RESEARCH REPORT

Dynamic Search and Working Memory in Social Recall

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What are the mechanisms underlying search in social memory (e.g., remembering the people one knows)? Do the search mechanisms involve dynamic local-to-global transitions similar to semantic search, and are these transitions governed by the general control of attention, associated with working memory span? To find out, we asked participants to recall individuals from their personal social networks and measured each participant’s working memory capacity. Additionally, participants provided social-category and contact-frequency information about the recalled individuals as well as information about the social proximity among the recalled individuals. On the basis of these data, we tested various computational models of memory search regarding their ability to account for the patterns in which participants recalled from social memory. Although recall patterns showed clustering based on social categories, models assuming dynamic transitions between representations cued by social proximity and frequency information predicted participants’ recall patterns best—no additional explanatory power was gained from social-category information. Moreover, individual differences in the time between transitions were positively correlated with differences in working memory capacity. These results highlight the role of social proximity in structuring social memory and elucidate the role of working memory for maintaining search criteria during search within that structure.

Keywords: working memory, executive function, search, social networks, individual differences

Recalling people we know is a key cognitive function. We recruit social memories to judge the frequency of a myriad of social events—ranging from diseases to consumer preferences (e.g., Hertwig, Pachur, & Kurzenhäuser, 2005; Pachur, Hertwig, & Rieskamp, in press)—to assess our relative positions in the social environment (e.g., with regard to happiness or income; Boyce, Brown, & Moore, 2010; Brown, Gardner, Oswald, & Qian, 2008), to establish whom we can trust to cooperate in future interactions (Stevens & Hauser, 2004), and to access others even beyond our own social circles (Kleinberg, 2000; Milgram, 1967). But how do we search social memory? And does this search reflect a general attentional process, as has been suggested for search in semantic memory?

Whereas social memory has often been studied relatively independently from other memory research, here we test the thesis that similar processes might apply for search in social memory as apply to search in semantic memory. Our argument involves two claims. First, search in social memory should dynamically transition between local and global search criteria (as implemented in models of semantic memory search, such as search of associative memory [SAM]; Raaijmakers & Shiffrin, 1981). Second, as proposed for a generalized cognitive search process (Hills, Todd, & Goldstone, 2008, 2010), transitions between local and global search criteria should recruit the general control of attention as measured by working memory capacity (WMC). This latter claim is also related to the proposal that working memory is involved in the guidance of strategically controlled search in long-term semantic memory (Unsworth & Engle, 2007).

The study presented here investigates these hypotheses by modeling the patterns in which people recall their social contacts and by investigating to what extent aspects of this search process correlate with WMC. Before describing our study in more detail, we briefly review previous research on the structure of social memory and highlight parallel ideas in research on semantic memory. We then describe in greater detail our hypotheses concerning dynamic search policies in social memory and the role of executive processing and working memory.

Search in Social Memory

How is social memory structured? And how do people navigate this internal structure? A common approach to studying social memory is to ask participants to “name the people you know” and to analyze the pattern in which these individuals are retrieved (e.g., Bond, Jones, & Weintrob, 1985; Brewer, 1995; Fiske, 1995). A typical finding in these studies is that individuals are recalled in clusters of related individuals (Bond et al., 1985). Several factors have been proposed to drive this clustering: The people we know

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This article was published Online First August 22, 2011.

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This research was supported by Swiss National Science Foundation Grant 100014 130397/1 awarded to Thomas T. Hills.

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1 An alternative approach is to present participants with various hypothesized structuring variables (e.g., locations, role relationships) as retrieval cues and to compare these cues in terms of their effectiveness in eliciting recall (e.g., Brewer & Garrett, 2001; Brewer, Garrett, & Rinaldi, 2002).
may be organized in terms of individual characteristics (such as gender, age, or hair color), spatial or geographical location, alphabetic similarity of their names, or factors concerning social relations (cf. Brewer, 1993; Brewer, Rinaldi, Mogoutov, & Valente, 2005; Fiske, 1995). Of these possible factors, structuring in terms of social relations seems to account for the data best (see Brewer et al., 2005).

However, there are at least two different ways in which social relations could influence social recall. On the one hand, people may use categorical search policies, in which individuals first think about a social category (e.g., one’s family), and then recall individuals “locally” from within this category, before switching to another social category (e.g., Bond & Brockett, 1987; Fiske, 1995; for a test of Fiske’s taxonomy of categories, see Brewer et al., 2005). Alternatively, recall may reflect an associative search policy, which recruits information about the social proximity among the individuals themselves (e.g., Brewer, 1995; Brewer et al., 2005). Such an associative policy implies a search through a cognitive representation of a person’s social network, with individuals connected and retrieved together not because they share the same category but because they know one another.

In this article, we use the computational tools developed for the study of semantic memory to study the search processes when people navigate social memory. Previous investigations have tended to consider social memory as relatively separate from recall of nonsocial material (Bond et al., 1985; Brewer, 1995; Fiske, 1995; but see Bahrick, Bahrick, & Wittlinger, 1975; Williams & Hollan, 1981). Because of its episodic character (Tulving, 2002) and potential differences in functionality (cf. Klein, Cosmides, Tooby, & Chance, 2002), social memory may indeed not completely overlap with other forms of memory, such as semantic memory. However, as we describe next, categorical and associative search policies have also been discussed in the context of semantic memory.

The distinction between categorical and associative forms of search was proposed for semantic memory (Pollio & Gerow, 1968) to account for clustering in patterns of recall found in Bousfield and Sedgewick’s (1944) pioneering studies of free recall from natural categories. In this context, categorical recall refers to search based on group membership (“dog” is in the category “pets”) and associative recall to search based on item-level associations (“dog” is similar to “cat,” which is similar to “lion,” and so on). The contrast between categorical and associative recall is still currently discussed. For instance, the notion of categorical recall is central to the cluster switching hypothesis (Troyer, Moscovitch, Winocur, Alexander, & Stuss, 1998) proposed in the context of category fluency tasks, in which people are instructed, for instance, to “say all the animals you can think of.” According to this hypothesis, people identify a subcategorical cluster (e.g., “pets”), harvest items locally from within this cluster, and then make a global transition to a new cluster (e.g., “birds”; see also Gruevewald & Lockhead, 1980). Alternatively, the associative character of search is a common assumption in many prominent memory frameworks, such as SAM (Raaijmakers & Shiffrin, 1981) and Adaptive Control of Thought—Rational (ACT-R; Anderson, 1993). Although authors have speculated about and found initial evidence for the combined influence of categorical and associative factors in social memory (e.g., Bond & Brockett, 1987; Brewer et al., 2005; Fiske, 1995), no prior studies have tested this possibility using cognitive modeling of the underlying retrieval mechanisms.

A further potential, and rather general, determinant of recall noted in many models of semantic memory (e.g., Anderson, 1993; Raaijmakers & Shiffrin, 1981) is the frequency with which an item—or a network member—is encountered (Brewer, 1995; Murray & Forster, 2004): Items that are more commonly encountered should be more easily accessed from long-term memory (Anderson & Schooler, 1991). Note that these three factors—categorical, associative, and frequency—are likely to be interrelated in social memory: People belonging to a particular social group (e.g., one’s family) are likely to know each other. Moreover, different social groups may differ in terms of the temporal pattern of one’s contacts to them: We may see members of a local club only once a week but see our partner on a daily basis. Because of these interdependencies between categorical, associative, and frequency factors, previous analyses of social recall were not always able to disentangle the individual influences of these factors (e.g., Fiske, 1995; but see Brewer et al., 2005; Brewer & Yang, 1994).

**The Dynamic Nature of Recall and the Role of Working Memory**

In addition to which factors structure social memory, it is also unclear how these factors are used during search. Specifically, it has been proposed that search is governed by a dynamic process, where search can switch between different search criteria (that activate different representational structures) over time. According to this view, search may transition from a local focus (with recall based on inter-item similarity) to a global focus (based on frequency) as the content of local areas becomes depleted (Raaijmakers & Shiffrin, 1981; Troyer et al., 1998). In the context of social memory, search might thus switch between a local cue—such as social-category or social-proximity—and a global cue—such as frequency.

If search follows a dynamic process, what components of cognitive control might govern transitions between local and global criteria? One proposal is that a key role is played by working memory and attentional control to maintain cues to guide local aspects of search. Rosen and Engle (1997) presented evidence that cluster switching in the animal fluency task (“name all the animals you can think of”) was governed by WMC (Kane & Engle, 2000; Unsworth & Engle, 2007). In their study, clusters were defined as items that were recalled in close temporal succession. Using this definition, Rosen and Engle found that individuals with higher WMC produced more items and showed larger clusters of related items than individuals with lower WMC. However, because this work used discontinuities in inter-item retrieval times to define clusters, the role of search criteria underlying these transitions was left unexplored.

Rosen and Engle’s (1997) proposal is similar to accounts of WMC that emphasize its role in the active maintenance of task goals in attention (Conway, Cowan, & Bunting, 2001; Hasher, Lustig, & Zacks, 2008; Kane & Engle, 2000). Moreover, Unsworth and Engle (2007) have speculated that “individual differences in WMC occur not only because of differences in active maintenance, but also because of differences in the ability to use cues to guide the search process from secondary memory [i.e., long-term memory]” (p. 125). By this account, a key function of working memory...
is to facilitate goal maintenance; as a corollary, working memory should govern search across various task domains—and might thus represent a general executive search process.

According to the theory of an executive search process (Hills et al., 2010), the maintenance of one goal requires the ability to inhibit competing goals. As competing goals represent noise (at least in the local function of manifesting action toward the purpose of the current dominant goal), goal maintenance is analogous to discriminating signal from noise. Individuals who have difficulty suppressing the noise will, ceteris paribus, have a greater tendency to transition between representations; that is, goal maintenance and thus the ability to focus search on one local area is jeopardized by the inability to inhibit competing goals. In the case of memory search, an inability to inhibit competing search criteria should manifest itself in more frequent global transitions and, thus, shorter periods of time between local-to-global transitions. Accordingly, the time between local-to-global transitions should be positively related to WMC.

Alternatively, it is also possible that social recall is unrelated to WMC. Moscovitch (1995) noted an important distinction between strategic, or effortful, recall—which involves working memory—and routine, or automatic recall processes—which are mainly driven by frequency (or familiarity) and do not involve working memory. If search in social memory is mainly driven by frequency, we should not expect to find a relation with WMC (see also Oberauer, 2005).

The Current Study

We examined the influence of categorical, associative, and frequency factors as well as the relationship between dynamic search in social memory and WMC by employing a social fluency task. In this task, we asked participants to recall “people that you know.” To model participants’ responses in the social fluency task, we additionally collected three types of information about the recalled individuals. First, we asked them to indicate each individual’s social category (partner, family member, friend, or acquaintance) as well as how frequently they have contact with each recalled individual. Additionally, each participant reconstructed the connections between these individuals (i.e., whether and how well they know each other). These three types of information—social category, frequency, and social proximity—served as the input for the computational models we tested and were taken to define retrieval structures, from which individuals may be sampled. To test the contribution of executive attentional capacities to social recall, participants returned to the laboratory approximately 2 weeks later to take an operation span task (Unsworth, Heitz, Schrock, & Engle, 2005), which measures WMC. In the operation span task, people have to remember a sequence of letters that must be solved (e.g., 1 × 2 + 1 = 2). For the purpose of reliability, at the second session, participants were also again presented with the social fluency task and again provided social-category, frequency, and social-proximity information.

This approach allowed us to construct possible representations of the social memory space for each of our participants and to then model the search process for each participant. Specifically, we tested (a) the influence of categorical, associative, and frequency-based search processes, and (b) whether, as predicted by a dynamic search process, individual differences in the time period between transitions are related to working memory span.

Method

Participants

Thirty-six students (31 women; mean age = 22.6 years) from the University of Basel participated in the experiment. One participant with an operation span of 9, being more than one standard deviation below the next lowest participant, was removed. The average operation span of the remaining participants was 43.06 (SD = 11.55), ranging between 23 and 68.

Materials and Procedure

In the social fluency task, participants were seated in front of a computer and provided with instructions (in German) to type in “the names of people that you know” in such a way that they could unambiguously identify the names later. After typing in a name, the name disappeared from the screen (i.e., participants could not review the persons they had already recalled). The time interval between finishing a name and typing the first letter of the next name was recorded. Participants were not told how many names to produce, but the task terminated after 35 entries. If no more individuals could be recalled before reaching 35, participants could terminate the task themselves (five participants recalled only 34 individuals, and two participants recalled 31 and 33 individuals, respectively). The social fluency task was followed by a series of further tasks that asked questions about the recalled individuals. First, participants were to indicate a social category for each individual (with categories ordered by social closeness to the participant, with lower numbers indicating greater closeness: 1 = partner, 2 = family, 3 = friend, 4 = acquaintance). Second, they were to report how frequently they encountered each individual (on a scale ranging from 1 to 5, with 1 = about once in 6 months or less, 2 = several times in 6 months, 3 = several times a month, 4 = several times a week, 5 = daily). Third, participants were presented with all pairwise comparisons of the recalled individuals (35 individuals yield 595 pairs) and were to indicate their social proximity, that is, how “familiar” the two individuals in each pair are to each other. The current study focused on the first 35 recalled individuals for each participant, with lower numbers indicating greater closeness. The clustering coefficient (35 individuals yield 595 pairs) and were to indicate their social proximity, that is, how “familiar” the two individuals in each pair are to each other.
were with one another (on a scale ranging from 1 = do not know each other at all to 4 = know each other well). This latter information allowed us to reconstruct the structure of (a part of) each participant’s personal social network (i.e., their ego network), corresponding to the recalled social contacts. Participants completed the experiment in approximately 45 min.

Participants visited the laboratory twice, separated by at least 2 weeks. During their first visit, they completed the social fluency task and answered the questions concerning the individuals recalled as described above. During their second visit, participants additionally completed an automated version of the operation span task presented on a computer. In this task, participants were presented with a sequence of letters (ranging from three to seven letters), which they were instructed to remember while simultaneously solving math operations. The operation span score was determined as the sum of all correctly recalled letter sets following correct math solutions. Higher scores indicate higher WMC.

Results

Participants took a mean time of 1.64 min ($SD = 0.56$) to complete the recall task, averaging 2.9 s ($SD = 1.0$) per individual recalled. Table 1 shows the average percentage of recalled individuals that were classified as belonging to the different social categories as well as the distribution across the different levels of contact frequency.

What are the patterns in which participants recalled members of their personal social networks in the social fluency task? For illustration, Figure 1 provides typical production patterns of two participants as well as a representation of the networks among the individuals the two participants recalled.4 In the networks, edges between individuals indicate individuals who knew one another (i.e., social proximity $> 1$). The production patterns in Figure 1 illustrate several interesting regularities. First, the participants tend to recall family and friends first, and acquaintances later. Second, social contacts belonging to the same social category seem to be retrieved clustered together (consistent with categorical recall). Third, these participants appear to recover individuals successively who know each other (i.e., social proximity $> 1$), as most recoveries are between individuals who share an edge in the social networks (consistent with associative recall). Fourth, individual differences in clustering may reflect differences in operation span; the upper individual has a higher operation span and appears to show more clustering both by category and social proximity. In the following, we evaluate the generality of these four patterns across all participants.

Recall by Social Category, Contact Frequency, and Social Proximity

Figure 2 shows for each social category the mean rank order in which an individual was recalled as well as the mean frequency of contact. As can be seen, participants tended to retrieve social contacts in the order of partner, family, friends, and acquaintances. At the same time, participants tended to retrieve individuals encountered frequently earlier than individuals encountered less frequently. A mixed regression analysis, using each participant as a grouping variable, showed that in predicting recall order, social category and contact frequency—which were positively correlated with each other (the average correlation across participants was significantly greater than zero, $r = .27, t(34) = 7.02, p < .001$)—have independent effects: social category, $B = 3.07, t(2324) = 12.11, p < .001$; contact frequency, $B = -10.73, t(2324) = -12.31, p < .001$. In other words, frequently contacted people are recalled earlier, irrespective of social category, and people in close social categories are recalled earlier, irrespective of the frequency of contact with them. These independent effects support both the frequency and category accounts of social recall.

However, there is also evidence for the influence of an associative search policy. A mixed regression analysis revealed that the recovery time (in seconds) between successively recalled individuals was inversely related to how well the two individuals know each other (i.e., their social proximity), $B = -1.1, t(2325) = -18.92, p < .001$.

To evaluate the influence of associative and categorical search policies along a common dimension, we used a measure of clustering frequently used in the social memory literature, the adjusted ratio of clustering (ARC; Brewer et al., 2005; Roenker, Thompson, & Brown, 1971). It expresses the degree to which recall is clustered with respect to a particular set of inter-item relations (e.g., categories or social proximity). ARC is computed as the difference in the observed clustering for a given participant ($O$) and the expected clustering if recall ordering were random ($E$), relative to the difference between the maximum potential clustering ($M$) and the expected clustering (for further details, see Brewer et al., 2005):

$$ARC = \frac{O - E}{M - E}$$

Table 1

Average Percentage of Participants Recalled in the Social Fluency Task Who Were Classified as Belonging to the Different Social Categories and Levels of Contact Frequency, Respectively

<table>
<thead>
<tr>
<th>Variable</th>
<th>% of recalled individuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social category</td>
<td></td>
</tr>
<tr>
<td>Partner</td>
<td>2.2 (0.78)</td>
</tr>
<tr>
<td>Family</td>
<td>23.6 (10.97)</td>
</tr>
<tr>
<td>Friends</td>
<td>46.0 (15.84)</td>
</tr>
<tr>
<td>Acquaintances</td>
<td>30.2 (14.05)</td>
</tr>
<tr>
<td>Frequency of contact</td>
<td></td>
</tr>
<tr>
<td>Daily</td>
<td>10.19 (9.41)</td>
</tr>
<tr>
<td>Several times a week</td>
<td>16.88 (7.70)</td>
</tr>
<tr>
<td>Several times a month</td>
<td>23.28 (8.67)</td>
</tr>
<tr>
<td>Several times in 6 months</td>
<td>25.88 (8.39)</td>
</tr>
<tr>
<td>About once in 6 months or less</td>
<td>23.77 (12.97)</td>
</tr>
</tbody>
</table>

Note. Standard deviations are in parentheses.

4 Brewer (1993) distinguished three aspects of recall patterns in a social fluency task: (a) clustering, that is, the relationship between consecutively recalled individuals; (b) the serial order in which individuals are recalled; and (c) the frequency with which individuals are recalled. In the following, we consider both clustering and serial order to examine the contributions of contact frequency and associative and categorical search policies. Our computational model, by contrast, focuses on clustering (i.e., it predicts the probability that search moves from one recalled individual to another).
For all three parameters—$O$, $E$, and $M$—clustering is computed as the number of adjacently recalled items that are from the same category (for categorical clustering) or that have social proximity $\geq 1$ (for clustering according to social proximity). ARC takes on the value of 1 if a person produces the smallest possible number of switches between clusters, and 0 if clustering is at the level expected by chance.\(^5\)

For social category, we found an average (across participants) ARC of .58 ($SD = .21$), significantly higher than zero, $t(34) = 14.46, p < .001$. This value is higher than what is usually observed for social categorical recall. For instance, in Sedikides and Ostrom’s (1988) meta-analysis, the average ARC was .14. This suggests that the social grouping into partner, family, friends, and acquaintances captures the influence of social categories rather well when compared with alternative grouping schemes. The average ARC for social proximity was .73 ($SD = .08$), significantly higher than zero, $t(34) = 56.22, p < .001$ (one-sample $t$ test), and also significantly higher than the ARC for social category, $t(34) = 4.34, p < .001$ (paired $t$ test).

One way to disentangle the contributions of social category and social proximity, which also controls for the simultaneous influence of contact frequency, is to use formal cognitive modeling (for an alternative approach, see Brewer & Yang, 1994). In the next section, we describe a computational modeling framework of memory recall and ask which type of search process based on the above search criteria offers the most parsimonious explanation for the observed sequence in which individuals were recalled.

\(^5\) Determining the amount of clustering expected by chance, $E$, for social proximity is computationally intensive and was solved using the graph-theoretic method described in Brewer et al. (2005).
Modeling Social Recall

To model how each participant recalled individuals, we used a modeling framework similar to the memory sampling process described by SAM (see Hills, Todd, & Jones, 2009; Raaijmakers & Shiffrin, 1981). SAM assumes that memory search is initiated by a cue (or a set of cues), $Q$, which activates a set of items (i.e., individuals), $I$, in memory in proportion to its similarity to those items, $S_k(Q, I)$, within a particular retrieval structure, $k$, of which there are $M$. Our data allowed us to describe three retrieval structures: one each for social category, social proximity, and frequency of contact, which are represented as matrices that describe how strongly an item in memory is activated in response to a given cue. Thus, the predicted probability that a given item, $I_i$, is sampled from memory is a function of the item’s similarity to one or more cues used to probe memory divided by the similarity of all other items activated by the same cue(s) (cf. Romney, Brewer, & Batchelder, 1993):

$$P(I|Q_1, Q_2, \ldots, Q_M) = \frac{\prod_{k=1}^{M} S_k(Q_k, I)^{w_k}}{\sum_{j=1}^{N} \prod_{k=1}^{M} S_j(Q_j, I)^{w_j}}.$$  \hfill (2)

$S_k(Q_k, I)$ represents the retrieval strength from cue $Q_k$ to individual $I_i$ in social memory, and $w_k$ represents the saliency (Raaijmakers & Shiffrin, 1981) of the $k$th retrieval structure. Higher values of $w_k$ lead to a stronger influence of the cue on the predicted probability.

Here, we consider two cues, representing the global and local aspects of memory search, respectively: a context cue and a cue representing the most recently recalled individual. The context cue represents a global search cue, activating each individual in proportion to his or her global strength of activation in the overarching category of “people that you know.” In line with previous work (Raaijmakers & Shiffrin, 1981), we assume that the global strength is best approximated by a retrieval structure defined by the frequency of contact with each individual. The local cue is represented by the most recently recalled individual and activates other individuals in retrieval structures defined by either social category (implementing categorical recall) or social proximity (implementing associative recall). For categorical recall, the activation strength of an individual corresponds to whether it shares the same category as the most recently recalled individual (e.g., family). For example, retrieval of a friend would preferentially activate other individuals that are also in the friends category. For associative recall, the activation strength of an individual corresponds to how well that person knows the most recently recalled individual. For example, if the most recently recalled individual was grandma, other individuals would be activated as a function of their social proximity to grandma; that is, if the participant indicates that “grandma” and “grandpa” know each other with a value of 4, then $S(“grandma,” “grandpa”) = 4$. Thus, each of the retrieval structures (representing either frequency, social category, or social proximity) is a matrix providing the retrieval
strength for each possible cue with all remaining social contacts.\(^6\)
Given a set of cues and a set of retrieval structures for each participant, we
determined the best fitting saliency parameter, \(w_c\), for each retrieval
structure, \(k\), for each participant, and we computed the predicted retrieval probability for each observed sequence of recalled individuals.

Using this framework, we tested several static and dynamic models that differed in terms of which retrieval structures guide search and how cues are used during the search process. Static models used the same combination of cues and retrieval structures over the entire production interval (e.g., always using the global context represented by frequency). Dynamic models, by contrast, transitioned between local and global cues. We defined local-to-global transitions as follows: When searching associatively, local-to-global transitions (i.e., from social proximity and frequency to frequency alone) occurred whenever an individual was produced who does not know the individual recalled immediately prior to him or her (closed circles in Figure 1). When searching categorically, local-to-global transitions (i.e., from social category and frequency to frequency alone) occurred whenever two successively recalled individuals did not share the same category (changes in color in Figure 1). In a dynamic model, the probability of recall during local and global search was thus computed based on different cues (for a related example, see Gronlund & Shiffrin, 1986).

Table 2 presents for static models the median (across participants) improvement over a random model\(^7\) in the Bayesian information criterion as well as the median \(w\) and number of free parameters. Note that the static and dynamic models are not strictly comparable, as to identify transition points, the dynamic models used information from the data about the to-be-retrieved items. We turn to the question of whether the data are better accounted for by a static or dynamic process in the next section.

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**Table 2**

*Median Improvement in the Bayesian Information Criterion (BIC) Relative to a Random Model for Static Recall Models That Use One or More Cues*

<table>
<thead>
<tr>
<th>Retrieval structure</th>
<th>BIC improvement ((Mdn))</th>
<th>(w) ((Mdn))</th>
<th>No. of free parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-cue models</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>32.30</td>
<td>1.01</td>
<td>1</td>
</tr>
<tr>
<td>Shared category</td>
<td>35.85</td>
<td>2.38</td>
<td>1</td>
</tr>
<tr>
<td>Social proximity</td>
<td>51.24</td>
<td>2.81</td>
<td>1</td>
</tr>
<tr>
<td>Multi-cue model</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency + Category</td>
<td>47.68</td>
<td>2.54</td>
<td>2</td>
</tr>
<tr>
<td>Frequency + Social proximity</td>
<td>49.93</td>
<td>2.57</td>
<td>2</td>
</tr>
<tr>
<td>Frequency + Social proximity + Category</td>
<td>44.13</td>
<td>3.74</td>
<td>3</td>
</tr>
</tbody>
</table>

*Note.* Models were fit using the maximum likelihood method to find the optimal \(w\) (medians reported) for each cue-retrieval structure combination for each individual. A plus sign indicates that the product of the retrieval strengths was computed in Equation 2 for the local memory search.

The results in Table 2 indicate that among the static models, the one that assumes that recall follows social proximity captures the data best. This is consistent with the ARC results from above. Although our approach also allows us to test static models that are based on multiple cues in combination, all of these models performed worse than the model using social proximity alone.

With regard to the dynamic models, the results indicate that the model that assumes a global structure defined by frequency and a local structure defined by social proximity and frequency captures the data best (see Table 3). Models assuming a local structure defined by social category, either alone or in combination with social proximity, performed worse. For all models, the \(w\) parameters were positive. In summary, both static and dynamic model comparisons converge on supporting a search process in which social proximity plays a key role, whereas social categories do not.

Next, we examine whether, as predicted by a dynamic (but not by a static) mechanism, the time period between transitions from local to global search criteria was correlated with WMC.

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**Working Memory and Local-to-Global Transitions**

Is there evidence that recall from social memory is governed by a dynamic local-to-global search policy? As described above, a domain-general executive search process predicts that for people with a high operation span, the time period between transitions from local to global search criteria is longer than for people with a low operation span. The reason is that low-span people should have a reduced ability to maintain cues that guide local search. To test this hypothesis, we examined the relationship between the individual differences in the time period between transitions and the operation span score. Transitions were defined as alternations between local and global cues as assumed in the best performing dynamic model, that is, between social proximity and frequency. Keeping in mind the moderate sample size of participants, regressing time between transitions (i.e., switches) on operation span indeed revealed a significant relationship, \(B = 117.6, t(34) = 2.18, p = .037, r = .35\) (see Figure 3A). In other words, participants with higher operation spans produced longer intervals of individuals who know each other than did participants with lower spans.

Importantly, the effect of working memory on the length of the time period between transitions was not due to high- and low-span participants having different network structures. As shown in Figure 3B, there was no association between operation span and clustering coefficient (which is a measure of the probability that, if

\(^6\) SAM, as proposed by Raaijmakers and Shiffrin (1981), uses sampling-with-replacement but also includes other assumptions to eliminate repetitions during recall. As none of our participants produced repetitions, and we are not simulating productions with additional assumptions to inhibit repetitions (but assign probabilities to each item produced), we use the more appropriate sampling-without-replacement. However, none of the conclusions we make here hinges on this assumption: The qualitative patterns of results are identical to those produced by a model with replacement.

\(^7\) This implementation is consistent with SAM (Raaijmakers & Shiffrin, 1981), which uses a local cue set that combines global and local information.

\(^8\) The random model assumes that all remaining items in the social network have an equal chance to be recalled.
an individual knows two other individuals in a network, those two individuals also know one another; \( r = -.04, p = .82 \). Moreover, operation span was unrelated to network density. We quantified network density for each participant as the number of connections between recalled individuals (defined as social proximity) in the participant’s ego network, relative to the maximal number of connections possible. The correlation between network density and operation span was not significant (\( r = -.28, p = .1 \)). The lack of associations between operation span and network characteristics indicates that the observed differences in recall patterns between high- and low-span participants are mainly driven by the executive control of memory and not by the idiosyncratic structure of their ego networks. Finally, participants with high and low operation spans did not differ with regard to the mean time spent to recall each individual (\( r = .10, p = .55 \); see Figure 3C).

**Discussion**

Memories of our social relations offer us a rich source of information about the world (Pachur et al., in press). Previous research has indicated that social memory is structured by factors such as social categories and social proximity (e.g., Brewer, 1995; Fiske, 1995). However, despite considerable developments of computational accounts for semantic memory, there have been very few analyses of social memory using cognitive modeling. In addition, whereas research in semantic memory found evidence for a dynamic retrieval process (e.g., Raaijmakers & Shiffrin, 1981), static and dynamic search policies have not been compared in previous research on social recall. In this article, we examined the relative contribution of the potential factors underlying social recall using a cognitive modeling framework developed for semantic memory. In line with previous results, social recall was clustered in terms of social categories (e.g., Fiske, 1995). Nevertheless, the best static account for the data assumed recall from retrieval structures based on associative relations (i.e., social proximity), supporting the conclusions in Brewer et al. (2005). Extending Brewer et al.’s findings, we showed that a dynamic model based on associative relations and frequency fit the data still better than the static model.

**Table 3**

Median Improvement in the Bayesian Information Criterion (BIC) Compared With the Random Model for Dynamic Recall Models Incorporating Different Global and Local Representations, and Different Switching Criteria (Associative or Categorical)

<table>
<thead>
<tr>
<th>Local retrieval structure</th>
<th>Switching criterion</th>
<th>Associative</th>
<th>Categorical</th>
<th>No. of free parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>w (Mdn)</td>
<td>BIC improvement (Mdn)</td>
<td>w (Mdn)</td>
<td>BIC improvement (Mdn)</td>
</tr>
<tr>
<td>Frequency +</td>
<td>4.89</td>
<td>52.93</td>
<td>3.43</td>
<td>41.21</td>
</tr>
<tr>
<td>Social proximity</td>
<td>2.76</td>
<td>3.19</td>
<td>3.69</td>
<td>41.75</td>
</tr>
<tr>
<td>Frequency +</td>
<td>3.30</td>
<td>29.51</td>
<td>52.15</td>
<td>45.92</td>
</tr>
<tr>
<td>Social category</td>
<td>3.50</td>
<td>4.43</td>
<td>49.29</td>
<td>2.79</td>
</tr>
<tr>
<td>Social category</td>
<td>1.81</td>
<td>1.67</td>
<td>31.78</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* A plus sign indicates the product of the retrieval strengths computed according to Equation 2 for the local memory search.

In all models, frequency was used as the global retrieval structure.

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**Figure 3.** Individual data for time per switch, clustering coefficient, and total time, as a function of operation span.
and, further, that the length of the time period between dynamic local-to-global transitions in the search process correlated with a measure of executive function, namely, WMC.

These findings are consistent with the proposal that working memory span is related to goal maintenance and the effective use of local cues during retrieval from long-term memory (see Rosen & Engle, 1997; Unsworth & Engle, 2007; Unsworth, Spillers, & Brewer, 2011). Moreover, the findings presented here, along with those found between WMC and dynamic search in other domains (e.g., Rakow, Demes, & Newell, 2008), support the thesis that executive processes may act as a domain-general search process, controlling goal abandonment in both external and internal domains (Hills et al., 2010, 2009).

An important aspect of our approach is that it allows a definition of clusters based on participant’s own idiosyncratic search environments—as opposed to analyses based on hand-coded categorizations (e.g., Troyer et al., 1998) or randomly generated search environments (e.g., Harbison, Dougherty, Davelaar, & Fayad, 2009; Raajmakers & Shiffrin, 1981). Because this approach makes explicit the putative internal representational environments over which participants may search, it allows us to compete alternative (categorical, associative, and frequency) representations against one another and, thus, to further infer the structure of individual memory representations. More general but less idiosyncratic representations of memory domains have been constructed to represent memory, for example, by using semantic space models, which capture semantic relations between words in natural text (e.g., Jones & Mewhort, 2007), or feature norms that allow objects to be associated based on shared features (e.g., feature norms; McRae, Cree, Seidenberg, & McNorgan, 2005). As here, such representations offer a powerful tool for future investigations of cognitive search processes and the representations over which they search.

Our results have implications for categorical versus associative accounts of long-term memory retrieval. In particular, they support previous findings indicating that social memory is based on associative relations between items in memory (Brewer et al., 2005), not on first identifying categories (e.g., family), and then identifying items with a category. This finding contrasts with some findings for semantic memory. Notably, much research has found support for categorical clustering using the hand-coded categories of Troyer et al. (1998; also see Lanting, Haugrud, & Crossley, 2009; Troyer, 2000). However, recent research on semantic memory has shown that recall patterns can appear to be categorical even when the underlying processes are more consistent with associative search policies (Hills et al., 2009). Whether the existing evidence for categorical search in semantic search is real or apparent is an important question for future research—as is the question of why the prevalence of different search policies might differ between social and semantic search (or even between individuals). Importantly, such insights into the structure of memory may be quite useful in improving recall, as has been shown by Pollio and Gerow (1968).

A second issue on which the present approach may be helpful refers to the factors underlying cognitive stopping rules in memory search. One prominent proposal is that people stop search when the number of retrieval failures reaches a certain threshold (Harbison et al., 2009; see also Dougherty & Harbison, 2007). Work on individual differences (e.g., Unsworth et al., 2011) and the work presented here indicate that additional factors may be at play, including the ability of individuals to use and maintain local cues during memory search. On the other hand, individual differences in cue maintenance might also be related to differences in the retrieval failure thresholds for determining when to abandon search. Relatedly, it is important to investigate “where” in a retrieval structure stopping is most likely to take place (for an attempt in this direction, see Hills et al., 2009).

Finally, the present research offers insights into how social memory might shape our inferences about the world. Traditionally, memory-based decision making has been suggested to mainly depend on the frequency and “availability” of traces in social memory (e.g., Tversky & Kahneman, 1973). Our results, by contrast, hint that search is not generally driven by a static and automatic process guided by frequency (Moscovitch, 1995). Rather, search seems to involve, in addition to an automatic process based on frequency, a strategic component based on inter-item associations—especially among people with high working span. It is likely that these relations also influence how our social memories shape our views of world.

References


automated version of the operation span task. *Behavior Research Methods, 37,* 498–505. doi:10.3758/BF03192720


Received April 27, 2011
Revision received July 1, 2011
Accepted July 11, 2011