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Maintaining Unintuitive Algorithmic Strategies within Human Culture: The Role of Selective Social Learning

Keywords: cultural evolution, human-machine collaboration, selective social learning, cognitive biases, artificial intelligence

Extended Abstract

Artificial intelligence (AI) is advancing astonishingly, leading us wonder how it will impact human culture. AlphaGo Zero, for example, surpassed human performance in the game of Go within days of training, starting from scratch. Professional GO players now train with these models, and there is evidence that humans have adopted new strategies inspired by AI [5]. However, whether algorithmic strategies will irreversibly influence human culture remains to be seen. A necessary condition is the maintenance of an algorithmic strategies or behavior in the absence of the AI “teacher.” Building on a rich literature of lab-based experiments on human culture [2], we recently showed that human biases could hinder the transmission of algorithmic solutions [1]. However, cultural tools such as selective social learning can maintain complex strategies that are difficult to learn [6]. This ongoing study investigates whether selective social learning can maintain unintuitive algorithmic strategies within human culture.

In this behavioral study, we aim to examine the maintenance and spread of an algorithm-derived strategy in a multi-generational population. In our earlier research, we constructed transmission chains involving both humans and algorithms and found that humans transmit solutions that mismatch their own biases with reduced fidelity and therefore, human participants tended to lose superior solutions induced by the algorithm during repeated transmission [1]. However, recent experimental evidence suggests that allowing participants to choose who to learn from is crucial to maintaining complex solutions within a multi-generational group experiment [6]. Such selective social learning allowed maintaining complex and high-performing solutions within the population despite considerable transmission loss. In the present study, we investigate the role of selective social learning as a cultural tool for maintaining algorithmic strategies. We conducted an agent-based simulation, which confirmed that selective social learning could enable the collective maintenance of unintuitive strategies that would otherwise be lost in linear transmission chains. We now intend to confirming these results in an online experiment.

Human cognition and algorithmic computation are subject to different constraints [3]. Biases and heuristics enable humans to make effective decisions despite limited experience. For instance, humans tend to avoid further exploration of a sequential solution that starts with a large loss [4]. In contrast, algorithms can leverage their computational speed to find strategies that may contradict human biases. To explore this idea further, we developed a version of the reward network task [4] that includes an optimal strategy that conflicts with human bias. We then created a reinforcement learning-based agent that reliably discovers and demonstrates this unintuitive strategy to human participants.

Our web-based experiment is designed to allow participants to learn both individually and socially, as well as to transmit learned strategies through both demonstration and written description. In initial pilot experiments, we found that humans struggle to

identify the optimal strategy for the task when learning independently. However, we also found that when humans were exposed to the optimal strategy, they could articulate it in written form. Drawing from these results and the agent-based simulation, we are currently conducting a larger version of the experiment with twenty multi-generational transmission networks, each consisting of five generations with eight participants in each generation. Participants in this experiment can choose two models from the previous generation to learn from. We provide them with the models' average performance on the task to enable selective learning from successful models.

In our experiment, we are testing two conditions: the hybrid and control conditions. In the hybrid condition, three of the first generation's players are replaced by algorithmic players, while in the control condition, all players are human. To minimize variance caused by differing performance within the first generation, some players of the first generation are shared between both conditions.

Our study investigates the role of selective social learning in cultural evolution and its implications for the evolution of an anticipated human-machine culture. We aim to provide insights into the potential for algorithmic strategies to influence human culture irreversibly and, more broadly, shed light on the interplay between human biases and selective social learning. In addition to these objectives, we also plan to investigate the role of different modes of communication in the spread of unintuitive strategies.

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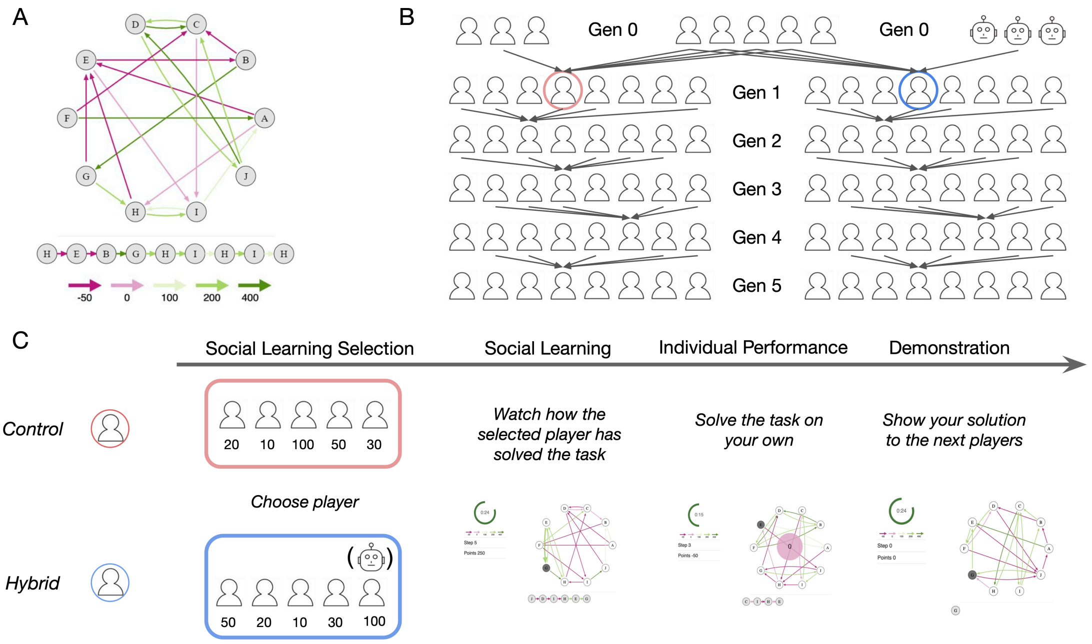

Figure 1: (A) Example of stimulus used in the experiment. The stimulus, referred to as reward network, comprises ten nodes. Each node has two outgoing edges associated with a numerical reward $r \in [-50, 0, 100, 200, 400]$. During a trial the task for a player is to navigate the network beginning from a starting node: using maximum eight steps the goal is to maximize the cumulative reward. (B) Overview of a single multi-generational transmission network. Within one transmission network the first generation, Generation 0, corresponds to the start of the experiment tree and comprises human players (control condition) and algorithmic players (hybrid condition). In addition, a subset of human players in Generation 0 is shared across the two conditions. Players complete and transmit solutions to the reward network task to the next generations, until the final Generation $n = 5$ is reached. (C) Overview of the experimental phases for the control (red) and hybrid (blue) condition. During the social learning selection phase, the player chooses a "teacher" among a set of model players, given their average score. Importantly, all model players are presented identically, including the algorithmic players in the hybrid condition. After observing the model player's solutions to the task in the social learning phase, the player moves on to trials testing individual performance. Finally, we record in a set of demonstrations trials solutions that are then shown in the social learning phase of the next generation.