# Linear Programming IV: More Duality and the Minimax Theorem

#### The Dual of a Linear Program

To take the dual: Label each primal constraint with a new dual variable. In our new linear program, each dual constraint will correspond to a primal variable. For the left-hand side, count up the appearances of this constraint's primal variable (e.g.,  $x_1$ ) in each of the primal constraints and multiply them by the dual variable for those constraints. That is, if  $x_1$  appears 5 times  $(5x_1)$  in constraint for  $y_1$ , then add  $5y_1$  to  $x_1$ 's constraint. Don't forget to include its appearance in the primal's objective function, but this will be the right-hand side of the constraint. Finally, the dual objective function is given by the right-hand side coefficients and their correspondence to the dual variables via the constraints in the primal.

The following is the normal form for a maximization problem primal and its primal:

$$\begin{array}{llll} \max & \mathbf{c}^T \mathbf{x} & \min & \mathbf{b}^T \mathbf{y} \\ \text{subject to} & \mathbf{A} \mathbf{x} \leq \mathbf{b} & \text{subject to} & \mathbf{A}^T \mathbf{y} \geq \mathbf{c} \\ & \mathbf{x} \geq \mathbf{0} & \mathbf{y} \geq \mathbf{0} \end{array}$$

#### **Example 3: Maximum Matching**

Given a graph G = (V, E) choose a maximum size matching—a set of edges S such that no vertex is covered by more than one edge.

Decision variables:  $x_e$  indicating whether edge e is in the matching.

Primal Linear Program:

$$\max \sum_{e \in E} x_e$$
 subject to 
$$\sum_{e: v \in e} x_e \le 1 \qquad \forall v \text{ (vertex matched at most once)}$$
 
$$x_e \ge 0 \qquad \forall e \text{ (non-negativity)}$$

Taking the dual of the above primal, we get what linear program?

# 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):

**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.

# 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  ${\bf A}$ ,

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

# From LP Duality to Minimax

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

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

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