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# Hybrid search in the temporal domain: Evidence for rapid, serial logarithmic search through memory

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**Abstract** In hybrid search, observers memorize a number of possible targets and then search for any of these in visual arrays of items. Wolfe (2012) has previously shown that the response times in hybrid search increase with the log of the memory set size. What enables this logarithmic search of memory? One possibility is a series of steps in which subsets of the memory set are compared to all items in the visual set simultaneously. In the present experiments, we presented single visual items sequentially in a rapid serial visual presentation (RSVP) display, eliminating the possibility of simultaneous testing of all items. We used a staircasing procedure to estimate the time necessary to effectively detect the target in the RSVP stream. Processing time increased in a log–linear fashion with the number of potential targets. This finding eliminates the class of models that require simultaneous comparison of some memory items to all (or many) items in the visual display. Experiment 3 showed that, similar to visual search, memory search efficiency in this paradigm is influenced by the similarity between the target set and the distractors. These results indicate that observers perform separate memory searches on each eligible item in the visual display. Moreover, it appears that memory search for one item can proceed while other items are being categorized as "eligible" or "not eligible."

**Keywords** Attention · Memory · Visual search · Visual attention · Categorization

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In the majority of studies of visual search, observers search for a single type of target that may or may not be present amongst distractor items (Chan & Hayward, 2012; Wolfe, 2012). However, in the real world, we frequently search for one of many possible targets in the same image. Thus, baggage screeners might search for liquids, knives, and guns, and radiologists search for bone fractures, cancerous tumors, blood clots, and so forth. Searching for items in the real world is often a "hybrid search," through both a memory set and the visual display.

In order to study hybrid search, Wolfe (2012) parametrically varied both the visual set size and the memory set size in a visual search experiment. Unsurprisingly, the search task becomes more difficult when the number of possible items increases: Searching for apples, peppers, avocados, and cherries is more difficult than searching for just apples. However, the cost of searching through additional items in memory seems to be qualitatively different from searching through additional items in visual space (Wolfe, 2012). In visual search, the cost of additional items in the display is typically roughly linear. In the Wolfe (2012) experiment, each additional item cost about 15 ms when observers were searching for a single target. In contrast, in search through a memory set, response times (RTs) increased linearly with the log of the memory set size, with each $log_2$ *item* costing about 56 ms when a single item was in the visual array (Wolfe, 2012).

What is the source of this logarithmic relationship? Such relationships occur when a constant proportion of possible options can be discarded on each step of a process. Thus, the average number of guesses required to guess a number between 1 and $N$ is $\log_2(N)$, if you ask questions of the form: Is it less than $N/2$? Than $N/4$?, and so forth. Perhaps hybrid search proceeds by asking "Is anything in the visual display like these $N/2$ similar items in memory?" Attention could be guided on the basis of similarity to subsets of the memory set, in something akin to this 20-question game.

Alternatively, a visual item might be matched against all items in the memory set at the same time. Recognition memory can be modeled as an accumulation of evidence toward a decision boundary (Leite & Ratcliff, 2010; Ratcliff, 1978; Ratcliff & Starns, 2013). The decision bound needs to be placed far enough from the start of the information accumulation that false alarm errors are prevented. The bound needs to be near enough to the start to avoid wasting time or committing miss errors. A hybrid search decision about whether this visual item is one of $N$ possible items in memory can be implemented as $N$ accumulators, operating in parallel. The chances of a false alarm error increase, given $N$ opportunities to go over a decision bound by mistake. It would be prudent, therefore, to raise the decision bound. The amount that the bound would need to be raised while holding error rates constant would lead to a pattern of RTs that increased apparently logarithmically with the number of items.

The basic hybrid data can be modeled in various other ways. The present study is an effort to constrain the space of the plausible models by presenting the visual subset over time in a rapid serial visual presentation (RSVP) mode. We wondered whether the log search through memory is specific to situations in which all potential targets are simultaneously available to the observer. Consider the "20-question" model sketched above: It proposes a form of "guided" search in which subsets of the memory set define the guidance: Are there any red items?, Any circular items?, and so forth.

If this process of spatial guidance based on the memory set attributes is critical to the observed log–linear search through memory space, then forcing the items to be considered independently should result in much less efficient search through memory space. Thus, we presented visual items, one after the other, in RSVP, distributing the items across time rather than space. Since we observed the same logarithmic relationship of memory set size to RTs (here measured as the threshold RSVP rate), we can eliminate this class of models.

Previous work has shown that increasing the number of possible target items results in increased difficulty with correctly noting the presence of a target item in RSVP (Akyürek, Abedian-Amiri, & Ostermeier, 2011; Akyürek & Hommel, 2005; Akyürek, Hommel, & Jolicœur, 2007; Shapiro, Raymond, & Arnell, 1994). These demonstrations were observed in attentional blink experiments. In this paradigm, a number of items are displayed in an RSVP stream, while the observer searches the stream for Target 1 (T1) and Target 2 (T2). The detection of the T1 leads to impaired performance on T2 when T2 follows within roughly 500 ms (Raymond, Shapiro, & Arnell, 1992; Shapiro et al., 1994).

Akyürek et al. (2007) showed that increasing the number of possible T1 items led to a larger impairment in T2 detection. More importantly, for the present purposes, the authors observed a large cost on T1 accuracy and speed as the number of possible T1 items increased from one to four items. The authors described the decrease in accuracy as being "fairly linear." However, without going to higher set sizes, it would be very difficult to determine whether the function was actually linear or log–linear. A similar issue can be seen in the early work on hybrid visual $X$ memory searches. When small numbers of alphanumeric characters were held in memory, visual search for any member of those small sets also looked essentially linear (Schneider & Shiffrin, 1977; Wickens, Moody, & Dow, 1981). It was only with larger set sizes that the relationship was revealed to be logarithmic (Burrows & Okada, 1975; Wolfe, 2012).

Since Akyürek et al. (2007) were interested in the role of working memory (WM) in the attentional blink, their T1 items changed prior to each trial. Given that WM is generally estimated to be ~3–4 items (Cowan, 2001; Luck & Vogel, 1997), it would be very difficult to increase the WM load high enough to confidently distinguish between linear and log–linear memory search. Sternberg (1966) faced a similar problem in some of the initial memory-scanning studies. These studies typically involved learning lists of words: a task in which it is difficult to hold more than ten items in memory without extensive practice. In the present study, we were able to avoid this issue by asking observers to search for unique objects held in "activated long-term memory (ALTM; Cowan, 1995) rather than WM. As the picture and object recognition literature has shown, with unique objects, observers can quickly encode hundreds, or even thousands, of items in ALTM without much difficulty (Brady, Konkle, Alvarez, & Oliva, 2008; Standing, 1973).

The general approach for this study was to extend the spatial hybrid search findings to an RSVP paradigm that emphasized sequential processing of individual items. Though previous work had suggested that memory search follows a linear function when the visual items are members of an RSVP stream, we suspected that this might be due to the relatively small memory set size manipulations in those experiments. In Experiments 1 and 2 below, we present converging evidence that hybrid search remains logarithmic when the items are presented sequentially. In the final experiment, we extended this work by showing that although memory search appears to be logarithmic, the efficiency of this search is strongly modulated by target–distractor similarity, in a manner similar to what is observed in the visual search literature.

## Experiment 1: Estimating processing time in hybrid search

### Method

*Observers* A total of 41 observers between 18 and 54 years of age gave informed consent and were paid $10/h to participate in the three experiments. We used 14 observers in Experiment 1, 13 in Experiment 2, and 14 in Experiment 3 (mean ages: Exp. 1, 30 years; Exp. 2, 35 years; Exp. 3, 27 years). All had at least 20/25 vision with correction, all passed the Ishihara Color Test, and all were fluent speakers and readers of English. One observer was excluded from Experiment 1 because he or she never reached a stable threshold in the set size 100 block of the experiment, generating an estimate that was seven standard deviations higher than any of the other observers in that condition. One observer was excluded from Experiment 2 after repeatedly not being able to successfully pass the 100-memory item test.

*Procedure* In all three experiments, observers were asked to complete a similar task (see Fig. 1). In part 1 of each block of the experiment, observers were asked to memorize between two and 100 target objects. The order of the memory blocks was randomized across observers. All objects were taken from a heterogeneous set of 3,000 unique photorealistic objects provided by Brady et al. (2008). Experimental sessions were carried out on a Macintosh G4 computer running Mac OS 10.5. The experiments were written in MATLAB 7.5 (The MathWorks, Natick, MA) using the Psychophysics Toolbox (Brainard, 1997; Pelli, 1997), version 3. Stimuli were presented on 20-in. CRT monitor (Mitsubishi Diamond Pro 91TXM) with a resolution set to 1,280 × 960 pixels and an 85-Hz refresh rate. Observers were placed so that their eyes were 57.4 cm from the monitor. At this distance, each object was centered in a virtual square that subtended 2.7 deg of visual angle. The actual sizes of the objects varied but were never smaller than 1.5 DVA on the long axis.

Following the procedure of Wolfe (2012), observers were taught their target objects by displaying each object from the target set individually at the center of the screen for 3 s. After this brief encoding, we tested observers to ensure that the target set was effectively in memory. For the memory test, we presented individual objects at the center of the screen and asked whether each object was part of the target set. Half of the items were from the target set, and the others were drawn


**Fig. 1** Schematic illustration of the methods

from the larger set of objects. This yielded a total of $2X$ trials for each memory test, where $X$ represents the size of the memory set. If accuracy was below 90 %, the observer viewed the learning phase once more before being tested again. Once the memory test was passed twice, the observer was allowed to proceed to the second part of the experiment.

In the second part of each block of the experiment, observers viewed an RSVP stream of 16 objects presented at the center of the screen. At the end of each trial, the observer was asked whether the RSVP stream had contained an object from the target set. Half of the trials contained a single target item that occurred randomly between Positions 4 and 14 in the stream. Each block was preceded by 12 practice trials. When the target set was 100 items (in Exps. 1 and 2), observers completed 240 trials in this part of the experiment. Otherwise, this part of the experiment contained 180 trials. Observers were asked to complete additional trials when the target set was 100 items because, in pilot testing, we found that our threshold estimation procedure did not stabilize within 180 trials for all observers when the target set size was 100. During the experimental block of trials, we manipulated the stimulus onset asynchrony (SOA) for each of the objects using an interlaced staircasing procedure. At the start of the experimental block, the SOAs were set to 15 ms per object for one stream and 200 ms for the other. We employed a 3-up, 1-down staircase with a fixed step size that targeted 79.4 % correct (García-Pérez, 1998). The initially slow and initially fast staircases were randomly interlaced. This reduced the ability of observers to anticipate the rate on the next trial on the basis of the answer to the current trial.

## Results and discussion

Figure 2 shows the staircase data, averaged across blocks of the experiment. It is clear that the interleaved staircase procedure worked: The two staircases converge for each memory set size by the end of the block. It is also clear that the final RSVP rate asymptote varies as a function of the memory set size. To estimate processing time, we used QUEST to estimate the final threshold on the basis of the observed performance (King-Smith, Grigsby, Vingrys, Benes, & Supowit, 1994; Watson & Pelli, 1983). QUEST is an adaptive psychometric procedure that uses Bayes's theorem to estimate a posterior probability function given the current data, which is treated as the prior. Although QUEST is often used to determine the stimulus intensity (stimulus duration, in this case) for each trial, here we used QUEST in to analyze the previously gathered data and generate a final threshold estimate for each individual in each block. To ensure that we had enough observations near the threshold for reliable estimates, we set the parameters of the QUEST algorithm to predict the SOA threshold for 79.4 % correct performance. We achieved qualitatively similar results if we analyzed all of the inflection

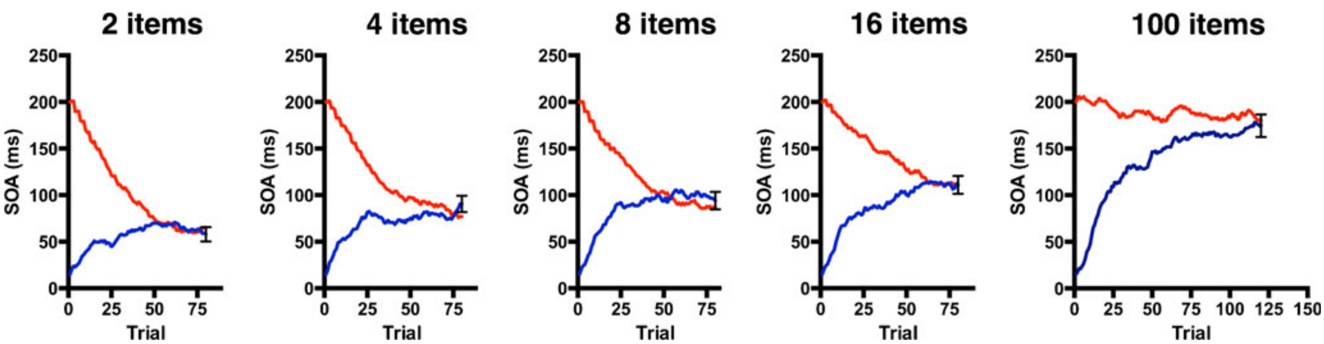


**Fig. 2** Average results for the initially slow (upper lines) and initially fast (lower lines) RSVP staircases in Experiment 1. Error bars represent standard errors of the means at the end of each block

points or if we averaged SOAs only over the final 30 trials of each block.

Figure 3A shows mean processing times as a function of memory set size in Experiment 1. Memory set size had a strong effect on processing time [$F(4, 48)=57.35$, $p<.001$, $\eta_G^2=.64$], which increased from 57 ms for memory set size 2 to 182 ms for memory set size 100. To evaluate whether the slope of this function followed a linear or log–linear function, we used the data from memory set sizes 2–16 to predict the performance on set size 100. As is shown in Fig. 3B, the log–linear prediction for set size 100 did not differ from the observed data significantly [161 vs. 182 ms; $t(12)=1.81$, $p=.09$], whereas the linear prediction (422 ms) was far higher than the observed value [$t(12)=4.61$, $p<.001$].

## Experiment 2: Forcing sequential processing in the RSVP hybrid search task

The results of Experiment 1 strongly suggest that search through memory occurs in a log–linear fashion, even when the items are presented in an RSVP stream. However, although each item was presented sequentially, it is possible that the items were not processed sequentially.[1] Perhaps potential target items were temporarily stored in memory, and a decision was made once each of these items had been compared to the target memory set. Along similar lines, rather than identifying any single target item, our observers might have made their decision at the end of each trial on the basis of the amount of "target-like" evidence that had accumulated over the sequence of items. Perhaps the observed evidence in favor of log–linear search through memory was a result of allowing observers to search through a memory space offline, at the end of each trial. If this were the case, requiring speeded online responses should result in a memory search that was less efficient, perhaps forcing a linear search through potential target items.

### Method

Unless otherwise stated, Experiment 2 was identical to Experiment 1. The only difference between the two experiments was the response method: Observers were instructed to respond as soon as they saw an object from their target set in the RSVP stream. Responses that occurred more than 2.5 s after the offset of the target item or prior to the onset of the target were coded as incorrect responses, and on slow responses observers were encouraged to try to respond more quickly. Less than 1 % of trials were marked as incorrect for these reasons.

### Results and discussion

As can be seen in Fig. 3C, the results from Experiment 2 are essentially identical to those of Experiment 1. As in Experiment 1, we found a significant effect of memory set size on estimated processing time [$F(4, 44)=57.66$, $p<.001$, $\eta_G^2=.73$], increasing from 64 ms for set size 2 to 214 ms for set size 100. Our data again suggest that the time for search through memory was a logarithmic function of set size, and not a linear function. The linear estimate based on memory set sizes 2–16 (537 ms) was significantly higher than the observed data [$t(11)=5.85$, $p<.001$], whereas the log–linear prediction (185 ms) was again not significantly different from the observed data [$t(11)=1.82$, $p=.09$]. In fact, when we directly compared the two experiments, although we found a large main effect of memory set size [$F(4, 92)=114.1$, $p<.001$, $\eta_G^2=.68$], there was no effect of experiment, and the two factors did not interact (both $p$s$>.1$, $\eta_G^2<.04$).

Our results indicate that pushing observers to process each object online, as soon as it was presented, had no effect on their ability to complete the task. This is strong evidence against the idea that groups of possible target objects were processed offline, after they were initially displayed. Note that this does not mean that each item was processed to completion before the next one appeared. The RSVP rates, especially for the smaller target set sizes, are inconsistent with estimates of the minimum "dwell time" required to fully process an item in

[1] We thank Karen Arnell for this idea.

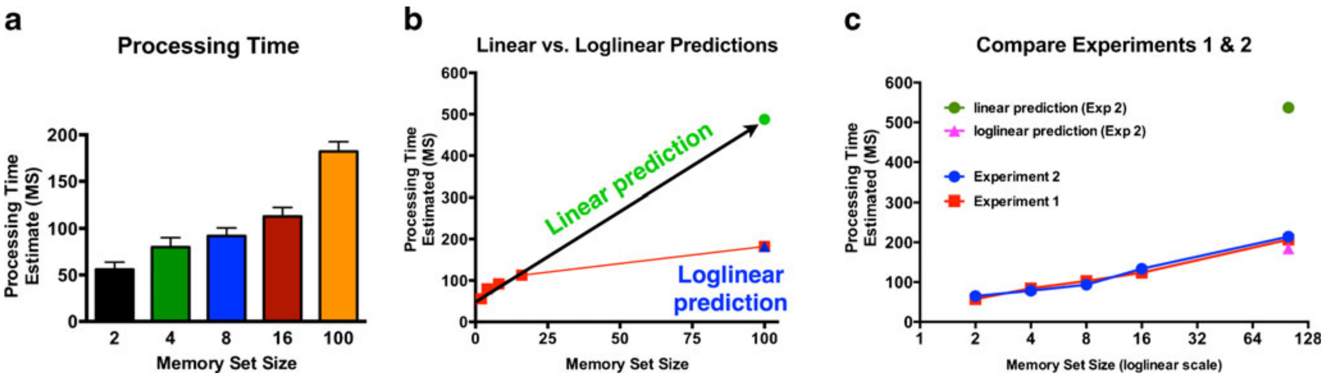


**Fig. 3** (**A**) QUEST-estimated processing times to correctly identify 79.4 % of all trials for each memory set size. (**B**) Predicted processing times for set size 100, based on a linear extrapolation from memory set sizes 2–16 (circle) or an extrapolation from $\log_2$(memory set size) (triangle). Clearly, the logarithmic prediction is closer to the data. (**C**) Estimated processing times for Experiments 1 and 2. Again, the logarithmic prediction is much closer to the data. The error bars here, as throughout the article, represent standard errors of the means. Errors bars are encompassed by the data points in panel C

an RSVP stream (Egeth & Yantis, 1997; Ward, Duncan, & Shapiro, 1996). The threshold RSVP durations reflect the rates at which items can enter and leave a processing pipeline; multiple items may be in the pipeline at one time (Moore & Wolfe, 2001; Wolfe, 2003).

## Experiment 3: Searching within and between categories

In spatial visual search, the efficiency of search is driven by both target–distractor similarity and distractor–distractor similarity (Duncan & Humphreys, 1989). In visual search for a single target, observers tend to search through only those items that share at least one feature with the target object (Egeth, Virzi, & Garbart, 1984; Wolfe, Cave, & Franzel, 1989; Zohary & Hochstein, 1989). Thus, observers can avoid wasting time on items that are never going to be targets.

The situation is somewhat different in the temporal search domain. In spatial visual search, items lacking the correct visual features are simply never selected in the course of the search. In RSVP, however, the items are presented to the spatial locus of fixation. We may assume that attention is directed to each object in turn, with little effective preattentive filtering. Nevertheless, it seems obvious that the relationship of the nontarget items to the items in the memory set would still influence the rate at which items can be presented in a hybrid RSVP search task. Suppose that the memory set consists of four red items (apple, car, cherry, and ball). It seems intuitively clear that the RSVP rate would be faster if all nontarget items were green than if all nontarget items were red. In this case, however, any benefit would seem to arise from a rapid process of identification and dismissal of irrelevant nontargets.

To test this hypothesis, we divided our object set into 223 animal items and 2,129 nonanimal items. In this experiment, all of the target items were drawn from the animal set. We then tested the ability to detect one of these animal targets in two types of RSVP streams. Either each item was an animal (within-category condition) or all but one item was a nonanimal (between-category condition). In the between-category condition, the one animal item that was presented was drawn from the target set on 50 % of trials.

### Method

Except where otherwise noted, the procedure for this experiment was identical to that of Experiment 1. Observers completed four blocks of trials in a randomized order. Prior to the threshold-estimating procedure used previously, 2, 4, 8, or 16 target items were memorized and tested, following the same procedure as in the previous experiments. In the previous experiments, each condition had featured two interlaced staircases. In Experiment 3, the two experimental conditions, between- and within-category, were interlaced in a single block (see Fig. 4). Each block contained ten practice trials, followed by 200 experimental trials. Again, we used a 3-up, 1-down staircase that guided performance toward 79.4 % correct. The SOA was set to 115 ms for both conditions at the start of each block. Processing time was estimated using the previously described QUEST procedure.

For the within-category condition, all 16 items in the RSVP stream, including the target (when present), were drawn from


**Fig. 4** Schematic illustration of the conditions in Experiment 3

the animal object set. For the between-category condition, 15 of the 16 items were drawn from the nonanimal object set. One item in every between-category stream was an animal. This animal item was a target animal on 50 % of the trials (otherwise, the task could be accomplished trivially by monitoring the stream for any animal).

## Results and discussion

As in Experiments 1 and 2, the estimated processing time increased with memory set size in both the between-category [$F(3, 39)=13.14$, $p<.001$, $\eta_G^2=.26$] and within-category [$F(3, 39)=40.78$, $p<.01$, $\eta_G^2=.41$] conditions (see Fig. 5A). Furthermore, search through memory appears to be better fit by a log–linear model than by a linear model (note that the *x*-axes in Fig. 5 are logarithmic).

Figure 5 shows strong effects of RSVP stream type [$F(1, 13)=113.9$, $p<.001$, $\eta_G^2=.57$] and target set size [$F(1, 13)=37.15$, $p<.001$, $\eta_G^2=.34$] on estimated processing times. These factors interacted significantly [$F(3, 39)=27.98$, $p<.001$, $\eta_G^2=.13$]. To better understand the interaction, we analyzed the change in processing times as a function of target size. This estimate of slope can be thought of as a measure of the cost of each additional $log_2$ item in memory on processing times. As can been seen in Fig. 5C, the slope was significantly higher in the within-category RSVP stream, when observers had to decide whether each animal in the visual stream was one of the memory set animals [$F(1, 13)=47.79$, $p<.001$, $\eta_G^2=.53$]. In the between-category case, it seems clear that observers could quickly determine that an item was categorically a nontarget without having to perform a memory search through the set of possible targets.

Figure 5 also shows that the rate of search through memory in Experiment 1 (22 ms/log item) falls between the rates observed in the two conditions in Experiment 3. This is what might be expected on the basis of the visual search literature. In Experiment 1, both targets and distractors were drawn from the complete, heterogeneous set of objects. Thus, a specific visual item would be unlikely to be rejected on the basis of its categorical status. This made Experiment 1 harder than the between-category condition. At the same time, Experiment 1 was easier than the within-category condition, because the target and distractor items were not as similar to each other. We have emphasized the role of semantic categories in influencing the rates of search through memory in this experiment. It is worth remembering that the items in our "animal" category were also more similar to one another than to items in the "nonanimal" category in terms of their basic visual features, and that this would also modulate search times (Duncan & Humphreys, 1989). If we return to the multiple-accumulator model sketched in the introduction, we can imagine that the decision bounds would need to be set quite high when we ask, "Is this animal one of the ten animals in my memory set?" The chances of a false alarm in this case would be higher than when we asked, "Is this object one of the ten objects in my very diverse memory set?"

The results of Experiment 2 suggested that requiring observers to respond to target presence does not influence the rate of search through memory when the target is embedded in a stream of heterogeneous objects. However, we wondered whether the results of Experiment 3 might have been influenced by the ability to hold a single animal item in memory, and then conduct a memory search once the trial had concluded. If observers engaged in this strategy, we should have found a strong relationship between RT and memory set size for the between-category trials; on those trials, observers could hold an animal in memory and do the memory search at the end of the trial. Our data do not support this prediction: We found no effect of memory set size on RTs for the between-category trials [$F(3, 52)=0.5$, $p=.71$].

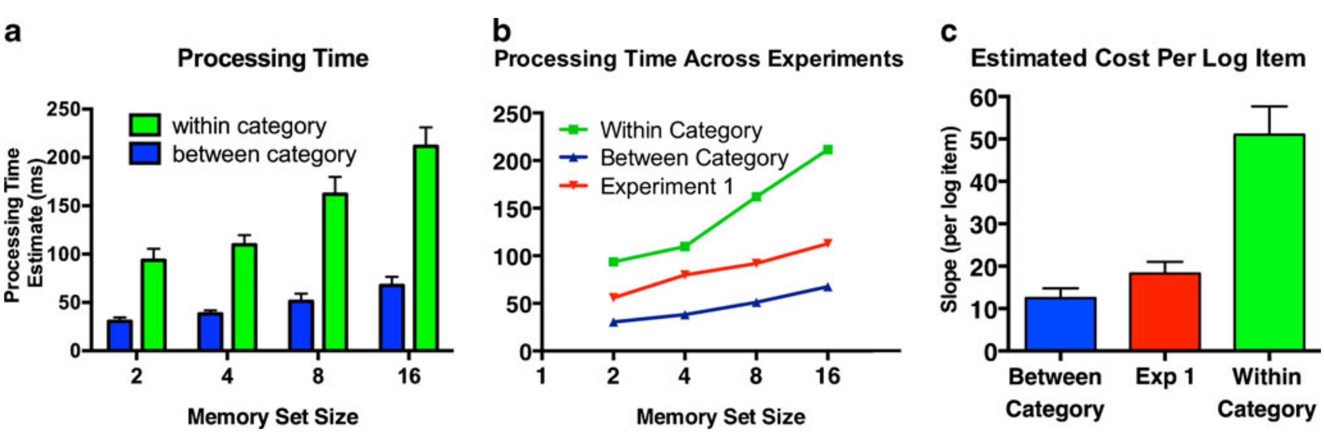


**Fig. 5** Results for Experiment 3, with comparisons to Experiment 1. (**A**) Estimated processing times for the within- and between-category streams, as a function of memory set size. (**B**) Estimated processing times for the two conditions in Experiment 3, as compared to the data from Experiment 1. Note that the data are plotted on a log–linear scale. (**C**) Slopes of the estimated processing times for Experiments 1 and 3. Slope here is an indication of the cost (in milliseconds) of searching through an additional $\log_2$ item

## General discussion

In Wolfe's (2012) data on combined visual and memory search, RT was a linear function of the visual set size, but rose linearly with the log of the memory set size. In a standard visual search, with all items present on the screen, one class of models could explain the result by proposing that some number of items in the memory set were being simultaneously matched to some or all of the items in the visual set. For instance, the observed log–linear function could be the consequence of breaking the memory set into subgroups and then completing the search for each subgroup in turn. The degree of feature overlap (for example) might inform which subgroup of memory items was searched first. The present study ruled out this class of theories by presenting items in an RSVP stream, thereby forcing items to be processed in series, though it remains possible that a small number of visual items could be processed at the same time, in a pipeline fashion.

Experiment 3 provides the clearest evidence that the memory search for one possible target item does not need to be completed before the next visual item appears (or is attended, in the spatial visual search case). When all of the items in the RSVP stream are animals, a memory search is needed for every (or almost every) item, in order to determine whether the animal is one of those in the memory set. The resulting RSVP rate that can be supported is relatively slow: <5 Hz when the memory set size is 16. When all but one of the visual items are nonanimals, presumably many fewer visual items provoke a memory search, and the rate is much faster: ~15 Hz when the memory set size is 16. Note, however, that a single animal was in the RSVP stream in the latter condition of Experiment 3. That item needed to be checked against the memory set. If that memory search needed to reach the same state that was reached by each item in the all-animal, within-category condition—so that the single animal should be a rate-limiting step in the one-animal, between-category condition—then the two conditions would have produced approximately the same results in RSVP, because that single memory search would be a rate-limiting step. Instead, the data show that the items could be presented much more quickly in the between-category stream. Unless the memory search became about 3 times faster in the between-category case, this suggests that the memory search for an animal in position $N$ can continue after the appearance of the next several items in RSVP.

This pattern of data is consistent with two-stage models of the attentional blink (Chun & Potter, 1995) and with Botella's model of illusory conjunctions in RSVP word lists (Botella, Barriopedro, & Suero, 2001). Both models propose high-capacity first stages during which all items are initially evaluated. Items that exceed a target threshold are sent to a limited-capacity second stage, and errors are typically attributed to situations in which the second stage is processing a nontarget when the target occurs. In this scheme, increasing the similarity of the distractor items increases the likelihood of an item that would appear similar to the target. This, in turn, leads to more errors, because of the increased likelihood that the second stage will be occupied when the target appears.

## Conclusions

Whereas the mechanisms that underlie this memory search are still very much in question, as a consequence of the log–linear search, observers were able to effectively determine whether a single object was one of 100 potential targets in memory when that target object was visible for less than 200 ms, despite strong forward and backward masking. On the basis of Wolfe's (2012) data, we can estimate that a visual search for a single target amongst 100 visual items from this set of objects would take ~1,500 ms. This represents converging evidence that search through memory is more efficient than search through visual space, and that this difference accelerates at higher set sizes. This is important, because although it may sometimes seem as though we have to search through many visual items (i.e., locations in a room) to find our target (i.e., car keys), this pales in comparison to the massive amount of information stored in memory that we must search through to find answers to mundane questions like "Who sings this song?" or "Whose car is that?" In both of these examples, a single stimulus is compared against a huge amount of information held in long-term memory. As in the temporal search task employed in the present set of experiments, spatial guidance based on target-set features is not useful in the evaluation of this single item. The data presented here suggest that we are to be able to answer these questions in a timely manner via a log–linear search through memory that is capable of evaluating multiple items simultaneously.

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