"Are You Ready Yet?!"
A Computational Model For Temporal Preparation

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Abstract

In this paper a computational model based on the ACT-R modules of time estimation and declarative memory is presented. These two components of the architecture have been combined in order to gain knowledge about how timing experiences that have occurred in the past have an influence on future experiences. This computational simulation reproduces the behavior of 18 subjects that have participated in a timing-based experiment. In the experiment they were required to react, as quickly as possible, to a visual stimulus that was presented at different time intervals.

Keywords: Timing, Declarative Memory, Memory Traces, ACT-R, Cognitive Modeling

Introduction

Research questions relating to the concept of time are some of the most researched in the whole field of science. The range of research papers pertaining to the concept are related to a broad range of fields such as theoretical physics and even, cognitive psychology. In this paper, time is considered from a cognitive modeling perspective. This work aims to understand how and why timing experiences that have occurred in the past can have an influence on future experiences. This is done by trying to establish the link that there is between the ACT-R cognitive mechanism that guides the human perception of time, proposed in the work of, (Taatgen & van Rijn, 2011) (Taatgen, Van Rijn, & Anderson, 2004), and its declarative memory system presented in the work of (Anderson, 1996). The latter has as its main objective, keeping track of past experiences. The major aim of this approach is to refute the *Hazard Function*, a theory that has been proposed in (Nobre, Correa, & Coull, 2007) that has as its main goal establishing the probability of expecting future stimuli according to how much time has passed between their presentations. The main assertion of this approach, is that, the likelihood of the occurrence of future events keeps increasing with the passing of time. The impact of this very intuitive perspective in timing tasks is very simple: whenever a person is expecting a stimulus to be presented, the chances that he thinks it will appear in the future keep getting higher after every moment that the cue that was supposed to precede it, has not been presented yet. However, as introduced previously, the *Hazard Function* is not the only possible explanation that aims to describe the mechanisms that lead humans to be ready to respond to a visual stimulus in timing tasks. The approach that is presented in this work states that timing behavior is driven by the memory traces of similar, previous, timing experiences. According to the strength of these traces, the likelihood of being ready to react to the presentation of a visual stimulus, changes. In contrast to the *Hazard* perspective, there is a more detailed combination of the aspects, how much time has passed between one stimulus and another, and how many times this has occurred in the past.

In order to investigate this phenomenon, this paper is mainly divided into two parts, the first one presents the methods and the results of a timing experiment that has as its main goal, to show how previous timing experiences have an influence on future ones. Once these effects have been identified, a computational model that is based on the ACT-R timing estimation and declarative memory modules is built in order to reproduce the participant's performances. This has been done to link the results obtained by the simulation, to the potential impact that more recent and common memory traces have on the participants performing the experiment.

Experiment & Methods

Eighteen students attending the Cognitive Modeling course at the Artificial Intelligence department of the Rijksuniversiteit Groningen have been the participants of an experiment that aimed to measure different response times, according to the presentation of a particular visual stimulus. The setup of the experiment is inspired by work (Los, Kruijne, & Meeter, 2016) and was as follows: the students had to watch a white screen on their computers where a black 0.6° plus (S1) was presented in the middle. After a variable amount of time a black 1.2° square (S2) appeared either 1.9° to the left of the plus or vice-versa. The goal of the students was to react as quickly and accurate as possible to the shown image of the black square by pressing the *z* letter of their keyboard, if the stimulus appeared on the left of the plus, and the *m* key if it appeared the other way around.

The experiment consisted of 5 different blocks that each consisted of 120 different trials. These blocks differed from each other according to the way that S2 was presented. In every block the black square appeared either to the right, or the left, of S1 after 400, 800, 1200 or 1600 milliseconds. However, the chances one particular foreperiod was chosen instead of another one differed between blocks. In the first, third and fifth block the foreperiods were presented in a uniform way, which means that the distribution of the different millisecond presentations were the same for every foreperiod: 30. In the second block, the distribution of the four foreperiods were different. They are considered as anti-exponential since the amount of the times that these were presented was: 64, 32, 16 and 8. Similarly, the forth block presented an exponential distribution based on the 8, 16, 32 and 64 amounts of presentations. The reason of presenting three different distributions of foreperiods is related to the research question explained in the previous section. Since the main goal of this work is to investigate how timing performances that have occurred in the past can influence the future ones, every block might have an effect on the response times of the next one. It is possible that the performances of the exponential and anti-exponential blocks have an effect on the uniform ones. If this is the case they will show some differences when compared to the first block which is not affected by any previous experience.

Reconsidering the setup of the experiment, 150 milliseconds passed between every foreperiod presentation while at the end of every block the participants could decide when to start with the next one, although they were asked to perform the whole experiment in one single continuous session. However, one important factor that should be taken into account, is that it is not possible to assert that this requirement has been adhered to. The students were provided with an *OpenSesame* executable and were asked to perform the experiment on their own laptops. They were also asked to reproduce an environment as similar as possible to one that they would have encountered in a research laboratory, but also in this case, there is no absolute certainty that all the subjects have followed this guideline.

Results

Figure 1 shows the results of the experiment for the five different blocks, on the x axis the four different foreperiods are represented, while on the y axes the average response time for every interval is shown, the scale of both axes is in milliseconds.

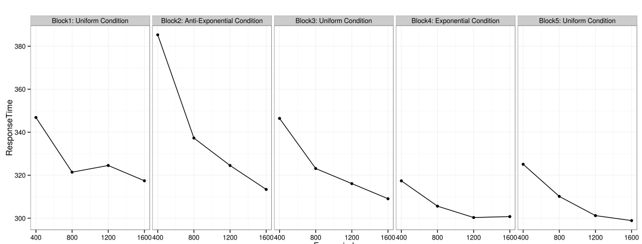

Figure 1: Experimental Results

As figure 1 shows, the range of the response times in Block 1 goes from 319 to almost 350 ms, the participants were slower when the 400 foreperiod was presented while performed pretty much the same for the other three. In Block 2 the results are significantly different, as at the one side it is true that the participants reacted slower to the 400 ms presentations as in Block 1, on the other hand, the average response time for the 400 foreperiod is much higher compared to the one of the previous block. Although there were more 400 stimuli (64) the students reacted slower to these presentations. A worst performance regards also the 800 ms foreperiod while a little bit quicker response time can be seen for foreperiod 1600. It is possible to define the behavior of this condition with a general exponential function:

$$f(x) = \left(\frac{1}{n}\right)^{x} \tag{1}$$

According to the research question of this work, Block 3 should show some influences of the anti-exponential response times on the uniform ones, and that was indeed the case. As it is possible to see although the average response time for the 400 foreperiod is the same one as in the first block, the general behavior of the function that represents the results is very similar to the one of the exponential block, while very different from the Block 1 condition where no function as (1) can be identified. This is remarkable since the stimuli that were presented in Block 3 were exactly the same ones as the ones presented in the first one. Block 4, that regarded the exponential presentation of the foreperiods, shows how the participants have been much quicker in reacting to the stimuli, this performance goes from an average response time of 317 ms for the 400 ms foreperiod to a 300 ms response time for the 1600 ms one. This kind of performance has a strong influence on the final uniform block of the experiment, it is in fact possible to see how quicker the overall performance in this final block has been and how also in this case the general function that defines the behavior of the response times has nothing in common with the one regarding the first block.

Computational Model

In order to reproduce the results of the experiment, a computational simulation has been built. It simulates the experimental procedure explained in the second section of this work by modeling how the participants perceive time, according to the ACT-R cognitive architecture (Taatgen et al., 2004) and how they store the results of this particular action in the declarative memory (Anderson, 1996). The basic way the model works is the following: before the experiment begins, every participant is provided with two main parameters: an empty declarative memory which is a matrix that will save the relevant information during the whole experiment, and a personal clock, a value that will keep track of the time that passes while the experiment is proceeding. Since every action a participant will perform will take some time this variable keeps increasing during the whole simulation (i.e. 50 ms are added whenever the DM is used and 150 ms are added after every foreperiod is presented). These foreperiods (400, 800, 1200, 1600) are presented according to the five different blocks and are converted into a pulse, a value that the human mind assigns to every time interval that is presented. This is done by recursively computing the following equation:

$$Actr_t = \sum_{actr_t}^{time} actr_t * 1.1 + \eta \tag{2}$$

The variables actr_t is initially set to 11 according to (Taatgen et al., 2004) and recursively updates itself until the end of the sum, every time the equation generates a result according to the sum's parameters, a pulse is counted. Regarding the other values, 1.1 also derives from Taatgen et al.'s research while η corresponds to a noise value that gives randomness to the output of the computation.
According to the personal clock parameter, every pulse is saved in the declarative memory together with the moment it has been presented. These values are used in a second instance in order to compute the activation rate (AcRate) of every pulse that has been estimated during the experiment with equation (3):

$$AcRate = \log(n/(1-d)) - d * \log(L) \tag{3}$$

N corresponds to the amount of times a pulse has been estimated (the number of times it is present in the DM), L is the difference between the moment the chunk has been estimated and the current moment this chunk has to be retrieved while d is the decay-rate that according to work (Gluck & Pew, 2006) has been set to the default value of 0.5. According to this equation every pulse has a different importance according to how many times it has occurred in the past and how long ago this happened, pulses that have occurred multiple times and recently have a higher chance to be expected by the participant during the experiment.
This process is defined as blending and works as follows: if the participant estimates a pulse that is already present in the DM, the blended value (BV) is given by the division of the sum of all the decay rates of that particular pulse (lenP) by the sum of the decay rates of all the pulses (totP). Finally, this value is multiplied by the pulse itself (P). This calculation can be expressed through the following equation which has as an outcome a new pulse:

$$BV = P * \frac{\sum_{i=1}^{lenP} a_i}{\sum_{i=1}^{totP} tota_i} \tag{4}$$

Similarly as has been done when estimating a pulse from a timing interval, it is also possible to infer a time period from a pulse by computing the following equation:

$$Time = \sum_{i=1}^{pulse} actr_t * 1.1 + \eta \tag{5}$$

In this case it is the variable *Time* that is recursively updated according to the result of the inner part of the equation. The meaning of this parameter for the participant coincides with the moment that he expects that the next stimulus will be presented on the screen. This is crucial for the computational model since according to this value the performances of the participants in the experiment change.
This performance is measured with a new variable that corresponds to the response time of each single participant, it has a baseline value of 300 ms and according to the value of the blending process it may or not increase. The case in which the response time increases regards the scenario in which the expected time estimation of the participant is higher then the foreperiod that is presented. This means that the participant didn't expect that particular stimulus at that moment in time and reacts slower when performing the reaction task.
In order to model this logic, different penalties are added to the reaction time variable, depending on the type of block. A penalty of 35 ms is added in block 1, 3 and 5, together with some random milliseconds in the range of 1 to 10, that make the data more varied. In the second and forth block the penalty that is added is higher and corresponds to 65 ms, this is related to the fact that these blocks don't present a uniform distribution of the foreperiods. The general idea behind this negative reinforcement theory is that since there are some foreperiods that are more common then others, according to the blending process the participants should be more prepared to react to these ones. In fact, they should react quicker to the 400 ms foreperiod in the second block and similarly in the forth one when it comes to the 1600 ms foreperiod, if they are not, a more important penalty is added to the variable that measures their response times.

Results & Discussion

Figure 2 shows the results of the computational simulation, the way the data is represented corresponds to the one used in the *Results* section but in this case every block has two different plots: the red one reproduces the way the participants performed in the experiment while the blue one corresponds to the computational model.
If the data is analyzed superficially it is possible to assert that the model reproduces at least the general behavior of the participants, however at a more detailed analysis, not all the blocks present as good simulated response times. Block 1 shows a significant difference regarding the 800 and 1200 foreperiods which in the real experiment had almost the same response time (320), while in the simulated one the second one the 800 foreperiod has been estimated much quicker. Block 2 and Block 3 show a satisfying fit, not only because the difference between the two plots isn't that big as in the previous one but mostly because Block 3's response times are influenced by the ones of Block 2, which is related to the main research question of this work. This idea is supported by the average response time of the 400 foreperiod, and by the general trend of the function that reproduces the response times that is very similar between the two blocks. Block 4 presents a satisfying result when it comes to the 800 1200 and 1600 foreperiods but the same cannot be said for the 400 one, apparently in the computational model the effect of the previous 2 blocks is still too strong, which makes the gap between the two different response times of almost 40 ms. The

same phenomenon can be seen in the last block even though it is less evident. The general behavior of the model seems to be more influenced by memory time traces of the past compared to the real participants.

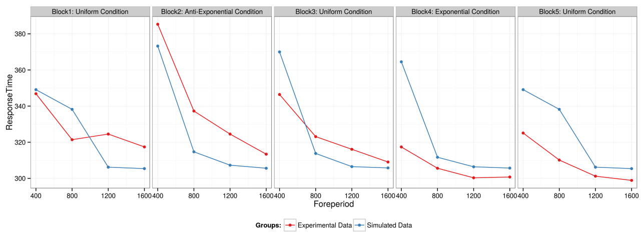

Figure 2: Simulated Results

In order to evaluate the goodness of the model some statistical parameters have been computed, namely $\mathbb{R}^2$ and the relative *p-value*. The first one measures how successful the computational fit is in explaining the variation of the real data and corresponds to the square of the correlation between the experimental values and the simulated values. The second parameter measures how statistically significant the first value is. This is the case if it is lower then 0.05.
Table 1 presents this statistical analysis:

	$\mathbb{R}^2$	*p-value*
Block 1	0.52	0.27
Block 2	0.96	0.01
Block 3	0.93	0.03
Block 4	0.95	0.02
Block 5	0.81	0.05

Table 1: Statistical Analysis

The first block presents a very low $\mathbb{R}^2$ value, 0.525, which means that the computational fit explains 52.5% of the real data, this cannot be considered as a good fit and according to the *p-value* it is neither significant since this value is too high. Better results are achieved in the other four blocks where the model explains between 81% and 95% of the real data together with a statistically significant *p-value*.

Conclusion

According to the ACT-R theory, the power of human cognition depends on two factors: the amount of knowledge encoded in memory and the effectiveness of this amount of information (Anderson, 1996). In this paper this guideline has been linked to the way humans perceive time and to the way they record this particular action.
The first part of this work has shown that there are indeed some differences related to the way humans react to particular stimuli in timing tasks if these stimuli have an impact on the declarative memory. The second part of this paper provides a possible explanation to this phenomenon with a computational simulation. Although the results obtained by the computer model don't fit perfectly with the experimental data it is still possible to assert that they generally match with the ACT-R guideline. More recent and recurring memory traces have indeed an impact on future timing based decisions.

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