university of groningen / faculty of mathematics and natural sciences / artificial intelligence

Error-driven learning in a language context

Graduation Project Proposal
(Cognitive language modelling)

Sanne Poelstra (s2901560)

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Internal Supervisor: Dr. Jacolien van Rij-Tange (University of Groningen)
External Supervisor: Dr. Jessie Nixon (University of Tübingen, Germany)

Human-Machine Communication
University of Groningen, The Netherlands

1 Introduction

There is still a lot that we do not know about intelligence. There are quite some theories on how it works, but looking at intelligence as a whole is a big task. People often focus on smaller theories that work in smaller domains and then try to extrapolate that to other forms of problem solving. One of these theories 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 Rescorla and Wagner state in their model of Error Driven Learning (Wagner & Rescorla, 1972). They suggest that if a cue does not appear, there is no change to the connection between the cue and the outcome. 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.

Ramscar et al. (2013) found that Error Driven Learning only works when we are not actively thinking about what the answer should be, thus leading to logical reasoning. This is similar to what Reber (1989) found, namely that learning in this manner (implicit learning) is best done when there is no conscious effort to learn.

While the Rescorla and Wagner model can successfully predict many phenomena, there are some that find issues with it. For example, should there not be different reactions when there is no cue depending on whether there is an outcome or not? What if there was no light on your smoke detector, but the battery beep did go off, should there still be no change in the connection? And should this be treated the in the same way as the case where there is no blinking light and no beep?

This is what Van Hamme and Wasserman (1994) try to explain with their model, in which they suggest that, in addition to the rules already stated by the Rescorla and Wagner model, there should be two extra calculations. The first one being a decrease in strength in connection when the cue is not there but the outcome is, and secondly an increase in connection strength when neither cue nor outcome is present.

While Van Hamme and Wasserman (1994) did find evidence in the right direction, this evidence was not significant. They also explicitly asked the participants for ratings after each trial. This would go against the assumption that was mentioned before, that Error Driven Learning is an implicit process and takes place when there is no conscious effort to learn. Therefore the results Van Hamme and Wasserman found, might not be the outcome of Error Driven Learning, but they might have been a result of logical reasoning. We want to test their experiment with adjustments to ensure that enforce unconscious learning and see if the model van Van Hamme and Wasserman still holds, or that their results can be explained by other phenomena.

2 Theoretical Framework

This project aspires to extend upon the research done in the field of Error Driven Learning and in specific to test if the model that (Van Hamme & Wasserman, 1994) propose is a reliable explanation for learning in humans. In their paper they gave participants different cues in the form of foods and they had to determine if compounds of these cues would result in an allergic reaction or not by rating for each food how likely it was that they resulted in an allergic reaction. 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. However as already mentioned, these results are not significant.
Ramscar et al. (2013) found in their paper that world learning in children is in line with error driven learning, however when given the same task to adults, they found that adults use reasoning. In the experiment they showed object A and B together with one label and B and C together with one label. Afterwards they asked for a label that had not been mentioned yet. According to error driven learning B occurred more often with the two other labels than A or B did, so the connection between the new label (outcome) and B should be the weakest. Therefore if error driven learning is taking place A and C both have an equal chance of getting picked as objects that could fit the new label. This is indeed what they found with the children. However if logical deduction is taking place then B would be the answer choosing, since both A and C have a clear label, but B does not have a clear label yet. This is what they found in adults.
Thus asking explicitly for ratings after each trail, as Van Hamme and Wasserman do, might lead to logical deduction instead of error driven learning.

As for modelling we will use a paper by D.B Hoppe et al. (still in press). 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 investigates whether the model proposed by Van Hamme and Wasserman is able to predict error driven learning, or if there are other phenomena that can explain the results found by them.
The following research question is proposed: Is the absence of cues indeed something that should be accounted for in a theory of Error Driven Learning?

4 Methods

To test this I will create an experiment in Python and have both human participants and a model partake in the experiment. The model 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 human participants I plan to create the experiment in an online environment (for example with a program like Gorilla (Anwyl-Irvine, Massonié, Flitton, Kirkham, & J.K, 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.
There will be three separate experiments. The first 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 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 it was not an issue related to the original stimuli in some way and test if the current stimuli are appropriate.
The second and third experiment will be similar, the only difference being how much time participants get for the task, thus enforcing implicit learning. In this they 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'll 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 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 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.

5 Scientific Relevance for Artificial Intelligence

Finding out what exactly intelligence is and how it works is needed to recreate it in systems that wish to replicate it. While figuring out intelligence as a whole is a very big task, adding to the evidence for a theory that might explain a small part of it will be relevant to Artificial intelligence as a whole.

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.

References

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