Title
Comparative analysis of visual category learning

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Authors
Freeman, John H.
Broschard, Matthew B.
Kim, Jangjin
et al.

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John H. Freeman (john-freeman@uiowa.edu)
Matthew B. Broschard (matthew-broschard@uiowa.edu)
Jangjin Kim (jangjin-kim@uiowa.edu)
Leyre Castro (leyre-castroruiz@uiowa.edu)
Edward A. Wasserman (ed-wasserman@uiowa.edu)
Department of Psychological and Brain Sciences, The University of Iowa
301 East Jefferson Street, Iowa City, IA 52242, USA

Vladimir M. Sloutsky (sloutsky.1@osu.edu)
Department of Psychology, The Ohio State University
1835 Neil Avenue, Columbus, OH 43210, USA

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Introduction

Categorization is critical for our ability to organize information. A comparative analysis may provide important insights into the cognitive and neural mechanisms underlying category learning. We have examined category learning in rats and pigeons because of differences in brain organization between mammals and birds. Species differences in category learning and representation can indicate how the differences in brain organization lead to differences in cognition.

Category structure and supervision are factors importantly influencing category learning and representation in humans (Kloos & Sloutsky, 2008; Love, 2002). Humans can learn categories with dense defining features with no supervision, but we need supervision to learn categories with sparse features. These finding have been interpreted as evidence for multiple category learning systems in the brain. The current study examined the roles of feature density and supervision in visual category learning in rats and pigeons.

Experiment 1

Rats were trained on a discrimination task earlier used for category learning with photographic stimuli (Brooks et al., 2013). Rats were trained with two visual categories in which feature density could be precisely manipulated (see Figure 1). One category was associated with a left response, whereas the other category was associated with a right response.

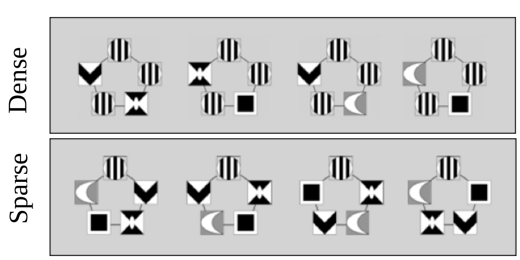

Figure 1: Exemplars of one high-density (dense) category (top) and one low-density (sparse) category (bottom).

Each stimulus category had five features. In the dense condition, three of the features were category-relevant, whereas the sparse condition had only one relevant feature. High supervision was defined as delivery of a food reward only after a correct choice. In contrast, low supervision was defined as delivery of a food reward regardless of whether or not the choice was "correct." Rats were trained in a 2 x 2 design with density and supervision as factors: dense–high supervision, sparse–high supervision, dense–low supervision, and sparse–low supervision. The rats were trained until reaching a criterion of 75% correct responding for both categories for 2 consecutive days or for a maximum of 60 days. After meeting the training criterion, the rats were given testing sessions in which training stimuli were mixed with probe trials. Probe trials included novel exemplars (novel irrelevant features), rotated stimuli (in which the relevant features appeared in different locations), and singleton stimuli (only one relevant feature was presented, in the absence of any other features).

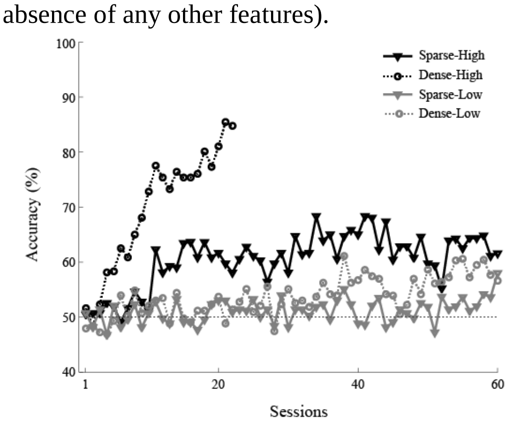

Figure 2: Mean accuracy of rats trained in the dense–high supervision (dense-high), sparse–high supervision (sparse-high), dense–low supervision (dense–low), and sparse–low supervision (sparse-low) conditions.

All rats in the dense–high supervision condition (6/6) showed rapid learning of the two categories (see Figure 2). They also showed very high accuracy with novel stimuli. Accuracy dropped significantly when rotated or singleton stimuli were presented, suggesting that the rats' representations of the categories included feature-location binding. Some of the rats in the sparse–high supervision condition (2/6) learned and showed substantial generalization to novel exemplars. Like rats in the dense–high supervision condition, the rats in the sparse–high supervision condition that learned showed a significant drop in accuracy during presentations of the rotated and singleton test stimuli. Rats trained in the low supervision conditions did not learn. Only one rat in the dense–low supervision condition reached criterion performance. Rats that did not learn showed a position bias and were slower to learn when switched to high supervision.

Experiment 2

Pigeons were trained and tested under identical conditions as the rats. This experiment is in progress and, currently, training and testing has been conducted with a limited number of animals: dense–high supervision (2), sparse–high supervision (3), dense–low supervision (2), and sparse–low supervision (3). All of these pigeons learned relatively quickly, compared to the rats.

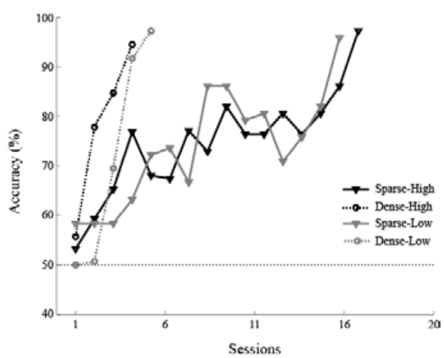

Figure 3: Mean accuracy of pigeons trained in the dense–high supervision (dense-high), sparse–high supervision (sparse-high), dense–low supervision (dense–low), and sparse–low supervision (sparse-low) conditions.

As can be seen in Figure 3, pigeons in the high density conditions learned rapidly, in five or fewer sessions, regardless of the level of supervision. They also showed very high accuracy to novel stimuli (above 90%), and to rotated and singleton stimuli as well (above 90%). Pigeons in the sparse conditions took longer to learn but, just as in the dense conditions, the level of supervision minimally affected their rate of learning. In both sparse conditions, accuracy to novel stimuli was high, albeit lower than in the dense conditions (85%). Accuracy to the singleton stimuli was high as well (85%), but it dropped a bit more for the rotated stimuli (75%). Pigeons' representations of the categories seemed to include feature-location binding as well, just as we observed in the rats; however, this factor played a much smaller role in the pigeons' performance.

Conclusions

The results indicate clear differences in category learning between rats and pigeons. Pigeons learned rapidly in all four conditions and their learning rate was not affected by the level of supervision. For pigeons, the most important factor was the density of category-relevant features—dense categories were learned faster than sparse categories. In contrast, rats showed robust learning only in the dense–high supervision condition. Statistical density is therefore a crucial factor for visual category learning in birds, rodents, and humans. The interaction of density and supervision is more complex, however, and may be related to whether the organism is remembering visual features, binding features and spatial locations, or learning category rules.

The differences in category learning between pigeons and rats may reflect differences in brain organization. Birds do not have a laminar cortex or a prefrontal cortex. Thus, the pigeons' insensitivity to the level of supervision might be related to the absence of prefrontal processing of differential reinforcement. The clear superiority in learning rate in the pigeons relative to the rats suggests, however, an advantage in memory for visual stimuli, which might be related to specializations within the visual areas of the avian brain.

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