Multi-Agent Reinforcement Learning

Multi-Agent Reinforcement Learning in Games: First Steps and Challenges

Stefano V. Albrecht, Filippos Christianos, Lukas Schäfer
Slides by: Leonard Hinckeldey

The MARL Book

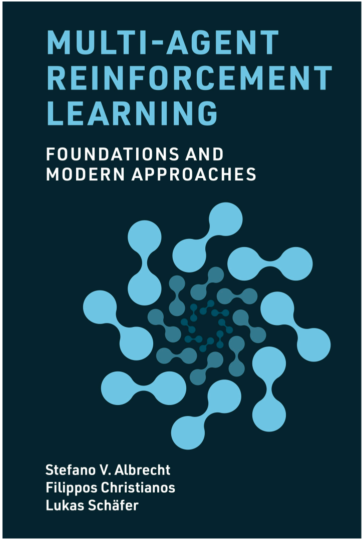
This lecture is based on

Multi-Agent Reinforcement Learning: Foundations and Modern Approaches

by Stefano V. Albrecht, Filippos Christianos and Lukas Schäfer

MIT Press, 2024

Download book, slides, and code at:
www.marl-book.com

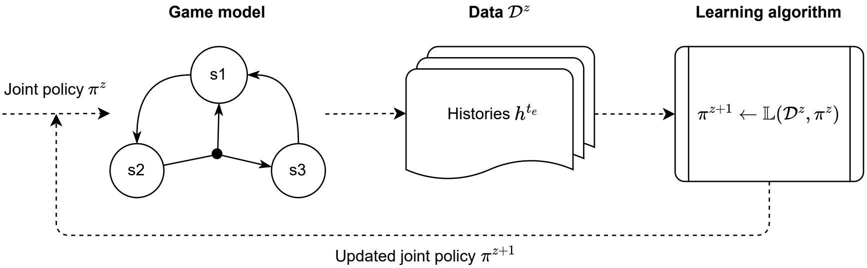


Lecture Outline

- Learning framework for MARL
- Independent learning
- Central learning
- Modes of learning
- Challenges of MARL

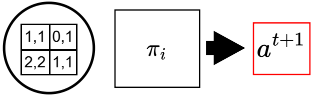
MARL Learning Framework

MARL Learning Process



- The game model defines the learning environment
- Interaction data from joint policy π^z are collected as $\mathcal{D}^z = \{h^{t_e} \mid e = 1, \ldots, z\}, z \geq 0$
- A learning algorithm updates the joint policy as $\pi^{z+1} = \mathbb{L}(\mathcal{D}^z, \pi^z)$
- The learning goal is a chosen solution concept, e.g. Nash equilibrium

Inputs of Policies Depend on Game Model



Normal-form games

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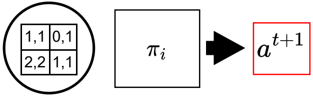

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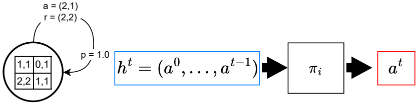

Repeated normal-form games

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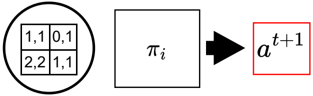

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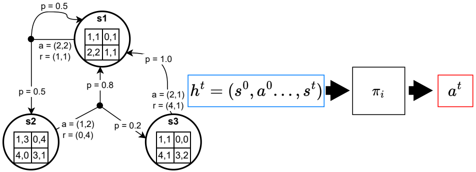
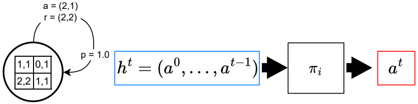


Stochastic games



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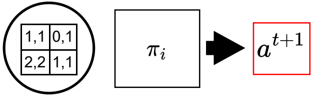

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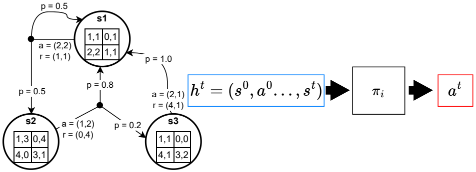

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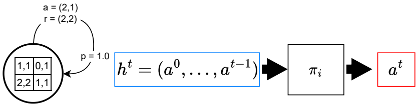

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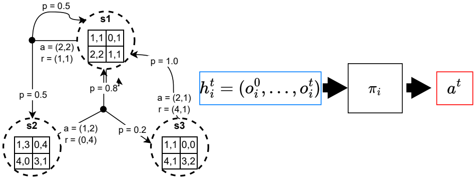

Partially observable stochastic games

Convergence

To evaluate the learning algorithm, we typically assess whether the learnt joint policy has **converged** to an optimal joint policy:

$$\lim_{z \to \infty} \pi^z = \pi^*$$

- Optimal joint policies may differ depending on the solution concept
- There may be many valid solutions $\Rightarrow$ e.g. multiple Nash equilibria
- In practice, we cannot collect infinite data $z \to \infty$

  $\Rightarrow$ Learning typically stops after a predefined 'budget' (e.g. training steps)

Single-Agent RL Reductions

The simplest way to apply RL algorithms in multi-agent settings is to reduce them to single-agent problems.

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Central learning:

- Apply one single-agent RL algorithm to control all agents centrally

  $\Rightarrow$ A central policy is learned over the joint action space

Independent learning:

- Apply single-agent RL algorithms to each agent independently

  $\Rightarrow$ Agents do not explicitly consider or represent each other

Central Learning

Central Learning

Central learning: learn a single central policy π_c which receives observations of all agents and selects an action for each agent (i.e. joint action $(a_1, ..., a_n)$).

- Requires transforming the joint reward $(r_1, \ldots, r_n)$ into a single scalar reward r

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- Mays not scale well with the number of agents, as the joint action space may grow exponentially with the number of agents
- May also not be suitable in environments that require agents to act independently based on local observations

Central Q-Learning

Algorithm Central Q-learning

Initialize: $Q(s, a) = 0$ for all $s \in S$ and $a \in A = A_1 \times \ldots \times A_n$
Repeat for every episode:
for $t = 0, 1, 2, \ldots$ **do**
    Observe current state s^t
    With probability ϵ: choose random joint action $a^t \in A$
    Otherwise: choose joint action $a^t \in \arg\max_a Q(s^t, a)$
    Apply joint action a^t, observe rewards $r_1^t, \ldots, r_n^t$ and next state s^{t+1}
    Transform $r_1^t, \ldots, r_n^t$ into scalar reward r^t
    $Q(s^t, a^t) \leftarrow Q(s^t, a^t) + \alpha[r^t + \gamma \max_{a'} Q(s^{t+1}, a') - Q(s^t, a^t)]$

Independent Learning

Independent Learning

Independent learning: each agent i learns its policy π_i using only its local history of observations.

- From the perspective of each agent i, the environment transition function looks like this:

$$\mathcal{T}_i(s^{t+1}|s^t, a_i) \propto \sum_{a_{-i} \in A_{-i}} \mathcal{T}(s^{t+1}|s^t, \langle a_i, a_{-i} \rangle) \prod_{j \neq i} \pi_j(a_j|s^t)$$

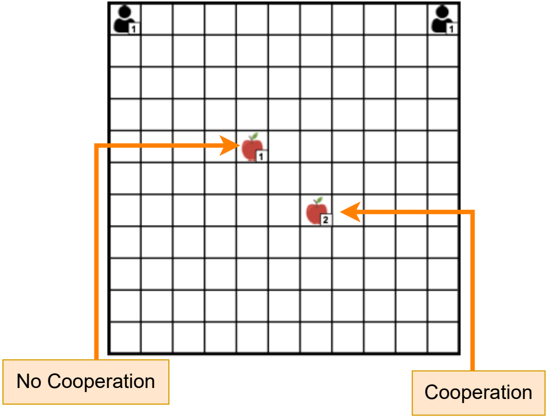
- As each agent j's policies are updated, the action probabilities π_j change
  $\Rightarrow$ From agent i's perspective, the transition function $\mathcal{T}_i$ appears non-stationary!

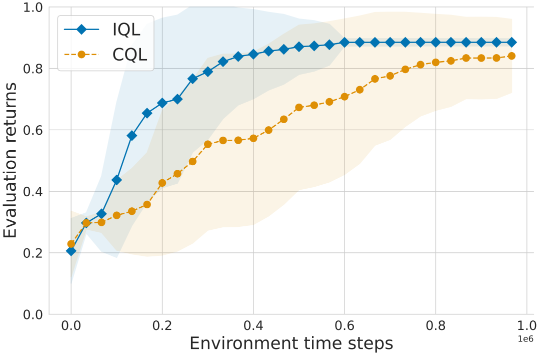
Independent Q-learning

Algorithm Independent Q-learning (IQL) for stochastic games

```
// Algorithm controls agent i
Initialize: Q_i(s, a_i) = 0 for all s ∈ S, a_i ∈ A_i
Repeat for every episode:
for t = 0, 1, 2, ... do
    Observe current state s^t
    With probability ε: choose random action a_i^t ∈ A_i
    Otherwise: choose action a_i^t ∈ arg max_{a_i} Q_i(s^t, a_i)
    (meanwhile, other agents j ≠ i choose their actions a_j^t)
    Observe own reward r_i^t and next state s^{t+1}
    Q_i(s^t, a_i^t) ← Q_i(s^t, a_i^t) + α[r_i^t + γ max_{a'_i} Q_i(s^{t+1}, a'_i) − Q_i(s^t, a_i^t)]
```

IQL and CQL in Level-Based Foraging





- IQL can learn more quickly, as CQL needs to explore $6^2 = 36$ actions in each state

Modes of Operation in MARL

Modes of Operation in MARL: **self-play** and **mixed-play**

Self-play:

- **Algorithm self-play:** all agents use the same learning algorithm (and parameters)
- **Policy self-play:** agent's policy is trained directly against itself

Mixed-play

- Agents use different learning algorithms

MARL Challenges

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Singe-Agent RL Challenges

- Unknown environment dynamics
- Exploration-exploitation dilemma
- Non-stationarity from bootstrapping
- Temporal credit assignment

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Multi-Agent RL Challenges

- Non-stationarity from multiple learning agents
- Equilibrium selection
- Multi-agent credit assignment
- Scaling tom many agents

Non-Stationarity

A stochastic process ${X^t}_{t\in\mathbb{N}^0}$ is stationary if:

- The probability distribution of $X^{t+\tau}$ does not depend on $\tau \in \mathbb{N}^0$, where t and $t+\tau$ are time indices
- This means that the dynamics of the process do not change over time

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Consider: X^t samples the state s^t at each time step t:

- In a MDP, X^t is completely defined by the state transition function $\mathcal{T}(s^t | s^{t-1}, a^{t-1})$ and the agent's policy π which selects an action $a \sim \pi(.|s)$

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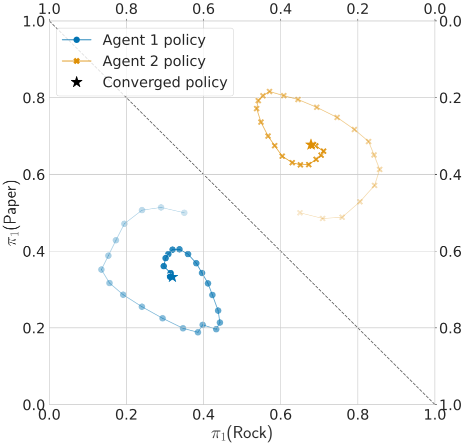
- However, in RL the policy does change over time through the learning $\pi^{z+1} = \mathbb{L}(\mathcal{D}^z, \pi^z)$, which leads to **non-stationarity** in X^t

Non-Stationarity in Multi-Agent Settings

In MARL, non-stationarity is exacerbated by multiple agents changing their policies!



- $\pi^{z+1} = \mathbb{L}(\mathcal{D}^z, \pi^z)$ updates an *entire* joint policy $\pi^z = (\pi_1^z, ..., \pi_n^z)$
- Environment is non-stationary from each agent's perspective
- Can cause cyclic learning dynamics where agents co-adapt to each other's changing policies

Equilibrium Selection

Equilibrium selection: a game may have multiple equilibria, which can yield different expected returns to the agents.

- **Example:** Stag Hunt matrix game
- Two hunters choose: cooperate to hunt stag (S) or go solo for hare (H)

	S	H
S	4,4	0,3
H	3,0	2,2

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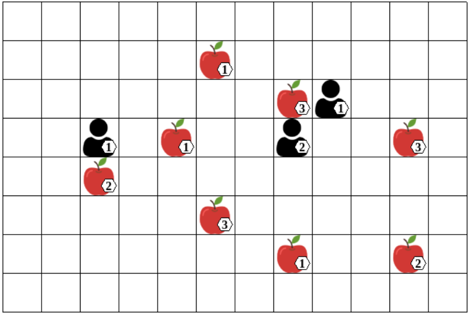
- Indep. Q-learning may bias towards (H,H) due to initial action uncertainty
- Early random actions can reinforce (H,H) since deviating from H is penalized if the other agent chooses H

Multi-Agent Credit Assignment

Multi-agent credit assignment: which agent's actions contributed to receved rewards?



- At time step t all agents perform *collect*, each receiving reward $+1$
- Whose actions led to the reward?
- The agent on the left did not contribute
- For a learning agent that only observes s^t, a^t, r^t, s^{t+1}, disentangling the action contributions is difficult

Joint Actions for Addressing Multi-Agent Credit Assignment

Joint actions can help disentangle agent contributions. Consider the RPS game:

	R	P	S
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2. Then agents choose $(a_1, a_2) = (R, P)$ $\Rightarrow$ agent 1 receives reward -1
3. Action value $Q(a_1)$ does not model agent 2, value for action R appears to be 0
4. Joint action value model $Q_1(a_1, a_2)$ can represent the effect of agent 2:
   $Q_1(R, S) = +1$ and $Q_1(R, P) = -1$

Problem

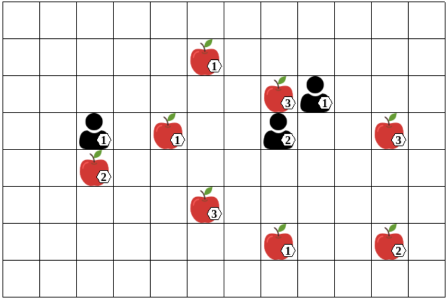
- **Joint action space** can grow **exponentially** with number of agents:

$$|A| = |A_1| \cdot \ldots \cdot |A_n|$$

- If agents have associated features in s (e.g. agent position) then $|S|$ also increases exponentially

$\Rightarrow$ How to scale efficiently to many agents?

Scaling to Many Agents



Changing number of agents from 3 to 5 increases the number of joint actions from 216 to 7776!

Summary

We covered:

- MARL learning process
- Independent and central learning
- Modes of operation in MARL
- Challenges of MARL

Next we'll cover:

- Foundational algorithms in MARL