CHAPTER

# 8

# The Neuropsychology of Perceptual Category Learning

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OUTLINE



## Abstract

There is widespread agreement that multiple qualitatively different category learning systems mediate the learning of different category structures. Two systems that have received support are a frontal-based explicit system that uses logical reasoning, depends on working memory and executive attention, and is mediated primarily by the anterior cingulate, the prefrontal cortex and the associative

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striatum, including the head of the caudate. The second is a basal ganglia-mediated implicit system that uses procedural learning, requires a dopamine reward signal and is mediated primarily by the sensorimotor striatum (i.e., the tail of the caudate and putamen). This chapter reviews a large body of work conducted in our laboratory and others that examines the details of the two proposed systems using neurological patients as experimental participants. Collectively the studies suggest significant involvement of the striatum and less involvement of the medial temporal lobes in category learning. They also suggest that, in striatal-damaged patients, the need to ignore irrelevant information is predictive of a rule-based category learning deficit, whereas the complexity of the rule is predictive of an information-integration category learning deficit.

## 8.1 INTRODUCTION

Category learning involves laying down a memory trace that can be used to improve the efficiency (i.e., accuracy and speed) of responding. It is now widely accepted that mammals have multiple memory systems (Schacter, 1987; Squire, 1992), and this fact alone makes it reasonable to postulate that multiple category learning systems might also exist. This chapter reviews a body of work that suggests that perceptual category learning is characterized by multiple systems each of which involves a set of diverse neurocognitive processes. This chapter builds upon the work outlined in the previous chapter by Ashby and Valentin, who reviewed a number of studies that tested a priori predictions from a successful neurobiologically plausible multiple systems theory called Competition between Verbal and Implicit Systems theory (COVIS; Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Waldron, 1999; for a review see Ashby & Maddox, 2005, 2011; Ashby, Paul, & Maddox, 2011; or Maddox & Ashby, 2004). In each study, a specific experimental manipulation was introduced that was predicted to affect processing in one system but not the other. All of these studies used healthy young adults as participants. These studies provide a nice foundation, but the next step is to examine the systems in greater detail. One way to achieve this goal is to examine category learning in neurological patients with damage to specific brain areas. The aim of this chapter is to review a body of work conducted in our and other laboratories that examined category learning in various patient populations.

This chapter was originally published in 2005 in the first edition of this Handbook. We continue to include much of the seminal work reviewed in the first edition in this second edition because it provides the necessary historical context. We then supplement this with a review of much of the exciting work conducted in the last decade. The chapter examines research in patients with amnesia, Parkinson's disease (PD), and Huntington's disease (HD), as well as schizophrenia and Alzheimer's disease (AD).

The chapter emphasizes work in Parkinson's disease because the striatum is the most critical brain region proposed in much recent theoretical and empirical work, and therefore this is a population that we have explored most extensively.

This chapter is organized as follows. In the first (next) section we briefly introduce COVIS and the proposed underlying neurobiology. A more detailed description is offered in the previous chapter and in the review papers cited above. The second section reviews briefly some of the seminal qualitative dissociations introduced in the previous chapter. Since the publication of the first edition of this Handbook, over 20 novel dissociations have been identified and supported empirically. The third section reviews a body of work that examines category learning in various patient populations. The third section is subdivided into sections devoted to rule-based and information-integration category learning in patients with amnesia, PD or HD, schizophrenia, and AD. The final section offers a brief summary and conclusions. It is important to note that this is not a substantive review of the field. Two excellent reviews are provided by Kéri (2003) and Poldrack and Packard (2003). Rather, this chapter reviews and integrates a large body of patient work that takes a systematic empirical approach, supplemented by the application of a series of quantitative models to the study of perceptual category learning.

### 8.1.1 COmpetition Between Verbal and Implicit Systems (COVIS)

A growing body of research suggests that the learning of different types of category structures is mediated by different systems with distinct but partially overlapping neurobiological substrates (Ashby & Ell, 2001, 2002; Erickson & Kruschke, 1998; Maddox & Ashby, 2004; Pickering, 1997; Reber & Squire, 1994; Smith, Patalano, & Jonides, 1998; however, see Nosofsky & Johansen, 2000). One of the most successful multiple systems models of category learning, and the only one that specifies the underlying neurobiology, is COVIS. COVIS postulates two systems that compete throughout learning: an explicit, hypothesis-testing system that uses logical reasoning and depends on working memory and executive attention, and a procedural learning-based system that relies more on incremental and feedback-learning processes. One intriguing aspect of the procedural learning-based system is its association with those processes involved in motor performance (e.g., Hazeltine & Ivry, 2001; Willingham, 1998), which leads to the important prediction that categories learned via a procedural learning-based system should have a close link to the motor response.

Much of the evidence for multiple category learning systems comes from two different types of categorization tasks. *Rule-based category learning tasks* are those in which the category structures can be learned via some explicit reasoning process that treats each stimulus dimension separately. Frequently, the rule that maximizes accuracy (i.e., the optimal rule) is easy to describe verbally (Ashby et al., 1998). For example, in Fig. 8.1A, the stimuli (with one presented on each trial) are composed of a single line that varies in length and orientation across trials. (Another popular set of stimuli are Gabor patches that vary across trials in spatial frequency and spatial orientation). Each symbol in Fig. 8.1 denotes the length and orientation of one stimulus. Also shown in Fig. 8.1 are the decision bounds that maximize categorization accuracy. In the rule-based task, the optimal bound requires observers to attend to length and ignore orientation. The vertical bound in Fig. 8.1A corresponds to the rule: "Respond A if the line is short and B if it is long."

*Information-integration category learning tasks* are those in which accuracy is maximized only if information from two or more stimulus components (or dimensions) is integrated at some predecisional stage (Ashby & Gott, 1988). Perceptual integration could take many forms — from treating the stimulus as a Gestalt to computing a weighted linear combination of the dimensional values.[1] In many cases, the optimal rule in information-integration tasks is difficult or impossible to describe verbally (Ashby et al., 1998). The information-integration task in Fig. 8.1 was generated by rotating the rule-based categories by 45°. Notice that the information-integration rule is linear. Fig. 8.1C depicts a case in which the information-integration rule is nonlinear. Category structures like these were used in the studies reviewed in the previous chapter and in some of the studies reviewed below.

COVIS assumes that learning in rule-based tasks is dominated by an explicit system that uses working memory and executive attention to generate and test hypotheses and is mediated primarily by the anterior cingulate, the prefrontal cortex, and the associative striatum, including the head of the caudate (see Fig. 7.2 from the previous chapter). Learning in information-integration tasks is dominated by a procedural learning-based system that relies heavily on the sensorimotor striatum (see Fig. 7.3 from the previous chapter; Ashby et al., 1998; Ashby & Ell, 2001; Ashby & Ennis, 2006; Willingham, 1998).

[1]A conjunction rule (e.g., respond A if the stimulus is small on dimension $x$ and small on dimension $y$) is a rule-based task rather than an information-integration task because separate decisions are first made about each dimension (e.g., small or large) and then the outcome of these decisions is combined (integration is postdecisional, not predecisional).

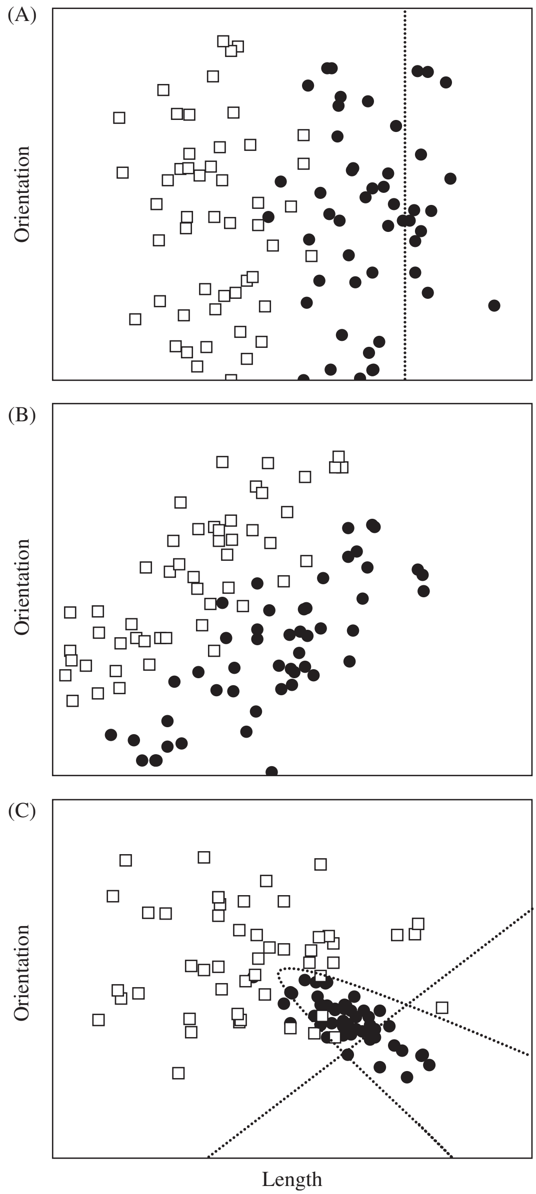


**FIGURE 8.1** Stimuli and optimal decision bound from a (A) rule-based, (B) linear information-integration, and (C) nonlinear information-integration categorization condition. Open squares denote category A items, and filled circles denote category B items.

### 8.1.2 Testing a Priori Predictions From COVIS

In this section we briefly review a number of studies that provided empirical tests of highly specific predictions derived from the proposed neurobiological underpinnings of COVIS. Because the hypothesis-testing system is under conscious control and has full access to working memory and executive attention, the placement and timing of the feedback signal should not be critical for rule-based category learning because this information can be held consciously in working memory. In contrast, a procedural learning system that relies on the striatum is far removed from working memory. As a result, it depends more heavily on the placement and timing of the feedback.

As a test of these predictions, rule-based and information-integration category learning have been compared across an observational training condition in which observers were informed of category membership before stimulus presentation, and a traditional feedback training condition in which the category label followed the response (Ashby, Maddox, & Bohil, 2003). Rule-based and information-integration category learning have also been compared across an immediate feedback condition in which corrective feedback was provided immediately following the response, and a delayed feedback condition, in which feedback was delayed by 2.5, 5, or 10 seconds after the response (Maddox, Ashby, & Bohil, 2003; Maddox & Ing, 2005; however, see: Ell, Ing, & Maddox, 2009; Worthy, Markman, & Maddox, 2013). In line with the COVIS predictions, observational training and delayed feedback negatively impacted information-integration category learning but had little effect on rule-based category learning.

The alternative to the explicit system in COVIS is assumed to be procedural learning-based. The quintessential paradigm for studying procedural learning is the serial reaction time (SRT) task. In a typical SRT task, one of $n$ stimuli is presented on each trial and each stimulus is associated with its own response key. The observer's task is to press the relevant key as quickly as possible. A large response time improvement is observed when the stimulus sequence is repeated, despite the observer's lack of awareness that a sequence exists. Willingham, Wells, Farrell, and Stemwedel (2000) showed that changing the location of the response keys interferes with SRT learning even when the sequence of stimulus positions is unchanged. In addition, they showed that SRT learning is unaffected by changing the sequence of finger movements as long as the location of the response keys remains fixed. If the nonexplicit system in COVIS is procedural learning-based, then it should be the case that changing the location of the response keys should adversely affect learning in this system, and thus information-integration category learning, whereas changing the finger press associated with each category response should not. On the other hand, hypothesis-testing systems are not typically linked to a specific motor response and should not be especially sensitive to procedures that change the mapping between category label and response location. Two studies directly tested these hypotheses. Ashby, Ell, and Waldron (2003) examined rule-based and information-integration category learning using a training-transfer procedure. There were three conditions: control, hand-switch, and button-switch. In the control condition, the response key assigned to category A was pressed with the left index finger and the response key assigned to category B was pressed with the right index finger during both training and transfer. In the hand-switch condition, the hands were crossed during training so that the response key assigned to category A was pressed with the right index finger and the response key assigned to category B was pressed with the left index finger. During transfer, the hands were uncrossed on the response keys. In the button-switch condition, training was identical to that in the control condition, but during transfer the locations of the buttons were switched. For the rule-based task, hand switching and button switching had no effect on performance. For the information-integration task, on the other hand, button switching led to a decrement in performance, but hand switching did not. These results suggest that the hypothesis-testing system learns abstract category labels, whereas the procedural-learning system learns response positions.

In a related study, Maddox, Bohil, and Ing (2004); also see: Maddox, Lauritzen, and Ing (2007), examined rule-based and information-integration category learning across two conditions. In the fixed response location condition, the response key assigned to category A was pressed with the left index finger, and the response key assigned to category B was pressed with the right index finger. In the variable response location condition, the response key assigned to category A was pressed with the left index finger on half the trials, and with the right index finger on the other half. In line with the predictions from COVIS, information-integration category learning, but not rule-based category learning was adversely affected in the variable response location condition.

Experimental manipulations that adversely affect rule-based, but not information-integration learning, have also been identified. Waldron and Ashby (2001); also see: Zeithamova and Maddox (2006), showed that rule-based category-learning was disrupted more than information-integration category learning by the simultaneous performance of a task that required working memory and executive attention (a numerical Stroop task). In addition, Maddox, Ashby, Ing, and Pickering (2004); also see: Filoteo, Lauritzen, and Maddox (2010); Zeithamova and Maddox (2007), showed that rule-based category learning was disrupted by a sequential memory scanning task whereas information-integration category learning was not.

Taken together, these studies provide strong support for the existence of hypothesis-testing and procedural-learning based systems of category learning and for the neurobiological underpinnings proposed in COVIS. These are only a small sampling of over 20 dissociations that have now been published in the literature. Collectively, these dissociation studies provide an excellent first step and help lay the groundwork for more detailed examinations of each system. Although several methods are available for studying each system in greater detail, our work has focused on applications to individuals with various neurological conditions. We turn now to a review of this work.

### 8.1.3 Perceptual Category Learning in Neurological Patients

In the 1980s and 1990s one of the most successful models of category learning and recognition memory was exemplar theory (e.g., Nosofsky, 1992). Exemplar models assume that people access memory traces (perhaps subconsciously) of exemplars when asked to recognize or categorize. This theory is parsimonious because it assumes that the same memory representation underlies both recognition and category learning. If exemplar theory is correct, people with impaired memory storage or consolidation processes should show deficits in recognition and category learning (Pickering, 1997). Amnesic patients have storage and consolidation problems, and they generally have damage to the hippocampus and connected structures (e.g., surrounding medial temporal lobe regions and the diencephalon), so amnesic patients should show both types of deficits. In a classic study, Knowlton, Squire, and Gluck (1994) examined probabilistic classification learning in a group of amnesic patients. The task (referred to as the weather prediction task) required participants to classify stimuli into one of two categories based on the relationship (or association) between multiple stimulus attributes. Specifically, participants were presented with one to three visual cues and were asked to predict whether there would be "rain" or "sun." Corrective feedback was provided following each response. There were 14 different combinations of four cues, and each combination was differentially associated with the probability of "rain" or "sun." Knowlton et al. (1994) found that amnesic patients with damage to the hippocampus or diencephalon performed normally on this "weather prediction" task (at least for the first 50 trials), whereas these same patients were impaired when asked specific questions about the learning context (i.e., an explicit memory task). Thus, amnesic patients were able to learn categories but were unable to recall consciously the circumstances surrounding their learning, suggesting that the hippocampus does not mediate early category learning.

It is important to note that amnesiacs showed normal category learning during the first 50 trials, but they did not perform as well as controls later in learning (i.e., during the last 200 trials). Because only 14 unique cue−stimulus combinations were utilized, Knowlton et al. (1994) suggested that this "late-training deficit" resulted because normal controls used explicit memory for the stimuli that arose from multiple stimulus presentations, whereas the amnesic patients were unable to use such information (for a related explanation, see Gluck, Oliver, & Myers, 1996). Recent work suggests also that there are a number of qualitatively different strategies that can be used to solve this task that range from strategies involving attention to a single stimulus attribute to the optimal strategy that involves attention to all attributes (Gluck, Shohamy, & Myers, 2002; see also Ashby & Maddox, 2005).

The Knowlton et al. (1994) study is important because it was one of the first to suggest that category learning and recognition memory might be mediated by different neural substrates. Even so, there are at least two problems with this study. First, the use of only 14 unique cue−stimulus combinations is problematic. This small number of stimuli allows the participant (with intact explicit memory) to use explicit memory processes to improve categorization performance. To control for the possibility that explicit memory processes will be invoked, and to provide a better test of category learning in amnesia, categories that contain a large number of stimuli should be used. Second, the fact that a large number of qualitatively different strategies can be used to accurately solve the task is problematic. A better approach would be to use a task in which a single uniquely identifiable optimal rule (i.e., the rule that maximizes long-run accuracy) can be identified, and for which other strategies yield worse accuracy. Similarly, it would be advantageous to utilize a model-based approach to identify the types of strategies that are being used and to help localize the cognitive processes that lead to any performance decrement.

### 8.1.4 Information-Integration Category Learning in Amnesia

Filoteo, Maddox, and Davis (2001a) took such an approach to study category learning in amnesic patients. Filoteo et al. (2001a) utilized the perceptual categorization task (also called the general recognition randomization technique; Ashby & Gott, 1988) that has been used extensively to study category learning in healthy young adults, and attentional processes in healthy older adults and patients with Parkinson's disease (see Filoteo & Maddox, 2007; Maddox, Filoteo, Delis, & Salmon, 1996;

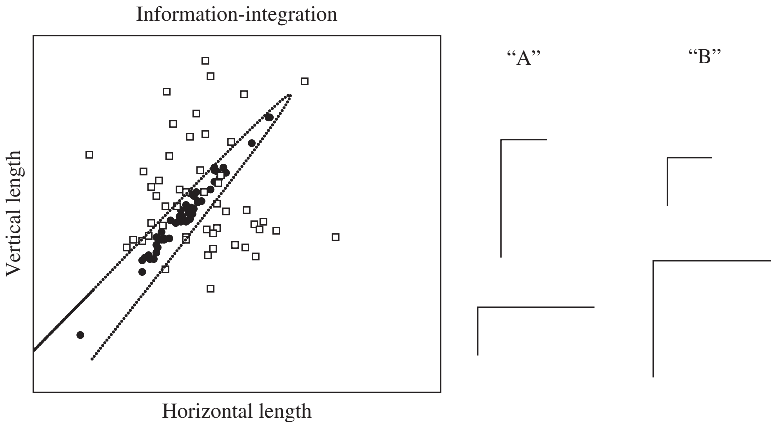


**FIGURE 8.2** Nonlinear information-integration category structures and representative stimuli used in Filoteo, Maddox, and Davis (2001a, 2001b). Open squares denote category A stimuli and filled circles denote category B stimuli. The broken quadratic curve denotes the optimal decision bound.

Maddox, Filoteo, & Huntington, 1998). In a typical perceptual categorization task, the participant is presented with simple stimuli such as a horizontal and vertical line connected at the upper left (see Fig. 8.2), and is asked to categorize the stimuli into one of two categories. Prior to the experiment, two bivariate normally distributed categories are specified, and a large number of stimuli are sampled randomly from each bivariate normal distribution. In the Filoteo et al. (2001a) study, 50 unique stimuli were sampled from category A and 50 from category B. With such a large number of unique stimuli, explicit memory processes cannot easily be invoked to improve categorization performance. Because the stimuli are two-dimensional, a unique point in a two-dimensional space can represent each. Fig. 8.2 depicts the distribution of stimuli used in this study in this two-dimensional space, where the x-axis represents the length of the horizontal line and the y-axis represents the length of the vertical line. Open squares denote category A stimuli and filled circles denote category B stimuli.

Because the categories are normally distributed, they overlap and a single experimenter-defined categorization rule (i.e., the rule that maximizes long-run accuracy) can be derived (e.g., Maddox & Ashby, 1993). The form of the rule is determined by the relationship between the two category distributions and thus, depends on the relationship between the two stimulus attributes. Filoteo et al. (2001a) examined an information-integration categorization rule that was based on a highly nonlinear relationship between the two stimulus attributes. The broken quadratic curve in Fig. 8.2 denotes the optimal categorization rule (or boundary), and yields 95% correct.

Because the category structures are defined a priori, the experimenter has a great deal of control over potentially important aspects of the categories, such as the optimal accuracy rate and the shape of the optimal categorization rule (e.g., linear or nonlinear), to name a few. An additional advantage of the perceptual categorization task is that a number of quantitative models of category learning have been developed specifically for application to data collected in this task (Ashby & Maddox, 1993; Maddox & Ashby, 1993). Categorization accuracy (i.e., per cent correct) is the typical metric used in neuropsychological studies of category learning, and although its use has several strengths there are at least two weaknesses of accuracy analyses. First, because accuracy analyses generally focus on averaged performance (e.g., ANOVA) important individual differences may be obscured. The model-based approach utilized by Filoteo et al. (2001a), on the other hand, allows one to identify and quantify performance at the individual participant level. Second, accuracy based analyses do not allow the researcher to tease apart the separate effects of various cognitive processes on performance. For example, categorization accuracy is affected not only by the participant's ability to learn the experimenter-defined categorization rule, but also by their ability to accurately apply the learned rule on each trial.[2] The first process we refer to as *categorization rule learning*. Difficulty learning the experimenter-defined categorization rule (denoted by the broken curve in Fig. 8.2) will lead to a reduced accuracy level. The second process we refer to as *rule application variability*. This has to do with the participant's ability to consistently apply from one trial to the next whatever categorization rule they might have learned. Greater variability in rule application can also lead to reduced accuracy. Both categorization rule learning and rule application variability will affect accuracy measures, and thus at the level of accuracy these two processes are nonidentifiable. The model-based approach utilized by Filoteo et al. (2001a) alleviates this problem because it allows one to *separate* categorization rule learning from rule application variability. The modeling approach will be summarized briefly after we review the experimental findings.

Filoteo et al. (2001a) had two amnesic patients and five matched controls complete 6 100-trial blocks of trials in the perceptual categorization task using the Fig. 8.2 category structures. On each trial a stimulus was selected at random and was presented on the computer screen, the participant generated a category A or category B response, and corrective feedback was provided.

The top panel of Fig. 8.3 displays the proportion correct for the amnesic and control participants during the first 100 trials and the final 100

[2]We are using the term "rule" more generally here than in COVIS. In the current application, the "rule" might be verbalizable or nonverbalizable. It might involve learning a decision bound or assigning responses to regions of perceptual space.

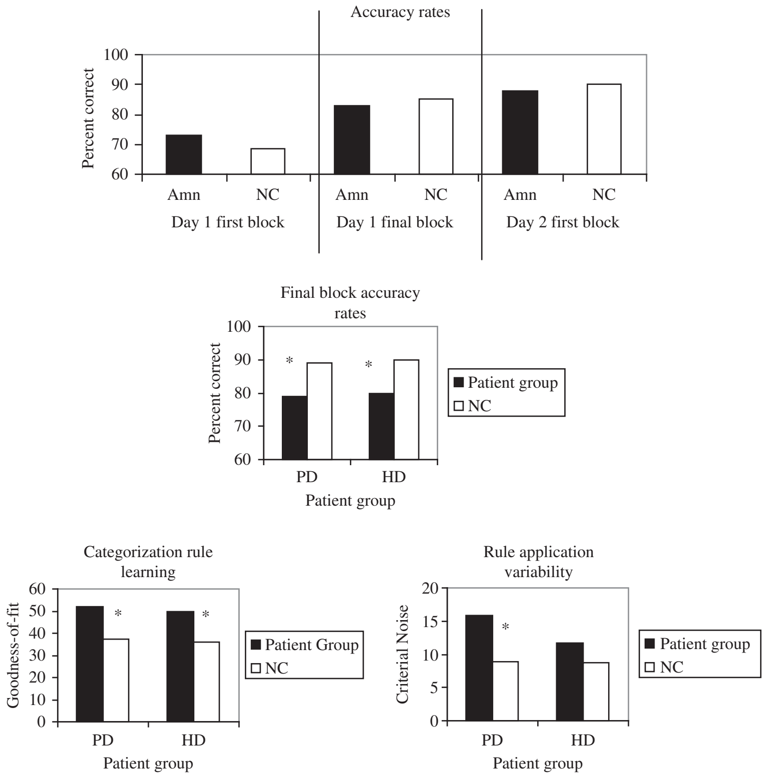


**FIGURE 8.3** Top panel: nonlinear information-integration per cent correct for the amnesiac and control participants from Filoteo et al. (2001a) during the first and final block of trials from Day 1 and the first block of trials from Day 2. Bottom panels: accuracy rates, categorization rule learning and rule application variability estimates from the nonlinear information-integration studies conducted by Filoteo et al. (2001b) and Maddox and Filoteo (2001). * Denotes a statistically significant performance difference ($p < 0.05$).

trials (i.e., 501–600) from the first experimental session. One of the amnesic patients and a matched control also completed a second session and the data from the first 100 trials are also presented in Fig. 8.3. Several comments are in order. First, during the first and final blocks from Day 1, the amnesic patients and controls showed equivalent performance. In fact, performance did not differ in any of the six blocks of trials. This finding is important because it suggests that amnesiacs can learn to categorize, and that the late-training deficit observed in the weather prediction task was likely due to the use of explicit memory processes by the control participants. Second, during the first block of trials from Day 2, the amnesic patient and control again showed equivalent performance, and in fact, performance during the first block of the second session was slightly better than that during the final block of trials from the first session. Some have suggested that amnesic patients learn categorization rules using working or short-term memory processes (Nosofsky & Zaki, 1999). For example, it has been suggested that amnesic patients are able to take advantage of the repeating stimuli during some categorization tasks and this information is then used to categorize (Nosofsky & Zaki, 1999). The Day 2 results from the Filoteo et al. study argue against this possibility because it is highly unlikely that participants were able to make use of working or short-term memory processes between the two days. Instead, these findings indicate that the categorization rule was retained over the one-day delay period, and given the severity of the memory deficit in our amnesic patient (e.g., on Day 2, the patient did not recall having been given the test on the previous day or even having been in the laboratory where the testing was conducted), brain systems not involved in explicit memory likely mediated the retention of this categorization rule.

#### *8.1.4.1 Model-Based Analyses*

The specifics of the modeling procedure are outlined in numerous articles (e.g., Ashby, 1992; Filoteo & Maddox, 2007). In this section we provide only an overview of the approach, highlighting aspects of the modeling that are relevant to the Filoteo et al. (2001a) study. Filoteo et al. tested amnesic patients and controls in their ability to learn a rule in which correct classification was based on a unique nonlinear (quadratic) relationship between the horizontal and vertical line lengths. This rule is depicted as the broken curve in Fig. 8.2. The aim of the modeling approach with these data was twofold. First, to determine how well a participant learned the optimal decision rule, we fit the optimal decision bound model to each block of data separately for each participant.[3] As a measure of *categorization rule learning* we examined the goodness-of-fit

[3]In two dimensions, a quadratic function takes the form $ax^2 + by^2 + cxy + dx + ey + f$, where $a - f$ denote the coefficients of the quadratic function, and x and y denote the horizontal and vertical line lengths, respectively. In the experimenter-defined, optimal quadratic categorization rule, the coefficients, a — f, are fixed, and are determined from the category structures. Maximum likelihood criteria were used to estimate model parameters (see Ashby, 1992). In essence, the maximum likelihood procedure attempts to maximize the “fit” of the model to the data by attempting to generate predictions from the model that most closely match the observed data. In Filoteo et al the data were the participant’s categorization responses for each presented exemplar. Thus, for each exemplar the observed probability of responding “Category A” was either 1 or 0. Assuming the optimal categorization rule is applied, and for a fixed value of the rule application variance (an estimate of the variability associated with a participant’s inability to accurately apply the same rule on every trials), the model generated a predicted probability of responding “Category A” for each exemplar. Because the coefficients are fixed in the optimal model, the rule application variance was the only parameter adjusted iteratively until the difference between the observed and predicted “Category A” response probabilities was minimized.

value (i.e., the maximum likelihood value, -lnL, negative log likelihood) from the optimal model. The smaller the fit, the better the optimal rule describes the data. Second, we were interested in quantifying the magnitude of any variability in the application of the participant's rule. To achieve this goal we fit a suboptimal model that assumed a quadratic decision bound, but allowed the coefficients of the quadratic decision bound to be estimated from the data. As a measure of *rule application variability*, we examined the noise variability estimate from this sub optimal model; the smaller the magnitude of the rule application variability, the less variable the participant's trial-by-trial application of the rule. To reiterate, at the level of accuracy rates these very different processes are nonidentifiable. Only with the model-based approach can these two subprocesses be teased apart and be made identifiable.

Because no accuracy differences were observed across amnesiac and control participants, Filoteo et al. predicted no differences in categorization rule learning or rule application variability, and none were observed. Since publication of the Knowlton et al. (1994) and Filoteo et al. (2001a) studies showing intact category learning in amnesia several challenges to these findings have been offered. For example, Hopkins, Myers, Shohamy, Grossman, and Gluck (2004) reported that amnesiacs were impaired at learning probabilistic categories, and Nosofsky and Zaki (1998) and Zaki (2004) suggested that exemplar theory can be used to account for the category learning/recognition memory dissociation observed in amnesia. However, Smith, and Minda (2000) and Poldrack and Foerde (2008) argued against these claims. In addition, Kitchener and Squire (2000) reported that amnesic patients were impaired at learning verbal (rule-based) categories, which is predicted by COVIS. Although conditions clearly exist for which amnesiacs will show an information-integration category learning deficit, the overwhelming body of patient data suggest that the medial temporal lobes are not involved. This has been supplemented recently with a large body of neuroimaging data suggesting little if any involvement of the medial temporal lobes in information-integration learning (Poldrack et al., 2001; Seger, Dennison, Lopez-Paniagua, Peterson, & Roark, 2011; Seger & Miller, 2010). There is neuroimaging evidence in support of MTL involvement in rule-based learning (Nomura et al., 2007).

The findings of Filoteo et al. were predicted by COVIS, which does not specify a direct role for the medial temporal lobes in category learning. COVIS does predict the striatum to be directly involved in category learning, however, and so an examination of striatal contributions to category learning was in order. We and others heeded this call and shifted our emphasis away from amnesia in favor of striatal-damaged patients.

### 8.1.5 Information-Integration Category Learning in Striatal-Damaged Patients

Knowlton, Mangels, and Squire (1996; see also Knowlton, Squire, et al., 1996) suggested that the striatum may play an important role in category learning. They found that patients with Parkinson's disease (PD), whose neuropathology results in a decrement in striatal functioning, demonstrate impaired probabilistic classification learning in the weather prediction task but intact recognition memory. In addition, Shohamy et al. (2004) showed that PD patients are impaired at feedback-based learning of a probabilistic classification task, compared to healthy controls, but not an observational version of the same task. These observations are also consistent with animal studies that implicate the striatum in certain aspects of category learning (McDonald & White, 1993; Packard & McGaugh, 1993). Notice that these data along with those from amnesic patients represent a double dissociation. PD patients show a deficit in category learning but intact recognition memory, whereas amnesic patients show intact category learning but a deficit in recognition memory. These results provide strong evidence for the involvement of the striatum, but not the medial temporal lobes in information-integration category learning.

Although the Knowlton et al. (1996) and Shohamy et al. (2004) studies suggest that the striatum is involved in category learning, other reports argue against this position. One important study conducted by Reber and Squire (1999) found that PD patients were normal in learning to classify dot patterns and artificial grammars. These results contradict the findings of Knowlton et al. (1996) who demonstrated that PD patients were impaired in probabilistic classification. In an attempt to reconcile these findings, Reber and Squire (1999) suggested that probabilistic classification is different from artificial grammar or dot pattern classification because the participants must learn the cue–outcome relations through trial-by-trial feedback (for an alternative explanation see Ashby & Maddox, 2005). In artificial grammar and dot pattern classification, on the other hand, individuals are simply exposed to members of a category, and are required to study these items. They are then tested on items that either "fit" or "do not fit" the trained category structure. Reber and Squire (1999) argue that the need to learn cue–outcome relations in probabilistic classification requires the striatal learning system i.e., impaired in PD. Since dopamine is dramatically reduced in the striatum of patients with PD (Cornford, Chang, & Miller, 1995), this interpretation would also be consistent with the proposed role of dopamine in reward-based learning mechanisms (Ashby et al., 1998).

It is very likely that the need to learn cue–outcome relations in probabilistic classification at least partially accounts for the poor performance of PD patients. Unfortunately, the artificial grammar and dot pattern classification tasks differ from the probabilistic classification task in a number of ways, any of which might fully or partially explain the performance dissociation observed in PD. First, the artificial grammar and dot pattern classification tasks usually require the learning of only a single category, whereas two categories must be learned in the probabilistic classification task (Ashby & Maddox, 2005). Second, perfect performance is possible in the artificial grammar and dot pattern classification tasks, whereas perfect performance is not possible in the probabilistic classification task. Third, all three tasks differ in the nature of the stimuli (dot pattern, artificial word, or cards with geometric forms), and the response requirements (point at the center dot, reproduce the artificial word on a piece of paper, choose a category "rain" or "sun"). Finally, the nature of the categorization rule is very different across the three tasks. Dot pattern classification can be solved by prototype extraction, and the artificial grammar task might involve perceptual priming of letter string chunks (Knowlton et al., 1996). The probabilistic classification task, on the other hand, appears to involve the learning of a complex categorization rule (although simpler strategies will suffice; Gluck et al., 2002). Thus, the performance dissociation could be due to any one of the following: reliance on striatal learning, effects of maximum attainable accuracy, differential stimulus characteristics and task requirements, categorization rule complexity, or any combination of these factors.

Because of these problems we decided to examine striatal involvement in category learning using the perceptual categorization task. In our earliest work, Maddox and Filoteo (2001) had PD patients and matched controls complete 6 100-trial blocks using the nonlinear information-integration category stimuli displayed in Fig. 8.2, and Filoteo, Maddox, and Davis (2001b) had HD patients and matched controls perform the same task. As with PD, HD also impacts striatal functioning (Vonsattel, Myers, Stevens, Ferrante, & Bird, 1985).

The asymptotic accuracy rates obtained during the final block of trials (i.e., trials 501−600) for the PD, HD and the relevant control participants are depicted in the middle panel of Fig. 8.3. Notice that both the PD and HD participants showed clear category learning deficits. To determine the locus of the nonlinear information-integration category learning deficit in PD and HD participants, we examined the categorization rule learning and rule application variability estimates from the final block of trials. These values are displayed in the bottom two panels of Fig. 8.3. The PD patients' evidenced categorization rule learning and rule application variability deficits, suggesting that their accuracy deficit was due to an inability to learn the optimal rule and greater variability in the application of the rule that they had learned. The HD patients showed categorization rule learning deficits but not rule application variability deficits (although the trend is in that direction) suggesting that their performance deficit was due primarily to an inability to learn the optimal rule.

Taken together with the Filoteo et al. (2001a) study, the results of this early work support the prediction that the striatum, but not the medial temporal lobes, is involved in nonlinear information-integration category learning when a large number of unique stimuli are utilized to minimize the influence of explicit memory processes. This follows since information-integration category learning appears to be mediated by the sensorimotor striatum, which is impacted in HD, and involves a dopamine-mediated reward signal, which is likely deficient in patients with PD. The results also suggest that the locus of the PD and HD deficits was in their ability to learn the optimal decision bound, with the additional difficulty for PD patients only to accurately apply the rule that they have learned.

The studies reviewed above all used a large number of unique stimuli with categories that overlapped and found that PD patients showed a consistent performance deficit across 6 100-trial blocks. Around the same time, Ashby and colleagues (Ashby et al., 2003) conducted a study that examined information-integration category learning in PD using 16 4-dimensional, highly discriminable, binary-valued dimension stimuli. To construct an information-integration rule, one dimension was irrelevant, and category assignment was based on the combination of information from the three remaining stimulus components. Using a learning criterion of 10 correct responses in a row, Ashby et al. found that similar percentages of PD patients and controls (50%) failed to learn the task, suggesting no deficit in information-integration category learning.

The conclusions from this study and Maddox and Filoteo (2001) differ, but the large number of task differences make it difficult to determine the locus of these contradictory findings. One aspect of the results that is of interest is the difference in complexity or difficulty of the two tasks. In Ashby et al. (2003), PD patients and controls who learned the task learned it in 80 trials on average. In Maddox and Filoteo (2001), on the other hand, PD patients showed a deficit relative to the controls across all 600 trials, and never reached 80% accuracy even after 600 trials. These data suggest that the information-integration rule used by Maddox and Filoteo (2001) is more complex and that this complexity might impact the likelihood of observing an information-integration category-learning deficit in PD. Even so the tasks differ along too many other dimensions to make any definitive claims.

To further explore the effects of information-integration rule complexity on PD patients category learning, Filoteo, Maddox, Salmon, and Song (2005) tested a group of PD patients and healthy elderly controls using the linear information-integration[4] and nonlinear information-integration conditions displayed in Figs 8.1B and C, respectively. The stimulus was a line that varied in length and orientation across trials. Each participant completed 6 100-trial blocks of trials in each condition. It is important to reiterate that because this work is couched within the framework of the perceptual categorization task, a number of important factors are equated across conditions (e.g., optimal accuracy), while only the form of the optimal decision bound is manipulated.

Before summarizing the results of this study, let us first describe the methods we used to model the data. Since publishing our early work on category learning in amnesia, PD and HD (Filoteo et al., 2001a, 2001b; Maddox, & Filoteo, 2001) the focus of our modeling approach has changed. Instead of focusing on estimates of categorization rule learning and rule application variability, we have begun attempting to characterize the strategy that participants are actually using. One conclusion that we have drawn from our parallel work using healthy young adults is that participants will often try to solve information-integration tasks using hypothesis-testing strategies when the experimental conditions are not conducive to learning with the procedural learning system (see Maddox & Ashby, 2004; Ashby & Maddox, 2005, 2011 for reviews). This might also occur with PD patients. Since the neurobiological machinery necessary to solve information-integration tasks is deficient in PD, it might be the case that PD patients attempt to use hypothesis-testing strategies. To investigate this possibility, we developed a large number of models that were applied to the data from each block of trials separately for each participant. Some of these models were hypothesis-testing models and some were information-integration models.

Fig. 8.4 displays hypothetical decision bounds and the resulting response regions from specific response strategies that might be applied in the linear information-integration condition. The four models in the left-most column are hypothesis-testing models and the three models on the right are information-integration models. The top two hypothesis-testing models instantiate *uni-dimensional* strategies. One assumes that the participant sets a criterion on length and ignores orientation, whereas the other assumes that the participant sets a criterion on orientation and ignores length. The bottom two hypothesis-testing models instantiate *two-dimensional, conjunctive* strategies. Each assumes that the participant sets a criterion on the length dimension and a

[4]In a linear condition the a, b, and c coefficients in footnote 2 would equal 0.

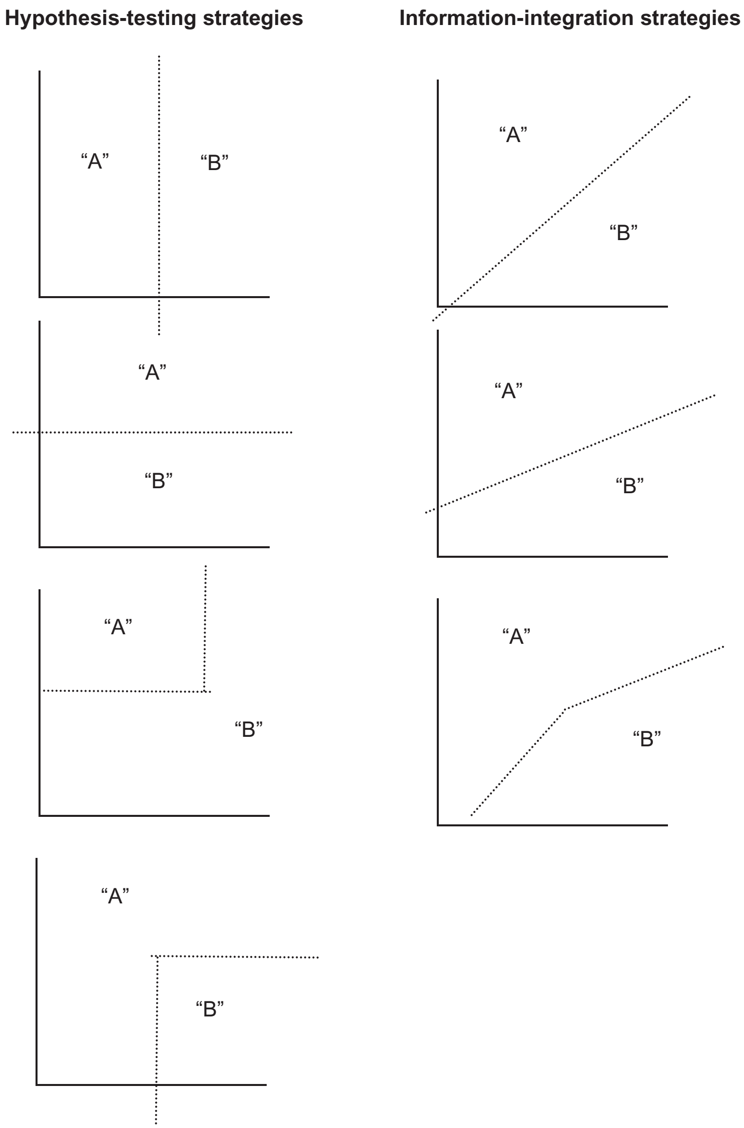


**FIGURE 8.4** Hypothetical response regions from participants using hypothesis-testing and information-integration strategies to solve the linear information-integration task.

separate criterion on the orientation dimension. In the first case, the participant responds A if the length is "short" and the orientation is "steep," otherwise the participant responds B. In the second case, the participant responds B if the length is "long" and the orientation is "shallow," otherwise the participant responds A. The top-most information-integration strategy assumes that the participant uses the optimal decision bound. The middle model assumes that the participant uses a suboptimal linear decision bound, but allows the slope and intercept to be suboptimal. The bottom model assumes that the participant uses two linear decision bounds.[5]

The hypothesis-testing models applied to the linear information-integration condition (Fig. 8.4) were also applied in the nonlinear information-integration condition. The information-integration models were identical as well, except that the optimal and suboptimal models assumed quadratic bounds.

#### *8.1.5.1 Brief Summary of the Results*

The asymptotic accuracy rates obtained during the final block of trials (i.e., trials 501−600) for the PD patients and controls is depicted in the top panel of Fig. 8.5 Notice that PD patients showed normal linear information-integration learning, but a deficit in nonlinear information-integration learning. Importantly, PD patients' deficit in the nonlinear condition but not the linear condition did not appear to be due to task difficulty *per se* in that the controls performed somewhat better in the nonlinear condition relative to the linear condition. The results of the model analyses can also be seen in Fig. 8.5. The middle left panel shows the percent of participants whose final block data was best fit by an information-integration model or a rule-based model. Notice that the model percentages are quite similar across PD and normal control participants for the linear and nonlinear information-integration conditions, but many fewer PD and normal control participants attempted to use hypothesis-testing strategies in the nonlinear condition. To gain additional insight into the locus of the PD nonlinear information-integration learning deficit we focused only on participants whose data was best fit by an information-integration model. We computed the accuracy rate for these participants (displayed in the middle right panel of Fig. 8.5), as well as the categorization rule learning and rule application variability indices (displayed in the bottom two panels of Fig. 8.5). These analyses suggest that PD patients who used information-integration

[5]This model is called the *Striatal Pattern Classifier* (SPC; Ashby & Waldron, 1999) and was developed as a computational model of the tail of the caudate. The model assumes that there are four "units" in the length-orientation space with two being assigned to category A and two to category B. On each trial the observer determines which unit is closest to the perceptual effect and gives the associated response. The model results in two "minimum-distance-based" decision bounds. This model has been found to provide a good computational model of observers response regions in previous information-integration category learning studies (e.g., Ashby & Waldron, 1999; Maddox, Filoteo, Hejl, & Ing, 2004).

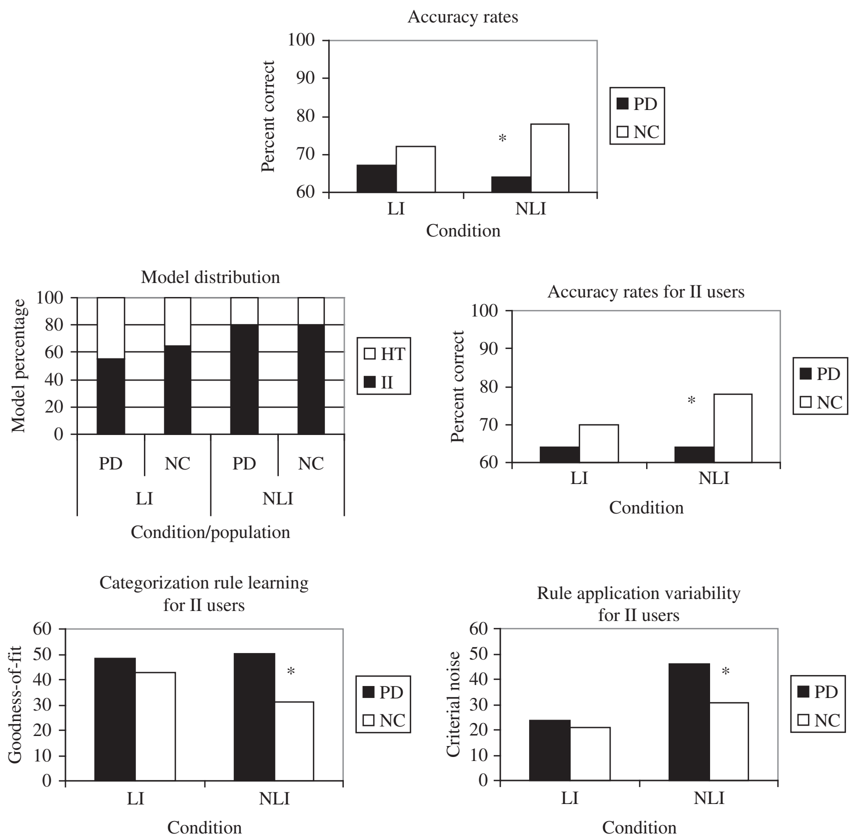


**FIGURE 8.5** Final block overall accuracy rates, model distributions, accuracy rates, categorization rule learning and rule application variability estimates for participants whose data was best fit by an information-integration model from Filoteo et al. (2004) (see text for details). * Denotes a statistically significant performance difference ($p < 0.05$).

strategies to solve the linear information-integration task were as accurate as controls, showed equivalent rule learning, and equivalent variability in the application of their rule. For PD patients who used information-integration strategies to solve the nonlinear information-integration task, on the other hand, accuracy was lower, categorization rule learning was poorer, and variability in the application of their rule was higher than that for controls.

Taken together these results suggest that PD patients are relatively normal at solving linear information-integration tasks (which was also the case in Ashby et al., 2003), but show clear and large deficits in their ability to solve more complex nonlinear information-integration tasks. Although this finding does not hint at the possible underlying mechanisms, it was tentatively hypothesized that this difference could be due to a lack of striatal resources to represent these more complex nonlinear rules. One way in which PD could create a lack of resources is if it decreases the number of medium spiny neurons in the striatum. Previous computational modeling work (Ashby & Waldron, 1999) has shown that a greater number of striatal neurons are needed to learn nonlinear categories than linear ones. With a diminished number of medium spiny neurons in the striatum, PD patients would be unable to adequately represent nonlinear information-integration categories in the striatum, and thus would perform more poorly than healthy controls. Another way PD could create a lack of resources would be by damaging communication between medium spiny neurons in the striatum, which would be more important as more striatal units are needed to learn members of a category.

To test between these two possible dysfunctions, Filoteo and Maddox (2014) compared PD patients' performance on four linearly separable categories versus two, and on discontinuous versus continuous categories. If the number of medium spiny neurons has decreased, then four categories should be more difficult for PD patients to learn than two, whereas if communication between different medium spiny neurons representing stimuli from the same category is damaged, discontinuous categories should be more difficult for PD patients than continuous categories. They found that PD patients were not impaired compared to healthy controls when learning either two or four linearly separated information-integration categories. However, PD patients were dramatically impaired when learning discontinuous categories compared to healthy controls. These findings support the hypothesis that communication and association between medium spiny neurons in the striatum is damaged in Parkinson's disease.

For those interested in the efficacy of information-integration category learning tasks in neuropsychological assessment work by Filoteo, Maddox, Salmon, and Song (2007) is relevant. Briefly in this study, nondemented PD patients completed an information-integration category learning task and were evaluated for dementia at time 1. Eighteen months later these same patients were reevaluated for dementia. Filoteo et al. (2007) found that performance in the nonlinear information-integration task at time 1 was a better predictor of global cognitive decline at time 2 than performance in the linear information-integration task. Interestingly, the Wisconsin Card Sort Task did not predict global cognitive decline although the trend was in that direction. In a reanalysis of these data Filoteo and Maddox (2007) included computational modeling results (i.e., whether each patient's data was best fit by an information-integration or rule-based model) along with information-integration accuracy in a simple regression and found that the models accounted for significant additional variance associated with decline in dementia.

### 8.1.6 Rule-Based Category Learning in PD

The work summarized above suggests that PD patients show information-integration category learning deficits when the optimal strategy is complex. In this section we examine the impact of striatal deficits on rule-based category learning. In addition to information-integration categories, Maddox and Filoteo (2001) also examined rule-based category learning in PD using the perceptual categorization task and the two-line stimuli. Their task required the participant to attend to both stimulus dimensions, and to use the following rule: respond A if the vertical line was longer than the horizontal line and respond B if the vertical line was shorter than the horizontal line. They found that PD patients were as good as controls at performing this task.[6]

This finding is at odds with predictions from COVIS and from the study conducted by Ashby, Noble, Filoteo, Ell, and Waldron (2003) that included both a rule-based and information-integration condition. COVIS predicts that PD patients will show impaired rule-based category learning because of depleted dopamine projections from the substantia nigra into the head of the caudate nucleus. As a test of this hypothesis, Ashby et al. had PD patients and controls learn a rule-based category structure with the 16 4 binary featured stimuli. Critically, one dimension was chosen to be relevant while the three remaining dimensional values varied randomly across trials. Using a learning criterion of 10 correct responses in a row, Ashby et al. found that approximately 50% of the PD patients failed to learn this rule-based task within 200 trials whereas only 10% of the controls failed to learn, suggesting a PD deficit in rule-based category learning. The findings from Ashby et al. (2003) and Maddox and Filoteo (2001) challenge the simplistic notion that PD patients will always show a rule-based category learning deficit.

Unfortunately, the Maddox and Filoteo (2001) and Ashby et al. (2003) studies differ in a number of important ways, each of which might explain the contradictory findings. For example, the Maddox and Filoteo study used a large number of overlapping, continuous-valued dimension stimuli that required that a unique decision criterion be learned but did not require that any dimensional information be filtered. On the other hand, the Ashby et al. study used a small number of nonoverlapping, binary-valued dimension stimuli that did not

[6] Filoteo et al. (2001b) examined HD patient learning in the same condition and found a small deficit in these patients.

require that a unique decision criterion be learned, but required that variation along three irrelevant dimensions be filtered.

To begin to shed some light on the locus of potential PD deficits in rule-based category learning, Maddox, Aparicio, Marchant, and Ivry (2005) examined PD patients learning in two rule-based category-learning conditions. Like Maddox and Filoteo (2001) they used the perceptual categorization task. Thus, they used a large number of overlapping, continuous-valued dimension stimuli that required that a unique decision criterion be learned (similar to that in Fig. 8.1A, but with different stimulus dimensions). However, unlike Maddox and Filoteo (2001) who required attention to both stimulus dimensions, Maddox et al. (2004) required the participant to learn a decision criterion along one stimulus dimension while filtering out (or ignoring) information from a second stimulus dimensions. Each participant completed five 50-trial blocks of trials in each condition. For ease of exposition we focus on asymptotic performance collapsed across the two rule-based conditions.

The asymptotic accuracy rates obtained during the final block of trials (i.e., trials 201–250) for the PD and control participants are depicted in the top panel of Fig. 8.6 Notice that the PD patients showed a clear rule-based category-learning deficit. To determine the locus of the rule-based category-learning deficit in PD we first applied

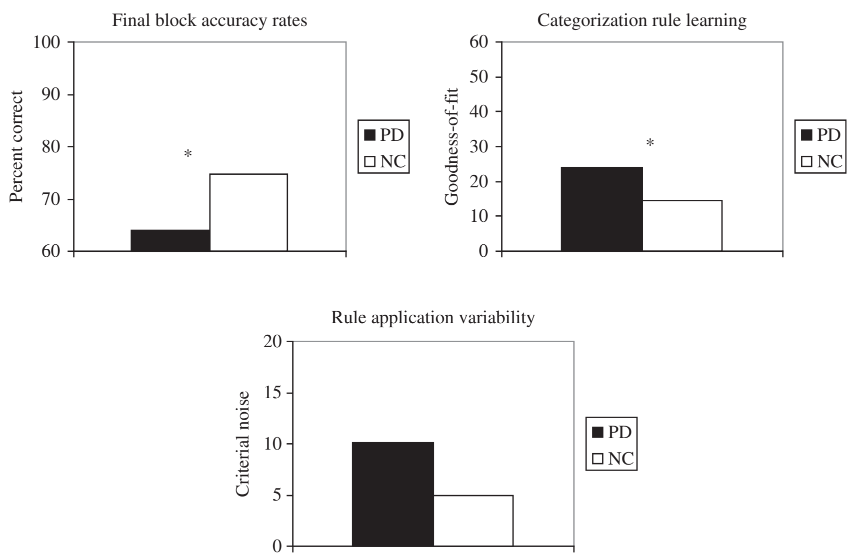


**FIGURE 8.6** Accuracy rates, categorization rule learning and rule application variability estimates from a rule-based category learning study conducted by Maddox, Aparicio, Marchant, and Ivry (2005) (see text for details). * Denotes a statistically significant performance difference ($p < 0.05$).

a series of models to determine whether PD patients' deficit was due to an inability to ignore variation along the irrelevant dimension. In other words, were PD patients more likely than controls to use a strategy that was qualitatively different from the optimal strategy—namely an information-integration strategy, when the optimal strategy was to attend selectively to only one dimension. To test this hypothesis, we fit three models. The optimal rule-based model assumes that the participant attended selectively and used the optimal decision criterion. The suboptimal rule-based model assumes that the participant attended selectively, but used a suboptimal decision criterion. The information-integration model assumes that the participant was unable to attend selectively and instead used a linear decision bound constructed from a weighted linear combination of the two-dimensional values.[7] The results were clear; for 84% of the PD patients and 81% of the control participants a rule-based model provided the best fit of the data suggesting that the PD deficit was not due to a bias to integrate information (i.e., use a qualitative different strategy from that of the optimal classifier) when the optimal strategy was to attend selectively.

To further examine the locus of the rule-based category-learning deficit in PD, we examined the categorization rule learning and rule application variability estimates from the final block of trials. The categorization rule-learning index was determined from the fit of the optimal rule-based model, and the rule application variability index was determined from the noise parameter estimate from the suboptimal rule-based models. These values are displayed in the bottom two panels of Fig. 8.6. The PD patients evidenced categorization rule learning deficits, but not rule application variability deficits (although this difference was marginally significant).

These analyses suggest that PD patients were as likely to select a task-relevant rule as control participants, but their use of this rule was less optimal. One way in which the rule might be used suboptimally is in the placement of the decision criterion. To assess this question, we examined the decision criterion estimates from the suboptimal rule-based model. Specifically, we examined the absolute deviation between the best-fitting decision criterion and the optimal decision criterion.

[7]The models are nested in the sense that the suboptimal rule-based model can be derived from the information-integration model by setting the slope of the information-integration model to the optimal slope (zero or infinity), and the optimal rule-based model can be derived from the suboptimal rule-based model by setting the decision criterion to the optimal value. Using nested modeling techniques (see Ashby, 1992), we identified the best-fitting model defined as the simplest model for which a more general model did not provide a statistically significant improvement.

By using the absolute deviation, the analyses assess the extent of a response bias independent of the direction of that bias. For the PD patients the absolute deviation from optimal was 34 pixels, whereas for controls the absolute deviation was 20 pixels, a reduction of nearly 50%. Thus, PD patients tended to exhibit larger suboptimality in decision criterion placement than the control participants.

It is worth mentioning that a group of patients with cerebellar lesions (CB) were also tested. CB patients showed no deficits in accuracy, categorization rule learning or rule application variability suggesting that the cerebellum is not involved in rule-based category learning. This finding was confirmed in a broader study of CB and categorization (Ell & Ivry, 2008). They found that patients with cerebellar lesions were not only not impaired on a rule-based categorization task, but they also showed no impairment on information-integration categorization or identification tasks.

The Maddox et al. (2004) study offered a straightforward extension of Maddox and Filoteo (2001) to a situation in which irrelevant dimensional information had to be filtered. In a related study, Filoteo, Maddox, Ing, Zizak, and Song (2004) offered a straightforward extension of Ashby et al. (2003). In Ashby et al. (2003) 16 4-dimensional, highly discriminable, binary-valued dimension stimuli were used. One dimension was selected as the relevant dimension, and the other three were irrelevant but varied randomly across trials. Ashby et al. (2003) found a large performance deficit for PD patients relative to matched controls. Filoteo et al. (2004) were interested in determining whether the number of randomly varying irrelevant dimensions might impact the magnitude of the PD rule-based category-learning deficit. In all conditions the stimuli were 4-dimensional, one dimension was relevant to solving the task, and the other three were irrelevant. However the number of irrelevant dimensions that could vary randomly was manipulated across conditions. In one condition, all three irrelevant dimension values could vary randomly across trials. This is analogous to the Ashby et al. (2003) condition. In a second condition, two of the three irrelevant dimension values varied randomly and the third was held fixed across trials. In the third and fourth conditions, one and none of the irrelevant dimension values varied randomly with the remaining (2 or 3, respectively) held fixed across trials. Using the Ashby et al. (2003) learning criterion of 10 correct responses, Filoteo et al. (2004) found that when no irrelevant dimensional variation occurred, PD patients and controls did not differ in the number of trials it took to learn to criterion, but as the number of irrelevant dimensions increased, PD patients' rule-based learning was impacted to a greater extent than that of controls. This suggests that as the selective attention load increases, the magnitude of the PD rule-based deficit increases.

While deficits in selective attention (i.e., difficulty in tuning out irrelevant dimensions) may underlie the explicit categorization impairments in PD patients, it has also been established that PD patients demonstrate a deficit in working memory (Owen et al., 1993), a key component of rule-based categorization. Therefore, another study was conducted to determine whether working memory deficits also contribute to PD patients' poorer performance on RB categorization tasks (Filoteo, Maddox, Ing, & Song, 2007). In this study, PD patients and healthy controls were tested in three category learning experiments. Stimuli that varied on two dimensions were used in all three conditions. In the first condition, only one dimension was relevant, and the other dimension was ignored. This was referred to as the *unidimensional* condition. In the other two conditions, participants had to attend to both dimensions to categorize accurately. In the second condition, the dimensions had to be combined in order to perform optimally on the task (i.e., stimuli that were high on the first dimension *and* the second dimension belonged to one category). This is referred to as the *conjunctive* condition. In the third, *disjunctive*, condition, participants had to compare the levels of the two dimensions in each stimulus: if the stimulus was high in the first dimension *or* the second dimension (but not both), it belonged to one category. These three conditions place increasing demands on working memory, with the first, unidimensional, condition placing the least load on working memory, and the third, disjunctive, placing the greatest load on working memory. So, if impaired working memory does indeed impair rule-based category learning, PD patients should show the largest deficit on the disjunctive condition, compared to healthy controls. Instead, PD patients demonstrated a large impairment on the unidimensional condition, but they were not impaired on the conjunctive or the disjunctive conditions, compared to controls. These results suggest that the deficit exhibited by PD patients on rule-based categories is related to impairment in selective attention, rather than impairment in working memory.

More recently, numerous studies have begun to clarify the previously murky and occasionally contradictory rule-based category learning in PD literature. A review by Price, Filoteo, and Maddox (2009) shows that many of the contradictions found in the literature may be due to differences in the severity of the disease and whether patients are participating in medication intervention. They summarized extensive research demonstrating that PD patients show impairments in rule generation, rule maintenance, rule shifting and rule selection, but medication can either exacerbate or ameliorate these impairments. For example, PD patients find it difficult to tune out irrelevant information in rule-based learning, and medication, which provides much-needed dopamine to the ventral striatum, over-inundates the dorsal striatum with dopamine in the early stages of the disease, making tuning out irrelevant information even more difficult. Another example of medication changing the apparent effects of the disease is in feedback processing; patients who are on medication appear to be less sensitive to *negative* feedback, whereas patients who are off medication appear to be less sensitive to *positive* feedback. Ell, Weinstein, and Ivry (2010) found that regardless of whether PD patients are on or off medication, they are impaired in tasks where working memory demand is high and in tasks where selective attention is high. In contrast, patients with focal lesions to the basal ganglia are only impaired in tasks where working memory demand is high.

## 8.1.7 Brief Summary of PD Category Learning Results

In summary, a large amount of work has been conducted examining category learning in PD. PD patients demonstrate impaired probabilistic classification learning but intact recognition memory. They are also not impaired at dot pattern or artificial grammar classification. The results of several studies show that PD patients are generally normal at linear information-integration tasks, but are impaired at more complex nonlinear information-integration tasks. PD patients also show deficits in rule-based categorization tasks, especially when they are required to filter out irrelevant information. Specifically, as the number of irrelevant dimensions increases, the impairment increases. This effect appears to be due to dysfunctional selective attention, rather than working memory.

## 8.1.8 Category Learning in Other Patient Groups

To this point, this review has focused on amnesic and striatal patients. This is in keeping with their theoretical importance. In this section, we very briefly review category learning research in other patient groups. Although some of this work examined rule-based and information-integration category learning, much of it uses the probabilistic category learning (weather prediction) task.

### *8.1.8.1 Probabilistic Category Learning in Schizophrenia*

The weather prediction task, although it ostensibly requires integration of information across multiple cue cards, and should therefore recruit procedural learning processes, in practice can be solved with reasonably high accuracy via explicit learning processes (Foerde, Knowlton, & Poldrack, 2006; Foerde, Poldrack, & Knowlton, 2007; Price, 2005). This makes it more difficult to use as a tool for isolating the neural networks involved in category learning. However, recently developed computational models have addressed some of these problems (Gluck et al., 2002). Price (2009) demonstrated that disrupting the explicit system impairs probabilistic category performance, but disrupting the procedural system has no effect.

Research on probabilistic category learning in patients with schizophrenia confirms that probabilistic category learning is more of an explicit task than a procedural one. Patients with schizophrenia display impaired cortical functioning, especially the higher-order judgment, decision-making and reality monitoring under the control of the prefrontal cortex. Therefore, it would be predicted that if probabilistic category learning depends on the prefrontal cortex, patients with schizophrenia should show impairment compared to healthy controls. A neuroimaging study conducted by Weickert et al. (2009) found that patients with schizophrenia as a group displayed impaired overall performance on a probabilistic category learning task. This lower overall performance appears to have been driven by the fact that significantly fewer patients with schizophrenia learned the task than healthy controls. Their neuroimaging results demonstrated that healthy controls relied more on a network including dorsolateral prefrontal cortex and the caudate nucleus than patients with schizophrenia. The subset of patients with schizophrenia who successfully learned the task recruited a "compensatory" network including the parahippocampal gyrus and parietal cortex. Foerde et al. (2008) also found that patients with schizophrenia are impaired at probabilistic category learning, although they are not impaired at basic motor skill learning.

#### *8.1.8.2 Category Learning in Alzheimer's Disease (AD)*

Alzheimer's disease is a progressive neurodegenerative disease that damages the hippocampus, posterolateral temporal-parietal cortex, and dorsolateral prefrontal cortex. These individuals commonly experience difficulties in retrieving semantic memory (Smith & Grossman, 2008). As a result, AD patients consistently show deficits in rule learning, and are impaired in some prototype distortion (dot pattern) tasks (Kéri et al., 1999). Koenig, Smith, Moore, Glosser, and Grossman (2007) ran AD patients, corticobasal degeneration (CBD) and age-matched controls in rule-based and similarity-based categories. AD patients were impaired at rule-based categorization, but achieved the same performance level as healthy controls for the similarity-based categories. This deficit in rule-based categorization was correlated with measures of executive functioning, suggesting a deficit in the cognitive resources necessary for rule-based category learning. It was also correlated with a measure of semantic memory. AD patients were unable to apply a rule even when they were reminded what the rule was. CBD patients were also impaired at rule-based categorization, but they were even more impaired at the similarity-based categories. In addition to AD, patients with frontotemporal dementia (which, as the name implies, affects primarily the frontal and temporal lobes) also displayed deficits in learning rule-based categories (Koenig, Smith, & Grossman, 2006).

The impact of Alzheimer's and other degenerative diseases on procedural learning is less clear but AD appears to have little if any effect on procedural learning and memory (Eldridge, Masterman, & Knowlton, 2002). In this particular experiment, a probabilistic classification task was used, and AD patients' performance did not differ significantly from that of healthy controls. They were, however, significantly impaired in an explicit memory test, suggesting that they may indeed have used the procedural system to perform this task.

## 8.2 GENERAL DISCUSSION

The work presented in this chapter builds upon that presented in the previous chapter by Ashby and Valentin. They reviewed the neurobiological underpinnings of a multiple systems model called COVIS. COVIS assumes that learning in rule-based tasks is dominated by an explicit system that uses working memory and executive attention and is mediated primarily by the anterior cingulate, the prefrontal cortex, and the head of the caudate nucleus, whereas learning in information-integration tasks is assumed to be dominated by a procedural learning-based system, which is mediated largely within the striatum and requires a dopamine-mediated reward signal. Ashby and Valentin reviewed a number of studies conducted using healthy young adults that tested and provided support for several a priori predictions derived from an examination of the neurobiological underpinnings of the two systems.

The current chapter reviewed a body of literature conducted in our and other laboratories that provides a more detailed examination of the systems using neurological patients. We focus on patients with damage to the medial temporal lobes or the striatum as these provide the best test of COVIS relative to single-system approach. However, we supplement this with brief reviews of other patient populations including schizophrenia and Alzheimer's disease. In addition, a quantitative model-based approach was taken in most of these studies that allowed us to tease apart the separate effects of various cognitive processes on performance that are nonidentifiable at the level of accuracy.

The ability of medial temporal lobe amnesic and striatal-damaged patients (PD and HD) to solve a nonlinear information-integration task was examined across three studies (Filoteo et al., 2001a, 2001b; Maddox & Filoteo, 2001). In each case a large number of stimuli were presented to alleviate the possibility that participants might recruit explicit memory processes, and participants completed a large number of experimental trials. As predicted from COVIS, medial temporal lobe amnesiacs showed no performance deficit throughout the learn session, whereas both PD and HD patients showed a consistent deficit. Because the optimal nonlinear information-integration rule was unique we used a model-based approach to determine whether the locus of the PD and HD accuracy deficit was due to an inability to learn the rule (categorization rule learning), an inability to apply consistently from trial to trial whatever categorization rule they might have learned (rule application variability), or both. PD and HD patients evidenced deficits in categorization rule learning and rule application variability suggesting that damage to the striatum affects both subprocesses.

The effect of complexity of the information-integration categorization task on PD performance was examined by comparing a linear information-integration rule with a nonlinear information-integration rule. A major focus was also on identifying the types of response strategies that PD patients and controls used to solve these problems. Work with healthy young adults suggests that hypothesis-testing strategies are often used to solve information-integration category learning problems when the learning situation is non-optimal. Because PD patients have depleted dopamine it is reasonable to suppose that they might show similar effects. PD patients showed normal category learning when the optimal decision bound was linear, but a deficit in category learning when the bound was nonlinear. The nonlinear information-integration deficit in PD was not due to an increase in the use of hypothesis-testing strategies (nearly the same proportion of PD and control participants used this type of strategy), but rather was due to worse performance for those PD patients using information-integration strategies relative to controls.

More recently, Filoteo and Maddox (2014) attempted to determine the locus of this effect by comparing PD patients' performance on four linearly separable categories versus two, and on discontinuous versus continuous categories. These were used to determine whether the hypothesis that poor nonlinear information-integration performance is due to a decrease in the number of medium spiny neurons in the striatum, or reduced communication between medium spiny neurons in the striatum, which would be more important as more striatal units are needed to learn members of a category. This initial test supported the hypothesis that communication and association between medium spiny neurons in the striatum is damaged in Parkinson's disease.

The ability of PD patients to solve rule-based category learning tasks was examined across two pairs of related studies (Ashby et al., 2003; Filoteo et al., 2004; Maddox et al., 2004; Maddox & Filoteo, 2001). One pair of studies used the perceptual categorization task that utilizes a large number of unique continuous-valued stimuli sampled from overlapping bivariate normally distributed categories. In Maddox and Filoteo (2001) the optimal rule-based strategy required the participant to attend to both stimulus dimensions, whereas in Maddox et al. (2004) the participant was required to attend to only one stimulus dimension while filtering out (or ignoring) information about the second. The two experiments were identical in all other important aspects. When no filtering was required, PD patients were normal at rule-based category learning, but when filtering was required they showed an accuracy deficit. This accuracy deficit was not due to PD patients' inability to attend selectively (PD patients used rule-based strategies to the same degree as controls), but rather was due to the use of a suboptimal decision criterion. These data suggest that PD patients show deficits when the rule-based task requires dimensional filtering.

Unlike the first pair of studies, the second pair of studies utilizes a small number of binary-valued stimuli that were highly discriminable (i.e., no category overlap). Ashby et al. (2003) used 16 stimuli composed of four binary-valued dimensions. One dimension was relevant to solving the task and the other three were irrelevant. PD patients showed a large rule-based category-learning deficit. Filoteo et al. (2004) utilized similar stimuli and a uni-dimensional rule-based category structure, but manipulated the number of irrelevant dimensions that could vary across trials from three (as in Ashby et al.) down to zero with the remaining dimensional values held fixed across trials. Filoteo et al. (2004) found that the magnitude of the PD deficit increased as the number of randomly varying irrelevant dimensions increased. Specifically, when zero or one irrelevant dimension varied PD patients showed normal rule-based category learning, but when two varied PD patients evidenced a rule-based category-learning deficit.

The chapter ended with a review of the much smaller literature on category learning in schizophrenia and AD. In contrast to PD, both diseases preferentially affect the cortex, especially prefrontal cortical areas. Therefore, as COVIS predicts, patients that suffer from each of these diseases show deficits in rule-based and probabilistic category learning tasks. Both Foerde et al. (2008) and Weickert et al. (2009) examined the performance of patients with schizophrenia on probabilistic category learning, and both groups found that they were impaired. Similarly, Koenig et al. (2007), and Koenig et al. (2006) found that patients with AD were impaired at learning rule-based categories, but not at similarity-based categories.

The application of rule-based and information-integration category learning in new neuropsychological populations continues to grow. For example, Xu et al. (2010) examined rule-based and information-integration category learning in patients with treated Wilson's disease. They found deficits in both forms of learning. Sperling, Lu, and Manis (2004) examined rule-based and information-integration category learning in dyslexia. Interestingly, dyslexics showed normal rule-based learning but deficient information-integration learning. The work reviewed in this chapter and these recent applications suggest that the dual-systems framework offered by COVIS provides a rich scaffolding for understanding many neuropsychological disorders. We fully expect the number of applications to grow in the coming years.

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