[working title] Calling it what it is: Novel categories are distinct from Not-categories

Anonymous CogSci submission

Abstract

[Need to write actual abstract] Include no author information in the initial submission, to facilitate blind review. The abstract should be one paragraph, indented 1/8 inch on both sides, in 9 point font with single spacing. The heading "**Abstract**" should be 10 point, bold, centered, with one line of space below it. This one-paragraph abstract section is required only for standard six page proceedings papers. Following the abstract should be a blank line, followed by the header "**Keywords:**" and a list of descriptive keywords separated by semicolons, all in 9 point font, as shown below.

Keywords: add your choice of indexing terms or keywords; kindly use a semicolon; between each term

Introduction

While researchers in categorization have primarily focused their effort on classification (i.e., associating an exemplar with a category given its features) and inference (i.e., predicting exemplar features given its category), work on category generation – predicting all exemplar features for a novel category – is relatively scarce. Recent work has established a few key findings. Most notably, Jern and Kemp (2013); Ward (1994); Thomas (1998) found that generated categories tend to share distributional statistics with learned categories. Austerweil, Conaway, Liew, and Kurtz (in preparation) also found that category contrast was an important factor in category generation – they found that models sensitive to the differences between categories were a better fit to observed data than models which did not take categories contrast into account.

Beyond these findings, the processes involved in category generation are still not well understood. In particular, it is currently unclear whether generating a new category involves identifying exemplar features that are simply *not* what was previously identified in a prior category, or if it involves generating exemplar features that are in some sense similar to the prior category. For instance, if a musician is creating a new album, is there a difference in the content of the new album when they are trying to compose something that is not one of their previous albums, compared to creating something that is a new genre?

the process of generating a new category is the result of specifying a category

In particular, whenever categories were requested to be generated in these studies, it is Although Jern and Kemp (2013); Austerweil et al. (in preparation) tested a series of computational models such as a hierarchical Bayesian model that assumes

The packing hypothesis would inform us that the variation in the range of feature values of 'Not Alpha' exemplars should be larger than than the variation in the range of feature values of 'Beta' and 'Gamma' exemplars.

Experiment

The primary objective of this experiment is to investigate the differences in the distribution of generated categories across three different instructional conditions. A secondary objective is observe if there are also differences in category distribution across the different Alpha conditions. This 3x3 design indicates a total of nine different conditions.

In the 'Not Alpha' condition, participants were told to generate exemplars that belonged to a category that is 'Not Alpha'. In the

Method

Participants and materials We recruited 240 participants through Amazon Mechanical Turk and randomly assigned them to one of the nine possible conditions. Specific numbers in each condition presented in Table 1.

Stimuli were squares that varied along two dimensions: color (grayscale 9.8%90.2%) and size (3.05.8cm on each side). The assignment of perceptual features (color, size) to axes of the domain space (x, y), as well as the direction of variation along each axis (e.g., increasing or decrasing size) was counterbalanced across participants. Feature values were evenly-spaced on a 50X50 grid, giving a near-continuous space from which exemplars can be generated.

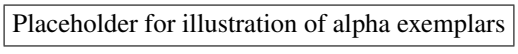

Figure 1: This is a figure.

Procedure In the first phase of the experiment, participants learned the 'Alpha' category exemplars by observing a unique 'Alpha' category exemplar on each trial. This was repeated over a total of three blocks (four trials per block – one corresponding to each unique exemplar), with the order of exemplar presentation randomized within each block. Participants were allowed to spend as much time as they wanted

on each trial and were also shown the full range of possible feature values prior to training.

The next phase comprised a series of generation trials. Depending on their instructional condition, participants were asked to generate either (a) eight exemplars from a category that was 'Not Alpha', (b) eight exemplars from a category called 'Beta', or (c) four exemplars from a category 'Beta' *and* four exemplars from a third category 'Gamma'. Exemplars were generated once per trial using two on-screen sliding scales, with each scale controlling the features (color and size) of the generated exemplar. Feature values could take any one of 50 evenly-spaced values between the specified boundaries. Previously generated exemplars were not allowed to be generated a second time. Participants were shown an on-screen preview of their exemplar on each trial as they interacted with the sliders.

Table 1: Sample sizes for each condition.

Instruction Condition	Cluster	Row	Diagonal
Not-Alpha	26	28	25
Beta-Only	30	27	25
Beta and Gamma	26	27	26

Results

The data revealed a series of individual differences indicating different category generation profiles. To provide a coarse overview of the different patterns of generated categories, we classified the generated categories into six different profiles: Positive, where the correlation between the dimensions is more than r; Negative, where the correlation between the dimensions is less than $-r$; Rows, where the range of values across the x dimension is at least five times more than the range across the y dimension; Columns, where the range of y dimension values is at least five times more than the range of x dimension values; Cluster, where the ranges across both dimensions are less than a; and Dispersed, where the ranges across both dimensions are more than a. We set $r = .7$ and $a = .25$. A sample of each profile is shown in Figure **??** and the frequency plot of the different profiles is presented in Figure 1.

By observing the distribution of these profiles, it is quite clear that

[Need to include stats!!! They're done, just need to plug them in here.]

Discussion

Overall, the results from the different Alpha conditions are similar to those observed in Austerweil et al. (in preparation). One notable difference is that while Austerweil et al. (in preparation) found evidence of negatively-correlated generated categories in their XOR condition, we found no evidence of negatively generated categories in our comparable Diagonal condition.

The differences in the distributional

Interestingly, the similarity in distributional statistics was clearest only in the Row conditions (i.e., participants in the Row conditions generated more row-like categories). This was not observed for participants in the Diagonal conditions, where the generated categories tended to adopt a dispersed profile.

Acknowledgments

In the **initial submission**, please **do not include acknowledgements**, to preserve anonymity. In the **final submission**, place acknowledgments (including funding information) in a section **at the end of the paper**.

References Instructions

Follow the APA Publication Manual for citation format, both within the text and in the reference list, with the following exceptions: (a) do not cite the page numbers of any book, including chapters in edited volumes; (b) use the same format for unpublished references as for published ones. Alphabetize references by the surnames of the authors, with single author entries preceding multiple author entries. Order references by the same authors by the year of publication, with the earliest first.

Use a first level section heading, "**References**", as shown below. Use a hanging indent style, with the first line of the reference flush against the left margin and subsequent lines indented by 1/8 inch. Below are example references for a conference paper, book chapter, journal article, dissertation, book, technical report, and edited volume, respectively.

References

Austerweil, J. L., Conaway, N., Liew, S. X., & Kurtz, K. J. (in preparation). Creating and learning something different: Similarity, contrast, and representativeness in categorization.

Jern, A., & Kemp, C. (2013). A probabilistic account of exemplar and category generation. *Cognitive Psychology*, *66*(1), 85–125.

Thomas, R. D. (1998). Learning correlations in categorization tasks using large, ill-defined categories. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *24*(1), 119–143.

Ward, T. B. (1994). Structured imagination: The role of category structure in exemplar generation. *Cognitive Psychology*, *27*(1), 1–40.

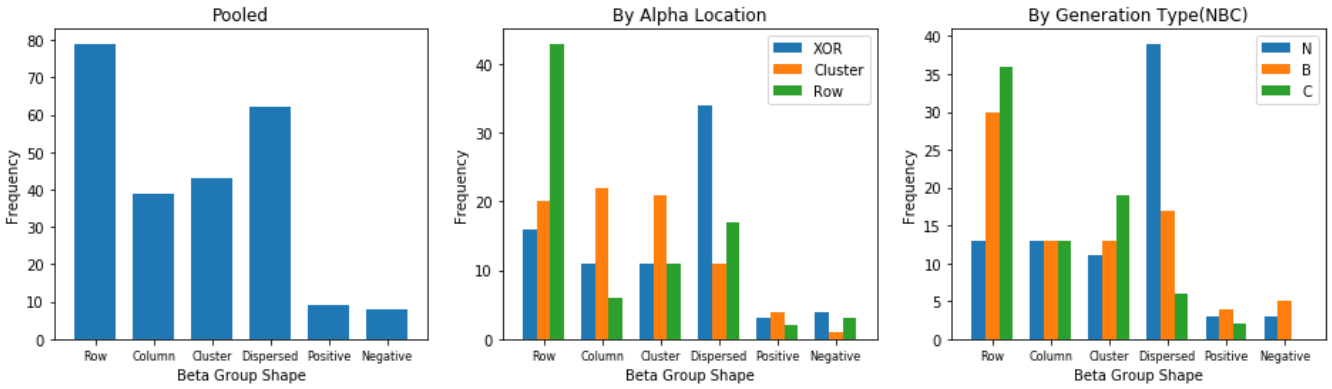

Figure 2: [insert caption].

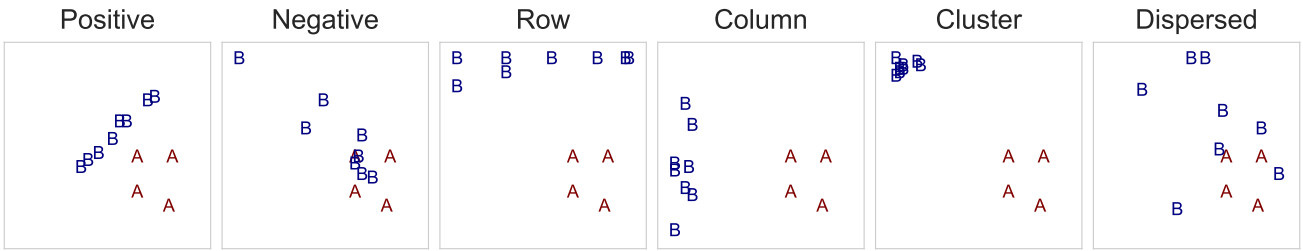

Figure 3: [insert caption].

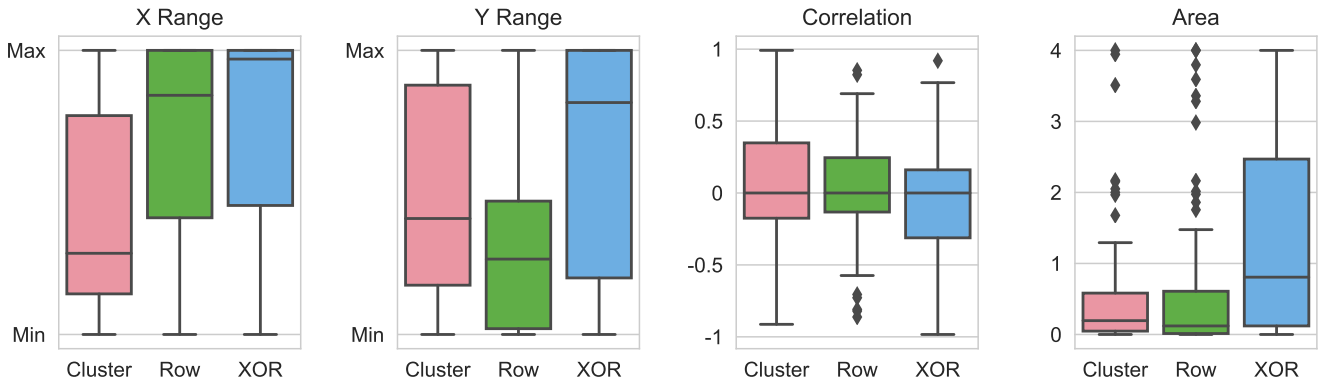

Figure 4: [insert caption].

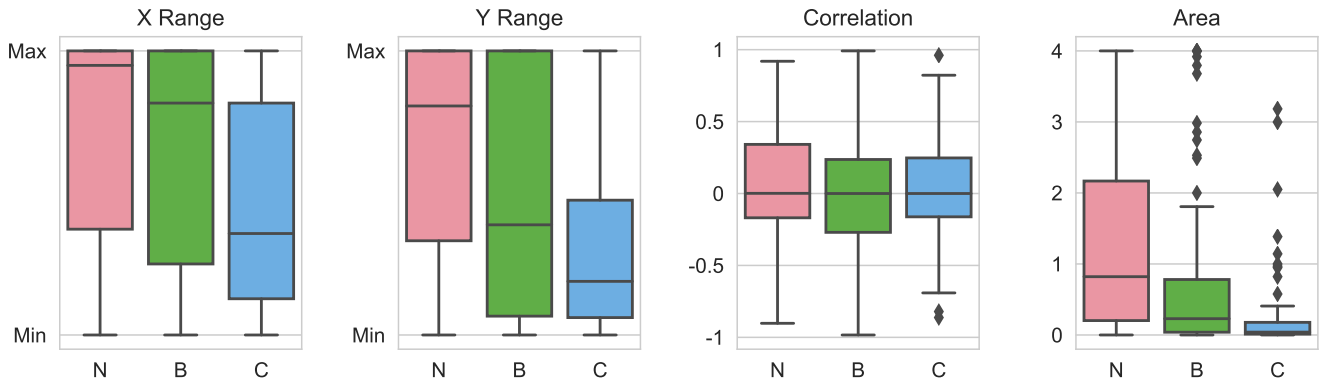

Figure 5: [insert caption].