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ABSTRACT

This research explored the role that dissociable associative learning and hypothesis-testing processes may play in human sequence learning. Two two-choice SRT tasks were conducted, one under incidental conditions and the other under intentional conditions. In both cases an experimental group was trained on four sub-sequences (i.e. XXX, XYY, YYX and YXY). To control for sequential-effects, sequence learning was assayed by comparing their performance to a control group that had been trained on a pseudo-random ordering, during a test-phase in which both groups experienced effectively the same trial-order. Under incidental conditions participants demonstrated learning of the sub-sequences that ended in an alternation, but not of those that ended in a repetition. In contrast, under intentional conditions XXX showed the greatest evidence of learning. This dissociation is explained using a two-process model of learning, with an associative process (the Augmented SRN) capturing the incidental pattern, and a rule-based process explaining the advantage for XXX under intentional conditions.

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The ability to learn the sequences within which events occur or in which actions need to be performed is clearly important to many aspects of human life. Thus the question of whether human sequence learning should be modelled by a unitary mechanism or functionally separable processes is of importance and interest. One popular means of exploring this question in the laboratory has been to employ the serial reaction time (SRT) task, which was developed by Nissen and Bullemer (1987) and Lewicki, Czyzewska and Hoffman (1987). In the standard version of this task, on each trial a stimulus appears in one of several locations on a computer screen. Participants simply have to press the response key that corresponds to its location, as quickly and accurately as possible. Crucially, the order of locations in which the stimulus appears follows a sequence, at least for the majority of the time -a fact that is usually concealed from the participants. It is commonly found that their reaction time (RT) on trials that obey the sequence becomes significantly faster either than their RT on probe trials that are inconsistent with the sequence, or the RT of a control group that experiences a pseudo-random ordering (e.g. Anastasopoulou & Harvey, 1999; Cleeremans & McClelland, 1991; Shanks, Green & Kolodny, 1994). This is taken to indicate that the participants have learnt at least part of the sequence, and that they are using this information to prepare for the stimulus' arrival on the next trial.

In many studies, the SRT task is followed by one or more 'direct' measures of the participants' knowledge of the sequence; these measures have included questioning the participants about their sequence knowledge (e.g. Nissen & Bullemer, 1987), testing their ability to predict what comes next in the sequence (e.g. Nissen & Bullemer, 1987; Willingham, Nissen & Bullemer, 1989), asking them to freely generate parts of the sequence (e.g. Jiménez, Méndez & Cleeremans, 1996; Perruchet & Amorim, 1992), and determining whether they recognise parts of

the sequence (e.g. Perruchet & Amorim, 1992; Shanks & Johnstone, 1999). In some of these studies, people's performance on the SRT task has appeared to dissociate from that on the direct measures, in that they seem to show evidence of sequence knowledge on the SRT task that they do not express on the direct tests (e.g. Jiménez et al., 1996; Reed & Johnson, 1994; Willingham et al., 1989). Some authors have taken this to indicate that some of the sequence learning during the SRT task can be unconscious and occurs by an unconscious learning process that is functionally distinct from the learning process that we have conscious access to and control of (e.g. Willingham, Greeley & Bardone, 1993). Following McLaren, Green and Mackintosh (1994), this stance raises the possibility that sequence learning in humans could be in part based on associative processes similar to those found in other animals, and that these operate independently of more rule-based, strategically controlled learning.

However, those studies that have shown a dissociation have either not been replicated or methodological concerns have been raised about them, which have included questions over whether the direct measure was sensitive enough (e.g. Shanks & St John, 1994), whether it was measuring the same knowledge as the SRT task (e.g. Shanks & St John, 1994), whether the participants may have had different response biases on the different tasks (Shanks & Johnstone, 1999), and whether sequential-effects had been adequately controlled for (Anastasopoulou & Harvey, 1999); this latter issue will be returned to in more detail shortly.

More recently, Destrebecqz and Cleeremans (2001) have applied Jacoby's (1991) process dissociation procedure to SRT sequence learning. Specifically, following an SRT task they asked human participants to generate a series of trials that contained sequences from the SRT task (the

inclusion phase) and then generate a trial order that did not contain any SRT sequences (the exclusion phase). Crucially, when the response to stimulus interval (RSI) was 0 ms, the participants showed evidence of sequence knowledge in the exclusion phase, suggesting that some of their sequence learning from the SRT task was not accessible to conscious control at that time. However, Wilkinson and Shanks (2004) have failed to replicate this finding, calling it into question.

Perhaps the strongest evidence for implicit influences on SRT performance comes from Shanks and Perruchet (2002), who followed their SRT task with a recognition test. On each trial of this test the participants had to react to a short series of stimuli as they would in an SRT task, before rating the extent to which they recognised that series of locations as having occurred in the preceding SRT task. Some of the series were novel, while others were taken from the SRT task. It was found that during the recognition test participants responded faster to old series than to novel series that they gave the same recognition rating to. This suggests that some of the sequence knowledge that they were using to improve their speed of responding during the recognition test was not accessible to consciousness at that time, since it did not affect their recognition judgements. However, this does not necessarily imply that sequence learning during the original SRT task occurred via separate conscious and unconscious learning processes because, as Shanks and Perruchet formally demonstrate, it is possible that this dissociation may simply reflect the operation of different, noisy, retrieval processes acting on one knowledge store (see also Shanks, 2003).

Stronger evidence to support dissociable sequence learning processes would be provided if it could be shown that participants learnt the same SRT sequences qualitatively differently under intentional and incidental learning conditions. Dominey, Lelekov, Ventre-Dominey and Jeannerod (1998) attempted to demonstrate this by training their participants on a sequence that had both a surface and more abstract structure. Participants in an intentional condition were told the abstract rule before the SRT task, while participants in the incidental condition were simply asked to react. Both groups showed some learning of the surface contingencies, but only the intentional group exhibited knowledge of the abstract rule on a transfer test in which the surface features were changed. This result is consistent with the operation of dissociable learning processes, with one process having acquired the rule and another being sensitive to surface contingencies, and this two-process view finds support from evidence from studies outside the domain of sequence learning (for reviews see Shanks, 1995; Shanks & St John, 1994). However, this result could also be explained by a single-process model that assumes that more abstract information is simply more difficult to learn and so will only be acquired under more favourable (i.e. intentional) conditions.

More recently, Jiménez, Vaquero and Lupiáñez (2006) have shown that participants trained on an SRT task under intentional conditions, in which they were instructed to search for sequences, were able to transfer their sequence learning when the task's surface features were changed, while incidental learners were not. On the other hand, when the transfer test retained the surface features but involved a substantial reduction in the proportion of trials that were consistent with the sequence, incidental learners showed transfer of learning while intentional learners did not, presumably because the latter withheld expression of their sequence knowledge. These findings

are consistent with the operation of separate, interacting learning processes, but do not necessitate this. For example, Jiménez et al. (2006) describe how they can be explained within a dynamic framework in which explicit learning can develop out of strengthening implicit learning.

Better evidence for dissociable sequence learning processes would be provided if it could be shown that some sub-sequences were learnt more strongly than others under incidental conditions and that this pattern reversed, or changed in some way, under intentional conditions. To the best of our knowledge such evidence does not currently exist. In fact, we have been unable to find any methodologically sound patterns of sub-sequence learning from the SRT literature. In part this is because, as has been pointed out by Anastasopoulou and Harvey (1999), the majority of SRT studies that have produced a pattern of sub-sequence learning as part of their dataset have failed to adequately control for 'sequential-effects'.

For the purposes of this paper, sequential-effects will be defined as the influence that the series of stimulus (and so also response) locations over the current and previous trials has on the participant's current response, in an SRT task in which the trial order is random or pseudo-random (cf. Jentzsch & Sommer, 2002; Soetens, Boer & Hueting, 1985). For example, in a two-choice SRT task with a long RSI, people will tend to respond more quickly when the stimulus keeps reappearing in the same location, or when it continues to alternate back and forth between the two locations (Soetens et al., 1985). Many previous SRT studies (e.g. Jiménez et al., 1996; Nissen & Bullemer, 1987) have failed to fully control for sequential-effects, because they have assayed sequence learning by comparing participants' performance on trials that obeyed the

sequence with either their performance on inconsistent probe trials or on a pseudo-random ordering**,** or with the performance of a pseudo-random control group (cf. Anastasopoulou & Harvey, 1999; Curran, Smith, DiFranco & Daggy, 2001; Shanks & Johnstone, 1999). In all these cases 'sequence' and 'control' performance was being assessed on different trial-orders and so differences in RT could arise as a consequence of changes in sequential-effects, as well as sequence learning. Some studies (e.g. Jiménez et al., 1996) have partially controlled for sequential-effects by disregarding those trials that contained immediate alternations or repetitions. However, this may not be sufficient because sequential-effects also occur following other trial-orders, albeit more subtly (e.g. Anastasopoulou & Harvey, 1999; Soetens et al., 1985). Furthermore, those studies that do appear to have adequately controlled for sequential-effects (Anastasopoulou & Harvey, 1999; Shanks & Johnstone, 1999) do not discuss the error data in sufficient detail to rule out the influence of speed-accuracy trade-off on the patterns of sub-sequence learning that they describe.

Therefore, one of the primary aims of the research reported in this paper was to establish patterns of SRT sub-sequence learning for incidental and intentional conditions, in order to determine whether these dissociated and so provided evidence consistent with the operation of separable sequence learning processes. A corollary issue addressed by this research was to offer some clue as to the nature of these dissociable processes if evidence for them was forthcoming. In particular, the question of whether it might be appropriate to use an associative / rule-based distinction to characterise learning under incidental / intentional conditions was very much in our minds.

If performance under incidental conditions is associative then we might expect the detailed pattern of sub-sequence learning to be governed by the principles suggested by other examples of human associative learning in the sequential domain (e.g. Spiegel & McLaren, 2006; Cleeremans & McClelland, 1991); specifically, that learning be driven by error-correction and be influenced by the short-term priming effect of learning on recent trials. Given this, our analysis suggests that we might expect to observe poor learning of sub-sequences comprising repetitions, relative to other sub-sequences, under incidental conditions. To illustrate this, it is worth briefly considering a connectionist instantiation of these principles.

The SRN (Simple Recurrent Network; Elman, 1990), which will be described in detail later, provides one such instantiation. Our initial expectations in relation to relatively poor performance on sub-sequences comprising repetitions were based on the APECS-SRN (e.g. Jones, Le Pelley & McLaren, 2002). However, we will model the sequence learning described in this paper using a variant of the SRN called the Augmented SRN (Cleeremans & McClelland, 1991), as this is a more established model. We will show that the Augmented SRN fails to learn a sub-sequence comprising repetitions (i.e. XXX), and argue that this is because, when the Augmented SRN is exposed to our sub-sequences, it repeatedly learns the mappings: [memory + first trial -> second trial] followed next trial by [memory + second trial -> third trial]. For sub-sequence XXX the mapping from first trial to second trial [irrelevant information + X -> X] and from second to third [memory of X + X -> X] are very similar. Therefore, we believe that the short term priming effect of the learning of the first mapping reduces the error term for the second mapping, thus reducing learning of this second mapping, since learning occurs by error-correction and so is proportional to the level of error. Furthermore, learning of this second

mapping is critical to learning sub-sequence XXX, since our sub-sequences (i.e. XXX, XYY, YYX and YXY) require the learner to be sensitive to the previous two trials, and only this second mapping contains information from the previous two trials. Therefore, difficulty learning the second mapping translates into difficulty learning the sub-sequence.

Thus, by this account, an associative mechanism employing error-correction and exhibiting short-term priming of recent learning should find sub-sequences comprising repetitions particularly difficult to learn. Therefore if, under incidental sequence learning conditions, human participants engage associative learning processes that follow these principles then we might expect to observe such an effect.

In contrast, we will also show that sub-sequences comprising repetitions are highly salient when participants are hypothesis-testing. Therefore, we will suggest that relative performance on sub-sequences comprising repetitions, such as XXX, has the potential to be used as a marker as to whether people are engaging error-correcting associative learning or rule-based hypothesis-testing.

EXPERIMENT ONE

Our first task was to identify the pattern of sub-sequence learning under incidental conditions to establish if it could in fact be modelled associatively; this was the purpose of Experiment One. In the majority of previous SRT studies the stimulus has appeared in four or more locations (e.g. Anastasopoulou & Harvey, 1999; Cleeremans & McClelland, 1991). However, to maximise the power of the inter-sub-sequence comparisons, it was decided to limit the number of locations to

two and the number of sub-sequences to four. Therefore the experiment comprised a two-choice SRT task, with Experimental and Control Groups. During training, the former were exposed to the sequential contingencies while the latter experienced a pseudo-random order. Both prior to and following training, the two groups received a test-phase during which the trial-order was pseudo-random. Thus, a pattern of sub-sequence learning could be established by comparing the post-training performance advantage of the Experimental Group over Control on each of the four sub-sequences. This design controlled for sequential-effects because the two groups experienced effectively the same trial-order on test, and so any reliable difference in their performance could only be due to the fact that one was previously exposed to the sequential contingencies while the other was not. Finally, as in other SRT studies (e.g. Nissen & Bullemer, 1987), after a short period of retraining the participants' verbalisable knowledge of the contingencies was assessed using a structured interview.

Method

Participants. The 24 participants, whose ages ranged between 18 and 47, were university students and members of the general public. Sixteen were randomly assigned to the Experimental Group, with the remainder forming the Control Group. Each participant's earnings were set to £15 Sterling at the start of the experiment, and to promote fast and accurate responding a bonus was added to this figure after every block. It was calculated using the formula:

$$\text{bonus} = (400 - \text{RT}) \times (\text{accuracy} - 90) / 100 \qquad 1$$

where the bonus, RT and accuracy were measured in pence, milliseconds and as a percentage respectively. Participants never received a negative bonus and they were paid a minimum of £24

after the six sessions, if their total earnings fell below that level (though they were not told this in advance).

Apparatus and Display. The two-choice SRT task was run on a Macintosh computer, with the display comprising the white outlines of two circles, 1.9cm in diameter, on a black background. These were positioned such that the centre of one was 2.2cm to the left of the middle of the screen, and the centre of the other was 2.2cm to the right of the middle. The stimulus was a white filled-circle, 1.9cm in diameter. On each trial this took the place of either the left or right outline circle, until the participant pressed a response key. The response keys were spatially compatible with the two stimulus locations, with the 'x' key on a QWERTY keyboard corresponding to the left location and the '>' key to the right.

Design. The two-choice SRT task lasted six sessions, with the inter-session interval typically being between 24 and 48 hours. Every session prior to the sixth consisted of 20 blocks. As shown in Table 1, blocks 1 to 10 of the first session and blocks 11 to 20 of the fifth session had a pseudo-random trial order, and formed the pre- and post-training test-phases respectively. The 80 blocks between these constituted the main training-phase. The purpose of session six was to provide a reminder treatment, following the pseudo-random blocks of the post-training test-phase, before participants' verbalisable sequence knowledge was assessed in a structured-interview.

---- Table 1, about here please. -----

Block Construction. To enable counterbalancing, the blocks were constructed in terms of Xs and Ys. For a randomly selected half of the participants in each group, X corresponded to the stimulus appearing on the left of the screen and Y the right, while the opposite assignment applied for the remainder. The pseudo-random SRT blocks were generated by concatenating 5 of each of the following trial triplets, in an arbitrary order: XXX, XYY, YYX, YXY, XXY, XYX, YYY and YXX. Sequence blocks were constructed in a similar manner except that they comprised 10 of each of the 'sub-sequences' XXX, XYY, YYX and YXY. Thus, in both cases continuous strings of 120 trials were produced. In addition, to compensate for initial variability in participants' responses (cf. Cleeremans & McClelland, 1991), if a block was to be the first of a session then its 120 trials were preceded by 5 further triplets, that were randomly selected from the pool used in pseudo-random block construction. However, this did not apply to the first session, since participants were given a pseudo-random practice block before beginning the experiment proper. The data from this practice block, and the 15 extra trials at the start of the other sessions, were not included in the analysis.

It is worth briefly considering a number of the consequences of this method of block construction that are important to the subsequent analysis of this experiment, and which have been confirmed by Monte-Carlo simulations. First, excluding the 15 extra trials at the start of a session, the identity of every third trial of a sequence block is predictable on the basis of the previous two trials and conforms to the rule: 'if the previous two trials are the same then it is an X, and if they differ then it is a Y'. Participants were not informed about this special status of the third trials in the sequence blocks and the response-stimulus interval following third trials was the same as after all the other trials.

Second, if a sequence block is considered on a trial-by-trial basis, the identity of approximately two-thirds of the trials is consistent with the above-mentioned rule. In other words, approximately two-thirds of the trials have the appropriate ending to the sub-sequence started by the previous two trials (i.e. XXX, XYY, YYX or YXY; where the underlined letter represents the stimulus' location on the current trial), while the remaining trials have endings that are inconsistent with the sub-sequences (i.e. XXY, XYX, YYY or YXX). The fraction two-thirds arises because the third trial of each triplet (and so one third of the total number of trials) must be consistent with the rule, due to the method of sequence block construction, and half of the remaining trials (another third) will also be consistent by chance. We thought that this combination of both probabilistic and deterministic structure might increase the chances of obtaining a dissociation in sub-sequence learning between incidental and intentional conditions.

Third, during sequence blocks, on average, participants received an equal amount of training on all four sub-sequences, both if just the third trials are considered and on a trial-by-trial basis. Thus, differential learning of the sub-sequences cannot trivially be attributed to differences in the amount of training.

Fourth, for each sub-sequence participants needed to be sensitive to the two previous trials to allow them to predict what was likely to come next; the two trial types, namely X and Y, were equally common; and the frequencies of repetitions and alternations were also, on average, equivalent. These properties eliminated a number of further unwanted, trivial, potential causes of differential sub-sequence learning.

Finally, during a pseudo-random block, whenever a participant was presented with the first two trials of a particular sub-sequence (e.g. XX), half of the time the next trial was consistent with the rule and so completed the sub-sequence (e.g. XXX) and the other half of the time it was inconsistent with it (e.g. XXY), on average. This applied both if the participants just tried to predict the third trials and if they prepared for every trial on the basis of the previous two. Hence, during the post-training test-phase, which comprised pseudo-random blocks, the extent to which the Experimental Group learnt a particular sub-sequence could be assessed both by measuring how much faster and more accurate their responding was relative to the Control Group on trials consistent with the sub-sequence and by observing how much slower and less accurate than Controls they were on trials inconsistent with the sub-sequence.

Procedure. The participants were told that the purpose of the experiment was to enable the experimenter to 'learn more about the effects of practice on people's ability to respond quickly to stimuli' and that on each trial they had to press the response key that corresponded to the stimulus' current location. They were instructed to respond as quickly as possible whilst avoiding errors, and informed that doing so would maximise the amount of money that they would be paid. No mention was made of any sequence. These instructions were followed by a practice phase that comprised a pseudo-random block, before the main SRT task commenced.

On each trial the stimulus remained on the screen until the participant had responded or was timed-out, not having pressed a key within 4.25s of the stimulus onset. RT was measured from the stimulus onset until the computer detected a key press, and the 500ms response-stimulus-

interval (RSI) was measured from the onset of the response until the next onset of the stimulus (and hence included 'time-on-key'). If participants pressed an incorrect key or were timed-out then the trial terminated and the computer issued a beep. Similarly, if they anticipated a stimulus, that is responded less than 100ms after its onset, then the trial was aborted and a beep sounded. In these cases, the 500ms interval before the next onset of the stimulus was measured from the start of the beep. Following each block, participants were told how fast and accurate they had been, given the new value for their total earnings up to that point, and had a rest break that lasted for a minimum of 30s.

The structured interview directly followed the last SRT block of session six. During this, the experimenter noted the participants' answers to a series of questions, including whether they thought that the trial-order was random and, if not, whether they could describe any of the sequences that it followed.

Results and Discussion

SRT Task. To determine whether sequence learning had occurred and, if it had, the consequent pattern of sub-sequence learning, the data from the 10 blocks of the post-training test-phase were analysed. The dependent measures were the mean of the RTs from trials on which correct responses were made and the proportion of errors. As in other studies (e.g. Buchner, Steffens, Erdfelder & Rothkegel, 1997), the data from any trial that immediately followed an error were excluded, given that an error can influence subsequent responding (Laming, 1979). Also, the data from any trial on which a participant was timed-out, made an

anticipatory response, or pressed a key other than the two designated were ignored, as were the data from the following trial. These exclusion principles were applied to all the analyses of SRT data presented in this paper. In addition, all the tests presented in this paper have been evaluated at the two-tailed level, and adjustments for violations of sphericity (e.g. Greenhouse-Geisser) or homogeneity of variance are only reported where these adjustments affected whether the p-value achieved significance or not.

The RT data from every third trial of the test-phase were divided up with respect to the identity of the previous two trials (i.e. XX, XY, YY and YX), and then further classified on the basis of whether the third trial was consistent with the sub-sequence begun by the previous two trials (e.g. XXX) or inconsistent with it (e.g. XXY). For the Control Group 'consistency' was a dummy variable that was determined by nominally assigning one version of the set of sub-sequences (i.e. RRR, RLL, LLR and LRL, where L=left and R=right) to a randomly selected half of the group, and allotting the counterbalanced set (i.e. LLL, LRR, RRL and RLR) to the remainder.

On a per participant basis, for each of the resulting eight trial types a mean RT was calculated. Then, for each of the four sub-sequences, a difference score was generated by subtracting the mean consistent RT from the mean inconsistent RT. This difference measure was employed in order to reduce variability, by subtracting out between-participant baseline differences in performance. If sequence learning occurs, it should produce longer RTs on inconsistent trials and shorter RTs on consistent ones, and so should inflate the difference scores of the Experimental Group relative to the Control Group.

Recall that during training the sequential contingencies could have been learnt on a trial-by-trial basis, since in sequence blocks approximately two-thirds of the trials represented the correct completion of the sub-sequence begun by the previous two trials. Therefore, RT difference scores for the data from 'first' and 'second' trials in the post-training test-phase were also calculated, using the same method as described above for third trials. This resulted in each participant having twelve RT difference scores (i.e. 4 sub-sequences x 3 trial-positions).

The same procedure was followed to create twelve proportion of errors difference scores for each participant. As with the RTs, sequence learning should produce larger difference scores for the Experimental Group than Control, because it should lead to more errors on trials that are inconsistent with the sub-sequences and fewer errors on trials consistent with them.

The RT and proportion of errors difference scores were each analysed using a mixed ANOVA, with 'group' (experimental vs. control) as a between-subject factor, and 'trial-position' (first, second or third) and sub-sequence (XXX, XYY, YYX and YXY) as within-subject factors. The main effect of group in both the RTs and errors revealed that the Experimental Group's difference scores were significantly larger than the Control Group's scores, indicating that sequence learning had occurred (RTs: $F(1,22)=45.69$, $p<.001$; errors: $F(1,22)=5.98$, $p<.05$).

For both the RTs and errors, the main-effect of trial-position and all the interactions involving this factor were not significant (all $p>.1$). Furthermore, an inspection of the means revealed that the trends in the difference scores were similar across the three trial-positions, suggesting that the

failure to reach significance was not due to a lack of power. Thus it appears that participants learnt the probabilistic version of the contingencies that occurred on a trial-by-trial basis and did not have knowledge of the special status of third trials, which is unsurprising since third trials were not marked in any way and the RSI following third trials was identical to that following first and second trials. Given the lack of difference, it is reasonable to consider the pattern of sub-sequence learning collapsed across trial-position. This is presented in Figure 1.

---- Figure 1, about here please. ----

The group by sub-sequence interaction was significant in the error data ($F(3,66)=2.92$, $p<.05$) and this was supported by a non-significant trend in the same direction in the RTs, excluding the possibility of speed-accuracy trade-off. Thus, there was evidence of differential sub-sequence learning. To elucidate this interaction a simple-effects analysis was conducted by performing trial-position by group ANOVAs separately on the error difference scores for each sub-sequence. To control for inflation of family-wise alpha due to multiple comparisons, the Bonferroni correction was applied by multiplying the p-values by four. This analysis revealed that the difference scores did not significantly differ between the Experimental and Control Groups for sub-sequences XXX and XYY (both main effects of group: $F(1,22)<1$), and an exploratory simple-effects analysis of the RTs revealed the same (main effect of group: $F(1,22)<1$ and $F(1,22)=1.70$, $p>.1$ respectively). Thus there was no evidence of reliable learning of sub-sequences XXX and XYY from the test-phase data.

In contrast, the simple-effects analysis of the errors revealed significant evidence of learning of YYX ($F(1,22)=11.75$, $p<.01$). Furthermore, the main effect of group was very close to significance for sub-sequence YXY ($F(1,22)=6.95$, $p=.06$), and arguably the failure of this to reach significance might represent a Type II error, as the Bonferroni correction can sometimes be overly conservative (Clark-Carter, 1997). The main effects of trial-position and the group by trial-position interactions were all non-significant ($p>.1$), with or without the Bonferroni correction, reinforcing the idea that participants had not learnt about the special status of third trials.

It is possible that the pseudo-random contingencies in the 10 blocks of the test-phase may have led to unlearning of some of the sequential contingencies or affected the expression of these. For example, without the potential unlearning effect of the pseudo-random blocks, the evidence for learning of YXY might well have achieved full significance. Therefore, it is worth also considering the pattern of sub-sequence learning in the 10 training blocks immediately prior to the post-training test-phase.

However, since the Experimental and Control Groups experienced different types of trial order during the training blocks, an analysis of sequence learning using the same method as for the test-phase would not control for sequential-effects. To illustrate, consider a trial that was inconsistent with sub-sequence XXX. In this case, the current trial and the two trials preceding it would have been the same for both the Experimental and Control Groups (i.e. XX**Y**, where the underlined letter represents the current trial and preceding letters denote previous trials). However, the likelihood of this triplet being preceded by an X or Y would have varied between

the groups, with XXX**Y** and YXX**Y** being equally probable in the Control Group, but XXX**Y** being more likely to occur than YXX**Y** in the Experimental Group. Thus, any difference in the groups' performance on XX**Y** could be attributable to sequential-effects rather than sequence learning.

Therefore, to control for sequential-effects, for each participant the RT difference score for sub-sequence XXX was calculated as follows. First, the mean RT for the last trial of each of the trial strings XXX**Y**, YXX**Y**, XXX**X** and YXX**X** was calculated; the data from every relevant trial of the 10 training blocks were included in these calculations, not just from every relevant fourth trial. Then, the mean RT for trials consistent with XXX was calculated, by averaging the mean RTs for YXX**X** and XXX**X**, and the mean RT for inconsistent trials determined by averaging the mean RTs for YXX**Y** and XXX**Y.** Finally, as in the analysis of the test-phase, the RT difference score for each participant was constructed by subtracting the mean RT for the consistent triplet (XX**X**) from the mean RT for the inconsistent one (XX**Y**).

By equally weighting each of the trial-orders four in length in this manner, sequential-effects up to the third order were controlled for. It was not possible to control for sequential-effects of a higher order, since some of the necessary trial-orders five in length did not occur during sequence blocks. However, through an examination of the Control Group data, we estimate that the potential artefact produced by not controlling for fourth-order sequential-effects is only of the order of 1 ms.

A similar process was followed to create the RT difference scores for the other sub-sequences, as well as the proportion of errors difference scores for all the sub-sequences. As with the previous analysis, consistency was a dummy variable for the Control Group. However, in contrast to this analysis, it was not possible to construct separate difference scores for each trial-position, since not all the necessary trial-orders occurred for every trial-position (e.g. YXXY could never end on a third trial in a sequence block, because third trials were always consistent with the sequential contingencies). Therefore, the data were analysed collapsed across trial-position. Given that there was no evidence for differing performance across trial-position in the test-phase, this did not seem problematic.

---- Figure 2, about here please. ----

The mean RT and error difference scores are shown in Figure 2. Group by sub-sequence ANOVAs were performed. These confirmed that sequence learning had occurred, since the Experimental Group's difference scores were significantly larger than the Control Group's (RTs: $F(1,22)=63.93$, $p<.001$; errors: $F(1,22)=21.91$, $p<.001$). There was also evidence of differential sub-sequence learning, since the sub-sequence by group interaction was significant in the RTs ($F(3,66)=3.07$, $p<.05$), and the non-significant trend in the same direction in the errors ruled out speed-accuracy trade-off.

To explore this interaction one-way ANOVAs, with group as a between-subject factor, were performed separately on the RT difference scores for each sub-sequence, and the Bonferroni correction was applied by multiplying the p-values by four. Consistent with the findings from the

test-phase, the ANOVAs provided no evidence of learning of XXX or XYY ($F(1,22)<1$ and $F(1,22)=4.77$, $p>.1$ respectively). To check that the error data did not contradict this, exploratory Bonferroni-corrected, one-way ANOVAs were conducted on the error difference scores for these sub-sequences. Again there was no evidence of learning ($F(1,22)<1$ and $F(1,22)=1.28$, $p>.1$ respectively).

Turning to YYX and YXY, the simple-effects analysis of the RT difference scores provided evidence of significant learning of both these sub-sequences ($F(1,22)=14.98$, $p<.01$ and $F(1,22)=20.78$, $p<.01$ respectively). And the exploratory simple-effects analysis of the errors again supported the pattern in the RTs ($F(1,22)=16.48$, $p<.01$ and $F(1,22)=10.92$, $p<.05$ respectively). Thus the pattern of differential sub-sequence learning in the training data is arguably very similar to that in the test-phase, with the marginally significant evidence of learning for YXY now reaching full significance; this improvement probably being due to the absence of unlearning produced by the pseudo-random contingencies in the test-phase. Moreover, the similarity in the patterns suggests that any artefact in the training data due to not controlling for sequential-effects above the third-order has not materially affected the findings.

However, the apparent absence of learning of XXX in the training and test difference score data might have been due to a floor effect, since control participants had particularly short RTs on trials consistent with XXX. To investigate this possibility, the data from only the inconsistent trials in the 10 training blocks immediately prior to the test-phase were examined. These data were selected because a floor effect could not have reduced the impact of sequence learning on inconsistent trials, since learning would have made the participants slower and less accurate on

these trials and so moved them away from floor. As illustrated in Figure 3, the pattern of sub-sequence learning remained the same. Moreover, a group by sub-sequence ANOVA again provided evidence of significant sequence learning (main effect of group: RTs: $F(1,22)=6.75$, $p<.05$; errors: $F(1,22)=4.83$, $p<.05$) and differential sub-sequence learning (group X sub-sequence: RTs: $F(3,66)=3.27$, $p<.05$; errors: $F(3,66)=0.72$, $p>.1$). And subsequent Bonferroni-corrected t-tests revealed significant learning of YXY and YYX (respectively, RTs: $t(22)=3.50$, $p<.01$ and $t(22)=2.86$, $p<.05$; errors: $t(22)=1.31$, $p>.1$ and $t(22)=3.35$, $p<.05$), while there was no evidence of learning of XXX or XYY (respectively, RTs: $t(22)=0.61$, $p>.1$ and $t(22)=1.87$, $p>.1$; errors: $t(22)=0.74$, $p>.1$ and $t(22)=1.27$, $p>.1$). Therefore, the pattern of sub-sequence learning was not an artefact produced by a floor effect.

---- Figure 3, about here please. ----

In summary, the pattern of sub-sequence learning demonstrated on the SRT task under incidental conditions seems clear: there was no evidence of learning of the sub-sequences that end in a repetition (i.e. XXX and XYY) while the sub-sequences that end in an alternation (i.e. YYX and YXY) do appear to have been learnt. We will present a formal simulation of this later, which demonstrates that the Augmented SRN can capture this pattern and that, therefore, it can be explained by an associative process that instantiates error-correction and the short-term priming effect of recent learning.

Structured Interview. The most striking finding from the structured interview was that, while the Experimental Group did not seem able to verbalise sufficient sequence knowledge to account

for their performance on the SRT task, the majority of them (9 out of 16) did report knowledge that they appeared not to use on the SRT task. Specifically, they stated that there were longer runs of Xs than Ys or described long strings of Xs (though obviously they phrased this in terms of lefts and rights). These observations were accurate, because the longest string of Ys possible during sequence blocks was produced by sub-sequence XYY followed by sub-sequence YYX, whereas far longer strings of Xs could have occurred if sub-sequence XXX repeated. It is worth noting that equivalent long runs of alternations cannot occur in sequence blocks, because YXY followed by YXY includes a repetition of Y at the join. The longest series of alternations possible in a sequence block would be that contained in YYX, followed by YXY, followed by XYY.

It seems reasonable to assume that if the participants had used their knowledge of the runs of Xs on the SRT task then they would have shown learning of sub-sequence XXX, since their expectation of an X following a string of Xs should have increased. Yet they did not demonstrate reliable learning of this sub-sequence. One possible explanation of this discrepancy runs as follows. It seems probable that at least some of the participants tried to improve their performance, and so inflate their monetary reward, by reducing the extent to which they consciously anticipated the next stimulus. At first sight this may seem paradoxical. However, the complexity of the contingencies and their non-deterministic nature on a trial-by-trial basis meant that the participants' anticipations would have frequently been wrong, and this could have reduced their speed and accuracy both on the anticipated trial and on subsequent trials if they made an error (cf. Laming, 1979). Moreover, even though they were not directly questioned about it, some participants did indeed report that they stopped trying to anticipate the next

stimulus location in order to improve their performance. This could explain why the participants refrained from expressing their knowledge of the longer strings of Xs.

But, if they were not trying to anticipate, why then did they demonstrate learning of those sub-sequences that ended in an alternation? Recall that Jiménez et al. (2006) have provided evidence that people are more likely to withhold intentional learning than incidental learning when the learning does not seem helpful to performance. Therefore, it does not seem unreasonable to assume that during Experiment One the participants' learning about those sub-sequences that ended in an alternation either was under weaker conscious control than their verbalisable knowledge of the long strings of Xs (which was a more global and perhaps more salient pattern), or was not amenable to conscious control at all.

These data are consistent with the existence of dissociable learning processes, since the sequence knowledge demonstrated on the SRT task could have been learnt by a separate process from that which detected the long strings of Xs. However, the data could also have been generated by a single learning process, in which different sequence knowledge was under different degrees of conscious control and only knowledge above a certain threshold level of control was not expressed. As outlined in the introduction, potentially stronger evidence for dissociable learning processes would be provided if the pattern of sub-sequence learning shown on the SRT task under intentional conditions dissociated from the advantage for sub-sequences that ended in an alternation that was observed under incidental conditions in Experiment One.

In order to set the stage for this comparison, it is helpful to first consider another experiment that we conducted, aimed at elucidating the relative salience of these sub-sequences under conditions that strongly biased participants towards hypothesis-testing.

EXPERIMENT TWO

In this experiment the task was based on the work of Kushner, Cleeremans and Reber (1991). On each trial the human participants saw the SRT stimulus appear twice and then had to predict where it would occur next, before it appeared for the third time. The four types of trial corresponded to the four sub-sequences. This task was chosen both because it forced the participants to hypothesis-test, and because the simplicity of the task and the contingencies meant that the participants would be able to learn the sub-sequences in a relatively short number of trials. Thus, many participants could be run, so increasing the power to detect differences in sub-sequence learning using post-hoc tests.

Method

Participants. Seventy new participants were drawn from the same pool as in the previous experiment and paid £1 Sterling for their participation. One of these participants was excluded from the analysis because when they were interviewed it became apparent that they had achieved criterion (see below) by accident, and another was excluded because they misunderstood the instructions.

Apparatus, Stimuli and Display. These were identical to those employed in Experiment One.

Design. The task comprised a single block that was constructed in batches of four trials, where each trial involved the SRT stimulus appearing twice, followed by participants predicting where it would occur next, before it appeared for the third time. The trial order was random but constrained, such that within every batch of four trials each of the four trial types (XXX, XYY, YYX and YXY) occurred once; the aim being to equate as much as possible the exposure to each trial type. The inter-trial-interval after every fourth trial was no different to that following other trials. The assignment of X and Y to right and left was counterbalanced. To ensure that a usable amount of data was collected, participants received a minimum of 40 trials. If, having reached this number, their responses for the last two batches had all been correct then the task ended. However, if this was not the case then the block continued until they did achieve two consecutive completely correct batches. This method of imposing the completion criterion ensured that all participants were presented with an equal number of each of the sub-sequences. The probability of reaching this criterion by chance is 0.5^8 (0.0039), and in the case of any participant who had not met criterion after 160 trials then the block ended regardless and they were excluded from the study.

Procedure. At the beginning of the experiment, instructions were displayed on the screen and the participants were given a practice trial. They were told that they had to learn by trial-and-error to predict where the circle would appear next after its first two presentations, and the importance of both speed and accuracy were emphasised. Each trial of the task began as

follows. The white outline circles were displayed for 500ms; one of the circles filled in for 250ms; the outlines then reappeared for a further 500ms; a circle again filled in for 250ms; and then the outlines reappeared with a 1.5cm tall question mark displayed in between them. Upon seeing the question mark, the participants had to press the 'x' key if they thought the next location in the sequence was left and the '>' key if they believed it was right. RT was measured from the appearance of the question mark until the onset of the response. Immediately following the response, the appropriate circle filled in for 500ms and a beep was emitted if the participant had failed to correctly predict its location. If they responded too quickly (sooner than 50ms after the appearance of the question mark), pressed a key other than the two designated, or were timed-out, having failed to respond within 4.25s of the question mark's onset, then the trial was aborted and an appropriate error message, which lasted for 1s, was displayed. The inter-trial-interval was 750ms, during which time the screen was blank. Once the criterion or the maximum number of trials had been reached, the task ended.

Results and Discussion

All the participants passed the task's termination criterion of responding completely correctly to two batches of four trials. To assess the pattern of sub-sequence learning, for each participant and per sub-sequence the mean RT, averaged across both correct and incorrect trials, and the proportion of errors were calculated. The data from trials on which participants made an anticipatory response, were timed-out or pressed a non-designated key were excluded; this totalled less than one percent of trials. The mean results are shown in Figure 4. Participants' scores were analysed using one-way ANOVAs with the within subject factor ‘sub-sequence’

(XXX, XYY, YYX and YXY). The main effect of sub-sequence was significant in both the RTs and errors ($F(3,201)=21.49$, $p<.001$ and $F(3,201)=12.76$, $p<.001$ respectively). Subsequent Tukey HSD tests demonstrated that the participants had learnt sub-sequence XXX significantly better than the other three (XYY: RT: $p<.01$, errors: $p<.01$; YYX: RT: $p<.01$, errors: n.s.; YXY: RT: $p<.01$, errors: n.s.); that their performance on XYY was also significantly worse than on YYX and YXY (XYY vs. YYX: RT: $p<.01$, errors $p<.01$; XYY vs. YXY: RT: $p<.01$, errors: $p<.01$); and that their learning of YYX and YXY did not reliably differ ($p>.05$).

----- Figure 4, about here please. ------

The most striking difference between this pattern and that demonstrated on the incidental SRT task in Experiment One is that XXX is now the most strongly learnt sub-sequence, whereas on the SRT task YXY and YYX had dominated. This change is consistent with previous studies that have suggested that runs of repetitions are one of the most salient patterns when participants are intentionally searching for sequences (e.g. Cleeremans, 1993; Garner & Gottwald, 1967). It is also consistent with the fact that the participants in the Experimental Group of Experiment One were most clearly able to verbalise knowledge related to sub-sequence XXX (i.e. the majority of them commented on the long runs of Xs), since a number of theories treat verbalisable knowledge as a hallmark of intentional hypothesis-testing (e.g. McLaren et al., 1994). Furthermore the results support the idea that relative performance on XXX can be used as a marker as to whether participants are learning by a hypothesis-testing or error-correcting associative process. With this in mind, we can now turn to the SRT task under intentional conditions with the aim of contrasting the results obtained with those under incidental conditions.

EXPERIMENT THREE

Experiment Three had the same core design as the incidental SRT task in Experiment One, but incorporated a number of modifications. First and foremost, following the pre-training test-phase the participants in both groups were informed that from now on the stimulus locations would follow a sequence that they should try to discover and then use to prepare for the stimulus' next appearance. The SRT task was also reduced in length to two sessions, in part because the learning effects in Experiment One did not appear to substantially strengthen during the latter training sessions of the SRT task. Also, it seemed likely that participants would find it difficult to maintain hypothesis-testing for the full six sessions used in Experiment One. Finally, the participants were no longer paid a performance bonus, since that could have encouraged them to concentrate on responding quickly and accurately, rather than on sequence learning and sequence expression.

Method

Participants. Thirty new human participants were drawn from a similar background as the previous experiments. Sixteen were randomly allocated to the Experimental Group and 14 to the Control Group. The first eight participants in each group were paid £4 Sterling, while the remainder agreed to participate without payment. An exploratory analysis on the difference score data, which included ‘payment’ as a factor, revealed that the presence or absence of payment had

no material effect on the amount of sequence learning or the pattern of sub-sequence learning (all the 'payment by group' and 'payment by group by sub-sequence' interactions: $F<1$, $p>.1$).

Display and Block Construction. These were identical to Experiment One.

Design. The experiment comprised two sessions, with the typical inter-session-interval being between 24 and 48 hours. The first session was identical to the first session in Experiment One, while the second session took the same form as the fifth session of Experiment One. Thus, a 10 block pre-training test-phase was followed by 20 training blocks and then a 10 block post-training test-phase.

Procedure. The procedure was the same as that in Experiment One except that, following the last block of the pre-training test-phase, the participants were told that 'for the rest of the experiment … it will be possible to predict which circle will fill in next based on the locations of the circles which have previously filled in'. Furthermore, they were asked to try to work out the sequences and to use them to prepare for the next appearance of the stimulus, and not to worry if doing so made them slightly slower and less accurate. In between the blocks the computer displayed the message 'please keep looking for patterns'.

The structured interview, which followed the SRT task, was similar in format to that in Experiment One.

Results and Discussion

Structured Interview. As with Experiment One, the majority (10 out of 16) of the Experimental Group reported noticing longer strings of Xs than Ys or described closely related patterns, like long strings of Xs (though obviously they phrased their statements in terms of rights and lefts).

SRT Task. The initial analysis of the SRT data takes the same form as for Experiment One. Specifically, RT and proportion of errors difference scores were constructed for each sub-sequence, per trial-position, for the post-training test-phase. The mean difference scores, collapsed across trial-position, are shown in the left panels of Figure 5. Mixed ANOVAs with the factors 'group', 'sub-sequence' and 'trial-position' were performed. The Experimental Group's RT difference scores were found to be significantly larger than the Control Group's scores (main effect of group: $F(1,28)=12.80$, $p<.01$), and this was supported by a non-significant trend in the same direction in the errors, excluding speed-accuracy trade-off. Thus there was evidence of sequence learning. As with Experiment One, none of the effects involving the factor trial-position were significant (all $p>.05$) and the trends were similar across all three trial-positions, suggesting that participants had learnt the sequential contingencies on a trial-by-trial basis and not learnt about the special status of third trials. The sub-sequence by group interaction was not significant (both RTs and errors: $F(3,84)<1$).

---- Figure 5, about here please. ----

The data from the 10 training blocks immediately before the test-phase were also analysed in the same manner to Experiment One, using sub-sequence by group ANOVAs. The mean difference scores are shown in the right panels of Figure 5. Again there was evidence of significant sequence learning (main effect of group: RTs: $F(1,28)=17.17$, $p<.001$; errors: $F(1,28)=10.75$, $p<.01$), while the sub-sequence by group interaction was not significant (both $F(3,84)<1$).

In addition, these training scores were compared with the difference scores from the test-phase, which were recomputed using the same method as for the training data to allow comparison. ANOVAs revealed that significantly more sequence learning was demonstrated over these 10 training blocks, since the phase by group interaction in the errors was reliable ($F(1,28)=9.30$, $p<.01$), and this was supported by a trend in the same direction in the RTs ($F(1,28)=4.08$, $p=.053$), excluding speed-accuracy trade-off. This difference seems most likely due to the pseudo-random contingencies in the test-phase causing unlearning or leading participants to withhold some of their learning.

Comparison Between the SRT Data of Experiments One and Three. Recall that previous research, participants' verbalisable knowledge of long runs of Xs, and the pattern of sub-sequence learning in Experiment Two all converge to suggest that participants will express greater relative learning of sub-sequence XXX under intentional conditions than incidental ones. To explore whether this was the case, performance on XXX relative to the other three sub-sequences was compared between Experiments One and Three. We decided to use the data from the 10 training blocks prior to the test-phase for this comparison, since the learning effects were stronger in the training blocks. To perform the comparison, for each participant a combined RT

difference score was created by calculating the mean of the RT difference scores for XYY, YYX and YXY. Combined proportion of errors difference scores were created in the same manner. The data were then analysed using mixed ANOVAs, with the between-subject factors 'experiment' (One vs. Three) and 'group' (Experimental vs. Control), and the within-subject factor 'sub-sequence' (XXX vs. combined score).

---- Figure 6, about here please. ----

The means are shown in Figure 6. It can be seen from this that the trends in the RTs and errors have moved in the direction of greater relative expression of learning of XXX in Experiment Three than One. Furthermore, this change was found to be significant in the RTs, as demonstrated by the reliable experiment by group by sub-sequence interaction ($F(1,50)=4.42$, $p<.05$). To elucidate this interaction, independent sample t-tests were performed on the RT difference scores separately for each sub-sequence, for the Experiment Three data (an equivalent analysis having already been conducted for Experiment One). Consistent with the results of Experiment Two, previous research, and participants' verbalisable knowledge of long strings of Xs, there was evidence of expression of learning of XXX ($t(28)=2.16$, $p<.05$). The difference in RT scores between the Experimental and Control Groups did not reach significance for the three other sub-sequences (XYY: $t(28)=1.90$, $p>.05$; YYX: $t(28)=0.49$, $p>.1$; YXY: $t(28)=1.10$, $p>.1$).[1]

Thus there was evidence of a dissociation between the patterns of sub-sequence learning shown on the SRT tasks in the two experiments, with learning of YXY and YYX being demonstrated

under the incidental conditions of Experiment One and learning of XXX being expressed under the intentional conditions of Experiment Three.

It might be objected that the pattern in Experiment Three could simply be a pattern that occurred earlier in training in Experiment One, given the longer training phase in the latter. Therefore, to check whether incidental participants had ever shown learning of XXX, independent sample t-tests were conducted separately on each set of 10 training blocks in Experiment One, for both the RT and proportion of errors difference scores for XXX. None of these t-tests approached significance (all $p>.2$), confirming that reliable learning of XXX had not been demonstrated on the SRT task across the whole of Experiment One. Thus it does not seem plausible to completely attribute the dissociation to different amounts of training in the two experiments.

One possible explanation of the dissociation and the detailed patterns of sub-sequence learning will be now offered in the following modelling sections.

MODELLING SUB-SEQUENCE LEARNING IN THE INCIDENTAL CONDITION

Connectionist networks have proven to be particularly adept at modelling SRT sequence learning under incidental conditions (e.g. Cleeremans, 1993; Cleeremans & McClelland, 1991; Dominey et al., 1998; Jones, Le Pelley & McLaren, 2002). Therefore, Experiment One was simulated using one of the leading connectionist models of SRT sequence learning, namely the Augmented SRN. The Augmented SRN is a modified version of Elman's (1990) SRN, which was developed by Cleeremans and McClelland (1991). As can be seen in Figure 7, this network comprises an

input layer, hidden layer and output layer. The units in each layer feed activation forward to every unit in the layer above.

---- Figure 7, about here please. ----

To model Experiment One, each of the two possible stimulus locations (X and Y) was assigned an input unit, and on every trial the unit that corresponded to the stimulus' current location was activated, by setting its activation to one while the other unit remained at zero. The input layer had an additional set of units that were matched in a one-to-one fashion to the hidden units. At the beginning of each trial, the pattern of activation across the hidden units from the previous trial was copied onto these 'context-units'; this process was implemented by one-to-one feedback connections. A consequence of recycling the hidden unit activity in this manner was that the pattern of activation across the context-units could be influenced by the locations of the stimulus over the previous series of trials. In this way, the context-units provide the SRN with the memory that is necessary to learn sequential contingencies. For our simulation, the two output units represented the model's prediction as to the location where the stimulus would appear on the next trial, and the activity of the output and hidden units was determined by the logistic activation function (Rumelhart, Hinton & Williams, 1986).

The weight of each of the feed-forward connections in the network was modifiable, and was divided into 'fast' and 'slow' components. In addition, each hidden unit had a 'bias'; a bias can be thought of as a modifiable inputting connection from a unit with a fixed activation of one. The biases also had fast and slow components. Following each trial, the fast and slow components of

the weights and biases were modified according to the back-propagation algorithm, without a momentum term, using the stimulus' location on the next trial as the training target (cf. Rumelhart et al., 1986). In this way, a combination of the stimulus' current location and the memory of the previous locations contained on the context-units could become associated with the stimulus' next location, and over a series of trials the network could improve in its ability to predict the next location in the sequence.

The fast components changed more quickly than the slow components, since they had a higher learning rate. However, unlike the slow components, they also decayed by half of their value each trial; we implemented this by halving the value of the fast components after the activations had been fed forward and errors back-propagated, but before the weights and biases were updated. Cleeremans and McClelland included these fast components in the Augmented SRN to allow recently learnt parts of the sequence to exert a short-term priming effect, since they observed that this occurred in their human SRT data. These data also showed a priming effect of the previous stimulus locations (or their associated responses); for example, participants tended to respond faster when the stimulus appeared in the same location as on the previous trial. To capture this Cleeremans and McClelland effectively included two 'response' units in the model, one corresponding to each stimulus location; these are not shown in Figure 7. The activation of each response unit depended both upon the activation of the corresponding output unit and upon a decaying trace of the response unit's activation on the previous trial. Specifically:

$$\text{response}_n(t) = \text{output}_n(t) + k \bullet \left(1 - \text{output}_n(t)\right) \bullet \text{response}_n(t-1) \qquad 2$$

where $\underline{\text{response}_n(t)}$ was the activation of the response unit corresponding to stimulus location $\underline{n}$ at the end of trial $\underline{t}$, and $\underline{\text{output}_n(t)}$ was the activation of the output unit corresponding to stimulus

location n at the end of trial t. Note that the activations of the response units at the end of trial t determined how fast the model reacted to the stimulus on trial t+1, because the network was predicting which stimulus-location (and so response) would come next in the sequence. Since we were only using this network to model RT data from correct trials, it was assumed that the response it made was always the correct one and that the activation of the response units solely influenced the RT (though for an example of a decision process that would also allow this network to model error data see Wills & McLaren, 1997, and Jones, Wills & McLaren, 1998). Furthermore, following Cleeremans and McClelland (1991), in order to allow executed responses to have a priming effect, after the response unit activations were recorded, the value of $response_n$ corresponding to the correct response was set to one, while the other $response_n$ remained unchanged.

Cleeremans and McClelland (1991), Cleeremans (1993) and Jiménez et al. (1996) have shown that this model can capture a number of aspects of human SRT data. To determine whether it could also model the pattern of sub-sequence learning demonstrated on the SRT task in Experiment One, 40 networks, half in the Experimental Group and half as Controls, were presented with an exact analogue of the experiment. Each network had 20 hidden units and a learning rate parameter of 0.4 for the slow weight components. This latter value was determined by a process of trial and error, in order to ensure that the networks showed significant sequence learning. It was somewhat larger than the slow learning rate of 0.15 that Cleeremans and McClelland used to model their SRT data. However, the RSI was shorter in their study and they employed a six-choice, rather than two-choice, SRT task. Following Cleeremans and McClelland, the fast learning rate parameter was 1.33 times larger than the slow learning rate parameter, and k was assigned the value 0.5. No attempt was made to alter the pattern of sub-

sequence learning by changing these parameters, since we wanted to see what pattern would 'naturally' fall out of the model.

As a first approximation the mean square error (MSE) was taken to be an index of the RT on the following trial; numerically:

$$\text{RT (t+1)} = \text{MSE (t)} = \left(\text{resptarget}_x - \text{response}_x(t)\right)^2 \bullet 0.5 + \left(\text{resptarget}_y - \text{response}_y(t)\right)^2 \bullet 0.5 \qquad 3$$

where resptarget_x and resptarget_y were assigned values of 1 and 0 respectively when the stimulus location on trial t+1 was an X, and the reverse when the location was a Y. Note that this was not the error term that was used in the determination of the weight changes. Following the standard back-propagation algorithm, the network's output activations were used in that calculation, rather than the response unit activations, and targets of 0.9 and 0.1 were employed. A decision rule or process (cf. Cleeremans & McClelland, 1991; Jones et al., 1998) was not used in case it obscured the sequence learning properties of the model. MSE was taken to be a sufficiently good index of RT because like RT it monotonically decreased as sequence learning strengthened.

The data from the post-training test-phase were analysed in the same manner as in Experiment One, by creating 'inconsistent MSE minus consistent MSE' difference scores for each sub-sequence, per trial-position, and then performing a 'group' by 'trial-position' by 'sub-sequence' ANOVA. The main-effect of group indicated that there was significant sequence learning ($F(1,38)=57.95$, $p<.01$). As with the human data, the main-effect of trial-position and all the interactions involving trial-position were not significant (all $p>.1$) and the trends were similar across all three trial-positions, suggesting that the networks had learnt the probabilistic

contingencies on a trial-by-trial basis, and had not learnt about the special status of third trials. The mean difference scores, collapsed across trial-position, are shown in Figure 8.

---- Figure 8, about here please. ----

The group by sub-sequence interaction was significant ($F(3,114)=15.69$, $p<.01$), providing evidence of differential sub-sequence learning. This was explored using the same simple-effects analysis as in Experiment One, including the Bonferroni correction. This revealed significant evidence of learning of YYX and YXY ($F(1,38)=56.65$, $p<.01$ and $F(1,38)=30.86$, $p<.01$ respectively), while XXX and XYY were not reliably learnt ($F(1,38)=5.67$, $p>.05$ and $F(1,38)=0.09$, $p>.1$ respectively). Again trial-position had no significant bearing on the findings (all $p>.1$). For some of these analyses the assumption of homogeneity of variance was substantially violated. However, we thought that this had not led to erroneously significant findings because of the large, equal group sizes and highly significant p-values. Heteroscedastic t-tests on the data for each sub-sequence, collapsed across trial-position, confirmed that the findings were genuinely significant. Thus the pattern of sub-sequence learning mirrored that demonstrated on the SRT task in Experiment One.

As outlined in the introduction, we believe that the interaction of error-correction and the short–term priming effect of recent learning plays an important role in determining the pattern of sub-sequence learning exhibited by the Augmented SRN. We are currently examining whether the Augmented SRN can fully account for all of the sequential-effects observed in two-choice RT tasks (e.g. Soetens et al., 1985), and the extent to which its pattern of sub-sequence learning is

parameter dependent. We also plan to explore whether the relatively small trend for the Experimental Group to perform worse than the Control Group on sub-sequence XXX, which would have reached significance without the Bonferroni correction, will increase in reliability and magnitude with a longer training phase. If this proves to be the case, in a way that is not highly parameter dependent, then we will have a novel prediction that could be the basis of a further test of the Augmented-SRN's ability to model incidental sequence learning.

However, regardless of the outcome of these investigations, it is clear that the pattern of sub-sequence learning observed on the SRT task in Experiment One can be explained in associative terms, by a model that combines short-term priming and error correction.

MODELLING INTENTIONAL SEQUENCE LEARNING

To model intentional sequence learning we followed the approach taken by Spiegel and McLaren (2003; see also Spiegel, Le Pelley, Suret & McLaren, 2002). Their SARAH framework includes a model that provides an account of the process by which participants induce abstract rules about sequences when they are deliberately trying to learn the sequences. Following the work of Hofstadter (1995), this model builds rules out of representational units called 'codelets'. Some codelets represent the surface features of stimuli, while others code for more abstract relationships.

When it is exposed to an analogue of the SRT task used in this study, the model employs codelets for the stimulus locations (i.e. an 'X' codelet and a 'Y' codelet) and codelets that

represent the relationship between adjacent stimulus locations (i.e. a 'same as previous' codelet and a 'different from previous' codelet). On each trial of the SRT task, there is a chance that the appropriate stimulus location codelet will be activated by the appearance of the stimulus. The activated codelet will be held in working memory, along with the codelets that were activated on some of the previous trials; the total number of codelets that can be retained is constrained by the capacity of working memory. In addition, if the codelets representing two consecutive stimulus locations are the same then there is a chance that a 'same as previous' codelet will be activated, and if they are different then a 'different from previous' codelet may be activated. Moreover, this process can occur recursively. For example, if two consecutive 'same as previous' codelets or two consecutive 'different from previous' codelets are activated then there is a chance that a 'same as previous' codelet will be activated. Similarly, a 'different from previous' codelet could be activated by adjacent 'same as previous' and 'different from previous' codelets. Thus, it is possible for the four sub-sequences to be represented by the hierarchical codelet structures shown in Figure 9.

---- Figure 9, about here please. ----

The more frequently the model is exposed to a particular sub-sequence, the more active the codelets within that sub-sequence's representation will tend to become. Once the activity of these codelets reaches a threshold level, the model is considered to have generated a complete representation of the sub-sequence. This complete representation is verbalisable, under conscious control and can be used as the basis for making predictions about where the stimulus will appear on the next trial.

Furthermore, if some generalisation of activity between identical codelets at different positions in the representation of a particular sub-sequence is allowed then the complete representation of sub-sequence XXX will tend to form before that of the other sub-sequences. This is because the representation of sub-sequence XXX contains fewer types of codelets than the other sub-sequences' representations, so there will be greater generalisation of activity between its codelets, resulting in them reaching threshold more quickly. This advantage for sub-sequence XXX means that the model can explain why learning of XXX was expressed in Experiment Three. Moreover, if it is assumed that the participants in Experiment One were engaged in some active searching for sequences (even though they had not been told that there were sequences), this model can also explain why the majority of them were able to report patterns related to the longer runs of Xs, since these runs were made up of XXX -the sub-sequence that is most salient to the model.

GENERAL DISCUSSION

To summarise, the main purpose of this research was to determine whether the pattern of sub-sequence learning that participants demonstrated on an SRT task dissociated between incidental and intentional learning conditions; a result that would be consistent with the existence of dissociable sequence learning processes. To this end, two two-choice SRT tasks were conducted, one under incidental conditions and the other under intentional conditions. In both cases an Experimental Group was trained on four sub-sequences (i.e. XXX, XYY, YYX and YXY). Sequence learning was assayed, in a manner that controlled for sequential-effects, through comparison with a pseudo-random Control Group. Under incidental conditions, in Experiment

One, the Experimental Group demonstrated learning of those sub-sequences that ended in an alternation (i.e. YYX and YXY) on the SRT task, but showed no learning of the other sub-sequences. Furthermore, the majority of the Experimental Group demonstrated awareness of the longer runs of Xs during the subsequent structured interview; yet they did not appear to have expressed this knowledge on the SRT task because they showed no learning of XXX. The pattern of sub-sequence learning exhibited under the intentional conditions of Experimental Three significantly differed from that in Experiment One, with learning of XXX being expressed.

The apparent dissociation between the patterns of sub-sequence learning exhibited during the two experiments, and the discrepancy between the participants' verbal reports and SRT performance in Experiment One, could probably be explained by a number of different multiple-process models of human learning (e.g. Dominey et al., 1998; Hayes & Broadbent, 1988; Reber, 1989; Willingham et al., 1989). However, we prefer McLaren et al.'s (1994) framework, which postulates that learning can occur either by an associative process, that is sensitive to statistical regularities in the surface features of the environment, or by a hypothesis-testing, rule-based process, that is under greater strategic control and can acquire more abstract information, provided that this information is simple enough to be held in working memory. There is evidence consistent with a distinction of this form (e.g. Dominey et al., 1998; Shanks & St John, 1994; Shanks, 1995; though for a critique see Hahn & Chater, 1998), and it may be used to understand the current results as follows.

The sequence learning that the Experimental Group demonstrated on the SRT task under the incidental conditions of Experiment One was predominantly associative in nature, and so was

difficult for them to verbalise and was relatively automatic. The associative processes learnt those sub-sequences that ended in an alternation but not those that ended in a repetition, at least in part due to the interaction of short term priming effects with error correction, as modelled by the simulations of the Augmented SRN. The probabilistic nature of the contingencies on a trial-by-trial basis combined with the incidental conditions made rule-based learning difficult. However, at least some of the participants did still actively search for patterns and their rule-based process was able to detect the longer runs of Xs. This was the most salient pattern because it comprised repeated occurrences of sub-sequence XXX, which was the most salient sub-sequence since it benefited most from inter-codelet generalisation. However, when the participants in Experiment One decided that attempting to predict the next trial worsened their SRT performance, expression of their rule-based knowledge was inhibited more than their associative learning, because the former was under greater conscious control. Thus, participants could verbalise their knowledge of the longer strings of Xs, but only showed evidence of their associative learning on the SRT task in Experiment One.

In contrast, under the intentional conditions of Experiment Three the participants were instructed to express all of their sequence learning, and so they expressed their rule-based knowledge of sub-sequence XXX. Furthermore, due to the fact that the training-phase in this experiment was shorter, the associative process had yet to reliably learn those sub-sequences that ended in an alternation.

The results derived from the incidental learning experiment in this paper complement those on sequence learning reported by Spiegel and McLaren (2006) that suggest a strong associative

component to sequence learning in human participants engaging in SRT tasks. The results from the intentional study fit well with the hypothesis-testing component of the hybrid SARAH model described in Spiegel and McLaren (2003). Moreover, the two sets of results combined suggest that relative performance on sub-sequences comprising only repetitions could be used as a marker of whether people are engaging associative or hypothesis-testing learning processes.

It is interesting to compare our findings with those of Perruchet, Cleeremans and Destrebecqz (2006), who presented human participants with a task in which a tone was followed by a square on a random half of the trials and occurred alone on the remaining trials. At the beginning of this task the participants were informed that the square followed the tone only half of the time, and over a series of experiments Perruchet et al. measured their conscious expectancy of the square appearing and their reaction time to the square when it did appear. They found that these dissociated, with a run of tone-square pairings leading to a lower expectancy of the square on the next trial, but faster reaction to it, if it did occur. Furthermore, comparison with a control group in which the presentation of tones and squares was randomly related suggested that the decrease in reaction times was due to the development of a tone-square association. Perruchet et al. argue that these findings provide evidence of independent processes: namely, an associative learning mechanism responsible for the reduction in reaction times, and a conscious expectancy process that exhibits gambler's fallacy.

We believe that the dual process account that we have offered of our data could be extended to explain Perruchet et al.'s findings. Specifically, in principle an associative model, such as the Augmented SRN, should be able to capture the decrease in reaction times following runs of tone-

square pairings. Here the issue is not so much the kind of long-term learning that we have studied in our experiments, but a short-term facilitation due to a run of trials of the same type. In Perruchet et al.'s experiments, all that is required to generate fast RTs after a run of stimulus-outcome pairings is fast learning over that series of the association between stimulus and outcome. The Augmented SRN lends itself to that well, as the fast weights will enable just this sort of learning to influence behaviour. In addition, gambler's fallacy could be modelled in codelet form, if the existence of more complex codelets is allowed. As an example, consider the case where a codelet of the type 'in a random ordering, expect an alternation after a few repetitions' is instantiated. This clearly would lead to conscious expectations similar to those captured by the concept of gambler's fallacy, and it is possible that such a codelet could contribute to the salience of runs of repetitions when participants are intentionally searching for patterns in sequence learning tasks, since a long run of repetitions would contradict this codelet and so might stand out.

Finally, regardless of how useful the explanations we have offered prove to be, we hope that the experiments presented in this paper have further demonstrated that it is important to control for sequential-effects when assaying the detailed pattern of sub-sequence learning (cf. Anastasopoulou, & Harvey, 1999; Curran et al., 2001). One way to achieve this is by comparing the Experimental and Control Groups' performance on the same trial-order. Furthermore, this research has generated patterns of sub-sequence learning that should serve as useful constraints on the development of models of human sequence learning.

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TABLE LEGENDS

Table 1: The composition of the sessions of the SRT task in Experiment One. ‘R’ refers to 10 pseudo-random blocks and ‘S’ refers to 10 sequence blocks.

Table 1

Session	1	2	3	4	5	6
Phase	Test	Main Training			Test	Train
Expt.	R	S S S S S S S S S			R	S
Control	R	R R R R R R R R R			R	R

FIGURE LEGENDS

Figure 1: The mean difference scores for each sub-sequence, collapsed across trial-position, from the post-training test-phase of Experiment One. Filled circles refer to the Experimental Group and open circles indicate the Control Group. Top Panel: Inconsistent RTs minus consistent RTs. Bottom Panel: Inconsistent proportion of errors minus consistent proportion of errors.

Figure 2: The mean difference scores for each sub-sequence, from the 10 training blocks immediately prior to the post-training test-phase of Experiment One. Filled circles refer to the Experimental Group and open circles indicate the Control Group. Top Panel: Inconsistent RTs minus consistent RTs. Bottom Panel: Inconsistent proportion of errors minus consistent proportion of errors.

Figure 3: The mean RTs and mean proportion of errors for each sub-sequence, on inconsistent trials in the 10 training blocks immediately prior to the post-training test-phase of Experiment One. Filled circles refer to the Experimental Group and open circles indicate the Control Group. Top Panel: RTs. Bottom Panel: Proportion of errors.

Figure 4: The mean RTs (top) and mean proportion of errors (bottom) for Experiment Two.

Figure 5: The mean difference scores for each sub-sequence from Experiment Three. Filled circles refer to the Experimental Group and open circles indicate the Control Group. Top Left Panel: RT difference scores from the post-training test-phase. Bottom Left Panel: Proportion of

errors difference scores from the post-training test-phase. Top Right Panel: RT difference scores from the 10 training blocks immediately prior to the post-training test-phase. Bottom Right Panel: Proportion of errors difference scores from these 10 training blocks.

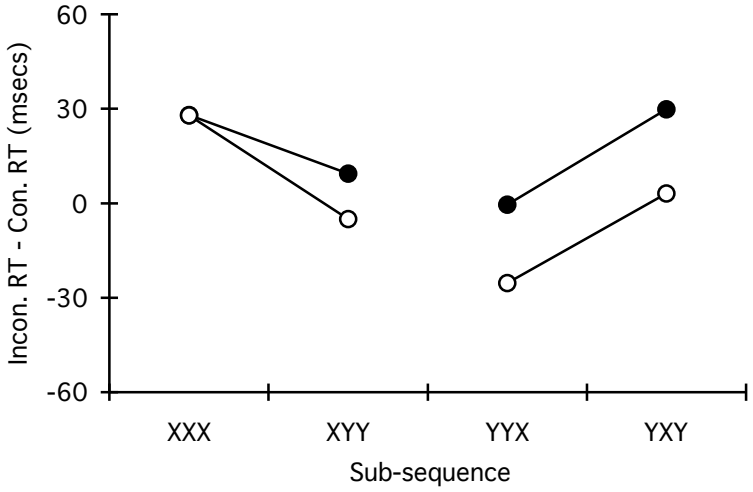
Figure 6: The change, between Experiments One and Three, in the difference score for sub-sequence XXX relative to the average of the difference scores for XYY, YYX and YXY. The data are from the 10 training blocks immediately prior to the post-training test-phase. Filled circles refer to the Experimental Group and open circles indicate the Control Group. Top Left Panel: RT difference scores from Experiment One. Bottom Left Panel: Proportion of errors difference scores from Experiment One. Top Right Panel: RT difference scores from Experiment Three. Bottom Right Panel: Proportion of errors difference scores from Experiment Three.

Figure 7: The architecture of an Augmented SRN, configured to model Experiment One. See the main text for an explanation. (Note: Not all the connections between units are drawn.)

Figure 8: The mean MSE difference scores for the sub-sequences, averaged across trial-position, from the post-training test-phase of the Augmented SRN simulation of Experiment One. Filled circles refer to the Experimental Group and open circles indicate the Control Group.

Figure 9: Panel A: The codelets needed to learn the sub-sequences, namely 'same as previous' (S), 'different from previous' (D), 'X' and 'Y'. Panel B: The possible codelet representations of the four sub-sequences. See the main text for more details.

Figure 1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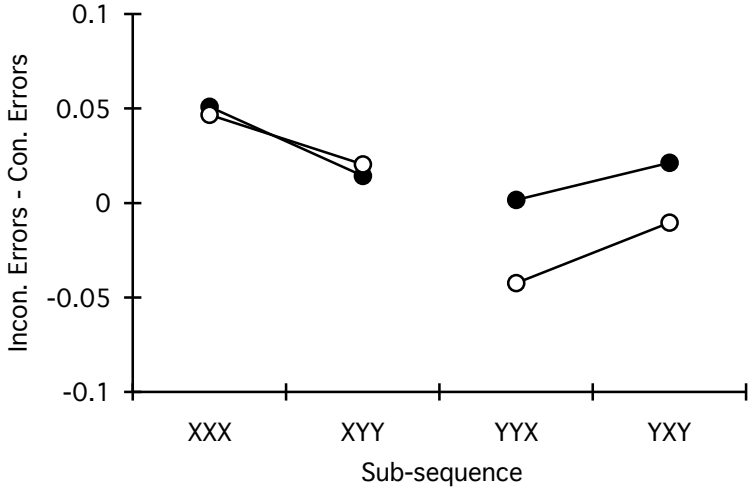
XXX
XYY
YYX
YXY
Sub-sequence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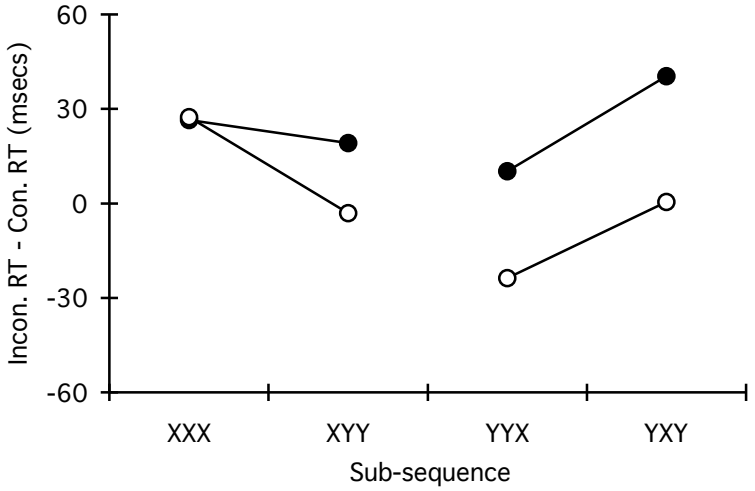
Incon. Errors - Con. Errors
XXX
XYY
YYX
YXY
Sub-sequence

Figure 2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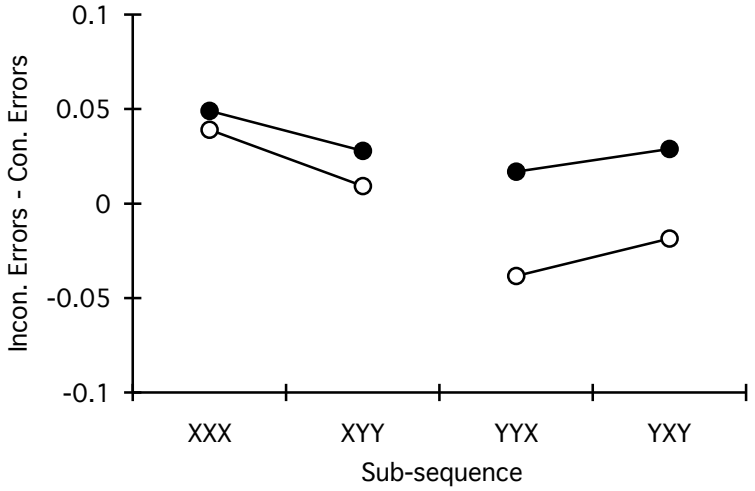
XYY
YYX
YXY
Sub-sequence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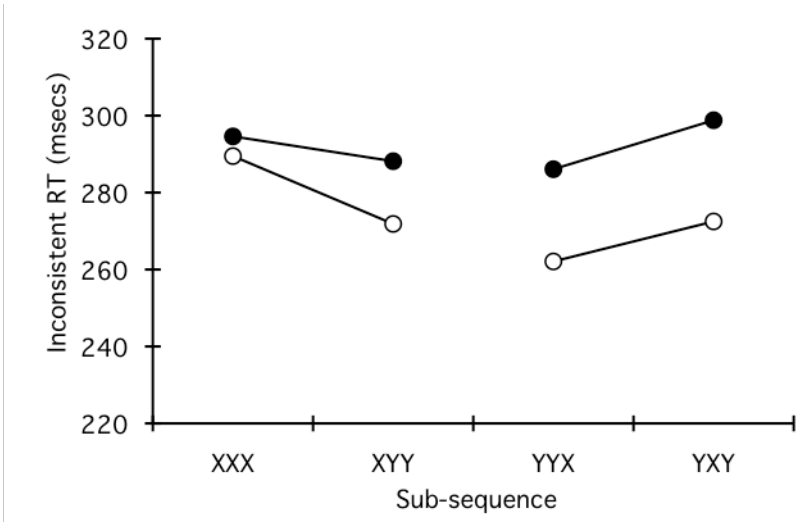
Incon. Errors - Con. Errors
XXX
XYY
YYX
YXY
Sub-sequence

Figure 3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240
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Inconsistent RT (msecs)
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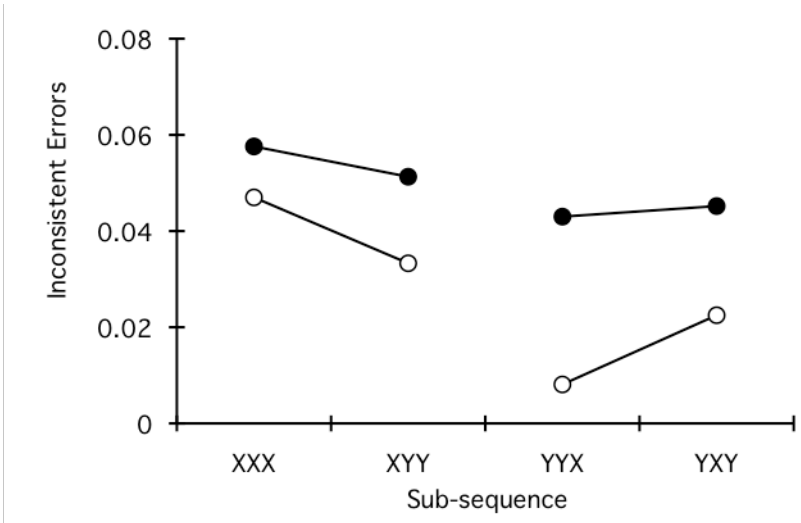
XYY
YYX
YXY
Sub-sequence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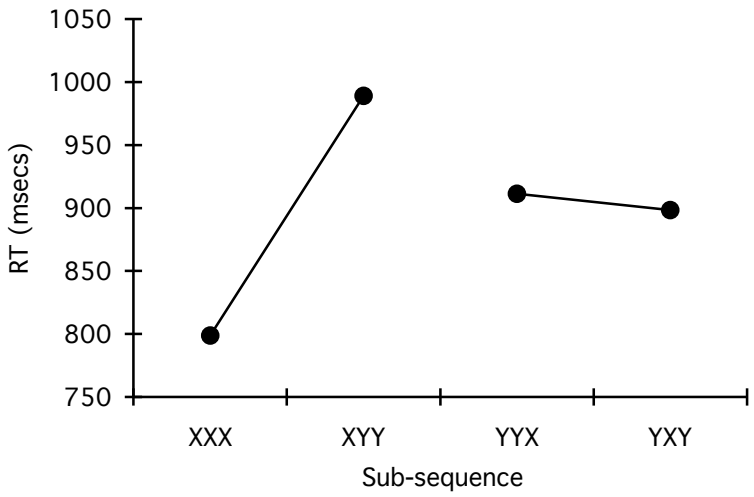
Inconsistent Errors
XXX
XYY
YYX
YXY
Sub-sequence

Figure 4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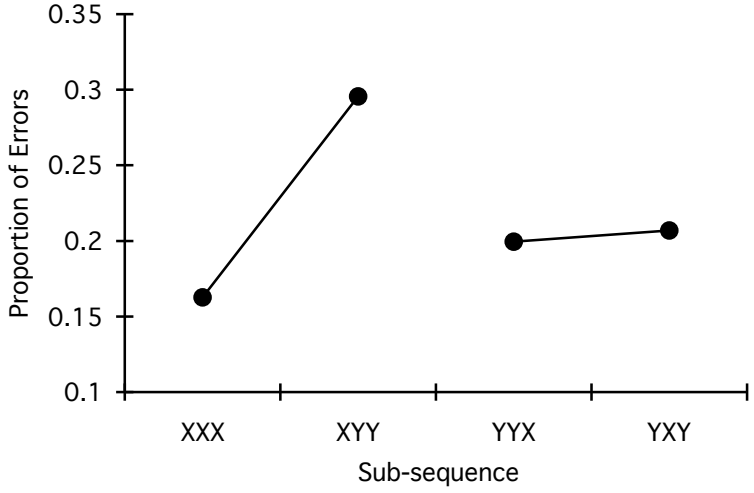
1000
950
900
850
800
750
RT (msecs)
XXX
XYY
YYX
YXY
Sub-sequence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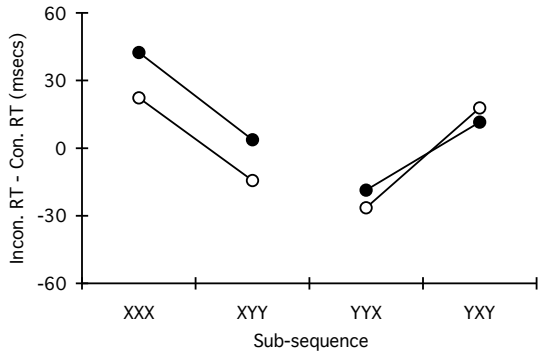
0.25
0.2
0.15
0.1
Proportion of Errors
XXX
XYY
YYX
YXY
Sub-sequence

Figure 5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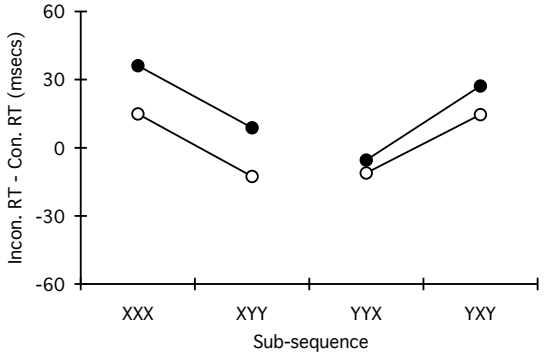
-60
Incon. RT - Con. RT (msecs)
XXX
XYY
YYX
YXY
Sub-sequence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30
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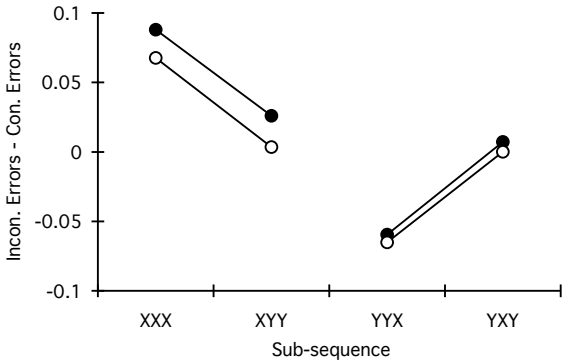
-30
-60
Incon. RT - Con. RT (msecs)
XXX
XYY
YYX
YXY
Sub-sequence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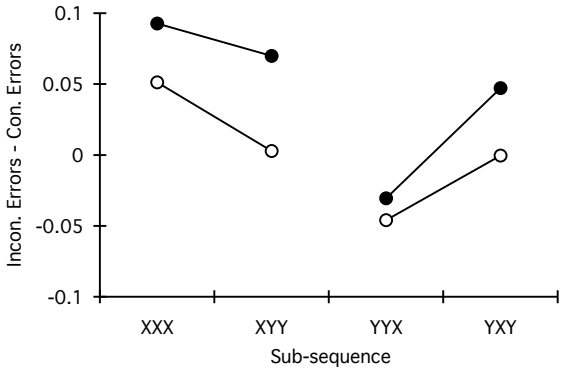
Incon. Errors - Con. Errors
XXX
XYY
YYX
YXY
Sub-sequence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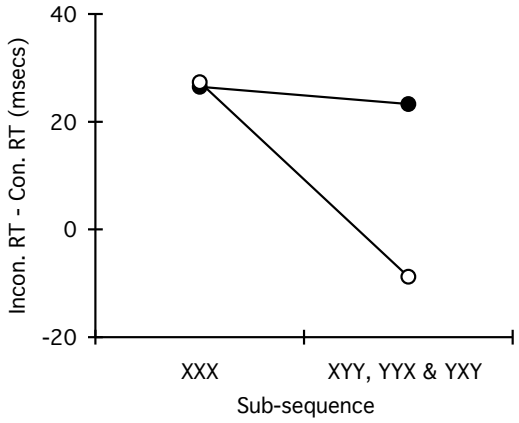
Incon. Errors - Con. Errors
XXX
XYY
YYX
YXY
Sub-sequence

Figure 6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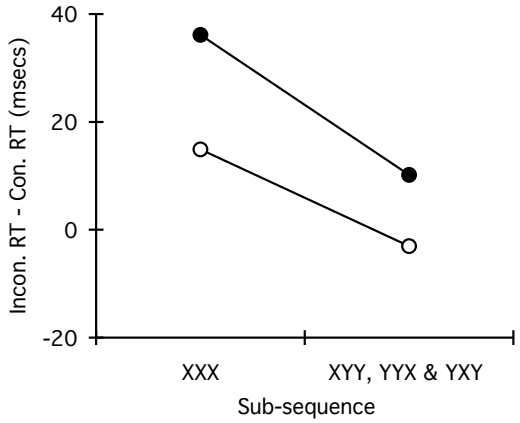
20
0
-20
Incon. RT - Con. RT (msecs)
XXX
XYY, YYX & YXY
Sub-sequence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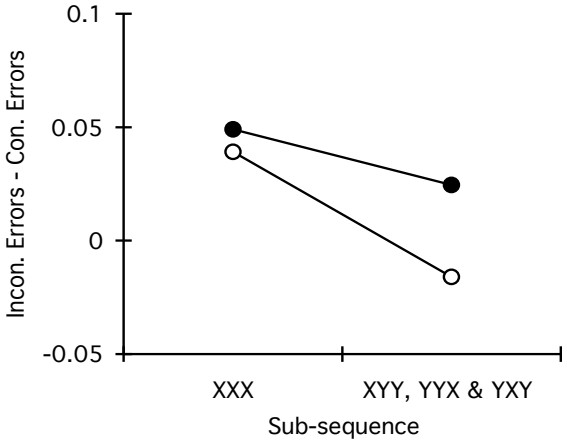
Incon. RT - Con. RT (msecs)
XXX
XYY, YYX & YXY
Sub-sequence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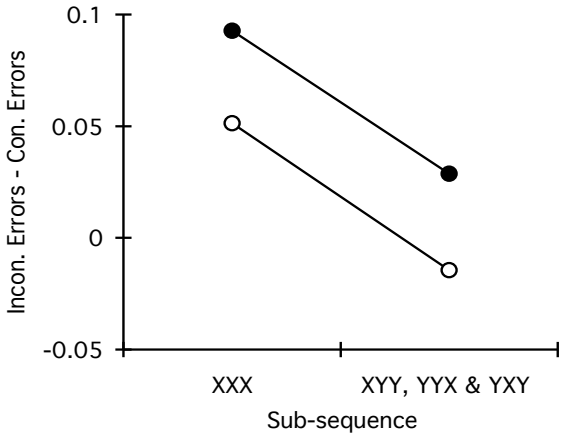
Incon. Errors - Con. Errors
XXX
XYY, YYX & YXY
Sub-sequence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XXX
XYY, YYX & YXY
Sub-sequence

Figure 7

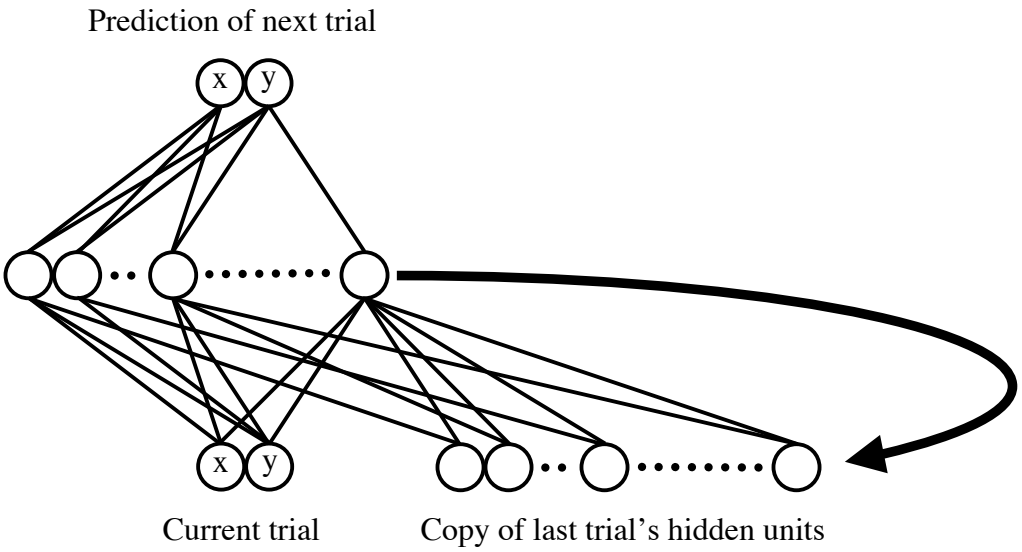
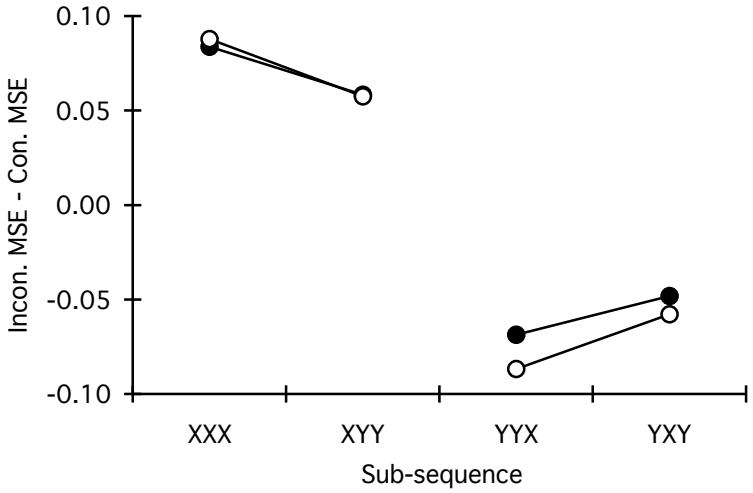

Prediction of next trial
x
y
x
y
Current trial
Copy of last trial's hidden units

Figure 8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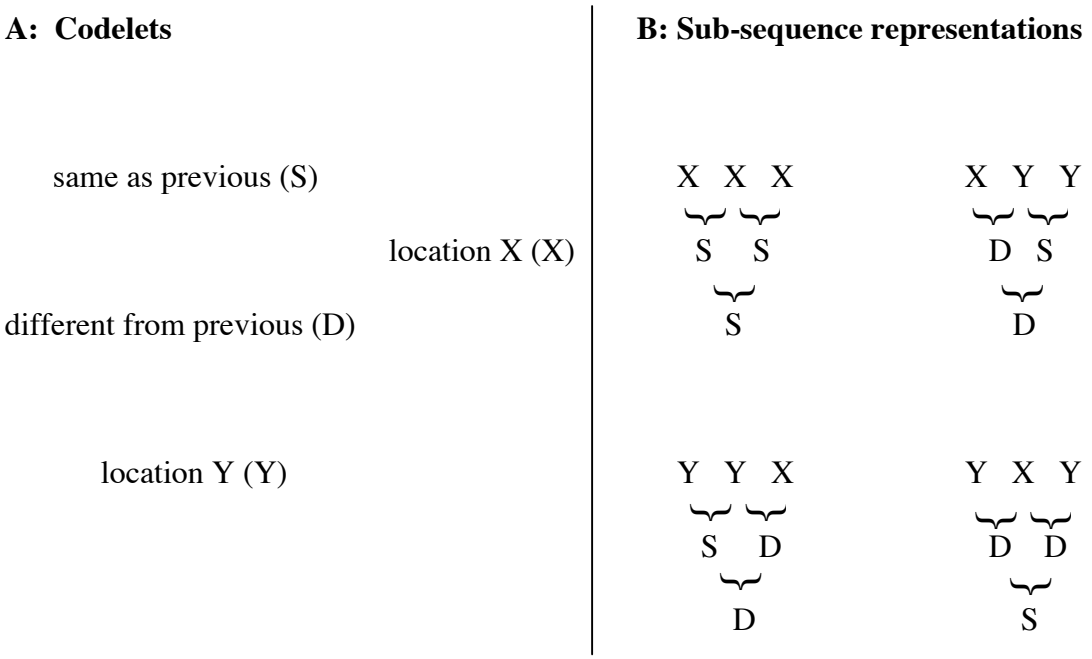
0.05
0.00
-0.05
-0.10
Incon. MSE - Con. MSE
XXX
XYY
YYX
YXY
Sub-sequence

Figure 9


A: Codelets
B: Sub-sequence representations
same as previous (S)
location X (X)
different from previous (D)
location Y (Y)
X X X
S S
S
X Y Y
D S
D
Y Y X
S D
D
Y X Y
D D
S

FOOTNOTE / ENDNOTE

[1] An exploratory analysis of the error difference scores revealed that the t-test for XYY was significant ($t(28)=2.83$, $p<.01$). However, this finding needs to be treated with caution because the initial interaction was not significant in the errors, nor could learning of XYY be expected on the basis of Experiment Two or previous literature, raising concerns that it might represent a Type I error as a result of multiple comparisons. Therefore, it is not considered further in the main text. That said, if a replication were to provide stronger evidence of learning of XYY then it would add weight to the dissociation in sub-sequence learning between incidental and intentional conditions, since sub-sequences ending in an alternation would be favoured in the former while sub-sequences ending in a repetition would be favoured in the latter. Although it would also mean that our modelling of the intentional condition (see later) might need to be modified.

In addition, prior to Experiment Three we had thought that the intentional conditions could lead to improved performance on YYX, as well as on XXX, since in principle knowledge of longer strings of Xs than Ys could be used by participants to expect an X after a short run of Ys. However, there was no evidence for this. On reflection, this is perhaps not surprising given that a re-examination of participants' verbal reports revealed little evidence of them adopting this strategy.