

lec43.

(测验). 证明: $\max_{v, \lambda_1, \lambda_2} -b^T v - \lambda_1^T u + \lambda_2^T l.$ 与 $\max_{v, \lambda_1, \lambda_2} -b^T v + l^T (A^T v + l)^+ - u^T (A^T v + l)^-$ 等价

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

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

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

无约束优化问题. $\min f(x).$

迭代算法. $x^{k+1} = x^k + \alpha^k d^k.$

(下降算法).

$\alpha^k = \arg \min_{\alpha} f(x^k + \alpha^k d^k)$

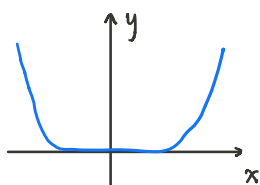
$\min f(x)$ $f(x)$ 一阶可微. 最优性条件.

$\nabla f(x) = 0.$ $\nabla f(\tilde{x}) \approx 0, x \rightarrow x^*? f(x) \rightarrow f(x^*).$

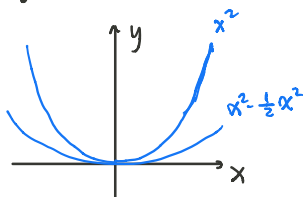
lec44.

假设 $f(x)$ 一阶可微且有强凸性.

$\exists m > 0, \forall x \in \text{dom } f, \nabla^2 f(x) \geq mI.$



不是强凸的



是强凸的.

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

当 $\nabla f(x) \rightarrow 0$ 时, $f(x) \rightarrow f(x^*)?$

x 给定, $f(x) + \nabla f^T(x)(y-x) + \frac{1}{2} m \|y-x\|_2^2$ 是 y 的凸函数.

$\nabla f^T(x) + m(\tilde{y} - x) = 0 \quad \tilde{y} = x - \frac{\nabla f^T(x)}{m}.$

$\geq f(x) - \frac{1}{2m} \|\nabla f(x)\|_2^2.$

$p^* \geq f(x) - \frac{1}{2m} \|\nabla f(x)\|_2^2$

$\underline{p^* + \frac{1}{2m} \|\nabla f(x)\|_2^2 \geq f(x) \geq p^*}.$

$$\|f(x) - p^*\|_2 \leq \frac{1}{2m} \|\nabla f(x)\|_2^2$$

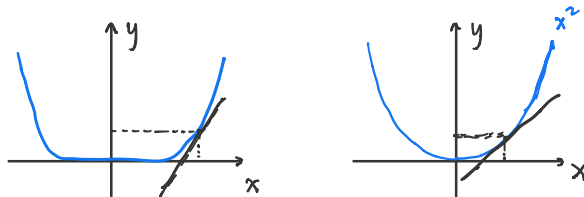
当 $\nabla f(x) \rightarrow 0$ 时, $x \rightarrow x^*$?

$$f(x) \geq p^* = f(x^*) \geq f(x) + \nabla f(x)(x^* - x) + \frac{m}{2} \|x^* - x\|_2^2 \quad \langle a, b \rangle + \|a\| \|b\| \geq 0.$$

$$\geq f(x) - \|\nabla f(x)\|_2 \|x^* - x\|_2 + \frac{m}{2} \|x^* - x\|_2^2.$$

$$f(x) \geq p^* \Rightarrow -\|\nabla f(x)\|_2 \|x^* - x\|_2 + \frac{m}{2} \|x^* - x\|_2^2 = 0.$$

$$\|x^* - x\|_2 \leq \frac{2}{m} \|\nabla f(x)\|_2.$$



$$\exists M > 0, \forall x \in \text{dom} f, \nabla^2 f(x) \leq M I.$$

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

$$p^* \leq f(x) - \frac{1}{2M} \|\nabla f(x)\|_2^2.$$

梯度下降法. $d^k = -\nabla f(x^k)$. 梯度大, 离最优值远

$$\text{Repeat } \left. \begin{array}{l} d^k = \arg \min_{0 \leq \alpha \leq \alpha_{\max}} f(x^k + \alpha d^k). \end{array} \right\} \rightarrow \begin{cases} \text{exact} \\ \text{inexact.} \end{cases}$$

$$x^{k+1} = x^k + \alpha^k d^k$$

Until Convergence.