Target Detection as an Online Measure of Adapting to Changing Statistical Regularities

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Abstract

Our environments are inherently structured, with certain stimuli or events having a higher probability of co-occurring. Statistical learning (SL), the ability to extract such regularities, is a powerful cognitive mechanism. The majority of SL studies to date, however, have treated our sensory environments as stable, assuming only a single set of to-be-learned regularities. In doing so, they overlooked the flexibility humans need to process and represent changes in the statistical patterns that make up our environments. In the current study, we exposed participants to visual and auditory sequences containing statistical regularities that changed throughout exposure. Our online learning measure, based on the reaction-time benefit in detecting predictable stimuli, showed that participants successfully learned both the initial and updated structure in the auditory modality. Our offline test, by contrast, only provided evidence for learning of the first structure in the auditory modality.

Keywords: Statistical learning; flexibility; target detection; pattern recognition; primacy effect; modality- and domain-specificity

Introduction

The environments we navigate are rife with regularities, ranging from certain sounds or words that tend to co-occur in natural language to predictable patterns of traffic flow. Statistical learning (SL), the ability to extract such regularities from sensory information (Frost et al., 2015), is a fundamental ability that subserves many of our cognitive functions, including attention (Theeuwes et al., 2022; Zhao et al., 2014; Jiang et al., 2013), linguistic abilities (Erickson & Thiessen, 2015; Siegelman, 2019) and prediction (Turk-Browne et al., 2010; Li et al., 2024). Previous studies extensively demonstrated that people are remarkably good at extracting and representing the statistical properties of their environments in unsupervised learning paradigms.

While the research on SL that followed the seminal work of Saffran et al. (1996) which showed that infants are sensitive to the transitional probabilities in continuous speech input has undoubtedly advanced our understanding of when and how learning of environmental structure is achieved (Frost et al., 2019), one important aspect of SL has been largely overlooked: its flexibility. Current approaches to SL have viewed the environment as static in terms of its structure, treating knowledge about the statistical properties of an environment as the end state. Many environments, however, are dynamic rather than fixed. Simply learning the structure of an environment without subsequently monitoring for and adapting to changes in regularities would be highly maladaptive (Frost et al., 2025).

To date, only a handful of studies have investigated the ability to adapt to changing regularities in the context of SL. A consistent finding in these experiments is a primacy effect: in a post-learning test, participants are typically worse at recognizing the patterns of a second compared to a first artificial language structure (Gebhart, Aslin & Newport, 2009; Franco, Cleeremans & Destrebecqz, 2011; Weiss et al., 2009). An important limitation of these so-called offline measures is that they only inform us about what pattern knowledge remains after learning, rather than how that knowledge is accumulated over time. Addressing this methodological limitation, Siegelman et al. (2018) used self-paced progression through a visual input stream as an online measure of learning an initial structure and adapting to a changed structure. Their results revealed that participants were generally slower to learn the updated structure compared to the first structure, but no difference was found in offline test performance. Note that self-paced exposure allows for varying exposure times per item/pair, likely impacting the learning process one is attempting to measure. In the current study, we used a target detection task as an online measure of adapting to changing regularities in both the auditory and visual modality.

Method and Results

Exposure Phase

Participants (N = 120) were first exposed to sequences of items, one item at a time. Depending on the modality, items were auditory consonant-vowel syllables or abstract visual shapes. All participants were exposed to both modalities, with the order of modalities counterbalanced across participants. Importantly, while individual items were presented at a fixed rate, the eight unique items of each stream formed 4 embedded pairs in the first half (structure 1 or S1), and were shuffled into 4 different pairs (structure 2 or S2) in the second half of each stream (see Figure 1). In addition to viewing the stream, participants were instructed to press a button as fast as possible upon detecting a prespecified target item. If participants are sensitive to the transitional probabilities between items, they should become faster at detecting targets in the second (predictable) position as opposed to the first (unpredictable) position of a pair. We used a linear mixed effects model to model reaction times in function of the modality (visual or auditory), structure (first or second) and position (predictable or unpredictable). The results suggest that participants learned the embedded pairs, both of the first and the second structure, but only in the auditory modality (see Figure 2).

Figure 1: Illustration of a visual and auditory stream

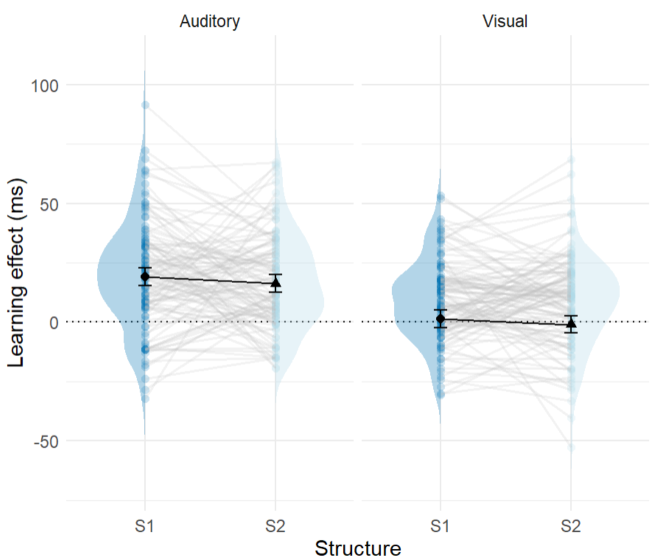

Figure 2: Estimated online learning effects per modality

Test Phase

After the target detection task, the majority of participants (*N* = 110) performed an old/new judgment task. On each trial, a combination of two items was presented and they had to indicate 1) whether the pair had been part of the input stream or not, and 2) how confident they felt in their decision. The combinations of items that formed the test items could be one of five types. Firstly, a test item could be a true pair of the first or the second structure of a stream which participants encountered during the exposure phase. Secondly, test items could be group foils, which were not encountered during the exposure phase, but did respect the group identity of either an S1 or S2 pair (i.e., a reversed true pair). Thirdly, test items could also be control foils, which were novel in every way as they did not respect the order or the group identity of any of the pairs. We found that participants were significantly better at recognizing pairs from the first structure, compared to both control foils and pairs of the second structure. We observed a similar pattern for the confidence ratings. Additionally, we observed no differences in group identity representations between both structures. These effects were once again solely driven by the auditory condition (see Figure 3 for estimated odds ratios of endorsing test items as old).

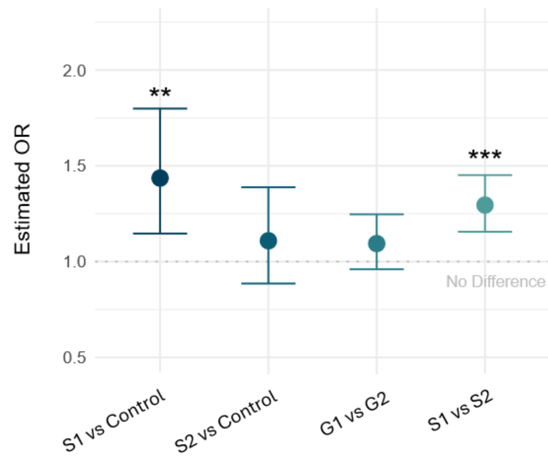

Figure 3: Estimated offline auditory learning effects

Discussion and Conclusion

Based on our online measure of learning, we found no evidence to support a primacy effect. Participants were able to learn the embedded patterns of both structures, at least in the auditory modality. Our offline learning measure, in contrast, revealed above chance performance in recognizing items of a first, but not of a second structure, pointing towards a primacy effect. Our findings align with and extend previous work arguing that on- and offline learning measures may tap into different aspects of the learning process (Batterink & Paller, 2017; Lukics & Lukács, 2021), and crucially, the adaptation in the face of structural changes (Siegelman et al., 2018). Relying solely on offline measures to gauge learning and adaptation therefore seems suboptimal, as these measures do not capture an important aspect of the learning process.

Finally, despite the comparable structure and structural change in speech and shape streams, we observed a different pattern of results, with no significant on- or offline learning in the visual modality. This finding points toward important modality or domain differences and lower-level constraints—for example, with temporal and spatial regularities being favorably learned in the auditory and visual modalities, respectively. (Conway & Christiansen, 2005; Frost et al., 2015).

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