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Characterizing rule-based category learning deficits in patients with Parkinson's disease

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Abstract

Parkinson's disease (PD) patients and normal controls were tested in three category learning experiments to determine if previously observed rule-based category learning impairments in PD patients were due to deficits in selective attention or working memory. In Experiment 1, optimal categorization required participants to base their decision on a single stimulus dimension and ignore irrelevant variation on another dimension, thus emphasizing selective attention processes. In Experiment 2, optimal categorization required participants to base their decision on both stimulus dimensions using a conjunction of unidimensional decisions. Thus, this task placed less emphasis on selective attention and more on working memory. In Experiment 3, optimal categorization again required participants to base their decision on both stimulus dimensions using a disjunction of two unidimensional decisions in which an additional verbal operation was needed, thereby placing even greater emphasis on working memory. Results indicated that PD patients were impaired in the unidimensional rule-based condition, but not the other two rule-based conditions. These results are consistent with previous studies that demonstrate that PD patients are impaired in learning rule-based categories when selective attention demands are greatest, whereas these patients are normal in learning rule-based tasks when working memory demands are emphasized. Overall, these findings help to delineate the conditions under which PD patients display rule-based category learning deficits.

Keywords: Parkinson's disease; Category learning; Rule-based; Selective attention; Working memory

A growing body of research indicates that patients with Parkinson's disease (PD) are impaired in their ability to learn new categories (Ashby, Noble, Filoteo, Waldron, & Ell, 2003; Filoteo, Maddox, Ing, Zizak, & Song, 2005; Filoteo, Maddox, Salmon, & Song, 2005; Knowlton, Mangels, & Squire, 1996; Maddox, Aparicio, Marchant, & Ivry, 2005; Maddox & Filoteo, 2001; Shohamy, Myers, Grossman, et al., 2004; Shohamy, Myers, Onlaor, & Gluck, 2004; Witt, Nuhsman, & Deuschl, 2002). However, not all studies have identified a generalized category learning deficit in these patients (Filoteo, Maddox, Ing, et al., 2005; Filoteo, Maddox, Salmon, et al., 2005; Maddox & Filoteo, 2001; Peigneux, Meulemans, Van der Linden, Salmon, & Petit, 1999; Reber & Squire, 1999; Smith, Siegert, McDowall, 2001; Witt, Nuhsman, & Deuschl, 2002). One potential reason for this discrepancy is the likelihood that there are multiple category learning systems (Asbhy & Maddox, 2005; Keri, 2003; Smith, Patalano, & Jonides, 1998), with some of these systems being impacted by the pathological changes to the striatum that occur in PD and other category learning systems not being affected. For example, PD patients' category learning abilities may be impaired to a greater extent when learning is based on trial-by-trial feedback (Filoteo, Maddox, Ing, et al., 2005; Shohamy, Myers, Onlaor, et al., 2004), but not when learning is based on simple observation of category exemplars (Reber & Squire, 1999). This difference may be due to PD patients experiencing a deficiency in the dopamine-mediated reward signal that likely drives trial-by-trial feedback learning (Aron et al., 2004), but having an intact perceptual priming system that is likely responsible for certain aspects of observational learning (Reber, Stark, & Squire, 1998).

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Another area that PD patients might experience a deficit is in their ability to learn *rule-based* categories. Rule-based categories are thought to be learned via an explicit *hypothesis-testing* system that seems to rely on hypothesis generation and testing, logical reasoning, working memory and executive attention. Rule-based categories are those where the rule defining category membership is salient and verbalizable, and can often be based on a single stimulus feature (e.g., the stimulus goes into one category if it is a certain color and another category if it is a different color; Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Bruner, Goodnow, & Austin, 1956; Smith et al., 1998). These tasks are often referred to as unidimensional rule-based tasks because information on a single dimension defines category membership. Perhaps the most well-known rule-based category learning task is the Wisconsin Card Sorting Test (WCST; Heaton, 1981), on which PD patients have been shown to be impaired in a number of previous investigations (Alevriadou, Katsarou, Bostantjopoulou, Kiosseoglou, & Mententopoulos, 1999; Bowen, Kamienny, Burns, & Yahr, 1975; Brown & Marsden, 1988; Caltagirone, Carlesimo, Nocentini, & Vicari, 1989). Although these studies might suggest a deficit in the learning of rule-based categories, one potential confound with the WCST is that the level of performance is often based on the ability to switch to a new rule after another rule has been established. The index measuring this sort of 'set-shifting' on the WCST is the number of preservative responses (i.e., the number of times a participant responds with a previously correct category although that category is no longer correct), and it is on this index that most studies report impairment in patients with PD. Thus, although PD patients are impaired on this test, their deficit may be due primarily to an inability to switch between rules and not necessarily in rule acquisition (see also Cools, Barker, Sahakian, & Robbins, 2001; Owen, Roberts, et al., 1993).

In a series of recent studies, we examined PD patients' ability to *learn* rule-based categories. In one study (Maddox & Filoteo, 2001), non-demented PD patients were normal in learning a rule-based task that required participants to compare the length of two lines and categorize the stimuli into one category if the vertical line was longer than the horizontal line, or into another category if the horizontal line was longer than the vertical line. These findings gave the initial impression that PD patients are normal at rule-based category learning. However, in a follow-up study (Ashby, Noble, et al., 2003) we found contradictory results. In that study, participants were asked to categorize single cards that consisted of colored geometric figures on a colored background. Each stimulus varied from trial-to-trial along four binary-valued dimensions. In the rule-based condition, category membership was defined by the value on a single dimension (e.g., color of the stimuli), thus the task was unidimensional. Interestingly, PD patients were impaired in learning, with fewer PD participants than controls being able to meet a specific learning criterion. Maddox et al. (2005) recently found that PD patients are impaired in learning a unidimensional rule-based task when correct categorization is based on either the distance between two lines or the length of a single line, results that again suggest PD patients are impaired in rule-based category learning. Thus, unlike our original finding in which PD patients were normal in rule-based category learning (Maddox & Filoteo, 2001), two subsequent studies indicate that PD patients are impaired in learning unidimensional rule-based tasks.

One possible explanation for these discrepant results is that the various rule-based tasks differ in terms of the presence or absence of irrelevant dimensional variation. That is, in our original study (Maddox & Filoteo, 2001), both of the stimulus dimensions were relevant to category membership (i.e., participants had to base their decision on the length of both lines), so there was no irrelevant dimensional variation. In contrast, in the study by Ashby, Noble, et al. (2003), one dimension of the stimulus was relevant, and three dimensions could vary randomly from trial-to-trial, and in the study by Maddox et al. (2005), one stimulus dimension was relevant but the other irrelevant dimension varied from trial-to-trial. Thus, the latter two studies potentially required greater selective attention than did the former study. Indeed, the WCST, on which PD patients are often impaired, also requires that the participant attend selectively to a single stimulus dimension when other irrelevant dimensions vary on a trial-by-trial basis. As such, a selective attention deficit might also underlie their impairment in shifting from one rule to another.

To examine the role of selective attention in PD patients' rule-based category learning more directly, we conducted a follow-up study (Filoteo, Maddox, Ing, et al., 2005) in which we systematically manipulated the selective attention requirements during the learning of a rule-based task. Specifically, participants were administered a rule-based task in which they were presented with stimuli that had 4 binary-valued dimensions (similar to those used in the study by Ashby, Noble, et al. (2003)) in four different conditions. In each of the conditions, one of the binary-valued dimensions determined category membership, and zero, one, two, or three irrelevant dimensions varied from trial-to-trial. Thus, there was a systematic difference among the four conditions in terms of the degree of irrelevant dimensional variation, and as such, the need for selective attention. PD patients' ability to learn the rule-based categories was impacted to a greater extent than controls as the number of varying irrelevant dimensions increased, suggesting that deficits in selective attention might contribute to the PD patients' rule-based category learning deficit. This characterization of the rule-based category learning deficit in PD is consistent with the observation that these patients are impaired on direct tests of selective attention (Dujardin, Degreef, Rogelet, Defebvre, & Destee, 1999; Filoteo & Maddox, 1999; Maddox, Filoteo, Delis, & Salmon, 1996; McDowell & Harris, 1997; Sharpe, 1990, 1992). In fact, in two previous studies using similar methods as those in the present study, we demonstrated that PD patients were impaired in attending selectively to a single dimension of a two-dimensional stimulus, whereas they were normal in attending to two relevant stimulus dimensions (Filoteo & Maddox, 1999; Maddox et al., 1996). The only difference between the present study and our two previous studies was that, in our previous work, we told the participants the categorization rule prior to the start of the experiment, thereby eliminating the need for learning.

Taken together, these findings raise the possibility that a selective attention impairment might contribute to any observed rule-based category learning deficit in patients with PD. These findings might then suggest a specific rule-based category learning deficit in PD, one that emerges when selective attention demands are emphasized. However, it is also known that PD patients are impaired in other cognitive processes known to be important for rule-based category learning. As noted above, rule-based category learning tasks not only require selective attention, but can also emphasize working memory processes (Ashby et al., 1998; Smith & Sloman, 1994). Working memory is believed to be important for rule-based category learning because participants must (a) maintain on-line a possible rule that dictates category membership, (b) test this possible rule by categorizing the stimuli, (c) incorporate feedback once a response is made, and (d) maintain on-line rejected rules that did not lead to correct category membership (Ashby et al., 1998; Smith & Sloman, 1994). Deficits in working memory have been reported in PD patients in a number of studies. For example, PD patients are impaired on n-back tasks (Costa et al., 2003), self-ordered pointing tasks (Gabrieli, Singh, Stebbins, & Goetz, 1996), delayed non-matching to sample tasks (Blanchet et al., 2000), span tasks (Gilbert, Belleville, Bherer, & Chouinard, 2005), delayed eye movement tasks (Armstrong, Chan, Riopelle, & Munoz, 2002; Chan, Armstrong, Pari, Riopelle, & Munoz, 2005), and planning tasks (Owen et al., 1992), to name a few. Thus, it is possible that working memory deficits might also contribute to PD patients' impaired rule-based category learning. However, the extent to which working memory deficits impact PD patients' category learning abilities has not been well-studied. As such, whether PD patients' rule-based category learning deficits are due primarily to selective attention deficits is unknown at this time.

The purpose of the present study was to further examine the nature of rule-based category learning in patients with PD and determine whether deficits in selective attention or working memory best account for their previously observed impairments. To this end, we examined the performance of non-demented PD patients in several different experiments in which selective attention and working memory demands on rule-based category learning varied. In each experiment, we administered a rule-based task in which participants were shown single stimuli that consisted of a Gabor patch (see Fig. 1) that could vary trial-by-trial in the orientation of the gratings and the spatial frequency of the gratings. Participants were shown a single stimulus and asked to categorize it as a member of Category A or Category B. In Experiment 1, participants were administered a unidimensional rule-based task where correct responding required that they attend to only the spatial frequency of the gratings and base their decision on this dimension while ignoring the trial-by-trial variation on the orientation dimension. Thus, selective attention demands were emphasized in Experiment 1. In Experiments 2 and 3, participants were administered two different rule-based tasks, a conjunctive and disjunctive task, respectively. In both of these tasks, optimal responding required that participants attend to both the spatial frequency and orientation of the stimulus and base their categorization decision on both dimensions. Thus, selective attention demands were minimized. However, the conjunctive and disjunctive rules placed greater demands on working memory. The working memory requirements of the three conditions can be demonstrated by a comparison of the logical expressions needed to describe the optimal rule:

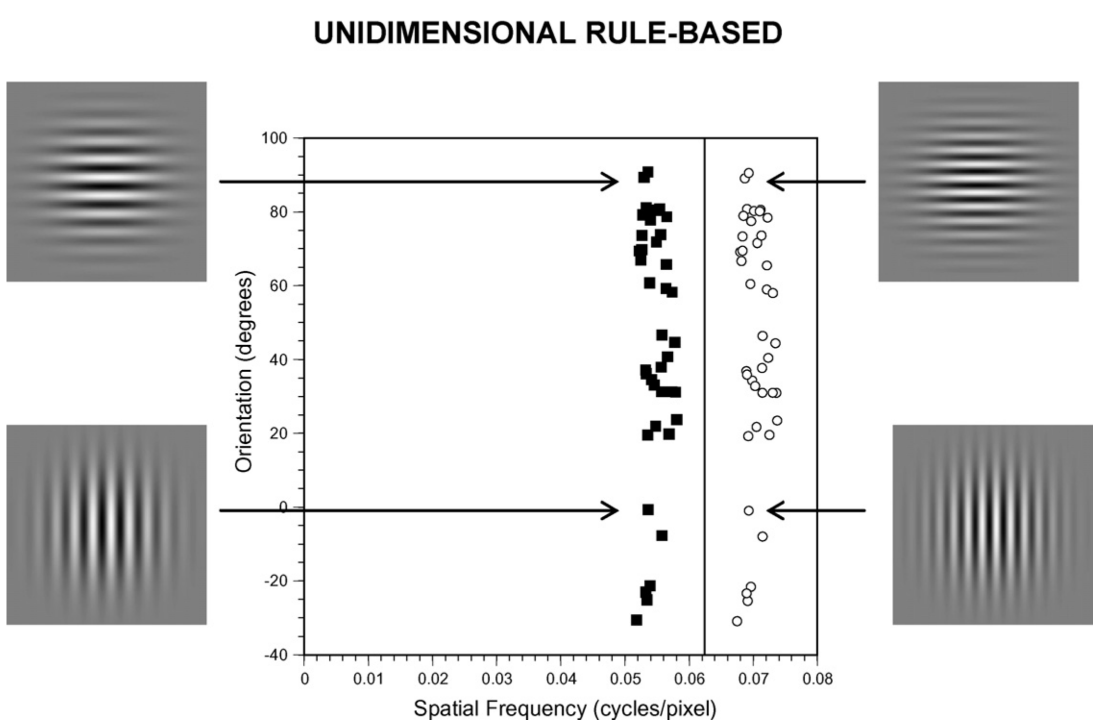

Fig. 1. Stimulus distributions and sample stimuli for Experiment 1. Filled squares represent stimuli from Category A and open circles represent stimuli from Category B. The solid line represents the optimal unidimensional rule-based rule. Arrows point from specific stimulus exemplars to their location in the two-dimensional stimulus space.

- *Unidimensional rule-based condition*: If the spatial frequency of the stimulus is small categorize it as A; if the spatial frequency of the stimulus is large categorize it as B.
- *Conjunctive rule-based condition*: If the spatial frequency of the stimulus is large *and* the orientation is relatively horizontal categorize it as A; if not then categorize it as B.
- *Disjunctive rule-based condition*: If the spatial frequency of the stimulus is large *and* the orientation is relatively horizontal *or* if the spatial frequency of the stimulus is small *and* the orientation is relatively vertical categorize it as A; if the spatial frequency of the stimulus is small *and* the orientation is relatively horizontal *or* if the spatial frequency of the stimulus is large *and* the orientation is relatively vertical categorize it as B.

Note that the main difference between the unidimensional rule as compared to the conjunctive and disjunctive rules is that the latter two require the participant to maintain in working memory two criteria—one for the orientation dimension and another for the spatial frequency dimension. These two criteria have to be maintained across trials while learning occurs, which results in the need for greater working memory capacity as compared to when only a single criterion is used. It is well established that conjunctive and disjunctive rules are considered more complex than unidimensional rules (Salatas & Bourne, 1974; Shepard, Hovland, & Jenkins, 1961) and thus likely require greater working memory or capacity (Kruschke, 1992; Maddox, Filoteo, Hejl, & Ing, 2004; Waldron & Ashby, 2001). In regard to the difference between the conjunctive and disjunctive rules, the main difference is not the number of criterion needed to be maintained in working memory, but rather the length of the logical expression needed to describe the rule. In particular, the need for the *or* statement in the disjunctive rule leads to a longer logical expression than the conjunctive rule. Previous research suggests that under many circumstances participants have a more difficult time learning disjunctive rules than conjunctive rules even when the logical rule length is equated, the speculation being that disjunctive rules require more working memory (Bourne, 1974; Haygood & Bourne, 1965; Pazzani, 1991). Importantly, rule-based tasks such as those in the present study are impacted by the performance of a secondary working memory demanding task (Zeithamova & Maddox, 2006) and more recent observations from Maddox and colleagues (unpublished data) suggest that, under most circumstances, conjunctive rules are impacted to a lesser degree than disjunctive rules by the performance of a secondary working memory task. These observations suggest that the learning of disjunctive rules likely emphasizes working memory to a greater extent than either conjunctive or unidimensional category structures.

Previous studies suggest that unidimensional, conjunctive and disjunctive rule-based tasks are learned using an explicit hypothesis-testing system (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). This assertion is based on past studies that have shown that the learning of these rules is not impacted by manipulations known to affect the learning of implicit categories, such as alterations in the timing of the feedback (Maddox, Ashby, & Bohil, 2003; Maddox & Ing, 2005) or the stimulus-response mappings (Ashby, Ell, & Waldron, 2003; Ashby, Noble, et al., 2003; Maddox, Bohil, & Ing, 2004), suggesting that rule-based tasks are not learned using perceptual or procedural-based learning processes. In contrast, rule-based category learning is impacted by manipulations that impact working memory, as noted above. The application of formal models (that will also be applied in the present study) to participants' category learning performance when learning unidimensional, conjunctive and disjunctive rule-based tasks also supports the contention that rule-based category structures are learned via a hypothesis-testing system (Ashby, Ell, et al., 2003; Maddox et al., 2003; Maddox, Bohil, et al., 2004; Maddox & Ing, 2005; Zeithamova & Maddox, 2006). The key brain regions for the hypothesis-testing system are the prefrontal cortex, anterior cingulate, and the anterior regions of the caudate nucleus; neural structures that underlie hypothesis generation and testing, logical reasoning, working memory and executive attention (Ashby et al., 1998; Asbhy & Maddox, 2005; Ashby & O'Brien, 2005; Smith et al., 1998), and previous functional imaging studies have implicated these regions (Filoteo, Maddox, Simmons, et al., 2005; Nomura et al., in press; Smith et al., 1998). This frontal–striatal circuitry has been shown to be abnormal in patients with PD and thought to underlie many of their cognitive deficits (Bosboom, Stoffers, & Wolters, 2004; Dubois & Pillon, 1997; Owen, 2004), so it is not surprising that these patients would be impaired in rule-based category learning. Nevertheless, the nature of rule-based category learning is poorly understood in PD.

If PD patients' rule-based category learning deficits are specific to tasks in which selective attention demands are emphasized, the patients should be impaired only in Experiment 1. However, if working memory deficits also contribute to PD patients' rule-based category learning performance, then they should also be impaired in Experiments 2 and 3, but more so in Experiment 3 in which working memory demands were even greater.

1. General methods

1.1. Participants

The number of individuals who participated in the three experiments were as follows: Experiment 1, 12 PD patients (6 males and 5 females) and 12 normal control (NC) participants (4 males and 8 females); Experiment 2, 10 PD patients (6 males and 4 females) and 11 NC participants (3 males and 8 females); Experiment 3, 9 PD patients (4 males and 5 females) and 9 NC participants (3 males and 6 females). The patients were recruited from Movement Disorder Clinics at UCSD and were diagnosed by a board-certified neurologist with subspecialty training in movement disorders. The diagnosis was based on the presence of at least two of the following symptoms: (1) resting tremor, (2) rigidity, or (3) bradykinesia. Patients were excluded if they presented with atypical findings. In Experiment 1, 10 patients were taking daily L-dopa medication, 7 were taking a dopamine receptor agonist, 2 were taking an MAO inhibitor, 3 were taking a COMT inhibitor as part of their L-dopa preparation, and 2 were taking amantadine. In Experiment 2, eight patients were taking daily L-dopa medication, eight were taking a dopamine receptor agonist, one was taking an MAO inhibitor, five were taking a COMT inhibitor as part of their L-dopa preparation, and three were taking amantadine. In Experiment 3, six patients were taking daily L-dopa medication, seven were taking a dopamine receptor agonist, three were taking an MAO inhibitor, 1 was taking a COMT inhibitor as part of their L-dopa preparation, and two were taking amantadine. Table 1 shows the mean age, years

Table 1
Demographic characteristics and dementia rating scale scores of the PD patients and normal controls in Experiments 1–4

	Age		Education		DRS		HY		LOI	
	M	S.E.M.	*M*	S.E.M.	*M*	S.E.M.	*M*	S.E.M.	*M*	S.E.M.
Experiment 1: unidimensional RB										
PD	66.3	2.9	15.8	0.6	139.0	1.8	1.8	0.2	5.9	1.1
NC	67.6	1.8	15.5	0.7	140.5	0.9	–	–	–	–
Experiment 2: conjunctive RB										
PD	64.7	3.4	16.8	0.5	140.7	0.9	1.9	0.3	7.3	1.6
NC	68.0	2.0	15.8	0.6	141.1	0.8	–	–	–	–
Experiment 3: disjunctive RB										
PD	64.4	2.7	15.9	0.7	140.7	0.7	1.9	0.2	5.0	1.2
NC	67.2	2.2	16.3	0.7	140.2	0.8	–	–	–	–

of education, and scores on the dementia rating scale (DRS; Mattis, 1988) for the PD patients and NC participants for the three experiments, and the mean Hoehn and Yahr (1967) rating score and the length of illness (years) for the PD patients. In all three experiments, the PD and NC groups did not differ in age, education, scores on the DRS, or gender distribution (all p's > 0.05). In addition, the PD samples in the three experiments did not differ age, education, on the DRS, gender distribution, Hoehn and Yahr rating scores, or length of illness (all p's > 0.05).

1.2. Stimuli and stimulus generation

All three experiments used the randomization technique introduced by Ashby and Gott (1988). For each experiment, an equal number of Categories A and B stimuli were generated by sampling randomly from two bivariate normal distributions. Each category distribution is specified by a mean and a variance on each dimension, and by a covariance between dimensions. For both category structures it was always the case that the covariance matrix for Category A was identical to the covariance matrix for Category B. The categories differed only in the location of their means. The exact parameter values for each experiment are listed in Table 2 (*Note*: these are in arbitrary units that were transformed into the stimulus units using the methods described below). The category structures for Experiments 1–3 are displayed in Figs. 1, 3 and 5, respectively. Each filled square in these figures denotes the spatial frequency and spatial orientation of a Gabor pattern from Category A, while each unfilled circle denotes the spatial frequency and spatial orientation of a Gabor pattern from Category B. The solid line in these figure denotes the location of the optimal decision bound(s). The use of the optimal bound(s) in each of the four experiments maximizes long-run accuracy. The nature of these bounds is described in detail below for each of the three experiments.

Table 2
Category distribution parameter values for Experiments 1–3

Category	μ_f	μ_o	σ_f^2	σ_o^2	$\text{cov}_{f,o}$
Experiment 1: unidimensional RB					
A	260	125	75	9000	0
B	339	125	75	9000	0
Experiment 2: conjunctive RB					
A	344	169	92	92	0
B_1	256	169	92	92	0
B_2	256	81	92	92	0
B_3	344	81	92	92	0
Experiment 3: disjunctive RB					
A_1	344	169	92	92	0
A_2	256	81	92	92	0
B_1	344	81	92	92	0
B_2	256	169	92	92	0

The stimuli were computer generated and displayed on a 21 in. monitor with 1360 × 1024 resolution. In each of the three experiments, the stimuli consisted of a single Gabor patch (see Fig. 1). Each of the stimuli varied in orientation and spatial frequency. Each Gabor patch was generated using MATLAB routines from Brainard's (1997) Psychophysics Toolbox. Each random sample (x_f, x_o) was converted to a stimulus by deriving the frequency, $f = 0.0025 + (x_f/5000)$ cycles per pixel, and orientation, $o = 0.36x_o$ degrees. The scaling factors were chosen in an attempt to equate the salience of frequency and orientation based on our past experience with these stimuli. Each Gabor patch was 7 cm in diameter, which subtended a visual angle of about 8.8° from a viewing distance of 45 cm.

1.3. Experimental procedure

For Experiments 1 and 3, 560 trials were presented and were broken down into seven blocks of 80 trials. For Experiments 2, 546 trials were presented and were broken down into seven blocks of 78 trials. At the start of the experiment, the participants were told that they were involved in a study that examined their ability to categorize simple stimuli, that a series of stimuli would be presented, and that they would be asked to categorize each as a member of either Category A or B. They were also told that at the beginning of the experiment they may feel as though they were guessing, but as the experiment progressed, their accuracy would likely increase. Participants indicated their categorization responses by pressing one key for Category A stimuli and another key for Category B stimuli. For each trial, the stimulus was presented until the participant's categorization response was made, then immediately following their response, they were given feedback for 1 s that consisted of the word "wrong" if their response was incorrect or "correct" if their response was correct. Once feedback was given, the next trial was initiated 1 s later.

1.4. Model-based analyses

Although the main dependent measure in this study was accuracy of participants' responses, we also applied a series of models to the data in each of the three experiments to better understand the category learning processes used by the PD patients and NC participants. These models have been developed to analyze data in this paradigm and have been used extensively to better understand the underlying processes in category learning in both normal and patient populations (for details see Ashby, 1992; Filoteo & Maddox, 1999; Filoteo, Maddox, & Davis, 2001; Maddox & Ashby, 1993; Maddox et al., 1996; Maddox, Filoteo, & Huntington, 1998; Maddox & Filoteo, 2001). The details of the modeling analyses are described in Appendix A. Briefly, the models are derived from general recognition theory (GRT; Ashby & Townsend, 1986), which is a multivariate generalization of signal detection theory (e.g., Green & Swets, 1966). Two classes of models were applied individually to each participant's data for each block of trials in the three experiments. One class of models, the *hypothesis-testing* (HT) models, is compatible with the assumption that participants used an explicit hypothesis-testing strategy, and the other class of models, the *procedural-based* (PB) learning models, is consistent with the assumption that participants used an implicit procedural-based learning strategy (described in Appendix A).[1]

For example, for data collected in Experiment 1, one HT model that was applied was the *optimal unidimensional model*, which assumed that the participant adopted the optimal rule by ignoring the irrelevant dimension, setting a criterion of 299.5 units (or 0.0624 in cycles/pixel units), and uses this criterion to partition Categories A and B responses. A second HT model that was applied in Experiment 1, the *suboptimal unidimensional model*, assumes that the participant also attends selectively to the relevant dimension, but that the participant does not use the optimal criterion of 299.5 units. Instead, the participant uses another criterion, which the model estimates based on the participant's responses. This second HT model assumes that the participant was able to base their categorization decision on the relevant dimension, but that the criterion they used to partition Categories A and B responses was suboptimal. For Experiment 1, the PB model that was applied was the *general linear classifier* (GLC). This model assumes that the participant's decision on each trial is based on a linear integration of information from both dimensions, although the weighting given to the two dimensions may be unequal. The HT and PB models applied to the data from the three experiments are described in detail in Appendix A.

2. Experiment 1: unidimensional rule-based category learning

The purpose of Experiment 1 was to examine unidimensional rule-based category learning in patients with PD and controls using a task in which selective attention demands were emphasized. In Experiment 1, correct responding required that the participant learn to set an appropriate criterion on the spatial frequency dimension and ignore the orientation dimension. Fig. 1 depicts the relationship between the stimulus attributes in this experiment. In this figure, a point represents a single stimulus, with the filled squares denoting Category A stimuli and the unfilled circles denoting Category B stimuli, and the x-axis representing the spatial frequency of the Gabor patch (cycles/pixel) and the y-axis representing the orientation of the frequency (in degrees, with 0 representing degrees from horizontal). The solid line in Fig. 1 represents the experimenter-defined (optimal) unidimensional categorization rule. Importantly, although the orientation of the stimuli did not provide any information regarding category membership, this dimension also varied from trial-to-trial. Thus, the rule-based task in Experiment 1 emphasizes selective attention but still required working memory to some extent (i.e., the participant had to maintain in working memory the relevant dimension and the criterion along that dimension).

As noted above, previous studies have demonstrated that PD patients are particularly impaired in learning unidimensional rule-based tasks in which selective attention demands are emphasized (Ashby, Noble, et al., 2003; Filoteo, Maddox, Salmon, et al., 2005; Maddox et al., 2005). In fact, in a previous study that used a methodology similar to that in the present study, Maddox et al. (2005) found a dramatic impairment in PD patients' ability to learn unidimensional rules. However, in that study even normal controls were unable to obtain greater than 80% accuracy after 250 trials. This was most likely due to the fact that optimal accuracy was only 90%, which was due to the overlap of the two category distributions. So one possible reason why PD patients may have been impaired relative to the controls in the study by Maddox and colleagues is that the task was more difficult. To evaluate this possibility, and to provide a starting point for further exploring rule-based category learning in PD, the task used in Experiment 1 had an optimal accuracy of 100% because the distributions of the two categories did not overlap (see Fig. 1). If the previously observed unidimensional rule-based deficit is due to task difficulty, we would anticipate no (or less) impairment in the PD patients relative to previous studies.

2.1. Accuracy results

Performance was examined by contrasting participants' accuracy (percent correct) across the entire 560 trials in 80 trial blocks using a 2 (group: PD versus NC) × 7 (blocks 1–7) mixed-design ANOVA. These data are depicted in Fig. 2. Results of this analysis identified a main effect of group, $F(1, 22) = 7.1$, $p < 0.05$, with PD patients performing worse than controls overall, and a main effect of block, $F(6, 132) = 18.0$, $p < 0.001$, with both PD and NC participants' performances improving across the trials, although it appears that both groups reached asymptotic performance by the second block of trials. There was no group × block interaction, $F = 0.5$. An examination of individual participants' performance indicated that three PD patients failed to perform above chance (>66%) by the final block of trials. To determine whether the group accuracy differences were due to these three individuals, we compared the two groups without these three PD patients using the same ANOVA as above and still found main effects of group, $F(1, 19) = 5.7$, $p < 0.05$, and block, $F(6, 114) = 23.0$, $p < 0.001$, but no interaction between these factors, $F = 0.7$.

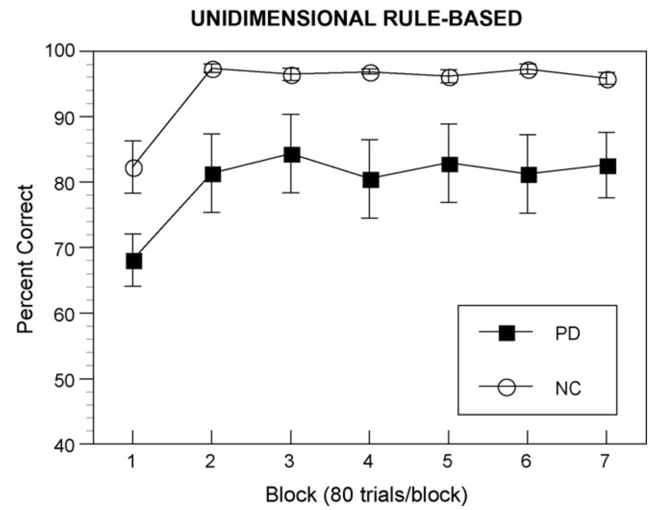

Fig. 2. Accuracy rates for PD patients and NC participants in Experiment 1. (Error bars are standard errors of the means.)

The finding that there was no group by block interaction might suggest that the deficit observed in PD patients was not due with learning *per se*, but rather just differences in performance. However, this likely had to do with the fact that learning differences were obscured by analyzing data in 80 trial blocks. To examine this issue in more detail, we looked at the earliest points in learning by comparing accuracy rates for the first 20 trials in 2, 10 trial blocks using a 2 × 2 ANOVA. Results indicated that there was a main effect of group, $F(1, 22) = 4.7$, $p < 0.05$, with PD patients performing less accurately than controls overall, a main effect of block, $F(1, 22) = 27.9$, $p < 0.001$, with both PD and NC participants' performances improving across the trials, and a significant group by block interaction, $F(1, 22) = 8.2$, $p < 0.01$. Follow-up t-tests indicated that the mean accuracy of the PD patients in the first 10 trials (40.8, S.E.M. = 5.6) was not significantly different than the mean of the NC participants (46.7, S.E.M. = 7.3), $t(22) = 0.6$, $p = 0.53$. In contrast, for the second 10 trials, PD patients (50.0, S.E.M. = 5.5) were significantly less accurate than the NC participants (77.5, S.E.M. = 5.7), $t(22) = 3.5$, $p < 0.01$. These results indicate that PD patients were impaired in *learning* the unidimensional rule-based task, and that this learning deficit was most evident at the earliest stages of acquisition.

2.2. Model results

To determine whether participants were using an appropriate unidimensional approach (either optimal or suboptimal) toward learning the rule, we examined the number of participants in each group whose data were best fit by one of the HT models described above (i.e., the optimal versus suboptimal models) versus the number of participants whose data were best fit by the PB model (i.e., the GLC model). If either of the two HT models best accounted for a participant's data, it would indicate that they based their decision on the frequency dimension only, whereas if the PB model best accounted for a participant's data, it would indicate that this individual based their decision on both the frequency and orientation dimensions.

[1] Note, although the focus of this study is not on procedural-based category learning, we nonetheless fit these types of models to the data because our previous work has demonstrated that participants will sometimes use a procedural-based approach to solve more complex rule-based tasks.

Table 3
Number of PD patients and NC participants for which one of the hypothesis-testing (HT) models or the procedural-based (PB) models best accounted for their data in the seven block of trials for each of the three experiments

	Block													
	1		2		3		4		5		6		7	
	HT	PB	HT	PB	HT	PB	HT	PB	HT	PB	HT	PB	HT	PB
Experiment 1: unidimensional RB														
PD	10	2	9	3	8	4	9	3	10	2	7	5	11	1
NC	11	1	9	3	10	2	11	1	8	4	11	1	9	3
Experiment 2: conjunctive RB														
PD	9	1	9	1	8	2	9	1	8	2	8	2	8	2
NC	9	2	9	2	9	2	10	1	5	6	8	3	8	3
Experiment 3: disjunctive RB														
PD	9	0	9	0	9	0	8	1	8	1	8	1	9	0
NC	9	0	9	0	8	1	9	0	9	9	8	1	9	0

The results of these analyses for each of the seven blocks are presented in Table 3. As can be seen, the data of both PD patients and controls tended to be best fit by one of the HT models. Fisher's Exact Tests indicated that, for each of the blocks, the frequency of PD patients and NC participants best fit by the two model types did not differ (all p's > 0.15). In general, these findings indicate that the majority of participants in both groups were able to attend selectively to the relevant dimension.

Next we examined whether there were any group differences in the ability to use the optimal rule. This was done by comparing the goodness-of-fit value from the optimal model using a 2 (group: PD versus NC) × 7 (blocks 1–7) mixed-design ANOVA.[2] Results of this analysis identified a main effect of group, $F(1, 19) = 6.8$, $p < 0.05$, with PD patients' overall fit value of 20.8 (S.E.M. = 3.1) being larger than the controls' value of 13.0 (S.E.M. = 1.2), and a main effect of block, $F(6, 114) = 24.0$, $p < 0.001$, with both PD and NC participants' fit values decreasing across blocks. There was no group × block interaction, $F = 0.8$. Thus, relative to the controls, the PD patients were less able to use an optimal approach to performing the unidimensional rule-based task.

Given that the PD patients were less able to use an optimal approach to learn the unidimensional rule, we attempted to determine whether this was due to the use of an inadequate decision criterion. That is, was there a difference between PD patients and controls in terms of where they placed the cut-off between Categories A and B stimuli? To examine this issue, we contrasted the groups' decision criterion estimates from the suboptimal unidimensional model in the seven blocks using a 2 (group: PD versus NC) × 7 (blocks 1–7) mixed-design ANOVA, which revealed a main effect of group, $F(1, 19) = 8.3$, $p < 0.05$, with PD patients' overall mean criterion value of 305.0 arbitrary units (S.E.M. = 1.6) being significantly different from the controls' mean criterion of 298.3 (S.E.M. = 1.7). The ANOVA did not identify a main effect of block, $F = 0.6$ nor a significant group × block interaction, $F = 1.9$. We next contrasted the overall mean criterion of the two groups with the optimal value of 299.5 arbitrary units and found that mean criterion of the PD patients differed significantly from the optimal criterion, $t(8) = 5.5$, $p < 0.01$, whereas the mean value of the controls did not differ from the optimal criterion, $t(11) = -1.2$, $p = 0.47$. These results indicate that the PD patients, on average, tended to overestimate the decision criterion relative to the optimal criterion, whereas the NC participants' criterion did not differ from the optimal criterion.

Next we determined the consistency with which the two groups applied their criterion. To do this, we examined the rule-application variability estimate derived from the suboptimal unidimensional model using a 2 (group: PD versus NC) × 7 (blocks 1–7) mixed-design ANOVA. This informed us as to how consistently the participant applied a criterion, regardless of whether that criterion was optimal. There was a trend for a main effect of group, $F(1, 19) = 3.8$, $p = 0.07$, with PD patients' variability estimates of 13.8 (S.E.M. = 3.0) being somewhat greater than the controls' variability estimates of 8.1 (S.E.M. = 1.1). There was a main effect of block, $F(6, 114) = 9.1$, $p < 0.001$, that demonstrated a reliable decrease in variability estimates across blocks, but there was no group × block interaction, $F = 1.1$.

Overall, the results of the model-based analyses suggested that, relative to NC participants, the presence of the irrelevant dimension resulted in the patients placing their criterion at a suboptimal location and that they had a tendency to be more variable in their trial-by-trial criterion placement. However, given that HT models provided a better accounting of patients' data than the PB models, the suboptimal placement and variability of the criterion did not completely result in an inability to attend selectively to the relevant dimension.

2.3. Discussion

The results from Experiment 1 indicated that PD patients are impaired in rule-based category learning when correct categorization is based on a unidimensional rule and there is irrelevant dimensional variation on a second dimension. These results build upon those from previous studies that also demonstrated that PD patients are impaired in learning unidimensional rule-based categories when there is irrelevant dimensional variation. Such findings have been demonstrated with a wide variety of stimuli and dimensions, including card stimuli with simple geometric shapes and colors (Ashby, Noble, et al., 2003), two lines that varied in distance (Maddox et al., 2005), individual lines that varied in length (Maddox et al., 2005), and simple drawings of objects (Filoteo, Maddox, Salmon, et al., 2005). Thus, the results from the current study show that PD patients are also impaired on a unidimensional rule-based task that used more basic perceptual dimensions (i.e., Gabor patches with spatial frequency as the relevant dimension and orientation as the irrelevant dimension), further supporting the notion that this type of category learning is particularly impaired in patients with PD.

Importantly, the results from previous studies of a unidimensional rule-based deficit in PD do not appear to be due simply to task difficulty. For example, in the study by Maddox et al. (2005), normal controls obtained no greater than 80% after 250 trials, whereas in Experiment 1 from this study, normal participants were able to obtain an accuracy level of approximately 97% by the 160th trial. Thus, given that PD patients were impaired on tasks across a range of accuracy levels obtained by normal controls, it does not appear that task difficulty can entirely account for PD patients' deficit on this type of rule-based task.

Although the PD patients' deficits in learning unidimensional rule-based categories is likely related to an impairment in selective attention, the modeling results suggest that deficit we observed in the present study is fairly subtle. Specifically, the majority of both PD patients and controls was best accounted for by either the optimal or suboptimal HT models, indicating that, overall, participants were able to attend selectively to the relevant dimension of the stimulus. However, the results from other aspects of the model-based analyses indicated that PD patients were less able to use the optimal rule (as determined by their fit values) and that their decision criterion was significantly different than both

[2] Note, the three PD patients who did not perform above chance in Block 7 were dropped from this analysis and subsequent model analyses because their parameter values were exceedingly large.

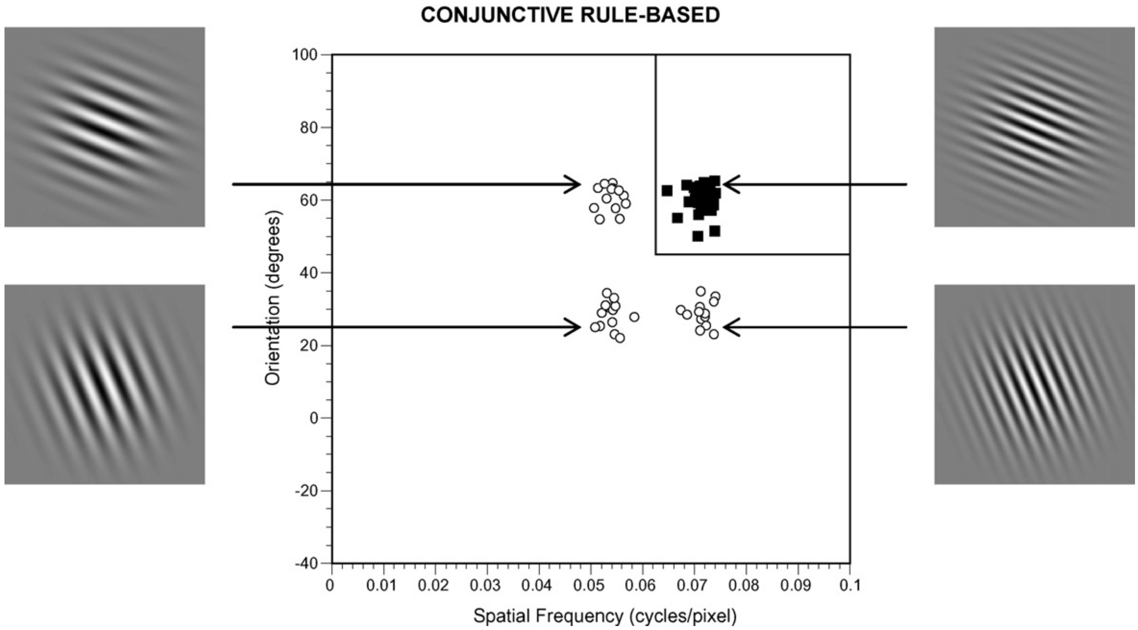

Fig. 3. Stimulus distributions and sample stimuli for Experiment 2. Filled squares represent stimuli from Category A and open circles represent stimuli from Category B. The two solid lines represent the optimal conjunctive rule. Arrows point from specific stimulus exemplars to their location in the two-dimensional stimulus space.

that of controls and the optimal criterion. Taken together, these results suggest that, when learning unidimensional rule-based categories, PD patients are able to attend selectively to the relevant stimulus dimension in that they do not integrate information from the irrelevant dimension, but that such irrelevant dimension variation will cause the patients to be less likely to use an optimal approach to solving the task and can cause them to adopt an inappropriate criterion, a conclusion that was also reached by Maddox et al. (2005). Interestingly, although the groups did not statistically differ in terms of the variability estimates from the suboptimal model, the PD patients had greater values than did the controls, suggesting that the trial-by-trial consistency at which they applied the criterion they adopted might also have contributed to PD patients' unidimensional rule-based deficit.

3. Experiment 2: conjunctive rule-based category learning

The results of Experiment 1 provide further evidence that PD patients are impaired in learning rule-based categories when selective attention demands are emphasized. However, it is unknown whether rule-based category learning is impaired in PD when working memory processes are emphasized. The purpose of Experiments 2 and 3 was to examine this issue. In Experiment 2, participants were administered a conjunctive rule-based task that used the same stimuli and response requirements as those used in Experiment 1. However, the use of the optimal rule in this experiment should place greater emphasis on working memory and less on selective attention because optimal responding required participants to base their categorization decision on both the spatial frequency dimension and the orientation dimension. Thus, there was no irrelevant dimensional variation. Correct responding required that participants maintain in working memory two different criteria: one associated with the orientation dimension and the other associated with the spatial frequency dimension. Specifically, for optimal responding, the participant was required to use one of two approaches to solving the task. First, they could set a criterion on orientation of the stimulus and if it was more vertical *and* had a larger spatial frequency, the participant should respond A, if not, they should respond B. Alternatively, the participant could first set a criterion on spatial frequency and if it was large *and* the orientation was more vertical the participant should respond A, if not, they should respond B. Note that either strategy is rule-based because the rule is easy to describe verbally and the integration of the information is performed sequentially—that is, participants first make a decision about one stimulus dimension and then combine that with a decision on the other dimension prior to categorizing the stimulus. Fig. 3 depicts the relationship between the stimulus attributes in Experiment 2. The solid lines represent the optimal conjunctive rule that shows the optimal criterion on the two dimensions. Because both dimensions are relevant, this task should place less emphasis on selective attention processes and more on working memory processes. If rule-based category learning deficits are also due to working memory impairment in PD, then the patients should be impaired in Experiment 2.

3.1. *Accuracy results*

Accuracy rates in 7, 80 trial blocks for Experiment 2 are displayed in Fig. 4 and were analyzed using a 2 (group: PD versus NC) × 7 (blocks 1–7) mixed-design ANOVA. Results revealed a main effect of block, $F(6, 114) = 2.7, p < 0.05$, with both PD and NC participants' performances improving across the trials. There was no main effect of group, $F = 0.1$, and no group × block interaction, $F = 0.9$. Early learning was also examined by analyzing the first 20 trials in 2, 10 trial blocks using a 2 × 2 ANOVA. Although there was a trend for learning to improve across the two blocks in both groups, $F = 3.3$, $p = 0.08$, there was no significant effect of group, $F = 1.5$, or group × block, $F = 1.4$.

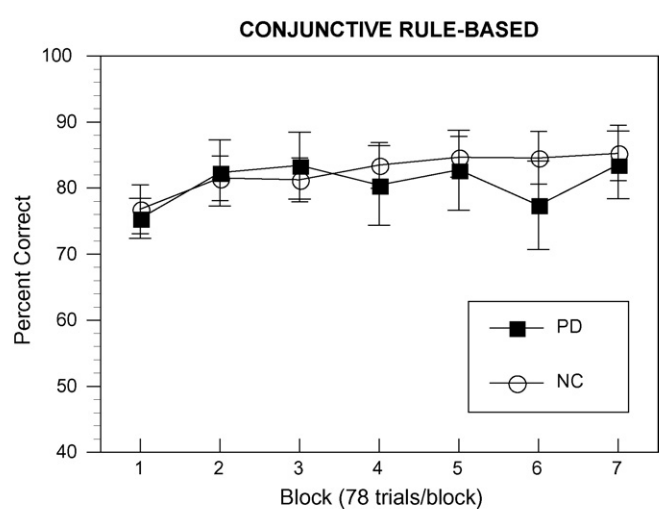

Fig. 4. Accuracy rates for PD patients and NC participants in Experiment 2. (Error bars are standard errors of the means.)

3.2. Model results

For Experiment 2, the HT models consisted of *optimal* and *suboptimal conjunctive models*, and *unidimensional models* (one each for the two dimensions). The optimal model assumed that the participant placed the optimal criteria on the two dimensions, which is depicted graphically as the use of the solid lines in Fig. 3. This rule results in the following logical expression: If the spatial frequency of the stimulus is large *and* the orientation is relatively horizontal categorize it as A; if not then categorize it as B. The suboptimal models also assumed that the participant used both dimensions, but either one, two, or both of the criteria were placed at a suboptimal point. In this case, the same logical expression as assumed by the optimal model would be used, but the placement of the criterion would be suboptimal. Unidimensional models were the same as those used in Experiment 1, with one model placing criterion on the spatial frequency dimension and the other placing the criterion on the orientation dimension. The PB models consisted of the GLC model along with the SPC model (see Appendix A for details), both of which assumed that participants used a procedural-based approach to solving the task. The inclusion of these latter two models is important for ruling out an implicit approach to learning these rules. As observed in previous studies, under rule-based learning conditions similar to those in Experiment 2, normal participants' data tend not to be best fit by these models, but rather are fit by HT models, suggesting they used a rule-based approach and not an implicit approach to learning these rules (Maddox, Bohil, et al., 2004; Zeithamova & Maddox, 2006).

The number of participants whose data were best fit by any of the HT models or the PB models for each block is shown in Table 3. The results indicated that one of the HT models tended to best fit most of the PD patients and NC participants' data in each of the seven blocks, and Fisher's exact tests indicated that there were no differences in these frequencies for all blocks (all p's > 0.18). Importantly, the data from the majority of participants in each group who used a HT approach to solving the task were best fit by one of the conjunctive models as compared to the unidimensional models. For example, in the final block of trials, seven out of the eight PD patients whose data was best fit by an HT model was best fit by one of the conjunctive models, and similarly seven out of the eight NC participants whose data was best fit by an HT model was best fit by one of the conjunctive models. In addition, the final-block accuracy of the PD patients and NC participants whose data were best fit by the conjunctive models did not differ (PD accuracy: $X = 84.3$, S.E.M. = 6.2; NC accuracy: $X = 84.6$, S.E.M. = 6.2, $t(12) = 0.04$, $p = 0.97$).

3.3. Discussion

The results from Experiment 2 indicate that PD patients are not impaired when learning conjunctive rule-based categories. Importantly, the model results indicated that the majority of participants in both groups used a conjunctive approach, and a direct comparison of the final-block accuracy rates indicated that the PD patients and NC participants who used such an approach did not differ. The finding that participants' performances tended to not be best accounted for by one of the two PB models suggests that participants did not use an implicit approach to learning the task. These results provide evidence that rule-based category learning is normal in PD patients when working memory demands are emphasized and selective attention requirements are deemphasized. However, one potential limitation of Experiment 2 is that the working memory demand was not sufficiently large to elicit a rule-based category learning deficit in PD. To further address this issue, PD patients and NC participants were tested in Experiment 3 using a disjunctive rule-based task that likely places even greater emphasis on working memory processes.

4. Experiment 3: disjunctive rule-based

In Experiment 3, participants were administered a disjunctive rule-based task in which optimal responding again required participants to attend to both stimulus dimensions. However, in the disjunctive rule-based task, membership in Category A or B could be determined by two different combinations of the stimulus dimensions. That is, optimal performance required that the participant respond A if the orientation of the stimulus was more vertical and had a smaller spatial frequency *or* if it was more horizontal and had a larger spatial frequency, or respond B if the orientation of the stimulus was more horizontal and had a smaller spatial frequency *or* if it was more vertical and had a larger spatial frequency. The solid lines represent the optimal disjunctive rule which depicts the optimal criterion on the two dimensions. As noted earlier, the length of this logical expression is greater than that in Experiments 1 and 2 because the number of operations necessary to instantiate the disjunctive rule (i.e., the need for the 'or' operation) has increased and therefore the learning of this rule should require greater working memory. Thus, Experiment 3 provides a stronger test of the hypothesis that PD patients are impaired in rule-based category learning when working memory demands are great. If working memory deficits contribute to PD patients' impaired rule-based category learning, the patients should display impairment in learning the disjunctive task.

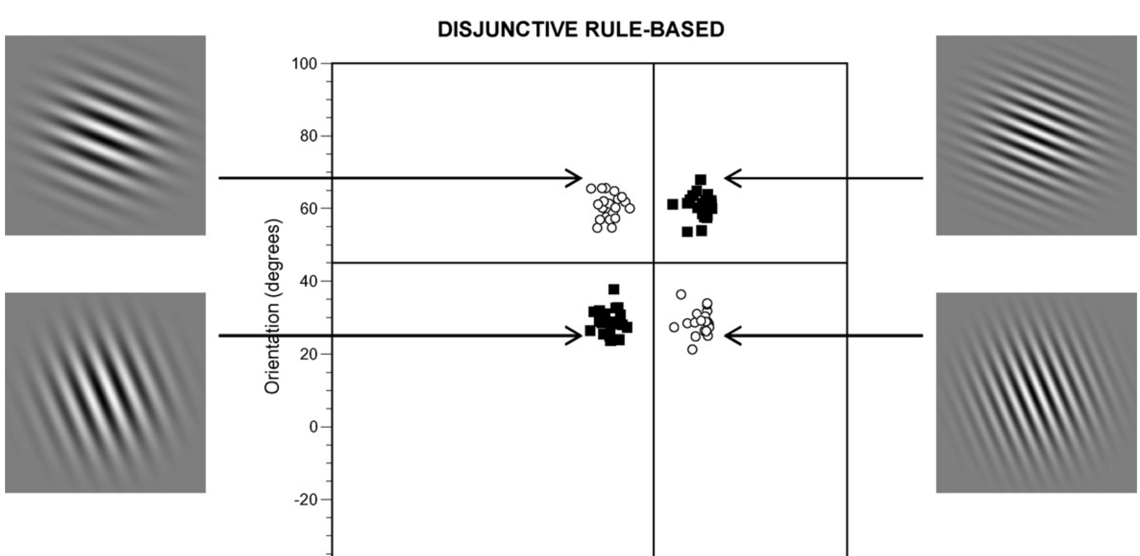

Fig. 5. Stimulus distributions for Experiment 3. Filled squares represent stimuli from Category A and open circles represent stimuli from Category B. The two solid lines represent the optimal disjunctive rule. Arrows point from specific stimulus exemplars to their location in the two-dimensional stimulus space.

Another benefit of examining PD patients and NC participants on the disjunctive rule-based task is to that participants in Experiment 2 could have used a similarity approach in which they simply learned to categorize Category A stimuli together because they were more similar in spatial frequency and orientation than Category B stimuli. Thus, participants may have adopted an approach that if the stimuli were similar, they responded ‘A’, if not similar they responded ‘B’, although the model-based results did not support this possibility. Nevertheless, such an approach could not be used in the disjunctive task because the degree of overlap between categories A and B stimuli are the same (see Fig. 5).

4.1. Results

Accuracy rates for Experiment 3 are displayed in Fig. 6 and were analyzed using a 2 (group: PD versus NC) × 7 (blocks 1–7) mixed-design ANOVA. Results revealed a main effect of block, $F(6, 96) = 3.7$, $p < 0.01$, with both PD and NC participants' performances improving across the trials. There was no main effect of group, $F = 0.1$, and no group × block interaction, $F = 1.0$. Early learning was also examined by analyzing the first 20 trials in 2, 10 trial blocks using a 2 × 2 ANOVA. Results failed to find a significant effect of group, $F = 0.15$, block, $F = 0.03$, or group × block, $F = 0.11$.

4.2. Model results

The HT models that were applied to participants' data included the *optimal* and *suboptimal disjunctive* model and *unidimensional* models (one each for the two dimensions). The PB models included the GLC and the SPC (see Appendix A for details). The outcome of the model results are shown in Table 3, which provides the frequency of the PD patients and NC participants whose data were best fit by the two classes of models for each of the seven blocks. In the majority of the cases, one of the HT models best fit the data from the participants in both groups, and these frequencies did not differ between the two groups in any of the blocks ($p > 0.10$). Importantly, the specific HT models that tended to best fit participants' data in each of the blocks was one of the disjunctive models (either optimal or suboptimal). For example, in the seventh block of trials, a disjunctive model provided the best accounting of both PD patients and NC participants' data seven out of nine times. In addition, the final-block accuracy of the PD patients and NC participants whose data were best fit by the disjunctive models did not differ (PD accuracy: $X = 69.6$, S.E.M. = 6.1; NC accuracy: $X = 71.1$, S.E.M. = 7.9, $t(12) = 0.04$, $p = 0.97$). Thus, the results of the model applications indicated that the majority of participants were indeed using a disjunctive approach, and for those that did, there were no accuracy differences between PD patients and controls.

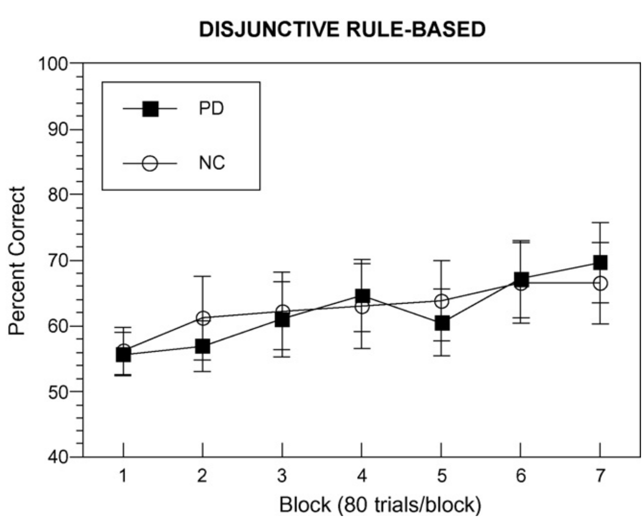

Fig. 6. Accuracy rates for PD patients and NC participants in Experiment 3. (Error bars are standard errors of the means.)

4.3. Discussion

The results of Experiment 3 are clear in demonstrating that the PD patients were not impaired in learning a disjunctive rule-based task. Thus, it appears that this task emphasized working memory in these participants, and as such, PD patients do not appear to be impaired in learning rule-based tasks that emphasize working memory and place less emphasis on selective attention. These findings, along with those from Experiment 2, are consistent with our initial study (Maddox & Filoteo, 2001) that showed that PD patients were not impaired on a rule-based task in which selective attention demands were also minimized. The findings from the model analyses from both Experiments 2 and 3 indicate that the majority of PD patients and NC participants were able to base their categorization on both the spatial frequency and orientation of the stimuli, suggesting that their working memory abilities were sufficient to carry out an explicit integration of the two dimensions. In contrast, models that assumed participants used an implicit approach to learning did not provide a good accounting of participants' data, suggesting that they did not use a perceptual integration to learn the categories. Thus, overall, the results from Experiments 2 and 3 suggest that PD patients are normal in learning rule-based categorization tasks that emphasize working memory.

4.4. General discussion

The main finding from the present set of experiments was that PD patients are impaired in learning rule-based categories when there is trial-by-trial irrelevant dimensional variation. In contrast, comparable PD patients are normal in learning rule-based categories when there is no trial-by-trial irrelevant dimensional variation and the task places moderate (conjunctive) or heavier (disjunctive) demands on working memory. It does not appear that the unidimensional rule-based deficit in PD is due to task difficulty *per se* in that their impairment was observed on the easiest of the three tasks (based on the performance of controls). Further, such deficits do not appear to be due to a generalized rule-based category learning impairment in that the patients and controls did not differ in Experiment 2 or 3, where optimal responding required the use of a highly verbalizable rule, but did require participants to use both stimulus dimensions in their categorization responses. Overall, the results suggest that a deficit in selective attention likely contributed to PD patients' impairment in Experiment 1. This interpretation is consistent with previous studies that demonstrate that these patients have deficits in selective attention (Dujardin et al., 1999; Filoteo & Maddox, 1999; Maddox et al., 1996; McDowell & Harris, 1997; Sharpe, 1990, 1992). Thus, it appears that a primary deficit in selective attention could underlie PD patients' impairment in learning unidimensional rule-based categories. Such an assertion is also consistent with a recent study where we showed a dose–response impact of irrelevant dimensional variation on the unidimensional rule-based learning abilities in PD patients (Filoteo, Maddox, Ing, et al., 2005), with greater levels of irrelevant dimensional variation resulting in worse performance in these patients.

An important question to address is the neuropathological underpinnings of PD patients' impaired unidimensional rule-based deficit. PD results in the loss of dopamine-producing cells within the pars compacta of the substantia nigra (Cornford, Chang, & Miller, 1995; Kish, Shannak, & Hornykiewicz, 1988). These cells project to the striatum, which consists of the caudate and the putamen, and loss of dopamine in PD results in dysfunction of these structures. So, one obvious possibility is that dysfunction within the striatum results in the selective attention deficit that resulted in PD patients' impairment in unidimensional rule-based category learning. Several lines of evidence support this possibility, including animal studies which have shown that lesions within these structures disrupts selective attention processes (Apicella, Legallet, Nieoullon, & Trouche, 1991; Boussaoud & Kermadi, 1997; Hassler, 1978; Kermadi & Boussaoud, 1995), and functional imaging studies in normals that have suggested that the striatum is involved in performing tasks of selective attention (Corbetta, Miezin, Dobmeyer, Shulman, & Petersen, 1991; Koski, Paus, Hofle, & Petrides, 1999; Pardo, Pardo, Janer, & Raichle, 1990; Vandenberghe et al., 1996). Indeed, functional imaging studies of rule-based category learning in normals have implicated the striatum in this process (Seger & Cincotta, 2002; Filoteo, Maddox, Simmons, et al., 2005; Nomura et al., in press).

The present findings are generally consistent with recent neurobiological accounts of rule-based category learning. Most neurobiological models of category learning argue for a system that is primarily responsible for learning rule-based category structures (Ashby et al., 1998; Asbhy & Maddox, 2005; Ashby & O'Brien, 2005; Smith et al., 1998) and that the key brain regions in this system are the dorsolateral prefrontal cortex, anterior cingulate, and the anterior regions of the caudate nucleus. These brain structures have been implicated in such processes as selective attention, working memory, and hypothesis testing, which are all important components of rule-based category learning. The present results suggest that the striatum, the area of greatest pathology in early PD, might mediate the selective attention processes needed for rule-based category learning, and raises the interesting possibility that frontal regions might be more involved in holding online the relevant rule needed to categorize information (i.e., the working memory component of rule-based category learning). It may be the case that frontal dopamine levels remain relatively normal in PD patients early in the disease process (Agid, Ruberg, Dubois, & Pillon, 1987; Kaasinen et al., 2000), so it is possible that working memory aspects of rule-based category learning are not impacted until the disease has progressed to a point where dopamine levels in frontal regions have decreased significantly. This possibility also suggests that selective attention and working memory aspects of rule-based category learning might be dissociable in PD patients, a possibility that has received some support in the literature. Specifically, using Positron emission tomography, Rinne et al. (2000) found that dopamine uptake in the caudate of PD patients was associated with performance on a selective attention task (i.e., the Stroop task), whereas a measure of verbal working memory (digit span backwards) was associated with dopamine activity in frontal cortex (but see Cheesman et al., 2005).

The present findings also help to clarify some recent discrepancies in the literature. First, Maddox and Filoteo (2001) initially reported that PD patients were normal in rule-based category learning, whereas a later study by Ashby, Noble, et al. (2003) and a recent study by Maddox et al. (2005) reported a deficit in their patients. One of the main differences between these studies was that optimal responding in the Maddox and Filoteo task required that the participant use both dimensions when categorizing the stimuli, whereas in the latter two studies, optimal responding required the participant to ignore trial-by-trial variation occurring on an irrelevant stimulus dimension. The results from the present report support the possibility that the presence or absence of such irrelevant dimensional variation may have contributed to these discrepancies. Specifically, when participants base their decision on all salient stimulus dimensions, as in Experiments 2 and 3, rule-based learning is normal in PD patients. However, when there is a high degree of irrelevant stimulus variability, such as in Experiment 1, then rule-based category learning is impaired. Interestingly, a contrast of these studies also indicates that the number of irrelevant dimensions needed to demonstrate an impairment in PD patients might be impacted by whether the stimulus dimensions are continuous or binary. Specifically, in the study by Filoteo, Maddox, Ing, et al. (2005), in which binary valued dimensions were used, PD patients did not demonstrate a deficit when only one irrelevant dimension varied, whereas they did demonstrate an impairment when two irrelevant dimensions varied. In contrast, in the present study and the study by Maddox et al. (2005), in which continuous valued dimensions were used, PD patients demonstrated a deficit when only one irrelevant dimension varied. These findings suggest that the saliency of the irrelevant dimension may be greater when it is a continuously valued dimension as compared to a binary valued dimension. However, it should also be pointed out that there are many fewer unique exemplars with binary-valued dimensions, suggesting that other mechanisms might also account for the differences observed among these studies.

Another line of evidence indicating that working memory does not contribute to PD patients' impairment in Experiment 1 is our finding in a previous study (Filoteo, Maddox, Ing, et al., 2005) that verbal working memory was not associated with PD patients' unidimensional rule-based deficit. Specifically, we found that performance on a supra-span word learning test was not associated with PD patients' performance on a unidimensional rule-based task. These findings suggest that verbal working memory did not likely contribute to the deficits observed in the patients. However, it is important to point out that there are other aspects of working memory that were not evaluated in this current study that also play a role in rule-based category learning and could be impaired in patients with PD. For example, the two dimensions used in this study were object features, and it is possible that if a spatial dimension was used as one of the relevant features PD patients would be impaired. Indeed, recent work has suggested that PD patients may be differentially impaired in spatial-based working memory (Owen, Beksinska, et al., 1993; Owen, Iddon, Hodges, Summers, & Robbins, 1997; Postle, Jonides, Smith, Corkin, & Growdon, 1997; Postle, Locascio, Corkin, & Growdon, 1997). Similarly, processes such as the manipulation or monitoring of working memory were not emphasized in this study, and patients with PD have been shown to be impaired in these processes as well (Bublak, Muller, Gron, Reuter, & von Cramon, 2002; West, Ergis, Winocur, & Saint-Cyr, 1998). Consistent with this possibility is a study by Lewis et al. (2003), who found that PD patients were only impaired in the manipulation aspects of working memory but not the maintenance or retrieval components, a finding that was later supported by an fMRI study in normal participants demonstrating striatal activity only during the manipulation of items in working memory (Lewis, Dove, Robbins, Barker, & Owen, 2004). Thus, it may be the case that deficits in working memory contribute to PD patients' ability to learn rule-based categories under experimental conditions different than those in the present study, such as when category membership is determined by a spatial-based dimension or participants must somehow manipulate the rule to learn the categories.

It is also important to point out that the PD patients who participated in our study were high functioning, did not demonstrate global cognitive impairment, and were relatively early in the course of the disease. Thus, it may be that a working memory impairment would contribute to category learning deficits in PD patients who are either later in the disease process or who are demonstrating cognitive impairment. In addition, our patients were optimally medicated at the time of testing, suggesting that PD patients 'off' medication might be impaired in rule-based category learning when working memory processes are emphasized. Previous studies have in fact shown that working memory in PD patients is worse when patients are 'off' medication as compared to 'on' (Costa et al., 2003; Fournet, Moreaud, Roulin, Naegele, & Pellat, 2000; Lange et al., 1992), suggesting that PD patients 'off' medication might be impaired on a rule-based category learning task that emphasized working memory processes. Future research should address this issue.

Although the present results suggest that selective attention deficits contribute to rule-based category learning deficits in PD, it is important to note that this may be only one component underlying rule-based category learning deficits in PD patients. For example, in a recent study, Price (2006) found that PD patients were impaired in generating potential solutions to a category learning problem, results that are consistent with previous studies demonstrating hypothesis generation deficits in these patients (Channon, Jones, & Stephenson, 1993). However, it is also important to note that Price (2006) found that, in addition to hypothesis generation deficits, PD patients were also impaired in rule selection and that both of these deficits were not associated with a measure of working memory. Thus, both hypothesis generation and selective attention impairments likely contribute to rule-based category learning deficits in patients with PD, and such impairments do not appear to be related to working memory *per se*.

The current findings are somewhat in contrast with those of previous studies that examined set shifting aptitude in patients with PD. For example, Owen, Roberts, et al. (1993) examined PD patients on a visual discrimination learning task in which participants had to learn to identify the appropriate stimulus dimension and then switch dimensions after a set had been established. The results of that study indicated that PD patients were normal in the initial aspects of learning the task and in performing an intra-dimensional attentional shift (i.e., when the relevant dimension remains the same, but the correct value on that dimension changes), a finding that was not surprising given the selective attention and working memory demands are fairly minimal during these phases of the task. However, medicated PD patients were found to be impaired when having to perform an extra-dimensional shift (i.e., when the relevant dimension shifts), but only when the relevant dimension after the shift consisted of the irrelevant dimension prior to the shift. These findings indicated that PD patients were unable switch their attention to a previously irrelevant dimension once it became relevant, suggesting that the patients overly inhibited the irrelevant dimension during the initial acquisition phase. In other words, the results of Owens and colleagues suggested *enhanced* selective attention during learning, findings that are not consistent with those of the present study. However, a more recent study conducted by Gauntlett-Gilbert, Roberts, and Brown (1999), indicated that PD patients deficits on such tasks are better characterized as a deficit in making extra-dimensional shifts, and that enhanced selective attention did not necessarily account for this deficit. Thus, it remains to be seen whether our present findings entirely contradict those of Owen, Roberts, et al. (1993).

The results of this study also contribute to the larger body of literature that has demonstrated dissociations in category learning in patients with PD. Specifically, past studies have shown that PD patients are impaired on some categorization tasks, such as probabilistic classification (Knowlton et al., 1996; Shohamy, Myers, Grossman, et al., 2004; Shohamy, Myers, Onlaor, et al., 2004; Witt et al., 2002a), but not on others, such as observational-based category leaning tasks (Reber & Squire, 1999; Shohamy, Myers, Grossman, et al., 2004; Smith et al., 2001; Witt et al., 2002b). This dissociation has been interpreted as an indication that patients with PD are more likely to be impaired on tests requiring feedback-based learning than on tasks that do not (Reber & Squire, 1999; Shohamy, Myers, Grossman, et al., 2004). Feedback-based learning is thought to be mediated primarily through the subcortical dopaminergic system that is damaged in PD, so it is not surprising that feedback-based learning is often impaired in these patients. However, our finding that PD patients are not impaired on *all* feedback-based learning tasks calls into question this generalized explanation of their category learning deficits, and strongly suggests that PD patients can be impaired in category learning for multiple reasons. The results of the present study suggest that selective attention must also be considered as an important factor when characterizing PD patients' category learning abilities.

One important assumption of our interpretation of these results is that selective attention and working memory represent two distinct, dissociable processes. This possibility is somewhat at odds with theories suggesting that selective attention and working memory potentially represent the same mechanism (e.g., Braver & Barch, 2002). For example, models of cognitive control argue that context representations are maintained in working memory and are used to direct control over other representations (i.e., selective attention), and that the appearance of separate processes is merely dependent on the task demands (Braver & Barch, 2002; Engle, Conway, Tuholski, & Shisler, 1995). However, at least one of these models also acknowledges the possibility that phasic and tonic dopamine activity might differentially impact selection and working memory processes (Braver & Barch, 2002; Cowen, Braver, & Brown, 2002), respectively, leaving open the possibility that behavioral dissociations among tasks that emphasize selective attention or working memory processes could occur. Whether the pattern of results we observed in PD is due to alterations in phasic or tonic dopamine levels remains to be seen.

In summary, the results of these three experiments suggest that PD patients do not demonstrate a generalized deficit in rule-based category learning in that they were impaired on a unidimensional rule-based task but normal on a disjunctive rule-based task. These results, taken along with the results of past studies, suggest that PD patients are more likely to be impaired on rule-based tasks that emphasize selective attention processes.

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Appendix A

For each experiment, different hypothesis-testing and procedural-based models were applied depending on the nature of the categories. All of the models allow us to examine the strategies that participants use to solve the task, and allow us to examine possible individual differences in performance. Because of concerns with modeling aggregate data (e.g., Ashby, Maddox, & Lee, 1994; Maddox, 1999; Smith & Minda, 1998), each model was fit block by block to the data from each subject.

A.1. Experiment 1

A.1.1. Hypothesis-testing models

Optimal unidimensional model. This model assumes that the participant used the rule depicted in Fig. 1 as the solid line. This model has one free parameter representing the rule application variability (i.e., perceptual and criterial noise or σ^2).

Suboptimal unidimensional model. This model assumes that the participant used a unidimensional approach to solving the task, but instead of assuming the use of the optimal rule depicted in Fig. 1, this model assumes a suboptimal placement of the decision criterion that is derived based on each participant's responses. This model has two free parameters, one representing the decision criterion on the spatial frequency dimension and a second representing the rule application variability (σ^2).

A.1.2. Procedural-based model

Hypothesis-testing models assume that any integration of information across dimensions is post-decisional. In other words, the participant first makes a separate decision about each dimension and then integrates those decisions to reach a final decision regarding category membership. Information–integration models, on the other hand, allow for pre-decisional integration. In other words, instead of assuming that the participant uses decision *criteria* along each dimension, we assume that the participant partitions the stimulus space using decision *bounds* that can have a non-zero or non-infinite slope.

General linear classifier. This model assumes that the participant's decision on each trial is based on a linear integration of information from both the spatial frequency and orientation dimensions, although the weighting given to the two dimensions may be unequal. Note that this model assumes that the participant based their decision on both of the dimensions, and thus, did not attend selectively to the relevant dimension. This model has three parameters, including the slope and intercept of the linear bound, and the rule application variability (i.e., σ^2).

A.2. Experiment 2

A.2.1. Hypothesis-testing models

Optimal conjunction model. This model assumes that the participant based their categorization decision on both dimensions and used the rule depicted as the two solid lines in Fig. 3. This model has one free parameter, σ^2, representing the rule application variability.

Suboptimal conjunction models. Three suboptimal conjunction models were applied, all of which assume that the participant based their categorization decision on both dimensions. One of these models assumes that the participant used the optimal criterion on the spatial frequency dimension but a suboptimal criterion on the other dimension, the second of these models assumes that the participant used the optimal criterion on the orientation dimension but a suboptimal criterion on the spatial frequency dimension, and the third of these models assumes that the participant used a suboptimal criterion on both dimensions. The two conjunction models that assumed optimal placement on one dimension and suboptimal placement on the other dimension had two free parameters, one for the decision criterion on the suboptimal dimension and σ^2. The third conjunction model had three free parameters, one each for the decision criteria on the two dimensions and σ^2.

Unidimensional models. Two unidimensional models were also applied, one that assumes the participant categorized the stimuli based only on the spatial frequency dimension and another that assumes the participant categorized the stimuli based only on the orientation dimension. These two models had two free parameters, a decision criterion on one of the dimensions and σ^2.

A.2.2. Procedural-based model

General linear classifier. This model was the same as that from Experiment 1, which has three parameters, including the slope and intercept of the linear bound, and σ^2.

Striatal pattern classifier (SPC; Ashby & Waldron, 1999). This model assumes that the participant constructs four decision bounds to separate the A and B categories by placing four "units" in the frequency–orientation stimulus space. On each trial, the participant determines which unit is closest to the perceptual effect and gives the associated response. When fitting the SPC to the conjunctive rule-based data, we assumed that one unit was associated with Category A and three units with Category B (since Category B consisted of three separate clusters of stimuli), which yielded four linear decision bounds. Because the location of one of the units can be fixed and a uniform expansion or contraction of the space will not affect the location of the resulting (minimum distance) decision bounds, in this case the SPC contains six free parameters, five that determine the location of the units, and thus the decision bounds, and one for the rule application variability (σ^2).

A.3. Experiment 3

A.3.1. Hypothesis-testing models

Optimal disjunctive model. This model assumes that the participant based their categorization decision on both dimensions and used the rule depicted as the two solid lines in Fig. 5. This model has one free parameter, σ^2, representing the rule application variability.

Suboptimal disjunctive models. Three suboptimal disjunction models were applied that were similar to the conjunction models from Experiment 2. Each of the disjunction models assumes that the participant based their categorization decision on both dimensions. One of these models assumes that the participant used the optimal criterion on the spatial frequency dimension but a suboptimal criterion on the other dimension, the second of these models assumes that the participant used the optimal criterion on the orientation dimension but a suboptimal criterion on the spatial frequency dimension, and the third of these models assumes that the participant used a suboptimal criterion on both dimensions. The two disjunction models that assumed optimal placement on one dimension and suboptimal placement on the other dimension had two free parameters, one for the decision criterion on the suboptimal dimension and σ^2. The third disjunction model had three free parameters, one each for the decision criteria on the two dimensions and σ^2.

Unidimensional models. The same two unidimensional models from Experiment 2 were also applied.

A.3.2. Procedural-based model

General linear classifier. This model was the same as that from Experiment 1, which has three parameters, including the slope and intercept of the linear bound, and σ^2.

Striatal pattern classifier (SPC; Ashby & Waldron, 1999). The SPC model applied was similar to the one in Experiment 2, except that two of the four units were associated with Category A and the other two units were associated with Category B.

A.4. Model fits

Each of the models from the three Experiments was fit to the data for each participant separately by block of trials. The model parameters were estimated using maximum likelihood (Ashby, 1992; Wickens, 1982) and the goodness of fit index was $-\ln L$ (negative log likelihood). The smaller the value of this fit index, the better the model fit the data. However, in order to directly compare the models we used the following goodness-of-fit statistic:

$$\mathrm{AIC} = 2r - 2\ln L$$

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 each free parameter by increasing the AIC value by a factor of two. In this way, 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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