Online Learning of Shaping Reward with Subgoal Knowledge

Extended Abstract

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ABSTRACT

SARSA-RS is a reward shaping method that updates the shaping through learning. However, the bottleneck of this method is the aggregation of states since designers need to design mappings from all states to abstract states. We propose a dynamic trajectory aggregation that uses subgoal series. The designer’s effort becomes minimal because only human input is the subgoal series. This makes application to environments with high-dimensional observations possible. We compared our method by using participants’ subgoal series with a baseline reinforcement learning algorithm and other subgoal-based methods in a navigation task. As a result, our reward shaping outperformed all other methods in learning efficiency.

KEYWORDS

Reinforcement Learning, Reward Shaping, Subgoal

ACM Reference Format:

1 INTRODUCTION

Reinforcement learning (RL) can acquire a policy maximizing long-term rewards. It is common for the state-action space to be quite large in a real environment. For that case, the learning becomes too slow to obtain optimal policies in a realistic amount of time. Since a human could have knowledge helpful to an agent in such cases, a promising approach is utilizing human knowledge [11, 15, 20].

The reward function is most related to learning efficiency. Most difficult tasks in RL have a sparse reward function [3]. Inverse reinforcement learning (IRL) [1, 18] is the most popular method for enriching the reward function. IRL uses an optimal policy to generate a dense reward function [13, 21].

2 SUBGOAL-BASED DYNAMIC TRAJECTORY AGGREGATION

We propose dynamic trajectory aggregation from states into abstract states with subgoal series. The method basically follows SARSA-RS [9], and the difference is mainly the aggregation function and minorly the accumulated rewards. Our method aggregates trajectories dynamically into abstract states during learning with subgoal series. We define a subgoal as a state \( s \) that is a subgoal if \( s \) is a goal in one of the subtasks decomposed from a task. A subgoal series is written formally as \((SG, \prec)\). \( SG \) is a set of subgoals and a sub-set of \( S \). There are two types of subgoal series, totally ordered and partially ordered. With totally ordered subgoals, a subgoal series is deterministically determined at any subgoal. In contrast, partially ordered subgoals have several transitions to the subgoal series from a subgoal. We use only the totally ordered subgoal series, but both types of ordered subgoals can be used for our method. Since an agent achieves a subgoal only once, the transition between subgoals is unidirectional. We assume that the subgoal series \((SG, \prec)\) is pre-defined, and \((SG, \prec) = \{sg_0 \prec sg_1 \prec \cdots \prec sg_n\}\).
2.1 Dynamic Trajectory Aggregation

We build abstract states to represent the achievement status of a subgoal series. If there are \( n \) subgoals, the size of abstract states is \( n + 1 \). The agent is in a first abstract state \( z_0 \) before it achieves a subgoal. Then, the abstract state \( z_0 \) transits to \( z_1 \) when the subgoal \( s_{g_0} \) is achieved. This means that trajectories are aggregated until subgoal \( s_{g_0} \) transits into \( z_0 \). The aggregated trajectories change dynamically every trial because of the policy with randomness. As the learning progresses, the aggregated trajectories become fixed. The value over abstract states is distributed to the values of states of the trajectory. Note that the trajectories for updating the value are different from those that the values are distributed to. The updated value function is not used for the current trial but for the next trials. An image of the dynamic trajectory aggregation is shown in Figure 1. As is shown, a circle is a state, and the aggregated states are in each gray background area. The bold circles express the states with which the designer deals. The number of bold circles in Figure 1(b) is much lower than Figure 1(a). “S” and “G” in the circles are a start and a goal, respectively. Figure 1(b) shows that the trajectory is separated into two sub-episodes, and each of them corresponds to abstract states.

2.2 Accumulated Reward Function

We clearly define the reward transformation function \( r_h \) because our method only updates the achievements of subgoals. We describe this formally as \( r_h = \sum_{i=0}^{N-1} \gamma^i r_i \), where \( N \) is the duration until subgoal achievement. The function accumulates rewards with discount \( \gamma \). Depending on the policy at the time, \( N \) is varied dynamically. This follows n-step temporal difference (TD) learning [19] because there are transitions between an abstract state \( z_i \) and another one \( z_{i+1} \).

3 EXPERIMENTS

We used a navigation task in pinball in OpenAI Gym [5]. Details can be found in [4]. We used a reward function generating a reward of +10000 when the agent reached the goal. This domain is difficult for humans because delicate control of the ball is necessary. We acquired ten patterns of two ordered subgoals from participants, and the evaluation was conducted using them with a PC [Core i7-7700 (3.6GHz), 16 GB of memory]. We compared our method with human subgoals (HRS) with three other methods, an actor-critic algorithm (AC) [14], our method with random subgoals (RRS), and naive subgoal reward shaping (NRS). The three reward shaping methods were implemented with AC. RRS used ten patterns of two randomly selected subgoals from the whole state space. NRS has the potential function \( \Phi(s) \) that outputs a scalar value \( \eta \) just when an agent has visited a subgoal state, and 0 otherwise. We set \( \eta \) as 10,000 so as to be the same value as the goal reward. The difference from our method is that there was a fixed value only for subgoals. All methods learned a total 100 times from scratch through 200 episodes. The learning took several tens of minutes. A subgoal had only a center position and a radius that was the same as the target. The agent achieved a subgoal when it entered the circle of the subgoal at any velocity. The setting of AC was the same as [4].

Figure 2 shows the subgoal distribution acquired from ten participants and from the random subgoals generated. In this figure, the color of the start point, the goal, and the subgoals are red, blue, and green, respectively. As shown in the figure, participants focused on four regions of branch points to set subgoals in comparison with random subgoals.

Figure 3 shows the learning curves of HRS, RRS, AC, and NRS. The learning indicator was the average number of steps per episode over learning 100 times. It took an average shift of 10 episodes. As is shown, HRS performed better than all other methods. RRS and NRS seemed to be almost the same as AC.

4 CONCLUSION

Although SARSA-RS incorporating state aggregation information into rewards is helpful, humans will rarely have to deal with all states in an environment with larger continuous observations. We proposed dynamic trajectory aggregation by which a human deals with several characteristic states as a subgoal. We evaluated a navigation task involving pinball with subgoals from participants. The experimental results revealed that our method with human subgoals enabled faster learning compared with the others. Our method could make SARSA-RS available without the mapping of all states, and learning was clearly accelerated. We plan to apply our method to an environment with image observations.
REFERENCES


