Multiagent Systems (BE4M36MAS)

Beyond the Normal and Extensive Forms

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Previously ... on multi-agent systems.

- **1** Sequence-Form Representations
- 2 Solving Extensive-Form Games

Let's assume that we want to play some normal-form game twice. For example, rock-paper-scissors:



Question

How can we model such games?

We can model the game as an extensive-form game.

Pros: we already know how to solve such a game. Cons: it is unnecessarily large.

RPS Played Twice as an Extensive-Form Games



We can use a model specific for repeated games.

Finitely Repeated Games

Definition

In repeated games we assume that a normal-form game, termed the *stage game*, is played repeatedly. If the number of repetitions (or rounds) is finite, we talk about *finitely repeated games*.

Question

How can we solve finitely repeated games?

We can use backward induction.

Why does this work if we have an extensive-form game with imperfect information?

Infinitely Repeated Games

Definition

Assume that a *stage game* is played repeatedly. If the number of repetitions (or rounds) is infinite, we talk about *infinitely repeated games*.

We cannot use extensive-form games as a underlying model. There are no leafs to assign utility values to. We need to define other utility measures:

Definition

Given an infinite sequence of payoffs $r_i^{(1)}, r_i^{(2)}, \ldots$ for player i, the *average reward* of i is

$$\lim_{k \to \infty} \frac{\sum_{j=1}^k r_i^{(j)}}{k}$$

Definition

Given an infinite sequence of payoffs $r_i^{(1)}, r_i^{(2)}, \ldots$ for player *i*, and a discount factor β with $0 \le \beta \le 1$, the *future discounted reward* is

$$\sum_{j=1}^{\infty} \beta^j r_i^{(j)}$$

Why do we use discount factor?

- a player cares more about immediate rewards
- \blacksquare a repeated game can terminate after each round with probability $1-\beta$

How can we represent the strategies in infinitely repeated games? (the game tree is infinite)

 a stationary strategy – a randomized strategy that is played in each stage game

Is this enough? Consider a repeated prisoners dilemma – what is the most famous strategy in repeated prisoners dilemma?

Tit-for-tat: the player starts by cooperating and thereafter chooses in round j + 1 the action chosen by the other player in round j.

We can have more complex strategies consisting of states/machines.

Strategies in Repeated Games

Definition

Given a game G = (N, A, u) that will be played repeatedly, an automaton M_i for player *i* is a four-tuple $(Q_i, q_i^0, \delta_i, f_i)$, where:

- Q_i is a set of states;
- q_i^0 is the start state;
- δ_i defines a transition function mapping the current state and an action profile to a new state, $\delta_i:Q_i\times A\to Q_i$
- f_i is a strategy function associating with every state an action for player $i, f_i : Q_i \to A_i$.



A strategy for Tit-for-Tat

Definition

A payoff profile $r = (r_1, r_2, ..., r_n)$ is *enforceable* if $\forall i \in \mathcal{N}$, $r_i \geq v_i$.

where v_i is a minmax value for player i

$$v_i = \min_{s_{-i} \in \mathcal{S}_{-i}} \max_{s_i \in \mathcal{S}_i} u_i(s_{-i}, s_i)$$

Definition

A payoff profile $r = (r_1, r_2, \ldots, r_n)$ is *feasible* if there exist rational, nonnegative values α_a such that for all i, we can express r_i as $\sum_{a \in \mathcal{A}} \alpha_a u_i(a)$, with $\sum_{a \in \mathcal{A}} \alpha_a = 1$.

Theorem (Folk Theorem)

Consider any *n*-player normal-form game G and any payoff profile $r = (r_1, r_2, \ldots, r_n)$.

- If r is the payoff profile for any Nash equilibrium s of the infinitely repeated G with average rewards, then for each player i, r_i is enforceable.
- If r is both feasible and enforceable, then r is the payoff profile for some Nash equilibrium of the infinitely repeated G with average rewards.

Let's generalize the repeated games. We do not have to play the same normal-form game repeatedly. We can play different normal-form games (possibly for infinitely long time).

Definition (Stochastic game)

- A stochastic game is a tuple $(Q,\mathcal{N},\mathcal{A},\mathcal{P},\mathcal{R})$, where:
 - Q is a finite set of games
 - ${\mathcal N}$ is a finite set of players
 - ${\mathcal A}$ is a finite set of actions, ${\mathcal A}_i$ are actions available to player i
 - $\mathcal P$ is a transition function $\mathcal P:Q\times \mathcal A\times Q:\to [0,1],$ where $\mathcal P(q,a,q')$ is a probability of reaching game q' after a joint action a is played in game q

 \mathcal{R} is a set of reward functions $r_i: Q \times \mathcal{A} \to \mathbb{R}$

Similarly to repeated games we can have several different rewards (or objectives):

- discounted
- average
- reachability/safety

In reachability objectives a player wants to visit certain games infinitely often.

Related to reaching some target state (for example attacking a target) in a game without a pre-determined horizon.

Stochastic Games - Examples

Repeated prisoners dilemma:





Equilibria in Stochastic Games

Definition (History)

Let $h_t = (q_0, a_0, q_1, a_1, \dots, a_{t1}, q_t)$ denote a history of t stages of a stochastic game, and let H_t be the set of all possible histories of this length.

Definition (Behavioral strategy)

A behavioral strategy $s_i(h_t, a_{i_j})$ returns the probability of playing action a_{i_j} for history h_t .

Definition (Markov strategy)

A Markov strategy s_i is a behavioral strategy in which $s_i(h_t, a_{i_j}) = s_i(h'_t, a_{i_j})$ if $q_t = q'_t$, where q_t and q'_t are the final games of h_t and h'_t , respectively.

Equilibria in Stochastic Games

Definition

A strategy profile is called a *Markov perfect equilibrium* if it consists of only Markov strategies, and is a Nash equilibrium.

Theorem

Every *n*-player, general-sum, discounted-reward stochastic game has a Markov perfect equilibrium.

Equilibria in Stochastic Games

For other rewards, Markov perfect equilibrium does not have to exist.



Standard algorithms from Markov Decision Processes, value and strategy iteration, translate to stochastic games.

Algorithm 1. Value Iteration

1: t := 02: $\tilde{v}^0 := (0, ..., 0, 1) // the vector \tilde{v}^0$ is indexed 0, 1, ..., N, N + 13: while true do 4: t := t + 15: $\tilde{v}^t_0 := 0$ 6: $\tilde{v}^t_{N+1} := 1$ 7: for $i \in \{1, 2, ..., N\}$ do 8: $| \tilde{v}^t_i := val(A_i(\tilde{v}^{t-1}))$

Algorithm 2. Strategy Iteration

1: t := 12: $x^1 :=$ the strategy for Player I playing uniformly at each position 3 while true do $y^t :=$ an optimal best reply by Player II to x^t 4: for $i \in \{0, 1, 2, \dots, N, N+1\}$ do 5: $v_i^t := \mu_i(x^t, y^t)$ 6: 7: t := t + 1for $i \in \{1, 2, ..., N\}$ do 8: if $\operatorname{val}(A_i(v^{t-1})) > v_i^{t-1}$ then 9: $x_i^t := \operatorname{maximin}(A_i(v^{t-1}))$ 10: 11: else $x_{i}^{t} := x_{i}^{t-1}$ 12:

compact representation of the game with $n = |\mathcal{N}|$ players

we want to reduce the input from $|\mathcal{S}|^{|\mathcal{N}|}$ to $|\mathcal{S}|^d$, where $d \ll |\mathcal{N}|$

it is less important which player plays which action, but how many players play certain action

examples of succinct representations :

- congestion games (network congestion games, ...)
- polymatrix games (zero-sum polymatrix games)
- graphical games (action graph games)

We have *n* players, set of edges *E*, strategies for each player are *paths* in the network (S), and there is a congestion function $c_e : \{0, 1, \ldots, n\} \to \mathbb{Z}^+$. When all players choose their strategy path $s_i \in S_i$ we have the load of edge e, $\ell_s(e) = |\{s_i : e \in s_i\}|$ and $u_i = -\sum_{e \in s_i} c_e(\ell_s(e))$.

Braess' paradox



100 drivers that want to go from s to t. What is Nash equilibrium? Now consider that we introduce a new edge between A and B, such that $c_{(A,B)}(x) = 0, \forall x \in \ell_{(A,B)}$.



What is Nash equilibrium?

Theorem

Every atomic congestion game has a pure Nash equilibrium.

We can find it by an algorithm where players iteratively switch to their pure best response. This holds for generalizations:

- weighted congestion games
- all games known as *potential games*

For some subclasses, it is polynomial to find a pure NE (e.g., for symmetric network congestion games due to min-cost flow).

Invitation - Algorithmic Game Theory (XEP36AGT)

XEP36AGT	Algorithmic Game Theory			Extent of teaching:	2+0+4
Guarantors:	Bošanský B.	Roles:	<u>s</u>	Completion:	ZK
Teachers:	Bošanský B.				
Responsible Department:	13136	Credits:	4	Semester:	

Anotation:

This course extends the knowledge in multiagent systems and game theory by focusing on the algorithmic and computational problems - the computational complexity and current algorithms for finding and approximating different solution concepts, the impact of different representations of games, and the applications of learning techniques in game theory. The course is suitable for students that have already completed the course on Multiagent Systems (AMM30MAS) and either wish to strengthen their knowledge in game theory, or they are working on related problems from artificial intelligence such as machine learning, decision theory, planning.

Course outlines:

- 1. Introduction to Game Theory
- 2. Fundamental Theorems (von Neumann, Nash, Kuhn)
- 3. Succinct Representations of Games
- 4. Finding Nash Equilibria
- 5. Approximating Nash Equilibria
- 6. Finding Correlated Equilibria
- 7. Finding Stackelberg Equilibria
- 8. Repeated Games
- 9. Learning and Dynamics in Games
- 10. Learning in Extensive-Form Games
- 11. Games of Incomplete Information, Auctions
- 12. Algorithmic Mechanism Design
- 13. Mechanisms Without Money
- 14. Stochastic Games

The structure of the lecutres covers the important algorithmic topics in game theory. Besides attending the lectures, the students are assumed to work on their homework assignments that strengthen the understanding of the topic (4h per week).