

Non-interacting particle systems and Wasserstein gradient flows

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Aim of the talk

the heat flow is the Wasserstein gradient flow of the entropy

- gradient flow
- Wasserstein
- convexity inequalities
- large deviations do a good job

References

- Jordan-Kinderlehrer-Otto, Otto, Otto-Villani, von Renesse-Sturm
- Ambrosio-Gigli-Savaré
- Adams-Dirr-Peletier-Zimmer
- joint work with J. Zimmer

Gradient flow in $\mathcal{X}$

- $\mathcal{X} = \mathbb{R}^n$

gradient flow equation

$$\begin{cases} \dot{\theta}_t &= -F'(\theta_t), & t \geq 0 \\ \theta_0 &= x_o \end{cases}$$

- hypothesis: F is K -convex $\iff F'' \geq K\text{Id}$, $K \in \mathbb{R}$
- semigroup: $\theta_t =: S_t(x_o)$, $t \geq 0$

- Lyapunov function: $\frac{d}{dt}F(\theta_t) = -I(\theta_t) \leq 0$, $I := |F'|^2$
- contraction: $|S_t(y) - S_t(x)| \leq e^{-Kt}|y - x|$, $\forall t, x, y$
- relaxation to equilibrium: $|S_t(x) - x_*| \leq e^{-Kt}|x - x_*|$, $\forall t, x$
 - ▶ $K > 0$
 - ▶ $F'(x_*) = 0$

Gradient flow in $\mathcal{X}$

F is K -convex

$$\iff t \in [0, 1] \mapsto F(\gamma_t^{xy}) \quad \text{is } K|y - x|^2\text{-convex}, \quad \forall x, y$$

$$\iff F'(x) \cdot (y - x) + \frac{K}{2}|y - x|^2 \leq F(y) - F(x), \quad \forall x, y$$

$$\iff \frac{d}{dt}\bigg|_{t=0} \frac{1}{2}|y - S_t(x)|^2 + \frac{K}{2}|y - x|^2 \leq F(y) - F(x), \quad \forall x, y$$

- geodesic: γ^{xy}
- recall: $\frac{d}{dt}\bigg|_{t=0} S_t(x) = -F'(x), \quad I := |F'|^2$

$$F(x) - F(y) \leq \sqrt{I(x)}|y - x| - K|y - x|^2/2, \quad \forall x, y$$

Gradient flow in $\mathcal{X}$

$$F(x) - F(y) \leq \sqrt{I(x)}|y - x| - K|y - x|^2/2, \quad \forall x, y$$

- equilibrium: $F'(x_*) = 0$, normalization: $F(x_*) = 0$

- $K|y - x_*|^2/2 \leq F(y), \quad \forall y$ (Talagrand)
- $F(x) \leq \sqrt{I(x)}|x - x_*| - K|x - x_*|^2/2, \quad \forall x$ (HWI)
- $F(x) \leq I(x)/(2K), \quad \forall x$ (log-Sobolev)

- relaxation to equilibrium: $|S_t(x) - x_*| \leq e^{-Kt}|x - x_*|, \quad \forall t, x$
- $t \mapsto F(S_t(x))$ decreases

$$\mathbb{R}^n \rightsquigarrow P(\mathcal{X})$$

- F : free energy, I : Fisher information
- $|\cdot| \rightsquigarrow W_2$: Wasserstein distance
- $(S_t)_{t \geq 0}$: Fokker-Planck semigroup
 - ▶ S is the W_2 -gradient flow of F

Gradient flow in $\mathcal{X}$

De Giorgi minimizing movement

- time step: $\tau > 0$
- $\xi_{k+1}^\tau = \operatorname{argmin} j^\tau(\xi_k^\tau, \cdot), \quad k \geq 0$
 - ▶ $j^\tau(x, y) := F(y) - F(x) + \tau^{-1}|y - x|^2/2$
- $\theta_t^\tau := \xi_{\tau \lfloor t/\tau \rfloor}^\tau, \quad t \geq 0, \quad \theta_0^\tau = \xi_0^\tau = x_o$

$$\lim_{\tau \downarrow 0} \theta_t^\tau = S_t(x_o), \quad t \geq 0$$

- hint: $\partial_y j^\tau(x, y) = 0 \iff (y - x)/\tau = -F'(y)$

Large deviations in $\mathcal{C}_{\mathcal{X}}$

- $\mathcal{C}_{\mathcal{X}} := C([0, \infty), \mathcal{X})$

$$\begin{cases} dX_t^\epsilon = -F'(X_t^\epsilon) dt + \sqrt{\epsilon} dW_t, & t \geq 0, \\ X_0^\epsilon = x_o \end{cases}$$

- almost sure limit: $\lim_{\epsilon \rightarrow 0} X^\epsilon = S(x_o)$

$$\mathbb{P}(X^\epsilon \in A) \underset{\epsilon \rightarrow 0}{\asymp} \exp(-\epsilon^{-1} \inf_A I), \quad A \subset \mathcal{C}_{\mathcal{X}}$$

- $I(\omega) = \iota_{\{\omega_0 = x_o\}} + \frac{1}{2} \int_{[0, \infty)} |\dot{\omega}_t + F'(\omega_t)|^2 dt$
- $\operatorname{argmin} I = S(x_o)$

Large deviations in $\mathcal{C}_{\mathcal{X}}$

- $\mathcal{X} = \mathbb{R}^n$
- time discretization: $X_t^{\epsilon, \tau} := X_{\lfloor t/\tau \rfloor \tau}^{\epsilon}, \quad t \geq 0$

$$\mathbb{P}(X^{\epsilon, \tau} \in \bullet) \underset{\epsilon \rightarrow 0}{\asymp} \exp \left(-\epsilon^{-1} \inf_{\bullet} I^{\tau} \right)$$

- $I^{\tau}(\eta) = \inf \{ I(\tilde{\eta}); \tilde{\eta}^{\tau} = \eta \}$
 $= \iota_{\{\eta \in \mathcal{C}_{\mathcal{X}}^{\tau, x_0}\}} + \sum_{k \geq 0} J^{\tau}(\eta_{k\tau}, \eta_{(k+1)\tau})$
- $J^{\tau}(x, y)$
 $= \inf \left\{ \frac{1}{2} \int_{[k\tau, (k+1)\tau]} |\dot{\eta}_t + F'(\eta_t)|^2 dt; \eta : \eta_{k\tau} = x, \eta_{(k+1)\tau} = y \right\}$
 $= F(y) - F(x) + \tau^{-1} C^{\tau}(x, y)$
- $C^{\tau}(x, y) = \inf \left\{ \frac{1}{2} \int_{[0,1]} |\dot{\omega}_s|^2 ds + \frac{\tau^2}{2} \int_{[0,1]} |F'(\omega_s)|^2 ds ; \omega \in \Omega^{xy} \right\}$
 - ▶ $\Omega^{xy} := \{ \omega \in C([0, 1], \mathcal{X}) : \omega_0 = x, \omega_1 = y \}$

Gradient flow in $\mathcal{X}$ revisited

$$C^\tau(x, y) = \inf \left\{ \frac{1}{2} \int_{[0,1]} |\dot{\omega}_s|^2 ds + \frac{\tau^2}{2} \int_{[0,1]} |F'(\omega_s)|^2 ds ; \omega \in \Omega^{xy} \right\}$$

- $C^{\tau=0}(x, y) = |y - x|^2/2$
- $j^\tau(x, y) = F(y) - F(x) + \tau^{-1} C^{\tau=0}(x, y)$
- $J^\tau(x, y) = F(y) - F(x) + \tau^{-1} C^\tau(x, y)$

LD minimizing movement

- $\xi_{k+1}^\tau = \operatorname{argmin} J^\tau(\xi_k^\tau, \cdot), \quad k \geq 0$
- $\theta_t^\tau := \xi_{\tau \lfloor t/\tau \rfloor}^\tau, \quad t \geq 0, \quad \theta_0^\tau = \xi_0^\tau = x_0$

$$\lim_{\tau \downarrow 0} \theta_t^\tau = S_t(x_0), \quad t \geq 0$$

- proof: $\Gamma\text{-}\lim_{\tau \downarrow 0} I^\tau = I$

Optimal transport

- $\mathcal{X} = \mathbb{R}^n, \quad \mathcal{Y} = M$
- $\mu_0, \mu_1 \in \mathcal{P}(\mathcal{X})$
- $\pi \in \Pi(\mu_0, \mu_1) \iff [\pi(dx \times \mathcal{Y}) = \mu_0(dx), \pi(\mathcal{X} \times dy) = \mu_1(dy)]$

Monge-Kantorovich problem

$$\inf_{\pi \in \Pi(\mu_0, \mu_1)} \int_{\mathcal{X}^2} d(x, y)^2 \pi(dxdy) =: W_2^2(\mu_0, \mu_1) \quad (1)$$

Benamou-Brenier formula

- $W_2^2(\mu_0, \mu_1) = \inf_{(\mu, \nabla \phi)} \int_{[0,1] \times \mathcal{X}} |\nabla \phi_t(x)|^2 \mu_t(dx) dt$
 - ▶ $\mu := (\mu_t)_{0 \leq t \leq 1}, \quad \mu_0, \mu_1 \text{ fixed}$
 - ▶ $\partial_t \mu + \nabla \cdot (\mu \nabla \phi) = 0$

Optimal transport

- $\Omega = C([0, 1], \mathcal{X}), \quad P \in \mathcal{P}(\Omega)$

$$\inf_{P: P_0=\mu_0, P_1=\mu_1} E_P \int_{[0,1]} |\dot{X}_t|^2 dt = W_2^2(\mu_0, \mu_1) \quad (2)$$

- $E_P \int_{[0,1] \times \mathcal{X}} |\dot{X}_t|^2 dt = \int_{\mathcal{X}^2} E_{P^{xy}} (\int_{[0,1] \times \mathcal{X}} |\dot{X}_t|^2 dt) P_{01}(dxdy)$
 $\geq \int_{\mathcal{X}^2} d(x, y)^2 P_{01}(dxdy)$
- $P \in \text{sol}(2) \iff \begin{cases} P(\cdot) = \int_{\mathcal{X}^2} \delta_{\gamma^{xy}}(\cdot) \pi(dxdy) \\ \pi \in \text{sol}(1) \end{cases}$
 $\iff \begin{cases} \ddot{X}_t = 0, & P\text{-a.s.} \\ P_{01} \in \text{sol}(1) \end{cases}$
- $\mu_t := P_t, \quad 0 \leq t \leq 1$ defines a *displacement interpolation*
 - ▶ natural candidate for a geodesic in $\mathcal{P}(\mathcal{X})$

Optimal transport

- $P \in \text{sol}(2)$, $\mu_t := P_t$
- P is Markov (uneasy)
 - ▶ hint: $v_t(X_t) = E_P(\dot{X}_t \mid X_t)$
 - ▶ $dX_t = v_t(X_t) dt$, P -a.s.
 - ▶ $\partial_t \mu + \nabla \cdot (\mu v) = 0$
 - ▶ no shock
- $v_t \in \overline{\{\nabla \phi\}}^{L^2(\mu_t)}$
 - ▶ $dX_t = \nabla \phi_t(X_t) dt$, P -a.s.
 - ▶ $\partial_t \mu + \nabla \cdot (\mu \nabla \phi) = 0$

Otto calculus

- $W_2^2(\mu_0, \mu_1) = \inf_{(\mu, \nabla \phi)} \int_{[0,1] \times \mathcal{X}} |\nabla \phi_t(x)|^2 \mu_t(dx) dt$
 - ▶ $\mu := (\mu_t)_{0 \leq t \leq 1}, \quad \mu_0, \mu_1 \text{ fixed}$
 - ▶ $\partial_t \mu + \nabla \cdot (\mu \nabla \phi) = 0$
- $d(x, y)^2 = \inf \left\{ \int_{[0,1]} |\dot{\omega}_t|_{\omega_t}^2 dt; \omega \in \Omega : \omega_0 = x, \omega_1 = y \right\}$
 - ▶ $\dot{\omega}_t \in T_{\omega_t} M$

Wasserstein metric (Otto)

- $\dot{\mu}_t := \nabla \phi_t, \quad \partial_t \mu + \nabla \cdot (\mu \dot{\mu}) = 0$
- $T_{\mu_t} P(\mathcal{X}) := \overline{\{\nabla \phi\}}^{L^2(\mu_t)}$
- $\dot{\alpha}_t = \nabla \phi_t, \dot{\beta}_t = \nabla \psi_t, \quad \left\langle \dot{\alpha}_t, \dot{\beta}_t \right\rangle_{\mu_t} := \int_{\mathcal{X}} \nabla \phi_t \cdot \nabla \psi_t d\mu_t$

W-gradient flow in $P(\mathcal{X})$

the heat flow is the Wasserstein gradient flow of the entropy

- heat equation: $\partial_t \mu = \Delta \mu$
- relative entropy: $H(\mu|m) := \int_{\mathcal{X}} \log(d\mu/dm) d\mu$
- entropy: $H(\mu) := H(\mu|\text{vol}) = \int_{\mathcal{X}} \mu \log \mu d\text{vol}$
- gradient flow: $\dot{\mu}_t = -\text{grad}_W H(\mu_t)$
- proof:
 - ▶ $\text{grad}_W H(\mu) = \nabla \log \mu$
 - ★ $\frac{d}{dt} H(\mu_t) = \int_{\mathcal{X}} \log \mu_t \partial_t \mu_t d\text{vol} = - \int_{\mathcal{X}} \log \mu_t \nabla \cdot (\mu_t \nabla \phi_t) d\text{vol}$
$$= \int_{\mathcal{X}} \nabla \log \mu_t \cdot \nabla \phi_t d\mu_t = \langle \nabla \log \mu_t, \dot{\mu}_t \rangle_{\mu_t}$$
 - ▶ $\dot{\mu}_t = -\text{grad}_W H(\mu_t)$
 - ★ $\dot{\mu}_t = -\nabla \log \mu_t$
 - ★ $0 = \partial_t \mu + \nabla \cdot (\mu \dot{\mu}) = \partial_t \mu - \nabla \cdot (\mu \nabla \log \mu) = \partial_t \mu - \Delta \mu$

W-gradient flow in $P(\mathcal{X})$

Fokker-Planck equation

$$\partial_t \mu - \nabla \cdot (\mu \nabla V / 2) = \Delta \mu / 2$$

- $\mu_t = e^{tL} \mu_0$, $L = [-\nabla V \cdot \nabla + \Delta] / 2$
- equilibrium: $m = e^{-V} \text{vol}$
- $R \in P(\mathcal{C}_{\mathcal{X}})$
 - ▶ $R_0 = m$
 - ▶ $dX_t = -\frac{1}{2} \nabla V(X_t) dt + dW_t^R$, R -a.s.
 - ▶ R is m -reversible
- $R_{\mu_0} := \int_{\mathcal{X}} R_x \mu_0(dx) \in P(\mathcal{C}_{\mathcal{X}})$
 - ▶ $\mu_t = (X_t)_{\#} R_{\mu_0}$

W -gradient flow in $P(\mathcal{X})$

- $F(\alpha) = H(\alpha|m)/2 = [H(\alpha) + \int_{\mathcal{X}} V d\alpha]/2$

$$J_{JKO}^{\tau}(\alpha, \beta) = F(\beta) - F(\alpha) + \tau^{-1} W_2^2(\alpha, \beta)/2$$

JKO minimizing movement

- $\xi_{k+1}^{\tau} = \operatorname{argmin} J_{JKO}^{\tau}(\xi_k^{\tau}, \cdot), \quad k \geq 0$
- $\mu_t^{\tau} = \xi_{\tau \lfloor t/\tau \rfloor}^{\tau}, \quad t \geq 0, \quad \mu_0^{\tau} = \xi_0^{\tau} = x_o$

JKO heuristic result

$$\lim_{\tau \downarrow 0} \mu^{\tau} = \mu$$

Large deviations in $\mathcal{C}_{\mathbb{P}(\mathcal{X})}$

- random dynamical particles: $Z^1, Z^2, \dots$ iid(R)
- empirical path measure: $\hat{Z}^N := \frac{1}{N} \sum_{1 \leq i \leq N} \delta_{Z^i} \in \mathbb{P}(\mathcal{C}\mathcal{X})$
- $\lim_{N \rightarrow \infty} \hat{Z}^N(0) = \mu_0, \quad \mathbb{P}\text{-a.s.}$

$$\mathbb{P}(\hat{Z}^N \in \bullet) \underset{N \rightarrow \infty}{\asymp} \exp \left(-N \inf_{P \in \bullet} [\ell_{\{P_0 = \mu_0\}} + H(P|R_{\mu_0})] \right)$$

Large deviations in $\mathcal{C}_{P(\mathcal{X})}$

- $\mathcal{C}_{P(\mathcal{X})} := C([0, \infty), P(\mathcal{X}))$
- empirical process: $Z^N = [t \in [0, \infty) \mapsto \bar{Z}^N(t)] \in \mathcal{C}_{P(\mathcal{X})}$

$$\mathbb{P}(\bar{Z}^N \in \bullet) \underset{N \rightarrow \infty}{\asymp} \exp\left(-N \inf_{\bullet} I\right)$$

- $I(\nu) = \iota_{\{\nu_0 = \mu_0\}} + \inf\{H(P|R_{\mu_0}); P \in P(\mathcal{C}_{\mathcal{X}}) : P_t = \nu_t, \forall t\}$
- $\operatorname{argmin} I = \mu$: solution of FP equation

Large deviations in $\mathcal{C}_{\mathbf{P}(\mathcal{X})}$

- $I(\nu) = \iota_{\{\nu_0=\mu_0\}} + \inf\{H(P|R_{\mu_0}); P \in \mathbf{P}(\mathcal{C}_{\mathcal{X}}) : P_t = \nu_t, \forall t\}$
- $\eta \in \mathcal{C}_{\mathcal{X}}, \quad \eta_t^\tau := \eta_{\tau \lfloor t/\tau \rfloor}$

$$\mathbb{P}(\bar{Z}^{N,\tau} \in \bullet) \underset{N \rightarrow \infty}{\asymp} \exp\left(-N \inf_{\bullet} I^\tau\right)$$

- $I^\tau(\nu) = \iota_{\mathcal{C}_{\nu_0}^\tau}(\nu) + \sum_{k \geq 0} J_{LD}^\tau(\nu_{k\tau}, \nu_{(k+1)\tau})$

$$J_{LD}^\tau(\alpha, \beta) = \inf\{H(\mathbf{p}|R_{[0,\tau]}); \mathbf{p} \in \mathbf{P}(\Omega^\tau) : \mathbf{p}_0 = \alpha, \mathbf{p}_\tau = \beta\} - H(\alpha|m)$$

$$\blacktriangleright \Omega^\tau = \mathcal{C}([0, \tau], \mathcal{X}), \quad R_{[0,\tau]} \in \mathbf{P}(\Omega^\tau)$$

LD gradient flow in $\mathcal{C}_P(\mathcal{X})$

- $\Gamma\text{-}\lim_{\tau \downarrow 0} I^\tau = I$
- $\mu^\tau := \operatorname{argmin} I^\tau$, μ : solution of FP equation

$$\lim_{\tau \downarrow 0} \mu^\tau = \mu$$

LD minimizing movement

- $\xi_{k+1}^\tau = \operatorname{argmin} J_{LD}^\tau(\xi_k^\tau, \cdot)$, $k \geq 0$
- $\mu_t^\tau = \xi_{\tau \lfloor t/\tau \rfloor}^\tau$, $t \geq 0$, $\mu_0^\tau = \xi_0^\tau = x_o$

LD gradient flow in $\mathcal{C}_P(\mathcal{X})$

heuristic result (JKO)

the FP flow is the W-gradient flow of the free energy

rigorous result

the FP flow is the LD-gradient flow of the free energy

LD gradient flow in $\mathcal{C}_P(\mathcal{X})$

$$J_{LD}^\tau(\alpha, \beta) = \inf\{H(p|R_{[0,\tau]}) ; p \in P(\Omega^\tau) : p_0 = \alpha, p_\tau = \beta\} - H(\alpha|m)$$

- Schrödinger problem

- time reversal, $\vec{v} = v^{\text{cu}} + v^{\text{os}}, \quad v^{\text{os}} = \nabla \log \sqrt{d\mu/d\text{vol}}$

- $H(p|R_{[0,\tau]}) - H(p_0|m)$

$$= E_p \int_{[0,\tau]} |\vec{v}_t|^2 / 2 \, dt$$

$$= [H(p_\tau|m) - H(p_0|m)]/2 + \underbrace{E_p \int_{[0,\tau]} |v_t^{\text{cu}}|^2 / 2 \, dt}_{O(\tau^{-1})} + \underbrace{E_p \int_{[0,\tau]} |v_t^{\text{os}}|^2 / 2 \, dt}_{O(\tau)}$$

$$J_{LD}^\tau(\alpha, \beta) = F(\beta) - F(\alpha) + \tau^{-1} W_2^2(\alpha, \beta)/2 + O(\tau)$$

- ▶ $F(\alpha) = H(\alpha|m)/2$
- ▶ $J_{JKO}^\tau(\alpha, \beta) = F(\beta) - F(\alpha) + \tau^{-1} W_2^2(\alpha, \beta)/2$

Perspectives

- numerical scheme: J_{LD}^τ is used in practice to compute J_{JKO}^τ
 - ▶ speedlight algorithm (Cuturi)
 - ▶ Mokaplan team (Benamou, Peyré, Brenier, Carlier, ...)
- gradient flows/curvature lower bound on graphs
- gradient flows related to nonlinear dissipative PDE's (biology?)
 - ▶ reaction-diffusion

happy birthday Sylvie