CHAPTER THREE

The Influence of Verbal and Nonverbal Processing on Category Learning

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Contents

Abstract

Categories are learned in a variety of ways and one important distinction concerns the effects of verbal and nonverbal processing on category learning. This chapter reviews the research from behavioral studies, computational modeling, and imaging studies that support this distinction. Although there is

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some consensus that subjects will often learn new categories by searching for verbal rules, there is less agreement in the literature about how categories are learned when a rule is not usable or when the subject has restricted access to verbal abilities. Accordingly, we outline a general theory of verbal and nonverbal category learning. We assume that verbal category learning relies on working memory and is primarily involved in rule-based categorization. Nonverbal category learning may rely on visual working memory and is primarily involved in similarity-based categorization. We present the results of several studies from our lab that test many of the predictions from this theory. Although we do not argue for two completely independent learning systems, we argue that the available evidence strongly supports the existence of these two approaches of learning categories.

1. Introduction

Categories are fundamental to cognition, and the ability to learn and use categories is present in all humans and animals. For example, when a physician offers a diagnosis to a sick patient, he or she is classifying that patient into a known disease category. In making the diagnosis, the physician can use the category to make other decisions, like how to treat the patient and how to help the patient manage his or her disease. The diagnosis is likely made on the basis of specific symptoms, and possibly by applying a set of diagnostic rules (e.g., blood-glucose level above a certain range, swelling in the ankles, etc.). The diagnosis may also be made via similarity of the patient to previously seen patients (Norman & Brooks, 1997). Choosing symptoms and applying rules is a verbally mediated process whereas calculating or assessing the similarity of the patient to memories of previous patients is a nonverbal process. Many factors likely influence the relative balance of these processes, and different categories probably rely on a different balance of these two processes. The investigation of verbal and nonverbal category learning is a primary focus of our research.

In this chapter, we outline a general theory that assumes that humans learn categories in a variety of ways, and that one of the most salient divisions occurs between verbal and nonverbal processing. Beyond the example discussed above, there are several reasons to support this verbal/nonverbal distinction. First and foremost, there is considerable behavioral evidence that some categories are primarily learnable by verbal means such as learning rules and hypothesis testing (Allen & Brooks, 1991; Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Bruner, Goodnow, & Austin, 1956; Minda, Desroches, & Church, 2008; Minda & Ross, 2004; Zeithamova & Maddox, 2006). That is, people utilize and rely on verbal abilities to assist in learning new categories. Any compromise in verbal processing could interfere with how these categories are learned.

Second, there is also a long tradition of research that focuses on the nonverbal learning of categories by implicit or indirect learning (Brooks, 1978; Jacoby & Brooks, 1984; Kemler Nelson, 1984, 1988; Smith & Shapiro, 1989; Smith, Tracy, & Murray, 1993; Ward, 1988; Ward & Scott, 1987). Category learning in these cases is thought to be nonverbal to the extent that learners are not actively verbalizing rules and testing hypotheses. Third, there is considerable support from neuroscience that has examined the separate contributions of verbal and nonverbal (i.e., visual) brain regions for learning categories (Ashby & Ell, 2001; Ashby, Ell, & Waldron, 2003; Maddox, Aparicio, Marchant, & Ivry, 2005; Maddox & Ashby, 2004; Patalano, Smith, Jonides, & Koeppe, 2001; Reber, Stark, & Squire, 1998b; Smith, Patalano, & Jonides, 1998). Finally, there is a literature examining the category learning abilities of humans and nonhuman species, that has noted similarities between humans and primates on categories that can be learned via nonverbal means but has noted an advantage by humans on categories that can be learned via verbal means (Smith, Minda, & Washburn, 2004; Smith, Redford, & Haas, 2008).

This verbal/nonverbal division in category learning is intuitive, as many objects can be described verbally and classified verbally, but also contain perceptual features that correspond to these verbal rules (Brooks & Hannah, 2006). Consider this example. A young angler might learn to classify two trout fish by describing important features verbally. In fact, these features might be explicitly learned and committed to memory. As an example, Figure 1 shows the distinguishing features between two common species of trout. This guide, adapted from the Province of Ontario's "Fish Identification Guide" (Fish and Wildlife Branch, 2009) mentions several key common features (e.g., the black dots on the body) and highlights a key distinguishing feature for the Brown Trout ("the only salmon or trout with orange on adipose fin"). This is a verbal rule or verbal feature list that can be consulted when a classification is being made. If an angler memorized this feature list, he or she would be able to make a correct classification.

But in practice, there are a lot of fish for the angler to distinguish and the rules are complicated. It is not hard to imagine that these explicit rules become less and less important as other processes and strategies take over. The angler may catch a fish and classify it because it has a "brown trout fin," which would be a simplification of the original rule and one that is more like specific feature selection than a verbal rule. Or a more experienced angler may quickly categorize the fish on sight. The rule may no longer be consulted and the classification may be performed solely on the basis of a quick comparison of the perceptual input to stored category representations (prototypes or instances). Still, however, the features that demand the most attention are likely to be those same features that were named in the original rule (Brooks & Hannah, 2006). Although the classification may no longer be rule based, the verbal process used during the initial rule learning may

Rainbow trout/inland

L: 15–40 cm (6–16 in.).
D: South of a line from Kenora to Kesagami Lake.
S: Brook and brown trout; juvenile Atlantic salmon.
K: Many small black spots on body; spots over tail in radiating rows; pink lateral stripe; leading anal fin ray extends the length of the fin; long, stocky caudal peduncle.

Favorite baits: Spinners, spoons, roe, worms, flies

Brown trout/inland

L: 20–40 cm (8–16 in.).
D: Occasional south of the French River, mostly in great lakes tributaries.
S: Rainbow and brook trout; juvenile Atlantic salmon.
K: Large black, blue or red spots on body, often surrounded by lighter ring; tail with few spots; only salmon or trout with orange on adipose fin; leading anal fin ray extends the length of the fin; short, stocky caudal peduncle.

Favorite baits: Spinners, spoons, worms, flies

Figure 1 An excerpt from Ontario's sport fish identification guide showing the key differences between two species of trout. The categories are defined by verbal rules, but there is strong visual similarity among category member. Used with permission. Note: L = length, D = distribution/habitat, S = similar fish, K = key identifying characteristics.

result in a category representation that was shaped by the initial rule. The point is that for some (the novice) the fish might be classified by the verbal rule. For a more seasoned angler, however, the classification might be based on a prototype or a collection of instance memories. These representations are probably not able to be described verbally and may even be accessed via implicit memory (Smith & Grossman, 2008).

As this example illustrates, there is reason to believe that people are able to base categorizations on information that can be described verbally as well as information that cannot be described verbally. Accordingly, we consider a wide range of research that investigates the same issue. This chapter is structured as follows. In the first section, we review research from behavioral studies, computational modeling, and from cognitive neuroscience that strongly suggests and supports the verbal/nonverbal distinction. In the second section, we provide a detailed discussion of a general theory of verbal and nonverbal category learning. This follows with an examination of empirical work from our lab that tests several predictions of this theory. Finally, we consider the relationship of our approach to other theories of concept learning.

2. Multiple Processes and Systems

2.1. Earlier Research

There has been a long tradition in cognitive psychology of comparing and contrasting two or more systems with each other. Research on category learning has often made a distinction regarding the learning of rules, inherently a verbal process, versus learning about overall similarity. For example, some of the earliest ideas of category and concept learning emphasized the learning of definitions (Bruner et al., 1956). These views were collectively called the *classical view* by Smith and Medin (1981) and remained a dominant view in the literature until several influential programs of research in the 1960s and 1970s.

The first of these was the dot pattern research of Posner and Keele, and Homa and colleagues (Homa, Cross, Cornell, & Shwartz, 1973; Homa & Cultice, 1984; Posner & Keele, 1968). In these experiments, subjects were shown various patterns of dots or polygons that were distortions of an original pattern (i.e., the prototype). These distortions were patterns that were similar to, but not exactly like, the original prototype. Small adjustments of the location of each dot resulted in items that were "low distortions" of the original prototype, and larger adjustments resulted in "high distortions." Subjects were generally trained on high-distortion items. Crucially, subjects were never shown the prototype during the training session. Later, during a test phase, subjects were usually shown the old patterns, some new distortions of varying levels of typicality, and the original prototype. Studies using these dot patterns have generally found a consistent pattern of results. First, subjects often performed as well on the prototype as they did on the old patterns, even though the prototype was originally unseen. Second, if the test was delayed by several hours or days, performance on the training items declined whereas performance on the prototype remained strong. Finally, the endorsement of new items showed a typicality effect, such that items that were closer to the prototype were endorsed more strongly as category members than items that were physically more distant (Homa et al.; Homa & Cultice; Posner & Keele; Smith & Minda, 2001; Smith et al., 2008). The most striking aspect of this research is how well subjects can learn these categories, given how difficult (or impossible) these stimuli are to describe verbally. This suggests that learning dot pattern stimuli may not require much verbal ability or verbal processing. Clearly, this would pose a difficulty for the assumptions of the classical view.

A second key development in cognition was Eleanor Rosch's influential work in the 1970s (Rosch & Mervis, 1975; Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). Rosch introduced the idea of "family resemblance" (FR) as an alternative to the classical rule-based models that were dominant at the time. In a FR category, the exemplars of a category share many features, just like members of a family might, but there is no one feature that can be used as a rule. Rosch argued that for many categories, the prototype was an abstract representation with highest FR to other category members. Although a person might be able to describe the category verbally, this verbal description might not correspond exactly to the prototype. Furthermore although the prototype might determine classification, a verbal description of the prototype need not enter into the classification decision. In other words, a decision could be made without reference to a verbal rule, but by nonverbal reference to a prototype. Rosch's work, in conjunction with Posner's and Homa's research, provided the groundwork for prototype theory's dominance in the 1970s and 1980s, and the tendency to assume that similarity, rather than rules, was the key factor in categorization.

2.2. Rules and Similarity

In contrast to Posner's and Rosch's emphasis on similarity, other research argued that similarity is insufficient to explain certain categorization phenomena (Rips, 1989; Smith & Sloman, 1994). For example, Rips asked subjects to consider a set of objects (e.g., a pizza, a quarter, and a 3-in. round object). One group of subjects indicated that the 3-in. round object was more similar to the quarter than to the pizza. Thus, their similarity judgments were correlated with perceptual and featural overlap. However, another group of subjects judged that the 3-in. round object was more likely to be a member of the pizza category. That is, categorization decisions did not track similarity. Rips suggested that similarity is insufficient as the sole driving mechanism for categorization and suggested that other factors can influence classification. In this case, he pointed to category variability and the possibility of a rule. Whereas quarters have very low variability (most are nearly exactly the same) pizzas come in a range of sizes and shapes (e.g., personal size, 18-in. round, square, on a bagel, etc.). The 3-in. round object, while perhaps more similar to the quarter category, was a more likely member of the pizza category. The greater variability of the pizza category allowed for more extreme members to be accepted. The lower variability of the quarter category undermined similarity-based categorization and encouraged rule application. This effect has been examined and demonstrated with other stimuli as well (Cohen, Nosofsky, & Zaki, 2001; Stewart & Chater, 2002).

Other research supported the distinction between rule-based category learning and exemplar-based category learning (Allen & Brooks, 1991). Subjects in this experiment learned to categorize artificial animals into two categories, BUILDERs and DIGGERs. The animals were composed from five binary attributes, and were cartoon-like. During the training phase, subjects were asked to learn the categories and one group was taught a rule (e.g., "If an animal has at least two of the following attribute values—long legs, angular body, spotted covering—it is a BUILDER; otherwise it is a DIGGER"). A second group, the exemplar-similarity group, was shown the same animals but not the rule. This group was instructed that the first time they saw an animal they would have to guess its category, but on subsequent trials they would be able to remember what it was.

Later, test stimuli were presented to examine any difference between rule and exemplar-similarity learning. For example, one kind of test item (the "positive match") followed the BUILDER rule and was also similar to an old BUILDER exemplar. A "negative match" was also a BUILDER according to the rule, but it was similar to an old DIGGER exemplar. Allen and Brooks reasoned that if rule subjects were really just following the rule, they should categorize both the positive and negative match items as member of the BUILDER category because they followed the same rule. That is, the rule should trump similarity. On the other hand, if exemplar-similarity subjects categorize novel items by retrieving the stored exemplar most similar to it and selecting the category associated with that of old exemplar, they should categorize positive matches as BUILDERs and negative matches as DIGGERs. Interestingly, Allen and Brooks found evidence for both rule use and exemplar use. For negative matches, rule subjects tended to follow the rule but still showed evidence of exemplar use and their data suggested that the rule and exemplar similarity were in conflict. For the exemplar-similarity group, categorization tended to follow the old-item similarity. These results provide strong evidence for the existence of two categorization processes, and additional work—described later in this chapter—has explored the neural underpinning regarding the same task (Patalano et al., 2001). Furthermore, these data have been taken by some to suggest the reliance on working memory (rules) and explicit, long-term memory (exemplars) in category learning (Smith & Grossman, 2008).

So it is clear that people sometimes rely on rules and may also rely on similarity when learning categories. Accordingly, researchers have examined the factors that might mediate between the nonverbal, FR category learning that subjects sometimes show, and the tendency to look for rules on many tasks that subjects also show. We examine some of this research below.

2.3. Analytic and Holistic Processing

Research that distinguishes between analytic and holistic styles of categorization offers one account of subjects' use of FR and rule-based categorization (Brooks, 1978; Jacoby & Brooks, 1984; Kemler Nelson, 1984, 1988; Smith & Shapiro, 1989; Smith et al., 1993; Ward, 1988; Ward & Scott, 1987). For example, Brooks provided an early account of analytic and nonanalytic concept identification. When analytic concept identification is used, the goal of the task is discovering a sweeping generalization (i.e., a rule) that can be applied to all new instances. In order to discover and apply this generalization, separate aspects/features of the stimulus are evaluated for their ability to predict category membership. The hypothesis testing process described by Brooks is likely to rely on verbal processing to engage in the testing and summarization. Brooks also described a nonanalytic mode of concept identification, in which an item's category membership is based on overall similarity. That is, an item is placed into the category with the item or cluster of items with which it is most similar. This is much like the FR categorization described earlier. While the nonanalytic/holistic mode does not preclude verbal processing, it may not require it either.

Research by Kemler Nelson and others (Kemler Nelson, 1984, 1988; Smith & Shapiro, 1989; Smith et al., 1993) linked analytic categorization to intentional learning (but see Ward, 1988; Ward & Scott, 1987), which occurs when subjects are explicitly trying to learn a new category. Intentional learning involves strategic, goal-directed categorization, often resulting in deliberate hypothesis testing. Since hypothesis testing is encouraged by the intentional learning, analytic processing is the result, and rule-based categories are learned easily. However, incidental learning occurs when subjects are not explicitly told the goal of the task. Rather, subjects learn to do an unrelated task, such as stimulus rating. Incidental learning often results in nonanalytic (holistic) learning since no deliberate hypothesis testing is necessary during the learning phase. Another explanation is that the subject's verbal abilities are simply not being engaged to learn categories because the subject is occupied with the stimulus rating.

Recently, Davis, Love, and Maddox (2009) have applied a similar analytic/holistic distinction to stimulus encoding rather than stimulus categorization. Just like during categorization, the holistic, image-based pathway encodes an object as a whole rather than breaking it down into its constituent parts. This process is rapid and automatic but only occurs with experience. The analytic, part-based pathway encodes an object by breaking it down and labeling important features. This type of encoding requires a sufficiently rich symbolic vocabulary for feature labeling and requires time and cognitive effort. According to this theory, the pathway that is used for stimulus encoding depends on the characteristics of the to-be-encoded object, the observer's level of expertise with the objects and the availability of cognitive resources. This theory makes many predictions that are similar to the analytic/holistic categorization theories discussed above, but also makes some predictions that are unique. For example, object features can affect the encoding pathway used, ultimately affecting categorization performance. When an object has features that are easily labeled, part-based encoding is favored and exception items can be learned quickly. When features are not easily labeled, Davis et al. argued that image-based encoding is favored and exception items are learned slowly. It is clear then, that many factors, such as task and stimulus structure, can influence whether categories are learned using analytic or holistic processing.

2.4. Multiple-Systems Theory

The research described above suggests that a reliance on higher order, verbal functioning, working memory for example, might result in the better learning of rules. If the reliance on verbal learning is downplayed or compromised, one might expect category learning to proceed in a more holistic fashion. The idea that working memory and executive functioning play a role in the learning of some categories but not in others is one of the central predictions of a multiple-systems theory of category learning called the Competition of Verbal and Implicit Systems, or COVIS (Ashby & Ell, 2001; Ashby et al., 1998). This model specifies that at least two broadly defined brain systems are fundamentally involved in category learning. The explicit, verbal system is assumed to learn rule-described categories. These are categories for which the optimal rule is relatively easy to describe verbally (Ashby & Ell). For example, consider a category set in which round objects belong to one group and angular objects belong to another group. These categories could be quickly mastered by the explicit system because a rule is easy to verbalize ("category 1 items are round"). According to COVIS, the explicit system is mediated by the prefrontal cortex and it requires sufficient cognitive resources (e.g., working memory and executive functioning) to search for, store, and apply a rule (Zeithamova & Maddox, 2006). Furthermore, this system is assumed to be the default approach for normally functioning adults learning new categories (Ashby et al.; Minda et al., 2008).

COVIS also assumes that an implicit system learns non-rule-described categories. These are categories for which no easily verbalizable rule exists or for which two or more aspects of the stimulus must be integrated at a predecisional stage (Ashby & Ell, 2001). According to COVIS, the neurobiology of the implicit system constrains the type of learning that can be done by this system. Once a to-be-categorized stimulus is viewed, the visual information is sent from the visual cortex to the tail of the caudate nucleus where a motor program is chosen to carry out the categorization. When an item is categorized correctly, the feedback acts as an unexpected reward and causes dopamine to be released, strengthening the association between the stimulus and the correct categorization response. When an item is categorized incorrectly, the release of dopamine is depressed and the association between the stimulus and categorization response is not strengthened (Ashby et al., 1998; Spiering & Ashby, 2008). The reliance of the implicit system on this type of dopamine-mediated learning has two implications. First, because dopamine plays a role in motor activation, the implicit system is well suited for procedural learning. Second, feedback causes the release of dopamine that is used for learning, so proper feedback is necessary for the implicit system to learn (Wickens, 1990).[1]

The procedural learning system described by COVIS makes several predictions. First, a consistent association between a stimulus and a response location facilitates learning. In a study by Ashby et al. (2003) subjects learned to categorize using one hand/button configuration and were later tested using another hand/button configuration. Similar to the results found in procedural memory studies (Willingham, Nissen, & Bullemer, 1989; Willingham, Wells, Farrell, & Stemwedel, 2000) learning by the implicit system was facilitated when each stimulus was associated with a consistent response location and hindered when no consistent response location existed. Other studies compared category learning with an ''A'' or ''B'' response to learning with a ''Yes'' or ''No'' response and found similar results (Maddox, Bohil, & Ing, 2004). As each exemplar was presented, the question ''Is this an A'' or ''Is this a B'' was also presented, and the subject was instructed to indicate yes or no. Subjects received feedback on this ''Yes''/''No'' response. In this way, each exemplar was equally associated with the ''Yes'' response and the ''No'' response and this interfered with the learning of consistent response locations. Second, the implicit system is also compromised when feedback is delayed. For the implicit system, it is imperative that feedback occurs soon after a categorization response so that the stimulus-response connections are still active when feedback causes dopamine to be released. Feedback timing is less important for the verbal system, which is able to store the categorization rule in working memory until feedback is provided and the effectiveness of the rule is evaluated. However, delaying feedback by as little as 2.5 s is detrimental to performance on non-rule-described categories but not rule-described categories (Maddox, Ashby, & Bohil, 2003). In contrast, once feedback is provided, the implicit system of COVIS does not require time and cognitive resources to process the feedback. Instead, feedback processing occurs through the automatic strengthening of synapses. The verbal system, on the other hand, relies on working memory, attention, and time to process feedback. Therefore, when working memory and attentional resources are made unavailable immediately following feedback, many subjects fail to learn using the verbal system but are able to learn using the implicit system (Maddox, Ashby, Ing, & Pickering, 2004; Zeithamova & Maddox, 2006).

Both the verbal and implicit systems are assumed to operate in normally functioning adults, and both can contribute to performance, even after learning has progressed. In general, COVIS assumes that the system with

[1] COVIS emphasizes the release of dopamine that accompanies a reward signal. Although error signals may also affect category learning, COVIS is relatively silent on the issue how errors may differ from rewards beyond simply not strengthening the connection.

the more successful responding will eventually dominate performance. For instance, although the verbal system is considered to be the default system for adults, some categories may not be easily learned by a verbal rule. In this case, the implicit system would produce more accurate responses and would take over. Also, if rule-based categories are learned under conditions in which the learner is distracted and working memory is being used for another task, the implicit system would have to take over for the struggling explicit system.

2.5. Other Models

Beyond the analytic/holistic distinction and COVIS, several other models have been proposed that make an assumption regarding the multiple cognitive processes involved in category learning. For example, Nosofsky and Palmeri proposed the RULEX model which is a model of rule and exception learning (Nosofsky & Palmeri, 1998; Nosofsky, Palmeri, & McKinley, 1994). RULEX assumes that subjects will begin learning categories by finding a simple rule that works reasonably well, and will fine-tune performance by learning exceptions to the rule at a later stage. In this case, rule learning is the default, and there is a premium on simplicity (i.e., single-dimensional rules). RULEX was not specifically designed as a "multiple systems" model, but the assumptions in RUELX are consistent with the other theories and models we have been discussing. Like COVIS, RULEX assumes that people first try to learn rules. Like the Allen and Brooks (1991) work, RULEX also places an importance on exemplars, though in this case, they are learned only as exceptions to the rule.

Another model that is closely related to RULEX, but assumes a larger role for exemplar similarity in category learning, is the ATRIUM model which combines rules and exemplars (Erickson & Kruschke, 1998). As with RULEX, ATRIUM also assumes an initial reliance on simple rules (typically single-dimensional rules), and stores exemplars that can also produce classifications. In ATRIUM, one pathway is designed to learn rules while the other pathway activates stored exemplars according to their similarity to the to-be-categories item. ATRIUM is notable for having a gating mechanism which allows both pathways (rules and exemplars) to operate simultaneously. The model determines category membership based on the mixture of evidence provided from both pathways and the gating mechanism can adjust the relative importance of these two sources of information. In other words, unlike COVIS, which makes a decision based on evidence from either the verbal *or* implicit system, ATRIUM can assume that a mixture is used. Like RULEX and COVIS, this model has been successful at accounting for a variety of categorization phenomena.

2.6. Neuroimaging Data

The preceding section makes clear that there is behavioral and theoretical precedence for the consideration of category learning as involving verbal rules and nonverbal similarity. There is also considerable evidence from cognitive neuroscience for the existence of separate verbal and nonverbal contributions in category learning. An early example was provided by Patalano and colleagues (Patalano et al., 2001), who asked subjects to learn a set of categories by either using a rule-based strategy or an exemplar-based strategy (Allen & Brooks, 1991). During the categorization, they tracked the cerebral blood flow with a PET scan and found distinct patterns of neural activation for each task. Rule-based classification showed increased activation of the occipital cortex, the posterior parietal cortex, and the prefrontal cortex, consistent with the cognitive functions of visual processing, selective attention, and working memory, respectively. In contrast, the exemplar-similarity learning showed activation in the occipital cortex, consistent with the primary role of visual memory when subjects were not using a verbal rule. Other recent evidence has indicated a strong role for the occipital cortex in the learning of dot pattern categories (Reber et al., 1998b; Reber, Stark, & Squire, 1998a), again suggesting a heavy contribution of visual areas when category learning does not depend of a rule.

Research has also examined the neural correlates to the learning of rule-defined and information-integration categories, which are commonly used by researchers who work on multiple-systems models. Figure 2A illustrates a rule-defined category for Gaussian blur stimuli that are defined by the frequency and orientation of the dark and light bands. Points (exemplars) on the left of the line are members of Category A and points to the right of the line are members of Category B. The vertical line separating Category A and Category B corresponds to a strategy that maximizes categorization accuracy. A single-dimensional rule, emphasizing frequency, can be verbalized and employed to correctly classify the exemplars. Figure 2B illustrates a type of non-rule-defined category set that is sometime known as an "information-integration" category set. Because both frequency and orientation contribute to category membership, the decision boundary is not parallel to either axis/feature, and these categories are not easily described by a verbal rule. Instead, for successful categorization, information from multiple dimensions must be combined before a categorization decision can be made.

Recent work by Nomura and colleagues (Nomura et al., 2007) asked subjects to learn rule-defined or information-integration categories while tracking their BOLD signal in an fMRI scanner. They found increased activation in the medial temporal lobe during correct categorization of rule-based stimuli, suggesting a role for declarative knowledge and underscoring

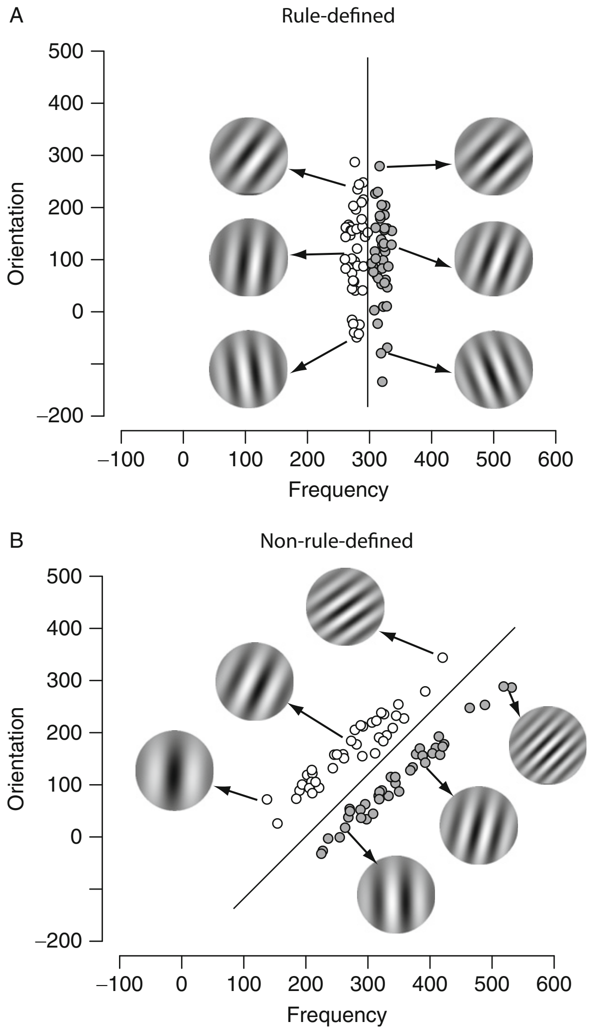

Figure 2 Panel A shows an example of a rule-defined category set of Gaussian blur stimuli that vary in terms of the spatial frequency and orientation of the light and dark bands. In the scatter plot, the open circles, represent Category A stimuli and the filled circles represent category B stimuli. Panel B shows an example of a non-rule-defined (sometime called information integration) category set.

the explicit, verbal nature of rule-based category learning. Subjects who correctly categorized information-integration stimuli showed increasing activation in the caudate, implicating a procedural learning style.

2.7. Summary

The research that we reviewed suggests that a multiple systems or multiple processes theory of category learning is not exactly new. In fact, the distinction between rules and similarity is one of the central aspects of the literature on concepts and category learning. A number of studies have pointed to the effects of different learning styles (the analytic/holistic distinction) or the effects of different cognitive processes (verbal ability and procedural learning mechanisms). Other research has suggested that some categories lend themselves well to verbal analysis and/or rules whereas others less so (categories with discernible features and low variability vs. dot patterns). Recent work with neuroimaging has shed light on the different brain systems that underlie the learning of new categories. Some of this work argues for a fairly strong distinction between the various systems (e.g., COVIS or ATRIUM) whereas other accounts have taken a more interactive approach (the rules and exemplar learning envisioned by Brooks and colleagues (Allen & Brooks, 1991; Brooks & Hannah, 2006)). In short, it seems an unavoidable conclusion that there is more than one way to learn categories and represent them as concepts. Accordingly, in the section that follows, we make a proposal that centers on the role of verbal processes and nonverbal processes on category learning.

3. A Theory of Verbal and Nonverbal Category Learning

The research reviewed above suggests that there are multiple categorization systems (or multiple processes, or dual pathways, etc.). Given this broad agreement on the existence of multiple processes, systems, or modes, how should one draw the dividing line? Our survey of the literature suggests that there is a clear distinction between categorization that is mediated by verbal processes (verbal descriptions of the stimuli, a reliance on verbal working memory, and hypothesis testing, etc.) and category learning that is primarily mediated by nonverbal processes (associations between stimuli and responses, visual pattern completion, visual working memory, and imagery). One of the central problems that we work on in our lab is discovering and delineating how this verbal/nonverbal distinction works, and discovering the fundamental cognitive processes involved in category learning. By fundamental cognitive processes, we mean constructs like selective attention, associative learning, working memory, etc. These are functions and processes available for many tasks and learning environments, including category learning.

3.1. Description and Main Assumptions of the Theory

We propose that there are two broadly defined systems or pathways by which new categories are learned and items are classified. A key distinction between these systems is that one relies heavily on verbal abilities and the other does not. That is, learners can make use of verbal descriptions and rules when learning categories but can also make use of nonverbal aspects of the stimulus or category. A possible conceptualization of the verbal/nonverbal distinction is shown in Figure 3. We have defined each of these pathways as a ‘‘cognitive system’’ and we define cognitive system as a collection of cognitive processes and functions, possibly mediated by distinct cortical structures, that work together to carry out an information processing task. We refer to one of the pathways as the ‘‘verbal system’’ and the other as the ‘‘nonverbal system.’’ The verbal system learns categories by trying to find a good verbal rule that will classify most of the stimuli. Of course, for rule-based categories reliance on this system will result in good category learning. For non-rule-based categories, like FR categories, this system may be less successful. The verbal system carries out this task by relying on working memory and hypothesis testing ability. The executive functioning assists in testing hypotheses, directing selective attention, inhibiting the responding to features and cues that are

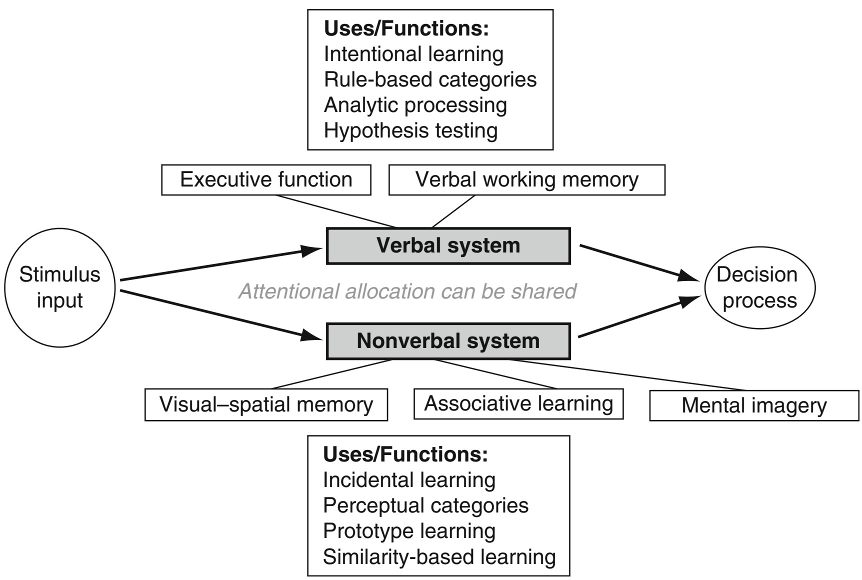

Figure 3 This figure shows a basic description of a verbal/nonverbal theory of category learning. The verbal system relies on verbal working memory as well as hypothesis testing abilities. The nonverbal system relies on visual working memory and associative learning.

not part of the rule, and inhibiting responses to rules that have been tried but are no longer being used.

Because these are verbal rules, some degree of verbal working memory is required to state the rule, consider feedback, etc. A good rule in this context has several characteristics. First, the rule should not exceed the limits of working memory capacity: shorter rules are better, longer rules are not. Second, the rule should be related to a feature that is readily discernible. That is, a rule that emphasizes a shape of a body part is better than a rule that emphasizes the size of an internal organ (even if the latter is very reliable). Third, a good rule should work: it should have relatively few exceptions and should produce reliably good performance. Consider again the example that we began the chapter with: the fish shown in Figure 1. The rules that are given are good in that they are reliable rules that are related to readily discernible features, but not good in the sense that they would surely exceed the capacity of working memory during a fishing trip. In other words, there are rules for these categories but they may not be very usable.

The other pathway is labeled as the nonverbal system. This system operates alongside the verbal system and would play a dominant role in the incidental learning of categories, for learning perceptual categories, and possibly for abstracting visual prototypes (as in the dot-pattern research discussed earlier). This system encompasses a broader range of abilities and functions relative to the verbal system. For example, there is evidence from animal learning work that selective attention plays a role in deciding which perceptual features matter most. But as we'll discuss below, in a full description of both systems, the attentional allocation that is part of the rule system can influence the attentional policy in nonverbal system (Harris & Minda, 2006). The nonverbal system can also learn stimulus and response associations. Like the implicit systems in COVIS (Ashby et al., 1998), our nonverbal system may rely on a close connection between the response and the reward to drive the learning processes. Strong stimulus/response/reward association facilitates learning by strengthening the neural connections between the visual neurons and response selection neurons. However, there is evidence that many non-rule-defined categories can be learned without feedback or with minimal feedback. First, dot-pattern categories can be acquired during test, without any training (Palmeri & Flanery, 1999). Second, there is evidence of non-rule-based category learning with indirect feedback (Minda & Ross, 2004) and in unsupervised conditions with no feedback at all (Love, 2002, 2003). Finally, the research reviewed above regarding holistic category learning also seems to result in learning FRs, even without feedback (Kemler Nelson, 1984). In other words, strong stimulus/response/reward association can be beneficial to the nonverbal learning of categories, but this may not be a requirement. But as we describe below, we think that other nonverbal processes—like visual working memory and possibly visual imagery—might allow for flexibility in this system.

3.2. Additional Assumptions

3.2.1. The Verbal System

The basic theory described above has a number of key assumptions beyond the basic verbal and nonverbal qualities of each system. In this section, we describe the core cognitive properties associated with each system.

First and foremost, the verbal system of category learning makes use of two components of the working memory system: the phonological loop—what we also refer to as verbal working memory—and the central executive. The phonological loop is described as a buffer for the temporary activation and storage of verbal information (Baddeley, 2003; Baddeley & Hitch, 1974; Baddeley, Lewis, & Vallar, 1984). Verbal information stored in the phonological loop fades quickly so rehearsal is used to keep information active and available for use. When rehearsal takes longer than the time capacity of the loop, some information will fade from memory. One implication of this limited capacity is that information stored in the phonological loop, such as categorization rules, must be simple enough to be kept active. Furthermore, if the phonological loop is involved in other tasks during category learning, rule-based learning should suffer. Therefore, there is limit to the complexity of verbal rules that can be learned. Another function of verbal working memory may be to store categorization responses and the corresponding feedback. In short, if aspects of the category-learning task can be described verbally, it is likely that verbal working memory is going to be occupied with the business of learning these categories.

The verbal system of category learning also makes use of the central executive, which operates as a control system for working memory (Baddeley, 2003; Baddeley & Hitch, 1974; Baddeley et al., 1984). Among other activities, the central executive is thought to be involved in the selection and inhibition of information (like rules and responses) and has limited resources. The verbal system that we are describing involves some degree of hypothesis testing during category learning. We assume that the central executive is used by verbal working memory to interpret feedback or generate new categorization rules. In short, if aspects of the learning task involve deliberation, considering alternatives, or inhibiting responses to features or rules then the central executive will be involved.

3.2.2. The Nonverbal System

The nonverbal system relies on several cognitive components. First, the nonverbal system relies on associative learning mechanisms—like strengthening the association between paired stimuli and responses—to learn categories. Learning by the nonverbal system will be especially enhanced when cues are maximally predictive. For example, in the FR category, no one feature can be used as a rule, but generally many features are predictive of category membership, and attention to multiple cues may result in forming a strong association between a set of cues and a category label. As we discussed earlier, the role of associative learning between a category and its response (i.e., procedural learning) has been investigated under the COVIS framework. In general, it has been found that procedural learning is important for the nonverbal system. However, a series of recent studies have shown that the nonverbal system may not be as reliant on procedural learning mechanisms as Ashby and colleagues originally thought. For example, category and task difficulty can explain nonverbal system impairments that were originally attributed to its reliance on procedural learning mechanisms (Nosofsky & Stanton, 2005; Spiering & Ashby, 2008). In addition, the claim that consistent response locations are important for the nonverbal system may not be as strong as once thought. Although consistent response locations are favored by the nonverbal system, any consistent category cue can be used for learning nonverbal categories (Spiering & Ashby). In reality, the nonverbal system is not entirely tied to the learning of motor responses, and can also rely on other types of associative learning. More to the point, procedural learning is only one kind of nonverbal category learning and a more complete account must explore additional mechanisms and processes.

Second, just like the verbal system, we assume that working memory also plays a role. In this case, however, we assume that only the visuo-spatial component is involved. The visuo-spatial sketchpad (Baddeley, 2003; Baddeley & Hitch, 1974; Baddeley et al., 1984) is a buffer in which visual and spatial information are stored and are thought to undergo rehearsal in much the same way as information within the phonological loop. Visuo-spatial working memory may be used during the initial processing of an object or to compare an object and a category representation during a categorization decision. The central executive does not play a role (or plays a minimal role) in the nonverbal system. Considerable evidence from comparative work, developmental work, and neuroimaging shows that non-rule-based categories can be learned with little or no contribution from the areas of the brain that mediate executive control, specifically the prefrontal cortex (Ashby et al., 1998; Minda et al., 2008; Reber et al., 1998b; Smith et al., 2004).

We suspect that mental imagery also plays a role in learning categories. Although it is unclear how this might differ from the visuo-spatial working memory already described. Perhaps the visuo-spatial working memory system and the imagery system work in conjunction so that the former is used for manipulation and short-term storage of stimulus information but the later is used over longer periods of time. One clear advantage to verbal learning is that the stimuli can be redescribed verbally, and can be categorized even if the perceptual information is lost. We suspect that there is a comparable role for mental imagery in this system, and we have begun to evaluate this claim in our lab. For example, we suspect that visual interference will disrupt learning by the nonverbal system more so than the verbal system. Whereas the verbal systems can recode aspects of the stimuli into verbal code and insulate it against any visual interference, the nonverbal systems might rely on an image-based code that would be more susceptible to visual interference.

3.2.3. Parallel Operation

One key additional assumption is that the two systems operate together, in parallel. There is no claim that categorization must proceed via one or the other pathway. At any given time, a stimulus might be encoded verbally ("a fish with large black fins") and nonverbally (visual memory, similarity to stored memory traces, or even mental imagery). This claim is reminiscent of the dual-coding hypothesis of Pavio (Pavio, 1986) which argues that both visual and verbal information are processed differently and along distinct channels with the human mind creating dual representations for each encoding. To be clear, though, we are not arguing for the necessity of dual representations, but rather for the inclusion of at least two kinds of input encoding. COVIS makes a similar prediction that the verbal and implicit systems both operate and are in competition with each other (Ashby et al., 1998). A prediction that follows from this assumption is that because both kinds of information are encoded and represented, then when one source is missing, categorization should proceed via the other system. In fact, several studies have shown these effects.

Although both pathways are operating during category learning, a decision is made from the evidence from only one pathway. In practice, this implies that the pathway that arrives at the answer first would produce the answer. Another possibility is that the pathway that arrives at the answer with the strongest source of evidence would drive the decision. In this sense, we make the same assumption as COVIS that the decision may involve a competition. Our theory differs from ATRIUM, which assumes a true mixture of responses. One prediction that follows is that when similarity information conflicts with a rule (Allen & Brooks, 1991; Minda & Ross, 2004), the decision may take longer. In reality, rules often correlate with similarity, but conflict and the need for disambiguation still arise. For example, consider two species of mushrooms (one poisonous and one edible) that appear very similar but can be distinguished on the basis of a single feature or set of features. In fact, the highly toxic and appropriately named "death cap" mushroom (*Amanita phalloides*) is extremely similar to the commonly consumed "straw mushroom" (*Volvariella volvacea*). In this case, the color of the spoors can be used to distinguish the two kinds of mushrooms (pink for the straw mushrooms, white for the death cap). In other words, the rule, rather than overall similarity, is used to differentiate the categories.

We assume that the two pathways can share an attentional allocation. This means that the features that are necessarily part of the rule or rule selection process (in the verbal system) will also be heavily weighted in the nonverbal system. There is already precedence in the literature for this idea. For example, Brooks and Hannah (2006) argued that verbal rules are essential for directing attention to the features that are relevant on categorization. Harris and Minda (2006) demonstrated that explicit classification encourages rule use and the same features that are important for the rule may be shared by other, non-rule-based processes and functions.

We assume that under most circumstances, the verbal system has an initial bias. This is in line with other research suggesting that explicit learning systems are the default (Ashby et al., 1998) or that subjects often start learning via analytic means (Jacoby & Brooks, 1984). Furthermore, explicit reasoning follows naturally from the expectations in a standard category learning experiment. We also assume that since the verbal system relies heavily on working memory and executive functioning, the bias will not be present (or at least less strong) in young children. This is because working memory and the prefrontal cortex (which mediates the key executive functions like selection and inhibition) is not fully developed.

3.3. Summary

Our theory is designed to account for the apparent division between the verbal and nonverbal processes that mediate category learning. The verbal system is characterized by the explicit search and application of verbally described rules. We do not mean that the rules will always be present or will always work and we do not mean that this system works to the exclusion of the other, nonverbal system. Learning by the verbal system means that people are using their verbal ability (and reasoning capacity) to the service of learning categories. The nonverbal system is characterized by associative learning, similarity, and visual memory and it operates in conjunction with the verbal systems. The allocation of attention for this system can be directed by the verbal system.

4. Experimental Tests of the Theory

We have discussed already a variety of evidence for the verbal/nonverbal distinction. Now we concentrate on experiments from our lab and from our collaborators' labs that test some specific predictions of our theory. First, we consider a variety of subject effects because verbal ability differs between humans and other primates and among various developmental groups. Second, we consider cognitive effects. Several different methods can interfere with the verbal system while leaving the nonverbal system intact, and there are some tasks that will interfere with visual processing and interfere with the nonverbal system while leaving the verbal system intact. Third, we consider the possibility that some modes of category learning that do not explicitly require a classification decision may divert resources from the verbal system onto the nonverbal system. Finally, we consider other, as yet untested predictions about differential roles of verbal and nonverbal processes.

One key thing to keep in mind is that the verbal/nonverbal distinction may not be the only explanation for these data. However, all of the studies we are about to discuss show how access to verbal processing abilities can shape the learning of categories. Another key thing to keep in mind is that we are not arguing for a dichotomy in which categories are learned via rules or similarity (though there may be cases when that is possible). Rather, we are arguing that in many learning scenarios, people can use verbal ability to assist in learning categories. The category learning process will ultimately involve an interaction between verbal and nonverbal processes in which verbal rules shape the attention to features and perceptual similarity can affect and sometimes override the rules.

4.1. Comparisons Across Species

One of the strongest sources of evidence for the role that verbal processing plays in category learning comes from the examination of category learning behavior in nonhuman primates. Nonhuman primates (in this case, *Rhesus Macaques*) share many cortical structures with humans [i.e., V1, V2, middle temporal area; (Preuss, 1999; Sereno & Tootell, 2005)]. But of course, monkeys do not have the ability to use verbal labels to help solve a category learning problem. They do not have the same ability to recode a visual stimulus into verbal descriptions, essentially employing a symbolic stand-in for the original stimuli. On the other hand, visual discrimination learning, visual classification learning, and stimulus response association should be equivalent between the two species. As a result, macaques should learn categories such that their performance can be described on the basis of the perceptual coherence of the categories to be learned. A category set with high within-category similarity and low between category similarity will be easy for macaques to learn whereas a category set that has overlapping members or a nonlinear boundary should be more difficult. Of course humans have many of the same constraints, but should also be able to put their verbal ability to work and should show a distinct advantage for categories that have an optimal verbal rule.

Smith et al. (2004) investigated this prospect by comparing the abilities of monkeys and humans on a set of categorization tasks. They used the six category sets originally used by Shepard, Hovland, and Jenkins (1961) and created six types of categories from a set of eight stimulus objects (see Figure 4). Each item was defined by three dimensions (size, color, and shape) and each category contained four objects. We will describe each of these six category sets in moderate detail, because they feature prominently in several of the studies described in the next few sections.

Under typical learning conditions, the relative ease with which subjects learn these categories follows the pattern (least difficult to most difficult): I < II < III = IV = V < VI (Shepard et al., 1961). Each category set presents specific information-processing demands, and the use of verbal processing affects each category set differently. Type I is a single-dimensional set and perfect performance can be attained by the formation of a straightforward verbal rule using a single proposition (e.g., if black then category 1). As such, a verbal/nonverbal theory predicts easy learning of this category by the verbal system. The nonverbal system could also learn this category without a verbal rule by learning to associate a cue (black) with a response (category 1), but learning might proceed more gradually.

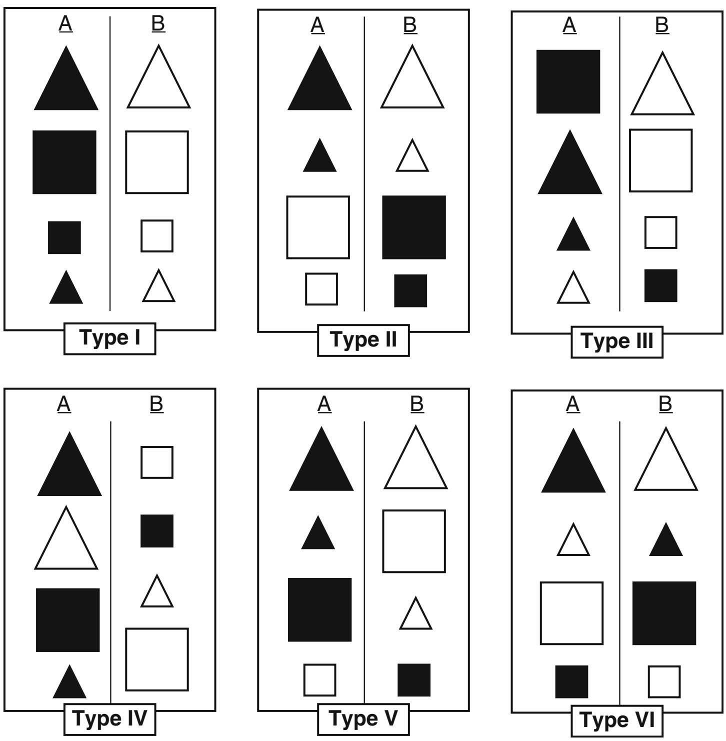

Figure 4 This figure shows an example of the kinds of stimuli originally used by Shepard et al. (1961), and used in many other studies since. The actual features that are used differ across studies, but the conceptual structure remains the same.

The Type II set is best described by a verbal, disjunctive rule that puts black triangles and white squares in the same category. This should still be relatively easy to learn via the verbal system, since the two-predicate rule is readily verbalized. The nonverbal system should have difficulty in learning these categories, because it would be undermined by the category structure. Specifically, the structure of this category set is such that items in a category are as perceptually distant from each other (e.g., black triangles and white squares) as they are similar to members of the opposite category (e.g., white triangles and black squares). Furthermore, each of the relevant cues is nonpredictive on its own and each is equally associated with both categories. As a result, these categories are difficult or impossible for the nonverbal system to learn because it relies in part on high within-category perceptual similarity, it benefits from greater perceptual distance between categories, and is helped by a consistent mapping between cue and response. If the verbal system is not present, not fully developed, or not accessible, a learner should have difficulty with this type of category since they would then have to rely on nonverbal learning.

Type III is a nonlinearly separable category set that is defined as having a rule and some exceptions. The verbal system learns this category accurately by finding the verbalizable rule and memorizing the exceptions. For example, one could learn "black objects and the small white triangle" as the rule for category 1. These categories should place a heavier demand on the verbal system than the Type I or Type II categories because the rule is more complex (Feldman, 2000, 2003). This heavier demand and complexity is a result of the extracognitive resources required to learn the exceptions and because attention to all three dimensions is needed in order to learn them. These categories require verbalizing multiple propositions to learn exclusively via the verbal system. This category set would be difficult for the nonverbal system to learn to perfection because of the nonlinear boundary and because there is no consistent association of cues and responses to correctly classify the exceptions. And so the similarity-based learning of the nonverbal systems would be compromised. As with the Type II set, if the verbal system is not fully developed or not fully accessible, the nonverbal system would take over and the learner would have difficulty with this type of category.

Type IV is a FR category set because all category members share the majority of their features with the other category members, but no one feature is perfectly diagnostic. Although this type of category might be able to be described by a complex rule with multiple propositions (possibly, "any two of the following three features" or "black objects and the large white triangle"), the rule is difficult to verbalize and learn. Unlike the nonlinearly separable Type III categories, which can also be learned by a rule and exception strategy, the Type IV categories have a FR structure that permits perfect performance by nonverbal, similarity-based mechanisms. Strengthening the association between the three cues ("large size," "black color," and "triangle-shaped") with a response ("category 1") will result in the correct response for all the items in the category. As a consequence, the nonverbal system can operate successfully and should dominate in the acquisition of these categories by learning the FR structure, even in cases when the verbal system would otherwise be compromised (Waldron & Ashby, 2001).

The Type V categories are also rule-plus-exception tasks, with the verbal rule leaving an exception item that requires additional cognitive processing to master (e.g., exemplar memorization). In this case, the exception is more difficult because it is less similar to the other category members. As with the Type III categories, these will be difficult for the verbal system because of the extra steps required to find the suboptimal rule and memorize the exceptions. These categories also pose a difficulty for the nonverbal system, since the nonlinear boundary will defeat a similarity-based system unless individual exemplars are learned.

The Type VI category set is a very ill-defined set because its category members have no FR to each other. Each category member shares only one feature with members of its own category but two features with several members of the other category. Neither verbal rules nor similarity-based categorization strategies will help performance. The only viable strategy is individual stimuli-response paring and/or exemplar memorization.

With respect to the availability of verbal resources, the Type II set is likely to benefit the most. It is poorly structured in terms of overall similarity, but because it has an optimal, verbalizable rule, it would be learned more readily than a category set with poor structure and no rule. Accordingly, Smith et al. (2004) expected humans to use their verbal resources (working memory and executive functioning) when learning that category set and to perform relatively well. They expected monkeys—who have no access to verbal resources—to perform poorly on Type II categories.

Smith et al. (2004) trained four macaques (over the course of a month) on each of these category sets. They also trained a group of human subjects as a comparison group. We'll highlight two of the most relevant comparisons. First, Smith et al. found that the humans performed as expected and they showed a rank-order difficulty of I < II < III = IV = V < VI. That is, unlike the similarity/generalization hypothesis (i.e., the idea that category difficulty should track perceptual coherence), which predicts difficult learning for Type II, humans performed well on Type II, and only Type I was easier. As we suggested earlier, Type II would be easy if one relied on a verbal description of the stimuli and the disjunctive rule. The four monkeys showed a different pattern, and their rank order difficulty was I < III = IV = V < II < VI, which is exactly what is predicted if these categories were being learned via stimulus generalization. In other words, whereas monkeys learned in a way that suggested associative learning, humans learned in a way that suggested verbal processes may have come into play.

However, another analysis made this point more clearly. Smith et al. looked for evidence of rule discovery in the Type I and Type II categories. Recall that Type I could be learned by a single-dimensional rule and Type II could be learned by a disjunctive rule. For each subject, they found the point at which that subject reached a criterion of one perfect block (eight correct stimuli in a row). This criterion block was set as block zero so that regardless of when an individual subject reached the criterion (because of individual performance differences), that criterion block was the starting point. Smith et al. then averaged across subjects for the blocks leading up to the criterion and the blocks following the criterion block and plotted these values with the pre- and postcriterion block on the *X* axis and proportion correct as the *Y* axis. Figure 5A and C shows the results of the monkeys on Type I and II. Their performance is indicative of similarity generalization. On both cases, the learning curve suggests a gradual acquisition, and the criterion block is probably due to chance (a few good "guesses"). The data from humans, shown in Figure 5B and D reveals a different pattern. Humans show gradually increasing performance with a spike to the criterion, and then near-perfect performance after that. Smith et al. suggested that this pattern was clear evidence of rule discovery by the humans. Once subjects learned this optimal rule they continued to use it, and their performance stayed nearly perfect.

This result strongly suggests that there are two ways to learn the same kind of category. Monkeys learned these categories, but without discovering the rule, and clearly without the reliance on any kind of verbal process. Humans showed a pattern that suggested rule use and we argue that this rule came about because the humans recruited verbal ability to find that rule. This difference is not present for categories that do not have a verbal rule. Both humans and monkeys found the Type IV categories to be moderately difficult because they have a moderate FR structure and no easily verbalizable rule. So both species resort to the similarity-based visual systems. Furthermore, both humans and monkeys displayed similar performance on dot-pattern categories (Smith & Minda, 2001; Smith et al., 2008), suggesting again that the fundamental difference between the two species is humans' access to verbal and executive processing.

4.2. Developmental Effects

The comparative research tests a core prediction about the existence of two category learning systems. That is, humans can use verbal ability to help in learning certain categories—those with an optimal verbal rule. But given that humans have access to verbal ability, working memory, and executive processing, how and when might these abilities reveal themselves developmentally? Surely infant categorization is not verbal but is similarity-based instead (Quinn, Palmer, & Slater, 1999; Sloutsky, 2003;

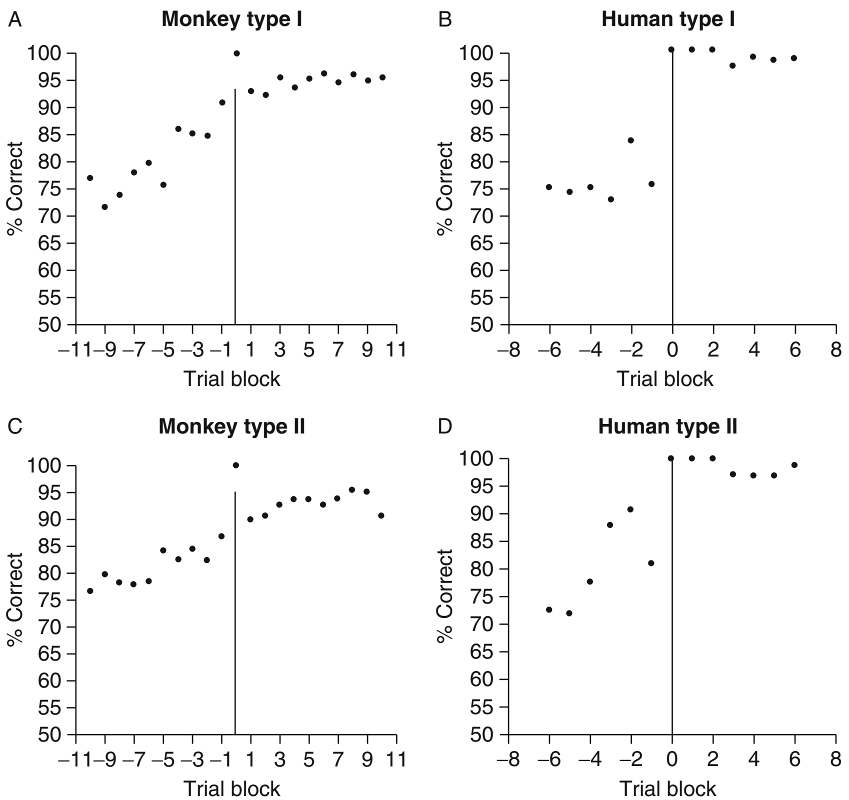

Figure 5 An example of rule discovery by humans (panels B and D) but not monkeys (panels A and C). This figure is adapted from the figure shown in Smith et al. (2004).

Sloutsky & Fisher, 2004). But with age comes a greater reliance on rules and probably a greater recruitment of verbal ability to learn categories.

We examined this idea in our lab (Minda et al., 2008) by comparing the abilities of children (3, 5, and 8 years old) and adults to learn a subset (Types I, II, III, and IV) of the same categories described above (Shepard et al., 1961; Smith et al., 2004), although the stimuli were now presented with faces. See Figure 6 for an example of the stimuli and the task design. The children were seated at the computer along with an experimenter and were told that they would be playing a game in which they would see pictures of different creatures on the screen. They were told that some of these creatures lived in the mountains and some lived in the forest. Their job was to help these creatures find their homes by pointing to the correct place on the screen. On each trial, the stimulus appeared in the center of the screen and the two category icons (mountains and trees) were shown to the left and the right of the stimulus. When the child pointed to a location on the screen, the experimenter made the selection with a mouse, and the stimulus moved to where the child had pointed. The stimulus was animated to show a smile for 2 s as feedback for a correct choice. For an incorrect classification, the stimulus frowned for 1 s and then moved to the correct location and smiled for 2 s as feedback.[2]

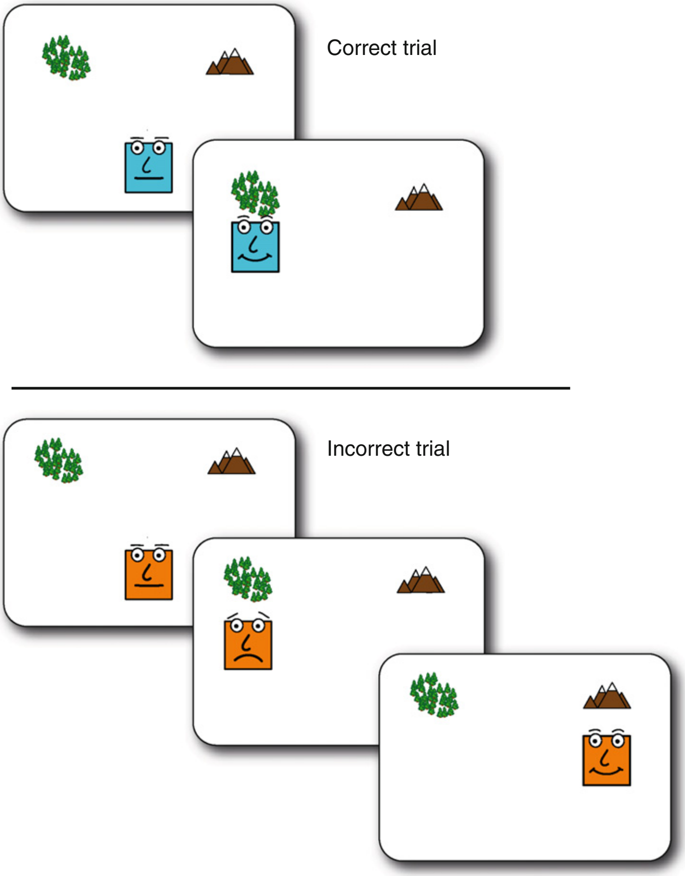

Figure 6 An example of a CORRECT trial and an INCORRECT trial in the Minda et al. (2008) experiments. Correct classifications were always indicated with a smiling stimulus and incorrect classifications were indicated by a frowning stimulus, after which the stimulus moved to the correct location and smiled.

[2] Note that although there were consistent mappings of stimulus to response, the feedback was not presented immediately after the response, since the experimenter required a second or two to make the selection. This would undermine the strictly procedural account of learning proposed by COVIS (Maddox et al., 2003).

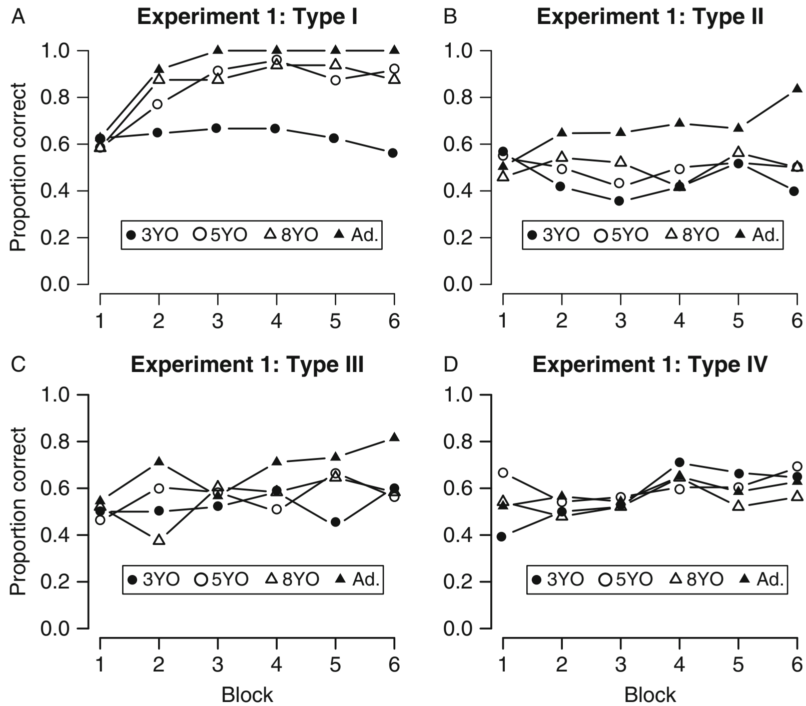

Figure 7 Average performance at each block (across subjects) for each category set and each age group. Note that 3YO = 3-year-old children, 5YO = 5-year-old children, 8YO = 8-year-old children, Ad. = Adult subjects.This figure is adapted from Minda et al. (2008).

The results from one experiment are shown in Figure 7. Adults and children differed on how well they learned the Type II categories, which required the formation of a disjunctive rule, and on the Type III categories, which required the formation of a rule and exception strategy. Adults performed relatively well on these categories whereas children performed very poorly. However, children and adults displayed similar levels of performance on the Type I categories, which were defined by a rule that was simple, easy to describe, and directly related to a perceptual cue information. Children and adults also displayed similar levels of performance on the Type IV FR categories because these categories were able to learned without verbal processing and could be learned by the nonverbal similarity-based systems instead. Consistent with the predictions of the verbal/nonverbal distinctions, children generally lagged behind adults when learning categories that depended on complicated verbal rules but not when learning categories that required a simple rule, or when the categories did not depend on verbal rules.

More recently (Minda & Miles, 2009), we asked children (age 5) and adults to learn a set of categories that could be acquired by finding a single-feature rule or by learning the overall FR structure. Subjects learned to classify drawings of bugs that varied along five binary dimensions: antenna (forward-facing or backward-facing), head (circle or square), wings (rounded or pointy), legs (bent or straight), and tail (bent or straight). The category set was made up of 10 objects with 5 objects belonging to each of two categories. The binary structure for Category A and Category B is shown in Table 1. The values 1 and 0 indicate the assigned feature values for each of the five dimensions. For example, round head, forward-facing antenna, rounded wings, straight legs and a straight tail were each assigned a value of 1, and the complementary set of features were assigned a value of 0. The item 1 1 1 1 1 represents the prototype for Category A and the item 0 0 0 0 0 represents the prototype for Category B while the remaining category members have four features in common with their own category's prototype and one feature of the opposite category's prototype. Note, the

Table 1 Stimuli Used by Minda and Miles (2009).

Stimulus	CA	d2	d3	d4	d5
Category A					
1	1	1	1	1	1
2	1	0	1	1	1
3	1	1	0	1	1
4	1	1	1	0	1
5	1	1	1	1	0
Category B					
6	0	0	0	0	0
7	0	1	0	0	0
8	0	0	1	0	0
9	0	0	0	1	0
10	0	0	0	0	1
Transfer					
11	0	1	1	1	1
12	0	0	1	1	1
13	0	1	0	1	1
14	0	1	1	0	1
15	0	1	1	1	0
16	1	0	0	0	0
17	1	1	0	0	0
18	1	0	1	0	0
19	1	0	0	1	0
20	1	0	0	0	1

first dimension is the criterial attribute (CA), upon which the optimal rule is based. The feature that corresponded to the CA was counterbalanced across participants. Perfect categorization performance could be attained by learning the CA (e.g. "round heads in Category A, otherwise Category B.") or by learning the FR structure.

Transfer stimuli were used to distinguish between CA and FR categorization strategies. That is, the feature corresponding to the CA indicated membership in one category but the overall FR indicated membership in the opposite category. As shown in Table 1, the first dimension of the first transfer stimulus (0 1 1 1 1) was consistent with CA evidence for category B, but the overall FR evidence is consistent with the evidence for Category A.

When we examined their learning data, we found that the children and adults did not differ from each other in terms of how well they had learned the categories. However, children and adults did differ in their classifications of the test stimuli. We also found that children were significantly less likely to classify the test stimuli according to the CA rule than were the adults (Figure 8). These results echo earlier developmental work on the holistic/analytic distinction in category learning, which found that children tended to prefer overall similarity and adults tended to prefer rules (Kemler Nelson, 1984). In addition, research using a similar category set found that adults who were asked to learn the categories in the presence of indirect feedback, or via incidental means were also less likely to find the CA, possibly because they were not relying on their verbal systems (Kemler Nelson; Minda et al., 2008).

The results of both of the studies we've just discussed are consistent with a verbal/nonverbal distinction. The verbal system should learn these categories by facilitating the testing of various rules and eventually allowing the subject to apply a verbal description for the correct single-dimensional rule. We assume that all of this testing, and considering, and applying happens within working memory. It is an active process. Subjects are explicitly aware and are trying to find a rule. Adults default to this verbal system under most classification learning conditions (Ashby et al., 1998; Minda et al., 2008; Zeithamova & Maddox, 2006), and so they apply the rule to classify the test stimuli. However, the nonverbal system could also learn these categories by relying on the good FR structure. The FR structure is difficult to verbalize because of the number of propositions in the verbal rules, but less difficult to learn nonverbally because of the straightforward relationship between features and responses. Children, unlike adults, have more difficulty relying on the verbal system in part because the prefrontal cortex has not sufficiently developed to allow the executive processing ability needed to search for rules (Bunge & Zelazo, 2006; Casey et al., 2004). The verbal system also relies on working memory and executive functioning to test and store hypotheses and rules. As such, the category learning differences between children and adults are consistent with other observed differences in working memory ability between children and

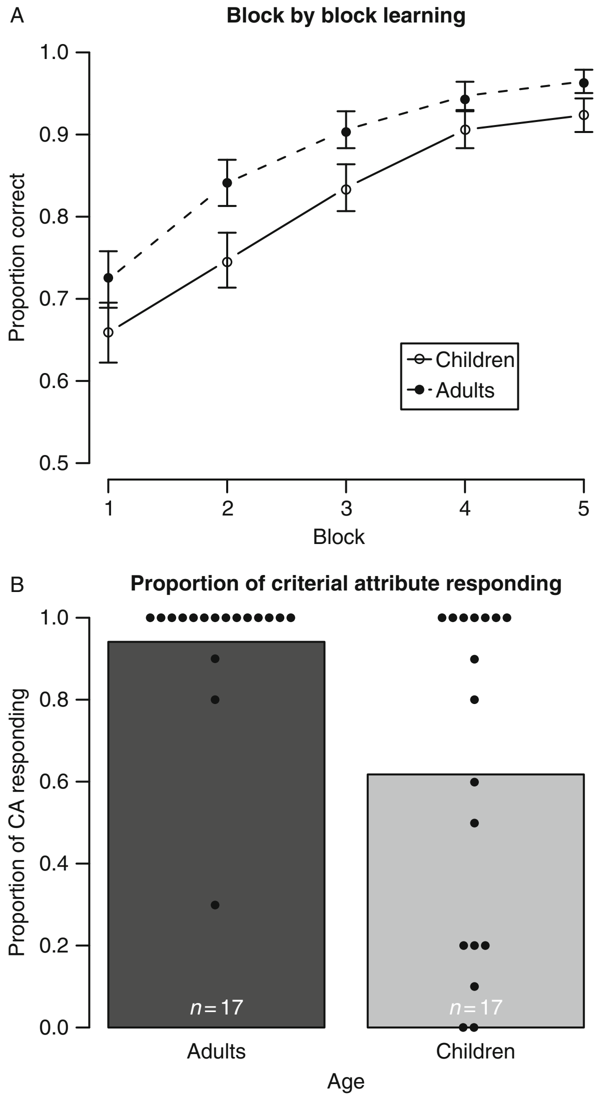

Figure 8 Panel A shows category learning performance for children and adults. Panel B shows the proportion of criterial attribute (CA) responding by children and adults in the transfer stage, with individual subject data shown as points. This figure was adapted from Minda and Miles (2009). Note: error bars denote *SEM*.

adults (Gathercole, 1999; Swanson, 1999). Working memory plays a large role in the verbal system and is required to learn categories for which the optimal rule is verbalizable (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). Adult subjects (but children less so) rely on verbal working memory to help learn these categories with the verbal system. Without the efficient use of the verbal system, the child is less able to efficiently engage in hypothesis testing. As a result, children could still learn these categories, but many of the children may have relied instead on the nonverbal system to learn the categories and subsequent classifications of the transfer stimuli were not likely to be based on a rule.

Although we claim that the verbal system is less effective in children, the results of our experiment suggest that it can (and does) operate. Some of the children in this study were able to learn rules, and many continued to make rule-based responses in the transfer phase. It is possible that some children did learn the rule, but were unable to resolve the conflict between the rule and FR during the transfer phase. This would be expected to happen in children, since their prefrontal cortex areas are less well developed (compared with adult) and they would have difficulty in inhibiting the response to the FR structure. Furthermore, Figure 8B reveals some subjects who relied on other non-rule-based strategies. These other strategies could be a mix of responses from the two systems (some rule-based, some similarity-based) or may also be imperfect exemplar-based strategies. At this point our data do not allow a strong conclusion about this subset of subjects and additional research is needed to understand the interaction of these two learning systems in general and at different stages in development.

4.3. Interference Effects

In order to test the hypothesis that the explicit system and verbal working memory play a crucial role in learning rule-defined categories but not non-rule-defined categories, we turned to a dual-task methodology. The rationale is that as subjects are engaged in the category learning task, they are also asked to engage in a secondary task. This task can be designed such that it will interfere with either verbal or visual resources, and so will interfere with learning by one system and not the other. We describe here another experiment from Minda et al. (2008) in which three groups of adults learned four category sets (originally presented to children and adults in the earlier study we discussed).

Participants were assigned to one of the three concurrent-task conditions and were assigned to learn one of the four category sets (Types I–IV from Figure 4). In the no concurrent-task condition, subjects saw a stimulus on the screen and were instructed to press the “1” or the “2” key to indicate category 1 or category 2, respectively. After responding, subjects were given feedback indicating a correct or an incorrect response. A verbal concurrent-task condition was similar to the no-task condition except that as subjects were learning to classify the stimuli, they performed a coarticulation task in which random letters appeared at the rate of one per second in the center of the screen, right below the stimulus. Subjects read these letters aloud as they were viewing the stimuli and making responses. A nonverbal concurrent-task condition was similar to the no-task condition except that as subjects were learning to classify the stimuli, subjects tapped their finger to match an asterisk that flashed on the screen at the rate of one per second.

The key finding, shown in Figure 9, was that subjects in the verbal concurrent-task group were impaired relative to both the nonverbal concurrent-task and the no-task groups on the Type II categories but not on the Type III or V categories. That is, verbal interference seriously interrupted the learning of categories that depended most strongly on access to verbal resources. These were also the same categories that were difficult for monkeys and difficult for children. However, the nonverbal concurrent-task did not appear to disrupt performance at all. This suggests that learning the Type II categories well depends on having access to verbal working memory. Learning the other categories does not seem to depend on verbal working memory as strongly. These results are consistent with other

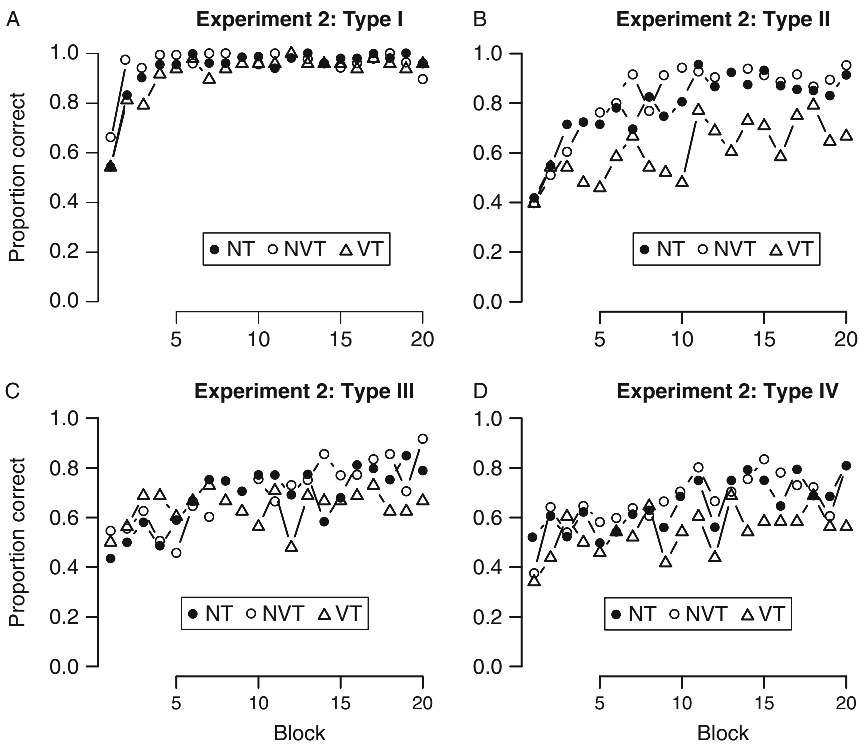

Figure 9 Average performance at each block (across subjects) for each category set and each experimental group.This figure is adapted from Minda et al. (2008). Note that NT = no task, VT = verbal task, and NVT = nonverbal task.

findings in the literature that demonstrate a role for verbal working memory in the learning of rule-described categories but not in the learning of non-rule-described categories (Waldron & Ashby, 2001; Zeithamova, Maddox, & Schnyer, 2008).[3]

4.4. Indirect Category Learning

A key prediction of our theory is that diverting verbal resources from the main task of learning categories will impair rule learning because it will knockout the verbal system. Instead, learning should proceed via the non-verbal system. Other multiple-systems theories make similar assumptions. In COVIS, for example, a procedural learning system takes over when the verbal system is not operating, in which case the response and feedback must be closely associated (Ashby et al., 1998). We do not make the same assumption and suggest that there are other nonverbal, similarity-based learning mechanisms in addition to the procedural systems envisioned by COVIS. If true, categories may be learned by the nonverbal system, even if the feedback is not directly connected to the stimuli and response.

Minda and Ross tested this prediction by devising an indirect learning paradigm (Minda & Ross, 2004). Unlike direct learning, in which a subject is explicitly instructed to learn a category and may be able to use verbal processing to do so, indirect learning occurs when the subjects are trying to learn something else about the stimuli. In this case, the subject may not be aware of the categories, but learning them will still be beneficial to succeeding in the task. Category learning occurs as a matter of course. For example, doctors may learn to categorize patients into a number of useful, but nondiagnostic, categories—such as patients who are not compliant or who have no prescription insurance. They may use the categories when making management decisions about the patient, but may never receive direct feedback on the classification *per se* (Devantier, Minda, Goldszmidt, & Haddara, 2009).

Minda and Ross carried out an experiment in which some subjects learned to first classify a series of imaginary creatures into two groups and then to predict how much food the creature would eat. The creatures appeared in three different sizes and larger animals always ate more than smaller animals. But animals in one category also ate more than the same sized animals in the other categories. Think of them as two species in which one has a higher metabolism (subjects just saw the label A and B, they were

[3] One might wonder why the nonverbal task did not seem to affect Type IV learning by the nonverbal system. We think this is because the secondary task was a purely motor task. This suggests that the hypothesized procedural learning systems of COVIS is incomplete and suggests something about the basic cognitive processes used by the nonverbal system. A visual task might affect FR learning, though. And that is something we're working on in our lab now.

not told about the connection between category and eating). Furthermore, the light-eater/heavy-eater categories were defined on the basis of good FR (4 out of 5 features) as well as a perfectly predictive single-feature rule. Another group of subjects did not perform the classification task but only made the food prediction. But since the correct amount of food depended on category, these subjects would have to learn the categories in order to perform well on the prediction task. This prediction-only condition tested the idea that indirect feedback (the correct food amount was indirectly related to the category) would encourage more similarity-based learning than the classification and prediction group because subjects' verbal abilities are occupied with the prediction task and not with learning to classify. In the classification-and-prediction group, subjects' verbal abilities were free to test hypotheses and search for the rule.

The test of these competing strategies (rule or overall similarity) was determined by transfer stimuli that presented a rule feature that was associated with one category but the rest of the features that were associated with the opposite category. This is the same idea used in other research we have already described (Allen & Brooks, 1991; Kemler Nelson, 1984; Minda & Miles, 2009). In other words, a creature might have a light-eater tail, but heavy eater head, eyes, antennae, etc. Minda and Ross found that subjects in both groups were able to learn the categories well (i.e., performance did not differ significantly between groups). However, subjects in the prediction only group were less likely to find the rule and more likely to learn the FR structure, which was not easily verbalized. Furthermore, computational modeling suggested a broader distribution of attention by subjects in the prediction only group. Subject who learns to classify first and then make a prediction tended to find the rule and as a result, tended to have a narrow attentional distribution.

In short, diverting resources from the main task of categorization resulted in less rule learning and more FR learning. This is similar to research by Brooks, Squire-Graydon, and Wood (2007) who used a different indirect learning paradigm to show that subjects who indirectly learn to categorize did not explicitly consider the category's structure. In their experiment, some subjects were explicitly instructed to categorize creatures and some subjects learned to determine the number of moves a creature needed to make to reach a goal. Critically, the type of move that a creature could make depended on its category membership, so that categorization was necessary to solve the problem. Brooks et al. reasoned that subjects in the indirect condition never explicitly considered a creature's category membership and so would be less knowledgeable of the category's non-rule-defined structure. Although both groups of subjects categorized the creatures equally well, subjects in the direct condition were aware that no feature was perfectly predictive of category membership because they had tried, and failed, to find the rule. Subjects in the indirect condition were not aware of this. This finding confirmed that when resources are diverted to another task during indirect category learning, the explicit testing of categorization rules does not take place, resulting in reduced knowledge of the category structure. Not only does an indirect task decrease rule learning by the verbal system, it also decreases explicit consideration of the category structure so that categories are learned in a less explicit manner using the nonverbal system.

4.5. Other Predictions

4.5.1. Mood Effects

We've described the results of testing a number of predictions that follow from the verbal/nonverbal approach to category learning. But there are several other predictions that remain to be tested and that we are working on in our lab. As an example, consider the effects of depression and mood. What people commonly refer to as "depression" is referred to as "major depression" in the DSM-IV. According to the DSM-IV, depression is a psychiatric syndrome comprised of multiple symptoms including sad mood and/or anhedonia, appetite and weight changes, sleep changes, decreased energy, psychomotor agitation, decreased ability to concentrate or think (American Psychiatric Association, 1994). A number of these symptoms are likely to have an effect on basic category learning, especially learning by the verbal system, since any reduction in executive functioning should impair the verbal system. Indeed, Ashby et al. (1998) predicted that depressed subjects should be impaired on rule-based, explicit category sets relative to controls. Earlier research has found some support for this idea. Smith, Tracy, and Murray (1993) compared the category learning performance of depressed subjects (with mean BDI scores ranging from 17.25 to 36.6) and a control group in two experiments. In both experiments, subjects learned a CA (verbal) category set and an FR (nonverbal) category set. As predicted, depressed subjects were impaired at rule-based categorization but unimpaired at FR categorization, relative to controls. These results confirm the importance of executive functioning for the verbal system, and show that the nonverbal system still functions well when executive functioning is depleted.

While the results of Smith et al. (1993) support the prediction that depressed subjects should be impaired on verbal, rule-based category learning, it is an open question whether or not mood, rather than depression, will affect categorization performance. Specifically, we predict that negative affect will impair performance on rule-based tasks because we expect rule selection and hypothesis testing abilities to be diminished relative to a control. At the same time, we speculate that positive affect may actually improve performance on rule-described categories, because of the enhanced processing capacity that may come from positive affect

(Ashby, Isen, & Turken, 1999). We are currently evaluating this set of predictions in our lab by inducing a positive (or negative) mood in subjects and then asking them to learn either a rule-defined category or a non-rule-defined category (as in Figure 2). In this case, we predict that positive mood will enhance learning in the rule-defined categories but not for the non-rule-defined categories.

4.5.2. Dot-Pattern Categories

A second prediction that follows from our verbal/nonverbal distinction concerns prototype learning by children. Because dot-pattern learning seems to require very little verbal processing or even executive processing, we predict that young children should be as good as adults on this task. This is a straight forward prediction, since good dot-pattern categorization has been observed in monkeys (Smith et al., 2008) and in amnesics (Knowlton & Squire, 1993). Furthermore, in the same way that the dual task methodology has been used to interfere with rule-based categories but not with information-integration categories, we expect that dot-pattern prototype abstraction will not be hindered by a dual verbal task, but may be hindered by a dual visual task. This type of finding would support our suspicion that some types of nonverbal categorization are particularly reliant on visual processing.

4.5.3. Language Effects

As another example, consider the condition known as specific language impairment (SLI). SLI is a diagnosis describing problems in the acquisition and use of language, typically in the context of otherwise normal development (Leonard & Deevy, 2006). These problems might reflect difficulty in combining and selecting speech sounds of language into meaningful units and might manifest as the use of short sentences, and problems producing and understanding syntactically complex sentences. SLI has been linked with working memory problems as well (Gathercole & Baddeley, 1990). Since these children have reduced verbal capacity, they should be impaired relative to control subjects in learning categories that are rule-defined as opposed to categories that are non-rule-defined. In fact, it is possible that these subjects might be better than age-matched controls in learning non-rule-defined categories like FR categories and information-integration categories because the nonverbal system would not have to compete with and overcome the verbal system. In fact, very recent research has examined individual working memory capacities and has found that subjects with lower working memory capacity actually perform better than other subjects on non-rule-described categories (DeCaro, Thomas, & Beilock, 2008).

5. Relationship to Other Theories

5.1. Verbal and Nonverbal Learning and COVIS

We have tried to highlight the relative importance of verbal and nonverbal processes for category learning. We've described a two-system model, and we suggest that these two systems operate simultaneously during category learning. Obviously, this description shares many assumptions with COVIS. Both share an assumption of a verbal system that relies on working memory and executive functioning. The overlap between COVIS and our verbal/nonverbal account is unavoidable. After all, there is converging evidence, discussed in the first section of this chapter, that one way to learn categories is to engage in hypothesis testing and to rely on verbal rules (Patalano et al., 2001; Smith et al., 1998). In other words, there are a number of models and theories that posit a verbal system.

But these two theories differ in how they describe the other, nonverbal category learning system. COVIS assumes that categories can also be learned by an implicit system. The implicit system is mediated by structures in the tail of the caudate nucleus and it seems to require a close connection between the stimulus, the response, and the reward. Whereas COVIS describes an implicit (procedural) learning system that learns to associate stimuli with various regions of perceptual space, we assume a much larger role for the nonverbal system. That is, we assume that categories can be learned by this system without feedback, or without the direct connection between stimulus and response. These are all viable ways of learning categories and these all end up producing performance that is similarity based. That is, these modes of category learning tend to result in performance that shows less of an emphasis on single-feature rules and shows more emphasis on overall FR.

Why do we suggest this expansion for nonverbal learning? Some of the evidence comes from our research on indirect learning. For example, the indirect learning paradigm employed by Minda and Ross (2004) did not have a direct connection between stimuli and response, as should be required by the implicit system in COVIS. Feedback was delayed, and the response and feedback were only indirectly related. And yet the subjects learned the categories as well as a direct classification group. Interestingly, the indirect learning subjects took a little longer and were more likely to learn FRs. In other words, they learned in much the same way as the implicit systems in COVIS predicts, but without the direct response and feedback connection. Consider also the learning of Shepard et al. stimuli by children and adults (Minda et al., 2008). The children were taught categories without the direct connection between response and feedback. Although they still received feedback, the experimenter, rather than the child, carried out the categorization response. Furthermore, the feedback took several second to be displayed (the stimulus smiled for a correct classification and frowned for an incorrect one). Yet the children still learned the FR categories as well as adults (and via a nonverbal system), even though the adults made their own response with a key press. We think that the basic version of COVIS may have difficulty in explaining these results, and we think that a more broadly construed nonverbal system explains these results better. In the case of indirect learning, for example, the verbal system was dealing with the predictions and so the categories were learned in a nonverbal way, despite the disconnect between the stimulus and response.

5.2. Single-System Models

A multiple-systems or dual process account of category learning, like what we are advocating for in this chapter, has traditionally been contrasted with a single-system account of category learning (Nosofsky & Johansen, 2002; Zaki & Nosofsky, 2001). In general, when two models or theories predict learning equally well, the model or theory that uses the simplest set of representational assumptions (i.e., a single system) is preferable. A common version of a single-system theory is exemplar theory—formalized as the Generalized Context Model or GCM—which assumes that people learn categories by storing exemplar traces and make classifications on the basis of similarity to these stored exemplars (Nosofsky, 1987, 1988, 1991). With respect to learning the Shepard et al. (1961) categories used by Smith et al. (2004) and Minda et al. (2008), the exemplar model can predict the basic ordering effect observed on the Type I–VI stimuli. That is, Type I is learned the most quickly, followed by Type II, etc. (Kruschke, 1992; Nosofsky, Gluck, Palmeri, McKinley, & Glauthier, 1994). For Type II categories, the exemplar model learns that only two dimensions are relevant, which reduces the amount of information to be learned, and so the GCM predicts good learning.

In its basic form, an exemplar model has no way to account for poor learning of Type II categories by monkeys and young children, nor can it predict the rule discovery observed in humans and shown in Figure 5. The GCM can make additional assumptions in order to predict poor learning of the Type II categories. For example, suppose the stimuli were created from integral dimensions (e.g., hue, saturation, and brightness) as opposed to separable dimensions (e.g., size, color, and shape) the GCM can adjust one of its parameters (the exponential in the distance equation) and the result is that Type II learning is slowed. Nosofsky and Palmeri (1996) found that when subjects learned the Shepard et al. (1961) categories with integral-dimension stimuli, learning on Type II was affected more than the learning of the other category types. So the GCM can account for the effects discussed earlier by treating the dimensions as integral because separable dimensions are able to be separately described by verbal processing; integral dimensions are not. Although the GCM is a single-system model, it can capture many of the same effects that we have discussed, albeit at the expense of simplicity.

So in the end the GCM solves this problem in a manner consistent with earlier work suggesting that children tend to perceive objects as integral wholes (Offenbach, 1990; Smith, 1989; Smith & Shapiro, 1989). However, an exemplar model does not make an *a priori* assumption about whether or not children or adults should perceive the stimulus dimensions as integral or separable, and it has no explanation for why an individual's ability to treat dimensions as integral versus separable should be impacted by working memory demands. On the other hand, a multiple systems approach, like the verbal/nonverbal distinction that we are proposing or like COVIS, makes clear predictions about both developmental and working memory load differences because of the role it assigns to prefrontal cortical areas for the use of the verbal system. As a result, we prefer a multiple systems account of category learning.

Another single-system model that can account for a variety of phenomena is the SUSTAIN model, which is a clustering model of category learning (Love, Medin, & Gureckis, 2004). This model does not make the assumption that categories are learned via different brain systems or even different processes. Instead, it assumes that categories can be learned as clusters of similar stimuli. A single cluster can represent one or many exemplars. As such, SUSTAIN has the ability to represent categories with a single prototype, several prototypes, or with many single exemplars. Furthermore, SUSTAIN has a mechanism for supervised learning (e.g., explicit, feedback-driven classification) and unsupervised learning. SUSTAIN has been successfully applied to a broad range of developmental and patient data (Love & Gureckis, 2007). In SUSTAIN, reduced memory capacity is modeled by reducing the number of clusters that the model forms (e.g., less memory = fewer possible clusters). In general, the mechanisms for forming new clusters are thought to be mediated in part by the prefrontal cortex as well as the hippocampus (Love & Gureckis). This means that tasks that impair or interfere with functions carried out by these areas (i.e., explicit memory and executive functions) should result in greater FR learning. For example, for Type II categories, a reduced number of clusters would result in impaired learning, similar to the impaired learning observed in the young children in Figure 7 (Minda et al., 2008). However, reduced numbers of clusters would not be expected to have as much effect on the FR categories, like the Type IV categories. In short, although SUSTAIN does not posit separate verbal and nonverbal systems, it accounts for the dissociations by appealing to many of the same cortical areas that most multiple systems approaches do. The obvious shortcoming is that

SUSTAIN, as with the GCM, has difficulty in making *a priori* predictions about working memory capacity, developmental differences, and cross-species comparisons. In addition, it is not clear how any single-system model would predict the rule-discovery behavior that subjects seem to show.

6. Conclusions

Throughout this chapter, we have been making the case that people learn categories by relying on verbal abilities but also by relying on nonverbal processes. As is clear from our review of the literature, this is not a new argument. It is an issue that has been central to many developments in the psychological study of category learning. We feel that our proposal—concentrating on how and why subjects rely on verbal processing and nonverbal processing—addresses a middle ground between the strongly, neurobiologically motivated models like COVIS and the single-system approaches like the GCM or SUSTAIN. Any complete model of category learning has to deal with the reality that people *do* recruit explicit reasoning abilities and verbal processes when they are learning new categories and when they are making classifications. In other words, subjects really try to find rules and may use them if they can. We are not claiming that this indicates the existence of a separate and abstract rule system. But we are claiming that this is one clear approach that people take when learning categories. Any complete model will also have to deal with the reality that some categories have no rule, or that subjects ignore the rules, or that subjects learn categories when they cannot or do not verbalize anything about them. In some cases, this nonverbal, similarity-based learning may be influenced by attempts to learn verbal rules and in other cases it may proceed implicitly. The review of literature we presented here, and our own work, suggests there is much exciting work to be done on how all of these cognitive processes come together in the behaviors of category learning and categorization.

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