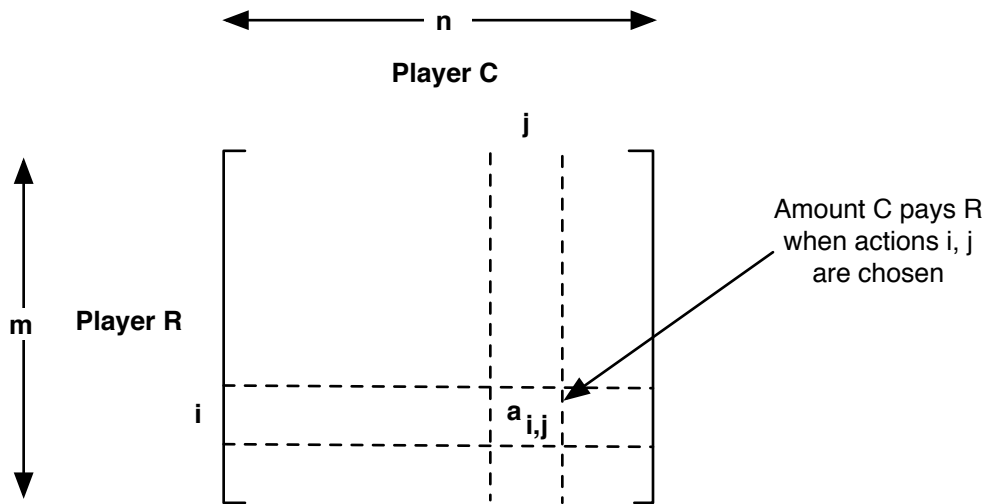


## Homework 4

### Problem 12.11

In this problem, we derive the minimax theorem using the LP-duality theorem. We are given a finite two-person zero-sum game, represented by matrix  $A$ . Player  $R$  can play actions from  $\{1, \dots, m\}$ , and player  $C$  can play actions from  $\{1, \dots, n\}$ .



Each player  $R$  and  $C$  will choose a strategy,  $\mathbf{x}$  and  $\mathbf{y}$  respectively, which is a vector that represents the probability of playing the action in each row or column.

$$\mathbf{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix}, \mathbf{y} = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \tag{1}$$

### Find the dual of the LP computing $R$ 's optimal strategy

We are given an LP  $Z$  that computes the optimal strategy for player  $R$ :

$$\begin{aligned} & \text{maximize} && z \\ & \text{s.t.} && z - \sum_{i=1}^m a_{ij}x_i \leq 0 \quad j = 1, \dots, n \\ & && \sum_{i=1}^m x_i = 1 \\ & && x_i \geq 0, \quad i = 1, \dots, m \end{aligned}$$

The dual of LP  $Z$  is:

$$\begin{array}{ll}
\text{minimize} & w \\
\text{s.t.} & w - \sum_{j=1}^n a_{ij}y_j \geq 0 \quad i = 1, \dots, m \\
& \sum_{j=1}^n y_j = 1 \\
& y_j \geq 0, \quad j = 1, \dots, n
\end{array}$$

### Show that the dual of $Z$ computes the optimal strategy for $C$

The optimal strategy for player  $C$  is the one that guarantees maximum possible expected winnings (or minimum expected losses), regardless of the strategy chosen by the other player. If player  $C$  plays strategy  $\mathbf{y}$ , he or she can be sure of losing no more than  $\max_{\mathbf{x}} \mathbf{x}^T \mathbf{A} \mathbf{y}$ , where the maximum is taken over all of player  $R$ 's possible strategies. A strategy  $\mathbf{y}$  that minimizes this value is an optimal strategy for player  $C$ .

We know that at least one of the optimal responses to player  $C$ 's strategy is a pure strategy:

$$\max_{\mathbf{x}} \mathbf{x}^T \mathbf{A} \mathbf{y} = \max_i \sum_{j=1}^n a_{ij} y_j \quad (2)$$

The goal is to find a strategy  $\mathbf{y}$  for player  $C$  that will minimize this value. This can be expressed as an optimization problem:

$$\begin{array}{ll}
\text{minimize} & \max_i \sum_{j=1}^n a_{ij} y_j \\
\text{s.t.} & \sum_{j=1}^n y_j = 1 \\
& y_j \geq 0, \quad (j = 1, \dots, n)
\end{array}$$

Expressed as an LP (call it  $W$ ), the problem of computing player  $C$ 's optimal strategy takes the form:

$$\begin{array}{ll}
\text{minimize} & w \\
\text{s.t.} & w - \sum_{j=1}^n a_{ij}y_j \geq 0 \quad i = 1, \dots, m \\
& \sum_{j=1}^n y_j = 1 \\
& y_j \geq 0, \quad j = 1, \dots, n
\end{array}$$

This LP (which computes  $C$ 's optimal strategy) is exactly the same as the dual of  $Z$ . Thus, the dual of  $Z$  computes the optimal strategy for  $C$ .

### Prove the minimax theorem using the LP-duality theorem

We first state the minimax theorem and the LP-duality theorem.

*Minimax theorem:* For every matrix  $\mathbf{A}$ ,

$$\max_{\mathbf{x}} \min_{\mathbf{y}} \mathbf{x}^T \mathbf{A} \mathbf{y} = \min_{\mathbf{y}} \max_{\mathbf{x}} \mathbf{x}^T \mathbf{A} \mathbf{y} \quad (3)$$

*LP-duality theorem:* The primal program has finite optimum iff its dual has finite optimum. Moreover, if  $\mathbf{x}^* = (\mathbf{x}_1^*, \dots, \mathbf{x}_n^*)$  and  $\mathbf{y}^* = (\mathbf{y}_1^*, \dots, \mathbf{y}_m^*)$  are optimal solutions for the primal and dual programs, respectively, then

$$\sum_{j=1}^n c_j x_j^* = \sum_{i=1}^m b_i y_i^* \quad (4)$$

From the LP-duality theorem, we know that the optimal solution of the primal is equal to the optimal solution to the dual.

We also have an LP  $Z$  that computes the optimal strategy for  $R$ , and we have shown that its dual is an LP  $W$  that computes the optimal strategy for  $C$ .

Putting these together, we know that the optimal solution of  $Z$  is equal to the optimal solution of  $W$ . Our  $Z$  is equal to  $\max_{\mathbf{x}} \min_{\mathbf{y}} \mathbf{x}^T \mathbf{A} \mathbf{y}$ , and our  $W$  is equal to  $\min_{\mathbf{y}} \max_{\mathbf{x}} \mathbf{x}^T \mathbf{A} \mathbf{y}$ , so we find that:

$$\max_{\mathbf{x}} \min_{\mathbf{y}} \mathbf{x}^T \mathbf{A} \mathbf{y} = \min_{\mathbf{y}} \max_{\mathbf{x}} \mathbf{x}^T \mathbf{A} \mathbf{y} \quad (5)$$

This gives us the minimax theorem. Thus, the minimax theorem is true.