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Computational models inform clinical science and assessment: An application to category learning in striatal-damaged patients

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ABSTRACT

In this article we develop a new model of classification that is intermediate between the static, single strategy decision-bound models and the dynamic trial by trial multiple systems model, dCOVIS. The new model, referred to as the sCOVIS model, assumes hypothesis-testing and procedural-based subsystems are active on each trial, but that the parameters that govern behavior of the system are fixed (static) within a block of trials. To determine the clinical utility of the model, it was applied to nonlinear information-integration classification data from patients with Parkinson's (PD) and Huntington's disease (HD). In one application, the models suggest that the locus of HD patients' nonlinear information-integration deficits is in their increased reliance on hypothesis-testing strategies, whereas the locus of PD patients' deficit is in the application of sub-optimal procedural-based strategies. In a second application, the weight associated with the hypothesis-testing subsystem is shown to account for a significant amount of the variance in longitudinal cognitive decline in non-demented PD patients above and beyond that predicted by accuracy alone. Together, the accuracy rate and this model index account for 72% of the total variance associated with cognitive decline in this sample of PD patients. Interestingly, the Wisconsin Card Sort task added no additional predictive power above and beyond that predicted by nonlinear accuracy alone.

1. Introduction

There has been a long standing interest in understanding the cognitive processes associated with clinical disorders. A prevalent class of clinical disorders is those associated with damage to the striatum,[1] such as Parkinson's disease (PD) or Huntington's disease (HD). Previous neuropsychological studies reveal a wide range of cognitive deficits in areas such as working memory, attention, set shifting, and procedural-based learning, even in patients who do not meet formal criteria for dementia (Dubois & Pillon, 1997; Lawrence et al., 1998; Owen, 2004; Salmon & Filoteo, 2007). These past studies suggest that cognition can be impacted early in the course of these diseases, and as such, the striatum plays a critical role in cognitive functioning.

Although traditional neuropsychological testing is extremely fruitful and informative, it tends to focus on comparisons of simple measures of performance, such as proportion correct and mean reaction time, to infer cognitive deficits. Unfortunately, in many domains, there are numerous (often qualitatively different) cognitive strategies that yield the same level of performance, with some strategies being associated with "deficient" cognitive processes and others being associated with intact cognitive processes. For example, patients with PD or HD tend to be impaired on the Wisconsin Card Sorting Test (WCST), a measure of executive functioning, but often the exact nature of their impairment cannot be determined by examining accuracy performance alone (Green et al., 2002; Owen, 2004; Paolo, Troster, Axelrod, & Koller, 1995).

Recently there has been a growing realization that mathematical modeling techniques – used successfully to examine cognitive processes in healthy (usually college age) individuals – can be fruitfully applied to the study of cognitive processing in individuals with brain damage (Busemeyer & Stout, 2002; Ell, Marchant, & Ivry, 2006; Maddox & Filoteo, 2005; Maddox, Filoteo, Delis, & Salmon, 1996; Maddox, Filoteo, & Huntington, 1998; Stout, Busemeyer, Lin, Grant, & Bonson, 2004; Stout, Rock, Campbell, Busemeyer, & Finn, 2005; Yechiam, Busemeyer, Stout, & Bechara, 2005). In fact, several recent "special issues" (including the current issue) and texts have been devoted to this topic (Neufeld, 1998, 2002, 2007). Over the past 10 years, our research team has contributed to this important endeavor by examining classification performance in PD, HD, as well as in normal aging and amnesia (for a review see Filoteo and

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[1] The striatum is the major input structure of the basal ganglia. It includes the caudate nucleus and the putamen.

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Maddox (2007) and Maddox and Filoteo (2005, 2007)). In brief, our studies indicate that patients with damage to the striatum, such as patients with PD or HD, are impaired in learning certain types of categorization tasks, whereas patients with damage to the medial temporal lobe memory system are not (Filoteo, Maddox, & Davis, 2001a,b; Maddox, Aparicio, Marchant, & Ivry, 2005; Maddox & Filoteo, 2001, 2007). These findings suggest an important role for the striatum in learning certain categorization tasks.

The application of mathematical models to data collected in our studies has greatly enhanced our understanding of the deficits associated with various diseases. We typically apply decision bound models (described in detail later) to the data collected from each participant, with each model instantiating a distinct cognitive strategy. Participants are often grouped based on the cognitive strategy that best accounts for their data, and performance measures as well as model parameter estimates are compared among these subgroups. This has been a very useful approach and has led to many important insights regarding striatal patients' category learning ability, and the specific cognitive processes associated with classification learning that are deficient. We focus on a few of these below, but the interested reader is directed to the original sources for details (Filoteo, Maddox, Ing, Zizak, & Song, 2005; Filoteo, Maddox, Salmon, & Song, 2005, 2007).

Even so, one weakness of this approach is that each model assumes a single fixed cognitive strategy. An overwhelming body of data suggests that participants have available multiple cognitive strategies (Erickson & Kruschke, 1998; Love & Gureckis, 2007; Nosofsky, Palmeri, & Mckinley, 1994; Smith, Patalano, & Jonides, 1998; Thomas, 1998), and recent evidence suggests that different neural systems sub-serve different classes of strategies (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Maddox, 2005; Ashby & O'Brien, 2005; Ashby & Spiering, 2004; DeGutis & D'Esposito, 2007; Filoteo et al., 2005; Maddox & Ashby, 2004; Nomura et al., 2007; Poldrack et al., 2001; Seger & Cincotta, 2002, 2005, 2006). Importantly, each neural system (and its associated strategy) is thought to be active on each trial, and to generate a candidate response. Thus, a more psychologically valid model would include multiple systems with each potentially influencing the response generated on each trial. The overriding aim of the current article is to develop and test such a model. Because the focus of this special issue is on applications to clinical science, our secondary aims are to encourage clinical scientists to embrace mathematical modeling techniques. As a step toward achieving this aim, we apply the model developed in this article to clinical data collected in our lab in hopes of providing some new conclusions regarding the cognitive deficits associated with striatal damage.

In Section 2 we briefly review the multiple system approach to classification and two types of classification learning tasks that we have utilized. More extensive reviews can be found elsewhere (Ashby et al., 1998; Ashby & Ennis, 2006; Ashby & Maddox, 2005; Ashby & O'Brien, 2005; Ashby & Spiering, 2004; Maddox & Ashby, 2004). In the Section 5, we develop our multiple systems modeling approach. To anticipate, the model builds upon the popular decision bound model framework developed by Ashby and colleagues (Ashby, 1992a; Ashby & Maddox, 1993; Maddox & Ashby, 1993) and can be thought of as a "static" version of Ashby et al.'s (1998) dynamic Competition between Verbal and Implicit Systems (COVIS) model. In the fourth section we apply the model framework to three sets of published data that examined classification learning in PD and HD patients, and that illuminate the utility of the model. We close with some general comments.

2. Multiple systems of classification

Classification involves learning to respond differently to objects and events in different groups (or categories). It provides information about which objects to approach or avoid, and how an object should be used or manipulated. Understanding the processes involved in classification is critical to understanding human cognition.

During the past decade there has been a surge of interest in the neural basis of classification learning (Ashby et al., 1998; Ashby & Maddox, 2005; Love & Gureckis, 2007; Poldrack & Rodriguez, 2004; Rodriguez, Aron, & Poldrack, 2006; Seger & Cincotta, 2005, 2006; Shohamy et al., 2004). Perhaps the most important discovery to come from this research is that humans have available multiple classification learning systems, with each system being best suited for learning a particular type of category structure, and each being sub-served by different neural circuits (Ashby et al., 1998; Ashby & O'Brien, 2005; Poldrack & Rodriguez, 2004; Reber, Gitelman, Parrish, & Mesulam, 2003). A two-system model was proposed by Ashby et al. (1998) that assumes a Competition between Verbal and Implicit Systems (COVIS). The verbal system is an explicit hypothesis-testing system that dominates the learning of rule-based categories, and the implicit system is procedural-based and dominates the learning of information-integration categories.

In *rule-based category-learning tasks* the categories can be learned via an explicit reasoning process. Frequently, the rule that maximizes accuracy (i.e., the optimal strategy) is easy to describe verbally. In the most common applications, only one stimulus dimension is relevant. The participant's task is to discover this relevant dimension and then to map the different dimensional values to the relevant categories (e.g., as in the WCST). Other rule-based tasks require attention to two or more dimensions. For example, in Fig. 1A the stimuli are lines that vary across trials in length and orientation. Fig. 1A displays some representative stimuli from each category, but in most applications each category contains many (50–100) unique stimuli. The correct rule (denoted by the broken horizontal and vertical line) is a conjunction of the line length and orientation and can be verbalized in the following manner: "the stimulus is in category A if the line is long and shallow and is in category B otherwise". The key requirement is that the correct categorization rule in rule-based tasks is one that can be discovered by a logical reasoning (explicit, hypothesis-testing) process that depends on working memory and executive attention (Ashby et al., 1998). This theory correctly predicts that rule-based learning is disrupted in normal participants by a concurrent or sequential working memory-demanding task and by individual differences in working memory span (Decaro, Thomas, & Beilock, 2008; Tharp & Pickering, 2008; Waldron & Ashby, 2001; Zeithamova & Maddox, 2006, 2007).

A variety of evidence implicates the prefrontal cortex, anterior cingulate, head of the caudate nucleus, and medial temporal lobe structures in rule-based category learning. This includes the results of neuroimaging studies (Filoteo et al., 2005; Konishi et al., 1999; Lombardi et al., 1999; Monchi, Petrides, Petre, Worsley, & Dagher, 2001; Nomura et al., 2007; Rao et al., 1997; Rogers, Andrews, Grasby, Brooks, & Robbins, 2000; Seger & Cincotta, 2006; Volz et al., 1997), single-unit recording studies (Asaad, Rainer, & Miller, 2000; Hoshi, Shima, & Tanji, 1998; Muhammad, Wallis, & Miller, 2006; Wallis, Anderson, & Miller, 2001; White & Wise, 1999), and studies with various neuropsychological patient groups (Ashby, Noble, Filoteo, Waldron, & Ell, 2003; Brown & Marsden, 1988; Cools, van den Bercken, Horstink, van Spaendonck, & Berger, 1984; Downes, Roberts, Sahakian, Evenden, Morris, & Robbins, 1989; Filoteo, Maddox, Ing, & Song, 2007; Kimberg, D'Esposito, & Farah, 1997; Snowden, Craufurd, Griffiths, Thompson, & Neary, 2001).

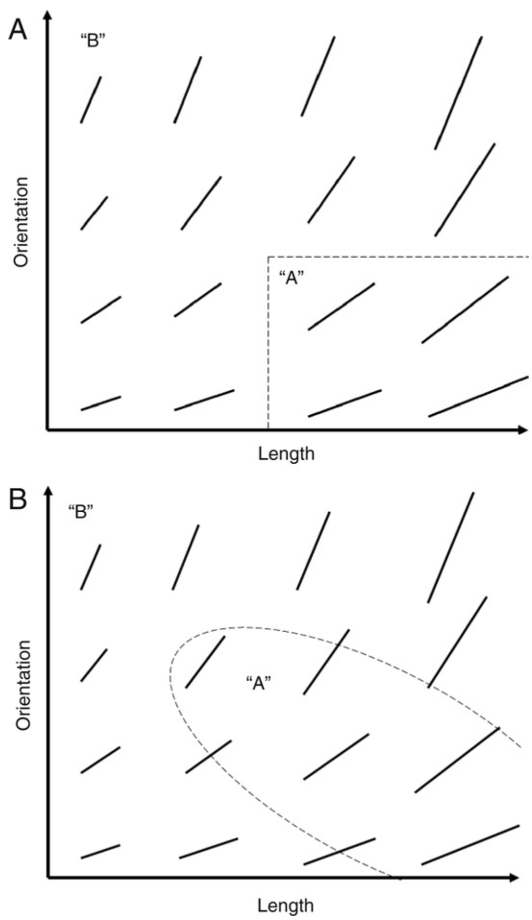

Fig. 1. (A) Representative stimuli and decision bounds associated with a conjunctive rule-based classification task. (B) Representative stimuli and decision bounds associated with a nonlinear information-integration classification task.

In contrast to rule-based tasks, *information-integration tasks* are optimally learned by integrating perceptual information across two or more non-commensurable stimulus dimensions at some pre-decisional stage. Typically, the optimal strategy in information-integration tasks is difficult or impossible to describe verbally (which makes it difficult to discover via logical reasoning). Rather, it is thought that participants learn to associate classification responses to different regions of perceptual space through a gradual, incremental learning process. An example in which the correct strategy requires nonlinear information-integration is shown in Fig. 1B.

The search for the neural basis of information-integration category learning has focused on the striatum. This follows because information-integration learning has many of the properties associated with forms of learning often attributed to the striatum, such as habit learning and procedural-based learning (Brown, Desimone, & Mishkin, 1995; Fernandez-Ruiz, Wang, Aigner, & Mishkin, 2001; Knowlton, Mangels, & Squire, 1996; Squire, 1992; Willingham, 1998). Ashby and colleagues (Ashby et al., 1998; Ashby, Ennis, & Spiering, 2007; Ashby & Waldron, 1999) proposed that the key site of information-integration learning was at cortical–striatal synapses between pyramidal cells from visual association cortex and medium spiny cells in the striatum. The direct pathway out of the striatum projects to premotor cortex (e.g., SMA and pre-SMA) via the internal segment of the globus pallidus and the ventral anterior/ventral lateral thalamic nuclei. The initial cortical–striatal projections are characterized by massive convergence, with about 10,000 visual cortical cells converging on each medium spiny cell (Wilson, 1995). Ashby et al. (1998) proposed that through a procedural-based learning process, each striatal unit associates an abstract motor program with a large group of visual cortical cells (i.e., all that project strongly to it) and that this learning is facilitated by a dopamine mediated training signal from the substantia nigra.

A variety of behavioral results with normal individuals support this general model (for a review, see Ashby and Maddox (2005) and Maddox and Ashby (2004)). For example, information-integration category learning is impaired if the feedback is delayed by as little as 2.5 s, whereas delays as long as 10 s have no effect on rule-based learning (Maddox, Ashby, & Bohil, 2003; Maddox & Ing, 2005), a finding that is highly consistent with what is known about the temporal dynamics of the dopamine reward signal (Gamble & Koch, 1987; MacDermott, Mayer, Westbrook, Smith, & Barker, 1986; Schultz, 1998; Schultz, Tremblay, & Hollerman, 1998). Consistent with the prediction that the striatum is involved in information-integration category learning, a number of studies have reported that patients with striatal dysfunction are impaired in information-integration tasks (Filoteo et al., 2001a; Filoteo, Maddox, Salmon et al., 2007; Maddox & Filoteo, 2001) and neuroimaging studies of information-integration learning have reported significant learning-related striatal activation (DeGutis & D'Esposito, 2007; Nomura et al., 2007; Seger & Cincotta, 2002, 2005).

sCOVIS: A Model Intermediate Between Static, Single Strategy Decision Bound Models and Dynamic, Trial-By-Trial COVIS (dCOVIS).

2.1. Decision bound theory

Decision bound theory is an extension of Ashby and Townsend's (1986) General Recognition Theory to categorization.[2] Consider two bivariate normally distributed categories, A and B and their associated probability density functions $f_A(x, y)$ and $f_B(x, y)$ with category means $\boldsymbol{\mu}_A$ and $\boldsymbol{\mu}_B$ and category covariance matrices $\boldsymbol{\Sigma}_A$ and $\boldsymbol{\Sigma}_B$. For any given stimulus, the optimal classifier computes the likelihood ratio, $l_o(x, y) = f_B(x, y)/f_A(x, y)$. Assuming no bias toward one category over the other, the optimal classifier uses the following decision rule:

$$\text{If } l_o(x, y) < 1.0 \quad \text{then respond "A", otherwise respond "B".} \tag{1}$$

With bivariate normally distributed categories the decision bound associated with the optimal classifier will always be linear or a quadratic curve.

Humans rarely use the optimal decision rule (e.g. Ashby and Maddox (1990, 1992) and Mckinley and Nosofsky (1996)) and so in decision bound theory it is assumed that participant uses a suboptimal strategy in the presence of perceptual and criterial noise. Perceptual noise exists because there is trial-by-trial variability in the perceptual information associated with each stimulus. We assume that the participant's percept of Stimulus i on any trial is $\mathbf{x}_{pi} = [x_{pi}, y_{pi}]'$, where $x_{pi} = x_i + e_p$, $y_{pi} = y_i + e_p$, and e_p is a univariate normal random variable with mean 0 and standard deviation σ_p, that represents the effect of perceptual noise. Criterial noise exists because there is trial-by-trial variability in the memory for the decision bound. The simplest decision bound model is the optimal decision bound model. The optimal decision bound model is identical to the optimal classifier (Eq. (1)) except that

[2] The reader interested in the details of General Recognition Theory is directed to a number of seminal works (Ashby, 1988, 2000; Ashby & Perrin, 1988; Ashby & Townsend, 1986; Kadlec & Townsend, 1992; Thomas, 1995).

perceptual and criterial noise are incorporated into the decision rule. Specifically,

$$\text{if } l_o(\mathbf{x}_{pi}) < 1 + e_c \quad \text{then respond "A", otherwise respond "B"}, \quad (2)$$

where e_c is a univariate normally distributed random variable with zero mean and standard deviation σ_c that represents the effects of criterial noise. The most general version of the model abandons the likelihood ratio on the left side of Eq. (2) for a general function $h(\mathbf{x}_{pi})$, although we generally assume h will be linear or quadratic. Because $h(\mathbf{x}_{pi})$ is linear or quadratic, the optimal likelihood ratio value of 1.0 is absorbed into the intercept of the linear bound or the constant term in the quadratic bound and we are left with

$$\text{if } h(\mathbf{x}_{pi}) + e_c < 0 \quad \text{then respond "A", otherwise respond "B"}. \quad (3)$$

Assuming the Eq. (3) decision rule, the probability of responding A, $P(R_A|\mathbf{x})$ is

$$P(R_A|\mathbf{x}) = P[h(\mathbf{x}_p) + e_c < 0 \mid \mathbf{x}]. \quad (4)$$

Assuming that $h(\mathbf{x}_p)$ is normally distributed, which holds exactly if $h(\mathbf{x}_p)$ is linear and is only approximate when $h(\mathbf{x}_p)$ is quadratic, then Eq. (4) can be evaluated from the cumulative normal distribution and reduces to

$$P(R_A|\mathbf{x}) = \Phi[\mu_{h(x)}/(\sigma^2_{h(x)} + \sigma^2_c)^{1/2}]. \quad (5)$$

The mean and variance depend upon the form of the $h(\mathbf{x}_p)$. These are derived in detail in Ashby (1992a, pgs. 459–467) and in the Appendix for the specific models applied in the empirical applications below.

2.2. Hypothesis-testing and procedural-based decision bound models

In keeping with the two system approach (Ashby et al., 1998), we outline two classes of decision rules; those that are congruent with an explicit reasoning (hypothesis-testing) process and those that are congruent with an implicit procedural based process.

Explicit hypothesis-testing models all involve linear decision bounds that are parallel to one or both of the coordinate axes. These include simple unidimensional rules that involve a single horizontal or vertical decision bound, and more complex conjunctive rules. Fig. 2A depicts an explicit hypothesis-testing strategy that involves a conjunctive rule on length and orientation. The conjunctive rule is defined by a criterion along the x dimension, x_o, and a criterion along the y dimension, y_o, and assumes that the participant responds "A" to long, shallow angle lines, and "B" to all others. Both criteria are free parameters in the model, along with the perceptual noise parameter, σ^2_p.[3] The equation for computing the predicted probability of responding A is included in Fig. 2A. This model is also referred to as an independent decisions classifier, and is detailed in Ashby (1992a, pgs. 465–467; see also Appendix).

Implicit procedural based models include linear and nonlinear decision bounds. Fig. 2B depicts an implicit procedural based strategy that involves a quadratic decision bound. The decision bound is defined as $h(x, y) = a_1x^2 + a_2y^2 + a_3xy + b_1x + b_2y + c_0$. All six constant terms are free parameters (although one can generally be set to 1), along with the perceptual noise, σ^2_p, and criterial noise, σ^2_c parameters. The equation for computing the predicted probability of responding A is included in Fig. 2B. This model is also referred to as a general quadratic classifier, and is detailed in Ashby (1992a, pgs. 460–462; see also Appendix).

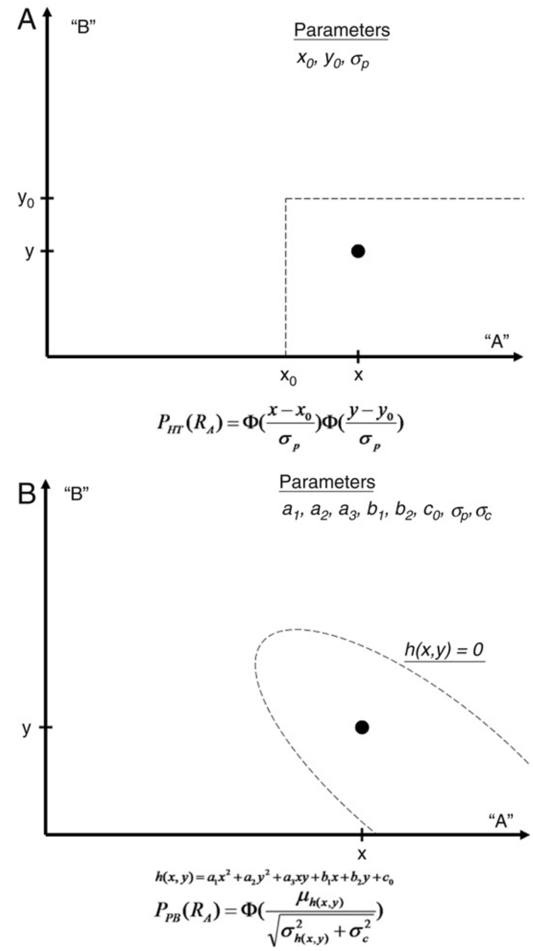

Fig. 2. Static, single system decision bound models. (A) Example of a conjunctive, hypothesis-testing model. (B) Example of a nonlinear, procedural-based model. (see text for details).

Decision bound models that instantiate hypothesis-testing and procedural based strategies are generally applied to the data from individual participants[4] on a block-by-block basis. In other words, a block of trials (usually 50 or more trials) is specified and the model parameters are adjusted in such a way that they best account for the full block of data. Fits of the models are then compared with each other and the best fitting model is assumed to represent the strategy that the participant used throughout the block. Thus, this approach assumes that the participant uses either a hypothesis-testing or a procedural-based strategy on each trial of the block, and assumes that the parameters that define the specific strategy (e.g., the x_o and y_o values in Fig. 2A, or the a_1, a_2, a_3, b_1, b_2, and c_0 values in Fig. 2B) remain fixed throughout the block.

2.3. dCOVIS

In their seminal article, Ashby et al. (1998) developed a dynamic trial-by-trial model that assumes that the hypothesis-testing and procedural-based systems are operative on each trial and that the parameters that governed behavior in each system (e.g., the decision bound parameters), as well as the parameters that governed the interaction between systems (e.g., the system

[3] When the decision bounds are linear, the perceptual and criterial noise parameters are not separately identifiable, and only the sum can be estimated (Ashby & Maddox, 1993).

[4] A large body of work shows that modeling data aggregated across participants can be misleading (Ashby, Maddox, & Lee, 1994; Estes, 1956; Maddox, 1999).

weights associated with each system) could change from trial-to-trial. The details of the model can be found in Ashby et al., but a brief summary is offered here. On each trial, the model generates an output from the hypothesis-testing and procedural based systems. The output is in the form of a response probability much like that generated from the decision bound models outlined above. Each response probability is scaled by its associated system weight,[5] and the weighted outputs are compared. The response associated with the hypothesis-testing system is selected on a given trial if its scaled output is larger than that generated from the procedural based system. Conversely, the response associated with the procedural-based system is selected on a given trial if its scaled output is larger than that generated from the hypothesis-testing system. Importantly, feedback provided to the model on each trial is propagated back through the system and is used to modify specific parameters. Thus, unlike the decision bound modeling approach, the dCOVIS model can change (a) the decision bound parameters associated with a particular strategy, (b) the nature of the strategy applied within a system (e.g., switch from a unidimensional rule on one trial to a conjunctive rule on the next), and/or (c) the system weight associated with the two systems on a trial-by-trial basis.

2.4. *sCOVIS*

In this section we develop a model that can be thought of as intermediate between the static, single strategy decision bound models, and the dynamic, multiple systems dCOVIS model. The new model, referred to as the sCOVIS model, is applied on a block by block basis and assumes that the parameters are fixed within a block of trials, like the decision bound models, but assumes that both the hypothesis-testing and procedural-based systems are operative on each trial, like dCOVIS (for a related model see Zeithamova, Filoteo, Simmons, Maddox, & Paulus, 2007).

It is important to be clear up front that we believe that classification learning is a dynamic process. In that sense, assuming that a static set of parameter values characterizes performance on each trial within a block of trials will clearly not capture the complexity of behaviors and changes to the neural systems that occur on a trial-by-trial basis. On the other hand, dynamic models can be extremely difficult to work with. Within the dCOVIS framework the nature of the system and its output on trial n depends on the nature of the system and its output on trial $n-1$, but the behavior on trial $n-1$ is probabilistic. Thus a large number of model simulations are needed for each set of initial parameter values, and a wide range of response patterns can emerge that are highly dependent on the initial subjective selection of these initial parameter values.

Unlike dCOVIS, sCOVIS is fairly easy to program and implement. With respect to clinical science and assessment, we feel that the simplicity of the sCOVIS model is a major strength given our hope that the application of this model will benefit neuropsychological researchers studying classification learning in various patient populations. It is also worth mentioning that as a participant gains experience with a particular classification problem, their behavior becomes more static in the sense that the parameters that describe the behavior of each subsystem (e.g., hypothesis-testing and procedural based) become more stable (Ashby et al., 1998). Thus, the sCOVIS parameter values become increasingly more psychologically valid as the participant gains experience with the task. Many of our clinical applications focus on later, as opposed to earlier, learning and thus take advantage of this property of the model.

Fig. 3 provides a schematic of the behavior of the sCOVIS model on trial *i*. At the initial stage of processing, the stimulus value on trial $i(x_i, y_i)$ is input into the hypothesis-testing and procedural based subsystem. As just one example, the hypothesis testing subsystem might instantiate a conjunctive rule like that in Fig. 2A, and the procedural based subsystem might instantiate a quadratic decision bound like that in Fig. 2B. Each subsystem then generates an output in the form of a response probability [i.e., $P_{HTi}(R_A)$ and $P_{PBi}(R_A)$; see Appendix A].

Two methods for combining the system level output were examined. The Competition Decision Rule is identical to that used in dCOVIS. It scales the output from each subsystem by a system weight (as described above) and applies the response probability associated with the largest subsystem output (see Fig. 3, left panel). The Cooperation Decision Rule, on the other hand, assumes that the response probability outputted on a trial is a weighted sum of the two subsystem outputs, and thus each subsystem contributes to the response given on each trial (see Fig. 3, right panel). Thus, whereas the competition version of the model assumes that one sub-system drives the response on each trial (although the "winning" subsystem can change across trials), the cooperation version instantiates more of a "mixture" model approach, assuming that the output from both sub-systems impacts the response on each trial. Mixture models of this sort are popular in the classification literature and are thus not without precedence (Estes, 1994; Minda & Smith, 2001; Nosofsky & Zaki, 2002; Rosseel, 2002).

Importantly, it has become increasingly clear that various forms of brain damage secondary to neurological conditions often results in increased neural activity above and beyond that seen in non-patient populations. This may represent some sort of compensation for damage to a particular neurocognitive system. Moody, Bookheimer, Vanek, and Knowlton (2004) provided some evidence for this in PD patients who performed a probabilistic category learning task while undergoing functional MRI. Thus, a cooperation model that takes into account the possibility of two systems contributing to a response could provide a more accurate accounting of categorization in patients with striatal damage (such as patients with HD or PD). This compensatory reaction to damage may also reveal itself as a deficit in patients' ability to transition away from hypothesis-testing strategies toward procedural-based strategies as they would need to do to perform optimally in the nonlinear information-integration tasks in Applications 1 and 2. This would result in larger estimates of the hypothesis-testing system weight. We examine each of these possibilities below.

3. Application 1: Nonlinear perceptual classification learning in PD and HD patients

In this section we briefly review the accuracy and modeling results from two published studies conducted in our lab that examined nonlinear information-integration classification learning in 10 non-demented PD patients and 5 age- and education-matched controls (Maddox & Filoteo, 2001), and 7 HD patients and 6 age- and education-matched controls (Filoteo et al., 2001a). Following the brief review, we apply the sCOVIS framework to the data and summarize the findings. A scatterplot of the stimuli and optimal decision bound used in these two studies are displayed in Fig. 4A. Each stimulus was composed of a horizontal and vertical line connected at the upper left with each line varying in length across trials. The optimal rule can not be verbalized and instead is defined by a quadratic function of the horizontal and vertical line lengths.

[5] In both original COVIS and in our Static COVIS implementation, the system weight associated with the hypothesis testing system, w_{HT}, is constrained to fall within the range 0–1, and the weight associated with the procedural based system is defined as $1 - w_{HT}$.

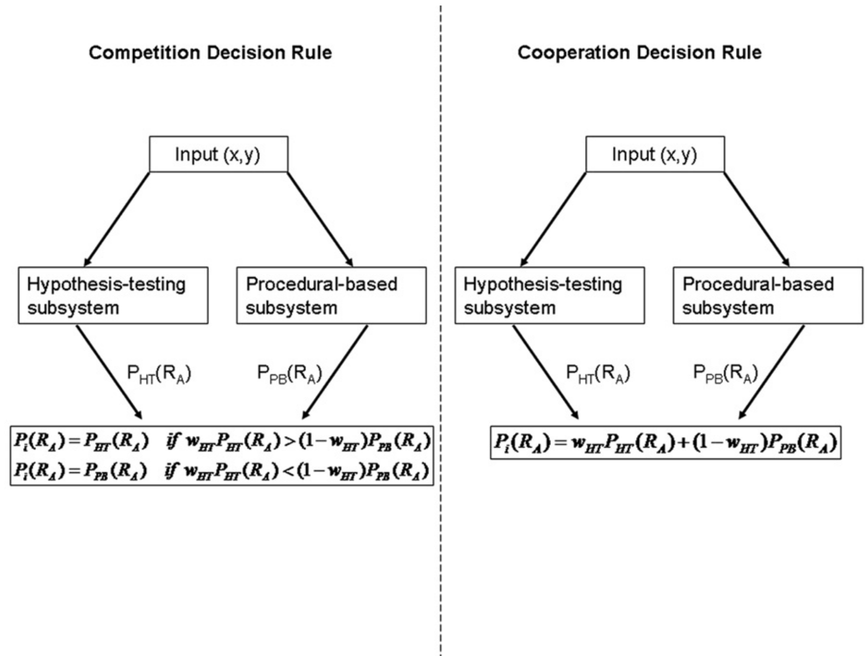

Fig. 3. Flow chart of the information stream associated with the sCOVIS model (see text for details).

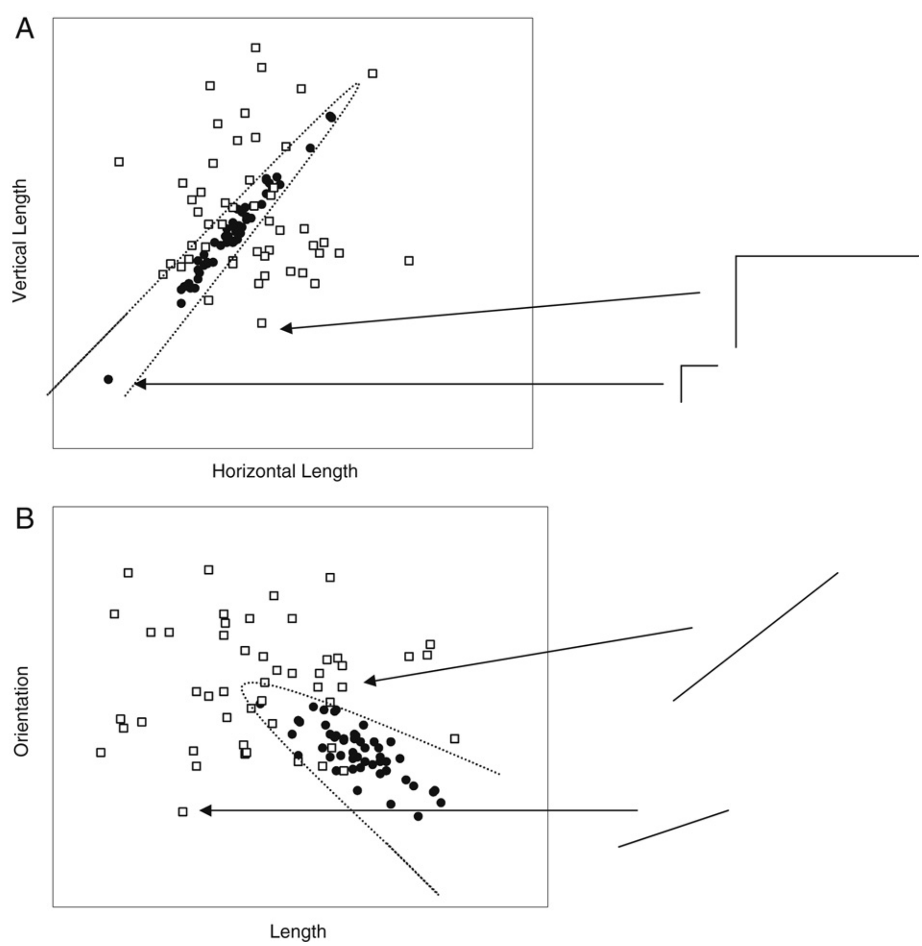

Fig. 4. (A) Non-linear information integration category structures used in Filoteo et al. (2001a) and Maddox and Filoteo (2001) (see text for details). (B) Non-linear information integration category structures used in Filoteo, Maddox, Salmon et al. (2007) (see text for details). Filled circles denote category A stimuli and open squares denote category B stimuli. The broken quadratic curve denotes the optimal decision bound.

In both conditions, optimal accuracy was 95%. Each experimental condition consisted of 6 100-trial blocks of trials.

PD and HD participants showed statistically significant non-linear information-integration classification learning deficits relative to controls. In fact, in the sixth block of 100-trials PD patients showed a 10% deficit [PD = 79%; controls = 89%; $F(1, 13) = 7.18$, $p < .05$; $\varepsilon^2 = .356$] while HD patients showed a 7% deficit [HD = 83%; controls = 90%; $F(1, 11) = 14.30$, $p < .01$; $\varepsilon^2 = .565$].

It is worth mentioning that our modeling approach to classification learning has evolved much over the past several years. In our original publication of these two studies we did not apply hypothesis-testing models to data from information-integration tasks. Instead we focused exclusively on the application of decision bound models that assumed a procedural-based strategy. The aim of our original modeling approach was two-fold. First, we were interested in determining how well a participant learned the optimal decision rule. To achieve this goal we fit the optimal decision bound model Eq. (3) to each block of data separately for each participant. As a measure of categorization rule learning we examined the goodness-of-fit value (i.e., the maximum likelihood value, $-\ln L$, negative log likelihood) from the optimal model. The smaller the fit value, the better the optimal rule describes the data. Second, we examined variability in the application of the best fitting decision bound, referred to as rule application variability. To achieve this goal we fit a sub-optimal model that assumed a quadratic decision bound, but allowed the decision bound parameters to be estimated from the data. As a measure of rule application variability, we examined the criterial noise estimate from this sub-optimal model. It is important to note that both poor categorization rule learning and high rule application variability will lead to comparable performance decrements at the level of accuracy. Thus at the level of accuracy rates these very different processes are non-identifiable. Only with the model-based approach can these two sub-processes be teased apart and be made identifiable.

In the original application, we applied the models to each of the six blocks of data, but focused on fits to the final (6th) block. The results can be summarized as follows. First, the HD patients showed categorization rule learning deficits but not rule application variability deficits (although the trend was in that direction) suggesting that their performance deficit was due primarily to an inability to learn the optimal rule. Second, the PD patients' evidenced categorization rule learning and rule application variability deficits, suggesting that their accuracy deficit was due to both an inability to learn the optimal rule and to greater variability in the application of the rule that they had learned. Interestingly, a regression analysis indicated that PD patients' goodness-of-fit values and criterial noise values uniquely predicted their accuracy performance on the categorization task, suggesting that both categorization learning and rule-application variability were each important factors in determining to what degree the rule was learned.

3.1. sCOVIS

Application of the sCOVIS framework began by applying some hypothesis-testing and procedural based decision bound models to the final block of data using maximum likelihood parameter estimation procedures. These include the optimal (2 parameters; perceptual and criterial noise) and sub-optimal quadratic (7 parameters; 5 decision bound, perceptual and criterial noise) procedural-based models, a unidimensional horizontal length hypothesis-testing model (2 parameters; horizontal length criterion and perceptual noise), a unidimensional vertical length hypothesis-testing model (2 parameters; vertical length and perceptual noise), and an equal line length bi-linear model (3 parameters; two intercepts and perceptual noise). The decision rule for this latter model is as follows: If the length of the two lines is approximately equal respond "A"; otherwise respond "B". This is a reasonable strategy because all members of category A have similar horizontal and vertical line lengths, whereas the members of category B have more disparate line lengths. More formally, this is a bi-linear categorization rule in which the slope of each categorization rule is equal to 1, one intercept is positive and the other is negative.[6]

We found that the sub-optimal quadratic procedural-based model provided a significantly better fit to the data than the optimal model for 9 of 10 PD patients, 7 of 7 HD patients, 4 of 5 PD controls and 6 of 6 HD controls. These conclusions were based on G^2 Likelihood Ratio Tests (Wickens, 1982) with a $p < .05$ minimum level of significance. In addition, we found that the bilinear model provided a significantly better fit to the data than either of the unidimensional models for all participants (again based on G^2 tests with a $p < .05$ level of significance). In light of these findings and following the approach taken in Application 1, we constructed a competitive and cooperative version of sCOVIS that assumed a quadratic procedural-based strategy and a bilinear hypothesis-testing strategy. Each model was applied to the data using maximum likelihood parameter estimation procedures.

Several aspects of the sCOVIS model results are worth highlighting and are summarized in Table 1. First, we compared the performance of the competitive and cooperative versions of sCOVIS. Although its original formulation assumed a competition between systems (Ashby et al., 1998), we know of no direct test of this assumption, or direct comparison with a cooperative version of the model. Table 2 displays the maximum likelihood values for competitive and cooperative versions of sCOVIS separately for each participant. Because these two models contain the same number of parameters, the fit values were compared directly. The best fitting model is in bold type. The results were clear. The cooperative version of the model provided a better account of the data than the competition model for 10 of 10 PD patients, 5 of 7 HD patients, 4 of 5 PD-controls and 6 of 6 HD-controls suggesting a clear advantage for the cooperative version of the model. Thus, the remainder of our analyses will focus on the cooperative version of sCOVIS.

Next we conducted nested model (χ^2) tests to determine whether the cooperative sCOVIS model provided a significant improvement in fit over the best of the quadratic procedural-based and the bilinear hypothesis-testing models (both of which are special cases of the sCOVIS model). The sCOVIS model provided a significant improvement in fit over the quadratic procedural-based and the bilinear hypothesis-testing models (based on G^2 tests with a $p < .05$ level of significance) for 9 of 10 PD patients, 6 of 7 HD patients, 2 of 5 PD-controls and 2 of 6 HD-controls. Interestingly, significantly more of the patient data than the control data was best fit by the cooperative sCOVIS model for both the PD [$\chi^2(1) = 4.261, p < .05$] and HD [$\chi^2(1) = 3.745, p = .053$] suggesting that the need to incorporate both the procedural based and hypothesis testing system was more critical for the patients than for the controls.

This finding supports our hypothesis above that patients are less able (or willing) to gradually transition away from

[6] The reader might note that this hypothesis-testing model does not assume decision bounds that are parallel with the coordinate axes of horizontal and vertical length and thus do not satisfy the definition outlined earlier. These two-line stimuli are unique in the sense that there are at least two different ways of dimensionalizing the stimuli. One dimensionalization is based on horizontal and vertical line length and is depicted in Fig. 4A. A second dimensionalization, however, is based on coordinate axes that are based on a 45 degree rotation of the horizontal and vertical line length space. These might be called the "shape" and "area" dimensions, with the shapes being more or less square-like and the area increasing in size. It is in this alternative dimensional space, that the bilinear model would be characterized as a version of hypothesis-testing.

Table 1
sCOVIS model fits in Application 1.

	PD	PD-control	HD	HD-control
Proportion of participants for which the Cooperation Model is superior to the Competition Model	1.00	0.80	0.71	1.00
Proportion of participants for which the Cooperation Model fits significantly better than the PB or HT Models	0.90[a]	0.40	0.86	0.33
Average HT system weight (Standard error)	0.46 (0.05)	0.41 (0.10)	0.50 (0.05)	0.23 (0.04)

[a] $p < .05$. Average PB system weight is 1-w_{HT}.

Table 2
Goodness-of-Fit ($-\ln L$) Values from the final block of trials for the cooperation (Coop) and competition (Comp) versions of sCOVIS for Application 1.

Participant	PD		PD-control		HD		HD-control	
	Coop	Comp	Coop	Comp	Coop	Comp	Coop	Comp
1	**22.07**	29.52	**8.15**	9.25	**17.38**	27.09	**8.70**	12.20
2	**19.63**	25.69	**6.45**	8.29	**16.81**	21.91	7.11	9.25
3	**18.91**	24.68	**6.73**	8.31	19.57	**19.38**	**6.11**	8.29
4	**22.50**	30.52	**18.42**	21.27	24.91	**24.04**	**3.01**	6.08
5	**18.76**	19.98	21.69	**20.80**	**29.54**	32.24	**10.95**	16.75
6	**39.65**	43.20			**14.31**	18.81	**0.00**	2.49
7	**44.24**	49.04			**31.32**	33.76		
8	**13.84**	15.34						
9	**19.34**	23.77						
10	**47.49**	50.38						

hypothesis-testing strategies toward procedural-based strategies as they would need to do to perform optimally in the nonlinear information-integration task yielding a larger impact of the hypothesis-testing system on performance. Such an impairment to transitioning away from hypothesis-testing approaches toward procedural-based approaches may be due to damage in the neural regions that subserve procedural-based learning (e.g., the striatum). In support of this claim, we found a consistent advantage for the sCOVIS model over the quadratic procedural-based and the bilinear hypothesis-testing models (based on G^2 tests with a $p <$ .05 level of significance) across blocks for the patients with 7, 6, 5, 6, 6, and 9 of the 10 PD patient's data being better fit by the sCOVIS in blocks 1–6, respectively and 4, 5, 5, 4, 6, and 5 of the 7 HD patient's data being better fit by the sCOVIS in blocks 1–6, respectively. On the other hand, we found a strong trend away from better fits of the sCOVIS model over the quadratic procedural-based and bilinear hypothesis-testing models (based on G^2 tests with a $p < .05$ level of significance) across blocks for the controls with 3, 3, 2, 2, 3, and 1 of the 5 PD-control patient's data being better fit by the sCOVIS in blocks 1–6, respectively and 4, 5, 2, 2, 2, and 1 of the 6 HD-control patient's data being better fit by the sCOVIS in blocks 1–6, respectively. It is possible that controls were able to undergo such a strategy transition because of a normal striatum.

We next examined the system weight associated with the hypothesis-testing subsystem. The average hypothesis-testing system weights (along with the standard errors) are displayed in Table 1. Several comments are in order. First, the average system weights are larger for the patient groups than for the controls. This is expected given the fact that the sCOVIS model was more likely to provide a significant improvement in fit over the static, single strategy models. Second, whereas the hypothesis-testing system weights were significantly larger in the HD patients than in their associated controls [$t(11) = 4.425, p < .001; \eta^2 = .64$], the weights did not differ significantly across the PD patients and their associated controls [$t(13) < 1.0; \eta^2 = .02$]. It is worth mentioning that this finding holds, not because the weights are larger for PD patients than for HD patients, but rather because the weights are smaller for the HD controls than for the PD controls. Given that these two groups differed in age (with HD controls being younger than PD controls), these findings suggest the possibility that age might also negatively impact one's ability to shift away from a hypothesis-testing strategy (Filoteo & Maddox, 2004).

We also examined the system weights across blocks. These values are displayed in Table 3 along with the standard errors. As expected, the system weights remained relatively constant across blocks for the patients remaining quite large even during the final block of trials. On the other hand, and also as expected, there was a general decline in the system weight values for the controls.

Finally, we examined the noise estimates from the model. We conducted t-tests comparing the noise estimates from the procedural-based system across patients and controls, and noise estimates from the hypothesis-testing system across patients and controls. None of the effects were significant due to large intra-group variability estimates. Despite the lack of significance, a few comments are in order. Interestingly, the noise estimates from the procedural based system were much larger for the patients than for the controls [average sum of perceptual and criterion noise: PD = 1.85 (s.e. = 1.50; PD controls = .69 (s.e. = .60); HD = 2.94 (2.15); HD controls = .58 (s.e. = .49)], whereas the group differences were much smaller for the noise estimates from the hypothesis-testing system [average perceptual noise: PD = 2.32 (s.e. = 1.25); PD controls = 1.76 (s.e. = .78); HD = 1.45 (s.e. = .93); HD controls = 1.03 (s.e. = .65)]. Although speculative, these data suggest that the patient group differences are larger in the procedural-based sub-system than in the hypothesis-testing sub-system. A visual examination of the best fitting quadratic decision bounds suggests that the locus of the PD patient deficit was due to poor learning of the optimal quadratic decision bound. Although both PD and HD patients were highly sub-optimal, the degree of suboptimality appeared larger for the PD patients. Thus, based on the fits of sCOVIS, it appears that the locus of HD patients' accuracy deficit in nonlinear information integration classification learning was due to too much reliance on the sub-optimal hypothesis-testing sub-system, whereas the locus of PD patients' deficit appeared to be in the use of a highly sub-optimal quadratic decision bound in the procedural-based subsystem.

3.2. Brief summary

First, a cooperation and competition version of sCOVIS was developed and applied to the nonlinear information-integration classification learning data from PD, HD, and healthy matched controls. Interestingly, the cooperative version of the model consistently outperformed the competition version for all participant groups suggesting that the system level interaction might differ from that originally proposed in dCOVIS. Second, inclusion of both

Table 3
Average (and Standard error) of hypothesis-testing system weights for Application 1.

		Block					
		1	2	3	4	5	6
PD	Average	0.49	0.62	0.45	0.65	0.47	0.46
	Standard error	0.07	0.08	0.07	0.09	0.06	0.05
PD-control	Average	0.68	0.67	0.55	0.80	0.51	0.41
	Standard error	0.09	0.10	0.21	0.16	0.15	0.10
HD	Average	0.64	0.40	0.44	0.52	0.47	0.50
	Standard error	0.09	0.07	0.10	0.08	0.09	0.05
HD-control	Average	0.67	0.56	0.36	0.75	0.29	0.23
	Standard error	0.07	0.09	0.13	0.05	0.07	0.04

the procedural-based and hypothesis-testing systems in the architecture of sCOVIS was more important in predicting the data from the patients than the controls. This is reflected by the fact that a larger proportion of patients' data, relative to the controls' data, was best fit by the sCOVIS framework as compared to the separate models alone. This finding supports our claim that both systems must be incorporated in clinical science investigations of classification learning. Finally, although we found analogous accuracy deficits for HD and PD patients, the sCOVIS framework suggests that the locus of the deficits might be different. Specifically, HD patients were relying too much on the sub-optimal hypothesis-testing system, with an average hypothesis-testing system weight of .50 for the HD patients and .23 for the controls. PD patients and controls hypothesis-testing system weights did not differ, but the locus of their deficit appeared to be in the use of highly sub-optimal quadratic decision bounds within the procedural-based subsystem.

This pattern of findings in the model parameters is congruent with what we know about the effects of PD and HD on the striatum. HD is characterized by cell loss in the striatum, whereas PD is characterized by striatal dysfunction that is secondary to loss of dopamine projecting into the striatum. In other words, in HD there is damage to the striatum, whereas in PD there is dysfunction in the striatum. If the striatum is damaged as in HD, then it is reasonable to predict a greater reliance on other learning systems, such as the hypothesis-testing system, as we observed in the sCOVIS modeling. In contrast, in a dysfunctional striatum, the procedural-based system may still be available to a certain extent, but it likely operates at a sub-optimal level. This would lead us to predict the use of less optimal quadratic decision bounds in the sCOVIS model as we observed.

One may argue that it is also possible that the model differences observed between PD and HD participants are due simply to the fact that all the PD patients were nondemented, whereas the HD patients had significant global cognitive deficits (with some meeting the criteria for dementia). Although we cannot rule this out, it is important to reiterate the basic accuracy results summarized above. HD patients yielded 83% accuracy and PD patients yielded 79% accuracy in the final block of training. Both of these accuracy rates reflect significant learning, with the HD patients achieving a higher performance level. In addition, the fits of all the models were comparable across PD and HD patient groups. If HD patients were simply more cognitively impaired, we would expect consistently poorer fits of the models to the HD data.

4. Application 2: Predicting cognitive decline in PD patients using sCOVIS

One of the most important challenges facing clinical scientists is to determine the clinical utility of their performance measures by ascertaining whether such measures are predictive of future cognitive decline in progressive diseases, such as PD or HD. In a recent study (Filoteo, Maddox, Salmon et al., 2007), we used performance on a nonlinear information-integration task to predict cognitive decline in PD patients. Seventeen non-demented PD patients were asked to complete six 100-trial blocks in the nonlinear information-integration task displayed in Fig. 4B.[7] The stimuli were lines that varied in length and orientation. Replicating our previous work (Maddox & Filoteo, 2001), we found PD patients to be impaired relative to matched controls in terms of accuracy. These patients also completed the Mattis Dementia Rating Scale (MDRS; Mattis, 1988), which is a measure of global cognitive functioning that has been used successfully with PD patients in both clinical and research settings (Brown, Rahill, Gorell, Mcdonald, Brown, & Sillanpaa, 1999). Upon initial testing, the PD patients did not differ from controls on the MDRS, despite their performance impairment in the nonlinear information-integration task.

Follow-up testing was conducted an average of 1.6 years after the initial testing, at which time the 17 PD patients were again administered the MDRS to determine whether performance on the nonlinear task (1.6 years earlier) predicted future cognitive decline based on the change in MDRS scores. During the initial testing period, the PD patients' mean MDRS total score was 139.0 and at the time of the second evaluation, their mean score was 134.2. Interestingly, poorer performance in the final block of the nonlinear information-integration task was highly predictive of future decline on the MDRS ($r = -.78$; 61% of the variance), whereas poorer performance (an increase in perseverative errors) on a more traditional classification learning task (the WCST) was less predictive of decline ($r = .42$; 18% of the variance). Importantly, none of the patients were considered to be demented at the time of their second evaluation and accuracy performance in the nonlinear condition did not correlate with patients' initial MDRS scores.[8]

In this section, we extend these analyses, by applying the sCOVIS model to these data. We will then use information garnered from these fits to determine whether significant additional variance in cognitive decline can be captured. Filoteo and Maddox (2007) showed that decision bound model fits, specifically identifying whether a hypothesis-testing model or a procedural based model provided the best account of the data, accounted for a significant additional 15% of the variance in cognitive decline in this sample. Thus, it is worth determining whether the more psychologically valid multiple systems approach will yield a similar result.

We took the same approach outlined in Application 1 to fitting of the sCOVIS model. We began by applying the optimal (2 parameters; perceptual and criterial noise) and sub-optimal quadratic (7 parameters; 5 decision bound, perceptual

[7] These 17 patients were a subset of 20 PD patients who completed the task (Filoteo et al., 2005), and were able to complete a follow up evaluation.

[8] Additional regression analyses verified that nonlinear information-integration performance continued to predict cognitive decline even after age, gender, motor impairment, mood, baseline performance on the MDRS, and performance on the WCST were taken into account.

Table 4
Goodness-of-Fit ($-\ln L$) Values from the Final Block of trials for the Cooperation (Coop) and Competition (Comp) versions of sCOVIS for Application 2.

Participant	PD	
	Cooperation	Competition
1	**58.20**	64.07
2	**20.41**	24.51
3	**42.31**	44.07
4	**58.87**	65.13
5	**62.81**	65.41
6	**50.64**	51.84
7	**58.99**	61.83
8	**25.63**	33.18
9	**59.41**	65.49
10	**12.23**	38.04
11	**45.62**	50.73
12	**35.31**	36.89
13	**38.35**	38.44
14	**27.36**	32.62
15	**64.16**	66.81
16	**60.30**	67.02
17	39.70	**35.54**

and criterial noise) procedural-based models, a unidimensional length hypothesis-testing model (2 parameters; length criterion and perceptual noise), a unidimensional orientation hypothesis-testing model (2 parameters; orientation criterion and perceptual noise), and a conjunctive model that assumes "A" responses to long shallow angled lines and "B" responses to all other stimuli (3 parameters; length criterion, orientation criterion, and perceptual noise) to the 6th block of data.[9]

As expected from Application 1, we found that the sub-optimal quadratic procedural-based model provided a significantly better fit to the data than the optimal model for 15 of 17 PD patients (based on G^2 tests with a $p < .05$ level of significance). In addition, we found that the conjunctive model provided a significantly better fit to the data than either unidimensional model for 14 of 17 PD patients (based on G^2 tests with a $p < .05$ level of significance). Thus, we examined a competitive and cooperative version of sCOVIS that assumed a quadratic procedural-based strategy and a conjunctive hypothesis-testing strategy.

Much like we found in Application 1, we found strong support for the cooperation version of the model over the competition version based on direct comparisons of the goodness-of-fit measure, with 16 of the 17 patients ($p < .001$ based on a sign test) being better fit by the cooperation model (see Table 4 for goodness-of-fit values). In addition, we found that the cooperation version of the model provided a significant improvement in fit over the quadratic and conjunctive single system models for 11 of the 17 patients (based on G^2 tests with a $p < .05$ level of significance). The average hypothesis-testing system weight was .51 (s.e. $= .055$) which is very similar to the .46 observed in Application 1.

As outlined above, Filoteo and Maddox (2007) showed that a stepwise regression that attempted to predict the change in MDRS scores from accuracy and a binary variable (coded as a 1 if a hypothesis-testing decision bound model provided the best account of the data or 2 if a procedural based decision bound model provided the best account of the data), accounted for 61% of the variance in cognitive decline from accuracy, and a significant additional 15% of the variance in cognitive decline from the binary model-based variable. In an attempt to model our approach after theirs, we created a binary variable that was coded as a 1 if the system weight on the hypothesis-testing system was greater than .50 (suggesting greater reliance on the output of the hypothesis-testing system on each trial and less reliance on the procedural system) and was coded as a 2 if the system weight on the hypothesis-testing system was less than .50 (suggesting less reliance on the output of the hypothesis-testing system on each trial and more reliance on the procedural system).

We conducted the same stepwise regression and found that the sCOVIS binary system weight variable predicted a significant additional 11% of the variance in cognitive decline above and beyond that predicted from the accuracy measure with those having a hypothesis-testing system weight that was greater than 0.5 showing greater cognitive decline. Thus, using a single category learning task and the sCOVIS framework, we were able to predict 72% of the total variance associated with future cognitive decline in a nondemented PD sample after a mean follow-up of just 1.6 years. These results clearly establish the clinical utility for the use of quantitative modeling for a better prediction of global cognitive decline in nondemented PD patients.

4.1. *Brief summary*

The aim of Application 2 was to apply the sCOVIS framework to the important task of predicting cognitive decline. Filoteo, Maddox, Salmon et al. (2007) found that performance on a nonlinear information-integration task predicted 61% of the variance in PD patients' cognitive decline over a 1.6 year period as measured by the MDRS. In this section, we applied the sCOVIS framework to the same data and found (a) that the sCOVIS model provided a significantly better account of the data than the single system decision bound models for 11 of 17 (65%) patients, and (b) that including a variable based on the estimated hypothesis-testing system weight from the model accounted for a significant additional 11% of the variance in PD patients' MDRS-based cognitive decline. Filoteo and Maddox (2007) found that classifying patients as hypothesis-testers or procedural-based classifiers based on fits of the single-system decision bound models accounted for slightly more of the variance (15%) in cognitive decline. Although it may seem that the additional 11% predicted from the sCOVIS framework is less than the 15% predicted from the decision bound framework, this difference is not significant. In addition, it is important to note that the sCOVIS framework provides a much better account of individual participant's data, and perhaps most importantly, comes from a more psychologically and neurally plausible model.

5. Summary and conclusions

A thorough understanding of the cognitive deficits in patients with brain dysfunction is critical for the development of therapies and interventions designed to improve these individuals' quality of life. Computational modeling approaches have been successfully applied to the study of healthy (college age) adults' cognitive functioning, and many important advances have been made. There has been a growing interest in applying these modeling techniques to the study of cognitive processes in clinical populations.

In this article we develop a new modeling approach and apply it to classification learning in patients with striatal dysfunction. The model can be thought of as intermediate between decision bound models that assume that a fixed hypothesis-testing or procedural-based strategy is applied on each trial in a block of trials, and a multiple system model (dCOVIS) that assumes that hypothesis-testing and procedural-based subsystems are active on each trial and that the parameters that govern inter- and intra-system processing can change on a trial by trial basis. The new model, referred to as the sCOVIS model, assumes that hypothesis-testing and procedural-based subsystems are active on each trial, but that the parameters that govern behavior of the system are fixed (static)

9 The bi-linear model used in Application 1 is not relevant here because the only valid dimensionalization of these data is length and orientation.

within a block of trials. We reiterate that we believe that category learning is a dynamic process and in that sense dCOVIS is a more psychologically plausible model. That said, as the participant gains experience with the task the dCOVIS parameter values tend to settle and thus may be more closely reflected in the block-by-block parameter estimates from sCOVIS (Ashby et al., 1998). Of course, a thorough empirical or simulation based comparison is in order to fully understand the practical similarities and differences between the two models.

We applied competition and cooperation versions of sCOVIS to nonlinear information-integration performance in PD and HD patients. There was strong support for the cooperation version of the model for both patient groups and their associated controls. To our knowledge this is the first ever attempt to directly compare these two decision rules within the framework of COVIS. In that sense, we need to be cautious in drawing any strong inference. Clearly, much more work is needed. Even so, these data suggest that the output of the two systems work in concert and do not compete to produce a categorization response. Future work should examine the nature of this cooperation.

In Application 1, we showed that the locus of HD patients' nonlinear information-integration deficits was in their increased reliance on the sub-optimal hypothesis-testing system, whereas the locus of PD patients' deficit was in the application of a sub-optimal quadratic decision bound. In Application 2, we showed that the weight on the hypothesis-testing subsystem accounted for a significant amount of the variance in global cognitive decline in non-demented PD patients above and beyond that predicted from non-linear information-integration accuracy. Importantly, the accuracy and model indices accounted for 72% of the total variance associated with cognitive decline in this sample. In contrast, regression analyses that included accuracy and performance measures from the WCST showed that the WCST did not account for any significant additional variance above and beyond that predicted from accuracy alone.

In summary, it is an exciting time to be involved in clinical science and assessment. Technological advances such as brain imaging, and the application of computational modeling approaches are already yielding numerous positive outcomes. Our hope in this article is to offer a relatively simple computational modeling technique that can be used as a window onto cognitive process in classification.

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Appendix A. Decision bound models applied in Application 1

The probability of responding A, $P(R_A|\mathbf{x})$ is given in Eq. (5) in the text. The mean and variance depend upon the form of the $h(\mathbf{x}_p)$ and is derived below for the models utilized in Application 1.

A.1. Suboptimal quadratic procedural-based model

In this model the decision bound, $h(\mathbf{x}_p)$ is quadratic. With two perceptual dimensions x and y, every quadratic bound satisfies

$$h(x, y) = a_1x^2 + a_2y^2 + a_3xy + b_1x + b_2y + c_o = 0 \tag{A.1}$$

with constants a_1, a_2, a_3, b_1, b_2, and c_0. Eq. (A.1) can be rewritten in vector notation as

$$h(\mathbf{x}) = \mathbf{x}'\mathbf{A}\mathbf{x} + \mathbf{b}'\mathbf{x} + c_o = 0. \tag{A.2}$$

Ashby and Maddox (1993) show that the mean and variance of $h(\mathbf{x}_p)$ are equal to

$$\mu_{h(x)} = \mathrm{trace}(\mathbf{A}\boldsymbol{\Sigma}_p) + \mathbf{x}'\mathbf{A}\mathbf{x} + \mathbf{b}'\mathbf{x} + c_o \tag{A.3}$$

and

$$\sigma^2_{h(x)} = 2\,\mathrm{trace}(\mathbf{A}\boldsymbol{\Sigma}_p)^2 + (\mathbf{b} + 2\mathbf{A}\mathbf{x})'\boldsymbol{\Sigma}_p(\mathbf{b} + 2\mathbf{A}\mathbf{x}). \tag{A.4}$$

Thus, the probability of responding A, $P(R_A|\mathbf{x})$ for each stimulus $\mathbf{x}$ can be approximated by Eq. (5) with $\mu_{h(x)}$ and $\sigma^2_{h(x)}$ given in Eqs. (A.3) and (A.4). The probability is approximate because $h(\mathbf{x}_p)$ is only approximately normally distributed when $h(\mathbf{x})$ is quadratic.

A.2. Optimal quadratic procedural-based model

The optimal quadratic procedural-based model is a special case of the sub-optimal quadratic procedural-based model with

$\mathbf{A} = 1/2(\boldsymbol{\Sigma}_A^{-1} - \boldsymbol{\Sigma}_B^{-1})$,

$\mathbf{b}' = \boldsymbol{\mu}_B'\boldsymbol{\Sigma}_B^{-1} - \boldsymbol{\mu}_A'\boldsymbol{\Sigma}_A^{-1}$,

and

$c0 = 1/2[\boldsymbol{\mu}_A'\boldsymbol{\Sigma}_A^{-1}\boldsymbol{\mu}_A - \boldsymbol{\mu}_B'\boldsymbol{\Sigma}_B^{-1}\boldsymbol{\mu}_B + \ln(|\boldsymbol{\Sigma}_A|/|\boldsymbol{\Sigma}_B|)]$.

A.3. Unidimensional horizontal length hypothesis-testing model

The unidimensional horizontal length hypothesis-testing model assumes that the participant sets a criterion on the horizontal length dimension and gives one response to "short" horizontal lines and another response to "long" horizontal lines. In this case the decision bound is linear, and thus Eq. (5) applies directly. In addition, because the decision bound is parallel with the coordinate axis, Eq. (5) can be simplified to

$P(R_A|\mathbf{x}) = \Phi[(x - x_o)/\sigma_p]$,

where x_o denotes the decision criterion that separates "short" from "long" horizontal lines.

A.4. Unidimensional vertical length hypothesis-testing model

This model is identical to the unidimensional horizontal length hypothesis-testing model except that the criterion is set on the vertical line length dimension (y). Thus the decision rule becomes

$P(R_A|\mathbf{x}) = \Phi[(y - y_o)/\sigma_p]$,

where y_o denotes the decision criterion that separates "short" from "long" vertical lines.

A.5. Equal line length bi-linear hypothesis-testing model

This model assumes that there are two linear decision bounds. When the decision bound is linear, Eq. (A.2) reduces to

$$h(\mathbf{x}) = \mathbf{b}'\mathbf{x} + c_o = 0 \tag{A.5}$$

with mean and variance equal to

$$\mu_{h(x)} = +\mathbf{b}'\mathbf{x} + c_o \tag{A.6}$$

and

$$\sigma^2_{h(x)} = \mathbf{b}'\boldsymbol{\Sigma}_p\mathbf{b}. \tag{A.7}$$

As outlined in the text, this model assumes that there are two linear decision bounds with a slope of 1. Thus, Eq. (5) along with A5–A7 would be applied separately for each stimulus, $\mathbf{x}$, under the constraint that the slope is 1 and the intercept is positive for one of the linear decision bounds, and is negative for the other decision bound. The "A" response region is associated with the area between the two linear decision bounds. Thus to determine the probability of responding "A" we estimate the probability of responding "A" for the linear decision bound with slope 1 and a positive intercept and subtract the probability of responding "A" for the linear decision bound with slope 1 and a negative intercept.

Appendix B. Decision bound models applied in Application 2

The decision bound models utilized in Application 1 were also utilized in Application 2 with the exception of the bilinear model that was replaced with a conjunctive rule based model.

B.1. Conjunctive hypothesis-testing model

The conjunctive hypothesis-testing model assumes that the participant sets a criterion on line length and on orientation giving one response to long/shallow orientation items and the other response to all other items. This model can be derived by combining the decision rule for the two uni-dimensional hypothesis-testing models. Thus, for this model Eq. (5) can be written as

$$P(R_A|\mathbf{x}) = \Phi[(x - x_o)/\sigma_p]\Phi[(y - y_o)/\sigma_p],$$

where x_o denotes the decision criterion that separates "short" from "long" horizontal lines, and y_o denotes the decision criterion that separates "shallow" from "steep" horizontal lines.

Appendix C. Goodness-of-Fit

Each of these models was fit separately to the six 100-trial blocks of data separately for each participant. The model parameters were estimated using maximum likelihood (Ashby, 1992b; Wickens, 1992). When the models had the same number of parameters, log likelihood values were compared directly. When models were nested G^2 likelihood ratio tests were use to determine the best model. When the models were not nested, AIC was used. The AIC goodness-of-fit statistic was:

$$AIC = 2r - 2\ln L,$$

where r is the number of free parameters and L is the likelihood of the model given the data (Akaike, 1974; Takane & Shibayama, 1992). The AIC statistic penalizes a model for extra free parameters in such a way that the smaller the AIC, the closer a model is to the "true model", regardless of the number of free parameters. Thus, to find the best model among a given set of competitors, one simply computes an AIC value for each model, and chooses the model associated with the smallest AIC value.

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