1 The PACKER Model: Producing Alike or Contrasting Knowledge with Exemplar Representations

This model assumes that people represent categories as exemplars in a multidimensional space, and that generation is constrained by both similarity to members of the category being generated *and* dissimilarity to members of other categories. The model assumes people generate categories that are dissimilar to known categories and have strong within-class similarity.

The similarity between exemplars x_i and x_j is computed using Shepard's law:

$$s\left(x_i, x_j\right) = \exp\left\{-c\left[\sum_k w_k \left|x_{ik} - x_{jk}\right|^r\right]^{1/r}\right\} \tag{1}$$

When prompted to make a generation decision, participants are thought to consider both similarity to examples from other categories as well as similarity to examples in the target category. More formally, the aggregated similarity a between candidate y and the model's stored exemplars x can be computed as:

$$a(y, x) = \sum_j f(x_j) s(y, x_j) \tag{2}$$

Where $f(x_j)$ is a function specifying each stored example's degree of contribution toward generation. Although $f(x_j)$ may be set arbitrarily, in PACKER it is set according to class assignment. For known members of the target category, $f(x_j) = \theta_t$. For members of contrast categories, $f(x_j) = -\theta_c$. θ_t and θ_c are free parameters $(0 \leq \theta_c, \theta_t)$ respectively controlling the within-class similarity and between-class dissimilarity: $\theta_t > 0, \theta_c = 0$ produces exclusive consideration of same-category members, and $\theta_t = 0, theta_c > 0$ produces exclusive consideration of opposite-category members. When $\gamma = 0.5$, the similarity to contrast categories is effectively subtracted from the similarity to the target category.

The probability that a given item y will be generated given the model's memory x is computed using relative summed similarity values across all generation candidates y_i:

$$p(y) = \frac{\exp\left\{\theta \cdot a\left(y, x\right)\right\}}{\sum_i \exp\left\{\theta \cdot a\left(y_i, x\right)\right\}} \tag{3}$$

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

1.1 An Older Version of PACKER: Didn't make it to any of the revisions, but was briefly considered

This model assumes that people represent categories as exemplars in a multidimensional space, and that generation is constrained by both similarity to members of the category being generated *and* dissimilarity to members of other categories. The model assumes people generate categories that are dissimilar to known categories and have strong within-class similarity.

The similarity between exemplars x_i and x_j is computed using Shepard's law:

$$s\left(x_i, x_j\right) = \exp\left\{-c\left[\sum_k w_k \left|x_{ik} - x_{jk}\right|^r\right]^{1/r}\right\} \tag{4}$$

When prompted to make a generation decision, participants are thought to consider both similarity to examples from other categories as well as similarity to examples in the target category. More formally, the aggregated similarity a between candidate y and the model's stored exemplars x can be computed as:

$$a(y, x) = \sum_j f(x_j) s(y, x_j) \tag{5}$$

Where $f(x_j)$ is a function specifying each stored example's degree of contribution toward generation. Although $f(x_j)$ may be set arbitrarily, in PACKER it is set according to class assignment. For known members of the target category, $f(x_j) = \gamma$. For members of contrast categories, $f(x_j) = \gamma - 1$. γ is thus a free parameter ($0 \leq \gamma \leq 1$) controlling the trade-off between within-class similarity and between-class dissimilarity: $\gamma = 1$ produces exclusive consideration of same-category members, and $\gamma = 0$ produces exclusive consideration of opposite-category members. When $\gamma = 0.5$, the similarity to contrast categories is effectively subtracted from the similarity to the target category.

The probability that a given item y will be generated given the model's memory x is computed using relative summed similarity values across all generation candidates y_i:

$$p(y) = \frac{\exp\left\{\theta \cdot a\left(y, x\right)\right\}}{\sum_i \exp\left\{\theta \cdot a\left(y_i, x\right)\right\}} \tag{6}$$

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