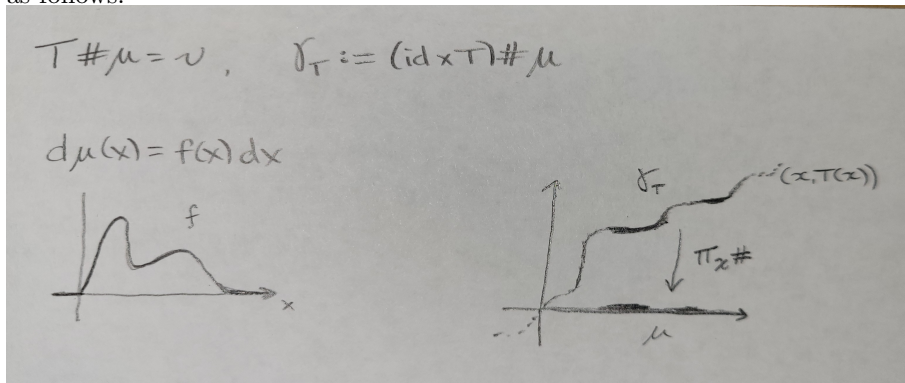


# Optimal Transport Seminar 7/26/23

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## Connection between Monge and Kantorovich

Every transport map  $T$  induces a transport plan  $\gamma_T$ , via  $\gamma_T := (\text{id} \times T)\#\mu$ , whose Kantorovich cost is the same as the Monge cost of  $T$ . It can be visualized as follows:



Thus there are more transport plans than transport maps, so the solution to the Kantorovich problem is no larger than that of the Monge problem:

$$\begin{aligned} (K) &= \min_{\gamma \in \Pi(\mu, \nu)} \int c(x, y) d\gamma(x, y) \leq \min_{T \# \mu = \nu} \int c(x, y) d\gamma_T(x, y) \\ &= \min_{T \# \mu = \nu} \int c(x, T(x)) d\mu(x) = (M). \end{aligned}$$

In fact, under certain conditions the solutions are the same.

**Theorem 1.** Suppose  $\mu$  is of the form  $d\mu(x) = f(x)dx$  and  $\Omega \subseteq \mathbb{R}^d$  is compact. Then the Kantorovich problem is a relaxation of the Monge problem. That is,

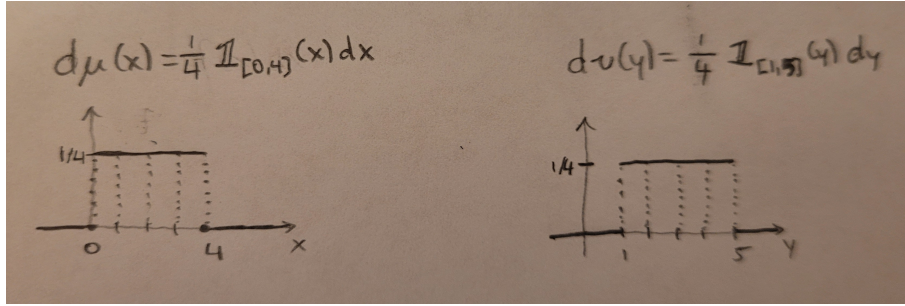
$$\min_{\gamma \in \Pi(\mu, \nu)} \int_{\Omega \times \Omega} c(x, y) d\gamma(x, y) = \min_{T \# \mu = \nu} \int_{\Omega} c(x, T(x)) d\mu(x)$$

**Remark 1.**  $\mu$  being of the form  $d\mu(x) = f(x)dx$  means  $\mu$  does not concentrate mass on  $d - 1$  dimensional subsets.

## Brenier's Theorem

The cost  $c(x, y) = |x - y|$  gives rise to a nice dual formulation. One problem with this cost is the non-uniqueness of the optimal transport map.

**Example 1** (Books on a shelf).



**Definition 1.** A function  $u : \mathbb{R}^d \rightarrow \mathbb{R}$  is called “convex” if for every  $x, y \in \mathbb{R}^d$  and  $\alpha \in [0, 1]$ ,

$$u((1 - \alpha)x + \alpha y) \leq (1 - \alpha)u(x) + \alpha u(y).$$

**Remark 2.** Equivalently, a function  $u : \mathbb{R}^d \rightarrow \mathbb{R}$  is convex if and only if its Hessian is positive semi-definite.

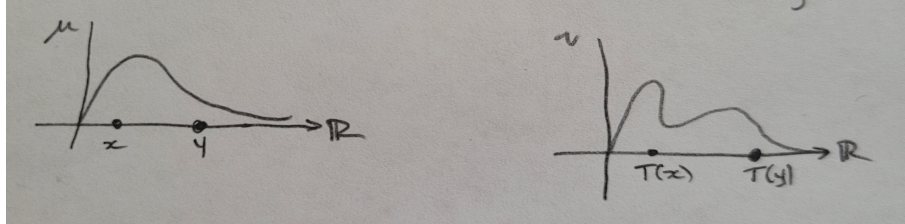
**Example 2.**  $u : \mathbb{R} \rightarrow \mathbb{R}$ ,  $u(x) = x^2$  is convex.

**Theorem 2** (Brenier). Let  $c(x, y) = \|x - y\|^2$  and  $\mu, \nu$  have finite second moment, i.e.  $\int_{\mathbb{R}^d} |x|^2 d\mu(x), \int_{\mathbb{R}^d} |y|^2 d\nu(y) < \infty$ . Suppose further  $\mu$  has the form  $d\mu(x) = f(x)dx$ . Then there exists a unique optimal transport map  $T$  of the form  $T = \nabla u$  where  $u$  is a convex function. Conversely, if  $T$  is a transport map and  $T = \nabla u$  then  $T$  is optimal.

**Remark 3.** The condition that  $d\mu(x) = f(x)dx$  is necessary, for if  $\mu$  concentrates mass on a  $d - 1$  dimensional subset uniqueness fails. Consider  $d = 2$ ,  $\mu = \frac{1}{2}\delta_{(0,0)} + \frac{1}{2}\delta_{(1,1)}$ ,  $\nu = \frac{1}{2}\delta_{(0,1)} + \frac{1}{2}\delta_{(1,0)}$ .

Discussion of the special case  $d = 1$ .

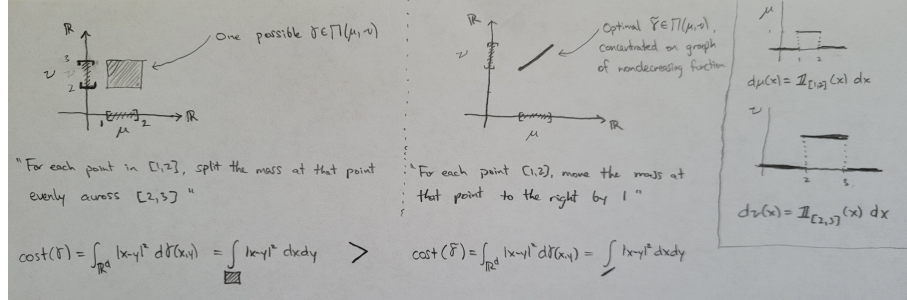
Fact: The derivative of a convex function  $u : \mathbb{R} \rightarrow \mathbb{R}$  is nondecreasing. Brenier's Theorem says the optimal rearrangement of  $\mu$  into  $\nu$  will not “cross over itself”.



Extension to Kantorovich problem:

The optimal  $\tilde{\gamma} \in \Pi(\mu, \nu) = \{\gamma : \pi_x \# \gamma = \mu, \pi_y \# \gamma = \nu\}$  concentrates its mass on the graph  $(x, T(x))$  of a function  $T$  which is the gradient of a convex function  $u$ . Namely this is via  $\tilde{\gamma} = (\text{id} \times T) \# \mu$ .

### Example 3.



## Translations and Dilations

In  $\mathbb{R}^d$ , a translation is the gradient of a convex function, namely

$$T_c(x) = x + c = \nabla \left[ \frac{1}{2} \|x\|^2 + c \cdot x \right].$$

By Brenier's Theorem, whenever a translation is a transport map, it is necessarily an optimal map and  $\gamma_T := (\text{id} \times T) \# \mu$  is the optimal transport plan. In this case one computes that the 2-Wasserstein distance between the original and translated measure is

$$\begin{aligned} W_2(\mu, T_c \# \mu) &= \left( \int |x - y|^2 d[(\text{id} \times T_c) \# \mu] \right)^{1/2} \\ &= \left( \int |x - T_c(x)|^2 d\mu \right)^{1/2} \\ &= \left( \int |c|^2 d\mu \right)^{1/2} \\ &= |c| \end{aligned}$$

as expected. Similarly scalings can be written as

$$T_a(x) = ax = \nabla \left[ \frac{a}{2} \|x\|^2 \right],$$

so the 2-Wasserstein distance between a measure  $\mu$  and its dilation  $\nu = T_a \# \mu$  is

$$\begin{aligned} W_2(\mu, T_a \# \mu) &= \left( \int |x - y|^2 d[(\text{id} \times T_a) \# \mu] \right)^{1/2} \\ &= \left( \int |x - T_a(x)|^2 d\mu \right)^{1/2} \\ &= |1 - a| \left( \int |x|^2 d\mu \right)^{1/2}. \end{aligned}$$