Algorithmic Game Theory

Repeated and Stochastic Games

Branislav Bošanský

Artificial Intelligence Center, Department of Computer Science, Faculty of Electrical Engineering, Czech Technical University in Prague

branislav.bosansky@agents.fel.cvut.cz

April 1, 2019

Repeated Games are the simplest type of a dynamic game that evolves over time.

Repeated Games are the simplest type of a dynamic game that evolves over time.

As such we can treat them as an extensive-form game (the finitely repeated case), or a stochastic game (the infinitely repeated case). However, such representations are very inefficient.

Repeated Games are the simplest type of a dynamic game that evolves over time.

As such we can treat them as an extensive-form game (the finitely repeated case), or a stochastic game (the infinitely repeated case). However, such representations are very inefficient.

Repeated games can thus be seen as an example of a compact representation.

Repeated Games are the simplest type of a dynamic game that evolves over time.

As such we can treat them as an extensive-form game (the finitely repeated case), or a stochastic game (the infinitely repeated case). However, such representations are very inefficient.

Repeated games can thus be seen as an example of a compact representation.

	C	D
C	(1,1)	(-1,2)
\overline{D}	(2,-1)	(0,0)

Repeated Games are the simplest type of a dynamic game that evolves over time.

As such we can treat them as an extensive-form game (the finitely repeated case), or a stochastic game (the infinitely repeated case). However, such representations are very inefficient.

Repeated games can thus be seen as an example of a compact representation.

	C	D
\overline{C}	(1,1)	(-1, 2)
\overline{D}	(2, -1)	(0,0)

Natural question: Is a NE of a single game the same as in the (in)finitely repeated game?



Definition

Definition

$$\blacksquare \mathcal{H} = \{\emptyset\} \cup \bigcup_{t=1}^{\infty} A^t \cup A^{\infty}$$

Definition

- $\blacksquare \mathcal{H} = \{\emptyset\} \cup \bigcup_{t=1}^{\infty} A^t \cup A^{\infty}$
- lacksquare $\mathcal{S}_i:\mathcal{H} o\mathcal{A}_i$

Definition

- $\blacksquare \mathcal{H} = \{\emptyset\} \cup \bigcup_{t=1}^{\infty} A^t \cup A^{\infty}$
- lacksquare $\mathcal{S}_i:\mathcal{H}\to\mathcal{A}_i$
- $g_i(s_i, s_{-i}) = (1 \delta) \sum_{t=1}^{\infty} \delta^t \mathbb{E}_{a_i \sim s_i, a_{-i} \sim s_{-i}} (u_i(a_i, a_{-i}))$

Definition

- $\blacksquare \mathcal{H} = \{\emptyset\} \cup \bigcup_{t=1}^{\infty} A^t \cup A^{\infty}$
- lacksquare $\mathcal{S}_i:\mathcal{H}\to\mathcal{A}_i$
- $g_i(s_i, s_{-i}) = (1 \delta) \sum_{t=1}^{\infty} \delta^t \mathbb{E}_{a_i \sim s_i, a_{-i} \sim s_{-i}} (u_i(a_i, a_{-i}))$
- \bullet $\delta \in (0,1)$ is the discount factor

We can define alternative utility functions in repeated games based on payoff vectors v_i^t for each:

We can define alternative utility functions in repeated games based on payoff vectors v_i^t for each:

lacksquare overtaking payoff: $\lim_{T o \infty} \sum_{t=1}^T v_i^t$

We can define alternative utility functions in repeated games based on payoff vectors v_i^t for each:

- \blacksquare overtaking payoff: $\lim_{T \to \infty} \sum_{t=1}^T v_i^t$
- lacksquare average payoff (or limit mean payoff): $\lim_{T o \infty} \sum_{t=1}^T v_i^t / T$

We can define alternative utility functions in repeated games based on payoff vectors v_i^t for each:

- lacksquare overtaking payoff: $\lim_{T o \infty} \sum_{t=1}^T v_i^t$
- lacksquare average payoff (or limit mean payoff): $\lim_{T \to \infty} \sum_{t=1}^T v_i^t / T$

Definition

Player i's min-max payoff is

$$\underline{v_i} = \min_{s_{-i}} \max_{s_i} g_i(s_i, s_{-i})$$



We can define alternative utility functions in repeated games based on payoff vectors v_i^t for each:

- lacksquare overtaking payoff: $\lim_{T o \infty} \sum_{t=1}^T v_i^t$
- lacksquare average payoff (or limit mean payoff): $\lim_{T \to \infty} \sum_{t=1}^T v_i^t / T$

Definition

Player i's min-max payoff is

$$\underline{v_i} = \min_{s_{-i}} \max_{s_i} g_i(s_i, s_{-i})$$

A strategy s is individually rational if $g_i(s) \geq \underline{v_i}$



Theorem (Nash Folk Theorem)

If v_i is a feasible and an individually rational payoff, then there exists a discount factor $\underline{\delta} < 1$ such that for all $\delta > \underline{\delta}$, there is a Nash equilibrium of G with payoff v_i .

Theorem (Nash Folk Theorem)

If v_i is a feasible and an individually rational payoff, then there exists a discount factor $\underline{\delta} < 1$ such that for all $\delta > \underline{\delta}$, there is a Nash equilibrium of G with payoff v_i .

Proof.

If v_i is feasible then there exist a strategy s such that $g_i(s)=v_i$ and let m_{-i} be the minmax strategy of other players to reach value $\underline{v_i}$ for player i. Let consider the following strategy:

Theorem (Nash Folk Theorem)

If v_i is a feasible and an individually rational payoff, then there exists a discount factor $\underline{\delta} < 1$ such that for all $\delta > \underline{\delta}$, there is a Nash equilibrium of G with payoff v_i .

Proof.

If v_i is feasible then there exist a strategy s such that $g_i(s) = v_i$ and let m_{-i} be the minmax strategy of other players to reach value \underline{v}_i for player i. Let consider the following strategy:

 \blacksquare play according to s_i as long as no one deviates

Theorem (Nash Folk Theorem)

If v_i is a feasible and an individually rational payoff, then there exists a discount factor $\underline{\delta} < 1$ such that for all $\delta > \underline{\delta}$, there is a Nash equilibrium of G with payoff v_i .

Proof.

If v_i is feasible then there exist a strategy s such that $g_i(s) = v_i$ and let m_{-i} be the minmax strategy of other players to reach value \underline{v}_i for player i. Let consider the following strategy:

- \blacksquare play according to s_i as long as no one deviates
- 2 let $\overline{v_i}$ be the maximum value player i can get by a deviation in step t

Theorem (Nash Folk Theorem)

If v_i is a feasible and an individually rational payoff, then there exists a discount factor $\delta < 1$ such that for all $\delta > \delta$, there is a Nash equilibrium of G with payoff v_i .

Proof.

If v_i is feasible then there exist a strategy s such that $g_i(s) = v_i$ and let m_{-i} be the minmax strategy of other players to reach value v_i for player i. Let consider the following strategy:

- 1 play according to s_i as long as no one deviates
- 2 let $\overline{v_i}$ be the maximum value player i can get by a deviation in step t

$$(1 - \delta)[v_i + \delta v_i + \ldots + \delta^t \overline{v_i} + \delta^{t+1} \underline{v_i} + \ldots] \le$$

$$\le (1 - \delta)[v_i + \delta v_i + \ldots + \delta^t v_i + \delta^{t+1} v_i + \ldots]$$

(Proof cont.)

By setting $\underline{\delta}$ sufficiently large approaching 1 the above inequality holds.

(Proof cont.)

By setting $\underline{\delta}$ sufficiently large approaching 1 the above inequality holds.

The Nash folk theorem says that essentially anything goes as a Nash equilibrium payoff in a discounted repeated game.

(Proof cont.)

By setting $\underline{\delta}$ sufficiently large approaching 1 the above inequality holds.

The Nash folk theorem says that essentially anything goes as a Nash equilibrium payoff in a discounted repeated game.

The players threat by playing grim trigger strategies.

Let's generalize the repeated games.

Let's generalize the repeated games. We do not have to play the same normal-form game repeatedly.

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).

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:

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

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:

 ${\cal Q}$ is a finite set of games

 ${\cal N}$ is a finite set of players

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:

 ${\it Q}\,$ is a finite set of games

 ${\cal N}$ is a finite set of players

 ${\cal A}$ is a finite set of actions, ${\cal A}_i$ are actions available to player i

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

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
- ${\cal N}$ is a finite set of players
- ${\cal A}$ is a finite set of actions, ${\cal A}_i$ are actions available to player i
- \mathcal{P} is a transition function $\mathcal{P}:Q\times\mathcal{A}\times Q:\rightarrow [0,1]$, 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):

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

discounted

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

- discounted
- average

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

- discounted
- average
- reachability/safety

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.

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

Stochastic Games - Examples

Repeated prisoners dilemma:

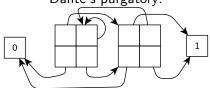


Stochastic Games - Examples

Repeated prisoners dilemma:



Dante's purgatory:



Definition (History)

Let $h_t=(q_0,a_0,q_1,a_1,\ldots,a_{t1},q_t)$ 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 (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 (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.

Definition

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

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.

Definition

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

Theorem

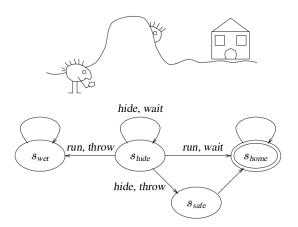
Every n-player, general-sum, discounted-reward stochastic game has a Markov perfect equilibrium.

Theorem

Problem of computing an optimal strategy in simple (turn-taking) stochastic games, where pure stationary strategies are known to be optimal, is in PLS.

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

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



Approximating Optimal Strategies in Stochastic Games

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



¹Pseudocode from [3].

Approximating Optimal Strategies in Stochastic Games

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

Algorithm 1. Value Iteration



¹Pseudocode from [3].

Approximating Optimal Strategies in Stochastic Games

Algorithm 2. Strategy Iteration

```
1 \cdot t := 1
2: 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
        for i \in \{0, 1, 2, \dots, N, N+1\} do
        v_i^t := \mu_i(x^t, y^t)
        t := t + 1
 7:
        for 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:
             else
11:
             x_i^t := x_i^{t-1}
12:
```

²Pseudocode from [3].

Extending stochastic games to imperfect information (known as partial observability, hence termed Partially Observable Stochastic Games (POSGs)) is lot more complicated compared to finite EFGs.

Extending stochastic games to imperfect information (known as partial observability, hence termed Partially Observable Stochastic Games (POSGs)) is lot more complicated compared to finite EFGs.

The problem lies with *Nested beliefs*. Consider a two-player game where each player has some private state unobserved by the opponent:

Extending stochastic games to imperfect information (known as partial observability, hence termed Partially Observable Stochastic Games (POSGs)) is lot more complicated compared to finite EFGs.

The problem lies with *Nested beliefs*. Consider a two-player game where each player has some private state unobserved by the opponent:

■ A player i has uncertainty about the exact state of the opponent -i – there is a belief (a probability distribution) over possible states.

Extending stochastic games to imperfect information (known as partial observability, hence termed Partially Observable Stochastic Games (POSGs)) is lot more complicated compared to finite EFGs.

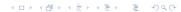
The problem lies with *Nested beliefs*. Consider a two-player game where each player has some private state unobserved by the opponent:

- A player i has uncertainty about the exact state of the opponent -i there is a belief (a probability distribution) over possible states.
- The optimal strategy of player i depends on the strategy of the opponent -i that depends on the belief over possible private states of player i.

Extending stochastic games to imperfect information (known as partial observability, hence termed Partially Observable Stochastic Games (POSGs)) is lot more complicated compared to finite EFGs.

The problem lies with *Nested beliefs*. Consider a two-player game where each player has some private state unobserved by the opponent:

- A player i has uncertainty about the exact state of the opponent -i there is a belief (a probability distribution) over possible states.
- The optimal strategy of player i depends on the strategy of the opponent -i that depends on the belief over possible private states of player i.
- Each player needs to consider beliefs, belief of beliefs, ... etc.



Solving general POSGs is not tractable (even solving related single-player decision problems is often undecidable [2]).

Solving general POSGs is not tractable (even solving related single-player decision problems is often undecidable [2]).

We can restrict to subclasses of games with limited partial observability:

Solving general POSGs is not tractable (even solving related single-player decision problems is often undecidable [2]).

We can restrict to subclasses of games with limited partial observability:

One-Sided Partially Observable Stochastic Games [4]

Solving general POSGs is not tractable (even solving related single-player decision problems is often undecidable [2]).

We can restrict to subclasses of games with limited partial observability:

- One-Sided Partially Observable Stochastic Games [4]
- Partially Observable Stochastic Games with Public Observations [5]

Theoretical results:

Theoretical results:

 Value function (function that assigns a belief point value of a (sub)-game) is convex (or convex-concave).

Theoretical results:

- Value function (function that assigns a belief point value of a (sub)-game) is convex (or convex-concave).
- We can define dynamic-programming operator a generalization of Bellman update.

$$[Hv](b) = \min_{\pi_2} \max_{\pi_1} \left(R_{\pi_1, \pi_2}^{\text{imm}} + \gamma \cdot R_{\pi_1, \pi_2}^{\text{subs}}(v) \right)$$

Theoretical results:

- Value function (function that assigns a belief point value of a (sub)-game) is convex (or convex-concave).
- We can define dynamic-programming operator a generalization of Bellman update.

 $a \in A_1 \ o \in \mathcal{O}$

$$[Hv](b) = \min_{\pi_2} \max_{\pi_1} \left(R_{\pi_1, \pi_2}^{\text{imm}} + \gamma \cdot R_{\pi_1, \pi_2}^{\text{subs}}(v) \right)$$

$$R_{\pi_{1},\pi_{2}}^{\text{imm}} = \sum_{s \in \mathcal{S}} \sum_{a \in \mathcal{A}_{1}} \sum_{a' \in \mathcal{A}_{2}} b(s) \cdot \pi_{1}(a) \cdot \pi_{2}(s, a') \cdot \mathcal{R}(s, a, a')$$

$$R_{\pi_{1},\pi_{2}}^{\text{subs}}(v) = \sum_{s \in \mathcal{S}} \sum_{a \in \mathcal{A}_{1}} \pi_{1}(a) \cdot \Pr[o|a, \pi_{2}] \cdot v(b_{\pi_{2}}^{a,o})$$

We can generalize value-iteration algorithms for POMDPs to POSGs.

Heuristic Search Value Iteration (HSVI):

```
Data: Game \langle S, A_1, A_2, \mathcal{O}, \mathcal{T}, \mathcal{R} \rangle, initial belief b^0,
           discount factor \gamma, desired precision \epsilon > 0,
           neighborhood parameter R
  Result: Approximate value function \hat{v}
1 Initialize \hat{v}
2 while gap(\hat{v}(b^0)) > \epsilon do
3 | Explore (b^0, \epsilon, R, 0)
4 return \hat{v}
5 procedure Explore (b, \epsilon, R, t)
       \pi_2 \leftarrow optimal strategy of player 2 in [Hv](b)
       (a, o) \leftarrow select according to forward exploration
         heuristic
       if excess(\hat{v}(b_{\pi_2}^{a,o}), t+1) > 0 then
       Explore (b_{\pi_0}^{a,o}, \epsilon, R, t+1)
   \Gamma \leftarrow \Gamma \cup \{L\Gamma(b)\}\
       \Upsilon \leftarrow \Upsilon \cup \{U\Upsilon(b)\}\ and make \overline{v}(U-L)-Lipschitz
   Algorithm 1: HSVI algorithm for one-sided POSGs
```

References I

(besides the books)

- M. Osborne and A. Rubinstein, A course in game theory.
 MIT press, 1994.
- [2] O. Madani, S. Hanks, and A. Condon, "On the undecidability of probabilistic planning and infinite-horizon partially observable Markov decision problems," in AAAI/IAAI, pp. 541–548, 1999.
- [3] K. A. Hansen, R. Ibsen-Jensen, and P. B. Miltersen, "The Complexity of Solving Reachability Games Using Value and Strategy Iteration," in International Computer Science Symposium in Russia, pp. 77–90, 2011.
- [4] Horák, K., Bošanský, B., and Pěchouček, M. (2017). Heuristic Search Value Iteration for One-Sided Partially Observable Stochastic Games. In *In Proceedings of AAAI Conference on Artificial Intelligence*, pages 558–564.

References II

[5] Horák, K., Bošanský, B. (2019).
Solving Partially Observable Stochastic Games with Public Observations.
In In Proceedings of AAAI Conference on Artificial Intelligence.