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Error-driven learning in a language context

Graduation Project Proposal
(Cognitive language modelling)

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1 Introduction

There is still a lot we don't know about learning. Research often focuses on smaller theories that explain how learning works in constrained domains and then tries to extrapolate that to other forms of problem solving and learning. One theory that actually does work over multiple domains, and is not constrained to only explaining one part of learning is Error Driven Learning. In this theory the main goal when learning something, is minimising the uncertainty about upcoming states in the world.

Say you have a smoke detector in your house and you see the light blink on it. You're not quite sure what it means, but the next day you hear it beep like it does when the batteries are empty. There is now a connection between the light blinking, the cue, and the batteries of the detector being empty, the outcome. However on that same day as you saw the lights blink you did just get out of the shower and the hallway was a bit steamy. So there is also a connection between the light and the shower steam. There is still uncertainty. The next time the lights blink, you do not come out of the shower and the next day the empty battery beep sounds. Now the connection between the light and the shower steam is weakened, while the connection between the light and the detector's batteries is strengthened. This way uncertainty about the world is reduced.

This is a practical example of what Error Driven Learning is. However there are different proposals on how the exact mechanism behind Error Driven Learning should work. In this research we will disentangle two of those mechanisms.

2 Theoretical Framework

The first of these two models that attempt to describe the underlying mechanisms of Error Driven Learning, is the Rescorla and Wagner model, by Wagner and Rescorla (1972). They suggest that if a cue does not appear, there is no change to the connection between the cue and the outcome. This can be seen in the first part of Equation 1, where ΔV_{ij}^t is the change in weights at a certain time. If a cue appears and the outcome also appears, then the connection between the two is strengthened, while if the cue appears but the outcome does not, then the connection is weakened. These two can be seen in the second and third part of Equation 1 respectively. η is the learning rate and act_j^t is the activation of outcome j. The latter is the sum of the connection weights for the present cue.

$$\Delta V_{ij}^t = \begin{cases} 0 & \text{, cue } i \text{ absent,} \\ \eta(1 - act_j^t) & \text{, cue } i \text{ and outcome } j \text{ are present,} \\ \eta(0 - act_j^t) & \text{, cue } i \text{ present but outcome } j \text{ absent} \end{cases} \tag{1}$$

Rescorla and Wagner focus on the informativeness of a certain cue. If a cue does not appear then that cue is not informative about a certain outcome, so there should be no updates to the weights.

The second of these two models of Error Driven Learning is given by Van Hamme and Wasserman (1994). They proposed that accounting for absent cues is something that *is* necessary in describing Error Driven Learning. While they agree on the second and third part of Equation 1, they propose

an addition.
If we take our smoke detector example, no light on the smoke detector and a low battery beep should be treated differently according to Van Hamme and Wasserman, than when there is no light and no beep. They propose a decrease in strength in connection when the cue is not there but the outcome is, as can be seen in the first part of Equation 2. And secondly an increase in connection strength when neither cue nor outcome is present, as in the second part of Equation 2.

$$\Delta V_{ij}^{t} = \begin{cases} \eta_1(1 - act_j^t) & \text{, cue } i \text{ absent but outcome } j \text{ present,} \\ \eta_1(0 - act_j^t) & \text{, cue } i \text{ and outcome } j \text{ absent,} \\ \eta_2(1 - act_j^t) & \text{, cue } i \text{ and outcome } j \text{ are present,} \\ \eta_2(0 - act_j^t) & \text{, cue } i \text{ present but outcome } j \text{ absent} \end{cases} \tag{2}$$

It is important to understand that Error Driven Learning might be an implicit process. Ramscar et al. (2013) looked at how adults and children learn in the context of Error Driven Le[illegible] found that adults had different responses than children. This was due to the fact th[illegible] context, the part of the brain responsible for processes such as logic or reasoning ([illegible] is not fully developed in children yet. The development of the prefrontal cortex m[illegible] for the difference in results between children and adults, since it interferes wit[illegible] Implicit learning, according to Reber (1989), is best done without interference fro[illegible] soning. Therefore explicit inference might get in the way of Error Driven Learning ta[illegible] Error Driven Learning is indeed an implicit process.

cortex

my understanding of the paper is that they asked participants to rate all three food items - even the absent one. this is based on the instructions on page 136 and the first sentence after the table on p. 137

However, in their paper Van Hamme and Wasserman (1994) explicitly asked participants for ratings after each trial. These ratings were based on how likely participants thought two out of three food items (compound cues) would result in an allergic reaction or not (outcome). These ratings were asked on a scale from 0 to 8, where 0 indicated that these foods were very unlikely to cause an allergic reaction, 4 was neutral and 8 was very likely. Participants were given as much time as they needed to fill in their ratings.
They found that if a certain cue is present, the ratings increase over time when there is an outcome present and decrease when there is not an outcome present. This is both in line with what they expected and with what the Rescorla Wagner model (1972) predicts. If there is no cue present and there is an outcome, then the ratings decreased over time. If there was no cue and no outcome, then the ratings increased. This is in line with the addition to the Rescorla and Wagner model that Van Hamme and Wasserman suggest.

inference

However asking these ratings in an explicit manner could lead to explicit interference in the process of implicit learning, as would be in line with what Reber found. Therefore it cannot be said for sure if the findings of Van Hamme and Wasserman's research are due to Error Driven Learning, or due to logic and reasoning.

The goal of this paper is to find out what kind of mechanism lies behind Error Driven Learning and to investigate if it is indeed an implicit process.

To model both the Rescorla Wagner model and the adjustment to the Rescorla and Wagner model that Van Hamme and Wasserman propose, we will use, amongst other papers, a paper by Hoppe et al. (n.d.). In this paper they go over the different ways to model Error Driven Learning with a simple neural network and on how to interpret the results.

3 Research Question

As described above, this graduation project aims to investigate which out of two proposed mechanisms for Error Driven Learning best describes learning. It also aims to investigate what the effects of cue complexity are.
The following research question is proposed: Do we find learning in the absence of cues?

We expect that by manipulating the presentation speed of the cues we will find a difference what participants learn between explicit interference and implicit learning.
To increase statistical power, we will add more stimuli and more trial types. This in turn will help mask the goal of the experiment, and will thus also help to reduce the amount of explicit reasoning happening during the experiment.

4 Methods

First we will create a model of the original experiment of Van Hamme and Wasserman with a limited set of stimuli. We will then use computational simulations to see if different stimuli matter and if the amount of stimuli matter. Based on the results from this model we design the different experiments to test the research question on.
To test this research question we will create three different experiment. The first of which will test the effect of cue complexity. The second and third are designed to enforce implicit learning by giving participants less time to think and thus giving them less or no time to reason.
The first experiment will be a replica of the original experiment by Van Hamme and Wasserman, but with different stimuli (linguistic) that we will also use in the other two experiments. The participants will be asked after each trail for all three cues how likely it is that it predicts the outcome on a scale from 0 to 8. This still includes the explicit asking, but this way we check if we can replicate this effect with different stimuli in humans as well as the models.
The second and third experiment will be similar to each other, the only difference being how much time participants get for the task, thus enforcing implicit learning. These two experiments have no rating scale, so we can test the effect of explicitly given ratings. In these experiments participants see two cues (pictures). There is also a bit of dirt on screen in which they can dig for a diamond. They can always do this, but it costs them a bit of money that they would otherwise get as a reward. If there is an outcome (a diamond) then they'll get that money back plus a little bit extra. This will discourage participants from always clicking and not paying any attention. The slow version of the

experiment can then be compared to the fast version of the experiment, to see if there are different results in how people predict the outcome (diamond) based on the cues (pictures).
In case the first experiment that we do with human participants gives very different results from the original experiment, the plan is to fully replicate their experiment, with the same stimuli, as to see where the difference in result comes from.

The experiments will be created in Python and tested on both human participants and two models. One that models learning according to Rescorla and Wagner, and the other that models it in line with Van Hamme and Wasserman. The models will be created in R (R Core Team, 2020) and will at least make use of the packages *ndl* (Antti Arppe et al., 2018) and *NDLvisualisations* (van Rij, 2018), which implement the Rescorla Wagner learning formulas and help visualise them.
As for testing the human participants I plan to create the experiment in an online environment (for example with a program like Gorilla (Anwyl-Irvine et al., 2019)) and then distribute it via science platforms such as Prolific, or mailing lists and Facebook. If it is safe to test again, this online experiment could be put on the lab computers as well.
The analysis of the results of both the model and the participants will be done in R. An analysis with Generalized Additive Mixed-effect Models (GAMMs) will be done over the ratings of the first experiment and over the participants responses and reaction times in the second and third. This way we can see if there is a significant difference in ratings between the different cues for the first experiment. For the second and third we will need to find out if people do indeed learn and unlearn the connections between cues and outcomes, while checking if they truly did respond faster as well.

5 Scientific Relevance for Artificial Intelligence

Cognitive Modelling is very important to the field of Artificial Intelligence. Creating models to test theories, generating new theories from those models, which can then be tested again with more models and humans, makes for a very informative loop. Figuring out how learning works as a whole is quite difficult, but if we can make this small part work and be predicted by a cognitive model, we will add on to the evidence of a theory that might bring us closer to understanding how exactly learning works.

6 Planning

Weeks	Date	General tasks
1,2	5 october - 18 october	Start on introduction and start with implementation model (design & cues and outputs design)
3-5	19 october - 8 november	Implement the model
6	9 november - 15 november	Buffer + hand in introduction
7-9	16 november - 6 december	Start on methods and the experiment
10	7 december - 13 december	Finetune the model and continue with experiment
11	14 december - 20 december	Buffer + hand in model/experiment part of the methods
12,13	21 december - 3 january	Vacation
14-16	4 january - 24 january	Testing the experiment, both on participants and the model Start writing script for the results if possible
17-19	25 january - 20 february	Analysis + start writing results + hand in participant part of the methods
20	15 february - 21 february	Buffer + hand in results
21-23	22 february - 14 march	Write discussion + write abstract and conclusion as far as I have not done it yet, update on feedback
24-26	15 march - 4 april	Hand in discussion, abstract, conclusion More feedback
27	5 april - 11 april	Finish thesis

Table 1: Master project planning

The general plan is to finish the experiment and model before the Christmas break, such that I can test after.
The absolute deadline for handing in my thesis (if I want to make the deadline before graduation in June) would be the 27^{th} of april, so I would have 2 more weeks as a buffer in case something really strange happens.

7 Resources and Support

My personal preference is to work at the designated area for master students of Artificial Intelligence and Human Machine Communication that want to work on their final project. However if, due to the Corona virus this is not feasible, then I can work from home at a PC. I will not need a laboratory setup or day-to-day supervision, but, especially in the beginning, there will be a weekly meeting to discuss proceedings. I do not have to agree on confidentiality.

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