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Deep multiagent reinforcement learning: challenges and directions

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Abstract

This paper surveys the field of deep multiagent reinforcement learning (RL). The combination of deep neural networks with RL has gained increased traction in recent years and is slowly shifting the focus from single-agent to multiagent environments. Dealing with multiple agents is inherently more complex as (a) the future rewards depend on multiple players' joint actions and (b) the computational complexity increases. We present the most common multiagent problem representations and their main challenges, and identify five research areas that address one or more of these challenges: centralised training and decentralised execution, opponent modelling, communication, efficient coordination, and reward shaping. We find that many computational studies rely on unrealistic assumptions or are not generalisable to other settings; they struggle to overcome the curse of dimensionality or nonstationarity. Approaches from psychology and sociology capture promising relevant behaviours, such as communication and coordination, to help agents achieve better performance in multiagent settings. We suggest that, for multiagent RL to be successful, future research should address these challenges with an interdisciplinary approach to open up new possibilities in multiagent RL.

Keywords Reinforcement learning · Deep learning · Multiagent systems · Evolutionary algorithms · Psychology · Survey

1 Introduction

Reinforcement learning (RL) is a machine-learning method in which one agent or a group of agents maximises its long-term return through repeated interaction with its environment. Agents are not told what actions to take and must learn their optimal behaviour via trial-and-error. Since rewards may be delayed, an agent has to make a trade-off between exploiting states with the current highest reward and exploring states that may potentially yield higher rewards (Bellman 1957). As agents learn by receiving rewards for desirable actions and penalties (negative rewards) for undesired actions, RL can automate learning and decision-making without supervision or having complete models of the environment.

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However, one drawback of RL methods is that they suffer from the *curse of dimensionality* (Bellman 1957): algorithms become less efficient as the dimensions of the state-action space increase (Sutton et al. 1998). In recent years the rise of deep reinforcement learning (DRL), a combination of RL and deep learning, has enabled artificial agents to surpass human-level performance in a wide range of complex decision-making tasks, such as in the board game Go (Silver et al. 2016) and the card game Poker (Brown and Sandholm 2018, 2019; Bowling et al. 2015). While prior RL applications required carefully handcrafted features based on human knowledge and experience (Sutton et al. 1998), deep neural networks can automatically find low-dimensional representations (features) of high-dimensional data (LeCun et al. 2015). This development has led to enormous growth in applying RL to more complicated problems. First in single-agent settings such as playing Atari (Mnih et al. 2015), resource management (Wen et al. 2015; Mao et al. 2016), indoor robot navigation (Zhu et al. 2017), cyber security (Huang et al. 2022), and trade execution (Nevmyvaka et al. 2006), and more recently in multiagent settings such as bidding optimization (Jin et al. 2018), traffic-light control (Chu et al. 2020), autonomous driving (Sallab et al. 2017), financial market trading (Bao and Liu 2019), energy usage (Prasad and Dusparic 2019), fleet optimization (Lin et al. 2018) and strategy games like Dota 2 (Berner et al. 2019) and Starcraft (Vinyals et al. 2019).

It is challenging to translate the successes of DRL in single-agent settings to a multiagent setting. Multiagent reinforcement learning (MARL) differs from single-agent systems foremost in that the environment's dynamics are determined by the joint actions of all agents in the environment, in addition to the uncertainty already inherent in the environment. As the environment becomes nonstationary, each agent faces the moving-target problem: the best policy changes as the other agents' policies change (Busoniu et al. 2008; Papoudakis et al. 2019). The violation of the stationarity assumption required in most single-agent RL algorithms poses a challenge in solving multiagent learning problems. The curse of dimensionality is also worse in a multiagent setting as every additional agent increases the state-action space. At the same time, MARL introduces a new set of opportunities as agents may share knowledge and imitate or directly learn from other learning agents (Da Silva and Costa 2019; Ilhan et al. 2019), which may accelerate the learning process and subsequently result in more efficient ways of arriving at a goal.

Deep multiagent reinforcement learning (DMARL) constitutes a young field that is rapidly expanding. Many real-world problems can be modelled as a MARL problem, and the emergence of DRL has enabled researchers to move from simple representations to more realistic and complex environments. This survey examines current research areas within DMARL, addresses critical challenges, and presents future research directions. Earlier surveys were driven by the theoretical difficulties in multiagent systems, including nonstationarity (Hernandez-Leal et al. 2019; Papoudakis et al. 2019), partial observability, and continuous state and action spaces (Nguyen et al. 2020). Others focus on how agents learn, such as transfer learning (Da Silva and Costa 2019), modelling other agents (Albrecht and Stone 2018), or a theoretical domain such as game theory (Yang and Wang 2021) and evolutionary algorithms (Bloembergen et al. 2015). A number of studies have looked into the applications of MARL (Canese et al. 2021; Feriani and Hossain 2021; Du and Ding 2021). This paper complements a group of surveys that provides a general framework to classify the deep learning algorithms used in recent DMARL studies (Hernandez-Leal et al. 2019; Gronauer and Diepold 2021).

When working on this survey, Google Scholar was the leading search engine for finding relevant papers containing keywords such as "multi-agent" or "multiagent", "reinforcement learning", and "deep learning". We cover works from leading journals, conference proceedings, relevant arXiv papers, book chapters, and PhD theses. We carefully evaluated the studies that came to our attention and developed a taxonomy based on the prominent research directions in the field.

In contrast to prior surveys, we propose a taxonomy based on the challenges inherent in multiagent problem formalisations and their solutions. Modelling a multiagent problem differs from the single-agent setting due to the violation of the stationarity assumption and the difference in learning objectives. Hence, alternative problem formalisations and solutions have been introduced. While other taxonomies also start from multiagent problem representations (Yang and Wang 2021; Zhang et al. 2021), these studies only focus on Markov and extensive-form games. Recent MARL research has used additional representations to model multiagent problems, such as the decentralised partially observable Markov game and the partially observable Markov game, which we will also cover in this survey.

The remainder of this paper is organised as follows. In Sect. 2 the preliminaries of single-agent RL are discussed. In Sect. 3 we present the most common DMARL problem frameworks. The taxonomy is introduced in Sect. 4. The discussion and recommendations for future research are given in Sect. 5. We end with the conclusion in Sect. 6.

2 Single-agent reinforcement learning

2.1 Markov decision process

Most RL problems can be framed as a Markov decision process (MDP) (Bellman 1957): a model for sequential decision-making under uncertainty that defines the interaction between a learning agent and its environment. Formally, it can be defined as a tuple $\langle S, A, P, R, \gamma \rangle$ where S is the set of states, A is the set of actions, P is the transition probability function, R is the reward function and $\gamma \in [0, 1]$ is the discount factor for future rewards. The learning agent interacts with the environment in discrete time steps. At each time step t, the agent is in some state $s_t \in S$ and selects an action $a_t \in A$. At time step t_{t+1} the agent receives a reward $r_{t+1} \in R$ and moves into a new state s_{t+1}. Specifically, the state transition function is defined as $P(s', r|s, a) = Pr\{S_t = s', R_t = r|S_{t-1} = s, A_{t-1} = a\}$ and describes the model dynamics. Each state in an MDP has the Markov property, which means that the future only depends on the current state and not on the history of earlier states and actions. MDPs further assume that the agent has full observability of the states and that the environment is stationary: the transition probabilities and rewards remain constant over time. A setting where the agent does not have full observability of the state is called a partially observable Markov decision process (POMDP) (Åström 1965).

A policy π is a mapping from states to probabilities of selecting each action and can be deterministic or stochastic. The goal of the agent is to learn a policy that maximises its performance and is typically defined as the expected return, computed as the expected discounted sum of rewards, in a trajectory $\tau = (s_0, a_0, s_1, a_1, ...)$, a sequence of states and actions in the environment:

$$\mathbb{E}_\tau \left[\sum_{t=0}^{T} \gamma^t r_t \right]. \tag{1}$$

The discount factor $\gamma \in [0, 1]$ describes how rewards are valued. A γ closer to 0 means that the agent places more value on immediate rewards, while a γ closer to 1 indicates that the agent favours future rewards. A policy that maximises the function above is optimal and is denoted as π^*.

Most MDP solving algorithms can be divided into one of three groups: value-based, policy-based, and model-based methods. This distinction is based on the three primary functions to learn in RL (Graesser and Keng 2019). Hybrid forms of the three primary functions also exist. We present a brief overview of each of the three classes.

2.2 Value-based methods

Value-based methods learn the value function and derive the optimal policy from the optimal value function. There are two kinds of value functions. The state-value function describes how good it is to be in a state, and it is the expected return from being in state s and then following policy π and is denoted as:

$$v_\pi(s) = \mathbb{E}_{s_0=s,\tau\sim\pi}\left[\sum_{t=0}^{T}\gamma^t r_t\right]. \tag{2}$$

The action-value function or sometimes called the Q-function describes how good it is to perform action a in state s and is denoted as:

$$q_\pi(s,a) = \mathbb{E}_{s_0=s,a_0=a,\tau\sim\pi}\left[\sum_{t=0}^{T}\gamma^t r_t\right]. \tag{3}$$

The optimal policy π^* maximizes the state-value function such that $v_{\pi_*}(s) > v_{\pi(s)}$ for all $s \in S$ and all policies π. If we have the optimal state-value function, the optimal policy can be extracted by choosing the action that gives the maximum action-value for state s. This relationship is given by $\pi^* = \max_\pi v_\pi(s) = \max_\pi q_\pi(s,a)$.

Deep Q-networks (DQN) (Mnih et al. 2015) belong to the value-based methods that have become increasingly popular as studies achieved remarkable results in more complicated environments such as Atari games. Recent developments in RL research show a preference for policy-based strategies, even though value-based methods can capture the underlying structure of the environment (Arulkumaran et al. 2017).

2.3 Policy-based and combined methods

In contrast to value-based methods, policy-based methods search directly for the optimal policy and the output is represented as a probability distribution over actions. The optimal policy is found by optimising a θ-parameterized policy with respect to the objective via gradient ascent. The policy network weights are updated iteratively so that state-action pairs that result in higher returns are more likely to be selected. The objective is the expected return over all completed trajectories and is defined as follows:

$$J(\theta) = \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T}\gamma^t r_t\right]. \tag{4}$$

Many policy gradient methods build upon REINFORCE (Williams 1992), one of the first policy gradient implementations which used Monte Carlo sampling to estimate the policy gradient.

Policy gradient methods perform better in continuous and stochastic environments, learn specific probabilities for each action, and learn the appropriate level of exploration (Sutton and Barto 2018). The main limitation of policy gradient methods is the large variance in the gradient estimators (Greensmith et al. 2004) due to sparse rewards and the fact that only a finite set of states and actions are tried. Policy gradient methods are not very sample-efficient since new estimates of the gradients are learned independently from past estimates (Konda and Tsitsiklis 2003; Peters and Schaal 2008).

Actor-critic methods (Konda and Tsitsiklis 2003; Grondman et al. 2012; Bahdanau et al. 2017) combine policy-based and value-based methods to address these limitations: Actor-critic methods preserve the desirable convergence properties while maintaining stability during learning. Actor-critic methods consist of an actor that learns a policy and a critic that learns a value function to evaluate the state-action pair. The critic approximates and updates the value function parameters w for either the state-value $v(s; w)$ or the action-value $q(a|s; w)$, and the actor updates the policy parameters θ for $\pi_\theta(a|s)$ in the direction suggested by the critic.

Popular actor-critic methods include Advantage Actor-Critic (A2C) (Wu et al. 2017a), Asynchronous Advantage Actor-Critic (A3C) (Mnih et al. 2016), Proximal Policy Optimization (PPO) (Schulman et al. 2017), Soft Actor-Critic (SAC) (Haarnoja et al. 2018) and Twin-Delayed Deep Deterministic Policy Gradient (TD3) (Dankwa and Zheng 2019). In A3C, multiple agents interact with a copy of the environment in parallel and update the global network parameters asynchronously (Mnih et al. 2016). In contrast, A2C performs the global network updates synchronously and is found to be more efficient on a GPU machine or when larger policies are trained (Wu et al. 2017b). PPO builds upon Trust Region Policy Optimization (TRPO) (Schulman et al. 2015), a method in which the gradient steps are constrained to prevent destructive policy updates. PPO uses first-order optimisation to compute the updates, simplifying the algorithm's tuning and implementation. In contrast to previous methods, SAC and TD3 are off-policy methods that efficiently reuse past experiences. SAC uses entropy maximization to encourage exploration, while TD3 is a combination of continuous Double Deep Q-Learning (Van Hasselt et al. 2016), Policy Gradient (Silver et al. 2014) and Actor-Critic (Sutton et al. 1999).

2.4 Model-based methods

Model-based approaches learn a model of the environment that captures the transition and reward function. The agent can then use planning, the construction of trajectories or experiences using the model (Hamrick et al. 2021) to find the optimal policy. While model-free methods focus on learning, where the agent improves a policy or value function from direct experiences generated by the environment, model-based methods focus on planning (Sutton and Barto 2018).

The environment model can either be given or learned. Games such as chess and Go belong to the first category. When there is no given model, the agent must learn it through repeated interaction with the environment using a base policy $\pi_0(a_t|s_t)$. The experiences are stored in historical data $\mathcal{D} = (s_t^i, a_t^i, s_{t+1}^i)$, which is then used to learn the dynamics model $P(s, a)$ by minimizing $\sum_i ||P(s_t^i, a_t^i) - s_{t+1}^i||^2$. Given the current state s and action a, the next state s_{t+1} is then given by $s_{t+1} = P(s_t, a_t)$. Planning is then performed through

$P(s, a)$ (Levine 2017; Chua et al. 2018). Planning methods generally compute value functions via updates or backup operations to simulated experiences to find the optimal policy (Sutton and Barto 2018).

Examples of model-based algorithms include AlphaZero (Silver et al. 2017) and MuZero (Schrittwieser et al. 2020) that achieved state-of-the-art performance in Atari, Go, chess and Shogi. For a recent overview of DRL in model-based games, see (Plaat 2020).

The main advantage of model-based approaches is better sample efficiency. Agents may use the model to simulate experiences to have fewer interactions with the environment, resulting in faster convergence. However, it is difficult to accurately represent the model, especially in real-world scenarios where the transition dynamics are unavailable. In addition, when bias and inaccuracies are present in the model, errors may accumulate for each step (Graesser and Keng 2019).

3 Multiagent problem representations

In MARL, a set of autonomous agents interact within the environment to learn how to achieve their objectives. While MDPs have proven helpful in modelling optimal decision-making in single-agent stochastic environments, multiagent environments require a different representation. The state dynamics and expected rewards change upon all agents' joint action, violating the core stationarity assumption of an MDP.

MDPs can be fully or partly visible to the agent. In a multiagent setting, the problem representation is also dependent on the nature of the interaction between agents, which can be cooperative, competitive or mixed, and whether agents take actions sequentially or simultaneously. Figure 1 shows an overview of the most common theoretical frameworks used in the DMARL literature. When agents have full observability of the state, the problem is usually represented by a Markov game. A particular type is the team Markov game, where agents collaborate to maximise a common reward. If agents collaborate but execute actions decentrally, it is represented by a decentralised POMDP. The partially observable variant for the mixed and competitive setting is known as the partially observable Markov game. The extensive-form game representation is used when agents take turns sequentially instead of simultaneously. The following sections outline the theoretical frameworks pertinent to the DMARL literature, which are visually depicted in Fig. 2.

3.1 Markov games

Markov games (e.g. Littman 1994), or Stochastic games (Shapley 1953),[1] provide a theoretical framework to study multiple interacting agents in a fully observable environment and can be applied to cooperative, collaborative and mixed settings. A Markov game is a collection of normal-form games (or matrix games) that the agents play repeatedly. Each state of the game can be viewed as a matrix representation with the payoffs for each joint action determined by the matrices.

In its general form, a Markov game is a tuple $\langle I, S, A, R, T \rangle$ where I is the set of N agents, S is a finite state space, $A = A_1 \times A_2 \times \cdots \times A_N$ is the joint action space of N

[1] The terms Markov game and stochastic game are used interchangeably in the literature. For consistency, we will continue using the term Markov game throughout the paper.

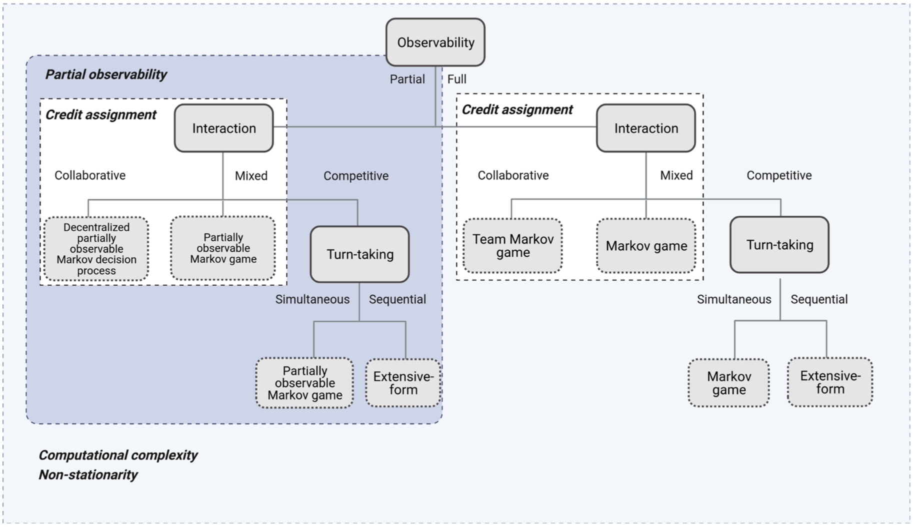


Fig. 1 Diagram of problem representations and their main challenges. multiagent problem representations can be categorised along a number of axes. First, whether the environment is fully or partially observable. Second, whether the nature of the interaction is collaborative, mixed or competitive. Third, whether turns are taken sequentially or simultaneously. Different problem representations come with different challenges. The four main challenges include computational complexity, nonstationarity, partial observability and credit assignment. Computational complexity and nonstationarity are challenges found in all problem representations, while partial observability and credit assignment are specific to some.Illustrations are created with BioRender.com

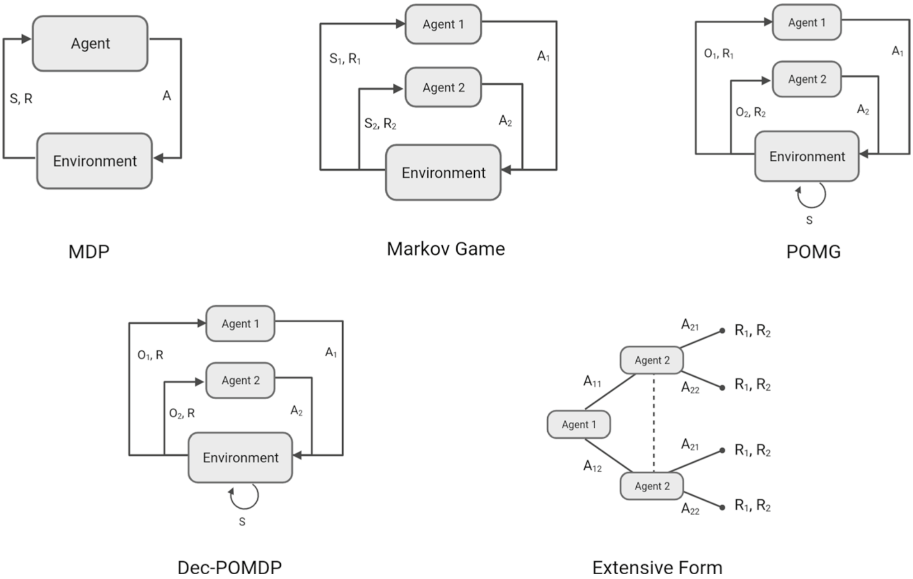


Fig. 2 Visual depiction of the main problem representations in multiagent reinforcement learning. The MDP is the primary framework used in the single-agent setting. An agent is in some state S, performs action A, and receives a reward R from the environment. In partially observable environments, the agent cannot view the true state S and receives an observation O instead. For simplicity, all figures display the interaction between two agents $i = 1, 2$ but can be extended to more agents

agents, $R = (r_1, r_2, \dots, r_N)$ where $r_i : S \times A \rightarrow \mathbb{R}$ is each agent's reward function and $T : S \times A \times S \rightarrow [0, 1]$ is the transition function. In a team Markov game, agents work together to achieve a goal and share the rewards function $r_1 = r_2 = \cdots = r_N$. A competitive Markov game is represented by a zero-sum game: the gains for one party automatically result in equal losses for the other. A Markov game is a normal-form game, which means that the game is represented in a tabular form, and all agents take their actions simultaneously.

One way to solve Markov games is to learn equilibria by optimising over an agent's reward function and ignoring others in the environment (Tan 1993; Littman 1994). Another approach involves best-response learners. Agents optimise their reward function while accounting for other agents' changing policies. If these algorithms converge during the play, then it must be an equilibrium (Bowling and Veloso 2001, 2002). However, equilibrium concepts either assume infinite computational resources or have been applied to smaller grid-word environments, as they do not scale well with the number of agents.

The majority of studies in DMARL focus on Markov games, such as Pong (Diallo et al. 2017), predator games (Zheng et al. 2018a) and the iterated prisoner's dilemma (Foerster et al. 2018a).

3.2 Extensive-form games

When agents take turns sequentially, this is modelled as an extensive-form game (Kuhn and Tucker 1953). An extensive-form game specifies the sequential interaction between agents in the form of a game tree. The game tree shows the order of the agents' moves and the possible actions at each point in time. Formally, an extensive-form game with finite and perfect information is given by the tuple $\langle P, A, H, Z, \chi, \rho, \sigma, u \rangle$ where P is a set of players or agents, A is a single set of actions, H is a set of non-terminal choice nodes, Z is a set of terminal outcome nodes, $\chi : H \rightarrow 2^A$ is an action function, representing the set of possible actions at each node, $\rho : H \rightarrow P$ is the player function, which assigns at each choice node a player $i \in P$ who is to take action at a given non-terminal node, $\sigma : H \times A \rightarrow H \cup Z$ is the successor function that maps a choice node and an action to a new choice node or terminal node, and u is a set of utility functions (Shoham and Leyton-Brown 2008).

When agents have incomplete information or a partial view of the global state, this can be formalised as an imperfect information extensive-form game in which decision nodes are portioned into information sets. When the game reaches the information set, the agent whose turn it is cannot distinguish between nodes within the information set nor tell which node in the tree has been reached. Formally, an imperfect information extensive-form game is a tuple $\langle P, A, H, Z, \chi, \rho, \sigma, u, I \rangle$ where $\langle P, A, H, Z, \chi, \rho, \sigma, u \rangle$ is a perfect information extensive-form game and $I = I_1, ..., I_N$ is the set of information partitions of all players.

A strategy maps each agent's information sets to a probability distribution over possible actions. The exploitability is a mean score over all the positions against a worst-case adversary who uses at each turn a best-response. In a Nash equilibrium, the exploitability is equal to 0, and no agents have an incentive to change their strategies (Johanson et al. 2013). Studies try to solve extensive-form games by approximating a Nash equilibrium, predominantly in the poker domain (Bowling et al. 2015; Heinrich et al. 2015; Moravčík et al. 2017; Heinrich and Silver 2016; Brown and Sandholm 2018, 2019) and board games such as Go (Silver et al. 2016, 2017) and Othello (Van Der Ree and Wiering 2013).

3.3 Decentralized partially observable Markov decision process

In a decentralised partially observable Markov decision process (Dec-POMDP), all agents attempt to maximise the joint reward function while having different individual objectives (Bernstein et al. 2002).

A Dec-POMDP is defined by the tuple $\langle I, S, A, \Omega, O, T, R \rangle$, where I is the set of N agents, S is the finite state space, A is the joint action set, Ω is the joint observations set, O is the observation probability function: $O : \Omega \times A \times S \rightarrow [0, 1]$ and $O(o_1, ..., o_N | a_1, ..., a_N, s')$ are observed by agents 1, ..., N, respectively, given that each action tuple $\langle a_1, ..., a_N \rangle$ was taken and led to state s'. Each agent i has a set of actions $A_i \in A$ for each observation $\Omega_i \in \Omega$. T is the state transition probability function $T : S \times A \times S \rightarrow [0, 1]$ that specify the transition probabilities $P(s' | s, a_1, ..., a_N)$. Finally, R is the reward function $R(s, a_1, ..., a_N)$.

At every time step, each agent takes an action and receives a local observation that is correlated with the state and an immediate joint reward. A local policy maps local histories of observations to actions, and a joint policy is a tuple of local policies.

The computational complexity of Dec-POMDPs presents a big challenge for researchers. These problems are not solvable with polynomial-time algorithms, and searching directly for an optimal solution in the policy space is intractable (Bernstein et al. 2002). One approach is to transform the Dec-POMDP into a simpler model and solve it with planning algorithms (Amato and Oliehoek 2015; Ye et al. 2017). For instance, using a centralised controller that receives all agents' private information converts the model into a POMDP, and allowing communication that is free of costs and noise reduces it to a multiagent POMDP (MPOMDP) (Amato and Oliehoek 2015; Gupta et al. 2017). Recent solutions also take advantage of the key assumption that planning can be centralised as long as execution is decentralised.

The Dec-POMDP has been used to represent riddles (Foerster et al. 2016), coordination of bipedal walkers (Gupta et al. 2017) and real-time strategy games such as Starcraft (Vinyals et al. 2019; Schroeder de Witt et al. 2019; Du et al. 2019), Dota 2 (Berner et al. 2019), and Capture the Flag (Jaderberg et al. 2019).

3.4 Partially observable Markov game

The partially observable Markov game (POMG) (Hansen et al. 2004), also known as the partially observable stochastic game (POSG), is the counterpart of the Dec-POMDP. Instead of a joint reward function, agents optimise their individual reward functions in a partially observable environment. The POMG implicitly models a distribution over other agents' belief states. Formally, a POMG is a tuple $\langle I, S, A, O, b^0, P, R \rangle$ where I is the set of N agents, S is the set of states, A_i is the action set of agent i and $A = A_1 \times A_2 \times \cdots \times A_N$ is the joint action set, O_i is a set of observations for agent i and $O = O_1 \times O_2 \times \cdots \times O_N$ is the joint observation set. The game's initial state, also called the initial belief, is drawn from a probability distribution b^0 over the states. P is a set of state transitions and observation probabilities, where $P(s', o | s, a)$ is the probability of moving into state s' and joint observation o when taking joint action a in state s. $R_i : S \times A \rightarrow \mathbb{R}$ is the reward function for agent i where S refers to the joint state $(s_1, ..., s_N)$ and A refers to the joint actions $(a_1, ..., a_N)$. The model can be reduced to a POMDP when $|I| = 1$.

Dynamic programming algorithms have been developed for POMG (Hansen et al. 2004; Kumar and Zilberstein 2009), in which agents maintain a belief over the actual state of the environment and other agents' policies. However, applying it to high-dimensional problems

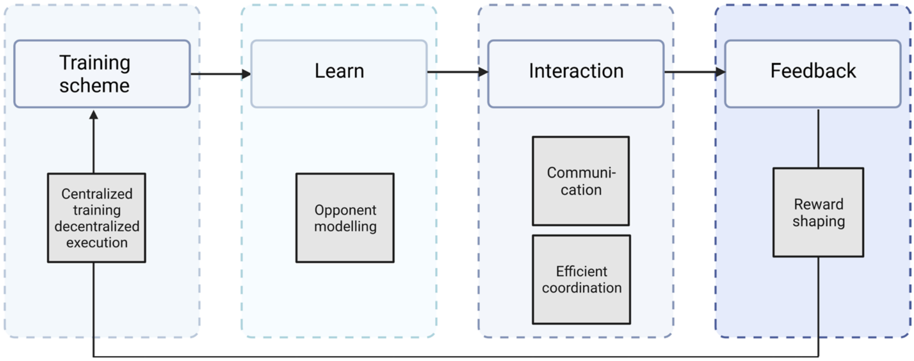


Fig. 3 Overview of taxonomy. This figure shows how the paper is organised. We start by discussing the main training scheme in DMARL: centralised training and decentralised execution. We then move to how agents learn through opponent modelling and interact with other agents via communication and coordination. Finally, we discuss how different reward shaping methods act as a feedback mechanism

becomes intractable, and assumptions are often relaxed or applied to simpler problems. Complexities such as competing goals, nonstationarity and incomplete information make the problem even harder. Examples of POMG include autonomous driving (Palanisamy 2020) and partially observable grid world games (Moreno et al. 2021).

4 Taxonomy of deep multiagent reinforcement learning algorithms

We will now introduce the taxonomy of this paper. We first discuss the four main challenges inherent in multiagent settings: (1) computational complexity, (2) nonstationarity, (3) partial observability and (4) credit assignment. We then provide an overview of current deep learning approaches and discuss how these algorithms address these challenges. The surveyed studies cover the whole learning process of an agent: starting from the training scheme, how it learns and interacts with the environment, to how an agent incorporates feedback, as shown in Figure 3. The reviewed algorithms have been categorised into one of the following groups: (1) centralised training and decentralised execution, (2) opponent modelling, (3) communication, (4) efficient coordination and (5) reward shaping. Figure 4 shows the relationship between the reviewed studies and the challenges that they address. Finally, Table 1 presents examples of some of the major studies along with their main challenges and solutions.

4.1 Challenges

Reinforcement learning in a multiagent environment comes with numerous challenges. Addressing these challenges is a prerequisite for the development of effective learning approaches. Despite promising results in the literature, computational complexity, nonstationarity, partial observability, and credit assignment remain largely unsolved.

The four challenges do not occur in isolation. In contrast, a multiagent problem usually deals with one or more challenges simultaneously. All multiagent problems deal with high computational demands, and the higher the number of agents, the more demanding it is on computing power. The problem of nonstationarity can lead to an infinite loop of agents

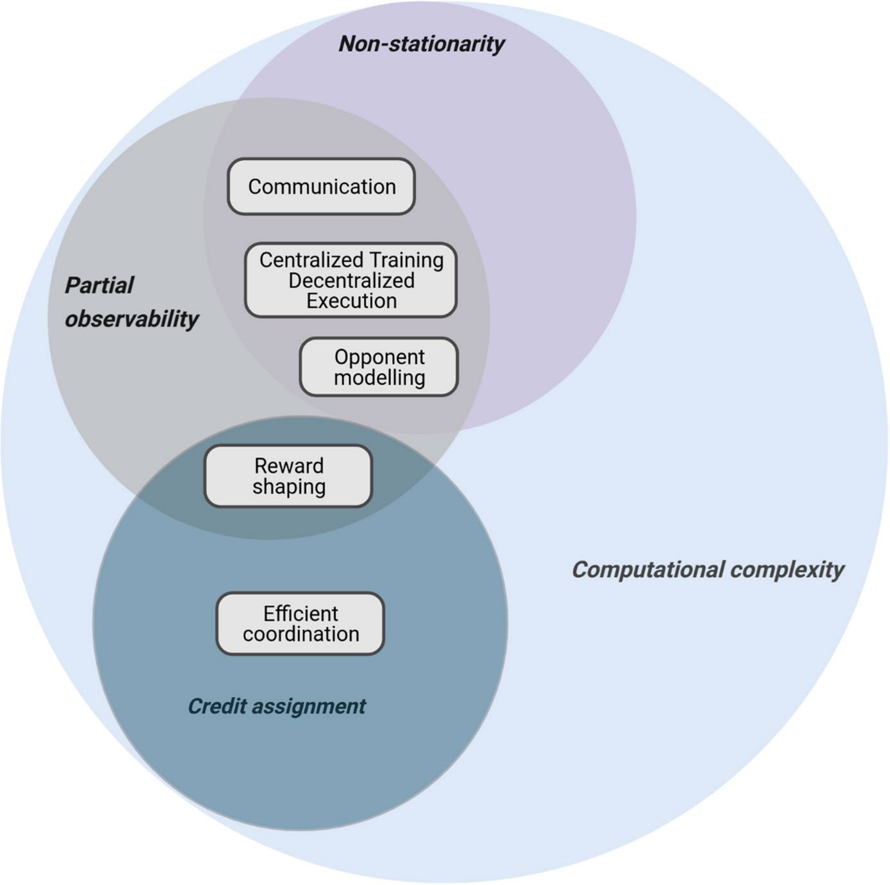


Fig. 4 Venn diagram of challenges and solutions. The taxonomy of DMARL algorithms comprises five groups: centralised training and decentralised execution, opponent modelling, communication, efficient coordination and reward shaping. Approaches may tackle one or more challenges: nonstationarity, partial observability, credit assignment and computational complexity. Computational complexity is a universal challenge for all approaches. This Venn diagram shows the relations between the surveyed groups of studies and the addressed challenges

adapting to other agents (Papoudakis et al. 2019), and this problem is exacerbated when agents have only a partial view of the state, which means they have less information, and it is even harder to distinguish the effects of their actions from that of other agents. Consequently, agents cannot distil the individual contribution to the team reward, also known as the credit assignment problem. We turn to each of these aspects next.

4.1.1 Computational complexity

A current limitation of RL algorithms is the low sample efficiency, which requires an agent to interact a vast amount of times with the environment to learn a useful policy (Yu 2018). For example, to teach an agent to play the game of Pong, at least ten thousand samples

Table 1 Overview of some of the major studies along with the problem representation, main challenges, evaluation domains and solutions

Study	Evaluation domain	Problem representation	Main challenge(s)	Approach	Method
Moreno et al. (2021)	Running with Scissors	POMG	PO	OM	Recursive belief models
Sukhbaatar et al. (2016)	Traffic Junction	Dec-POMDP	PO, NS	Cm	Communication with backpropagation
Sunehag et al. (2018)	Switch	Dec-POMDP	PO, NS	CTDE	Value-Decomposition Networks
Heinrich et al. (2015)	Leduc Poker	IIEFG	PO, CC	OM	Neural fictious self-play
Bowling et al. (2015)	Heads-up limit hold'em Poker	IIEFG	PO, CC	OM	Self-play with counterfactual regret minimization
Brown and Sandholm (2019)	No-limit Texas hold'em Poker	IIEFG	PO, CC	OM	Self-play with counterfactual regret minimization
Silver et al. (2017)	Go	CIEF	CC	OM	Self-play and Monte Carlo tree search
Nguyen et al. (2018)	Matching taxi supply and demand	Dec-POMDP	CA, PO, NS	RS	Difference rewards: wonderful life utility and aristocratic utility
Leibo et al. (2017)	Sequential social dilemma	Markov game	CA	EC	Learn policy dynamics of DQN agents by altering variables
Vinyals et al. (2019)	StarCraft	Dec-POMDP	CA, PO, NS, CC	OM	Population-based self-play
Jaderberg et al. (2019)	Capture the flag	Dec-POMDP	CA, PO, NS, CC	OM	Population-based self-play
Berner et al. (2019)	Dota 2	Dec-POMDP	CA, PO, NS, CC	OM	Self-play against self and past selves

IIEFG incomplete information extensive-form game, *CIEF* complete information extensive-form game, *PO* partial observability, *NS* non-stationarity, *CC* computational complexity, *CA* credit assignment, *OM* opponent modelling, *Cm* communication, *CTDE* centralized training and decentralized execution, *RS* reward shaping, *EC* efficient coordination are needed, while humans, on average, can master the game in dozens of trials (Ding and Dong 2020). The sample complexity of reinforcement, or the amount of data an agent needs to collect to learn a successful policy (Kakade 2003), worsens when multiple interacting agents are learning simultaneously. Computational complexity in RL is then how much computation, in terms of time and memory requirements, is required to collect sufficient data samples to output an approximation to the target (Kakade 2003). A challenge of MARL research is to develop algorithms that can handle this high level of computational complexity. In particular, on complex or continuous-space problems, we face slow learning of new tasks and, in the worst-case, tasks even become infeasible to master. Hence, many studies focus on designing better sample efficiency and scalability of algorithms to deal with the computational complexity in RL.

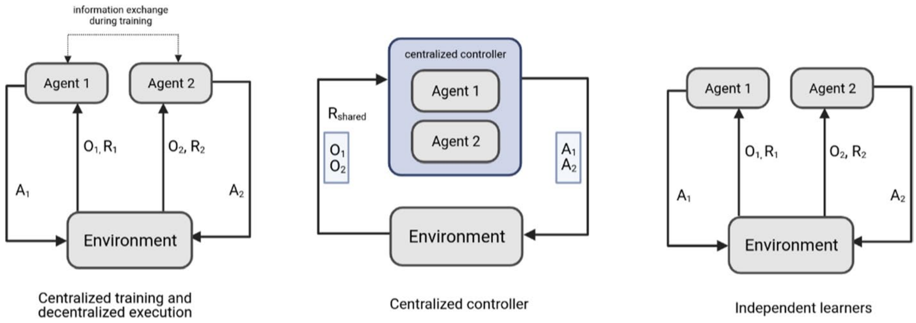
4.1.2 Nonstationarity

In a multiagent environment, all agents learn and interact with the environment concurrently. The state transitions and rewards are no longer stationary for an agent since the new state of the environment is dependent on the joint action of all agents instead of the agent's own behavior. Consequently, agents need to keep adapting to other agents' changing policies. The Markov assumption is violated as the state of the environment no longer gives sufficient information for optimal decision-making (Van Otterlo and Wiering 2012), which is problematic since most RL algorithms assume a stationary environment to guarantee convergence.

Recent works have addressed nonstationarity differently, focusing on various variables: such as the setting, which can be cooperative (Son et al. 2019), competitive (Berner et al. 2019) or mixed (Leibo et al. 2017), whether and how opponents are modelled (Brown 1951; Bowling et al. 2015), the availability of opponent information (Foerster et al. 2018b; He et al. 2016), and whether the execution of actions is centralised (Foerster et al. 2018b; Lowe et al. 2019) or decentralised (Tan 1993). There is also a wide range of sophistication across algorithms: some algorithms ignore that the environment is nonstationary, assuming that other agents are part of the environment, while more complex methods involve opponent modelling with recursive reasoning (Hernandez-Leal et al. 2019). One way to address nonstationarity is to learn as much as possible about the environment, for example, using centralised training with decentralised execution (Sect. 4.2), through opponent modelling (Sect. 4.3), and exchanging information between agents (Sect. 4.4). For a thorough overview of how algorithms model and cope with nonstationarity, we refer to recent surveys on nonstationarity (Papoudakis et al. 2019; Hernandez-Leal et al. 2019).

4.1.3 Partial observabilty

In a partially observable environment, agents cannot access the global state and must make decisions based on local observations. This results in incomplete and asymmetric information across agents, which makes training difficult. Other agents' rewards and actions are not always visible, making it difficult to attribute a change in the environment to an agent's own action. Partial observability has been mainly studied in the setting where a group of agents maximises a team reward via a joint policy (e.g. in the Dec-POMDP setting). The two main approaches for dealing with partial observability are the centralised training and decentralised execution paradigm (Kraemer and Banerjee 2016; Mahajan et al. 2019;



Centralized training and decentralized execution

Centralized controller

Independent learners

Fig. 5 Overview of training schemes. The three main training schemes in multiagent settings are centralised training and decentralised execution, using a centralised controller and independent learning. The most popular approach is centralised training with decentralised execution, where agents can share information during training, but actions are executed decentrally based on local observations. Using a centralised controller reduces the problem to a single-agent problem but is computationally infeasible. Finally, independent learners consider other agents part of the environment but ignore the nonstationarity problem

Foerster et al. 2018b; Lowe et al. 2017) and using communication to exchange information about the environment (Foerster et al. 2016; Mao et al. 2017; Peng et al. 2017).

4.1.4 Credit assignment

Two credit assignment problems are inherent in multiagent settings. The first problem is that an agent cannot always determine its individual contribution to the joint reward signal due to other concurrently acting agents in the same environment (Minsky 1961). This makes learning a good policy more difficult as the agent cannot tell whether changes in the global reward were due to its own actions or others in the environment. An alternative to the global reward structure is to let agents learn based on a local reward: a reward based on the part of the environment that an agent can directly observe. However, while an agent may increase its local reward more quickly, this approach encourages selfish behaviour that may lower overall group performance. Hence, reward shaping methods, the practice of supplying the agent with additional rewards beyond those given by the underlying environment to improve learning, have been introduced to deal with the credit assignment problem (Ng et al. 1999).

The second problem involves constructing a reward function to promote effective collaborative behaviour. This is especially difficult when mixed incentives exist in an environment, such as social dilemmas. The lazy agent problem is also undesirable (Sunehag et al. 2018): when multiple agents interact simultaneously, and one agent learns a good policy, the second agent can hold back to avoid affecting the performance of the first agent.

4.2 Centralised training and decentralised execution

We will now turn to the approaches developed to address these challenges.

The main challenge in DMARL is to design a multiagent training scheme that is efficient and that can deal with the nonstationarity and partial observability problem. Figure 5 shows the three most common training schemes. One of the most simple multiagent training schemes is to train multiple collaborating agents with a centralised controller and to reduce it to a single-agent problem. All agents send their observations and policies to a central controller, and the central controller decides which action to take for each agent. This method mitigates the problem of partial observability when agents have incomplete information about the environment. However, using a centralised controller is computationally expensive in large environments and risky as it is a single point of failure. Conversely, all agents can learn an individual action-value function and view other agents as part of the environment (Tan 1993). This method does not allow agents to coordinate with each other and ignores the nonstationarity problem.

An approach combining centralised and decentralised processing is centralised training and decentralised execution (Kraemer and Banerjee 2016). The main idea is that agents can access extra information during training, such as other agents' observations, rewards, gradients and parameters. Agents then execute their policy based on local observations. Centralised training and decentralised execution mitigate nonstationarity and partial observability, as access to additional information during training stabilises agents' learning, even when other agents' policies are changing. Centralised training and decentralised execution methods can be divided into value-based and policy-based methods. Single-agent value-based methods focus on learning and derive the optimal policy via the learned value function. In MARL, cooperating agents have to optimise a team value function, and studies investigate the best way to decompose and optimise this value function. On the other hand, traditional policy-based methods search directly for the optimal policy. In a multiagent setting, nonstationarity makes learning more challenging as all agents update their policies simultaneously. Hence, most policy-based methods use the actor-critic architecture, in which a centralised critic is used to exchange extra information during training.

Value-based methods focus on how to decouple centrally learned value functions and use them for decentralised execution. Value-function factorisation is one of the most popular methods in this category (Sunehag et al. 2018; Rashid et al. 2020b; Son et al. 2019; Mahajan et al. 2019; Rashid et al. 2020a; Yang et al. 2020a). Value Decomposition Networks (VDN) (Sunehag et al. 2018) decompose the team value function into a sum of linear, individual value functions. The optimal policy arises by acting greedily with respect to the Q-value, an estimate of how good it is to take an action in a particular state during execution. QMIX (Rashid et al. 2020b) improves VDN's performance by treating the joint value function as a nonlinear combination of individual value functions and a monotonic constraint. However, this constraint limits the performance of collaborating agents that require significant coordination (Rashid et al. 2020a). QTRAN (Son et al. 2019) employs a different factorisation method that can escape the monotonicity and additivity constraints. However, it relies on regularisations to maintain tractable computations, which may impede performance in complex multiagent settings (Mahajan et al. 2019). Numerous algorithms build further upon QMIX. For instance, Weighted QMIX extends QMIX to nonmonotonic environments by placing more weight on joint actions with higher rewards (Rashid et al. 2020a). Multiagent Variational Exploration (MAVEN) (Mahajan et al. 2019) addresses the inefficient exploration problem in QMIX via committed exploration: coordinated exploratory actions over extended time steps in dealing with environments that require long-term coordination. MAVEN uses a hybrid value and policy-based method approach by conditioning value-based agents on the shared latent variable controlled by a hierarchical policy. Value-Decomposition Actor-Critic (VDAC) enforces the same monotonic relationship between the global state-value and the local state-values as QMIX. However, unlike QMIX, VDAC is compatible with A2C, which makes sampling more efficient. In addition, the study demonstrates that following a simple gradient calculated from a temporal-difference advantage, the policy can converge to a local optimal (Su et al. 2021). Q-DPP (Yang et al. 2020b) do not rely on constraints to decompose the global value function. Instead, it builds upon determinantal point processes: probabilistic models that capture both quality and diversity when a subset is sampled from a ground set, allowing for a natural factorisation of the global value function.

Policy-based methods mainly focus on the actor-critic architecture (see Sect. 2.3). These studies use a centralised critic to train decentralised actors. Counterfactual multiagent (COMA) (Foerster et al. 2018b) uses a centralised critic to approximate the Q-function and decentralised actors to optimise policies. The centralised critic has access to the joint action and all available state information, while each agent's policy only depends on its historical action-observation sequence. Along the same line, multiagent Deep Deterministic Policy Gradient (MADDPG) extends the Actor-Critic algorithm so that the critic has access to extra information during training and the actor only has access to local information (Lowe et al. 2017). As opposed to COMA, which uses one centralised critic for all agents, MADDPG has a centralised critic for each agent to have different reward functions in competitive environments. MADDPG can learn continuous policies, whereas COMA focuses on discrete policies. Several studies build upon MADDPG. For instance, R-MADDPG (Wang et al. 2019) extends the MADDPG algorithm to the partially observable environment by having both a recurrent actor and critic that keep a history of previous observations, and M3DDPG (Li et al. 2019) incorporates minimax optimisation to learn robust policies against agents with changing strategies. Since these methods concatenate all the observations in the critic, the input dimension increases exponentially with each agent. Hence, several studies have devised more efficient methods to deal with this problem. For instance, Mean-Field Actor-Critic (Yang et al. 2018) factorises the Q-function using only the interaction with the neighbouring agents based on mean-field theory (Stanley 1971), and the idea of dropout[2] can be extended to MADDPG to handle the large input space (Kim et al. 2019).

Centralised training and decentralised execution have been applied to solve complex strategy games such as StarCraft Micromanagement (Foerster et al. 2018b) and hide-and-seek (Baker et al. 2019).

4.3 Opponent modelling

Opponent modelling belongs to the class of model-based methods (Markovitch and Reger 2005) and refers to the construction of models of the beliefs, behaviours, and goals of other agents in the environment (Albrecht and Stone 2018). An agent can use these opponent models to guide decision-making. Opponent modelling algorithms generally take a sequence of interactions with the modelled opponent as input and predict action probabilities as output. After generating the opponent's model, an agent can derive its policy based on that model. This method helps an agent discover the competitor's intentions and weaknesses. Learning the model is generally considered more data-efficient than model-free approaches in which the policy is updated from direct observations (Markovitch and Reger 2005). Opponent modelling mitigates the nonstationarity and partially observability problem as agents collect historical observations to learn about the environment (i.e. opponents), allowing agents to track and switch between policies. This method is especially beneficial in the adversarial setting when the opponent has opposing interests, and other approaches, such as communication and centralised training that require the opponents'

[2] Randomly dropping units in the neural network to avoid overfitting (Srivastava et al. 2014).

information, are unlikely. For a comprehensive overview of opponent modelling, we refer to other work (Albrecht and Stone 2018).

Early opponent modelling methods assumed fixed play of opponents. Neural Fictitious Self-Play (NFSP) extends the idea of fictitious play (Brown 1951) with neural networks to approach a Nash equilibrium in imperfect information games such as Poker (Heinrich and Silver 2016). The main idea is to keep track of the opponents' historical behaviours and to choose a best-response to the opponents' average strategies.

While NFSP requires actual interaction with the opponent, other methods do not. For instance, counterfactual regret minimisation has achieved success in poker (Bowling et al. 2015). AlphaZero achieved remarkable results in Go, chess, and Shogi, using a neural network with self-play and Monte Carlo Tree Search (Silver et al. 2017). MuZero was able to achieve this without a given model. Instead of modelling the entire environment, it focused on the three core elements most relevant for planning: the value, policy and reward (Schrittwieser et al. 2020). Still, these studies assume that the opponent follows a stationary strategy.

Later approaches look at nonstationary environments in which an agent has to track, switch, and possibly predict behaviour. Several studies achieved superhuman performance using self-play in real-time strategy games characterised by long time horizons, nonstationary environments, partially-observed states, and high dimensional state and action spaces. OpenAI Five employs a similar method to fictitious play in playing Dota 2, a video game in which two teams compete to conquer each other's base, but the algorithm learns a distribution over opponents and uses the latest policy instead of the average policy (Berner et al. 2019). This infrastructure has also been used to solve hide-and-seek, but hide-and-seek agents can act independently as the training scheme is centralised training and decentralised execution (Baker et al. 2019). In Capture-the-Flag and StarCraft II, a population of agents is trained to introduce variation. Policies are made more robust by letting agents play with sampled opponents and teammates from this population in a league (Jaderberg et al. 2019; Vinyals et al. 2019).

Some studies assume that the opponent switches between a set of stationary policies over time (He et al. 2016; Everett and Roberts 2018; Zheng et al. 2018b). These algorithms derive the optimal policy based on the learned opponent's model and identify when the opponent changes the behaviour, and the agent has to relearn a new policy. Over time, the agent has a library of inferred opponent strategies and associated best-response policies. The two main challenges are designing a policy detection mechanism and learning a best-response policy. Some studies use a variant of Bayes' rule to learn opponent models and assign probabilities to the opponent's available actions. An agent starts with a prior belief that is continually updated during interaction to make it more accurate. Switching Agent Model (SAM) learns opponent models from observed state-action trajectories in combination with a Bayesian neural network (Everett and Roberts 2018). A Deep Deterministic Policy Gradient algorithm (Lillicrap et al. 2016) is used to learn the best-response. Distilled Policy Network-Bayesian Policy Reuse+ (DPN-BPR+) (Zheng et al. 2018b) extends the Bayesian Policy Reuse+ algorithm (BPR+) (Hernandez-Leal et al. 2016) with a neural network to detect the opponent's policy via both its behaviour and the reward signal. The latter uses policy distillation (Rusu et al. 2016) to learn and reuse policies efficiently. Others use a form of deep Q-learning (Mnih et al. 2013). Deep Reinforcement Opponent Network (DRON) (He et al. 2016) uses one network to learn the Q-values to derive an optimal policy and a second network to learn the opponent policy representation, in addition to expert networks that capture different types of opponent strategies. A drawback of DRON is that it relies on handcrafted opponent features. Previous methods assume that the opponent remains stationary within an episode. Deep Policy Inference Q-Network (DPIQN) and Deep Recurrent Policy Inference Q-Network (DRPIQN) (Hong et al. 2018) incorporate policy features as a hidden vector into the deep Q-network to adapt itself to unfamiliar opponents. DRPIQN uses a Long Short Term Memory (LSTM) layer so agents can learn in partially observable environments. This LSTM layer utilises a recurrent neural network architecture that can take observations as input and allow agents to model time dependencies and capture the underlying state (Hausknecht and Stone 2015).

Previous approaches do not consider an intellectual and reasoning opponent. According to the theory of mind, people attribute mental states to others, such as beliefs, intents and emotions (Premack and Woodruff 1978). These models help to analyse and infer others' behaviours and are essential in social interaction (Frith and Frith 2005). Learning with Opponent-Learning Awareness (LOLA) (Foerster et al. 2018a) anticipates and shapes opponents' behaviour. Specifically, it includes a term that considers the impact of an agent's policy on the learning behaviour of opponents. One drawback is that LOLA assumes access to the opponent's parameters, which is unlikely in an adversarial setting. Others focus on recursive reasoning by learning models over the belief states of other players, a nesting of beliefs that can be represented in the form: "I believe that you believe that I believe" (Wen et al. 2019; Tian et al. 2021). The Probabilistic Recursive Reasoning (PR2) framework (Wen et al. 2019) first reflects on the opponent's perspective: what the opponents would do given that the opponents know the agent's current state and action. Given the potential actions of the opponent, the agent selects a best-response. The recursive reasoning process can be viewed as a hierarchical process with k-levels of reasoning. At level $k = 0$, agents take random actions (Dai et al. 2020) or act based on historical interactions, the main assumption in traditional opponent modelling methods (Wen et al. 2019). At $k = 1$, an agent selects its best-response to the agents acting at lower levels. Studies show that it pays off to reason about an opponent's intelligence levels (Tian et al. 2021) and that reasoning at a higher level is beneficial as it leads to faster convergence (Dai et al. 2020) and better performance (Moreno et al. 2021).

4.4 Communication

Through communication, agents can pass information to reduce the complexity of finding good policies. For instance, agents exploring different parts of the environment can share observations to mitigate partial observability and share their intents to anticipate each others' actions to deal with nonstationarity. Communication can also be used for transfer learning so that more experienced agents can share their knowledge to accelerate the learning of inexperienced agents (Taylor and Stone 2009). One of the fundamental questions in communication is how language emerges between agents with no predefined communication protocol (Lazaridou et al. 2017) and, subsequently, how meaning and syntax evolve through interaction (Jaques et al. 2019). Learning this process will help researchers better understand human language evolution and contribute to more efficient problem-solving in a team of interacting agents (Lazaridou and Baroni 2020).

Several studies investigate how agents learn a successful communication protocol. A communication protocol should inform agents about which concepts to communicate and how to translate these concepts into messages (Hausknecht and Stone 2016). Many studies approach this problem as a referential game (Lazaridou et al. 2017; Havrylov and Titov 2017). A referential game involves two or more agents in which speakers and listeners must develop a communication protocol to refer to an object (Fig. 6). In the basic version

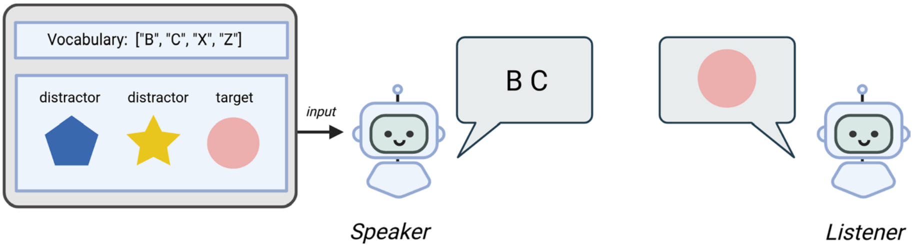


Fig. 6 Basic referential game. In this basic referential game example, two agents have to develop a communication protocol so that the speaker can translate the target into a message and the listener can understand which one is the target. The game works as follows. The speaker receives as input three images. One is the target, and the other two are distractions. The speaker has to use the symbols in the vocabulary, which consists of the symbols “B”, “C”, “X” and “Z”, to send a message to the listener. The listener sees the messages and has to guess the target message. If the target is correct, both agents receive a reward

of this game with two agents, the speaker sends two images and a message from a fixed vocabulary to the receiver. One of the images is the target, which the listener has to identify based on the message. Both agents receive a reward when the classification is correct (Lazaridou et al. 2017). To succeed in this game, agents must understand the image content and express the content through a common language. The language can be discrete, where messages are a single symbol (Lazaridou et al. 2017) or a sequence of symbols (Havrylov and Titov 2017), or continuous, where messages are continuous vectors (Sukhbaatar et al. 2016).

Using DRL, end-to-end policies can be learned in which agents receive image pixels as input and a corresponding message as output. For example, two agents represented as simple feed-forward networks can learn a communication protocol to solve the basic referential game (Lazaridou et al. 2017). Language also emerges in more complicated versions of the game that require dialogue (Jorge et al. 2017; Das et al. 2017; Kottur et al. 2017) or negotiation (Cao et al. 2018) between agents. Agents trained with deep recurrent Q-networks (DRQN) (Jorge et al. 2017) and REINFORCE (Das et al. 2017; Kottur et al. 2017) are able to learn a communication protocol from scratch. Since communication is not always meaningful, it is important to develop metrics for emergent communication. An example is when an agent sends a message that has no actual impact on the environment. Agents with the capacity to communicate should exhibit positive signalling and positive listening (Lowe et al. 2019). Positive signalling means that messages correlate with observations or actions, and positive listening refers to updating beliefs or behaviour after receiving a message. Most studies focus solely on positive signalling metrics. However, positive signalling may occur without positive listening (Lowe et al. 2019), which indicates that there was no actual communication.

In contrast to earlier works that consider communication as the primary learning goal, other works consider communication an instrument for learning a specific task. Most of these studies focus on coordination in collaborative environments and show that communication improves overall performance. Differentiable Interagent Learning (DIAL) (Foerster et al. 2016) uses centralised training and decentralised execution. Communication is continuous during training and discrete during the execution of the task. Continuous communication during training is particularly effective as it enables the exchange of gradients between agents, which improves performance. CommNet shows that the exchange of discrete symbols is less efficient than continuous communication, as the latter enables the use of backpropagation to train agents efficiently (Sukhbaatar et al. 2016). While DIAL and CommNet base their approach on DQRN, later studies propose the Actor-Critic architecture, including Actor-Coordinator-Critic Net (ACCNet) (Mao et al. 2017), Bidirectionally Coordinated Network (BiCNet) (Peng et al. 2017) and MADDPG (Lowe et al. 2017). This architecture can solve more complex problems than previous approaches and works for continuous actions. In addition, when critics are individually learned (Jiang and Lu 2018) instead of centrally computed (Iqbal and Sha 2019), agents have different reward functions, which is suitable for competitive settings.

Communication also allows peer-to-peer teaching. More experienced agents communicate their knowledge to learning agents, accelerating the learning of a new task (Da Silva et al. 2017; Omidshafiei et al. 2019; Ilhan et al. 2019; Amir et al. 2016). However, having agents send messages to all agents is costly and inefficient. Thus, an important question is how to filter the most important messages and to whom to send them. One approach is to limit communication bandwidth (Foerster et al. 2016; Kim et al. 2020) or use a communication budget (Ilhan et al. 2019; Omidshafiei et al. 2019). Others use metrics to identify relevant messages, such as attention mechanisms. In its simplest form, this is a vector of importance weights (Peng et al. 2018; Gu et al. 2021; Mao et al. 2020). An alternative is to keep confidence scores about states (Da Silva et al. 2017). However, communication comes at a cost and increased complexity. Negative transfer can also happen, for example, when the message contains inaccurate or noisy information so that performance may become worse (Taylor and Stone 2009). Therefore, it is essential to trade off benefits and costs or find a better way to filter valuable information.

4.5 Efficient coordination

Another group of studies investigate agents' emergent behaviours and look at how cooperating agents can coordinate actions most efficiently. These studies are conducted in mixed environments with elements of both cooperation and competition.

A key question is how to design reward functions so that agents adapt to each others' actions, avoid conflicting behaviour and achieve efficient coordination. By engineering the reward function, competitive or cooperative behaviours can be stimulated (Tampuu et al. 2017). While early studies look at how agents can maximise external rewards, recent works assume that agents are intrinsically motivated.

Most studies look at multiagent behaviour in social dilemmas (Eccles et al. 2019; Lerer and Peysakhovich 2018; Leibo et al. 2017; McKee et al. 2020; Jaques et al. 2019; Peysakhovich and Lerer 2018). Earlier studies, mainly influenced by game theory, have looked at social dilemmas as a matrix game in which agents choose pure cooperation or pure defect. Recent studies generalise these social dilemmas to temporally and spatially extended Markov games, also known as a sequential social dilemma (Leibo et al. 2017). This setting is more realistic as people can adapt and change their strategies. One notable example is the repeated prisoner's dilemma. In each turn, each agent decides whether to cooperate or defect. When both agents cooperate, both agents get good rewards. Contrary, defection improves one agent's reward at the expense of the other agent. Thus, an agent can decide to retaliate or trust the opponent, dependent on the actions in the previous round.

One of the first sequential social dilemma studies examined how policies change due to environmental factors or agent properties (Leibo et al. 2017). They found that agents learn more aggressive policies when resources are limited. In addition, manipulating the discount rate over the rewards, batch size, and the number of hidden units in the network affected emerging social behaviour. While this study took a descriptive approach to understand how behaviours change to different rules and conditions, others took a prescriptive approach in which agents learn to cooperate without being exploited (Lerer and Peysakhovich 2018; Wang et al. 2018). The general approach comprises two steps: first, detect the level of cooperation of the opponent, and then mimic or reciprocate with a slightly higher-level cooperation policy to induce cooperation without getting exploited. This approach is based on the Tit-for-Tat principle (Axelrod and Hamilton 1981): the strategy suggests cooperation in the first round and copies the opponent's behaviour afterwards.

Previous approaches assume that the only incentive for cooperation is the external reward. However, there is a rapidly growing literature where cooperation occurs from social behaviour and intrinsic motivation (McKee et al. 2020; Jaques et al. 2019; Peysakhovich and Lerer 2018; Hughes et al. 2018).

Psychology research has shown that people do not always seek to maximise utility (Dovidio 1984). In addition, an intrinsic reward may be a good alternative in sparse environments. Several attempts have been made to design these internal rewards. For instance, inequity aversion, which refers to the preference for fairness and resistance against inequitable outcomes (Fehr and Schmidt 1999), has improved coordination in social dilemmas (Hughes et al. 2018). The main idea is to punish agents that deviate too much from the average behaviour. Underperforming and overperforming agents are both undesirable, as the first may exhibit free-riding behaviour while the latter may be operating a defective policy. Another approach is to make agents care about the rewards of teammates (Peysakhovich and Lerer 2018; Jaques et al. 2019).

Pro-social behaviour improves the convergence probabilities of policy gradient-based agents, even if only one of the two players displays social behaviour (Peysakhovich and Lerer 2018). In addition, rewarding actions that lead to a relatively more significant change in the other agent's behaviour may lead to increased cooperation (Jaques et al. 2019). Another study introduces heterogeneity in intrinsic motivation (McKee et al. 2020). Specifically, the study compares a team of homogeneous agents, who share the same degree of social value orientation, to a heterogeneous group of agents with different degrees of social value orientation. The results show that homogeneous altruistic agents earn relatively high rewards, yet it appears that they adopt a lazy agent approach and produce highly specialised agents. This problem is not evident in heterogeneous groups. Hence, it shows that the widely adopted joint return approach may be undesirable as it masks high levels of inequality amongst agents.

While studies show that shaping reward functions can lead to better coordination (Devlin et al. 2011; Holmesparker et al. 2016; Peysakhovich and Lerer 2018; Tampuu et al. 2017; Jaques et al. 2019; Liu et al. 2019), it is very challenging to tune the trade-off between the intrinsic and external reward, and whether it gives rise to cooperative behaviour may depend on the actual task and environment.

4.6 Reward shaping

The credit assignment problem refers to the situation when individual agents cannot view their contribution to the joint team reward due to a partially observable environment. Researchers have introduced implicit and explicit reward shaping methods to deal with this problem. Table 2 gives an overview of the reviewed reward shaping methods.

The general solution to this problem is reward shaping, with difference rewards and potential-based reward shaping as the two main classes. Difference rewards consider

Table 2 Overview of solutions to the credit assignment problem

Study	Implicit/ explicit	Approach	Algorithm
Foerster et al. (2018a)	Explicit	Difference rewards	COMA: uses a counterfactual baseline to marginalise out the action of an agent
Yu et al. (2019)	Explicit	Potential-based rewards	MA-AIRL: extends maximum entropy inverse reinforcement learning to Markov games. A potential-based function is used to deal with reward shaping ambiguity
Devlin et al. (2014)	Explicit	Difference rewards and potential-based rewards	DriP: uses potential based reward shaping to improve difference rewards
Sunehag et al. (2018)	Implicit	Value-based: deep Q-learning	VDN: decomposes the team value function into a sum of linear, individual value functions
Zhou et al. (2020)	Implicit	Policy-based: actor-critic	LICA: a centralized critic maps current state information into a set of weights, and in turn, mixes individual action vectors into the joint action value estimate

both the individual and the global reward (Foerster et al. 2018b; Proper and Tumer 2012; Nguyen et al. 2018; Castellini et al. 2021) and help an agent understand its impact on the environment by removing the noise created by other acting agents. Specifically, it is defined as $D_i(z) = G(z) - G(z - z_i)$ where D_i is the difference reward of agent i, $G(z)$ is the global reward considering the joint state-action z, and $G(z - z_i)$ is a modified version of the state-action vector z in which agent i takes a default action, or more intuitively, the global reward without the contribution of agent i (Yliniemi and Tumer 2014). COMA (Foerster et al. 2018b) takes inspiration from difference rewards. The centralised critic uses a counterfactual baseline to reason about counterfactuals or alternatives to the state when only that agent's actions change. To marginalise out the action of an agent, an expected value is calculated over all the actions of an agent while keeping other agents' actions constant. Potential-based reward shaping has also received attention lately (Suay et al. 2016; Devlin et al. 2014). Formally, it is defined as $F(s, s') = \gamma\Phi(s') - \Phi(s)$ (Ng et al. 1999) where $\Phi(s)$ is a potential function which returns the potential for state s and γ is the discount factor. It is a method to incorporate additional information into the reward function to accelerate learning. This approach has been proven not to alter the set of Nash equilibria in a Markov game (Devlin and Kudenko 2011), even when the potential function changes dynamically during learning (Devlin and Kudenko 2012), and combining the two approaches allows agents to converge significantly faster than using difference rewards alone (Devlin et al. 2014). However, these reward shaping methods require manual tuning for each environment, which is inefficient. Some studies have therefore started looking into the automatic generation of reward shaping, for example, through abstractions derived from an agent's experience (Burden 2020) or via meta-learning on a distribution of tasks (Zou et al. 2021).

Previous approaches evaluate an agent's action against a baseline to extract its individual effect and belong to the class of explicit credit assignment. In contrast, implicit methods do not work with baselines. Value-based methods decompose the global value function into individual state-action values, also known as value mixing methods, such as VDN

(Sunehag et al. 2018), QMIX (Rashid et al. 2020b) and QTRAN (Son et al. 2019) to filter out agent's individual contribution. However, these methods may not handle continuous action spaces effectively. Policy-based algorithms include Learning Implicit Credit Assignment (LICA) (Zhou et al. 2020) and Decomposed multiagent Deep Deterministic Policy Gradient (DE-MADDPG) (Sheikh and Bölöni 2020). LICA extends the idea of value mixing to policy-based methods. Under the centralised training and decentralised execution framework, a centralised critic is represented by a hypernetwork that maps state information into a set of weights that mixes individual action values into the joint action value. DE-MADDPG extends previous deterministic policy gradient methods using a dual-critic framework. The global critic takes as input all agents' observations and actions and estimates the global reward. The local critic receives as input only the local observation and action of an agent and estimates the local reward. This framework achieves better and more stable performance than earlier deterministic policy gradient methods.

5 Discussion

We have surveyed a range of studies in DMARL. While integrating deep neural networks in RL has dramatically improved agents' learning in more complex and larger environments, we wish to highlight current limitations and open challenges in the field.

- In the development from single-agent reinforcement learning to multiagent reinforcement learning, most earlier studies used a game-theoretic lens to study interactive decision-making, assuming perfectly rational agents who maximise their behaviour through a deliberate optimisation process. However, while game theory's strength lies in its generalizability and mathematical precision, experiments have shown that it is often a poor representation of actual human behaviour (Colman 2003). Researchers must consider irrational and altruistic decision-making, especially if we wish to extend artificial intelligence (AI) to more realistic environments or design applications for human-AI interaction in larger and more complex problems. We have seen that pro-social agents can achieve better group outcomes (Peysakhovich and Lerer 2018; Hughes et al. 2018). However, studies are still limited, and we encourage fellow researchers to deepen our understanding in this field.
- We also want to bring attention to the design and assumptions in current research. Many studies assume homogeneous agents; from a practical viewpoint, this may accelerate learning since agents can share policies and parameters. Agents thus only need to learn one policy and may better anticipate the behaviour of other agents. However, whether this also leads to better performance in the final task is an open question. For instance, a soccer team usually consists of forwards, midfielders, defenders and a goalkeeper. The team's success is partly determined by how well each fulfils these different roles. Thus, an interesting question is whether letting each agent learn its own policy and have heterogeneous teams pays off. While homogeneous agents can still act differently due to different observations input, the observation space must be the same size. This assumption does not always hold. For instance, agents have different observation spaces in soccer as individuals occupy different positions on the field. Preliminary results show that despite making the learning slower at the beginning, heterogeneous teams perform better at the final task (Kurek and Jaśkowski 2016). Another study provides formal proof

for parameter sharing between heterogeneous agents (Terry et al. 2021), which may mitigate the slow start problem.

- Studies may also rely on unrealistic assumptions. For instance, multiple studies require access to opponents' information, such as trajectories or parameters, while their problem domain actually gives an incentive to hide information. Others assume fixed behaviours of agents or that agents can view the global state.
- Another issue is the generalizability of studies. For example, many studies require handcrafted features or rewards specific to the environment. In addition, a majority of the studies are evaluated in two-player games. As a result, a danger exists that the agent's policy overfits to the behaviour of the second agent (i.e. the lazy agent problem) and does not generalise to other settings. Future research should integrate more realistic assumptions and work on the generalizability of studies to settings with more players or different environments.

While DMARL has seen a significant improvement in the types and complexities of challenges it can address, several hurdles remain. For example, problems associated with large search spaces, partially observable environments, nonstationarity, sparse rewards and the exploration-exploitation trade-off remain challenging. These issues are partly due to computational constraints, such that assumptions are often relaxed. We want to point out two other research areas, namely evolutionary algorithms and psychology, that may help researchers address some of the open questions.

5.1 Evolutionary algorithms

Evolutionary algorithms (EAs) are inspired by nature's creativity and simulate the process of organic evolution to solve optimisation problems. In simple terms, a randomly initialised population of individual solutions evolves toward better regions of the search space via selection, mutation and recombination operators. A fitness function evaluates the quality of the individuals and favours the reproduction of those with a higher fitness score, while mutation maintains diversity in the population (Bäck and Schwefel 1993). An early study sheds light on how EAs deal with RL problems (Moriarty et al. 1999) and has been confirmed by recent studies (Bloembergen et al. 2015; Drugan 2019; Arulkumaran et al. 2019; Lehman et al. 2018a, b, c; Such et al. 2018; Zhang et al. 2017). EAs offer a novel perspective to scaling RL multiagent systems as it is highly parallelisable, and there is no need for backpropagation (Such et al. 2018; Majumdar et al. 2020).

EAs have been compared with popular value-based and policy-gradient algorithms such as DQN and A3C (Such et al. 2018). Novelty search (Such et al. 2018; Lehman et al. 2018c) is a promising area (Lehman and Stanley 2008) since it encourages exploration on tasks with sparse rewards and deceptive local optima—problems that remain an issue with conventional reward-maximising methods. EAs have been shown to work well with nonstationarity and partial observability, as it continually uses and evolves a population of agents instead of a single agent (Moriarty et al. 1999; Liu et al. 2020). EAs can evolve agents with different policies (Gomes et al. 2017, 2014; Nitschke et al. 2012), such that heterogeneity can be introduced in team-based learning. Population-based training has proven powerful in achieving superhuman behaviour in Capture the Flag (Jaderberg et al. 2019), and StarCraft (Vinyals et al. 2019).

5.2 Psychology

Many key ideas in RL, such as operant conditioning and trial-and-error, originated in psychology and cognitive science research (Sutton et al. 1998). Interestingly, recent DMARL studies started moving towards more human-like agents, showing that characteristics like reciprocity and intrinsic motivation pay off.

We believe psychology may provide more valuable insights into current problems in DMARL. For instance, bounded rationality models (Simon 1990, 1957) describe how individuals make decisions under a finite amount of knowledge, time and attention. To deal with bounded rationality, people use heuristics, or mental shortcuts, to solve problems quickly and efficiently (Gigerenzer and Goldstein 1996). While RL research already uses heuristics to deal with large and complex problems (Cheng et al. 2021; Ma et al. 2021), selecting suitable heuristics is still insufficiently explored. Psychology has a long tradition of investigating heuristics and may offer new perspectives. In addition, heuristics aid in filtering relevant information in a complex world, which may benefit agents in partially observable environments or counter negative knowledge transfer (Marewski et al. 2010). However, intuitive judgement can also lead to biases and suboptimal decision-making (Gilovich et al. 2002).

Humans are also capable of creative problem-solving, a prerequisite for innovation. Likewise, agents need to explore the environment to find more optimal solutions. A first approach of combining creativity with RL shows that creativity offers the potential to explore promising solution spaces, whereas traditional methods fail (Colin et al. 2016).

Lastly, psychology can play an essential role in helping researchers understand how agents make decisions and tackle the black-box problem of deep neural networks. Cognitive psychologists have developed robust models of human behaviour, such as decision-making, attention and language, without observing these processes directly but through controlled behavioural experiments in which cognitive functions can be isolated (Taylor and Taylor 2021). Open-source platforms are now also available (Leibo et al. 2018) that allow researchers to use methods from cognitive psychology to study the behaviours of artificial agents in a controlled environment. We encourage researchers to draw from psychology research and its methodologies to analyse agents' complex interactions and better understand and improve their decision-making.

6 Conclusion

The current survey has presented an overview of the challenges inherent in multiagent representations. We have identified five different research areas in DMARL that aim to mitigate one or multiple of these challenges: (1) centralised training and decentralised execution, (2) opponent modelling, (3) communication, (4) efficient coordination, and (5) reward shaping. While early studies drew inspiration from game theory and were evaluated on grid-based games, the field is moving towards more sophisticated and realistic representations. Nevertheless, dealing with large problem spaces and sparse rewards in nonstationary and partially observable settings remains an open issue.

Existing research has approached this problem mainly from traditional, computational, RL perspectives. While combining deep learning with value-based and policy-based methods has been shown to mitigate the problem, they seem to be only part of the answer. We encourage researchers to take an interdisciplinary perspective on developing new solutions and benefit from the knowledge of other research domains. Specifically, evolutionary algorithms offer insights into dealing with larger, nonstationary and partially observable environments. At the same time, sociology and psychology increase our understanding of agents' reasoning patterns and offer us alternatives for dealing with sparse rewards, such as intrinsic motivation. Finally, we believe that integrating multiple research disciplines leads to more realistic scenarios humans encounter in practice, so the findings may eventually be fruitful in real-world applications.

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References

Albrecht SV, Stone P (2018) Autonomous agents modelling other agents: a comprehensive survey and open problems. Artif Intell 258:66–95

Amato C, Oliehoek F (2015) Scalable planning and learning for multiagent pomdps. Proc AAAI Conf Artif Intell 29:1995–2002

Amir O, Kamar E, Kolobov A, Grosz B (2016) Interactive teaching strategies for agent training. In: Proceedings of the twenty-fifth international joint conference on artificial intelligence 2016. https://www.microsoft.com/en-us/research/publication/interactive-teaching-strategies-agent-training/

Arulkumaran K, Deisenroth MP, Brundage M, Bharath AA (2017) Deep reinforcement learning: a brief survey. IEEE Signal Process Mag 34(6):26–38

Arulkumaran K, Cully A, Togelius J (2019) Alphastar: an evolutionary computation perspective. In: Proceedings of the genetic and evolutionary computation conference companion, pp 314–315

Åström KJ (1965) Optimal control of markov decision processes with incomplete state estimation. J Math Anal Appl 10:174–205

Axelrod R, Hamilton WD (1981) The evolution of cooperation. Science 211(4489):1390–1396

Bäck T, Schwefel HP (1993) An overview of evolutionary algorithms for parameter optimization. Evol Comput 1(1):1–23

Bahdanau D, Brakel P, Xu K, Goyal A, Lowe R, Pineau J, Courville A, Bengio Y (2017) An actor-critic algorithm for sequence prediction. In: International conference on learning representations. https://openreview.net/forum?id=SJDaqqveg

Baker B, Kanitscheider I, Markov T, Wu Y, Powell G, McGrew B, Mordatch I (2019) Emergent tool use from multi-agent autocurricula. In: Eigth international conference on learning representations (ICLR)

Bao W, Liu Xy (2019) Multi-agent deep reinforcement learning for liquidation strategy analysis. arXiv preprint. arXiv:1906.11046

Bellman R (1957) A markovian decision process. J Math Mech 6(5):679–684

Berner C, Brockman G, Chan B, Cheung V, Debiak P, Dennison C, Farhi D, Fischer Q, Hashme S, Hesse C, Józefowicz R, Gray S, Olsson C, Pachocki JW, Petrov M, de Oliveira Pinto HP, Raiman J, Salimans T, Schlatter J, Schneider J, Sidor S, Sutskever I, Tang J, Wolski F, Zhang S (2019) Dota 2 with large scale deep reinforcement learning. arXiv preprint. arXiv:1912.06680

Bernstein DS, Givan R, Immerman N, Zilberstein S (2002) The complexity of decentralized control of Markov decision processes. Math Oper Res 27(4):819–840

Bloembergen D, Tuyls K, Hennes D, Kaisers M (2015) Evolutionary dynamics of multi-agent learning: a survey. J Artif Intell Res 53:659–697

Bowling M, Veloso M (2001) Rational and convergent learning in stochastic games. In: International joint conference on artificial intelligence, Citeseer, vol 17, pp 1021–1026

Bowling M, Veloso M (2002) Multiagent learning using a variable learning rate. Artif Intell 136(2):215–250

Bowling M, Burch N, Johanson M, Tammelin O (2015) Heads-up limit hold'em poker is solved. Science 347(6218):145–149

Brown GW (1951) Iterative solution of games by fictitious play. Activity Anal Prod Allocation 13(1):374–376

Brown N, Sandholm T (2018) Superhuman ai for heads-up no-limit poker: Libratus beats top professionals. Science 359(6374):418–424

Brown N, Sandholm T (2019) Superhuman ai for multiplayer poker. Science 365(6456):885–890

Burden J (2020) Automating abstraction for potential-based reward shaping. PhD thesis, University of York

Busoniu L, Babuska R, De Schutter B (2008) A comprehensive survey of multiagent reinforcement learning. IEEE Trans Syst Man Cybern Part C (Appl Rev) 38(2):156–172

Canese L, Cardarilli GC, Di Nunzio L, Fazzolari R, Giardino D, Re M, Spanò S (2021) Multi-agent reinforcement learning: a review of challenges and applications. Appl Sci 11(11):4948

Cao K, Lazaridou A, Lanctot M, Leibo JZ, Tuyls K, Clark S (2018) Emergent communication through negotiation. In: International conference on learning representations (ICLR) (Poster), https://openreview.net/forum?id=Hk6WhagRW

Castellini J, Devlin S, Oliehoek FA, Savani R (2021) Difference rewards policy gradients. In: Proceedings of the 20th international conference on autonomous agents and multiagent systems, international foundation for autonomous agents and multi agent systems, AAMAS '21, Richland, SC, pp 1475–1477

Cheng CA, Kolobov A, Swaminathan A (2021) Heuristic-guided reinforcement learning. Adv Neural Inf Process Syst 34:13550–13563

Chu T, Wang J, Codecá L, Li Z (2020) Multi-agent deep reinforcement learning for large-scale traffic signal control. IEEE Trans Intell Transp Syst 21(3):1086–1095

Chua K, Calandra R, McAllister R, Levine S (2018) Deep reinforcement learning in a handful of trials using probabilistic dynamics models. In: Bengio S, Wallach H, Larochelle H, Grauman K, Cesa-Bianchi N, Garnett R (eds) Advances in neural information processing systems, vol 31. Curran Associates, Red Hook, pp 4759–4770

Colin TR, Belpaeme T, Cangelosi A, Hemion N (2016) Hierarchical reinforcement learning as creative problem solving. Robot Autonom Syst 86:196–206

Colman AM (2003) Cooperation, psychological game theory, and limitations of rationality in social interaction. Behav Brain Sci 26:139–198

Da Silva FL, Costa AHR (2019) A survey on transfer learning for multiagent reinforcement learning systems. J Artif Intell Res 64:645–703

Da Silva FL, Glatt R, Costa AHR (2017) Simultaneously learning and advising in multiagent reinforcement learning. In: Proceedings of the 16th international conference on autonomous agents and multiagent systems (AAMAS 2017), pp 1100–1108

Dai Z, Chen Y, Low BKH, Jaillet P, Ho TH (2020) R2-B2: recursive reasoning-based bayesian optimization for no-regret learning in games. In: Proceedings of the 37th international conference on machine learning, PMLR, pp 2291–2301

Dankwa S, Zheng W (2019) Twin delayed DDPG: a deep reinforcement learning technique to model a continuous movement of an intelligent robot agent. In: Proceedings of the 3rd international conference on vision, image and signal processing, pp 1–5

Das A, Kottur S, Moura JM, Lee S, Batra D (2017) Learning cooperative visual dialog agents with deep reinforcement learning. In: Proceedings of the IEEE international conference on computer vision, pp 2951–2960

Devlin S, Kudenko D (2011) Theoretical considerations of potential-based reward shaping for multi-agent systems. In: The 10th International conference on autonomous agents and multiagent systems. ACM, New York, pp 225–232

Devlin S, Kudenko D, Grześ M (2011) An empirical study of potential-based reward shaping and advice in complex, multi-agent systems. Adv Complex Syst 14(02):251–278

Devlin S, Yliniemi L, Kudenko D, Tumer K (2014) Potential-based difference rewards for multiagent reinforcement learning. In: Proceedings of the 2014 international conference on autonomous agents and multi-agent systems, pp 165–172

Devlin SM, Kudenko D (2012) Dynamic potential-based reward shaping. In: Proceedings of the 11th international conference on autonomous agents and multiagent systems, IFAAMAS, pp 433–440

Diallo EAO, Sugiyama A, Sugawara T (2017) Learning to coordinate with deep reinforcement learning in doubles pong game. In: 2017 16th IEEE international conference on machine learning and applications (ICMLA). IEEE, Piscataway, pp 14–19

Ding Z, Dong H (2020) Challenges of reinforcement learning. Springer, Singapore

Dovidio JF (1984) Helping behavior and altruism: an empirical and conceptual overview. Adv Exp Soc Psychol 17:361–427

Drugan MM (2019) Reinforcement learning versus evolutionary computation: a survey on hybrid algorithms. Swarm Evol Comput 44:228–246

Du W, Ding S (2021) A survey on multi-agent deep reinforcement learning: from the perspective of challenges and applications. Artif Intell Rev 54(5):3215–3238

Du Y, Han L, Fang M, Liu J, Dai T, Tao D (2019) Liir: Learning individual intrinsic reward in multi-agent reinforcement learning. Adv Neural Inf Process Syst 32:4403–4414

Eccles T, Hughes E, Kramár J, Wheelwright S, Leibo JZ (2019) Learning reciprocity in complex sequential social dilemmas. arXiv preprint. arXiv:1903.08082

Everett R, Roberts S (2018) Learning against non-stationary agents with opponent modelling and deep reinforcement learning. In: 2018 Association for the advancement of artificial intelligence spring symposium series

Fehr E, Schmidt KM (1999) A theory of fairness, competition, and cooperation. Q J Econ 114(3):817–868

Feriani A, Hossain E (2021) Single and multi-agent deep reinforcement learning for AI-enabled wireless networks: a tutorial. IEEE Commun Survey Tutor 23(2):1226–1252

Foerster J, Assael IA, De Freitas N, Whiteson S (2016) Learning to communicate with deep multi-agent reinforcement learning. Adv Neural Inf Process Syst 29:2137–2145

Foerster J, Chen RY, Al-Shedivat M, Whiteson S, Abbeel P, Mordatch I (2018a) Learning with opponent-learning awareness. In: Proceedings of the 17th international conference on autonomous agents and multiagent systems, AAMAS '18, pp 122–130

Foerster J, Farquhar G, Afouras T, Nardelli N, Whiteson S (2018b) Counterfactual multi-agent policy gradients. In: Proceedings of the AAAI conference on artificial intelligence, vol 32

Frith C, Frith U (2005) Theory of mind. Curr Biol 15(17):644–645

Gigerenzer G, Goldstein DG (1996) Reasoning the fast and frugal way: models of bounded rationality. Psychol Rev 103(4):650

Gilovich T, Griffin D, Kahneman D (2002) Heuristics and biases: the psychology of intuitive judgment. Cambridge University Press, Cambridge

Gomes J, Mariano P, Christensen AL (2014) Avoiding convergence in cooperative coevolution with novelty search. In: Proceedings of the 2014 international conference on autonomous agents and multi-agent systems, pp 1149–1156

Gomes J, Mariano P, Christensen AL (2017) Dynamic team heterogeneity in cooperative coevolutionary algorithms. IEEE Trans Evol Comput 22(6):934–948

Graesser L, Keng WL (2019) Foundations of deep reinforcement learning: theory and practice in Python. Addison-Wesley Professional, Boston

Greensmith E, Bartlett PL, Baxter J (2004) Variance reduction techniques for gradient estimates in reinforcement learning. J Mach Learn Res 5(9):1471–1530

Gronauer S, Diepold K (2021) Multi-agent deep reinforcement learning: a survey. Artif Intell Rev 55(6):1–49

Grondman I, Busoniu L, Lopes GA, Babuska R (2012) A survey of actor-critic reinforcement learning: Standard and natural policy gradients. IEEE Trans Syst Man Cybern Part C (Appl Rev 42(6):1291–1307

Gu S, Geng M, Lan L (2021) Attention-based fault-tolerant approach for multi-agent reinforcement learning systems. Entropy 23(9):1133

Gupta JK, Egorov M, Kochenderfer M (2017) Cooperative multi-agent control using deep reinforcement learning. In: International conference on autonomous agents and multiagent systems. Springer, Cham, pp 66–83

Haarnoja T, Zhou A, Hartikainen K, Tucker G, Ha S, Tan J, Kumar V, Zhu H, Gupta A, Abbeel P et al (2018) Soft actor-critic algorithms and applications. arXiv preprint. arXiv:1812.05905

Hamrick JB, Friesen AL, Behbahani F, Guez A, Viola F, Witherspoon S, Anthony T, Buesing LH, Veličković P, Weber T (2021) On the role of planning in model-based deep reinforcement learning.

In: International conference on learning representations. https://openreview.net/forum?id=IrM64DGB21

Hansen EA, Bernstein DS, Zilberstein S (2004) Dynamic programming for partially observable stochastic games. Am Assoc Artif Intell 4:709–715

Hausknecht M, Stone P (2015) Deep recurrent q-learning for partially observable mdps. In: 2015 AAAAI fall symposium series

Hausknecht M, Stone P (2016) Grounded semantic networks for learning shared communication protocols. In: International conference on machine learning (workshop)

Havrylov S, Titov I (2017) Emergence of language with multi-agent games: learning to communicate with sequences of symbols. In: Advances in neural information processing systems (NIPS 2017) proceedings, vol 30

He H, Boyd-Graber J, Kwok K, Daumé III H (2016) Opponent modeling in deep reinforcement learning. In: International Conference on Machine Learning, Proceedings of Machine Learning Research, pp 1804–1813

Heinrich J, Silver D (2016) Deep reinforcement learning from self-play in imperfect-information games. arXiv preprint. arXiv:1603.01121

Heinrich J, Lanctot M, Silver D (2015) Fictitious self-play in extensive-form games. In: International conference on machine learning, PMLR, pp 805–813

Hernandez-Leal P, Rosman B, Taylor ME, Sucar LE, Munoz de Cote E (2016) A Bayesian approach for learning and tracking switching, non-stationary opponents. In: Proceedings of the 2016 international conference on autonomous agents & multiagent systems, pp 1315–1316

Hernandez-Leal P, Kartal B, Taylor ME (2019) A survey and critique of multiagent deep reinforcement learning. Autonom Agents Multi-Agent Syst 33(6):750–797

Holmesparker C, Agogino AK, Tumer K (2016) Combining reward shaping and hierarchies for scaling to large multiagent systems. Knowl Eng Rev 31(1):3–18

Hong ZW, Su SY, Shann TY, Chang YH, Lee CY (2018) A deep policy inference Q-network for multi-agent systems. In: Proceedings of the 17th international conference on autonomous agents and multiagent systems, international foundation for autonomous agents and multi agent systems, AAMAS '18, pp 1388–1396

Huang Y, Huang L, Zhu Q (2022) Reinforcement learning for feedback-enabled cyber resilience. Annu Rev Control 53:273–295

Hughes E, Leibo JZ, Phillips M, Tuyls K, Dueñez-Guzman E, García Castañeda A, Dunning I, Zhu T, McKee K, Koster R, et al. (2018) Inequity aversion improves cooperation in intertemporal social dilemmas. In: Advances in neural information processing systems, vol 31

Ilhan E, Gow J, Perez-Liebana D (2019) Teaching on a budget in multi-agent deep reinforcement learning. In: 2019 IEEE conference on games (CoG). IEEE, Piscataway pp 1–8

Iqbal S, Sha F (2019) Actor-attention-critic for multi-agent reinforcement learning. In: International conference on machine learning, PMLR, pp 2961–2970

Jaderberg M, Czarnecki WM, Dunning I, Marris L, Lever G, Castaneda AG, Beattie C, Rabinowitz NC, Morcos AS, Ruderman A et al (2019) Human-level performance in 3d multiplayer games with population-based reinforcement learning. Science 364(6443):859–865

Jaques N, Lazaridou A, Hughes E, Gulcehre C, Ortega P, Strouse D, Leibo JZ, De Freitas N (2019) Social influence as intrinsic motivation for multi-agent deep reinforcement learning. In: International conference on machine learning, PMLR, pp 3040–3049

Jiang J, Lu Z (2018) Learning attentional communication for multi-agent cooperation. In: Advances in neural information processing systems, vol 31

Jin J, Song C, Li H, Gai K, Wang J, Zhang W (2018) Real-time bidding with multi-agent reinforcement learning in display advertising. In: Cuzzocrea A, Allan J, Paton NW, Srivastava D, Agrawal R, Broder AZ, Zaki MJ, Candan KS, Labrinidis A, Schuster A, Wang H (eds) Proceedings of the 27th ACM international conference on information and knowledge management. ACM, New York, pp 2193–2201

Johanson M, Burch N, Valenzano R, Bowling M (2013) Evaluating state-space abstractions in extensive-form games. In: Proceedings of the 2013 international conference on autonomous agents and multi-agent systems, pp 271–278

Jorge E, Kågebäck M, Johansson FD, Gustavsson E (2017) Learning to play guess who? and inventing a grounded language as a consequence. arXiv preprint. arXiv:1611.03218

Kakade SM (2003) On the sample complexity of reinforcement learning. University of London, University College London, London

Kim DK, Liu M, Omidshafiei S, Lopez-Cot S, Riemer M, Habibi G, Tesauro G, Mourad S, Campbell M, How JP (2020) Learning hierarchical teaching policies for cooperative agents. In: Proceedings of the

19th international conference on autonomous agents and multiagent systems, international foundation for autonomous agents and multi agent systems, Richland, SC, AAMAS '20, pp 620–628

Kim W, Cho M, Sung Y (2019) Message-dropout: An efficient training method for multi-agent deep reinforcement learning. In: Proceedings of the AAAI conference on artificial intelligence, vol 33, pp 6079–6086. https://doi.org/10.1609/aaai.v33i01.33016079

Konda VR, Tsitsiklis JN (2003) Actor-critic algorithms. J Control Optim 42(4):1143–1166

Kottur S, Moura JMF, Lee S, Batra D (2017) Natural language does not emerge 'naturally' in multi-agent dialog. In: Conference on empirical methods in natural language processing (EMNLP), pp 2962–2967. https://aclanthology.info/papers/D17-1321/d17-1321

Kraemer L, Banerjee B (2016) Multi-agent reinforcement learning as a rehearsal for decentralized planning. Neurocomputing 190:82–94

Kuhn HW, Tucker AW (1953) Contributions to the theory of games, vol 2. Princeton University Press, Princeton

Kumar A, Zilberstein S (2009) Dynamic programming approximations for partially observable stochastic games. In: Proceedings of the 22nd international FLAIRS conference, pp 547–552

Kurek M, Jaśkowski W (2016) Heterogeneous team deep q-learning in low-dimensional multi-agent environments. In: 2016 IEEE conference on computational intelligence and games (CIG). IEEE, Piscataway, pp 1–8

Lazaridou A, Baroni M (2020) Emergent multi-agent communication in the deep learning era. arXiv preprint, arXiv:2006.02419

Lazaridou A, Peysakhovich A, Baroni M (2017) Multi-agent cooperation and the emergence of (natural) language. In: International conference on learning representations. https://openreview.net/forum?id=Hk8N3Sclg

LeCun Y, Bengio Y, Hinton G (2015) Deep learning. Nature 521(7553):436–444

Lehman J, Stanley KO (2008) Exploiting open-endedness to solve problems through the search for novelty. In: Artificial Life XI, Citeseer, pp 329–336

Lehman J, Chen J, Clune J, Stanley KO (2018a) Es is more than just a traditional finite-difference approximator. In: Proceedings of the genetic and evolutionary computation conference, pp 450–457. https://doi.org/10.1145/3205455.3205474

Lehman J, Chen J, Clune J, Stanley KO (2018b) Safe mutations for deep and recurrent neural networks through output gradients. arXiv preprint. arXiv:1712.06563

Lehman J, Chen J, Clune J, Stanley KO (2018c) Safe mutations for deep and recurrent neural networks through output gradients. In: Proceedings of the genetic and evolutionary computation conference, association for computing machinery, New York, NY, USA, GECCO '18, pp 117–124. https://doi.org/10.1145/3205455.3205473

Leibo JZ, Zambaldi V, Lanctot M, Marecki J, Graepel T (2017) Multi-agent reinforcement learning in sequential social dilemmas. In: Proceedings of the 16th conference on autonomous agents and multiagent systems, international foundation for autonomous agents and multi agent systems, Richland, SC, AAMAS '17, pp 464–473

Leibo JZ, d'Autume CdM, Zoran D, Amos D, Beattie C, Anderson K, Castañeda AG, Sanchez M, Green S, Gruslys A, et al. (2018) Psychlab: a psychology laboratory for deep reinforcement learning agents. arXiv preprint .arXiv:1801.08116

Lerer A, Peysakhovich A (2018) Maintaining cooperation in complex social dilemmas using deep reinforcement learning. arXiv preprint. arXiv:1707.01068

Levine S (2017) Berkeley CS 294-112, Lecture notes: model-based reinforcement learning. http://rail.eecs.berkeley.edu/deeprlcourse-fa17/f17docs/lecture_9_model_based_rl.pdf. Last visited on 12 May 2021

Li S, Wu Y, Cui X, Dong H, Fang F, Russell S (2019) Robust multi-agent reinforcement learning via minimax deep deterministic policy gradient. In: Proceedings of the AAAI conference on artificial intelligence, vol 33, pp 4213–4220

Lillicrap TP, Hunt JJ, Pritzel A, Heess N, Erez T, Tassa Y, Silver D, Wierstra D (2016) Continuous control with deep reinforcement learning. In: The international conference on learning representations. http://arxiv.org/abs/1509.02971

Lin K, Zhao R, Xu Z, Zhou J (2018) Efficient large-scale fleet management via multi-agent deep reinforcement learning. In: Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining, pp 1774–1783

Littman ML (1994) Markov games as a framework for multi-agent reinforcement learning. In: 11th International conference on machine learning. Elsevier, Amsterdam, pp 157–163

Liu S, Lever G, Merel J, Tunyasuvunakool S, Heess N, Graepel T (2019) Emergent coordination through competition. arXiv preprint. arXiv:1902.07151

Liu Z, Chen B, Zhou H, Koushik G, Hebert M, Zhao D (2020) Mapper: multi-agent path planning with evolutionary reinforcement learning in mixed dynamic environments. In: 2020 IEEE/RSJ international conference on intelligent robots and systems (IROS). IEEE, Piscataway, pp 11748–11754

Lowe R, Wu YI, Tamar A, Harb J, Pieter Abbeel O, Mordatch I (2017) Multi-agent actor-critic for mixed cooperative-competitive environments. In: Advances in neural information processing systems, vol 30

Lowe R, Foerster J, Boureau YL, Pineau J, Dauphin Y (2019) On the pitfalls of measuring emergent communication. In: Proceedings of the 18th international conference on autonomous agents and multiagent systems, international foundation for autonomous agents and multi agent systems, Richland, SC, AAMAS '19, pp 693–701

Ma Z, Luo Y, Ma H (2021) Distributed heuristic multi-agent path finding with communication. In: 2021 IEEE international conference on robotics and automation (ICRA). IEEE, Piscataway, pp 8699–8705

Mahajan A, Rashid T, Samvelyan M, Whiteson S (2019) Maven: Multi-agent variational exploration. In: Advances in neural information processing systems, vol 32

Majumdar S, Khadka S, Miret S, Mcaleer S, Tumer K (2020) Evolutionary reinforcement learning for sample-efficient multiagent coordination. In: International conference on machine learning, PMLR, pp 6651–6660

Mao H, Alizadeh M, Menache I, Kandula S (2016) Resource management with deep reinforcement learning. In: Ford B, Snoeren AC, Zegura EW (eds) Proceedings of the 15th ACM workshop on hot topics in networks, ACM Press, New York, pp 50–56. https://doi.org/10.1145/3005745.3005750

Mao H, Gong Z, Ni Y, Xiao Z (2017) Accnet: Actor-coordinator-critic net for "learning-to-communicate" with deep multi-agent reinforcement learning. arXiv preprint. arXiv:1706.03235

Mao H, Zhang Z, Xiao Z, Gong Z, Ni Y (2020) Learning multi-agent communication with double attentional deep reinforcement learning. Autonom Agents Multi-Agent Syst 34(1):1–34

Marewski JN, Gaissmaier W, Gigerenzer G (2010) Good judgments do not require complex cognition. Cogn Process 11(2):103–121

Markovitch S, Reger R (2005) Learning and exploiting relative weaknesses of opponent agents. Autonom Agents Multi-Agent Syst 10(2):103–130

McKee KR, Gemp I, McWilliams B, Duèñez Guzmán EA, Hughes E, Leibo JZ (2020) Social diversity and social preferences in mixed-motive reinforcement learning. In: Proceedings of the 19th international conference on autonomous agents and multiagent systems, international foundation for autonomous agents and multi agent systems, Richland, SC, AAMAS '20, pp 869–877

Minsky M (1961) Steps toward artificial intelligence. Proc IRE 49(1):8–30. https://doi.org/10.1109/JRPROC.1961.287775

Mnih V, Kavukcuoglu K, Silver D, Graves A, Antonoglou I, Wierstra D, Riedmiller M (2013) Playing Atari with deep reinforcement learning. arXiv preprint. arXiv:1312.5602

Mnih V, Kavukcuoglu K, Silver D, Rusu AA, Veness J, Bellemare MG, Graves A, Riedmiller M, Fidjeland AK, Ostrovski G et al (2015) Human-level control through deep reinforcement learning. Nature 518(7540):529–533

Mnih V, Badia AP, Mirza M, Graves A, Lillicrap T, Harley T, Silver D, Kavukcuoglu K (2016) Asynchronous methods for deep reinforcement learning. In: Balcan MF, Weinberger KQ (eds) Proceedings of the 33rd international conference on machine learning, PMLR, New York, pp 1928–1937

Moravčík M, Schmid M, Burch N, Lisỳ V, Morrill D, Bard N, Davis T, Waugh K, Johanson M, Bowling M (2017) Deepstack: expert-level artificial intelligence in heads-up no-limit poker. Science 356(6337):508–513

Moreno P, Hughes E, McKee KR, Pires BA, Weber T (2021) Neural recursive belief states in multi-agent reinforcement learning. arXiv preprint. arXiv:2102.02274

Moriarty DE, Schultz AC, Grefenstette JJ (1999) Evolutionary algorithms for reinforcement learning. J Artif Intell Res 11:241–276

Nevmyvaka Y, Feng Y, Kearns M (2006) Reinforcement learning for optimized trade execution. In: Proceedings of the 23rd international conference on machine learning, pp 673–680

Ng AY, Harada D, Russell S (1999) Policy invariance under reward transformations: Theory and application to reward shaping. ICML 99:278–287

Nguyen DT, Kumar A, Lau HC (2018) Credit assignment for collective multiagent rl with global rewards. In: Proceedings of the 31th advances in neural information processing systems. MIT, Cambridge

Nguyen, T. T., Nguyen, N. D., & Nahavandi, S. (2020). Deep reinforcement learning for multiagent systems: A review of challenges, solutions, and applications. IEEE Ttrans cybernetics 50(9):3826–3839

Nitschke GS, Eiben A, Schut MC (2012) Evolving team behaviors with specialization. Genet Program Evol Mach 13(4):493–536

Omidshafiei S, Kim DK, Liu M, Tesauro G, Riemer M, Amato C, Campbell M, How JP (2019) Learning to teach in cooperative multiagent reinforcement learning. Proceedings of the AAAI conference on artificial intelligence, vol 33, pp 6128–6136

Palanisamy P (2020) Multi-agent connected autonomous driving using deep reinforcement learning. In: International joint conference on neural networks. IEEE, Piscataway, pp 1–7

Papoudakis G, Christianos F, Rahman A, Albrecht SV (2019) Dealing with non-stationarity in multi-agent deep reinforcement learning. arXiv preprint. arXiv:1906.04737

Peng P, Wen Y, Yang Y, Yuan Q, Tang Z, Long H, Wang J (2017) Multiagent bidirectionally-coordinated nets: emergence of human-level coordination in learning to play starcraft combat games. arXiv preprint. arXiv:1703.10069

Peng Z, Zhang L, Luo T (2018) Learning to communicate via supervised attentional message processing. In: Proceedings of the 31st international conference on computer animation and social agents, pp 11–16

Peters J, Schaal S (2008) Natural actor-critic. Neurocomputing 71(7–9):1180–1190

Peysakhovich A, Lerer A (2018) Prosocial learning agents solve generalized stag hunts better than selfish ones. In: International foundation for autonomous agents and multi agent systems, Richland, SC, AAMAS ’18, pp 2043–2044

Plaat A (2020) Learning to play: reinforcement learning and games. Springer, Cham

Prasad A, Dusparic I (2019) Multi-agent deep reinforcement learning for zero energy communities. In: 2019 IEEE PES innovative smart grid technologies Europe (ISGT-Europe). IEEE, Piscataway, pp 1–5

Premack D, Woodruff G (1978) Does the chimpanzee have a theory of mind? Behav Brain Sci 1(4):515–526

Proper S, Tumer K (2012) Modeling difference rewards for multiagent learning. In: Proceedings of the 11th international conference on autonomous agents and multiagent systems), Conitzer, Winikoff, Padgham, pp 1397–1398

Rashid T, Farquhar G, Peng B, Whiteson S (2020) Weighted qmix: Expanding monotonic value function factorisation for deep multi-agent reinforcement learning. In: Advances in neural information processing systems, vol 33, pp 10199–10210

Rashid T, Samvelyan M, Schroeder de Witt C, Farquhar G, Foerster JN, Whiteson S (2020b) Monotonic value function factorisation for deep multi-agent reinforcement learning. J Mach Learn Res 21:1–51

Rusu AA, Colmenarejo SG, Gulcehre C, Desjardins G, Kirkpatrick J, Pascanu R, Mnih V, Kavukcuoglu K, Hadsell R (2016) Policy distillation. arXiv preprint. arXiv:1511.06295

Sallab AE, Abdou M, Perot E (2017) Yogamani S (2017) Deep reinforcement learning framework for autonomous driving. Electron Imaging 19:70–76

Schrittwieser J, Antonoglou I, Hubert T, Simonyan K, Sifre L, Schmitt S, Guez A, Lockhart E, Hassabis D, Graepel T et al (2020) Mastering atari, go, chess and shogi by planning with a learned model. Nature 588(7839):604–609

Schroeder de Witt C, Foerster J, Farquhar G, Torr P, Boehmer W, Whiteson S (2019) Multi-agent common knowledge reinforcement learning. In: Advances in neural information processing systems, vol 32, pp 9927–9939

Schulman J, Levine S, Abbeel P, Jordan M, Moritz P (2015) Trust region policy optimization. In: International conference on machine learning, PMLR, pp 1889–1897

Schulman J, Wolski F, Dhariwal P, Radford A, Klimov O (2017) Proximal policy optimization algorithms. arXiv preprint. arXiv:1707.06347

Shapley LS (1953) Stochastic games. Proc Natl Acad Sci USA 39(10):1095–1100

Sheikh HU, Bölöni L (2020) Multi-agent reinforcement learning for problems with combined individual and team reward. In: 2020 international joint conference on neural networks (IJCNN). IEEE, Piscataway, pp 1–8

Shoham Y, Leyton-Brown K (2008) Multiagent systems: algorithmic, game-theoretic, and logical foundations. Cambridge University Press, Cambridge

Silver D, Lever G, Heess N, Degris T, Wierstra D, Riedmiller M (2014) Deterministic policy gradient algorithms. In: International conference on machine learning, PMLR, pp 387–395

Silver D, Huang A, Maddison CJ, Guez A, Sifre L, Van Den Driessche G, Schrittwieser J, Antonoglou I, Panneershelvam V, Lanctot M et al (2016) Mastering the game of go with deep neural networks and tree search. Nature 529(7587):484–489

Silver D, Schrittwieser J, Simonyan K, Antonoglou I, Huang A, Guez A, Hubert T, Baker L, Lai M, Bolton A et al (2017) Mastering the game of go without human knowledge. Nature 550(7676):354–359

Simon HA (1957) Models of man, social and rational: mathematical essays on rational human behavior in a social setting. Wiley, New York

Simon HA (1990) Bounded rationality. Springer, New York

Son K, Kim D, Kang WJ, Hostallero DE, Yi Y (2019) Qtran: Learning to factorize with transformation for cooperative multi-agent reinforcement learning. In: International conference on machine learning, PMLR, pp 5887–5896

Srivastava N, Hinton G, Krizhevsky A, Sutskever I, Salakhutdinov R (2014) Dropout: a simple way to prevent neural networks from overfitting. J Mach Learn Res 15(1):1929–1958

Stanley HE (1971) Phase transitions and critical phenomena. Clarendon Press, Oxford

Su J, Adams S, Beling P (2021) Value-decomposition multi-agent actor-critics. In: Proceedings of the AAAI conference on artificial intelligence, vol 35, pp 11352–11360

Suay HB, Brys T, Taylor ME, Chernova S (2016) Learning from demonstration for shaping through inverse reinforcement learning. In: Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems, pp 429–437

Such FP, Madhavan V, Conti E, Lehman J, Stanley KO, Clune J (2018) Deep neuroevolution: Genetic algorithms are a competitive alternative for training deep neural networks for reinforcement learning. arXiv preprint. arXiv:1712.06567

Sukhbaatar S, Fergus R, et al. (2016) Learning multiagent communication with backpropagation. In: Advances in neural information processing systems, vol 29

Sunehag P, Lever G, Gruslys A, Czarnecki WM, Zambaldi V, Jaderberg M, Lanctot M, Sonnerat N, Leibo JZ, Tuyls K, Graepel T (2018) Value-decomposition networks for cooperative multi-agent learning based on team reward. In: Proceedings of the 17th International conference on autonomous agents and multiagent systems, international foundation for autonomous agents and multi agent systems, Richland, SC, AAMAS '18, pp 2085–2087

Sutton RS, Barto AG (2018) Reinforcement learning: an introduction. MIT, Cambridge

Sutton RS, Barto AG, et al. (1998) Introduction to reinforcement learning, vol 135. MIT, Cambridge

Sutton RS, McAllester D, Singh S, Mansour Y (1999) Policy gradient methods for reinforcement learning with function approximation. In: Advances in neural information processing systems, vol 12

Tampuu A, Matiisen T, Kodelja D, Kuzovkin I, Korjus K, Aru J, Aru J, Vicente R (2017) Multiagent cooperation and competition with deep reinforcement learning. PLoS ONE 12(4):1–15. https://doi.org/10.1371/journal.pone.0172395

Tan M (1993) Multi-agent reinforcement learning: Independent vs. cooperative agents. In: Proceedings of the 10th international conference on machine learning, pp 330–337

Taylor ME, Stone P (2009) Transfer learning for reinforcement learning domains: a survey. Journal of Machine Learning Research 10(1):1633–1685

Taylor JET, Taylor GW (2021) Artificial cognition: how experimental psychology can help generate explainable artificial intelligence. Psychon Bull Rev 28(2):454–475

Terry JK, Grammel N, Hari A, Santos L, Black B (2021) Revisiting parameter sharing in multi-agent deep reinforcement learning. arXiv preprint. arXiv:2005.13625

Tian R, Tomizuka M, Sun L (2021) Learning human rewards by inferring their latent intelligence levels in multi-agent games: a theory-of-mind approach with application to driving data. In: 2021 IEEE/RSJ international conference on intelligent robots and systems (IROS). IEEE, Piscataway, pp 4560–4567

Van Der Ree M, Wiering M (2013) Reinforcement learning in the game of othello: Learning against a fixed opponent and learning from self-play. In: 2013 IEEE symposium on adaptive dynamic programming and reinforcement learning (ADPRL). IEEE, Piscataway, pp 108–115

Van Hasselt H, Guez A, Silver D (2016) Deep reinforcement learning with double q-learning. In: Proceedings of the AAAI conference on artificial intelligence, vol 30

Van Otterlo M, Wiering M (2012) Reinforcement learning and markov decision processes. In: Wiering M, van Otterlo M (eds) Reinforcement learning. Adaptation, learning, and optimization, vol 12. Springer, Berlin, pp 3–42

Vinyals O, Babuschkin I, Czarnecki WM, Mathieu M, Dudzik A, Chung J, Choi DH, Powell R, Ewalds T, Georgiev P et al (2019) Grandmaster level in starcraft II using multi-agent reinforcement learning. Nature 575(7782):350–354

Wang W, Hao J, Wang Y, Taylor M (2018) Towards cooperation in sequential prisoner's dilemmas: a deep multiagent reinforcement learning approach. arXiv preprint. arXiv:1803.00162

Wang RE, Everett M, How JP (2019) R-MADDPG for partially observable environments and limited communication. In: International conference on machine learning 2019 workshop (RL4RealLife)

Wen Z, O'Neill D, Maei H (2015) Optimal demand response using device-based reinforcement learning. IEEE Trans Smart Grid 6(5):2312–2324

Wen Y, Yang Y, Luo R, Wang J, Pan W (2019) Probabilistic recursive reasoning for multi-agent reinforcement learning. In: 7th international conference on learning representations, ICLR 2019

Williams RJ (1992) Simple statistical gradient-following algorithms for connectionist reinforcement learning. Mach Learn 8(3–4):229–256

Wu Y, Mansimov E, Grosse RB, Liao S, Ba J (2017a) Scalable trust-region method for deep reinforcement learning using kronecker-factored approximation. In: Advances in neural information processing systems, vol 30, pp 5279–5288

Wu Y, Mansimov E, Liao S, Radford A, Schulman J (2017b) OpenAI Baselines: ACKTR & A2C. https://openai.com/blog/baselines-acktr-a2c//. Accessed 16 Dec 2021

Yang Y, Luo R, Li M, Zhou M, Zhang W, Wang J (2018) Mean field multi-agent reinforcement learning. In: International conference on machine learning, PMLR, pp 5571–5580

Yang Y, Hao J, Chen G, Tang H, Chen Y, Hu Y, Fan C, Wei Z (2020a) Q-value path decomposition for deep multiagent reinforcement learning. In: International conference on machine learning, PMLR, pp 10706–10715

Yang Y, Wen Y, Wang J, Chen L, Shao K, Mguni D, Zhang W (2020b) Multi-agent determinantal Q-learning. In: International conference on machine learning, PMLR, pp 10757–10766

Yang Y, Wang J (2020) An overview of multi-agent reinforcement learning from game theoretical perspective. arXiv preprint arXiv:2011.00583

Yang Y, Wang J (2021) An overview of multi-agent reinforcement learning from game theoretical perspective. arXiv preprint. arXiv:2011.00583

Ye N, Somani A, Hsu D, Lee WS (2017) Despot: Online pomdp planning with regularization. J Artif Intell Res 58:231–266

Yliniemi L, Tumer K (2014) Multi-objective multiagent credit assignment through difference rewards in reinforcement learning. In: Asia-Pacific conference on simulated evolution and learning. Springer, Cham, pp 407–418

Yu Y (2018) Towards sample efficient reinforcement learning. In: International joint conference on artificial intelligence, pp 5739–5743

Yu L, Song J, Ermon S (2019) Multi-agent adversarial inverse reinforcement learning. In International Conference on Machine Learning (pp. 7194–7201). PMLR

Zhang X, Clune J, Stanley KO (2017) On the relationship between the openai evolution strategy and stochastic gradient descent. arXiv preprint. arXiv:1712.06564

Zhang K, Yang Z, Başar T (2021) Multi-agent reinforcement learning: a selective overview of theories and algorithms. Springer, Cham, pp 321–384. https://doi.org/10.1007/978-3-030-60990-0_12,

Zheng Y, Meng Z, Hao J, Zhang Z (2018a) Weighted double deep multiagent reinforcement learning in stochastic cooperative environments. In: Pacific RIM international conference on artificial intelligence. Springer, Berlin, pp 421–429

Zheng Y, Meng Z, Hao J, Zhang Z, Yang T, Fan C (2018b) A deep bayesian policy reuse approach against non-stationary agents. In: Proceedings of the 32nd international conference on neural information processing systems, pp 962–972

Zhou M, Liu Z, Sui P, Li Y, Chung YY (2020) Learning implicit credit assignment for cooperative multi-agent reinforcement learning. In: Advances in neural information processing systems, vol 33, pp 11853–11864

Zhu Y, Mottaghi R, Kolve E, Lim JJ, Gupta A, Fei-Fei L, Farhadi A (2017) Target-driven visual navigation in indoor scenes using deep reinforcement learning. In: 2017 IEEE international conference on robotics and automation (ICRA). IEEE, Piscataway, pp 3357–3364

Zou H, Ren T, Yan D, Su H, Zhu J (2021) Learning task-distribution reward shaping with meta-learning. In: Proceedings of the AAAI conference on artificial intelligence, Vancouver, BC, Canada, pp 2–9