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Review

A review of medial temporal lobe and caudate contributions to visual category learning

E.M. Nomura[a,b], P.J. Reber[a,b,*]

[a]Department of Psychology, Northwestern University, 2029 Sheridan Road, Evanston, IL 60201, USA
[b]Institute for Neuroscience, Northwestern University, Chicago, IL 60611, USA

Abstract

Here we review recent functional neuroimaging, neuropsychological and behavioral studies examining the role of the medial temporal lobe (MTL) and the caudate in learning visual categories either by verbalizeable rules or without awareness. The MTL and caudate are found to play dissociable roles in different types of category learning with successful rule-based (RB) categorization depending selectively on the MTL and non-verbalizeable information-integration (II) category learning depending on the posterior caudate. These studies utilize a combination of experimental cognitive psychology, mathematical modeling (Decision Bound Theory (DBT)) and cognitive computational modeling (the COVIS model of Ashby et al. [1998. A neuropsychological theory of multiple systems in category learning. Psychological Review 105, 442–481]) to enhance the understanding of data obtained via functional magnetic resonance imaging (fMRI). The combination of approaches is used to both test hypotheses of the cognitive model and also to incorporate hypotheses about the strategies used by participants to direct analysis of fMRI data. Examination of the roles of the MTL and caudate in visual category learning holds the promise of bridging between abstract cognitive models of behavior, systems neuroscience, neuropsychology, and the underlying neurophysiology of these brain regions.

Keywords: Decision bound modeling; Categorization; Rule-based; Information-integration

Contents

1. Introduction

Categorization is a skill that allows us to respond similarly to distinct objects in the environment that share certain features. In visual categorization, novel stimuli are

*Corresponding author. Department of Psychology, Northwestern University, 2029 Sheridan Road, Evanston, IL 60201, USA.
Tel.: +1 847 467 1624; fax: +1 847 491 7859.
E-mail address: preber@northwestern.edu (P.J. Reber).

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evaluated based on their perceptual features and treated as members of a category of related items (e.g., cats or dogs). Through experience with category members, new category representations can be formed that allow further identification of novel category members. The category learning process is a topic of broad and active investigation (Ashby and Maddox, 2005) for experimental cognitive psychology, computational cognitive models and cognitive neuroscience.

The process of creating a representation of category structure can be described as partitioning perceptual space and assigning category labels (or motor responses) to regions that encompass a collection of similar stimuli. One formulation of this process is decision-bound theory (DBT) of category learning first proposed by Ashby and Gott (1988). The basis of DBT is that people learn to assign motor responses to different regions in perceptual space. When presented with a to-be-categorized stimulus, subjects determine in what region the stimulus has fallen and produce the associated response. In this approach, learning the categories amounts to identifying the decision-boundary that separates the categories in the perceptual space. One consequence of this decision boundary is that those category members that are perceptually far from the boundary are categorized more easily and with higher confidence than those that are close to the boundary.

A number of reports supported DBT as an effective model of visual category learning (Ashby and Gott, 1988; Ashby and Maddox, 1990, 1992). Typically, the stimuli in these experiments vary on two dimensions. For example, in one task, subjects are asked to categorize rectangular stimuli that vary in either the length or the width (Fig. 1a). In another task, the stimuli are circles of different diameters that have an internal line that varies in orientation (Fig. 1b). The stimuli can also be perceptually more complex, such as sine wave gratings (Fig. 1c). All of

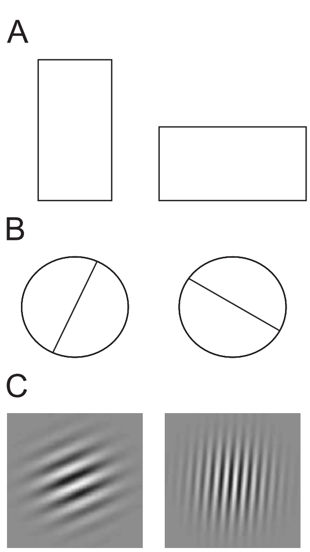

Fig. 1. (A) Rectangular stimuli that vary in width and length. (B) Circular stimuli that vary in diameter and line orientation. (C) Sine wave stimuli that vary in frequency and orientation.

these examples can come from the same category structure, only differing in the stimulus dimensions. The two-dimensional perceptual space is partitioned into two (or more) categories by decision boundaries that can be linear or non-linear. A non-linear boundary requires a more complex representation, but even linear boundaries can vary in the demands placed on the category learner.

A linear boundary that segments the perceptual space along one dimension (e.g., a horizontal or vertical boundary) creates two categories that can be easily described by a verbal rule. In contrast, a linear decision boundary that does not fall along a cardinal orientation requires the learner to integrate information across the two dimensions in order to determine category membership. In the first case, the category structure is considered rule-based (RB) in that a simple rule describes the categories. In the second case, determining the category structure requires information-integration (II) and cannot be accomplished using a simple rule. In RB category structures, participants tend to use an explicit reasoning process consisting of one or more verbalizable rules to learn the category (Ashby et al., 1998). Typically, only one of several stimulus features is relevant, so participants can systematically test the different features to discover a rule that will allow for accurate categorization. For example, in Fig. 2a the optimal decision boundary is a uni-dimensional rule that only depends on the frequency of the stimuli. In II tasks, category membership is best determined by integrating two or more stimulus dimensions before making a category judgment (Ashby et al., 1998). An important characteristic of the II task is that the optimal strategy is very difficult to verbalize and may not be available to conscious awareness. As you can see in Fig. 2b, accurate categorization can only be achieved by incorporating both frequency and orientation information. Learning II category structures may rely on an implicit, procedural-learning-based system that gradually associates response labels with regions in stimulus space (Ashby and Waldron, 1999).

The COmpetition between Verbal and Implicit Systems model (COVIS model) proposed by Ashby et al. (1998) provides a specific hypothesis about the neural basis of RB and II categorization. In this model, two learning systems compete to provide the output response: an explicit, RB system dependent upon working memory and attention; and an implicit, II procedural learning system.

While the COVIS theory is based on the connections and computational properties of cortico-striatal circuits, the parallels between the multiple neural systems theory of categorization and multiple memory systems of the brain is of note. Studies of memory dating to Scoville and Milner (1957; Squire, 1992) have established an important difference between conscious, declarative memory based on the medial temporal lobe (MTL) and a collection of heterogeneous non-declarative memory systems. Studies of non-declarative memory have shown the importance of the basal ganglia for some non-declarative memory tasks,