How Visible are Different Variations of Spatial Features and Relations in Logos and How Does Visibility Affect Prototype Generation?

Ute Schmid[1*], Peter Grossmann[1], Markus Wachter[1], Marius Raab[2], Claus-Christian Carbon[2], and Stella J. Faerber[2]

[1] Faculty Information Systems and Applied Computer Science
[2] Department of General Psychology and Methodology
University of Bamberg
⟨firstname⟩.⟨lastname⟩@uni-bamberg.de

Abstract. We present an approach to prototype construction and prototype change for complex object representations including visual form, metrical and categorial features as well as metrical and categorial relations. This approach is intended as a computational model for dynamic similarity-based aesthetical judgements as proposed by Carbon (2010, 2005). In the context of modeling aesthetic judgements of brand logos, we conducted a psychological experiment to determine which aspects of objects (visual, metric/abstract, featural/relational) are dominant in similarity judgements. In this work in progress report we present the psychological background and the computational model. Furthermore, we present the application domain of brand logos and the experimental results.

1 Introduction

Categorization is a basic human ability which is central to many cognitive tasks such as communication, inference, or decision making (Sternberg & Ben-Zeev, 2001). For example, by categorizing an object as "chair", we identify this object as something to sit on and at the same time differentiate it from other categories as "stool" or "bench". A prominent cognitive approach to categorization is prototype theory (Rosch, 1978). Categories are assumed to be represented by a prototypical object which represents an average over the exemplars belonging to this category. There is strong empirical evidence that categories are learned from experience (Medin & Heit, 1999; Ashby & Maddox, 2005). Consequently, categories differ – slightly or strongly – between different humans.

Prototype theory is criticized because it does not take into account contextual information. For example, Labov (1973) could show that drawings of cups and cup-like objects with different width-to-depth ratios and *presence* or *no presence* of a handle were categorized differently in different functional contexts, such

* Corresponding author: Ute Schmid, Fakultät Wirtschaftsinformatik und Angewandte Informatik, Otto-Friedrich-Universitt Bamberg, 96045 Bamberg

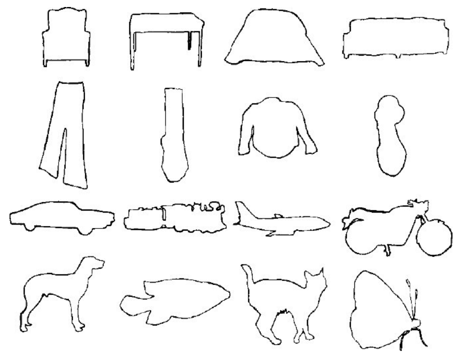

Fig. 1. Averaged shapes of objects (figure from Rosch et al. 1976, fig.1, p. 402)

as holding tea, food or flowers. Furthermore, prototype theory in its pure form does not consider information concerning the number of objects and their variability. Both aspects are covered in exemplar theory (Nosofsky, 1988). From the perspective of machine learning (Mitchell, 1997), prototype construction corresponds to eager generalization while example theory is reflected in lazy learning approaches such as k-nearest neighbors.

While prototype and exemplar theory differ with respect to their assumptions about what kind of experience is stored in memory, both theories postulate that categorization is based on *similarity assessments* between given objects and entities stored in memory (Goldstone & Son, 2004). Consequently, objects which are more similar to a stored concept are rated more typical, can be identified faster, and are acquired earlier (Smith & Medin, 1981) .

When designing a computational model for similarity-based categorization, the decision of what aspects of real-world objects are to be included in the internal representation is a fundamental issue, since it determines the type of similarity measure which can be applied. The kind of information which is used to construct prototypes varies widely between different studies and models. For example, prototype theory is used to model averaging over visual information such as shapes. In a series of experiments in the context of natural categories, Rosch could show, that humans average over visual shape information for base categories (see Figure 1) – such as chair (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). Posner and Keele (1968) could show that humans form prototypes over abstract visual patterns. In other studies and models, prototypes are characterized by simple visual features such as size or color (Smits, Storms, Rosseel, & De Boeck, 2002). Further proposals consider categorial information or abstract semantic features, such as *can sing* (Rosch & Mervis, 1974).

In general, features and relations can be either metrical or categorial. Metrical features or relations represent properties that allow quantitative orderings, while categorial features or relations represent nominal information. Dependent on which information is used, different types of similarity measures are applicable. For instance, similarity between metrical features typically is assessed as Euclidian distance, similarity between categorial features with the contrast model (Tversky, 1977). For relational representations structural similarity measures, such as alignment based approaches are used (Goldstone & Son, 2004).

Intuitively, for real-world objects, humans might refer to a variety of information when classifying an object. For example, a mental representation of a car might contain

- **holistic visual information** such as shape, which characterize a car as racy, comfortable, etc.
- **metrical visual features** such as length,
- **metrical visual relations** such as the proportion of length to breadth ,
- **metrical non-visual features** such as weight or horsepower,
- **categorial visual features** such as color (which typically is perceived qualitative and not as a metrical feature representing wave length),
- **categorial non-visual features** such as availability of a parking assistant,
- **qualitative spatial relations** such as that the radiator grill is *between* the headlights (which might be *below* them in another car).

There are no empirical findings which clearly indicate which of these different types of information influence similarity judgements of real-world objects. Since different subsets of these information types might be used in different domains, a general computational model of similarity-based categorization should be flexible enough to deal with all of them.

To our knowledge, no such computational model exists. We constructed such a model in the context of similarity-based aesthetic judgements based on a theory of dynamic prototype change of Carbon (2010), Carbon and Leder (2005). In the following we first introduce the psychological background and the general structure of the computational model. Afterwards we describe the domain of brand logos and an instantiation of our model for that domain. Finally, we present a first psychological experiment where we investigated which kind of the information types given above are used when judging similarity between brand logos.

2 Aesthetic Judgements and Prototype Similarity

When making aesthetical judgements, novelity and familiarity are the most important predictors. Novelity –measured as distance from the established prototype – is crucial for innovative design (Hekkert, Snelders, & Wieringen, 2003). When buying everyday objects, familiarity can be considered a key feature for predicting consumer behavior (Whitfield & Slatter, 1979).

Based on the observation that attractiveness ratings of artefacts – such as cars or clothes – change over time, Carbon and Leder (2005), Carbon (2010) proposed the Repeated Evaluation Technique (RET) which allows to investigate the dynamics of aesthetic appreciation by systematic inspection and elaboration of the material under standardized conditions.

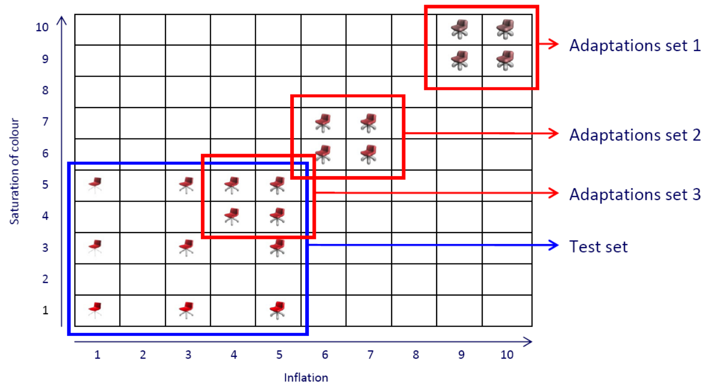

Fig. 2. Illustration of a typical experiment on varying the position of the adaptation set within the whole object space

An application of RET in the context of an adaptation experiment was realised by Faerber and Carbon (2010): Initially (t_1), subjects are presented a set of stimuli (e.g., chairs) which vary on some dimensions (e.g., inflatedness of form and saturation of color, see Figure 2). Some objects are similar to standard, that is, prototypical artefacts, others highly deviate from typical appearance. Subjects have to rate the attractiveness of the given objects. In a second phase (E), subjects are induced to engage with another set of artefacts which deviate not, moderately or strongly (see adaptation sets 1, 2, 3 in Figure 2) from the typical objects. For example, they have to rate pleasantness and functionality. Afterwards (T_2), subjects have to rate the attractiveness of the objects in the initial set again. Over several experiments, Carbon and his coworkers could show, that if subjects were engaged with strongly deviating objects during the evaluation phase, at T_2 the more deviating stimuli are rated more attractive as at T_1 while the more standard objects are rated less attractive. This result cannot be explained by mere exposure, since in the evaluation phase (E) different objects were presented than the ones used at T_1 and T_2.

Carbon and colleagues explain this effect by recalibration or dynamic prototype change: When confronted with a new artefact, which deviates too much from the prototype for this class of objects (e.g., very angular car shape, belly-bottom trouser legs), initially such new artefacts are rated as not attractive (T_1). However, if one gains more experience with such innovative objects (E), the prototype undergoes a dynamic change, incorporating the new objects. Consequently, after a while (T_2), the objects which were originally similar to the prototype at (T_1) are now more distant and the objects which originally strongly deviated from prototype are now similar to the updated prototype (T_2).

A computational model which captures these empirical observations can be constructed as follows:

– Given the ratings at T_1 a prototype over the object set is constructed such that the similarity of the objects to the prototype correspond to the attractiveness rating of these objects.
– Based on this initial prototype and the set of objects presented in the evaluation phase E, the prototype is recalibrated.
– The similarities of the objects in the initial set to the new prototype are calculated and used to predict the attractiveness ratings at T_2.

Whether the model can predict attractiveness ratings with satisfying accuracy crucially depends on the type of information included in the representation of the objects as well as the used similarity measure. Since it is plausible to assume that the type of information included depends strongly on the domain as well as the used experimental manipulation of objects, our aim is to work on very rich representations which allow us to use different subsets of information to model prototype change for different domains. We propose a dual visual/abstract representation for objects and prototypes (see Figure 4 for an example representation for brand logos): The visual representation can be realized as a simple mesh representing the visual shape of objects (see Figure 1). Often a 2D mesh capturing the coordinates which determinate each component of an object might be sufficient. For some cases, a more complex 3D mesh might be necessary. The abstract representation is a partonomy with the category name (e.g., chair) as root node and child nodes representing parts of which an object can be composed (e.g., back, seat, legs). When representing a given object, leaf nodes give specific values, when representing prototype objects, leaf nodes represent average values for metrical features and attribute sets for categorial features. Each node of the partonomy has a link to the visual representation. Within the partonomy, a second type of nodes represent relations between objects.

In the next section, a specific realization of this representation format is given for our application domain of brand logos. There we will also introduce the similarity measures.

3 A Computational Model Of Featural and Relational Prototypes for Brand Logos

The four logos we analyzed in our study are from the brands Adidas [3], Aldi (Süd) [4], Deutsche Post [5] and Shell [6] (see Figure 3). Every logo can be seen in a holistic way and as a composition of specific logo parts. Typically, there are many alternatives how objects can be decomposed. As usual in knowledge representation, we will decide on one suitable way of decomposition and apply it to all entities belonging to a given class (be it a car, a chair, or a logo).

[3] http://www.adidas.com
[4] http://www.aldi.com/
[5] http://www.deutschepost.de/
[6] http://www.shell.de/

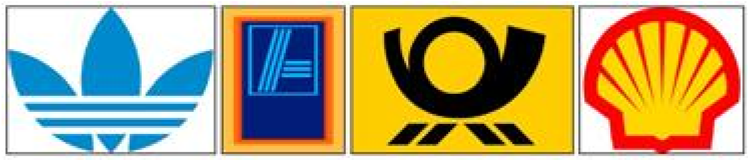

Fig. 3. Logos of Adidas, Aldi (Süd) , Deutsche Post and Shell

In the following, we only describe the instantiation of our model for the Adidas logo. This logo is represented by three specific components *LeftLeaf*, *MiddleLeaf* and *RightLeaf*.

A logo as well as its components do have properties, such as the size (the width and height), which is a metric feature, or a color, which is a categorial feature. Furthermore, there exist relations between components, which also can be metric (e.g., ratio between areas) or qualitative (e.g., component x is left of component y).

In the first experiment (see section 4) we focussed on the question whether featural or relational aspects of objects contribute more to similarity assessments. Therefore, objects were varied only with respect to metrical features and relations.

3.1 Logo Representation via MeshPoints

Logos are given as bit-images. Every logo is labeled with a set of specific points on its image representation, the *MeshPoints*. For the Adidas logo (see Figure 4, the set of stimuli logos is defined as $T_{Adidas} = \{t_1, t_2, ..t_N\}$. For every logo t_i we have a set of *MeshPoints*. Every mesh point is represented by two coordinates x and y. We define three points for every leaf of the Adidas logo and one point for the dimension of the logo – the size – which is the point of the bottom right corner. The x-coordinate represents the width, the y-coordinate the height. So the set

$$t_i = \{(x_{size}, y_{size}), (x_{LeftLeaf_{TP}}, y_{LeftLeaf_{TP}}), (x_{LeftLLeaf_{LP}}, y_{LeftLeaf_{LP}})..\}$$

describes the logo. To capture the holistic impression of a logo, we consider all mesh points. Furthermore, we consider its three components *Left-*, *Middle-* and *RightLeaf*. There we selected three specific mesh points which are easily extractable from the image: the tip of a leaf and the left and right bottom. The *Curviness* of a leaf is heuristically approximated by the ratio between the Euclidian distance of tip and left bottom and the actual length of the border line (see the illustration for the middle leaf in Figure 4).

3.2 Prototype Calculation

Prototype calculation is performed over the set T of the logos: For the visual holistic representation we calculate the arithmetic average value for the

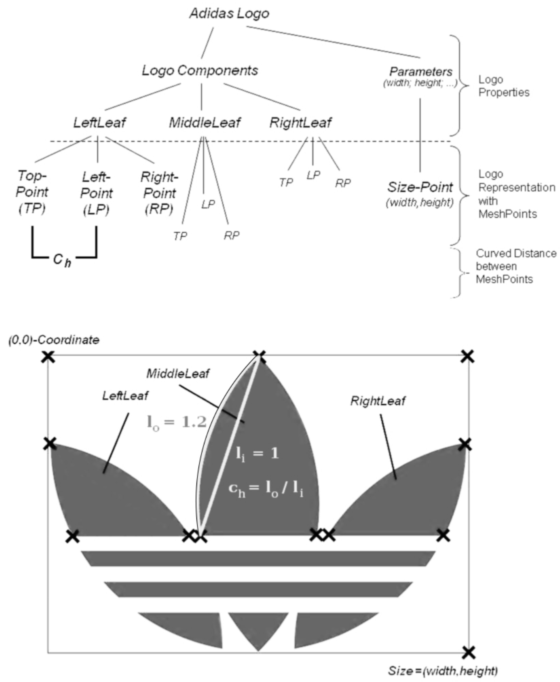

Fig. 4. Visual/Abstract representation of the Adidas logo

x-coordinate and the y-coordinate of the same mesh point of the different logos over all mesh points. For example, the size is represented by one mesh point (x_{size}, y_{size}). Assume we have N logos in T, the x-coordinate for the size, or the width of the prototype, is the value

$$x_{size_{prototype}} = \frac{1}{N}\sum_{i=0}^{N} x_{size_{t_i}}$$

and the height is

$$y_{size_{prototype}} = \frac{1}{N}\sum_{i=0}^{N} y_{size_{t_i}}.$$

We do likewise for calculating the component values of the prototype. Besides averaging over the mesh points, we average over the curvature heuristic.

3.3 Features, Simple, and Complex Relations

For our first experiment, logos where varied along three metrical dimensions. Starting with the original logo, each dimension was varied in five decreasing and five increasing steps (see Figure 5).

Feature Change (Dimension 1) Height was selected as a simple example of a featural variation. In one direction, the logo is vertically compressed, in the other direction it is stretched.

Simple Relational Change (Dimension 2) We define a simple relation such that it only affects a single component of an object. In our experiment, curvature (and area) of the middle leaf was decreased or increased.

Complex Relational Change (Dimension 3) We define a complex relation such that two or more components change relative to each other. Here, an increase of the curvature of the middle leaf occurs with a simultaneous decrease of the curvature of the outer leafes and vice versa.

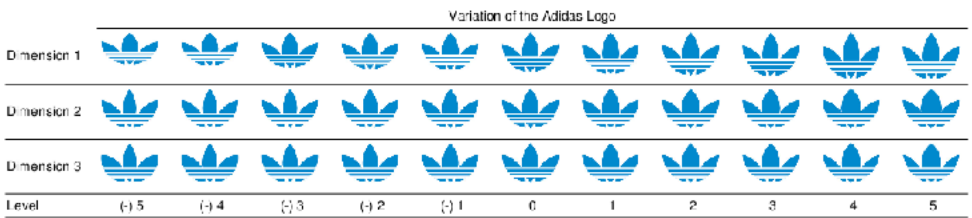

Fig. 5. Variations of the Adidas Logo

3.4 Similarity of New Objects to the Prototype

For a given prototype for a class of objects, the similarity S of a new object $L_{new} \notin T$ can be calculated in different ways. Either, similarity might be assessed in a rather general way, based on the holistic impression. In our first experiment, we were interested whether human subjects base their similarity judgement on simple features, simple relations, or complex relations. We give the definitions of these types of similarity below, again for the Adidas logo.

Holistic Similarity Currently, holistic similarity is calculated over the mesh points only. The measure is extendable to take into account further metrical information, such as curvature, and categorial information, such as color.

For now, we use all mesh points m of the logo and calculate the *Average Euclidian Distance* d_{avg}, that is, the Euclidian Distance of all x-coordinates of all mesh points of the prototype P to all corresponding x-coordinates of all mesh points of the logo L_{new} and the y-coordinates respectively. We calculate d_{avg} as follows,

$$d_{avg} = \frac{\sum\limits_{k \in K} d_k(P, L_{new})}{m},$$

where $k \in K = \{size, LeftLeaf_{TP}, LeftLeaf_{LP}, LeftLeaf_{RP}, MiddleLeaf_{TP}, \ldots, RightLeaf_{RP}\}$ are the mesh points of the components,

$$d_k(P, L_{new}) = \sqrt{(x_{P_k} - x_{L_{new_k}})^2 + (y_{P_k} - y_{L_{new_k}})^2}$$

is the distance of every mesh point within these components, and m is the count of all mesh points within the logo, so all points of $t_{L_{new}}$.

To obtain a similarity value $S_{holistic}$ such that $0 \leq S_{holistic} \leq 1$, we need to normalize the calculated value d_{avg}. To do so, we create a point M_{max} such that $x_{M_{max}} = max(x_{prototype}, x_{L_{new}})$ and $y_{M_{max}} = max(y_{prototype}, y_{L_{new}})$ are the maximum x- and y-coordinates, a mesh point can have. Now we calculate the distance of this point M to the minimal point $O = (0, 0)$, the zero point, as the *Normfactor*

$$d_{normfactor}(O, M) = \sqrt{(0 - x_{M_{max}})^2 + (0 - y_{M_{max}})^2}.$$

Finally, for the holistic similarity, based on mesh points, we get

$$S_{holistic} = 1 - (\frac{d_{avg}}{d_{normfactor}}).$$

Featural Similarity To calculate featural similarity $S_{featural}$, only the size (respectively the height) of the prototype and a new logo is considered. Again, similarity is calculated as Average Euclidian Distance of only the mesh points representing the size of the prototype and the size of the new logo. This similarity value will be normalized as mentioned before.

Simple Relational Similarity The simple relational similarity $S_{singleRelation}$ is the similarity of a component of the prototype to the same component of the new logo. All mesh points of the component are considered to calculate the Average Euclidian Distance for this component. The value will be normalized as before.

Complex Relational Similarity To calculate complex relational similarity, a pre-processing step is needed. For the case of the Adidas logo, the relation between curvature (value) of an outer leaf and the middle leaf has to be determined to capture the relational dependency between components. This relation, for a new object, as well as for the logo prototype is calculated as ratio:

$$relValue = \frac{value_{LeftLeaf}}{value_{MiddleLeaf}}.$$

Relational similarity is then

$$S_{relational} = 1 - (\frac{relValue_{L_{new}} - relValue_{L_{proto}}}{max(relValue_{L_{new}}, relValue_{L_{proto}})}),$$

where we need the maximum value of $relValue_{L_{proto}}$ and $relValue_{L_{new}}$ to normalize the similarity in order to get values of $0 \leq S_{relational} \leq 1$.

It is an open question, whether humans base their similarity assessment on one of the similarity measures proposed above or on a combination of them. Furthermore, combination could be realised as cascade from a rough holistic judgement to more detailed comparisons, or as a weighted sum over the different similarity measures where the weight parameters represent the empirically assessed influence of the different aspects.

3.5 Implementation of the Model

We implemented a prototype in Java which is based on XML-representations of the objects. For a given category of objects, for example, Adidas logos, an XML-schema has to be provided which predefines the features and relations which represent the objects and their prototype. The prototype is calculated over the XML-representations and stored as a Java object that holds the required values and their getter- and setter-methods. To calculate the similarity of a new set of objects to the prototype, these objects again are given as XML-files. Output of our system are the similarity values of each object to the prototype.

4 Visibility and Similarity

In the future, we plan to apply our model to adaptation experiments as described in section 2. To reach this goal, we propose the following series of experiments: (1) Assessing which features and relations are taken into account when comparing objects, i.e., which are visible when judging similarities; (2) tuning our similarity measures in such a way that a high correlation with empirical similarity judgements can be achieved; and (3) applying the model to predict aesthetical judgements by similarity to prototype and novelty with high accuracy.

We conducted a first experiment to explore how featural, simple relational and complex relational changes contribute to the overall assessment of similarity between objects. The four brand logos given in Figure 3 were systematically varied in ten steps on three dimensions. The experiment was conducted in June 2010 with 8 students of psychology from University of Bamberg. We used a signal detection design: For each brand logo, subjects received pairs presented in varying positions on the monitor and had to decide whether the two logos are identical or not. One logo always was the original logo, the other one of the 30 manipulated logos.

Results show that subjects detect differences between logos on all three dimension (see Table 1). For no logo, the smallest variation on each dimension was detected. For Adidas, featural variation was identified from the second smallest variation onwards; simple and complex relational variation was identified from the third variation onwards.

Table 1. Degree of variation from which on a logo was identified different from original

	Featural	Simple Relation	Complex Relation
Adidas	2	3	3
Aldi	2	2	2
Post	2	2	3
Shell	2	4	3

5 Conclusions

We proposed a computational approach which can model generation and updating of prototypes based on complex visual and symbolic representations. The model can be applied to data obtained with experiments on changes of attractiveness ratings based on the RET approach. In a first step, we realized the model for simple brand logos, restricted to metrical features and relations. A signal-detection experiment showed that subjects use featural as well as relational information to determine similarity between objects.

Next steps include follow-up experiments to validate our modelling approach. We plan to take into account more complex artefacts such as cars. Furthermore, we want to explore the potential of the model to guide innovative design. Given a current prototype for some class of objects, the model can be used to assess the novelty of new designs and ultimately, the appreciation such novel design might receive.

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