



MODELING THE EFFECT OF CO-OCCURRING DISTRACTOR REFERENTS ON WORD LEARNING USING THE RESCORLA-WAGNER MODEL AND PROPOSE-BUT-VERIFY

Bachelor's Project Thesis

Rijk van Braak, s2050188, K.D.van.Braak@student.rug.nl,
 Supervisors: Dr J.K. Spenader & Dr J.C. van Rij-Tange

Abstract: Word learning is an actively studied subject of research in linguistics and cognition. Several theories have been proposed to describe word learning. Two of these theories are *cross situational learning* and *propose-but-verify*. Roembke and McMurray (2016) conducted experiments studying the effects of co-occurring distractor referents on word learning. This current research will study the effects of co-occurring distractor referents by modeling the experiments of Roembke and McMurray (2016) using models of *cross situational learning* and *propose-but-verify* in the form of *Rescorla-Wagner learning* and a model of *propose-but-verify* as proposed by Trueswell, Medina, Hafri, and Gleitman (2013). Both models predict that co-occurring distractor referents impede word learning. The *Rescorla-Wagner* however can not be directly related to choice accuracy but can be used as predictor for the most likely choice. The *propose-but-verify* model does predict accuracy but seems to lack a gradual learning component. A combination of both models might be necessary to accurately predict the effect of co-occurring distractor referents on word learning.

1 Introduction

Word learning is an actively studied subject of research in linguistics and cognition. Word learning is not straightforward and might be influenced by for example sentence structure (Ramscar, Dye, Popick, and O'Donnell-McCarthy, 2011), informativity of the learning environment (Ramscar, Dye, and Klein, 2013) or co-occurring referents (e.g., Roembke and McMurray, 2016; Dautriche and Chemla, 2014).

Word learning is being investigated in experiments with adult or child participants. In these studies participants are trained to learn novel words with the corresponding referents. (e.g., Yu and Smith, 2007; Roembke and McMurray, 2016; Trueswell et al., 2013; Dautriche and Chemla, 2014) Another method of studying word learning is the computational modeling of word learning (Ramscar, Yarlett, Dye, Denny, and Thorpe, 2010; Ramscar et al., 2011, 2013; Trueswell et al., 2013). These experiments are used to explore or form theories of word learning. Yu and Smith (2007) for example pro-

posed a theory of word learning which describes how possible referents are tracked across different learning instances. A referent is in their account determined by comparing the co-occurrence of different referents with the word. They named this theory *cross situational learning*. This theory will be further explored in Section 1.1.

Trueswell et al. (2013) offer an alternative theory of word learning which describes how a conjecture is made about the correct the referent for a word. In succeeding learning instances this conjecture will be either confirmed and further solidified or rejected after which a new conjecture will be made. This theory, named *propose-but-verify*, thus tracks just one referent as opposed to *cross situational learning* which tracks multiple referents across learning instances. The *propose-but-verify* theory will be further explored in 1.2.

One factor that may influence word learning is the co-occurrence of distractor referents with the correct reference across learning instances. A learning instance is an instance where a subject is exposed

to a word and its possible referents. For example a child sitting at a dinner table might hear the word "knife"; the child will see a lot of objects that might be the correct referent for the word "knife". A child may hear the word "knife" in many learning instances. In this situation however the referent "knife" might often co-occur with the referent "fork" and "spoon". These co-occurring referents can be considered *distractor referents* as they distract from the correct referent. The research question for this current research is what the influence of co-occurring distractor referents on word learning is.

Both Dautriche and Chemla (2014) and Roembke and McMurray (2016) researched similar questions regarding the influence of co-occurring distractor referents on word learning. Dautriche and Chemla (2014) focused on the context these co-occurring distractors might provide for word learning. They found that if the distractor referents were present in the first learning instances but not on later instances than these distractor referents might provide context for the correct referent and learning will improve. Roembke and McMurray (2016) focused on different co-occurrence rates for the distractors, simulating situations wherein distractor referents are present across learning instances and not only in the first learning instances. Roembke and McMurray found that co-occurring distractors in word learning impede the learning process through experiments wherein the co-occurrence rate of the distractors with the words was influenced. They compared their results with the two aforementioned theories and concluded that both theories might be at play during word learning. These experiments will be further explored in Section 1.5 As this current research will attempt to answer a very similar question as Roembke and McMurray (2016), the experiments of Roembke and McMurray (2016) will be modeled using computational models of *cross situational learning* and *propose-but-verify* in the form of the *Rescorla-Wagner model* (Rescorla and Wagner, 1972) and a model of *propose-but-verify* as proposed by Trueswell et al. (2013) to study to what extent these models predict the influence of co-occurring distractors on word learning. These models are implemented in R version 3.4.3 (R Core Team, 2017). For the model of *Rescorla-Wagner learning* the existing *NDLvisualization* (van Rij,

2018) R-package is used, the proposed *propose-but-verify* model is implemented in R. The next subsections will further discuss the learning theories, the corresponding models and the experiments by Roembke and McMurray (2016).

1.1 Cross situational learning

One theory that describes word learning, as mentioned earlier, is *cross situational learning*. This theory describes how new words are learned over time across different learning instances. Cross situational learning states that a subject will learn the meaning of the word by tracking the word and all its possible referents across different learning instances. Over time the correct referent is learned by comparing the co-occurrences of the referents with the word. The most frequent co-occurring referent is eventually selected as the correct referent of the word in question. This is a form of associative learning where different referents compete for relevance through different learning instances. A very simple example of cross-situational learning can be seen in figure 1.1 from Vogt (2012). Suppose a subject

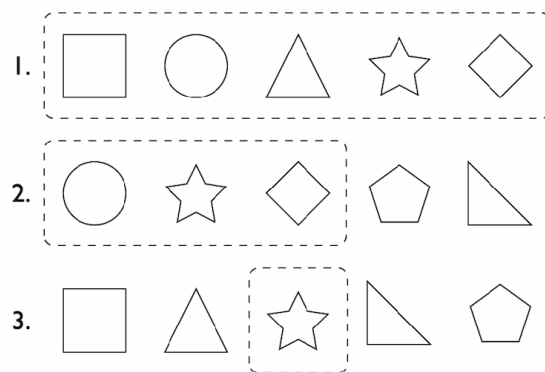


Figure 1.1: An example of cross-situational learning across three trials. (Vogt, 2012)

is tasked with learning the correct referent for the novel word 'wakabu'. The first row depicts the first learning instance wherein a subject hears the novel word and sees the possible referents square, circle, triangle, star and diamond. Since this is the first learning instance all the referents have the same co-occurrence rate with the novel word depicted by the dotted line around the possible referents. In the second learning instance, depicted by the sec-

ond row, not all referents from the previous learning instance are present. Since the circle, star and diamond were present in the previous learning instance, they have a higher co-occurrence rate with the novel word than the new referents pentagon and rectangular triangle. The dotted line again represents the referents with the highest co-occurrence rate with the novel word. Now in the third learning instance, depicted by the third row, the star referent has the highest co-occurrence rate with the novel word, again depicted by the dotted line, since the star was present in all learning instances as opposed to the other referents. As shown in this example, the co-occurrence rate of the novel word with all the possible referents is tracked and a choice for the correct referent can be made based on the co-occurrence rate after multiple learning instances. Yu and Smith (2007) describe several possible mechanisms that might be the underlying process of this type of learning. One of the possibilities is a purely associative process wherein every co-occurrence of a word with a referent increases the association between that word and the referent and after enough exposures the referent with the highest association is considered to be the correct referent. A second possibility is a more complex associative process wherein the association between word and referent can not only be increased by co-occurrence of a word with the referents but also inhibited by competition with other words and referents. An example of this process is *Rescorla-Wagner learning* (Rescorla and Wagner, 1972) which will be discussed in Section 1.3.

1.2 Propose but verify

Although the theory of *cross situational learning* might be supported by some experimental data (e.g. Yu and Smith, 2007) it is not without criticism. One point of criticism on *cross situational learning* by Trueswell et al. (2013) is that the tracking of the co-occurrence between a word and all possible referents might be too memory intensive for real life learning situations because the amount of possible referents in these real life situations are far larger than in any experimental environment as suggested by Medina, Snedeker, Trueswell, and Gleitman (2011). Another point of criticism is that in experiments to support *cross situational learning* only the final performance of the subjects

was evaluated and not the performance per trial which is necessary to determine how learning unfolds across trials. Trueswell et al. (2013) offer an alternative theory which they call *propose-but-verify* which finds its initial support in research by Medina et al. (2011). *Propose-but-verify*, in contrast to *cross situational learning*, does not require storing multiple hypotheses about the correct referent in memory. As figure 1.2 clarifies, *propose-but-verify* states that in a learning instance with a word and possible referents, one of the referents is proposed as the correct referent (As shown in the "First exposure" box in 1.2). In the following learning instances this conjecture is either confirmed because it again co-occurs with the word or rejected because it does not co-occur with the word. If it is confirmed, the conjecture is solidified in memory. If it is rejected a new conjecture is made. If the

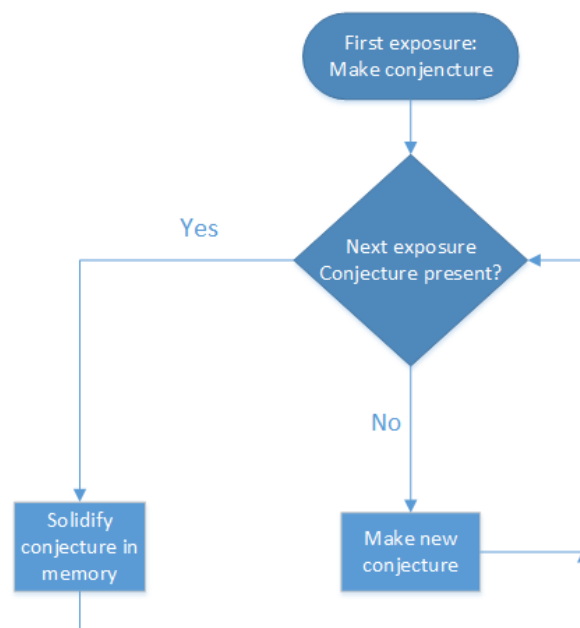


Figure 1.2: Flowchart of the propose-but-verify theory.

co-occurrence between the word and correct referent is consistent across learning instances, at some point the correct referent will be the conjecture that will be confirmed and thus solidified in memory. Trueswell et al. (2013) modeled the experiments they conducted that seem to support the theory by modeling *propose-but-verify*. This will model will be explored in Section 1.4.

1.3 Modeling cross situational learning

As this research aims to study the influence of co-occurring distractors on word learning using the aforementioned theories *cross situational learning* and *propose-but-verify*, we would like to implement simulations of word learning under the assumption of these two theories. In this research *Rescorla-Wagner learning* (Rescorla and Wagner, 1972) is used to model *cross situational learning*. As mentioned in Section 1.1 this model is one of the possible learning mechanisms suggested by Yu and Smith (2007). The Rescorla-Wagner model is a learning model of formal learning developed based on classical Pavlovian conditioning (Rescorla and Wagner, 1972). This model is used to formally describe the association between conditioned stimuli and unconditioned stimuli often referred to as cues and outcomes respectively. It emerged to explain phenomena seen in experiment results that could not be explained by mere co occurrence of a cue and outcome such as the Kamin blocking effect (Kamin, 1969). It is not only used to model animal learning but it is also used to model word learning phenomena (Ramscar et al., 2010, 2011, 2013). As Section 1.1 described the co-occurrence of referents and a word is tracked across learning instances in *cross situational learning*. The *Rescorla-Wagner model* describes this as the association strength between cues and outcome changing across trials. The association strength between a cue and outcome thus represents to what extent an outcome is expected given a cue. This association strength can be increased or inhibited based on the co-occurrence of cues and outcomes or absence of an outcome given a cue. In every learning instance one of three learning rules is used:

1. If a cue is not present, the association strength does not change
2. If a cue is present and so is an expected outcome, the association strength is increased
3. if a cue is present but an expected outcome is not, the association strength is inhibited.

This can formally be described in the formula $V_i^{t+1} = V_i^t + \Delta V_i^t$ where ΔV is defined as:

$$\Delta V = \begin{cases} 0 & \text{if } ABSENT(C_{j,t}) \\ \alpha_i \beta_1 (\lambda - \sum_{PRESENT(C_j)} V_j) & \text{if } PRESENT(C_{j,t}) \ \& \ PRESENT(O_{j,t}) \\ \alpha_i \beta_2 (0 - \sum_{PRESENT(C_j)} V_j) & \text{if } PRESENT(C_{j,t}) \ \& \ ABSENT(O_{j,t}) \end{cases} \quad (1.1)$$

Where V is the association strength between cue C and outcome O , α the salience of the cue, β the learning rate and λ the maximum association strength. The salience parameter α was set to the default value of 0.1, the learning rate parameters β_1 and β_2 were set to the default value 0.1 and these values stayed the same throughout the experiments as the relative difference between cues are of interest. The maximum association strength λ was set to the default value 1.

Table 1.1: Example of matrices generated by the RW model applied on figure 1.1

	Wakabu		Wakabu		Wakabu	
	Circle	0.01	Circle	0.0197	Circle	0.0197
	Diamond	0.01	Diamond	0.0197	Diamond	0.0197
1	Square	0.01	2 Square	0.01	3 Square	0.019409
	Star	0.01	Star	0.0197	Star	0.029109
	Triangle	0.01	Triangle	0.0097	Triangle	0.019409
			Pentagon	0.0097	Pentagon	0.019109
			Rectangular	0.0097	Rectangular	0.019109
			Triangle		Triangle	

Applying the formula across trials will result in matrices representing the association strength between every cue and outcome for the learning instances. The outcome with the highest association strength for a cue will thus be the most expected outcome. An example of this can be seen in table 1.1. This table shows how the association strength between the symbol-cues and novel word outcome shown in figure 1.1 changes across the three trials using the *Rescorla-Wagner model* resulting in the Star-cue having the highest association strength with the novel word 'Wakabu'.

1.4 Modeling propose-but-verify

Trueswell et al. (2013) not only propose an abstract theory of word learning, but also a provide a concrete model that formalizes their theory. This

model, in line with their theory and in contrast to the *Rescorla-Wagner model*, only keeps track of one conjecture. The algorithm for the model of *propose-but-verify* is described as following:

1. In a new learning instance: make a conjecture at random.
2. In the next learning instance of the word: remember the previous conjecture with probability α_1 .
3. If the previous conjecture is present in this learning instance (i.e. confirmed) increase probability to α_2 ; otherwise make a new conjecture at random.

With $\alpha = (accuracy - chance)/(1 - chance)$. α is a free parameter that can only be determined from experimental data with α_1 using the average accuracy of those learning instance where participants were correct on the previous learning instance but not on earlier learning instances. α_2 is based on the average accuracy of those learning trials where participants were correct on the two previous learning instances. If the co-occurrence of the word and

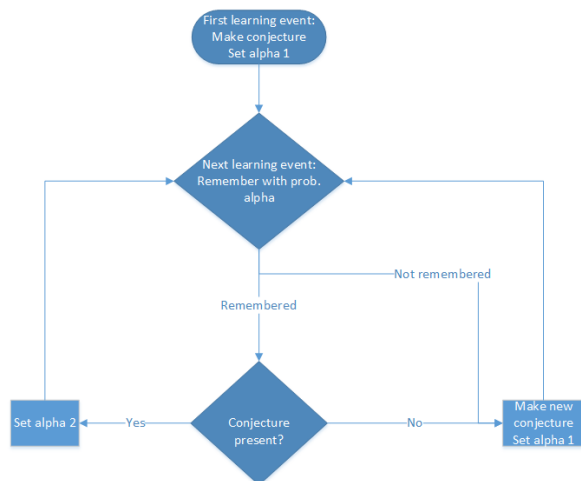


Figure 1.3: Flowchart of the propose-but-verify model.

the target-referent is consistent, eventually the correct conjecture will be made and solidified in memory. Trueswell et al. (2013) supported their theory and model with experiments wherein participants were tasked with learning novel words for existing objects. Every novel word was repeated 5

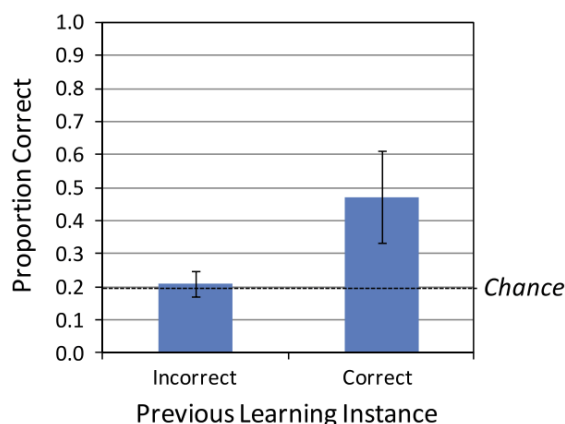


Figure 1.4: Example trial analysis of word learning. (Trueswell et al., 2013)

times throughout the experiment. Figure 1.4 shows the accuracy analysis of one the experiments of Trueswell et al. (2013) which supports the theory that the accuracy will be at chance level after an incorrect choice but higher than chance after a correct choice in the previous trial.

1.5 Experiments by Roembke and McMurray

This research will study the effect of co-occurring distractor referents on word learning by computational modeling the research of Roembke and McMurray (2016) using the models described in Section 1.3 and Section 1.4. In their research Roembke and McMurray conducted two experiments of word learning wherein eight word-referent pairings were learned by the participants.

Table 1.2: Novel words used (Roembke and McMurray, 2016)

Written form	IPA
Mefa	/meifa/
Goba	/gouba/
Jifei	/dzifer/
Bure	/bu:er/
Naida	/naida/
Zati	/zæti/
Lubou	/lubo/
Pacho	/patʃou/

The eight words were novel words as shown in table 1.2 and the referents were eight novel objects. Each experiment consisted of 480 trials divided into 4 blocks of 120 trials such that every word was repeated 60 times. In every trial a participant first saw the target object with 2 distractor objects on a screen and shortly after heard the novel word. A participant then clicked on the object they thought was the target object. The distractors were chosen from the 7 other novel objects.

In the first experiment the co-occurrence rate of the distractors with the novel word was manipulated such that every novel word had one high co-occurring distractor (HC) that co-occurred in 60% of the trials with the novel word, one low co-occurring distractor (LC) that co-occurred 40% of the trials with the novel word and random distractors (RO) that co-occurred 20% of the trials with the novel word. The target object co-occurred 100% of the trials with the novel word. An example of these statistics can be found in 1.5. This means that there are four different trial types in the first experiment: the target with a HC and a LC (HCLC-trial), the target with a HC and a RO (HC-trial), the target with a LC and a RO (LC-trial) and the target with 2 RO's (RO-trial). The trial types were randomized per block and each block consisted of 16 HCLC-trials, 56 HC-trials, 32 LC-trials and 16 RO-trials.

In the second experiment the 2 distractor objects were chosen at random such that the co-occurrence of the random distractors with the novel word was approximately 28%.

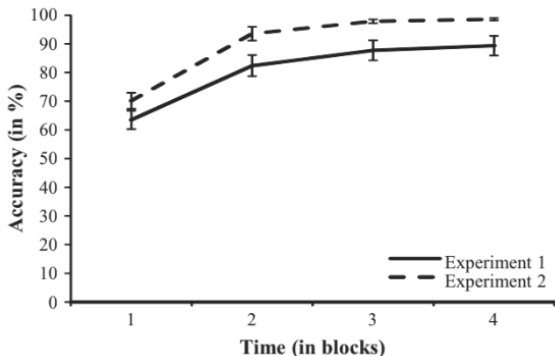


Figure 1.6: Average accuracy across blocks for Experiments 1 and 2 (Roembke and McMurray, 2016)

The average accuracy results of the first and second experiment as shown in figure 1.6 show a difference in accuracy between the experiments. The lower accuracy of the first experiment shows that the high co-occurrence rate of the distractor objects in experiment one impede learning. Another finding relevant for the current research can be seen in figure 1.7. This plots the accuracy as a function of how participants responded on previous trials as Trueswell et al. (2013) used in figure 1.4. In the first 5 repetitions of the novel words (A) Roembke and McMurray find the same results as Trueswell et al. but in the last 5 repetitions of the novel word the results differ from the first repetitions. There is a gradual growth in accuracy despite an incorrect choice on the previous trial, contradicting the findings of Trueswell et al. (2013).

By modeling the experiments of Roembke and McMurray (2016), this research will compare the aforementioned models of word learning to the experimental data of the influence of co-occurring distractors on word learning.

2 Modeling experiment 1

The experiments of Roembke and McMurray (2016) were modeled by implementing the experiment setup and the models described in section 1.3 and section 1.4 in R version 3.4.3 (R Core Team, 2017). For the *Rescorla-Wagner model* the existing R-package *NDLvisualization* (van Rij, 2018) was used; the *propose-but-verify* model was implemented based on the algorithm described by Trueswell et al. (2013).

2.1 Data setup

To model the first experiment of Roembke and McMurray (2016), we constructed the trials according to the experiment setup as described in Section 1.5. Even though the novel words are not relevant in modeling as previous association do not exist and won't influence learning, the same eight novel words were used in modeling the experiment for the sake of consistency. The eight novel objects were represented as "novelObject1" etc. resulting in the word-object pairings that can be found in Table 2.1. For every novel word a high co-occurring

	Object 1	Object 2	Object 3	Object 4	Object 5	Object 6	Object 7	Object 8
Mefa	60	36	24	12	12	12	12	12
Goba	12	60	36	24	12	12	12	12
Jifei	12	12	60	36	24	12	12	12
Bure	12	12	12	60	36	24	12	12
Naida	12	12	12	12	60	36	24	12
Zati	12	12	12	12	12	60	36	24
Lubou	24	12	12	12	12	12	60	36
Pacho	36	24	12	12	12	12	12	60

Figure 1.5: Example of co-occurring statistics over all 4 blocks (Roembke and McMurray, 2016)

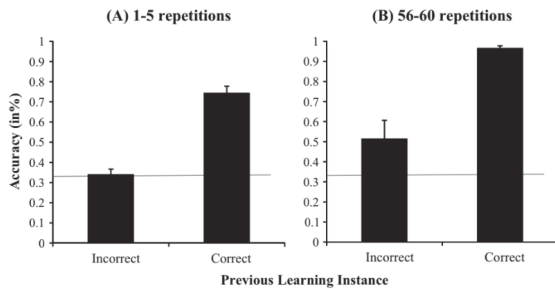


Figure 1.7: Accuracy as a function of how participants responded on previous trials with the same target for five target replications at beginning of experiment (A) and at the end of the experiment (B). Error bars indicate the standard error of the mean. (Roembke and McMurray, 2016)

(HC) and a low co-occurring (LC) distractor was selected according to the co-occurrence statistics of Roembke and McMurray (2016) as described in 1.5, an example of which is presented in Figure 1.5. A

Table 2.1: Novel words and target novel objects used

Novel word	Novel object
Mefa	novelObject1
Goba	novelObject2
Jifei	novelObject3
Bure	novelObject4
Naida	novelObject5
Zati	novelObject6
Lubou	novelObject7
Pacho	novelObject8

data frame was setup containing the different trial types (HCLC, HC, LC, RO see Section 1.5) for every novel word. The trials were then distributed

over the 480 trials and divided over 4 blocks of 120 trials according to Figure 2.1. This results in every block containing 2 HCLC trials per novel word, 7 HC trials per novel word, 4 LC trials per novel word and 2 RO trials per novel word such that the co-occurrence statistics of Roembke and McMurray (2016) described in Section 1.5 hold true. Since there are 8 novel words there were 64 HCLC trials, 224 HC trials, 128 LC trials and 64 RO trials in the experiment. Each word was therefore repeated 60 times throughout the experiment. The trials were

Trial-type	Object types on screen	Repetitions/block and word	Repetitions
HCLC	Target HC competitor LC competitor	2	64
HC	Target HC competitor Random object	7	224
LC	Target LC competitor Random object	4	128
RO	Target Random object 1 Random object 2	2	64

Figure 2.1: The four trial-types and the number of times each is repeated in a single block and over the course of the experiment. (Roembke and McMurray, 2016)

randomized per block. The trial setup was determined for every run (or simulated participant).

2.2 Rescorla-Wagner model

To model the experiment using the *Rescorla-Wagner equations* it is necessary to determine what the cue and outcome represent. In the experiments by Roembke and McMurray (2016) the participants first saw the novel objects on the screen and then

heard the novel word. We therefore considered the novel objects as cues and the novel word as outcome in every trial. An extra background cue was added, that was named 'experiment', to capture the effects of non-relevant background cues and experiment context as is usual in modeling experiments of word learning.

The salience parameter α was set to the default value of 0.1, the learning rate parameters β_1 and β_2 were set to the default value 0.1 and these values stayed the same throughout the experiment as the relative difference between cues are of interest. The maximum association strength λ was set to the default value 1.

2.3 Rescorla-Wagner model results

The association strength calculated by the *Rescorla-Wagner model* between the novel object cues and the novel word outcome are plotted across all 480 trials of experiment 1. Because every plot showed the same pattern, only the plot of the novel word 'mefa' is shown in Figure 2.2. The other plots can be seen in Appendix A. Each show the highest association strength for their target object followed by the HC distractor, 'experiment' cue and LC distractor. The association strength of the RO distractors are even lower with the majority having a negative association strength after 480 trials. This can be seen more clearly in Figure 2.3 in which the final association strength after 480 trials is plotted.

2.4 Propose-but-verify model

To use the *propose-but-verify* model, the α_1 and α_2 parameters need to be determined. α is a free parameter ($\alpha = (accuracy - chance)/(1 - chance)$) that can only be determined from experimental data with α_1 using the average accuracy of those learning instance where participants were correct on the previous learning instance but not on earlier learning instances. α_2 is based on the average accuracy of those learning trials where participants were correct on the two previous learning instances. As the raw data of the experiments of Roembke and McMurray was not available, the parameters were determined based on the results from the experiments of Roembke and McMurray (2016) as shown in Figure 1.7. α_1 was chosen based on the first 5

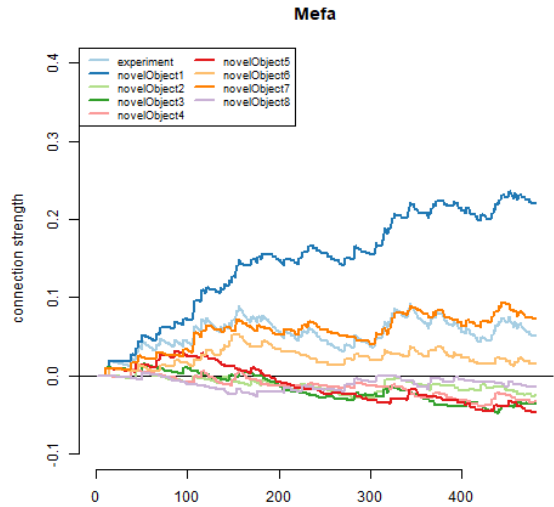


Figure 2.2: Association strength between novel object cues and novel word 'mefa' for 480 trials. Target object: 'novelObject1' HC distractor: 'novelObject7, LC distractor: 'novelObject6'

experiments as seen in Figure 1.7(A) wherein the average accuracy was approximately 0.7 when the participants were also correct on the previous learning instance of the novel word and not based on the first confirmation as described in Section 1.4. Using the aforementioned formula and the average accuracy of 0.7 the α_1 is determined to be 0.55. α_2 was chosen based on Figure 1.7(B) wherein the average accuracy was approximately 0.9 when the participants were also correct on the previous learning instance of the novel word and not based on the second confirmation as described in 1.4. Using the aforementioned formula and the average accuracy of 0.9 the α_2 is determined to be 0.85.

This does mean however that α parameters might be higher than the raw data of the Roembke and McMurray experiments shows because the α could not be determined exactly. This is especially true for the α_2 parameter because this is based on results of the final five repetitions of the first experiment by Roembke and McMurray and they show that there is a gradual increase in accuracy during the trials. This means that it is likely that the α_2 parameter is higher than the average accuracy of those learning trials where participants were cor-

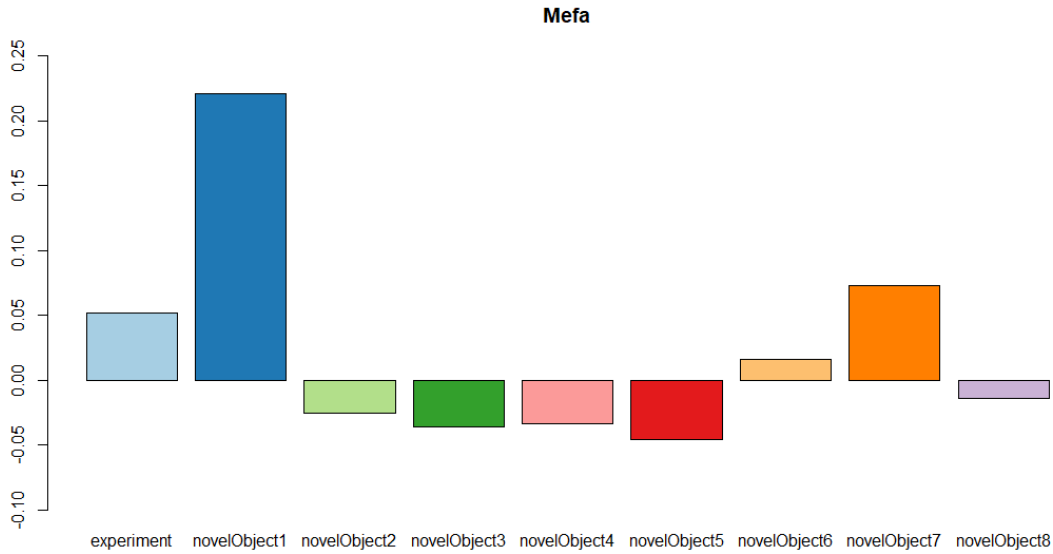


Figure 2.3: Barplot of the final association strength between novel object cues and novel word 'mefa'. Target object: 'novelObject1' HC distractor: 'novelObject7, LC distractor: 'novelObject6'

rect on the two previous learning instances. The model was run 1000 times to simulate 1000 participants.

2.5 Propose-but-verify model results

Every conjecture of every run in every trial is tracked. Every conjecture that was the target object was treated as a correct choice. The mean of these correct choices for every trial across the 1000 runs is plotted in Figure 2.4 . Figure 2.5 shows the mean of these correct choices across 1000 runs for every block of 120 trials.

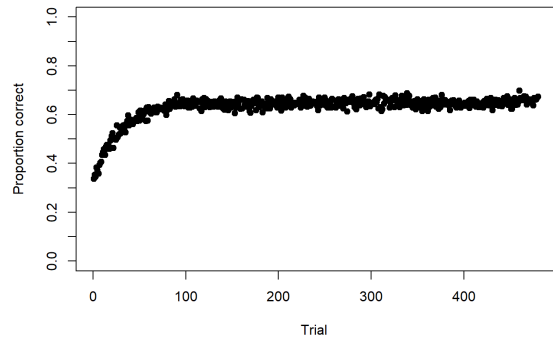


Figure 2.4: Accuracy of the word-object pairings across the 480 trials for Experiment 1 for 1000 runs

2.6 Experiment 1 discussion

The results of the *Rescorla-Wagner model* can not be directly related to accuracy as it represents association strength and not choice accuracy. However association strength is a predictor of the most likely choice. In all the results, an example of which can be seen in Figure 2.2 and Figure 2.3 the target object has the highest association strength with the novel word after 480 trials so the target object

will be the most likely choice. The HC distractor however also has a relatively high positive association meaning that it will be competing with the target object. The LC distractor has a low positive association with the novel word and will offer little competition to the target object and HC distractor. Because there is competition for the target

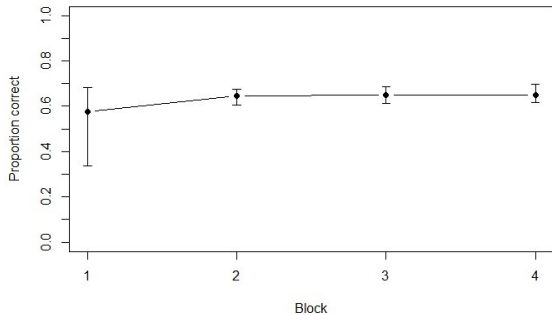


Figure 2.5: Accuracy of the word-object pairings across blocks for Experiment 1 for 1000 runs

object the accuracy will be lower than if there was no competition as the competition means that it is more likely that the distractor is chosen instead of the target object.

The results of the *propose-but-verify model* show a rapid accuracy increase in the first block as can be seen in Figure 2.4 and Figure 2.5 but it levels off after the first block. This contrasts with the results of Roembke and McMurray (2016) seen in Figure 1.6 which shows a negatively accelerated curve across all trials. This is because the α parameters in the *propose-but-verify model* are fixed which limits the maximum accuracy because it is directly dependent on the accuracy determined by experimental data as seen in Section 1.4.

To see the influence of the distractors a comparison needs to be made to the results of modeling learning without the manipulated co-occurrence rate as will be done in experiment two.

3 Modeling experiment 2

In the second experiment the co-occurrence of distractors with the novel word are not manipulated and therefore the distractors randomly co-occur with the novel word leading to a co-occurrence rate of approximately 28% for every distractor.

3.1 Data setup

Again the trials were setup according to the experiment setup described in Section 1.5. Again the novel words and target object of Table 2.1 were

used. A data frame was setup containing the trials in which every target object was combined with two random distractor objects of the same set of words. The trial setup was done for every run (or simulated participant).

3.2 Rescorla-Wagner model

As the second experiment was conducted in the same manner as experiment 1 the same settings for the *Rescorla-Wagner model* were used as described in Section 2.2.

3.3 Rescorla-Wagner model results

The association strength calculated by the *Rescorla-Wagner model* between the novel object cues and the novel word outcome are plotted across all 480 trials of Experiment 2. Because every plot showed the same pattern, only the plot of the novel word 'mefa' is shown shown in Figure 3.1. The other plots can be seen in Appendix A. Each show the highest association strength for their target object and a small or negative association strength for the random distractors. This can be seen more clearly in Figure 3.2 in which the final association strength after 480 trials is plotted.

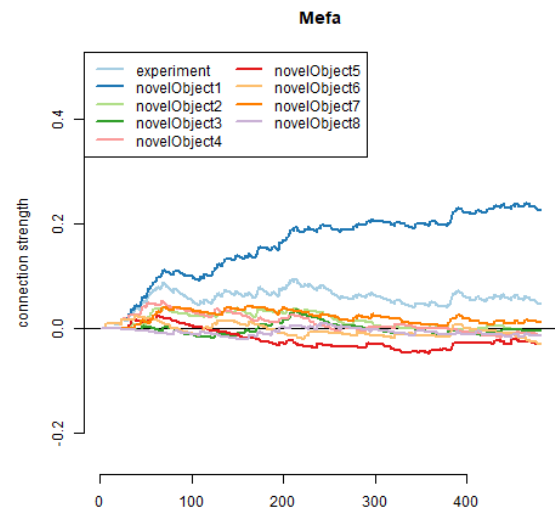


Figure 3.1: Association strength between novel object cues and novel word 'mefa' for 480 trials. Target object: 'novelObject1'

3.4 Propose-but-verify model

Again the α parameters had to be determined but since the raw data was not available, an estimate had to be made. It is known from the Roembke and McMurray (2016) results in Figure 1.6 that the accuracy of the second experiment was higher than the first experiment. The accuracy is increased by $\sim 5\text{-}10\%$ we therefore chose to use a conservative increase of 5% to the accuracy used in Section 2.4 increasing α_1 to 0.625 and α_2 to 0.925. Again the model was run to simulate 1000 participants.

3.5 Propose-but-verify model results

Every conjecture of every run in every trial is tracked. Every conjecture that was the target object was treated as a correct choice. The mean of these correct choices for every trial across the 1000 runs is plotted in Figure 3.3. Figure 3.4 shows the mean of these correct choices across 1000 runs for every block of 120 trials.

3.6 Experiment 2 discussion

The results of the *Rescorla-Wagner model*, an example of which is shown in Figure 3.1 and Figure 3.2, clearly show that the target object has the highest association with the novel word for all novel word and novel object pairings after 480 trials. The RO distractors all have a low or negative association strength meaning that they hardly offer any competition for the target object. As there is less competition for the target object than there is in experiment 1, the accuracy of experiment 2 will be higher.

The results of the *propose-but-verify model* again show a rapid accuracy increase in the first block as can be seen in Figure 3.3 and Figure 3.4 but it levels off after the first block. As discussed in Section 2.6 this is due to the fixed α parameters. The overall accuracy is higher however because the α parameters are set higher than in experiment 1. Both models predict a higher accuracy in the second experiment compared to the first experiment. We can thus conclude that both models predict that co-occurring distractors impede learning.

4 Discussion

The results of both computational models show that a clear influence of co-occurring distractor referents on learning. The results show that the distractor referents impede learning. This corresponds to the findings of the experiments by Roembke and McMurray. This can be seen in the results of the *Rescorla-Wagner model* through competition between cues because the association strength cannot be related directly to accuracy. In the results of modeling the first experiment with the *Rescorla-Wagner model* there is competition for the target object as discussed in Section 2.6 whereas the result of Experiment 2 shows hardly any competition as discussed in 3.6. As there is less competition for the target object, it is more likely that the target object will be the object of choice and Experiment 2 will therefore have a higher accuracy than Experiment 1.

The results of the *propose-but-verify model* do show the accuracy. The results of Experiment 2 show increased accuracy relative to the results of Experiment 1. The results however do not show the same pattern as the results of Roembke and McMurray (2016) as seen in Figure 1.6 because learning stops after the first block. As discussed in Section 2.6 and 3.6 this is due to the fixed α parameters. The *propose-but-verify model* seems to only be able to model a few trials as after one block accuracy ceases to increase. In order to see the gradual learning of Figure 1.6 at least the α_2 needs to increase after every confirmation as can be seen in Figure 4.1. For these results the α_2 parameter was increased after every confirmation of the conjecture using the following formula: $\alpha_{2\ new} = 0.1 * (\alpha_{2\ old})$ where $\alpha_{2\ new}$ is the increased α_2 and $\alpha_{2\ old}$ the α_2 of the previous learning instance of the novel word. The α_2 parameter is reset to the initial value if a conjecture is rejected. This gradual learning rule demonstrates the effect a gradual learning might have on the results of the *propose-but-verify model*.

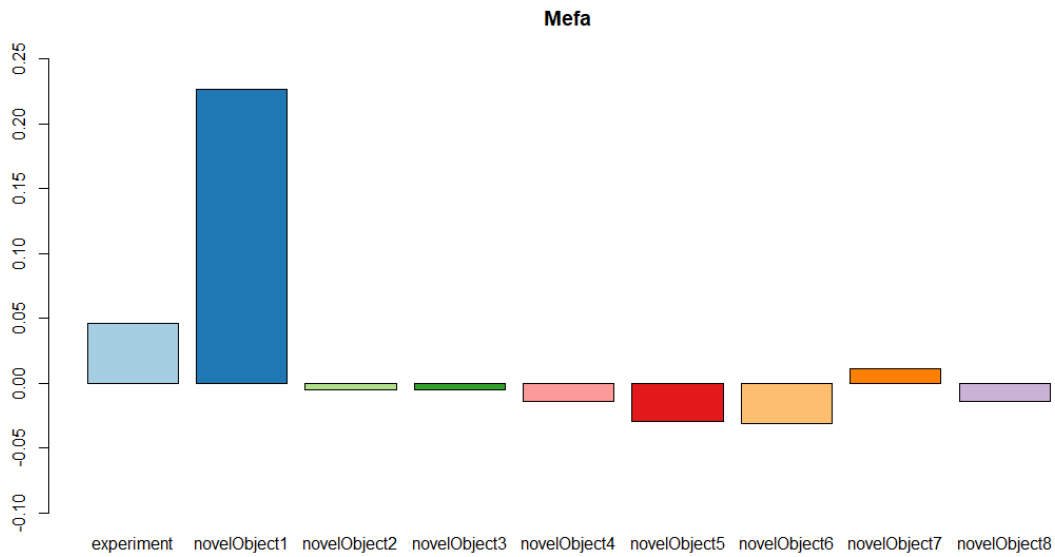


Figure 3.2: Barplot of the final association strength between novel object cues and novel word 'mefa'. Target object: 'novelObject1'

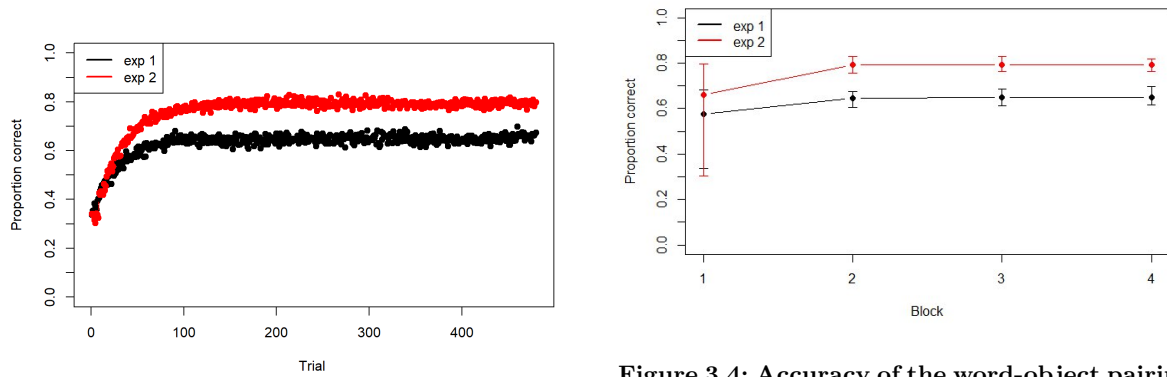


Figure 3.3: Accuracy of the word-object pairings across the 480 trials for Experiment 1 and 2 for 1000 runs

Figure 3.4: Accuracy of the word-object pairings across blocks for Experiment 1 and 2 for 1000 runs

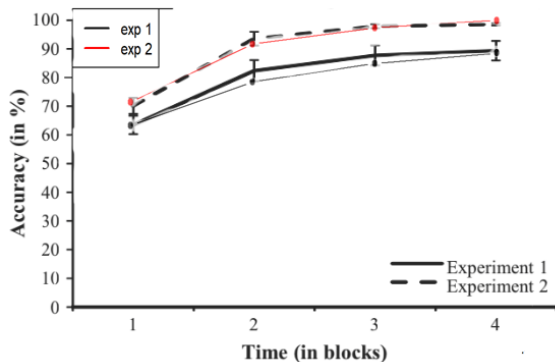


Figure 4.1: Comparison of the results of Roembke and McMurray (2016) as seen in Figure 1.6 and the accuracy of the word-object pairings across blocks for Experiment 1 and 2 with added gradual learning rule for 1000 runs

The difference in results of the *Rescorla-Wagner model* modeling Experiment 1 and Experiment 2 emerges because of the change in trial setup as the model parameters are kept the same for both experiments. The difference in results of the *propose-but-verify model* modeling Experiment 1 and Experiment 2 emerges mostly because of the changes to the α parameters and not because of the change in trial setup. Figures 4.2 and 4.3

show the results of modeling experiment one and two wherein the α parameters were consistent across both experiments. The α parameters of experiment one were used such that $\alpha_1 = 0.55$ and $\alpha_2 = 0.85$. These were also used for modeling experiment two. The results hardly show any difference between experiment one and two if the α parameters are kept consistent across trials.

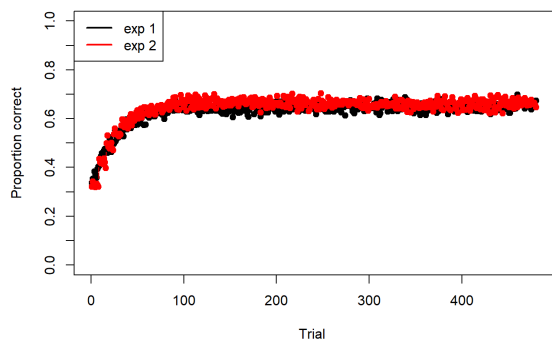


Figure 4.2: Accuracy of the word-object pairings across the 480 trials for Experiment 1 and 2 with consistent α for 1000 runs

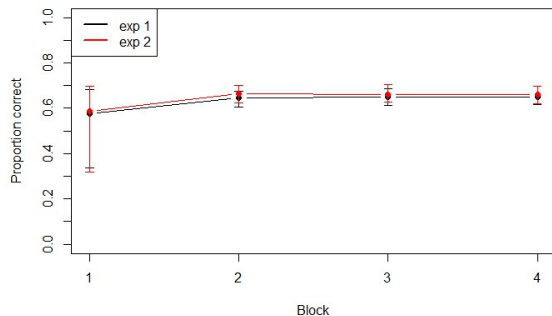


Figure 4.3: Accuracy of the word-object pairings across blocks for Experiment 1 and 2 with consistent α for 1000 runs

The trials used in the experiment might be unrealistically consistent as the co-occurrence rate of the target object with the novel word is 100% where in real learning situation the target object might not be encountered in every learning instance as the target object might not be visible

or overlooked. In the *Rescorla-Wagner model* this would mean that the association of the target object with the word mistakenly does not increase based on the first rule of the formula seen in Formula 1.1. This will have a slight effect on learning whereas in the *propose-but-verify model* the target object will not be one of the possible conjectures and will therefore be rejected. This might have a big effect on learning as a learned word-object pairing will be unlearned after one inconsistent learning instance. The *propose-but-verify model* therefore is not a robust model as one error will unlearn any previous learning whereas the *Rescorla-Wagner model* is robust as one error will only slightly chance the association strength and not unlearn all previous learning.

Roembke and McMurray (2016) suggest that the effect of last-encounter performance, which is the cornerstone of the *propose-but-verify* might be a product of learning and not a mechanism of learning based on their autocorrelation analyses. The results of this research show that the *propose-but-verify model* lacks a gradual learning component which is necessary for modeling the experimental result of Roembke and McMurray (2016) (as can be seen by comparing Figures 3.3 and 3.4 with Figure 1.6). The *Rescorla-Wagner model* can account for the gradual learning effect but can not be directly related to accuracy. Further research might explore combining the *Rescorla-Wagner model* with the *propose-but-verify model* as a learning strategy wherein the conjecture is not only based on the last encounter but also based on the association strength. This might mean that, using the results of the first experiment as seen in Figure 2.2, in the first trials a new conjecture might be random as the association strength between all objects and the word will be roughly the same but as the trials progress the higher association strength of the target and HC object will increase the accuracy as they have a higher probability of being selected as the new conjecture reducing the probability of choosing the incorrect object. Furthermore increasing the α parameters based on the increasing associative strength will lead to the gradual increase of accuracy seen in Figure 4.1.

The results show that consistent co-occurring distractor referents will impede learning. The "knife" example of the introduction is often seen with "fork" and "spoon". These can be seen as high co-

occurring distractors as described in Experiment 1 (Section 2). The results of the *Rescorla-Wagner model* in Section 2.3 show that high co-occurring distractors are competitors to the correct referent. If the "knife" would also be encountered in different settings, the co-occurrence rate of "knife" with "fork" and "spoon" will be lower. The results of Section 3.3 show that a lower co-occurrence rate will result in less competition for the correct referent and therefore less influence on word learning. This suggests that it might be better for word learning if a referent that is often encountered with distractors is also seen in a different setting without the distractors as this will result in less influence of the distractor referents on word learning.

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A Results of the Rescorla Wagner model for the first experiment

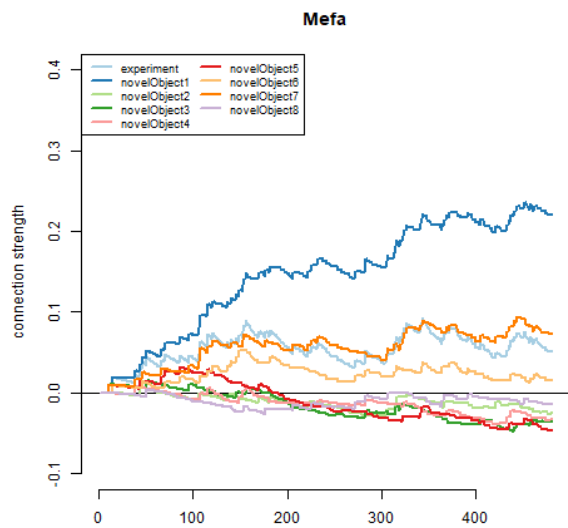


Figure A.1: Association strength between novel object cues and novel word 'mefa' for 480 trials. Target object: 'novelObject1' HC distractor: 'novelObject7', LC distractor: 'novelObject6'

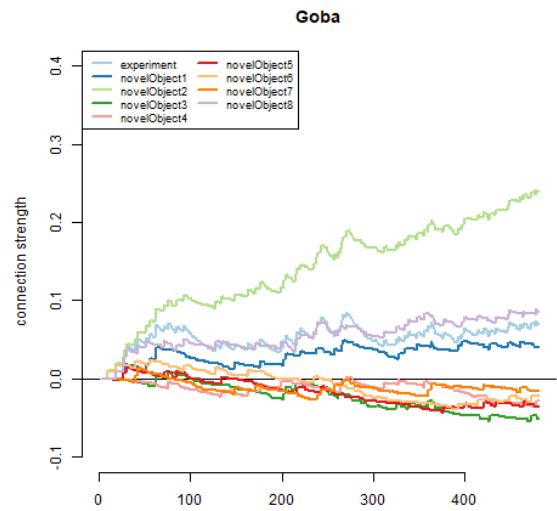


Figure A.2: Association strength between novel object cues and novel word 'goba' for 480 trials. Target object: 'novelObject2' HC distractor: 'novelObject8', LC distractor: 'novelObject1'

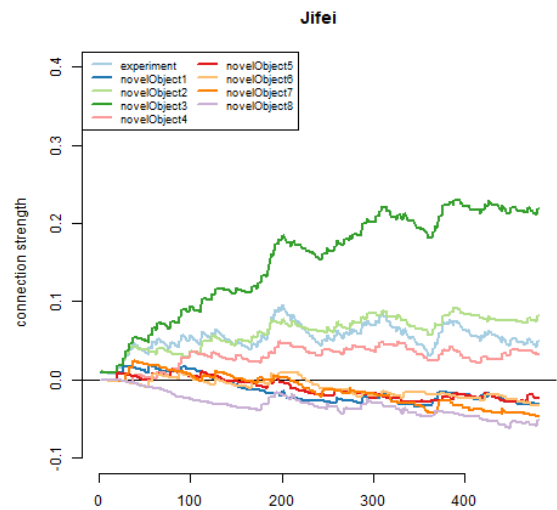


Figure A.3: Association strength between novel object cues and novel word 'jifei' for 480 trials. Target object: 'novelObject3' HC distractor: 'novelObject2', LC distractor: 'novelObject4'

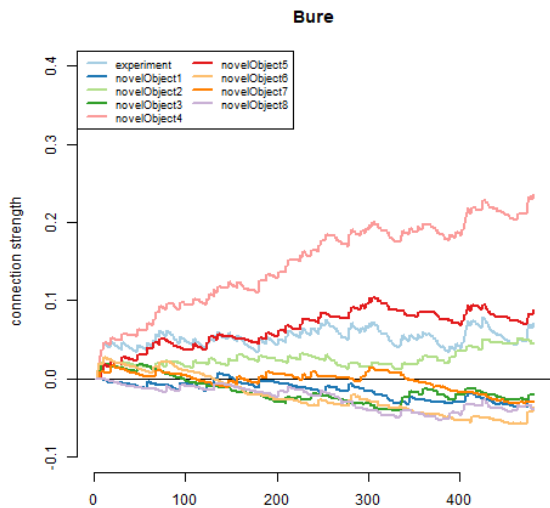


Figure A.4: Association strength between novel object cues and novel word 'bure' for 480 trials. Target object: 'novelObject4' HC distractor: 'novelObject5, LC distractor: 'novelObject2'

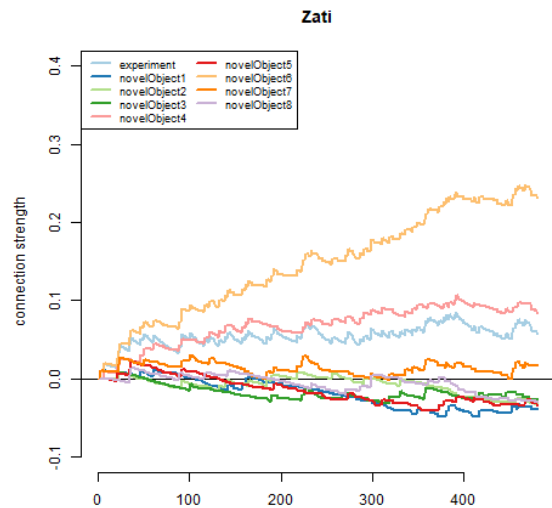


Figure A.6: Association strength between novel object cues and novel word 'zati' for 480 trials. Target object: 'novelObject6' HC distractor: 'novelObject4, LC distractor: 'novelObject7'

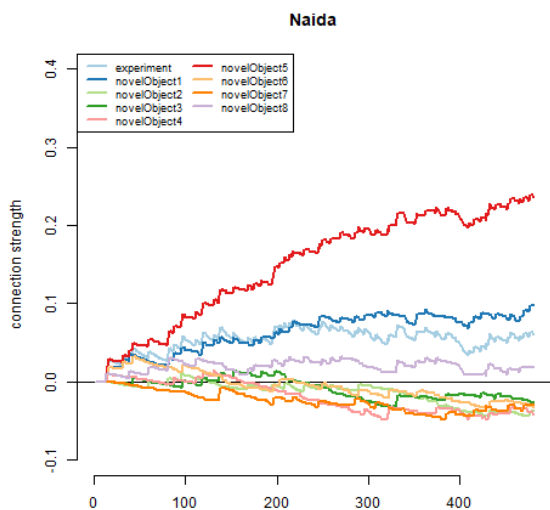


Figure A.5: Association strength between novel object cues and novel word 'naida' for 480 trials. Target object: 'novelObject5' HC distractor: 'novelObject1, LC distractor: 'novelObject8'

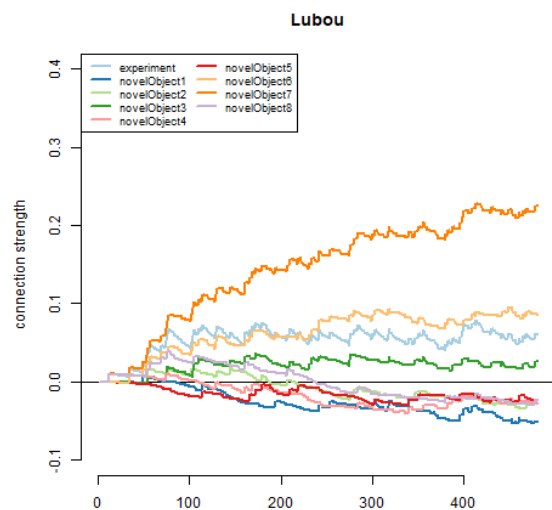


Figure A.7: Association strength between novel object cues and novel word 'lubou' for 480 trials. Target object: 'novelObject7' HC distractor: 'novelObject6, LC distractor: 'novelObject3'

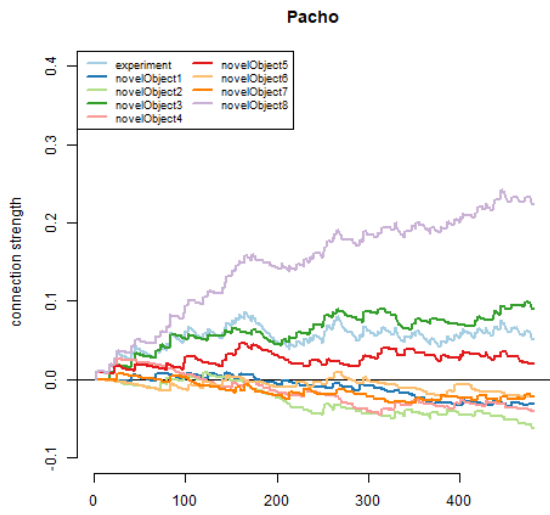


Figure A.8: Association strength between novel object cues and novel word 'pacho' for 480 trials. Target object: 'novelObject8' HC distractor: 'novelObject3, LC distractor: 'novelObject577'

B Results of the Rescorla Wagner model for the second experiment

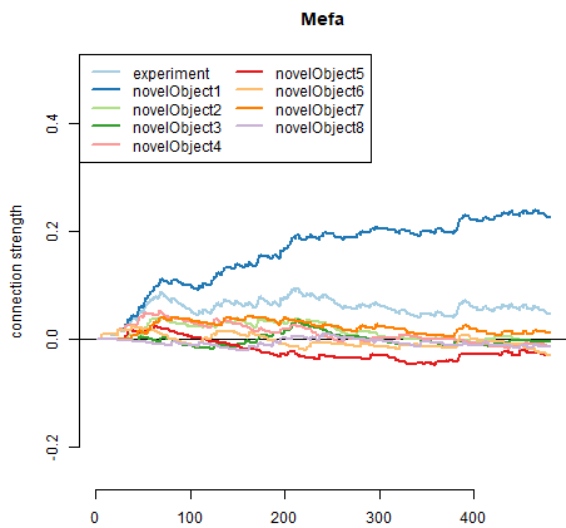


Figure B.1: Association strength between novel object cues and novel word 'mefa' for 480 trials. Target object: 'novelObject1'

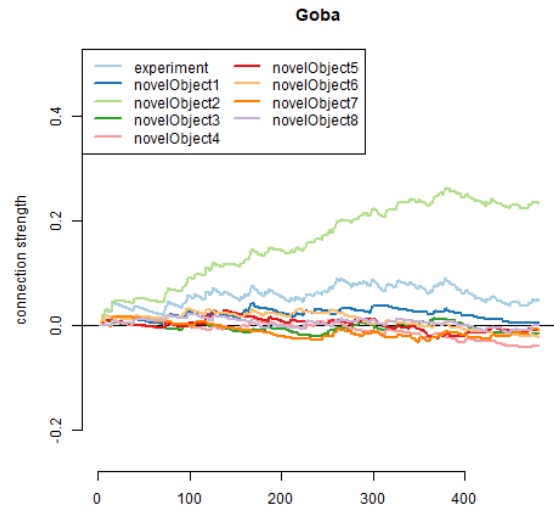


Figure B.2: Association strength between novel object cues and novel word 'goba' for 480 trials. Target object: 'novelObject2'

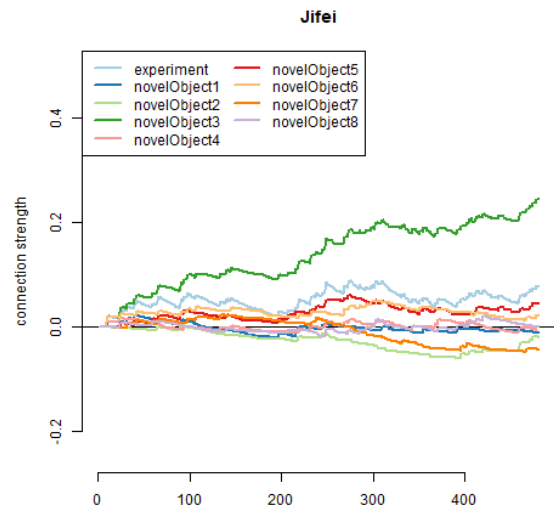


Figure B.3: Association strength between novel object cues and novel word 'jifei' for 480 trials. Target object: 'novelObject3'

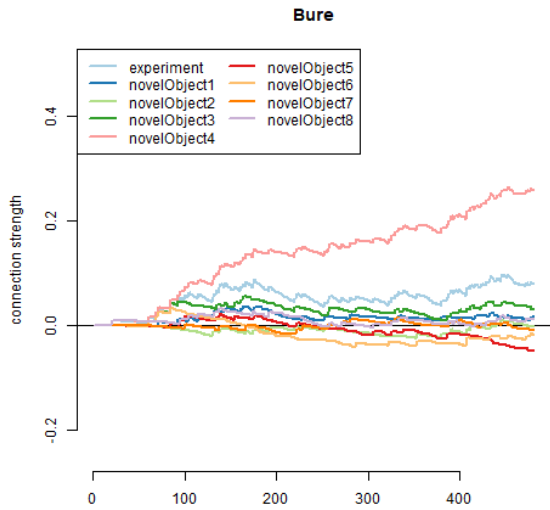


Figure B.4: Association strength between novel object cues and novel word 'bure' for 480 trials. Target object: 'novelObject4'



Figure B.6: Association strength between novel object cues and novel word 'zati' for 480 trials. Target object: 'novelObject6'

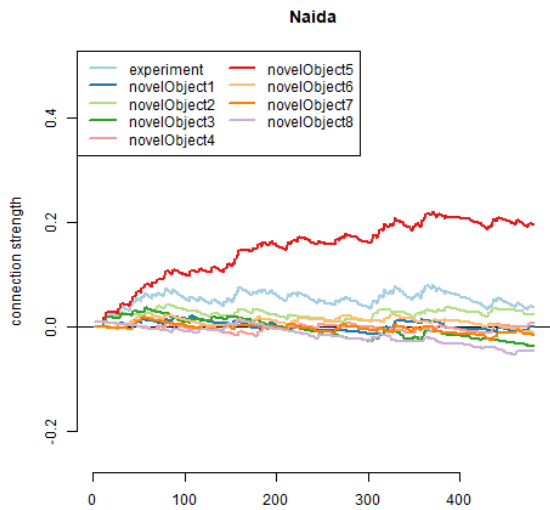


Figure B.5: Association strength between novel object cues and novel word 'naida' for 480 trials. Target object: 'novelObject5'

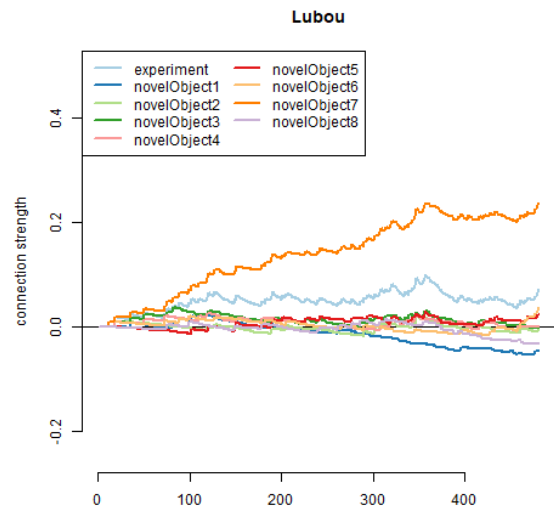


Figure B.7: Association strength between novel object cues and novel word 'lubou' for 480 trials. Target object: 'novelObject7'

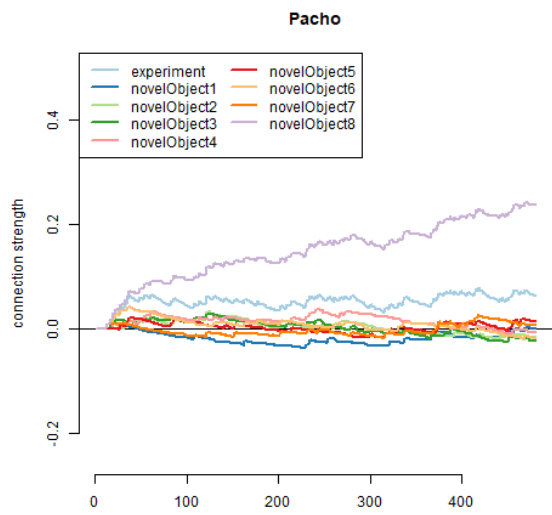


Figure B.8: Association strength between novel object cues and novel word 'pacho' for 480 trials. Target object: 'novelObject8'