

f-div:  $D_f(P \parallel Q) = \int f(P/Q) Q dx$

$f: \mathbb{R}_+ \rightarrow \mathbb{R}$  convex  $\downarrow$

$f(x) = x \log x \quad \int \frac{P}{Q} \log \frac{P}{Q} \cdot Q = \int P \log \frac{P}{Q}$

$f(x) = -\log x \quad \Rightarrow \int Q \log \frac{Q}{P}$

$P_t = P * N(0, 2t) \quad , \quad Q_t = Q * N(0, 2t)$

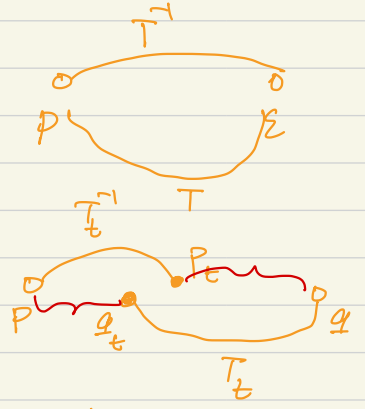
$\frac{d D_f(P_t \parallel Q_t)}{dt} = - \square$

$P \sim N(0, I) \quad , \quad Q \sim X_0$

$Q = T_{\#}^{-1} P \Leftrightarrow P = T_{\#} Q$

$P_t = (T_t^{-1})_{\#} P$

$Q_t = (T_t)_{\#} Q$



$\min_{T_t} KL(Q \parallel P_t) = KL(Q_t \parallel P)$   
 $\quad \quad \quad \underbrace{\quad}_{(T_t^{-1})_{\#} P} \quad \quad \quad \underbrace{\quad}_{(T_t)_{\#} Q}$   
 $\quad \quad \quad \text{apply } T_t \Rightarrow \quad \geq \quad \leq \quad \text{apply } T_t^{-1}$

$$KL(q \parallel P_t) = \int q(x) \log \frac{q(x)}{P_t(x)} dx = KL(q_t \parallel P)$$

$$= \int q_t(x) \log \frac{q_t(x)}{P(x)} dx$$

$$= \int q_t(T_t y) \log \frac{q_t(T_t y)}{P(T_t y)} dT_t y$$

$$\boxed{q_t(T_t y) \cdot |\det T_t'| = q(y)} \Rightarrow$$

$$= \int q(y) \log \frac{q_t(T_t y)}{P(T_t y)} dy$$

$$\frac{\delta KL}{\delta T} = \frac{d}{d\varepsilon} \int q(y) \log \frac{q_t((T+\varepsilon S)y)}{P((T+\varepsilon S)y)} dy \Big|_{\varepsilon=0}$$

$$= \int q(y) \nabla \log q_t(Ty) \cdot \frac{d(T+\varepsilon S)}{d\varepsilon} \Big|_{\varepsilon=0}$$

...

$$= \int q(y) \underbrace{[S_{q_t}(Ty) - S_P(Ty)]}_{\text{...}} \cdot \underbrace{S(y)}_{\text{...}} dy$$

$$\langle f, g \rangle \triangleq \int f(y) g(y) dy \quad \parallel \quad \frac{\delta KL}{\delta T}$$

$$\nabla f(x) =$$

$$= \nabla_i f(x)$$

$$\vec{x} \in \mathbb{R}^d$$

$$x: \{1, 2, \dots, d\} \rightarrow \mathbb{R}$$

$$x(1) = x_1$$

$$x(2) = x_2$$

$$\vdots$$

$$x(d) = x_d$$

$$\left. \frac{df(x + \varepsilon \cdot e_i)}{d\varepsilon} \right|_{\varepsilon=0} = \partial_i f(x)$$

$$= \langle \nabla f(x), e_i \rangle$$

$$\left. \frac{df(x + \varepsilon \cdot d)}{d\varepsilon} \right|_{\varepsilon=0} = \langle \nabla f(x), d \rangle$$

$$\parallel$$
$$\nabla f(x)^T d$$

$$\langle x, y \rangle_{(n)} = \sum x_i^T y_i$$

under  $\langle x, y \rangle_{(n)}$  we have  $\nabla_{(n)} f = \frac{1}{2} \nabla f(x)$

$$\begin{aligned} \nabla_{L_2} KL &= [S_{q_t}(T_t x) - S_p(T_t x)] q(x) \\ &= [S_{q_t}(T_t x) - S_p(T_t x)] \cdot q(T_t x) \cdot \cancel{[d(T_t x)]} \end{aligned}$$

$$\dot{T}_t = -b(T_t), \text{ where } b(z) = [S_{q_z}(z) - S_p(z)] q(z)$$

$$T_t(x; u)$$

Neural ODE (Chen et al '2018)

$$t \in [0, 1] \quad \dot{x}_t = \vec{f}(t, x_t, u) \quad x_0 \sim P_{\text{data}}$$

$$\partial_t P_t = -\nabla \cdot (P_t \vec{f})$$

discretize

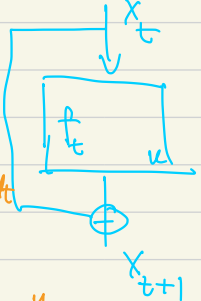
$$x_{t+1} = x_t + \vec{f}(x_t, u)$$

min  $u$

$$g(x_1)$$

$$L(t, x, u, \rho) = g(x_1) + \int_0^1 \langle \dot{x}_t - \vec{f}, \vec{p}(t) \rangle dt$$

$$\tilde{u} = u + \varepsilon \cdot v \quad \int_0^1 \langle \dot{x}_t, \vec{p}_t \rangle dt - \int_0^1 H(t, x_t, u, \rho) dt$$

$$\tilde{x} = x + \varepsilon \cdot y + o(\varepsilon)$$


$$\frac{dL(t, \tilde{x}, \tilde{u}, \tilde{\rho})}{d\varepsilon} \Big|_{\varepsilon=0} = \langle \nabla g(x_1), y_1 \rangle + \langle \rho, \theta_1 \rangle - \int_0^1 \langle x_t, \dot{p}_t \rangle dt$$

$$\frac{dL}{dt} \Big|_{t=0} = \underbrace{\langle \nabla g(x_1) + p_1, y_1 \rangle}_{=0} - \int_0^1 \underbrace{\langle \dot{p} + H_x, y \rangle}_{=0} + \langle H_u, v \rangle dt$$

$$\left\{ \begin{array}{l} \textcircled{2} \dot{p} = -H_x, \quad p_1 = -\nabla g(x_1) \\ \textcircled{1} \dot{x} = +H_p \\ p_u L = -\int_0^1 H_u dt = -\int_0^1 \nabla_u f \cdot p dt \end{array} \right.$$

$$\begin{aligned} \frac{d \log P_t(x_t)}{dt} &= \frac{1}{P_t(x_t)} \cdot \left[ \underbrace{\partial_t P_t + \partial_x P_t \cdot \underbrace{\dot{x}_t}_{\vec{f}_t}}_{\substack{-\nabla \cdot (P_t \vec{f}_t) \\ \parallel \\ -\cancel{\nabla_x P_t \vec{f}_t} - \cancel{P_t \nabla \cdot \vec{f}_t}} \right] \\ &= -\nabla \cdot \vec{f}_t \quad \vec{f}_t = \nabla \phi \end{aligned}$$

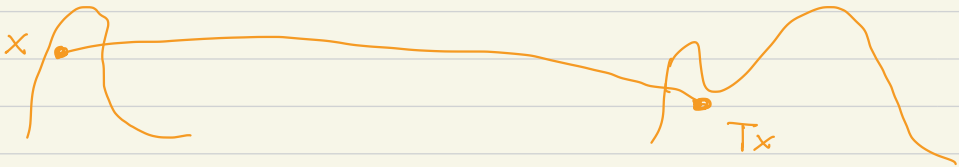
$$\left\{ \begin{array}{l} \dot{x}_t = \vec{f}_t \\ \log P_t(x_t) = -\nabla \cdot \vec{f}_t \end{array} \right.$$

$$\begin{aligned} \nabla \cdot \vec{f} &= \text{tr}(\nabla^2 \phi) \\ &\parallel = E[\sum_i \partial_i^2 \phi] \\ \begin{pmatrix} \partial_1 \\ \partial_2 \\ \vdots \\ \partial_d \end{pmatrix}^T \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_d \end{pmatrix} &= \sum_i \partial_i \frac{\partial \phi}{\partial x_i} \end{aligned}$$

$\rho_0, \rho_1$  two densities

$$W_2^2(\rho_0, \rho_1) = \min_T \mathbb{E} \|Tx - x\|_2^2, \quad T_{\#}\rho_0 = \rho_1$$

Brenier  $T = \nabla \Phi$ ,  $\Phi$  convex



$$f(x) = \sum_i \omega_i \sigma\left(\sum_j u_j^i x_j\right) \quad \omega \geq 0$$

$\downarrow$   
 $\int \rho du$

$$\dot{X}_t = \vec{b}_t(X_t)$$

$$\partial_t \rho_t = -\nabla \cdot (\rho_t \vec{b}_t)$$

$$\rho_0 = \rho_0, \quad \rho_1 = \rho_1$$

$$\begin{aligned} \int \int_0^1 \rho_t(x) \|\vec{b}_t(x)\|_2^2 dt dx &= \int \int_0^1 \|\vec{b}_t(X_t)\|_2^2 dt \cdot \rho_0(x) dx \\ &= \int \int_0^1 \|\dot{X}_t\|_2^2 dt \cdot \rho_0(x) dx \\ &\geq \int \|\int_0^1 \dot{X}_t\|_2^2 \rho_0(x) dx \\ &= \int \|x_1 - x_0\|_2^2 \rho_0(x) dx \geq W_2^2 \end{aligned}$$

$$W_2^2(p_0, p_1) = \min_{P_t, \vec{b}_t} \int \int_0^1 P_t(x) \|\dot{b}_t(x)\|_2^2 dt dx$$

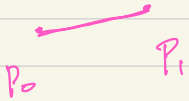


$$\partial_t P_t = -\nabla \cdot (P_t \vec{b}_t) \quad (2)$$

$$P_0 = p_0, P_1 = p_1 \quad (1)$$

$$= \min_{P_t(1)} \int_0^1 \left[ \min_{\vec{b}_t(2)} \int P_t \cdot \|\dot{b}_t\|_2^2 dx \right] dt$$

$f(b)$



$$\frac{df(b + \epsilon d)}{d\epsilon} \Big|_{\epsilon=0} = 2 \int \cancel{P_t} \cdot \left\langle \dot{b}_t, \cancel{\frac{d}{d\epsilon}} \right\rangle dx = 0$$

$b \perp Pd$

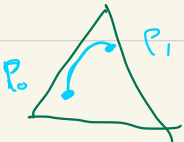
$$\cancel{\partial_t P_t} = -\nabla \cdot (P_t (b_t + \epsilon d_t)) = -\nabla \cdot (\cancel{P_t} b_t) - \epsilon \nabla \cdot (\cancel{P_t} d_t) = 0$$

Helmholtz decomposition  $\Rightarrow b = \nabla \varphi$

$$W_2^2 = \min_{P_t(1)} \int_0^1 \min \int P_t \cdot \|\nabla \varphi\|_2^2 dx dt$$

$\nabla \cdot (P \nabla \varphi) = 0$

$\|\partial_t P_t\|_{P_t}^2$



$$h_1, h_2: \mathbb{R}^d \rightarrow \mathbb{R}$$

$$Q_i: \mathbb{R}^d \rightarrow \mathbb{R}$$

Weinstein inner product

$$\langle h_1, h_2 \rangle_P = \int \langle \nabla \varphi_1(x), \nabla \varphi_2(x) \rangle P(x) dx$$

$$\boxed{\nabla \cdot (P \nabla \varphi_i) = -h_i}$$

$$f(p): \text{density} \rightarrow \mathbb{R}$$

$$\partial_t P(t, x) \Big|_{t=0}$$

$$\frac{df(P_t)}{dt} \Big|_{t=0} = \left\langle \nabla_{W_2} f(p), \frac{dP_t}{dt} \Big|_{t=0} \right\rangle_P$$

$$\boxed{\langle f, g \rangle_{L_2} = \int f(x) g(x) dx}$$

$$= \left\langle \nabla_{L_2} f(p), \underbrace{\frac{dP_t}{dt} \Big|_{t=0}}_{-\nabla \cdot (P \nabla \varphi_1)} \right\rangle_{L_2}$$

$h_1$

$$= \left\langle \nabla (\nabla_{L_2} f(p)), P \nabla \varphi \right\rangle_{L_2}$$

$$= \int \langle \nabla (\nabla_{L_2} f(p)), \nabla \varphi \rangle P(x) dx$$

$$\underbrace{\nabla_{W_2} f(p)}_{h_2} = -\nabla \cdot \left( P \nabla \underbrace{(\nabla_{L_2} f(p))}_{\varphi_2} \right)$$



$$f(p) = \int u(p(x)) dx, \quad u: \mathbb{R}_+ \rightarrow \mathbb{R}$$

$$= \int p(x) \log p(x) dx, \quad u(t) = t \log t$$

$$\frac{df(p + \varepsilon q)}{d\varepsilon} = \int u'(p(x)) \cdot q(x) dx$$

$$= \langle u'(p), q \rangle_{L_2}$$

$$\nabla_{L_2} f = u'(p)$$

$$\nabla_{u_2} f(p) = -\nabla \cdot (p \nabla (\nabla_{L_2} f))$$

$$= -\nabla \cdot (p u''(p) \cdot \nabla p)$$

$$\nabla_{u_2} f(p) = -\Delta p$$



$$q(x) \propto \exp(-\beta \cdot \varphi(x))$$

$$dx_t = -\nabla \varphi(x_t) dt + \sqrt{2\beta^{-1}} dB_t$$

$$\partial_t P = +\nabla \cdot (P \nabla \varphi(x_t)) + \frac{1}{2} \nabla^2 \cdot (P 2\beta^{-1} I)$$

$$= \nabla \cdot (P \nabla \varphi) + \beta^{-1} \Delta P$$

$$= \nabla \cdot (P (\nabla \varphi + \beta^{-1} S_P)) = 0$$

$$\nabla \log P = -\nabla (\beta^{-1} \varphi)$$

$$\Leftrightarrow P \propto e^{-\beta \varphi}$$

$$\frac{dP_t}{dt} = -\nabla_{w_2} KL(P_t \parallel q)$$

$$\frac{1}{2} \|P_t - q\|_1^2 \leq KL(P_t \parallel q) \leq e^{-\beta t} KL(P_0 \parallel q)$$

Pinsker