

上节课两道题.

$$\textcircled{1} \max -b^T v - \lambda_1^T u + \lambda_2^T c.$$

$$\text{s.t. } A^T v + \lambda_1 - \lambda_2 + c = 0.$$

$$\lambda_1 \geq 0, \lambda_2 \geq 0.$$

$$\max -v^T b + \underbrace{c^T (A^T v + c)^+}_{\lambda_2} - \underbrace{u^T (A^T v + c)^-}_{\lambda_1}$$

$$\Leftrightarrow \max -v^T b + c^T \lambda_2 - u^T \lambda_1.$$

$$\text{s.t. } \left. \begin{array}{l} \lambda_2 = (A^T v + c)^+ \\ \lambda_1 = (A^T v + c)^- \end{array} \right\} \rightarrow \left\{ \begin{array}{l} \lambda_1 \geq 0, \lambda_2 \geq 0. \\ \lambda_2 - \lambda_1 = A^T v + c \end{array} \right.$$

②. 若 $g(x, u, w)$ 为凸, 则 $p(u, w) = \inf_x g(x, u, w)$ 为凸.

$$\forall \theta \in (0, 1), \inf_{x_1, x_2} (\theta g(x_1, u_1, w_1) + (1-\theta) g(x_2, u_2, w_2))$$

$$\geq \inf_{x_1, x_2} g(\theta x_1 + (1-\theta)x_2, \theta u_1 + (1-\theta)u_2, \theta w_1 + (1-\theta)w_2).$$

$$\theta p(u_1, w_1) + (1-\theta)p(u_2, w_2) \geq p(\theta u_1 + (1-\theta)u_2, \theta w_1 + (1-\theta)w_2). \text{ 凸函数.}$$

函数性质的分析 $f(x)$.

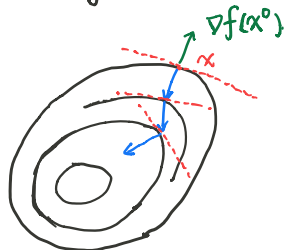
$$\text{强凸性: } \exists m, \forall x \in \text{dom} f, \nabla^2 f(x) \succeq mI.$$

$$\Leftrightarrow \forall x, y \in \text{dom} f, f(y) \geq f(x) + \nabla f(x)^T (y-x) + \frac{1}{2} m \|y-x\|_2^2.$$

$$\text{相应的, } \exists M, \forall x \in \text{dom} f, \nabla^2 f(x) \preceq MI.$$

$$\Leftrightarrow \forall x, y \in \text{dom} f, f(y) \leq f(x) + \nabla f(x)^T (y-x) + \frac{1}{2} M \|y-x\|_2^2.$$

梯度下降法. gradient decent.



$$d^k = -\nabla f(x^k)$$

分析算法的收敛性. $\forall x \in \text{dom} f, MI \succeq \nabla^2 f(x) \succeq mI.$

1) exact line search.

$$\tilde{f}(\alpha) = f(x^k + \alpha d^k) = f(x^k - \alpha \nabla f(x^k)).$$

$$\Downarrow x^{k+1}.$$

$$\underbrace{f(x^{k+1})}_y \leq \underbrace{f(x^k)}_x + \nabla f^T(x^k) (-\alpha \nabla f(x^k)) + \frac{M}{2} \|\alpha \nabla f(x^k)\|_2^2$$

$$\Leftrightarrow \tilde{f}(\alpha) \leq f(x^k) - \alpha \|\nabla f(x^k)\|_2^2 + \frac{M}{2} \alpha^2 \|\nabla f(x^k)\|_2^2.$$

$$-\|\nabla f(x^k)\|_2^2 + M\alpha \|\nabla f(x^k)\|_2^2 = 0. \Rightarrow \alpha = \frac{1}{M}$$

$$\min_{\alpha} \tilde{f}(\alpha) \leq f(x^k) - \frac{1}{M} \|\nabla f(x^k)\|_2^2 + \frac{1}{2M} \|\nabla f(x^k)\|_2^2$$

$$\begin{cases} f(x^{k+1}) \leq f(x^k) - \frac{1}{2M} \|\nabla f(x^k)\|_2^2. \\ p^* \geq f(x^k) - \frac{1}{2m} \|\nabla f(x^k)\|_2^2 \end{cases}$$

$$\frac{1}{2M} \|\nabla f(x^k)\|_2^2 + \underbrace{f(x^{k+1}) - p^*}_{\geq 0} \leq \underbrace{f(x^k) - p^*}_{\geq 0} \quad \times M$$

$$-\frac{1}{2m} \|\nabla f(x^k)\|_2^2 + \underbrace{f(x^k) - p^*}_{\geq 0} \leq 0. \quad \times m.$$

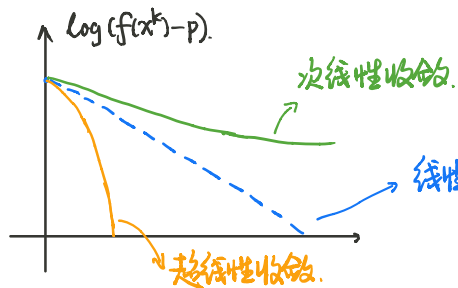
$$M(f(x^{k+1}) - p^*) + m(f(x^k) - p^*) \leq M(f(x^k) - p^*).$$

$$\Leftrightarrow \underbrace{(f(x^{k+1}) - p^*)}_{\geq 0} \leq (1 - \frac{m}{M}) \underbrace{(f(x^k) - p^*)}_{\geq 0}. \quad \text{越来越接近最优值.}$$

$$\left\| \frac{f(x^{k+1}) - p^*}{f(x^k) - p^*} \right\| \leq \left\| 1 - \frac{m}{M} \right\|.$$

given ε , 何时 $\left\| \frac{f(x^{k+1}) - p^*}{f(x^k) - p^*} \right\| \leq \varepsilon$ (经过 τ 步, 十分接近最优解).

$$(1 - \frac{m}{M})^\tau = \varepsilon. \Rightarrow \tau = \frac{\log \varepsilon}{\log(1 - \frac{m}{M})} \approx \frac{m}{M}.$$



$6 \rightarrow 5 \rightarrow 4 \rightarrow 3 \rightarrow \dots$ 不是线性收敛.

$6 \rightarrow 6 \times 0.9 \rightarrow 6 \times 0.9^2 \rightarrow \dots$ 线性收敛

2). Inexact line search (Armijo Rule).

当 $0 \leq \alpha \leq \frac{1}{m}$ 时, 迭代必然停止.

$$\tilde{f}(\alpha) = f(x^{k+1}) \leq f(x^k) + r\alpha \cdot \nabla f^T(x^k) d^k \text{ 时接受 } \alpha.$$

当 $0 \leq \alpha \leq \frac{1}{M}$ 时, 必有 $(-\alpha + \frac{M\alpha^2}{2}) \leq -\frac{\alpha}{2}$

$$\tilde{f}(\alpha) = f(x^{k+1}) \leq f(x^k) - \alpha \|\nabla f(x^k)\|_2^2 + \frac{M\alpha^2}{2} \|\nabla f(x^k)\|_2^2.$$

$$\leq f(x^k) - \frac{\alpha}{2} \|\nabla f(x^k)\|_2^2$$

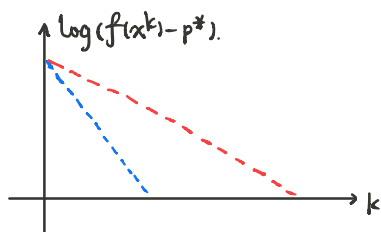
$$\leq f(x^k) - r\alpha \|\nabla f(x^k)\|_2^2$$

$$\alpha_{\text{inexact}} = \alpha_{\text{max}} \text{ 或 } \geq \frac{\beta}{M}.$$

$$f(x^{k+1}) = \tilde{f}(\alpha_{\text{exact}}) \leq f(x^k) - \frac{1}{2M} \|\nabla f(x^k)\|_2^2$$

$$f(x^{k+1}) \leq f(x) - \min\left\{r\alpha_{\text{max}}, \frac{r\beta}{M}\right\} \|\nabla f(x)\|_2^2$$

$$\frac{f(x^{k+1}) - p^*}{f(x^k) - p^*} \leq 1 - \min\left\{2mr\alpha_{\text{max}}, \frac{2mr\beta}{M}\right\} \rightarrow 1$$



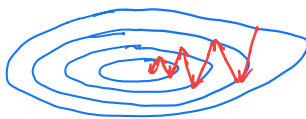
例: $f(x) = \frac{1}{2} x^T P x$, $P \in S_+^n$

$$\nabla^2 f(x) = P.$$

$$\begin{matrix} MI \geq P \geq mI. \\ \uparrow \quad \quad \uparrow \\ \lambda_{\text{max}} \quad \lambda_{\text{min}}. \end{matrix}$$

$\frac{M}{m}$ 小, 收敛快.

$$P = \begin{pmatrix} 100 & 0 \\ 0 & 1 \end{pmatrix}$$



收敛慢. zig-zag.