Exploring the Role of Language in Two Systems for Categorization

Kayleigh Ryherd, PhD
University of Connecticut, 2019

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

Exploring the Role of Language in Two Systems for Categorization

Kayleigh Ryherd

B.A., The George Washington University, 2014
M.S., University of Connecticut, 2016

A Dissertation
Submitted in Partial Fulfillment of the
Requirements for the Degree of
Doctor of Philosophy
at the
University of Connecticut
2019

APPROVAL PAGE

Doctor of Philosophy Dissertation

Exploring the Role of Language in Two Systems for Categorization
Kayleigh Ryherd, M.S.

Major Advisor: ____________________
Nicole Landi

Associate Advisor: ____________________
Letitia Naigles

Associate Advisor: ____________________
James Magnuson

Associate Advisor: ____________________
Eiling Yee

Associate Advisor: ____________________
Clinton Johns

2019

Acknowledgments

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

Contents

List of Figures

List of Tables

1 General Introduction

Categories help us organize the world. They help us predict and hypothesize about category members, helping us quickly select the most appropriate response for each situation. We also rely on language during these processes. As Lupyan (2012) puts it, language augments our thought. For categories, language provides structure in the form of category labels, but language also affects how we think about and even perceive the categories themselves. Thus any thorough investigation of how we learn categories must consider the role of language.

Indeed, many theoretical frameworks of category learning involve language – some even reference it right in the name. For example, a key theory in perceptual category learning, COVIS, stands for "competition between verbal and implicit systems"' (Ashby et al., 1998). Similarly, a theory put forth by Minda and colleagues is called "A theory of verbal and nonverbal category learning" (Minda & Miles, 2010). However, to date most theories of category learning that consider language primarily determine whether language has an influence on systems for category learning, rather than further defining the role language plays in these systems.

Thus, the current work seeks to both define a theory of category learning and explore the role language has in this theory. In this review I will synthesize multiple approaches to category learning, all of which have some type of dual-systems model. Following the synthesis, I will review relevant literature that provides suggestions as to how language might be involved in category learning in a dual-systems model. Through these efforts, I will provide a theoretical framework and hypotheses for this dissertation.

1.1 Dual-systems model for category learning

Multiple theories converge on the idea that there are two systems for category learning. In this section, I will first describe a generalized dual-systems model that pulls threads from all of these theories and then go on to describe how each theory fits into the overarching framework.

1.1.1 Proposed model

The proposed model involves two systems for category learning. The first, which I title the **associative system**, uses associative mechanisms in an iterative manner to learn distributions of features. This system is best suited for learning multidimensional *similarity-based* categories such as natural kinds, where it is difficult to describe necessary and sufficient rules for inclusion. Similarity-based categories have features that are correlated and probabilistic, such that a category instance may not have all of the category-relevant features but tends to have some distribution of them. For example, Manx cats do not have tails, a typical feature of cats, but are still undeniably members of the category *cat*. Thus, the associative system must be able to extract the most frequent pattern of features over many instances in order to learn a category.

The second one is called the **hypothesis-testing system**. This system uses a more explicit learning method to test and adjust hypotheses about category boundaries. This method relies on selection of relevant features rather than representation of a distribution of feature probabilities. As such, it is most suited for learning rule-based categories, which typically have one or a few easily verbalizable rules for inclusion. For example, the *ad hoc* category *things to be sold at the garage sale* has a simple rule for inclusion that perfectly separates members from non-members.

Thus, we have two systems for category learning, each one ideal for learning a different type of category (similarity-based vs. rule-based). In the upcoming sections, I will describe theoretical and empirical evidence for a dual-systems model from five different approaches to category learning. I will show how each approach informs the current theoretical framework.

1.1.2 COVIS

COVIS stands for COmpetition between Verbal and Implicit Systems and is a prominent theoretical framework for perceptual category learning first proposed by Ashby et al. in 1998. This framework provides a dual-systems model that is grounded in neuropsychological data, allowing it to suggest neurobiological underpinnings for the two systems. It is important to note from the beginning that this framework is mostly concerned with perceptual categories, which are defined as "a collection of similar objects belonging to the same group" (Ashby & Maddox, 2005, p. 151). This is in contrast to concepts, which they define as groups of related ideas. Thus, this approach focuses on categorizing objects that can be encountered and perceived in the real world.

As can be inferred from the title, the two category learning systems in COVIS are the **verbal** and **implicit** systems. The verbal system is COVIS' answer to our hypothesis-testing system. It is a declarative learning system that uses a hypothesis-testing method to learn category rules, typically for rule-based stimuli. Under COVIS, rule-based stimuli must have inclusion rules that are easy to describe verbally. Typically, rule-based stimuli used by Ashby and colleagues have a single rule for inclusion or two rules combined by "and" or "or." When a rule-based category involves multiple dimensions, decisions about each dimension are made separately, and these decisions are used to evaluate the logical operators. In other words, each dimension is considered on its own before their combination. These guidelines for rule-based categories ensure that an explicit, verbalizable hypothesis-testing method can be used to learn them. When learning a new category, the verbal system holds candidates for category inclusion rules in working memory, which are tested as stimuli are encountered. Over time, the hypotheses are tested and switched until they reflect the optimal strategy for categorization.

The implicit system from COVIS is most similar to our associative system. Like the associative system, it uses incremental learning to find category boundaries. It is most ideal for learning information-integration categories, which are like similarity-based categories but have also some specific guidelines. Information-integration categories are defined by some combination of dimensions, like some rule-based categories. However, while each dimension can be considered separately in rule-based categories, all dimensions must be considered simultaneously for information-integration categories. Information-integration category membership depends on both the values associated with each dimension as well as the relationship between these values. Information-integration category boundaries are difficult or impossible to describe verbally. COVIS suggests that the implicit system relies on an information stream that connects stimuli, motor responses, and feedback to learn category membership.

One of the most substantial contributions of COVIS is its strong grounding in neurobiology. In the original paper, Ashby and colleagues proposed specific brain regions involved the verbal (hypothesis-testing) and implicit (associative) systems, supported by neuroimaging and patient studies. The verbal (hypothesis-testing) system relies on the prefrontal cortex (PFC), anterior cingulate cortex (ACC), striatum, hippocampus, and the head of the caudate nucleus. Information about the stimuli are processed in fronto-striatial loops and potential category rules are generated. The PFC keeps these rules in working memory while the ACC and the head of the caudate nucleus mediate switching between rules based on feedback. Finally, the hippocampus stores longer-term memory of which rules have already been tested it is only involved when the task is complex enough that previously tested rules cannot all be stored in working memory (Ashby & Maddox, 2005, 2011). Patient data shows that individuals with frontal damage as well as individuals with Parkison's disease, which affects the basal ganglia including the caudate nucleus, show difficulty in rule-based tasks such as the Wisconsin Cart Sorting Test (Robinson et al., 1980) and an experimental rule-based category learning task (Ashby et al., 2003). This suggests that both frontal regions and the basal ganglia are involved in rule-based categorization. More recent neuroimaging work, however, is still mixed as to the involvement of different areas specifically for rule-based categorization. Soto et al. (2013) found that two separate rule-based tasks could be differentiated based on activation in ventro-lateral PFC, suggesting that specific rules are stored in that region. Nomura et al. (2007) found activation in the medial temporal lobe (MTL), which contains the hippocampus, specifically for rule-based categorization. However, a later study failed to find any activation that was specifically greater for rule-based categorization (Carpenter et al., 2016). Thus, the neural underpinnings of the verbal (hypothesis-testing) system are still under debate.

The implicit (associative) system from COVIS has a different neurobiolgoical pathway for category learning. It uses incremental learning rather than hypothesis testing to learn information-integration (similarity-based) categories. The main structure involved in this procedural learning system is the striatum, which is involved in reinforcement learning with dopamine as the reinforcement signal. From the striatum, information about the category is sent to the thalamus and the globus pallidus, which is within the basal ganglia. From the thalamus, information also runs to motor and premotor cortex. This procedural system links stimuli, motor responses during categorization, and feedback to allow the participant to learn categories. Neuroimaging studies using the implicit system again are mixed, with some finding activation in the caudate body while others fail to find that activation, instead seeing activity in parahippocampal regions (Carpenter et al., 2016; Nomura et al., 2007). A separate study also found a role for the putamen in similarity-based category learning (Waldschmidt & Ashby, 2011).

Thus, COVIS provides us with a few key insights. First, it is one of the most studied dual-systems theories of categorization. While Ashby and colleagues generally use visual stimuli for their tasks, this paradigm has been extended to other perceptual domains such as hearing/speech (Chandrasekaran et al., 2014, 2016). As such, research on the current theoretical framework (associative/hypothesis-testing systems) has much COVIS literature which we can compare it to. It also makes clear claims about the neurobiological basis of the two systems of category learning. While the specifics of these claims are still under debate in the literature, they at least provide regions of interest for researchers who want to conduct neuroimaging research on a dual-systems model of category learning. Finally, this approach is one of the only ones to consider how the two systems interact.

As its name suggests, COVIS also accounts for interactions between the declarative and procedural systems. Behavioral studies encouraging participants to switch between the verbal and implicit systems show that unless participants are cued towards which type of strategy to use on a given trial, they tend to use verbal strategies for all trials (Ashby & Crossley, 2010; Erickson, 2008). This suggests that use of the verbal system may inhibit use of the implicit system. Indeed, neuroimaging studies and animal models seem to support this interpretation (Foerde et al., 2006; Packard & McGaugh, 1996). Other research suggests that switching between systems uses the left cerebellum as well as regions involved in the default mode network, including posterior cingulate cortex, medial prefrontal cortex (Turner et al., 2017).

1.1.3 Dimensionality

Considering categories in terms of their dimensionality is primarily the work of Lupyan and colleagues. Low-dimensional categories are those that cohere on one or a small number of dimensions, such as color, while allowing other dimensions to vary. In this way, low-dimensional categories are similar to rule-based categories, as they can be described using relatively simple rules. In fact, some of Lupyan's papers define low-dimensional categories as those that have a single dimension that can distinguish targets from non-targets (Lupyan & Mirman, 2013). Examples of low-dimensional categories from this study include *things made of wood* and *things with handles*.

In contrast, high-dimensional categories are those that cohere on multiple dimensions, often so many that category rules are difficult to describe. Examples of high-dimensional categories from the previously-mentioned study include *birds*, *tools*, *things that fly*, and *objects that hold water*. Most natural kinds and artifacts are high-dimensional, as well as some *ad hoc* categories.

The core prediction tested using this approach is that low-dimensional categorization should rely more heavily on language than high-dimensional categorization. Similar to the model proposed in this paper, the dimensionality approach postulates that language helps an individual select features, which is a process only helpful for low-dimensional categorization. High-dimensional categorization relies on creating associations across multiple features, which does not involve language as highly.

To explore this prediction, Lupyan and colleagues interfered with language ability in multiple ways across studies. Lupyan & Mirman (2013) measured categorization ability in individuals with aphasia for both low- and high-dimensional categories. They found that the individuals with aphasia performed similarly to unimpaired controls on the high-dimensional categories, but showed significantly lower accuracy on the low-dimensional categories. Lupyan (2009) used a concurrent verbal load to reduce the verbal resources available during a categorization task. He found that individuals showed significantly poorer categorization with a verbal load as compared to a visuospatial load specifically for category judgments based on a single dimension (color or size) but not for those based on multiple dimensions (theme). Other studies manipulated language ability by using transcranial direct current stimulation (tDCS). tDCS can raise or lower cortical excitability, depending on the polarity of the stimulation. One study found that cathodal stimulation, which tends to lower excitability, over the left inferior frontal gyrus led to poorer performance on low-dimensional but not high-dimensional categorization (Lupyan et al., 2012). Another study used stimuli that could either be categorized using a uni-dimenional or a bi-dimensional strategy. Cathodal tDCS over Wernicke's area made participants more likely to chose the bi-dimensional strategy, indicating that interfering with language functioning resulted in participants using higher-dimensional categorization (Perry & Lupyan, 2014).

The dimensionality approach to category learning and the studies done to test it provide multi-method evidence for the role of language in low-dimensional categorization. Unlike COVIS, where the verbal system largely uses language to describe and rehearse candidate category rules, the dimensionality approach states that language is used to select relevant features for a category. This idea has highly influenced this paper's dual-systems model, in which the hypothesis-testing system does select category-relevant features. However, the evidence for this approach is largely unable to speak for the system underlying high-dimensional categorization, as most of the effects for this system are null. Thus, it is not clear from this approach whether the hypothesized broad inter-item association building is in fact how individuals learn high-dimensional categories.

1.1.4 Statistical Density

A third framework for dual-systems category learning was created by Sloutsky and colleagues. He describes two category learning systems that are each used to extract different types of regularities from a stream of information, allowing for flexibility in the data collected (Sloutsky, 2010). Sloutsky's main metric for describing categories is called *statistical density*. In this section, I will describe statistical density in a broad sense; for more detailed information on how to calculate it, see Appendix A (p. 14).

The statistical density of a category is related to the ratio between the amount of entropy seen within a target category and the entropy seen between the target category and other categories in the set. In this context, entropy refers to variation within features. Consider a set of shapes. These shapes can vary in shape, size, and color. The within-category entropy for squares is all of the different sizes and colors that squares in this set have. The between-category entropy is the sizes and colors of all shapes in the set. **Sparse** categories have lots of within-category entropy; the items in the category cohere on only one or a few dimensions. All other dimensions are allowed to vary freely. In our shape example, a sparse square category would have squares of all color and sizes, such that color and size was not related to shape. Thus, to find the category *square*, an individual would have to isolate the "shape" feature.

In contrast, **dense** categories have little within-category entropy; their members have multiple intercorrelated features that togetehr are predictive of category membership. There are few irrelevant features in dense categories. Within our set of shapes, the square category would be considered dense if all squares shared the same color and size. You may notice here that technically color and size are not relevant to the actual definition of square. However, the distribution of these other features are what determine the statistical density of a category, rather than the category's "actual" rules for inclusion. If the other irrelevant features are correlated with the relevant features, the category is dense. If they vary independently of the relevant features, the category is sparse. Thus, the statistical density expresses the relationships between features within a category as well as within an entire set of items. A particularly interesting feature of this metric is that statistical density is a continuous spectrum: categories can be very dense, very sparse, or anywhere in between.

This framework also outlines two systems hypothesized to be used for learning categories with different densities. Dense categories are best learned by the compression-based system, which takes input and reduces it by representing some but not all features. With more instances, relevant features for a given category will be represented more frequently and survive the compression. In contrast, features that appear infrequently will be mostly filtered out. The compression-based system does not use conscious selection to determine which features are represented; instead, it is just more likely that redundant and probable features continue on. The many correlated features of a dense category are easily extracted using this system. This system is quite similar to the current paper's associative system.

The second learning system is called the selection-based system. This system directs attention towards relevant features, sampling those features for later representation and learning by aiming to reduce error. As feedback is encountered, the system shifts attention from those dimensions that create categorization errors to those that do not. This system relies heavily on multiple aspects of executive function, including inhibition and selection. It is best for learning sparse categories. While over time the compression-based system could be able to learn sparse categories, as the freely varying irrelevant features would eventually be less frequent than relevant features, this process would be much more inefficient than selecting and testing individual features. This is Sloutsky's version of our hypothesis-testing system. Some research shows that sparse categorization is correlated with performance on a flanker task, which is often used to measure selection and inhibition (Perry & Lupyan, 2016). This suggests that at least some executive functions are related to sparse categorization.

Sloutsky's framework also discusses the development of these two systems. He suggests that children have access to the compression-based (associative) system early in development, as its mechanisms involve brain structures that develop relatively early, such as inferiotemporal cortex (Rodman, 1994). In contrast, the selection-based (hypothesis-testing) system involves more frontal regions that develop later, such as dorsolateral prefrontal cortex and anterior cingulate cortex (Eshel et al., 2007; Lewis, 1997; Segalowitz & Davies, 2004). Thus, this framework posits that the compression-based system develops before the selection-based system. Sloustky and others have done some studies on different age groups testing the two systems with categories of different densities to verify this claim.

Kloos & Sloutsky (2008) tested both of these systems in children and adults. They engaged the two systems separately by modifying task demands. Some participants learned novel categories by being taught the rules for inclusion (e.g., "Ziblets have a short tail."). This activated the selection-based (hypothesis-testing) system. Other participants learned these categories by viewing multiple members, engaging the compression-based (associative) system. Thus, the authors could test how well individuals could learn novel categories of different densities depending on whether the category density matched the system being engaged. For both children and adults, learning performance was high when the category density and task instructions matched. However, while the adults were able to adapt and learn the categories in mismatch conditions, children were specifically unable to learn sparse categories just by viewing multiple instances. This suggests that children are not able to use the selection-based system without direct guidance. Other evidence comes from a study of infants and adults which used a switching paradigm to investigate whether individuals were selecting specific features (using the selection-based/hypothesis-testing system) or processing the entire stimulus holistically (using the compression-based/associative system). They found that when viewing sparse categories, adults showed a significant switch cost as the category-relevant feature was changed, while infants did not. However, eye movement data did suggest that infants were able to learn the categories and were simply not selectively attending to category-relevant features (Best et al., 2013).

One consequence of the developmental trajectories of these systems is that sometimes children outperform adults on some tasks. One study tested adults and children on a change-detection task. Two differently-colored shapes were overlaid onto a screen, and participants were told to pay attention to one of the shapes. Then participants saw a short mask followed by two different shapes. Next, participants indicated if the cued shape was familiar. Finally, participants were asked to indicate if the picture (consisting of the two shapes) changed. For some trials, the cued shape changed, while in others the uncued shape changed or there was no change. This allowed the authors to determine whether participants attended to the cued and uncued shapes. Both adults and children showed high performance on change detection for the cued shapes (A' >.85), but adults did show significantly better performance on these trials. However, children showed significantly better performance than adults on change detection for uncued shapes. Similar results were found when children and adults were asked to perform familiarity judgments on items seen during a visual search task: high performance for both groups when probing items with changed relevant features, and higher performance for children than adults when probing items with changed irrelevant features (Plebanek & Sloutsky, 2017). The results from both of these experiments suggest that children attend to a stimulus in a diffuse manner, even when task demands suggest a selective strategy. This is consistent with a later-developing selection-based system, as children may be using the compression-based system for processing these features. The compression-based system preserves even category-irrelevant features.

Thus, Sloutsky's statistical density approach to category learning provides two major points for consideration. First, the statistical density metric itself emphasizes the idea that there aren't two distinct types of categories (e.g., rule-based and similarity-based). Instead, categories exist on a spectrum ranging between these extremes. It is still unknown how a dual-system model would deal with stimuli that lie directly in the middle of this spectrum, however. Second, this framework is one of few that describes a developmental trajectory for a dual-systems framework of category learning.

1.1.5 Verbal/nonverbal

Like some of approaches discussed above, the verbal/nonverbal approach is a dual-systems model of category learning. While other approaches discuss the role of language in category learning, none make it as central as this approach by Minda & Miles (2010). The two systems in this approach are called the **verbal** and

nonverbal systems. These systems align well both with the framework outlined in this paper as well as with other approaches. The verbal system uses hypothesis testing to determine the verbal rules best suited to characterize a category. In contrast, the nonverbal system uses associative mechanisms to learn categories, iteratively learning which features go together in predicting category membership.

A unique feature of this approach to category learning is its emphasis on traditional models of working memory and their role in the category learning process. Minda & Miles (2010) state that the verbal system relies heavily on working memory, especially the phonological loop and central executive, to rehearse and select potential rules (Baddeley & Hitch, 1974). The nonverbal system, meanwhile, uses the visuospatial sketchpad to store and rehearse visual information, but overall uses working memory to a lesser extent than the verbal system. Evidence for these hypotheses comes from a study of children and adults showing that children showed adult-like performance when learning categories that could be learned by the nonverbal system and reduced learning for categories that required use of the verbal system. This study also showed that adults showed more child-like performance when learning categories suited to the verbal system while under concurrent verbal load, suggesting that the verbal system indeed needs verbal working memory resources (Minda et al., 2008).

While the two systems described in Minda & Miles (2010) are quite similar to the systems hypothesized in this paper, there remains a core difference: the nonverbal system does not posit a role for language. This is likely due to the way Minda & Miles (2010) ground their dual-systems model in working memory. As will be discussed shortly, language can be very useful even for iterative, association-based learning, although perhaps not in the form of a verbal working memory resource. Thus, the verbal/nonverbal dual-systems model of category learning provides us with evidence that verbal working memory and executive resources support rule-based category learning but does not fully consider the ways in which language may influence category learning.

1.1.6 Taxonomic/thematic

As these previous frameworks have shown, when considering categories we must think carefully about how the items in a category relate to each other. The taxonomic/thematic framework is yet another way to consider relations within categories. **Taxonomically** related items are those we might think of as belonging to the same everyday category (e.g., animals, plants, tools, etc.). **Thematically** related items are those that go together in everyday life but are not necessarily part of the same category (e.g., needle and thread, apple and worm).

Similar to and perhaps even more so than the statistical density approach, the taxonomic/thematic framework has been able to provide many valuable insights about the developmental trajectory of categorization. Early research on this topic suggests that children are not sensitive to taxonomic relations, primarily categorizing items using thematic relations in kindergarten and switching to taxonomic relations later in childhood (Piaget et al., 1964; Vygotsky, 1962). **EXPLAIN TASK HERE**. Smiley & Brown (1979) found that the preference for taxonomic versus thematic relations switches between first and fifth grade as well as between college and old age, such that the very young and the elderly both show a preference for thematic relations. However, in another study, college-aged adult participants chose a taxonomically-related item more frequently in a triad task across ten different experiments, including one with the same stimuli used in Smiley and Brown's paper (Lin & Murphy, 2001).

1.2 Vocabulary/labels and category learning

1.3 Executive function and category learning

2 Experiment 1

2.1 Methods

2.1.1 Participants

Data was collected from 236 undergraduate psychology students at the University of Connecticut (161 Female, 67 Male, mean age = 18.94). Data for the category learning task was lost for 7 subjects due to technical errors. Thus, the final sample size was 229. Each subject was placed into one of six groups. Each group completed two blocks of the category learning task in a specific order. For more details, see Table 2. Unequal group sizes result from lost data due to technical errors.

Table 1. Group sizes for each order

Effect	Group	*N*
1	1	40
	2	38
2	3	39
	4	39
3	5	36
	6	37

2.1.2 Category Learning Task

This task measures learning of dense and sparse categories and is based off of a paradigm from previous research (Kloos & Sloutsky, 2008). Participants learn novel categories of items in four possible conditions in a 2 x 2 design. The first manipulation is learning type (supervised vs. unsupervised). In *supervised* learning, participants learn the categories by being instructed on the relevant features (e.g., All friendly aliens have big noses.). Images of the relevant features are provided along with the descriptions. In *unsupervised* learning, participants learn the categories by viewing sixteen instances of the category.

The second manipulation is category type (sparse vs. dense). Category type is measured by statistical density, which ranges from zero (where all features vary freely) to one (where all features co-occur perfectly). It is based on a comparison between within- and between-category entropy (Sloutsky, 2010). All categories in this experiment have seven dimensions. The *sparse* categories cohere on a single dimension, while the other dimensions vary freely (density = .25). In contrast, the *dense* categories cohere on six of the seven dimensions (density = .75). The seventh dimension is allowed to vary freely. For more details on how density was calculated, see Appendix A. Stimuli for each of the four blocks are different. See Fig. 1 for examples of the experimental manipulations.

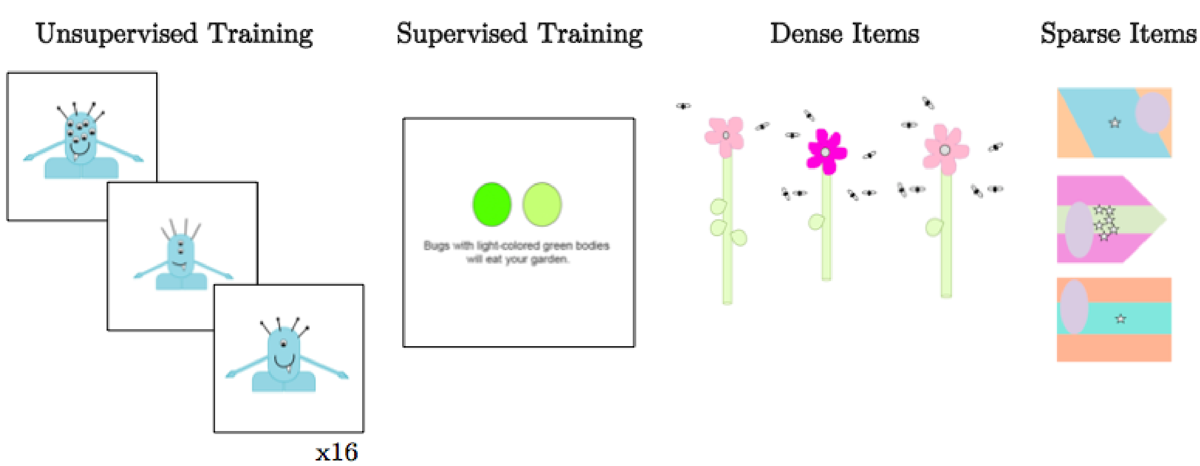

Figure 1. Examples of learning type and category type manipulations for category learning experiment.

This task is within-subjects. Based on the group they were placed into, participants completed two of the four possible learning-category type combinations. In this experiment, I tested three main order effects. First, I tested order effects for the matching conditions (unsupervised-dense and supervised-sparse).The second order effect used unsupervised-dense and supervised-dense blocks. Finally, the third order effect tested the same sparse stimuli, testing unsupervised-dense and supervised-sparse blocks. This design led to six possible order groups that each participant could be placed into. See Table 2 for a summary.

Table 2. Block orders for statistical density task

Effect	Group	Block 1	Block 2
1	1	Unsupervised-dense	Supervised-sparse
	2	Supervised-sparse	Unsupervised-dense
2	3	Unsupervised-dense	Supervised-dense
	4	Supervised-dense	Unsupervised-dense
3	5	Unsupervised-sparse	Supervised-sparse
	6	Supervised-sparse	Unsupervised-sparse

In each block, participants were introduced to the task through a short cover story. They were told to learn which items go with a certain property (e.g., which aliens are friendly). Crucially, no labels were attached to the categories (e.g., some aliens are Ziblets). Then, participants completed a training block (either supervised or unsupervised). After training, participants completed 40 test trials (16 target, 16 distractor, 8 catch), following the design of Kloos & Sloutsky (2008) . In each trial, participants saw a single item and used the keyboard to indicate whether the item matched the category they had just learned (e.g., if the alien is friendly). Catch items looked significantly different than both the target and competing categories, so participants should have always rejected them as members of the learned category. This experiment was presented using PsychoPy v.1.84.2 (Peirce, 2007).

2.1.3 Behavioral Measures

I used multiple assessments to test participants' language ability. The choice of assessments was based on the epiSLI criteria for language impairment (Tomblin et al., 1996), which includes comprehension, expression, vocabulary, grammar, and narrative. I adapted these requirements from a kindergarten population to a college-aged population. The epiSLI criteria have been shown to be robust for diagnosis of specific language impairment (SLI). In addition, other studies of language impairment more broadly have adapted a similar multidimensional approach to measuring language ability, sometimes including measures of phonological skills (Catts et al., 2006). Thus, using assessments that the many domains of language outlined in epiSLI criteria will allow me to get a fuller picture of individual differences in language ability. See Table 3 for a summary of the assessments and which domains of the epiSLI criteria they cover. The specific tests used in this experiment are detailed below.

Test of word reading efficiency (TOWRE) phonemic decoding subtest. TOWRE is a test of nonword fluency (Torgesen et al., 1992). This test is a part of the comprehension aspect of epiSLI, since the comprehension measure is reading-based. In the TOWRE, individuals have 45 seconds to read as many nonwords as possible. The nonwords become longer and more difficult as the list goes on.

Woodcock Johnson-III word attack (WA) subtest. This task measures nonword decoding ability (Woodcock et al., 2001). Like the TOWRE, it is helpful for measuring the comprehension aspect of epiSLI. However, while the TOWRE measures word fluency, this task measures decoding accuracy. Participants read a list of nonwords out loud at their own pace.

Computerized reading comprehension. This test covers the comprehension and narrative aspects of epiSLI. This computerized reading comprehension test is based on the Kaufman Test of Educational Achievement (KTEA) reading comprehension subtest (Kaufman & Kaufman, 2004). To create this test, I copied the passages and questions contained in the KTEA reading comprehension subtest into E-Prime (Schneider et al., 2002) for presentation on a computer. I created multiple choice answers for the KTEA questions that did not already have them. In this task, participants read short expository and narrative texts and answered multiple-choice comprehension questions about them. Some questions are literal, while others require participants to make an inference. Because this task is a modified version of the KTEA, I use raw scores in analysis rather than standardized scores based on the KTEA norms.

Nelson-Denny vocabulary subtest. The Nelson-Denny vocabulary sub-test is a written assessment of vocabulary (Brown et al., 1981). This test covers the vocabulary aspect of epiSLI. This test has been used in multiple studies of college-aged adults and provides sufficient variability for individual difference investigations in this population (e.g., Boudewyn et al. 2015; Stafura & Perfetti 2014). In this test, participants are asked to choose the word closest to a target vocabulary word.

Clinical Evaluation of Language Fundamentals recalling sentences subtest. I will use the recalling sentences subtest from the Clinical Evaluation of Language Fundamentals (CELF; Semel et al. 2006; Stafura & Perfetti 2014). This test covers the grammar and expression aspects of epiSLI. In this subtest, participants hear sentences and are asked to repeat them. Scoring is based on how many errors the participant makes in their repetition.

Finally, I used Set II of Raven's Advanced Matrices to measure nonverbal IQ (Raven, 1998). In this task, participants see a grid containing eight images and an empty space. The images are arranged in the grid according to some rule or rules. Participants must choose one of eight additional images that fits in the empty space.

Table 3. Assessments of language and their corresponding epiSLI domains.

Test	epiSLI Criteria
TOWRE WA	Comprehension (decoding aspect)
Computerized Reading Comprehension	Comprehension, narrative
ND Vocab	Vocabulary
CELF RS	Grammar, expression

2.2 Procedure

Each participant completed the category learning task as well as all of the behavioral measures. TOWRE, WA, and CELF were audio-recorded to allow for offline scoring. To allow multiple subjects to be run in a single timeslot, some participants received tasks they could complete on their own (category learning, ND, Computerized reading comprehension, Raven's) first while others completed tasks with the experimenter first (WA, CELF, TOWRE). All together, the seven tasks took approximately one hour.

2.3 Results

For all analyses shown below, accuracy was converted to *d'* values (Macmillan & Creelman, 2004) using the R package **neuropsychology** (Makowski, 2016). Correction for extreme values was done following (Hautus, 1995). Following prior research, all blocks where 5 or fewer catch items were correctly rejected were dropped from analysis. This resulted in 22 total missing blocks (out of 458 total), including both blocks from a single subject in group 5.

2.3.1 Order Effect 1: Matching Conditions

The first analysis investigated order effects for blocks in which the learning type (supervised vs. unsupervised) and category type (sparse vs. dense) both engaged the same category learning system (hypothesis testing vs. associative). Participants completed supervised-sparse and unsupervised-dense blocks.

I used linear mixed-effects models to examine the effects of block and order on accuracy at test. The relationship between accuracy and block/order showed significant variance in intercepts across participants $SD = 0.26$. Adding block and order as fixed effects significantly increased model fit, $\chi^2(2) = 13.04$, $p = 0.001$. Adding the interaction between block and order further improved model fit $\chi^2(1) = 6.05$, $p = 0.014$. Thus, the final model had fixed effects of block, order, and the interaction between block and order as well as random intercepts for subject.

The final model revealed three significant effects. First, there was not a significant main effect of block,

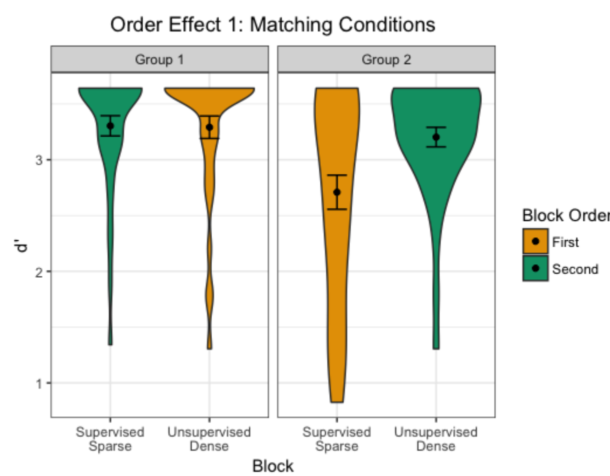

Figure 2. Accuracy (d') for each block completed by each group for the first order effect. Colors indicate which block was encountered first by each group. Points indicate means with error bars reflecting standard error. Shaded portions represent the distribution of accuracy values; wider portions indicate more subjects with that accuracy value.

b = -0.52, SE = 0.32, $t(74)$ = -1.60, p = 0.12. This model also showed a significant main effect of order, b = -0.59, SE = 0.16, $t(141)$ = -3.76, p = 0.0002. Finally, there was a significant interaction between block and order, b = 0.51, SE = 0.20, $t(72)$ = 2.48, p = 0.016. This interaction was broken down by conducting two separate models for each of the orders (unsupervised-dense first and supervised-sparse first). These analyses showed that when the associative system was engaged first (unsupervised-dense first), there was no significant main effect of block, b = -0.0064, SE = 0.11, $t(34)$ = -0.057, p = 0.95. When the hypothesis testing system was used first (supervised-sparse first), there is a significant effect of block, b = 0.50, SE = 0.17, $t(37)$ = 2.92, p = 0.0059. Inspection of means shows that when participants complete the supervised-sparse block first, performance on the supervised-sparse block is lower than in the unsupervised-dense block (see Figure 2).

2.3.2 Order Effect 2: Dense Stimuli

The second order effect analysis compared groups 3 and 4. All participants learned only dense categories, with the order of learning types differing between groups. Again, I used linear-mixed effects models to investigate the effects of block and order on accuracy at test. The variance in intercepts across participants had a standard deviation of 0.62. Adding the fixed effects to the model did not significantly improve fit $\chi^2(2) = 0.24$, $p = 0.89$. Inspection of coefficients confirmed this finding. Block was not a significant predictor of accuracy, b = 0.03, SE = 0.10, $t(145)$ = 0.27, p = 0.79. Similarly, order was not a significant predictor of accuracy, b = -0.04, SE = 0.10, $t(145)$ = -0.11, p = 0.68. Thus, accuracy at test on dense categories was similar regardless of training type or block order (see Figure 3).

Figure 3. Accuracy (d') for each block completed by each group for the second order effect.

2.3.3 Order Effect 3: Sparse Stimuli

The third order effect investigated differences in learning sparse categories based on learning type order, using data from groups 5 and 6. I used the same type of linear mixed-effect models as the prior two order effects. Random intercepts for subject had a standard deviation of 0.11. Adding block as a fixed effect significantly increased model fit, $\chi^2(1) = 59.44$, $p < 0.00001$. Adding order to this model did not further improve model fit $\chi^2(1) = 0.05$, $p = 0.82$. Thus, the final model had a fixed effects of block as well as random intercepts for subject, but no fixed effect of order or interaction between block and order. This model revealed a significant main effect of block, b = -1.14, SE = 0.13, $t(72)$ = -8.91, $p < 0.00001$. Inspection of means showed that participants exhibited better performance in supervised-sparse blocks than in unsupervised-dense blocks (see Figure 4).

2.3.4 Exploratory Order Analyses

An interesting feature of this experimental design is that both manipulations (learning type and category type) push individuals towards a certain category learning system. Supervised and sparse blocks encourage use of the hypothesis-testing system, while unsupervised and dense blocks evoke the associative system. Thus, mismatch blocks (i.e., unsupervised-sparse and supervised-dense) have conflicting information on which category learning system to use and thus likely are less effective at evoking that system. To investigate this possibility, I completed some exploratory analyses.

First, I compared unsupervised-dense blocks completed by groups 2 and 4. Group 2 completed a supervised-sparse (matching, hypothesis-testing) block before their supervised-dense block, while group 4 completed a supervised-dense (mismatch, hypothesis-testing) block before their unsupervised-dense block. If matching blocks more strongly evoke the category learning system and the hypothesized order effect (where activating the hypothesis-testing system first interferes with later use of the associative system) holds, then performance in group 2 on the unsupervised-dense block should be worse than performance in group 4 on the same block. A two-sample t-test indicated that this hypothesis did not hold – the two groups had equivalent performance ($t(73)$ = -0.62, p = 0.54).

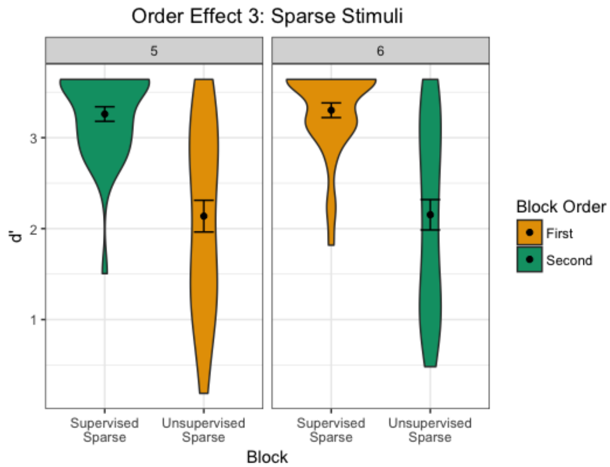

Figure 4. Accuracy (d') for each block completed by each group for the third order effect.

I extended this analysis by doing the sample thing for groups 1 and 5, who both completed the supervised-sparse block second. Group 1 completed an unsupervised-dense (match, associative) block before their supervised-sparse block and group 4 completed an unsupervised-sparse (mismatch, associative) block first. Again, a two-sample t-test indicated that the two groups had equivalent performance ($t(69) = 0.36$, $p = 0.71$).

As an additional check, I looked at two more comparisons. First, I compared the unsupervised-dense blocks for the two groups who completed it first, group 1 and group 3. There should be no difference between these groups on this block, since it was the first block each group encountered. A two-sample t-test confirmed this hypothesis ($t(70) = 0.097$, $p = 0.92$). I then checked the same thing for the supervised-sparse blocks within groups 2 and 6. Interestingly, these two groups were found to be different ($t(54)$ = -3.43, p = 0.001).

2.4 Discussion

2.4.1 Order Effects

The primary analyses looked at three different order effect. Each effect compared different ways to engage the hypothesis testing system before the associative system and vice versa. The first order effect used category learning blocks whose learning type and category type matched (i.e., supervised-sparse/hypothesis-testing, unsupervised-dense/associative). A significant interaction was found between block and order. Individuals who completed the unsupervised-dense/associative block first showed similar performance on both blocks. However, participants who completed the supervised-sparse/hypothesis-testing blocks first showed reduced performance in the supervised-sparse/hypothesis-testing block, with considerable recovery by the time they got to the unsupervised-dense/associative blocks. This result may be spurious, however, because the individuals in group 2 showed atypically low accuracy on their first block (supervised-sparse/hypothesis-testing), as compared to participants in group 6 that received the same block first and exhibited higher performance.

Overall, few order effects were found in accuracy. Most performance was close to ceiling. The main effect of block found in the third order analysis indicated that the unsupervised-sparse block may be more difficult overall. This is consistent with prior between-subjects research showing the worst performance in the unsupervised-sparse condition (Kloos & Sloutsky, 2008).

2.4.2 Individual Differences

3 Experiment 2

3.1 Methods

3.1.1 Participants

3.1.2 Category Learning Tasks

3.1.3 Behavioral Measures

3.2 Procedure

3.3 Results

3.4 Discussion

4 General Discussion

5 Appendix A: Statistical Density Calculations

5.1 Statistical Density Formulae

Statistical density is the method that Sloutsky and colleagues use to define categories (Sloutsky, 2010). Dense categories have multiple intercorrelated features, while sparse categories have few relevant features. Statistical density can vary between 0 and 1. Higher values (closer to 1) are dense, while lower values (closer to 0) are sparse. We calculate statistical density (D) with the following formula, where H_{within} is the entropy within the category and $H_{between}$ is the entropy between the category and contrasting categories.

$$D = 1 - \frac{H_{within}}{H_{between}}$$

To find total entropy(H), we sum entropy due to varying dimension and entropy due to varying relations among dimensions.

$$H = H^{dim} + H^{rel}$$

This equation is the same whether you are calculating within-category entropy or between-category entropy. To find entropy due to dimensions, you use the following formulas, where M is the total number of varying dimensions, w_i is the attentional weight of a particular dimension (assumed to be 1), and p_j is the probability of value j on dimension i.

$$H_{within}^{dim} = \sum_{i=1}^{M} w_i[\sum_{j=0,1} within(p_j log_2 p_j)]$$
$$H_{between}^{dim} = \sum_{i=1}^{M} w_i[\sum_{j=0,1} between(p_j log_2 p_j)]$$

To find entropy due to relations, you use a similar set of formulas, where O is the total number of possible dyadic relations among the varying dimensions, w_k is the attentional weight of a relation (assumed to be 0.5), and p_{mn} is the probability of the co-occurrence of values m and n on dimension k.

$$H_{within}^{rel} = -\sum_{k=1}^{O} w_k[\sum_{\substack{m=0,1\\n=0,1}} within(p_{mn} log_2 p_{mn})]$$
$$H_{between}^{rel} = -\sum_{k=1}^{O} w_k[\sum_{\substack{m=0,1\\n=0,1}} between(p_{mn} log_2 p_{mn})]$$

All categories have 7 dimensions. For dense categories, 6 of these dimensions are correlated. The seventh dimensions is allowed to vary randomly. For sparse categories, 6 of the dimensions vary randomly. The seventh dimension is category-relevant and defines the category. All dimensions have two levels (e.g., for hair shape in aliens – curly and straight).

5.2 Statistical Density Calculations – Sparse

First, we calculate the entropy due to dimensions. We have 7 dimensions, so $M = 7$. Between categories (i.e., across all categories), each level of each dimension has a 0.5 probability of being present.

$$H_{between}^{dim} = -7 * 1(2 * 0.5 log_2 0.5)$$
$$H_{between}^{dim} = -7 log_2 0.5$$
$$H_{between}^{dim} = 7$$

Within categories, the relevant dimension does not vary – thus it does not contribute to the entropy. Its value goes to zero, leading to the following calculations.

$$H^{dim}_{within} = -6 * 1(2 * 0.5log_2 0.5)$$
$$H^{dim}_{within} = -6log_2 0.5$$
$$H^{dim}_{within} = 6$$

To find the entropy due to relations, we start by calculating O.

$$O = \frac{M!}{(M-2)! * 2!}$$
$$O = 21$$

Between categories, all dyadic relations have the same probability of co-occurrence (0.25). For each relation between dimensions, there are 4 possible combinations of the levels of those dimensions. They're all equally probable. Recall that for relations, we use an attentional weight of 0.5. So, we end up with the following.

$$H^{rel}_{between} = -21 * 0.5(4 * 0.25log_2 0.25)$$
$$H^{rel}_{between} = -10.5log_2 0.25$$
$$H^{rel}_{between} = 21$$

Within the target category, 15 of the dyadic relationships don't include the relevant feature. Thus, their probability of co-occurrence is .25. For 6 of the dyadic relations (any including the relevant feature), there is perfect co-occurrence: probability is either 0 or 1. This makes these terms go to zero, because $log_2 1 = 0$, and anything multiplied by zero is zero.

$$H^{rel}_{within} = -15 * 0.5(4 * 0.25log_2 0.25)$$
$$H^{rel}_{within} = -7.5log_2 0.25$$
$$H^{rel}_{within} = 15$$

Now, we use these calculated values to find entropy between and within categories.

$$H_{within} = 6 + 15$$
$$H_{within} = 21$$
$$H_{between} = 7 + 21$$
$$H_{between} = 28$$

Finally, we use the within- and between-category entropy to calculate the density.

$$D = 1 - \frac{21}{28}$$
$$D = 0.25$$

5.3 Statistical Density Calculations – Dense

The between category entropy for dense categories is the same as for sparse categories. $H_{between} = 28$

Next, we will consider within-category entropy due to dimensions. Six of the seven dimensions do not vary, so they do not contribute to the entropy. Their value goes to zero.

$$H^{dim}_{within} = -1 * 1(2 * 0.5log_2 0.5)$$
$$H^{dim}_{within} = -log_2 0.5$$
$$H^{dim}_{within} = 1$$

Entropy due to relations is similar. Within the target category, 6 of the dyadic relationships don't include the relevant feature. Thus, their probability of co-occurrence is .25. For 15 of the dyadic relations, there is perfect co-occurrence, so their values go to zero.

$$H^{rel}_{between} = -6 * 0.5(4 * 0.25log_2 0.25)$$
$$H^{rel}_{between} = -3log_2 0.25$$
$$H^{rel}_{between} = 6$$

Next, we calculate the within-category entropy.

$$H_{within} = 1 + 6$$
$$H_{within} = 7$$

Finally, we use the within- and between-category entropy to calculate the density.

$$D = 1 - \frac{7}{28}$$
$$D = 0.75$$

References

Ashby, F. G., Alfonso-Reese, L. A., Turken, U., & Waldron, E. M. (1998). A neuropsychological theory of multiple systems in category learning. *Psychological Review*, *105*(3), 442–481. doi: 10.1037/0033-295X.105.3.442

Ashby, F. G., & Crossley, M. J. (2010). Interactions between declarative and procedural-learning categorization systems. *Neurobiology of Learning and Memory*, *94*(1), 1–12. doi: 10.1016/j.nlm.2010.03.001

Ashby, F. G., & Maddox, W. T. (2005). Human Category Learning. *Annual Review of Psychology*, *56*(1), 149–178. doi: 10.1146/annurev.psych.56.091103.070217

Ashby, F. G., & Maddox, W. T. (2011). Human category learning 2.0. *Annals of the New York Academy of Sciences*, *1224*(1), 147–161. doi: 10.1111/j.1749-6632.2010.05874.x

Ashby, F. G., Noble, S., Filoteo, J. V., Waldron, E. M., & Ell, S. W. (2003). Category learning deficits in Parkinson's disease. *Neuropsychology*, *17*(1), 115–124. doi: 10.1037/0894-4105.17.1.115

Baddeley, A. D., & Hitch, G. (1974). Working Memory. In *The psychology of learning and motivation* (Vol. 8, pp. 47–89). doi: 10.1016/S0079-7421(08)60452-1

Best, C. A., Yim, H., & Sloutsky, V. M. (2013). The cost of selective attention in category learning: Developmental differences between adults and infants. *Journal of Experimental Child Psychology*, *116*(2), 105–119. doi: 10.1016/j.jecp.2013.05.002

Boudewyn, M. A., Long, D. L., Traxler, M. J., Lesh, T. A., Dave, S., Mangun, G. R., ... Swaab, T. Y. (2015). Sensitivity to Referential Ambiguity in Discourse: The Role of Attention, Working Memory, and Verbal Ability. *Journal of Cognitive Neuroscience*, *27*(12), 2309–2323.

Brown, J. I., Bennett, J. M., & Hanna, G. (1981). *The Nelson-Denny Reading Test.* Chicago, IL: Riverside Publishing.

Carpenter, K. L., Wills, A. J., Benattayallah, A., & Milton, F. (2016). A Comparison of the neural correlates that underlie rule-based and information-integration category learning. *Human Brain Mapping*, *37*(10), 3557–3574. doi: 10.1002/hbm.23259

Catts, H. W., Adlof, S. M., & Weismer, S. E. (2006). Language deficits in poor comprehenders: a case for the simple view of reading. *Journal of Speech, Language, and Hearing Research*, *49*(2), 278–293. doi: 10.1044/1092-4388(2006/023)

Chandrasekaran, B., Yi, H.-G., & Maddox, W. T. (2014). Dual-learning systems during speech category learning. *Psychonomic bulletin & review*, *21*(2), 488–95. doi: 10.3758/s13423-013-0501-5

Chandrasekaran, B., Yi, H.-G., Smayda, K. E., & Maddox, W. T. (2016). Effect of explicit dimensional instruction on speech category learning. *Attention, Perception, & Psychophysics*, *78*(2), 566–582. doi: 10.3758/s13414-015-0999-x

Erickson, M. A. (2008). Executive attention and task switching in category learning: Evidence for stimulus-dependent representation. *Memory & Cognition*, *36*(4), 749–761. doi: 10.3758/MC.36.4.749

Eshel, N., Nelson, E. E., Blair, R. J., Pine, D. S., & Ernst, M. (2007). Neural substrates of choice selection in adults and adolescents: Development of the ventrolateral prefrontal and anterior cingulate cortices. *Neuropsychologia*, *45*(6), 1270–1279. doi: 10.1016/j.neuropsychologia.2006.10.004

Foerde, K., Knowlton, B. J., & Poldrack, R. A. (2006). Modulation of competing memory systems by distraction. *Proceedings of the National Academy of Sciences*, *103*(31), 11778–11783. doi: 10.1073/pnas.0602659103

Hautus, M. J. (1995). Corrections for extreme proportions and their biasing effects on estimated values ofd. *Behavior Research Methods, Instruments, & Computers*, *27*(1), 46–51. doi: 10.3758/BF03203619

Kaufman, A. S., & Kaufman, N. L. (2004). *Kaufman test of educational achievement - comprehensive form.* American Guidance Service.

Kloos, H., & Sloutsky, V. M. (2008). What's behind different kinds of kinds: effects of statistical density on learning and representation of categories. *Journal of Experimental Psychology: General*, *137*(1), 52–72. doi: 10.1037/0096-3445.137.1.52

Lewis, D. (1997). Development of the Prefrontal Cortex during Adolescence: Insights into Vulnerable Neural Circuits in Schizophrenia. *Neuropsychopharmacology*, *16*(6), 385–398. doi: 10.1016/S0893-133X(96)00277-1

Lin, E. L., & Murphy, G. L. (2001). Thematic relations in adults' concepts. *Journal of Experimental Psychology: General*, *130*(1), 3–28. doi: 10.1037/0096-3445.130.1.3

Lupyan, G. (2009). Extracommunicative functions of language: verbal interference causes selective categorization impairments. *Psychonomic bulletin & review*, *16*(4), 711–718. doi: 10.3758/PBR.16.5.986

Lupyan, G. (2012). What Do Words Do? Toward a Theory of Language-Augmented Thought. In B. Ross (Ed.), *Psychology of learning and motivation - advances in research and theory* (Vol. 57, pp. 255–297). Academic Press. doi: 10.1016/B978-0-12-394293-7.00007-8

Lupyan, G., & Mirman, D. (2013). Linking language and categorization: Evidence from aphasia. *Cortex*, *49*(5), 1187–1194. doi: 10.1016/j.cortex.2012.06.006

Lupyan, G., Mirman, D., Hamilton, R., & Thompson-Schill, S. L. (2012). Categorization is modulated by transcranial direct current stimulation over left prefrontal cortex. *Cognition*, *124*(1), 36–49. doi: 10.1016/j.cognition.2012.04.002

Macmillan, N. A., & Creelman, C. D. (2004). *Detection theory: A user's guide.* Psychology press.

Makowski, D. (2016). Package 'neuropsychology': An r toolbox for psychologists, neuropsychologists and neuroscientists [Computer software manual]. Retrieved from `https://github.com/neuropsychology/neuropsychology.R` (0.5.0)

Minda, J. P., Desroches, A. S., & Church, B. A. (2008). Learning rule-described and non-rule-described categories: A comparison of children and adults. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*(6), 1518–1533. doi: 10.1037/a0013355

Minda, J. P., & Miles, S. J. (2010). The influence of verbal and nonverbal processing on category learning. In B. H. Ross (Ed.), *The psychology of learning and motivation* (Vol. 52, pp. 117–162). Burlington: Academic Press. doi: 10.1016/S0079-7421(10)52003-6

Nomura, E. M., Maddox, W. T., Filoteo, J. V., Ing, A. D., Gitelman, D. R., Parrish, T. B., ... Reber, P. J. (2007). Neural correlates of rule-based and information-integration visual category learning. *Cerebral Cortex*, *17*(1), 37–43. doi: 10.1093/cercor/bhj122

Packard, M. G., & McGaugh, J. L. (1996). Inactivation of Hippocampus or Caudate Nucleus with Lidocaine Differentially Affects Expression of Place and Response Learning. *Neurobiology of Learning and Memory*, *65*(1), 65–72. doi: 10.1006/nlme.1996.0007

Peirce, J. W. (2007). PsychoPyPsychophysics software in Python. *Journal of Neuroscience Methods*, *162*(1-2), 8–13. doi: 10.1016/j.jneumeth.2006.11.017

Perry, L. K., & Lupyan, G. (2014). The role of language in multi-dimensional categorization: Evidence from transcranial direct current stimulation and exposure to verbal labels. *Brain and Language*, *135*, 66–72. doi: 10.1016/j.bandl.2014.05.005

Perry, L. K., & Lupyan, G. (2016). Recognising a zebra from its stripes and the stripes from zebra: the role of verbal labels in selecting category relevant information. *Language, Cognition and Neuroscience*, *3798*, 1–19. doi: 10.1080/23273798.2016.1154974

Piaget, J., Inhelder, B., & Lunzer, E. A. (1964). *The early growth of logic in the child: Classification and seriation.* Routledge & Kegan Paul.

Plebanek, D. J., & Sloutsky, V. M. (2017). Costs of Selective Attention: When Children Notice What Adults Miss. *Psychological Science*, *28*(6), 723–732. doi: 10.1177/0956797617693005

Raven, J. C. (1998). *Raven's progressive matrices.* Oxford: Oxford Psychologists Press.

Robinson, A. L., Heaton, R. K., Lehman, R. A., & Stilson, D. W. (1980). The utility of the Wisconsin Card Sorting Test in detecting and localizing frontal lobe lesions. *Journal of Consulting and Clinical Psychology*, *48*(5), 605–614. doi: 10.1037//0022-006X.48.5.605

Rodman, H. R. (1994). Development of Inferior Temporal Cortex in the Monkey. *Cerebral Cortex*, *4*(5), 484–498. doi: 10.1093/cercor/4.5.484

Schneider, W., Eschman, A., & Zuccolotto, A. (2002). *E-prime: User's guide.* Psychology Software Incorporated.

Segalowitz, S. J., & Davies, P. L. (2004). Charting the maturation of the frontal lobe: An electrophysiological strategy. *Brain and Cognition*, *55*(1), 116–133. doi: 10.1016/S0278-2626(03)00283-5

Semel, E. M., Wiig, E. H., & Secord, W. (2006). *CELF 4: clinical evaluation of language fundamentals.* Pearson: Psychological Corporation.

Sloutsky, V. M. (2010). From Perceptual Categories to Concepts: What Develops? *Cognitive Science*, *34*(7), 1244–1286. doi: 10.1111/j.1551-6709.2010.01129.x

Smiley, S. S., & Brown, A. L. (1979). Conceptual preference for thematic or taxonomic relations: A nonmonotonic age trend from preschool to old age. *Journal of Experimental Child Psychology*, *28*(2), 249–257. doi: 10.1016/0022-0965(79)90087-0

Soto, F. A., Waldschmidt, J. G., Helie, S., & Ashby, F. G. (2013). Brain activity across the development of automatic categorization: A comparison of categorization tasks using multi-voxel pattern analysis. *NeuroImage*, *71*, 284–297. doi: 10.1016/j.neuroimage.2013.01.008

Stafura, J. Z., & Perfetti, C. A. (2014). Word-to-text integration: Message level and lexical level influences in ERPs. *Neuropsychologia*, *64*(11), 41–53. doi: 10.1016/j.neuropsychologia.2014.09.012

Tomblin, J. B., Records, N. L., & Zhang, X. (1996). A System for the Diagnosis of Specific Language Impairment in Kindergarten Children. *Journal of Speech Language and Hearing Research*, *39*(6), 1284–1294. doi: 10.1044/jshr.3906.1284

Torgesen, J. K., Wagner, R., & Rashotte, C. (1992). *TOWRE-2: test of word reading efficiency.* Austin, TX: Pro-Ed.

Turner, B. O., Crossley, M. J., & Ashby, F. G. (2017). Hierarchical control of procedural and declarative category-learning systems. *NeuroImage*, *150*, 150–161. doi: 10.1016/j.neuroimage.2017.02.039

Vygotsky, L. S. (1962). Language and thought. *Massachusetts Institute of Technology Press, Ontario, Canada*.

Waldschmidt, J. G., & Ashby, F. G. (2011). Cortical and striatal contributions to automaticity in information-integration categorization. *NeuroImage*, *56*(3), 1791–1802. doi: 10.1016/j.neuroimage.2011.02.011

Woodcock, R. W., McGrew, K. S., Mather, N., & Schrank, F. (2001). *Woodcock-Johnson III NU tests of achievement.* Rolling Meadows, IL: Riverside Publishing.