Comparing social learning strategies in collective search: simulation and empirical evidence in patent data

NK landscape, social network, social learning, innovation, simulation

Extended Abstract

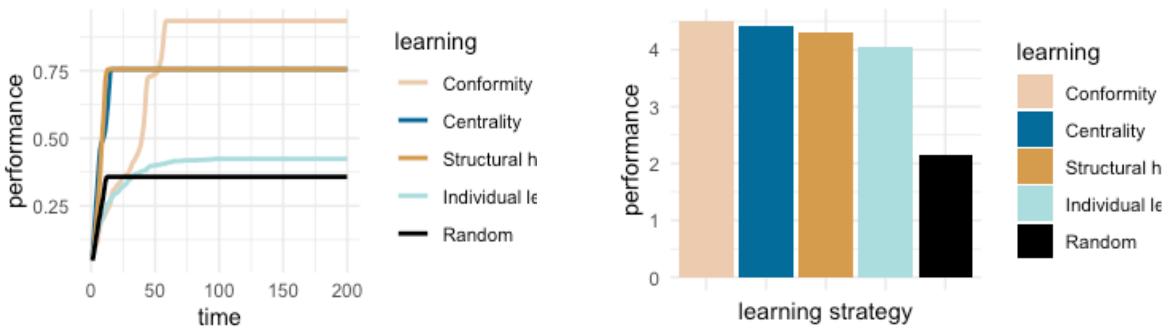
How learning biases influence learning results in complex environments is a long-standing question in social science. One approach is to search for the optimal solution based on the complexity of the environment and find the balance between exploitation and exploration (Kauffman & Weinberger, 1989). Another common approach uses cultural evolution to understand the mechanism and evolution of different individual and social learning biases (Boyd & Richerson, 1985). Recent work combines two approaches to understand how groups improve their performance through social learning strategies in a rugged landscape (Mason & Watts, 2012; Barkoczi & Galesic, 2016), with a focus on payoff-biased learning and frequency-biased learning. However, in fast-evolving stochastic areas like science, innovation, and art creation, payoffs can be hard to observe or predict immediately. Thus, indirect bias, including prestige and influence, are more likely to be used as visible "role model" traits for individuals to imitate. Social network theory provides a rich theoretical framework that connects network positions with indirect biases, including prestige, power, and influence. Do learning biases toward advantageous network positions, including high-centrality nodes and structural holes, lead to better group performance in complex environments?

In this research, we model indirectly-biased network learning strategies in an NK landscape based on theories in cultural evolution and social networks to search for the optimal network learning strategy in complex environments. We then construct intra-organizational inventor network and develop measures for search, learning and performance in US patent data to validate the modeling result. Our simulation is based on Kauffman's NK model, a classic model for complex system and collective intelligence. We first develop a model of problem-solving in which a group of agents repeatedly search for the best solutions in a rugged landscape with N components and K dimensions. When the environment is complex, agents can be stuck in several local maxima, which stops them from finding the global optimal solution. Social learning enables the exchange of information, allowing the group to search for the best solution. Extended on Barkoczi and Galesic's social learning model (2016), we compare the group performances between indirectly-biased network learning strategies (bias towards high centrality and bias towards structural holes), frequency-biased learning strategy, individual learning strategy and random strategy. We found that in complex environments and efficient networks, bias towards the majority produce better outcomes than bias towards high centrality or structural holes (See Figure 1a).

We then test the conclusions from simulation models on the empirical data of technological inventions (i.e., patent data, provided by the United States Patent and Trademark Office). Individuals and organizations in innovation are strategic actors who try to generate the most influential and applicable technologies, yet cannot easily achieve this goal due to the complexity and uncertainty in the environment. Social network position and prestige are more visible and thus are more likely to be used as learning bias in such contexts. Previous studies show that the NK model serves as an useful representation of innovative search (Ganco, 2017) for patent data, and empirical coding of the NK landscape based on technological classifications successfully replicates the parameter relationships embedded in the NK framework. As most patents are assigned to organizations (firms, governments and NGOs), the organizational boundary provides a natural cut of inventor networks for searching and learning (Paruchuri & Awate, 2017). To measure individual network learning, we divide the patent data into three periods (1985-1995, 1995-2005 and 2006-2015) and focus on the organizations (assignees) with more than 50 patents in all three time periods. We then construct intra-organization inventor networks by their collaborations to estimate social learning pathways. Overall, those networks follow efficient network structures.

To quantify knowledge, we construct a high-dimensional vector of technological classes for each inventor based on their knowledge expertise. We then measure knowledge shifts by calculating the distance of the inventor's knowledge vectors between two time periods. To estimate the knowledge transmission pathway, we regress an individual's knowledge shift on their neighbors' knowledge vector, estimating the direction and strength of neighbors' influences on the ego actor's knowledge shift. For example, a significant positive coefficient on high centrality neighbors indicates successful centrality-biased network learning. In the case where several strategies are valid, we choose the one with the highest positive coefficient; in the case where no strategy is valid, we assume that the focal inventor goes with "random" because the strategies, even existing, seem to be impossible to identify. Finally, we use five-year forward citations as the measure of patent impact (Kaplan & Vakili, 2015), and aggregate it to the inventor level to measure the inventor's performance in the next period.

Matching the network structure and environmental complexity to the modeling parameter space, our empirical data supports the modeling results that learning from the majority leads to better performance than learning from structural holes or high-centrality neighbors. The random strategy always has the worst performance, followed by individual learning(See Figure 1b). The preliminary results show that the network learning model provides credible explanations for learning pathways in the complex environments of innovation and opens up opportunities for further understanding of learning biases and performances in networks.



(a)simulation result

(b) Empirical patent data result

Figure1. Simulation and empirical result comparison

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