Systems Factorial Analysis of Item and Associative Retrieval

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Abstract

Using hierarchical Bayesian estimation of RT distributions, we present a novel application of Systems Factorial Technology (Townsend & Nozawa, 1995) to the retrieval of item and associative information from episodic memory. We find that item and associative information are retrieved concurrently, with positive memory evidence arising from a holistic match between the test pair and the contents of memory, in which both item and associative matches are pooled together into a single source. This retrieval architecture is inconsistent with both strictly serial processing and independence of item and associative information. Pooling of item and associative matches implies that while item and associative information may be separable, they are not qualitatively different, nor are qualitatively different processes (e.g., familiarity vs. recollection) used to retrieve these kinds of information.

Keywords: Memory models; associative recognition; systems factorial technology; Bayesian statistics.

Introduction

Associations have served as important theoretical constructs throughout the study of cognition. The present work is concerned with the distinction made in memory between memory for isolated events—which we refer to as "items"—and memory for combinations of events—which we refer to as "associations". Given that myriad phenomena in human learning depend on being able to store and retrieve both of these kinds of information and a dissociation between item and associative memory is important for a variety of neurological diagnoses, it is crucial to understand the representations and processes behind memory for items and associations. In this paper, we use qualitative properties of response dynamics to determine what kind of processing is involved in item and associative retrieval and how the two could be represented in order to support such processing.

Various theories posit that item and associative information are qualitatively different and are retrieved using independent processes. Linearities in receiver-operating characteristic (ROC) functions obtained in associative recognition have been argued to reflect the operation of an "all-or-none" recall process for associative information that is independent of the continuous-valued familiarity process used to assess item information (Yonelinas, 1997). Unfortunately, beyond the difficulty of statistically determining whether a ROC curve is linear or curvilinear, such functional forms are not, in fact, diagnostic of the type of processing involved: Curvilinear ROCs are consistent with discrete-state processing (Province & Rouder, 2012) and linear ROCs are consistent with continuous-valued processes (Wixted, 2007). Process-dissociation procedures (Jacoby, 1991) have also been used to assess whether associative information must be retrieved using a distinct recall process, but such procedures do not lead to accurate estimates of the contribution of different processes even with simulated data (Ratcliff, Van Zandt, & McKoon, 1995), nor has any strong evidence been found for the operation of multiple retrieval processes in item recognition (Dunn, 2004; Pratte & Rouder, 2012).

While there is little evidence for a qualitative distinction between item and associative information, there is good evidence for a *quantitative* difference. Item recognition accuracy decreases faster over time than associative recognition accuracy (Hockley, 1991, 1992), suggesting that associative recognition gives less weight to context (Murdock, 1997) or that it begins from a baseline that is defined by item information (Humphreys, Bain, & Pike, 1989). A focus on studying items impairs associative memory, but a focus on associative study has no negative impact on item memory (Hockley & Cristi, 1996), and associative recognition depends on the strength of *both* items and pairs (Buchler, Light, & Reder, 2008). Studies of retrieval dynamics find that the ability to discriminate between studied and unstudied items begins earlier than the ability to distinguish intact from rearranged pairs (Gronlund & Ratcliff, 1989; Rotello & Heit, 2000; Nobel & Shiffrin, 2001). While this delay has been attributed to a qualitatively different "recall-to-reject" process (Rotello & Heit, 2000; Malmberg, 2008), such a process cannot explain why stronger associations are not retrieved more quickly (Wickelgren & Corbett, 1977; Dosher, 1984; Nobel & Shiffrin, 2001) nor why participants do not use partial cues to aid associative recognition (i.e., using a singly presented word to retrieve its studied associate; Gronlund & Ratcliff, 1989). Instead, such dynamics are more consistent with the need to augment an item-only retrieval cue with compound associative information (Cox & Shiffrin, 2015).

Thus, associative information appears to be at least partially dependent on item information at both storage and retrieval, consistent with the fact that associative interference occurs only among pairs comprised of the same types of items (Criss & Shiffrin, 2004; Aue, Criss, & Fischetti, 2012). At the same time, item information is also affected by the presence of an association such that recognition of intact item groups is superior to rearranged item groups even when associative information is irrelevant (Tulving & Thompson, 1973; Clark & Shiffrin, 1987). Modeling these and other data required an assumption that presenting a pair/triplet intact at test led to an enhancement for memory for the component items, and that a holistic pair/triplet cue was used during tasks requiring retrieval of associative information (Clark & Shiffrin, 1992). Priming studies suggest that this holistic cue may be configural in nature, in that it is only effective when *all* of the component items are present and there is no effect of a partial overlap between study and test (Dosher & Rosedale, 1989, 1997).

It is clear that, despite attempts to dissociate item and associative memory, the two appear to be closely related. Unfortunately, extant empirical and theoretical work is not sufficient to fully characterize their relationship nor whether the processes used to retrieve item and associative information are in fact separable. The present work is a novel application of Systems Factorial Technology (SFT; Townsend & Nozawa, 1995) to associative recognition in which we use qualitative properties of response dynamics to determine what kinds of processing and interactions are present during the retrieval of item and associative information from event memory.

Experiment

SFT is a set of experimental and analytical techniques designed to identify the class of model to which an information processing system belongs (for an overview, see Houpt, Blaha, McIntire, Havig, & Townsend, 2014). It does so by comparing how processing dynamics differ as the presence and strength of different information sources is varied. To use SFT to describe item and associative retrieval, we employ an associative recognition paradigm in which participants study a list of pairs. After study, participants are presented with a series of test pairs and must give a positive response only to test pairs that exactly match one of the studied pairs. We separately manipulate the strength of the item and associative information in each test pair, implementing a double factorial paradigm. This paradigm allows for the computation of several key SFT statistics needed to characterize the processes underlying item and associative retrieval.

Two broad classes of processing architecture are parallel models, in which both item and associative information are retrieved simultaneously, and serial models, in which one type of information is not retrieved until the first retrieval process is finished. For example, many dual-process theories assume that associative retrieval does not begin until item retrieval has completed, an example of serial processing (Diller, Nobel, & Shiffrin, 2001; Malmberg, 2008). If either item or associative information can be used to make a response, the system is called "self-terminating". If, however, both types of information must be retrieved to generate a response, the system is "exhaustive".

Item and associative retrieval can also interact. For example, if positive evidence from both item and associative retrieval is pooled into a single "match" accumulator, we say that positive responses are facilitated whereas negative responses are inhibited, and vice versa. In the extreme case, both match and mismatch information might be pooled from both sources, termed "coactive" processing; in this case, item and associative information are effectively inseparable, since it is impossible to tell whence a particular bit of information arose. Just as interactions blur the line between item and associative retrieval, they make it impossible to make a meaningful distinction between serial and parallel processing

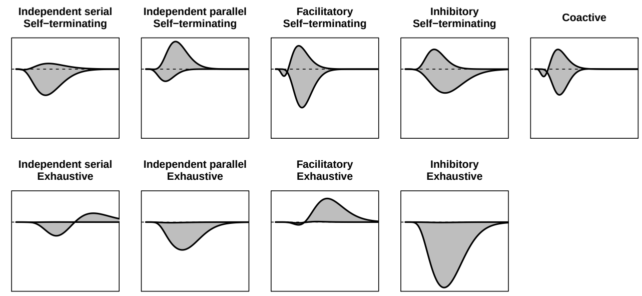

Figure 1: Allowed forms of the survivor interaction contrast (SIC) function for each processing architecture with time along the x-axis and dashed line at zero.

(Townsend, 1976); interactive serial processes are functionally equivalent to parallel cascade processing (McClelland, 1979). We refer to interactive processes as parallel, however, since the defining feature of parallel processing is that the two processes are able to operate concurrently, which is required by our notion of interaction.

Two SFT statistics can help us diagnose the architecture and interactions present in item and associative retrieval. First is the Survivor Interaction Contrast (SIC) function:

$$SIC(t) = [S_{LL}(t) - S_{LH}(t)] - [S_{HL}(t) - S_{HH}(t)]$$

where $S_{LL}(t)$ is the survivor function of the response time distribution for correct responses to test pairs with low (L) item strength and low (L) associative strength, and the other terms are defined similarly. This statistic represents how the processing dynamics of one factor (item retrieval) change as the other factor (associative retrieval) changes, taking particular forms depending on the architecture of the system. In situations where the two factors are selectively influenced by experimental manipulations and accuracy is high, the form of the SIC function can be found analytically (Townsend & Nozawa, 1995). However, when item and associative retrieval may interact—possibly leading to violations of selective influence—and/or demonstrate low to moderate accuracy, the predicted forms of the SIC function can vary. To that end, we followed Eidels, Houpt, Altieri, Pei, and Townsend (2011) and Fific, Nosofsky, and Townsend (2008) and obtained SIC predictions for various architectures by simulating accumulator models with a wide variety of parameter values. These simulations yielded an allowed set of SIC functions for each architecture, depicted in Figure 1, which allows models to be ruled out if the observed SIC is not among the allowed set.

The other statistic we use to characterize item and associative retrieval is the capacity function, specifically, the capacity function adapted to low-accuracy settings given by Equation 2 in Townsend and Altieri (2012). This function compares processing dynamics when two sources of information are present (i.e., in an intact pair, there is both an item match and an associative match) to what would be expected if a parallel unlimited capacity system processed the two sources separately. As shown in Figure 2, this function, termed the "assessment" function, also takes characteristic forms depend-

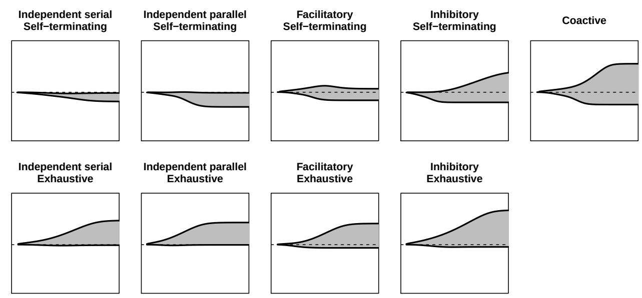

Figure 2: Allowed forms of the OR correct-and-fast assessment function for each processing architecture with time along the *x*-axis and dashed line at one.

Table 1: Design of studied pairs. Numerals denote either the left or right half (at random) of a particular image.

Image half A	Image half B	Item strength	Associative strength
1	2	H	H
3	4	H	L
5	6	H	H
7	8	H	H
9	10	H	L
11	12	H	L
13	14	L	H
15	16	L	L
17	18	L	H
19	20	L	H
21	22	L	L
23	24	L	L
25	26	H	H
27	28	H	L
29	30	L	H
31	32	L	L

ing on the type of processing architecture. Generally speaking, values of the assessment function greater than one reflect facilitation while values less than one indicate inhibition. Jointly, the SIC and assessment functions characterize how information is combined between item and associative retrieval and the manner in which it is processed dynamically.

Method

Participants 135 Syracuse University students took part in this experiment in exchange for course credit.

Materials Stimuli consisted of indoor and outdoor scene images, 256×256 pixels in size, chiefly derived from image sets used by Konkle, Brady, Alvarez, and Oliva (2010). The images were first screened to remove any legible writing (to preclude this as a strategy to remember particular images) as well as people (since these were particularly salient relative to other scene content). While space constraints prevent describing the procedure in detail, we used the color histograms of the images to select a pool of 512 to use in the experiment. Our criteria were designed to simultaneously maximize within-image symmetry (so the left and right halves would be similar to each other) and between-image dissimilarity (to reduce interference from other items).

Design Each study/test list was comprised of 16 unique pairs of image halves, divided evenly into four strength conditions, summarized in Table 1: High associative strength/high item strength (HH), high associative strength/low item strength (HL), low associative strength/high item strength (LH), and low associative strength/low item strength (LL).

Table 2: Design of test lists. Numerals refer to the same images in the study design in Table 1, with apostrophes denoting the unstudied half of the image labeled by the numeral.

		Associative strength			
		H	L	N_H	N_L
Item strength	H	1, 2	3, 4	5, 8	9, 12
		Quadrant 1 (Intact pairs)		*Quadrant 2 (Rearranged pairs)*	
	L	13, 14	15, 16	17, 20	21, 24
	N_H	25’, 26’	27’, 28’	7’, 6’	11’, 10’
		Quadrant 3 (Novel pairs)		*Quadrant 4 (Novel rearranged pairs)*	
	N_L	29’, 30’	31’, 32’	19’, 18’	23’, 22’

High associative strength pairs were presented 3 times during the study list while low associative strength pairs were presented only once during study. Item strength was manipulated by presenting the two image halves comprising the pair separately, paired with themselves. The image halves in a low item strength pair appeared *only* as part of the study pair. The image halves in a high item strength pair were shown during study paired with themselves twice. Thus, in total, the study list comprised 64 pair presentations: 8 low strength pair presentations, 24 high strength pair presentations (8 pairs repeated 3 times), and 32 self-pairings of an image half (2 presentations each of the 2 halves of 8 high item strength pairs).

Test lists were comprised of 16 pairs, summarized in Table 2. The 4 pairs in the upper left quadrant are presented intact and should be given a positive response. The remaining 12 pairs in the other 3 quadrants are foils: Rearranged pairs (quadrant 2) are created by swapping the left and right image halves of two pairs, as in normal associative recognition studies. Intact novel pairs (quadrant 3) are created by replacing each image half in an intact pair with the unstudied half of the respective images. Rearranged novel pairs (quadrant 4) apply both of these transformations: A pair is rearranged and then each of its component image halves is replaced with the unstudied image half.

Procedure Participants engaged in 10 study/test blocks. Prior to each study block, participants were told that they would be shown sets of image pairs and that they should try to remember which images appeared together. Study pairs were then presented on a white background for 2 seconds at a time, with a 0.5 second blank between each pair presentation. Presentation order was randomized under the constraint that two successive pairs did not contain any of the same image halves. The two image halves subtended approximately 3 degrees of visual angle, with approximately 0.5 degrees of blank space between them. Although the image pairs were centered horizontally on the screen, the left and right halves were independently offset from vertical center by random values sampled uniformly from [-0.25, 0.25] degrees of visual angle. This offset served two purposes: first, to emphasize that the two image halves were not meant to be treated as part of the same image; second, to avoid confusion between successive pair presentations.

After presentation of all study pairs, participants were informed that they would be shown another set of image pairs and should give a positive response only to pairs of images

Table 3: Observed mean proportion of positive responses and mean of median correct RTs (in seconds, in parentheses) for each pair type.

Item strength	Associative strength: H	L	N_H	N_L
H	0.75 (*1.071*)	0.54 (*1.162*)	0.37 (*1.216*)	0.34 (*1.194*)
L	0.72 (*1.095*)	0.46 (*1.197*)	0.31 (*1.209*)	0.22 (*1.105*)
N_H	0.26 (*1.157*)	0.21 (*1.111*)	0.15 (*1.094*)	0.16 (*1.123*)
N_L	0.27 (*1.151*)	0.22 (*1.082*)	0.14 (*1.101*)	0.12 (*1.060*)

that had appeared together at the same time on the most recent list (they were told that each test would only be for the most recent list). Positive and negative responses were randomly mapped to the "F" or "J" keys for each participant. Participants were instructed to respond as quickly and accurately as possible. Test instructions appeared on screen for a minimum of 15 seconds, after which participants could press "enter" to proceed to the test list. Each test trial began with a fixation cross centered on the screen for 0.5 seconds followed by presentation of the test pair (which followed the same sizing and random vertical offset procedure used during study). The test pair remained on screen until a response was made, after which feedback was given. Participants were told whether their response was "correct" or "incorrect", with font color green if correct and red if incorrect. Regardless of correctness, if the response was made in under 300 ms, feedback included a statement to "please take more time to respond" and if the response was made in over 4 seconds, feedback included a statement to "please try to respond more quickly". Feedback appeared for a minimum of 1 second, an additional 0.5 seconds if the participant was incorrect, and an additional 3 seconds if the response was too fast. A random time sampled at uniform between 0.25 and 0.75 seconds preceded the onset of the next test trial.

Results

Prior to analysis, we excluded trials in which the response time was shorter than 200 ms (47 out of 21,369 trials) or longer than 5 s (127 trials). Based on the remaining trials, we excluded participants who failed to give a higher rate of positive responses to intact pairs than to foils or who did not give any correct responses in at least one condition. All subsequent analyses were carried out on the remaining 18,760 trials from 118 participants.

Mean proportion of positive responses and median correct RT for each combination of item and associative strength are given in Table 3. A 4 (item strength) × 4 (associative strength) within-subjects ANOVA on the proportion of positive responses finds main effects of item strength ($F(3,351) = 298.4$, $p \sim 0$) and associative strength ($F(3,351) = 238.3$, $p \sim 0$) as well as a significant interaction ($F(9,1053) = 42.4$, $p \sim 0$). Using the same 4×4 ANOVA to analyze median correct RT, we again find main effects of item strength ($F(3,351) = 10.44$, $p \sim 0$) and associative strength ($F(3,351) = 3.01$, $p \approx 0.03$) as well as a significant interaction ($F(9,1053) = 8.99$, $p \sim 0$).

Systems Factorial Analysis

Precision terms: $\tau_{a:b} \sim \Gamma(1.01, 0.01)$

Intercept: $m_0 \sim \mathcal{N}(0, 0.001)$

For each level of item strength i, associative strength j, response r, subject s...

First-order main effects

$$m_i \sim \mathcal{N}(0,\tau_{1:1}),\ m_j \sim \mathcal{N}(0,\tau_{1:2}),\ m_r \sim \mathcal{N}(0,\tau_{1:3}),\ m_s \sim \mathcal{N}(0,\tau_{1:4})$$

Second-order interactions

$$m_{i:j} \sim \mathcal{N}(0,\tau_{2:1}),\ m_{i:r} \sim \mathcal{N}(0,\tau_{2:2}),\ m_{i:s} \sim \mathcal{N}(0,\tau_{2:3}),$$
$$m_{j:r} \sim \mathcal{N}(0,\tau_{2:4}),\ m_{j:s} \sim \mathcal{N}(0,\tau_{2:5}),\ m_{r:s} \sim \mathcal{N}(0,\tau_{2:6})$$

Third-order interactions

$$m_{i:j:r} \sim \mathcal{N}(0,\tau_{3:1}),\ m_{i:j:s} \sim \mathcal{N}(0,\tau_{3:2}),\ m_{i:r:s} \sim \mathcal{N}(0,\tau_{3:3}),\ m_{j:r:s} \sim \mathcal{N}(0,\tau_{3:4})$$

Fourth-order interaction

$$m_{i:j:r:s} \sim \mathcal{N}(0,\tau_4)$$

Linear combination of predictors:

$$m_{i,j,r,s} = m_0 + m_i + m_j + m_r + m_s + m_{i:j} + m_{i:r} + m_{i:s} + m_{j:r} + m_{j:s} + m_{r:s} + m_{i:j:r} + m_{i:j:s} + m_{i:r:s} + m_{j:r:s} + m_{i:j:r:s}$$

Likelihood, given item strength $I[n]$, associative strength $A[n]$, response $R[n]$, and subject $S[n]$ on trial n:

$$\mathrm{RT}_n \sim \text{Ex-Gaussian}\left(m_{I[n],A[n],R[n],S[n]}, s_{I[n],A[n],R[n],S[n]}, t_{I[n],A[n],R[n],S[n]}\right)$$

Figure 3: Hierarchical model structure for RT distributions; although the model structure is depicted for only the m parameter of the Ex-Gaussian, the same structure was applied to $\log s$ and $\log t$, the logarithmic transformation required because the Ex-Gaussian is defined only for $s, t > 0$. Group-level RT distributions are obtained by marginalizing each parameter over subjects, which amounts to excluding terms involving the subject factor s (all of which have mean 0), e.g., $\bar{m}_{i,j,r} = m_0 + m_i + m_j + m_r + m_{i:j} + m_{i:r} + m_{j:r} + m_{i:j:r}$.

Hierarchical parametric RT distribution estimation In contrast to most applications of SFT, we have a large number of participants but few observations per participant. We therefore estimate RT distributions using a hierarchical Bayesian model (Rouder, Lu, Speckman, Sun, & Jiang, 2005), which also enables robust statistical tests. We assume that RT distributions have an Ex-Gaussian form, with likelihood

$$f(x) = \frac{1}{t\sqrt{2\pi}} \exp\left(\frac{s^2}{2t^2} - \frac{x-m}{t}\right) \int_{-\infty}^{\frac{x-m}{s} - \frac{s}{t}} \exp\left(-\frac{y^2}{2}\right) dy,$$

where x is the response time and m, s, and t are the parameters of the distribution. The Ex-Gaussian has been found to provide a good description of RT distributions in recognition memory (Ratcliff & Murdock, 1976) and can accommodate a variety of distribution shapes. For each participant, there are a total of $4 \times 4 \times 2 = 32$ RT distributions defined by the factorial combination of item strength, associative strength, and positive/negative response. We estimate these parameters for each participant according to the multilevel model described in Figure 3. We report SFT statistics at the group level, based on the Ex-Gaussian distributions obtained by marginalizing the three parameters (m, $\log s$, and $\log t$) for each of the 32 distributions over participants (see caption of Figure 3). The model was implemented in JAGS (Plummer, 2013), which was used to obtain 10,000 posterior samples split over 10 parallel chains after 2000 iterations of "burn-in" each.

Correct acceptance architecture The SIC function for correct acceptance of intact pairs (Figure 4, upper left) demonstrates a credible positive peak (95% credible interval [CI] of the maximum is [0.024, 0.142]) but no evidence for any negative deflections (95% CI of the minimum is [-0.013, 0]). We can thus rule out all forms of exhaustive process-

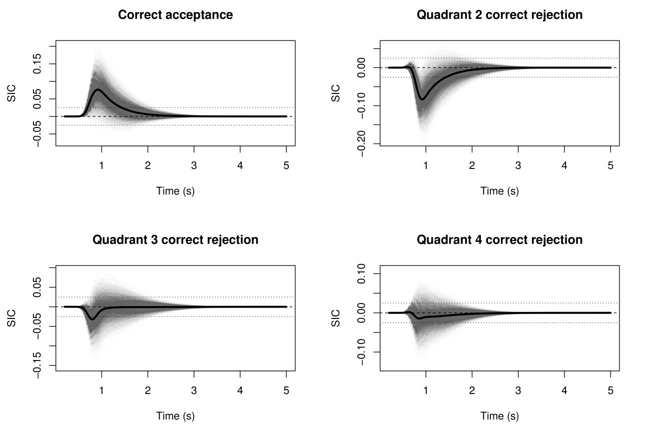

Figure 4: Posterior distributions over SIC functions for correct responses in each quadrant (see Table 2). Solid lines are posterior means while faded lines are posterior samples.

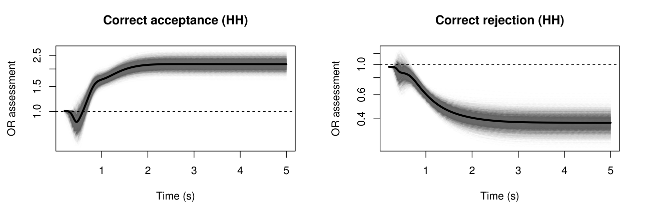

Figure 5: Posterior distributions over capacity assessment functions for correct responses. Solid lines are posterior means while faded lines are posterior samples.

ing except facilitatory, since each of these requires either a flat SIC or one with a credible negative deflection. In addition, coactive and facilitatory self-terminating processing, while they allow for SIC's that are majority positive, require at least a small early negative deflection; nonetheless, we withhold ruling these out since this negative deflection may be too small to detect. The assessment function (Figure 5, left) is everywhere greater than or equal to one, which is impossible under independent serial or parallel self-terminating processing and implies facilitation of positive responses. In sum, the SIC and capacity functions for correct acceptance are most consistent with facilitatory exhaustive and inhibitory self-terminating processing, but may allow for coactive or facilitatory self-terminating processing.

Correct rejection architecture While participants should give a positive response to pairs in the upper left quadrant of Table 2, they should give negative responses to pairs in the remaining three quadrants. Within each of these quadrants, item and associative strength is still varied but must be viewed in reverse: a high strength is actually *low* evidence in favor of the correct (negative) response. For example, the SIC for Quadrant 2 is given by $[S_{HN_H}(t) - S_{HN_L}(t)] - [S_{LN_H}(t) - S_{LN_L}(t)]$. Similarly, whenever positive responses are self-terminating, negative responses must be exhaustive; and facilitation of positive responses is inhibition for negative responses. Therefore, based on the remaining possible correct acceptance architectures, correct rejections could arise from inhibitory self-terminating (reverse of facilitatory exhaustive) or facilitatory exhaustive (reverse of inhibitory self-terminating) processing, as well as possibly inhibitory exhaustive or coactive processing.

The SIC's for the three types of correct rejection (Figure 4) differ quantitatively but are qualitatively similar. None demonstrate any credible positive deflections (95% CI of the maximum for quadrant 2 is [0, 0.017], for quadrant 3 is [0, 0.044], and for quadrant 4 is [0, 0.042]), and the SIC for quadrant 2—correct rejection of rearranged pairs—demonstrates a credible *negative* deflection (95% CI of the minimum is [-0.146, -0.030]). This pattern rules out facilitatory exhaustive processing, since this does not allow for any negative deflections. The assessment function for correct rejections (Figure 5, right) is never greater than one, consistent with the remaining possible architectures and implying inhibition of negative responses.

Complete picture We have so far examined the SIC and assessment functions without regard to the task demands, namely, that correct acceptances by definition require exhaustive processing of both item and associative information—only correct rejections can be made on the basis of a single source. After thus ruling out self-terminating processing for correct acceptances—particularly as facilitatory self-terminating processing entails a negative SIC deflection that we did not observe—we are left with two remaining architectures that can account for the complete qualitative pattern of response dynamics: Parallel facilitatory processing where positive responses are exhaustive; and fully coactive processing. In both architectures, positive match information is pooled between item and associative sources, but in the case of facilitatory processing, mismatch (negative) information arises separately from item and associative retrieval.

Discussion

Based on measures from Systems Factorial Technology (Townsend & Nozawa, 1995; Townsend & Altieri, 2012), we found that item and associative information are retrieved concurrently, with match information pooled between both sources. It is also possible that mismatch information is pooled, resulting in fully coactive processing, making item and associative information effectively indistinguishable. While our results allow for the possibility that associative information may be retrieved more slowly than item information (Gronlund & Ratcliff, 1989), our results are inconsistent with strictly serial processing, such as the proposal that item familiarity is assessed prior to the retrieval of associative information (e.g., Rotello & Heit, 2000; Malmberg, 2008). We can also rule out independence of item and associative retrieval. The assumption of independence lies at the core of both the process dissociation procedure (Jacoby, 1991) and mixture analysis of ROC curves (Yonelinas, 1997). Because this assumption is violated, any conclusions drawn within those frameworks are invalid with respect to item and associative retrieval (for additional arguments along these lines, see Curran & Hintzman, 1995; Hillstrom & Logan, 1997).

Match information—and possibly mismatch information in the case of coactive processing—was found to be pooled between item and associative sources, suggesting that positive memory evidence derives from a holistic match between the pair and the contents of memory. This is consistent with priming studies that find that multiple memory cues are combined in an interactive fashion (Ratcliff & McKoon, 1988; Dosher & Rosedale, 1989, 1997). The ability for mismatch information to arise separately from multiple sources has previously been implicated in short-term memory search (Mewhort & Johns, 2000), and may well apply in the context of long-term associative recognition, particularly as some of the critical mismatch information in Mewhort and Johns (2000) was relational in nature. Taken together, separate processing of mismatch information and pooling of match information suggests that while item and associative information may be separable, they cannot be qualitatively different, otherwise it would not be possible to combine them into a single holistic match. While this representational schema is not entailed by any extant memory theory, TODAM's allowance for separate item and associative traces (Murdock, 1982) allows that theory the flexibility to construct such a representation.

Our conclusions are based on model-independent qualitative properties of response dynamics, demonstrating how SFT can be applied in situations in which the number of observations per individual is limited and responses are more error-prone. By using Bayesian hierarchical estimation of RT distributions, we can accurately characterize group-level response dynamics. We are limited, however, in what we can say about the degree to which individuals may vary in their retrieval architectures; we are currently employing quantitative individual RT modeling (e.g., Ratcliff, 1978; Brown & Heathcote, 2008) to address this issue. Nonetheless, we have shown how tools from SFT can be used to answer critical questions in novel domains.

References

Aue, W. R., Criss, A. H., & Fischetti, N. W. (2012). Associative information in memory: Evidence from cued recall. *Journal of Memory and Language*, *66*, 109–122.

Brown, S., & Heathcote, A. (2008). The simplest complete model of choice response time: Linear ballistic accumulation. *Cognitive Psychology*, *57*, 153–178.

Buchler, N. G., Light, L. L., & Reder, L. M. (2008). Memory for items and associations: Distinct representations and processes in associative recognition. *Journal of Memory and Language*, *59*, 183–199.

Clark, S. E., & Shiffrin, R. M. (1987). Recognition of multiple-item probes. *Memory & Cognition*, *15*(5), 367–378.

Clark, S. E., & Shiffrin, R. M. (1992). Cuing effects and associative information in recognition memory. *Memory & Cognition*, *20*(5), 580–598.

Cox, G. E., & Shiffrin, R. M. (2015). A dynamic approach to secondary processes in associative recognition. In D. Noelle et al. (Eds.), *Proceedings of the 37th annual conference of the Cognitive Science Society.* Austin, TX: Cognitive Science Society.

Criss, A. H., & Shiffrin, R. M. (2004). Pairs do not suffer interference from other types of pairs or single items in associative recognition. *Memory & Cognition*, *32*(8), 1284–1297.

Curran, T., & Hintzman, D. L. (1995). Violations of the independence assumption in process dissociation. *Journal of Experimental Psychology: Learning. Memory, and Cognition*, *21*(3), 531–547.

Diller, D. E., Nobel, P. A., & Shiffrin, R. M. (2001). An ARC-REM model for accuracy and response time in recognition and recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *27*(2), 414–435.

Dosher, B. A. (1984). Degree of learning and retrieval speed: Study time and multiple exposures. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *10*(4), 541–574.

Dosher, B. A., & Rosedale, G. (1989). Integrated retrieval cues as a mechanism for priming in retrieval from memory. *Journal of Experimental Psychology: General*, *118*(2), 191–211.

Dosher, B. A., & Rosedale, G. (1997). Configural processing in memory retrieval: Multiple cues and ensemble representations. *Cognitive Psychology*, *33*, 209–265.

Dunn, J. C. (2004). Rememberknow: A matter of confidence. *Psychological Review*, *111*(2), 524–542.

Eidels, A., Houpt, J. W., Altieri, N., Pei, L., & Townsend, J. T. (2011). Nice guys finish fast and bad guys finish last: Facilitatory vs. inhibitory interaction in parallel systems. *Journal of Mathematical Psychology*, *55*, 176–190.

Fific, M., Nosofsky, R. M., & Townsend, J. T. (2008). Information-processing architectures in multidimensional classification: A validation test of the systems factorial technology. *Journal of Experimental Psychology: Human Perception and Performance*, *34*(2), 356–375.

Gronlund, S. D., & Ratcliff, R. (1989). Time course of item and associative information: Implications for global memory models. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *15*(5), 846–858.

Hillstrom, A. P., & Logan, G. D. (1997). Process dissociation, cognitive architecture, and response time: Comments on Lindsay and Jacoby (1994). *Journal of Experimental Psychology: Human Perception and Performance*, *23*(5), 1561–1578.

Hockley, W. E. (1991). Recognition memory for item and associative information: A comparison of forgetting rates. In *Relating theory and data: Essays on human memory in honor of Bennet B. Murdock* (pp. 227–248).

Hockley, W. E. (1992). Item versus associative information: Further comparisons of forgetting rates. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *18*(6), 1321–1330.

Hockley, W. E., & Cristi, C. (1996). Tests of encoding tradeoffs between item and associative information. *Memory & Cognition*, *24*(2), 202–216.

Houpt, J. W., Blaha, L. M., McIntire, J. P., Havig, P. R., & Townsend, J. T. (2014). Systems factorial technology with R. *Behavior Research Methods*, *46*, 307–330.

Humphreys, M. S., Bain, J. D., & Pike, R. (1989). Different ways to cue a coherent memory system: A theory for episodic, semantic, and procedural tasks. *Psychological Review*, *96*(2), 208–233.

Jacoby, L. L. (1991). A process dissociation framework: Separating automatic from intentional uses of memory. *Journal of Memory and Language*, *30*, 513–541.

Konkle, T., Brady, T. F., Alvarez, G. A., & Oliva, A. (2010). Conceptual distinctiveness supports detailed visual long-term memory for real-world objects. *Journal of Experimental Psychology: General*, *139*(3), 558–578.

Malmberg, K. J. (2008). Recognition memory: A review of the critical findings and an integrated theory for relating them. *Cognitive Psychology*, *57*, 335–384.

McClelland, J. L. (1979). On the time relations of mental processes: An examination of systems of processes in cascade. *Psychological Review*, *86*(4), 287–330.

Mewhort, D. J. K., & Johns, E. E. (2000). The extralist-feature effect: Evidence against item matching in short-term recognition memory. *Journal of Experimental Psychology: General*, *129*(2), 262–284.

Murdock, B. B. (1982). A theory for the storage and retrieval of item and associative information. *Psychological Review*, *89*(3), 609–626.

Murdock, B. B. (1997). Context and mediators in a theory of distributed associative memory (TODAM2). *Psychological Review*, *104*(4), 839–862.

Nobel, P. A., & Shiffrin, R. M. (2001). Retrieval processes in recognition and cued recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *27*(2), 384–413.

Plummer, M. (2013). *JAGS: Just another Gibbs sampler.* Retrieved from `http://mcmc-jags.sourceforge.net/`

Pratte, M. S., & Rouder, J. N. (2012). Assessing the dissociability of recollection and familiarity in recognition memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*(6), 1591–1607.

Province, J. M., & Rouder, J. N. (2012). Evidence for discrete-state processing in recognition memory. *Proceedings of the National Academy of Sciences*, *109*(36), 14357–14362.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108.

Ratcliff, R., & McKoon, G. (1988). A retrieval theory of priming in memory. *Psychological Review*, *95*(3), 385–408.

Ratcliff, R., & Murdock, B. B. (1976). Retrieval processes in recognition memory. *Psychological Review*, *83*(3), 190–214.

Ratcliff, R., Van Zandt, T., & McKoon, G. (1995). Process dissociation, single-process theories, and recognition memory. *Journal of Experimental Psychology: General*, *124*(4), 352–374.

Rotello, C. M., & Heit, E. (2000). Associative recognition: A case of recall-to-reject processing. *Memory & Cognition*, *28*(6), 907–922.

Rouder, J. N., Lu, J., Speckman, P. L., Sun, D., & Jiang, Y. (2005). A hierarchical model for estimating response time distributions. *Psychonomic Bulletin & Review*, *12*(2), 195–223.

Townsend, J. T. (1976). Serial and within-stage independent parallel model equivalence on the minimum completion time. *Journal of Mathematical Psychology*, *14*, 219–238.

Townsend, J. T., & Altieri, N. (2012). An accuracy-response time capacity assessment function that measures performance against standard parallel predictions. *Psychologial Review*, *119*(3), 500-516.

Townsend, J. T., & Nozawa, G. (1995). Spatio-temporal properties of elementary perception: An investigation of parallel, serial, and coactive theories. *Journal of Mathematical Psychology*, *39*, 321–359.

Tulving, E., & Thompson, D. M. (1973). Encoding specificity and retrieval processes in episodic memory. *Psychological Review*, *80*(5), 352–373.

Wickelgren, W. A., & Corbett, A. T. (1977). Associative interference and retrieval dynamics in yes-no recall and recognition. *Journal of Experimental Psychology: Human Learning and Memory*, *3*(2), 189–202.

Wixted, J. T. (2007). Dual-process theory and signal-detection theory of recognition memory. *Psychological Review*, *114*(1), 152–176.

Yonelinas, A. P. (1997). Recognition memory ROCs for item and associative information: The contribution of recollection and familiarity. *Memory & Cognition*, *25*(6), 747–763.