Does error-driven learning occur without cues? Investigation of the effects of updating connection weights to absent cues

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Abstract

Keywords: error-driven learning; discriminative learning; associative learning; Rescorla-Wagner model; delta rule; absent cues; cue competition

Introduction

The Rescorla-Wagner learning equations (Rescorla & Wagner, 1972, also developed independently by Widrow & Hoff, 1960) were initially developed to explain findings from several decades of animal learning research. However, in the half century since its publication, the model has had a vast influence, not only in animal learning, but also in several other areas of psychology and human learning (see e.g. Siegel & Allan, 1996; Miller, Barnet, & Grahame, 1995, for reviews). While earlier models had assumed that 'associative learning' (often called 'conditioning' in the animal learning literature) resulted from contiguity or co-occurrence of stimuli, a number of findings demonstrated that contiguity was neither necessary nor sufficient for learning. The Rescorla-Wagner model has proven remarkably successful in predicting human contingency judgements ... [other effects... refs.] The model has recently been used as an account of human language acquisition [refs] and other linguistic phenomena [refs]. [other perceptual learning?].

Although several phenomena are known to not be captured by the model (Miller et al., 1995), it has been so successful that it has inspired numerous adaptations, which either attempt to capture some of its successes or attempt to address some of its shortcomings. One such proposal for an adaptation to the Rescorla-Wagner model comes from Van Hamme and Wasserman (1994).

Van Hamme and Wasserman (1994) noted that previous work had suggested that human participants in causal judgement tasks are able to take into account both occurrence and non-occurrence of potential causal factors (Arkes & Harkness, 1983; Levin, Wasserman, & Kao, 1993; Wasserman, Dorner, & Kao, 1990). They proposed that human learning in causal judgement tasks not only involves changes in judgement of the causal relation between *cues* and *outcomes* for the particular cues that occur on a given trial, but also for cues that do not occur on that trial. They set out to test this hypothesis with a causal judgement task. On each trial, participants were presented with two out of three food types. One food type occurred on every trial. (That is, trials were either AX or BX). Participants were told whether or not the allergy occurred on that trial and were asked to give a rating (on a scale of 0-8) how likely they thought each of the three food types was the cause of the allergy.

Van Hamme and Wasserman (1994) conceptualise learning as symmetrical. They argue that the Rescorla-Wagner model does not utilise all the covariation information in the 'four cells' of the contingency table; that is, the occurrence vs. non-occurrence of cues and outcomes.

However, there is good evidence that learning is not 'symmetrical' in this sense. In other words, learning is not simply an association between two stimuli, but is an *asymmetrical* process in which cues predict outcomes (Ramscar, Yarlett, Dye, Denny, & Thorpe, 2010; Nixon, 2020, 2018; Hoppe, van Rij, Hendriks, & Ramscar, 2020). That is, temporally earlier events may be used to predict temporally later events, but not the other way around.

Importantly, Van Hamme and Wasserman (1994) did not present simulations of their experiment. They presented only verbal predictions. Therefore, it is useful to get numerical predictions for the learning trajectories in the original and adapted versions of the Rescorla-Wagner model, in order to tease apart which version of the model more effectively captures the experimental results.

Below we first introduce the experiment design and data collected in the Van Hamme and Wasserman (1994) study. We then present the simulations with the Rescorla-Wagner model and the adjusted version proposed by Van Hamme and Wasserman (1994).

Experimental data

Participants

Forty-eight undergraduate students participated in the experiment for course credit.

Stimuli

The cues consisted of food items and the outcomes were whether the allergy occurred that day (i.e. trial) or not. A complete list of the stimuli is presented in Table 1.

Experiment design and procedure

Each participant was presented with three different foods in each block (see Table 1), of which two occurred on each trial. One of the foods occurred on every trial in the block, so that

Food Conditions

Food condition	AX–BX	Stimulus element X	A	B
1	.00	Shrimp	Strawberries	Peanuts
2	.50	Yogurt	Bran	Cabbage
3	1.00	Bananas	Chicken	Mustard
4	.00	Wheat	Walnuts	Peaches
5	.50	Corn	Horseradish	Lobster
6	1.00	Blueberries	Cheese	Pork

Figure 1: Table: list of food items – Note! I will do this as a proper table later - using pdf to save time for now.

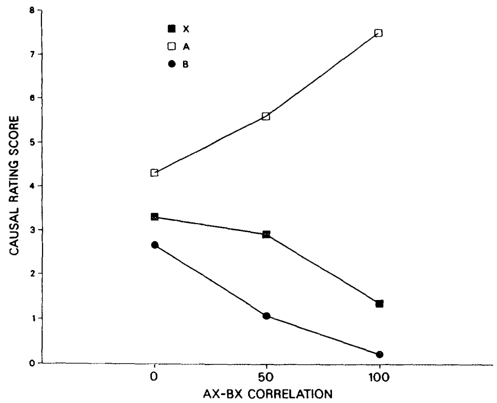

Figure 2: Experiment results for each contingency condition, averaged over trial and participant.

each trial was either AX (e.g. strawberries and shrimp) or BX (e.g. peanuts and shrimp). There were three blocks and all the foods changed between blocks.

The two foods and the outcome (allergic or not) were presented on a computer screen for 15 seconds. Participants were asked to give a rating (0-8) how likely each of all *three* of the foods was to cause the allergy, not just the two foods presented on screen.

Three within-participant contingency conditions were used, one condition per block. The order of contingency condition differed between participants. The three conditions were: AX and BX both predicted the allergy on 50% of the trials (50-50 condition); AX predicted the allergy on 75% of trials and BX on 25% of trials (75-25 condition) and AX predicted the allergy on 100% of trials and BX on 0% of trials (100-0 condition).

Experiment results

Figure 2 shows the ratings averaged over food condition, trial and participant, for each contingency condition (50-50, 75-25, 100-0) and each food type A, B and X. Figure 3 shows the trial-by-trial ratings, averaged over food condition and participant, for the 50-50 contingency condition (left panel), the 75-25 condition (middle panel) and the 100-0 condition (right panel).

Computational modelling

Original Rescorla-Wagner learning equations

We will first describe the learning equations as proposed independently by both Widrow and Hoff (1960) and Rescorla and Wagner (1972) and then the adaptation proposed by Van Hamme and Wasserman (1994). The Rescorla-Wagner equations estimate the connection strength, or *weights* $\mathcal{W}$, between the input *cues* C ($C \in c_k, k = 1,2,...,K$), and a set of *outcomes* O ($O \in o_n, n = 1,2,...,N$). The network grows incrementally with each training trial. At the end of training with k cues and n outcomes, the network consists of a $k \times n$ matrix of connection weights. On each training trial, weights are adjusted between all and only cues present on that trial and all outcomes present or encountered previously. The adjustment to the connection weight between a cue c_i and outcome o_j on a given trial, or learning event, t, is given by the Rescorla-Wagner equations:

$$w_{ij}^{(t)} = w_{ij}^{(t-1)} + \Delta w_{ij}^{t}. \tag{1}$$

The connection strength at the end of learning event t is equal to the connection strength at the end of the previous learning event, $t-1$, plus any change during the current learning event.

The change in weights during the current learning event, Δw_{ij}^{t}, is given by the Rescorla-Wagner equations:

$$\Delta w_{ij}^{t} = \begin{cases} \text{a) } 0 & \text{if } Absent(c_i,t), \\ \text{b) } \alpha_i \beta_j \left(\lambda - \sum_{[Present(c_k,t)]} w_{kj}\right) & \text{if } Present(c_i,t) \\ & \quad and\ Present(o_i,t), \\ \text{c) } \alpha_i \beta_j \left(0 - \sum_{[Present(c_k,t)]} w_{kj}\right) & \text{if } Present(c_i,t) \\ & and\ Absent(o_i,t), \\ \text{d) } 0 & \text{otherwise.} \end{cases} \tag{2}$$

in which λ is the maximum learnability of the outcome; and α_i and β_j refer to cue and outcome salience, respectively.

Put simply, the above equation says that a) for any cue not present in a given learning event, no adjustment is made; b) if a cue is present and an outcome is also present, the cue-outcome weight increases; c) if a cue is present and an outcome is not present, cue-outcome weight decreases; d) for any cues or outcomes that have not yet been encountered, no adjustment is made. The amount of adjustment made (in b and c) depends on the history of learning: the size of increase or decrease in strength is calculated based on the sum of connection strengths from the previous learning events of all present cues (subtracted either from λ or from 0 and multiplied by the learning rate).

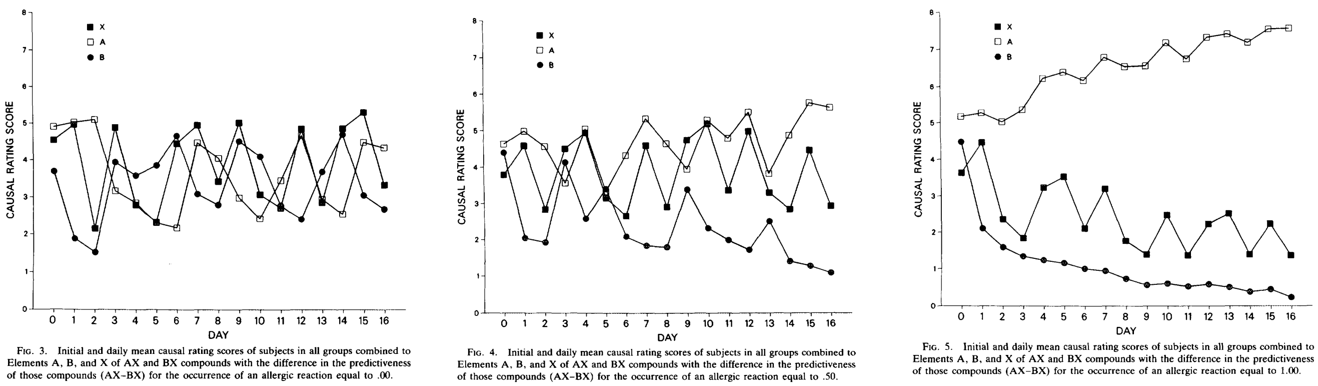

Figure 3: Trial-by-trial experiment results over block averaged over participant for contingency .

Adaptation proposed by Van Hamme & Wasserman

$$\Delta w_{ij}^{t} = \begin{cases} \text{a) } \alpha_i \beta_j \left(\lambda - \sum_{[Present(c_k,t)]} w_{kj}\right) & \text{if } Present(c_i,t) \\ & \quad and\ Present(o_i,t), \\ \text{c) } \alpha_i \beta_j \left(0 - \sum_{[Present(c_k,t)]} w_{kj}\right) & \text{if } Present(c_i,t) \\ & \text{and } Absent(o_i,t), \\ \text{c) } \alpha_i \beta_j \left(0 - \sum_{[Present(c_k,t)]} w_{kj}\right) & \text{if } Absent(c_i,t), \\ & \quad and\ Present(o_i,t), \\ \text{c) } \alpha_i \beta_j \left(\lambda - \sum_{[Present(c_k,t)]} w_{kj}\right) & \text{if } Absent(c_i,t), \\ & \quad and\ Absent(o_i,t), \\ \text{d) } 0 & \text{otherwise.} \end{cases} \tag{3}$$

Simulations

Simulations were run using the `edl` package in R (R Core Team, 2020). The trial-by-trial development of weights was visualised using `NDLvisualisations` (van Rij, 2018). The eta parameter was set to 0.001 and lambda was set to 1 (both the default parameters). Cues were created for each of the nine foods that occurred during the experiment - three food types for each of three blocks. On each trial of the simulation, two cues were presented, as well as a background cue that was present on all trials to model the experiment environment, as specified in the Rescorla-Wagner model (Rescorla & Wagner, 1972). There were two outcomes, allergic reaction and no allergic reaction, one of which occurred on every trial. The order of cues and outcomes followed the order set out in (Van Hamme & Wasserman, 1994). Following the experiment, the order of cues was the same for all participants and all blocks. The order of outcomes depended on the contingency condition (see Table XXX). All three blocks were run as a single simulation to model the learning of one participant. This was done for each of the contingency condition orders.

Results

Figure 4 shows the simulation results for both the original Rescorla-Wagner model (middle panel) and the adjusted Van Hamme and Wasserman version (right panel). For comparison, the experimental data are also shown (left panel). The responses or estimated weights to allergic minus not allergic are averaged over trials and participants and are shown for each contingency condition (50-50, 75-25, 100-0) separately. The predictions of the two versions of the model are almost indistinguishable. The only difference is the absolute magnitude of the weights, the VHW model with greater values; the pattern is essentially the same. Essentially, both models make the same predictions about the average responses between conditions. However, it is still possible that the two models make different predictions about the development of weights over the course of a block or over the course of the experiment. These are examined below.

Figure 5

Discussion

Future work

References

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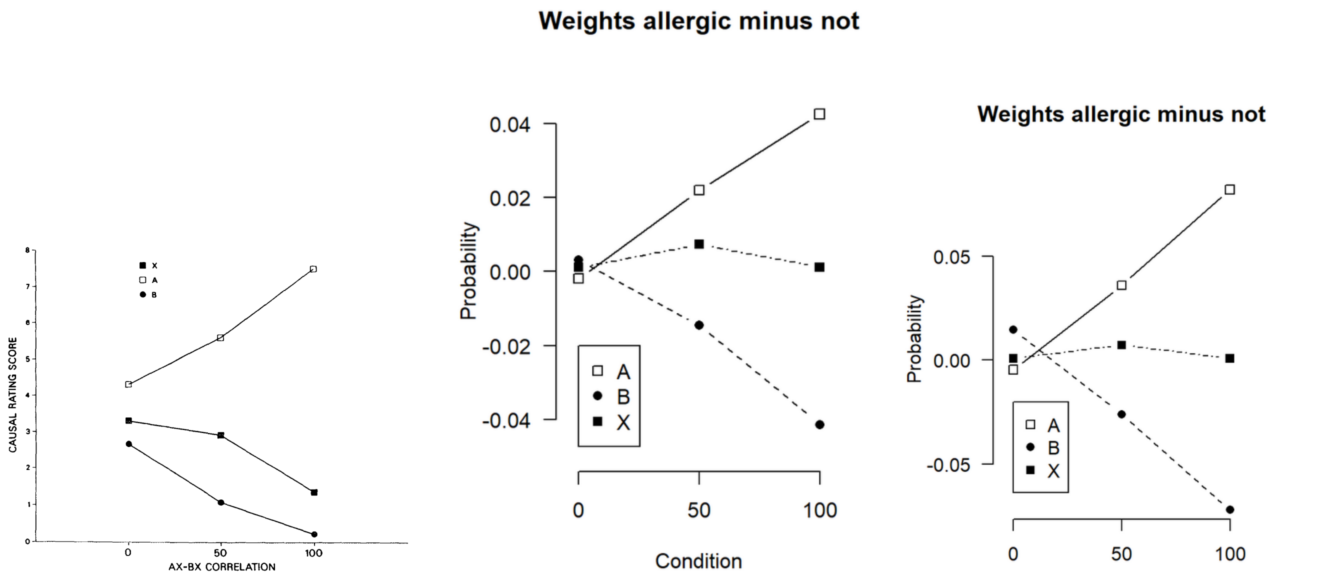

Figure 4: Connection weights to allergic minus not allergic for the three food types in the three conditions, averaged over subject and trial. Left: experiment data; middle: Rescorla-Wagner model predictions; right: Van Hamme & Wasserman adaptation predictions.

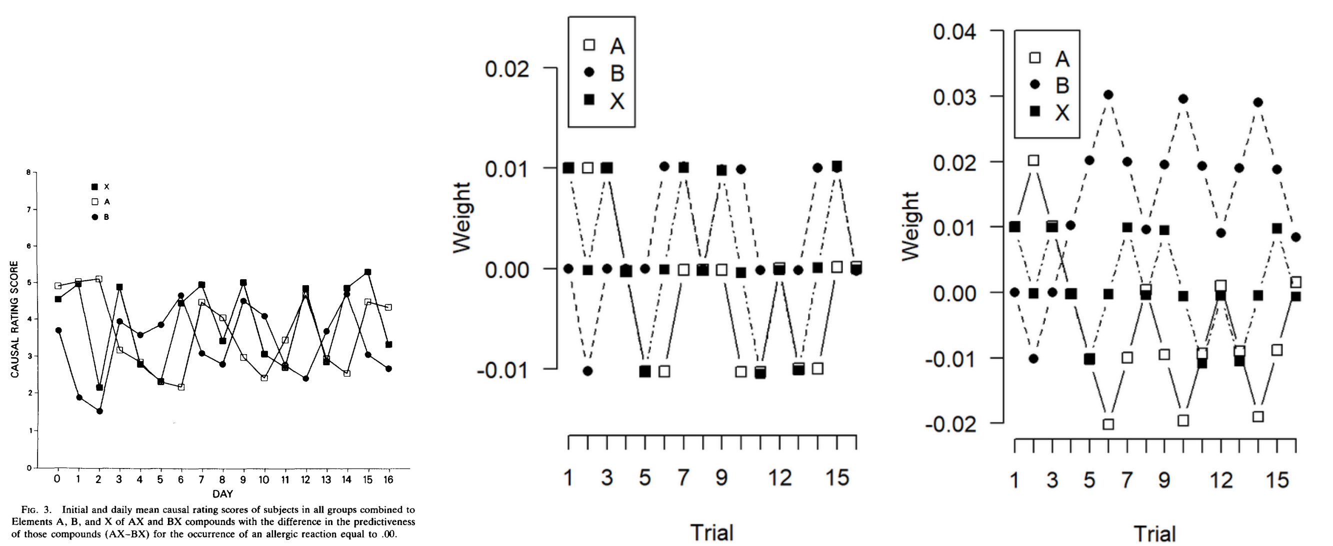

Figure 5: Connection weights to allergic minus not allergic for the three food types over one block (16 trials), averaged over subject, in the 50-50 condition. Left: experiment data; middle: Rescorla-Wagner model predictions; right: Van Hamme & Wasserman adaptation predictions.

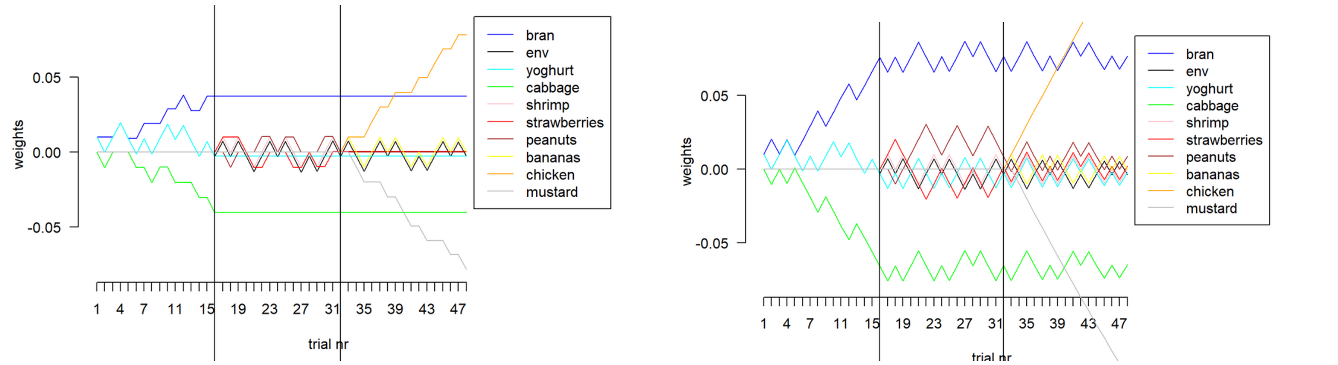

Figure 6: Connection weights to allergic minus not allergic for the different food types over all blocks (48 trials). Left: Rescorla-Wagner model predictions; right: Van Hamme & Wasserman adaptation predictions.

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