

a) Ising Model

b) Metropolis algo.

c) Glauber algo or dynamics.

↑
(Heat bath dynamics.)

$$G = (V, E)$$

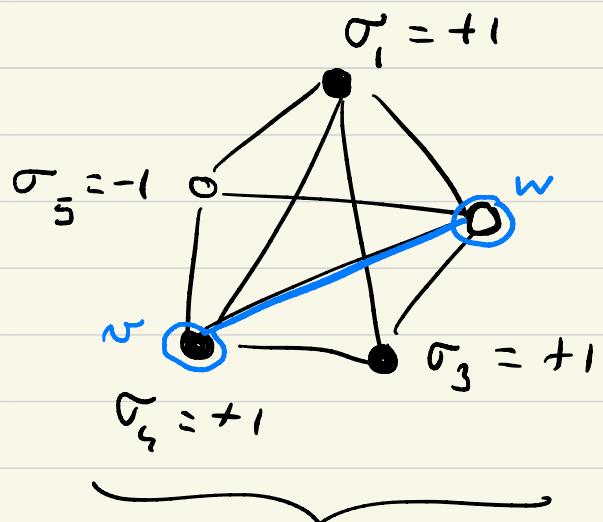
$$V = \{1, 2, 3, \dots, N\}$$

binary alphabet $X = \{-1, +1\}$ and

"degrees of freedom" or "spins" $\sigma_v \in X$.

$$v \in V$$

Complete graph for example:



$$\pi(\underline{\sigma}) = \frac{e^{-\beta H(\underline{\sigma})}}{Z}$$

$$H(\underline{\sigma}) = - \sum_{(v,w) \in E} J_{vw} \sigma_v \sigma_w - \sum_{v \in V} h_v \sigma_v$$

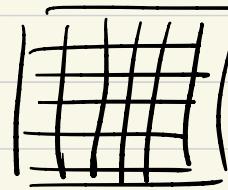
$$Z = \sum_{\underline{\sigma} \in \mathcal{X}^N} e^{-\beta H(\underline{\sigma})}$$

assignment or "spin configuration"

$$\underline{\sigma} = (\sigma_1, \sigma_2, \dots, \sigma_N)$$

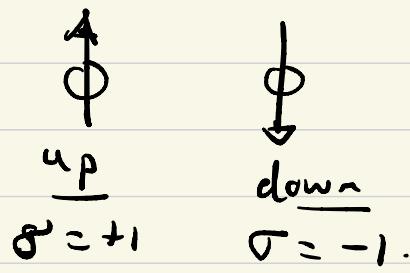
"Partition function":

Another important example: square grid. $\subset \mathbb{Z}^d$.



Some intuition: (from physics)

- The "spins" represent magnetic moments, which are carried by atoms in a crystal say.



Gross simplification with only two direction for the mag. moments.

- These "spins" interact.

anti-ferromagnetic interaction

$$J_{rw} > 0$$

$$J_{rw} < 0$$

Energy of a configuration of two spins

w w



$$-\overbrace{J_{rw}}^{+1} \sigma_w \sigma_w = -J_{rw}$$

favorable

unfavorable



$$-\overbrace{J_{rw}}^{-1} \sigma_w \sigma_w = +J_{rw}$$

unfavorable
favorable



$$-\overbrace{J_{rw}}^{-1} \sigma_w \sigma_w = +J_{rw}$$

unfavorable
favorable



$$-\overbrace{J_{rw}}^{+1} \sigma_w \sigma_w = -J_{rw}$$

favorable
unfavorable

- The ferromagnetic model : all $J_{vw} > 0$

Consider the special case $h_v = 0$:

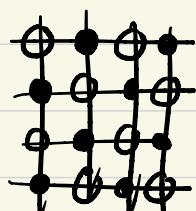
$$H(\sigma) = - \sum_{(vw) \in E} J_{vw} \sigma_v \sigma_w$$

has two minima (all $\sigma_v = +1$) or (all $\sigma_v = -1$).

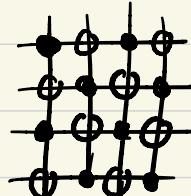


- The anti-ferromagnetic ; all $J_{vw} < 0$.

Situation more complicated and will depend on the graph. E.g.



is a minimum



second min.

Staggered configuration

Frustration:

difficulty will come for large graphs because you cannot min all terms simultaneously in $H(\sigma)$.

- The study of optimization of $H(\underline{\sigma})$ and of sampling $\pi(\underline{\sigma}) = \frac{e^{-\beta H(\underline{\sigma})}}{Z}$ is a difficult problem specially for "frustrated" systems with all possible signs for $J_{mn} > 0$ and $J_{mn} < 0$.

- Interpretation of β^0 : inverse of the temperature of the system $\beta = \frac{1}{kT}$

β small: corresponds to a nearly high temperature uniform measure on state space X^N .

Typical spin configurations will be more or less uniform at random from $\mathbb{X}^N = \{-1, +1\}^N$.

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | • | 0 | 0 | 0 | 0 | 0 |
| • | 0 | • | 0 | 0 | 0 | 0 |
| 0 | • | 0 | • | • | • | 0 |
| • | 0 | • | • | • | 0 | 0 |

β large: $\frac{e^{-\beta H(\underline{\sigma})}}{Z}$ is peaked around the Minima of $H(\underline{\sigma})$ ($\beta \rightarrow +\infty$).

Typical spin conf with fluctuations around Minima.

Formal definitions:

- Magnetization:

$$m(\beta) = \frac{1}{N} \sum_{n=1}^N \langle \sigma_n \rangle \quad \dots$$

where Notation $\langle \sigma_n \rangle = \underbrace{\mathbb{E}_{\pi}}_{\text{bracket notation.}} (\sigma_n) := \sum_{\Omega \in \chi^n} \sigma_n \pi(\Omega)$

→ Intuitively this is the total $\underbrace{\text{average}}$ magnetic moment.

- If $m(\beta) \approx 0$ the system is not magnetized.
- If $m(\beta) \neq 0$ the system is magnetized.

Model displays transition between these two

situations typically as β varies from high temp to low high temp β .

- How would you calculate $m(\beta)$?

Remark (exercise): $\langle \sigma_n \rangle = \frac{1}{\beta} \frac{\partial}{\partial h_n} (\ln Z)$

$$Z = \sum_{\Omega \in \chi^n} \exp \left\{ \beta \sum_{\text{NNEE}} J_{nn} \sigma_n \sigma_n + \beta \sum_{n \in \Omega} h_n \sigma_n \right\}$$

But computing Z is difficult and in general impossible.

Instead we go back to:

$$m(\beta) = \left\langle \frac{1}{N} \sum_{v \in V} \sigma_v \right\rangle = \mathbb{E}_{\sigma} \left(\frac{1}{N} \sum_{v \in V} \sigma_v \right).$$

and consider an estimator based on an MCMC algo.

$$\hat{m}(\beta) = \lim_{t \rightarrow +\infty} \left\{ \frac{1}{N} \sum_{v \in V} \sigma_v(t) \right\}.$$

where $\sigma_v(0), \sigma_v(1), \dots, \sigma_v(t), \dots$ is

an MCMC chain with stat dist $\pi(\sigma)$.

We can also compute any sort of average:

$$\langle A(\sigma) \rangle \text{ e.g. } \underbrace{\frac{1}{N} \langle H(\sigma) \rangle}_{\text{internal energy per vertex per site.}}$$

$$\text{again: } \lim_{t \rightarrow +\infty} \left\{ \frac{1}{N} \sum_{v \in V} H(\sigma^{(t)}) \right\}.$$

A bit of background on the phase transition phenomena

(scratch the surface of the subject .).

$$\left\{ \begin{array}{l} G = (V, E) \text{ is a } \underline{\text{complete graph}}. \\ J_{vw} = \frac{J}{N} > 0 \text{ for all } (v, w) \in E \\ h_v = h \in \mathbb{R} \text{ for all } v \in V. \end{array} \right.$$

Ferromagnetic Ising Model on a complete graph.

$$H(\sigma) = -\frac{J}{2N} \underbrace{\sum_{v, w \in V^2} \sigma_v \sigma_w}_{\text{complete graph.}} - h \underbrace{\sum_{v \in V} \sigma_v}_{\text{acts like a bias}}.$$

$\frac{1}{2} \left(\underbrace{\sum_{v \in V} \sigma_v}_{\text{in } e^{-\beta H(\sigma)}} \right)^2 - N$

→ It possible to in fact compute \mathbb{P} and also average and in particular

$$m(\beta) = \left\langle \frac{1}{N} \sum_{v \in V} \sigma_v \right\rangle.$$



Show the result.

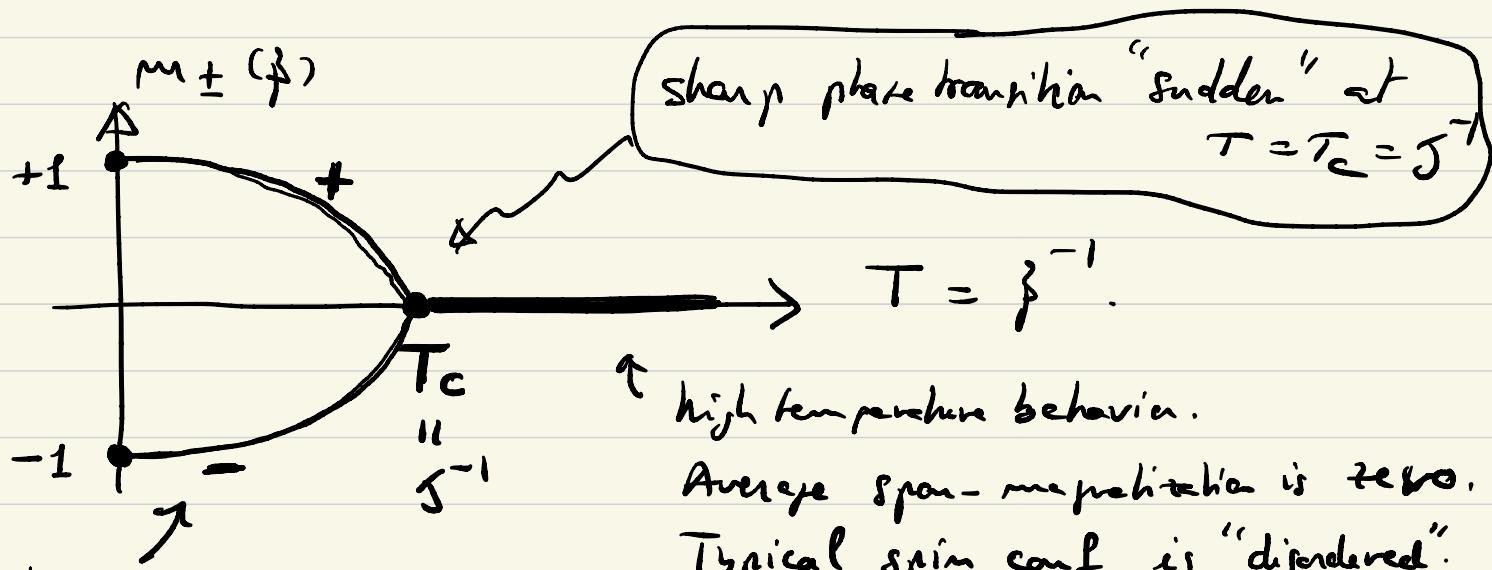
Finding is eventually :

$$\underline{m(\beta, h)} = \left\langle \frac{1}{N} \sum_{n \in v} \downarrow \sigma_n \right\rangle.$$

for $\langle - \rangle$ for the complete ^{graph} ferro-magnetic model

You can plot $m_{\pm}(\beta) = \lim_{h \rightarrow 0^{\pm}} m(\beta, h)$.

The spontaneous magnetization or zero bias mag
or zero-magnetic field magnetization.



Low temp behavior

Average spin Magn ≠ 0.

Typical spin conf are
fluctuations of (all +1)
and (all -1).

↑ high temperature behavior.

Average spin-magnetization is zero.

Typical spin conf is "disordered".

b) Metropolis algorithm (Ising) ✓

c) Glauber dynamics

c_{bis}). Heat bath dynamics in general.

d) Simulation results.

·

Metropolis algo.

Hamiltonian (energy or cost).

$$H(\underline{\sigma}) = - \sum_{(v,w) \in E} J_{vw} \sigma_v \sigma_w - \sum_{v \in V} h_v \sigma_v.$$

$$\underline{\sigma} = (\sigma_1, \dots, \sigma_N) \in \{-1, +1\}^N$$

$$G = (V, E).$$

algo:
run

- Select a vertex $v \in V$ uniformly random (with prob $1/N$).
- Propose the move $\underline{\sigma} \rightarrow \underline{\sigma}'$: $\sigma'_w = \sigma_w \quad w \neq v$
 $\sigma'_v = -\sigma_v \quad \underline{\text{flip at } v \in V}$
- Compute the cost difference: $\Delta E(\underline{\sigma} \rightarrow \underline{\sigma}') = H(\underline{\sigma}') - H(\underline{\sigma})$.
- Accept the move with probability $A(\underline{\sigma} \rightarrow \underline{\sigma}') = \min(1, e^{-\beta \Delta E})$.

$$H(\underline{\sigma}) = - \sum_{(v,w) \in E} J_{vw} \sigma_v \sigma_w - \sum_{v \in V} h_v \sigma_v.$$

$$\Delta E(\underline{\sigma} \rightarrow \underline{\sigma}') = \underbrace{H(\underline{\sigma}')}_{\text{New energy}} - \underbrace{H(\underline{\sigma})}_{\text{old energy}}.$$

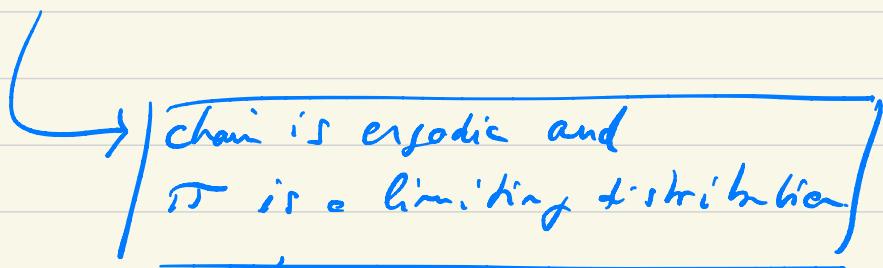
$$A(\underline{\sigma} \rightarrow \underline{\sigma}') = \min \left(1, e^{-\beta \frac{\Delta E(\underline{\sigma} \rightarrow \underline{\sigma}')}{} } \right)$$

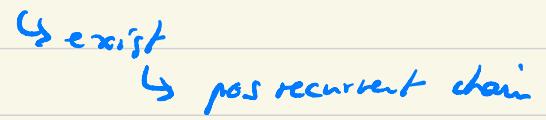
$$= \begin{cases} 1 & \text{if } \Delta E(\underline{\sigma} \rightarrow \underline{\sigma}') < 0 \quad \text{New Energy} < \text{Old Energy} \\ e^{-\beta \Delta E} & \text{if } \Delta E > 0 \quad \text{New Energy} \geq \text{Old Energy}. \end{cases}$$

Remark

$$\bullet e^{-\beta \Delta E} = \frac{e^{-\beta H(\underline{\sigma}')}}{e^{-\beta H(\underline{\sigma})}} = \frac{\pi(\underline{\sigma}')}{\pi(\underline{\sigma})} \quad \text{Metropolis rule.}$$

- chain is irreducible, aperiodic (self loops), detailed balance is satisfied and π is stationary.

 chain is ergodic and
 π is a limiting distribution

 \hookrightarrow ergodic \hookrightarrow limiting distribution

- This is certainly true for N finite and time (<# of steps) large

- Final important point,

$$\Delta E(\underline{\sigma} \rightarrow \underline{\sigma}') = H(\underline{\sigma}') - H(\underline{\sigma}).$$

$$= \left\{ - \sum_{(k,l) \in E} J_{kl} \frac{\sigma'_k \sigma'_l}{\sigma_k \sigma_l} - \sum_{k \in V} h_k \sigma'_k \right\}$$

$$- \left\{ - \sum_{(k,l) \in E} J_{kl} \frac{\sigma_k \sigma_l}{\sigma_k \sigma_l} - \sum_{k \in V} h_k \sigma'_k \right\}.$$

We have selected vertex w and $\sigma'_w = \sigma_w \neq w \neq w$

if $(k,l) \not\ni w$ and $k \neq w$ then terms simplify.

and it remains only:

$$= \left(\sum_w J_{ww} \sigma_w \frac{\sigma'_w}{\sigma_w} - h_w \sigma'_w \right) - \left(\sum_w J_{ww} \sigma_w \frac{\sigma_w}{\sigma_w} - h_w \sigma_w \right)$$

$$= 2 \left(\sigma_w \sum_w J_{ww} \sigma_w + h_w \right).$$

For interaction you get only neighbors of w that share an edge count // For the bias only the vertex w enters.

Glauber dynamics or algo.

- Select a vertex w at random unif among
 $V = \{1, \dots, N\}$

- Propose the move $\underline{\sigma} \rightarrow \underline{\sigma}'$ s.t

$$\sigma'_w = \sigma_w \cup w \neq w$$

$$\sigma'_w = -\sigma_w \quad \text{flip of } w \text{ spin.}$$

- Accept the move with acceptance probability

$$A(\underline{\sigma} \rightarrow \underline{\sigma}') = \frac{1}{2} \left\{ 1 - \tanh \left(\frac{\overbrace{\beta \Delta E(\underline{\sigma}' \rightarrow \underline{\sigma})}^{\text{blue}}}{2} \right) \right\} \quad \checkmark \checkmark \checkmark$$

$$\begin{aligned} & \left[\text{Reject the move with prob } 1 - A(\underline{\sigma} \rightarrow \underline{\sigma}') \right] \\ &= \frac{1}{2} \left\{ 1 + \tanh \frac{\beta \Delta E}{2} \right\}. \end{aligned}$$

$$\Delta E(\underline{\sigma}' \rightarrow \underline{\sigma}) = H(\underline{\sigma}') - H(\underline{\sigma})$$

$$= 2 \left(\sum_w J_{ww} \sigma_w + h_w \sigma_w \right) \quad (\text{as before}).$$

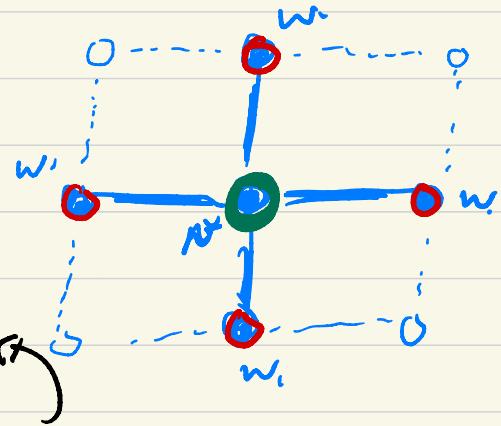
Again this chain is irred.; aperiodic.

Exercise: detailed balance is satisfied again.

$\Rightarrow \exists$ stat dist which is π

.... \Rightarrow chain is irred, aperiodic, per rec i.e. ergodic
and π is a limiting dist.

Remark:



$$A(\underline{\sigma} \rightarrow \underline{\sigma}') = \frac{1}{2} \left(1 - \tanh \frac{\beta \Delta E}{2} \right)$$

$$\Delta E = 2\sigma_N \sum_w S_{Nw} \sigma_w + 2h_N \sigma_N$$

$$\Rightarrow A(\underline{\sigma} \rightarrow \underline{\sigma}') = \frac{1}{2} \left(1 - \tanh \frac{\beta \sigma_N}{2} \left\{ \sum_w S_{Nw} \sigma_w + h_N \right\} \right)$$

$$\underbrace{\tanh(-x)}_{=} = -\tanh x$$

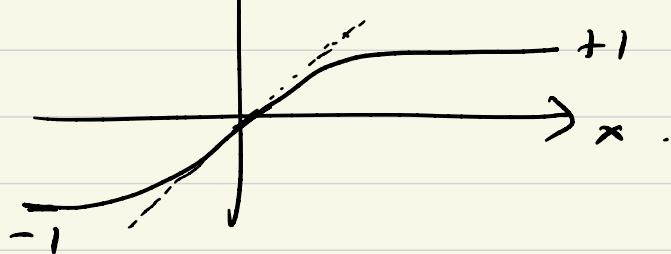
$$\tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

$$A(\underline{\sigma} \rightarrow \underline{\sigma}') = \frac{1}{2} \left(1 - \sigma_N \tanh \frac{\beta h_N^{loc}}{2} \right)$$

$$h_N^{loc} = \sum_w S_{Nw} \sigma_w + \underline{h_N}$$

Total effective bias on spin.

"Total local magnetic field".



$$A(\underline{\sigma} \rightarrow \underline{\sigma}') = \frac{1}{2} \left(1 - \sigma_w \tanh \beta h_w^{\text{loc}} \right) . \text{ accept prob}$$

Reject move with prob

$$1 - A(\underline{\sigma} \rightarrow \underline{\sigma}') = \frac{1}{2} \left(1 + \sigma_w \tanh \beta h_w^{\text{loc}} \right) \equiv R(\underline{\sigma} \rightarrow \underline{\sigma}').$$

Cases :

- $\sigma_w = +1$ initially and $\underline{h_w^{\text{loc}}} = \sum_w J_{\text{now}} \sigma_w + h_w > 0$.

$R(\underline{\sigma} \rightarrow \underline{\sigma}') > A(\underline{\sigma} \rightarrow \underline{\sigma}')$. i.e tendency is not to flip.

- $\sigma_w = -1$ initially and $\underline{h_w^{\text{loc}}} > 0$.

$R(\underline{\sigma} \rightarrow \underline{\sigma}') < A(\underline{\sigma} \rightarrow \underline{\sigma}')$ i.e tendency is to flip.

In Glauber dynamics at the end what controls the move or the spin flip at a vertex is the "local bias or mean field".

|| The spin bias the tendency to flip so as to align with
|| h_w^{loc} .

Heat bath dynamics or Gibbs sampling.

- can be viewed as a generalization of Glauber to general measures and general alphabets.
- really useful when π is of "Gibbs type" or Markov Random Field.

Algo:

- Select an initial assignment $\underline{x} = (x_1, \dots, x_N)$.
- Select a vertex $v \in V \in \{1, \dots, N\}$ uniformly at random
- Compute the conditional probability of \underline{y} conditioned on ($y_w = x_w$ for $w \neq v$)
and make the move $\underline{x} \rightarrow \underline{y}$ with this
conditional probability :

$$P(\underline{y} | \{y_w = x_w, w \neq v\}) = \frac{\pi(x_1, \dots, x_{v-1}, y_v, x_{v+1}, \dots, x_N)}{\sum_{\underline{y}_v \in X} \pi(x_1, \dots, x_{v-1}, y_v, x_{v+1}, \dots, x_N)}.$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

Exercise : Detailed Balance & General Qo Reduction to Glauber for Init.