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Dissimilarity is used as evidence of category membership in multidimensional perceptual categorisation: A test of the similarity-dissimilarity generalised context model

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Abstract

In exemplar models of categorisation, the similarity between an exemplar and category members constitutes evidence that the exemplar belongs to the category. We test the possibility that the dissimilarity to members of competing categories also contributes to this evidence. Data were collected from two two-dimensional perceptual categorisation experiments, one with lines varying in orientation and length and the other with coloured patches varying in saturation and brightness. Model fits of the similarity-dissimilarity generalised context model were used to compare a model where only similarity was used with a model where both similarity and dissimilarity were used. For the majority of participants the similarity-dissimilarity model provided both a significantly better fit and better generalisation, suggesting that people do also use dissimilarity as evidence.

Using dissimilarity as evidence for category membership in multidimensional perceptual categorisation: A test of the similarity-dissimilarity generalised context model

What is it that constitutes evidence of category membership in perceptual categorisation? According to one very successful account - exemplar models (e.g., Medin & Schaffer, 1978; Nosofsky, 1986) - the evidence that a stimulus belongs to a particular category is given by the stimulus's similarity to each stored member of that category. We test the possibility that a second factor - the dissimilarity between the stimulus and exemplars from competing categories - can also be used as evidence for category membership. All other things being equal we propose that, if a stimulus is highly dissimilar to members of competing categories, then this too should be taken as positive evidence for membership in the remaining category.

There is already evidence from other domains that dissimilarity may be used as evidence. In recognition memory, dissimilarity between a novel test item and previous items might provide the basis for rejection of the test item in some circumstances (e.g., Mewhort & Johns, 2000). In identification, Murdock's (1960) distinctiveness model assumed that ease of item identification is a function of relative distinctiveness, where distinctiveness is effectively a measure of the summed difference between the target item and other contextual items. In Stewart, Brown, and Chater's (2005) model of unidimensional absolute identification, the difference between the current stimulus and the immediately preceding stimulus is used to derive a response to the current stimulus. In his contrast model of similarity, Tversky (1977) argued that the similarity and dissimilarity judgements and the effects of context on these judgements are a function of the number of common features and also the number of differing or unique features. In judging prototypicality, Rosch and Mervis (1975) found that judgements are a positive function of the number of features in common with members of the target category and a negative function of the number of features in common with members of other categories.

There is some evidence from perceptual categorisation tasks that dissimilarity information might be used. Stewart, Brown, and Chater (2002) and Stewart and Brown (2004) found that a stimulus on the category borderline is significantly more likely to be classified into the opposite category to that of a previous dissimilar stimulus when stimuli were both from the same category (the category contrast effect, see also Jones, Love, & Maddox, 2006; Hampton, Estes, & Simmons, 2005). Stewart and Brown (2005) showed that this observation is consistent with the predictions of a model in which dissimilarity evidence is used (the similarity-dissimilarity generalised context model, hereafter SD-GCM), but not a model in which only similarity information is used (the generalised context model, hereafter GCM, Nosofsky, 1986). When only similarity is used in modelling, a distant exemplar counts as small - but none-the-less positive - evidence that the target exemplar belongs in the same category as the distant exemplar. Participants instead behaved as if the distant exemplar was evidence against membership of the same category.

The purpose of the two experiments presented in this paper is to test whether the additional use of dissimilarity as evidence will allow a significantly better description of multidimensional perceptual categorisation data. To this end, the accompanying modelling provides the first comparison of the GCM against the SD-GCM.

The Similarity-Dissimilarity Generalised Context Model

Here we describe the SD-GCM (Stewart & Brown, 2005) for an *N*-dimensional perceptual classification. This model is a generalisation of the GCM (Nosofsky, 1986), which itself was a generalisation of Medin and Schafer's (1978) context model. The perceptual distance between two stimuli S_i and S_j is defined as

$$d_{ij}=\left(\sum_{k=1}^{N} w_k \left|x_{ik}-x_{jk}\right|^r\right)^{(1/r)} \tag{1}$$

where x_{ik} is the magnitude of Stimulus S_i on Dimension k. The attentional weighting of dimension k is w_k and $\sum_{k=1}^{N} w_k = 1$. The Minkowski metric parameter r gives a city block metric when $r = 1$ (used for separable-dimension stimuli) and a Euclidean metric when $r = 2$ (used for integral-dimension stimuli) . The similarity η_{ij} between S_i and S_j is a function of the perceptual distance between them:

$$\eta_{ij} = \mathrm{e}^{-c\, d_{ij}^{q}} \tag{2}$$

where c is a scaling parameter, $q = 1$ gives an exponential function and $q = 2$ gives a Gaussian function. The evidence v_{iA} for S_i's membership of Category C_A is

$$v_{iA} = s \sum_{x_j \in C_A} t_j \eta_{ij} + (1-s) \sum_{x_j \in \neg C_A} t_j \left(1 - \eta_{ij}\right) \tag{3}$$

where the first term gives the summed similarity to Category C_A and the second term gives the summed dissimilarity to the remaining categories. (Though here dissimilarity = 1 - similarity, dissimilarity could, for example, be calculated over one set of features while similarity is calculated over another.) The s parameter represents the relative contributions of similarity and dissimilarity evidence. When $s = 1$, only similarity evidence is used, when $s = 0$ only dissimilarity evidence is used. The t_j parameter represents the weighting of exemplar S_j and decays with the time since S_j was encountered. Specifically,

$$t_j = \mathrm{e}^{-n\tau} \tag{4}$$

where n is the number of trials since S_j and τ is the decay rate. Finally, the evidences are used in the choice rule to give the probability of responding C_A.

$$\mathrm{P}(C_A | S_i) = \frac{\left(\beta_A v_{iA}\right)^{\gamma}}{\sum_{all\, C} \left(\beta_C v_{iC}\right)^{\gamma}} \tag{5}$$

where β_A is the response bias for Category C_A and $\sum_{all\, C} \beta_C = 1$. The γ parameter varies the degree of determinism in responding (e.g., Ashby & Maddox, 1993). When $\gamma = 1$ the response rule reduces to the special case originally proposed for the context model (Medin & Schaffer, 1978; see Nosofsky, 1986, p. 42) and the GCM. For $\gamma > 1$ responding is increasingly deterministic.

Table 1 gives a summary of the free parameters in the SD-GCM. When $s = 1$ (so only similarity evidence is weighted) and $\tau = 0$ (so all stimuli are weighted equally) the SD-GCM reduces to the deterministic GCM which was first proposed by Ashby and Maddox (1993). Fixing $\gamma = 1$ gives the original GCM.

(Table 1 about here)

Experiments

The two experiments differed only in the stimuli that were presented. In Experiment 1, the stimuli were lines varying in orientation and length (separable dimensions, Garner & Felfoldy, 1970). In Experiment 2, the stimuli were coloured patches varying in saturation and brightness (integral dimensions, Garner & Felfoldy, 1970).

Experiment 1 Method

Participants. Eighteen undergraduate psychology students from the University of Warwick took part in this experiment.

Stimuli. The stimulus set consisted of 56 lines, constructed from the factorial combination of eight levels of line length and seven levels of line orientation. The first line length level started at 2 cm and lines increased in length by 22% at each level to reach 8.05 cm on level eight. The seven levels of line orientation started with at 80° (measured anticlockwise from horizontal), decreasing in steps of 5° to 50°. The 56 lines were divided into two categories (Figure 1). Stimuli were displayed using E-prime on a Sony G400 Multiscan monitor (75 Hz vertical refresh rate, 1024x768 resolution).

(Figure 1 about here)

Procedure. Participants were tested individually in a quiet room. Participants were informed that they would see lines differing in length and orientation, one after the other. They were told that after each line they would be asked to respond with the category they thought the line came from. Participants were not told about the category structure, but had to learn the structure from trial-by-trial feedback. Although at first participants would have to guess, they were informed that by attending to the correct answer displayed on the screen after each response, they could learn which lines belonged to which category.

There were four blocks each of 168 trials, with a break between each block. Each trial began with the presentation of a 1000 ms fixation cross. Stimuli were presented in a random order with the constraint that each stimulus appeared once in every set of 56 trials (i.e., three times per block). Stimuli were presented at a random location on the screen. Participants were able to respond with either “1” or “2” (labelled “A” and “B”, counterbalanced across participants) on a standard keyboard. The line remained on the screen until participants responded, whereupon it disappeared. After the participant had responded the screen went blank for 1000 ms followed immediately by the correct answer (either “A” or “B”) for 500 ms. Feedback was given throughout the experiment. The next trial began immediately.

Experiment 2 Method

Participants. Nineteen undergraduate psychology students from the University of Warwick took part in this experiment.

Stimuli. The stimulus set consisted of 56 Munsell colour patches measuring 10cm x 10 cm, all of 10PB (purple-blue) hue but varying in saturation and brightness. These stimuli were constructed from the factorial combination of eight levels of brightness (values 4, 4.5, 5, 5.5, 6, 6.5, 7, and 7.5) and seven levels of saturation (chromas 2, 3, 4, 5, 6, 7, and 8). A Minolta CS100 colorimeter was used to measure the colour of the patches and adjust them to match the Munsell values.

Procedure. The procedure was identical to Experiment 2 except that the colour patches were always presented in the middle of the screen.

Results of Experiment 1

The first 20 trials from each block were considered to be practice trials and were not analysed. The mean proportion of correct responses averaged across participants on the remaining trials was .77 (SE = .01) and ranged from .66 to .85. Figure 2A plots the mean proportion of A responses averaged across participants as a surface above the stimulus space. As expected, stimuli furthest from the category boundary were categorised most accurately, with performance at about chance for stimuli on the category boundary. There were individual differences in the relative weighting of the two dimensions, with a few participants placing a large reliance upon only Dimension 1 and a few placing a large reliance upon only Dimension 2. These differences were captured very well by the dimension weighting parameter w_1 in the model fitting below.

(Figure 2 about here)

It was possible to test whether the category contrast effect, which previously has only been shown in one-dimensional stimulus structures, also occurred for this two-dimensional stimulus structure. Recall that, in the category contrast effect, accuracy on a borderline stimulus which follows an extreme stimulus is higher when the extreme stimulus was from the opposite category. In this analysis, stimuli immediately adjacent to the stimulus boundary were considered to be borderline stimuli (i.e., (1, 7), (2, 6), ..., (7, 1) for Category A). The three stimuli in each category most distant from the category boundary were grouped together as extreme stimuli (i.e., (1, 1), (2, 1), and (1, 2) for Category A). Accuracy was indeed higher when a borderline stimulus was preceded by an extreme stimulus from the opposite category

(M = .63, SE = .03) compared to when a borderline stimulus was preceded by an extreme stimulus from the same category (M = .51, SE = .03), $t(17) = 2.76$, $p = .013$.

We have deferred until now the discussion of an important finding by Jones et al. (2006) who found that the category contrast effect was mainly due to perceptual contrast and not decisional contrast. It is possible to test between perceptual and decisional accounts here. Consider a pair of consecutive borderline stimuli. Perceptual contrast of these stimuli should shift the representation of the second stimulus parallel to the category borderline, and predicts no change in categorization accuracy. However decisional contrast predicts that when these borderline stimuli differ greatly, this should be taken as evidence that the current stimulus belongs in the opposite category from the previous stimulus, and thus that the accuracy with which the current stimulus is categorised should depend on the similarity to the previous stimulus. This is the pattern found in the data (Figure 3A). For consecutive stimuli on the category borderline (e.g., on a line between (1, 7) and (7, 1) or between (1, 6) and (6, 1) for Category A) high similarity increases accuracy if stimuli are from the same category but decreases accuracy if stimuli are from different categories. This description is confirmed by a similarity (high or low) x category (same or different) ANOVA, which gives a significant main effect of category [$F(1, 17) = 12.47$, $p = .0026$], no main effect of similarity [$F(1, 17) = 1.88$, $p = .1882$], and importantly a significant category x similarity interaction [$F(1, 17) = 31.22$, $p < .0001$]. Considering only stimuli from the same category, accuracy is significantly lower when stimuli differ, $t(17) = 8.66$, $p < .0001$. Considering only stimuli from different categories, accuracy is significantly lower when stimuli are similar, $t(17) = 2.84$, $p = .0112$.

(Figure 3 about here)

Results of Experiment 2

The pattern of results was very similar to that observed in Experiment 1. Data from three participants performing at levels very close to chance (mean proportion of correct responses at .47, .49, and .55) were omitted from the following analysis, though doing so did not alter the pattern of results.

The mean proportion of correct responses averaged across participants on the remaining trials was .80 (SE = .02) and ranged from .66 to .90. Figure 2B plots the mean proportion of A responses averaged across participants as a surface above the stimulus space. Just as in Experiment 1, stimuli furthest from the category boundary were categorised most accurately, with performance at about chance for stimuli on the category boundary. Individual differences in the relative weighting of the two dimensions were captured well by the w_1 parameter.

The category contrast effect was examined in the same way as for Experiment 1 and a similar result was found. Accuracy was higher when a borderline stimulus was preceded by an extreme stimulus from the opposite category (M = .62, SE = .04) compared to when a borderline stimulus was preceded by an extreme stimulus from the same category (M = .51, SE = .02), $t(15) = 3.20$, $p = .006$.

Figure 3B shows that, as in Experiment 1, dissimilarity between consecutive borderline stimuli is taken as evidence that the stimuli belong in different categories. This description is confirmed by a similarity (high or low) x category (same or different) ANOVA, which gives a significant main effect of category [$F(1, 15) = 5.04$, $p = .0403$], no main effect of similarity [$F(1, 15) = 0.02$, $p = 0.8930$], and a significant category x similarity interaction [$F(1, 15) = 8.39$, $p = .0111$]. Considering only stimuli from the same category, accuracy is significantly lower when stimuli differ, $t(15) = 2.73$, $p = .0156$. Considering only stimuli from different categories, accuracy is not quite significantly lower when stimuli are similar, $t(15) = 1.79$, $p = .0933$.

Modelling

We examine whether there is evidence for the use of dissimilarity information by comparing fits of the SD-GCM with fits of a restricted version of the model in which only similarity information is used (i.e., $s = 1$). The free parameters were best-fitted to the trial-by-trial raw data separately for each participant using the Nelder-Mead simplex algorithm to maximise the likelihood of the data given the model. For parameters bounded in the range 0 - 1, seed simplex coordinates were selected randomly from a uniform distribution with range 0 - 1. For parameters bounded in the range 0 - ∞, coordinates were log transformed and selected from the range e^{-5} - e^{5}. Outside this range, changes in the parameter values had essentially no effect on model predictions. The fitting process was repeated 1000 times for each participant and the best fit was selected. The best-fitting parameter values for the unrestricted models (with s free) are given in Tables 2 and 3.

(Tables 2 and 3 about here)

In the fits presented, we assume a Euclidean distance metric ($r = 2$) and a Gaussian generalisation function ($q = 2$). This provided a better fit than when a city-block distance metric ($r = 1$) and exponential generalisation function ($q = 1$) were assumed for 14 out of 18 participants in Experiment 1 and 14 out of 16 participants in Experiment 2. However, a very similar pattern of results is obtained if a city-block distance metric and exponential generalisation function are used instead.

We compared the fit of the unrestricted SD-GCM with a restricted version where only similarity information was used (i.e., $s = 1$). These models are said to be "nested". Obviously, the more general model will always fit the data better. To test the significance of the improvement in fit, generalised likelihood ratio tests were used to test the null hypothesis that s differed significantly from 1 in just the same way that a single sample t-test tests whether the population mean parameter differs significantly from some hypothesised value. (Indeed, t-tests, ANOVA, contingency table chi-squared tests, etc., are all special cases of the likelihood ratio test.)

Those fits that were significantly better by likelihood ratio test are marked in the *s* columns of Tables 2 and 3. For Experiment 1, 17 of the 18 participants' data fitted significantly better when *s* was allowed to vary freely. The average probability of the model predicting an observed response correctly was higher when when *s* was free (M = .718, SE = .012) than when *s* was fixed (M = .700, SE = .012). For Experiment 2, all participants' data was fitted significantly better when *s* was allowed to vary freely (free: M = .742, SE = .017; fixed: M = .720, SE = .015). In summary, for all but one participant, there is significant evidence that they used both similarity and dissimilarity evidence in their categorisation decisions.

Because of the importance of this conclusion, we have tested it using an alternative methodology: cross validation. In this procedure, a model is best-fitted to part of the data. The best-fitting parameters are then used to predict the remaining data. If the model is the correct model and is not too flexible, it will generalise well to the remaining data. In our analysis, for each participant, the data was randomly split in half. The likelihood of one half of the data was calculated using the parameters that best-fitted the other half of the data. This procedure was repeated for 100 different partitionings of the data and the average likelihood was calculated. In Experiment 1, the similarity and dissimilarity model was found to generalise better than the similarity only model for 16 out of 18 participants. In Experiment 2, the similarity and dissimilarity model was found to generalise better than the similarity only model for 14 out of 16 participants. This cross validation analysis essentially replicates the analysis of the likelihood tests, providing strong evidence for the use of both similarity and dissimilarity information.

General Discussion

In these experiments, participants categorised stimuli that varied on two dimensions into one of two categories. In Experiment 1, stimuli were lines varying in their orientation and length. In Experiment 2, stimuli were coloured patches varying in saturation and brightness. In both experiments, there was significant evidence that dissimilarity information was used in addition to similarity information. That is, if a stimulus was dissimilar to an exemplar of Category A this counted as evidence that the stimulus belonging to Category B rather than counting as infinitesimally small evidence that the stimulus belonged to Category A. We reach this conclusion on the basis of two pieces of evidence. First, in both experiments, performance on borderline stimuli was more accurate after a distant stimulus from the opposite category compared to a distant stimulus from the same category. This finding replicates the category contrast effect that has been found for unidimensional stimuli (Hampton et al., 2005; Stewart et al., 2002; Stewart & Brown, 2004) and cannot be explained by the use of similarity information only (Stewart & Brown, 2005). Second, for almost every participant in Experiments 1 and 2, model comparisons found a significant advantage for a model in which both similarity and dissimilarity information was used (the SD-GCM) in comparison to a nested version in which only similarity information was used (the GCM).

Models of the Time Course of Categorisation

There are two main models of the time course of perceptual categorisation, and each could be modified to incorporate the use of dissimilarity information in a relatively straightforward manner. In exemplar-based random walk model (Nosofsky & Palmeri, 1997), the categorisation decision process is modelled as a random walk in which stored exemplars race one another to be retrieved and add to the evidence for their category. There are at least two ways in which the use of dissimilarity information might be incorporated into this model. First, the size of each step in the random walk could be made to depend upon the similarity (activation) of the retrieved exemplar. If the exemplar is very similar, a step could be taken towards the exemplar's category bound. If the exemplar is very dissimilar, a step could be taken away from the exemplar's category bound. Second, the dissimilarity could influence the retrieval time. In the model, similar exemplars are more activated and thus more likely to be retrieved sooner. It might also be the case that highly dissimilar exemplars might also be retrieved more quickly. This modification would cause highly dissimilar exemplars to have an influence early on during the categorisation process.

In the extended GCM (Lamberts, 2000), response times depend not upon the decision process, but rather upon the accumulation of stimulus information. Stimulus elements are repeatedly sampled, with similarity to each category calculated after each sample. The probability that sampling stops depends upon the relative similarity to each category. When the similarity to one category is high sampling stops and a response is emitted. The most obvious way to include dissimilarity information is to modify the choice rule, so that the evidence for each category includes the summed dissimilarity to exemplars of competing categories.

Multiple Systems Categorisation Models

Performance in the information integration experiments of the sort presented in this article is dominated by similarity (or dissimilarity) based processes in which exemplars or regions of perceptual space are associated with category labels (see Ashby & Maddox, 2005, for a review). But there is good evidence that categorisation involves multiple systems or strategies (e.g., Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Erickson & Kruschke, 1998; Nosofsky, Palmeri, & McKinley, 1994). What these models have in common is the assumption that one system detects single-dimension categorisation rules and that another system categorises stimuli from multiple dimensions. In Ashby et al.'s COVIS model, unidimensional verbal rules are augmented with a procedural learning mechanism with associates regions of perceptual space with responses (essentially, a decision bound model). In Erickson and Kruschke's ATRIUM model, a person learns to weight the output of unidimensional categorisation rules with the output of a connectionist implementation of the GCM. In Nosofsky et al.'s RULEX model, people are hypothesised to learn the exceptions to unidimensional classification rules. The SD-GCM could be viewed as an alternative to the multi-dimensional systems in COVIS and ATRIUM. There is no generalisation in the RULEX model - stimuli either match a stored exception or not - and so incorporating the use of similarity and dissimilarity information would require further elaboration of the model.

Conclusion

We have been concerned with whether dissimilarity information is used as evidence in perceptual categorisation. In two experiments we found the category contrast effect which cannot be explained without recourse to the use of dissimilarity information. In addition, nested model comparison and cross validation both revealed significantly better performance for a model that included both dissimilarity and similarity information (the SD-GCM) compared to a restricted similarity-only model (the GCM). This result provides strong evidence that people use dissimilarity information as evidence in perceptual categorisation.

References

Ashby, F. G., Alfonso-Reese, L. A., Turken, A. U., & Waldron, E. M. (1998). A neuropsychological theory of multiple systems in category learning. *Psychological Review, 105,* 442-481.

Ashby, F. G., & Maddox, W. T. (1993). Relations between prototype, exemplar, and decision-bound models of categorization. *Journal of Mathematical Psychology, 37,* 372-400.

Ashby, F. G., & Maddox, W. T. (2005). Human category learning. *Annual Review of Psychology, 56,* 149-178.

Erickson, M. A., & Kruschke, J. K. (1998). Rules and exemplars in category learning. *Journal of Experimental Psychology: General, 127,* 107-140.

Garner, W. R., & Felfoldy, G. L. (1970). Integrality of stimulus dimensions in various types of information processing. *Cognitive Psychology, 1,* 225-241.

Hampton, J. A., Estes, Z., & Simmons, C. L. (2005). Comparison and contrast in perceptual categorization. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 31,* 1459-1476.

Jones, M., Love, B. C., & Maddox, W. T. (2006). Recency effects as a window to generalization: Separating decisional and perceptual sequential effects in category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 32*, 316-332.

Lamberts, K. (2000). Information-accumulation theory of speeded classification. *Psychological Review, 107,* 227-260.

Medin, D. L., & Schaffer, M. M. (1978). Context theory of classification learning. *Psychological Review, 85,* 207-238.

Mewhort, D. J. K., & Johns, E. E. (2000). The extralist-feature effect: Evidence against item matching in short-term recognition memory. *Journal of Experimental Psychology: General, 129,* 262-284.

Murdock, B. B. (1960). The distinctiveness of stimuli. *Psychological Review, 67,* 16-31.

Nosofsky, R. M. (1986). Attention, similarity and the identification-categorization relationship. *Journal of Experimental Psychology: General, 115,* 39-57.

Nosofsky, R. M., & Palmeri, T. J. (1997). An exemplar-based random walk model of speeded classification. *Psychological Review, 104,* 266-300.

Nosofsky, R. M., Palmeri, T. J., & McKinley, S. C. (1994). Rule-plus-exception model of classification learning. *Psychological Review, 101,* 53-79.

Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology, 7,* 573-605.

Stewart, N., & Brown, G. D. A. (2004). Sequence effects in categorizing tones varying in frequency. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 30,* 416-430.

Stewart, N., & Brown, G. D. A. (2005). Similarity and dissimilarity as evidence in perceptual categorization. *Journal of Mathematical Psychology, 49,* 403-409.

Stewart, N., Brown, G. D. A., & Chater, N. (2002). Sequence effects in categorization of simple perceptual stimuli. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 28,* 3-11.

Stewart, N., Brown, G. D. A., & Chater, N. (2005). Absolute identification by relative judgment. *Psychological Review, 112,* 881-911.

Tversky, A. (1977). Features of similarity. *Psychological Review, 84,* 327-352.

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Table 1

SD-GCM Free Parameters

Parameter	Description	Range
w_k	Weighting of dimension k	0 - 1
c	Generalisation parameter	0 - ∞
s	Relative weighting of similarity and dissimilarity evidence	0 - 1
τ	Rate of decay of effect of past stimuli	0 - ∞
β_A	Response bias for Category C_A	0 - 1
γ	Response determinism parameter	0 - ∞

Table 2

Best Fits of the SD-GCM to Experiment 1 Data

Subject	-ln L	c	β_A	γ	w_1	τ	s
1	327.46	0.09	0.48	0.98	0.61	0.72	0.80
2	209.17	0.11	0.61	3.77	0.57	0.01	0.52*
3	262.86	0.06	0.48	3.30	0.29	0.06	0.29*
4	208.91	0.07	0.54	4.99	0.26	0.03	0.41*
5	214.09	0.00	0.58	3.12	0.97	0.11	0.00*
6	232.14	0.47	0.48	1.67	0.78	0.02	0.93*
7	332.73	0.19	0.41	1.40	0.16	0.23	0.64*
8	229.64	0.00	0.57	3.62	0.69	0.07	0.00*
9	256.71	0.12	0.52	2.62	0.54	0.12	0.56*
10	286.67	0.33	0.62	1.39	0.99	0.09	0.83*
11	327.53	0.14	0.52	1.67	0.30	0.09	0.69*
12	277.22	0.07	0.59	1.80	1.00	0.23	0.38*
13	242.22	0.22	0.46	2.69	0.36	0.04	0.68*
14	231.61	0.19	0.62	2.64	0.58	0.10	0.76*
15	204.46	0.15	0.59	3.73	0.54	0.04	0.54*
16	263.09	0.03	0.67	3.65	0.11	0.02	0.18*
17	236.46	0.14	0.43	3.14	0.50	0.10	0.53*
18	277.81	0.62	0.50	1.27	0.71	0.05	0.93*

Note. * indicates s significantly less than 1 (p <.05).

Table 3

Best Fits of the SD-GCM to Experiment 2 Data

Subject	-ln L	c	β_A	γ	w_1	τ	s
1	183.38	0.24	0.40	4.08	0.34	0.04	0.68*
2	200.77	0.11	0.64	3.82	0.69	0.13	0.47*
3	209.89	0.25	0.48	2.81	0.42	0.00	0.80*
4	258.72	0.29	0.56	2.32	0.41	0.10	0.74*
5	189.59	0.40	0.53	3.36	0.53	0.01	0.75*
6	301.16	0.10	0.55	2.18	0.48	0.08	0.63*
7	223.76	0.19	0.50	3.19	0.26	0.07	0.67*
8	183.39	0.24	0.54	3.61	0.50	0.00	0.73*
9	362.80	0.20	0.51	1.08	0.67	0.04	0.65*
10	213.40	0.17	0.60	3.30	0.65	0.02	0.59*
13	267.56	0.00	0.68	2.12	0.80	0.01	0.00*
14	181.55	0.00	0.59	3.54	1.00	0.03	0.01*
15	234.68	0.18	0.41	3.22	0.22	0.03	0.60*
16	234.40	0.19	0.49	3.15	0.33	0.02	0.63*
18	282.31	0.20	0.25	0.31	0.58	0.24	0.00*
19	293.16	0.00	0.61	3.15	0.27	0.00	0.82*

Note. * indicates s significantly less than 1 (p <.05).

Figure Captions

Figure 1. The category structure used in Experiments 1 and 2. In Experiment 1, Dimension 1 was length and Dimension 2 was orientation. In Experiment 2, Dimension 1 was brightness and Dimension 2 was saturation.

Figure 2. The mean proportion of A responses as a function of stimulus for (A) Experiment 1 and (B) Experiment 2.

Figure 3. Proportion of correct responses for a borderline stimulus following immediately after another borderline stimulus for (A) Experiment 1 and (B) Experiment 2. Plots are parameterised by whether the two consecutive borderline stimuli are from the same category or not and are similar or dissimilar.

Figure 1

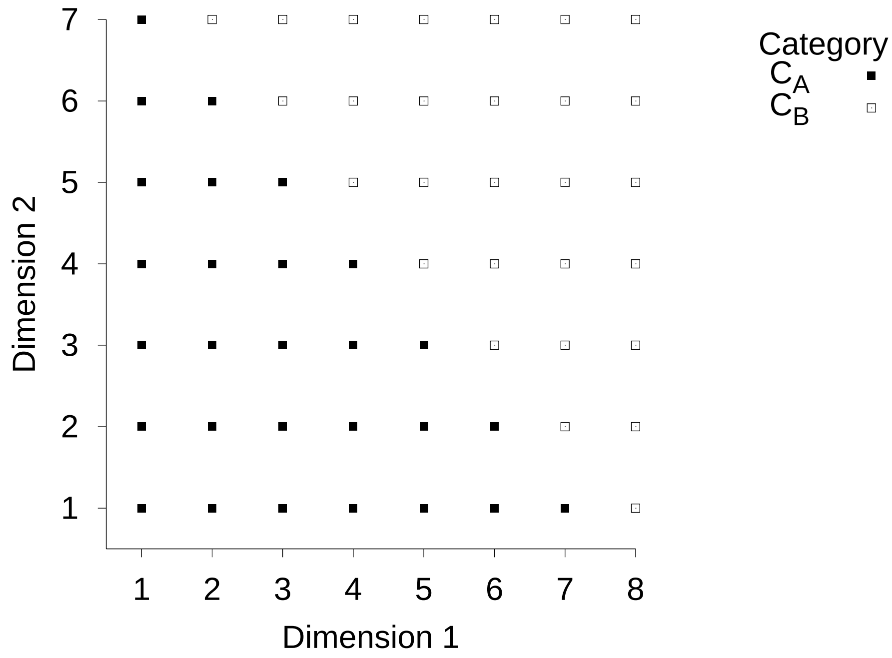
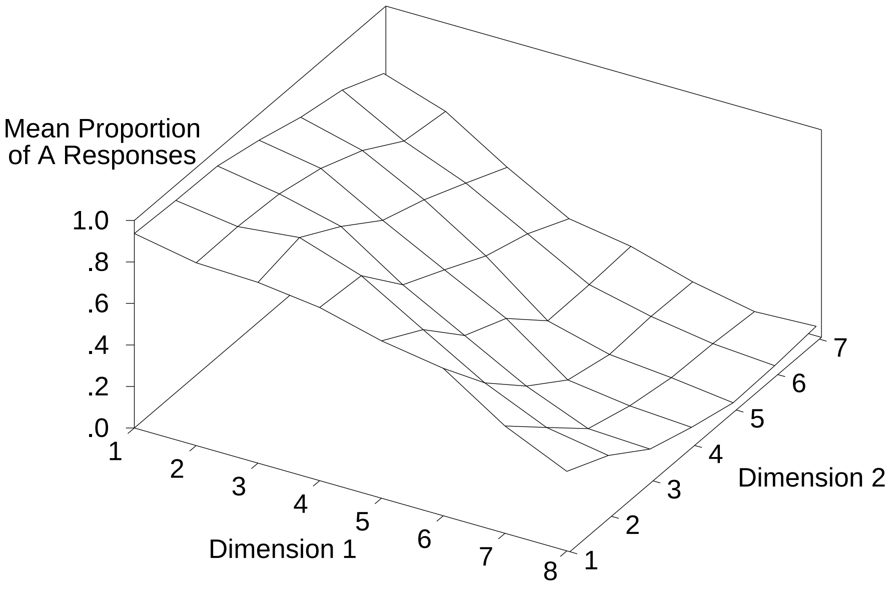


Figure 2

A


Mean Proportion
of A Responses
1.0
.8
.6
.4
.2
.0
1
2
3
4
5
6
7
8
Dimension 1
1
2
3
4
5
6
7
Dimension 2

B

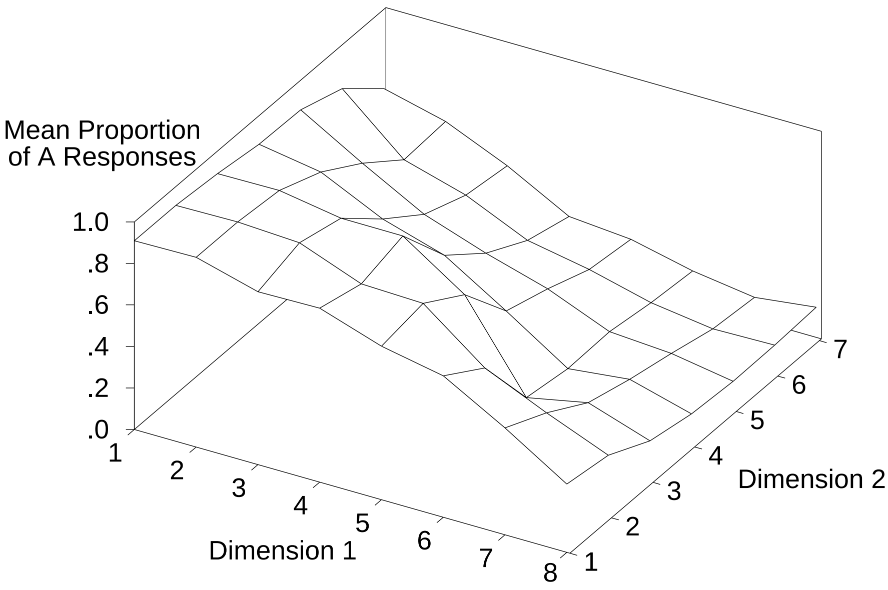
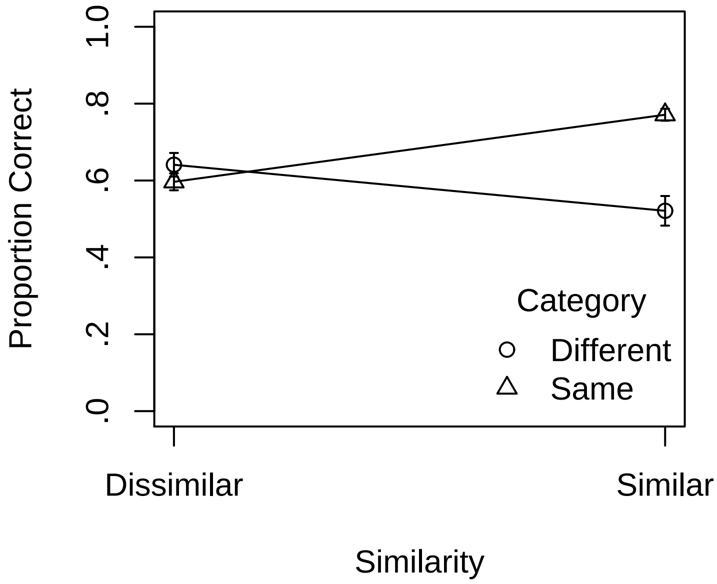
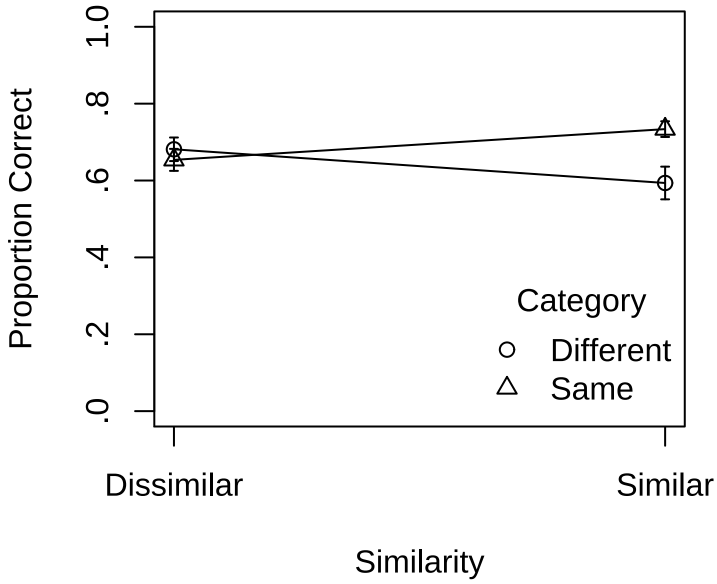

Mean Proportion
of A Responses
1.0
.8
.6
.4
.2
.0
1
2
3
4
5
6
7
8
Dimension 1
1
2
3
4
5
6
7
Dimension 2

Figure 3

A


Proportion Correct
.0
.2
.4
.6
.8
1.0
Category
Different
Same
Dissimilar
Similar
Similarity

B


Proportion Correct
.0
.2
.4
.6
.8
1.0
Category
Different
Same
Dissimilar
Similar
Similarity