The Report of AAAI 2025 Workshop 11: Cooperative Multi-Agent Systems Decision-Making and Learning: Human-Multi-Agent Cognitive Fusion*

Qin Yang[1], Giovanni Beltrame[2], Alberto Quattrini Li[3], Christopher Amato[4]

[1] Computer Science and Information Systems Department, Bradley University
[2] Department of Computer Engineering and Software Engineering, Polytechnique Montreal
[3] Department of Computer Science, Dartmouth College
[4] Khoury College of Computer Sciences, Northeastern University
is3rlab@gmail.com, giovanni.beltrame@polymtl.ca, alberto.quattrini.li@dartmouth.edu, camato@ccs.neu.edu

Abstract

Many domains of AI and its effects are established, which mainly rely on their integration modeling cognition of human and AI agents, collecting and representing knowledge using them at the human level, and maintaining decision-making processes towards physical action eligible to and in cooperation with humans. Especially in human-robot interaction, many AI and robotics technologies are focused on human-robot cognitive modeling, from visual processing to symbolic reasoning and from reactive control to action recognition and learning, which will support human-multi-agent cooperative achieving tasks. However, the main challenge is efficiently combining human motivations and AI agents' purposes in a sharing architecture and reaching a consensus in complex environments and missions. To fill this gap, this workshop brings together researchers from different communities interested in multi-agent systems (MAS) and human-robot interaction (HRI) to explore potential approaches, future research directions, and domains in human-multi-agent cognitive fusion.

Workshop Topic

Cooperative MAS needs cognitive science because it provides a better understanding and more accessible models of individual cognition, based on which it can develop better models of aggregate processes through multi-agent interaction. Specifically, when we analyze natural agents, such as humans, they are usually combined motivation entities. They have biological motivations, including physiological, safety, and existence needs; social motivation, such as love and esteem needs; and cognitive motivation, like self-actualization or relatedness and growth needs (Merrick and Maher 2009). The combined motivation theories include Maslow's Hierarchy of Needs (Maslow 1958) and Alderfer's Existence Relatedness Growth (ERG) theory (Alderfer 1972). Especially those combined motivations drive humans to develop various behaviors and strategies, such as self-interest and altruism, satisfying their diverse needs and presenting different personalities and characteristics in their interactions. As higher-level intelligent creatures globally, humans have more complex and diversified needs such as personal security, health, friendship, love, respect, and recognition. Considering humans and AI agents, like robots, working as a team, organizing their needs and getting a common ground is necessary for human-robot collaboration in complex and uncertain environments (Yang and Parasuraman 2020a, 2024). In the invited speakers section, Pro. Katia Sycara (Carnegie Mellon University) discussed the modeling trust in Human-Swarm collaboration and Pro. Peter Stone (University of Texas at Austin) introduced the advances in Ad Hoc Teamwork: multi-agent collaboration without pre-coordination.

On the other hand, decision-making and learning in human-multi-agent cooperation motivate the collaboration of researchers from MAS and HRI using AI. The related topics include modeling human-multi-agent cognitive fusion, building robust, stable, and reliable cognitive trust networks, and implementing deep reinforcement learning in human-multi-agent interaction. Considering the interactions between human agents and artificial intelligence agents like human-robot interaction (HRI), building stable and reliable relationships is of utmost importance in MAS cooperation, especially in adversarial environments and rescue missions (Yang and Parasuraman 2020b, 2021). Pro. Benjamin Kuipers (University of Michigan) discussed the relationship between trust and utility. From the game theory perspective, Pro. Panagiotis Tsiotras (Georgia Institute of Technology) introduced the training multi-agent reinforcement learning games with mean field interactions and Pro. Kevin Leyton-Brown (University of British Columbia) discussed the Human-Like Strategic Reasoning via ML. From the cognitive modeling perspective (Sun, Merrill, and Peterson 2001; Sun 2001), it may provide a more realistic basis for understanding human-multi-agent cooperation by embodying realistic constraints, capabilities, and tendencies of individual agents in their interaction, including physical and social environments. Pro. Sven Koenig (University of Cali-

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fornia, Irvine) talked about multi-robot systems – ant robots and auction robots. The other crucial problem is how to build a robust, stable, and reliable cognitive trust network among humans and AI agents, such as trust among robots and between humans and robots, evaluating their performance and status in a common ground when they make collective decisions and learn from interactions in complex and uncertain environments. Pro. Maria Gini (University of Minnesota) introduced the topic about "Can I trust my teammates? Are they friends or foes?". Moreover, to explore practical and efficient reinforcement learning methods, Pro. Matthew E. Taylor (University of Alberta) talked about how to design and examine the rewards rewards via a multi-agent lens.

One important issue we address in this workshop is how to model human-multi-agent cognitive fusion from the individual intrinsic values perspective, such as agent needs and innate values (presenting as various expected utilities) (Fishburn, Fishburn et al. 1979; Merrick 2013), in their decision-making and learning. The paper "Innate-Values-driven Reinforcement Learning" proposed a new RL model that supports the AI agent's lifelong development to bridge the gap in the traditional RL. Fourteen peer-reviewed papers were presented in the workshop, including five oral and nine poster presentations. They covered types like MAS RL in communication, Smart Manufacturing, Bayesian Trust Metric, multi-agent imperfect-information games, cognitive MAS RL, innate-values-driven RL, etc. Some were accepted by the IEEE CogSIMA conference and other AI journals. The recording, photos and papers, of the workshop are available at workshop site:

https://www.is3rlab.org/aaai25-cmasdl-workshop.github.io/

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