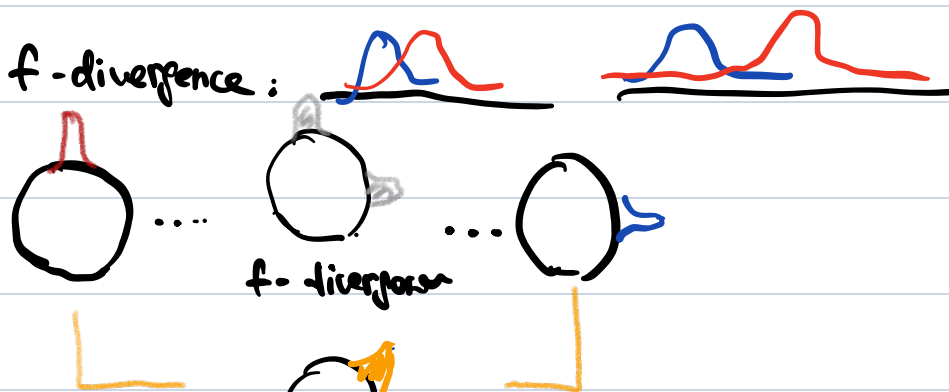


# Introduction to Optimal Transport (and Particle Systems)

Motivation

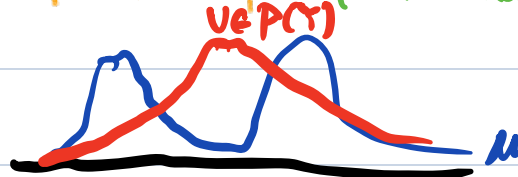
f-divergence:



Optimal Transport (Earth Moving distance, Wasserstein Distance)

Monge

$\mu \in P(X)$



$v \in P(Y)$

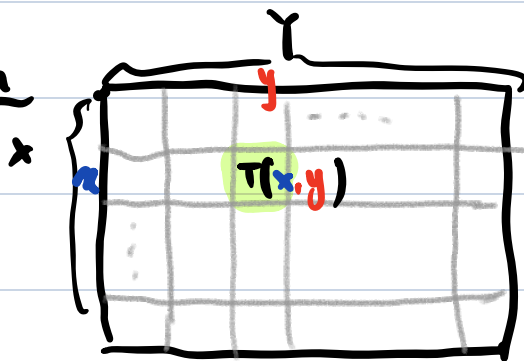
measurable map:  $T: X \rightarrow Y$

$$① \quad \nu(A) = \mu(T^{-1}(A))$$

$$② \quad \text{minimize} \quad \int_X c(x, T(x)) d\mu(x).$$

$c(x, y)$  is a cost function.

Kantorovich's Problem



$T(x, y)$ : how many products I transport from  $x \rightarrow y$

$$\min_{T \geq 0} \int_{x, y} T(x, y) c(x, y) dx dy \longrightarrow \min_{T \geq 0} \int T(x, y) c(x, y) dx dy$$

$$\text{s.t.} \quad \sum_y T(x, y) = \mu(x)$$

$$\sum_x T(x, y) = \nu(y)$$

$$\text{s.t.} \quad \sum_y T(x, y) dy = \mu(x) \quad \forall x$$

$$\sum_x T(x, y) dx = \nu(y) \quad \forall y$$

coupling

$$\sum_x \psi(x) [\sum_y T(x, y) - \mu(x)]$$

# Optimal Transport as IPM (Kantorovich Duality)

$$\begin{aligned}
 & \min_{T \geq 0} \sup_{\varphi, \psi} \left[ \int T(x, y) c(x, y) dx dy \right. \\
 & \quad + \int_{x \times Y} \varphi(x) T(x, y) dx dy - \int_x \varphi(x) \mu(x) dx \\
 & \quad \left. + \int_{x \times Y} \psi(y) T(x, y) dx dy - \int_Y \psi(y) \nu(y) dy \right] \\
 & = \sup_{\varphi, \psi} \min_{T \geq 0} \int_{x \times Y} T(x, y) [c(x, y) + \varphi(x) + \psi(y)] dx dy \\
 & \quad - \int_x \varphi(x) \mu(x) dx - \int_Y \psi(y) \nu(y) dy \\
 & = \sup_{\varphi(x) + \psi(y) + c(x, y) \geq 0} \int_x -\varphi(x) \mu(x) dx - \int_Y \psi(y) \nu(y) dy.
 \end{aligned}$$

$$\Leftrightarrow \min_{\varphi(x) - \psi(y) \geq c(x, y)} \int_x \varphi(x) \mu(x) dx - \int_Y \psi(y) \nu(y) dy$$

Shadow price

(proof provided at Appendix)

if  $c(x, y) = \|x - y\|$ .

Optimal Transport cost

IPM.

$$= \sup_{\varphi(x) - \varphi(y) \leq \|x - y\|} \int_x \varphi \mu(x) dx - \int_Y \varphi \mu(y) dy$$

the shadow price is Lipschitz.

[hw for these week]

Optimal Transport Distance. between empirical and population.  
can be bounded by the covering number of Lipschitz function

$$\Rightarrow W(\hat{P}_n, P_n) \propto n^{-1/d} \quad \text{"Curse of dimensionality"}$$

Shadow price has too much free dom.

§ Gradient flow is Wasserstein Space. advance things.

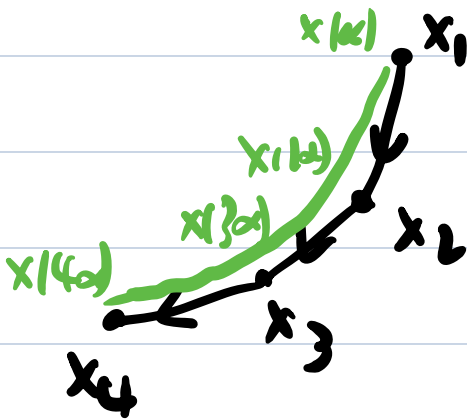
What is Gradient flow:

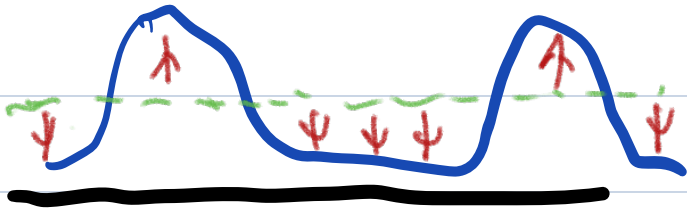
Gradient descent.  $x_{t+1} = x_t - \alpha \nabla f(x_t)$

$$\Rightarrow \frac{x_{t+1} - x_t}{\alpha} = -\nabla f(x_t)$$

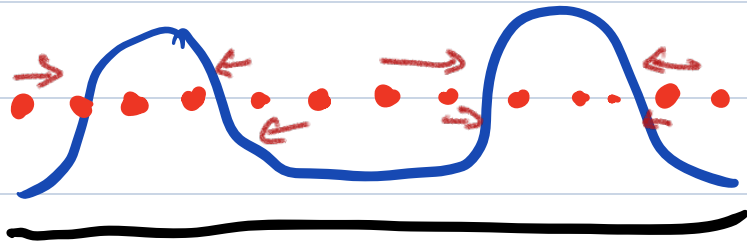
$$x_t \approx x(\alpha t) \quad \frac{x(\alpha(t+1)) - x(\alpha t)}{\alpha} \approx \left. \frac{dx}{dt} \right|_{\alpha t}$$

Gradient flow:  $\frac{dx(t)}{dt} = -\nabla f(x(t))$



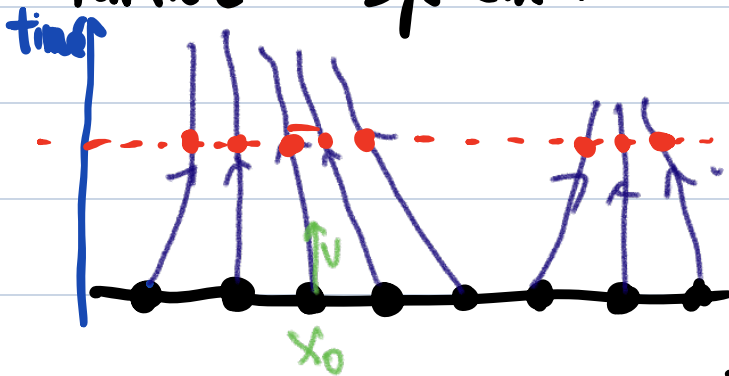


①  $\uparrow \downarrow$  Consider in  $f$ -direction / as a vector



② Transporting the particles.

Particle System.



assume every particle moves

$$\begin{cases} x(0) = x_0 \\ \frac{dx}{dt} = \vec{V}_t(x) \end{cases}$$

$x$  is the position,  $v$  is the speed

Question! How does the density move?

$$\partial_t P_t = - \nabla \cdot (\vec{V}_t P_t)$$

$$\nabla \cdot \begin{pmatrix} \vec{v}_x \\ \vec{v}_y \end{pmatrix} = \frac{d\vec{v}_x}{dx} + \frac{d\vec{v}_y}{dy}$$

★ Introduce a test function.  $\psi$

then we keep track of  $\int_x \psi(x) P_t(x) dx = \mathbb{E}_{P_t} \psi$

$$\frac{d}{dt} \int_x P_t(x) \psi(x) dx \quad \underline{\text{write down in particle side!!}}$$

$$\int_x \frac{d}{dt} P_t(x) \psi(x) dx$$

$$\frac{d}{dt} \int \psi(X(t)) P_0(x) dx$$

we first sample  $X(0) \sim P_0(x)$

run  $\frac{dX(t)}{dt} = \vec{V}_t(X(t))$  till times

$$= \int \underbrace{\nabla \psi(X(t))}_{\text{chain rule: } \frac{d}{dt} \psi(X(t)) = \nabla \psi(X(t)) \frac{dX}{dt}} \underbrace{V_t(X_t)}_{= V_x} P_0(x) dx$$

$$= - \int \psi \nabla \cdot (V P)$$

Thus  $\frac{d}{dt} P_t = -\nabla \cdot (V P)$ .

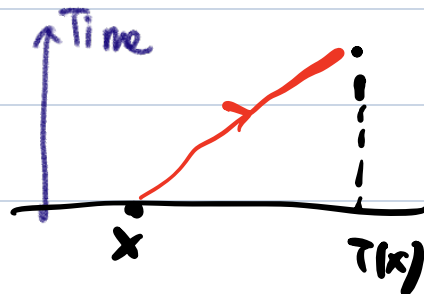
Benamou - Brenier. If  $c(x, y) = \|x - y\|^2$ , then optimal transport can be characterize as

$$\min. \int_0^1 \int_x |V_t(x)|^2 P_t(x) dx dt.$$

$$\text{s.t.} \quad \partial_t P_t + \nabla \cdot (V_t P_t) = 0.$$

$$P(\cdot, 0) = \mu, \quad P(\cdot, 1) = \nu$$

$$X(t, x) = x + t(T(x) - x),$$



## Gradient Descent in Wasserstein Space.

$F(P)$  is a function of distribution  $P$ .

$\frac{dF(P)}{dP}$  is a function  $f$ , actually satisfies.

$$F(P + \varepsilon P_0) = F(P) + \varepsilon \int f \cdot P + o(\varepsilon)$$

$\frac{dP}{dt} = - \frac{dF(P)}{de}$  (If I run the gradient in vector space - not exactly Fisher-Rao Flow)

Wasserstein Gradient Descent:

Particles,  $x(t)$ .

$$\frac{dx}{dt} = - \nabla \left( \frac{dF(P)}{de} \right).$$

If  $F(P) = \int \psi(x) P(x)$  is a linear function of  $P$

$$\frac{dF(P)}{dP} = \psi$$

$$\Rightarrow \frac{dx}{dt} = - \nabla \psi$$

## [Appendix] Duality of Optimal Transport when $C(x,y) = \|x - y\|$

If  $g$  is 1-Lipschitz: then

$$\rightarrow \underbrace{\inf_x \{ \|x - y\| - g(x) \}}_{\text{must be 1-lipschitz}} = -g(y)$$

if  $\varphi$  is the shadow price for  $x$ , then the shadow price for  $y$  is  $\varphi(y) = \inf_x \{ \|x - y\| - \varphi(x) \}$