Network Structure shapes the Impact of Diversity in Collective Learning

skill diversity, network density, collective performance, social learning, complexity

Extended Abstract

In today's world, people communicate more frequently than ever before. And the denser social networks get, the more diverse problem-solving teams become. Despite the importance of both concepts – network structure and diversity – we do not yet have a clear understanding of how they interact to shape group performance. While most empirical studies on diversity have not taken into account network structure as a factor [1, 2], most previous theoretical efforts have focused on populations of identical individuals [3, 4, 5].

To fill this gap, we model skill diversity within the paradigm of social learning, that has been used in empirical as well as theoretical studies [6, 7, 8, 9, 4]. From a theoretical perspective, the dynamics of social learning can be mapped onto a collective search process in an underlying solution space [3, 5], where the quality of a particular solution S is assessed using a payoff function $P(S)$: the higher the payoff $P(S)$, the better the solution S. Importantly, we assume that an agent's skill set determines how much value P they can extract from S, and contribute to the collective performance of the group. From this assumption it follows that the same solution S is generally not evaluated equally by two agents with different skill sets, see Fig. 1A.

We investigate the dynamics of collective problem solving along three dimensions: (i) task complexity, (ii) network structure, and (iii) group composition with regard to skill diversity. Using the NK model [10], we generate different payoff landscapes with tuneable complexity, where simple tasks correspond to smooth payoff landscapes and complex tasks correspond to rugged payoff landscapes. As for the network structure, we focus on the density of links in random networks. And finally, to increase the level of skill diversity in a population we add more and more groups of agents with different skills. Collective performance is then quantified in terms of both speed (time to reach best solution) and quality (payoff of best solution).

Our results show that skill diversity consistently impairs collective performance in simple tasks. While the optimum solution is always reached by all populations, diverse populations need more time to reach it (Fig. 1B). This effect holds independent of the network density and increases with the level of diversity. In complex tasks, the situation is different and diversity can also boost collective performance. Specifically, we find that link density modifies the effect of diversity: while homogeneous populations outperform diverse ones in sparse networks, the opposite is true in dense networks, where diversity boosts collective performance. This can be seen in Fig. 1C, where we depict the average final performance for homogeneous and diverse groups depending on the link density of the network.

Noise from a variety of sources originating from different social learning strategies, less well-connected networks, or distrust between individuals has been shown to lead to better exploration of the solution space and thus better performance [5, 11, 3, 12]. Here we identify skill diversity as another way to boost collective performance. Different skill sets that map onto distinct payoff functions allow agents to mutually assist each other in overcoming sub optimal solutions, a benefit of diversity that is made possible through the information exchange among dissimilar peers.

Overall, our findings suggest that diversity offers a pathway to boost collective performance in complex tasks. Specifically, we have shown that the more we are connected, the more we can benefit from diversity to solve complex problems – a finding which informs the compilation of problem solving teams in an increasingly interconnected and diverse world.

References

[1] Suzanne T Bell, Anton J Villado, Marc A Lukasik, Larisa Belau, and Andrea L Briggs. Getting specific about demographic diversity variable and team performance relationships: A meta-analysis. *Journal of Management*, 37(3):709–743, 2011.

[2] Alberto Alesina and Eliana La Ferrara. Who trusts others? *Journal of Public Economics*, 85(2):207–234, 2002.

[3] David Lazer and Allan Friedman. The network structure of exploration and exploitation. *Administrative Science Quarterly*, 52(4):667–694, 2007.

[4] Duncan J Watts and Steven H Strogatz. Collective dynamics of 'small-world'networks. *Nature*, 393(6684):440–442, 1998.

[5] Daniel Barkoczi and Mirta Galesic. Social learning strategies modify the effect of network structure on group performance. *Nature Communications*, 7(1):1–8, 2016.

[6] Robert Boyd and Peter J Richerson. *Culture and the evolutionary process*. University of Chicago press, 1988.

[7] Maxime Derex and Robert Boyd. Partial connectivity increases cultural accumulation within groups. *Proceedings of the National Academy of Sciences*, 113(11):2982–2987, 2016.

[8] Maxime Derex, Charles Perreault, and Robert Boyd. Divide and conquer: intermediate levels of population fragmentation maximize cultural accumulation. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 373(1743):20170062, 2018.

[9] Abdullah Almaatouq, Mohammed Alsobay, Ming Yin, and Duncan J Watts. Task complexity moderates group synergy. *Proceedings of the National Academy of Sciences*, 118(36):e2101062118, 2021.

[10] Stuart Kauffman and Simon Levin. Towards a general theory of adaptive walks on rugged landscapes. *Journal of Theoretical Biology*, 128(1):11–45, 1987.

[11] Winter Mason and Duncan J Watts. Collaborative learning in networks. *Proceedings of the National Academy of Sciences*, 109(3):764–769, 2012.

[12] Giovanni F Massari, Ilaria Giannoccaro, and Giuseppe Carbone. Are distrust relationships beneficial for group performance? the influence of the scope of distrust on the emergence of collective intelligence. *International Journal of Production Economics*, 208:343–355, 2019.

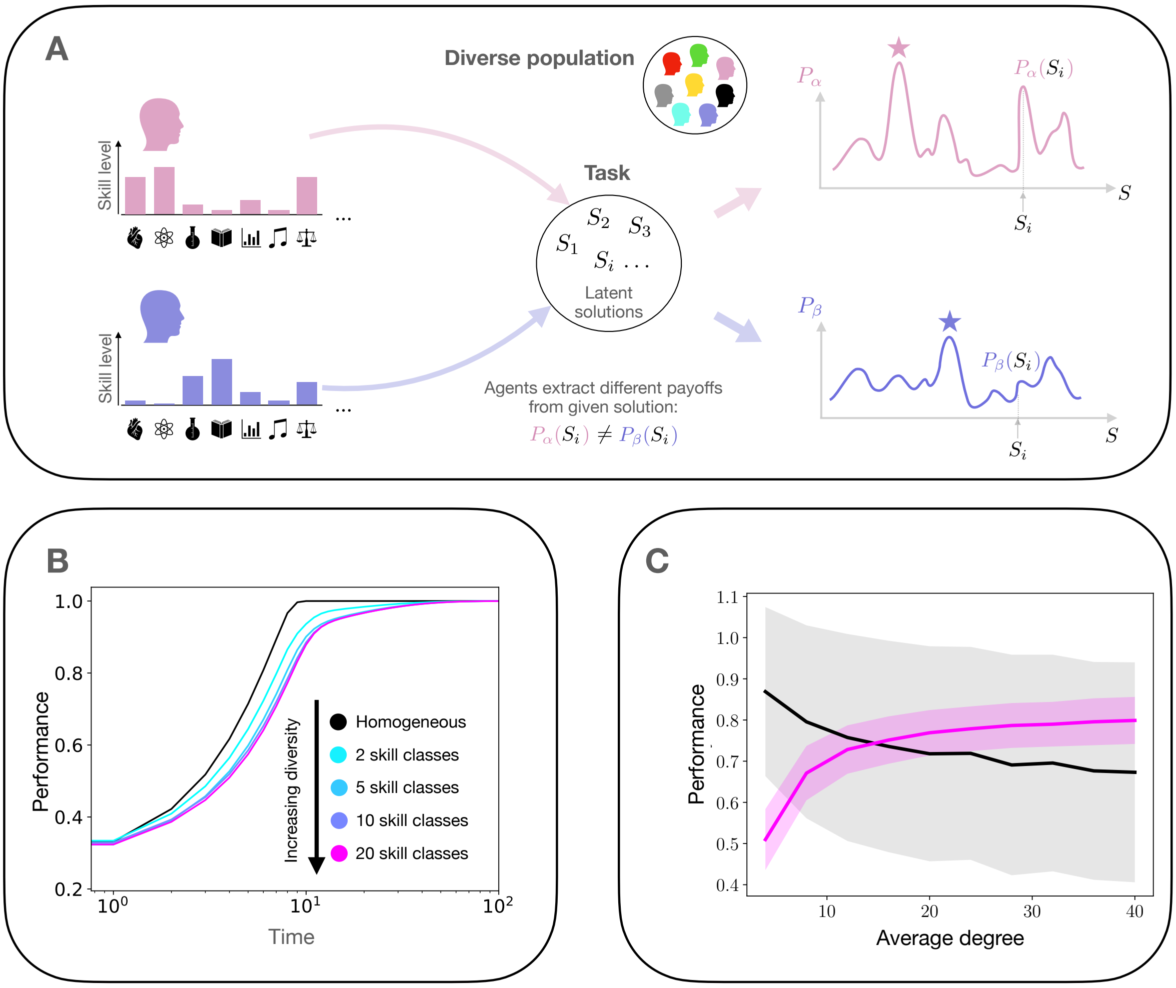

Figure 1: Panel A: The skill set of an agent determines how much payoff they can extract from a particular solution S. Panel B: In simple problems diversity harms in terms of speed: diverse populations need more time to reach optimal solutions. Panel C: In complex tasks, link density modifies the effect of diversity on average performance: the more we are connected, the more we benefit from diversity.