

Dynamics for the Random-cluster Model

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Joint work with Alistair Sinclair (UC Berkeley)

Random-cluster model (Fortuin & Kasteleyn, 1969)

- Probability distribution over the subgraphs of a graph $G = (V, E)$.
- Given parameters $p \in [0, 1]$ and $q > 0$, for each subgraph $(V, \mathcal{A} \subseteq E)$:

$$\mu_G(\mathcal{A}) \propto p^{|\mathcal{A}|} (1-p)^{|E \setminus \mathcal{A}|} q^{c(\mathcal{A})}$$

[$c(\mathcal{A})$]: # of cmts in (V, \mathcal{A})]



$$p(1-p)^3 q^3$$



$$p^2(1-p)^2 q^2$$



$$p^4 q$$

$$\mu_G(A) \propto p^{|A|} (1-p)^{|E \setminus A|} q^{c(A)}$$

Unifying framework for studying several important distributions:

- When $q = 1$, bond percolation model. [$G = K_n$, $G(n, p)$ model]
- For integer $q \geq 2$, “dual” to ferromagnetic Ising/Potts model.
- When $q \rightarrow 0$, the set of (weak) limits that arises includes:

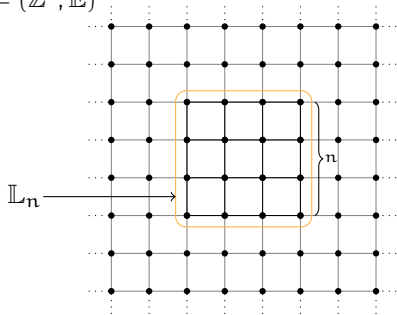
$$\mu_G \rightarrow \text{UST}(G), \quad \mu_G \rightarrow \text{USF}(G), \quad \text{or} \quad \mu_G \rightarrow \text{UCS}(G)$$

Random-cluster model in infinite graphs

Infinite measure: If $\{G_n\} \rightarrow G$, then $\mu_G := \lim_{n \rightarrow \infty} \mu_{G_n}$

Example:

$$\mathbb{L} = (\mathbb{Z}^2, \mathbb{E})$$



Then, $\{\mathbb{L}_n\} \rightarrow \mathbb{L}$ and $\mu_{\mathbb{L}} := \lim_{n \rightarrow \infty} \mu_{\mathbb{L}_n}$

Phase transition

Phase transition: $\exists p_c(q)$ such that w.h.p.,

- $p < p_c(q) \implies$ all components are finite;
- $p > p_c(q) \implies$ there is at least one infinite component.

In \mathbb{Z}^2 :

$$p_c(q) = \frac{\sqrt{q}}{\sqrt{q} + 1} \quad [\text{Beffara, Duminil-Copin 2012}]$$

Finite setting: corresponds to the emergence of a **giant component**.

Our focus: Markov chains on the random-cluster configurations of a graph G with stationary distribution μ_G .

Mixing time: Number of steps T_{mix} until total variation distance from μ_G is small ($\leq 1/4$), starting from any initial configuration.

Motivation:

- Connection between phase transitions and mixing times.
- Algorithms for sampling configurations (MCMC).
- Random-cluster dynamics challenge current techniques.

Heat-bath (HB) dynamics

Given a random-cluster configuration $A \subseteq E$:

1. pick an edge $e \in E$ u.a.r.;
2. replace A by $A \cup \{e\}$ with probability

$$\frac{\mu_G(A \cup \{e\})}{\mu_G(A \cup \{e\}) + \mu_G(A \setminus \{e\})};$$

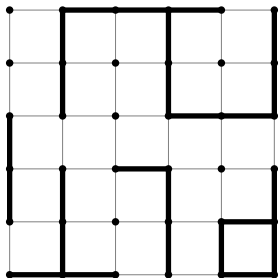
3. else replace A by $A \setminus \{e\}$.

Heat-bath (HB) dynamics (cont.)

$$\frac{\mu_G(A \cup \{e\})}{\mu_G(A \cup \{e\}) + \mu_G(A \setminus \{e\})} = \begin{cases} p & \text{if } e \text{ is not a cut-edge;} \\ \frac{p}{p + q(1-p)} & \text{otherwise.} \end{cases}$$

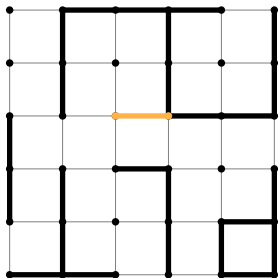
Heat-bath (HB) dynamics (cont.)

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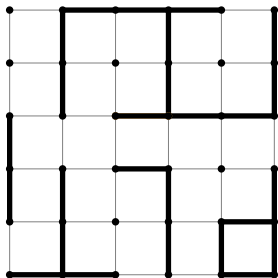
Heat-bath (HB) dynamics (cont.)

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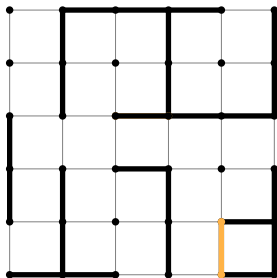
Heat-bath (HB) dynamics (cont.)

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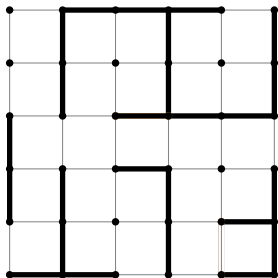
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Heat-bath (HB) dynamics (cont.)

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Chayes-Machta (CM) dynamics

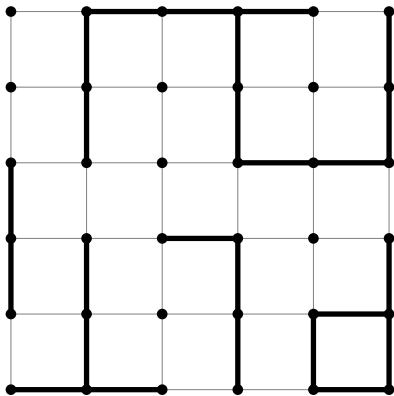
Given a random-cluster configuration $A \subseteq E$:

1. Activate each component of A independently with prob. $1/q$;
2. Add each active edge with prob. p ; remove it otherwise.

- Straightforward to check that μ_G is the stationary measure.
- It is well-defined for any $q \geq 1$.

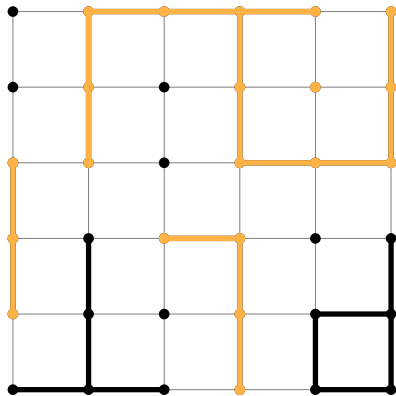
CM dynamics: example

$$G = \mathbb{L}_6, p = 1/2, q = 2$$



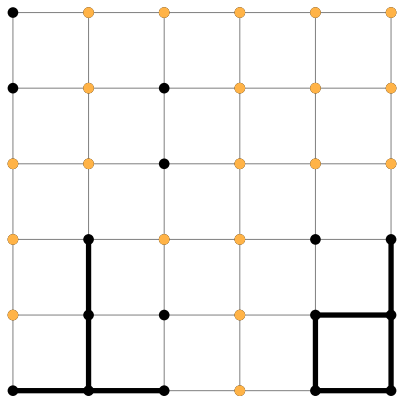
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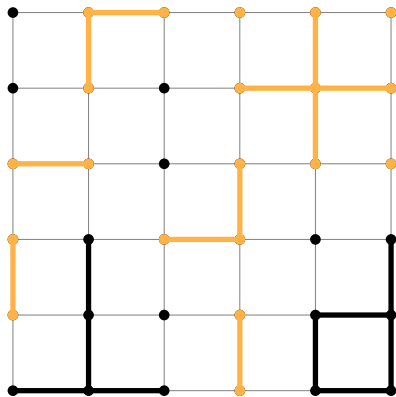
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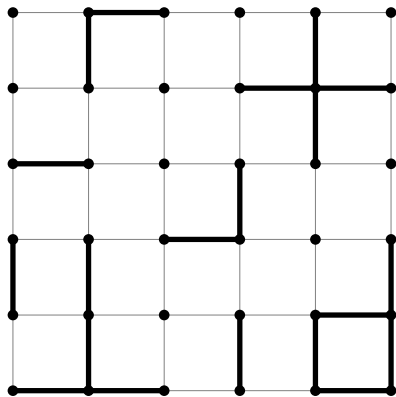
CM dynamics: example

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CM dynamics: example

$$G = \mathbb{L}_6, p = 1/2, q = 2$$



Local and Global dynamics

- The HB dynamics is a **local** Markov chain, while the CM is **global**.
- In spin systems, global Markov chains mix fast in regimes where local dynamics are slow.

Theorem 1

$$\frac{T_{\text{mix}}(\text{CM})}{\tilde{O}(|E|^2)} \leq T_{\text{mix}}(\text{HB}) \leq \tilde{O}(|E|^2) \cdot T_{\text{mix}}(\text{CM})$$

Proof idea. Follows by generalizing a technique of [Ullrich 2013].

Part I: Chayes-Machta dynamics in the mean-field [$G = K_n$]

Part II: Heat-bath dynamics in \mathbb{Z}^2

Mean-field theory

Mean-field: $G = K_n$ [useful non-trivial starting point]

Phase transition: If $p = \lambda/n$, then $\exists \lambda_c(q)$ such that w.h.p.:

- $\lambda < \lambda_c(q) \implies$ all components have size $O(\log n)$.
- $\lambda > \lambda_c(q) \implies$ there is a component of size $\sim \theta_r n$.

Critical value:

$$\lambda_c(q) = \begin{cases} q & \text{if } 0 < q \leq 2, \\ 2 \left(\frac{q-1}{q-2} \right) \log(q-1) & \text{if } q > 2. \end{cases}$$

[Bollobás, Grimmett, Janson 1996] [Łuczak, Łuczak 2006]

Mean-field mixing: Previous work

Previous work on mixing times:

- Most previous results are for Swendsen-Wang (SW) dynamics.
[similar to CM dynamics, but only for integer q]
- Mixing time of SW dynamics for $q = 2$ fully understood.
[Cooper, Dyer, Frieze, Rue 2006]
[Long, Nachmias, Ning, Peres 2011]
- Until recently, only partial results for integer $q \geq 3$.
[Gore, Jerrum 1996], [Huber 2003]
- Independently, mixing time of SW dynamics for integer $q \geq 3$ also fully understood. [Galanis, Štefankovič, Vigoda 2015]

Mean-field mixing: Our results

Theorem 2

If $q \in (1, 2]$:

$$T_{\text{mix}}(\text{CM}) = \Theta(\log n) \quad \text{for } \lambda \neq \lambda_c$$

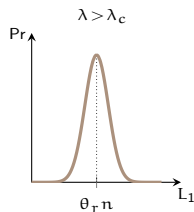
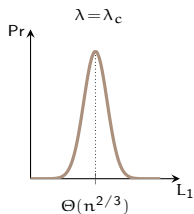
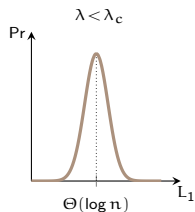
If $q > 2$:

$$T_{\text{mix}}(\text{CM}) = \begin{cases} \exp(\Omega(\sqrt{n})) & \text{for } \lambda \in (\lambda_L, \lambda_R) \\ \Theta(\log n) & \text{for } \lambda \notin [\lambda_L, \lambda_R] \\ \Theta(n^{1/3}) & \text{for } \lambda = \lambda_L \end{cases}$$

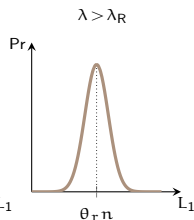
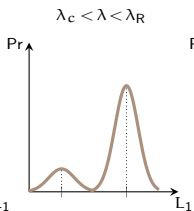
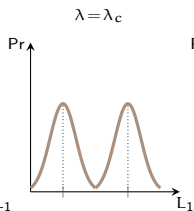
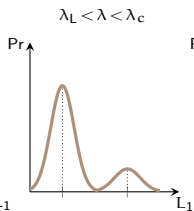
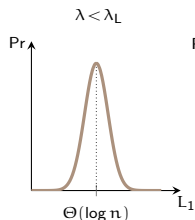
$$[\lambda_L < \lambda_c < \lambda_R]$$

Mean-field mixing: Interpretation of results

Second order phase transition for $1 < q \leq 2$:



First order phase transition for $q > 2$:



Mean-field mixing: Proof ideas

Technique:

- **Couple** two copies $\{X_t\}, \{Y_t\}$ of the CM dynamics, starting from arbitrary initial configurations X_0, Y_0 .
- If $\Pr[X_T \neq Y_T] \leq 1/4$ then $T_{\text{mix}} \leq T$.

Coupling has two main phases:

1. Run $\{X_t\}$ and $\{Y_t\}$ **independently** until the sizes of largest components are close to expectation. $[\Theta(\log n)$ if $\lambda < \lambda_c$, and $\sim \theta_T n$ if $\lambda > \lambda_c$]
2. **Coupled** the evolution of $\{X_t\}, \{Y_t\}$ until $X_T = Y_T$.

Phase 1: Independent evolution

Observation: If A_t is the set of active vertices at time t , the configuration in A_t is replaced by a $G(A_t, p)$ random graph.

Phase 1a: After $O(\log n)$ steps $\{X_t\}$ has at most one large component.

Phase 1b: Analyze the expected change in size of the largest component.

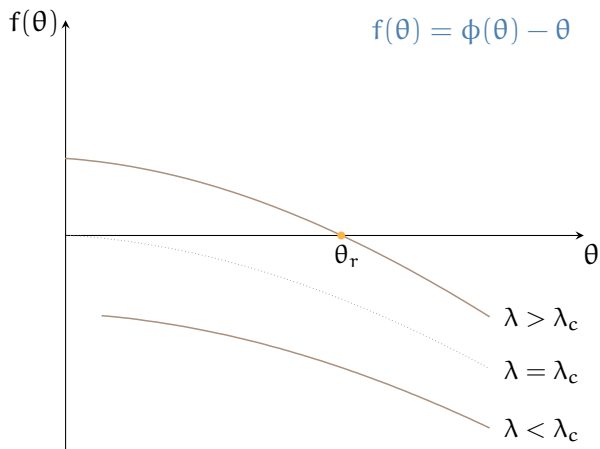
$\mathcal{L}(X_t)$ largest component of X_t , and $L_1(X_t) =: \theta_t n$

- If $\mathcal{L}(X_t)$ is **inactive**: $\mathcal{L}(X_{t+1}) = \mathcal{L}(X_t)$ w.h.p.
- If $\mathcal{L}(X_t)$ is **active**: # of active vertices $\approx \theta_t n + \frac{(1 - \theta_t)n}{q} =: M$

$$E[L_1(X_{t+1}) \mid \mathcal{L}(X_t) \text{ active}] \approx L_1(G(M, p)) =: \phi(\theta_t)n.$$

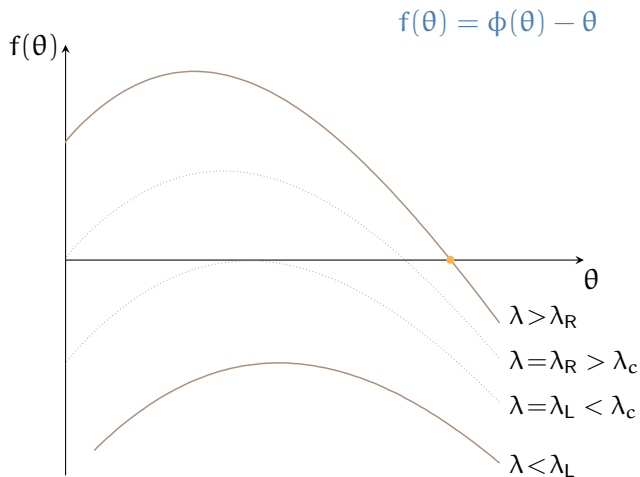
- Drift given by the function $f(\theta) := \phi(\theta) - \theta$.

Phase 1: Drift function ($1 < q \leq 2$)



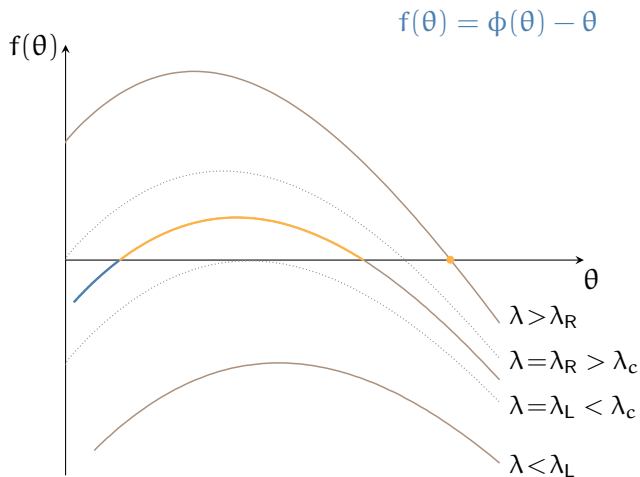
The drift function f has the desired sign.

Phase 1: Drift function ($q > 2$)



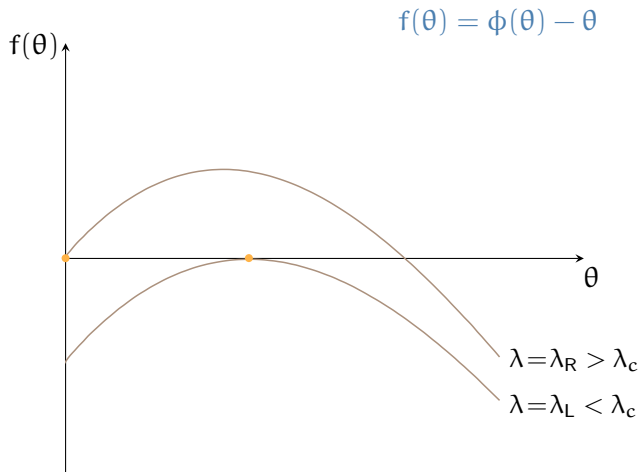
When $\lambda < \lambda_L$ and $\lambda > \lambda_R$ drift always has desired sign.

Phase 1: Drift function ($q > 2$)



When $\lambda_L < \lambda < \lambda_R$, drift **does not** always have desired sign.

Phase 1: Drift function ($q > 2$)



When $\lambda = \lambda_L$ or $\lambda = \lambda_R$, drift can be 0.

Proofs: Phase 2 - Coupled evolution

Phase 2a: Coupling to achieve the same component structure.

[Assuming $L_1(X_0) \approx L_1(Y_0)$]

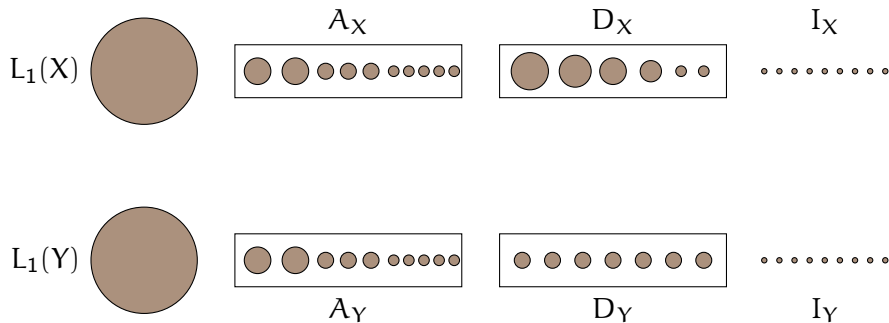
1. Couple the **activation** of components in a way such that both active subgraphs have the same size w.h.p.
2. Couple **edge resampling** using arbitrary bijection between active edges.

Observations:

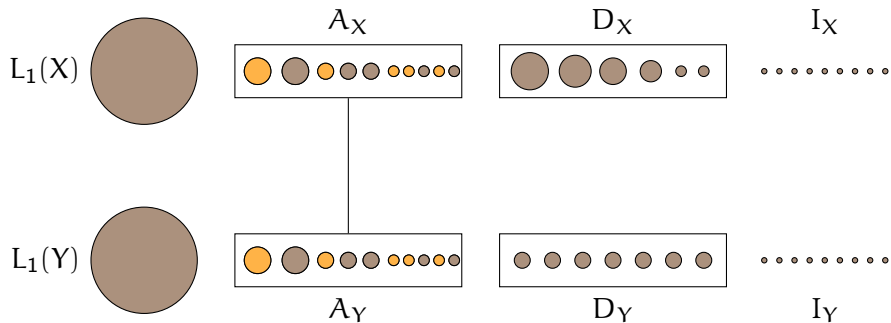
- If activation coupling succeeds, the activated subgraphs will have the same component structure after step 2.
- After $T = O(\log n)$ consecutive **successes** of the activation coupling X_T and Y_T have the same component structure w.h.p.

Phase 2b: If X_0 and Y_0 have the same component structure, $\{X_t\}, \{Y_t\}$ can be coupled such that $X_T = Y_T$ for some $T = O(\log n)$ w.h.p.

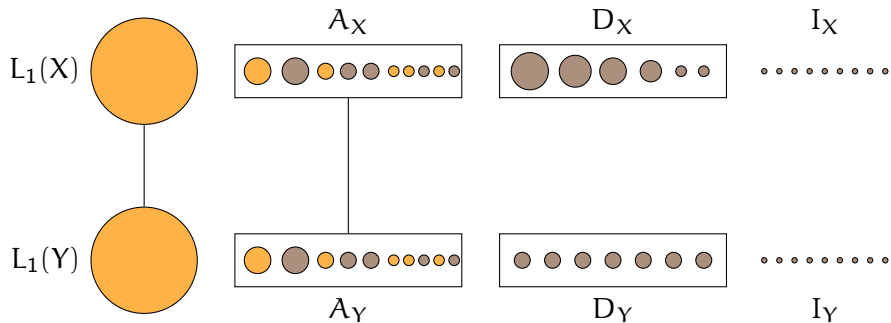
Proofs: Phase 2 - Activation coupling



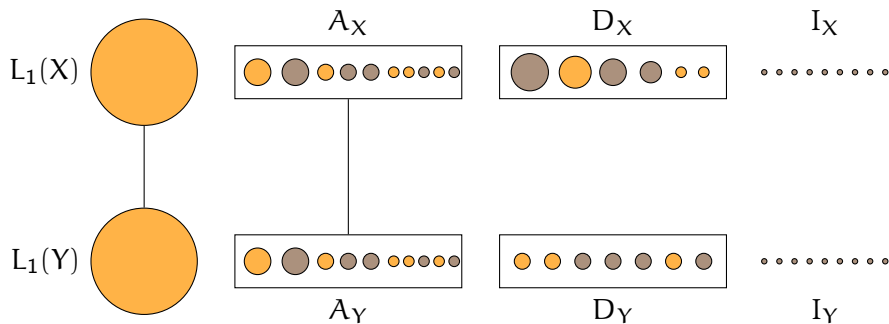
Proofs: Phase 2 - Activation coupling



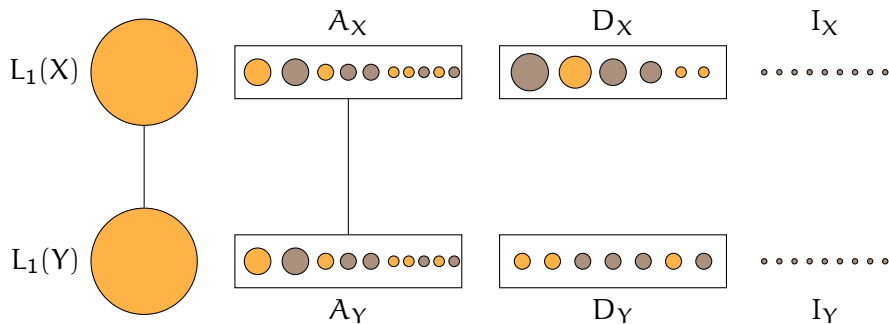
Proofs: Phase 2 - Activation coupling



Proofs: Phase 2 - Activation coupling

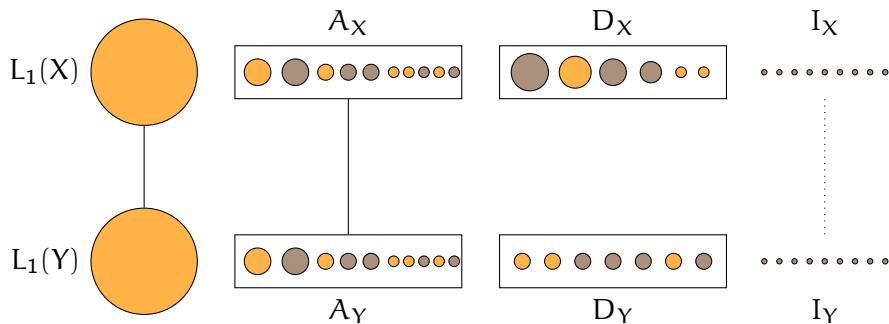


Proofs: Phase 2 - Activation coupling



- First part of activation creates a discrepancy $\mathcal{D} = O(\sqrt{n})$.

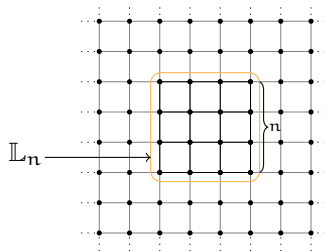
Proofs: Phase 2 - Activation coupling



- First part of activation creates a discrepancy $\mathcal{D} = O(\sqrt{n})$.
- Correct \mathcal{D} using coupling of binomial distributions on I_X and I_Y .

Part II: Random-cluster dynamics in \mathbb{Z}^2

Heat-bath dynamics in \mathbb{L}_n



Given a random-cluster configuration $A \subseteq E_n$ of \mathbb{L}_n :

1. pick an edge $e \in E$ u.a.r.;

2. replace A by $A \cup \{e\}$ with probability $\frac{\mu_G(A \cup \{e\})}{\mu_G(A \cup \{e\}) + \mu_G(A \setminus \{e\})}$;

3. else replace A by $A \setminus \{e\}$.

Heat-bath dynamics in \mathbb{L}_n : Mixing times

Previous work: [Ullrich 2014]

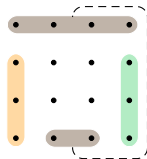
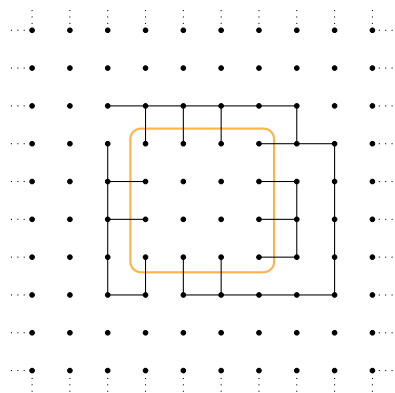
$T_{\text{mix}}(\text{HB}) = O(n^6 \log^2 n)$, for all integer $q \geq 1$ and all $p \neq p_c(q)$.

Holds only for **integer** q , produces **weak bounds**, and the proof is **indirect**.

Theorem 3

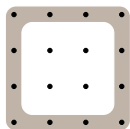
$T_{\text{mix}}(\text{HB}) = \Theta(n^2 \log n)$, for all $q \geq 1$ and all $p \neq p_c(q)$.

Boundary conditions

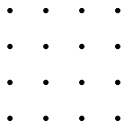


Boundary condition: A **partition** of the vertices in $\partial\mathbb{L}_n$ that encodes the connectivities from \mathbb{L}_n^c .

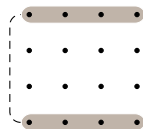
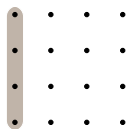
Boundary conditions: examples



wired

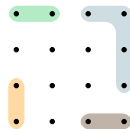
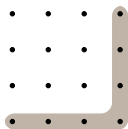
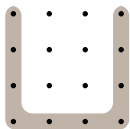


free



A boundary condition η is **side-homogeneous** if:

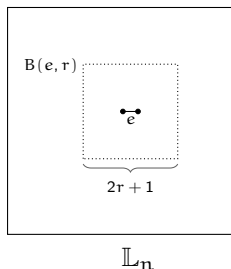
1. all wired vertices in η belong to the same component of \mathbb{L}_n^c ; and
2. η is either free or wired along each side of \mathbb{L}_n



not side-homogeneous!

Spatial Mixing (SM)

Let $B(e, r)$ be a square box of radius r around e :



SM holds if for all e and all pairs of configurations A_1^c, A_2^c on $B^c(e, r)$:

$$| \mu_{\mathbb{L}_n}^\eta(e = 1 | A_1^c) - \mu_{\mathbb{L}_n}^\eta(e = 1 | A_2^c) | \leq e^{-\Omega(r)}$$

Spatial Mixing (cont.)

Exponential decay of connectivities (EDC): [Beffara, Duminil-Copin 2012]

For $p < p_c(q)$, $q \geq 1$ and all $u, v \in \mathbb{Z}^2$,

$$\mu_{\mathbb{L}}(u \leftrightarrow v) \leq e^{-d(u,v)}$$

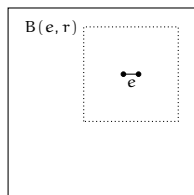
Previous work on SM: [Alexander 2004]

- EDC holds in finite volumes with arbitrary boundary conditions.
- SM holds for certain restricted class of boundary conditions, for all $p < p_c(q)$ and all integer $q \geq 1$.

Lemma 1. SM holds for side-homogeneous boundary conditions, for all $p < p_c(q)$ and all $q \geq 1$.

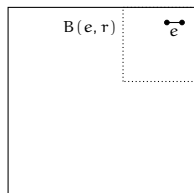
Proof of Lemma 1 (SM)

Case 1: $\partial\mathbb{L}_n \cap B(e, r) = \emptyset$



- Influence on e from $B^c(e, r)$ iff there are paths from ∂B to e .
- EDC ensures that influence decays exponentially with r .

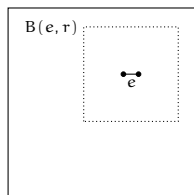
Case 2: $\partial\mathbb{L}_n \cap B(e, r) \neq \emptyset$



- Influence on e also from the boundary condition on \mathbb{L}_n .

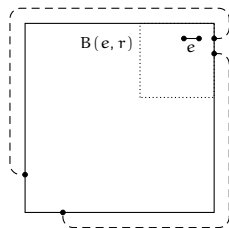
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- Influence on e from $B^c(e, r)$ iff there are paths from ∂B to e .
- EDC ensures that influence decays exponentially with r .

Case 2: $\partial\mathbb{L}_n \cap B(e, r) \neq \emptyset$



- Influence on e also from the boundary condition on \mathbb{L}_n .
- Far regions could affect the state of e .
- Side-homogeneous boundaries avoid this!

Outline of proof of Theorem 3

Theorem 3

$T_{\text{mix}}(\text{HB}) = \Theta(n^2 \log n)$, for all $p \neq p_c$ and all $q \geq 1$.

Proof Sketch.

Lemma 2. SM implies that $T_{\text{mix}} = O(n^2 \log n (\log \log n)^2)$.

Lemma 3. If $T_{\text{mix}} = O(n^{2+\varepsilon})$, then $T_{\text{mix}} = O(n^2 \log n)$.

Therefore, $T_{\text{mix}} = O(n^2 \log n)$ for all $p < p_c$ and all $q \geq 1$.

Lemma 4. If $T_{\text{mix}} \leq M$ for $p < p_c$, then $T_{\text{mix}} = O(M)$ for $p > p_c$.

Lemma 5. $T_{\text{mix}} = \Omega(n^2 \log n)$.

Proof of Lemma 2: SM implies fast mixing

On spin systems: [Martinelli, Olivieri, Schonmann 1994]
[Dyer, Sinclair, Vigoda, Weitz 2004]
[Mossel, Sly 2013]

Proof idea.

- **Couple** two copies $\{X_t\}, \{Y_t\}$ of the heat-bath Markov chain, starting from arbitrary initial configurations.
- If $\Pr[X_T \neq Y_T] \leq 1/4$ then $T_{\text{mix}} \leq T$.

Identity Coupling: Use same random edge e and same uniform random number to decide if add/remove e .

Monotonicity: If $Y_t \subseteq X_t$, then $Y_{t+1} \subseteq X_{t+1}$.

Therefore, it is sufficient to consider the starting states $Y_0 = \emptyset, X_0 = E_n$.

Proof of Lemma 2: SM implies fast mixing (cont.)

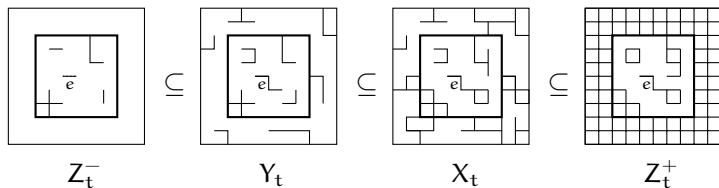
- A **union bound** implies:

$$\Pr[X_t \neq Y_t] \leq \sum_{e \in E} \Pr[X_t(e) \neq Y_t(e)]$$

- Consider $\{Z_t^-\}, \{Z_t^+\}$ such that:

$$\emptyset = Z_0^- = Y_0 \subseteq X_0 = Z_0^+ = E_n$$

- $\{X_t\}, \{Y_t\}, \{Z_t^-\}, \{Z_t^+\}$ are coupled via the **identity coupling**.
- $\{Z_t^-\}, \{Z_t^+\}$ ignore updates in $B^c = B^c(e, r)$ for a suitable r .



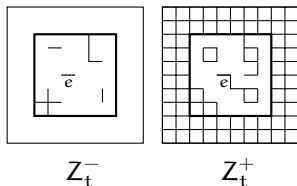
Proof of Lemma 2: SM implies fast mixing (cont.)

$$\Pr[X_t(e) \neq Y_t(e)] \leq \Pr[Z_t^-(e) \neq Z_t^+(e)]$$

Stationary measures:

$$\{Z_t^-\} \rightarrow \mu_{\mathbb{L}_n}^\eta(\cdot | B^c = 0)$$

$$\{Z_t^+\} \rightarrow \mu_{\mathbb{L}_n}^\eta(\cdot | B^c = 1)$$



For sufficiently large T :

$$Z_T^-(\cdot) \approx \mu_{\mathbb{L}_n}^\eta(\cdot | B^c = 0)$$

$$Z_T^+(\cdot) \approx \mu_{\mathbb{L}_n}^\eta(\cdot | B^c = 1)$$

SM with $r = O(\log n)$:

$$\left| \mu_{\mathbb{L}_n}^\eta(e = 1 | B^c = 1) - \mu_{\mathbb{L}_n}^\eta(e = 1 | B^c = 0) \right| \leq e^{-\Omega(r)} = O(n^{-2})$$

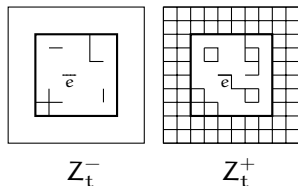
Proof of Lemma 2: SM implies fast mixing (cont.)

$$\Pr[X_t(e) \neq Y_t(e)] \leq \Pr[Z_t^-(e) \neq Z_t^+(e)]$$

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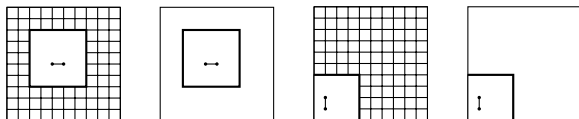
T should be large enough s.t. $\{Z_t^-\}, \{Z_t^+\}$ are well mixed.

SM with $r = O(\log n)$:

$$\left| \mu_{\mathbb{L}_n}^\eta(e = 1 | B^c = 1) - \mu_{\mathbb{L}_n}^\eta(e = 1 | B^c = 0) \right| \leq e^{-\Omega(r)} = O(n^{-2})$$

Proof of Lemma 2: SM implies fast mixing (cont.)

- $\{Z_t^-\}$ and $\{Z_t^+\}$ are “lazy” heat-bath dynamics in $B(e, r)$ with **side-homogeneous boundary conditions**:



- If $T_{\text{mix}}(\mathbb{L}_n) \leq F_0(n)$ for all side-homogeneous boundaries, then:

$$T = F_0(\log n) \log n \cdot \frac{n^2}{\log^2 n} = F_1(n)$$

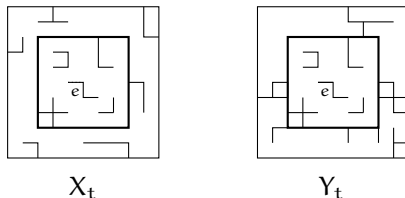
- If $F_0(n) \leq e^{n^2}$ [crude bound], then: $F_4(n) = O(n^2 \log n (\log \log n)^2)$

Proof of Lemma 3

Lemma 3. If $T_{\text{mix}} = O(n^{2+\varepsilon})$, then $T_{\text{mix}} = O(n^2 \log n)$.

Proof Sketch. Establish recurrence for $\max_{e \in E} \Pr[X_t(e) \neq Y_t(e)]$

Main new ingredient: Bound the speed of propagation of disagreements.

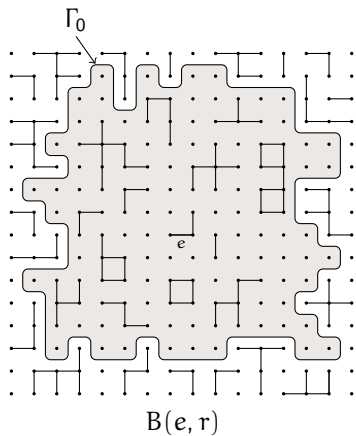


If $X_t(B(e, r)) = Y_t(B(e, r))$, how many steps until $X_T(e) \neq Y_T(e)$?

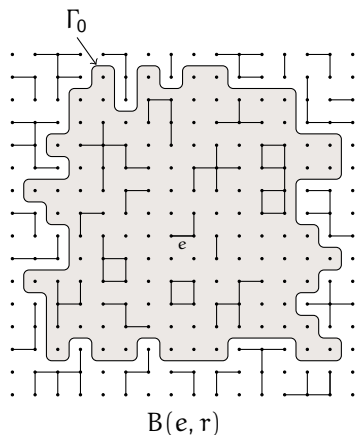
Lemma 6. If $X_0(B(e, r)) = Y_0(B(e, r))$ and $Y_0 \sim \mu_{\mathbb{L}_n}^\eta$, then:

$$\Pr[X_{kn^2}(e) \neq Y_{kn^2}(e)] \leq e^{-\Omega(r^{1/4})} \quad [\text{for } k < r^{1/4}]$$

Speed of propagation of disagreements: Proof



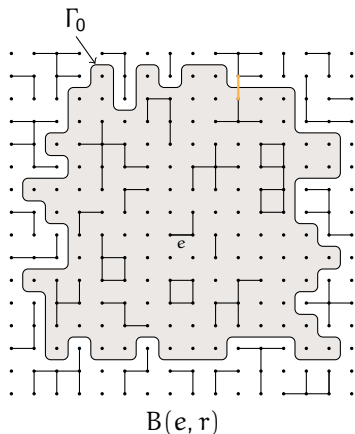
Speed of propagation of disagreements: Proof



1. If $e_t \notin \partial\Gamma_t$, then $\Gamma_{t+1} = \Gamma_t$;
2. o.w., $\Gamma_{t+1} = \Gamma_t \setminus c_t$.

Key observation: $X_t(\Gamma_t) = Y_t(\Gamma_t)$

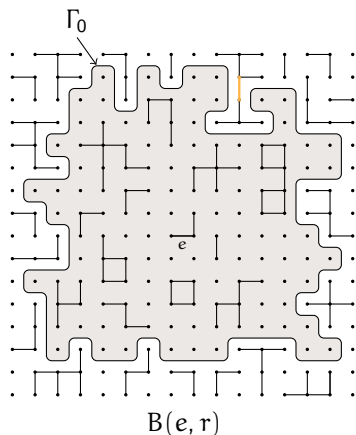
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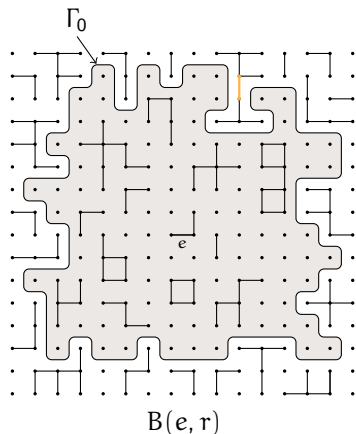
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Speed of propagation of disagreements: Proof

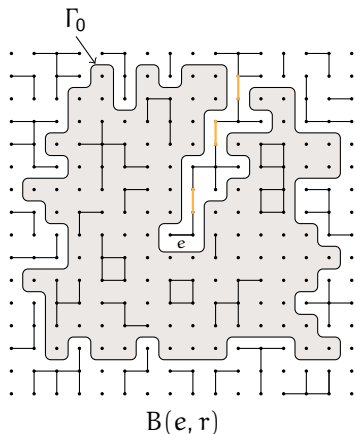


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- Since $Y_t \sim \mu_{\mathbb{L}_n}^\eta$, **EDC** only small clusters in $B(e, r)$.
- Hence, many updates to $\partial\Gamma_t$ are required to reach e .

Open problems

Mean-field:

- Better upper bounds for the mixing time of local dynamics.
[Should be $\tilde{O}(n^2)$, instead of $\tilde{O}(n^4)$]

\mathbb{Z}^2 :

- Mixing time of the heat-bath at the critical point $\lambda = \lambda_c(q)$.
[Conjecture: polynomial for $q \leq 4$, exponential for $q > 4$]
[Duminil-Copin, Sidoravicius, Tassion 2015]
[Laanait, Messenger, Miracle-Solé, Ruiz, Shlosman 1991]

General Graphs:

- Dynamics for $q \in (0, 1)$?
- Analysis of dynamics in other graphs.

Thanks!