CS 470 Introduction To Artificial Intelligence

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Outline

- Introduction
 - Model games
- 2 Basic of Game Theory
 - Dominance
 - Strategies
- Turn-taking games
 - Model games
 - Alpha-beta pruning



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Multi-Agent in a Game

- $s \in \mathsf{State}$: states
 - S_0 : initial state
 - \bullet S_t erminate : terminal state
- $p \in PLAYER$: players
- $a \in Actions$: actions
- $c \in \text{Consequence}(s, a)$: consequences transition model
- $u \in \text{UTILITY}(c, p)$: utility utility function



Payoff matrix

- Two players
- Player 1 has *m* actions
- Player 2 has *n* actions

	P2 P1	a_1^{P2}		a_n^{P2}
•	a_1^{P1}	$(u_{1,1}^{P1}, u_{1,1}^{P2})$	• • •	$(u_{1,n}^{P1}, u_{1,n}^{P2})$
	•••	:	• • •	÷
	a_m^{P1}	$(u_{m,1}^{P1}, u_{m,1}^{P2})$	• • •	$(u_{m,n}^{P1}, u_{m,n}^{P2})$



Zero-sum game

Zero-sum game

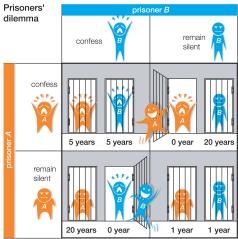
- The total payoff to all players is the same for every instance of the game
- Equivalence : the sum is zero
- One player's profit is the other player's loss
- Show only the utility of Player 1 in the payoff matrix

P1 P2	a_1^{P2}		a_n^{P2}
a_1^{P1}	$u_{1,1}^{P1}$		$u_{1,n}^{P1}$
		•	:
a_m^{P1}	$u_{m,1}^{P1}$		$u_{m,n}^{P1}$

Non zero-sum game



Prisoners' dilemma



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Battle of sexes

Woman Baseball Ballet Baseball (3, 2) (1, 1) Ballet (0, 0) (2, 3)

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Strategic dominance

For player i, a strategy $s^* \in S_i$ and another strategy $s' \in S_i$

- s^* weakly dominates s'
 - for any strategy of the other player S_i
 - None worse $\forall s_{-i} \in S_{-i}, u_i(s^*, s_{-i}) \geq u_i(s', s_{-i})$
 - At least one better $\exists s_{-i} \in S_{-i}, u_i(s^*, s_{-i}) > u_i(s', s_{-i})$
- s* strictly dominates s'
 - for any strategy of the other player S_i
 - All better $\forall s_{-i} \in S_{-i}, u_i(s^*, s_{-i}) > u_i(s', s_{-i})$



Pareto dominance

strategy profile

- a set of strategies for all the players
- one and only strategy for every player
- $\bullet \ (s_i, s_{-i})$

Strategy profile *S* **Pareto dominates** strategy profile *S'*

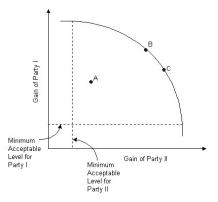
- no player gets a worse payoff with S than with S' $\forall i, U_i(S) \geq U_i(S')$
- at least one player gets a better payoff with S than with S' $\exists i, U_i(S) > U_i(S')$



Pareto optimal

Strategy profile S^* is **Pareto optimal**

• No there strategy S' that Pareto dominates S^*





Nash equilibria

For player i, s_i is a **best response** to S_{-i}

$$\bullet \ \forall s_i' \in S_i, U_i(s_i, S_{-i}) \geq U_i(s_i', S_{-i})$$

A strategy profile $S=(s_1,\cdots,s_n)$ is a Nash equilibrium

- no agent can do by better unilaterally changing his/her strategy
- $\forall i, s_i$ is a best response to S_{-i} .



Maximin strategy

Maximin strategy

- maximizes a player's worst possible outcome
- $\bullet \ s^* = \arg\max_{s \in S} \min_{t \in T} \mathit{u}(s,t)$



Minimax strategy

Minimax strategy

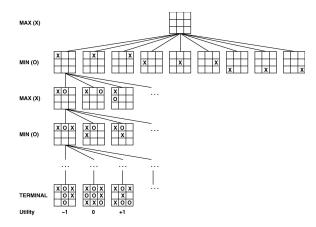
- minimizes opponent player's best possible outcome
- $t^* = \arg\min_{t \in T} \max_{s \in S} u(s, t)$
- Minimax theorem John Von Neumann
 - zero-sum game
 - optimal strategy

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Tic-Tac-Toe game





- game tree
 - initial state S_0 is the root
 - each state maps to a node
 - each action maps to an edge
 - minimax tree
 - optimal strategy minimax
- evaluation function approximates the utility of a state without a complete search

Alpha-beta pruning

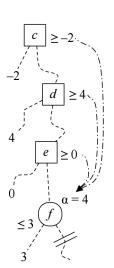
- exponential growth in minimax tree
- <u>pruning</u>: removes away branches that cannot possibly influence the final decision
- minimax search ⇒ depth-first
 - Alpha-beta pruning



Alpha-beta pruning

Alpha cutoff

- $oldsymbol{lpha}$ = the value of the best choice at any node for the MAX algorithm
- biggest lower bound
- Example
 - At node f, MAX get utility ≤ 3
 - At node f, $\alpha = 4$
 - Node f will never be reached
 - Pruning Node f

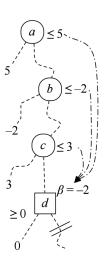




Alpha-beta pruning

Beta cutoff

- $\beta =$ the value of the best choice at any node for the MIN algorithm
- smallest upper bound
- Example
 - At node d, MIN get utility ≥ 0
 - At node d, $\beta = -2$
 - Node d will never be reached
 - Pruning Node d





Alpha-beta pruning

Example