

Optimal Transport in a Nutshell (3h!)

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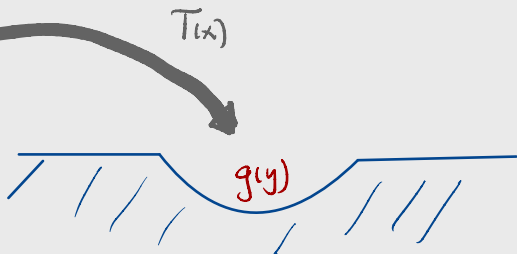
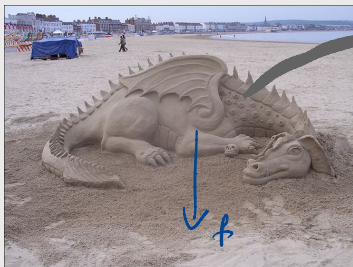


Doomed to fail
Part 1

ICMS workshop on
'Connections between interacting particle dynamics and data science'

Monge's problem (1781):

How to move a pile of sand to a hole (both having the same volume) at minimal cost?



More mathematical: given two positive densities f and g , with $\int_{\mathbb{R}^d} f(x)dx = \int_{\mathbb{R}^d} g(y)dy = 1$, find a map $T : \mathbb{R}^d \rightarrow \mathbb{R}^d$ minimising the cost

$$M(T) := \int_{\mathbb{R}^d} |T(x) - x| f(x) dx,$$

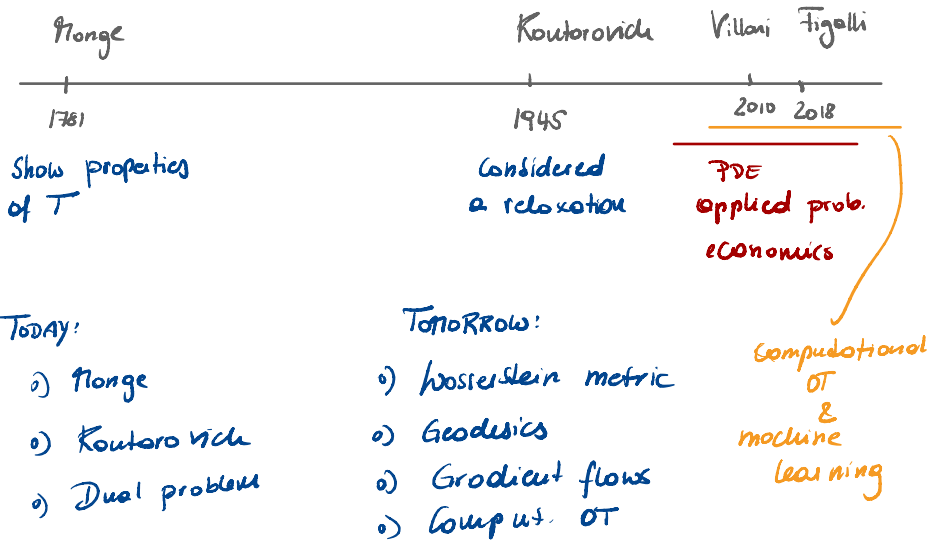
displacement of particle located at x
mass taken from pre-image of A

subject to the constraint

$$\int_A g(y) dy = \int_{T^{-1}(A)} f(x) dx \text{ for any Borel subset } A \subset \mathbb{R}^d.$$

mass clumped in A

Timeline



Notation

- More general, let's replace f and g by measures

$$\mu \in \mathcal{M}^+(X) \text{ and } \nu \in \mathcal{M}^+(Y),$$

where X and Y are Polish spaces.

- Consider a general cost function $c : X \times Y \rightarrow \mathbb{R}$
- Spaces: $\mathcal{M}(X)$ space of finite measures on X

$$\begin{aligned} c(x,y) &= |x-y| \\ c(x,y) &= |x-y|^p \quad p=2 \\ c(x,y) &= h(x-y) \text{ \& \textit{convex}} \end{aligned}$$

$$\mathcal{M}^+(X) := \{\mu \in \mathcal{M}(X) : \mu \geq 0\},$$

$$\mathcal{P}(X) := \{\mu \in \mathcal{M}^+(X) : \mu(X) = 1\}. \Leftrightarrow \text{probability measures}$$

- Push forward operator: Let $\mu, \nu \in \mathcal{P}(X)$ and $T : X \rightarrow Y$ be a measurable map. The push-forward $T_{\#}\mu$ is defined as

$$\nu(A) = \mu(T^{-1}(A))$$

for all measurable sets $A \subseteq Y$.

Equivalent: $d\mu = f dx$ $d\nu = g dy$

$$\int_Y \varphi(y) d\nu(y) = \int_X \varphi(T(x)) d\mu(x)$$

$\varphi : Y \rightarrow \mathbb{R}$
measurable
bdd.

$$\varphi = \mathbb{1}_A \quad \int_A g(y) dy = \int_{T^{-1}(A)} f(x) dx$$

The Monge Problem

Given two probability measures $\mu \in \mathcal{P}(X)$ and $\nu \in \mathcal{P}(Y)$ and a cost function $c : X \times Y \rightarrow [0, \infty]$ find

$$\inf \left(M(T) := \left(\int c(x, T(x)) d\mu(x) \right) \right) \quad (\text{MP})$$

over all measurable maps $T : X \rightarrow Y$ such that $T_{\#}\mu = \nu$.

Monge is hard \otimes slightly nonlinear

$d\mu = f dx$ $dr = g dx$, $T \in C^1$ diffeomorphisms

$$T_{\#}\mu = \nu \quad \Rightarrow \quad f(x) = g(T(x)) |\det T'(x)|$$

change of variable

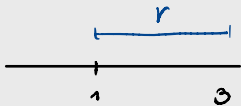
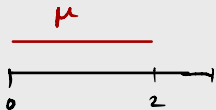
if $T = \nabla \varphi$

$$\det \nabla^2 \varphi = \frac{f(x)}{g(\nabla \varphi)} \quad \Leftarrow \quad \text{Monge-Ampere equation}$$

Figalli, Coferreli, ...

Example [Non-uniqueness] Let $X = [0, 2]$, $Y = [1, 3]$, $\mu = \frac{1}{2}\mathbf{1}_{[0,2]}$, $\nu = \frac{1}{2}\mathbf{1}_{[1,3]}$ and $c(x, y) = |x - y|$. Let T_1 and T_2 denote two transportation maps, given by $T_1(x) = x + 1$ and

$$T_2(x) = \begin{cases} x + 2 & \text{if } x \in [0, 1] \\ x & \text{if } x \in (1, 2]. \end{cases}$$



T_1 ... linear translation

T_2 ... only move mass from $(0, 1]$ to $[2, 3]$

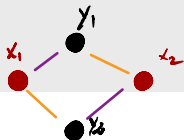
$$\pi(T_1) = \frac{1}{2} \int_0^2 |x+1-x| dx = 1$$

$$\pi(T_2) = 1$$

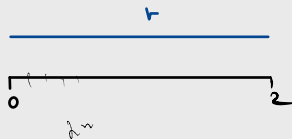
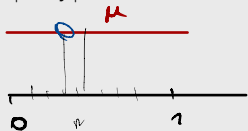
} $\pi(T) = 1$ the best possible

$\Rightarrow T$ might not be UNIQUE

Exd.



Example [Non-existence] Let $X = [0, 1]$ and $Y = [0, 2]$ and $\mu = \mathbf{1}_{[0,1]}$ and $\nu = \frac{1}{2}\mathbf{1}_{[0,2]}$ and cost $c(x, y) = |x - y|^{\frac{1}{2}}$.



\Rightarrow mass can't be split



Why is (MP) difficult?

- Class of admissible transportation maps might be empty.
- Solution may not be unique.
- There's no notion of convergence, which makes the class of admissible transportation maps sequentially closed and compact.

The Kantorovich problem:

Given two probability measures $\mu \in \mathcal{P}(X)$ and $\nu \in \mathcal{P}(Y)$ and a cost $c : X \times Y \rightarrow [0, \infty]$ find

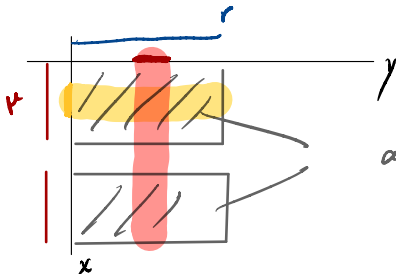
$$\inf \left(K(\pi) := \int_{X \times Y} c(x, y) d\pi(x, y) \right) \quad (\text{KP})$$

among all admissible transportation plans $\pi \in \Pi(\mu, \nu)$, where

$$\Pi(\mu, \nu) := \{ \pi \in \mathcal{P}(X \times Y) : (P_X)_\# \pi = \mu, (P_Y)_\# \pi = \nu \}$$

and P_X and P_Y are the projections of $X \times Y$ onto X and Y , respectively.

Transportation plan $\pi(x, y)$ how much mass was moved from x to y ,

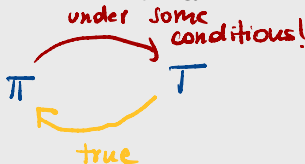


admissible π

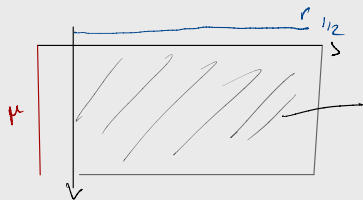
Why is (KP) easier?

$$\Pi = \mu \otimes \nu$$

- The set $\Pi(\mu, \nu)$ is not empty, and compact and convex wrt to the narrow topology.
- The mapping $\pi \rightarrow \int c(x, y) d\pi(x, y)$ is linear.
- Transportation plans π 'include' transportation maps T .
- Problem is symmetric.



Example Let $X = [0, 1]$ and $Y = [0, 2]$ and $\mu = \mathbf{1}_{[0,1]}$ and $\nu = \frac{1}{2}\mathbf{1}_{[0,2]}$ and cost $c(x, y) = |x - y|^{\frac{1}{2}}$.



$$\Pi = \frac{1}{2} \mathbb{1}_{[0,1] \times [0,2]} \quad \text{admissible}$$

Hongre

$$\min \frac{1}{n} \sum c(x_i, T(x_i))$$

↓

$$\min \frac{1}{n} \sum c(x_i, y_{\pi(i)}) \quad \text{e... permutation}$$

Kantorovich

$$\min \frac{1}{n} \sum c_{ij} \pi_{ij}$$

$$\Pi(\mu, \nu) = \left\{ \pi \in \mathbb{R}^{n \times n} : \sum_i \pi_{ij} = \sum_j \pi_{ij} = \frac{1}{n} \right\}$$

⇒ Birkhoff's theorem: extremal points of the set of bistochastic matrices are induced by permutation

Hongre and Kantorovich agree

Relax, Monge!

Every transportation map T (in the sense of Monge) induces a transportation plan π :

$$\pi_T := (\text{Id}, T)_{\#} \mu. \quad \Leftarrow \quad d\pi_T = \int_{y=T(x)} d\mu$$

If T^+ is optimal $\Rightarrow \pi_{T^+}$

$$\pi_{T^+}(A \times Y) = \int_A d_{y=T(x)} d\mu(x) = \mu(A) \quad \checkmark$$

} marginal
constr.
satisfied

$$\pi_{T^+}(X \times B) = \underbrace{\quad}_{K(\pi)}$$

since

$$\begin{aligned} \int_{X \times Y} c(x, y) d\pi(x, y) &= \int \int c(x, y) d_{y=T(x)} dy d\mu \\ &= \int_X c(x, T(x)) d\mu(x) = \eta(T) \end{aligned}$$

Therefore

$$\inf K(\pi) \leq \inf W(\bar{\pi})$$

\Rightarrow Transport map induces transport plan π

Converse? If on plan π can be written

$$d\pi(x,y) = \int_{y=T(x)} d\mu(x)$$

$\Rightarrow T$ is an OT map

Theorem (Existence of transportation plans)

Let X and Y be compact metric spaces, $\mu \in \mathcal{P}(X)$ and $\nu \in \mathcal{P}(Y)$ and $c : X \times Y \rightarrow \mathbb{R}$ be a lower semi-continuous function. Then (KP) admits a unique solution.

Direct method of calculus of variations

Kantorovich

$$\min_{\nu \in V} F(\nu)$$

$$\min_{\pi \in \Pi} K(\pi)$$

- Check that $\{\nu \in V : F(\nu) < \infty\} \neq \emptyset$.
- Consider a minimising sequence $\{\nu_n\}$ in V with $F(\nu_n) \rightarrow \inf F(\nu)$.
- Show that V is compact in a suitable topology. ← the weaker the topology
- F is lower semicontinuous wrt this topology. ← the easier conv. of subseq.

the stronger the easier the set

Put together

$$\inf \{F(\nu) \mid \nu \in V\} \stackrel{\text{min. seq.}}{=} \lim_{n \rightarrow \infty} F(\nu_n) \stackrel{\text{conv. subseq.}}{=} \lim_{k \rightarrow \infty} F(\nu_{n_k}) \stackrel{\text{low-semi cont.}}{\geq} F(\nu^+) \geq \inf \{F(\nu) \mid \nu \in V\}$$

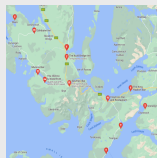
$$F(\nu^+) = \inf \{F(\nu) \mid \nu \in V\}$$

Example

- We wish to transport bottles of whiskey from a given number of distilleries and a given number of pubs.
- Let $c(x, y)$ denote the cost of transporting one unit of whiskey from distillery x to pub y .



(c) Distilleries



(d) Pubs

Outsourcing to contractor

a) $\varphi(x)$ price to pick up whiskey at x

b) $\varphi(y)$ — the drop off — at y

$$\varphi(x) + \varphi(y) \leq c(x, y) \quad \forall x, y$$

The Dual Problem

Given two probability densities $\mu \in \mathcal{P}(X)$ and $\nu \in \mathcal{P}(Y)$ and a cost function $c : X \times Y \rightarrow [0, \infty)$ consider

$$\max_{\varphi, \psi \in \Phi_c} \left(\int_X \varphi(x) d\mu(x) + \int_Y \psi(y) d\nu(y) \right) : \varphi \in C_b(X), \psi \in C_b(Y), \quad (\text{DP})$$

where $\Phi_c = \{(\varphi, \psi) \in C_b(X) \times C_b(Y) : \varphi(x) + \psi(y) \leq c(x, y)\}$.

$$\text{Since } \varphi(x) + \psi(y) \leq c(x, y) \quad \varphi \oplus \psi = \varphi(x) + \psi(y)$$

$$\begin{aligned} \int_X \varphi(x) d\mu + \int_Y \psi(y) d\nu &= \int_{X \times Y} (\varphi \oplus \psi) d\pi \\ &\leq \int_{X \times Y} c(x, y) d\pi \end{aligned}$$

$$\sup \text{DP} \leq \min \text{KP}$$

If $\sup \text{DP} = \min \text{KP} \Leftrightarrow$ strong duality

Optimality & Monodonicity

$\exists \pi = \pi_{ij}$ amount of whiskey going to x_i to y_j

Assume my Cost is too high

o) $x_1 \rightarrow y_1$ decide $x_1 \rightarrow y_2$

o) $x_2 \rightarrow y_2$ decide $x_2 \rightarrow y_3$

BENEFIT

$$C(x_1, y_1) - C(x_1, y_2)$$

$$C(x_2, y_2) - C(x_2, y_3)$$

⋮

$$C(x_1, y_2) + \dots + C(x_n, y_1) \leq C(x_1, y_1) + \dots + C(x_n, y_n)$$

$\Rightarrow \pi$ CAN'T BE OPTIMAL

Definition (C-Cyclical monotonicity)

Let X, Y be arbitrary sets and $c: X \times Y \rightarrow (-\infty, \infty]$ be a function. A subset $\Gamma \subset X \times Y$ is called c -cyclically monotone if for any $m \in \mathbb{N}$ and any family $(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)$ of points in Γ

$$\sum_{i=1}^m c(x_i, y_i) \leq \sum_{i=1}^m c(x_i, y_{i+1})$$

with $y_{m+1} = y_1$. A transportation plan is c -cyclically monotone if its concentrated on a c -cyclically monotone set.

$\Rightarrow \pi$ is optimal $\rightarrow \text{spt}(\pi)$ is a c -cyclically monotone set

Definition (C-Transforms)

Let $\varphi: X \rightarrow \mathbb{R} \cup \{\infty\}$, then its c -transform $\varphi^c: Y \rightarrow \mathbb{R} \cup \{\infty\}$ is defined as

$$\varphi^c(y) = \inf_{x \in X} c(x, y) - \varphi(x) \quad \varphi(x) + \varphi^c(y) \leq c(x, y)$$

The \bar{c} -transform of $\psi: Y \rightarrow \mathbb{R} \cup \{\infty\}$ is given by $\psi^{\bar{c}}(x) = \inf_{y \in Y} c(x, y) - \psi(y)$.

Theorem

Let X and Y be Polish spaces and assume that $c: X \times Y \rightarrow \mathbb{R}$ is uniformly continuous and bounded. The (DP) admits a solution (φ, φ^c) and $\max(\text{DP}) = \min(\text{KP})$.

$(\varphi, \varphi^c) \leftarrow$ Kantorovich potential

Theorem

Let μ and ν be two probability measures on a compact domain $\Omega \subset \mathbb{R}^d$ and the cost $c(x, y) = h(x - y)$ with h strictly convex.

Then there exists a unique transportation plan π of the form $(id, T)_{\#}\mu$ if μ is absolutely continuous and $\partial\Omega$ negligible. The corresponding Kantorovich potential φ is linked via

$$T(x) = x - (\nabla h)^{-1}(\nabla\varphi(x)).$$

Duality: Assume there exist JOT plan π & Kantorovich plan φ

$$\varphi(x) + \varphi^c(y) \leq c(x, y) \quad \text{on } \Omega \times \Omega$$

$$\varphi(x) + \varphi^c(y) = c(x, y) \quad \text{on } \text{spt}(\pi)$$

Consider (x_0, y_0) on $\text{spt}(\pi)$

$$x \mapsto \varphi(x) - c(x, y_0) \text{ is min at } x_0$$

$$\text{If } \varphi \text{ \& } c \text{ diff.} \quad \nabla\varphi(x_0) = \nabla_x c(x_0, y_0) = \nabla_x h(x_0 - y_0)$$

if h is strictly convex

$$x_0 - y_0 = (\nabla h)^{-1} (\nabla \varphi(x_0))$$

$$T(x) = x - (\nabla h)^{-1} (\nabla \varphi(x))$$

NOT working $c(x,y) = |x-y|$

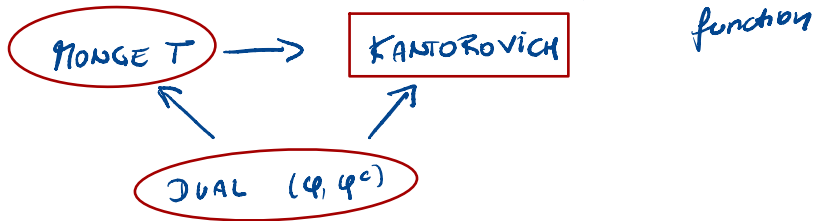
Theorem (Brenier's Theorem)

Let $\mu \in \mathcal{P}(X)$, $\nu \in \mathcal{P}(Y)$ with $X, Y \subset \mathbb{R}^d$, assume that both have finite second moments and that μ does not give mass to small sets, and let $c(x, y) = |x - y|^2$.

Then there exists a unique solution π to the Kantorovich problem (KP). This plan is uniquely supported on the graph $(x, T(x))$, that is $\pi = (Id, T)_{\#}\mu$. Furthermore there exists an $L^1(\mu)$, convex, lower-semicontinuous function $\bar{\varphi}$ such that $\pi = (Id \times \nabla \bar{\varphi})_{\#}\mu$.

Quadratic cost. $T(x) = x - \nabla \varphi(x) = \nabla \left(\underbrace{\frac{x^2}{2}}_{:= u} - \varphi \right)$ u convex
Lsc.

\Rightarrow Transportation map is the gradient of a
convex & lsc



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Python libraries

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URL: <https://www.cvxpy.org/index.html>
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R. Flamary et al. *POT Python Optimal Transport library*, Journal of Machine Learning Research, 22(78):18, 2021.
URL: <https://pythonot.github.io/>
- OTT Optimal Transport Toolbox
M. Cuturi et al. *Optimal Transport Tools (OTT): A JAX Toolbox for all things Wasserstein*, arXiv:2201.12324, 2022
URL: <https://github.com/ott-jax/ott>