Linear Programming III: Duality Theory and Zero-Sum Games Conditions for Optimality

$$\begin{array}{lll} \max & \mathbf{c}^T\mathbf{x} & \min & \mathbf{b}^T\mathbf{y} \\ \text{subject to} & \mathbf{A}\mathbf{x} \leq \mathbf{b} & \text{subject to} & \mathbf{A}^T\mathbf{y} \geq \mathbf{c} \end{array}$$

Weak Duality

Theorem 1. If \mathbf{x} is feasible in (P) and \mathbf{y} is feasible in (D) then $\mathbf{c}^T \mathbf{x} \leq \mathbf{b}^T \mathbf{y}$.

Give an upper bound on maximum matching:

Give a lower bound on vertex cover:

Strong Duality

Theorem 2 (Strong Duality). A pair of solutions $(\mathbf{x}^*, \mathbf{y}^*)$ are optimal for the primal and dual respectively if and only if $\mathbf{c}^T \mathbf{x}^* = \mathbf{b}^T \mathbf{y}^*$.

Proof.
$$(\Rightarrow)$$
 Skip. (\Leftarrow)

Complementary Slackness

Primal
$$(P)$$
: Dual (D) :

Theorem 3 (Complementary Slackness). A pair of solutions $(\mathbf{x}^*, \mathbf{y}^*)$ are optimal for the primal and dual respectively if and only if the following complementary slackness conditions (1) and (2) hold:

Proof.

Using Linear Programming for a Vertex Cover Approximation

$$\min \sum_{i \in V} w_i x_i$$
 s.t. $x_i + x_j \ge 1$
$$(i, j) \in E$$

$$x_i \in [0, 1]$$
 $i \in V$.

Claim 1. Let S^* denote the optimal vertex cover of minimum weight, and let x^* denote the optimal solution to the Linear Program. Then $\sum_{i \in V} w_i x_i^* \leq w(S^*)$.

Proof. The vertex cover problem is equivalent to the integer program, whereas the linear program is a *relaxation*. Then there are simply more solutions allowed to the linear program, so the minimum can only be smaller. \Box

max
$$4x_1 + x_2$$

subject to $-x_1 + x_2 \le 2$
 $8x_1 + 2x_2 \le 17$
 $x_1, x_2 \ge 0$

Claim 2. The set $S = \{i : x_i \ge 0.5\}$ is a vertex cover, and $w(S) \le 2 \sum_{i \in V} w_i x_i^*$.

Zero-Sum Games and the Minimax Theorem

	Rock	Paper	Scissors
Rock	0	-1	1
Paper	1	0	-1
Scissors	-1	1	0

The Minimax Theorem

Theorem 4 (Minimax Theorem). For every two-player zero-sum game A,

$$\max_{\mathbf{x}} \left(\min_{\mathbf{y}} \mathbf{x}^T \mathbf{A} \mathbf{y} \right) = \min_{\mathbf{y}} \left(\max_{\mathbf{x}} \mathbf{x}^T \mathbf{A} \mathbf{y} \right). \tag{1}$$