

# Lecture 28: Matrix Games

Game theory has many applications: economics, computer science, physics, etc.

Founders: J. von Neumann, ...., J. Nash (Nobel prize and Abel prize),

....



John von Neumann



John Nash

# Matrix Games

## Example (Rock-Paper-Scissors)

The payoff matrix for the row player:

		column player		
		$r$	$p$	$s$
row player	$r$	0	-1	1
	$p$	1	0	-1
	$s$	-1	1	0



## [Morra] (Ch. 15 in [Chvatal])

- ▶ Each player hides 1 or 2 dollars and guess how much the other player has hidden
- ▶ If neither player guess correctly, then no one wins. Repeat.
- ▶ If both player guess correctly, then no one wins. Repeat.
- ▶ If only one player guess correctly, then the player wins **from the other player**, an amount the same as the total hidden \$\$.

**Payoff matrix (for the row player).**

[hide, guess]

		column player			
		[1, 1]	[1, 2]	[2, 1]	[2, 2]
row player	[1, 1]	0	2	-3	0
	[1, 2]	-2	0	0	3
	[2, 1]	3	0	0	-4
	[2, 2]	0	-3	4	0

# Mixed strategies and Stochastic vectors

Mixed strategies:

- ▶ May give weights (frequencies) on each strategy, say when they play the game **many many times**.
  - ▶ At a given time, players choose their strategy **randomly**.
  - ▶ Player 1 (row player) chooses strategy  $i$  for  $x_i$  fraction of times;
  - ▶ Player 2 (column player) chooses strategy  $j$  for  $y_j$  fraction of times;
  - ▶  $x_i$  = probability for player 1 (row player) to choose  $i$ ;
  - ▶  $y_j$  = probability for player 2 (column player) to choose  $j$ .

$\vec{x} = (x_1, \dots, x_m)$  is **stochastic**, that is,

$$x_1, \dots, x_m \geq 0 \quad \& \quad x_1 + \dots + x_m = 1.$$

$\vec{y} = (y_1, \dots, y_n)$  is **stochastic**, that is,

$$y_1, \dots, y_n \geq 0 \quad \& \quad y_1 + \dots + y_n = 1.$$

- ▶ Player 1 chooses a stochastic vector  $\vec{x}$ .
- ▶ Player 2 chooses a stochastic vector  $\vec{y}$ .

**Assume** Player 1 and Player 2 choose their strategies **independently**:

$$\begin{aligned}\Pr[\text{row} = i \ \& \ \text{column} = j] &= \Pr[\text{row} = i] \times \Pr[\text{column} = j] \\ &= x_i y_j\end{aligned}$$

**Then**, for

- ▶  $\vec{x} = (x_1, \dots, x_m)$ : player 1's strategy
- ▶  $\vec{y} = (y_1, \dots, y_n)$ : player 2's strategy
- ▶  $A = [a_{ij}]$ : the payoff matrix for row player (player 1),

**the average payoff for Player 1** (row player) is

$$\begin{aligned}&= \sum \text{"payoff for } (i, j) \text{"} \times \text{"probability for } (i, j) \text{"} \\ &= \sum_{i=1}^m \sum_{j=1}^n a_{ij} x_i y_j \\ &= \vec{x}^T A \vec{y}\end{aligned}$$

and **the average payoff for Player 2** (column player) =  $-\vec{x}^T A \vec{y}$ .

## Mixed strategies: Rock-Paper-Scissors Example

If Player 1 chooses  $\vec{x}^T = \begin{matrix} & r & p & s \\ \begin{bmatrix} 1/3 & 1/3 & 1/3 \end{bmatrix} \end{matrix}$

and Player 2 chooses  $\vec{y}^T = \begin{matrix} & r & p & s \\ \begin{bmatrix} 1/2 & 0 & 1/2 \end{bmatrix} \end{matrix}$

Then, the payoff for play 1 is

$$\begin{aligned} & \begin{bmatrix} 1/3 & 1/3 & 1/3 \end{bmatrix} \begin{matrix} & r & p & s \\ \begin{bmatrix} 0 & -1 & 1 \\ 1 & 0 & -1 \\ -1 & 1 & 0 \end{bmatrix} \end{matrix} \begin{bmatrix} 1/2 \\ 0 \\ 1/2 \end{bmatrix} \\ &= \begin{bmatrix} 1/3 & 1/3 & 1/3 \end{bmatrix} \begin{bmatrix} 1/2 \\ 0 \\ -1/2 \end{bmatrix} \\ &= 1/6 - 1/6 = 0. \end{aligned}$$

# Optimization problems

- ▶ Player 1 (row player)  
tries to maximize  $\vec{x}^T A \vec{y}$  by choosing good  $\vec{x}$ .
- ▶ Player 2 (column player)  
tries to maximize  $-\vec{x}^T A \vec{y}$ , equivalently, minimize  $\vec{x}^T A \vec{y}$  by choosing good  $\vec{y}$ ,
- ▶ Each player does not affect/control the other player's decision:  
They are independent!



# Remarks

$$\min_{\vec{y} \text{ stochastic}} (\vec{x}^*)^T A \vec{y} \leq (\vec{x}^*)^T A \vec{y}^* \leq \max_{\vec{x} \text{ stochastic}} \vec{x}^T A \vec{y}^*$$

- ▶ The left inequality will be strict if  $\vec{y}^*$  is not the solution of the min. problem.
- ▶ The right inequality will be strict if  $\vec{x}^*$  is not the solution of the max. problem.

## Remark

- ▶ *Such strategies  $(\vec{x}^*, \vec{y}^*)$  with*

$$\min_{\vec{y} \text{ stochastic}} (\vec{x}^*)^T A \vec{y} = \max_{\vec{x} \text{ stochastic}} \vec{x}^T A \vec{y}^*$$

*is called a **Nash equilibrium**. These are special strategies.*

# Optimization problems

Given strategy  $\vec{x}$  (a stochastic vector),



$$\text{Player 1's payoff} \geq \min_{\vec{y} \text{ stochastic}} \vec{x}^T A \vec{y}.$$

The right is “the worst-case scenario” for player 1.

- ▶ The right is the best-case scenario for player 2, which she can choose.
- ▶ Player 1 cannot avoid the possibility of such a worst-case scenario.

**Objective for player 1** : “ Find the best of the worst scenarios”.

**Definition (Optimization problem for player 1 (row player))**

- ▶ To find a mixed strategy  $\vec{x}$  (a stochastic vector) that maximizes  $\min_{\vec{y} \text{ stochastic}} \vec{x}^T A \vec{y}$ .
- ▶ That is,

$$\max_{\vec{x} \text{ stochastic}} \left[ \min_{\vec{y} \text{ stochastic}} \vec{x}^T A \vec{y} \right].$$

Remark:

- ▶ If the player 1 chooses the optimal strategy  $\vec{x}^*$  then **no matter what the player 2 chooses** the player 1 will **gain at least**

$$\max_{\vec{x} \text{ stochastic}} \left[ \min_{\vec{y} \text{ stochastic}} \vec{x}^T A \vec{y} \right].$$

# Optimization problems for player 2's point of view

Given strategy  $\vec{y}$  (a stochastic vector),



$$\text{Player 2's payoff} \geq - \max_{\vec{x} \text{ stochastic}} \vec{x}^T A \vec{y}.$$

The right is “the worst-case scenario” for player 2.

- ▶ The right is the best-case scenario for player 1, which she can choose.
- ▶ Player 2 cannot avoid the possibility of such a worst-case scenario.

**Objective for player 2** : “ Find the best of the worst scenarios”.

Definition (Optimization problem for player 2 (column player))

- ▶ To find a mixed strategy  $\vec{y}$  (a stochastic vector) that minimizes  $\max_{\vec{x} \text{ stochastic}} \vec{x}^T A \vec{y}$ .
- ▶ That is,

$$\min_{\vec{y} \text{ stochastic}} \left[ \max_{\vec{x} \text{ stochastic}} \vec{x}^T A \vec{y} \right].$$

Remark:

- ▶ If the player 2 chooses the optimal strategy  $\vec{y}^*$  then **no matter what the player 1 chooses** the player 2 will **loose at most**

$$\min_{\vec{y} \text{ stochastic}} \left[ \max_{\vec{x} \text{ stochastic}} \vec{x}^T A \vec{y} \right].$$