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Towards Explaining Sequences of Actions in Multi-Agent Deep Reinforcement Learning Models

Extended Abstract

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ABSTRACT

Although Multi-agent Deep Reinforcement Learning (MADRL) has shown promising results in solving complex real-world problems, the applicability and reliability of MADRL models are often limited by a lack of understanding of their inner workings for explaining the decisions made. To address this issue, this paper proposes a novel method for explaining MADRL by generalizing the sequences of action events performed by agents into high-level abstract strategies using a spatio-temporal neural network model. Specifically, an interval-based memory retrieval procedure is developed to generalize the encoded sequences of action events over time into short sequential patterns. In addition, two abstraction algorithms are introduced, one for abstracting action events across multiple agents and the other for further abstracting the episodes over time into short sequential patterns, which can then be translated into symbolic form for interpretation. We evaluate the proposed method using the StarCraft Multi Agent Challenge (SMAC) benchmark task, which shows that the method is able to derive high-level explanations of MADRL models at various levels of granularity.

KEYWORDS

Multi Agent Deep Reinforcement Learning; Explainable Artificial Intelligence; Explainable Deep Reinforcement Learning.

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1 INTRODUCTION

Multi-agent Deep Reinforcement Learning (MADRL) [5, 6, 22] has been demonstrated to solve complex real-world problems. However, MADRL models use black-box neural networks [17, 25, 29, 31, 39], making the explanation of the learned knowledge contained in such models challenging [9, 14, 23]. Explainable AI (XAI) systems or models aim to offer the predictions in a form that is explainable

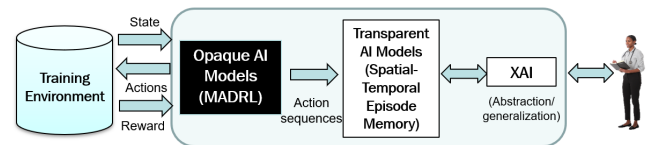


Figure 1: A general framework for explaining opaque MADRL models using transparent self-organizing neural network models and post-hoc abstraction algorithms.

and understood by humans [1, 3, 21] without a significant amount of additional knowledge from the human participants [15, 16, 33].

Under the umbrella of XAI, various methods have been proposed for explaining Deep Reinforcement Learning (DRL) models [8, 11, 18, 27, 36]. These methods differ in the form of interpretation and explanation of the implicit knowledge in the DRL models [2, 10, 24]. Some recent work have discussed how low-level sequences of actions can be converted to a high-level explainable form [28, 34]. Although these works are able to abstract agent's action sequences, they are not applicable to the multi-agent domain. On the other hand, Heuillet et al. have proposed using Shapley Values for MADRL model interpretation [20], leading to a general approach for explaining cooperative strategies and agent contribution in a multi-agent system. However, Shapley values cannot explain the actions taken by the agents and the episodic behaviour [7, 12].

This study aims to explain the behavior of MADRL models through interpreting the sequences of action events performed across multiple agents over time. Specifically, we adopt an *explanation by simplification* [19] approach which translates the sequences of low-level primitive action (called episodes) into short and high-level sequences (called abstracted episodes). For empirical evaluation, we have conducted extensive experiments using the SMAC [26, 38, 40] game environment. The results show that the proposed approach can simplify the sequences of action events performed by multiple agents and transform them into comprehensible strategies. More importantly, the abstracted and simplified strategies could potentially be adopted by another multi-agent team to produce performance comparable to those of the original MADRL agents in playing the game.

2 APPROACH AND METHODOLOGY

Our approach to explaining MADRL models is by transferring the learned behaviour into a more transparent episodic memory model

and explaining in terms of the sequence of action events performed by the multiple agents. As illustrated in Figure 1, we propose a general framework, wherein the knowledge and behaviour of the black-box MADRL agents (in the forms of the sequences of action events performed by the agents over time) are transferred into a collective sequential memory model based on spatio-temporal neural networks. The memory model, considered as a more transparent AI model, also serves to generalize the sequences of action events across multiple episodes before they are further simplified and abstracted by XAI algorithms for interpretation. Accordingly, the research problems to be addressed can be defined as (1) to design a sequential memory model to learn and abstract the collective trajectories and action events of multi-agent units and (2) to interpret the spatio-temporal action patterns across multiple agents learned by the sequential memory model in symbolic form.

To this end, we present a spatio-temporal neural network model based on a modification of Episodic Memory–Adaptive Resonance Theory (EM-ART) model [32, 37] for encoding and generalizing sequences of action events performed by MADRL agents *across multiple episodes*. In addition, by encoding the time stamp of the action events explicitly using complement coding [30] in a time field [13], an interval-based memory retrieval procedure is developed to generalize the encoded actions and behaviour patterns of the agents over a selected time interval into short abstract sequential patterns. Previously used for retrieving events over a selected time interval in Spatio-Temporal Episodic Memory (STEM) model [4], the *interval-based memory retrieval* method averages the features values of all events occurring within the time interval so as to abstract and discern dominant events. For tuning the degree of abstraction over time, the method incorporates a parameter called *abstraction factor* which can be chosen according to the length of abstracted sequences (and time interval) as preferred by the user.

Furthermore, two new algorithms called Significant Event Selection for Episode Abstraction (SESEA) and Repeated Event Reduction for Episode Abstraction (REREA) are presented for abstracting the episodes of action events encoded by EM-ART into *sequences of significant action events* and *sequences of unique action events* respectively. The combination of various abstraction algorithms serves to transform the long sequences of action events performed by MADRL models into short abstract episodes of notable events (strategies).

3 EXPERIMENTS

Our experiments are conducted using the StarCraft Multi-Agent Challenge (SMAC) [26] which is a set of mini-games developed based on the StarCraft II (SC2) [35, 41] real-time strategy (RTS) game platform. We consider a combat scenario called **4t**, wherein two groups of identical units, namely the allied group trained by MADRL model and the enemy group based on built-in rules, are symmetrically placed on the map and the objective of the game is to maximize the win rate. The agents are homogeneous in the reported experiments wherein the type of actions they can perform are the same. To train the MADRL team, we employ QMIX [25], which has produced competitive performance in the SMAC environment.

In our experiments, a collection of 1,100 episodes performed by MADRL model is recorded after learning is completed. Subsequently, we built EM-ART models using various EM-ART vigilance

Time Interval	Action	Time Interval	Action
t1-t3	WWWW	t16-t18	$A_3A_3A_3A_3$
t4-t6	SNNS	t19-t21	$A_1A_3A_1A_1$
t7-t9	WWWW	t22-t24	$A_1A_1A_2A_1$
t10-t12	EEEE	t25-t27	$A_2A_2A_2A_2$
t13-t15	$A_0A_0A_0A_0$	t28-t30	$A_2A_2A_2E$

Table 1: A set of abstracted events extracted by EM-ART using time-based memory retrieval. Legend of actions: N, S, E, and W indicate move[north], move[south], move[east], and move[west], respectively; A_i indicates attack[enemy_ i]; - indicates stop; and X indicates no_op.

parameter values to study their effects on learning and generalization of events and episodes. Table 1 shows a set of abstracted events from winning episode extracted by the EM-ART model using the interval-based memory retrieval algorithm with an abstraction factor of 10. Based on the extracted episode, the two abstraction algorithms are further applied and the final episode abstracted over agents and time is shown in Table 2.

Time Interval	Action	Time Interval	Action
t1-t3	W	t13-t15	A_0
t4-t6	SN	t16-t18	A_3
t7-t9	W	t19-t24	A_1
t10-t12	E	t25-t30	A_2

Table 2: A winning strategy derived with event abstraction over agents and episode abstraction over time.

We note that the sequence of low-level actions performed by the MADRL agents can be explained in terms of high-level abstracted strategies as follows. At the group level, the multi-agent team performs a series of the move actions before proceeding with the attack actions. At the subgroup level, agents also perform strategic positioning before engaging in firing. During the combat, the agents perform coordinated attack on the same enemy unit by always attacking enemies in a specific order (A_0 , A_3 , A_1 followed by A_2). Though the reported evaluation is based on the **4t** scenario, our method can be used to explain both single agent and multi-agent models and can be scaled according to the number of agents.

4 CONCLUSION

To explain how a team of trained MADRL agents selects their actions cooperatively, a spatial-temporal memory called EM-ART can be used to encode the sequences of actions performed by the team of decentralized agents trained using the MADRL model. More importantly, the action sequences can be further generalized and abstracted using the time-based retrieval method and the two episode abstraction algorithms. The results have shown that the proposed approach is able to explain the behavior of the multi-agent team by means of the generalized and abstracted episodes. The developed methods are also generalizable to other scenarios as the abstraction factor (across time) and the level of abstraction (across agents) parameters enable the methods to be applicable to episodes of different length and any number of agents. Beyond explaining the action sequences observed, it will be interesting in the future to also consider contextual information captured in the state attributes, for further explaining the decision-making process of MADRL agents.

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