Explainability in autonomous pedagogically structured scenarios

Minal Suresh Patil
Umeå universitet
UNIVERSITETSTORGET 4
907 36 Umeå, Sweden
minal.patil@umu.se

Abstract
In this work, we present the notion of explainability for decision-making processes in a pedagogically structured autonomous environment. Multi-agent systems that are structured pedagogically consist of pedagogical teachers and learners that operate in environments in which both are sometimes not fully aware of all the states in the environment and beliefs of other agents thus making it challenging to explain their decisions and actions with one another. This work emphasises the need for robust and iterative explanation-based communication between the pedagogical teacher and the learner. Explaining the rationale behind multi-agents decisions in an interactive, partially observable environment is necessary to build trustworthy and reliable communication between pedagogical teachers and the learners. On-going research is primarily focused on explanations of the agent’s behaviour towards humans, and there is a lack of research in inter-agent explainability.

Introduction
Pedagogy refers to “the interplay between teachers, students and the learning environment and the learning tasks” (Murphy, Hall, and Soler 2012). Pedagogy includes how teachers and students relate together through instructional methods implemented in a classroom-like setting. There are two primary approaches to pedagogy: teacher-centred and learner-centred. Though at first sight, these two approaches seem on the opposite side of the spectrum, however, they often can accompany each other in achieving objectives. For instance, a teacher-centred pedagogy is crucial when the teacher is introducing a new theme and objective to the learners and whilst learner-centred pedagogy allows for these learners to explore and gain a deeper understanding of these objectives on their own. In a learning scenario, the learner-centered approach will allow agents to create new knowledge by integrating prior knowledge of the environment with unique experiences of its own. The pedagogical teacher not only enables this process but also generates and structures the settings for learning the environment. Another approach which is a relatively new pedagogical method is the learning-centred pedagogy (Bremner 2019) combines the best of both worlds, where the pedagogical teacher considers local and contextual information of the environment, such as the availability of resources, time and cost. In Multi-Agent Systems (MAS), the learning-centred approach is more effective since the pedagogical teacher ensures adaptability of their pedagogical approaches based on the environment. For example, MAS have become an integral part of the defence industry and play an active role in various military activities such as path planning, surveillance, assessment and attack. However, agents’ explanation generation in uncertain and dynamic environments is a challenging problem for MAS. Early relevant works have demonstrated the power of explanations (Van Lent, Fisher, and Mancuso 2004) for combat purposes, which recorded decisions made by agents during a combat mission, provide reasons for the decisions and handle counterfactual queries through a knowledge guided execution as opposed to plans generated by the agents. As pedagogical MAS become more self-supporting and independent of human intervention, explanation generation between agents becomes a pivotal point in understanding their interactions with each other and the environment.

Problem Identification
Explainable inter-agent pedagogy involves a teacher(s) communicating and assigning tasks to a learner(s), and these agents produce explanations for their decisions during their course of action. Through this work, we define a mandate as instructions communicated and explanations generated by the teacher to the learner and vice-versa in a human-style format. However, understanding the internal representations and beliefs between learners is an essential aspect for inter-agent explainability (Omicini 2020). Thus an explainable pedagogically structured environment must have the following attributes:

- Learners that can counterfactually think and communicate with the pedagogical teacher. Counterfactual thinking considers alternative scenarios for past or future events: what might transpire or what might have transpired? This allows learners to gain valuable experience from their mistakes, enabling them to do better in similar tasks in the future. This allows for the learners to rigorously test the environment for the optimal reward through
trustworthy and reliable communication with other learners.

- Open MAS must allow for agents to enter and leave the environment at any instance without the need for human intervention through robust and reliable explanations during a planning or scheduling task.
- In scenarios where the teachers have complete knowledge of the system, they must have the ability to break down a labyrinth task into a series of simple and explainable sub-tasks under resource, time and cost constraints.

**Theory of Mind for Learners**

Theory of Mind (ToM) ([Premack and Woodruff 1978](#)) is an important concept that involves thinking about mental states, both of your own and those of others. This enables humans to infer intentions of others, and also understand what is going in someone’s mind, such as beliefs, expectations and fears. The ToM concept is critical in providing explanations to other agents in terms of beliefs and expectations and be able to update their beliefs using optimal explanations. It is rather necessary to adequately understand inter-agent communication for an effective collaborative planning task and provide explanations when necessary. A significant development in the explainability of agent’s decision and communication ability is to integrate ToM since it is a well-established framework when humans collaborate and generate explanations for their actions whilst achieving their objectives as well as the team’s objectives. To be able to measure the trust of an explanation in a multi-agent environment, a Partially-Observable Markov decision process (POMDP) was implemented to generate explanations and measure the trust using survey data ([Wang, Pynadath, and Hill 2016](#)). Furthermore, ([Chakraborti et al. 2017](#)) proposed a framework where explanations produced by a robot were reconciled to a human’s model.

Thus, we can see it is critical to understand not only trust but also the technique used to produce the explanation. Intelligent multi-agent systems are fundamental elements of an autonomous environment. According to ([Wooldridge 2009](#)), the purpose of an agent is to achieve a its objectives in a stochastic environment through computational processes in a flexible and self-governing manner without the need for regular human intervention. Preferably, learners should learn from their experience of the environment in a continuous manner and must be able to possess the ability to cooperate and interact with each other. We propose an extension of Wooldridge’s work ([Wooldridge 2009](#)) identifying four essential contextual capabilities of learners in a learning-centred approach environment:

- **Autonomy:**
  The ability to perform complex tasks and subtasks without the need for humans to intervene by using their own internal beliefs and intentions.

- **Awareness:**
  The ability for agents to perceive and be aware of their environment and take appropriate decisions to achieve their objectives.

- **Proactivity:**
  An agent’s ability to take control of its actions to achieve its goals.

- **Sociability:**
  An agent’s ability to interact with other agents to understand their beliefs and intentions whilst achieving their objectives.

**Beliefs, Desires and Intentions for Learners**

The Beliefs, Desires and Intentions (BDI) model ([Georgeff et al. 1998](#)) is a framework commonly used whilst building intelligent agents. The underlying philosophical argument for using BDI for MAS is that humans interact with the environment using the following criteria: a set of beliefs consist of knowledge of the environment, a set of desires consist of motivation to complete objectives and a collection of intentions consist of plans to achieve the agent’s objectives. Beliefs represent interim knowledge of the agents and usually is subject to change as and when the agent explores the world, i.e. environment. The BDI model uses core concepts that humans use to reason and act in everyday situations, thus integrating this framework for the learning-centred approach in MAS is necessary. Desires of an agent represent the top priority objective that must be achieved during its lifetime, i.e. a planning episode. Intentions of agents are resource bound and represent the commitment to achieving the objective. According to Torsun ([Torsun 1995](#)), to achieve goals, the agents must have the ability to undertake the following: Commitment; Communication; Conflict Resolution; Cooperation; Interaction; Negotiation. The need for coordinated behaviour between the teacher and the learner and how they share and explain information such as objectives, knowledge, strategies and plans to make decisions and take necessary actions is important to achieve the common objective. Taking forward the learning-centred approach for an explainable pedagogically structured environment we define four important desiderata:

- **Behavioural Explanations:**
  Behavioural explanations must be generated by the agents to explain their behaviour to the teacher as well as to other agents in the system. These explanations could be developed through their past experiences whilst planning a similar task or produce explanations based on agents that have planned similar tasks. Agents could also provide contrastive explanations and reasons for their behaviour in achieving one objective over another to their teacher.

- **Intention Explanations:**
  Intention explanations are necessary explanations for determining the course of action to achieve objectives of one’s self and the overall goal. Post-hoc explanations for choosing a certain of action to achieve could provide insights into how agents prioritise planning tasks on the fly.

- **Timely Explanations:**
  Timely explanations must be provided by the learner to the teacher. It is possible in planning scenarios, where constant monitoring of all the agents is not feasible.
Trustworthiness: Building trust into MAS is critical in planning applications for defence and military purposes. One of the significant challenges of multi-agent explainable AI Planning is agents exhibiting malicious behaviour by sharing false plans or strategies. Often, MAS comprises of asynchronous agents and heterogeneous agents. In asynchronous MAS, updates are executed asynchronously whilst maintaining the overall/global objective and heterogeneous MAS, updates are executed asynchronously whilst maintaining the overall/global objective and heterogeneous agents. In asynchronous MAS, false plans or strategies can arise due to internal conflicts, faults, environmental conditions or when agents are stressed to achieve a particular objective, thus making agents untrustworthy of their actions and decisions. Chang and Kuo proposed a Markov Chain Trust Model (Chang and Kuo 2008) that uses the trust level of an agent as a state, and through the agent’s experience and behaviour, the trust level is computed.

Perceptual Explanations: Perceptual explanations are explanations that agents must be provided once they gather their own as well as the other agents’ knowledge (beliefs, desires or intentions) of the environment after the teacher has issued a set of instructions. Learners must have the ability to explain how and why it decided to merge or discard knowledge or strategies from other learners.

Challenges and Opportunities

Curse of Dimensionality during Belief Augmentation of Agents: In a MAS planning environment, the issue of belief augmentation occurs when agents interact and exchange information about the agent's states. According to Gmytrasiewicz and Doshi (Gmytrasiewicz and Doshi 2005) they propose an Interactive-POMDP which maintains their own belief as well the beliefs about other agents. This often results in an increase in the complexity of the belief space due to nesting of beliefs of all the agents, which often leads to intractability. Partially Observable Markov Decision Processes (POMDPs) provide a natural model for sequential decision and planning under uncertainty. However, finding exact solutions for finite-horizon POMDPs are PSPACE-complete (Papadimitriou and Tsitsiklis 1987) and for infinite-horizon POMDPs is undecidable (Madani, Hanks, and Condon 1999). For I-POMDPs the complexity is at least PSPACE-complete because it can be accounted for the fact that an I-POMDP can consist of multiple POMDPs of other learners in the system. As the size of belief dimension increases, a solution that accommodates the agent’s beliefs over all other agents’ actions, intentions and beliefs are still open to research.

Conclusion

This work has introduced four important explainable desiderata which can provide a road-map for multi-agent systems in a pedagogically structured environment. Overall, establishing a standard metric for explanations for a pedagogically structured environment is of paramount importance. In critical domains such as defence and marine, Situational-Awareness (SA), Context-Awareness (CA) and Active Perception (AP) describe an agent’s awareness and perception and to be able to explain their actions and decisions during planning are of utmost importance and almost life-saving. Existing works from sociology, psychology, and cognitive science can be leveraged to make pedagogically structured environments explainable, transparent and reliable.

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