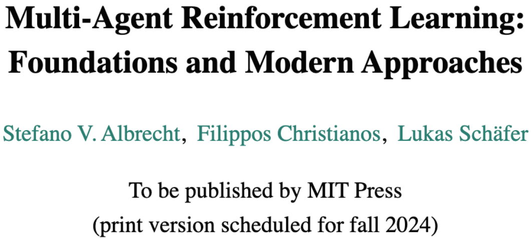
# Multi-Agent Reinforcement Learning

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

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

# MARL Book



**Multi-Agent Reinforcement Learning: Foundations and Modern Approaches**

Stefano V. Albrecht, Filippos Christianos, Lukas Schäfer

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This lecture is based on *Multi-Agent Reinforcement Learning: Foundations and Modern Approaches* by Stefano V. Albrecht, Filippos Christianos and Lukas Schäfer

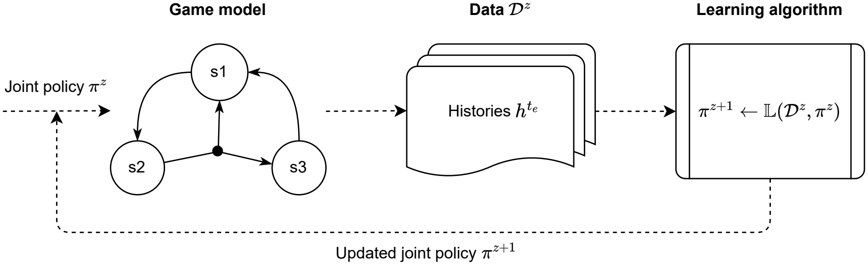
The book can be downloaded for free here.

# Lecture Outline

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

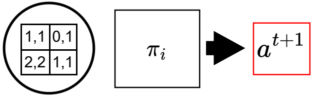
# The MARL learning framework

# MARL Learning Process



- The game model defines agent interaction
- Data of these interactions are collected as $\mathcal{D}^z = \{h^{t_e} \mid e = 1, \ldots, z\}, z \geq 0$
- A learning algorithm updates each agent’s policy $\pi^{z+1} = \mathbb{L}(\mathcal{D}^z, \pi^z)$
- The learning goal is a chosen solution concept, e.g. Nash equilibrium

# Game Model's and Joint Policy



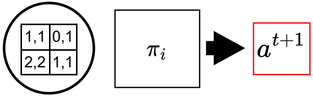
|  |  |
|---|---|
| 1,1 | 0,1 |
| 2,2 | 1,1 |

$\pi_i$

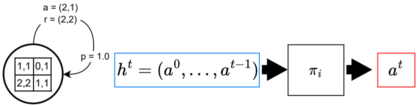
$a^{t+1}$

Normal-form games

# Game Model's and Joint Policy

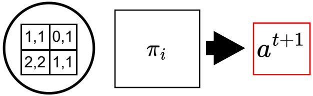


Normal-form games

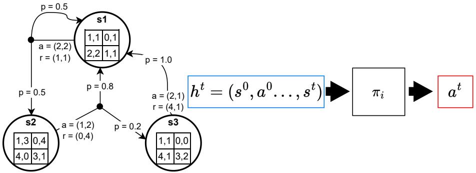


Repeated normal-form games

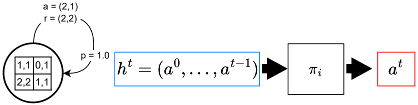
# Game Model’s and Joint Policy



Normal-form games

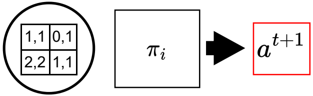


Stochastic games

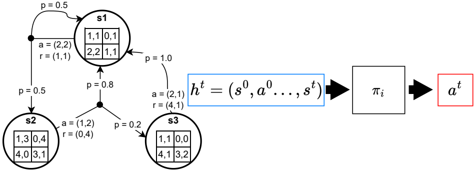


Repeated normal-form games

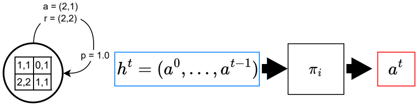
# Game Model's and Joint Policy



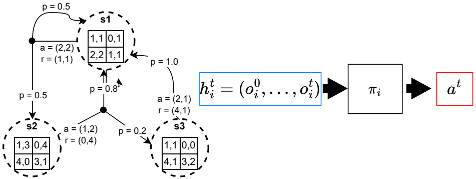
Normal-form games



Stochastic games



Repeated normal-form games



Partially observable stochastic games

# Convergence

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

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

- The optimal joint policy may differ depending on the chosen game solution
- There may be many valid solutions, e.g., multiple Nash equilibria
- In practice, we cannot collect infinite data
- Learning typically stops after a predefined ’budget’ (e.g. training steps) is reached or changes in the policy are below a predefined threshold

# Single-Agent RL Reductions

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

- We can apply single-agent RL algorithms to each agent independently
    - This is known as **independent** learning; agents do not explicitly consider each other instead they treat other agents as part of the environment
- Alternatively, we can apply one single-agent RL to all agents centrally
    - This is referred to as **central** learning, where a central policy is learned, providing action probability across all agents' actions

# Central Learning

# Central Learning

In the central learning framework, we learn a single central policy $\pi_c$, which receives observations of all agents and selects an action for each agent.

- Requires transforming the joint reward $(r_1, \ldots, r_n)$, into a single scalar reward $r$
- This can be easy in some settings, e.g. in games with common rewards $r = r_i$, but difficult in zero-sum or general-sum games
- Central learning does not scale well with the number of agents as the joint action space grows exponentially with the number of agents
- This framework may also not be suitable in environments that require agents to act independently based on localized 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 $\epsilon$: 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

In the independent learning framework, each agent $i$ learns its policy $\pi_i$ using only its local history of observations, treating the effects of other agents' actions as part of the environment.

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

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

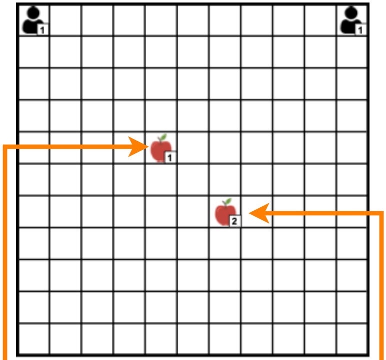
- As each agent $j$'s policies are updated, the action probabilities $\pi_j$ change
- From agent $i$'s perspective its transition function $\mathcal{T}_i$ thus appears to be non-stationary

# Independent Q-learning

**Algorithm** Independent Q-learning (IQL) for stochastic games

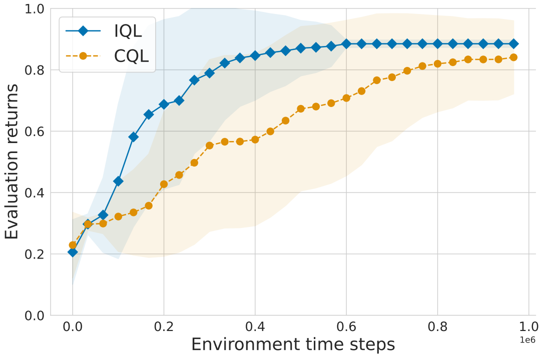
```
// Algorithm controls agent i
Initialize: $Q_i(s, a_i) = 0$ for all $s \in S$, $a_i \in A_i$
Repeat for every episode:
for $t = 0, 1, 2, \ldots$ do
    Observe current state $s^t$
    With probability $\epsilon$: choose random action $a_i^t \in A_i$
    Otherwise: choose action $a_i^t \in \arg\max_{a_i} Q_i(s^t, a_i)$
    (meanwhile, other agents $j \neq i$ choose their actions $a_j^t$)
    Observe own reward $r_i^t$ and next state $s^{t+1}$
    $Q_i(s^t, a_i^t) \leftarrow Q_i(s^t, a_i^t) + \alpha[r_i^t + \gamma \max_{a_i'} Q_i(s^{t+1}, a_i') - Q_i(s^t, a_i^t)]$
```

# IQL and CQL in Level-based Foraging



No Cooperation

Cooperation



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

# Modes of Operation in MARL

# Modes of Learning

In addition to independent and central learning, there are different modes of learning algorithms. Algorithms can use **self-play** or **mixed-play**.

Self-play:

- Refers to two related but distinct modes of operation in MARL, **algorithm self-play** and **policy self-play**
- **Algorithm self-play** assumes that all agents use the same learning algorithm
- **Policy self-play** is more literal and means that an agent's policy is trained directly against itself

Mixed-play

- Refers to instances where agents use different learning algorithms

# MARL Challenges

# MARL Challenges

MARL algorithms inherit issues from single-agent RL, such as:

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

In addition to this, MARL algorithms face challenges that arise from learning in a dynamic multi-agent system.

# Non-Stationarity

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

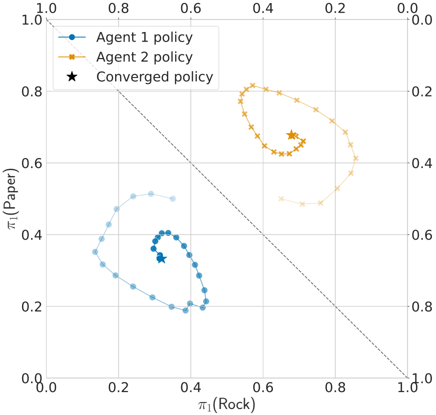
- The probability distribution of $X^{t+\tau}$ does not depend on $\tau \in \mathbb{N}^0$, where t and $t + \tau$ are time indices
- This means that the dynamics of the process do not change over time

Now $X^t$ 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 agents policy $\pi$ which selects an action $a \sim \pi(.|s)$
- The **Markov property** means that this property is stationary in that $s^t$ depends only on $s^{t-1}$, $a^{t-1}$ and $a^{t-1}$ depends only on $s^{t-1}$ via $\pi(.|s^{t-1})$
- In RL, the policy does, however, change over time through the learning process $\pi^{z+1} = \mathbb{L}(\mathcal{D}^z, \pi^z)$, 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 over time.



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

# Equilibrium Selection

A game might have multiple equilibrium solutions, each of which might yield different expected returns to the agents in the game. This leads to the problem of **equilibrium selection**

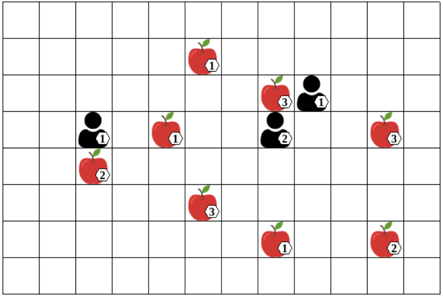
- Consider the stag hunt game
- Two hunters choose: cooperate to hunt stag (S) or go solo for hare (H)
- Nash equilibria: reward-dominant (S,S) maximizes reward, risk-dominant (H,H) minimizes risk
- (S,S) requires trust; (H,H) offers a safe, lower reward

| | S | H |
|---|---|---|
| S | 4,4 | 0,3 |
| H | 3,0 | 2,2 |

- Independent 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

Credit assignment in single-agent RL refers to determining which past action contributes to receiving rewards. In MARL, determining which agent has contributed to receiving rewards is an additional challenge.



- At time step *t* all agents simultaneously perform *collect*, each receiving reward $+1$
- Whose action led to the reward?
- The agent on the left did not contribute
- For a learning agent which 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

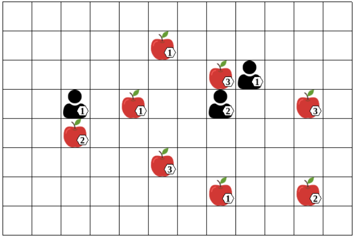
**Joint actions** can help disentangle agent contributions. Consider the RPS game:

| | R | P | S |
|---|---|---|---|
| R | 0,0 | -1,1 | 1,-1 |
| P | 1,-1 | 0,0 | -1,1 |
| S | -1,1 | 1,-1 | 0,0 |

1. Agents choose actions $(a_1, a_2) = (R, S)$ with agent 1 receiving reward $+1$
2. Agents choose $(a_1, a_2) = (R, P)$ with agent 1 receiving reward $-1$
3. Using $Q(s, a_1)$ does not model agent 2's action's effects and thus the value for action $R$ appears to be 0
4. $Q_1(s, a_1, a_2)$ can represent the effect of agent 2 thus ascribing different values to joint action $(R, S)$ and $(R, P)$

# Scaling to Many Agents

The ability to scale to many agents is an important goal in MARL. Scaling agents is, however, a significant challenge for MARL as:



- # of **joint action** can grow **exponentially** with # agents since $|A| = |A_1| \cdot \ldots \cdot |A_n|$
- Changing # agents from 3 to 5 increases the number of joint actions from 216 to 7776
- If agents have associated features in s (e.g. agent position) then $|S|$ also increases exponentially
- In CL, this increases the decision problem, while in IL this increases issues of non-stationarity and multi-agent credit assignment

# Summary

We covered:

- MARL Learning Process
- Independent and central learning
- Modes of learning in MARL
- Challenges of MARL

Next we’ll cover:

- Foundational algorithms in MARL