Exploring the Role of Language in Two Systems for Categorization

Kayleigh Ryherd, PhD
University of Connecticut, 2019

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Blablabla said Nobody ?.

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2.1 Methods

2.1.1 Participants

2.1.2 Category Learning Task

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

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

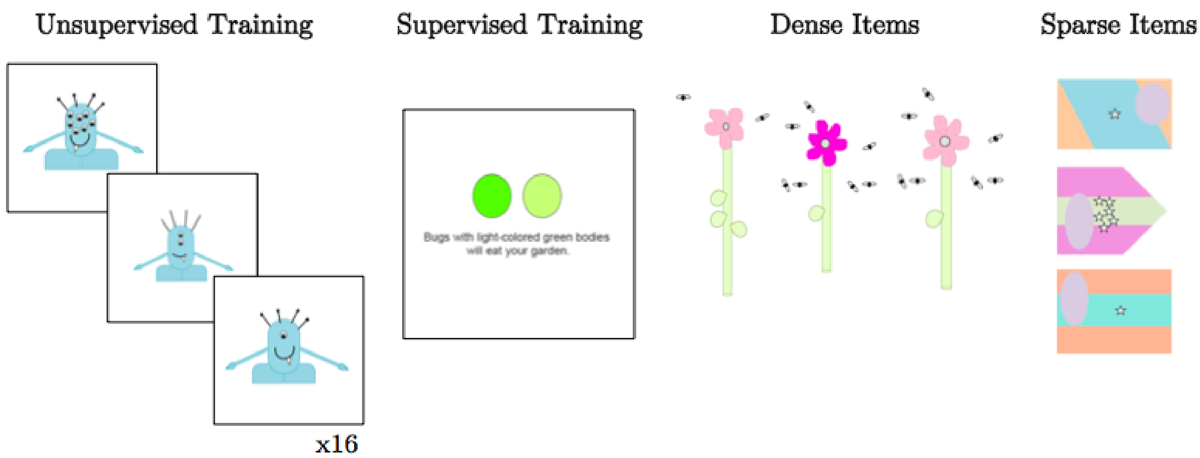

Figure 1. Examples of learning type and category type manipulations for category learning experiment.

This task is within-subjects. Based on the group they were placed into, participants will complete two of the four possible learning-category type combinations. In this experiment, I tested three main order effects. First, I tested order effects for the matching conditions (unsupervised-dense and supervised-sparse).The second order effect used unsupervised-dense and supervised-dense blocks. Finally, the third order effect tested the same sparse stimuli, testing unsupervised-dense and supervised-sparse blocks. This design led to six possible order groups that each participant could be placed into. See Table 1 for a summary.

Table 1. Block orders for statistical density task

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

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

2.1.3 Behavioral Measures

I used multiple assessments to test participants' language ability. The choice of assessments was based on the epiSLI criteria for language impairment (Tomblin et al., 1996), which includes comprehension, expression, vocabulary, grammar, and narrative. I adapted these requirements from a kindergarten population to a college-aged population. The epiSLI criteria have been shown to be robust for diagnosis of specific language impairment (SLI). In addition, other studies of language impairment more broadly have adapted a similar multidimensional approach to measuring language ability, sometimes including measures of phonological skills (Catts et al., 2006). Thus, using assessments that the many domains of language outlined in epiSLI criteria will allow me to get a fuller picture of individual differences in language ability. See Table 2 for a summary of the assessments and which domains of the epiSLI criteria they cover. The specific tests used in this experiment are detailed below.

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

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

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

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

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

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

Table 2. Assessments of language and their corresponding epiSLI domains.

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

2.2 Procedure

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

2.3 Results

2.4 Discussion

3 Experiment 2

3.1 Methods

3.1.1 Participants

3.1.2 Category Learning Tasks

3.1.3 Behavioral Measures

3.2 Procedure

3.3 Results

3.4 Discussion

4 General Discussion

5 Appendix A: Statistical Density Calculations

5.1 Statistical Density Formulae

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

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

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

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

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

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

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.

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

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.

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

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

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

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

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

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

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

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

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

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

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

5.3 Statistical Density Calculations – Dense

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

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

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

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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