Noise sensitivity questions in percolation-like models

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Noise sensitivity of Boolean functions

 $f: \{-1,1\}^N \longrightarrow \{-1,1\}$ a Boolean function, usually monotone. Input is i.i.d. Bernoulli(p).

Take critical density $p = p_c(N)$, where $\mathbf{P}_p[f(\omega) = 1] = 1/2$.

Resample each input bit with probability ϵ , independently, get ω^{ϵ} .

Given a typical ω , can we predict what $f(\omega^{\epsilon})$ will be? What is the correlation between $f(\omega^{\epsilon})$ and $f(\omega)$? Three simple examples:

Dictator_n($\omega_1, \ldots, \omega_n$) := ω_1 . Here $p_c(n) = 1/2$. Here Corr $[\operatorname{Dic}_n(\omega), \operatorname{Dic}_n(\omega^{\epsilon})] = 1 - \epsilon$, hence noise-stable.

$$\begin{split} \mathsf{Majority}_n(\omega_1,\ldots,\omega_n) &:= \mathrm{sgn}\,(\omega_1+\cdots+\omega_n). \text{ Again, } p_c(n) = 1/2. \\ \mathsf{Here } \operatorname{Corr}\big[\operatorname{Maj}_n(\omega),\operatorname{Maj}_n(\omega^\epsilon)\big] = 1 - O(\sqrt{\epsilon}), \text{ hence noise-stable.} \end{split}$$

 $\begin{aligned} &\mathsf{Parity}_n(\omega_1,\ldots,\omega_n) := \omega_1 \cdots \omega_n. \text{ Again, } p_c(n) = 1/2. \\ &\mathsf{Here } \mathsf{Corr} \big[\mathsf{Par}_n(\omega), \mathsf{Par}_n(\omega^\epsilon) \big] = (1-\epsilon)^n, \text{ very sensitive to noise.} \end{aligned}$

Noise sensitivity of Boolean functions

A sequence of Boolean functions $f_k : \{-1, 1\}^{N_k} \longrightarrow \{-1, 1\}$ is called noise sensitive at density p if

$$\forall \epsilon > 0: \quad \operatorname{Corr} \left[f_k(\omega^{\epsilon}), f_k(\omega) \right] \to 0 \quad \text{as} \quad k \to \infty,$$

and noise stable if

$$\lim_{\epsilon \to 0} \sup_{k} \mathbf{P}_{p} \left[f_{k}(\omega^{\epsilon}) \neq f_{k}(\omega) \right] = 0.$$

Could be insensitive but not stable.

Give a monotone noise sensitive example!

Percolation and noise



At $p_c = 1/2$, left-right crossing has non-trivial probability.

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Naive idea: how many pivotals are there?

A bit is pivotal for f in ω if flipping it changes the output.

Do the ϵ -noise by switching bits one-by-one. In order to change the output, need at least one pivotal switch; in fact, need an odd number of them.

Complete decorrelation \Leftrightarrow so many pivotal switches that you don't know their parity.

Naively, "the more pivotals there are, the more noise sensitive the function should be".

First issue: Maj_{2k+1} typically has no pivotal bits at all; with probability $\approx 1/\sqrt{k}$, it has k + 1, hence $\mathbf{E}|\text{Piv}_{\text{Maj}_{2k+1}}| \approx \sqrt{k}$. This matters for sharp thresholds by the Russo-Margulis formula,

$$\frac{d}{dp}\mathbf{P}_p\big[f(\omega) = 1\big] = \mathbf{E}_p\big[|\mathsf{Piv}_f|\big],$$

but apparently not for noise sensitivity.

Naive idea: how many pivotals are there?

A site is pivotal for left-right crossing in ω if it has the alternating 4-arm event to the sides. $\mathbf{E}|\operatorname{Piv}_n| \simeq n^2 \alpha_4(n) \quad (= n^{3/4+o(1)}).$

Furthermore, $\mathbf{E}[|\mathsf{Piv}_n|^2] \leq C (\mathbf{E}|\mathsf{Piv}_n|)^2$. So, $\mathbf{P}[|\mathsf{Piv}_n| > \lambda \mathbf{E}|\mathsf{Piv}_n|] < C/\lambda^2$, any λ .

And not only $\exists \epsilon \mathbf{P} [|\operatorname{Piv}_n| > \epsilon \mathbf{E} |\operatorname{Piv}_n|] > \epsilon$, but $\mathbf{P} [0 < |\operatorname{Piv}_n| < \epsilon \mathbf{E} |\operatorname{Piv}_n|] \asymp \epsilon^{11/9 + o(1)}$, as $\epsilon \to 0$ (exponent only for Δ).



If $\epsilon_n \mathbf{E}[|\mathsf{Piv}_n|] \to 0$, then $\mathbf{E}[\mathsf{number of pivotal switches}] \to 0)$ \implies asymptotically full correlation

If $\epsilon_n \mathbf{E}[|\mathsf{Piv}_n|] \to \infty$, then $\mathbf{E}[\mathsf{number of pivotal switches}] \to \infty$ $\implies \mathbf{P}[\mathsf{hit (many) pivotals}] \to 1 \implies \mathsf{asymptotic independence}!!$

Dynamical 2nd Moment Method for pivotal switches

Make $m = t/\alpha_4(n)$ switches, $\omega = \omega_0, \ldots, \omega_m$, so that

 $\mathbf{E}[S_t] = \mathbf{E}[$ number of pivotal switches $] \simeq t$.

Want to show $\mathbf{P}[S_t = \text{odd}] > c_t > 0$, uniformly in n, because then $\operatorname{Corr}[f(\omega), f(\omega_m)] < 1 - \tilde{c_t}$.

Will prove $\mathbf{E}[S_t^2 - S_t] = O(t^2)$.

Then note $\mathbf{E}[S_t^2] \ge \mathbf{P}[S_t = 1] + 2(\mathbf{E}S_t - \mathbf{P}[S_t = 1])$. Rearranging gives $\mathbf{P}[S_t = 1] \ge 2\mathbf{E}[S_t] - \mathbf{E}[S_t^2] \simeq t - O(t^2) > 0$ for t > 0 small enough. Also done for all t, since correlation is monotone decreasing in t.

And the second moment calculation:

$$\begin{split} \mathbf{E}[S_t^2 - S_t] &\asymp \sum_{\substack{i,j=1\\i \neq j}}^m \sum_{\substack{x,y \in V_n\\x \neq y}} n^{-4} \mathbf{P} \big[x \in \mathsf{Piv}(\omega_i); \ y \in \mathsf{Piv}(\omega_j) \big] \\ &\leqslant n^{-4} \sum_{i,j=1}^m \sum_{r=0}^{\lceil \log_2 n \rceil} \sum_{\substack{x,y\\2^r \leqslant d(x,y) < 2^{r+1}}} \mathbf{P} \big[A_x^r(\omega_i) \big] \mathbf{P} \big[B_y^r(\omega_j) \mid A_x^r(\omega_i) \big] \\ &\leqslant n^{-4} m^2 n^2 \sum_{r=0}^{\lceil \log_2 n \rceil} O(1) \, 2^{2r} \alpha_4(1, 2^r)^2 \, \alpha_4(2^r, n) \\ &\leqslant n^{-2} m^2 \, \alpha_4(n) \sum_{r=0}^{\lceil \log_2 n \rceil} O(1) \, 2^{2r} \alpha_4(2^r) \,, \ \mathsf{recall} \ k^2 \alpha_4(k) = k^{3/4 + o(1)}, \\ &\asymp O(1) \, \alpha_4(n)^2 \, m^2 = O(t^2) \,, \end{split}$$

where

 $A_x^r(\omega_i) := \{ \text{alternating 4 arms in } A_x(1, 2^{r-1}) \text{ and in } A_x(2^{r+2}, n) \text{ in } \omega_i \},$

 $B_y^r(\omega_j) := \{ \text{alternating 4 arms in } A_y(1, 2^{r-1}) \text{ in } \omega_j \}.$

Same for weakly dependent input?

This was a robust argument! Critical FK-Ising and critical spin-Ising on \mathbb{Z}^2 also satisfy

 $\mathbf{P}\left[B_y^r(\omega_j) \mid A_x^r(\omega_i)\right] \asymp \alpha_4(1, 2^r),$

for their natural Glauber / heat-bath / Gibbs sampler dynamics.

Moreoever, the exponents $\alpha_4^{\text{FK-Ising}}(n) = n^{-35/24+o(1)}$ and $\alpha_4^{\text{spin-Ising}}(n) = n^{-21/8+o(1)}$ are known (Chelkak, Duminil-Copin, Hongler, Garban).

For FK-Ising, because of 35/24 < 2, which means many pivotal points in the discrete world and self-touches of SLE(16/3) in the continuum, the previous argument works fine. Hence $t n^{-13/24+o(1)}$ is the good space-time scaling to watch macroscopic connections start changing, and Garban-P (2015+) proves that there is a Markovian scaling limit of the dynamics.

For spin-Ising Glauber dynamics, because of 21/8 > 2, we do not know anything. Btw, the mixing time of the *entire* system is known to be polynomial (Lubetzky-Sly 2010), but the exponent is not known.

Noise sensitivity of percolation

All results use Fourier analysis of Boolean functions:

Theorem (Benjamini, Kalai & Schramm 1998). If $\epsilon > 0$ is fixed, and f_n is the indicator function for a left-right percolation crossing in an $n \times n$ square, then as $n \to \infty$

$$\mathbf{E}[f_n(\omega)f_n(\omega^{\epsilon})] - \mathbf{E}[f_n(\omega)]^2 \to 0.$$

This holds for all $\epsilon = \epsilon_n > c/\log n$.

Theorem (Schramm & Steif 2005). Same if $\epsilon_n > n^{-a}$ for some positive a > 0. If triangular lattice, may take any a < 1/8.

Theorem (Garban, P & Schramm 2008). Same holds if and only if $\epsilon_n \mathbf{E}[|\mathsf{Piv}_n|] \to \infty$. For triangular lattice, this threshold is $\epsilon_n = n^{-3/4+o(1)}$.

What is the Fourier spectrum and why is it useful?

 $f_n: \{\pm 1\}^{V_n} \longrightarrow \{\pm 1\}$ indicator of left-right crossing, $V = V_n$ vertices.

 $(N_{\epsilon}f)(\omega) := \mathbf{E}[f(\omega^{\epsilon}) | \omega]$ is the noise operator, acting on the space $L^{2}(\Omega, \mu)$, where $\Omega = \{\pm 1\}^{V}$, μ uniform measure, inner product $\mathbf{E}[fg]$.

Correlation: $\mathbf{E}[f(\omega^{\epsilon})f(\omega)] - \mathbf{E}[f(\omega)]\mathbf{E}[f(\omega^{\epsilon})] = \mathbf{E}[f(\omega)N_{\epsilon}f(\omega)] - \mathbf{E}[f(\omega)]^2$. So, we would like to diagonalize the noise operator N_{ϵ} .

Let χ_i be the function $\chi_i(\omega) = \omega(i)$, $\omega \in \Omega$.

For $S \subset V$, let $\chi_S := \prod_{i \in S} \chi_i$, the parity inside S. Then

$$N_{\epsilon}\chi_{i} = (1-\epsilon)\chi_{i}; \qquad N_{\epsilon}\chi_{S} = (1-\epsilon)^{|S|}\chi_{S}.$$

Moreover, the family $\{\chi_S, S \subseteq V\}$ is an orthonormal basis of $L^2(\Omega, \mu)$.

Any function $f \in L^2(\Omega, \mu)$ in this basis (Fourier-Walsh series):

$$\hat{f}(S) := \mathbf{E}[f\chi_S]; \qquad f = \sum_{S \subseteq V} \hat{f}(S) \chi_S.$$

The correlation:

$$\mathbf{E}[fN_{\epsilon}f] - \mathbf{E}[f]^{2} = \sum_{S} \sum_{S'} \hat{f}(S) \, \hat{f}(S') \, \mathbf{E}[\chi_{S} N_{\epsilon} \chi_{S'}] - \mathbf{E}[f\chi_{\emptyset}]^{2}$$
$$= \sum_{\emptyset \neq S \subseteq V} \hat{f}(S)^{2} \, (1-\epsilon)^{|S|} = \sum_{k=1}^{|V_{n}|} (1-\epsilon)^{k} \sum_{|S|=k} \hat{f}(S)^{2}.$$

By Parseval, $\sum_{S} \hat{f}(S)^2 = \mathbf{E}[f^2] = 1$. So can define probability measure $\mathbf{P}[\mathscr{S}_f = S] := \hat{f}(S)^2 / \mathbf{E}[f^2]$, the spectral sample $\mathscr{S}_f \subseteq V$.

If, for some functions f_n and numbers k_n , we have $\mathbf{P}[0 < |\mathscr{S}_n| < tk_n] \to 0$ as $t \to 0$, uniformly in n, then $(1 - \epsilon)^k \sim \exp(-\epsilon k)$ implies that for $\epsilon_n \gg 1/k_n$ we have asymptotic independence. Maybe with $k_n = \mathbf{E}|\mathscr{S}_n|$?

Pivotals versus spectral sample

$$\nabla_{i}f(\omega) := f(\sigma_{i}(\omega)) - f(\omega) \in \{-2, 0, +2\} \text{ gradient.}$$

$$\nabla_{i}f(\omega) = \sum_{S}\hat{f}(S)[\chi_{S}(\sigma_{i}(\omega)) - \chi_{S}(\omega)], \text{ hence } \widehat{\nabla_{i}f}(S) = -2\hat{f}(S)\mathbf{1}_{i\in S}.$$

$$\mathbf{P}[i \in \mathsf{Piv}_{f}] = \frac{1}{4} \|\nabla_{i}f\|_{2}^{2} = \frac{1}{4}\sum_{S}\widehat{\nabla_{i}f}(S)^{2} = \sum_{S\ni i}\hat{f}(S)^{2} = \mathbf{P}[i \in \mathscr{S}_{f}].$$
Thus, $\mathbf{E}[\mathscr{S}_{i}] = \mathbf{E}[\mathsf{Piv}_{i}].$ So, the pivotal upper bound for poise sensitivity.

Thus, $\mathbf{E}|\mathscr{S}_f| = \mathbf{E}|\operatorname{Piv}_f|$. So, the pivotal upper bound for noise sensitivity is sharp if there is tightness around $\mathbf{E}|\mathscr{S}|$.

Alos, $\mathbf{P}[i, j \in \mathsf{Piv}_f] = \mathbf{P}[i, j \in \mathscr{S}_f]$, hence $\mathbf{E}|\mathscr{S}_f|^2 = \mathbf{E}|\mathsf{Piv}_f|^2$.

Not for more points and higher moments! Both random subsets measure the "influence" or "relevance" of bits, but in different ways.

For percolation, $\mathbf{E}[|\operatorname{Piv}_n|^2] \leq C (\mathbf{E}|\operatorname{Piv}_n|)^2$, hence $\exists c > 0 \text{ s.t. } \mathbf{P}[|\mathscr{S}_n| > c \mathbf{E}|\mathscr{S}_n|] > c$. That's why one hopes for tightness around mean.



The earlier simple examples

Dictator_n(
$$\omega_1, \ldots, \omega_n$$
) := ω_1 . Here $p_c(n) = 1/2$.
Here Corr $[Dic_n(\omega), Dic_n(\omega^{\epsilon})] = 1 - \epsilon$, hence noise-stable. And $\mathbf{P}[\mathscr{S}_n = \{x_1\}] = 1$.

$$\begin{split} \mathsf{Majority}_n(\omega_1,\ldots,\omega_n) &:= \mathrm{sgn}\,(\omega_1+\cdots+\omega_n). \text{ Again, } p_c(n) = 1/2. \\ \mathsf{Here } \operatorname{Corr}\big[\operatorname{Maj}_n(\omega),\operatorname{Maj}_n(\omega^\epsilon)\big] = 1 - O(\sqrt{\epsilon}), \text{ hence noise-stable.} \\ \mathsf{And } \mathbf{P}\big[\mathscr{S}_n = \{x_i\}\big] &\asymp 1/n, \text{ most of the weight is on singletons.} \\ \mathsf{On the other hand, } \mathbf{E}|\mathscr{S}_n| &= \mathbf{E}|\operatorname{Piv}_n| \asymp \frac{1}{\sqrt{n}}n \asymp \sqrt{n}. \end{split}$$

$$\begin{aligned} &\mathsf{Parity}_n(\omega_1,\ldots,\omega_n) := \omega_1 \cdots \omega_n. \text{ Again, } p_c(n) = 1/2. \\ &\mathsf{Here } \operatorname{Corr} \big[\operatorname{Par}_n(\omega), \operatorname{Par}_n(\omega^\epsilon) \big] = (1-\epsilon)^n, \text{ very sensitive to noise.} \\ &\mathsf{And } \mathbf{P} \big[\mathscr{S}_n = \{x_1,\ldots,x_n\} \big] = 1. \end{aligned}$$

Benjamini, Kalai & Schramm 1998

Using hypercontractivity of the noise operator N_{ϵ} :

Theorem 1. A sequence f_n of monotone Boolean functions is noise sensitive, iff it is asymptotically uncorrelated with all weighted majorities $\operatorname{Maj}_w(\omega_1, \ldots, \omega_n) = \operatorname{sign} \sum_{i=1}^n \omega_i w_i$.

Theorem 2. A sequence f_n of monotone Boolean functions is noise sensitive at density p = 1/2, iff $\sum_x \mathbf{P}[x \in \operatorname{Piv}_n]^2 \to 0$ as $n \to 0$.

Extended to $p_c(n) \approx 1/\text{poly}(\log n)$ by Keller-Kindler '10 and Bouyrie '14.

Corollary. The left-right percolation crossing in an $n \times n$ square is noise sensitive, even with $\epsilon = \epsilon_n > c/\log n$.

Schramm & Steif 2005

Theorem. If $f : \Omega \longrightarrow \mathbb{R}$ can be computed with a randomized algorithm with revealment δ (each bit is read only with probability $\leq \delta$), then

$$\sum_{S:|S|=k} \hat{f}(S)^2 \leq \delta k \, \|f\|_2^2.$$

For left-right crossing in $n \times n$ box on the hexagonal lattice, exploration interface with random starting point gives revealment $n^{-1/4+o(1)}$ (it has length $n^{7/4+o(1)}$, given by 2-arm exponent), while $\sum_{k \leq m} k \asymp m^2$, thus:

Corollary. Left-right crossing on the triangular lattice is noise sensitive under $\epsilon_n > n^{-a}$, with any a < 1/8. Even on square lattice, can take some positive a > 0.

The revealment is at least $n^{-1/2+o(1)}$ for any algorithm computing the crossing (O'Donnell-Servedio '07, plus $n^{3/4}$ pivotals), hence this method can give only $n^{-1/4+o(1)}$ -sensitivity, far from the conjectured $\epsilon_n = n^{-3/4+o(1)}$.

Garban, P. & Schramm 2008

Although goal is to understand size, Gil Kalai suggested trying to understand entire distribution of \mathscr{S}_f . A strange random set of bits.

[Smirnov '01] + [Tsirelson '04] + [Schramm-Smirnov '10] implies that it has a conformally invariant scaling limit.

How to prove tightness for the size of strange random fractal-like sets?

For
$$A \subseteq V$$
: $\mathbf{E}[\chi_S \mid \mathscr{F}_A] = \begin{cases} \chi_S & S \subseteq A, \\ 0 & \text{otherwise.} \end{cases}$

Therefore, $\mathbf{E}[f \mid \mathscr{F}_A] = \sum_{S \subseteq A} \widehat{f}(S) \chi_S$, a nice projection.

$$\mathbf{P}\big[\mathscr{S}_f \subset U\big] = \sum_{S \subset U} \hat{f}(S)^2 = \mathbf{E}\Big[\left(\sum_{S \subset U} \hat{f}(S) \chi_S\right)^2\Big] = \mathbf{E}\Big[\mathbf{E}\big[f \mid \mathscr{F}_U\big]^2\Big]$$

From this, for disjoint subsets A and B, can try to give percolation meaning to $\mathbf{P}[\mathscr{S}_f \cap B \neq \emptyset = \mathscr{S}_f \cap A]$. Very restricted independence.

Influence notions of subsets

Besides resampling a random subset U_{ϵ} , could also use any fixed subset U. Influence:

 $I(U) := \mathbf{P}[U \text{ is pivotal}] = \mathbf{P}[U^c \text{ does not determine the value of } f].$

Significance: the amount of information missing if the bits in U^c are known,

$$\operatorname{sig}(U) := \frac{\operatorname{E}\left[\operatorname{Var}[f \mid \mathscr{F}_{U^c}]\right]}{\operatorname{Var} f} = \frac{\operatorname{P}[\mathscr{S} \cap U \neq \emptyset]}{\operatorname{Var} f}$$

Clue: the amount of information we gain from the bits of U,

$$\mathsf{clue}(U) := \frac{\operatorname{Var}\big[\mathbf{E}[f \mid \mathscr{F}_U]\big]}{\operatorname{Var} f} = \frac{\mathbf{P}[\emptyset \neq \mathscr{S} \subseteq U]}{\operatorname{Var} f}$$

Clearly, $I(U) \ge \operatorname{sig}(U) \ge \operatorname{clue}(U)$. Also, $\operatorname{clue}(U) = 1 - \operatorname{sig}(U^c)$.

Influence notions of subsets

A few examples:

 U_n is all the vertical edges in \mathbb{Z}^2 bond percolation. Then $sig(U_n) \to 1$ and $clue(U_n) \to 0$.

 U_n has a scaling limit of Hausdorff-dimension γ : If $\gamma < 5/4$, then $\operatorname{sig}(U_n) \to 0$, or $\operatorname{clue}(U_n^c) \to 1$. If $5/4 < \gamma < 2$, then usually $\operatorname{sig}(U_n) \to 1$, but also $\operatorname{sig}(U_n^c) \to 1$, hence $\operatorname{clue}(U_n) \to 0$.

For Majority_n, any subset U of size ϵn has sig $(U) \asymp \sqrt{\epsilon}$.

Benjamini: does $|U_n| = o(n^2)$ imply also for percolation that $clue(U_n) \rightarrow 0$?

If we can choose the revealed bits adaptively, then, using the exploration interface, $n^{7/4+o(1)}$ bits suffice.

Small subsets are clueless (Galicza & P.)

If $f : {\pm 1}^V \longrightarrow {\pm 1}$ is *transitive*, and $U \subset V$, then

$$\mathsf{clue}(U) \cdot \operatorname{Var} f = \mathbf{P}[\emptyset \neq \mathscr{S} \subseteq U] \leqslant \mathbf{P}[X \in U] = \sum_{u \in U} \mathbf{P}[X = u] = \frac{|U|}{|V|}.$$

Percolation left-right crossing is *not transitive*, but if we consider an $n \times n$ torus, then the indicator F of the event that {there is a translate of the square on the torus where the left-right crossing happens} is transitive.

Now F_{ϵ} , the indicator of {there is a good translate by some vector $(k, \ell)\epsilon n$, $k, \ell \in \{0, 1, \dots, 1/\epsilon\}$ } is a good approximation to F, because of low probability of half-plane 3-arm events etc.

If a small subset U had a clue about left-right crossing in a square, then its $1/\epsilon \times 1/\epsilon$ translates, using FKG, would have a clue about F_{ϵ} , so also about F, which is impossible, since $1/\epsilon^2 |U|$ is still small.

The clue of random subsets

It Ain't over till it's over (Mossel, O'Donnell, Oleszkiewicz '10). For any density $0 < \rho < 1$ and $\epsilon > 0$ there is a δ and a τ such that for every Boolean function f satisfying $\mathbf{P}[i \in \mathsf{Piv}_f] \leq \tau$ for all $i \in V$, we have

 $\mathbf{P}[\operatorname{clue}(U_{\rho}) \geqslant 1 - \delta] < \epsilon \,.$

This is a deep result, though obvious for noise sensitive functions. Our easy method gives the result when $\sum_i \mathbf{P}[i \in \text{Piv}_f]^2 = o(1)$, via an Azuma-Hoeffding concentration argument:

$$\mathbf{E}[\operatorname{clue}(U_{\rho})] \cdot \operatorname{Var} f = \mathbf{P}[\emptyset \neq \mathscr{S} \subseteq U_{\rho}] \leqslant \mathbf{P}[X \in U_{\rho}] = \rho.$$

And if U and U' differ only in bit i, then

$$|\mathsf{clue}(U) - \mathsf{clue}(U')| \leq \mathbf{P}[i \in \mathscr{S}] = \mathbf{P}[i \in \mathsf{Piv}].$$

Hence we get concentration around the mean on the scale $\sum_i \mathbf{P}[i \in \mathsf{Piv}]^2$.

Bootstrap percolation on infinite graphs

Infinite transitive graph. Start with Bernoulli(p) percolation of occupied sites. If a site has at least k occupied neighbors, then gets occupied. Repeat ad infinitum. For what p do we occupy the entire graph, with probability 1?

van Enter '87, Schonmann '90. $p_c(\mathbb{Z}^d, k) = 0$ for $k \leq d$, and 1 for k > d.

Probably also true for the Heisenberg group (observation by Rob Morris).

Balogh, Peres & P. '06. For any non-amenable group Γ that has a free subgroup F_2 , there exists a symmetric finite generating set and a k-neighbor rule such that $G = \text{Cayley}(\Gamma, S)$ has $0 < p_c(G, k) < 1$.

On *d*-regular tree $p_c(T_d, k)$ can be explicitly calculated, since unsuccessful occupation is equivalent to having a d - k + 1- regular vacant subtree in the initial configuration.

Question. What about non-amenable graph without free subgroups? Conversely, on amenable transitive graphs, does $p_c < 1$ imply $p_c = 0$?

Bootstrap percolation on infinite graphs



Bootstrap percolation on finite graphs

Aizenman, Lebowitz '88. $p_c(\mathbb{Z}_n^d, 2) \simeq \frac{1}{\log^{d-1} n}$.

More general and sharper results by Cerf, Cirillo, Manzo, Holroyd, Balogh, Bollobás, Morris, Duminil-Copin, . . .

Balogh, Pittel '07. For the random *d*-regular graph on *n* vertices, $p_c(G_{n,d},k) \rightarrow p_c(T_d,k)$ for any $2 \leq k \leq d-2$. The threshold window around $p_c(n)$ is of size $O(1/\sqrt{n})$.

Bartha & P. '14. (1) At $p_c(\mathbb{Z}_n^d, 2)$, the process is noise sensitive. (2) At $p_c(G_{n,d}, k)$, the process is noise insensitive.

Rough sketch of sensitivity on \mathbb{Z}_n^2

Will use the condition that $\sum_{i} \mathbf{P}[i \in \mathsf{Piv}]^2$ is small.

Complete occupation is roughly equivalent to having an internally spanned rectangular seed of side lengths $\approx \log n$, because this will keep growing.

Hence, again using an "almost transitivity" argument,

$$\mathbf{P}[i \in \mathsf{Piv} \text{ and } \omega_i = 1] \leqslant rac{C \, \log^2 n}{n^2}.$$

And we have $\mathbf{P}[i \in \mathsf{Piv} \text{ and } \omega_i = 1] \asymp \frac{1}{\log n} \mathbf{P}[i \in \mathsf{Piv} \text{ and } \omega_i = -1]$. So, altogether,

$$\mathbf{P}[i \in \mathsf{Piv}] \leqslant \frac{C \, \log^3 n}{n^2}$$

Should hold for k > 2, too, but seeds are much more complicated.

Revealment does not work: for negative result, need to reveal a lot.

Sketch of stability on $G_{n,d}$

The very narrow threshold window $O(1/\sqrt{n})$ implies that it is correlated with a weighted majority: if majority at level $p_c(n)$ is fulfilled, then with positive probability we overshoot by density $O(1/\sqrt{n})$, but that raises the probability of complete occupation noticeably.

But this used the Balogh-Pittel explicit ODE calculation, relying on the lot of independent randomness in $G_{n,d}$.

A more intuitive reason for (2) is that it should hold for many expander graphs: for 2d-regular expanders, with $k \ge d$, by the perimeter trick, all positive witnesses have size at least c n, and this is often also true for the negative witnesses, which already should imply insensitivity — that would be a converse to the revealment method.

However, there are expanders where each vertex is part of large piece of a square lattice, hence $p_c(G_n, 2) \rightarrow 0$. I do not know whether to expect noise stability or not.