Exploring the Role of Language in Two Systems for Categorization

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University of Connecticut, 2019

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Exploring the Role of Language in Two Systems for Categorization

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A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

at the

University of Connecticut

2019

2019

APPROVAL PAGE

Doctor of Philosophy Dissertation

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2019

Acknowledgments

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1 General Introduction

Categories help us organize the world. They help us predict and hypothesize about category members and aid us in selecting the most appropriate response for each situation. Language plays a key role in categorization and category learning. It provides structure in the form of category labels and affects how we think about and even perceive the categories themselves. As Lupyan (2012) puts it, language augments our thought. Thus, any thorough investigation of how we learn categories must consider the role of language. Many theoretical frameworks do just this, often by separating categorization which involves language from that which does not. For example, COVIS, a key theory in perceptual category learning, emphasizes the competition between verbal and implicit systems for categorization (Ashby et al., 1998). Another theory explicitly separates category learning into verbal and nonverbal(Minda & Miles, 2010). However, this approach results in an all-or-none viewpoint of language's effect on category learning; language either influences category learning or it does not. In this process, the question of how language affects category learning is left unanswered.

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. Following the synthesis, I will review relevant literature that provides suggestions as to how language might be involved in category learning. 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 given category instance may not have all of the category-relevant features but does tend to have some distribution of them. For example, although Manx cats do

not have tails, a typical feature of cats, they 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.

In contrast, the **hypothesis-testing 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. First proposed by Ashby et al. in 1998, it is a prominent theoretical framework for perceptual category learning. 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 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 Ashby and colleagues 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 hypothesis-testing method can be used to learn them. When learning a new category, the

verbal system holds potential category inclusion rules in working memory that are then tested as stimuli are encountered. Over time, 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), suggesting that the verbal system relies at least partially on executive function.

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. 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. The structure of information-integration categories require an iterative, associative learning method. 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, where 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. The hippocampus 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 specific to rule-based categorization in the medial temporal lobe (MTL), which contains the hippocampus. 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 neurobiological 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. Information then runs to motor and premotor cortex. This 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). As with the verbal system, the neural basis of the implicit system requires more study.

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, a topic which will be discussed further below.

1.1.3 Dimensionality

The dimensionality approach, led by Lupyan and colleagues, considers categories in terms of the dimensions on which they cohere. Low-dimensional categories are the same on one or a small number of dimensions (e.g., color) and allow other dimensions to vary. Low-dimensional categories are similar to rule-based categories, as they can be described using relatively simple rules (e.g., *things that are red*). In fact, some of Lupyan's papers define low-dimensional categories as those that have a single dimension that can distinguish category members from non-members (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. Like similarity-based categories, high-dimensional categories require their members to be the same on most (but not all) relevant dimensions.

The core prediction tested using this approach is that low-dimensional categorization relies more heavily on language than high-dimensional categorization. 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 require language.

To explore this prediction, Lupyan and colleagues interfered with language ability in multiple ways across studies. In each study, they found that a reduction in language ability was associated with poorer performance on low- but not high-dimensional categorization. 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 but not for those based on multiple dimensions. Other studies manipulated language ability by using transcranial direct current stimulation (tDCS). One study found that reducing excitability in a language-critical region (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. Reducing excitability 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 strategies (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 suggests 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. In addition, while the authors claim that poorer low-dimensional categorization performance reflects difficulty in selecting category-relevant dimensions, the studies mentioned above do not directly test how interfering with language ability affects selection or inhibition ability.

1.1.4 Statistical Density

The statistical density framework focuses on the structure of categories defined by the relationships among members and non-members. Pioneered by Sloutsky, it proposes 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. 44).

The statistical density of a category is related to the ratio between the amount of entropy within a target category and the entropy between the target category and other categories in the set. In this context, entropy refers to variation within features. As an example, 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 the squares come in. The between-category entropy includes all of the variation in size, color, and shape for the items 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 together 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. The distribution of these other features are what determine the statistical density of a category. If irrelevant features (here, color and size) are correlated with the relevant feature(s), the category is dense. If they vary independently of the relevant features, the category is sparse. Thus, 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 used to learn 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, redundant and probable features are more likely to continue on. The many correlated features of a dense category are easily extracted using this system, which is quite similar to our 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 learns 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. The selection-based 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 would 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. The selection-based system 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 category learning.

The statistical density framework also discusses the development of these two systems. It 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. Sloutsky 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 a series of instances, engaging the compression-based (associative) system. Thus, the authors tested how well individuals could learn novel categories of different densities depending on whether the category density matched the system being en-

gaged. 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 from task instructions.

Other evidence for the developmental course of the two systems comes from a study of infants and adults. This study 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. This indicates that adults viewing sparse categories were focusing on a specific feature, while infants were processing the entire stimulus. Eye movement data also suggested that even though infants were processing stimuli holistically, they were still able to learn sparse categories (Best et al., 2013). Thus, this study found that adults and infants used different systems for learning the same categories.

A similar finding comes from a study of change detection. One study found that while both children and adults showed high accuracy when detecting change in a cued stimulus, children were better than adults at detecting change in task-irrelevant stimuli. 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 relevant features, and higher performance for children than adults when probing 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 processing these features using the compression-based system, which preserves even category-irrelevant features.

Thus, the 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 only a 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 showing that children, who have fewer working memory resources than adults, exhibited adult-like performance when learning categories using the nonverbal system and reduced performance 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 similarity-based 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 suggested that children primarily categorize items using thematic relations in kindergarten and switch 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.

1.2 The role of the label in 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, or 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 features that are specific to a given instance. 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 (a less typical bird). 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 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 the type of 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 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 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 Language and executive function in category learning

Most of the approaches discussed above specifically posit a role of language in the hypothesis-testing system. For example, interfering with language resources specifically affects the low-dimensional, rule-based categorization most suited to this system (Lupyan, 2009; Minda et al., 2008). However, these studies tend to focus on tying up language processing resources during categorization. This taps a different aspect of language than studies like Lupyan et al. (2007), which focuses on the presence or absence of a language-related feature. I propose that the language resources necessary for the hypothesis-testing system are those involved in and supporting executive functions. The hypothesis-testing system involves many executive functions (e.g., selecting and maintaining relevant category rules, inhibiting irrelevant rules). Additionally, both inhibitory control and working memory have been shown to be related to rule-based category learning (Rabi & Minda, 2014). Below, I will show how language and executive function work together, especially for tasks relevant to the hypothesis-testing system.

Language ability and executive function have been shown to be related to varying degrees in multiple studies. 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 subtests 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 been shown to have some executive function deficits, specifically in updating and inhibition (Im-Bolter et al., 2006). However, 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, suggesting that language and executive function are not directly influencing each other (Gooch et al., 2016). However, another study found that language ability at 2-3 years predicts executive function at 4 years (L. J. Kuhn et al., 2014). Thus, it is possible that the relationship between executive function and language ability changes over development. Regardless, language and executive function at least develop concurrently.

More evidence for the relationship between executive function and language comes from research in adults showing that interfering with verbal resources, usually through articulatory suppression, can negatively impact task switching, an executive function useful for switching between potential category rules during rule-based category learning (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 (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. In summary, language and executive function interact to support processing that is used by the hypothesis-testing system for rule-based category learning. While labels are the most important aspect of language for the associative system, language processing and its interaction with executive function are most important for the hypothesis-testing system.

1.4 Interaction between category learning systems

While much research has focused on outlining dual-systems models of categorization, very little research has investigated how these two systems might interact. Both COVIS and the verbal/nonverbal approach suggest that the two systems in a dual-systems model operate in parallel. Stimuli are processed by both systems, but category decisions are made using the faster system or the system with the strongest evidence. However, some research suggests that the hypothesis-testing system may be the default. Behavioral studies encouraging participants to switch between hypothesis-testing and associative strategies in a perceptual category learning task show that unless participants are cued towards which type of strategy to use on a given trial, they tend to use hypothesis-testing strategies for all trials (Ashby & Crossley, 2010; Erickson, 2008). This suggests that the hypothesis-testing system can overpower the associative system when both are equally activated. Still, this line of research requires much more empirical evidence before definitive claims can be made.

1.5 Summary and overview of the current study

So far, I shown evidence across theoretical approaches for a dual-systems model of category learning. Further, I have discussed literature suggesting that different aspects of language are involved in the two systems. Finally, I have pointed out the need for more within-subjects research on how these two systems interact. This document addresses these ideas and predictions with two experiments, which I will explain below.

Experiment 1 investigates the relationship between the associative and hypothesis-testing systems. Almost all of the studies discussed above utilize a between-subjects design to avoid transfer effects in learning. As such, it is still unclear how an individual switches between the systems in response to task demands and stimulus characteristics. Furthermore, some research suggests that low-language individuals have difficulty switching category learning strategies (Ryherd & Landi, 2019). Thus, this experiment tests effects of order on category learning performance across language ability. Given the results discussed in section 1.4, I expect that individuals will show specific difficulty disengaging the hypothesis-testing system but not the associative system. This will be reflected in poorer performance in associative blocks that take place after hypothesis-testing blocks than those that are before hypothesis-testing blocks. Furthermore, I expect that this difficulty will be greater for individuals with lower overall language ability. The results of this experiment will provide useful theoretical insight as well as practical insight into order considerations for dual-systems category learning tasks in a within-subjects design.

I use **Experiment 2** to answer two questions. First and foremost, I test the core hypothesis that the associative system is shaped by labels while the hypothesis-testing system relies on the interaction between language and executive functioning. I use vocabulary as a proxy for labeling in this experiment. Thus, I expect to see a strong relationship between vocabulary and associative category learning as well as between executive function and hypothesis-testing category learning. I expect to see either a weak relationship or no relationship between associative category learning and executive function and between hypothesis-testing category learning and vocabulary.

Finally, **Experiment 2** will also be one of the first studies to directly compare category learning approaches within subjects. I use three different category learning paradigms (from the COVIS, statistical density, and taxonomic-thematic approaches) to measure category learning ability. I expect to see significant effects of system (associative vs. hypothesis-testing) on performance within each paradigm, but no effects of paradigm on performance. This would suggest that these approaches, which appear theoretically similar, also tap the two systems in a similar manner empirically.

2 Experiment 1

The goals for this experiment were twofold. First, I hoped to test order effects in a paradigm originally designed to test a dual-systems model of categorization. Despite the fact that many approaches posit such a model, only one approach (COVIS) has explicitly tested how a given individual switches between systems for categorization (e.g., Ashby & Crossley, 2010; Erickson, 2008, described above). Most other studies that compare different types of categorization do so in a between-subjects manner (e.g., Kloos & Sloutsky (2008)). Thus, this study is one of the first to look at the relationship between two categorization systems using a non-COVIS within-subjects design. This task is also the first to test how individual differences in language ability modulate this relationship.

This experiment also has a more practical purpose. One of the overarching goals of this dissertation is to compare different paradigms of category learning. However, all studies using a statistical density approach have been done between subjects, so we do not yet know if there are any transfer effects for this type of task. In addition, no studies to date have tested for transfer effects along the spectrum of language ability. This experiment carefully conducts three order analyses to fully understand the statistical density category learning task. This will benefit both practical understanding of this task as well as its underlying theoretical framework.

An interesting feature to the statistical density task is its two manipulations, each of which engages or requires one of the two category learning systems. First, the instruction type engages either the associative or the hypothesis-testing system by placing different task demands. Second, the stimulus requires a certain category learning system. Recall that dense and sparse stimuli are best learned by different systems. Thus, each block can either be a match (where the instruction type engages the ideal system for the stimulus type) or a mismatch (where the instruction type engages the wrong system for the stimulus type).

To fully understand this task, I tested for order effects in both matching and mismatching conditions. First, I tested order for the matching conditions. This analysis is the most simple and straightforward test of order; can participants switch between systems when both the stimulus type and the learning type cue a certain system? The second order analysis tested dense stimuli to see whether participants were able to engage the associative system even when the learning instructions sometimes cued the hypothesis-testing system. Further, if participants were unable to overcome the learning instructions and ended up using the hypothesis-testing system in their first block, this analysis investigated whether they could switch to the associative system in subsequent blocks following task demands. Finally, the third order analysis tested sparse stimuli. Similarly, I tested whether participants could engage the hypothesis-testing system to learn sparse stimuli even when task demands cued the associative system. This order analysis also tested the

participants' ability to subsequently switch away from the associative system.

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, which led to slightly unequal group sizes. 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 3.

Table 1

Group sizes for each order.

Analysis	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 (learning type) x 2 design (stimulus type). Table 2 summarizes how each experimental manipulation corresponds to the theorized category learning systems. Learning type can be either supervised or 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.

Table 2

Relationship between learning systems and experimental manipulations.

Experimental feature	Hypothesis-testing	Associative
Learning type	Supervised	Unsupervised
Stimulus type	Sparse	Dense

Categories in this experiment can either be sparse or dense. Category density ranges from zero (where all features vary freely) to one (where all features co-occur perfectly), 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. **??** for examples of the experimental manipulations.

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 conducted three different order analyses. This design led to six possible order groups that each participant could be placed into; see Table 3 for a summary.

Table 3

Block orders for statistical density task.

Analysis	Group	First Block	Second Block
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 (supervised or unsupervised). During training, only members of the target category or its features were shown. 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 cover the many domains of language outlined in epiSLI criteria allowed me to get a fuller picture of individual differences in language ability. See Table 4 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 (Gough & Tunmer, 1986). In this subtest of 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. The raw score from the TOWRE was calculated by counting the number of words correctly pronounced before the time limit. These raw scores were then converted to standard scores using age-based norms. The standard scores for this task are based on a distribution with a mean of 100 and a standard deviation of 15. In the current age range, a perfect raw score (63) on the TOWRE returns a standard score of ">120." For the purposes of this study, scores of ">120" were trimmed to 120.

Woodcock Johnson-III word attack (WA) subtest. This task measures nonword decoding accuracy (Woodcock et al., 2001). Like the TOWRE, it is helpful for measuring the comprehension aspect of epiSLI. Participants read a list of nonwords out loud at their own pace. Raw scores were calculated by counting the number of words the participant said correctly. Raw scores were converted to standard scores using age-based norms. The standard score distribution has a mean of 100 and a standard deviation of 15.

Computerized reading comprehension. This test covers the comprehension and narrative aspects of epiSLI. This computerized reading comprehension (CRC) 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. Then, 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 answer multiple-choice comprehension questions about them. Some questions are literal, while others require participants to make an inference. Participants completed as many questions as they could in 10 minutes. Once 10 minutes had elapsed, the participant was allowed to answer the question currently on the screen and then the assessment closed. Because this task is a modified version of the KTEA, I used raw scores in analysis rather than standardized scores based on the KTEA norms. Raw scores were calculated by counting the number of correctly answered questions for each participant.

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. The test has a total of 80 items. Participants were allowed unlimited time to complete all items. Raw scores were generated by counting the total number

of correctly answered items. The raw scores were then converted to standard scores based upon a norming sample including students in 10th, 11th, and 12th grade as well as two- and four-year college students. The standard scores for this assessment have a mean of 200 and a standard deviation of 25.

Clinical Evaluation of Language Fundamentals recalling sentences subtest. I used the Recalling Sentences subtest from the Clinical Evaluation of Language Fundamentals - Fourth Edition (CELF; Semel et al. 2006) to cover the grammar and expression aspects of epiSLI. In this subtest, participants hear sentences and are asked to repeat them. Scoring was based on how many errors the participant makes in their repetition. Raw scores were calculated by adding up the number of points achieved for each item. These were then converted to standard scores using age-based norms. The standard scores are based on a distribution with a mean of 10 and a standard deviation of 3.

Table 4

Assessments of language and their corresponding epiSLI domains.

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

Raven's Advanced Matrices. Finally, I used Set II of Raven's Advanced Matrices (RAM) 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. Due to time constraints, I restricted participants to 10 minutes in this task. Since this administration is different than the standard administration, I did not use standard scores. Raw scores were calculated by counting the number of correct answers given within 10 minutes.

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). Together, the seven tasks took approximately one hour.

2.3 Results

2.3.1 Category Learning Task Data Processing

First, 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. 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). For reaction time, all incorrect trials were discarded. Then, outliers were removed on a by-trial basis by calculating the mean and standard deviation of RTs within a given subject and block. Any trial with an RT more than 2 SDs away from the mean was discarded. For basic descriptive statistics on the category learning task, see Table 5.

Table 5

Descriptive statistics for the category learning task.

Analysis	Group	Block	Mean (SD) Accuracy	Mean (SD) RT (ms)
1	1	Unsupervised-dense	0.91 (0.19)	958 (291)
		Supervised-sparse	0.93 (0.14)	705 (291)
	2	Supervised-sparse	0.72 (0.34)	759 (385)
		Unsupervised-dense	0.90 (0.18)	742 (370)
2	3	Unsupervised-dense	0.91 (0.18)	963 (499)
		Supervised-dense	0.91 (0.23)	834 (429)
	4	Supervised-dense	0.90 (0.21)	854 (482)
		Unsupervised-dense	0.92 (0.18)	777 (394)
3	5	Unsupervised-sparse	0.57 (0.35)	1166 (600)
		Supervised-sparse	0.93 (0.14)	715 (311)
	6	Supervised-sparse	0.93 (0.12)	752 (353)
		Unsupervised-sparse	0.53 (0.38)	917 (470)

2.3.2 Behavioral Measures

For basic descriptive statistics on the behavioral measures, see Table 6. Before performing any statistical analyses using these measures, I checked their normality using the D'Agostino normality test from the R package **fBasics** (Wuertz et al., 2017). Four measures (CRC, ND Vo-

Table 6

Descriptive Statistics for Behavioral Measures

Assessment	Mean	SD	Range
CELF Recalling Sentences SS	10.7	1.86	3-14
Computerized Reading Comprehension	21.7	5.12	7-48
Nelson-Denny Vocabulary SS	229	14.0	175-255
TOWRE SS	96.2	9.86	59-120
Word Attack SS	99.7	9.04	75-120
Raven's Advanced Matrices	15.1	4.58	0-26

cab, CELF RS, RAM) were significantly

skewed. These measures were centered, scaled, and transformed using Yeo-Johnson transformations from R package **caret** (M. Kuhn, 2017). The remaining measures (TOWRE, WA) were not skewed and thus were simply scaled and centered.

Since my goal was to create a composite measure of language ability, I investigated the relationship between the behavioral measures. First, I constructed a correlation matrix between all of the behavioral measures (see Table 7). All pairs of measures had a significant positve correlation with the exception of CELF RS and RAM. To further test whether the behavioral measures could be combined into a single composite, I ran a principal components analysis (PCA) on the 5 assessments related to epiSLI (i.e., all assessments except RAM). The Kaiser-Meyer-Olkin overall measure of sampling adequacy was 0.69, above the commonly accepted threshold of 0.6. Bartlett's test of sphericity was also significant $\chi^2(10) = 236.16$, $p < 0.001$. Both suggest that the 5 behavioral assessments were suitable for a PCA.

The first component in the PCA accounted for 47.74% of the variance and had an eigenvalue of 2.38. All of the factor loadings for this component were quite similar, ranging from -0.41 to -0.51. The second factor accounted for an additional 20.5% of the variance and had an eigenvalue of 1.02. This factor separated the two measures involved in decoding (TOWRE and WA) from the other measures (CRC, ND Vocab, and CELF RS). The remaining components had eigenvalues below 1. Thus, of the two significant components, the first component explained almost half of the variance and had an eigenvalue more than double the second component, which largely represented decoding ability. Since the first component indicated that most of the measures loaded similarly, I decided to take a simple means approach to creating a language composite measure.

The language composite measure was created by averaging the 5 scaled, centered, and/or transformed measures. For participants with missing behavioral measures, the composite was created by averaging the remaining available measures. No subject was missing more than 1 measure. This composite measure was then scaled but not centered. This language composite measure and the centered, scaled, and transformed RAM measure are used in the analyses investigating order effects reported below.

Table 7

Correlations between behavioral measures.

	1	2	3	4	5	6
1. Computerized Reading Comprehension	-					
2. Nelson-Denny Vocabulary	0.57***	-				
3. CELF Recalling Sentences	0.31***	0.40***	-			
4. Raven's Advanced Matrices	0.31***	0.34***	0.09	-		
5. TOWRE	0.22**	0.28***	0.26***	0.16***	-	
6. Word Attack	0.22**	0.38***	0.29***	0.22***	0.53***	-

Note. $p < 0.05$, $^{**}p < 0.001$, $^{***}p < 0.0001$

2.3.3 Order Analysis 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 (hypothesis-testing) and unsupervised-dense (associative) blocks.

Sensitivity. I used linear mixed-effects models to examine the effects of block and order on sensitivity at test. Sensitivity in these models was measured by *d'* values for each subject by block. The base model included random intercepts for subject. Adding block and order as fixed effects significantly increased model fit, $\chi^2(2) = 13.21$, $p = 0.001$. Adding the interaction between block and order further improved model fit, $\chi^2(1) = 6.03$, $p = 0.014$. Thus, the final model including only experimental conditions had fixed effects of block, order, and the interaction between block and order as well as random intercepts for subject.

This model revealed two significant effects. First, there was a significant main effect of order, $F(1,75) = 8.60$, $p = 0.004$. There was also a significant interaction between block and order, $F(1,74) = 6.10$, $p = 0.02$. There was not a significant main effect of block, $F(1,76) = 2.61$, $p = 0.11$. The 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, $F(1,36) = 0.014$, $p = 0.91$. When the hypothesis testing system was used first (supervised-sparse first), there was a significant effect of block, $F(1,37) = 7.52$, $p = 0.009$. This shows that when participants complete engage the hypothesis-testing system first, performance on the supervised-sparse (hypothesis-testing) block is lower than in the unsupervised-dense (associative) block.

To investigate the effect of individual differences in language ability on the order effect, I used the final model above which included main effects for block and order as well as their interaction. I then added the

language composite measure as a fixed effect. I also added RAM to control for nonverbal IQ. This model revealed no significant effects for RAM or the language composite; there remained a significant interaction between block and order.

Reaction time. Again, I used linear-mixed effects models to look at the effects of block and order on reaction time at test. While the sensitivity measure was at the block level, reaction time here is modeled at the item level. The base model included random intercepts for subject and for block nested within subject. Adding the fixed effects of block and order increased the model fit, $\chi^2(2) = 25.02$, $p < 0.001$. Further, adding the interaction between block and order improved model fit, $\chi^2(1) = 33.11$, $p < 0.001$.

This model showed three significant effects. There was a significant main effect of block, $F(1,72) = 62.50$, $p < 0.001$. There was also a significant main effect of order, $F(1,77) = 4.17$, $p = 0.04$. Finally, there was a significant interaction between block and order, $F(1,72) = 40.49$, $p < 0.001$. To break down this interaction, I ran follow-up models for each of the two orders. This showed that when the associative system was engaged first (unsupervised-dense first), there was a significant main effect of block, $F(1,36) = 69.46$, $p < 0.001$. When the hypothesis testing system was used first (supervised-sparse first), there was no significant effect of block, $F(1,36) = 0.02$, $p = 0.88$. This result is the opposite of what was found in accuracy. When the associative system is engaged first, we see a difference in reaction time between blocks, but when the hypothesis-testing system in engaged first, there is no difference in reaction time.

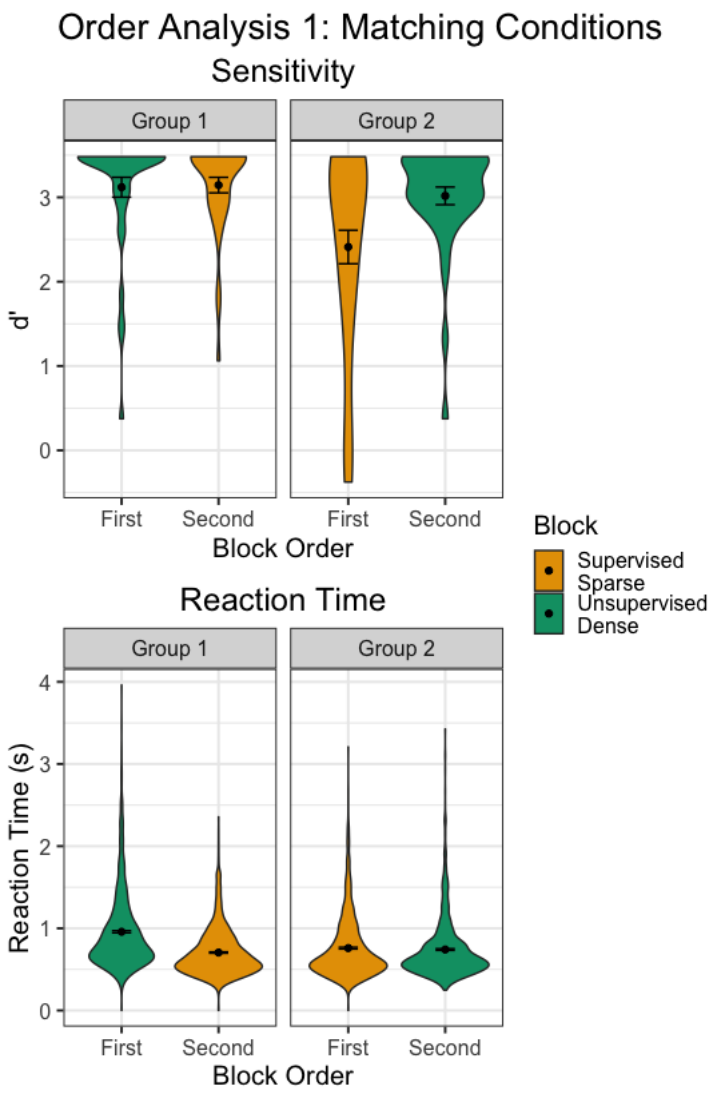

Figure 1. Sensitivity (d') and reaction time for each block completed by each group for order analysis 1. Points indicate means with error bars reflecting standard error. Shaded portions represent the distribution of sensitivity or reaction time values.

Similar to the sensitivity analysis, I added RAM and language ability as fixed effects to the final reaction time model from above. Neither had any effect on reaction time. The main effects and interactions from above stayed significant.

Summary (see Fig. 1). While the findings from sensitivity and reaction time seem to be opposing, they may in fact tell the same story. Group 1 engaged the associative system first. This group showed similar accuracy for both blocks but slower reaction time in their first block (unsupervised-dense/associative). Group 2 engaged the hypothesis-testing system first. They showed similar reaction times for both blocks, but lower accuracy in their first block (supervised-sparse/hypothesis-testing). Thus, both groups showed reduced performance (reflected in either reaction time or sensitivity) in their first block, regardless of which system it engaged, perhaps reflecting a general learning effect across the task as a whole. Importantly, this learning effect is not modulated by language ability.

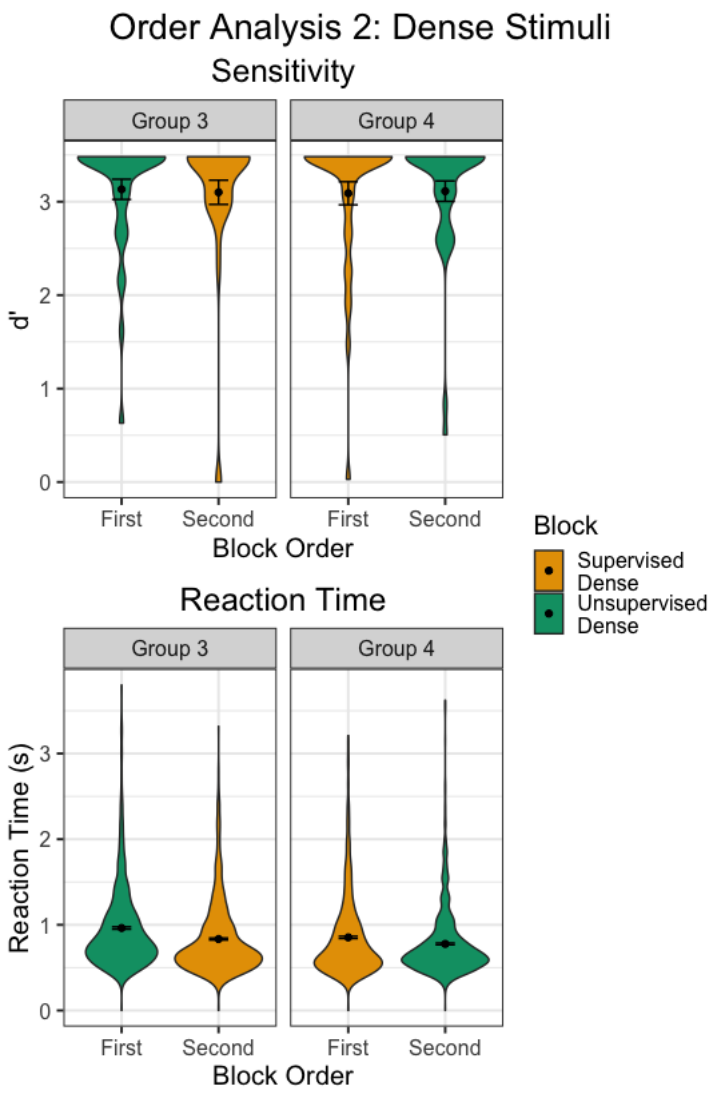

Figure 2. Sensitivity (d') and reaction time for each block completed by each group for order analysis 2. Points indicate means with error bars reflecting standard error. Shaded portions represent the distribution of sensitivity or reaction time values.

2.3.4 Order Analysis 2: Dense Stimuli

The second order analysis compared groups 3 and 4. All participants learned only dense categories, with the order of learning types differing between groups.

Sensitivity. Again, I used linear-mixed effects models to investigate the effects of block and order on sensitivity at test. The base model included random intercepts for subject. Adding the fixed effects to the model did not significantly improve fit $\chi^2(2) = 0.07$, $p = 0.97$. Indeed, neither block, $F(1,145) = 0.053$, $p = 0.82$, nor order, $F(1,145) =$

0.016, p = 0.90, were significant predictors of accuracy. Thus, sensitivity at test on dense categories was similar regardless of training type or block order. Next, I conducted the individual differences analysis. Since the goal of this investigation was to see whether the relationship between order and sensitivity in each block changed as a function of language ability, I created a model with fixed effects for block, order, and language ability as well as RAM. The model showed no significant effects of any of the predictors.

Reaction time. I used the same linear mixed-effects model as above, with random intercepts for subject and for block nested within subject in the base model. Adding fixed effects of order and block did not significantly improve model fit, $\chi^2(2) = 3.38$, $p = 0.18$. Block, $F(1,71) = 1.12$, $p = 0.29$, and order, $F(1,76) = 2.28$, $p = 0.13$, did not have any effect on reaction time. Adding language ability and RAM to the model also did not improve fit. These measures were not significant predictors of reaction time for dense stimuli.

Summary (see Fig. 2). There were no significant effects of block, order, or language ability found for dense stimuli. This may suggest that learning dense stimuli engages a single system regardless of the instructions. Alternatively, it may be that learning dense stimuli is overall an easy task, evidenced by the high sensitivity values seen in these blocks.

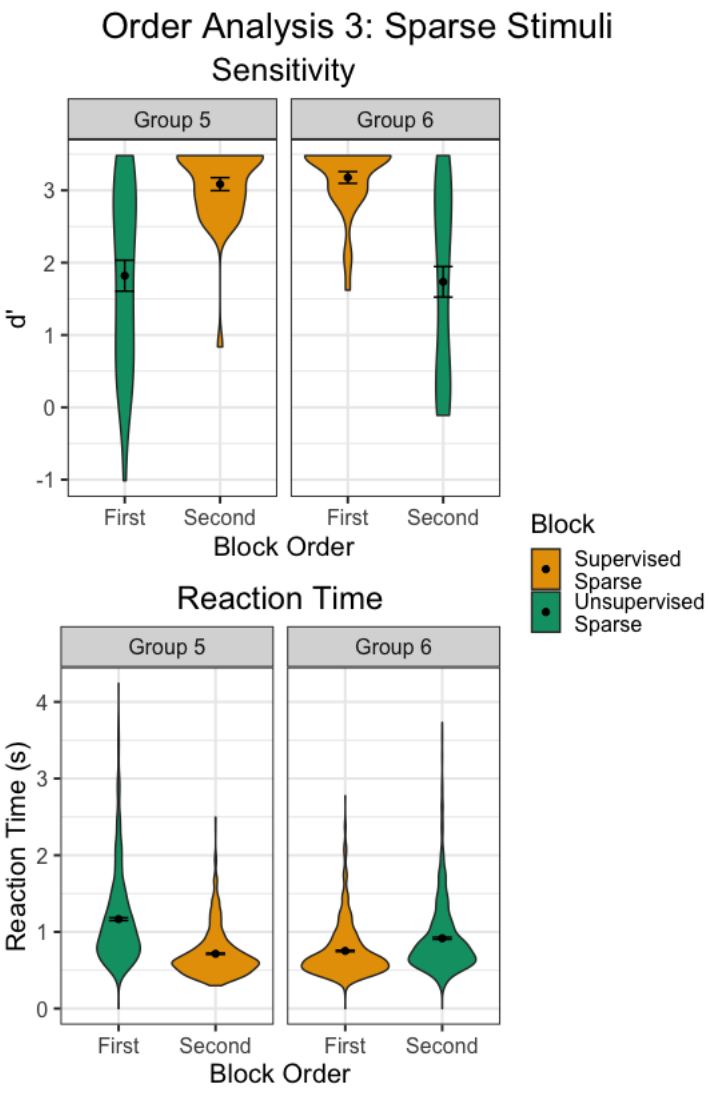

Figure 3. Sensitivity (d') and reaction time for each block completed by each group for order analysis 3. Points indicate means with error bars reflecting standard error. Shaded portions represent the distribution of sensitivity or reaction time values.

2.3.5 Order Analysis 3: Sparse Stimuli

The third order analysis investigated differences in learning sparse categories based on learning type order, using data from groups 5 and 6.

Sensitivity. I used the same type of linear mixed-effect models as the prior two order effects, with random intercepts for subject. Adding block and order significantly increased model fit, $\chi^2(2) = 57.5$, $p < 0.001$. However, adding the interaction between block and order did not increase model fit, $\chi^2(1) = 0.33$, $p = 0.56$. Thus, the final model included fixed effects for order and block but not their interaction. This model revealed a significant main effect of block, $F(1,67) = 75.69$, $p < 0.0001$, but no significant main effect of order, $F(1,67) = 0.0008$, $p = 0.98$. Participants showed significantly higher sensitivity in supervised-sparse blocks than in unsupervised-sparse blocks (see Table 5).

As in the two previous analyses, I added RAM and language ability to the final model above. Adding the language composite improved model fit even after adding RAM, $\chi^2(2) = 5.34$, $p = 0.02$. However, adding the block x language and order x language interactions did not improve model fit, $\chi^2(2) = 1.94$, $p = 0.38$. The final model, which included no interactions, showed the same main effect of block seen above as well as a significant main effect of language ability, $F(1,63) = 5.21$, $p = 0.03$. The effect of language ability was associated with a positive coefficient ($b = 0.19$, $SE = 0.09$), suggesting that sensitivity and language ability were positively related. There was no main effect of RAM.

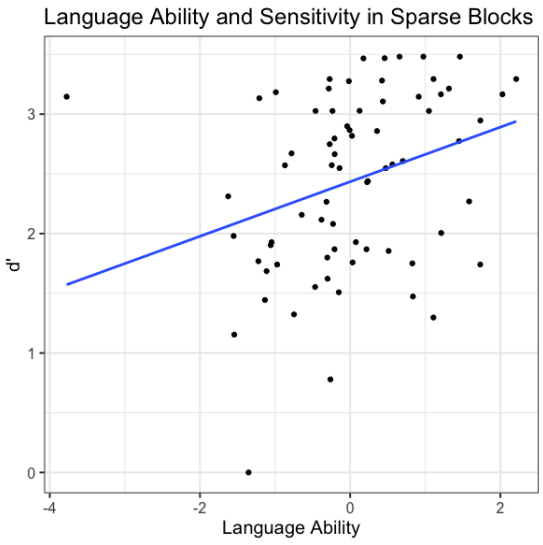

Figure 4. Language ability is a significant predictor of sensitivity (*d'*) for blocks in order analysis 3 (all containing sparse stimuli).

Reaction time. As above, I used a linear mixed-effect model with random intercepts for subject and block nested within subject as the base model. Adding the fixed effects of order and block significantly improved fit, $\chi^2(2) = 55.08$, $p < 0.0001$. In addition, adding the interaction between block and order improved fit, $\chi^2(1) = 20.00$, $p < 0.0001$. The final model showed significant main effects for block, $F(1,68) = 31.22$, $p < 0.0001$, order, $F(1,70) = 5.04$, $p = 0.03$, and a significant interaction between block and order, $F(1,68) = 22.25$, $p < 0.0001$. Follow-up models showed that there was a significant difference in reaction time by block for each order. However, the difference between mean reaction time of the two blocks for group 5 (unsupervised-sparse first) was 415 ms, while the difference for group 6 (supervised-sparse first) was 163 ms. This suggests that the interaction represents a greater difference in reaction time between blocks for participants who received the unsupervised-sparse block first.

For the individual differences analysis, I added RAM and the language composite to the final model from above. Adding the language composite did not improve the model fit. There was no effect of language

ability on reaction time for sparse stimuli.

Summary (see Fig. 3 and Fig. 4). In terms of accuracy, participants showed higher sensitivity during the supervised-sparse block than during the unsupervised-sparse block, regardless of order. In addition, sensitivity on all blocks was positively related to language ability. This relationship did not vary by block or order. For reaction time, there was an interaction between block and order, but no effect of language ability. The unsupervised-sparse block was by far the most difficult block for all participants who received it. Thus, this interaction may reflect this block difference crossed with learning effects. Participants who received the unsupervised-sparse block second were perhaps more comfortable with the task overall than participants who received the unsupervised-sparse block first, which lead to faster reaction times for those receiving unsupervised-sparse second.

2.4 Discussion

In this experiment, I tested three different order effects to see whether the order in which an individual engages the two category learning systems affects their learning using that system. The two manipulations in the statistical density task encouraged participants to use a particular system in two ways (learning type and stimulus type; see Table 2 for a summary). The first analysis investigated whether block order affected performance when both the learning type engaged and the stimulus type required the same system. The second analysis tested the effect of block order on performance when all stimuli were dense, and the third analysis did the same for only sparse stimuli.

2.4.1 Order Effects

The three analyses revealed what appears to be a general learning effect. It is most apparent in the first analysis, which showed that when both learning type and stimulus type engage the same category learning system, performance is better on the second block than on the first. Group 1 (unsupervised-dense first) showed slower reaction times in their first block, while Group 2 (supervised-sparse first) showed poorer sensitivity in their first block, even though the first block for each of these groups was different. This result was also seen in a block by order interaction in the third analysis, where the difference between blocks in reaction times attenuated when the more difficult block (unsupervised-dense) was encountered second. Finally, while there were no significant effects in the second analysis, the mean reaction times were numerically higher for first blocks than for second.

The core hypothesis for this experiment was that engaging the hypothesis-testing system before the associative system would lead to reduced performance during associative blocks and that the reverse effect

would not appear. This hypothesis was based on previous research that showed that when participants were required to switch between categories built using different category rules, they tended to rely more on executive function even if they were not actually switching between rule types (Erickson, 2008). Other research also has shown that when participants are asked to learn a hybrid category that combines different rule types, they end up using only a simple rule-based strategy (Ashby & Crossley, 2010). Thus, when individuals are bombarded with cues towards different systems on a trial-to-trial basis, they default to the more explicit strategies, reflecting reliance on the hypothesis-testing system. However, this type of result was not found in the current study. Instead of defaulting to the hypothesis-testing system and thus showing reduced performance on unsupervised or dense blocks that occurred second, better performance was almost always seen in second blocks. This may reflect a broad learning effect that was not seen in prior studies.

Differences in experimental paradigm may at least partially explain why this study shows learning effects while other studies show reliance on a single system. In the studies mentioned above, stimulus characteristics encouraged participants to switch between systems on a trial-by-trial basis. In the current study, trials were blocked and a single system was engaged for that block. Participants had short transition periods between blocks were new instructions and examples or rules were presented. The results presented here suggest that these transition periods were sufficient for participants to switch to a new system as stimulus and task demands changed.

2.4.2 Individual Differences

The original hypothesis for this analysis was that individuals with poorer language ability would show stronger order effects than those with better language ability. My prior research showed that low-language individuals showed difficulty switching away from suboptimal learning strategies that were developed in the absence of guided instruction (Ryherd & Landi, 2019). Thus, I expected to see an interaction between language ability and order such that individuals with better language skills would show minimal costs when switching between unsupervised and supervised tasks, while those with poorer language skills would show a large switch cost. However, no interactions between language ability and order were found.

The third analysis revealed the only significant effect of language ability. This analysis showed that language ability was positively related to sensitivity when all items in both blocks were sparse. Recall that sparse items are best learned by the hypothesis-testing system. Since both blocks in the third order effect analysis were sparse, an individual could succeed by only using this system. The effect of language on category learning is often found only for the hypothesis-testing system (Lupyan, 2009; Lupyan & Mirman,

2013). Thus, this result is most in line with previous findings.

This finding is especially interesting because it is one of the first to relate category learning performance to individual differences in language ability in an adult sample. This topic has been much more extensively studied in children and infants. For example, vocabulary and categorization have been shown to be positively correlated in 20-month-olds (Nazzi & Gopnik, 2001) and 24-month-olds (Jaswal, 2007). In addition, infants' categorization ability at 12 months predicts their concurrent and future (18 month) vocabulary size (Ferguson et al., 2015). However, much of the individual differences category learning literature focuses on things like working memory or strategy use rather than language ability. Thus, this study is one of the first to find that individual differences in language ability are related to categorization accuracy for novel rule-based categories in adults.

3 Experiment 2

This experiment tests the core hypothesis of this dissertation. Namely, I use a within-subjects design to test whether executive function is specifically related to categorization in the hypothesis-testing system while verbal labels are specifically related to associative system categorization. This experiment also uses three different category learning tasks, allowing me compare different category learning paradigms and to test the core hypothesis for multiple approaches.

In this experiment, I use vocabulary as a proxy for labeling. Vocabulary measures should reflect the link between a word and its meaning. Further, this link should be more elaborated than those built in a paired-associate learning task. Thus, individual differences in vocabulary should give some insight into how well participants use labels in learning categories. For executive function, I selected three different measures. Multiple studies have shown that while executive function is sometimes talked about as a single construct, it actually is made up of separable components (Karr et al., 2018; Miyake et al., 2000). The components I chose to focus on were inhibition, switching, and planning.

I chose to compare the COVIS, statistical density, and taxonomic-thematic approaches to category learning. These three approaches represent a broad spectrum of category learning. COVIS exclusively focuses on perceptual categories, while the statistical density approach uses constructed stimuli that can be mapped onto real-world objects at least somewhat. Finally, the taxonomic-thematic approach is almost always applied to real-world objects with which participants have experience. Since these three approaches are so different in the types of categories they try to explain, results showing similarities between them would be strong evidence for an overarching dual-systems framework. I decided to use common paradigms from each approach as a starting point for comparison. Given the theoretical similarities between the approaches, I hypothesize that task differences will not be sufficient to affect the relationship between the two systems differently for each approach.

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.. **Nelson-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 I: Cross-Paradigm Comparison

Descriptive statistics for accuracy and reaction time in all category learning tasks can be found in Table TABLE HERE.

3.3.1 Data Processing

Concordant with an *a priori* power analysis and pre-registration, only the first 84 undergraduate students with complete data were included in the analyses reported in this section.

Ashby perceptual category learning task. For this task, II blocks were labeled as associative and RB as hypothesis-testing. Accuracy and reaction time were measured for this task. Accuracy was summarized by subject and system. For reaction time, only accuracy trials were used. Outliers were removed on a by-trial basis using the same method described in the cross-paradigm analysis. Then, reaction time was summarized by subject and system. Next, we constructed boxplots to summarize mean RTs for each

system and paradigm. Subjects who were clear outliers for both systems within a given paradigm were excluded (1 participant) and replaced with the next participant. Accuracy and reaction time were then Yeo-Johnson transformed to reduce skewness, as well as centered and scaled. At this point, any subjects with a z-score of less than -3 or greater than 3 were considered outliers and removed from further analysis.

Sloutsky statistical density task. In this task, the unsupervised-dense block was considered to engage the associative system, and the supervised-sparse block was considered to engage the hypothesis-testing system. The other two blocks were discarded. Any participants who did not respond correctly to at least 6 of the 8 catch trials for a given block were removed from future analyses. Thus, all subjects reported in analyses using this task had at least 75% accuracy on catch trials in both blocks. Accuracy was summarized by subject and system. Reaction time outliers were removed on a by-trial basis as described in the cross-paradigm analysis and reaction time was then summarized by subject and system. Next, we constructed boxplots to summarize mean RTs for each system and paradigm. No subjects for this task were clear outliers. Accuracy and reaction time were then transformed, centered, and scaled. At this point, any subjects with a z-score of less than -3 or greater than 3 were considered outliers and removed from further analysis.

Taxonomic/thematic task. For this task, taxonomic blocks were associative and thematic blocks were hypothesis-testing. Practice trials were discarded before analysis. Accuracy was summarized by subject and system. Reaction time outliers were removed using the same method as above, and then reaction time was summarized by subject and system. Next, we constructed boxplots to summarize mean RTs for each system and paradigm. Subjects who were clear outliers for both systems within a given paradigm were excluded (2 participants) and replaced with the next 2 participants. Accuracy and reaction time were then transformed, centered, and scaled. At this point, any subjects with a z-score of less than -3 or greater than 3 were considered outliers and removed from further analysis.

3.3.2 Accuracy

To investigate whether accuracy was comparable across paradigms, we constructed a mixed-effects model with random intercepts for subject. Adding the fixed effects of paradigm and system significantly improved model fit, $\chi^2(3) = 32.24$, $p < 0.0001$. Adding the interaction between paradigm and system further increased fit, $\chi^2(2) = 75.60$, $p < 0.0001$. Thus, the final model predicted the accuracy z-scores from paradigm, system, and their interaction. This model revealed a significant main effect of system, $F(1,415) = 38.37$, $p < 0.0001$, as well as a significant interaction between paradigm and system, $F(2,415) = 41.00$, $p < 0.0001$. To further investigate this interaction, we conducted three follow-up models each testing the effect of system within a

given paradigm.

The first model revealed a significant main effect of system in the perceptual category learning paradigm, $F(1,83) = 210.27$, $p < 0.0001$. A follow-up t-test confirmed that accuracy was significantly higher for the hypothesis-testing system, $t(133) = -11.90$, $p < 0.0001$. The second model revealed no main effect of system in the statistical density paradigm, $F(1,83) = 0.92$, $p = 0.34$. A follow-up t-test confirmed this result, $t(135) = 0.91$, $p = 0.36$. Finally, the third model showed no main effect of system in the taxonomic-thematic paradigm, $F(1,83) = 0.73$, $p = 0.40$. This was confirmed by a follow-up t-test, $t(164) = -0.66$, $p = 0.51$.

Overall these results suggest that these three paradigms are not comparable. While no differences between systems were found for the statistical density and taxonomic-thematic tasks, the perceptual category learning task showed a different pattern. However, the statistical density task may have been suffering from ceiling effects. Of the 84 total subjects, we saw average accuracy values of 0.9 or higher during the statistical density paradigm in 76 subjects for the associative block and 58 subjects for the hypothesis-testing block. Thus, the statistical density task may not be sufficiently difficult to detect differences between systems in accuracy.

3.3.3 Reaction Time

To investigate whether reaction time was comparable across paradigms, we constructed a mixed-effects model with random intercepts for subject. Adding the fixed effects of paradigm and system significantly improved model fit, $\chi^2(3) = 13.48$, p = 0.003. Adding the interaction between paradigm and system further increased fit, $\chi^2(2) = 44.65$, $p < 0.0001$. Thus, the final model predicted the accuracy z-scores from paradigm, system as well as their interaction. This model revealed a significant main effect of system, $F(1,415) = 14.62$, $p = 0.0001$, but no main effect of paradigm, $F(2,415) = 0.017$, $p = 0.84$. The interaction between system and paradigm was also significant, $F(2,415) = 23.30$, $p < 0.0001$. To further investigate this interaction, we conducted three follow-up models each testing the effect of system within a given paradigm.

The first model revealed a significant main effect of system in the perceptual category learning paradigm, $F(1,83) = 29.96$, $p < 0.0001$. A follow-up t-test confirmed that reaction time was significantly faster for the hypothesis-testing system, $t(141) = 3.73$, $p = 0.0002$. The second model revealed a significant main effect of system in the statistical density paradigm, $F(1,83) = 44.00$, $p < 0.0001$. A follow-up t-test showed that again reaction time was faster for the hypothesis-testing system, $t(165) = 4.62$, $p < 0.0001$. Finally, the third model also showed a main effect of system in the taxonomic-thematic paradigm, $F(1,83) = 14.96$, $p = 0.0002$. However, for this paradigm the pattern was flipped. Reaction times were faster for the associative system, $t(162) = -2.68$, $p = 0.008$.

3.4 Discussion I: Cross-Paradigm Comparison

This analysis aimed to directly compare three dual-systems approaches to category learning. From a theoretical standpoint, considerable similarities can be drawn between these approaches. They each consider two category structure types, which can be mapped onto similarity- and rule-based categories. In addition, two of the approaches posit very similar systems for learning these categories, each specifically adapted to one type of category. One system best learns similarity-based categories by integrating and compressing multiple features using an iterative and associative process. The other system uses higher-order skills like working memory and executive functions to select and test hypotheses about category-relevant features. This system is best for learning rule-based categories. Each approach uses a different paradigm to measure how individuals learn these different category structures. I hypothesized that while there are considerable task-related differences among the paradigms, each paradigm would engage the relevant category learning system in a given block. Thus, I expected to see a main effect of system but no effect of paradigm, indicating that each task separately engaged the two systems in different blocks.

I did not find these hypothesized results in either accuracy or reaction time. In accuracy, two of the paradigms showed no difference while one showed a different pattern. For perceptual category learning, accuracy was much lower for the associative system than for the hypothesis-testing system. In fact, mean accuracy in the associative block of the perceptual task was barely above chance, indicating that participants showed little learning of these categories. In contrast, no accuracy differences were seen between the two blocks in the taxonomic/thematic and statistical density task. The statistical density paradigm also suffered from considerable ceiling effects. In reaction time, we again saw paradigm-related differences. In both the perceptual task and the statistical density task, participants were significantly faster in the hypothesis-testing block than in the associative block. However, this pattern was reversed for the taxonomic/thematic task.

A key takeaway from this study is that despite the theoretical similarities behind these approaches, the tasks they use to measure category learning are not directly comparable. Even after accounting for scaling considerations by using *z*-scores, the relationship between category learning in the two systems is not consistent across paradigms. This could simply be explained by task and stimuli differences; perhaps each approach is indeed trying to measure the same types of processing, but they are taxing the systems differently. Another possibility is that each approach is fundamentally trying to explain different, albeit related, phenomena. We will consider both of these possibilities in the general discussion.

3.5 Results II: Individual Differences

Descriptive statistics for all individual difference measures can be found in Table TABLE HERE.

3.5.1 Data Processing

An *a priori* power analysis showed that 132 subjects would be needed for this experiment. As is noted above, more than 132 subjects participated in the experiment. Due to the many assessments being collected, issues with the experimental paradigm, and experimental time constraints, there was a considerable amount of data missingness. Thus, each analysis discussed below uses the first 132 subjects with full data for all measures included in that analysis.

Ashby perceptual category learning task. For this task, II blocks were labeled as associative and RB as hypothesis-testing. Accuracy and reaction time were measured for this task. Accuracy was summarized by subject and system. For reaction time, only accuracy trials were used. Outliers were removed on a by-trial basis using the same method described in the cross-paradigm analysis. Then, reaction time was summarized by subject and system. A single subject had reaction times 8 SD higher than the mean; this subject's data was removed and replaced with another subject. Accuracy and reaction time were then Yeo-Johnson transformed to reduce skewness, as well as centered and scaled.

Sloutsky statistical density task. In this task, the unsupervised-dense block was considered to engage the associative system, and the supervised-sparse block was considered to engage the hypothesis-testing system. The other two blocks were discarded. Again, participants were removed for failure to reach criterion on catch trials (as described above). Accuracy was summarized by subject and system. Reaction time outliers were removed on a by-trial basis as described in the cross-paradigm analysis and reaction time was then summarized by subject and system. Accuracy and reaction time were then transformed, centered, and scaled.

Taxonomic/thematic task. For this task, taxonomic blocks were associative and thematic blocks were hypothesis-testing. Practice trials were discarded before analysis. Accuracy was summarized by subject and system. Reaction time outliers were removed using the same method as above, and then reaction time was summarized by subject and system. Accuracy and reaction time were then transformed, centered, and scaled.

Flanker task. The flanker effect was calculated by first selecting only incongruent or congruent trials. Then, the average reaction time was calculated for each subject for both trial types. Finally, the average reaction time for congruent trials was subtracted from the average reaction time for incongruent trials for each subject. This measure was then centered and scaled but not transformed.

Switcher task. The switcher effect was calculated by selecting the 3-dimension ordered and 3-dimension random blocks. Average reaction time was calculated for each subject in each of these blocks. Then, the reaction time for 3-dimension ordered was subtracted from the reaction time for 3-dimension random. This measure was then transformed, centered, and scaled.

Tower of London task. The main metric calculated for this task was the ratio of planning time to total trial time for each subject. Planning time and total trial time were summarized for each subject. Next, planning time was divided by total trial time. This measure was then transformed, centered, and scaled.

Nelson-Denny, CELF, RAM. Nelson-Denny and CELF were both standardized using their respective norms. Raven's was not standardized. All 4 measures (Nelson-Denny vocabulary, CELF Recalling Sentences, CELF Formulated Sentences, and Raven's Advanced Matrices) were all transformed, centered, and scaled.

3.5.2 Accuracy

Ashby perceptual category learning task.

Sloutsky statistical density task. To investigate how the individual difference measures related to task performance, I constructed a mixed-effects model with random intercepts for subject. Adding the fixed effect of system marginally improved model fit, $\chi^2(1) = 3.38$, p = 0.07. In the next step, I added RAM, vocabulary, and the three executive function tasks as fixed effects. This step significantly improved fit, $\chi^2(5) = 20.24$, $p = 0.001$. However, adding the interactions between system and the individual difference measures (except RAM) did not further improve fit, $\chi^2(4) = 3.03$, p = 0.55. Thus, the final model predicted accuracy in this task from system and the individual difference measures, but not their interactions. This model revealed a significant main effect of flanker, $F(1,126) = 4.93$, $p = 0.03$, and a significant main effect of switcher, $F(1,126) = 9.70$, $p = 0.003$. The coefficient associated with flanker was positive ($b = 0.16$, $SE = 0.07$), while the coefficient associated with switcher was negative, ($b = -0.21$, $SE = 0.07$). There were also marginally significant effects of system, $F(1,126) = 3.40$, $p = 0.07$, Tower of London, $F(1,126) = 3.56$, $p = 0.06$, and vocabulary, $F(1,126) = 2.82$, $p = 0.10$. Thus, accuracy on the Sloutsky statistical density task is positively related to flanker performance and negatively related to switcher performance. However, as in the prior analysis, these results should be interpreted with caution, as large ceiling effects were found in accuracy for this task.

Taxonomic/thematic task. Again I constructed a mixed-effects model with random intercepts for subject. Adding the fixed effect of system significantly improved model fit, $\chi^2(1) = 8.59$, p = 0.003. Adding the individual difference measures also significantly improved fit, $\chi^2(5) = 11.46$, $p = 0.04$. However, adding the

interactions between system and the individual difference measures (except RAM) did not further improve fit, $\chi^2(4) = 1.81$, p = 0.77. Thus, the final model predicted accuracy in this task from system and the individual difference measures, but not their interactions. This model revealed a significant main effect of system, $F(1,131) = 8.80$, $p = 0.003$, and a significant main effect of RAM, $F(1,126) = 4.78$, $p = 0.031$. The coefficient associated with RAM was positive ($b = 0.17$, $SE = 0.08$), while the coefficient associated with switcher was negative. Thus, accuracy on the taxonomic/thematic task is positively related to performance on RAM.

3.5.3 Reaction Time

Ashby perceptual category learning task.

Sloutsky statistical density task. Once again I constructed a mixed-effects model with random intercepts for subject. Adding the fixed effect of system significantly improved model fit, $\chi^2(1) = 53.01$, p $<$0.001. Adding the individual difference measures as fixed effects also significantly improved fit, $\chi^2(5) = 17.62$, $p = 0.003$. However, adding the interactions between system and the individual difference measures (except RAM) only marginally improved fit, $\chi^2(4) = 8.13$, p = 0.09. Thus, the final model predicted accuracy in this task from system and the individual difference measures, but not their interactions. This model revealed a significant main effect of system, $F(1,131) = 64.75$, $p <$0.001, a main effect of RAM, $F(1,126) = 4.26$, $p = 0.04$, and a significant main effect of Tower of London, $F(1,126) = 9.18$, $p = 0.003$. The coefficient associated with RAM was positive ($b = 0.16$, $SE = 0.08$), as was the coefficient associated with Tower of London, ($b = 0.22$, $SE = 0.07$). Thus, participants who took longer to respond in this task also performed better on RAM and spent a larger portion of their total time planning in Tower of London.

Taxonomic/thematic task. I constructed a mixed-effects model with random intercepts for subject. Adding the fixed effect of system significantly improved model fit, $\chi^2(1) = 19.70$, p $<$0.001. However, adding the individual difference measures did not further improve fit, $\chi^2(4) = 3.89$, p = 0.42. Indeed, the only effect even close to significant in this model was a marginal main effect of Tower of London, $F(1,127) = 3.17$, $p = 0.08$. Thus, reaction time on the taxonomic/thematic task is not related to any of the individual difference measures.

3.6 Discussion II: Individual Differences

4 General Discussion

4.1 Language in a dual-systems model: summary of results

4.1.1 Language and the interaction between two systems

4.1.2 Individual differences and dual-systems category learning

4.1.3 Levels of processing and the dual-systems model

4.2 Rethinking the dual-systems model of categorization

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*.

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

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

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.

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

$$H^{dim}_{between} = -7 log_2 0.5$$

$$H^{dim}_{between} = 7$$

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.

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

$$H^{dim}_{within} = -6 log_2 0.5$$

$$H^{dim}_{within} = 6$$

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.

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

$$H^{rel}_{between} = -10.5 log_2 0.25$$

$$H^{rel}_{between} = 21$$

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.

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

$$H^{rel}_{within} = -7.5 log_2 0.25$$

$$H^{rel}_{within} = 15$$

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.

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

$$H^{dim}_{within} = -\log_2 0.5$$

$$H^{dim}_{within} = 1$$

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.

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

$$H^{rel}_{between} = -3 \log_2 0.25$$

$$H^{rel}_{between} = 6$$

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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