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Detection of Regularities in a Random Environment

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Abstract

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Regularity detection, or statistical learning, is regarded as a fundamental component of our cognitive system. To test the ability of human participants to detect regularity in a more ecological situation (i.e., mixed with random information), we used a simple letter-naming paradigm in which participants were instructed to name single letters presented one at a time on a computer screen. The regularity consisted of a triplet of letters that were systematically presented in that order. Participants were not told about the presence of this regularity. A variable number of random letters were presented between two repetitions of the regular triplet making this paradigm similar to a Hebb repetition task. Hence, in this Hebb-naming task, we predicted that if any learning of the triplet occurred, naming times for the predictable letters in the triplet would decrease as the number of triplet repetitions increased. Surprisingly, across four experiments, detection of the regularity only occurred under very specific experimental conditions and was far from a trivial task. Our study provides new evidence regarding the limits of statistical learning and the critical role of contextual information in the detection (or not) of repeated patterns.

Keywords: regularity detection, statistical learning, implicit learning

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We often encounter the same objects, symbols, sounds and sensations time and time again, and they tend to show up in a variety of contexts. One of the basic functions underlying human cognitive processes is our ability to detect such invariant or regular information within environmental variations. *Regularity detection*, also often labelled *statistical learning* (SL), *implicit learning*, or *implicit statistical learning* (Christiansen, 2019; Monaghan & Rebuschat, 2019; Perruchet & Pacton, 2006; Thiessen, Kronstein, & Hufnagle, 2013; Rey, Minier, Malassis, Bogaerts, & Fagot, 2018) is commonly assumed to be a gradual process by which individuals experience a patterned sensory input and, by mere repeated exposure to this regularity, implicitly derive knowledge of its underlying structure, using it to update their predictions of future events (e.g., Fine & Jaeger, 2013; Misyak, Christiansen, & Tomblin, 2010).

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Standard SL tasks involve a visual or auditory familiarization stream, comprising a set of regularities, that is usually followed by an offline test phase (e.g., Aslin, Saffran, & Newport, 1998; Fiser & Aslin, 2001; Reber, 1967; Saffran, Aslin & Newport, 1996). In the test phase, participants are asked to judge the familiarity of sequences that are either consistent or inconsistent with the familiarization stream. The test score captures the total amount of learning that occurred by the end of the familiarization phase (see Siegelman, Bogaerts, Christiansen, & Frost, 2016). The seminal findings of Saffran and colleagues inspired a large research community to focus on the ability to extract adjacent patterns of visual or auditory input, with little variation in the information contained in the stream. In most experiments, therefore, the familiarization phase featured a set of regular patterns of different kinds that were combined in a semirandom manner to form a continuous familiarization stream (e.g., 11 syllables arranged in six triplets; Batterink, Reber, Neville, &

Paller, 2015; 24 abstract shapes arranged in eight triplets; Bogaerts, Siegelman, & Frost, 2016; 12 aliens arranged in four triplets; Arciuli & Simpson, 2012).

The present study featured a slightly different situation - possibly slightly more ecological - in which a single regular pattern was inserted into random information. Participants were shown a series of single letters displayed one at a time in the centre of a computer screen, and were simply instructed to name each letter. A single triplet of letters repeatedly appeared, in between random sequences of other letters. Participants were not, however, informed about the presence of a repeated pattern. If participants started to anticipate the predictable letters in the triplet (i.e., the second and third letters for which the transitional probability was equal to 1), then naming onsets for these letters would gradually decrease over time.

The presentation of a single regularity interspersed by noise sequences is very similar to the Hebb repetition task (Hebb, 1961). Hebb asked his participants to perform an immediate serial recall task in which one specific supraspan sequence was repeated every third trial. He found that the recall performances improved with the repetition of the regular pattern (for more recent studies using the Hebb task, see Bogaerts, Siegelman, Ben-Porat, & Frost, 2017; Ordonez Magro, Attout, Majerus, & Szmalec, 2018; Page & Norris, 2009; Szmalec, Duyck, Vandierendonck, Mata, & Page, 2009). Our experimental paradigm differed from the Hebb task on the nature of the regularity (letter triplet vs. supraspan sequence of items), the process elicited by the task (serial recall vs. naming), and the dependent variable (recall performance vs. response times). However, due to its similarities with the Hebb repetition task, it could be identified as a “Hebb-naming task”.

Studying regularity extraction under these specific conditions as opposed to standard offline tasks has two main advantages. First, if learning is observed with standard SL tasks, it is usually difficult to determine what has been learned exactly (e.g., did participants learn a

little about each of the patterns, or did they pick up on just a few? see Siegelman, Bogaerts, Armstrong, & Frost, 2019), whereas the answer to that question should be more straightforward in the present situation. Second, the naming task could serve as an online learning measure, allowing us to trace the trajectory of learning. The reasoning here was that if participants managed to extract the regularity, the predictability of its constituent elements would increase over time (i.e., with repeated presentations of the regularity), leading to a decrease in naming latencies for predictable letters. By looking at the change in naming latencies across repeated presentations of the regularity, we would be able to study the temporal dynamics of regularity detection under different learning conditions.

Although the idea of using naming as an online measure of regularity detection is relatively novel, the idea of measuring regularity extraction *online* is not. Several recent studies have used other novel behavioural experimental strategies to track learning as it unfolds, in both SL and artificial grammar learning (AGL) paradigms. These strategies typically involve asking participants to detect a target (e.g., Batterink, 2017; Gómez, Bion, & Mehler, 2011; Turk-Browne, Jungé, & Scholl, 2005) or presenting an auditory sequence where the participants' task is to select the written equivalent of the auditory stimuli from a grid of options on the monitor (e.g., Dale, Duran, & Morehead, 2012; Misyak et al., 2010). Additional examples are self-paced SL and AGL tasks (Karuza, Farmer, Fine, Smith, & Jaeger, 2014; Siegelman, Bogaerts, Kronefeld, & Frost, 2016), in which participants follow the familiarization sequence at their own speed. In all these paradigms, faster button press or mouse click responses for predictable stimuli than for unpredictable stimuli are assumed to be an indication of (implicit) regularity learning¹.

We know from the extensive SL, AGL and implicit learning literature that individuals are able to extract structure, and two main theoretical approaches to regularity learning have

¹ Several studies also used EEG recordings to track online changes in event-related potentials when participants are exposed to an artificial language (e.g., Abla, Katahira, & Okanoya, 2008; François et al., 2017; Rodríguez-Fornells, Cunillera, Mestres-Missé, & de Diego-Balaguer, 2009).

been applied to date: the bracketing approach and the clustering approach (Swingley, 2005; see also Frank, Goldwater, Griffiths, & Tenenbaum, 2010). The *bracketing approach*, with the simple recurrent network (SRN, Elman, 1990) as its most famous computational instance, assumes that we learn to predict the next stimulus in a given context, based on the transitional probabilities between sequence elements. The *clustering approach*, by contrast, assumes that sensitivity to co-occurrences arises from the chunking that results from the repetition of groups of elements. PARSER (Perruchet & Vinter, 1998) and TRACX (French, Addyman, & Mareschal, 2011) are probably the best known models instantiating this approach (see also McCauley & Christiansen, 2019).

Although they assume different learning mechanisms, these approaches are actually quite hard to tell apart, as they make similar predictions regarding most experimental SL settings. Interestingly, they do make different predictions regarding the temporal dynamics of learning small regular sequences embedded within larger ones (e.g., a sequence of three items, ABC, where A was consistently followed by B, and B by C). Based on the assumption that prior contextual information can influence pattern extraction, the *SRN model* predicts an advantage for the final part of an embedded sequence (e.g., slower learning of the first two items than of the final one). By contrast, *PARSER* assumes that the input material is subjected to random attentional exploration, and predicts that there will be no difference between the beginning and end of the sequence. *TRACX* assumes that chunks are constructed on a left-to-right basis, leading to the prediction that AB will be learned before BC.

Evidence accumulated over the past decade supports the chunking approach (e.g., Giroux & Rey, 2009; Orbán, Fiser, Aslin, & Lengyel, 2008; but see also Franco & Destrebecqz, 2012), and TRACX has been proved to outperform the other models in simulating several benchmark effects of regularity extraction (French et al., 2011). However, the results of some recent studies have highlighted new constraints for chunking-based

models (Kim, Seitz, Feenstra, & Shams, 2009; Turk-Browne et al., 2005; see also Minier, Fagot, & Rey, 2016, for similar results in baboons). These studies of learning 3-item patterns found that C is learned faster than B, which can be interpreted as an effect of the strong contextual information AB preceding C, compared with the weaker contextual information A preceding B. This can be accounted for by an associative learning mechanism, but runs counter to the predictions by the aforementioned chunking models. However, to date, it is not clear whether the learning advantage for the final stimulus in a repeated pattern is observed in other learning situations, such as the extraction of a single regular pattern hidden in noise. The first goal of the present set of experiments was therefore to study the detection dynamics of a regular letter triplet and to test the replicability of previous findings showing faster learning for the letter in the last position of the triplet (i.e., C) compared with the one in the second position (i.e., B).

The second goal was to ask how regularity extraction is influenced by different learning conditions, that is, how do the characteristics of the pattern and its environment affect learning? Interestingly, SL models (e.g., SRN, PARSER or TRACX) state that if the contextual information is made up of different elements of the regular pattern, then the critical factors for detecting this regularity will be the number of repetitions and the amount of interfering information inserted between two repetitions of the regular pattern. With a sufficient number of repetitions and a limited amount of interfering information, these models therefore predict that participants will have no difficulty detecting the regular pattern. We examined whether the evidence yielded by the present set of experiments supported this claim.

Overview of the Experiments

Our study comprised four experiments. Experiment 1 tested the extraction of a repeated triplet made up of consonants that alternated with random noise (sequences of two to

five letters, randomly selected from a set of five different consonants). Experiment 2 tested the extraction of a similar statistical regularity, but in contrast to the first experiment, the repeated triplet was made up of vowels. In Experiment 3, we changed the nature of the random (i.e., unstructured) noise separating the triplet repetitions, such that although the noise sequences were still two to five letters long, these were drawn from a set of 14 consonants. Finally, Experiment 4 was identical to Experiment 3, except that the random sequences between repetitions of the triplet were shorter (no more than three letters). The data yielded by these four experiments are available on Open Science Framework at https://osf.io/dyb4u/?view_only=d35620f91740450b9a915643f6c49308.

Experiment 1

Method

Participants

A total of 21 adults (7 men, 14 women; $M_{\text{age}} = 20.15$ years), all native French speakers and students at Aix-Marseille University, took part in the study in exchange for a course credit. All reported normal or corrected-to-normal vision, and none reported a history of attention problems or reading disabilities.

Procedure and materials

The experiment was run on a portable computer equipped with a serial response box and an Audio-Technica microphone. The microphone was fixed to an adjustable stand and positioned approximately 3 cm from the participant's mouth.

The naming task, administered via E-Prime 2.0 (Schneider, Eschman, & Zuccolotto, 2002), involved the sequential presentation of individual letters in 70-point Arial white font in the centre of a black background. Participants were instructed to read aloud each letter as fast as possible. Speech onset and accuracy were recorded for each letter. Accuracy was scored by an experimenter present in the testing room, who scored errors but also (rare)

microphone failures as incorrect responses. Each letter stayed on the screen until the microphone was triggered at speech onset. The next letter then appeared after a fixed interstimulus interval (ISI) of 800 ms.

Participants first performed a microphone test, which also allowed them to familiarize themselves with the task. The microphone test consisted of 12 randomly selected naming trials. The actual rapid naming experiment consisted of 3 blocks of 100 trials (i.e., individual letter presentations) each. The letter stream that participants were exposed to was constructed from a set of printed consonants (F, H, L, M, N, P, R, S, T). Eight letters were randomly drawn from this set for each participant: three letters were used for the repeated triplet, and triplet repetitions (15 per block, 45 in total) were always separated by two to five random consonants, chosen from the five remaining letters. Frequency was balanced across the noise letters for each block of 100 trials. The repeated triplet was never a three-letter alphabetic run (e.g., LMN) or a well-known (French) abbreviation. The letters making up the triplet and their serial order were counterbalanced across participants.

Participants could take a break after every block. After Blocks 1 and 2, participants received oral feedback telling them that they were performing well, but had to try to speed up (this feedback was given independently of their actual performance or speed). In total, the naming task lasted approximately 10-15 minutes.

All participants responded to a short questionnaire after completing the naming task. In standard SL experiments participants are typically tested after the exposure phase with a 2-alternative forced choice task, testing the recognition of regular patterns against different foils. Given that our focus is on a learning situation with only one regular triplet, building a 2-AFC task was problematic because it would be impossible to control for the frequency of the regular triplet and the foils. We therefore opted for a questionnaire to get information about the participants' explicit knowledge of the regularity (acknowledging that this might be

qualitatively different from the ability to recognise a regularity).

The experimenter asked them “Did you notice anything in particular in this experiment? Yes/No” and, in case of a “Yes” answer, the follow-up question “Can you explain what you noticed?” If participants reported noticing the repeated presentation of a sequence or sequences of letters, they were asked “Can you recall which sequence(s) of letters was repeated?” If the answer to the first question was “No”, or participants provided an explanation that was unrelated to the presence of repeated patterns, the experimenter explicitly asked them “Did you notice the repetition of a sequence of letters? Yes/No” and “Can you recall which sequence of letters was repeated?”

Results

Speech onset latency

Only trials with correct naming responses (97.97% of the data) were analysed. Those where the stimulus presentation onset was delayed by more than 10 ms were excluded (0.96% of the data). Figure 1 shows that the distribution of speech onset latencies (SOLs) was close to normal in our task². Given that we expected anticipatory naming responses, we included fast responses, and excluded only 6 data points with a SOL exceeding 800 ms.

The summary statistics are set out in Table 1, and further results are provided in Figure 2.

-- Table 1 about here --

-- Figure 1 about here --

-- Figure 2 about here --

First, to study the learning trajectory across triplet repetitions as a function of the position of the stimulus (within the triplet), we used the lme4 package in R (CRAN project; R Foundation for Statistical Computing, 2009) to run a linear mixed model with SOL as the

² This was due to the presence of anticipatory responses that distorted to the left the usually right-skewed distribution.

dependent variable. The fixed effect variables included in the model were position (1-3) and repetition number (1–45), as well as their two-way interaction. Position was sum-coded (Position 1: -1 1; Position 2: 1 0; Position 3: 0 1), and repetition was mean-centred here and in all subsequent models. The model included the maximum random effect structure that allowed convergence (Barr, 2013; Barr et al., 2013): $SOL \sim Position + Repetition + Position:Repetition (1 + Position + Repetition + Position:Repetition | Participant)^3$. In other words, we had a random intercept for participant and a random by-participant slope for position, repetition and the Position x Repetition interaction. It should be noted that triplet learning was predicted to result in a main effect of position (with faster SOLs for predictable 2nd and 3rd positions) and a Position x Repetition interaction.

The results of the model are summarized in Table 2. We only found a significant effect of repetition, with the negative coefficient for this effect reflecting an acceleration (faster SOLs) over the course of the experiment. Model comparison with a likelihood-ratio test (following the guidelines established by Barr et al., 2013) revealed that neither the main effect of position, $\chi^2(2) = 0.58, p = 0.75$, nor the Position x Repetition interaction effect, $\chi^2(2) = 3.25, p = 0.20$, significantly improved the model fit.

-- Table 2 about here --

In a second analysis, we tested whether there was evidence for significant learning at the group level for each of the blocks. Learning was quantified as the difference score between mean log-transformed naming SOLs for unpredictable letters (Position 1) versus predictable letters (Positions 2 and 3). As such, a positive score could be interpreted as evidence for learning. We opted for the use of log-transformed SOLs (rather than the raw

³ It should be noted that we did not include letter identity as a random effect in the model, as this would have led to many instances of nonconvergence (across the four experiments). Although this could potentially have left us with more unexplained variance, it was not a concern, as in each experiment, the triplets were either randomly selected for each participant and/or letter position was counterbalanced, ensuring that any biases for individual letters were averaged out.

values) to control for the baseline differences in the speed of participants' naming responses (see Siegelman et al., 2019).⁴ When we compared the mean learning difference score for each of the three blocks (see Table 1) with the hypothetical mean 0 using a one-sample *t* test, and found no evidence of significant learning (i.e., mean SOL difference score significantly greater than zero) in any of the blocks (all *ts* > 1 and *p*_{one-tailed} > .10).

Questionnaire

Eight of the 21 participants reported noticing a repeated pattern. Only one of them correctly recalled the triplet (i.e., all three letters in the right order), but five other participants correctly reported one subsequence (either Letters 1&2 or Letters 2&3).

Discussion

Surprisingly, the results of this first experiment showed that there was no significant acceleration for predictable letters. Furthermore, SOLs were not influenced by the serial position of the letter within the triplet. A number of participants noticed the presence of a repeated sequence, but most were unable to accurately recall the triplet. Although the presence of the repeated triplet looked obvious from the point of view of the experimenters, the majority of participants did not even notice it. Regularity detection in this specific experimental situation, in which attentional processing was oriented toward the naming of each letter, was apparently very limited for most participants.

This surprising result is at odds with the predictions of current SL models. Assuming that participants have to pay attention and process each letter in order to retrieve and produce

⁴ To exemplify the influence of the log transformation, let us consider two participants with a mean difference of 100 ms between unpredictable and predictable letters, but a different baseline SOL: P1 unpredictable = 500 ms, predictable = 400 ms; P2 unpredictable = 300 ms, predictable = 200 ms. Because of the baseline difference, P2's relative acceleration for predictable stimuli was far greater. The difference between predictable and unpredictable stimuli after log-transforming the SOLs reflects this, with 0.22 for P1 and 0.41 for P2.

its name, these models predict that the residual activation for Letter 1 generated at trial $t-1$ should enhance the activation of Letter 2 at trial t , merely through associative learning mechanisms. With sufficient repetitions, these transient memory traces should be reinforced, and the activation of Letter 1 should gradually come to predict and pre-activate the neural population coding for Letter 2. Apparently, for the majority of participants, the present experimental conditions were ineffective in producing this mandatory associative learning of adjacent patterns, indicating that we reached the limit of these mechanisms here.

The three following experiments were conducted to clarify this surprising result. In Experiment 2, we tested the extraction of a repeated triplet of vowels (e.g., A, O, U). Given that the letters for the triplet were drawn from a different category than the set of random letters, which were all consonants, we expected the repeated triplet to be more salient, and the detection of the regularity more efficient.

Experiment 2

Method

Participants

A different sample of 21 native French adults (2 men, 19 women; $M_{\text{age}} = 19.81$ years) took part in the experiment in exchange for a course credit or payment. As in the previous experiment, all the participants had normal or corrected-to-normal vision, and none of them reported a history of attention problems or reading disabilities.

Procedure and materials

The naming task procedure was identical to the one used in Experiment 1. The material, however, was different, in that the regular triplet was made up of three vowels. We always used the same three vowels (A, O, U), but their order was counterbalanced across participants. The regular triplet was inserted into a random sequence of consonants drawn from a set of five consonants (F, L, N, R, S), and the triplet repetitions (15 per block) were

always separated by two to five random consonants.

Results

Only correct responses (97.22% of the data) were analysed. Trials where the stimulus presentation onset was delayed by more than 10 ms were excluded (0.98% of the data), as were four data points with SOLs exceeding 800 ms.

Table 3 summarizes the results of Experiment 2. The plot in Figure 3 suggests that letter predictability had a strong effect on SOLs, and this was confirmed by the results of our statistical analysis.

-- Table 3 about here --

-- Figure 3 about here --

The mixed model used to analyse the data of Experiment 2 was identical to the model we used in Experiment 1. Its results are summarized in Table 4.

-- Table 4 about here --

We found a significant effect of repetition, with the negative coefficient for this effect reflecting a decrease in SOLs. The coefficients for the effect of Position 3 reflect the fact that SOLs were significantly faster for predictable Position 3 letters relative to the mean SOL across all positions. Finally, a significant negative interaction coefficient indicated a significantly greater acceleration for Position 3 letters relative to the mean acceleration across all positions. Model comparison revealed that both the main effect of position, $\chi^2(2) = 21.80$, $p < 0.001$, and the Position x Repetition interaction effect, $\chi^2(2) = 70.43$, $p < 0.001$, were significant. A follow-up analysis revealed that pairwise position contrasts were significant for Position 1 - Position 2, $t(21.01) = 4.58$, Tukey-adjusted $p < 0.001$, and Position 1 - Position 3, $t(20.13) = 5.99$, Tukey-adjusted $p < 0.001$, but not for Position 2 - Position 3, $t(19.97) = 2.38$, Tukey-adjusted $p = 0.07$).

When we looked at learning as the difference score between log-transformed SOLs for unpredictable and predictable letters, we found strong evidence for learning even in the first block, $t(20) = 5.09$, $p_{\text{one-tailed}} < .001$, and learning increased further with exposure, $t(20) = 3.21$, $p_{\text{one-tailed}} < .001$ for Block 2; $t(20) = 4.03$, $p_{\text{one-tailed}} < .001$ for Block 3 (see Table 3)⁵.

Questionnaire

Nineteen of the 21 participants reported noticing a repeated pattern, and 14 of them correctly recalled the triplet. Two other participants correctly reported one subsequence (Letters 1&2 or Letters 2&3).

Discussion

The results of Experiment 2, in contrast to those of our first experiment, revealed clear effects of predictability on SOLs. Shorter SOLs were observed for the second and third letters in the repeated triplet, and this difference increased across repetitions. Results further showed an increased naming advantage for Position 3 over Position 2—a pattern consistent with previous findings (e.g., Minier et al., 2016).

The use of different letter categories for the structured and unstructured material (vowels in the triplet and consonants in the noise) may, of course, have served as a cue that facilitated the parsing of the continuous sequence and the extraction of the regular triplet pattern. Participants' responses to the awareness questionnaire suggest that, for at least 90% of them, the resulting knowledge about the structure was conscious. This result therefore indicates that regularity detection is possible within this experimental paradigm, though only if the regular triplet is made more salient than the random information.

Returning to the question of why no learning was observed in Experiment 1, one possible explanation is that the regularity was presented within noise that was still relatively

⁵ It should be noted that we only compared predictable versus unpredictable vowels here, so even though vowels and consonants may not trigger the voice key in the same way (thus affecting SOLs), this could not bias our analyses.

structured. That is, given that the noise letters were drawn from a set of just five consonants, the theoretical mean transitional probability between the different noise letters was .25. Participants' responses on the post-task questionnaire indicated that regularities were also detected in the unstructured noise material. We tentatively suggest that the structure perceived in the noise may have interfered with the extraction of the actual triplet. In Experiment 3, we sought to increase the signal-to-noise ratio, without giving any cues for the regular triplet. We tested whether we could find evidence for regularity detection in a consonant-only version of the task using *noisier* noise. Therefore, instead of selecting them from a set of five consonants, we drew the noise letters from a set of 14 consonants, making the transitional probabilities between noise letters much smaller than they were in Experiment 2.

Experiment 3

Method

Participants

A sample of 22 native French speakers (7 men, 15 women; $M_{\text{age}} = 21.73$ years) took part in the study in exchange for either a course credit or a payment.

Procedure and materials

The procedure was identical to the one used in Experiments 1 and 2. The letter stream was constructed with the full set of 20 French consonant letters minus W (referred to in French as *double V* [double U], and the low-frequency letters Q and X (hence, a set of 17). Three letters were used to construct the triplet (as before, the letter organization of the triplet was counterbalanced across participants), while the 14 remaining letters were used for the unstructured noise. Triplet repetitions (15 per block) were always separated by two to five randomly structured consonants, as in the previous experiments.

Results

Only correct responses (96.27 % of the data) were analysed. Trials where the stimulus presentation onset was delayed by more than 10 ms were excluded (0.94% of the data). One participant was excluded from the analysis as she failed to give rapid naming responses. Her mean SOL for triplet letters (493.29 ms) exceeded the sample's mean (391.26 ms) + 1.5**SD* (58.31 ms).

Table 5 summarizes the results of Experiment 3. The plot in Figure 4 suggests a learning effect, but a substantially smaller one than the effect we observed in Experiment 2.

-- Table 5 about here --

-- Figure 4 about here --

The mixed model we used was identical to the ones used in Experiments 1 and 2. The results of the model are summarized in Table 6.

-- Table 6 about here --

Results were somewhat mixed. Only the position coefficient for Position 3 approached the significance threshold ($\beta = -12.3$, CI [-23.7, -0.9], $p = .06$) indicating that SOLs were faster for predictable Position 3 letters relative to the mean SOL across positions. Model comparisons revealed that the main effect of position was also approaching significance, $\chi^2(2) = 5.66$, $p = .058$, while the Block x Position interaction did not significantly improve the model fit, $\chi^2(2) = 2.49$, $p = .29$. A follow-up analysis contrasting Position 1, 2 and 3 revealed similar trends: Position 1 - Position 2, $t(18.97) = 1.81$, Tukey-adjusted $p = 0.19$; Position 1 - Position 3, $t(18.99) = 2.49$, Tukey-adjusted $p = 0.055$; Position 2 - Position 3, $t(18.99) = 1.69$, Tukey-adjusted $p = 0.23$.

One-sample t tests revealed that in Block 1, participants did not exhibit learning of the

underlying statistical structure of the letter stream – as reflected by a difference score between SOLs for unpredictable and predictable letters that was significantly greater than zero, $t(20) = .99$, $p_{\text{one-tailed}} = .17$. Significant learning was apparent in the subsequent learning blocks: $t(20) = 2.64$, $p_{\text{one-tailed}} < .01$ for Block 2, and $t(20) = 1.69$, $p_{\text{one-tailed}} = .05$ for Block 3 (see Table 5).

Questionnaire

Thirteen of the 21 participants reported noticing a recurrent letter sequence. Three of them could recall the whole triplet, and two others correctly recalled one subsequence (Letters 1&2 or Letters 2&3).

Discussion

In line with the results of Experiment 2, the difference in SOLs between unpredictable and predictable letters increased across blocks. It should be noted that the online learning effect was substantially smaller than the one observed for the vowel triplet. Significant learning also emerged later (in the second block rather than in the very first). Unsurprisingly, in the absence of any cue other than the statistical properties of the stream, far fewer participants were able to explicitly recall the repeated triplet (3/21 vs. 14/21 for Experiment 2).

A key result of these first three experiments was that the context in which the regular patterns were presented influenced online learning performances. To account for the lack of online learning in our first experiment, we tentatively hypothesized that the statistical structure in the noise interfered with the extraction of the actual triplet. The fact that we found learning under nearly identical learning conditions, the only difference being the set of letters used to construct the noise sequences, suggests that the degree of latent structure in the

noise sequences affected the detection of the regularity⁶. This result is problematic for most SL models. Recall of the letters making up the regular triplet should not have been affected by the manipulation of the noise information in Experiment 3, and results should have been the same as those in Experiment 1.

Previous research has demonstrated that learners form expectations about the kind of structure present in an information stream, based on previous exposure to other streams (Lew-Williams & Saffran, 2012), and may therefore fail to learn structures that conflict with their expectations (Gebhart, Aslin, & Newport, 2009). A similar conflict may occur within a single stream when wrong expectations are formed on the basis of the noise information (which was not sufficiently noisy in Experiment 1). In that case, participants may keep in mind a random repetition (which is more likely to occur in Experiment 1 due to the small number of filler letters) and this expectation may interfere with the discovery of the genuine regularity. An alternative (though not necessarily mutually exclusive) interpretation relates to memory constraints (Frank & Gibson, 2011; Frank, Goldwater, Griffiths, & Tenenbaum, 2010). The presence of quasi-regularities in the noise sequences may be disadvantageous if they are being kept active in working memory. This could be especially true in the context of a demanding task such as rapid naming that presumably takes up capacity itself.

In the fourth and final experiment, we aimed to determine the effect of reducing the distance between occurrences of the regular pattern. All SL models predict that shorter noise sequences between triplet repetitions should lead to improved learning.

⁶ It should be noted that although the triplet was repeated the same number of times (45) in each of the experiments, the relative frequency of triplet letters versus noise letters was higher in Experiment 3 than in Experiment 1. This factor may have contributed to participants' better learning performances. Faster SOLs for Position 1 than for noise letters (see Fig. 5) suggest that participants also picked up on the greater frequency of the first letter in the triplet. However, given that the difference between unpredictable Position 1 and predictable Positions 2 and 3 increased, this frequency effect cannot fully account for the data.

Experiment 4MethodParticipants

A sample of 24 native French speakers (4 men, 20 women; $M_{\text{age}} = 20.1$ years) took part in the study in exchange for a course credit.

Procedure and materials

The procedure used in Experiment 4 was identical to the one used in Experiment 3, except that triplet repetitions were always separated by no more than three randomly arranged consonants (rather than the two to five randomly arranged consonants in Experiments 1-3). As the total number of trials was identical to the number in the three previous experiments (300 trials in three blocks of 100 trials), there were 62 rather than 45 triplet repetitions.

Results

Only correct responses (97.17% of the data) were analysed. Trials where the stimulus presentation onset was delayed by more than 10 ms were excluded (0.97% of the data), as were 11 data points with SOLs exceeding 800 ms.

The results of Experiment 4 are summarized in Table 7 and Figure 5.

-- Table 7 about here --

-- Figure 5 about here --

The model included the maximum random effect structure that allowed convergence (Barr, 2013; Barr et al., 2013): $\text{SOL} \sim \text{Position} + \text{Repetition} + \text{Position} \times \text{Repetition} (1 + \text{Position} + \text{Position} \times \text{Repetition} \mid \text{Participant})$. The results of the model are summarized in Table 8.

-- Table 8 about here --

There was a significant effect of repetition and the predicted effect of position: overall

SOLs were significantly faster for the predictable Position 3 compared with the mean across all positions. Finally, the significant negative interaction coefficient indicated greater acceleration for Position 3 across repetitions, relative to the mean acceleration for all positions. Model comparisons revealed a significant main effect of position, $\chi^2(2) = 12.82$, $p < .01$, and a significant Position x Repetition interaction, $\chi^2(2) = 8.05$, $p = .018$. Pairwise position contrasts were significant for Position 1 - Position 2, $t(23.02) = 3.85$, Tukey-adjusted $p < 0.01$, and Position 1 - Position 3, $t(22.98) = 3.647$, Tukey-adjusted $p < 0.01$, but not for Position 2 - Position 3, $t(22.94) = 1.32$, Tukey-adjusted $p = 0.40$.

One-sample t tests revealed that participants already exhibited significant learning of the underlying statistical structure of the letter stream in the first block, $t(23) = 2.94$, $p_{\text{one-tailed}} < .01$, which remained significant in subsequent learning blocks, with $t(23) = 2.89$, $p_{\text{one-tailed}} < .001$ for Block 2, and $t(23) = 3.84$, $p_{\text{one-tailed}} < .001$ for Block 3 (see Table 7).

To directly compare learning in the current experiment with learning in Experiment 3, we ran another linear mixed model on the data for the two experiments, subsetting the data of Experiment 4 to include only the first 45 repetitions. In this model, learning score was the dependent variable, and experiment, repetition and the Experiment x Repetition interaction were fixed effects with a random by-participant intercept. Experiment was sum-coded (Experiment 3: -1; Experiment 4: 1). We found significant main effects of Experiment ($\beta = 0.04$, $SE = 0.01$, $p < .001$) and Repetition ($\beta = 0.005$, $SE = 0.001$, $p < .001$), and a significant interaction effect ($\beta = 0.002$, $SE = 0.001$, $p < .001$), confirming stronger learning in Experiment 4 than in Experiment 3 (see also Fig. 6).

-- Figure 6 about here --

Questionnaire

Nineteen of the 24 participants reported noticing a recurrent letter sequence. Thirteen

could recall the whole triplet, while four others correctly recalled one subsequence (Letters 1&2 or Letters 2&3).

Discussion

In Experiment 4, we tested the prediction that shorter noise sequences between triplet repetitions would further improve learning in the naming task. Results showed that overall learning scores were indeed higher than in Experiment 3. With its 17 additional repetitions, the present experiment also provided information regarding the trajectory of SOLs in the later stages of pattern learning. Interestingly, the decrease in SOLs for predictable letters continued unabated across the 62 repetitions (no sign of reaching asymptote).

General Discussion

In the present study, participants had to name out loud single letters that were displayed one at a time on a computer screen. Unbeknownst to them, the stream contained a repeated letter triplet. Our data suggest that SOLs were sensitive to online statistical computations: with exposure, SOLs for the predictable second and third letters in the repeated triplet decreased. However, this effect was only present when the information stream had what could be described as a high signal-to-noise ratio. To be detected, the triplet either had to have a salient feature compared with the noise information (Exp. 2), or the noise sequences between successive presentations of the regular pattern had to be sufficiently noisy (Exp. 3) or short (Exp. 4). Otherwise, the regular pattern remained undetectable for most participants (Exp. 1).

Taken together, the results of our four experiments have two main implications for models of implicit SL. First, they show that although SL mechanisms are powerful, they also have limitations. The detection of co-occurrences and regularities does not systematically take place when participants are exposed to a repeated regular pattern of adjacent items, even if this pattern is relatively simple. Mere repetition is not a sufficient condition for a regularity

to stand out from a stream of variable information, and for participants to detect it. The regular pattern will be detected either because of a feature that makes it salient with respect to the surrounding variable information (i.e., vowels vs. consonants; Exp. 2) or because the mean interval between two repetitions is small enough for the memory trace of the co-occurrences to be sufficiently reinforced (Exp. 4). This raises important issues, such as the role of regularity learning in more natural contexts, as well as educational ones. In language learning in particular, a field in which SL has become a dominant theoretical construct in recent years, the current findings point to the limitations of our implicit co-occurrence learning abilities.

Second, the present results indicate that the context or surrounding information in which the regularities are presented may matter for SL (Exp. 1 & 3). If the variable context is not variable enough, associative learning mechanisms may extract co-occurrences that have sufficiently strong transitional probabilities, but which are irrelevant. This is an issue that has so far received too little attention, as almost all previous research has used input streams with a similar latent structure, repeating n (usually between four and eight) triplets or pairs with a transitional probability of 1 between the items within each one (Siegelman et al., 2016).

The present data also replicate previous findings on the dynamics of regularity extraction. The results of Experiment 2, where we tested a vowel triplet in consonant noise, revealed greater acceleration for Position 3 versus Position 2 letters, and we saw a similar trend in Experiments 3 and 4. This could be interpreted as an effect of context on the learning of the final stimulus in a repeated triplet (i.e., the final stimulus benefits from the contextual information provided by the stimuli that consistently precede it), in line with the effect described by Minier et al. (2016) in the motor sequence learning trajectory of baboons. It therefore suggests that in a verbal SL task, greater contextual information facilitates prediction (see also Rey, Minier, Malassis, Bogaerts, & Fagot, 2018). As argued by Minier et

al. (2016), this learning advantage for the final item or embedded pattern is predicted by the SRN model, but poses challenges for chunking models such as PARSER, which predicts no difference between learning for the initial (Letters 1&2 in a triplet) and final (Letters 2&3) embedded patterns, or TRACX, which predicts faster learning for the initial one (Letters 1&2) - the opposite of what we found.

Prospects and limitations

We believe that the Hebb-naming paradigm described here offers a simple behavioural approach to studying learning dynamics online, suitable for studying how fast and with which trajectory learners capture the statistical properties of incoming sensory information. It could be used to complement existing offline measures and might help to overcome some of the psychometric shortcomings of offline measures, such as test interference. As a more implicit and direct measure (see also Isbilen, Frost, Monaghan, & Christiansen, 2018), SOL might prove particularly useful for studying SL in young children (e.g., Arnon, 2019; Lammertink, van Witteloostuijn, Boersma, Wijnen, & Rispens, 2018) or certain patient groups (e.g., amnesic patients; Schapiro, Gregory, Landau, McCloskey, & Turk-Browne, 2014) who have difficulty with the 2-AFC testing format. It also has a considerable advantage (over for example the RT-based measure in an SRT task) due to the many degrees of freedom in constructing the regular sequence (e.g., contrary to the SRT task, it is possible to have several sequences with transitional probabilities of 1). It could be employed with all sorts of nameable stimuli with large set sizes (e.g., pictures, words) and with different types of regularities. By extension, this measure could also be included in verbal AGL and Hebb repetition paradigms.

The above formulation “as a more implicit and direct measure” requires some further clarification. We worked on the premise that faster SOLs for predictable letter stimuli can occur when learning is implicit, that is, when the stream of letters is processed without “the

conscious intention to find out whether the input information contains regularities” (Hulstijn, 2005, p. 131). However, this does not mean that the learning trajectories we observed were uniquely shaped by implicit learning processes (Andringa & Rebushat, 2015). In each of the experiments, by the end of the task (i.e., after several dozen repetitions) several participants displayed conscious knowledge of the regularity that had been learned, and the pattern of questionnaire results across our four experiments suggests that either awareness emerged with increased implicit learning, or some emerging awareness of the regularity (while participants were engaged in the naming task) amplified the online learning effect as we measured it. Splitting participants from Experiment 4 in two groups of similar sizes (i.e., participants who could recall *vs.* who could not recall the repeated sequence of letters (with $N = 13$ and $N = 11$, respectively), we indeed found that the interaction between Position 3 and Repetition was significant for those who could recall the sequence ($\beta = -1.22$, CI $[-2.06, -0.37]$, $p < .02$) but not for the other group ($\beta = -0.51$, CI $[-1.23, 0.21]$, $p = 0.191$).

Although the present investigation goes some way toward the development of a Hebb naming SL task, future research will have to examine whether the task can be adapted to other types of verbal stimuli and to the auditory modality (where the participants are asked to shadow rather than to name), and whether it can also be employed to study different types of regularities (e.g., nonadjacent co-occurrences). Furthermore, from a psychometric perspective, it is important to examine whether the online naming measure can reliably tap into individual performances on the task and predict offline performance.

Conclusion

We asked participants to name letters presented in continuous letter sequences and measured their SOLs in four experiments. Overall, our data suggest that SOLs are sensitive to stimulus predictability and to online statistical computations. Our results also highlight the influence of the context in which a regular pattern is presented, and a major limitation of

599 implicit co-occurrence learning abilities in the context of an active naming task.

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Open Practices Statements

Data and materials for all the experiments are available on Open Science Framework. None of the experiments were preregistered.

Conflict of Interest

AR, LB, LT, GB, AF, and BF declare that they have no conflict of interest.

Ethical Approval

All procedures in the present experiments involving human participants were performed in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards.

Informed Consent

Informed consent was obtained from each of the participants included in the study.

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Table 1

Means and Standard Deviations for Raw Speech Onset Latencies (SOLs) and Learning

Scores in Experiment 1

	Block 1	Block 2	Block 3	Total
Raw SOL				
Position 1	411 (68)	382 (67)	376 (71)	389 (70)
Position 2	413 (73)	388 (67)	364 (84)	388 (77)
Position 3	415 (67)	389 (73)	376 (72)	393 (72)
Learning score	0	-.02	.02	

Table 2

Results of the Mixed Model for Experiment 1

Predictor	β	CI	SE	<i>p</i>	
(Intercept)	390.3	[376.3 , 404.3]	7.1	< .001	***
Position 2	-1.9	[-8.7 , 4.8]	3.4	.58	
Position 3	2.9	[-4.8 , 10.6]	3.9	.47	
Repetition	-1.2	[-1.7 , -0.8]	0.2	< .001	***
Position 2: Repetition	-0.2	[-0.5 , 0.1]	0.2	.14	
Position 3: Repetition	0	[-0.3 , 0.3]	0.2	.99	

Note. Position was sum-coded.

Table 3*Means and Standard Deviations for Raw Speech Onset Latencies (SOLs) and Learning**Scores in Experiment 2*

	Block 1	Block 2	Block 3	Total
Raw SOL				
Position 1	382 (66)	343 (64)	334 (73)	352 (71)
Position 2	364 (76)	299 (84)	270 (93)	311 (93)
Position 3	352 (75)	284 (106)	248 (107)	295 (106)
Learning score	.07	.16	.25	

Table 4*Results of the Mixed Model for Experiment 2*

Predictor	β	CI	SE	p	
(Intercept)	320.2	[299.9 , 340.5]	10.3	< .001	***
Position 2	-8.9	[-17.2 , -0.7]	4.2	.04	*
Position 3	-24.3	[-33.1 , -15.4]	4.5	< .001	***
Repetition	-2.5	[-3.3 , -1.8]	0.4	< .001	***
Position 2: Repetition	-0.4	[-0.8 , -0.02]	0.2	.05	*
Position 3: Repetition	-0.8	[-1.2 , -0.3]	0.2	0.004	***

Note. Position was sum-coded.

776 Table 5777 *Means and Standard Deviations for Raw Speech Onset Latencies (SOLs) and Learning*778 *Scores in Experiment 3*

	Block 1	Block 2	Block 3	Total
Raw SOL				
Position 1	404 (57)	397 (66)	396 (66)	399 (63)
Position 2	404 (59)	377 (72)	376 (80)	386 (72)
Position 3	390 (58)	363 (92)	370 (89)	375 (82)
Learning score	.01	.07	.09	

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780

781 Table 6782 *Results of the Mixed Model for Experiment 3*

Predictor	β	CI	SE	<i>p</i>	
(Intercept)	386	[351 , 421]	17.91	< .001	***
Position 2	-0.9	[-5.6 , 3.7]	2.37	.71	
Position 3	-12.3	[-23.7 , -0.9]	5.81	.06	
Repetition	-0.5	[-1.4 , 0.35]	0.45	.26	
Position 2: Repetition	-0.3	[-0.68 , 0.09]	0.19	.16	
Position 3: Repetition	-0.1	[-0.64 , 0.44]	0.28	.72	

783 *Note.* Position was sum-coded.

Table 7

Means and Standard Deviations for Raw Speech Onset Latencies (SOLs) and Learning

Scores in Experiment 4

	Block 1	Block 2	Block 3	Total
Raw SOL				
Position 1	429 (64)	414 (69)	418 (75)	420 (70)
Position 2	405 (78)	377 (95)	344 (120)	375 (102)
Position 3	404 (82)	357 (122)	328 (127)	363 (116)
Learning score	.08	.21	.34	

Table 8

Summary of the Fixed Effects in the Mixed Model for Experiment 4

Predictor	β	CI	SE	<i>p</i>	
(Intercept)	395.3	[374.3 , 416.4]	10.2	< .001	***
Position 2	-7.3	[-14.9 , 0.4]	3.8	.07	
Position 3	-17.8	[-30.6 , -5]	6.1	< .01	**
Repetition	-1.4	[-2.2 , -0.6]	0.4	< .001	***
Position 2: Repetition	-0.05	[-0.3 , 0.2]	0.14	.74	
Position 3: Repetition	-0.8	[-1.4 , -0.3]	0.2	< .01	**

Note. Position was sum-coded.

Figure Captions

Figure 1. Density plot of speech onset latencies showing the fitted normal distribution in blue, with a red line indicating our cut-off score.

Figure 2. Plot with smoothed estimate of mean speech onset times in Experiment 1 as a function of letter position and number of repetitions. Grey-shaded areas indicate 95% confidence intervals around linear regression lines. Dashed lines represent the best linear fit.

Figure 3. Plot with smoothed estimate of mean speech onset times in Experiment 2 as a function of letter position and number of repetitions. Grey-shaded areas indicate 95% confidence intervals around linear regression lines. Dashed lines represent the best linear fit.

Figure 4. Plot with smoothed estimate of mean speech onset times in Experiment 3 as a function of letter position and number of repetitions. Grey-shaded areas indicate 95% confidence intervals around linear regression lines. Dashed lines represent the best linear fit.

Figure 5. Plot with smoothed estimate of mean speech onset times in Experiment 4 as a function of letter position and number of repetitions. Grey-shaded areas indicate 95% confidence intervals around linear regression lines. Dashed lines represent the best linear fit.

Figure 6. Comparison of learning scores and their changes across repetitions for all-consonant triplet in consonant-noise experiments. Grey-shaded areas indicate 95% confidence intervals around linear regression lines. Dashed lines represent the best linear fit.

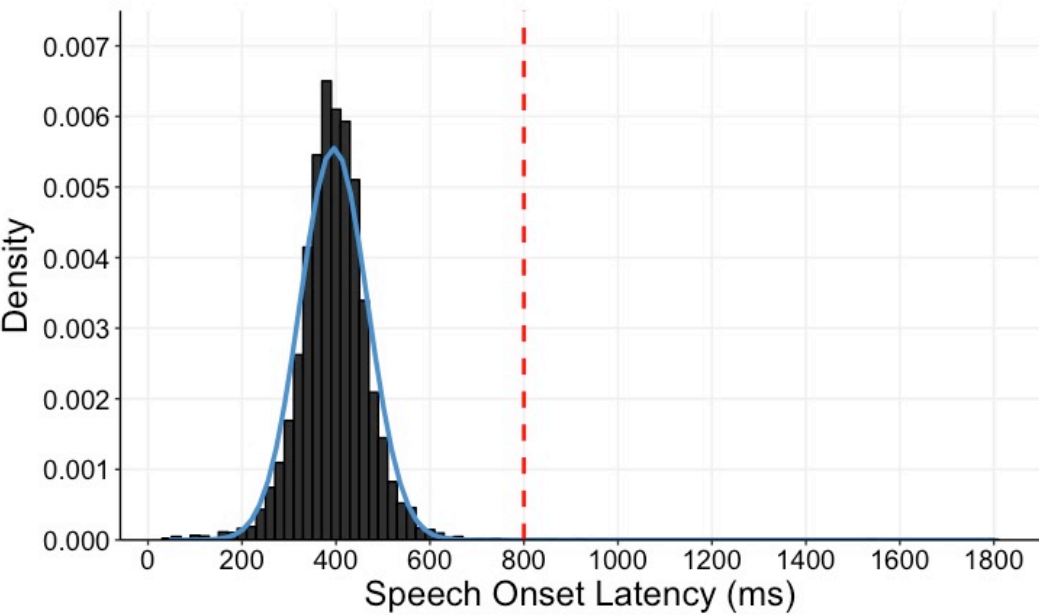
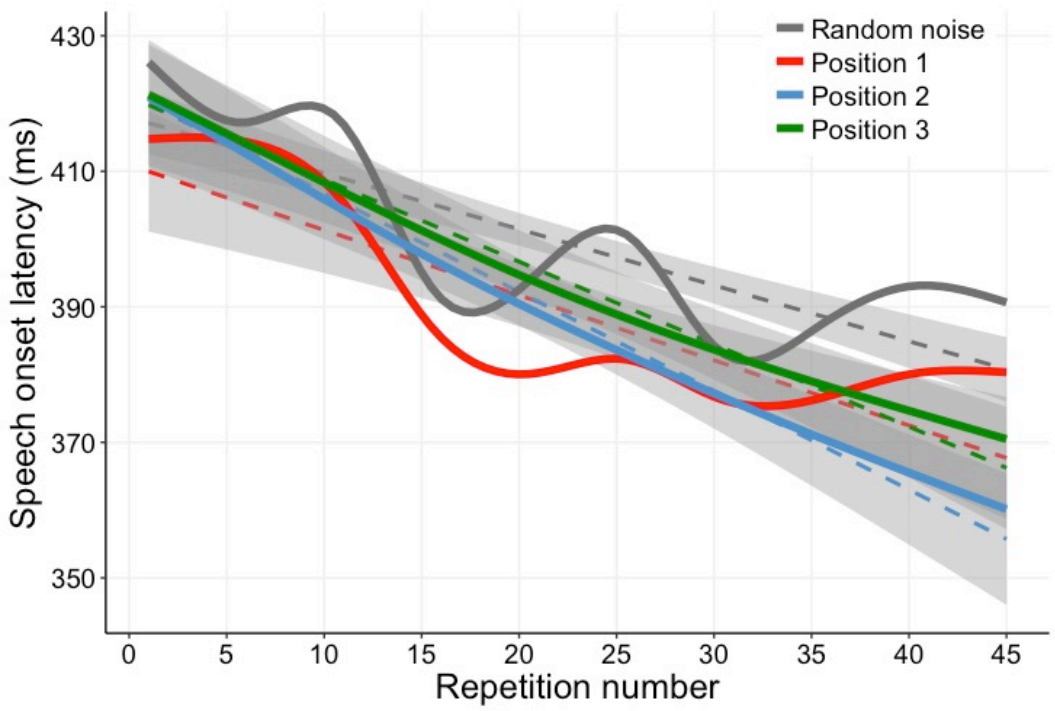


Figure 1

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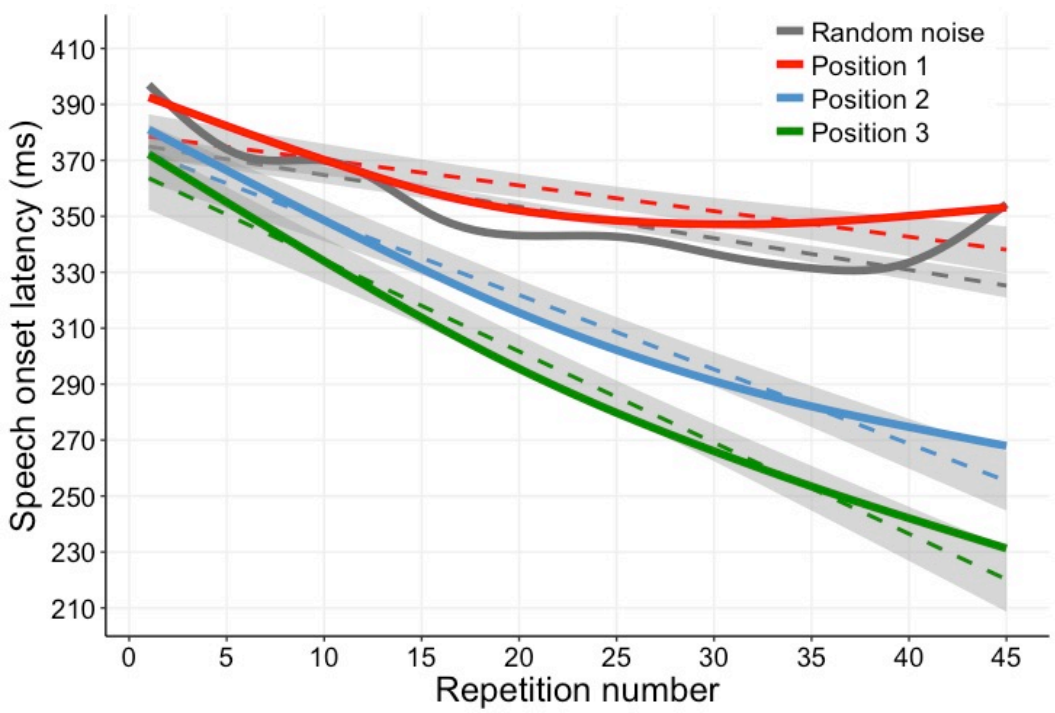
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Figure 2

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831 Figure 3

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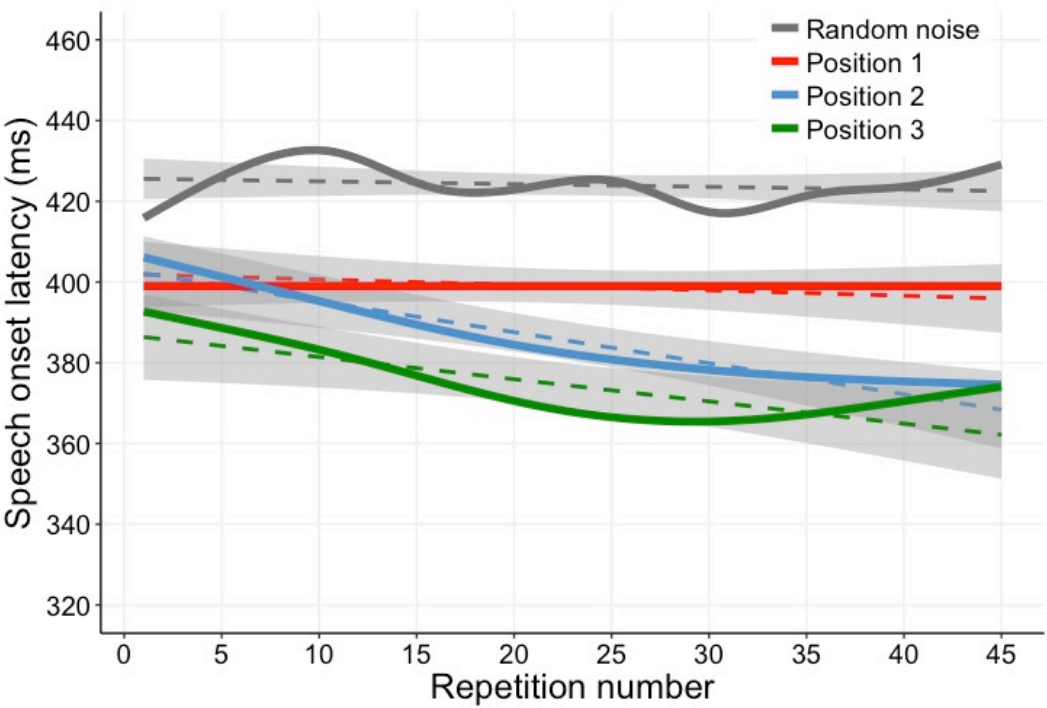


Figure 4

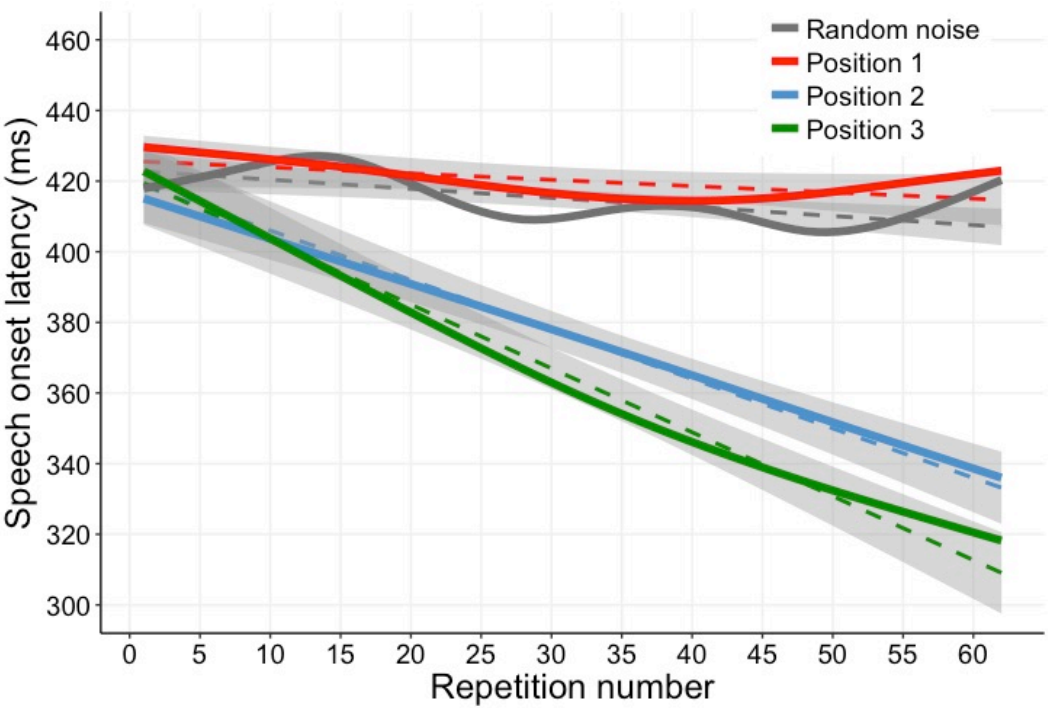
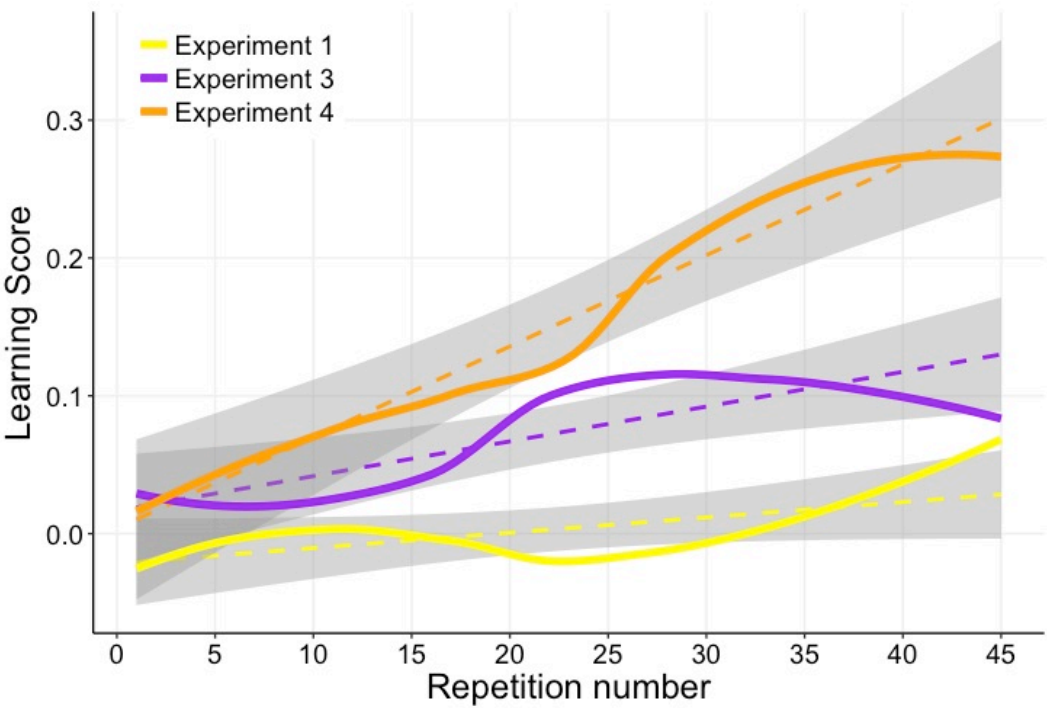


Figure 5

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850 Figure 6

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