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Perceptual vs conceptual categorization*

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The study considered whether Ss use the same strategies in categorizing biographical descriptions as in perceptual classifications. A biographical description consisted of a person's age, income, number of children, and years of education. The Ss were asked to classify these descriptions as residents of two different suburbs in order to compare the results with a previous study using schematic faces. The 123 Ss were assigned to one of three alternative organizations of the descriptions: a table, a "name" organized paragraph in which each person was successively described, or an "attribute" organized paragraph in which each attribute was successively described. Essentially the same results were obtained for schematic faces and biographical descriptions, except for a few differences which were attributed to the use of more realistic categories (suburbs) in the present study. When more realistic categories are used, a S's prior experience can influence which attributes he emphasizes and possibly his formation of an abstract prototype.

The perception-conception relation has been a popular topic of discussion in psychology (see Wohlwill, 1962, for a summary of the views of Bruner, Brunswik, Piaget, and the Gestaltists). The issue which we examine in this paper is Bruner's (1957) proposal that there is a continuity in the rules of inference used at both the perceptual and conceptual levels. According to Bruner, categorization at both levels consists of an act of identification by placing a stimulus input into a certain class on the basis of its defining attributes. A rule for classifying objects should specify the critical attributes of the stimulus, the manner in which the attributes are combined, the weights assigned to various attributes, and the acceptance limits of each category. Although there is a continuity in the inference rules used for perceptual and conceptual categorization, the two processes are not identical. One of the principal differences between the two forms of categorization is the immediacy of the attributes (Bruner, Goodnow, & Austin, 1956, p. 9). In the perceptual case, the attributes are given more immediately—an orange is round, of such and such a size, nubbly in texture, and orange in color. In contrast, the "conceptual" categorization of a 19th century statesman as a Whig or a Tory involves attributes which are less immediate.

Would Ss use the same decision strategies in perceptual and conceptual categorization tasks if the patterns in both tasks consisted of immediately given, well-defined attributes? Our objective was to examine this question and extend the application of some categorization models proposed by Reed (1972). All the models assume that a pattern can be represented by a vector of attribute values: $X = (x_1, x_2, x_m, \ldots x_d)$. An example of a *perceptual pattern* are the schematic faces in Fig. 1, which shows one of the problems used in a previous study on perceptual classification (Reed, 1972). The attributes are the height of the forehead, the distance between the eyes, the length of the nose, and the height of the mouth. An example of a nonfigural *conceptual pattern* are the biographical descriptions shown in Table 1. The attributes are the age of a person, his income in thousands of dollars, the number of children in his family, and his education beyond high school (years). Both problems define two categories, and the S's task was to classify new patterns into one of the two categories. Before examining the two categories in more detail, we first consider alternative strategies that a S might use in a classification task.

CLASSIFICATION MODELS

The following decision models were tested to determine which model could best predict Ss' classifications. A brief formulation is given here, and a more extensive formulation is given in Reed (1972, 1973).

The *cue validity model* considers for each attribute of the test pattern the probability of the alternative categories. Different models were tested in which the number of cues compared across the two categories varies from 1 to d, where d is the number of attributes. In the one-cue case, the cue with the highest validity (probability in favor of Category 1) is compared with the cue with the highest validity for Category 2. In the two-cue case, the two cues with the highest validity in

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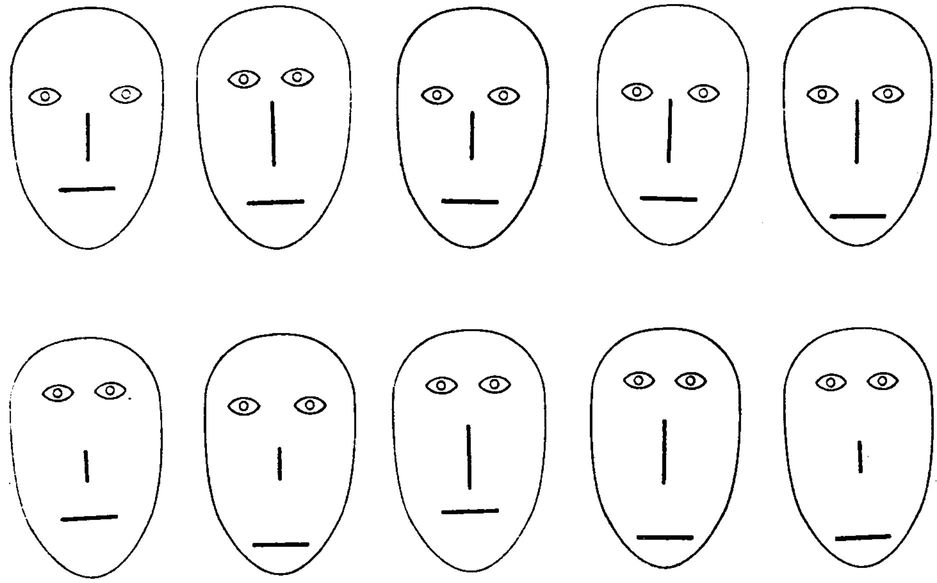

Fig. 1. Schematic faces used in Problem 2A (Reed, 1972). The upper faces represent Category 1 and the lower faces represent Category 2.

favor of Category 1 are compared with the two cues with the highest validity for Category 2. In the d-cue case, all cues are compared. The average cue validity is calculated when more than one cue is evaluated, and the test pattern is assigned to the category which yields the highest cue validity.

The *proximity algorithm* assumes that each pattern can be represented as a point in a multidimensional space. The procedure simply counts the number of patterns in the immediate area of the test pattern. If the majority of patterns belongs to Category 1, the test pattern is placed in Category 1. If the majority of patterns belongs to Category 2, the test pattern is placed in Category 2. We consider three cases of the model in which the decision is based on either the closest pattern (closest match), the three closest patterns, or the five closest patterns to the test pattern.

The *average distance model* assumes that Ss utilize all the patterns in each category in making their decisions instead of just a local subset as in the preceding model. The decision rule states: "Decide the test pattern belongs to Category 1 if the average distance of the test pattern from members in Category 1 is less than or equal to the average distance of the test pattern from members in Category 2; otherwise place the test pattern in Category 2." An alternative version of the average distance model involves differentially weighting the attributes when calculating the distance between two patterns. The weights are calculated from a normative solution which maximally discriminates between the two categories (Sebestyen, 1962, pp. 37-43). The psychological implications of the model are that Ss differentially emphasize those attributes of a pattern which best enable them to discriminate among different categories.

The *prototype model* proposes that Ss create an internal pattern to represent each category. The created pattern, or prototype, represents the central tendency of the category. The decision rule is: "Decide that a test pattern belongs to Category 1 if its distance from the Category 1 prototype is less than or equal to its distance from the Category 2 prototype. Decide that the test pattern belongs to Category 2 otherwise." We also consider a weighted-features version of the prototype model in which the weights are identical to the weights calculated for the average distance model.

The cue validity model is an example of a probability model, whereas the proximity algorithm, the average distance model, and the prototype model are examples of distance models. The two most popular distance metrics are the city block metric ($r = 1$) and the euclidean metric ($r = 2$), and we test both metrics in formulating the distance models (cf. Torgerson, 1958, pp. 251-253). Altogether, 18 models were compared: (1) the cue validity model, four versions depending on whether the decision is based on one, two, three, or all four attributes; (2) the proximity algorithm, six versions depending on the metric ($r = 1$ or $r = 2$) and the size of the local subset ($k = 1, 3,$ or 5); (3) the average distance rule, four versions depending on the metric and weighted

Table 1
Composition of the Two Suburbs

	Age	Income	Children	Education
		Suburb A		
Adams	40	10	5	0
Ames	40	10	3	2
Austin	35	8	5	2
Allen	40	10	5	2
Andrews	40	12	3	4
		Suburb B		
Baker	30	8	1	0
Bell	35	10	1	0
Bolden	30	8	5	0
Brown	30	8	1	4
Butler	30	8	5	4

vs nonweighted features; and (4) the prototype rule, four versions depending on the metric and weighted vs nonweighted features.

The eighteen models were also compared in a previous study in which schematic faces were used as stimuli (Reed, 1972). The results of that study revealed that the weighted-features average distance model and the weighted-features prototype model were the best-predicting models for three of the four problems. Additional converging operations suggested that Ss predominantly used the prototype strategy since (1) many Ss reported using that strategy and (2) Ss were more accurate in classifying the prototype pattern than an equidistant control pattern.

CONCEPTUAL CATEGORIZATION

Replication

The objective of this study was to replicate one of the problems (Problem 2A, shown in Fig. 1) in Reed (1972) using biographical descriptions as patterns instead of schematic faces. The experiment was a replication because there was a one-to-one correspondence between the attributes of the two sets of patterns. This procedure is illustrated in an experiment by Hollier and Evans (1967). The Es used a computer program to generate a sequence having as elements the numbers 1-7. A *schema* was introduced by arranging high transitional probabilities so as to favor a particular sequence. Each number corresponded to one of the syllables PA, HA, RO, GE, KO, ME, LA; the numbers were translated into sequences 15 syllables in length. On each trial, the S was given three sequences (two from the same schema) and had to decide which of the sentences was from a "language" different from the "language" of the other two sentences. In another experiment (Evans & Edmonds, 1966), the same numbers were translated into column heights of histoform patterns. Again the Ss had to indicate on each trial which pattern was from a different schema. The procedure allowed the investigators to study schema learning in two experiments which were identical except for the change in patterns.

One difficulty in using these patterns in the current study is that column heights preserve the ordinal properties of the numbers, whereas the syllables do not. A column height of 7 units is more similar to a height of 6 units than it is to a height of 1 unit, but the same relation does not exist for the syllables. In the current study, it was necessary to insure not only that a one-to-one relation existed among attribute values, but that the relation preserved the ordinal properties of corresponding attributes. The use of biographical descriptions was motivated by a study by Himmelfarb and Senn (1969). Ss in this experiment judged the social class of a series of persons each described by occupation, income, and education.

The attributes in the current study were age (30, 35, 40), income (8, 10, 12 thousand), number of children (1, 3, 5), and number of years of education beyond high school (0, 2, 4). Each attribute was paired with a perceptual attribute of the schematic faces (age-forehead, income-eyes, children-nose, education-mouth), and the ordinal values along each attribute were preserved in the pairing. For example, a short nose corresponded to 1 child, a medium nose to 3 children, and a long nose to 5 children. The correspondence can be seen by comparing the faces in Fig. 1 with the biographical descriptions in Table 1.

Organization

There are different ways to present the information in Table 1, and the manner of presentation could possibly influence Ss' classification strategies. The use of a cue validity or prototype rule requires Ss to organize the information by columns in order to compute the cue validities or the category prototypes. Alternatively, the use of a rule involving the comparison of the similarity between the test pattern and category patterns (such as the proximity and average distance rules) requires Ss to organize the information by rows. We therefore decided to use three types of organization to test whether Ss' classification strategies would be influenced by how we presented the material. The *table* organization was exactly as shown in Table 1. The *attribute* organization involved presenting the information in a paragraph which successively described the values of each of the four attributes. The following paragraph uses this type of organization in describing Suburb A.

Five people were interviewed in Suburb A. Austin is 35 and Adams, Ames, Allen, and Andrews are 40. Austin earns 8 thousand a year; Adams, Ames, and Allen earn 10 thousand a year; and Andrews earns 12 thousand a year. Ames and Andrews have 3 children and Adams, Austin, and Allen have 5 children. Adams attended 0 years of college; Ames, Austin, and Allen attended 2 years of college; and Andrews attended 4 years of college.

The *name* organization involved presenting the information in a paragraph which successively described each of the five persons in a suburb. The following paragraph uses this type of organization in describing Suburb A.

Five people were interviewed in Suburb A. Adams is 40, earns 10 thousand a year, has 5 children, and attended 0 years of college. Ames is 40, earns 10 thousand a year, has 3 children, and attended 2 years of college. Austin is 35, earns 8 thousand a year, has 5 children, and attended 2 years of college. Allen is 40, earns 10 thousand a year, has 5 children, and attended 2 years of college. Andrews is 40, earns 12 thousand a year, has 3 children, and attended 4 years of college.

Experimenters (Frase, 1969; Friedman & Greitzer, in press) have studied the effects of name and attribute

Table 2
Best Fitting Models for Each of Six Groups

		p
	Table Group	
1	Average Distance (r = 1)	--
2	Closest Match (r = 1)	.37
3	Weighted Average Distance (r = 1)	.09
	Attribute Group	
1	Average Distance (r = 1)	--
2	Prototype (r = 2)	.11
3	Closest Match (r = 1)	.10
	Name Group	
1	Weighted Average Distance (r = 1)	--
2	Prototype (r = 2)	.60
3	Weighted Prototype (r = 1)	.52
4	Cue Validity (one cue)	.17
	Faces Group	
1	Weighted Average Distance (r = 1)	--
2	Weighted Prototype (r = 1)	.84
3	Cue Validity (one cue)	.71
4	Prototype (r = 2)	.07
	Objective Group	
1	Weighted Average Distance (r = 1)	--
	Prototype (r = 2)	--
2	Average Distance (r = 1)	.29
3	Cue Validity (one cue)	.09
4	Average Distance (r = 2)	.08
	Subjective Group	
1	Average Distance (r = 1)	--

organization on the ability of Ss to remember material. Although learning and retention of facts have been studied, little is known about how Ss make inferences from written passages (Glaser & Resnick, 1972, p. 261). The present experiment may therefore provide information regarding whether paragraph organization influences the inference rules used by Ss in classifying new patterns.

EXPERIMENT I

Method

The Ss were obtained from an introductory psychology course at Case Western Reserve University. The 123 Ss who participated in the experiment were tested in small groups, averaging about 8 Ss per group. They were randomly assigned to the table organization (N = 40), the attribute organization (N = 41), or the name organization (N = 42). Except for the use of nonfigural patterns, the experimental procedure was identical to the procedure used by Reed (1972). The instructions indicated that the purpose of the experiment was to determine how people make classifications. Each S was initially given a description of the two categories (a table, a "name" organized paragraph, or an "attribute" organized paragraph) and had several minutes to study the two suburbs. They were informed that they would see descriptions of similar people and that their task was to decide whether each new person belonged to Suburb A or Suburb B. The E told the Ss that they could consult the categories throughout the experiment but encouraged them to study the categories carefully because they would have only 12 sec to classify each pattern.

A test booklet contained descriptions of the test patterns, which were chosen so as to discriminate maximally among alternative models. Test patterns did not have names, but consisted of a description of the four attributes. One test pattern appeared on each page of the booklet, and Ss were told every 12 sec to turn to the next page. Ss classified 10 practice patterns, studied the categories for 1 additional min, classified 24 test patterns, and answered several questions about their classification strategies.

Results

The 18 models were initially compared by calculating the percentage of correct predictions for each model. The percentage is limited by the extent to which Ss agree in classifying the patterns, since the optimal predictions are to always choose the category selected by the majority of Ss. Ss agreed more in classifying the faces, since the maximum percentage of correct predictions was 71% for the faces experiment (Reed, 1972) but only 64% for the table, attribute, and name groups. The fact that the same percentage was obtained for the latter three groups indicates that organization had no effect on the extent to which Ss agreed in classifying the patterns. The best-fitting model predicted 59% of the classifications for the table group, 59% for the attribute group, and 62% for the name group.

Table 2 shows the best-fitting models for the table, attribute, and name groups and for the faces group reported previously (Reed, 1972). The predictions of the distance models were based on the assumption that one unit of distance separated the adjacent values on each dimension. Predictions based on psychologically scaled distances are reported in Experiment II. The average distance (r = 1) model was the best-predicting model for the table and attribute groups, and the weighted average distance (r = 1) model was the best-predicting model for the name and faces groups. A z score was calculated to test which models predicted significantly worse than the best-fitting model, and those models which could not be rejected at the p = .05 level are also listed in Table 2.

The finding that a weighted-features model was not the best-predicting model for the table and attribute group contrasts with previous research findings using schematic faces in which the weighted-features models were generally superior (Reed, 1972). Ss' reports about which features they emphasized revealed two alternative determinants of feature emphasis. Some Ss' explanations clearly indicated that the information presented in the problem influenced which attributes they emphasized, whereas other Ss' explanations indicated that their differential emphasis of dimensions was determined by their own beliefs about what factors determine where people live. The term "objective" will be used to refer to the use of problem information, and the term "subjective" will be used to refer to the use of one's own beliefs. The following explanation illustrates subjective weighting of features. "I emphasized education more because of a person's background and how it influences a community. Age was also emphasized because people in my opinion prefer to live surrounded by their same range of age." The next explanation illustrates objective weighting of features. "It seemed that in the two suburbs Group A had mostly 40 year olds and one 35. Group B, 30 year olds and one 35 so I used age as my first attribute. Group A mostly had some college education whereas in Group B only two had 4 years. Age and education seemed to me to be important factors for where the person lived." Although both Ss reported emphasizing the same attributes in this case, the first S was oriented toward information which was not in the problem, whereas the second S was oriented toward the problem.

Of the 123 Ss tested, 48 gave explanations suggesting an "objective" weighting of attributes and 54 Ss gave explanations suggesting a "subjective" weighting of attributes. The explanations of the remaining 21 Ss could not be clearly classified. The normative weights derived from the composition of the two categories were age, 0.46; income, 0.24; children, 0.24; and education, 0.06. The Ss rated how much they emphasized each attribute on a scale ranging from 1 (very little) to 7 (very much). The mean ratings of the objective Ss were age, 5.3; income, 4.8; education, 4.0; and children, 3.7. The ratings correspond fairly well to the normative ordering except for the low rating given to children. The mean ratings of the subjective Ss were income, 5.4; age, 4.8; education, 4.3; and children, 3.3. The ratings differ from the ratings of the objective Ss and the normative ordering, since income was rated most important and there was a larger difference between the ratings given to education and children.

The explanations given by the Ss reveal why a weighted-features model was superior for the name group but not for the table and attribute groups. Table 3 shows that Ss in the name group primarily utilized objective weighting, whereas Ss in the other two groups primarily utilized subjective weighting ($\chi^2 = 11.74$, $p < .01$). The weighted-features models should apply only for the objective weighting of features, since the normative weights are based on category information. The superiority of the weighted-features models in the previous research on schematic faces can be explained by the artificiality of these categories, providing less opportunity for subjective weighting based on prior beliefs. It is less clear why the name organization of the current study should have resulted in more objective weighting, and we have no explanation of this finding. It is of interest, however, that the verbal reports and the model predictions were consistent with respect to feature weighting across the three types of organization. Further confirmation of this consistency was provided by comparing the models for the objective and subjective groups. Table 2 shows that the weighted average distance (r = 1) model was one of the two best-predicting models for the objective group, whereas the average distance (r = 1) model was the best predictor for the subjective group.

Table 3
Objective vs Subjective Weighting of Attributes

	Table	Attribute	Name	Total
Objective	10	13	25	48
Subjective	23	20	11	54

Table 4
Percentage of Correct Classifications of the Prototype and Control Patterns

Problem	Pattern	Percent Correct	Difference p
Faces	Prototype 1	92	.02
	Control 1	75	
	Prototype 2	88	.001
	Control 2	46	
Table	Prototype 1	95	n.s.
	Control 1	95	
	Prototype 2	85	n.s.
	Control 2	85	
Attribute	Prototype 1	90	n.s.
	Control 1	93	
	Prototype 2	78	n.s.
	Control 2	66	
Name	Prototype 1	98	n.s.
	Control 1	95	
	Prototype 2	85	n.s.
	Control 2	85	

The previous study on schematic faces revealed that the weighted average distance models and the weighted prototype models were the best predictors in three of the four experiments. It was difficult in that study to distinguish between the predictions of the two models, but additional converging operations supported the formation of a prototype. First, Ss correctly classified the category prototype significantly more often than an equally distant control pattern, and secondly, more Ss reported using a prototype strategy than an average distance strategy. The first result was not confirmed for the conceptual categories. Table 4 shows the previous results for the faces experiment and the corresponding results for the table, attribute, and name groups. The significant results for faces contrast with the nonsignificant results for the three conceptual categories. A second converging operation, Ss' verbal reports, supported the prototype strategy, since 57% of the Ss reported using a prototype strategy, 21% reported using a cue validity strategy, 13% reported using an average distance strategy, and 8% reported using a closest match strategy.

EXPERIMENT II

The prediction of the distance models greatly improved when scaled distances were used in the previous study on perceptual categorization (Reed, 1972, p. 399). The objective of Experiment II was to determine whether the use of scaled distances would result in a similar improvement for the classification of biographical patterns.

Table 5
Stress Measures for the Six Scaling Solutions

S	r = 1 (Percent)	r = 2 (Percent)
1	14	12
2	14	12
3	14	10
4	15	12
5	15	14
Mean Ratings	13	11

Method

Five Ss participated in the experiment. All Ss were male undergraduates at Case Western Reserve University. They were told that they would be paid $2/h for participation in a scaling experiment and that a $2 bonus would be given to those Ss who performed well on the task.

In the scaling experiment, Ss judged the similarity of all possible pairs (496) of the patterns used in Experiment I. The task was to judge the similarity of each pair of patterns on a scale ranging from "1" to "20." Both ends of the scale were anchored, and Ss knew the range of values along each of the four attributes. All Ss completed the scaling experiment in two sessions.

Results

The TORSCA-9 multidimensional scaling program (Young, 1968) was used to analyze the similarity ratings. Scaled solutions were obtained for the individual Ss in four dimensions. Table 5 shows the resulting stress measures for both the city block (r = 1) and euclidean metrics (r = 2). The stress values for the two metrics are close, but the euclidean metric was always lower in stress. The range in stress values using the euclidean metric varied from 10% to 14% for the five Ss. The scaled solution fit the data somewhat better for the biographical descriptions than for the schematic faces, which resulted in a 14% to 18% range for six Ss. There were also fewer violations of the triangle inequality for the biographical descriptions. The triangle inequality states that any two patterns A:C should be judged more similar than the sum of the judged similarities of Pairs A:B and B:C. The number of judgments which violated the triangle inequality ranged from 3% to 17% for the five Ss who rated the biographical descriptions and from 10% to 32% for the six Ss who judged the schematic faces. Both the lower stress measures and the lower number of violations of the triangle inequality suggest that Ss were more consistent in judging the similarity of biographical descriptions than in judging the similarity of schematic faces.

The mean similarity ratings were also used as input to the scaling program, and the resulting distances were used to make predictions for the distance models. Although the individual subject scaling solutions were better for the biographical descriptions than for the schematic faces, the mean ratings resulted in nearly identical solutions. For biographical descriptions, the stress was 13% for the city block metric and 11% for the euclidean metric. Five percent of the mean ratings violated the triangle inequality. For schematic faces, the stress was 13% for the city block metric, 12% for the euclidean metric, and 5% of the mean ratings violated the triangle inequality (Reed, 1972, p. 398).

The euclidean distances were used to test the distance models since the euclidean solution could be rotated to correspond to the physical dimensions. The correspondence is necessary for the weighted-features models since the difference in values along each dimension must be appropriately weighted. In order to determine whether scaled distances would improve the fit of the models, we compared the scaled distances with the physical distances for the objective and subjective groups. Table 6 shows the results. In contrast to the large improvement found for schematic faces, the use of scaled distances had little effect on the model predictions for biographical descriptions.

DISCUSSION

In summarizing the major implications of the study, the results generally support Bruner's (1957) suggestion that the same decision strategies are used to classify both perceptual and conceptual patterns. The best-predicting models for both studies were the prototype model and the average distance model. The average distance rule received more support in the present study than in the previous study since it was the best-predicting model for all three types of organization, and the control patterns were classified as well as the prototype patterns for all three types of organization. This latter finding contrasts with the results for visual patterns in which Ss were more accurate in classifying the category prototypes (Posner & Keele, 1968; Reed, 1972). There was also support for the prototype model, however, since the majority of Ss reported using that strategy and a prototype model could not be rejected as predicting significantly worse than an average distance rule for two of the three groups. Furthermore, the fact that the average distance model was the best-predicting model for the attribute group is surprising, since it would take

Table 6
Percentage of Correct Predictions of the Euclidean Distance Models Based on Physical and Scaled Dimensions

Model	Physical (Percent)	Scaled (Percent)
Objective Group		
Weighted Average Distance	57	56
Weighted Prototype	54	56
Average Distance	53	56
Prototype	54	59
Subjective Group		
Weighted Average Distance	56	52
Weighted Prototype	52	52
Average Distance	55	53
Prototype	56	55

considerable reorganization to use the average distance rule when the paragraph is organized by attributes.

Previous studies using a recognition memory paradigm indicated that abstraction is often utilized for representing both visual patterns (Franks & Bransford, 1971) and linguistic ideas (Bransford & Franks, 1971). The visual patterns were spatial configurations of geometric forms, produced by applying transformations to a prototype pattern. During an acquisition task, Ss were shown a series of patterns which varied in their transformational distance from the prototype. In a subsequent recognition task, Ss were most confident of having seen the prototype (even when it was not presented), and their confidence ratings of other patterns were inversely related to their transformational distance from the prototype. Bransford and Franks obtained corresponding results for sentences. Ss read a paragraph containing a number of ideas presented in different sentences. When tested later, they were most confident of having seen a sentence which did not occur but which contained all the main ideas.

The major difference between the present study and the previous study (Reed, 1972) was that the superiority of the weighted-features models found previously was obtained in only one of the three groups in the current study. This finding seems to be due to differences in the *artificiality* of the two tasks rather than to the use of numerical, as opposed to figural, patterns. The categories of faces apparently had little extraexperimental meaning which would encourage Ss to assign validities to the features which did not reflect the experimental validities. Differences in feature saliency might influence selection, but the success of the models based on scaled distances suggests that psychological scaling could compensate for these differences. In contrast, attributes such as age, income, number of children, and education have real-world validities with respect to where people live. The weighted-features models were successful when Ss used the experimental validities, but they were not successful when Ss used subjective validities.

The distinction between artificial and natural categories has been made recently by Heider (1972). Heider emphasized the importance of a prototype which was the best example or focal point of a category, but proposed that the focal point of natural categories (concepts designable by words) need not be the central tendency of the experimentally defined categories. Although she used schematic faces as one of the examples of an artificial category, a reformulation of the task might meet her definition of a natural category. If the categories were formed on the basis of a verbal concept such that happy faces were in one category and sad faces were in the other category (cf. Bradshaw, 1969), Ss might form two abstract images which best represented their predefined concept of a happy face and a sad face. The abstractions might not be the central tendency of each experimentally defined category and might vary across Ss.

Perhaps one factor which limited the number of correct predictions of the prototype model in the current study was the use of natural categories (suburbs). Although many Ss reported using an abstract image, the abstraction may not have represented the central tendency used in the model predictions. In addition, the current results suggest that the use of natural categories influences the weighting of attributes whenever Ss use subjective weighting. Each S brings to the experiment prior knowledge about natural categories, and either his prior knowledge or the information presented in the experiment can influence his formation of an abstract image and his differential weighting of attributes.

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