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# Category Number Impacts Rule-Based but Not Information-Integration Category Learning: Further Evidence for Dissociable Category-Learning Systems

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Category number effects on rule-based and information-integration category learning were investigated. Category number affected accuracy and the distribution of best-fitting models in the rule-based task but had no effect on accuracy and little effect on the distribution of best-fitting models in the information-integration task. In the 2 category conditions, rule-based learning was better than information-integration learning, whereas in the 4 category conditions, unidimensional and conjunctive rule-based learning was worse than information-integration learning. Rule-based strategies were used in the 2-category/rule-based condition, but about half of the observers used rule-based strategies in the 4-category unidimensional and conjunctive rule-based conditions. Information-integration strategies were used in the 4-category/information-integration condition and by the end of training were used in the 2-category/information-integration condition.

Every day, organisms make thousands of categorization responses that are remarkably quick and accurate (Ashby & Maddox, 1998). Despite the widespread influence of category-learning abilities on survival, and the varied nature of category-learning problems facing the organism, research on category learning has been narrowly focused (see Markman & Ross, in press, for a review). For example, nearly all category-learning studies have focused on situations in which two categories are relevant, and to our knowledge, none have systematically manipulated the number of categories while holding the nature of the category structures fixed. In addition, few studies have systematically examined the learning of qualitatively different types of category structures while holding structural aspects of the categories constant (e.g., the coherence of the categories, optimal accuracy, etc).[1] Both of these factors vary widely in nature. For example, moving vehicles can be classified as two- or four-wheeled, or as cars, trucks, SUVs, or motorcycles. Similarly, rabbits categorize other animals as friend or foe, or as flying predators, fast-running predators, potential mates, and so on. One reason for this lack of interest in qualitatively different types of category structures, and the focus on two-category problems, is that until recently the focus had been on testing predictions from single-process models of category learning. Traditionally, the approach has been to examine category learning in a condition where two single-process models make different predictions (e.g., Maddox & Ashby, 1993).

A large body of research supports a multiple-process approach to category learning, suggesting that observers have available different processing modes that can be used during category learning (Allen & Brooks, 1991; Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Ell, 2001; Erickson & Kruschke, 1998;

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[1] A few seminal studies have been conducted that compare category learning across different category structures. Perhaps the most influential was conducted by Shepard, Hovland, and Jenkins (1961; see also Alfonso-Reese, Ashby, & Brainard, 2002; Love, 2002; Nosofsky, Gluck, Palmeri, McKinley, & Gauthier, 1994). In that study, perfect performance was possible in all conditions, but the structural aspects of the categories varied across conditions. In addition, only a small number of exemplars were utilized (e.g., eight in Shepard et al., 1961). Under those conditions, it is difficult to separate pure category-learning processes from memorization processes.

Nosofsky, Palmeri, & McKinley, 1994; Pickering, 1997; Reber & Squire, 1994; Rehegr & Brooks, 1993; E. E. Smith, Patalano, & Jonides, 1998). Over the past several years, several researchers have extended this multiple-process approach to a multiple-systems approach by suggesting that the learning of different types of category structures is mediated by different categorization systems that are associated with distinct (but partially overlapping) neurobiological substrates (Ashby & Ell, 2001; Pickering, 1997; Reber & Squire, 1994; E. E. Smith et al., 1998). Although the number of potential category-learning systems and the details of the underlying neurobiology remain controversial, most multiple-systems theorists agree that one system is explicit and another is implicit (e.g., Ashby et al., 1998; Ashby & Ell, 2001, 2002; Erickson & Kruschke, 1998; Reber, Stark, & Squire, 1998).

In this article, we focus on two different types of category structures (Ashby & Ell, 2001). *Rule-based/category-learning tasks* are those in which the category structures can be learned through some explicit reasoning process. Frequently, the rule that maximizes accuracy (i.e., the optimal rule) is easy to describe verbally (Ashby et al., 1998). In the most common applications, only one stimulus dimension is relevant, and the observer's task is to discover this relevant dimension and then to map the different dimensional values to the relevant categories. Rule-based tasks have a long history in cognitive psychology, and not surprisingly, they have been popular with proponents of the so-called classical theory of categorization, which assumes category learning is the process of discovering the set of necessary and sufficient conditions that determine category membership (e.g., E. E. Smith & Medin, 1981).

*Information-integration/category-learning tasks,* on the other hand, are those in which accuracy is maximized only if information from two or more stimulus components (or dimensions) is integrated at some predecisional stage (Ashby & Gott, 1988). Perceptual integration could take many forms, from treating the stimulus as a Gestalt to computing a weighted linear combination of the dimensional values. In many cases, the optimal rule in information-integration tasks is difficult or impossible to describe verbally (Ashby et al., 1998). In contrast to information-integration rules, a conjunctive rule (e.g., respond A if the stimulus is small on dimension $x$ and small on dimension $y$) is one where the observer applies separate decisions about each dimension (e.g., small or large) and then combines the outcome of these decisions when making a categorization decision (integration is not predecisional). Such rules can be applied to information-integration conditions, but they generally lead to suboptimal levels of accuracy. Unlike information-integration rules, conjunctive rules are highly "verbalizable."

Several recent studies have examined rule-based and information-integration category learning across a variety of experimental conditions (Ashby, Maddox, & Bohil, 2002; Ashby, Queller, & Berretty, 1999; Maddox, Ashby, & Bohil, 2003; Waldron & Ashby, 2001). The aim of those studies was to test predictions from a neurobiologically plausible multiple-systems model of category learning. A discussion of the neurobiology will be reserved for the General Discussion, and for now, only a brief overview will be offered. The theory assumes that learning in rule-based tasks is dominated by an explicit system that uses working memory and executive attention, which is mediated by the frontal lobes. This system appears to learn through a conscious process of hypothesis generation and testing. In contrast, learning in information-integration tasks is assumed to be dominated by an implicit procedural learning-based system, which is mediated largely within the tail of the caudate nucleus (Ashby et al., 1998; Ashby & Ell, 2001; Willingham, 1998). It has been proposed that a dopamine-mediated reward signal is critical for learning in this system. The idea is that an unexpected reward causes dopamine to be released from the substantia nigra into the tail of the caudate nucleus, and that the presence of this dopamine strengthens recently active synapses (e.g., Schultz, 1992; J. Wickens, 1993).

The rule-based/category-learning system proposed above is under conscious control and has full access to working memory and executive attention. As a result, the placement and timing of the feedback signal should not be as critical in rule-based tasks because this information can be held consciously in working memory. In contrast, an information-integration/category-learning system that is mediated within the tail of the caudate nucleus would not be accessible to conscious awareness and is far removed from working memory.[2] As a result, it would depend more heavily on local learning mechanisms that are likely associated with stimulus–response type learning, which is not available to consciousness, and in which the timing of the feedback would be much more critical. As a test of these predictions, Ashby, Maddox, and Bohil (2002) compared rule-based and information-integration category learning across an observational training condition (in which participants were informed before stimulus presentation of what category the ensuing stimulus was from) and a traditional feedback training condition (in which the category label followed the response). In a related study, Maddox, Ashby, and Bohil (2003) compared rule-based and information-integration category learning across an immediate feedback condition (in which corrective feedback was provided immediately following the response) and a delayed feedback condition (in which corrective feedback was delayed by 2.5, 5, or 10 s following the response). In line with predictions from the multiple-systems model, observational training and delayed feedback negatively impacted information-integration category learning, but had little effect on rule-based category learning. Furthermore, in a related study, Ashby, Queller, and Berretty (1999) showed that unidimensional rule-based categories (in which the optimal rule is to set a criterion along one dimension while ignoring the other) can be learned with no feedback of any kind, whereas information-integration categorization performance was at chance, and all observers used some sort of unidimensional rule, even when explicitly encouraged to use both stimulus dimensions.

Experimental manipulations that adversely affect rule-based, but not information-integration learning, have also been observed. Waldron and Ashby (2001) showed that rule-based category learning was disrupted more than information-integration category learning by the simultaneous performance of a task that required working memory and executive attention (a numerical Stroop task). In addition, Maddox, Ashby, Ing, and Pickering (2003) showed that rule-based category learning was disrupted by a

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[2] Crick and Koch (1990, 1995, 1998) offered a cognitive neuroscience theory of consciousness that states that one can have conscious awareness only of activity in brain areas that project directly to the prefrontal cortex. The caudate nucleus does not project to the prefrontal cortex (it first projects through the thalamus), so the Crick–Koch hypothesis predicts that we are not aware of activity within the caudate nucleus.

sequential memory-scanning task, whereas information-integration category learning was not. Overall, those studies indicate that rule-based and information-integration category learning can be disrupted differentially by various experimental manipulations, results that provide strong evidence in support of multiple category-learning systems. However, in all of those studies, only two categories were relevant, and the rule-based task was unidimensional. The present study extends this line of research by examining the effects of category number on rule-based and information-integration category learning. For reasons discussed in the following, it was anticipated that manipulations of category number would impact rule-based, but not information-integration, category learning.

## Experiment 1

Experiment 1 combined factorially the number of categories (two vs. four) with the nature of the category structures (rule-based vs. information-integration) within observers. In all experimental conditions the stimulus was a single line that varied across trials in length and orientation. These dimensions are separable and are generally processed independently (Maddox, 1992). The category structures for the four experimental conditions are described in Figure 1, and the associated category-distribution parameters are detailed in Table 1. Each symbol in Figure 1 denotes the length and orientation of a single line. Notice that there are four "clusters" of stimuli in each condition. In the rule-based/two-category (RB2) condition and the information-integration/two-category (II2) condition, two clusters are associated with one category label, and two clusters are associated with the other category label. In the rule-based/four-category (RB4) condition and the information-integration/four-category (II4) condition, each cluster of stimuli is associated with a unique category label. Because our focus was on examining the interaction between the number of categories and the type of category structure, it was important to control as many extraneous factors as possible. Of central importance was to equate the conditions on several measures of complexity by equating a number of structural aspects of the categories. These included optimal accuracy, the number of stimulus clusters, within-cluster scatter, and cluster coherence (i.e., the distributional parameters within a category; Fukunaga, 1990). In all four conditions, optimal accuracy was 95%. In addition, cluster scatter and coherence were held constant by first generating the stimuli for the RB2 condition (described in detail in the *Methods* section), and then generating the stimuli in the three remaining conditions by applying simple scatter- and coherence-preserving transformations. By taking these steps we were able to ensure that the four category-learning conditions differed only in the number of category labels and nature of the category structure while equating important measures of complexity, such as optimal accuracy, within-category scatter, and category coherence.

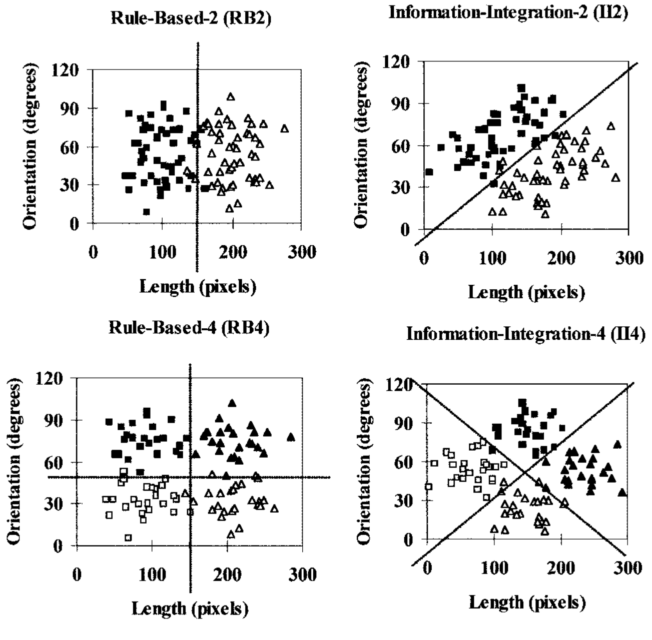

*Figure 1.* Scatter plots in the length and orientation space for the categorization stimuli from each of the four conditions from Experiment 1. For the two-category conditions, the filled squares denote stimuli from Category A, and the open triangles denote stimuli from Category B. For the four-category conditions, the open squares denote stimuli from Category A, the filled squares denote stimuli from Category B, the open triangles denote stimuli from Category C, and the filled triangles denote stimuli from Category D. The dashed lines in each plot denote the optimal decision bound(s).

Also shown in Figure 1 are the decision bounds that maximize categorization accuracy. In the RB2 condition, the optimal bound requires the observer to set a criterion on line length while ignoring line orientation (referred to as a unidimensional rule) and to use the following decision rule: Respond A if the line length is short, and respond B if the line length is long. Because the II2 stimuli were generated by rotating the RB2 stimuli, the optimal decision bound in the II2 condition is a simple rotation of the RB2 decision bound. Notice that the II2 decision bound is linear and requires the observer to integrate length and orientation information. Notice also that there is no simple verbal description of the optimal decision rule. In the RB4 condition, the observer must set a criterion on line length and line orientation and use the following decision rule: Respond A if the length is short and the orientation is shallow, respond B if the length is short and the orientation is steep, respond C if the length is long and the orientation is shallow, and respond D if the length is long and the orientation is steep. Finally, the decision bounds in the II4 condition are a simple rotation of the RB4 decision bounds, but notice that there is no simple verbal description of the optimal decision rule in this condition.

The multiple-systems model (described previously) makes several a priori predictions with respect to the conditions in this study. First, RB4 category learning is predicted to be poorer than RB2 category learning for the following reasons: In the RB2 condition the observer must set a single decision criterion along the length dimension that partitions the length dimension into two response regions while ignoring orientation; in the RB4 condition, on the other hand, the observer must set a single decision criterion along the length dimension and a single decision criterion along the orientation dimension. This information must then be integrated at a postdecisional stage, effectively partitioning the space into four response regions. The greater complexity of the RB4 decision rule (two decision bounds instead of one) places additional demands on working memory and hypothesis-testing systems, and thus should lead to poorer category learning. Second, category learning in the II2 and II4 conditions is predicted to be the same, although II4

Table 1
*Category-Distribution Parameters From Experiment 1*

| Category | $\mu_l$ | $\mu_o$ | $\sigma_l$ | $\sigma_o$ | $\text{cov}_{lo}$ |
|---|---|---|---|---|---|
| Rule-Based-2 (RB2) | | | | | |
| $A_1$ | 100 | 100 | 30 | 30 | 0 |
| $A_2$ | 100 | 200 | 30 | 30 | 0 |
| $B_1$ | 200 | 100 | 30 | 30 | 0 |
| $B_2$ | 200 | 200 | 30 | 30 | 0 |
| Rule-Based-4 (RB4) | | | | | |
| A | 91 | 91 | 30 | 30 | 0 |
| B | 91 | 209 | 30 | 30 | 0 |
| C | 209 | 91 | 30 | 30 | 0 |
| D | 209 | 209 | 30 | 30 | 0 |
| Information-Integration-2 (II2) | | | | | |
| $A_1$ | 80 | 150 | 30 | 30 | 0 |
| $A_2$ | 150 | 220 | 30 | 30 | 0 |
| $B_1$ | 150 | 80 | 30 | 30 | 0 |
| $B_2$ | 220 | 150 | 30 | 30 | 0 |
| Information-Integration-4 (II4) | | | | | |
| A | 66 | 150 | 30 | 30 | 0 |
| B | 150 | 233 | 30 | 30 | 0 |
| C | 150 | 66 | 30 | 30 | 0 |
| D | 233 | 150 | 30 | 30 | 0 |

*Note.* Optimal accuracy was held constant at 95% in all conditions.

category learning might be poorer early in learning due to the decreased level of chance performance (25% for II4 vs. 50% for II2). The reasoning is as follows: Learning in the II2 and II4 conditions relies on an implicit, procedural learning-based system, which is mediated largely within the tail of the caudate nucleus. This system links clusters of "percepts" to categorization responses (the details of this process are reserved for the General Discussion). Because the complexity of the categories was held constant across conditions (i.e., the number of stimulus clusters was fixed at four), and because each observer was informed of the number of categories prior to each condition, there is no a priori reason to expect a performance difference between information-integration category learning with two versus four categories. It was also of interest to contrast rule-based and information-integration performance to determine if, under the present conditions, information-integration performance might exceed rule-based performance. One might anticipate that the additional processes required by working memory in the RB4 condition could in fact lead to poorer performance as compared with the II4 condition.

In this study, category learning is assessed first through traditional accuracy-based analyses and next by the application of a series of quantitative models to each observer's data. Each model instantiates a different set of assumptions regarding the type of strategy used by the observer to solve the task. Because our focus is on rule-based and information-integration category learning, we will use the models to instantiate different types of rule-based strategies and different types of information-integration strategies. It is important to be clear that we are using the term *strategy* to define a particular type of partitioning of the stimulus space into response regions, and are not claiming that this implies conscious awareness. In fact, we argue that an observer using a rule-based strategy will be consciously aware of that strategy, whereas an observer using an information-integration strategy will not be consciously aware of that strategy (E. E. Smith et al., 1998). It is these model-based analyses that provide important insights into the strategies used by observers to solve these tasks and suggests that important individual and task differences exist. (Details of the model-based approach are discussed later.)

## Method

### Observers and Design

Twenty-four observers (12 women and 12 men) were solicited from the University of Texas community and received $30 for participating in this study. Each observer completed all four experimental conditions with the condition order being determined from a Latin square. Only one of the four conditions (approximately 60 min) was completed during a single test day, and one rest day was required between testing sessions. Visual acuity was tested in each observer, and all observers had 20/20 vision, or vision corrected to at least 20/20.

### Stimuli and Stimulus Generation

The experiment used the randomization technique introduced by Ashby and Gott (1988). The two- and four-category/rule-based and information-integration category structures are displayed in Figure 1 along with the optimal decision bound(s). The category-distribution parameters are outlined in Table 1. The stimuli for RB2 categories were generated by randomly sampling 25 stimuli from each of the four bivariate normal distributions for a total of 100 unique stimuli. The stimuli for the II2 categories were generated by rotating the RB2 stimuli clockwise by 45°. Thus, optimal accuracy, within-category scatter, and category coherence are identical in both conditions. The stimuli for the RB4 categories were generated from the RB2 stimuli by shifting each stimulus by nine units in the appropriate direction (see Table 1). The RB4 categories were shifted in this manner to equate optimal accuracy (at 95%) across all four experimental conditions. The stimuli for the II4 categories were generated by rotating the RB4 stimuli clockwise by 45°. Each experimental condition consisted of six 100-trial blocks where each of the 100 unique stimuli was presented once in each block in a random order.

The stimuli were computer generated and displayed on a 21 in. (53.34 cm) monitor with 1,360 × 1,024 resolution. Each line was presented in white on a black background. To minimize line jaggedness, Alfonso-Reese's (1997, 2001) anti-aliasing routine, developed for use with Brainard's (1997) Psychophysics Toolbox was applied. Each stimulus was created by converting the *x* value into a line length (measured in pixels), and the *y* value (after applying a scaling factor $\pi/500$) into a line orientation. The scaling factor $\pi/500$ was chosen to (approximately) equate the salience of line length and line orientation (see also Alfonso-Reese, 2001).

### Procedure

All observers were tested individually in a dimly lit room with an approximate viewing distance of 35 cm. They were informed that there were two categories in the two-category conditions or four categories in the four-category conditions, and that each category was equally likely. They were informed that perfect performance was impossible but that high levels of accuracy could be achieved. They were instructed to learn about the categories, to be as accurate as possible, and not to worry about speed of responding. At the start of each trial, a fixation point was displayed for 1 s. and then the stimulus appeared. The stimulus remained on the screen until the observer generated a response by pressing one of two keys in the two-category cases, or one of four keys in the four-category cases. The correct category label was then presented on the screen for 1 s along with the word “wrong” for incorrect responses or “right” for correct responses. Once feedback was given, the next trial was initiated.

## *Accuracy Results*

Analyses were performed separately on each of the six 100-trial blocks of data. A Category Number (2 vs. 4 categories) × Category Structure (rule-based vs. information-integration) × Block (six 100-trial blocks) within-observer analysis of variance (ANOVA) was conducted on the accuracy rates. The accuracy rates averaged across observers are presented in Figure 2A. The main effects of category number, $F(1, 23) = 35.33$, $p < .001$, and block, $F(5, 115) = 62.02$, $p < .001$, were significant, whereas the main effect of category structure was not ($F < 1$). Performance was superior in the two-category (86.8%) condition relative to the four-category condition (80.8%), and improved over blocks (73.7%, 83.7%, 85.4%, 86.3%, 87.1%, and 86.7% for Blocks 1–6, respectively). These main effects were qualified by a significant category number by block interaction, $F(5, 115) = 13.97$, $p < .001$, and a significant category number by category structure interaction, $F(1, 23) = 8.05$, $p < .01$. The category structure by block interaction and the three-way interaction were nonsignificant (both $F$s $< 1$). As suggested by Figure 2A, the category number by block interaction was characterized by faster learning in the two-category relative to the four-category conditions, and was likely due to the lower chance level in the four-category case.

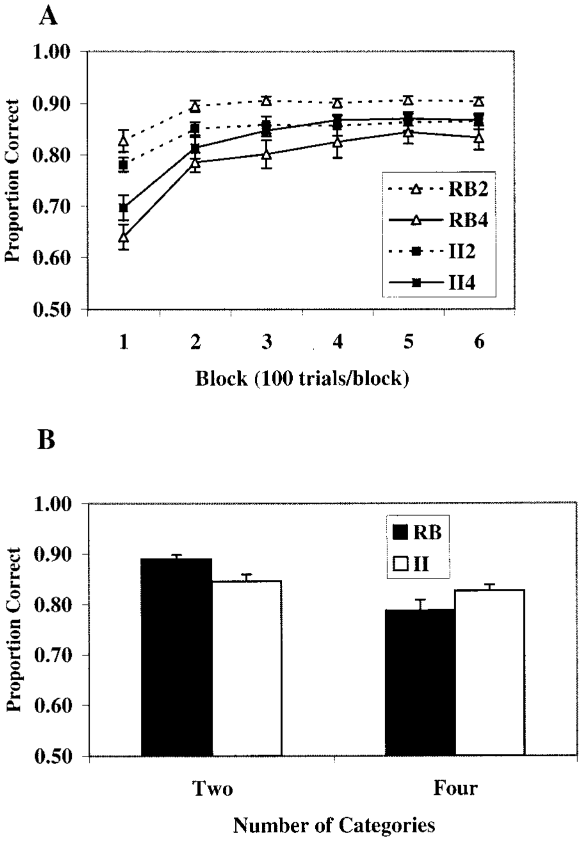

*Figure 2.* A: Proportion correct for the two- and four-category/rule-based and information-integration category structures for each block from Experiment 1 (standard error bars included). The solid lines denote the four-category conditions, and the dashed lines the two-category conditions. The filled squares denote the information-integration conditions, and the open triangles denote the rule-based conditions. RB2 = rule-based-2, RB4 = rule-based-4, II2 = information-integration-2, and II4 = information-integration-4. B: Proportion correct for the same conditions averaged over blocks (standard error bars included). RB = rule based; II = information integration.

The most important finding from the preceding analysis was the category number by category structure interaction, which is displayed graphically in Figure 2B. To determine the locus of this interaction we conducted a number of *t* tests on the accuracy rates collapsed across blocks. First, we conducted *t* tests comparing two- versus four-category performance separately for the rule-based and information-integration conditions. RB2 performance (89.0%) was significantly better than RB4 performance (78.8%), $t(23) = 5.21$, $p < .001$, whereas II2 performance (84.6%) was statistically equivalent to II4 performance (82.7%), $t(23) = 1.18$, $p = .25$. Second, we conducted *t* tests comparing rule-based versus information-integration category performance separately for the two- and four-category cases. RB2 performance (89.0%) was significantly better than II2 performance (84.6%), $t(23) = 2.90$, $p < .01$, whereas RB4 performance (78.8%) was significantly worse than II4 performance (82.7%), $t(23) = 2.08$, $p < .05$.

Three general conclusions can be drawn from these accuracy-based analyses. First, and foremost, the type of category structure interacted strongly with the number of categories, yielding opposite effects. Specifically, in the two-category case, rule-based category learning was significantly better than information-integration category learning, whereas in the four-category case, rule-based category learning was significantly worse than information-integration category learning. Second, the number of categories had a strong effect on rule-based category learning, yielding significantly better two-category/rule-based learning than four-category/rule-based learning, whereas the number of categories had no effect on information-integration category learning. Finally, the best and worst category learning emerged for rule-based categories, with intermediate levels of learning emerging for information-integration categories, that is, two-category/rule-based learning was significantly better than information-integration learning (two- or four-category), and information-integration learning was significantly better than four-category/rule-based learning. Taken together, these results suggest a strong dissociation between rule-based and information-integration category learning as a function of the number of categories.

## *Modeling Results*

The accuracy-based analyses provide important information regarding overall performance but they tell us little about the types of strategies observers might use to solve these tasks. An understanding of strategy use and how these strategies might be affected by both the nature of the category structures and the number of categories is of central importance to a complete understanding of category learning. To gain insight into these issues, a number of different decision-bound models (Ashby, 1992a; Ashby & Maddox, 1992, 1993; Maddox & Ashby, 1993) were fit to the data separately by category structure, block, and observer. All analyses were performed at the individual-observer level because of concerns with modeling aggregate data (e.g., Ashby, Maddox, & Lee, 1994; Estes, 1994; Maddox, 1999; Maddox & Ashby, 1998; J. D. Smith & Minda, 1998).

Decision-bound 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). The fundamental assumption of GRT is that there is trial-by-trial variability in the perceptual information obtained from every stimulus, no matter what the viewing conditions (Ashby & Lee, 1993). On each trial, it is assumed that the percept can be represented as a point in a multidimensional psychological space. Decision-bound theory assumes each observer partitions the perceptual space into response regions. On each trial, the observer determines which region the percept is in, and then emits the associated response. Despite this deterministic decision rule, decision-bound models predict probabilistic responding because of trial-by-trial perceptual and criterial noise (Maddox & Ashby, 1993).

Two different classes of decision-bound models were fit to each observer's responses (see Ashby, 1992a, and Maddox & Ashby, 1993, for a more formal treatment of these models; see Ashby, Maddox, & Bohil, 2002, and Maddox, Ashby, & Bohil, 2003, for applications similar to those outlined here). One type is compatible with the assumption that observers used an explicit rule-based strategy and one type assumes an information-integration strategy. Even so, it is important to note that these models make no detailed process assumptions in the sense that a number of different process accounts are compatible with each of the models (e.g., Ashby, 1992a; Ashby & Waldron, 1999). For example, if an information-integration model fits significantly better than a rule-based model, then we can be reasonably confident that observers did not use a rule-based strategy, but we learn little about which information-integration strategy might have been used (e.g., decision-bound, exemplar, or prototype interpretations would all be compatible with such results). In contrast, if a rule-based model fits significantly better than the information-integration models, then we gain confidence that observers used a rule-based strategy, but we cannot rule out all information-integration strategies because some of these can mimic rule-based responding. In summary, the modeling described in this section provides a powerful vehicle by which to test hypotheses about the decision strategies used by observers, but is limited in its ability to provide a process interpretation.

We now describe the models that were fit to each observer's responses (see Ashby, 1992a, and Maddox & Ashby, 1993, for a more formal treatment of these models). We organize this section around the four experimental conditions because every model was not applied to data from every condition.

### Rule-Based/Two-Category Condition

*Rule-based models.* Two models were compatible with the assumption that the observer used an explicit rule-based strategy. The optimal decision-bound model assumes that the observer used the unidimensional decision bound that maximizes accuracy (i.e., the vertical bound shown in Figure 1). This model has one free parameter: the variance of internal (perceptual and criterial) noise (i.e., $\sigma^2$). The unidimensional length model assumes that the observer sets a criterion on the length dimension and then makes an explicit decision about the level of the stimulus on that dimension (Ashby & Gott, 1988; Shaw, 1982). For example, the observer might use the rule: Respond A if the line is short, and B if it is long, but the decision criterion that separates "short" from "long" lines might be set at a suboptimal length value. The unidimensional length model has two free parameters: a decision criterion on the length dimension and the noise variance.

*Information-integration models.* The general linear classifier (GLC) assumes that the observer used a linear decision bound to separate the A and B categories. This produces an information-integration decision strategy because it requires linear integration of perceived length and orientation. The GLC has three parameters (i.e., the slope and intercept of the linear bound and $\sigma^2$).

### Information-Integration/Two-Category Condition

*Rule-based models.* Five models were compatible with the assumption that observers used an explicit rule-based strategy to solve the II2 category-learning problem. Two unidimensional models were examined. The unidimensional length model was applied to these data and was defined previously. The unidimensional orientation model assumes that the observer sets a criterion on the orientation dimension and then makes an explicit decision about the level of the stimulus on that dimension (Ashby & Gott, 1988; Shaw, 1982). For example, the observer might use the rule: Respond A if the orientation is steep, and B if it is shallow. The unidimensional orientation model has two free parameters (one orientation decision criterion and the noise variance).

Three conjunctive rule models were applied to the data. The conjunctive(1) model and the conjunctive(2) model assume that the observer uses a conjunctive rule in which he or she makes one decision about the length of the line (short or long), a separate decision about the orientation of the line (shallow or steep), and then integrates this information postdecisionally (i.e., after deciding whether the line is short or long and after deciding whether the orientation is shallow or steep). The two models differ only in how this information is integrated to generate a categorization response. The conjunctive(1) model assumes that the observer uses the following rule: Respond A if the length is short and the orientation is steep, otherwise respond B. The conjunctive(2) model assumes that the observer uses the following rule: Respond B if the length is long and the orientation is shallow, otherwise respond A. The conjunctive(1) and conjunctive(2) models contain three parameters (one length criterion, one orientation criterion, and the noise variance). The conjunctive(3) model instantiates an "extreme values" type of decision rule.[3] This model assumes that the observer sets two criteria along the length dimension that partitions the length dimension into three regions. The model assumes that the observer sets a criterion along the orientation dimension that is invoked only when the perceived length falls into the intermediate length region. The model assumes that the observer uses the following rule: Respond A if the length is short, respond B if the length is long, if the length is intermediate then respond A if the orientation is steep, and respond B if the orientation is shallow. The conjunctive(3) model contains four parameters (two length criteria, one orientation criterion, and the noise variance).

*Information-integration models.* Three information-integration models were applied to the data. The optimal model assumes that

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[3] We are indebted to Art Markman for suggesting this model.

the observer uses the optimal decision bound (see Figure 1) and contains the single noise parameter. The GLC (described previously) assumes that the observer uses a suboptimal linear decision bound and contains three parameters (the slope and intercept of the linear decision bound and the noise variance). The minimum distance classifier (MDC) assumes that the observer constructs two decision bounds to separate the A and B categories. In fitting this model we assume that there are four "units" in the length–orientation space. On each trial the observer determines which unit is closest to the perceptual effect and gives the associated response. When fitting the MDC to the II2 category data, we assume that each category has two associated units (because each category consists of two separate clusters of stimuli), which yield two linear decision bounds. Because the location of one of the units can be fixed, and because a uniform expansion of contraction of the space will not affect the location of the resulting (minimum distance) decision bounds, the MDC contains six free parameters (i.e., five that determine the location of the units, and one noise variance). This model has been found to provide a good computational model of observers' response regions in previous information-integration/category-learning studies (e.g., Ashby & Waldron, 1999; Waldron & Ashby, 2001; for applications to stimulus identification, see Ashby, Waldron, Lee, & Berkman, 2001; Maddox, 2001, 2002). In addition, the assumptions of this model have strong neurobiologically plausibility. We reserve a discussion of the neurobiological details for the General Discussion.

### Rule-Based/Four-Category Condition

*Rule-based models.* Four models were compatible with the assumption that observers used an explicit rule-based strategy. The optimal model assumes that the observer sets a criterion on the length dimension, sets a criterion on the orientation dimension, and integrates that information postdecisionally. The model assumes that these decision criteria are those that maximize accuracy (i.e., the decision bounds shown in Figure 1). The optimal model uses the following decision rule: Respond A if the line length is short and the orientation is shallow, respond B if the line length is short and the orientation is steep, respond C if the line length is long and the orientation is shallow, and respond D if the line length is long and the orientation is steep. The optimal model has only one free parameter (i.e., noise variance). Three additional rule-based models that used the same decision rule were tested. The suboptimal length model assumes that the observer used the optimal decision criterion along the orientation dimension, but used a suboptimal decision criterion along the length dimension. The suboptimal orientation model assumes that the observer used the optimal decision criterion along the length dimension, but used a suboptimal decision criterion along the orientation dimension. These two models contain two free parameters (i.e., one criterion and the noise variance). The suboptimal length–orientation model assumes that the observer used a suboptimal decision criterion along the length dimension and a suboptimal decision criterion along the orientation dimension. This model contains three free parameters (i.e., two decision criteria and the noise variance).

*Information-integration models.* The MDC was also applied to these data. When fitting the MDC to the RB4 category-learning data we assume that each category has a single associated unit. The MDC contains six free parameters (i.e., five that determine the location of the units and the noise variance).

### Information-Integration/Four-Category Condition

*Rule-based models.* Two models were compatible with the assumption that observers used an explicit rule-based strategy to solve the II4 category-learning problem, and both were conjunctive rule models. The conjunctive(3) model (described previously) was applied to the data with the following amended decision rule: Respond A if the length is short, respond B if the length is intermediate and the orientation is steep, respond C if the length is intermediate and the orientation is shallow, and respond D if the length is long. The assumptions of the conjunctive(4) model are identical to those from the suboptimal length–orientation model (applied to the RB4 category-learning data) and assumes that the observer sets a decision criterion along the length dimension, a decision criterion along the orientation dimension, and integrates that information postdecisionally. The model assumes that the observer used the following decision rule: Respond A if the line length is short and the orientation is shallow, respond B if the line length is short and the orientation is steep, respond C if the line length is long and the orientation is shallow, and respond D if the line length is long and the orientation is steep.

*Information-integration models.* The optimal model assumes that the observer used the optimal decision bounds (see Figure 1) and contains the single noise parameter. The MDC was also applied to the data. When fitting the MDC to the II4 category-learning data, we assume that each category has one associated unit, yielding a total of six free parameters (i.e., five that determine the location of the units and one noise variance).

### Model Fits

For each of the four experimental conditions, the relevant models were fit separately to the data from each of the six blocks of trials for every observer. The model parameters were estimated using maximum likelihood (Ashby, 1992b; T. D. Wickens, 1982) and the goodness-of-fit statistic was $AIC = 2r - 2lnL$, where $r$ is the number of free parameters and $L$ is the likelihood of the model given the data (Akaike, 1974; Takane & Shibayama, 1992). Akaike's information criterion (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 (for a discussion of the complexities of model comparisons, see Myung, 2000; Pitt, Myung, & Zhang, 2002).

For each of 576 data sets (2 category structures × 2 numbers of categories × 24 observers × 6 blocks), we determined which model provided the best account of the data. For ease of exposition, we then summarized the data by collapsing across the different rule-based and different information-integration models. The number of observers' data sets for which a rule-based or an information-integration model provided the best account of the data by experimental condition and block are presented in Table 2. To provide insight into the categorization performance achieved with the different types of response strategies, we computed the average accuracy rate obtained by observers whose data were best

Table 2
*Number of Observers for Which a Rule-Based or Information-Integration Model Provided the Most Parsimonious Account of Each Block of Data and the Average Accuracy Rate Associated With These Data Sets for Experiment 1*

| | Block | | | | | |
|---|---|---|---|---|---|---|
| Best-fitting model type | 1 | 2 | 3 | 4 | 5 | 6 |
| Rule-based/2 categories | | | | | | |
| Rule based | | | | | | |
| Frequency | 21 | 19 | 22 | 18 | 21 | 21 |
| Average accuracy | .84 | .91 | .90 | .90 | .91 | .90 |
| Information integration | | | | | | |
| Frequency | 3 | 5 | 2 | 6 | 3 | 3 |
| Average accuracy | .73 | .85 | .93 | .90 | .87 | .91 |
| Information-integration/2 categories | | | | | | |
| Rule based | | | | | | |
| Frequency | 11 | 9 | 5 | 6 | 4 | 3 |
| Average accuracy | .73 | .85 | .79 | .77 | .74 | .76 |
| Information integration | | | | | | |
| Frequency | 13 | 15 | 19 | 18 | 20 | 21 |
| Average accuracy | .83 | .85 | .88 | .89 | .89 | .88 |
| Rule-based/4 categories | | | | | | |
| Rule based | | | | | | |
| Frequency | 11 | 15 | 14 | 18 | 19 | 14 |
| Average accuracy | .64 | .83 | .87 | .82 | .88 | .84 |
| Information integration | | | | | | |
| Frequency | 13 | 9 | 10 | 6 | 5 | 10 |
| Average accuracy | .64 | .72 | .70 | .85 | .70 | .82 |
| Information-integration/4 categories | | | | | | |
| Rule based | | | | | | |
| Frequency | 1 | 0 | 0 | 1 | 0 | 0 |
| Average accuracy | .49 | | | .88 | | |
| Information integration | | | | | | |
| Frequency | 23 | 24 | 24 | 23 | 24 | 24 |
| Average accuracy | .71 | .81 | .85 | .87 | .87 | .87 |

fit by each type of model.[4] For example, in the rule-based/two-category condition, 21 observers' data from Block 1 were best fit by a rule-based model with an average accuracy rate of 84% (see Table 2). An examination of Table 2 suggests several interesting results, which we summarize separately for each of the four experimental conditions.

*Rule-based/two-category condition.* In the RB2 condition, a rule-based strategy almost always provided the best account of the data across all six blocks of trials, and those observers who used a rule-based strategy achieved high levels of accuracy (over 90% in all but the first block of trials). In fact, the optimal model that assumes the observer used the decision criterion that maximizes categorization accuracy (in the presence of perceptual and criterial noise) provided the best account of the data for about half of the observers (specifically, 10, 13, 17, 10, 17, and 14 of the 24 observers in Blocks 1–6, respectively). Clearly, observers found category learning under these conditions straightforward. They quickly learned the optimal decision criterion and quickly achieved high levels of accuracy.

*Information-integration/two-category condition.* In the II2 condition there was a shift from a nearly even split between observers whose data were best fit by rule-based or information-integration strategies early in learning, toward almost exclusive use of information-integration strategies later in learning. About one-third of the observers learned the optimal information-integration decision bound (specifically, 7, 8, 8, 13, 10, and 8 of the 24 observers' data in Blocks 1–6, respectively, were best fit by the optimal model). In addition, when a rule-based strategy provided the best account of the data, the best-fitting rule-based model was almost always the conjunctive(3) model that instantiates the

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[4] We could take a different data-analytic approach. In particular, we could identify the strategy used by each observer in each condition first, and then examine the accuracy rates for different subgroups of observers (such as rule-based vs. information-integration users). This is a reasonable approach and one that should be pursued in future research. We chose not to take this approach here for several reasons. First, it precludes us from taking full advantage of the within-observer design. Because the focus at this early stage of scientific endeavor is on performance accuracy, we deemed it most important to take full advantage of the within-observer design. Second, a detailed understanding of the relevant individual differences in strategy use would require a much larger sample size than was used in this research. Even so, we are including the accuracy rates broken down by strategy subgroup for the interested reader.

extreme value strategy (this model provided the best account of the data for 8, 8, 4, 5, 3, and 2 of the 24 observers in Blocks 1–6, respectively). Interestingly, the accuracy rate achieved by observers who used a rule-based strategy was much lower than that of observers using an information-integration strategy.

*Rule-based/four-category condition.* In the RB4 condition there was a fairly even split between observers whose data were best fit by a rule-based or information-integration strategy early in learning, as in the II2 condition. However, unlike the II2 condition, this pattern held across all six blocks of trials. Thus, even later in learning both rule-based and information-integration strategies were being used extensively. In addition, the number of observers learning the optimal rule-based strategy was much smaller than in the RB2 condition, and was slightly smaller than that observed in the II2 condition, although the number increased across blocks (specifically, 4, 7, 4, 6, 8, and 8 of the 24 observers' data in Blocks 1–6, respectively, were best fit by the optimal model). The accuracy rates observed for the two classes of models was also somewhat mixed, although there was a general tendency for the rule-based strategies to yield higher accuracy. In addition, none of the three suboptimal rule-based models seemed to dominate the others, with a fairly even split among the three suboptimal rule-based strategies.

*Information-integration/four-category condition.* In the II4 condition, an information-integration strategy provided the best account of the data across all six blocks of trials. Notice that this is the same pattern observed in the RB2 condition. Specifically, in both the II4 and RB2 conditions, strategies of the same form as the optimal (i.e., information-integration in the II4 condition and rule-based in the RB2 condition) dominated throughout learning. The number of observers learning the optimal information-integration decision bounds was similar to that observed in the RB4 condition with a general increase over blocks (specifically, 3, 7, 6, 7, 11, and 8 of the 24 observers' data in Blocks 1–6, respectively, were best fit by the optimal model). The accuracy rate for observers using an information-integration strategy increased gradually from 71% to a high of 87%.

### Response Time Analyses

Observers were explicitly instructed to respond as accurately as possible and not to worry about speed of responding. In light of this fact, any analyses of the response time data should be interpreted with caution. Even so, we decided to examine the response time data briefly to determine whether the results that held in the accuracy data might be mimicked in the response time data. For each observer in each condition and block, we computed the mean response time for correct responses only, and performed a series of *t* tests. First, we conducted *t* tests comparing two- versus four-category response times separately for the rule-based and information-integration conditions. RB2 responses (1,007 ms) were significantly faster than RB4 responses (1,773 ms), $t(23) = 5.64$, $p < .001$, and II2 responses (1,049 ms) were significantly faster than II4 responses (1,341 ms), $t(23) = 3.55$, $p < .01$. Although both of these latter *t* tests were significant, the significance of the overall category number by category structure interaction indicates that the differences in response times between the RB2 and RB4 responses (response time difference = 766 ms) was greater than the differences in response times between the II2 and II4 responses (response time difference = 292 ms). Second, we conducted *t* tests comparing rule-based versus information-integration category response times separately for the two- and four-category cases. RB2 response times were statistically equivalent to II2 response times, $t(23) = 0.40$, *ns,* whereas RB4 response times were significantly slower than II4 response times, $t(23) = 3.78$, $p < .01$. These findings generally support the conclusions drawn from the accuracy data.

### Discussion

The results from Experiment 1 indicate a strong interaction between the number of categories and the nature of the category structures on category learning. Whereas no accuracy difference was observed across the II2 and II4 conditions, there was a large accuracy difference observed across the RB2 and RB4 conditions. Performance in the RB2 condition was a full 10% better than in the RB4 condition (see Figure 2B). In fact, the best category learning resulted in the RB2 condition, which was significantly better than in the II2 and II4 conditions, which were both significantly better than in the RB4 condition. Importantly, the observed interaction cannot be attributed to differences in objective measures of complexity because a number of structural aspects of the categories were equated across conditions, including optimal accuracy, cluster number, within-cluster scatter, and cluster coherence (Fukunaga, 1990). The large accuracy difference observed in the rule-based conditions was mirrored by a large difference in the best-fitting model profile. Whereas a rule-based strategy dominated across all blocks in the RB2 condition, and in fact the optimal model was best for nearly half of the observers, there was a nearly even split between observers using rule-based and information-integration strategies across all blocks in the RB4 condition. Previous research suggests that unidimensional rules are easier to learn than conjunctive rules (although all of that work focused only on conditions with two categories; e.g., Shepard et al., 1961) and so the observed accuracy difference was not surprising. What is unique about this study is that the model-based analyses suggest that the accuracy difference may be due (in part) to the fact that nearly half of the observers in the RB4 condition (that required the application of a more complex rule) did not utilize a rule-based strategy, but rather relied on an information-integration strategy to solve the task. Although speculative, it appears that many observers were unable (or unwilling) to expend the conscious effort necessary to apply the complex optimal rule-based strategy. Those observers appeared to rely instead on the more unconscious information-integration system to perform the task.

The response time data generally supported the conclusions derived from the accuracy data, and ruled out possible speed–accuracy trade-off explanations. For example, response times were fastest in the RB2 condition, were intermediate in the II2 and II4 conditions, and were slowest in the RB4 condition. Thus, response times increased as accuracy declined. This very dramatic increase in response times for the RB4 condition as compared to the RB2 condition mimicked the accuracy results. Overall, these findings suggest that increasing category number places a greater demand on executive processes and working memory, and such demands result in performance decrements that can be seen in both accuracy rates and reaction times.

There are two problems with Experiment 1's attempt to compare two- with four-category/rule-based learning. First, the pattern of differences observed in the four conditions in Experiment 1 may not be due to category number per se, but rather due to the relevant stimulus dimension in the RB2 condition. Recall that optimal performance in the RB2 condition depended on the observer setting a criterion on the length dimension, and it may be that the high level of accuracy observed in this condition was due to the saliency of the length dimension. Thus, the question arises as to whether the pattern of results would remain the same if optimal responding in the RB2 condition was based on setting a criterion on the orientation dimension. We address this issue in Experiment 2 where we had observers learn a rule-based/two-category task in which length was relevant (RB2L), a rule-based/two-category task in which orientation was relevant (RB2O), and a rule-based/four-category task in which both length and orientation were relevant (RB4). If the specific relevant dimension in RB2 had no impact on the pattern of results in Experiment 1, then in Experiment 2 we would expect there to be no performance differences between RB2L and RB2O, whereas performance in both these conditions should be better than in RB4.

A second potential problem with Experiment 1 is that the RB2 and RB4 conditions differed not only in the number of categories, but also in the number of dimensions that are relevant to solving the task. Thus, the observed performance difference across the RB2 and RB4 conditions might be due to the difference in category number, the difference in the number of dimensions that are relevant, or both. To shed some light on this issue, Experiment 3 examined rule-based category learning across four rule-based conditions (described in detail later).

## Experiment 2

Experiment 2 was conducted to determine whether RB4 performance was significantly worse than RB2L and RB2O performance, and to determine whether RB2L and RB2O performance was statistically equivalent. This finding would strengthen our conclusion that category number affects rule-based category learning. The RB2L and RB4 stimuli were identical to those used in Experiment 1. In the RB2O condition, we simply reversed the category assignments for $A_2$ and $B_1$ from the RB2 condition (see Table 1). Specifically, the $A_2$ stimuli became members of Category B and the $B_1$ items became members of Category A.

### *Method*

### *Observers and Design*

Six observers (3 women and 3 men) were solicited from the University of Texas community and received $25 for participating in this study. Each observer completed all three experimental conditions in a different order. Only one of the three conditions (approximately 60 min) was completed during a single test day, and one rest day was required between testing sessions. Visual acuity was tested in each observer, and all observers had 20/20 vision, or vision corrected to at least 20/20.

### *Stimuli, Stimulus Generation, and Procedure*

The stimuli, stimulus generation, and procedures were identical to those in Experiment 1.

### *Results and Discussion*

Analyses were performed separately on each of the six 100-trial blocks of data. A Condition (RB2L, RB2O, and RB4) × Block (six 100-trial blocks) within-observer ANOVA was conducted on the accuracy rates. The accuracy rates averaged across observers are presented in Figure 3A separately by block, and collapsed over blocks in Figure 3B. The main effects of condition, $F(2, 5) = 9.51$, $p < .01$, block, $F(5, 25) = 4.92$, $p < .01$ and the interaction, $F(10, 50) = 2.13$, $p < .05$, were all significant. Most importantly, performance was significantly worse in the RB4 condition (81.0%) than in both the RB2L (88.3%) and the RB2O (89.8%) conditions, with the latter two yielding statistically equivalent performance levels. The model-based and response time analyses mimicked those from Experiment 1 with faster, more nearly optimal responding in the RB2L and RB2O conditions than in the RB4 condition.

These results suggest that the significant performance difference observed in Experiment 1 between the RB2 and RB4 conditions holds regardless of which dimension (length or orientation) is relevant in the RB2 condition. We turn now to Experiment 3, which examines rule-based category learning in more detail.

## Experiment 3

Experiment 3 was conducted to determine whether the poor performance observed in the RB4 condition relative to the RB2 condition from Experiment 1 was due to the difference in category number, the difference in the number of relevant dimensions, or

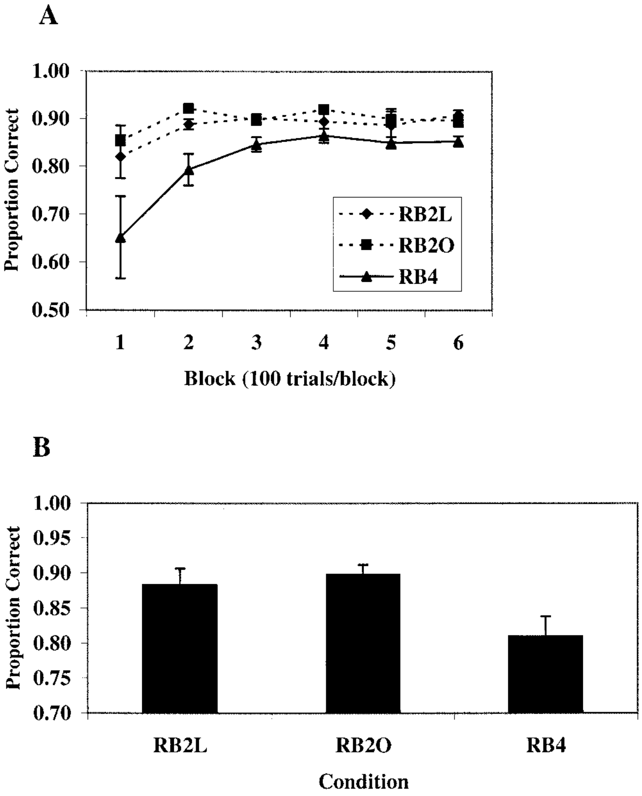

*Figure 3.* A: Proportion correct for the two-category/rule-based structures and the four-category/rule-based structure for each block from Experiment 2 (standard error bars included). The solid lines denote the four-category conditions, and the dashed lines the two-category conditions. B: Proportion correct for the same conditions averaged over blocks (standard error bars included). RB2L = rule-based-2, length relevant, RB2O = rule-based-2, orientation relevant, and RB4 = rule-based-4.

both. Experiment 3 included four rule-based categories constructed from the factorial combination of category number (two or four) with the number of relevant dimensions (one or two), also termed the *nature of the optimal rule* (unidimensional or conjunctive). In the unidimensional/two-category condition (UD2), there were two categories, and the optimal strategy was to set a criterion along the length dimension while ignoring the orientation dimension, yielding one relevant dimension. Notice that this condition is analogous to the RB2 condition from Experiment 1 and the RB2L condition from Experiment 2. In the conjunctive/two-category condition (CJ2), there were two categories, and the optimal strategy was to set one criterion along the length dimension and a second criterion along the orientation dimension, yielding two relevant dimensions, and to respond A to short/shallow lines or long/steep lines, and to respond B to long/shallow lines or short/steep lines. In the unidimensional/four-category condition (UD4), there were four categories, and the optimal strategy was to set three criteria along the length dimension while ignoring the orientation dimension, yielding one relevant dimension. These three criteria were used to partition the length dimension into four response regions. Finally, in the conjunctive/four-category condition (CJ4), there were four categories, and the optimal strategy was to set a criterion along the length dimension and to set a criterion along the orientation dimension, yielding two relevant dimensions. The two criteria were used to partition the length–orientation space into four response regions. Notice that this condition is analogous to the RB4 condition from Experiments 1 and 2. If category learning differs across the UD2 and CJ4 conditions, as predicted from the results of Experiments 1 and 2, a comparison of performance across the UD2 and UD4 conditions will allow us to determine whether category number impacts rule-based learning when one dimension is relevant, and a comparison of performance across the UD4 and CJ4 conditions will allow us to determine whether the number of relevant dimensions impacts rule-based learning when there are four categories. We anticipate that increasing the number of categories while holding the number of relevant dimensions fixed at one (i.e., UD2 vs. UD4) will adversely affect performance because of the increased attentional and working memory load required for three, as opposed to one, decision bound. In addition, we predict that increasing the number of relevant dimensions while holding the number of categories fixed at four (i.e., UD4 versus CJ4) will adversely affect performance because of the increased attentional and working memory load. Tests of this prediction are especially interesting because the CJ4 condition requires only two decision bounds, whereas the UD4 condition requires three decision bounds. Our sense is that the need to include both dimensions in the CJ4 condition will lead to a much greater increase in attentional and working memory load than simply increasing from one to three decision bounds along one dimension as in the UD2 versus UD4 comparison.

Following the approach taken in Experiments 1 and 2, we equated the conditions on several measures of complexity by equating a number of structural aspects of the categories. These included optimal accuracy, the number of stimulus clusters, within-cluster scatter, and cluster coherence (Fukunaga, 1990). In all four conditions, optimal accuracy was 95%. In addition, cluster scatter and coherence was held constant by first generating the stimuli for the UD2 condition (described in detail in the *Method* section), and then generating the stimuli in the three remaining conditions by applying simple scatter- and coherence-preserving transformations.

## Method

### Observers and Design

Sixteen observers (8 women and 8 men) were solicited from the University of Texas community and received $30 for participating in this study. Each observer completed all four experimental conditions with the condition order being determined from a Latin square. Only one condition (approximately 60 min) was completed during a single test day, and one rest day was required between testing sessions. Visual acuity was tested in each observer, and all observers had 20/20 vision, or vision corrected to at least 20/20.

### Stimuli and Stimulus Generation

The stimuli and stimulus generation procedures were identical to those in Experiments 1 and 2. The two- and four-category unidimensional/rule-based and conjunctive/rule-based category structures are displayed in Figure 4 along with the optimal decision bound(s). The category-distribution parameters are outlined in Table 3. A total of 16 bivariate normal distributions were specified. The stimuli for UD2 categories were generated by sampling randomly 36 stimuli from each of the 16 bivariate normal distributions for a total of 576 unique stimuli. The stimuli for the remaining three conditions were generated from the UD2 stimuli by applying scatter- and coherence-preserving shifts of the location of each stimulus in such a way as to equate optimal accuracy (at 95%) across all four conditions. Each experimental condition consisted of six, 96-trial blocks.

### Procedure

The procedures were identical to those used in Experiments 1 and 2.

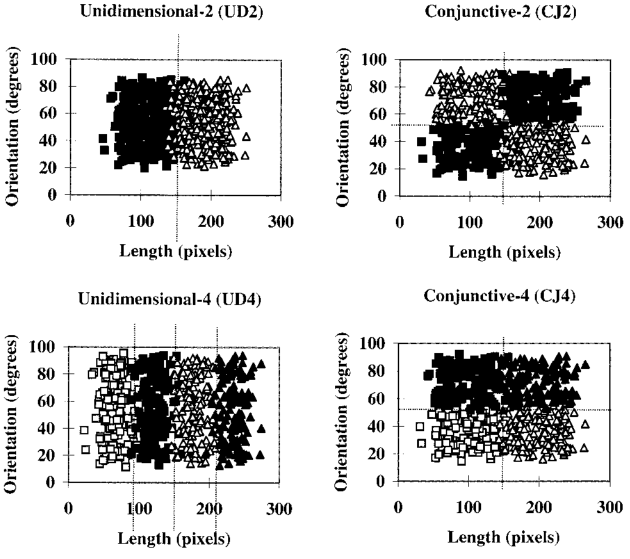

*Figure 4.* Scatter plots in the length and orientation space for the categorization stimuli from each of the four conditions from Experiment 3. For the two-category conditions, the filled squares denote stimuli from Category A, and the open triangles denote stimuli from Category B. For the four-category conditions, the open squares denote stimuli from Category A, the filled squares denote stimuli from Category B, the open triangles denote stimuli from Category C, and the filled triangles denote stimuli from Category D. The dashed lines in each plot denote the optimal decision bound(s).

Table 3
*Category-Distribution Parameters From Experiment 3*

| Category | $\mu_l$ | $\mu_o$ | $\sigma_l$ | $\sigma_o$ | $\text{cov}_{lo}$ | Category | $\mu_l$ | $\mu_o$ | $\sigma_l$ | $\sigma_o$ | $\text{cov}_{lo}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Unidimensional-2 (UD2) | | | | | | Conjunctive-2 (CJ2) | | | | | |
| $A_1$ | 90 | 90 | 15 | 15 | 0 | $A_1$ | 75 | 75 | 15 | 15 | 0 |
| $A_2$ | 90 | 130 | 15 | 15 | 0 | $A_2$ | 75 | 125 | 15 | 15 | 0 |
| $A_3$ | 90 | 170 | 15 | 15 | 0 | $A_3$ | 125 | 75 | 15 | 15 | 0 |
| $A_4$ | 90 | 210 | 15 | 15 | 0 | $A_4$ | 125 | 125 | 15 | 15 | 0 |
| $A_5$ | 130 | 90 | 15 | 15 | 0 | $A_5$ | 175 | 175 | 15 | 15 | 0 |
| $A_6$ | 130 | 130 | 15 | 15 | 0 | $A_6$ | 175 | 225 | 15 | 15 | 0 |
| $A_7$ | 130 | 170 | 15 | 15 | 0 | $A_7$ | 225 | 175 | 15 | 15 | 0 |
| $A_8$ | 130 | 210 | 15 | 15 | 0 | $A_8$ | 225 | 225 | 15 | 15 | 0 |
| $B_1$ | 170 | 90 | 15 | 15 | 0 | $B_1$ | 75 | 175 | 15 | 15 | 0 |
| $B_2$ | 170 | 130 | 15 | 15 | 0 | $B_2$ | 75 | 225 | 15 | 15 | 0 |
| $B_3$ | 170 | 170 | 15 | 15 | 0 | $B_3$ | 125 | 175 | 15 | 15 | 0 |
| $B_4$ | 170 | 210 | 15 | 15 | 0 | $B_4$ | 125 | 225 | 15 | 15 | 0 |
| $B_5$ | 210 | 90 | 15 | 15 | 0 | $B_5$ | 175 | 75 | 15 | 15 | 0 |
| $B_6$ | 210 | 130 | 15 | 15 | 0 | $B_6$ | 175 | 125 | 15 | 15 | 0 |
| $B_7$ | 210 | 170 | 15 | 15 | 0 | $B_7$ | 225 | 75 | 15 | 15 | 0 |
| $B_8$ | 210 | 210 | 15 | 15 | 0 | $B_8$ | 225 | 125 | 15 | 15 | 0 |
| Unidimensional-4 (UD4) | | | | | | Conjunctive-4 (CJ4) | | | | | |
| $A_1$ | 66 | 66 | 15 | 15 | 0 | $A_1$ | 75 | 75 | 15 | 15 | 0 |
| $A_2$ | 66 | 122 | 15 | 15 | 0 | $A_2$ | 75 | 125 | 15 | 15 | 0 |
| $A_3$ | 66 | 178 | 15 | 15 | 0 | $A_3$ | 125 | 75 | 15 | 15 | 0 |
| $A_4$ | 66 | 234 | 15 | 15 | 0 | $A_4$ | 125 | 125 | 15 | 15 | 0 |
| $B_1$ | 122 | 66 | 15 | 15 | 0 | $B_1$ | 75 | 175 | 15 | 15 | 0 |
| $B_2$ | 122 | 122 | 15 | 15 | 0 | $B_2$ | 75 | 225 | 15 | 15 | 0 |
| $B_3$ | 122 | 178 | 15 | 15 | 0 | $B_3$ | 125 | 175 | 15 | 15 | 0 |
| $B_4$ | 122 | 234 | 15 | 15 | 0 | $B_4$ | 125 | 225 | 15 | 15 | 0 |
| $C_1$ | 178 | 66 | 15 | 15 | 0 | $C_1$ | 175 | 75 | 15 | 15 | 0 |
| $C_2$ | 178 | 122 | 15 | 15 | 0 | $C_2$ | 175 | 125 | 15 | 15 | 0 |
| $C_3$ | 178 | 178 | 15 | 15 | 0 | $C_3$ | 225 | 75 | 15 | 15 | 0 |
| $C_4$ | 178 | 234 | 15 | 15 | 0 | $C_4$ | 225 | 125 | 15 | 15 | 0 |
| $D_1$ | 234 | 66 | 15 | 15 | 0 | $D_1$ | 175 | 175 | 15 | 15 | 0 |
| $D_2$ | 234 | 122 | 15 | 15 | 0 | $D_2$ | 175 | 225 | 15 | 15 | 0 |
| $D_3$ | 234 | 178 | 15 | 15 | 0 | $D_3$ | 225 | 175 | 15 | 15 | 0 |
| $D_4$ | 234 | 234 | 15 | 15 | 0 | $D_4$ | 225 | 225 | 15 | 15 | 0 |

*Note.* Optimal accuracy was held constant at 95% in all conditions.

### *Accuracy Results*

Analyses were performed separately on each of the six, 96-trial blocks of data. A Category Number (2 versus 4 categories) × Nature of Optimal Rule (unidimensional versus conjunctive) × Block (six 96-trial blocks) within-observer ANOVA was conducted on the accuracy rates. The accuracy rates averaged across observers are presented in Figure 5A. The main effects of nature of the optimal rule, $F(1, 15) = 52.78$, $p < .001$, and block, $F(5, 75) = 59.86$, $p < .001$, were significant, whereas the main effect of category number was nonsignificant ($p > .25$). Performance was superior in the unidimensional/rule-based conditions (83.9%) relative to the conjunctive/rule-based conditions (69.8%), and improved over blocks (67.3%, 72.5%, 78.7%, 80.9%, 80.0%, and 81.7% for Blocks 1–6, respectively). These main effects were qualified by a significant category number by nature of the optimal rule interaction, $F(1, 15) = 33.70$, $p < .001$, a significant nature of the optimal rule by block interaction, $F(5, 75) = 6.65$, $p < .001$, a significant category number by block interaction, $F(5, 75) = 3.78$, $p < .01$, and a significant three-way interaction, $F(5, 75) = 3.19$, $p < .05$. The three-way interaction, and the two-way interactions with block, suggest different learning rates across conditions, and are most likely due to the very quick learning in the UD2 condition relative to all others.

The most important finding from this analysis was the category number by nature of the optimal rule interaction, which is displayed graphically in Figure 5B. To determine the locus of this interaction we conducted a number of *t* tests on the accuracy rates collapsed across blocks. First, we conducted *t* tests comparing two- versus four-category performance separately for the unidimensional/rule-based and conjunctive/rule-based conditions. UD2 performance (88.8%) was significantly better than UD4 performance (79.0%), $t(15) = 4.44$, $p < .001$, whereas CJ2 performance (67.5%) was statistically equivalent to CJ4 performance (72.1%), $t(15) = 1.62$, $p = .13$. Second, we conducted *t* tests comparing unidimensional/rule-based versus conjunctive/rule-based category performance separately for the two- and four-category cases. UD2 performance was significantly better than CJ2 performance, $t(15) = 9.23$, $p < .001$, and UD4 performance was significantly better than CJ4 performance, $t(15) = 2.98$, $p < .01$.

These data also allow us to determine whether superior performance in the RB2 condition relative to the RB4 condition observed in Experiment 1, was due to the difference in category number,

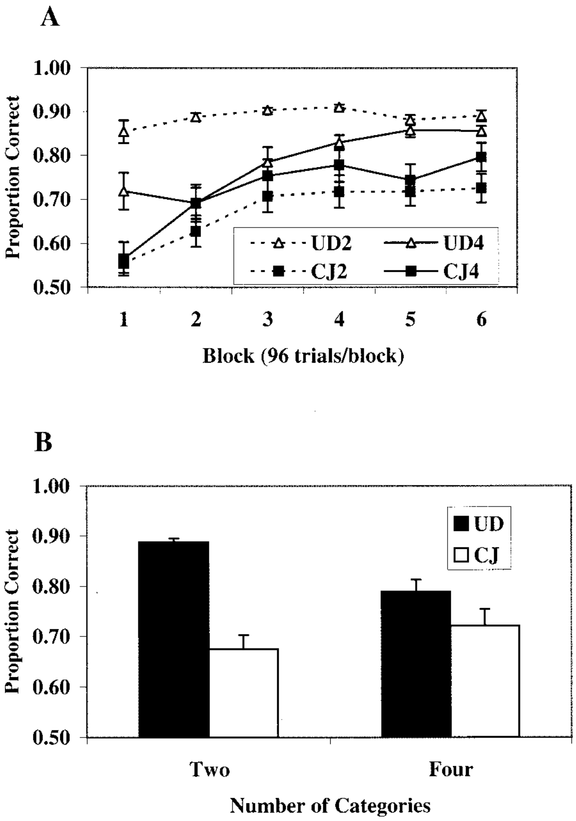

*Figure 5.* A: Proportion correct for the two- and four-category/unidimensional and conjunctive/rule-based category structures for each block from Experiment 3 (standard error bars included). The solid lines denote the four-category conditions, and the broken lines the two-category conditions. The filled squares denote the conjunctive/rule-based conditions, and the open triangles denote the unidimensional/rule-based conditions; UD2 = unidimensional-2, UD4 = unidimensional-4, CJ2 = conjunctive-2, and CJ4 = conjunctive-4. B: Proportion correct for the same conditions averaged over blocks (standard error bars included). UD = unidimensional; CJ = conjunctive.

number of relevant dimensions (and hence, nature of the optimal rule), or both. These data suggest that both factors were important. The fact that UD2 performance was significantly better than UD4 performance suggests that category number has a significant effect on performance when the number of relevant dimensions was held fixed at one, likely due to the need to learn three as opposed to one decision bound. In addition, the fact that UD4 performance was significantly better than CJ4 performance suggests that the number of relevant dimensions, and hence the nature of the optimal rule (unidimensional versus conjunctive), has a significant effect on performance, above and beyond the effect due to category number. The fact that CJ4 performance that required the learning of two decision bounds was worse than UD4 performance that required the learning of three decision bounds suggests that the need to learn one decision bound on each of two dimensions is harder than learning three decision bounds along a single dimension. Interestingly, increasing the number of categories (and decision bounds) in a rule-based task does not always lead to poorer performance. Notice that performance in the CJ2 condition is worse (albeit nonsignificantly) than in the CJ4 condition.

### *Modeling Results*

Following the approach taken in Experiments 1 and 2, a number of different decision-bound models (Ashby, 1992a; Maddox & Ashby, 1993) were fit to the data separately by condition, block, and observer. The models applied to the RB2 condition from Experiment 1 were applied to the UD2 condition from Experiment 3, and the models applied to the RB4 condition from Experiment 1 were applied to the CJ2 and CJ4 conditions from Experiment 3.

Two rule-based models were applied to the UD4 data. The optimal decision-bound model assumes that the observer used the three unidimensional decision bounds that maximize accuracy (i.e., the three vertical bounds shown in Figure 4). This model has one free parameter: the variance of internal (perceptual and criterial) noise (i.e., $\sigma^2$). A generalization of the unidimensional length model was also applied to the data that assumes that the observer sets three criteria on the length dimension, but that these criteria can be placed at suboptimal locations. This model has four free parameters: three decision criteria on the length dimension and the noise variance. One information-integration model was applied to the UD4 data, and is identical to the MDC. It assumes that the observer constructs four decision bounds. In fitting this model we assume that there are four "units" (one per category) in the length–orientation space. The MDC contains six free parameters (i.e., five that determine the location of the units and one noise variance).

### *Model Fits*

For each of 384 data sets (2 optimal rule types × 2 numbers of categories × 16 observers × 6 blocks), we determined which model provided the best account of the data (using the AIC statistic), then summarized the data by collapsing across the different rule-based and different information-integration models. The number of observers' data sets for which a rule-based or an information-integration model provided the best account of the data by experimental condition and block are presented in Table 4. In addition, we computed the average accuracy rate achieved by observers whose data were best fit by each type of model. An examination of Table 4 suggests several interesting results, which we summarize separately for each of the four experimental conditions.

*Unidimensional/two-category condition.* In the UD2 condition a rule-based strategy almost always provided the best account of the data across all six blocks of trials, and those observers who used a rule-based strategy achieved high levels of accuracy (over 89% in all but the first block of trials). This pattern of results mirrors those from the RB2 condition from Experiment 1, and suggests that observers found category learning under these conditions easy and quickly achieved high levels of accuracy.

*Conjunctive/two-category condition.* As in the UD2 condition, rule-based strategies dominated throughout learning. Interestingly, though, the few observers who used information-integration strategies to solve this category-learning problem tended to achieve higher accuracy levels than those observers who used rule-based strategies. The small sample makes it difficult to draw any strong conclusions from these data. One speculation, though, is that this "rule" is extremely complex and difficult for observers to implement, and for those observers who had difficulty, the unconscious information-integration system might have dominated.

*Unidimensional/four-category condition.* In the UD4 condition there was a fairly even split between observers whose data

Table 4

*Number of Observers for Which a Rule-Based or Information-Integration Model Provided the Most Parsimonious Account of Each Block of Data and the Average Accuracy Rate Associated With These Data Sets for Experiment 3*

| | Block | | | | | |
|---|---|---|---|---|---|---|
| Best-fitting model type | 1 | 2 | 3 | 4 | 5 | 6 |
| **Unidimensional/2 categories** | | | | | | |
| Rule based | | | | | | |
| Frequency | 10 | 13 | 13 | 14 | 13 | 11 |
| Average accuracy | .84 | .89 | .90 | .91 | .88 | .90 |
| Information integration | | | | | | |
| Frequency | 6 | 3 | 3 | 2 | 3 | 5 |
| Average accuracy | .88 | .87 | .91 | .92 | .88 | .87 |
| **Conjunctive/2 categories** | | | | | | |
| Rule based | | | | | | |
| Frequency | 15 | 13 | 12 | 14 | 13 | 11 |
| Average accuracy | .54 | .59 | .69 | .72 | .73 | .71 |
| Information integration | | | | | | |
| Frequency | 1 | 3 | 4 | 2 | 3 | 5 |
| Average accuracy | .76 | .78 | .77 | .70 | .67 | .76 |
| **Unidimensional/4 categories** | | | | | | |
| Rule based | | | | | | |
| Frequency | 7 | 6 | 9 | 6 | 8 | 12 |
| Average accuracy | .74 | .64 | .75 | .82 | .86 | .85 |
| Information integration | | | | | | |
| Frequency | 9 | 10 | 7 | 10 | 8 | 4 |
| Average accuracy | .71 | .72 | .82 | .84 | .86 | .86 |
| **Conjunctive/4 categories** | | | | | | |
| Rule based | | | | | | |
| Frequency | 7 | 9 | 10 | 5 | 10 | 7 |
| Average accuracy | .67 | .73 | .81 | .86 | .79 | .86 |
| Information integration | | | | | | |
| Frequency | 9 | 7 | 6 | 11 | 6 | 9 |
| Average accuracy | .49 | .64 | .65 | .74 | .66 | .75 |

were best fit by a rule-based or information-integration strategy in all but the final block of trials. The accuracy rates observed for the two classes of models were nearly equivalent, with a small, but consistent, advantage for the information-integration strategy.

*Conjunctive/four-category condition.* In the CJ4 condition, like the UD4 condition, there was a fairly even split between observers whose data were best fit by a rule-based or information-integration strategy across all six blocks of trials. Interestingly, in this condition, and contrary to the results from the CJ2 condition, the accuracy rates for the observers who used rule-based strategies were consistently higher than those from observers who used information-integration strategies. This pattern of results mirrors those from the RB4 condition from Experiment 1.

### *Response Time Analyses*

Although the response time data should be interpreted with caution (observers were instructed to ignore speed of responding), we decided to examine the response time data from Experiment 3 in the same way that we examined the response time data from Experiments 1 and 2. For each observer in each condition and block, we computed the mean response time for correct responses only and computed a series of $t$ tests. First, we conducted $t$ tests comparing two- versus four-category response times separately for the unidimensional and conjunctive/rule-based conditions. UD2 responses (785 ms) were significantly faster than UD4 responses (1,166 ms), $t(15) = 3.42$, $p < .01$, whereas CJ2 responses (1,414 ms) were statistically equal to CJ4 responses (1,389 ms), $t(15) = 0.20$, *ns.* Second, we conducted $t$ tests comparing unidimensional versus conjunctive/rule-based category response times separately for the two- and four-category cases. UD2 response times were significantly faster than CJ2 response times, $t(15) = 4.04$, $p < .01$, whereas UD4 response times were marginally significantly faster than CJ4 response times, $t(15) = 1.81$, $p = .09$.

### *Discussion*

Experiment 3 was conducted to determine whether the rule-based performance difference observed in Experiments 1 and 2 was due to a difference in category number, number of relevant dimensions (and hence nature of the optimal rule), or some combination of the two. The results from Experiment 3 suggest that both category number and the number of dimensions relevant to the rule affect performance. Specifically, performance in the two-category/unidimensional condition was better than performance in the four-category/unidimensional condition, and performance in the four-category/unidimensional condition was better than performance in the four-category/conjunctive condition. Thus, when the rule-based task is unidimensional, increasing the number of categories adversely affects performance, and when there are four categories, increasing the number of dimensions relevant to solving the rule-based problem adversely affects performance. The response time generally supported the conclusions derived from the accuracy data, and ruled out possible speed–accuracy trade-off explanations. For example, response times were faster in the UD2 condition than in the UD4 condition, and were faster in the UD4 condition than in the CJ4 condition.

Although both category number (UD2 vs. UD4) and the number of relevant dimensions (UD4 vs. CJ4) each lead to a significant reduction in performance, the effect of category number was larger than the effect of number of dimensions for both accuracy and response time. Specifically, accuracy was 10% higher in the UD2 condition than in the UD4 condition, but was only 7% higher in the UD4 condition than in the CJ4 condition. In addition, response time was 380 ms faster in the UD2 condition than in the UD4 condition, but was only 223 ms faster in the UD4 condition than in the CJ4 condition. (Of course, this might be due partially to the fact that three decision bounds were relevant in the UD4 condition, but only two were relevant in the CJ4 condition.) This finding provides further evidence to support the hypothesis that category number affects rule-based, but not information-integration category learning.

It is worth mentioning that CJ4 performance was somewhat lower than RB4 performance from Experiment 1 with accuracy rates of 78.8% for RB4 and 72.1% for CJ4 collapsed across blocks. This difference is much smaller for the final block of trials with accuracy rates of 83.3% for RB4 and 79.6% for CJ4. This slight difference is likely due to the difference in the density of the stimuli across the two studies, but does not affect our overall conclusions because the important comparisons are within experiment.

The CJ2 condition was not necessary to determine whether the category number effect on rule-based category learning in Experiment 1 was due to the number of categories or number of relevant dimensions. This condition was included mainly to complete the factorial design. Even so, the results from this condition suggest that increasing the number of categories in a rule-based task does not always lead to worse performance. In fact, CJ2 performance was 4.6% worse than CJ4 performance, although this difference was nonsignificant. It is worth mentioning, though, that the CJ2 condition is unique in the sense that it requires the observer to give the same categorization response to stimuli that fall in separate, nonoverlapping response regions. This was not the case in any other condition in Experiments 1–3. Even so, the fact that the category number effect is in the opposite direction for unidimensional and conjunctive conditions is interesting, and suggests that future work should focus on this issue.

## General Discussion

The results from this study indicate that there is a strong interaction between the number of categories and the nature of the category structures on category learning. Whereas there was no effect of category number on information-integration category learning, category number had a large effect on rule-based category learning. In Experiments 1 and 2, performance in the RB2 condition was significantly better than in the RB4 condition. However, the RB4 and RB2 conditions differed in the number of categories and number of relevant dimensions, and so the effect could be due to one factor or both. In Experiment 3, performance in the UD2 condition was significantly better than performance in the UD4 condition, suggesting that category number does affect unidimensional/rule-based category learning. In addition, in Experiment 3, performance in the UD4 condition was significantly better than performance in the CJ4 condition, suggesting that the number of relevant dimensions also affects rule-based category learning. Importantly, the observed interaction between category number and category structure cannot be attributed to differences in objective measures of complexity because a number of structural aspects of the categories were equated across conditions, including optimal accuracy, the number of stimulus clusters, within-cluster scatter, and cluster coherence (Fukunaga, 1990). The model-based analyses allowed us to examine the detailed nature of this accuracy-based interaction because we were able to identify the type of response strategy used by each observer in the various experimental conditions. The model-based results provided important insights into the locus of the observed performance interaction and have implications for information-integration and rule-based category learning, single- versus multiple-system approaches to category learning, and the underlying neurobiology of category learning. We turn now to a discussion of these issues.

### *Single- and Multiple-System Models of Category Learning*

A wide variety of evidence now indicates that the learning of rule-based and information-integration category structures might be mediated by different neural circuits, and that literature provides further reason to expect that the experimental manipulations studied here might have different effects on these two types of tasks (Ashby et al., 1998; Ashby & Ell, 2002; Erickson & Kruschke, 1998; E. E. Smith et al., 1998; Waldron & Ashby, 2001). In particular, Ashby and his colleagues have proposed that with rule-based structures, learning is mediated by a circuit that includes the anterior cingulate, the prefrontal cortex, and the head of the caudate nucleus, whereas in information-integration tasks, learning is mediated largely within the tail of the caudate nucleus for visual stimuli (Ashby et al., 1998; Ashby & Ell, 2001; Ashby, Isen, & Turken, 1999; Ashby & Waldron, 1999) and the body of the caudate for auditory stimuli (Maddox, Molis, & Diehl, 2002). In primates, all of the extrastriate visual cortex projects directly to the tail of the caudate nucleus, with about 10,000 visual cortical cells converging on each caudate cell (Wilson, 1995). Cells in the tail of the caudate (medium spiny cells) then project to prefrontal and premotor cortex (via the globus pallidus and thalamus; e.g., Alexander, DeLong, & Strick, 1986). Ashby and Waldron (1999) hypothesized that, through a procedural learning process, each caudate unit learns to associate a category label, or perhaps a response location, with a large group of visual cortical cells (i.e., all that project to it).

We reviewed several studies that support this theory in the introduction. For example, we reviewed three studies that showed that the nature and timing of the feedback was critical for efficient information-integration category learning. Ashby, Queller, and Berretty (1999) showed that two-category/information-integration structures cannot be learned without trial-by-trial feedback, whereas two-category/unidimensional rule-based structures can. Similarly, Ashby, Maddox, and Bohil (2002) and Maddox, Ashby, and Bohil (2003) showed that the timing of the feedback was important for information-integration but not rule-based category learning, with observational training procedures and delayed feedback adversely affecting information-integration but not rule-based category learning. In addition, Ashby, Ell, and Waldron (in press) and Maddox, Bohil, and Ing (2003) showed a direct association between procedural learning and information-integration category learning by demonstrating that information-integration category learning was adversely affected by changes in the response location associated with unique category labels. Studies were also reviewed that suggested that rule-based category learning, but not information-integration category learning is adversely affected by tasks known to recruit frontal structures, such as the Stroop task (Waldron & Ashby, 2001) and working memory tasks (Maddox, Ashby, Ing, & Pickering, 2003).

These results are important because the mechanisms that mediate learning-related changes in synaptic efficacy within these two neural circuits are qualitatively different, and such differences suggest that category number may have different effects on rule-based and information-integration tasks. The rule-based/category-learning system proposed previously is under conscious control and has full access to working memory and executive attention, and accurate rule-based category learning depends upon good use of these processes. As the complexity of the rule increases, the reliance on working memory and executive attention resources increases, and performance is expected to decline when observers use a rule-based strategy. When the optimal rule is simple, as in the RB2 and UD2 conditions, the amount of working memory and executive attentional resources required to learn is low. Under these conditions, nearly all observers performed the task with high accuracy and used the optimal rule. On the other hand, as the complexity of the optimal rule increases, the working memory and executive attentional resource requirements are much greater. For example, in the UD4 condition, only one dimension is relevant (as in the RB2 and UD2 conditions), but three decision criteria must be learned and stored in working memory. Under these conditions, overall performance is significantly lower than in the RB2 or UD2 conditions, and some observers even apply an information-integration strategy, although the majority still apply a rule-based strategy. As the complexity of the rule increases even more, as in the CJ4 relative to the UD4 condition, performance continues to decline significantly, and the number of observers applying information-integration strategies increases. The information-integration system is not under conscious control, and instead learns through a gradual incremental learning process. For those observers who are unable (or unwilling) to expend the resources necessary to learn the complex rule, the information-integration strategy dominated.

This multiple-systems approach also offers a reasonable explanation for the equivalent category learning in the II2 and II4 conditions. Ashby and Waldron (1999; see also Ashby et al., 2001; Maddox, 2001, 2002; Waldron & Ashby, 2001) proposed a neurobiologically plausible model of information-integration category learning with visually presented stimuli (for a generalization to auditory stimuli, see Maddox et al., 2002). In short, visual stimuli are represented perceptually in higher-level visual areas, such as the inferotemporal cortex (IT). Because as many as 10,000 cells in visual cortex project to the same cell in the striatum (specifically, the caudate nucleus; Wilson, 1995), it is assumed that a low-resolution map of the perceptual space is represented among the striatal units. As the observer gains experience with the task, each unit becomes associated with a particular response through gradual incremental learning processes. Thus, the striatum can be thought of as associating a categorization response with a cluster of visual cortical cells. Recall that each observer was informed of the number of categories prior to each condition, and across conditions the complexity of the categories was held constant (i.e., the number of stimulus clusters held constant). In light of this fact, and given the proposed neurobiology of this information-integration learning system, there is no a priori reason to expect a performance difference between information-integration category learning with two versus four categories. The early accuracy difference is likely due to differences in the level of chance performance (50% in the two-category case and 25% in the four-category case), but by the third block of trials performance was statistically equivalent.

It is an open question whether there would be category number effects on information-integration learning if the number of stimulus clusters was not held constant. It is reasonable to propose that four-category/information-integration performance might be worse then two-category/information-integration performance if the two-category problem had two stimulus clusters, whereas the four-category problem had four stimulus clusters. Future research should address this issue.

It is important to point out that the decision rule proposed in this striatal learning system is mathematically equivalent to that of the minimum distance classifier (MDC) outlined in the *Modeling* section. In fact, when Ashby and Waldron (1999) originally proposed their model, they referred to it as the striatal pattern classifier (SPC). The MDC (or SPC) provided an excellent account of the data from many observers in both the II2 and II4 conditions. Specifically, the MDC provided the best account of the data from 3, 5, 9, 4, 8, and 11 of the 24 observers in Blocks 1–6, respectively, in the II2 condition, and from 20, 17, 18, 16, 13, and 16 of the 24 observers in Blocks 1–6, respectively, in the II4 condition. The excellent performance of the MDC in accounting for these data provides additional evidence in support of the multiple-systems model and for the assumption that information-integration learning relies on the striatum. In fact, this same model has been applied successfully to identification learning (Ashby et al., 2001; Maddox, 2001, 2002; Maddox & Dodd, in press), and information-integration category learning with auditory stimuli (Maddox et al., 2002).

It is unclear how a single-system approach could account for these data. For example, Nosofsky (1986; Nosofsky, Clark, & Shin, 1989) argued that an exemplar-similarity approach can account for both unidimensional/rule-based and ill-defined (i.e., information-integration) category-structure learning by postulating differences in attentional processes. The key is that in a unidimensional/rule-based task, attention can be placed along the relevant dimension. This single-system approach offers an explanation for the performance difference observed between RB2/UD2 and RB4/CJ4 conditions because all attention can be placed on the relevant dimension to improve RB2 performance, whereas equal attention is necessary to solve the RB4/CJ4 task. However, it is unclear how this approach could account a priori for the performance difference observed between the RB4/CJ4 and II4 (or II2) conditions. The II4 condition requires equal attention to both dimensions, and the category clusters are a simple rotation of the RB4 clusters. The only reasonable a priori prediction would be for identical performance, yet II4 performance was significantly better than RB4 performance. In addition, it is unclear how this approach could account a priori for the performance difference observed between the UD2 and UD4 conditions. As both require that all attention be placed on a single dimension, the most reasonable a priori prediction would be for identical performance. Of course it is possible that some version of a single-system model might be able to account for our results via a post hoc manipulation of its parameters. We would argue, however, that models making such post hoc accounts are less parsimonious than models making parameter-free a priori predictions, regardless of the number of systems assumed by the two models.

### *Across-Condition Modeling Comparisons*

Averaged across blocks, performance was statistically equivalent in the II2 and II4 conditions, although learning was slower in the II4 condition during the first two blocks of trials. Despite the fact that performance was equivalent during Blocks 3–6, one eighth to one fourth of the II2 observers used a rule-based strategy to solve the task, whereas at most 1 observer used a rule-based strategy to solve the II4 task. When observers used a rule-based strategy to solve the II2 task, the predominant strategy was the extreme values strategy instantiated by the conjunctive(3) model. This raises the question as to why the extreme values strategy was not used to solve the II4 task. One might speculate that an observer using this strategy would be able to achieve a higher level of accuracy in the II2 condition than an observer using the same strategy in the II4 condition. This is not the case. In fact, because the II4 categories were shifted slightly away from the center of the length–orientation space (to equate optimal accuracy across all conditions), the extreme values strategy could yield a slightly higher accuracy in the II4 condition than in the II2 condition. A second possibility, supported by a large body of work on the effects of rule complexity on concept learning (e.g., Alfonso-Reese, Ashby, & Brainard, 2002; Neisser & Weene, 1962; Nosofsky et al., 1989; Shepard et al., 1961), suggests that the extreme values strategy is more complex when applied to the II4 condition than to the II2 condition, mainly because there are more category labels in the II4 condition, and thus a more complex decision rule. So, despite the fact that the extreme value strategy could yield (slightly) higher accuracy in the II4 than in the II2 condition, it was sufficiently more complex that observers were unwilling (or unable) to expend the effort to utilize this strategy.

The results of the II2 and II4 comparison are in sharp contrast to those observed for the RB2/UD2 and RB4/CJ4 comparisons. Whereas no accuracy difference was observed across the II2 and II4 conditions, there was a large accuracy difference observed across the RB2/UD2 and RB4/CJ4 conditions. Performance in the RB2/UD2 condition was over 10% better than in the RB4/CJ4 condition (see Figures 2B, 3B, and 5B). This accuracy difference was mirrored by a large difference in the best-fitting model profile. Whereas a rule-based strategy dominated across all blocks in the RB2/UD2 condition, there was a nearly even split between observers using rule-based and information-integration strategies across all blocks in the RB4/CJ4 condition. Comparison of the UD2 with UD4, and the UD4 with CJ4 conditions provides additional insight into this effect. As stated earlier, performance was better in the UD2 than in the UD4 condition, and performance was better in the UD4 than in the CJ4 condition, suggesting that both category number and the number of dimensions relevant to solving a rule-based problem affect rule-based category learning. Interestingly, the best-fitting model profile differed across the UD2 and UD4 conditions, with roughly equal numbers of observers using rule-based and information-integration strategies in the UD4 condition in all but the final block, which was dominated by rule-based strategies. In contrast, the model profile for the CJ4 condition was similar to that for the UD4 condition, suggesting a larger effect of category number on rule-based learning than the number of relevant dimensions.

One might argue that the accuracy-based performance interaction between category number and the category structures (rule-based vs. information-integration) is an artifact of the different distributions of best-fitting models across conditions. Recall that the RB2/UD2 and II4 conditions yielded the most consistent use of a single class of response strategies. Specifically, across all blocks of trials, rule-based strategies dominated in the RB2/UD2 condition and information-integration strategies dominated in the II4 condition. On the other hand, there was a nearly even split between the use of rule-based and information-integration strategies across all blocks in the RB4/CJ4 condition, and an even distribution of rule-based and information-integration strategies early in learning for the II2 condition, which during the latter blocks, shifted toward a dominance for information-integration strategies. Thus, one might argue that the differences in the distribution of best-fitting models resulted in the finding that performances were best in the RB2/UD2 condition, worst in the RB4/CJ4 condition, and intermediate in the II2 and II4 conditions. Clearly, the best-fitting model frequency distributions impacted overall performance, and in fact, one might argue that there was an interaction between category number and category structure in the distribution of best-fitting models in addition to an interaction at the level of accuracy. Our ability to identify differences in best-fitting model frequencies is an advantage, not a weakness of our approach. Even so, to examine this issue further we decided to revisit the accuracy data from only those observers who used a response strategy of the same form as the optimal one for a given condition (i.e., a rule-based strategy in the RB2/UD2 and RB4/CJ4 conditions, and an information-integration strategy in the II2 and II4 conditions). Although we are unable to apply formal statistical analyses to these data because they no longer remained within-subjects (i.e., we could not perform paired-sample *t* tests because not all observers whose data were fit by the various models were also in the other subgroups), an examination of the accuracy means generally converges with the results outlined in Figure 2B (see also Figure 5B) to suggest an interaction between category number and category structure. For example, averaged across blocks, RB2/UD2 accuracy for rule-based users was highest (RB2 = 89.6%; UD2 = 88.8%), and RB4/CJ4 accuracy for rule-based users was lowest (RB4 = 81.4%; CJ4 = 78.7%). An intermediate level of accuracy was observed for the information-integration users in the II2 (86.9%) and II4 (82.9%) conditions. In addition, it is worth mentioning that accuracy for rule-based users was 77.6% in the UD4 condition from Experiment 1. The fact that this value is so much lower than that observed in the RB2 and UD2 conditions, and is so similar to that observed in the RB4 and CJ4 conditions, suggests again, that category number has a larger effect than the number of relevant dimensions on rule-based performance.

## *Conclusions*

To summarize, category number impacted rule-based category learning but not information-integration category learning. RB2/UD2 category learning was significantly better than II2 category learning, but RB4/CJ4 category learning was significantly worse than II4 category learning. II2 and II4 category learning were statistically equal. The distribution of best-fitting models differed across conditions. In the RB2/UD2 and II4 conditions, models of the same form as the optimal model (i.e., rule-based models in the RB2/UD2 condition, and information-integration models in the II4 condition) dominated throughout learning. Even in the II2 condition, information-integration models dominated later in learning. Only in the RB4/CJ4 condition was there nearly an even split between observers using rule-based and information-integration strategies that held across all blocks of trials. Taken together, these results suggest that category number interacts with category structure learning at the level of overall accuracy and in the distribution of best-fitting model strategies. Furthermore, the notion of multiple-category systems is supported by these results.

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