Title

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Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 35(35)

ISSN

1069-7977

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Publication Date

2013

Peer reviewed

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Abstract

This study examined the effect of an explicit relational rule on sequence learning in a 3-choice serial reaction time task. Simple probabilistic contingencies between pairs of response cues were used in such a way that the sequence of cues moved predominantly in one direction (i.e. either clockwise or counterclockwise). Performance on cued and miscued responses was compared for a group given a hint about the abstract rule describing the relationship between the response cues, and a group given no information about this relationship. Experiment 1A demonstrated that XYZ and XYX subsequences showed performance differences when the location of the target on each trial was random. Experiment 1B showed that giving participants the explicit hint affected XYZ subsequences more than XYX subsequences. Implications for sequence learning and, specifically, the interaction between rule and instance learning are discussed.

Keywords: serial reaction time; awareness; motor learning; volitional control; sequence learning; rule vs. instance learning

Introduction

Humans are remarkably capable at learning about sequential material, such as the underlying sequence of locations of a target in a serial reaction time (SRT) task (Nissen & Bullemer, 1987). A typical paradigm involves participants pressing keys corresponding to the location of a target as it appears in positions on a computer screen. Speed and accuracy of responses are emphasized. Unbeknownst to participants, some or all of the positions can be predicted using deterministic or probabilistic rules. Participants exposed to this structured material generally show a reduction in reaction times (RTs) for predicted locations, relative to unpredicted (random) locations, suggesting that they have learned about the underlying sequence. The SRT task is an example of an implicit learning paradigm that appears to show robust learning in the absence of verbalizable knowledge (e.g. Destrebecqz & Cleeremans, 2001; Willingham, Nissen & Bullemer, 1989) and intention to learn (Jiménez, Méndez, & Cleeremans, 1996; Jones & McLaren, 2009). Since implicit learning is, according to some definitions, unconscious (Reber, 1993), this classification implies that learning is independent of explicit knowledge, and should not be susceptible to cognitive influences (Lewicki, 1986).

However, the implicit status of sequence learning has been challenged by later studies showing that sequence knowledge is reportable when appropriate tests are used (e.g. Jimenez, Mendez, & Cleeremans, 1996; Perruchet & Amorim, 1992). The results from several studies (e.g. Dominey, Lelekov, Ventre-Dominey, & Jeannerod, 1998; Jimenez, Vaquero, & Lupianez, 2006; Jones & McLaren, 2009) suggest that while learning is generally automatic (in that it does not require an intention to learn and occurs under a variety of learning conditions), giving participants knowledge about the sequence or instructions to search for an underlying rule can change what is learned, implying that learning is under some degree of volitional control. Conflicting results and ongoing disagreement about appropriate methodology has meant that no firm conclusions can be made about the status of implicit learning and what learning mechanisms it embodies (Shanks & St. John, 1994).

A corollary of the implicit/explicit distinction made by several researchers is between the learning of rules and instances. Explicit learning is assumed by some to involve knowledge in the form of symbolic propositions that are apt for describing abstract relations between events (Mitchell, De Houwer, & Lovibond, 2009). In contrast, implicit learning can be seen as the accumulation of statistical information in an incremental fashion, and many have argued is better suited for learning the surface structure or physical properties of events in a sequence rather than abstract relations (McLaren, Green, & Mackintosh, 1994; Perruchet & Amorim, 1992). Conceptualizing implicit learning in this way allows it to be explained using the same simple associative learning mechanisms that have been postulated to explain animal learning (McLaren, Green, & Mackintosh, 1994). In support of this conceptualization, models such as Elman's (1990) Serial Recurrent Network (SRN) have been quite successful in modeling human performance in the SRT task using associative mechanisms (e.g. Cleeremans & McClelland, 1991). The SRN captures statistical regularities in the pattern of responses and allows predictions to be made based on a limited temporal context of responses. However, models such as these presuppose that explicit representation of sequence knowledge is limited, and assume rule learning to be a separate, higher-order process. While it seems obvious that humans are capable of rule learning and hypothesis testing, the question of interest is whether these explicit processes have any place in sequence learning.

Where abstract relations between events can be described in ways that do not depend on the physical properties of those events, the content of rule learning often differs from that of instance learning (e.g. Natal, McLaren, & Livesey, 2013; Livesey & McLaren, 2009; Shanks & Darby, 1998;). It is possible to derive evidence for both rule and instance learning in an SRT task with appropriately constructed sequences. For example, Dominey et al. (1998) found that participants under implicit and explicit learning conditions were able to learn about surface contingencies in an SRT task, but only those in the explicit condition were able to learn about, and transfer their knowledge of, the underlying abstract rule. This study shows that what is learned in an SRT task depends on the learning conditions imposed, and while rule learning requires appropriate learning conditions (sufficient cognitive resources, or in this case, explicit instructions to search for a rule), instance learning can occur automatically.

In Dominey et al.'s (1998) study, evidence of a dissociation between the learning of abstract and surface structure was sought by testing transfer to sequences containing different surface features but the same abstract rule. An alternative approach used by Jones and McLaren (2009) is to allow participants to make a prediction about the target's location before the onset of the target, with the assumption that some sequences will benefit from an intentional search for sequences more than others. In a two-choice (X,Y) SRT task, Jones and McLaren found that participants given incidental learning conditions showed the strongest evidence of learning for subsequences containing an alternation (e.g. YYX, YXY) and the least evidence of learning for subsequences consisting of runs of the same response (XXX). However, when participants were presented with two cue positions and given instructions to predict what would happen on the next trial, this pattern of results was reversed, with the best learning occurring for the more salient XXX subsequences. This study shows that the effect of explicit instructions can differentially affect certain subsequences. Giving participants the intention to learn or alluding to the existence of sequences does not entail that all subsequences will benefit from these manipulations. However, the fact that learning in the SRT task is even affected by these manipulations suggests that sequence learning cannot be considered implicit in the traditional sense.

The translation of abstract rules to the performance of a concrete action is not necessarily a straightforward task, even when the rule is explicitly identified. Many researchers have assumed that it requires intentional mental effort (Gick & Holyoak, 1983; Gomez, 1997; Shanks & St. John, 1994). Although the rules used in the studies by Dominey et al. (1998) and Jones and McLaren (2009) could be explained verbally and symbolically, they were relatively complex. Once known, implementation of the rule involved retention of at least two items in working memory in order to use the abstract relationship to determine the next response.

In contrast, in this study a relatively simple rule was used; the sequence of response cues moved clockwise most of the time for some participants, and moved counterclockwise most of the time for others. This rule can be applied purely on the basis of the preceding response but was still abstract in the sense that it involved a relationship between at least two events and can be applied flexibly to any of the response cues in the sequence. Although the rule was probabilistic in nature and not necessarily obvious to participants performing the task, it was easy to describe and (we assumed) easy to implement once recognized explicitly. Thus the primary aim of current study was to explore the degree to which learning in an SRT task could be affected by explicit knowledge of an abstract rule describing the probabilistic contingencies in the task.

Experiment 1

Experiment 1 used a simplified version of the SRT task with three response locations (A, B and C, see Figure 1) and probabilistic contingencies to minimize hypothesis-testing strategies and the development of explicit sequence knowledge during training (see Jiménez & Méndez, 2001). The target never appeared in the same location twice in a row, meaning that each set of three consecutive responses in the sequence contained either three unique responses (XYZ, e.g. ACB, ABC) or a repetition of one response as the first and third in the set (XYX, e.g. ABA, ACA).

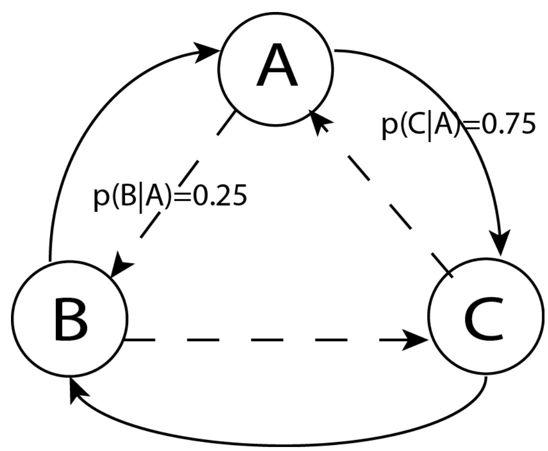

Figure 1. Illustration of the target positions (A, B, C) and an example of the contingencies arranged between them (in this case, resulting in a predominantly clockwise direction of motion). Curved, bold lines indicate cued trials (p = .75) and dotted straight lines indicate miscued trials (p = .25).

Experiment 1A sought to establish performance differences on these two subsequences using a single control group that performed the SRT task with a randomly generated sequence. Experiment 1B compared learning between two groups: a group given a hint before the experiment about the nature of the contingencies embedded within the target locations (hint group), and a group who did not receive a hint (no hint group). The contingencies were arranged such that most of the time, the target appeared to be moving in one direction (clockwise or counterclockwise), with the direction of motion randomly chosen for each participant. If the target was moving clockwise, for example, there was a .75 probability that the next location would be the next clockwise position (cued trials), and a .25 probability that the next location would be the next counterclockwise direction (miscued trials, and vice versa for counterclockwise, see Figure 1).

Since the contingencies were probabilistic, an explicit hint about the direction of motion would still mean that the location of the target on any given trial could not be predicted with complete accuracy. We expected that both groups in Experiment 1B would learn the sequence, but the group given the hint would show both better overall learning (a larger cueing effect) and higher levels of awareness in subsequent tests. Furthermore, we hypothesized that even with a simple abstract rule its application on each trial would not be straightforward. Since responses are made rapidly, there is little time to prepare for the next response based on the direction of motion. Thus, although the directional rule is applicable to every response, we expected that the effectiveness of the hint when applied to specific instances would be greater on the more salient XYZ subsequences than the XYX subsequences because the presence of a consistent direction of motion for several responses would facilitate the use of the rule.

Method

Participants and Apparatus In Experiment 1A, fifteen University of Sydney staff and students participated. In Experiment 1B, forty-six University of Sydney first year Psychology students participated in exchange for course credit. The experiment was programmed using PsychToolbox for Matlab (Brainard, 1997; Pelli, 1997) and run on Apple Mac Mini desktop computers connected to 17 inch CRT monitors, refreshed at a rate of 85 Hz. Participants made responses using a standard Apple keyboard and mouse. Testing was conducted in individual cubicles in groups of up to six.

Procedure For both experiments, participants performed a SRT task where they were asked to respond to a series of targets appearing in one of three positions (on the left, top and right) on the computer screen by pressing corresponding arrow keys. Training in both experiments was presented to participants in one continuous block of 720 responses. In Experiment 1A, the position of the target was completely random, such that no learning could occur. In Experiment 1B, the sequence of locations followed a probabilistic rule such that the sequence of response locations usually moved in a clockwise or counterclockwise direction around the screen, and each trial was either cued (75% of the time) or miscued (25% of the time, see Table 1). The direction of motion was randomly chosen for each participant.

Participants in Experiment 1B were allocated to either a hint or no hint group. The hint group received written instructions at the beginning of the experiment that stated that the target moved in either a clockwise or counterclockwise direction most of the time, and that their task was to work out which direction it went. The no hint group did not receive any explicit instructions about the possibility of an underlying sequence, nor did the control group in Experiment 1A. All participants were informed that they would have to respond as quickly and as accurately as possible to the targets appearing around the screen.

After the training phase, both groups in Experiment 1B were told that there was a pattern in the sequence of locations in the training phase, and they would now be asked questions about the sequence. Participants completed a recognition test and a prediction test, in counterbalanced order. Participants in Experiment 1A did not complete any awareness tests, as there were no contingencies to assess.

Table 1. *Probability of occurrence for each triplet type and conditional probability of the last response cue (cue t) in each triplet given the preceding cue (cue t-1).*

	p(triplet)	p(cue t | cue t-1)
XYZ – Cued	0.5625	0.75
XYZ – Miscued	0.0625	0.25
XYX – Cued	0.1875	0.75
XYX – Miscued	0.1875	0.25

Recognition Test On each trial in the recognition test, participants were presented with two sequences in which they had to respond to the target in the same way as in training. One of the two sequences was the same sequence they saw in training, and the other sequence was the opposite (the direction of motion was reversed). Each sequence contained 12 response cues and participants completed 10 trials. After responding to the two sequences, participants were asked to press a key to indicate which of the two sequences they thought was most similar to their training sequence.

Prediction Test The prediction test simply presented participants with the target in one of the three positions and asked which of the remaining two positions they would predict the next position to be. This test consisted of 3 trials (one for each of the target positions).

Results

All of the following RT analyses refer to response times on correct trials only, excluding responses > 1 second.

Experiment 1A Participants in Experiment 1A took on average 317ms to respond on XYZ trials (with 98% accuracy), and 363ms to respond on XYX trials (with 94% accuracy). Thus participants were both faster, $F(1,14)=119.91$, $p<.001$, and more accurate, $F(1,14)=21.81$, $p<.001$, on XYZ trials, relative to XYX trials. These performance differences indicated that the repetition of a recently-performed response on XYX trials interfered with fast and accurate responding, or conversely that performing all three responses without repetition facilitated responding. This effect was not based on differential contingencies (after each response, the remaining two cues were equally likely) and is similar to alternation effects found in other choice response tasks, which are most likely not based on sequence learning effects (e.g. see Barrett & Livesey, 2010). In any case, performance differences provided further impetus for examining the XYX and XYZ subsequences separately.

Experiment 1B: Training All trials were classified as being either cued or miscued, and the cueing effect taken as the difference between the cued and miscued trials.

Figure 2 shows the mean RTs for cued and miscued trials in Experiment 1B for both the hint (*n*=23) and no hint (*n*=23) groups, and the mean RTs for the control group (*n*=15) in Experiment 1A, across the 4 training quarters. It is evident that in both the hint and no hint groups, participants were slower to make a response on miscued trials, and faster to make a response on cued trials, relative to what would be expected without any contingencies (the control group). An ANOVA with group (hint x no hint) as a between-subjects factor, and cueing (cued x miscued) and quarter (1-4) as within-subjects factor revealed an overall cueing effect, $F(1,44)=344.15$, $p<.001$, and a marginal interaction with group, $F(1,44)=3.99$, $p=.05$, with the hint group exhibiting a larger cueing effect overall. There was also a significant linear trend in the cueing effect, $F(1,44)=74.17$, $p<.001$, which did not interact with group, $F<1$, indicating that the cueing effect increased during training.

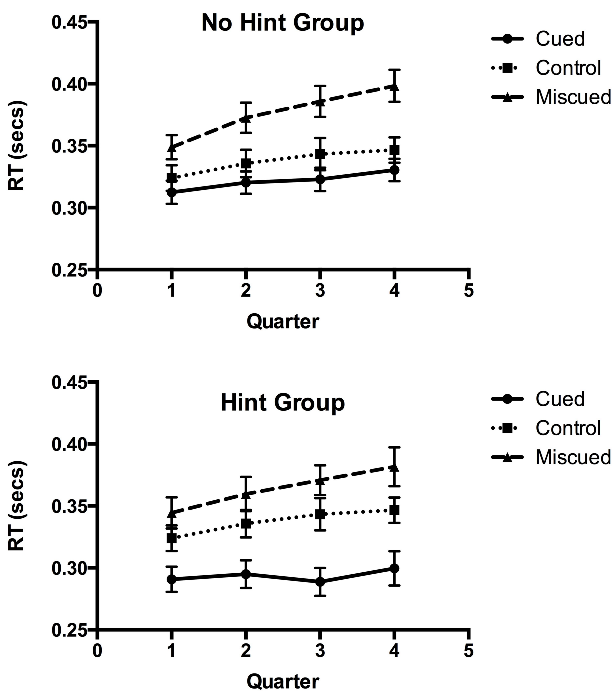

Figure 2. Mean reaction times for the hint and no hint groups in Experiment 1B, and mean reaction times for the control group in Experiment 1A.

To examine whether the effect of the hint differed between the two subsequences, a repeated measures ANOVA with cueing (cued x miscued), subsequence type (XYZ x XYX) and quarter (1-4) as within-group factors and group (hint x no hint) as a between-subjects factor was performed. As hypothesized, a significant 4-way interaction was found $F(3,132)=3.37$, $p=.02$. The cueing effect for both subsequence types and for both groups is shown in Figure 3. It is evident that while both the hint and no hint groups obtain similar cueing effects for the XYX subsequences across training, the hint group's cueing effect increased sharply in the 3rd quarter. This may be because it took participants in the hint group some time to translate the hint given at the start of the SRT task into confident knowledge about the direction of motion, and therefore for this knowledge to affect their performance.

There was a significant group difference for XYZ cueing, $F(1,44)=7.29$, $p=.001$, but not for XYX cueing, $F<1$. Thus it appears that the effect of the hint increased cueing for XYZ subsequences but not for XYX subsequences, relative to the no hint group.

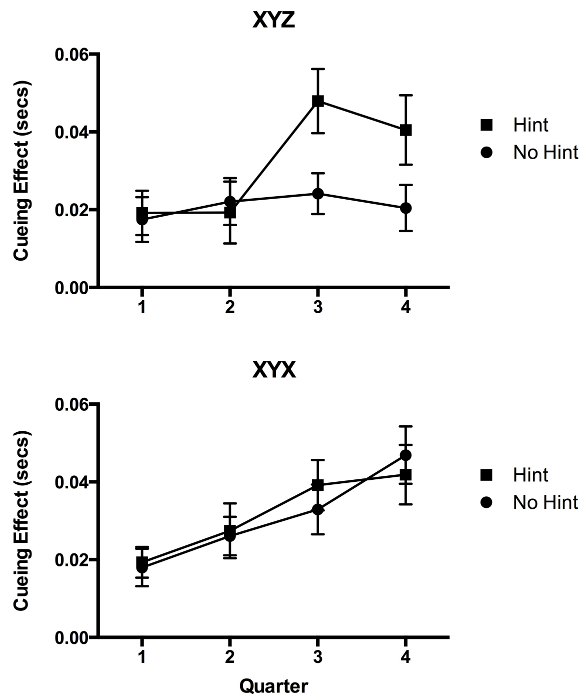

Figure 3. Cuing effect by training quarter in Experiment 1B, for both groups and subsequence types, showing a significant difference between hint and no hint groups for XYZ cuing, but not for XYX cuing.

Recognition Test The hint group showed a recognition score (61.1%) that was statistically above chance, $F(1,21)=8.56$, $p=.008$, while the no hint group did not (55.2%, $F<1$).

Prediction Test Mirroring the recognition test, the hint group showed a level of performance (65.4%) that was statistically higher than chance, $F(1,21)=8.06$, $p=.01$, and the no hint group did not (59.4%, $F(1,21)=1.58$, $p=.22$).

Cueing and Awareness To examine the relationship between awareness and cuing, each participant's recognition score was correlated with their cuing effect for XYZ and XYX sequences separately (Figure 4). There was a significant correlation between recognition and cuing for the

XYZ subsequences in the hint group only, $r(23)=.45$, $p=.03$. Comparing the correlation coefficients between groups, there was a stronger relationship between awareness and cuing in the hint group for XYZ subsequences ($r(22)=.45$) than the no hint group ($r(22)=.2$), $z=2.2$, $p=.028$.

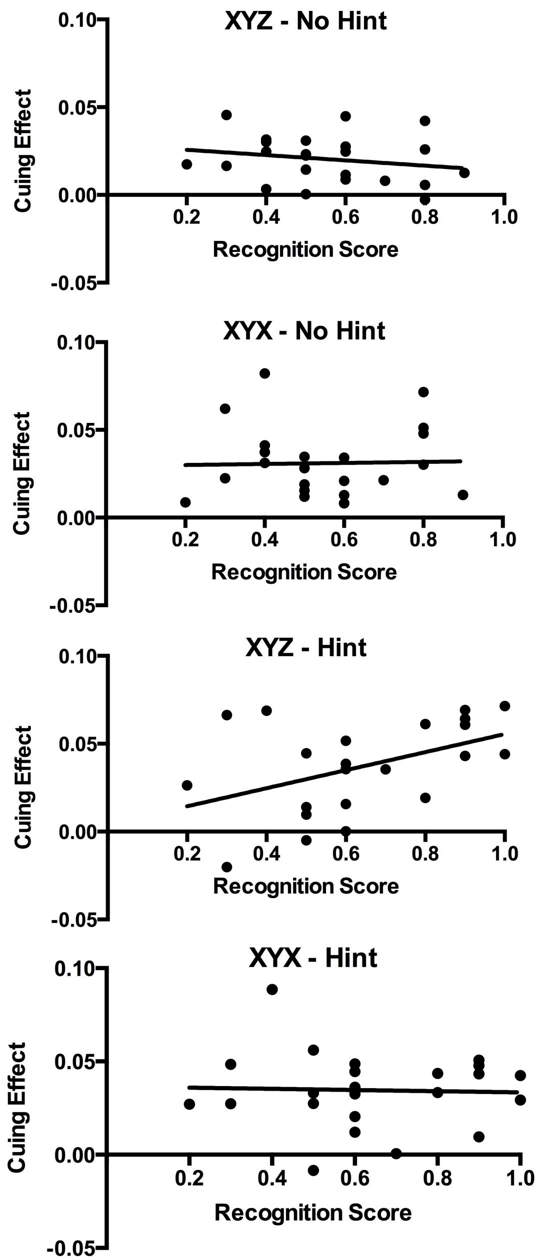

Figure 4. Scatterplots of the cuing effect (in seconds) as a function of recognition accuracy for each subsequence type (XYX and XYZ) and each group (Hint and No Hint) in Experiment 1B.

General Discussion

In this study, we observed a robust sequence learning effect using probabilistic contingencies arranged between 3 target locations in both a group given an explicit hint about an abstract rule underlying the contingencies and a no hint group who performed the task as usual. The hint group exhibited a marginally larger cuing effect overall and produced above-chance results on both a recognition and prediction test.

Experiment 1A demonstrated that participants were both faster and more accurate to respond on XYZ subsequences (consisting of 3 unique responses) than on XYX subsequences (when the response on the current trial is the same as the response 2 trials back) when there were no contingencies present. Closer inspection of the different subsequences indicated that the benefit of the hint group over the control group in Experiment 1B was only evident on subsequences that did not contain a repetition (XYZ), and that participants in both groups learned about subsequences with a repetition (XYX) equally well. While the hint group were able to produce results on the awareness tests at a level greater than chance, there was a significant correlation between cueing and recognition on XYZ subsequences only.

The results from this study suggest that the relationship between explicit abstract knowledge and performance in sequence learning tasks is complex. The SRT task utilized in this experiment shows a strong dissociation between two subsequence types – participants given an explicit hint about the underlying contingencies could use this knowledge to produce a larger cueing effect (relative to those given no hint) on XYZ subsequences, and the amount of cueing was related to how well those in the hint group performed in the recognition test. On the other hand, whether or not participants received the hint did not make any difference to the magnitude of the cueing effect on XYX trials, and the cueing effect was not correlated with recognition performance.

These results indicate that while the hint may have been successful in helping participants to discover the abstract rule amongst the contingencies, this knowledge could only be applied to XYZ trials and not XYX trials. One potential reason for this may be that certain subsequences are learned better in intentional learning conditions because they are more salient (see Jones & McLaren, 2009). The repetition of two clockwise or counterclockwise positions in the XYZ subsequences may be particularly salient if participants are searching for the correct direction of the target. This is in line with our initial prediction that the abstract information provided by the hint would be easier to implement (and thus produce a greater facilitatory effect) on trials where the direction of motion was consistent for several cues. An alternative reason may be simply that XYX subsequences are harder to respond to in general, and therefore applying explicit knowledge on these trials may also be more difficult. According to this explanation, whatever property of the XYX subsequences that produced the slower reaction time and lower accuracy in Experiment 1A might also be responsible for interfering with the expression of any knowledge of the sequence that participants had acquired.

While Experiment 1B demonstrated that giving participants explicit knowledge did affect their SRT performance, it is also obvious that this knowledge is not necessary to display a cueing effect. In fact, very robust cueing effects were evident in the no hint group, along with poor performance (not differing significantly from chance) on awareness tests. However, the fact that giving participants an explicit hint about the underlying sequence affected performance suggests that there is some degree of volitional control in sequence learning, and that learning is not impervious to cognitive influences such as intention to learn. However, whether or not explicit knowledge about an abstract rule can be expressed in sequence learning seems to be dependent on the properties of the subsequences to be learned.

In summary, this experiment demonstrates that sequence learning does not appear to be independent of explicit knowledge of the abstract relations between the cues in the sequence. However, participants are not able to apply their knowledge equally to all subsequences even when, in principle, the abstract relation applies to all instances. These results are most consistent with an explanation in which simple associations between events are learned and expressed relatively automatically, but explicit symbolic knowledge has a strong influence on performance only when specific conditions permit its use.

Acknowledgments

This research was supported by a University of Sydney Bridging Support Grant to EJL. The authors would like to thank Lauren Shone and Dorothy Kwok for helpful comments on an earlier version of this manuscript.

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