

Metastability for Glauber dynamics with inhomogeneous coupling disorder

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(with A. Bovier, F. den Hollander, S. Mareello and M. Slowik)

Analysis and Simulations of Metastable Systems

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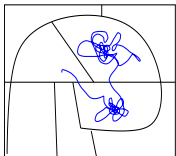


What is metastability?

Metastability is a phenomenon where a system, under the influence of a stochastic dynamics, moves between different regions of its state space on **different time scales**.

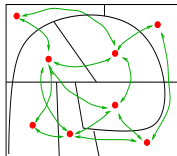
Fast time scale:

quasi-equilibrium within single subregion



Slow time scale:

transitions between different subregions

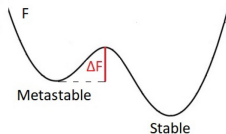


In Physics: metastability is the dynamical manifestation of a **phase transition**.

How to study metastability?

Given F the free energy, the quantities of interest are

- 1 Metastable parameter regime \rightarrow multiple minima of F
- 2 Critical points of F :
 - local minima (metastable states)
 - global minimum (stable state)
 - local maxima/saddle points
- 3 **Mean hitting time:** the mean time the system (subject to a stochastic dynamics) needs to “hit” the stable state starting from a metastable state.
Arrhenius law: $\mathbb{E}(\tau) \sim \exp(N\Delta F)$, in the limit $N \rightarrow \infty$.



Monographs:

- Olivieri and Vares 2005
- Bovier and den Hollander 2015

The quenched model

Mean-field version of Ising type spin model with inhomogeneous bond disorder.

N spins, $[N] = \{1, 2, \dots, N\}$

Configuration space $\mathcal{S}_N = \{-1, +1\}^N$

Configuration $\sigma = (\sigma_i)_{i \in [N]} \in \mathcal{S}_N$, $\sigma_i \in \{-1, +1\}$

$h > 0$ constant magnetic field.

Hamiltonian of **quenched/dilute** model

$$H_N^{\text{que}}(\sigma) = -\frac{1}{N} \sum_{1 \leq i < j \leq N} J_{ij} \sigma_i \sigma_j - h \sum_{i=1}^N \sigma_i$$

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Mean-field version of Ising type spin model with **inhomogeneous bond disorder**.

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Configuration space $\mathcal{S}_N = \{-1, +1\}^N$

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Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a **probability space** and let $(J_{ij})_{1 \leq i, j < \infty}$ a triangular array of **random variables**.

The quenched model

Hamiltonian

$$H_N^{\text{que}}(\sigma) = -\frac{1}{N} \sum_{1 \leq i < j \leq N} J_{ij} \sigma_i \sigma_j - h \sum_{i=1}^N \sigma_i$$

We take

$$J_{ij} = A_{ij} B_{ij}$$

where $(A_{ij}), (B_{ij}), (P_{ij})$ are sequences of random variables such that

- $|A_{ij}| \leq a, \quad B_{ij} \in [0, b], \quad P_{ij} \in (0, 1], \quad \mathbb{P}\text{-a.s.}, \quad \forall i, j$
- (B_{ij}) are mutually independent
- $B_{ij} \perp\!\!\!\perp \mathcal{F}_A$ and $\mathbb{E}[B_{ij} | \mathcal{F}_P] = P_{ij} \quad \mathbb{P}\text{-a.s.}, \quad \forall i, j$

Notation: \mathcal{F}_A and \mathcal{F}_P are the σ -algebras generated by (A_{ij}) and (P_{ij}) .

The quenched model

Hamiltonian

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- $B_{ij} \perp\!\!\!\perp \mathcal{F}_A \quad \text{and} \quad \mathbb{E}[B_{ij} | \mathcal{F}_P] = P_{ij} \quad \mathbb{P}\text{-a.s.}, \quad \forall i, j$

Three possible randomness levels:

- 1 B_{ij} random
- 2 $\mathbb{E}[B_{ij} | \mathcal{F}_P] = P_{ij}$ random (quenched on this)
- 3 A_{ij} random (quenched on this)

Example: Ising model on random graphs

$$J_{ij} = A_{ij}B_{ij},$$

$$H_N^{\text{que}}(\sigma) = -\frac{1}{N} \sum_{1 \leq i < j \leq N} J_{ij} \sigma_i \sigma_j - h \sum_{1 \leq i \leq N} \sigma_i,$$

Example: Ising model on random graphs

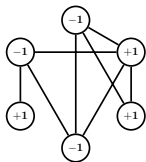
$J_{ij} = A_{ij}B_{ij}$, if $A_{ij} \equiv 1$, $B_{ij} \sim \text{Be}(P_{ij}) \in \{0, 1\}$

$$H_N^{\text{que}}(\sigma) = -\frac{1}{N} \sum_{1 \leq i < j \leq N} B_{ij} \sigma_i \sigma_j - h \sum_{1 \leq i \leq N} \sigma_i,$$

Example: Ising model on random graphs

$$J_{ij} = A_{ij}B_{ij}, \quad \text{if } A_{ij} \equiv 1, B_{ij} \sim \text{Be}(P_{ij}) \in \{0, 1\}$$

$$\begin{aligned} H_N^{\text{que}}(\sigma) &= -\frac{1}{N} \sum_{1 \leq i < j \leq N} B_{ij} \sigma_i \sigma_j - h \sum_{1 \leq i \leq N} \sigma_i, \\ &= -\frac{1}{N} \sum_{(i,j) \in \mathcal{E}} \sigma_i \sigma_j - h \sum_{1 \leq i \leq N} \sigma_i \end{aligned}$$



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

\implies Ising model on dense (inhomogeneous) random graphs:

$$\mathbb{P}((i, j) \in \mathcal{E}) = \mathbb{P}(B_{ij} = 1) = P_{ij}.$$

Examples:

- Curie–Weiss model: $B_{ij} \equiv 1 \implies$ Ising on the complete graph
- $B_{ij} \sim \text{Be}(p)$ i.i.d. $\implies (P_{ij} \equiv p)$ Ising on the Erdős–Rényi random graph
- $B_{ij} \sim \text{Be}(V_i V_j)$, V_i i.i.d. $\implies (P_{ij} \equiv V_i V_j)$ Ising on the Chung-Lu r. g.

Example: dilute Hopfield model

Hopfield model, with n patterns.

Let $(\xi_i)_{i \in \mathbb{N}}$, $\xi_i \in \{-1, 1\}^n$ *random* (typically $\mathbb{P}(\xi_i^k = 1) = \frac{1}{2}$):

$$\xi = \begin{pmatrix} +1 & -1 & -1 & +1 & -1 & -1 & -1 & \dots \\ -1 & -1 & -1 & +1 & -1 & +1 & -1 & \dots \\ -1 & +1 & -1 & -1 & +1 & -1 & +1 & \dots \\ -1 & -1 & -1 & +1 & +1 & -1 & -1 & \dots \\ +1 & +1 & +1 & +1 & -1 & +1 & -1 & \dots \end{pmatrix}$$

$$H_N^{\text{Hop}}(\sigma) = -\frac{1}{N} \sum_{1 \leq i < j \leq N} \sum_{k=1}^n \sigma_i \sigma_j \xi_i^k \xi_j^k \quad \sigma \in \{-1, 1\}^N$$

[Anton Bovier, Veronique Gayraud, Pierre Picco...]

Example: dilute Hopfield model

Randomly **dilute** Hopfield model, with n patterns.

Let $(\xi_i)_{i \in \mathbb{N}}$, $\xi_i \in \{-1, 1\}^n$ *random* (typically $\mathbb{P}(\xi_i^k = 1) = \frac{1}{2}$):

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$J_{ij} = A_{ij} B_{ij}$. Taking $A_{ij} = \sum_{1 \leq k \leq n} \xi_i^k \xi_j^k$, $B_{ij} \sim \text{Be}(p)$, $p \in (0, 1)$

$$H_N^{\text{que}}(\sigma) = -\frac{1}{N} \sum_{1 \leq i < j \leq N} A_{ij} B_{ij} \sigma_i \sigma_j - h \sum_{1 \leq i \leq N} \sigma_i, \quad \sigma \in \{-1, 1\}^N.$$

The annealed model

Notation: $\mathbb{P}_B[\cdot] = \mathbb{P}[\cdot \mid \mathcal{F}_{A \cup P}]$.

Then the Hamiltonian of the (*partially annealed model*) is

$$H_N^{\text{ann}}(\sigma) = \mathbb{E}_B [H_N^{\text{que}}(\sigma)] = -\frac{1}{N} \sum_{1 \leq i < j \leq N} A_{ij} \mathbb{E}_B [B_{ij}] \sigma_i \sigma_j - h \sum_{i=1}^N \sigma_i$$

The annealed model

Notation: $\mathbb{P}_B[\cdot] = \mathbb{P}[\cdot \mid \mathcal{F}_{AUP}]$.

Then the Hamiltonian of the (*partially annealed model*) is

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Examples:

- Ising on Erdős–Rényi, $\xrightarrow{\text{annealed}}$ Curie-Weiss

[Bovier, Marello, P. (2021), den Hollander, Jovanovski (2021), BdHMPS (2022+)]

- Ising on Chung–Lu random graph: $B_{ij} \sim \text{Be}(V_i V_j)$, V_i iid

$\xrightarrow{\text{annealed}}$ Ising with product disorder: $B_{ij} = V_i V_j$, V_i iid

[BdHMSP (2022+), Bovier, den Hollander, Marello (2022)]

- Dilute Hopfield $\xrightarrow{\text{annealed}}$ Hopfield

[BdHMSP (2022+), an der Heiden (2007)]

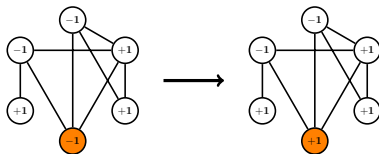
The Glauber dynamics

At equilibrium we define the Gibbs measure, $\sigma \in \mathcal{S}_N$,

$$\mu_{N,\beta}(\sigma) = \frac{e^{-\beta H_N(\sigma)}}{Z_{N,\beta}} \quad \text{with} \quad Z_{N,\beta} = \sum_{\sigma \in \mathcal{S}_N} e^{-\beta H_N(\sigma)}$$

where $\beta \in (0, \infty)$ is the inverse temperature and $Z_{N,\beta}$ the partition function. Continuous-time Glauber dynamics on \mathcal{S}_N with Metropolis transition rates

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



$\mu_{N,\beta}$ is the unique invariant and reversible measure.

Assume metastability of the annealed model.

Questions:

- 1 Is the random model metastable too?

In particular, denoting by P the law of the Markov chain, let $\tau_{\mathcal{A}}$ be the first return time to \mathcal{A} and define last exit-biased distribution

$$\nu_{\mathcal{A},\mathcal{B}}(\sigma) = \frac{\mu(\sigma) P_{\sigma}[\tau_{\mathcal{B}} < \tau_{\mathcal{A}}]}{\sum_{\sigma \in \mathcal{A}} \mu(\sigma) P_{\sigma}[\tau_{\mathcal{B}} < \tau_{\mathcal{A}}]}, \quad \sigma \in \mathcal{A}.$$

- 2 What is the mean hitting time of the more stable set \mathcal{B} , i.e.

$$E_{\nu_{\mathcal{A},\mathcal{B}}}[\tau_{\mathcal{B}}] ?$$

Two kind of results: **tail behaviour** of the distribution and sharp estimates of the **moments**. All results quenched in A_{ij} and P_{ij} .

Definition of metastability

Consider a simple case where $\mathcal{M} = \{m_1, \dots, m_k\} \subset \mathcal{S}$ is a set of points, e.g. minima of F . Then a Markov process $X = \{X_t : t \geq 0\}$ is said to be ρ -metastable with respect to the set of metastable points \mathcal{M} if

$$\frac{\max_{m \in \mathcal{M}} \mathbb{P}_m \left[\tau_{\mathcal{M} \setminus m} < \tau_m \right]}{\min_{A \subset \mathcal{S} \setminus \mathcal{M}} \mathbb{P}_{\mu|A} \left[\tau_{\mathcal{M}} < \tau_A \right]} \leq \rho \ll 1,$$

Definition from Schlichting and Slowik ('19). More classical definition in BdH.

Results: metastability for the random model

Assumption

For \mathbb{P} -a.e. realization of the r.v.'s, there exist $N_0 < \infty$ and $\forall N$ disjoint subsets $\mathcal{M}_{1,N}, \dots, \mathcal{M}_{K,N}$ of \mathcal{S}_N such that, for all $N \geq N_0$, the **annealed model** is $\tilde{\rho}_N := e^{-c_1 N}$ -**metastable** with respect to $\{\mathcal{M}_{1,N}, \dots, \mathcal{M}_{K,N}\}$.

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Theorem 1 (BdHMPS)

*Under the Assumption and for \mathbb{P} -a.e. realization of the r.v.'s and any $c_2 \in (0, c_1)$, there exists $N_1(c_2) < \infty$ such that, for all $N \geq N_1(c_2)$ the random model is $\rho_N := e^{-c_2 N}$ -**metastable** with respect to $\mathcal{M} = \{\mathcal{M}_{1,N}, \dots, \mathcal{M}_{K,N}\}$.*

Results: tail estimates

Fix $i \in \{2, \dots, K\}$ and take $\mathcal{A} = \mathcal{M}_{i,N}$. Choose \mathcal{B} as the union of all the other metastable sets with lower free energy.

Notation: all quantities which refer to the annealed model have the tilda.

Theorem 2 (BdHMPS)

Under the Assumption, for any $s > 0$ and \mathbb{P} -a.e. realization of the r.v.'s

$$\lim_{N \rightarrow \infty} \mathbb{P}_B \left[e^{-s - \alpha_N} (1 + o(1)) \leq \frac{\mathbb{E}_{\nu_{\mathcal{A},B}}[\tau_{\mathcal{B}}]}{\tilde{\mathbb{E}}_{\tilde{\nu}_{\mathcal{A},B}}[\tilde{\tau}_{\mathcal{B}}]} \leq e^{s + 2\alpha_N} (1 + o(1)) \right] \geq 1 - 4e^{-\bar{c}s^2}$$

where $\bar{c} := 1/(\beta a b)^2$ and

$$\alpha_N := \frac{\beta^2}{2N^2} \sum_{1 \leq i < j \leq N} A_{ij}^2 \text{Var}_B[B_{ij}].$$

Theorem 3 (BdHMPS)

For any $q \geq 1$ and \mathbb{P} -a.e. realization of the r.v.'s

$$e^{-\alpha_N} (1 + o(1)) \leq \frac{\mathbb{E}_B \left[\mathbb{E}_{\nu_{\mathcal{A}, \mathcal{B}}} [\tau_{\mathcal{B}}]^q \right]^{1/q}}{\tilde{\mathbb{E}}_{\tilde{\nu}_{\mathcal{A}, \mathcal{B}}} [\tilde{\tau}_{\mathcal{B}}]} \leq e^{4q\alpha_N} (1 + o(1))$$

for all $N \geq N_1(c_2, \omega)$.

Target result: tail estimates

$$\lim_{N \rightarrow \infty} \mathbb{P}_B \left[e^{-s - \alpha_N} (1 + o(1)) \leq \frac{\mathbb{E}_{\nu_{\mathcal{A}, \mathcal{B}}} [\tau_{\mathcal{B}}]}{\tilde{\mathbb{E}}_{\tilde{\nu}_{\mathcal{A}, \mathcal{B}}} [\tilde{\tau}_{\mathcal{B}}]} \leq e^{s + 2\alpha_N} (1 + o(1)) \right] \geq 1 - 4e^{-\bar{c}s^2}$$

First step: concentration inequality

$$\mathbb{P}_B \left[\left| \log \mathbb{E}_{\nu_{\mathcal{A}, \mathcal{B}}} [\tau_{\mathcal{B}}] - \mathbb{E}_B \left[\log \mathbb{E}_{\nu_{\mathcal{A}, \mathcal{B}}} [\tau_{\mathcal{B}}] \right] \right| > s \right] \leq 4e^{-\bar{c}s^2} + o(1),$$

Second step: annealed estimates

$$-\alpha_N(1 + o(1)) \leq \mathbb{E}_B \left[\log \mathbb{E}_{\nu_{\mathcal{A}, \mathcal{B}}} [\tau_{\mathcal{B}}] \right] - \log \tilde{\mathbb{E}}_{\tilde{\nu}_{\mathcal{A}, \mathcal{B}}} [\tilde{\tau}_{\mathcal{B}}] \leq 2\alpha_N(1 + o(1)),$$

Translates the problem of understanding the metastable behaviour of Markov processes to the study of capacities of electric networks. Link between **mean metastable crossover time** and **capacity**.

For \mathcal{A}, \mathcal{B} disjoint subsets of \mathcal{S}_N , the **key formula** is

$$\mathbf{E}_{\nu_{\mathcal{A}, \mathcal{B}}}[\tau_{\mathcal{B}}] = \sum_{\sigma \in \mathcal{A}} \nu_{\mathcal{A}, \mathcal{B}}(\sigma) \mathbf{E}_{\sigma}[\tau_{\mathcal{B}}] = \frac{1}{\text{cap}(\mathcal{A}, \mathcal{B})} \sum_{\sigma' \in \mathcal{S}_N} \mu(\sigma') h_{\mathcal{A}\mathcal{B}}(\sigma'),$$

where

$$\text{cap}(\mathcal{A}, \mathcal{B}) = \sum_{\sigma \in \mathcal{A}} \mu_N(\sigma) \mathbf{P}_{\sigma}(\tau_{\mathcal{B}} < \tau_{\mathcal{A}})$$

and $h_{\mathcal{A}\mathcal{B}}$ is called *harmonic function*

$$h_{\mathcal{A}\mathcal{B}}(\sigma) = \begin{cases} \mathbf{P}_{\sigma}(\tau_{\mathcal{A}} < \tau_{\mathcal{B}}) & \sigma \in \mathcal{S}_N \setminus (\mathcal{A} \cup \mathcal{B}), \\ \mathbf{1}_{\mathcal{A}}(\sigma) & \sigma \in \mathcal{A} \cup \mathcal{B}. \end{cases}$$

\Rightarrow we need to prove the two steps (concentration and annealed estimates) for $\text{cap}(\mathcal{A}, \mathcal{B})$ and $h_{\mathcal{A}\mathcal{B}}$.

One related problem

Metastability for the **dilute Curie-Weiss Potts** model: spins in $\{1, \dots, q\}$ and random couplings (together with Johan Dubbeldam, Vicente Lenz and Martin Slowik)

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Thank you for your attention!

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Variational principles for the capacity

Dirichlet principle

$$\text{cap}(\mathcal{A}, \mathcal{B}) = \inf_{g \in \mathcal{H}_{\mathcal{A}\mathcal{B}}} \frac{1}{2} \sum_{\sigma, \sigma' \in \mathcal{S}_N} \mu_N(\sigma) p_N(\sigma, \sigma') [g(\sigma) - g(\sigma')]^2.$$

$$\mathcal{H}_{\mathcal{A}\mathcal{B}} := \{g : \mathcal{S}_N \rightarrow [0, 1] : g|_{\mathcal{A}} = 1, g|_{\mathcal{B}} = 0\}$$

Thomson principle

$$\text{cap}(\mathcal{A}, \mathcal{B}) = \sup_{\phi \in \mathcal{U}_{\mathcal{A}\mathcal{B}}} \frac{1}{\mathcal{D}(\phi)},$$

where

$$\mathcal{D}(\phi) = \sum_{(\sigma, \sigma') \in E} \frac{\phi(\sigma, \sigma')^2}{\mu_N(\sigma) p_N(\sigma, \sigma')}$$

$\mathcal{U}_{\mathcal{A}\mathcal{B}}$ is the space of all unit flows from \mathcal{A} to \mathcal{B}

McDiarmid concentration inequality

Classical concentration inequality for functionals of independent random variables satisfying a bounded difference estimate

Theorem 4 (McDiarmid's inequality)

Let \mathcal{X} be a Polish space. Consider a vector $X = (X_1, \dots, X_n)$ of independent \mathcal{X} -valued random variables and suppose that $f: \mathcal{X}^n \rightarrow \mathbb{R}$ satisfies, for any $i \in \{1, \dots, n\}$, the bounded differences inequality, i.e.

$$|f(X_1, \dots, X_n) - f(X_1, \dots, X_{i-1}, X'_i, X_{i+1}, \dots, X_n)| \leq c_i \in [0, \infty) \quad \mathbb{P}\text{-a.s.},$$

where (X'_1, \dots, X'_n) is an independent copy of (X_1, \dots, X_n) . Then, \mathbb{P} -a.s. for any $t \geq 0$,

$$\mathbb{P}[f(X) - \mathbb{E}[f(X)] > t] \leq e^{-t^2/2v},$$

where $v := \frac{1}{4} \sum_{i=1}^n c_i^2$.

Concentration inequality for the capacity

Consider two disjoint subsets $\mathcal{X}, \mathcal{Y} \subset \mathcal{S}_N$. Then, \mathbb{P} -a.s., for any $t \geq 0$,

$$\mathbb{P}_B \left[\left| \log(Z_{\text{cap}}(\mathcal{X}, \mathcal{Y})) - \mathbb{E}_B \left[\log(Z_{\text{cap}}(\mathcal{X}, \mathcal{Y})) \right] \right| > t \right] \leq 2 e^{-2t^2 \bar{c}},$$

where $\bar{c} = 1/(\beta a b)^2$.

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where $\bar{c} = 1/(\beta a b)^2$.

Proof: the map

$$(B_{ij}) \longmapsto F((B_{ij})) := \log(Z^B \text{cap}^B(\mathcal{X}, \mathcal{Y}))$$

satisfies a bounded difference inequality:

$$|F((B_{ij})) - F((B'_{ij}))| \leq \frac{\beta ab}{N} \quad \mathbb{P}\text{-a.s.},$$

when $B'_{ij} = B_{ij}$ for any $(i, j) \neq (k, \ell)$ and $B'_{k\ell}$ independent copy of $B_{k\ell}$.

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$$Z^B \text{cap}^B(\mathcal{X}, \mathcal{Y}) = \inf_f \frac{Z}{2} \sum_{\sigma, \eta \in \mathcal{S}_N} e^{-\beta(H^B(\sigma) \vee H^B(\eta))} (f(\sigma) - f(\eta))^2$$

Concentration inequality for the capacity

Consider two disjoint subsets $\mathcal{X}, \mathcal{Y} \subset \mathcal{S}_N$. Then, \mathbb{P} -a.s., for any $t \geq 0$,

$$\mathbb{P}_B \left[\left| \log(Z_{\text{cap}}(\mathcal{X}, \mathcal{Y})) - \mathbb{E}_B \left[\log(Z_{\text{cap}}(\mathcal{X}, \mathcal{Y})) \right] \right| > t \right] \leq 2 e^{-2t^2 \bar{c}},$$

where $\bar{c} = 1/(\beta a b)^2$.

Proof: the map

$$(B_{ij}) \longmapsto F((B_{ij})) := \log(Z^B \text{cap}^B(\mathcal{X}, \mathcal{Y}))$$

satisfies a bounded difference inequality:

$$|F((B_{ij})) - F((B'_{ij}))| \leq \frac{\beta a b}{N} \quad \mathbb{P}\text{-a.s.}$$

Obtain BDI via: Dirichlet principle, comparison of Dirichlet forms and

$$\max_{\sigma \in \mathcal{S}_N} |H^B(\sigma) - H^{B'}(\sigma)| \leq |A_{k\ell}| \frac{|B_{kl} - B'_{kl}|}{N} \leq \frac{a b}{N}$$

Annealed estimates for the capacity

Consider two disjoint subsets $\mathcal{X}, \mathcal{Y} \subset \mathcal{S}_N$. Then, \mathbb{P} -a.s.,

$$\left| \mathbb{E}_B [\log(Z_{\text{cap}}(\mathcal{X}, \mathcal{Y}))] - \log(\tilde{Z}_{\text{cap}}(\mathcal{X}, \mathcal{Y})) \right| = \alpha_N + O\left(\frac{1}{\sqrt{N}}\right)$$

Annealed estimates for the capacity

Consider two disjoint subsets $\mathcal{X}, \mathcal{Y} \subset \mathcal{S}_N$. Then, \mathbb{P} -a.s.,

$$\left| \mathbb{E}_B [\log(Z \text{cap}(\mathcal{X}, \mathcal{Y}))] - \log(\tilde{Z} \widetilde{\text{cap}}(\mathcal{X}, \mathcal{Y})) \right| = \alpha_N + O\left(\frac{1}{\sqrt{N}}\right)$$

Via comparison of the Dirichlet form for functions $\mathcal{E}_N(f)$ and the Dirichlet form for unit-flows $\mathcal{D}_N(\varphi)$

$$\begin{aligned} \mathbb{E}_B [Z_N \mathcal{E}_N(f)] &= \tilde{Z}_N \tilde{\mathcal{E}}_N(f) e^{\alpha_N} (1 + O(N^{-1/2})) & \forall f \in \mathcal{H}_{\mathcal{X}, \mathcal{Y}}, \\ \mathbb{E}_B [Z_N^{-1} \mathcal{D}_N(\varphi)] &= \tilde{Z}_N^{-1} \tilde{\mathcal{D}}_N(\varphi) e^{\alpha_N} (1 + O(N^{-1/2})) & \forall \varphi \in \mathcal{U}_{\mathcal{X}, \mathcal{Y}}. \end{aligned}$$

And via annealed estimates on $\Delta_N(\sigma) := H_N(\sigma) - \tilde{H}_N(\sigma)$, i.e. for any $\sigma \in \mathcal{S}_N$ and \mathbb{P} -a.s.,

$$\mathbb{E}_B \left[e^{\pm \beta \Delta_N(\sigma)} \right] = e^{\alpha_N} (1 + O(N^{-1})).$$