

# Dissociable Processes for Learning the Surface Structure and Abstract Structure of Sensorimotor Sequences

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## Abstract

■ A sensorimotor sequence may contain information structure at several different levels. In this study, we investigated the hypothesis that two dissociable processes are required for the learning of surface structure and abstract structure, respectively, of sensorimotor sequences. Surface structure is the simple serial order of the sequence elements, whereas abstract structure is defined by relationships between repeating sequence elements. Thus, sequences ABCBAC and DEFEDF have different surface structures but share a common abstract structure, 123213, and are therefore isomorphic. Our simulations of sequence learning performance in serial reaction time (SRT) tasks demonstrated that (1) an existing model of the primate fronto-striatal system is capable of learning surface structure but fails to learn abstract structure, which requires an additional capability, (2) surface and abstract structure can be learned independently by these independent processes, and (3) only abstract structure transfers to isomorphic sequences.

We tested these predictions in human subjects. For a sequence with predictable surface and abstract structure, subjects in either explicit or implicit conditions learn the surface structure, but only explicit subjects learn and transfer the abstract structure. For sequences with only abstract structure, learning and transfer of this structure occurs only in the explicit group. These results are parallel to those from the simulations and support our dissociable process hypothesis. Based on the synthesis of the current simulation and empirical results with our previous neuropsychological findings, we propose a neurophysiological basis for these dissociable processes: Surface structure can be learned by processes that operate under implicit conditions and rely on the fronto-striatal system, whereas learning abstract structure requires a more explicit activation of dissociable processes that rely on a distributed network that includes the left anterior cortex. ■

## INTRODUCTION

Essentially all aspects of cognitive function are embedded in a sequential context, as seen in the perception and production of language, game playing, problem solving, and motor control. In such domains, humans regularly perceive and produce novel legal sequences, relying on a capacity to manipulate rules that permit generalization to new instances. An open question in cognitive science is whether there are distinct forms of knowledge related to rules versus instances, with the corresponding question in cognitive neuroscience as to whether these distinct forms of knowledge must be treated by distinct neural systems (e.g., Gomez & Schvaneveldt, 1994; Knowlton & Squire, 1993, 1996; Shanks & St. John, 1994). The current research explores this question in the do-

main of sensorimotor sequence learning, with results that argue for the necessity of distinct processes to accommodate instance versus rule-based knowledge.

We will explore this processing distinction in the domain of serial reaction time (SRT) sequence learning. In the SRT paradigm, subjects perform a series of manual responses to the successive elements in a series of visual stimuli. Nissen and Bullemer (1987) demonstrated that the reaction times (RTs) for these responses are significantly reduced if the stimuli appear in a repeating sequence, as opposed to in a random order. This reduction in RTs between responses for sequential versus random series is a measure of the sequence learning.

Within the SRT domain, we approach the instance versus rule dissociation in terms of “surface” and “abstract” structure in sensorimotor sequences. Surface

structure is defined by the serial order of the sequence elements, at the level of verbatim and aggregate structure as defined by Stadler (1992). In contrast, abstract structure is defined by the relations between elements that repeat within a sequence. In this context, the two sequences ABCBAC and DEFEDF share the same abstract structure 123213 and have completely unrelated surface structures (i.e., they are isomorphic). If we consider two such isomorphic sequences in terms of what is predicted by the abstract structure, we observe that in both sequences the last three elements are predictable by the first three, which themselves are unpredictable. In an SRT protocol with a repeating sequence like ABCBAC, surface structure learning should be manifest by a uniform RT reduction for both the predictable and unpredictable elements. Learning of the abstract structure should be manifest by a nonuniform profile, with additional RT reduction for the predictable versus unpredictable elements that should transfer to new isomorphic sequences.

### **A Theoretical Basis for Dissociable Processes**

From a theoretical perspective, there is an important relation between the structure of information to learn (e.g., surface or abstract structure) and the class of machines or architectures that are capable of learning or processing this structure (e.g., Chomsky, 1959; Turing, 1936). This would predict, for example, that there is a system capable of learning surface structure that cannot learn abstract structure. Here we describe a neural network model based on the primate fronto-striatal system (Dominey, 1995; Dominey, Arbib, & Joseph, 1995) and present simulation results demonstrating that this system is capable of learning surface structure but is not capable of learning and transferring abstract structure, which requires separate processing capabilities (Dominey 1997b; Dominey, Ventre-Dominey, Broussolle, & Jeanerod, 1995a, 1995b).

Based on these results and our initial hypothesis, we predict that there are two independent and behaviorally dissociable mechanisms for learning surface and abstract structure in humans. As noted by Shanks and St. John (1994), the learning of rules or abstract structure is characterized by a conscious effort to discover and exploit the appropriate rules, an effort that can be invoked by specific instructions to make such a conscious effort (Gick & Holyoak, 1983). This position is supported by studies of analogical transfer in problem solving that involve the extraction of an abstract structure common to several problems with different surface structures (Gick & Holyoak, 1983; Holyoak, Junn, & Billman, 1984; Holyoak, Novick, & Melz, 1994). Such studies demonstrate that this process requires the explicit intention to find the abstract structure. In contrast, the learning of instances or surface structure is oriented toward memorization of the instances themselves (Shanks & St. John,

1994), without a conscious processing effort to search for common, rule-based structure (e.g., Cohen, Ivry, & Keele, 1990, Curran & Keele, 1993). These studies suggest the existence of dissociable mechanisms for processing surface and abstract structure.

Several studies of artificial grammar learning (AGL) have also provided convincing evidence for the existence of dissociable mechanisms for surface versus abstract structure representations (Gomez, 1997; Gomez & Schvaneveldt, 1994; Knowlton & Squire, 1996). Knowlton and Squire demonstrated that both rule adherence (abstract structure) and chunk strength, that is, similarity of letter bigram and trigram distribution (surface structure), influence grammaticality judgments. Likewise, Gomez and Schvaneveldt's results indicate that training on legal letter pairs is sufficient for classification with the same letter set, but that training with longer strings is required to allow transfer of abstract structure to a changed letter set. This suggests that pairs provide a source of surface structure, whereas abstract structure is only available in strings. These results thus indicate that in AGL there are dissociable forms of representation for surface and abstract structure, respectively.

Although AGL tasks are often considered to test implicit learning, it is important to note that during the test phase the subjects are explicitly instructed to apply a set of rules to classify the new objects, and it is likely that some rule abstraction takes place during this explicit testing phase (Perruchet & Pacteau, 1991; Reddington & Chater, 1996). Likewise, Mathews et al. (1989) have demonstrated that this grammatical knowledge can become at least partially explicit and that for grammars that exploit relational properties like the ones used in our current studies, learning can only occur in truly explicit conditions. This relation between explicit processing and AGL has recently been further clarified by Gomez (1997), who demonstrated that subjects' ability to transfer abstract structure learning to changed letter sets was invariably accompanied by explicit knowledge as revealed in direct tests. Conversely, subjects who learned first-order surface structure dependencies but failed to display transfer of the abstract structure in the changed letter set condition did not differ from naive controls on the direct tests. Finally, Gomez demonstrated that for the same testing materials presented either in a whole-string AGL task or a letter-by-letter sequence learning task, transfer and the associated acquisition of explicit knowledge occurred only in the AGL task. This indicates that, especially in sequencing tasks, the acquisition of abstract structure and its transfer to isomorphic sequences involves explicit processing.

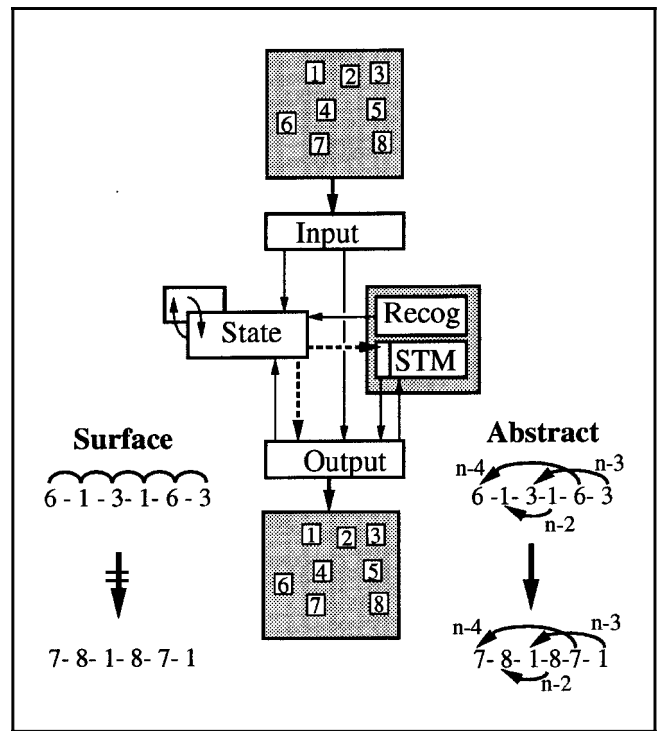
We thus predict, for our sequence learning task, that in completely uninformed, implicit conditions, processes that are capable of learning surface structure but not abstract structure will be accessible, whereas in explicit conditions both will be accessible. In response to these predictions, we will report the results of three experi-

ments in human subjects, demonstrating that surface structure can be learned in implicit conditions but that learning and transferring abstract structure occur only in explicit conditions. Based on a synthesis of these observations with our previous neuropsychological findings (Dominey & Georgieff, 1997; Dominey & Jeannerod, 1997; Dominey et al., 1995a, 1995b; Dominey, Ventre-Dominey, Broussolle, & Jeannerod, 1997), we propose a neurophysiological basis for the dissociable processing of surface and abstract structure observed in the simulation and human experiments.

## A DUAL PROCESS MODEL OF SURFACE AND ABSTRACT STRUCTURE LEARNING

An important class of sequence learning models demonstrates the capability to predict future events by encoding the context or the history of previous events via recurrent connections or self-connections (e.g., Cleeremans & McClelland, 1991; Dominey, 1995, 1998a, 1998b; Elman, 1990). In these recurrent networks, the context is sensitive to events several positions in the past, allowing the networks to resolve ambiguities, as in determining the successor to B in the sequence ABCBAC. More generally, these recurrent systems are ideally suited for learning surface structure. However, this recurrent context mechanism appears to be insufficient to represent the common relation between two isomorphic sequences ABCBAC and DEFEDF. The ability to represent this abstract structure requires the capacity to recognize the structure of repeating elements and to let this information be the source of the context. This distinction will be clarified in the following description of the dissociable models for surface and abstract structure processing that together make up the dual process model.

The surface model (Figure 1 & "Appendix") consists of the Input, State, and Output units and falls into the general category of recurrent networks described above (Dominey, 1995, 1998a; Dominey, Arbib, et al., 1995). The model architecture is based closely on the neuroanatomy of the primate fronto-striatal system, and the model has been used to explain detailed electrophysiological activity in the primate prefrontal cortex and basal ganglia during sequence processing tasks (Dominey, Arbib, et al., 1995; Dominey & Boussaoud, 1997). Input, Output, and State each consist of  $5 \cdot 5$  arrays of leaky integrator units whose response latency (i.e., reaction time) is a function of the strength of their input signals. State is influenced by Input and Output (Equations 1 & 2; see "Appendix" for all equations) and has recurrent excitatory and inhibitory connections. State thus plays the crucial role of encoding sequence context, corresponding to the prefrontal cortex in the fronto-striatal system, whereas Output corresponds to the striatum (Dominey, Arbib, et al., 1995). Sequences are presented to the model by activating individual units (1 to 25) in the Input array. Input units are directly



**Figure 1.** Schematic representation of an anatomically structured model for learning surface and abstract structure. Surface model: Presentation of sequence stimuli to Input activates both State (corresponding to prefrontal cortex in Dominey, Arbib, et al., 1995) and Output (corresponding to Caudate nucleus of striatum in Dominey, Arbib, et al., 1995). State is a recurrent network whose activity over time encodes the sequence context, that is, the history of previous sensory (Input) and motor (Output) events. At the time of each Output response there is a specific pattern of activity, or context, in State. Connections from State to Output (dotted line) are modified during sequence learning, thus binding each sequence context in State with the corresponding response in Output for each sequence element, yielding reduced reaction times (RTs). Abstract model extension: A short-term memory (STM) encodes the  $7 \pm 2$  previous responses. Recog detects repetitions between current response and previous responses in and provides this input to State. Modifiable connections (dotted line) from State gate the contents of appropriate STM elements to Output when repetitive structure is predictable, reducing RTs for predictable elements in isomorphic sequences. Left: The surface model can learn the serial order of sequence elements 613163 but cannot transfer this knowledge to isomorphic sequence 781871. Right: The abstract model learns the relations between repeating elements in 613163 as u, u, u,  $n - 2$ ,  $n - 4$ ,  $n - 3$  (where "u" signifies unpredictable, and " $n - 2$ " indicates a repetition of the element two places behind, etc.). This abstract structure transfers completely to the isomorphic sequence 781871.

connected to their corresponding Output units. These connections are responsible for the baseline reaction times (RTs) for responses in Output to stimuli presented to Input. This baseline reaction time is modulated by connections from State to Output that are modifiable by learning (Equations 3 & 4). These connections correspond to cortico-striatal synapses that are modifiable by reward-related dopamine release in the striatum (Dominey, Arbib, et al., 1995).

## Learning Surface Structure

In the SRT task simulations, each element in a sequence is presented in Input, which thus generates a response in Output with the baseline reaction time. When a response is generated, active units in State encode the current sequence context, and connections from these State units to units in Output coding the response are strengthened, thus binding the sequence context to the current element in the sequence. The result of this learning is that the next time this same pattern of sequence context activity in State occurs (i.e., the next time the sequence of elements that precede the current element is presented) the strengthened State-Output connections will cause State to increasingly activate the appropriate Output units (effectively predicting the current sequence element), resulting in a reduced RT for this response. By this mechanism, the learning of surface structure will be demonstrated as RT reductions for all elements in the learned repeating sequence. Indeed, we have recently demonstrated that this model is robust in its ability to simulate SRT learning in normal and “distraction” conditions for surface structure, based on its sensitivity to temporal as well as serial sequence organization (Dominey, 1998a, 1998b). The model fails, however, to learn abstract structure (Dominey 1997b; Dominey et al., 1995a, 1995b).

## Learning Abstract Structure

To permit the representation of abstract structure as we've defined it, the model must be capable of comparing the current response with previous responses to recognize repetitive structure (i.e., u, u, u,  $n - 2$ ,  $n - 4$ ,  $n - 3$  for ABCBAC, where “u” signifies unpredictable, and “ $n - 2$ ” indicates a repetition of the element two places behind, etc.). These functions would rely on the more nonsensorimotor associative areas of the anterior cortex and would permit the generalization of grammarlike rules to new, but “legal,” sensorimotor sequences (Dominey, 1997b). To make this possible, we introduced a short-term memory (STM) mechanism (Equation 5) that is continuously updated to store the previous  $7 \pm 2$  responses (see Lisman & Idiart, 1995) and a Recognition mechanism (Equation 6) that compares the current response to the stored STM responses to detect any repeated elements (Dominey et al., 1995a, 1995b). This permits the recoding of sequences in terms of their abstract structure that is now provided as input to State (Equation 1'). Thus, in terms of the recoded abstract structure representation provided to State, the two sequences ABCBAC and DEFEDF are equivalent: u, u, u,  $n - 2$ ,  $n - 4$ ,  $n - 3$ . For sequences that follow this “rule,” the pattern of activation (context) produced in State by subsequence u, u, u,  $n - 2$  will reliably be followed by that context associated with  $n - 4$ . To exploit this predictability, the system should then take the contents of

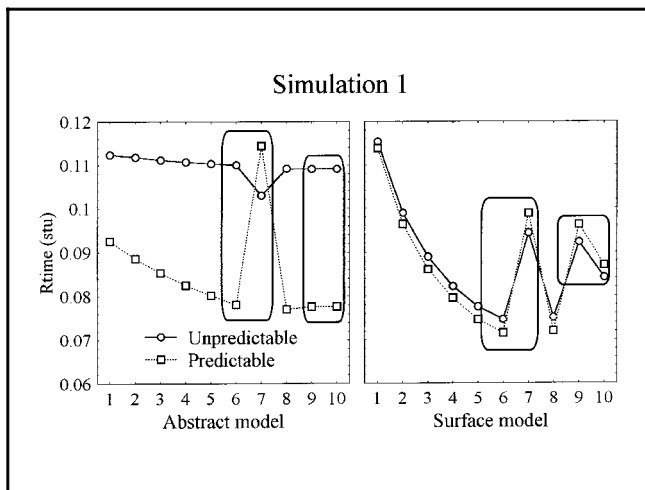
the STM for the  $n - 4$ th element and direct it to the output, yielding an RT reduction. This is achieved in the following manner: For each STM element (i.e., the structures that store the  $n - 1$ ,  $n - 2$ , ..., responses) there is a unit that modulates (Equation 8) the contents of this structure to Output. If one of these units is active, the contents of the corresponding STM structure is directed to Output (Equation 4').

Now, during learning, each time a match is detected between the current response and an STM element (Equation 6), the connections are strengthened between State units encoding the current context and the modulation unit for the matched STM element (Equation 7). The result is that the next time this same pattern of activation in State occurs (i.e., before a match  $n - 4$  corresponding to the learned rule), the contents of the appropriate STM will be directed to Output in anticipation of the predicted match, thus yielding a reduced RT. In the same sense that the surface model learns to anticipate specific elements that define a given sequence, the abstract model learns to anticipate a repetitive abstract structure that defines a class of isomorphic sequences.

We have now defined two formal models for the treatment of surface and abstract structure, respectively, that together make up the dual process model. By using different randomized starting conditions for the models' connections, we can generate multiple model subjects that permit the same statistical analysis to be performed in parallel on human and model populations. In the following section we will demonstrate a double dissociation in the models' processing capabilities. That is, we will show that the surface model learns surface but not abstract structure and that the opposite is true for the abstract model. We will make a special effort to argue that, indeed, there is no feasible combination of parameter settings, etc., that can yield a single model that is capable of both types of processing. These observations concerning the dual process model then provide the basis for a series of predictions that are subsequently tested in human subjects.

## SIMULATION 1 RESULTS: LEARNING SURFACE AND ABSTRACT STRUCTURE

This SRT test, using sequences with both surface and abstract structure, was performed on groups of five surface and five abstract models, with results supporting the hypothesis that dissociable systems are required to treat surface and abstract structure. The mean RTs for predictable and unpredictable responses in blocks 1 through 10 are presented in Figure 2 for the two model groups. Recall that “predictable” and “unpredictable” refer to the abstract structure, whereas all responses are “predictable” by the surface structure. The abstract model (group) displays reduced RTs only for the predictable



**Figure 2.** Simulation 1. Mean RTs for predictable and unpredictable responses in the 10 blocks of trials for Surface and Abstract model groups. Blocks 1 through 6 and 8 have the same surface and abstract structure. The isomorphic sequence in blocks 9 and 10 retains this abstract structure but has a different surface structure. Block 7 is random. The critical blocks for learning and transfer assessment are marked in the rounded boxes. The surface model learns only the surface structure and does not transfer to the isomorphic sequence. The abstract model learns only the abstract structure and transfers this knowledge to the isomorphic sequence. Rtime expressed in simulation time units (stu) where one network update cycle corresponds to 0.005 stu.

versus unpredictable responses in blocks 1 through 6, evidence for pure abstract structure learning. The surface model displays reductions for both, evidence for surface structure learning. In the test of transfer to random material in block 7, both models display negative transfer for the predictable elements, whereas for the unpredictable elements only the surface model shows negative transfer. In the test of transfer to a new isomorphic sequence with the same abstract structure in blocks 9 and 10, the abstract model displays complete transfer to the new sequence, whereas the surface model displays negative transfer in block 9 with some improvement in block 10.

### Statistical Confirmation of Observations

The observations about learning and transfer were confirmed by a 2 (Model: abstract, surface) · 2 (Predictability) · 6 (Block: 1-6) analysis of variance (ANOVA). The interaction between Model and Predictability was reliable,  $F(1, 336) = 289, p < 0.0001$ . The effect of Model,  $F(1, 336) = 183, p < 0.0001$ , was also reliable, as were the effects for Predictability,  $F(1, 336) = 430, p < 0.0001$ , and for Block,  $F(5, 336) = 118, p < 0.0001$ .

The observations about negative transfer to a random series for both models was confirmed by a 2 (Model: abstract, surface) · 2 (Predictability) · 2 (Block: 6 and 7) ANOVA. The three main effects were reliable, as was the

interaction between Model, Block, and Predictability,  $F(1, 112) = 55, p < 0.0001$ , reflecting the striking absence of learning and negative transfer for the abstract model with unpredictable elements.

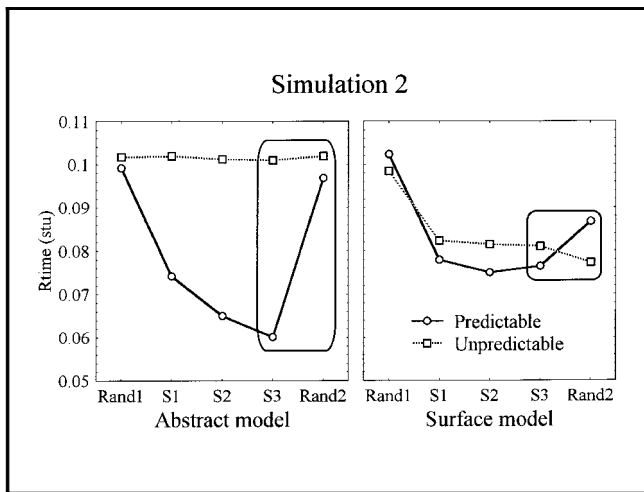
The observation about transfer of acquired knowledge to the new sequence was confirmed by a 2 (Predictability) · 2 (Model: surface, abstract) · 2 (Block: 9 and 10) ANOVA. The Model effect was reliable,  $F(1, 112) = 4.58, p < 0.05$ , as were those for Predictability,  $F(1, 112) = 75.12, p < 0.0001$ , and Block,  $F(1, 112) = 6.93, p < 0.01$ . The interaction between Model and Predictability was reliable,  $F(1, 112) = 116.3, p < 0.0001$ . In separate ANOVAs for the two models we confirmed a significant Predictability effect for the abstract model ( $F(1, 56) = 295.6, p < 0.0001$ ) but not for the surface model ( $F(1, 56) = 1.6, p = 0.2$ ). This indicates that only for the abstract model did the abstract knowledge of the rule transfer to the new isomorphic sequence.

### Discussion

In theory, different types of information structure must be treated by different processes, and, the inverse, a given processing architecture must be capable of treating some but not other information structures. These simulation results demonstrate that for surface and abstract structure, as we have defined them, there are two corresponding sequence learning models, each of which is capable of learning only one of these types of sequential structure. Specifically, the abstract model was sensitive only to the sequence elements that were predictable by the abstract structure and demonstrated strictly no learning for the sequence elements that were unpredictable by the abstract structure, despite the fact that these elements recurred in a regular fashion in the surface structure. For this reason it was not sensitive to the change in surface structure in blocks 9 and 10. In contrast, the surface model was insensitive to the predictable/unpredictable distinction in the abstract structure, displaying reduced RTs for both types of elements, indicative of learning the surface structure. This knowledge, however, was seen to be inadequate for supporting transfer to the isomorphic sequence of blocks 9 and 10, which was effectively treated as a new sequence.

### SIMULATION 2 RESULTS: LEARNING ABSTRACT STRUCTURE ALONE

Here we consider performance of the two models when only an abstract structure is present in repeating sequences. Figure 3 displays the mean RT values for predictable and unpredictable elements for the Surface and Abstract models. During training in blocks 2 through 4, the predictable structure had a large effect on RTs, primarily for the abstract model, although there appears to be some effect of predictability in the surface models as



**Figure 3.** Simulation 2. Mean RTs for predictable and unpredictable responses in the five blocks of trials for surface and abstract model groups. The first (Rand1) and last (Rand2) of the five blocks of 120 trials are random. Block 2–4 (S1, S2, and S3) are made up of three different repeating isomorphic sequences, one per block. The critical blocks for learning and transfer assessment are marked in the rounded boxes. The abstract model learns and transfers the abstract structure, and the surface model does not. Rtime expressed in simulation time units (stu) where one network update cycle corresponds to 0.005 stu.

well. There was a negative transfer to the final random block but only for the predictable elements in the abstract model.

### Statistical Confirmation of Observations

The observations about learning were confirmed by a 2 (Model: surface, abstract)  $\cdot$  2 (Predictability: predictable, unpredictable)  $\cdot$  3 (Block: 2–4) ANOVA. The Model  $\cdot$  Predictability interaction was reliable,  $F(1, 78) = 53.7$ ,  $p < 0.0001$ , reflecting the performance benefit of the predictable abstract structure only for the abstract model. The main effect of Model,  $F(1, 78) = 5.9$ ,  $p < 0.05$ , was reliable, as was that for Predictability,  $F(1, 78) = 96.9$ ,  $p < 0.0001$ .

The observations about negative transfer to the random material in block 5 were confirmed by a 2 (Model: surface, abstract)  $\cdot$  2 (Predictability: predictable, unpredictable)  $\cdot$  2 (Block: 4 and 5) ANOVA. The Model  $\cdot$  Predictability  $\cdot$  Block interaction was reliable,  $F(1, 52) = 6.8$ ,  $p < 0.05$ . A posthoc test (Scheffe) revealed that the negative transfer was significant only for the abstract model with predictable elements.

The observation that the surface model may have displayed a prediction effect was confirmed by a 2 (predictable, unpredictable)  $\cdot$  3 (Block: 2–4) ANOVA. Indeed, the surface model displayed a reliable effect for Predictability,  $F(1, 39) = 5.35$ ,  $p < 0.05$ , indicating that this architecture is capable of acquiring some of the predictable structure of the isomorphic sequences.

### Discussion

These results confirm that even in the absence of surface structure, the abstract model learns and transfers knowledge of this abstract structure and that the surface model fails to do so at the same level. However, the observation that the surface model does acquire some knowledge of the abstract structure requires explanation.

This observation is counter to our position that the surface model should be incapable of exploiting the abstract structure. The explanation for this observation lies in the potential capacity of the surface model to exploit the weak but present surface structure of these sequences in terms of single-item recency. Consider the following sequence fragment . . . ABC BCD CDE . . . in which the first two elements of each triplet are predictable and the third is unpredictable by the abstract structure “ $n - 2, n - 2, u$ .” Note the single-item recency of lag  $- 1$  for predictable elements (e.g., B and C in BCD) versus the single-item recency of lag  $- 19$  for unpredictable elements, (e.g., D in BCD). All sequence elements that are predictable by the abstract structure are also favored in terms of single-item recency. Because the surface model cannot represent the abstract structure as defined above, its small but significant predictability effect appears to be purely a function of single-item recency differences between predictable and nonpredictable elements (surface structure) and does not correspond to the abstract structure and thus cannot provide the basis for transfer of learning to isomorphic sequences. Indeed in Simulation 1, the single-item recency difference for predictable versus unpredictable elements is smaller (lag  $- 2$  and lag  $- 8$  versus lag  $- 1$  and lag  $- 19$  in Simulation 2), and there is no predictability effect for the surface model in Simulation 1 ( $F(1, 196) = 3.18$ ,  $p > 0.1$ ), nor is there any transfer to the isomorphic sequence in blocks 9 and 10.

With respect to our argument that two models are necessary to accommodate surface and abstract structure, one might argue that in Simulation 2, a single model could produce both types of behavior based on single-item recency, with a simple gain reduction responsible for the smaller predictability effect in the implicit/surface condition. This argument fails, however, when we apply it to Simulation 1. There the difference between the Abstract and Surface models is a difference of kind, not quantity, demonstrating behaviors that cannot be attributed to a common system.

### TESTING SIMULATION PREDICTIONS IN HUMANS

By extending these observations, which support dissociable systems, to human SRT performance we can now test the hypothesis that surface and abstract structure are processed by dissociable systems in humans. An important issue in testing this hypothesis is to develop

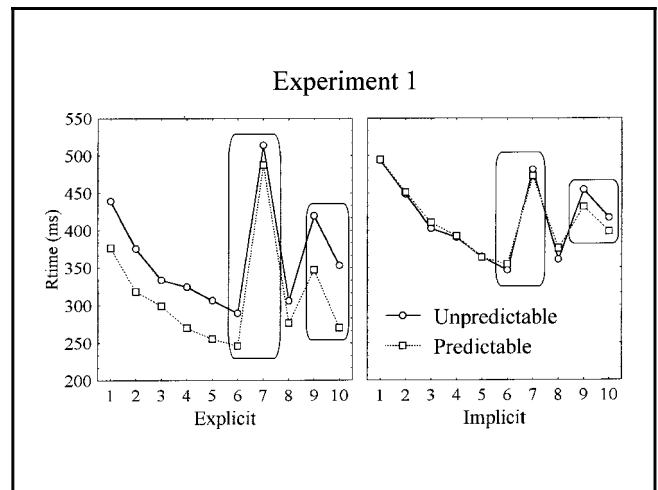
a method to isolate such processes in humans. As mentioned above, several recent studies demonstrate that abstract rule processing involves explicit intentional effort in mapping the appropriate rule onto the target problem (Gick & Holyoak, 1983; Gomez, 1997; Mathews et al., 1989; Shanks & St. John, 1994), whereas surface structure processing is likely to be a more automatic, implicit function (e.g., Cohen et al., 1990; Curran & Keele, 1993). We consider that in implicit conditions, primarily processes capable of learning surface but not abstract structure will be accessible, whereas in explicit conditions both will be accessible.

We thus employ two experimental conditions to dissociate the effects of surface structure versus abstract structure learning. In the Explicit condition, the subjects were shown a diagram visually depicting the abstract structure in question and were told before and once during the examination that such a rulelike structure might be found in the subsequent testing and that searching for and finding such a structure could aid their performance. In the Implicit condition the subjects were simply told that they should respond as quickly and accurately as possible. In the following three experiments, we compare explicit and implicit human performance in SRT tasks that manipulate surface and abstract structure, with the goal of demonstrating that learning surface and abstract structure rely on functionally dissociable mechanisms. Experiment 1 thus repeats the protocol that was used in Simulation 1.

### Experiment 1 Results: Learning Surface and Abstract Structure

The analysis focused on the RT data for predictable and unpredictable events. The mean RTs for predictable and unpredictable responses in blocks 1 through 10 are presented in Figure 4 for the Explicit and Implicit groups. Both groups display progressively reducing RTs in blocks 1 through 6, with an additional reduction for the predictable elements seen only in the Explicit group. This suggests that although both groups profit from the surface structure, only the Explicit group benefits additionally from the abstract structure. This predictability advantage in the Explicit group does not appear to change over blocks 1 through 6. Both groups display negative transfer to random material in block 7 and positive transfer to block 8, which is constructed as blocks 1 through 6. The test of transfer involves new material with different surface structure but the same abstract structure in blocks 9 and 10. The explicit group transfers knowledge of the abstract structure as revealed by significantly reduced RTs for predictable elements in block 9 and 10, whereas the implicit group shows no evidence of learning or transfer of the abstract information.

In posttest interviews, all of the Explicit group subjects reported awareness of a repeating structure in the



**Figure 4.** Experiment 1. Mean RTs for predictable and unpredictable responses in the 10 blocks of trials for Explicit and Implicit subjects. Blocks 1 through 6 and 8 have the same surface and abstract structure. Blocks 9 and 10 retain this abstract structure but have a different surface structure. Block 7 is random. The critical blocks for learning and transfer assessment are marked in the rounded boxes. Explicit subjects learn surface and abstract structure and display transfer to blocks 9 and 10. Implicit subjects learn only surface structure, with no transfer.

sequence blocks and were able to sketch a figure that reflected ABCBAC structure. The sketches were considered to reflect reasonable awareness if they included at least two of the three repetitions  $n - 2$ ,  $n - 4$ , and  $n - 3$ . None of these subjects reported a specific awareness of the 12-element sequence ABCBACDEFEDF, and our interview did not attempt to quantify partial knowledge. None of the Implicit group subjects reported any awareness of the underlying abstract structure or a specific awareness of the 12-element sequence ABCBACDEFEDF.

### Statistical Confirmation of Observations

The observations about learning in blocks 1 through 6 were confirmed by a 2 (Group: Explicit, Implicit)  $\cdot$  2 (Predictability)  $\cdot$  6 (Block: 1-6) ANOVA. The effect of Group,  $F(1, 696) = 155.8, p < 0.0001$ , was reliable, as were the effects for Predictability,  $F(1, 696) = 10.7, p < 0.005$ , and for Block,  $F(5, 696) = 36.0, p < 0.0001$ . The interaction between Group and Predictability was reliable,  $F(1, 696) = 14.2, p < 0.0005$ , corresponding to the observation of a Predictability effect in the Explicit but not Implicit group. This was confirmed by the absence of a Predictability effect for the Implicit group ( $F(1, 348) = 0.11, p = 0.7$ ). The observation that the predictability effect did not vary with block was confirmed by the nonsignificant interaction between Predictability and Block (1 through 6) for the Explicit group,  $F(5, 348) = 0.18, p > 0.9$ .

The observations about negative transfer to a random series in block 7 for both groups were confirmed by a

2 (Group: explicit, implicit) · 2 (Predictability) · 2 (Block: 6 and 7) ANOVA. The interaction between Group and Block was reliable,  $F(2, 232) = 22.4, p < 0.0001$ . Planned comparisons revealed significant differences in both groups between RTs in blocks 6 and 7 for predictable and unpredictable events. The effect for Block was also reliable,  $F(1, 232) = 257.9, p < 0.0001$ , as was that for Group,  $F(1, 232) = 6.7, p < 0.05$ .

The observation about transfer of acquired knowledge to the new sequence was confirmed by a 2 (Predictability) · 2 (Group: explicit, implicit) · 2 (Block: 9 and 10) ANOVA. The Group effect was reliable,  $F(1, 232) = 38.7, p < 0.0001$ , as were those for Predictability,  $F(1, 232) = 15.37, p < 0.0005$ , and Block,  $F(1, 232) = 18.5, p < 0.0001$ . The interaction between Group and Predictability was reliable,  $F(1, 232) = 5.2, p < 0.05$ . Separate ANOVAs for the two groups confirmed a significant Predictability effect for the Explicit group ( $F(1, 116) = 17.6, p < 0.0001$ ), but not for the Implicit group ( $F(1, 116) = 1.7, p = 0.23$ ).

### Discussion

The results from the Implicit and Explicit groups provide clear evidence for a dissociation between processing of the surface and abstract structures of a sequence that has both structures. Explicit subjects acquired and used both types of knowledge and transferred the abstract knowledge to a new, isomorphic sequence. Note that transfer does not imply improvement on the transfer block but simply the maintenance of the previously established performance. The Implicit group acquired only the surface structure and did not transfer this information to the isomorphic sequence. It is important to note that with respect to the abstract structure, the group difference is a difference of kind, not of degree. There is no evidence of acquisition of the abstract structure in the Implicit group. In contrast, both groups demonstrate a significant learning of the surface structure. The fact that surface structure can be acquired independently of abstract structure argues strongly for the existence and use of distinct processes for treating surface and abstract structure.

Because our Explicit subjects were briefed on the rule, their performance improvement for predictable elements could be attributed to their learning to apply the rule rather than their learning or discovery of the rule itself. The point of interest, however, is that knowledge of the rule yields a performance advantage for predictable but not unpredictable elements both in the initial training sequence and in a new, isomorphic sequence, indicating a transfer of the rule-based information.

### Comparing Simulation and Human Performance

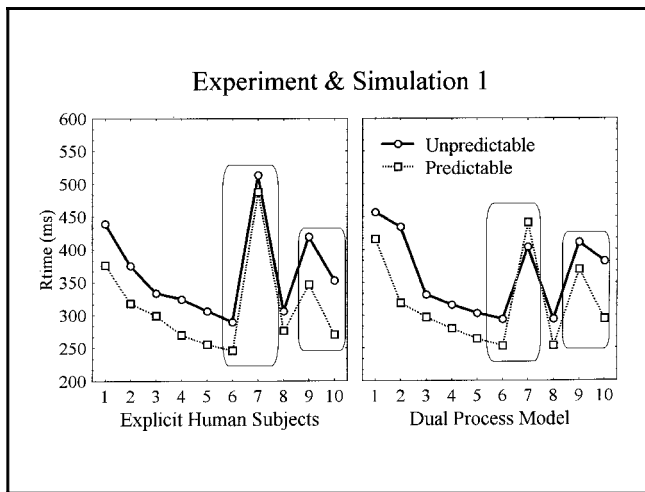
It is of interest to note the difference between the human and simulation data in these conditions. Whereas

the surface model predicts the behavior of the Implicit group rather well, the abstract model differed from the Explicit group in two major ways. First, it displayed no learning for the unpredictable elements, whereas the Explicit group showed significant learning. To understand this difference we note that the simulations allow a complete isolation of the surface and abstract systems, but this is not possible in humans. That is, for explicit learning in humans, we cannot prevent the surface (implicit) system from operating in parallel with the abstract (explicit) system. This is demonstrated by the significant learning effect in the Explicit group for elements that have surface structure but are unpredictable by the abstract structure. This, along with the Group · Block (6 and 7) interaction, allows us to consider that there is an additive effect between these two systems in humans (Mathews et al., 1989).

The second major difference is the lack of negative transfer for predictable elements in block 9 for the Abstract model as compared to the Explicit subjects. The abstract model does not, in fact, make any distinction between blocks 8 and 9 because it operates entirely in terms of abstract structure, which is identical for these two isomorphic sequences. Explicit subjects' performances on predictable elements of the abstract structure on block 9, however, are influenced by the change in surface structure, even though the abstract structure remains the same, demonstrating the additive effect between surface and abstract structure processing mechanisms in humans.

As we previously stated, simulation of the abstract model alone is psychologically invalid in the sense that although the processes related to abstract structure can be engaged (or not) as a function of the pretrial instructions and intention, the processes that treat surface structure are engaged by default. Thus we should consider the combined behavior of both of the dual processes to simulate what occurs in explicit conditions. We simulate the performance of such a dual process model as a nonlinear combination of the performance of the surface and abstract models. This performance and that of explicit human subjects were compared by a piecewise linear regression on the 20 data points defined by the RTs for predictable and unpredictable elements for the dual-process model and the Explicit group, yielding a significant correlation,  $r^2 = 0.79, p < 0.00001$  versus the correlation  $r^2 = 0.33, p = 0.0093$  for the Abstract versus Explicit comparison. Figure 5 displays the resulting behavior for the dual process model. We now see humanlike performance regarding learning for the unpredictable events, and negative transfer in block 9 is now seen in the hybrid model. A linear regression analysis for the Surface model and Implicit group revealed a correlation of  $r^2 = 0.853, p < 0.0001$ .





**Figure 5.** Experiment 1. Comparison of explicit human performance and dual process model performance. Same format as Figure 4, see text.

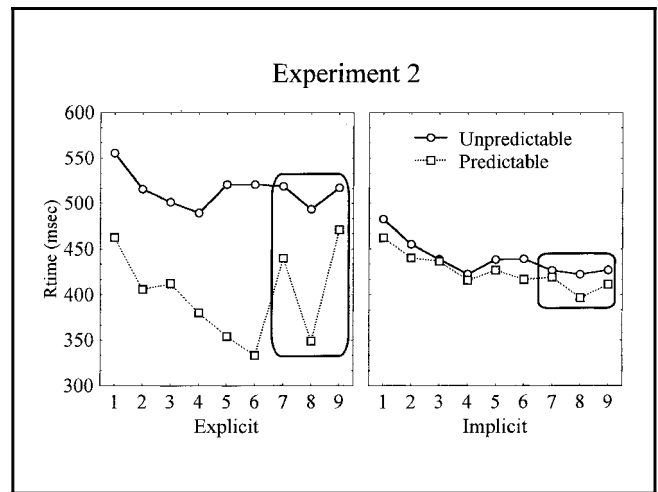
### Experiment 2 Results: Learning Abstract Structure Alone

We now test the learning and transfer of abstract structure (ABCBAC) with continuously changing surface structure. The mean RTs for predictable and unpredictable responses in blocks 1 through 9 are presented in Figure 6 for the Explicit and Implicit groups. The Explicit group displays greatly reduced RTs for the predictable versus unpredictable responses in blocks 1 through 6, whereas such a reduction is not seen for the Implicit group. In the test of transfer to a new but similar abstract structure (ABACBC) in block 7 and transfer to random material in block 9, the Explicit group displayed a large RT increase for the predictable elements but not for the unpredictable ones. This effect appears absent in the Implicit group. This difference in behavior for transfer to the new abstract structure (block 7) indicates that the Explicit group learns the abstract structure itself, but the Implicit group does not.

In the posttest interviews, all of the Explicit subjects reported awareness of a repeating structure in the sequence blocks and were able to sketch a figure that reflected some knowledge of the ABCBAC structure. The sketches were considered to reflect reasonable awareness if they included at least two of the three repetitions  $n - 2$ ,  $n - 4$ , and  $n - 3$ . As in Experiment 1, none of the Implicit subjects reported any awareness of the underlying structure.

#### Statistical Confirmation of Observations

The observations about learning and transfer of the abstract structure were confirmed by a 2 (Group: explicit, implicit)  $\cdot$  2 (Predictability: predictable, unpredictable)  $\cdot$  6 (Block: 1-6) ANOVA. The interaction between Group



**Figure 6.** Experiment 2. Mean RTs for predictable and unpredictable responses in the nine blocks of trials for Explicit and Implicit subjects. There is no repetitive surface structure throughout the nine blocks. Block 7 uses a different abstract structure than that in blocks 1 through 6 and 8, and block 9 is random. The critical blocks for learning and transfer assessment are marked in the rounded boxes. Only Explicit subjects learn the abstract structure and display negative transfer to the novel abstract structure in block 7.

and Predictability was reliable,  $F(1, 336) = 70.5$ ,  $p < 0.0001$ , corresponding to the observation that the prediction effect is seen primarily in the Explicit group. The effect of Group,  $F(1, 336) = 4.8$ ,  $p < 0.05$ , was also reliable, as were the effects for Predictability,  $F(1, 336) = 106.8$ ,  $p < 0.0001$ , and for Block,  $F(5, 336) = 8.5$ ,  $p < 0.0001$ .

The observations about negative transfer to a different abstract structure and to a random series for the Explicit subjects were confirmed by a 2 (Group: explicit, implicit)  $\cdot$  2 (Predictability: predictable, unpredictable)  $\cdot$  3 (Block: 7-9) ANOVA. The Group effect was reliable,  $F(1, 168) = 42.8$ ,  $p < 0.0001$ , as were those for Predictability,  $F(1, 168) = 53.11$ ,  $p < 0.0001$ , and Block,  $F(2, 168) = 12.6$ ,  $p < 0.0001$ , and all three of the two-way interactions. Planned comparisons revealed significant differences between RTs in blocks 7 and 8 (new versus learned abstract structure) and blocks 8 and 9 (learned abstract structure versus random) only for the Explicit subjects and only for the predictable elements.

The observation about a possible Predictability effect in the Implicit group was confirmed by a 2 (Predictability)  $\cdot$  6 (Block: 1-6) ANOVA. The effect for Predictability was just reliable,  $F(1, 168) = 3.97$ ,  $p = 0.048$ . However, the lack of negative transfer in block 7 as revealed by planned comparison indicates that the predictability effect for the Implicit group is in fact due to single-item recency as described in Simulation 2, rather than learning that is specific to the abstract structure.

## Discussion

This experiment demonstrated that abstract knowledge can be acquired by the Explicit subjects even in the absence of repeating surface structure and that this knowledge is specific to a given abstract structure and does not transfer to related but different abstract structure. Indeed, for the predictable elements, the Explicit group showed negative transfer to a new abstract structure and to random material, ruling out the possibility that their predictability effect is due to single-item recency. In contrast, in the Implicit group there was no change in the small predictability effect when the abstract structure was changed, indicating the use of recency cues in the surface structure. This allows us to conclude that the relatively small predictability effect in the Implicit group is not due to weak learning of the abstract structure but rather to single item recency effects. Note again, however, that the single-item recency explanation does not hold for the Explicit group because the negative transfer in block 7 is unexplained.

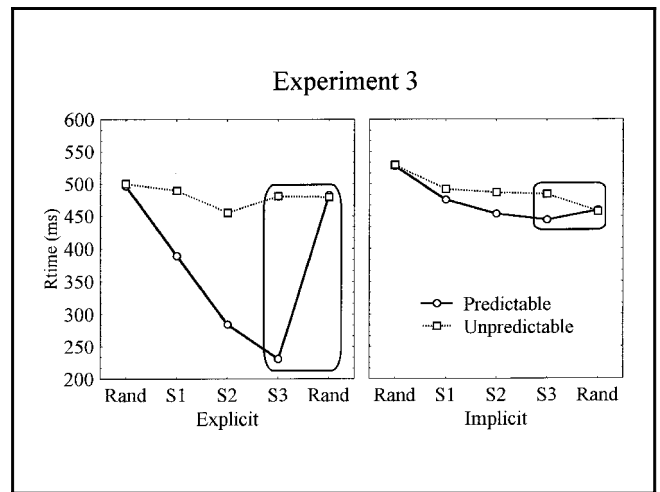
### Experiment 3 Results: Learning Abstract Structure Alone

Figure 7 displays the mean RT values for predictable and unpredictable elements for the Explicit and Implicit groups in the task described in Simulation 2. During training in blocks 2 through 4, the predictable structure had a large effect on RTs, primarily for the Explicit group, as learning accumulated over the three sequence blocks, although there appears to be some effect of predictability in the Implicit group as well. There was a large negative transfer to the final random block but only for the predictable elements in the Explicit group.

In the posttest interviews, all of the Explicit subjects reported awareness of a repeating structure in the three sequence blocks and were able to sketch a figure that reflected the “ $n - 2, n - 2, u$ ” structure. The sketches were considered to reflect reasonable awareness if they included a directed graph representing the pattern A-B-A-B-C. In contrast, none of the Implicit subjects reported any awareness at all of the underlying analogical schema. Several reported that if there was any pattern, it was too long and complicated to be learned.

#### Statistical Confirmation of Observations

The observations about training were confirmed by a 2 (Group: explicit, implicit)  $\cdot$  2 (Predictability: predictable, unpredictable)  $\cdot$  3 (Block: 2-4) ANOVA. The Group  $\cdot$  Predictability interaction was reliable,  $F(1, 78) = 37.3$ ,  $p < 0.0001$ , indicating that the performance benefit of the predictable abstract structure is dependent, as predicted, on Group. The main effect of Group,  $F(1, 78) = 51$ ,  $p < 0.0001$ , was reliable, as were those for Predictability,  $F(1, 78) = 74.6$ ,  $p < 0.0001$ , and for Block,  $F(2, 78)$



**Figure 7.** Experiment 3. Mean RTs for predictable and unpredictable responses in the five blocks of trials for Explicit and Implicit groups. The first and last of the five blocks of 120 trials are random (Rand). Block 2-4 (S1, S2, and S3) are made up of three different repeating isomorphic sequences, one per block. The critical blocks for learning and transfer assessment are marked in the rounded boxes. Only Explicit subjects learn the abstract structure.

$= 7.2$ ,  $p < 0.005$ , and for the Predictability  $\cdot$  Block interaction,  $F(2, 78) = 4.48$ ,  $MSE = p < 0.005$ . The observations about a progressive improvement in the Explicit group were confirmed by a 2 (Predictability)  $\cdot$  3 (Block: 2-4) ANOVA, with a significant interaction ( $F(2, 39) = 5.69$ ,  $p < 0.0001$ ).

The observations about negative transfer to the random material in block 5 were confirmed by a 2 (Group: explicit, implicit)  $\cdot$  2 (Predictability: predictable, unpredictable)  $\cdot$  2 (Block: 4 and 5) ANOVA. The Group  $\cdot$  Predictability  $\cdot$  Block interaction was reliable,  $F(1, 52) = 11.4$ ,  $p < 0.005$ , reflecting the observed negative transfer from block 4 to 5 only for the Explicit group with predictable elements. A post hoc test (Scheffe) revealed that the negative transfer was significant only for the Explicit group with predictable elements.

The observation that the Implicit group may have displayed a Predictability effect was not confirmed by a 2 (predictable, unpredictable)  $\cdot$  3 (block 2-4) ANOVA. However, the implicit group displayed a nearly reliable effect for Predictability,  $F(1, 39) = 3.9$ ,  $MSE = 8880$ ,  $p = 0.055$ , suggesting that like the Surface model, they exploited single-item recency effects in the isomorphic sequences. Neither the Block effect nor the interaction were reliable.

## Discussion

To compare the results of the surface model with those from the Implicit subjects, a linear regression was applied to the 10 RT means (predictable and unpredictable in the five blocks), demonstrating a significant correla-

tion with  $r^2 = 0.76$ ,  $p = 0.001$ . The same analysis for the abstract model and Explicit subjects also yielded significant correlation with  $r^2 = 0.93$ ,  $p = 0.000005$ .

These data reconfirm the observation that explicit learning conditions are necessary to encode and transfer abstract structure. Likewise, simulation data indicate that only the abstract model architecture is adequate for learning the abstract structure that is common to the three sequence blocks and also imply that small predictability effects in the Implicit group might be due to single-item recency. This suggests that in explicit learning a processing capability—corresponding to that of the abstract model—is enabled, whereas it is not enabled in the implicit learning conditions.

## GENERAL DISCUSSION

A given sequence of stimuli can encode different types of information or structure. Depending on the type of encoded structure, different mechanisms may be required to extract that structure (e.g., Chomsky, 1959; Turing, 1936). We define surface structure in terms of the straightforward serial order of sequence elements. In contrast, abstract structure is defined in terms of ordered relations between repeating sequence elements. Thus, although the two sequences ABCBAC and DEFEDF have different surface structures, their abstract structures are identical. The purpose of the current research has been to test the hypothesis that, as defined, surface and abstract sequential structure are processed by distinct and dissociable systems. Separate results from simulation and related human experiments support this hypothesis and, combined with recent neuropsychological results, provide a framework for an initial specification of the underlying neurophysiology.

### Simulation Evidence for Dissociable Processes

It has been clearly demonstrated that although our “surface model” of sequence learning, based on the functional neuroanatomy of the primate fronto-striatal system (Dominey, Arbib, et al., 1995), is quite capable of displaying humanlike performance for learning surface structure (Dominey, 1995, 1998a, 1998b) as well as explaining primate cortical electrophysiological results in cognitive sequencing tasks (Dominey, Arbib, et al., 1995; Dominey & Boussaoud, 1997), it fails to learn abstract structure (Dominey, 1997b; Dominey et al., 1995a, 1995b). This provides a formal argument for the independence of processes that learn surface and abstract structure, respectively. Part of what is missing in the surface model is a specialized short-term or working memory that has been proposed to be necessary to construct the mapping from source to target problems in analogical reasoning (Holyoak et al., 1994; Holyoak & Thagard, 1989; Thagard, Holyoak, Nelson, & Gochfeld, 1990). When the surface model is modified to include a short-term mem-

ory of the previous responses that can be compared with current responses, so as to encode the repetitive structure, the resulting abstract model is capable of learning and exploiting the abstract structure of sequences, independently of the surface structure (Dominey, 1997a, 1997b, 1998c; Dominey et al., 1995a, 1995b). This provides the second half of the dissociation. The surface model learns surface but not abstract structure, and the abstract model learns abstract but not surface structure, with the surface model simulating performance of the implicit group, and the combined surface and abstract models simulating performance of the explicit group.

One might argue, however, that the more powerful Abstract model could simulate both groups' performance. If the extent of the short-term memory is increased to accommodate the 12 previous events, the Abstract model could learn the surface structure of sequence ABCBACDEFEDF from Experiment 1, based on the abstract structure “ $n - 12, n - 12, \dots, n - 12$ .” In this sense, one might suggest that the same model could explain behavior attributed to distinct processes for surface and abstract structure, with explicit and implicit human performance modeled by a simple gain modification in the single model. There are, however, at least two flaws in this approach.

First, as we recall from Experiment 1, the Implicit and Explicit groups' performances are different in kind, not in degree. The highly visible predictability effect in the Explicit group does not exist in the Implicit group. Thus a simple “gain” change in the abstract model can account for this difference. Second, for the implicit group, the data could be explained by the abstract model only if (1) the size of the STM is raised to 12 elements (versus a minimal STM size of only 4 required for the explicit group) and (2) the implicit group is modeled by a much more complex and memory-intensive system than the explicit group (i.e., STM extent of 12 versus  $7 \pm 2$ ). Thus, the single-model approach requires one to defend the idea that a system that is quite “overqualified” is at work in all manipulations of surface structure. In taking this position, one is forced to reject a large body of work on recurrent network learning (e.g., Cleeremans & McClelland, 1991; Dominey, 1995, 1998a, 1998b; Elman, 1990) and obliged to say that even though recurrent networks can simulate SRT and related results, a more complex model must be proposed to avoid a dual-process explanation.

We clearly admit, however, that the dual-process model as proposed is by no means complete. That is, there are related forms of rule-based abstract structures that cannot be processed by the abstract model. For example, consider the sequence “A-B-C, left of A, left of B, left of C.” The first three elements are unpredictable, and the next three are predictable, based their spatial relations with the first three. Although humans are likely to pick up on this rule and transfer it to isomorphic sequences, the abstract model in its current state would

not because it doesn't have the representational hardware to exploit these spatial relations.

### **Experimental Evidence for Dissociable Processes from Healthy Subjects**

The results of manipulation of surface and abstract structure in three experiments with human subjects provide evidence that two distinct mechanisms are required to treat surface and abstract structure, respectively, in humans. Experiment 1 provided the crucial test of whether knowledge of surface structure could be acquired independently of knowledge of abstract structure while both were present. In agreement with the proposed hypothesis, implicit subjects, although capable of significant learning of surface structure, did not learn the abstract structure nor display transfer to the new isomorphic sequences. Experiments 2 and 3 demonstrated that in the absence of surface structure, only explicit subjects are capable of extracting the abstract structure and transferring it to isomorphic sequences, and Experiment 2 demonstrated that this learning is highly specific to the learned abstract structure.

It is important to note that we do not claim that explicit learning is equal to abstract structure learning, nor that implicit learning is equal to surface structure learning. Our point is to demonstrate the existence of distinct processes for distinct types of information processing. To do so we choose to observe performance in the functional modes (implicit versus explicit) in which these processes may be expressed or liberated. Our choice is supported by the observation of Gomez (1997) that in an implicit sequence learning task, surface structure was learned but no learning or transfer of abstract structure occurred. This suggests that holistic exposure to entire strings permits additional processing that is not possible in an element-by-element presentation as in our SRT tasks. Likewise, in an AGL task using the same material but presented in letter strings, Gomez observed that surface structure (first-order dependencies) learning can occur without explicit awareness, whereas learning abstract structure (supporting transfer to changed letter sets) is invariably linked to explicit knowledge. The debate over the possibility of transfer with implicit learning, however, is not yet resolved (Gomez, 1997; Knowlton & Squire, 1993) and is likely to require the use of control subjects in the testing conditions and a careful control over nongrammatical cues that could bias transfer scores. In this framework, although AGL has been often considered a test of implicit learning, we recall that the testing phase includes an instruction to exploit rule-based regularities that probably invokes explicit abstraction processes (Perruchet & Pacteau, 1991; Reddington & Chater, 1996). It is just this kind of explicit instruction to direct one's attention that can lead subjects in problem-solving studies to abstract a shared rule based on previous problems to solve the current problem (Gick

& Holyoak, 1983). Such behavioral process shifting is consistent with recent observations that attentional state and awareness can influence the selection of neurophysiological cognitive processes (Grafton, Hazeltine, & Ivry, 1995; Treue & Maunsell, 1996).

### **Toward a Neurophysiological Basis for Dissociable Systems**

We can now begin to specify a neurophysiological basis for these dissociable systems for surface and abstract structure processing in terms of recent results from neuropsychological experiments. Patients with fronto-striatal dysfunction due to Parkinson's disease are significantly impaired in a SRT task that requires learning surface structure under implicit conditions, yet they have near normal performance when the task becomes explicit (Pascual-Leone et al., 1993). More interestingly, these patients display an intact capability to learn abstract sequential structure in explicit conditions (Dominey et al., 1997; Dominey & Jeannerod 1997). This indicates that although the fronto-striatal system provides part of the neurophysiological basis for implicit processes that can acquire surface structure, it is less involved in explicit processes that treat abstract structure. This is supported by the demonstration that our model of the primate cortico-striatal system that explains prefrontal electrophysiology during primate sequence learning tasks (Dominey, Arbib, et al., 1995; Dominey & Boussaoud, 1997) is also capable of learning surface structure, yet fails to learn abstract structure (Dominey, 1997b; Dominey et al., 1995a, 1995b).

In comparison to the Parkinson's disease patients, schizophrenic patients yield an opposite profile and another piece of the puzzle. That is, although schizophrenic patients display significant learning of surface structure, they fail to learn abstract structure (Dominey & Georgieff, 1997). Because schizophrenia is characterized in part by a hypoactivity of the left anterior cortex (Suzuki, Kurachi, Kawasaki, Kiba, & Yamaguchi, 1992), we can consider that the impaired abstract structure learning in these participants might be related to this left hypofrontality. Such an interpretation fits well with the initial motivation behind the development of the abstract model, which was to account for the ability to generalize between "grammatically" related, but novel, sensorimotor sequences (Dominey, 1997b). This work was based in part on related ideas from Greenfield (1991) suggesting that linguistic syntax, and abstract aspects of motor control, are treated in Broca's area and adjacent cortical motor areas in the left anterior cortex. It is thus of interest to note that the left hypofrontality may contribute not only the failed processing of abstract structure that we observed in schizophrenic patients (Dominey & Georgieff, 1997) but also to their impairment in grammatical language processing (e.g., Portnoff, 1982). We thus propose that surface structure can be learned by

processes that can operate under implicit conditions and rely on the fronto-striatal system, whereas learning abstract structure requires a more explicit activation of dissociable processes that rely on a network that includes the left anterior cortex.

## Conclusion

From the theoretical perspective that fundamentally different information structures must be treated by distinct computational machines, we predicted the existence of computationally, behaviorally, and neurophysiologically dissociable systems for treating surface and abstract structure in sensorimotor sequences. Starting with a recurrent network that is based on the functional neuroanatomy of the fronto-striatal system, we demonstrated that surface structure can be learned independently of abstract structure and that only after undergoing modifications that provide distinct representational capabilities can the updated model learn abstract structure. We propose that the surface (fronto-striatal) model corresponds to human processes that are accessible in implicit conditions and that the abstract model corresponds to human processes that must be deliberately put into play in explicit conditions. This concurs with an increasing body of evidence that transfer performance in artificial grammar and sequence learning is linked to explicit knowledge and processing (Gomez, 1997; Mathews et al., 1989; Perruchet & Pacteau, 1991; Reddington & Chater, 1996). Three human experiments designed around these assumptions demonstrated that the processing of surface and abstract structure can be behaviorally dissociated in human subjects, corresponding to the dissociation between the surface and abstract models. These results support our initial hypothesis that surface and abstract structure are treated by distinct mechanisms. Combined with our neuropsychological results, the current results are consistent with the position that implicit processes for surface structure learning depend on the fronto-striatal system, whereas processes for abstract structure learning that are revealed in explicit conditions rely in a dissociated fashion on a network that includes the left anterior cortex. This is in agreement with the general position that instances versus rules or categories are probably treated by dissociable information processing systems in humans (e.g., Knowlton & Squire, 1993, 1996; Shanks & St. John, 1994).

## METHODS

### Simulation 1: Learning Surface and Abstract Structure

The first simulation is designed to test the models' ability to learn surface and abstract structure when both are present in the same sequence to determine if it is possible to learn surface structure independently of abstract

structure. The SRT test we employ consists of 10 blocks of 108 trials each, where each trial corresponds to the presentation of a single-sequence element. Blocks 1 through 6, and 8 use an abstract structure of the form  $u, u, u, n - 2, n - 4, n - 3$  (where "u" signifies unpredictable, and "n - 2" indicates a repetition of the element two places behind, etc.). This abstract structure recurs twice in the 12-element sequence ABCBACDEFEDF that repeats nine times in each block. Thus, each repetition of the sequence contains two repetitions of the abstract structure and one repetition of the surface structure. In this sequence, predictable elements have a mean single-item recency of lag - 2, while the unpredictable elements are lag - 8. Block 7 is a random series of elements. Blocks 9 and 10 each use nine repetitions of a new, 12-element sequence, isomorphic to that used in blocks 1 through 6 and 8 (i.e., with the same abstract structure but with a different surface structure), by using a different mapping of A through F to elements in the input array.

In evaluating the performance of the models, the following constraints should be kept in mind. For the abstract structure in question (ABC BAC), the first three elements (ABC) are considered to be unpredictable, whereas the second three are completely predictable (BAC). Pure abstract structure learning should be manifest as a reduction in RTs for the predictable but not the unpredictable elements, with a high degree of transfer to the isomorphic sequence in blocks 9 and 10. Pure surface structure learning should be manifest as an RT reduction for both predictable and unpredictable elements because that distinction is valid only with respect to the abstract structure. In addition, there should not be significant transfer of surface structure learning to the isomorphic sequence in blocks 9 and 10. This experiment was performed on five surface and five abstract models.

### Simulation 2: Learning Abstract Structure Alone

The first simulation experiment demonstrated the dissociation of surface and abstract structure processing when both are present in the same sequence. In this simulation, we address two resulting questions: First, in the absence of surface structure, is the abstract model still capable of learning the abstract structure? Second, is there truly no information that is available to the surface model in a sequence that has abstract but not surface structure?

These questions are addressed through the use of sequences that have a low degree of surface structure and a high degree of abstract structure. The experiment consists of five blocks of 120 trials each. Blocks 1 and 5 are randomly organized, and blocks 2 through 4 are sequence blocks. Sequence blocks are based on 24-element sequences of the form ABC BCD CDE DEF EFG FGH GHA HAB repeated five times to make a block of

120 trials. To appreciate the surface structure complexity of this 24-element sequence, note that each of the eight (A through H) elements appears three times, with two different successors, yielding a complex, or ambiguous, sequence. We thus consider that this sequence has a surface structure that should be relatively difficult to learn. In contrast, a clear form of abstract structure becomes evident if we note that the first two elements of each triplet (e.g., B and C in BCD) are predictable repetitions of the elements two places behind them ( $n - 2$ ), whereas the third is unpredictable (u). This abstract structure “ $n - 2, n - 2, u$ ” repeats throughout the sequence. The predictable elements have a mean single-item recency of lag  $- 1$ , whereas the unpredictable elements are at lag  $- 19$ .

To study the transfer of abstract structure knowledge, we construct three isomorphic sequences by using the 24-element pattern described above with three different mappings of A through H onto eight locations on the  $5 \cdot 5$  Input array. Thus, the three resulting 24-element sequences differ completely in their surface structure (i.e., the serial ordering of their spatial targets). However, they are *isomorphic* in that they all share the abstract structure “ $n - 2, n - 2, u$ .” This sequence learning experiment was performed on five surface and five abstract models.

## Human Experiments

### *Apparatus*

In each of the three experiments, subjects are seated in front of a touch-sensitive computer screen (Micro-Touch™) on which we can display the sequence elements ( $2.5 \text{ cm}^2$ ), and record response time (from target onset until subject's contact with the screen). The eight sequence elements are spatially distributed in a pseudorandom fashion over a  $25 \cdot 25$ -cm surface of the screen, as illustrated in Figure 1. The tasks are piloted by a PC using Cortex software (NIH, Robert Desimone). The tasks are based on the SRT protocol (Nissen & Bullemer, 1987) and involve pointing to successively illuminated sequence elements on the touch-sensitive screen as quickly and accurately as possible. In a given trial, one of the eight sequence elements is illuminated. After an element is touched, it is extinguished, the reaction time is recorded, and the next element is displayed.

### *Experiment 1: Learning Surface and Abstract Structure*

Simulation 1 demonstrated that the surface model learned the surface structure of the sequence but made no distinction between elements that were predictable versus unpredictable by the abstract structure and displayed no transfer of performance to the new, isomorphic sequence. In contrast, the abstract model learned only the elements that were predictable by the abstract

structure and transferred this knowledge quite effectively to the isomorphic sequence. Experiment 1 employs the same task in Explicit and Implicit groups of human subjects to determine if the same processing dissociation demonstrated in the models can be replicated in humans, in order to further demonstrate the dissociation between processes for treating surface versus abstract structure.

*Experiment 1 Method.* This experiment uses the same procedure as that of Simulation 1 with two groups of 10 subjects each, in the Implicit (surface) and Explicit (abstract) conditions as defined above. Blocks 1 through 6, and 8 use an abstract rule of the form  $u, u, n - 2, n - 4, n - 3$  that recurs in the 12-element sequence, ABCBACDEFEDF (where elements ABCDEF are mapped to elements 285613 in Figure 1), that repeats nine times in each block. Thus, each repetition of the sequence contains two repetitions of the abstract structure and one repetition of the surface structure. Predictable elements have single-item recency of lag  $- 2$ , and unpredictable elements, lag  $- 8$ . Block 7 is a random series of elements. Blocks 9 and 10 each use nine repetitions of a new, 12-element sequence (ABCBACDEFEDF with A through F mapped to elements 781365), isomorphic to that used in blocks 1 through 6 and 8 (i.e., with the same abstract structure but with a different surface structure). The delay between a response and the next stimulus (response to stimulus interval, or RSI) was 200 msec within a six-element subsequence and 500 msec between subsequences.

Subjects in the Explicit group ( $N = 10$ ) were shown a schematic representation of the rule and asked to demonstrate knowledge of the rule by pointing to BAC given ABC. They were told to actively try to use such a rule to help them go as fast as possible. Subjects in the Implicit group ( $N = 10$ ) were simply told to go as fast as possible and were given no hint that there might be an underlying structure in the stimuli.

### *Experiment 2: Learning Abstract Structure Alone*

Experiment 1 provides evidence that abstract structure can be learned and exploited in an SRT setting when both surface and abstract structure are present. There are two potential criticisms to this interpretation. First, the learning of the abstract structure may still require a coherent, repeating surface structure, and in the absence of this surface structure, the learning of abstract structure may fail. Second, performance that we are attributing to abstract structure learning may be something much simpler related to a single-item recency effect. That is, the reduced RTs for predictable elements may simply be due to the fact that all predictable elements have a mean single-item recency of lag  $- 2$ , whereas the unpredictable elements have a recency of lag  $- 8$ . Thus, the reduced RT for predictable elements may simply be

due to a recency effect, rather than the learning of a specific abstract structure. If so, this effect should be insensitive to a change in abstract structure in transfer tests with new sequences, provided that the new sequence maintains a similar degree of exploitable recency information. Experiment 2 specifically addresses these questions in the following manner. During training, a continuously changing surface structure and a fixed abstract structure are used. Testing then occurs with a continuously changing surface structure and a new fixed abstract structure that maintains roughly the same degree of single-item recency. If the abstract structure itself is being learned, we will see negative transfer to the new abstract structure, with no such negative transfer if it is primarily recency information that is being exploited. It is worth mentioning that although some related studies focus on the learning of rules versus smaller “chunks” of information (e.g., Knowlton & Squire, 1994), we rule out any learning effect due to element chunking in the current experiment because there are no regularly repeating chunks (i.e., no repeating surface structure).

**Experiment 2 Method.** The methods used in Experiment 2 are similar to those in Experiment 1 with the following exceptions. The test is divided into nine blocks of 90 trials each. Blocks 1 through 6, and 8 use an abstract structure of the form ABCBAC (u, u, u, n - 2, n - 4, n - 3) that repeats 15 times. Although the abstract structure is always the same, the surface structure changes continuously within each block so that the same sequence is never repeated. Specifically, the mapping between ABC and elements 1 through 8 changes for each sequence and is never repeated. Block 7 uses an abstract structure of the form ABACBC (u, u, n - 2, u, n - 4, n - 2), also with continuously changing surface structure, and serves as a transfer test. Block 9 uses a random series. Predictable elements in the first abstract structure have a mean single-item recency of lag - 2, versus lag - 1.6 for the transfer abstract structure.

Subjects in the Explicit group ( $N = 5$ ) were shown a schematic representation of the rule and told to actively try to use such a rule to help them go as fast as possible as in Experiment 1. Subjects in the Implicit group ( $N = 5$ ) were simply told to go as fast as possible and were given no hint that there might be an underlying structure in the stimuli.

### Experiment 3: Learning Abstract Structure Alone

Simulation 2 demonstrated that for sequences with a low degree of surface structure and a high degree of abstract structure, only the abstract model could learn the abstract structure, and neither model learned the surface structure. Experiment 3 uses the same protocol as Simulation 2 and allows further testing of the prediction that abstract structure can be learned independently of surface structure by the Explicit group and that some re-

cency information may be extracted from the surface structure by the Implicit group.

**Experiment 3 Method.** As in Simulation 2, the task is divided into five blocks of 120 trials. Blocks 1 and 5 are randomly organized, and blocks 2 through 4 are sequence blocks. Each of the three isomorphic sequence blocks is made by taking the 24-element sequence ABCBCDCDE . . . and mapping A through H to different elements and repeating it five times, yielding a total of 120 trials per block. The mappings of A through H for the three isomorphic sequences are, respectively, 28561374, 54123867, and 71486253. The test starts with a block of 120 trials in random order, followed by the three isomorphic sequence blocks of 120 trials each, and a final block of 120 trials in random order. The RSI was 500 msec.

Subjects in the Explicit group ( $N = 5$ ) were shown a schematic representation of the rule and told to actively try to use such a rule to help them go as fast as possible. Subjects in the Implicit group ( $N = 5$ ) were simply told to go as fast as possible and were given no hint that there might be an underlying structure in the stimuli.

## Appendix: Specification of Surface and Abstract Models

### Surface Model

**Recurrent State Representation.** The model is implemented in Neural Simulation Language (NSL 2.1, Weitzenfeld, 1991). Equation 1a and 1b describe how the representation of sequence context in the  $5 \cdot 5$  State is influenced by external inputs from Input, responses from Out, and a recurrent inputs from State<sub>D</sub>. In Equation 1a the leaky integrator,  $s()$ , corresponding to the membrane potential or internal activation of State is described. In Equation 1b the output activity level of State is generated as a sigmoid function,  $f()$ , of  $s(t)$ . The term  $t$  is the time,  $\Delta t$  is the simulation time step, and  $\tau$  is the time constant. As  $\tau$  increases with respect to  $\Delta t$ , the charge and discharge times for the leaky integrator increase. The  $\Delta t$  is 5 msec. For Equations 1 through 4, the time constants are 10 msec, except for Equation 2, which has five time constants that are 100, 600, 1100, 1600, and 2100 msec (see below).

$$s_i(t + \Delta t) = \left( 1 - \frac{\Delta t}{\tau} \right) s_i(t) + \frac{\Delta t}{\tau} \left( \sum_{j=1}^n w_{ij}^{IS} \text{Input}_j(t) + \sum_{j=1}^n w_{ij}^{SS} \text{StateD}_j(t) + \sum_{j=1}^n w_{ij}^{OS} \text{Out}_j(t) \right) \quad (1a)$$

$$\text{State}(t) = f(s(t)) \quad (1b)$$

The connections  $w^{IS}$ ,  $w^{SS}$ , and  $w^{OS}$  define the projections from units in Input, State<sub>D</sub>, and Out to State. These connections are one-to-all, are mixed excitatory and in-

hibitory, and do not change with learning. This mix of excitatory and inhibitory connections ensures that the State network does not become saturated by excitatory inputs and also provides a source of diversity in coding the conjunctions and disjunctions of input, output, and previous state information. Recurrent input to State originates from the layer State<sub>D</sub>. State<sub>D</sub> (Equation 2a and 2b) receives input from State, and its 25 leaky integrator neurons have a distribution of time constants from 100 to 2100 msec (20 to 420 simulation time steps), whereas State units have time constants of 10 msec (2 simulation time steps). This distribution of time constants in State<sub>D</sub> yields a range of temporal sensitivity similar to that provided by using a distribution of temporal delays (KQhn & van Hemmen, 1992).

$$sd_i(t + \Delta t) = \left(1 - \frac{\Delta t}{\tau}\right) sd_i(t) + \frac{\Delta t}{\tau} (\text{State}_i(t)) \quad (2a)$$

$$\text{State}_D = f(sd(t)) \quad (2b)$$

*Associative Memory.* During learning, for each correct response generated in Out, the pattern of activity in State at the time of the response becomes linked, via reinforcement learning in a simple associative memory, to the responding element in Out. The required associative memory is implemented in a set of modifiable connections ( $w^{SO}$ ) between State and Out. Equation 3 describes how these connections are modified during learning. The first response in Out above a certain threshold is selected by a “winner take all” (WTA) function and is evaluated. Thus, Equation 3 is executed only once for each response. When a response is evaluated, the connections between units encoding the current state in State and the unit encoding the current response in Out are strengthened as a function of their rate of activation and learning rate R. R is positive for correct responses and negative for incorrect responses. Weights are normalized to preserve the total synaptic output weight of each State unit.

$$w_{ij}^{SO}(t + 1) = w_{ij}^{SO}(t) + R * \text{State}_i * \text{Out}_j \quad (3)$$

The network output is thus directly influenced by the Input, and also by State, via learning in the  $w^{SO}$  synapses, as in Equation 4a and 4b where  $f(\cdot)$  includes a WTA function.

$$o_i(t + \Delta t) = \left(1 - \frac{\Delta t}{\tau}\right) o_i(t) + \frac{\Delta t}{\tau} \left( \text{Input}_i(t) + \sum_{j=1}^n w_{ij}^{SO} \text{State}_j(t) \right) \quad (4a)$$

$$\text{Out} = f(o(t)) \quad (4b)$$

*Abstract Structure Learning Model.* To represent and learn abstract structure, a system must (1) compare the

current sequence element with previous elements to recognize repetition and (2) maintain a representation of this recoded context to predict future repetitions. To provide a record of the previous responses with which the current response can be compared, the model of Figure 1 is augmented with a continuously updated short-term memory (STM) of the five previous responses. Each time a response is generated in Out, the STM is updated, as described in Equation 5a and 5b so that STM always contains the five previous responses in Out. Each of the five STM elements is thus a  $5 \cdot 5$  array.

$$\text{for } i = 5 \text{ to } 2, \text{STM}(i) = \text{STM}(i - 1) \quad (5a)$$

$$\text{STM}(1) = \text{Out} \quad (5b)$$

To detect if the current response is a repetition of one of the five previous responses, it is compared with each of the five previous responses encoded in STM (prior to update of Equation 5). The result is stored in a six-element vector called Recognition (Recog in Figure 1). Each Recognition element  $i$ , for  $1 \leq i \leq 5$ , is either 0 if Out is different from  $\text{STM}(i)$  or 1 if they are the same, as described in Equation 6. If no match is detected in STM for a given response in Out,  $\text{Recog}_0$  is set to 1, indicating that a unique (u) response has occurred.

$$\text{Recog}_i = \text{STM}(i) * \text{Out} \quad (6)$$

After Recognition compares a response in Output with the contents of the STM, the results of this comparison (e.g., u, u, u, n - 2, n - 4, n - 3 for ABCBAC) is provided as input to State from Recognition, as described in the updated version of Equation 1a'. Thus the abstract structure is encoded and represented in the sequence context.

$$s_i(t + \Delta t) = \left(1 - \frac{\Delta t}{\tau}\right) s_i(t) + \frac{\Delta t}{\tau} \left( \sum_{j=1}^n w_{ij}^{IS} \text{Input}_j(t) + \sum_{j=1}^n w_{ij}^{SS} \text{StateD}_j(t) + \sum_{j=1}^n w_{ij}^{OS} \text{Out}_j(t) + \sum_{j=1}^n w_{ij}^{RS} \text{Recog}_j(t) \right) \quad (1a')$$

The result is that now the abstract structure of sequences is represented in State and thus can be exploited. For example after training with sequence(s) with the abstract structure u, u, u, n - 2, n - 4, n - 3, when the model is exposed to a subsequence with the structure u, u, u, n - 2, it should predict that the next element will be the same as the element stored in  $\text{STM}_4$  (i.e., n - 4). To exploit this predictive abstract structure that is represented in the State pattern, we want to selectively take the contents of the STM that are predicted to match the upcoming element and direct this STM content to Out. To achieve this, a new learning rule



is developed. Each time a repetition is recognized, connections are strengthened between the active context (State) units and units in a four-element vector, Modulation (described below), that modulate the contents of the matched STM element to the output. The result is that this State pattern becomes increasingly associated with, and thus predicts, the occurrence of the matched element, before it occurs. This learning rule is described in Equation 7.

$$w_{ij}^{SM}(t+1) = w_{ij}^{SM}(t) + \text{State}_i * \text{Recog}_j \quad (7)$$

The goal of this learning is to allow State to modulate the contents of specific, predicted STM elements into Out. To permit this, a five-element vector, Modulation, is introduced such that for  $i = 1$  to 5, if  $\text{Modulation}_i$  is nonzero, the contents of  $\text{STM}(i)$  are modulated or directed to Out. This leads to an updated version of Equation 4a.

$$o_i(t + \Delta t) = \left(1 - \frac{\Delta t}{\tau}\right) o_i(t) + \frac{\Delta t}{\tau} \left(\text{Input}_i(t) + \sum_{j=1}^n w_{ij}^{SO} \text{State}_j(t) + \sum_{k=1}^m \text{Modulation}_k \text{STM}(k)_i\right) \quad (4a')$$

Based on the learning in Equation 7, State now directs this modulation of the STM contents into Out via State's influence on Modulation, as described in Equation 8.

$$\text{Modulation}_i = \sum_{j=1}^n w_{ij}^{SM} \text{State}_j(t) \quad (8)$$

After training on sequence ABCBAC, when the model is exposed to a new isomorphic sequence DEFEDF, the abstract structure  $u, u, u, n - 2, n - 4, n - 3$  will be recognized. After exposure to subsequence DEFE, the active State units will drive the Modulation unit corresponding to the  $n - 4$  STM element,  $\text{STM}(4)$ , directing its contents D to the output, leading to a reduced RT for the response to D. By the same type of context coding with which the surface model predicts elements of a learned sequence, the abstract model can predict element repetitions in a learned class of isomorphic sequences.

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