

# The Gaussian Free Field: Properties and Applications

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# The Discrete Gaussian Free Field

Let us have  $G = (V, E)$  be a finite undirected graph. Let there be non-negative weights on the edges,  $(w_e)_{e \in E}$ . Let us also distinguish a set of vertices  $\partial V \subset V$  and call this set of vertices “the boundary.” Let  $\hat{V} = V \setminus \partial V$  be “the interior” of  $V$ .

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Let us define a matrix,  $Q = (q_{x,y})_{x,y \in V}$  such that

$$q_{x,y} = \begin{cases} w_{x,y}, & x \neq y \\ -\sum_{z \sim x} w_{x,z}, & x = y \end{cases}. \quad (1)$$

This is the **graph Laplacian**.

# The Discrete Gaussian Free Field

Let us define the **Green's function**,

$$G(x, y) = \frac{1}{-q_{y,y}} \mathbb{E}_x \left[ \sum_{n=0}^{\infty} \mathbf{1}_{\{Y_n=y; \tau > n\}} \right], \quad (2)$$

where  $Y_n$  is a random walk on  $G$ , which jumps from  $z$  to  $w$  with probability proportional to  $w_{z,w}$ , and is killed at time  $\tau = \min\{k : Y_k \in \partial V\}$ .

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It is true that

$$G(x, y) = (-\hat{Q})^{-1}(x, y), \quad x, y \in \hat{V} \quad (3)$$

where  $\hat{Q}$  is the restriction of  $Q$  to  $\hat{V} \times \hat{V}$ .

# The Discrete Gaussian Free Field

A function  $h : V \rightarrow \mathbb{R}$  is **harmonic** if

$$Qh(x) = \sum_y q_{x,y} h(y) = 0, \quad \forall x \in \hat{V}. \quad (4)$$

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Let us define the **Dirichlet energy** of  $h$  as

$$\mathcal{E}[h] = \frac{1}{2} \sum_{x,y \in V} q_{x,y} (h(x) - h(y))^2. \quad (5)$$

Recall: given any boundary condition, the harmonic function satisfying the boundary constraints is also the minimizer of  $\mathcal{E}[h]$ .

# The Discrete Gaussian Free Field

## Theorem

The law of the **discrete GFF** is absolutely continuous with respect to Lebesgue measure on  $\mathbb{R}^{|V|}$ . The joint density with respect to Lebesgue measure is proportional to

$$\exp \left( -\frac{1}{4} \sum_{x,y \in V} q_{x,y} (h(x) - h(y))^2 \right) \quad (6)$$

$$= \exp \left( -\frac{1}{2} h(\hat{\mathbf{x}})^T G^{-1} h(\hat{\mathbf{x}}) \right), \quad (7)$$

with  $h(x) = 0$  for  $x \in \partial V$ .

Notice,  $h : \hat{V} \rightarrow \mathbb{R}$  is a centered Gaussian on the interior of  $V$  with a covariance structure given by the Green's function.



# The 2-d GFF: Preliminaries

Facts about the Green's function in 2 dimensions.

Let  $D \subset \mathbb{R}^2$ .

①  $G_0^D(x, y) \rightarrow 0$  as  $y \rightarrow y_0 \in \partial D$ .

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- ③  $G_0^{\mathbb{D}}(0, z) = -\log |z|$ .
- ④ As  $y \rightarrow x$

$$G_0^D(x, y) = -\log(|x - y|) + \log(R(x; D)) + o(1), \quad (8)$$

where  $R(x; D)$  is the conformal radius of  $x \in D$ .

# The 2-d GFF: As a Stochastic Process

Let  $D \subset \mathbb{R}^2$  be any domain on which the Green's function is finite. Let  $\mathcal{M}_0^+$  be the set of non-negative measures with compact support such that

$$\int_{D^2} G_0^D \rho(dx) \rho(dy) < \infty.$$

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Let  $\mathcal{M}_0$  be the set of signed measures  $\rho = \rho_- + \rho_+$ . For  $\rho_1, \rho_2 \in \mathcal{M}_0$  let

$$\Gamma_0(\rho_1, \rho_2) := \int_{D^2} G_0^D(x, y) \rho_1(dx) \rho_2(dy). \quad (9)$$

Note that  $\mathcal{M}_0$  includes the case that  $\rho(x) = f(x)dx$  where  $f(x)$  is a continuous function with compact support, but does not include any point masses due to logarithmic singularity of  $G_0^D$  on the diagonal.

# The 2-d GFF: As a Stochastic Process

## Theorem

There exists a unique stochastic process  $(h_\rho)_{\rho \in \mathcal{M}_0}$ , such that for every choice of  $\rho_1, \dots, \rho_n$ , the vector  $(h_{\rho_1}, \dots, h_{\rho_n})$  is a centered Gaussian vector with covariances structure  $\text{Cov}(h_{\rho_i}, h_{\rho_j}) = \Gamma_0(\rho_i, \rho_j)$ .

Recalling from last slide that,

$$\Gamma_0(\rho_1, \rho_2) := \int_{D^2} G_0^D(x, y) \rho_1(x) \rho_2(y). \quad (10)$$

The finite dimensional marginals are enough to uniquely characterize the infinite dimensional process by Kolmogorov's extension theorem.

# The 2-d GFF: As a Random Distribution

The GFF defined as a stochastic process cannot realize all values of  $h_\rho$  simultaneously. So, we would like to work with a version of  $h$  which lives in some function space.



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$$\begin{cases} -\Delta f_n = \lambda_n f_n, & D \\ f_n = 0, & \partial D. \end{cases} \quad (12)$$

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Reasoning then goes

- For  $-\Delta f = 2\pi\rho$  with  $\rho, f \in C_0^\infty(D)$  we have that  $\|f\|_\nabla^2 = \Gamma_0(\rho, \rho)$ .

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- Polarization would then suggest that  $\text{Cov}(\langle h, f \rangle_\nabla, \langle h, g \rangle_\nabla) = \langle f, g \rangle_\nabla$ .
- So,  $f_n$  and  $f_m$  should be uncorrelated unit variance Gaussians, so  $h$  could be understood as a random series,

$$h_N = \sum_{n=1}^N X_n f_n,$$

with  $X_n$  i.i.d.  $\mathcal{N}(0, 1)$ .

What kind of convergence do we get as  $N \rightarrow \infty$ ?

# The 2-d GFF: As a Random Distribution

Does  $h_N$  converge in  $H_0^1(D)$ ? No! But, does  $\langle h_N, f \rangle_{\nabla}$  converge? Yes! It converges almost surely, and in  $L^2(\mathbb{P})$ .



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## Theorem

Suppose  $D$  is bounded. If  $(X_n)_{n \geq 1}$  are i.i.d standard Gaussian random variables and  $(f_n)_{n \geq 1}$  is any orthonormal basis of  $H_0^1(D)$ , then the series  $\sum_{n \geq 1} X_n f_n$  converges almost surely in  $H_0^s(D)$ , where

$$s = 1 - \frac{d}{2} - \epsilon,$$

for any  $\epsilon > 0$ . In particular, for  $d = 2$ , the series converges in  $H_0^{-\epsilon}$  for any  $\epsilon > 0$ .

This also implies that  $h_N$  converges in the space of distributions,  $(C_0^\infty)'(D)$ .

# The 2-d GFF: Conformal Invariance

## Theorem

The Dirichlet inner product is conformally invariant. That is, for  $\phi : D \rightarrow D'$  a conformal map, and  $f, g : D \rightarrow \mathbb{R}$  we have

$$\int_{D'} \nabla(f \circ \phi^{-1}) \cdot \nabla(g \circ \phi^{-1}) = \int_D \nabla f \cdot \nabla g.$$

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## Theorem

If  $h$  is a random distribution on  $(C_0^\infty)'(D)$  with the law of the Gaussian free field on  $D$ , the the distribution of  $h \circ \phi^{-1}$  defined by setting  $(h \circ \phi^{-1}, f) = (h, |\phi'|^2(f \circ \phi))$  for  $f \in C_0^\infty(D)$ , has the law of a GFF on  $D'$ .

# The 2-d GFF: Circle Averages

Let us fix  $z \in D$ . Let  $\rho_{z,\epsilon}$  denote the uniform distribution on the circle of radius  $\epsilon$  around  $z$ . Note,  $\rho_{z,\epsilon} \in \mathcal{M}_0$ . Set  $h_\epsilon(z) = (h, \rho_{z,\epsilon})$ .

## Theorem

Let  $h$  be a GFF on  $D$ . Let  $0 < \epsilon_0 < d(z, \partial D)$ . For  $t \geq t_0 = \log(1/\epsilon_0)$ , set

$$B_t = h_{e^{-t}}(z).$$

Then  $(B_t, t \geq t_0)$  has the law of a Brownian motion started from  $B_{t_0}$ .

# The 2-d GFF: Thick Points

We let  $h$  be a GFF on  $D \subset \mathbb{C}$  simply connected and let  $\alpha > 0$ . We say a point  $z \in D$  is  $\alpha$ -**thick** if

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## Theorem

Let  $\mathcal{T}_\alpha$  denote the set of  $\alpha$ -thick points. Then almost surely,

$$\dim(\mathcal{T}_\alpha) = (2 - \frac{\alpha^2}{2})_+$$

and  $\mathcal{T}_\alpha$  is empty if  $\alpha > 2$ .

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# Liouville Quantum Gravity

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We define approximating measures

$$\mu_\epsilon(dz) := e^{\gamma h_\epsilon(z)} \epsilon^{\gamma^2/2} dz. \quad (14)$$



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## Theorem

Suppose  $0 \leq \gamma < 2$ . If  $D$  is bounded, then the random measure  $\mu_\epsilon$  converges weakly almost surely to a random measure  $\mu$ , the (bulk) Liouville measure, along the subsequence  $\epsilon = 2^{-k}$ .  $\mu$  a.s. has no atoms, and for any  $A \subset D$  open, we have  $\mu(A) > 0$  almost surely. In fact, we have  $\mathbb{E}(\mu(A)) = \int_A R(z, D)^{\gamma^2/2} dz$ .

## Theorem

Suppose  $D \subset \mathbb{C}$  is bounded. Let  $z$  be a point sampled according to the Liouville measure  $\mu$ , normalized to be a probability measure. Then, a.s.,

$$\lim_{\epsilon \rightarrow 0} \frac{h_{\epsilon}(z)}{\log(1/\epsilon)} = \gamma.$$

That is,  $z$  is almost surely a  $\gamma$ -thick point.

So the  $\gamma$ -Liouville measure is supported on the set  $\mathcal{T}_{\gamma}$ . Thick points with  $\alpha < \gamma$  don't carry enough weight, and there aren't enough thick points with  $\alpha > \gamma$  to matter in the measure.

## Theorem

Let  $f : D \rightarrow D'$  be a conformal map, and let  $h$  be a GFF in  $D$ . Then  $h' = f \circ f^{-1}$  is a GF in  $D'$ , and

$$\mu_h \circ f^{-1} = e^{\gamma Q \log |(f^{-1})'|} \mu_{h'}$$

where  $Q = \frac{\gamma}{2} + \frac{2}{\gamma}$ .

# LQG: Convergence of planar maps to LQG

- Spanning tree decorated planar map converges to  $\sqrt{2}$ -LQG
- Uniform Random Triangulations converge to  $\sqrt{8/3}$ -LQG
- Conjectures on other maps such as the critical bond percolation decorated uniform map and critical Ising model decorated map.