

Stein Operator

$$(\mathcal{J}_p f)(x) := \langle \nabla_x \log p(x), f(x) \rangle + \nabla_x \cdot f(x)$$

we know  $\mathbb{E}_p[\mathcal{J}_p f(x)] = \int \langle \nabla_x p, f \rangle + p \cdot \nabla_x \cdot f = \int \nabla \cdot (p f) = 0, \forall f$

$$\min_{\{x_i\}} KL[\{x_i\} \| p], \text{ given } p$$

$$x_i' \leftarrow x_i + \varepsilon \phi(x_i), \quad \phi = \underset{q \in \mathcal{G}}{\text{argmax}} \{ KL[q \| p] - KL[q_{\varepsilon \phi} \| p] \}$$

$$= \underset{q \in \mathcal{G}}{\text{argmax}} \left\{ - \frac{d}{d\varepsilon} KL[q_{\varepsilon \phi} \| p] \Big|_{\varepsilon=0} \right\}$$

$$\stackrel{\text{ex}}{=} \mathbb{E}_{x \sim q} [\mathcal{J}_p \phi(x)]$$

$q(x) = \frac{1}{n} \sum_{i=1}^n \delta(x - x_i)$  empirical dist. of  $x'$

Proof:

$$T(x) \stackrel{\Delta}{=} x + \varepsilon \phi(x)$$

$$KL[q_{\varepsilon T} \| p] = KL[q \| p_{\varepsilon T}] = \int q \cdot (\log q - \log p_{\varepsilon T}(x)) dx$$

$$\log p_{\varepsilon T}(x) = \log \det(I + \varepsilon \nabla \phi(x)) + \log p(x + \varepsilon \phi(x))$$

$$= \varepsilon \cdot \text{Tr}(\nabla \phi) + \log p(x) + \varepsilon \cdot \nabla \log p(x)^T \phi(x)$$

$$\Rightarrow \frac{d}{d\varepsilon} KL[q_{\varepsilon T} \| p] = \frac{d}{d\varepsilon} [- \int q(x) \log p_{\varepsilon T}(x) dx]$$

$$= - \int q(x) \cdot [\text{Tr}(\nabla \phi) + \nabla \log p(x)^T \phi(x)] dx$$

Functional derivative in RKHS

$$T(x) := x + f(x) \quad \langle \mathcal{J}_p k(x, \cdot), f(\cdot) \rangle$$

$$KL[q \| p_{\varepsilon T}] = \int q(x) \cdot [\log q(x) - \log p(x) - \langle \mathcal{J}_p f(x), \cdot \rangle] dx \quad (\text{when } f \neq 0)$$

$$\Rightarrow \delta_{f, \cdot} KL[q_{\varepsilon T} \| p] \Big|_{f=0} = - \int q(x) \mathcal{J}_p k(x, \cdot) dx = \phi_{q, p}^*$$

(kernelized) Stein Discrepancy

$$D_{\mathcal{G}}(p \| q) := \max_{\phi \in \mathcal{G}} \mathbb{E}_{x \sim q} [\mathcal{J}_p \phi(x)] \stackrel{\mathcal{G}=\mathcal{H}}{=} \max_{\phi \in \mathcal{H}} \{ \mathbb{E}_{x \sim q} \mathcal{J}_p \phi(x) \mid \|\phi\|_{\mathcal{H}} \leq 1 \}$$

$$\Rightarrow \phi^*(\cdot) \propto \mathbb{E}_{x \sim q} [\mathcal{J}_p k(x, \cdot)] \quad \mathbb{E}_{x \sim q} \langle k(x, \cdot), \mathcal{J}_p \phi(\cdot) \rangle_{\mathcal{H}}$$

$$\Rightarrow D_{\mathcal{G}}^2(p \| q) = \mathbb{E}_{x, x' \sim q} [\mathcal{J}_p^* \mathcal{J}_p^* k(x, x')] \quad \langle \mathbb{E}_{x \sim q} \mathcal{J}_p k(x, \cdot), \phi(\cdot) \rangle_{\mathcal{H}}$$

$$\Rightarrow D(\{x_i\} \| p) = \frac{1}{n(n-1)} \sum_{i \neq j} \mathcal{J}_p^* \mathcal{J}_p^* k(x_i, x_j) \quad (\langle k(x, \cdot), \phi(\cdot) \rangle = \phi(x))$$

Goodness of fit test:

whether  $D(\{x_i\} \| p) \geq \dots$

SVGD

$$x_j \leftarrow x_j + \varepsilon \cdot \mathbb{E}_{x \sim \{x_i\}_{i \neq j}} [\mathcal{J}_p k(x, x_j)]$$

$$= [\nabla \log p(x) \cdot k(x, x_j) + \nabla_x k(x, x_j)]$$

repulsive force

(MAP:  $x_j \leftarrow x_j + \varepsilon \nabla \log p(x_j)$ ) move to high  $p(x)$ , general case of MAP

de-Bruijn's Identity

$$\begin{aligned} \text{If } \phi_{q,p}(x) &:= \nabla_x \log \frac{p(x)}{q(x)}, \quad T(x) = x + \varepsilon \phi_{q,p}(x) \\ \frac{d}{d\varepsilon} K[\phi_{q,p}(\cdot)]|_{\varepsilon=0} &= -\mathbb{E}_{x \sim q} [\mathcal{J}_p \phi(x)] = -\int \frac{q}{p} \nabla(p\phi) = \int \nabla\left(\frac{q}{p}\right) \cdot p\phi \\ &= \int \frac{\nabla q \cdot p - q \nabla p}{p} \phi = \int q(\nabla \log q - \nabla \log p) \phi = -\mathbb{E}_{x \sim q} [\|\nabla \log \frac{p(x)}{q(x)}\|_2^2] \\ &\qquad\qquad\qquad \text{Fisher divergence} \end{aligned}$$

Fokker-Planck Eq. derivation

$$dx/dt = \phi(x) \Rightarrow \frac{dP(x)}{dt} = -\nabla \cdot (p(x)\phi(x)) \quad \hookrightarrow \neq dP(x)/dt$$

$$T(x) := x + \varepsilon \phi(x) \Rightarrow T^{-1}(x) = x - \varepsilon \phi(x) + o(\varepsilon)$$

$$\log \tilde{p}(x) = \log p(T^{-1}(x)) + \log \det(\nabla_x T^{-1}(x))$$

$$= \log p(x - \varepsilon \phi(x)) + \log \det(I - \varepsilon \nabla \phi(x)) + o(\varepsilon)$$

$$= \log p(x) - \varepsilon \nabla \log p^T \phi(x) - \varepsilon \text{Tr}(\nabla \phi) + o(\varepsilon)$$

$$\hookrightarrow -(\mathcal{J}_p \phi)(x)$$

$$\Rightarrow \frac{d}{dt} \log p_t(x) = -(\mathcal{J}_p \phi)(x)$$

$$\Rightarrow \frac{d}{dt} p_t(x) = -p(x) \cdot \mathcal{J}_p \phi(x) = -\nabla \cdot (p(x)\phi(x))$$

Regularized Stein Discrepancy

$$\text{RSD}(p||q; f) = \mathbb{D}(p||q; f) - \frac{1}{2} \|f\|_{L^2(q)}^2$$

$$= \mathbb{E}_q [\nabla \log p^T f + \text{div}(f)] - \frac{1}{2} \mathbb{E}_{x \sim q} [\|f(x)\|^2]$$

$$= \mathbb{E}_q [(\nabla \log \frac{p}{q})^T f] - \frac{1}{2} \mathbb{E}_q [\|f(x)\|^2]$$

$$\Rightarrow f^* = \nabla \log \frac{p}{q}$$

Gradient Flows

$$P_2(\mathcal{M}) = \{ \rho: \mathcal{M} \rightarrow \mathbb{R}_{\geq 0} \mid \int_{\mathcal{M}} \rho = 1, \int_{\mathcal{M}} |x|^2 \rho(x) dx < +\infty \}$$

$$D_{KL}(\rho, \pi) = \int_{\mathcal{M}} (\log \rho(x) - \log \pi(x)) \cdot \rho(x) dx$$

$$W_2^2(\mu, \nu) = \inf_{\rho \in \Pi(\mu, \nu)} \int |x - y|^2 d\rho(x, y)$$

SVGD

$$dx/dt = \int [k(x', x) \nabla_{x'} \log \pi(x') + \nabla_{x'} k(x', x)] \rho(x') dx'$$

Gradient Flows

$$= \int k(x', x) \nabla_{x'} \log \pi(x') \rho(x') dx' + \int \nabla_{x'} k(x', x) \rho(x') dx'$$

mean-field limits

$$\leftarrow - \int k(x', x) \nabla_{x'} \rho(x') dx'$$

$$= \int k(x', x) \nabla_{x'} [\log \pi(x') - \log \rho(x')] \rho(x') dx'$$

$$dx/dt = \mathbb{E}_{x' \sim \rho} [k(x', x) \nabla_{x'} (\log \pi(x') - \log \rho(x'))] = \mathcal{K}_\rho \nabla_x (\log \pi(x) - \log \rho(x))$$

$$(\mathcal{K}_\rho \phi)(x) := \mathbb{E}_{x' \sim \rho} [k(x', x) \phi(x')]$$

Liouville Eq.

$$\partial \rho(x) / \partial t = -\nabla \cdot [ \downarrow ]$$

$$= \nabla \cdot [ \int k(x', x) \nabla_{x'} \frac{\delta}{\delta \rho} D_{KL}(\rho, \pi) \rho(x') dx' ] = \nabla \cdot (\rho(x) \mathcal{K}_\rho \nabla_x \frac{\delta}{\delta \rho} D_{KL}(\rho, \pi))$$

只是把 KL 为 objective, 在 Wasserstein metric 下 的梯度流

$$? \quad \nabla_{\rho} D_{KL}(\rho, \pi)$$

Liouville Eq.

$$\partial \rho(x) / \partial t = \nabla \cdot [ \rho(x) \nabla \frac{\delta}{\delta \rho} D_{KL}(\rho, \pi) ] = \nabla \cdot [ \rho(x) \nabla (\log \rho(x) - \log \pi(x)) ]$$

$$= -\nabla \cdot [ \rho(x) \nabla \log \pi(x) ] + \nabla^2 \rho(x)$$

$$\rightarrow dx/dt = -\nabla \cdot [ \log \rho(x) - \log \pi(x) ]$$

$$\tilde{x}_i \leftarrow x_i - \varepsilon \cdot [ \nabla \log \rho(x_i) - \nabla \log \pi(x_i) ]$$

$$\rho(x) \approx \frac{1}{n} \sum_{i=1}^n k(x, x_i) \Rightarrow \nabla \log \rho(x) = \nabla \rho(x) / \rho(x) \approx \frac{\sum_i \nabla_x k(x, x_i)}{\sum_i k(x, x_i)}$$

mean-field

Wasserstein

dynamics

$W_2$  grad flow  $\partial_t \rho_t = \nabla \cdot (\rho_t \nabla_{W_2} F[\rho_t])$   $\nabla_{W_2} F[\rho] \stackrel{?}{=} \nabla \cdot \frac{\delta}{\delta \rho} F[\rho]$

continuity Eq.  $\partial_t \rho_t = \text{div}(\rho_t \frac{dx}{dt}) \Rightarrow \frac{dx}{dt} = -\nabla_{W_2} F[\rho_t]$

$\partial_t F[\rho_t] = \partial_t \rho_t \cdot \delta F[\rho_t] = \nabla \cdot (\rho_t \frac{dx}{dt}) \cdot \delta F[\rho_t] = \mathbb{E}_{\rho_t} [\langle \nabla_{W_2} F[\rho_t], \frac{dx}{dt} \rangle]$   
 $= -\mathbb{E}_{\rho_t} [\|\nabla_{W_2} F[\rho_t]\|^2]$

not sure 分步积分符号对上

f-divergence  $D_f [p||\pi] = \mathbb{E}_{\pi} [f(\rho/\pi)]$   
 $D_f [p + \epsilon u || \pi] - D_f [p || \pi] = \int \pi \cdot [f(\frac{\rho}{\pi} + \epsilon \frac{u}{\pi}) - f(\frac{\rho}{\pi})] \approx \int \pi \cdot f'(\frac{\rho}{\pi}) \cdot \frac{u}{\pi} \cdot \epsilon$   
 $\Rightarrow \frac{\delta}{\delta p} D_f [p || \pi] = f'(\rho/\pi)$   
 $\Rightarrow \nabla_{W_2} D_f [p || \pi] = \nabla \cdot \frac{\delta}{\delta p} D_f [p || \pi] = \nabla f'(\rho/\pi)$

KL:  $f(t) = t \log t, f'(t) = \log t + 1$   $\chi^2: f(t) = t^2, f'(t) = 2t$

结论:  $\nabla_{W_2} KL [p || \pi] = \nabla_x \log \frac{p}{\pi}$   $\nabla_{W_2} \chi^2 [p || \pi] = 2 \nabla (\frac{p}{\pi})$

We know SGD is kernelized KL grad flow

kernelized  $-\frac{dx}{dt} = \mathcal{K}_{\pi} \nabla_{W_2} \chi^2 [p || \pi] = \mathbb{E}_{x \sim \pi} [k(x, x') 2 \nabla (\frac{p(x')}{\pi(x')})]$   
 $\chi^2$  grad flow  $= 2 \int k(x, x') [\nabla p(x') - \nabla \log \pi(x') p(x')] dx'$   
 $= 2 \int k(x, x') \nabla \log \frac{p(x')}{\pi(x')} p(x') dx' = 2 \mathcal{K}_{\rho} \nabla_{W_2} KL [p || \pi]$

本质上是  $\int \pi \nabla (\frac{p}{\pi}) = \int p \nabla (\log \frac{p}{\pi})$