

# Properties of the gradient squared of the discrete Gaussian free field



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# Abelian sandpile

The height-one field

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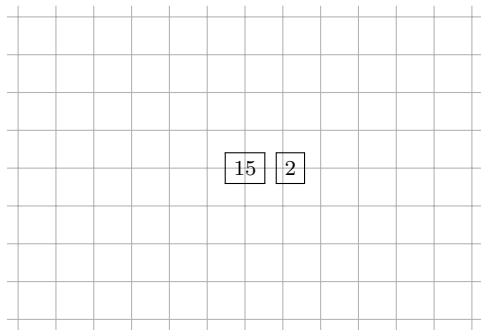
This Markov chain has a unique stationary measure  $\mathbb{P}$ . We look at

**Definition (Height-one field)**

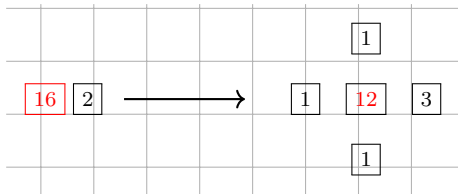
$h_\Lambda(x) := \mathbf{1}_{\{s(x)=1\}}$  under  $\mathbb{P}$

## An example

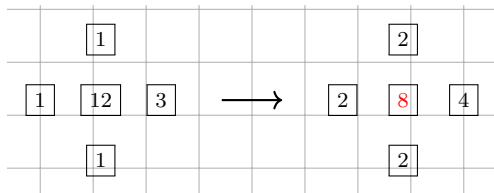
$$s(x) = 15\delta_{x=(0,0)} + 2\delta_{x=(1,0)}$$



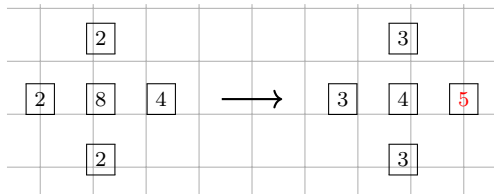
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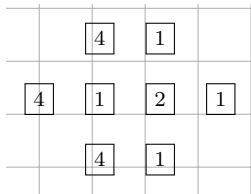
## An example



## An example

	3	1	
3	5	1	1
	3	1	

## An example



Stable configuration!

## Going larger

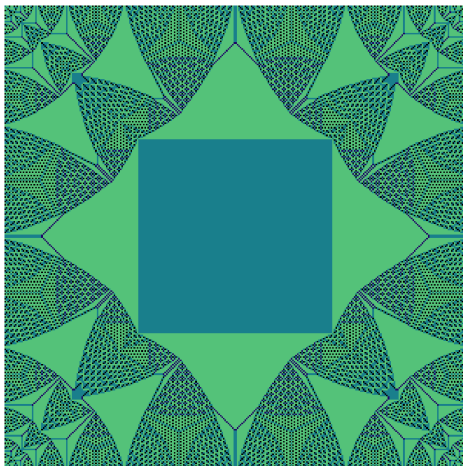


Figure: Sandpile configuration on a  $300 \times 300$  box.



# The height one field

	4	1	
4	1	2	1
	4	1	

## Joint cumulants

Joint cumulants  $\kappa$  for r. v.'s  $X_1, \dots, X_n$  are defined by

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

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We are going to study

$$\kappa(h(x_1), \dots, h(x_n))$$

## Question

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- Regardless of the microscopic details of the model, what is the “driving force” behind height one?

# Abelian sandpile

## Ingredients

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

$$U \ni u \mapsto u_\epsilon = \lfloor u/\epsilon \rfloor \in U_\epsilon$$

- Let  $g_U(\cdot, \cdot)$  be the harmonic Green's function on  $U$  with Dirichlet boundary conditions

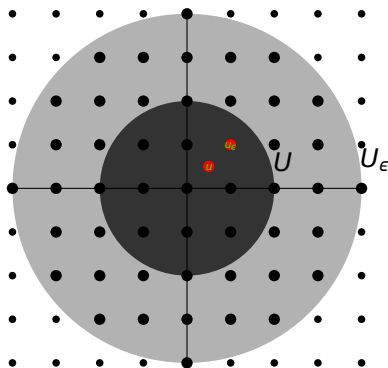


Figure:  $U = B(0, 1), U_\epsilon = B(0, 2) \cap \mathbb{Z}^2, \epsilon = 1/2, u = (1/2, 1/2), u_\epsilon = (1, 1)$

# Abelian sandpile

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  $|V| \geq 2$ . Then as  $\epsilon \rightarrow 0$  the rescaled joint cumulant  $\epsilon^{-2|V|} \kappa(h_{U_\epsilon}(v_\epsilon) : v \in V)$  converges to*

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

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

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



# Abelian sandpile

The connection to GFF

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

## Definition (GFF)

$\Psi$  is the centered Gaussian random distribution with

$$\mathbb{E}[\Psi(x)\Psi(y)] = g_U(x, y), \quad x \neq y \in U.$$

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We investigated this conjecture

# Grad squared DGFF

## Definition (DGFF)

Let  $(\Gamma_\epsilon(v) : v \in U_\epsilon)$  be the **discrete** GFF on  $U_\epsilon$ :

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

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

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The field  $(\Phi_\epsilon(v) : v \in U_\epsilon)$  is defined as

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We will work in  $d \geq 2$  ( $d = 1$ : manual calculations)

# Grad squared DGFF

## Covariances

Call  $[d] := \{1, \dots, d\}$ .

$$\mathbb{E} [\Phi_\epsilon(x_\epsilon) \Phi_\epsilon(y_\epsilon)] = 2 \sum_{i,j \in [d]} \left( \nabla_i^{(1)} \nabla_j^{(2)} G_{U_\epsilon}(x_\epsilon, y_\epsilon) \right)^2$$

# Main results

## Convergence of cumulants

Theorem (Cipriani, Hazra, Rapoport, Ruszel 2023)

*Let  $\mathcal{E}$  be the set of coordinate vectors of  $\mathbb{R}^d$ . Let  $\{x^{(1)}, \dots, x^{(k)}\} \subset U$ . Let  $S_{\text{cycl}}^0(B)$  be the set of cyclic permutations of a set  $B$  without fixed points. If  $x^{(i)} \neq x^{(j)}$  for all  $i \neq j$ , then*



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$$\lim_{\epsilon \rightarrow 0} \epsilon^{-dk} \kappa \left( \Phi_{\epsilon} \left( x_{\epsilon}^{(j)} \right) : j \in [k] \right) =$$
$$2^{k-1} \sum_{\sigma \in S_{\text{cycl}}^0([k])} \sum_{\eta: [k] \rightarrow \mathcal{E}} \prod_{j=1}^k \partial_{\eta^{(j)}}^{(1)} \partial_{\eta^{(\sigma(j))}}^{(2)} g_U \left( x_{\epsilon}^{(j)}, x_{\epsilon}^{(\sigma(j))} \right)$$

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

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Comparison in  $d = 2$

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- Dürre:

$$\lim_{\epsilon \rightarrow 0} \epsilon^{-2k} \kappa(h_{U_\epsilon}(x_\epsilon^{(j)})) : j \in [k] = -C^k \sum_{\sigma \in S_{\text{cycl}}^0([k])} \sum_{\eta: [k] \rightarrow \mathcal{E}} \prod_{j=1}^k \partial_{\eta(j)}^{(1)} \partial_{\eta(\sigma(j))}^{(2)} g_U(x^{(j)}, x^{(\sigma(j))})$$

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- CHRR:

$$\lim_{\epsilon \rightarrow 0} \epsilon^{-2k} \kappa(\Phi_{\epsilon}(x_{\epsilon}^{(j)}) : j \in [k]) = 2^{k-1} \sum_{\sigma \in S_{\text{cycl}}^0([k])} \sum_{\eta: [k] \rightarrow \mathcal{E}} \prod_{j=1}^k \partial_{\eta(j)}^{(1)} \partial_{\eta(\sigma(j))}^{(2)} g_U(x^{(j)}, x^{(\sigma(j))})$$

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## Corollary

$$-2 \lim_{\epsilon \rightarrow 0} \epsilon^{-2k} \kappa\left(\frac{C}{2} \Phi_\epsilon(x_\epsilon^{(j)}) : j \in [k]\right) = \lim_{\epsilon \rightarrow 0} \epsilon^{-2k} \kappa(h_{U_\epsilon}(x_\epsilon^{(j)}) : j \in [k])$$

# Main results

Convergence as random distribution

Consider for  $f \in C_c^\infty(U)$ ,  $U \subset \mathbb{R}^d$ ,

$$\langle \Phi_\epsilon, f \rangle = \int_U \Phi_\epsilon(x_\epsilon) f(x) dx.$$

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Theorem (C, Hazra, Rapoport, Ruszel 2022)

$$\chi^{-1/2} \epsilon^{-d/2} \Phi_\epsilon \xrightarrow{d} \text{white noise on } U,$$

in  $C_{\text{loc}}^\alpha(U)$  for any  $\alpha < -d/2$ , and the constant  $\chi$  is

$$\chi := 2 \sum_{v \in \mathbb{Z}^d} \sum_{i, j \in [d]} \left( \nabla_i^{(1)} \nabla_j^{(2)} G_0(0, v) \right)^2 \in (0, +\infty)$$

where  $G_0(\cdot, \cdot)$  is the  $\begin{cases} \text{infinite-volume discrete Green's function} & \text{in } d \geq 3 \\ \text{potential kernel} & \text{in } d = 2 \end{cases}$

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Comparison in  $d = 2$

- Dürre:

$$\frac{\epsilon^{-1}}{\sqrt{\chi}}(h_{U_\epsilon} - \mathbb{E}[h_{U_\epsilon}]) \xrightarrow{d} \text{white noise}$$



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# Recap

What we have so far

Random distribution Scaling  $\epsilon^{-d/2}$  and limit are the same as height-one field

Cumulants Scaling  $\epsilon^{-d}$  and limit are the same as height-one field **up to sign**

# Proofs

Why white noise?

- Finite susceptibility ( $\iff \chi \in (0, +\infty)$ ) suggests CLT-type rescaling and WN convergence [Bauerschmidt et al. \(2014\)](#), [Newman \(1980\)](#)...

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- [Kassel–Wu \(2013\)](#) derive Gaussian fluctuations for models related to the spanning tree measure (reprove Dürre)
- We are not able to apply K–W’s results directly, but this hints at a universality class of models related to the spanning tree measure via the **transfer current matrix**  $T(\cdot, \cdot)$

$$\mathbb{E} [\nabla_i \Gamma_\epsilon(v) \nabla_j \Gamma_\epsilon(u)] = T((v, v + e_i), (u, u + e_j))$$

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Useful facts: white noise

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$$\bullet \mathbb{E} [\Phi_\epsilon(v)\Phi_\epsilon(w)] \leq c \cdot \begin{cases} |v - w|^{-2d} & v \neq w, \\ 1 & v = w. \end{cases}$$



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Useful facts: white noise

For  $v, w \in U_\epsilon$  "away from the boundary"

- $E[\Phi_\epsilon(v)\Phi_\epsilon(w)] \leq c \cdot \begin{cases} |v-w|^{-2d} & v \neq w, \\ 1 & v = w. \end{cases}$
- $\left| \nabla_i^{(1)} \nabla_j^{(2)} G_{U_\epsilon}(v, w) - \nabla_i^{(1)} \nabla_j^{(2)} G_0(v, w) \right| \leq c\epsilon^d,$

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  - ▶ the limiting covariance structure is the  $L^2(U)$  inner product

# Proofs

Why these cumulants?

To answer, we need to look at the proof first...



# Proofs

Useful facts: cumulants

- $T((x_\epsilon, x_\epsilon + e), (y_\epsilon, y_\epsilon + e')) = \epsilon^d dg_U|_{(x,y)}(e, e') + o(\epsilon^d)$  (Kassel–Wu, 2013).

# Proofs

## *k*-point functions

We derive cumulants from *k*-point functions:

$$\mathbb{E} \left[ \prod_{j=1}^k \Phi_{\epsilon}(x_{\epsilon}^{(j)}) \right] = \sum_{\pi \in \Pi([k])} \prod_{B \in \pi} \kappa \left( \Phi_{\epsilon}(x_{\epsilon}^{(j)}) : j \in B \right)$$

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- 🔗 For ASP the proof uses explicitly the relation with the spanning tree measure
  - 🔗 Kassel–Wu generalize this to models related to the spanning tree measure conjecturing a universal and conformally covariant limit

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We derive cumulants from *k*-point functions:

$$\mathbb{E} \left[ \prod_{j=1}^k \Phi_\epsilon(x_\epsilon^{(j)}) \right] = \sum_{\pi \in \Pi([k])} \prod_{B \in \pi} \kappa \left( \Phi_\epsilon(x_\epsilon^{(j)}) : j \in B \right)$$

1. Decompose *k*-point functions as **Feynman diagrams**
  2. Expand the products of covariances in terms of the transfer matrix
  3. Use the transfer matrix expansion
- 
- 🔗 For ASP the proof uses explicitly the relation with the spanning tree measure
  - 🔗 Kassel–Wu generalize this to models related to the spanning tree measure conjecturing a universal and conformally covariant limit



# Proofs

## Cumulants: another viewpoint

In the proof we (loosely) obtain that the  $k$ -point function is

$$\sum_{\gamma \text{ FD on } [2k]} \prod_{((x_\epsilon^{(j)}, x_\epsilon^{(j)} + e), (x_\epsilon^{(m)}, x_\epsilon^{(m)} + e')) \in \gamma} \epsilon^{-d} T\left((x_\epsilon^{(j)}, x_\epsilon^{(j)} + e), (x_\epsilon^{(m)}, x_\epsilon^{(m)} + e')\right)$$

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## Fermionic (or Grassmannian) calculus

### Definition (Grassmanian variables)

Let  $\{\xi_i, \bar{\xi}_i : i \in \Lambda\}$  be symbols that satisfy for all  $i, j$

$$\xi_i \xi_j = -\xi_j \xi_i, \quad \xi_i \bar{\xi}_j = -\bar{\xi}_j \xi_i, \quad \bar{\xi}_i \bar{\xi}_j = -\bar{\xi}_j \bar{\xi}_i$$

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## Example

Used in physics to model Fermi–Dirac statistics (opposed to Bose–Einstein statistics)

# Fermionic Gaussian free field

## Definition (fGFF)

For every function  $F$  of  $\{\xi, \bar{\xi}\} = \{\xi_i, \bar{\xi}_i : i \in \Lambda\}$  the expectation of  $F$  under the fGFF is defined as

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

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## “Fermionic gradient squared”

For  $v \in \Lambda = U_\epsilon$

$$X_v = \frac{1}{2d} \sum_{e \ni v \text{ edges}} \zeta(e)$$

$$\zeta(e) = (\xi_v - \xi_u) (\bar{\xi}_v - \bar{\xi}_u), \quad e = \{v, u\}$$

Theorem (CCRR, 2023)

$$\lim_{\epsilon \rightarrow 0} \epsilon^{-2n} \kappa \left( h_{U_\epsilon}(v_\epsilon^{(1)}), \dots, h_{U_\epsilon}(v_\epsilon^{(n)}) \right)$$
$$\lim_{\epsilon \rightarrow 0} \epsilon^{-2n} \kappa \left( -CX_{v_\epsilon^{(1)}}, \dots, -CX_{v_\epsilon^{(n)}} \right).$$

# Summary & open questions

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We studied the scaling limit of  $\Phi_\epsilon$  as a random distribution and the scaling limit of its  $k$ -point functions/cumulants

- As a random distribution the limit is WN as height-one field: common decay of correlations

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- As a random distribution the limit is WN as height-one field: common decay of correlations
- The cumulants have the same limit as in the height-one field (up to sign) and conformal covariance property
- the Fermionic free field kind of identifies the height-one field and gives an alternative the gradient free field squared.

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**Thank you!**