

Multi-Agent Reinforcement Learning

Multi-Agent Deep Reinforcement Learning – Part 1

Stefano V. Albrecht, Filippos Christianos, Lukas Schäfer

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

- Training and execution modes
- Independent learning with deep reinforcement learning
- Multi-agent policy gradient algorithms
- Policy gradient algorithms
- Value decomposition in common-reward games

Training and Execution Modes

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We often distinguish between training and execution modes in MARL:

- **Training:** what information is available to agents during learning?
- **Execution:** what information is available to agents for action selection?

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- **Independent learning:** each agent learns its policy independently → decentralized training and decentralized execution

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- **Independent learning:** each agent learns its policy independently → decentralized training and decentralized execution
- **Central learning:** learn single policy over the joint action space conditioned on joint histories → centralized training and centralized execution

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- **Independent learning:** each agent learns its policy independently → decentralized training and decentralized execution
- **Central learning:** learn single policy over the joint action space conditioned on joint histories → centralized training and centralized execution

But we can also have **centralised training with decentralised execution (CTDE)**!

Independent Learning with Deep Reinforcement Learning

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Reminder

In the independent learning framework, each agent i learns its policy π_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:

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

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How about we do this with deep RL? We have already seen several single-agent deep RL algorithms: DQN, REINFORCE, A2C, PPO, etc.

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Independent Deep Q-Networks

Algorithm Independent deep Q-networks

- 1: Initialize n value networks with random parameters $\theta_1, \dots, \theta_n$
 - 2: Initialize n target networks with parameters $\bar{\theta}_1 = \theta_1, \dots, \bar{\theta}_n = \theta_n$
 - 3: Initialize a replay buffer for each agent D_1, D_2, \dots, D_n
 - 4: **for** time step $t = 0, 1, 2, \dots$ **do**
 - 5: Collect current observations o_1^t, \dots, o_n^t
 - 6: **for** agent $i = 1, \dots, n$ **do**
 - 7: With probability ϵ : choose random action a_i^t
 - 8: Otherwise: choose $a_i^t \in \arg \max_{a_i} Q(h_i^t, a_i; \theta_i)$
 - 9: Apply actions (a_1^t, \dots, a_n^t) ; collect rewards r_1^t, \dots, r_n^t and next observations $o_1^{t+1}, \dots, o_n^{t+1}$
 - 10: **for** agent $i = 1, \dots, n$ **do**
 - 11: Store transition $(h_i^t, a_i^t, r_i^t, h_i^{t+1})$ in replay buffers D_i
 - 12: Sample random mini-batch of B transitions $(h_i^k, a_i^k, r_i^k, h_i^{k+1})$ from D_i
 - 13: **if** s^{k+1} is terminal **then**
 - 14: Targets $y_i^k \leftarrow r_i^k$
 - 15: **else**
 - 16: Targets $y_i^k \leftarrow r_i^k + \gamma \max_{a_i' \in A_i} Q(h_i^{k+1}, a_i'; \bar{\theta}_i)$
 - 17: Loss $\mathcal{L}(\theta_i) \leftarrow \frac{1}{B} \sum_{k=1}^B \left(y_i^k - Q(h_i^k, a_i^k; \theta_i) \right)^2$
 - 18: Update parameters θ_i by minimizing the loss $\mathcal{L}(\theta_i)$
 - 19: In a set interval, update target network parameters $\bar{\theta}_i$
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- Almost identical to DQN from Chapter 8 but with n agents!

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- Almost identical to DQN from Chapter 8 but with n agents!
- Replay buffer contains off-policy experiences due to changing policies
- In MARL, the policies of **all** agents are changing \rightarrow training can be unstable

Independent Advantage Actor-Critic

Algorithm Independent A2C with synchronous environments

- 1: Initialize n actor networks with random parameters ϕ_1, \dots, ϕ_n
 - 2: Initialize n critic networks with random parameters $\theta_1, \dots, \theta_n$
 - 3: Initialize K parallel environments
 - 4: **for** time step $t = 0 \dots \text{do}$
 - 5: Batch of observations for each agent and environment:
$$\begin{bmatrix} o_1^{t,1} & \dots & o_1^{t,K} \\ & \ddots & \\ o_n^{t,1} & \dots & o_n^{t,K} \end{bmatrix}$$
 - 6: Sample actions $\begin{bmatrix} a_1^{t,1} & \dots & a_1^{t,K} \\ & \ddots & \\ a_n^{t,1} & \dots & a_n^{t,K} \end{bmatrix} \sim \pi(\cdot \mid h_1^t; \phi_1), \dots, \pi(\cdot \mid h_n^t; \phi_n)$
 - 7: Apply actions; collect rewards $\begin{bmatrix} r_1^{t,1} & \dots & r_1^{t,K} \\ & \ddots & \\ r_n^{t,1} & \dots & r_n^{t,K} \end{bmatrix}$ and observations $\begin{bmatrix} o_1^{t+1,1} & \dots & o_1^{t+1,K} \\ & \ddots & \\ o_n^{t+1,1} & \dots & o_n^{t+1,K} \end{bmatrix}$
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 - 10: Advantage $Adv(h_i^{t,k}, a_i^{t,k}) \leftarrow r_i^{t,k} - V(h_i^{t,k}; \theta_i)$
 - 11: Critic target $y_i^{t,k} \leftarrow r_i^{t,k}$
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- Almost identical to single-agent A2C from Chapter 8
- Similar adaptation can be done for independent REINFORCE and independent PPO

Challenges of Multi-Agent Reinforcement Learning

Reminder

MARL algorithms suffer from multi-agent specific challenges:

- **Non-stationarity:** exacerbated due to changing policies of all agents
- **Equilibrium selection:** how to converge to a stable equilibrium?
- **Multi-agent credit assignment:** how to attribute rewards to agents' actions? (especially in common-reward settings)
- **Scaling to many agents:** how to efficiently scale to large numbers of agents?

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Centralised training with decentralised execution (CTDE) can help address some of these challenges.

Multi-Agent Policy Gradient Algorithms

The Policy-Gradient Theorem

Reminder

Follow this gradient to optimise the parameters ϕ of the policy π to maximise the expected return:

$$\begin{aligned}\nabla_{\phi} J(\phi) &\propto \sum_{s \in \mathcal{S}} \Pr(s \mid \pi) \sum_{a \in \mathcal{A}} Q^{\pi}(s, a) \nabla_{\phi} \pi(a \mid s; \phi) \\ &= \mathbb{E}_{s \sim \Pr(\cdot \mid \pi), a \sim \pi(\cdot \mid s; \phi)} [Q^{\pi}(s, a) \nabla_{\phi} \log \pi(a \mid s; \phi)]\end{aligned}$$

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Does this also hold for MARL?

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Does this also hold for MARL? Yes, with minor modifications!

The Multi-Agent Policy-Gradient Theorem

Solution

In MARL, the expected returns of agent i under its policy π_i depends on the policies of all other agents $\pi_{-i} \rightarrow$ the multi-agent policy gradient theorem defines an expectation over the policies of **all** agents:

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\rightarrow Derive policy update rules by finding estimators for expected returns $Q_i^\pi(\hat{h}, \langle a_i, a_{-i} \rangle)$.

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But can we do better? Perhaps by leveraging more information?

Note

In actor-critic algorithms, only the policy/actor is used during execution and the critic is used only during training → the critic can be conditioned on centralised information z without compromising decentralised execution.

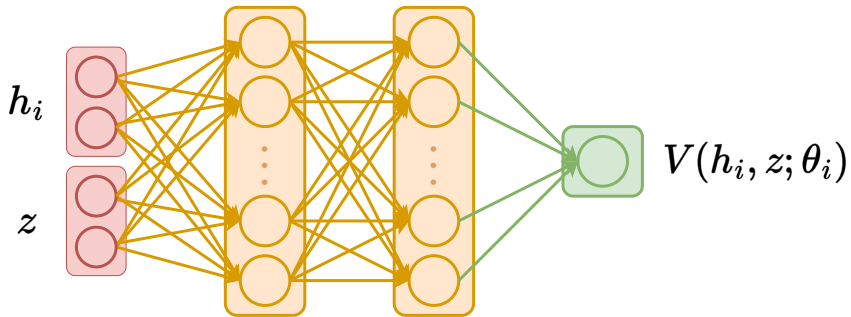
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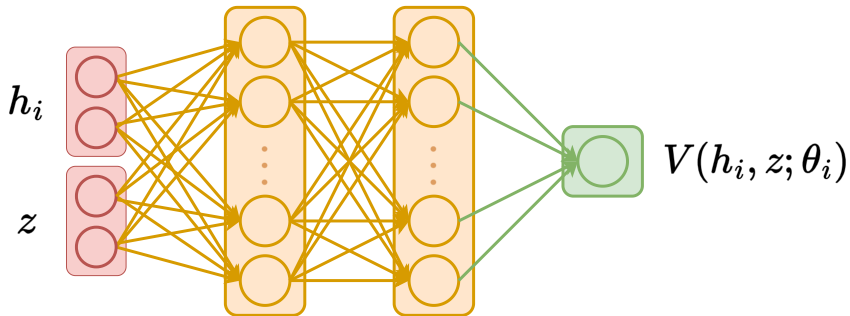
This might include:

- Global state s
- Joint action a
- Joint observation history h
- ...

Centralized Critics



Centralized Critics



Now we can integrate centralized critics into multi-agent policy gradient algorithms.

Centralized Advantage Actor-Critic

Algorithm Centralized A2C with synchronous environments

```

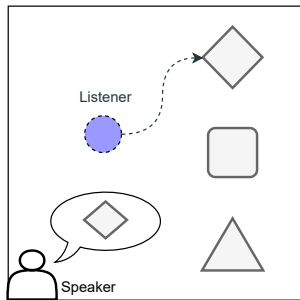
1: Initialize  $n$  actor networks with random parameters  $\phi_1, \dots, \phi_n$ 
2: Initialize  $n$  critic networks with random parameters  $\theta_1, \dots, \theta_n$ 
3: Initialize  $K$  parallel environments
4: for time step  $t = 0 \dots$  do

5:   Batch of observations for each agent and environment:  $\begin{bmatrix} o_1^{t,1} \dots o_1^{t,K} \\ \vdots \\ o_n^{t,1} \dots o_n^{t,K} \end{bmatrix}$ 
6:   Batch of centralized information for each environment:  $[z^{t,1} \dots z^{t,K}]$ 
7:   Sample actions  $\begin{bmatrix} a_1^{t,1} \dots a_1^{t,K} \\ \vdots \\ a_n^{t,1} \dots a_n^{t,K} \end{bmatrix} \sim \pi(\cdot \mid h_1^t; \phi_1), \dots, \pi(\cdot \mid h_n^t; \phi_n)$ 
8:   Apply actions; collect rewards  $\begin{bmatrix} r_1^{t,1} \dots r_1^{t,K} \\ \vdots \\ r_n^{t,1} \dots r_n^{t,K} \end{bmatrix}$ , observations  $\begin{bmatrix} o_1^{t+1,1} \dots o_1^{t+1,K} \\ \vdots \\ o_n^{t+1,1} \dots o_n^{t+1,K} \end{bmatrix}$ , and
   centralized information  $[z^{t+1,1} \dots z^{t+1,K}]$ 
9:   for agent  $i = 1, \dots, n$  do
10:     if  $s^{t+1,i}$  is terminal then
11:        $Adv(h_i^{t,i}, z^{t,i}, a_i^{t,i}) \leftarrow r_i^{t,i} - V(h_i^{t,i}, z^{t,i}; \theta_i)$ 
12:       Critic target  $y_i^{t,i} \leftarrow r_i^{t,i}$ 
13:     else
14:        $Adv(h_i^{t,i}, z^{t,i}, a_i^{t,i}) \leftarrow r_i^{t,i} + \gamma V(h_i^{t+1,i}, z^{t+1,i}; \theta_i) - V(h_i^{t,i}, z^{t,i}; \theta_i)$ 
15:       Critic target  $y_i^{t,i} \leftarrow r_i^{t,i} + \gamma V(h_i^{t+1,i}, z^{t+1,i}; \theta_i)$ 
16:     Actor loss  $\mathcal{L}(\phi_i) \leftarrow \frac{1}{K} \sum_{k=1}^K Adv(h_i^{t,i}, z^{t,i}, a_i^{t,i}) \log \pi(a_i^{t,i} \mid h_i^{t,i}; \phi_i)$ 
17:     Critic loss  $\mathcal{L}(\theta_i) \leftarrow \frac{1}{K} \sum_{k=1}^K (y_i^{t,i} - V(h_i^{t,i}, z^{t,i}; \theta_i))^2$ 
18:     Update parameters  $\phi_i$  by minimizing the actor loss  $\mathcal{L}(\phi_i)$ 
19:     Update parameters  $\theta_i$  by minimizing the critic loss  $\mathcal{L}(\theta_i)$ 

```

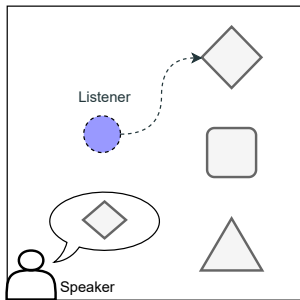
- Simple extension of independent A2C.
- Centralized information z is added to the critic input.

Centralized Critics in Action

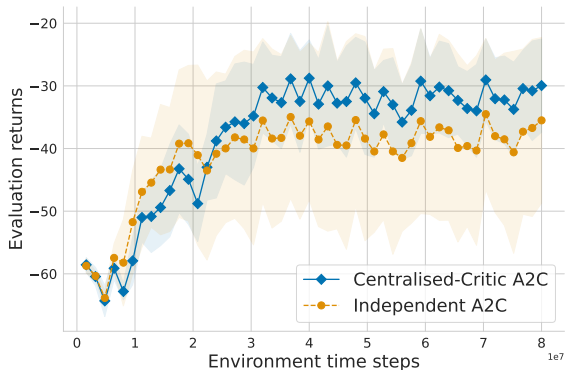


(a) Speaker-listener game

Centralized Critics in Action



(a) Speaker-listener game

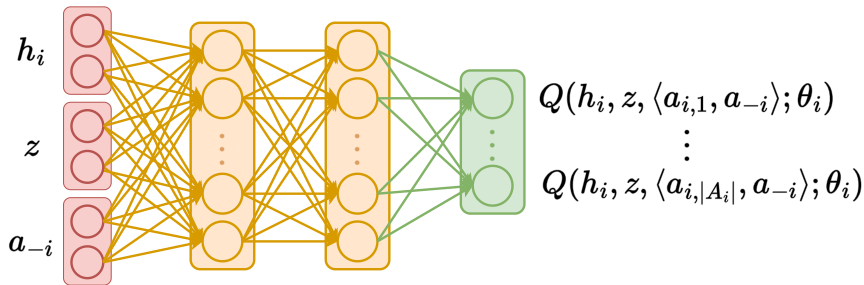


(b) Training curves

Agents with centralized critics converge to higher returns than agents with independent critics in the partially observable speaker-listener game.

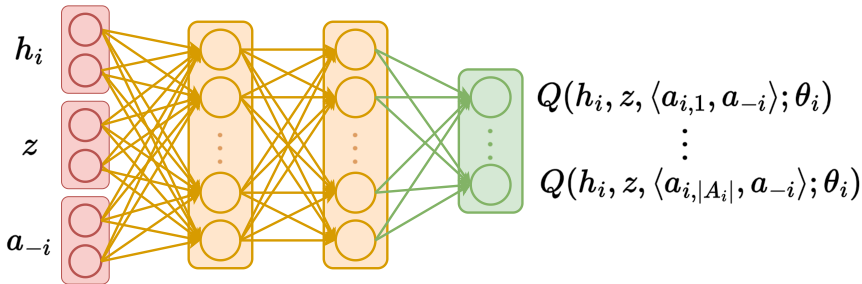
Centralized Action-Value Critics

Similarly, we can learn an action-value function that receives additional centralized information z .



Centralized Action-Value Critics

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But what for? The centralized action-value critic can reason about the joint action space!

Counterfactual Multi-Agent Policy Gradient

For example, we can compute a counterfactual advantage for agent i

$$\text{Adv}_i(h_i, z, a) = Q(h_i, z, a; \theta) - \underbrace{\sum_{a'_i \in A_i} \pi(a'_i \mid h_i; \phi_i) Q(h_i, z, \langle a'_i, a_{-i} \rangle; \theta)}_{\text{counterfactual baseline}}$$

with the following components:

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Identify contribution of agent i 's action a_i to received rewards \Rightarrow help to address the **credit assignment problem** in common-reward games

The Equilibrium Selection Problem

Problem

Many multi-agent games have multiple equilibria. In such games, it is difficult for all agents to agree on and stably converge to a single equilibrium. This is known as the **equilibrium selection problem**.

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	A	B
A	4,4‡	0,3
B	3,0	2,2†

Figure: Stag Hunt

	A	B	C
A	11‡	-30	0
B	-30	7†	0
C	0	6	5

Figure: Climbing

The Stag Hunt and Climbing matrix games have multiple equilibria.

†: Pareto-dominated equilibria

‡: Pareto-optimal equilibria

Example for the Equilibrium Selection Problem

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- Pareto-optimal equilibrium (‡):
(A, A) with +11
- Pareto-dominated equilibrium
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How can we overcome this problem and robustly

Pareto Actor-Critic for Equilibrium Selection

Both shown matrix games are **no-conflict games** where agents agree on the optimal policy:

$$\arg \max_{\pi} U_i(\pi) = \arg \max_{\pi} U_j(\pi) \quad \forall i, j \in I$$

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We can compute π_{-i}^+ using a centralized critic that receives the joint action a as input:

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$$\pi_{-i}^+ \in \arg \max_{a_{-i}} Q(h_i^t, z^t, \langle a_i^t, a_{-i} \rangle)$$

During training, agent i optimises its policy π_i by minimising the following loss:

$$\mathcal{L}(\phi_i) = -\mathbb{E}_{a_i^t \sim \pi_i, a_{-i}^t \sim \pi_{-i}^+} \left[\log \pi(a_i^t \mid h_i^t; \phi_i) \left(Q^{\pi^+}(h_i^t, z^t, \langle a_i^t, a_{-i}^t \rangle; \theta_i^q) - V^{\pi^+}(h_i^t, z^t; \theta_i^v) \right) \right]$$

Pareto Actor-Critic for Equilibrium Selection in Climbing Game

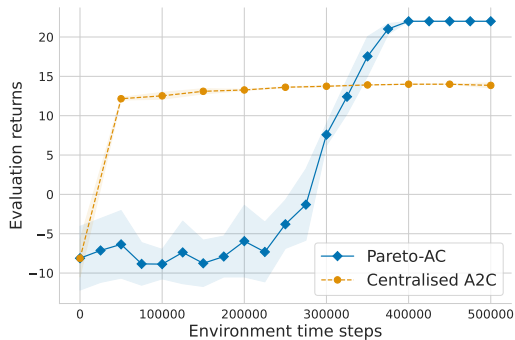
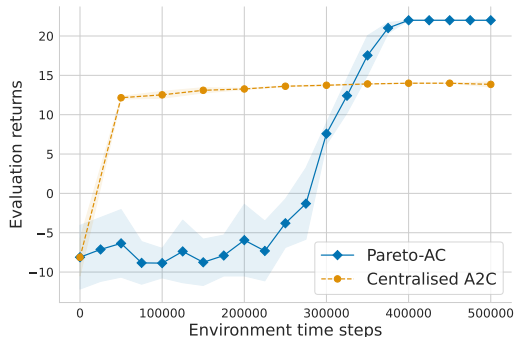


Figure: Learning curves in the Climbing game.

Pareto Actor-Critic for Equilibrium Selection in Climbing Game



- A2C with centralized state-value critic converges to the Pareto-dominated equilibrium (B, B) with +7 (per agent).

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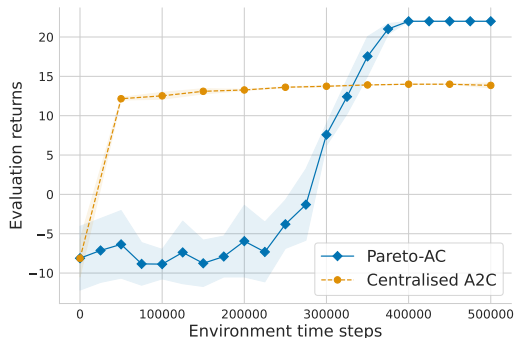


Figure: Learning curves in the Climbing game.

- A2C with centralized state-value critic converges to the Pareto-dominated equilibrium (B, B) with +7 (per agent).
- **Pareto actor-critic** converges to the Pareto-optimal equilibrium (A, A) with +11 (per agent).

Value Decomposition in Common-Reward Games

Centralized Value Functions in Value-Based MARL

We addressed MARL challenges in policy gradient algorithms by leveraging centralized critics. Can we also use centralized value functions in value-based MARL algorithms?

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In value-based MARL algorithms, e.g. IDQN, agents learn value functions and derive their policy from them. However, learning and deriving a policy from centralized value functions would prevent decentralized execution.

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How can we overcome this limitation and leverage the benefits of centralized value functions in value-based MARL algorithms?

Value Decomposition

We will focus on **value decomposition** methods for common-reward games. These methods aim to decompose a centralized action-value function of all agents

$$Q(h^t, z^t, a^t; \theta) = \mathbb{E} \left[\sum_{\tau=t}^{\infty} \gamma^{\tau-t} r^{\tau} \mid h^t, z^t, a^t \right]$$

into individual utility functions of each agent: $Q(h_i, a_i; \theta_i)$ for $i \in I$

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into individual utility functions of each agent: $Q(h_i, a_i; \theta_i)$ for $i \in I$

This decomposition has several benefits:

- Agents benefit from centralized information during training
- Simplify learning by decomposing the centralized value function
- Agents learn their individual utility functions to represent their contribution to the centralized value function, helping to address the **credit assignment problem**

Individual-Global-Max Property

How do we ensure that decentralized action selection with respect to the agents' individual utility functions leads to effective joint actions with respect to the decomposed centralized action-value function?

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Solution

Let \hat{h} be a full history with joint-observation histories $h = \sigma(\hat{h})$, individual observation histories, $h_i = \sigma_i(\hat{h})$, and centralized information z . The **individual-global-max (IGM) property** is satisfied if and only if:

$$\forall a = (a_1, \dots, a_n) \in A : a \in A^*(h, z; \theta) \iff \forall i \in I : a_i \in A_i^*(h_i; \theta_i)$$

with $A^*(h, z; \theta) = \arg \max_{a \in A} Q(h, z, a; \theta)$ and $A_i^*(h_i; \theta_i) = \arg \max_{a_i \in A_i} Q(h_i, a_i; \theta_i)$.

The Importance of the Individual-Global-Max Property

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Note

It is not guaranteed that for a given environment, there exists a decomposition of the centralized action-value function that satisfies the IGM property.

Linear Value Decomposition

Value decomposition networks (VDN) uses a simple linear decomposition of the centralized action-value function:

$$Q(h^t, z^t, a^t; \theta) = \sum_{i \in I} Q(h_i^t, a_i^t; \theta_i)$$

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This decomposition satisfies the IGM property and we can jointly optimise the parameters of all networks by minimising the following loss on sampled batches of experiences \mathcal{B} :

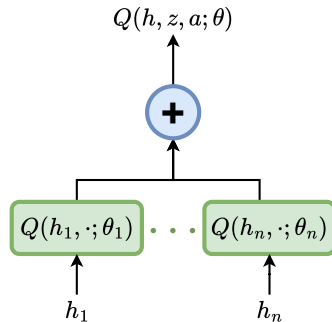
$$\mathcal{L}(\theta) = \frac{1}{B} \sum_{(h^t, a^t, r^t, h^{t+1}) \in \mathcal{B}} \left(r^t + \gamma \sum_{i \in I} \max_{a_i \in A_i} Q(h_i^{t+1}, a_i; \bar{\theta}_i) - \sum_{i \in I} Q(h_i^t, a_i^t; \theta_i) \right)^2$$

with $\bar{\theta}_i$ denoting the parameters of agent i 's target network.

Value Decomposition Networks

Algorithm Value decomposition networks (VDN)

- 1: Initialize n utility networks with random parameters $\theta_1, \dots, \theta_n$
 - 2: Initialize n target networks with parameters $\bar{\theta}_1 = \theta_1, \dots, \bar{\theta}_n = \theta_n$
 - 3: Initialize a shared replay buffer D
 - 4: **for** time step $t = 0, 1, 2, \dots$ **do**
 - 5: Collect current observations o_1^t, \dots, o_n^t
 - 6: **for** agent $i = 1, \dots, n$ **do**
 - 7: With probability ϵ : choose random action a_i^t
 - 8: Otherwise: choose $a_i^t \in \arg \max_{a_i} Q(h_i^t, a_i; \theta_i)$
 - 9: Apply actions; collect shared reward r^t and next observations $o_1^{t+1}, \dots, o_n^{t+1}$
 - 10: Store transition (h^t, a^t, r^t, h^{t+1}) in shared replay buffer D
 - 11: Sample mini-batch of B transitions (h^k, a^k, r^k, h^{k+1}) from D
 - 12: **if** s^{k+1} is terminal **then**
 - 13: Targets $y^k \leftarrow r^k$
 - 14: **else**
 - 15: Targets $y^k \leftarrow r^k + \gamma \sum_{i \in I} \max_{a_i' \in A_i} Q(h_i^{k+1}, a_i'; \bar{\theta}_i)$
 - 16: Loss $\mathcal{L}(\theta) \leftarrow \frac{1}{B} \sum_{k=1}^B \left(y^k - \sum_{i \in I} Q(h_i^k, a_i^k; \theta_i) \right)^2$
 - 17: Update parameters θ by minimizing the loss $\mathcal{L}(\theta)$
 - 18: In a set interval, update target network parameters $\bar{\theta}_i$ for each agent i
-



Monotonic Value Decomposition

A more general decomposition (that also ensures the IGM property) can be formulated by assuming that the centralized action-value function is a (strictly) monotonically increasing function with respect to any individual utility function:

$$\forall i \in I, \forall a \in A : \frac{\partial Q(h, z, a; \theta)}{\partial Q(h_i, a_i; \theta_i)} > 0$$

Monotonic Value Decomposition

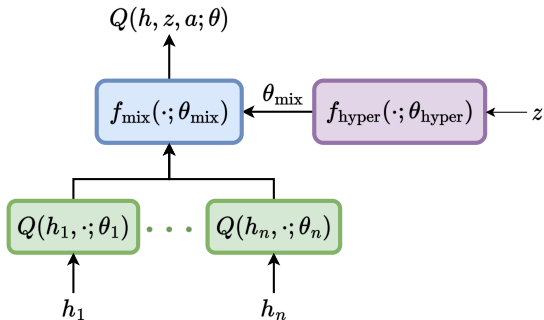
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The **QMIX** algorithm implements this assumption using a mixing function f_{mix} that aggregates individual utilities to approximate the centralized action-value function:

$$Q(h, z, a, \theta) = f_{\text{mix}}(Q(h_1, a_1; \theta_1), \dots, Q(h_n, a_n; \theta_n); \theta_{\text{mix}})$$

QMIX Architecture



The centralized action-value function is monotonic with respect to individual utilities if all weights of f_{mix} are positive \rightarrow ensure positive weights by obtaining the parameters of the mixing function from a hypernetwork f_{hyper} conditioned on centralized information z

The parameters of all utility functions and the hypernetwork are jointly optimised by minimising the following loss on batches of experiences \mathcal{B} sampled from a replay buffer:

$$\mathcal{L}(\theta) = \frac{1}{B} \sum_{(h^t, z^t, a^t, r^t, h^{t+1}, z^{t+1}) \in \mathcal{B}} \left(r^t + \gamma \max_{a \in A} Q(h^{t+1}, z^{t+1}, a; \bar{\theta}) - Q(h^t, z^t, a^t; \theta) \right)^2$$

with the following decomposed value estimates:

$$Q(h^t, z^t, a^t, \theta) = f_{\text{mix}}(Q(h_1^t, a_1^t; \theta_1), \dots, Q(h_n^t, a_n^t; \theta_n); \theta_{\text{mix}})$$
$$\max_{a \in A} Q(h^{t+1}, z^{t+1}, a; \bar{\theta}) = f_{\text{mix}} \left(\max_{a_1 \in A_1} Q(h_1^{t+1}, a_1; \bar{\theta}_1), \dots, \max_{a_n \in A_n} Q(h_n^{t+1}, a_n; \bar{\theta}_n); \bar{\theta}_{\text{mix}} \right)$$

Value Decomposition in Matrix Games

To better understand how value decomposition works in practise, we will look at several exemplary tasks and the learned decompositions of both VDN and QMIX.

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A	1	5
B	5	9

Figure: Linear game

	A	B
A	0	0
B	0	10

Figure: Monotonic game

	A	B	C
A	11	-30	0
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	Linear game	Monotonic game	Climbing game
Linearly decomposable	✓	✗	✗
Monotonically decomposable	✓	✓	✗

Value Decomposition in Linearly Decomposable Matrix Game

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(a) True rewards

	0.12	4.12
0.88	1.00	5.00
4.88	5.00	9.00

(b) VDN decomposition

	-0.21	0.68
0.19	1.00	5.00
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- VDN and QMIX are able to learn the true centralized action-value function

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We can make several observations from the learned decompositions:

- VDN and QMIX are able to learn the true centralized action-value function
- The learned decompositions are not unique and can vary between different runs

Value Decomposition in Linearly Decomposable Matrix Game

	A	B
A	1	5
B	5	9

(a) True rewards

	0.12	4.12
0.88	1.00	5.00
4.88	5.00	9.00

(b) VDN decomposition

	-0.21	0.68
0.19	1.00	5.00
0.96	5.00	9.00

(c) QMIX decomposition

We can make several observations from the learned decompositions:

- VDN and QMIX are able to learn the true centralized action-value function
- The learned decompositions are not unique and can vary between different runs
- Individual utility values, in particular for QMIX, can be difficult to interpret (besides larger values indicating higher return estimates)

Value Decomposition in Monotonically Decomposable Matrix Game

	A	B
A	0	0
B	0	10

(a) True rewards

	-1.45	3.45
-0.94	-2.43	2.51
4.08	2.60	7.53

(b) VDN decomposition

	-4.91	0.82
-4.66	0.00	0.00
1.81	0.00	10.00

(c) QMIX decomposition

Value Decomposition in Monotonically Decomposable Matrix Game

	A	B
A	0	0
B	0	10

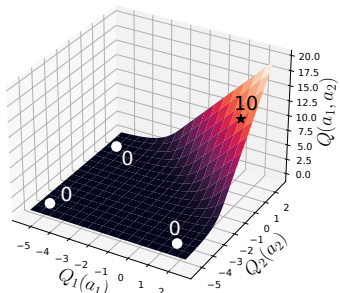
(a) True rewards

	-1.45	3.45
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(b) VDN decomposition

	-4.91	0.82
-4.66	0.00	0.00
1.81	0.00	10.00

(c) QMIX decomposition



Only QMIX is able to represent the non-linear but monotonic relationship between the individual utility functions and the centralized action-value function.

Value Decomposition in Climbing Game

	A	B	C
A	11	-30	0
B	-30	7	0
C	0	6	5

Figure: True rewards

In the Climbing game, neither VDN nor QMIX are able to learn the true centralized action-value function and converge to sub-optimal policies.

	-4.56	-4.15	3.28
-4.28	-8.84	-8.43	-1.00
-6.10	-10.66	-10.25	-2.82
5.31	0.75	1.16	8.59

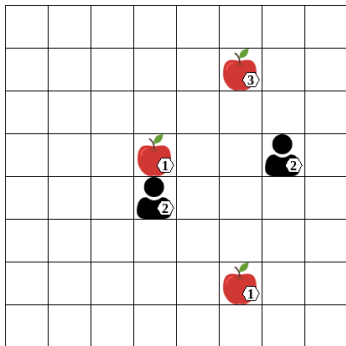
(a) VDN decomposition

	-16.60	-0.24	-4.68
-7.44	-11.16	-11.16	-11.16
7.65	-11.15	2.34	-1.37
11.27	-4.95	8.72	5.01

(b) QMIX decomposition

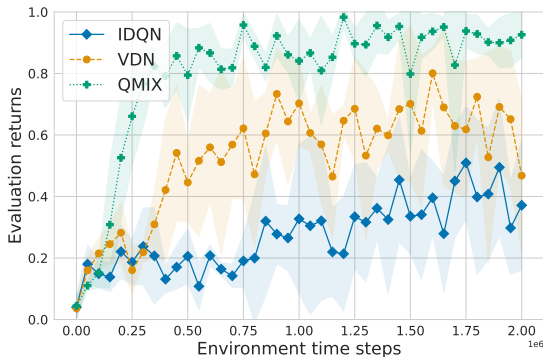
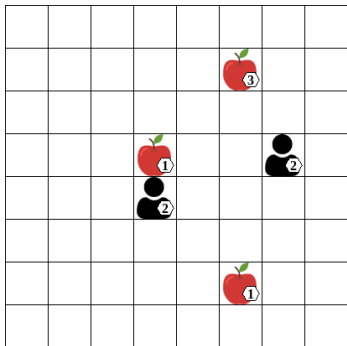
Value Decomposition in LBF

So far, we looked at simple single-step matrix games. We will now compare IDQN, VDN and QMIX in a common-reward level-based foraging task where two agents need to collect three items in a 8×8 grid world:



Value Decomposition in LBF

So far, we looked at simple single-step matrix games. We will now compare IDQN, VDN and QMIX in a common-reward level-based foraging task where two agents need to collect three items in a 8×8 grid world:



Summary

We covered:

- Training and execution modes
- Independent learning with deep reinforcement learning
- Multi-agent policy gradient algorithms
- Value decomposition in common-reward games

Next we'll cover:

- Agent modeling with deep learning
- Parameter and experience sharing
- Policy self-play in zero-sum games
- Population-based training