Mnemonic convergence in social networks: The emergent properties of cognition at a collective level

Alin Coman[a,1], Ida Momennejad[a,b], Rae D. Drach[c], and Andra Geana[a,b]

[a]Department of Psychology, Princeton University, Princeton, NJ 08544; [b]Princeton Neuroscience Institute, Princeton University, Princeton, NJ 08544; and [c]Department of Psychology, University of Albany, State University of New York, Albany, NY 12222

Edited by Danielle S. Bassett, University of Pennsylvania, Philadelphia, PA, and accepted by Editorial Board Member Michael S. Gazzaniga May 31, 2016 (received for review December 26, 2015)

The development of shared memories, beliefs, and norms is a fundamental characteristic of human communities. These emergent outcomes are thought to occur owing to a dynamic system of information sharing and memory updating, which fundamentally depends on communication. Here we report results on the formation of collective memories in laboratory-created communities. We manipulated conversational network structure in a series of real-time, computer-mediated interactions in fourteen 10-member communities. The results show that mnemonic convergence, measured as the degree of overlap among community members' memories, is influenced by both individual-level information-processing phenomena and by the conversational social network structure created during conversational recall. By studying laboratory-created social networks, we show how large-scale social phenomena (i.e., collective memory) can emerge out of microlevel local dynamics (i.e., mnemonic reinforcement and suppression effects). The social-interactionist approach proposed herein points to optimal strategies for spreading information in social networks and provides a framework for measuring and forging collective memories in communities of individuals.

mnemonic reinforcement effect | socially-shared retrieval-induced forgetting | social networks | collective memories | emergent phenomena

From recounting personal stories (1) to discussing historical events (2), people often share their memories with one another. This social sharing leads to widespread transmission of knowledge and memories among members of human communities (3). It is how families, organizations, and even nations come to remember group-relevant events in similar ways (4). Because of their importance for both individual and collective behavior, collective memories have been extensively explored across the social sciences (5, 6), and have been found to affect people's attitudes (7), their decisions (8), and the way in which they collectively solve problems (9, 10). Despite this wide interest, however, there has been very little empirical research into the dynamical processes involved in their formation (11). Questions ranging from basic, such as how a community's collective memories are measured, to more complex, such as how cognitive phenomena or conversational dynamics contribute to the emergence of collective memories, have remained unanswered.

We propose that the formation of collective memories is dependent on how conversations shape individuals' memories. Jointly remembering the past can selectively reinforce and selectively weaken the conversational partners' memories of the experienced events, which in turn can reshape their memories and bring them into alignment. Thus, collective memories grow out of a dynamic system that fundamentally depends on communication (3). At present, most empirical work on communicative influences on memory focuses on dyadic interactions, examining how a speaker can shape the memories of one or more listeners (12); however, a burgeoning literature has shown that collective-level phenomena cannot be explored by simply studying isolated dyadic or small group interactions (13, 14). Rather, it is essential to investigate the mechanisms by which the communicative influences at the dyadic level affect the formation of collective memories in larger groups of individuals.

During social remembering, only part of what a speaker is capable of recalling is actually recollected; that is, any act of remembering is selective, producing what scholars call mnemonic silences (15, 16). This incomplete remembering reshapes the memories of the interactants in very specific ways. On one hand, if a speaker in a conversation repeats something already known to the speaker and/or listeners, then, by virtue of the repetition, both speaker and listener are likely to subsequently better remember the preexisting memory, an indication of a mnemonic reinforcement effect (17). On the other hand, this selective retrieval practice leads to the forgetting of unpracticed material that is related to the practiced material to a greater degree than the unpracticed material that is unrelated to the practiced material (18), a phenomenon aptly termed "retrieval-induced forgetting" (19). More importantly, and relevant to our interest in the emergence of collective memories, previous research has shown that conversational remembering produces the same pattern of reinforcement and retrieval-induced forgetting in listeners as in speakers (12).

Referred to as the socially shared reinforcement effect (SS-R) and socially shared retrieval-induced forgetting effect (SS-RIF) when they occur in the listeners, these phenomena have been found to result in overlap between the memories of the two conversation partners (7, 20). There is no published research on how these dyadic alignment processes lead to the emergence of collective memories in larger communities of individuals, however. In the present study, we examined how the formation of collective memories is dependent on the individual-level cognitive mechanisms described above (i.e., reinforcement and retrieval-induced forgetting effects), and on the conversational network structure that characterizes a community's interactions. Thus, we developed

Significance

Human memory is highly malleable. Because of this malleability, jointly remembering the past along with another individual often results in increased similarity between the conversational partners' memories. We propose an approach that examines the conversation between a pair of participants as part of a larger network of social interactions that has the potential to reveal how human communities form collective memories. Empirical evidence indicating that dyadic-level conversational alignment processes give rise to community-wide shared memories is presented. We find that individual-level memory updating phenomena and social network structure are two fundamental factors that contribute to the emergence of collective memories.

Author contributions: A.C. and R.D.D. designed research; R.D.D. performed research; I.M. and A.G. contributed new analytic tools; A.C. analyzed data; and A.C., I.M., R.D.D., and A.G. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission. D.S.B. is a guest editor invited by the Editorial Board.

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[1]To whom correspondence should be addressed. Email: acoman@princeton.edu.

This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1525569113/-/DCSupplemental.

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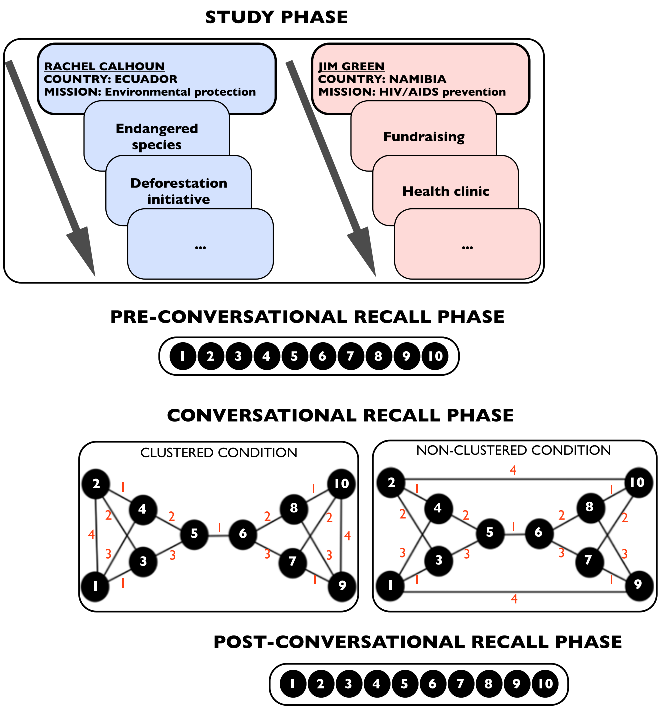


Fig. 1. Phases of the experimental procedure. Participants' first study information about the four Peace Corps volunteers (only two shown here). In the preconversational and postconversational phases, 10 participants individually recall the studied information. In the conversational recall phase, participants are part of either the clustered (left) or the nonclustered (right) condition. Circles represent participants, and links represent conversations. Numbers in red indicate the sequence of conversations.

a paradigm to investigate the formation of collective memories in laboratory-created 10-member communities. We assessed the impact of network structure by manipulating the clustering parameters of the conversational networks in these laboratory-created communities. We also explored how the reinforcement and retrieval-induced forgetting effects triggered during conversations influence the emergence of collective memories. To do so, we used naturalistic stimuli characterized by a category-exemplar structure, a requirement for measuring the two mnemonic effects.

A total of 140 participants enrolled in the study through Princeton University's online recruitment system. Each session was conducted with 10 participants and consisted of four phases, all completed on laboratory computers (*Materials and Methods*). In the study phase, participants first learned four pieces of information about each of four Peace Corps volunteers. Then, in the preconversational recall test phase, participants were provided with the name of each volunteer as a cue and were asked to individually recall the studied information. In the conversational recall phase that followed, participants in the 10-member communities were paired up for a series of dyadic conversations (each with a different partner), during which they jointly remembered the studied materials. Conversations took the form of interactive exchanges in a chat-like computer-mediated environment in which participants typed their responses. Finally, in the postconversational recall phase, participants were asked to individually remember the initially studied information when presented with the name of each volunteer as a cue. Both preconversational and postconversational recalls were self-paced, whereas conversational recalls were time-constrained.

During the conversational recall phase, each participant engaged in a sequence of three 150-s conversations, during which he or she was asked to collaboratively remember as much information from the initially studied materials as possible. In the clustered condition (n = 70 participants; seven 10-member networks), the individuals communicated according to a network structure characterized by two subclusters, whereas in the nonclustered condition (n = 70 participants; seven 10-member networks), the interactions involved only a single large cluster (Fig. 1). The number of participants per network (n = 10), the sequencing of the conversational interactions, and the number of conversations engaged in by each participant in the network (i.e., three) was kept constant between the two conditions. The global clustering coefficient, C (21, 22), differed between the clustered condition (C = 0.40) and the nonclustered condition (C = 0.00).

For each 10-member network, to quantify the formation of collective memories, mnemonic convergence scores were computed separately for the preconversational and postconversational individual recalls (20). First, a mnemonic similarity score for each pair of participants in the network was calculated by adding the number of items remembered in common and the items forgotten in common by both participants, and then dividing this sum by the total number of items studied (Eq. **1** in Fig. 2). The network mnemonic convergence score was calculated by averaging the mnemonic similarity scores among all of the pairs of participants in the network, separately for the preconversational and postconversational recalls (Eq. **2** in Fig. 2).

We predicted that the conversational network structure and the sociocognitive mechanisms triggered during conversations would impact the formation of collective memories, measured as the increase in mnemonic convergence from the preconversational recall to the postconversational recall. More specifically, mnemonic convergence would be (*i*) larger in nonclustered networks than in the clustered networks, (*ii*) circumscribed by a degree of separation effect, and (*iii*) dependent on the degree of reinforcement and retrieval-induced forgetting effects triggered during dyadic conversational remembering.

Results

Mnemonic Convergence Is Dependent on Network Structure.

Comparing mnemonic convergence in clustered and nonclustered networks. To explore whether the differences in clustering between the two conditions influenced the degree of mnemonic convergence

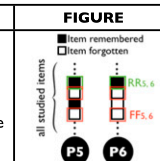
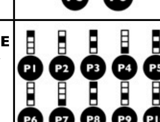
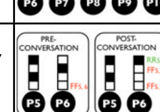
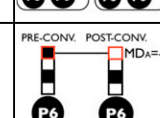
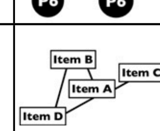
MEASURE/DEFINITION	FIGURE	FORMULA
MNEMONIC SIMILARITY Similarity between the memories of any two participants, computed both pre and post-conversation.		$MS_{i,j} = \frac{RR_{i,j} + FF_{i,j}}{N_{total}}$ (1) *RR* - number of items participants i and j remembered (black squares) in common *FF* - number of items participants i and j forgot (white squares) in common *N* - total number of items studied
MNEMONIC CONVERGENCE Average of mnemonic similarity scores across a network, computed both pre and post-conversation.		$MC_{i:j} = \frac{\sum_j^i MS_{i:j}}{N_{i:j}}$ (2) $MS_{i:j}$ - mnemonic similarity for all i-j pairs in a network $N_{i:j}$ - number of i-j pairs
MNEMONIC ALIGNMENT Changes in mnemonic similarity scores between any two participants from pre to post conversation		$MA_{i,j} = MS_{i,j}^{Post} - MS_{i,j}^{Pre}$ (3) *MS* - mnemonic similarity between participants i and j, pre and post-conversational recall
MNEMONIC DIFFERENCE The difference between a participant's pre- and post-conversational recall, separate for each item		$MD_i = Rec\ A_i^{Post} - Rec\ A_i^{Pre}$ (4) *Rec Ai* - Recall status of item A, for participant i, pre and post-conversational recall
ITEM CENTRALITY The centrality of an item in the collective memory of a community, computed both pre and post-conversation.		$C'_{(A)} = \frac{N-1}{\sum_{P=1}^{N} d(A,P)}$ (5) A - item N - number of items P - all other items except A d(A,P) - shortest path between A and all items P

Fig. 2. Definitions, figures, and equations for the dependent variables.

that the communities reached, we conducted a mixed factorial ANOVA, with time (preconversation vs. postconversation) as a within-network variable and network type (clustered vs. nonclustered) as a between-network variable. This analysis was performed at the network level, with the mnemonic convergence score as a dependent variable. We found a significant main effect for time, [$F_{(1,\ 12)} = 85.62$, $P < 0.001$] and marginally significant effects for network type [$F_{(1,\ 12)} = 4.27$, $P = 0.061$] and for the interaction between time and network type [$F_{(1,\ 12)} = 4.56$, $P = 0.054$]. The degree of mnemonic convergence increased from preconversation to postconversation for both the clustered ($P < 0.002$) and the nonclustered ($P < 0.001$) conditions. As the interaction suggests, the increase was larger in the nonclustered condition than in the clustered condition ($P = 0.054$) (Fig. 3 *A* and *B*). These effects were in the hypothesized direction, but only marginally significant; thus, we conducted additional analyses to more precisely explore the effect of network structure on mnemonic convergence.

Mnemonic similarity is dependent on the degree of separation. An important difference between the two network structures is the distance between the participants in the conversational network. The degree of separation, defined as the number of links in the shortest path between two nodes, ranges from 1 to 5 in the clustered condition and from 1 to 3 in the nonclustered condition. We posit that the smaller the degree of separation between any two participants, the more similar their mnemonic representations should become after network conversations. For instance, if participant P1 interacts with participant P3, and P3 interacts with P5, but P1 does not interact with P5, then the mnemonic similarity between P1 and P3 would be expected to be larger than the mnemonic similarity between P1 and P5. Such a prediction, if confirmed, could explain the difference in mnemonic convergence between the two network structures.

To test for a degree of separation effect, we first computed a mnemonic alignment score by subtracting the preconversational mnemonic similarity score from the postconversational mnemonic similarity score for each pair of participants (Eq. **3**). This mnemonic alignment score, computed at a dyadic level, constituted the dependent variable for this analysis. We used separate linear mixed model analyses for the clustered and the nonclustered conditions, given the differing degrees of separation between the two conditions. The degree of separation, a between-subjects factor, constituted an independent variable and was nested by network. We found a significant effect for degree of separation in the clustered condition [$F_{(1,\ 288.717)} = 10.27$, $P < 0.002$], but not in the nonclustered condition [$F_{(1,\ 74.936)} = 1.75$, $P = 0.19$]. A polynomial contrast revealed that the effect was linear in the clustered condition ($P < 0.006$), but not in the nonclustered condition ($P = 0.20$) (Fig. 3 *C* and *D*). Despite this difference in the linear nature of the effect, there was no statistical difference between the two conditions in the pattern of mnemonic alignment when the analyses were restricted to 1–3 degrees of separation. In both conditions, only participants who were 1, 2, or 3 degrees of separation away from one another had alignment scores significantly larger than 0 ($P < 0.001$ for all three comparisons). These results provide support for the hypothesis that the conversational network structure impacts the alignment of participants' memories. (An analysis that solidifies this conclusion is provided in *SI Materials and Methods*; see Fig. S1.) The question then becomes what are the processes by which conversations align the participants' memories?

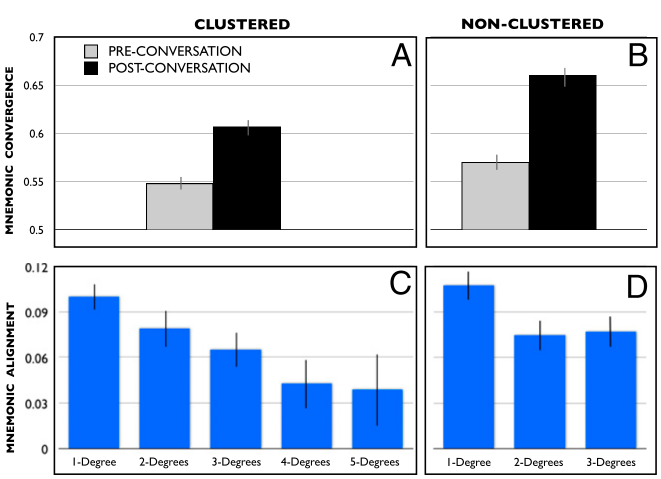


Fig. 3. Mnemonic convergence and mnemonic alignment scores. (*A* and *B*) Mnemonic convergence scores for the clustered (*A*) and nonclustered (*B*) conditions. (*C* and *D*) Mnemonic alignment scores, computed as the difference between postconversational and preconversational mnemonic similarity, by degree of separation, in the clustered condition (*C*; range, 1–5) and the nonclustered condition (*D*; range 1–3). Error bars represent ± 1 SEM.

Cognitive Phenomena Affect Mnemonic Convergence.

Conversational alignment: From dyads to networks. As discussed above, a burgeoning literature has shown that jointly remembering previously studied information makes mentioned information more likely to be remembered by the conversational partners in subsequent individual recollections (7, 12, 20). At the same time, unmentioned information related to what is discussed during the conversation is less likely than unmentioned and unrelated information to be subsequently remembered by the interactants. It follows, then, that the reinforcement and retrieval-induced forgetting effects triggered during conversational interactions could similarly affect the interactants' memories, thereby impacting the emergence of collective memory.

To test for this possibility, we analyzed the content of all participants' conversations. Following Cuc et al. (12), we first classified, for each conversation, all of the items of information that the participants studied as a function of their conversational retrieval practice status, as follows: (*i*) items mentioned during the conversation were labeled Rp+ (retrieval practice plus), (*ii*) items not mentioned during the conversation but related to the mentioned items, that is, those from the same category as the practiced ones, were labeled Rp− (retrieval practice minus), and (*iii*) items unmentioned during the conversation and unrelated to those mentioned were labeled Nrp (no retrieval practice). The labeling of items was relative to each of the three conversations in which a participant was involved during the conversational remembering phase, such that an item coded as Rp+ during the participant's first conversation could be coded as Rp− during that participants' subsequent conversation. We did not account for the source of the information during the conversation (i.e., who was the speaker and who was the listener), because previous research showed that during conversational recall tasks, the speakers and listeners experience similar degrees of reinforcement and retrieval-induced forgetting effects (12).

Using the foregoing labeling scheme, we computed reinforcement/suppression (R/S) scores for each of the 16 initially studied items for each participant. If an item was mentioned during a conversation, and was thus an Rp+ item, it received a (+1) score on the R/S scale. Similarly, if an item was not mentioned during a conversation but was related to the mentioned item (i.e., Rp–), it received a (−1) score on the R/S scale. Items unmentioned and unrelated to the mentioned items (i.e., Nrp) received a score of 0 on the R/S scale. The final R/S score for each participant was cumulated across the three conversations that he or she had in the network. For instance, if an item was mentioned in all three conversations that a participant had in the network, then that item was coded as having a (+3) R/S cumulative score, whereas if the item was part of the category mentioned during a participant's conversations but itself was never mentioned in any of the three conversations, then that item was coded as having a (−3) R/S cumulative score. Importantly, each item was categorized based on its R/S score, which could range from −3 to +3. The scores computed using this procedure are designated as

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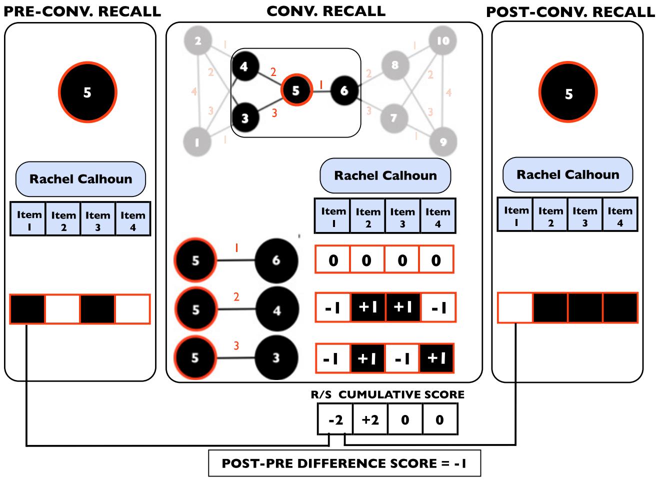

Fig. 4. Computation of the R/S score. Participant 5's recall pattern of one of the four Peace Corps volunteers (i.e., Rachel Calhoun) as a hypothetical example. In the boxes highlighted in red, black boxes indicate recalled items, white boxes indicate unrecalled items. Participant 5 recalls items 1 and 3 in the preconversational recall, then has a series of three conversational recalls with participants 6, 4, and 3, and then recalls items 2, 3, and 4 postconversation. R/S scores were assigned based on whether the item was mentioned in the conversation (+1), was related to a mentioned item (−1), or was not mentioned and unrelated to a mentioned item (0).

"mixed" R/S cumulative scores, because the status of an item could change from Rp− to Rp+ to Nrp in the different conversations in which participants were involved. Based on previous studies that used a selective practice paradigm, we predicted that items with positive R/S scores would experience a reinforcement effect, whereas items with negative R/S scores would experience a retrieval-induced forgetting effect. To capture these effects, for each item we computed a mnemonic difference score by subtracting the preconversational recall score from its postconversational recall score (Fig. 4 and Eq. **4** in Fig. 2). A positive value for this mnemonic difference score indicates a reinforcement effect, whereas a negative value indicates a retrieval-induced forgetting effect.

We conducted a mixed factorial ANOVA with R/S item type as a within-network variable with five levels (+2, +1, 0, −1, and −2) and network type (clustered vs. nonclustered) as a between-network independent variable. For this analysis, we aggregated individual-level scores into network-level scores to avoid missing-data issues derived from using a five-level repeated-measures variable. To do so, we computed mnemonic difference scores for each participant and then averaged these scores across all participants within each network, separately for each R/S item type. These network-level scores constituted the dependent variable for this analysis. Even though the R/S scores ranged from −3 to +3, we only ran analyses with a range between −2 and +2, owing to an insufficient number of data points for the extreme scores (less than 3% of data points had R/S scores of +3 and −3). We found a main effect for R/S item type [$F_{(4, 9)} = 21.68$, $P < 0.001$], but not for network type ($P = 0.81$) or for the interaction ($P = 0.96$). Furthermore, the effect was qualified by a linear trend, with mnemonic difference scores decreasing as R/S scores decreased [$F_{(1, 12)} = 51.72$, $P < 0.001$] (Fig. 5*A*, black line), showing the expected pattern.

To disentangle the effects of reinforcement and retrieval-induced forgetting on subsequent memories, we conducted the same analysis as before, but this time using a subset of the data for which we could compute "pure" R/S cumulative scores. To compute these scores, we calculated the mnemonic difference scores for only the items that could be unequivocally categorized as reinforced, suppressed, or baseline, based on each participant's three conversations. Thus, if an item constituted an Rp+ item in two of the three conversations of a participant and an Nrp item in the remaining conversation, then the item was twice reinforced and experienced no suppression, for a pure R/S cumulative score of +2. Similarly, if an item constituted an Rp− item in one conversation of a participant and an Nrp in the other two conversations of that participant, then the item was suppressed once and experienced no reinforcement—a pure R/S cumulative score of −1. Items that were categorized as Nrp items for all three conversations of a participant constituted baseline items and were assigned a pure R/S score of 0.

Because the analysis was conducted at a network level, we averaged the mnemonic difference scores across the 10 participants in the network, separately for the different types of R/S items. Importantly, 75% of the data points entered into the mixed R/S scores analysis were categorized as pure R/S instances. As in the above analysis, we found a main effect for R/S item type [$F_{(4, 6)} = 38.19$, $P < 0.001$], but not for network type ($P = 0.51$) or for the interaction ($P = 0.61$). Furthermore, the effect was qualified by a linear trend, with mnemonic difference scores decreasing as the pure R/S scores decreased [$F_{(1, 9)} = 70.95$, $P < 0.001$] (Fig. 5*A*, red line). Items that were twice or once suppressed had a significantly lower mnemonic difference score compared with the baseline items ($P < 0.05$). Items that were twice reinforced had a significantly higher mnemonic difference score than the baseline items ($P < 0.03$), unlike once-reinforced items ($P = 0.35$) (Fig. 5*A*, red line). Of note, the analyses involving pure R/S scores were performed for 11 of the 14 networks, because three networks had no items that could be designated pure Nrp items.

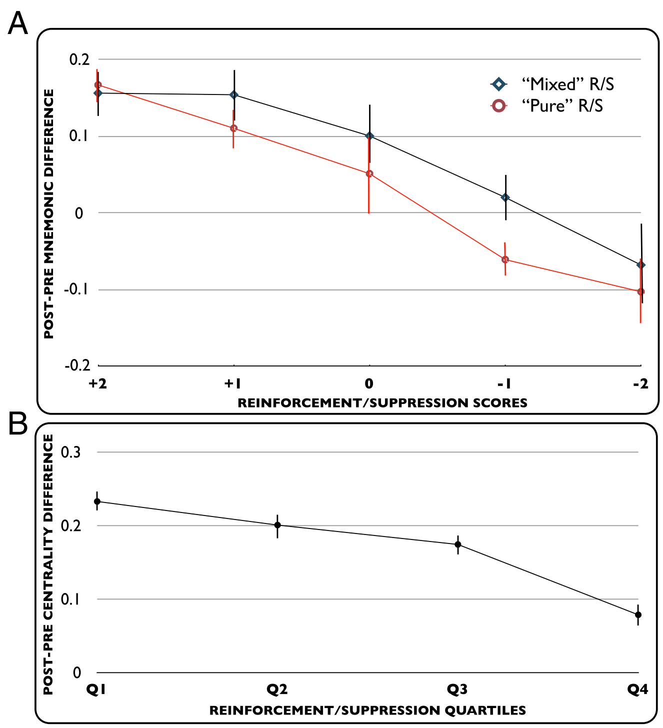

Fig. 5. (*A*) The effect of conversational remembering on subsequent individual recall. The difference between postconversational and preconversational recall (*y* axis) as a function of the R/S score (*x* axis). The R/S scores could range from (+3) (item mentioned in all three conversations of a participant) to (−3) (item not mentioned, but related to a mentioned item in all three conversations of a participant). Mixed R/S scores are in black, and pure R/S scores are in red. (*B*) Item centrality dynamics. The difference between postconversational and preconversational centrality scores (*y* axis) as a function of the quartile split of R/S scores (*x* axis). Quartile 1 represents items with the highest mixed R/S scores. Error bars represent ±1 SEM.

R/S scores predict the emergence of collective memory. We have provided evidence that cognitive mechanisms triggered during conversational remembering (i.e., reinforcement and retrieval-induced forgetting effects) influence the participants' subsequent memories. But do the sociocognitive processes triggered during conversations affect mnemonic convergence at a network level? To answer this question, we followed Weldon (23), who pioneered the use of social network methodology to explore the formation of collective memories. According to this approach, collective memories could be represented as the aggregation of individual memories of the members who belong to the community (i.e., a participants-by-memory items matrix). By transposing this matrix into an item-by-item matrix containing the number of participants that remembered the items in common, and then dichotomizing the matrix using a majority rule ($n > 5$ for a 10-member network), we obtain a binary matrix that captures the community's collective memory. In a visual representation of such a network, nodes are items, and connections indicate that the members' linked nodes (items) are remembered by a majority of the community (in our case $n > 5$; Fig. 2, last row).

We computed such binary matrices separately for each network, for both preconversational and postconversational recalls. Based on these binary matrices, we calculated item-level closeness centrality scores for each of the 16 items (21). Defined as the graph-theoretic distance of a given node to all other nodes, this measure captures how central each of the 16 items is to the collective memory of a community. We used a normalized measure for closeness centrality (21), such that high closeness centrality scores indicate higher centrality in the network's collective memory (Fig. 2, Eq. **5**). We then subtracted the preconversation closeness centrality from the postconversation closeness centrality to capture item-level closeness centrality dynamics from preconversation to postconversation.

For a measure of conversationally triggered reinforcement and retrieval-induced forgetting effects, we used the mixed R/S scores as described above. We computed item-level mixed R/S cumulative scores by averaging the R/S scores over all of the 15 conversations that took place in the conversational recall phase for each network. To investigate whether the R/S scores predict closeness centrality difference scores, we ran separate regression analyses for each of the 14 networks. Both the R/S scores and the closeness centrality difference scores were computed at an item level for each of the 16 items that participants studied. We did not expect to find differences between the two conditions in the degree to which an item's R/S score predicts its closeness centrality difference score. To control for item memorability effects, we included the item's preconversational recall score in the regression analysis. For 11 of the 14 networks (six clustered and five nonclustered), the R/S scores were significant predictors of closeness centrality difference scores ($P < 0.05$); for two networks, the R/S scores were marginally significant ($P = 0.08$ and 0.11); and for one network, the R/S score was not a significant predictor ($P = 0.47$).

To provide further support linking the conversationally triggered sociocognitive processes with the network level effects, we conducted a more fine-grained analysis. As described above, the average R/S scores were computed at a network level, with a single cumulative R/S score corresponding to each of the 16 items studied by the participants. Based on these R/S scores, for each network we categorized the 16 items into quartiles, from highest to lowest R/S scores. As before, for each of the 16 items, we subtracted the preconversation closeness centrality from the postconversation closeness centrality. This difference captured item-level closeness centrality dynamics from preconversation to postconversation. We then averaged these centrality difference scores separately for the four R/S quartiles. Using these network level closeness centrality difference scores as a dependent variable, we conducted a mixed factorial ANOVA with R/S quartiles as a within-network variable and network type (clustered vs. nonclustered) as a between-network independent variable. We only found a main effect of R/S quartiles [$F_{(3,\ 10)} = 70.43$, $P < 0.001$], qualified by a linear trend [$F_{(1,\ 12)} = 160.20$, $P < 0.001$], as expected (Fig. 5*B*). Taken together, these two latter analyses indicate that the emerging collective memory is shaped by the sociocognitive processes triggered during conversational remembering. Items that become central to the collective memory of a community are those that are mentioned frequently and thus are reinforced in conversations among the members of the community. In contrast, the items that become peripheral to the collective memory of a community are those that are suppressed during conversational remembering.

Discussion

The present study constitutes one of the first cognitively grounded investigations of large-scale social dynamics. We have shown that both the conversational network structure and the individual-level sociocognitive phenomena triggered during conversational recall influence the emergence of collective memories in laboratory-created communities of individuals. This exploration meaningfully extends existing research by measuring interactional outcomes that are nonobservable to individual social actors. Research on information propagation (22), imitation (24), and social influence (25) study large-scale dynamics by focusing on behavior manifested in a social context (e.g., observed, interpreted, and acted on); however, this excludes a large class of situations that involve unobservable cognitive consequences of social interactions, such as mnemonic reinforcement and retrieval-induced forgetting effects. In this study, we fill this gap and provide a framework for investigating the emergent properties of individual cognition at a social level.

It is important to acknowledge that even though the manipulation of the network structure was aimed at differentially affecting the clustering of the two types of communities, this manipulation unavoidably resulted in changes in other network parameters. Diameter, betweenness centrality, and average path length are three network features that differed between the two conditions and could have plausibly impacted mnemonic convergence (26). By using targeted analyses, for instance, we have shown that differences in diameter between the two types of network structures affect the degree of mnemonic convergence. Thus, we caution that the present investigation is only a first step in a programmatic investigation of the independent contribution of these network parameters to the emergence of collective memories.

With recent advances in psychological approaches to the formation of collective memories, we are now in a position to overcome both the theoretical and methodological limitations that have hindered the field (27). This would allow researchers interested in investigating micro-macro processes to ask more nuanced research questions regarding the interaction between individual-level cognitive phenomena and structural features of social formations (28–30). Can sampling procedures be designed to minimize data collection efforts and still reveal a community's collective memories? What type of network structures result in maximal mnemonic convergence? Are there sociocultural conditions that accelerate mnemonic convergence (e.g., intergroup conflict) or attenuate this convergence (e.g., organizational mergers)? These are just some of the many questions that become empirically tractable with the social-interactionist approach proposed herein.

Finally, understanding the formation of collective memories is of utmost importance, because they are central to human functioning. On one hand, these shared memories affect people's attitudes (7), their decisions (8), and how they collectively solve problems (9). On the other hand, systematically investigating these dynamics is of wide social importance. Policy makers could use these findings to measure and forge convergent memories in communities affected by biological or social epidemics (31). In public health, disease outbreaks such as Ebola and Zika that have the potential to reach pandemic proportions require rapid and widespread dissemination of information. Community convergence on information about symptoms, risk factors, and preventive measures could save lives. Equally important, strategies aimed at facilitating social justice in open societies could benefit from the approach proposed herein. Our findings could lead to interventions aimed at diminishing the propagation and maintenance of stereotype-consistent information in communities of individuals (32). Given its large-scale nature, our approach could prove more impactful from a policy perspective than current interventions aimed at an individual level (31, 33).

Materials and Methods

Participants. One hundred and forty students affiliated with Princeton University (61% female; mean age, 20.19 y; range, 18–30 y) participated in this experiment for either research credits or compensation. Seventy participants were assigned, in groups of 10, to the clustered condition, and the remaining 70 participants were assigned to the nonclustered condition. All subjects gave informed consent for the protocol, which was approved by the Institutional Review Board at Princeton University.

Stimuli. Using the Qualtrics survey platform, we created a presentation describing a fictional but realistic humanitarian aid program initiated by the American Peace Corps. The presentation consisted of an introductory section outlining the program, followed by descriptions of four Peace Corps volunteers, each with a different mission, stationed on a different continent. The four volunteers were Rachel (environmental protection, South America), Alex (refugee assistance, Europe), Christine (postdisaster recovery, Asia), and Jim (HIV/AIDS prevention, Africa). For each volunteer, four of their projects with the program were presented in separate brief paragraphs ($M_{word\text{-}number}$, 36.75; range, 23–52). A photo illustrated each project. For instance, Rachel was involved in protecting endangered species, preventing deforestation, distributing natural fertilizer, and cleaning beaches. We treated each volunteer as a unitary category, and each project undertaken by the volunteer as an exemplar within the category. We conducted two preliminary studies over Mechanical Turk to balance the 16 activities on relevance and memorability across the four categories.

Design and Procedure. Participants signed up for the study through Princeton University's online recruitment system. Each session was conducted with 10 participants who went through the experimental procedure in a computer laboratory on the university's campus. All of the participants within each network were physically present in the same room and carried out the study on the designated computer terminals throughout. In the study phase, participants first learned information about the four Peace Corps volunteers. The order of presentation of these volunteers (categories), as well as that of their missions (items) was random across participants. Importantly, the exemplars were blocked, such that items pertaining to that volunteer were presented on the same screen. Then, in a preconversational recall phase, participants were provided with the name and background information for each of the four volunteers and were instructed to individually remember the initially presented information (preconversation recall). After this phase, participants took part in a sequence of conversations for which they were instructed to jointly remember the initially studied materials (conversational recall). These computer-mediated chat conversations took place in dyads, such that each participant in a 10-member community engaged in a sequence of three interactions. The conversations were characterized by turn-taking, with virtually all conversational recall instances involving collaboration between the interacting partners. A qualitative analysis of the conversations revealed that all of the participants stayed on task throughout the duration of the study and engaged in collaboratively remembering the initially studied materials, as instructed.

We manipulated the network structure of conversational interactions as illustrated in Fig. 1. A software platform was specifically designed for this project to allow for fluent computer-mediated interactions among participants (i.e., Software Platform for Human Interaction Experiments; SoPHIE). We kept the number of participants, the number of conversations in which each participant was engaged, and the sequence of conversations constant across the two conditions. Each conversation lasted for 150 s, which in preliminary studies provided ample time for information to be exchanged. A final recall test similar to the preconversational recall test was administered following the conversational phase (postconversational recall). The preconversational and postconversational recall phases presented the volunteer name cues in random order. Coding of all of the recall protocols was performed by a research assistant who was blinded to the study's hypotheses and involved a binary system in which an item was labeled as either remembered or not remembered. Ten percent of the data were double-coded for reliability (Cohen $\kappa > 0.89$ for all of the recall phases). Three- to 5-min distracter tasks, in which participants completed unrelated questionnaires, were inserted between any two phases described above.

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