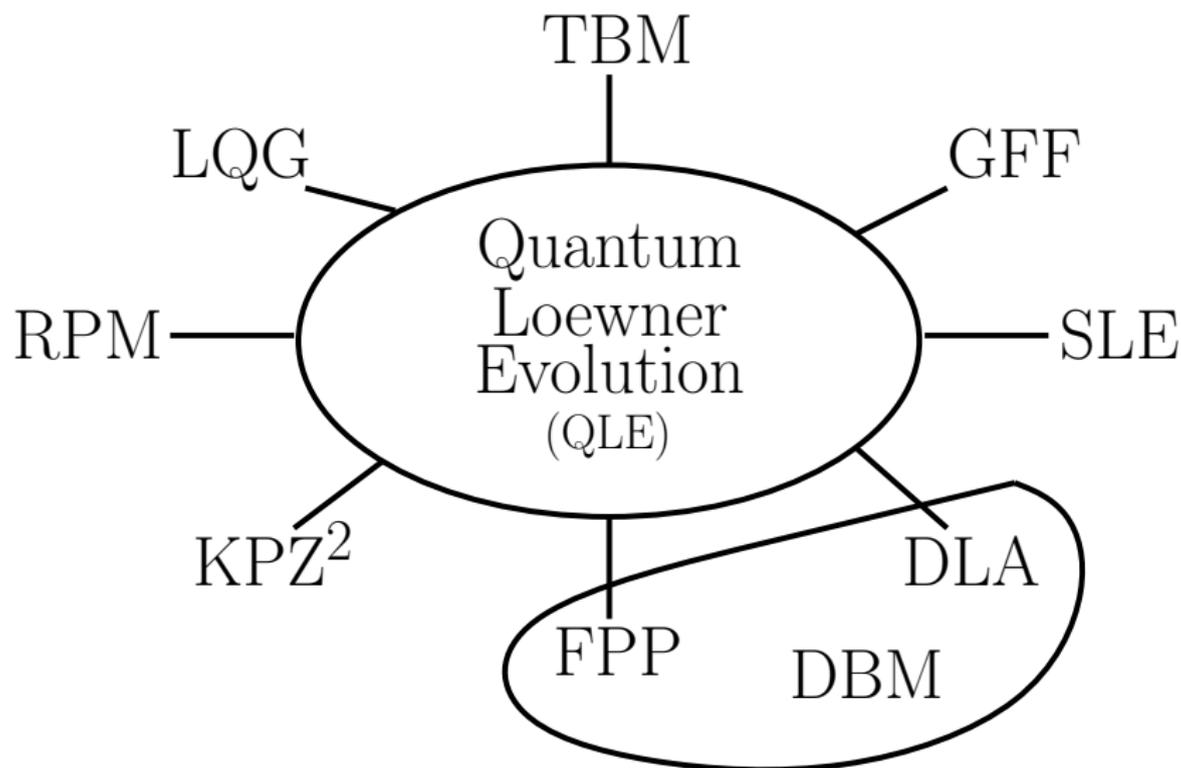
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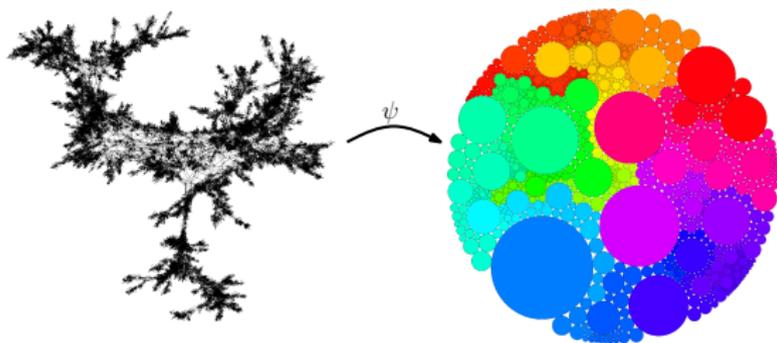
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What we would like to do: construct and study $\text{QLE}(\gamma^2, \eta)$ for (γ^2, η) pairs off the orange curves

QLE is connected to other topics in probability





Thanks!