

# MAT3220: Operation Research

## Homework 1

李肖鹏 (116010114)

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**Problem 1.** Consider a general form linear program,

$$\begin{aligned} \max_{x_j} \quad & \sum_{j=1}^n c_j x_j \\ \text{s.t.} \quad & \sum_{j=1}^n a_{ij} x_j \leq b_i, \quad i \in I \\ & \sum_{j=1}^n a_{ij} x_j = b_i, \quad i \in E \\ & x_j \geq 0, \quad j \in S \end{aligned}$$

Show that it is possible to equivalently formulate it into the following standard form,

$$\begin{aligned} \max_{\vec{x}} \quad & \vec{c}^T \vec{x} \\ \text{s.t.} \quad & \bar{A} \vec{x} = \vec{b} \\ & \vec{x} \geq 0 \end{aligned}$$

First, we transform the original form into matrix form as follows

$$\begin{aligned} \max_{\vec{x}} \quad & \vec{c}^T \vec{x} \\ \text{s.t.} \quad & A_I \vec{x} \leq \vec{b}_I \\ & A_E \vec{x} = \vec{b}_E \\ & \vec{x} \geq 0 \end{aligned}$$

Let  $\vec{s} = \vec{b}_I - A_I \vec{x}$ , it is equivalent to the following form

$$\begin{aligned} \max_{\vec{x}} \quad & \vec{c}^T \vec{x} \\ \text{s.t.} \quad & A_I \vec{x} + \vec{s} = \vec{b}_I \\ & A_E \vec{x} = \vec{b}_E \\ & \vec{x}, \vec{s} \geq 0 \end{aligned}$$

We can further compact the above two equality constraints into a block matrix form, which is

$$\left[ \begin{array}{c|c} A_I & I \\ \hline A_E & 0 \end{array} \right] \cdot \begin{bmatrix} \vec{x} \\ \vec{s} \end{bmatrix} = \begin{bmatrix} \vec{b}_I \\ \vec{b}_E \end{bmatrix} \iff \bar{A} \cdot \vec{x} = \vec{b}$$

Similarly, we can replace the objective function as follows

$$\vec{c}^T \vec{x} = \begin{bmatrix} \vec{c}^T & \vdots & 0 \end{bmatrix} \cdot \begin{bmatrix} \vec{x} \\ \vec{s} \end{bmatrix} = \vec{c}^T \vec{x}$$

Therefore, we could obtain the equivalent form of the original formulation as follows

$$\begin{aligned} \max_{\vec{x}} \quad & \vec{c}^T \vec{x} \\ \text{s.t.} \quad & \vec{A} \vec{x} = \vec{b} \\ & \vec{x} \geq 0 \end{aligned}$$

**Problem 2.**

- Consider the following primal linear program ( $P$ ) and its dual problem ( $D$ ),

$$\begin{aligned} (P) \quad \max_{\vec{x}} \quad & \vec{c}^T \vec{x} \\ \text{s.t.} \quad & \vec{A} \vec{x} + \vec{s} = \vec{b} \\ & \vec{x} \geq 0, \vec{s} \geq 0 \end{aligned} \qquad \begin{aligned} (D) \quad \min_{\vec{y}} \quad & \vec{b}^T \vec{y} \\ \text{s.t.} \quad & \vec{A}^T \vec{y} - \vec{w} = \vec{c} \\ & \vec{y} \geq 0, \vec{w} \geq 0 \end{aligned}$$

Prove the following theorem (aka. the theorem of complementary slackness).

Suppose ( $P$ ) and ( $D$ ) are both feasible. Then,

- ( $P$ ) and ( $D$ ) both have optimal solutions.
- Denote a pair of their respective optimal solutions to be  $(\vec{x}^*, \vec{s}^*)$  and  $(\vec{y}^*, \vec{w}^*)$ . Show that

$$s_i^* y_i^* = 0, 1 \leq i \leq m, \text{ and } w_j^* x_j^* = 0, 1 \leq j \leq n$$

The first part is easy to prove. Since both ( $P$ ) and ( $D$ ) are feasible, they are either optimal or unbounded. If ( $P$ ) is unbounded, then by weak duality theorem, all feasible solution of ( $P$ ) should be less than or equal to any of solutions to ( $D$ ), which is impossible. This is because positive infinity cannot be bounded by any fixed value. If ( $D$ ) is unbounded, then the solution to ( $D$ ) tends to negative infinity. By weak duality again, this is impossible, because negative infinity cannot be an upper bound of solution to ( $P$ ).

Consider the second part, since  $(\vec{x}^*, \vec{s}^*)$  and  $(\vec{y}^*, \vec{w}^*)$  are feasible solutions, we have

$$\begin{cases} \vec{s}^* = \vec{b} - \vec{A} \vec{x}^* \geq \vec{0} \\ \vec{w}^* = \vec{A}^T \vec{y}^* - \vec{c} \geq \vec{0} \end{cases}$$

Since  $\vec{y}^*$  and  $\vec{x}^*$  are both nonnegative, we have

$$\begin{cases} \vec{y}^{*\top}(\vec{b} - A\vec{x}) \geq \vec{0} \\ \vec{x}^{*\top}(A^\top\vec{y}^* - \vec{c}) \geq \vec{0} \end{cases}$$

which shows that

$$\begin{cases} \vec{y}^{*\top}\vec{b} \geq \vec{y}^{*\top}A\vec{x} \\ \vec{x}^{*\top}A^\top\vec{y}^* \geq \vec{x}^{*\top}\vec{c} \end{cases}$$

Since  $\vec{y}^{*\top}A\vec{x}$  is a real number, so its transpose will be equal to itself, i.e.,

$$\vec{y}^{*\top}A\vec{x} = (\vec{y}^{*\top}A\vec{x})^\top = \vec{x}^{*\top}A^\top\vec{y}^*$$

Hence, we have

$$\vec{y}^{*\top}\vec{b} \geq \vec{y}^{*\top}A\vec{x} \geq \vec{x}^{*\top}A^\top\vec{y}^* \geq \vec{x}^{*\top}\vec{c}$$

By strong duality,  $\vec{y}^{*\top}\vec{b} = \vec{x}^{*\top}\vec{c}$ , thus, we conclude that

$$\vec{y}^{*\top}\vec{b} = \vec{y}^{*\top}A\vec{x} = \vec{x}^{*\top}A^\top\vec{y}^* = \vec{x}^{*\top}\vec{c}$$

Hence,

$$\begin{cases} \vec{y}^{*\top}(\vec{b} - A\vec{x}) = \vec{0} \\ \vec{x}^{*\top}(A^\top\vec{y}^* - \vec{c}) = \vec{0} \end{cases}$$

which is equivalent to say

$$\begin{cases} \vec{y}^{*\top}\vec{s}^* = \vec{0} \\ \vec{x}^{*\top}\vec{w}^* = \vec{0} \end{cases}$$

Since each entry of  $\vec{x}^*$ ,  $\vec{y}^*$ ,  $\vec{s}^*$ , and  $\vec{w}^*$  is nonnegative, we have

$$s_i^* y_i^* = 0, \quad 1 \leq i \leq m, \quad \text{and} \quad w_j^* x_j^* = 0, \quad 1 \leq j \leq n$$

- Apply the same upper bounding process to formulate the dual of the following general linear programming problem,

$$\begin{aligned} \max_{x_j} \quad & \sum_{j=1}^n c_j x_j \\ \text{s.t.} \quad & \sum_{j=1}^n a_{ij} x_j \leq b_i, \quad i \in I \\ & \sum_{j=1}^n a_{ij} x_j = b_i, \quad i \in E \\ & x_j \geq 0, \quad j \in S \end{aligned}$$

First, we transform the original form into matrix form as follows

$$\begin{aligned} \max_{\vec{x}} \quad & \vec{c}^\top \vec{x} \\ \text{s.t.} \quad & A_I \vec{x} \leq \vec{b}_I \\ & A_E \vec{x} = \vec{b}_E \\ & \vec{x} \geq \vec{0} \end{aligned}$$

Choose  $\vec{y}_I \geq 0$  and  $\vec{y}_E$  free, as long as  $\vec{y}_I^T A_I + \vec{y}_E^T A_E \geq \vec{c}^T$ , from  $\vec{x} \geq \vec{0}$ , we have

$$\vec{y}_I^T A_I \vec{x} + \vec{y}_E^T A_E \vec{x} \geq \vec{c}^T \vec{x} \implies \vec{y}_I^T A_I \vec{x} + \vec{y}_E^T \vec{b}_E \geq \vec{c}^T \vec{x}$$

Also, since  $\vec{y}_I \geq \vec{0}$  and  $A_I \vec{x} \leq \vec{b}_I$ , we have

$$\vec{y}_I^T \vec{b}_I + \vec{y}_E^T \vec{b}_E \geq \vec{c}^T \vec{x}$$

Thus, the dual problem is to minimize the upper bound, i.e.,

$$\begin{aligned} \min_{\vec{y}_I, \vec{y}_E} \quad & \vec{y}_I^T \vec{b}_I + \vec{y}_E^T \vec{b}_E \\ \text{s.t.} \quad & \vec{y}_I^T A_I + \vec{y}_E^T A_E \geq \vec{c}^T \\ & \vec{y}_I \geq 0, \vec{y}_E \text{ free} \end{aligned}$$

or equivalently,

$$\begin{aligned} \min_{\vec{y}_I, \vec{y}_E} \quad & \vec{b}_I^T \vec{y}_I + \vec{b}_E^T \vec{y}_E \\ \text{s.t.} \quad & A_I^T \vec{y}_I + A_E^T \vec{y}_E \geq \vec{c} \\ & \vec{y}_I \geq 0, \vec{y}_E \text{ free} \end{aligned}$$