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Learn locally, think globally: Exemplar variability supports higher-order generalization and word learning

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Abstract

Research suggests variability supports successful categorization, however, the scope of variability's support at the level of higher-order generalization remains unexplored. A longitudinal study examined the role of exemplar variability in first- and second-order generalization in the context of early nominal-category learning. Sixteen eighteen-month-old children were taught twelve categories. Half were taught with sets of highly similar exemplars; half with sets of more variable exemplars. Participants' learning and generalization of trained labels and their development of more general word-learning biases were tested. All children learned labels for trained exemplars, but children trained with variable exemplars generalized to novel exemplars of these categories, developed a discriminating word-learning bias generalizing labels of novel solid objects by shape and nonsolids by material, and accelerated in vocabulary acquisition. These data demonstrate that variability leads to better abstraction of individual and global category organization, increasing learning outside the laboratory.

Philosophers, poets, and playwrights have long proclaimed the role of variability in giving life meaning, from Euripides' (408 BCE) "The variety of all things forms a pleasure," to Cowper's (1785) "Variety's the very spice of life that gives it all its flavor." Empirical evidence similarly suggests that variability enhances the quality of learning and plays a critical role in generalization (e.g., Estes & Burke, 1953; Munsinger & Kessen, 1966). The idea that variability helps learners form a category abstraction leading to more successful generalization has roots in seminal work by Posner and Keele (1968) and is related to classical accounts of categorization (see Murphy, 2002)[1]. Further, variability has a pervasive role: helping non-native speakers learn new perceptual categories (Lively, Logan, & Pisoni, 1993), and being critical in same/different discrimination in humans and animals (Castro, Young, & Wasserman, 2007).

Perhaps nowhere is the role of variability in learning more evident than in early development, leading some to propose that variability is the driving force of development (Siegler, 1996). This is supported by work showing variability plays an essential role in domains ranging from motor development (Thelen, Corbetta, Kamm, Spencer, Schneider, & Zernicke, 1993) to problem solving (Siegler, 2007) to studies probing children's ability to learn grammatical features of natural and artificial languages (Gomez, 2002; Hudson Kam & Newport, 2005). Further, infant research demonstrates that the amount of variability present

[1]We note that while variability often overlaps with typicality, typicality emerges out of experience with a learned category and its members. Thus, in an examination of novel category learning, exemplar-typicality should depend on presentation frequency—if a child sees all exemplars equally often, as is the case in our experiment, they should be equally typical. For these reasons, we make no claims about separating these dimensions here but discuss our work in terms of variability as is common in developmental literature.

in a learned category impacts breadth of generalization. For example, Oakes Coppage, & Dingel (1997) found that familiarizing infants with highly similar exemplars led to a strict basis for category organization. Likewise, work by Gentner and colleagues suggests that similarity promotes comparison, leading to more accurate generalization of part names (Gentner, Loewenstein, & Hung, 2007). On the other hand, using variable exemplars leads children to extend both novel verbs (Childers & Paik, 2009) and spatial mappings (Loewenstein & Gentner, 2001) farther.

Clearly, variability plays a central role in development. However, prior work has focused on generalization to novel instances of the trained learning set. Less understood is how variability at one level of cognitive organization impacts learning and generalization at other levels. This is a central issue in development where multiple cognitive abilities are emerging in parallel. Thus, in the present study, we examined whether the amount of variability present in a learned category impacts, not only the breadth of generalization for the trained set, but how children learn about object categories *in general*. We examined this issue in the context of children's acquisition of object names.

At the local level of individual nominal categories, it is clear that variability among learning exemplars could influence learning. To learn the nominal category *chair*, for example, a child must come to understand that the word "chair" refers not just to one item, but applies across all examples of chairs she has experienced. This seems difficult when one considers the variety of chairs a child might encounter. One might think it easier to learn the category chair from a set of similar instances that clearly shared commonalities central to the category. In fact, research has demonstrated that adults learning similar instances of novel categories are faster than those learning diverse instances (Hahn, Bailey, & Elvin, 2005; Posner, Goldsmith, & Welton, 1967). On the other hand, more variation across exemplars has been shown to lead to better abstraction of the invariant features of the category (Zentall, Wasserman, Lazareva, Thompson, & Rattermann, 2008; Posner & Keele, 1968). Thus, learning the category chair by seeing a number of variable instances named "chair" might promote generalization of the newly-acquired nominal category to new instances (see also Smith, 2005).

At a higher level of abstraction, recent theoretical proposals suggest a means by which variability at the level of individual nominal categories may influence second-order generalizations. In particular, Smith and colleagues proposed that children's acquisition of a bias to attend to shape when learning novel object names—a second-order generalization—is the developmental product of prior learning of individual nominal categories (Samuelson, 2002; Smith, Jones, Landau, Gershkoff-Stowe & Samuelson, 2002). More specifically, Smith and colleagues (2002) proposed a four-step process to describe how the shape bias is acquired from the child's productive vocabulary. The fact that many early nouns children learn name solid objects in categories well-organized by similarity in shape (Samuelson & Smith, 1999) helps children get from learning words for individual instances (step 1) and individual categories (step 2) to acquiring a bias to attend to shape when learning novel names (step 3). This bias, then, helps children acquire new words more quickly (step 4).

Support for the four-step process comes from studies of the statistics of the early vocabulary (Gershkoff-Stowe & Smith, 2004; Samuelson & Smith, 1999), cross-linguistic studies showing that the biases learned depend on the language being learned (Smith, Colunga, & Yoshida, 2003; Yoshida & Smith, 2003), data suggesting atypical learners do not develop the same word-learning biases as typically developing children (Jones & Smith, 2005), and connectionist models of the learning process (Samuelson, 2002; Colunga & Smith, 2005). Further support comes from a series of longitudinal training studies (Smith et al., 2002; Samuelson, 2002) showing that teaching children names of multiple categories organized by shape similarity helps them develop a precocious shape bias and acquire vocabulary outside the lab more quickly than those not given such training. Results from these training studies suggest between-category similarity—the fact that many earlyacquired nominal categories are organized by similarity in shape—is important for children's higher-order generalizations such as the shape bias. Left unexplained, however, is how factors impacting learning of individual categories—such as exemplar variability—influence the extraction of a higher-order generalization.

A starting point for examining this issue comes from Samuelson's (2002) prior finding that children taught names for many categories well-organized by shape similarity overgeneralized the shape bias to nonsolid stimuli. Rather than teaching children that shape is particularly critical for categories of solid things, training children with names for similar categories may have taught them to attend to shape indiscriminately. The fact that variability promotes extraction of the invariant features of a category (e.g. Posner & Keele, 1968) may mean category training with more variable instances will help children learn both when to attend to shape, *and* when not to; thereby promoting appropriate generalization at the global level.

The goal of the current study, therefore, is to examine the role of exemplar variability on each step of the four-step process of shape bias development; that is, to examine how learning at the local level of individual categories influences global learning about what to attend to in the context of a novel noun. More specifically, we ask how training children with sets of highly similar category exemplars versus more variable exemplars, affects their learning of names for individual exemplars (step 1), generalization to novel within-category exemplars (step 2), generalization of novel names for novel stimuli (step 3), and acquisition of new words outside the laboratory (step 4). In this way, then, we examine whether variability at the local level has consequences for the entire developmental cascade that underlies early nominal category learning and generalization.

Experiment

We taught children the names of 12 categories of common solid objects not usually learned until after 26 months (Dale & Fenson, 1993) (see Table 1). The categories were ones adults judged to be well-organized by similarity in shape (Samuelson & Smith, 1999). Category exemplars used in training were either highly similar (tight condition) or more variable (variable condition). We then tested children's learning of exemplar names, generalization to new instances, novel noun generalization (NNG), and overall vocabulary acquisition.

Method

Participants—Sixteen typically developing English-learning children (*M*= 18mos., range: 15-21mos., 10 females) participated in one of two between-subjects conditions. Children were matched across conditions based on their productive noun vocabularies at week one (tight: *M*=17.25, range: 3-37; variable: *M*=17.75, range: 4-37; $t(14)=.19$, *ns*). Children were recruited via birth records and received a toy for participation after each session.

Stimuli—Twelve sets of objects, each made up of 10 exemplars, were used in training and testing (see Table 1). Within-category similarity of exemplars was determined by adult judgments using a placement method with the actual objects (Perry, Cook & Samuelson, 2010; see also, Goldstone, 1994). Adults judged similarity by arranging the objects on a table such that more similar objects were closer together and more dissimilar objects were farther apart. A multi-dimensional scaling solution was created for each category using the average pairwise distances. Using these solutions, the three most similar exemplars of each category were used for training in the tight condition, and the most dissimilar were used in the variable condition (see Figure 1). The remaining four exemplars in each set were used in tests of generalization.

Novel noun generalization was tested with five sets of solid stimuli and five sets of nonsolid stimuli. Each set consisted of an exemplar, two items matching the exemplar in shape only, and two items matching the exemplar in material only (see Figure 2). Additionally, two of a possible twenty sets of common familiar objects were used as warm up stimuli at each session. Each set consisted of two identical items (e.g. purple plastic eggs) and one completely different item (e.g. a red wooden block).

Procedure—We used the same training procedure as prior longitudinal studies of this kind (e.g. Samuelson, 2002). Children came to the lab for 9 weekly visits and a 1-month follow up. Using naturalistic play, they were taught 12 object names. Training was broken into three three-week blocks with four training words. The order of training words was randomized across participants. We periodically tested individual exemplar learning with our learning test and individual category learning with our extension and exclusivity tests (see below). We also periodically tested novel noun generalization (NNG). Noun vocabulary development was measured by parent-report on a subsection of the MacArthur-Bates Communicative Development Inventory, Words and Sentences (Fenson et al., 1994). Table 2 presents a breakdown of training and test sessions over the course of the study.

Step 1: Learning: The learning test examined acquisition of names for training exemplars. Children were presented with one exemplar previously used to teach a target word, a second item previously used to teach one of the other trained words, and asked to get the target item.

Step 2: Firstorder generalization: We examined generalization of trained labels to novel exemplars in two ways. In the *extension* test, children were presented with an exemplar belonging to a trained target category and a second item belonging to another trained category, neither of which were used in training. In the *exclusivity* test, children were presented with an exemplar from a trained category that had not been used in training, and a second item from a highly similar, but untrained category (e.g, for the trained category "bucket," the foil category was "box"). In both tests children were asked to get the target item.

Step 3: Higherorder generalization: The NNG task examined development of children's attention to shape when generalizing novel nouns for both solid and nonsolid exemplars. Children were presented with a novel solid or nonsolid exemplar object that was given a novel name (e.g. "This is a wug"). Then two novel test objects, one matching the exemplar in shape only and another in material only, were presented and the child was asked to "Get the wug!" The order of solid and nonsolid sets was counterbalanced across participants.

Coding & Analysis—Children's choices were coded off-line. One-third of all data were re-coded for reliability purposes. Inter-coder reliability was 95%. Learning, extension, and exclusivity test results are reported as proportion correct. NNG test results are reported as proportion shape responding.

We examined the effects of condition and links between the four steps using mixed logistic regression for forced-choice tasks and mixed linear regression for rate of vocabulary acceleration. We took this approach because recent arguments suggest ANOVA's on categorical outcome variables such as ours are inappropriate (see Jaeger, 2008). Additionally, these models enable control for individual differences in children's vocabulary and prior experiences with the potentially familiar stimuli via the inclusion of random subject and item effects. We report one model per step including condition and performance in the previous step as predictors of performance in the current step. We removed collinearity from the models by sum-coding data and scaling continuous variables. We began with a completely specified random effects structure including random slopes for all variables included in a given model. Using model comparison we systematically removed uninformative random effects to find an appropriate model (c.f. http://hlplab.wordpress.com/2009/05/14/random-effect-structure/). All final models included random intercepts for subject and items, unless otherwise specified.

Results and Discussion

Steps 1 & 2: Learning and Firstorder generalizations—Children in both conditions learned labels of trained exemplars at levels significantly better than chance (.50), tight: M= .63; $t(7)$=7.49, p<.0001, d=2.5; variable: M= .67; $t(7)$=4.13, p<.005, d=1.42. A logit model including the interaction between vocabulary size and condition as predictors found only vocabulary size predicted learning, z= 2.59 p<.01. Children in both conditions learned names of trained exemplars equally well, but those with higher vocabularies learned best (see Figure 3).

Next we asked how variability influenced generalization to new instances. Because both our extension and exclusion tests are measures of this second step in the four-step process, we created a combined generalization score for each child such that higher values indicated extension of the name to novel category members and appropriate exclusion of non-members. A logit model revealed a significant interaction between condition and learning, z=−2.01, p<.05, such that children in the variable condition who previously showed more learning had higher generalization scores. Thus, it was not just successful learning of trained categories, but rather successful learning of categories in the *variable* condition that led to the most accurate generalization to novel exemplars (see Figure 3).

To summarize, although children in both conditions evidenced learning of trained exemplars' names, children in the variable condition who learned these names best were more likely to generalize names to novel category instances and exclude members of other similar categories. This suggests that more variable instances lead to better generalization at the local level.

Step 3: Higherorder generalizations—Neither group evidenced a shape bias at the start of the study, solids—tight: M= .54, $t(7)$=.36, ns; variable: M= .56, $t(7)$=.51, ns; nonsolids—tight: M= .44, $t(7)$=.55, ns; variable: M=.56, $t(7)$=.51, ns. However, those in the variable condition were more likely to develop a discriminating shape bias by the end, attending to shape with solid stimuli and material with nonsolid stimuli. A mixed logit model including random slopes for condition for both subjects and items, in addition to the random intercepts, showed that individual children's combined generalization score did not predict whether they demonstrated a shape bias in the NNG test with solid stimuli, z=.03, ns. However, the interaction between condition and combined generalization did *negatively* predict shape responding with nonsolid stimuli, z=−1.97, p<.05. That is, in the variable condition children with higher combined generalization scores were more likely to generalize by material while those in the tight condition were significantly more likely to generalize novel nouns for *nonsolid* things by shape, thus evidencing an overgeneralized shape bias (see Figure 3).

Thus, the more successful a child was at generalizing trained labels to novel exemplars but not other similar things—which requires knowing when a feature indicates something is a member of a category and when it does not—the more likely she was to form a discriminating shape bias, learning when to generalize by shape and when not to. And recall, it was children in the variable condition who were more discriminating in their generalizations of learned labels to novel instances. Thus, training with variable categories supported more precise second-order generalizations.

Step 4: Vocabulary growth—As can be seen in Figure 4, during the first 3 weeks, children in both conditions learned new words outside the lab at roughly the same rate, tight: 3.63 words per week; variable: 4.44 words per week, $F(1, 14)=.09$, ns. During training, however, the rate of new word acquisitions began to change markedly such that children in the variable condition acquired new words at a significantly faster rate than children in the tight condition between week 9 and the 1-month follow-up visit, tight: 4.03 words per week; variable: 9.78 words per week, $F(1,14)=5.45$, $p<.04$, $h^2=.28$. This rate of change for the tight group compares to a matched set of participants from the no training condition (4.68 words per week) of Samuelson's (2002) training study, while the rate of change for the variable group is even higher than that of a matched set of participants from the natural statistics condition (7.64 words per week) of that study.

A mixed linear model of the link between Steps 3 and 4—how individual children's performance in the NNG task predicted rate of vocabulary acceleration between the end of training and the one-month follow-up visit—showed that individuals who had a discriminating shape bias evidenced greater acceleration in vocabulary development $t=5.31$, $p<.0002$[2]. This suggests that it was the variable group's abstraction of a precise second-order generalization that led to their acceleration.

The developmental cascade

Finally, we tested the cascading influence of variability by putting the individual steps in the four-step sequence together, creating a model including training condition, learning, combined generalization, and NNG task performance as predictors of vocabulary acceleration. A mixed linear model using these standardized predictors was significantly stronger than models that excluded Learning, $X^2_{(1)}=53$, $p<.0001$, or Combined Generalization, $X^2_{(1)}=290$, $p<.0001$. Thus, each predictor was necessary to capture differences in children's learning and development over time. Critically, in the best model (according to our model comparison), having a *discriminating* shape bias (generalizing novel names for nonsolids by material rather than shape) was the strongest predictor of acceleration in vocabulary development, $t=4.31$, $p<.0004$.

General Discussion

The current study makes important contributions to our understanding of both the processes supporting early word learning and the role of variability in category development. By concretely establishing links between the steps in Smith et al.'s four-step process, we have shown how variability in individual nominal categories leads to a cascade of effects that build from the learning of individual words to the development of general word-learning biases to an acceleration in vocabulary development. These findings complement prior work on the development of the shape bias demonstrating that the similarity *between categories* in the language environment (most early-learned nouns name categories well-organized by shape similarity) guides children to attend to shape when learning names, and subsequently helps them learn new names more quickly (Samuelson, 2002; Smith et al., 2002; Colunga & Smith, 2005). The current data add to this account by demonstrating that children trained with low *within-category* variability learned individual exemplars and extracted a general

[2]Because of the difficulty in determining degrees of freedom in mixed linear models, we conducted MCMC sampling to find p-values (see Baayen et al., 2008).

basis for category organization, but over-applied this bias. These children also did not accelerate in their vocabulary development outside the laboratory. In contrast, children trained with more *variable within-category* exemplars were more likely to discriminate in their application of the shape bias, applying it only to novel solid things. These children did accelerate in vocabulary development outside the laboratory. In this way, then, we have shown how individual children's current developmental state has a cascading influence on each step in the learning process and then on subsequent vocabulary learning—a finding that goes beyond the original four-step process and highlights how individual developments provide the foundation for later learning.

Importantly, this is the first demonstration of the benefits of variability in making both first- and second-order generalizations. Prior research had focused on the local level and shown that training with less variable exemplars speeds learning, but training with more variable instances increases accurate generalization to novel category members. The exciting effect shown here is that local learning influenced something global—children in the variable condition not only showed better generalization for learned categories, but also discriminating second-order generalizations. Thus, we have linked a manipulation of local learning directly to a global learning effect.

This is an important contribution and a remarkable one because we have demonstrated how teaching children about individual nominal categories can change the word learning biases they develop, which in turn, has consequences for their vocabulary development outside the laboratory. Children in both conditions learned something more than the importance of particular shapes for particular noun categories. Children in the tight condition learned to attend to shape when generalizing novel nouns—even nouns that referred to nonsolid things. However, children in the variable condition learned even more than that—they learned when *not* to attend to shape. Thus, variable training seems to have uniquely pushed children to a more context sensitive shape-bias, something usually not seen until older ages (Jones & Smith, 1993; Samuelson, Horst, Schutte & Dobbertin, 2008). Although this study does not reveal the details of the processes by which this occurred, we suggest two complementary ways in which training at the local level with variable instances may have lead to differences at the global level of attentional biases and word learning.

One way local variability may have influenced global learning is by moving the focus from a specific value on a feature dimension to considering a range of acceptable values for category inclusion. For example, the buckets presented in the tight condition were highly similar in overall shape; they all were cylindrical with smaller bottoms than tops (see Figure 1). In contrast, the buckets presented in the variable condition varied more in shape: the trash bucket had a smaller bottom than top, the bottom of the plastic bucket was almost the same diameter as the top, and the pumpkin was round. This greater variability between exemplars possibly caused children to focus not on a specific shape, but on an abstract range of shape—thus highlighting the dimension of shape in general.

A second way variability may have pushed the level of processing to dimensions is by highlighting what features are *not* critical for a category. A variable set of category instances is more likely to differ on non-critical features. Thus, when we labeled a beige paper bucket, a clear plastic bucket, and an orange cloth pumpkin bucket all "bucket" for children in the variable condition, we were, effectively, telling them buckets differ in color, material, size, and whether they have a handle, and thus, that these dimensions are *not* the ones to attend to when deciding if something is a bucket. In contrast, the things labeled "bucket" in the tight condition were all roughly the same size, all had a handle, and they were made of either plastic or paper. This training eliminated fewer dimensions by presenting fewer contrasts between stimuli at the level of dimensions.

These suggestions about how variability pushes attention to dimensions fit with recent data from Rost and McMurray (2009). They found that speaker variability improved learning of novel word-object mappings and discrimination between lexical neighbors. They suggested that slight variability along the relevant dimension (differences in voice onset time) gave infants better representations of categorical boundaries and helped them attend to a range along the key dimension rather than a specific instance. Furthermore, variability along irrelevant dimensions (e.g. pitch and formants) helped draw infants' attention to the invariant information. The current data add to these ideas by demonstrating that local variability has cascading consequences for subsequent development at higher levels of abstraction.

Clearly, more work is needed to reveal the details of the processes by which variability at the local level helps children find more global relations. Nevertheless, the current data suggest that variability adds more than local spice; it can have a direct impact on the emergence of global cognitive abilities in development.

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Figure 1.
Exemplars used in training and testing for one sample set: the buckets. The Tight training set for each category contained the three most similar exemplars while the Variable training set contained the three most dissimilar exemplars. The remaining four exemplars from each category were used in the Extension and Exclusivity tests, counterbalanced across participants so that each item appeared in both tests.

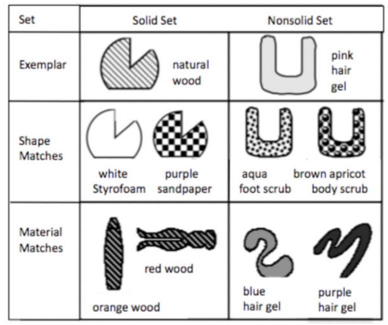

Figure 2.
Example solid and nonsolid stimulus sets used in the Novel Noun Generalization task.

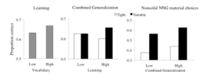

Figure 3.

Performance for tests of learning, combined generalization (both reported as proportion correct), and Novel Noun Generalization of nonsolid substances (reported as proportion material choices). Data are grouped based on the relevant main effect from the regression models: learning grouped by low and high vocabulary size; combined generalization grouped by condition and low and high learning performance; and Nonsolid novel noun generalization grouped by condition and low and high combined generalization performance

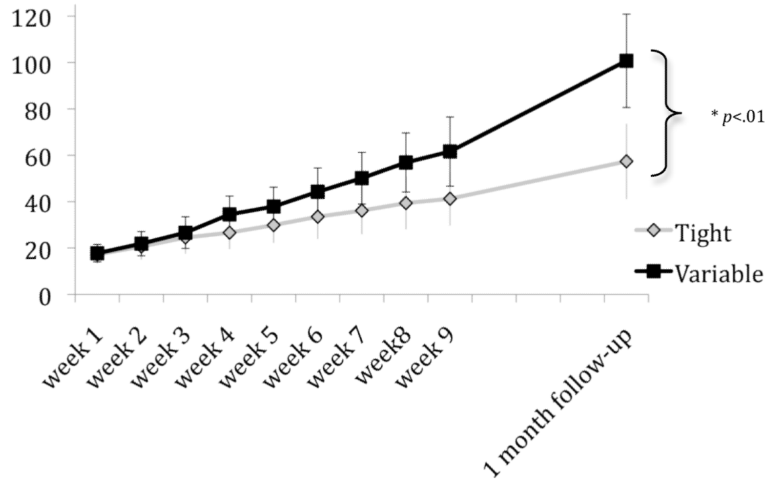

Figure 4.

Changes in noun vocabulary over the course of the study for children in the two training conditions.

Table 1

The 12 words and 2 alternate words used in category training for the study.

Words Used in Training	
Bead	Funnel
Boot	Hammer
Bowl	Key
Bucket	Necklace
Can	Toothbrush
Comb	Tractor
Ladder (alternate)	Spoon (alternate)

Table 2

Order of training and testing procedures across experimental sessions.

Session	Tests
Week 1	NNG, word training
Week 2	Word training, learning, extension
Week 3	NNG, learning, extension, exclusivity
Week 4	Word training
Week 5	Word training, learning, extension
Week 6	NNG, learning, extension, exclusivity
Week 7	Word training
Week 8	Word training, learning, extension
Week 9	NNG, learning, extension, exclusivity
1-month follow-up	NNG