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Abmarl: Connecting Agent-Based Simulations with Multi-Agent Reinforcement Learning

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Summary

Abmarl is a package for developing Agent-Based Simulations and training them with Multi-Agent Reinforcement Learning (MARL). We provide an intuitive command line interface for engaging with the full workflow of MARL experimentation: training, visualizing, and analyzing agent behavior. We define an Agent-Based Simulation Interface and Simulation Manager, which control which agents interact with the simulation at each step. We support integration with popular reinforcement learning simulation interfaces, including gym.Env (Brockman et al., 2016) and MultiAgentEnv (Liang et al., 2018). We leverage RLlib's framework for reinforcement learning and extend it to more easily support custom simulations, algorithms, and policies. We enable researchers to rapidly prototype MARL experiments and simulation design and lower the barrier for pre-existing projects to prototype Reinforcement Learning (RL) as a potential solution.

Statement of need

In 2016, Brockman et al. (2016) published OpenAI Gym, an interface for single-agent simulations. This interface quickly became one of the most popular connections between simulation and training in RL experimentation. It has been used by many simulation benchmarks for single-agent reinforcement learning, including the Arcade Learning Environment (Bellemare et al., 2013). Since then the field of Deep Reinforcement Learning (DRL) has exploded in both algorithm development and simulation design, and over the past few years researchers have been extending their interest to Multi-Agent Reinforcement Learning (MARL). Surprisingly complex and hierarchical behavior emerges in the interaction among multiple agents, especially when those agents differ in their objectives (Bowen Baker, 2020).

To train agents with Multi-Agent Reinforcement Learning, one needs two components: simulation and algorithm (also commonly referred to as environment and agent). Much effort has been given to the development of MARL algorithms, which has brought us exciting breakthroughs and enhancements in the field of artificial intelligence. Our aim, however, focuses on the simulation component of MARL.

Several projects have attempted to define a standard set of benchmark scenarios for Multi-Agent problems. In their groundbreaking work, Lowe et al. (2020) introduced MADDPG, a "centralized training, decentralized execution" multi-agent algorithm. Along with their algorithmic development, they created Multi-Particle Environment (MPE) (now managed as a part of PettingZoo) as a benchmark suite that includes continuous movement and communication features. Zheng et al. (2018) produced scalable grid-based simulations and demonstrated emergent behavior in multi-team games on the order of millions of agents. Samvelyan et al. (2019) and Perez-Liebana et al. (2019) brought RL research closer to home, giving researchers access to dozens of multi-agent scenarios in the popular games StarCraft and Minecraft, respectively. Suarez et al. (2019) also targeted video games by supporting MARL in MMORPG-styled simulations with persistent, open-ended tasks among multiple agents. Zhou et al. (2020) brought us realistic traffic simulation scenarios to lead society towards autonomous driving.

Each of these efforts and more are great milestones in RL simulation. Naturally, each of them couples the simulation interface with the underlying simulation. Terry et al. (2020) have attempted to unify some of the more popular simulations under a single interface, giving researchers easier access to these simulations. While this is a step towards a standard multi-agent interface, most simulation efforts are tied to a specific set of already-built simulations with limited flexibility.

Abmarl defines an interface for multi-agent simulations that is versatile, extendible, and intuitive. Rather than adapting gym's interface for a targeted multi-agent simulation, we have built an interface from scratch that allows for the greatest flexibility while connecting to one of the most advanced, general-purpose, and open-source libraries: RLlib (Liang et al., 2018). Our interface manages the loop between agents and the trainer, enabling the researcher to focus on simulation design and algorithmic development without worrying about the data exchange.

We developed and tuned Abmarl's intuitive command-line interface through practical experience while working on (Dawson et al., 2021). Our interface gives researchers a running-start in MARL experimentation. We handle all the workflow elements needed to setup, run, and reproduce MARL experiments, providing direct access to train, visualize, and analyze experiments. We streamline the savvy-practitioner's experience and lower the barrier for new researchers to join the field. The analysis module sets Abmarl apart from others as it provides a simple command line interface to add analytics to trained policies, allowing researchers to generate additional statistics and visualizations of agent and simulation metrics after the policy has been trained.

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