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Abstraction of Ill-Defined Form

Donald Homa
Arizona State University

Category abstraction for ill-defined form patterns was investigated in two experiments. In Experiment 1, subjects initially classified 18 different patterns into three categories containing 3, 6, and 9 members, followed by a transfer test containing old, new, prototype, and random patterns. In Experiment 2, an observational learning paradigm was used, in which categories were defined by 4, 8, 16, and 32 different exemplars, followed by a transfer test containing unrelated and new patterns at each of six distortion levels. In both experiments, transfer was enhanced by prior training on numerous exemplars. Tendencies toward overgeneralization were correlated with greater abstraction in Experiment 1, although this tendency was absent in Experiment 2. The general importance of exemplar variance on category abstraction and the implausibility that transfer is mediated by comparison to stored exemplars are discussed.

The present research was concerned with the abstraction of form from ill-defined categories. Since previous research in category abstraction has usually employed dot pattern stimuli (e.g., Barresi, Robbins, & Shain, 1975; Homa & Chambliss, 1975; Posner & Keele, 1968, 1970), part of the thrust of the present research was to determine if results obtained for the dot pattern stimuli could be replicated with the form stimuli employed in the present study. For example, it has been possible to demonstrate with the dot pattern stimuli that categories *evolve* with (or are modified by) exemplar experience (Homa, Cross, Cornell, Goldman, & Shwartz, 1973), and that the *boundary* of an ill-defined category can be extended by sampling a more variable set of stimuli from the category domain (Homa & Vosburgh, 1976). In contrast, the evolution of a category cannot be readily studied for well-defined, rule-based concepts (e.g., Hayes-Roth & Hayes-Roth, 1977) in the sense that learning is complete once the rule is discovered, that is, all stimuli are classifiable without error by continued application of the rule. Since it has been argued that most natural categories are ill defined (Neisser, 1967), it seemed useful to investigate category abstraction for a stimulus type that was more formlike

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Requests for reprints should be sent to Donald Homa, Department of Psychology, Arizona State University, Tempe, Arizona 85281.

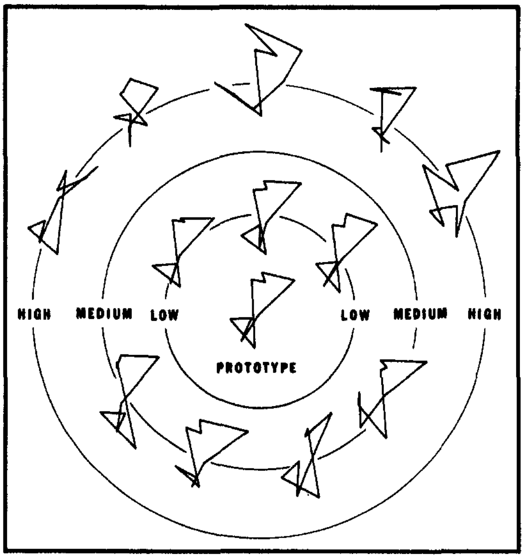

Figure 1. A prototypical form, surrounded by exemplars of varying distortion (low, medium, high) from the prototype.

than the dot patterns, while maintaining the ill-definedness property of a category.

The stimulus type explored here was a nine-sided polygon. Due to the method of generation of these stimuli, any sample of forms from a given category belongs to a population of infinite size. Furthermore, the degree of similarity among patterns within a particular category can be made as close or distant as desired. The method of construction of these stimuli closely mirrors the procedure described by Attneave and Arnoult (1956, Method 8), but the distortion rule applied to a prototypical shape is borrowed from Posner, Goldsmith, and Welton (1967) for the generation of dot patterns. In brief, a prototypical shape containing nine dots is initially determined by the random placement of nine dots in a matrix, and the points are then connected in an arbitrary manner. Distorted exemplars of the prototype are then determined by displacing each of the dots according to a statistical decision rule, and the points are then connected in the same order as the prototype. The magnitude of the distortion level for a given pattern is determined in a manner similar to that described by Posner et al. (1967), that is, the average distance moved per dot from the corresponding dots in the prototype. Figure 1 shows an example of a prototypical form, surrounded by exemplars of varying distortion from the prototype. Since each pattern consists of nine dots, where each dot has two coordinate values, the pattern can be exactly located in an 18-dimensional hyperspace. Pattern variations from the prototype are located on concentric hyperspheres, where the radius from the prototype to a particular exemplar is equal to the distortion level for that exemplar. Although Posner et al. (1967) originally used a discrete distortion rule to generate exemplars (each dot of the prototype could be moved to one of five areas), we have subsequently found it more convenient to supplant the discrete movement rule with one that allows for continuous change, that is, the dots are free to move to any location. The overall distance moved, then, determines the degree of distortion for that pattern.

The present method for generating forms may provide some advantages over previous attempts to construct variable form stimuli (Zusne, 1970, Chapter 5), including the dot pattern stimuli or the free-forms devised by Shepard and Cermak (1973). One useful property is that the degree of distortion of a particular pattern to a prototype can be precisely measured. Although the dot pattern stimuli also have this property, it is not always clear (from the subject's point of view) *which* dots have been moved in a pattern. For example, when a small distortion is used to generate a number of patterns, it is obvious which dots in the distorted patterns correspond to each other and which dots in the prototype correspond to the dots in each pattern. However, with larger distortion levels, the 1:1 mapping between dots in the prototype and the corresponding dots in the exemplars may be obscured. With the form patterns used here, this mapping is always maintained, since the dots are connected in the same order for each pattern in the class of patterns defined by the prototype. The obvious difference between the form polygon explored for the present study and the free-forms of Shepard and Cermak is that the free-form stimuli have smooth contours. Perhaps the major advantage of the form polygon is that a considerable data base in category abstraction has been obtained with the closely related dot pattern stimuli. In contrast, little is known about the functional utility of the free-form patterns in category abstraction.

Two experiments on form abstraction were investigated. In Experiment 1, subjects initially classified 18 different forms into three categories, followed by an immediate transfer test. Each category was represented by a different prototype, and the transfer test was administered once learning criterion had been reached (no errors on two consecutive trials). One major manipulation concerned the number of different forms that had to be classified into each category; one category contained 3 stimuli, another 6, and a third, 9 stimuli. It was hypothesized that the categories defined by more exemplars would result in enhanced category abstraction as revealed by an immediate transfer test. On the transfer test, the subject was presented with four stimulus types: (a) *old* patterns, that is, stimuli classified during original learning; (b) *new* patterns derivable from the three prototypes but heretofore unseen by the subject; (c) the *prototype* for each category; and (d) *unrelated* patterns. Except for the use of form stimuli, this experiment was a close replication of an earlier study (Homa et al., 1973), with the additional modification that half of the transfer patterns were unrelated to any of the three learned categories. Thus, it was possible to determine if a better-abstracted category was also characterized by a greater tendency to exclude unrelated stimuli. In a previous study (Homa & Hibbs, 1978), no systematic difference was found in the assignment of unrelated patterns to categories differing in category size. However, only two categories were learned in that experiment, and category size differed only slightly (three vs. six patterns/category). As was the case in the experiment by Homa et al. (1973), both the training and transfer patterns were high-level (7.7 bit/dot) distortions of the prototype. Unlike that study, subjects were given the option of classifying any pattern in the transfer task to a "junk" category rather than to one of the learned categories.

In Experiment 2, a much wider range of category size on prototype abstraction was explored (4, 8, 16, and 32 different patterns for four categories). In addition, transfer patterns included new patterns at each of six distortion levels (1.0–6.0 units, where 4.6 units = 7.7 bit/dot distortion).[1] It was hoped that generalization gradients across the six distortion levels for categories differing in category size would clearly isolate the advantages of a well-abstracted category. The major difference between Experiment 2 and previous experiments in abstraction was that the learning phase was observational, that is, subjects did not have to learn to classify the patterns but were simply shown the patterns in a random order and told which category was being represented. Since many natural categories are learned in an observational setting, it seemed useful to determine the effects of category size for this paradigm. As was the case in Experiment 1, a large percentage of the transfer patterns were unrelated to the learned categories, and each subject was given the option of assigning any pattern to a "junk" category.

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[1] Although Posner, Goldsmith, and Welton (1967) originally defined the degree of pattern distortion in informational terms (bits/dot), we have subsequently found it more convenient to measure pattern distortion in terms of the average distance moved per dot. The correspondence between bits/dot and distance moved is contained in Table 1 of the Posner et al. article. Except for this change, our patterns are generated in much the same manner as originally described, for example, a prototype is initially determined by the random placement of 9 dots on a 50×50 matrix. Our use of both measures (bits/dot and distance moved per dot) is done primarily because other researchers have stated their pattern distortions in terms of bits/dot.

Experiment 1

Method

Subjects. The subjects were 30 Arizona State University undergraduates who participated to fulfill a course requirement. One subject who required an abnormally long time to reach learning criterion was replaced.

Materials. The basic stimulus pool consisted of 84 stimuli, 14 for each of the three training prototypes and 42 stimuli that functioned as foils during the transfer test. The 42 foils were evenly divided among six unrelated prototypes.[2] The 42 positive stimuli consisted of the prototype and 13 high-level distortions for each of the three categories. All patterns corresponded to 7.7 bit/dot distortions (Posner et al., 1967), that is, the average distance moved per dot was about 4.60 units. All stimuli were drawn in black ink by the university Cal-Comp plotter, and were mounted on 6 × 9 in. (15.24 × 22.86 cm) cards. The maximum size of any pattern was 5 in. (12.70 cm) in either the vertical or horizontal direction.

Procedure. The subject was told that a series of patterns would be shown in which the task was to determine which patterns belonged to the same category. The subject was instructed to classify the forms into three groups, called A, B, and C, and told not to expect an equal number of patterns in each group. Stimuli were presented one at a time, and learning was self-paced. Each response was followed by correct feedback ("no, that is a B pattern"), and learning was terminated once two consecutive errorless trials had occurred (a minimum of 36 consecutive classifications).

During the learning phase, each trial contained 18 different stimuli that had to be classified into three groups, where each group contained 3, 6, or 9 stimuli. All stimuli classified together were derived from the same prototype (P). The same 18 stimuli were presented in five different random orders. Learning trials were rotated across these five random orders until criterion was reached.

For the transfer task, a total of 84 stimuli were presented, 42 that were positive and 42 that were negative. The 42 positive stimuli were equally divided among the three learned categories, where each learned category was represented by the prototype, 3 old, and 10 new patterns. The 42 negative stimuli were drawn from six unrelated prototypes, each with 7 exemplars. The 84 transfer patterns were presented in one of four random orders, and no feedback was provided. Prior to the transfer test, the subject was told, in part: "A number of patterns, in fact, belong to none of the three categories you've learned. If you feel that any pattern I show you doesn't belong to one of the three categories, indicate that by calling the pattern 'junk.' If, however, the pattern looks like it belongs to one of the three categories you've learned, indicate so by assigning it to that category." The subject was also told that there would be about the same number of patterns in each of the learned categories.

Across the 30 subjects, each of the three prototypes were used equally often to represent the categories containing 3, 6, and 9 instances.

Results

The mean number of trials to reach criterion was 19.87, with an individual subject range from 9 to 38 trials. For each subject, the number of classifications into each category (3, 6, 9, junk) was determined for each stimulus type (old, new, prototype, unrelated). The left panel of Figure 2 shows the mean percent correct for each stimulus type as a function of category size; the right panel shows the complete classification performance of the new patterns only, with the category response indicated on the x-axis. As can be seen from the left panel of Figure 2, mean performance systematically increased across category size for both new and prototypical stimuli. Performance of the prototype stimuli (.711) surpassed that of the new stimuli at all category sizes, and overall, classification accuracy for the prototype was intermediate between the old (.878) and new (.446) patterns. This general patterning of results closely mir-

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[2] Although the Euclidean distance between any two patterns from the same category can be precisely measured, it is a nontrivial problem to measure the distance between two *unrelated* prototypes (or two patterns from different prototypes). Since each pattern consists of 9 two-dimensional values (9 dots on a two-dimensional plane), what is required for distance measurement is a rational way to represent each pattern as an *ordered* set of 18 coordinate values. However, there is no logical way to order the set of coordinates when comparing two unrelated patterns. We have attempted to resolve this issue by having subjects provide similarity values between patterns, letting them use whatever basis for similarity they desire. In one experiment, a total of 20 subjects rated the similarity of 20 random prototypes on an 11-point similarity scale. All prototypes used in the two experiments reported here, including the unrelated prototypes, were included in this set of 20. The resulting similarity matrix was subsequently multidimensionally scaled. The correlations involving scaled distance in Experiment 2 were computed using the Euclidean distance between prototypes from the multidimensionally scaled configuration of 20 prototypes.

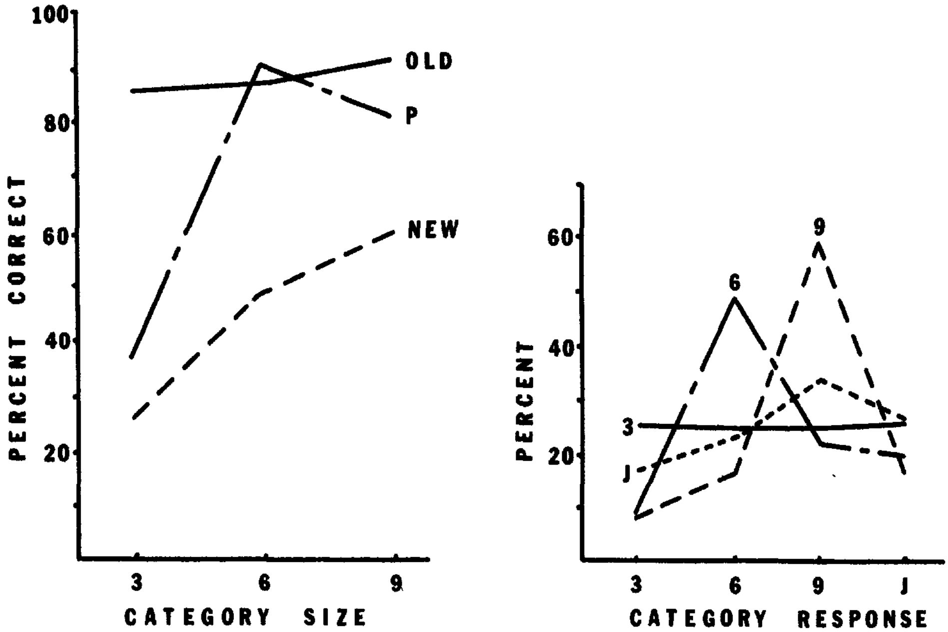

Figure 2. Classification of patterns on the transfer test. (Left panel: Mean percent correct for each stimulus type as a function of category size. Right panel: Category response for new patterns, for patterns belonging to 3-, 6-, 9-instance, or junk categories. P = prototype; J = junk.)

rored that found earlier employing dot pattern stimuli at the same level of distortion (Homa et al., 1973).

The right panel of Figure 2 shows that unrelated patterns were more likely to be classified into the larger categories; the classification of unrelated patterns into the 3, 6, 9, and junk categories was .174, .232, .333, and .261, respectively. To determine if the greater tendency for classifying unrelated patterns into the larger categories nullified the apparent facilitation of category size, performance for each subject at each category size was converted to a d' value (Green & Swets, 1966) using classification of unrelated patterns as an estimate of a guessing bias. This analysis resulted in mean d' values of .29, .71, and .66, for category sizes 3, 6, and 9, respectively, differences that were highly significant, $F(2, 58) = 4.09$, $MS_e = .4298$, $p < .025$. Although the conversion to d' values resulted in no difference in classification accuracy between the 6- and 9-instance categories, both of these categories exceeded the performance for the 3-instance category ($p < .05$).

The overall classification performance shown in the right panel of Figure 2 highlights the composition of the four categories, including the junk category. For example, the category defined by 3 instances is largely undifferentiated in that a stimulus from this category was equally likely to be assigned to any category. Thus, the likelihood of classifying a pattern drawn from the 3-instance category into the 3, 6, 9, and junk categories was .257, .247, .243, and .253, respectively. Although the categories defined by 6 and 9 instances were more prone to accept unrelated patterns, these categories were, nonetheless, better differentiated.

Analysis of bias. At least two explanations may account for the greater tendency to assign unrelated patterns to the categories defined by 6 and 9 instances. First, subjects could have adopted the strategy in which any unidentifiable pattern was assigned to that category containing the most patterns, that is, a simple bias explanation. Another possibility, however, is that some of the unrelated patterns actually appeared more similar to a category defined by more instances. Support for a simple bias explanation would be obtained if patterns from each unrelated category (P4–P9) were assigned to the learned categories (P1–P3) at a rate that mirrored the overall false-alarm rate for each category size (.171, .232, and .333 for 3, 6, and 9, respectively). Support for the latter explanation (perceived similarity) would be obtained if *most* of the exemplars from *some* of the unrelated categories were classified into the learned categories with a consistency that matched the classification of appropriate members. An analysis of classification of unrelated patterns into the learned categories revealed two interesting cases, both involving Prototype 1 as a 9-instance category. Patterns from two unrelated prototypes (P5 and P9) were incorporated into the 9-instance category at unusually high rates (P5 = .56 and P9 = .53). This rate nearly matched the classification of appropriate new patterns into the 9-instance category (new = .59). Since the other unrelated categories were incorporated into the 9-instance category at much lower rates (.24–.36), it appeared that these two unrelated categories were perceived as belonging to P1, but only when P1 was defined by 9 exemplars; when P1 was defined by 3 exemplars, the false-alarm rates for P5 and P9 were .17 and .24; when defined by 6 exemplars, these rates were .24 and .23, respectively.

Finally, the number of trials to reach learning criterion was not significantly correlated with either the degree of abstraction, as determined by the d' values for classification ($r = .16$), or the likelihood of assigning unrelated patterns into the learned categories ($r = .06$). The former result is at variance with an earlier study (Homa & Chambliss, 1975), which found that rapid learners were better abstractors. The latter result suggests that rapid learners were as likely to assign numerous unrelated patterns into the learned categories as were slow learners.

Discussion

For the most part, classification performance on the transfer test mirrored that found previously with dot pattern stimuli (Homa et al., 1973). The major surprise was the tendency to assign a greater percentage of unrelated patterns into the categories defined by more instances during learning. Although this tendency seems partly attributable to a bias or criterion explanation, it is also possible that unrelated categories are more likely to contain information in common with those categories defined by more exemplars. The inclusion of entire unrelated categories into the learned category would be consistent with this view. If category abstraction involves the isolation of common components, and if the detection of these common components is largely mediated by the number of learning patterns that define a category, then overgeneralization (to unrelated categories) may be a natural consequence for categories at moderate levels of abstraction. In effect, the information common to a category may not have been disciminating with regard to other categories (Homa & Chambliss, 1975). In contrast, tendencies toward generalization to *any* patterns may be minimal for poorly abstracted categories. When a category is minimally abstracted, it is unlikely that common components are detected. A number of subjects mentioned that they sorted few patterns into the smallest category simply because that category lacked definition.

Ultimately, enhanced category abstraction should be evidenced by an increased tendency to incorporate appropriate members while correctly rejecting unrelated stimuli. In Experiment 2, category size was manipulated across a much wider range than in Experiment 1, and transfer patterns included novel stimuli at each of six distortion levels (average distance/dot = 1.0, 2.0, 3.0, 4.0, 5.0, or 6.0). Rather than requiring active classification during the learning phase, each pattern was viewed only once in an observational learning paradigm in Experiment 2. The transfer test contained new, prototypical, and unrelated patterns.

Experiment 2

Method

Subjects. The subjects were 20 Arizona State University undergraduates, none of whom had participated in Experiment 1. All subjects were drawn from the same pool as Experiment 1.

Materials. The population of stimuli for Experiment 2 was expanded to include the four prototypes to be learned (P1–P4), and 12 unrelated prototypes (P5–P16) that served to provide foils during the transfer test. All stimuli were generated in a manner identical to that described for Experiment 1.

Procedure. The major difference between Experiments 1 and 2 was the use of an observational study phase in Experiment 2. The subject was presented 60 stimuli, one at a time, for about 3 sec each, followed by an immediate transfer test. In the study phase, the presentation of each stimulus was accompanied by the name of the category (A, B, C, D) containing that stimulus. On the transfer test, the subject was simply told to classify the pattern into the categories represented by the exemplars from the study phase. Each subject was also informed that a substantial percentage of all transfer patterns were, in fact, unrelated to the learned categories, and that a pattern could be assigned to any of the four learned categories or to a junk category.

Design. A within-subject design was used, in which the variables of category size (4, 8, 16, 32) and degree of distortion level of the transfer patterns (1.0–6.0) were combined in a factorial manner. Unlike Experiment 1, each category was represented by an equal proportion of stimuli at each of four distortion levels (1.0, 2.0, 3.0, 4.0) during learning. For example, a category containing 4 exemplars had one pattern that was 1.0 units (distance/dot) from the prototype, another that was 2.0 units from the prototype, a third that was 3.0 units from the prototype, and a fourth exemplar that was 4.0 units from the prototype. A category defined by 32 exemplars had 8 patterns at each of the four distortion levels. On the transfer test, 5 patterns at each of the six distortion levels for each of the four learned prototypes were presented, that is, 120 new transfer patterns in all. In addition, another 120 foils were presented, 10 from each of the 12 unrelated prototypes. The four prototypes were also presented on the transfer test, resulting in 244 transfer stimuli in all.

A Greco-Latin square was used to assign the four prototypes (P1, P2, P3, P4) and four category names (A, B, C, D) to each category size (4, 8, 16, 32). With 20 subjects, it was possible to assign 5 subjects to each of the four rows of the resulting square. The order of presentation of stimuli during the observational and transfer phases was randomized for each row of the square.

Results

The classification performance for the new patterns at each category size is shown in Figure 3 as a function of the distortion level of the exemplars; also shown is the likelihood that each new pattern was misclassified as a junk pattern or as a member of one of the other learned categories. For example, new patterns that belonged to the 4-instance category (left panel) that were 1.0, 2.0, 3.0, 4.0, 5.0, and 6.0 units from the prototype were correctly classified at rates of .60, .45, .42, .35, .37, and .27, respectively. These same patterns were misclassified as junk at rates of .23, .35, .32, .41, .37, and .49. The likelihood that these patterns were misclassified into one of the other learned categories (8, 16, 32) was usually less than 10%. Unlike Experiment 1, the assignment of unrelated patterns into the learned categories (not shown in Figure 3) was approximately equal across category size: the likelihood that unrelated patterns were sorted into categories defined by 4, 8, 16, and 32 instances was .136, .094, .136, and .120, respectively. The unrelated patterns were properly assigned to the junk category with a likelihood of .517. Since bias seemed to be unrelated to category size, an analysis was performed on the errors for each combination of category size (4, 8, 16, 32), distortion level (1.0–6.0), and prototype (P1–P4), using the Greco-Latin square analysis suggested by Winer (1971, pp. 745–747). This analysis revealed that both category size, $F(3, 48) = 8.01$, $MS_e = 5.76$, and distortion level, $F(5, 80) = 63.44$, $MS_e = 1.02$, were highly significant, $p < .001$ in each case. The significant Category Size $\times$ Distortion Level interaction, $F(15, 240) = 2.92$, $MS_e = .88$, $p < .05$, was largely due to the minimal facilitation provided by category size at the extreme levels of distortion (5.0 and 6.0 units).

The patterning of results illustrated in Figure 3 indicates that exemplars from

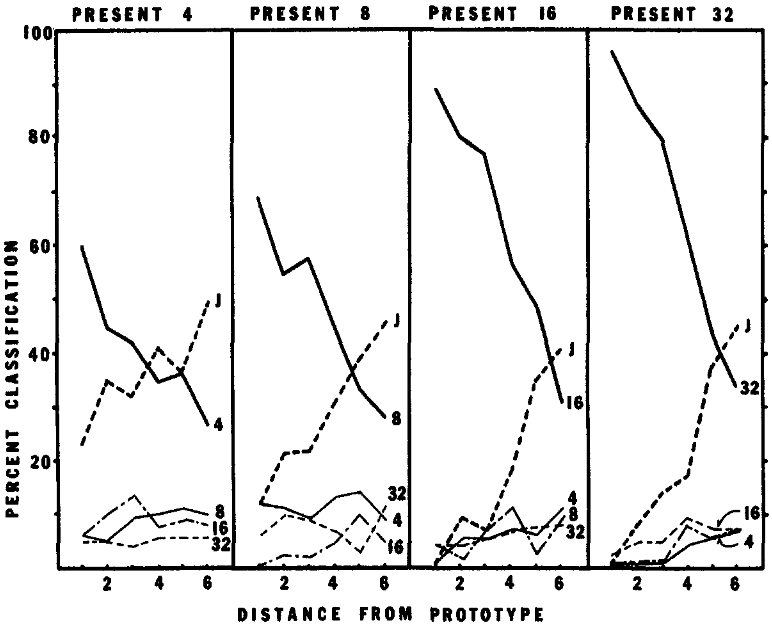

Figure 3. Mean classification performance for new patterns at each category size, as a function of the distance (in units) from the prototype. (4-, 8-, 16-, and 32-instance categories are indicated by respective numerals; J = junk.)

learned categories were rarely confused with another learned category. Rather, most errors were the result of classifying an appropriate pattern into the junk category. This tendency was enhanced by increasing distortion level and decreasing category size.

The classification of unrelated patterns (P5–P16) into the four learned prototypes (P1–P4) was analyzed as a function of category size. Unlike Experiment 1, none of the unrelated categories were incorporated into a learned category at a rate equal to the classification of appropriate patterns. For example, when P1 represented a category containing 4, 8, 16, or 32 patterns, the mean rate of including unrelated patterns was .105, .062, .062, and .090, respectively, and none of the individual unrelated categories were incorporated into a learned category to any great extent; for example, P5 and P9, which had more than 50% of their patterns classified into the largest category in Experiment 1 when P1 was the learned prototype, had only 16% and 20%, respectively, of their patterns included in the 32-instance category.

In another analysis, the multidimensionally scaled distance between the learned and unrelated categories proved to be a mild predictor of classification of unrelated patterns.[3] For the categories defined by 4, 8, 16, and 32 exemplars, the correlations between foil distance and foil classification into a learned category were $-.26$, $-.42$, $-.32$, and $-.34$, respectively, $p < .05$ in each case. However, all category sizes tended to be equally affected by the derived distance of the foil categories, and all category sizes tended to have many close foil categories that were rarely incorporated into the learned category; for example, P12 had 10% of its patterns incorporated into P4, although the scaled distance to P4 was relatively small (distance = .93), whereas 20% of the patterns from P5 were classified into P4, although the scaled distance to P4 was relatively large (distance = 1.81).

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[3] It should be noted that interpoint distances were computed between prototypes, and not between an unrelated pattern and a prototype. Conceivably, these correlations might be improved by taking exemplar distances into consideration.

General Discussion

Taken together, the results from both experiments support the view that the ill-defined patterns used here can be successfully employed in studies of category abstraction. The results of Experiment 1 tended to match the essential outcomes of a previous study (Homa et al., 1973), which employed stimuli composed of nine dots, whereas the results of Experiment 2 support the view that category abstraction can be investigated in an observational paradigm. In fact, for categories defined by 16 and 32 exemplars, the transfer to new patterns at high levels of distortion (e.g., patterns at 4.0 units from the prototype) was quite accurate. In contrast to Experiment 1, categories defined by many exemplars were no more prone to accept unrelated patterns than categories defined by few exemplars. Previously, we have argued that category abstraction involved both the detection of features common to the exemplars of a category as well as the isolation of distinctive features among categories, where common features were determined by exemplar experience, and distinctive features were determined by exposure to contrasting categories (Homa & Chambliss, 1975). The tendency to overgeneralize when categories were defined by a moderate number of exemplars (such as may have been the case in Experiment 1) may reflect no more than a category at an intermediate stage of abstraction. With further within-category experience (as in Experiment 2), the tendency to accept unrelated patterns was reduced. However, it may be the case that tendencies toward overgeneralization can be further counteracted only by additional training on a greater number of contrasting categories.

The results of the present study, together with the structure of the ill-defined categories employed here, are relevant to the issues of *what* is abstracted during exemplar learning and *what information* is utilized on the transfer test. It is possible to measure the Euclidean distance between a prototype and an exemplar, as well as the distance between any two exemplars from the same category. For a random sample of patterns from a given category, it is possible to determine the distribution of distances between patterns. Table 1 shows the interstimulus distances for (a) low-level distortions (patterns about 1.15 units from the prototype) to high-level distortions (patterns about 4.85 units from the prototype), and (b) high-level distortions to high-level distortions. The distributions shown in Table 1 were generated from a sample of 30 patterns at these two distortion levels, including all patterns from Experiment 2 at these distances. The most interesting aspect of Table 1 is that it shows that low-level distortions are more similar to high-level distortions than are high-level distortions to each other. In other words, a low-level and a high-level distortion have more in common (smaller interstimulus distance) than do high-level distortions to each other (larger interstimulus distance). This conclusion is unchanged if one considers subsets of a pattern rather than the entire stimulus, since the distances between patterns are computed in terms of average distance moved per dot. Now, previous research (Homa & Vosburgh, 1976) has

Table 1
Interstimulus Distances between Low-Level (1.15 units) and High-Level (4.85 units) Distortions to other High-Level Distortions

Interstimulus distance	Probability: Low to high	Probability: High to high
1.00– 1.99	.002	.000
2.00– 2.99	.029	.000
3.00– 3.99	.147	.000
4.00– 4.99	.270	.044
5.00– 5.99	.329	.137
6.00– 6.99	.201	.266
7.00– 7.99	.021	.268
8.00– 8.99	.000	.189
9.00– 9.99	.000	.076
10.00–10.99	.000	.020
M interstimulus distance	5.07	7.23
Mdn interstimulus distance	5.17	7.19

demonstrated that transfer to new patterns at all levels of distortion is enhanced if training has occurred with a large sample of the more variable and more distant high-level distortions. Two outcomes seem warranted by these results: (a) Transfer cannot occur to old, stored exemplars, since transfer would be greater when training had occurred on the low-level distortions; and (b) if the stored exemplars mediate transfer via common and distinctive components (Homa & Chambliss, 1975) or diagnostic parts (Hayes-Roth & Hayes-Roth, 1977), then the variance of these components is crucial. For ill-defined categories, even features must be abstractions, since identical features never occur in two patterns from the same category, and with increasing distortion levels (which produces greater transfer), feature similarity must become increasingly remote. Since the strategy of counting features seems to be an implausible outcome when patterns become increasingly distorted, a fruitful explanation may be that subjects are averaging exemplar information (Goldman & Homa, 1977; Reed, 1972). With increasingly large samples, the average of all patterns asymptotes to the prototypical shape, regardless of whether the exemplars were low-level or high-level distortions of the prototype. Alternatively, if something akin to features are being counted, then whatever is counted must include the concept of variance, that is, the allowable range of feature and/or exemplar distortion. Regardless, the advantage of training on high-level distortions is that *only* the high-level distortions exhibit the variance that is permissible for the population of stimuli belonging to a given category. In this regard, we have argued that pattern variance and distortion effectively increase the boundary of an evolving category (Homa & Vosburgh, 1976).

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