Optimal Transport: Theory, Computation and Applications

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Optimal Transport

Principal concern: the distance between two probability measures.

First introduced in 1781 by Monge.

Relative subjects: probability theory, geometry, graph theory, machine learning...

Applications:

- Image registration and warping;
- Reflector design;
- Retrieving information from shadowgraphy and proton radiography;
- Seismic tomography and reflection seismology.

Some well-known researchers:

- Gasoard Monge (France);
- Leonid Kantorovich (Russia);
- Yann Brenier (France);
- Xianfeng Gu (顾险峰, China);

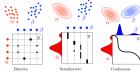


Fig. 1. Three main scenarios for Kantorovich OT

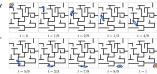


Fig. 2. Solving maze with OT



Fig. 3. 2D shape interpolation with OT

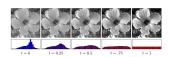


Fig. 4. Histogram equalization with OT



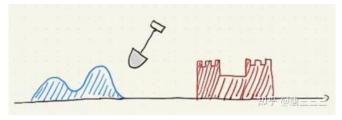


The sand-moving problem

A child wants to make a pile of sand in the shape of a castle.

Cost: 1 kcal per shovel and per meter horizontally.

Target: Minimize the total cost.



 $\textbf{Fig. 5.} \ \ \textbf{The sand-moving problem}.$



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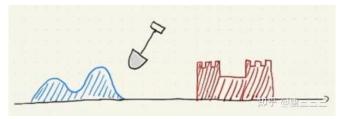


Fig. 5. The sand-moving problem.

Let's denote the source shape by f(x) and the target by g(x). The sand-moving problem cound be formulated as: find a **transport mapping** $T:\mathbb{R}\to\mathbb{R}$ to minimize

$$\int_{\mathbb{R}} |T(x) - x| f(x) \ dx,\tag{1}$$

which satisfies

$$\int_{T(U)} g(x) \ dx = \int_{U} f(x) \ dx \text{ for all open interval } U \subset \mathbb{R}. \tag{2}$$

The allocation problem

There are some steel coils to be transported from warehouses to factories. The transport cost is \$1 per coil and per kilometer. How to minimize the total cost?

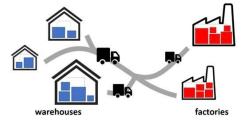


Fig. 6. The allocation problem.

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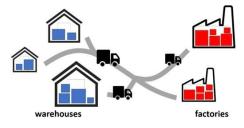


Fig. 6. The allocation problem.

Assume the i-th warehouse has a_i coils and the j-th factory needs b_i coils. And assume the distance between the i-th warehouse and the j-th factory is d_{ij} . The allocation problem could be formulated as: find a **transport matrix** v_{ij} to minimize

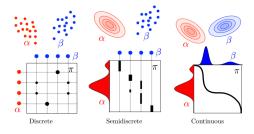
$$\sum_{i,j} d_{ij} v_{ij} \tag{3}$$

which satisfies

$$a_i = \sum_j v_{ij}, \quad orall i, \qquad ext{and} \qquad b_j = \sum_i v_{ij}, \quad orall j.$$

The Kantorovich formulation

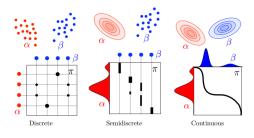
To give an general formulation of OT, we first recall the three main scenarios for OT.



¹ Leonid Kantorovich. "On the transfer of masses". In: Doklady Akademii Nauk 37.2 (1942).□ ▶ ◀ 🗗 ▶ ◀ 🚡 ▶ ◀ 👼 ▶ 🥞 🤟 🗨 🔾

The Kantorovich formulation

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Given two probability measures μ on $\mathcal X$ and ν on $\mathcal Y$, and a cost function c(x,y). The Kantorovich formulation of OT is

$$\mathcal{L}_{c}(\mu,\nu) = \min_{\pi} \int_{\mathcal{X} \times \mathcal{Y}} c(x,y) \ d\pi(x,y), \tag{5}$$

where π is a measure on $\mathcal{X} \times \mathcal{Y}$, whose marginals are μ and ν , that is,

$$\mu = \int_{\mathcal{Y}} \pi(\cdot, y) \, dy, \qquad \nu = \int_{\mathcal{X}} \pi(x, \cdot) \, dx. \tag{6}$$

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Metric properties of OT

Here we assume $\mathcal{X} = \mathcal{Y}$ and $c(x,y) = d(x,y)^p$ (p > 1), where d is a distance on \mathcal{X} . Denote $\mathcal{M}^1_+(\mathcal{X})$ the set of probability measures on \mathcal{X} .

²Cédric Villani. Optimal Transport: Old and New. Vol. 338. Springer Verlag, 2009.



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Theorem (Wasserstein distance)

Under the above assumptions, $\mathcal{L}_c(\mu, \nu)^{1/p}$ is a distance on $\mathcal{M}^1_+(\mathcal{X})$.

The distance $\mathcal{W}_p(\mu,\nu):=\mathcal{L}_c(\mu,\nu)^{1/p}$ is called $p ext{-Wasserstein}$ distance.

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Definition (Weak convergence)

Assume $\mathcal X$ is compact. Say $(\mu_k)_{k\geq 1}\subset \mathcal M^1_+(\mathcal X)$ converges weakly to $\mu\in \mathcal M^1_+(\mathcal X)$ if

$$\int_{\mathcal{X}} g \ d\mu_k \to \int_{\mathcal{X}} g \ d\mu, \quad \forall g \in \mathcal{C}(\mathcal{X}). \tag{7}$$

Theorem (Wasserstein distance and weak convergence²)

On a compact domain \mathcal{X} , $(\mu_k)_{k\geq 1}\subset \mathcal{M}^1_+(\mathcal{X})$ converges weakly to $\mu\in \mathcal{M}^1_+(\mathcal{X})$ if and only if $\mathcal{W}_p(\mu_k,\nu)\to 0$.

²Cédric Villani. Optimal Transport: Old and New. Vol. 338. Springer Verlag, 2009. ◀ □ ▶ ◀ ∰ ▶ ◀ 臺 ▶ ▼ ▼ ♀ ♀ ♀

Thank You