

A Fourier-analytic approach to transport inequalities

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Definitions

Definition. Let μ and ν be probability measures on a separable metric space (M, ρ) . The Kantorovich transport distance:

$$W(\mu, \nu) = \inf_{\lambda} \int \int \rho(x, y) d\lambda(x, y),$$

where the inf is over all λ on $M \times M$ with marginals μ and ν .

Discrete measures with atoms x_1, \dots, x_n and y_1, \dots, y_n :

$$\mu_n = \frac{1}{n} (\delta_{x_1} + \dots + \delta_{x_n}), \quad \nu_n = \frac{1}{n} (\delta_{y_1} + \dots + \delta_{y_n}),$$

2

$$W(\mu_n, \nu_n) = \frac{1}{n} \inf_{\sigma \in S_n} \sum_{k=1}^n \rho(x_k, y_{\sigma(k)}).$$

The case $M = \mathbb{R}$ with $\rho(x, y) = |x - y|$. Arranging $x_1^* \leq \dots \leq x_n^*$, $y_1^* \leq \dots \leq y_n^*$, one has

$$W(\mu_n, \nu_n) = \frac{1}{n} \sum_{k=1}^n |x_k^* - y_k^*|.$$

Random samples and empirical measures

Given i.i.d. X_1, \dots, X_n and Y_1, \dots, Y_n (independent samples) distributed according to the law μ on M , let

$$\mu_n = \frac{1}{n} (\delta_{X_1} + \dots + \delta_{X_n}), \quad \nu_n = \frac{1}{n} (\delta_{Y_1} + \dots + \delta_{Y_n}),$$

so that

$$W(\mu_n, \nu_n) = \frac{1}{n} \inf_{\sigma \in S_n} \sum_{k=1}^n \rho(X_k, Y_{\sigma(k)}).$$

Theorem (Varadarajan 1958). With probability one, $\mu_n \Rightarrow \mu$ as $n \rightarrow \infty$.

³ **Variant:** If $\int \rho(x, x_0) d\mu(x) < \infty$, then $W(\mu_n, \mu) \rightarrow 0$ a.s.

Matching problem: $\mathbb{E} W(\mu_n, \mu) = ?$ or $\mathbb{E} W(\mu_n, \nu_n) = ?$

The case $M = \mathbb{R}$: In terms of distribution functions of μ_n and μ ,

$$W(\mu_n, \mu) = \int_{-\infty}^{\infty} |F_n(x) - F(x)| dx,$$
$$\mathbb{E} W(\mu_n, \mu) \leq \frac{1}{\sqrt{n}} J, \quad J = \int_{-\infty}^{\infty} \sqrt{F(x)(1-F(x))} dx.$$

Theorem (B-L). $\mathbb{E} W(\mu_n, \mu) = O(\frac{1}{\sqrt{n}})$ if and only if $J < \infty$.

Sampling from the uniform distribution

Let X_1, \dots, X_n and Y_1, \dots, Y_n be drawn from $M = [0, 1]^d$ with Euclidean distance according to the uniform distribution, and let

$$\mu_n = \frac{1}{n} (\delta_{X_1} + \dots + \delta_{X_n}), \quad \nu_n = \frac{1}{n} (\delta_{Y_1} + \dots + \delta_{Y_n}).$$

Case $d = 1$: $\mathbb{E} W(\mu_n, \nu_n) \sim \frac{1}{\sqrt{n}}$.

Case $d = 2$: AKT theorem (Ajtai-Komlós-Tusnády 1984)

$$\mathbb{E} W(\mu_n, \nu_n) \sim \sqrt{\frac{\log n}{n}}.$$

Other proofs: Shor (mid 1980's), Talagrand-Yukich (1993)
Extension to arbitrary laws μ on $[0, 1]^d$: Talagrand (1992)

Majorizing measure approach: Talagrand (1994)

Fourier-analytic approach: B-Ledoux (2019)

PDE approach, exact asymptotics for $\mathbb{E} W_2^2(\mu_n, \nu_n)$: Ambrosio, Stra, Trevisan (2019)

Case $d \geq 3$: $\mathbb{E} W(\mu_n, \nu_n) \sim n^{-1/d}$.

Kantorovich-Rubinstein theorem

Theorem. Given μ and ν on (M, ρ) ,

$$W(\mu, \nu) = \sup_u \left| \int u d\mu - \int u d\nu \right|$$

where the sup is over all Lipschitz u on M with $\|u\|_{\text{Lip}} \leq 1$.

For empirical measures

$$\mu_n = \frac{1}{n} (\delta_{X_1} + \dots + \delta_{X_n}), \quad \nu_n = \frac{1}{n} (\delta_{Y_1} + \dots + \delta_{Y_n}),$$

for independent samples drawn from μ on $M = [0, 1]^d$,

$$nW(\mu_n, \nu_n) = \sup_u \left[\sum_{k=1}^n u(X_k) - \sum_{k=1}^n u(Y_k) \right]$$

$$n \mathbb{E} W(\mu_n, \nu_n) \sim \mathbb{E} \sup_u \left[\sum_{k=1}^n \varepsilon_k u(X_k) \right]$$

Subgaussian process (in Talagrand's proof): $\xi(u) = \sum_{k=1}^n \varepsilon_k u(X_k)$.

Fourier-Stieltjes transform

Any probability measure μ on $Q^d = (-\pi, \pi]^d$ is uniquely determined by the sequence (characteristic function)

$$f_\mu(m) = \int_{Q^d} e^{im \cdot x} d\mu(x), \quad m = (m_1, \dots, m_d) \in \mathbb{Z}^d.$$

Theorem 1 (Fourier-analytic inequality). If μ, ν are supported on $[0, \pi]^d$, for any $t > 0$,

$$W(\mu, \nu) \leq \left(\sum_{m \neq 0} e^{-t|m|^2} \frac{|f_\mu(m) - f_\nu(m)|^2}{|m|^2} \right)^{1/2} + 2\sqrt{dt}.$$

Other variants (smoothings): For any $T > 0$,

$$W(\mu, \nu) \leq \left(\sum_{1 \leq \|m\|_\infty \leq T} \frac{|f_\mu(m) - f_\nu(m)|^2}{|m|^2} \right)^{1/2} + \frac{c\sqrt{d}}{T}.$$

Application to empirical measures

Let

$$\mu_n = \frac{1}{n} (\delta_{X_1} + \dots + \delta_{X_n}), \quad \nu_n = \frac{1}{n} (\delta_{Y_1} + \dots + \delta_{Y_n}).$$

Corollary 1. Let $(X_1, Y_1), \dots, (X_n, Y_n)$ be pairwise independent with values in $[0, 1]^d \times [0, 1]^d$ such that X_k and Y_k have equal distributions $\forall k \geq 1$. Then

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

Proof. By Fourier-analytic inequality,

$$\mathbb{E} W(\mu_n, \nu_n) \leq \left(\sum_{m \neq 0} e^{-t|m|^2} \mathbb{E} \frac{|f_{\mu_n}(m) - f_{\nu_n}(m)|^2}{|m|^2} \right)^{1/2} + 2\sqrt{dt}.$$

Here

$$f_{\mu_n}(m) - f_{\nu_n}(m) = \frac{1}{n} \sum_{k=1}^n (e^{im \cdot X_k} - e^{im \cdot Y_k}),$$

$$\mathbb{E} |f_{\mu_n}(m) - f_{\nu_n}(m)|^2 \leq \frac{4}{n}.$$

Reduction to torus

Kantorovich-Rubinstein theorem:

$$W(\mu, \nu) = \sup_{\|u\|_{\text{Lip}} \leq 1} \left| \int_{Q^d} u d\mu - \int_{Q^d} u d\nu \right|.$$

Let \mathcal{L}_d be the set of all (2π) -periodic functions u on \mathbb{R}^d with $\|u\|_{\text{Lip}} \leq 1$. Put

$$\widetilde{W}(\mu, \nu) = \sup_{u \in \mathcal{L}_d} \left| \int_{Q^d} u d\mu - \int_{Q^d} u d\nu \right|.$$

∞ **Lemma 1.** If μ and ν are supported on $[0, \pi]^d$, then $W(\mu, \nu) = \widetilde{W}(\mu, \nu)$.

Proof. Let $\|z\| = \text{dist}(z, 2\pi\mathbb{Z}^d)$, $z \in \mathbb{R}^d$. Then $u \in \mathcal{L}_d$ iff u is 1-Lip with respect to $\rho(x, y) = \|x - y\|$. Since it is a metric on Q^d , by the Kantorovich-Rubinstein theorem,

$$\widetilde{W}(\mu, \nu) = \inf_{\lambda} \iint \|x - y\| d\lambda(x, y).$$

If μ, ν are supported on $[0, \pi]^d$, then λ is supported on $[0, \pi]^d \times [0, \pi]^d$, while

$$\|x - y\| = |x - y|, \quad x, y \in [0, \pi]^d.$$

Fourier-analytic inequality on the torus

Lemma 2. For all μ and ν on Q^d ,

$$\widetilde{W}(\mu, \nu) \leq \left(\sum_{m \neq 0} \frac{|f_\mu(m) - f_\nu(m)|^2}{|m|^2} \right)^{1/2}.$$

Proof. Given a (smooth) function u participating in Lemma 1 for $\widetilde{W}(\mu, \nu)$, expand it as a multiple Fourier series

$$u(x) = \sum_{m \in \mathbb{Z}^d} a_m e^{im \cdot x}.$$

Hence

$$\int_{Q^d} u d\mu - \int_{Q^d} u d\nu = \sum_{m \in \mathbb{Z}^d} a_m (f_\mu(m) - f_\nu(m)).$$

Also, since $\partial_{x_l} u(x) = i \sum_{m \in \mathbb{Z}^d} m_l a_m e^{im \cdot x}$, we have

$$\frac{1}{(2\pi)^d} \int_{Q^d} |\partial_{x_l} u(x)|^2 dx = \sum_{m \in \mathbb{Z}^d} m_l^2 |a_m|^2,$$

$$\frac{1}{(2\pi)^d} \int_{Q^d} |\nabla u(x)|^2 dx = \sum_{m \in \mathbb{Z}^d} |m|^2 |a_m|^2 \leq 1.$$

It remains to apply Cauchy's inequality and take the sup over all $u \in \mathcal{L}_d$.

Convolution

Identifying $(-\pi, \pi]$ with the circle S^1 via $x \rightarrow e^{ix}$, and $Q^d = (-\pi, \pi]^d$ with $(S^1)^d$, one may introduce the convolution for prob. measures μ and γ on Q^d :

$$\int u d(\mu * \gamma) = \iint u(x + y) d\mu(x) d\gamma(y)$$

in the class of all continuous (2π) -periodic functions u on \mathbb{R}^d . Applying this equality to $u(x) = e^{im \cdot x}$, it becomes

$$f_{\mu * \gamma}(m) = f_\mu(m) f_\gamma(m), \quad m \in \mathbb{Z}^d.$$

“Gaussian” measures on the torus: For each $t > 0$, there is γ_t on Q^d with Fourier-Stieltjes transform

$$f_{\gamma_t}(m) = e^{-t|m|^2/2}, \quad m \in \mathbb{Z}^d.$$

Construction ($d = 1$): γ_t is the image of $N(0, t)$ under the map

$$T(x) = x - 2\pi k \quad \text{for } \pi(2k - 1) < x \leq \pi(2k + 1).$$

In particular, $|T(x)| \leq |x|$, so,

$$\int x^2 d\gamma_t(x) \leq t.$$

Smoothing inequality. Proof of Theorem 1

Put $\mu_t = \mu * \gamma_t$, so that $f_{\mu_t}(m) = f_\mu(m) e^{-t|m|^2/2}$, $m \in \mathbb{Z}^d$.

If u is (2π) -periodic and $\|u\|_{\text{Lip}} \leq 1$,

$$\begin{aligned} \left| \int u d\mu_t - \int u d\mu \right| &= \left| \iint (u(x+y) - u(x)) d\mu(x) d\gamma_t(y) \right| \\ &\leq \int |y| d\gamma_t(y). \end{aligned}$$

Conclusion (smoothing inequality): $\widetilde{W}(\mu_t, \mu) \leq \sqrt{dt}$.

Proof of Theorem 1 (FA inequality): Using the triangle inequality for \widetilde{W} , the smoothing inequality, and applying Lemma 1 to (μ, ν) , and Lemma 2 to (μ_t, ν_t) , we have

$$\begin{aligned} W(\mu, \nu) &= \widetilde{W}(\mu, \nu) \leq \widetilde{W}(\mu_t, \nu_t) + \widetilde{W}(\mu_t, \mu) + \widetilde{W}(\nu_t, \nu) \\ &\leq \left(\sum_{m \neq 0} e^{-t|m|^2} \frac{|f_\mu(m) - f_\nu(m)|^2}{|m|^2} \right)^{1/2} + 2\sqrt{dt}. \end{aligned}$$

Non-Euclidean metrics

Let the metric

$$\rho(x, y) = \omega(|x - y|), \quad x, y \in \mathbb{R},$$

be generated by the modulus of continuity $\omega : \mathbb{R}_+ \rightarrow \mathbb{R}_+$, i.e. a non-decreasing continuous function such that $\omega(0) = 0$ and $\omega(\delta_1 + \delta_2) \leq \omega(\delta_1) + \omega(\delta_2)$ for all $\delta_1, \delta_2 \geq 0$.

Kantorovich transport distance:

$$W_\omega(\mu, \nu) = \inf_\lambda \iint \omega(|x - y|) d\lambda(x, y),$$

where the inf is over all λ on $\mathbb{R}^d \times \mathbb{R}^d$ with marginals μ and ν .

Theorem 1' (FA inequality). If μ, ν are supported on $[0, \pi]^d$, for any $t > 0$,

$$W(\mu, \nu) \leq \sqrt{d} \left(\sum_{m \neq 0} \omega^2 \left(\frac{\pi}{|m|} \right) e^{-t|m|^2} |f_\mu(m) - f_\nu(m)|^2 \right)^{1/2} + 6\omega(\sqrt{dt}).$$

Empirical measures

Kantorovich distance:

$$W_\omega(\mu_n, \nu_n) = \frac{1}{n} \inf_{\sigma \in S_n} \sum_{k=1}^n \omega(|X_k - Y_{\sigma(k)}|),$$

$$\mu_n = \frac{1}{n} (\delta_{X_1} + \dots + \delta_{X_n}), \quad \nu_n = \frac{1}{n} (\delta_{Y_1} + \dots + \delta_{Y_n}),$$

Corollary 1'. Let $(X_1, Y_1), \dots, (X_n, Y_n)$ be pairwise independent with values in $[0, 1]^d \times [0, 1]^d$ such that X_k and Y_k have equal distributions for each $k \geq 1$. For any $t > 0$,

$$\mathbb{E} W_\omega(\mu_n, \nu_n) \leq \frac{2\sqrt{d}}{\sqrt{n}} \left(\sum_{m \neq 0} \omega^2 \left(\frac{\pi}{|m|} \right) e^{-tm^2} \right)^{1/2} + 6\omega(\sqrt{dt}).$$

If all X_j, Y_k are independent, a similar inequality also holds for the ψ_2 -norm of $W_\omega(\mu_n, \nu_n)$.

Dimension one (Zolotarev metrics)

For power moduli of continuity $\omega(\delta) = \delta^\alpha$, $0 < \alpha \leq 1$,

$$\begin{aligned} W_\omega(\mu, \nu) &= \zeta_\alpha(\mu, \nu) = \inf_\lambda \iint |x - y|^\alpha d\lambda(x, y) \\ &= \sup_{\|u\|_{\text{Lip}(\alpha)} \leq 1} \left| \int u d\mu - \int u d\nu \right|. \end{aligned}$$

Corollary 1''. We have

$$\begin{aligned} \sqrt{2\alpha - 1} \mathbb{E} \zeta_\alpha(\mu_n, \nu_n) &\leq \frac{c}{\sqrt{n}}, & \text{if } \frac{1}{2} < \alpha \leq 1, \\ \mathbb{E} \zeta_\alpha(\mu_n, \nu_n) &\leq \frac{c}{\sqrt{n}} \sqrt{\log(2n)}, & \text{if } \alpha = \frac{1}{2}, \\ \sqrt{1 - 2\alpha} \mathbb{E} \zeta_\alpha(\mu_n, \nu_n) &\leq \frac{c}{n^\alpha}, & \text{if } 0 < \alpha < \frac{1}{2}. \end{aligned}$$

If all X_j, Y_k are independent, similar bounds also hold for the ψ_2 -norm of the random variable $\zeta_\alpha(\mu_n, \nu_n)$.

The iid case: N. Fournier and A. Guillin (2015).

Comparison with Bernstein's theorem

S. Bernstein's theorem (1914): If a (2π) -periodic function

$$u(x) \sim \frac{a_0}{2} + \sum_{n=1}^{\infty} (a_n \cos(nx) + b_n \sin(nx))$$

belongs to the Lipschitz class of order $\alpha > \frac{1}{2}$, i.e.,

$$|u(x) - u(y)| \leq L\omega(|x - y|) = L|x - y|^\alpha,$$

then

$$\sum_{n=1}^{\infty} (|a_n| + |b_n|) < \infty.$$

Comparison with order statistics

Given two independent samples X_1, \dots, X_n and Y_1, \dots, Y_n drawn from the law μ on $[0, 1]$, consider

$$\xi_n = \zeta_\alpha(\mu_n, \nu_n) = \frac{1}{n} \inf_{\sigma} \sum_{k=1}^n |X_k - Y_{\sigma(k)}|^\alpha,$$

In case $\alpha = 1$, it is simplified to

$$\zeta_1(\mu, \nu) = W(\mu_n, \nu_n) = \frac{1}{n} \sum_{k=1}^n |X_k^* - Y_k^*|$$

via order statistics $X_1^* \leq \dots \leq X_n^*$ and $Y_1^* \leq \dots \leq Y_n^*$. Define

$$\xi_n^* = \frac{1}{n} \sum_{k=1}^n |X_k^* - Y_k^*|^\alpha,$$

so that $\xi_n^* \geq \xi_n$, and we have $\xi_n^* = \xi_n$ in case $\alpha = 1$.

Corollary 2. Let $0 < \alpha < 1$. If μ is log-concave, then

$$\mathbb{E} \xi_n^* \geq \frac{c}{n^{\alpha/2}} \text{Var}(X_1).$$

Hence, if n is large, then $\xi_n^* > \xi_n$ with positive probability.

Minimax grid matching

Minimax matching length: Given two unordered collections $X = \{x_1, \dots, x_n\}$ and $Y = \{y_1, \dots, y_n\}$ of points in \mathbb{R}^d , define the distance

$$L(X, Y) = \min_{\sigma \in S_n} \max_{1 \leq k \leq n} |x_k - y_{\sigma(k)}|.$$

Comparison with Kantorovich: $W \leq L$.

Minimax grid matching problem: Find the rate of $\mathbb{E} L(X, Y)$ at which it tends to zero as $n \rightarrow \infty$, when X and Y are independent samples drawn from μ . Of a special interest – the uniform distribution on $[0, 1]^d$.

Case $d \geq 3$ (Shor and Yukich 1991):

$$c_0 \left(\frac{\log(2n)}{n} \right)^{1/d} \leq \mathbb{E} L(X, Y) \leq c_1 \left(\frac{\log(2n)}{n} \right)^{1/d}.$$

Case $d = 2$ (Leighton and Shor 1989):

$$c_0 \frac{\log^{3/4}(2n)}{\sqrt{n}} \leq \mathbb{E} L(X, Y) \leq c_1 \frac{\log^{3/4}(2n)}{\sqrt{n}}.$$

Case $d = 1$:

$$c_0 \frac{1}{\sqrt{n}} \leq \mathbb{E} L(X, Y) \leq c_1 \frac{1}{\sqrt{n}}.$$

Restricted minimax grid matching

One can improve the rate in dim. one, if counting not all, but most of the points in perfect matchings. For a (non-empty) subset I of $\{1, \dots, n\}$, define

$$L_I(X, Y) = \min_{\sigma} \max_{k \in I} |x_k - y_{\sigma(k)}|,$$

where the minimum is over all permutations σ of $\{1, \dots, n\}$.

Let $Y = (Y_1, \dots, Y_n)$ be an independent copy of the random vector $X = (X_1, \dots, X_n)$ which has independent coordinates with values in $[0, 1]$.

Corollary 3. For each $\varepsilon > 0$, with high probability there is a (random) set $I \subset \{1, \dots, n\}$ of $|I| \geq (1 - \varepsilon)n$ such that

$$L_I(X, Y) \leq C \frac{\log^2(2n)}{\varepsilon^2 n}.$$

“With high probability” means the probability $1 - n^{-p}$, where p can be chosen to be large by a proper choice of C . By Corollary 1” with $\alpha = \frac{1}{2}$, for some σ ,

$$|X_k - Y_{\sigma(k)}|^{1/2} \leq \frac{C}{\sqrt{n}} \sqrt{\log(2n)}$$

on average with respect to k .