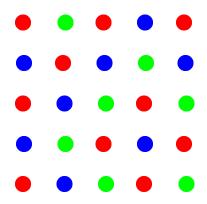
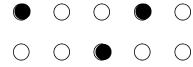
EFFICIENT ALGORITHMS FOR FINDING A RANDOM NEEDLE IN A COMBINATORIAL HAYSTACK

Dana Randall

GEORGIA TECH

Models from Statistical Mechanics



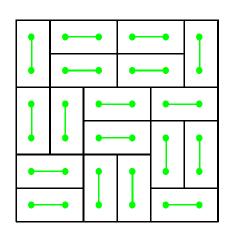




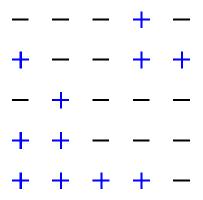


3-Colorings

Independent Sets



Dimer Model

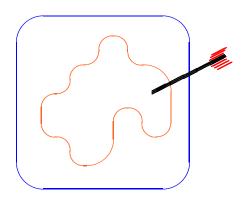


Ising Model

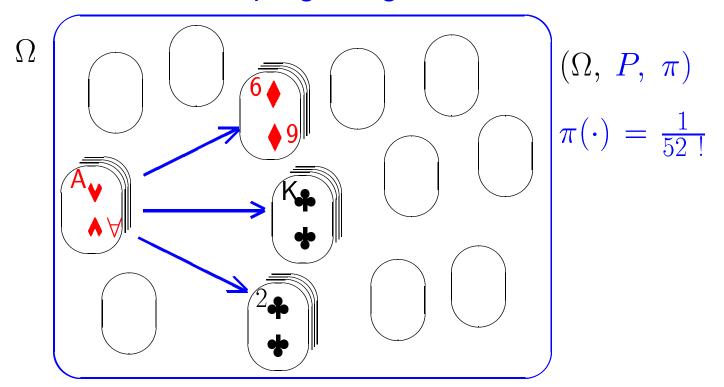
What does a "typical" element look like?

Sampling can be used to:

- Evaluate thermodynamic properties.
- Determine properties of "typical" elements.
- Estimate the cardinality of a set.
 ("Markov chain Monte Carlo")



Random Sampling Using Markov Chains



<u>Thm:</u> If a finite, reversible M.C. \mathcal{M} with transition probs P is ergodic on Ω , then it converges to a unique stationary distribution.

The Metropolis Algorithm:

Thm: If P is defined so that

$$P(x,y) = \frac{1}{\Delta} \min \left(1, \frac{\pi(y)}{\pi(x)}\right),$$

then the stationary distribution will be π .

Bounding Convergence Time

Def: The total variation distance

$$||\pi, \pi'||_{\text{TV}} = \max_{A \subseteq \Omega} (\pi(A) - \pi'(A)).$$

Def: The mixing time is

$$\tau(\epsilon) = \max_{x} \min\{t : ||P^{t}(x, \cdot), \pi||_{\text{TV}}\} \le \epsilon.$$

Def: A Markov chain is rapidly mixing if

$$\tau(\epsilon) \le \text{poly}(n, \epsilon^{-1}).$$

Some methods:

- spectral gap $\longrightarrow \operatorname{\mathsf{Gap}}(P) = \lambda_1 |\lambda_2|,$
- (path) coupling $(\lambda_1 \ge |\lambda_2| \ge ... \ge |\lambda_{|\Omega|}|).$
- canonical paths / flows
- conductance / isoperimetry
- comparison
- decomposition
- stopping rules

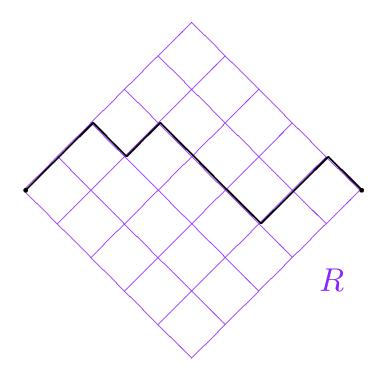
Examples:

The efficiency and limitations of various sampling algorithms for:

- 1. Lattice paths
- 2. Dimer models and 3-colorings
- 3. Ising / Potts models

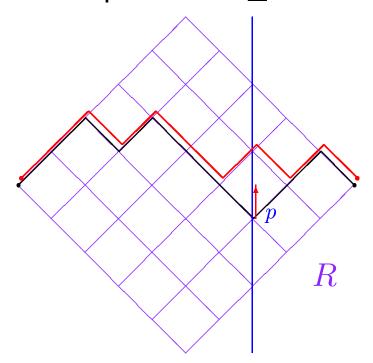
Example 1: Lattice paths

Find a shortest path in $R \subseteq \mathbb{Z}^2$.



Example 1: Lattice paths

Find a shortest path in $R \subseteq \mathbb{Z}^2$.



The Mountain/Valley Chain

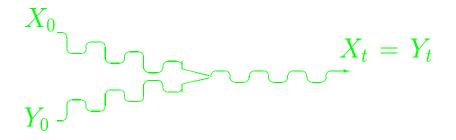
Repeat:

- Pick vertical line uniformly.
- If path intersect is "mountain" or "valley,"
 invert it with probability 1/2;
 else do nothing.

(This is ergodic for any simply connected R, and the stationary distribution is uniform.)

Coupling (To bound convergence rates)

For a Markov chain $\mathcal{M} = (\Omega, P, \pi)$:



<u>Def:</u> A <u>coupling</u> is a stochastic process $(X_t, Y_t)_{t=0}^{\infty}$ on $\Omega \times \Omega$ s.t.:

- 1. X_t and Y_t are each faithful copy of \mathcal{M} ;
- 2. If $X_t = Y_t$ then $X_{t+1} = Y_{t+1}$.

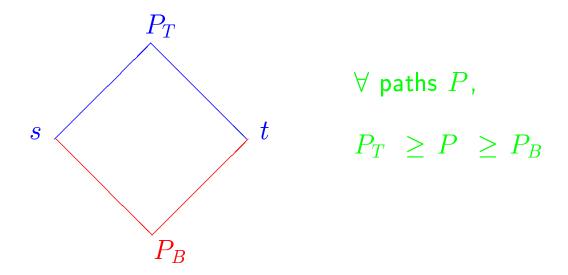
Def: The coupling time

$$T = \max_{X_0, Y_0} E \left[\min\{t : X_t = Y_t | X_0, Y_0 \} \right].$$

Thm: [Aldous]

$$\tau(\epsilon) \leq c T \ln \epsilon^{-1}.$$
 mixing time coupling time

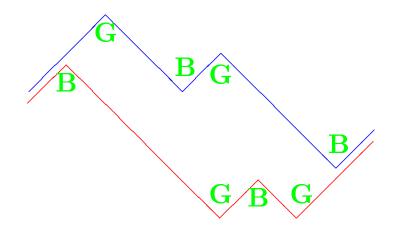
Proof of Fast Mixing



To couple, choose the same vertical line and the same direction for both processes.

- 1. Initially, vol = vol $[P_T, P_B] = n$.
- *2. $E \left[\Delta \text{vol} \right] \leq 0$.
 - 3. Pr [vol changes in 1 step] $\geq \frac{1}{n}$ (if vol $\neq 0$).
 - 4. $vol = 0 \Leftrightarrow paths agree.$
- \Rightarrow Mixing Time \leq O (n^3) .

Pf. cont.: (* $E[\Delta vol] \leq 0$)



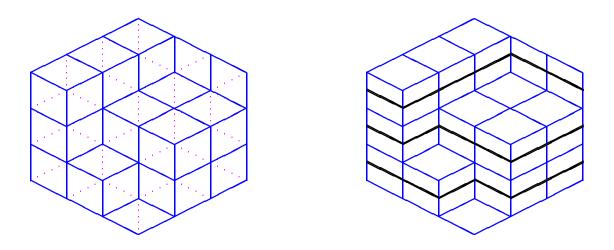
On P_1 : Label Mtns w/ \mathbf{G} ; Valleys w/ \mathbf{B} . On P_2 : Label Mtns w/ \mathbf{B} ; Valleys w/ \mathbf{G} .

$$E [\Delta vol] = \frac{1}{2m} [(\#B) - (\#G)] \le 0.$$

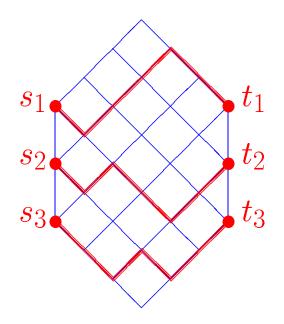
$$\begin{array}{c|c} G \\ \hline G \\ \hline G \\ \hline \end{array} \begin{array}{c} G \\ \hline G \\ \hline \end{array} \begin{array}{c} G \\ \\ \end{array} \begin{array}{c} G \\ \end{array} \begin{array}{c}$$

$$\implies (\#G) \ge (\#B)$$

Ex. 2: Lozenge tilings

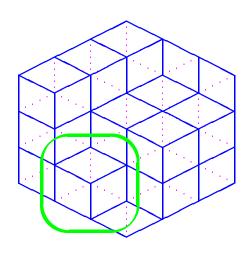


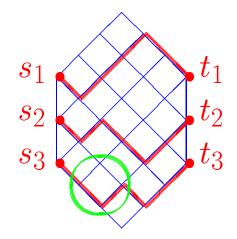
The dimer model on the triangular lattice



The "routing" interpretation

Two Markov chains on lozenge tilings

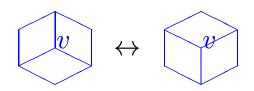




Markov chain 1: Glauber dynamics

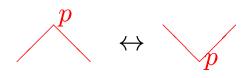
Repeat:

- Pick $v \in_u S$;
- Add/remove the "cube" at v w.p. $\frac{1}{2}$, if possible.

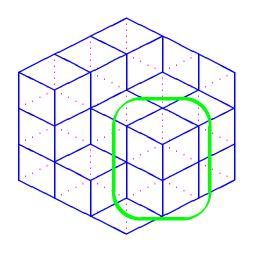


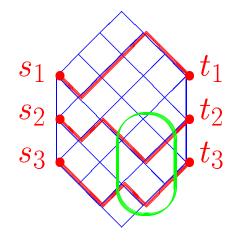
Repeat:

- Pick p on one of the paths uniformly;
- at v w.p. $\frac{1}{2}$, if possible. Invert Mountain/Valley, w.p. $\frac{1}{2}$, if possible.



Two Markov chains on lozenge tilings

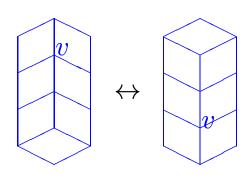




Markov chain 1: "Tower" moves

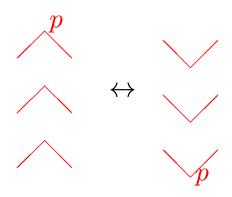
Repeat:

- Pick $v \in_u S$;
- Invert "tower" (ht h) at v w.p. $\frac{1}{2h}$, if pos.

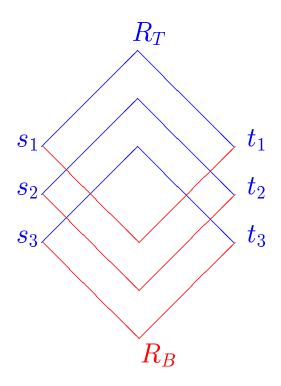


Repeat:

- Pick p on one of the paths uniformly;
- Invert the Mtn/val tower, w.p. $\frac{1}{2h}$, if possible.



Analysis of Markov chain 2 (Towers) [Luby, R., Sinclair]

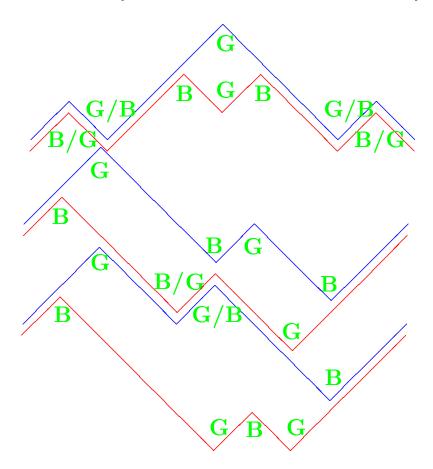


 \forall routings R,

$$R_T \geq R \geq R_B$$

- 1. Initially, vol = vol $[R_T, R_B] = n^{1.5}$.
- *2. $E[\Delta vol] \leq 0$.
 - 3. Pr [vol changes in 1 step] $\geq \frac{1}{n}$ (if vol $\neq 0$).
 - 4. $vol = 0 \Leftrightarrow paths agree.$
- \Rightarrow Mixing Time \leq O (n^4) .

Proof (cont.): (* $E[\Delta vol] \leq 0$)



On
$$P_1$$
: Label Mtns w/ \mathbf{G} ; Valleys w/ \mathbf{B} . On P_2 : Label Mtns w/ \mathbf{B} ; Valleys w/ \mathbf{G} .

$$\begin{array}{c} \text{change due to inversion} \\ & \text{prob of inversion} \\ \text{E} \left[\Delta \text{vol} \right] = \frac{1}{2m} \left(\sum_{\text{bad } t} h_t \left(\frac{1}{2h_t} \right) - \sum_{\text{good } t} h_t \left(\frac{1}{2h_t} \right) \right). \\ &= \frac{1}{4m} \left((\#B) - (\#G) \right) \leq 0. \end{array}$$

⇒ The tower chain is rapidly mixing.

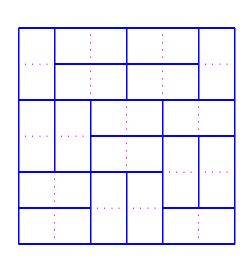
Extensions

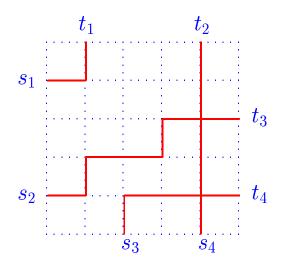
<u>Thm:</u> [R., Tetali] Glauber dynamics (MC 1) is also rapidly mixing on 3-colorings.

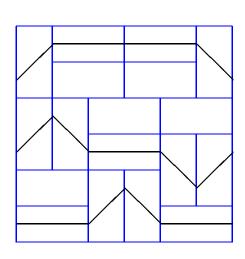
By the Comparison Thm of [Diaconis, Saloff-Coste].

Same ideas also work for <u>3-colorings</u> (with fixed boundary cond'ns) and <u>domino tilings</u>.

2	1	0	1	2	1	0
_1	0	2	0	1	0	2
0	2	0	1	2	.1.	0
_1	0	1	2	1	0	2
2	1	0	1	2	1	0
_1	0	1	0	1	0	2
0	2	0	2	0	2	0







Example 3: Ising and Potts models

The Ising Model

$$\sigma \in \Omega = \{+, -\}^N$$

(Hamiltonian)

$$\begin{array}{l} \bullet \ H(\sigma) = \sum_{i \sim j} \sigma_i \sigma_j \\ \text{(Gibbs measure)} \quad \swarrow (\beta = 1/T) \\ \bullet \ \pi_\beta(\sigma) = e^{\beta H(\sigma)}/Z_\beta \end{array}$$

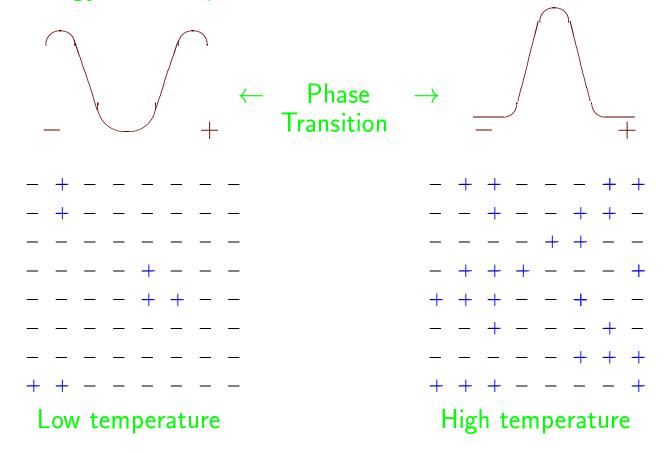
$$/(\beta = 1/T)$$

$$\bullet \ \pi_{\beta}(\sigma) = e^{\beta H(\sigma)} / Z_{\beta}$$

(Partition function)

•
$$Z_{\beta} = \sum_{\sigma' \in \Omega} e^{\beta H(\sigma')}$$

Energy landscapes:



Glauber dynamics on Ising configurations

Repeat:

- Pick v uniformly;
- Change the sign of v (going from σ to τ) w.p. $\min\left(1, \frac{\pi(\tau)}{\pi(\sigma)}\right)$.

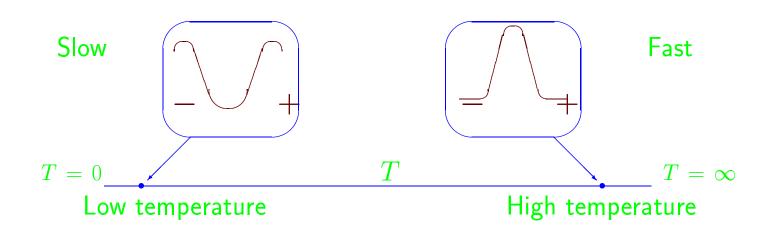
Conductance:

For
$$S\subseteq\Omega,$$
 let
$$\Phi_S=\frac{\sum_{x\in S,y\in\overline{S}}\pi(x)P(x,y)}{\sum_{x\in S}\pi(x)}$$

$$\Phi=\min_{S:\ \pi(S)\leq\frac{1}{2}}\Phi_S.$$

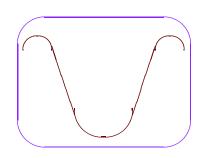
Thm: [Jerrum, Sinclair]

$$\frac{\Phi^2}{2} \le Gap \le 2\Phi.$$

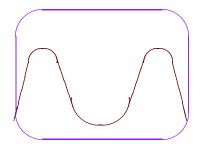


Tempering / Swapping

$$\beta_M = \beta$$

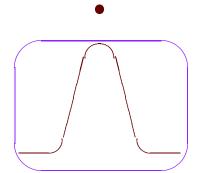


$$\beta_{M-1}$$



$$\beta_{M-2}$$

 β_0



$$\widehat{\Omega} = \Omega^{M+1}$$

$$\beta_i = \frac{i}{M} \beta$$

$$\pi_i(\sigma_i) = \pi_{\beta_i}(\sigma_i)$$

$$\widehat{\pi}(\sigma) = \prod_{i=0}^{M} \pi_i(\sigma_i)$$

The Swap Algorithm

Repeat:

w.p. 1/2: Do a LEVEL move:

Pick i; update σ_i

w.p. 1/2: Do a SWAP move:

Pick (i, i + 1);

"swap" σ_i and σ_{i+1}

$$\sigma = (\sigma_0,...,\sigma_i,\sigma_{i+1},...,\sigma_M)$$

$$\sigma = (\sigma_0,...,\sigma_{i+1},\sigma_i,...,\sigma_M)$$

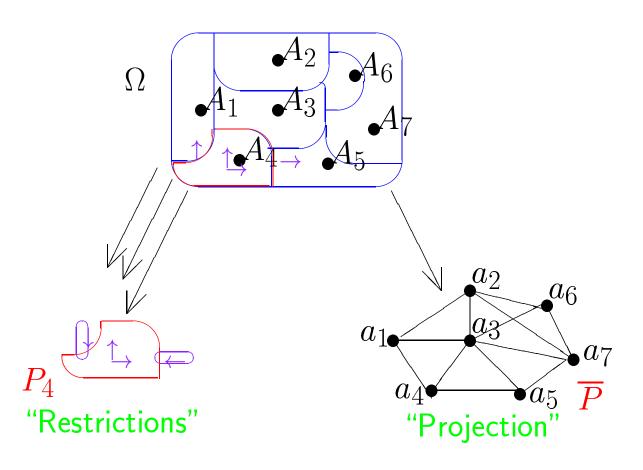
Swapping on the Mean-Field Ising Model

In the Mean-field model, the underlying graph is $G = K_n$.

Thm: [Madras, Zheng] Swap is fast for the mean-field Ising model for all β .

Disjoint Decomposition

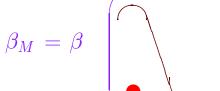
[Caracciolo, Pelisetto, Sokal], [Madras, R.], [Martin, R.]

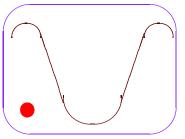


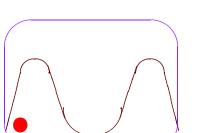
$$\overline{\overline{R}}(a_i) = \overline{\pi}(A_i) \atop \overline{P}(a_i, a_j) = \sum_{\substack{x \in A_i, \\ y \in A_j}} \frac{\pi(x)P(x, y)}{\pi(A_i)}$$

<u>Thm:</u> $Gap(P) \ge \frac{1}{2} Gap(\overline{P}) (\min_{i} Gap(P_{i}))$

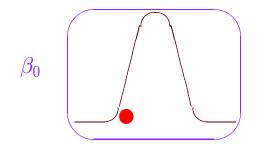
Tempering / Swapping







$$eta_{M-2}$$



$$Tr(\sigma) = (0, ..., 1, 0, 0)$$

$$\widehat{\Omega} = \Omega^{M+1}$$

$$\beta_i = \frac{i}{M}\beta$$

$$\pi_i(\sigma_i) = \pi_{\beta_i}(\sigma_i)$$

$$\widehat{\pi}(\sigma) = \prod_{i=0}^M \pi_i(\sigma_i)$$

Def: The trace

$$\operatorname{Tr} \colon \widehat{\Omega} \, \to \, \{0,1\}^{M+1},$$

$$\mathsf{Tr}(\sigma) = (b_0,...,b_M)$$
,

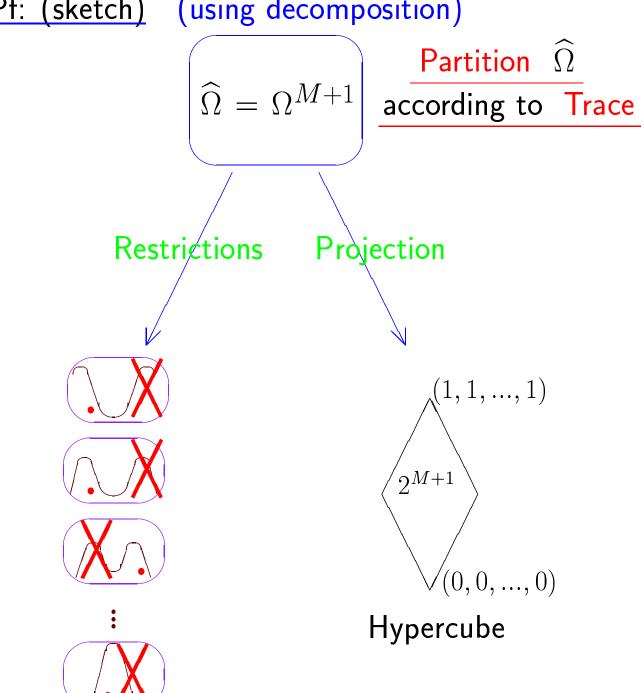
$$b_i = 0$$
 if σ_i is mostly –;

$$b_i = 1$$
 if σ_i is mostly $+$.

Thm: [Madras, Zheng] Swap is fast for the mean-field Ising model for all β .

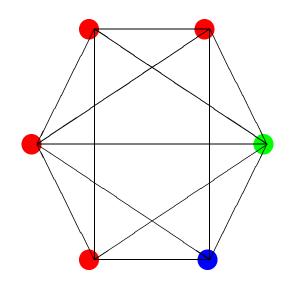


Fixed Trace



Swapping (Tempering): the Magic Answer?

The Potts Model



$$\sigma \in \Omega = \{R, B, G\}^N$$

(Hamiltonian)

•
$$\pi_{\beta}(\sigma) = e^{\beta H(\sigma)}/Z_{\beta}$$

(Partition function)

$$\bullet Z_{\beta} = \sum_{\sigma' \in \Omega} e^{\beta H(\sigma')}$$

Thm: [Bhatnagar, R.] The swap algorithm can be slow for the mean-field 3-state Potts model.

(Because of the <u>first order</u> (discontinuous) phase transition.)

Moreover, it can be exponentially slower than fixed-temperature Glauber dynamics

Comments

1. There is a different way to sampling Ising states:

[Jerrum, Sinclair]: \exists an efficient algorithm for estimating the partition function of an Ising system on any graph for any β .

[R., Wilson]: \exists an efficient sampler for the Ising model for any graph, any β .

(But almost nothing is known for Potts!)

2. Phase trans'ns also exist for the uniform dist'n:

[Luby, Vigoda]: Glauber dynamics is fast for the Independent Set model on $R \subseteq \mathbb{Z}^2$.

[Galvin, Kahn] Above some sufficiently large dimension, Glauber dynamics is exponentially slow for the Independent Set model on \mathbb{Z}^d .

Future challenges ...

- 1. Characterize which sampling problems are computationally intractable.
- 2. Determine when specific Markov chain algorithms are <u>inefficient</u>.
- 3. Develop <u>new techniques</u> for analyzing potentially fast chains.
- 4. Design fast(er) Markov chains.

