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The role of extensional information in conceptual combination

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Abstract

In this study, we evaluated the role of extensional information in the representation of complex concepts. For 10 complex concepts, typicality was predicted using a traditional feature-based prototype model, an instantiation-based spatial exemplar model and an instantiation-based spatial prototype model. Results clearly indicated that the extension of a complex concept plays an important role in its representation, and little or no variance in the observed typicality gradient was accounted for exclusively by the prototype model.

Keywords: natural language categories; conceptual combination; computational models;

Two important aspects of human language are compositionality and productivity. In everyday conversation, simple semantic concepts (e.g. 'sports', 'weapons', 'clothing') are continuously combined, adapted and specified into more complex concepts ('outdoor sports', 'dangerous weapons', 'warm clothing') that better fit the intended meaning. The resulting linguistic structures are generally effortlessly comprehended by listeners or readers. Indeed, language comprehension and production seem to necessarily imply "… the combination of concepts into larger and larger structures as guided by the syntax of language" (Murphy, 2002, p. 443).

An important topic in research concerning semantic concept representation – and moreover, an important test of the generality of theories on natural language concepts – is how people arrive at the interpretation of complex concepts, such as 'homicidal green penguin' (Osherson & Smith, 1981). While context and language syntax definitely play a role in interpreting these larger structures, it is obvious that the interpretation of the combination of relatively simple concepts into more complex concepts is for a large part determined by the meaning, and thus the representation, of the relatively simple[1] concepts 'penguin', 'homicidal' and 'green' (e.g. Hampton, 1997).

[1] We use the term 'simple' to denote concepts for which a well established, lexicalized expression exists.

Challenges to a prototype view of complex concepts

Following the main approach in research concerning natural language categories, theories of conceptual combination are traditionally based on a prototype view on concepts. In this view it is assumed that simple, semantic concepts are represented by a prototype a summary representation often assumed to be the average of the category (e.g., Hampton, 1993). The concept 'weapons', for example, is assumed to be a summary representation of what weapons are like on average.

Extending this approach to the domain of conceptual combination, several models have been developed that use this notion of a prototype to give an account of how people interpret complex concepts such as 'dangerous weapons' or 'red apple' (Murphy, 1990; Smith, Osherson, Rips & Keane, 1988). In these models, a concept is typically seen as a schema, consisting of dimensions (e.g. color, shape, size) and possible values on these dimensions. The schema representation of a concept such as apple may contain the dimensions colour, shape, texture and size. The dimension for color, would contain possible values 'red', 'green' and 'brown', each of which has a certain salience within the concept. When the concept 'apple' is combined with another concept to form for example the complex concept 'red apple', the dimension 'color' becomes dominated by the value 'red', and the dimension of color is weighed more heavily. The net result is that the dimension 'color' becomes more diagnostic in determining whether something is a red apple than the dimension color would be in a judgment of whether something is an apple. In short, the conceptual combination 'red apple' results in a modification – essentially a reweighing of features – of the prototype of the concept of 'apple'.

There are however two major challenges for these prototype models of complex concepts. First, several intuitions and observations suggest that the extension of complex concepts – i.e., the set of things in the world the concept refers to – also plays in the representation (Murphy, 1990; Gray & Smith, 1995). For example, Medin and

Shoben (1988) have shown that a metal spoon is judged to be more typical of 'spoons' than is a wooden spoon, whereas a wooden spoon is judged more typical of 'large spoons' than is a metal spoon. This is problematic for the prototype based models since there is no a priori reason why modifying the size dimension of the concept 'spoon' affects the salience of a certain value on another dimension. However, many instances of the category 'large spoon' are made of wood, and it seems people use their knowledge of the extension of the concept 'large spoon' to judge typicality. The importance of extensional information in conceptual combination is often referred to as extensional feedback (e.g. Hampton, 1997). Despite clear evidence, well specified and empirically grounded ways of implementing 'extensional feedback' in models of conceptual combination have yet to be developed.

A second and perhaps even greater challenge for prototype models of conceptual combination, is the recent rise of the exemplar view in semantic concept research. According to this view, categories are represented by previously encountered instances of a category. The concept 'weapons' thus is assumed to be represented by members of the category. Recent research contrasting prototype models and exemplar models in the prediction of typicality strongly suggests that semantic concepts are represented by instances rather than by an abstract summary representation (e.g., Voorspoels, Vanpaemel & Storms, 2008). Obviously, these findings are problematic for the traditional models of conceptual combinations, since these theories are based on prototype representations of simple concepts.

Outline

Both the notion of extensional feedback and the success of the exemplar view in studies concerning simple concepts, point to the necessity of a systematic study of extensional information in conceptual combination. The present study aims at a systematic evaluation of the role of extensional information in conceptual combination, starting from recent models used in simple concept research. More specifically, we contrasted two different prototype models –which neglect extensional information – with an instantiation based exemplar model – which takes the category extension into consideration – in the prediction of the typicality gradient of 10 complex concepts.

One prototype model is based on the idea of conceptual combination as the modification of a prototype in the sense of a reweighing of the features of the modified concept. This model will be referred to as the *feature-based prototype model.* The two other models – the second prototype model and the exemplar model– are based on an underlying spatial representation. The key idea behind the exemplar model is that a complex concept is represented by a number of instances that are activated. In the spatial prototype model, a complex concept is represented by the average of a set of instances. The spatial models both rely on an instantiation principle (Heit & Barsalou, 1994), which essentially posits that certain judgments about concepts are made by activating 1 or more members of the category the concept refers to.

We used the typicality gradient of the complex concepts as an evaluation criterion for the models. The notion of typicality gradient refers to the observation that some members of a category are better examples of the category than are others. Cows are generally seen as more typical examples of the category 'mammals' than are duckbilled platypi, or whales. Typicality has been shown to be an influential variable in a wide range of cognitive tasks (for a review see Hampton, 1993), and one of the most important variables in semantic concept research. As such, typicality can be considered an important criterion in evaluating theories of concepts: a theory of concept representation that can not account for the typicality gradient is no good.

In the next sections we will first give an overview of the data we used in the present study followed by a detailed overview of the three models. After this, we will present and discuss the results of the model evaluations.

Data

The dependent variable in this study is a measure of graded structure. To derive a feature-based prototype measure of typicality for the complex concepts, we used previously published feature applicability ratings and newly collected feature importance ratings. To obtain a spatial representation, we used previously published similarity ratings. To implement the instantiation principle, we collected categorization decisions.

Stimulus set Complex concepts were created starting from 5 common, simple natural language categories ('sports', 'musical instruments', 'vehicles', 'clothing' and 'weapons') taken from a recent norm study (De Deyne et al., 2008). Each of these categories contains between 20 and 30 (verbal) instances.

For each of the 5 common concepts, we construed two intuitively non-overlapping complex concepts, (i.e., not sharing instances), resulting in 10 complex concepts, which were specifications of the basic categories: 'indoor sports' and 'outdoor sports', 'musical instruments used in rock music' and 'musical instruments used in classical music', 'vehicles used for the transport of people' and 'vehicles used for the transport of goods', 'summer clothes' and 'winter clothes', 'weapons used in wars' and 'weapons used for sports'.[2] The complex concepts construed in this way contained at least some of the members of the simple concepts from which they were derived. For example, the simple concept 'sports' entails members such as 'basketball', 'voleyball' and ballet – which intuitively are 'indoor sports' – but also members such as 'rugby', 'skiing' and 'sailing' – which intuitively are 'outdoor sports'.

[2] These are (free) translations of the stimuli that were actually used.

Typicality ratings We used a goodness-of-example[3] measure to assess the typicality of an instance for a category. All instances of each simple concept were rated for goodness-of-example for each associated complex concepts by 20 to 26 participants. Reliabilities, estimated using split half correlations and corrected with the Spearman-Brown formula ranged from .91 to .98. A typicality score for each instance towards the relevant complex concept was obtained by averaging the typicality ratings across participants.

Feature applicability and feature importance ratings For each of the simple concepts, De Deyne et al., 2008 report an exemplar by feature matrix, containing between 32 and 39 features for the concepts used in this study. These matrices contain judgments – elicited from 4 participants – of the applicability of each feature for each exemplar of a simple concept. The reliability of the applicability judgments per concept was evaluated applying Spearman-Brown formula to split-half correlations, resulting in estimated reliabilities between .83 and .88 (De Deyne et al., 2008).

We collected additional data capturing the importance of the features of each simple concept for the derived complex concepts. For each of the complex concepts in this study, we asked 10 to 15 participants to rate the importance of the relevant features[4]. Applying the Spearman-Brown formula to the split-half correlations, all reliabilities except one were estimated between .81 and .93. For 'weapons used for sports', the reliability was .64, which is rather low. These feature importance ratings will be used as weights for the calculation of the feature-based prototype model.

Similarity ratings and underlying representations For the 5 simple concepts pairwise similarity ratings were available from the norm studies (De Deyne et al., 2008). For each category, all pairwise similarities were judged by 14 to 25 participants. Reliability of the ratings was evaluated using split half correlations, corrected with the Spearman-Brown formula, and ranged between .89 and .96.

Categorization decisions Using a simple computerized categorization task, 35 participants were presented with the instances of a simple concept and were asked to indicate to which of the appropriate 2 complex concepts the instance belonged. The task thus consisted of 5 blocks, one for each simple concept, and each block consisted of all instances of a simple concept (thus ranging from 20 to 30 instances). In each trial, a fixation cross was presented in the middle of the screen, followed by the stimulus. The stimulus remained on the screen until an answer was given, for a maximum of 10 seconds. The order of presentation of the instances was random, as well as the order of the 5 blocks. Categorization proportions were derived for each of the instances of a simple concept with respect to the appropriate complex concepts.

[3] Typicality ratings and goodness-of-example ratings are both measures of graded structure in concepts. They are often seen as synonymous.

[4] i.e. the features of the simple concept from which the complex concept was derived.

Model review

Feature-based prototype model

In the feature-based prototype model the representation of a concept is assumed to consist of a set of (weighed) features. As noted earlier, prototype modification as proposed by traditional theories of conceptual combination (e.g. Smith et al., 1988) essentially comes down to a reweighing of the feature structure. Typicality of an instance towards the modified concept then is the similarity of the instance towards the (re-)weighed feature representation. This can easily be calculated by summing the importance of a feature multiplied by the degree to which a certain instance has this feature.

Formally, for an instance i with F features, the typicality towards complex concept *A* is given by:

$$T_{(i,A)} = \sum_{j=1}^{F} \left(I_{jA} \times T_{ji} \right) \qquad (1)$$

in which I_{jA} is the importance of feature *j* for complex concept *A*, and T_{ji} is the applicability of feature *j* to instance *i*.

Spatial models

The predictions of typicality of the exemplar model and the spatial prototype model are based on underlying spatial representations of the simple concepts from which the complex concepts are derived. In such similarity spaces, the instances of a category are represented as points in an M-dimensional space and the distance between two instances in the space is inversely related to the similarity between the instances. Depending on the model – a prototype or an exemplar model – typicality is translated as the distance (i.e., the inverse of similarity) towards the average point of a category, (i.e., the prototype), or the summed distance of the instance towards all other instances of the. Spatial models have already been proven to be quite successful in the representation of basic semantic concepts and more specifically in accounts of typicality (e.g., Verheyen, Ameel & Storms, 2007; Voorspoels, Vanpaemel & Storms, 2008).

We obtained an underlying spatial representation for each of the 5 simple concepts, using the pairwise similarity ratings as input for a SAS MDS analysis (SAS, V9). Since determining the optimal number of dimensions for semantic concepts is not an easy task (Verheyen, Ameel & Storms, 2007), solutions were calculated in 2 to 6 dimensions for all concepts. Stress values decreased monotonically as a function of dimensionality, indicating the routine did not get trapped in a local minimum for any of the solutions.

In the present study we used underlying spatial representations of the simple concepts – implying that two complex concepts that are derived from the same simple

concept, share the same underlying spatial representation, which contains all members of the simple concept. For example, 'winter clothes' and 'summer clothes' have the same underlying spatial representation – i.e., the underlying representation for the simple concept 'clothes' – yet they will not have the same members. The complex concept 'winter clothes' contains instances such as 'scarf', 'mittens' and 'beanie', while the complex concept 'summer clothes' contains members like 't-shirt', 'shorts' and 'top'.

The concept representation of a complex concept was built using an instantiation process, in which a certain subset of exemplars in the underlying spatial representation is used. We will in turn describe the spatial prototype model, the exemplar model and the instantiation principle that is applied in both models.

Exemplar model According to the exemplar view a concept representation consists of all members of a category. Typicality of an instance to a category then is the summed similarity of the instance towards all members of the category. For stimulus *i* with M dimensions, the typicality to complex concept A is predicted to be:

$$T_{(i,A)} = -\sum_{j=1}^{n}\left(\sum_{k=1}^{M}\left(x_{ik} - x_{jk}\right)^2\right)^{1/2}, \qquad (2)$$

where the instances *j* are members of the set (of size *n*) that make up the category representation and x_{ik} is the coordinate of instance *i* on dimension k...

Prototype model A prototype of a category can be conceptualized as the average instance of the category. Typicality of an instance to a category according to the prototype view is the similarity of that instance to the prototype. Formally, the predicted typicality of instance *i* to complex concept *A* is given by:

$$T_{(i,A)} = -\left(\sum_{k=1}^{M}\left(x_{ik} - p_{Ak}\right)^2\right)^{1/2}, \qquad (3)$$

where x_{ik} is the coordinate of instance i on dimension k, p_{Ak} is the coordinate of the prototype of category *A* on dimension *k* and *M* is the number of dimensions of the underlying representation. The prototype is found by averaging across the coordinates of these instances on each dimension:

$$p_{Ak} = \frac{1}{n}\sum_{i=1}^{n} x_{ik}, \qquad (4)$$

in which *i* is an element of the set of instances, with size *n*, that are included in the representation of category A. Note that the instances included in the calculation of the prototype will determine the location of the prototype.

The instantiation principle In semantic concept research, an instantiation principle has been proposed (Heit & Barsalou, 1996) that essentially states that for category decisions – such as categorization decisions, but also typicality judgments – one (optimal) category member is activated. This principle is generalized in De Wilde, Vanoverberghe, Storms and De Boeck (2003), such that an optimal subset of members of the category is activated instead of only one. As a fictive example: in evaluating whether a whale is a fish, people might instantiate 'trout', 'shark' and 'gold fish' and base their evaluation on the similarity of a whale to these instantiated members of the categoy 'fish' rather than activating all previously encountered examples of fish, as is assumed by traditional exemplar models.

In the present study, both the prototype and the exemplar models require a specification of the exact set of category members that are included in the representation (see equation (2) and (4)). A proces inspired by the instantiation principle is easily implemented in formulas (2) and (4) by choosing the number of instances included and the specific instances that are instantiated. Based on the categorization proportions, we made a ranking of instances for each complex concept in terms of the proportion of people that judged them as belonging to the category. For each complex concept we then selected the *n* (ranging from 2 to 20) instances which were most agreed upon to belong to the category (i.e. with the highest categorization proportion for the category). The resulting set of *n* "optimal" instances was then used in the exemplar (equation 2) and prototype model (equation 4).

Results

The performance of the different models was assessed by computing the correlation between the empirically observed and the predicted typicality. For the models based on an underlying similarity space, predictors of typicality were calculated for each concept representation including 2 to 20 instances – and this was done for underlying spatial representations in dimensionalities 2 to 6. This procedure resulted in two (exemplar or prototype predictor) by 5 (Dimensionality 2 to 6) by 19 (different number of instances included) predictors for each complex concept. For each dimensionality the optimal number of instances (i.e., resulting in the concept representation that produces the best correlation with observed typicality) was chosen. Note that the two models can have optimal subsets with a different number of instances given a certain dimensionality, since the optimal set was chosen separately for each model and for each dimension.

In Figure 1 the performance of these two models is presented, separately for each dimension. Figure 1 also shows the performance of the feature-based prototype model. Since this model is not based on the underlying spatial representation, it yields only one prediction for each complex concept, presented by the horizontal dashed line. In 'outdoor sports' and 'weapons used for sports', the feature-based prototype model yielded a (slightly) negative correlation with typicality, and was not added in the graph. As for 'weapons used for sports', this might be due to the low reliability (.62) of the feature importance ratings, which are essential in the calculation of this measure.

It is clear from Figure 1 that the exemplar model (solid line) generally outperforms the feature-based prototype model (dashed line) in all but one category ('vehicles for transporting people'). For 'musical instruments used in rock music', the exemplar model predicts typicality better than the prototype model from Dimensionality 4 onwards, and for 'summer clothes' from Dimensionality 5 onwards. These findings are in strong favor of the use of extensional information in the representation of complex concepts.

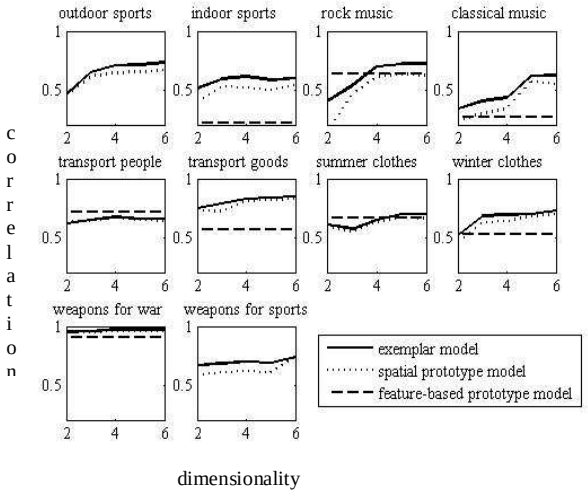

Figure 1. Correlation between observed and predicted typicality for the 3 models as a function of dimensionality.

A potential concern in the comparison between the feature-based prototype model and the exemplar model is that the feature-based prototype model might have suffered from the lack of freedom available to the exemplar model. However, this difference is non-existent for the comparison between the two spatial models. Note that the prototype model is based on the same underlying spatial representations, and uses the same information to select a subset of instances. The only difference between these two models is that the exemplar model uses optimally selected instances as representation, and the prototype model averages over an optimally selected subset of instances. Figure 1 shows that the exemplar model also outperforms the spatial prototype model (dotted line) for the 10 complex concepts. While differences are rather small for some complex concepts, the exemplar model consistently predicts the observed typicality better.

Apart from looking at the performance of each model separately, it is also worthwhile to investigate whether the exemplar and the prototype models capture a different aspect of the variance in typicality. Indeed, it might be that some important aspect of the typicality gradient is not explained by the exemplar model, but is only captured by the prototype model. To check this, we entered the predictions of both the exemplar model and the feature-based prototype model[5] as predictors in a regression analysis with the observed typicality as criterion. In this way, we can investigate the differential contribution of the exemplar and prototype model in the prediction of typicality. The results of these analyses are shown in Table 1.

Table 1 shows that in the regression analyses the exemplar model is clearly the dominant predictor. In all complex concepts, the exemplar model contributes significantly (at level .01) to the prediction of typicality, while the feature-based prototype model does not contribute significantly at level .01 and only in 3 of the 10 concepts, at level .05. These results strongly suggest that there is little or no variance in the observed typicality ratings explained by the feature-based prototype model that is not accounted for by the exemplar model.

Table 1. R-squared and b-coefficients of the feature-based prototype predictor and the exemplar predictor for the 10 complex concepts. Note that for the exemplar predictor, the dimensionality was set at 5.

concept	R-squared	prototype	exemplar
Outdoor sports	0,51	-0,005	9,351**
Indoor sports	0,36	0,080	5,814**
Rock music	0,61	0,141*	6,911**
Classical music	0,39	0,021	4,326**
Transport people	0,70	0,080*	4,194**
Transport goods	0,70	-0,010	8,684**
Summer clothes	0,53	0,089	3,479**
Winter clothes	0,57	0,067*	4,088**
War weapons	0,95	0,052	4,183**
Sport weapons	0,53	0,163	7,549**

* $p < .05$ ** $p < .01$

Discussion

The main aim of the present study was to evaluate the role of extensional information in the representation of complex concepts. We compared an exemplar model, which included extensional information, to two prototype-like models which deny an explicit role of extensional information, on their ability to predict typicality in 10 complex concepts. The feature-based prototype model was based on reweighing of the features of the concept from which the complex concept was derived. This model resembles traditional prototype modification models of conceptual combination (e.g. Murphy, 1990; Smith et al., 1988). The spatial instantiation prototype model was based on an underlying spatial representation, in which the prototype is defined as the average of a set of optimally chosen instances. In the instantiation-based spatial exemplar model, the representation of the complex category was made up by

[5] We did not include the spatial prototype model in these analyses due to problems of colinearity.

a set of optimally chosen instances. In each of the three models, typicality was defined as the similarity towards the category for which the predictions were made.

The results clearly favored the exemplar model. First, considering the performance of the three models separately, the exemplar model consistently outperformed both prototype models in the prediction of typicality for all the complex concepts. These findings suggest that the extension of a complex concept indeed plays an important role in its representation. Second, regression analyses including both the exemplar model's prediction and the feature-based prototype model's prediction demonstrated that only a small proportion of the variance in the observed typicality ratings was uniquely accounted for by the feature-based prototype model. This finding is in line with expectation that extensional information might play a role more fundamental than is currently acknowledged in the traditional theories of conceptual combination – consequently acknowledging the importance of notions such as extensional feedback.

Three concluding remarks are appropriate here. First, we observed considerable differences in succes of predicting typicality for the complex concepts used in the present study. The role of extensional information however was obvious for all complex concepts, which does not imply that other factors – not included in the present study – might also be important.

Secondly, in this study we left open the essential question of how the right members of the complex concept are instantiated. We do not in any way claim that the categorization data we used in the instantiation process has any explanatory value nor do we at the moment have a viable alternative. While the instantiation-based exemplar model performed well, the crucial question for this model is: how can we construct novel, unfamiliar complex concept representations if we have no remembered instances to call to mind (Hampton, 1997; Rips, 1995). For now, this obviously is an important shortcoming of the exemplar model as presented here.

On the other hand, the model is not restricted to using categorization data. Other variables – such as familiarity or association strength – with more explanatory strength can be implemented in the same way. In this sense, the instantiation-based exemplar model allows the explicit study of such variables, and could perhaps be a valuable tool in the systematic study of conceptual combination.

Third, an obvious strength of the instantiation-based exemplar approach evaluated in this study is that it is compatible with models used in simple concept research. The same model can be applied to both the study of common, simple concepts and the study of conceptual combination. In this sense, the model could be a step towards a more unified theory of concepts, covering a broader range of phenomena.

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