

## Beyond the Normal and Extensive Forms

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Previously ... on multi-agent systems.

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

# Extensive-Form Games

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

	<b>R</b>	<b>P</b>	<b>S</b>
<b>R</b>	(0, 0)	(-1, 1)	(1, -1)
<b>P</b>	(1, -1)	(0, 0)	(-1, 1)
<b>S</b>	(-1, 1)	(1, -1)	(0, 0)

## Question

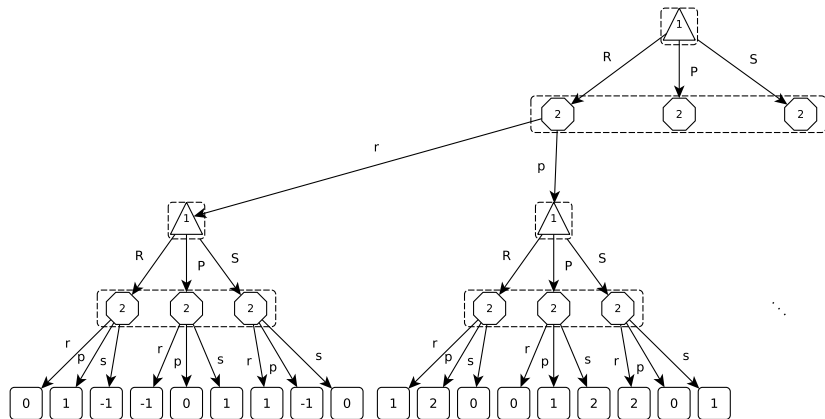
How can we model such games?

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  $r_i^{(1)}, r_i^{(2)}, \dots$  for player  $i$ , the *average reward* of  $i$  is

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

# Infinitely Repeated Games

## Definition

Given an infinite sequence of payoffs  $r_i^{(1)}, r_i^{(2)}, \dots$  for player  $i$ , and a discount factor  $\beta$  with  $0 \leq \beta \leq 1$ , 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
- a repeated game can terminate after each round with probability  $1 - \beta$

# Strategies in Repeated Games

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

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

# Nash Strategies in Repeated Games

## Theorem (Folk Theorem)

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

- 1** *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.*
- 2** *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.*

# Stochastic 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:

$Q$  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  $\mathcal{P} : Q \times \mathcal{A} \times Q \rightarrow [0, 1]$ , 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  $r_i : Q \times \mathcal{A} \rightarrow \mathbb{R}$

# Stochastic Games

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

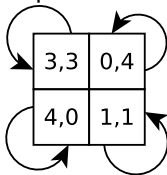
- discounted
- average
- reachability/safety

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

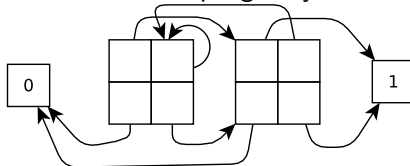
Related to reaching some target state (for example attacking a target) in a game without a pre-determined horizon.

# Stochastic Games - Examples

Repeated prisoners dilemma:



Dante's purgatory:



# Equilibria in Stochastic Games

## Definition (History)

Let  $h_t = (q_0, a_0, q_1, a_1, \dots, a_{t-1}, q_t)$  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 (Stationary strategy)

A stationary strategy  $s_i$  is a Markov strategy in which  $s_i(h_{t_1}, a_{i_j}) = s_i(h_{t_2}, a_{i_j})$  if  $q_t = q'_t$ , where  $q_t$  and  $q'_t$  are the final games of  $h_{t_1}$  and  $h_{t_2}$ , respectively.

## Definition

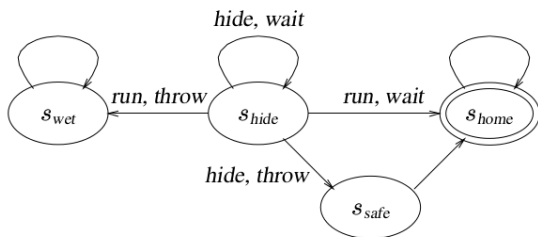
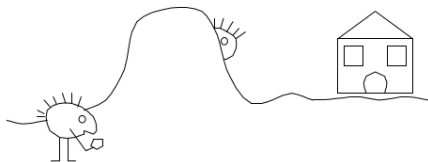
A strategy profile is called a *Markov perfect equilibrium* if it consists of only Markov strategies, and is a Nash equilibrium.

## 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.





# Approximating Optimal Strategies in Stochastic Games

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

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**Algorithm 1.** Value Iteration

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```
1:  $t := 0$ 
2:  $\tilde{v}^0 := (0, \dots, 0, 1)$  // the vector  $\tilde{v}^0$  is indexed  $0, 1, \dots, N, N + 1$ 
3: while true do
4:    $t := t + 1$ 
5:    $\tilde{v}_0^t := 0$ 
6:    $\tilde{v}_{N+1}^t := 1$ 
7:   for  $i \in \{1, 2, \dots, N\}$  do
8:      $\tilde{v}_i^t := \text{val}(A_i(\tilde{v}^{t-1}))$ 
```

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# Approximating Optimal Strategies in Stochastic Games

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## Algorithm 2. Strategy Iteration

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

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# Succinct Representations

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  $d \ll |\mathcal{N}|$

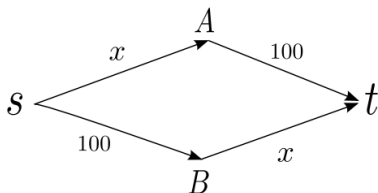
examples of succinct representations :

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

# Atomic Congestion Games

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

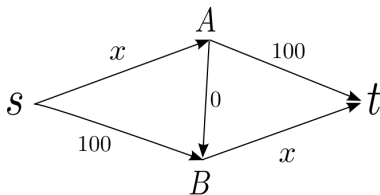
Braess' paradox



100 drivers that want to go from  $s$  to  $t$ .  
What is Nash equilibrium?

# Atomic Congestion Games

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?

# Atomic Congestion Games

## 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).