Frequency Effects on Categorization and Recognition

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Abstract

An experiment investigating effects of familiarity (indicated by presentation frequency) on categorization and recognition behavior is presented. Results show frequency influenced performance under speeded response conditions only, producing increased categorization of new, similar items with the frequent item, and differentiation (a decrease in false alarms to these same items) in recognition. These results are evaluated with respect to different versions of an exemplar model of categorization and recognition (Medin & Schaffer, 1978; Nosofsky, Clark & Shinn, 1989). Models that include a mechanism for *differentiation*, or changes in the similarity computation to a familiar example, provided better descriptions of both categorization and recognition behavior than models without this added aspect. The addition of a differentiation mechanism improved fits to categorization data of all three versions of exemplar models considered: the *type* model (in which repetitions do not produce separate memory traces), the *token* model (which posits individual memory traces for each repetition of an item) and the frequency parameter model (which includes frequency weighting as a free parameter).

Introduction

If you live in the Midwest, you are probably familiar with species of birds different from someone living in another geographic location. For example, you see geese and ducks throughout winters and cardinals heralding every spring. A person from Florida, in contrast, would probably have more encounters with seagulls, egrets and pelicans, birds you only see on vacations. An interesting question to ask is, does your *bird* concept differ from a Floridian's because of your familiarity with different birds?

One possibility is that your concept of bird is influenced by your exposure to geese, and you are more likely to think of a goose-like bird when someone mentions the category *bird*. A second possibility is that your experience has led you to differentiate your bird category into the two categories of *geese* and *birds*. This would leave your bird category unaffected, or possibly even less goose-like than the Floridian's. A last possible effect of your experience might be no effect at all. That is, your first encounter with a new bird would affect your concept, but repeated encounters with that animal might not. This would happen if the category structure is more important in people's concept formation than category familiarity (Rosch, Simpson & Miller, 1976).

In this paper, I present an experiment that investigates effects of familiarity (as measured by frequency of encounter) on categorization and recognition, and evaluate these results with respect to different versions of an exemplar model of categorization and recognition. In particular, I will compare models which include a mechanism for differentiation, or changes in the similarity metric to a familiar example, to models without this added aspect.

The modeling framework employed was the context theory of classification (Medin & Schaffer, 1978). According to this theory, people's representations of categories consist of stored memory traces of every category exemplar observed. Categorization decisions are made by comparing an item's summed similarity to members of different categories. Nosofsky (1988, 1991) has extended the exemplar-based classification theory to account for recognition performance. Recognition of a stimulus item is predicted by summing its similarity to all exemplars stored in memory. One variant of exemplar theory is a *type* model, in which repetitions of examples are not stored in memory as additional traces. This kind of model predicts that there are no effects of repetitions, or familiarity on categorization or recognition. A type model can be contrasted with a *token* model, in which every experience produces an additional memory trace. A *differentiation* model was constructed by allowing likelihood of retrieval of a stored example (a function of similarity to the exemplar, in this model) to vary with familiarity of an item. In the differentiation model, similarity to a familiar exemplar is computed separate from similarity to other items in the sense that the dimension weightings that make up similarity are different. For example, if geese are differentiated from your bird category, a duck-like animal might not cause you to retrieve geese, but rather ducks and other birds. Whereas, a person who is not as familiar with geese might retrieve a memory trace of a goose in response to presentation of a duck.

Frequency Effects on Classification and Recognition

Nosofsky (1988, 1991) found exemplar frequency effects on both categorization and recognition behavior. Furthermore, an exemplar model with a free parameter for frequency weighting provided the best fit (over a straight type or token model) to his data (Nosofsky, 1991). Nosofsky (1991) found exemplar frequency had less pronounced effects on recognition when compared with effects on classification. Furthermore, Ratcliff, Clark & Shiffrin (1990) conducted studies in which they increased an item's study time or frequency of presentation relative to other items. Recognition accuracy (d') to the frequently presented items increased with presentation frequency. However, Ratcliff et al. expected to find a greater effect of frequency when lists consisted of frequent and infrequent items than when lists of all frequent and all infrequent items were compared. Frequency improved recognition performance in both cases, and sometimes even more for the pure lists (all frequent vs. all infrequent presentations) than mixed lists. Shiffrin, Ratcliff & Clark (1990) account for these data with a variant of the exemplar model SAM which includes differentiation of exemplars. Differentiation is accomplished in this model by reducing the activation of a "strengthened" target item in memory in response to presentation of an unrelated item.

In the present experiment, the effects of exemplar frequency on categorization and recognition under both speeded and unspeeded response conditions was studied. In previous research we found minimal effects of exemplar frequency when subjects were given as much time as they needed to respond. Therefore, we included two more conditions in which subjects were forced to respond quickly. Decreased response time was expected to produce less accurate recognition performance, or more false alarms to foils similar to the frequent exemplar (Ratcliff, 1978). Categorization models predict a corresponding effect on categorization performance; that is, more categorization of those same items with the frequent exemplar.

Method

Design. This experiment used geometric figures comprised of four dimensions, as stimuli. Two categories were constructed, each consisting of three exemplars. The stimulus dimensions were pattern (striped or shaded), form (oval or rectangular), size (small or big) and orientation (horizontal or vertical).

In the Frequent condition, one exemplar was presented with tripled frequency relative to the other five items. In the Control condition, all exemplars were presented with equal frequency. Both a recognition test and a classification test consisting of new and old items were given. New transfer items were either similar to the frequent exemplar (matching on 3 of the 4 dimensions), or neutral in similarity to the frequent exemplar (mismatching on 2 or 3 dimensions).

Procedure. During the learning phase, a subject categorized the six category items, receiving feedback, until a block of 18 or 24 (for control and frequency conditions, respectively) was completed without any errors. Next, subjects were tested on recognition or classification of seen and unseen items. This test phase was followed by a second learning phase (which ended under the same criterion as the first) and the remaining test. Subjects who were tested under speeded conditions were instructed to respond as quickly as possible. In addition, these subjects were alerted after 1.5 seconds that they were taking too long to respond to an item. (Test order, dimension coding, and category labels were counterbalanced.)

Subjects. Subjects were 113 University of Michigan undergraduates who participated as a course requirement for an introductory psychology class. The subjects were randomly assigned to the four experimental conditions.

Results and Discussion

Figure 1 shows the proportion of categorization responses of new transfer items into the same category as the frequent exemplar. There is an interaction between test conditions (speeded versus unspeeded) and frequency condition on categorization responses; $F(1,109)=15.05$, $p=0.0002$. That is, under speeded conditions, exemplar presentation frequency produced an increase in the categorization of new exemplars with the frequent item (from .63 in the control condition to .70 in the triple frequency condition). This did not occur under unspeeded response conditions (which yielded categorization probabilities of .65 and .60 in the control and triple frequency conditions, respectively).

Figure 1 also shows results of the recognition test. Speeded response conditions had the unexpected effect of increased recognition accuracy in the frequent condition. False alarms to new items which were similar to the frequently presented exemplar decreased with exemplar presentation under speeded conditions. False alarm probabilities were

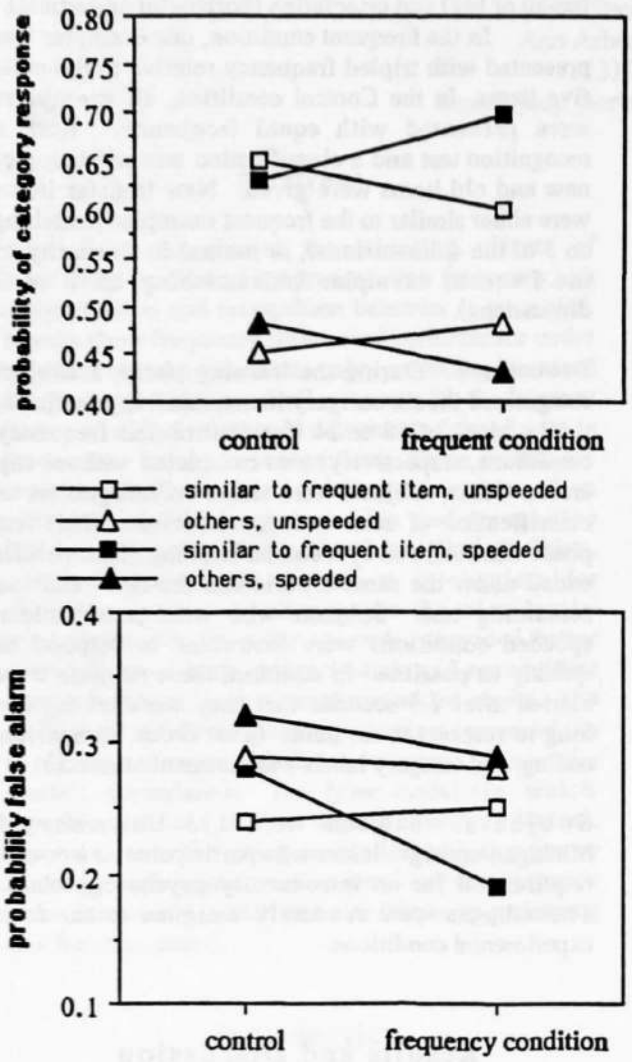

Figure 1. Classification (Top Graph) and Recognition Results (Bottom Graph).

.28 in the control condition and .19 in the triple frequency condition under speeded response conditions. Under unspeeded conditions, exemplar presentation frequency did not affect false alarm rate to similar new items. False alarm rates were .24 in the control condition, and .25 in the triple frequency condition when responses were not speeded. Again, this interaction between exemplar frequency and response conditions was significant; $F(1,109)=11.76$, $p=.0009$.

Modeling of Classification Results. Various versions of the context model of categorization (Medin & Schaffer, 1978; Nosofsky, Clark & Shinn, 1989) were fit to both classification and recognition data. Table 1 contains a summary of the observed data and the results of model fits, including values of G^2 which is a measure of goodness of fit of the model. Decreases in G^2 can be used as a measure of significant improvement of a model with added parameters because it conforms to a χ^2-distribution with degrees of freedom equal to the number of additional parameters. Reductions in G^2 exceeding expectation according to a χ^2-distribution are used here to identify significant improvements in model fits.

The first comparison which can be made is between the fits of the type model, in which exemplar repetitions are not included, and the token model, in which each repetition is included as an additional exemplar in the model. The type model provides a better fit to the data than the token model, which predicts large effects of exemplar frequency. A third model included frequency as a free parameter weighting of the repeated exemplar. This third model, called the *frequency parameter* model, fared no better than the type model, however.

An additional variant (called the differentiation model) of each model (type, token and frequency parameter) was fit to the data by calculating similarity to the frequent item with a separate computation from similarity to other stored items. In the context model, similarity between two items is computed by multiplying similarity measures for each dimension, with a match along any dimension yielding a similarity value of 1 and a mismatch being assigned a value between 0 and 1. (These similarity measures are free parameters in the model.) In the differentiation model, these similarity values of mismatched dimensions are different for the frequently seen item than for other learned items. That is, the differentiation model allows the similarity space around the familiar item to differ from the similarity space of other exemplars. This model can account for differentiation, or decreases in item retrieval in response to a probe with increases in familiarity, if mismatches along dimensions are assigned small similarity values. This would have the effect of drastically reducing similarity between a target and probe item, thereby suppressing memory retrieval of the target item. In this experiment, categorization performance of similar new items decreased with increases in frequency of presentation under unspeeded conditions.

Columns 5-7 of Table 1 show the results of the differentiation model simulations. For all three kinds of models (type, token, and frequency parameter), the addition of exemplar-specific similarity parameters for the frequent exemplar

Table 1.

Summary of Observed and Predicted Category Response Probabilities (top portion) and "Old" Recognition Probabilities (bottom portion) for Test Items by Similarity to Frequent Example.[a]

	Observed	Type Model	Token Model	Frequency Parameter Model	Type Model with Differentiation	Token Model with Differentiation	Frequency Parameter Model with Differentiation	Type Model with Differentiation + Accessibility	Token Model with Differentiation + Accessibility	Frequency Parameter Model + Differentiation + Accessibility
Classification:										
New Exemplars Similar To Frequent Item:										
Unspeeded, Control	.65	.64	.63	.64	.64	.64	.64	.64	.64	.64
Unspeeded, Triple Freq.	.60	.64	.72	.67	.66	.64	.65	.63	.60	.63
Speeded, Control	.63	.64	.63	.64	.64	.64	.64	.64	.64	.64
Speeded, Triple Freq.	.70	.64	.72	.67	.66	.64	.65	.69	.70	.69
Other New Exemplars:										
Unspeeded, Control	.45	.44	.44	.44	.44	.44	.44	.44	.44	.44
Unspeeded, Triple Freq.	.47	.44	.49	.45	.45	.41	.41	.43	.41	.41
Speeded, Control	.48	.44	.44	.44	.44	.44	.44	.44	.44	.44
Speeded, Triple Freq.	.43	.44	.49	.45	.45	.41	.41	.45	.41	.41
G^2 =		176.2	199.5	174.1	161.4[b]	155.8[b]	151.8[b]	158.7[b]	151.9[b]	151.0[b]
Recognition:										
New Exemplars Similar To Frequent Item:										
Unspeeded, Control	.24	.25	.21	.25	.25	.25	.25	.25	.25	.26
Unspeeded, Triple Freq.	.25	.25	.33	.23	.22	.22	.22	.24	.25	.24
Speeded, Control	.28	.25	.21	.25	.25	.25	.25	.25	.25	.26
Speeded, Triple Freq.	.19	.25	.33	.23	.22	.22	.22	.19	.18	.18
Other New Exemplars:										
Unspeeded, Control	.29	.29	.27	.29	.29	.29	.29	.29	.29	.29
Unspeeded, Triple Freq.	.28	.29	.28	.29	.30	.30	.30	.30	.30	.30
Speeded, Control	.32	.29	.27	.29	.29	.29	.29	.29	.29	.29
Speeded, Triple Freq.	.29	.29	.28	.29	.30	.30	.30	.30	.29	.30
G^2 =		57.7	88.1	57.0	55.8	57.6[b]	55.4	53.9	53.8[b]	53.6

[a]Note that model fittings were to performance on individual transfer items, and only a summary of this data is presented here.

[b]This model provides a significantly better fit to the data than the model without added parameters (i.e., type, token or frequency parameter models), $p<.05$.

provided a significant increase in the model's fit to the data. An interesting observation is that the token model which includes similarity parameters specific to the frequent exemplar now provides a better fit than the type model ($G^2 = 155.8$ versus 161.4).

A further variant of each of the three models was fit to the data in an attempt to predict the effect of response conditions. This variant included a weighting (referred to as *accessibility*) of the frequent exemplar under speeded response conditions only, because the data show an effect of frequency under these conditions. The results of these simulations are shown in columns 8-10 of Table 1. With the additional accessibility parameter, the differentiation model predicts the observed interaction between presentation frequency and response conditions. That is, the effect of frequency on categorization is different under speeded and unspeeded conditions, and the accessibility parameter allows prediction of that interaction. However, the additional parameter did not provide a significant quantitative improvement in the model's fit to the data, when compared with the models with exemplar specific similarity parameters.

Modeling of Recognition Results. The frequency parameter model was able to model differentiation of items, or decreases in false alarms to similar, new items, from the frequent exemplar. (See the bottom half of column 4 of Table 1.) The differentiation versions of the type, token and frequency parameter models also predicted differentiation with frequency. This qualitative improvement of the differentiation model is only statistically significant for the token model, however. With the addition of an accessibility parameter (which is a weighting of the frequent exemplar under speeded response conditions only), all three models were able to account for the interaction between response conditions and frequency.

Conclusion

In sum, effects of exemplar frequency were best described by exemplar models having a differentiation mechanism. These models fared better than a type, a token or a model which included frequency as a free parameter. Without a differentiation mechanism, the type and frequency parameter models fared better than a token model, in which every repetition produces an additional memory trace. An interesting observation is that once differentiation is added to the straight token model, its fit became as good as the other two. Therefore, multiple-trace models that store memory traces for each repetition may not be as inadequate as previously found. An additional parameter representing accessibility of a familiar item over the course of responding was necessary to fit the interaction between response conditions (speeded vs. unspeeded) and exemplar frequency observed in the data.

In addition, categorization and recognition tests were fit separately because subjects' strategies on these two tasks diverged. Differentiation, or decreased retrieval, of a frequent item occurred on the recognition test under speeded conditions, but generalization, or increased retrieval, occurred on the test of categorization.

It should be noted that the SAM model of recall and recognition also has a mechanism for differentiation with increased presentation strength (Gillund & Shiffrin, 1984; Shiffrin et al., 1990). In this variant of SAM, the parameter signifying activation of a trace by any stimulus item is allowed to change as trace strength increases in response to such factors as frequency or length of presentation. In addition, repetitions of items are captured in one trace representation in this model. However, the SAM model with differentiation does not capture changes in similarity between items in response to increased frequency. Rather, SAM predicts decreases in overall activation with increases in exemplar strength. In the differentiation model presented here, the parameters comprising similarity varied with exemplar strength, so the similarity space surrounding a strengthened exemplar could change. The model fits suggest that this kind of differentiation is necessary to model classification performance.

In another experiment, the position of exemplar repetitions during the learning phase (throughout or only after learning had occurred) was manipulated. In this experiment, the frequency effects observed above were replicated. That is, categorization of similar items increased in response to presentation frequency, and recognition accuracy was greater for the frequent item. However, when exemplar repetitions occurred after learning, they did not affect categorization or recognition. Therefore, repetition probably has a greater effect on categorization and recognition early in learning (Medin & Bettger, 1991). Therefore, total frequency does not appear to be producing the frequency effects observed. Further research will hopefully determine what leads to frequency effects at different points in learning.

Acknowledgments

This research was supported by National Science Foundation Grant 91-10245. I thank Doug Medin for numerous discussions of this project and Evan Heit for comments on an earlier version of this paper.

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