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1 **ACQUISITION AND PROCESSING OF AN ARTIFICIAL MINI-LANGUAGE**
2 **COMBINING SEMANTIC AND SYNTACTIC ELEMENTS**

3

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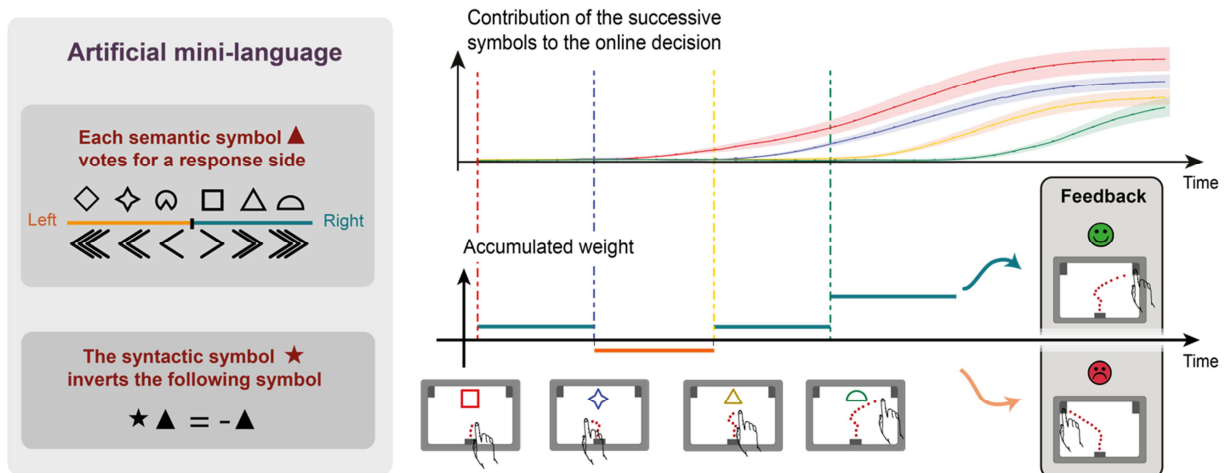
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1 **Abstract**

2 Most artificial grammar tasks require the learning of sequences devoid of
3 meaning. Here, we introduce a learning task that allows studying the acquisition
4 and processing of a mini-language of arithmetic with both syntactic and
5 semantic components. In this language, symbols have values that predict the
6 probability of being rewarded for a right or left response. Novel to our paradigm
7 is the presence of a syntactic operator which changes the sign of the subsequent
8 value. By continuously tracking finger movement as participants decided
9 whether to press left or right, we revealed the successive cognitive stages
10 associated with the sequential processing of the semantic and syntactic
11 elements of this mini-language. All participants were able to understand the
12 semantic component, but only half of them learned the rule associated with the
13 syntactic operator. Our results provide an encouraging first step in elucidating
14 the way in which humans acquire non-verbal syntactic structures and show how
15 the finger tracking methodology can shed light on real-time artificial language
16 processing.

17 **Keywords:** syntax, finger tracking, sequence learning, artificial grammar

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1 **1. Introduction**

2 Infant and adult humans are able to extract and compress the information present in
3 their rich environment. From a small number of samples, they can identify the abstract
4 hierarchical rules that govern the structure of the incoming information (Amalric et al.,
5 2017). This ability lies at the heart of the human ability to acquire the syntactic and
6 semantic structures of human language. It has therefore been proposed that humans,
7 contrary to other animals, possess the specific ability to acquire recursive rules (Fitch,
8 2004; Hauser, 2002; ten Cate & Okanoya, 2012).

9 To study this ability in the laboratory, researchers have used mini-languages involving
10 minimal lexicons and grammatical rules. This artificial grammar approach (Reber, 1969)
11 has led to important advances in understanding the mechanisms of rule acquisition and
12 generalization in infants. For instance, it showed that infants can use transition
13 probabilities to identify the chunks that form words and the abstract patterns that govern
14 sequences of syllables or tones (Marcus et al., 1999; Saffran, Johnson, Aslin, & Newport,
15 1999). The comparison of such data with formal models of children's learning (Frank &
16 Tenenbaum, 2011) is currently being used to clarify the statistical learning mechanism and
17 the language primitives that drive human language learning.

18 To understand which rule learning abilities allow humans to acquire and use complex
19 languages, many studies compare them with their closest phylogenetic relatives, non-
20 human primates, in similar tasks of sequence processing and artificial grammar learning
21 (Wilson, Marslen-Wilson, & Petkov, 2017). Several of the mechanisms involved in sequence
22 processing seem to be shared by human and non-human primates and could reflect
23 domain-general abilities contributing to rule learning and language acquisition in humans.
24 For instance, a recent study suggests that primates may process sequential relationships in
25 a way strikingly similar to human infants (Milne et al., 2016). Moreover, non-human
26 primates have been shown to extract the statistical properties of syllable transition
27 probabilities in a continuous speech stream in a manner comparable to humans (Hauser,
28 Newport, & Aslin, 2001). Furthermore, when processing the order relationships between

1 nonsense words in rule-based sequences, frontal brain regions activate similarly in
2 macaques and humans (Wilson, Kikuchi, et al., 2015).

3 However, primates' grammatical abilities seem to diverge from those of humans whenever
4 embedding and recursion are needed to process the sequences (Penn, Holyoak, & Povinelli,
5 2008). For instance, human and non-human primates have been shown to master simple
6 grammars devoid of embedding. Yet, only humans succeeded to do so when the grammar
7 contained center-embedded sequences (Fitch, 2004). Furthermore, both macaques and
8 humans showed sensitivity to adjacent relationships, but significant sensitivity to the non-
9 adjacent relationships of a mixed-complexity artificial grammar was found only in a
10 subgroup of humans (Wilson, Smith, & Petkov, 2015). We note that both humans and
11 monkeys failed to learn the nonadjacent dependencies using a similar paradigm but with
12 different stimuli (Milne, Petkov et al. 2017). Other works seem to show that non-human
13 primates can process nonadjacent dependencies in some artificial grammar learning tasks
14 (e.g. see Newport, Hauser et al. 2004, Ravignani, Sonnweber et al. 2013, Sonnweber,
15 Ravignani et al. 2015, Milne, Mueller et al. 2016). Finally, a recent fMRI study suggested
16 that both humans and macaques are capable of representing the number and sequence
17 patterns underlying simple auditory sequences, but that only humans possess an
18 integrated representation of those two features in the inferior frontal gyrus (Wang, Uhrig,
19 Jarraya, & Dehaene, 2015).

20 One issue with such artificial grammar studies is that they typically require only the
21 learning of the surface structure of sequences (their 'syntax', i.e. the rules governing the
22 valid or invalid arrangement of their elements), but the sequences do not convey any
23 meaning. Indeed, in these artificial grammars, no semantic component is present and only a
24 minimal form of syntax, often reduced to a finite-state automaton, is needed in order to
25 detect grammatical violations (for rare exceptions, see (Friederici, Steinhauer, & Pfeifer,
26 2002; Moeser & Olson, 1974; Mueller, Hahne, Fujii, & Friederici, 2005)). As the primary
27 role of syntax is to convey meaning, these studies may fail to engage some crucial
28 mechanisms involved in semantic processing and language acquisition in humans. Our goal
29 in the present work was to fill this gap. To do so, we designed a simple language with

1 elementary syntactic and semantic features and studied its learnability in human adults.
2 Such a study is a first step prior to comparing its learnability by human and non-human
3 primates.

4 We designed an artificial mini-language reminiscent of elementary symbolic
5 arithmetic, and studied whether it could be learned by trial-and-error, in the absence of
6 explicit instructions. Each ‘sentence’ of the language was a sequence of semantic and
7 syntactic elements, represented by visual symbols. The first part of the experiment was
8 very similar to Yang and Shadlen (2007): on each trial, participants saw a sequence of 1, 2
9 or 4 symbols (sampled randomly out of a set of six symbols) and had to point to a left or
10 right response button. The rewarded response was determined by merging all symbols:
11 each symbol was associated with a certain weight-of-evidence (*WOE*) favoring a decision
12 to the right or to the left, and the probability of the rewarded response being left or right
13 was determined by summing the *WOEs* of all symbols in the sequence (Fig. 1a,b). For
14 instance, if symbol A strongly favored a rightward response and symbol B slightly favored a
15 leftward response, then participants had to compute that the sequence AB still slightly
16 favored a rightward response (according to a precise quantitative equation, see Section
17 2.2). Note that the syntax here is essentially non-existent, because the semantics is order-
18 independent: all symbol sequences are meaningful, and their meaning is simply the sum of
19 the weights attached to each symbol, which is a commutative operation. Previous work by
20 Yang and Shadlen (2007) demonstrated that even rhesus macaques could learn such a
21 language: they acquired a lexicon of 10 symbols, learned their weights, and learned how to
22 sum these weights for decisions – yet with training that required more than 130,000 trials.
23 In the first part of this study, we will see that humans can learn this language too, within
24 about an hour and ~ 1000 trials.

25 The second part of this study aimed to examine how humans learn a language with both
26 syntax and semantics. To this end, we added to the language above a syntactic operator,
27 represented by another visual symbol. Unlike the other symbols, this symbol did not have a
28 fixed value, but its function was to invert the sign of the *WOE* of the subsequent symbol.
29 For instance, if this symbol is denoted by the \star sign, and symbols A and B are defined as

1 above ($A \rightarrow$ right, $B \rightarrow$ left), then the sequence of the 3 symbols $A * B$ strongly favored a
2 rightward response, whereas the sequence $B * A$ strongly favored a leftward response. The
3 analysis of the participants' responses to this order-dependent (non-commutative) mini-
4 language allowed us to determine whether they were able to learn the meaning of the
5 syntactic symbol. A participant who fails to learn the symbol may come up with an
6 alternative interpretation for it – e.g. assign a *WOE* (weight of evidence) to the syntactic
7 symbol just like to any other semantic symbol. Because this mini-language is an extension
8 of the language considered in Yang and Shadlen (2007), which is learnable by monkeys, we
9 reasoned that the extended language, if easily learnable by humans, could pave the way to a
10 future investigation of syntactic abilities in non-human primates.

11 The present work was additionally designed to show that a purely behavioral measure,
12 namely continuous finger tracking, can be sensitive to the covert mechanisms that are
13 engaged in the sequential processing of symbols. On each trial, we recorded the finger
14 movement while participants saw symbol sequences and pointed to one of two response
15 buttons on a touchscreen. Crucially, the participants had to move their finger continuously
16 without ever stopping. We also enforced a minimal finger speed, in order to encourage
17 intuitive decisions and dissuade explicit calculations. Previous research has repeatedly
18 shown that intermediate points in the pointing trajectory reflect the real-time unfolding of
19 internal decision processes (Berthier, 1996; Erb, Moher, Sobel, & Song, 2016; Friedman,
20 Brown, & Finkbeiner, 2013; Pinheiro-Chagas, Dotan, Piazza, & Dehaene, 2017; Resulaj,
21 Kiani, Wolpert, & Shadlen, 2009; Song & Nakayama, 2009). We therefore hypothesized that
22 the continuous finger tracking would provide insights into the online processing of the
23 symbol sequence, without requiring invasive neurophysiological recordings of single unit
24 activity (Yang & Shadlen, 2007), which are typically not available in human subjects.

25 **2. Methods**

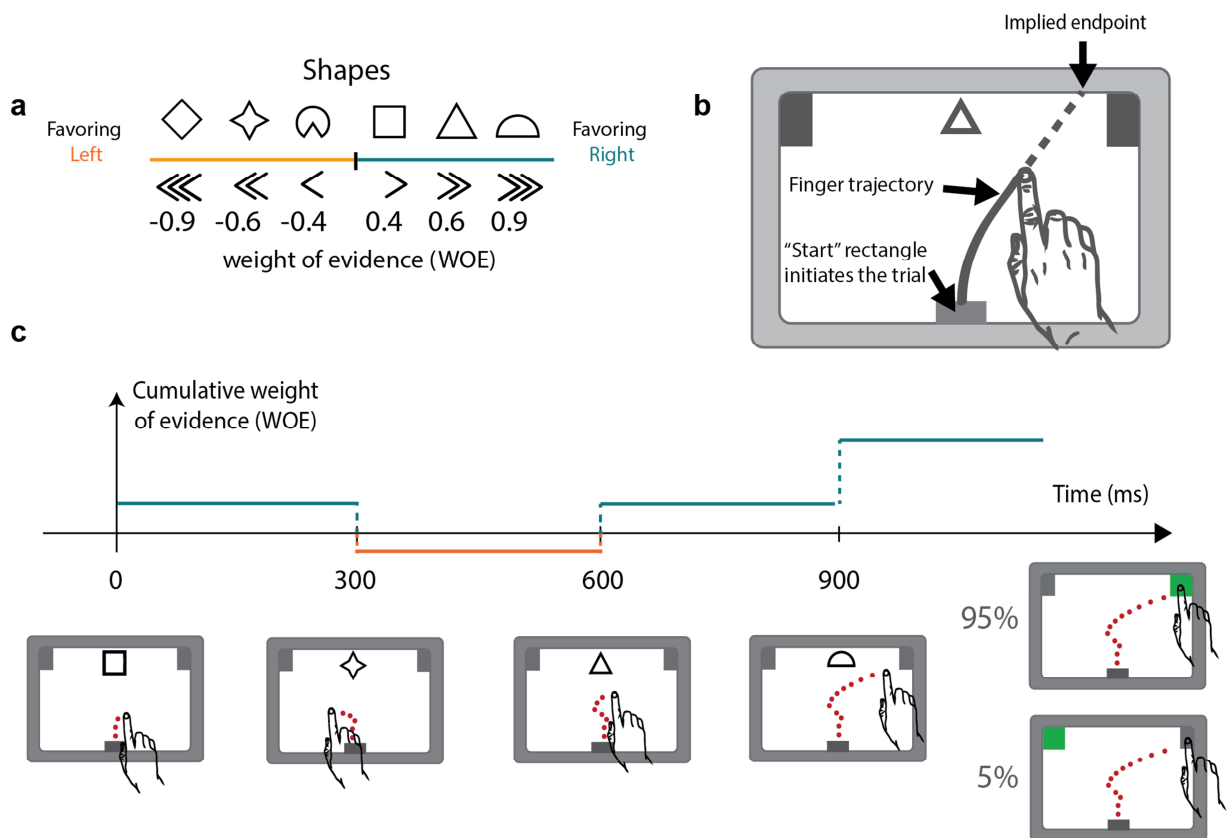
26 **2.1. Participants.**

1 The participants were 30 French right-handed adults (this number was determined based
2 on past experience with similar paradigms (Dotan, Meyniel, & Dehaene, 2018)). We
3 excluded 3 participants who performed poorly in the length-1 sequences of Day 1 (2
4 standard deviations below the mean). 27 participants (16 females, mean age = 23.7 years,
5 SD = 2.8) took part to the first day of the experiment, and 25 returned on the successive day
6 for the second part. All participants gave informed consent prior to participating. The study
7 was approved by the local ethical committee.

8 2.2. Stimuli.

9 On each trial, the participants saw 1, 2 or 4 symbols, presented sequentially, and were
10 instructed to point to one of two response buttons (Figure 1). In most experimental blocks,
11 one of the buttons was rewarded by presenting correct/incorrect feedback at the end of the
12 trial. As explained above, each sequence of symbols was associated with a certain
13 probability that the rewarded response button would be the one on the right
14 (hereby P^{right}). There were 6 “content symbols”, each associated with a certain weight of
15 evidence (hereby WOE), and the sum of WOE , ΣWOE , determined $P^{right} = (1 +$
16 $10^{-\Sigma WOE})^{-1}$ (Figure 1a). The sequences of stimuli were pseudo randomized, such that each
17 “content symbol” appeared the same number of times at each position. A 7th symbol,
18 denoted \star , was not associated with a fixed WOE , but had a syntactic role: it inverted the
19 sign of the WOE of the subsequent symbol (but left the WOE of the other symbols
20 unchanged). Namely, the \star operator acted locally, affecting only the symbol following it.
21 Throughout this article, \blacktriangle denotes any content symbol, and \star denotes the syntactic
22 operator. Specific content symbols are denoted, according to their WOE , as $\ll\ll$, \ll , \lt , \gt ,
23 \gg , $\gg\gg$.

24 An ideal observer should choose the response button corresponding to the side that agrees
25 with $sign(\Sigma WOE)$. Such a “maximizing strategy” does not guarantee a positive feedback,
26 because even the highest ΣWOE did not reach a P^{right} value of 1.0 or 0.0, but it does
27 maximize the chances of getting such feedback.



1
 2 **Figure 1: Experimental paradigm.** On each trial, one, two or four symbols were presented
 3 sequentially on an iPad. Participants dragged their finger from the starting point to either a left or a
 4 right response button. **a.** Meaning of the symbols. Each of the 6 content symbols was assigned a
 5 certain weight-of-evidence (*WOE*) that determined the probabilities of reward. The symbol-*WOE*
 6 mapping was fixed for each subject. The 6 content symbols are represented in the text according to
 7 their *WOE* as <<<, <<, <, >, >>, and >>>. **b.** Screen layout. Finger movement was continuously
 8 recorded. The onset of the first symbol was triggered by finger movement. After touching a
 9 response button, feedback was provided. **c.** Sample trial flow. The probability that the right or left
 10 button would be rewarded was a sigmoid function of the sum of the weights of the symbols in the
 11 sequence. For the specific sequence of symbols shown here, the probability of obtaining a positive
 12 feedback is 95%.

13

14

1

2 **2.3. Trial Flow.**

3 Touching the “start” rectangle (Figure 1c) triggered the onset of a fixation dot at the
4 symbols’ intended location (top center, see Figure 1b). When the participant started
5 moving their finger upwards, the symbol sequence started appearing. Each symbol was
6 presented for 100 ms, with a stimulus onset asynchrony (SOA) of 300 ms. As soon as the
7 finger touched one of the response buttons, feedback was provided: the button that should
8 have been selected flickered in green, and a pleasant/unpleasant sound was played. A trial
9 was considered as failed if the participant lifted the finger before reaching the top of the
10 screen, moved the finger backwards, started the trial with sideways (rather than upward)
11 movement or moved too slowly (less than 3 s per trial or less than 1.5 s to reach the first
12 third of the screen, with linear interpolation; except a grace period of the trial’s first 300
13 ms). In such cases, the trial immediately terminated and was presented again later in the
14 experiment.

15 **2.4. Training.**

16 To get acquainted with the motor aspects of the task, the participants initially performed a
17 similar task in which the stimulus was a single arrow pointing left or right, which
18 unambiguously indicated the response button that would be rewarded.

19 **2.5. Experiment stages.**

20 The experiment was organized in two sessions, held on two consecutive days. Each session
21 lasted approximately 90 minutes and was organized in 4 parts (see Table 1). During the
22 first day, only the 6 content symbols were presented; in the 2nd day the * operator was
23 added.

24 To examine whether the participants genuinely understood the syntactic operator *, rather
25 than just memorized specific symbol combinations, we tested their ability to generalize the
26 syntactic operator to untrained combinations. Thus, in all blocks with feedback, the *

1 operator never occurred prior to the symbol << or >>. Such combinations of * followed by
 2 << or >> were presented only during the last stage in day 2 (with length-4 trials), in which
 3 no feedback was provided.

4

5 **2.6. Questionnaire.**

6 At the end of the second day, participants filled out a questionnaire where they were asked
 7 for the meaning of each of the 7 symbols, i.e. how each symbol contributed to their
 8 left/right decision. We used this questionnaire to divide the participants into two groups –
 9 those who managed to figure out explicitly the meaning of the syntactic operator (G⁺
 10 participants) and those who did not (G⁻ participants).

DAY 1				DAY 2		
	Sequences	#Trials	Feedback	Sequences	#Trials	Feedback
length-1	▲	480	Yes	▲	240	Yes
length-2	▲▲	360	Yes	*▲	360	Yes
				▲▲		
length-4	▲▲▲▲	360	Yes	*▲▲▲	480	Yes
				▲*▲▲		
		360	No	▲▲*▲	360	No
				▲▲▲▲		

11

1 **Table 1:** The experiment design. The experiment took place during two consecutive days. In the
2 first day, only semantic symbols were presented (each denoted here by ▲). In the second day, the
3 sequences also included the syntactic operator *.

4 **2.7. Data Encoding.**

5 The position of the finger was sampled at 60 Hz and resampled to 100 Hz using cubic spline
6 interpolation. The x and y coordinates were then separately smoothed with a Gaussian
7 filter with $\sigma = 20$ ms. At each time point, we calculated the implied endpoint (*iEP*) – the top-
8 of-screen position that the finger would reach if it kept moving in its current direction. As a
9 measure of the online decision, we used either the actual horizontal position of the finger,
10 denoted by x, or the implied endpoint. The x coordinates and the *iEP* are measured on a
11 scale ranging from -1 (left end of screen) to +1 (right end), with x=0 being at the middle of
12 the screen. The y coordinates use the same scale (1 unit = 9.84 cm).

13 **2.8. Data Analysis.**

14 We start by considering only the participants' final responses (left or right). Performance
15 scores are given as the proportion of *ideal responses*, i.e. responses where the participant
16 chose the side that agrees with $sign(\sum WOE)$. Note that, because of the probabilistic nature
17 of the task, the rewarded button was not always the ideal response. However, choosing the
18 ideal response maximized the likelihood to obtain a reward.

19 Logistic regressions were computed on the proportion of rightward responses, with one
20 predictor corresponding to each of the symbols that appeared in the sequence.

21 The analysis of trajectories followed the method introduced in our earlier publications
22 (Dotan & Dehaene, 2013). The dependent variable was the implied endpoint (*iEP*) and the
23 predictors indicated the different symbols in the sequence (details about specific
24 predictors appear in the text below). One regression was run for each participant and time
25 point, in 30ms intervals. To determine whether a predictor had a significant group-level
26 effect at a specific time point, we compared, for each time point and each predictor, the per-
27 participant regression coefficients to zero using a t-test.

3. Results

3.1. Day 1. Acquisition of the semantic elements of the mini-language

3.1.1. Analysis of the responses

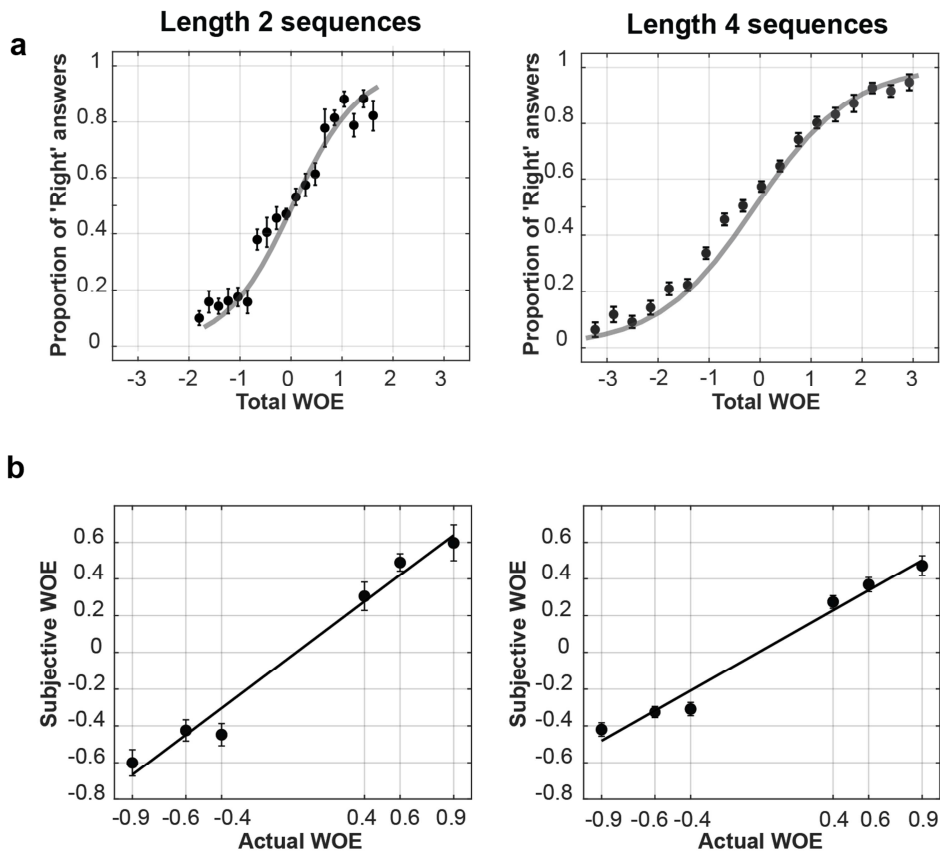
During Day 1, the participants saw only content symbols. We first analyzed the participants' final decision, i.e. whether they ultimately hit the left or right response button. When seeing length-1 sequences, after only a few trials, participants learned to associate each symbol to the corresponding response. The percentage of ideal responses increased from 83% in the first half of Part 1 to 90% in the second half (paired $t(26) = 5.20$, $p < 0.001$).

For length-2 and length-4 sequences, participants also quickly learned to combine the content symbols. They favored the right response button when the total WOE (ΣWOE) was positive and the left response button when ΣWOE was negative (Figure 2a). The proportion of ideal responses was higher in trials with larger ΣWOE , but participants still performed better than chance even on trials in which ΣWOE was close to zero. We fitted the proportion of 'right' responses as a sigmoidal function of ΣWOE :

$$\log_{10} \left(\frac{p^{right}}{1-p^{right}} \right) = const + b \times \Sigma WOE.$$

In this regression, the intercept reflects a general leftward or rightward bias, and the slope measures the participants' capacity to accurately base their decision on ΣWOE . The higher the slope, the closer to optimality: a participant with infinite slope would base his decision on $sign(\Sigma WOE)$. As the slope of the sigmoidal fit was significantly greater than 0, we conclude that they chose the ideal response more often for larger $|\Sigma WOE|$ (for length-2 sequences, mean $b = 0.67$, $t(26) = 9.93$, $p < 0.001$; for length-4 sequence, mean $b = 0.45$, $t(23) = 12.0$, $p < 0.001$). Furthermore, participants performed better for length-2 than for length-4 sequences, as the slope was higher for length-2 than for length-4 sequences (paired $t(23) = 4.7$, $p < 0.001$, mean $b = 1.5$ for length-2 sequences and mean $b = 1.0$ for length-4 sequences). There was no left or right bias – the intercepts were not significantly different from zero, neither for length-2 nor for length-4 sequences (all $p > 0.1$).

1 To determine whether participants assigned a larger subjective weight to the most reliable
2 symbols (e.g. a larger weight to >>> than to >), we performed a linear regression on the log
3 odds of “right” responses. Unlike the previous analysis, in which ΣWOE was the only
4 predictor, here there was one predictor for each of the 6 semantic symbols. These
5 predictors were defined as 1 when the corresponding symbol was present in the sequence,
6 and as 0 otherwise (Figure 2b). The regression coefficients thus reflect the contribution of
7 each symbol to the participant’s final decision. Below, we refer to these regression
8 coefficients as the “subjective *WOE*” of the symbol. To determine whether the participants
9 based their decision on the *WOE* of each symbol, we examined how well their
10 subjective *WOEs* were correlated with the true *WOE*. This was done with linear regression
11 on the per-participant subjective *WOE* as a function of the true *WOE* (Figure 2). In this
12 regression, the intercept did not significantly differ from 0 ($p > 0.3$ both in length-2 and in
13 length-4 sequences), meaning that there was no general leftward or rightward bias. The
14 slope was significantly higher than 0 (2-symbol sequences: mean $b = 0.76$, $t(26) = 9.13$, $p <$
15 0.001 ; 4-symbol sequences: mean $b = 0.53$, $t(23) = 12.2$, $p < 0.001$). The order of
16 subjective *WOE* agreed with that of the true *WOEs*, indicating that participants were able
17 to attribute a higher weight to the symbols that were more strongly associated with a
18 reward. Furthermore, the participants’ behavior suggests that they estimated the *WOE* of
19 the symbols better for length-2 than for length-4 sequences: the slope was significantly
20 higher in the length-2 sequences than in the length-4 sequences (paired t-test $t(23) = 3.50$,
21 $p = 0.002$).



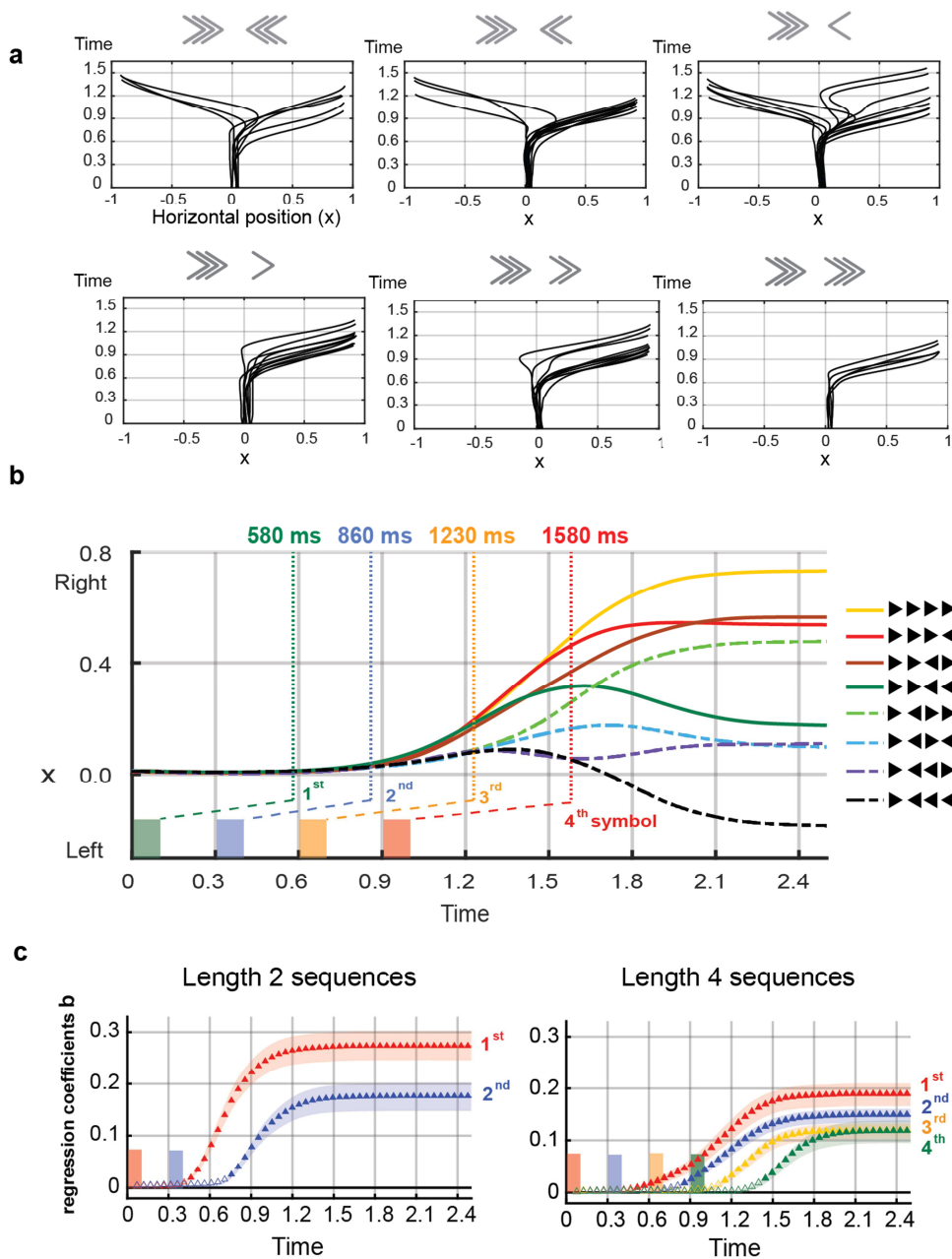
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2 **Figure 2: Evidence that the participants' final decision in day 1 resulted from a summation of**
 3 **the symbols' WOE.** **a.** Proportion of responses to the 'right' response button as a function of the
 4 total *WOE*. A sigmoidal fit was obtained for the average regression coefficients over participants.
 5 Error bars indicate the standard error on the estimation of the mean (SEM). **b.** Average subjective
 6 *WOE* as a function of the true *WOE*, as determined by regression. The positive regression slope
 7 indicates that participants learned the *WOE*s and managed to combine them.

8 3.1.2. Analysis of the finger trajectories

9 Examination of the raw trajectories suggested that they contained rich information on the
 10 processing of the sequences of symbols (Figure 3a) as they seemed to strongly depend on
 11 the presented sequences of symbols. This effect can be seen in Figure 3b, which shows the
 12 finger horizontal position (x coordinate) as a function of time, separately for each unique
 13 sequence of $sign(WOE)$ (e.g. the sequences $>$, $>>$ and $>>>$, $>$ were averaged together into a
 14 single line in Figure 3b, and separately from the sequence $>$, $<<$).

1 We looked for the time point where each symbol started affecting the finger movement.
2 First we ran, for each position in the sequence (1st, 2nd, 3rd, or 4th symbol), a two-way
3 repeated measures ANOVA with the x coordinate as the dependent variable and with two
4 within-participant factors: the symbol's *sign(WOE)*, and the specific sequence of
5 *sign(WOE)* of the preceding symbols. One ANOVA was run for each time point, in 10 ms
6 intervals. The onset time of a symbol's effect on the finger movement was defined as the
7 first time-point in which this ANOVA showed a significant main effect of *sign(WOE)*
8 ($p < 0.05$), which remained significant for at least 50 ms. This analysis revealed that, for 4-
9 symbol sequences, each successive symbol started affecting the finger movement about
10 600 ms after its onset (see Figure 3b). The average interval between the effects of
11 consecutive symbols was ~ 330 ms, closely corresponding to the actual SOA of 300 ms.
12 These results indicate that the symbols were considered one by one as they appeared, and
13 affected the finger movement even before the full sequence was presented. The finger
14 movements were thus sensitive to intermediate accumulation of evidence.



1

2 **Figure 3: Finger trajectories in day 1 reveal a sequential accumulation of evidence.** **a.** Sample
 3 single-trial trajectories for one participant in length-2 sequences. The stimulus is indicated on the
 4 top of each panel. The raw trajectories strongly depend on the *WOEs* of both symbols. **b.** Mean *x*
 5 coordinate per time point. Each line shows the average trajectory for trials with the same sequence
 6 of $\text{sign}(WOE)$ s. The colored rectangles at the bottom show each symbol's onset time and duration.
 7 The colored vertical lines denote the times at which each symbol started having a significant effect

1 on the trajectory. **c.** The sequential accumulation of evidence is also captured by regression results.
2 The implied endpoint (*iEP* cf. Figure 1c) were regressed against the *WOE* of each position. The
3 regression coefficients were averaged over participants and plotted as a function of time (filled
4 markers indicate values significantly higher than 0). The plots show how, depending on their
5 position in the sequence, symbols successively contribute to the decision.

6 We next examined how the effect of each symbol developed during a trial and affected the
7 finger trajectory. For each time point and participant, we ran a linear regression on the
8 implied endpoint (*iEP*). There was one predictor for each position – the *WOE* of the symbol
9 at that position. This analysis (Figure 3c) showed that the effects of each symbol built up
10 gradually over the course of the trial. For 4-symbol sequences, each symbol had a
11 significant effect on the trajectory ($p < .05$ when comparing the per-participant regression
12 coefficients to 0) starting from about 500 ms after the symbol's appearance. The average
13 interval between the effects of consecutive symbols was close to the actual SOA (300 ms).
14 These results are consistent with the previous analysis of the symbols' effect onset times
15 and indicate that evidence was accumulated incrementally.

16 Remarkably, the asymptote values of the regression coefficients decreased with symbol
17 position (Figure 3c), i.e. earlier symbols affected the finger movement more than symbols
18 that appeared later in the sequence. The contribution of the symbols of the sequence to the
19 intermediate decision, captured by these regression coefficients, probably reflects the
20 contribution of several mechanisms. First of all, this analysis was run on all the length-2
21 trials of Day 1, while participants were still learning the *WOEs*. The down-weighting of the
22 late symbols in the sequence may thus be partly due to the difficulty of memorization and
23 calculation with symbols that have an uncertain and noisy meaning. However, this
24 explanation may only partially account for this observation, as a similar effect was
25 observed in an experiment where the symbols were not arbitrary shapes but arrows
26 pointing left or right (Dotan et al., 2018). Another explanation comes from the fact that
27 when the *WOE* of the first symbol is large enough, a decision can be reached without
28 considering the next symbols. Once enough evidence is accumulated, an ideal observer may
29 ignore the later symbols, which are not going to change the outcome. For length-2

1 sequences, this situation affected 33 % of the trials, so for an ideal observer knowing the
2 *WOEs* of the symbols, it should result in the second symbol's regression coefficient being
3 $\frac{2}{3}$ the size of the first.

4 To determine if this strategy could explain the regression coefficients profiles, we ran the
5 previous analysis on two subsets of trials: those for which enough evidence was provided
6 by the first symbol, and those for which it was not. Figure S2 shows that the regression
7 coefficient associated with the second symbol was higher when the second symbol was
8 necessary to determine the ideal response (two-tailed paired t-test on second position
9 regression coefficients depending on first-position weight: $p < 0.05$ from 0.91 seconds on).
10 Nonetheless, even when enough evidence was provided by the first symbol, the last symbol
11 still had a sizable influence on the decision.

12 A logistic regression on the final decision confirmed these results: the regression coefficient
13 of the second position significantly decreased as the evidence carried by the first symbol
14 increased (paired t-test between the distributions of regression coefficients when $|WOE|$
15 position 1 = 0.4 and when $|WOE|$ position 1 = 0.9 : $t(26) = -3.5$, $p = 0.0015$; when $|WOE|$
16 position 1 = 0.6 and when $|WOE|$ position 1 = 0.9: $t(26) = -3.7$, $p = 0.001$). The converse
17 analysis did not show any significant modulation of the first position regression coefficient
18 as a function of the second symbol's weight ($p > 0.5$), confirming the importance of the
19 temporal constraints of this task in the decision process. To sum up, the participants'
20 behavior was logical (they assigned more weight to earlier symbols), but the degree of this
21 underweighting was smaller than that expected from an optimal observer. It is possible
22 that participants did not manage to adopt an optimal strategy due to the high presentation
23 speed, which may have been too fast to respond as soon as evidence sufficed to determine
24 the ideal response (conscious strategical stopping, de Lange, van Gaal, Lamme, & Dehaene,
25 2011). Moreover, as this analysis captures the learning stages of the semantic symbols,
26 subjects may still have a noisy representation of the *WOE* of the different symbols. In this
27 context, the best strategy to compensate for the uncertainty of the task would be to get a
28 maximum of information by waiting for more symbols, which is apparently what
29 participants do.

1 Finally, the results were remarkably similar to the ones obtained in Dotan et al. (2018)
2 where the stimuli were sequences of arrows pointing left or right and the participants had
3 to point according to the majority of arrows. Even in Dotan et al.'s task, where the *WOE* of
4 each symbol in the sequence ($+\infty$ or $-\infty$, where ∞ denotes infinity) was clearly indicated by
5 the arrow, the earlier symbols in the sequence were over-weighted relatively to later
6 symbols.

7 **3.2. Day 2: Acquisition of the syntactic operator**

8 In the post-experiment questionnaire, 15 out of 26 participants reported the correct
9 interpretation of the operator \star , i.e. that it changes the sign of the *WOE* of the subsequent
10 symbol, thus inverting its meaning. From now on, the syntactic operator will equivalently
11 be called inversion operator. This group of participants will be denoted as $G^{\star+}$. In the
12 complementary group, denoted as $G^{\star-}$, 8 participants reported that the \star symbol was
13 different from the other symbols but said that the difference was that \star was not associated
14 with any preferred direction of response (i.e. that it had $WOE = 0$). The remaining 2 $G^{\star-}$
15 participants said that \star favored a certain direction of response with a small weight, like the
16 6 other semantic symbols.

17 **3.2.1. Analysis of the responses**

18 If the participant's behavior was consistent with the questionnaire answers, the $G^{\star-}$ group
19 should attribute $WOE = 0$ to the \star symbol, whereas the $G^{\star+}$ group should treat \star as a
20 inversion operator. To examine whether this was the case, we considered 'critical' trials.
21 These are trials where correctly interpreting \star as changing the sign of the subsequent *WOE*
22 would lead to one response (the ideal response), whereas interpreting \star as having $WOE =$
23 0 would lead to the opposite response. In the $G^{\star+}$ group, the mean accuracy in the critical
24 trials (70.6 %) was significantly better than chance (two-tailed t-test to chance level,
25 $t(14) = 6.4, p < 0.001$), indicating that these participants correctly interpreted \star as changing
26 the sign of the *WOE* of the subsequence symbol. Conversely, the $G^{\star-}$ group performed on
27 average at chance level for such 2-symbol sequences (45 %). Thus, consistently with their

1 explicit report, they did not treat \star as an inversion operator. However, because their
2 performance was not significantly lower than the chance level of 50 % (mean accuracy:
3 45.0 %, one-tailed t-test to chance level, $t(10) = -1.23$, $p > 0.1$), we cannot conclude that
4 they adopted the $WOE = 0$ interpretation consistently across the block. For length-4 trials,
5 the $G^{\star-}$ participants answered below chance, in agreement with the $WOE = 0$ hypothesis
6 (mean accuracy = 37.4 %, one-tailed t-test to chance level of 50 %, $t(9) = -5.1$, $p < 0.001$). In
7 contrast, the $G^{\star+}$ participants performed at chance level (mean accuracy 50.4 %, two-tailed
8 t-test to chance level of 50 %: $t(12) = 0.1$, $p > 0.1$) – i.e. they did not fully treat \star as an
9 inversion operator. As we will elaborate in the Discussion, the reason for this may be that
10 long sequences were too hard for them to apply the inversion operation.

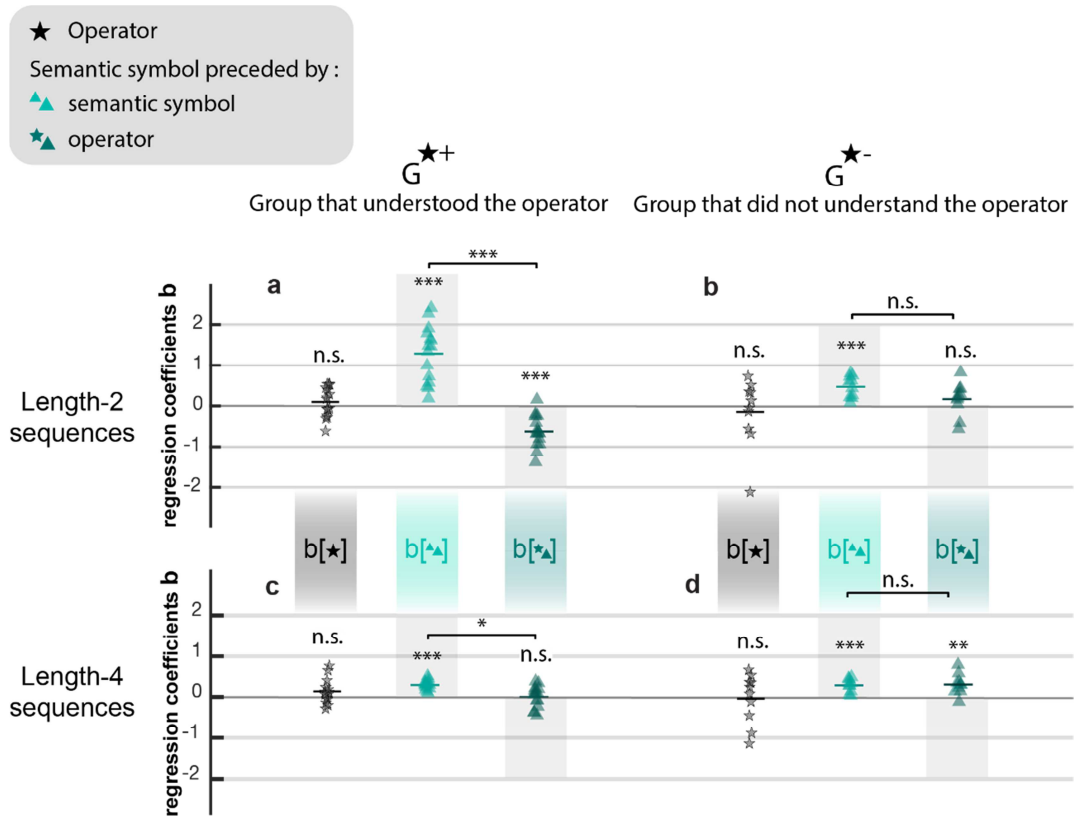
11 To understand in more details how the participants interpreted the syntactic operator, we
12 investigated the contribution of each symbol to the decision. This analysis was first run for
13 length-2 sequences: with logistic regression, the log odds of a rightward response were
14 regressed against 4 predictors: the presence of \star (coded as 0 or 1), the WOE of the
15 semantic symbol at position 1 (\blacktriangle), the WOE of the symbol at position 2 when preceded by
16 \star (denoted $\star\blacktriangle$), and the WOE of the symbol at position 2 when preceded by a content
17 symbol (denoted $\blacktriangle\blacktriangle$). For observer participants who understand the symbols fully – the
18 inversion operator, the meaning of the content symbols, and how to combine them – we
19 expect regression coefficients $b[\blacktriangle\blacktriangle] > 0$ (i.e. processing the standard WOE when the
20 operator did not appear), $b[\star\blacktriangle] < 0$ (i.e. applying the inversion implied by the operator),
21 and $b[\star] = 0$ (understanding that the syntactic operator does not have any weight of its
22 own). This was the case in the $G^{\star+}$ group, as shown in Figure 4a. First, $b[\star]$ did not
23 significantly differ from 0 ($p > 0.3$). Second, $b[\blacktriangle\blacktriangle]$ was higher than zero (mean $b = 1.29$,
24 $t(14) = 7.2$, $p < 0.001$), indicating that the change of sign of the WOE was specifically
25 triggered by the \star operator, and in its absence the participants accumulated the WOE
26 normally. Third, crucially, $b[\star\blacktriangle]$ was lower than 0 (mean $b = -0.6$, $t(14) = -6.11$, $p < 0.001$),
27 indicating that these participants changed the sign of the WOE of the symbol that appeared
28 after \star . We recomputed these regression coefficients on the second half of the block, once
29 the syntactic operator had been learned (*cf* learning curves in Figure S3). $b[\star]$ still did not

1 significantly differ from 0 ($p > 0.9$), $b[\blacktriangle]$ was higher than zero (mean $b = 1.78$,
2 $t(14) = 4.29$, $p < 0.001$) and $b[\star\blacktriangle]$ was even more negative (mean $b = -1.17$, $t(14) = -6.34$,
3 $p < 0.001$), confirming that subjects processed the syntactic operator better in the second
4 half of the block than in the first.

5 In the $G^{\star-}$ group, interpreting \star as having $WOE = 0$ should lead to $b[\star] = 0$, which was
6 indeed the case (mean $b[\star] = -0.25$, $t(10) = -1.0$, $p > 0.3$; Fig. 4b). Subjective $WOE = 0$ should
7 also lead to $b[\star\blacktriangle] > 0$, because \star would simply be ignored. Figure 4b shows that this was
8 not the case: $b[\star\blacktriangle]$ did not significantly differ from 0 either (mean $b[\star\blacktriangle] = 0.16$,
9 $t(10) = 1.3$, $p > 0.1$). This pattern suggests that the participants in this group may have
10 responded randomly for sequences with \star rather than attributed $WOE = 0$ to the \star symbol.

11 A similar analysis was run on length-4 trials. In the $G^{\star+}$ group (Figure 4c), contrary to the
12 predictions, $b[\star\blacktriangle]$ was not significantly lower than zero (mean $b[\star\blacktriangle] = 0.036$,
13 $t(12) = 0.44$, $p = 0.7$). Still, the \star operator significantly decreased the weight of the
14 subsequent symbol ($b[\star\blacktriangle] < b[\blacktriangle\blacktriangle]$, $t(12) = 2.84$, $p = 0.02$). Thus, although the results
15 were not as clear as for the 2-symbol sequences, even here the $G^{\star+}$ group considered \star as
16 affecting the subsequent content symbol in a direction opposite to the content symbol's
17 WOE . In the $G^{\star-}$ group (Figure 4d), no significant change of sign of the WOE of the next
18 symbol could be measured: $b[\star\blacktriangle]$ was significantly positive (mean = 0.37, $t(9) = 6.8$, $p <$
19 0.001). Moreover, \star did not reduce the weight of the subsequent symbol: $b[\star\blacktriangle]$ was not
20 significantly lower than $b[\blacktriangle\blacktriangle]$ ($t(9) = 0.58$, $p = 0.6$).

21



1

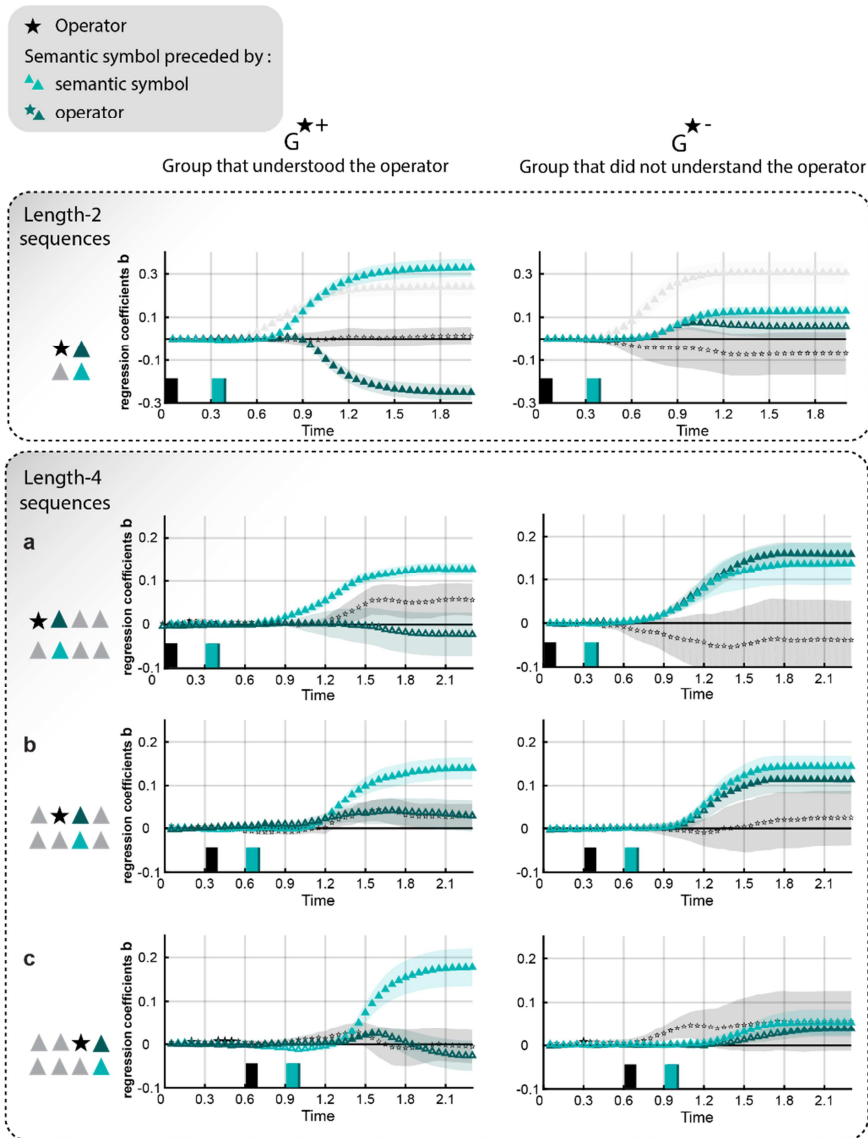
2 **Figure 4 : Understanding of the * operator, which changes the sign of the subsequent symbol.**

3 Two groups of participants were distinguished according to their explicit reports, at the end of the
 4 experiment, of understanding (G^{*+}) or failing to understand (G^{*-}) the * operator. Each panel shows
 5 the weights of a logistic regression on the final decisions during Day 2 for the G^{*+} and G^{*-} groups.
 6 The regression coefficients presented here are: the presence or absence of * (coded as 0 or 1,
 7 denoted *), the *WOE* of the symbol at position 2 when preceded by a content symbol (denoted
 8 \blacktriangle), and the *WOE* of the symbol at position 2 when preceded by * (denoted $\star\blacktriangle$). Horizontal
 9 segments represent the mean value. Shaded areas represent the range where the regression
 10 coefficients should fall for an observer that understands the meaning of the syntactic operator. **a.**
 11 For G^{*+} participants in length-2 sequences, the operator * was not assigned any *WOE* of its own,
 12 but it significantly inverted sign(*WOE*) of the subsequent symbol $\star\blacktriangle$. **b.** For G^{*-} participants in
 13 length-2 sequences, * did not invert sign(*WOE*) of the subsequent symbol, and did not even reduce
 14 the *WOE*. **c.** For G^{*+} participants in the length-4 sequences, * decreased significantly the *WOE* of
 15 the subsequent symbol $\star\blacktriangle$, yet without inverting its sign. **d.** In the G^{*-} participants in length-4
 16 sequences, * did not change the *WOE* of the following symbol.

1 **3.2.2. Analysis of the finger trajectories**

2 **3.2.2.1. Length-2 sequences, $G^{\star+}$ participants**

3 We next analyzed the finger trajectories, starting with the length-2 sequences. We ran
4 linear regressions on the implied endpoints (iEP) in each time point with 4 predictors: the
5 presence of \star (coded as 0 or 1), the *WOE* of the symbol at position 1 (\blacktriangle), the *WOE* of the
6 symbol at position 2 when preceded by \star ($\star\blacktriangle$), and the *WOE* of the symbol at position 2
7 when preceded by a content symbol ($\blacktriangle\blacktriangle$). This was done separately for the $G^{\star+}$ and $G^{\star-}$
8 groups.



1

2 **Figure 5 : Finger trajectories reveal how participants processed the syntactic operator.** We
 3 ran linear regressions on the implied endpoint (*iEP* cf. Figure 1c) on length-2 and length-4
 4 sequences for the G^{*+} and G^{*-} groups (respectively left and right columns). The *iEP* was regressed
 5 against the presence or absence of the syntactic operator \star and against the *WOE* of the content
 6 symbols at each position in presence or absence of the operator. The shaded areas represent the
 7 inter-subject SEM, and filled markers indicate regressors significantly different from 0. For length-
 8 2 sequences (top), the regression coefficient $b[\star \blacktriangle]$ changed its sign for the G^{*+} group but not for
 9 the G^{*-} group. Namely, consistently with their report, G^{*+} participants processed the \star operator as
 10 an inversion operation whereas G^{*-} did not. Fitting with a sigmoid the per-participant regression

1 coefficients, we estimated the processing time of the \star -induced inversion operation as 140 ± 50 ms.
2 For length-4 sequences, (bottom), in the $G^{\star+}$ group, but not in the $G^{\star-}$ group, the operator
3 significantly decreased the weight of the subsequent semantic symbol.

4 The results for length-2 sequences are presented in the top part of Figure 5. For the
5 subgroup $G^{\star+}$, $b[\star]$ was not significantly different from zero in any time point, confirming
6 our earlier conclusion that the participants did not treat \star as a semantic symbol having its
7 own *WOE*. Moreover, consistent with the results of the logistic regression, the regression
8 coefficient associated with $\star \blacktriangle$ had a significantly negative value starting from ~ 400 ms
9 after the appearance of \blacktriangle . We note the onset of $b[\star \blacktriangle]$'s significant effect was ~ 150 ms
10 after the onset of $b[\blacktriangle \blacktriangle]$. This 150 ms delay could be a rough estimation of the processing
11 time of the \star operator. To get a more precise estimation of the operator's processing time,
12 we fitted the regression coefficients to a common exponential profile $A(1 - \exp(-[t -$
13 $t_0]/\tau))$ and estimated A, t_0, τ for $b[\star \blacktriangle](t)$ and $b[\blacktriangle \blacktriangle](t)$. The parameter t_0 , which
14 represents the onset time of a symbol's effect on the finger movement, was significantly
15 higher for $b[\star \blacktriangle]$ than for $b[\blacktriangle \blacktriangle]$. This delay, which is a measure of the processing time of
16 the \star operator, was estimated as 140 ± 50 ms. No difference was found between $b[\star \blacktriangle]$
17 and $b[\blacktriangle \blacktriangle]$ for the parameter that represents the steepness of the slope ($\tau = 250 \pm 40$ ms
18 for both $b[\star \blacktriangle]$ and $b[\blacktriangle \blacktriangle]$).

19 Initially, the \star operator was novel to the participants. It could be argued that novelty, rather
20 than syntactic function, was at the origin of the observed delay. To provide insight into the
21 learning dynamics of the $G^{\star+}$ group, we analyzed separately the trials belonging to the first
22 and the second half of the length-2 trials of Day 2, the \star operator being presented in half of
23 the trials of this block (Figure S4). We observed an increase in the ability to process the
24 syntactic operator, as $b[\star \blacktriangle]$ was much larger in amplitude in the second half of the block
25 ($p < 0.05$ from 800 ms on, uncorrected paired t-test). Moreover, novelty could not account
26 for the \star -induced delay because it was also observed in the second half of the block (the
27 delay is then equal to 120 ± 40 ms), when $G^{\star+}$ participants had already learned the
28 meaning of the \star operator (*cf* learning curves in Figure S3). These results suggest that it

1 took the G^{*+} participants about 120 ms to carry out the inversion indicated by the $*$
2 operator.

3 **3.2.2.2. Length-2 sequences, G^{*-} participants**

4 The same analysis was ran for the G^{*-} group and showed that $b[*]$ was not significantly
5 different from zero in any time point, meaning that these participants did not assign the
6 operator any *WOE* of its own. Furthermore, there was no significant difference between
7 $b[* \blacktriangle]$ and $b[\blacktriangle \blacktriangle]$ in any time point (in one-tailed t-test, $p > 0.1$ in all time points), i.e. $*$ did
8 not reduce the weight of the subsequent symbol. This confirms the results obtained in the
9 logistic regressions: G^{*-} participants did not process the $*$ operator as an inversion
10 operator, neither did they consistently assign it a left or right *WOE*.

11 **3.2.2.3. Length-4 sequences**

12 The analysis was extended to length-4 sequences. The dependent variable was the implied
13 endpoint and the 8 predictors were the presence or absence of $*$ (coded as 1 and 0) and the
14 *WOE* of the content symbols at each position in presence or absence of the operator
15 (Figure 5 bottom part). For participants in G^{*+} , $b[*]$ was not significantly different from
16 zero for any position of $*$. Similarly, $b[* \blacktriangle]$ was not significantly different from 0 in any
17 time point, except a short time window when $*$ was in third position. Nonetheless, the
18 operator $*$ significantly decreased the effect of the subsequent semantic symbol: $b[* \blacktriangle]$
19 was significantly lower than $b[\blacktriangle \blacktriangle]$ ($p < .05$ in per time-point one-tailed t-tests) for all
20 positions of $*$, starting from 1.35 s, 1.30 s and 1.40 s for $*$ in position 1, 2 and 3, respectively
21 (Figures 5a, 5b and 5c).

22 For the participants in the G^{*-} subgroup, $b[*]$ was not significantly different from zero in
23 any time point, for any position of $*$. Moreover, $*$ did not significantly reduce the weight of
24 the subsequent symbol: $b[* \blacktriangle]$ and $b[\blacktriangle \blacktriangle]$ did not significantly differ in any time point
25 (one-tailed paired t-test, $p > 0.05$).

1 The syntax of our mini-language was such that the \star operator applied only to the semantic
2 symbol that immediately followed it. To determine whether the $G^{\star+}$ participants
3 inappropriately interpreted \star as affecting the other symbols too, we examined their
4 regression coefficients for the content symbols that were at a distance of 2 or 3 from the \star
5 operator (Figure S1). We could not observe any significant decrease in the regression
6 coefficients when the operator was present (all $p > 0.05$), confirming that $G^{\star+}$ participants
7 understood that \star acted locally, i.e., only on the subsequent symbol.

8 **3.2.3. Generalization of the \star operator**

9 Two content symbols, \ll and \gg , were preceded by the \star operator only in trials in which
10 feedback was not provided (in Day 2 length-4 trials). This aspect of our design allowed
11 examining whether participants who learned the meaning of \star generalized it to previously-
12 unseen symbol combinations. Such a finding would rule out the possibility that participants
13 learned specific combinations of \star with certain symbols, and would unequivocally show
14 that the participants indeed learned the syntactic meaning of \star .

15 Thus, we now restricted our analysis to trials in which \star was followed by \ll or \gg . For the
16 $G^{\star+}$ group (2 out of 15 participants did not perform this block), we observed a significant
17 difference $b[\star \blacktriangle] < b[\blacktriangle \blacktriangle]$ (paired $t(12) = 2.45$, $p = 0.03$, mean $b[\star \blacktriangle] = 0.04$, mean
18 $b[\blacktriangle \blacktriangle] = 0.38$), i.e. \star decreased the weight of the subsequent symbol. Furthermore, when
19 examining the regression coefficient normalized by the WOE, no significant difference was
20 found between \ll and \gg and the other symbols (paired $t(12) = 1.4$, two-tailed t-test
21 $p = 0.2$). Namely, the $G^{\star+}$ participants understood the true syntactic meaning of \star and
22 applied it to previously-unrewarded symbol combinations exactly as they did with the
23 explicitly-rewarded combinations.

24 For $G^{\star-}$ participants, \star did not significantly decrease the weight of the subsequent symbol
25 (mean $b[\star \blacktriangle] = 0.44$, mean $b[\blacktriangle \blacktriangle] = 0.41$, paired $t(9) = 0.45$, two-tailed $p > 0.5$). No
26 significant difference was found between the regression coefficients for \ll and \gg and the
27 other symbols (paired $t(9) = 0.1$, two-tailed $p > 0.5$).

3.2.4 The origins of the differences between the $G^{\star+}$ and $G^{\star-}$ groups

To understand why $G^{\star+}$ and $G^{\star-}$ groups differed in their report and processing of \star , we first compared their performance when processing sequences of semantic symbols during Day 1. An inaccurate representation of the WOE of the semantic symbols may make it difficult to learn the \star operator, because participants learn its meaning in conjunction with semantic symbols. No significant difference between the two groups was found in movement time (two-tailed $p > 0.1$) and performance for length-4 sequences of Day 1 ($t(23) = 1.5$, two-tailed $p > 0.1$). However, the $G^{\star-}$ group had significantly fewer ideal responses than the $G^{\star+}$ group for length-1 trials of Day 1 ($t(23) = 2.2$, one-tailed t-test $p = 0.02$) and length-2 trials of Day 1 ($t(23) = 2.0$, one-tailed t-test $p = 0.03$). To understand whether the lower accuracy for $G^{\star-}$ group was due to a difficulty in integrating the semantic symbols, we regressed the *iEP* of the length-2 sequences in Day 1 against the weights associated with each position, separately for each group of participants. The $G^{\star-}$ group assigned a much smaller weight to the second symbol than the $G^{\star+}$ group (Fig. S5), suggesting a difficulty in integrating the two symbols. This difficulty may be responsible for their failure to learn the syntactic operator.

This conclusion is further supported by an additional result: we examined whether a participant's ability to integrate the WOE of the semantic symbols correlated with their ability to process the syntactic symbol as an inversion operator. The first ability was quantified as the regression coefficient of the total WOE in a logistic regression on the decision for length-2 sequences of Day 1. The second was quantified as the regression coefficient of a semantic symbol preceded by \star in a logistic regression on the decision for length-2 sequences of Day 2. These two measures correlated ($R^2 = 0.27$, $p < 0.01$), thereby showing a link between WOE-integration and the processing of \star .

Additional differences between $G^{\star+}$ and $G^{\star-}$ groups were revealed by the evolution of accuracy while learning the meaning of \star . Here, accuracy was defined as the average ideal responses over 30 consecutive '*critical trials*' of the length-2 sequences of Day 2. In the first trials, the accuracy of the $G^{\star+}$ group did not differ from chance (mean: 47%, two tailed

1 $p > 0.1$), whereas it was significantly below chance for the $G^{\star-}$ group (mean : 40% , $t(9)=-$
2 3.0, one-tailed $p < 0.01$). Namely, the $G^{\star-}$ group did not answer randomly, but initially
3 considered \star as a semantic symbol and consistently assigned it a null WOE. For both
4 groups, accuracy increased from the 30 first trials to the 30 last trials ($G^{\star+}$: paired $t(14) =$
5 7.0, one-tailed $p < 0.001$, $G^{\star-}$: paired $t(9)=-3.5$, one-tailed $p < 0.01$), but only the $G^{\star+}$ group
6 ended the block with accuracy above chance level ($G^{\star+}$ mean : 81% , $t(14)=7.9$, $p < 0.01$;
7 $G^{\star-}$ mean: 54%, $p > 0.1$). These results indicate that $G^{\star+}$ quickly grasped the syntactic
8 function of \star , whereas $G^{\star-}$ seem to have initially considered it as a semantic symbol with
9 null WOE. For a full overview of the dynamics of performance, see Figure S3.

10 **4. Discussion**

11 We used continuous tracking of finger movement to investigate the covert stages of
12 semantic and syntactic processing in an artificial mini-language. During the first part of the
13 experiment, we investigated how human adults learned the meaning of semantic symbols
14 associated with different weights of evidence favoring left or right response buttons, and
15 the rules to combine sequences of such symbols. All participants understood the semantic
16 component of the artificial mini-language: they understood whether each symbol favored a
17 left or a right response, and their decisions attributed higher weights to symbols that were
18 more predictive of a reward. After a short amount of training, all participants based their
19 decisions on the combined weights of the symbols presented in the sequence. Just like the
20 two rhesus macaques studied in Yang and Shadlen (2007), our participants were able to
21 combine the *WOEs* of the symbols and figure out which response button was the most
22 likely to be rewarded. However, humans required only about an hour of training and
23 ~1000 trials – much faster than the monkeys, who needed several months and ~130,000
24 training trials.

25 Yang and Shadlen (2007) showed that the instantaneous firing rate of LIP neurons in
26 monkeys reflected the evidence accumulated so far, indicating a continuous summation
27 process. The present results show that a similar on-line monitoring of evidence

1 accumulation can be achieved non-invasively, solely using finger trajectory monitoring.
2 Furthermore, the trajectory data provided information about the effects of discrete
3 symbols at various points within the sequence: for instance, participants assigned less
4 weight to symbols presented later in the sequence, replicating the results from monkeys
5 (Figure S6 of Yang & Shadlen, 2007). Similar to rhesus macaques, adult humans did not
6 behave ideally. The subjective *WOE* that they assigned to the different symbols
7 underestimated their real weights. Additionally, the weights attributed to the positions in
8 the sequence did not reflect the symbol's optimal contribution to the ideal response. The
9 difficulty of accumulating evidence from several symbols with uncertain meanings in a
10 short amount of time is likely to be at the origin of this non-ideal behavior.

11 In the second part of the experiment, to investigate the acquisition of a syntactic rule, we
12 incorporated a syntactic operator that reversed the weight of the subsequent symbol. Only
13 15 out of the 26 participants (the $G^{\star+}$ group) reported to have understood the meaning of
14 this operator. Their subjective introspection was confirmed by objective analyses: in the
15 $G^{\star+}$ group only, left/right responses indicated that the \star symbol was indeed interpreted as
16 inverting the meaning of the subsequent symbol. Finger trajectories showed that in this
17 group, the \star operator significantly affected the subsequent symbol, either changing the sign
18 of its *WOE* (in short sequences), or at least decreasing its amplitude (in longer sequences).
19 As for the $G^{\star-}$ group, the analyses of decision and of trajectories indicated that, on average,
20 they did not process \star as an inversion operator, but rather as a neutral semantic symbol
21 with *WOE* = 0.

22 Importantly, the $G^{\star+}$ group did not interpret the \star operator as a global inverter of all
23 subsequent symbols, but correctly applied it only to the symbol following \star . Moreover, we
24 ruled out the possibility that the $G^{\star+}$ group learned the meaning of \star by memorizing all
25 combinations of \star with each content symbol: this group managed to generalize the
26 inversion induced by the \star operator to content symbols that were not presented after \star
27 during the learning stages, thereby showing that they truly understood the syntactic
28 meaning of \star .

1 Within the $G^{\star+}$ group, the \star symbol had slightly different effects in the length-2 and length-
2 4 sequences. In the short sequences, it inverted the weight of the subsequent symbol, but in
3 the long sequences it only decreased its weight. This could be explained by assuming two
4 type of trials: presumably, in some trials the participants were able to process the \star
5 operator, whereas in other trials they were not. The regression, which averages the two
6 types of trials, would show a reduced $b[\star\blacktriangle]$ rather than a strictly negative $b[\star\blacktriangle]$. This
7 difference between short and long sequences is likely to be due to an overall increase in
8 task difficulty as the sequence becomes longer. Even in the long sequences, the
9 participants' performance would have probably improved had we provided them with
10 further training or longer SOA. However, longer SOAs could have allowed for more explicit
11 strategies, which we wanted to avoid.

12 The trajectory analysis revealed that in the $G^{\star+}$ group, the \star operator not only inverted the
13 meaning of the subsequent symbol, but also delayed the subsequent symbol's effect on
14 finger movement. Novelty of the \star symbol could not account for this delay as it was still
15 present and estimated to 120 ± 40 ms when we restricted the analysis to the second part
16 of the length-2 trials, i.e. when $G^{\star+}$ participants had already learned the meaning of the
17 operator (*cf* Figure S4). Furthermore, this was a pure delay – we did not observe a
18 transient activation of the positive value of the symbol, followed by activation of its
19 negative value. Thus, participants who understood the meaning of the inversion operator
20 managed to apply it to the next symbol, but it took about additional 120 ms to invert the
21 symbol before adding its value to the ongoing accumulation of evidence. This finding
22 predicts that, should monkeys be able to learn this mini-language, the firing rate of LIP
23 neurons should also show an additional ~ 120 ms delay before reflecting the value with
24 opposite sign. As currently designed, this task does not allow us to determine to which
25 extent the processing or memory load associated with the syntactic symbol contributed to
26 the measured delay. Further experiments could explore this aspect by varying the SOA
27 between symbols. Indeed, a refractory period associated to the comprehension of the
28 syntactic operator itself should decrease for large SOA while any delay induced by the
29 application of the inversion operation to the next semantic symbol should stay constant.

1 By adding the non-commutative operator \star , we increased the complexity of the artificial
2 language. We could thus distinguish the human participants that were able to represent
3 syntactic functions, the $G^{\star+}$ group, from those who were only able to attach quantities to
4 symbols, the $G^{\star-}$ group, and who attached a null weight to the operator symbol. Similar
5 intra-species variability was observed in Wilson, Smith, et al. (2015), where only some of
6 the human participants showed sensitivity to the longer-distance relationships present in
7 sequences generated from an artificial grammar with mixed complexity. In our case, the
8 difference in learning the syntactic symbol can be partly explained by differences in the
9 acquisition of the semantic part of the language, i.e. the meaning of the semantic symbols
10 and the combination rule (Section 3.2.4): participants who did not learn the semantic
11 symbols well enough also had difficulty in learning the syntactic symbol. In particular,
12 these participants (the $G^{\star-}$ group) seemed to have initially considered the \star operator as a
13 semantic symbol with null WOE. Furthermore, although these participants did not perform
14 above chance even in the end of the length-2 block in Day 2, they still performed better in
15 the end of the block than in its beginning.

16 Why were these participants unable to understand the syntactic operator? One possibility
17 is that for humans, some minimal mastery of the semantic symbols is required before the
18 syntactic operator can be learned. This suggests that, with additional time, even the non-
19 knowers would have been able to sharpen their knowledge of semantic symbols and then
20 discover the meaning of \star . Another possibility is that the non-knowers failed to formulate a
21 proper hypothesis about its meaning (e.g. they kept trying to assign it a value rather than a
22 syntactic function). This hypothesis predicts that they would have been able to use this
23 symbol if they had been explicitly told its meaning.

24

25 One of the goals of this study was to create a paradigm that allows comparing the
26 mechanisms of syntax acquisition between humans and monkeys, given that monkeys have
27 been shown to be able to acquire the semantic part of this artificial mini-language (Yang &
28 Shadlen, 2007). Nevertheless, we cannot exclude the possibility that our adult human

1 participants simply matched the syntactic operator \star to their pre-existing knowledge of the
2 minus sign in arithmetic. Thus, even if an advantage is observed for human compared to
3 non-human primates, such advantage could reflect prior education rather than a human-
4 unique ability to understand the syntactic operator. This criticism could be addressed by
5 teaching the same language to adults with limited access to formal schooling in
6 mathematics (e.g. Mundurucu Indians; Amalric et al., 2017; Dehaene, Izard, Pica, & Spelke,
7 2006) or to unschooled children. Alternatively, the present study could be replicated with
8 another syntax unfamiliar to most human adults: the Postfix Polish notation, in which
9 operators follow their operands, may be a good candidate.

10 Contrary to most artificial grammar studies, our mini-language contains both semantic and
11 syntactic elements and may, as such, involve brain networks similar to the ones of natural
12 language processing. However, the function of our syntactic operator is closer to an
13 arithmetical minus sign (multiplication by -1) than to a linguistic operation of negation
14 (reversal of truth value; Grisoni, Miller, & Pulvermüller, 2017; Kaup & Zwaan, 2003;
15 Tettamanti et al., 2008). It would therefore be interesting to determine, using functional
16 MRI, whether the underlying brain circuits involve classical language areas (left-
17 hemispheric superior temporal sulcus and inferior frontal gyrus) or the distinct math-
18 responsive regions (bilateral parietal, inferior temporal and dorsal prefrontal cortices)
19 (Amalric & Dehaene, 2016, 2017).

20 Moreover, our mini-language is extremely simple compared to natural languages: it
21 contains a single syntactic operator, whose effect is limited to the subsequent symbol, and
22 does not involve long-distance relations or embeddings of the kinds that exist in natural
23 language. As such, it may be learnable by non-human primates, since recent studies suggest
24 that they can master grammars that involve local sequential regularities extending to
25 neighboring units (Fitch, 2004; Wilson, Smith, et al., 2015). Wilson et al. (2015) suggest
26 that the macaque brain regions involved in the processing of such rule-based sequences are
27 the counterparts of the ones associated with the initial stages of syntactic processing in
28 humans (Uhrig, Janssen, Dehaene, & Jarraya, 2016). There is, however, a debate as to
29 whether human-specific language areas such as Broca's area can be activated by simple

1 artificial languages such as the local-global paradigm (Wang et al., 2015) or require more
2 complex human-like center-embedded grammars (Bahlmann, Schubotz, & Friederici,
3 2008). Indeed, TMS and fMRI studies suggest an involvement of Broca’s area (and its right-
4 hemispheric homologue) in complex motor tasks involving sets of hierarchical rules
5 (Alamia et al., 2016; Clerget, Andres, & Olivier, 2013; Clerget, Poncin, Fadiga, & Olivier,
6 2011; Koechlin & Jubault, 2006). Further studies will determine whether the present
7 paradigm suffices to reveal important differences between human and non-human
8 primates, or whether it should be extended to syntactical operators that act at distance and
9 involve embedding.

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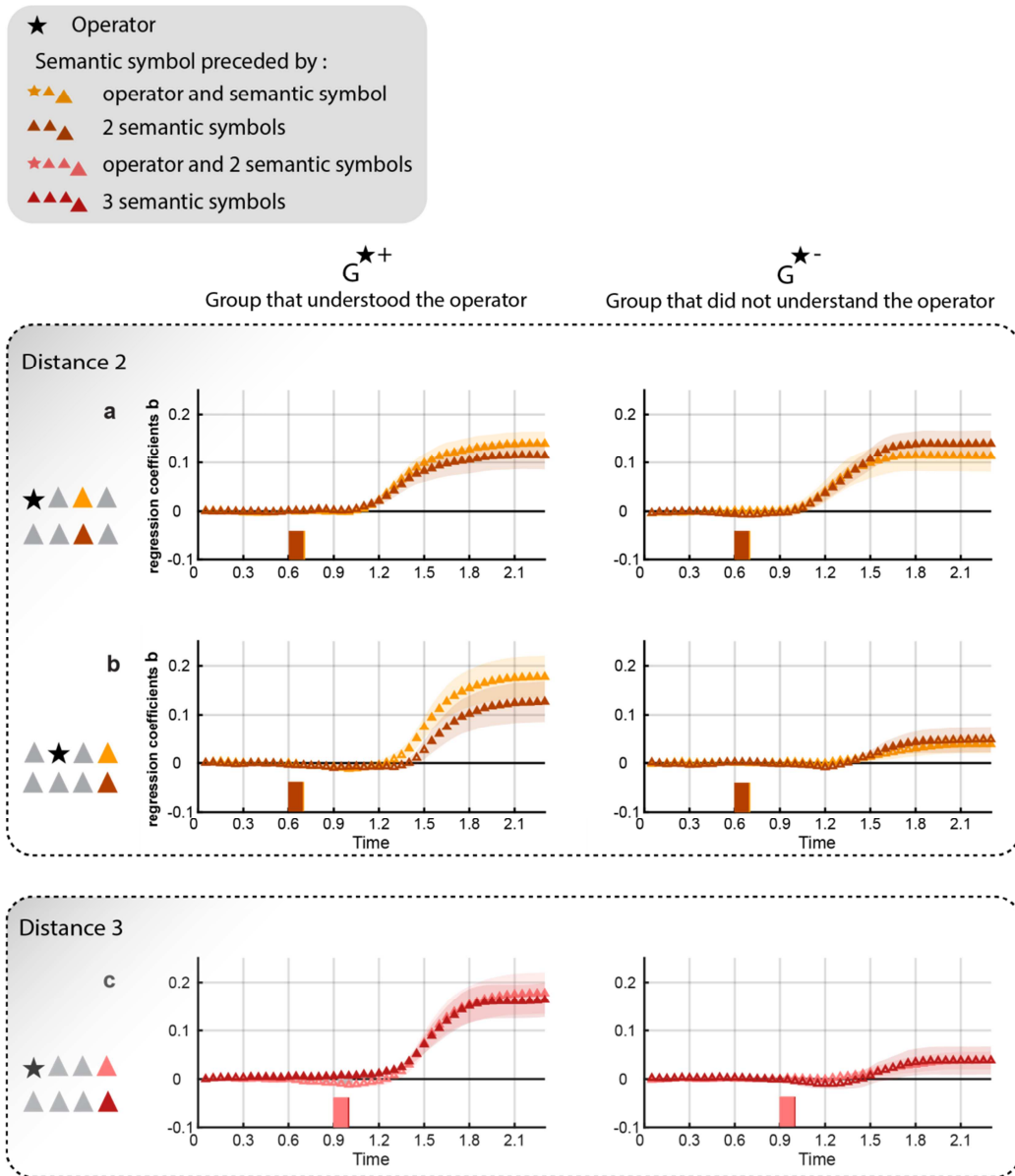
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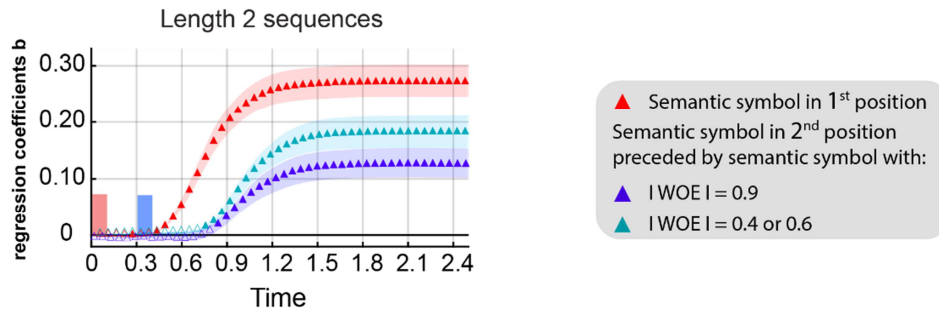
2 Supplementary figures



3

4 **Figure S1: The syntactic operator acts only on the subsequent semantic symbol.** To determine
5 if the participants applied the \star operator only to the immediately following symbol, we considered
6 the regression coefficients for the content symbols that were at a distance of 2 (Figures a. and b.) or
7 3 (Figures c.) from \star . The operator did not decrease significantly the amplitude of the regression

1 coefficient, confirming that G^{*+} participants understood that the $*$ operator acted only on the
2 subsequent symbol ($p > 0.05$)



3

4 **Figure S2: The accumulation of evidence is affected by the weights of the preceding**
5 **symbols.** Regression coefficients obtained from the linear regression of the implied
6 endpoint (*iEP* cf. Figure 1c) as a function of the first symbol (in red), the second symbol
7 when the first symbol did not suffice to compute the correct response (i.e. when its
8 *WOE* was equal to ± 0.4 or ± 0.6 ; in turquoise); and the second symbol when the first
9 symbol provided enough evidence to compute the correct response (i.e. when the *WOE* of
10 the first symbol was equal to ± 0.9 ; in purple). The regression coefficient associated to the
11 second symbol was higher when the second symbol was necessary to determine the ideal
12 response. Nevertheless, even when enough evidence was provided by the first symbol, the
13 second symbol still had a sizable influence on the decision.

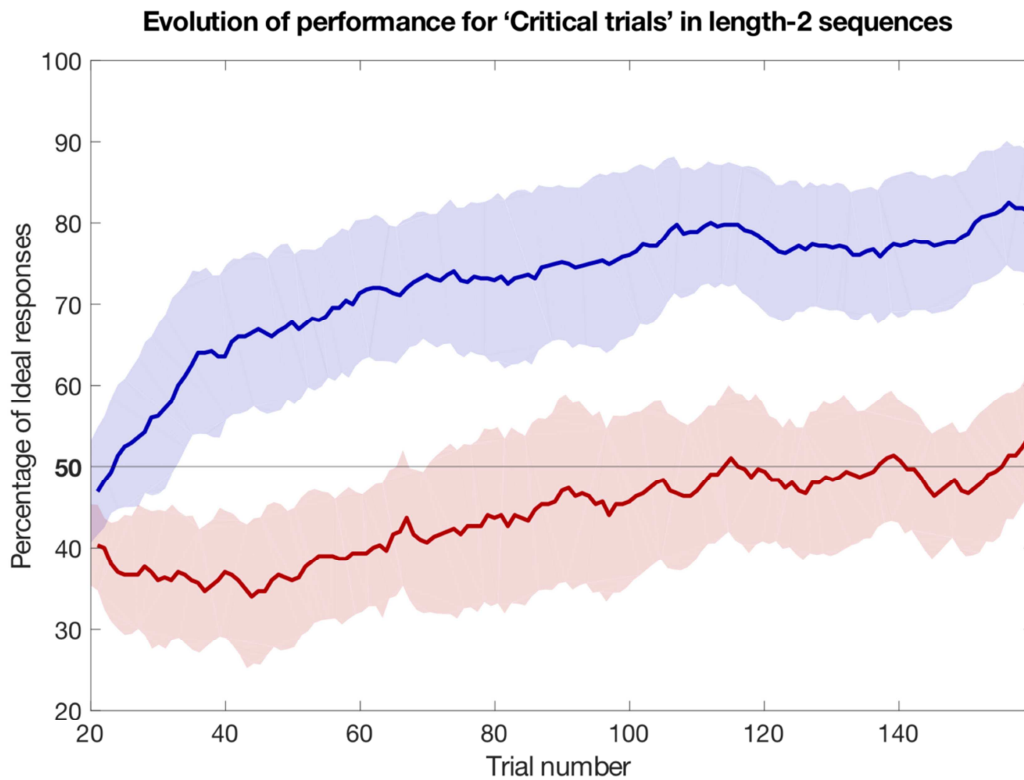
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2 **Figure S3: Tracking the learning of the syntactic symbol from the dynamics of performance.**

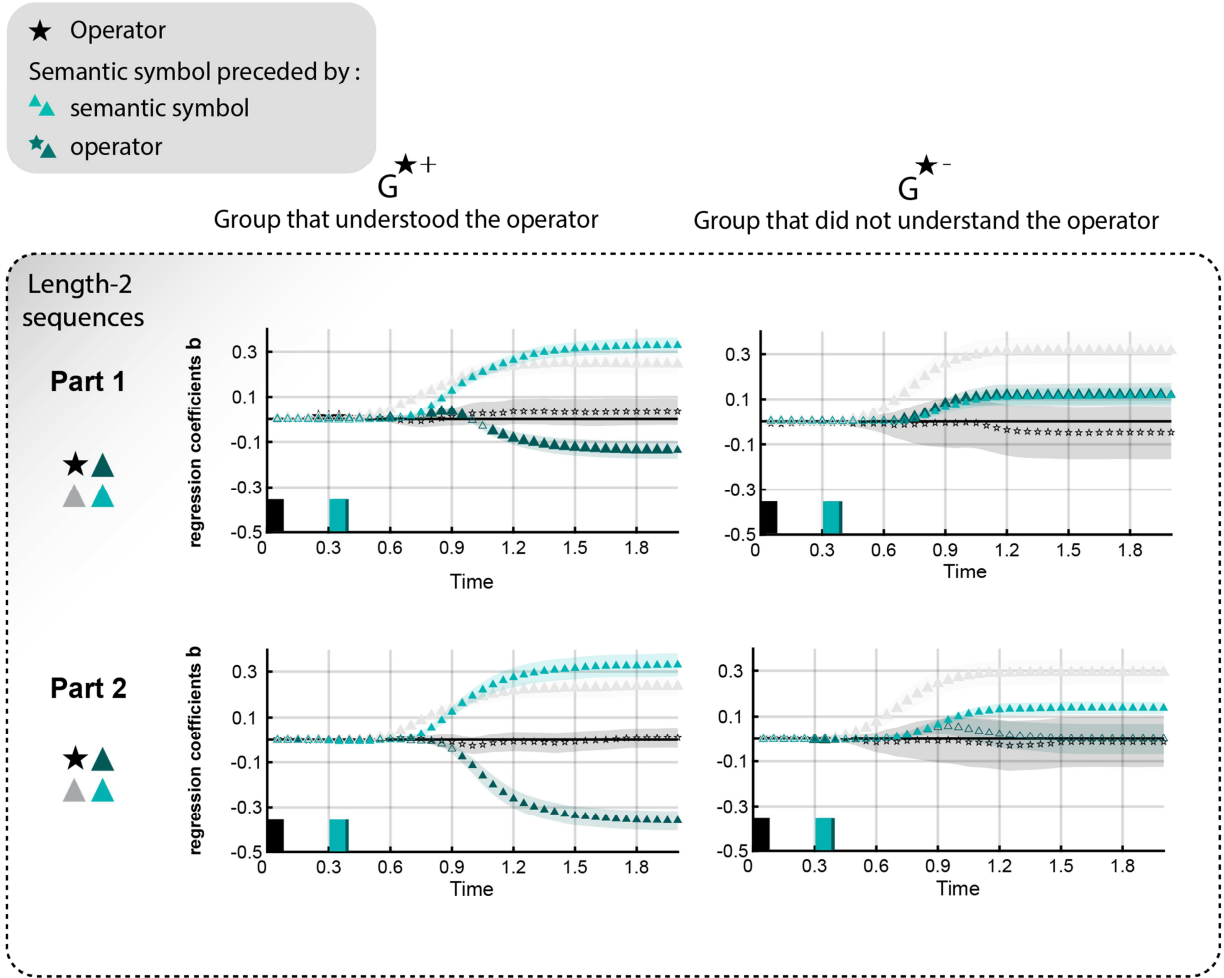
3 Average percentage of ideal responses for 'critical trials' in length-2 sequences. The average is
 4 performed over 30 trials. Blue and red curves correspond to the performance of the G^{*+} and G^{*-}
 5 participants. Shaded areas correspond to the inter-subject SEM. We observe that, contrary to the
 6 performance of the G^{*+} group, that quickly reaches above chance values, the performance of G^{*-}
 7 group starts significantly below chance and increases much slower. These observations, which are
 8 compatible with the reports of the two groups, suggest that G^{*+} participants quickly grasp the
 9 function of the operator and G^{*-} participants initially considered it as a semantic symbol with null
 10 WOE.

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Figure S4: Finger trajectories reveal the learning dynamics of the syntactic operator. We ran

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linear regressions on the implied endpoint (*iEP* cf. Figure 1c) for the first and the second parts of

4

length-2 sequences of Day 2 for $G^{\star+}$ and $G^{\star-}$ groups (respectively left and right columns). The *iEP*

5

was regressed as a function of the presence or absence of the syntactic operator ★ and *WOE* of the

6

content symbols at each position in presence or absence of the operator. The symbols in the

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schematic representation of the sequence (on the left of the graphics) have matching colors with

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the corresponding regression coefficients. The shaded areas represent the inter-subject SEM. For

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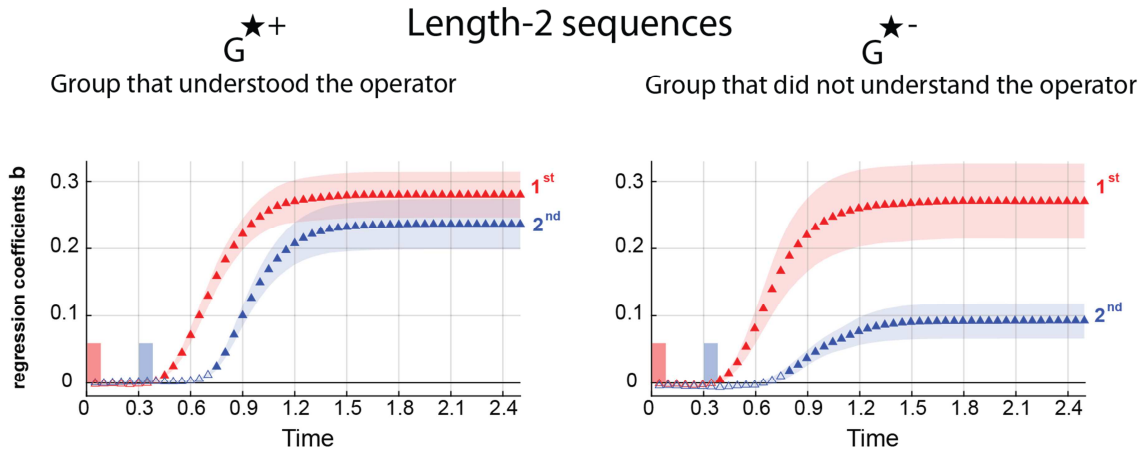
the $G^{\star+}$ group, we observe an increase in the capacity to process the syntactic operator for the first

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to the second part of the block. For $G^{\star-}$ participants, both during the first and the second part of the

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block, ★ does not significantly affect the processing of the semantic symbol at second position.



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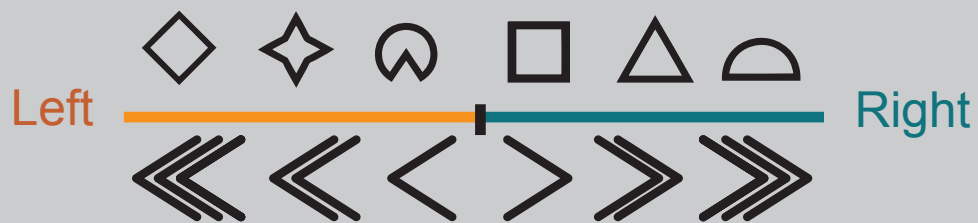
2 **Figure S5: $G^{\star+}$ and $G^{\star-}$ participants do not give the same weight to the second symbol in**
 3 **length-2 sequences.** Time evolution of the regression coefficients for $G^{\star+}$ and $G^{\star-}$ participants
 4 obtained from the linear regression of the implied endpoint (*IEP* cf. Figure 1c) as a function of the
 5 weights associated to each position for length-2 sequences of Day 1. Strong differences across
 6 groups can be observed. Namely, $G^{\star+}$ and $G^{\star-}$ participants do not give the same weight to the
 7 second symbol presented in the sequence. The difficulty to integrate the meaning of the second
 8 symbol to make a decision may contribute to their failure to learn the syntactic operator.

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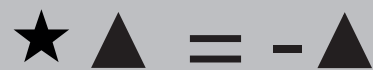
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Artificial mini-language

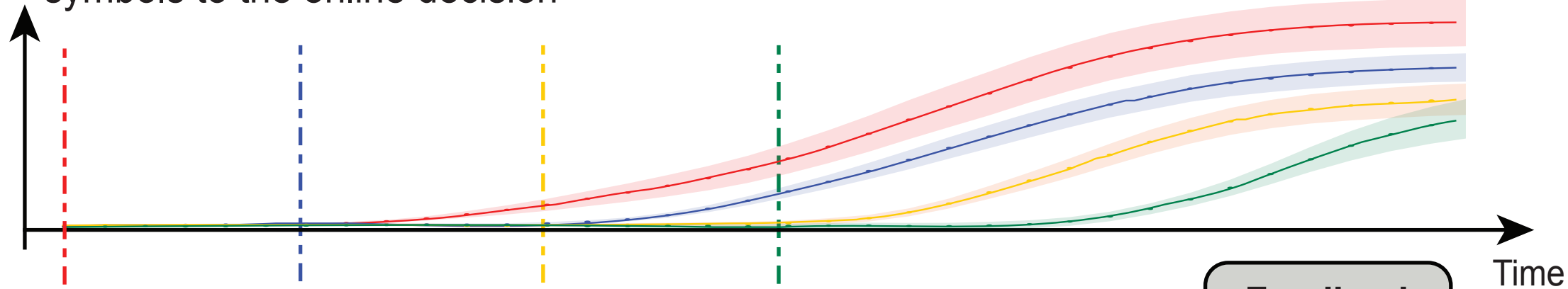
Each semantic symbol ▲ votes for a response side



The syntactic symbol ★ inverts the following symbol



Contribution of the successive symbols to the online decision



Accumulated weight

