Learning Progress Driven Multi-Agent Curriculum

Wenshuai Zhao\textsuperscript{1}, Zhiyuan Li\textsuperscript{2}, and Joni Pajarinen\textsuperscript{1}

\textsuperscript{1}Department of Electrical Engineering and Automation, Aalto University
\textsuperscript{2}School of Computer Science and Engineering, University of Electronic Science and Technology of China

Abstract

Curriculum reinforcement learning (CRL) aims to speed up learning by gradually increasing the difficulty of a task, usually quantified by the achievable expected return. Inspired by the success of CRL in single-agent settings, a few works have attempted to apply CRL to multi-agent reinforcement learning (MARL) using the number of agents to control task difficulty. However, existing works typically use manually defined curricula such as a linear scheme. In this paper, we first apply state-of-the-art single-agent self-paced CRL to sparse reward MARL. Although with satisfying performance, we identify two potential flaws of the curriculum generated by existing reward-based CRL methods: (1) tasks with high returns may not provide informative learning signals and (2) the exacerbated credit assignment difficulty in tasks where more agents yield higher returns. Thereby, we further propose self-paced MARL (SPMARL) to prioritize tasks based on learning progress instead of the episode return. Our method not only outperforms baselines in three challenging sparse-reward benchmarks but also converges faster than self-paced CRL.

Keywords Curriculum reinforcement learning \cdot Multi-agent reinforcement learning \cdot Credit assignment

1 Introduction

Curriculum reinforcement learning (CRL) \cite{1} generally consists of a teacher generating a sequence of tasks with various difficulties to train the agents, which helps to overcome the exploration difficulty in target tasks with sparse rewards. In single-agent CRL, the teacher usually controls the initial states or environmental parameters to change the task difficulties. When considering curriculum learning in MARL settings, it is natural to employ the number of agents as a potential curriculum in addition to the environmental parameters in single-agent CRL, as the number of agents is critical to form the difficulty of MARL tasks. However, prior work is limited to controlling the number of agents manually or heuristically, for example, FewToMore \cite{2} and EPC \cite{3} simply train the agents starting from tasks with fewer agents and gradually move to the target task in a predefined way. VAACL \cite{4} proposes a general automatic CRL method that can control both the initial states and the number of agents. However, in their paper, the number of agents is still manually set in a linear scheme.

Moreover, existing work typically assumes that the curriculum used should start from tasks with fewer agents and then progress to more agents. This assumption could be partially true as many MARL methods rely on centralized training and decentralized execution (CTDE) \cite{5,6,7}, where the centralized value function can be unstable as more agents are changing their policies in the learning process. However, this assumption is in general not true. In the MPE Simple-Spread \cite{5} task, several agents (purple circles) try to cover as many landmarks (black dots) as possible, shown in Figure 1. Intuitively, if the number of agents increases sufficiently, the most naive policy such as random moving can work well. On the contrary, with fewer agents, they have to learn a complicated cooperation strategy to accomplish the task. We argue in this paper that more sophisticated control of the number of agents is needed in curriculum learning for MARL.

Therefore, we first propose to apply the state-of-the-art single-agent ACRL method, self-paced RL (SPRL) \cite{8}, to adaptively control the number of agents. SPRL explores a range of tasks with different contexts \cite{8} and finds easier...
ones with higher performance while progressing towards the target task, hence generating a reasonable task sequence as a curriculum. In our experiments, such a direct extension works well and outperforms the heuristic baselines by successfully generating suitable task distributions without being limited to pre-defined task sequences. However, as existing ACRL methods including SPRL typically evaluate the difficulty of tasks based on the expected returns, we show that this inductive bias may incur two problems in the MARL settings. First, a curriculum pursuing higher rewards could result in uninformative learning signals. For example, in the extreme case of the Simple-Spread task with infinite agents, the initial random policy is sufficient to be optimal, while the policy gradient estimated on this task will be zero despite the maximum return. Second, in many MARL tasks formulated as Dec-POMDP [10] where agents share the same reward, more agents may achieve higher returns but also lead to harder credit assignments.

Inspired by the above findings, we further introduce the self-paced MARL (SPMARL) method. In order to tackle the incurred credit assignment problem in reward-based ACRL methods, SPMARL improves SPRL in the MARL settings by optimizing a novel measurement indicating the learning progress instead of the difficulty measured by expected returns. Specifically, we instantiate a metric to quantify the learning progress based on the critic loss, i.e. value loss in MARL. Our method works by employing the property of value function $V^*(s)$. As $V^*(s)$ shows the performance of the current policy, the corresponding critic loss across different tasks naturally indicates how much policy change has been made on these tasks since converged value estimation usually means no change of policy updates.

We evaluate our methods on three benchmarks including the XOR matrix game [11], MPE Simple-Spread [5], and SMAC-v2 Protoss 5 vs. 5 task [12]. Note that all of the benchmarks are modified with severe sparse rewards and raise significant exploration challenges. The experimental results show that the number of agents can be an effective curriculum to overcome the hard exploration problem. While both SPMARL and the straight extension of SPRL consistently succeed and outperform the heuristic baselines by adaptively changing the number of agents over different tasks, SPMARL further demonstrates a faster convergence than SPRL.

Our contribution is threefold: (1) We extend single-agent SPRL to a multi-agent setting and show that a principled curriculum over the number of agents outperforms the manually designed baselines; (2) We identify two flaws in the straight extension of SPRL and propose SPMARL to address the problems; (3) Our experiments on three distinct benchmarks show that SPMARL converges faster than SPRL.

2 Related Work

In this section, we discuss general ACRL methods and existing work that applies curriculum learning on multi-agent tasks, especially those employing the number of agents as a curriculum variable in order to scale the current MARL methods to tasks with more agents.

Automatic curriculum reinforcement learning (ACRL): Curriculum learning has been extensively studied in the single-agent realm. A set of automatic curriculum generation methods are proposed [11] to control either the initial states [13], goal positions [14] or environment dynamics [15 8]. There are several possible objectives proposed to optimize over the controllable contexts in the current literature such as reward [16 8] and difficulty [14], where the difficulty differs from reward based methods by pursuing tasks with intermediate difficulty but not the easiest tasks. Similar to the learning progress concept proposed in this paper, several works [13 17] also employ the same idea to maximize the learning progress. However, we note that these methods still measure the learning progress based on the reward increases, while our method measures learning progress based on the critic loss from the underlying MARL
updates. In the following, we simply refer to these ACRL methods as reward-based ACRL methods and mainly build our work on one representative ACRL method, SPRL [8]. However, we argue that the improvement we make in the proposed SPMARL can be also applied to other reward-based ACRL methods when employed for MARL tasks.

Multi-agent curriculum reinforcement learning: Compared to extensive study in single-agent realm, only a few works have explored the multi-agent curriculum reinforcement learning. Dynamic Multi-Agent Curriculum Learning (DyMA-CL) [2] solves large-scale problems by starting learning from a small-size multi-agent scenario and progressing to the target number of agents, where the number of agents is manually chosen. EPC [3] increases the number of agents in the order of \( N \rightarrow 2N \), and proposes to train multiple parallel agents in each stage which are then crossed to select the best ones for the next stage. Variational Automatic Curriculum Learning (VACL) is principal method for curriculum learning [4] that formulates optimizing a curriculum distribution as a variational inference problem. While VACL provides a general method for controlling environment parameters, in their paper, it still follows a presumed order \( k^j = k + 1 \) or \( k^i = 2k \) to adapt the number of agents. Therefore, we abstract these curriculum MARL works as a Liner baseline, where we consider the increasing (from few to more) and decreasing (from more to few) curriculum in our experiments. Recently, [16] proposes selecting tasks based on the performance and the similarity to the target tasks. However, the similarity is measured based on the state visitation distribution which is hard to directly apply to tasks with different state spaces when the number of agents varies.

## 3 Background

In this section, we introduce the problem framework Dec-POMDP and the underlying MARL method we use, MAPPO [7]. As the underlying framework of curriculum learning, contextual reinforcement learning is also included.

### 3.1 Dec-POMDP

We study the decentralized partially observable Markov decision process (Dec-POMDP) problem [10], which can be formulated as a tuple: \((\mathcal{S}, \{\mathcal{O}^i\}_{i \in \mathcal{N}}, \{\mathcal{A}^i\}_{i \in \mathcal{N}}, r, \mathcal{P}, \gamma)\), where \(\mathcal{N} = \{1, \ldots, n\}\) denotes a set of agents. At time step \(t\) of each agent \(i\) observes local observation \(o^i_t\) from the full state \(s_t\) in the state space \(\mathcal{S}\) of the environment and performs an action \(a^i_t\) in the action space \(\mathcal{A}^i\) based on its policy \(\pi(\cdot|s^i_t) = \pi^1 \times \cdots \times \pi^n\). The environment takes the joint action of all agents \(\mathbf{a}_t = \{a^1_t, \ldots, a^n_t\}\), changes its state following the dynamics function \(\mathcal{P}: \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow [0, 1]\) and generates a common reward \(r: \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}\) for all the agents. \(\gamma \in [0, 1]\) is a reward discount factor. The agents learn their individual policies and maximize the expected return: \(\pi^* = \arg \max_{\pi} \mathbb{E}_{s, a \sim \pi, t}[\sum_{l=0}^{\infty} \gamma^l r(s_t, a_t)]\), where \(a_t^i\) is the joint action at time step \(t\) sampled from decentralized policies \(\pi^i(\cdot|s^i_t)\).

### 3.2 MAPPO

Multi-agent PPO (MAPPO) [7] is a popular MARL algorithm with strong performances on various benchmarks. MAPPO works in a straightforward way by applying single-agent PPO [19] to multi-agent learning while using a centralized critic with additional full-state information. In MAPPO, each agent learns a centralized state value function \(V(s)\), and the individual policy is updated by maximizing the following objective

\[
\max_{\pi_{\theta}} \mathbb{E}_{(s, a^i) \sim \pi^i}[\min(r(\theta)A(s, a^i), \text{clip}(r(\theta), 1 \pm \epsilon)A(s, a^i))] ,
\]

where \(r(\theta)\) is the importance ratio between the current policy and the previous policy used to generate the data,

\[
r(\theta) = \frac{\pi_{\theta'}(a^i_t | h^i_t)}{\pi_{\theta^i}(a^i_t | h^i_t)}
\]

The advantage \(A(s, a^i)\) is usually estimated by the generalized advantage estimator (GAE) [20] defined as Equation 3 where we use the full state information \(s\) thanks to the centralized training and decentralized execution (CTDE) [5] framework,

\[
A^\text{GAE}(\lambda, \gamma) = \sum_{l=0}^{\infty} (\gamma \lambda)^l \delta_{t+l},
\]

and \(\delta_t\) denotes the TD error

\[
\delta_t = r_t + \gamma V(s_{t+1}) - V(s_t).
\]
Figure 2: The paradigm of SPRL involves a two-stage optimization, where a teacher controls the context of tasks, i.e. the number of agents in the MARL setting, and a student interacts with the environment specified by the number of agents $n$ from the teacher and performs policy updates. In the first stage, before the expected performance achieves the threshold $V_{LB}$, the teacher maximizes the performance over the number of agents. The context distribution $p(c|\nu)$ is updated based on the episode returns of the sampled tasks, which results in an updated distribution $p(c'|\nu')$ moving towards tasks with higher returns. In the second stage when the pre-defined performance threshold once achieved, the teacher moves the context distribution to the target task denoted by the Dirac delta distribution $\mu(c)$ while maintaining the performance above the threshold $V_{LB}$. In both stages, the context updates are constrained by a KL divergence $\epsilon$.

3.3 Contextual Reinforcement Learning

Different from a typical Markov decision process (MDP) with fixed transition properties $M = \langle S, A, P, r, P_0 \rangle$, contextual reinforcement learning [21, 9] parameterizes MDPs by a contextual parameter $c \in \mathcal{C} \subseteq \mathbb{R}^m$ which can be certain environmental parameters, goals or initial states, while assuming a shared state-action space over these MDPs, $M(c) = \langle S, A, P_c, r_c, P_{0,c} \rangle$. The objective of contextual RL is defined as: $
abla \theta J(\theta, c) = \nabla \theta \mathbb{E}_{\nu}(\mathbb{E}_{\mu(c)}[V_{\theta}(s, c)])$, where we have the target context distribution $c \sim \mu(c)$ and initial state distribution $s \sim P_{0,c}(s)$. The value function $V_{\theta}(s, c)$ denotes the expected discounted return in states $s$ and under the context $c$ following the conditioned policy $\pi(a|s, c, \theta)$. Generally, contextual RL aims to generalize behavior over different tasks by exploiting the continuation between MDPs. In curriculum learning, we usually set the target context distribution $\mu(c)$ as a Dirac delta function, since we are interested in solving one specific task with fixed context $c$ while exploiting other tasks from different distributions $\nu(c)$ as curriculum.

4 Method

We first introduce self-paced reinforcement learning (SPRL) [8] and apply it directly to MARL by optimizing the number of agents w.r.t. the performance. Nonetheless, we show the ineffective learning problem and increased credit assignment difficulty in SPRL raised by simply pursuing tasks with higher returns. To address these problems, we further propose self-paced MARL (SPMARL) with a new objective indicating agents’ learning progress.

4.1 SPRL

Intuitively, in tasks where directly learning from the target context $\mu(c)$ is difficult, i.e. the maximization of the following objective is hard due to sparse reward under the target contexts,

$$
\max_{\theta} \mathbb{E}_{\mu(c)}[J(\theta, c)] = \max_{\theta} \mathbb{E}_{\mu(c), P_{0,c}(s)}[V_{\theta}(s, c)],
$$

(5)
While the straightforward SPRL for MARL is supposed to be able to successfully find easier tasks with high performance, we improve SPRL by proposing self-paced MARL (SPMARL) to optimize a new objective measuring the expected performance.

Our first proposed method directly applies SPRL to control the number of agents as context variables instead of the regular environmental parameters used in single-agent CRL. In practice, this constrained optimization problem in Equation 6 can be solved in a two-stage paradigm as shown in Figure 2. At first, when the expected performance is lower than $V_{LB}$, we maximize $E_p[J(\theta, c)]$ under the constraint $D_{KL}(p(c|\nu) \parallel p(c|\nu')) \leq \epsilon$ and obtain the new context distribution $p(c|\nu')$, which can be solved by the existing trust-region algorithms [22]. Secondly, once the performance achieves the threshold $V_{LB}$, we start to progress to the target context distribution $\mu(c)$ by minimizing $D_{KL}(p(c|\nu) \parallel \mu(c))$, under the KL divergence constraint. Note that in this stage, SPRL maintains the performance always above $V_{LB}$ by setting the context distribution unchanged until the performance is higher than the threshold again.

Our first proposed method directly applies SPRL to control the number of agents as context variables instead of the regular environmental parameters used in single-agent CRL.

4.2 SPMARL

While the straightforward SPRL for MARL is supposed to be able to successfully find easier tasks with high performance, and eventually mitigate the hard exploration problem due to sparse reward, we argue that the objective purely depending on the rewards in SPRL could lead to slow learning progress. This problem has been intuitively explained by the Simple-Spread task in Section 1. Motivated to address the problem, we improve SPRL by proposing self-paced MARL (SPMARL) to optimize a new objective measuring the learning progress.

---

**Algorithm 1** Self-Paced Multi-Agent Reinforcement Learning (SPMARL)

**Input:** Initial context with number of agents distribution $\nu_0$, initial policy parameters $\theta_0$, target context with number of agents distribution $\mu(c)$, expected performance threshold $V_{LB}$, number of iterations $K$, rollouts $M$ for each policy update, relative entropy bound $\epsilon$

for $k = 1$ to $K$ do

Policy Learning:

for $i = 1$ to $M$ do

Sample context, i.e., number of agents, $c_i \sim p(c|\nu_k)$

Rollout trajectory $\tau_i \sim p(\tau_i|\theta_k)$

end for

Obtain $\theta_{k+1}$ by the chosen MARL method and collected trajectories $D_k = \{(c_i, \tau_i) | i \sim [1, M]\}$

Estimate $V_{\theta_{k+1}}(s_{i0}, c_i)$ for context $c_i, i \sim [1, M]$

Context Distribution Update:

▷ Stage 1: Optimize the learning progress

if $\frac{1}{M} \sum_{i=1}^{M} V_{\theta_{k+1}}(s_{i0}, c_i) < V_{LB}$ then

Obtain $\nu_{k+1}$ from Equation 6 under the KL divergence constraint

end if

▷ Stage 2: Progress to the target

Obtain $\nu_{k+1}$ from Equation 6

end if

end for

---
progress over different tasks instead of the initial state values. The learning progress (LP) should be able to quantify the effective learning signal on each task.

**Intuition on the learning progress:** We are inspired by the nice property of value function $V^\pi(s)$ as it estimates the expected return of current policy $\pi_\theta$. The value loss, or critic loss, naturally measures how much policy change has been made over a specific task. Therefore, we believe the critic loss can be a favorable instantiation of learning progress. The critic loss used in SPMARL is following the one in MAPPO, which is defined as the following:

$$LP(c) = \frac{1}{2} E_{s,a \sim \pi(a|s,c)} [\| R(s, a) - V(s) \|^2],$$  

(8)

where $R(s, a)$ is the discounted return since state action pair $(s, a)$. We find that thanks to the CTDE framework allowing us to access the full state information during training, the estimation is sufficiently accurate. Moreover, learning progress exploits all the data samples for the estimation and hence results in more stable and effective context updates, while SPRL only updates based on sparse trajectory returns.

In SPMARL, we follow the two-stage optimization scheme in SPRL, but replace the reward objective of Equation 7 in the first stage with our new learning progress measurement

$$\max_{\nu_{k+1}} \frac{1}{M} \sum_{i=1}^{M} \frac{p(c_i|\nu_{k+1})}{p(c_i|\nu_k)} LP_\theta(c_i).$$  

(9)

We keep the second stage optimization the same as SPRL, i.e. keeping the same performance threshold $V_{LB}$. This is reasonable because even though we do not directly optimize returns over different contexts, the optimized learning progress objective will implicitly result in higher performance. As validated in our experiments, the curriculum generated by SPMARL even triggers a faster performance increase than SPRL. The detailed SPMARL is shown in Algorithm 1.

### 4.3 Implementation Factors

Several implementation details need to be considered when applying curriculum learning to control the number of agents. First, the changing number of agents usually leads to varying vector lengths of agents’ observation and we need to handle the new coming agents. Second, the context distribution in SPRL is usually implemented as a Gaussian distribution which is continuous while we need to optimize the discrete number of agents. Third, the existing MARL benchmarks rarely support setting different numbers of agents in a convenient way.

In SPMARL, we tackle the first difficulty by simply setting a fixed observation range for each agent when it doesn’t impact the performance much [23] or padding zeros to the state vectors. To handle the new coming agents, we adopt parameter sharing for all the agents so that the new agents can use the learned policy. For the second problem, we keep using the Gaussian distribution and simply discretize the sampled float contexts, which works well enough in practice. In the third problem, we create a set of environment wrappers for existing MARL benchmarks to easily change the number of agents. We believe these empirical tips together with the new environment wrappers can benefit the community for the curriculum MARL research. We open source our code in order to make it easier to reuse the environments and replicate the experiment results.

In addition, $V_{LB}$ is an important hyper-parameter in our algorithm. In our experiments, $V_{LB}$ can be usually set as the value of the expected return on the target task. The details can be found in our code.

### 5 EXPERIMENTS

We evaluate our method on three challenging benchmarks with severe sparse rewards, including 1) XOR game [11] with 10 agents, 2) MPE Simple-Spread task [5] with 8 agents, and 3) SMAC-v2 Protoss 5 vs. 5 task [12]. We compare SPMARL with both the straight application of SPRL and several heuristic baselines:

- **SPRL:** As a state-of-the-art automatic curriculum learning method, SPRL is directly applied to MARL settings to adaptively control the number of agents. SPRL also represents a set of general automatic CRL methods based on rewards [11].
- **Linear:** The linear scheme can be seen as an abstract of existing multi-agent curriculum learning works [2, 3, 4]. In Simple-Spread and XOR matrix game, we set a linearly increasing curriculum while in SMAC-v2 Protoss 5 vs. 5 task we use a linearly decreasing scheme in order to diversify the baselines.

\[^2\]Code is available: [https://anonymous.4open.science/r/spmarl-EE00](https://anonymous.4open.science/r/spmarl-EE00)
• Random: We set a Gaussian distribution in the random curriculum baseline. The random baseline can be strong as we set superior parameters with human knowledge. For example, in Simple-Spread and Protoss 5 vs. 5, the random baselines are set with a higher mean than the target task while in XOR a lower mean, which make the tasks much easier to learn.

• W/O teacher: This is the default MARL algorithm MAPPO trained directly on the target task without any curriculum.

5.1 MPE Simple-Spread

As shown in Figure 1, Simple-Spread involves several agents trying to cover all the landmarks as soon as possible. The original Simple-Spread task is designed with a dense reward function denoted by the negation of summed distances to each landmark. However, we test our method on a modified version which has quite sparse rewards and becomes challenging, where the agents can only obtain rewards when at least 4 landmarks are covered and the reward is the number of landmarks successfully covered at each timestep. We set the target task with 8 agents and 8 landmarks.

Analysis of the evaluation performance: The experiment results are shown in Figure 5 from which we can find the number of agents works as an effective curriculum variable to help overcome the sparse reward problem. In Figure 5a showing the episode returns evaluated on the target task during training, our method SPMARL outperforms SPRL by a faster convergence due to the faster-updated context distribution, which is analyzed in the following paragraph. It is reasonable that two baselines, Linear and W/O teacher, completely fail to learn any valid policies because of the severe sparse rewards. Linear generating curriculum from few to more agents even exacerbates the problem as in this task few agents have less chance to receive any non-zero rewards. We surprisingly find the random curriculum (Random) works pretty well. However, this is also reasonable as the average of the sampled number of agents is set sufficiently high around 10 agents, which means the random policy takes advantage of a human prior while our method and SPRL can automatically find the effective curriculum. Figure 5b presents the generated curriculum from different methods, from which we can find that SPMARL generates more agent tasks in a short time when SPRL is still exploring. Figure 5c shows the episode returns on the training tasks. The random policy achieves the highest because it always samples tasks with more agents as SPMARL and SPRL converge to the target tasks with 8 agents.

Analysis of the generated curriculum: It is interesting to observe the different curriculum generated by SPMARL and SPRL in Figure 5b. We can see that SPMARL updates the context distribution to more agents quickly while SPRL keeps exploring for a longer time. Consequently, SPMARL starts early to converge to the target task after achieving the performance threshold $V_{15}$ of 50. The resulting faster context updates in SPMARL can be attributed to two substantial advantages empowered by our proposed learning progress objective compared to the performance objective in SPRL. 1) Dense signal: In SPRL, the context update is based on the episode returns (i.e. the initial state values) of each
sampled context. However, at the beginning of training, the initial policies can rarely receive informative reward signals on most tasks, especially in tasks with extremely sparse rewards. Therefore, SPRL can only perform useful updates after sufficient policy improvement. Differently, SPMARL employs the critic loss from the underlying MAPPO as the learning progress measurement, which can be reliably obtained at any stage of training. 2) **Stable estimation:** The estimation of expected returns in SPRL is usually noisy as each episode can only correspond to one return. However, the critic loss over each context used in SPMARL is estimated based on all the state-action pairs, which helps to achieve a much more stable estimation than SPRL.

**Analysis of the training process:** The episode returns over the training tasks are closely related to the generated curriculum from different teachers. As shown in Figure 5c, Random achieves the highest training episode returns due to that it continuously samples tasks with more agents without caring about the target task. Even with the advantage of more agents prior, we find that Random does not lead to a better evaluation on the target task, which means that a principled curriculum learning method can benefit the agents more than imperfect prior.

### 5.2 XOR Matrix Game

In this subsection, we consider a cooperative game called $N$-player XOR game, where each player has $N$ possible actions and they will get a positive reward only if they output different actions. A simple example of 2-player XOR game is given by the payoff matrix shown in Figure 4. Although it could be easy to learn the optimal policy for 2-player XOR game, as $N$ increases, it becomes increasingly difficult to solve due to exponentially scaled policy space. In this case, a curriculum learning approach becomes necessary. In our experiments, we set the target task with 10 players.

As shown in Figure 5a, the default MAPPO without curriculum learning (W/O teacher) fails to learn any valid strategy, which confirms the necessity of curriculum learning. The same negative result can also be observed from the random policy (Random). For Random, since the context sampling heavily depends on human prior, it may fail to find the effective context, which eventually leads to poor performance. In the baseline with linear curriculum Linear (from few to more), as the contexts are drawn step by step, effective curriculum may be occasionally found, which leads to the case where it can find the optima eventually. However, since the linear scheme explores the entire context space, it is inefficient and unstable (Figure 5c). In contrast, for self-paced curriculum learning, the curriculum are found automatically. As a result, we can see from Figure 5b that SPRL and SPMARL do not need to traverse the entire space to find effective curriculum. More importantly, the SPRL and SPMARL significantly outperform the Linear in convergence speed.

**Figure 4:** Payoff Matrix of 2-player XOR game.

**Figure 5:** Comparison on the 10-player XOR game where each agent needs to output different actions to succeed. The left figure shows the evaluation returns on the target task with 10 agents, where the default MAPPO without curriculum learning (W/O teacher) and the baseline with random curriculum (Random) fail to learn any meaningful policy. Note that the plots of Random and W/O teacher are overlapped. While the linear curriculum from few to more (Linear) successfully achieves optima eventually, the SPRL and SPMARL demonstrate a faster convergence thanks to the automatic curriculum.

### 5.3 SMAC-v2
We further test our method on a more complex benchmark. We consider SMAC-v2 [12], a new version of the StarCraft Multi-Agent Challenge (SMAC), which increases the difficulty of SMAC by imposing higher stochasticity. Specifically, we evaluate SPMARL on the Protoss 5 vs. 5 task (Figure 6) with sparse reward. In this setting, the agents can only receive $1$ if win or $-1$ if lose at the end of the game.

As shown in Figure 7, due to the sparse reward significantly increasing the difficulty of learning in SMACv2, the default MAPPO without curriculum learning fails to learn any meaningful policies. In general, baselines with teachers can successfully learn qualified policies, demonstrating the necessity of curriculum learning in this task. Among curriculum learning methods, the automatic curriculum learning methods, i.e., SPRL and SPMARL, outperform the rule-based curriculum learning algorithms, i.e., Linear and Random, in both convergence speed and performance. We also observe that although SPMARL and SPRL achieve comparable final performance, SPMARL is superior in terms of convergence speed.

It is notable that in the Linear baseline, even though with superior prior knowledge designing curriculum from sufficiently high as high as 15 agents to the target number of 8 agents, it fails to show better evaluation performance on the target task. These can be attributed to the exacerbated credit assignment difficulty due to too many agents. On the contrary, our method SPMARL learns to decrease the number of agents when the current context distribution has a sufficient number of agents to meet the performance threshold. This pattern is also observed from SPRL. However, SPMARL shows a faster context change even though with the same KL divergence constraints as SPRL.

Figure 6: Screenshot from Protoss 5 vs. 5 in SMACv2 showing agents battling the built-in AI.

Figure 7: Comparison on Protoss 5 vs. 5 task of SMACv2 with sparse reward. The left figure shows the mean test win rate on the target task with 5 agents versus 5 enemies. Note that the default MAPPO without curriculum learning (W/O teacher) fails to learn any meaningful policy under sparse reward. The rule-based curriculum learning methods, i.e., Linear (from more to few) and Random, achieve satisfying performance, which is reasonable as we have employed superior human knowledge to set a higher mean of the random curriculum and a high-to-low linear scheme for the Linear baseline. Compared with Linear and Random, the self-paced curriculum learning methods demonstrate superior performance. In particular, SPMARL outperforms SPRL in convergence speed.

6 Discussion

The particular difficulty of MARL comes from the involving multiple agents. Curriculum learning provides a framework for solving difficult tasks by training agents starting from easier tasks. In the context of multi-agent learning, we seek the potential of employing a controllable number of agents to mitigate the pains arising from the multiple agents themselves. Our second proposed method, SPMARL, improves the convergence speed of the first straightforward SPRL for multi-agent learning by a novel learning progress objective but remains the two-stage optimization paradigm under the KL constraint, as shown in Figure 2. While the KL constraint was originally proposed to keep the performance continuity between context updates, the proposed SPMARL shows better performance improvement when not optimizing the performance directly. In spite we believe the KL constraint helps stabilize the training and benefits the initial attempt of this work, it is possible to further question the necessity of the KL constraint when employing our learning progress as the new optimization objective.
7 Conclusion

In this paper, we investigate how to control the number of agents as an effective curriculum. As existing works are limited to a pre-defined curriculum with heuristics such as a liner scheme, we first propose to directly apply the state-of-the-art CRL method SPRL to MARL. Although with satisfying performance, our analysis shows two potential flaws of general reward-based CRL methods for MARL: ineffective task generation despite high returns, and the increased credit assignment difficulty when more agents tend to yield higher returns. These problems can eventually lead to slow learning progress. Therefore, we further propose a SPMARL that prioritizes tasks based on learning progress instead of the episode returns to tackle these problems. The proposed method SPMARL optimizes one instantiated learning progress measurement, the critic loss, over the context distribution. Consequently, SPMARL can generate tasks that benefit the learning as much as possible. While not focusing on the performance directly, SPMARL turns out to implicitly increase the episode returns more effectively by improving the learning progress. The evaluation on three challenging benchmarks confirms our hypothesis of SPMARL by a faster convergence compared to the baselines. Moreover, SPMARL generates a set of interpretable tasks that are consistent with human priors.

References

[1] Rémy Portelas, Cédric Colas, Lilian Weng, Katja Hofmann, and Pierre-Yves Oudeyer. Automatic curriculum learning for deep rl: A short survey. In Christian Bessiere, editor, Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI-20, pages 4819–4825. International Joint Conferences on Artificial Intelligence Organization, 7 2020. Survey track.

[2] Weixun Wang, Tianpei Yang, Yong Liu, Jianye Hao, Xiaotian Hao, Yujing Hu, Yingfeng Chen, Changjie Fan, and Yang Gao. From few to more: Large-scale dynamic multiagent curriculum learning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 7293–7300, 2020.

[3] Qian Long, Zihan Zhou, Abhibav Gupta, Fei Fang, Yi Wu, and Xiaolong Wang. Evolutionary population curriculum for scaling multi-agent reinforcement learning. arXiv preprint arXiv:2003.10423, 2020.

[4] Jiayu Chen, Yuanxin Zhang, Yuanfan Xu, Huimin Ma, Huazhong Yang, Jiaming Song, Yu Wang, and Yi Wu. Variational automatic curriculum learning for sparse-reward cooperative multi-agent problems. Advances in Neural Information Processing Systems, 34, 2021.

[5] Ryan Lowe, Yi Wu, Aviv Tamar, Jean Harb, Pieter Abbeel, and Igor Mordatch. Multi-agent actor-critic for mixed cooperative-competitive environments. arXiv preprint arXiv:1706.02275, 2017.

[6] Tabish Rashid, Mikayel Samvelyan, Christian Schroeder, Gregory Farquhar, Jakob Foerster, and Shimon Whiteson. Qmix: Monotonic value function factorisation for deep multi-agent reinforcement learning. In International Conference on Machine Learning, pages 4295–4304. PMLR, 2018.

[7] YU Chao, A VELU, E VINITSKY, et al. The surprising effectiveness of ppo in cooperative, multi-agent games. arXiv preprint arXiv:2103.01955, 2021.

[8] Pascal Klink, Hany Abdulsamad, Boris Belousov, Carlo D’Eramo, Jan Peters, and Joni Pajarinen. A probabilistic interpretation of self-paced learning with applications to reinforcement learning. arXiv preprint arXiv:2102.13176, 2021.

[9] Tom Schaul, Daniel Horgan, Karol Gregor, and David Silver. Universal value function approximators. In International conference on machine learning, pages 1312–1320. PMLR, 2015.

[10] Christopher Amato, Girish Chowdhary, Alborz Geramifard, N. Kemal Üre, and Mykel J. Kochenderfer. Decentralized control of partially observable markov decision processes. In 52nd IEEE Conference on Decision and Control, pages 2398–2405, 2013.

[11] Wei Fu, Chao Yu, Zelai Xu, Jiqiqi Yang, and Yi Wu. Revisiting some common practices in cooperative multi-agent reinforcement learning. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvari, Gang Niu, and Sivan Sabato, editors, Proceedings of the 39th International Conference on Machine Learning, volume 162 of Proceedings of Machine Learning Research, pages 6863–6877. PMLR, 17–23 Jul 2022.

[12] Benjamin Ellis, Skander Moalla, Mikayel Samvelyan, Mingfei Sun, Anuj Mahajan, Jakob N Foerster, and Shimon Whiteson. Smacv2: An improved benchmark for cooperative multi-agent reinforcement learning. arXiv preprint arXiv:2212.07489, 2022.

[13] Carlos Florensa, David Held, Markus Wulfmeier, Michael Zhang, and Pieter Abbeel. Reverse curriculum generation for reinforcement learning. In Conference on robot learning, pages 482–495. PMLR, 2017.
[14] Carlos Florensa, David Held, Xinyang Geng, and Pieter Abbeel. Automatic goal generation for reinforcement learning agents. In *International conference on machine learning*, pages 1515–1528. PMLR, 2018.

[15] Tambet Matiisen, Avital Oliver, Taco Cohen, and John Schulman. Teacher–student curriculum learning. *IEEE transactions on neural networks and learning systems*, 31(9):3732–3740, 2019.

[16] Cédric Colas, Pierre Fournier, Mohamed Chetouani, Olivier Sigaud, and Pierre-Yves Oudeyer. Curious: intrinsically motivated modular multi-goal reinforcement learning. In *International conference on machine learning*, pages 1331–1340. PMLR, 2019.

[17] Siddharth Mysore, Robert Platt, and Kate Saenko. Reward-guided curriculum for robust reinforcement learning. In *Workshop on Multi-task and Lifelong Reinforcement Learning at ICML*, 2019.

[18] Jizhou Wu, Tianpei Yang, Xiaotian Hao, Jianye Hao, Yan Zheng, Weixun Wang, and Matthew E Taylor. Portal: Automatic curricula generation for multiagent reinforcement learning. In *Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems*, pages 2460–2462, 2023.

[19] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

[20] John Schulman, Philipp Moritz, Sergey Levine, Michael Jordan, and Pieter Abbeel. High-dimensional continuous control using generalized advantage estimation. *arXiv preprint arXiv:1506.02438*, 2015.

[21] Gerhard Neumann et al. Variational inference for policy search in changing situations. In *Proceedings of the 28th International Conference on Machine Learning, ICML 2011*, pages 817–824, 2011.

[22] Pauli Virtanen, Ralf Gommers, Travis E Oliphant, Matt Haberland, Tyler Reddy, David Cournapeau, Evgeni Burovski, Pearu Peterson, Warren Weckesser, Jonathan Bright, et al. Scipy 1.0: fundamental algorithms for scientific computing in python. *Nature methods*, 17(3):261–272, 2020.

[23] Wenshuai Zhao, Eetu-Aleksi Rantala, Joni Pajarinen, and Jorge Peña Queralta. Less is more: Robust robot learning via partially observable multi-agent reinforcement learning. *arXiv preprint arXiv:2309.14792*, 2023.