Trajectory Diversity for Zero-Shot Coordination

Extended Abstract

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ABSTRACT

We study the problem of zero-shot coordination (ZSC), where agents must independently produce strategies for a collaborative game that are compatible with novel partners not seen during training. In particular, our first contribution is to consider the need for diversity in generating such agents. Because self-play agents control their own trajectory distribution during training, their policy only performs well on this exact distribution. As a result, they achieve low scores in ZSC, since playing with another agent is likely to put them in situations they have not encountered during training. To address this issue, we train a common best response (BR) to a population of agents, which we regulate to be as diverse as possible. For that purpose, we introduce *Trajectory Diversity* (TrajeDi) - a differentiable objective for generating diverse reinforcement learning (RL) policies. We present TrajeDi as a generalization of the Jensen-Shannon divergence (JSD) between policies and motivate it experimentally in a simple matrix game, where it allows to find the unique ZSC-optimal solution.

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1 INTRODUCTION

In this paper, we use policy diversity within population based training (PBT) to improve cross-play (XP) scores in the ZSC framework.

ZSC [8] is the problem of independently training two or more agents in a cooperative game such that their strategies are compatible and achieve high return when paired together at test time. Since it is impossible to agree on an arbitrary strategy with all humans ahead of time, solving ZSC is required for human-AI cooperation, such as in rescue robots or self-driving cars.

The challenge of the ZSC framework arises from the fact that many collaborative settings admit multiple joint strategies that are optimal yet incompatible. Then, if we naively train two independent agents in self-play (SP) [10], there is no guarantee that they will converge to compatible policies.

To address this problem, we can rely on the game-theoretic relationships between the optimal SP policies. Notably, if we have access to the entire solution space, we can train an agent to be the common BR to the largest possible subset of that space. The resulting agent would then be robust to the maximum number of potential partners, making it a prime candidate for ZSC.

This approach allows to train good policies for ZSC, but requires access to a diverse pool of optimal policies to serve as the training set for the BR. To that end, we introduce *TrajeDi*, a differentiable objective allowing to drive diversity within a pool of policies in the context of PBT. Specifically, TrajeDi works as a generalization of the JSD between the different policies and, unlike other methods, is especially designed for use in partially observable multi-agent settings.

2 RELATED WORKS

There is a growing corpus of works featuring a measure of diversity in RL. Many leverage it as a means of exploration [2, 5, 7] or to learn less redundant options, in the case of hierarchical RL [4, 6, 9]. Diversity has also been used in a reward-free context as a method of pre-training [3].

Regardless of the application, past works tend to formulate diversity either per state ($\pi(a|s)$) [2, 7], as a function of state distributions ($\mathbb{P}(s|\pi)$) [3, 4, 9] or of state-action distributions ($\mathbb{P}(s,a|\pi)$) [5]. Unfortunately, these formulations are inadequate for multi-agent RL [1, 11], where non-Markovian dynamics require actions to be conditioned on the entire observation history. Since multi-agent settings are ultimately our main concern, we formulate TrajeDi accordingly, making it the first trajectory-based ($\mathbb{P}(\tau|\pi)$) diversity objective, to the best of our knowledge.

Finally, our work addresses directly the challenges of the ZSC framework introduced by Hu et al., which we summarize in section 3. For this setting, Hu et al. propose a suitable training method called "*Other-Play*" that leverages domain knowledge of the game symmetries to find unambiguous solutions that perform well. Since symmetries are not always present or known, we instead rely on the structure of the policy space to find such solutions. That being said, the two methods are compatible, and they address different aspects of ZSC. As such, we expect to use them jointly when applying TrajeDi to more complex settings in the future.

3 SETTING AND BACKGROUND

We assume a collaborative Dec-POMDP $\mathcal{M} = (k, \mathcal{S}, \mathcal{A}, P, r, o, \gamma_{\mathcal{M}}, T)$, where a joint-policy π over the k agents selects joint-actions $a = (a^1, ..., a^k) \in \mathcal{A}$ based on observations $o(s) = (o^1(s), ..., o^k(s))$ of environment states $s \in \mathcal{S}$, with probability $\pi(a|s)$. The environment dynamics are governed by unknown transition probabilities $P(s_{t+1}|s_t, a_t)$, upon which all agents receive a reward $r(s_t, a_t)$. Finally, $\gamma_{\mathcal{M}} \in [0, 1]$ and T are the reward discount factor and horizon, respectively, and so we let $R = \sum_{t=0}^{T} \gamma_{\mathcal{M}}^t r(s_t, a_t)$ be the discounted return.

[1] Work done while at Facebook AI Research.

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