PACKER: An Exemplar Model of Category Generation

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Abstract

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Introduction

One of the most intriguing capabilities of human cognition is the ability to creatively generate new ideas and concepts. The creative use of knowledge has, however, scarcely been the subject of scientific inquiry in the field of categorization. Most research on concepts and categorization has conformed to a traditional artificial classification learning paradigm (Kurtz, 2015), wherein the primary use of category knowledge is to discriminate between two or more experimenter-defined classes.

In one of the earliest explorations on the creative use of conceptual knowledge, Ward & colleagues (Marsh, Ward, & Landau, 1999; Smith, Ward, & Schumacher, 1993; Ward, 1994; Ward, Patterson, Sifonis, Dodds, & Saunders, 2002) provided clear evidence of the role of prior knowledge in concept generation. In a canonical study, Ward (1994) asked participants to draw and describe novel species of plants and animals that might exist on other planets. Generation was strongly constrained by prior knowledge of Earth plants and animals: people generated alien species using the same structural forms found on Earth (e.g., eyes, legs, wings), exemplars tended to obey the same feature correlations observed on Earth (e.g., feathers tended to co-occur with wings), and exemplars drawn from the same species were less variable than animals drawn from different species (as is the case on Earth).

In a more recent report, Jern and Kemp (2013) developed a hierarchical model capable of explaining the influence of prior knowledge observed by Ward (1994). In their model, categories are represented as distributions in multi-dimensional space, where known exemplars are assumed to have been generated from the underlying category distribution. Category distributions are in turn thought to be generated by an underlying domain distribution, representing common distributional characteristics of known categories (e.g., feature variance, feature correlations). When asked to generate exemplars from a novel category, people are thought to sample a new category from the domain distribution, and then sample exemplars from the category distribution. Thus, the generated exemplars tend to obey the same distributional properties of known categories.

Jern and Kemp (2013) reported several experiments in support of their model's predictions. In their paradigm, participants are first exposed to members from a set of known categories within a k-dimensional feature space (in their experiments, $k = 3$). After observing the assigned examples, participants are asked to generate exemplars from a new category within the domain. Participants presented with k scales that can be used to adjust the feature values of the generated stimulus, and are given unlimited time to create each example. As in the classic Ward (1994) experiment, Jern and Kemp (2013) found that people generated categories possessing the same feature correlations as the known categories in the domain.

PACKER: An Exemplar Model

The work presented by Ward & Colleagues, as well as that of Jern and Kemp (2013), undoubtedly captures a core principle of the creative use of conceptual knowledge: category generation is informed by the distributional characteristics of known concepts in the target domain. However, this work fails to describe the inverse: how do generated categories *differ* from known categories? In this paper, we introduce a novel exemplar-based approach to category generation, the PACKER model (*Producing Alike and Contrasting Knowledge using Exemplar Representations*), which creates new categories by balancing two constraints: (1) new categories should be different from known categories (minimizing between-class similarity), and (2) new categories should be internally coherent (maximizing within-class similarity).

The PACKER model is in many senses an extension of the highly influential Generalized Context Model of category learning (GCM; Nosofsky, 1984). The model assumes that each category is represented by a collection of exemplars within in a k-dimensional stimulus space, and that generation is constrained by both similarity to members of the category being generated as well as similarity to members of other categories.

As in the GCM, the similarity between two examples, $s(x_i, x_j)$, is defined as an inverse-exponential function of distance:

$$s(x_i,x_j) = exp(-c\sum_k |x_{ik} - x_{jk}|w_k) \qquad (1)$$

where w_k is a vector of attention parameters ($\sum_k w_k = 1$), weighting to the importance of each feature in the similarity computation. The c parameter controls the specificity of examples: larger values of c produce more *specific* representations (exemplars that do not generalize broadly). The attention weights are of interest in explaining individual differences in generation strategy (discussed below), but for our formal simulations they are set uniformly.

When prompted to generate a new example, the model considers both the summed similarity to examples from other categories as well as the summed similarity to examples in the target category. More formally, the summed similarity ss between generation candidate y and the model's stored exemplars x_j can be computed as:

$$ss(y,x) = \sum_j \hat{f}_j s(y,x_j) \quad (2)$$

where $\hat{f}_j$ is a function specifying each example's degree of contribution toward generation. Although $\hat{f}_j$ may be set arbitrarily, in PACKER it is set according to class assignment. For known members of contrast categories, $\hat{f}_j = \phi$. For known members of the target category, $\hat{f}_j = \gamma$. ϕ and γ are free parameters ($-\infty \leq \phi, \gamma \leq \infty$) controlling the contribution of target- and contrast-category similarity to generation. Larger absolute values for either parameter produce greater consideration of that type of similarity, with values of 0 producing no effect. Negative values produce a 'repelling' effect (exemplars are less likely to be generated nearby). Conversely, positive values produce a 'pulling' effect (exemplars are more likely to be generated nearby).

Because the model's main proposals are that new categories should be different from existing categories, and exemplars belonging to the same category should be similar to one another, PACKER is commonly simulated under the constraints that $\phi < 0, \gamma > 0$, thus, similarity to contrast categories is effectively subtracted from similarity to the target category. When $-\phi = \gamma$, negative summed similarities indicate that y is more similar to members of contrast categories, and positive values indicate y is more similar to members of the target category.

The probability that a given candidate y will be generated is evaluated using the Luce (1977) choice axiom. Candidates with larger summed similarity are more likely to be generated compared to candidates with smaller summed similarity:

$$p(y) = \frac{exp(\theta \cdot ss(y,x))}{\sum_i exp(\theta \cdot ss(y_i,x))} \quad (3)$$

where θ (≥ 0) is a free parameter controlling overall response determinism.

Summary. The PACKER model described above explains exemplar and category generation through exemplar similarity (one of the field's oldest traditions). The model proposes that people generate categories by maximizing within-category similarity and minimizing between-category similarity. Unlike the model proposed by Jern and Kemp (2013), the distributional properties of known categories affects performance only insofar as it constrains inter-exemplar similarities. Instead, the *location* of known categories in the domain is crucial because it constrains remaining possible locations for new categories. See Figure 1 for a depiction of the model's behavior.

Behavioral Experiment

The behavioral experiment described below was designed to test a core prediction of the PACKER model: that the *location* of contrast categories (as opposed to their structure), influences generation. The experiment follows the paradigm set by Jern and Kemp (2013): first, participants are exposed to members of a known category ('Alpha', or 'A'), and are then asked to generate exemplars belonging to a new category ('Beta', or 'B').

Because the goal of the study was to determine if the structure of known categories is the only determinant of generation, our experiment manipulated only the location of the Alpha category within the domain (the structure of the category was held constant). See Figure 2 for a depiction of the experimental conditions. In both conditions, members of the Alpha category are tightly clustered, with equal variance on both features and no correlation between features. Our manipulation is fairly 'weak' – the conditions have only a slight difference in the Y-Axis position of the Alpha category: in the 'Middle' condition the Alpha category is placed in the center of the space, in the 'Bottom' condition the Alpha category is placed in the bottom-center of the space.

By consequence, the Jern and Kemp (2013) model predicts that there should be no difference in the generated categories, as the distributional characteristics of the domain do not differ between the two conditions. However, the PACKER model can predict strong between-condition differences. Assuming exemplars are generated such that each category has strong within-class similarity and weak between-class similarity, top areas of the stimulus space should be used for generation more frequently in the Bottom condition (compared to Middle), as stimuli in this area possess weaker similarity to members of the Alpha category. Conversely, the bottom areas of the space should be less frequently used for generation in the Bottom condition (compared to Middle), as stimuli in this area possess greater similarity to the Alpha category.

Participants & Materials

We recruited 122 participants from Amazon Mechanical Turk. All participants were located in the United States. 61 Participants were assigned to the 'Middle' condition, 61 were assigned to the 'Bottom' condition. Stimuli were squares varying in color (RGB 25–230) and size (3.0–5.8cm), see Figure 3 for samples. The assignment of perceptual features (color, size) to axes of the domain space (x, y) was counterbalanced across participants.

Procedure

Participants began the experiment with a short training phase (3 blocks of 4 trials), where they iteratively observed exemplars belonging to the 'Alpha' category. Participants were instructed to learn as much as they can about the Alpha category, and that they would answer a series of test questions afterwards. On each trial, a single exemplar from the Alpha category was presented, and participants were given as much time as they desired before moving on.

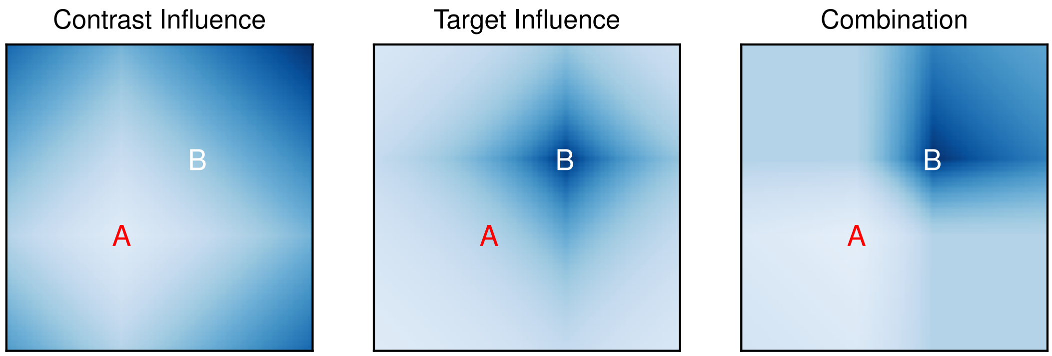

Figure 1: Predicted generation of a category 'B' example, following exposure to one member of category 'A' and one member of category 'B'. Areas in which generation is not likely are shaded white; high probability areas are shaded blue. *Left*: Predictions given $\{\phi = -1, \gamma = 0\}$ (contrast influence only). *Center*: Predictions given $\{\phi = 0, \gamma = 1\}$ (target influence only). *Right*: Predictions given $\{\phi = -1, \gamma = 1\}$ (both constraints considered).

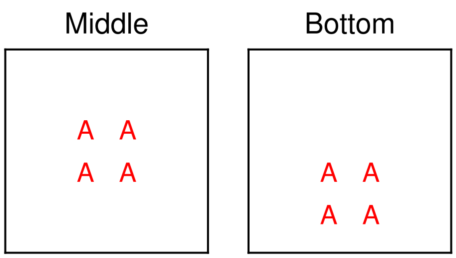

Figure 2: Experiment conditions.

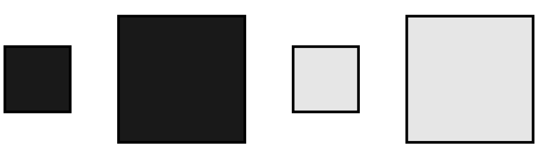

Figure 3: Sample stimuli (not drawn to scale).

Following the training phase, participants were asked to generate four examples belonging to another category called 'Beta'. Participants were instructed that members of the Beta category could be quite similar or different depending on what they think makes the most sense for the category, but that they were not allowed to make the same example twice.

As in the Jern and Kemp (2013) experiments, generation was completed using a sliding-scale interface. Participants were presented with two scales that could be used to change the color and size of the generated example. An on-screen preview of the example updated whenever one of the features was changed. Participants could generate any example along an evenly-spaced 9x9 grid, and they could change the example as much as they wanted before moving on. Neither the members of the Alpha category nor the previously generated Beta examples were visible during generation.

Results

Because the conditions differ only in their location along the Y (vertical) axis (see Figure 2), our main interest is in generation of Beta examples above and below the contrast category.

Table 1 contains the number of participants in each condition who generated at least one example possessing one of the

Fisher's Exact Tests reveal that a greater number of participants assigned to the Middle condition generated at least one Beta example in the bottom rows of the space, $p < 0.001$. Similarly, a greater number of Middle participants generated all four Beta examples in the bottom rows of the space, $p = 0.003$. Participants in the Bottom condition were more marginally more likely to generate at least one Beta example in the top rows of the space, $p = 0.088$, and they were significantly more likely to generate all four examples in the top rows of the space, $p = 0.017$. The conditions did not differ in the number of participants who placed at least one Beta example in the top rows *and* at least one Beta example in the bottom rows, $p = 0.14$.

Table 1: Behavioral results.

Middle	Used top rows	No top rows
Used bottom rows	31	18
No bottom rows	11	1

Bottom	Used top rows	No top rows
Used bottom rows	22	8
No bottom rows	29	2

Summary

Simulations

Discussion

Acknowledgments

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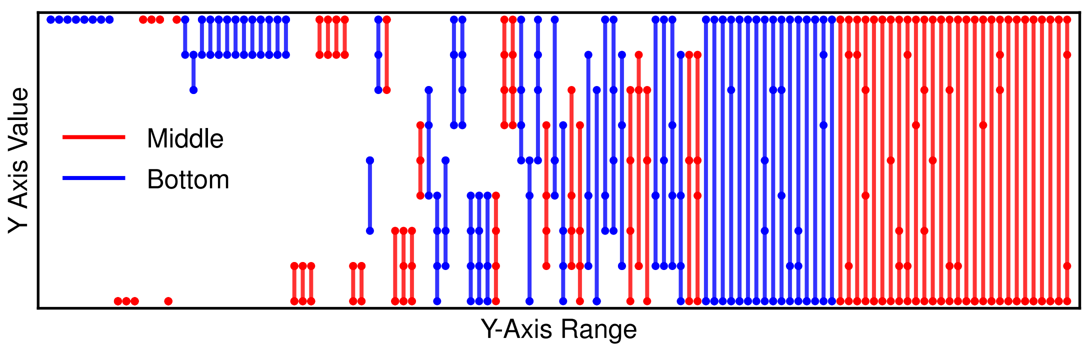

Figure 4: Behavioral results. Each line shows the minimum and maximum value of a generated category along the Y (vertical) axis. Dots along each line represent the positions of individual exemplars in the category, and each participant's category is shown on a separate line. Participants are sorted by overall Y axis range, and then by condition.