

Proof of Weak Duality
Richard Anstee

Theorem (Weak Duality) Let \mathbf{x}^* be a feasible solution to the primal and let \mathbf{y}^* be a feasible solution to the dual where

$$\begin{array}{ll} \max & \mathbf{c} \cdot \mathbf{x} \\ \text{primal} & \begin{array}{l} A\mathbf{x} \leq \mathbf{b} \\ \mathbf{x} \geq \mathbf{0} \end{array} \end{array} \quad \begin{array}{ll} \min & \mathbf{b} \cdot \mathbf{y} \\ \text{dual} & \begin{array}{l} A^T\mathbf{y} \geq \mathbf{c} \\ \mathbf{y} \geq \mathbf{0} \end{array} \end{array}$$

Then $\mathbf{c} \cdot \mathbf{x}^* \leq \mathbf{b} \cdot \mathbf{y}^*$.

Proof: We note that $A^T\mathbf{y} \geq \mathbf{c}$ and $\mathbf{x} \geq \mathbf{0}$ yields $\mathbf{x}^T A^T\mathbf{y} \geq \mathbf{x}^T \mathbf{c}$ which we write as $\mathbf{c} \cdot \mathbf{x} = \mathbf{x}^T \mathbf{c} \leq \mathbf{x}^T A^T\mathbf{y}$. Similarly $A\mathbf{x} \leq \mathbf{b}$ and $\mathbf{y} \geq \mathbf{0}$ yields $\mathbf{y}^T A\mathbf{x} \leq \mathbf{y}^T \mathbf{b}$ which we write as $\mathbf{y}^T A\mathbf{x} \leq \mathbf{y}^T \mathbf{b} = \mathbf{b} \cdot \mathbf{y}$. Now $\mathbf{x}^T A^T\mathbf{y}$ is a 1×1 matrix and so $\mathbf{x}^T A^T\mathbf{y} = (\mathbf{x}^T A^T\mathbf{y})^T = \mathbf{y}^T (A^T)^T ((\mathbf{x}^T)^T) = \mathbf{y}^T A\mathbf{x}$. We obtain

$$\mathbf{c} \cdot \mathbf{x} = \mathbf{x}^T \mathbf{c} \leq \mathbf{x}^T A^T\mathbf{y} = \mathbf{y}^T A\mathbf{x} \leq \mathbf{y}^T \mathbf{b} = \mathbf{b} \cdot \mathbf{y}.$$

We read off $\mathbf{c} \cdot \mathbf{x} \leq \mathbf{b} \cdot \mathbf{y}$. ■

The case of equality is of course of great interest and Strong Duality and Complementary Slackness deal with equality. Nonetheless, Weak Duality is of independent interest and is a model for other optimization problems for which we have no Strong Duality.