# Properties of the (fermionic) gradient squared of the Gaussian free field

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#### UCL

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#### fGFF gradient squared

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# Section 1

# Motivation

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The height-one field

1. Choose at time zero a function  $s: \Lambda \to \mathbb{N}$ ,  $\Lambda \Subset \mathbb{Z}^d$ 



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The height-one field

- 1. Choose at time zero a function  $s: \Lambda \to \mathbb{N}$ ,  $\Lambda \Subset \mathbb{Z}^d$
- 2. Choose a site x uniformly at random

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3.  $s(x) \rightsquigarrow s(x) + 1$ 

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- 4. If s(x) > 2d (instability), topple x sending one "grain" to each neighbor

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  - Grains outside  $\Lambda$  are lost

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- 5. Go to 2.

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- 5. Go to 2.

This Markov chain has a unique stationary measure  $\mathbb{P}$ .

Definition (Height-one field)

 $h_\Lambda(x) := \mathbf{1}_{\{s(x) = 1\}}$  under  $\mathbb P$ 

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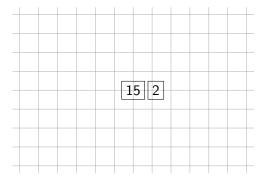
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### $s(x) = 15\,\delta_{x=0} + 2\,\delta_{x=(1,0)}$



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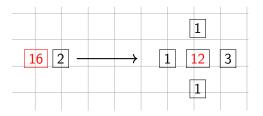
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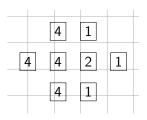
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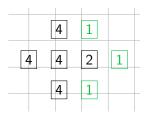
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Stable configuration!

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Ingredients

# • Let $U \subset \mathbb{R}^2$ be smooth connected bounded and $\Lambda := U_{\epsilon} := {}^{u}\!/_{\epsilon} \cap \mathbb{Z}^2$

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• Let  $U \subset \mathbb{R}^2$  be smooth connected bounded and  $\Lambda := U_{\varepsilon} := {}^{u}\!/_{\varepsilon} \cap \mathbb{Z}^2$ 

Let

$$U \ni \mathfrak{u} \mapsto \mathfrak{u}_\varepsilon = \lfloor \mathfrak{u}/ \varepsilon \rfloor \in U_\varepsilon$$

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Let g<sub>U</sub>(·, ·) be the harmonic Green's function on U with Dirichlet boundary conditions fGFF gradient squared

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- Let g<sub>U</sub>(·, ·) be the harmonic Green's function on U with Dirichlet boundary conditions
- Joint cumulants κ for r. v.'s X<sub>1</sub>, ..., X<sub>n</sub> are defined by

$$\mathsf{E}\left[\prod_{i=1}^{n} X_{i}\right] = \sum_{\pi \text{ partition of } \{1, ..., n\}} \prod_{B \in \pi} \kappa(X_{i} : i \in B)$$

Eg.  $\kappa(X) = E[X]$ ,  $\kappa(X, Y) = cov(X, Y)$ .

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Height-one field in d = 2

### Theorem (Dürre (2009))

**Theorem 2** (Scaling Limit for the Height One Joint Cumulants). Let V be as in Theorem 1 and suppose  $|V| \ge 2$ . Then as  $\epsilon \to 0$  the rescaled joint cumulant  $\epsilon^{-2|V|} \kappa \left( h_{U_{\epsilon}}(v_{\epsilon}) : v \in V \right)$ converges to

$$\kappa_U(v:v\in V):=-C^{|V|}\sum_{\sigma\in S_{\mathrm{cycl}}(V)}\sum_{(k^v)_{v\in V}\in \{x,y\}^V}\prod_{v\in V}\partial_{k^v}^{(1)}\partial_{k^{\sigma(v)}}^{(2)}g_U\left(v,\sigma(v)\right).$$

Here  $C := (2/\pi) - (4/\pi^2)$ . That is, if we write  $\kappa_U(v) := 0$  for all  $v \in V$ , then

$$\lim_{\epsilon \to 0} \epsilon^{-2|V|} \mathbb{E} \left[ \prod_{v \in V} \left( h_{U_{\epsilon}}(v_{\epsilon}) - \mathbb{E}[h_{U_{\epsilon}}(v_{\epsilon})] \right) \right] = \sum_{\Pi \in \Pi(V)} \prod_{B \in \Pi} \kappa_{U}(v : v \in B)$$

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The connection to GFF

Let  $\Psi$  be a Gaussian free field with 0-boundary conditions:

# Definition (GFF)

 $\boldsymbol{\Psi}$  is the centered Gaussian random distribution with

 $\mathbb{E}[\Psi(\mathfrak{u})\Psi(\nu)]=g_{U}(\mathfrak{u},\nu),\quad \mathfrak{u}\neq\nu\in U.$ 

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Formal computations show that

 $\lim_{\varepsilon \to 0} \varepsilon^{-2|V|} \kappa(h_{U_\varepsilon}(\nu) \, \nu \in V) = \kappa(: \|\nabla \Psi(\nu)\|^2:, \ \nu \in V)$ 

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$$: \|\nabla \Psi(\nu)\|^2 := \sum_{i=1}^2 \vartheta_i \Psi(\nu)^2 - \mathbb{E}[\vartheta_i \Psi(\nu)^2]$$

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# Definition (DGFF)

Let  $(\Gamma_{\varepsilon}(\nu): \nu \in U_{\varepsilon})$  be the discrete GFF on  $U_{\varepsilon}$ :

$$\mathbb{E}[\Gamma_{\varepsilon}(\nu)] = 0, \quad \mathbb{E}[\Gamma_{\varepsilon}(\nu)\Gamma_{\varepsilon}(u)] = G_{U_{\varepsilon}}(u, \nu)$$

where  $G_{U_\varepsilon}(\cdot,\,\cdot)$  is the discrete harmonic Green's function with Dirichlet b.c.

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### Definition (Grad squared DGFF) The field $(\Phi_{\epsilon}(\nu), \nu \in U_{\epsilon})$ is defined as

$$\Phi_{\varepsilon}(\nu) := \sum_{i=1}^{d} : \nabla_{i} \Gamma_{\varepsilon}(x)^{2} := \sum_{i=1}^{d} : \left(\Gamma_{\varepsilon}(\nu + e_{i}) - \Gamma_{\varepsilon}(\nu)\right)^{2} :$$

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We will work in  $d \ge 2$ 

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Covariances

C = [1 ] [1]

$$\mathbb{E}\left[\Phi_{\epsilon}(\mathbf{x}_{\epsilon})\Phi_{\epsilon}(\mathbf{y}_{\epsilon})\right] = 2\sum_{i,j\in[d]} \left(\nabla_{i}^{(1)}\nabla_{j}^{(2)}G_{\mathbf{u}_{\epsilon}}(\mathbf{x}_{\epsilon},\,\mathbf{y}_{\epsilon})\right)^{2}$$

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### Main results

Convergence of cumulants,  $d \geqslant 2$ 

Theorem (C, Hazra, Rapoport, Ruszel 2022) Let  $\mathcal{E}$  be the set of coordinate vectors of  $\mathbb{R}^d$ . Let  $\{v^{(1)}, \ldots, v^{(k)}\} \subset U$ . Let  $S^0_{cycl}(B)$  be the set of cyclic permutations of a set B. If  $v^{(i)} \neq v^{(j)}$  for all  $i \neq j$ , then fGFF gradient squared A. C. Motivation Model 1 Results model 1

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### Main results

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$$\begin{split} &\lim_{\varepsilon \to 0} \varepsilon^{-dk} \kappa \Big( \Phi_{\varepsilon} \big( \nu_{\varepsilon}^{(j)} \big) : j \in [k] \Big) \\ &= 2^{k-1} \sum_{\sigma \in S^{0}_{cvcl}([k])} \sum_{\eta: [k] \to \mathcal{E}} \prod_{j=1}^{k} \vartheta_{\eta(j)}^{(1)} \vartheta_{\eta(\sigma(j))}^{(2)} g_{U} \big( \nu_{\varepsilon}^{(j)}, \nu_{\varepsilon}^{(\sigma(j))} \big) \end{split}$$

In d = 2 the limit is conformally covariant with scale dimension 2

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# Main results model 1

Comparison in d = 2

Dürre:

$$-C^k \sum_{\sigma \in S^0_{cycl}([k])} \sum_{\eta: [k] \to \mathcal{E}} \prod_{j=1}^k \vartheta^{(1)}_{\eta(j)} \vartheta^{(2)}_{\eta(\sigma(j))} g_U(\nu^{(j)}, \nu^{(\sigma(j))}$$

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# Main results model 1

#### Comparison in d = 2

Dürre:

$$-C^k\sum_{\sigma\in S^0_{\text{cycl}}([k])}\sum_{\eta:[k]\to \mathcal{E}}\prod_{j=1}^k \vartheta^{(1)}_{\eta(j)}\vartheta^{(2)}_{\eta(\sigma(j))}g_{U}\big(\nu^{(j)},\nu^{(\sigma(j))}\big)$$

CHRR:

$$2^{k-1}\sum_{\sigma\in S^0_{cycl}([k])}\sum_{\eta:[k]\to \mathcal{E}}\prod_{j=1}^k \vartheta^{(1)}_{\eta(j)}\vartheta^{(2)}_{\eta(\sigma(j))}g_u\big(\nu^{(j)},\nu^{(\sigma(j))}\big)$$

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# Main results model 1

Comparison in d = 2

#### Corollary

$$\begin{split} &\lim_{\varepsilon \to 0} \varepsilon^{-2k} \kappa \Big( h_{U_{\varepsilon}} \big( \nu_{\varepsilon}^{(j)} \big) : j \in [k] \Big) \\ &= -2 \lim_{\varepsilon \to 0} \varepsilon^{-2k} \kappa \Big( \frac{C}{2} \Phi_{\varepsilon} \big( \nu_{\varepsilon}^{(j)} \big) : j \in [k] \Big) \end{split}$$

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# Model 2

## **Discrete Laplacian**

Discrete Laplacian: for i,  $j\in\Lambda$ 

$$\Delta_{\Lambda}(\mathfrak{i},\,\mathfrak{j}) = \begin{cases} 1 & |\mathfrak{i}-\mathfrak{j}| = 1 \\ -2d & \mathfrak{i} = \mathfrak{j} \\ 0 & \text{otherwise} \end{cases}$$

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Fermionic variables

# Definition (Grassmanian variables) Let $\{\xi_i, \overline{\xi}_i : i \in \Lambda\}$ be symbols that satisfy $\xi_i \xi_i = -\xi_i \xi_i, \quad \xi_i \overline{\xi}_i = -\overline{\xi}_i \xi_i, \quad \overline{\xi}_i \overline{\xi}_i = -\overline{\xi}_i \overline{\xi}_i$

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# Definition (fGFF)

For every function F of  $\{\xi_i,\,\bar\xi_i\}$  the expectation of F under the fGFF is defined as

$$[F] = \int_{\text{Berezin}} \partial_{\bar{\xi}} \partial_{\xi} e^{(\xi, (-\Delta_{\Lambda})\bar{\xi})} F.$$

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Example:

$$[1] = \int \partial_{\bar{\xi}} \partial_{\xi} e^{(\xi, (-\Delta_{\Lambda})\bar{\xi})} = \det(-\Delta_{\Lambda}).$$

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Let **P** be the law of the uniform spanning tree T on  $\Lambda$ .



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Let  ${\bf P}$  be the law of the uniform spanning tree T on  $\Lambda.$  Proposition

Let S be any subset of edges of  $\Lambda$ .

$$\mathbf{P}(S \subseteq \mathsf{T}) = \frac{1}{\mathsf{det}(-\Delta_{\Lambda})} \left[ \prod_{e \in S} \nabla_e \xi \nabla_e \overline{\xi} \right]$$

where

$$abla_e\xi = \xi_{e^+} - \xi_{e^-}, \quad 
abla_e\overline{\xi} = \overline{\xi}_{e^+} - \overline{\xi}_{e^-}$$

is the gradient of the fGFF along the edge e.

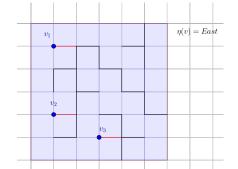
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UST & ASM

Proposition (Dhar–Majumdar, Járai–Werning) Let  $V \subseteq \Lambda$ . Let  $\eta : V \rightarrow [2d]$  be a choice of a direction. Then the height-one field satisfies

$$\mathbb{E}\left(\prod_{\nu\in V}h_{\Lambda}(\nu)\right) = \mathbf{P}((\nu, \nu + e) \notin \mathsf{T} \text{ if } e \neq \eta(\nu), \nu \in \mathsf{V}).$$



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Now we are able to connect ASM and fGFF via the UST.

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## Theorem (Chiarini, C, Rapoport, Ruszel, 2023)

$$\mathbb{E}\left[\prod_{\nu \in V} h_{\Lambda}(\nu)\right] = \frac{1}{\det(-\Delta_{\Lambda})} \left[\prod_{\nu \in V} X_{\nu} Y_{\nu}\right]$$

where

$$\begin{split} X_{\nu} &= \sum_{e \ni \nu} \nabla_{e} \xi \nabla_{e} \bar{\xi} \\ Y_{\nu} &= \prod_{e \ni \nu} \left( 1 - \nabla_{e} \xi \nabla_{e} \bar{\xi} \right) \end{split}$$

#### Proof.

Key: inclusion-exclusion principle over edges.

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Theorem (CCRR, 2023) ln d = 2

$$\begin{split} &\lim_{\varepsilon \to 0} \varepsilon^{-2k} \kappa \Big( -C_2 X_{\nu_{\varepsilon}^{(j)}} : j \in [k] \Big) \\ &= \lim_{\varepsilon \to 0} \varepsilon^{-2k} \kappa \Big( h_{U_{\varepsilon}} \big( \nu_{\varepsilon}^{(j)} \big) : j \in [k] \Big), \quad C_2 = 2/\pi - 4/\pi^2 \end{split}$$

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We also have a closed form expression for the limiting cumulants of  $-C_d X_v$  in  $d \ge 3$ .

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#### Proof.

Wick's theorem for fermionic variables and combinatorics of partitions/permutations.  $\hfill \Box$ 

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Theorem (CCRR, 2023) ln d = 2

$$\begin{split} &\lim_{\varepsilon\to 0}\varepsilon^{-2k}\kappa\Big(X_{\nu_{\varepsilon}^{(j)}}Y_{\nu_{\varepsilon}^{(j)}}:\,j\in[k]\Big)\\ &=\lim_{\varepsilon\to 0}\varepsilon^{-2k}\kappa\Big(h_{U_{\varepsilon}}\big(\nu_{\varepsilon}^{(j)}\big):\,j\in[k]\Big). \end{split}$$

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We also have a closed form expression for the limiting cumulants of  $X_{\nu}Y_{\nu}$  in  $d \ge 3$  and in turn those of the height-one field in  $d \ge 3$ .

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#### Proof.

The proof generalizes that for  $X_{\nu}$ . It is alternative and independent to Dürre's. Essentially, " $Y_{\nu}$  becomes -C".

# Extension/1

Universality

Our proofs in the limit  $\varepsilon \to 0$  hold for the triangular and hexagonal lattice as well:

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- translation invariance (homogeneity)
- isotropy

# Extension/2

We have on  $\mathbb{Z}^d$ 

$$\kappa\left(X_{\nu}\text{, }\nu\in V\right)=\kappa\left({}^{\mathsf{deg}_{\mathsf{UST}}\left(\nu\right)}\!/_{2\mathsf{d}}\text{, }\nu\in V\right).$$

- $\blacktriangleright$  Analogous results obtained for the "degree field" in  $\mathbb{Z}^d$  and triangular lattice
- Other observables of UST can be studied (ongoing)

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# Thank you!