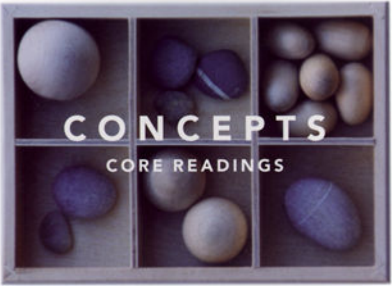


CONCEPTS

CORE READINGS

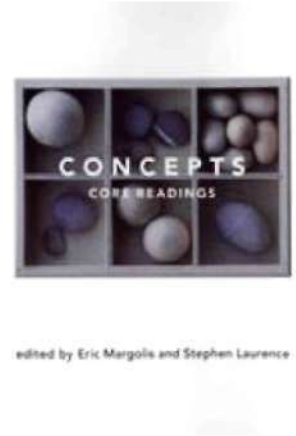
edited by Eric Margolis and Stephen Laurence

< BACK

Concepts

Core Readings

Edited by Eric Margolis and Stephen Laurence



July 1999
ISBN 0-262-63193-8
664 pp., 26 illus.
$50.00/£32.95 (PAPER)

ADD TO CART

Other Editions

Cloth (1999)

Series

Bradford Books

Related Links

Contributor List

Request Exam/Desk Copy

Table of Contents

Chapter 9

The Exemplar View

Edward Smith and Douglas Medin

In this chapter we take up our third view of concepts, the exemplar view. Since this view is quite new and has not been extensively developed, we will not give separate treatments of featural, dimensional, and holistic approaches. Instead, we will sometimes rely on featural descriptions, other times on dimensional ones.

Rationale for the Exemplar View

As its name suggests, the exemplar view holds that concepts are represented by their exemplars (at least in part) rather than by an abstract summary. This idea conflicts not only with the previous views but also with common intuitions. To talk about concepts means for most people to talk about abstractions; but if concepts are represented by their exemplars, there appears to be no room for abstractions. So we first need some rationale for this seemingly bold move.

Aside from a few extreme cases, the move is nowhere as bold as it sounds because the term *exemplar* is often used ambiguously; it can refer either to a specific instance of a concept or to a subset of that concept. An exemplar of the concept clothing, for example, could be either "your favorite pair of faded blue jeans" or the subset of clothing that corresponds to blue jeans in general. In the latter case, the so-called "exemplar" is of course an abstraction. Hence, even the exemplar view permits abstractions.[1]

A second point is that some models based on the exemplar view do not exclude summary-type information (for example, the context model of Medin and Schaffer, 1978). Such models might, for example, represent the information that "all clothing is intended to be worn" (this is summary information), yet at the same time represent exemplars of clothing. The critical claim of such models, though, is that the exemplars usually play the dominant role in categorization, presumably because they are more accessible than the summary information.

These rationales for the exemplar view accentuate the negative—roughly speaking, the view is plausible because its representations are *not* really restricted to specific exemplars. Of course, there are also positive reasons for taking this view. A number of studies in different domains indicate that people frequently use exemplars when making decisions and categorizations. In the experiments of Kahneman and Tversky (1973), for example, it was found that when subjects try to estimate the relative frequencies of occurrence of particular classes of events, they tend to retrieve a few

1 While "your favorite pair of faded blue jeans" is something of an abstraction in that it abstracts over situations, it seems qualitatively less abstract than blue jeans in general, which abstracts over different entities.

exemplars from the relevant classes and base their estimates on these exemplars. To illustrate, when asked if there are more four-letter words in English that (1) begin with *k* or (2) have *k* as their third letter, subjects consistently opt for the former alternative (which is incorrect); presumably they do so because they can rapidly generate more exemplars that begin with *k*. In studies of categorization, subjects sometimes decide that a test item is *not* an instance of a target category by retrieving a counterexample; for example, subjects base their negative decision to "All birds are eagles" on their rapid retrieval of the exemplar "robins" (Holyoak and Glass, 1975). And if people use exemplar retrieval to make negative decisions about category membership, they may also use exemplars as positive evidence of category membership (see Collins and Loftus, 1975; Holyoak and Glass, 1975).

The studies mentioned above merely scratch the surface of what is rapidly becoming a substantial body of evidence for the use of exemplars in categorical decisions (see, for example, Walker, 1975; Reber, 1976; Brooks, 1978; Medin and Schaffer, 1978; Kossan, 1978; Reber and Allen, 1978. This body of literature constitutes the best rationale for the exemplar view.

Concept Representations and Categorization Processes

The Critical Assumption

There is probably only one assumption that all proponents of the exemplar view would accept: The representation of a concept consists of separate descriptions of some of its exemplars (either instances or subsets). Figure 9.1 illustrates this assumption. In the figure the concept of bird is represented in terms of some of its exemplars. The exemplars themselves can be represented in different ways, partly depending on whether they are themselves subsets (like robin, bluejay, and sparrow) or instances (the pet canary "Fluffy"). If the exemplar is a subset, its representation can consist either of other exemplars, or of a description of the relevant properties, or both (these possibilities are illustrated in Figure 9.1). On the other hand, if the exemplar is an instance, it must be represented by a property description. In short, the representation is explicitly disjunctive, and the properties of a concept are the sum of the exemplar's properties.

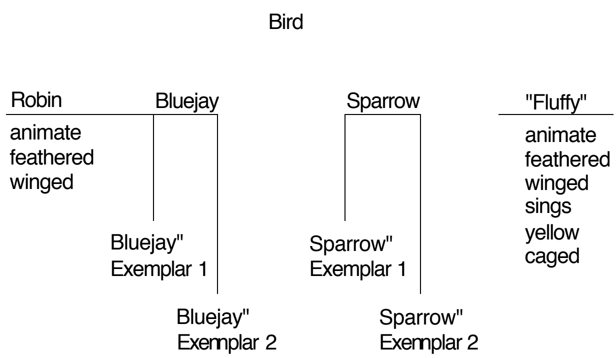


Figure 9.1
An exemplar representation

This assumption conflicts with that of a summary representation, and it is useful to pinpoint the extent of the conflict. Recall that we use three criteria for a summary representation: it is the result of an abstraction process, it need not correspond to a specific instance, and it is always applied when a question of category membership arises. To what extent is each of these criteria violated by the above assumption? We can best answer this by considering each criterion in turn.

The representation in Figure 9.1 shows a clear-cut lack of abstraction in two respects. First, it contains a specific instance, "Fluffy"; second, it contains subsets (for example, robin and bluejay) whose properties overlap enough to permit some amalgamation. Note, however, that the very fact that some exemplars are subsets means that some abstraction has taken place. Thus lack of abstraction is a matter of degree, and our safest conclusion is that exemplar-based representations show a substantially greater lack of abstraction than representations based on the classical or the probabilistic view. This aspect, as we shall see, is the only thing common to all present models based on the exemplar view; so it is the real meat of the critical assumption.

The representation in Figure 9.1 also seems at odds with our second criterion, for it contains a component corresponding to a specific instance. Again, the offender is our friend "Fluffy." But if we remove this instance, the representation still qualifies as an exemplar one. That is, some models based on the exemplar view (for example, Medin and Schaffer, 1978) permit representations with no specific instances. Thus, whether or not part of a representation corresponds to a instance is a point on which various exemplar models vary, not a criterion for being an exemplar model.

Finally, there is the summary-representation criterion that the same information is always accessed when category membership is being determined. This issue concerns categorization processes, so the sample representation in Figure 9.1 is neutral on this point. Once we consider categorization models based on the exemplar view, it turns out that some violate this criterion (for example, different test items would access different exemplars in the representation in Figure 9.1), while others are consistent with the criterion (for example, the entire representation in Figure 9.1 would always be accessed when there is a question of birdhood). Again, then, the criterion is really a choice point for various exemplar models.

The Proximity Model as an Extreme Case

We have seen that the critical assumption behind the present view is that the representation lacks abstraction and is "needlessly disjunctive." All exemplar models violate this criterion of a summary representation. Exemplar models differ among themselves, however, with respect to the other two criteria of summary representations; consequently some exemplar models depart from previous views more than others. To appreciate this, it is useful to consider briefly an extreme case of the exemplar view, the *proximity* model (see Reed, 1972). This model violates all three criteria of a summary representation.

In the proximity model each concept is represented by all of its instances that have been encountered. When a novel test item is presented along with a target category, the test item automatically retrieves the item in memory that is most similar to it. The test item will be categorized as an instance of the target concept if and only if the retrieved item is a known instance of that concept. Thus: (1) the concept representation is lacking entirely in abstraction; (2) every exemplar in the representation is realizable as an instance; and (3) the information retrieved in making a decision about a particular concept varies with the test item presented.

Since the proximity model leaves no room at all for abstraction, it conflicts with the intuitions we mentioned earlier. There is another obvious problem with the model. Adults have experienced an enormous number of instances for most natural concepts, and it seems highly implausible that each instance would be a separate part of the representation; the memory load seems too great. For an exemplar model to be plausible, then, there must be some means of restricting the exemplars in the representation. The models that we now consider attempt to do this.

Models of Categorization

Best-Examples Model

Assumptions Though Rosch explicitly disavows a concern with models (1975, 1978), her work—and that of her collaborator, Mervis, (1980)—points to a particular kind of categorization model. In the following discussion, we will try to develop it.

In addition to the assumption of exemplar descriptions, the best-examples model assumes that the representation is restricted to exemplars that are typical of the concept—what Rosch often refers to as the *focal instances* (1975). More specifically:

> (1) The exemplars represented are those that share some criterial number of properties with other exemplars of the concept; that is, the exemplars have some criterial family resemblance score. (Since family resemblance is highly correlated with typicality, this amounts to assuming that the exemplars represented meet some criterial level of typicality.)

This assumption raises some questions. First, why leave room for multiple typical exemplars rather than restricting the representation to the single best example? A good reason for not using such a restriction comes directly from data. Inspection of actual family resemblance scores indicates that usually a few instances share the highest score (Rosch and Mervis, 1975; Malt and Smith, 1981). Similarly, inspection of virtually any set of typicality ratings (for example, Rips, Shoben, and Smith, 1973; Rosch, 1975) shows that two or more instances attain comparable maximal ratings. Another reason for permitting multiple best examples is that some superordinate concepts seem to demand them. It is hard to imagine that the concept of animal, for instance, has a single best example; at a minimum, it seems to require best examples of bird, mammal, and fish.

A second question about our best-examples assumption is, How does the learner determine the best exemplars? This question is difficult to answer; all we can do is to mention a few possibilities. At one extreme, the learner might first abstract a summary representation of the concept, then compare this summary to each exemplar, with the closest matches becoming the best exemplars, and finally discard the summary representation. Though this proposal removes any mystery from the determination of best examples, it seems wildly implausible. Why bother with determining best examples when you already have a summary representation? And why ever throw the latter away? A second possibility seems more in keeping with the exemplar view. The learner stores whatever exemplars are first encountered, periodically computes the equivalent of each one's family resemblance score, and maintains only those with high scores. The problem with this method is that it might attribute more computations to the learner than are actually necessary. Empirical data indicate that the initial exemplars encountered tend to have high family resemblance scores; for instance, Anglin's results (1977) indicate that parents tend to teach typical exemplars before atypical ones. This suggests a very simply solution to how best examples are learned—namely, they are taught. The simplicity is misleading, however; for now we need an account of how the teachers determine the best examples. No doubt they too were taught, but this instructional regress must stop somewhere. At some point in this account there must be a computational process like the ones described above.

In any event, given a concept representation that is restricted to the most typical exemplars, we can turn to some processing assumptions that will flesh out the model. These assumptions concern our paradigm case of categorization—an individual must decide whether or not a test item is a member of a target concept. One possible set of assumptions holds that:

(2a) All exemplars in the concept representation are retrieved and are available for comparison to the test item.

(2b) The test item is judged to be a concept member if and only if it provides a sufficient match to at least one exemplar.

If the matching process for each exemplar is like one of those considered in previous chapters [of Smith and Medin 1981—EM&SL]—for example, exemplars and test item are described by features, and a sufficient match means accumulating a criterial sum of weighted features—then our exemplar-based model is a straightforward extension of models considered earlier. Since few new ideas would arise in Heshing out this proposal, we will adopt an alternative set of processing assumptions.

The alternative is taken from Medin and Schaffer's context model (1978). (Since this is the only exemplar model other than the best-examples model that we will consider, it simplifies matters to use the same set of processing assumptions.) The assumptions of interest are as follows:

(3a) An entity X is categorized as an instance or subset of concept Y if and only if X retrieves a criterial number of Y's exemplars before retrieving a criterial number of exemplars from any contrasting concept.

(3b) The probability that entity X retrieves any specific exemplar is a direct function of the similarity of X and that exemplar.

To illustrate, consider a case where a subject is given a pictured entity (the test item) and asked to decide whether or not it is a bird (the target concept). To keep things simple, let us assume for now that categorization is based on the first exemplar retrieved (the criterial number of exemplars is 1). The presentation of the picture retrieves an item from memory—an exemplar from some concept or other. Only if the retrieved item is a known bird exemplar would one categorize the pictured entity as a bird (this is assumption 3a). The probability that the retrieved item is in fact a bird exemplar increases with the property similarity of the probe to stored exemplars of bird (this is assumption 3b). Clearly, categorization will be accurate to the extent that a test instance is similar to stored exemplars of its appropriate concept and dissimilar to stored exemplars of a contrast concept.

The process described above amounts to an induction based on a single case. Increasing the criterial number of exemplars for categorization simply raises the number of cases the induction is based on. Suppose one would classify the pictured entity as a bird if and only if k bird exemplars are retrieved. Then the only change in the process would be that one might retrieve a sample of n items from memory $(n > k)$ and classify the pictured item as a bird if and only if one samples k bird exemplars before sampling k exemplars of another concept. Categorization will be accurate to the extend that a test instance is similar to several stored exemplars of the appropriate concept and dissimilar to stored exemplars of contrasting concepts; these same factors will also govern the speed of categorization, assuming that the sampling process takes time.

Note that processing assumptions 3a and 3b differ from the previous ones (2a and 2b) in that the present assumptions postulate that different information in the concept is accessed for different test items. This is one of the theoretical choice points we mentioned earlier.

One more issue remains: How is the similarity between a test instance and an exemplar determined? The answer depends, of course, on how we describe the properties of representation—as features, dimension values, or templates. In keeping with the spirit of Rosch's ideas (for example, Rosch and Mervis, 1975; Rosch et al., 1976), we will use feature descriptions and assume that the similarity between a test instance and an exemplar is a direct measure of shared features.

Explanations of Empirical Phenomena In this section we will briefly describe how well the model of interest can account for the seven phenomena that troubled the classical view.

Disjunctive concepts Each concept representation is explicitly disjunctive—an item belongs to a concept if it matches this exemplar, *or* that exemplar, and so on.

Unclear cases An item can be an unclear case either because it fails to retrieve a criterion number of exemplars from the relevant concept, or because it is as likely to retrieve a criterion number of exemplars from one concept as from another.

Failure to specify defining features There is no reason why the feature of one exemplar should be a feature of other exemplars; that is, the features need not be necessary ones. And since the concept is disjunctive, there is no need for sufficient features.

Simple typicality effect There are two bases for typicality ratings. First, since the representation is restricted to typical exemplars, a typical test item is more likely to find an exact match in the concept. Second, for cases where a test item is not identical to a stored exemplar, the more typical the test item the greater is its featural similarity to the stored exemplars. Both factors should also play a role in categorization; for example, since typical instances are more similar to the stored exemplars of a concept, they should retrieve the criterial number of exemplars relatively quickly. And the same factors can be used to explain why typical items are named before atypical ones when concept members are being listed. That is, the exemplars comprising the concept representation function as retrieval cues, and the cues themselves should be named first, followed by instances most similar to them. As for why typical exemplars are learned earlier, we have already considered means by which this could come about; for example, the learner may use a kind of family-resemblance computation to decide which exemplars to maintain.

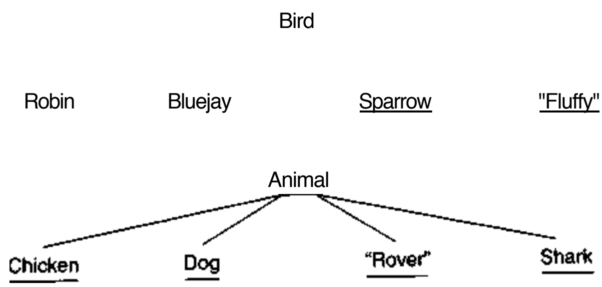


Figure 9.2
Representations that can explain similarity ratings for nested triples.

Determinants of typicality The fact that typical instances share more features with other concept members is essentially presupposed by the present model.

Use of unnecessary features As already noted, there is no requirement that the features of one exemplar be true of all other exemplars.

Nested concepts Figure 9.2 illustrates why some instances (for example, robin) are judged more similar to their immediate than their distance superordinates, while other instances (for example, chicken) manifest the reverse similarity relations. In this illustration robin is one of the represented exemplars for bird, but not for animal. This alone makes it likely that robin is rated more similar to bird than to animal. On the other hand, chicken is a represented exemplar of animal but not of bird, thereby making it likely that chicken is rated as being more similar to animal. In essence, the set of exemplars in a concept may shift with the level of concept.

Context Model

The context model of Medin and Schaffer (1978) differs from the preceding proposal in two critical respects. One concerns the learning of exemplar representations; the other deals with the computation of similarity in categorization processes. We will consider each issue in turn.

Nature of the representation To understand the representational assumptions of the context model, we will begin with a simple case. Suppose that subjects in an experiment on artificial concepts have to learn to classify schematic faces into two categories, A and B; the distribution of facial properties for each category is presented abstractly at the top of Figure 9.3. Here the relevant properties will be treated as dimensions. They correspond to eye height (EH), eye separation (ES), nose length (NL), and mouth height (MH). Each dimension can take on one of two values, for example, a short or a long nose; these values are depicted by a binary notation in Figure 9 3. For example, a nose length of 0 indicates a short nose, a value of 1 signals a long nose. The structure of concepts A and B is presumably that of natural concepts—though A and B lack defining conditions, for each concept there are certain dimension values that tend to occur with its instances. The instances of A, for example, tend to have large noses, while those of B favor small noses.

How, according to the context model, is this information represented by the concept learner? The answer depends on the strategies employed. If our concept learner

Category A					Category B				
Instances	Dimension values				Instances	Dimension values			
	EH	ES	NL	MH		EH	ES	NL	MH
1	1	1	1	0	1	1	1	0	0
2	1	0	1	0	2	0	1	1	0
3	1	0	1	1	3	0	0	0	1
4	1	1	0	1	4	0	0	0	0
5	0	1	1	1					

Category A				Category B			
Instances	Dimension values			Instances	Dimension values		
	EH	ES	NL		EH	ES	NL
1'	1	1	1	1'	1	1	0
2'	1	0	1	2'	0	1	1
3'	1	1	0	3'	0	0	0
4'	0	1	1				

Category A	Category B
.8[a] high eyes	.75" low eyes

a = weight associated with dimension value.

Figure *9.3*
Representational assumptions of the context model.

attends equally to all instances and their dimension values, her final representation should be isomorphic to what is depicted in the top part of Figure 9.3—each exemplar would be represented by its set of values. However, if our concept learner selectively attends to some dimensions more than others—say she ignores mouth-height entirely—her representation should be isomorphic to the middle part of Figure 9.3. Here instances 2 and 3 of concept A have been collapsed into a single exemplar, and the same is true for instances 3 and 4 of concept B (remember, exemplars can be abstract). This strategy-based abstraction can be even more extensive. To take the extreme case, if our learner attends only to eye height, she will end up with concept representations like those at the bottom of Figure 9.3. Here there is no trace of exemplars; instead, the representations are like those in models based on the probabilistic view.

The notion of strategy-based abstraction gives the context model a means of restricting representations to a limited number of exemplars when natural concepts are at issue. (Recall that a plausible exemplar model needs such a restriction.) In particular, suppose that a learner when acquiring a natural concept primarily attends to properties that occur frequently among concept members; then the learner will end up with detailed representations of typical exemplars, which contain the focused properties, but with only incomplete or collapsed representations of atypical exemplars, which do not contain the focused properties. In this way the context model can derive the notion that typical exemplars dominate the representation, rather than assuming this notion outright as is done in the best-examples model. In addition, the context model can assume that in the usual artificial concept study, where there are very few items, each exemplar is fully represented (unless instructions encourage otherwise). Hence in artificial-concept studies, the context model's representations may differ substantially from those assumed by the best-examples model.

Similarity Computations in Categorization The general assumptions about categorization processes in the present model are identical to those in the best-examples model (this is no accident, since we deliberately used the context model's assumptions in developing the best-examples proposal). To reiterate these assumptions:

(3a) An entity X is categorized as an instance or subset of the concept Y if and only if X retrieves a criterial number of Y's exemplars before retrieving a criterial number of exemplars from any constrasting concept.

(3b) The probability that entity X retrieves any specific exemplar is a direct function of the similarity of X and that exemplar.

There is, however, an important difference between the context model and the previous one with regard to how these assumptions are instantiated. The difference concerns how similarity, the heart of assumption 3b, is computed.

Thus far, whenever we have detailed a similarity computation we have used an *additive* combination. In featural models, the similarity between a test item and a concept representation (whether it is summary or an exemplar) has been some additive combination of the individual feature matches and mismatches. In dimensional models, similarity between test item and concept representation has been measured by an additive combination of differences on component dimensions. This notion of additivity is rejected by the context model. According to the present model, computing the similarity between test instances and exemplar involves *multiplying* differences along component dimensions.

This process is illustrated in Figure 9.4. The top half repeats some representations given in the previous figure. Associated with each dimensional difference is a similarity parameter, a_{if} with high values indicating high similarity. Thus a_{NL} is a measure of the similarity between a long and a short nose. Two factors can decrease the size of each parameter, that is, decrease the similarity between the values of a dimension. One factor is the psychophysical difference between the two values of a dimension; the other is the salience of the dimension, which is itself determined by the attentional and strategy considerations that we discussed earlier. Given a fixed set of parameters, one computes similarity between test item and exemplar by multiplying the four parameters. As examples, the similarity between a test item and exemplar that have different values on every dimension would be a_{EH} • «ES • «NL • «MH, while the similarity between a test item and exemplar that have identical values on all dimensions would be 1 • 1 • 1 • 1 = 1. Some intermediate cases are shown in the middle part of Figure 9.4. The bottom part of Figure 9.4 shows how these similarity computations between test item and exemplar are cumulated over all relevant exemplars to derive a final categorization of the test item. The probability of assigning test item to, say, concept A is equal to the sum of the similarities of the test items to all stored exemplars of A, divided by the sum of the similarities of the test item to all stored exemplars of both A and B (this instantiates assumption 3b).

How much hinges on computing similarity by a multiplicative rule rather than by an additive one? Quite a bit, as the two cases illustrated in the middle part of Figure

Sample representations

Category A instances	EH	ES	NL	MH	Category B Instances	EH	ES	NL	MH
1	1	1	1	0	1	1	1	0	0
2	1	0	1	0	2	0	1	1	0
3	1	0	1	1	3	0	0	0	1
4	1	1	0	1	4	0	0	0	0
5	0	1	1	1					

(Dimension values)

Sample compulations for Category A exemplars

S(A1,A1)* = 1 1 1 . 1 = 1 0 S(A2,A1) = 1 a ES 1 1 = a ES

S(A1.A2) = 1 a ES 1 1 = s ES S(A2,A2) = 1 • 1 • 1 • 1 = 1.0

S(A1,A3) = 1-a ES-1-oc MH S(A2.A3) = 11 1 oc MH
= «ES • £*MH

S(A1,A4) = 1 - 1 - « NL · a MH S(A2.A4) = 1 • o ES • a NL • a MH
= *ES ' «NL • tZMH

S(A1,A5) = a EH-1 -1-OMH S(A2, A5) = a EH • a ES • 1 a MH
= *EH " XMH = *EH • <*MH

Final categorization

P(A1 c Category A)**

_ 1.0 + a ES + a ES *MH + a NL ' *MH + «EH • 0<MH
I;S(AI,X)

P(A2 <= Category A)

_ *ES + 1 0 + 5<MH + a ES ' «NL ' «MH + =<EH • a FS • I u u
^S(A2,X)
X

*S(i, j) = Similarity between i and j
"P(i c Category A) = Probability that i is assigned to Category A

Figure 9.4
How the context model computes similarity.

9.4 demonstrate. Following the multiplicative rule, instance 2 should be easier to learn and categorize than instance 1. This essentially reflects the fact that instance 2 is highly similar (that is, differing on only one dimension) to two exemplars of category A (instances 1 and 3) but is not highly similar to any exemplar of concept B- instance 1 on the other hand, is highly similar to only one exemplar in A (instance 2) but to the first two exemplars in B. Had we computed similarity by an additive rule this prediction would reverse. This can be seen by noting that instance 1 shares an average of more than two values with other exemplars of A, while instance *2* shares an average of exactly two values with other A exemplars. (Both instances share the same average number of values with B exemplars.) These contrasting predictions were tested in a number of artificial-concept experiments by Medin and Schaffer 1978) and the results uniformly supported the multiplicative rule: instance 2 was learned faster and categorized more efficiently than instance 1. In a follow-up study

(Medin and Smith, 1981) we found that the superiority of instance 2 held across widely different instructions, including ones that implicitly suggested an additive rule to subjects.

Admittedly this particular contrast between multiplicative and additive similarity computations is highly specific, and is probably only realizable with artificial materials Still it provides some basis for favoring the context model's way of instantiating the exemplar-based processing assumptions over that specified by the best-examples model. Other reasons for favoring the multiplicative rule will be given later in the chapter.

Explanations of Empirical Phenomena There is no need to detail how the context model handles our standard list of phenomena, since these accounts are virtually identical to those given for the best-examples model. Again, the explicitly disjunctive nature of an exemplar-based representation immediately accounts for the existence of disjunctive concepts, the failure to specify defining properties, and the use of nonnecessary properties during categorization. And to the extent that the learning strategies posited by the context model eventuate in a representation dominated by typical exemplars, the model would explain typicality effects in the same manner as the best-examples model.

Criticisms of the Exemplar View

Having discussed some of the strengths of the exemplar view, we now consider its weaknesses. We will first take up those difficulties that the present view shares with the probabilistic one; that is, problems in (1) representing all the knowledge in concepts (2) constraining possible properties, and (3) accounting for context effects. Then we will consider a fourth set of problems—those that are specific to the exemplar view's critical assumption that a concept is represented by a disjunction of exemplars.

Representing More Knowledge in Concepts

To return to our standard example, how can we represent the knowledge that the properties "small" and "sings" tend to be correlated across exemplars of the concept of bird? Note that the solutions we considered in conjunction with the probabilistic view such as labeling relations between properties, are irrelevant here. For in the present view exemplars tend to be represented separately, so how can we represent something that pertains to all exemplars?

The most promising solution appears to be this: knowledge about a correlation between properties is *computed* from an exemplar-based representation when needed, rather than *prestored* in the representation. We can illustrate with the kind of representation used in the best-examples model. Suppose that the concept of bird is represented by two best examples, one corresponding to robin, the other to eagle. Then one can compute the negative correlation between size and singing ability by noting that the best example that is small (robin) also sings, while the best example that is large (eagle) does not. More generally, to the extent that each best example contains properties that characterize a particular cluster of instances (for example many of a robin's properties also apply to bluejays and sparrows), then property differences between best examples reflect correlations among properties in the instances at large.

Another kind of additional knowledge that we have routinely been concerned with has to do with variability in properties associated with a concept. Some knowledge of this sort is implicit in any exemplar representation. The different exemplars represented must manifest some differences in their features or dimension values, and one can use these differences to compute estimates of property variability. The problem, though, is that these computations would probably yield smaller estimates of variability than those actually obtained in relevant experiments (Walker, 1975). This would clearly be the case for computations based on best-examples representations, since only a few highly typical exemplars are represented here, and typical exemplars show only limited variation in their properties (see Rosch and Mervis, 1975). The situation seems more promising for the contest model: it is at least compatible with a concept representation containing multiple exemplars, some of which may be atypical, and its representations therefore permit a more realistic computation of property-variability.

Lack of Constraints

There really are two problems involving constraints with the exemplar view: a lack of constraints on the properties associated with any exemplar, and a lack of constraints on the relations between exemplars included in the same representation. We will treat only the first problem here, saving the second for our discussion of problems specific to the exemplar view.

We start with the obvious. For exemplars corresponding to instances, there is no issue of specifying constraints in the form of necessary or sufficient properties, since we are dealing with individuals. So the following applies only to exemplars that correspond to subsets of a concept, for example, the exemplars "chair" and "table" of the concept "furniture." With regard to the latter kind of exemplar, the problem of unconstrained properties *vis-a-vis* an exemplar is identical to that problem *vis-a-vis* a summary representation. This is so because a subset-exemplar is a summary representation of that subset—there need be no difference between the representation of chair when it is included as one component of an exemplar representation of furniture and when it stands alone as a probabilistic representation. Hence, all our suggestions about how to constrain properties in probabilistic representations apply *mutatis mutandis* to exemplar representations. For the best-examples model, then, there may be a need to specify some necessary features, *or* some sufficient ones, for each exemplar represented in a concept; otherwise we are left with problems such as the exemplar permitting too great a degree of disjunctiveness.

The same, of course, holds for the context model, but here one can naturally incorporate necessary properties via similarity parameters and the multiplicative rule for computing similarity. Specifically, a dimension is a necessary one to the extent that its similarity parameter goes to zero when values on the dimension increasingly differ; and given a near-zero value on one parameter, the multiplication rule ensures that the product of all relevant parameters will also be close to zero. An illustration should be helpful: a creature 90 feet tall might possibly be classified as a human being, but one 9,000 feet tall would hardly be. In the former case, the parameter associated with the height difference between the creature and known human beings would be small but nonzero; in the latter case, the parameter for height difference might be effectively zero, and consequently the overall, multiplicative similarity between creature and human being would be effectively zero regardless of how many other properties they shared. In essence, we have specified a necessary range of values along the height dimension for human beings. To the extent that this is a useful means of capturing property constraints, we have another reason for favoring multiplicative over additive rules in computing similarity.

Context Effects

Thus far little has been done in analyzing context effects of the sort we described in conjunction with the probabilistic view. We will merely point out here what seems to us to be the most natural way for exemplar models to approach context effects.

The basic idea is that prior context raises the probability of retrieving some exemplars in representation. To return to our standard example of "The man lifted the piano," the context preceding "piano" may increase the availability of exemplars of heavy pianos (that is, exemplars whose representations emphasize the property of weight), thereby making it likely that one of them will actually be retrieved when "piano" occurs. This effect of prior context is itself reducible to similarity consideration; for example, the context in the above sentence is more similar to some piano exemplars than to others. Retrievability is thus still governed by similarity to stored exemplars, and our proposal amounts to increasing the factors that enter into the similarity computation.

The above proposal seems workable to the extent that a representation contains numerous exemplars. If there are only a few exemplars, then many contexts will fail to activate a similar exemplar. To illustrate, consider the sentence "The holiday platter held a large bird," where the context seems to activate a meaning of bird akin to chicken or turkey. If the representation of bird is restricted to a few typical exemplars, like robin and eagle, there is no way the preceding context effect can be accounted for. Since the best-examples model is restricted in just this way, it will have difficulty accounting for many context effects through differential retrievability of exemplars. The context model is less committed to this kind of restriction, and thus may fare better.

Problems Specific to Exemplar Representations

We see two major problems that stem from the assumption that a concept is represented by a disjunction of exemplars. The first concerns the relation between the disjunctions; the second, the learning of summary information. Both can be stated succinctly.

According to the ideas presented thus far, the only relation between the exemplars in a given representation is that they all point to the same concept. But "exemplars that point to the same concept" can be a trait of totally unnatural concepts. For example, let FURDS be the "concept" represented by the exemplars of chair, table, robin, and eagle; again each exemplar points to the same "concept," but this collection of exemplars will not meet anyone's pretheoretical notion of a concept. The point is that the exemplar view has failed to specify principled constraints on the relation between exemplars that can be joined in a representation.

Since any added constraint must deal with the relation between concept exemplars, the constraint must be something that applies to all exemplars. For the concept of furniture, it might be that all the exemplars tend to be found in living spaces, or are likely to be used for some specific purpose. Positing such a constraint therefore amounts to positing something that *summarizes* all exemplars. In short, any added constraint forces a retreat from a pure exemplar representation toward the direction of a summary representation. The retreat, however, need not be total. The summary constraints may be far less accessible than the exemplars themselves (perhaps because the former are less concrete than the latter), and consequently categorization might be based mainly on exemplars. This proposal would leave the currently formulated exemplar models with plenty of explanatory power; it also seems compatible with Medin and Schaffer's statement of the context model (1978), which does not prohibit properties that apply to the entire concept. But whether our proposal is compatible with the spirit behind the best-examples model (that is, the work of Rosch and her colleagues) is at best debatable.

With regard to learning summary information, we are concerned with the situation where someone (say, an adult) tells a concept learner (say, a child) something like "All birds lay eggs." What, according to the exemplar view, is the learner to do with such information—list it separately with each stored bird exemplar and then throw away the summary information? This seems implausible. What seems more likely is that when one is given summary information, one holds onto it as such. Again, we have a rationale for introducing a bit of a summary representation into exemplar-based models.

Conclusions

With regard to those problems it shares with probabilistic approaches, the exemplar view offers some new ideas about potential solutions. Thus computing property correlations from exemplars that represent different clusters is an interesting alternative to prestoring the correlation, say, by means of a labeled relation. Similarly, accounting for context effects via differential retrieval of exemplars seems a viable alternative to the context-sensitive devices proposed for the probabilistic view. And the context model's multiplicative rule for computing similarity offers a particularly natural way of incorporating necessary properties into representations that can also contain nonnecessary ones. But the exemplar view has two unique problems—specifying relations between disjuncts and handling summary-level information—and the solution to these problems seems to require something of a summary representation. This suggests that it would be a useful move to try to integrate the two views.

References

Anglin,). M. (1977) *Word, Object and Conceptual Development*. New York: Norton.

Brooks, L. (1978) "Nonanalytic Concept Formation and Memory for Instances." In *Cognition and Categorization,* ed. E. Rosch and B. Lloyd. Hillsdale, NJ: LEA.

Collin, A., and Loftus, E. (1975) "A Spreading Activation Theory of Semantic Processing." *Psychological Review,* 82: 407-28.

Holyoak, K,, and Glass, A. (1975) "The Role of Contradictions and Counterexamples in the Rejection of False Sentences." *Journal of Verbal Learning and Verbal Behavior,* 14: 215-39.

Kahneman, D,, and Tversky, A. (1973) "On the Psychology of Prediction." *Psychological Review,* 80: 237-51.

Kossan, N. (1978) "Structure and Strategy in Concept Acquisition." Ph.D. Dissertation, Stanford University.

Malt, B., and Smith, E. (1981) "Correlations Structure in Semantic Categories."

Medin, D., and Schafer, M. (1978) "A Context Theory of Classification Learning." *Psychological Review,* 85: 207-38.

Medin, D., and Smith, E. (1981) "Strategies and Classification Learning." *Journal of Experimental Psychology: Human Learning and Memory*.

Mervis, C. (1980) "Category Structure and the Development of Categorization." In *Theoretical Issues in Reading Comprehension,* ed. R. Spiro, B. Bruce, and W. Brewer. Hillsdale, NJ: LEA.

Reber, A. (1976) "Implicit Learning of Synthetic Languages: The Role of Instructional Set." *Journal of Experimental Psychology: Human Memory and Learning,* 2: 88-94.

Reber, A., and Allen, R. (1978) "Analogical and Abstraction Strategies in Synthetic Grammar Learning: A Functionalist Interpretation." *Cognition* 6: 189-221.

Reed, S. (1972) "Pattern Recognition and Categorization." *Cognitive Psychology* 3: 382-407.

Rips, L., Shoben, E., and Smith, E. (1973) "Semantic Distance and the Verification of Semantic Relations." *Journal of Verbal Learning and Verbal Behavior,* 12: 1-20.

Rosch, E. (1975) "Cognitive Representations of Semantic Categories." *Journal of Experimental Psychology: General,* 104: 192-233.

Rosch, E. (1978) "Principles of Categorization." In: *Cognition and Categorization,* ed. E. Rosch and B. Lloyd, 27-48. Hillsdale, NJ: LEA.

Rosch, E., and Mervis, C. (1975) "Family Resemblance Studies in the Internal Structure of Categories." *Cognitive Psychology, 7:* 573-605.

Rosch, E,, Mervis, C. Gray, W. Johnson, D., and Boyes-Braem, P. (1976) "Basic Objects in Natural Categories." *Cognitive Psychology,* 3: 382-439.

Smith, E., and Medin, D. (1981) *Categories and Concepts.* Cambridge, MA: Harvard University Press.

Walker, J. (1975) "Real World Variability, Reasonableness Judgements, and Memory Representations for Concepts." *Journal of Verbal Learning and Verbal Behavior,* 14: 241-52.