



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)

September 24, 2020

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 now 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 the Rescorla and Wagner state (Wagner & Rescorla, 1972) in their model of error-driven learning. They suggest that if a cue does not appear then 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.

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 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. Could there be any other factors that could have caused the results that they found? Therefore we want to test if this model is indeed a reliable explanation for the way that humans learn. We want to do this by testing both a model that implements error driven learning and human participants with an experiment and comparing the results.

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.

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 consists of ...

We are interested in finding X and investigating the theory of Y

The following RQ is proposed:

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 visualize 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, Massoné, Flitton, Kirkham, & J.K, 2019)) and then distribute it via science platforms such as Prolific, or mailing lists and facebook.

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.

Still need to add things like what the experiment will be like, what things I'm measuring. Maybe also GAMMS packages in R, but I first wanted to see if this was the right direction.



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 27th 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

- Antti Arppe, Peter Hendrix, Petar Milin, R. Harald Baayen, Tino Sering, & Cyrus Shaoul. (2018). ndl: Naive discriminative learning [Computer software manual]. Retrieved from <https://CRAN.R-project.org/package=ndl> (R package version 0.2.18)
- Anwyl-Irvine, A., Massoné, J., Flitton, E., Kirkham, N., & J.K, E. (2019). *Gorilla experiment builder*. Retrieved from <https://gorilla.sc/>
- R Core Team. (2020). R: A language and environment for statistical computing [Computer software manual]. Vienna, Austria. Retrieved from <https://www.R-project.org/>
- van Rij, J. (2018). Ndlvisualization: Additional visualization functions for the ndl framework [Computer software manual]. (R package version 0.4)
- Van Hamme, L. J., & Wasserman, E. A. (1994). Cue competition in causality judgments: The role of nonpresentation of compound stimulus elements. *Learning and motivation*, 25(2), 127–151.
- Wagner, A., & Rescorla, R. (1972). A theory of pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. *Classical conditioning ii*, 64, 99.
-