

第 11 周: P280 2/1), 补充题 (见邮箱), P328 3 (用最优步长) 4, 5

P280 2/1): $\min \varphi(\lambda) = 3\lambda^4 - 4\lambda^3 - 12\lambda^2$, $\lambda_1 = -1.2$ 解: $\varphi'(\lambda) = 12\lambda^3 - 12\lambda^2 - 24\lambda$, $\varphi''(\lambda) = 36\lambda^2 - 24\lambda - 24$

$$\varphi'(\lambda_1) = -9.216, \varphi''(\lambda_1) = 56.64, \lambda_2 = \lambda_1 - \frac{\varphi'(\lambda_1)}{\varphi''(\lambda_1)} = -1.037,$$

$$\varphi'(\lambda_2) = -1.398, \varphi''(\lambda_2) = 39.601, \lambda_3 = \lambda_2 - \frac{\varphi'(\lambda_2)}{\varphi''(\lambda_2)} = -1.002$$

$$\varphi'(\lambda_3) = -0.072, \varphi''(\lambda_3) = 36.192, \lambda_4 = \lambda_3 - \frac{\varphi'(\lambda_3)}{\varphi''(\lambda_3)} = -1.000$$

补充题: 用两种可接受一维搜索方法求解:

$$\min_{\lambda \geq -4} \varphi(\lambda) = 3\lambda^4 - 4\lambda^3 - 12\lambda^2$$

取初始点 $\lambda_1 = -1.2$, $\sigma_1 = 0.2, \sigma_2 = \sigma_3 = 0.6, \alpha = 1.2$ 。解: 令 $\mu = \lambda + 4$, 则原问题变为

$$\min_{\mu \geq 0} \varphi(\mu - 4) = 3(\mu - 4)^4 - 4(\mu - 4)^3 - 12(\mu - 4)^2$$

其中 $\varphi'(\mu - 4)|_{\mu=0} < 0, \mu_1 = 2.8$ 。A-G 准则: $\mu_1 = 2.8$ 时, $\varphi(\mu_1 - 4) \leq \varphi(-4) + \sigma_1 \varphi'(-4)\mu_1$, $\varphi(\mu_1 - 4) \geq \varphi(-4) + \sigma_2 \varphi'(-4)\mu_1$, 因此 $\tilde{\mu} = \mu_1 = 2.8$, $\tilde{\lambda} = \tilde{\mu} - 4 = -1.2$ 。W-P 准则: $\mu_1 = 2.8$ 时, $\varphi(\mu_1 - 4) \leq \varphi(-4) + \sigma_1 \varphi'(-4)\mu_1$, $\varphi'(\mu_1 - 4) \geq \sigma_3 \varphi'(-4)$, 因此 $\tilde{\mu} = \mu_1 = 2.8$, $\tilde{\lambda} = \tilde{\mu} - 4 = -1.2$ 。

P328/3 (用最优步长):

$$\nabla f(\mathbf{x}) = \begin{pmatrix} 2x_1 - 2x_2 + 1 \\ -2x_1 + 8x_2 - 3 \end{pmatrix}, \mathbf{H} = \nabla^2 f(\mathbf{x}) = \begin{pmatrix} 2 & -2 \\ -2 & 8 \end{pmatrix} \text{ 正定}$$

$$k=1: \mathbf{x}^1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \nabla f(\mathbf{x}^1) = \begin{pmatrix} 1 \\ 3 \end{pmatrix}, \mathbf{d}^1 = \begin{pmatrix} -1 \\ -3 \end{pmatrix}, \lambda_1 = -\frac{\nabla f(\mathbf{x}^1)^T \mathbf{d}^1}{(\mathbf{d}^1)^T \mathbf{H} \mathbf{d}^1} = \frac{5}{31}, \mathbf{x}^2 = \mathbf{x}^1 + \lambda_1 \mathbf{d}^1 = \begin{pmatrix} 26/31 \\ 16/31 \end{pmatrix}.$$

$$k=2: \mathbf{x}^2 = \begin{pmatrix} 26/31 \\ 16/31 \end{pmatrix}, \nabla f(\mathbf{x}^2) = \frac{17}{31} \begin{pmatrix} 3 \\ -1 \end{pmatrix}, \text{ 取 } \mathbf{d}^2 = \begin{pmatrix} -3 \\ 1 \end{pmatrix}, \lambda_2 = -\frac{\nabla f(\mathbf{x}^2)^T \mathbf{d}^2}{(\mathbf{d}^2)^T \mathbf{H} \mathbf{d}^2} = \frac{17}{31} \frac{5}{19},$$

$$\mathbf{x}^3 = \mathbf{x}^2 + \lambda_2 \mathbf{d}^2 = \begin{pmatrix} 239/589 \\ 389/589 \end{pmatrix}.$$

P328/4:

$$(1) \text{ 等值线 (略), } \nabla f(\mathbf{x}) = \begin{pmatrix} 2x_1 - 4 \\ 8x_2 - 8 \end{pmatrix}, \mathbf{H} = \nabla^2 f(\mathbf{x}) = \begin{pmatrix} 2 & 0 \\ 0 & 8 \end{pmatrix} \text{ 正定, } f \text{ 严格凸, 最优解 } \bar{\mathbf{x}} = \begin{pmatrix} 2 \\ 1 \end{pmatrix}.$$

(2) 若存在 $\mathbf{x}^{k+1} = \bar{\mathbf{x}}$, 则 $\nabla f(\mathbf{x}^{k+1}) = \mathbf{0}$, 即

$$\mathbf{0} = \nabla f(\mathbf{x}^{k+1}) = \mathbf{H} \mathbf{x}^{k+1} + \mathbf{c} = \mathbf{H}(\mathbf{x}^k + \lambda_k \mathbf{d}^k) + \mathbf{c} = \nabla f(\mathbf{x}^k) + \lambda_k \mathbf{H} \mathbf{d}^k = -\mathbf{d}^k + \lambda_k \mathbf{H} \mathbf{d}^k$$

即 $\mathbf{H} \mathbf{d}^k = \frac{1}{\lambda_k} \mathbf{d}^k$, 即 \mathbf{d}^k 是 \mathbf{H} 的特征向量, 即 $\mathbf{d}^k // (1 \ 0)^T$ 或 $\mathbf{d}^k // (0 \ 1)^T$ 。但取初始点为 $\mathbf{x}^1 = (0, 0)^T$, 搜

索方向 $\mathbf{d}^k // (1, 2)^T$ 或 $\mathbf{d}^k // (-2, 1)^T$ 。因此不会经过有限步迭代得到 $\bar{\mathbf{x}}$ 。

(3) $\mathbf{d}^1 // (1, 0)^T$ 或 $\mathbf{d}^1 // (0, 1)^T$ ，即 $2x_1^1 - 4 = 0$ 或 $8x_2^1 - 8 = 0$ ，即 $x_1^1 = 2$ 或 $x_2^1 = 1$ ，即 $\mathbf{x}^1 = (2, x_2^1)^T$ 或 $\mathbf{x}^1 = (x_1^1, 1)^T$ 。

P328/5:

$$(1) \nabla f(\mathbf{x}^1) = \mathbf{A}\mathbf{x}^1 + \mathbf{b} = \mathbf{A}(\bar{\mathbf{x}} + \mu\mathbf{p}) + \mathbf{b} = \nabla f(\bar{\mathbf{x}}) + \mu\mathbf{A}\mathbf{p} = \mu\lambda\mathbf{p}。$$

$$(2) \lambda_1 = -\frac{\nabla f(\mathbf{x}^1)^T \mathbf{d}^1}{(\mathbf{d}^1)^T \mathbf{A} \mathbf{d}^1} = \frac{\|\nabla f(\mathbf{x}^1)\|^2}{\nabla f(\mathbf{x}^1)^T \mathbf{A} \nabla f(\mathbf{x}^1)} = \frac{\mu^2 \lambda^2 \|\mathbf{p}\|^2}{\mu^2 \lambda^2 \mathbf{p}^T \mathbf{A} \mathbf{p}} = \frac{\mu^2 \lambda^2 \|\mathbf{p}\|^2}{\mu^2 \lambda^3 \mathbf{p}^T \mathbf{p}} = \frac{1}{\lambda}，$$

$$\mathbf{x}^2 = \mathbf{x}^1 + \lambda_1 \mathbf{d}^1 = \bar{\mathbf{x}} + \mu\mathbf{p} - \lambda_1 \nabla f(\mathbf{x}^1) = \bar{\mathbf{x}} + \mu\mathbf{p} - \frac{1}{\lambda} \mu\lambda\mathbf{p} = \bar{\mathbf{x}}。$$

第 12 周: P328 2 (用牛顿法求解, 迭代 1 次), P330 12, 13, 14/2)4)

P328/2 (用牛顿法求解, 迭代 1 次)

$f(\mathbf{x}) = (6 + x_1 + x_2)^2 + (2 - 3x_1 - 3x_2 - x_1x_2)^2$ 凸函数

$$\nabla f(\mathbf{x}) = \begin{pmatrix} 2(6 + x_1 + x_2) + 2(2 - 3x_1 - 3x_2 - x_1x_2)(-3 - x_2) \\ 2(6 + x_1 + x_2) + 2(2 - 3x_1 - 3x_2 - x_1x_2)(-3 - x_1) \end{pmatrix}$$

$$\nabla^2 f(\mathbf{x}) = \begin{pmatrix} 2(x_2^2 + 6x_2 + 10) & 2(2x_1x_2 + 6x_1 + 6x_2 + 8) \\ 2(2x_1x_2 + 6x_1 + 6x_2 + 8) & 2(x_1^2 + 6x_1 + 10) \end{pmatrix}$$

$$\mathbf{x}^1 = \hat{\mathbf{x}} = \begin{pmatrix} -4 \\ 6 \end{pmatrix}: \nabla f(\mathbf{x}^1) = \begin{pmatrix} -356 \\ 24 \end{pmatrix}, \nabla^2 f(\mathbf{x}^1) = \begin{pmatrix} 164 & -56 \\ -56 & 4 \end{pmatrix}, \nabla^2 f(\mathbf{x}^1)^{-1} = -\frac{1}{2480} \begin{pmatrix} 4 & 56 \\ 56 & 164 \end{pmatrix},$$

$$\text{牛顿方向 } \mathbf{d}^1 = -[\nabla^2 f(\mathbf{x}^1)]^{-1} \nabla f(\mathbf{x}^1) = \begin{pmatrix} 22/31 \\ -126/31 \end{pmatrix}, \mathbf{x}^2 = \mathbf{x}^1 + \mathbf{d}^1 = \begin{pmatrix} -102/31 \\ 60/31 \end{pmatrix}$$

P330/12:

设 \mathbf{p}^i 是 \mathbf{A} 对应于特征值 λ_i 的特征向量, 即 $\mathbf{A}\mathbf{p}^i = \lambda_i \mathbf{p}^i$, 则 $j \neq i$ 时,

$$(\mathbf{p}^j)^T \mathbf{A} \mathbf{p}^i = \lambda_i (\mathbf{p}^j)^T \mathbf{p}^i = 0$$

P330/13: 用归纳法。

$k=2$ 时, $\mathbf{d}^2 = \mathbf{p}^2 - \frac{(\mathbf{d}^1)^T \mathbf{A} \mathbf{p}^2}{(\mathbf{d}^1)^T \mathbf{A} \mathbf{d}^1} \mathbf{d}^1$, $(\mathbf{d}^1)^T \mathbf{A} \mathbf{d}^2 = (\mathbf{d}^1)^T \mathbf{A} \mathbf{p}^2 - \frac{(\mathbf{d}^1)^T \mathbf{A} \mathbf{p}^2}{(\mathbf{d}^1)^T \mathbf{A} \mathbf{d}^1} (\mathbf{d}^1)^T \mathbf{A} \mathbf{d}^1 = 0$, 即 $\mathbf{d}^1, \mathbf{d}^2$ 是 \mathbf{A} -共轭的。

设 $\mathbf{d}^1, \dots, \mathbf{d}^k$ 是 \mathbf{A} -共轭的, 则

$$\mathbf{d}^{k+1} = \mathbf{p}^{k+1} - \sum_{i=1}^k \frac{(\mathbf{d}^i)^T \mathbf{A} \mathbf{p}^{k+1}}{(\mathbf{d}^i)^T \mathbf{A} \mathbf{d}^i} \mathbf{d}^i, \quad j=1, \dots, k \text{ 时,}$$

$$\begin{aligned}
(d^j)^T A d^{k+1} &= (d^j)^T A p^{k+1} - \sum_{i=1}^k \frac{(d^i)^T A p^{k+1}}{(d^i)^T A d^i} (d^j)^T A d^i \\
&\stackrel{(d^j)^T A d^i = 0, i \neq j}{=} (d^j)^T A p^{k+1} - \frac{(d^j)^T A p^{k+1}}{(d^j)^T A d^j} (d^j)^T A d^j = 0
\end{aligned}$$

即 d^1, \dots, d^{k+1} 是 A -共轭的。由归纳法知, d^1, \dots, d^n 是 A -共轭的。

P330/14(2):

$$\min f(\mathbf{x}) = x_1^2 + 2x_2^2 - 2x_1x_2 + 2x_2 + 2, \quad \mathbf{x}^1 = \begin{pmatrix} 0 \\ 0 \end{pmatrix}.$$

$$\nabla f(\mathbf{x}) = \begin{pmatrix} 2x_1 - 2x_2 \\ 4x_2 - 2x_1 + 2 \end{pmatrix}, \quad \mathbf{H} = \nabla^2 f(\mathbf{x}) = \begin{pmatrix} 2 & -2 \\ -2 & 4 \end{pmatrix} \text{ 正定, } f \text{ 是严格凸函数。}$$

$$k=1: \quad \mathbf{x}^1 = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \nabla f(\mathbf{x}^1) = \begin{pmatrix} 0 \\ 2 \end{pmatrix}, \quad \mathbf{d}^1 = \begin{pmatrix} 0 \\ -2 \end{pmatrix}, \quad \lambda_1 = -\frac{\nabla f(\mathbf{x}^1)^T \mathbf{d}^1}{(\mathbf{d}^1)^T \mathbf{H} \mathbf{d}^1} = \frac{1}{4}, \quad \mathbf{x}^2 = \mathbf{x}^1 + \lambda_1 \mathbf{d}^1 = (0, -1/2)^T.$$

$$k=2: \quad \mathbf{x}^2 = \mathbf{x}^1 + \lambda_1 \mathbf{d}^1 = \begin{pmatrix} 0 \\ -1/2 \end{pmatrix}, \quad \nabla f(\mathbf{x}^2) = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \quad \beta_1 = \frac{\|\nabla f(\mathbf{x}^2)\|^2}{\|\nabla f(\mathbf{x}^1)\|^2} = \frac{1}{4}, \quad \mathbf{d}^2 = -\nabla f(\mathbf{x}^2) + \beta_1 \mathbf{d}^1 = \begin{pmatrix} -1 \\ -1/2 \end{pmatrix},$$

$$\lambda_2 = -\frac{\nabla f(\mathbf{x}^2)^T \mathbf{d}^2}{(\mathbf{d}^2)^T \mathbf{H} \mathbf{d}^2} = 1, \quad \mathbf{x}^3 = \mathbf{x}^2 + \lambda_2 \mathbf{d}^2 = (-1, -1)^T.$$

$$k=3: \quad \mathbf{x}^3 = \begin{pmatrix} -1 \\ -1 \end{pmatrix}, \quad \nabla f(\mathbf{x}^3) = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \mathbf{x}^3 \text{ 是平稳点。又 } f \text{ 是严格凸函数, 因此 } \mathbf{x}^* = \mathbf{x}^3 \text{ 是最优解。}$$

P330/14(4):

$$\min f(\mathbf{x}) = 2x_1^2 + 2x_1x_2 + x_2^2 + 3x_1 - 4x_2, \quad \mathbf{x}^1 = (3, 4)^T.$$

$$\nabla f(\mathbf{x}) = \begin{pmatrix} 4x_1 + 2x_2 + 3 \\ 2x_1 + 2x_2 - 4 \end{pmatrix}, \quad \mathbf{H} = \nabla^2 f(\mathbf{x}) = \begin{pmatrix} 4 & 2 \\ 2 & 2 \end{pmatrix} \text{ 正定, } f \text{ 是凸函数。}$$

$$k=1: \quad \mathbf{x}^1 = \begin{pmatrix} 3 \\ 4 \end{pmatrix}, \quad \nabla f(\mathbf{x}^1) = \begin{pmatrix} 23 \\ 10 \end{pmatrix}, \quad \mathbf{d}^1 = \begin{pmatrix} -23 \\ -10 \end{pmatrix}, \quad \lambda_1 = -\frac{\nabla f(\mathbf{x}^1)^T \mathbf{d}^1}{(\mathbf{d}^1)^T \mathbf{H} \mathbf{d}^1} = \frac{629}{3236} \approx 0.194,$$

$$\mathbf{x}^2 = \mathbf{x}^1 + \lambda_1 \mathbf{d}^1 = (-1.462, 2.06)^T.$$

$$k=2: \quad \mathbf{x}^2 = \begin{pmatrix} -1.462 \\ 2.06 \end{pmatrix}, \quad \nabla f(\mathbf{x}^2) = \begin{pmatrix} 1.272 \\ -2.804 \end{pmatrix}, \quad \beta_1 = \frac{\|\nabla f(\mathbf{x}^2)\|^2}{\|\nabla f(\mathbf{x}^1)\|^2} = 0.015,$$

$$\mathbf{d}^2 = -\nabla f(\mathbf{x}^2) + \beta_1 \mathbf{d}^1 = \begin{pmatrix} -1.617 \\ 2.654 \end{pmatrix}, \quad \lambda_2 = -\frac{\nabla f(\mathbf{x}^2)^T \mathbf{d}^2}{(\mathbf{d}^2)^T \mathbf{H} \mathbf{d}^2} = 1.287, \quad \mathbf{x}^3 = \mathbf{x}^2 + \lambda_2 \mathbf{d}^2 = (-3.543, 5.476)^T.$$

$$k=3: \quad \mathbf{x}^3 = \begin{pmatrix} -3.543 \\ 5.476 \end{pmatrix}, \quad \nabla f(\mathbf{x}^3) \approx \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \mathbf{x}^3 \text{ 是近似平稳点。又 } f \text{ 是凸函数, 因此 } \mathbf{x}^* = \mathbf{x}^3 \text{ 是近似最优解。}$$