The Metric side of Optimal Transport

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 - The Wasserstein distance
 - Dudley Lemma
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 - Iterated Dudley Lemma
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 - Wasserstein ∞ metric
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The Wasserstein distance for finite p

As a reminder, we have for any $p \in [1, \infty[$

$$\mathcal{P}_p(X) := \left\{ \mu \in \mathcal{P}(X) \mid \int_X d^p(x, x_0) \, \mathrm{d}\mu(x) < \infty \right\}$$

and the following will be a metric on this space.

Definition

For any $p \in [1, \infty[$ and $u, \mu \in \mathcal{P}_p(X)$

$$W_p^p(\mu,\nu) := \min \left\{ \int_{X \times X} d^p(x,y) \mathrm{d}\pi(x,y) \mid \pi \in \Gamma(\mu,\nu) \right\}.$$

Theorem

 $(\mathcal{P}_p(X), W_p)$ is a metric space!

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Proof of Theorem

We assume p = 2, which makes it less messy, the other cases are similar.

- 1. $W_2(\mu, \nu) < \infty$ always
- 2. $\mu = \nu \Leftrightarrow W_2(\mu, \nu) = 0$
- 3. $W_2(\mu, \nu) = W_2(\nu, \mu)$
- 4. Dudley Lemma for triangle inequality
- 5. $W_2(\mu_1, \mu_3) \leq W_2(\mu_1, \mu_2) + W_2(\mu_2, \mu_3)$.

Reminder

Let $T:X\to Y$ be a measurable function and let μ,ν be measures on X,Y, then we have the Change of Variables Formula:

$$\int_{Y} f(y) d(T_{\#}\mu)(y) = \int_{X} f(T(x)) d\mu(x).$$

Additionally, for any metric d on X it holds for any $x_0 \in X$ that

$$d^{2}(x,y) \leq (d(x,x_{0}) + d(x_{0},y))^{2} \leq 2(d^{2}(x,x_{0}) + d^{2}(x_{0},y))$$

because $2ab < a^2 + b^2$ always.

The Dudley Lemma

In the Literature this is often called Gluing Lemma!

Lemma

Let $(X_1, \mu_1), (X_2, \mu_2), (X_3, \mu_3)$ be Polish and $\pi^{1,2} \in \Gamma(\mu_1, \mu_2)$ and $\pi^{2,3} \in \Gamma(\mu_2, \mu_3)$. Then there exists some $\pi \in \mathcal{P}(X_1 \times X_2 \times X_3)$ such that

$$p_{\#}^{1,2}(\pi) = \pi^{1,2}$$
 and $p_{\#}^{2,3}(\pi) = \pi^{2,3}$

where
$$p^{1,2}(x_1, x_2, x_3) = (x_1, x_2)$$
 and $p^{2,3}(x_1, x_2, x_3) = (x_2, x_3)$.

Proof is essentially just taking the product measures of the Disintegration's of $\pi^{2,3}$ and $\pi^{1,2}$ and "Gluing" them together with μ_2 .

Let $\mu_1, \mu_2, \mu_3 \in \mathcal{P}_2(X)$, $\pi^{1,2} \in \Gamma_o(\mu_1, \mu_2)$ and $\pi^{2,3} \in \Gamma_o(\mu_2, \mu_3)$ and π is the measure we get from gluing $\pi^1, 2$ with $\pi^2, 3$. Let $p_\#^{1,3}(\pi) = \pi^{1,3} \in \Gamma(\mu_1, \mu_3)$.

$$W_2(\mu_1, \mu_3) \le \left(\int_{X \times X} d^2(x_1, x_3) d\pi^{1,3}(x_1, x_3)\right)^{1/2}$$

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$$\stackrel{!}{=} \left(\int_{X \times X \times X} d^{2}(x_{1}, x_{3}) d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2}$$

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$$\leq \left(\int_{X \times X \times X} [d(x_{1}, x_{2}) + d(x_{2}, x_{3})]^{2} d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2}$$

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$$W_{2}(\mu_{1}, \mu_{3}) \leq \left(\int_{X \times X} d^{2}(x_{1}, x_{3}) d\pi^{1,3}(x_{1}, x_{3})\right)^{1/2}$$

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$$\leq \left(\int_{X \times X \times X} \left[d(x_{1}, x_{2}) + d(x_{2}, x_{3})\right]^{2} d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2}$$

$$\stackrel{*}{\leq} \left(\int_{X \times X \times X} d^{2}(x_{1}, x_{2}) d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2} + \left(\int_{X \times X \times X} d^{2}(x_{2}, x_{3}) d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2}$$

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$$\begin{aligned} W_{2}(\mu_{1}, \mu_{3}) &\leq \left(\int_{X \times X} d^{2}(x_{1}, x_{3}) d\pi^{1,3}(x_{1}, x_{3})\right)^{1/2} \\ &\stackrel{!}{=} \left(\int_{X \times X \times X} d^{2}(x_{1}, x_{3}) d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2} \\ &\leq \left(\int_{X \times X \times X} \left[d(x_{1}, x_{2}) + d(x_{2}, x_{3})\right]^{2} d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2} \\ &\stackrel{*}{\leq} \left(\int_{X \times X \times X} d^{2}(x_{1}, x_{2}) d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2} + \left(\int_{X \times X \times X} d^{2}(x_{2}, x_{3}) d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2} \\ &\stackrel{!}{=} \left(\int_{X \times X} d^{2}(x_{1}, x_{2}) d\pi^{1,2}(x_{1}, x_{2})\right)^{1/2} + \left(\int_{X \times X} d^{2}(x_{2}, x_{3}) d\pi^{2,3}(x_{2}, x_{3})\right)^{1/2} \end{aligned}$$

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$$W_{2}(\mu_{1}, \mu_{3}) \leq \left(\int_{X \times X} d^{2}(x_{1}, x_{3}) d\pi^{1,3}(x_{1}, x_{3})\right)^{1/2}$$

$$\stackrel{!}{=} \left(\int_{X \times X \times X} d^{2}(x_{1}, x_{3}) d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2}$$

$$\leq \left(\int_{X \times X \times X} [d(x_{1}, x_{2}) + d(x_{2}, x_{3})]^{2} d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2}$$

$$\stackrel{*}{\leq} \left(\int_{X \times X \times X} d^{2}(x_{1}, x_{2}) d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2} + \left(\int_{X \times X \times X} d^{2}(x_{2}, x_{3}) d\pi(x_{1}, x_{2}, x_{3})\right)^{1/2}$$

$$\stackrel{!}{=} \left(\int_{X \times X} d^{2}(x_{1}, x_{2}) d\pi^{1,2}(x_{1}, x_{2})\right)^{1/2} + \left(\int_{X \times X} d^{2}(x_{2}, x_{3}) d\pi^{2,3}(x_{2}, x_{3})\right)^{1/2}$$

$$= W_{2}(\mu_{1}, \mu_{2}) + W_{2}(\mu_{2}, \mu_{3}).$$

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Comparing L^2 norm and Wasserstein distance

Let $\nu \ll \lambda^n$ with Radon Nikodym derivative f such that $supp(f) \subseteq \overline{B_1}$.

Additionally, let $\mu_h \ll \lambda^n$ such that $f_h(x) = f(x+h)$. Then we have

$$||f_h - f||_{L^2(\mathbb{R}^n)}^2 = 2||f||_{L^2(\mathbb{R}^n)}^2$$

but on the other hand

$$W_2(\mu_h,\mu)=\|h\|_2$$

which for large ||h|| implies

$$W_2(\mu_h,\mu) \gg ||f_h - f||_{L^2(\mathbb{R}^n)}.$$

In case of small ||h|| we can also find $W_2(\mu_h, \mu) \ll ||f_h - f||_{L^2(\mathbb{R}^n)}$.

Wasserstein distance for normal distributions

For any $\mu_X, \mu_Y \in \mathcal{P}_2(\mathbb{R}^d)$ with $\mathcal{L}(X) = \mu_X$ and $\mathcal{L}(Y) = \mu_Y$ where X and Y are normally distributed, the Wasserstein distance can be calculated as follows

$$W_2^2(\mu_X, \mu_Y) = \|m_X - m_Y\|^2 + \operatorname{tr}\left(\Sigma_X - 2 \cdot \left(\Sigma_Y^{1/2} \Sigma_X \Sigma_Y^{1/2}\right)^{1/2} + \Sigma_Y\right)$$

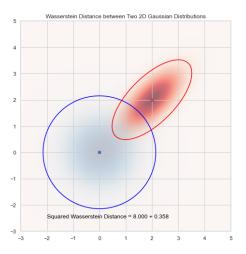
If Σ_X and Σ_Y commute, this simplifies to

$$W_2^2(\mu_x, \mu_Y) = \|m_X - m_Y\|^2 + \sum_{i=1}^d \left(\sqrt{\lambda_i^X} - \sqrt{\lambda_i^Y}\right)^2$$

where λ_i^X and λ_i^Y are the Eigenvalues of Σ_X and Σ_Y respectively.

Normally distributed examples

Assume
$$\Sigma_X = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$
 and $\Sigma_Y = \begin{pmatrix} \frac{1}{2} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{2} \end{pmatrix}$ with $m_X = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$ and $m_Y = \begin{pmatrix} 2 \\ 2 \end{pmatrix}$.



Lifting completeness from X to $\mathcal{P}_p(X)$

We remind ourselves of the metric version of the L^p spaces.

$$L^p(\Omega,\mathcal{F},P,X) \coloneqq \left\{ f: \Omega \to X \mid f \text{ measurable }, \int_{\Omega} d^p(f,z_0) dP < \infty \right\}$$

with

$$d_{L^p}^p(f,g) := \int_{\Omega} d^p(f,g) dP$$

These are not necessarily vector spaces, but one can show that this more general notion of L^p space is still complete if (X, d) is.

This completeness is important for the following Theorem.

Theorem

Let (X, d) be a complete metric space, then $(\mathcal{P}_p(X), W_p)$ is complete.

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Iterated Dudley Lemma

We want to represent a sequence of measures (μ_n) as the marginals of some measure in an infinite product space.

For that we need the iterated Dudley Lemma. Note that we also allow $N=\infty$ in this Lemma, in that case, the \leq become <.

Lemma

Let $N \geq 3$ and for any $n \leq N$ (X_n, d_n) Polish, $\mu_n \in \mathcal{P}(X_n)$ and $\theta_n \in \Gamma(\mu_{n-1}, \mu_n)$. Then there exists $\pi_n \in \mathcal{P}(X_1 \times ... \times X_n)$ for any $n \leq N$ such that.

- 1. $p_{\#}^{1,...,n-1}\pi_n = \pi_{n-1}$ for $2 \le n \le N$
- 2. $p_{\#}^{i}\pi_{n}=\mu_{i}$ for $1 \leq i \leq n \leq N$
- 3. $p_{\#}^{i-1,i}\pi_n = \theta_i \text{ for } 2 \le i \le n \le N$

Proof is just applying the Dudley Lemma iteratively (hence the name :).

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Prove of completeness

We again consider p = 2. Assume $(\mu_n) \subseteq \mathcal{P}_2(X)$ is Cauchy.

- 1. Applying Iterated Dudley on (X, μ_n) to get $(\pi_n)_{n \in \mathbb{N}}$
- 2. Get π_{∞} on $\mathbb{X} = \prod_{i=1}^{\infty} X$ with $p_{\#}^{(1,\ldots,n)}(\pi_{\infty}) = \pi_n$.
- 3. Show that the projections (p_n) are Cauchy in $L^2(\mathbb{X}, \mathcal{B}_{\infty}, \pi_{\infty}, X)$
- 4. Use that $L^2(\mathbb{X},\mathcal{B}_\infty,\pi_\infty,X)$ is complete to get $p_n\to p_\infty$
- 5. Define $\mu_{\infty} = (p_{\infty})_{\#}(\pi_{\infty})$ and prove $\mu_n \xrightarrow{W_2} \mu_{\infty}$.

Reminder

If
$$\sum_{k=1}^{\infty} d(x_n, x_{n+1}) < \infty$$
 then (x_n) is Cauchy.

Also earlier in the Book, we had

$$S_{\#}(P) = \mu$$
 and $T_{\#}(P) = \nu \Rightarrow (S, T)_{\#}(P) \in \Gamma(\mu, \nu)$.

Duality for the Wasserstein Distance

By the Kantorovich-Rubinstein Duality we have

$$W_1(\mu, \nu) = \sup_{(\phi, \psi) \in I_c} \left\{ \int_X \phi d\mu + \int_X \psi d\nu \right\}$$

$$= \sup_{\|\phi\|_{Lip} \le 1} \left\{ \int_X \phi d\mu + \int_X \phi^c d\nu \right\}$$

$$= \sup_{\|\phi\|_{Lip} \le 1} \left\{ \int_X \phi d\mu - \int_X \phi d\nu \right\}$$

where the first equality holds for any W_p distance, the latter need that c=d.

Wasserstein distance for $p = \infty$

If we restrict ourselves to $\mathcal{P}_{\infty}(X)$, the space of probability measures with bounded support. We can also define W_{∞} as the limit of W_p .

$$\begin{split} \lim_{\rho \to \infty} W_{\rho}(\mu, \nu) &= W_{\infty}(\mu, \nu) = \inf\{\|d(x, y)\|_{L^{\infty}}(\pi) \mid \pi \in \Gamma(\mu, \nu)\} \\ &= \inf_{\pi \in \Gamma(\mu, \nu)} \inf\{C \geq 0 \mid |d(x, y)| \leq C \text{ for } \pi \text{ almost all } (x, y)\} \end{split}$$

and we have

$$(\mathcal{P}_{\infty}(X), W_{\infty})$$
 is a metric space