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HW #1: Multiagent Literature Review

1. Neural Networks or Deep Learning

Wu, Y., Fan, M., Cao, Z., Gao, R., Hou, Y., & Sartoretti, G. (2024). Collaborative Deep Reinforcement Learning for Solving Multi-Objective Vehicle Routing Problems. *Autonomous Agents and Multiagent Systems (AAMAS 2024)*, *IFAAMAS*, 10 pages.

Solving Multi-Objective Vehicle Routing Problems (MOVRPs), which involve optimizing conflicting objectives, has been paid attention over time. These problems are essential to various industries for minimizing cost and require balancing multiple conflicting factors, making them significantly complex. It is challenging that solving MOVRPs involve conflicting objectives that need to be optimized simultaneously. Current deep reinforcement learning (DRL) methods for MOVRPs typically divide them into smaller subproblems with respective preferences, and then train policies to solve corresponding subproblems. Conventional DRL is still less efficient in addressing the complex interactions between subproblems. To handle the gap, Wu et al.(2024) proposed Preference-based Attention Network (PAN) consisting of an encoder shared by Single-Objective VRPs (SOVRPs) and a decoder tailored for each SOVRP by the hybrid intervention and designed a Collaborative Active Search (CAS) to improve the solution quality through imitation learning. For effective optimization, the authors used collaborative learning mechanism where agents can communicate and exchange insights of elite solutions each other. The outcome is that the proposed approach outperformed existing DRL methods, particularly in configurations beyond the training scenarios.

2. Teaming or Team Formation

Seo, S., Han, B., & Unhelkar, V. (2023). Automated Task-Time Interventions to Improve Teamworkusing Imitation Learning. *Autonomous Agents and Multiagent Systems (AAMAS 2023)*, *IFAAMAS*, 10 pages.

Human-autonomy teaming (HAT) has been essential for interacting with autonomous technology. It focuses on improving coordination in teamwork. Effective teamwork is crucial in fields where time pressure and efforts to form well-coordination are needed to manage critical tasks. The challenges are particularly relevant in time pressures that can make coordination substantially difficult to achieve goals and imperfect coordination that can bring about poor performance. Current approaches include team training, self-assessment, and debriefing to improve coordination. These methods are either pre-planned or post-hoc and fail to provide real-time interventions to help teams adapt during task execution. According to the paper, Seo et al. (2023) presented Task-time Interventions for Improving Collaboration (TIC), a system that uses a multi-agent imitation learning to learn team behavior from past and current task executions and generate real-time interventions to improve teamwork. The use of real-time intervention generation is a novel approach to address the problem, detecting poor coordination and suggesting intervention during tasks, which is important to time-critical collaborative environments. The authors demonstrated and proved their algorithm improving team performance in simulation. The automated interventions are effective in trading off intervention costs with task performance gains, enhancing teamwork.

3. Multi-Robot Coordination

Dong, Y., Li, Z., Zhao, X., Ding, Z., & Huang, X. (2023). Decentralised and Cooperative Control of Multi-Robot Systems through Distributed Optimisation. *Autonomous Agents and Multiagent Systems (AAMAS 2023)*, *IFAAMAS*, 9 pages.

Extensive research on achieving multi-robot cooperative control system has been crucial due to its various applications in security and military domain. It is to enable a group of robots to coordinate and perform tasks optimally while using only information from local communication between neighboring robots. The challenges include managing restricted communication among robots, ensuring global optimality despite decentralized information, and addressing heterogeneous systems where different robots have not similar dynamics. Current approaches often rely on formulated consensus problems in which robots converge to common value based on their initial positions and on continuous-time systems, which are limited by assumptions about initial conditions. The gap of existing approaches depends on initial states of the robots, limiting flexibility. Dong et al. (2023) designed an output-regulation based distributed optimization algorithm to control the physical multi-robot systems, allowing the system to find out global optimal solution and operate effectively in heterogeneous discrete-time systems through local communication with neighbor robots. The combination of distributed optimization and output regulation for heterogeneous, discrete-time systems, allowing robots to independently manage their local objectives. The proposed algorithm was validated both in simulation and real-world experiments with Turtlebot robots, resulting in successful optimization of multi-robot coordination against errors and noise.