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Abstract

An important component of many, if not all, real-word retrieval tasks is the decision to terminate memory search. However, despite its importance, no systematic evaluation of the potential rules for terminating search (i.e., potential stopping rules) has been undertaken. Using computational methods and recent results from a new memory retrieval paradigm, we evaluated four potential stopping rules in a reduced SAM framework. We focused on two measures of memory search termination: the total time spent in search before termination and the exit latency (the time between the last retrieved item and the point of search termination). The results of our analysis favor a rule that is sensitive to the number of retrieval failures during memory search.

Keywords: free recall; memory retrieval; stopping rules; exit latency.

Introduction

Every memory search is eventually terminated. Sometimes this termination is due entirely to an external cause (e.g., an interruption), but often it is determined by the individual searching memory. Therefore, it is not surprising that computational models of the memory retrieval process often include stopping rules to terminate memory search.

Despite the ubiquity of termination decisions and the presence of stopping rules in models of memory retrieval, little empirical data has been collected on search termination decisions. Indeed, the traditional memory retrieval paradigm gives participants a fixed retrieval-interval (e.g., 30 seconds) during which to retrieve. After the interval, the participant is moved on to the next list by the experimenter. This methodology allows for no measurement of memory search termination decisions. Recently, research has begun to examine termination decisions by altering the traditional retrieval paradigm through the use of an open-ended, rather than a fixed, retrieval interval (Dougherty & Harbison, 2007). In the present paper, we use results from this new paradigm to evaluate previously proposed stopping rules.

Open-Ended Retrieval Paradigm

The open-ended retrieval paradigm, introduced by Dougherty and Harbison (2007), is shown in Figure 1. The only change relative to the traditional free-recall paradigm is that participants determine the length of the retrieval interval instead of the experimenter. That is, instead of giving participants a fixed amount of time during which to retrieve, participants in the open-ended paradigm are free to stop search whenever they judge themselves finished. This decision is signaled (e.g., by pressing the SPACE bar) and the participant continues on to the next part of the experiment.

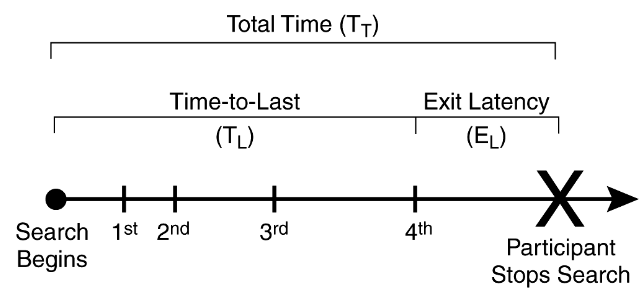

Figure 1: Open-ended Retrieval Paradigm.

Since participants signal their memory search termination, this paradigm allows for the measurement of the termination decision (Dougherty & Harbison, 2007). The most obvious measurement of this decision is the total time (T_T) that the participant spends in search. In the fixed retrieval interval paradigm, T_T is determined by the experimenter. Participants may continue to search throughout the entire fixed retrieval interval or they may stop earlier; there is no way to tell if or when participants terminate search. With the open-ended paradigm, T_T is determined by the participant searching memory and therefore, becomes a dependent measure of how long participants *are willing* to continue searching memory. However, T_T is in some ways necessarily confounded with other variables. Particularly, as the number of items a participant retrieves increases, an increase in T_T is expected.

As shown in Figure 1, T_T can be divided into two components, the time up to the last retrieval (time-to-last or T_L) and the time between the final retrieval and search termination. This latter variable is referred to as the exit latency (E_L; Dougherty & Harbison, 2007). T_L is the component of T_T that naturally relates to the number of items retrieved. E_L, on the other hand, does not relate to the number retrieved in any necessary way. Indeed, reasonable arguments could be made for E_L to increase, decrease, or be independent of the number of items retrieved (Harbison, Dougherty, & Fayyad, submitted).

Research using the open-ended paradigm has found that as the number of items retrieved increases T_T also increases, as might be expected. However, while T_T is increasing, E_L decreases (Dougherty & Harbison, 2007; Harbison, Dougherty, & Fayyad, submitted). That is, the more items that are retrieved, the less time passes between the final retrieval and search termination.

The increase in T_T (due to T_L) and the decrease in E_L as more items are retrieved has been found now in four independent experiments (Dougherty & Harbison, 2007; Harbison, Dougherty, & Fayyad, submitted). This data pattern provides strong constraints against which to test potential stopping rules.

Stopping Rules

Atkinson and Shiffrin (1968, page 121) suggested a number of stopping rules, which have been implemented in models by several authors. These different stopping rules are: an internal time limit (Davelaar et al., 2005; Davelaar, 2007; Diller, Nobel & Shiffrin, 2001; Farrell & Lewandowsky, 2002; Metcalfe & Murdock, 1981), a strength threshold (Anderson et al. 1998; Diller, Nobel & Shiffrin, 2001), and an event-counter that would terminate search after a prespecified number of events (Raaijmakers & Shiffrin, 1980; Rundus, 1973; Shiffrin, 1970).

Despite the tacit assumptions regarding stopping rules embodied in models of memory, surprisingly little is known about the mechanisms underlying the termination of memory retrieval. Consequently, computational models developed to account for retrieval dynamics have employed a variety of rules, with little empirical justification for the choice of the selection (Davelaar et al., 2005; Metcalfe & Murdock, 1981; Raaijmakers & Shiffrin, 1980, 1981). Satisfying solutions may involve more pragmatic considerations rather than theoretical, such as minimizing simulation time. Moreover, modelers traditionally have been relatively more concerned with accounting for recall probabilities at various levels of granularity, from cumulative recall functions (e.g., Gronlund & Shiffrin, 1986) to conditional recall probabilities (Howard & Kahana, 1999). Since the empirical results the models were evaluated against were from experiments using the fixed interval retrieval paradigm, the potential contribution of the stopping rule or rules that a participant would normally use would likely have little impact on recall probabilities.

Given the varied assortment of stopping rules employed across the literature, it is clear that little heed has been paid to how a chosen stopping rule might affect the model's *retrieval dynamics.* To date, there has been no justifiable way to narrow the set of plausible stopping rules. We argue that data obtained from the open-ended retrieval paradigm provides the necessary, finer-grained analysis of free recall data that allows us to whittle down the set of potential stopping rules. We now turn to the comparative analysis of four stopping rules.

Comparative Modeling Study

We compared the results from one of the open-ended retrieval paradigm experiments against the predictions of four different stopping rules. Each of these stopping rules has been proposed previously in the literature.

S1. Total time—the decision to terminate search is a function of the total time spent retrieving (Davelaar et al., 2005; 2006).

S2. Time since last retrieved item—the decision to terminate search is a function of the time since the last retrieval (Metcalfe & Murdock, 1981; Rundus, 1973; Thomas, Dougherty, Sprenger, & Harbison, 2008).

S3. Last Inter-Retrieval Time (IRT)—the stopping time decreases as the duration of the last IRT increases. The final IRT tends to be of constant length, independent of the number of items retrieved (Rohrer, 1996). Furthermore, the final IRT tends to be substantially larger than earlier IRTs. Therefore, it is possible that once the most recent retrieval takes a sufficient amount of time, search would be terminated. Young (2004) suggested that it is the relative increase in the IRT between the initial and final retrievals may lead to search termination.

S4. Number of retrieval failures—the decision to terminate search is a function of the number of failed retrieval attempts (Raaijmakers & Shiffrin, 1980; 1981).

For the purpose of the present simulations, each rule was implemented to make stopping decisions through a probabilistic function

$$P(G) = \frac{1}{1+e^{-g(X-\theta)}},$$

in which P(G) is the probability of giving-up, g and theta are the gain and threshold parameters respectively and X is either the total time (for S1), the time since the last retrieved item (for S2), the last IRT (for S3), or the number of failures (for S4).

Method

To evaluate the stopping rules, all rules were implemented in a reduced search of associative memory (SAM) framework (Raaijmakers & Shiffrin, 1980).

Search of Associative Memory (SAM)

The two central aspects of SAM are the acquisitions of associations during learning and the random-sampling with replacement process during retrieval. During list presentation SAM learns associations between context and images and between images that are co-active in the short-term buffer. Images are combinations of features from item and context representations. Specifically, the association between the current context and an image in the short-term buffer is incremented by the value a, that is a free parameter within the framework, for each second the image is present in the buffer. Similarly, the inter-image associations are incremented for each second they are both present in the short-term buffer. However, as discussed below, we removed the inter-image associations for the purposes of the present simulations.

During retrieval, the context is used to search for images in the long-term store. Search for not-yet retrieved images proceeds through a random-sampling with replacement process, where the probability of sampling an image is dependent on the association strength between that image and the current context. Specifically, the probability of sampling an image, I_i, given the context, C, is

$$P_s(I_i \mid C) = \frac{S(C, I_i)}{\sum_j S(C, I_j)},$$

which is the relative strength of image I_i in the search set delineated by context C. Since images retrieved are not excluded from subsequent sampling, the probability of sampling a previously retrieved image increases with the total number of images retrieved. Note that for the purposes of S4, sampling a previously retrieved image counts as a retrieval failure.

If the sampled image has not previously been retrieved, the second stage of retrieval, item recovery, is performed. Recovery of the sampled item depends on the absolute strength of the image and succeeds with probability

$$P_r(I_i) = 1 - e^{-S(C, I_i)}.$$

If the recovery process is successful (i.e., a randomly chosen number between 0 and 1 is less than $P_r(I_i)$), then the item has successfully been retrieved and that item is outputted. Otherwise, the recovery is deemed unsuccessful and the retrieval attempt is counted as a failure.

Note that for comparison with the temporal data we assume that each retrieval attempt takes a fixed amount of time whether or not that retrieval attempt was successful. This assumption is consistent with previous applications of the SAM model to temporal data (Raaijmakers & Shiffrin, 1980).

For our comparative analysis, we are interested in the termination of the search and not in the associative path traversed during memory retrieval. We therefore exclude encoding of inter-image association strengths, the use of retrieved images for further retrieval and post-retrieval incrementing. In terms of the SAM model, this eliminated the contribution of the inter- and intra-image associations. Doing so allowed us to isolate the contribution of the stopping rules themselves, as any differences in patterns of latencies across stopping rules could not be attributed to interactions between the rules and these mechanisms. However, introducing the various SAM components did not alter the major qualitative patterns. We do note that these components are critical in capturing finer-grained retrieval dynamics.

Data

The data to be fitted in the model comparison was taken from Experiment 2 of Harbison, Dougherty, and Fayyad (submitted). This experiment made use of the open-ended retrieval paradigm. Each participant was shown six lists of ten, fifteen, and twenty items one at a time. List-length was randomized so that each block of three lists contained a list of each length. The lists were created randomly for each participant and consisted of high frequency (KF 30 to 300), single syllable words from the MRC psycholinguistic database (Wilson, 1988). Between presentation of the list and recall, participants performed timed math problems for at least 30 seconds, making it a delayed free recall task.

The list length effect was found in this experiment; the percent of items retrieved from the lists decreased as list length increased. No differences in T_T or E_L were found due to list length; therefore, the data was collapsed over this variable. Figure 2 shows mean total time (as solid circles) and exit latency (as open circles) across participants for retrieval totals of zero through nine in each of the four panels. It is important to note that the same qualitative pattern of results (increasing T_T and decreasing E_L as more items were retrieved) was found in the within-participant data as well.

Procedure

We conducted 1000 simulation runs of delayed free recall for each of the four rules. Delayed free recall was modeled by presenting 10 list items followed by 10 distracter items to the model and at retrieval having the search set be comprised of only the first 10 items. No items were retrieved from the short term store or buffer. This procedure was used in previous models (Davelaar et al., 2005; 2006) and is consistent with the theoretical position that distracter items displace list items from the buffer (Murdock, 1967). The number of items retrieved (N_{stop}), the T_T (in iterations) and the E_L (in iterations) were recorded for all simulations.

The strength for each image increased by 0.18 for every timestep that the item resided in the buffer (i.e., a = 0.18 in terms of the SAM model). A baseline value (or the d parameter) of 0.18/5 = 0.036 was used as the residual memory strength. These values were chosen after extensive exploration of the parameter space. However, the space is quite flat and many possible combinations of parameter values produced similar levels of fit. To avoid any parameter tradeoffs, all encoding parameters were kept fixed across the four simulations. The fitting routine minimized the sum of squared deviations of all 20 data points using the simplex method repeatedly until the parameter values stabilized. First, θ was allowed to vary alone (with g = 100) and then g was allowed to vary alone (with θ fixed to the best value). After this both parameters were allowed to vary, but this cycle did not change the values much. For rules S2 and S3, the initial values for comparison were set to zero, thereby those points are based on the probability of terminating search only.

During the retrieval phase, an image can be resampled, but will not be re-recovered, leading to an extra time-step during the retrieval. In following Raaijmakers and Shiffrin (1980), we assume that the number of sampling attempts is linearly related to the retrieval time (here one time-step equals one second). Only the time-stamps for the first correct retrievals were used in the analyses.

Results

The results of the simulations are presented in Figure 2 and are based on 10000 simulation runs of the respective simulation (100k for model S3). We calculated the adjusted R^2 for each model. Although we aimed at fitting the four models quantitatively, the models differ in their qualitative fits to the data. In the data, T_T is an increasing function of N_{stop}, which is captured by models S2, S3, and S4. In the data, E_L is a negatively decelerating function of N_{stop}, which is captured by models S1 and S4. Therefore of these four models, model S4 has the best qualitative and quantitative fit.

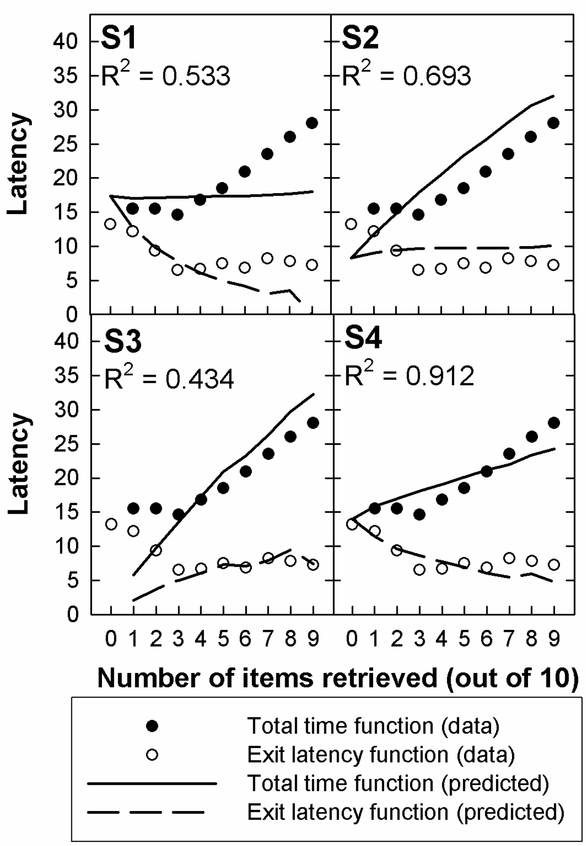

Figure 2: Data (dots) and simulation (lines) results.

The qualitative fit to the data is especially important given the robustness of the within-participant analyses (Dougherty & Harbison, 2007; Harbison, Dougherty, & Fayyad, submitted). The consistent finding that T_T increases systematically with the number of items retrieved cannot be predicted by S1. Indeed, S1 cannot predict any systematical variability in T_T. Similarly, S2 cannot predict systematic variability in E_L. Therefore, we believe the empirical results successful rule out S1 and S2. While S3 does not have these restrictions, the qualitative predictions of this rule remain in error.

Control Simulation

The comparative simulation study shows that the stopping rule introduced by Raaijmakers and Shiffrin (1980; 1981) is superior to the other three rules. A criticism to these results is that the maximum number of failures rule is inherent to the SAM framework and thus the rule already had an advantage over the other rules. Although we reduced SAM to its essentials, we conducted a control simulation with the smallest retrieval model we could employ: a simple sampling-with-replacement model.

We ran 20000 trials of a sampling-with-replacement model using only the S4 rule (stop when number of failures equals 5). Our only assumption with this model is that memory retrieval involves sampling items in memory and allowing memories to be resampled (see also, Indow & Togano, 1970; Wixted & Rohrer, 1994). More specifically, this model assumes equal association strengths between every item in memory and the context. Therefore, every item has the same probability of being sampled. This removed any additional assumptions concerning the nature of the learning process. Furthermore, there is no recovery process or, put another way, the probability of recovering an item given that it is sampled is set to one. This allowed us to test whether a two-step process is critical in obtaining the qualitative patterns.

Note that only the S4 rule was tested. As discussed above, the particular assumptions of the model will have no impact on the qualitative predictions of rules S1 and S2. Each of these rules, by definition predicts a lack of systematic variance in a variable where systematic variance is clearly and repeatedly found (T_T and E_L, respectively). The S3 rule was excluded because it has already been demonstrated to make predictions inconsistent with the results. What is of interest is whether the predictions of the S4 rule is robust to variations in retrieval assumptions, not whether a model can be devised that allows S3 to make accurate predictions. In addition, we wanted to check whether the mere assumption of sampling-with-replacement is sufficient to capture the qualitative patterns seen in the data. Previously, one of us noted that a sampling-*without*-replacement model, in which the search set becomes smaller after every correct retrieval, produces incorrect predictions for inter-response time distributions in free recall (Davelaar, 2007).

As can be seen in Figure 3, the model captures the qualitative pattern of T_T being an increasing function of N_{stop} and E_L being a negatively decelerating function of N_{stop}. This simulation also shows that the two temporal measures are sensitive to accumulated costs (in case of rule S4, these are failures), and could therefore be informative measures for investigating memorial processes in more high-level decision processes (e.g., Thomas et al., 2008).

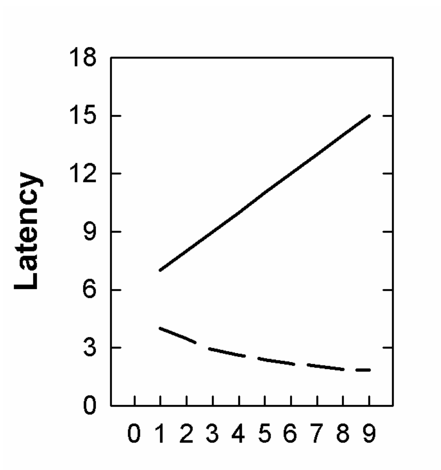

Figure 3: Simulation results using the sampling-with-replacement model and the S4 rule. Note the similarity in the qualitative profiles with the data shown in figure 2.

Conclusion

The purpose of this paper was to examine stopping rules that might characterize the psychological basis of how people terminate memory search. We argue that the decision to terminate search is ubiquitous in real-world memory retrieval. Therefore, memory search termination decisions are important for understanding the underlying processes involved in memory search as well as how long a physician might spend when generating possible diagnostic hypotheses (Thomas et al., 2008), or how long a survey respondent will spend retrieving episodes of alcohol consumption so that he or she can estimate frequency of use (Brown, 1995; 1997; Brown & Sinclair, 1999; Conrad, Brown, & Cashman, 1998). Nevertheless, the question of how people terminate memory search has gone largely unstudied.

Our goal was to provide an initial starting point for understanding how people terminate memory search. The systematicity of the empirical data (Dougherty & Harbison, 2007; Harbison, Dougherty, & Fayyad, submitted) suggests that participants employ a decision rule to terminate memory search. In this paper, we sought to address the nature of this stopping rule by evaluating four rules that have been featured in the analytical literature on free recall memory. Only one of the four rules leads to the model capturing the qualitative pattern in the data. The fits are quite remarkable despite the relative simplicity of our assumptions and suggest that decisions for terminating memory search are made on events occurring during the retrieval phase itself. This is made even clearer in the control simulation in which despite the lack of any memorial process, the model captures the important qualitative patterns.

The four stopping rules we compared by no means represent an exhaustive list, but we feel that these rules represent a range of rules that seem plausible and were explored during development of process models of free recall memory. Interestingly, although some successful models use an internal time limit (Davelaar, 2007; Davelaar et al., 2005; Diller, Nobel & Shiffrin, 2001; Farrell & Lewandowsky, 2002; Metcalfe & Murdock, 1981), the simulations show that such a stopping rule does not capture the empirical findings. This issue was raised by Metcalfe and Murdock (1981) who commented that participants do not use a total time stopping rule (rule S1). However, this is not to say that such a stopping rule will never be used. For example, Diller et al. (2001) were able to quantitatively fit retrieval time data using an internal time limit that was conditioned on the strength of the last-sampled image and the experimenter-imposed response deadline. Granted that Diller et al. (2001) were only concerned with cued recall, the possibility remains that 1) different recall paradigms require different stopping rules, 2) experimenter-imposed deadlines affect participant's choice of stopping rule, or 3) type of material and list composition affects the choice of stopping rule. In this paper, we only focused on stopping rules in a free recall paradigm in the absence of an experimenter-imposed deadline. Further research, both at the empirical and computational levels, is needed to identify which stopping rules are employed across different paradigms and under different conditions.

In our simulations, we did not include inter-image transitions through which items can be retrieved. We acknowledge the importance of associative path in accounting for detailed memory performance, but the results presented here suggest that associative paths may have relative smaller impact on the decision for terminating search, at least for the retrieval from a random word list. For example, we only focused on the stopping rule for retrieval of a whole set of items. SAM incorporates a stopping rule that governs the use of a previously retrieved item in further retrieval. This rule affects the timing of conditional responses. Here, we took a list-wise view and we are currently working on comparing stopping rules that affect the more finer-grained temporal dynamics.

Anderson and colleagues provided a rational analysis of the free recall task (Anderson & Milson, 1989; Anderson & Schooler, 1991), in which each item has a need probability associated with it. Only those items are retrieved whose need probability is larger than a certain criterion, which increases with the time spent inspecting an item before accepting or rejecting it. Anderson and Milson (1989) were able to capture a number of basic memory phenomena using their adaptive perspective. However, their analysis only provided the time of the last retrieved item, T_L, and not of the exact time of terminating memory search. One possibility would be to use the criterion to estimate the termination time, but this would require knowing the functional form of how the criterion changes during item inspection. Nevertheless, the success of Anderson's rational analysis and our current results warrants investigating how these can be combined and would allow analyzing the consequences of different retrieval processes on stopping rules. We leave such an endeavor for the future.

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