

# Concepts in Stochastic Models & Processes.

Mathematics gr #4.

'23.9.10.

Younghun Jo.

## I. Stochastic model. & process.

- Why is it important?

- Statistical mechanics :

If we solve it deterministically, then we have to work w/ system of  $N$  mols of equations.

$\leadsto$  let them behave randomly, and study their macroscopic behavior!

- Ising model, percolation, random graph, Brownian motion, .....

- Preliminary : Probability theory.

- Probability space :  $(\Omega, \mathcal{F}, \mathbb{P})$ .

- $\Omega$  : space of states.
  - $\mathcal{F}$  :  $\sigma$ -algebra.
  - $\mathbb{P}$  : probability measure ( $\mathbb{P}[\Omega] = 1$ ).

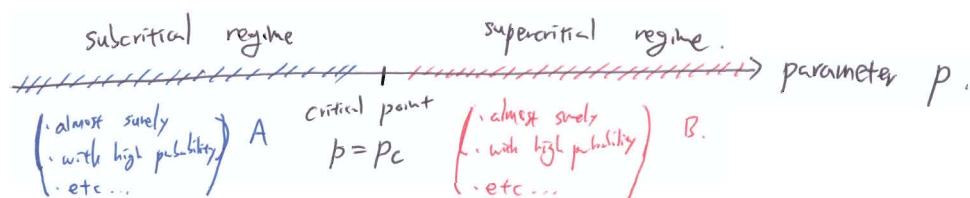
- $A \in \mathcal{F}$  : event.

- $X$  :  $\mathcal{F}$ -measurable function on  $\Omega$  : random variable.

- $\mathbb{E}[X] := \int_{\Omega} X d\mathbb{P}$  : expectation.

## II. Phase transition.

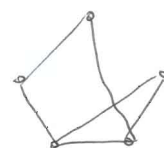
- When we have a family of models, parametrized by a variable, we often can observe a "phase transition" phenomenon.



- e.g. 1. Erdős-Rényi graph.

Erdős-Rényi graph  $G_{n,p} \subseteq K_n$  ( $p \in [0, 1]$ ).

$$\mathbb{P}_p[G_{n,p} = G] = p^{\# \text{edges in } G} \cdot (1-p)^{\binom{n}{2} - \# \text{edges in } G}.$$



- Q. Given a graph  $H$ , what is the probability that  $H \subseteq G_{n,p}$ ?

$H = \Delta$ : let  $T = \# \text{ of } \Delta \text{ in } G_{n,p}$ .

$$\mathbb{E} T = \binom{n}{3} \cdot p^3 \rightarrow \begin{cases} 0 & \text{if } p \ll \frac{1}{n} \\ \infty & \text{if } p \gg \frac{1}{n} \end{cases}$$

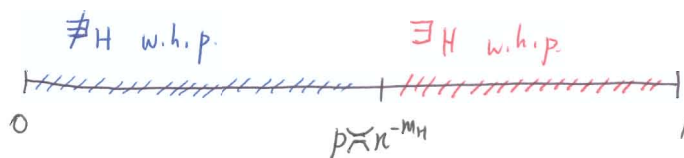
$$\mathbb{E} T^2 = \sum_{\Delta} \mathbb{E} \Delta^2 + \sum_{\Delta_i \neq \Delta_j} \mathbb{E} \Delta_i \Delta_j = \binom{n}{3} \cdot p^3 + 3 \binom{n}{3} (n-3) \cdot p^5 + \left[ \binom{n}{3} \binom{n-3}{3} + 3 \binom{n}{3} \binom{n-3}{2} \right] \cdot p^6$$

(Second moment method)  $\mathbb{P}[T=0] \leq \mathbb{P}[|T - \mathbb{E} T| \geq \mathbb{E} T] \stackrel{\text{Chebyshev}}{\leq} \frac{\text{Var } T}{(\mathbb{E} T)^2} \rightarrow 0 \text{ if } p \gg \frac{1}{n}$

$$\Rightarrow \mathbb{P}[H \subseteq G_{n,p}] \rightarrow \begin{cases} 0 & \text{if } p \ll \frac{1}{n} \\ 1 & \text{if } p \gg \frac{1}{n} \end{cases}$$

(Erdős-Rényi, Bollobás)  $\forall H$ ,  $m_H := \min \left\{ \frac{v_K}{e_K} : K \subseteq H \right\}$ .

$$\mathbb{P}[H \subseteq G_{n,p}] \rightarrow \begin{cases} 0 & \text{if } p \ll n^{-m_H} \\ 1 & \text{if } p \gg n^{-m_H} \end{cases}$$





• e.g. 2. Percolation.

•  $d$ -dim'l hypercubic lattice  $L^d = (\mathbb{Z}^d, E^d)$ ,  $p \in [0, 1]$ .

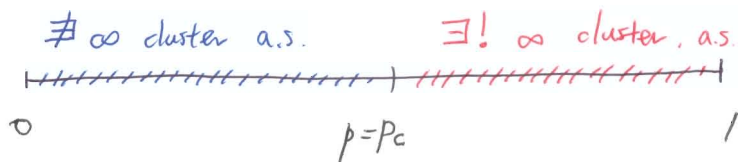
• Percolation:  $\omega \in \Omega = \{0, 1\}^{E^d}$ ,  $\omega(e) \sim \text{Ber}(p)$  i.i.d.  $\forall e \in E^d$ .

• Q. What is the probability that we have an infinite cluster?

•  $\theta(p) := \mathbb{P}_p[0 \text{ is in an } \infty \text{ cluster}]$ .

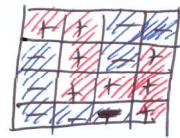
$p_c := \sup\{p : \theta(p) = 0\}$ .

• FACT)



( $\because \#$ ,  $\exists$ : Use 0-1 law.  
 $\exists!$ : Pretty complicated... Read [Grimmett '99 - Percolation].)

• e.g. 3. 2-dim'l Ising model.



-  $\Lambda = [0, L]^2 \subseteq \mathbb{Z}^2$  box,  $\sigma \in \{+1, -1\}^\Lambda = \Sigma$ .

- Hamiltonian:  $H(\sigma) = -J \sum_{x \sim y} \mathbb{1}_{\{\sigma_x = \sigma_y\}} - h \sum_x \mathbb{1}_{\{\sigma_x = +1\}}$ .  
*Annotations:  $J > 0$  interaction strength;  $h$  external magnetic field.*

-  $P_\beta[\sigma] = \frac{1}{Z_\beta} e^{-\beta H(\sigma)}$  "Gibbs measure" inverse temperature  $\beta = \frac{1}{k_B T} > 0$ .

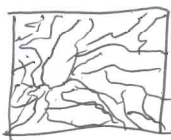
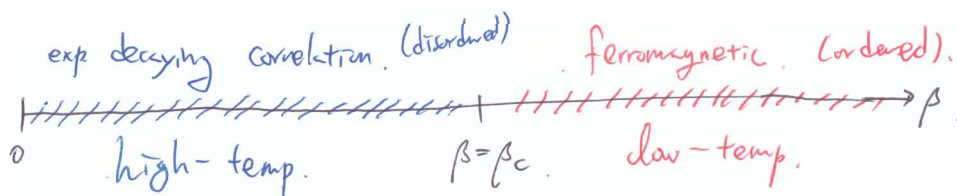
- let  $h=0$ . (Zero magnetic field),  $J=1$ .

Passing to weak limit as  $L \rightarrow \infty$ ,

we can define an Ising model on  $\mathbb{Z}^2$ .

- Q. For two sites  $x, y \in \mathbb{Z}^2$ , how are  $\sigma_x, \sigma_y$  correlated?

- FACT) For  $\beta_c = \log(1+\sqrt{2})$ ,

$$P_\beta[\sigma_x = \sigma_y] - \frac{1}{2} \xrightarrow{|x-y| \rightarrow \infty} \begin{cases} 0 & \text{exponentially fast, if } \beta < \beta_c \\ c(\beta) > 0 & \text{if } \beta > \beta_c. \end{cases}$$


### III. Glauber dynamics. & mixing time

- Random process.

÷ Basically, it is a collection of random variables  $(X_t)$ , where  $t \in \mathbb{Z}_{\geq 0}$  or  $\mathbb{R}_{\geq 0}$ .

- It is called a Markov chain if it is "memoryless",

i.e., the conditional distribution of future states depends only upon the present state:

$$\mathbb{P}[X_t \in A \mid \mathcal{F}_s] = \mathbb{P}[X_t \in A \mid X_s] \quad \forall A \in \mathcal{F}, s \leq t.$$

- Markov Chain Monte Carlo algorithm.

- Q. Given a stochastic model, how can we sample (simulate) it?

- Idea: Markov Chain Monte Carlo (MCMC).

Construct a Markov chain on the state space

whose stationary measure is the probability measure we want.

Classical FACT) If an ergodic Markov chain  $X_t$  has stationary measure  $\mathbb{P}$ ,  
then  $\mathbb{P}_{X_0}^t \xrightarrow{t \rightarrow \infty} \mathbb{P} \quad \forall X_0 \in \Omega.$

\* Total variation distance

$$\|\mathbb{P}_1 - \mathbb{P}_2\|_{TV} := \sup_{A \in \mathcal{F}} |\mathbb{P}_1[A] - \mathbb{P}_2[A]| \quad (\in [0, 1]).$$

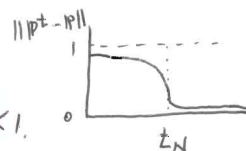
- Mixing time.

$$t_{\text{mix}}(\varepsilon) := \inf \left\{ t : \max_{X_0 \in \Omega} \|\mathbb{P}_{X_0}^t - \mathbb{P}\|_{TV} \leq \varepsilon \right\} \quad 0 < \varepsilon < 1.$$

Conventionally, write  $t_{\text{mix}} = t_{\text{mix}}(\frac{1}{4})$ . (We may pick any  $\varepsilon < \frac{1}{2}$ ).

- Cutoff:

: A family of process exhibits cutoff if  $\lim_{N \rightarrow \infty} \frac{t_{\text{mix}}(\varepsilon)}{t_{\text{mix}}(1-\varepsilon)} = 1 \quad \forall 0 < \varepsilon < 1.$



- Glauber dynamics.

- Return to the finite-volume Ising model on  $\Lambda = [0, L]^2$ .

- Equip  $\Omega = \{\pm 1\}^\Lambda$  w/ a set of undirected edges  $E$

:  $\sigma \sim \sigma'$  if  $\sigma_x \neq \sigma'_x$  exactly at one site.

- Glauber dynamics  $(\sigma_t)$  on  $\Omega$ :

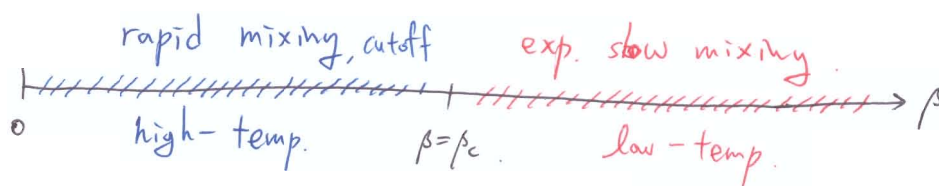
: continuous time Markov process w/ transition rates

$$c_\beta(\sigma, \sigma') = \begin{cases} e^{-\beta[H(\sigma') - H(\sigma)]_+} & \text{if } \sigma \sim \sigma' \\ 0 & \text{otw.} \end{cases}$$

"single spin flip"

$\leadsto$  We have stationary measure  $\mathbb{P}$ , that is reversible & ergodic.

- FACT)  $\beta < \beta_c$ :  $t_{\text{mix}} = O(L^2 \log L)$  : "coupon-collecting time" & cut-off.  
 $\beta > \beta_c$ :  $t_{\text{mix}} \geq e^{c(\beta) \cdot L}$   $\exists c(\beta) > 0$ . [Lubetzký-Sly '14].



$\hookrightarrow$  This is a pretty universal picture!

# IV. Metastability.

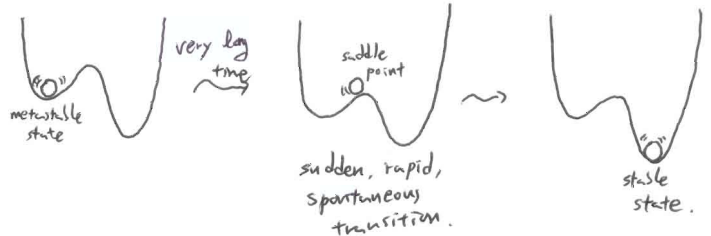
## • Metastability

= "Spontaneous transition from a 'fake' stable state to the stable state"

- e.g. • supercooled water



• diffusion w/ gradient drift



- Common indicators.



• exponential hitting time :  $\tau_n = \inf \{t : X_t^n \in S\}$ .

$$\Rightarrow \frac{\log E_m \tau_n}{n} \xrightarrow{n \rightarrow \infty} \exists C > 0.$$

(cf. large deviations, Friedman-Wentzell theory.)

• "independent" attempts :  $\frac{\tau_n}{E \tau_n} \xrightarrow{n \rightarrow \infty} \text{Exp}(1)$  in distribution.

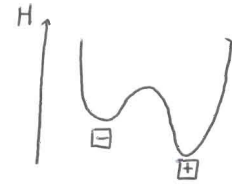


asymptotically Poisson.

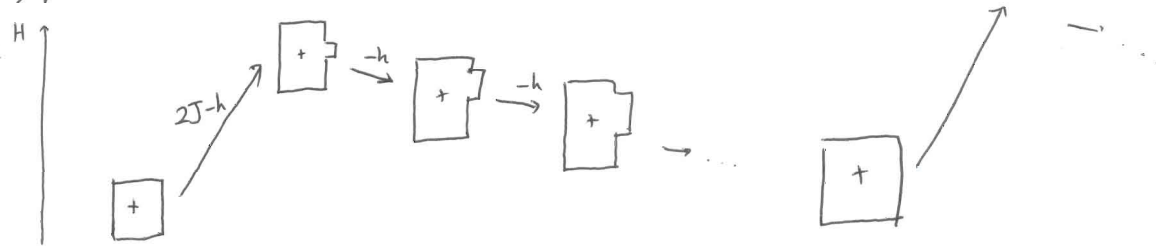
- Metastability of Glauber dynamics.

- Now we consider  $\Lambda = [0, L]^2$  torus,  $J > 0$ ,  $h \in (0, 2J)$ .

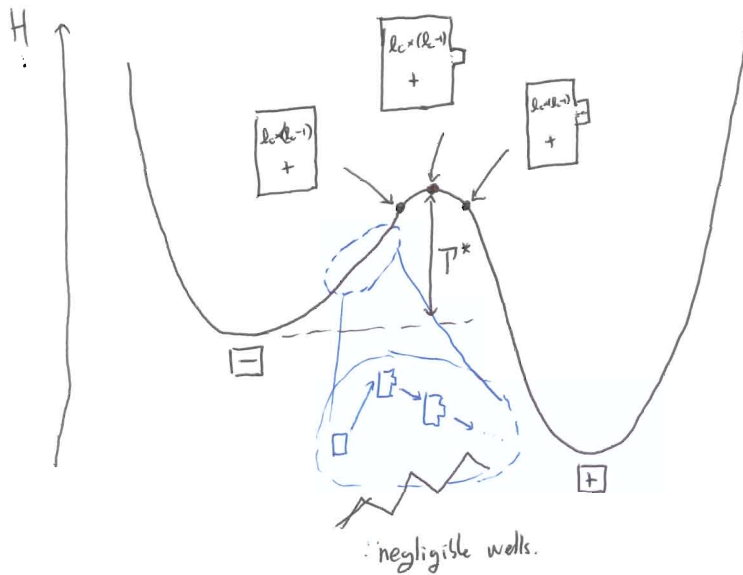
- metastable state  $\square \stackrel{h}{\rightleftharpoons} \sigma_x = -1 \quad \forall x$   
 stable state  $\boxplus : \sigma_x = +1 \quad \forall x$



- typical (most-likely) path  $\square \rightarrow \boxplus$ .



- critical droplet size  $l_c = \lceil \frac{2J}{h} \rceil$ .



FACT)

$$\mathbb{E} \tau_{\square \rightarrow \boxplus} \sim K e^{\beta T^*} \quad \text{where}$$

$$T^* = J \cdot [4l_c] - h \cdot (l_c(l_c-1) + 1)$$

$$K = \frac{3}{4(2l_c-1)} \frac{1}{|\Lambda|}$$

(See [Bovier-Hollander '15 - Metastability].)