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Memory Transmission in Small Groups and Large Networks: An Agent-Based Model

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Abstract

The spread of social influence in large social networks has long been an interest of social scientists. In the domain of memory, collaborative memory experiments have illuminated cognitive mechanisms that allow information to be transmitted between interacting individuals, but these experiments have focused on small-scale social contexts. In the current study, we took a computational approach, circumventing the practical constraints of laboratory paradigms and providing novel results at scales unreachable by laboratory methodologies. Our model embodied theoretical knowledge derived from small-group experiments and replicated foundational results regarding collaborative inhibition and memory convergence in small groups. Ultimately, we investigated large-scale, realistic social networks and found that agents are influenced by the agents with which they interact, but we also found that agents are influenced by nonneighbors (i.e., the neighbors of their neighbors). The similarity between these results and the reports of behavioral transmission in large networks offers a major theoretical insight by linking behavioral transmission to the spread of information.

Keywords

memory, computer simulation, social influences, social structure

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The spread of social influence in large groups has long been an interest of social scientists (Bartlett, 1932; Cialdini, 2001; Gladwell, 2000; Schelling, 2006). Work from a variety of disciplines (for a review, see Christakis & Fowler, 2009) has revealed that behavior is powerfully influenced, not only by the people you know, but also by the people they know (and the people *they* know, etc.). Despite the pervasiveness of such findings, the mechanisms underlying the spread of behavior are not well understood. It has been suggested that "social networks function . . . by giving us access to what flows within them" (Christakis & Fowler, 2009, p. 91). But what exactly flows within our social networks, allowing for these powerful influences on our behavior, is unknown, which hampers our ability to ground large-scale phenomena such as collective memory (Hirst & Manier, 2008; Wertsch & Roediger, 2008), collective action (Lopez-Pintado & Watts, 2008; Strang & Soule, 1998), and the contagion of complex behaviors (Centola, 2010, 2011; Christakis & Fowler, 2009; Wisdom, Song, & Goldstone, 2014) in well-understood psychological processes.

In this article, we examine the transmission of information within social networks and propose that information transmission may act as one of the fundamental mechanisms underlying the transmission of behavior. Over the past decade, collaborative-memory researchers have begun to investigate how information is transmitted between individuals in small groups during social interactions. These researchers have uncovered a variety of novel phenomena, as well as insights into the key mechanisms that facilitate or inhibit information transmission (Rajaram, 2011). However, the practical constraints entailed by laboratory paradigms, such as small groups and a protracted measurement phase, hinder the ability to extrapolate findings to realistically large groups.

Here, we circumvent these constraints by introducing a novel theoretical approach that uses an agent-based

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model in which individuals are simulated as computational agents capable of representing information, communicating with other agents, and learning (Coman, Kolling, Lewis, & Hirst, 2012; Goldstone & Janssen, 2005; Smith & Collins, 2009). In our model, large numbers of agents can be allowed to interact with one another, and we can evaluate the patterns of information flow that emerge at the group level. This final step fulfills the promise of our computational approach, providing psychologically grounded results at scales unreachable by experimental methodologies and suggesting that our model may account for the social transmission of memory as well as a variety of aggregate-level behaviors.

We first describe the theoretical and empirical advances made in the study of information flow with small-group memory experiments. We then lay out the details of our computational model, emphasizing how our agent model is endowed with psychologically realistic memory processes. We validate our agent model by demonstrating that the model exhibits counterintuitive phenomena previously observed in behavioral experiments (e.g., collaborative inhibition) and also provide insights into the mechanisms behind these surprising patterns (Study 1). Having validated our model, we explore collaborative inhibition beyond the confines of laboratory paradigms (Study 2). Finally, we explore our theoretical model's predictions about how these memory processes manifest themselves in realistic social networks (Study 3). We find that memory representations cascade across social networks: Agents' memories are influenced by the agents with which they have interacted and also by the agents with which those agents previously interacted (and so on). Given that such patterns are pervasive in the literature on behavioral transmission (e.g., Christakis & Fowler, 2009, we argue that information transmission is a critical mechanism underlying the social transmission of behavior.

Collaborative Memory in Small Groups

The collaborative-memory paradigm is a robust method for measuring the transmission of information in small groups and has been used to identify several key mechanisms that facilitate or inhibit information transmission in small groups (Rajaram & Pereira-Pasarin, 2010). In the collaborative-memory paradigm, each participant is first exposed to experimenter-provided stimuli (e.g., words, pictures, narratives). Participants then form groups of two or three and recall items collaboratively. Finally, participants recall items individually to assess the representations retained by each participant after the collaborative recall. In this study, we select key phenomena that have emerged from these small-group experiments and examine how the mechanisms that give rise to these phenomena scale up to large, real-world social networks.

The first phenomenon of interest is the effect of collaboration on group memory. The behavioral findings in this area are counterintuitive. Although a collaborating group recalls more than a given individual, the group recalls significantly less than its potential, a phenomenon called *collaborative inhibition* (Weldon & Bellinger, 1997). To estimate a collaborative group's potential, one compares its performance with that of a noncollaborative group, or *nominal group*, containing the same number of participants. The performance of the nominal group is defined as the total, nonredundant recall of the group's participants, each of whom recalls individually (Blumen & Rajaram, 2008; Weldon & Bellinger, 1997). Although suboptimal performance could reasonably be attributed to a lack of accountability (Latane, Williams, & Harkins, 1979), experimental findings show that this is not the case (Weldon, Blair, & Huebsch, 2000). Instead, the suboptimal performance of collaborative groups has been attributed largely to the process of retrieval disruption, which occurs when the output of one participant's recall disrupts other participants' ongoing retrieval processes, which prevents the group from performing up to its potential (Basden, Basden, Bryner, & Thomas, 1997). Our first aim was to simulate this counterintuitive yet highly robust finding (for a review, see Rajaram & Pereira-Pasarin, 2010) using an agent-based model. Replicating the least intuitive empirical finding to come out of the literature on collaborative memory would support the validity of our model.

The second intriguing phenomenon, one that is particularly suited to computational exploration, is the effect of group size on collaborative inhibition in recall. Even within small groups, research shows that as group size increases (from two to three or four members), collaborative inhibition increases (Basden, Basden, & Henry, 2000; Thorley & Dewhurst, 2007). This raises the question of whether this decline becomes exaggerated in larger social situations. The fact that retrieval disruption (see the preceding paragraph) should increase with group size would also predict this outcome. However, the ultimate outcome of collaborative retrieval reflects the complex interplay of several mechanisms that operate during collaboration (Rajaram & Pereira-Pasarin, 2010). For example, despite the emphasis on the disruptive consequences of collaboration that lower recall, research has also highlighted mechanisms that may act to enhance the quantity and accuracy of postcollaboration representations. One such mechanism is *reexposure*, in which collaboration acts to expose each participant to items he or she might not have remembered otherwise (Blumen & Rajaram, 2008, 2009; Congleton & Rajaram, 2011). Thus, the mechanisms of retrieval disruption and reexposure encourage opposing effects on postcollaboration recall. We focus on these two well-studied mechanisms.

The third phenomenon of interest is the extent to which collaboration produces convergence or similarity in the postcollaboration memories of individuals who previously engaged in collaborative recall. Experimental evidence from dyadic and triadic collaborations shows that one or two sessions of collaborative recall increase the similarity or the overlap in items that former members recall in a session after the collaborative recall (Coman, Manier, & Hirst, 2009; Congleton & Rajaram, 2014). Recent results also show that when individuals collaborate twice in groups of three, but each time with a different set of partners, their eventual postcollaboration recall is influenced not only by what their immediate partners recalled but also by what their partners' previous partners had recalled initially. In other words, immediate partners can act as conduits for transmitting memory between two individuals who never collaborated (Choi, Blumen, Congleton, & Rajaram, 2014; Yamashiro & Hirst, 2014). By taking a computational approach, we intend to study such transmission in large social networks without the loss of experimental control typically associated with large-scale field studies. Of particular interest is investigating how far such transmission effects extend.

Current Approach

The agent-based modeling approach taken in the investigations reported here represents individuals as simplified units that are endowed with the ability to encode and retrieve stimuli. Large groups of these agents can then interact in ways designed to mimic both laboratory settings (e.g., the collaborative-memory paradigm) and ecologically realistic environments (a tutorial on agent-based modeling and further detail about the current model can be found in the Supplemental Material available online).

Simulating these settings has several obvious benefits. First, because we control the nature of the agents' memory, we have direct access to the psychological mechanisms that underlie the individual and collective behavior that we observe. Second, computational simulations need not be constrained to paradigms that are methodologically feasible in a laboratory setting. For example, simulations involving hundreds of agents are no more difficult to perform than simulations involving small groups. This allows us to seamlessly transition between small group settings, about which we already have a wealth of empirical knowledge, and large, real-world settings, which have been difficult to study empirically, without sacrificing experimental rigor.

Agent Model

Our computational agents are endowed with a simplified memory model capable of storing a set of N items (e.g., words). Each agent's memory consists of two separate representations. First, $\mathbf{A}$ denotes a vector of N activations. Each activation in $\mathbf{A}$ represents the probability that the corresponding item will be retrieved. Second, $\mathbf{S}$ denotes a matrix representing interitem associations. These associations represent preexperimental knowledge, such as semantic associations between words. Because we did not explore the influence of preexperimental knowledge per se in our simulations, the interitem associations in $\mathbf{S}$ were assigned random values between −0.2 and 0.2. If prior knowledge is expected to play a systematic role, $\mathbf{S}$ can be formulated to reflect the structure of this prior knowledge. For example, categorized words can be simulated by constructing high within-category associations and low between-category associations, a strategy we have successfully used in recent modeling (Luhmann, Congleton, Zhou, & Rajaram, 2015).

Agents have two behaviors. First, they can encode an item. If the item to be encoded is not the maximally active item, the activation of the maximally active item is first reduced according to Equation 1:

$$\Delta\mathbf{A}_{\max} = -\beta\mathbf{A}_{\max} \tag{1}$$

$\mathbf{A}_{\max}$ is the activation of the most active item, and β is a learning rate. Next, semantic associates of the maximally active item have their activations modified:

$$\Delta\mathbf{A}_j = -\beta\mathbf{S}_{\max,j}\mathbf{A}_j \tag{2}$$

$\mathbf{S}_{\max,j}$ is the strength of the association between the maximally active item and item j. Activation of the to-be-encoded item is increased:

$$\Delta\mathbf{A}_i = \alpha\left[1-\mathbf{A}_i\right] \tag{3}$$

$\mathbf{A}_i$ is the activation of the encoded item and α is a learning rate. Finally, $\mathbf{A}$ is normalized so that $\Sigma_i\mathbf{A}_i = 1$. This allows each entry in $\mathbf{A}$ to be interpreted as a proper probability.

Agents can also retrieve an item. Each time an agent has an opportunity to retrieve an item, it does so with probability γ. If retrieval is successful, a random item is selected in proportion to the activations in $\mathbf{A}$ (i.e., more active items are more likely to be retrieved) and generated (e.g., spoken out loud). Finally, the activations in $\mathbf{A}$ are modified in response to successful retrieval. Specifically, four separate modifications are made. First, semantic associates of the successfully retrieved item have their activations modified:

$$\Delta\mathbf{A}_j = \beta\mathbf{S}_{i,j}\mathbf{A}_j \tag{4}$$

$\mathbf{A}_j$ is the activation of an associate of the successfully retrieved item (item i) and $\mathbf{S}_{i,j}$ is the strength of the association between items i and j. Second, if the retrieved item is not the most active item in **A**, the activation of the most active item is reduced according to Equation 1, and semantic associates of this nearly retrieved item are modified according to Equation 2. The successfully retrieved item is then encoded; its activation is increased according to Equation 3. Finally, **A** is normalized so that $\Sigma_i \mathbf{A}_i = 1$.

The agent model has three parameters: α, β, and γ. In the current simulations, the values of these parameters were .2, .05, and .75, respectively, and were held constant across all simulations. In this way, we ensured that the patterns observed in the context of small groups and those observed in the context of larger social structures were related in a nontrivial manner. In seeking to generalize, we intentionally focused on simulating the quintessential pattern of collaborative inhibition observed across a plethora of empirical studies (Rajaram & Pereira-Pasarin, 2010) rather than one particular data set from one particular experiment.

Study 1: Validating the Agent Model

Task design

Our first study addressed the collaborative-memory task and was designed to reflect the standard laboratory paradigm as closely as possible. Each agent was first allowed to encode a study list of 40 items, presented in a random order. Groups of three agents were then allowed to interact. The interaction was structured into 20 rounds. During each round, each agent was given an opportunity to retrieve an item. The order in which the agents executed the retrieval was determined randomly in each round. If an agent successfully retrieved an item, it was encoded by the other two agents. If an agent attempted to retrieve a previously retrieved item, this retrieval failed (no changes were made to the activations in **A**), and the next agent was given an opportunity to retrieve. This turn-taking paradigm allowed all group members to participate in the collaborative recall task without having to specify how a more free-form interaction might unfold and has been used in experimental studies of collaborative memory (e.g., Basden et al., 1997; Thorley & Dewhurst, 2007).

As in the prior collaborative-memory experiments, we compared the performance of our collaborating agents with the performance of three individual agents, each of which studied and recalled in isolation. The nonredundant output of this nominal group of agents was taken as the expected output of three individual agents against which the collaborative group could be compared. Unlike behavioral investigations of collaborative memory, the current paradigm made it possible to construct the nominal and collaborative groups using identical agents by creating three agents and presenting each with the list of items to study in isolation. Identical clones (which had identical activation vectors, etc.) of these three agents were then generated. This yielded a pair of groups consisting of identical agents. One of these groups retrieved collaboratively whereas the other group retrieved individually. As in all the simulations reported in the current article, we simulated 1,000 separate pairs of groups (i.e., 1,000 collaborative groups and 1,000 nominal groups). These sample sizes obviously provide substantially greater statistical power than past behavioral studies, which have typically used fewer than 60 participants per condition.

Results

The simulated agents exhibited the pattern of collaborative inhibition reported in the literature. That is, collaborative groups retrieved significantly fewer items than their counterparts in nominal groups, $t(999) > 100$, $p < .0001$, $d = 6.32$.[1] We attribute this finding to several factors, chief among them the homogenization of group members' memory during collaboration. After completing the initial individual study phase, each agent possessed an idiosyncratic pattern of activation over the set of items. Diversity in these activations ought to facilitate overall group performance because it allows each agent to contribute unique items to the group's nonredundant output. In the collaborative groups, however, the learning that occurred during the interaction tended to reduce the diversity of agents' representations, which ultimately lowers recall performance.

To explore this explanation further, we computed the precollaboration similarity between the agents by calculating the Pearson correlation coefficient of the activation vectors for each pair of agents within the triad ($\mathbf{A}_1$ vs. $\mathbf{A}_2$, $\mathbf{A}_2$ vs. $\mathbf{A}_3$, and $\mathbf{A}_1$ vs. $\mathbf{A}_3$) and averaging across these three correlations. Because correlation coefficients are nonnormally distributed, we converted the set of 1,000 average correlations to *z*-scores. Figure 1 illustrates how these intragroup precollaboration similarities are related to group performance. The greater the similarity between agents before collaborating, the lower the recall performance of the nominal groups, $r = -.39$, 95% confidence interval, or CI = [−.44, −.34], $p < .0001$. Precollaboration similarity was not related to the performance of collaborative groups as strongly, $r = -.12$, 95% CI = [−.17, −.05], $p = .0002$. Indeed, intragroup precollaboration similarity predicted nominal-group performance significantly better than it predicted collaborative-group performance, $t(998) = 5.41$, $p < .0001$, $d = 0.34$ (for method, see Steiger, 1980).

We attribute this pattern to the fact that agents' memories become more similar as they collaborate; indeed, group members were significantly more similar after collaborating ($M = .91$, $SD = .02$) than before ($M = -.004$, $SD = .09$), $t(999) > 1{,}000$, $p < .0001$, $d = -14.42$. In

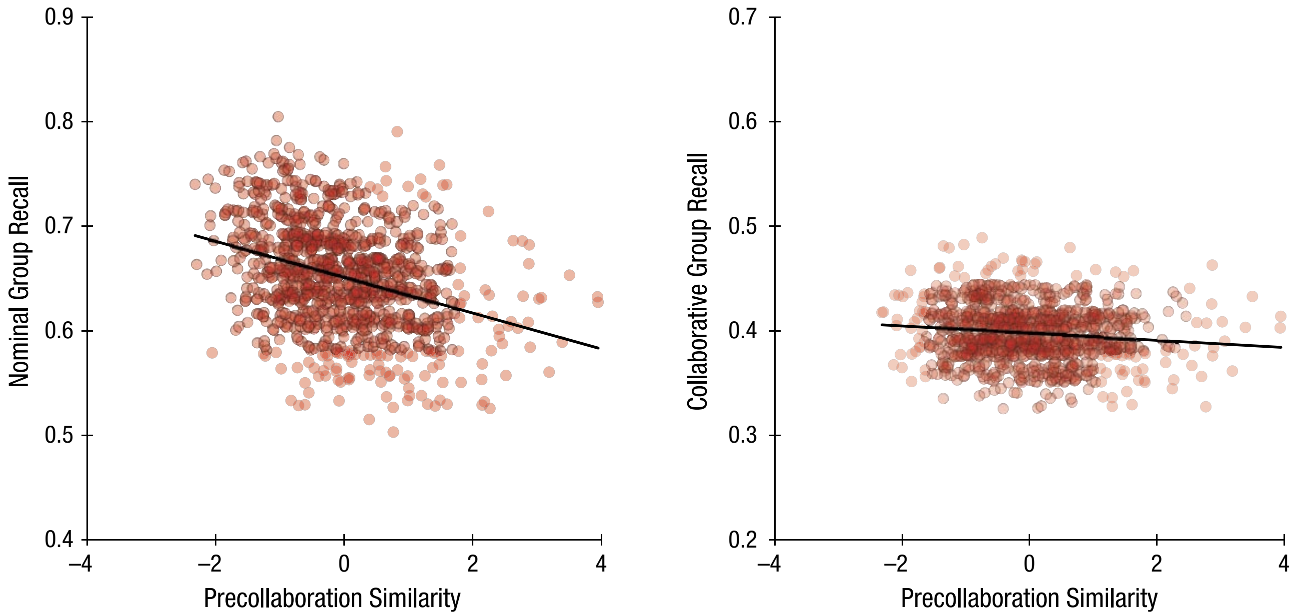

Fig. 1. Results from Study 1: relationship between group members' normalized precollaboration similarity and the proportion of items recalled. Results, with best-fitting regression lines, are plotted separately for the nominal groups (left) and collaborative groups (right). Note that the data points have been jittered vertically to improve comprehension and that the two plots do not use a common *y*-axis.

contrast, nominal-group members showed no such increase, $t(999) = 1.38$, $p = .17$, $d = -0.06$. These findings suggest that collaborative recall leads to convergence among group members and that this convergence is ultimately responsible for collaborative groups' lower recall.

Study 2: Group Size

Design

We systematically investigated how group size influences collaborative inhibition. In only two studies has group size been manipulated (Basden et al., 2000; Thorley & Dewhurst, 2007), and both suggested that larger groups produce more detrimental collaborative effects. However, the groups tested in these studies were limited to no more than 4 participants, which makes it difficult to extrapolate to larger groups.

The current simulations used the same agents and task design as in Study 1. We constructed collaborative groups ranging in size from 2 to 128 agents as well as analogous nominal groups. As in Study 1, the entire list of 40 items was first presented to each agent. All the agents within a group were then allowed to simultaneously interact as described in Study 1. We performed 1,000 simulations for each group size.

Results

The standard collaborative-inhibition effect was observed for all group sizes (Fig. 2). However, the relationship between group size and collaborative inhibition was not entirely straightforward. As groups grew from 2 to 7 agents, collaborative inhibition increased (a finding that replicates and extends those of Basden et al., 2000, and Thorley & Dewhurst, 2007). In this range, the performance of both collaborative and nominal groups increased steadily. However, each additional group member conferred a much larger benefit to nominal groups than to collaborative groups. This effect of group size was probably driven by the relative balance between the facilitative effects offered by collaboration (i.e., more agents increased the probability that the group would retrieve a given item) and the detrimental effects of retrieval disruption (i.e., more collaborators meant more opportunities to be disrupted). Collaborative inhibition decreased as group size increased beyond 7. This effect was driven by the fact that nominal groups reached ceiling far earlier than the collaborative groups. Nonetheless, the continued deficiencies exhibited by even large collaborative groups suggest that the cognitive factors that hurt retrieval diversity in small groups could not easily be overcome by the addition of group members.

Study 3: Transmission of Memory in Social Networks

Design

In Study 3, we used the power and flexibility of our agent-based model to address questions beyond those previously explored in the literature. First, we explored

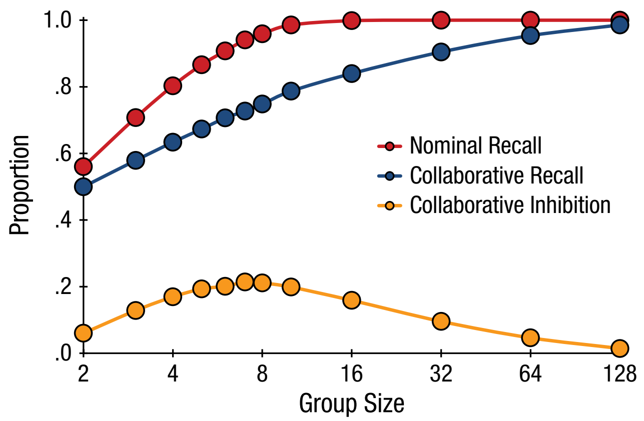

Fig. 2. Results from Study 2: influence of group size on collaborative inhibition (collaborative recall minus nominal recall). Note that the *x*-axis is logarithmic.

large, complex social structures, which is simply not possible in behavioral studies because of practical constraints. Second, we drew on the memory-convergence findings from Study 1 to investigate the similarity of agents' memory representations and to seek evidence of hyperdyadic spread (i.e., the similarity between individuals who have never interacted but share a common neighbor; Christakis & Fowler, 2009). To accomplish these goals, we placed agents into large, realistic social networks and allowed them to interact with their neighbors (i.e., those to which they were directly connected in the network). Because spread beyond immediate neighbors is pervasive in the literature on the social transmission of behavior, the novel theoretical aim of the study was to determine whether similar patterns would emerge from our model of memory transmission. Such similarities would suggest that behavioral "contagion" is related to the social transmission of information.

To increase the realism of the current simulations, we used three different networks. The first was a so-called small-world network. Small-world networks are a class of random graphs that are generated algorithmically (Watts & Strogatz, 1998). These graphs, like natural social networks, exhibit a high degree of clustering and a short average path length. That is, the shortest distance between two nodes is short, on average, despite the network's relatively sparseness (i.e., most nodes are not neighbors). These features give rise to the well-known six-degrees-of-separation phenomenon (Dodds, Muhamad, & Watts, 2003; Milgram, 1967). The Watts-Strogatz algorithm takes three parameters: number of nodes, average degree (i.e., number of connections), and a rewiring probability. We created networks with 100 nodes. Average degree was set to 4, meaning that agents were, on average, connected to 4 other agents. The rewiring probability was set to .1, a value that yields the high levels of clustering observed in real-world social networks (Watts & Strogatz, 1998).

The second and third networks were empirically derived. The second was a network of friendships between members of a karate club at a U.S. university (Zachary, 1977). This network contains information about 34 individuals and the 78 connections among them. The third network describes the coauthorship relationships among scientists who study networks (Newman, 2006). This network includes 376 nodes with 914 connections among them. Given that these networks are empirically derived, they have been the subject of intense scrutiny within the literature on social-network analysis (e.g., Barabasi, 2003; Christakis & Fowler, 2009; Watts, 2003).

Each simulation began by presenting the entire 40-item list to each agent individually. In this simulation, unlike those preceding, we wished to have the agents interact in a way that was constrained by their location within the network. To achieve this, we set the current simulations to 800 time steps. During each step, each agent and one of its randomly selected neighbors interacted (i.e., each agent took a turn retrieving an item, etc.). This interaction was just like that in the collaborative groups simulated in Studies 1 and 2. In this simulation, each agent collaboratively retrieved items with only a single other agent and never with the entire network. This technique was intended to approximate the way in which individuals interact with their peers in the real world. For example, two scientists might share information about a new statistical technique as they work on a manuscript together. Each of these scientists might subsequently share such information with their colleagues, and so on.

To assess the diffusion of information across the network, we evaluated the similarity of agents on the basis of the agents' proximity in the network. Specifically, we calculated the correlation between activation vectors, **A**, at the conclusion of the simulations. This measure increases when items are strongly active in both agents' memories but also when items were strongly inactive in both agents' memories (i.e., they are jointly forgotten). Conversely, this measure of similarity decreases when one agent forgets an item (i.e., $\mathbf{A}_i$ is low) that the other agent still remembers (i.e., $\mathbf{A}_i$ is high). Thus, this correlation can be considered a measure of collective memory (Choi et al., 2014; Stone, Barnier, Sutton, & Hirst, 2010).

We computed the similarity between all possible pairs of agents, sorted by the two agents' proximity in the network. Specifically, we used the minimum spanning distance, which is the minimum number of "hops" (i.e., edges) required to traverse the network from one agent to another. Neighboring agents were separated by a distance of one hop. Two nonneighboring agents that shared a common neighbor were separated by a distance of two hops, and so forth. We conducted 1,000 simulations with each of the three networks, each time using newly initialized agents (and in the case of the small-world network, newly generated networks).

Results

Results illustrate that the representations of directly connected agents (those at a distance of one hop) were significantly more similar than those of agents at a distance of two hops. This is not particularly surprising because neighboring agents directly interacted, and Study 1 demonstrated that interaction increases similarity of agents' memories. Perhaps more surprising is that agents separated by a distance of two hops were more similar than those separated by a distance of three hops. These pairs consist of agents that never interacted, so direct communication cannot explain this similarity. Instead, the two agents' common neighbor presumably acted as a conduit through which information was transmitted, allowing nonneighbors to indirectly influence one another. Overall, distance in the network modulated the agent similarity. Each additional hop separating a pair of agents was associated with a significant reduction in similarity, ts(999) > 2.73, ps < .01, until reaching a minimum at a distance of seven hops in the authorship network and a distance of six hops in the small-world network. Once agents were farther apart, there was no relationship between similarity and distance (e.g., agents separated by seven hops were just as similar as agents separated by nine hops; Fig. 3).

General Discussion

The current studies aimed to develop a computational model firmly grounded in psychological theory to investigate the transmission of information within large groups. Past work using the collaborative-memory paradigm has provided a wealth of insights into the social influences on the transmission of learning and memory, including such mechanisms as retrieval disruption and reexposure as well as such phenomena as collaborative inhibition and collective memory. However, the practical constraints of behavioral paradigms have limited past work to the study of small-scale social contexts (e.g., groups of two or three).

In the current study, we instead took an agent-based modeling approach, simulating individuals as psychologically realistic information-processing units capable of

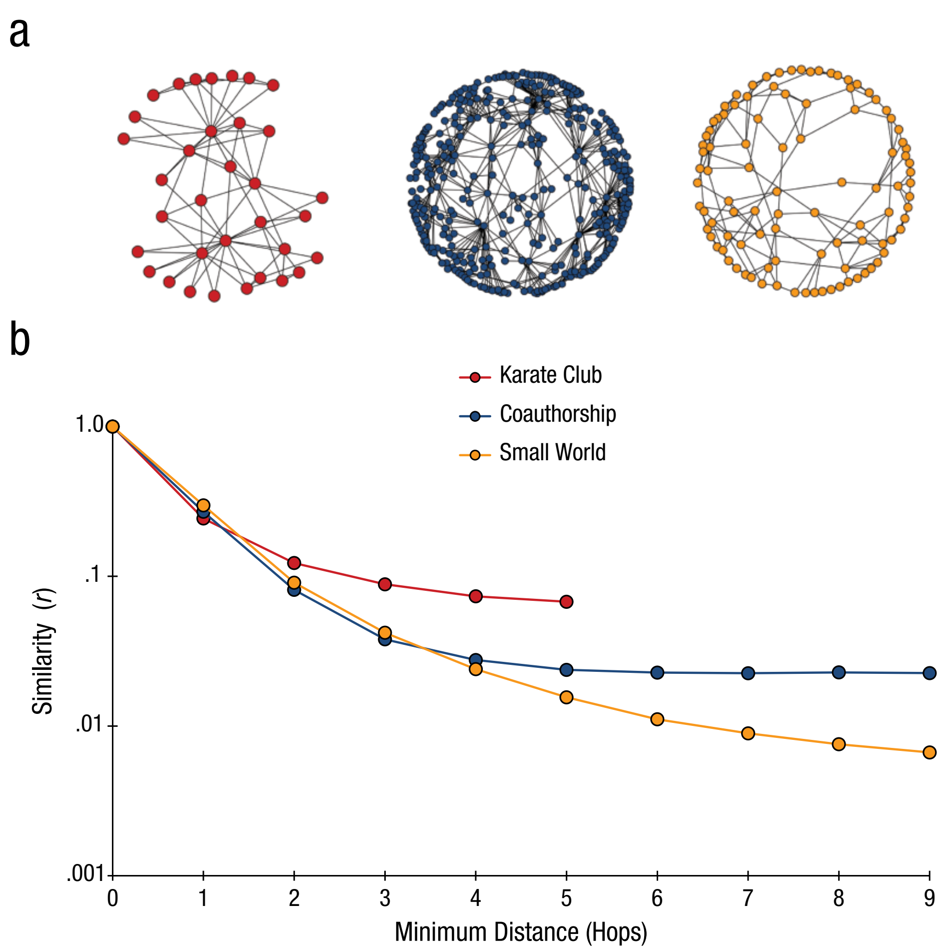

Fig. 3. Networks (a) and results (b) for Study 3. For each network, similarity between pairs of agents is plotted as a function of minimum distance between them.

representing information, learning from experience, and interacting with other agents. To investigate the transmission of information, we explored three different phenomena. We first investigated the robust collaborative-inhibition effect. Our simulations replicated the standard pattern of results: Collaborative groups underperformed relative to the nominal groups. However, we also provided novel insights into the relationship between collaborative inhibition and the increasing similarity of collaborators (insights that dovetail nicely with recent behavioral work, Congleton & Rajaram, 2014).

Having validated our model, we explored collaborative inhibition in groups larger than allowed by laboratory paradigms. Finally, we explored the patterns that emerge when these memory processes operate in realistic social networks and found that memory influence spreads beyond immediate neighbors. This final step allowed us our biggest theoretical advance: We argue that information transmission is a critical mechanism underlying the social transmission of a variety of behaviors. Taken together, the findings of the current study leverage the successful simulation of laboratory results to develop a much-needed theoretical account of behavior in larger social networks.

The psychologically realistic nature of our model is a critical step forward in the study of behavioral transmission. Given the attention garnered by this phenomenon, computational models for it have been developed, and they show the role that basic mimicry mechanisms may play (Easley & Kleinberg, 2010; Granovetter, 1978; Jackson, 2008; Lopez-Pintado & Watts, 2008). In contrast, our model is purpose-built to include key psychological mechanisms that were not identified previously, and it was validated against patterns observed in the empirical literature (Sun, 2001, 2006). In this way, our model has more in common with other agent-based models developed within psychology. For example, models (Barr, 2004) have been developed on the basis of behavioral work (e.g., Fay, Garrod, Roberts, & Swoboda, 2010) to account for the emergence of communication systems. These models have shown that large groups can develop a single, global communication system even if individuals interact only locally. Other work has explored how opinions form in large groups of individuals (see Hegselmann & Krause, 2002), with a particular focus on convergence and polarization. The focus in these prior reports, as in our current report, is on the emergence of group-level phenomena from relatively basic but psychologically plausible mechanisms. Unlike our model, these previous models were not intended as broad explanations for behavioral transmission.

Our large-scale simulations demonstrate that agent-based modeling can be used to study social influences on memory and opens new avenues for exploring individual- and population-level phenomena. Such linkages allow large-scale phenomena to be grounded in psychologically identifiable mechanisms and provide well-informed predictions about patterns that emerge at large scales.

Author Contributions

Both authors developed the study concept. C. C. Luhmann designed and executed the simulations and analyzed the data. Both authors contributed to writing the manuscript and approved the final version of the manuscript for submission.

Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

Additional supporting information can be found at http://pss.sagepub.com/content/by/supplemental-data

Note

1. We report statistics for completeness despite our large and ultimately unconstrained sample sizes (see Macdonald, 1997; Oakes, 1986).

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