

Solution 3

1. The Lagrangian function is

$$L(x, \mu) = (x_1 - 4)^2 + (x_2 - 4)^2 + \mu_1(x_1 + x_2 - 4) + \mu_2(x_1 + 3x_2 - 9)$$

Then the KKT condition is

$$\begin{aligned} 2(x_1 - 4) + \mu_1 + \mu_2 &= 0 \\ 2(x_2 - 4) + \mu_1 + 3\mu_2 &= 0 \\ 0 &\leq (-x_1 - x_2 + 4) \perp \mu_1 \geq 0 \\ 0 &\leq (-x_1 - 3x_2 + 9) \perp \mu_2 \geq 0 \end{aligned}$$

For the point $x^* = \left(\frac{3}{2}, \frac{5}{2}\right)^T$, we can get that $\mu_1 = 6, \mu_2 = -1 < 0$.

Therefore, it is not a KKT point.

2. (1) Denote the objective function as $f(x) = (x_1 - 1)^2 + (x_2 + 1)^2$, then gradient is

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

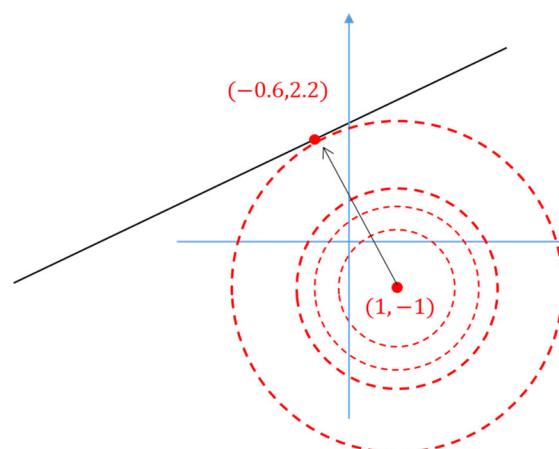
And the Hessian matrix is

$$H(x) = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \succ 0$$

So $f(x)$ is a convex function. Denote $g(x) = x_1 - 2x_2 + 5$, then the constraint can be represented as $g(x) \leq 0$.

Since both $f(x)$ and $g(x)$ are convex functions, the problem is a convex optimization.

(2) The feasible region and the contours of the objective function are



Therefore, $x^* = (-0.6, 2.2), f^* = 12.8$.

(3) The Lagrangian function is

$$L(x, \mu) = (x_1 - 1)^2 + (x_2 + 1)^2 + \mu(x_1 - 2x_2 + 5)$$

The KKT condition is

$$\begin{aligned} 2(x_1 - 1) + \mu &= 0 \\ 2(x_2 + 1) - 2\mu &= 0 \\ 0 \leq \mu \perp (-x_1 + 2x_2 - 5) &\geq 0 \end{aligned}$$

If $\mu^* = 0$, then $x_1^* = 1, x_2^* = -1$, and $-x_1^* + 2x_2^* - 5 = -1 - 2 - 5 = -8 < 0$, the constraint is not satisfied.

If $\mu^* \neq 0$, then we have $-x_1^* + 2x_2^* - 5 = 0$. Together with the first two equations, we

can obtain $x^* = (-0.6, 2.2), \mu^* = 3.2, f^* = 12.8$.

(4) The Lagrangian function is

$$\begin{aligned} L(x, \mu) &= (x_1 - 1)^2 + (x_2 + 1)^2 + \mu(x_1 - 2x_2 + 5) \\ &= x_1^2 - 2x_1 + 1 + x_2^2 + 2x_2 + 1 + \mu x_1 - 2\mu x_2 + 5\mu \\ &= x_1^2 + (\mu - 2)x_1 + \frac{(\mu - 2)^2}{4} + x_2^2 + (2 - 2\mu)x_2 + (1 - \mu)^2 + 5\mu - \frac{(\mu - 2)^2}{4} - (1 - \mu)^2 \\ &= \left(x_1 - \frac{\mu - 2}{2}\right)^2 + (x_2 - (1 - \mu))^2 + 5\mu - \frac{(\mu - 2)^2}{4} - (1 - \mu)^2 \end{aligned}$$

Therefore,

$$\min_x L(x, \mu) = 5\mu - \frac{(\mu - 2)^2}{4} - (1 - \mu)^2 = -\frac{5}{4}\mu^2 + 8\mu - 2$$

The dual problem is

$$\begin{aligned} \max_{\mu} \quad & -\frac{5}{4}\mu^2 + 8\mu \\ \text{s.t.} \quad & \mu \geq 0 \end{aligned}$$

3. (1) Given any two points $x = [x_1, x_2] \in S, y = [y_1, y_2] \in S$. For any $0 \leq \lambda \leq 1$, we have

$$\lambda x + (1 - \lambda)y = [\lambda x_1 + (1 - \lambda)y_1, \lambda x_2 + (1 - \lambda)y_2]$$

Then we check whether $\lambda x + (1 - \lambda)y$ is in S .

$$\begin{aligned} 2[\lambda x_1 + (1 - \lambda)y_1] + [\lambda x_2 + (1 - \lambda)y_2] &= \lambda(2x_1 + x_2) + (1 - \lambda)(2y_1 + y_2) \\ &\leq 4\lambda + 4(1 - \lambda) = 4 \end{aligned}$$

Therefore, $\lambda x + (1 - \lambda)y \in S$, so S is a convex set.

(2) We can minimize the square distance instead, and the optimization problem is

$$\begin{aligned} \min_{x_1, x_2} \quad & (x_1 - 4)^2 + (x_2 - 4)^2 \\ \text{s.t.} \quad & 2x_1 + x_2 \leq 4 \end{aligned}$$

The Lagrangian function is

$$L(x, \mu) = (x_1 - 4)^2 + (x_2 - 4)^2 + \mu(2x_1 + x_2 - 4)$$

The KKT condition is

$$\begin{aligned} 2(x_1 - 4) + 2\mu &= 0 \\ 2(x_2 - 4) + \mu &= 0 \\ 0 \leq \mu \perp (4 - 2x_1 - x_2) &\geq 0 \end{aligned}$$

If $\mu = 0$, we have $x_1 = x_2 = 4$, the constraint is not met.

If $\mu > 0$, we have

$$\begin{aligned} 2x_1 - 8 + 2\mu &= 0 \\ 2x_2 - 8 + \mu &= 0 \\ 2x_1 + x_2 - 4 &= 0 \end{aligned}$$

Therefore, $x^* = (\frac{4}{5}, \frac{12}{5})$.

Since the optimization is a convex optimization, x^* is global optimal.