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# A Dynamic Approach to Secondary Processes in Associative Recognition

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## Abstract

Associative recognition—the ability to discriminate between studied and novel associations—has been attributed to the operation of a recall-like process that is not engaged during recognition of single items. An alternative mechanism for associative recognition is the formation of a compound memory cue that incorporates relational information between the two elements of the association. These alternatives make different predictions about the dynamics of associative recognition as revealed by speed-accuracy trade-off (SAT) functions: if recall were operating, SAT functions should approach asymptotic performance at a faster rate for stronger associations, whereas a compound cue mechanism predicts that only asymptotic performance, not rate, should be affected by strength. In a review of the literature, we find that only asymptotic performance, not rate, is affected by the strength of studied associations, supporting the operation of a compound cue mechanism. We present a formal model of this mechanism as a direct outgrowth of a model of single-item recognition (Cox & Shiffrin, 2012) and use it to predict observed SAT curves for both single-item and associative recognition in a variety of experiments.

**Keywords:** Recognition memory; associative recognition; episodic memory; memory models.

## Introduction

Recognition is a critical function performed by the memory system, and must therefore form part of the bedrock upon which any theory of memory can be constructed. When engaging in a recognition task, a participant must decide whether a given test item was or was not present in a particular study context. Recognition judgments thus indicate the ability of a participant to discriminate between experienced and unexperienced events, where an “event” is defined by the conjunction of an item and context. By characterizing the situations in which studied items can be correctly detected and unstudied items can be correctly rejected, we gain understanding of how memory is organized and how it is accessed.

Several theories posit that recognition can be accomplished via two routes: The first route involves a comparison between the test item and the contents of memory which produces a value of “familiarity” or “memory strength”. An item is called “old” if the familiarity it evokes is sufficiently high relative to a criterion value; this familiarity process has been characterized by a variety of memory models (e.g., Murdock, 1982; Gillund & Shiffrin, 1984; Hintzman, 1988; Shiffrin & Steyvers, 1997; McClelland & Chappell, 1998; Dennis & Humphreys, 2001). A second route involves retrieving a specific event from memory and directly comparing it to the test item, responding “old” only if the test item and the retrieved memory match. This route, often termed “recall” or “recollection”, forms a component of dual-process theories of memory (e.g., Atkinson & Juola, 1974; Reder et al., 2000;

Malmberg, 2008) and is typically invoked to explain situations in which familiarity alone is presumed to be insufficient to distinguish between studied and unstudied test items.

An important exemplar of such a case is associative recognition. In associative recognition, the study list is comprised of sets of items, e.g., word pairs. Participants are subsequently tested on “intact” pairs consisting of two items that had been studied as part of the same pair (denoted AB) as well as “rearranged” pairs in which the two items had both been studied, but not in the same pair (denoted AB’). Thus, both items of a rearranged pair are “familiar” in that both had been seen at study, so additional information is needed in order to distinguish rearranged from intact pairs. This information could be available via a secondary recall route if participants use one of the items (e.g., item A) to cue recall of the item it had been studied with (B); if the recalled item matches the other item at test, the pair is judged to have been studied, but if the recalled item does not match, the pair is rejected (Rotello & Heit, 2000; Malmberg, 2008). Alternatively, if studying a pair results in storage not just of the individual elements of the pair, but of relational information representing the compound of the two items, this would also provide the necessary information to distinguish between intact and rearranged pairs: rather than comparing each item individually to memory, a participant could compare the relational information in the pair to the relations stored in memory (Murdock, 1982; Doshier & Rosedale, 1989, 1997).

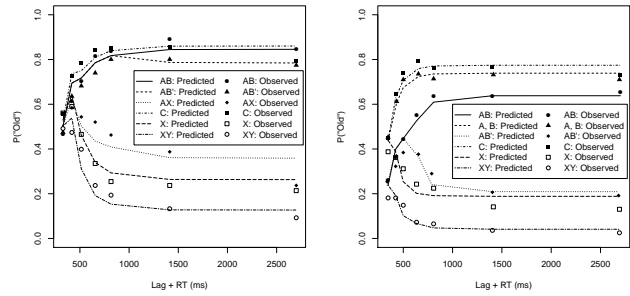
A wealth of research has attempted to distinguish between these two views of associative recognition on the basis of accuracy alone. The shape of receiver-operating characteristic (ROC) curves has been argued to support the involvement of recall in associative recognition (Yonelinas, 1997), but these data are equally consistent with a signal detection process that combines two sources of evidence, as in a compound cue model (Wixted, 2007). Process-dissociation procedures (Jacoby, 1991) have also been used to argue in favor of a recall-like process in associative recognition. However, process-dissociation will produce high estimates of the contribution of recollection even when the data are simulated from a single-process model where it is known that recollection did not generate the data; and when a model with recollection is used to generate the data, the process dissociation estimates of recollection’s contributions are incorrect (Ratcliff, Van Zandt, & McKoon, 1995). Process-dissociation also relies on the strong assumption that familiarity and recall are stochastically independent of one another; when the assumption is violated, estimates obtained from this procedure are uninterpretable (Curran & Hintzman, 1995; Hillstrom &

Logan, 1997). The assumption of independence is also inconsistent with positive correlations between the probability of correct recall and that of correct recognition (Tulving & Wiseman, 1975). Finally, even if the assumptions of the process dissociation procedure are satisfied, it is insufficient for identifying the relevant processing components (Humphreys, Dennis, Chalmers, & Finnigan, 2000).

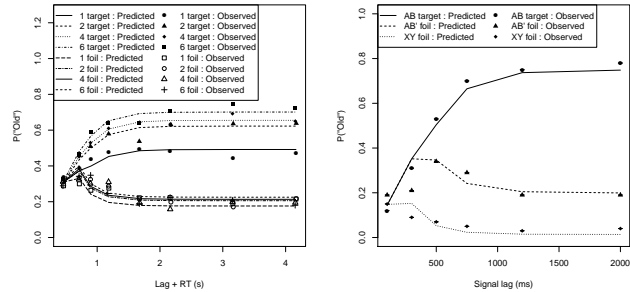
Because accuracy data alone is insufficient, we believe the most promising approach toward understanding the secondary processes involved in associative recognition is a *dynamic* approach. By this, we mean that we must examine not just the final recognition decision, but the dynamics of the mnemonic and decision processes that lead to that decision. If associative recognition involves secondary processes beyond those involved in single-item recognition, those processes should have characteristic dynamics which affect not only the final decision, but response time and the form of speed-accuracy trade-off (SAT). This kind of approach has yielded insights into various aspects of single-item recognition, such as the form of memory-evidence distributions (Starns & Ratcliff, 2014) and short-term memory decay (Donkin & Nosofsky, 2012). In this article, we examine evidence from a wide variety of studies and argue that while the evidence demonstrates the operation of secondary processes in associative recognition, such processes are not well-described by a recall-like process. Instead, the secondary process involved in associative recognition is best described as the formation of a compound cue. We present a formal model of this process and show that it provides excellent quantitative and qualitative fits to SAT data in both single and associative recognition, with parameter values that provide additional insight into the cognitive processes underlying recognition.

### Evidence for Secondary Processes in Associative Recognition

In the speed-accuracy trade-off (SAT) paradigm, a test item is presented on each trial for a varying length of time at which point a response signal occurs instructing participants to respond immediately based on whatever information they had acquired during the lag between stimulus onset and response signal (Reed, 1973). The SAT procedure thus provides a measure of the dynamics of processing and can, thereby, provide compelling evidence for the involvement of a secondary process in associative recognition, as shown in Figure 1. In Gronlund and Ratcliff (1989, Exp. 1), participants were instructed to endorse a test pair if both of its members had been studied, regardless of whether they had been studied together (labeled AB and AB', in contrast to novel pairs XY or pairs with one novel member AX); this decision involves only item-level information. In addition, participants were tested on single items and had to distinguish between studied (C) and unstudied (X) words, where associative information is once again irrelevant. In Experiment 2, participants were told to endorse a pair only if its two members had actually been studied together (only AB); this decision requires associative



(a) Gronlund and Ratcliff (1989, Exp. 1). (b) Gronlund and Ratcliff (1989, Exp. 2).



(c) Doshier (1984, Exp. 2). (d) Rotello and Heit (2000, Exp. 1).

Figure 1: Probability of responding “old” to a test word or pair over time, along with predictions from our dynamic recognition model. Parameters used to generate these predictions are given in Table 1; model details are given in the main text.

information (although participants were, again, also tested on single-item recognition). Under the Experiment 2 exclusion instructions, participants initially endorsed rearranged pairs (AB') before this tendency reversed at later signal lags. The nonmonotonic false alarm curve to AB' pairs under exclusion instructions, also evident in Figures 1c and 1d, indicates the involvement of a secondary process or source of information that is not available early in associative recognition.

The critical difference between a recall and a compound cue mechanism is the *source* of the new information that becomes available: For a recall-like process, new information is retrieved from memory, so the rate at which this information becomes available should be related to the strength of the memory from which it is being retrieved. Specifically, as the target memory gets stronger—perhaps as a function of increased study time or repetition—information should be retrieved more quickly (e.g., Raaijmakers & Shiffrin, 1981; Anderson, 1983; Sederberg, Howard, & Kahana, 2008). In terms of SAT, this would be reflected in faster rise to asymptotic performance and/or an earlier inflection point in the false alarm curve to AB' pairs. On the other hand, the formation of a compound cue depends only the test pair, and is independent of the contents of memory, and thus predicts that there should be no difference in the dynamics of associative recognition as a function of memory strength.

These predictions were directly tested by Doshier (1984), who presented pairs for varying amounts of time at study and tested participants on both intact pairs and rearranged pairs formed by mixing the left and right members from pairs that had been studied for equal amounts of time. The results,

shown in Figure 1c, demonstrate a similar albeit less dramatic nonmonotonic false alarm curve to rearranged pairs, but there is no evidence that either the inflection point or rate of approach to asymptote changes as a function of study time. Instead, only asymptotic accuracy is affected. This mirrors the findings of Nobel and Shiffrin (2001) and Wickelgren and Corbett (1977), in which memory strength was manipulated both by study time and by list length, yet had no effect on the dynamics of associative recognition, only on asymptotic accuracy. An additional test of a recall-based account of associative recognition was conducted by Gronlund and Ratcliff (1989, Exp. 4), in which the first word of each test pair was presented 200 ms before the second; if participants were using a recall-like strategy, they should use the first word to cue recall of the second, allowing them to correctly reject a rearranged pair much faster after the second word appeared and, perhaps, without any nonmonotonic false alarm curve. Instead, although participants could reject completely novel foils (XY) more quickly when given a 200 ms head start, the extra time conferred no advantage in rejecting AB foils. When item information alone could enable participants to reject a foil (AB vs. XY), a single unstudied word is sufficient, but when associative information is necessary (AB vs. AB'), both members of the pair have to be present, as would be expected if a compound cue were necessary for associative recognition.

In sum, the dynamics of associative recognition do not resemble those that would be expected if recall were operating. Instead, associative recognition seems to depend on a secondary cuing process, such as the formation of a compound cue. We now present a formal model of this process and show that it provides an excellent qualitative and quantitative account of associative recognition performance.

## Model

The model for associative recognition that we present is a direct outgrowth of the model for single-item recognition proposed by Cox and Shiffrin (2012) and expanded in Cox (2015). We first describe the assumed structure of long-term episodic memory, then the model for single-item recognition, and finally describe how it is extended to address pair and associative recognition.

### Structure of long-term memory

Studying a single word leads to the formation in long-term episodic memory of a “memory trace”. This trace is represented as a vector of feature values, which can derive from two sources: The *content* of the study event, which includes semantic, phonological, and orthographic features of the word; and the *context* of the event, which pertains to the general study situation in which the word was encountered. Additional study time or repetitions increase the probability that a content feature will be stored in the trace; the probability of content feature storage is denoted  $u$ , and the total number that may be stored is  $N_C$ . We assume that the relevant context features do not change over the course of a study-test

block and that they are persistent in the participant’s environment; therefore, all available  $N_X$  context features are assumed to be stored in the trace. Features are assumed to be binary with each value having equal base-rate probabilities, such that the probability that two different items will have matching values for a particular feature is  $\frac{1}{2}$ . If a feature is stored, it is stored correctly with probability  $c$ , otherwise a random value (e.g., “0” or “1”) is stored instead.

Studying a pair results in the storage of *two* traces in memory, one for each of the two words. However, in addition to the content and context features that would have been stored had the words been presented in isolation, both traces contain *associative* features. The values of these features are equal in the two traces and represent emergent compound features that arise from the joint encoding of the two words. As with content features, additional study time or repetition increases the probability that an associative feature will get stored in each of the two traces. We emphasize, however, that the “memory system” treats content, associative, and context features identically and does not “know” whence these features of a trace arose.

### Single-item recognition

To make a recognition decision about a single word, a participant constructs a “memory probe”. As with a memory trace, the probe consists of both content features and context features. At the beginning of the trial, time  $t = 0$ , the probe contains only context features, since these are presumed to be persistent in the environment. At some later time  $t_0$ , content features begin to enter the probe as the test word is processed. On each time-step within the model, one of the  $N_C$  available content features is sampled uniformly at random. If the probe does not contain a value for that feature, the sampled value is stored; otherwise, whatever value was already in the probe remains. Thus, over time, the probe will become saturated when no new content features are available.

**Likelihood** On each time-step  $t$ , the current probe is compared in parallel to all traces in episodic memory. The probe-trace comparison depends only on the features that are in *both* the probe and the trace, and takes the form of a likelihood ratio reflecting the relative probability that the probe and trace encode the *same* event versus the probability that they encode *different* events (cf. Shiffrin & Steyvers, 1997; McClelland & Chappell, 1998). If the probe and trace encode the same event, the probability that they will match on a particular feature is  $p_{M|S} = c + (1 - c)\frac{1}{2}$  while the probability that they will mismatch is  $p_{N|S} = (1 - c)\frac{1}{2}$ . If the probe and trace encode different events, the probability that they will either match or mismatch is simply  $p_{M|D} = p_{N|D} = \frac{1}{2}$ , i.e., chance. We assume for simplicity that features are stored independent of one another, such that the likelihood ratio is the product

$$\begin{aligned} \lambda_i(t) &= (p_{M|S}/p_{M|D})^{N_M^i(t)} (p_{N|S}/p_{N|D})^{N_N^i(t)} \\ &= (1 + c)^{N_M^i(t)} (1 - c)^{N_N^i(t)}, \end{aligned} \quad (1)$$

where  $\lambda_i(t)$  is the likelihood ratio between the probe and trace  $i$  at time  $t$  and  $N_M^i(t)$  and  $N_N^i(t)$  denote the number of matching and mismatching features, respectively, between the probe and trace  $i$  at time  $t$ .

**Memory evidence** Recognition decisions depend on the overall match between the probe and memory, however most traces (e.g., those from years ago) will not match the probe very well. Thus, we assume that only traces with likelihood ratios greater than one contribute to the match. This match value is the logarithm of the average likelihood ratio for those traces whose likelihoods exceed this threshold value,

$$\phi(t) = \log \langle \lambda_i(t) : \lambda_i(t) > 1 \rangle, \quad (2)$$

which may be considered a form of “log-odds”. At time  $t_0$ , when the probe contains only context features,  $\phi(t_0)$  reflects the match between the test context and the contents of memory. As content features are sampled and join the probe,  $\phi(t)$  will evolve, governed by the order and timing with which features are sampled, as well as the properties of the traces stored during study. Each new feature provides more statistical evidence about whether there is a trace in memory that encodes the same event as the probe. The number of mismatching features ( $N_N^i(t)$ ) between the probe and traces of different items will tend to increase over time, thus decreasing their likelihood ratios. If there is a trace stored from the test word, its likelihood ratio will tend to increase beyond the initial match to context as more matching features are sampled ( $N_M^i(t)$ ); this single trace that matches well on both content and context will grow to dominate the average likelihood<sup>1</sup>.

On average, then,  $\phi(t)$  increases for targets and decreases for foils. The change in familiarity over time is thus statistically diagnostic of whether an item had been studied or not, and we presume this is the basis for a recognition decision. The accumulated change is simply the difference between the current value  $\phi(t)$  and the value before any content features had been sampled:

$$x(t) = \sum_{\tau=t_0}^{t-1} \phi(\tau+1) - \phi(\tau) = \phi(t) - \phi(t_0). \quad (3)$$

By making recognition dependent on the *change* in evidence over time, rather than on its absolute level, one need not assume differing criteria across experimental conditions or stimulus classes which may differ in their absolute memory strength (Cox & Shiffrin, 2012). One can also view  $x(t)$  as conditionalizing  $\phi(t)$  on an initial value determined by context,  $\phi(t_0)$ . Because context features are persistent in the environment, rather than changing rapidly like content features, they provide a natural baseline level against which to judge new information.

**Predicting SAT data** Although more complex assumptions are possible (cf. Meyer, Irwin, Osman, & Kounios, 1988;

<sup>1</sup>Traces formed in contexts before the experiment are also present in memory, but in practice such traces contribute little and so we do not model them here.

Ratcliff, 1988), we assume that participants continue to sample features into their memory probe until a response signal is given, at which point they stop. Each model time-step is presumed to take a constant amount of time  $\rho$ . If the accumulated changes  $x(t)$  at the time of the response signal are greater than a threshold value  $\theta$ , the participant responds “old”, otherwise they respond “new”. If a response signal occurs before sampling begins at time  $t_0$ , the participant guesses “old” with probability  $1/[1 + \exp(-\theta)]$ . We assume feature sampling only occurs between  $t_0$  and the response signal, and that the additional time required for a participant to make their response after the signal does not allow for additional processing of the test item(s). Although this is surely an oversimplification, response times are typically quite brief (200 ms), are unrelated to the stimulus itself, and only vary at earlier lags. These considerations, plus the good fits obtained, suggest this simplification does not harm any conclusions reported here.

### Pair and associative recognition

When a pair is presented at test, a participant processes each item in its own parallel channel, using the same mechanisms just described for single-item recognition (Figure 2). Participants only make an “old” response if the accumulated change in familiarity for each item is sufficient to call *both* of them “old”. In each channel, the probe begins at time  $t_0$  with  $N_X$  context features and there is available capacity for  $N_C$  content features. In associative recognition, a certain proportion of the  $N_C$  content features, denoted  $p_A$ , are given over to representing the association between the two items; the remaining features are used to represent the content features of the individual items. Due to constraints on short-term memory capacity, it is possible that not all item-specific features can be sampled into the two probes; we denote the proportion of the maximum number of item features (of which there are  $(1 - p_A)N_C$ ) that can be sampled in pair recognition by  $p_S$ .

Associative recognition begins just like pair recognition, but at some time  $t_A$  after the start of processing, the  $p_A N_C$  associative features become available for sampling. At that point, both item and associative features can be sampled into each probe. The only difference between item and associative features from the perspective of the retrieval process is that the values of the associative features match between the two probes. Just as in pair recognition, a participant only responds “old” if both probes result in sufficiently high accumulated change in familiarity. This model is flexible enough to allow us to explain both single- and multiple-item recognition within the same modeling framework, and enables one to infer the degree to which associative information is used ( $p_A$ ), when it is available ( $t_A$ ), and to what extent it interferes with item-level processing ( $p_S$ ).

### Model Fits

We fit this model to the data from the first two experiments reported by Gronlund and Ratcliff (1989) and described above, where Experiment 1 involved only pair recognition while Experiment 2 required associative information. These experi-

Table 1: Best-fitting parameters of the dynamic model for associative recognition to SAT datasets, as well as fit diagnostic  $R^2$ . In Doshier (1984, Exp. 2), multiple study times were used, entailing multiple values of  $u_P$ ; study times were 1, 2, 4, and 6 seconds per pair. In all models,  $N_C = N_X = 30$ .

Experiment	$u_S$	$u_P$	$c$	$p_A$	$t_A$	$p_S$	$\theta_S$	$\theta_P$	$t_0$	$\rho$	$R^2$
Gronlund and Ratcliff (1989, Exp. 1)	0.316	0.339	0.988	0.017	751.655	0.937	-0.118	-0.891	89.047	5.880	0.898
Gronlund and Ratcliff (1989, Exp. 2)	0.414	0.388	0.980	0.170	411.847	0.869	0.245	0.048	94.477	4.096	0.936
Rotello and Heit (2000, Exp. 1)	—	0.439	0.984	0.162	437.489	—	—	1.097	82.982	7.899	0.923
Doshier (1984, Exp. 2)	—	0.356, 0.420, 0.437, 0.463	0.969	0.190	447.302	—	—	-0.228	187.346	9.639	0.881

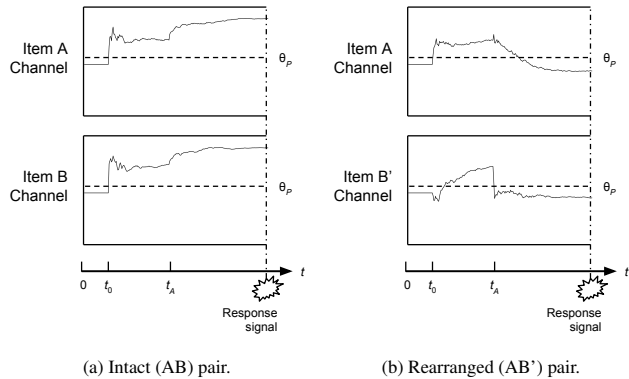


Figure 2: Schematic depiction of our model for associative recognition. Each member of the pair is processed in parallel channels that each operate as single-item recognition processes; sample paths for memory evidence  $x(t)$  are shown for each channel.

ments involved studying both pairs and single items, and thus represent a strong test of the model’s ability to jointly fit data from putatively different tasks. We fit a single encoding noise parameter  $c$ , start time  $t_0$ , and time-step duration  $\rho$  across all conditions in each experiment, but allowed the probability of feature encoding to differ between single items ( $u_S$ ) and pairs ( $u_P$ ). Even though participants did not need to use associative information in Experiment 1, we fit values of  $p_A$ , the proportion of content features used to represent associations, and  $t_A$ , the delay in availability of associative features, to verify that the model is sensitive to the different task demands. Two criterion parameters were also required, one for single-item recognition  $\theta_S$  and another that applied to both parallel channels in pair recognition  $\theta_P$ . Model predictions are shown in Figures 1a and 1b, showing that the model closely matches the data, with the fitted parameter values in Table 1. Estimates of  $u_S$  and  $u_P$  are similar to each other within each experiment, consistent with the fact that participants were given twice as long to study a pair as they were a single item. As expected,  $p_A$  is much lower in Experiment 1, where associative information is not required, although the fact that it is non-zero suggests that some associative information is nonetheless encoded (this would account for the slight increase in asymptotic hit rate for AB pairs compared to AB’). It would also appear the increase in  $p_A$  in Experiment 2 is accompanied by a decrease in  $p_S$ , suggesting that a greater focus on associative features entails a smaller capacity for item features.

We also fit our model to two experiments that only tested pair recognition<sup>2</sup>. In Rotello and Heit (2000, Exp. 1), participants had to distinguish between intact pairs (AB), rearranged pairs (AB’), and novel pairs (XY), rejecting both novel and rearranged pairs. Thus, as in the experiments from Gronlund

<sup>2</sup>For these experiments, we set  $p_S = 1$  since, without tests of *both* single items and pairs, this parameter becomes unidentifiable.

and Ratcliff (1989), participants could make use of item-level information to reject certain (XY) foils. Predictions and data are shown in Figure 1d. Finally, in Doshier (1984, Exp. 2), item information is made irrelevant: participants studied pairs for varying amounts of time (1, 2, 4, or 6 seconds per pair) and foils were created by rearranging pairs within each level of study time. As shown in Figure 1c, an increase in study time does not affect the rate of approach to asymptotic performance. Our cue-formation model predicts this result both quantitatively and qualitatively, in contrast to a recall-based model which must predict a relationship between SAT dynamics and pair strength.

The estimated parameters are consistent with the task demands in each experiment. Where associative information is not needed (Gronlund & Ratcliff, 1989, Exp. 1), the probe is given over to mostly item features (low  $p_A$ ); associative features, to the extent that they are involved at all, are not available until quite late (high  $t_A$ ). When associative information is required, it becomes available at roughly the same time ( $t_A$ ) across all experiments—between 400 and 450 ms after stimulus onset. Finally, when item information is not at all informative (Doshier, 1984, Exp. 2), participants delay the onset of feature sampling ( $t_0$ ) by 100 ms and increase the proportion of associative features used (high  $p_A$ ). This effectively reduces the influence of item features by diminishing the time between the onset of processing and the time at which associative features become available.

## Discussion

We have extended a dynamic model for recognition of single items to the recognition of pairs, showing how it can account for single-item, pair, and associative recognition. Pair recognition results from the parallel operation of two single-item recognition processes in which changes in familiarity are accumulated as features of each item are sampled. If the accumulated changes for both items are sufficiently large, the pair is judged “old”, otherwise it is called “new”. In associative recognition, an additional set of features becomes available later in the processing of the two items; these features represent an associative binding between the two items. Our model can thus be considered a form of compound cue formation (Doshier & Rosedale, 1989, 1997).

The consistency of parameter estimates across experiments is remarkable and, coupled with good quantitative fits, suggests that this model is capturing something important about associative recognition. In particular, associative features, regardless of other aspects of the experiment, are generally available 400-500 ms after stimulus onset, which is intriguing because it lies on the border between the two temporal regions supposed to reflect “familiarity” (typically 300-500

ms) and “recollective” (typically 500-800 ms) processing in event-related EEG (Rugg & Curran, 2007). If associative features become available 400-500 ms after stimulus onset, on some trials they will be sampled quickly and fall into the early “familiarity” bin, while on other trials they will be sampled more slowly and affect the later “recollective” ERP components. This potential confusion is reflected in the ERP literature on associative recognition in which associative recognition performance is sometimes related only to late positive ERPs (Donaldson & Rugg, 1998) and sometimes with both early negative and late positive ERPs (Speer & Curran, 2007).

Difficulties in interpreting such data may result from the a priori assumption that associative recognition *must* entail qualitatively different familiarity and recollection processes. Rather than assuming such a conclusion—as in behavioral ROC and process-dissociation analyses—we believe more progress may be made by developing explicit formal models of the processes involved in memory, as we have demonstrated here. Doing so allows for much more specific statements to be made about the mechanisms involved, and enables stronger tests of the predictions of various theories. For this reason, we believe such an approach will be a boon to the understanding not just of behavioral data, but of neural measures like EEG. Conversely, the ability of EEG to probe ongoing cognitive processes at a much finer level than behavioral paradigms could allow for more detailed theories to be specified, enabling even deeper insights into the dynamics of retrieval.

We hardly dispute the operation of at least two processes in associative recognition, but we have shown that the secondary process is better characterized as compound cue formation, rather than recall/recollection. There are a variety of other memory tasks that may entail the operation of secondary processes, such as rejecting highly-similar foils (Hintzman & Curran, 1994), list discrimination (Hintzman, Caulton, & Levitin, 1998), and source memory (Hintzman & Caulton, 1997), which we have also explored within the dynamic model framework outlined here (Cox, 2015). Although a full description would go beyond the scope of the present article, we find that although secondary processes beyond those found in single-item recognition are necessary to explain these phenomena, only in the case of source memory does this secondary process resemble a kind of recall. In general, it would appear that memory retrieval can involve a multitude of processes depending on the decision required of the participant, but that only through rigorous quantitative modeling can we begin to characterize these processes and develop a deeper understanding of memory.

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