

LEC. 1: WASSERSTEIN GRADIENT FLOWS

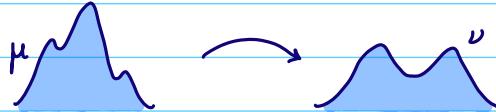
I. Basics of optimal transport

DEF.

Given two probability measures μ, ν over \mathbb{R}^d with finite second moment (written $\mu, \nu \in P_2(\mathbb{R}^d)$), the 2-Wasserstein distance between μ and ν is defined to be:

$$W_2(\mu, \nu) := \inf_{\gamma \in C(\mu, \nu)} \int \|x-y\|^2 \gamma(dx, dy)$$

where $C(\mu, \nu)$ is the set of couplings of μ and ν .



FACTS:

- For $\mu, \nu \in P_2(\mathbb{R}^d)$, an optimal coupling γ always exists (not unique)
- $(P_2(\mathbb{R}^d), W_2)$ is a metric space
- $W_2(\mu_n, \mu) \rightarrow 0 \Leftrightarrow \mu_n \rightarrow \mu$ weakly and $\int \| \cdot \|^2 d\mu_n \rightarrow \int \| \cdot \|^2 d\mu$
- $x \mapsto \delta_x$ is an isometric embedding (i.e., $W_2(\delta_x, \delta_y) = \|x-y\|$)

FUNDAMENTAL THM. OF OPTIMAL TRANSPORT

Assume μ has a density w.r.t. Lebesgue measure (written $\mu \in P_{2,ac}(\mathbb{R}^d)$). Then, the optimal transport plan between μ and ν is induced by a transport map:

$$W_2(\mu, \nu) = \int \|x-y\|^2 \gamma^*(dx, dy) = \int \|x-T^*(x)\|^2 \mu(dx)$$

$$\nu = T^* \# \mu \Leftrightarrow \text{if } X \sim \mu, \text{ then } T^*(X) \sim \nu$$

Moreover, T^* is characterized as the (μ -a.e.) unique gradient of a convex function which pushes μ to ν . We call T^* the Brenier map.

EXAMPLES:

$$\bullet T^* \# \delta_x = \delta_{T(x)}$$

- If $\mu = N(m_1, \Sigma_1)$ and $\nu = N(m_2, \Sigma_2)$, then

$$T^*(x) = m_2 + \Sigma_1^{-1/2} (\Sigma_1^{1/2} \Sigma_2 \Sigma_1^{1/2})^{1/2} (x - m_1) \quad (\text{exercise})$$

2. Curves of measures

curve in \mathbb{R}^d



\dot{x}_t is the tangent vector
to the curve

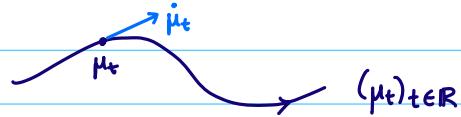
Think of $(x_t)_{t \in \mathbb{R}}$ as the trajectory of a particle

x_t = position at time t

\dot{x}_t = velocity at time t

"LAGRANGIAN" perspective

curve in $P_{2,\text{ac}}(\mathbb{R}^d)$



what is $\dot{\mu}_t$?

Think of μ_t as a collection of particles

$\mu_t(x) =$ mass density at time t , location x

$v_t(x) =$ velocity at time t , location x

v_t is the velocity vector field

"EULERIAN" perspective

Joining the two perspectives:

Now think of X_t as a random variable, $X_t \sim \mu_t$

Then, $\dot{X}_t = v_t(X_t)$

PROP. If $X_0 \sim \mu_0$ and $\dot{X}_t = v_t(X_t)$, then $\mu_t = \text{law}(X_t)$ satisfies

$$\partial_t \mu_t + \text{div}(\mu_t v_t) = 0 \quad (\text{continuity eq.})$$

Proof. The "weak" form of the PDE is:

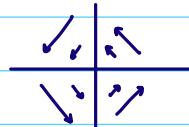
$$\partial_t \int \varphi d\mu_t = \int \langle \nabla \varphi, v_t \rangle d\mu_t, \quad \forall \varphi \in C_c^\infty(\mathbb{R}^d)$$

$$\text{But } \partial_t \int \varphi d\mu_t = \partial_t \mathbb{E}[\varphi(X_t)] = \mathbb{E}[\langle \nabla \varphi(X_t), v_t(X_t) \rangle] = \int \langle \nabla \varphi, v_t \rangle d\mu_t. \quad \square$$

Q: Can we think of v_t as the tangent vector at μ_t ?

Non-uniqueness: $\mu_t = N(0, I)$ for all $t \in \mathbb{R}$

$$v_t = 0 \quad \text{vs.} \quad v_t = \text{rotation}$$



Selection criterion: choose v_t to minimize the kinetic energy

$$v_t = \operatorname{argmin}_{V: \mathbb{R}^d \rightarrow \mathbb{R}^d} \left\{ \frac{1}{2} \int \|v\|^2 d\mu_t : \operatorname{div}(\mu_t v_t) = -\partial_t \mu_t \right\} \quad (*)$$

PROP. There is a unique v_t satisfying (*). It is characterized by " $v_t = \nabla \psi_t$ " for some $\psi_t: \mathbb{R}^d \rightarrow \mathbb{R}$.
 (More precisely, $v_t = \lim_{k \rightarrow \infty} \nabla \psi_t^{(k)}$, where $\psi_t^{(k)} \in C_c^\infty(\mathbb{R}^d)$.)

Proof. Uniqueness follows from strict convexity of (*).

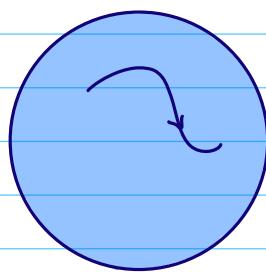
Then, note that the constraint in (*) is

$$\int \langle \nabla \varphi, v_t \rangle d\mu_t = \partial_t \int \varphi d\mu_t, \quad \forall \varphi \in C_c^\infty(\mathbb{R}^d)$$

If we replace v_t by its projection onto $\overline{\{\nabla \varphi : \varphi \in C_c^\infty(\mathbb{R}^d)\}}^{L^2(\mu_t)}$

then it still satisfies the constraint but has smaller norm. \square

3. Elements of Riemannian geometry



A Riemannian manifold M has, at each point $p \in M$, an associated vector space—the tangent space $T_p M$ —equipped with an inner product $\langle \cdot, \cdot \rangle_p$.

The inner product gives rise to distances:

$$d(p_0, p_1)^2 := \inf \left\{ \int_0^1 \|\dot{p}_t\|_{p_t}^2 dt : \text{Curves } p: [0, 1] \rightarrow M \text{ joining } p_0 \text{ to } p_1 \right\}$$

A minimizer $(p_t)_{t \in [0, 1]}$ to this variational problem is a (const.-speed) geodesic or shortest path.

The exponential map $\exp_p: T_p M \rightarrow M$ maps $v \in T_p M$ to the endpoint of the geodesic leaving p w/ velocity v for unit time.

The logarithmic map $\log_p: M \rightarrow T_p M$ is the inverse mapping.

Given $f: M \rightarrow \mathbb{R}$, the gradient $\nabla f(p)$ at $p \in M$ is the element of $T_p M$ s.t. for all curves $(p_t)_{t \in \mathbb{R}}$ with $p_0 = p$,

$$\partial_t f(p_t) \Big|_{t=0} = \langle \nabla f(p), \dot{p}_0 \rangle_p.$$

The Hessian $\nabla^2 f(p)$ is such that for all geodesics $(p_t)_{t \in \mathbb{R}}$,

$$\partial_t^2 f(p_t) \Big|_{t=0} = \nabla^2 f(p) [\dot{p}_0, \dot{p}_0].$$

A set $C \subseteq M$ is (geodesically) convex if for all $p, q \in C$, the geodesic joining p to q lies in C .

The function $f: M \rightarrow \mathbb{R}$ is α -convex if one of the following holds:

- for all geodesics $(p_t)_{t \in [0,1]}$,

$$f(p_t) \leq (1-t)f(p_0) + t f(p_1) - \frac{\alpha t(1-t)}{2} d(p_0, p_1)^2$$

- for all $q \in M$,

$$f(q) \geq f(p) + \langle \nabla f(p), \log_p(q) \rangle_p + \frac{\alpha}{2} d(p, q)^2$$

- for all $p \in M$, $v \in T_p M$,

$$\nabla^2 f(p)[v, v] \geq \alpha \|v\|_p^2$$

4. Otto calculus

We now define the tangent space

$$T_p P_{2,ac}(\mathbb{R}^d) := \overline{\{\nabla \psi : \psi \in \mathcal{C}_c^\infty(\mathbb{R}^d)\}}^{L^2(\mu)}$$

equipped with the $L^2(\mu)$ norm: $\|\nabla \psi\|_\mu^2 := \int \|\nabla \psi\|^2 d\mu$

Q: What are the geodesics?

THM. The Benamou-Brenier formula holds:

$$W_2^2(\mu_0, \mu_1) = \inf \left\{ \int_0^1 \|v_t\|_{\mu_t}^2 dt : (\mu, v) \text{ solve the cont. eq.} \right\}$$

The geodesic joining μ_0 to μ_1 is described as follows:

$$\mu_t = ((1-t)\text{id} + t\nabla\varphi)_\# \mu_0, \quad \nabla\varphi = \text{Brenier map}$$

Proof. Let (μ, v) solve the cont. eq. Then,

$$\int_0^1 \|v_t\|_{\mu_t}^2 dt = \int_0^1 \mathbb{E} \|\dot{x}_t\|^2 dt \quad (\dot{x}_t = v_t(x_t))$$

$$\geq \mathbb{E} \left\| \int_0^1 \dot{x}_t dt \right\|^2 \quad (\text{equality if } t \mapsto \dot{x}_t \text{ is const.})$$

$$= \mathbb{E} \|x_1 - x_0\|^2$$

$$\geq W_2^2(\mu_0, \mu_1). \quad (\text{equality if } X_1 = \nabla\varphi(X_0)) \quad \square$$

Hence, we have obtained a Riemannian structure associated with the 2-Wasserstein distance.

$$\exp_\mu(\nabla\psi) = (\text{id} + \nabla\psi)_\# \mu$$

$$\log_\mu(v) = \nabla\varphi_{\mu \rightarrow v} - \text{id}$$

Now, let $F: P_{2,\text{ac}}(\mathbb{R}^d) \rightarrow \mathbb{R}$ be a functional. What is the gradient?

DEF. The first variation of F at μ is a function

$\delta F(\mu): \mathbb{R}^d \rightarrow \mathbb{R}$ s.t. for all X w/ $\int dX = 0$ and $\mu + \varepsilon X \in P(\mathbb{R}^d)$ for sufficiently small $\varepsilon > 0$,

$$\lim_{\varepsilon \downarrow 0} \frac{F(\mu + \varepsilon X) - F(\mu)}{\varepsilon} = \int \delta F(\mu) dX \quad (\text{defined up to an additive const.})$$

How to compute $\delta F(\mu)$: let $(\mu_t)_{t \in \mathbb{R}}$ be a curve, $\mu_0 = \mu$.

Compute $\partial_t F(\mu_t)$ and write it in the form

$$\partial_t F(\mu_t) \Big|_{t=0} = \int (\dots) \partial_t \mu_t \Big|_{t=0} \Rightarrow (\dots) = \delta F(\mu)$$

THM. The Wasserstein gradient $\nabla_{W_2} F(\mu)$ of F at μ is the vector field

$$\nabla_{W_2} F(\mu) = \nabla \delta F(\mu).$$

Proof. By defn., $\nabla_{W_2} F(\mu)$ satisfies:

- for $\partial_t \mu_t + \operatorname{div}(\mu_t \nabla \psi_t) = 0$,

$$\partial_t F(\mu_t) = \langle \nabla_{W_2} F(\mu_t), \nabla \psi_t \rangle_{\mu_t}.$$

- $\nabla_{W_2} F(\mu) \in T_\mu P_{2,\text{ac}}(\mathbb{R}^d) \Leftrightarrow \nabla_{W_2} F(\mu)$ is a grad. vector field.

Then, note that

$$\partial_t F(\mu_t) = \int \delta F(\mu_t) \partial_t \mu_t = - \int \delta F(\mu_t) \operatorname{div}(\mu_t \nabla \psi_t)$$

$$= \int \langle \nabla \delta F(\mu_t), \nabla \psi_t \rangle d\mu_t = \langle \nabla \delta F(\mu_t), \nabla \psi_t \rangle_{\mu_t}. \quad \square$$

COR. The Wasserstein gradient flow of F satisfies

$$\partial_t \mu_t = \operatorname{div}(\mu_t \nabla \delta F(\mu_t)) \Leftrightarrow \dot{x}_t = -\nabla \delta F(\mu_t)(x_t)$$