Bidirectional Interactions between Evidence Accumulation and Rule Learning during Sensory Predictions

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Abstract:

Learning to structure incoming sensory input is crucial to build an appropriate mental model of one's environment. An abundant literature has shown that, when faced with sequences of stimuli, humans can accumulate sensory evidence, learn statistical dependencies between consecutive or non-consecutive elements, or even find abstract rules in an efficient fashion. However, although each system has been tested using ad-hoc paradigms, we lack theory and data on how these abilities might articulate with each other. While recent work has begun to investigate the relationship between statistical inference and rule learning, here we propose an experimental framework to jointly investigate evidence accumulation and rule learning in the same sensory prediction task. To do so, we presented participants with sequences of 10 Gabor patterns whose orientations could or could not follow a hidden rule in the form of a +45° switch in the middle of the sequence. Participants were always asked to estimate the angle of the last (10th) element in the sequence, while the presentation stopped after 3, 5, 7 or 9 elements, forcing them to make predictions more or less deep into the future. Computational modeling shows that this design correctly separates different inference strategies, making different assumptions about the interactions between evidence accumulation and rule learning. Pilot data suggests that human behavior in this task has the required diversity to investigate this question.

Introduction

Humans are facing a complex, yet highly organized sensory environment from which they learn to extract many relevant information. Three main types of learning in sequences have been studied: perceptual accumulation of evidence from repeated noisy sensory stimuli (Morillon et al., 2014; Wyart et al., 2012), learning statistical properties between consecutive elements (Saffran et al., 1996) or high-order statistical structure of the sequence (Benjamin et al., 2024), and learning rules where the temporal order of the elements follow a deterministic pattern that can be compressed in a language like manner (Al Roumi et al., 2021; Quilty-Dunn et al., 2022). In most studies, these learning capacities are described as relying on different cognitive and neural mechanisms (for counterpoint see Fiser & Lengyel, 2022), but they have rarely been studied conjointly, resulting in a lack of theory and data on how they articulate to form a comprehensive learning system.

Recent work started to investigate this question by presenting sequences with both statistical properties and rules (Maheu et al., 2020) and showed a discrete arbitration between those two systems. However, to our knowledge no studies have addressed the question of simultaneous perceptual accumulation of evidence and rule learning. In fact, investigating both learning mechanisms simultaneously is not trivial given the differences in paradigms used in those two literatures: perceptual learning is often studied with ambiguous, noisy, heterogeneous stimuli, whereas rules are learnt in paradigm with discrete, prototypical categories of stimuli. Here we aim at mixing both approaches by presenting participants with sequences following a rule AAAAABBBBB but where A and B are not discrete categories, but probability distributions with significant overlap.

We hypothesize that, on the one hand, evidence accumulation properties could influence rule learning. Indeed, a high level of overlap between categories, and of internal noise during inferences (Drugowitsch et al., 2016) could prevent participants from differentiating between categories A and B, thus preventing them from finding the rule. On the other hand, the discovery of the rule could radically alter the way in which items are accumulated. Another hypothesis being that the discovery of the rule does not modify the evidence accumulation system itself, but only participants' subsequent response selection. Computational modeling will allow testing and differentiating these distinct hypotheses.

Method & Results

Method

Experimental Paradigm In this task, participants must always estimate the angle of the last element of a sequence of 10 Gabor patches. The experiment consists two different types of blocks: in *stay* blocks (blue), each element of the sequence is drawn from a normal distribution around a random target with a std of 10°. In *switch* blocks (purple), we added a +45° rotation from the middle of the sequences. In other words, the last five elements were drawn from the +45°-shifted distribution compared to the five firsts. In each block, after the presentation of 6 full sequences, participants were presented with incomplete sequences, stopping after 3, 5, 7 or 9 elements, and had to estimate the angle of the last one by rotating a bar, and click on their confidence level. After each trial, they saw feedback with the answer. They performed a total of 240 trials (30 in each condition).

Preliminary data A group of n=15 (8f, $\overline{age} = 27.6\, yo$) pilot subjects performed the behavioral task at the lab and answered a questionnaire indicating what they thought the structure of the *switch* sequences was. We separated subjects in two groups based on the questionnaire answer: 4 subjects explicitly described the switching rule, while the other 11 were unable to report any significant rule. For both groups, we computed the distribution of the difference between the given answer and the average angle of the first part of the sequence. We fitted von Mises distribution to estimate the location (θ) and concentration (κ) of these angular differences for each condition and assessed between group significance using bootstrap replacement method between trials.

Computational modeling Each concentration κ could be decomposed in terms of inference noise and response noise. We performed a parameter recovery analysis to estimate how distinguishable those two sources of variability are with our design. Moreover, we distinguish three assumptions about participants' behavior: 1. Because of too high inference noise, participants are unable to distinguish A from B categories and thus ignore the rule in their responses 2. Participants used the rule to apply an offset to each given item during the inference computation 3. Participants only use their evidence accumulation system, and latter apply an offset to their response, when necessary. These three strategies reflect three different assumptions about how perceptual learning and rule learning can interact. We have modeled these three strategies and performed model recovery and parameter recovery analysis.

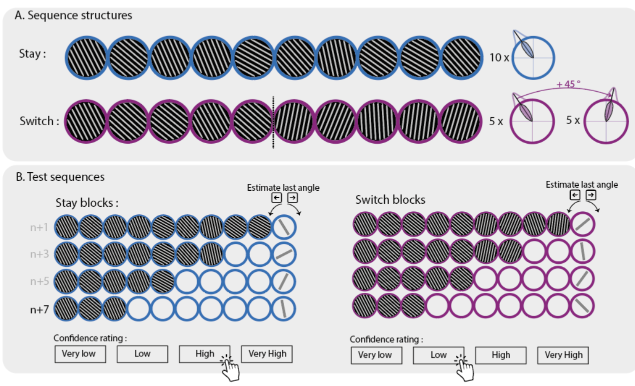

*Figure 1: **Experimental framework. A.** Participants are presented with two types of blocks : 'stay', in blue where the angle of each element is drawn from a normal distribution around the target, and 'switch' sequences, in purple, where the five last elements are +45° shifted **B.** After 6 training sequences at the beginning of each of the 12 blocks, subjects are presented with incomplete sequences stopping after 3, 5, 7 or 9 elements and asked to estimate the angle of the last item.*

Results

Recovery analyses We implemented our three models including two distinct sources of behavioral variability: inference noise and response noise. (Findling & Wyart, 2021). We first checked that the two sources of variability could be reliably estimated by carrying out a recovery analysis of the noise parameters (inference noise correlation = 0.69, response noise correlation = 0.54). We then performed a model recovery analysis: we created 150 synthetic subject data by simulating each model 50 times. We then fitted each data item to each of our three models and compared the best-fitting model to the model used for simulation. For all those synthetic subjects, the winning model corresponded correctly to the model used for the simulation, which shows that our three hypotheses are correctly dissociable with this paradigm.

Behavioral analyses Our aim is to find a difficulty level where some participants will explicitly find the rule, while others will not. This intermediate difficulty would enable us to study which parameters of evidence accumulation can trigger or prevent rule learning. Preliminary data analysis showed that explicit learners were less noisy during evidence accumulation even in the absence of any rule (κ is greater for those subjects in the *Stay* conditions n+1 and n+3). Moreover, they exhibited clearly dissociable response patterns in the *Switch* condition compared to non-explicit learners. This suggests that the task parameters are well suited to our needs. By fitting our models to human data, we found that the inference offset and response offset significantly differed between our two groups, correctly capturing their different behavior in the switch condition. Next steps include testing a full set of new subjects in the lab (n~30) and a large online dataset (n~150) to better cover the full range of possible strategies, and to fit their behavior using our three models.

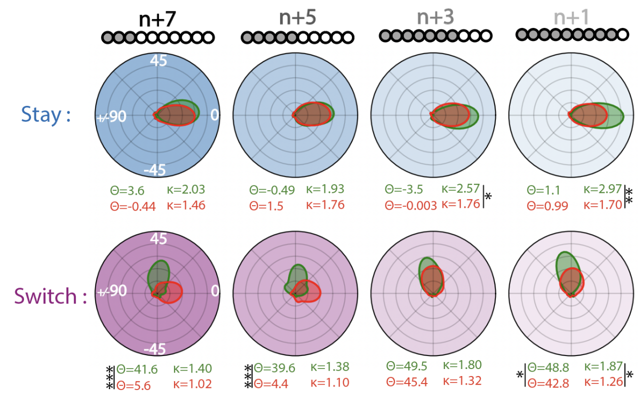

*Figure 2: **Pilot data:** For each condition, we report the distribution of the differences between the answer and the first elements of the sequence. Subject are divided in two groups bases on their post-experiment questionnaire : n=4 who explicitly found the hidden rule (green) and n=11 unable to describe the structure of the sequences (red). We observe difference in precision between both groups (κ is greater for explicit learners in the stay conditions n+1 and n+3, and switch n+1) We also see separable response locations (θ) in the switch condition n+7 and n+5. Below each plot are the fit of von Mises parameters, significance is assessed using bootstrapping (*p<.05 **p<.01 ***p<.001).*

Conclusion

Preliminary data and models suggest that this task is well suited to studying the interaction that might exist between evidence accumulation and rule learning during sensory predictions. We specifically hypothesize that this interaction occurs in both directions: inference noise during evidence accumulation impairs rule learning, whereas the discovery of abstract rules shapes how sensory inferences are made.

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