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Error-driven learning in a language context

Graduation Project Proposal
(Language acquisition)

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September 17, 2020

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1 Introduction

A paper by Van Hamme and Wasserman (1994) proposes a model for error driven learning which, apart from cues and outcomes/non-outcomes, also takes non-cues into account. They found evidence that this model reflects human learning better than the Rescorla and Wanger model (Wagner & Rescorla, 1972). To see if this also holds for a language setting, in this research I am going to recreate their experiment but in a language setting and test this experiment on both human participants and a cognitive model.
I hope to find similar results to theirs and also compare my results to the Rescorla and Wagner model, such that it can be seen which of these reflects human language learning better.

2 Theoretical Framework

Error driven learning -¿ definition.
While this has been shown to work in animals, it has also been shown to work in humans, and more specifically in language learning. One approach of error driven learning in language is given by Wagner and Rescorla (1972) whose model states that there is a connection between cues and outcomes. If a certain cue is present and an outcome is too, then the associative strength between those two increases. However if a cue is present and there is no outcome, then the associative strength between that cue and that outcomes decreases. Kamin (1967) states that if there is a very strong associative strength between a cue and an outcome, then a new cue that also leads to this outcome will not be able to make this connection. This is called *blocking*.
While the Rescorla and Wagner model is very influential, there is critique on the fact that it does not include what happens in the absence of a cue in combination with the absence or presence of an outcome. Therefore Van Hamme and Wasserman (1994) propose a new model that includes not only the presence of a cue, but also the absence of one.

They base their current model on a model from Markman (1989). This model uses the Delta P theory (Wasserman, Elek, Chatlosh, & Baker, 1993) to get to the formulas for the no cue in combination with present and absent outcomes. Which then gives us a contingency table that looks like Figure 1, where only square A and B are directly predicted by the original Rescorla and Wagner model, but all squares are directly predicted by the Markman's model. However in his model all of the squares have the same weight in the decision. What Van Hamme and Wasserman change here, is that not all the squares have the same weight, but A weighs stronger than B and C stronger than D.

Cue Outcome A	Cue No outcome B
C No cue Outcome	D No cue No Outcome

Figure 1: Contingency table of the cues and outcomes

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: This RQ requires a partial reproduction of the experiment van Hamme and Wasserman did in their 1994 paper.

4 Methods

Create a model in python?
Also an experiment in python
Explain experiment approx here, since it should be similar to H and W
Hopefully distribute it online in some way
Analysis presumably with GAMMs

5 Scientific Relevance for Artificial Intelligence

6 Planning

Weeks	Date	General tasks
1,2	5 october - 18 october	Start on introduction and start with implementation experiment (design & adjust experiment to language)
3-5	19 october - 8 november	Implement the experiment
6	9 november - 15 november	Buffer + hand in introduction
7-9	16 november - 6 december	Start on methods and the model
10	7 december - 13 december	Fine tune the model
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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