

# CS257 Linear and Convex Optimization

## Homework 8

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1. (a) Substitute the constraint  $x_1 = 1 - 2x_2$  into the quadratic function

$$\begin{aligned} f(1 - 2x_2, x_2) &= (1 - 2x_2)^2 + (1 - 2x_2)x_2 + x_2^2 - (1 - 2x_2) - 3x_2 \\ &= 3x_2^2 - 4x_2 \\ &= 3\left(x_2 - \frac{2}{3}\right)^2 - \frac{4}{3} \end{aligned}$$

Thus, the minimum value is

$$f^* = -\frac{4}{3}$$

where the optimal solution is

$$x_1^* = -\frac{1}{3}, x_2^* = \frac{2}{3}$$

- (b) Write down the Lagrangian

$$\mathcal{L}(x_1, x_2, \lambda) = x_1^2 + x_1x_2 + x_2^2 - x_1 - 3x_2 + \lambda(x_1 + 2x_2 - 1)$$

By the Lagrange condition

$$\begin{cases} \frac{\partial \mathcal{L}}{\partial x_1} = 2x_1 + x_2 + \lambda - 1 = 0 \\ \frac{\partial \mathcal{L}}{\partial x_2} = x_1 + 2x_2 + 2\lambda - 3 = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda} = x_1 + 2x_2 - 1 = 0 \end{cases}$$

which yields

$$x_1^* = -\frac{1}{3}, x_2^* = \frac{2}{3}, \lambda^* = 1$$

Since the Hessian matrix

$$\nabla^2 f(\mathbf{x}) = \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} \succ \mathbf{0}$$

The problem is convex, so the solution is the optimal solution.

2. Since  $f$  is continuous and the feasible set is compact, the global minimum must exist. Let

$$h(x_1, x_2) = x_1^2 + \frac{1}{8}x_2^2 - 1$$

then

$$\nabla h(\mathbf{x}) = \begin{pmatrix} 2x_1 \\ \frac{1}{4}x_2 \end{pmatrix} \neq \mathbf{0}$$

Thus, any  $x^*$  will be regular point of  $h$ . Write down the Lagrangian

$$\mathcal{L}(x_1, x_2, \lambda) = x_1x_2 + x_1^2 + \lambda(x_1^2 + \frac{1}{8}x_2^2 - 1)$$

By the Lagrange condition

$$\begin{cases} \frac{\partial \mathcal{L}}{\partial x_1} = 2(1 + \lambda)x_1 + x_2 = 0 \\ \frac{\partial \mathcal{L}}{\partial x_2} = x_1 + \frac{1}{4}\lambda x_2 = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda} = x_1^2 + \frac{1}{8}x_2^2 - 1 = 0 \end{cases}$$

which yields 4 solutions

$$\begin{cases} x_1 = \frac{1}{\sqrt{3}} \\ x_2 = -\frac{4}{\sqrt{3}} \\ \lambda = 1 \end{cases}, \quad \begin{cases} x_1 = -\frac{1}{\sqrt{3}} \\ x_2 = \frac{4}{\sqrt{3}} \\ \lambda = 1 \end{cases}, \quad \begin{cases} x_1 = \frac{\sqrt{2}}{\sqrt{3}} \\ x_2 = \frac{2\sqrt{2}}{\sqrt{3}} \\ \lambda = -2 \end{cases}, \quad \begin{cases} x_1 = -\frac{\sqrt{2}}{\sqrt{3}} \\ x_2 = -\frac{2\sqrt{2}}{\sqrt{3}} \\ \lambda = -2 \end{cases}$$

where the first 2 solutions are the minimum. Therefore, the minimum value is  $f^* = -1$ , where the optimal solutions are  $x^* = \left(\frac{1}{\sqrt{3}}, -\frac{4}{\sqrt{3}}\right)^T$  and  $x^* = \left(-\frac{1}{\sqrt{3}}, \frac{4}{\sqrt{3}}\right)^T$ .

3. (a) Write down the Lagrangian

$$\mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}) = \frac{1}{2}\mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{g}^T \mathbf{x} + c + \boldsymbol{\lambda}^T (\mathbf{A} \mathbf{x} - \mathbf{b})$$

The Lagrange condition is

$$\begin{cases} \nabla_{\mathbf{x}} \mathcal{L} = \mathbf{Q} \mathbf{x} + \mathbf{g} + \mathbf{A}^T \boldsymbol{\lambda} = \mathbf{0} \\ \nabla_{\boldsymbol{\lambda}} \mathcal{L} = \mathbf{A} \mathbf{x} - \mathbf{b} = \mathbf{0} \end{cases}$$

(b) Since  $\mathbf{Q} \succ \mathbf{O}$ ,  $\mathbf{Q}^{-1} \succ \mathbf{O}$ , for any  $\mathbf{y} \neq \mathbf{0}$  we have

$$\mathbf{y}^T \mathbf{Q}^{-1} \mathbf{y} > 0$$

Since  $\text{rank}(\mathbf{A}) = k$ , for any  $\mathbf{x} \neq \mathbf{0}$  we have  $\mathbf{A}^T \mathbf{x} \neq \mathbf{0}$ , thus

$$\mathbf{x}^T \mathbf{A} \mathbf{Q}^{-1} \mathbf{A}^T \mathbf{x} > 0$$

which yields  $\mathbf{A} \mathbf{Q}^{-1} \mathbf{A}^T \succ \mathbf{O}$  and hence is invertible.

From the first equation we have

$$\mathbf{x} = -\mathbf{Q}^{-1}(\mathbf{g} + \mathbf{A}^T \boldsymbol{\lambda})$$

Substitute it into the second equation

$$-\mathbf{A}\mathbf{Q}^{-1}(\mathbf{g} + \mathbf{A}^T \boldsymbol{\lambda}) = \mathbf{b}$$

which yields

$$\boldsymbol{\lambda}^* = -(\mathbf{A}\mathbf{Q}^{-1}\mathbf{A}^T)^{-1}(\mathbf{A}\mathbf{Q}^{-1}\mathbf{g} + \mathbf{b})$$

Substitute it into the initial expression

$$\mathbf{x}^* = \mathbf{Q}^{-1}\mathbf{A}^T(\mathbf{A}\mathbf{Q}^{-1}\mathbf{A}^T)^{-1}(\mathbf{A}\mathbf{Q}^{-1}\mathbf{g} + \mathbf{b}) - \mathbf{Q}^{-1}\mathbf{g}$$

(c) Let  $\mathbf{Q} = \mathbf{I}$ ,  $\mathbf{g} = -\mathbf{x}_0$ ,  $c = \frac{1}{2}\mathbf{x}_0^T \mathbf{x}_0$ , and we have

$$\text{Proj}_S(\mathbf{x}_0) = \mathbf{x}^* = \mathbf{x}_0 - \mathbf{A}^T(\mathbf{A}\mathbf{A}^T)^{-1}(\mathbf{A}\mathbf{x}_0 - \mathbf{b})$$

(d) Let  $\mathbf{Q} = \mathbf{I}$ ,  $\mathbf{g} = -\mathbf{x}_0$ ,  $c = \frac{1}{2}\mathbf{x}_0^T \mathbf{x}_0$ ,  $\mathbf{A} = \mathbf{x}^T$  and we have

$$\text{Proj}_P(\mathbf{x}_0) = \mathbf{x}^* = \mathbf{x}_0 - \mathbf{w}(\mathbf{w}^T \mathbf{w})^{-1}(\mathbf{w}^T \mathbf{x}_0 - \mathbf{b}) = \mathbf{x}_0 - \frac{\mathbf{w}^T \mathbf{x}_0 - \mathbf{b}}{\|\mathbf{w}\|^2} \mathbf{w}$$

Therefore, the distance between  $\mathbf{x}_0$  and  $P$  is

$$d(\mathbf{x}_0, P) = \|\text{Proj}_P(\mathbf{x}_0) - \mathbf{x}_0\| = \left\| \frac{\mathbf{w}^T \mathbf{x}_0 - \mathbf{b}}{\|\mathbf{w}\|^2} \mathbf{w} \right\| = \frac{|\mathbf{w}^T \mathbf{x}_0 - \mathbf{b}|}{\|\mathbf{w}\|}$$