# Random Surfaces and Quantum Loewner Evolution 

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January 23, 2014

## 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, TBM, LQG, GFF, SLE, DLA, FPP, DBM, KPZ, KPZ

## Part I: Picking surfaces at random

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- In this talk, interested in uniformly random quadrangulations - random planar map (RPM).
- First studied by Tutte in 1960s while working on the four color theorem
- Combinatorics: enumeration formulas
- Physics: statistical physics models: percolation, Ising, UST ...
- Probability: "uniformly random surface," Brownian surface

Random quadrangulation with 25,000 faces

(Simulation due to J.F. Marckert)

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Brownian map also described in terms of trees (CRT)
(Markert-Mokkadem)

## Random quadrangulation



Sampled using Sheffield's H-C bijection.

## Red tree



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## Red and blue trees



Sampled using Sheffield's H-C bijection.

Red and blue trees alone do not determine the map structure


## Sampled using Sheffield's H-C bijection.

## Random quadrangulation with red and blue trees



## Sampled using Sheffield's H-C bijection.

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 subivide each quadrilateral to obtain a triangulation without multiple edges.


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

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- Natural perturbation of a harmonic function
- Fine mesh limit: converges to the continuum GFF, i.e. the standard Gaussian wrt the Dirichlet inner product

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

## Liouville quantum gravity

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- Can compute areas of regions and lengths of curves

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2. Coding functions: put a space-filling path and coding function on LQG and show that it is the limit of the coding functions for the RPMs
3. Metric spaces: put a metric on LQG and show that it is isometric to TBM, the metric space limit of RPMs

## Continuum space-filling path



Space-filling SLE SL $_{6}$ on a LQG surface. Random path which encodes the limit of a RPM.

## Recap

Two natural ways to pick surfaces at random

- Discrete: random planar maps
- Continuum: Liouville quantum gravity $e^{\gamma h(z)} d z, h$ 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

Part II:

## Quantum Loewner Evolution

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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
- $Z^{2}$ 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 tesselation 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 $\partial C_{n}$, and then adding the vertex which is attached to it.

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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 ${ }_{6}$ )


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- Color vertices on rest of map blue or yellow with prob. $\frac{1}{2}$
- Explore percolation (blue/yellow) interface
- Forget colors
- Repeat

- This exploration also respects the Markovian structure of the map.


## First passage percolation on random planar maps III

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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


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Ansatz Image of random map converges to a $\sqrt{8 / 3}-L Q G$ surface and the image of the interface converges to an independent $\mathrm{SLE}_{6}$.

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- Start off with $\sqrt{8 / 3}$-LQG surface
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- Know the conditional law of the LQG surface at each stage



## Continuum analog of first passage percolation on LQG

- Start off with $\sqrt{8 / 3}$-LQG surface
- Fix $\delta>0$ small and a starting point $x$
- Draw $\delta$ units of SLE 6
- Resample the tip according to boundary length
- Repeat
- Know the conditional law of the LQG surface at each stage

$\operatorname{QLE}(8 / 3,0)$ 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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$\operatorname{QLE}(8 / 3,0)$ is SLE $_{6}$ with tip re-randomization.


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

## What is $\operatorname{QLE}\left(\gamma^{2}, \eta\right)$ ?

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

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- $\eta$-dieletric breakdown model: general values of $\eta$


Euclidean DLA


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

## Diffusion limited aggregation

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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.

## $\operatorname{QLE}\left(\gamma^{2}, \eta\right)$ processes we can construct



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

## Results

## What we can do:

- Existence of $\operatorname{QLE}\left(\gamma^{2}, \eta\right)$ on the orange curves as a Markovian exploration of a $\gamma$-LQG surface.
- Derive an SPDE which the measure valued diffusion satisfies
- Continuity of the outer boundary of the growth at a given time
- Phases for sample path behavior: which QLEs are trees, have holes, and fill space


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## What we think we can do:

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What we would like to do: construct and study $\operatorname{QLE}\left(\gamma^{2}, \eta\right)$ for $\left(\gamma^{2}, \eta\right)$ pairs off the orange curves

QLE is connected to other topics in probability



