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Category Breadth and the Abstraction of Prototypical Information

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The abstraction of prototypical information and the development of category breadth was investigated for categories defined by low-level distortions from the prototype or by a mixing of distortion levels. In the uniform-low condition, low-level distortions were classified into three categories containing 3, 6, and 9 stimuli; in the mixed condition, an equal number of stimuli at each of three distortion levels was classified into categories of sizes 3, 6, and 9. Subsequent transfer to old, new, and prototype stimuli was investigated immediately and after delays of 1 and 10 wk. It was found that degree of positive transfer to new instances interacted with category size such that a mixing of distortions resulted in superior transfer for the categories defined by a larger number of stimuli; transfer was greater for the uniform-low condition only when the category was defined by 3 instances. The influence of category size was maintained across the 10-wk delay for the mixed condition, and, overall, the mixed categories tended to resist deterioration following long delays better than categories defined by low-level distortions.

The isolation of potent variables which underlie the learning of concepts has proceeded along two divergent paths, those in which the concept is well-defined and interest is focused upon hypothesis testing strategies (e.g., Bourne, 1966), and those in which the concept is ill-defined (Neisser, 1967), and primary concern is with the abstraction of prototypical information (Posner & Keele, 1968, 1970). When categories are well-defined, stimuli typically vary along highly discriminable and easily verbalizable dimensions, where the subject's task is frequently one of discovering a rule which allows for the classification of objects into predesignated categories; for example, Category A might be defined as consisting of those objects which are both red and large, whereas Category B might be everything else. Once the rule is discovered, all stimuli can then be classified without error.

In contrast, research in the area of ill-defined categories goes back to the view of Bartlett (1932) in that conceptual experiences are somehow integrated, and a schema or abstracted prototype for that category is formed. Evidence that the protoype is abstracted during learning has been determined from the retention characteristics of the prototype. When a delay of 4–7 days is inserted between learning and test, significant forgetting is obtained for the old stimuli, whereas the classification accuracy for the prototype is unaffected (Homa, Cross, Cornell, Goldman, & Schwartz, 1973; Posner & Keele, 1970; Strange, Kenney, Kessel, & Jenkins, 1970). If the prototype were classified via generalization to the old, stored, instances at the time of test, any performance decrement on the old instances should have been accompanied by a similar decrement for the prototype. Since this was not the case, the most likely explanation is that the abstracted prototype is formed during learning and is simply more resistant to forgetting than the old instances.

Although the abstracted prototype may be thought of as a rule, the abstracted prototype is, in a strict sense, neither correct nor incorrect but rather, appropriate for the information which defines the concept. Consistent with this view is the finding that the abstracted prototype can be modified and enhanced as the experience with the exem-

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plars of a concept is increased (Homa et al., 1973). More recently, it has been demonstrated that category size (i.e., category experience) and the number of categories which have to be discriminated during learning both facilitate subsequent classification of prototypical and new information (Homa & Chambliss, 1975).

A descriptive model for abstraction which involves the sampling of stimulus features during classification has been used to account for prototype abstraction and classification of new and old stimuli (Homa & Chambliss, 1975), where the most important variables are category experience (i.e., the number of different exemplars classified together which define the concept) and category distinctiveness. In this model, the abstracted prototype is that set (or integration) of features which occur most often among the stimuli classified together, where the weightings of featural information are determined by their commonality and categorical discriminability. Crucial to this model is the reliance on stimulus sampling, that is, a sufficient number of stimuli must be classified together before common and distinctive features can be determined.

An intriguing question which has received little attention is whether ill-defined categories can have a boundary and a breadth. A category boundary might be defined as the degree of distortion a stimulus can undergo and still be identified as a member of a particular category; category breadth would then be defined as the range of stimulus distortion that is acceptable to that category. In terms of the feature model, the likelihood that an allowable but severely distorted new stimulus would be correctly identified should be a function of the number and type of stimuli originally sampled to define the concept. Thus, category exemplars that were, in some sense, too close together would not provide adequate experience with the potential range of stimulus distortion and variability. It might be hypothesized that the category boundary is not fixed but can be extended with appropriate kinds of learning experiences, much in the same manner that an abstracted prototype can be modified by experience (Homa et al., 1973).

The present study investigated category breadth by focusing upon the generalizability of different learning experiences to the classification of new exemplars. In an attempt to deal with this issue, Peterson, Meagher, Chait, and Gillie (1973) concluded that prototype abstraction and degree of positive transfer to new category instances of varying distortion levels was most facilitated by training on low-level distortions. However, this conclusion should be tempered by a number of methodological and theoretical considerations: (a) Criterion learning was not always equated for their various conditions, and subsequent transfer to prototype and new instance stimuli could very well reflect this initial learning difference. For example, in Experiment 1, immediate classification of old instances (generated from random patterns) varied from about 87% to about 64% for groups trained on low-level (1-bit) and high-level (7.7-bit) distortions, respectively. (b) A delayed test was not administered in any of their experiments, and it is not obvious that differences on an immediate test would be maintained at later testing. (c) Minimal category experience was provided, since each category was defined by only three exemplars; at best, their conclusions should be restricted to learning situations which offer minimal category experience.

In a theoretical sense, one might also be bothered by the logic of training on low-level distortions, especially the minimal, 1-bit distortions used by Peterson et al. If the view is taken that a prototype has no objective reality, in the sense that one is unlikely to encounter a prototype walking the streets, then the experiential analogue of low-level distortions is a far-fetched one; for example, the search for the "near prototypical" dog would be an ominous task, at least when ill-defined concepts are being considered. An alternative consideration, and the one preferred here, is that concepts and abstracted prototypes are formed from exemplars of a concept, and that, in fact, abstraction cannot occur without these experiences. In effect, training on low-level distortions may guarantee accurate prototype classification but at the expense of classification of new exemplars, especially for those stimuli which are at an intermediate or high level of distortion.

If category experience is a variable of fundamental importance for abstraction, it seems likely that increasing the number of exemplars which define a category would be beneficial only if the exemplars broadly sampled the domain of acceptable distortions. To assess this possibility, the present experiment investigated the generalizability to new and prototypical stimuli for concepts defined by different category sizes and stimuli having varying amounts of distortion. In the uniform-low condition, categories were defined by 3, 6, and 9 instances, where all category instances were low-level distortions from each of three prototypes. In the mixed condition, the 3-, 6-, and 9-instance categories were represented by an equal number of low-, medium-, and high-level distortions. It was hypothesized that transfer to the prototype and new instances of varying distortion level would be positively related to category size only for the categories defined by a mixing of distortion levels, and that, for the larger categories, positive transfer would be higher for the mixed condition. Furthermore, the retention of conceptual information was assessed following delays of 1 and 10 wk; thus, it was possible to determine the decay of conceptual information following substantial time delays for these two conditions.

Method

Subjects. The subjects were 72 undergraduates from New College who were paid $1.50 for their participation. Half of the subjects were run in the mixed condition and half in the uniform-low condition. Following the classification session, all subjects were tested immediately and after a delay of 1 wk. In addition, 28 subjects in each condition were also tested after a delay of 10 wk.[1]

Materials and apparatus. Construction of the stimuli has been described previously (Homa et al., 1973), and closely mirrors the procedure outlined in Posner, Goldsmith, and Welton (1967). Briefly, each prototype is defined as the random placement of nine dots on a 30 $\times$ 30 matrix; distortions from each prototype are determined by movement of each of the dots according to statistical decision rules. The basic stimulus pool for the present experiment consisted of 12 stimuli at each of three distortion levels (3.5, 5.6, and 7.7 bit) for each of the three different prototypes. For purposes of simplicity, the three levels of distortion employed here will be referred to as low-, medium-, and high-level distortions of the prototype. Stimuli were mounted in slides and presented via a Kodak 650 Carousel projector.

Procedure. The subject was seated in an adjoining room and informed that a series of dot patterns would be shown, where the task was to determine which dot patterns were to be grouped together. The subject was instructed to classify the dot patterns into three groups, labeled A, B, and C, and to not expect an equal number of patterns in each group during the study trials. Stimuli were presented one at a time, and learning was self-paced. Each response was followed by yes–no feedback, and learning was terminated once two consecutive errorless trials had occurred.

During the learning phase, each trial consisted of 18 different stimuli which had to be classified into three groups containing 3, 6, and 9 stimuli. All of the stimuli classified together were derived from the same prototype. The same 18 stimuli were presented in four different random orders. In the uniform-low condition, all 18 stimuli were low-level (3.5-bit) distortions; in the mixed condition, each category contained an equal number of low- (3.5-bit), medium- (5.6-bit), and high-level (7.7-bit) distortions. Thus, in the mixed condition, a category defined by 3 stimuli contained one low-, one medium-, and one high-level distortion; a category of size 6 contained two low-, two medium-, and two high-level distortions, etc.

During the testing phase, a total of 39 stimuli were shown on each of two test trials, 9 of which were stimuli classified during original learning (old instances), 27 of which were new, and 3 of which were the prototypes for the three categories. For both conditions, the 27 new stimuli were derivable from the prototypes which also generated the old instances. Of these 27 new stimuli, 9 each belonged to each of the three prototypes, 3 at a low-level distortion (3.5-bit), 3 at a medium-level (5.6-bit), and 3 at a high-level (7.7-bit). For the uniform-low condition, the 9 old instances were composed of 3 low-level distortions for each of the categories. For the mixed condition, the 9 old instances were composed of 1 low-, medium-, and high-level distortion for each of the categories. Each of the two test trials contained the same

[1] Of the original 36 subjects who provided data on the immediate and 1-wk delay test, 28 in each condition could be located for the 10-wk delayed test. Although the 8 missing subjects in each condition were randomly dispersed among the treatments, e.g., prototypes serving as the 3-, 6-, and 9-instance categories, results for the 10-wk test should be treated with some caution.

stimuli but in different random orders. The subject was instructed to classify the patterns as A, B, or C, and was informed that there would be approximately the same number of A, B, and C patterns. During the test trials, no feedback was provided.

Design. Across the 36 subjects in each condition, each of the three prototypes was represented equally often for categories containing 3, 6, and 9 instances. With three prototypes and three variations in category size, two possible 3 × 3 Latin squares can be generated. For both the mixed and uniform-low conditions, a total of six subjects were then randomly assigned to each of the resulting six rows of the matrix. Stimuli which represented the categories during the learning and test phases were then randomly selected from the basic stimulus pool and maintained for three of the six subjects for one of the rows of the Latin square. For the other three subjects in that row, stimuli were again randomized for the learning and test phase. This procedure was then repeated for each of the remaining rows of the matrix and insured that each stimulus occurred approximately equally often as a new or old stimulus at each category size.

Results

Original learning. The mean number of trials to criterion for the mixed and uniform-low conditions was 17.8 and 6.6, respectively, a difference which was highly significant, $t(70) = 5.85$, $p < .001$. Thus, the two conditions differed considerably in ease of learning, an expected outcome since only the subjects in the mixed condition classified the more difficult medium- and high-level distortions. In spite of the uneven learning difficulty of the two conditions, a partial check on whether the degree of learning was approximately equated by having both groups learn to criterion can be gauged by subsequent classification of the old instances on the immediate test. If this comparison is restricted to only the low-level distortions, since the uniform-low concepts were defined solely by low-level distortions, the percentage correct for the mixed and uniform-low conditions was .944 and .963, respectively. If the comparison is made by combining the medium- and high-level distortions for the mixed condition, overall performance on the old instances for this condition is reduced slightly to .926. Thus, as indexed by classification accuracy of the old instances on an immediate test, performance for the two conditions was high and roughly comparable.

Immediate test. For each subject, errors were tabulated for each combination of category size (3, 6, 9), distortion level (low, medium, high), stimulus type (old, new, prototype), and time of test (immediate, 1 wk delay, 10 wk delay). The mean percentage correct for the new and prototype stimuli on Trial 1 for the immediate test is shown in Figure 1 for the mixed and uniform-low conditions separately.[2] The most obvious result is the strong effect of category size at each distortion level for the mixed condition and the apparent inffectiveness of this variable for the uniform-low condition. Separate analyses were initially computed for the mixed and uniform-low conditions, with distortion level, category size, and stimulus type as within-subject variables for the mixed condition; for the uniform-low condition, the stimulus type variable was not included in the analysis since old instances could only appear as a low-level distortion. In order to enhance data reliability, the errors for each of the three subjects who received identical stimuli in the learning and test phases were combined and treated as a single subject. In addition, errors on the old instances (for the mixed condition) were multiplied by a factor of three since the opportunity for errors on the test trials was one third that of the new instances. Essentially, the analysis was performed on 12 pseudosubjects in each condition.

For the mixed condition, the main effects of category size, $F(2, 22) = 9.73$, $p < .01$ ($MS_e = 7.65$), stimulus type, $F(1, 11) = 5.96$, $p < .05$ ($MS_e = 18.19$), and distortion level, $F(2, 22) = 5.92$,, $p < .01$, ($MS_e = 5.64$), were all highly significant. The Stimulus Type × Distortion Level interac-

[2] There was a slight but consistent increase in performance from Trial 1 to Trial 2 for both the mixed (+2.8%) and uniform-low (+2.5%) conditions. Although analyses based on Trial 1 alone or averaged across Trials 1 and 2 resulted in identical statistical outcomes, the results shown in all figures included in this article are based on Trial 1 performance. It was felt that Trial 1 data was more sensitive to pure experimental manipulations, whereas Trial 2 performance was slightly influenced by classification on Trial 1.

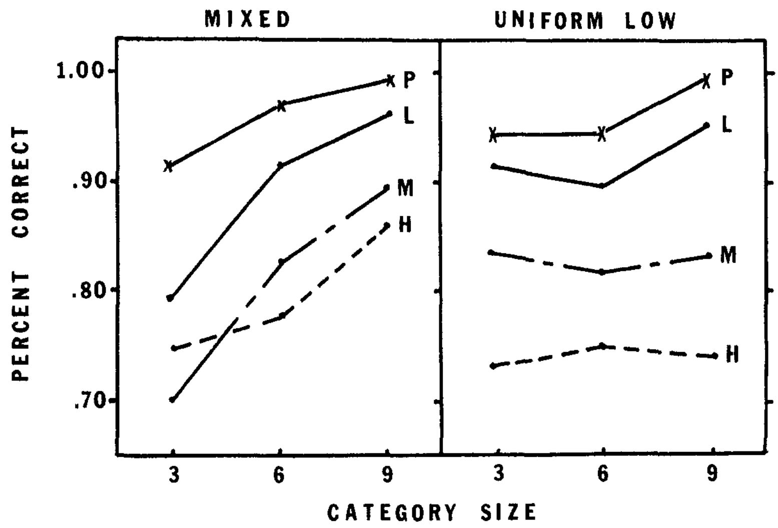

FIGURE 1. Mean percentage correct on an immediate test for new and protoype stimuli on Trial 1 as a function of category size, distortion level, and training condition. (P = prototype; L = low-level distortion; M = medium-level distortion; H = high-level distortion.)

tion was also significant, $F(2, 22) = 4.74$, $p < .03$ ($MS_e = 5.42$), and reflected the fact that new stimuli were much more affected by distortion level than were the old instances. If the analysis is restricted to new instances, the essential statistical outcomes are maintained, with category size, $F(2, 22) = 11.99$ ($MS_e = 5.44$), and distortion level, $F(2, 22) = 8.78$ ($MS_e = 5.09$), again highly significant, both $p < .01$.

For the uniform-low condition, the only significant source was that of distortion level, $F(2, 22) = 40.11$, $p < .001$ ($MS_e = 2.75$); neither the main effect of category size nor the Distortion Level × Category Size interaction proved to be significant, $F(2, 22) = .86$ ($MS_e = 6.90$, and $F(4, 44) = .28$ ($MS_e = 3.85$), both $p > .25$. Although the mixed and uniform-low conditions did not differ in terms of overall performance (.836 for mixed and .837 for uniform-low new stimuli), an analysis with condition (mixed and uniform-low), category size, and distortion level as main variables revealed a significant Condition × Category Size interaction, $F(2, 44) = 5.62$, $p < .01$ ($MS_e = 6.17$). This interaction reflects the strong influence of category size for the mixed condition but not for the uniform-low condition. The tendency for the two conditions to be differentially affected by category size resulted in the uniform-low condition being superior for size 3 category (.827 vs. .750) but poorer on the size 9 category (.843 vs. .907). As expected, both conditions showed a strong effect of distortion level, with separations between low and medium and medium and high distortions averaging about 5–10% at each category size.

Delayed testing. All subjects were again tested after a period of 1 wk. In addition, 28 of the 36 subjects in each condition provided data after a 10-wk delay. It was possible, therefore, to determine whether the patterning of results on the immediate test was maintained after a considerable passage of time. The mean percentage correct for the new and prototype stimuli is shown in Figure 2, as a function of category size and distortion level, for delays of 1 and 10 wk.

Following a delay of 1 wk, the effect of category size, $F(2, 22) = 7.09$ ($MS_e = 5.12$), and distortion level, $F(2, 22) = 9.05$ ($MS_e = 3.67$), were again highly significant for the mixed condition, both $p < .01$, whereas only the effect of distortion level was significant for the uniform-low condition, $F(2, 22) = 21.97$, $p < .01$ ($MS_e = 4.33$). Thus, after a period of 1 wk, the effect of category size was maintained for the mixed condition.

Following an interval of 10 wk, the most obvious trends for the mixed condition was the continuation of a strong category-size effect for the low- and medium-level distortions, with overall performance maintaining their original levels. On the immediate test, classification accuracy for low- and medium-level distortions was .892 and .809, respectively; after 10 wk, these percentages were .901 and .806. The magnitude of the facilitation due to category size was also maintained after 10 wk; on the immediate test, the difference in classification accuracy for categories of sizes 9 and 3 was +.167 and +.194 for low and medium distortions, respectively; after 10 wk, the size of the facilitation was +.142 and +.226. The most notable exception to the relative stability of performance for the mixed condition was the washing out of a category-size enhancement for the high-level distortions; after an immediate test, this enhancement was +.111 but after 10 wk, the difference between categories of sizes 3 and 9 was 0.

For the uniform-low condition, the effect of a 10-wk delay was more detrimental, in that performance dropped at all levels of stimulus distortion, especially for categories of sizes 6 and 9; for example, for the high-

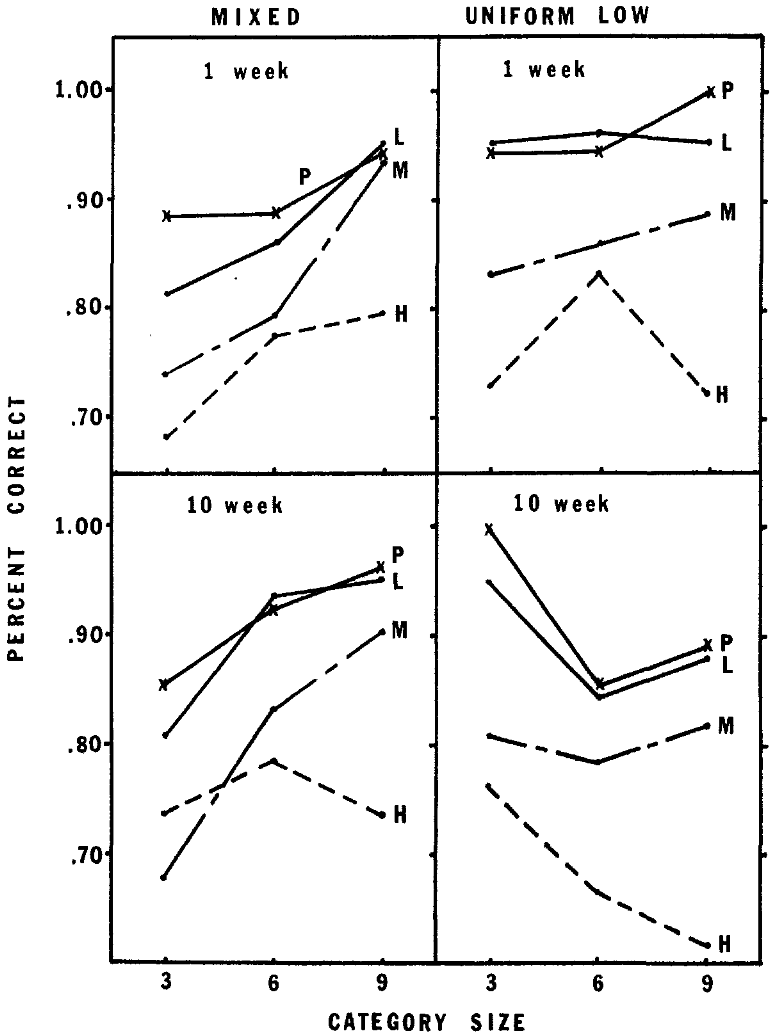

FIGURE 2. Mean percentage correct for new and prototype stimuli on Trial 1, as a function of category size, distortion level, and training condition, for delays of 1 and 10 wk. (P = prototype; L = low-level distortion; M = medium-level distortion; H = high-level distortion.)

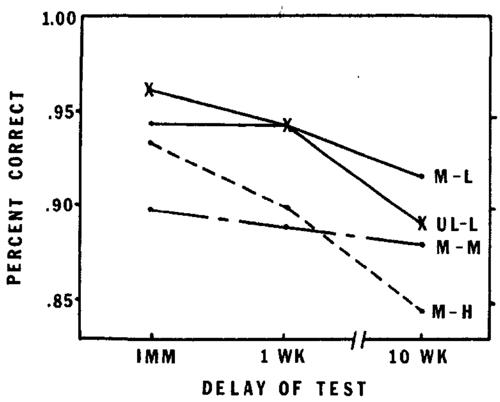

FIGURE 3. Mean percentage correct for old stimuli on Trial 1 on an immediate test and delays of 1 and 10 weeks, for both training conditions. (M–L = mixed condition–low-level stimuli; UL–L = uniform-low condition–low-level stimuli; M–M = mixed condition–medium-level stimuli; M–H = mixed condition–high-level stimuli; IMM = immediate.)

level distortions, the magnitude of deterioration was −.083 and −.122 for categories of sizes 6 and 9, respectively. Even performance on the low-level distortions showed a performance decline, averaging −.063 for categories of sizes 6 and 9. Although the 10-wk delay was based on only a subset of the original sample, it would appear that the mixed condition fared better across a substantial delay than the uniform-low condition.

Retention of old stimuli. Figure 3 shows the temporal course of retention for the old stimuli at each distortion level for both conditions. Although forgetting does appear to have occurred, its magnitude is relatively small, especially after a delay of 1 wk. For the uniform-low condition, the difference in classification accuracy for old low-level stimuli on an immediate test and one 10 wk later was about 7%; although 61% of the subjects in the uniform-low condition made no classification errors for old stimuli on an immediate test, only 39% managed errorless performance 10 wk later. For the mixed condition, differences on an immediate and 10-wk delay test was negligible for low- and medium-level distortions (3% and 2% decline); however, classification of old high-level distortions did decline about 9%. It is interesting to speculate that classification in the mixed condition was mediated primarily by abstracted information after 10 wk, since the ordering of performance curves for distortion levels is haphazard following an immediate test (e.g., high distortions are more accurately classified than medium ones), but, after 10 wk, is similar to that for new instances (low distortions more accurate than medium, medium more accurate than high).

Response bias. The possibility of response bias operating during the test phase, for example, a tendency to classify more test stimuli into the 9-instance category than the 3- or 6-instance ones, was investigated by adding to the end of each test session 10 stimuli that were unrelated to the three training prototypes, that is, 10 random patterns. For the mixed condition, the percentages of these random patterns, grouped into 3-, 6-, and 9-instance categories, were .305, .350, and .345 after an immediate test, .297, .303, and .400 after a delay of 1 wk, and .379, .289, and .332 after 10 wk. Since .333 would be chance or random assignment, there is only a slight bias to classify stimuli into the 9-instance category in the 1 wk delay session; otherwise, there does not appear to be any general trend toward a bias in classification.

For the uniform-low condition, these percentages for the 3-, 6-, and 9-instance categories were .375, .242, and .383 after an immediate test, .400, .264, and .336 after a delay of 1 wk, and .425, .271, and .304 after 10 wk. Thus, for reasons unclear, there was a bias to classify random patterns into the 3-instance category, as well as a slight tendency for this bias to increase with increasing time delays.

DISCUSSION

These results clarify the question of whether abstraction is facilitated by training on highly similar or highly variable category exemplars. When a category is defined by only a few exemplars, subsequent transfer to new stimuli, especially those at a low or intermediate level of distortion, is better if the original training set consists of minimal stimulus distortions of the prototype. With more distorted and highly variable training stimuli, subsequent transfer to all stimulus patterns, including those at a low level of distortion from the prototype, is relatively poor.

However, the limitations of training on minimally distorted stimuli come to the surface once the effects of category experience are considered. Categories defined by low-level distortions show no appreciable benefit in terms of subsequent transfer to new stimuli, as category size is increased. In fact, it would appear that *no* amount of category experience would result in high levels of positive transfer for categories defined solely by low-level distortions, especially for those new patterns which are at an intermediate or high level of distortion. In marked contrast, categories defined by a mixing of distortion levels showed significant and substantial positive transfer to new stimuli as category size was increased. For categories of size 6 and 9, the mixed condition resulted in performance superior to the uniform-low condition; with even greater amounts of category experience than manipulated here, differences between these two training methods would probably continue to increase.

With regard to the retention of conceptual information, the substantial time delays investigated here seemed to be more detrimental to the uniform-low concepts; deterioration was manifested at all levels of stimulus distortion, including new stimuli at low levels of distortion, a distortion level which defined the original training stimuli. For the mixed condition, the effects of category size and classification accuracy for low- and medium-level distortions were maintained across a 10-wk delay; only those stimuli at high distortion levels were classified less well than originally. If categories are to be formed that are tightly knit and relatively resistant to forgetting, the results obtained here would suggest that categories defined by stimuli of varying distortion levels are more likely to achieve this outcome than categories defined by stimuli of minimal prototype distortion. In conclusion, the main hypothesis of this study was supported: Abstraction is facilitated by training on a highly variable range of stimuli once the number of stimuli defining a concept has reached a sufficiently large size; when the number of exemplars defining a concept is small, a high degree of stimulus distortion may be deleterious rather than facilitative.

Although the conclusions reached here are opposite to those of Peterson et al. (1973), the results of their study are replicated if only those categories defined by three instances are considered. Thus, the failure of Peterson et al. to find greater generalization for concepts defined by a mixing of distortion levels than for those defined by low-level distortions is likely attributable to their failure to consider category size as a variable of fundamental importance in abstraction.

A feature model of abstraction proposed to account for the effects of category experience and category discriminability on subsequent transfer and prototype abstraction (Homa & Chambliss, 1975) can be extended to accommodate the results of stimulus distortion obtained for the present study. If each stimulus can be represented by a collection of features, then those stimuli classified together define a set of common, distinctive, and idiosyncratic features. Those features which ultimately become the best predictors for category inclusion can be determined only after sufficient experience with the exemplars of the category has been provided. Since the breadth of a category can be abstracted only from its exemplars, it seems clear that a representative sample would better indicate the allowable set of features than would a sample which is tightly constrained. This would certainly be true for the special case where the sample is tightly constrained around the objective prototype. However, a restrictive sample such as this would only guarantee accurate classification of the objective prototype; other new instances which are sufficiently distorted to fall outside the defined boundary for the exemplars but within the allowable limits of distortion for that prototype cannot be expected to be readily recognized. The importance of category experience for this model is crucial since, for minimally distorted patterns, increased category experience would most likely be duplicative for those features already sampled, that is, a small sample would be as poorly representative as would a large one.

For categories defined by more variable and distorted stimuli, the size of the category is critical in determining subsequent generalization. With a small sample of highly distorted stimuli, the collection of features are likely to be idiosyncratic. Only as the size of the category is increased will the range of allowable common features, and hence, the category boundary, be defined. Once the range of allowable features has been established through experience, the likelihood that new and highly distorted stimuli will contain these features is increased. Although a feature model such as this, with emphasis on feature sampling, would seem capable of accommodating the results of this and other experiments (e.g., Barresi, Robbins, & Shain, 1975; Homa et al., 1973), it is worth emphasizing that a model of abstraction which involves some integration of features such as a feature-averaging model (Reed, 1972) can make similar predictions.

Finally, the results of the present study highlight some theoretical ideas which should be considered in attempting to assess the degree of abstraction underlying conceptual learning. It may be misleading to gauge the degree of prototype abstraction on the basis of the classification accuracy of the prototype alone. The results of this experiment have shown that accuracy of classification of new instances may be higher in one condition (mixed), even though performance differences may be minimal for the prototype. The interpretation favored here is that abstraction must incorporate a notion of category breadth as gauged by the transferability to new instances. In a similar vein, it may be misleading to ignore the distinction between the abstracted prototype and the objective prototype. The objective prototype (nine dots on a 30×30 matrix) cannot simply be assumed to be the most accurate representation of what information has been abstracted. Although it seems obvious that training on low-level distortions of a prototype is likely to insure accurate classification of the objective prototype, it is not clear that abstraction has occurred. The fact that forgetting of old instances for the uniform-low condition was correlated with growing inaccuracy in the classification of the prototype suggests that classification of the prototype may have been mediated by generalization from the old instances at the time of test; that is, a prototype was not abstracted during learning for this condition. Alternatively, *what* was abstracted was so closely bound by the slight variations provided by the low-level distortions that any subsequent forgetting of old information was also reflected in the general deterioration of the abstracted prototype.

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