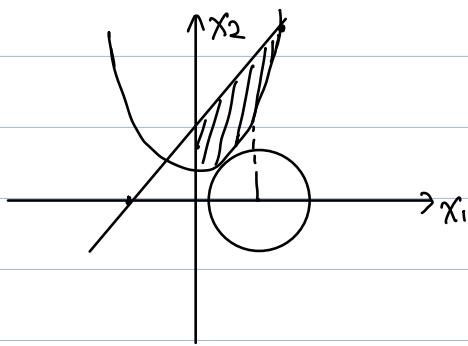


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4-2 $\max S = 3.6x_1 - 0.4x_1^2 + 1.6x_2 - 0.2x_2^2$

s.t. $\begin{cases} x_1 + 0.5x_2 \leq 5 \\ x_1 \geq 0, x_2 \geq 0 \end{cases}$

4-4(2) $\min S = x_1^2 + x_2^2 - 4x_1 + 4 = (x_1 - 2)^2 + x_2^2$ 即到 $(2, 0)$ 距离平方



由图知以 $(2, 0)$ 为圆心圆与抛物线相切时, 取到最小值

$$\begin{cases} (x_1 - 2)^2 + x_2^2 = a \\ x_2 = x_1^2 + 1 \end{cases}$$

即 $2x_1' \cdot \frac{x_1'^2 + 1}{x_1' - 2} = -1$ 得 $x_1' = 0.5536$

即 $X = (0.5536, 1.31)^T$, $\min = 3.81$

4-5(1) $\nabla f(x) = (2x_1 - 4x_3, 4x_2, 6x_3 - 4x_1)^T$

$$\nabla^2 f(x) = \begin{pmatrix} 2 & 0 & -4 \\ 0 & 4 & 0 \\ -4 & 0 & 6 \end{pmatrix}$$

4-5(2) $\nabla f(x) = (3x_2^2 + x_2 e^{x_1 x_2}, 6x_1 x_2 + x_1 e^{x_1 x_2})^T$

$$\nabla^2 f(x) = \begin{pmatrix} x_2^2 e^{x_1 x_2}, 6x_2 + e^{x_1 x_2} + x_1 x_2 e^{x_1 x_2} \\ 6x_2 + e^{x_1 x_2} + x_1 x_2 e^{x_1 x_2}, 6x_1 + x_1^2 e^{x_1 x_2} \end{pmatrix}$$

4-8 证明:

$$\nabla f(x_1, x_2) = (8x_1 - 2x_1 x_2, 2x_2 - x_1^2)^T, \nabla^2 f(x_1, x_2) = \begin{pmatrix} 8 - 2x_2 & -2x_1 \\ -2x_1 & 2 \end{pmatrix}$$

$\therefore \nabla f(0, 0) = (0, 0)^T, \nabla^2 f(0, 0) = \begin{pmatrix} 8 & 0 \\ 0 & 2 \end{pmatrix}, A > 0, AC - B^2 > 0$

$\therefore x^* = (0, 0)^T$ 是 $f(x_1, x_2)$ 的严格局部极小值点

$\therefore \nabla f(x_1) = \nabla f(x_2) = (0, 0)^T, \nabla^2 f(x_1) = \begin{pmatrix} 0 & 4\sqrt{2} \\ 4\sqrt{2} & 2 \end{pmatrix}, \nabla^2 f(x_2) = \begin{pmatrix} 0 & -4\sqrt{2} \\ -4\sqrt{2} & 2 \end{pmatrix}$

$AC - B^2 < 0$, 故 $f(x_1, x_2)$ 在 x_1, x_2 未取到极值

$\therefore x_1, x_2$ 是驻点, 不是极值点

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4-10 (1) $\nabla f(x) = -3(4-x)^2$, $\nabla^2 f(x) = 6(4-x)$

$x \leq 4$, $\nabla^2 f(x)$ 半正定, 故 $f(x)$ 为凸函数

4-10 (2) $\nabla f(x) = [2x_1 + 2x_2, 2x_1 + 6x_2]^T$, $\nabla^2 f(x) = \begin{pmatrix} 2 & 2 \\ 2 & 6 \end{pmatrix}$

$\nabla^2 f(x)$ 正定, 故 $f(x)$ 是严格凸函数

4-10 (3) $\nabla f(x) = (x_2, x_1)^T$, $\nabla^2 f(x) = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$ 不定

故 $f(x)$ 既不是凸函数也不是凹函数

4-13

n	a	b	λ_1	λ_2	$F(\lambda_1)$	$F(\lambda_2)$	$b-a$
0	0	10	3.82	6.18	-6.3	3.1	10
1	0	6.18	2.36	3.82	-6.6	-6.3	6.18
2	0	3.82	1.46	2.36	-4.6	-6.6	3.82
3	1.46	3.82	2.36	2.92	-6.6	-7	2.36
4	2.36	3.82	2.92	3.26	-7	-6.93	1.46
5	2.36	3.26	2.7	2.92	-6.91	-7	0.9
6	2.7	3.26	2.92	3.05	-6.9936	-6.9975	0.56
7	2.92	3.26	3.05	3.13	-6.9975	-6.9831	0.34
8	2.92	3.13					0.21

$0.21 < 10 \times 3\% = 0.3$ $[a, b] = [2.92, 3.13]$

求得 $f(x) = x^2 - 6x + 2$ 极小点为 $x = 3.025$

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$$4-14 \quad f(x) = x_1^2 + 2x_2^2 \quad Q = \begin{bmatrix} 2 & 0 \\ 0 & 4 \end{bmatrix}$$

$$g(x) = \nabla f(x) = [2x_1, 4x_2]^T$$

$$p^{(1)} = -\nabla f(x^0) = [-8, -16]^T$$

$$\lambda_1 = -\frac{g^{(1)T} p^{(1)}}{p^{(1)T} Q p^{(1)}} = \frac{5}{18}$$

$$x_1 = x_0 + p^{(1)} \lambda_1 = \left[\frac{16}{9}, -\frac{4}{9} \right]^T$$

$$g^{(2)} = \left[\frac{32}{9}, -\frac{16}{9} \right]^T, \quad p^{(2)} = \left[-\frac{32}{9}, \frac{16}{9} \right]^T, \quad \lambda_2 = -\frac{g^{(2)T} p^{(2)}}{p^{(2)T} Q p^{(2)}} = \frac{5}{12}$$

$$x_2 = x_1 + p^{(2)} \lambda_2 = \left[\frac{8}{27}, \frac{8}{27} \right]^T$$

$$g^{(3)} = \left[\frac{16}{27}, \frac{32}{27} \right]^T, \quad p^{(3)} = \left[-\frac{16}{27}, -\frac{32}{27} \right]^T, \quad \lambda_3 = -\frac{g^{(3)T} p^{(3)}}{p^{(3)T} Q p^{(3)}} = \frac{5}{18}$$

$$x_3 = x_2 + p^{(3)} \lambda_3 = \left[\frac{32}{243}, -\frac{8}{243} \right]^T = [0.132, -0.03]^T$$

$$4-15(1) \quad f(x) = \frac{1}{2} x^T Q x + b^T x + c$$

$$g(x) = \nabla f(x) = [2x_1 - 2, 8x_2, 18x_3 + 18]^T$$

$$G(x) = \nabla^2 f(x) = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 8 & 0 \\ 0 & 0 & 18 \end{bmatrix}$$

$$\text{取 } x^{(0)} = (1, 1, 1)^T$$

$$g(x^{(0)}) = (0, 8, 36)^T, \quad G(x^{(0)}) = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 8 & 0 \\ 0 & 0 & 18 \end{bmatrix}$$

$$x_1 - x^{(0)} = -G(x^{(0)})^{-1} g(x^{(0)}) = \begin{bmatrix} 0 \\ -1 \\ -2 \end{bmatrix}$$

$$p x^{(1)} = (1, 0, -1)^T \quad g(x^{(1)}) = 0, \quad \text{即极值点为 } (1, 0, -1)^T$$

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$$4-16 \quad x^{(0)} = (2, 2)^T$$

$$g(x) = \begin{bmatrix} 2x_1 - x_2 + 2 \\ -x_1 + 2x_2 - 4 \end{bmatrix} \quad Q = \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix}$$

$$p^{(0)} = -g^{(0)} = \begin{bmatrix} -4 \\ 2 \end{bmatrix} \quad \lambda_0 = \frac{g^{(0)T} g^{(0)}}{p^{(0)T} Q p^{(0)}} = \frac{5}{14}$$

$$x^{(1)} = x^{(0)} + \lambda_0 p^{(0)} = \begin{bmatrix} \frac{4}{7} \\ \frac{19}{7} \end{bmatrix} \quad g^{(1)} = \begin{bmatrix} \frac{3}{7} \\ \frac{6}{7} \end{bmatrix}$$

$$\beta_0 = \frac{g^{(1)T} Q p^{(0)}}{p^{(0)T} Q p^{(0)}} = \frac{9}{196} \quad p^{(1)} = -g^{(1)} + \beta_0 p^{(0)} = \begin{bmatrix} -\frac{30}{49} \\ -\frac{75}{98} \end{bmatrix}$$

$$\lambda_1 = \frac{g^{(1)T} g^{(1)}}{p^{(1)T} Q p^{(1)}} = \frac{14}{15}$$

$$x^{(2)} = x^{(1)} + \lambda_1 p^{(1)} = \begin{bmatrix} 0 \\ 2 \end{bmatrix} \quad g^{(2)} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \text{迭代终止}$$

$$\text{最优解 } x^* = x^{(2)} = \begin{bmatrix} 0 \\ 2 \end{bmatrix} \quad \min(x_1^2 - x_1 x_2 + x_2^2 + 2x_1 - 4x_2) = -4$$