Difference Rewards Policy Gradients

Extended Abstract

Jacopo Castellini
Dept. of Computer Science
University of Liverpool
Liverpool, United Kingdom
J.Castellini@liverpool.ac.uk

Sam Devlin
Microsoft Research Cambridge
Cambridge, United Kingdom
Sam.Devlin@microsoft.com

Frans A. Oliehoek
Dept. of Intelligent Systems
Delft University of Technology
Delft, The Netherlands
F.A.Oliehoek@tudelft.nl

Rahul Savani
Dept. of Computer Science
University of Liverpool
Liverpool, United Kingdom
rahul.savani@liverpool.ac.uk

ABSTRACT

Policy gradient methods have become one of the most popular classes of algorithms for multi-agent reinforcement learning. A key challenge, however, that is not addressed by many of these methods is multi-agent credit assignment: assessing an agent's contribution to the overall performance, which is crucial for learning good policies. We propose a novel algorithm called Dr.Reinforce that explicitly tackles this by combining difference rewards with policy gradients to allow for learning decentralized policies when the reward function is known. By differencing the reward function directly, Dr.Reinforce avoids difficulties associated with learning the Q-function as done by Counterfactual Multiagent Policy Gradients (COMA), a state-of-the-art difference rewards method. For applications where the reward function is unknown, we show the effectiveness of a version of Dr.Reinforce that learns a reward network that is used to estimate the difference rewards.

KEYWORDS

Multi-Agent Reinforcement Learning; Policy Gradients; Difference Rewards; Multi-Agent Credit Assignment; Reward Learning

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1 INTRODUCTION

Many real-world problems [23, 24, 27], can be naturally modelled as *cooperative multi-agent systems* [4]. Such problems have commonly been approached with *(deep) multi-agent reinforcement learning* (MARL) [3, 12, 13, 15]. In the paradigm of *centralized training with decentralized execution* (CTDE) [13, 19] agents use global information during training, but then only rely on local sensing during execution, thus avoiding the prohibitive complexity of a centralized solution [2, 18]. Multi-agent policy gradients (MAPG) [20] methods have become one of the most popular CTDE approaches [11, 14].

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However, one key problem that agents face with CDTE that is not directly tackled by many MAPG methods is *multi-agent credit assignment* [7, 17, 25, 28]. With a shared reward signal, an agent cannot readily tell how its own actions affect the overall performance. *Difference rewards* [9, 10, 21, 26] were proposed to tackle this problem: agents learn from a shaped reward that allows them to infer how their actions contributed to the shared reward.

Counterfactual Multiagent Policy Gradients (COMA) [11] is a state-of-the-art algorithm that does this differencing with a learned action-value function $Q(s, a)$. However, there are potential disadvantages to this approach: learning the Q-function is a difficult problem due to compounding factors of bootstrapping, the moving target problem [16], and Q's dependence on the joint actions [6, 8].

To overcome these potential difficulties, we propose *difference rewards REINFORCE (Dr.Reinforce)*, a new MARL algorithm that combines decentralized policy gradients directly with differencing of the reward function. Additionally, we provide a practical variant, called Dr.ReinforceR, that learns a centralized reward network during training for settings where the reward function is not known upfront. Although the dimensionality of the reward function is the same as the Q-function, and similarly depends on joint actions, learning the reward function is a simple regression problem and it does not suffer from the moving target problem.

2 DIFFERENCE REWARDS POLICY GRADIENTS

If the reward function $R(s, a)$ is known, we can directly use difference rewards with policy gradients. We define the *difference return* ΔG_t^i for agent i as the discounted sum of the difference rewards $\Delta R^i(a_t^i|s_t, a_t^{-i})$ from time step t onward:

$$\Delta G_t^i(a_{t:t+T}^i|s_{t:t+T}, a_{t:t+T}^{-i}) \triangleq \sum_{l=0}^{T} \gamma^l \Delta R^i(a_{t+l}^i|s_{t+l}, a_{t+l}^{-i}), \quad (1)$$

where $\Delta R^i(a_t^i|s_t, a_t^{-i})$ is the difference rewards for agent i, computed using the aristocrat utility [26]:

$$\Delta R^i(a^i|s, a^{-i}) = R(s, a) - \sum_{b^i \in A^i} \pi_{\theta^i}(b^i|s_t) R(s, \langle a^{-i}, b^i \rangle). \quad (2)$$

To learn the decentralized policies π_θ, we follow a modified version of the distributed policy gradients [20] that uses our difference return, optimizing each policy by using the update target:

$$\theta^i \leftarrow \theta^i + \alpha \gamma^t \Delta G_t^i(a^i_{t:t+T}|s_{t:t+T}, a^{-i}_{t:t+T}) \nabla_{\theta^i} \log \pi_{\theta^i}(a^i_t|s_t). \quad (3)$$

This way, each policy is guided by an update that takes into account its individual contribution to the shared reward, and an agent thus takes into account the real value of its own actions [1].

In many settings however, complete access to the reward function to compute the difference rewards is not available. Thus, we propose Dr.ReinforceR, which is similar to Dr.Reinforce but additionally learns a *centralized reward network* R_ψ, parametrized by a vector ψ, that is used only during training to estimate the value $R(s, \langle a^i, a^{-i} \rangle)$ for every local action $a^i \in A^i$. The reward network is trained to reproduce the sampled reward value $r_t \sim R(s_t, a_t)$ by minimizing a standard MSE regression loss:

$$\mathcal{L}_t(\psi) = \frac{1}{2} \Big(r_t - R_\psi(s_t, a_t) \Big)^2 . \quad (4)$$

Although the dimensionality of the function $R(s, a)$ that we are learning with the reward network is the same as that of $Q(s, a)$ learned by the COMA critic, learning R_ψ is a regression problem that does not involve bootstrapping or moving targets, thus avoiding many of the problems faced with an action-value function critic.

We can now compute an estimated ΔR^i_ψ to use in (1) as:

$$\Delta R^i_\psi(a^i_t|s_t, a^{-i}_t) \triangleq r_t - \sum_{b^i \in A^i} \pi_{\theta^i}(b^i|s_t) R_\psi(s_t, \langle b^i, a^{-i}_t \rangle). \quad (5)$$

Lemma 1. *Using difference return ΔG^i_t as the learning signal for policy gradients in* (3) *is equivalent to subtracting an unbiased baseline $b^i(s_{t:t+T}, a^{-i}_{t:t+T})$ from the distributed policy gradients in [20].*

Proofs of Lemma 1 and convergence are available in [5].

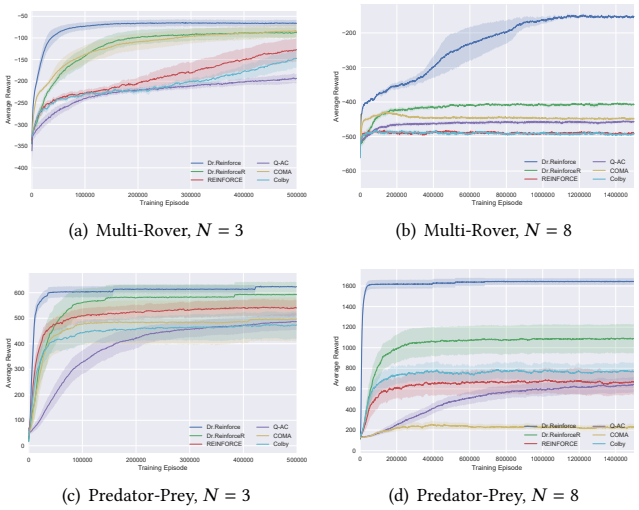
3 EXPERIMENTS

We are interested in investigating the following questions:

(1) How does Dr.Reinforce compare to existing approaches?
(2) How does the use of a learned reward network R_ψ instead of a known reward function affect performance?
(3) Is learning the Q-function (as in COMA) more difficult than learning the reward function $R(s, a)$ (as in Dr.ReinforceR)?

To investigate these questions, we tested our methods on the multi-rover domain [10], in which agents have to spread across a series of landmarks, and a variant of the classical predator-prey problem with a randomly moving prey [22]. We compare to a range of other policy gradients methods, including COMA [11] and an adaptation of the algorithm proposed by Colby et al. [9]. Additional results and analysis of the reward network are available in [5].

Multi-Rover Domain. While both COMA and Dr.ReinforceR easily learn good policies with three agents, when the system gets larger both begin to struggle, achieving sub-optimal performance. On the other hand, Dr.Reinforce learns high return policies. Given that this represents an upper bound to Dr.ReinforceR performance in case the reward network R_ψ learns a correct approximation, we can hypothesize that the gap in performance are due to a reward network: computing the difference rewards requires very accurate reward estimates, but the reward network may end up overfitting to the training reward samples and not exhibit appropriate generalization capabilities.



(a) Multi-Rover, $N = 3$ (b) Multi-Rover, $N = 8$

(c) Predator-Prey, $N = 3$ (d) Predator-Prey, $N = 8$

Figure 1: Training curves on the two problems, showing the mean reward and 90% confidence interval across 10 seeds.

Predator-Prey. In this environment, Dr.ReinforceR outperforms all the other methods, achieving performance that is equal or close to these of the Dr.Reinforce upper bound. In contrast, COMA struggles in learning something useful when more agents are introduced. This points out how accurately learning an optimal Q-function may be problematic in many settings: to compute the counterfactual baseline, estimates of Q-values need to be accurate even on state-action pairs that the policies do not visit often, rendering the learning problem more difficult. From this side, learning the reward function is an easier regression problem not involving bootstrapped estimates or moving target problems.

4 CONCLUSIONS

In cooperative multi-agent systems agents face the problem of figuring out how they are contributing to the overall performance of the team in which only a shared reward signal is available. We proposed Dr.Reinforce, a novel algorithm that tackles multi-agent credit assignment by combining policy gradients and differencing of the reward function. When the true reward function is known, our method outperforms all compared baselines and scales much better with the number of agents. For settings in which such reward function is not known, we proposed Dr.ReinforceR, that learns a centralized reward network used for estimating the difference rewards, which scales significantly better than COMA in the predator-prey benchmark.

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