

Field dynamics: a new tool to boost mixing results

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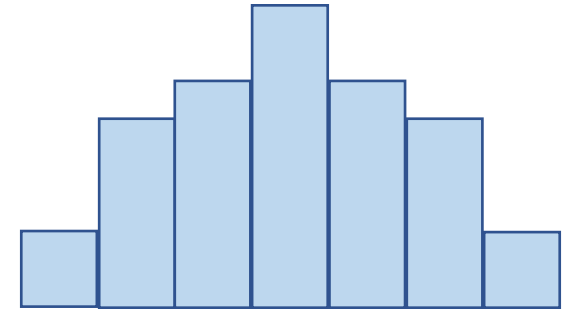
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(Nanjing University)

Summer school at UCSB, Santa Barbara, CA, US, 12th August 2022

Sampling, counting and phase transition

Boolean variables set V , weight function $w: \{-, +\}^V \rightarrow \mathbb{R}_{\geq 0}$
joint distribution μ :

$$\forall X = (X_v)_{v \in V} \in \{-, +\}^V, \quad \mu(X) \propto w(X)$$

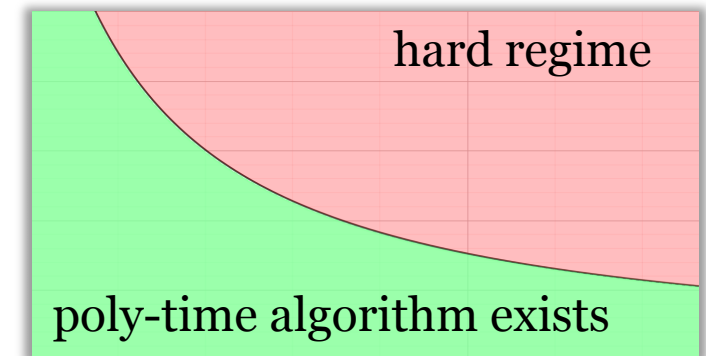


Sampling problem

Draw (approximate) random samples from distribution μ

Goal:

Prove *optimal* mixing results up to the computational phase transition threshold



Example: Hardcore model

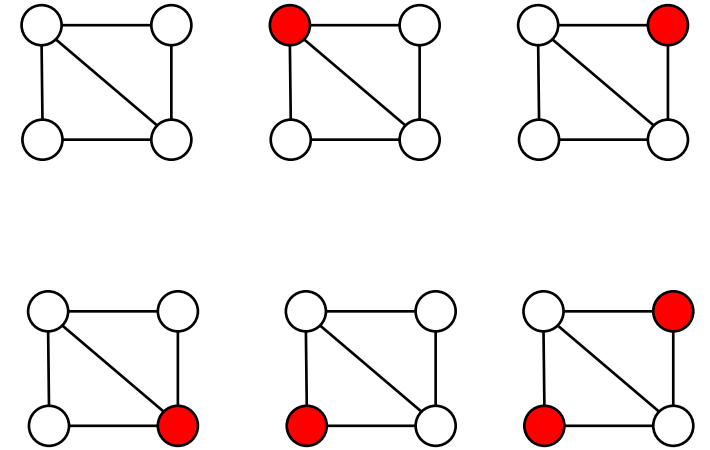
- graph $G = (V, E)$, parameters λ ;

- Gibbs distribution μ :

$$\forall \text{independent set } I \subseteq V, \quad \mu(I) \propto \lambda^{|I|}.$$

- Equivalent state space of μ :

$$\{-, +\}^V = \{\text{occupied}, \text{unoccupied}\}^V$$



Computational phase transition

- $\lambda < \lambda_c(\Delta)$: **poly-time algorithm** for sampling [Weitz06]
- $\lambda > \lambda_c(\Delta)$: **no poly-time algorithm** unless $NP = RP$ [Sly10]

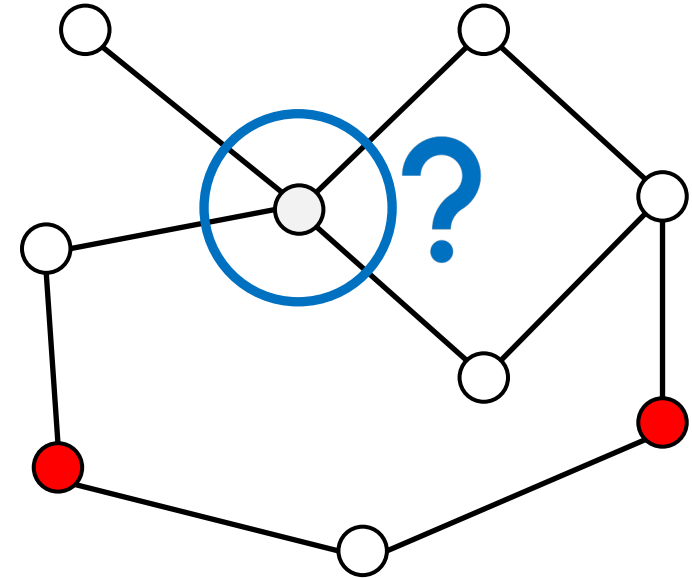
$$\lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta-1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta}$$

Glauber dynamics for hardcore model

Start from an arbitrary independent set X ;

For each transition step **do**

- Lazy w.p. $\frac{1}{2}$, otherwise do as follows:
- Pick a vertex v uniformly at random;
- **If** $X_u = -$ for all neighbors u **then**
$$X_v = \begin{cases} + & \text{w.p. } \lambda/(1 + \lambda) \\ - & \text{w.p. } 1/(1 + \lambda) \end{cases}$$
- **Else** $X_v \leftarrow -$



Mixing time: $T_{\text{mix}} = \max_{X_0 \in \Omega} \min \left\{ t \mid d_{TV}(X_t, \mu) \leq \frac{1}{4e} \right\},$

$d_{TV}(X_t, \mu)$: the *total variation distance* between X_t and μ .

Previous works

Work	Condition	Mixing Time
Dobrushin 1970	$\lambda \leq \frac{1 - \delta}{\Delta - 1}$	$O\left(\frac{1}{\delta} n \log n\right)$
Luby, Vigoda, 1999	$\lambda \leq \frac{2(1 - \delta)}{\Delta - 2}$	$O\left(\frac{1}{\delta} n \log n\right)$
Efthymiou <i>et al</i> , 2016	$\lambda \leq (1 - \delta)\lambda_c(\Delta)$ $\Delta \geq \Delta_0(\delta), \text{ girth} \geq 7$	$O\left(\frac{1}{\delta} n \log n\right)$

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Anari, Liu, Oveis Gharan, 2020 improved by Chen, Liu, Vigoda, 2020	$\lambda \leq (1 - \delta)\lambda_c(\Delta)$	$n^{O(1/\delta)}$
Chen, Liu, Vigoda, 2021	$\lambda \leq (1 - \delta)\lambda_c(\Delta)$	$\Delta^{O(\Delta^2/\delta)} n \log n$

Open question:

Can we prove the fast (optimal) mixing for all degrees ?

Mixing time of Glauber dynamics when $\lambda \leq (1 - \delta)\lambda_c$

Work	Mixing Time	Technique
Anari, Liu, Oveis Gharan, 2020 improved by Chen, Liu, Vigoda, 2020	$n^{O(1/\delta)}$	Spectral Independence (SI)
Chen, Liu, Vigoda, 2021	$\Delta^{O(\Delta^2/\delta)} n \log n$	
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3 Chen, Eldan, 2022	$e^{O(1/\delta)} n \log n$	Localization Scheme

1

Zongchen Chen

2

Xiaoyu Chen

3

Yuansi Chen

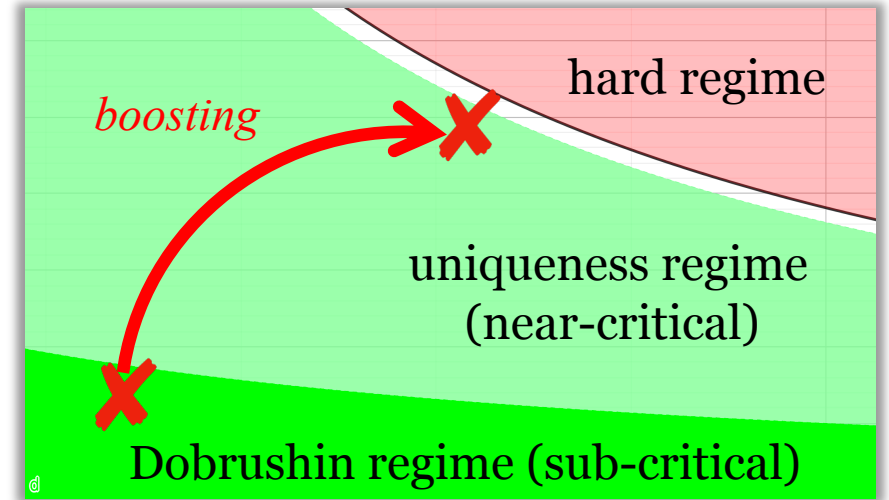
Hardcore model in uniqueness regime

If λ is *close* to $\lambda_c(\Delta)$, e.g., $\lambda = 0.999\lambda_c$ (**near-critical**)

analyzing mixing time is *hard*

- If λ is *far-away* from $\lambda_c(\Delta)$, e.g., $\lambda \leq 0.1\lambda_c$ (**sub-critical**)

analyzing mixing time is *easy*



Boosting Theorem

Boosting mixing results from **sub-critical regime** to **near-critical regime**

- Boost *spectral gap* of Glauber dynamics [CFYZ21]
- Boost *modified log-Sobolev constant* of Glauber dynamics [CFYZ22]

Proved by a new Markov chain: field dynamics

Revisit Chen-Liu-Vigoda's technique

Simpler task: poly-time sampling algorithm

Input: hardcore model with $\lambda \leq (1 - \delta)\lambda_c(\Delta)$ and Δ can be unbounded;

Output: random sample X s.t. $d_{TV}(X, \mu) = \frac{1}{\text{poly}(n)}$.

θ -fractional block dynamics

Parameter: $\theta \in (0,1)$

Initialization: arbitrary $X \in \{-, +\}^V$

Update: for each $t = 1$ to T

- pick $S \subseteq V$ with $|S| = \theta n$ u.a.r.;
- $X_S \sim \mu_S(\cdot | X_{V \setminus S})$;

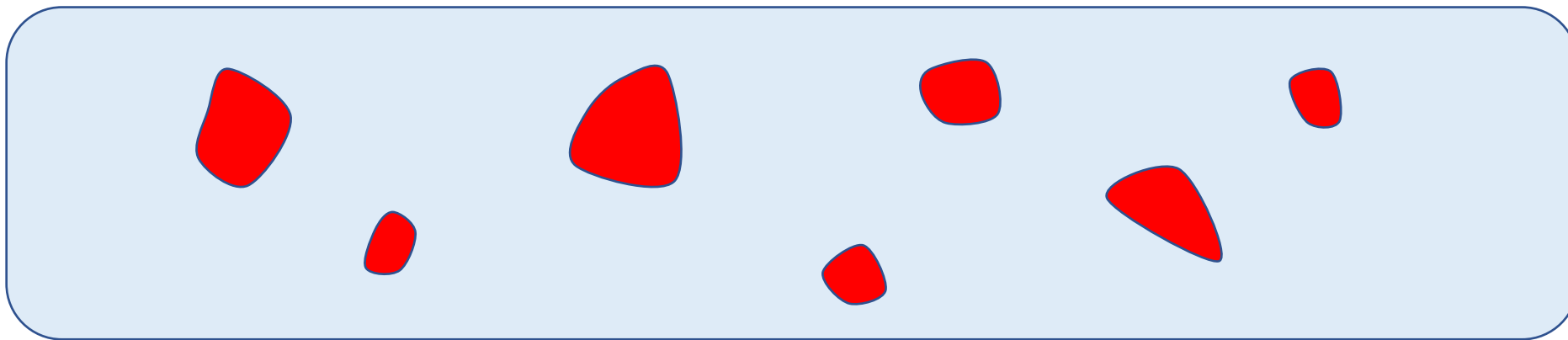
Mixing result [CLV21]

$$\lambda_{\text{gap}} \geq \theta^{O(1/\delta)}$$

$$d_{TV}(\mu, X) \leq \frac{1}{\text{poly}(n)} \text{ if } T = \left(\frac{1}{\theta}\right)^{O(1/\delta)} n \log n$$

Question: how to *efficiently* simulate the transition step $X_S \sim \mu_S(\cdot | X_{V \setminus S})$?

Update step $X_S \sim \mu_S(\cdot | X_{V \setminus S})$: sample from hardcore model $(G[S], \lambda)$ with boundary condition $X_{V \setminus S}$



Observation [Chen, Liu and Vigoda, 2021]

If $\theta = O\left(\frac{1}{\Delta}\right)$, then w.h.p., $G[S]$ is a set of small connected components

Mixing time

$\theta = O(1/\Delta)$ -fractional block dynamics
 $T = \Delta^{O(1/\delta)} n \log n$ steps

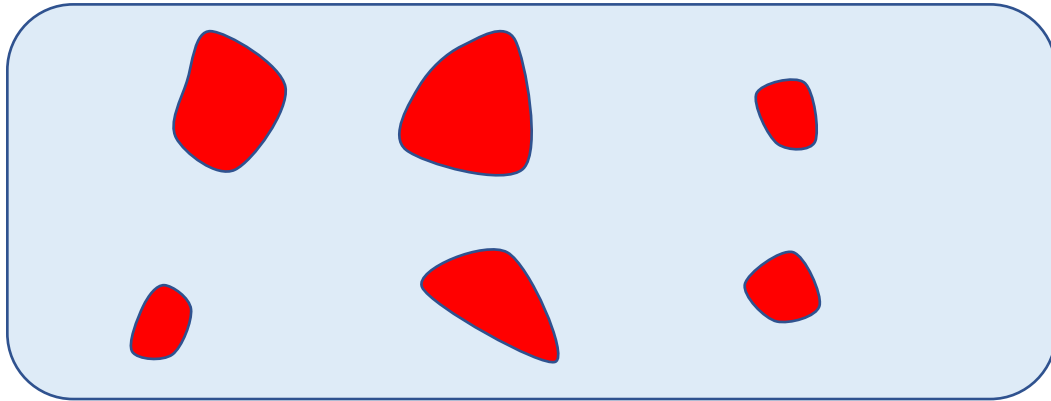
Simulation of each step

brute force on each component
Expected cost = $O(n)$

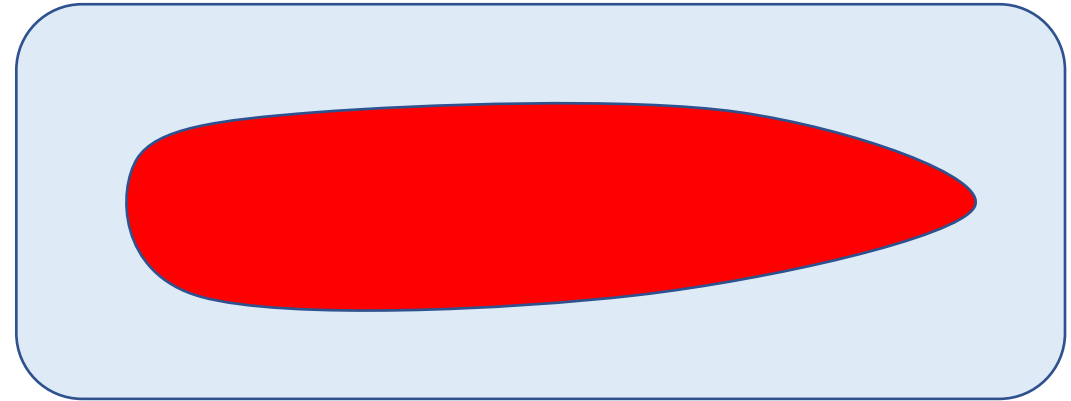
Total expected running time of the algorithm: $\Delta^{O(1/\delta)} n^2 \log n$



Natural idea: set $\theta = \frac{1}{100}$ \longrightarrow Mixing time $T = 2^{O(1/\delta)} n \log n = O_\delta(n \log n)$



$$\theta = O(1/\Delta)$$



$$\theta = O(1)$$

Issue : how to sample from hardcore model $(G[S], \lambda)$ with boundary condition $X_{V \setminus S}$?

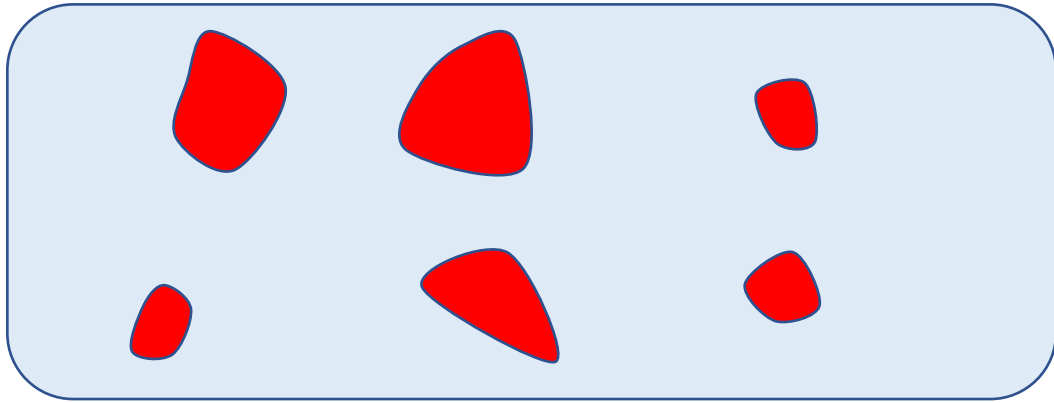
Observation [Chen, F. Yin and Zhang, 2021]

The maximum degree of $G[S]$ can be small.

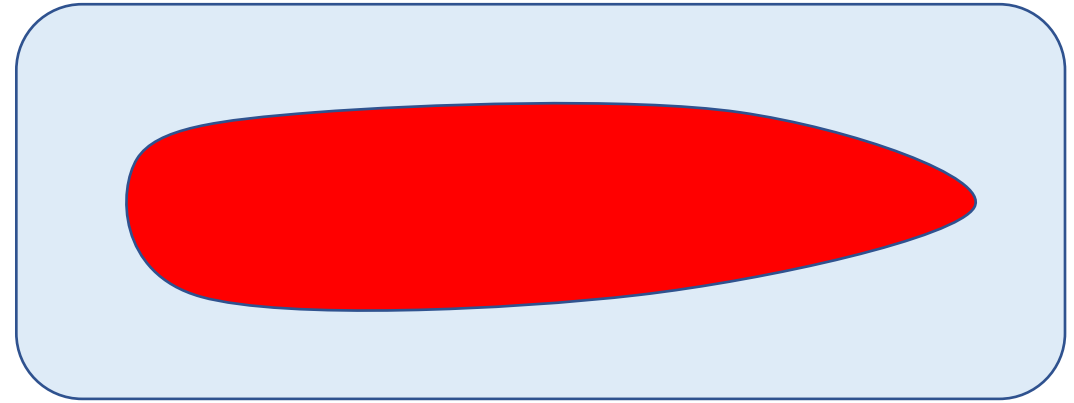
For any $v \in S$,

$$\begin{aligned} \mathbb{E}[\text{degree of } v \text{ in } G[S]] &\approx \theta \deg_G(v) \\ &= \frac{\deg_G(v)}{100} \end{aligned}$$

Natural idea: set $\theta = \frac{1}{100}$  Mixing time $T = 2^{O(1/\delta)} n \log n = O_\delta(n \log n)$



$$\theta = O(1/\Delta)$$



$$\theta = O(1)$$

Issue : how to sample from hardcore model $(G[S], \lambda)$ with boundary condition $X_{V \setminus S}$?

$$\lambda \leq \lambda_c(\Delta_G) \approx \frac{e}{\Delta_G}$$

uniqueness condition in (λ, Δ_G)

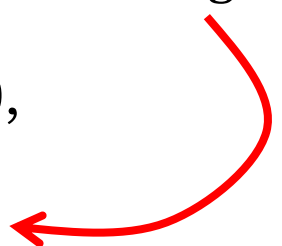
If we can show

$$\Delta(G[S]) \ll \Delta_G$$

the $(G[S], \lambda)$ is **easy** to sample from

Case 1: the maximum degree Δ_G of original graph G satisfies $\Delta_G \geq 100 \log n$

- By **concentration**, for any $v \in S$, expected degree $\leq \Delta_G/100$,

$$\Pr \left[\text{degree of } v \text{ in } G[S] \leq \frac{\Delta_G}{10} \right] \geq 1 - \frac{1}{n^{10}}$$


- Bound a **union bound**, w.h.p. (prob $\geq 1 - \frac{1}{n^7}$)

In every transition step, the **maximum degree of $G[S]$** is **at most $\frac{\Delta_G}{10}$**

- The hardcore model $(G[S], \lambda)$ satisfies **Dobrushin's condition**
simulate the Glauber dynamics for $O(n \log n)$ steps.

$\theta = 1/100$ -fractional block dynamics
 $T = 2^{O(1/\delta)} n \log n$ steps

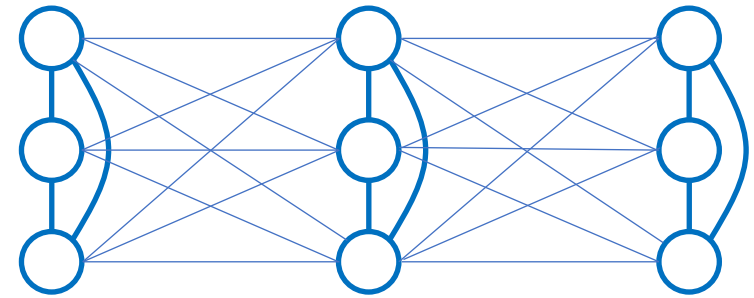
simulation cost of each step
 $O(n \log n)$

Total running time of the algorithm: $2^{O(1/\delta)} n^2 \log^2 n$

Case 2: $\Delta_G < 100 \log n$



$$\mu = (G, \lambda)$$



$$\mu_k = (G_k, \lambda_k)$$

- Graph G_k : $v \in V \longrightarrow$ size k clique C_v ; $\{u, v\} \in E \longrightarrow$ connect C_u and C_v ;
- Parameter: $\lambda_k = \lambda/k$;

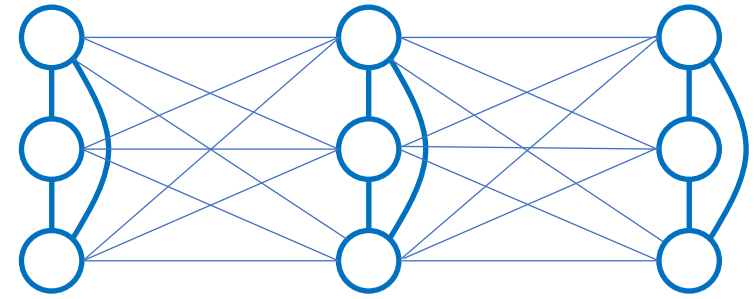
Properties of the k -transformation:

- μ_k is $O(1/\delta)$ **spectrally independence** \longrightarrow block dynamics on μ_k is **rapid mixing** [CLV21]
- if $k = \Omega(\log n)$, the **max degree** of G_k is **large** $\longrightarrow \mu_k = (G_k, \lambda_k)$ is in **Case 1**
- if $X \sim \mu_k$, then $X' = f_k(X) \sim \mu$

Case 2: $\Delta_G < 100 \log n$



$$\mu = (G, \lambda)$$

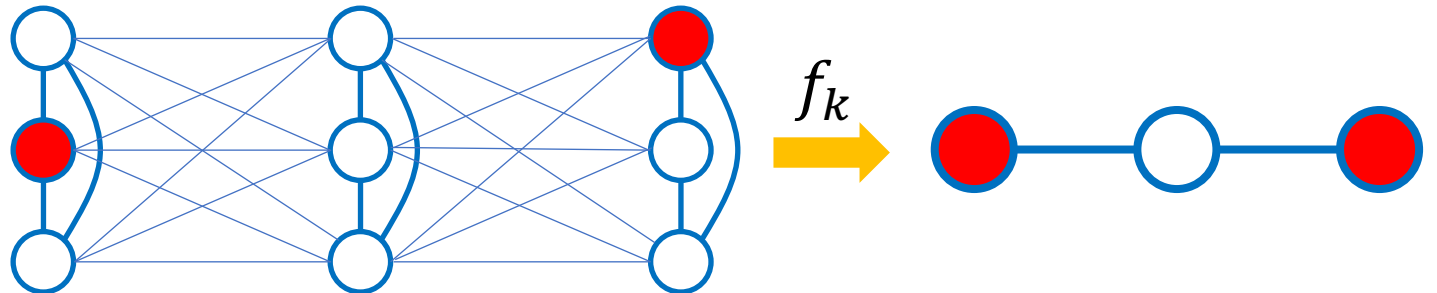


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Properties of the k -transformation:

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- if $k = \Omega(\log n)$, the **max degree** of G_k is **large** $\longrightarrow \mu_k = (G_k, \lambda_k)$ is in **Case 1**
- if $X \sim \mu_k$, then $X' = f_k(X) \sim \mu$
 - $X'_v = +$ if $\exists u \in C_v$ s.t. $X_u = +$
 - $X'_v = -$ if $\forall u \in C_v, X_u = -$



Algorithm for sampling from the hardcore model

Input: graph $G = (V, E)$ and parameter $\lambda \leq (1 - \delta)\lambda_c(\Delta)$

- apply $k = \Omega(\log n)$ -transformation to get μ_k ;
- simulate $\left(\theta = \frac{1}{100}\right)$ -fractional **block dynamics** $(X_t)_{t=0}^T$ on μ_k :
 - $T = 2^{O(1/\delta)}(nk)^2 \log(nk)$;
 - every transition is simulated by an $O(nk \log(nk))$ -step **Glauber dynamics**
- output $f_k(X_T)$

$$(f_k(X_t))_{t=0}^T$$

Apply the mapping f_k on
every step of block dynamics

$$k \rightarrow \infty$$



Field Dynamics

New Markov chain for
sampling from $\mu = \text{Hardcore}(G, \lambda)$

Field Dynamics

Input: hardcore model $\mu = (G, \lambda)$, a parameter $\theta \in (0,1)$

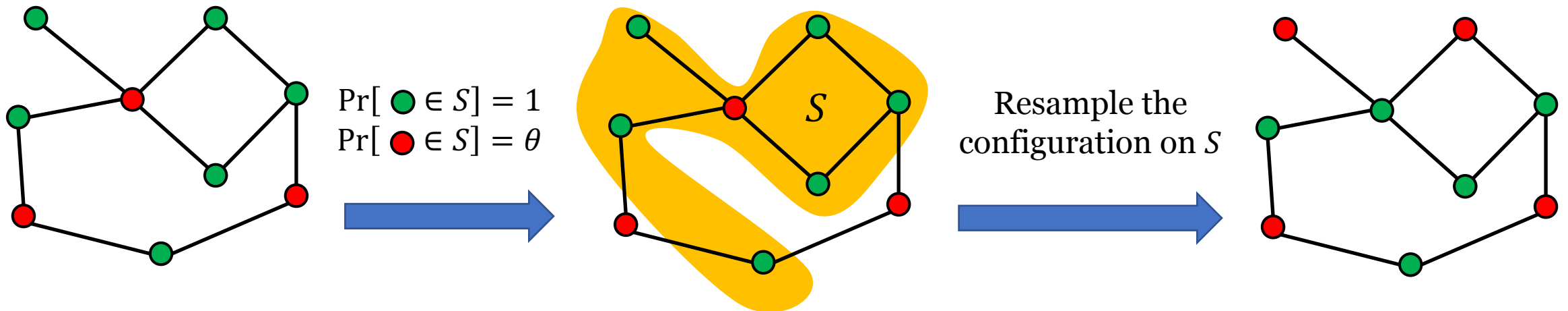
Start from an arbitrary feasible configuration $X \in \{-, +\}^V$

For each t from 1 to T **do**

Down-Walk • Construct $S \subseteq V$ by selecting each $v \in V$ independently with probability

$$p_v = \begin{cases} 1 & \text{if } X_v = - \\ \theta & \text{if } X_v = + \end{cases}$$

Up-Walk • Resample $X_S \sim \pi_S(\cdot \mid X_{V \setminus S})$ π : hardcore model $(G, \theta\lambda)$



Field Dynamics

Input: a **general distribution** μ over $\{-1, +1\}^V$, a parameter $\theta \in (0,1)$

Start from an arbitrary feasible configuration $X \in \{-, +\}^V$

For each t from 1 to T **do**

- Construct $S \subseteq V$ by selecting each $v \in V$ independently with probability

$$p_v = \begin{cases} 1 & \text{if } X_v = - \\ \theta & \text{if } X_v = + \end{cases}$$

- Resample $X_S \sim \pi_S(\cdot \mid X_{V \setminus S})$

$$\forall \sigma \in \{-, +\}^V, \quad \pi(\sigma) \propto \mu(\sigma) \prod_{v \in V: \sigma_v = +} \theta$$

π : distribution μ with external field θ

Field Dynamics

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- Resample $X_S \sim \pi_S(\cdot \mid X_{V \setminus S})$

Proposition (Field Dynamics): for any $\theta \in (0,1)$

Field dynamics has the **unique stationary distribution** μ .

(irreducible, aperiodic and reversible)

Spectral gap of Glauber dynamics

Mixing lemma

If $\lambda \leq (1 - \delta)\lambda_c(\Delta)$, for any $\theta \in (0,1)$

$$\text{Gap}_{\text{field}}(\lambda, \theta) \geq \theta^{O(1/\delta)}$$

Comparison lemma

For any $\lambda \geq 0$, for any $\theta \in (0,1)$

$$\text{Gap}_{\text{Glauber}}(\lambda) \geq \text{Gap}_{\text{field}}(\lambda, \theta) \cdot \text{Gap}_{\text{Glauber}}(\theta\lambda)$$

Boosting theorem

If $\lambda \leq (1 - \delta)\lambda_c(\Delta)$, for any $\theta \in (0,1)$

$$\text{Gap}_{\text{Glauber}}(\lambda) \geq \theta^{O(1/\delta)} \cdot \text{Gap}_{\text{Glauber}}(\theta\lambda)$$

Near-Critical Regime

Boosting with cost $O(1)$

Easy Regime

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$$\text{Gap}_{\text{Glauber}}(\lambda) \geq \text{Gap}_{\text{field}}(\lambda, \theta) \cdot \text{Gap}_{\text{Glauber}}(\theta\lambda)$$

*Proved by
a calculation*

$$\theta = \frac{1}{10}$$

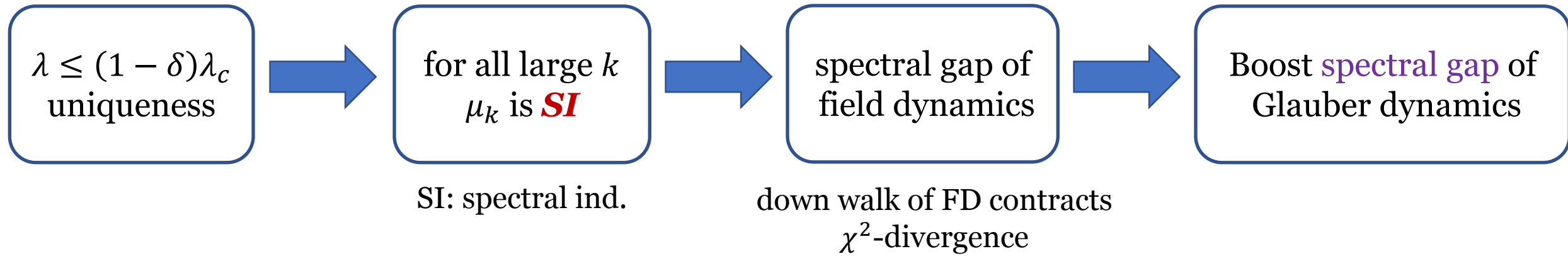


$$\begin{aligned} \text{Gap}_{\text{Glauber}}(\theta\lambda) &= \Omega\left(\frac{1}{n}\right) \\ \theta\lambda &\in \text{Dobrushin's regime} \end{aligned}$$

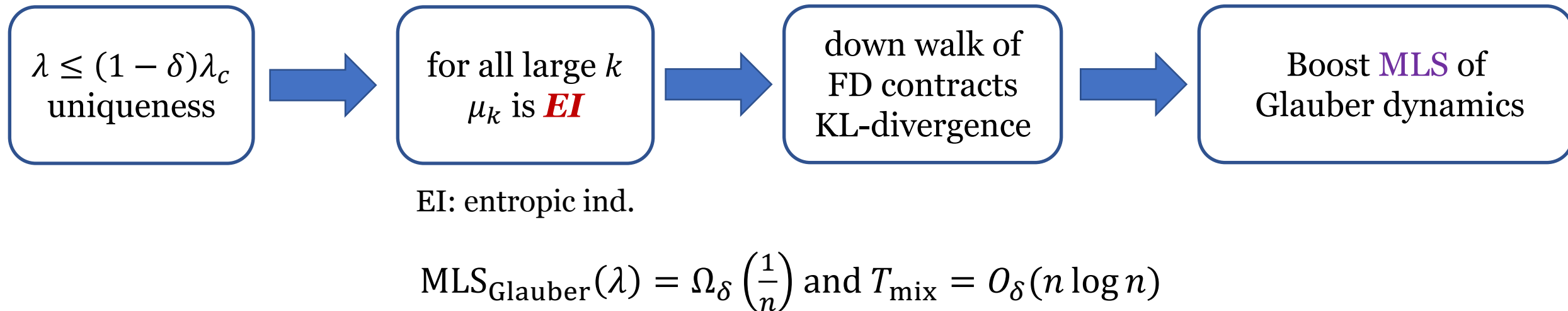


$$\begin{aligned} \text{Gap}_{\text{Glauber}}(\lambda) &= \Omega_{\delta}\left(\frac{1}{n}\right) \\ T_{\text{mix}} &= O_{\delta}(n^2 \log n) \end{aligned}$$

Boosting spectral gap of Glauber dynamics



Boosting modified log-Sobolev constant of Glauber dynamics



Summary

- Hardcore model in the **uniqueness regime**
 - Optimal spectral gap and $O(n^2 \log n)$ mixing time
 - Optimal modified log-Sobolev constant and $O(n \log n)$ mixing time
- General distributions
 - Complete SI \longrightarrow boost spectral gap
 - Complete SI + marginal ratio bound \longrightarrow boost MLS constant
- A new Markov chain **field dynamics**

Thank you!

Open problem

- More applications of field dynamics
 - Algorithmic applications (e.g., random cluster model [Chen and Zhang 2022])
- Extend our technique to **general distributions** beyond the Boolean domain i.e., q -coloring