

# Metastability for the Curie-Weiss model on inhomogeneous random graphs: results and challenges

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Based on ongoing joint work with Anton Bovier and Frank den Hollander

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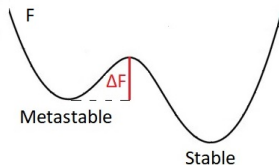


# Metastability: quantities of interest

Given  $F$  free energy

- 1 Metastable parameter regime ( $\rightarrow$  multiple minima of  $F$ )
- 2 Critical sets/points  $F$ :
  - ▶ local minima (metastable state), global minimum (stable state)
  - ▶ local maxima/saddle points
- 3 **Metastable exit time**: metastable  $\rightarrow$  (more) stable.
  - ▶ Mean
  - ▶ Distribution

In the limit  $N \rightarrow \infty$  it is usually exponential  $\sim \exp(N\Delta F)$ .



# Ferromagnetic Ising model on a lattice of size $N$

Spin flip model on a lattice of size  $N$ :  $N$  particles/spins.

Configurations  $\sigma = (\sigma_i)_{1 \leq i \leq N} \in \{-1, 1\}^N = \mathcal{S}_N$ .

Energy/Hamiltonian:

$$H_N(\sigma) = -\frac{1}{2N} \sum_{i,j=1}^N J(i,j) \sigma_i \sigma_j - h \sum_{i=1}^N \sigma_i, \quad \sigma \in \{-1, 1\}^N$$

$J(i,j) \geq 0$  interaction/coupling coefficients,  $h \geq 0$  external magnetic field.

We use **Glauber dynamics** with **Metropolis transition** rates and  $\beta > 0$  inverse temperature

$$p_N(\sigma, \sigma') = \begin{cases} \exp(-\beta[H_N(\sigma') - H_N(\sigma)]_+) & \text{if } \sigma \sim \sigma' \text{ single spin flip,} \\ 0 & \text{otherwise.} \end{cases}$$

The Gibbs measure  $\mu_N(\sigma) \propto e^{-\beta H_N(\sigma)}$  is the **invariant** and **reversible measure**.

# Curie–Weiss on graphs

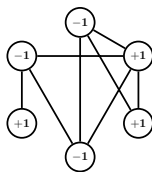
$$H_N(\sigma) = -\frac{1}{2N} \sum_{i,j=1}^N J(i,j) \sigma_i \sigma_j - h \sum_{i=1}^N \sigma_i, \quad \sigma \in \{-1, 1\}^N$$

The **interaction graph**  $G = (\mathcal{E}, [N]) : (i, j) \in \mathcal{E} \iff J(i, j) \neq 0$ .

When  $J(i, j) \in \{0, 1\}$ , we can write

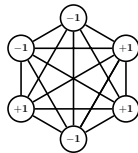
$$H_N(\sigma) = -\frac{1}{2N} \sum_{(i,j) \in \mathcal{E}} \sigma_i \sigma_j - h \sum_{i=1}^N \sigma_i$$

$\implies$  *Curie–Weiss on the graph*  $G = (\mathcal{E}, [N])$ .



Models from the previous talk:

- Curie–Weiss model:  $J(i, j) \equiv 1$   
 $\implies$  complete graph
- Randomly dilute CW:  $J(i, j) \sim Be(p)$  i.i.d.  
 $\implies$  CW on the Erdős–Rényi random graph



Complete graph

# Results for CW on the Erdős–Rényi random graph

## From the previous talk

### Theorem (Mean metastable exit time for CW on E-R, in [BMP21])

For  $\beta > 1$ ,  $h > 0$  small enough and for all  $s > 0$ ,

$$\lim_{N \uparrow \infty} \mathbb{P}_J \left( C_1 e^{-s} \leq \frac{\mathbb{E}_{\nu_{m_-, m_+}^{ER}} [\tau_{\mathcal{S}_N[m_+(N)]}]}{\mathbb{E}_{m_-(N)}^{CW} [\tau_{m_+(N)}]} \leq C_2 e^s \right) \geq 1 - k_1 e^{-k_2 s^2}.$$

where

$$\mathbb{E}(H_N^{ER}(\sigma)) = p H_N^{CW}(\sigma)$$

### Ideas:

- compare  $\text{cap}(A, B)$  and  $\sum_{\sigma' \in \mathcal{S}_N} \mu_N(\sigma') h_{AB}(\sigma')$  of the target model with its “mean” correspondents, using **concentration**.
- use potential-theoretic approach

$$\mathbb{E}_{\nu_{A,B}}[\tau_B] = \frac{1}{\text{cap}(A, B)} \sum_{\sigma' \in \mathcal{S}_N} \mu_N(\sigma') h_{AB}(\sigma')$$

# Conjecture for CW on inhomogeneous random graphs

## Conjecture

In the metastable regime, let  $J(i, j)$  be independently distributed Bernoulli, and  $A, B$  metastable sets for the “mean” model. Then for all  $s > 0$ ,

$$\lim_{N \uparrow \infty} \mathbb{P}_J \left( C_1 e^{-s} \leq \frac{\mathbb{E}_{\nu_{A,B}} [\tau_B]}{\mathbb{E}_{\nu_{A,B}^{\mathbb{E}}} [\tau_B]} \leq C_2 e^s \right) \geq 1 - k_1 e^{-k_2 s^2}.$$

where

$$\mathbb{E}(H_N(\sigma)) = H_N^{\mathbb{E}}(\sigma)$$

Ideas:

- compare  $\text{cap}(A, B)$  and  $\sum_{\sigma' \in \mathcal{S}_N} \mu_N(\sigma') h_{AB}(\sigma')$  of the target model with its “mean” correspondents, using **concentration**;
- use potential-theoretic approach

$$\mathbb{E}_{\nu_{A,B}} [\tau_B] = \frac{1}{\text{cap}(A, B)} \sum_{\sigma' \in \mathcal{S}_N} \mu_N(\sigma') h_{AB}(\sigma').$$

# Results for inhomogeneous random graphs

$$\text{Target quantity: } \mathbb{E}_{\nu_{A,B}}[\tau_B] = \frac{1}{\text{cap}_N(A,B)} \sum_{\sigma' \in \mathcal{S}_N} \mu_N(\sigma') h_{AB}(\sigma')$$

where

$$\text{cap}_N(A,B) = \sum_{x \in A} \mu_N(x) \mathbb{P}_x(\tau_B < \tau_A).$$

## Theorem (Capacity estimates)

Assume  $J(i,j) \sim \text{Be}(v_N(i,j))$  independent. Then, for any disjoint  $A, B$  and any  $s > 0$

$$\lim_{N \rightarrow \infty} \mathbb{P}_J \left( c_1 e^{-s} \leq \frac{Z_N \text{cap}_N(A,B)}{Z_N^{\mathbb{E}} \text{cap}_N^{\mathbb{E}}(A,B)} \leq c_2 e^s \right) \geq 1 - k_1 e^{-k_2 s^2}.$$

where  $c_1, c_2$  are both  $O(1)$ , explicit and depend on  $\beta, h, \sum_{i,j} \text{Var}J(i,j)$ .

Idea of the **proof**: use Dirichlet and Thomson variational principles, together with **concentration**.

**Challenge**: estimates on  $\sum_{\sigma' \in \mathcal{S}_N} \mu_N(\sigma') h_{AB}(\sigma')$

# Concentration

Extension of the concentration results proven in [BMP21]

$$H_N(\sigma) = -\frac{1}{2N} \sum_{i,j=1}^N J(i,j)\sigma_i\sigma_j - h \sum_{i=1}^N \sigma_i, \quad \sigma \in \{-1, 1\}^N$$

with  $J(i, j) \sim Be(v_N(i, j))$ .

## Theorem (Concentration)

Assume  $(J(i, j))_{i,j}$  are independent. Then there exist absolute constants  $k_1, k_2 > 0$  such that, for any  $g: \mathcal{S}_N \rightarrow [0, \infty)$  and any  $s > 0$

$$\lim_{N \rightarrow \infty} \mathbb{P}_J \left( e^{-s+\kappa(N)} \leq \frac{\sum_{\sigma \in \mathcal{S}_N} g(\sigma) e^{-\beta(H_N(\sigma) - \mathbb{E}[H_N(\sigma)])}}{\sum_{\sigma \in \mathcal{S}_N} g(\sigma)} \leq e^{s+\alpha(N)} \right) \geq 1 - k_1 e^{-k_2 s^2},$$

where  $\alpha(N) = \frac{\beta^2}{8N^2} \sum_{i,j=1}^N \text{Var}(J(i, j))$  and  $\kappa(N) = \alpha(N) - \varepsilon(\alpha(N))$ .



# Ideas of the proof

$$\lim_{N \rightarrow \infty} \mathbb{P} \left( e^{-s+\kappa(N)} \leq \frac{\sum_{\sigma \in \mathcal{S}_N} g(\sigma) e^{-\beta(H_N(\sigma) - \mathbb{E}[H_N(\sigma)])}}{\sum_{\sigma \in \mathcal{S}_N} g(\sigma)} \leq e^{s+\alpha(N)} \right) \\ \geq 1 - k_1 e^{-k_2 s^2},$$

is equivalent to

## Target result

$$e^{\mathcal{Y}_N} e^{\kappa(N)} \sum_{\sigma \in \mathcal{S}_N} g(\sigma) \leq \sum_{\sigma \in \mathcal{S}_N} g(\sigma) e^{-\beta(H_N(\sigma) - \mathbb{E}[H_N(\sigma)])} \leq e^{\mathcal{Y}_N} e^{\alpha(N)} \sum_{\sigma \in \mathcal{S}_N} g(\sigma)$$

with  $\mathcal{Y}_N$  sub-Gaussian r.v. i.e.  $\mathbb{P}_J (|\mathcal{Y}_N| \geq s) \leq k_1 \exp(-k_2 s^2)$ , for any  $s > 0$ .

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$$\sum_{\sigma \in \mathcal{S}_N} g(\sigma) e^{-\beta[H_N(\sigma) - \mathbb{E}[H_N(\sigma)]]} \\ \equiv \exp(N\mathcal{F}_N) = \exp(N(\mathcal{F}_N - \mathbb{E}\mathcal{F}_N)) \cdot \exp(N\mathbb{E}\mathcal{F}_N)$$

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## Step 1. Proof **stochastic part**

### Proposition

$N(\mathcal{F}_N - \mathbb{E}\mathcal{F}_N)$  is a sub-Gaussian r.v., i.e. for any  $s > 0$

$$\mathbb{P}_J \left( N |\mathcal{F}_N - \mathbb{E}\mathcal{F}_N| \geq s \right) \leq k_1 \exp \left( - \frac{8k}{\beta^2} s^2 \right).$$

Proof: 
$$\begin{aligned} N\mathcal{F}_N &= \log \sum_{\sigma \in \mathcal{S}_N} g(\sigma) e^{-\beta[H_N(\sigma) - \mathbb{E}[H_N(\sigma)]]} \\ &= \log \sum_{\sigma \in \mathcal{S}_N} g(\sigma) \exp \left[ \frac{\beta}{2N} \sum_{i,j=1}^N [J(i,j) - \mathbb{E}J(i,j)] \sigma_i \sigma_j \right] \end{aligned}$$

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Proof: 
$$N\mathcal{F}_N = \log \sum_{\sigma \in \mathcal{S}_N} g(\sigma) \exp \left[ \frac{\beta}{2N} \sum_{i,j=1}^N [J(i,j) - \mathbb{E}J(i,j)] \sigma_i \sigma_j \right]$$

### Talagrand's concentration inequality

$$\mathbb{P} \left( |G(g) - \mathbb{E}G(g)| \geq tK \right) \leq k_1 \exp \left( - k_2 t^2 \right),$$

for  $G : \mathbb{R}^n \rightarrow \mathbb{R}$  convex and 1-Lipschitz, and  $g = (g_i)_{i \in [n]}$  **independent** r.v.'s uniformly bounded by  $K > 0$ .

with  $G = \frac{2\sqrt{2}}{\beta} N\mathcal{F}_N$  and the r.v.'s  $[J(i,j) - \mathbb{E}J(i,j)]_{ij}$ .

## Step 2. Proof **deterministic part**

### Proposition

$$e^{\kappa(N)} \sum_{\sigma \in \mathcal{S}_N} g(\sigma)(1 + o(1)) \leq \exp(N \mathbb{E}_J \mathcal{F}_N) \leq e^{\alpha(N)} \sum_{\sigma \in \mathcal{S}_N} g(\sigma)(1 + o(1))$$

Lower bound:

- $\mathbb{E}_J[\exp(N \mathcal{F}_N)]$
- $\mathbb{E}_J[\exp(2N \mathcal{F}_N)] \leq k \mathbb{E}_J^2[\exp(N \mathcal{F}_N)]$
- Talagrand's concentration inequality

Upper bound:

- $\mathbb{E}_J[\exp(N \mathcal{F}_N)]$
- Jensen's inequality

## Step 2. Proof **deterministic part**: upper bound

### Upper bound

$$\exp(N\mathbb{E}_J\mathcal{F}_N) \leq \mathbb{E}_J[\exp(N\mathcal{F}_N)] = e^{\alpha(N)} \sum_{\sigma \in \mathcal{S}_N} g(\sigma)(1 + o(1))$$

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$$\exp(N\mathcal{F}_N) = \sum_{\sigma \in \mathcal{S}_N} g(\sigma) \prod_{i,j=1}^N \exp\left[\frac{\beta}{2N}[J(i,j) - \mathbb{E}J(i,j)]\sigma_i\sigma_j\right]$$



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$$\begin{aligned}\mathbb{E}_J \exp\left[\frac{\beta}{2N}[J(i,j) - \mathbb{E}J(i,j)]\sigma_i\sigma_j\right] &= 1 + \frac{1}{2} \left(\frac{\beta}{2N}\sigma_i\sigma_j\right)^2 \text{Var}[J(i,j)] + o\left(\frac{1}{N^2}\right) \\ &= \exp\left[\frac{\beta^2}{8N^2} \text{Var}[J(i,j)] + o\left(\frac{1}{N^2}\right)\right]\end{aligned}$$

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### Upper bound

$$\exp(N\mathbb{E}_J \mathcal{F}_N) \leq \boxed{\mathbb{E}_J[\exp(N\mathcal{F}_N)] = e^{\alpha(N)} \sum_{\sigma \in \mathcal{S}_N} g(\sigma)(1 + o(1))}$$

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$$\begin{aligned}\implies \mathbb{E}_J[\exp(N\mathcal{F}_N)] &= \sum_{\sigma \in \mathcal{S}_N} g(\sigma) e^{\frac{\beta^2}{8N^2} \sum_{i,j=1}^N \text{Var}(J(i,j))} (1 + o(1)) \\ &= e^{\alpha(N)} \sum_{\sigma \in \mathcal{S}_N} g(\sigma) (1 + o(1))\end{aligned}$$

# An inhomogeneous random graph: the Chung-Lu r. g.

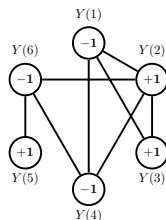
## Chung-Lu random graph

$$G = (\mathcal{E}, \{1, 2, \dots, N\})$$

Assign random weights on vertices

$$Y: \{1, 2, \dots, N\} \rightarrow [0, 1].$$

$$\mathbb{P}((i, j) \in \mathcal{E}) = Y(i)Y(j), \quad i, j \in \{1, 2, \dots, N\}$$



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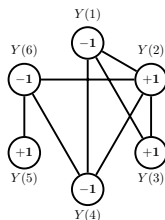
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## Hamiltonian of CW on the Chung-Lu random graph

$$H_N(\sigma) = -\frac{1}{2N} \sum_{i,j=1}^N J(i,j) \sigma_i \sigma_j - h \sum_{i=1}^N \sigma_i, \quad \sigma \in \{-1, 1\}^N$$

$$\text{with } J(i,j) \sim \text{Be}(Y(i)Y(j)).$$

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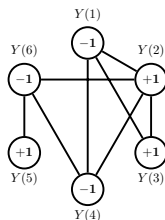
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$$\text{with } J(i, j) \sim \text{Be}(Y(i)Y(j)).$$

The mean w.r.t.  $J$  is

$$\mathbb{E}(H_N(\sigma)) = -\frac{1}{2N} \sum_{i,j=1}^N Y(i)Y(j) \sigma_i \sigma_j - h \sum_{i=1}^N \sigma_i, \quad \sigma \in \{-1, 1\}^N$$

It is the Hamiltonian of **CW with disorder**.

# Recap: Curie–Weiss model and stochastic modifications

$$H_N(\sigma) = -\frac{1}{2N} \sum_{i,j=1}^N J(i,j) \sigma_i \sigma_j - h \sum_{i=1}^N \sigma_i, \quad \sigma \in \{-1, 1\}^N$$

Curie-Weiss model (CW) [1]

$$J(i,j) \equiv 1$$

complete graph

Randomly Dilute CW (RDCW) [2]

$$J(i,j) \sim \text{Be}(p) \text{ iid}$$

Erdős–Rényi random graph

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Erdős–Rényi random graph

CW on the Chung–Lu r.g. [3]

$$J(i,j) \sim \text{Be}(Y(i)Y(j)), \quad Y(i) \geq 0 \text{ iid r.v.}$$

Chung–Lu random graph

# Recap: Curie–Weiss model and stochastic modifications

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**CW with disorder** [2]

$$J(i,j) = Y(i)Y(j), \quad Y(i) \geq 0 \text{ iid r.v.}$$

CW on the Chung–Lu r.g. [3]

$$J(i,j) \sim \text{Be}(Y(i)Y(j)), \quad Y(i) \geq 0 \text{ iid r.v.} \quad \text{Chung–Lu random graph}$$



# Model reduction in CW-Dis: coarse graining and magnetisation

**Coarse-graining in CW-Dis with finite support**  $\{a_1, \dots, a_k\}$  of  $Y(i)$ .

Partition:  $A_\ell = \{i \in \{1, \dots, N\} : Y(i) = a_\ell\}$ ,  $\ell \in \{1, \dots, k\}$ .

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$Y(i) = \sum_{\ell=1}^k a_\ell \mathbb{1}(i \in A_\ell)$ . Then

$$\begin{aligned} H_N(\sigma) &= -\frac{N}{2} \left( \frac{1}{N} \sum_{i=1}^N Y(i) \sigma_i \right)^2 - h \sum_{i=1}^N \sigma_i, \quad \sigma \in \{-1, 1\}^N \\ &= -\frac{N}{2} \left( \frac{1}{N} \sum_{\ell=1}^k a_\ell \sum_{i \in A_\ell} \sigma_i \right)^2 - h \sum_{\ell=1}^k \sum_{i \in A_\ell} \sigma_i \end{aligned}$$

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**Magnetisation**  $m : \{-1, 1\}^N \rightarrow M_N \subset [-1, 1]^k$ ,  $m = (m_1, \dots, m_k)$ ,

$$\boxed{m_\ell(\sigma) = \frac{1}{|A_\ell|} \sum_{i \in A_\ell} \sigma_i}, \quad \ell \in \{1, \dots, k\}, \sigma \in \{-1, 1\}^N.$$

$$H_N(\sigma) = -N \left[ \frac{1}{2} \left( \sum_{\ell=1}^k a_\ell \frac{|A_\ell|}{N} m_\ell(\sigma) \right)^2 + h \sum_{\ell=1}^k \frac{|A_\ell|}{N} m_\ell(\sigma) \right] = NE_N(m(\sigma))$$

# Well-known results in CW

$$J(i, j) \equiv 1$$

## Theorem (Metastability)

- **Metastable regime**

$$\beta \in (1, \infty), \quad h \in [0, \bar{h}_c(\beta)).$$

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# Results in CW with finite disorder

$J(i, j) = Y(i)Y(j)$ ,  $Y(i) \geq 0$  iid r.v. with **finite support**  $\{a_1, \dots, a_k\}$  and  $\omega_\ell = \mathbb{P}(Y(1) = a_\ell)$ .

## Theorem (Metastable regime and critical points)

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$$\beta \in (\beta_c, \infty), \quad h \in [0, h_c(\beta)),$$

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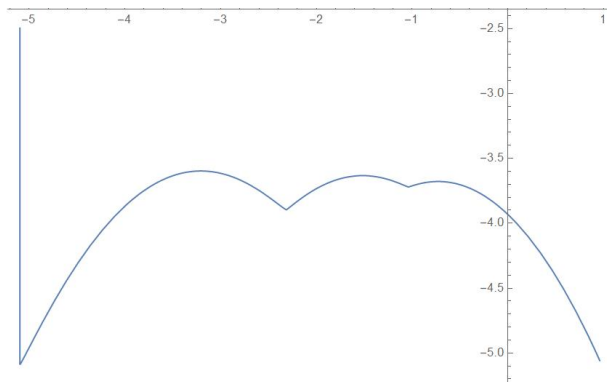
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# Results in CW with finite disorder: example critical points

Example of free energy with more than three critical points



Energy functional. 1-dim. example:  $k=4$ , 7 critical points

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Within the metastable regime, uniformly in  $\sigma \in \mathcal{S}_N[\mathbf{m}_N]$  and with  $\mathcal{P}^N$ -probability tending to 1, as  $N \rightarrow \infty$

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[A. Bovier, F. den Hollander and S. M., “Metastability for Glauber dynamics on the complete graph with coupling disorder”, 2021. [arXiv:2107.04543](https://arxiv.org/abs/2107.04543)]

# Techniques: Potential-theoretic approach

Lumpable:  $H_N(\sigma) = E_N(m(\sigma))$ .

Magnetisation:  $m = (m_1, \dots, m_k)$ ,  $m_\ell(\sigma) = \frac{1}{|A_\ell|} \sum_{i \in A_\ell} \sigma_i$ .

$\forall \sigma \in m^{-1}(\mathbf{m})$ ,

$$\mathbb{E}_\sigma[\tau_{m^{-1}(\mathcal{B})}] = \boxed{\mathbb{E}_{m(\sigma)}^*[\tau_{\mathcal{B}}^*] = \frac{\tilde{\mu}_N^*(m(\sigma))}{\text{cap}^*(m(\sigma), \mathcal{B})}}$$

Same technique for any lumpable model (e.g. CW, finite RFCW, ...).

Challenge for not lumpable models (infinite RFCW, RDCW, ...): we can use only

$$\mathbb{E}_{\nu_{A,B}}[\tau_B] = \frac{1}{\text{cap}(A, B)} \sum_{\sigma' \in \mathcal{S}_N} \mu_N(\sigma') h_{AB}(\sigma').$$

# Summary and outlook

## Summary of results:

- Extension of some results for CW on E-R r.g. to general inhomogeneous r.g.
- Focus on CW on the Chung-Lu r.g. and detailed study on its mean, the CW with (finite) disorder

## Outlook of next challenges:

- Conclude the proof of our conjecture
- Find other  $J(i, j)$  s.t. the mean model is sufficiently solvable (problems with randomness on edges)



Thanks for your attention!

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