

Sharp noise stability in continuum percolations via Spectra of Poisson functionals

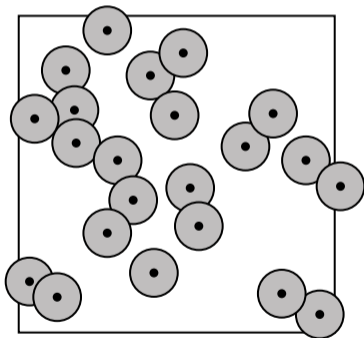
Joint with G. Peccati (Luxembourg) and D. Yogeshwaran (ISI Bangalore)

Chinmoy Bhattacharjee

25.10.2024

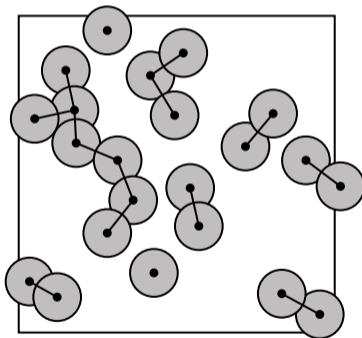
Boolean percolation

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Naturally gives rise to a random geometric graph.

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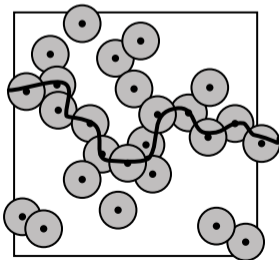
Non-trivial at criticality : \exists critical parameter $\lambda_c > 0$, such that for $\lambda > \lambda_c$, \exists a unique unbounded occupied component. Fix $\lambda = \lambda_c$.

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Non-trivial at criticality : \exists critical parameter $\lambda_c > 0$, such that for $\lambda > \lambda_c$, \exists a unique unbounded occupied component. Fix $\lambda = \lambda_c$.

Let $f_L = \pm 1$ indicator of a **L-R occupied crossing** of $W_L = [-L, L]^2$:



Noise stability

To study the sensitivity of a system to random noise, one can measure its **stability**. For η the original configuration, let η^ε be its ε -noisy version.

Definition: $(f_L)_{L>0}$ is **noise stable** if

$$\lim_{\varepsilon \rightarrow 0} \sup_L \mathbf{P} \{f_L(\eta) \neq f_L(\eta^\varepsilon)\} = 0.$$

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We consider the **Ornstein-Uhlenbeck** dynamics to perturb the system.

Ornstein Uhlenbeck dynamics

Given marked configuration η , noisy version η^ε is given by

$$\eta^\varepsilon = \eta_1 + \eta_2, \quad t > 0,$$

- η_1 a **thinning** of η [delete each point independently w.p. $(1 - e^{-\varepsilon})$],
- η_2 an **independent Poisson process** with intensity $(1 - e^{-\varepsilon})$.

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Motivation: Show sharp results for the OU dynamics.

Sharp noise instability

Sharp noise instability in Boolean percolation (B., Peccati, Yogeshwaran '24+)

There exists $A_L \rightarrow \infty$ such that under the OU dynamics, $(f_L)_{L>0}$ exhibits **sharp noise instability** at time-scale $1/A_L$, i.e., for $\varepsilon_L A_L \rightarrow 0$,

$$\lim_{L \rightarrow \infty} \mathbf{P} \{f_L(\eta) \neq f_L(\eta^{\varepsilon_L})\} = 0,$$

while if $\varepsilon_L A_L \rightarrow \infty$,

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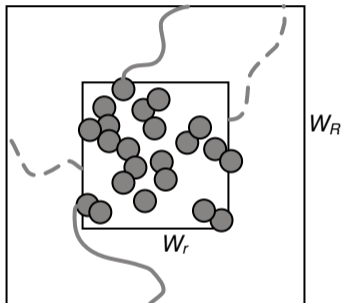
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Here, one can take $A_L = L^2 \alpha_4(1, L) \rightarrow \infty$, where α_4 is the **4-arm probability**.

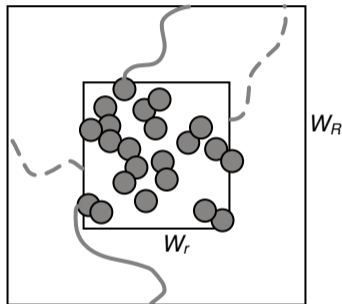
4-arm probability : Quasi-multiplicativity

Recall $A_L = L^2 \alpha_4(1, L)$: For $1 \leq r \leq R < \infty$, $\alpha_4(r, R)$ is the probability of the event



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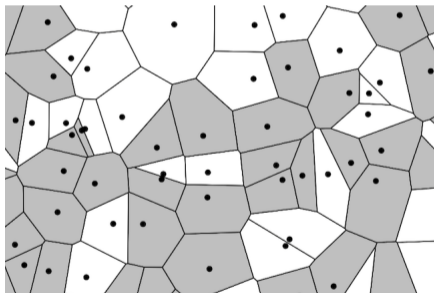
Quasi-multiplicativity of α_4 (B., Peccati, Yogeshwaran '24+)

In critical Boolean percolation,

$$\alpha_4(r_1, r_3) \asymp \alpha_4(r_1, r_2) \alpha_4(r_2, r_3), \quad 1 \leq r_1 \leq r_2 \leq r_3.$$

Voronoi percolation

Given a homogeneous *Poisson process* with **intensity 1** on \mathbb{R}^2 , independently, colour each cell black or white with probabilities p and $1 - p$ (marked process η).



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$$\begin{aligned}\mathbf{P}_{1/2}(f_L(\eta) = 1) &= \mathbf{P}_{1/2}(\text{L-R black crossing of } W_L) \\ &= \mathbf{P}_{1/2}(\text{Top-Bottom white crossing of } W_L) = \frac{1}{2}.\end{aligned}$$

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Definition: $(f_L)_{L>0}$ is **noise sensitive** (NS) under the dynamics η^ε if $\forall \varepsilon > 0$,

$$\lim_{L \rightarrow \infty} \text{Cov}(f_L(\eta), f_L(\eta^\varepsilon)) = 0.$$

Frozen dynamics

- Sample the unperturbed random configuration according to $\eta \subset \mathbb{R}^2 \times \{\pm 1\}$.
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Sharp NS under frozen dynamics (Vanneuille '21)

For the critical Voronoi percolation, $L^2\alpha_4(L) \rightarrow \infty$ and under the frozen dynamics,

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Only non-sharp results by Ahlberg, Baldasso '18; Last, Peccati, Yogeshwaran '23 under the OU dynamics.

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For the proof of no noise sensitivity, we study the associated **spectral point process**.

Main tool : Concentration of spectral mass

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For N_L with $\mathbf{P} \{N_L = k\} = k! \|u_k\|^2$, sharp noise instability follows by showing concentration of N_L around $\mathbf{E} N_L \asymp L^2 \alpha_4(1, L)$.

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The size of the spectral process can be neatly related to the number of **Pivotal points**, i.e., those $x \in \eta$ such that $D_x^- f_L(\eta) \neq 0$.

Further remarks

Our results imply asymptotic **Volatility** (infinitely many jumps) of the crossing functional f_L over time intervals of length $t_L \gg (L^2 \alpha_4(1, L))^{-1} \rightarrow 0$. Also has implications in **critical windows** for phase transition of f_L .

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It is typically easier to prove sharp noise stability. Showing sharp noise sensitivity under OU dynamics requires a precise understanding the lower tail of N_L : to conclude noise sensitivity when $\varepsilon_L \mathbf{E}N_L \rightarrow \infty$, it suffices to show that

$$\lim_{c \rightarrow 0} \liminf_{L \rightarrow \infty} \mathbf{P} \{N_L \geq c \mathbf{E}N_L\} = 1.$$

Thank you!

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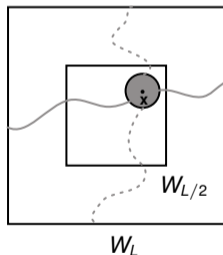
One can show for all $B \in \mathcal{X}$,

$$\mathbf{E} [|\gamma_L(B)|] = 4\mathbf{E} [|\mathcal{P}_L(B)|] = 4 \int_B \mathbf{P}\{D_x f_L(\eta) \neq 0\} \lambda(dx).$$

Moment estimations

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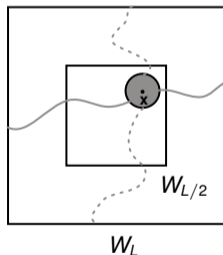
In particular, $\mathbf{E}N_L = \mathbf{E}|\gamma_L| \geq \mathbf{E}|\gamma_L(W_{L/2})| \asymp L^2 \alpha_4(1, L/2) \asymp L^2 \alpha_4(1, L)$.



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Indeed, $\mathbf{E}N_L \asymp L^2 \alpha_4(1, L)$. A more careful second moment estimate then yields a desired concentration result in the Boolean model.

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$$\text{Cov}(f_L(\eta), f_L(\eta^\varepsilon)) \leq \text{Cov}(f_L(\eta), f_L(\eta_\varepsilon)).$$

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Noise sensitivity in the OU dynamics, when $\varepsilon_L L^2 \alpha_4(1, L) \rightarrow \infty$, now follows from the same for the frozen dynamics (Vanneuille '21).

Voronoi: no noise sensitivity when $\varepsilon_L L^2 \alpha_4(1, L) \rightarrow 0$

Let $f_L = \sum_{k=1}^{\infty} I_k(u_k)$. By Mehler's formula,

$$\mathbf{E}[f_L(\eta^\varepsilon) | \eta] = \sum_{k=1}^{\infty} e^{-k\varepsilon} I_k(u_k).$$

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$$\begin{aligned} \text{Cov}(f_L(\eta), f_L(\eta^\varepsilon)) &= \mathbf{E}[f_L(\eta)f_L(\eta^\varepsilon)] \stackrel{\text{Orth.}}{=} \sum_{k=1}^{\infty} e^{-k\varepsilon} \mathbf{E}[I_k(u_k)^2] \\ &= \sum_{k=1}^{\infty} e^{-k\varepsilon} k! \|u_k\|^2 = \mathbf{E}[e^{-\varepsilon N_L}] \stackrel{\text{Jensen}}{\geq} e^{-\varepsilon \mathbf{E}N_L}. \end{aligned}$$

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Since $\mathbf{E}N_L \asymp L^2 \alpha_4(1, L)$, it follows that f_L is **not noise sensitive** when $\varepsilon_L L^2 \alpha_4(1, L) \rightarrow 0$.