Amnesia and the Declarative/Nondeclarative Distinction: A Recurrent Network Model of Classification, Recognition, and Repetition Priming

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Abstract

A key claim of current theoretical analyses of the memory impairments associated with amnesia is that certain distinct forms of learning and memory are spared. Supporting this claim, B. J. Knowlton and L. R. Squire found that amnesic patients and controls were indistinguishable in their ability to learn about and classify strings of letters generated from a finite-state grammar, but that the amnesics were impaired at recognizing the training strings. We show, first, that this pattern of results is predicted by a single-system connectionist model of artificial grammar learning (AGL) in which amnesia is simulated by a reduced learning rate. We then show in two experiments that a counterintuitive assumption of this model, that classification and recognition are functionally identical in AGL, is correct. In three further simulation studies, we demonstrate that the model also reproduces another type of dissociation, namely between recognition memory and repetition priming. We conclude that the performance of amnesic patients in memory tasks is better understood in terms of a nonselective, rather than a selective, memory deficit.

INTRODUCTION

For some time, an important goal of research in cognitive psychology has been to identify distinct memory and learning systems that operate independently of each other and that mediate different kinds of behavior. A prominent distinction has been made between declarative and nondeclarative memory (for an overview, see Squire, Knowlton, & Musen, 1993). Declarative (or explicit) memory typically is characterized by the conscious recollection of previously encoded information. By contrast, nondeclarative (or implicit) memory is thought to influence behavior in the absence of conscious recollection. The most compelling evidence for the existence of these two distinct and independent systems has been accumulated in studies with amnesic patients: Amnesics, whose declarative memory is poor, have been demonstrated to show intact learning in various tasks of nondeclarative memory (for an overview, see Gabrieli, 1998). These studies are particularly convincing if the same type of stimulus materials is used in the declarative and in the nondeclarative memory test, and if the tests differ principally in the kind of instructions. This was achieved, for example, in a study carried out by Knowlton and Squire (1995). In their experiments, they used dot patterns generated from a prototype by employing the classic statistical distortion methods of Posner and Keele (1968). Amnesic participants performed normally on a task where they had to classify random dot patterns while their performance on recognizing the same type of stimuli was significantly impaired. This result was interpreted by Knowlton and Squire as evidence that performance on the two tasks is indeed mediated by different memory systems, one of which is impaired and the other of which is spared in the patients.

Recently, however, Nosofsky and Zaki (1998) seriously challenged this conclusion by demonstrating that a single-system model, the Generalized Context Model (GCM), accounts for the observed dissociation. According to the GCM, there is only a single memory system in which representations of entire training stimuli are stored. In Nosofsky and Zaki’s modeling approach, only a single parameter of the GCM, the sensitivity parameter, was varied in order to account for a general difference in the memory abilities of the two groups of participants. Nosofsky and Zaki showed that decreasing the value of this parameter only slightly reduced classification performance but considerably reduced recognition performance. Thus, the GCM successfully accounts for the dissociation between classification and recognition observed by Knowlton and Squire (1993). By showing that a single-system model can explain this dissociation, Nosofsky and Zaki made it clear that a dual-system interpretation is not compelled by the data.

The study by Knowlton and Squire, however, is only a single example in which amnesic patients show intact

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classification performance but are impaired in recognition tasks. Further studies have been conducted in the domain of artificial grammar learning (AGL) and in studies of repetition priming. We return later in this article to the evidence (e.g., Hamann & Squire, 1997a) that repetition priming and recognition can be dissociated in amnesia. The overall aim of our research, like that of Nosofsky and Zaki (1998), is to show that dissociations between declarative tasks (e.g., recognition) and nondeclarative ones (e.g., classification, repetition priming) can be explained on the basis of a unitary computational system with a single form of knowledge representation.

Classification and Recognition in Artificial Grammar Learning

In AGL experiments, letter strings are presented that have been generated using an artificial or finite-state grammar (see Figure 1). Typically, participants first memorize a subset of all strings that can be generated by the grammar. Then they are informed about the existence of a complex set of rules that determine letter order and are asked to classify new grammatical strings, which they did not see during training, and new non-grammatical strings. Knowlton, Ramus, and Squire (1992) and Knowlton and Squire (1994, 1996) report several AGL experiments showing that classification performance in amnesic patients is similar to that in control participants. In contrast, two experiments reported by the same authors showed amnesic patients to be significantly impaired in recognition, both of whole training strings (Knowlton et al., 1992) and of fragments of those strings (Knowlton & Squire, 1996, Experiment 2). Thus, results of AGL experiments are consistent with those obtained in other tasks in supporting the notion of two distinct memory systems.

In AGL, participants base their judgments on distributed information from the entire set of training strings rather than on similarity to specific training exemplars. This conclusion is based on the fact that similarity to specific training items does not influence grammaticality judgments when distributed information is held constant (Johnstone & Shanks, 2001; Kinder, 2000; Shanks, Johnstone, & Staggs, 1997; Knowlton & Squire, 1994). Therefore, the GCM as well as other exemplar models do not give an appropriate account of performance at test (see Dienes, 1992). Thus, Nosofsky and Zaki’s demonstration that an exemplar-based single-system model can reproduce the dissociation between recognition and classification observed with dot patterns does not directly challenge the evidence in support of separate memory systems found in AGL studies.

In this article we pursue an alternative to Nosofsky and Zaki’s approach by exploring whether a connectionist model of AGL, the Simple Recurrent Network (SRN) model (see Figure 2), can produce the dissociation between recognition and classification found in the experiments reported by Knowlton et al. The SRN is a connectionist model, which was designed to store sequences of symbols or even (Cleeremans & McClelland, 1991; Cleeremans, 1993; Elman, 1990). At present, it appears to be the most successful computational model of AGL (see Kinder, 2000; Redington & Chater, 1998, for comparisons of computational models of AGL). For a detailed description of the model, see the Appendix. Following a suggestion by McClelland and Rumelhart (1986), we vary only a single parameter of the SRN—the learning rate—to simulate amnesia.

**Figure 1.** An artificial grammar. Letter strings are generated by following the arrows from the input state until the structure is left at an output state. Each time an arrow is chosen, the associated letter is appended to the string. Letter strings that are generated this way are called grammatical, whereas all other letter strings are called nongrammatical.

**Figure 2.** The architecture of the SRN.

**OVERVIEW OF THE SIMULATION STUDIES AND GENERAL ASSUMPTIONS**

Four of the six simulation studies reported in this article deal with the declarative/nondeclarative distinction in AGL. In all of these simulations, we assume classification and recognition in AGL to be functionally equivalent. First, we assume that on both tasks an identically structured system is used, which can be depicted as an SRN. Second, we assume that the information stored in...
that system is used in identical ways independent of whether a classification or a recognition response is given. Thus, our simulations follow from the assumption that a single system mediates performance both in classification and in recognition of stimuli generated by an artificial grammar. In accord with this assumption, we varied only one single parameter, the learning rate, to account for a general difference in memory efficiency between amnesic patients and control participants. Identical parameter values were chosen in both tasks.

We then report two additional simulation studies (5 and 6) concerned with repetition priming and recognition. In these, we apply our model to memory for illegal nonwords that resemble AGL strings. With these stimuli, amnesics show intact repetition priming but impaired recognition memory (Hamann & Squire, 1997a), supporting the notion that performance on these tasks is mediated by different memory systems. In simulating this experiment, we again assumed that there is only a single memory system and that amnesic patients are generally, not selectively, impaired in their learning and memory capabilities. Finally, we consider evidence from patients who show intact recognition memory combined with impaired priming (Gabrieli, Fleischman, Keane, Reminger, & Morrell, 1995) and we show that the model can also reproduce this performance pattern.

Simulation Study 1: Knowlton et al. (1992)

Knowlton et al. (1992) report an AGL experiment in which amnesic patients and control participants were tested on their performance both in recognition and in classification. In the classification task, participants had to judge whether or not letter strings adhered to a finite-state grammar after they had memorized strings generated from that grammar. The two groups did not differ significantly in classification performance, although numerically, performance of the controls was higher (see Figure 3, top, left portion). In the second task, too, participants were trained on grammatical items. In this task, however, a recognition test was administered with the stimuli being old grammatical

Figure 3. Top: Classification and recognition performance (percentage of correct responses) in the amnesic patients and the control participants reported by Knowlton et al. (1992). Bottom: Percentage of correct responses with different learning rates when the SRN was tested on either the recognition stimuli (old grammatical and new nongrammatical) or the classification stimuli (new grammatical and new nongrammatical) used by these authors. The error bars indicate the 95% confidence intervals.

Knowlton, Ramus, & Squire (1992), Experimental Results

![Experimental Results](image1)

Knowlton, Ramus, & Squire (1992), Simulation Results

![Simulation Results](image2)
items and new nongrammatical items. In this test, the amnesic patients performed significantly more poorly than the control participants (see Figure 3, top, right portion).

The SRN was trained and tested on the identical stimuli as the participants in the experiment. Parameters were set to identical values for both groups and for both tasks except for the learning rate that was set to a lower value when the performance of the amnesics was simulated (see the Appendix for parameter values). The simulation results (Figure 3, bottom) resemble the experimental data very closely. Whereas there was only a small difference in classification performance, recognition performance was considerably better when the learning rate had been set to a high value. Thus, in the simulations, a dissociation between recognition and classification emerged merely as a result of the target test stimuli being different in the two tasks (old grammatical items in the recognition task and new grammatical items in the classification task). No differences in the mechanisms being used in these two tasks needed to be assumed in order to account for the pattern of results.

Simulation Study 2: Knowlton and Squire (1994, Experiment 1)

In this experiment, Knowlton and Squire again showed that amnesic patients and controls performed similarly in a classification task (no recognition test was administered in this experiment). However, in contrast to all other experiments of this kind, amnesic patients exhibited a slightly higher level of performance. Although this difference was extremely small and far from being statistically significant, it is an interesting question whether the SRN can also reproduce a result in this direction. Since amnesics and controls are simulated using different learning rates (a lower one for the amnesics than the controls), the crucial question is whether a decrease in classification performance can be obtained as the learning rate increases. In Knowlton and Squire’s (1994) Experiment 1, only a single grammar was used, which was identical to grammar A employed by Knowlton et al. (1992). Figure 4 shows the simulated classification (new grammatical and nongrammatical) and recognition (old grammatical and new nongrammatical) performance as a function of the learning rate with this grammar (all other parameters were identical to the ones in the last simulation; each data point represents the average outcome of 100 simulations). Figure 4 reveals that there is a small but steady decrease in classification between a learning rate of 0.2 and 0.7, consistent with Knowlton and Squire’s results. What might be the reason for this decrease? With very high levels of learning efficiency, the model exhibits an increasing ability to discriminate between the items it has been trained on, the old grammatical items, and new grammatical items. This is because the network becomes more and more sensitive to fragments larger than bigrams and trigrams such as quadruples. Whereas old and new grammatical items are rather similar with respect to global chunk strength (old grammatical strings: 8.57, new grammatical strings: 7.68; see Knowlton & Squire, 1994, for details on the method of computing chunk strength), they differ to a larger extent with respect to quadruples, which are not considered in the measure of chunk strength proposed by Knowlton and Squire (1994). New grammatical strings contain an average of 1.46 quadruples presented during training whereas old grammatical strings contain an average of 2.77 quadruples, which is almost twice as many. The network’s increasing sensitivity to larger fragments results in a decreasing endorsement rate for new grammatical items that contain a low number of familiar quadruples. Paradoxically, therefore, the model actually predicts a decrease in classification performance when the targets are new grammatical items as the learning efficiency increases. With recognition, because the target stimuli in the test are the old grammatical stimuli that the network was trained on, there is no such decrease of the learning rate function. The behavior shown by the SRN reflects a general property of distributed connectionist models: When a network becomes increasingly sensitive to more specific information (either as a result of increasing the number of training trials or—as in our case—by increas-

![Figure 4](http://direct.mit.edu/jocn/article-pdf/13/5/648/1760401/089892901750363217.pdf)
ing the learning rate), its ability to show generalization tends to decline. Since endorsing new grammatical items requires generalization whereas endorsing old grammatical items does not, in the current simulations the decrease occurs only with classification stimuli.

Figure 4 also makes it clear why the SRN is capable of accounting for the dissociation between recognition and classification found by Knowlton et al. (1992). Both learning rate functions, the one for classification as well as the one for recognition, are negatively accelerated until they finally reach a maximum. The maximum is at a considerably higher value for recognition than for classification. This is because of the target stimuli being old in recognition but new in classification. As a general rule, the predicted endorsement rate of a test string is positively related to its chunk strength (Knowlton & Squire, 1994). Since old grammatical strings have higher values of chunk strength than new grammatical strings, the model predicts them to be endorsed more readily. Because non-targets are identical in both tasks and, therefore, are predicted to be endorsed equally often, lower percentages of correct responses are predicted for classification than for recognition. With low learning rates (e.g., .1), classification performance is already near its maximum value whereas recognition performance is not. Classification and recognition performance are very similar. With high learning rates, both functions are at asymptote or are even decreasing again. With the two functions being shaped like this, there will be only a small difference in classification when the learning rate is varied from low to high, but a much larger difference in recognition.

**Simulation Study 3: Knowlton and Squire (1996, Experiment 2)**

Knowlton and Squire (1996, Experiment 2) tested whether amnesic patients were not only impaired in recognition of whole training strings but also in recognition of chunks that had comprised these strings. On that test, amnesic patients performed considerably worse than control participants (57.7% correct vs. 67.4% correct). Together with other results showing normal classification performance in amnesia, Knowlton and Squire interpreted these data as further evidence that in AGL, declarative knowledge does not contribute to classification.

Simulating these results, we used largely the same parameters as in the two previous simulations (we regarded a small change in parameter values when simulating different experiments as justified1). Both the learning items and the test items were the original ones used by Knowlton and Squire (1996). As can be seen in Figure 5, the simulation results closely resemble the experimental data. Thus, the SRN is capable of yielding a considerable difference in chunk recognition when low and high learning rates are used. At the same
time, rather similar high and low learning rates produce only a small difference in classification performance. The simulation results provide evidence that it is not necessary to assume two different processes in order to account for the results in chunk recognition and classification.

So far, we have presented simulation results showing that a single-system model reproduces the observed dissociations between recognition and classification in AGL. Thus, in order to explain these dissociations, it is not necessary to assume that there are two separate memory systems mediating recognition and classification. However, our simulations of course do not rule out the dual-system account. In the second part of this article, we therefore report two experiments that were conducted to directly test the dual-system against the single-system account. The key assumption of our single-system account is that participants do not discriminate between classification and recognition in AGL experiments, whereas the dual-system account requires unequivocally that they do. Thus, evidence that participants treat recognition and classification identically would support the single-system view.

**Experiment 1**

All participants in Experiment 1, who were not memory-impaired, experienced an identical training procedure, in which they had to memorize items generated by an artificial grammar. In the test phase, we instructed one group of participants to classify test strings as grammatical or nongrammatical and the other group to judge them as old or new. Three types of test strings were presented to both groups: old grammatical strings (the training strings), new grammatical strings, and new nongrammatical strings. From a dual-system point of view, different results would be expected for the two tasks. Participants performing classification should have high endorsement rates for both types of grammatical strings.
and a much lower endorsement rate for nongrammatical strings. By contrast, participants performing recognition should only have a high endorsement rate for old grammatical strings and low endorsement rates for both new grammatical and new nongrammatical strings.

A strong prediction that can be derived from the single-system account is that the experimental results should be identical in both tasks, since participants get exactly the same information during training and test, and the stimuli are identical in both cases. Furthermore, participants in both groups should use similar kinds of information for making their judgments during test. A regression analysis (see Johnstone & Shanks, 1999) computed to assess the sources of information participants use to make their judgments should, therefore, reveal no differences between the two groups. However, if two different memory systems mediate performance on the two tasks, subjects should use different information for making their judgments: In recognition, the old/new status of items should be important, whereas in classification, subjects should rely on several sources of information that have been previously shown to be important in grammaticality judgments (for an overview, see Johnstone & Shanks, 1999).

Results
The level of significance was set to .05 in all statistical analyses. Table 1 shows the mean endorsement rates for both groups (classification or recognition instructions) and all three item types (old grammatical, new grammatical, and new nongrammatical). Under both instructions, endorsement rates for nongrammatical items were much lower than endorsement rates for the old and new grammatical items. The two types of grammatical items differed only slightly from each other. A 2 × 3 factorial analysis of variance (ANOVA) was computed with type of instruction as a between-subject variable and item type as a within-subject variable. Unsurprisingly, this ANOVA revealed a significant effect of item type, indicating that endorsement rates of the three item types were different, $F(2,60) = 158.41$, $MSE = 102.2$. There was no main effect of instructions, indicating that the probability of calling an item old under recognition instructions did not differ from the probability of calling an item grammatical under classification instructions. A significant Item Set × Instructions interaction would have indicated a different pattern of endorsement rates under the two instructions. This interaction, however, was not statistically significant, $F(2,60) = 1.39$, $MSE = 102.2$.

Next, we computed for both groups the percentage of correct responses in two different ways, either using only those stimuli that would typically be presented in classification (new grammatical and new nongrammatical) or only those typically presented in recognition (old grammatical and new nongrammatical strings). These values can be seen in Table 1. Two $t$ tests were computed to compare the percentages of correct responses under classification instructions and under recognition instructions. Neither of them revealed a statistically significant difference (percent correct old grammatical/new nongrammatical: $t(30) = 1.60$; percent correct new grammatical/new nongrammatical: $t(30) = .86$).

In order to explore whether or not participants performing classification and recognition rely on different kinds of information, regression analyses using the method suggested by Lorch and Myers (1990) were performed (see Johnstone & Shanks, 1999, for a detailed explanation of this method). Eleven predictor variables were defined reflecting the attributes of the test items: (1) grammaticality, (2) a variable indicating whether the string was old or new, (3) global chunk strength, (4) anchor chunk strength, (5) chunk novelty, (6) novel chunk positions, (7) length, (8) specific item similarity, (9) a variable indicating whether or not the string contained the letter J, (10) a variable indicating whether the first letter of the string had appeared in that position in the training strings, and (11) a variable indicating whether the string’s pattern of repetitions was a familiar one. Global chunk strength, anchor chunk strength, chunk novelty, and novel chunk positions were computed as described by Johnstone and Shanks (1999). Specific item similarity of a string was defined as the number of positions in which it diverged from its most similar training string. The most similar training string could be of identical or of different length. The test string VTV, e.g., was assigned a specific item similarity value of 1, because there was a training string VT. To code the occurrence of Js in the string seemed reasonable since of the letters used in the grammar, J was the only one from the first half of the alphabet whereas the other letters (T, V, and X) were taken from the second half of the alphabet. Thus, J possibly had a special impact on endorsement rates. The validity of the starting letter was coded because with only two different initial letters, a new letter occurring at the first position of a

| Table 1. Endorsement Rates and Percentages of Correct Responses in Experiment 1 |
|------------------------|------------------------|------------------------|
|                        | Recognition            | Classification          |
| Old grammatical strings| 68.2 (± 3.9)           | 64.9 (± 5.9)           |
| New grammatical strings| 61.7 (± 4.5)           | 63.0 (± 5.9)           |
| New nongrammatical strings| 23.1 (± 4.9)         | 28.3 (± 4.3)           |
| All strings            | 51.0 (± 2.9)           | 52.1 (± 2.7)           |
| Percent correct old grammatical/new nongrammatical | 72.6 (± 2.9) | 68.3 (± 4.1) |
| Percent correct new grammatical/new nongrammatical | 69.3 (± 2.5) | 67.4 (± 3.5) |

The values in brackets are the 95% confidence intervals.
Table 2. Regression Weights (*B Values*) Averaged Across All Participants and Across Participants in Each of the Instruction Groups in Experiment 1

<table>
<thead>
<tr>
<th>Variables</th>
<th>Overall Regression Weights</th>
<th>Regression Weights Recognition</th>
<th>Regression Weights Classification</th>
<th>t Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grammaticality</td>
<td>0.575* (± 0.345)</td>
<td>0.635* (± 0.498)</td>
<td>0.514* (± 0.490)</td>
<td>0.34</td>
</tr>
<tr>
<td>Old/new</td>
<td>−0.210 (± 0.314)</td>
<td>−0.277 (± 0.306)</td>
<td>−0.142 (± 0.557)</td>
<td>0.42</td>
</tr>
<tr>
<td>Global chunk strength</td>
<td>0.093 (± 0.125)</td>
<td>0.103 (± 0.137)</td>
<td>0.085 (± 0.216)</td>
<td>0.16</td>
</tr>
<tr>
<td>Anchor chunk strength</td>
<td>0.286* (± 0.231)</td>
<td>0.093 (± 0.341)</td>
<td>0.479* (± 0.312)</td>
<td>1.69</td>
</tr>
<tr>
<td>Chunk novelty</td>
<td>−0.205 (± 0.384)</td>
<td>−0.411* (± 0.651)</td>
<td>0.001 (± 0.404)</td>
<td>1.06</td>
</tr>
<tr>
<td>Novel chunk positions</td>
<td>0.171 (± 0.235)</td>
<td>0.301 (± 0.343)</td>
<td>0.041 (± 0.321)</td>
<td>1.08</td>
</tr>
<tr>
<td>Length</td>
<td>−0.003 (± 0.192)</td>
<td>0.215 (± 0.220)</td>
<td>−0.220 (± 0.282)</td>
<td>2.38*</td>
</tr>
<tr>
<td>Specific item similarity</td>
<td>−0.178 (± 0.425)</td>
<td>−0.525 (± 0.570)</td>
<td>0.170 (± 0.598)</td>
<td>1.65</td>
</tr>
<tr>
<td>String contains letter J</td>
<td>−0.430* (± 0.218)</td>
<td>−0.353* (± 0.265)</td>
<td>−0.507* (± 0.553)</td>
<td>0.68</td>
</tr>
<tr>
<td>Valid starting letter</td>
<td>1.739* (± 0.713)</td>
<td>2.224* (± 1.017)</td>
<td>1.254* (± 0.974)</td>
<td>1.35</td>
</tr>
<tr>
<td>Familiar pattern of repetitions</td>
<td>0.527* (± 0.165)</td>
<td>0.493* (± 0.276)</td>
<td>0.560* (± 0.192)</td>
<td>0.39</td>
</tr>
</tbody>
</table>

The values in brackets are the 95% confidence intervals.

*p < .05, df = see bottom line.

The third and the fourth columns of Table 2 show the mean regression weights computed separately for each group of participants. For each predictor variable, a *t* test between the means of the two groups was computed. As the final column of Table 2 shows, neither the *B* values for the variable old/new nor the *B* values for the variable grammaticality differed significantly between the two groups of participants, which had been expected from the two-system view, neither did any of the other *t* tests yield a statistically significant result, except in the case of the predictor variable length. This reflects a marginal tendency for endorsing more long strings than short strings in classification but endorsing more short strings than long strings in recognition. To evaluate this result, it must be noted that a single significant result is quite likely to occur by chance when 11 *t* tests are performed, even if the population means are identical. We nevertheless refrained from adjusting the alpha value since a liberal way of testing seemed to be more adequate to test the hypothesis that the *B* values did not differ between the two groups. Moreover, we will see in Experiment 2 that the differential effect of string length is not replicated.

**Discussion**

The purpose of Experiment 1 was to investigate whether or not different memory systems are used for classification and recognition in AGL. In contrast to other studies, these tasks were designed to be as similar as possible: Not only was the training stage...
identical but also the stimuli used in the test stage. In both conditions all three types of stimuli were presented, old grammatical strings, new grammatical strings, and new nongrammatical strings. The results of Experiment 1 clearly do not support the dual-system hypothesis. Neither the analysis of endorsement rates for the three types of test stimuli nor the analysis of the regression coefficients indicated that participants performed the two tasks in different ways. Thus, the more parsimonious hypothesis that only a single learning system is used for the two tasks cannot be rejected on the basis of our data. The results of Experiment 1, therefore, support the key assumption of our single-system SRN model, which is that the processes guiding classification and recognition in AGL are identical.

Experiment 2

We have argued that the results of Experiment 1, which showed that under recognition instructions participants tended to endorse new grammatical items as much as they did under classification instructions, support the single-system rather than the dual-system account of memory. However, one might object that we did not take into account the possible influence of similarity on declarative memory processes. Participants might have been using their declarative memory in the recognition condition but nevertheless endorsed new grammatical stimuli that looked familiar because they were similar to some of the training stimuli. Actually, the stimuli of Knowlton et al. (1992), which we used in Experiment 1, were not controlled for specific-item similarity: On average, new grammatical items were more similar to specific training items than new nongrammatical items. To rule out a similarity-based explanation, in Experiment 2 we used the stimulus materials of Vokey and Brooks (1992) in which grammatical and nongrammatical test items are balanced in terms of similarity to specific study items. Therefore, differences between new grammatical and new nongrammatical stimuli under recognition instructions could not occur as a result of the new grammatical items being more similar to specific training items than the new nongrammatical items.

The testing procedure was also changed. Participants were no longer instructed to give equal numbers of “yes” and “no” responses (see Methods). Moreover, they were not presented with all three types of test items but only with two of them. One group of participants received old grammatical and new nongrammatical test strings and the other group received new grammatical and new nongrammatical test strings. By crossing the independent variables item type and instructions, we created four experimental conditions. Four independent groups of participants were tested, one group under each condition.

What pattern of results would be expected under the assumption that there are two different memory systems? Participants tested on new grammatical and new nongrammatical strings should show similarly low endorsement rates for new nongrammatical strings in both classification and recognition since these items are non-targets under both instructions. However, endorsement rates for new grammatical strings should be higher in classification than in recognition because these items are targets in classification but nontargets in recognition. Thus, endorsement rates on this item type should depend on the instructions. As a result, in the groups exclusively presented with new items, the percentage of correct responses should be higher under classification than under recognition instructions. Conversely, if we assume that there is only a single system mediating both classification and recognition, we would expect instructions to have no effect on endorsement rates at all.

What are the predictions for the two groups tested on old grammatical and new nongrammatical items? If the single-system assumption is true, we would again expect no differences between the two groups. If we assume instead that classification and recognition are controlled by separate systems, the predictions for these groups are less clear. For both groups, half of the items are targets (namely the old grammatical strings) and half of them are nontargets (namely the new nongrammatical strings). However, we might expect the endorsement rates for old grammatical strings to be higher under recognition than under classification instructions. To understand why this hypothesis is plausible, it is necessary to think of the kinds of representations that are assumed to emerge in the two memory systems. In the declarative memory system, exemplar-specific information is thought to be stored in separate memory traces (e.g., Squire et al., 1993). By contrast, the representations in the implicit learning system are thought to contain abstract information about the common properties of the training strings. Although the exact nature of these representations is unclear, there is some consensus that they do not include information about specific exemplars (Meulemans & Van der Linden, 1997; Knowlton & Squire, 1996). If we now assume that a particular test item has already been presented in the training phase and the participant is given recognition instructions, he or she might retrieve this item from declarative memory. In that case, the participant will call that item “old.” If, conversely, the participant is given classification instructions, he or she will utilize representations not including information about that specific exemplar. Thus, whether or not the participant will endorse that item will strongly depend on how many “typical” features it contains. Therefore, the probability of “yes” responses to old grammatical items will plausibly be lower under classification instructions than under recognition instructions.

Further important hypotheses can be derived from the two theories regarding the information participants
use to make classification and recognition judgments. Under the dual-system assumption, old/new status should be important in recognition judgments. Conversely, grammaticality and chunk strength or chunk novelty should play a significant role in classification. If we assume that a single system mediates both classification and recognition, we would expect participants to use identical types of information in both tasks.

**Results**

Table 3 shows the mean endorsement rates, the mean percentages of ‘yes’ responses (endorsement rates averaged across the three item types), and the mean percentages of correct responses in the four experimental groups. Participants had higher percentages of correct responses when they had to assess old grammatical and new nongrammatical items than when they had to assess new grammatical and new nongrammatical items, consistent with our assertion that the former is an easier discrimination. This effect occurred both when participants were instructed to recognize the strings and when they had to classify them as grammatical or nongrammatical. A 2 × 2 factorial ANOVA on percent correct scores including the variables instructions and item set showed a significant effect of item set on the percentage of correct responses, F(1,71) = 79.9, MSE = 44.8. The percentages of correct responses in the two groups of participants tested with new grammatical items were almost identical (note that ‘yes’ responses to new grammatical items were counted as correct, even if participants were instructed to recognize). Participants who were presented with old grammatical items showed a slightly higher percentage of correct responses when they were instructed to recognize the strings. However, the ANOVA showed neither a main effect of instructions, F(1,71) = 1.5, MSE = 44.8, nor an Item Set × Instructions interaction, F(1,71) = 3.1, MSE = 44.8. Two t tests showed that the percentage of correct responses was not significantly affected by the type of instructions, neither in participants presented with new grammatical items, t(34) = .45, p > .60, nor in participants presented with old grammatical items, t(37) = 1.83, p > .07. However, although the latter difference did not reach statistical significance, it can be regarded as being marginally significant.

In this experiment, participants were not instructed to give equal numbers of ‘yes’ and ‘no’ responses. The percentage of ‘yes’ responses in the four groups indicated that participants were more likely to call strings ‘grammatical’ than to call strings ‘old.’ An ANOVA indeed showed a significant effect of the instructions on the proportion of ‘yes’ responses, F(1,71) = 7.8, MSE = 84.3. There was no significant main effect of the item set on the proportion of ‘yes’ responses, F < 1, and no significant Item Set × Instructions interaction, F(1,71) = 1.7, MSE = 84.3.

As in Experiment 1, a multiple regression analysis was computed in order to investigate whether participants used different types of information when they were tested under different instructions. Since every test item was presented twice in Experiment 2, there were not only endorsement rates of 0 and 1, but also of 0.5 (when a participant gave different answers on the two presentations of an item). Therefore, a standard multiple regression was computed instead of the logistic regression employed in Experiment 1. The predictor variables were identical with those used in the analysis of Experiment 1 with a few exceptions. In the subsamples tested on new grammatical and new nongrammatical strings, the predictor variable ‘old/new’ was omitted since all items were new. In the subsample tested on old grammatical and new nongrammatical strings, the variable ‘grammaticality’ was omitted because it was entirely confounded with the variable ‘old/new.’ The variable ‘string includes letter M’ was exchanged for the variable ‘string includes letter J’ and was dropped from the first half of the alphabet. The variable ‘valid starting letter’ was dropped since only two items started with invalid letters. The mean regression coefficients of participants in all four groups can be seen in

| Table 3. Endorsement Rates and Percentages of Correct Responses in Experiment 2 |
|---------------------------------|---------------------------------|
|                                | **Old Grammatical and**          | **New Grammatical and**          |
|                                | **New Nongrammatical Test Strings** | **New Nongrammatical Test Strings** |
| **Recognition**                | **Classification**              | **Recognition**                  | **Classification**              |
| Old grammatical                | 72.9 (± 6.1)                    | 71.4 (± 5.1)                     | –                                | –                                |
| New grammatical                | –                               | –                                | 52.0 (± 5.1)                     | 61.5 (± 3.9)                     |
| New nongrammatical            | 24.7 (± 5.5)                    | 32.5 (± 4.1)                     | 37.0 (± 5.3)                     | 44.9 (± 5.7)                     |
| Percentage of ‘yes’ responses  | 48.8 (± 4.5)                    | 52.0 (± 3.1)                     | 44.5 (± 4.9)                     | 53.2 (± 3.9)                     |
| Percent correct a              | 74.1 (± 3.5)                    | 69.5 (± 3.5)                     | 57.5 (± 1.8)                     | 58.3 (± 2.9)                     |

The values in brackets are 95% confidence intervals.

aThe ‘yes’ responses to new grammatical items were also counted as correct when participants were instructed to recognize strings.
Table 4. Regression Weights (β Values) Averaged Across Participants in Experiment 2

<table>
<thead>
<tr>
<th>Variables</th>
<th>Old Grammatical/New Nongrammatical Items</th>
<th>New Grammatical/New Nongrammatical Items</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall β</td>
<td>β Weights</td>
</tr>
<tr>
<td></td>
<td>Weights</td>
<td>Recognition</td>
</tr>
<tr>
<td>Grammaticality</td>
<td>0.177* (± 0.149)</td>
<td>0.164 (± 0.202)</td>
</tr>
<tr>
<td>Old/new</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Global chunk strength</td>
<td>0.050 (± 0.084)</td>
<td>-0.010 (± 0.096)</td>
</tr>
<tr>
<td>Anchor chunk strength</td>
<td>-0.077 (± 0.084)</td>
<td>-0.035 (± 0.143)</td>
</tr>
<tr>
<td>Chunk novelty</td>
<td>0.092 (± 0.141)</td>
<td>0.051 (± 0.210)</td>
</tr>
<tr>
<td>Novel chunk positions</td>
<td>0.014 (± 0.184)</td>
<td>-0.067 (± 0.265)</td>
</tr>
<tr>
<td>Length</td>
<td>-0.086* (± 0.061)</td>
<td>-0.100* (± 0.082)</td>
</tr>
<tr>
<td>Specific item similarity</td>
<td>-0.125 (± 0.165)</td>
<td>-0.072 (± 0.190)</td>
</tr>
<tr>
<td>String contains letter M</td>
<td>0.113* (± 0.053)</td>
<td>0.069 (± 0.194)</td>
</tr>
<tr>
<td>Familiar pattern of repetitions</td>
<td>0.422* (± 0.120)</td>
<td>0.473* (± 0.075)</td>
</tr>
<tr>
<td>df</td>
<td>38</td>
<td>19</td>
</tr>
</tbody>
</table>

The left-hand portion of the table contains the regression weights for participants tested on old grammatical and new nongrammatical items. The right-hand portion contains the regression weights for participants tested on new grammatical and new nongrammatical items.

The values in brackets are the 95% confidence intervals. Dashes in the left-hand portion of the table indicate that the variable ‘grammaticality’ was entirely confounded with the variable ‘old/new.’ Dashes in the right-hand portion indicate that the variable ‘old/new’ had only one value because all items in this condition were new.

* p < .05, df = see bottom line.
Table 4. With both stimulus sets, \( t \) tests were computed to compare the regression coefficients of participants tested under classification instructions and tested under recognition instructions.

In the sample of participants tested on old grammatical and new nongrammatical items, four predictor variables turned out to be statistically significant. In contrast to Experiment 1, the variable “old/new” and the variable “length” were statistically significant predictors. Furthermore, the variable “string contains letter M” reached statistical significance. However, whereas in Experiment 1 strings containing the letter J were rejected more readily than other strings, strings containing the letter M were more likely to be accepted than other strings. This effect might be due to all old strings containing the letter M and old strings being more likely to be accepted than new strings. As in Experiment 1, the variable “familiar pattern of repetitions” was a statistically significant predictor. This variable gained the highest regression weight among all predictors. The crucial result, though, is that there was no statistically significant difference between the regression weights of participants tested under the two different instructions.

In the sample of participants tested on new grammatical and new nongrammatical items, five variables were statistically significant predictors. These were “anchor chunk strength,” “chunk novelty,” “length,” “string contains letter M,” and “familiar pattern of repetitions.” “Grammaticality” was not a statistically significant predictor in this sample. Anchor chunk strength was also statistically significant in Experiment 1. In contrast to participants tested on old grammatical strings, participants tested on new grammatical strings rejected strings containing letter M more readily. This result strengthens the assumption that the positive weight in the other subsample was due to the variable “string contains letter M” being confounded with the variable “old/new.” “Familiar pattern of repetitions” was a statistically significant predictor in Experiment 1 and in both subsamples of Experiment 2. Thus, this variable seems to influence responding to test strings reliably and independently of the stimulus set presented. The regression weights for this variable were the only ones that depended significantly on the instructions when participants were tested on new grammatical and new nongrammatical strings: In participants instructed to recognize these stimuli, the regression weight was significantly higher than in participants instructed to classify these stimuli as grammatical or nongrammatical. To evaluate this result, it must again be noted that a single significant difference is quite likely to occur by chance when 18 \( t \) tests are computed. Furthermore, the value of this predictor did not differ significantly between the two groups in Experiment 1. Note that neither the \( \beta \) weights of the variable old/new nor the \( \beta \) weights of the variable grammaticality differed significantly between the two groups, in contrast to the predictions of the two-system view. In particular, the old/new status of the items was not even a statistically significant predictor in recognition.

**Discussion**

First, we discuss the results of participants tested on new grammatical and new nongrammatical items. In these groups, the dual-system account predicts a lower percentage of correct responses in recognition than in classification, since in recognition all items were actually nontargets. However, there was no significant difference between the two groups. But the results seem to be at variance with the strong version of the single-system view as well, because both types of items were endorsed less readily in recognition than in classification. According to a very strict interpretation of the single-system account, no difference between the groups would have been expected.

The results of participants tested on old grammatical and new nongrammatical strings also do not support the dual-system view. We have argued that if explicit, examplar-specific knowledge is used on the recognition task, and implicit, abstract knowledge on the classification task, the endorsement rates of old grammatical strings should be higher under recognition instructions than under classification instructions. Although participants in the recognition group showed marginally better performance, this superiority was exclusively due to a “lower rate” of incorrect “yes” responses to new nongrammatical strings. This pattern of results is different from the one that would be expected on the dual-memory systems account, namely that there should be a difference in old grammatical items but not in new nongrammatical ones. It might be argued, however, that the results do not support the single-system view either, which predicts no differences between the two groups.

Therefore, it is important to take a close look at the regression data that contain fine-grained information about the type of knowledge used in classification and recognition. The results of these analyses did not indicate that participants used different types of knowledge in the two tasks. In particular, the old/new status of the items was not a statistically significant predictor in recognition, which would have been expected from the dual-system view. Numerically, this predictor was even larger in classification than in recognition. In both tasks, it seemed to be important whether the test strings had the same properties as the training strings, for example, the same pattern of repetitions. Overall, the regression data clearly support the single-system account. In the following section, we will investigate whether or not the endorsement rates are in accord with our single-system account if we further assume that participants bring
different response criteria to the two tasks that might influence their readiness to accept items.

**Simulation Study 4: Simulation of Experiment 2**

Can the pattern of results found in Experiment 2 be explained by a single-system model solely by assuming differences in participants’ response bias while performing classification and recognition? This question can be answered in a straightforward way since the SRN model has a threshold parameter that exclusively affects its bias (see Appendix). In this simulation study, we simulated the results of Experiment 2 by keeping all other parameters constant and solely varying the model’s threshold. The mean simulated endorsement rates together with the empirical values can be seen in Figure 6. Figure 6 shows that the simulation results rather closely resemble the empirical ones with all the simulated mean values lying within the 95% confidence intervals of the corresponding empirical means. Thus, the simulation results show that the SRN model accounts for the empirical data obtained in Experiment 2 by only assuming bias differences between the groups. Since bias differences are not related to the information stored in memory but only reflect the fact that participants have different thresholds for endorsing items, the simulation results support the notion of a single memory system mediating both classification and recognition.

**REPETITION PRIMING AND RECOGNITION IN AMNESIA**

The simulation studies reported above have shown that a single-system model can explain dissociations between tests of declarative and nondeclarative knowledge in AGL. It might be argued, however, that only a small subset of neuropsychological evidence supporting the declarative/nondeclarative distinction comes from AGL studies. Experiments in which amnesic patients, who are impaired on tests of recognition memory, show intact repetition priming also support the notion of two separate learning systems. Repetition priming is defined as the improvement in identification, detection, or production of a stimulus resulting from its prior experience (see Schacter & Buckner, 1998; Tenpenny, 1995). It is thought to be mediated by nondeclarative memory because it occurs even if there is no conscious recollection of the prior learning episode (Gabrieli, 1998). Neuropsychological theories assume priming to be mediated by neocortical structures that are independent from the brain structures lesioned in amnesic patients (e.g., McClelland, McNaughton, & O’Reilly, 1995). In an experiment reported by Hamann and Squire (1997a, Experiment 1), amnesic patients and controls first viewed four-letter consonant strings (e.g., KKZL), which were presented for 3 sec each. Then, these stimuli as well as new stimuli were presented very briefly (~170 msec) and participants had to identify them. Priming was defined as the difference between identification accuracy for old and new stimuli. After two priming tests each including a study and a test phase, participants were tested on their recognition memory for the stimuli presented in the two study phases. A two-alternative forced-choice recognition test was administered in which pairs of old and new stimuli were presented. As expected, amnesics showed a normal amount of priming but were significantly impaired in recognizing the strings. It is especially interesting in these results that performance on the explicit memory task was not significantly above chance. According to Hamann and Squire, these results support the notion that priming is based on nondeclarative memory as well as the assumption that it can involve the for-
formation of novel stimulus representations (because consonant letter strings are unlikely to activate preexisting word representations).

**Simulation Study 5: Simulating Repetition Priming With Nonword Stimuli**

Whereas we agree with the latter conclusion, we have some concerns about the first one. As our simulation studies of AGL have shown, a dissociation between two tests does not unequivocally prove that they are performed on the basis of different memory systems. The illegal nonword stimuli presented in Hamann and Squire’s study are similar to those presented in AGL experiments. We therefore presumed that memory for these stimuli can again be simulated by the SRN model. As in the studies reported above, we tried to simulate the results by assuming that there is only a single memory system both controlling recognition of the strings and having a facilitating effect on identification. As in the experiment, we simulated two priming tests each consisting of a study and a test phase. In the training phases, we trained the network on the same stimuli as in Hamann and Squire’s experiment. In simulating the test phases, we had to account for the presentation durations being extremely short. In accord with the framework of cascaded processing (McClelland, 1979), we assumed that short presentation times result in presymptomatic activation values in the input units. In the priming tests, activation values of the input units were, therefore, set to values of 0.7 (instead of 0.9) for the presence of a letter and 0.3 (instead of 0.1) for its absence. In simulating identification accuracy, we assumed that it is positively related to the accuracy with which the network predicts the actual stimulus from the degraded input it receives.

Finally, we simulated a recognition test in which the model was tested on old stimuli, which had been presented in the two study phases, and on new stimuli. Like the participants, the network was presented with pairs of stimuli, one old and the other new. The input was no longer degraded since the presentation time of old/new pairs was not limited in Hamann and Squire’s experiment.

Again, the two groups of participants were simulated by varying the learning rate, assuming that the amnesics have a general, rather than a specific, memory and learning deficit. The parameters affecting learning were identical for both types of test (since no separate training phase was run for the recognition test). The parameter values are given in the Appendix.

Figure 7 shows the experimental data as well as the simulation results. The upper panel depicts the empirical and simulated priming effects. In the empirical data, the amounts of priming in the amnesics and the controls were almost identical. The same result was found in the simulations, despite the fact that there was a considerable difference between the learning rates used to simulate the two groups of participants (0.1 and 0.4). The lower panel shows empirical and simulated percentages of correct responses in recognition. The empirical results showed the amnesics to be substantially impaired in recognizing the training stimuli. The same result was obtained in the simulations, where recognition performance with the low learning rate (0.1) was considerably worse than with the high learning rate (0.4).

Figure 8 depicts performance in both tests when the learning rate was varied systematically. The upper panel shows that the amount of priming rises strongly as learning rate is increased from zero but soon reaches a plateau. Thus, the model predicts that participants should show similar levels of priming over a large range of learning efficiency. The lower panel shows that recognition performance rises continuously from a zero learning rate to a learning rate of 0.5. Thus, the model predicts recognition performance to vary considerably as a function of learning rate. This pattern of results is predicted despite the fact that the same knowledge base underlies performance on both types of task. It emerges solely from the two testing procedures being different. In the identification task, the network has to reconstruct the actual input from the degraded input it receives, a task that it has not been trained for. Thus, the task is not optimal for measuring the model’s knowledge and as a result, the network is not very sensitive in differentiating...
between different levels of knowledge and, therefore, the very flat learning rate function emerges. By contrast, in the recognition task, exactly the same information is presented that the model was trained on before. As a result, this task provides a good measure of the model’s knowledge and clearly differentiates between different knowledge levels. Hence, the performance function increases across almost the whole range of learning rates. A second reason for the two functions having different shapes is that in identification only a single stimulus is presented on each trial whereas a choice between two stimuli is required in recognition. Whereas it depends on the parameters chosen whether the forced-choice task or the yes/no task is predicted to be easier, the forced choice task is—Independently of the set of parameters—more sensitive to variations of the learning rate.

Figure 8 reveals another very interesting prediction of the model. Although both tasks are accomplished using a single knowledge base, the model predicts that when learning efficiency is low, priming is at a normal level while recognition performance is indistinguishable from chance for all practical purposes: With a learning rate of 0.1, a priming effect of 11% occurs while only 51% of the items are recognized correctly (which is only 1% above chance level). Thus, our single-system model can explain the observation that participants show chance performance in an explicit memory task but above-chance performance in an implicit memory task. This pattern of results was shown not only in Hamann and Squire’s (1997a) study but also in another study by the same authors (Hamann & Squire, 1997b) testing patient EP. Note that this very pattern of results is typically taken as compelling evidence for a two-system view of memory.

To summarize, this simulation study shows that our single-system explanation of dissociations between tests of declarative and nondeclarative memory is not confined to AGL. Furthermore, the results show that dissociations between priming and recognition performance do not compel a dual-system account of learning and memory, but might equally reflect differences between the two testing procedures.

Repetition Priming in Patients With Occipital Lobe Lesions

Our simulations show that a single dissociation between recognition and priming in a perceptual identification procedure does not necessarily contradict the notion that both are mediated by a single memory system. A serious challenge to our model, however, would be a double dissociation demonstrating that one group of participants shows impaired priming and intact recognition whereas another group shows the reverse pattern of intact priming and impaired recognition. Gabrieli et al. (1995) obtained exactly this pattern with MS, a patient with a right occipital lesion, and a pair of amnesic patients. Whereas MS performed normally on a recognition test, he did not show priming in a perceptual identification procedure. The result was interpreted as having its origin in a selective deficit of perceptual implicit memory. In the same experiment, the amnesic patients showed a normal level of priming but were impaired on recognition. However, there are two problems with the data reported by Gabrieli et al. One is the fact that the pattern of impaired priming and intact recognition pertains to a single subject and thus might not be generalizable. The other is that the statistical analysis of the data reported by Gabrieli et al. is rather incomplete. The recognition data, for example, were not analyzed statistically at all, so that it is not clear whether the amnesics actually were impaired on recognition.

A further problem is that it remains unclear whether or not MS’s visual processing capacities are normal. Given the size of his lesion, it seems rather unlikely that he has no deficit in visual processing at all. Although he
identified the test stimuli in Gabrieli et al.’s study nearly as quickly as the normal controls, possible differences in visual processing speed might have been masked by a floor effect (controls had mean identification times of only about 30 msec). His lack of priming might then have its origin in a visual-processing deficit rather than in a selective deficit of perceptual implicit memory.

If MS actually has a selective deficit of visuoperceptual implicit memory, one would expect his deficit to appear after all types of training in which items are presented visually but not after training that does not involve visual presentation. By contrast, if his priming deficit has its origin in a perceptual deficit rather than a memory deficit, one would expect that it appears on testing tasks involving visual processing whether or not the training stimuli were presented visually. A study reported by Fleischman et al. (1995) tested MS and controls on a perceptual identification task after different types of training. In one experiment, he and the control participants did not see the training stimuli but generated them (orally) from a definition. In terms of multiple-system views of memory this training should lead to conceptual rather than to perceptual implicit memory (since no visual input was given). MS, having no deficit of conceptual implicit memory, should acquire intact implicit knowledge on this task. After training, participants were tested on an perceptual identification task and control participants showed significant priming on this task. This is a replication of other findings showing that conceptual implicit memory can be measured by means of a perceptual identification procedure (e.g., Jacoby, 1983). Interestingly, however, MS did not show any priming at all. Thus, MS’s priming deficit seems to be related to the testing task (the perceptual identification procedure) rather than to the type of training (perceptual vs. conceptual). This suggests that MS has a visual-processing deficit rather than a selective perceptual memory deficit.

An explanation in terms of a visual-processing deficit is even more plausible in the case of LH, another patient with a (bilateral) occipital lobe lesion. Keane, Gabrieli, Mapstone, Johnson, and Corkin (1995) report that LH showed no priming in a perceptual identification procedure although he exhibited normal recognition performance. Thus, he also showed a reversal of the amnesics’ pattern of results. However, LH’s mean response time was 10 times longer than the mean response times of the controls, which suggests that this patient has a severe visual-processing deficit.

**Simulation Study 6: Reduced Priming as a Function of Input Degradation**

We hypothesized that our single process model can reproduce the dissociation between priming and recognition found in patients with occipital lobe lesions by assuming that these patients have a visual-processing deficit rather than a deficit of perceptual implicit mem-

![Figure 9. Results of simulation study 6: priming as a function of the amount of input degradation.](image-url)

ory. In our model, this visual-processing deficit can be simulated by increasing the amount of degradation in the perceptual identification procedure. In simulation study 5, the input during the priming task was degraded by 0.2 (0.9 activation values were set to 0.7 and 0.1 activation values were set to 0.3). In the present simulation study, we used levels of degradation ranging from 0 to 0.4. We ran simulations using Hamann and Squire’s (1997a) stimulus materials and the same parameters as in simulation study 5 (the parameters are given in the Appendix). Figure 9 reveals a strong negative relationship between the size of the priming effect and the degree of degradation. Because the input is not degraded in simulating recognition, the manipulation of degradation leaves recognition performance unaffected. Thus, our model can account for priming being selectively impaired in patients with occipital lobe lesions on the assumption that these patients have a visual-processing deficit. Together with our simulations of amnesia, the model then is able to produce a double dissociation. Thus, not even a double dissociation between recognition and priming seems to compel a dual-system view.

**GENERAL DISCUSSION**

The main goal of the present article was to demonstrate that a single-system model is sufficient to explain categorization and recognition of stimuli generated by an artificial grammar. We took a two-pronged approach to meet this goal. In the first part of the article, we dealt with the question of whether a single-system model of AGL, the SRN model, is capable of reproducing the dissociation between classification and recognition observed in studies with amnesic patients (Knowlton et al., 1992; Knowlton & Squire, 1994, 1996). In the simula-
tions reported in this article, we made two key assumptions: First, we assumed that the processes mediating classification and recognition in AGL are identical. Second, we assumed that amnesic patients have a general memory and learning deficiency rather than a specific deficit of declarative memory. This general deficiency was simulated by reducing the learning rate parameter and thus impairing the system’s general learning capabilities. We demonstrated that by variation of this single parameter, the model was capable of reproducing the observed dissociations. Thus, these dissociations are not only in accord with a dual-system account but can also be explained on the assumption that a single memory system underlies performance in both classification and recognition.

One might argue that a more straightforward way to simulate damage to the medial temporal lobe or the diencephalic system in amnesic patients would be to literally lesion the model by removing some of the processing units and their connections. The model would have to be lesioned before, not after, training, because of course the amnesics received their lesions before the learning stages of the various experiments. The “memory” of the SRN model depends on the hidden and the copy units because it is located in the connections belonging to these units. As an alternative way to simulate amnesia, we lesioned the model by removing a portion of the hidden layer as well as the copy layer units before training it. It turned out that removing these units had a similar effect to reducing the learning rate: Recognition performance deteriorated much more than classification performance. Thus, by literally lesioning the model a dissociation-like pattern emerged, just as with a reduction of the learning rate.

Although our simulation studies provide a single-system account of the observed dissociations, they of course do not rule out the possibility that two separate systems mediate classification and recognition performance. In order to directly test the dual-system assumption against the single-system view, we conducted two experiments. In these experiments, we directly compared recognition and classification of stimuli generated by an artificial grammar. Except for the different instructions, the procedure and the stimuli in both groups were exactly the same. If recognition is mediated by a different memory system than classification, we would have expected the results to depend on the instructions. In recognition, the “old/new” status of items should have been especially important whereas in classification grammaticality as well as surface features of the training strings should have been relevant. However, neither the analyses of the endorsement rates nor the regression analyses we performed showed this pattern of results. In recognition as well as in classification participants showed a high probability of endorsing all grammatical items and a low probability of endorsing new items. Furthermore, the regression analyses showed that participants relied on surface features of the test strings (and not on their “old/new” status) whether they made grammaticality or old/new judgments. In Experiment 2, there were small differences between mean endorsement rates in classification and recognition but these could be attributed to differences in bias as simulation study 4 showed. Thus, our findings support the notion of a single memory system mediating both classification and recognition.

In summary, on the one hand, our simulation results have shown that the observed dissociations—which at first sight pose a serious problem for a single-system account—in fact, do not rule out this account. Our experimental data, on the other hand, provide empirical support for a single-system account over the dual-system view. Thus, our findings are a serious challenge for a dual-system view assuming that recognition is mediated by declarative memory while classification is achieved on the basis of nondeclarative memory (e.g., Gabrieli, 1998; Knowlton et al., 1992).

However, there are alternative dual-system accounts of memory that might be more in accord with our findings. Over the last few years, there has been considerable interest in the possibility that two distinct processes may be involved in recognition memory, one based on genuine recollection (which is often thought to be synonymous with declarative memory) and the other based on familiarity (which is often thought to be synonymous with nondeclarative memory). A good deal of evidence is consistent with the separability of these processes as revealed by the process dissociation procedure (e.g., Jacoby, Toth, & Yonelinas, 1993). One possible response to the results we have reported here, therefore, is to concede that classification and recognition do not dissociate in AGL experiments, but to maintain that the reason for this is that both normal participants and amnesics perform AGL recognition purely on the basis of familiarity. A defender of this view would then go on to suggest that in other situations in which recollection does contribute to recognition performance it would be possible to obtain more compelling dissociations across normals and amnesics between direct and indirect tests of memory.

Although we ourselves do not strongly subscribe to the two-process view of recognition, it is important to realize that the above response to our findings is extremely unlikely to be tenable. This is because when the process dissociation procedure is applied to AGL, it yields significant contributions of both recollection and familiarity (A. Buchner, unpublished data). Thus the recognition performance of amnesic and normal participants in our experiments and those of Knowlton and Squire cannot plausibly be attributed solely to familiarity. In that case, there is no reason to believe that AGL experiments are biased against obtaining the sought-for dissociation.
Although we can rule out the possibility that both tasks were accomplished exclusively on the basis of familiarity, one still might argue that both declarative memory (i.e., genuine recollection) and nondeclarative memory (i.e., familiarity) were involved in both tasks. Participants performing classification and faced with an old grammatical item might recollect this item and since they know that all training items are grammatical, call it grammatical. Participants performing recognition might reject items that—as a result of implicit memory processes—seem unfamiliar. Indeed, our pattern of results could be explained by assuming declarative and nondeclarative memory processes to be involved in both recognition and classification to approximately the same extent. Of course, any pattern of results that is in accord with a single-system view can also be explained by a dual-system view assuming that both systems are equally involved in different tasks. However, a single-system explanation that allows only for differences in bias between different tasks obviously is more parsimonious and, therefore, preferable.

According to another dual-system view of memory one can differentiate between forms of memory requiring cognitive binding and other forms that do not (see Cohen et al., 1999; Kroll, Knight, Metcalfe, Wolf, & Tulving, 1996). Cognitive binding is assumed to be crucial in episodic memory in that it links several aspects of an episode so as to create a new, coherent memory representation. This function is thought to be impaired in amnesia caused by hippocampal lesions. It is difficult, however, to determine whether or not learning letter strings generated by an artificial grammar involves binding. Participants’ classification and recognition performance shows that they must have built some kind of representations of the training strings. Because these representations must be composed of several single letters one could argue that binding must have taken place. However, in that case binding would be a prerequisite of both classifying and recognizing AGL stimuli. Therefore, our work does not allow for any obvious conclusions with regard to binding.

In order to demonstrate that our approach can be extended to a different type of dissociation, we simulated results reported by Hamann and Squire (1997a). These authors measured priming in a perceptual identification procedure as well as performance on a recognition task both in amnesics and control participants. The results, which showed no difference in priming but a difference in recognition performance between the two groups, were interpreted in terms of two distinct memory systems. By contrast, we again assumed in our simulations that a single knowledge base underlies performance in the two tasks and that amnesics have a general rather than a specific learning deficit. Consistent with this assumption, a dissociation similar to the empirical one emerged in simulation study 5 simply as a result of the different characteristics of the two tasks. Simulation study 6 showed that the reverse pattern found in patients with occipital lobe lesions, who exhibit impaired priming in the presence of normal recognition performance, can also be simulated by our single-system model.

Our simulation results cast doubt on the view that single or double dissociations between priming and recognition provide unequivocal evidence for distinct memory systems. However, although most evidence for priming mediated by a distinct memory system comes from neuropsychological studies relying on dissociation logic, there is also some evidence from brain imaging studies (see Ungerleider, 1995, for an overview). It has been shown that neocortical activity elicited by stimuli that have been processed before is reduced compared to novel stimuli. The fact that neocortical activity is (negatively) related to familiarity can be interpreted as evidence that these neural structures mediate priming. On the other hand, if priming were a purely neocortical phenomenon, we would expect it always to be spared in amnesia. However, there is evidence that under certain testing conditions priming is impaired in amnesic patients (Ostergaard, 1999). This implies that the medial temporal and diencephalic brain structures can be involved in priming.

A type of dissociation not addressed in the present work is the dissociation between skill learning and recognition performance. In several experiments, it has been shown that amnesic patients who are impaired on recognition tasks showed intact acquisition of sensorimotor skills such as mirror reading and rotary pursuit (for an overview see Gabrieli, 1998). On the basis of our present work, we cannot say whether or not the dissociations between skill learning and recognition are genuine evidence for separate memory systems. To account for acquisition of sensorimotor skills one would have to simulate not only the memory processes but also the motor processes involved. But, since the SRN has been successfully used to model motor skill learning (Cleermans, 1993), we would anticipate that it might account for this sort of dissociation too.

To summarize, on the basis of our present work we cannot conclude that there is only a single system mediating performance on all types of memory tasks. However, our findings show that dissociations may not provide unambiguous evidence for separate memory systems. Also, our findings suggest that the declarative/nondeclarative distinction—proposing one memory system to be characterized by conscious recollection and another to influence behavior in the absence of conscious recollection—might be inappropriate.

In recent years, other approaches similar to ours have been reported. We already have mentioned McClelland and Rumelhart’s (1986) work in which they simulated amnesia in a simple connectionist model by reducing the learning rate. They showed that reducing the learning rate had no effect on asymptotic performance if the
testing task required generalization to new stimuli, but impaired performance on old stimuli, which is the very pattern of results found in amnesics. More recently, Nosofsky and Zaki (1998) took a similar approach using a completely different type of model. As noted before, they showed that dissociations observed in recognition and classification of dot patterns can be well reproduced by a single-system exemplar model. There was one finding Nosofsky and Zaki could not explain on the basis of their single-system account, though: EP, a patient with profound anterograde and retrograde amnesia, was shown to be completely unable to recognize random dot patterns but exhibited normal performance when categorizing these stimuli (Squire & Knowlton, 1995). However, Palmeri and Flanery (1999) showed that even this finding might be explained without assuming two distinct memory systems. They “induced” amnesia by falsely informing normal participants that they had viewed subliminally presented stimuli. When participants were given the same tasks as EP, recognition performance was at chance, as would be expected, but classification performance was quite good. Although this result seems to be quite puzzling on first glance there is a simple way to explain it: In the classification materials, targets were more similar to one another than non-targets, thus allowing participants to detect the family resemblance of the targets and hence discriminate them from nontargets without having received any training. Thus, EP’s intact categorization performance could reflect processes at test, merely requiring an intact working memory, rather than an intact implicit memory system.

These (and other) examples suggest that we should be cautious in too readily interpreting data as evidence for separate learning or memory systems. On closer examination, at least some of the observed dissociations might be in accord with a single-system assumption as well. As our AGL simulations have shown, this might especially be true if different stimuli are presented in the two tasks. A further problem arises if the testing procedures differ substantially from each other (e.g., repetition priming vs. recognition).

METHODS
Experiment 1
Participants
Thirty-two students from University College London participated in the experiment, 16 in each group. They were from 18 to 31 years old and had a mean age of 20.7.

Stimuli
There was one set of training stimuli and three sets of test stimuli, each of which contained 23 items. The first set of test strings contained old grammatical strings, the second new grammatical strings, and the third new nongrammatical strings. The old grammatical strings were identical to the training stimuli. The training stimuli, the new grammatical and new nongrammatical stimuli were those used by Knowlton et al. (1992, grammar A) for the classification task.

Training Stage: Procedure
Participants were told that they were taking part in a simple short-term memory experiment. Each training stimulus was presented on the computer screen for 3 sec. When it disappeared, participants had to type the string on the keyboard. If they were correct, a new string was presented again. If they made a mistake, the old string was presented again. After the third incorrect entry, participants were reminded to try not to make mistakes and a new string was presented on the next trial. The training strings were presented in a randomized order. Every string was presented twice during training.

Test Stage: Classification Instructions
Participants were told that the strings they had just seen had been generated using a complex set of rules that constrained letter order. They were instructed to classify each test string according to whether or not it followed these rules. Adopting a paragraph of the instructions given by Knowlton et al. (1992), we encouraged participants to rely on their “gut feeling” while making their judgment. To avoid response biases, participants were told that 50% of the items conformed to the rules and 50% did not and that they should thus try to give approximately equal numbers of “yes” and “no” responses. The 69 test items were presented in random order.

Test Stage: Recognition Instructions
Participants were told that they would see items which they either had seen before or which were new and that they should classify them accordingly. The instructions said that 50% of the items were old and that they thus should try to give approximately equal numbers of “old” and “new” responses. The 69 test items were presented in the same random order as to the participants in the classification group.

Experiment 2
Participants
Seventy-nine students from University College London participated in Experiment 2 in order to fulfill a part of their course requirement. Due to technical problems, the data of four participants were not recorded properly. The remaining participants were from 18 to 31 years old and had a mean age of 19.6 years.
Stimuli

There was one set of training stimuli and three sets of test stimuli each of which contained 16 items. As in Experiment 1, test stimuli were old grammatical, new grammatical, and new nongrammatical strings. The training set was identical to training set A used in Experiment 1 reported in Vokey and Brooks (1992). The new grammatical and the new nongrammatical strings were identical with the second set of test stimuli used in that experiment. Each of these test stimuli differed from its most similar training item in at least two positions.

Procedure and Design

The training stage was identical to that of Experiment 1 except for the kind and number of training stimuli presented. In the test phase, almost the same instructions as in Experiment 1 were given: Participants were instructed either to classify the items as grammatical or nongrammatical or to judge them as old or new. The instructions were only changed in one respect: Participants were no longer told to give 50% “yes” responses. Whereas participants in Experiment 1 were presented with all three types of test stimuli, participants in Experiment 2 saw only two types of these items. Thus, the test stage contained either old grammatical and new nongrammatical strings or new grammatical and new nongrammatical strings. By additionally varying the instructions, four experimental conditions emerged, which differed with respect to the grammatical test stimuli presented (old or new) and the kind of instructions given (classification or recognition). A total of 19 participants were tested under recognition instructions on old grammatical items, 20 under recognition instructions on new grammatical items, 20 under classification instructions on old grammatical items, and 16 under classification instructions on new grammatical items.

APPENDIX

The Simple Recurrent Network Model

The SRN model of AGL can be depicted as a multilayered network that learns by error backpropagation (see Figure 2). It is designed to be trained with a sequence of stimuli, with the target output at time $t$ equaling the input at time $t+1$. Thus, the model is trained always to predict the next stimulus in the sequence. Its architecture consists of an input layer where the current stimulus is coded, a hidden layer where an internal representation is generated, and an output layer where the response is represented. The special feature of the model is the context layer, which contains a copy of the hidden layer’s activation pattern on the last presentation. Because of this context layer, the network is capable of predicting a stimulus not only from its immediate predecessor but also from several previous stimuli.

To simulate AGL, the network is trained with the same stimuli as participants (e.g., Kinder, 2000; Kinder & Assmann, 2000). The input layer consists of a number of units, each of which locally represents one letter from the grammar. Additionally, there are two units coding the beginnings and endings of the letter strings. The output layer contains the same number of units also representing all the letters and the beginning and ending of a string. Each string is presented letter-by-letter from left to right. A letter (or the beginning or ending of a letter string) is coded by setting the unit representing it to an activation of .9 while setting all other units to an activation of .1. On the presentation of each letter, the network’s goal is to predict the next letter in the string.

Before a new string is presented, activation values of all copy layer units are set to 0.5 (they can be set to zero as well, which has only a small impact on the results).

During testing, the model predicts an endorsement rate for each test string. This endorsement rate is related to the accuracy with which the model predicts the letters comprising that string. To obtain a measure of prediction accuracy, first, all the output vectors, which represent the letters predicted by the network, are concatenated. The length of the resulting vector corresponds to the length of a single output vector times the length of the test string plus 1 (since the end of the string is predicted as well). The target vectors, which represent the correct predictions, are also concatenated. Next, the cosine of the angle $\theta$ between the global output vector and the global target vector is computed. The value of the cosine is translated into an endorsement rate by the logistic function:

$$p(g) = \frac{1}{1 + e^{-a \cos \theta + b}}$$

(1)

where $a$ is a scaling parameter and $b$ is the model’s threshold for endorsing an item as grammatical or old.

There are two different sets of free parameters in the SRN, one of which affects learning and the other of which exclusively influences performance at test. Parameters that affect learning are (1) the learning rate parameter, (2) the momentum term, (3) the number of learning epochs, and (4) the number of hidden units. The learning rate and the momentum term enter directly into the backpropagation algorithm. These parameters have to be varied to simulate any experimental variation concerning the training stage (such as the type of training procedure, the letter set, or the type of grammar). They also should be allowed to vary when performance of groups differing in age, intelligence or, as in the present case, in memory impairment, is simulated. Although these parameters are not synonymous, varying them has a rather similar effect on performance. For example, instead of reducing the learning rate, the number of hidden units can be reduced.
In contrast to these parameters, the parameters in Equation 1 (which converts the cosine of the angle between the output vector and the target vector into an endorsement rate) exclusively change performance at test. The scaling parameter $a$ has an impact on the model's sensitivity in discriminating between grammatical and nongrammatical items (or old and new items). This parameter might be changed as a function of different testing conditions, for instance. The threshold $b$ has an impact on the percentage of test items classified as grammatical or old, and thus on the bias. This parameter can be varied in order to obtain an average of about 50% of items being classified as grammatical or old.

**Parameters Used in the Simulations**

*Parameters identical in simulation studies 1–4:*

- starting weights: randomly varying from $-0.5$ to $+0.5$
- momentum: $0.4$
- number of hidden units: $10$
- learning epochs: $100$

**Simulation studies 1 and 2**

- learning rate: $0.6$ (high) / $0.05$ (low)
- logistic function parameters: $a = 15$, $b = 10.5$

**Simulation study 3**

- learning rate: $0.58$ (high) / $0.05$ (low)
- logistic function parameters: $a = 15$, $b = 8.5$

**Simulation study 4**

- learning rate: $0.6$
- $a = 15$
- mean $b$: old grammatical/new nongrammatical stimuli
- classification instructions: $10.38$
- old grammatical/new nongrammatical stimuli
- recognition instructions: $10.58$
- new grammatical/new nongrammatical stimuli
- classification instructions: $9.47$
- new grammatical/new nongrammatical stimuli
- recognition instructions: $9.94$

**Simulation studies 5 and 6**

- starting weights: randomly varying from $-0.5$ to $+0.5$
- momentum: $0.9$
- number of hidden units: $20$
- learning epochs: $10$
- learning rates: in Figure 7, $0.4$ (high) / $0.1$ (low)
  - in simulation study 6, $0.6$
- logistic function parameters: $a = 30$, $b = 18.6$
- scaling parameter $\Phi$ in simulating recognition: $2$

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**Notes**

1. The third task, a classification task that was performed under similarity instructions, is not reported here because its results were not subsequently replicated (Knowlton & Squire, 1994, Experiment 1).
2. As in the experiment, two different grammars were used. Half of the simulations used grammar A and the other half grammar B. Each simulated network was tested on both tasks, recognition and classification. We averaged across 100 simulations to reproduce performance of each group and with each grammar. Because Knowlton, Ramus, and Squire (1992) used two different sets of letters in the two grammars, all letters of both grammars were coded. All simulations were performed with our own simulator, which we checked against “learn” (Plunkett & Elman, 1997). Small differences between the simulation results reported here and those of “learn” might emerge from different procedures in resetting the context layer: In “learn,” context layer units are reset to zero between letter string presentations, whereas in our simulations they were reset to $0.5$.
3. Our model produces a dissociations-like pattern not only with Knowlton, Ramus, and Squire’s (1992) materials. We also performed simulations using Meulemans and Van der Linden’s (1997) and Vokey and Brooks’ (1992) materials (who used a different grammar) and got similar results when we compared performance on old grammatical and new nongrammatical stimuli with performance on new grammatical and new nongrammatical stimuli. Thus, the pattern of results seems to be a rather general phenomenon.
4. Two of the parameters used in the previous simulations were changed. First, the threshold parameter had to be set to a lower level. This was necessary because the old and new chunks generally were less similar to the training strings than the test strings. Therefore, the network was less likely to endorse the chunks as old than the strings. Adapting the threshold resembles a criterion-adjustment process that participants plausibly do as well in order to show approximately equal numbers of “yes” and “no” responses. Second, both learning rate parameters were reduced by a small amount. All other parameters were kept constant. When the simulations on the data reported by Knowlton, Ramus, and Squire were repeated with the previous learning rate parameters, a dissociation still emerged.
5. We ran 100 simulations in each condition. For each of these simulations, the threshold was estimated by minimizing the difference between the empirical and the simulated endorsement rates according to a least-mean-squares criterion.
6. In their Experiment 1, Hamann and Squire also presented pseudowords and words to the participants. Since the pattern of results in all three stimulus conditions was qualitatively the same, the data in these conditions present exactly the same problem for a computational model.
7. The response rule was exactly the same as before (see Appendix): Prediction accuracy was defined as the cosine of the angle between the vector representing the actual stimuli.
and the vector representing the output of the network (thus, we chose the same measure of accuracy as in the AGL simulations). We transformed this cosine value into a probability of correct identification by means of the logistic function.

8. For both items, the cosine between the target and the output vector was computed. We employed an exponential Luce choice function to transform these cosine values into a choice probability, 

\[ p(\text{old}) = 1 / (1 + e^{-\Phi (\text{cos} \text{ target} - \text{cos} \text{ new})}) \]

where \( p(\text{old}) \) is the probability that the old item is chosen and \( \Phi \) is a scaling constant.

9. With a level of 0, the original activation values of 0.9 and 0.1 were used, with a level of 0.05, activation values of 0.85 and 0.15 were used, etc.

10. Though note that Squire (e.g., Squire, 1994) would not accept this proposal since he views familiarity as being dependent on declarative memory.

11. This theory would, therefore, predict that amnesias should be impaired at both recognition and classification if identical test items are used in the two cases.

REFERENCES


