PACKER: An Exemplar Model of Category Generation

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Generating new concepts is an intriguing yet understudied topic in cognitive science. In this paper, we present a novel exemplar model of category generation: PACKER (Producing Alike and Contrasting Knowledge using Exemplar Representations). PACKER's core design assumptions are (1) categories are represented as exemplars in a multidimensional psychological space, (2) generated items should be similar to exemplars of the same category, and (3) generated categories should be dissimilar to existing categories. A behavioral study reveals strong effects of contrast- and target-class similarity. These effects are novel empirical phenomena, which are directly predicted by the PACKER model but are not explained by existing formal approaches.

How do people create new concepts?

Classic paradigm: Ps draw pictures of new categories (e.g., alien plants and animals), experimenter analyzes what they created. (Ward, 1994).

Artificial categorization paradigm: Ps learn about categories in an artificial domain, then generate new categories (Jern & Kemp, 2013). Designed to enable testing of formal models.

Common finding. Generated categories are distributionally similar to known categories:

- People generate categories using known features.
- Features vary as in known categories.
- Features are correlated as in known categories.

Existing Accounts (Jern & Kemp, 2013; Ward, 1995)

- *Path Of Least Resistance / Copy & Tweak*: Generated category members are copied from known members.
- *Hierarchical Bayesian*: New categories are samples from a common, but latent, domain-wide distribution.

How do people create *new* concepts?

No existing work on how generated categories *differ* from what is already known. New concepts should be distinct from known ones.

How do people ensure their creations are unique?

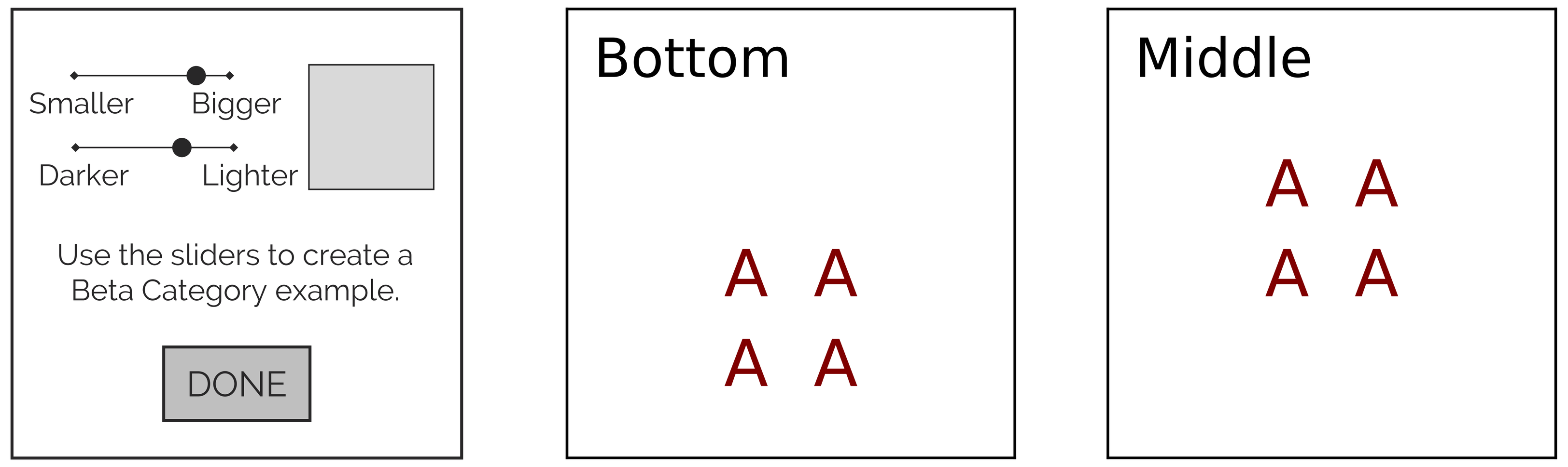
Our Contributions:

1. Proposed contrast as a core principle of generation.
2. Developed an exemplar-based model including contrast as a mechanism for generating categories.
3. Tested the model in a behavioral experiment. We found strong support for our model, supporting contrast as core constraint in category generation.

Behavioral Experiment

Questions: Does contrast with a previously learned category influence generation? Is distributional emulation the only factor?

Participants (MTurk; N=122) learned about an experimenter-defined category ('Alpha') composed of squares varying in size and color.



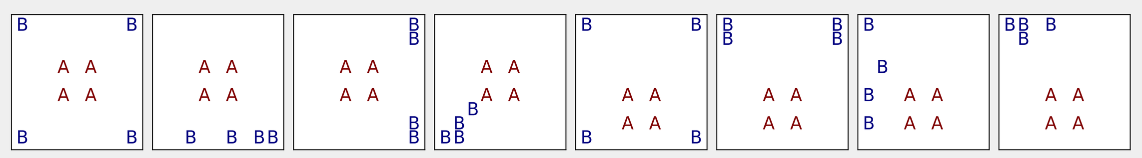
Two conditions (Between-Ps) differed only in category location. *Differences cannot be explained by sharing distributional info.*

After training, Ps generated four examples of a new 'Beta' category. *Generation using sliding-scale interface (as in Jern & Kemp, 2013).*

If category contrast is a factor, the *unoccupied space* is important

- All Ps should generate items distant from the Alphas.
- Middle Ps should create categories spanning the entire Y-axis.

Behavioral Results

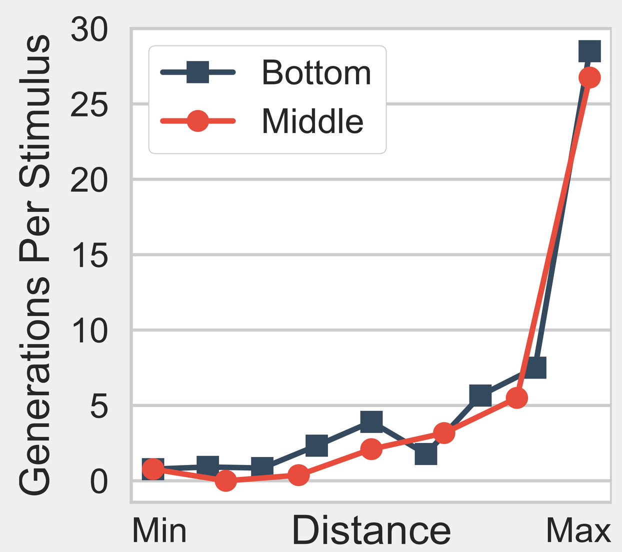


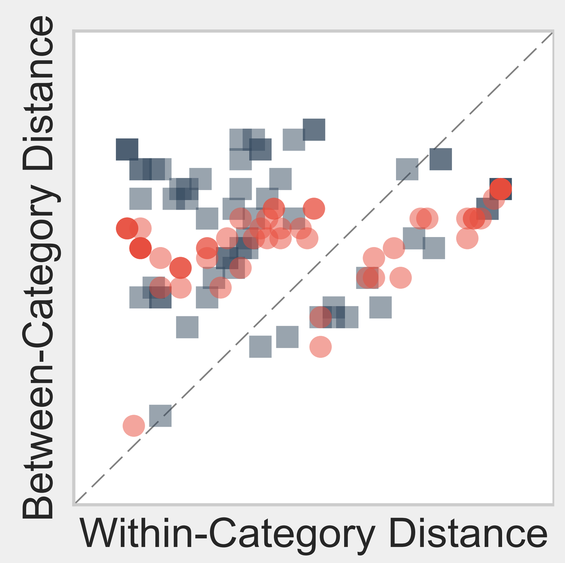
Exemplars that are highly distant from Alpha category members were more likely to be generated.

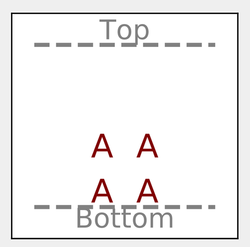
Generated category members were more similar to each other than to Alphas.

Middle Ps were more likely to create categories spanning the entire Y-axis.

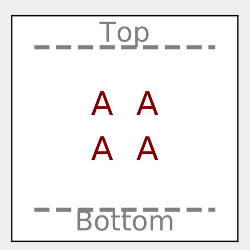
The *location* of known categories impacts the *distribution* of generated categories.







Bottom	Top Used	Top Not Used
Bottom Used	16	8
Bottom Not Used	31	6



Middle	Top Used	Top Not Used
Bottom Used	28	18
Bottom Not Used	11	4

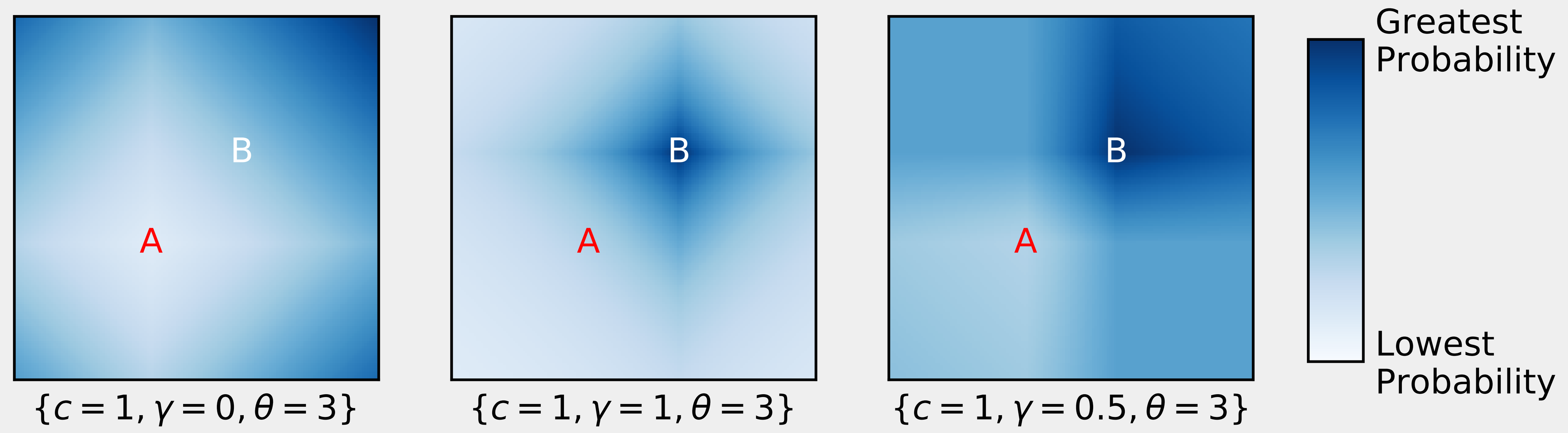
PACKER: Producing Alike and Contrasting Knowledge using Exemplar Representations

Extension of the Generalized Context Model (GCM; Nosofsky, 1984).

Proposal: Generation is constrained by within- and between-class similarity.

- Similarity computed as: $s(x_i, x_j) = \exp\{-c\sum_k |x_{ik} - x_{jk}| w_k\}$
- Generation based on aggregated similarity: $a(y, x) = \sum_j f(x_j) s(y, x_j)$
- $f(x_j)$ based on class membership: γ for x_j in target class, $\gamma - 1$ otherwise.
- Generation probability $p(y)$ computed via softmax among $\theta \cdot a(y, x)$

Implication: Prioritization of within-class and between-class similarity is parametrized. Distinct γ values reflect different generation approaches.

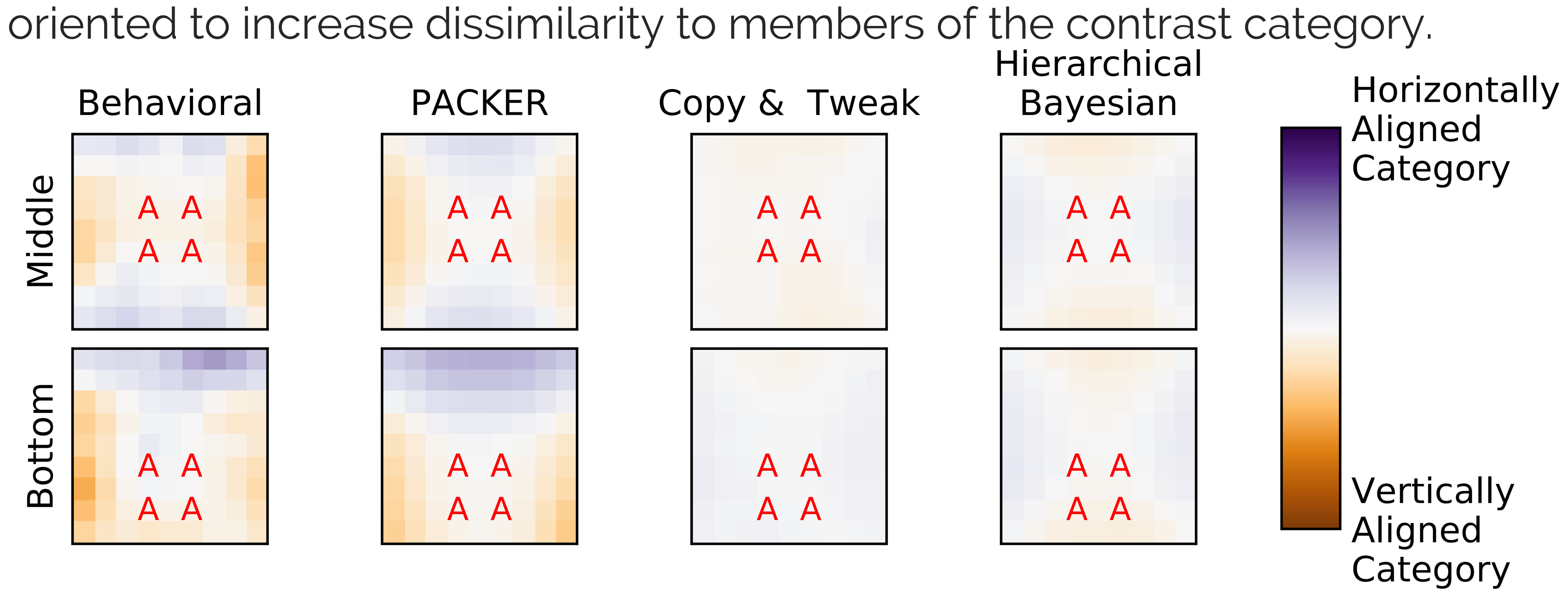


Modeling Results

We fit the **PACKER**, **Copy and Tweak**, and **Hierarchical Bayesian** models, maximizing log-likelihood to every response in our dataset. PACKER's fit greatly outperformed the other models (~11% larger log-likelihood).

Category Structure vs. Category Location

We computed, for each stimulus, the difference between the X- and Y-axis ranges of each category it was generated in. **Result**: Categories were oriented to increase dissimilarity to members of the contrast category.



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