Linear Programming III: Duality Theory and Zero-Sum Games

Conditions for Optimality

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):

$$\begin{array}{cccc} \max & \mathbf{c}^T \mathbf{x} & \min & \mathbf{b}^T \mathbf{y} \\ \text{subject to} & \sum_i a_{ji} x_i \leq b_j & \forall j & (y_j) & \text{subject to} & \sum_i a_{ij} y_i \geq c_i & \forall i & (x_i) \\ & x_i \geq 0 & \forall i & y_j \geq 0 & \forall j \end{array}$$

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. $x_i + x_j \ge 1$
 $x_i \in [0, 1]$
 $(i, j) \in E$
 $i \in V.$

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



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,

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

From LP Duality to Minimax

Issues:

(1)

(2)

Observation:

$$\max_{\mathbf{x}} \left(\min_{\mathbf{y}} \mathbf{x}^T \mathbf{A} \mathbf{y} \right) = \max_{\mathbf{x}} \left(\min_{j=1}^n \mathbf{x}^T \mathbf{A} \mathbf{e}_j \right)$$
(2)

$$= \max_{\mathbf{x}} \left(\min_{j=1}^{n} \sum_{i=1}^{m} a_{ij} x_i \right)$$
(3)