

# Global Similarity Predicts Dissociation of Classification and Recognition: Evidence Questioning the Implicit–Explicit Learning Distinction in Amnesia

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Dissociation of classification and recognition in amnesia is widely taken to imply 2 functional systems: an implicit procedural-learning system that is spared in amnesia and an explicit episodic-learning system that is compromised. We argue that both tasks reflect the global similarity of probes to memory. In classification, subjects sort unstudied grammatical exemplars from lures, whereas in recognition, they sort studied grammatical exemplars from lures. Hence, global similarity is necessarily greater in recognition than in classification. Moreover, a grammatical exemplar's similarity to studied exemplars is a nonlinear function of the integrity of the data in memory. Assuming that data integrity is better for control subjects than for subjects with amnesia, the nonlinear relation combined with the advantage for recognition over classification predicts the dissociation of recognition and classification. To illustrate the dissociation of recognition and classification in healthy undergraduates, we manipulated study time to vary the integrity of the data in memory and brought the dissociation under experimental control. We argue that the dissociation reflects a general cost in memory rather than a selective impairment of separate procedural and episodic systems.

*Keywords:* memory, amnesia, recognition, classification, dissociation

Memory is often conceived as a set of interconnected parts with separate explicit and implicit systems for learning (Schacter & Tulving, 1994). The dual-systems position derives, in part, from performance by people with amnesia who cannot recognize studied items but who show evidence of having learned them when tested in a classification or judgment-of-grammaticality (JOG) task. The dual-systems idea claims that (a) recognition reflects an explicit learning system, called *episodic memory*; (b) JOG reflects an implicit system, called *procedural memory*; and (c) only the episodic system is damaged in amnesia (i.e., the procedural system is spared; see Knowlton & Squire, 1993; Squire, 1994).

Although the recognition–classification dissociation is widely taken to imply two systems, the form of evidence—dissociation—cannot force the conclusion (Dunn & Kirsner, 1988, 2003; Van Orden & Kloos, 2003; Van Orden, Pennington, & Stone, 2001). It has been known for two decades that a single-system account can accommo-

date the basic facts of amnesia (McClelland & Rumelhart, 1986), and, more recently, single-system accounts of learning have mimicked the recognition–classification dissociation (e.g., Kinder & Shanks, 2001, 2003; Malmberg, Zeelenberg, & Shiffrin, 2004; Zaki & Nosofsky, 2001; see Cleeremans & Dienes, 2008; Pothos, 2007).

Although single-system accounts can be parameterized to mimic the dissociation, they are often special-purpose models crafted to show that a single-system account can accommodate the dissociation. Kinder and Shanks (2001), for example, simulated the dissociation with a simple recurrent network (SRN), an associative network designed to learn serial-order information (see also Botvinick & Plaut, 2006). Reber (2002) objected to their approach because such models require extensive training and, therefore, do not map onto standard procedures for recognition memory. Hence, to support the single-system position, we need a single-system model that is consistent with standard procedures and that explains the dissociation in terms of established principles of storage in and retrieval from memory.

Our analysis of the source of the recognition–classification dissociation has roots in Brooks' (1978; see also Vokey & Brooks, 1992) account of performance in JOG. In his analysis, JOG is based on the similarity of a probe to the studied items. Similarity ideas derived from Brooks' analysis have been formalized in models of both *classification* (e.g., Nosofsky & Zaki, 1998; Pothos & Bailey, 2000) and *retrieval* (e.g., Jamieson & Mewhort, 2009a, 2009b, 2010).

The classification approach is based on Nosofsky's (1988) generalized context model. To apply the model, one (a) estimates interexemplar similarity, (b) uses the similarity estimates to construct a psychological space (Shepard, 1987), and (c) applies the model's classification algorithm to derive decisions. Nosofsky and

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The experiment reported in this article was presented as part of Signy Holmes's honors thesis. The research was supported by grants from the Natural Sciences and Engineering Research Council of Canada to Randall K. Jamieson and D. J. K. Mewhort. We thank Brian Hauri for help in collecting some of the data, and we thank E. E. Johns and J. P. Leboe for comments.

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Zaki (1998) argued that the recognition–classification dissociation is explained in terms of the confusability of items in memory, rather than in terms of selective impairment to one of two memory systems. To test the idea, Nosofsky and Zaki used perceptual dot patterns to assess the performance of healthy subjects in both classification and recognition. Following Graf, Mandler, and Haden (1982), they delayed the test to simulate amnesic symptoms in healthy undergraduates. Performance in both recognition and classification decreased with increased time between study and test, but the reduction was larger for recognition than classification. Nosofsky and Zaki concluded that “a single-system exemplar-memory model that allows for a parameter change to represent the differential sensitivities of normal and amnesic individuals is capable of reproducing the classification and recognition probabilities that Knowlton and Squire . . . observed” (p. 252). It is unclear how time affects distinctiveness of items in memory, and time has long been notorious as an agent of loss from memory (e.g., McGeoch, 1932).

Jamieson and Mewhort’s (2009a, 2010) retrieval approach is based on Minerva 2 (Hintzman, 1986, 1988), a standard account of recognition memory. They represented the symbols of an artificial grammar with vectors of random elements. To represent studied exemplars, Jamieson and Mewhort concatenated the symbol vectors to assemble exemplar vectors.<sup>1</sup> In their account, JOG is not based on knowledge of the grammar. Instead, both recognition and JOG are based on global similarity, an index of the probe’s similarity to the studied exemplars.<sup>2</sup>

The retrieval and classification approaches differ in both when and how similarity is calculated. The generalized context model assumes that estimates of interexemplar similarity are available and that the similarity structure of the exemplars is static. The retrieval approach starts with a representation of the exemplars (i.e., concatenated symbol vectors) and computes similarity on the fly in response to each probe. As a result, the similarity structure is dynamic; it reflects the state of memory when the probe is applied.

In the present article, we develop the retrieval approach to show how it handles the dissociation of recognition and classification. Our aim is to bring the dissociation under experimental control in healthy subjects to develop evidence that it reflects the integrity of data in memory rather than selective impairment of a separate episodic memory system.

### Retrieval When Data in Memory Are Compromised

Knowlton, Ramus, and Squire (1992) provided a now-classic demonstration of the recognition–classification dissociation in amnesia. In their study, subjects with amnesia and matched control subjects studied 23 letter strings; each string conformed to the rules of a finite-state grammar (see Figure 1). After they studied, the subjects had their knowledge assessed with a JOG classification test and a recognition test. The JOG test required the subjects to discriminate unstudied grammatical probes from unstudied ungrammatical probes. The recognition task required them to discriminate studied grammatical probes from unstudied ungrammatical probes.

Knowlton et al.’s (1992) results are reproduced in the top panel of Figure 2. Performance by the subjects with amnesia and the control subjects was not reliably different in the classification test,

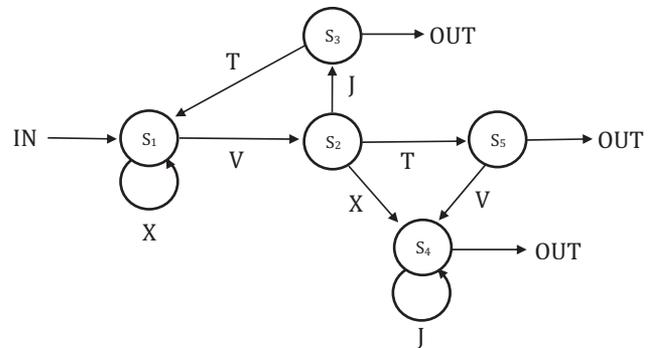


Figure 1. An artificial grammar. A grammatical stimulus is generated by starting at the leftmost node marked  $S_1$  and following the paths (indicated by arrows) until reaching one of the “out paths” from nodes  $S_3$ ,  $S_4$ , or  $S_5$ . The grammar is redrawn from “Intact Artificial Grammar Learning in Amnesia: Dissociation of Classification Learning and Explicit Memory for Specific Instances,” by B. J. Knowlton, S. J. Ramus, and L. R. Squire, 1992, *Psychological Science*, 3, p. 175. Copyright 1992 by the American Psychological Society. Adapted with permission of SAGE Publications.

but the control subjects were much better in the recognition test. Knowlton et al. argued that classification is supported by an implicit procedural-learning system, intact in both the control subjects and the subjects with amnesia, whereas recognition is supported by an explicit episodic-learning system, intact only in the control subjects. Accordingly, selective impairment in amnesia produced a selective deficit to performance in recognition.

Knowlton et al.’s (1992) procedure may seem to provide a fair comparison, but from the perspective of global-similarity theory, it is biased in favor of recognition. The bias occurs because JOG required subjects to distinguish *unstudied* grammatical targets from *unstudied* ungrammatical lures, whereas recognition required subjects to distinguish *studied* grammatical targets from *unstudied* lures. Because the targets were studied in the recognition task but unstudied in the classification task, targets’ global similarity in recognition must be greater than it is in classification (see Higham & Vokey, 1994; see Knowlton & Squire, 1994, for a rebuttal).

To calculate the effect of changes in data integrity on recognition and classification, we simulated Knowlton et al.’s (1992) two tasks. Details of the simulation model can be found in Jamieson and Mewhort (2009a, 2010). Briefly, we represented each letter

<sup>1</sup> If it was important to capture both the intersymbol similarity as well as the structure of the multisymbol exemplars, the symbol vectors could be adjusted. For example, if an exemplar involved the symbols *CESO* and subjects were to encode it phonetically, the vectors for *C* and *E* could be made more similar to each another than to the vectors for *S* and *O*. Of course, if the subjects used a visual code, one might prefer to make *C* and *O* similar rather than *C* and *E*. Similarly, depending on what subjects encode, vectors may represent conjunctions of letters to represent bigram information (cf. Kinder, 2000).

<sup>2</sup> Decision in Minerva 2 assumes that subjects accept a probe if it is sufficiently familiar and reject it otherwise. Recent evidence suggests, however, that subjects use contradiction to reject probes. The two possibilities are correlated, but recent experiments have begun to tease them apart (e.g., Johns & Mewhort, 2002, 2003, 2009; Mewhort & Johns, 2000, 2005; Rotello, Macmillan, & Van Tassel, 2000).

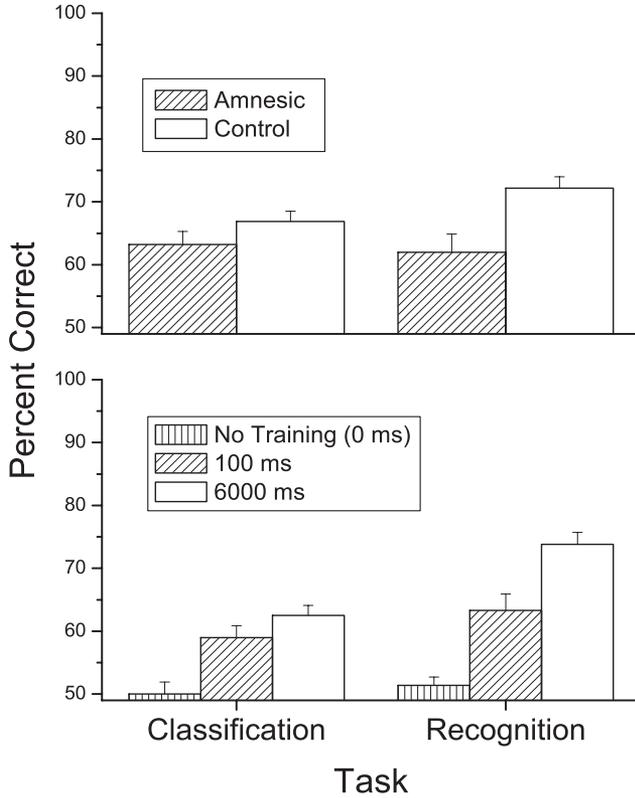


Figure 2. Accuracy as a function of task, subject type, and presentation conditions. The top panel presents data from Knowlton, Ramus, and Squire’s (1992) study and shows performance in classification and recognition for both subjects with amnesia and control subjects. The bottom panel shows performance by healthy undergraduates as a function of study time per training exemplar. Whiskers indicate standard errors. Data in the top panel are redrawn from Table 3 in “Intact Artificial Grammar Learning in Amnesia: Dissociation of Classification Learning and Explicit Memory for Specific Instances,” by B. J. Knowlton, S. J. Ramus, and L. R. Squire, 1992, *Psychological Science*, 3, p. 175. Copyright 1992 by the American Psychological Society. Adapted with permission of SAGE Publications.

used in the grammar with a unique vector of 20 random binary values  $[-1, +1]$  and constructed each exemplar by concatenating the vectors that correspond to its constituent letters; a string of six letters, for example, was coded by the concatenated letter vectors, yielding a vector of dimensionality 120.

Training was implemented by copying each of the training strings to a memory matrix, one row per string. Data integrity was manipulated by randomly replacing a proportion  $(1 - L)$  of elements in memory with 0s. As  $L$  increased, data integrity improved.

All retrieval is cued in the model. When a cue is presented, it activates all memory traces in proportion to their similarity to the cue. The activation from all traces is aggregated into a composite trace (the echo). The echo’s intensity,  $I$ , is a function of the probe’s similarity to all items in memory:

$$I = \sum_{i=1}^m \left( \frac{\sum_{j=1}^n P_j \times M_{ij}}{N_r} \right)^3,$$

where  $P_j$  is the value of the  $j$ th feature in the probe,  $M_{ij}$  is the value of  $j$ th feature of the  $i$ th row in memory,  $m$  is the number of traces in memory,  $n$  is the number of features in a trace, and  $N_r$  is the number of features in the probe and memory traces that are both nonzero. Echo intensity quantifies a probe’s global similarity to its training set. In recognition, it serves as evidence prompting an old response. In a JOG task, it is evidence prompting a grammatical response.

Classification (JOG) required subjects to distinguish unstudied grammatical targets from unstudied ungrammatical lures, whereas recognition required them to distinguish studied grammatical targets from unstudied lures. Accordingly, we ran separate simulations for each task and estimated global similarity across a full range of data integrity. The top panel in Figure 3 shows global similarity for targets and lures as a function of encoding quality ( $L$ ) and task.

As shown in Figure 3, the lure conditions for both tasks sit on top of each other. Global similarity for the studied grammatical strings (targets in the recognition test) was systematically greater than for the unstudied grammatical strings (targets in the classification test).<sup>3</sup> Finally, the advantage for the studied strings over the unstudied strings was increasingly exaggerated as data quality improved.

The bottom panel in Figure 3 recasts the simulation data to show the difference in global similarity for targets and lures in the classification (closed symbols) and recognition tasks (open symbols). The difference measure indexes how well global similarity discriminates targets from lures in each task. As shown, discrimination of targets from lures was systematically better in recognition than in classification, and the advantage for recognition increased exponentially with data integrity. When data integrity was poor (e.g.,  $L < .5$ ), the model predicted discrimination of targets and lures to be no better in classification than recognition. Discrimination improved as data integrity improved, but the improvement was faster in recognition than in classification.

With the simulation in mind, recall that recognition by Knowlton et al.’s (1992) control subjects was 72%, indicating that even with ample study time, control subjects’ memory for the studied items was less than perfect; presumably, data integrity for patients with amnesia is even lower than data integrity for the control subjects. Suppose, then, that data integrity for patients with amnesia is captured when  $L \leq .4$ , whereas data integrity for normal subjects is captured when  $L \geq .6$ . As shown in Figure 3, with data integrity as poor as  $L = .4$ —the situation that we associate with the amnesic group—global similarity predicts a very small advantage for recognition over classification. With data integrity better than  $L = .6$ —the situation that we associate with Knowlton et al.’s control subjects—global similarity predicts a strong advantage for recognition over classification. Thus, if data integrity for Knowlton et al.’s control subjects was better than data integrity for their

<sup>3</sup> In an article addressing JOG for individual exemplars, we analyzed tasks that tested both studied and unstudied grammatical strings (e.g., Dienes, 1992). Consistent with Figure 3, people rated studied grammatical test items as more grammatical than unstudied grammatical test items (see Jamieson & Mewhort, 2010, Table 8). The difference confirms the model’s prediction: Rated grammaticality is larger for studied grammatical items than for unstudied ones.

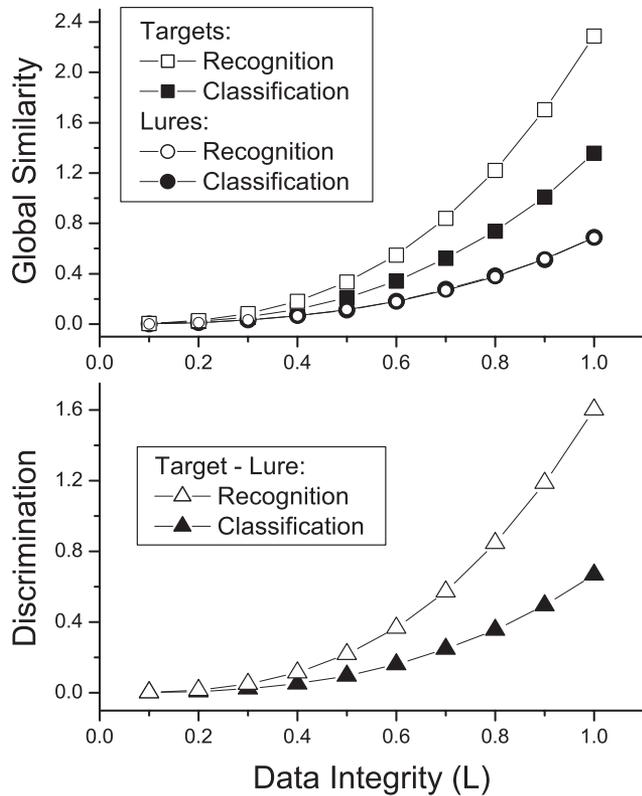


Figure 3. Simulation of Knowlton, Ramus, and Squire's (1992) recognition and classification tasks. The top panel presents global similarity for the targets and lures in both the tasks as a function of data integrity. The bottom panel shows the discrimination computed by subtracting lure from target values for both tasks as a function of data integrity.

patients with amnesia, the global-similarity idea anticipates the dissociation.

Both the dual systems and retrieval positions acknowledge that a deficit follows from amnesia. At issue is what the deficit reveals about the architecture of memory. The dual-systems position postulates that one of two systems is damaged in amnesia. The retrieval view postulates a data deficit in amnesia without postulating a second learning system. From the dual-systems perspective, the dissociation of recognition and classification in amnesia reflects selective impairment of one system. From the retrieval perspective, the dissociation is an artifact reflecting a bias favoring recognition combined with a nonlinear function relating global similarity and data integrity. Fortunately, the idea that the dissociation reflects an artifact admits to a direct empirical test: Manipulating data integrity should induce the dissociation in normal subjects.

### Bringing the Dissociation Under Experimental Control

To test the idea that the recognition–classification dissociation reflects a bias for recognition over classification that interacts with the quality of the data in memory, we conducted a conceptual replication of Knowlton et al. (1992) using healthy undergraduates. During training, subjects memorized 23 training strings taken

from the target experiment. Each string was presented for 0 ms, 100 ms, or 6,000 ms. The 0-ms condition was intended to establish baseline performance in classification and recognition, independent of viewing the training items. The 100-ms condition was chosen to produce a severe data deficit of the sort associated with amnesia; the 6,000-ms condition was chosen to allow for the better data integrity that is associated with control subjects. After training, the subjects completed either a recognition test for the studied grammatical items or a classification test in which they discriminated novel grammatical items from novel ungrammatical items, the same tests that Knowlton et al. used.

### Method

**Participants.** Ninety undergraduates from the University of Manitoba subject pool participated in the study. They were assigned in equal numbers to the six experimental conditions defined by the factorial combination of encoding time (0 ms, 100 ms, and 6,000 ms) and test type (classification vs. recognition). All reported normal or corrected-to-normal vision.

**Stimuli.** The stimuli were derived from Knowlton et al.'s (1992) Grammar A (see Figure 1), the same grammar that we used for the simulation. There were 46 grammatical strings and 46 ungrammatical strings. The grammatical strings make up the entire set of strings of six characters or fewer that can be produced from the grammar. Because Knowlton et al. did not list their ungrammatical stimuli, we generated 46 ungrammatical strings matched for length against the grammatical ones. To generate a string, we sampled one of the four consonants used in the grammatical items—*J*, *T*, *X*, and *V*—randomly to each serial position in the string. If the resulting string was ungrammatical, it was used; otherwise, it was discarded and replaced.

For each subject, the 46 grammatical strings were divided randomly into two sets. In recognition, the 23 grammatical strings presented in training also served as the studied grammatical targets. In classification, the 23 grammatical strings that were not presented in training served as the unstudied grammatical targets. For both tests, 23 of the 46 ungrammatical strings were selected randomly to serve as the unstudied ungrammatical lures; the 23 ungrammatical items were sampled randomly for each subject.

**Procedure.** The experiment was administrated on computers. Participants were tested in groups of four to seven; each subject used a different computer.

The subjects were told that they would be shown strings of letters and that they should try to remember the strings. Participants in the 0-ms condition were told the strings would be presented subliminally and that they should keep their eyes on the screen over the training phase.

The subject initiated the training phase of the experiment by clicking on the word *Start* displayed at the center of the computer's screen. When the trial started, the screen was cleared for 750 ms; immediately thereafter, a training string was presented at the center of the screen. The training string remained on the screen for 0, 100, or 6,000 ms, depending on the condition to which the subject had been assigned. Next, the screen was cleared for 750 ms, and (in the 100- and 6,000-ms conditions) the next string was displayed. The training cycle repeated until all of the training strings had been presented.

After training, the subjects in the recognition test were asked to distinguish the studied strings from unstudied lures. In classification, the subjects were first informed that the studied strings were constructed using rules and were asked to distinguish novel strings that conformed to the rules from novel strings that violated the rules. Participants were invited to ask for clarification if the instructions were unclear; otherwise, they were instructed to click on a button labeled *Begin* to initiate the test procedure.

At the start of the test, the screen was cleared for 1 s, after which the first test string was displayed at the center of the screen. Two buttons appeared below the string, one on the left and another on the right. For the recognition condition, the buttons were labeled *Old* and *New*. For the classification condition, the buttons were labeled *Correct* and *Incorrect* (the same labels Knowlton et al., 1992, used). The subjects used their computer's mouse to click on the appropriate button. After the subject's response had been recorded, the screen was cleared; 1 s later, the next test string was displayed. The test cycle continued until the subject had responded to each of the test strings.

After the test, a text editor was provided on the computer's screen, and, prompted by a message that the training items had been constructed using the rules of an artificial grammar, the subjects were invited to describe the rules.

## Results and Discussion

Mean percentage correct classification and recognition scores are presented in the bottom panel of Figure 2. First, classification performance was equivalent in the 100-ms and 6,000-ms conditions,  $t(28) = 1.078$ ,  $p = .291$ ,  $d = 0.394$ , replicating the null difference reported for Knowlton et al.'s (1992) patient and control groups. Second, recognition performance was reliably worse in the 100-ms training group as compared with the 6,000-ms training group,  $t(28) = 3.234$ ,  $p = .003$ ,  $d = 1.181$ , replicating the deficit of Knowlton et al.'s patients with amnesia relative to their control subjects. Third, performance was better in the 100-ms over the 0-ms conditions for both recognition,  $t(28) = 4.091$ ,  $p = .001$ ,  $d = 1.443$ , and classification,  $t(28) = 3.07$ ,  $p = .005$ ,  $d = 1.119$ , confirming that performance in the 100-ms conditions reflected an advantage based on memory of the training items rather than learning over the course of the test phase. Fourth, performance was above chance ( $M = 50\%$ ) in all but the 0-ms control conditions, matching the better than chance performance by subjects with amnesia in Knowlton et al.'s study ( $\alpha = .05$ ). Finally, comparison of performance in the 100- and 6,000-ms conditions in our experiment against that of Knowlton et al.'s subjects with amnesia and control subjects, respectively, shows a close match to both the means and standard errors.

The pattern of results is remarkably consistent with Knowlton et al.'s (1992) data. There is, of course, a key difference: We used study time, a proxy for data integrity, as the dissociating factor. From our perspective, both classification and recognition reflect an incomplete memory of the training exemplars. The dissociation of recognition and classification in both studies reflects the nonlinear function of data integrity and global similarity.

The experiment tested the idea that the dissociation of recognition and classification reflects a difference in data quality rather than selective impairment to a dedicated learning system. To confirm the data quality idea, we replicated the dissociation by

manipulating study time in a sample of healthy undergraduates. Our evidence not only confirms that the dissociation can be explained without assuming a specialized procedural learning system but also brings it under experimental control.

## General Discussion

We are not alone in arguing against dual-system accounts of the recognition–classification dissociation. However, the present work extends the argument in three ways. First, we explain the dissociation in terms of a bias in the design of the dissociation experiment combined with nonlinear growth in similarity as data integrity improves (Kinder & Shanks, 2001). Second, because our model is based on an established account of retrieval, we have described retrieval in amnesic subjects with the same principles as retrieval in normal subjects (see Clark & Gronlund, 1996). For the same reason, our approach escapes the criticism that Reber (2002) leveled against Kinder and Shanks's (2001) network account. Finally, we have encapsulated the argument by producing the dissociation in healthy subjects. The demonstration shows, at a minimum, that the dissociation does not imply two systems. In light of the present data, to argue for two systems, one needs a form of evidence that is not based on the dissociation between recognition and classification.

Our manipulation of study time per exemplar was designed to compromise the integrity of our subjects' memory for the training strings. We are agnostic about details of the corresponding data loss in amnesia: It may reflect an encoding deficit or it may reflect rapid loss after initial encoding (see Mayes, Downes, Shoqeirat, Hall, & Sagar, 1993). Likewise, our account is agnostic about the order in which aspects of a verbal stimulus might be encoded (see Criss & Malmberg, 2008). We note, however, that the sequences of letters in both grammatical and ungrammatical exemplars conflict with English usage. Hence, encoding is unlikely to include what Criss and Malmberg (2008) described as late-stage or semantic encoding.

Our retrieval-based approach contrasts with the SRN serial-learning account developed by Kinder and Shanks (2001). The SRN learns regularities in training items over multiple presentations at study and bases decisions on that information at test (e.g., Cleeremans, Servan-Schreiber, & McClelland, 1989). In contrast, Minerva 2 stores once-presented events: The structure in those events emerges retrospectively and on the fly during retrieval. In Redington and Chater's (2002) terminology, the SRN is an eager and prospective account whereas ours is a lazy and retrospective one.

Despite differences, Minerva 2 and the SRN share a prediction. If both control subjects and subjects with amnesia were tested using studied grammatical targets and unstudied ungrammatical lures under both recognition and classification instructions, performance of the subjects with amnesia should fall below that of the control subjects, and the dissociation of recognition and classification should disappear. At least for healthy undergraduates, Kinder and Shanks (2001, Experiment 1) showed that judgment of grammaticality for studied grammatical, unstudied grammatical, and unstudied ungrammatical test items did not differ under recognition and classification instructions. If performance by subjects with amnesia and control subjects is mediated by different systems, however, there is no reason to expect the dissociation to

change when studied items are used in both recognition and classification. Control subjects should still benefit from the availability of both systems, and subjects with amnesia should continue to benefit from the implicit system.

Finally, to reduce performance of control subjects to the level of subjects with amnesia, we used a tachistoscopic study time (100 ms). The study time allowed material to be encoded—performance was better than the 0-ms control—but data integrity was poor. Nevertheless, even under such extreme conditions, our subjects performed above chance, a feat that is remarkable itself and that underscores an important insight that Hintzman (1986, 1988) built into Minerva 2: Even when the data in memory are sparse, Minerva's retrieval algorithm supports above-chance performance in both recognition and classification.

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Received May 22, 2009

Revision received March 11, 2010

Accepted June 22, 2010 ■