# 5.2 Simplex and Duality

The following linear programs form a primal dual pair:

$$z = \max\{c^T x \mid Ax = b, x \ge 0\}$$
$$w = \min\{b^T y \mid A^T y \ge c\}$$

This means for computing the dual of a standard form LP, we do not have non-negativity constraints for the dual variables.

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## **Proof of Optimality Criterion for Simplex**

$$\tilde{c} = c^T - c_R^T A_R^{-1} A \le 0$$

This is equivalent to  $A^T(A_R^{-1})^Tc_B \ge c$ 

 $\gamma^* = (A_R^{-1})^T c_B$  is solution to the dual  $\min\{b^T \gamma | A^T \gamma \ge c\}$ .

$$b^{T}y^{*} = (Ax^{*})^{T}y^{*} = (A_{B}x_{B}^{*})^{T}y^{*}$$
$$= (A_{B}x_{B}^{*})^{T}(A_{B}^{-1})^{T}c_{B} = (x_{B}^{*})^{T}A_{B}^{T}(A_{B}^{-1})^{T}c_{B}$$
$$= c^{T}x^{*}$$

Hence, the solution is optimal.

## **Proof**

#### Primal:

$$\max\{c^{T}x \mid Ax = b, x \ge 0\}$$

$$= \max\{c^{T}x \mid Ax \le b, -Ax \le -b, x \ge 0\}$$

$$= \max\{c^{T}x \mid \begin{bmatrix} A \\ -A \end{bmatrix} x \le \begin{bmatrix} b \\ -b \end{bmatrix}, x \ge 0\}$$

### Dual:

$$\begin{aligned} \min \{ \begin{bmatrix} b^T - b^T \end{bmatrix} y \mid \begin{bmatrix} A^T - A^T \end{bmatrix} y \geq c, y \geq 0 \} \\ &= \min \left\{ \begin{bmatrix} b^T - b^T \end{bmatrix} \cdot \begin{bmatrix} y^+ \\ y^- \end{bmatrix} \mid \begin{bmatrix} A^T - A^T \end{bmatrix} \cdot \begin{bmatrix} y^+ \\ y^- \end{bmatrix} \geq c, y^- \geq 0, y^+ \geq 0 \right\} \\ &= \min \left\{ b^T \cdot (y^+ - y^-) \mid A^T \cdot (y^+ - y^-) \geq c, y^- \geq 0, y^+ \geq 0 \right\} \\ &= \min \left\{ b^T y' \mid A^T y' \geq c \right\} \end{aligned}$$



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Suppose that we have a basic feasible solution with reduced cost

$$\tilde{c} = c^T - c_B^T A_B^{-1} A \le 0$$

$$b^{T}y^{*} = (Ax^{*})^{T}y^{*} = (A_{B}x_{B}^{*})^{T}y^{*}$$
$$= (A_{B}x_{B}^{*})^{T}(A_{B}^{-1})^{T}c_{B} = (x_{B}^{*})^{T}A_{B}^{T}(A_{B}^{-1})^{T}c_{B}$$