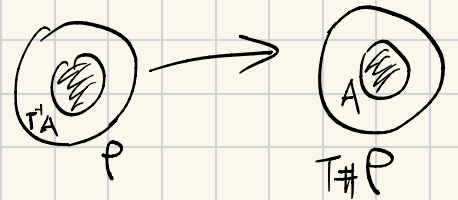


数学基础

邻域: $O_x^\varepsilon = \{y: d(x,y) < \varepsilon\}$



开集: U , $\forall x \in U$, $\exists \varepsilon$, $O_x^\varepsilon \subset U$

闭集: $U \Leftrightarrow X \setminus U$ 是开集

推前算子: $\int_{y \in A} T\#P(y) dy = \int_{T(x) \in A} P(x) dx$

变量替换

$$T\#P(T(x)) |T'(x)| = P(x)$$

$$P(x) dx = \tilde{P}(T(x)) dT(x)$$

概率测度空间的度量

搬运沙子

① 全变差距离

$P, P' \in C^0$

$$d_{TV}(P, P') = 0 \Leftrightarrow \|P - P'\|_{L^1} = 0 \Leftrightarrow P - P' = 0$$

$$d_{TV}(P, P') = d_{TV}(P', P)$$

$$d_{TV}(P_1, P_2) = \frac{1}{2} \int |P_1 - P_2| d\theta$$

$$= \frac{1}{2} \int |P_1 - P_3 + P_3 - P_2| d\theta$$

$$\leq \frac{1}{2} \int |P_1 - P_3| d\theta + \frac{1}{2} \int |P_3 - P_2| d\theta$$

② Hellinger 距离

$$d_H(P_1, P_2)^2 = \frac{1}{2} \int |\sqrt{P_1} - \sqrt{P_2}|^2 d\theta$$

$$= \frac{1}{2} \int |\sqrt{P_1} - \sqrt{P_3} + \sqrt{P_3} - \sqrt{P_2}|^2 d\theta$$

$$= \frac{1}{2} \int |\sqrt{P_1} - \sqrt{P_3}|^2 d\theta + \frac{1}{2} \int |\sqrt{P_3} - \sqrt{P_2}|^2 d\theta$$

$$+ \int |\sqrt{P_1} - \sqrt{P_3}| |\sqrt{P_3} - \sqrt{P_2}| d\theta$$

$$= d_H(p_1, p_3)^2 + d_H(p_3, p_2)^2 + \int |\sqrt{p_1} - \sqrt{p_3}| |\sqrt{p_3} - \sqrt{p_2}| d\theta$$

下证:

$$\int |\sqrt{p_1} - \sqrt{p_3}| |\sqrt{p_3} - \sqrt{p_2}| d\theta \leq 2 d_H(p_1, p_3) d_H(p_3, p_2)$$

使用 Cauchy 不等式

$$\int |f g| \leq \sqrt{\int f^2 d\theta} \sqrt{\int g^2 d\theta}$$

良定性:

$$d_{TV}(p, p') = \frac{1}{2} \int |p - p'| d\theta \leq \frac{1}{2} \left(\int |p| d\theta + \int |p'| d\theta \right) = 1$$

$$\begin{aligned} d_H(p, p') &= \left(\frac{1}{2} \int |\sqrt{p} - \sqrt{p'}|^2 d\theta \right)^{\frac{1}{2}} \\ &= \left(\frac{1}{2} \int p + p' - 2\sqrt{pp'} d\theta \right)^{\frac{1}{2}} \\ &\leq 1 \end{aligned}$$

为什么不用 L_2 距离?

等价性:

$$\frac{1}{\sqrt{2}} d_{TV}(p, p') = \frac{1}{\sqrt{2}} \int (\sqrt{p} + \sqrt{p'}) |\sqrt{p} - \sqrt{p'}| d\theta$$

$$\leq \frac{1}{2\sqrt{2}} \sqrt{\int (\sqrt{p} + \sqrt{p'})^2 d\theta} \int (\sqrt{p} - \sqrt{p'})^2 d\theta$$

$$\leq \frac{1}{2} \sqrt{4} d_H(p, p')$$

$$d_H(p, p')^2 = \frac{1}{2} \int |\sqrt{p} - \sqrt{p'}|^2 d\theta$$

$$d_{TV}(p, p') = \frac{1}{2} \int |p - p'| d\theta$$

$$\text{由于 } |\sqrt{p} - \sqrt{p'}|^2 \leq |\sqrt{p} - \sqrt{p'}| |\sqrt{p} + \sqrt{p'}|$$

$$= |p - p'|$$

其它估计

首先证明

$$\frac{1}{2} |E_p f - E_{p'} f| \leq d_{TV}(p, p')$$

$$\Leftrightarrow \left| \int f(p - p') d\theta \right| \leq \int |f| |p - p'| d\theta \quad (|f|_\infty \leq 1)$$

$$\leq \int |p - p'| d\theta$$

再证明

$$\sup_{|f|_\infty \leq 1} \frac{1}{2} |E_p f - E_{p'} f| \geq d_{TV}(p, p')$$

$$\text{取 } f = \text{sign}(p - p')$$

$$\begin{aligned}
|\mathbb{E}_e f - \mathbb{E}_{e'} f| &= \left| \int f(e - e') d\theta \right| \\
&\leq \int |f| |e - e'| d\theta \\
&\leq 2 \|f\|_\infty d_{TV}(e, e')
\end{aligned}$$

$$\begin{aligned}
|\mathbb{E}_e f - \mathbb{E}_{e'} f| &= \left| \int f(\sqrt{p} - \sqrt{p'}) (\sqrt{p} + \sqrt{p'}) d\theta \right| \\
&\leq \left(\int f^2 (\sqrt{p} + \sqrt{p'})^2 d\theta \int (\sqrt{p} - \sqrt{p'})^2 d\theta \right)^{\frac{1}{2}} \\
&\leq \left(\int f^2 (p + p') d\theta \cdot 2 \right)^{\frac{1}{2}} d_H(e, e')
\end{aligned}$$

最优传输问题

Kantorovich 问题, 有 $\gamma(\theta_1, \theta_2)$ 的沙子从 θ_1 运到 θ_2 .

Kantorovich 对偶, 引入拉格朗日乘子, f, g (离散)

$$\Phi(f, g) = \inf_{\gamma_{ij} \geq 0} \left\{ \sum_{ij} c_{ij} \gamma_{ij} + \sum_i f_i (a_i - \sum_j \gamma_{ij}) + \sum_j g_j (b_j - \sum_i \gamma_{ij}) \right\}$$

$$= \inf_{\gamma_{ij} \geq 0} \left\{ \sum_i f_i a_i + \sum_j g_j b_j + \sum_{ij} \gamma_{ij} (c_{ij} - f_i - g_j) \right\}$$

$$\textcircled{1} \text{ Kantorovich} = \inf_{\gamma_{ij} \geq 0, \sum_j \gamma_{ij} = a_i, \sum_i \gamma_{ij} = b_j} \left\{ \sum_i f_i a_i + \sum_j g_j b_j + \sum_{ij} \gamma_{ij} (c_{ij} - f_i - g_j) \right\} \geq \Phi(f, g)$$

$$\begin{aligned} \text{Kantorovich} &\geq \sup_{f, g} \Phi(f, g) = \sup_{f_i, g_j \leq c_{ij}} \Phi(f, g) \\ &= \sup_{f_i, g_j \leq c_{ij}} \left\{ \sum_i f_i a_i + \sum_j g_j b_j \right\} \end{aligned}$$

② 线性归化

$$\min \left\{ c^T x : Ax = b, x \geq 0 \right\}$$

$$\max \left\{ b^T y : A^T y \leq c \right\}$$

下面证明 Wasserstein - P 距离是距离

假设我们有 P_A, P_B, P_C

$$W_p(p_A, p_C) \leq W_p(p_A, p_B) + W_p(p_B, p_C)$$

那么有 $\gamma(x_A, x_B, x_C)$ 的边缘分布为 γ_{AB}^* γ_{BC}^*

$x_B \sim p_B$ $x_A \sim p(\cdot | x_B)$ 根据 γ_{AB}^*

再生成 $x_C \sim p(\cdot | x_B)$ 根据 γ_{BC}^*

$$\begin{aligned} W_p(p_A, p_C) &\leq \left(\int \|x_A - x_C\|_2^p \gamma(x_A, x_B, x_C) dx_A dx_B dx_C \right)^{\frac{1}{p}} \\ &\leq \left(\int \left[\|x_A - x_B\|_2 + \|x_B - x_C\|_2 \right]^p \gamma(x_A, x_B, x_C) \right)^{\frac{1}{p}} \\ &\leq W_p(p_A, p_B) + W_p(p_B, p_C) \end{aligned}$$

这里用了 $p \geq 1$

Minkowski 不等式

Holder 不等式 $\left(\int (\|f\|_2 + \|g\|_2)^p \gamma d\theta \right)^{\frac{1}{p}}$

$$\leq \left(\int \|f\|_2^p \gamma d\theta \right)^{\frac{1}{p}} + \left(\int \|g\|_2^p \gamma d\theta \right)^{\frac{1}{p}}$$

思考: $\begin{matrix} \frac{1}{2} & \frac{1}{2} \\ \cdot & \cdot \\ -1 & 0 \end{matrix} \Rightarrow \begin{matrix} \frac{1}{2} & \frac{1}{2} \\ \cdot & \cdot \\ 1 & 2 \end{matrix}$

$$w_1 = 2$$

$$w_2 = \sqrt{2^2 \cdot \left(\frac{1}{2} + \frac{1}{2}\right)} = 2$$

对 $c = \|\theta_1 - \theta_2\|_2$, 下界的证明

$$\sup_h \int (p_A(\theta) - p_B(\theta)) h(\theta) d\theta$$

$$\begin{aligned}
&= \sup_h \int \gamma(\theta_1, \theta_2) (h(\theta_2) - h(\theta_1)) d\theta_1 d\theta_2 \\
&\leq \sup_h \int \gamma(\theta_1, \theta_2) |h(\theta_2) - h(\theta_1)| d\theta_1 d\theta_2 \\
&\leq \sup_h \int \gamma(\theta_1, \theta_2) \|\theta_1 - \theta_2\|_2 d\theta_1 d\theta_2 \\
&\leq W_1(P_A, P_B)
\end{aligned}$$

上界的证明, 目标

$$\begin{aligned}
&\sup E_{P_A} f + E_{P_B} g \\
&f(\theta_1) + g(\theta_2) \leq \|\theta_1 - \theta_2\|_2 \\
&\leq \sup E_{P_A} h - E_{P_B} h \\
&\quad |h(\theta_1) - h(\theta_2)| \leq \|\theta_1 - \theta_2\|_2
\end{aligned}$$

构造

$$k(\theta) = \inf_u [\|\theta - u\|_2 - g(u)] \quad \text{由于 } f(\theta_1) + g(\theta_2) \leq \|\theta_1 - \theta_2\|_2$$

$$f(\theta_1) \leq \inf_{\theta_2} \|\theta_1 - \theta_2\|_2 - g(\theta_2) = k(\theta_1)$$

$$k(\theta_2) = \inf_{\theta_1} \|\theta_2 - \theta_1\|_2 - g(\theta_1)$$

$$\leq \|\theta_2 - \theta_2\|_2 - g(\theta_2) = -g(\theta_2)$$

我们还有

$$\sup_{f(\theta) + g(\theta) \leq \|\theta_1 - \theta_2\|_2} E_{P_A} f + E_{P_B} g$$

$$\leq E_{P_A} k - E_{P_B} k$$

下证 $|k(\theta_1) - k(\theta_2)| \leq \|\theta_1 - \theta_2\|_2$

$$k(\theta_1) = \inf_u \|\theta_1 - u\|_2 - g(u)$$

$$\leq \inf_u \|\theta_1 - u\|_2 - g(u)$$

$$\leq \inf_u \|\theta_1 - \theta_2\|_2 + \|\theta_2 - u\|_2 - g(u)$$

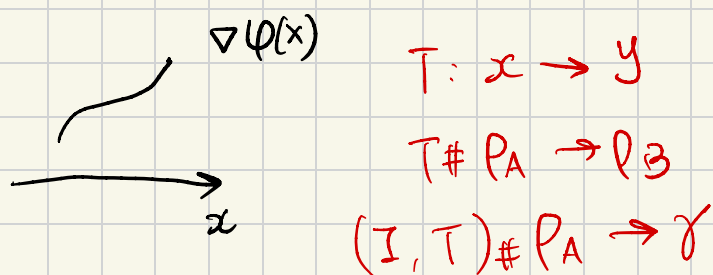
$$\leq \|\theta_1 - \theta_2\|_2 + k(\theta_2)$$

因此 $k(\theta_1) - k(\theta_2) \leq \|\theta_1 - \theta_2\|_2$

再由对称性可证。

$$(I \nabla \varphi): x \rightarrow (x, \nabla \varphi(x))$$

$$(I \nabla \varphi): P_A(x) \rightarrow \gamma(x, y)$$



Wasserstein 2 距离

测地线

$$T_0: (\theta_1, \theta_2) \rightarrow \theta_1, \quad T_0 \# \gamma^*(A) = \gamma^*(T_0^{-1}(A)) \\ = \gamma^*(\theta_1 \in A) = \rho_A$$

同理 $T_1 \# \gamma^* = \rho_B$

下证 $W_2(\rho_s, \rho_t) \leq (t-s) W_2(\rho_A, \rho_B) (s \leq t)$

定义 $\gamma_{s,t}^* = (T_s, T_t) \# \gamma^*$

$$(\theta_1, \theta_2) \rightarrow ((1-s)\theta_1 + s\theta_2, (1-t)\theta_1 + t\theta_2)$$

验证是
耦合

$$\begin{aligned} \iint_{(\theta_1, \theta_2) \in (A, \mathbb{R}^d)} \gamma_{s,t}^*(\theta_1, \theta_2) d\theta_2 &= \int_{(\theta_1, \theta_2) \in (A, \mathbb{R}^d)} \gamma_{s,t}^*(\theta_1, \theta_2) d\theta_1 d\theta_2 \\ &= \int_{\substack{[(1-s)x_1 + s x_2, \\ (1-t)x_1 + t x_2] \in (A, \mathbb{R}^d)}} \gamma^*(x_1, x_2) dx_1 dx_2 \\ &= \int_{\substack{(1-s)x_1 + s x_2 \in A \\ (1-t)x_1 + t x_2 \in \mathbb{R}^d}} \gamma^*(x_1, x_2) dx_1 dx_2 \end{aligned}$$

$$\int_{\theta_1 \in A} \rho_s(\theta_1) d\theta_1 = \int_{(1-s)\theta_1 + s\theta_2 \in A} \gamma^*(\theta_1, \theta_2) d\theta_2 d\theta_1$$

$$W_2(P_s, P_t)^2 \leq \int \|\theta_1 - \theta_2\|^2 \gamma_{s,t}^*(\theta_1, \theta_2) d\theta_1 d\theta_2$$

$$\text{换元} \quad = \int \|\mathbb{T}_s(\theta_1, \theta_2) - \mathbb{T}_t(\theta_1, \theta_2)\|^2 \gamma^*(\theta_1, \theta_2) d\theta_1 d\theta_2$$

$$= (s-t)^2 \int \|\theta_1 - \theta_2\|^2 \gamma^*(\theta_1, \theta_2) d\theta_1 d\theta_2$$

$$= (s-t)^2 W_2(P_A, P_B)$$

因此

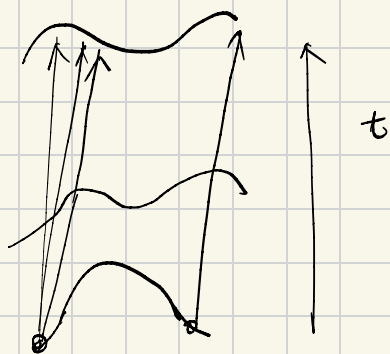
$$W_2(P_A, P_B) \leq W_2(P_A, P_s) + W_2(P_s, P_t) + W_2(P_t, P_B)$$

$$\leq s W_2(P_A, P_B) + (t-s) W_2(P_A, P_B) + (1-t) W_2(P_A, P_B)$$

$$= W_2(P_A, P_B)$$

所以全部取等

这对于 W_p 距离也成立。



动力学观点

两点之间的距离

$$X(s) = (1-s)x_0 + s x_1 \quad \text{满足}$$

$$\inf_X \int_0^1 X'(s)^2 ds \quad (\text{能量最小})$$

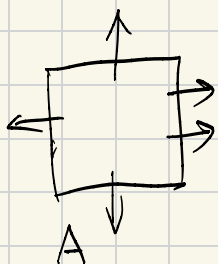
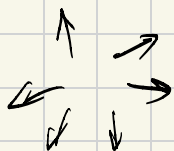
每一项放缩

$$\int_0^1 X'(s)^2 ds \int_0^1 1 ds \geq \sum_i \left(\int_0^1 X'_i(s) ds \right)^2$$
$$= \|x_1 - x_0\|_2^2$$

$$\int_0^1 (X'(s))^2 ds \geq \|x_1 - x_0\|_2^2$$

两个概率密度之间，有速度场 v_t

粒子随着 v_t 演化， p_t 也随之演化



$$\frac{\partial}{\partial t} \int_A p_t(\theta) d\theta = - \int_{\partial A} p_t v \cdot n d\theta$$
$$= - \int_{\Omega} \nabla p_t \cdot v_t d\theta$$

$$\Rightarrow \partial_t p_t + \nabla_{\theta} (p_t v_t) = 0$$

定义 $T_t: \mathbb{R}^d \rightarrow \mathbb{R}^d$ 满足

$$\partial_t T_t(\theta) = v_t(T_t(\theta)), \quad T_0(\theta) = \theta$$

那么 $p_t = T_t \# p_0$, 在时刻 t , 粒子

从 $\theta \rightarrow T_t(\theta)$

因为粒子 $T_t(\theta)$ 下一时刻 $T_{t+\Delta t}(\theta)$

速度为 $v_t(T_t(\theta))$

$$p_0(\theta) d\theta = p_t(T_t(\theta)) dT_t(\theta)$$

给定 v_t , 在时间 0 到 1 , 把 $p_0 = p_A$ 演化到 $p_1 = p_B$, 定义能量

$$A(p, v) = \int_0^1 \int \|v_t\|_2^2 p_t d\theta dt$$

$$\textcircled{1} \text{ 我们有 } = \int_0^1 \int \|v_t(T_t(\theta))\|_2^2 p_t(T_t(\theta)) dT_t(\theta) dt$$

$$= \int_0^1 \int \left\| \frac{\partial}{\partial t} T_t(\theta) \right\|_2^2 p_0(\theta) d\theta dt$$

$$\text{由于 } \int_0^1 \left\| \frac{\partial}{\partial t} T_t(\theta) \right\|_2^2 dt \geq \int_0^1 dt$$

$$\text{每一项放缩} \geq \left(\int_0^1 \frac{\partial}{\partial t} T_t(\theta) dt \right)^2 = \|T_1(\theta) - T_0(\theta)\|_2^2$$

$$\geq \int \|T_1(\theta) - T_0(\theta)\|_2^2 p_0(\theta) d\theta$$

$$\geq W_2^2(p_A, p_B)$$

② 另一方面，如果有最优映射 T ，定义
 $T_t(\theta) = (1-t)\theta + tT(\theta)$ ($T = \nabla\psi$)

$$\begin{aligned} \text{定义 } V_t &= \frac{d}{dt} T_t(\theta) \circ T_t^{-1}(\theta) \\ &= (T - \text{Id}) \circ T_t^{-1} \end{aligned}$$

我们有 $\frac{d}{dt} T_t(\theta) = V_t(T_t(\theta))$ ， p_t, V_t
满足连续性方程，且

$$\begin{aligned} A(p, \nu) &= \int_0^1 \int \| \frac{d}{dt} T_t(\theta) \|_2^2 p_0(\theta) d\theta dt \\ &= \int \| T(\theta) - \theta \|_2^2 p_0(\theta) d\theta \\ &= W_2^2(p_A, p_B) \end{aligned}$$

KL 散度 $p^* = \frac{1}{Z} e^{-\Phi_R(\theta)}$

$$\begin{aligned} \text{KL}[p \parallel p^*] &= \int p \log \frac{p}{e^{-\Phi_R}} + p \log Z d\theta \\ &= \int p \log p + p \log \Phi_R d\theta + \log Z \end{aligned}$$

KL 散度的强凸性

$$(1-t) \text{KL}[p_0 \| p^*] + t \text{KL}[p_1 \| p^*] - \text{KL}[(1-t)p_0 + tp_1 \| p^*] \\ \geq \frac{(1-t)t}{2} \|p_0 - p_1\|_1^2$$

$$\text{KL}[p \| p^*] = \int p^* f\left(\frac{p}{p^*}\right) d\theta$$

$$f(x) = x \ln x$$

$$f'(x) = \ln x + 1$$

$$f''(x) = \frac{1}{x}$$

定义

$$x_t = \frac{p_t}{p^*} = \frac{(1-t)p_0 + tp_1}{p^*}$$

$$a_i(\eta) = f((1-\eta)x_t + \eta x_i)$$

$$a_i(\eta) = a_i(0) + a_i'(0)\eta + \int_0^\eta a_i''(\tau)(\eta-\tau) d\tau$$

$$\eta = 1$$

\Rightarrow

$$f(x_i) = f(x_t) + f'(x_t)(x_i - x_t) + (x_i - x_t)^2 \int_0^1 f''((1-\tau)x_t + \tau x_i) (1-\tau) d\tau$$

$$(1-t)f(x_0) + tf(x_1)$$

$$= f(x_t) + (1-t)(x_0 - x_t)^2 \int_0^1 f''((1-\tau)x_t + \tau x_0) (1-\tau) d\tau \\ + t(x_1 - x_t)^2 \int_0^1 f''((1-\tau)x_t + \tau x_1) (1-\tau) d\tau$$

$$= f(x_t) + (1-t)t (x_0 - x_1)^2 \int_0^1 \left(\frac{t}{(1-\tau)x_t + \tau x_0} + \frac{1-t}{(1-\tau)x_t + \tau x_1} \right) (1-\tau) d\tau$$

Titik

$$\int (p_0 - p_1)^2 \int_0^1 \left(\frac{t}{(1-\tau)p_t + \tau p_0} + \frac{1-t}{(1-\tau)p_t + \tau p_1} \right) (1-\tau) d\tau$$

$$= \int_0^1 (1-\tau) d\tau \int \frac{t(p_0 - p_1)^2}{(1-\tau)p_t + \tau p_0} + \frac{(1-t)(p_0 - p_1)^2}{(1-\tau)p_t + \tau p_1} d\theta$$

$$\geq \int_0^1 (1-\tau) d\tau \left[t \left(\int |p_0 - p_1| d\theta \right)^2 \right.$$

$$\left. + (1-t) \left(\int |p_0 - p_1| d\theta \right)^2 \right]$$

$$= \frac{1}{2} \left(\int |p_0 - p_1| d\theta \right)^2$$

随机过程:

$$E dB_t = E (B_{t+dt} - B_t) = 0$$

$$E dB_t^2 = E (B_{t+dt} - B_t) (B_{t+dt} - B_t) \approx dt$$

Ito 公式

$$dX_t = \partial_t f(t, \theta_t) dt + \nabla_{\theta} f(t, \theta_t) d\theta_t$$

$$+ \frac{1}{2} \nabla_{\theta} \nabla_{\theta} f(t, \theta_t) d\theta_t \cdot d\theta_t$$

$$= \partial_t f(t, \theta_t) dt + \nabla_{\theta} f(t, \theta_t) (b_t dt + \beta_t dB_t)$$

$$+ \frac{1}{2} (G_t dB_t)^T \nabla_{\theta}^2 f(t, \theta_t) (\beta_t dB_t)$$

$$= \partial_t f(t, \theta_t) dt + \nabla_{\theta} f(t, \theta_t) b_t \cdot dt + \nabla_{\theta} f(t, \theta_t) \beta_t dB_t$$

$$+ \frac{1}{2} dB_t^T \beta_t^T \nabla_{\theta}^2 f(t, \theta_t) \beta_t dB_t$$

$$\frac{1}{2} \nabla_{\theta}^2 f(t, \theta_t) (\beta_t dB_t + dB_t^T \beta_t^T)$$

$$dB_t \cdot dB_t^T \approx dt I$$

Fokker Planck 方程

$$d f(\theta_t) = \nabla_{\theta} f(\theta_t) b_t dt + \frac{1}{2} \nabla_{\theta}^2 f(\theta_t) : \delta_t \delta_t^T dt + \nabla_{\theta} f(\theta_t)^T \delta_t dB_t$$

$$\mathbb{E} f(\theta_t) = \int f(\theta) p_t(\theta) d\theta$$

$$= \int f(\theta_t) p_t(\theta) d\theta \quad \theta_t = \theta_t(\theta)$$

$$\partial_t \mathbb{E} f(\theta_t) = \mathbb{E} \left[\nabla_{\theta} f(\theta_t) b_t + \frac{1}{2} \nabla_{\theta}^2 f(\theta_t) : \delta_t \delta_t^T \right]$$

$$= \int p_t \left(\nabla_{\theta} f(\theta) b_t + \frac{1}{2} \nabla_{\theta}^2 f(\theta) : \delta_t \delta_t^T \right) d\theta$$

$$= - \int f(\theta) \nabla_{\theta} (p_t b_t) d\theta + \int \partial_{ij} f(\theta) p_t(\theta) D_{ij} d\theta$$

$$= - \int f(\theta) \nabla_{\theta} (p_t b_t) d\theta + \int f(\theta) \partial_{ij} (p_t(\theta) D_{ij}) d\theta$$

$$\Rightarrow \frac{\partial}{\partial t} p_t(\theta) = - \nabla_{\theta} (p_t b_t) + \sum \partial_{ij} (p_t D_{ij})$$

带约束问题

$$\min f(x)$$

$$g(x) = 0$$

$$h(x) \leq 0$$

(P)

拉格朗日乘子

(Q)

$$L(x, \lambda_g, \lambda_h) = f(x) + \lambda_g g(x) + \lambda_h h(x)$$

$$\max_{\lambda_g, \lambda_h} \min_x L(x, \lambda_g, \lambda_h)$$

$$\lambda_h \geq 0$$

$$\lambda_h \geq 0$$

① 对于 P 的极小 x^*

$$f(x^*) \geq \min_{\substack{g(x)=0 \\ h(x) \leq 0 \\ \lambda_h \geq 0}} L(x, \lambda_g, \lambda_h)$$

$$\text{因为 } f(x^*) \geq \min_{\lambda_h \geq 0} L(x^*, \lambda_g, \lambda_h)$$

② 如果 P 是凸问题，那么两个问题极值相等

下面有KKT条件

$$\partial_x L(x^*, \lambda_g^*, \lambda_h^*) = 0$$

$$g(x^*) = 0$$

$$h(x^*) \geq 0$$

$$\lambda_h^* h(x^*) = 0 \quad \lambda_h^* \geq 0$$

KKT是充分条件 $\Rightarrow P$

KKT是必要条件(如果P是凸) $\Leftarrow P$

因此 x^* 满足问题 1 的条件,

$$L_1 \leq L_2$$

② 接下来我们考虑问题 2 的解

$$\text{满足 } \nabla_x f(x) - \lambda_g \nabla_x g(x) - \lambda_h \nabla_x h(x) = 0$$

$$g(x) = 0$$

$$h(x) \geq 0$$

是一个鞍点