

# Introduction to Artificial Intelligence

## Lecture 18: Games and strategies

November 6, 2025



# Lecture plan

- **Games and strategies**
  - **Zero-sum game**
  - None-zero-sum game: Nash equilibrium
  - Cooperative games



# Recap: Two-player zero-sum games

- Players = {agent, opponent}
- **Definition: two-player zero-sum game**
  - $s_{start}$ : starting state
  - Action( $s$ ): possible actions from state  $s$
  - Successor( $s, a$ ): resulting state if choose action  $a$  in state  $s$
  - IsEndState( $s$ ): whether  $s$  is an end state
  - Utility( $s$ ): agent's utility for end state  $s$
  - Player( $s$ )  $\in$  Players: player who controls state  $s$



# Two-finger Morra

- Players **A** and **B** each show 1 or 2 fingers
  - If both show 1, **B** gives **A** 2 dollars
  - If both show 2, **B** gives **A** 4 dollars
  - Otherwise, **A** gives **B** 3 dollars



# Two-finger Morra

- What are the possible actions?
  - Player *A* chose 1, player *B* chose 1
  - Player *A* chose 1, player *B* chose 2
  - Player *A* chose 2, player *B* chose 1
  - Player *A* chose 2, player *B* chose 2



# Payoff matrix

- Definition: single-move simultaneous game
  - Players =  $\{A, B\}$
  - Actions: all possible actions
  - $V(a, b)$ :  $A$ 's utility if  $A$  chooses action  $a$ ,  $B$  choose  $b$  (Let  $V$  be the payoff matrix)
- Example: two-finger Morra payoff matrix

Player $A$	1 finger	2 fingers
1 finger	2	-3
2 fingers	-3	4

Player $B$	1 finger	2 fingers
1 finger	-2	3
2 fingers	3	-4



# Strategies

- Definition:
  - **Pure strategy:** a pure strategy is a single action:  $a \in Actions$
  - **Mixed strategy:** a mixed strategy is a probability distribution over all possible actions

$$0 \leq \pi(a) \leq 1 \text{ for } a \in Actions$$

- Example: two-finger Morra strategies
  - Always play action 1:  $\pi = [1, 0]$
  - Always play action 2:  $\pi = [0, 1]$
  - Uniformly chosen at random:  $\pi = \left[\frac{1}{2}, \frac{1}{2}\right]$



# Game evaluation

- Definition: game evaluation
  - The value of the game if player  $A$  follows  $\pi_A$  and player  $B$  follows  $\pi_B$  is

$$V(\pi_A, \pi_B) = \sum_{a,b} \pi_A(a) \pi_B(b) V(a, b)$$

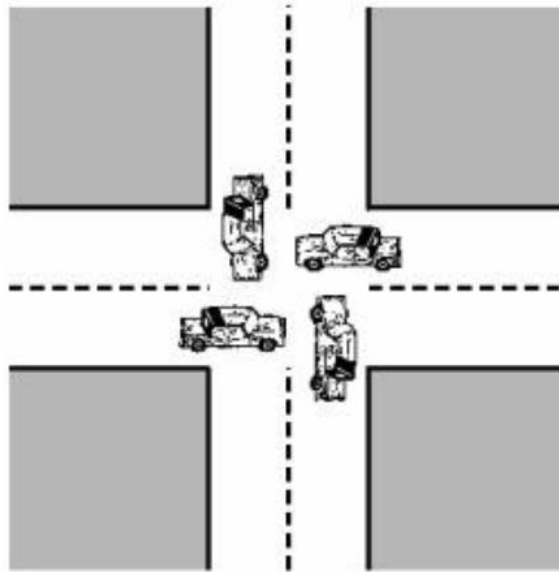


# How to optimize the game value?

- Game value:

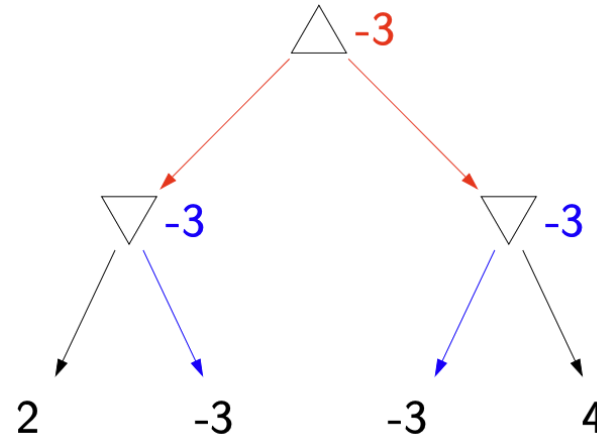
$$V(\pi_A, \pi_B)$$

- Challenge: player **A** wants to **maximize**, whereas player **B** wants to **minimize**



# Pure strategies: Who goes first?

- Player **A** goes first:

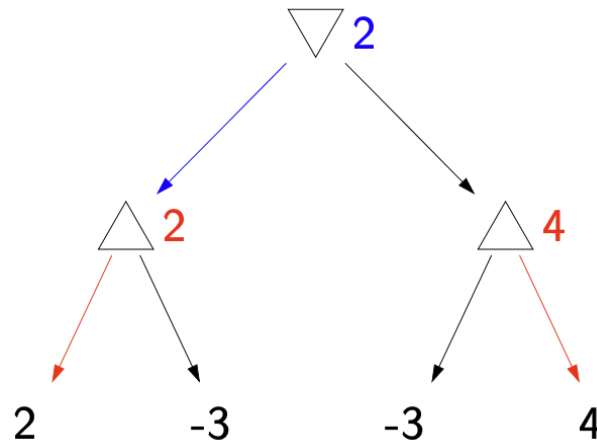


Going second is no worse!

$$\max_a \min_b V(a, b) \leq \min_b \max_a V(a, b)$$

Proof: For any fixed  $a, b$

- Player **B** goes first:



$$\min_{b'} V(a, b') \leq V(a, b) \leq \max_{a'} V(a', b)$$

Now we may take max on the left inequality, and min on the right inequality, to conclude the minimax inequality



# Mixed strategies

- Player A reveals:  $\pi_A = \left[\frac{1}{2}, \frac{1}{2}\right]$
- Value  $V(\pi_A, \pi_B) = \pi_B(1) \times \left(-\frac{1}{2}\right) + \pi_B(2) \times \left(\frac{1}{2}\right)$
- Optimal strategy for player B is  $\pi_B = [1, 0]$ , it's a pure strategy!
- **Claim:** For any fixed mixed strategy  $\pi_A$ :

$$\min_{\pi_B} V(\pi_A, \pi_B)$$

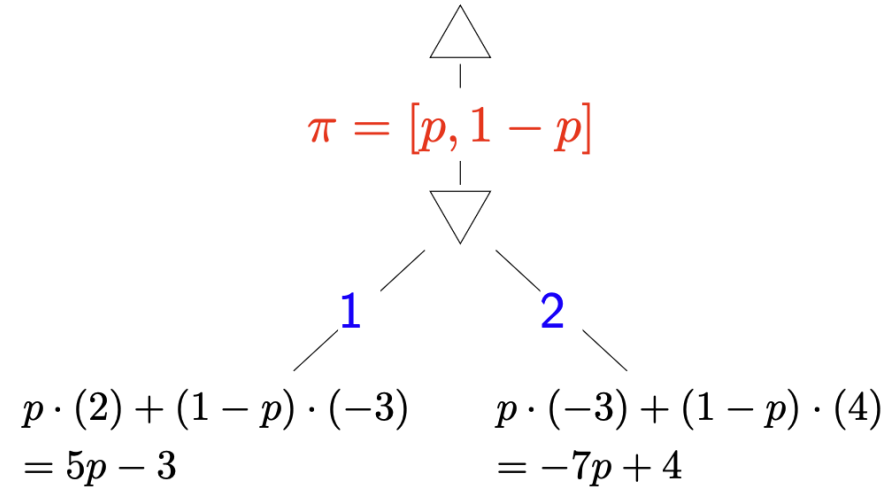
can be attained by a pure strategy  $\pi_B$

Can you convince yourself that this statement is correct?



# Mixed strategies

- Player *A* first reveals his or her mixed strategy



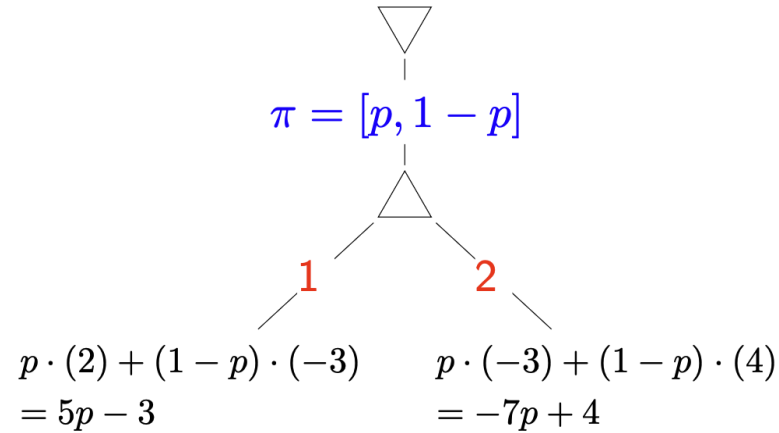
- Player *B* chooses the minimum of the two, leading to the maximin value of game:

$$\max_{0 \leq p \leq 1} \min\{5p - 3, -7p + 4\} = -\frac{1}{12} \text{ (with } p = \frac{7}{12}\text{)}$$



# Mixed strategies

- Player **B** first reveals his or her mixed strategy



- Player **A** chooses the maximum of the two, leading to the minimax value of game:

$$\min_{p \in [0,1]} \max\{5p - 3, -7p + 4\} = -\frac{1}{12} \text{ (again with } p = \frac{7}{12}\text{)}$$

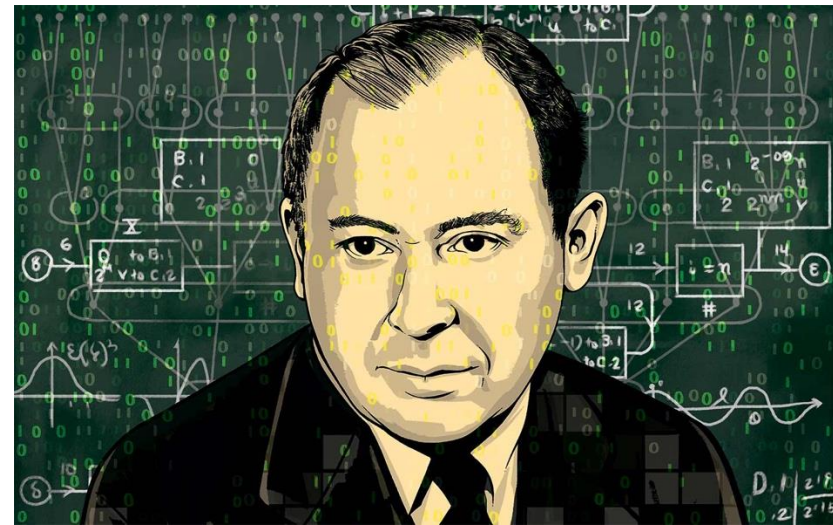


# Minimax theorem

- Theorem: the minimax theorem [John von Neumann, 1928]
  - For every simultaneous two-player zero-sum game with a finite number of actions

$$\max_{\pi_A \in \Delta_m} \min_{\pi_B \in \Delta_n} V(\pi_A, \pi_B) = \min_{\pi_B \in \Delta_n} \max_{\pi_A \in \Delta_m} V(\pi_A, \pi_B),$$

where  $\pi_A, \pi_B$  range over mixed strategies over a finite set



Hungarian-American mathematician and physicist, 1903 - 1957

# Proof of minimax theorem

- Let  $M$  be the payoff matrix for player  $A$ . Suppose  $A$  and  $B$  use mixed strategies  $x \in \Delta_m$  and  $y \in \Delta_n$ , where  $\Delta_m$  and  $\Delta_n$  refer to the simplex on the unit sphere in the positive orthant

- The expected payoff for player  $A$  is
$$f(x, y) = x^\top M y$$

- First, fix  $x$ . Because  $x^\top M$  is linear, its minimum is attained at a vertex, i.e., at some pure column  $e_j$ . Thus

$$\min_{y \in \Delta_n} f(x, y) = \min_{1 \leq j \leq n} x^\top M e_j$$



# Proof of minimax theorem

- Define  $F(x) = \min_{1 \leq j \leq n} x^\top M e_j$ .  $F$  is the pointwise minimum of linear functions. One can verify that
  - $F(x)$  is concave
  - $F(x)$  is continuous in the simplex  $\Delta_m$
- Therefore, there exists some  $x^* \in \Delta_m$  that maximizes  $F(x)$ . Let

$$v := F(x^*) = \min_{1 \leq j \leq n} x^{*\top} M e_j$$

- Consider the set of “tight” columns  $J = \{j: x^{*\top} M e_j = v\}$ . Take any probability vector  $y^*$  supported on  $J$ . Then

$$x^{*\top} M y^* = v$$

because every column in the support gives payoff  $v$  to  $x^*$



# Proof of minimax theorem

- For every  $y \in \Delta_m$ ,  $F(x^*) \leq f(x^*, y)$ . With  $y = y^*$ , we get  $f(x^*, y^*) = v$ . Hence

$$\max_{x \in \Delta_m} \min_{y \in \Delta_n} f(x, y) \geq \min_{y \in \Delta_n} f(x^*, y) = v = f(x^*, y^*)$$

- Next, we have that

$$\min_{y \in \Delta_n} \max_{x \in \Delta_m} f(x, y) \leq \max_{x \in \Delta_m} f(x, y^*) \leq v = \max_{x \in \Delta_m} F(x)$$

The second part is because on every  $j \in J$ ,  $f(x^*, e_j) = v$

- Since  $\max_{x \in \Delta_m} \min_{y \in \Delta_n} f(x, y) \geq v$ , we have

$$\max_{x \in \Delta_m} \min_{y \in \Delta_n} x^\top M y \geq \min_{y \in \Delta_n} \max_{x \in \Delta_m} x^\top M y$$



# Proof of minimax theorem

- Finally, recall the minimax inequality, which asserts that
$$\max_{\pi_A} \min_{\pi_B} V(\pi_A, \pi_B) \leq \min_{\pi_B} \max_{\pi_A} V(\pi_A, \pi_B)$$

Combined together, we thus complete the proof



# Lecture plan

- **Games and strategies**
  - Zero-sum game
  - **None-zero-sum game: Nash equilibrium**
  - Cooperative games



# Prisoner's dilemma

- Prosecutor asks  $A$  and  $B$  individually if each will testify against the other
  - If both testify, then both are sentenced to 5 years in jail
  - If both refuse, then both are sentenced to 1 year in jail
  - If only one testifies, then he or she gets out for free; the other gets a 10 year sentence



# Prisoner's dilemma

- What are the possible outcome?
  - Player *A* testified, player *B* testified
  - Player *A* testified, player *B* refused
  - Player *A* refused, player *B* testified
  - Player *A* refused, player *B* refused



# Prisoner's dilemma

- Payoff matrix

	testify	refuse
testify	$A = -5, B = -5$	$A = -10, B = 0$
refuse	$A = 0, B = -10$	$A = -1, B = -1$

- Let  $V_p(\pi_A, \pi_B)$  be the utility for player  $p$



# Prisoner's dilemma

- If both players had refused, then one of the players could testify to improve his/her payoff (from  $-1$  to  $0$ )
- If one player testified, then the other had to choose testified, otherwise he/she would be in the jail for **10** years instead of **5** years
- This is not the highest possible reward, but it is stable in the sense that neither player would want to change his or her strategy
- This kind of situation is commonly known as the **Nash equilibrium**



# Nash equilibrium

- Different from zero-sum games, a Nash equilibrium is a kind of fixed-point state, where no player has any incentive to change his or her policy unilaterally
- **Definition:** A Nash equilibrium is any kind of policies  $(\pi_A^*, \pi_B^*)$  such that no player has an incentive to change his or her strategy, conditioned on the other player's strategy

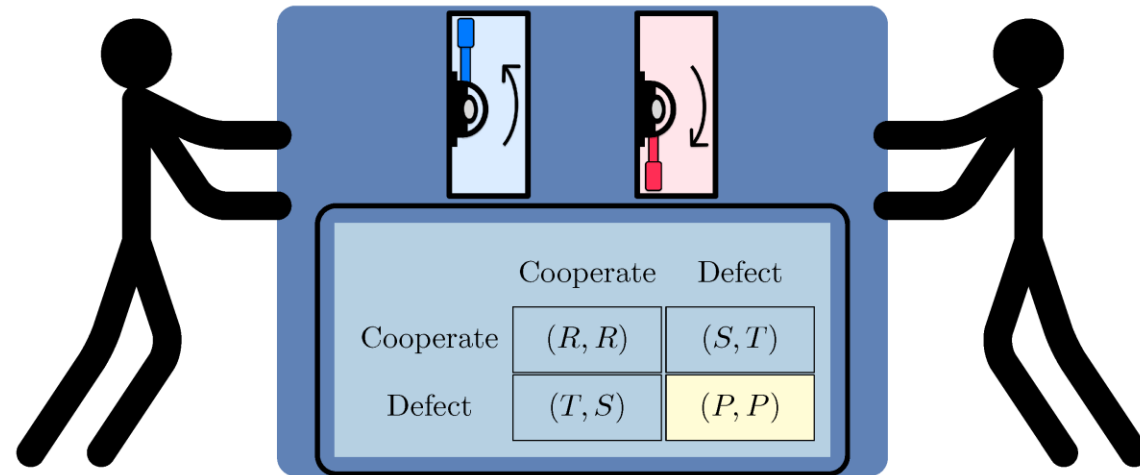
$$V_A(\pi_A^*, \pi_B^*) \geq V_A(\pi_A, \pi_B^*) \text{ for all } \pi_A$$

$$V_B(\pi_A^*, \pi_B^*) \geq V_B(\pi_A^*, \pi_B) \text{ for all } \pi_B$$



# Nash equilibrium

- Since the game is no longer a zero-sum game, we cannot apply the minimax theorem, but we can still get a weaker result
- **Theorem:** Nash's existence theorem [1950]
  - In any finite-player game with finite number of actions, there exists **at least one (mixed-strategy)** Nash equilibrium



- Proof uses Kakutani's fixed-point theorem (skipped)

# Examples of Nash equilibria

- The minimax strategies for zero-sum are also equilibria and they are simultaneously the global optima ([exercise question](#))

- **Example 1:** Two-finger Morra

- Nash equilibrium: A and B both play  $\pi = \left[\frac{7}{12}, \frac{5}{12}\right]$

$$\min_{p \in [0,1]} \max\{5p - 3, -7p + 4\} = -\frac{1}{12} \text{ (again with } p = \frac{7}{12}\text{)}$$

- **Example 2:** Collaborative two-finger Morra

- Two Nash equilibria:
    - A and B both play 1 (value is 2)
    - A and B both play 2 (value is 4)



# Summary

- **Two-player zero-sum games**
  - Von Neumann's minimax theorem
  - Multiple minimax strategies, single game value
- **Two-player non-zero-sum games**
  - Nash's existence theorem or fixed-point theorem
  - Multiple Nash equilibria, multiple game values



# Other examples: AlphaGo



- Supervised learning: on human games
- Reinforcement learning: on self-play games
- Evaluation function: convolutional neural network (value network)
- Policy: convolutional neural network (policy network)
- Monte Carlo Tree Search: search/lookahead

# Coordination games

- Hanabi: players need to signal to each other and coordinate in a decentralized fashion to collaboratively win. So, unlike most games, **you cannot see your own hand** — only your teammates can. You must rely on **limited communication** to figure out which cards to play



- Hide-and-Seek: OpenAI has developed multi-agent RL in which two teams of agents (hiders vs seekers) compete in a simulated physics-based world



# Cooperative games

- A cooperative game is typically defined as a pair  $(N, v)$ , where
  - $N = \{1, 2, \dots, n\}$  is the set of players
  - $v: 2^N \rightarrow \mathbb{R}$  is the characteristic function, which assigns a value to every coalition
- Applications:
  - **Resource allocation:** given a budget (e.g., one million dollars) and a list of public projects, allocate the budget on a subset of projects to maximize social welfare
  - **Robotics:** multi-agent cooperation



# Solution concepts in cooperative games

- **Core:** A payoff vector  $x = (x_1, x_2, \dots, x_n)$  is in the core if  $\sum_{i \in N} x_i = v(N)$ , and  $\sum_{i \in S} x_i \geq v(S)$ ,  $\forall S \subseteq N$ 
  - Example: in resource allocation games, this corresponds to solving a linear program
- **Shapley value:** ensures fair division  
[https://en.wikipedia.org/wiki/Shapley\\_value](https://en.wikipedia.org/wiki/Shapley_value)

