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Generalization in an evidence accumulation task

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Generalization in an Evidence Accumulation Task

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Abstract:

Humans are capable of generalizing using the similarity between the abstract features of external stimuli. The neural mechanisms underlying generalization using abstract representations are unclear, and future discoveries would be facilitated by studies in animal models. Here we developed a rat model of generalization by leveraging an existing pulse-based evidence accumulation task, with the abstract rule of choosing the side with the greater number of light pulses. We trained rats (n=14) on different curricula that limit the stimulus-action associations presented during learning and then used test trials to evaluate generalization to novel stimuli. The performance of rats was consistent with a hybrid Exemplar-to-Prototype model of learning. In this model, sensory evidence in the training trials is altered by internal noise providing an expanded perceptual experience to guide generalization. Overall, our study suggests that pulse-based accumulation tasks may be used to study the neural mechanisms of generalization in animals and highlights how noise may support cognition.

Introduction

A prominent theory suggests that perceptual generalization entails identifying similar stimuli that lead to the same outcome, with similarity defined as the distance between the stimuli in a multidimensional representation space (Shepard, 1987). This account of generalization sparked a lot of debate, as researchers disagree on the definition of similarity in abstract feature space, a space of abstract variables including but not limited to political affinity, cultures, styles and structures (i.e. mental constructs) (Ashby & Perrin, 1988; Hahn et al., 2003; Krumhansl, 1978; Nosofsky, 1986; Pothos et al., 2013; Tversky, 1977). Studying generalization in the context of evidence accumulation might enrich the dialogue, since accumulated evidence is an abstract variable, a mental construct that is inferred and calculated from sensory percepts (Nieh et al., 2021). Furthermore, there has been significant progress made in characterizing the neural correlates of decisions with accumulated evidence in animal models (Gold & Shadlen, 2007). Therefore, we studied generalization by leveraging an existing pulse-based evidence accumulation task, which can be learned by both humans and rats (Do et al., 2023; Scott et al., 2015), allowing for future comparative and circuit manipulation studies. It is however unclear if rats show generalization in the task. Here we evaluated the generalization capability of rats and tested Shepard's theory.

Methods

Rats were trained to initiate a trial and wait for a fixed duration (~1.4s) where up to 10 brief (10ms) randomly timed light pulses were presented to either side of the visual field (max of 20 pulses total). After stimulus presentation, rats selected the side with the greater number of pulses to obtain a reward (10% sucrose; Figure 1a). We trained rats (n=6) using a restricted number of light pulses (Curriculum 1, high count of 10 or 9 and low count of 1 or 0, Figure 1b). We also trained another cohort of rats (n=8) on a new curriculum (Curriculum 2, high count of 10 or 9 and low count of 1 or 0, interleaved with 1 vs 2 and 2 vs 3, Figure 1b) that ensured rats are waiting and paying even attention to all the light pulses. Generalization was evaluated using a 95% binomial confidence interval of rat's performance on test trials (3 vs 7, 4 vs 6) that have a low probability of occurrence (5%) and random reward (Figure 1c).

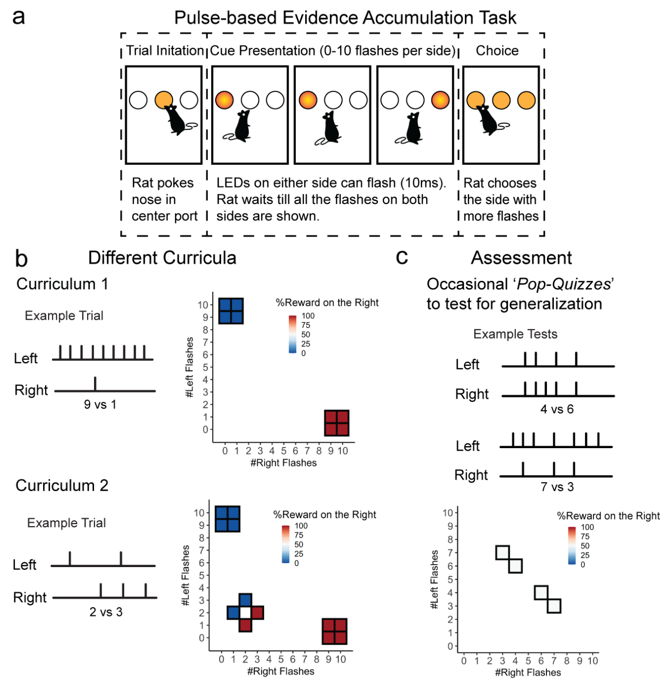

Figure 1: a) Schematic of the evidence accumulation task used in this study. b) Different curricula to control and limit the stimulus-action associations acquired by rats during learning. c) Occasional pop-quizzes with random feedback to test for generalization.

Results

Rats generalized but varied in performance due to curriculum differences.

We found that rats' performance was consistent with generalization and that their performance was consistent across the first 100 test trials (linear regression, intercept = 0.61, slope of accuracy against number of trials is not significantly different from 0, p=0.122). We expected that rats whose strategy is to memorize the stimulus-action pairings will perform at chance on the test trials, whereas rats that learned a rule will have a mean accuracy of 65.90%. This expected value was taken from the data of 14 rats trained on the same task but on all the stimulus-actions pairings and evaluated on the same trials as the test trials. We compared rats to the expected memorizer and rule learner. We found rats from both Curricula are significantly different from memorizers (p<2.2e-16, Figure 2). We found no significant difference between Curriculum 1 rats and rule learners (66.80% vs 65.90% accuracy, respectively, p=0.1, Figure 2). Surprisingly, rats trained on Curriculum 2 underperformed rats trained on Curriculum 1 on the test trials (60.14% vs 66.80% accuracy, respectively, p<2.2e-16, Figure 2).

Initially, we had expected that experiencing more stimulus-action pairings during training would help rats generalize better, but that was not the case.

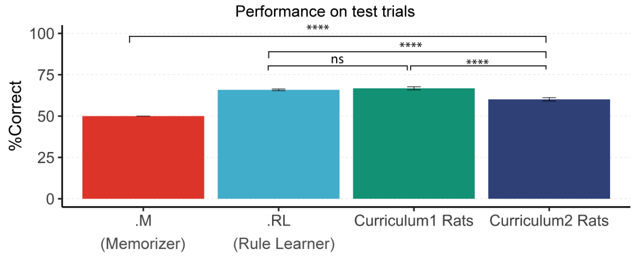

Figure 2: Rats trained on different curriculum differ in generalization's performance. Rats on both curricula are compared against the expected rule learner and memorizer.

Rats learned an evidence accumulation rule.

We regressed choice on the test trials on three different strategies that rats could use with the light pulses: primacy (first flash), recency (last flash) or perfect accumulation. For rats trained on either curriculum, we found that the best predictor of choice on the test trials is an evidence accumulation strategy (AIC = 444 vs 480 and 498, $p<0.01$ in Curriculum 1, and AIC=551 vs 568 and 570, $p<0.05$ in Curriculum 2, Figure 3a,b).

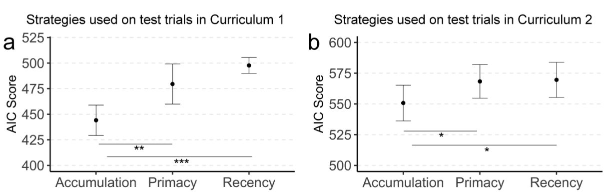

Figure 3: a, b) AIC score comparing strategies rats could use on the test trials. Lower AIC indicates better fit. Error bars (standard errors) indicate rat-to-rat variability, across the same number of test trials.

Generalization behavior in rats is consistent with an Exemplar-to-Prototype model.

Previous works suggest that rats and humans accumulate evidence with non-linear noise (Do et al., 2023; Koay et al., 2020; Scott et al., 2015). Inspired by exemplar theory (Nosofsky, 1986), we hypothesized that rats could use this noise to generate similar examples to the training trials, essentially expanding the training set to facilitate generalization (Figure 4a). We therefore trained linear classifiers on the same curricula rats are trained on, where the classification features are the noisy accumulated evidence. The classifiers however cannot predict the curriculum differences (Figure 4d). We replaced the linear classifier with a Radial Basis Function (RBF) classifier to add Shepard's similarity-by-distance constraint (Wu et al., 2019) to the accumulated evidence. The RBF kernel also cannot explain the curriculum differences (Figure 4d). Steering away from the classifier approach, inspired by prototype theory (Posner & Keele, 1968; Rosch & Mervis, 1975), we then averaged the noise-generated examples and resulting actions into a summary lookup table, which can be used to guide generalization (Figure 4b,c). Notably, our hybrid Exemplar-to-Prototype (E2P) model can explain the curriculum differences (Figure 4c,d).

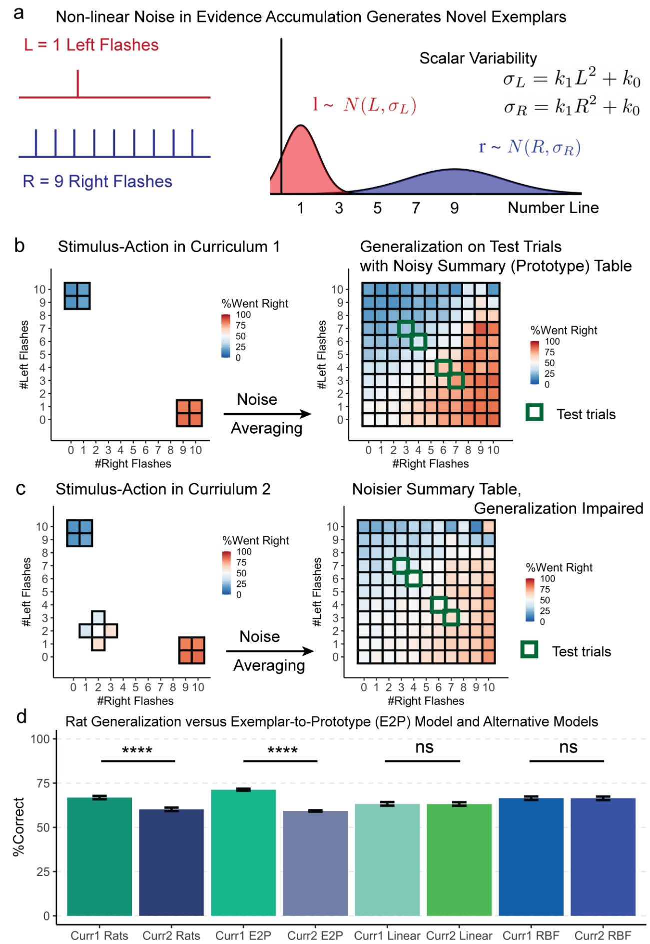

Figure 4. a) Rats accumulate evidence with noise, which generates training examples that extend beyond the stimuli presented by the experimenters. b) The stimulus-action in Curriculum 1 as observed by the experimenters versus the stimulus-action pairings as perceived by rats due to noise. The noisy accumulated evidence and the resulting actions are averaged and stored in a table, essentially a summary of the information learned. Rats can generalize on the test trials since rats have a summary table to guide choice. c) With harder training trials in Curriculum 2, the summary table that rats perceived is noisier, hence generalization is impaired. d) Performance of rats on test trials are comparable with performance on test trials as predicted by the Exemplar-to-Prototype (E2P) model across different curriculum. Support Vector Classification with Linear and Radial Basis Function (RBF) Kernels on the noisy accumulated evidence do not predict performance of rats on the test trials.

Conclusions

Our results indicate that rats can generalize in a modified pulse-based accumulation task. Surprisingly, generalization was impaired when rats were given a more diverse training set. Our results challenge the similarity-as-a-function-of-distance theory. Instead, our results are consistent with a model of generalization that combines both exemplar and prototype categorization using noise and averaging.

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