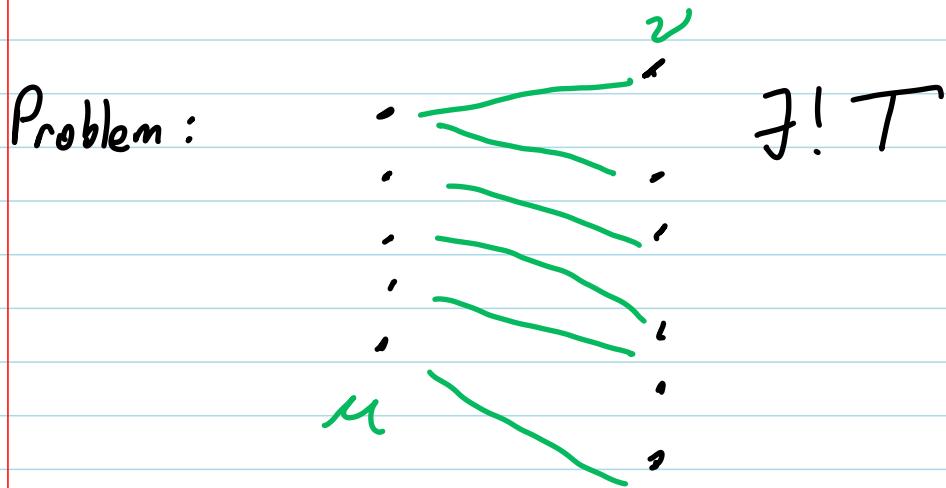


# Wasserstein-2 Menge Problem

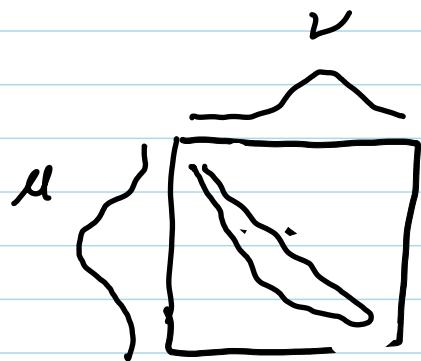
$$W_2^2(\mu, \nu) = \inf_{\substack{T: \\ \uparrow \uparrow \\ \in P_2(\mathbb{R}^d)}} \int \|x - T(x)\|^2 d\mu$$

$T_\# \mu = \nu$



# Kantorovich Problem

$$W_2^2(\mu, \nu) = \inf_{\gamma \in \Pi_{\mu}^{\nu}} \int \|x - y\|^2 d\gamma(x, y)$$



Definition of  $\Pi_{\mu}^{\nu}$ :

$\gamma \in \Pi_{\mu}^{\nu}$  : if

(\*)  $\gamma \in P(X \times Y)$

$\gamma(A \times \mathbb{R}^d) = \mu(A)$

$\gamma(\mathbb{R}^d \times B) = \nu(B)$

# Dual Problem

$$\sup_{f, g \in L^1(\mathbb{R}^d)} \int f(x) d\mu + \int g(y) d\nu$$

$$f(x) + g(y) \leq \|x - y\|^2$$

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$$(*) \sup_{f, g \in C_b} \int f d\mu + \int g d\nu - \int f(x) + g(y) d\delta(x, y)$$
$$= \begin{cases} 0 & \text{if } \delta \in \Pi_\mu^\nu \\ \infty & \text{else} \end{cases}$$

$$(KP) \text{ if } \left\{ \int \|x - y\|^2 d\delta + (*) \right\}$$
$$\delta \in M_+$$

$$(KP) \geq \sup_{f,g} \left\{ \int f d\mu + \int g d\nu + \inf_y \left\{ \int \|x-y\|^2 \cdot (-f(x)-g(y)) d\lambda \right\} \right\}$$

$$(**) = \begin{cases} 0 & \text{if } f(x) + g(y) \leq \|x-y\|^2 \\ -\infty & \text{else} \end{cases}$$

$\Rightarrow D KP$

Brenier Thm (1992)

$\mu, \nu \in \mathcal{P}_2(\mathbb{R}^d)$ , &  $\mu$  has dens. ty.

$X \sim \mu$ . The following are equiv.

i)  $\bar{\sigma}$  is opt coupling for  $K\mathcal{P}$

ii)  $\exists$  convex fctn  $\varphi$  s.t.

$$(X, \nabla \varphi(X)) \sim \bar{\sigma}$$

i.e  $T(x) = \nabla \varphi(x)$ , then  $T_{\#} \mu = \nu$ .

$$\text{iii) } K\mathcal{P} = D K\mathcal{P} + \bar{f}(x) = \|x\|^2 - 2\varphi(x)$$
$$\bar{g}(x) = \|x\|^2 - 2\varphi^*(x)$$

## Cyclic Monotonicity

$$\text{On } \mathbb{R}: \quad \varphi \text{ convex} \Rightarrow (x - y)(\varphi'(x) - \varphi'(y)) \geq 0$$

$$\text{On } \mathbb{R}^d: \quad \text{if } \Rightarrow \langle x - y, \tilde{\nabla} \varphi(x) - \tilde{\nabla} \varphi(y) \rangle \geq 0$$

$$\tilde{\nabla} \varphi \in \partial \varphi$$

For  $\{x_i\}_{i=1}^K \subseteq \mathbb{R}^d$ ,  $\varphi$  convex  $\Rightarrow$

$$\sum_{i=1}^K \langle x_i - x_{i+1}, \nabla \varphi(x_i) \rangle \geq 0$$

$$\text{w/ } x_{K+1} = x_1$$

Def:  $(x_i, y_i)$  is cyc. monotone if

$$\sum_{i=1}^K \langle x_i - x_{i+1}, y_i \rangle \geq 0$$

Rockafellar Thm:

$A$  is cyc monotone iff  $\exists \varphi$   
Convex s.t

$$A \in \partial \varphi$$

||

$$\{(x, g) : x \in \mathbb{R}^d, g \in \partial f(x)\}$$

$Opt \bar{\sigma} \in \Pi_{\mu}^{\nu} \Rightarrow supp(\bar{\sigma})$  is C.M.

Prop: Let  $\bar{\sigma} \in \Pi_{\mu}^{\nu}$  be opt coupling

Then  $supp(\bar{\sigma})$  is cyc. monotone.

Intuition: CM  $\Rightarrow$

$$\sum_{i=1}^K \|x_i - y_i\|^2 \leq \sum_{i=1}^K \|x_{i+1} - y_i\|^2$$

Discrete OT:  $\sigma$  is opt perm.

$$\sum_{i=1}^K \|a_i - b_{\sigma(i)}\|^2 \leq \sum_{i=1}^K \|a_i - b_{\tau(i)}\|^2$$

i  $\Rightarrow$  ii

$\bar{\delta}$  be opt coupling

$\Rightarrow \text{supp}(\bar{\delta})$  is cyc monotone

$\Rightarrow \exists$  convex  $\varphi$  s.t.

$$\bar{\delta}(Y \in \partial \varphi(x)) = 1$$

$\Rightarrow$  If assume domain is bdd & compact

then  $\varphi$  is diff a.e.

$$\Rightarrow \bar{\delta}(Y = \nabla \varphi(x)) = 1 \Rightarrow (X, \nabla \varphi(x)) \sim \bar{\delta}$$

$\hat{c} \geq \hat{c}_i$

$$\|\mathbf{x} - \nabla \varphi(\mathbf{x})\|^2 = \|\mathbf{x}\|^2 + \|\nabla \varphi(\mathbf{x})\|^2 - 2\langle \mathbf{x}, \nabla \varphi(\mathbf{x}) \rangle$$

Convex conj of  $\varphi$ :  $\varphi^*(\mathbf{y}) = \sup_{\mathbf{x}} \{\langle \mathbf{x}, \mathbf{y} \rangle - \varphi(\mathbf{x})\}$

$$\varphi^* \text{ sat is L; os } \underbrace{\varphi(\mathbf{x})}_{\bar{F}} + \varphi^*(\nabla \varphi(\mathbf{x})) = \langle \nabla \varphi(\mathbf{x}), \mathbf{x} \rangle$$

$$\|\mathbf{x} - \nabla \varphi\|^2 = \underbrace{\|\mathbf{x}\|^2 - 2\varphi(\mathbf{x})}_{\bar{F}(\mathbf{x})} + \underbrace{\|\nabla \varphi(\mathbf{x})\|^2 - \varphi^*(\nabla \varphi(\mathbf{x}))}_{\bar{g}(\nabla \varphi(\mathbf{x}))}$$

$$\int \|\mathbf{x} - \mathbf{y}\|^2 d\mu = \int \bar{F}(\mathbf{x}) d\mu + \underbrace{\int \bar{g}(\nabla \varphi(\mathbf{x})) d\mu}_{\int \bar{g}(\mathbf{y}) d\nu}$$

(continued)

$(\bar{F}, \bar{g})$  satisfies const.

$$\bar{f}(x) + \bar{g}(y) \leq \|x\|^L + \|y\|^2 - 2(\varphi(x) + \varphi^*(y))$$

↑

$\langle x, y \rangle$

$$= \|x - y\|^2$$

iii  $\Rightarrow$  i

$$\begin{aligned}\int \|x - y\|^2 d\bar{\sigma} &= \int \tilde{f}(x) d\lambda_x + \int \bar{g} d\nu \\ &= \int (\tilde{f}(x) + \bar{g}(y)) d\sigma \quad \nwarrow_{\text{any coupling}} \\ &\leq \int \|x - y\|^2 d\sigma\end{aligned}$$

$\bar{\sigma}$  is op +



## Uniqueness

Thm: Some asspt.

$$(x, \nabla \varphi(x)) \sim \bar{x} \text{ is opt.}$$

$\nabla \varphi$  is unique in sense that

$$\exists \text{ convex } \psi \text{ s.t. } \nabla \psi \# \mu = \gamma$$

$$\text{thus } \nabla \varphi = \nabla \psi \text{ a.e.}$$

## Application I : 1D OT

Thm:  $\mu, \nu \in \mathcal{P}(\mathbb{R})$ ,  $\mu$  has density

$$W_2^2(\mu, \nu) = \int_0^1 |F_{\mu}^+(u) - F_{\nu}^+(u)|^2 du$$

where  $F_{\mu}$  is CDF of  $\mu$

$F_{\mu}^+$  is inverse CDF

Pf:  $\mu$  density  $\Rightarrow F_{\mu} \circ F_{\mu}^+ = \text{Id}$

$$(u \sim \text{Unif}(0, 1)), \quad X \sim F_{\mu}^+(u) \quad Y \sim F_{\nu}^+(u)$$

(continued)

$$X \sim \mu, Y \sim \nu$$
$$Y = F_\nu^+ \circ F_\mu(x) + F_\nu^+ \circ F_\mu \text{ is } (*)$$

monotone inc.

$\Rightarrow (*)$  is grad of convex fctn

$$\Rightarrow (x, F_\nu^+ \circ F_\mu(x)) \sim \mathcal{D} \text{ opt } \square$$

Application II: OT for Gaussians

$$\mu = \mathcal{N}(m_1, \Sigma_1)$$

$$\nu = \mathcal{N}(m_2, \Sigma_2)$$

$$T(x) = Ax + b$$

$$T^*(x) = \sum_i^{V_2} \left( \Sigma_1^{\frac{1}{2}} \Sigma_2 \Sigma_1^{\frac{1}{2}} \right)^{\frac{1}{2}} \sum_i^{\frac{1}{2}} (x - m_i)$$

$$+ m_2$$

$$W_2^2(\mu_1, \nu) = \|m_1 - m_2\|^2$$

$$+ \text{tr}(\Sigma_1 + \Sigma_2 - 2(\Sigma_1^{\frac{1}{2}} \Sigma_2 \Sigma_1^{\frac{1}{2}})^{\frac{1}{2}})$$

(continued)

Lower bound  $W_2(\nu_1, \nu_2)$ :

## Application III: ICNNs

$\exists$  NN w/ skip connection s.t.

$f_\theta : \mathbb{R}^d \rightarrow \mathbb{R}$  is convex

$$\mu = \mathcal{N}(0, I), \quad \nu = p_{\text{data}}$$

Train NN to minimize

$$W_2(\nu, (\nabla f_\theta)_* \mu)$$

then  $\nabla f_\theta$  is approximate OT map







