

# Transportation-information inequalities for continuum Gibbs measures

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# $L^p$ -Wasserstein distance

$(\mathcal{X}, \mathcal{B})$  a Polish space,  $d$  a lower semi-continuous metric on  $\mathcal{X} \times \mathcal{X}$ .

$\mathcal{M}_1(\mathcal{X})$  the space of all probability measures on  $\mathcal{X}$ .

$\mathcal{M}_1^p(\mathcal{X}, d) := \{\nu \in \mathcal{M}_1(\mathcal{X}); \int d^p(x, x_0) d\nu < +\infty\}$ , where  $x_0$  is some fixed point of  $\mathcal{X}$ .

Given  $p \geq 1$  and two probability measures  $\mu$  and  $\nu$  on  $\mathcal{X}$ , we define the quantity

$$W_{p,d}(\mu, \nu) = \inf \left( \iint d(x, y)^p d\pi(x, y) \right)^{1/p}.$$

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# Fisher-Donsker-Varadhan information

Given a Dirichlet form  $\mathcal{E}$  on  $L^2(\mu) := L^2(\mathcal{X}, \mu)$  with domain  $\mathcal{D}(\mathcal{E})$ , the Fisher-Donsker-Varadhan information of  $\nu$  with respect to  $\mu$  is given as:

$$I(\nu|\mu) = \begin{cases} \mathcal{E}(\sqrt{f}, \sqrt{f}) & \text{if } \nu = f\mu, \sqrt{f} \in \mathcal{D}(\mathcal{E}) \\ +\infty & \text{otherwise} \end{cases}$$

# Transportation-information inequality

$\alpha$  a nondecreasing left-continuous function on  $\mathbb{R}^+ = [0, +\infty)$  which vanishes at 0.

Probability measure  $\mu$  satisfies a transportation-information inequality  $W_1$  / if

$$\alpha(W_{1,d}(\nu, \mu)) \leq I(\nu|\mu), \quad \forall \nu \in M_1(\mathcal{X}),$$



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# GLWY's equivalence for $W_1 I$ -inequality

The following properties are equivalent:

- (a) The transportation-information inequality holds.
- (b) The following concentration inequality holds for each  $g \in b\mathcal{B}$  with  $\|g\|_{\text{Lip}(d)} \leq 1$  and any initial distribution  $\nu \ll \mu$ ,

$$\mathbb{P}_\nu \left( \frac{1}{t} \int_0^t g(X_s) ds > \mu(g) + r \right) \leq \left\| \frac{d\nu}{d\mu} \right\|_2 e^{-t\alpha(r)}, \quad \forall t, r > 0,$$

where  $\|\cdot\|_2$  is the norm of  $L^2(\mu)$ .

# Configuration space

$\Omega$  the space of all point measures  $\sum_i \delta_{x_i}$  (finite or countable) with  $x_i$  different in  $\mathbb{R}^d$ ;

$\mathcal{F}_A = \sigma\left(\omega(B) : B(\text{Borelian}) \subset A\right)$  for each  $A \in \mathcal{B}_b(\mathbb{R}^d)$

Borel  $\sigma$  field on  $\mathbb{R}^d$  is  $\mathcal{F} = \mathcal{F}_{\mathbb{R}^d}$

Given a bounded open subset  $\Lambda$  of  $\mathbb{R}^d$  and  $\omega \in \Omega$ ,

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# Poisson point measures

Give the activity  $z > 0$ , let  $P$  be the law of Poisson point process on  $\mathbb{R}^d$  with intensity measure  $zdx$ .

The image measure  $P_\Lambda$  of  $P$  by  $\omega \rightarrow \omega_\Lambda$  is the law of Poisson point process on  $\Lambda$  with intensity measure  $zdx$ .



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# The Gibbs measure

The Gibbs measure for a given boundary condition  $\eta \in \Omega$  on  $\Lambda^c$  is a probability given by

$$\mu_\Lambda^\eta(d\omega_\Lambda) := (Z_\Lambda^\eta)^{-1} \exp\{-\beta H_\Lambda^\eta(\omega_\Lambda)\} P_\Lambda(d\omega_\Lambda)$$

where  $Z_\Lambda^\eta$  is the normalization constant, and

$$H_\Lambda^\eta(\omega_\Lambda) := \frac{1}{2} \iint_{\Lambda^2} \phi(x-y) \omega_\Lambda(dx) \omega_\Lambda(dy) + \int_\Lambda \omega_\Lambda(dx) \int_{\Lambda^c} \phi(x-y) \eta(dy)$$

is the Hamiltonian.

# Difference operator

For a real  $\mathcal{F}$ -measurable function  $f$ , consider the difference operators

$$D_x^+ f(\omega) := f(\omega + \delta_x) - f(\omega), \quad \omega \in \Omega_\Lambda, x \in \Lambda;$$

$$D_x^- f(\omega) := f(\omega - \delta_x) - f(\omega), \quad \omega \in \Omega_\Lambda, x \in \text{supp } \omega.$$

# Generator and Dirichlet form

Generator:

$$\mathcal{L}_\Lambda^\eta f(\omega_\Lambda) = \int_\Lambda D_x^- f(\omega_\Lambda) \omega_\Lambda(dx) + z \int_\Lambda e^{-\beta D_x^+ H_\Lambda^\eta(\omega_\Lambda)} D_x^+ f(\omega_\Lambda) dx.$$

Dirichlet form:

$$\begin{aligned} \mathcal{E}_\Lambda^\eta(f, g) &:= \langle f, -\mathcal{L}_\Lambda^\eta g \rangle_{\mu_\Lambda^\eta} \\ &= \int_{\Omega_\Lambda} d\mu_\Lambda^\eta(\omega_\Lambda) \int_\Lambda D_x^- f(\omega_\Lambda) D_x^- g(\omega_\Lambda) \omega_\Lambda(dx) \\ &= \int_{\Omega_\Lambda} d\mu_\Lambda^\eta(\omega_\Lambda) \int_\Lambda e^{-\beta D_x^+ H_\Lambda^\eta(\omega_\Lambda)} D_x^+ f(\omega_\Lambda) D_x^+ g(\omega_\Lambda) z dx. \end{aligned}$$

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# $M/M/\infty$ queue system

Generator:  $\mathcal{L}f(n) = \lambda(f_{n+1} - f_n) + n(f_{n-1} - f_n)$

Invariant measure:  $\mu_n = e^{-\lambda} \lambda^n / n!$

Dirichlet form:  $\mathcal{E}(f, g) = \sum_{n=0}^{\infty} \lambda \mu_n (f_{n+1} - f_n)(g_{n+1} - g_n)$ .

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# Optimal $W_1 I$ -inequality for $M/M/\infty$

**Theorem.** Consider  $\rho$  the classical Euclidean distance on  $\mathbb{N}$ . Then

$$W_{1,\rho}(\nu, \mu) \leq I + 2\sqrt{\lambda I}, \quad \forall \nu \in \mathcal{M}_1(\mathbb{N}_+),$$

where  $I = I(\nu/\mu)$ .

The inequality is optimal since

- ▶ Gao, Guillin and Wu proved that  $\nu(g_0) - \mu(g_0) \leq 2\sqrt{\lambda I} + I$  for  $g_0(n) = n - \lambda$  is optimal (motivation).
- ▶ Take  $\nu$  a Poisson distribution with parameter  $a\lambda$ ,  $a > 1$ . Then  $W_{1,\rho}(\nu, \mu) = 2\sqrt{\lambda I} + I = \lambda(\sqrt{a} - 1)^2$ .

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# Some key points

- ▶ Lipschitzian spectral gap:  $\|(-\mathcal{L})^{-1}\|_{\text{Lip}(\rho)} = 1$
- ▶ Lyapunov test function: take  $V_n = \kappa^n$  ( $\kappa > 1$ ), s.t.

$$(1 + \delta)n + \left(1 + \frac{1}{\delta}\right)\lambda \leq -a \frac{\mathcal{L}V}{V}(n) + b$$

with  $a = (1 + \delta)\kappa/(\kappa - 1)$  and  $b = ((1 + \delta)\kappa + (1 + \frac{1}{\delta}))\lambda$   
 + for any function  $V \geq 1$ , if  $-\frac{\mathcal{L}V}{V}$  is lower bounded, then

$$\int -\frac{\mathcal{L}V}{V} d\nu \leq I(\nu|\mu), \quad \forall \nu.$$

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+ for any function  $V \geq 1$ , if  $-\frac{\mathcal{L}V}{V}$  is lower bounded, then

$$\int -\frac{\mathcal{L}V}{V} d\nu \leq I(\nu|\mu), \quad \forall \nu.$$

# Sketch of the Proof

Given any function  $g$  on  $\mathbb{N}$  with  $\mu(g) = 0$ ,  $\|g\|_{\text{Lip}(\rho)} = 1$ ,  $G$  satisfies  $-\mathcal{L}G = g$  with  $\mu(G) = 0$ . For any  $\delta > 0$ , we have

$$\begin{aligned}
 \nu(g) - \mu(g) &= \langle g, f \rangle_{\mu} = \mathcal{E}(G, f) = \sum_{n=0}^{\infty} \lambda \mu_n (G_{n+1} - G_n) (f_{n+1} - f_n) \\
 &\leq \sqrt{\sum_{n=0}^{\infty} \lambda \mu_n (\sqrt{f_{n+1}} - \sqrt{f_n})^2} \cdot \sqrt{\sum_{n=0}^{\infty} \lambda \mu_n (G_{n+1} - G_n)^2 (\sqrt{f_{n+1}} + \sqrt{f_n})^2} \\
 &\leq \sqrt{I \sum_{n=0}^{\infty} \lambda \mu_n \left( (1 + \delta) f_{n+1} + \left(1 + \frac{1}{\delta}\right) f_n \right)} = \sqrt{I \sum_{n=0}^{\infty} \mu_n f_n \left( (1 + \delta) n + \left(1 + \frac{1}{\delta}\right) \lambda \right)} \\
 &\leq \sqrt{I \sum_{n=0}^{\infty} \mu_n f_n \left( -a \frac{\mathcal{L}V}{V}(n) + b \right)} \leq \sqrt{I(aI + b)}.
 \end{aligned}$$

# Lipschitzian space

The metric  $d$  on  $\Omega_\Lambda$  : for any  $\omega, \omega' \in \Omega_\Lambda$ ,

$$d(\omega, \omega') = \|\omega - \omega'\|_{\text{TV}}.$$

Given any functional  $F \in r\mathcal{F}_\Lambda$ ,  $F$  is Lipschitzian with respect to  $d$  if

$$\|F\|_{\text{Lip}(d)} := \sup_{\omega \neq \omega'} \frac{|F(\omega) - F(\omega')|}{d(\omega, \omega')} < \infty$$

$$\Leftrightarrow \|F\|_{\text{Lip}(d)} = \sup_{x \in \Lambda, \omega_\Lambda \in \Omega_\Lambda} |D_x^+ F(\omega_\Lambda)| < \infty.$$



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Upper bound of  $\|(-\mathcal{L}_\Lambda^\eta)^{-1}\|_{\text{Lip}(d)}$ 

**Lemma.** Suppose that the Dobrushin's uniqueness condition holds, i.e.,

$$D = z \int_{\mathbb{R}^d} (1 - e^{-\beta\varphi(x)}) dx < 1.$$

We have

$$\|(-\mathcal{L}_\Lambda^\eta)^{-1}\|_{\text{Lip}(d)} \leq \frac{1}{1-D}.$$

# Lyapunov test function

**Lemma.** Take  $V(\omega_\Lambda) = \kappa^{N_\Lambda(\omega_\Lambda)}$ . Given any  $\delta > 0$ , then

$$(1 + \delta)N_\Lambda(\omega_\Lambda) + (1 + \frac{1}{\delta})z|\Lambda| \leq -a \frac{\mathcal{L}_\Lambda^\eta V(\omega_\Lambda)}{V(\omega_\Lambda)} + b, \quad \omega_\Lambda \in \Omega_\Lambda$$

where  $a = (1 + \delta) \frac{\kappa}{\kappa - 1}$ ,  $b = ((1 + \delta)\kappa + (1 + \frac{1}{\delta}))z|\Lambda|$ .

# $W_1 I$ -inequality for $\mu_\Lambda^\eta$

**Theorem.** Suppose that the Dobrushin uniqueness condition holds, i.e.

$$D = z \int_{\mathbb{R}^d} (1 - e^{-\beta\varphi(x)}) dx < 1.$$

The Gibbs measure  $\mu_\Lambda^\eta$  satisfies the transportation-information inequality  $W_1 I$

$$W_{1,d}(\nu, \mu_\Lambda^\eta) \leq \frac{1}{1-D} \left( I + 2\sqrt{z|\Lambda|I} \right),$$

where  $I = I(\nu/\mu_\Lambda^\eta)$ .

**Remark.** The transportation-information inequality for  $\mu_\Lambda^\eta$  is sharp. If  $\varphi = 0$ , then  $D = 0$  and  $N_\Lambda(X_t)$  is just the  $M/M/\infty$  queue system with  $\lambda = z|\Lambda|$ .

# The discrete spin system

$T$  a finite subset of  $\mathbb{Z}^d$

$\gamma : \mathbb{Z}^d \times \mathbb{Z}^d \rightarrow \mathbb{R}^+$  a nonnegative interaction function satisfying  $\gamma_{ij} = \gamma_{ji}$  and  $\gamma_{ii} = 0$  for all  $i, j \in \mathbb{Z}^d$ .

The Gibbs measure on  $\mathbb{N}^T$  with boundary condition  $(x_k)_{k \in T^c}$  is defined by

$$\mu_T(dx_T | x) = \frac{e^{-\frac{1}{2} \sum_{\{i,j\} \cap T \neq \emptyset} \gamma_{ij} x_i x_j}}{Z(x_{T^c})} \prod_{i \in T} \sigma_{\lambda_i}(dx_i)$$

where  $\{\sigma_{\lambda_i}(\cdot)\}_{i \in \mathbb{Z}^d}$  are the given Poisson measures on  $\mathbb{N}$  with means  $\{\lambda_i > 0\}_{i \in \mathbb{Z}^d}$ , and  $Z(x_{T^c})$  is the normalization factor.

When  $T = \{i\}$ ,  $\mu_T(dx_T | x)$  noted as  $\mu_i(dx_i | x)$ , is the Poisson distribution with parameter  $\lambda_i e^{-\sum_{j \neq i} \gamma_{ij} x_j}$ .

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$T$  a finite subset of  $\mathbb{Z}^d$

$\gamma : \mathbb{Z}^d \times \mathbb{Z}^d \rightarrow \mathbb{R}^+$  a nonnegative interaction function satisfying  $\gamma_{ij} = \gamma_{ji}$  and  $\gamma_{ii} = 0$  for all  $i, j \in \mathbb{Z}^d$ .

The Gibbs measure on  $\mathbb{N}^T$  with boundary condition  $(x_k)_{k \in T^c}$  is defined by

$$\mu_T(dx_T | x) = \frac{e^{-\frac{1}{2} \sum_{\{i,j\} \cap T \neq \emptyset} \gamma_{ij} x_i x_j}}{Z(x_{T^c})} \prod_{i \in T} \sigma_{\lambda_i}(dx_i)$$

where  $\{\sigma_{\lambda_i}(\cdot)\}_{i \in \mathbb{Z}^d}$  are the given Poisson measures on  $\mathbb{N}$  with means  $\{\lambda_i > 0\}_{i \in \mathbb{Z}^d}$ , and  $Z(x_{T^c})$  is the normalization factor.

When  $T = \{i\}$ ,  $\mu_T(dx_T | x)$  noted as  $\mu_i(dx_i | x)$ , is the Poisson distribution with parameter  $\lambda_i e^{-\sum_{j \neq i} \gamma_{ij} x_j}$ .

# Dobrushin interdependence matrix

$C := (c_{ij})_{i,j \in T}$  w.r.t.  $d_{\mathbb{N}}$  on  $\mathbb{N}$  is

$$c_{ij} = \sup_{x=x' \text{ off } j} \frac{W_{1,\rho} \left( \mu_i(dx_i|x), \mu_i(dx'_i|x') \right)}{|x_j - x'_j|} = \lambda_i(1 - e^{-\gamma_{ij}}).$$

Dobrushin's uniqueness condition

$$D := \sup_{j \in T} \sum_{i \in T} c_{ij} = \sup_{j \in T} \sum_{i \in T} \lambda_i(1 - e^{-\gamma_{ij}}) < 1.$$

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The Dirichlet form of  $\mathcal{E}_T$  is defined as

$$\mathcal{E}_T(g, g) := \int_{\mathbb{N}^T} \sum_{i \in T} \mathcal{E}_i(g_i, g_i) d\mu_T, \quad g \in \mathcal{D}(\mathcal{E}_T) \quad \text{with}$$

$$\mathcal{D}(\mathcal{E}_T) := \left\{ g \in L^2(\mu_T) : g_i \in \mathcal{D}(\mathcal{E}_i), \mu_T - \text{a.e. } \hat{x}_i, \int_{\mathbb{N}^T} \sum_{i \in T} \mathcal{E}_i(g_i, g_i) d\mu_T < +\infty \right\}$$

where  $g_i(x_i) := g(x_i, \hat{x}_i)$  with  $\hat{x}_i := x_{T \setminus \{i\}}$  fixed.

# Tensorization result for $W_1$

**Lemma.** Assume the Dobrushin's uniqueness condition

$$D = \sup_{j \in T} \sum_{i \in T} \lambda_i (1 - e^{-\gamma_{ij}}) < 1.$$

Then for all  $\nu_T \in \mathcal{M}_1^+(\mathbb{N}^T)$ ,

$$W_{1, d_{11}}(\nu_T, \mu_T) \leq \frac{1}{1-D} \mathbb{E}^{\nu_T} \sum_{i \in T} W_{1, \rho}(\nu_i, \mu_i)$$

where  $\nu_i$  is the conditional distribution of  $x_i$  knowing  $(x_j)_{j \neq i}$ .

# Additivity property of the Fisher information

Let  $\nu_T, \mu_T$  be probability measures on  $\mathbb{N}^T$  such that  $I_T(\nu_T | \mu_T) < +\infty$ , and let  $\mu_i, \nu_i$  be the conditional distributions of  $x_i$  knowing  $\hat{x}_i$  under  $\mu, \nu$  respectively. Then

$$I_T(\nu_T | \mu_T) = \mathbb{E}^{\nu_T} \sum_{i \in T} I_i(\nu_i | \mu_i)$$

where  $I_i(\nu_i | \mu_i)$  is the Fisher-Donsker-Varadhan information related to the Dirichlet form  $(\mathcal{E}_i, \mathcal{D}(\mathcal{E}_i))$ .

# $W_1 I$ -inequality for discrete spin system

**Theorem.** Assume the Dobrushin uniqueness condition

$$D = \sup_{j \in T} \sum_{i \in T} \lambda_i (1 - e^{-\gamma_{ij}}) < 1.$$

Then for any  $\nu_T \in \mathcal{M}_1^1(\mathbb{N}^T, d_{l_1})$ , it holds that

$$W_{1, d_{l_1}}(\nu_T, \mu_T) \leq \frac{1}{1-D} \left( 2 \sqrt{\sum_{i \in T} \lambda_i I} + I \right)$$

where  $I = I_T(\nu_T | \mu_T)$ .



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*Thank you for your attention*