Temporal dynamics of Cognitive processes: Case studies on Sequence learning and Affective adaptation of emotions

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by

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CERTIFICATE OF AUTHORSHIP

I, Sneha Kummetha, declare that the thesis, titled "Temporal dynamics of Cognitive processes: Case studies on Sequence learning and Affective adaptation of emotions", and the work presented herein are my own. I confirm that this work was done wholly or mainly while in candidature for a research degree at IIIT-Hyderabad.

Date

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It is certified that the work contained in this thesis, titled "Temporal dynamics of Cognitive processes: Case studies on Sequence learning and Affective adaptation of emotions" by Sneha Kummetha, has been carried out under my supervision and is not submitted elsewhere for a degree.

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To *My Family*

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Abstract

This thesis aims to investigate different aspects of timing in Sequence Learning and Adaptation to certain emotional responses. Sequencing and processing of emotions are fundamental to human behaviour and hence are important fields to explore.

To investigate the influence of temporal factors in Sequence learning, we conducted a behavioural study using the paradigm of Serial Reaction Time (SRT) task and introduced delay in presentation of successive stimuli, referred to as *Response-to-Stimulus Interval* (RSI). By varying the RSI between successive elements of a sequence over a few temporal windows, we attempted to explore what effects this systematic varying of the RSI would have on the sequence learning process. We have also conducted post-experimental debriefing sessions to see if such learning is *implicit* or *explicit*. The SRT task requires the participants to simply respond to a stimulus that appears on the screen by clicking a key corresponding to the location at which it appeared. Reaction times were recorded for all the stimuli and reduction in this would imply learning. Statistical analysis of the reaction time data showed that learning did not get impaired in the various temporal groups despite delays experienced due to variable RSI. Post-experimental results showed that the knowledge acquired in smaller RSIs was implicit while for larger RSIs it was explicit. The results are in general agreement with the existing literature with fixed RSIs and hence we can conclude from the empirical study that varying RSIs do not impair sequence learning and that the sequential knowledge might have become explicit with larger RSIs. Additionally, we proposed a biologically realistic computational model in the form of a simple recurrent neural network (SRN) to obtain a functional account of the empirical findings. The proposed model has spatial representation of time for incorporating RSI in the neural network. The model illustrates how explicit learning could emerge due to a longer temporal window between stimuli that could potentially give insights into the mechanisms of sequence learning in variable RSI conditions.

In the second part of the thesis, we investigated the duration aspect of timing. Specifically, how different kinds of emotional reactions last for different duration. For this, we conducted an empirical study with a sad and self-relevant stimulus and compared the results to a sad but not-so-self-relevant stimulus. We found that the emotional reaction in the current study lasted longer because it is perhaps difficult for human beings to adapt to an emotional response when they can relate to the stimulus that elicited the emotion. The emotional intensity and its duration are thus determined by two factors, the self-relevance of the affective stimulus and how well or poorly understood the stimulus is to the person experiencing it. The greater the self-relevance and poorer the understanding, the stronger the emotion

and longer will be its duration. We also describe a preliminary study conducted to collect Physiological data as an attempt to strengthen this observation.

The thesis ends with a summary of the work and a general discussion of the findings. Limitations and future work have also been discussed.

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Chapter 1

Introduction

Cognition is the process of acquiring knowledge and understanding through senses, thought and experience. It includes processes such as knowledge formation, memory, attention, judgment and evaluation, reasoning, problem solving and decision making, comprehension and production of language. Cognitive processes use existing knowledge and generate new knowledge. Cognition occurs over widely varying time scales spanning milliseconds to days. Cognitive processing is generally influenced by many behavioral variables and many times this produces behavioral patterns that are unpredictable. This makes understanding the underlying temporal factors influencing cognition a valuable area of scientific inquiry.

In this thesis, we investigate one important aspect of time: Duration. *Duration* refers to the amount of time elapsed between any two events or the amount of time an event continues to exist. In the first part of the thesis we will investigate how duration elapsed between two stimuli will affect the cognitive process of learning sequences. In the second part, we discuss the factors that influence the duration of an elicited emotion.

1.1 Investigation of duration in Learning

To investigate the impact duration has on learning, we first conducted an empirical study by introducing and manipulating duration between successive stimuli and subsequently built a computational model to explain the observations of the empirical study.

1.1.1 Human learning processes

Our ability to learn is probably one of the most commonly observable and noteworthy phenomenon of the human mind. We can acquire language, concepts and motor skills to such a complex and extensive degree that these learned processes and information are themselves the subject of intensive study. How our mind understands and is capable of interacting with the world relies on learning which is a process of vital importance to human beings.

Learning and memory are dependent on each other. People learn new knowledge or information and put it into their memory using their memory encoding processes. Additionally, people recall the information that they already know from memory: 1) To relate with new information 2) To make new information meaningful, and 3) Finally, in order to learn it effectively.

The memory system is broadly divided into two subsystems: Declarative and Non-declarative memory systems (Figure 1.1). Conscious memory processes are part of the *declarative memory* system and non-conscious information processes are part of the *non-declarative memory* system. Declarative memory is subdivided into episodic and semantic memory which refers to day-to-day memory functions like memory of facts and events. It primarily relies on the medial temporal lobe structures including the hippocampus. Non-declarative memory is also sub-divided into various components, of which *procedural memory* or formation of motor memories is the most prominent. Non-declarative memory depends mostly on the cerebellum, the striatum, and cortical association areas [14]. Procedural memory also includes associative learning forms, such as operant and classical conditioning, and non-associative learning forms such as habituation, priming, and learning of cognitive and perceptual processes. Historically, the distinction between *explicit* and *implicit memory* has been associated with declarative and non-declarative memory, respectively. It is often argued that declarative memory corresponds to explicit memories that are conscious and verbally transmittable. On the other hand, non-declarative memory is thought to represent an implicit and non-verbal type of memory that is acquired sub-consciously.

One well-studied sub-component of non-declarative memory is procedural memory. The difference between declarative memory and procedural memory is what is famously known as the difference between ”knowing that” and ”knowing how”. Procedural learning describes the formation of habits and skills and is one of the most primitive forms of learning, in fact the first to develop in infancy [91]. As it requires extensive practice, procedural learning system is slow and inflexible that eventually becomes automatic or reflexive. Despite its slowness, it is long-lasting and reliable, as any bike rider knows that even after years of not riding a bicycle, he/she never loses the skill. This slowness of acquisition but robustness of memory (once learned) makes procedural learning a particularly interesting field of study. In this thesis we investigate a paradigmatic example of procedural memory, namely, associative learning of successive stimuli or sequence learning.

1.1.2 Sequence learning

Sequence learning is defined as the ability to learn sequential structures present in an environment. There are two main reasons why sequence learning is a topic of interest:

1) Sequencing of information and actions is a fundamental human ability

We use sequences of information or sequences of action in many everyday tasks like, sequencing movements in playing instruments or typing on a keyboard, sequencing sounds in speech and sequencing actions in driving a vehicle.

2) Sequence learning could be a complex form of implicit learning

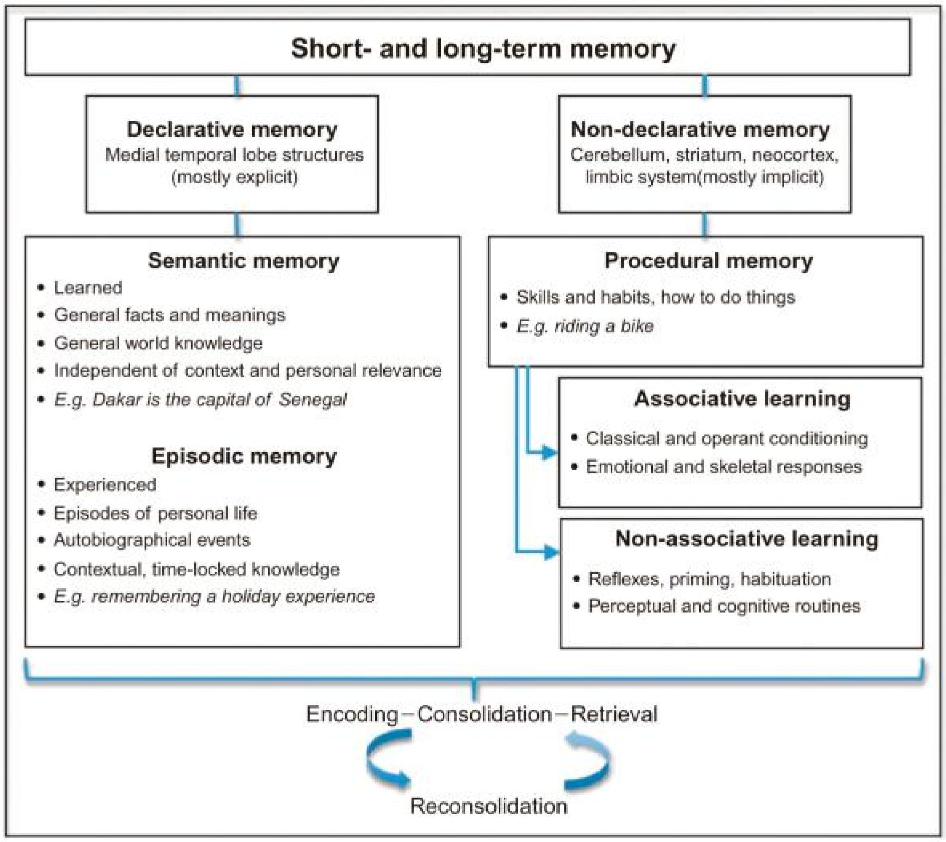


Figure 1.1: Taxonomy of multiple memory systems. Taken from [5]

If sequence learning is accepted as sometimes occurring without awareness, then it provides an intriguing example of non-conscious learning of a complex cognitive task. Initial evidence seemed to suggest we could. In Nissen and Bullemers original study [57], subjects demonstrated sequence learning in the absence of conscious awareness of a sequence. Indeed the study also found preserved learning in amnesic patients despite their lack of awareness of the sequence. These findings rapidly led to the conclusion that sequence learning can occur implicitly.

In this thesis, we were specifically focused on how sequence learning might be affected by introducing varying durations of time between successive stimuli. The duration of time introduced is known as RSI (Response-to-Stimulus Interval). We also tried to examine whether the knowledge acquired through such learning is available to consciousness. We have conducted an empirical study to investigate these points and then built a computational model to simulate the results observed in the empirical study.

1.2 Investigation of duration in Emotional Adaptation

Emotion experienced by a person is defined as a complex feeling that can result in physiological and psychological changes in that person. Emotions are constructed from multiple interacting components such as physiological arousal, appraisal/meaning-making, conscious experience, expression, and action tendencies [50] that each unfold along their own respective time scales. These temporal dynamics are integral to most major theories of emotion. For example, process models of emotion and emotion regulation emphasize their endurance and change over time and hold that temporal approaches will yield discoveries about how emotions are processed [35, 49]. Though timing is generally considered to be an important factor in understanding emotional experience, the overwhelming majority of studies that examine the neural basis of emotions ignore time as a central parameter.

Investigating the temporal dynamics of some process is to investigate how that process and its outputs change over time. Since time stretches infinitely in both the directions, there would be infinite ways of characterizing how a process would change. But these infinite possibilities can be narrowed down to highlight a couple of temporal dynamic features relevant for understanding how emotions are processed in the brain.

Emotions begin after the onset of a stimulus because they are coordinated responses to the stimulus. Since emotions aren't always synchronous with the stimuli that elicited them, one temporal dynamic feature of interest is the timing of the onset of an emotion after the onset of the stimulus, or, the time it takes for the emotion to reach a supra-threshold state [16].

Once an emotional process begins, the next temporal dynamic feature of interest is the duration of that process. Emotions are not static responses but rather emerge from the dynamic interplay between the person and their environment (internal or external) [1] and their duration will often be different from that of the event or stimulus that elicited the emotion [16]. The study described in this thesis focuses on the duration aspect of the emotional process.

Emotional experiences endure for variable amounts of time past their initial onset, from a few seconds to several hours and in some cases much longer, and only recently have we begun to understand determining factors of different durations of emotion [93]. Assessing this duration is very important for understanding how people recover from emotional events and individual differences that influence the recovery process [16]. For example, behavioral and psychophysiology studies have provided evidence that people diagnosed with depression recover from negative events more slowly than people never diagnosed with depression [8].

Affective adaptation is the process of weakening of the affective response of a constant or repeated affective stimulus by cognitive processes. As adaptation to an affective stimulus progresses, one would think less frequently about it, and when he/she does, it would result in a relatively weak affective response. The adaptation process depends on the intensity of the elicited emotion. It also depends on certain characteristics of the stimulus itself that cause the emotional response. In this thesis, we discuss one such stimulus characteristic: The self-relevance of the stimulus presented. We conducted a study where the stimulus is non-fiction (self-relevant) and compared it with a study where the stimulus is fiction (not-self-relevant). In both the studies, the initial emotional intensity was the same in both the cases and we hypothesized that the non-fiction condition will take longer duration of time compared to the fiction condition. This aspect of stimulus self-relevance was not investigated much, especially for negative stimuli which forms the main contribution of this part of the thesis.

1.3 Thesis Overview

This thesis consists of 5 chapters. Chapter 2 describes the empirical study conducted to understand the temporal effects on sequence learning. Chapter 3 covers the computational model that was built to explain the data observed in the empirical study on sequence learning. Chapter 4 talks about the temporal aspect (duration) of elicited emotions. Chapter 5 concludes the thesis and discusses future work.

Chapter 2

Empirical Investigation of the effects of RSI on Sequence Learning

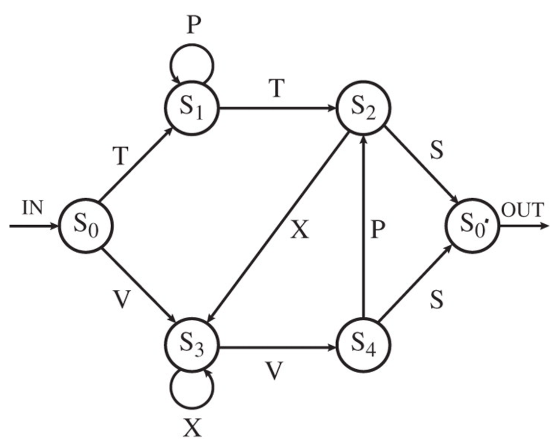
In this chapter, we discuss the experimental study conducted to test the effects of variable Response-to-Stimulus Interval (RSI) on Sequence Learning.

2.1 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*. Whereas, if it is not available to conscious access, the learning is said to be *implicit*.

Implicit learning or procedural learning is an important topic since most human learning takes place without the conscious awareness of learning something [12, 43]. An example of implicit learning would be typing on a keyboard where people are not able to verbalize how the letters are arranged on the keyboard, even though they are able to use the keys to type words precisely and at a high speed. Their knowledge of where the letters are on the keyboard is implicit. Many everyday skills also rely heavily on implicit learning processes, i.e., language [58]. Language acquisition is implicit because children start learning a language and apply the grammar correctly at a very early age even though they have neither intended to learn the grammar nor are they aware of the fact that they are learning it. While the idea of learning something without awareness is accepted intuitively, the idea that humans are capable of learning with, as well as, without awareness is heavily contested [3, 6, 17, 56, 76, 77].

The term "implicit learning" was coined by Reber[65] when he used artificial grammar to train the participants (see Figure 2.1). He presented the participants with six to eight length strings for seven blocks which were constructed from a Markovian grammar. When asked to reproduce the strings, the participants who were presented with strings constructed from the grammar performed better than those in the control group who were presented with random set of letter strings. Since the participants were unable to verbalize the rules of the grammar, Reber[65, 66] suggested the existence of an unconscious system that was capable of acquiring abstract knowledge.



example strings:

TTS
TPPTS
TPPPTXVS
VXVS
VVS
TTXVPXVPS
TPPPPPPPTS
VXXXXXVS
TPPTXVPXXXXXVPXVPS

Figure 2.1: The Artificial Grammar used by Reber [65], illustrated by its corresponding finite state automaton and a few sample strings generated from the grammar

2.1.1 Serial Reaction Time task (SRT)

Serial Reaction Time (SRT) task is one of the most popular paradigms used for implicit sequence learning [10]. It was first used by Nissen and Bullemer [57]. In the original experiment, the participants react to stimuli presented on a computer screen. Stimuli occur in different locations which are horizontally aligned in the middle of the screen. These locations are mapped to keys on a keyboard and it is the participants task to react to each stimulus with the corresponding key. Participants were not informed that stimuli follow a sequence.

As a result, Nissen and Bullemer (1987) found that the participants showed a learning effect in their performance while not reporting any knowledge of the existence of a sequence. Implicit knowledge of the underlying sequence is commonly shown by changes in reaction times over time. But this reduction in reaction time (RT) could be due to a practice effect [55, 57] and not because the participants are learning the underlying sequence. It is a common practice to insert a random block at the end of training to show that when the sequence changes, RTs abruptly increase [13] (see Figure 2.2). Many different kinds of sequences were implemented into SRTs to see how robust sequence learning is, for example, probabilistic sequences [39]. Sequence learning could be demonstrated for probabilistic sequences, too, though the learning is slower [11, 15, 59, 69] and is less likely to become explicit [18].

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. Verbal reports [37, 38, 57], Recognition task [61, 62, 95] and Generation task [11, 61, 80, 94] are widely used for this purpose. These tests are conducted to determine if the knowledge base acquired through the learning is implicit or explicit. In the recognition task, participants are presented with small fragments such

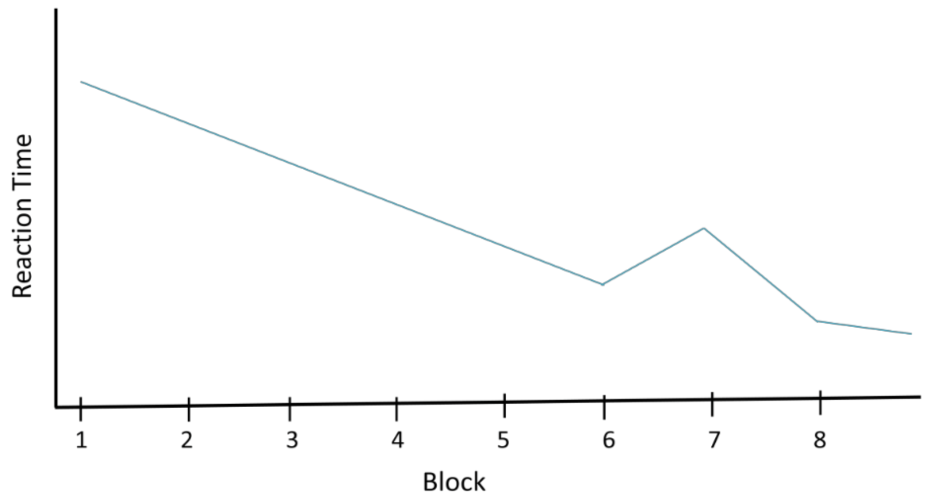


Figure 2.2: An explanation of how Reaction Time progresses over a period of Eight blocks in an SRT task. The first six blocks show reduction in RTs either due to practice effect or due to sequence learning and in order to see if it's not mere practice effect, a different sequence is introduced in the 7th block. The increase in RT observed in the 7th block shows that the sequence, indeed, was learned. (adapted from [23])

that some of them are part of the training sequence while the others are not and they are asked to rate how familiar the fragments looked. In generation task, they are asked to freely generate trials that they encountered during SRT task. The ability to generate the sequence in the free generation task and the ability to distinguish between various fragments was taken as proof that the knowledge is explicit.

2.1.2 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) [7, 18, 19, 22, 27, 28, 47, 54, 81, 85, 86]. In these studies, RSI is the time interval between a participants response to a stimulus and the appearance of the subsequent stimulus.

Temporal factors were initially used as a way of understanding the effects of a secondary task on sequence learning. Some studies claimed that the secondary task impairs sequence learning because it exhausts participants' attentional resources [57]. Stadler (1995) [86] however claimed that the secondary task impairs sequence learning because the secondary task introduces variability in RSI. The lengthening of the RSI that happens due to the secondary task would have similar effects compared to those resulting from actually inserting pauses between the trials. The pauses that were introduced incidentally would disrupt participants' ability to chunk the sequence which is essential to sequence learning [86].

Frensch and Miner (1994)[27] attributed the effects of secondary task on learning to the limitations of memory resources. Secondary tasks impair sequence learning because they lengthen the RSI which makes it more difficult for participants to link the memory traces corresponding to successive elements of the sequence in memory. They reported that sequence learning is impaired when RSI is increased to a very high value of 1500ms because the memory trace linking is affected due to that high a value.

The experiments of Destrebecqz and Cleeremans [18, 19] 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 post-hoc 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 [41].

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. There aren't any studies that investigate how disrupting the temporal rhythm of a sequence might affect its learning and what would the nature of such learning be (implicit or explicit) in various temporal groups. The temporal rhythm was disrupted by varying the RSI throughout the experiment. RSIs were systematically varied in various temporal windows in this study: first 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 [18, 19], the hypothesis of the current study was that learning, if it does happen, would lead to a knowledge base that is 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.

2.2 Method

2.2.1 Participants

35 participants were recruited from International Institute of Information Technology, Hyderabad, India. They 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. All the participants were right-handed and had normal or corrected-to-normal vision. All the participants received monetary compensation for their participation. Participants gave informed consent before the start of the experiment.

2.2.2 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). These sequences consisted of second order conditional transitions [67] and were balanced for location frequency, transition frequency, reversal frequency and rate of full coverage [67] but differed in sub-sequences of three elements that they contained. Each location formed a trial and a sequence constituted 12 trials. Participants were presented with 14 blocks of 97 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 12th block (transfer block) SEQ2 was used and vice versa.

2.2.3 Procedure

Informed consent and demographic profile were taken from all the participants according to the guidelines of the local Ethics Committee of the Cognitive Science Lab, International Institute of Information Technology, Hyderabad, India. 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 which constituted the main experiment. The experiment consisted of 14 training blocks with a serial four choice SRT task. Each block consisted of 97 trials for a total of 1358 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 first trial in each block appeared in a random location and was not considered for further analysis. The other trials in each block had 8 repetitions of one of the two 12 length sequences (SEQ1 or SEQ2). Half of the participants were trained on SEQ1 during the first 11 blocks and during blocks 13 and 14; and on SEQ2 during block 12. This was reversed for the other half of the participants. Reaction times of the participants were recorded. After the experiment, participants were given the following debrief session to assess the knowledge of the learned sequence.

2.2.3.1 Verbal Reports

After the SRT task, participants were presented with the following five choices and asked to choose the one that described the movement of stimulus the best:

1. The sequence of stimuli was random.

2. Some positions occurred more often than others.

3. The movement was often predictable.

4. The same sequence of movements would often appear.
5. The same sequence of movements occurred throughout the experiment.

This questionnaire is adapted from the one used by Curran et al [15]. After completing the questionnaire they were asked to perform the free generation task.

2.2.3.2 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. They were asked to rely on their intuition when unable to recall the exact location of the next stimulus and were asked not to repeat their responses. 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.

2.2.3.3 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 the following six-point scale [79]:

1. "I'm certain that this fragment was part of the training sequence"
2. "I'm fairly certain that this fragment was part of the training sequence"
3. "I believe that this fragment was part of the training sequence"
4. "I believe that this fragment was not part of the training sequence"
5. "I'm fairly certain that this fragment was not part of the training sequence"
6. "I'm certain that this fragment was not part of the training sequence"

2.3 Results

2.3.1 SRT task

In the analysis of the RT data, the first trial in each block was discarded as it was presented in a random location. The analysis was done on 11 participants in Group 1 and 12 each in Groups 2 and 3. Means of median RTs during the 14 blocks are displayed in Figure 2.3.

Faster responses 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

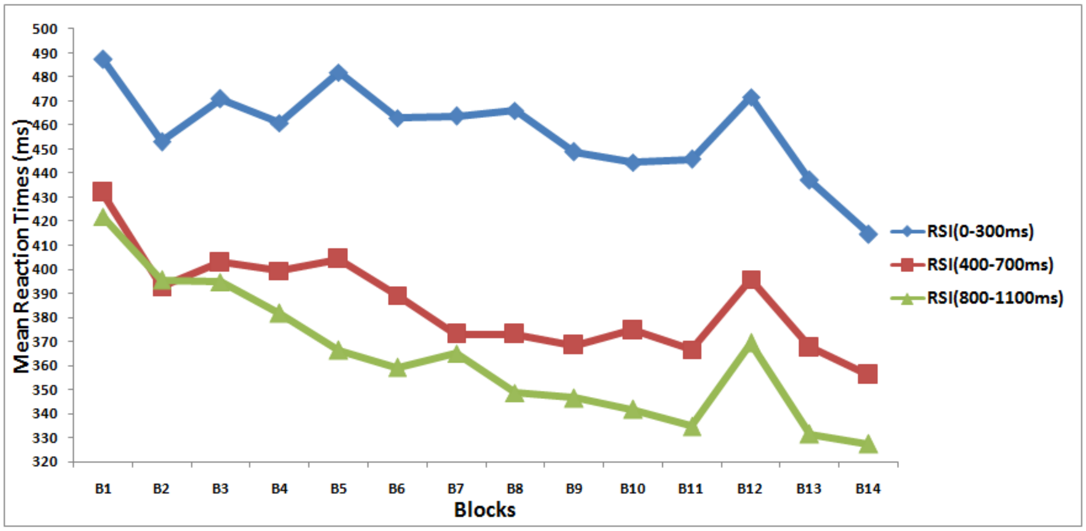


Figure 2.3: Mean of median RTs across the blocks with an RSI of 0-300ms (blue), 400-700ms (red) and 800-1100ms (green). B12 is the transfer block.

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 *post-hoc* results showed that there was significant difference between Group1 (M=462.379, SE=20.727) and Group2 (M=388.750, SE=19.845) ($p = 0.046$) and Group1 (M=462.379, SE=20.727) and Group3 (M=368.796, SE=19.845) ($p = 0.008$) but there was no significant difference between Group2 (M=388.750, SE=19.845) and Group3 (M=368.796, SE=19.845) ($p > 0.05$).

The improvement in RTs across the blocks could be due to the general improvement of motor performance and not necessarily due to improved learning. However, 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.

2.3.2 Verbal Reports

In general, high scores in verbal reports suggest that the participants might be aware of the sequence and low scores suggest that they might not be. Average of the choices for the three groups: Group1: 2.64, Group2: 2.83 and Group3: 3.58. Although Group3 had a higher score, overall the average scores were not statistically significantly different in the pair-wise comparisons.

2.3.3 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 2.4 reports the average scores for the three groups.

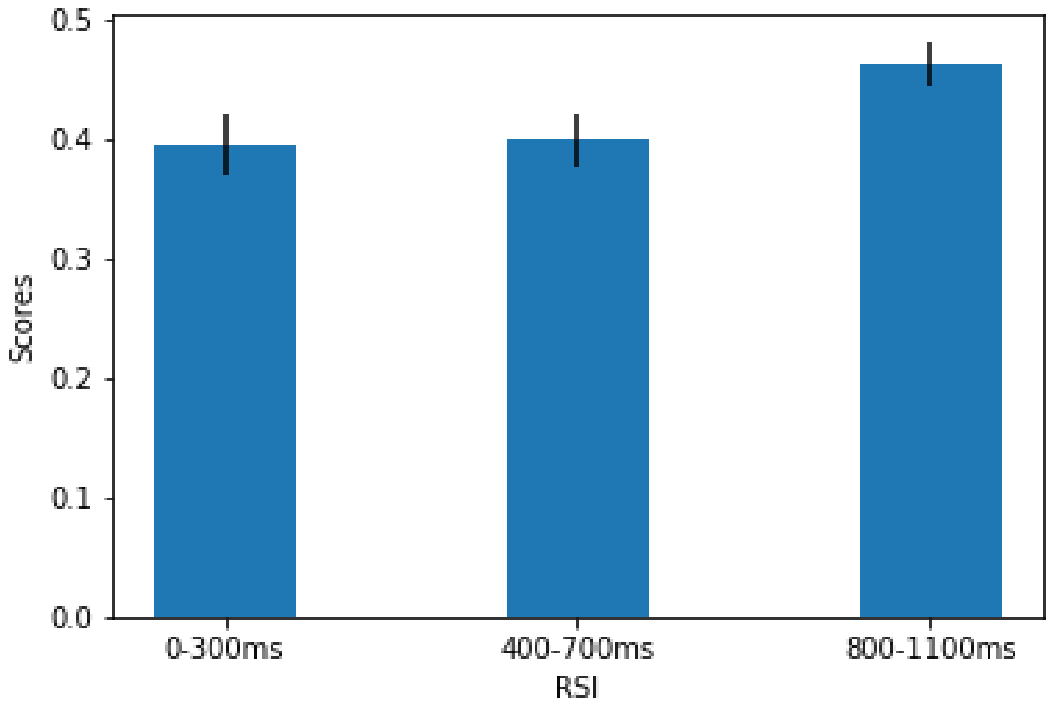


Figure 2.4: Average free generation scores shows that the first and the second group have similar performance but the second group has better performance compared to the other two

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.

2.3.4 Recognition Task

Mean recognition ratings for the three conditions and for both the old and new triplets are shown in Figure 2.5

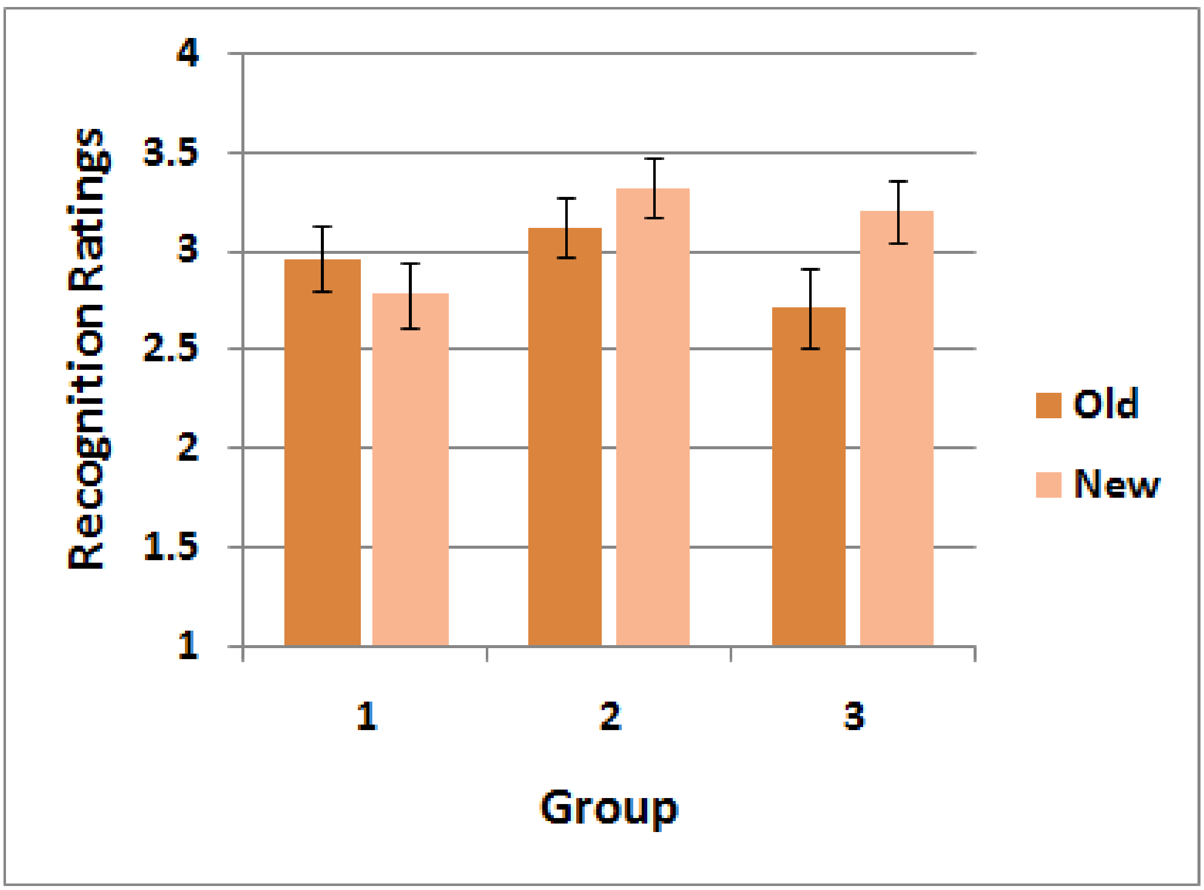


Figure 2.5: Average recognition ratings shows that the first and second groups have almost similar ratings for the old and new fragments. Whereas for the third group, the ratings look quite different

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.

2.4 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 show that irrespective of the RSIs, participants were able to learn the sequences in all the three groups. This was evident from the transfer effect that was observed when the sequence was changed in B12 and also from the significant reduction in RTs across the blocks.

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.

The recognition task results show that the participants in Group1 and Group2 have an implicit knowledge of the sequence while the participants in Group3 have explicit knowledge. This was clear from the fact that the participants in Group1 and Group2 were not able to distinguish between the old and new fragments (ratings for old and new fragments were not significantly different in the two groups). Whereas in Group3, the ratings were significantly different which implies that the knowledge the participants acquired was accessible to conscious recall and hence were able to distinguish between the old and new fragments. This was not the case for Groups 1 and 2. Hence the participants' knowledge of the learned sequence might have been implicit.

To summarize, the explicitness of the knowledge increases as the RSIs increase which is consistent with the existing literature [18, 19, 41]. This is evident from the results of the pairwise comparative tests that were performed on the free generation scores of all the three groups. The scores were comparable for Groups 1 and 2 while they were significantly different from that of Group3. These results together with the recognition task results give us more evidence to say that higher RSI does in fact make the knowledge base explicit. These results imply that the switch from implicit to explicit perhaps happened somewhere between the RSI ranges of 400-700ms and 800-1100ms. This concept of switch from implicit is explicit is consistent with the recent theoretical framework proposed by Savalia et al [72] which is discussed in the next section.

2.5 A Theoretical Account of the Implicit-to-Explicit Switch

The concept of the switch from implicit to explicit is consistent with the recent theoretical framework proposed by Savalia et al [72]. The framework claims that explicit learning follows a model-based mechanism which is slower because the subject is required to deliberate over the choices that lead to the goal. Whereas implicit learning which is said to be habitual follows a model-free mechanism which is much faster as the participant has to merely (habitually) follow the stimuli that appear in sequence.

Based on this, it was proposed that response-stimulus interval plays an important role in the model-based and model-free learning. It was proposed that higher RSIs would allow the participants to form a model and deliberate over their actions during the SRT task and hence learning would happen through a model-based mechanism. Whereas in the presence of lower RSIs, subjects do not get enough time to form a model and hence model-free learning would be initiated in this case. This proposal relies on the hierarchical chunking mechanism in which learning begins implicitly and in a model-free manner at the smallest possible fragment. As the chunk formation proceeds up the hierarchy, at a particular point, the size of the chunk which is defined in terms of the time it takes to execute the set of actions within the chunk, crosses a threshold. At this point, the attentional resources of the subject start to get engaged and explicit learning (model based learning) starts to take control of behaviour.

This engagement of attention happens when the chunk size becomes equivalent to what is known as the temporal window. This temporal window includes RSI for an SRT task and hence during bottom-up learning, larger RSIs need fewer actions to reach the threshold size of the temporal window. This leads to the engagement of attentional resources towards the underlying sequential pattern much sooner than in the case of a trial with smaller RSIs. According to their proposal, implicit learning in the first(lowest) level of the hierarchy proceeds without any attentional engagement. The hierarchical architecture of the bottom-up processing is depicted in Figure 2.6. The results of the current study tend to support this theoretical account which posits that as with increased RSI, more attentional resources are engaged, thereby making the learning process more explicit.

In the next chapter, we propose a computational model that tries to explain the phenomena observed in the empirical study. We will try to explore the extent to which the model is capable of simulating the temporal effects that were observed in the SRT task and the generation task to which our human participants were exposed to.

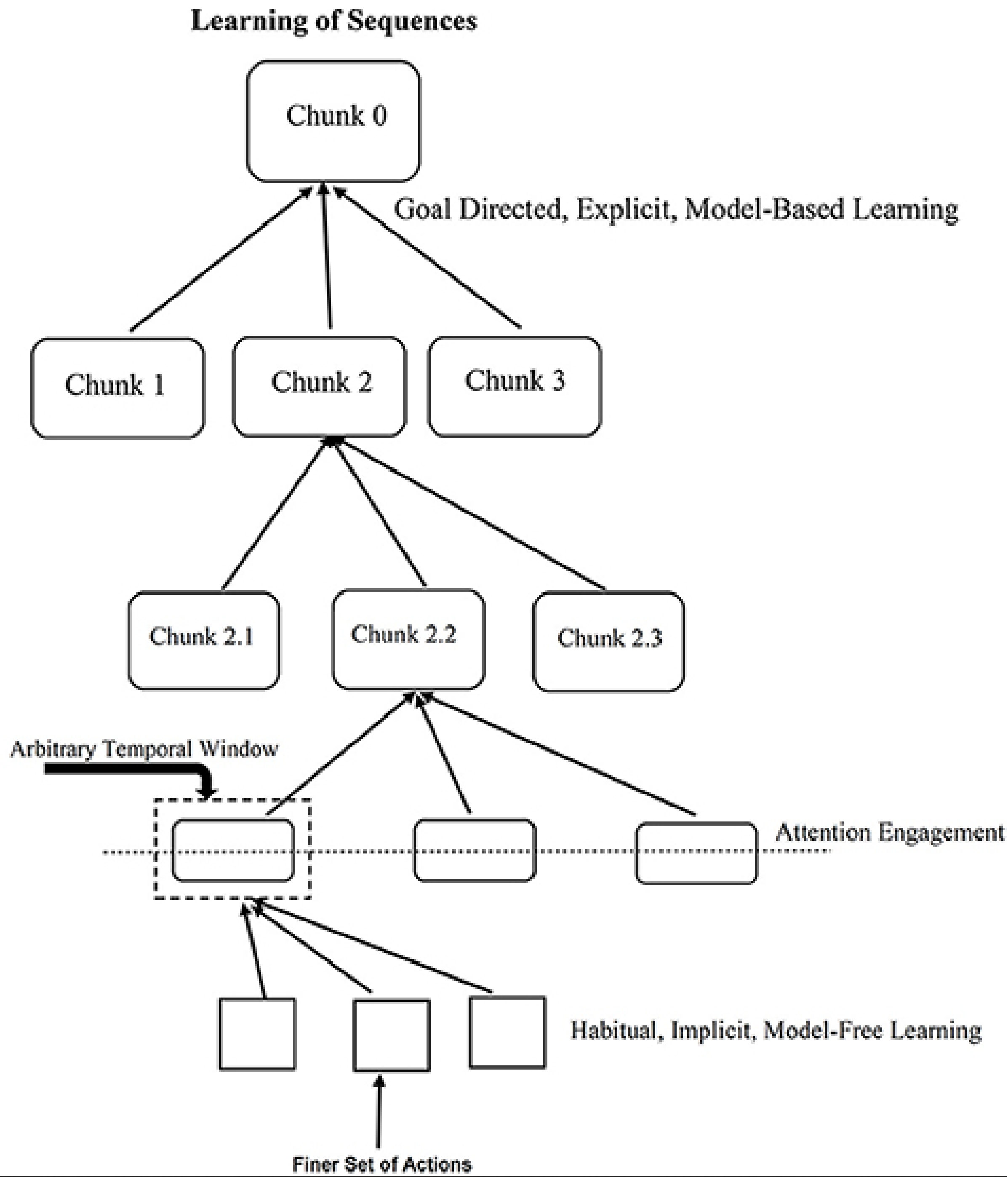


Figure 2.6: Acquisition of sequences from bottom-to-top where attention gets gradually engaged as you go up the hierarchy. Temporal window where switch from implicit to explicit happens is also depicted. [Adapted from [72]]

Chapter 3

Computational Model

In this chapter, we describe our attempts to emulate the empirical data observed in the previous chapter by building a biologically realistic Neural network model.

3.1 Introduction

Neural-network models are widely used as models of implicit learning. A number of architectures have been applied to the existing implicit learning paradigms. Dienes [20] found that several versions of simple auto-associator networks trained to memorize artificial grammar stimuli were able to classify new strings better than competing exemplar-based models.

The most prominent models of sequence learning are based on Elmans simple recurrent network (SRN) [25]. The SRN (Figure 3.1) is a three-layer, backpropagation network that is typically assigned the task of predicting the next item in a sequence. This prediction task requires that the network is sensitive to the temporal context in which successive elements occur. The SRN develops such sensitivity by means of fixed one-to-one recurrent connections between the hidden units and a pool of context units, which, on each time-step through a sequence, contain a representation of the previous time steps hidden unit activation vector. Over training, the network learns to base its predictions on the combined effect of the associations between current input and the next element (due to Backpropagation) and an increasingly large and self-developed temporal window (due to recurrent connections). The model has been successfully applied to numerous findings in sequence learning [9, 11] as well as in artificial grammar learning (AGL) situations [20]. As an extension to the model, Diens [21] showed that the model can be used to account for performance in AGL tasks involving transfer to strings composed entirely of new letters. This model by Diens showed that the transfer could also be accounted for without resorting to abstract, symbolic mechanisms. Other influential models of sequence learning include Jordans network [45], a model introduced by Dominey [22] and a few others [46].

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 section.

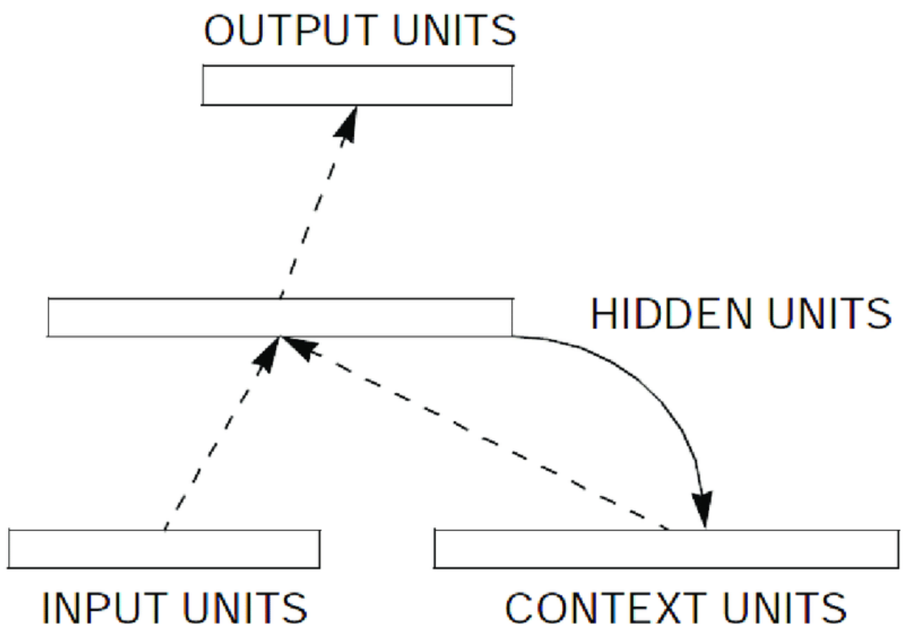


Figure 3.1: Elman Network with feed-forward connections from input and context layers to the hidden layer, and from hidden layer to the output layer. Recurrent connection exists from the hidden layer to the context layer [25].

3.2 Description of the model

To simulate Response-to-Stimulus Intervals (RSIs), 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 elements 3 and 4 is taken as 2 and that between elements 4 and 1 is taken as 3. Thus 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.

3.2.1 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 inappropriate 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. The backpropagation learning process is continued during the presentation of all the input and RSI elements.

3.2.2 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 section, we describe the simulations performed to compare SRT task and generation performance for the three groups.

3.3 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, i.e., the unit corresponding to the input has a value of 1 and the rest of the units were set to 0. 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:

$$f(x) = 0.9^x \tag{3.1}$$

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 which saturates to 1 at around 100^{th} block. The function is represented by a sigmoid function below:

$$f(x) = \sigma(\frac{x}{30} - 1) \tag{3.2}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{3.3}$$

where $x = Blocknumber$

The parameters used were: Learning rate: 0.01, Momentum=0.4, Number of hidden and context units=20. We used local representation (one-hot encoding) of input and output and since the sequence is made up of only four values, the number of input and output units was 4. Sigmoid activation function was used for all the networks.

After training, generation task was performed as described earlier.

3.4 Results

We used root mean squared error (RMSE) as a measure of learning since we did not simulate reaction times for the model. Figure 3.2 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 larger RSI conditions compared to the smaller RSI condition.

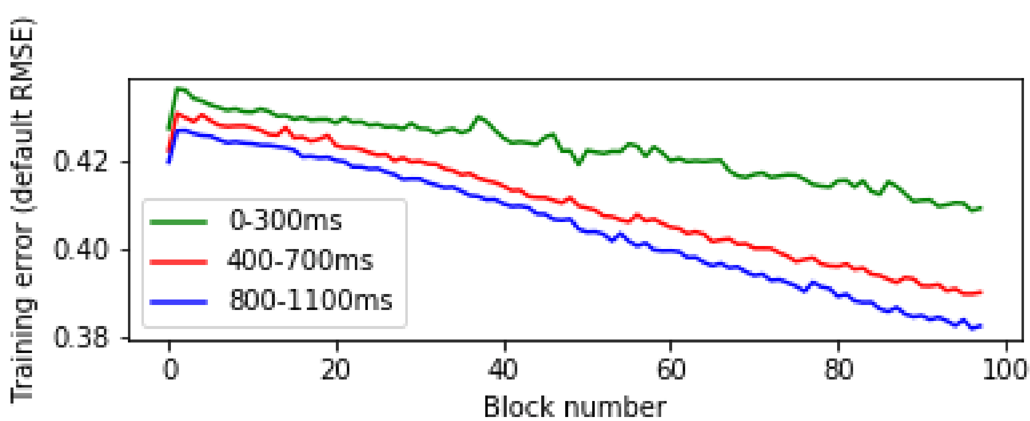


Figure 3.2: Root mean square errors simulated in the three RSI conditions

These differences in training influence generation performance as well. Figure 3.3 illustrates the average scores of the free generation task for the three groups. The scores were calculated using the method employed in the empirical study. 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.

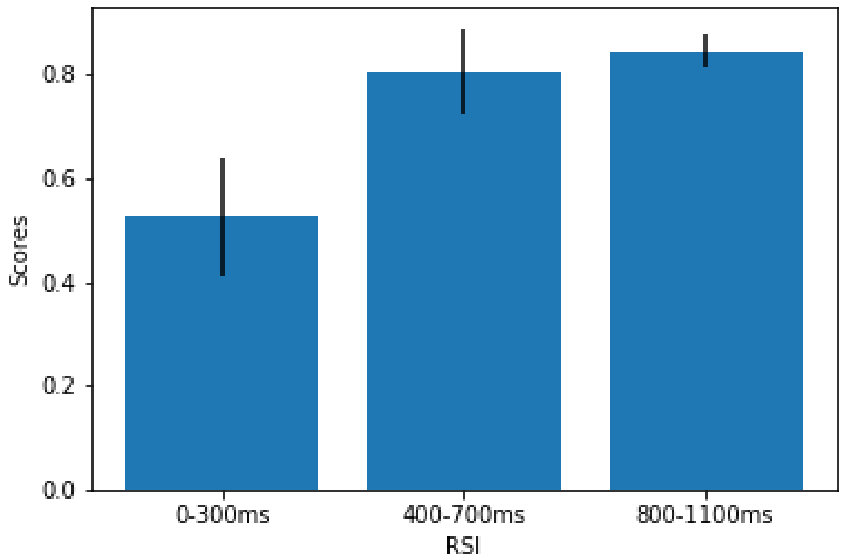


Figure 3.3: Mean free generation scores simulated in the three conditions

3.5 Analysis of hidden layer representations

In this section we discuss a qualitative analysis done on the hidden layer activations of the three networks to unravel the hidden representation learned by the network in the different learning contexts corresponding to different RSIs.

To predict accurately, a neural network takes advantage of the representations that have developed on the hidden units which are copied back onto the context layer. At any point in the sequence, these patterns must somehow encode the position of the current input in the grammar on which the network was trained. One approach to understanding how the network uses these patterns of activation is to perform a cluster analysis. We recorded the patterns of activation on the hidden units following the presentation of each sequence element in the three length chunks present in the original sequence. There are 12 distinct chunks present in the sequence and they were all presented to the three networks. The matrix of Euclidean distances between each pair of vectors of activation served as input to a cluster analysis program.

Cluster analysis is a method that finds the optimal partition of a set of vectors according to some measure of similarity (in this case, Euclidean distance). On the graphical representation of the obtained clusters, the contrast between two groups is indicated by the length of the vertical links.

The graphical results of the cluster analysis performed on the three networks can be seen in Figures 3.4, 3.5 and 3.6. Each leaf in the tree corresponds to a particular chunk and the middle element in each chunk indicates the element that has just been presented. For example, if a leaf is identified as

”324”, ”2” is the current element, its predecessor was ”3” and the network is supposed to predict ”4”. In all the graphs, the Y-axis represents distance and the X-axis represents the input to the networks.

From the figures below, it can be seen that for Group2 and Group3, some patterns that produce the same prediction are grouped together independent of the current input. For example, in Group2 ”324” and ”214” are grouped together because they are both supposed to predict ”4” as the output. Similarly, for Group3 ”312”, ”342” and ”432” are grouped together because all three inputs should have ”2” as their prediction. In all of these clusters, similarity in the patterns that result in similar prediction element are grouped together. Therefore when one of the hidden layer patterns is copied back onto the context layer, the network is provided with information about the temporal context of the chunk. That information is combined with the input representing the current element of the chunk to produce a pattern on the hidden layer that is a representation of the next element in the chunk which is to be predicted. This is not the case for Group1. All the chunks that have the same input are grouped together. For example, ”121”, ”324” and ”423” have ”2” as the current input and they form a cluster. The hidden layer representations for Group1 are not able to capture the temporal context of the sequence but are based primarily on the current input and hence the clusters are grouped only based on the current input.

Overall, the results of cluster analysis of hidden unit activations seem to point out that networks that learned sequences with larger RSIs tended to develop an internal predictive context that could be the basis for their superior performance as seen in Figures 3.2 and 3.3. On the other hand, relying primarily on the current input may have made it difficult for networks trained with smaller RSI because of the absence of sequential predictive ability from the hidden unit representations.

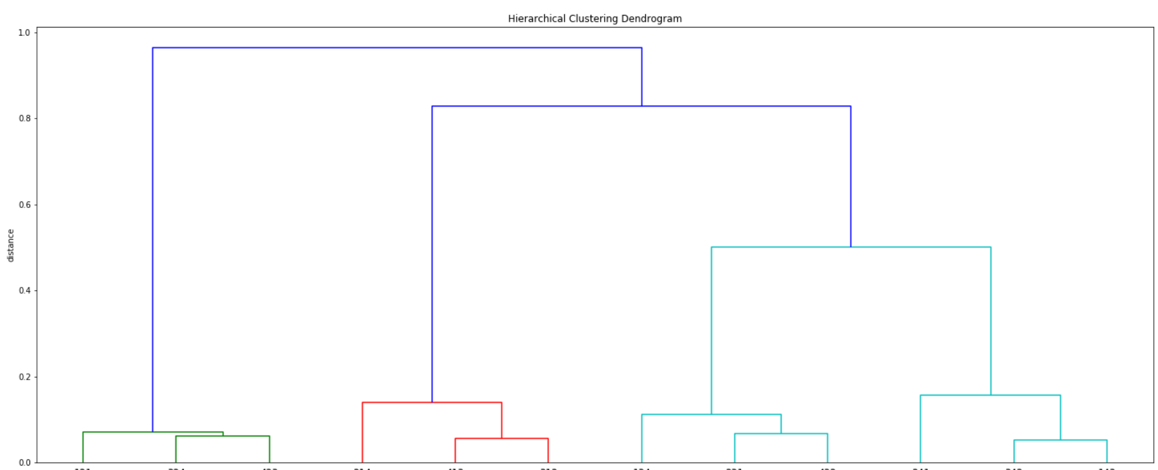


Figure 3.4: Hierarchical Cluster Analysis of the hidden unit activations for the network trained on Group1 conditions

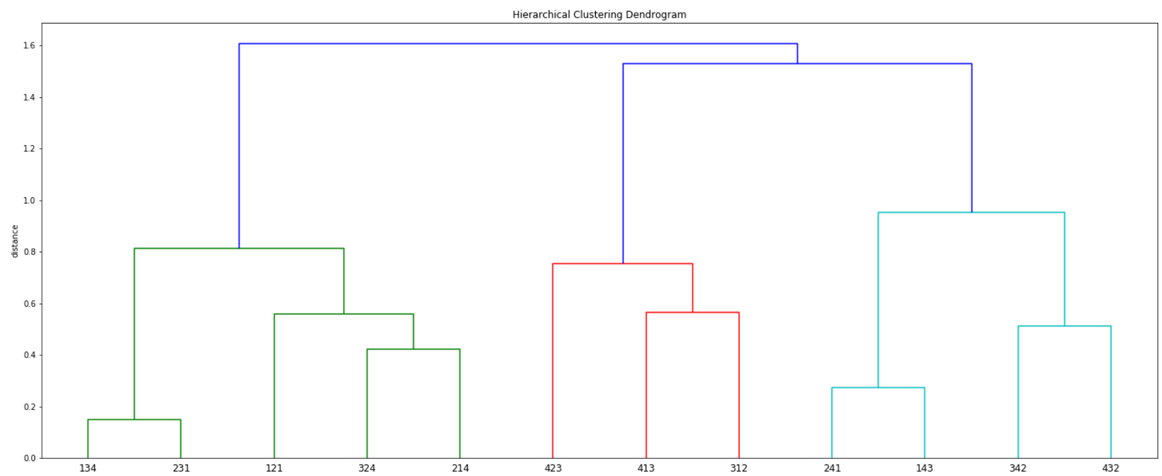


Figure 3.5: Hierarchical Cluster Analysis of the hidden unit activations for the network trained on Group2 conditions

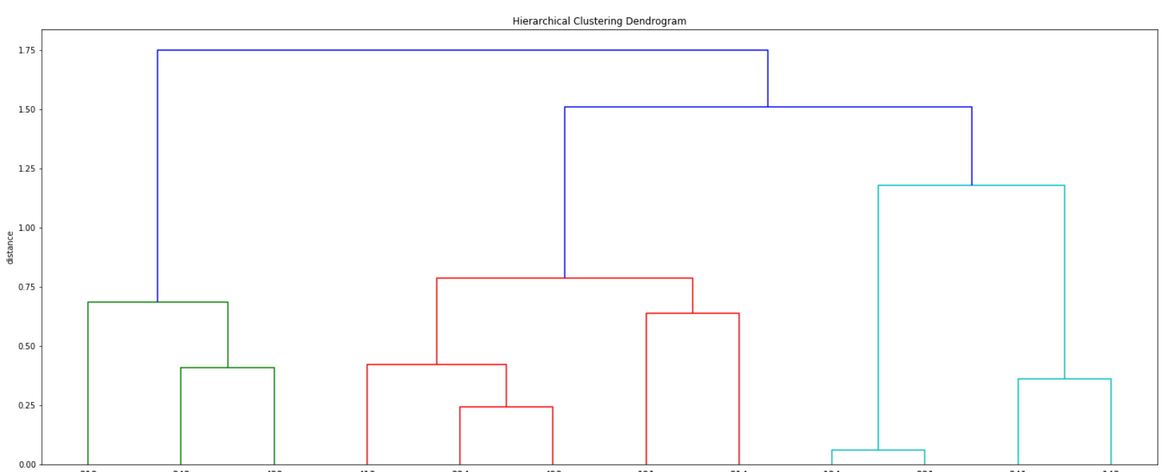


Figure 3.6: Hierarchical Cluster Analysis of the hidden unit activations for the network trained on Group3 conditions

Chapter 4

Emotion

In this chapter, we discuss an empirical study that was conducted to investigate the temporal aspects of Emotions.

4.1 Introduction

The overall emotional experience of an event results from both the intensity and duration of the elicited emotion. Yet, while making daily choices, we may be tempted to focus a lot more on emotion intensity than how long it is likely to last, often leading to poorer decisions in life. The duration aspect has received only a limited attention even from cognitive scientists in spite of it being a pertinent feature of an emotional response. For instance, research that evaluates the efficacy of different stimuli in mood induction appears to focus only on the initial emotion strength and not how long it would last [36]. While several studies and appraisal theories of emotion [24, 73, 82] have focused on its causes and elicitation, its duration has often been ignored [84, 97]. Studies that tried to elucidate the relation between the intensity and duration of an emotional response have been even fewer.

Different emotions have been reported to have different durations. For instance, it has been reported that joy and sadness generally last longer than fear and anger [29, 31]. It has also been reported that negative emotions have a longer duration than positive emotions [26, 29, 52, 53, 88]. It has been suggested [33, 84] and one would intuitively expect, that within an emotion type, the duration of an emotional experience would increase with its intensity. For instance, in a study by Gilbert, Lieberman, Morewedge, & Wilson [34], subjects expected the duration of their emotional response to correlate positively with its initial in-tensity.

There is some empirical evidence for this expected relation between intensity and duration. For instance, Sonnemans & Frijda [84] reported that the duration of an emotional response correlates with its intensity for positive emotions, disappointment, and sadness as long as there is no change in the situation that induced the emotion. The lengths of episodes of depressed mood also have been positively correlated with the severity of depression. The duration of the startle response has been reported to parallel stimulus strength, suggesting the same for the experienced fear underlying it [29]. A study by Rasinski, Berktold, Smith, & Albertson [64] showed that Americans who were more affected psychologically and emotionally by the 9/11 attacks retained the corresponding symptoms for a longer period on average. The amount of mental rumination and its duration have been observed to increase with initial emotion intensity [29, 70]. A prolonged duration of emotional consequences have also been found for extremely strong emotional events [29]. All these suggest a positive correlation between emotion intensity and its duration.

On the other hand, it has been reported that humans sometimes have a tendency to recover more quickly from deeply distressing incidents than the less painful ones [2, 32, 100]. Sonnemans & Frijda [84] observed a negative correlation between intensity and duration for fear. Rasinski et al. [64] found that Americans who knew someone killed or injured in the 9/11 attacks showed faster recovery from high stress levels as compared to those who did not. The experiments of Gilbert et al. [33, 34] provided additional evidence for this counter-intuitive phenomenon, who called this negative correlation the region- paradox. Brandon & Silke [4] suggested that this paradox is perhaps present for anxiety problems as well, on the basis of the findings of Smith, Perrin, Yule, & Rabe-Hesketh [83] and Thabet & Vostanis [90]. Thus it is clear that a simple relation does not exist between emotion intensity and its duration and the conflicting reports and arguments in the literature are hard to merge into a unifying hypothesis. We refer to this as the intensity-duration problem of emotion. The duration of an emotional response is primarily controlled by affective adaptation, the process by which active and passive psychological processes weaken emotional responses with time [26, 53, 97]. In addition to anecdotal accounts on affective adaptation, studies have demonstrated that we adapt to both pleasant (such as receiving an award or getting a promotion) and unpleasant (such as incarceration or losing money in a casino) incidents of life with time [26, 53]. The rate at which adaptation happens is known to differ across persons [88] and substantially between affective events [52, 88]. Three principles have been suggested to underlie affective adaptation on the basis of decades of research [97]. According to the antagonism principle, affective responses trigger conscious and subconscious processes that antagonize and weaken them. As per the attention principle, as subsequent events draw the attention from an emotional event, its emotional impact progressively decreases [97]. According to the adaptation-level principle or theory, emotional response decays as a result of the difference between stimulus strength and a reference point called adaptation-level, which is a function of past stimulus levels, reducing with time [26, 40, 63, 97].

In 2008, a simple affective adaptation model called AREA was proposed by Wilson & Gilbert [97]. According to AREA, if an affective event is self-relevant and poorly understood, it grabs our attention. Attending to it results in both an emotional reaction and an attempt at explaining the event. The process of explanation involves learning the nature of the event, determining its causes and understanding its consequences for our goals and self-concept. This results in the transformation of the event from being perceived as an extraordinary event to an ordinary one. As the event gets better and better understood by our attempts at explaining it, our attention to it also progressively reduces, resulting in our emotional reaction getting weaker with time. Once the event is completely explained successfully, it will no longer hold our attention and we will not have an emotional reaction anymore. The process of adaptation is now complete. In this model, emotion intensity and its duration are determined by two factors, the self-relevance of the affective stimulus and how well or poorly understood the stimulus is to the experiencer. The greater the self-relevance and poorer the understanding, the stronger the emotion and longer its duration.

To strengthen this proposition that affective adaptation is slower for more self-relevant and difficult to explain events than for less self-relevant and easy to explain events and to address the lacuna that this has not been shown for negative emotions, we conducted an empirical study. In this study, a documentary clip which is highly self-relevant but has difficult to explain events was used. These results were compared with a study that was conducted in University of Hyderabad (UoH) where a less self-relevant and easy to explain stimulus (movie clip) was used. Documentaries are about real people in real situations which can happen to anyone. One can almost always relate to them. Movies are fictional and are therefore not very relevant. Hence a documentary clip was used as a highly relevant stimulus. The protocol followed in both the studies is exactly the same and the only difference is the stimulus that was used.

Emotional states of the participants were recorded at various stages of the experiment and these values were compared with the values recorded in the UoH study. We expected the subjects in the current study to adapt slower compared to the UoH study because the documentary clip used in this study is an actual recorded event unlike the movie clip used in the UoH study which is merely a made-up story. Consequently, we hypothesized that subjects in both the studies would be comparably sad immediately after watching the clip, but that the subjects in the current study would remain sad longer.

4.2 Method

4.2.1 Participants

Twenty-eight volunteers (14 females and 14 males) participated in this experiment. Average age of the participants was 21.6. Average age of females was 21 and average age of males was 22. The experiment was conducted at International Institute of Information Technology. Similarly, the experiment conducted in UoH had Twenty-eight volunteers (14 females and 14 males). Average age of males was 25.1 and that of females was also 25.1. Written informed consent forms were obtained from all the participants who volunteered for both the studies.

4.2.2 Stimulus Preparation

The stimulus for this study was a sad self-relevant video. The saddest part from the documentary called ”The Suicide Tourist” was edited to make an eight minute video out of it. In the study conducted in UoH, the stimulus was the final scene from the movie ”The Champ”. This was also an eight minute long video. The presentation of stimuli and collection of data were controlled using the PsychoPy software program [60].

4.2.3 Procedure

The participants were shown pictures of the rating scales that they were going to see during the experiment and were briefly explained what they were expected to do. They were asked to wear the headphones throughout the duration of the experiment.

At the beginning of the experiment, the participant was asked to mark his/her emotional state (T1) on the rating scale. After that, a series of faces were flashed one after the other. Figure 4.1 shows a few sample images shown during the task. After a face was flashed on the screen, a rating scale would appear on the screen on which the participant was asked to mark the emotion expressed by the face. Both the rating scales ranged from extremely sad (-1) to extremely happy (1). The middle of the scale was neutral (0). All the values in between were values lying in the interval [-1 , 1]. After 48 faces were flashed, a rating scale would appear on the screen asking the participant to mark his/her emotional state (T2).

He/she was then instructed to read a small passage describing the video and then watched the video (the documentary clip which was the stimulus for the study). Right after the video, the emotional state of the participant was recorded (T3). After that, the procedure with the faces flashing on the screen would happen again. The task to rate these faces had no purpose other than to keep the participants busy and while away some time (filler task). This filler task is necessary because it gives time for the affective adaptation to happen.

After the filler task, the emotional state (T4) of the participant was recorded on the rating scale. A very short cartoon clip was shown to the participant and then he/she was asked to mark his/her emotional state (T5). The cartoon clip serves the purpose of lifting the participants' mood. In the experiment there were many instruction pages to guide the participant throughout. The participants were asked not to reveal the nature of the study to anybody else. The procedure followed in the UoH study is exactly the same as the current study.

4.3 Exclusion Criteria

After the experiment was done, all the participants were asked if they had seen the video before. If anyone had seen it before the experiment, then he/she would have gotten adapted to the stimulus and would not have felt as sad as he/she did the first time they had seen the video. None of the participants reported to have seen the video before the experiment.

There were certain entries with $T3 - T2 \geqslant -0.01$ where T2 represents the participant's emotional state just before watching the video and T3 represents their emotional state right after watching the video. $T3 - T2 \geqslant -0.01$ implies that the participant was not sad after watching the video. Such entries were removed because the objective of the experiment was to see adaptation when a selfrelevant sad video is seen. If a participant was not even sad when he/she saw it, then we can definitely not observe adaptation. There were 3 rejects (2 females and 1 male). Excluding these rejects there were 14 male and 14 female participants.

Figure 4.1: Sample images that were presented during the filler task

4.4 Results

For this study (IIIT experiment), the mean of T3 values was -0.519 ($SEM = \pm0.063$) and the mean of T4 values was -0.186 ($SEM = \pm0.061$). For the study that was conducted in University of Hyderabad (UoH experiment), the mean of T3 values was -0.528 ($SEM = \pm0.068$) and the mean of T4 values was 0.010 ($SEM = \pm0.057$). T3 is the emotional state of the participants just after watching the clip. T4 is the emotional state of the participants after the filler task.

Figure represents a line graph of UoH and IIIT experiments T3 and T4 means along with their respective SEM (standard error of the mean). The blue line joins the mean values of T3 and T4 in UoH experiment and the orange line joins the mean values of T3 and T4 in IIIT experiment. As expected, the emotional state of the participants in both the studies just after watching their respective videos is almost the same (intensity of sadness is almost the same) and the emotional state of the participants in the current study is lower than that of the participants in UoH study (the participants in the current study were sadder compared to the participants in the UoH study, after the filler task).

To test statistically that T4 value is smaller in the current study and that there is not much difference in T3 values in both the studies, two way ANOVA test for both T3 and T4 values was performed. The two factors were Gender (male and female) and Experiment type (IIIT experiment and UoH experiment).

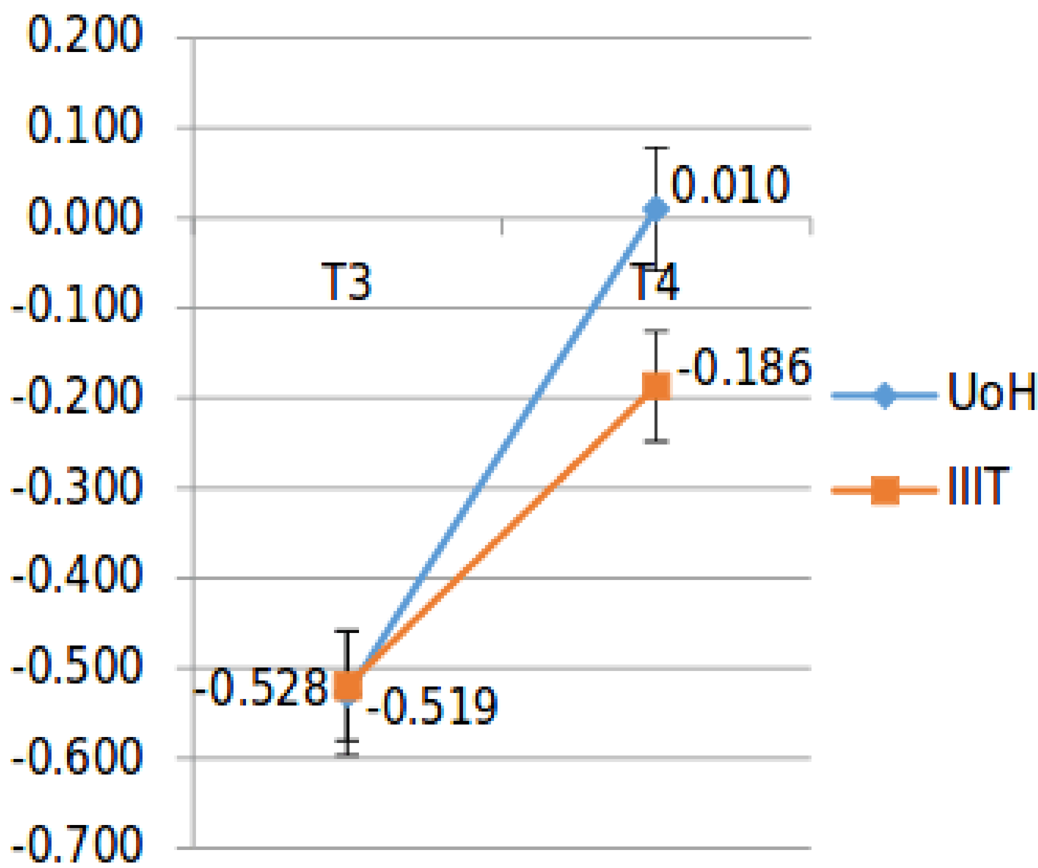


Figure 4.2: Difference in mean values of T3 and T4 for UoH experiment and IIIT experiment

From the ANOVA test we could say that there was no significant difference in T3 values in both the genders [F(1,52) = 1.82, $p = .18$]. Same was the case for T4 values between both the genders [F(1,52) = 1.08, $p = .30$]. There was no significant difference in T3 values of the two experiments [F(1,52) = .01, $p = .93$]. Also, the ANOVA shows that T4 is smaller in the IIIT experiment compared to that in the UoH experiment [F(1,52) = 5.48, $p = .02$]. Further there was no interaction between Gender and Experiment type in both T3 [F(1,52) = .04, $p = .84$] and T4 [F(1,52) = .09, $p = .76$]. Thus, there was no significant difference in T3 values of the two experiments while T4 is larger in the current study.

4.5 Discussion

This study was conducted to test the hypothesis that adaptation is slower for more self-relevant and difficult to explain events compared to that in less self-relevant events. To test this, the results obtained from this study were compared to those obtained in the study conducted in University of Hyderabad in which less self-relevant stimulus was used.

The results indicate that there is no significant difference between the emotional states of the participants recorded right after watching the video in both the experiments. While there is significant difference between the emotional states recorded after a certain period of time following the video. No significant difference was observed between the values obtained in males and females. No interaction between gender and experiment type (experiment with highly self relevant stimulus and experiment with less self relevant stimulus) was observed.

Since the final emotional intensity is larger for the current experiment (the participants were sadder for longer duration in the current experiment) for similar initial emotional intensities, it can be said that it takes longer for the emotion to die down with highly self-relevant stimulus. Thus, this study supports the hypothesis that affective adaptation is slower in sad - more self-relevant poorly explained events compared to sad - less self relevant easily explained events. It is consistent with the idea proposed by Wilson and Gilbert, 2008 [97]. The experiment strengthened the conjecture that duration is not dependent on intensity alone and consequently that stimulus features that determine intensity and duration are not exactly the same. Secondly, the experiment showed that this conjecture is valid for negative emotions as well. Future work could include investigation into more stimulus features that determine duration of an emotional response.

These results have been part of a larger study that lead to a publication recently [87].

4.6 Physiological Data

As an extension to the study described above, we conducted a pilot study to strengthen the results observed above by collecting and analyzing physiological data of the participants. We integrated Electrodermal Activity (EDA) with the experiment for this purpose.

Electrodermal activity (EDA) is the property of the human body that causes variations in the electrical characteristics of the skin. EDA has also been known as skin conductance, skin conductance response (SCR), galvanic skin response (GSR), psychogalvanic reflex (PGR), sympathetic skin response (SSR), electrodermal response (EDR) and skin conductance level (SCL). The theory of EDA holds that skin resistance varies with the state of sweat glands in the skin. Sweating is controlled by a part of the nervous system called as the sympathetic nervous system. Skin conductance is an indication of psychological or physiological arousal. If the sympathetic branch of the autonomic nervous system is highly aroused, then the activity of sweat glands also increases, which in turn increases skin conductance. In this way, skin conductance can be used as a measure of emotional responses.

We used BIOPAC system [89] for collecting EDA data. We first setup the EDA device on the subject by attaching the BioNomadix transmitter (PPGED), which is wireless, near or on the subject's wrist via a Velcro strap and the lead set into the EDA socket. Then, two isotonic gel electrodes would be stuck to the tips of the fore-finger and the middle finger of the subject. The lead set has two wires which have clips. Both the wires are clipped to the electrodes. If the subjects dominant hand is right, everything must be on his left hand and vice-versa. A button must be pushed on the transmitter for it to start transmitting signals. When the subject is emotionally aroused, sweat is secreted from the sweat glands which increases the conductance.

After this, the channels need to be setup. BIOPAC comes with a software called AcqKnowledge which is installed on the system connected to the receiver. The channel that is selected for collecting the EDA data must be the same on the receiver as well as on the system. The receiver receives the signals that the transmitter on the subject transmits. When the start button is pressed, the software plots the signals on the screen.

BIOPAC system needs to be integrated with the PsychoPy experiment inorder to get the EDA values at specific points during the experiment. In the experiment, the subjects are asked to mark their emotional states at five different points as explained in the procedure. The first point was at the very beginning of the experiment (T1), the second time was after all the faces were displayed which was right before the video was played (T2), the third time was right after the video (T3), the fourth time was after the second set of faces were displayed (T4) and the fifth time was at the end of the experiment (T5).

From the results that we got in the last experiment, we expect the EDA value at T2 to be less than that at T3 because the skin conductance generally increases after watching an emotional video. Also, we expect the EDA value at T4 to be less than that at T3 because of affective adaptation. The EDA values for the five participants who took part in the pilot study are displayed in Table 4.1. All the values are in microsiemens. The emotional responses marked by the subjects on the rating scale at T1, T2, T3, T4 and T5 are displayed in Table 4.2.

From Table 4.2, the results are similar to what were observed in the experiment. T3 values (emotional state are right after the clip) are all lower than T2 values (emotional state just before watching the clip) and T4 values (emotional state after a certain period of time following the video) are higher than T3 values. Adaption did happen.

From Table 4.1, we can make some inferences. Note that the EDA values will be higher when there is an emotional response. For Participant1, the EDA value increases from T2 to T3 as expected but there isn't much change in the subjects emotional response from T3 to T4. For Participant2, the emotional responses were, as expected, increase from T2 to T3 and decrease from T3 to T4. For Participant3, the emotional responses are as expected but the EDA values from T2 to T3 decrease instead of increasing. For Participant4 and Participant5, the emotional responses are as they are expected to be. For Participant5 the EDA values were negative which is quite surprising because we do not expect conductance to be negative.

There are several reasons for negative EDA values:

1. Calibration is incorrect.

2. Interference from another channel.

	T1	**T2**	**T3**	**T4**	**T5**
Participant1	10.63837	10.17603	12.21766	12.12458	12.79291
Participant2	0.09458	0.07474	0.41501	0.37686	0.36466
Participant3	0.96281	0.296000	0.08390	0.04881	0.00914
Participant4	0.08692	0.11133	1.03907	0.76898	1.66162
Participant5	2.73733	-2.61239	-1.29098	-0.56161	-2.34231

Table 4.1: EDA readings of the five participants at various points in the experiment

3. Interaction with bio-impedance measurements. If recording with NICO100C or EBI100C, improper connections could be the reason for negative EDA.

4. The recording is in AC mode. While tonic skin conductance can never be less than zero, phasic skin conductance can. A negative phasic skin conductance means that the tonic skin conductance is decreasing. Most of the automated analysis routines and much of the science of skin conductance requires a measure of tonic skin conductance. To measure this signal, the switches must be set to DC position which in case of PPGED is dip switch 6 on the receiver. It should be in the down position.

In our case, 1 can not be the reason because for an AcqKnowledge version later than 4.0, calibration is performed automatically. 2 also can not be the reason because only one channel was used for the

	T1	**T2**	**T3**	**T4**	**T5**
Participant1	0.09	-0.17	-0.19	0	0.04
Participant2	0.21	0.01	-0.64	-0.22	-0.13
Participant3	0.75	0.57	-0.61	-0.41	-0.31
Participant4	0	0.13	-0.21	0.22	0.09
Participant5	0.12	0.1	-0.19	0.11	0.05

Table 4.2: Rating Scale readings marked by the participants at various points in the experiment

experiment, and hence no interference. 3 can not be the reason either because neither NICO100C nor EBI100C was used in the experiment. The most probable reason for the negative EDA in our case is 4. The dip switch 6 on the receiver might not have been in the down position which might have resulted in negative EDA.

There was also a lot of noise observed in the graphs. A possible reason could be that the participants made movements during the experiment, even though they were instructed not to. With our limited pilot study with 5 participants, no correlation was found between subjective reports and the EDA values. This could be because the method that was used to collect the EDA data is not very accurate. There is probably a different way of collecting EDA data which might give better results. For example, instead of attaching the electrodes to the fingertips, they could be attached on the lower part of the palm. There might be certain precautions that need to be taken which may improve the results. Finding a way to remove the noise will also result in more accurate results. These could be taken up as future improvements.

Chapter 5

Conclusion and Future Work

In this thesis, we aimed to explore temporal aspects of two fundamental human capabilities : 1) Sequence learning 2) Affective Adaptation of emotions.

In the **Sequence Learning section**, we discussed the role of Response-to-stimulus interval (RSI) on sequence learning by describing an empirical study and then building a computational model. In the empirical study, there were three groups with various temporal windows. Apart from looking at whether sequence learning itself is affected by varying the RSI (disrupting the temporal rhythm), we also conducted post-experimental studies to investigate if the learning is implicit or explicit. The empirical study demonstrated that the sequence learning becomes more explicit when RSIs are larger. It was also evident that disrupting the temporal rhythm does not affect sequence learning as a whole which was the main objective of the study.

One limitation of this study could be that, even though we know that the implicit-to-explicit switch happens somewhere between the RSI ranges of 400-700ms and 800-1100ms, we do not know the exact value. To figure out where exactly the switch happens, this experiment must be extended to other temporal windows too. It is also possible that there are individual differences in switching intervals and this needs to be investigated in the future.

The **computational model** was a modified Elman network with spatial representation of time as RSI. The network with certain parameters behaved similar to the participants in the empirical study with higher RSIs developing more explicit representations.

The difference between the larger and smaller RSI groups in the computational model occurs due to more number of backpropagation learning iterations that happen during large RSI condition which could be interpreted as more time available to build better representations of the available stimuli. The computational model proposed in this study uses fewer number of components compared to the existing models [19], with a single SRN unit accounting for both perception and memory. Nevertheless, the simple architecture of the model captures various aspects of sequence learning like: 1) Faster reduction of root mean squared error (which corresponds to reaction times) for higher RSIs as compared to lower ones 2) Better scores for sequence generation indicating better learning of the underlying grammar in the higher RSI group. The model is also more biologically feasible because it incorporates: 1) Perceptual trace and 2) Increased exposure to the sequence with practice (monotonically increasing function in the output unit) which were not included in Destrebecqz (2003) model.

To investigate the claim that increased RSI leads to better and more explicit representations of the sequence, hidden layer representations were studied to see any differences among the three networks representing different RSI conditions. Hidden layer representations were studied using clustering techniques utilized earlier [75]. Hierarchical cluster analysis of the hidden unit activations revealed that indeed the networks that were trained with larger RSIs seem to have learned sequential context that depends on the previous element that enables prediction of the next element when the network is presented with the current element. The context that successfully embeds the past-present-future triad enables accurate prediction when learning sequences and as a result accuracy and post-hoc generation test performances were superior in these networks as compared to networks trained with smaller RSI. Networks trained with smaller RSI seemed to overly rely on the current input and did not seem to develop robus sequential context.

One of the limitations of the proposed computational model is that it does not capture reaction times proposed in the earlier models [19]. Future work could include modeling reaction times in a more robust manner.

In the next section, we discussed the duration aspect of **affective adaptation in emotions**. We hypothesized that affective adaptation is slower for self-relevant events compared to less self-relevant events. To test this, we conducted an experiment with the stimulus as a documentary and compared its results with another study which followed the same protocol but with the stimulus as a movie clip. As expected, participants were relatively more sad after certain period after watching the documentary clip.

Though the two sections are not completely related to each other, there is a unifying concept of time involved in both the studies. Emotion and Sequence learning are part of the fundamental aspects of human psychology.

As a future work, one could explore how emotions might affect sequence learning.

1. Sneha Kummetha, Pramod Kaushik, Anuj Shukla and Bapi Raju Surampudi.”Experimental and Computational Investigation of the Effects of Variable RSI on Sequence Learning.” Cognitive Computational Neuroscience, 2018. (Accepted for Poster Presentation)

2. J. E. Steephen, S. C. Obbineni, S. Kummetha, and R. S. Bapi. ”An Affective Adaptation Model Explaining the intensity-duration Relationship of Emotion.” *IEEE Transactions on Affective Computing*, 2018. ISSN 1949-3045. doi: 10.1109/TAFFC.2018.2848656.

3. Sneha Kummetha, Anuj Shukla, and Raju Bapi ”Effects of Variable Response-Stimulus Interval (RSI) On Sequence Learning” In G. Gunzelmann, A. Howes, T. Tenbrink, and E.J. Davelaar, editors, Proceedings of the 39^{th} Annual Meeting of the Cognitive Science Society, CogSci 2017, London, UK, 16- 29 July 2017. (Abstract)

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