Exploring the Role of Language in Two Systems for Categorization

Kayleigh Ryherd, PhD
University of Connecticut, 2019

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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. Individual differences in rule-based category learning have been shown to be related to an individual's cognitive flexibility (Reetzke et al., 2016).

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. 19).

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 (A. D. 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. The typical task in this line of research is a grouping task, where individuals are given a set of items and asked to group the ones that are ”alike” or ”the same.” Early research on this topic suggests that children primarily categorize items using thematic relations in kindergarten and switching to taxonomic relations later in childhood, although even this early work indicated that young children are able to learn taxonomic relations if necessary (Piaget et al., 1964; Vygotsky, 1962). 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 thematically-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).

Rather than being tied directly to age or ability, the preference for thematic or taxonomic classification may depend on an individual’s goals. Markman & Hutchinson (1984) had children between the ages of 2 and 4 complete a triad task. The children were shown a target picture (e.g. a tennis shoe) as well as two options: one that was taxonomically related (e.g., a high-heeled shoe) and one that was thematically related (e.g., a foot). The children were then asked to ”find the one that is the same.” With these directions, the children chose the thematically-related object about half of the time. However, when a novel label was applied to the task (e.g., This is a *dax*. Can you find another *dax*?), the children were more likely to choose the taxonomically related item. Thus, having a category label focused the task and directed attention towards taxonomic category structure rather than thematic relations. Further research in children between the ages of 2 and 4 manipulated many parts of the typical triad task, including experimenter instructions and medium of presentation (pictures vs. physical objects). They found that the thematic preference seen in Smiley & Brown (1979) seemed to be strongly affected by task instructions and age (Waxman & Namy, 1997). Some research suggests that what is developing in young childhood is not a sensitivity to different types of relations but instead the ability to flexibly switch between thematic and taxonomic relations according to task demands (Blaye & Bonthoux, 2001).

Taxonomic and thematic categories and processing share many similarities with the approaches discussed above. Taxonomic categories are like similarity-based categories. Both are what a typical individual would consider to be a "category;" they include natural kinds and artifacts. In contrast, thematic categories are more similar to rule-based categories. Both can be defined using a rule like "usually found in a kitchen" or "used for sewing." Thinking about rule-based categories in terms of thematic relations brings a new aspect to these categories: situational similarity. Often, rule-based categories are *ad hoc*, or created for and bound to a certain situation (e.g., "things to be sold at the garage sale"). Thus, when we think about how we learn and process rule-based categories using the hypothesis-testing system, we should keep in mind how we use our knowledge of situations or episodes in categorization.

To start to understand how processing taxonomic and thematic relations may differ, we can look to the brain. Much neuroimaging research has looked at how the brain responds to these two types of categories.

1.2 Vocabulary/labels and category learning

Much theory and research has considered how having a single word for a category or concept affects how an individual learns and processes that category. In this document, we will consider the word form associated with a given category (either spoken or written) to be the **category label**. Thus, a category has two potential pieces. First, there is the category's meaning. This refers to the way in which members belong to a category. As discussed previously, this can be a set of defined rules (e.g., anything you plan to sell is a part of the category *things to sell at the garage sale*) or an implicit set of fuzzy category boundaries (e.g., the ways in which you judge whether an item is a *chair*). The second piece of the category is its label. Individuals learning new categories often learn both the meaning and the label.

There have been multiple viewpoints on just how labels interact with the category or concept they describe and refer to. One line of thought postulates that labels are attached to concepts that can be formed in their absence (Gillette et al., 1999; Snedeker & Gleitman, 2004). This framework tends to focus on early-acquired object concepts, which are thought to be built nonverbally in the infant before language is acquired. Experiments done under this framework reveal interesting and important findings about the information that best supports a mapping between a category meaning and its label (e.g., having a syntactic frame for a category label leads to much quicker learning than just observing the use of the label in multiple situations). However, this viewpoint places little importance on the interplay between the label and the meaning; at best, the label is an additional way to access the meaning but does not seem to differ from any other feature.

Other researchers suggest that labels dynamically interact with meanings, and that having a single word for a meaning fundamentally changes how individuals think about and even perceive a category. In the words of Waxman & Markow (1995), words (labels) are "invitations to form categories". When a child encounters a novel word form applied to an object, they are initially biased to interpret that word form as a label for a category rather than the name of that singular object. Indeed, receiving a label for a category helps 12-month-old infants focus on common features more than just directive speech (Althaus & Mareschal, 2014). In adults, labels promote category learning even when they are redundant, and they do so even more than additional nonverbal features (Lupyan et al., 2007). Even more interestingly, having a label can change perceptual processing across development. Infants shown a certain set of objects without an accompanying label will sort these objects into multiple categories using visual features. However, if a single label is applied to the same set of objects, the infants will create only one category (Plunkett et al., 2008). In adults, hearing category labels affects visual perception. Participants asked to find 2s or 5s in a visual display showed better accuracy and shorter reaction time when hearing “two” or “five” immediately before the display appeared (Lupyan & Spivey, 2010).

The evidence cited above suggests that labels are special in some way. They are not simply additional features of fully-formed concepts. This may be because labels encourage individuals to focus on features that are more diagnostic (i.e., more often associated with members of a category) rather than instance-specific variation. A number of studies from Lupyan and colleagues support this idea. For example, Edmiston & Lupyan (2015) found that adults tended to look at more typical instances of a category when hearing a label. Thus, when hearing the word ”bird,” participants were more likely to look at a robin (a more typical bird) than a penguin. They also found that when listening to sounds associated with a category (e.g., bird chirp), participants tended to look at more likely sources of the sound (e.g., images of birds with their mouths open). This suggests that labels activate a typical, abstracted representation of a category while other sounds activate a more specific instance of that category that is congruent with the sound itself.

Similar findings come from a study looking at the formal category triangles. Triangles are by definition figures with three sides – any figure with three sides can be labeled a triangle. However, Lupyan (2017) found that typicality effects for triangles in multiple tasks were introduced when the word “triangle” was used. When asked to draw a triangle, participants most often drew isosceles or equilateral triangles with their base parallel to the horizontal (i.e., more canonical triangles). However, when instructed to draw a three-sided figure, participants drew a variety of triangles. The same typicality-related pattern of results was found for multiple other tasks, including typicality judgments, speeded recognition, and shape judgment. Another study found that pairing category instances with labels increased fixations on category-relevant features, as compared to pairing them with random words or silence, even for sparse categories (Barnhart et al., 2018). This study used an associative learning environment, where participants viewed many instances, were not asked to make category judgments, and were not provided any feedback on categorization. Thus, when the associative system is engaged, labels draw attention towards the most category-relevant features available.

This phenomenon is related to other research showing that other seemingly rule-based categories (e.g., grandmothers, odd numbers) show typicality effects (Armstrong et al., 1983; Lupyan, 2013). Armstrong and colleagues suggest that typicality effects are seen in what might be considered rule-based categories because these categories are defined both by rules for inclusion (e.g., having a grandchild) as well features that are used in identification (e.g., gray hair, tendency to bake cookies). This line of reasoning implies a continuum between rule-based and similarity-based categories, where categories with definite and verbalizable rules for inclusion are subject to processing most often associated with similarity-based categories. Thus, having a label for a category changes how individuals process that category, even when it has clearly-defined rules for inclusion.

Insight into why this might be the case comes from the Attentional Learning Account (ALA; Smith et al., 2002; Yoshida & Smith, 2005). The ALA posits that infants and young children extract statistical regularities from their environment and then use that knowledge to direct their attention towards future learning. For example, early-acquired words in English often refer to objects that are grouped based on their shape (e.g., ball). This regularity teaches the child to direct their attention towards shape when they learn a novel word. Children who are taught this regularity specifically in the laboratory also show greater vocabulary growth than untrained peers (Smith et al., 2002).

When thinking about the ALA, it is important to discuss the use of the word ”attention.” Attention can be driven either by the individual (endogenous) or by the environment (exogenous). In the endogenous case, the individual expends effort to focus on specific aspects of the stimulus (Engle & Kane, 2004). Alternatively, the environment can direct an individual’s attention to these different aspects. This exogenous case is perhaps more similar to the way attention is described in the ALA. As the individual learns that certain features tend to co-occur in a given stimulus (e.g., the name and shape of an object), an instance of one of those features draws attention towards the other. Since the label of a category is perhaps its most frequent feature, it co-occurs most often with other frequent (i.e., typical) features of that category. Thus, the typicality effects seen by Lupyan and colleagues specifically for category labels may be the result of individuals learning statistical regularities between labels and features.

This type of iterative learning where feature distributions are learned over time closely matches the associative system. In contrast, the hypothesis-testing system is much more focused on selecting one or a few relevant features and discarding those that do not characterize category membership. In fact, many of the categories best learned by the hypothesis-testing system (e.g., *ad hoc* categories) do not have a single-word category label. Thus, a core hypothesis of this dissertation is that category labels affect learning in the associative system but not in the hypothesis-testing system. In the next section, I will discuss how language might play a role in the hypothesis-testing system.

1.3 Executive function and category learning

The hypothesis-testing system involves many executive functions (e.g., selecting and maintaining relevant category rules, inhibiting irrelevant rules). Both inhibitory control and working memory have been shown to be related to rule-based category learning (Rabi & Minda, 2014). In addition, interfering with language resources specifically affects the low-dimensional, rule-based categorization that is best processed by the hypothesis-testing system (Lupyan, 2009; Minda et al., 2008). This suggests that language is important for this system. Thus, it is possible that language and executive functions work together in the hypothesis testing system.

Indeed, language ability and executive function have been shown to be related in multiple studies to varying degrees. For example, Figueras et al. (2008) found significant positive correlations between language measures such as vocabulary and receptive grammar and a wide variety of executive function tasks for school-age children. Berninger et al. (2017) found that performance on inhibition and verbal fluency sub-tests of the D-KEFS, a standardized measure of executive function, was correlated with language outcomes in children between the ages of 9 and 15. Children with specific language impairment have also been shown to have some executive function deficits, specifically in updating and inhibition (Im-Bolter et al., 2006). Findings have been more mixed for the nature of the causal relationship between these skills. One study found a strong concurrent relationship between language and executive function longitudinally for children between ages 4 and 9, but no cross-lagged effects (Gooch et al., 2016). This suggests that language and executive function are not directly influencing each other. However, another study found that language ability at 2-3 years predicts executive function at 4 years (Kuhn et al., 2014). Thus, it is possible that the relationship between executive function and language ability changes over development. Regardless, it appears as though language and executive function at least develop concurrently.

More evidence for the relationship between executive function and language comes from research on adults showing that interfering with verbal resources, usually through articulatory suppression, can negatively impact task switching (A. Baddeley et al., 2001; Emerson & Miyake, 2003). In a task-switching paradigm, performance typically decreases when an individual has to switch between tasks as compared to when they can perform the same task repeatedly. This decrease in performance is known as the switch cost. Articulatory suppression provides verbal interference by having the participant use language-related resources to repeat a nonsense string (e.g. “the the the”). In 6- and 9-year-old children, articulatory suppression has been shown to impair performance during task-switching but not during a flanker (inhibition) task (Fatzer & Roebers, 2012).

Interestingly, the negative effect of articulatory suppression on task switching is specific to instances where the individual must represent the task rules internally. For example, if participants must switch between different arithmetic functions such as addition and subtraction, verbal interference does not have an effect when the plus, minus, and equal signs are printed on the page A. Baddeley et al. (2001). A similar effect is found in a task-switching paradigm where participants must pay attention to different features of a stimulus. When the cue is the whole word (e.g., shape, color, etc.), articulatory suppression has no effect on switch cost. However, when the cue is just one letter (e.g., S, C, etc.), articulatory suppression increases the switch cost (Miyake et al., 2004). This effect suggests that task switching in these instances require a participant to use language to represent and formulate task rules (Cragg & Nation, 2010). These results indicate that language is important for representing and selecting rules, which may be similar to how the hypothesis testing system learns rule-based categories.

1.4 Overview of the current studies

2 Experiment 1

2.1 Method

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.

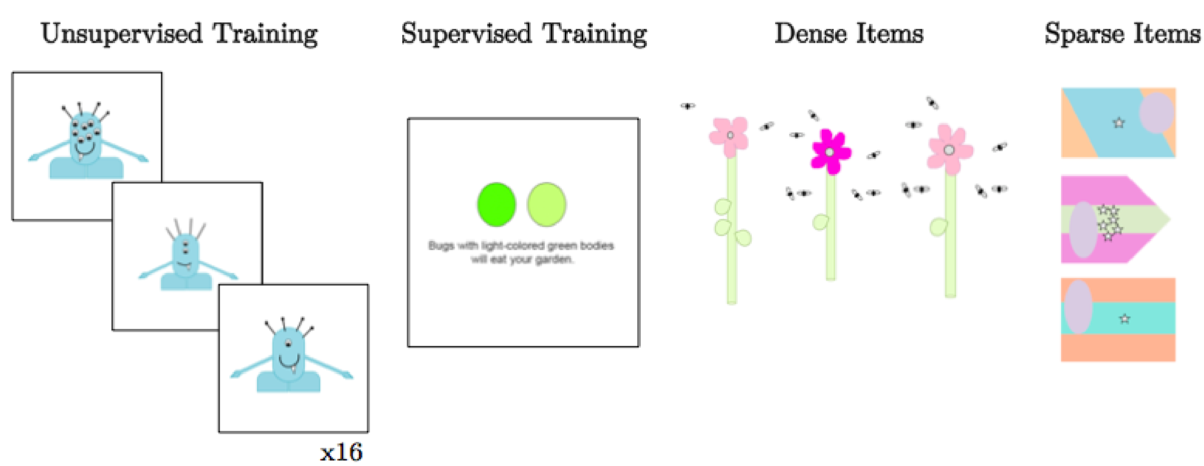

Figure 1. Examples of learning type and category type manipulations for category learning experiment.

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.

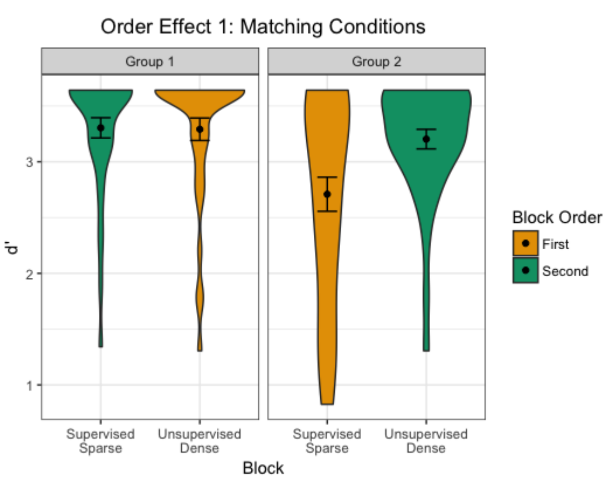

Figure 2. Accuracy (d') for each block completed by each group for the first order effect. Colors indicate which block was encountered first by each group. Points indicate means with error bars reflecting standard error. Shaded portions represent the distribution of accuracy values; wider portions indicate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

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

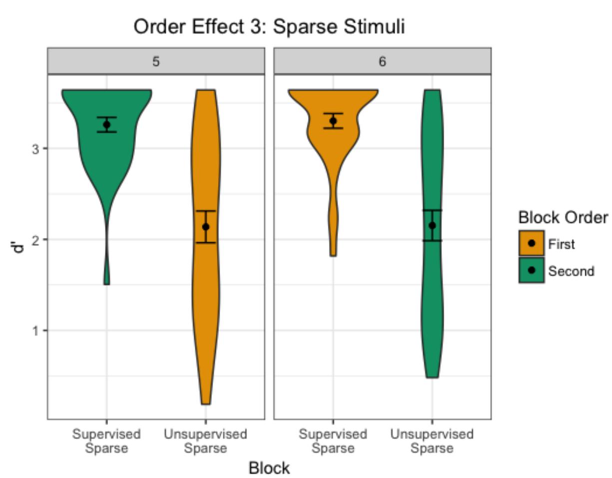

Figure 4. Accuracy (d') for each block completed by each group for the third order effect.

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 ($t(73) = -0.62$, $p = 0.54$).

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 Method

3.1.1 Participants

XX participants were recruited from the psychology undergraduate participant pool at the University of Connecticut (X Female, X Male, mean age = X).

3.1.2 Category Learning Tasks

This experiment used three different category learning tasks, each based on a different approach to category learning. We used these three tasks to investigate whether the paradigms used in different approaches engage category learning systems in a similar way. The order of category learning tasks was counterbalanced across participants. All category learning tasks were presented using PsychoPy v.1.84.2 (Peirce, 2007).

Sloustky statistical density task. This task used the same procedure and stimuli as the task described in Experiment 1. However, instead of completing only two blocks, participants completed all four blocks. Because the previous experiment showed few significant order effects, the order of the four blocks was randomly generated for each participant.

Ashby perceptual category learning task. There were two versions to this task: Information-Integration (II) and Rule-Based (RB). Participants completed the II version and then the RB version. Prior research has shown that when participants are asked to switch between the declarative (hypothesis-testing) and implicit (associative) systems, they end up using rule-based strategies from the declarative system for all trials. Thus, by engaging the implicit system first, we aimed to reduce transfer effects between versions as much as possible.

In each version of the task, participants were told that they would be learning two categories and that perfect performance was possible. They were also told to be as quick and accurate as possible. In each trial, participants viewed a Gabor patch that belonged to one of the two categories. Each patch subtended 11°of visual angle. The stimuli were generated using category parameters from Maddox et al. (2003). The participant then had 5000ms to press a key, indicating which category they believed the stimulus belonged to. After a response, the participant received feedback (”Correct” or ”Incorrect”). Feedback was presented for 1000ms, and then the next trial began. If the participant took more than 5000ms to respond, they saw ”Too Slow” and proceeded to the next trial. Participants completed five runs of each version. Each run had 80 trials (40 from each category) presented in a random order. Thus, in total participants completed 400 II trials and 400 RB trials.

Taxonomic/thematic task. This task was adapted from Murphy (2001) and Kalénine et al. (2009). There were also two versions of this task: one taxonomic and one thematic. Version order was counterbalanced across subjects, with some participants getting the taxonomic version first and others the thematic version first. Most versions of this type of task allow participants to choose the item that is most ”semantically related,” and thus do not ask participants to make either taxonomic or thematic choices on any given trial. As such, little research has looked at switching between taxonomic and thematic semantic judgments. Thus, counterbalancing was applied to control for order effects.

The stimuli were images taken from Konkle et al. (2010). We chose to use images in order to avoid automatic language processing. While participants likely did engage linguistic resources during the task, this should be due to how language relates to categorization rather than the features of the stimuli themselves. In each trial, four images were presented: a target, a taxonomically-related item, a thematically-related item, and an unrelated item. Taxonomically- and thematically-related items were chosen based on norms from Landrigan & Mirman (2016) where available. The Landrigan & Mirman (2016) norms were based on word stimuli rather than the images available from Konkle et al. (2010); as such, not all of the available images were normed. For images without norming information, we used our best judgment to pick items for each type of relation.

For each version, participants were told that they would be categorizing objects. They were told to pick the option that ”goes best with” (thematic) or is ”most similar to” (taxonomic) the target item. We chose these instructions based on previous research showing that slight differences in task instructions affect taxonomic and thematic judgments (Lin & Murphy, 2001). After instructions, participants got five practice trials. In each trial, the images were shown for 5000ms and participants had unlimited time to make a response. The practice trials were identical for the taxonomic and thematic versions of the task. After each response, participants received feedback (”Correct!” or ”Oops!”) for 1000ms. Once the practice trials were completed, participants received 24 test trials. While some images were seen in multiple trials, the 4-image combination for each trial was unique across the taxonomic and thematic versions of the task.

3.1.3 Executive Function Tasks

To measure executive function, we used three different tasks taken from the Psychology Experiment Building Language (PEBL) test battery (Mueller & Piper, 2014). We chose three tasks to try and tap multiple aspects of executive function, including inhibition, planning, and task-switching. All three tasks were presented using the PEBL software.

Flanker task (inhibition). This task was an implementation of the Eriksen & Schultz (1979) flanker task, using a method similar to Stins et al. (2007). In each trial, participants viewed a set of five arrows and were asked to respond based on the direction in which the center arrow was pointing (left or right). In congruent trials, all arrows faced the same way. In incongruent trials, the four distractor arrows pointed in the opposite direction of the target (center) arrow. In neutral trials, the four distractor arrows were just horizontal lines without arrowheads. Participants completed 20 trials for each condition in a 2 (direction; left vs. right) x 3 (condition; congruent vs. incongruent vs. neutral) design, for a total of 120 trials. **how many empty trials??** Each trial began with a 500 ms fixation, followed by the stimulus which appeared for 800ms. Participants were only allowed to respond during the 800ms that the stimulus was on the screen. After a response, there was an inter-trial interval of 1000ms. Participants received 12 practice trials before the actual experiment to get used to the timing of each trial. During practice trials, each response was followed by feedback (”Correct”, ”Incorrect”) as well as a number indicating RT for that trial. This feedback was not provided for the test trials.

Switcher task (task-switching). This task was taken from Anderson et al. (2012). In this task, participants are presented with an array of colored shapes. Each colored shape has a single letter inside. For each trial, a single shape was indicated to be the target shape. Based on instructions at the top of the screen, participants were told to select a shape that matched the target shape on one of three dimensions (color, shape, or letter). Research from Miyake et al. (2004) has shown that cueing a dimension using its entire name (e.g. ”shape”) does not require as many language resources as cueing a dimension using a single letter (e.g., ”s”). Since one of the core hypotheses of this study was that language supports executive functions in the hypothesis-testing system, we used a version of the switcher task that cued dimension using just a single letter. We expect that this version of the task requires individuals to represent dimensions/selection rules internally, similar to how they might represent possible category rules when learning rule-based categories.

The task consisted of nine different arrays of ten shapes. For each array, participants made ten responses. In the first three arrays, participants switched between two of the three dimensions in a fixed order (e.g., C - S - C - S, etc.). The relevant dimensions were different for each array. For the second three arrays, participants switched between all three dimensions still in a fixed order (e.g., S - C - L - S - C - L, etc). The specific order was different for each array. Finally, in the last three arrays participants switched between all three dimensions in a random order. Unlike previous arrays, in the last three participants were unable to anticipate the upcoming relevant dimension.

Tower of London task (planning). This task was a computerized version of the one described in Shallice (1982). In this task, participants were shown a setup of colored disks in three stacks as well as a target setup. They were given a limited number of moves to make their setup match the target setup. Participants could only have one disk in their ”hand” at a time, and they could only pick the top disk up off of any stack. The trials varied in the number of steps required to match the target setup from 2 to 5, with easier (2 step) trials at the beginning of the task and harder (5 step) trials at the end of the task. Participants were encouraged to take their time and plan out their moves before beginning each trial.

3.1.4 Behavioral Measures

Finally, we used four different behavioral assessments to measure vocabulary, syntax, and nonverbal IQ.. **Neson-Denny vocabulary subtest.** To measure vocabulary, we used the same Nelson-Denny vocabulary subtest described in experiment 1.

Clinical Evaluation of Language Fundamentals recalling sentences and formulated sentences subtests. We used the CELF here to measure individuals differences in syntax production and perception. The recalling sentences subtest allowed us to look at receptive grammar, while the formulated sentences subtest provided a measure of expressive grammar. In the formulated subtest, participants view a scene and are asked to make a sentence containing a target word about that scene. Often, the target word encourages certain syntactic structures (e.g., ”because”).

Raven’s Advanced Matrices. We used Raven’s Advanced matrices to measure nonverbal IQ, as described in Experiment 1.

3.2 Procedure

Each participant completed all of the category learning and executive function tasks, as well as all of the behavioral measures. CELF responses were audio-recorded to allow for offline scoring. To allow multiple subjects to be run in a single timeslot, some participants received tasks in a shuffled order. All together, the tasks and behavioral measures took about an hour and a half.

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*.

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

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

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*.

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

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

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.

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

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.

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

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