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A cognitive model for predicting esthetical judgements as similarity to dynamic prototypes ☆

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Abstract

We present a framework for cognitive modeling of esthetic decision making based on dynamic prototypes. Starting point of our work is empirical evidence which shows that subjects' initial ratings of attractiveness of objects can be influenced by adapting them to new, typically more innovative objects. The framework consists of three steps: (1) Estimating an initial prototype from the ratings, (2) adapting the prototype due to the impact of the new objects, and (3) predicting the attractiveness ratings for subsequently presented object by their similarity to the adapted prototype. The framework allows representation of prototypes and objects as feature vectors containing metrical or categorial attributes or as structural representations. Within the framework, a variety of similarity measures and similarity-to-rating mappings can be explored to gain more precise insight into the cognitive processes underlying esthetical appreciations. We instantiated the framework for a first set of data obtained in a psychological experiment. In this experiment subjects rated the attractiveness of an initial set of chairs which varied in length of the backrest and the saturation of the color. Subjects then were adapted to a new set of chairs with extreme values on both dimensions. Finally, subjects again rated the initial objects. The framework was instantiated with an e-function to model the non-linear effects of variations in length and saturation on the judgements. Although there were only 25 data points per subject, we got satisfying results in predicting the shift of esthetical judgements due to adaptation to novel stimuli.

Keywords: Prototypes; Esthetic decision making; Cognitive modeling

1. Introduction

Esthetical judgements are not only underlying the evaluation of works of art but also guide our purchase decisions for mundane objects (Whitfield & Slatter, 1979; Hekkert, Snelders, & Wieringen, 2003). Whenever we buy something – may it be clothing, furniture, a phone, or a car – our decision is influenced by esthetical aspects. That is, given a class of objects with comparable functionality, price range, and brand image, we still prefer one object over another. Often, this preference is based on visual cues and, more often than not, we cannot give a clear justification for our preference.

One possible explanation for such esthetical preferences is the similarity of objects to our individual prototype for the

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object category (Rosch, 1978; Kruschke, 2008). Such prototypes are constructed over personal experience and therefore dynamic (Medin & Heit, 1999; Ashby & Maddox, 2005; Blijlevens, Carbon, Mugge, & Schoormans, 2012). This is reflected, for example, in the way we are affected by changes of fashion. The majority of people typically does not like a new style in clothing or car design if it is freshly introduced to the market. However, if they are exposed to the new design over some time, their esthetical judgement adapts and the previously liked designs appear less attractive while the new design gains attractiveness (Carbon, 2010).

Experimental evidence for adaptation effects in esthetical judgements was, for example, given by Faerber and Carbon (2010). An experimental procedure for an adaptation experiment can be realized in the following way: Initially (T_1), subjects are presented a set of stimuli (e.g., chairs) which vary on some dimensions (e.g., length of backrest and saturation of color, see Fig. 3). Some objects are similar to the common standard – that is, prototypical – artefacts, others deviate to some degree from typical appearance. Subjects have to rate the attractiveness of the given objects. In a second phase (adaptation phase A), subjects are induced to engage with artefacts which usually deviate strongly from the prototype. For example, they have to rate different functional and aethetical features of these objects. 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 adaptation phase, at T_2 attractiveness ratings shifted towards a preference of the objects in the adaptation phase.

Carbon and colleagues (Carbon, 2011) explain this effect by recalibration or dynamic prototype change (see Fig. 1): 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), such new artefacts are rated as not attractive (T_1). However, if one gains more experience with such innovative objects (A), the prototype undergoes a dynamic change, incorporating the new objects. Consequently, after having inspected and processed the adapting stimuli, the objects which were originally similar to the prototype at (T_1) are now more distant and the objects which originally deviated more from prototype are now similar to the updated prototype (T_2).

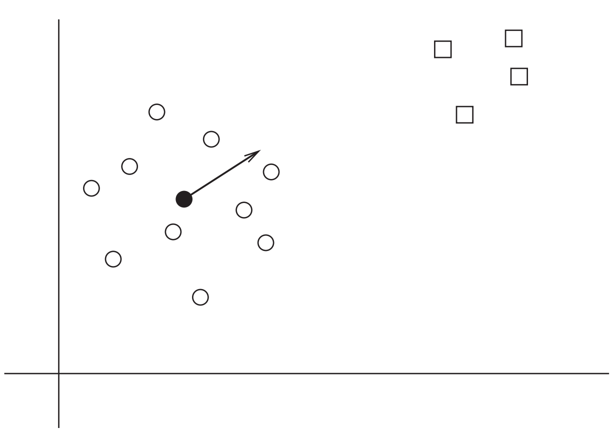

Fig. 1. Illustration of a prototype-shift in feature space due to adaptation to novel objects (prototype represented as black circle, novel objects represented as white squares).

To gain more precise insights into the dynamic changes of prototype representations and their impact on esthetical decision making, we propose a cognitive modeling framework which allows (1) to estimate an initial prototype from esthetical judgements of objects at the time of the first exposure (T_1), (2) to adapt this initial prototype with respect to the adaptation set (A), and (3) to use this prototype to predict subsequent esthetical judgements of objects (T_2). Such a model can help to gain a deeper understanding of esthetical decision making. Furthermore, it can provide an initial building block for an assistant system which allows designers to evaluate the possible market success of new design lines.

In the following, we first propose a general framework for prototype based generation of esthetical judgements. Afterwards, we present a first instantiation of the framework where we model data gained from a psychological experiment. We conclude with a short discussion and further work to be done.

2. A framework for generating esthetical judgements

Given the proposition that an individual generates his/her esthetical judgement of an object with respect to its similarity to his/her prototype, the general framework can be expressed as

$$\forall o \in O : K(\sigma(o,p)) = a(o) \quad (1)$$

where $\sigma(o,p)$ is the similarity of the object o to prototype p, K is a kernel function, and $a(o)$ is the resulting attractiveness rating for the object. To simplify matters, we do not discriminate between $a(o)$ as the mental representation of the attractiveness of the object and $a(o)$ as the externally expressed judgement which, for instance, is given as a rating on a Likert scale.

To instantiate the general approach, the following questions must be answered:

- What kind of information of the real-world objects is included in the prototype?
- How is the prototype represented?
- With what type of measure is the similarity between prototype and object established?
- Which kernel function is used to map the similarity to the attractiveness rating?

2.1. Illustration

We illustrate these aspects using the material which will be presented in more detail in Section 3. The objects under consideration are chairs. A chair might be represented using:

- **holistic visual information** such as shape, which characterize a chair as elegant, and comfortable.
- **metrical visual features** such as length of the backrest,
- **metrical visual relations** such as the proportion of length of the beackrest to depth of the seat,
- **metrical non-visual features** such as weight,
- **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 producing country,
- **qualitative spatial relations** such as that the back legs of the chair are *under* the backrest or *in front* of the backrest.

Each subset of these different types of information implies a different representational format (Schmid, Ragni, Gonzalez, & Funke, 2011). If only metric features are considered, each object can be represented as a feature vector and the prototype can be represented by an average value for each feature.

Under the – in most domains not valid – assumption (Nosofsky, 1988), that the features are not correlated and that the variability of feature values is comparable, a standard distance metric, such as Euclidian distance or Manhatten distance could be used to calculate the similarity between an object and a prototype. However, it is an open question, whether one of these measures is guiding the mental similarity assessment or whether more complex similarity measures are needed. Maybe, different features have different salience which would result in a measure with different weights for the different features. In general, the similarity measure should not only take into account the isolated features but also interaction terms.

Finally, there are many possible mappings from similarity to esthetical judgements. In the most simple case, this might be a linear regression $\beta_0 + \beta_1(\sigma(o,p)) = a(o)$. In the case of a similarity measure which deals with different components of object-representation differently, σ and β_1 might be vectors. Alternatively, the mapping might be non-linear and only captured by specific non-linear functions. A typical obeservation is that ratings of attractiveness are based on the MAYA (most advanced yet acceptable) principle (Hekkert et al., 2003). That is, objects which are very similar to the prototype are not perceived as highly, but only medium attractive (because they are somewhat boring) and objects which deviate too far from the prototype are considered as highly unattractive.

The proposed general model can be viewed as a guideline for exploring empirical data to obtain more specific information about the processes underlying esthetical decision making.

2.2. Identifying the similarity and mapping functions

In the context of an experimental setting researching adaptation as described above (see Section 1), the ratings obtained during initial representation (T_1) of objects are used to determine $K(\sigma(o,p))$ in such a way that the ratings of each individual can be reproduced as exactly as possible. To identify σ and K, we propose the following procedure:

- Predefine a set of plausible measures $\Sigma = \{\sigma_1, \ldots, \sigma_n\}$ and functions $\kappa = \{K_1, \ldots, K_m\}$.
- For each combination $K_j(\sigma_i(o,p))$ estimate p such that the prediction error of $a(o)$ is minimal over all objects o in O_1. How the estimation can be performed depends on the form of σ_i and K_j. In the most simple case, it might be possible to gain the estimate analytically. Alternatively, the prototype values could be identified by gradient descent, or – if non-derivable functions are involved – by Monte Carlo studies.
- Select the most simple function K_j and measure σ_i which produces minimal errors.

We believe it reasonable to assume that the functions found to be fitting the individual ratings best should be kept constant for the attractiveness ratings after the prototype adaptation phase (at T_2).

2.3. Predict esthetical judgements due to dynamic shift of the initial prototype

To include the dynamic change of the initial prototype due to adaptation to novel objects, the framework is extended to

$$\forall o \in O : K(\sigma(o, S(p, O_A))) = a(o) \tag{2}$$

where $S(p, O_A)$ is a function modeling the shift of the initial prototype due to adaptation.

The form of the shift function is dependent on the similarity measure and mapping function obtained from the initial ratings. If, for instance, the similarity measure is based on independent, equally salient features and the kernel is a linear function, than the prototype is shifted in the direction of the feature vector of the average over all objects in the adaptation phase (see Fig. 1). However – again – things can get more complex. Therefore, different shift functions S should be investigated in the context K_j and σ_i identified in the previous step. The general procedure for selecting a suitable S is analogous to the previous step.

3. Experiment

The stimuli used in the experiment are chairs which were constructed by varying length of the backrest ($l(o)$) and saturation ($s(o)$). A matrix of chairs where length and saturation is varied in ten equi-distant steps is given in Fig. 2. For the experiment, chairs for every second variation were selected as test sets – that is, saturations are −60, −30, 0, 30, 60 and lengthes are 1, 3, 5, 7, 9. This selection was made to ensure that the visual variations were perceivable when presenting the objects at a computer monitor. To refer to a specific chair o, we give its feature vector $\langle l(o), s(o)\rangle$.

21 Subjects participated in the study. In a first session (T_1), subjects rated each of the 25 chairs of the test set

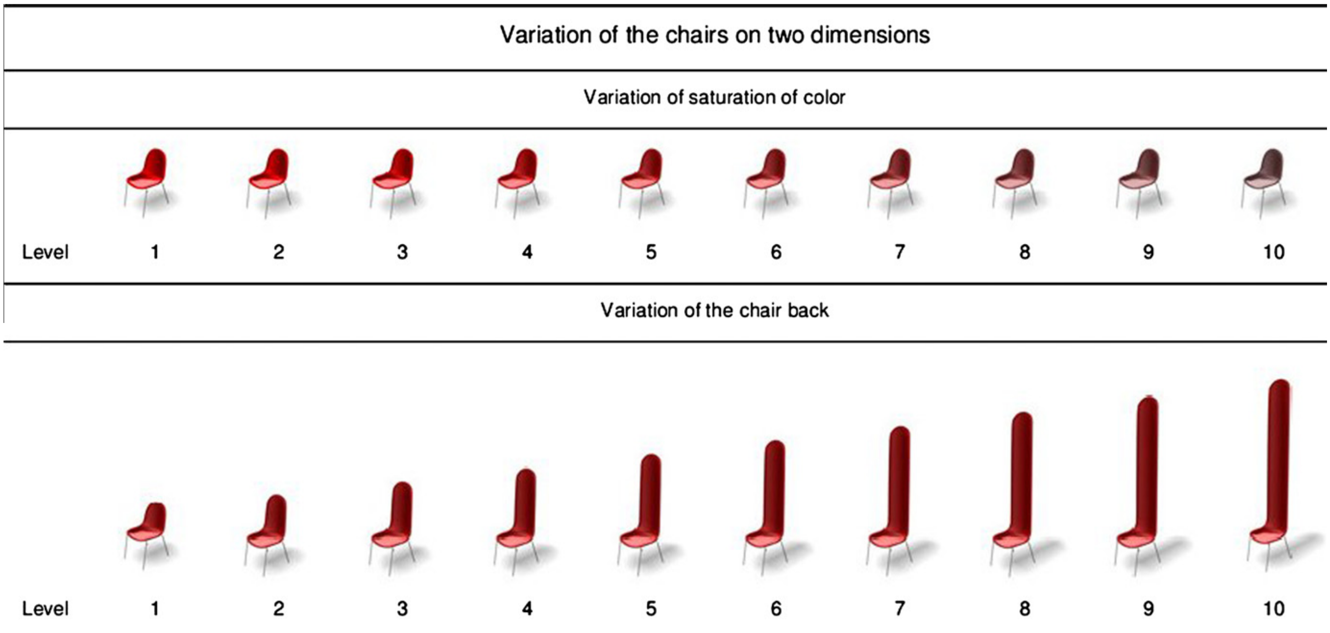

Fig. 2. Variations of length and saturation.

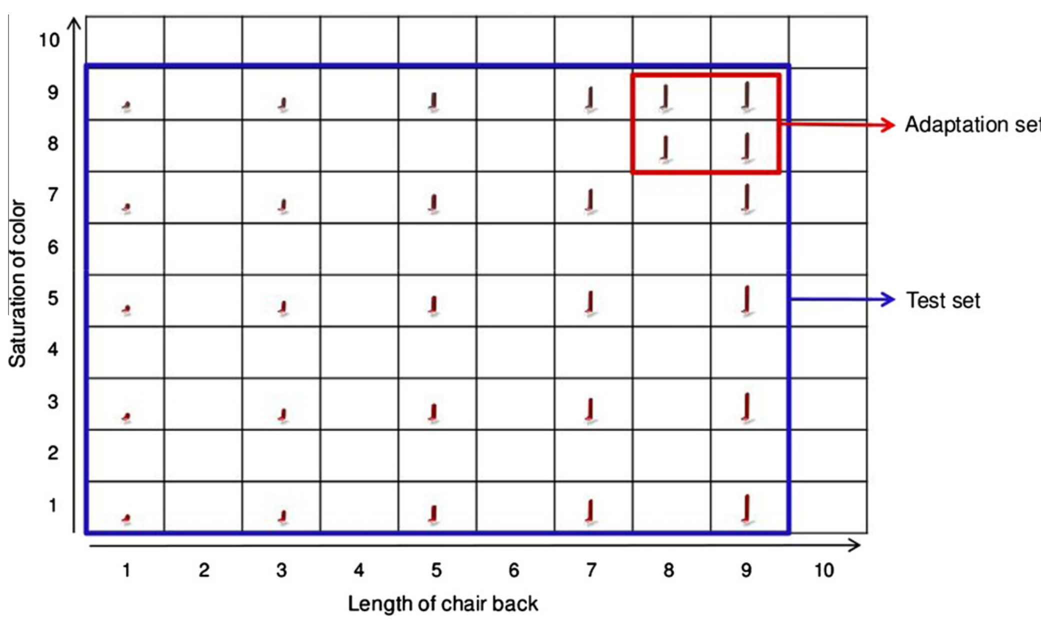

Fig. 3. Object space with 10 equi-distant variations of the two dimensions length of chairback and saturation (only every second variation per dimension was included in the initial object set).

on a 7-step Likert scale. Afterwards (A), subjects were adapted to four chairs with extreme values: the most extreme chair with $\langle 9, -60\rangle$ was already contained in the test set, the other three chairs were the neighbors $\langle 8, -60\rangle$, $\langle 8, -45\rangle$, and $\langle 9, -45\rangle$ (see Fig. 3). After a time-lag of seven days, this adaptation set was presented again (A) and afterwards (T_2), attractiveness ratings for the 25 test chairs were obtained the second time.

The experiment was not specifically designed to explore our cognitive framework. With one rating for each of the 25 chairs in the test set, we have a rather small number of data available for individual models. Consequently, we can only explore similarity measures and mapping functions which involve a small number of free parameters. Furthermore, it can be assumed that saturation is perceived more dominantly for chairs with longer backs than for chairs with shorter ones. Finally, there might be some impact of the amount of space taken by a presented chair in relation to the background. With these caveats, we now will present the cognitive models.

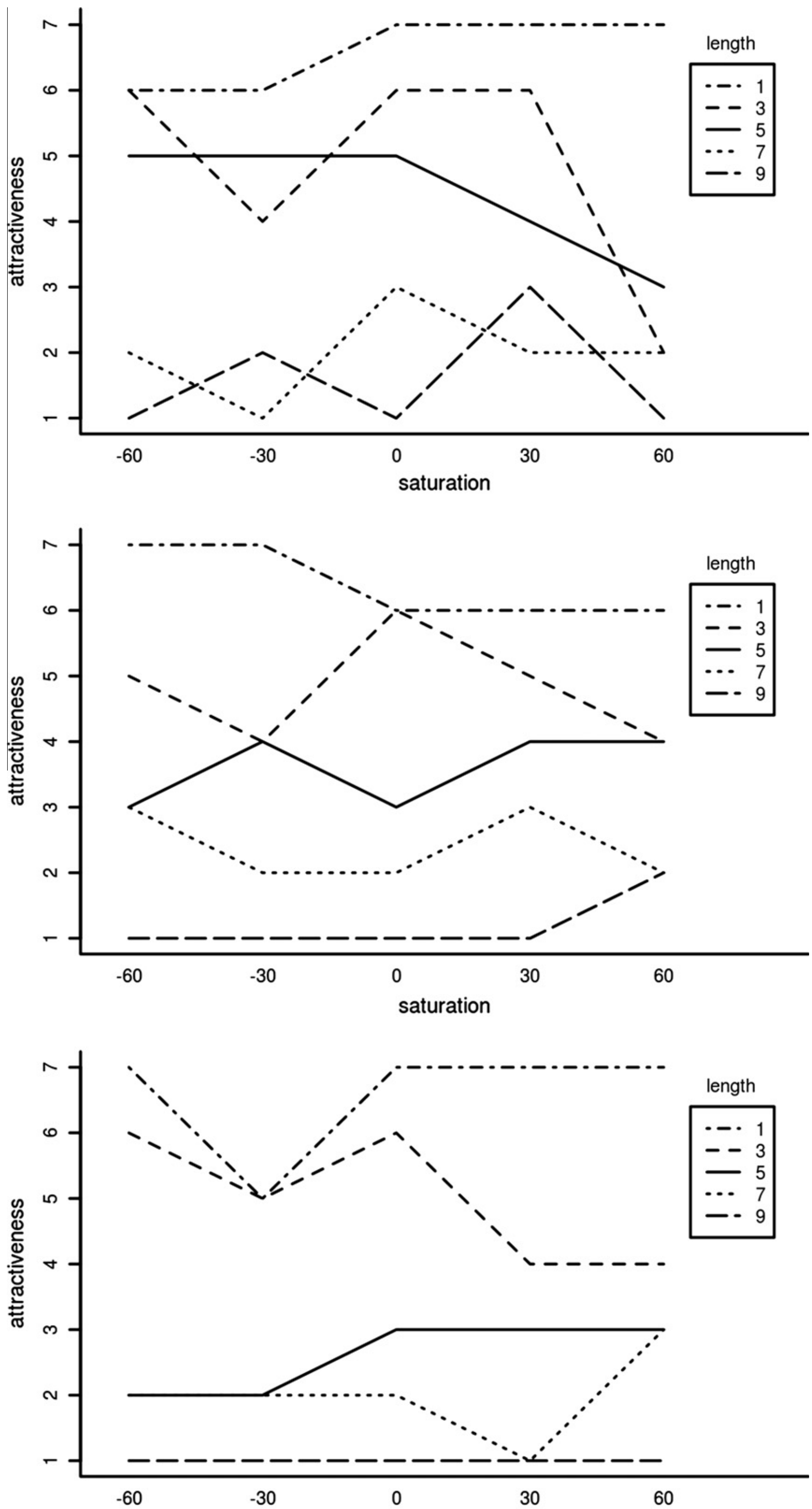

Fig. 4. Interaction between length $l(o)$, saturation $s(o)$ and initial attractiveness rating $a(o)$ for three subjects.

4. A model for attractiveness ratings of chairs

To generate a model based on our framework presented in Eq. (1), the values of length and saturation were normalized via z-transformation.

4.1. Excluding a simple linear model

Applying the Occam's razor principle of simplicity, the first choice for modeling was to assume that ratings of attractiveness are linearly dependent on similarity. That there is no simple linear relation between prototypicallity and attractiveness is obvious from the interaction diagrams of $l(o)$, $s(o)$ and $a(o)$ (see Fig. 4).

4.2. Approximating a first model for the initial prototype

To capture the non-linear effect of variations in length and saturation, we propose the following instantiation of the framework given in Eq. (1):

$$\sigma(o,p) = \begin{pmatrix} |l(o) - l_p| \\ |s(o) - s_p| \end{pmatrix} \quad (3)$$

$$K(\langle x_l, x_s \rangle) = \beta_0 + \beta_1 e^{-x_l} + \beta_2 e^{-x_s} + \beta_3 e^{-x_l x_s} \quad (4)$$

Using the e function (instead of a polynomial) is reasonable because it results in the fewest possible number of free parameters in the models. It also is supported by the usage of Shepard's exponential law in prototype and exemplar theories of similarity and categorization (Jäkel, Schlkopf, & Wichmann, 2008). When taking into account two feature dimensions and their interaction the minimal number of free parameters is 4. The initial prototypes were estimated by minimizing

$$\frac{1}{2}\sum_{i=1}^{25}(a(o_i) - K(\sigma(o_i,p)))^2 \quad (5)$$

for each subject where o_i and p are vectors $\langle l, s \rangle$. The values for the initial prototypes $\langle l_p, s_p \rangle$ were calculated using gradient descend with decaying learning rate η with initial value $\eta = 0.025$ and momentum $\alpha = 0.25$ iterating over 500 cycles. Values l_p and s_p were initialized to the means of the highest rated objects.

The estimated prototypes produced acceptable small deviations between predicted and observed attractiveness ratings (see Table 1). The estimated initial prototypes are given in Fig. 5. Note, that there are three subjects (11, 15, 21) who preferred chairs with long backrests from the beginning.

4.3. Predicting attractiveness ratings from the shifted initial prototypes

Given the estimates for the individual initial prototypes, in the next step the model was applied to predict the attractiveness ratings after shifting the initial prototype due to the adaptation set. Eq. (2) as proposed above was used for estimation. The parameters β estimated for the initial prototype were kept as it is reasonable to assume that the individual influence of the different features is constant within subjects. Again, gradient descent was applied with initial $\eta = 0.0005$.

With the exception of three subjects (6, 11, 15), the predicted attractiveness ratings again have acceptable small deviations from the observed ratings. For these three subjects it might be possible that the good fit for the initial prototype was due to a local minimum.

The prototype shifts are given in Fig. 5. For the majority of subjects the shift is in the direction of longer chairs. This is plausible because the adaptation set consisted of four chairs with lengths 8 and 9. Only subjects 11, 17, and 21 show a shift towards shorter lengthes. However, this shift is very small for 17 and 21. In the direction of saturation (which was −60 and −45 in the adaptation set) there is no clear pattern for the shift. This might be due to the fact that the visual salience of saturation is more variable between subjects than the visual salience of length.

Table 1
Estimated values $\langle l_p, s_p \rangle$ for the initial prototype and estimated values $\langle l_s, s_s \rangle$ for the shifted prototype with mean squared residuals.

Pb	l_p	s_p	MSSQ (a_1)	l_s	s_s	MSSQ (a_2)
1	1.42	41.08	17.29	1.75	41.07	39.22
2	1.00	−0.07	6.81	1.73	−0.004	48.51
3	1.54	9.67	27.22	2.79	−0.005	65.62
4	1.43	32.34	37.58	1.56	32.34	24.10
5	1.56	−51.09	10.19	2.13	−51.09	17.67
6	1.66	59.58	13.97	3.91	59.61	100.42
7	2.24	57.63	10.57	2.37	57.65	25.88
8	1.95	51.28	7.64	2.53	32.35	45.06
9	1.25	−4.78	29.46	3.00	−5.18	31.66
10	1.99	−50.52	18.93	5.00	−50.51	45.09
11	6.38	48.60	9.91	5.00	30.00	108.15
12	1.54	9.78	11.79	1.60	18.31	23.93
13	3.88	−35.14	17.86	4.74	−35.13	34.03
14	1.53	55.55	11.26	1.89	55.55	89.45
15	8.21	−56.70	44.86	8.33	−56.75	103.34
16	1.97	−59.97	14.97	3.14	−58.13	24.49
17	1.33	−25.16	2.66	1.23	−25.16	11.77
18	3.72	54.17	8.34	4.02	47.23	14.09
19	2.17	40.46	38.44	2.25	40.46	37.94
20	1.00	−44.86	6.02	1.90	−44.86	33.56
21	7.05	29.91	19.24	6.72	29.00	21.11

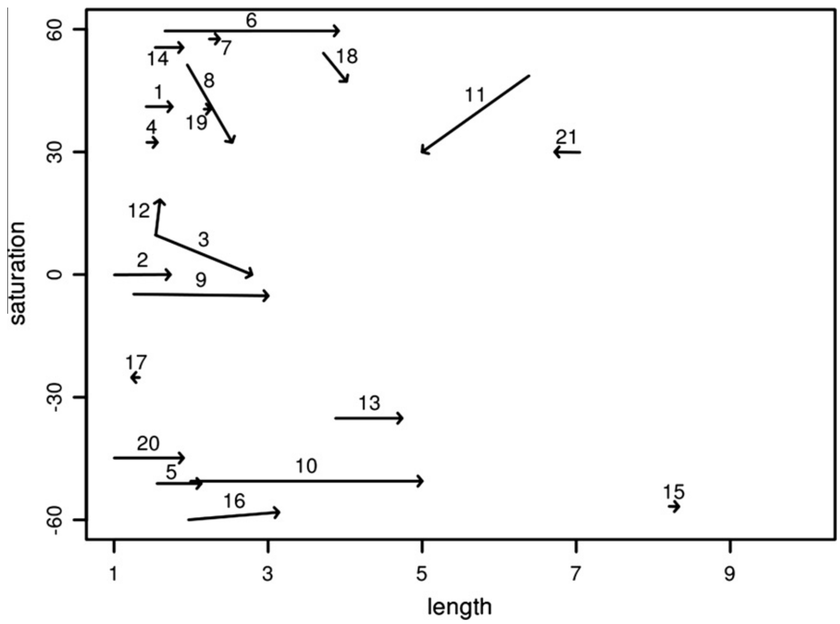

Fig. 5. Initial prototypes and their shift which predict initial attractiveness ratings and attractiveness ratings after adaptation.

5. Conclusion

Given empirical findings which demonstrate that esthetical preferences change dynamically over time, we proposed a cognitive framework. Within this framework it is claimed that esthetical judgements are based on similarity to prototype. Similarity assessment and mapping of similarity to attractiveness are proposed as sub-processes underlying esthetical decision making. The framework therefore gives a guideline to explore empirically which types of similarity measures and mapping functions are realized when subjects perform ratings of attractiveness.

We explored the framework with empirical data which were obtained in an experiment where subjects rated the attractiveness of chairs which varied in the length of the backrest and the saturation of color. Although there were only 25 data points per subject, we got satisfying results in predicting the shift of esthetical judgements due to adaptation to novel stimuli.

Based on this initial work, there are several aspects which we plan to explore in future work: In the current model the shift of the prototype is estimated in a single time step over all objects of the adaptation set. A psychological more plausible approach would be to model an *incremental* shift. However, for an incremental model, it is necessary to determine in advance (a) the degree of the shift – that is, how strong a new object pulls the prototype in its direction – and (b) the direction of the shift – that is, the possible different weights of the dimensions in the object space. Such an incremental model would have an additional advantage since it allows a new way to combine empirical evidence of mere exposure respectively the exemplar theory of categorization and prototype theory: Because each presented object induces a shift, the prototype updates are sensitive not only to variations in object attributes but also to frequency of object presentation. That is, if the same objects is presented several times, each presentation would induce a shift.

Another aspect we plan to explore in the future is to investigate more sophisticated measures of similarity, e.g., using different similarity measures for the different aspects of the objects. Another alternative could be to replace the similarity measure by fuzzy memberships. Furthermore, we are interested in models which capture a mixture of metrical and categorial features and in models which capture the holistic visual impression.

Finally, the experiment was not specifically designed to test the proposed framework. Therefore, we plan to conduct more specific experiments to explore the explanatory power of our framework. Especially, we plan to investigate attractiveness ratings when object appearance is varied on different kinds and numbers of dimensions. Stimuli should be obtained from different artificial and natural domains.

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