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Association and Abstraction in Sequential Learning: “What is Learned?” Revisited

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Evidence from serial pattern learning research has been used to support the controversial claim that rats detect, encode, and use abstract rules. To understand why the evidence indicates that rats' "rules" are abstract, we examine the basis of "pattern structure" in sequential tasks, how rats respond to pattern structure in highly-organized sequences, the role of "rules" in rats' representation of patterned sequences, and the notion that rats' "rules" differ from generalization. We show that "pattern structure" reflects systematic abstractions from stimuli that can be described by abstract relationships, that rats are flexible in representing sequential patterns, that rats use "rules" along with other forms of representation concurrently in serial pattern learning, and that associative/generalization models do not always predict rats' "rule-governed" behavior. Both behavioral and neurobiological evidence suggest that "rules" are not simply emergent properties of associative networks, that instead rule abstraction and associative processes are mediated by separate concurrently active systems in serial pattern learning. It is not known how "rules" are instantiated in the nervous system, and a key problem at a more molar level of analysis is what determines the output of multiple concurrently active cognitive systems in serial pattern learning.

"Serial pattern learning" is an interesting term, especially when it is used as the designation for a learning paradigm employed to study various aspects of sequential behavior in nonhuman animals. In serial pattern learning tasks for animals, as in analogous tasks for humans, the goal is to learn to predict a series of events. The term "pattern" is particularly problematic in this context. We humans perceive patterns in every stimulus dimension and on scales from infinitesimal to cosmic. In contrast, when we examine rat serial pattern learning, one might reasonably ask whether a rat brain ever has any inkling of "pattern," that is, the "form" or "structure" of the sequential stimuli the animal encounters in the task. We are asking, then, whether the rat is capable of "going beyond the information given," as Bruner (1957) famously put it. Or, in a broader sense, we are asking whether the rat learns by abstraction. The claim that rats learn "rules" in serial pattern learning tasks and related paradigms is in fact a claim that rats induce, encode, and use abstractions, whether or not they also employ more stimulus-specific associations in addition. In this paper, first we briefly discuss the basis of pattern structure and conditions conducive to rule abstraction in sequential tasks, and then we present what we consider to be strong evidence for abstraction in rat serial pattern learning. We follow with evidence for the additional claim that rats use both processes of abstraction and stimulus-specific association concurrently. Afterwards, we take on the problems of distinguishing between "rules" and

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generalization, that ubiquitous workhorse of associative theory, and determining whether or not “rules” are simply an emergent property of an associative system at work. Finally, we consider the implications of multiple concurrent cognitive systems in sequential behavior, ultimately returning to the question — “What is learned?” — at a more molar level of analysis.

The Basis of Rule Abstraction: Stimulus “Alphabets” and Formal Structure

Some kinds of sequences, especially serial patterns, encourage cognitive learning strategies that involve rule abstraction. The defining property of such a sequence is the ordinal or interval nature of the *alphabet* (Hulse & O’Leary, 1982; Jones, 1974), or ordered set of stimuli, from which the elements of the sequence are drawn. Most generally, an alphabet consists of a set of stimuli which a) are discriminable from one another, and b) have the properties, at a minimum, of an ordinal scale (Hulse & O’Leary, 1982; Jones, 1974). This means that the elements of a serial pattern are all drawn from the same stimulus dimension and that they are related in some quantifiable way, for example, some elements of the pattern are larger or smaller, brighter or dimmer, more to the left or right, greater than or less than others. The elements of serial patterns are quantitatively different, and can thus be related to each other by quantitative descriptions such as “greater than,” “less than,” “+1,” or “-1.” These kinds of quantitative descriptions are one kind of rule that the learner can use to encode information about the pattern beyond the qualitative identity of each list element. Also, some instructional descriptions, such as “alternate,” “repeat,” “reverse,” or “transpose” may be used as rules to describe the relationships of whole subsets of pattern elements. A rule, then, is a principle for establishing a relationship among the elements of a set of stimuli, a set drawn from an alphabet in the present case. The view that serial patterns of stimuli may be built by the action of rules operating on alphabets has been developed earlier in several detailed, related theoretical forms (e.g., Hulse & O’Leary, 1982; Jones, 1974; Restle & Brown, 1970a; Simon & Kotovsky, 1963).

Formal structure is a systematic relationship or set of relationships among rules relating pattern elements, such as the repeated occurrence of a single rule or of a set of rules always found in the same order. Rules that relate pattern elements are called lower-order rules. Rules that relate whole sets of rules, and thus whole sets of pattern elements, are called higher-order rules. In the formally simple pattern of digits, 1 2 3 4 5 6, for example, the lower order “+1” rule adequately describes the relationships between all pairs of successive pattern elements. This type of formal structure is the simplest that can be devised. Formal structure becomes more complex as the number of different rules needed to describe a pattern is increased. The highest-order rules relate the largest number of pattern elements and sets of elements, with lower-order structure nested within the higher-order structure. Some patterns may be perfectly symmetrical with lower-order rules completely nested within higher-order rules, forming structural trees (Restle & Brown, 1970a). An example of such a pattern is:

12345-34567-76543-54321

where elements within the first 5-element chunk start with “1” and obey a first-order “+1” rule, then a second-order “+2” rule applied to all members of the first chunk produces the second chunk, and a third-order “reverse” rule applied to the first half of the pattern creates the second half. Other patterns may have incompletely nested rule structures. Whatever the form, the presence of any formal structure provides a potential means of reducing memory load, and the learner need only have the capacity and predilection to use it to substantially increase pattern learning efficiency. This memory load hypothesis assumes that the learner actively searches for simple or recurring structures of patterns that can be encoded by abstracting and learning a representation of formally simple rule structures. When simple structures are found, the learner may choose to use a rule learning strategy if doing so substantially reduces the total amount of information that must be committed to memory to learn the pattern.

The difficulty of a pattern is assumed to be directly related to pattern complexity, but may be affected by many other, often conflicting, factors. Among the factors that are likely to contribute to pattern difficulty are pattern length, element discriminability, and the relative and absolute timing of events that compose the pattern. Hulse (1980) suggested that each of these factors may affect rats' choice of strategy — rule abstraction versus stimulus-specific association — in pattern learning.

Combining the foregoing ideas, the implication is that rats will be biased to use a rule learning strategy and will find a pattern easy to learn to the extent that the pattern contains many closely spaced elements that are related by many exemplars of few rules. The concept of reduced memory load (Hulse, 1980; Jones, 1974) summarizes the conditions that should predispose rats to adopt rule learning strategies. All the conditions outlined above simplify the learning process by functionally reducing the number of units of information that must be processed and remembered to learn a serial pattern. We suggest that in the interest of reducing memory load, rats actively search for simple or recurring pattern structure which they can encode by rule abstraction.

Evidence for Abstraction in Rat Serial Pattern Learning

Several methods of studying serial pattern learning in rats have been established. Rats have been trained to anticipate sequences of food quantities in runway and operant studies (e.g., Capaldi & Molina, 1979; Fountain, Evensen, & Hulse, 1983; Hulse, 1978), to anticipate sequences of quantities of brain-stimulation reward (Fountain & Annau, 1984), to anticipate the sequential positions of flashing lights in an array (Fountain, 1990), and to anticipate the successive correct positions of levers or nose-poke receptacles in an 8-position circular array. Using these methods, it became possible to conduct tests to determine whether rats would show evidence of abstracting rules when learning serial patterns that had structure.

Several early studies showed that rats learned structured serial patterns faster than unstructured patterns. For example, Hulse and Dorsky (1977, 1979) created patterns from a stimulus "alphabet" of various quantities of food. The patterns they created varied in formal structure. Rats learned to anticipate the

successive elements of a “simple” consistently decreasing pattern of food quantities faster than sequences with less structure. Hulse and Dorsky rejected a variety of pattern learning strategies the rats might have adopted to learn the simple pattern in favor of the hypothesis that rats reduced memory load by abstracting a single rule rather than learning a larger number of associations (see Hulse & Dorsky, 1977). A number of other studies have shown that rats' pattern acquisition can be predicted by the complexity of pattern structure when patterns to be learned are sequences composed of food quantities (Fountain et al., 1983), brain-stimulation reward quantities (Fountain & Annau, 1984; Fountain, Schenk, & Annau, 1985; Fountain, Raffaele, & Annau, 1986), flashing lights (Fountain, 1990), and spatial locations in a circular array (Fountain & Rowan, 1995a, b).

Two early studies were taken as particularly strong evidence that what rats learned when presented highly structured patterns in these paradigms was, in fact, abstract rules. In one study (Hulse & Dorsky, 1979) rats demonstrated the ability to generalize a rule learned in one setting to a different pattern composed of entirely different elements. In a second study, after learning short patterns, rats were able to predict a new element added to the end of a structured pattern, but not less structured patterns. That is, rats showed the ability to *extrapolate* a pattern of consistently decreasing food quantities to anticipate an even smaller quantity of food, but were not able to extrapolate a less structured pattern of food quantities (Fountain & Hulse, 1981). Rule generalization and extrapolation results in rats paralleled analogous results obtained with human subjects. Restle and Brown (1970c) reported results of transfer studies indicating that human subjects could generalize rule structures from one pattern to another. Thus rats and humans appeared to have functionally similar, though not equivalent, rule generalization and extrapolation capacities.

The preceding discussion describes examples of rats' ability to abstract rules from formally-simple structures described by a single rule. A sophisticated rule learner should also be able to use rules to describe the organization of other more complex pattern structures. Humans, for example, are able to encode and use hierarchical structures composed of many levels. In such patterns, rules at higher levels describe rules at lower levels of the structure, thus creating a nested organization, an example of which is a hierarchical "tree structure" (Restle, 1972). Because hierarchical serial patterns are described by more than one rule, changes in rule structure occur at various points throughout the pattern. Changes in rule structure mark the boundaries of sets of related pattern elements, or "chunks" (Miller, 1956; Simon, 1974). A common assumption is that people are active information processors, that is, people actively search for structure when they learn a serial pattern. When structure is found in a pattern, people "chunk" the pattern into subpatterns that reflect the underlying formal properties of the sequence (Bower & Winzenz, 1969; Miller, 1956; Simon, 1974). Chunking is reorganization imposed on the pattern by the learner; it is the result of active information processing. The chunking process allows the learner to detect and abstract the structure of groups of structurally related elements sometimes widely separated in the pattern.

Three types of recent studies provide strong evidence that rats search patterns for structure, namely, studies showing that hierarchical structure is a

determinant of learning rate, that rats can learn structures from nonadjacent pattern elements, and that experimental manipulations can systematically bias rats' ability to detect structure in serial patterns. Here we present evidence that rats actively search serial patterns for structure.

Evidence that Rats Abstract Hierarchical Structure

In these studies, we used a *serial multiple choice* (SMC) task in an octagonal operant chamber in order to examine how rats acquire long and often difficult patterns of responses. Rats were presented with the problem of responding in 8 unique spatial locations arranged in a circular array using a specific pattern of required actions (e.g., lever pressing or nose pokes) in order to receive reinforcement. Rats were required to seek out the "correct" spatial location and receive reinforcement for each correct response. The structure and cueing of the pattern were systematically manipulated to measure rats' error rates and error types throughout acquisition to test the hypothesis that rats abstract hierarchical structure from highly structured serial patterns. Two commonly studied patterns that we have employed in a number of studies to examine rat serial pattern learning consisted of a 24 elements that comprised eight 3-element chunks with either perfect hierarchical structure or a single element that violated otherwise perfect hierarchical structure:

Perfect:	123-234-345-456-567-678-781-812
Violation:	123-234-345-456-567-678-781-81 <u>8</u>

Digits in the pattern correspond to elements of the pattern consisting of unique spatial locations numbered 1-8 in a clockwise direction within the octagonal chamber. Dashes between chunks made up of three digits indicate the positions of temporal pauses that served as *phrasing cues* positioned at formal boundaries between structured chunks. These patterns contain both *chunk-boundary elements*, the first element of each chunk of three elements, and *within-chunk elements*, which are the remaining two elements in each chunk. The pattern is considered to be hierarchical because multiple hierarchically-related rules are required to describe the organization of the pattern (*cf.* Leeuwenberg, 1969). In the perfect pattern, within-chunk elements obey a "+1" rule. Chunks are related by a higher-order "+1" rule which increments all elements of the first chunk to generate the second chunk as a whole, which requires rats to turn left rather than right at chunk boundaries where the rule structure changes. In the violation pattern, the final element of the perfect pattern can be replaced with an element not predicted by pattern structure to create a *violation element*, which is shown underlined in the example pattern. By including the violation element, we are better able to determine whether rule learning has occurred because, according to rule-learning theory, learning such an element should be more difficult than learning a rule-consistent element and rats' errors should be predicted by pattern structure.

Using this methodology, better understanding of rat rule acquisition and complex pattern production has been achieved. Since rats in this study were never shaped to produce these patterns, but instead were presented the entire pattern from

the first day of training, it was possible to examine the types of errors made by the rat and what these errors may mean for the process of pattern acquisition. Rats in this type of procedure are able to acquire hierarchical, linear, and interleaved patterns (Fountain & Rowan, 1995a, 1995b; Fountain, Rowan, & Benson, 1999; Fountain & Benson, 2006; Fountain, Rowan, & Carman, 2007; Kunder & Fountain, 2010).

In one such task, groups of rats in the octagonal operant chamber learned either a pattern consisting of “runs” or “trills” structures (Fountain & Rowan, 1995a). Two groups received “runs” or “trills” patterns with perfect structure and two groups received patterns which ended with a violation element that was not compatible with the “runs” or “trills” structure of the rest of the pattern, as shown in Table 1. The goal of this experiment was to determine whether rats would have difficulty learning the violation element of each pattern as predicted by rule-learning theory. If rats were sensitive to the violation of the pattern, then more errors should occur on the final element of the violation pattern when compared to the final element in the corresponding perfect pattern. The results demonstrated that rats were sensitive to the structure of the pattern and to violations of pattern structure (Fountain & Rowan, 1995a). Subjects in the violation groups for both the “runs” and “trills” groups tended to make many more errors at the final violation element compared to rats with no violation element in that position in the corresponding pattern. In addition, rats in both “runs” and “trills” groups made errors on the violation trial that were consistent with the structure of their pattern. That is, “runs” rats made predominantly “runs errors” and “trills” rats made predominantly “trills errors” on the violation element. Of particular interest was the fact that rats in the “trills” group made very high rates of “8” errors on the violation element despite the fact that an “8” response was never reinforced on a trial following a “1” response. The fact that the results were similar for “runs” and “trills” structured patterns is evidence that rats are able to abstract rules and have difficulty responding to elements incompatible with pattern structure. These results led to a series of experiments to further explore rats’ rule abstraction capabilities and the nature of the processes rats utilized to form potential rules.

Table 1
Serial patterns of “runs” or “trills” that were either structurally perfect or contained a single violation element that was inconsistent with pattern structure (underlined).

	Runs	Trills
Perfect Pattern	123-234-345-456-567-678-781-812	121-232-343-454-565-676-787-818
Violation Pattern	123-234-345-456-567-678-781-81 <u>8</u>	121-232-343-454-565-676-787-81 <u>2</u>

Rats’ sensitivity to pattern structure was also demonstrated in an experiment comparing performance between rats and humans (Fountain & Rowan, 1995b). In this study, both rats and humans learned either a hierarchical pattern with completely nested rule structure or a linear pattern without hierarchical structure. As shown in Figure 1, the nested hierarchical pattern was composed of three levels of rules so that the elements within 3-element chunks were organized by a first order “+1” rule (elements and rules indicated in **green text**), those

chunks within the first and second half of the pattern, respectively, were organized by a second order “+1” rule (elements and rules indicated in **blue text**), and the two halves of the pattern were organized by a third-order “mirror” rule (elements and rule indicated in **red text**). Thus, rats and humans assigned to this completely nested pattern were required to learn to produce the pattern:

123 234 345 456 567 876 765 654 543 432

Other rats and humans learned a linear pattern created by swapping the two chunks underlined in the pattern above and below, as shown in Figure 1 (enclosed in rectangles). This manipulation preserved pairwise associations but disrupted the completely nested hierarchical structure present in the hierarchical pattern. The correct response sequence for this pattern was:

123 234 543 456 567 876 765 654 345 432

Thus, the training patterns were identical with the exception of the two chunks that were swapped in the linear pattern.

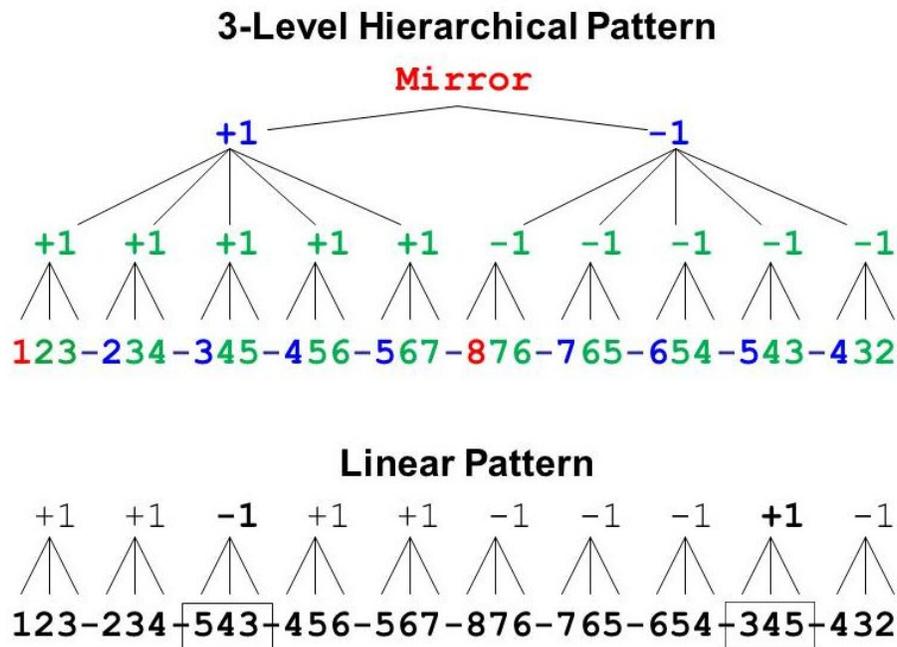


Figure 1. The structures of the 3-level hierarchical and the linear patterns rats learned in the octagonal operant chamber. The hierarchical pattern is described by a formally simple completely nested rule structure: elements within 3-element chunks are related by first-order rules (**green text**), chunks within the first and second halves of the pattern, respectively, are related to each other by second-order rules (**blue text**), and the first half of the pattern is related to the second half of the pattern by a third-order “mirror” rule (**red text**). The incompletely nested linear pattern was generated by exchanging two 3-element chunks of the hierarchical pattern (boxed chunks with rules in **bold text**). In this structure, elements within any chunk are related by a rule, but chunks are not related to each other systematically.

Rats and humans were both able to acquire these patterns with rats learning the completely nested hierarchical pattern with fewer overall errors compared to the linear pattern. Thus, rats learned the more structured sequence faster than the less structured sequence, a result consistent with the idea that rats are sensitive to the relative structural properties of the patterns they learned. More interesting in this regard, however, were rats' relative error rates on an element-by-element basis.

Rats' mean percent errors for each element of the pattern for the first week of the experiment are shown in Figure 2. There are multiple interesting things to note within this figure. First of all, we are able to determine the hierarchical level in the structure of the rule that each element in the pattern followed simply by how many errors were made in that serial position of the pattern. The top panel of the figure are those errors made by rats presented with the nested hierarchical pattern and within this pattern, the most frequent errors occurred on those elements that followed the application of the highest-level rule in the hierarchy, namely, "mirror" (**red-filled circles**). Rats in this procedure found finishing one "half" of the pattern and predicting the next element extremely difficult compared to all other elements. Predicting chunk boundaries, following application of the second-order "+1" rule (**blue-filled circles**) was also more difficult than anticipating within-chunk elements described by the simplest lower-order rule, "+1" (**green-filled circles**). Thus, within the hierarchical pattern, there was also a hierarchy of difficulty reflected in the errors rats made. Similar results were found for the chunk and within chunk error rates of the linear pattern (bottom panel) with the exception of the two exchanged linear chunks, but higher error rates were not observed at the beginning and midpoint of the pattern presumably because of the linear pattern structure.

Evidence that Rats Learn Structures from Nonadjacent Pattern Elements

Another study that demonstrated rats' ability to actively search for structure in a pattern showed that rats can learn rules to describe elements widely scattered in a pattern of food quantities if the structure describing the scattered pattern elements is formally simple (Fountain & Annau, 1984). More recent work employed the SMC task to examine multiple cognitive processes and rule learning in interleaved patterns (Fountain et al., 1999; Fountain & Benson, 2006; Kunder & Fountain, 2011). For humans, chunking together seemingly separate (nonadjacent) familiar pieces of information is quite common. When presented with the pattern, AMBNCODPE__, most humans familiar with the Latin alphabet have little difficulty detecting the two interleaved subpatterns of ABCDE and MNOP__ and extrapolating the correct subpattern to correctly predict that the next element should be Q.

In an analogous task, we examined how the organization of nonadjacent items would affect the rate of serial pattern learning when presented as elements in an interleaved pattern (Fountain et al., 1999). Half the rats in this experiment learned a structured (ST) hierarchical subpattern, 123-234-345-456-567, interleaved with repeating "8" elements, 182838-283848-485868-586878. A second group learned an unstructured (UNST) subpattern in which the position of

two pairs of elements from the structured pattern were exchanged, 153-236-345-426-547, and likewise interleaved with repeating “8” elements, 185838-283868-384858-483868-584878.

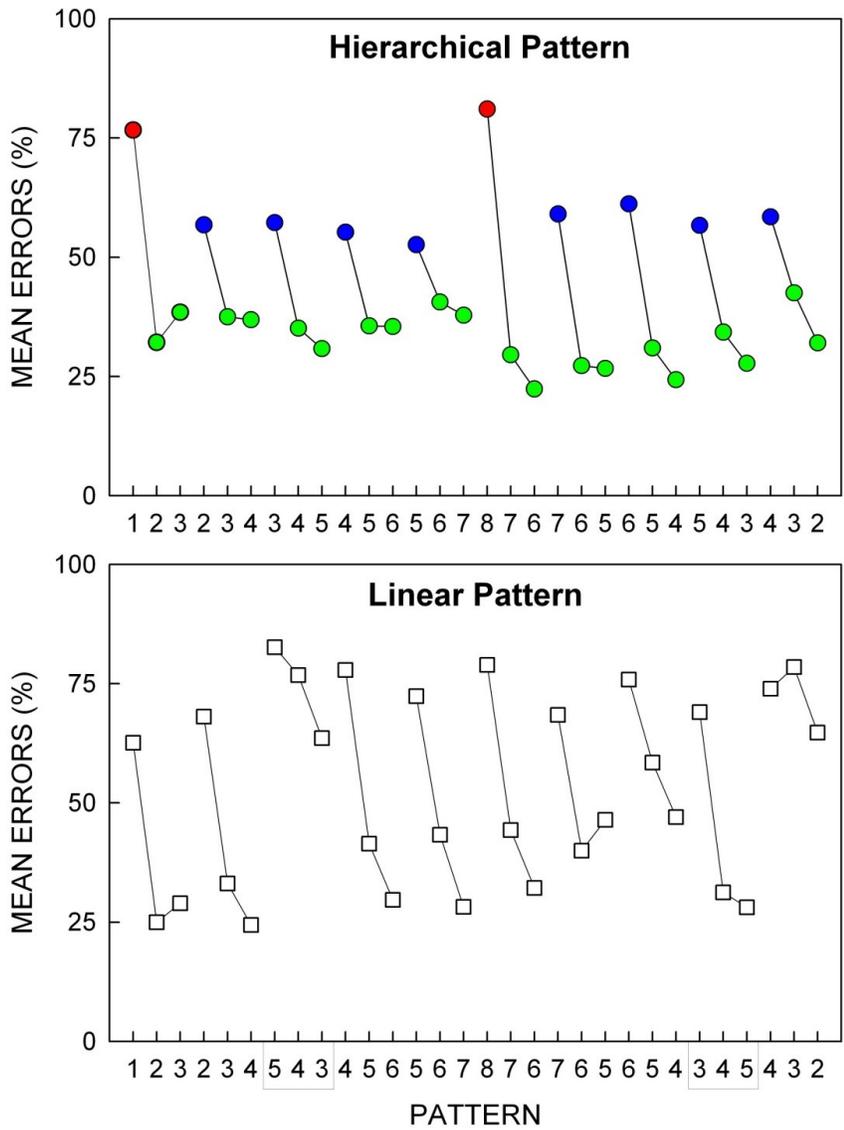


Figure 2. Rats' mean percentage of pattern tracking errors for hierarchical and linear patterns (top and bottom panels, respectively) as a function of the 30 items of the patterns. Mean percentage of errors are shown for the first week of training. Note that in the hierarchical pattern data, errors were most frequent at the highest-level 3rd order rule transitions at the beginning of each half of the pattern (red-filled circles), next most frequent at the 2nd order rule transitions at the beginning of other chunks (blue-filled circles), and least frequent at 1st order rule transitions within chunks (green-filled circles), as predicted by rule learning theory. Adapted from *Coding of hierarchical versus linear pattern structure in rats and humans* (p. 187-202), by S. B. Fountain and J. D. Rowan, 1995b, *Journal of Experimental Psychology: Animal Behavior Processes*, 21. Copyright 1995 by American Psychological Association. Adapted with permission.

During acquisition, rats in the ST group acquired the interleaved pattern more quickly and accurately compared to rats in the UNST group. This is especially evident in Figure 3 when examining the mean percent errors made for each element in the interleaved pattern averaged over three weeks of training. When presented with the unstructured interleaved pattern, rats performed poorly and made many more errors on the unstructured subpattern, producing a serial position-like effect with fewer errors occurring in the earlier and later parts of the pattern and more errors occurring in the middle. This is interesting when compared to the ST group results and especially so when comparing the middle chunk between the two groups. Although the middle chunk was the same for the two groups, the structural context of that chunk determined how easily the rats learned that chunk. In the structured group, the middle chunk presented in the context of a subpattern with perfect hierarchical structure was learned quickly and at the same rate as other chunks of the pattern that necessarily had the same formal structure. In the unstructured group, on the other hand, the same series of elements presented as the middle chunk in the context of a pattern with no hierarchical structure was quite difficult. Thus, consistent with the view that rats abstract rules, subpattern structure predicted the differential difficulty of the same series of elements in the two cases. In addition, it is interesting to note that both groups were equally able to acquire the interleaved subpattern of repeating “8” responses easily but were differentially affected by structured and unstructured subpattern formal structure. This result suggests that rats were able to separate the two subpatterns cognitively and track each subpattern separately, that is, that rats were able to chunk the pattern into subpatterns based on their different subpattern structures.

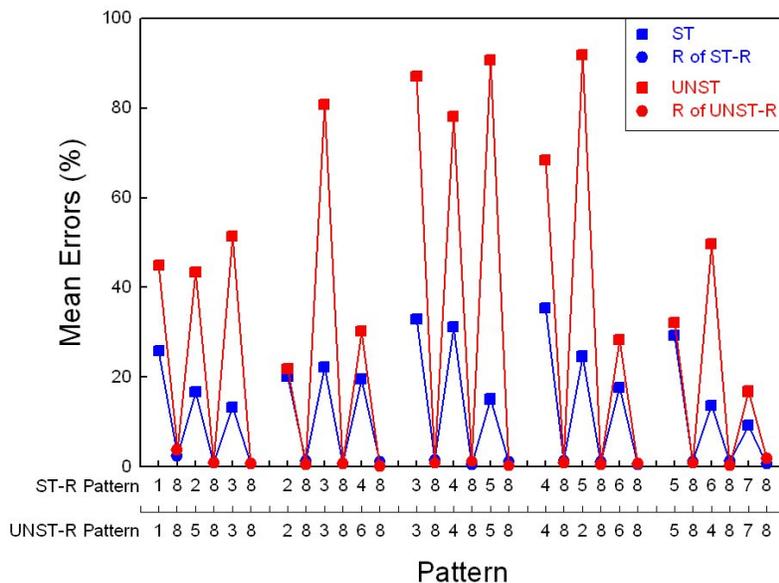


Figure 3. Group mean element-by-element errors for the interleaved structured-repeating (ST-R, blue curves) and unstructured-repeating (UNST-R, red curves) patterns averaged across Week 3 of training. Adapted from *Rule learning in rats: Serial tracking in interleaved patterns* (p. 41-54), by S. B. Fountain, J. D. Rowan, and D. M. Benson, Jr., 1999, *Animal Cognition*, 2. Copyright 1999 by Springer-Verlag. Adapted with permission.

But what happens when rats are required not only to separate and track two interleaved subpatterns, but also violation elements that may occur within one of the two subpatterns? Fountain and Benson (2006) asked whether rats presented with interleaved patterns with violations would track and acquire both the structure of the subpatterns and the violation elements in the pattern. In order to answer this question, rats were assigned to groups that learned either completely structured (S), twice violated (2V), or four times violated (4V) subpatterns interleaved with a second structured (S) subpattern, thus creating the S-S, 2V-S, and 4V-S interleaved patterns shown in Table 2. Consistent with rule-learning theory, rats in the (S-S) group were able to acquire their pattern quickly and more accurately compared to groups with violation elements, namely, 2V-S and 4V-S, with difficulty of the first subpatterns increasing monotonically from S to 2V to 4V, as predicted by rule-learning theory.

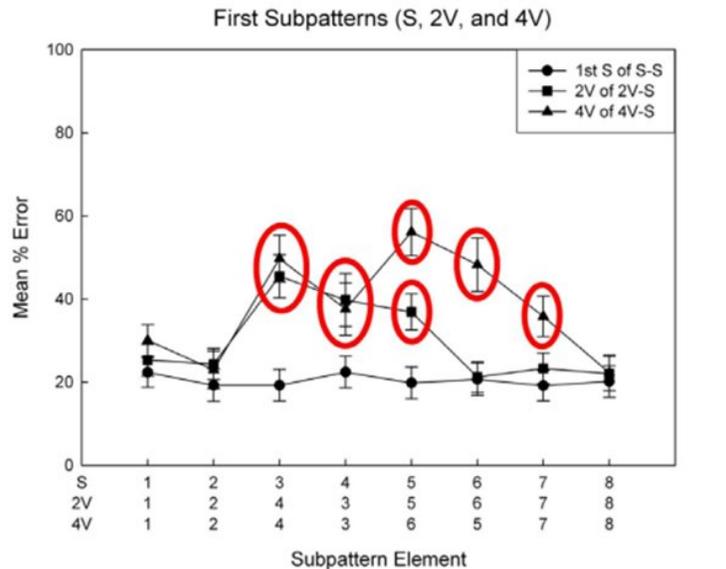
Table 2

Interleaved patterns composed of two subpatterns; the first subpattern had 0, 2, or 4 violation elements whereas the second subpattern was always structured without violation elements. The Structured/Structured (S-S) Pattern was composed of two structured subpatterns without violation elements. Two Violation/Structured (2V-S) and Four Violation/Structured (4V-S) Patterns had one and two pairs, respectively, of successive elements in the first subpattern reversed, as indicated by underlined elements.

Group	Interleaved Pattern
Structured/Structured (S-S) Pattern	1526374851627384
Two Violation/Structured (2V-S) Pattern	1526 <u>4</u> 7 <u>3</u> 851627384
Four Violation/Structured (4V-S)Pattern	1526 <u>4</u> <u>7</u> <u>3</u> <u>8</u> <u>6</u> <u>1</u> <u>5</u> 27384

Evidence for chunking and rule learning also came from results of the intrusion error analysis. Rats' group mean element-by-element percent error rates collapsed across all days of the experiment are shown in Figures 4 and 5. The data shown in these figures are organized by first and second subpatterns of the interleaved patterns, respectively, by presenting the data from first subpatterns (1st S of S-S, 2V, and 4V) in Figure 4 and data from the second subpatterns (2nd S of S-S, S of 2V-S, and S of 4V-S) in Figure 5. In violation subpatterns (Fig. 4), the highest-frequency errors on violation elements were responses consistent with the +1 rule describing simple subpattern structure (indicated by **red circles** for trials where this was true, also shown underlined in the training patterns below the graph). For example, in the 2V-S and 4V-S pattern, rats had high rates of errors on the third element of the S subpattern, and the predominant error was “3,” an apparent extrapolation of the “+1” rule of the subpattern, 1→2→3. It should be noted by reference to the actual patterns in Table 2, however, that rats in both groups produced this high rate of “3” error response as the last element of the actual response sequence, 1→5→2→6→3, even though a “3” response was never reinforced after a “6” response at any point in the 2V-S or 4V-S pattern. Thus, high error rates for this “3” response are not consistent with associative predictions because “6” signals only “4,” “2,” or “1” at different points in the 2V-S and 4V-S training patterns. On the other hand, a “3” response is a direct prediction of

applying the “+1” rule common to both S and most trials of 2V and 4V subpatterns. Thus, such responses fit well with predictions of rule learning theory, but are not easily explained by common associative mechanisms of discrimination learning.



2V-S Pattern 1526473851627384

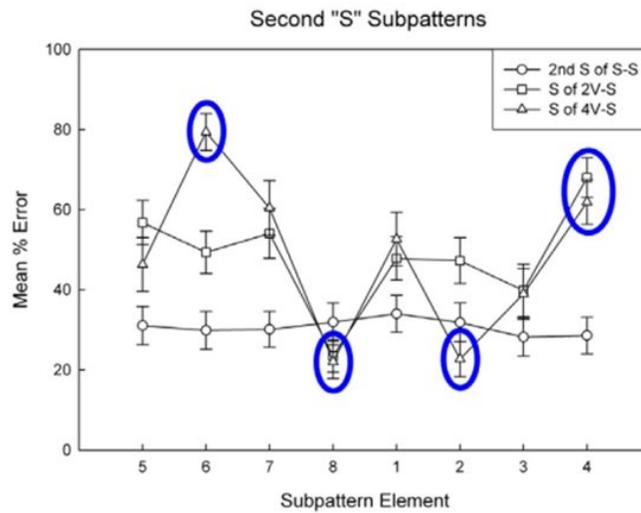
4V-S Pattern 1526473861527384

Figure 4. Rats' group mean element-by-element percent error rates collapsed across all 5 weeks of the experiment for the first subpattern of the S-S, 2V-S, and 4V-S interleaved patterns. **Red-circled points** indicate unusually high rates of errors attributable to rule learning. Adapted from *Chunking, rule learning, and multiple item memory in rat interleaved serial pattern learning* (p. 95-112), by S. B. Fountain and D. M. Benson, Jr., 2006, *Learning and Motivation*, 37. Copyright 2006 by Elsevier. Adapted with permission.

Evidence for stimulus-specific associations can be seen if we ignore subpattern structure and treat the patterns as an undifferentiated series of events. Several of the easiest and most difficult elements for rats to learn can be accounted for by multiple adjacent-item associations (indicated by **blue circles** in Fig. 5 for trials where this was true, also shown underlined in the training patterns below the graph). When multiple cues consistently signaled the same correct outcome (as shown color-coded in **green digits** in the patterns below the graph), the target elements were among the easiest to learn. In contrast, when multiple cues signaled different outcomes at different points in the sequence (as shown color-coded in **red digits** and **blue digits** in the patterns below the graph), creating a difficult “branching” problem (Restle & Brown, 1970b), the target elements were among the most difficult to learn due to generalization of errors across instances where the

same cues predicted different outcomes. Thus, we find strong evidence that sequential adjacent-element associations and remote associations controlled rats' sequential choices in these cases. This associative view, however, cannot account for the foregoing phenomena implicating chunking and rule learning. Instead, the results taken together fit better with the idea that rats used rule learning and associative learning concurrently.

Rats appeared to learn about the formally simple rules that described the underlying interleaved structures of the sequences and governed long strings of elements. They also used associative memory of multiple items as compound cues to anticipate specific pattern elements where those cues were particularly distinctive. Thus, the behavioral evidence suggests that rats used chunking, rule learning, and interitem association learning concurrently to master these complex patterns.



2V-S Pattern 1526473851627384

4V-S Pattern 1526473861527384

2V-S Pattern 1526473851627384

4V-S Pattern 1526473861527384

Figure 5. Rats' group mean element-by-element percent error rates collapsed across all 5 weeks of the experiment for the second simple (S) subpattern of the S-S, 2V-S, and 4V-S interleaved patterns. **Blue-circled points** indicate unusually high or low rates of errors attributed to multiple item associations. Adapted from *Chunking, rule learning, and multiple item memory in rat interleaved serial pattern learning* (p. 95-112), by S. B. Fountain and D. M. Benson, Jr., 2006, *Learning and Motivation*, 37. Copyright 2006 by Elsevier. Adapted with permission.

Evidence that Experimental Manipulations can Systematically Bias Rats' Ability to Detect Pattern Structure

In another SMC task study, we examined the effects of phrasing a structurally ambiguous pattern as either a series of “runs” or “trills” (Fountain et al., 2007). A 1234345656787812 pattern phrased as “runs” (1234-3456-5678-7812...) was easier to learn than when it was phrased as “trills” (1212-3434-5656-7878), a result that resembles a similar “run bias” reported in the human sequential learning literature and in earlier studies of rats’ response to “run” versus “trill” structures (Fountain & Rowan, 1995b). Whereas rats learning the “runs”-phrased pattern showed rapid learning and little tendency to make trills errors, rats learning the “trills”-phrased version of the pattern produced inflated rates of both trills and runs errors (Fountain et al., 2007). The results show that rats represented the “runs”- and “trills”-phrased versions of the pattern differently. These results add to the evidence that, in addition to serving as discriminative cues (Stempowski, Carman, & Fountain, 1999), phrasing cues can bias pattern perception in rat serial pattern learning resulting in memory representations characterized by different interpretations of the same pattern.

Irrelevant relations in serial patterns are inferred relationships between sequential elements that obscure actual pattern structure (Hersh, 1974). For example, in a sequence such as MMMNMO, it is difficult to abstract the underlying structure of two interleaved sequences, namely, MMM and MNO, because of the natural bias to detect an incorrect “identity” or “repeat” rule in the first three successive elements of the series. In contrast, when irrelevant relations are avoided by presenting the same structure with different elements, such as MAMBMC, the correct structure is much easier to detect and learn. Kundey and Fountain (2011) examined the impact on rat serial pattern learning of irrelevant relations positioned at the beginning or end of a serial pattern. If rats learn such sequences by abstracting rules, irrelevant relations at the beginning of a pattern should bias rats toward an incorrect interpretation of the pattern and should thus retard pattern learning. In contrast, irrelevant relations positioned at the end of the pattern should cause less retardation of learning because early in the pattern rats should be “biased” toward the correct interpretation of the pattern, as reported in college students by Hersh (1974). Rats learned the same structured serial pattern, 123-234-345-456-567, interleaved with repeating responses on lever 2 to produce irrelevant relations at the beginning of the pattern, on lever 6 to produce irrelevant relations at the end of the pattern, or on lever 8 to produce little or no irrelevant relations, as shown in Table 3. Figure 6 shows that irrelevant relations significantly retarded learning regardless of their placement within the pattern. However, irrelevant relations retarded learning significantly more when placed at the beginning of the pattern versus the end (Kundey & Fountain, 2011). The results are strong evidence that rats and humans actively search sequences of events for pattern structure and that the chunking and rule abstraction processes involved are sensitive to structural ambiguity created by irrelevant relations in patterns.

Table 3

Interleaved patterns with repeating elements that created little or no irrelevant relations (No Irrelevant Relations, NoIR), that created irrelevant relations at the beginning of the interleaved pattern (Beginning Irrelevant Relations, B, underlined), and that created irrelevant relations at the end of the interleaved pattern (End Irrelevant Relations, E, underlined).

Group	Interleaved Pattern
No Irrelevant Relations (NoIR)	182838 283848 384858 485868 586878
Beginning Irrelevant Relations (B)	<u>122232</u> <u>223242</u> <u>324252</u> 425262 526272
End Irrelevant Relations (E)	162636 263646 364 <u>656</u> 465 <u>666</u> <u>566676</u>

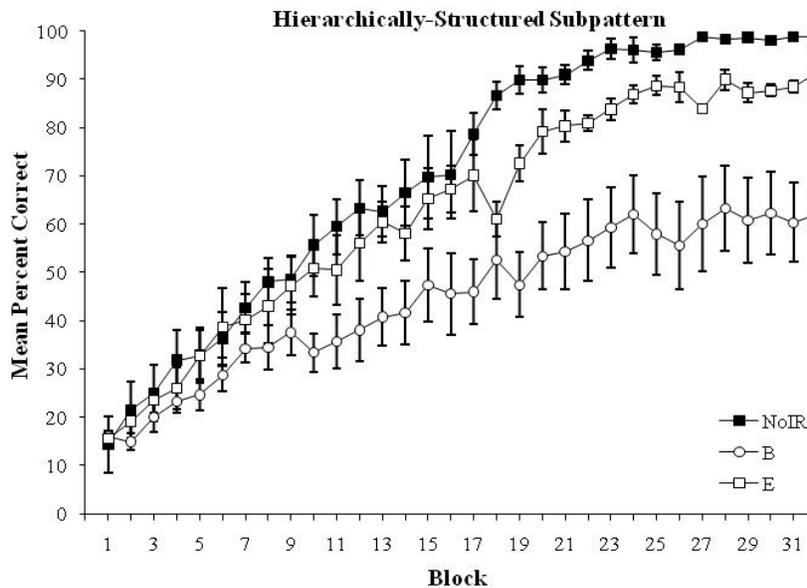


Figure 6. Acquisition curves depicting block-by-block group mean correct response rates for Group NoIR (having No Irrelevant Relations), Group B (having Beginning Irrelevant Relations), and Group End (having End Irrelevant Relations) for the hierarchically-structured subpattern of the interleaved pattern. Adapted from *Irrelevant relations and the active search for pattern structure in rat serial pattern learning* (p. 359-368), by S. M. A. Kundery and S. B. Fountain, 2011, *Animal Cognition*, 14. Copyright 2011 by Springer-Verlag. Adapted with permission.

What is Learned in Rat Serial Pattern Learning? “Rules” versus Associations and Generalization

As the previous two experiments demonstrated, there is sensitivity to elements that violate the rule structure in patterns, but we should not be blind to the fact that rats are able to acquire and respond accurately to the violation element after many blocks of training (Fountain & Rowan, 1995a, b, 2000; Kundery & Fountain, 2010; Muller & Fountain, 2010). If we have evidence that rats are

abstracting rules from patterns and are using these rules to respond accurately, how is the acquisition of violation element responses explained? One explanation is that rats may be using multiple learning processes to accurately produce the pattern (Muller & Fountain, 2010). It should be mentioned that this conclusion follows logically from the notion that if there are no rules to learn that predict violation elements, the only alternative is for the rat to use serial position, timing, associations, or some other strategy to anticipate violation elements. Recent strong evidence against the serial position and timing idea (Muller & Fountain, 2010) and other evidence for stimulus-specific associations in anticipating violation elements (Kunder & Fountain, 2010) are consistent with the idea that rats learn both rules and associations concurrently.

One approach to determining whether complex behavior can be described by a few simple assumptions is to use a mathematical model to simulate the behavior. To help us determine whether pairwise association and generalization of cues might account for rat reward magnitude serial pattern learning, we recently sought to use a computational model to conduct simulation studies. In considering how to begin to model serial pattern learning processes, a variety of different computational approaches were considered from simple stochastic models, to connectionist models, to production system approaches. Each of these varieties of computational models has been applied to sequential learning and memory problems at one time or another. For example, “random walk” models have been advanced by Roitblat (1984) and, more recently, Neath and Capaldi (1996), connectionist models have been advanced by Roitblat (2002), and a forerunner of production system models was pioneered on serial-pattern learning problems studied in humans by Simon, Newell, and their associates (Newell & Simon, 1961; Simon & Kotovsky, 1963). The principal concern was that the model should associate specific items in “memory” and produce generalization phenomena. Stochastic models and production systems were rejected because they are not easily stated in terms consistent with basic principles of discrimination learning. Several varieties of connectionist and related models have the desired properties and, thus, are also analogous to Capaldi’s item association and cue generalization ideas. In particular, the TODAM model developed by Bennett Murdock (Murdock, 1982, 1983) and the CHARM model developed by Janet Metcalfe (Metcalfe Eich, 1982; Metcalfe, 1990) have these properties. These models have the added advantage that both Murdock’s and Metcalfe’s models have also been used successfully to simulate a broad array of human associative learning and memory phenomena (Metcalfe, 1990, 1993; Murdock, 1983, 1992), including some rote sequential learning phenomena (Murdock, 1983, 1992, 1995).

We conducted simulation studies with a computational model of sequential learning we called the Sequential Pairwise Associative Memory (SPAM) model (Wallace & Fountain, 2002, 2003). SPAM includes all of the essentials of the TODAM model described by Murdock (1982, 1983) and Metcalfe (Metcalfe Eich, 1982; Metcalfe, 1990) and subsequently used by Metcalfe (1990) as the model known as CHARM in her simulations of eyewitness misinformation effects and “blending” of memories that depend on stimulus association and generalization. The model is described in great detail by Murdock (1982, 1983, 1985) and Metcalfe (Metcalfe Eich, 1982; Metcalfe, 1990) and also in our studies (Wallace &

Fountain, 2002; 2003). SPAM is also one possible instantiation of the item memory view because encoding is based on pairwise associations of items in memory and because generalization occurs between similar cue items.

When successive pairs of items are associated in SPAM, the result of the association process is added to a common trace. Because the trace is a composite of all prior associations, retrieval can result in generalization when the same or similar cue items were earlier associated with two or more different items. This is the basis of generalization in SPAM. For example, items are represented by vectors in SPAM. Items such as "14 pellets," "7 pellets," "3 pellets," "1 pellet," and "0 pellets" are represented by vectors. Since these items represent quantities of food that presumably vary systematically in similarity to each other, we used vectors that varied systematically in similarity to represent them (as Metcalfe, 1990, did in her studies of "blended memories" in eyewitness testimony). Under these conditions, if the composite trace contains information about the association of "1" and "0" only, cueing the composite trace with "1" retrieves "0." On the other hand, if the composite trace contains the associations "3" with "7" and "1" with "0," cueing the trace with "1" retrieves both "0" (retrieved directly by "1") and, to a lesser degree, "7" (cued by generalization of "1" to "3," since "1" and "3" are similar). This generalization would result in an "anticipation" of a quantity greater than "0." This effect is analogous to generalization typically observed in discrimination learning and it is also analogous to Capaldi's idea of cue generalization, where the capacity to signal reward or nonreward can generalize from one cue to other similar cues. Because SPAM is an associative model that has characteristics of simple associative systems, namely, pairwise associations and generalization, it was used to test whether an instance of this type of mechanisms could account for the phenomena that various investigators have reported in their studies of rat reward magnitude pattern learning.

In a series of simulation studies (Wallace & Fountain, 2002), we used SPAM to test whether simple associative processes, namely, pairwise association and generalization, could account for some of the fundamental behavioral evidence supporting rule learning in rat serial pattern learning. In two simulation studies (Wallace & Fountain, 2002), SPAM predicted that a short pattern with highly discriminable elements would be learned better than one with less discriminable elements even though the former was nonmonotonic, that is, formally complex, and the latter was monotonic, that is, formally simple (Capaldi & Molina, 1979). This prediction from the model might be expected given the similarities of SPAM and item memory theory, but SPAM also predicted that a long, strongly monotonic pattern of food quantities should be tracked better than a long nonmonotonic pattern, as observed by Hulse and Dorsky (1977). In two other simulation studies (Wallace & Fountain, 2002), SPAM also successfully simulated behavioral "rule generalization," "extrapolation," and associative transfer data (*cf.* Fountain & Hulse, 1981; Haggbloom, 1985; Haggbloom & Brooks, 1985; Hulse & Dorsky, 1979).

The critical point of this discussion is that over a broad range of parameter values (Wallace & Fountain, 2002, 2003) SPAM simulations demonstrated the power of simple associative principles of pairwise association and stimulus generalization to account for rats' performance in patterns of different length and

item arrangements, “rule generalization”, and pattern “extrapolation” (Wallace & Fountain, 2002; 2003). SPAM is nearly the simplest possible formulation of this associative memory model because it does not store information about remote associations between sequential events, the effects of extraneous cues like phrasing, or about the passage of time or serial position. This is not to say that these factors play no role in serial-pattern learning; our SPAM simulations simply tested whether a model without these features could be sufficient to describe what may be considered the critical phenomena for the rule learning versus item memory debate in the reward magnitude serial pattern learning literature (Wallace & Fountain, 2002). It should be noted that we also concluded that SPAM is likely not unique; it is likely a member of a class of formally equivalent or similar associative models that share common features—association and generalization—that should produce common behavioral outcomes in sequential learning paradigms (Wallace & Fountain, 2002). Prior unpublished work in our lab restating SPAM with an error-correcting rather than a Hebbian learning rule supports this contention (Wallace, Lewis, Fountain, & Block, 1999). The important conclusion is that there exists at least one subsymbolic mechanism—SPAM—that can explain sequential behavior of a type previously thought to require rule induction processes (Gallistel, 1995; Hulse, 1978; Lashley, 1951; Roitblat & von Fersen, 1992).

Although rats may in fact use rule induction processes to learn serial patterns of food quantities, SPAM simulations indicate that this is not a necessary conclusion from the classical behavioral studies on reward magnitude sequential learning. A natural question is whether SPAM simulations can account for the results described above from the SMC task that support the view that rat serial pattern learning of highly structured response sequences is mediated at least in part by rule induction processes. Although rats can learn the serial patterns described above to a high level of performance (no more than 10% errors on any element of the pattern), recent unpublished simulation studies indicate that SPAM failed to do so despite attempts to code sequences as series of distinct lever spatial locations or as a series of left and right turns (Kundey, Rowan, & Fountain, 2007). The insurmountable problem appears to be the highly branching nature of the serial patterns. Because SPAM depends on pairwise associations and cannot use compound or configural cues to disambiguate branching sequences, generalization is complete across instances where the same cue signals different outcomes resulting in high error rates that cannot be reduced by further “training” in SPAM. For SPAM to have any chance of simulating rats’ performance for even simple branching sequences, the model will need to be modified to encode compound or configural cues, but it is not at all clear that such a model would then be capable of simulating reward magnitude serial pattern learning or that it would produce results that simulate the foregoing data with structured response sequence learning in the octagonal chamber paradigm. Work to add compound or configural cue encoding to SPAM is currently underway.

Evidence that “Rules” are Not Simply an Emergent Property of Associative Networks

One question is whether “rules” are an emergent property of the activity of associative networks in the brain. One argument against this idea is that SPAM and association theory have failed to account for many aspects of the foregoing data and often logically predict incorrect experimental outcomes. For example, interleaved data in Figure 5, especially the high rates of “3” responses on the “4” trial discussed above, make no sense from an associative perspective, so logically the associative mechanism that generates high rates of associative-based errors and correct responses on some trials in Figure 6 cannot also be responsible for rule-based responding that violates associative principles in Figure 5. This is especially problematic when the same pattern elements are clearly involved in the performance of both rule- and association-governed responses. In this case, the hypothesis that separate systems for rule abstraction and association formation mediate serial pattern learning is the more parsimonious explanation.

Perhaps the strongest evidence that “rules” are not an emergent property of the same neural network responsible for associative learning in rat serial pattern learning is that neurobehavioral evidence indicates that rule abstraction and association formation are dissociable by neurobiological manipulations. For example, Fountain and Rowan (2000) examined the effects of the drug MK-801 on sequential learning. MK-801 is a systemically administered drug that blocks a specific type of glutamate receptor, namely, the NMDA receptor, which plays a critical role in a type of neuronal plasticity, known as long-term potentiation, in the hippocampus, basal ganglia, and other brain structures. Rats were trained on the perfect and violation “runs” patterns used before by Fountain and Rowan (1995a) with the violation response located consistently in the same position in the spatial array. Rats from one group for each pattern condition were injected with 0.0625 mg/kg MK-801 daily before training. MK-801 had little effect on learning to respond to rule-based items within chunks, but it did impair responding on the first trial of chunks and, most dramatically, for the violation element (Fountain & Rowan, 2000). Although rats showed no signs of learning to respond to the violation element, throughout the 7-day experiment they produced rule-based errors on the violation trial by responding “2” instead of “8” at the end of the sequence (Fountain & Rowan, 2000). Similar effects have been observed with anticholinergic drugs and, with much smaller effects, in adult rats following adolescent nicotine exposure (Fountain, Rowan, Kelley, Willey, & Nolley, 2008). Earlier we presented evidence that violation elements recruit associative discrimination learning processes in normal rats. Although rats can with difficulty learn to anticipate violation elements to near perfect performance, because violation elements are not predicted by pattern structure, rats learn to anticipate them via associative mechanisms (Fountain & Rowan, 1995a; Kundery & Fountain, 2010). Thus the fact that MK-801 blocks acquisition yet results in high rates of rule-based “2” intrusion errors on the violation element provides strong evidence that MK-801 impairs associative learning while sparing the rule abstraction

processes necessary to abstract pattern structure and extrapolate the sequence on the violation trial.

Implications of Multiple Concurrently Active Cognitive Systems

We have shown that “pattern structure” reflects systematic abstractions from stimuli described by abstract relationships, that rats abstract simple and hierarchical rules from serial patterns, that rats are flexible in representing sequential patterns, that rats use “rules” along with associations concurrently in serial pattern learning, and that associative models including generalization do not always predict rats’ “rule-governed” behavior. Both behavioral and neurobiological evidence suggests “rules” are not simply emergent properties of associative networks. Instead, evidence suggests that rule abstraction and associative processes are mediated by separate concurrently active systems in serial pattern learning. It is not known how “rules” are instantiated in the nervous system, and this is one key problem that demands attention in both behavioral and neurobiological research. However, perhaps a more interesting implication of multiple concurrently active cognitive systems is that such a view raises another key question about what is learned at yet a higher level of analysis, namely, at the level of output of multiple competing cognitive systems. Whereas our work has focused primarily on questions related to whether rats learn abstract rules, associations, or both, we have barely mentioned the problem of what determines the output of multiple concurrently active cognitive systems in serial pattern learning. For example, when rule-based and associative-based systems predict different events at the same time, which response is expressed? Much attention has been directed to this problem recently in the cognitive literature on human skilled performance in the serial reaction time task with theories that emphasize multiple information processing and response systems, multiple memory stores, and the role of attention (*cf.* Abrahamse, Jimenez, Verwey, & Clegg, 2010; Willingham, 1998). Similar attention should be directed toward characterizing the processes involved in higher-level interactions between multiple cognitive systems that determine behavior in the “simple preparation” of serial pattern learning in the serial multiple choice task in the rat.

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