

Dynamic Optimal Transport

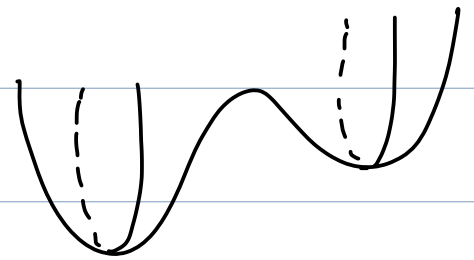
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Plan

Dynamic 2-Wasserstein Metric

→ geometry

→ gradient flows



Generalizations of W_2

① Graph Wasserstein Metric

② Hellinger Kantorovich Metric

③ Vector-valued Optimal Transport

References

AGS Ambrosio, Gigli, Savaré, Gradient Flows, 2005

M Mass, "Gradient flows of the entropy", 2011

Em Erbar, Maas, "Ricci Curvature...", 2012

GLM Gangbo, Li, Mou, "Geodesic of Minimal...", 2017

Dynamic 2-Wasserstein Metric

Given $\mu, \nu \in \mathcal{P}_2(\mathbb{R}^d)$

Kantorovich:

$$W_2^2(\mu, \nu) = \inf_{\gamma \in \Gamma(\mu, \nu)} \int |x_1 - x_2|^2 d\gamma$$

Dynamic (Benamou-Brenier):

$$W_2^2(\mu, \nu) = \inf \int_0^1 \int_{\mathbb{R}^d} |v_t(x)|^2 d\rho_t(x) dt$$

Kinetic energy

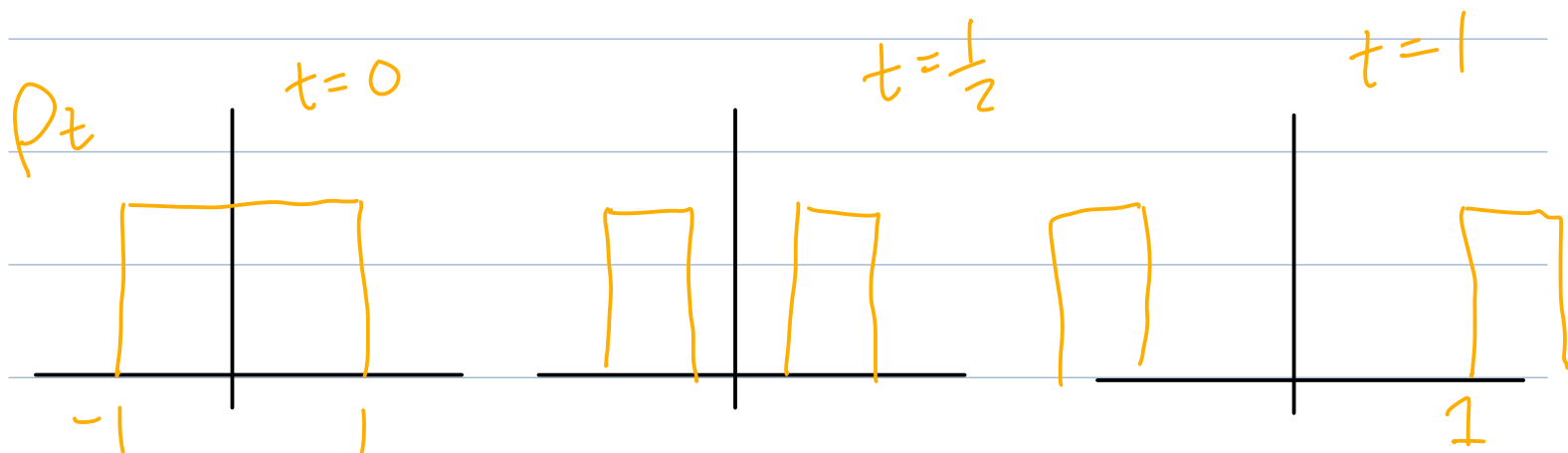
$(\rho_t(x), v_t(x))$ $v_t(x)$ tells which direction $\rho_t(x)$

continuity
eqn
(weak
sense)

$$\partial_t \rho_t + \nabla \cdot (\rho_t v_t) = 0$$

$\rho_0 = \mu$, $\rho_1 = \nu$ at time t , location x

Ex: $\rho_0 = \frac{1}{2} \mathbb{1}_{[-1,1]}(x) dx$, $v_t(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ -1 & \text{if } x < 0 \end{cases}$



$$\int_0^1 \int_{\mathbb{R}} |v_t(x)|^2 d\rho_t(x) dt = 1 = W_2^2(\rho_0, \rho_1)$$

Key properties of dynamic formulation:

- the minimum is achieved by geodesics
- if there exists an OT map T_μ^ν , the the unique minimum is

$$\rho_t = ((1-t)x + t T_\mu^\nu(x)) \# \mu$$

$=: T_t(x)$

$$v_t(x) = T_\mu^\nu(T_t^{-1}(x)) - T_t^{-1}(x)$$

Geodesics on Metric Spaces

Given a metric space (X, d) , a curve $x: [0, 1] \rightarrow X$ is a (constant speed) geodesic if $d(x_t, x_s) = |t - s|d(x_0, x_1)$, $\forall t, s \in [0, 1]$.

Geometry:

Thm (AGS) Given $p: [0, 1] \rightarrow \mathcal{P}_2(\mathbb{R}^d)$ smooth in time,
 $\exists!$ v s.t. (p, v) satisfy cty eqn and
 $v_t \in \{\nabla \varphi: \varphi \in C_c^\infty(\mathbb{R}^d)\}$ for a.e. t .

$$\parallel$$
$$\text{Tan}_{p_t} \mathcal{P}_2(\mathbb{R}^d)$$

This leads to a heuristic Riemannian structure...

$$W_2^2(\mu, \nu) = \inf \int_0^1 \langle \dot{\nu}_t, \dot{\nu}_t \rangle \rho_t dt$$

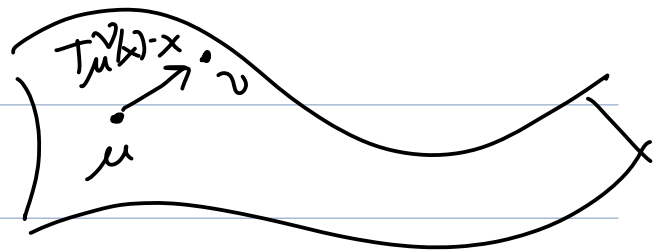
$\rho: [0, 1] \rightarrow \mathcal{P}_2(\mathbb{R}^d)$ smooth in time
 $\rho_0 = \mu, \rho_1 = \nu$

the unique $\dot{\nu}_t$ guaranteed by ABS

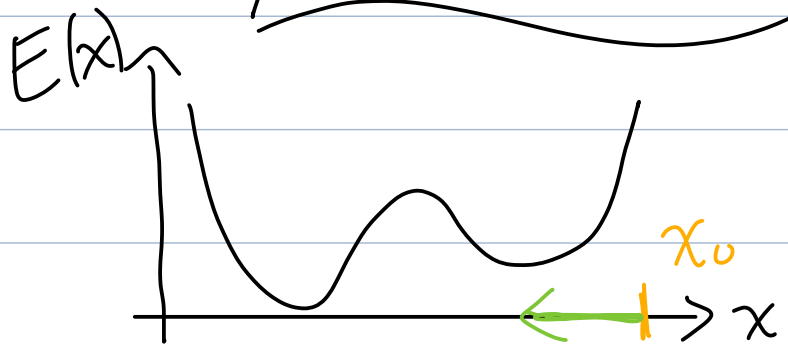
"Riemannian metric" $\langle v, u \rangle_\rho = \int v(x) \cdot u(x) d\rho$

Utility of perspective, e.g. logarithmic map:

$$\text{Log}_\mu(\nu) = T_\mu^{-1}(x) - x$$



Gradient Flows:



Given $E: \mathcal{P}_2(\mathbb{R}^d) \rightarrow \mathbb{R}$ smooth, $\rho_0 \in \mathcal{P}_2(\mathbb{R}^d)$, what smooth curve $\rho: [0, 1] \rightarrow \mathcal{P}_2(\mathbb{R}^d)$ makes E decrease as quickly as possible?

Finite Dimensional Warmup:

Consider $E: \mathbb{R}^d \rightarrow \mathbb{R}$ smooth

$$\text{Gradient descent: } \begin{cases} \dot{x}_t = -\nabla E(x_t) \\ x_t|_{t=0} = x_0 \end{cases}$$

Why is this the best path?

$$\frac{d}{dt} E(x_t) = \nabla E(x_t) \cdot \dot{x}_t = -|\nabla E(x_t)|^2$$

Cauchy Schwarz guarantees this is the best choice of $\dot{x}_t$ for making $\frac{d}{dt} E(x_t)$ as small as possible (up to normalization of magnitude).

Functional derivative

Given $E: L^2(\mathbb{R}^d) \rightarrow \mathbb{R}$, $f \in L^2(\mathbb{R}^d)$, if

$\exists \varphi \in L^2(\mathbb{R}^d)$ s.t.

$$\lim_{h \rightarrow 0} \frac{E(f+hg) - E(f)}{h} = \int_{\mathbb{R}^d} \varphi g dx, \quad \forall g \in L^2(\mathbb{R}^d),$$

then we define $\frac{\delta E}{\delta f} := \varphi$.

Note: If $dp_t = p_t(x) dx$ for $p_t(x) \in L^1 \cap L^\infty$, then $p_t \in L^2(\mathbb{R}^d)$.

What is the best curve to decrease E as fast as possible?

$$\begin{aligned} \frac{d}{dt} E(p_t) &= \lim_{h \rightarrow 0} \frac{E(p_{t+h}) - E(p_t)}{h} \\ &= \lim_{h \rightarrow 0} \frac{E(p_t + h \dot{p}_t + O(h^2)) - E(p_t)}{h} \\ &= \int_{\mathbb{R}^d} \frac{\delta E}{\delta p_t} \dot{p}_t dx \end{aligned}$$

$$\partial_t p_t = -\nabla \cdot (v_t p_t)$$

$$= - \int_{\mathbb{R}^d} \frac{\delta E}{\delta p_t} \nabla \cdot (v_t p_t)$$

$$= \int_{\mathbb{R}^d} \nabla \frac{\delta E}{\delta p_t} \cdot v_t p_t$$

$$= \left\langle \nabla \frac{\delta E}{\delta p_t}, v_t \right\rangle_{p_t}$$

Best choice of $v_t = -\nabla \frac{\delta E}{\delta p_t}$

General heuristic PDE for
2-Wasserstein GFs:

$$\partial_t p_t - \nabla \cdot \left(\nabla \frac{\delta E}{\delta p_t} | p_t \right) = 0.$$

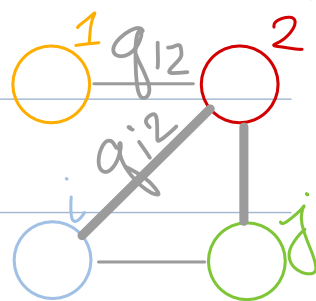
Ex: $E(p) = \int p(x) \log(p(x)) dx$

$$\partial_t p_t = \Delta p_t$$

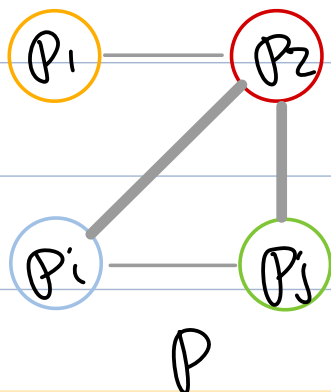
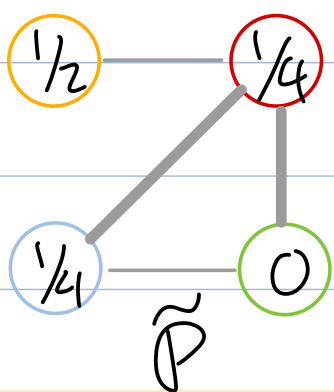
Graph Wasserstein Metric

Let G denote an n node, connected, symmetric, weighted graph.

$$q_{ij} = q_{ji}$$



Let $\mathcal{P}, \tilde{\mathcal{P}} \in \mathcal{P}(G) = \{p \in \mathbb{R}_+^n : \sum_{i=1}^n p_i = 1\}$



Graph operators

Given $\phi \in \mathbb{R}^n$, $\nabla_G \phi = [\phi_i - \phi_j]_{i,j=1}^n \in \mathbb{M}_{n \times n}$

Given $v \in \mathbb{M}_{n \times n}$, $\text{div}_G(v) = \left[\frac{1}{2} \sum_{j=1}^n (v_{ij} - v_{ji}) q_{ij} \right]_{i=1}^n$

Key facts:

- $\langle \nabla_G \phi, v \rangle_G = - \langle \phi, \text{div}_G v \rangle_{\mathbb{R}^n}$
- $\text{div}_G \nabla_G \phi = \Delta_G \phi$

Dynamic Wasserstein metric: $\boxed{m}$

$$W_G^2(p, \tilde{p}) = \inf_{(p_t, v_t)} \frac{1}{2} \sum_{i,j=0}^n \int_0^1 |v_{ij,t}|^2 \check{p}_{ij,t} q_{ij} dt$$
$$\partial_t p_t + \operatorname{div}_G(v_t \check{p}_t) = 0$$
$$p_0 = p, p_1 = \tilde{p}$$

where $\check{p} = [\check{p}_{ij}]_{i,j=1}^n = [\Theta(p_i, p_j)]_{i,j=1}^n$

Examples of Θ :

① $\Theta(p_i, p_j) \in \mathbb{R}^+_{\frac{p_i + p_j}{2}}$, ② $\Theta(p_i, p_j) = \sqrt{p_i p_j}, \dots$

Role of edge weights:

After a change of variables...

$$W_G^2(p, \tilde{p}) = \inf \frac{1}{2} \sum_{i,j} \int_0^1 |v_{ij,t}|^2 \check{p}_{ij,t} q_{ij}^{-1} dt$$
$$\partial_t p_t + \operatorname{div}_{[n]}(v_t \check{p}_t) = 0$$
$$p_0 = p, p_1 = \tilde{p}$$

Geometry:

there is a heuristic Riemannian structure

Thm (m) $(\mathcal{P}_{>0}(G), W_G)$ is a smooth Riemannian manifold.

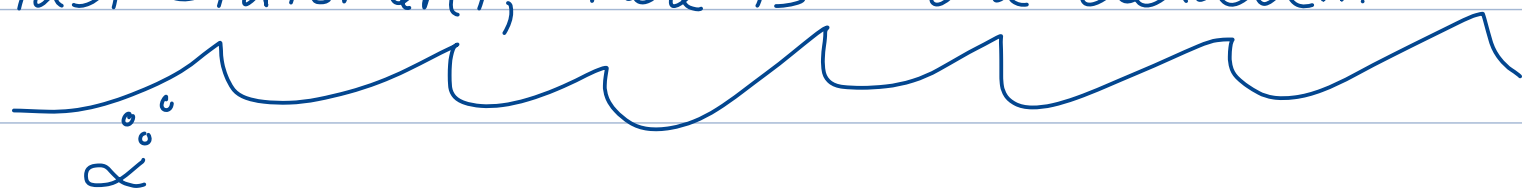
Bad News:

- $(\mathcal{P}_{>0}(G), W_G)$ is not complete; geodesics between points in interior can touch bdy. GLM
- the minimizer of dynamic problem does not necessarily exist, but if it exists and is strictly positive, it is a geodesic.

(as a curve in the space of probability measures)



For those who want a deep dive into this last statement, here is more detail...



① If one further restricts the constraint set of the dynamic formulation of WG to only consider solutions of the graph continuity equation satisfying $p_t \in \mathcal{P}(G) \forall t \in (0, 1)$, then minimizers exist. GLM, Thm 4.5

② I believe that the following example should show that the minimizing curve is not always a curve in $\mathcal{R}(G)$. Moreover, understanding the structure of WG geodesics is important to understanding when the space may be branching, which is relevant in applications of vector-valued OT.

Graph $\overset{1}{0} \xrightarrow{q_{12}=1} \overset{2}{0} \xrightarrow{q_{23}=1} \overset{3}{0}$, $P = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix}$, $\tilde{P} = \begin{bmatrix} \tilde{P}_1 \\ \tilde{P}_2 \\ \tilde{P}_3 \end{bmatrix}$

$$\Theta(P_i, P_j) = \frac{P_i + P_j}{2}$$

Continuity eqn constraint

$$\partial_t P_t + \nabla_G \cdot (\tilde{P} v) = 0$$

$\Downarrow$

$$\partial_t P_{1,t} - v_{12} \left(\frac{P_{1,t} + P_{2,t}}{2} \right) = 0$$

$$\partial_t P_{2,t} + v_{12} \left(\frac{P_{1,t} + P_{2,t}}{2} \right) + v_{23} \left(\frac{P_{2,t} + P_{3,t}}{2} \right) = 0$$

$$\partial_t P_{3,t} - v_{23} \left(\frac{P_{2,t} + P_{3,t}}{2} \right) = 0$$

$\Downarrow$

$$q_t = P_{1,t} + P_{2,t}, \quad r_t = P_{2,t} + P_{3,t}$$

$$\dot{q}_t + \frac{1}{2} v_{23} r_t = 0$$

$$= 1 - P_{1,t}$$

$$r_t + \frac{1}{2} v_{12} q_t = 0$$

Objective function

$$\int_0^1 \sum_{i,j} v_{ij,t}^2 \ddot{p}_{ij,t} q_{ij} dt = \int_0^1 v_{12,t}^2 q_t + v_{23,t}^2 r_t dt$$

applying cty
eqn constraint

$$= 4 \int_0^1 \frac{(\dot{r}_t)^2}{q_t} + \frac{(\dot{q}_t)^2}{r_t} dt$$

$$r_t = 1 - p_{1,t}, \quad \dot{r}_t = -\dot{p}_{1,t}$$

$$q_t = 1 - p_{3,t}, \quad \dot{q}_t = -\dot{p}_{3,t}$$

By symmetry,

$$p_{3,t} = p_{1,1-t}$$

$$= 4 \int_0^1 \frac{(\dot{p}_{1,t})^2}{1 - p_{3,t}} + \frac{(\dot{p}_{3,t})^2}{1 - p_{1,t}} dt$$

$$= 8 \int_0^1 \frac{(\dot{p}_{1,t})^2}{1 - p_{1,1-t}} dt$$

This leads to the problem

$$\min 8 \int_0^1 \frac{(\dot{p}_{1,t})^2}{1 - p_{1,1-t}} dt$$

$$p_1: [0,1] \rightarrow \mathbb{R}$$

$$\text{s.t. } p_1(0) = p_1$$

$$p_1(1) = \tilde{p}_1$$

This should be solvable (at least numerically??).

Once we solve this, we obtain

$$p_{3,t} = p_{1,1-t}$$

$$p_{2,t} = 1 - p_{1,t} - p_{3,t}.$$

I expect that $p_{2,t}$ will be zero for some values of t , which will prove existence of a minimizer that leaves $\mathcal{P}(G)$.