Maintaining transient diversity is a general principle for improving collective problem solving

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Abstract
Humans regularly solve complex problems in cooperative teams. A wide range of mechanisms have been identified that improve the quality of solutions achieved by those teams upon reaching consensus. We argue that all of these mechanisms work via increasing the *transient diversity* solutions while the group attempts to reach a consensus. These mechanisms can operate at the level of individual psychology (e.g., behavioral inertia), interpersonal communication (e.g., transmission noise), or group structure (e.g., sparse social networks). Transient diversity can be increased by widening the search space of possible solutions or by slowing the diffusion of information and delaying consensus. All of these mechanisms increase the quality of the solution at the cost of increased time to reach it. We review specific mechanisms that facilitate transient diversity and synthesize evidence from both empirical studies and diverse formal models—including multi-armed bandits, NK landscapes, cumulative innovation models, and evolutionary transmission models. Apparent exceptions to this principle occur primarily when problems are sufficiently simple that they can be solved by mere trial and error, or when the incentives of team members are insufficiently aligned. This work has implications for our understanding of collective intelligence, problem solving, innovation, and cumulative cultural evolution.

Keywords: diversity; networks; formal models; collective intelligence

1. Introduction

Humans and other social animals often solve problems in teams or collectives. They forage for food or nesting sites. They explore technological designs. They deliberate over evidence to make decisions. Case studies, behavioral experiments and formal models have been used to identify a wide variety of mechanisms that allow teams to reach higher-quality solutions. We argue that evidence from across several different modeling paradigms indicates a general principle for collective problem solving: any mechanism that extends the *transient diversity* of solutions in the population will improve the quality of the solution upon which the group ultimately converges.

Diversity is a term with many possible implications. Here we refer to the diversity of solutions to a well-specified problem. That is, the diversity of a population is an instantaneous measure of the variation of solutions under consideration. Why does transient diversity lead to higher quality solutions? When a wider area of the solution space is explored, the population becomes more likely to find an optimal or high-quality solution and less likely to become stuck on a local optimum. The longer that diversity persists, the larger the *total* area of solution space being explored becomes. Rapid consensus can be important when decisions must be made quickly, but consensus also precludes certain questions from being asked and certain ideas from being explored. This highlights the important tradeoff between speed and accuracy in problem solving. Increasing transient diversity means that a solution is more likely to be of higher quality, but it also increases the time it takes for a team to reach consensus. A similar phenomenon is well known for cases of individual-level problem solving (Hourihan & Benjamin, 2010; Vul & Pashler, 2008; Raviv et al., 2022). The overall value of transient diversity therefore depends on the relative importance of solution quality versus timely decision making. In this paper, we focus on solution quality alone, but this tradeoff should be kept in mind.

There are numerous mechanisms that can produce more diverse populations or maintain high levels of diversity for longer times. These are often studied in isolation as separable mechanisms that improve the solutions discovered by cooperative teams. Our proposal is that these are better appreciated as mechanisms for increasing transient diversity. We can draw an analogy from research on social evolution. Over several decades, researchers identified numerous mechanisms to facilitate the evolution or maintenance of altruistic cooperation. These include kin selection, direct and indirect reciprocity, group structure, limited dispersal, and partner choice. All of these mechanisms are now understood to be different ways of generating *positive assortment*, which means that interactions occur between individuals using the same behavioral strategies at rates higher than predicted by chance (Nowak, 2006; Fletcher and Doebeli, 2009; Apicella and Silk, 2019), allowing the benefits of cooperation to be preferentially bestowed upon cooperative individuals. We propose that transient diversity operates similarly as a unifying principle for improving the quality of collective problem solving.

We anchor our review on findings from formal modeling studies. Formal models are mathematical and/or computational systems that can capture essential features applicable to a wide variety of teams and problems and can be used to explore the logical consequences of particular theoretical assumptions (Smaldino, 2017; 2020). There are quite a few different modeling paradigms used to study collective problem solving. Such a many-model approach is useful for investigating systems at different scales and levels of organization (Page, 2018). Moreover, convergence on similar results using different models indicates the presence of a general principle for systems with the properties shared among the different models. Below, we first review the types of models we use as evidence, which originate from a wide range of disciplines, including organizational behavior, philosophy of science, and evolutionary biology. We then enumerate specific mechanisms for generating transient diversity and explore how each does so. Third, we briefly review some of the relevant empirical work and discuss the extent to which model assumptions are met in these studies. Finally, we discuss limitations to our proposal.

2. Models of Collective Problem Solving

The models we consider have several core assumptions in common. First, the problem being solved is assumed to be well-specified, such that solutions can be directly compared and assessed for quality. Second, the problem is assumed to be sufficiently complex so that individuals are unlikely to find the best solution on their own. Third, each individual is assumed to prefer to adopt the best solution they know of, and individuals will agree on the quality of a particular solution. And fourth, teams are assumed to be cooperative, such that individuals' goals are aligned, and they willingly share information with others. Even constrained by these assumptions, there are several ways a system of collective problem solvers can be formalized. Below, we describe some of the best known and widely used of these models (see Table 1).

2.1. NK Landscapes

The NK landscape was first conceived as a way to characterize epistasis in gene regulatory networks (Kauffman and Levin 1987; for a primer see Csaszar 2018). Social scientists starting with Lazer and Friedman (2007) have used the NK landscape as a model of problem solving, where each of N bits represents the presence or absence of some solution element and the parameter K represents the number of interdependencies between those elements. Landscapes where K is close to zero can be solved by hill climbing and are viewed as "simple" problems, while K close to $N/2$ characterizes "complex" problems where hill climbers get stuck on local optima (when K is close to $N – 1$, the values of neighboring solutions become completely uncorrelated, and the optimal solution can only found via brute force search). Models typically assume a networked team of solvers, each starting with a unique solution and searching individually via hill climbing while also sharing information socially with network neighbors. A strength of this model is that the complexity of the problem and the size of the solution space can be easily manipulated.

2.2. The Hong-Page Model

Hong and Page (2001; 2004) considered a model in which, like the NK Landscape, solutions are represented as bitstrings and the value of each bitstring is derived from a randomly generated mapping. Their model focuses on individual differences regarding the heuristics each agent uses to search the solution space. In particular, each of n solutions is effectively mapped to a point on a discrete circle, and each agent has a unique strategy for exploring nearby solutions. Unlike the NK landscape, there is no relationship between the distance between solutions and the similarity of their assigned values. Each member of a team starts with the previous agent's best solution and searches from there. Solutions are translated to individual cognitive representations and individuals can vary in their search heuristics. In this way, some agents are individually more likely to find high-quality solutions than others when searching alone, which explicitly affords a comparison of group-level diversity with individual-level talent.

2.3. Organizational Learning Models

In March's (1991) model of organizational learning, individual agents are tasked with learning about an external reality comprised of m dimensions, each with a binary value of 1 or −1. Individuals hold beliefs about the value of each dimension of reality. As individuals are part of a larger organization with its own code of beliefs, at each time step each individual can change their beliefs to that of the organization's code with some probability. Similarly, the code of the organization adapts to the beliefs of the group of individuals in the organization who hold more accurate beliefs about external reality. Investigations typically focus on how quickly an organization can converge on a model of external reality and how accurate this model of reality is. As this model involves both the influence of individuals on an organization and the influence of the organization on those individuals, it has been useful for understanding ideal arrangements of individual contributors to collective problems.

2.4. Network Epistemology Models

A standard benchmark problem in machine learning is the multi-armed bandit, where each "arm" yields payoffs drawn from a unique distribution function. In the simplest versions, there are two choices (a two-armed bandit), each of which yields a fixed payoff with a unique probability. The learner's goal is to maximize its cumulative payoff by consistently choosing the best option with the least amount of exploration. Researchers interested in social learning have considered networked populations of learners who can explore solutions individually but also learn about payoffs from observing the consequences of others' actions, where the focus is typically on the (adaptive) value of social learning (Bala and Goyal 1998; Rendell et al. 2010; Turner et al. in prep). Individuals can update their estimates of each arm's payoff through Bayesian learning. These models have gained interest from philosophers interested in social epistemology and the sociology of science, starting with (Zollman 2007). A strength of this model is that it incorporates uncertainty and the idea that individual observations can be misleading.

2.5. The Potions Model

The models described above assume that the ability to adopt a solution is independent of prior history, such that any individual could adopt any solution. However, many technologies and behaviors are only possible with specific prior knowledge. This idea was formalized in the Potions Model, first introduced by Derex and Boyd (2016) as a multi-player game using human participants and later explored as an agent-based model with artificial players (Migliano et al. 2018; Moser and Smaldino in prep). Each agent begins with a set of ingredients that can be combined in triads to make a potion to stop the spread of a harmful virus. The efficacy of the potion depends on the ingredients used. Critically, once an efficacious recipe is found, it can then serve as a stand-alone ingredient to be combined with two other ingredients for a future potion. These innovations can accumulate iteratively, resulting in potions of ever-increasing efficacy. Agents in the potions model explore combinations of ingredients through individual trial and error but can also learn from others with whom they share network connections. Not only does this model allow for the consideration of cumulative innovation, but it also affords the consideration of path dependency at the population level, as different subgroups may discover different cumulative solutions that can then be further combined when the subgroups interact and learn from one another.

2.6. Evolutionary Models

The paradigmatic model of evolution by natural selection, commonly known as the replicator dynamic, explicitly links the variance in strategies within a population with the intensity of selective pressure the population experiences (Taylor & Jonker, 1978; Schuster & Sigmund 1983). Early perspectives on the fixation of beneficial alleles and novelty in populations and the optimization problem were typified in theories of Sewall Wright (Wright 1948, Wade & Goodnight, 1998). As the originator of the "adaptive landscape" analogy, now commonly used in machine learning and computational models of collective intelligence, Wright saw populations as inhabiting landscapes of optimal and sub-optimal adaptations (Wright 1931). More successful strategies generate more replicates of themselves relative to less successful strategies, leading to a decrease in strategy diversity as selection acts on the population. In this way, a population can converge to local optima (the "peaks") of the fitness landscape. However, finding a global optimum given a current environment will often not be as straightforward a task, because the environmental features and the space of possible strategies can translate into rugged, difficult-to-traverse fitness landscapes (Gavrilets, 2004). By exploiting mechanisms that generate diversity (like random mutations in individual strategies), populations can get "nudged" beyond local peaks onto potentially more advantageous ones. Similar arguments have also been formalized for human cultural evolution (Boyd & Richerson, 1985).

Table 1. Summary of models considered.

Model	Key characteristics	Key References
NK Landscapes	Frames the search for solutions to a problem as travelling through a landscape and finding the optimum of the landscape.	Lazer and Friedman (2007), Barkoczi and Galesic (2016), Gomez and Lazer (2019)
The Hong-Page Model	Conceptualizes the problem solving system as a collection of individual problem solvers with different perspectives (initial beliefs) and heuristics (solution generating algorithms).	Hong and Page (2001; 2004)

Organizational Learning Models	Models the feedback individuals have on a larger organization and the subsequent feedback organizations have on individuals.	March (1991), Miller et al. (2006), Fang et al. (2010)
Network Epistemology Models	Models the quest for the best solution to a problem as a choice between different slot machines (bandit problems) in a social context	Bala and Goyal (1998), Zollman (2007; 2010), Kummerfeld and Zollman (2016)
The Potions Model	Thinks of generating new solutions to a problem as synergizing previous innovations to cumulatively reach better solutions.	Derex and Boyd (2016), Migliano et al. (2020), Moser and Smaldino (in prep)
Evolutionary Models	Models the fixation of adaptations and the discovery of novelty by populations of replicators in a fitness context.	Wright (1931), Boyd and Richerson (1985), Taylor and Jonker (1978)

3. Mechanisms for Increasing Transient Diversity

There are a wide range of mechanisms that produce transient diversity. Here we review several of these, providing evidence from across modeling frameworks and explaining how each mechanism leads to transient diversity (see Table 2). This is not meant to be a complete or definitive list. Indeed, it is likely that there are mechanisms that fit the bill that have yet to be identified. Instead, we use it to illustrate how the unifying characteristic among seemingly disparate mechanisms is that they all work by increasing transient diversity.

3.1. Higher variance of initial solutions

One way to increase transient diversity is to simply begin with a greater diversity of initial solutions. Another way is through the use of larger teams, which are likely to involve more perspectives through sheer force of numbers. Using an NK Landscape, Boroomand and Smaldino (2021) showed that increasing both the diversity of initial solutions and the overall team size improve solution quality for complex problems. Gomez and Lazer (2019) further showed that this type of diversity may in fact work best when like-minded people are placed in connected subnetworks, which allows for local consensus but maintains the overall diversity of the network for longer. Zollman (2010), using a network epistemology approach, showed that populations with wider (more uncertain) priors were more likely to reach consensus on the correct solution**.** In evolutionary biology, the evolution of more robust polymorphisms can be facilitated through processes that increase diversity of phenotypes, including as mutation, frequency dependence and the colonization of and migration among heterogeneous environments (Walter, Aguirre, Blows, Ortiz-Barrientos, 2018; Campbell Clarke, 1979). In economics, Wärneryd (2002) showed that in a population of risk-sensitive rational actors performing in winner-takes-all types of situations, a broad initial distribution of risk preferences (in which diversity is maximized) leads to efficient rent dissipation as the system evolves to a distribution where all attitudes to risk are represented.

3.2. Greater diversity of individual search strategies

Another way to maintain diversity is to have people search in different directions even if they start at the same location. Having a diversity of strategies (also referred to as diversity of abilities or heuristics) means that individuals search in fundamentally different ways, and therefore can explore a wider area of solution space. In March's (1991) organizational learning model, introducing heterogeneity to individuals' learning rates allowed organizations to produce more accurate models of reality than organizations composed exclusively of fast- or slow-learning individuals. Hong and Page (2001; 2004) showed that a team of problem solvers who were diverse in the way they explored the solution space could outperform a less diverse team, even when the members of the latter team reached higher quality solutions when searching individually. Gomez and Lazer (2019) found similar results using an NK landscape model, showing that a diversity of search strategies led to higher quality solutions, and moreover that teams performed better when individuals with diverse abilities were intermixed within network clusters, as this could counteract local consensus achieved through sharing information. Boroomand and Smaldino (2021), also using an NK landscape, showed that the presence of risk-taking agents, who simultaneously varied multiple solution elements chosen at random, also increased solution quality by increasing transient diversity. Kummerfeld and Zollman (2016), using a network epistemology approach, similarly showed that moderate amounts of random exploration on the parts of individuals could improve the likelihood that the group reached consensus on the correct solution. In cultural evolution, models have shown that the introduction of diversity through migration makes directional social learning biases adaptive with respect to individual and unbiased social learning (McElreath, Wallin & Fasolo, 2013), unless migration is so strong that diversity itself is stifled. When extended to environmental stochasticity in time, these models show that strategies that combine individual and social learning can lead to a tangible evolutionary advantage over pure strategies, as they spread risk out across the learning sub-strategies.

3.3. Sparse networks

It is a well-known result that information spreads more rapidly on densely connected networks and on networks with short average path lengths (Lind et al., 2007). If a problem is sufficiently simple that a single individual can quickly find a solution and the key concern is therefore communicating that solution throughout the network, then dense networks are best (Centola 2022; Lazer and Friedman 2007). However, when problems are complex, such that individual search is likely to become stuck on a local optimum, rapid consensus becomes less desirable. Sparser networks (i.e., those with lower average degree and/or longer average path length) facilitate slower percolation of information, which leaves time for disparate regions of the network to explore different regions of solution space. Early relevance of this idea to the search problem in population genetics was recognized by Sewall Wright. In his shifting-balance theory, Wright (1948) proposed that a global population split into subpopulations with limited gene flow between them allows for the global population to explore non-optimal areas of solution space and therefore discover otherwise inaccessible novelty. This influence of network sparsity on solution quality has been similarly observed using NK landscape models (Lazer and Friedman, 2007); organization learning models (Fang et al., 2010), network epistemology models (Zollman 2007; 2010,) and the potions model (Migliano et al. 2020; Moser and Smaldino in prep).

3.4. Slow or intermittent interactions

Network models often assume that connections are fixed and that transmission between connected nodes is deterministic. However, solution quality can be improved if the communication or diffusion rate is decreased, so that learning from neighbors becomes probabilistic. This is analogous to reducing the transmissibility of a contagion in an epidemiological model. Reducing the communication rate means that individuals do more individual search and less social learning, which decreases the correlation in solutions among neighbors and thereby helps maintain higher levels of solution diversity in the population. In his seminal paper on organizational learning, March (1991) altered learning rates between individuals and their organization, finding that slower learning rates led to better organizational performance, albeit at a loss to time until the organization obtained consensus. A similar way to achieve such diversity is to isolate different groups or network clusters and allow them to connect with other clusters only intermittently. Separation affords each cluster path independency, allowing each to converge on a distinct solution. This is particularly important in models that allow for the cumulative recombination of solutions, in which the combination of two solutions can be valued more highly than either solution in isolation (Derex and Boyd 2016; Migliano et al. 2020; Moser and Smaldino in prep).

3.5. Communication noise

Models very often assume that communication is perfect, and do not account for errors of either transmission or perception. However, diversity can be maintained purely by accident if a solution is copied with error. Boroomand and Smaldino (in prep) studied a NK landscape model in which, during social learning, each element of a target solution was correctly learned with probability $1 - c$, and otherwise the learner substituted the solution element from their current solution. Though framed as noise, this could be viewed in other ways, including as a form of strategic selective copying. Either way, it was found that increasing noise levels (up to 50% considered) improved the overall solution quality by maintaining a higher diversity of solutions in the population. This result is similar to the verbal predictions made by Eisenberg (1984) and others suggesting an adaptive role for ambiguity in communication.

3.6. Behavioral inertia

Individuals can sometimes be stubborn, favoring their own ideas over the ideas of others even when their own ideas are inferior. Pragmatically, it may also be costly to abandon one's own "good enough" solution for someone else's solution that is only slightly better, yielding a negative net benefit. Either of these factors can lead to a form of behavioral inertia in which another solution must be substantially better than one's current solution to justify its adoption. Interestingly, this reluctance to learn socially can maintain a diversity of solutions and keep potential pathways in solution space open for longer. In other words, behavioral inertia can increase transient diversity. This effect has recently been demonstrated to improve solution quality in both NK landscape models (Borooman and Smaldino, in prep) and network epistemology models (Gabriel and O'Connor 2022). Similarly, in a model of cultural innovation where agents could either copy the strategies of others or innovate their own strategies, Walker et al. (2021) found that the introduction of a third strategy, "maintain", led to stronger population-level adaptation than groups which only copied or innovated standing strategies.

3.7. Context biases for social learning

Conditions for learning that impede efficient information flow appear to prolong transient diversity. Another mechanism that produces this impediment is nonrandom social learning strategies. In particular, *context dependent biases* are proclivities to learn preferentially from certain people or to aggregate multiple sources of information in nonuniform ways (Kendal et al. 2018). Barkoczi and Galesic (2016) studied an NK landscape model in which agents sampled a subset of their neighbors and employed either success-biased or conformist social learning strategy. While all of the considered strategies outperformed pure individual learning, the strategy that produced the best solutions to complex problems was conformist transmission with small samples. The conformist rule reverted to individual learning when there was no majority among the sampled solutions, and so copying only occurred when multiple agents converged to the same high-quality solution. This allowed the diversity of solutions to be maintained for long enough that high-quality solutions were vetted by receiving "votes" from multiple searchers. Note that a conformist learning bias differs from social pressures to conform, which are likely to reduce diversity. And indeed, using a network epistemology model, Fazelpour and Steel (2022) showed that pressure to conform to the solution of one's neighbors reduces the probability that the group reaches consensus on a high-quality solution.

3.8. Outgroup distrust

In addition to holding individual-level biases for self vs. other, as with behavioral inertia, individuals can also exhibit group-level biases. If members of one group give less weight to information from outgroup individuals, they maintain their current beliefs for longer. If this bias is very strong, individuals ignore useful information which can lead to consensus on poor solutions or even polarization (O'Connor and Weatherall 2018). However, a small amount of outgroup distrust might serve merely to prolong transient diversity and by doing so improve group-level outcomes. Using a network epistemology approach with a two-group population, Fazelpour and Steel (2022) demonstrated that small levels of distrust for information from outgroup members improves the probability of consensus on high quality solutions. Complicating this matter, Wu (2022) considered a similar two-group network epistemology model, in which a "dominant" group completely ignored information from the "marginalized" group, while the latter group used information from the former. Because the dominant group updates on less evidence, it maintains its diversity of belief for longer. However, it is the marginalized group that benefits from this exploration. Compared with a similar population without any group biases, the marginalized group was more likely to converge upon the correct belief, while the dominant group was less likely. This indicates that groups may not always be the ones to benefit from their own diversity when informational asymmetries exist.

Table 2. Summary of mechanisms that promote transient diversity.

Mechanism	**Description**	**Key References**
Diversity of initial beliefs	Diversity is maintained by simply having agents with different starting point.	Boroomand and Smaldino (2021); Gomez and Lazer (2019); Zollman (2010); Walter, Aguirre, Blows, Ortiz-Barrientos (2018); Campbell Clarke (1979)
Diversity of search strategies	By having a diverse set of individual search strategies, more of the search space can be explored.	March (1991); Hong and Page (2001; 2004); Gomez and Lazer (2019); Boroomand and Smaldino (2021); Zollman (2016); McElreath, Wallin & Fasolo (2013)
Sparse networks	Sparser networks (i.e., those with lower average degree and/or longer average path length) slow the diffusion of information compared to more connected networks. This gives distant parts of the network time to explore different parts of the solution space without assimilating each other's solutions.	Wright (1931, 1932, 1948); Lazer and Friedman (2007); Derex & Boyd, (2016); Fang et al. (2010); Zollman (2007; 2010); Migliano et al. (2020); Moser and Smaldino in prep
Slow or intermittent interactions	When communication rates between individuals are reduced, social learning is attenuated. This leads to a decrease in how much solutions are alike between	March (1991); Derex and Boyd (2016); Migliano et al. (2020); Moser and Smaldino in prep

	neighbors, which helps maintain higher levels of solution diversity.	
Communication noise	Imperfect copying of candidate solutions makes perfect conforming less likely, and results in more variance of solutions.	Boroomand and Smaldino in prep
Behavioral inertia	Reluctance to adopt the solutions of others, except if they are substantially better than one's own, keeps potentially beneficial pathways of innovation open for longer.	Boroomand and Smaldino in prep; Gabriel and O'Connor (2022); Walker et al. (2021)
Context biases for social learning	Preferentially learning from certain people or aggregating multiple sources of information can decrease the proclivity to adopt marginally better solutions, prolonging the maintenance of varied suboptimal strategies.	Kendal et al. (2018); Barkoczi and Galesic (2016); Fazelpour and Steel (2022)
Outgroup distrust	By distrusting the information given from an outgroup, a group of members can maintain their current beliefs for longer periods of time.	Fazelpour and Steel (2022); Wu (2022)

4. Empirical Evidence

The recognition that the maintenance of transient diversity contributes to group success has been long recognized in studies of organizational behavior and group psychology. Empirical studies of this phenomenon date at least as far back as the 1950s, when an analysis by Bavelas (1950) showed a relationship between more fragmented group structures and task efficiency. This relationship was then explored experimentally by Guetzkow & Simon (1955) who developed a task whereby individuals in groups of six were each given a card with various symbols and the task of the group was to find the symbol they all had in common. Between three different organizational arrangements, they found that the most subdivided arrangement (the one with the fewest open communication channels) performed best.

Other empirical studies of the phenomenon of transient diversity for collective problem solving have shown that its benefits are mixed. One constant challenge is that it is often difficult to disentangle factors that lead to greater diversity of solutions from other types of diversity, including those which may reduce the alignment of incentives and goals. Stasser & Titus (1985) found that in a simulated caucus task where university students were asked to elect an ideal candidate from a pool of applicants, initial distributions of diverse unshared information about candidates did not alter who was actually elected, as most people shared and discussed only the information that others in the group already shared. Known as *shared* *information bias*, this effect has also been found in ratings of guilty parties in mock criminal trials (Stasser & Stewart, 1992) and in selecting ideal job applicants (Wittenbaum, 1998).

In a larger meta-analysis, Joshi & Roh (2009) examined the role that both relations-oriented (gender, race, etc.) and task-oriented (function, education, tenure) diversities played in group performance. Across all studies, task-oriented diversity related to function was the only positive predictor of team performance. The effect of relations-oriented diversity was either negative or virtually zero while the effect for non-functional forms of task-oriented diversity was similarly negative or virtually zero. While real-world complexities of diversity in this form of a meta-analysis make an assessment of diversity's impact on real-world performance difficult, the authors found at least one case where non-functional diversity had a significant positive impact on team-performance: when individuals had a finite amount of time to complete their tasks, relations-oriented diversity had a positive effect on performance. Worth noting here is that such conditions in this meta-analysis may be the most relevant to the transient diversity of solutions and therefore the most akin to the tasks laid out in the models discussed above.

In several real-world systems, striking a balance between introducing too much diversity or maintaining too little of it is critical for collective problem solving. In other words, the relationship between diversity and real-world performance may be non-monotonic. Aggarwal et al. (2019) studied the diversity of cognitive styles in an experimental game where individuals in small groups who could not communicate with each other had to choose from a set of options to receive a group payoff that depended on the choices of each group member. They found that teams with an *intermediate* level of diversity outperformed teams with both low and high levels of diversity (teams with the highest levels of diversity performed worst, perhaps as an inability to coordinate in the absence of communication). These empirical results somewhat resemble findings from models of organizational learning (Fang et al., 2010) and cultural accumulation (Derex et al., 2018; Moser and Smaldino, in prep), which found that intermediate levels of connectivity within networks are ideal for group performance; similar concepts have been expressed in the framing of "optimum mutation rates" in biological populations (Crow 1986).

Empirical studies have also tested the effect of specific network structures on the ability of human groups to solve tasks. Mason et al. (2008) found that in monotonic problems (problems with only one solution), fully-connected networks outcompeted small-world networks. When the landscape was more complex with more local solutions, small-world networks outperformed fully-connected networks. Similar findings were discovered in experimental versions of the Potions Game where the authors found that not a single fully-connected group was able overcome the inherent path dependencies in the game whereas over half of the partially-connected groups were able to do so (Derex & Boyd, 2016). Nonetheless, a much larger-scale study by Mason & Watts (2012) failed to find a positive role for partial connectivity; finding instead that fully-connected networks performed best in complex tasks with local maxima. While such a result can be considered as a strike against transient diversity as improving collective problem solving, it is critical to consider the behavior of the agents themselves: unlike the agents in agent-based models, individuals in the fully-connected group maintained a diversity of strategies despite their fully-connectedness. In order to explore this phenomenon further, Shore et al. (2015) developed a similar task on networks, asking about the role that clustering, rather than simply connectedness, plays on these tasks. They found that, unlike simulated agents, human players in their task possessed an awareness of what their neighbors were doing; instead of copying their neighbors, they employed a strategy of limiting wasteful redundant exploration of the solutions that were known.

5. Limitations

While we have argued that transient diversity is an important concept in a wide variety of collective problem-solving frameworks, it is also necessary to explore the situations in which it can fall short of its proposed virtues, some of which are illustrated in the empirical examples above. In scenarios where rapid consensus is important, marginal increases in solution quality must be weighed against the costs of further exploration. We also note that the mechanisms we listed may not contribute additively to solution quality. For example, several studies have indicated that efficient rather than sparse networks are preferable when other mechanisms for maintaining transient diversity are present (Foley & Riedl, 2015; Barkoczi & Galesic, 2016; Zollman, 2010). The value of transient diversity also relies on the assumption that the interests of team members are all aligned. However, diversity of interests can erode cooperation. For example, O'Connor and Weatherall (2018) examine a network epistemology model in which agents devalue information from those with differing beliefs. They show this can lead to polarization in which a large proportion of the population holds an incorrect belief. Relatedly, we have not considered scenarios like optimal behavior during collective behaviors like voting, in which diversity may translate into an inability to reach consensus.

6. Conclusion

Given the convergence from multiple models and mechanisms for maintaining it, the use of transient diversity by groups of agents to improve solutions likely represents a general principle for collective problem solving. The multiple mechanisms which can be used to create and maintain it can be shown to transfer across a number of models and a diversity of tasks. A critical consideration for the use of transient diversity for leveraging group abilities is the ideal level of diversity which should be maintained within a population. With too little diversity, populations may rapidly and prematurely converge on non-ideal solutions, leading to deadlocks, polarization, and path dependent lock-in at local optima. With too much diversity, consensus may be difficult to obtain and, under situations which require speedy solutions, may simply be too costly. An important assumption of most studies reviewed here is a *lack* of diversity in agent goals, such that interests were always perfectly aligned. The interaction of multiple types of diversity is an important consideration for future research on collective problem solving.

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