Abstraction in Natural Language Categories

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Keywords: formal models; categorization; concepts; typicality.

Introduction

A long lasting debate in research on the fundamental human capacity to categorize, regards the degree of abstraction in the mental category representations of a cognitive agent. In its extremes, this debate translates into the decades-old discussion between advocates of the exemplar view (Nosofsky, 1984) and the prototype view (Minda & Smith, 2001). Recently, a number of models have been developed that go beyond these extremes (Griffiths, Canini, Sanborn, & Navarro 2007; Love Medin & Gureckis, 2004; Rosseel, 2002; Vanpaemel & Storms, 2008). One of them is the Varying Abstraction Model (VAM) proposed by Vanpaemel and Storms (2008) in which a whole range of category representations (including the prototype and exemplar representation) can be tested and compared with one another. In this way, the VAM can be used to quantify the degree of abstraction in artificial categories.

Surprisingly, these and other formal models that have been extensively used to investigate the category representations of artificial categories are rarely used to study the category representations of natural language categories such as *fruits* and *birds*. This is odd, since ultimately the goal of investigating artificial categories is to better understand how people learn and use everyday concepts, that is, natural language categories. Given that natural language categories can be expected to be different from artificial categories in a number of respects (Malt & Smith, 1984), the results from artificial categorization experiments may not easily generalize to natural language categories

In the present study we test whether we can find evidence for partial abstraction in natural language categories. We adapt the VAM to make it applicable to the domain of natural language categories and test it in two categories: *fruits and birds.*

The Varying Abstraction Model

The VAM starts from the assumption that the prototype and exemplar representation are two extremes on a continuum ranging from maximal abstraction (prototype) to minimal abstraction (exemplar) and furthermore states that besides these two extremes also intermediate representations on this continuum should be considered as valuable category representations. These intermediate category representations correspond to representations in which some exemplars are merged to form a set of prototypes and where other exemplars can be represented individually.

The category representations of the VAM are formed by subprototypes. To define subprototypes, VAM uses a multidimensional space to represent the exemplars of a category. Subprototypes are formed by dividing the points, that make up a category in the MDS space, in clusters and by averaging the coordinates of the points that were clustered together.

The more subprototypes that make up a representation the less abstract the representation is. The least abstract representation of the VAM, is the exemplar representation for which no exemplars are merged together. If all the exemplars are merged in one cluster the obtained representation is the most abstract representation of the VAM namely, the prototype representation and a representation with two subprototypes is, for example, slightly less abstract than a prototype representation but still more abstract than an exemplar representation.

Given a category representation, the VAM uses the processes of the well-known Generalized Context Model (GCM) of Nosofsky (1984) to determine the category decisions a subject makes for a particular stimulus. The VAM derives, in the same way as the GCM, similarities from the MDS space and uses, like the GCM, the Luce choice rule to derive category decisions from these similarities. The only difference is that the VAM contains not only the exemplar representation but also the prototype and all the possible intermediate representations lying between the prototype and exemplar representation.

Vanpaemel and Storms (2008,2010) fitted the VAM to category decisions made for artificial categories and showed that an intermediate representation provided a better fit to the data in some of the artificial categories they studied, suggesting that these intermediate category representations are valuable category representations for artificial categories.

Varying abstraction in natural language categories

When applying the VAM to the domain of natural language concepts, two considerations are in place. First, whereas in category learning experiments with artificial stimuli the dependent variable typically is a categorization decision, this variable seems rather awkward for semantic concept research since people are generally in good agreement of the exemplars that belong to a particular category and those that do not. Category decisions are, therefore, not the primary variable studied in natural language categories. Researchers investigating natural language categories usually use typicality as a dependent variable in their studies. Typicality is a measure of how good an exemplar is an example of a category. Typicality has been used extensively in the studies about the category representations of natural language categories and is known to predict performance in a variety of cognitive tasks (for a review see Hampton, 1993).

In order to obtain typicality predictions for each exemplar from the representations of the VAM model we calculate the similarity of the exemplars to the category, which in case of the VAM corresponds to summing the similarity of the exemplar to all the subprototypes that make up the category.

Second, everyday concepts have an extension that greatly outnumbers the largest artificial categories generally studied. This greatly increases the complexity of studying varying abstraction in these categories. There is no a priori restriction in the VAM in the way that exemplars of a category are merged into subprototypes. This means that in a category with a extensive number of exemplars the number of possible category representations quickly becomes untenable. A category with 30 exemplars for example yields 8.4675 10^{23} different category representations. One way to solve this issue is to assume that some category representations are more plausible than others. It is for example much more likely that similar members of a category will be clustered together in a category representation while dissimilar members will be kept separate. This idea is elegantly captured by applying k-means clustering, in which similar members are assigned to the same cluster and dissimilar members are kept separate from each other. By using k-means clustering we were able to select a single category representation for every number of subprototypes.

Data

In our study we investigated the natural language categories *fruits* and *birds* with respectively 44 and 41 exemplars. To construct an MDS space for each category we gathered pairwise similarity ratings for each category by asking four subjects to rate the similarity between each pair of exemplars on a scale from 1 (not at all similar) to 9 (very similar). Typicality ratings for each exemplar were obtained by asking subjects to rate the typicality of the exemplars on a scale from 1 (not at all typical for the category) to 20 (very typical for the category).

Results

For each of the categories, we optimized the correlation between observed and model-based typicality scores for each representation at each level of abstraction separately. This results in 44 model fits for the category fruits and 41 model fits for the category *birds*.

The results of the model analyses will be discussed in the light of earlier findings.

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