

1

将此非线性规划问题化为标准型，得

$$\begin{aligned} \min & -b^T x, x \in R^n \\ \text{s.t.} & 1 - x^T x \geq 0 \end{aligned}$$

$$\text{KKT 条件为} \begin{cases} -b + wx = 0 \\ w(1 - x^T x) = 0 \\ w \geq 0 \end{cases}$$

得KKT点为 $x = \frac{b}{||b||}$ ，且此规划为凸规划， \therefore 此点满足最优性充分条件

2

经过观察可知， f 是线性函数，可行域是半空间和圆的交集，是凸集， \therefore 是个凸规划

\therefore 必存在最优解，且在边界达到，将原问题化为

$$\begin{aligned} \min & c^T x \\ \text{s.t.} & Ax = 0 \\ & -x^T x + r^2 = 0 \end{aligned}$$

$$\text{KKT 条件} \begin{cases} c - A^T v + 2v_{m+1}x = 0 \\ Ax = 0 \\ -x^T x + r^2 = 0 \end{cases}$$

$$\text{解得 } f_{\min} = -r\sqrt{c^T(c - A^T v)}$$

$$\text{最优解 } x = \frac{r^2}{f_{\min}}(c - A^T v)(f_{\min} \neq 0)$$

当 $c = A^T v$ 时， $f_{\min} = 0$ ，此时最优解不唯一

3

先求梯度

$$\nabla f(x) = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \nabla g(x) = \begin{bmatrix} -2x_1 \\ -2(x_2 - 4) \end{bmatrix}, \nabla h(x) = \begin{bmatrix} 2(x_1 - 2) \\ 2(x_2 - 3) \end{bmatrix}$$

$$\text{Lagrange 函数 } L(x, w, v) = x_2 - w(-x_1^2 - (x_2 - 4)^2 + 16) - v((x_1 - 2)^2 + (x_2 - 3)^2 - 13)$$

$$\nabla_x^2 L(x, w, v) = \begin{bmatrix} 2(w-v) & 0 \\ 0 & 2(w-v) \end{bmatrix}$$

对 $x^{(1)} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ 来说, 两个约束都是 active constraint

$$KKT \text{ 条件为 } \begin{cases} 4v = 0 \\ 1 - 8w + 6v = 0 \\ w \geq 0 \end{cases}$$

解得 $w = \frac{1}{8} > 0, v = 0$, 因此满足一阶必要条件

$$\Leftrightarrow \begin{cases} \nabla g(x^{(1)})^T d = 0 \\ \nabla h(x^{(1)})^T d = 0 \end{cases}, \text{ 解得 } d = 0$$

即方向集 $G = \{d \mid d \neq 0, \nabla g(x^{(1)})^T d = 0, \nabla h(x^{(1)})^T d = 0\} = \emptyset, \therefore x^{(1)}$ 是局部最优解

$$\text{对 } x^{(2)} = \left(\frac{16}{5}, \frac{32}{5}\right)^T, \text{ 两个约束都是 active constraint}$$

$$\nabla f(x^{(2)}) = (0, 1)^T, \nabla g(x^{(2)}) = \left(-\frac{32}{5}, -\frac{24}{5}\right)^T, \nabla h(x^{(2)}) = \left(\frac{12}{5}, \frac{34}{5}\right)^T$$

$$KKT \text{ 条件 } \begin{cases} \frac{32}{5}w - \frac{12}{5}v = 0 \\ 1 + \frac{24}{5}w - \frac{34}{5}v = 0 \\ w \geq 0 \end{cases} \text{ 的解为 } w = \frac{3}{40} > 0, v = \frac{1}{5}, \therefore x^{(2)} \text{ 是 KKT 点}$$

$$\text{方向集 } \begin{cases} \nabla g(x^{(2)})^T d = 0 \\ \nabla h(x^{(2)})^T d = 0 \end{cases}, \text{ 解得 } d = 0, \therefore x^{(2)} \text{ 是局部最优解}$$

$$\text{对 } x^{(3)} = (2, 3 + \sqrt{13})^T, \text{ 只有等式约束是 active constraint}$$

$$KKT \text{ 条件 } 1 - 2\sqrt{13}v = 0 \Rightarrow v = \frac{\sqrt{13}}{26}$$

$$\text{方向集 } G = \{d \mid d = \begin{bmatrix} d_1 \\ 0 \end{bmatrix}, d_1 \neq 0\}$$

$$\text{Lagrange 函数的 Hessian 矩阵 } \nabla_x^2 L(x^{(3)}, w, v) = \begin{bmatrix} -2v & 0 \\ 0 & -2v \end{bmatrix} = \begin{bmatrix} -\frac{1}{\sqrt{13}} & 0 \\ 0 & -\frac{1}{\sqrt{13}} \end{bmatrix}$$

$$d^T \nabla_x^2 L(x^{(3)}, w, v) d = (d_1, 0) \begin{bmatrix} -\frac{1}{\sqrt{13}} & 0 \\ 0 & -\frac{1}{\sqrt{13}} \end{bmatrix} \begin{bmatrix} d_1 \\ 0 \end{bmatrix} = -\frac{1}{\sqrt{13}} d_1^2 < 0,$$

$\therefore x^{(3)}$ 不满足二阶条件, 不是局部最优解

4

令目标函数 = $f(x)$, 等式约束 = $h(x)$

$$\nabla f(x) = \begin{bmatrix} x_1 - 1 \\ x_2 \end{bmatrix}, \nabla h(x) = \begin{bmatrix} -1 \\ 2\beta x_2 \end{bmatrix}$$

$$\text{Lagrange 函数为 } L(x, v) = \frac{1}{2}((x_1 - 1)^2 + x_2^2) - v(-x_1 + \beta x_2^2)$$

$$\nabla_x^2 L(x, v) = \begin{bmatrix} 1 & 0 \\ 0 & 1 - 2\beta v \end{bmatrix}$$

$$\text{KKT 条件} \begin{cases} x_1 - 1 + v = 0 \\ x_2 - 2\beta v x_2 = 0 \end{cases}, \text{ 将 } x = (0, 0)^T, \text{ 得 } v = 1$$

$$\text{方向集 } G = \left\{ d \mid d = \begin{bmatrix} 0 \\ d_2 \end{bmatrix} \right\}$$

$$d^T \nabla_x^2 L(x, v) d = (1 - 2\beta) d_2^2 > 0 \Rightarrow \beta < \frac{1}{2}$$

$$\text{当 } \beta = \frac{1}{2} \text{ 时, 原问题} = \min \frac{1}{2} (x_1^2 + 1)$$

易知当 $x_1 = 0$ 时, 原问题取得极小值. 综上, 当 $\beta \leq \frac{1}{2}$ 时, \bar{x} 是最优解

5

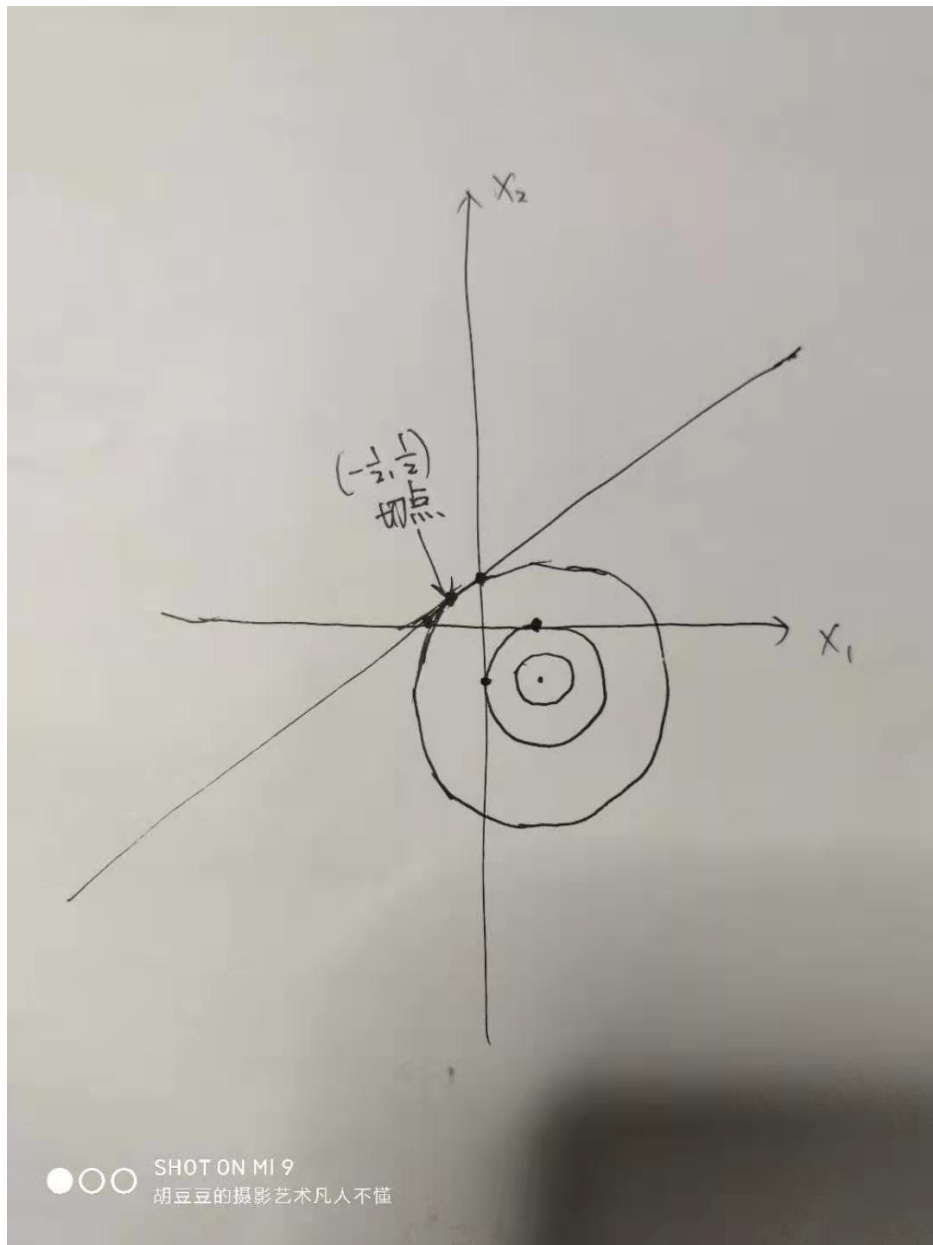
(1)

最优性条件法: 令 $f(x)$ = 目标函数, $g(x)$ = 不等式约束

$$\therefore \nabla f(x) = \begin{bmatrix} 2(x_1 - 1) \\ 2(x_2 + 1) \end{bmatrix}, \nabla g(x) = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

$$\text{KKT 条件} \begin{cases} 2(x_1 - 1) + w = 0 \\ 2(x_2 + 1) - w = 0 \\ w(-x_1 + x_2 - 1) = 0, \text{ 解得 } x = \left(-\frac{1}{2}, \frac{1}{2}\right)^T, w = 3, f_{\min} = \frac{9}{2} \\ w \geq 0 \\ -x_1 + x_2 - 1 \geq 0 \end{cases}$$

图解法:



如图, 切点为最优解 $x = \left(-\frac{1}{2}, \frac{1}{2}\right)^T$, 最优值为 $\frac{9}{2}$

(2)

$$\text{Lagrange 函数 } L(x, w) = (x_1 - 1)^2 + (x_2 + 1)^2 - w(-x_1 + x_2 - 1)$$

$$\text{对偶问题的目标函数 } \theta(w) = \inf\{(x_1 - 1)^2 + (x_2 + 1)^2 - w(-x_1 + x_2 - 1) | x \in R^2\}$$

$$= \inf\{x_1^2 - 2x_1 + wx_1\} + \inf\{x_2^2 + 2x_2 - wx_2\} + w + 2$$

$$\text{令 } w \geq 0$$

$$\text{则 } \inf\{x_1^2 - 2x_1 + wx_1\} = -\frac{1}{4}(w^2 - 4w + 4) = \inf\{x_2^2 + 2x_2 - wx_2\}$$

$$\theta(w) = -\frac{1}{2}w^2 + 3w, \text{ 对偶问题为}$$

$$\begin{aligned} \max & -\frac{1}{2}w^2 + 3w \\ \text{s.t. } & w \geq 0 \end{aligned}$$