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Highly Interpretable GNNs for Deploying Real-World Multi-Agent Systems

Multi-Agent (MA) problems have been demonstrated in a wide range of applications including surveying and exploration[1], [2], aiding construction management[3], water quality monitoring[4] and assisting disaster evacuation[5]. Many techniques have been employed to these ends with some more common approaches including expert designed model based controllers[6]–[9] and Multi-Agent Reinforcement Learning (MARL)[10]–[14]. MARL has been the subject of increased attention recently, with groups its applicability demonstrated in simulation and lab environments[10], [15], [16], as well as in controlled real-world settings[4], [12], [17]. However, the most commonly identified shortcoming of MARL is a lack of human interpretable explanations for why an agent is taking a certain action, although developing metrics for this is an active research area[18]–[20]. This work is crucial for systems to operate in unstructured and uncontrolled real-world human environments where the ability to both prevent and diagnose errors are incredibly important.

Both traditionally designed model-based controllers and MARL controllers have advantages and drawbacks. For example, model-based controllers are highly interpretable; they depend on a designer specifying a fixed set of rules and constraints who then derives controls laws which satisfy them. However, they suffer in terms of generality as a change in system dynamics often means rederiving the control laws, and implementation for complicated tasks often requires devising complicated decentralized logic to drive cooperation. MARL has an almost converse set of issues with policies often lacking interpretability but being highly general given proper training. Developing better tools to interpret the behavior of MARL algorithms is one of the major roadblocks to wide-scale real-world implementation. There are many ways to improve interpretability of MARL techniques, with various authors doing this by carefully designing network structures or employing post-hoc reasoning to rationalize decisions, among other methods[18], [20]. One promising approach from the past few years has been the use of Graph Neural Networks (GNNs) to improve model interpretability [12], [17], [21]. These models achieve better interpretability by representing MA systems as graphs where agents are nodes with information stored as relations between nodes, which proves to be a very interpretable perspective in MARL. To that end, the proposed research is the development and testing of interpretable GNNs for use in MA Systems acting in unstructured real-world environments.

The goal of this study is to produce a GNN based MARL framework which is capable of coordinating communication to allow agents to pathfind in partially observable real-world environments. The work extends current implementations of MARL to allow for better integration into everyday unstructured environments containing people. Phase 1 (6 months) will focus on development and in-lab verification of a set of interpretability metrics for MA systems. Phase 2 (6 months) focuses on deployment in unstructured but access-controlled real-world environments to ensure the algorithm behaves safely while giving interpretable rationale. Finally, phase 3 (1 year) will focus on scaling the study to real-world, human environments where uncontrolled interaction between agents and humans may occur. The required resources would be a collection of unmanned vehicles with hardware to enable decentralized communication and coordination and controlled spaces for experiments.

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