

答案

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问题1

证明. 记 $x_0 = (0.1, 1)^T, f'(x) = 2(10x_1, x_2)^T$ 根据最速下降法的迭代公式 $x_k = x_{k-1} - \alpha f'(x_{k-1})$, 得:

$$\|x_k\|^2 = (1 - \frac{\alpha}{10})^2 (x_{k-1}^1)^2 + (1 - \alpha)^2 (x_{k-1}^2)^2,$$

选取 $0 < \alpha < 1$ 有 $\|x_k - 0\| \leq (1 - \frac{\alpha}{10}) \|x_{k-1} - 0\|$, 此时最速下降法线性收敛。□

问题2

证明. 由利普希兹连续的性质, $\forall x$,

$$f(x - \alpha \nabla f(x)) \leq f(x) - \alpha(1 - \frac{L\alpha}{2}) \|\nabla f(x)\|^2, \quad (1)$$

记 $\tilde{x} = x - \alpha \nabla f(x)$ 并限制 $0 < \alpha < \frac{1}{L}$, 有:

$$\begin{aligned} f(\tilde{x}) &\leq f(x) - \frac{\alpha}{2} \|\nabla f(x)\|^2 \\ &\leq f^* + \nabla f(x)^T (x - x^*) - \frac{\alpha}{2} \|\nabla f(x)\|^2 \\ &= f^* + \frac{1}{2\alpha} (\|x - x^*\|^2 - \|x - x^* - \alpha \nabla f(x)\|^2) \\ &= f^* + \frac{1}{2\alpha} (\|x - x^*\|^2 - \|\tilde{x} - x^*\|^2), \end{aligned}$$

取 $x = x^{i-1}$, 则 $\tilde{x} = x^i$ 。并将 $i = 1, 2, \dots, k$ 求和得到

$$\begin{aligned} \sum_{i=1}^k (f(x^i) - f^*) &\leq \frac{1}{2\alpha} \sum_{i=1}^k (\|x^{i-1} - x^*\|^2 - \|x^i - x^*\|^2) \\ &= \frac{1}{2\alpha} (\|x^0 - x^*\|^2 - \|x^k - x^*\|^2) \\ &\leq \frac{1}{2\alpha} \|x^0 - x^*\|^2. \end{aligned}$$

由(1)知 $f(x^i)$ 是非增的, 所以

$$f(x^k) - f^* \leq \frac{1}{k} \sum_{i=1}^k (f(x^i) - f^*) \leq \frac{1}{2k\alpha} \|x^0 - x^*\|^2.$$

□

问题3

1. 给点初始点 $x_0, \epsilon > 0, k = 1$ 。
2. 若终止准则满足, 则输出有关信息, 停止迭代。
3. $x_{k+1} = x_k - G_K^{-1} g_k, k = k + 1$, 转2

$f'(x) = 4x^3 - 12x^2 - 12x - 16, f''(x) = 12(x^2 - 2x - 1)$ 计算过程如下:

1. $x_1 = x_0 - \frac{f'(x_0)}{f''(x_0)} = 5.167$;
2. $x_2 = x_1 - \frac{f'(x_1)}{f''(x_1)} = 4.335$;
3. $x_3 = x_2 - \frac{f'(x_2)}{f''(x_2)} = 4.040$;
4. $x_4 = x_3 - \frac{f'(x_3)}{f''(x_3)} = 4.001$ 。

问题4 $G_0 = \begin{pmatrix} 0 & 1 \\ 1 & 2 \end{pmatrix}, G_0 + \bar{v}I = \begin{pmatrix} \bar{v} & 1 \\ 1 & \bar{v} + 2 \end{pmatrix}$ 要使 $G_0 + \bar{v}I$ 正定只需 $\bar{v} > 0, |G_0 + \bar{v}I| > 0$, 解得: $\bar{v} > \sqrt{2} - 1$ 令 $v_0 = 1$ 得

$$d_0 = -(G_0 + I)^{-1} g_0 = - \begin{pmatrix} 1 & 1 \\ 1 & 3 \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ 2 \end{pmatrix} = \begin{pmatrix} 1 \\ -1 \end{pmatrix},$$

从而 $f(x_0 + d_0) = 0 < f(0, 0) = 1$, 最后由LM算法可知 $x_0 + d_0 = \begin{pmatrix} \frac{2}{\bar{v}^2 + 2\bar{v} - 1} \\ \frac{-2\bar{v}}{\bar{v}^2 + 2\bar{v} - 1} \end{pmatrix}$ 编程计算可得 $\bar{v} < 0.9004$ 。

问题 5

证明. 先证 $\forall k$, 有 $H^k y^{k-1} = s^{k-1}$.

$$\begin{aligned} H^k y^{k-1} &= H^{K-1} y^{k-1} + \frac{(s^{k-1} - H^{k-1} - y^{k-1})(s^{k-1} - H^{K-1} y^{k-1})^T}{(s^{k-1} - H^{K-1} y^{k-1})^T y^{K-1}} y^{k-1} \\ &= H^{k-1} y^{k-1} + s^{k-1} - H^{k-1} y^{k-1} \\ &= s^{k-1}, \end{aligned}$$

考虑 $j = k - 2$ 的情况:

$$\begin{aligned} H^k y^{k-2} &= H^{K-1} y^{k-2} + \frac{(s^{k-1} - H^{k-1} - y^{k-1})(s^{k-1} - H^{K-1} y^{k-1})^T}{(s^{k-1} - H^{K-1} y^{k-1})^T y^{K-1}} y^{k-2} \\ &= s^{k-2} + \frac{(s^{k-1} - H^{k-1} - y^{k-1})(s^{k-1} - H^{K-1} y^{k-1})^T}{(s^{k-1} - H^{K-1} y^{k-1})^T y^{K-1}} y^{k-2}, \end{aligned}$$

由于

$$\begin{aligned} (s^{k-1} - H^{K-1} y^{k-1})^T y^{k-2} &= (s^{k-1})^T y^{k-2} - (y^{k-1})^T (H^{k-1})^T y^{k-2} \\ &= (s^{k-1})^T y^{k-2} - (y^{k-1})^T H^{k-1} y^{k-2} \\ &= (s^{k-1})^T y^{k-2} - (y^{k-1})^T s^{k-1} = 0 \end{aligned}$$

从而 $j = k - 2$ 时成立, 类似可证 $\forall j = 1, 2, \dots, k - 1$ 成立。 \square

问题 6 解: $\nabla f(x) = \begin{pmatrix} 2x_1 \\ 8x_2 \end{pmatrix}, \nabla^2 f(x) = \begin{pmatrix} 2 & 0 \\ 0 & 8 \end{pmatrix}$

(1) $\nabla f(x^0) = \begin{pmatrix} 2 \\ 8 \end{pmatrix}, d^0 = -\nabla f(x^0) = \begin{pmatrix} -2 \\ -8 \end{pmatrix}$

$\phi(\alpha) = f(x^0 + \alpha d^0) = (1 - 2\alpha)^2 + 4(1 - 8\alpha)^2$

令 $\phi'(\alpha) = 0$, 得 $\alpha = \frac{68}{520} = 0.13077$

进而有 $x^1 = x^0 + \alpha_0 d^0 = \begin{pmatrix} 1 \\ 1 \end{pmatrix} - 0.13077 \begin{pmatrix} 2 \\ 8 \end{pmatrix} = \begin{pmatrix} 0.73846 \\ -0.04616 \end{pmatrix}$

$\nabla f(x^1) = (1.47692, -0.36923)^T, \|\nabla f(x^1)\| = 1.52237$

由于 $\|\nabla f(x^1)\|$ 较大, 因此还需要迭代下去。(2)先确定搜索方向, 为此需要按公式计算

$$H_1 = H_0 + \frac{\delta_1 \delta_1^T}{\delta_1^T \gamma_1} - \frac{H_0 \gamma_1 \gamma_1^T H_0}{\gamma_1^T H_0 \gamma_1}$$

$$\text{又 } \delta_1 = x^1 - x^0 = \begin{pmatrix} -0.26154 \\ -1.04616 \end{pmatrix}, \gamma_1 = \nabla f(x^1) - \nabla f(x^0) = \begin{pmatrix} -0.52308 \\ -8.36923 \end{pmatrix}$$

$$\text{故 } H_1 = \begin{pmatrix} 1.00380 & -0.03149 \\ -0.03149 & 0.12697 \end{pmatrix}$$

下面再确定步长:

利用 $\frac{df(x^1 + \alpha d^1)}{d\alpha} = 0$, 得到 $\alpha_1 = 0.49423$

$$\text{所以 } x^2 = x^1 + \alpha_1 d^1 = \begin{pmatrix} 0.00000 \\ 0.00000 \end{pmatrix}$$

由于 $\|\nabla f(x^2)\| < \epsilon$, 因此停止迭代, 最优解为 $x^* = x^2$.

问题 7

证明. 定理的证明归结于用归纳法证明如下不等式:

$$-\sum_{j=0}^k \sigma^j \leq \frac{g_k^T d_k}{\|g_k\|^2} \leq -2 + \sum_{j=0}^k \sigma^j \quad (2)$$

对于所有 k 成立, 其中 $\sigma \in (0, \frac{1}{2})$. 事实上, 若(2)成立, 由于

$$\sum_{j=0}^k \sigma^j < \sum_{j=0}^{\infty} \sigma^j = \frac{1}{1-\sigma} \quad (3)$$

由此可知(2)式右侧为负, 从而

$$g_k^T d_k < 0 \quad (4)$$

下降性质成立. 显然, 当 $k=0$ 时, (2)式成立. 今设对任何 $k \geq 0$, (2)成立.

由FR算法的迭代过程, 有

$$\frac{g_{k+1}^T d_{k+1}}{\|g_{k+1}\|^2} = -1 + \frac{g_{k+1}^T d_k}{\|g_k\|^2} \quad (5)$$

则有

$$-1 + \sigma \frac{g_k^T d_k}{\|g_k\|^2} \leq \frac{g_{k+1}^T d_{k+1}}{\|g_{k+1}\|^2} \leq -1 - \sigma \frac{g_k^T d_k}{\|g_k\|^2} \quad (6)$$

再由归纳法假设(2), 有

$$-\sum_{j=0}^{k+1} \sigma^j = -1 - \sigma \sum_{j=0}^k \sigma^j \leq \frac{g_{k+1}^T d_{k+1}}{\|g_{k+1}\|^2} \leq -1 + \sigma \sum_{j=0}^k \sigma^j = -2 + \sum_{j=0}^{k+1} \sigma^j. \quad (7)$$

于是, 对于 $k+1$, 不等式(2)成立.

□

问题 8 解: $g(x) = (3x_1 - x_2 - 2, x_2 - x_1)^T, G(x) = \begin{pmatrix} 3 & -1 \\ -1 & 1 \end{pmatrix}$

因 $g_0 = (-2, 0)^T \neq 0$, 故取 $p_0 = (2, 0)^T$, 从 x_0 出发, 沿 p_0 做一维搜索, 也就是求

$$\min f(x_0 + \alpha p_0) = 6\alpha^2 - 4\alpha$$

的极小点, 得步长 $\alpha_0 = \frac{1}{3}$. 于是得到 $x_1 = x_0 + \alpha_0 p_0 = (\frac{2}{3}, 0), g_1 = (0, -\frac{2}{3})^T$. 由FR公式得

$$\beta_0 = \frac{g_1^T g_1}{g_0^T g_0} = \frac{1}{9}$$

故 $p_1 = -g_1 + \beta_0 p_0 = (\frac{2}{9}, \frac{2}{3})^T$. 从 x_1 出发, 沿 p_1 作一维搜索, 求

$$\min f(x_1 + \alpha p_1) = \frac{4}{27}\alpha^2 - \frac{4}{9}\alpha + \frac{2}{3}$$

的极小点, 解得 $\alpha_1 = \frac{3}{2}$, 于是 $x_2 = x_1 + \alpha_1 p_1 = (1, 1)^T$ 此时 $g_2 = (0, 0)^T$, 故 $x^* = x_2 = (1, 1)^T, f^* = -1$