

Motivation (Jordan-Kinderlehrer-Otto 1998) . S. Mars 19/01/2014.

Concise b/w:

• 2-Wasserstein metric

$$W_2(\mu, \nu) = \inf_{\gamma} \left\{ \iint_{\mathbb{R}^n \times \mathbb{R}^n} |x-y|^2 d\gamma(x,y) : \begin{array}{l} \gamma(A \times \mathbb{R}^n) = \mu(A) \\ \gamma(\mathbb{R}^n \times B) = \nu(B) \end{array} \right\}.$$

• Boltzmann entropy for $\mu \in \mathcal{P}(\mathbb{R}^n)$.

$$H(\mu) = \begin{cases} \int \mu(dx) x \log \mu(dx) & \text{if } \mu \neq \delta_x \\ +\infty & \text{otherwise.} \end{cases}$$

I_h^h , the heat equation $\partial_t f = \Delta f$ in \mathbb{R}^n is the gradient flow of H w.r.t. to W_2 .

One interpretation: for $\mu \in \mathcal{P}(\mathbb{R}^n)$, define

$$\mathcal{J}_h \mu = \underset{\nu}{\operatorname{argmin}} \left\{ H(\nu) + \frac{1}{2h} W_2^2(\mu, \nu) \right\}.$$

Then, $\mu_t := \lim_{h \rightarrow 0} (\mathcal{J}_h)^n \mu$ exists and satisfies

$$\partial_t \mu_t = \Delta \mu_t, \quad \mu_{t=0} = \mu.$$

Point: It holds in very general metric ~~metric~~ ^{measure} spaces. (Ambrosio-Gigli-Savaré).

What about discrete spaces?

Example: $X = \{0, 1\}$, $P(x) = \{\mu_x = (1-\alpha)\delta_0 + \alpha\delta_1 : \alpha \in [0, 1]\}$.

Then. $W_2(\mu_\alpha, \mu_\beta) = \sqrt{|\alpha - \beta|}$. Thus, $(P(X), W_2) \cong ([0, 1], \sqrt{| \cdot - 1 |})$

Very bad metric space.

Now, let $f: [0, 1] \rightarrow \mathbb{R}$ smooth, endow $[0, 1]$ with

$d(x, y) = \sqrt{|x - y|}$. Then, try minimisation scheme:

$$\forall x \in [0, 1].$$

$$\underset{y}{\operatorname{arg\,min}} \{ f(y) + \frac{1}{2h} |x - y| \} \geq x.$$

If $h > 0$ is small. ~~for~~.

i.e., all gradient flows are just constant!

Discrete Setting

• X finite set.

• \mathcal{L} generator of continuous-time Markov chain.

$$\mathcal{L}_Q(u) = \sum_y Q(u, y) (\gamma(y) - \gamma(u)).$$

$$Q(u, y) \geq 0, \quad Q(u, x) = 0.$$

of discrete analogs
of heat kernel.

• \exists prob measure π on X s.t. $\forall u, y$.

$$\pi(u) Q(u, y) = \pi(y) Q(y, u). \quad (\text{detailed balance eq's}).$$

• Heat Semigroup $(e^{t\mathcal{L}})_{t \geq 0}$ is self-adjoint on $L^2(X, \pi)$.

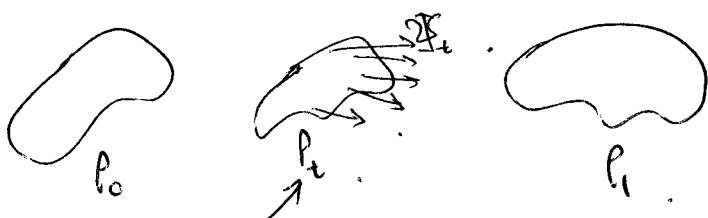
• Dirichlet energy $\mathcal{E}: L^2(\Omega, \alpha) \rightarrow \mathbb{R}$.

$$\mathcal{E}(u) = \frac{1}{2} \sum_{x,y} (u(x) - u(y))^2 w(x,y).$$

Exercise: the heat equation $\partial_t u = \Delta u$. is the gradient flow of \mathcal{E} w.r.t $L^2(\Omega, \alpha)$.

Back to \mathbb{R}^n : for $\rho_0(d\mathbf{x}) = \rho_0(\mathbf{x}) d\mathbf{x}$, $\rho_1(d\mathbf{x}) = \rho_1(\mathbf{x}) d\mathbf{x}$.

Brenier-Poincaré formula:



Follow entire trajectory.

but consider as a cloud of particles.
at set velocity vector \vec{F}_t

$$\text{Then, } W_2(P_0, P_1)^2 = \inf_{P, \vec{F}} \left\{ \int_{\mathbb{R}^n} \int_0^1 |\vec{F}_t|^2 dP_t(\mathbf{x}) dt : \right.$$

$$\left. \begin{aligned} \partial_t P + \operatorname{div}(P\vec{F}) &= 0, \\ P|_{t=0} &= P_0, \quad P|_{t=1} = P_1 \end{aligned} \right\}.$$

Use this as motivation for discrete case.

[N.b. At each t , \vec{F}_t s.t. $\vec{D}_t = \nabla^2 u_t$.]

Notation: • $\mathcal{E} = \{(u, v) \in X \times X : Q(u, v) > 0\}$.

• for function $u: X \rightarrow \mathbb{R}$, set (Gradient is vector,
so defined on
edges (u, v))

$$\nabla u(x, y) = u(y) - u(x).$$

• for vector fields $\vec{B}: \mathcal{E} \rightarrow \mathbb{R}$, set.

~~$$(\operatorname{div} \vec{B})(u) = \frac{1}{2} \sum_y ((\vec{B}(u, y) - \vec{B}(y, u))^T Q(u, y)).$$~~

$$\text{Also, } \langle \nabla \Phi, \Psi \rangle_{L^2(E, \omega)} = \langle \Phi, \operatorname{div} \Psi \rangle_{L^2(x, \pi)},$$

$$\text{and } \nabla \Psi = \operatorname{div} \nabla \Phi.$$

Need: How to multiply functions and vectorfields?



Fix $\Omega: \mathbb{R}_+ \times \mathbb{R}_+ \rightarrow \mathbb{R}_+$ smooth, symmetric. and $\Omega(s, t) > 0$ for $s, t > 0$.

For $p: x \rightarrow \mathbb{R}_+$, set $\hat{p}(x, y) = \Omega(p(x), p(y))$.

$$\mathcal{P}(x) = \{p: x \rightarrow \mathbb{R}_+ : \sum p(x) \pi(x) = 1\}.$$

Prop Let $p \in \mathcal{P}_{>0}(x) = \{p \in \mathcal{P}(x) : p > 0\}$. and

$(p_\epsilon)_{\epsilon \in (-\varepsilon, \varepsilon)}$ be smooth with $p_0 = p$. Then $\exists! \Psi: \varepsilon \rightarrow \mathbb{R}$.

s.t.

$$\cdot \nabla \Psi = \nabla \Phi \text{ for some } \Phi: x \rightarrow \mathbb{R}.$$

$$\cdot \dot{p}_0 + \nabla \cdot (\hat{p} \nabla \Psi) = 0. \quad (\text{continuity eq.})$$

Note: This depends on choice of Ω .

A Riemannian structure:

(I) for any probability density $P > 0$, identify tangent space at P with $\{\nabla \Phi: \Phi: x \rightarrow \mathbb{R}\}$. where differentiation given by continuity equation.

(II). For $p \in \mathcal{P}_0(x)$, define $\langle \nabla \Phi, \nabla \Psi \rangle_p := \langle \hat{p} \nabla \Phi, \nabla \Psi \rangle_{L^2(x, \mu)}$.

Note: The Riemannian distance is given by

$$d(p_0, p_1)^2 = \inf \left\{ \int_0^1 \langle \hat{p}_t \nabla \Phi_t, \nabla \Psi_t \rangle_{L^2(x, \mu)} dt \mid \begin{array}{l} \Phi_t \in \mathcal{P}_0(x) \\ \Phi_0 = P_0, \Phi_1 = P_1 \\ \dot{\Phi}_t + \nabla \cdot (\hat{p}_t \nabla \Phi_t) = 0 \end{array} \right\}.$$

$$\boxed{4}$$

Taylor gen.

Note: Typically, differentiation at $p \in P_0(X)$,

We find curv P and wh. a vector

$$\partial_t|_{t=0} p_t.$$

But continuity eqⁿ:

$$\partial_t p_t + \nabla \cdot (\hat{p}_t \nabla \varphi) = 0.$$

means that we can identify such ans with
 $\{\nabla \varphi\}$.

Note: $W(p_0, p_1)$ is not Wasserstein metric in discrete
setting.

Def: $H(p) = \sum_y p(y) \log p(y)$.

The: The heat eq. $\partial_t p = F_p$ is the ~~heat~~ gradient
flow equation of H w.r.t. W , provided that

$$O(s, t) = \int_0^1 s^{1-\alpha} t^\alpha d\alpha = \frac{s-t}{\log(s)-\log(t)}.$$

Pl. let (p_t) satisfy $\partial_t p_t + \nabla \cdot (\hat{p}_t \nabla \varphi) = 0$. Then,

$$\begin{aligned} \partial_t H(p_t) &= \langle 1 + \log p_t, \partial_t p_t \rangle_\pi = \langle 1 + \log p_t + \nabla \cdot (\hat{p}_t \nabla \varphi) \rangle_\pi \\ &= \langle \nabla \log p_t, \hat{p} \cdot \nabla \varphi \rangle_W. \end{aligned}$$

$$\Rightarrow \text{grad}_W H(p_t) = \nabla \log p_t.$$

Thus, the gradient flow of H is given by

$$\partial_t p_t - \nabla \cdot (\hat{p}_t \nabla \log p_t) = 0.$$

$$\text{Num: } \hat{p}(x,y) \nabla \log p(x,y) = o(p(x), p(y)) (\log p(x) - \log p(y)) = p(x) - p(y).$$

14

Exercise Show that the discrete porous medium equation

$\partial_t p = \Delta \psi(p)$, $\psi: \mathbb{R} \rightarrow \mathbb{R}$ measure
is the gradient flow of the functional

$$\tilde{F}(p) = \sum_n f(p(n)) \cdot \pi(n). \quad \text{w.r.t. } W.$$

$$\text{if } \theta(s,t) = \frac{\psi(s) - \psi(t)}{f'(s) - f'(t)}.$$

①