# 1   General Introduction

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

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

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

## 1.1   Dual-systems model for category learning

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

### 1.1.1   Proposed model

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

feature of cats, but are still undeniably members of the category *cat*. Thus, the associative system must be able to extract the most frequent pattern of features over many instances in order to learn a category.

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

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

### 1.1.2   COVIS

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

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

strategy for categorization.

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

One of the most substantial contributions of COVIS is its strong grounding in neurobiology. In the original paper, Ashby and colleagues proposed specific brain regions involved the verbal (hypothesis-testing) and implicit (associative) systems, supported by neuroimaging and patient studies. The verbal (hypothesis-testing) system relies on the prefrontal cortex (PFC), anterior cingulate cortex (ACC), striatum, hippocampus, and the head of the caudate nucleus. Information about the stimuli are processed in fronto-striatial loops and potential category rules are generated. The PFC keeps these rules in working memory while the ACC and the head of the caudate nucleus mediate switching between rules based on feedback. Finally, the hippocampus stores longer-term memory of which rules have already been tested – it is only involved when the task is complex enough that previously tested rules cannot all be stored in working memory (**??**). 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 (**?**) and an experimental rule-based category learning task (**?**). 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. **?** 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. **?** found activation in the medial temporal lobe (MTL), which contains the hippocampus, specifically for rule-based categorization. However, a later study failed to find any activation that was specifically greater for rule-based categorization (**?**). Thus, the neural underpinnings of the verbal (hypothesis-testing) system are still under debate.

The implicit (associative) system from COVIS has a different neurobiolgoical pathway for category learning. It uses incremental learning rather than hypothesis testing to learn information-integration (similarity-based) categories. The main structure involved in this procedural learning system is the striatum, which is

3

involved in reinforcement learning with dopamine as the reinforcement signal. From the striatum, information about the category is sent to the thalamus and the globus pallidus, which is within the basal ganglia. From the thalamus, information also runs to motor and premotor cortex. This procedural system links stimuli, motor responses during categorization, and feedback to allow the participant to learn categories. Neuroimaging studies using the implicit system again are mixed, with some finding activation in the caudate body while others fail to find that activation, instead seeing activity in parahippocampal regions (**??**). A separate study also found a role for the putamen in similarity-based category learning (**?**).

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

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

### 1.1.3 Dimensionality

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

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

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

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

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

### 1.1.4  Statistical Density

A third framework for dual-systems category learning was created by Sloutsky and colleagues. He describes two category learning systems that are each used to extract different types of regularities from a stream of information, allowing for flexibility in the data collected (**?**). Sloutsky'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. **??**).

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

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

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

features continue on. The many correlated features of a dense category are easily extracted using this system. This system is quite similar to the current paper's associative system.

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

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

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

holistically (using the compression-based/associative system). They found that when viewing sparse categories, adults showed a significant switch cost as the category-relevant feature was changed, while infants did not. However, eye movement data did suggest that infants were able to learn the categories and were simply not selectively attending to category-relevant features (**?**).

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

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

### 1.1.5 Verbal/nonverbal

Like some of approaches discussed above, the verbal/nonverbal approach is a dual-systems model of category learning. While other approaches discuss the role of language in category learning, none make it as central as this approach by **?**. 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. **?** state that the verbal system relies heavily on working memory, especially the phonological loop and central executive, to rehearse and select potential rules (**?**). The nonverbal system, meanwhile, uses the visuospatial sketchpad to store and rehearse visual information, but overall uses working memory to a lesser extent than the verbal system. Evidence for these hypotheses comes from a study of children and adults showing that children showed adult-like performance when learning categories that could be learned by the nonverbal system and reduced learning for categories that required use of the verbal system. This study also showed that adults showed more child-like performance when learning categories suited to the verbal system while under concurrent verbal load, suggesting that the verbal system indeed needs verbal working memory resources (**?**).

While the two systems described in **?** 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 **?** ground their dual-systems model in working memory. As will be discussed shortly, language can be very useful even for iterative, association-based learning, although perhaps not in the form of a verbal working memory resource. Thus, the verbal/nonverbal dual-systems model of category learning provides us with evidence that verbal working memory and executive resources support rule-based category learning but does not fully consider the ways in which language may influence category learning.

### 1.1.6 Taxonomic/thematic

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

Similar to and perhaps even more so than the statistical density approach, the taxonomic/thematic framework has been able to provide many valuable insights about the developmental trajectory of categorization. Early research on this topic suggests that children are not sensitive to taxonomic relations,

9

primarily categorizing items using thematic relations in kindergarten and switching to taxonomic relations later in childhood (**??**). **EXPLAIN TASK HERE**. **?** 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 (**?**).

Rather than being tied directly to age or ability, the preference for thematic or taxonomic classification may depend on an individual's goals. **?** 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 **?** seemed to be strongly affected by task instructions and age (**?**). 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 (**?**).

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

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

## 1.2 Vocabulary/labels and category learning

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

There have been multiple viewpoints on just how labels interact with the category or concept they describe and refer to. One line of thought postulates that labels are attached to concepts that can be formed in their absence (**??**). 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 **?**, 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 (**?**). In adults, labels promote category learning even when they are redundant, and they do so even more than additional nonverbal features (**?**). 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 (**?**). 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 (**?**).

The evidence cited above suggests that labels are special in some way. They are not simply additional

features of fully-formed concepts. This may be because labels encourage individuals to focus on features that are more diagnostic (i.e., more often associated with members of a category) rather than instance-specific variation. A number of studies from Lupyan and colleagues support this idea. For example, **?** found that adults tended to look at more typical instances of a category when hearing a label. Thus, when hearing the word "bird," participants were more likely to look at a robin (a more typical bird) than a penguin. They also found that when listening to sounds associated with a category (e.g., bird chirp), participants tended to look at more likely sources of the sound (e.g., images of birds with their mouths open). This suggests that labels activate a typical, abstracted representation of a category while other sounds activate a more specific instance of that category that is congruent with the sound itself. Similar findings come from a study looking at the formal category triangles. Triangles are by definition figures with three sides – any figure with three sides can be labeled a triangle. However, **?** found that typicality effects for triangles in multiple tasks were introduced when the word "triangle" was used. When asked to draw a triangle, participants most often drew isosceles or equilateral triangles with their base parallel to the horizontal (i.e., more canonical triangles). However, when instructed to draw a three-sided figure, participants drew a variety of triangles. The same typicality-related pattern of results was found for multiple other tasks, including typicality judgments, speeded recognition, and shape judgment. This is related to other research showing that other seemingly rule-based categories (e.g., grandmothers, odd numbers) show typicality effects (**??**). Armstrong and colleagues suggest that typicality effects are seen in what might be considered rule-based categories because these categories are defined both by rules for inclusion (e.g., having a grandchild) as well features that are used in identification (e.g., gray hair, tendency to bake cookies). This line of reasoning implies a continuum between rule-based and similarity-based categories, where categories with definite and verbalizable rules for inclusion are subject to processing most often associated with similarity-based categories. Thus, having a label for a category changes how individuals process that category, even when it has clearly-defined rules for inclusion.

Insight into why this might be the case comes from the Attentional Learning Account (ALA; **??**).

## 1.3 Executive function and category learning