**CS861: Theoretical Foundations of Machine Learning** Lecture 27 - 11/06/2024 University of Wisconsin–Madison, Fall 2024

Lecture 27: Learning in games (cont'd)

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Continuing from the end of last time, we will keep talking about game theory and its connection to online learning. We will start by introducing **two-player normal form game**. Then, we will talk about two solution concepts: **Nash equilibrium** and **Safety strategies**. And we will see how we can use online learning method to establish the proof of **Minimax theorem**.

**Definition 1** (Normal Form Game). In a finite two-player NFG, player 1 has m available actions and player 2 has n available actions. If player 1 chooses  $a_1 \in [m]$  and player 2 chooses  $a_2 \in [n]$ , they receive payoffs  $Q^{(1)}(a_1, a_2), Q^{(2)}(a_1, a_2)$  respectively. Here,  $Q^{(1)}, Q^{(2)} \in \mathbb{R}^{m \times n}$ .

**Example 1** (Rock-Paper-Scissors). Let's consider the Rock-Paper-Scissors game. The following is the payoff (or utility) table for Player 1 and Player 2.

(P1, P2)	R	Р	$\mathbf{S}$
R	(0,0)	(-1,1)	(1,-1)
Р	(1,-1)	(0,0)	(-1,1)
$\mathbf{S}$	(-1,1)	(1, -1)	(0,0)

(Question) How to Choose a Strategy/Action for each player?

Thoughts: A player's best action depends on the other player's action.

**Example 2** (Deer/Stag Hunt). There are two players, who both go out hunting. Here, two players must independently choose whether to hunt a deer or a rabbit. Hunting a deer requires both players' cooperation to succeed and offers a greater reward, but also carries risk since each hunter depends on the other to commit. Hunting a rabbit, on the other hand, can be done individually and is less risky but provides a smaller reward. The following is the reward table:

$$\begin{array}{c|ccc} D & R \\ \hline D & (4,4) & (0,2) \\ R & (2,0) & (1,1) \end{array}$$

**Example 3** (Driver vs. Inspector). Consider driver and inspector as two opposing players. Driver can choose to drive "legally" or "illegally". And inspector can choose "don't inspect" or "inspect". The following is the payoff table:

	Don't Inspect	Inspect
Legal	(0,0)	(0,-1)
Illegal	(10,-10)	(-90,-6)

**Definition 2** (Mixed Strategies). Instead of choosing an action (pure strategy), players can choose distributions over the actions. For example,  $P_1 : x \in \Delta([m]), P_2 : y \in \Delta([n])$ . Later, we can think of all strategy as mixed strategy.

With above definition, we can consider the expected payoffs of x, y.

$$P_1: x^T Q^{(1)} y \qquad P_2: x^T Q^{(2)} y$$

Several solution concepts arise from the strategies of two players. We will look specifically at 2 of them:

- Nash equilibrium
- Safety strategy

**Definition 3** (Nash equilibrium). A strategy x for player 1 is a best response to strategy y of player 2, if it maximizes player 1's utility. *i.e.*,

$$x^T Q^{(1)} y \ge x'^T Q^{(2)} y \quad , \quad \forall x' \in \Delta([m])$$

Similarly, for player 2, y is a best response to x if

$$x^T Q^{(2)} y \ge x^T Q^{(1)} y' \quad , \quad \forall y' \in \Delta([n])$$

A pair  $(x_*, y_*)$  is a **Nash Equilibrium** (NE) if:  $x_*$  is player 1's best response to  $y_*$  and  $y_*$  is player 2's best response to  $x_*$ . That is, no player can unilaterally deviate and do better.

Here are some NE choices for previous examples:

- 1. Rock-Paper-Scissors:  $x_* = y_* = (1/3, 1/3, 1/3)$  is a NE.
- 2. Deer/Stag Hunt:  $x_* = y_* = (1, 0), (D,D)$   $x_* = y_* = (0, 1), (R,R)$  $x_* = y_* = (1/3, 2/3)$  is a mixed NE.
- 3. Driver vs. Inspector:  $x_* = (0.8, 0.2), y_* = (0.9, 0.1)$

**Definition 4** (Safety Strategies). Define  $g_1(x) \stackrel{\Delta}{=} \min_{y \in \Delta([n])} x^T Q^{(1)} y$ ,  $g_2(y) = \min_{x \in \Delta([m])} x^T Q^{(2)} y$ . Then P1 and P2's safety strategies are:

$$x^* = \arg \max_{x \in \Delta([m])} g_1(x) = \arg \max_x \min_y x^T Q^{(1)} y$$
$$y^* = \arg \max_{y \in \Delta([n])} g_2(y) = \arg \max_y \min_x x^T Q^{(2)} y$$

Some safety strategy choice for previous examples:

• RPS:

$$x_* = y_*(1/3, 1/3, 1/3)$$

• Driver vs. Inspector:

 $x_* = (1,0), y_* = (0,1)$ 

(Question): When are Safety Strategies always equal to NE ? Answer: Two-player zero-sum games (TPZSG) Definition 5 (Two-player zero sum game (TPZSG)). In a two-player zero-sum-game,

$$Q^{(1)} = -Q^{(2)} \stackrel{\Delta}{=} Q$$

• NE in TPZSG:

$$x^T Q y \leq x_*^T Q y_* \leq x_*^T Q y \qquad \forall x \in \Delta([m]), y \in \Delta([n])$$

• Safety strategy in TPZSG:

(1): 
$$\tilde{x} = \arg \max_{x} \min_{y} x^{T} Q y$$
  
(2):  $\tilde{y} = \arg \min_{y} \max_{x} x^{T} Q y$ 

Interpretation of  $\tilde{x}, \tilde{y}$ :

P1 has to announce their strategy first. P1 knows P2 will choose  $\arg \min_y x^T Qy$  if she announces x. Therefore, she will choose:

$$\tilde{x} = \arg\max_{x}\min_{y} \quad x^{T}Qy$$

P1's expected payoff (utility):

$$(*): \max_{x} \min_{y} x^{T} Q y$$

Similarly, if P2 announces first, P2's expected utility is:

$$-\min_{y}\max_{x}x^{T}Qy$$

P1's expected utility is:

$$(**): \min_{y} \max_{x} x^{T} Q y$$

The following is a brief argument to show that  $(*) \leq (**)$ :

For any continuous function f(x, y),

$$g_1(x) \stackrel{\Delta}{=} \min_y f(x, y)$$
$$g_2(y) \stackrel{\Delta}{=} \max_x f(x, y)$$

If  $g_1$  and  $g_2$  are also continuous, we have:

$$\begin{split} \min_{y} f(x,y) &\leq f(x,y') \quad \forall y' \in \Delta([n]) \\ \max_{x} \min_{y} f(x,y) &\leq \max_{x} f(x,y') \quad \forall y' \\ \max_{x} \min_{y} f(x,y) &\leq \min_{y'} \max_{x} f(x,y') \end{split}$$

We can also show (\*) = (\*\*). We will use the following theorem:

Theorem 4 (Von-Neumann's MiniMax). In any TPZSG,

$$(*) = \max_{x} \min_{y} x^{T} Q y = \min_{y} \max_{x} x^{T} Q y = (**)$$

This value, denoted V(Q), is called the value of the game.

**Proof:** Since we have shown  $(*) \leq (**)$  before, we will show  $(*) \geq (**)$  in the following. Consider the following multi-round game:

- On each round,  $P_2$  chooses a mixed strategy  $y_t \in \Delta([n])$ , via some policy  $\pi$ .
- After this,  $P_1$  chooses the best response

$$x_t = \arg \max_{x \in \Delta([n])} x^T Q y_t$$

• We will define  $P_2$ 's regret as

$$R_T(\pi, E) = \sum_{t=1}^T x_t^T Q y_t - \min_{y \in \Delta([n])} \sum_{t=1}^T x_t^T Q y_t$$

where E refers to the estimate:  $Q, P_1$ 's behavior, what is known to  $P_2$ .

**Claim 1.** If there exists a policy  $\pi$  which achieves sublinear regret, then

$$\max_{x} \min_{y} x^{T}Qy \geq \min_{y} \max_{x} x^{T}Qy$$

## Proof of the claim:

Let  $x_1, ..., x_T, y_1, ..., y_T$  be the strategies used by both players on each round. Let

$$\bar{x} = \frac{1}{T} \sum_{t=1}^{T} x_t$$
$$\bar{y} = \frac{1}{T} \sum_{t=1}^{T} y_t$$

$$\begin{split} \min_{y} \max_{x} x^{T} Qy &\leq \max_{x} x^{T} Q \bar{y} \\ &= \max_{x} \frac{1}{T} \sum_{t=1}^{T} x^{T} Q y_{t} \\ &= \frac{1}{T} \sum_{t=1}^{T} \max_{x} x^{T} Q y_{t} \\ (\text{by choice/definition of } x_{t}) &= \frac{1}{T} \sum_{t=1}^{T} x_{t}^{T} Q y_{t} \\ &= \frac{1}{T} \left( \min_{y \in \Delta([n])} \sum_{t=1}^{T} x_{t}^{T} Q y + R_{T}(\pi, E) \right) \\ &= \min_{y \in \Delta([n])} \bar{x}^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \min_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} \max_{y} x^{T} Q y + \frac{1}{T} R_{T}(\pi, E) \\ &\leq \max_{x} x^{T} Q x + \frac{1$$

So,  $\forall \epsilon > 0$ , we can find any policy  $\pi$  s.t.  $\frac{R}{T} \leq \epsilon$ . Then,  $(*) \leq (**)$