Abstract

Learning agents that are not only capable of taking tests but are also innovating are becoming a hot topic in artificial intelligence (AI). One of the most promising paths towards this vision is multi-agent learning, where agents act as the environment for each other, and improving each agent means proposing new problems for others. However, the existing evaluation platforms are either not compatible with multi-agent settings, or limited to a specific game. That is, there is not yet a general evaluation platform for research on multi-agent intelligence. To this end, we introduce Arena, a general evaluation platform for multi-agent intelligence with 35 games of diverse logic and representations. Furthermore, multi-agent intelligence is still at the stage where many problems remain unexplored. Therefore, we provide a building toolkit for researchers to easily invent and build novel multi-agent problems from the provided games set based on a GUI-configurable social tree and five basic multi-agent reward schemes. Finally, we provide python implementations of five state-of-the-art deep multi-agent reinforcement learning baselines. Along with the baseline implementations, we release a set of 100 best agents/teams that we can train with different training schemes for each game, as the base for evaluating agents with population performance. As such, the research community can perform comparisons under a stable and uniform standard.

1 Introduction

Modern learning algorithms are more of outstanding test-takers, but less of innovators [4], i.e., the ceiling of an agent’s intelligence may be limited by the complexity of its environment [52]. Thus, the emergence of innovation is becoming a hot topic for artificial intelligence (AI). One of the most promising paths towards such a vision is learning via social interaction, i.e., multi-agent learning. In multi-agent learning, how the agents should beat the opponents or collaborate with each other is not defined by the builder of the environment, e.g., the inventor of the ancient Go [21] never defines what strategies are good. However, enormous and sophisticated strategies are invented while a population of human players/artificial agents evolve by improving themselves over the others, i.e., each agent is acting as an environment for the others and improving itself means proposing new problems for the others [19, 38, 70, 86].

To study a new class of intelligence, general evaluation platforms that contain a set of games of diverse logics and representations are always the milestones that push forward the research to a new stage.
For example, ALE [7], Retro [64], GVG-AI [74], OpenAI Universe [69], Mujoco [94], and Deepmind Control Suite [91] are the most spread general evaluation platforms that greatly accelerate the research of general reinforcement learning (RL). However, there is no such general evaluation platform for multi-agent intelligence. Although some platforms support multi-agent settings [8, 45, 83, 97, 104], they are not general evaluation platforms, i.e., built for specific games. Thus, in this paper, we propose the first general evaluation platform for multi-agent intelligence, called Arena, containing 35 multi-agent games in total with diverse logics and representations, as shown in Fig. 1.

Apart from training and evaluation, multi-agent intelligence research is still at a stage where many problems remain undiscovered or unexplored. Thus, the second vision of Arena is a building toolkit for multi-agent intelligence, easily enabling the creation of different multi-agent scenarios after the basic game scene has been established. For example, in the example game in Fig. 2(a), after defining the basic behavior of the agent (moving and turning) and the alive condition of the agent (staying on the playground), it should be extensible with little effort to different multi-agent scenarios. For example, (1) 5 players fight each other until only one agent is alive (see Fig. 2(b)), or (2) $5 \times 2$ players form into 2 teams and each agent fights for its own team until all players in a team are dead (see Fig. 2(c)), or (3) multiple players form into multiple teams in hierarchies where the collaboration and competition relationships between the teams are customized (see Fig. 3). In this way, Arena is not just a research platform for the evaluation with a fixed set of games, but also a building toolkit for researchers to invent and build novel multi-agent problems.

To achieve the above vision of building a toolkit for multi-agent intelligence, (1) we provide a GUI-configurable tree that defines the social structure of agents, called social tree; and (2) based on the social tree, we propose 5 basic multi-agent reward schemes (BMaRSs) that define different social paradigms at each node in the social tree. Specifically, each BMaRS is a restriction applied to the reward function, so it corresponds to a batch of reward functions that can lead to a specific social paradigm. For each BMaRS, Arena provides multiple ready-to-use reward functions, simplifying the construction of games with complex social relationships. Besides, when the agent is controlling each joint of a robot, it has long been a burden for researchers that low-level intelligence (such as the basic skill of moving) must first be built before one can study high-level multi-agent intelligence.
Thus, Arena provides many ready-to-use dense reward functions in each BMaRS that handle such low-level intelligence. Apart from providing reward functions, Arena also offers a verification option for customized reward functions, so that one can make sure that the programmed reward functions lie in one of the BMaRSs and produce a specific social paradigm. Thus, with the above efforts towards a building toolkit for multi-agent intelligence and the provided set of 35 games for a general evaluation platform, one can easily customize a set of games of a new social paradigm to study a yet unexplored problem.

Finally, we provide python implementations of several state-of-the-art deep multi-agent reinforcement learning baselines, which can be used as starting points for the development of novel multi-agent algorithms, as well as the validation of new environments. Along with the baseline implementations, we also release a set of 100 best agents/teams that we can train with different training schemes for each game, as the base for evaluating agents with population performance [3, 4]. Consequently, the research community can perform comparisons under a stable and uniform standard.

To summarize, this paper’s contributions are as follows: (1) a general evaluation platform for multi-agent intelligence with a set of diverse games, most of which are new to the community or still stand as a challenge for state-of-the-art algorithms; (2) a building toolkit for multi-agent games, enabling the easy creation of new social paradigms based on GUI-configurable social trees and BMaRSs; (3) the baseline implementations of 5 state-of-the-art multi-agent algorithms for both competitive and collaborative settings; and (4) the sets of benchmark agents/teams for the community to conduct stable and uniform population evaluation [3]. Code for both the platform and the baselines are released at https://sites.google.com/view/arena-unity/.

2 The Platform

State-of-the-Art Engine. The engine behind Arena is the world-leading game engine Unity [41], which provides Arena with several desirable features on rendering, physics, customizability, and community. There are also other choices of popular engines. Some platforms contain a wide set of diverse games [7, 64, 69, 74]; however, they are designed mostly for single agent scenarios and extremely hard to customize (adding multiple players or creating new games), since the games are provided as compiled binary ROMs. Other downsides of these choices include deterministic environments, unrealistic rendering, and unrealistic physics. Other platforms [91, 94] are, in nature, more physics engines than game engines, which lack a visual editor for easily creating customized games, and cannot handle more “game-like” features, such as instantiating and destroying objects in real-time during the simulation. The rest of the platforms are limited in the sense that they are built for specific tasks, such as first person shooting [104], Real-Time Strategy (RTS) [93], vision understanding [76], in-door scene understanding [12, 15, 29, 80], and interaction [43, 81, 103], or specific games, such as driving [20, 105], handling blocks [53], Pac-Man [99], Starcraft [16, 19, 97, 102], Capture the Flag [58], and Dota2 [70]. Thus, creating a general evaluation platform on these engines is not a reasonable choice. DeepMind Lab [6], Psychlab [51], and Malmo [39] are the most possible choices when making a customizable general evaluation platform. However, the main drawbacks of the above engines are tied to their dated nature. The rendering system of these engines are either low-polygon pixelated (Malmo, based on Minecraft) or low-qualified (DeepMind Lab and Psychlab, based on Quake III). The physics systems of these engines are either rudimentary (Malmo), or have a gap [41] to the physical world (DeepMind Lab and Psychlab). Besides, they are all incompatible with a visual editor, making it very cumbersome to define customized scenarios.

To summarize, built on Unity, Arena has the following advantages over other platforms: (1) realistic rendering, so that features, such as complex lighting, textures, and shaders, etc., are fully handled by the background engine and easily produced in a customized game; (2) realistic physics, so that enough and realistic stochasticity is introduced in the game and transferring a policy learned within a simulator to the real world is easier; (3) user-friendly visual editor, so that building new multi-agent scenarios in Arena is easy; and (4) a large and active development community, so that creating new games is easy with millions of off-the-shelf assets.
We assume that the random seed of all sampling operations is \( k \) where \( 0 \leq k \leq |\mathcal{S}| - 1 \), which is a deterministic function \( r(\text{normal-form game}) \), the reward scheme serves a similar purpose as the payoff matrix \([63]\), which is also represented as a tabular. See Lemma 2 in the supplementary material \([2]\) for how the payoff matrix is aligned with BMaRSs. In the following, we define 5 different BMaRSs. Along defining these BMaRSs, we also describe a ready-to-use GUI-configurable social tree that defines how BMaRSs are applied on each node in the social tree, so that different social relationships can be easily built and verified, and low-level intelligence (like motor skills) can be handled (see isolated BMaRSs in Sec. \( 3 \)). Sec. \( 3 \) first introduces the BMaRSs, and then shows the social tree with an example of how the BMaRSs are applied on it.

### 3 Basic Multi-Agent Reward Schemes and Social Trees

#### Preliminaries

We consider a Markov game as defined in \([54]\), consisting of multiple agents \( x \in \mathcal{X} \), a finite global state space \( s_t \in \mathcal{S} \), a finite action space \( a_{x,t} \in \mathcal{A}_x \) for each agent \( x \), and a bounded-step reward space \( r_{x,t} \in \mathbb{R} \) for each agent \( x \). For the environment, it consists of a transition function \( g : \mathcal{S} \times \{ \mathcal{A}_x : x \in \mathcal{X} \} \rightarrow \mathcal{S} \), which is a stochastic function \( s_{t+1} \sim g(s_t, \{a_{x,t} : x \in \mathcal{X}\}) \) (see paragraph on stochasticity in Sec. \( 5 \)), a reward function for each agent \( f_x : \mathcal{S} \times \{ \mathcal{A}_x : x \in \mathcal{X} \} \rightarrow \mathbb{R} \), which is a deterministic function \( f_{x,t+1} = f_x(s_t, \{a_{x,t} : x \in \mathcal{X}\}) \), a joint reward function \( f = \{f_x : x \in \mathcal{X}\} \), and episode reward \( R^f_x = \sum_{t=1}^{T} r_{x,t} \) for each agent \( x \) under the joint reward function \( f \). For the agent, we consider that it observes \( s_{x,t} \in \mathcal{S}_x \), where \( \mathcal{S}_x \) consists of a part of the information from the global state space \( \mathcal{S} \). Thus, we have a policy \( \pi_x : \mathcal{S}_x \rightarrow \mathcal{A}_x \), which is a stochastic function \( a_{x,t} \sim \pi_x(s_{x,t}) \). Besides, we consider that agent \( x \) can take a policy \( \pi_x \) from a set of policies \( \Pi_x \). We assume that the random seed of all sampling operations is \( k \), which is sampled from the whole seed space \( \mathcal{K} \).

We investigate the effect of \( \{x : x \in \mathcal{X}\} \) and \( \{\pi_x : \Pi_x\} \) on \( \{R^f_x : x \in \mathcal{X}\} \). By applying different restrictions on the effect, we have different BMaRSs, each one of which is a set of joint reward functions \( \mathcal{F} = \{f : \} \) that produce a similar effect on the population \( \mathcal{X} \). The term reward scheme first appears in \([90]\) as a tabular, which is applied to a special case of Pong. While we define it in a general form and show many cases as examples within this general form. In a non-sequential setting (normal-form game), the reward scheme serves a similar purpose as the payoff matrix \([63]\), which is also represented as a tabular. See Lemma 2 in the supplementary material \([2]\) for how the payoff matrix is aligned with BMaRSs. In the following, we define 5 different BMaRSs. Along defining these BMaRSs, we also describe a ready-to-use \( f \) within these BMaRSs, which is provided by Arena as a dropdown list.

**Non-learnable BMaRSs** \( (\mathcal{F}^{NL}) \) are a set of joint reward functions \( f \) as follows:

\[
\mathcal{F}^{NL} = \{ f : \forall k \in \mathcal{K}, \forall x \in \mathcal{X}, \forall \pi_x \in \Pi_x, \partial R^f_x / \partial \pi_x = 0 \},
\]

where \( 0 \) is a zero matrix of the same size and shape as the parameter space that defines \( \pi_x \). Intuitively, \( \mathcal{F}^{NL} \) means \( R^f_x \) for any agent \( x \in \mathcal{X} \) is not optimizable by improving its policy \( \pi_x \).
Isolated BMaRSs ($F^{IS}$) are a set of joint reward functions $f$ as follows:

$$F^{IS} = \{ f : f \notin F^{NL} \text{ and } \forall k \in K, \forall x \in X, \forall x' \in X \setminus \{x\}, \forall \pi_x \in \Pi_x, \forall \pi_{x'} \in \Pi_{x'}, \frac{\partial R^f_x}{\partial \pi_{x'}} = 0 \},$$

(2)

where \(\setminus\) is the set difference. Intuitively, $F^{IS}$ means that the episode reward $R^f_x$ received by any agent $x \in X$ is not related to any policy $\pi_{x'}$ taken by any other agent $x' \in X \setminus \{x\}$. Reward functions $f_x$ in $F^{IS}$ are often called internal reward functions in other multi-agent approaches\(^5\),\(^36\),\(^38\), meaning that apart from the reward functions applied at a population level (such as win/lost), which are too sparse to learn, there are also reward functions directing the learning process towards receiving the population-level rewards, yet are more frequently available, i.e., more dense\(^32\),\(^87\),\(^88\). $F^{IS}$ is especially practical when the agent is a robot requiring continuous control of applying force on each of its joints, which means basic motor skills (such as moving) need to be learned before generating population-level intelligence. Thus, we provide $f$ in $F^{IS}$ of: energy cost, punishment of applying a big force, encouragement of keeping a steady velocity, and moving distance towards target.

Competitive BMaRSs ($F^{CP}$) are inspired by\(^14\) and defined as

$$F^{CP} = \{ f : f \notin F^{NL} \cup F^{IS} \text{ and } \forall k \in K, \forall x \in X, \forall \pi_x \in \Pi_x, \forall \pi_{x'} \in \Pi_{x'}, \frac{\partial R^f_x}{\partial \pi_{x'}} = 0 \},$$

(3)

which intuitively means that for any agent $x \in X$, taking any possible policy $\pi_x \in \Pi_x$, the sum of the episode reward of all agents will not change. If the episode length is 1, it expresses classic a multi-player zero-sum game\(^14\). Useful examples of $f$ within $F^{CP}$ are: (1) agents fight for a limited amount of resources that are always exhausted at the end of the episode, and the agent is rewarded for the amount of resources that it gained; and (2) fight till death, and the reward is given based on the order of death (the reward can also be based on the reversed order, so that the one departing the game first receives the highest reward, such as in some poker games, the one who first discards all cards wins). Rock, Paper, and Scissors in normal-form game\(^63\) and Cyclic Game in\(^4\) are both special cases of $F^{CP}$; see Lemmas 2 and 3 in the supplementary material\(^2\).

Collaborative BMaRSs ($F^{CL}$) are inspired by\(^14\) and defined as

$$F^{CL} = \{ f : f \notin F^{NL} \cup F^{IS} \text{ and } \forall k \in K, \forall x \in X, \forall \pi_x \in \Pi_x, \forall \pi_{x'} \in \Pi_{x'}, \frac{\partial R^f_x}{\partial \pi_x} \geq 0 \},$$

(4)

which intuitively means that there is no conflict of interest ($\partial R^f_x / \partial R^f_{x'} < 0$) for any pair of agents $(x', x)$. Besides, since $f \notin F^{NL} \cup F^{IS}$, there is at least one pair of agents $(x, x')$ that makes $\partial R^f_x / \partial R^f_{x'} > 0$. This indicates that this pair of agents shares a common interest, so that improving $R^f_x$ for agent $x$ means improving $R^f_{x'}$ for agent $x'$. The most common example of $f$ within $F^{CL}$ is that $f_x$ for all $x \in X$ is identical, such as the moving distance of an object that can be pushed forward by the joint effort of multiple agents, or the alive duration of the population (as long as there is at least one agent alive in the population, the population is alive). Thus, we provide $f$ in $F^{CL}$: living time of the team (both positive and negative, since some games require the team to survive as long as possible, while other games require the team to depart as early as possible, such as poker).

Competitive and Collaborative Mixed BMaRSs ($F^{CC}$) are defined to be any situation other than the above four ones. First, the term $\int_{x' \in X} \frac{\partial R^f_{x'}}{\partial \pi_x} dx' / \partial \pi_x = 0$ in\(^3\) can be written as $\int_{x' \in X} \frac{\partial R^f_{x'}}{\partial \pi_x} dx' = 0$ (see Lemma 1 in supplementary material\(^2\)), which makes an alternative\(^5\). Considering $F^{CP}$ in this alternative\(^5\) and $F^{CL}$ in\(^4\), an intuitive explanation of $F^{CC}$ is that there exist circumstances when $\partial R^f_{x'} / \partial R^f_{x'} < 0$, meaning that the agents are competitive at this point. But the derivative of total interest $\int_{x' \in X} \partial R^f_{x'} / \partial R^f_{x'} dx'$ is not always 0, thus, the total interest can be maximized with specific policies, meaning that the agents are collaborative at this point.

Apart from providing several practical $f$ in each BMaRS, we also provide a verification option for each BMaRS, meaning that one can customize an $f$ and use this verification option to make sure that the programmed $f$ lies in a specific BMaRS. How the verification option is implemented can be found in Sec. 1 in\(^2\).

The Social Tree. The BMaRSs defined above apply to a group of agents of any number. To define more complex and structured social paradigms, we use a tree structure (social tree) to organize the
agents and apply BMaRSs on each node of the tree. We illustrate this by an example. The GUI interface in Fig. 3(a) defines a tree structure in Fig. 3(b), representing a population of 4 agents. The tree structure can be easily reconfigured by dragging, duplicating, or deleting in the GUI interface in Fig. 3(a). In this example, each agent has an agent-level BMaRS. The agent is a robot ant, so that the agent-level BMaRSs are $F^{IS}$, specifically, the option of *ant-motion* that directs the learning towards basic motion skills such as moving forward, as shown in Fig. 3(c). Each two agents form a *team* (which is a set of agents or teams), the two agents have team-level BMaRSs. In this example, the two robot ants collaborate with each other to push a box forward, as shown in Figure 3(d). Thus, the team-level BMaRSs are $F^{CL}$, specifically, the moving distance of the box. On the two teams, we have global-level BMaRSs. In this example, the two teams are set to have a match regarding which team pushes its box to the target point first, as shown in Figure 3(e). Thus, the global-level BMaRSs are $F^{CP}$, specifically, the ranking of the box reaching the target. The final reward function applied to each agent is a weighted sum of the above three BMaRSs at three levels. One can imagine defining a social tree of more than three levels, where small teams form into bigger teams, and BMaRSs are defined at each node to give more complex and structured social problems. After defining the social tree and applying BMaRSs on each node, the environment is ready for use with abstraction layer handling everything else, such as assigning viewports to each agent in the window, applying the team color, displaying the agent ID, and generating a top-down view.

4 The Learning Agents

The Baselines. We provide the python implementations of several state-of-the-art baselines, which can be used as starting points for the development of novel multi-agent algorithms, as well as the validation of new environments. Specifically, we first implement a fully decentralized system where each agent is a self-contained PPO [82], with independent rollout, critic, actor, and optimizer. Based on the above fully decentralized PPO (D-PPO), for competitive agents, we implement 2 state-of-the-art methods based on self-play in [70] (SP) and population-based training in [19, 38] (PB). For collaborative agents, we implement two state-of-the-arts of centralized critic [57] (CC) and centralized critic with a counterfactual baseline [25] (CF).

The Evaluation Metric. It is recently raising attention that evaluating an agent against a single agent or hand-coded bot is unstable and misleading [3, 4]. Thus, the population performance is introduced to evaluate an agent’s (or an agent group’s) performance among a base population. To enable population evaluation, we release 100 best agents that we can train with different training schemes for each game as the base population. One can call the provided function to get the ranking of one’s agent among the base population, or get the averaged ranking of one’s population among the base population. Moreover, we provide a human ranking among the base population, which gives an indication of human level intelligence in the game. We will accept the submissions of agents from the community as well as keep implementing algorithms introduced in the future, so that the base population will be upgraded, as the level of research in multi-agent intelligence advances.

5 Experiments

Experiments are conducted from three aspects. First, we evaluate our games set from the perspective of realistic rendering, stochasticity, and simulation speed. Other advantages from the Unity engine have been verified by [41]. Second, we evaluate our design of the extensible multi-agent building toolkit with a case study, showing that by applying different social trees and BMaRSs, different population-level strategies can be learned. Third, we report the experimental results of 5 baselines that we implemented and show that by using the provided population performance evaluation metric, the training progress can be visualized in a less noisy and more analyzable way.
Realistic Rendering. Providing a realistic rendering effect in the game is gaining more consideration, as one is generally paying more attention to transferring the algorithms to a real-world scenario. Some of the platforms are built towards this effort [12, 45, 76, 103, 107]. In Fig. 4 we show an objective comparison of the most realistic scenes provided in these works against that in our platform. It shows that our platform provides a realistic rendering effect at the same level as the best of them.

Simulation Speed. Simulation speed and parallelizability of an environment are important for carrying out research. Thus, we compare our game Boomer in Fig. 5 (a) with MsPacman in Fig. 5 (b) from the most widely used general evaluation platform ALE [7], which are both run on our parallelized implementatin of the PPO (D-PPO) baseline on a server with 32 CPU threads. We compare these two games, because they are of similar complexity. The result in Fig. 5 (c) shows that Arena is well parallelized with a similar simulation speed as ALE [7] under the games of similar complexity, when the number of concurrent threads is below the number of CPU threads of the machine, i.e., smaller than 32.

Stochasticity. As being addressed by [38], having enough stochasticity is essential for researchers to verify that their algorithms are learning general knowledge, instead of memorizing action sequences. Thus, we conduct a stochasticity study on the existing general evaluation platforms ALE [7], Retro [64], GVG-AI [74], Mujoco [94], and Deepmind Control Suite [91], by running a fixed sequence of 1000 actions repeatedly for 1000 times and investigate how many branches are produced (averaged over all games in the corresponding platform). Table 1 shows that our platform generates most stochasticity among them. This is accomplished by introducing stochasticity from the initial setup (e.g., a randomly generated map), the rendering effect (e.g., randomized light conditions and particle systems), and the physics system (e.g., randomized physics properties).

Case Study of Social Tree and BMaRSs. We use Crossroads from Arena to study the effectiveness of the proposed social tree and BMaRSs via designing different social paradigms. Specifically, in the game Crossroads shown in Fig. 6 (a), the agent can move and turn, the final goal of the agent is to reach the target on the other side of the crossroad. By defining different social trees and applying different BMaRSs, as shown in Fig. 6 (b,c,d), the agents learn different strategies. In Fig. 6 (b), isolated BMaRSs ($F^{IS}$) are applied to all agents, i.e., each agent minimizes the time that it takes to reach the target. The result shows that the learned agents simply rush forward and they easily crash with each other at the center of the crossroad, producing a traffic jam. In Fig. 6 (c), collaborative BMaRSs ($F^{CL}$) are applied to the parent node of all agents, i.e., all agents are rewarded with the time that the last one of them takes to reach the target. The result shows that the agents learn to wait for each other to go across the crossroad, so that they can all get across as efficiently as possible. In Fig. 6 (d), collaborative BMaRSs ($F^{CL}$) are applied on the parent node of every 4 agents (which form a team), and competitive BMaRSs ($F^{CP}$) are applied on the parent node of the two teams. Specifically speaking, each two agents in the same team are rewarded with the same reward, and the reward is 1 for the team who gets all of its agents to the target first, 0 for the other team. The results show that
each team learns to block the road of the other team with one agent, so that the other agents in the team can get across undisturbed. Then, the agent that blocks the road leaves for the target, after all its teammates have reached the target.

**Baselines and Evaluation Metric.** We compare 5 baselines on two games: (1) *Crossroads* in Fig. 6 (a) with the BMaRS settings of Fig. 6 (d); and (2) *PushBox* in Fig. 3 (e) with the BMaRS settings of Fig. 3 (b). The BMaRS settings of both games contain competitive as well as collaborative social relationships, i.e., multiple agents form into collaborative teams, and teams compete with each other. Thus, we can investigate SP and PB baselines at the level of teams competing with each other, as well as investigate CC and CF baselines at the level of agents collaborating with each other in a team. As can be seen, the curve of episode reward shown in Fig. 7 (a,b) is extremely noisy, as the environment is non-stationary with the strategy of other collaborators and/or competitors evolving during the training. However, in Fig. 7 (c,d), which is the curve of ranking in the released base population, i.e., population performance, all methods are comparable with clear performance gaps.

## 6 Related Work

Surveys of multi-agent intelligence research can be found here [13, 71, 84, 95]. Different ideas have been explored on competitive and collaborative multi-agent settings, respectively.

**Collaborative Settings.** The simplest way to deploy multi-agent collaborative systems is to make each agent have a completely independent learning process (fully decentralized) [1, 37, 48, 59, 67, 68, 90]. However, collaborative behaviors are hardly observed under such fully decentralized setting; thus, a fully centralized system is utilized in [73, 96], where the policy has access to the global state and is shared by all agents. However, it is impractical, since the global state is mostly unavailable in the real world, and the system does not support extending the number of agents. Thus, centralized training and decentralized execution are gaining attention, which is a standard paradigm for multi-agent planning [47, 66]. At the multi-agent learning side, this idea is mostly explored under actor-critic algorithms [23, 25, 28, 57]. Other ideas include using joint action-value function [17, 26, 39, 53] and value function factorization [27, 44, 77], addressing the variance problem by a large batch size [5], learning grounded cooperative communication protocols between agents [18, 22, 30, 40, 50, 62, 89].

**Competitive Settings.** Competitive multi-agent intelligence originally comes from computational game theory [9, 11, 60, 79]. Later on, deep multi-agent reinforcement learning (D-MARL) is preferred, due to its scalability, and as it achieves notable advances on two-player turn-based games, such as Poker and Go [61, 85, 106]. D-MARL is then applied to more diverse problems, such as high-dimensional video games [19, 70] and those involving physics control [5, 75, 90]. When solving more practical problems, many issues have been raised, such as ensuring diversity amongst agents [58, 93], avoiding overfitting to the policy of the opponents [46, 48, 59, 65, 78]. Many ideas have been raised to address such issues [10, 42, 43, 55, 72]. Following on D-MARL, a most promising direction raised recently is self-play [22]. Fictitious Self-Play [33, 34, 35] first shows promising performance on the competitive game Leduc Poker. However, as the stability and parallelizability are improving with the invention of new RL algorithms, state-of-the-art approaches adopt a simpler form of self-play [70], which produces a superior-human intelligence on large video games like Dota2. Another promising idea raised recently is population-based training, as adopted in StarCraft [19, 58].
Other less commonly adopted ideas include predicting the opponent’s behavior [100, 101] and giving the agents information on their opponents [24, 31].

7 Summary and Outlook

The paper has introduced the first general evaluation platform for multi-agent intelligence research. Besides, with the efforts on a building toolkit of multi-agent environments, the platform also allows for easily building new multi-agent problems. Additionally, with the released implementations of several state-of-the-art baselines, researchers can start their adventure instantly. Finally, by releasing a base population, the community can conduct comparison under a stable and uniform evaluation metric. We are open to suggestions for new games/baselines from the community, and update Arena to introduce more novel and practical problems, as well as more powerful and general algorithms.

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