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Maximizing Cooperative Behavior in Collective Action Games Through a Deep Q-Learning AI Agent

Keywords: collective action game, reinforcement learning, public goods game, conditional cooperation, game theory

Extended Abstract

Collective action problems are a class of frequently occurring problems in society where individual interests within a group clash with the group's optimal outcome. These difficulties emerge when cooperation among group members would bring about maximum benefit for the group, but self-interest takes precedence. Scenarios showcasing these problems range from simple, such as seating arrangements at a concert, to complex, like global carbon emissions, water conservation, and military spending (collectively, every country benefits if nobody invests heavily in the military but individually countries have incentives to invest heavily in their militaries for personal protection).

Following prior research in economics, there are three groups of people who behave differently in conditionally cooperative games: free riders, cooperators, and conditional cooperators. Cooperative and free-riding behaviors can be observed in real examples of collective-action games. Consider these scenarios: At a movie theater, audience members cooperate by staying seated for a comfortable viewing experience. However, in the realm of industrial development, many businesses prioritize their own interests over managing climate impact, an example of free-riding behavior since they are acting selfishly while hoping others act in a manner beneficial for the climate.

Conditionally cooperative behavior, on the other hand, "depend[s] on the subjects' perception of future behavior", which is established via group behavior. [2]. Typically, in situations where conditionally cooperative actors have the chance to contribute varying amounts of resources over the course of multiple rounds, conditionally cooperative agents will decrease their contributions over time [1] [2] to a level approaching free riding. As a consequence, conditionally cooperative actors cannot be trusted to cooperate amongst themselves. One approach to influence them into cooperative behavior can be using AI posing as a fellow agent.

The premise of AI masquerading as a human to help individual behavior was established in 2016 when researchers developed chatbots that masqueraded as an expert, a curious peer, and a mentor in an online class to help students learn. The researchers found that the introduction of the agents "led to significant changes in learning and motivation" [3]. While this principle has been applied to education - a largely individual endeavor for each student - prior research has not explored application of a similar idea to collective action problems and group collaborations.

This begs the question, which has been unanswered in prior research: Is there a way that an AI agent, which has learned from past experiences in training as opposed to definite rules, could trigger conditionally cooperative humans to act cooperatively instead of selfishly? Humans in this situation tend to behave in the manner their group does, which shows there is room for the group to influence each human, especially early on in the collective action game while humans have not ascertained the group dynamic. An individual actor, whose singular objective is to manifest the collective outcome, may be able to use their actions to foster a cooperative environment early and thus drive group members towards a cooperative strategy in the collective action game.

The setup of the collective action game is as follows: the four agents that play are 3 Bush-Mosteller agents (agents that emulate human conditional cooperators) [1] and a fourth agent. The fourth agent is another Bush-Mosteller agent in the control group or one of two reinforcement learning agents in each of the test groups. The reinforcement learning agents used the PPO algorithm to maximize the objective functions they were given, which were either the sum of the Bush-Mosteller agents' contributions or the number of contributions the hBush-Mosteller agents made that were over 0.5. For the purposes of this paper, the first one will be referred to as the ”sum” agent and the second one will be referred to as the ”prop” AI agent. It is worth noting that neither of these reward functions directly factor in the amount of tokens each agent has for itself.

Both the sum AI agent and the prop AI agent significantly increased the sums and proportions of contributions, respectively, with notable statistical significance (see Table 1). The sum AI agent performed slightly better in terms of both the total sum of the human agents' contributions as well as the number of contributions the human agent made over 0.5.

The key difference in the baseline games where only Bush-Mosteller agents played and the games where AI agents influenced the Bush-Mosteller agents was the trend in contributions each round. In the baseline games, the Bush-Mosteller agents would decrease their contributions by about 0.015 each round on average. When the sum AI agent played, the agents would increase their contributions by about 0.072 on average, and when the prop AI agent played, the Bush-Mosteller agents would increase their contributions by about 0.062 on average. By increasing the rate that the Bush-Mosteller agents upped their contributions each round, especially in the later rounds, the AI agents were able to increase the sum of contributions the Bush-Mosteller agents made as well as the number of contributions over 0.5 they made.

In conclusion, we find that reinforcement learning has the potential to significantly improve the outcomes of conditionally cooperative agents, which most humans are. We also find that precisely what the AI agent tries to maximize - the net sum of the other agents' contributions or the proportion of contributions over 0.5 - appeared to have minimal impact on the net result. It is possible that the strategies for maximizing both from the perspective of the AI agent are the same, which is why the differences are negligible.

References

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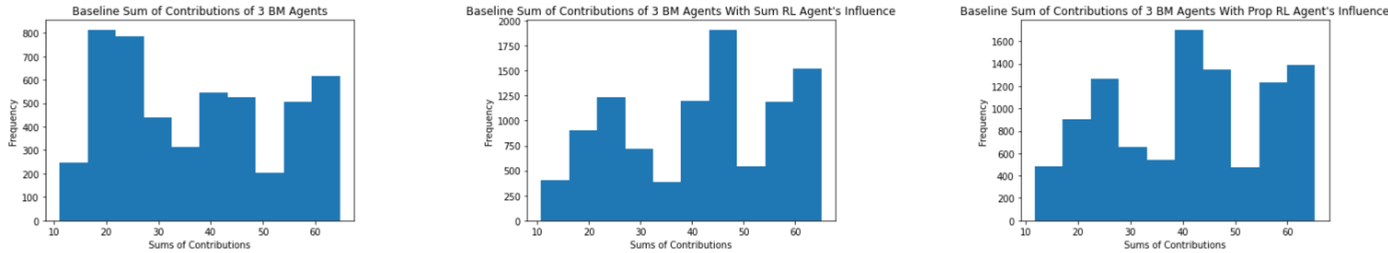

Fig. 1: The distributions of the average sums of contributions of Bush-Mosteller agents with a baseline (Bush-Mosteller) agent’s influence, sum AI agent’s influence, and prop AI agent’s influence.

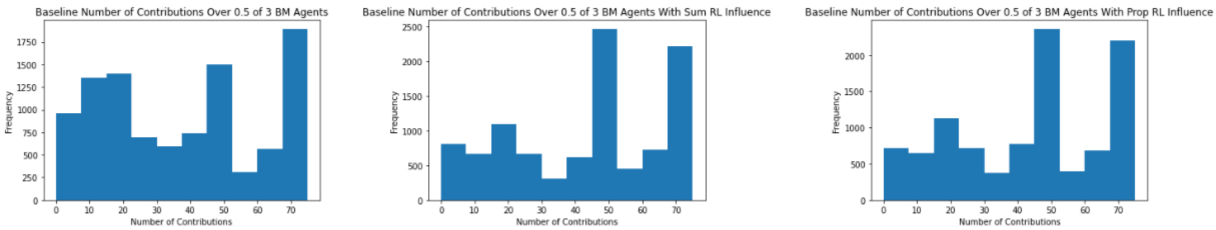

Fig. 2: The distributions of the average number of contributions over 0.5 by Bush-Mosteller agents with a baseline (Bush-Mosteller) agent’s influence, sum AI agent’s influence, and prop AI agent’s influence.

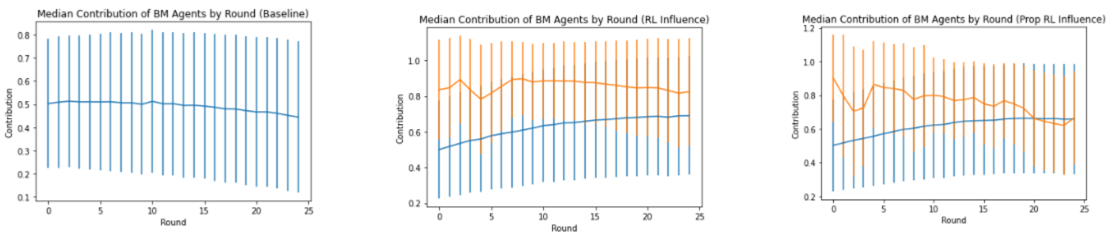

Fig. 3: The amount the AI agents contributed each round on average (orange) and the amount each Bush-Mosteller (BM) agent contributed in each round on average (in blue).

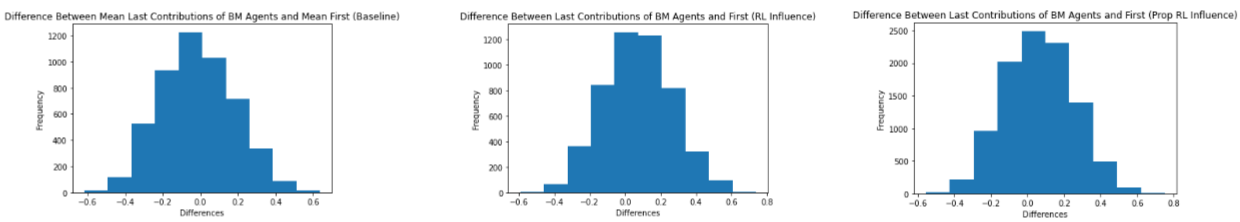

Fig. 4: The mean difference between the first and last contribution of the Bush-Mosteller agents in baseline game and under the influence of each of the AI agents.

Table 1: **Results of Baseline (Bush-Mosteller) Agent, Sum RL Agent, and Prop RL Agent**

Value	Baseline Mean	Mean With Sum RL Agent Influence	Mean With Prop RL Agent Influence
Sum of Contributions	37.229	41.314 (improved with p = 3.673e-60)	41.071 (improved with p = 3.722e-66
Number of Contributions Over 0.5	37.5014	43.352 (improved with p = 5.386e-58)	43.2426 (improved with p = 2.564e-64)