

On optimal matching of random samples

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optimal matching: minimal transportation cost
between two sets of (random) points

$X_1, \dots, X_n, Y_1, \dots, Y_n$ two samples of points in \mathbb{R}^d

$$\min_{\sigma} \frac{1}{n} \sum_{i=1}^n c(X_i, Y_{\sigma(i)})$$

σ permutation of $\{1, \dots, n\}$

$c(\cdot, \cdot) \geq 0$ cost function

$$c(x, y) = |x - y|^p, \quad 1 \leq p < \infty$$

$X_1, \dots, X_n, Y_1, \dots, Y_n$ iid random points in \mathbb{R}^d

order of growth in n of

$$\mathbb{E} \left(\min_{\sigma} \frac{1}{n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^p \right)$$

dependence

- ▶ dimension d
- ▶ $1 \leq p < \infty$ (mostly $p = 1$ and $p = 2$)
- ▶ common distribution of X_i, Y_i

$X_1, \dots, X_n, Y_1, \dots, Y_n$ iid random points in \mathbb{R}^d

order of growth in n of

$$\mathbb{E} \left(\min_{\sigma} \frac{1}{n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^p \right)$$

X_i, Y_i uniform on $[0, 1]^d$

typical distance between n uniform points in $[0, 1]^d \asymp \frac{1}{n^{1/d}}$

expected: $\mathbb{E} \left(\min_{\sigma} \frac{1}{n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^p \right) \asymp \frac{1}{n^{p/d}}$

only true when $d \geq 3$

Ajtai-Komlós-Tusnády (1984)

$X_1, \dots, X_n, Y_1, \dots, Y_n$ independent, uniform on $[0, 1]^2$

$$\mathbb{E} \left(\min_{\sigma} \frac{1}{n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^p \right) \asymp \left(\frac{\log n}{n} \right)^{p/2}$$

$$1 \leq p < \infty$$

$$A \asymp B \iff \frac{1}{C} B \leq A \leq C B \quad (C \text{ independent of } n)$$

(hungarian) combinatorics on dyadic partitions

Ajtai-Komlós-Tusnády (1984)

$X_1, \dots, X_n, Y_1, \dots, Y_n$ independent, uniform on $[0, 1]^2$

$$\mathbb{E} \left(\min_{\sigma} \frac{1}{n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^p \right) \asymp \left(\frac{\log n}{n} \right)^{p/2}$$

$$1 \leq p < \infty$$

alternate generic chaining ideas

Shor, Leighton (1989-91), Talagrand (1992-94)

$X_1, \dots, X_n, Y_1, \dots, Y_n$ iid random points in \mathbb{R}^d

order of growth in n of

$$\mathbb{E} \left(\min_{\sigma} \frac{1}{n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^p \right)$$

dependence

- ▶ dimension d
- ▶ $1 \leq p < \infty$ (mostly $p = 1$ and $p = 2$)
- ▶ common distribution of X_i, Y_i

$$c(x, y) = |x - y|^p, \quad 1 \leq p < \infty$$

$$\mu_n = \frac{1}{n} \sum_{i=1}^n \delta_{X_i}, \quad \nu_n = \frac{1}{n} \sum_{i=1}^n \delta_{Y_i}$$

$$\min_{\sigma} \frac{1}{n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^p = W_p^p(\mu_n, \nu_n)$$

Monge-Kantorovich metric

$$W_p^p(\mu, \nu) = \inf_{\pi} \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} |x - y|^p d\pi(x, y)$$

π with respective marginals μ and ν

what is the cost of optimal matching

$$\mathbb{E}(W_p^p(\mu_n, \nu_n))$$

between two independent samples $X_1, \dots, X_n, Y_1, \dots, Y_n$?

statistics: if the samples are iid with common law μ

what is the speed of convergence of

$$\mathbb{E}(W_p^p(\mu_n, \mu))?$$

$$\mu_n = \frac{1}{n} \sum_{i=1}^n \delta_{X_i}$$

$$X_1, \dots, X_n \text{ iid in } \mathbb{R}^d \text{ with law } \mu, \quad \mu_n = \frac{1}{n} \sum_{i=1}^n \delta_{X_i}$$

first order study of

$$\mathbb{E}(W_p^p(\mu_n, \mu)) \quad \text{or} \quad \mathbb{E}(W_p(\mu_n, \mu))$$

- ▶ dimension d
- ▶ mostly $p = 1$ and $p = 2$ $(W_1 \leq \sqrt{W_2^2})$
- ▶ distribution μ

standard rates: comparison with the known uniform example

specific representations of Monge-Kantorovich metrics

$$W_1(\nu, \mu) = \int_{-\infty}^{+\infty} |G(x) - F(x)| dx$$

G, F distribution functions of ν, μ on \mathbb{R}

quantile representation for $W_p(\nu, \mu)$, $p \geq 1$

$$W_p^p(\nu, \mu) = \int_0^1 |G^{-1}(t) - F^{-1}(t)|^p dt$$

(order statistics)

μ on \mathbb{R} with distribution function F

$$\mathbb{E}(W_1(\mu_n, \mu)) \asymp \frac{1}{\sqrt{n}}$$

if and only if

$$\int_{-\infty}^{+\infty} \sqrt{F(x)(1-F(x))} dx < \infty$$

(for example $\int_{\mathbb{R}} |x|^q d\mu < \infty$, $q > 2$)

$$\mu_n = \frac{1}{n} \sum_{i=1}^n \delta_{X_i}, \quad \nu_n = \frac{1}{n} \sum_{i=1}^n \delta_{Y_i}$$

$$W_p^p(\mu_n, \nu_n) = \min_{\sigma} \frac{1}{n} \sum_{i=1}^n |X_i - Y_{\sigma(i)}|^p = \frac{1}{n} \sum_{i=1}^n |X_i^* - Y_i^*|^p$$

order statistics $X_1^* \leq \dots \leq X_n^*, \quad Y_1^* \leq \dots \leq Y_n^*$

$$\mathbb{E}(W_p^p(\mu_n, \mu)) \asymp \frac{1}{n} \sum_{i=1}^n \mathbb{E}(|X_i^* - \mathbb{E}(X_i^*)|^p)$$

$$1 \leq p < \infty$$

$$\mathbb{E}(W_p^p(\mu_n, \mu)) \asymp \frac{1}{n} \sum_{i=1}^n \mathbb{E}(|X_i^* - \mathbb{E}(X_i^*)|^p)$$

μ uniform on $[0, 1]$

X_i^* beta $(i, n - i + 1)$

$$\mathbb{E}(W_p^p(\mu_n, \mu)) \asymp \frac{1}{n^{p/2}}$$

$$1 \leq p < \infty$$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) = \frac{6}{n}$$

bipartite $\mathbb{E}(W_2^2(\mu_n, \nu_n)) = \frac{1}{3(n+1)}$

$$n W_2^2(\mu_n, \mu) \rightarrow \chi = \int_0^1 B^2(t) dt \quad \text{in distribution}$$

B Brownian bridge on $[0, 1]$

$$\mathbb{E}(\chi) = \frac{1}{6}, \quad \text{Var}(\chi) = \frac{1}{45}$$

μ on \mathbb{R} with distribution function F , density f

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{1}{n}$$

if and only if

$$\int_{-\infty}^{+\infty} \frac{F(x)(1 - F(x))}{f(x)} dx < \infty$$

μ on \mathbb{R} with distribution function F

$$\mathbb{E}(W_1(\mu_n, \mu)) \asymp \frac{1}{\sqrt{n}}$$

if and only if

$$\int_{-\infty}^{+\infty} \sqrt{F(x)(1-F(x))} dx < \infty$$

(for example $\int_{\mathbb{R}} |x|^q d\mu < \infty$, $q > 2$)

μ on \mathbb{R} with distribution function F , density f

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{1}{n}$$

if and only if

$$\int_{-\infty}^{+\infty} \frac{F(x)(1-F(x))}{f(x)} dx < \infty$$

$$\int_{-\infty}^{+\infty} \frac{F(x)(1-F(x))}{f(x)} dx = \int_0^1 \frac{t(1-t)}{I(t)^2} dt$$

$$I(t) = f \circ F^{-1}(t) \quad (\text{isoperimetric profile})$$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{1}{n}$$

if and only if

$$\int_0^1 \frac{t(1-t)}{I(t)^2} dt < \infty$$

μ log-concave ($d\mu = e^{-v}dx$, v convex)

accurate two-sided bounds

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{1}{n} \int_{1/(n+1)}^{n/(n+1)} \frac{t(1-t)}{I(t)^2} dt$$

order statistics $X_1^* \leq \dots \leq X_n^*$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{1}{n} \sum_{i=1}^n \text{Var}(X_i^*)$$

density of distribution of X_i^*

$$f_i(x) = n \binom{n-1}{i-1} F(x)^{i-1} (1-F(x))^{n-i} f(x), \quad x \in \mathbb{R}$$

log-concave

$$\text{Var}(X_i^*) \asymp \frac{1}{\sup_{x \in \mathbb{R}} f_i(x)^2} \asymp \frac{1}{n} \frac{t(1-t)}{I(t)^2}, \quad t = \frac{i}{n}$$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{1}{n} \int_{1/(n+1)}^{n/(n+1)} \frac{t(1-t)}{I(t)^2} dt$$

- μ standard normal, $I(t) \asymp t\sqrt{\log \frac{1}{t}}$, $t \rightarrow 0$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{\log \log n}{n}$$

- μ exponential, $I(t) \asymp t$, $t \rightarrow 0$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{\log n}{n}$$

general 1-d investigation **Bobkov-L (2016)**

μ uniform on $[0, 1]$

$$\mathbb{E}(W_p^p(\mu_n, \mu)) \asymp \frac{1}{n^{p/2}} \quad 1 \leq p < \infty$$

μ standard normal on \mathbb{R}

$$\mathbb{E}(W_p^p(\mu_n, \mu)) \asymp \begin{cases} \frac{1}{n^{p/2}} & \text{if } 1 \leq p < 2 \\ \frac{\log \log n}{n} & \text{if } p = 2 \\ \frac{1}{n(\log n)^{p/2}} & \text{if } p > 2 \end{cases}$$

W_2 more sensitive to distribution than W_1

μ uniform on $[0, 1]^d$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{1}{n} \quad d = 1$$

AKT $\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{\log n}{n} \quad d = 2$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{1}{n^{2/d}} \quad d \geq 3$$

(of the order of the uniform spacings $\frac{1}{n^{1/d}}$)

Dereich-Scheutzow-Schottstedt (2013)

Fournier-Guillin (2015)

general μ , enough moments

$$\mathbb{E}(W_2^2(\mu_n, \mu)) = O\left(\frac{1}{n^{2/d}}\right) \quad d \geq 4 \quad (d = 3?)$$

dyadic partitions (local irregularities)

also results for W_p

general bounds

μ enough moments

$$\mathbb{E}(W_2^2(\mu_n, \mu)) = O\left(\frac{1}{\sqrt{n}}\right)$$

Ajtai-Komlós-Tusnády theorem

μ uniform on $[0, 1]^2$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{\log n}{n}$$

μ enough moments $(\int_{\mathbb{R}^2} |x|^q d\mu < \infty, \quad q > 1)$

$$\mathbb{E}(W_1(\mu_n, \mu)) = O\left(\sqrt{\frac{\log n}{n}}\right)$$

generic chaining methodology Talagrand (1992), Yukich (1992)

Ajtai-Komlós-Tusnády theorem

μ uniform on $[0, 1]^2$

$$\mathbb{E}(W_1(\mu_n, \mu)) \asymp \sqrt{\frac{\log n}{n}}$$

some (unknown) limits may exist

$$\lim_{n \rightarrow \infty} n^{1/d} \mathbb{E}(W_1(\mu_n, \mu)) = \gamma_d \quad d \geq 3$$

$$\lim_{n \rightarrow \infty} n^{2/d} \mathbb{E}(W_2^2(\mu_n, \mu)) = \tau_d \quad d \geq 5$$

modified subadditivity arguments

Dobric-Yukich (1995), Boutet de Monvel-Martin (2002) W_1

Barthe-Bordenave (2013),

Dereich-Scheutzw-Schottstedt (2013) $W_p, \quad p < \frac{d}{2}$

(absolutely continuous distributions)

Ajtai-Komlós-Tusnády (1984)

 μ uniform on $[0, 1]^2$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{\log n}{n}$$

$$A \asymp B \iff \frac{1}{C} B \leq A \leq C B \quad (C \text{ independent of } n)$$

Ambrosio-Stra-Trevisan (2016)

 μ uniform on $[0, 1]^2$

$$\lim_{n \rightarrow \infty} \frac{n}{\log n} \mathbb{E}(W_2^2(\mu_n, \mu)) = \frac{1}{4\pi}$$

bipartite

$$\lim_{n \rightarrow \infty} \frac{n}{\log n} \mathbb{E}(W_2^2(\mu_n, \nu_n)) = \frac{1}{2\pi}$$

Ambrosio-Stra-Trevisan (2016)

(M, g) compact Riemannian manifold, dimension 2

μ (normalized) Riemannian volume element

$$\lim_{n \rightarrow \infty} \frac{n}{\log n} \mathbb{E}(W_2^2(\mu_n, \mu)) = \frac{\text{vol}(M)}{4\pi}$$

2-sphere/torus [Holden-Peres-Zhai \(2017\)](#) gravitational allocation

bipartite [Ambrosio-Glaudo \(2018\)](#)

pde ansatz by Caracciolo, Lucibello, Parisi, Sicuro (2014)

$$T = \nabla\psi : \rho_0 \mapsto \rho_1$$

Monge-Ampère equation

$$\rho_1(\nabla\psi) \det \nabla^2\psi = \rho_0$$

linearization as $\rho_i \sim 1$, $\psi \sim \frac{1}{2}|x|^2 + f$

Poisson equation

$$-\Delta f = \rho_1 - \rho_0$$

W_2 approximated by H^{-1} Sobolev norm

upper bound

$$\mathbb{E}(W_2^2(\mu_n, \mu)) = \mathbb{E}\left(\inf_{\pi} \int_M \int_M \rho(x, y)^2 d\pi(x, y)\right) = O\left(\frac{\log n}{n}\right)$$

- regularization
- energy estimate

(Sobolev-type inequality, heat kernel estimates)

(M, g) compact Riemannian manifold, dimension d

(weighted manifold, RCD space, Markov triple)

$p_t(x, y)$, $t > 0$, $x, y \in M$ heat kernel $(t = t(n) \rightarrow 0)$

$$\mu_n = \frac{1}{n} \sum_{i=1}^n \delta_{X_i} \rightarrow d\mu_n^t = \frac{1}{n} \sum_{i=1}^n p_t(X_i, \cdot) d\mu$$

standard convexity of W_2

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \leq D_t + \mathbb{E}(W_2^2(\mu_n^t, \mu))$$

dispersion contribution

$$D_t = \int_M \int_M \rho(x, y)^2 p_t(x, y) d\mu(x) d\mu(y), \quad t > 0$$

$$\mathbb{E}(W_2^2(\mu_n^t, \mu))$$

density $d\mu_n^t = \frac{1}{n} \sum_{i=1}^n p_t(X_i, \cdot) d\mu$

$$f = f(y) = \frac{1}{n} \sum_{i=1}^n p_t(X_i, y)$$

f random densities

law of large numbers, $\int_M p_t(\cdot, y) d\mu = 1$

$$f \approx 1$$

$$\mathbb{E}(W_2^2(\mu_n^t, \mu))$$

density $d\mu_n^t = \frac{1}{n} \sum_{i=1}^n p_t(X_i, \cdot) d\mu$

central limit theorem heuristics

$$f = f(y) = \frac{1}{n} \sum_{i=1}^n p_t(X_i, y) \sim 1 + \frac{1}{\sqrt{n}} G(y)$$

$$G = G(t, y), \quad t > 0, y \in M$$

Gaussian Free Field

infinitesimals

$$f = 1 + \varepsilon g, \quad \int_M g \, d\mu = 0$$

$$\lim_{\varepsilon \rightarrow 0} \frac{1}{\varepsilon^2} W_2^2(f\mu, \mu) = \int_M |\nabla((-\Delta)^{-1}g)|^2 \, d\mu$$

$$d\nu = f \, d\mu$$

$$W_2^2(\nu, \mu) \leq 4 \|f - 1\|_{H^{-1}(\mu)}^2$$

dual Sobolev norm $\int_M g \, d\mu = 0$

$$\|g\|_{H^{-1}(\mu)} = \left(\int_M |\nabla((-\Delta)^{-1}g)|^2 \, d\mu \right)^{1/2}$$

$$d\nu = f d\mu$$

$$W_2^2(\nu, \mu) \leq 4 \|f - 1\|_{H^{-1}(\mu)}^2$$

$$\frac{1}{2} W_2(\nu, \mu)^2 = \sup \left(\int_M Q_1 \varphi d\nu - \int_M \varphi d\mu \right)$$

$\varphi : M \rightarrow \mathbb{R}$ bounded continuous

$$Q_u \varphi(x) = \inf_{y \in M} \left[\varphi(y) + \frac{d(x, y)^2}{2u} \right], \quad x \in M, u > 0$$

Hamilton-Jacobi $\frac{d}{du} Q_u \varphi = -\frac{1}{2} |\nabla Q_u \varphi|^2$

$$\frac{1}{2} W_2(\nu, \mu)^2 = \sup \left(\int_M Q_1 \varphi d\nu - \int_M \varphi d\mu \right)$$

$$\theta : [0, 1] \rightarrow [0, 1] \text{ increasing, } g = f - 1$$

$$\begin{aligned} & \int_M Q_1 \varphi d\nu - \int_M \varphi d\mu \\ &= \int_0^1 \frac{d}{du} \int_M (1 + \theta(u)g) Q_u \varphi d\mu du \\ &= \int_0^1 \int_M \left[\theta'(u)g Q_u \varphi - (1 + \theta(u)g) \frac{1}{2} |\nabla Q_u \varphi|^2 \right] d\mu du \\ &= \int_0^1 \int_M \left[-\theta'(u) \nabla((-\Delta)^{-1}g) \cdot \nabla Q_u \varphi - (1 + \theta(u)g) \frac{1}{2} |\nabla Q_u \varphi|^2 \right] d\mu du \\ &\leq \int_0^1 \int_M \frac{1}{2} \frac{\theta'(u)^2}{1 + \theta(u)g} |\nabla((-\Delta)^{-1}g)|^2 d\mu du \end{aligned}$$

infinitesimals

$$f = 1 + \varepsilon g, \quad \int_M g \, d\mu = 0$$

$$\lim_{\varepsilon \rightarrow 0} \frac{1}{\varepsilon^2} W_2^2(f\mu, \mu) = \int_M |\nabla((-\Delta)^{-1}g)|^2 \, d\mu$$

$$d\nu = f \, d\mu$$

$$W_2^2(\nu, \mu) \leq 4 \|f - 1\|_{H^{-1}(\mu)}^2$$

dual Sobolev norm $\int_M g \, d\mu = 0$

$$\|g\|_{H^{-1}(\mu)} = \left(\int_M |\nabla((-\Delta)^{-1}g)|^2 \, d\mu \right)^{1/2}$$

$$\|g\|_{H^{-1}(\mu)}^2 = \int_M |\nabla((-\Delta)^{-1}g)|^2 d\mu = \int_M g(-\Delta)^{-1}g d\mu$$

trace formula

$$(-\Delta)^{-1} = \int_0^\infty P_s ds$$

$$\int_M g(-\Delta)^{-1}g d\mu = 2 \int_0^\infty \int_M (P_s g)^2 d\mu ds$$

$$d\nu = f d\mu, \quad g = f - 1$$

$$W_2^2(\nu, \mu) \leq 4 \|f - 1\|_{H^{-1}(\mu)}^2 = 8 \int_0^\infty \int_M (P_s g)^2 d\mu ds$$

$$W_2^2(\nu, \mu) \leq 8 \int_0^\infty \int_M (P_s g)^2 d\mu ds$$

density $d\nu = f d\mu$

$$g = g(y) = f(y) - 1 = \frac{1}{n} \sum_{i=1}^n [p_t(X_i, y) - 1]$$

$$P_s g = \frac{1}{n} \sum_{i=1}^n [p_{t+s}(X_i, y) - 1]$$

average of the sample (CLT heuristics)

$$\mathbb{E}((P_s g)^2) = \frac{1}{n} \mathbb{E}([p_{t+s}(X_1, y) - 1]^2) = \frac{1}{n} [p_{2(t+s)}(y, y) - 1]$$

$$\mathbb{E}(W_2^2(\mu_n^t, \mu)) \leq \frac{4}{n} \int_{2t}^\infty \int_M [p_s(y, y) - 1] d\mu(y) ds$$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \leq D_t + \mathbb{E}(W_2^2(\mu_n^t, \mu)), \quad t > 0$$

dispersion

$$D_t = \int_M \int_M \rho(x, y)^2 p_t(x, y) d\mu(x) d\mu(y)$$

energy (trace) estimate

$$\mathbb{E}(W_2^2(\mu_n^t, \mu)) \leq \frac{4}{n} \int_{2t}^{\infty} \int_M [p_s(y, y) - 1] d\mu(y) ds$$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \leq D_t + \frac{4}{n} \int_{2t}^{\infty} \int_M [p_s(y, y) - 1] d\mu(y) ds$$

(M, g) compact Riemannian manifold, dimension d

$$D_t = \int_M \int_M \rho(x, y)^2 p_t(x, y) d\mu(x) d\mu(y) \leq Ct$$

heat kernel bounds $p_s(y, y) \leq \frac{C}{s^{d/2}} \quad 0 < s \leq 1$

optimization $t \sim \frac{1}{n^{2/d}} \left(\frac{\log n}{n} \text{ if } d = 2 \right)$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) = \begin{cases} O\left(\frac{1}{n}\right) & \text{if } d = 1 \\ O\left(\frac{\log n}{n}\right) & \text{if } d = 2 \\ O\left(\frac{1}{n^{2/d}}\right) & \text{if } d \geq 3 \end{cases}$$

heat kernel bounds

$$p_s(y, y) \leq \frac{C}{s^{d/2}} \quad 0 < s \leq 1$$

reflect the dimensional rates

similar (optimal) conclusions for $\mathbb{E}(W_p^p(\mu_n, \mu))$

μ uniform on $[0, 1]^d$

$$\mathbb{E}(W_p^p(\mu_n, \mu)) \asymp \begin{cases} \frac{1}{n^{p/2}} & \text{if } d = 1 \\ \left(\frac{\log n}{n}\right)^{p/2} & \text{if } d = 2 \\ \frac{1}{n^{p/d}} & \text{if } d \geq 3 \end{cases}$$

$$1 \leq p < \infty$$

Ambrosio-Stra-Trevisan (2016)

(M, g) compact Riemannian manifold, dimension 2

μ Riemannian volume element ($\text{vol}(M) = 1$)

$$\lim_{n \rightarrow \infty} \frac{n}{\log n} \mathbb{E}(W_2^2(\mu_n, \mu)) = \frac{1}{4\pi}$$

more precise arguments

common heat kernel asymptotics

$$\lim_{s \rightarrow 0} 4\pi s \int_M p_s(x, x) d\mu = 1$$

Ambrosio-Stra-Trevisan (2016)

(M, g) compact Riemannian manifold, dimension 2

μ Riemannian volume element ($\text{vol}(M) = 1$)

$$\lim_{n \rightarrow \infty} \frac{n}{\log n} \mathbb{E}(W_2^2(\mu_n, \mu)) = \frac{1}{4\pi}$$

only for $p = 2, d = 2$

pde ansatz by [Caracciolo, Lucibello, Parisi, Sicuro \(2014\)](#)

$$\lim_{n \rightarrow \infty} \left(\frac{n}{\log n} \mathbb{E}(W_2^2(\mu_n, \mu)) - \frac{1}{4\pi} \right) \log n = \xi \in \mathbb{R}$$

finer estimates [Ambrosio, Glaudo \(2018\)](#)

$$\liminf_{n \rightarrow \infty} \left(\frac{n}{\log n} \mathbb{E}(W_2^2(\mu_n, \mu)) - \frac{1}{4\pi} \right) \frac{\log n}{\log \log n} > -\infty$$

$$\limsup_{n \rightarrow \infty} \left(\frac{n}{\log n} \mathbb{E}(W_2^2(\mu_n, \mu)) - \frac{1}{4\pi} \right) \left(\frac{\log n}{\log \log n} \right)^{1/2} < \infty$$

concentration arguments

$$\frac{n}{\log n} W_2^2(\mu_n, \mu) \rightarrow \frac{1}{4\pi} \quad \text{in probability}$$

further conjecture

$$n \left[W_2^2(\mu_n, \mu) - \mathbb{E}(W_2^2(\mu_n, \mu)) \right] \rightarrow \chi \quad \text{in distribution}$$

χ (recentered) chi-square type distribution (L^2 -norm of GFF)

$$n W_2^2(\mu_n, \mu) - \frac{1}{4\pi} \log n \rightarrow \xi + \chi$$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) = \frac{6}{n}$$

bipartite $\mathbb{E}(W_2^2(\mu_n, \nu_n)) = \frac{1}{3(n+1)}$

$$n W_2^2(\mu_n, \mu) \rightarrow \chi = \int_0^1 B^2(t) dt \quad \text{in distribution}$$

B Brownian bridge on $[0, 1]$

$$\mathbb{E}(\chi) = \frac{1}{6}, \quad \text{Var}(\chi) = \frac{1}{45}$$

X_1, \dots, X_n independent

with standard Gaussian law μ in \mathbb{R}^2

order of

$$\mathbb{E}(W_2^2(\mu_n, \mu)) ?$$

μ uniform on $[0, 1]$

$$\mathbb{E}(W_p^p(\mu_n, \mu)) \asymp \frac{1}{n^{p/2}} \quad 1 \leq p < \infty$$

μ standard normal on \mathbb{R}

$$\mathbb{E}(W_p^p(\mu_n, \mu)) \asymp \begin{cases} \frac{1}{n^{p/2}} & \text{if } 1 \leq p < 2 \\ \frac{\log \log n}{n} & \text{if } p = 2 \\ \frac{1}{n(\log n)^{p/2}} & \text{if } p > 2 \end{cases}$$

W_2 more sensitive to distribution than W_1

μ standard Gaussian on \mathbb{R}^d

pde-transportation approach

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \leq D_t + \frac{4}{n} \int_{2t}^{\infty} \int_{\mathbb{R}^d} [p_s(y, y) - 1] d\mu(y) ds$$

$p_s(x, y), \quad s > 0, \quad x, y \in \mathbb{R}^d$ Mehler kernel

$$p_s(x, y) = \frac{1}{(1 - e^{-2s})^{d/2}} \exp \left(- \frac{e^{-2s}}{1 - e^{-2s}} [|x|^2 + |y|^2 - 2e^s x \cdot y] \right)$$

no uniform bounds

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \leq D_t + \frac{4}{n} \int_{2t}^{\infty} \int_{\mathbb{R}^d} [p_s(y, y) - 1] d\mu(y) ds$$

$$D_t = \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} |x - y|^2 p_t(x, y) d\mu(x) d\mu(y) \leq 2dt$$

$$\int_{\mathbb{R}^d} p_s(y, y) d\mu(y) = \frac{1}{(1 - e^{-s})^d} \sim \frac{1}{s^d}$$

optimization in t

$$\mathbb{E}(W_2^2(\mu_n, \mu)) = O\left(\frac{1}{n^{1/d}}\right) \quad \text{if } d \geq 2$$

μ^R normalized restriction of μ to the ball $B = B(0, R)$, $R \sim \sqrt{\log n}$

Z_1, \dots, Z_n independent with law μ^R

$$X_i^R = \begin{cases} X_i & \text{if } |X_i| \leq R \\ Z_i & \text{if } |X_i| > R \end{cases}$$

$$\mathbb{E}(W_2^2(\mu_n, \mu_n^R)) = O\left(\frac{1}{n}\right), \quad \mu_n^R = \frac{1}{n} \sum_{i=1}^n \delta_{X_i^R}$$

$$\int_{\mathbb{R}^d} p_s(y, y) d\mu^R(y) = \frac{1}{(1 - e^{-s})^{d/2}} \frac{\mu(\theta B)}{\theta^d}$$

$$\theta \sim s^{1/2} \quad \text{as } s \rightarrow 0$$

$$\frac{\mu(\theta B)}{\theta^d} \sim \lambda(B) \sim R^d \quad \text{as } \theta R \leq 1$$

μ standard Gaussian on \mathbb{R}^d

$$\mathbb{E}(W_2^2(\mu_n, \mu)) = \begin{cases} O\left(\frac{\log \log n}{n}\right) & \text{if } d = 1 \\ O\left(\frac{(\log n)^2}{n}\right) & \text{if } d = 2 \\ O\left(\frac{\log n}{n^{2/d}}\right) & \text{if } d \geq 3 \end{cases}$$

good enough to cover $d = 1$

extra factor $R^2 = \log n$ for $d \geq 2$

λ uniform on $[0, 1]^2$

U_1, \dots, U_n independent with law λ , $\nu_n = \frac{1}{n} \sum_{i=1}^n \delta_{U_i}$

$$\lambda = \Phi^{\otimes 2}(\mu)$$

$$\Phi(x) = \int_{-\infty}^x e^{-u^2/2} \frac{du}{\sqrt{2\pi}}, \quad x \in \mathbb{R}, \quad \|\Phi\|_{\text{Lip}} \leq 1$$

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \geq \mathbb{E}(W_2^2(\nu_n, \lambda))$$

$$\text{AKT} \quad \mathbb{E}(W_2^2(\nu_n, \lambda)) \asymp \frac{\log n}{n}$$

μ standard Gaussian on \mathbb{R}^2

$$\frac{1}{C} \frac{\log n}{n} \leq \mathbb{E}(W_2^2(\mu_n, \mu)) \leq C \frac{(\log n)^2}{n}$$

some support for the left-hand side

$$\mathbb{E}(W_2^2(\mu_n, \mu)) = O\left(\frac{\log n}{n^{2/d}}\right) \quad d \geq 3$$

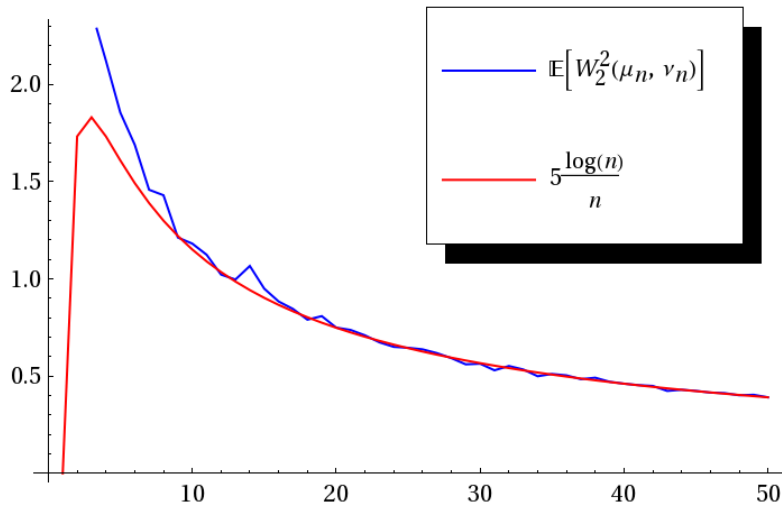
general moment bounds

$$\mathbb{E}(W_2^2(\mu_n, \mu)) = O\left(\frac{1}{n^{2/d}}\right) \quad d \geq 4$$

same pde-transportation methodology

$$\mathbb{E}(W_p^p(\mu_n, \mu)) \asymp \left(\frac{\log n}{n}\right)^{p/2} \quad d = 2, \quad 1 \leq p < 2$$

(same as for uniform)



μ standard Gaussian on \mathbb{R}^2

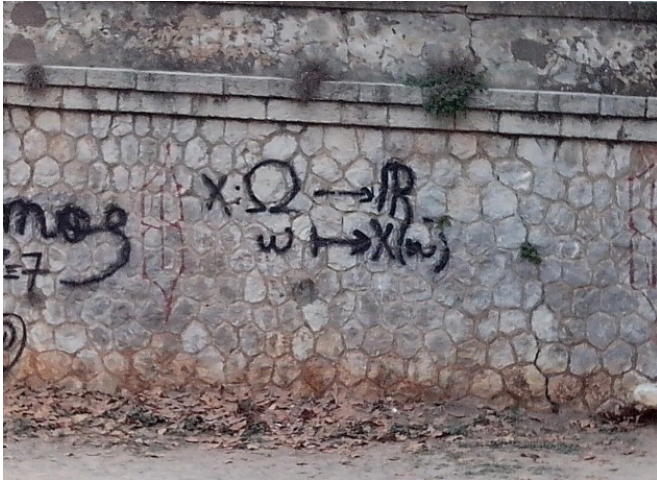
$$\frac{1}{C} \frac{\log n}{n} \leq \mathbb{E}(W_2^2(\mu_n, \mu)) \leq C \frac{(\log n)^2}{n}$$

M. Talagrand (2018)

$$\mathbb{E}(W_2^2(\mu_n, \mu)) \asymp \frac{(\log n)^2}{n}$$

AKT method + scaling argument

(also by the pde approach – limit?)



Thank you for your attention

Vershik (2013) wrote a historic essay explaining why it is more fair to fix the name “Kantorovich distance” for all metrics like W_p (calling them Kantorovich power metrics).

Some general topological properties of W_1 were studied in 1970 by Dobrushin, who re-introduced this metric with reference to [Vasershtein 1969]; apparently, that is why the name “Wasserstein distance” has become rather traditional.

As Vershik writes, “Leonid Vasershtein is a famous mathematician specializing in algebraic K -theory and other areas of algebra and analysis, and ... he is absolutely not guilty of this distortion of terminology, which occurs primarily in Western literature”.