Experimental And Computational Investigation of the Effects of Variable RSI on Sequence Learning

Sneha Kummetha[1] **(kummetha.sneha@research.iiit.ac.in)**

Pramod Kaushik[1] **(pramod.sivaram@research.iiit.ac.in)**

Anuj Shukla[1] **(anuj.shukla@research.iiit.ac.in)**

Bapi Raju Surampudi[1,2] **(raju.bapi@iiit.ac.in)**

[1]Cognitive Science Lab, International Institute of Information Technology, Hyderabad, India

[2]School of Computer and Information Sciences, University of Hyderabad, Hyderabad, India

Abstract

In this study, we investigated the effects of variable Response-to-Stimulus interval (RSI) on sequence learning using both empirical and computational methods. In the empirical study, the serial reaction time task (SRT) was conducted which was followed by free generation and recognition tasks. Results showed that learning becomes explicit with increase in RSI despite its varying temporal nature. We constructed a computational model based on modified Elman network architecture to obtain a functional account of the empirical findings. The model illustrates how explicit learning could emerge due to a longer temporal window between stimuli which could potentially give insights into the mechanisms of sequence learning in variable RSI conditions.

Keywords: Sequence Learning; RSI; Implicit Learning; Elman;

Introduction

Information sequencing is a fundamental human capability. It has been observed that when participants were asked to respond to stimuli that followed a certain sequence, they were faster compared to when they were asked to respond to stimuli that were presented randomly. Such learning is called sequence learning - the ability to learn the regularities present in the environment. If the knowledge base acquired through this learning is available to conscious access, then the learning is called explicit learning, else, it is said to be implicit.

Serial Reaction Time (SRT) task is one of the most popular paradigms used for implicit sequence learning. In this task, a stimulus would appear in one of the four spatial locations and the participants would be asked to respond as fast as possible by pressing the corresponding key. The stimulus would follow a particular sequence unknown to the participant. Progressive decrease in reaction times (RT) with practice on a given sequence but an increase in RT when the sequence is modified, indicates that the participants are indeed learning the sequence. Since the participants were not told about the presence of a sequence, the learning observed in such a case is said to be incidental.

The outcome of learning could now be investigated using direct measures of assessing sequence knowledge. These involve tests that are conducted after completing the SRT task. Recognition and generation tasks are widely used for this purpose. These tests are conducted to determine if the learning is implicit or explicit.

Response-to-Stimulus Interval (RSI) in Sequence Learning

Timing plays a crucial role in acquiring the hidden regularities present in the environment. There have been many studies that looked at the influence of temporal factors in sequential behaviour by manipulating the Response-to-Stimulus Interval (RSI) (Stadler, 1995; Destrebecqz & Cleeremans, 2001, 2003; Willingham, Greenberg, & Thomas, 1997). In these studies, RSI is the time interval between a participants response to a stimulus and the appearance of the subsequent stimulus.

The experiments of Destrebecqz and Cleeremans (Destrebecqz & Cleeremans, 2001, 2003) have provided strong evidence that extending RSI from 0ms to 1500ms increased the processing time, thereby facilitating the acquisition of explicit sequence knowledge as evidenced by the improvement in the recognition scores of sequences.

More recently, studies conducted to investigate the gradual change of awareness states in implicit sequence learning showed that higher stimulus onset asynchrony (equivalent to RSI) leads to greater awareness (Huang et al., 2017).

In all these studies, a pre-determined but fixed RSI was used throughout the experiment. This could have led the participants to get adapted to the task for that particular RSI. The motivation for the study reported in this paper was to see what effects disrupting this temporal rhythm would have on the implicit or explicit acquisition of sequential knowledge. The temporal rhythm was disrupted by varying the RSI throughout the experiment. RSIs were systematically varied in various temporal windows in this study: one with low RSIs (0-300ms), second with medium RSIs (400-700ms) and the third with high RSIs (800-1100ms).

Based on the results of the earlier studies with fixed RSI, the hypothesis of the current study was that learning would be more explicit in the high RSI group compared to the other two groups because of the increased processing time available for the stimuli being presented sequentially for the high RSI group.

Experiment

Method

Participants 35 participants were randomly assigned to one of the three experimental conditions [(RSI (0-300ms), RSI (400-700ms) and RSI (800-1100ms)], with eleven participants in Group1 and twelve each in the other two. Participants gave informed consent before the start of the experiment.

Stimulus A black circle (target) appeared in one of the four boxes located horizontally on the computer screen. The target positions were numbered 1 to 4 from the extreme left being 1 and the extreme right being 4. Participants' task was to press the corresponding key as soon as the target appeared in one of the four target locations. In this experiment, we used two different sequences: 342312143241 (SEQ1), 341243142132 (SEQ2) (Reed & Johnson, 1994). Each location formed a trial and a sequence constituted 12 trials. Participants were presented with 14 blocks of 96 trials. In each group, half of the participants were trained on SEQ1 whereas the other half was trained on SEQ2. For those participants who received training on SEQ1, in the 12^{th} block (transfer block) SEQ2 was used and vice versa.

Procedure Participants were asked to look at the target, in this case, a black dot, which would appear at one (out of four) predefined box on the computer display. Participants were not informed about the repeating sequence.

After the instructions, the training (practice) phase started. It consisted of 14 training blocks with a serial four choice SRT task where each block consisted of 96 trials. On each trial, stimulus appeared in one of the four locations and the participants were asked to respond to it by pressing the corresponding key as fast as they could. The stimulus would disappear as soon as the participant had pressed a key and appeared in the next location after an RSI depending on the condition (0-300, 400-700 or 800-1100). The RSI value between any two stimuli was a value belonging to the range. For example: In Group1, RSI value can be 0ms, 100ms, 200ms or 300ms and within a block these RSI values were randomized between any two stimuli with no two successive pairs having the same RSI value.

The trials in each block had 8 repetitions of one of the two 12 length sequences (SEQ1 or SEQ2) and reaction times of the participants were recorded for each trial. After the experiment, participants were asked to perform generation and recognition tasks to assess the knowledge of the learned sequence.

Generation task In this task, participants were asked to freely generate the sequential regularities they might have encountered during the main task in a series of 96 trials. The stimulus appeared wherever the participant pressed the corresponding key and as soon as the participant pressed the key corresponding to the next location, it would appear in the next one.

Recognition task In this task, participants were presented with 24 fragments of 3 trials where 12 fragments belonged to SEQ1 and 12 belonged to SEQ2. The participants were asked to respond to the stimuli like they did in the SRT task and were then asked to rate how confident they were that the fragment that they just encountered was part of the training sequence. Ratings were given on a six-point scale described in (Shanks & Johnstone, 1999).

Results

SRT task The analysis was done on 11 participants in Group1 and 12 each in Groups 2 and 3. Means of median RTs during the 14 blocks are displayed in Figure 1.

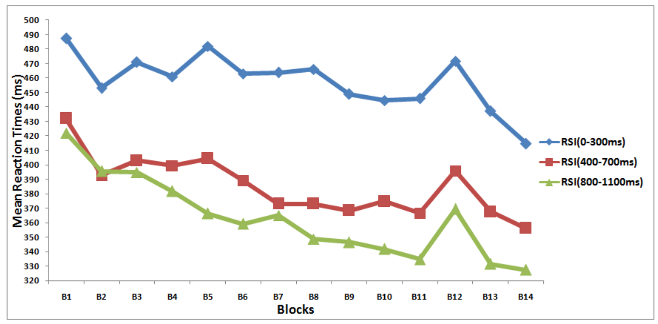

Figure 1: Mean of median RTs across the blocks with an RSI of 0-300ms (blue), 400-700ms (red) and 800-1100ms (green). B12 is the transfer block.

Faster RTs were observed observed for higher RSI groups compared to the lower RSI groups. A one-way repeated measures ANOVA was conducted on blocks 1-11 (within-subject) and group as a between-subject factor. A significant effect of block [F(10,320) = 12.161, $p < 0.05$, η^2=0.275] and group [F(2,32) = 5.831, $p = 0.007$, η^2=0.267] were observed. The interaction between block and group was found to be insignificant [F(20,320) = 1414.882, $p = 0.137$, η^2=0.0079].

The increase in RTs from Block 11 to Block 12 suggests that the participants learned the sequence in all the 3 groups. To assess this, paired t-tests were conducted between RTs of transfer block (B12) with the average of RTs obtained for B11 and B13, separately for each of the three groups. The tests showed significant transfer effect in all three groups (Group1: t(10) = 3122, $p = 0.011$, Group2: t(11) = 2.669, $p = 0.022$ and Group3: t(11) = 4.886, $p < 0.01$). The results confirm that sequence learning did take place in all the three groups.

Generation task In the free generation task, the number of generated chunks of length that were part of the training sequence was computed. The maximum number of three length chunks that can be present in a generated sequence of 96 trials is 94. Correct chunks generated were divided by 94 to compute the scores. The chance level is 0.33 as the participants were asked to not repeat their responses in both the tasks. Figure 2 reports the average scores for the three groups.

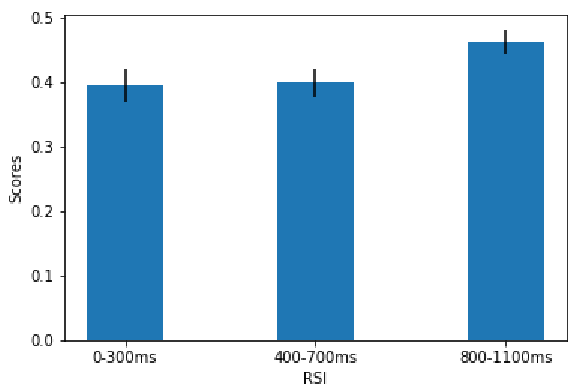

Figure 2: Average free generation scores

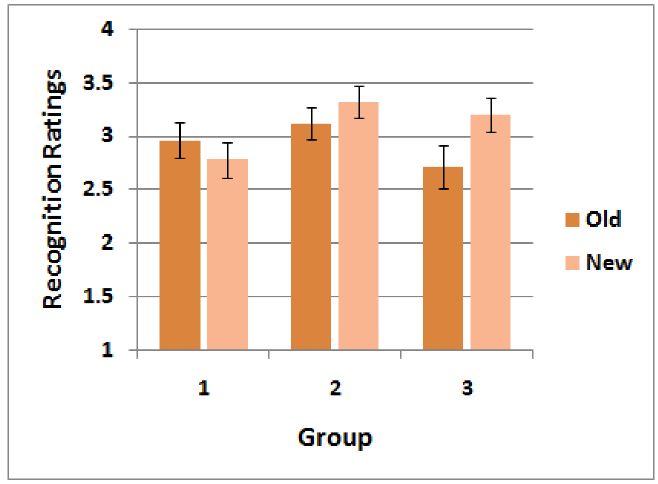

Figure 3: Average recognition ratings

The scores were compared with the chance level (0.33) and were significantly above chance level in all the three groups (Group1: t(10) = 2.419, $p = 0.036$, Group2: t(11) = 3.002, $p = 0.012$ and Group3: t(11) = 6.612, $p < 0.05$).

Pairwise comparative tests done on the scores showed significant differences between Group2 (M=0.399 and SD=0.0795) and Group3 (M=0.462 and SD=0.0692) ($p = 0.05$) and Group1 (M=0.394 and SD=0.088) and Group3 (M=0.462 and SD= 0.0692) ($p = 0.04$) while there was no significant difference between Group1 (M=0.394 and SD=0.088) and Group2 (M=0.399 and SD=0.0795) ($p > 0.05$).

The scores were above chance level in all the three groups which gives us more proof that sequence was successfully acquired in all the three groups. The pairwise results of the scores show that the participants in Group3 have more knowledge of the sequence compared to that of the other two groups.

Recognition Task Mean recognition ratings for the three conditions and for both the old and new triplets are shown in Figure 3

Paired t-tests were conducted to compare the ratings on the old and new fragments in each group. There was no significant difference between ratings of the new and old triplets in Group1 (t(10) = 0.868, $p > 0.05$) and Group2 (t(11)= 1.508, $p > 0.05$) but there was a significant difference in Group3 (t(11) = 2.358, p=0.04). Since there is a significant difference between the ratings of old and new fragments in Group3, we can say that the participants were able to distinguish old and the new fragments. We can hence conclude that the knowledge acquired by Group3 participants is explicit.

Discussion

The purpose of the study was to investigate the effects of varying RSI on sequence learning. For this, we chose three separate groups based on RSI (interval between the participants' response to a stimulus and appearance of the next one) : 0-300ms, 400-700ms and 800-1100ms. These RSIs were randomized within each RSI group. Results showed that irrespective of the RSIs, participants were able to learn the sequences in all the three groups.

The free generation scores were significantly above the chance level for all three groups which indicates that the participants were able to express the knowledge they acquired when directly instructed to do so. Pair wise comparisons showed that the participants in higher RSI group had acquired more knowledge compared to the lower RSI groups.

In the recognition task, since the the ratings for old and new fragments were significantly different for Group3, it that the participants were able to distinguish between them. Hence we can conclude that conscious knowledge of the sequence led them to distinguish between the old and new fragments. This wasn't the case for Group1 and Group2.

To summarize, the explicitness of the knowledge increases as the RSIs increase which is consistent with the existing literature (Destrebecqz & Cleeremans, 2001, 2003). In the next section, we propose a computational model that tries to explain the phenomena observed in the empirical study.

Computational Model

We used the simple recurrent network (SRN) introduced by Elman (Elman, 1990) to capture our empirical results. Elman network is a connectionist network which is trained to predict the next element in a sequence based on the current input using backpropagation learning algorithm (Rumelhart, Hinton, & Williams, 1986) and a set of units called as context units that store the context of the sequence. The Elman network was first used for sequence learning by Cleeremans and McClelland (Cleeremans & McClelland, 1991)

The SRN architecture, however, does not have intrinsic mechanisms to support RSI which is crucial for the current study. We addressed this shortcoming by using an explicit spatial representation of time in the network i.e. by introducing RSI assuming it to be one of the inputs to the network.

This is explained in detail in the next subsection.

Description of the model

To simulate Response-to-Stimulus Intervals, we approximated every 100ms to 1 unit of time. Equivalent RSIs for Group 1 (0-300ms) would be: [0, 1, 2, 3], Group 2 (400-700ms) : [4, 5, 6, 7] and Group 3 (800-1100ms) : [8, 9, 10, 11]. We introduced these RSIs between any two stimuli by repeating the first stimulus, the corresponding RSI number of times. For example, if the input sequence is [3, 4, 1] and RSI value between 3,4 is 2 and 4,1 is 3, the input that is sent into the network would be: [3, 3, 3, 4, 4, 4, 4, 1]. It should be noted that the RSI values were randomized in the same way described in the empirical study. Target for the stimulus element and the RSI values would be the next element in the sequence. For the above example input, the target would be [4, 4, 4, 1, 1, 1, 1]. Using this representation of RSI, our goal was to simulate the effects of RSI on 1) Serial Reaction Time Task and 2) Generation task.

Serial Reaction time task To simulate the performance of the SRT task, element $t-1$ of a sequence is presented to the model. Both the context layer and the input layer contribute to the activation of hidden layer, which in turn activates the output layer. In the original Elman network, hidden activations get copied on to the context layer but in our model, the copying only happens at the end of the RSI i.e. when the input is the last RSI element. This was done to avoid inapproapriate grammar being learned by the network. Since the RSIs are randomized, changing the context for all inputs disrupts the underlying grammar of the sequence, thereby hampering learning.

Generation Task After training, the network is presented with a randomly selected stimulus. The output unit with the maximum activation value is presented as the next stimulus to the SRN.

In the next subsection, we describe the simulations performed.

Methods and Parameters

Twenty different networks for each of the three groups were each initialized with random weights. All networks were then trained on SEQ1 (342312143241), where each block contains 8 repetitions of the sequence. Variable RSIs were incorporated as described earlier. Local representation (one-hot encoding) was used to represent the input to the network. To make the model and the input process more ecologically realistic, a decay function was added to the input layer during the RSI. This progressively decreases the input vector value during the duration of the RSI acting as a perceptual trace of the original input. The decay function is represented as :

$$f(x) = 0.9^x \tag{1}$$

where $x =$ RSI

Another deviation from the standard Elman network is that the target values of the output units also increase with respect to the block number. Humans can not predict what the next element will be, without any prior exposure to the sequence. To capture this, we used an exponentially increasing function. The function is represented by a sigmoid below :

$$f(x) = sigmoid(\frac{x}{30} - 1) \tag{2}$$

where $x = Blocknumber$

The parameters used were: Learning rate: 0.01, Momentum=0.4, Number of hidden and context units=20, Number of input and output units=4 and activation function = sigmoid. After training, generation task was performed as described earlier.

Results

We used root mean square error as a measure of learning since we did not simulate reaction times for the model. Figure 4 shows the root mean squared errors averaged over twenty simulations for the three groups where error is the difference between target and output. As the figure illustrates, root mean square error tends to decrease in Group2 and Group3 conditions, but remains relatively stable in the Group1 condition. The error also decreases more with practice in the high RSI condition compared to the small RSI condition.

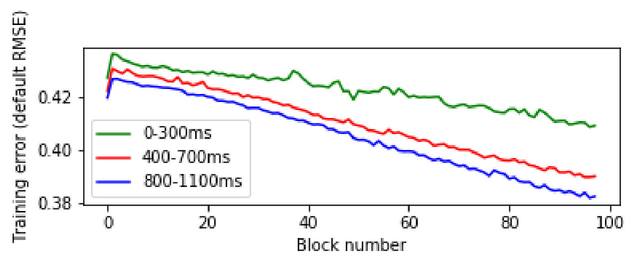

Figure 4: Root mean square errors simulated in the three conditions

These differences in training influence generation performance as well. Figure 5 illustrates the average scores of the free generation task for the three groups. The figure shows that the model can offer a good qualitative account of participants' behavior in the generation task, as higher RSI group has higher scores.

Discussion & Conclusion

The empirical study demonstrated that the sequence learning becomes more explicit when the RSIs are larger. It was also evident that disrupting the temporal rhythm does not affect sequence learning. The difference between the higher and lower RSI groups in the computational model occurs due to more number of backpropagation learning iterations that happen during high RSI, which could be interpreted as more time available to build better representations of the available stimuli. The computational model proposed in this study is a simplified version of existing models (Destrebecqz & Cleeremans,

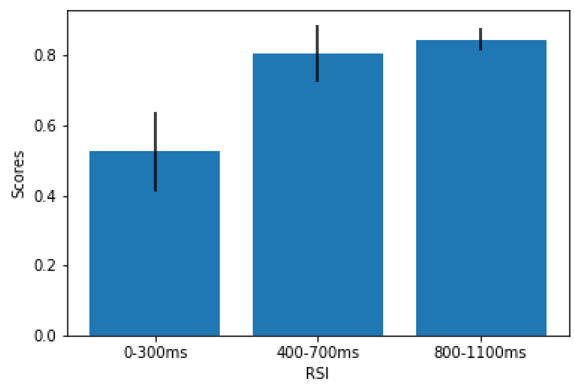

Figure 5: Mean free generation scores simulated in the three conditions

2003) with a single SRN unit accounting for both perception and memory and a monotonically increasing function in the output unit. Nevertheless, the simple architecture of the model captures various aspects of sequence learning like: 1) Faster reduction of root mean square error (which corresponds to reaction times) for higher RSIs compared to lower ones 2) Better scores for sequence generation indicating better learning of the underlying grammar in the higher RSI group.

Future work could include modeling the target vectors in detail with a learning function and capturing reaction times with integrators similar to earlier models (Destrebecqz & Cleeremans, 2003). To investigate the claim that increased RSI leads to better and more explicit representations of the sequence, hidden layer representations could be studied to see the differences among the three networks representing different RSI conditions (Servan-Schreiber, Cleeremans, & McClelland, 1989).

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