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Typicality and the Classical View of Categories

The Classical View

When you were in junior high school or even earlier, you probably had a teacher who tried to get you to define words. Given a word like *wildebeest*, you might say "It's a kind of animal." Your teacher would not be satisfied with this definition, though. "A frog is also a kind of animal," she might point out, "Is it the same as a frog?" "No," you would reply sheepishly, "it has four legs and is about the size of a cow and has horns and lives in Africa." Well, now you're getting somewhere. My teacher used to tell us that a definition should include everything that is described by a word and nothing that isn't. So, if your description of a wildebeest picks out all wildebeest and nothing else, you have given a successful definition. (In fact, most definitions in dictionaries do not meet this criterion, but that is not our problem.)

Definitions have many advantages from a logical standpoint. For example, the truth or falsity of "Rachel is a wildebeest" is something that can be determined by referring to the definition: Does Rachel have all the properties listed in the definition—four legs, horns, and so on? By saying "Rachel is not a wildebeest," we are saying that Rachel lacks one or more of the definitional properties of wildebeest. And we could potentially verify statements like "Wildebeest can be found in Sudan" by looking for things in Sudan that meet the definition. Philosophers have long assumed that definitions are the appropriate way to characterize word meaning and category membership. Indeed, the view can be traced back as far as Aristotle (see Apostle 1980, pp. 6, 19–20). In trying to specify the nature of abstract concepts like fairness or truth, or even more mundane matters such as causality and biological kinds, philosophers have attempted to construct definitions of these terms. Once we have a definition that will tell us what exactly is and is not a cause, we will have come a long way toward understanding causality. And much philosophical argu-

Figure 2.1
Two concepts from Hull's (1920) study. Subjects learned 12 concepts like this at a time, with different characters intermixed. Subjects were to respond to each stimulus with the name at left (*oo* and *yer* in this case). Note that each example of a concept has the defining feature, the radical listed in the "concept" column.

mentation involves testing past definitions against new examples, to see if they work. If you can find something that seems to be a cause but doesn't fit the proposed definition, then that definition of cause can be rejected.

It is not surprising, then, that the early psychological approaches to concepts took a definitional approach. I am not going to provide an extensive review, but a reading of the most cited work on concepts written prior to 1970 reveals its assumption of definitions. I should emphasize that these writers did not always explicitly *say*, "I have a definitional theory of concepts." Rather, they took such an approach for granted and then went about making proposals for how people learned concepts (i.e., learned these definitions) from experience.

For example, Clark Hull's (1920) Ph.D. thesis was a study of human concept learning—perhaps surprisingly, given his enormous later influence as a researcher of simple learning, usually in rats. Hull used adapted Chinese characters as stimuli. Subjects viewed a character and then had to respond with one of twelve supposedly Chinese names (e.g., *oo* and *yer*). Each sign associated with a given name contained a radical or component that was identical in the different signs. As figure 2.1 shows, the *oo* characters all had the same radical: a kind of large check mark with two smaller marks inside it. Clearly, then, Hull assumed that every example of a concept had some element that was critical to it.

There are two aspects to a definition that these items illustrate. The first we can call *necessity*. The parts of the definition must be in the entity, or else it is not a member of the category. So, if a character did not have the check-mark radical, it would not be an *oo*. Similarly, if something doesn't have a distinctive attribute of chairs, it is not a chair. The second aspect we can call *sufficiency*. If something has all the parts mentioned in the definition, then it must be a member of the category. So, anything having that radical in Hull's experiment would be an *oo*, regardless of what other properties it had. Note that it is not enough to have one or two of the

parts mentioned in the definition—the item must have all of them: The parts of the definition are "jointly sufficient" to guarantee category membership. So, it wouldn't be enough for something to be as big as a cow and be from Africa to be a wildebeest; the item must also be an animal, with four legs and horns, if those things are included in our definition.

Hull (1920) explicitly adopted these aspects of a definition (without calling them by these names) in one of the principles he followed in creating his experiment (p. 13): "All of the individual experiences which require a given reaction, must contain certain characteristics which are at the same time common to all members of the group requiring this reaction [i.e., necessary] and which are NOT found in any members of the groups requiring different reactions [i.e., sufficient]." (Note that Hull adopted the behaviorist notion that it is the common response or "reaction" that makes things be in the same category. In contrast, I will be talking about the mental representations of categories.) Hull believed that this aspect of the experiment was matched by real-world categories. He describes a child who hears the word *dog* used in a number of different situations. "At length the time arrives when the child has a 'meaning' for the word dog. Upon examination this meaning is found to be actually a characteristic more or less common to all dogs and not common to cats, dolls and 'teddy-bears.' But to the child, the process of arriving at this meaning or concept has been largely unconscious. He has never said to himself 'Lo! I shall proceed to discover the characteristics common to all dogs but not enjoyed by cats and "teddy-bears"'" (p. 6). Note that although Hull says that "Upon *examination* this meaning is . . .," he does not describe any examination that has shown this, nor does he say what characteristics are common to all dogs. These omissions are significant—perhaps even ominous—as we shall soon see.

In the next major study of concept learning, Smoke (1932—the field moved somewhat more slowly in those days) criticized the definitional aspect of Hull's concepts. He says quite strongly that "if any concepts have ever been formed in such a fashion, they are very few in number. We confess our inability to think of a single one" (p. 3). He also quotes the passage given above about how children learn the concept of dog, and asks (pp. 3–4): "What, we should like to ask, is this 'characteristic more or less common to all dogs and not common to cats, dolls, and "teddy-bears"' that is the '"meaning" for the word dog' . . . What is the 'common element' in 'dog'? Is it something within the *visual* stimulus pattern? If exact drawings were made of all the dogs now living, or even of those with which any given child is familiar, would they 'contain certain strokes in common' [like Hull's characters] which could be 'easily observed imbedded in each'?"

One might think from this rather sarcastic attack on Hull's position that Smoke is going to take a very different position about what makes up a concept, one that is at odds with the definitional approach described. That, however, is not the case. Smoke's objection is to the notion that there is a single, simple element that is common to all category members. (Although Hull's stimuli do have such a simple element in common, it is not so clear that he intended to say that all categories were like this.) Smoke says "As one learns more and more about dogs, [one's] concept of 'dog' becomes increasingly rich, not a closer approximation to some bare 'element' " (p. 5). What Smoke feels is missing from Hull's view is that the essential components of a concept are a complex of features that are connected by a specified relationship, rather than being a single common element. Smoke gives this example of a concept called "zum," which he feels is more realistic: "Three straight red lines, two of which intersect the third, thereby trisecting it" (p. 9). You may judge for yourself whether this is more realistic than Hull's Chinese characters. In teaching such concepts, Smoke made up counterexamples that had some of the components of the concept but not all of them. Thus, for a nonzum, he might make up something with only two lines or something with three lines but that did not intersect one another in the required way. Thus, he created a situation that precisely follows the definitional view: Zums had all the required properties, and for the items that did not, subjects had to learn not to call them zums. Thus, the properties of zums were necessary and sufficient.

In short, although Smoke seems to be rejecting the idea of concepts as being formed by definitions, he in fact accepts this view. The main difference between his view and Hull's is that he viewed the definitions as being more complex than (he thought) Hull did. I have gone through these examples in part to show that one can tell whether experimenters had the definitional view by looking at their stimuli. In many older (pre-1970) studies of concepts, all the members have elements in common, which are not found in the nonmembers. Thus, even if such studies did not explicitly articulate this definitional view, they presupposed it.

The work of Hull and Smoke set the stage for research within American experimental psychology's study of concepts. In addition to their view of concepts, the techniques they developed for concept learning studies are still in use today. Another influence that promoted the use of definitions in the study of concepts was the work of Piaget in cognitive development. Piaget viewed thought as the acquisition of logical abilities, and therefore he viewed concepts as being logical entities that could be clearly defined. Again, Piaget did not so much argue for this view of concepts as simply assume it. For example, Inhelder and Piaget's (1964, p. 7) theory relied on

constructs such as: "the 'intension' of a class is the set of properties common to the members of that class, together with the set of differences, which distinguish them from another class"—that is, a definition. Following this, they provide a list of logical properties of categories which they argued that people must master in order to have proper concepts. (Perhaps not surprisingly, they felt that children did not have true concepts until well into school age—see chapter 10.) Piaget's work was not directly influential on most experimental researchers of adult concepts, but it helped to bolster the definitional view by its extraordinary influence in developmental psychology.

Main Claims of the Classical View

The pervasiveness of the idea of definitions was so great that Smith and Medin (1981) dubbed it the *classical view* of concepts. Here, then are the main claims of the classical view. First, concepts are mentally represented as definitions. A definition provides characteristics that are a) necessary and b) jointly sufficient for membership in the category. Second, the classical view argues that every object is either in or not in the category, with no in-between cases. This aspect of definition was an important part of the philosophical background of the classical view. According to the *law of the excluded middle*, a rule of logic, every statement is either true or false, so long as it is not ambiguous. Thus, "Rachel is a wildebeest" is either true or false. Of course, we may not know what the truth is (perhaps we don't know Rachel), but that is not the point. The point is that in reality Rachel either is or isn't a wildebeest, with no in-between, even if we don't know which possibility is correct. Third, the classical view does not make any distinction between category members. Anything that meets the definition is just as good a category member as anything else. (Aristotle emphasized this aspect of categories in particular.) An animal that has the feature common to all dogs is thereby a dog, just the same as any other thing that has that feature. In a real sense, the definition *is* the concept according to the classical view. So all things that meet the definition are perfectly good members of the concept, and all things that do not fit the definition are equally "bad" members (i.e., nonmembers) of the concept, because there is nothing besides the definition that could distinguish these things. As readers are no doubt thinking, this all sounds too good to be true.

Before confirming this suspicion, it is worthwhile to consider what kind of research should be done if the classical view is true. What is left to understand about the psychology of concepts? The basic assumption was that concepts were acquired by learning which characteristics were defining. However, unlike Hull's assumption (and more like Smoke's), it became apparent that any real-world concepts would

involve multiple features that were related in a complex way. For example, dogs have four legs, bark, have fur, eat meat, sleep, and so on. Some subset of these features might be part of the definition, rather than only one characteristic. Furthermore, for some concepts, the features could be related by rules, as in the following (incomplete) definition of a strike in baseball: "the ball must be swung at and missed OR it must pass above the knees and below the armpits and over home plate without being hit OR the ball must be hit foul (IF there are not two strikes)." The use of logical connectives like AND, OR, and IF allows very complex concepts to be defined, and concepts using such connectives were the ones usually studied in psychology experiments. (There are not that many experiments to be done on how people learn concepts that are defined by a single feature.) Often these definitions were described as *rules* to tell what is in a category.

Bruner, Goodnow, and Austin (1956) began the study of this sort of logically specified concept, and a cottage industry sprang up to see how people learned them. In such experiments, subjects would go through many cards, each of which had a picture or description on it. They would have to guess whether that item was in the category or not, usually receiving feedback on their answer. For difficult concepts, subjects might have to go through the cards a dozen times or more before reaching perfect accuracy on categorizing items; for easy concepts, it might only take four or five run-throughs (blocks). Research topics included how learning depended on the number of attributes in the rule, the relations used in the rule (e.g., AND vs. OR), the way that category examples were presented (e.g., were they shown to the subject in a set order, or could the subject select the ones he or she wished?), the complexity of the stimuli, and so on. But whether this research is of interest to us depends on whether we accept the classical view. If we do not, then these experiments, although valid as examples of learning certain abstract rules, do not tell us about how people learn normal concepts. With that foreshadowing, let us turn to the problems raised for the classical view.

Problems for the Classical View

The groundbreaking work of Eleanor Rosch in the 1970s essentially killed the classical view, so that it is not now the theory of any actual researcher in this area (though we will see that a few theorists cling to it still). That is a pretty far fall for a theory that had been the dominant one since Aristotle. How did it happen? In part it happened by virtue of theoretical arguments and in part by the discovery of data that could not be easily explained by the classical view. Let us start with the arguments. Because this downfall of the classical view has been very ably described by Smith and Medin (1981) and others (e.g., Mervis and Rosch 1981; Rosch 1978), I will spend somewhat less time on this issue than could easily be spent on it. Interested readers should consult those reviews or the original articles cited below for more detailed discussion.

In-Principle Arguments

The philosopher Wittgenstein (1953) questioned the assumption that important concepts could be defined. He used the concept of a game as his example. It is maddeningly difficult to come up with a definition of games that includes them but does not include nongame sports (like hunting) or activities like kicking a ball against a wall. Wittgenstein urged his readers not to simply say "There *must* be something in common," but to try to specify the things in common. Indeed, it turns out to be very difficult to specify the necessary and sufficient features of *most* real-world categories. So, the definition we gave earlier of dogs, namely, things that have four legs, bark, have fur, eat meat, and sleep, is obviously not true. Does something have to have four legs to be a dog? Indeed, there are unfortunate dogs who have lost a leg or two. How about having fur? Although most dogs do have fur, there are hairless varieties like chihuahuas that don't. What about barking? Almost all dogs bark, but I have in fact known a dog that "lost" its bark as it got older. This kind of argument can go on for some time when trying to arrive at necessary features. One can find some features that seem a bit "more necessary" than these—abstract properties such as being animate and breathing appear to be true of all dogs (we are talking about real dogs here, and not toy dogs and the like). However, although these features may be necessary, they are not nearly sufficient. In fact, all animals are animate and breathe, not just dogs. So, features like these will not form adequate definitions for dogs—they won't separate dogs from other similar animals. Also, sometimes people will propose features such as "canine" as being definitional of dogs. However, this is just cheating. "Canine" is simply a synonym for the dog concept itself, and saying that this is part of the definition of dog is not very different from saying that the dogs all have the property of "dogginess." Clearly, such circular definitions explain nothing.

Wittgenstein's argument, which is now widely accepted in the field, does have a problem, however (Smith and Medin 1981): It is primarily negative. It says something like "I can't think of any defining features for games or dogs," but this does not prove that there aren't any. Perhaps it's just that we are not clever enough to think of the defining features. Perhaps there are defining features that will be

realized or discovered in 100 years. This may be true, but it is incumbent on someone who believes the classical view to explain what the defining features are, *and* why we can't easily think of them. If our concept of dogs is a definition, why are we so bad at saying what it is even when we know the concept? Why is it that we can use this definition for identifying dogs and for thinking about them, but the properties we give for dogs are not definitional? The classical view has considerable trouble explaining this.

I used to think that the arguments against the classical view might be somewhat limited. In particular, it seemed likely to me that in certain technical domains, concepts might be well defined. For example, the rules of baseball are written down in black and white, and they look very much like the rules of old category-learning experiments (think of the disjunctive rule for a strike). Perhaps in the physical sciences, one will find classical concepts, as the scientists will have figured out the exact rules by which to decide something is a metal or a member of a biological genus. However, my own experience has always been that whenever one explores these domains in greater depth, one finds more and more fuzziness, rather than perfectly clear rules.

For example, consider the following portion of a lecture on metals by a distinguished metallurgist (Pond 1987). He begins by attempting, unsuccessfully, to get audience members to define what a metal is.

> Well, I'll tell you something. You really don't know what a metal is. And there's a big group of people that don't know what a metal is. Do you know what we call them? Metallurgists! ... Here's why metallurgists don't know what metal is. We know that a metal is an element that has metallic properties. So we start to enumerate all these properties: electrical conductivity, thermal conductivity, ductility, malleability, strength, high density. Then you say, how many of these properties does an element have to have to classify as a metal? And do you know what? We can't get the metallurgists to agree. Some say three properties; some say five properties, six properties. We really don't know. So we just proceed along presuming that we are all talking about the same thing. (pp. 62–63)

And in biology, biologists are constantly fighting about whether things are two different species or not, and what species belong in the same genus, and so on. There is no defining feature that identifies biological kinds (Mayr 1982). In 2000, there was a dispute over whether Pluto is really a planet (apparently, it isn't, though it is too late to do anything about it now). Students in the town of Pluto's discoverer put up a web site demanding Pluto's retention as a full-fledged planet. Among their points was that the astronomers critical of Pluto's planethood "don't even have a definition of what a planet really is!" (Unfortunately, they did not provide their own definition.) The very fact that astronomers can argue about such cases is evidence that the notion of planet is not well defined. The idea that all science consists of hard-and-fast logical categories, in contrast to those of everyday life, may be a romantic illusion.

One might well hope that legal concepts have a classical nature, so that definitions can be evenly applied across the board. One does not want judges and juries having to make decisions in fuzzy cases where there is no clear boundary between the legal and illegal. However, legal practice has found that in practice the law is sometimes very fuzzy, and legal theorists (e.g., Hart 1961) suggest that this is inevitably the case, because lawmakers cannot foresee all the possibilities the law will have to address, some of which do not exist at the time the law is passed (e.g., laws on intellectual property were written before the invention of the internet). Furthermore, since laws are written in language that uses everyday concepts, to the degree that these concepts are fuzzy, the law itself must be fuzzy. So, if one has a rule, "No vehicles in the park" (Hart 1961), does one interpret that to include wheelchairs? Maintenance vehicles? Ambulances? Bicycles? Although the law is stated in a simple, clear-cut manner, the fuzziness of the vehicle category prevents it from being entirely well-defined.[1]

Even artificial domains may have rules that are not particularly well defined. In 1999, Major League Baseball made a much publicized effort to clean up and standardize the strike zone, suggesting that my belief that strikes were well defined prior to that was a delusion. Perhaps the only hope for true classical concepts is within small, closed systems that simply do not permit exceptions and variation of the sort that is found in the natural world. For example, the rules of chess may create classical concepts, like bishops and castling. Baseball, on the other hand, has too much human behavior and judgment involved, and so its categories begin to resemble natural categories in being less well defined than the purist would like.

Empirical Problems

Unfortunately for the classical view, its empirical problems are even greater than its theoretical ones. One general problem is that the neatness envisioned by the classical view does not seem to be a characteristic of human concepts. As mentioned above, the notion of a definition implies that category membership can be discretely determined: The definition will pick out all the category members and none of the nonmembers. Furthermore, there is no need to make further distinctions among the members or among the nonmembers. In real life, however, there are many things that are not clearly in or out of a category. For example, many people express uncertainty about whether a tomato is a vegetable or a fruit. People are not sure about

whether a low, three-legged seat with a little back is a chair or a stool. People do not always agree on whether sandals are a kind of shoe. This uncertainty gets even worse when more contentious categories in domains such as personality or aesthetics are considered. Is *Sergeant Pepper's Lonely Hearts Club Band* a work of art? Is your neighbor just shy or stuck up? These kinds of categorizations are often problematic.

Research has gone beyond this kind of anecdote. For example, Hampton (1979) asked subjects to rate a number of items on whether they were category members for different categories. He did not find that items were segregated into clear members and nonmembers. Instead, he found a number of items that were just barely considered category members and others that were just barely not members. His subjects just barely included sinks as members of the kitchen utensil category and just barely excluded sponges; they just included seaweed as a vegetable and just barely excluded tomatoes and gourds. Indeed, he found that for seven of the eight categories he investigated, members and nonmembers formed a continuum, with no obvious break in people's membership judgments.

Such results could be due to disagreements among different subjects. Perhaps 55% of the subjects thought that sinks were clearly kitchen utensils and 45% thought they were clearly not. This would produce a result in which sinks appeared to be a borderline case, even though every individual subject had a clear idea of whether they were category members or not. Thus, the classical view might be true for each individual, even though the group results do not show this. However, McCloskey and Glucksberg (1978) were able to make an even stronger argument for such unclear cases. They found that when people were asked to make repeated category judgments such as "Is an olive a fruit?" or "Is a dog an animal?" there was a subset of items that individual subjects changed their minds about. That is, if you said that an olive was a fruit on one day, two weeks later you might give the opposite answer. Naturally, subjects did not do this for cases like "Is a dog an animal?" or "Is a rose an animal?" But they did change their minds on borderline cases, such as olive-fruit, and curtains-furniture. In fact, for items that were intermediate between clear members and clear nonmembers, McCloskey and Glucksberg's subjects changed their mind 22% of the time. This may be compared to inconsistent decisions of under 3% for the best examples and clear nonmembers (see further discussion below). Thus, the changes in subjects' decisions do not reflect an overall inconsistency or lack of attention, but a bona fide uncertainty about the borderline members. In short, many concepts are not clear-cut. There are some items that one cannot make up one's mind about or that seem to be "kind of" members. An avo-

The Necessity of Category Fuzziness

The existence of unclear examples can be understood in part as arising from the great variation of things in the world combined with the limitations on our concepts. We do not wish to have a concept for every single object—such concepts would be of little use and would require enormous memory space. Instead, we want to have a fairly small number of concepts that are still informative enough to be useful (Rosch 1978). The ideal situation would probably be one in which these concepts did pick out objects in a classical-like way. Unfortunately, the world is not arranged so as to conform to our needs.

For example, it may be useful to distinguish chairs from stools, due to their differences in size and comfort. For the most part, we can distinguish the two based on the number of their legs, presence of a back or arms, and size. However, there is nothing to stop manufacturers from making things that are very large, comfortable stools; things that are just like chairs, only with three legs; or stools with a back. These intermediate items are the things that cause trouble for us, because they partake of the properties of both. We could try to solve this by forming different categories for stools with four legs (stegs), for chairs with three legs (chools), stools with backs (stoocks), stools with backs and arms (stoorms), and so on. But by doing so, we would end up increasing our necessary vocabulary by a factor of 5 or 10, depending on how many distinctions we added for every category. And there would still be the problem of intermediate items, as manufacturers would no doubt someday invent a combination that was between a stoock and a stoorm, and that would then be an atypical example of both. Just to be difficult, they would probably also make stools with no back, with very tiny backs, with somewhat tiny backs, ... up to stools with enormous, high backs. Thus, there would be items in between the typical stools and stoocks where categorization would be uncertain.

The gradation of properties in the world means that our smallish number of categories will never map perfectly onto all objects: The distinction between members and nonmembers will always be difficult to draw or will even be arbitrary in some cases. If the world existed as much more distinct clumps of objects, then perhaps our concepts could be formed as the classical view says they are. But if the world consists of shadings and gradations and of a rich mixture of different kinds of properties, then a limited number of concepts would almost have to be fuzzy.

cado is "kind of a vegetable," even if it is not wholeheartedly a vegetable. The classical view has difficulty explaining this state of affairs; certainly, it did not predict it.

Another problem for the classical view has been the number of demonstrations of *typicality effects*. These can be illustrated by the following intuition. Think of a fish, any fish. Did you think of something like a trout or a shark, or did you think of an eel or a flounder? Most people would admit to thinking of something like the first: a torpedo-shaped object with small fins, bilaterally symmetrical, which swims in the water by moving its tail from side to side. Eels are much longer, and they slither; flounders are also differently shaped, aren't symmetrical, and move by waving their body in the vertical dimension. Although all of these things are technically fish, they do not all seem to be equally good examples of fish. The *typical* category members are the good examples—what you normally think of when you think of the category. The *atypical* objects are ones that are known to be members but that are unusual in some way. (Note that *atypical* means "not typical," rather than "a typical example." The stress is on the first syllable.) The classical view does not have any way of distinguishing typical and atypical category members. Since all the items in the category have met the definition's criteria, all are category members. (Later I will try to expand the classical view to handle this problem.)

What is the evidence for typicality differences? Typicality differences are probably the strongest and most reliable effects in the categorization literature. The simplest way to demonstrate this phenomenon is simply to ask people to rate items on how typical they think each item is of a category. So, you could give people a list of fish and ask them to rate how typical each one is of the category fish. Rosch (1975) did this task for 10 categories and looked to see how much subjects agreed with one another. She discovered that the reliability of typicality ratings was an extremely high .97 (where 1.0 would be perfect agreement)—though later studies have suggested that this is an overestimate (Barsalou 1987). In short, people agree that a trout is a typical fish and an eel is an atypical one.

But does typicality affect people's use of the categories? Perhaps the differences in ratings are just subjects' attempt to answer the question that experimenters are asking. Yes, a trout is a typical fish, but perhaps this does not mean that trouts are any better than eels in any other respect. Contrary to this suggestion, typicality differences influence many different behaviors and judgments involving concepts. For example, recall that I said earlier that McCloskey and Glucksberg (1978) found that subjects made inconsistent judgments for only a subset of their items. These items could be predicted on the basis of typicality. Subjects did not change their minds about the very typical items or the clear nonitems, but about items in the middle of the scale, the atypical members and the "close misses" among the nonmembers. For

example, waste baskets are rated as atypical examples of furniture (4.70, where 1 is low and 10 is high), and subjects changed their minds about this item a surprising 30% of the time. They never changed their minds about tables, a very typical member (rated 9.83), or windows, a clear nonmember (rated 2.53).

Rips, Shoben, and Smith (1973) found that the ease with which people judged category membership depended on typicality. For example, people find it very easy to affirm that a robin is a bird but are much slower to affirm that a chicken (a less typical item) is a bird. This finding has also been found with visual stimuli: Identifying a picture of a chicken as a bird takes longer than identifying a pictured robin (Murphy and Brownell 1985; Smith, Balzano, and Walker 1978). The influence of typicality is not just in identifying items as category members—it also occurs with the production of items from a category. Battig and Montague (1969) performed a very large norming study in which subjects were given category names, like *furniture* or *precious stone* and had to produce examples of these categories. These data are still used today in choosing stimuli for experiments (though they are limited, as a number of common categories were not included). Mervis, Catlin and Rosch (1976) showed that the items that were most often produced in response to the category names were the ones rated as typical (by other subjects). In fact, the average correlation of typicality and production frequency across categories was .63, which is quite high given all the other variables that affect production.

When people learn artificial categories, they tend to learn the typical items before the atypical ones (Rosch, Simpson, and Miller 1976). Furthermore, learning is faster if subjects are taught on mostly typical items than if they are taught on atypical items (Mervis and Pani 1980; Posner and Keele 1968). Thus, typicality is not just a feeling that people have about some items ("trout good; eels bad")—it is important to the initial learning of the category in a number of respects. As we shall see when we discuss the explanations of typicality structure, there is a very good reason for typicality to have these influences on learning.

Learning is not the end of the influence, however. Typical items are more useful for inferences about category members. For example, imagine that you heard that eagles had caught some disease. How likely do you think it would be to spread to other birds? Now suppose that it turned out to be larks or robins who caught the disease. Rips (1975) found that people were more likely to infer that other birds would catch the disease when a typical bird, like robins, had it than when an atypical one, like eagles, had it (see also Osherson et al. 1990; and chapter 8).

As I will discuss in chapter 11, there are many influences of typicality on language learning and use. Just to mention some of them, there are effects on the order of word production in sentences and in comprehension of anaphors. Kelly, Bock, and

Keil (1986) showed that when subjects mentioned two category members together in a sentence, the more typical one is most likely to be mentioned first. That is, people are more likely to talk about "apples and limes" than about "limes and apples." Garrod and Sanford (1977) asked subjects to read stories with category members in them. For example, they might read about a goose. Later, a sentence would refer to that item with a category name, such as "The bird came in through the front door." Readers took longer to read this sentence when it was about a goose (an atypical bird) than when it was about a robin (a typical bird). Rosch (1975) found that typical items were more likely to serve as *cognitive reference points*. For example, people were more likely to say that a patch of off-red color (atypical) was "virtually" the same as a pure red color (typical) than they were to say the reverse. Using these kinds of nonlinguistic stimuli showed that the benefit of the more typical color was not due to word frequency or other aspects of the words themselves. Similarly, people prefer to say that 101 is virtually 100 rather than 100 is virtually 101.

This list could go on for some time. As a general observation, one can say that whenever a task requires someone to relate an item to a category, the item's typicality influences performance. This kind of result is extremely robust. In fact, if one compares different category members and does *not* find an effect of typicality, it suggests that there is something wrong with—or at least unusual about—the experiment. It is unfortunate for the classical view, therefore, that it does not predict the most prevalent result in the field. Even if it is not specifically disproved by typicality effects (see below), it is a great shortcoming that the view does not actually explain why and how they come about, since these effects are ubiquitous.

Revision of the Classical View

As a result of the theoretical arguments and the considerable evidence against the classical view, a number of writers have attempted to revise it so that it can handle the typicality data and unclear members. The main way to handle this has been to make a distinction between two aspects of category representation, which I will call the *core* and *identification procedures* (following Miller and Johnson-Laird 1976; see Armstrong, Gleitman, and Gleitman 1983; Osherson and Smith 1981; Smith and Medin 1981; and Smith, Rips, and Shoben 1974 for similar ideas). The basic idea is as follows. Although concepts do have definitions (which we have not yet been able to discover), people have also learned other things about them that aren't definitional. This kind of information helps us to identify category members or to

use information that is not defining. For example, not all dogs have fur, so having fur cannot be part of the definition of the dog category. However, it is still useful to use fur as a way of identifying dogs, because so many of them do have it. Thus, "fur" would be part of the identification procedure by which we tell what actual dogs are, but it would not be part of the concept core, which contains only the definition. One could call "fur" a *characteristic feature*, since it is generally true of dogs even if not always true: Characteristically, dogs have fur.

Part of the problem with this proposal is that it is not clear what the concept core is supposed to do. If it isn't used to identify the category members, then what is it for? All the typicality effects listed above must arise from the identification procedure, since the category core by definition (sic) does not distinguish typicality of members. One proposal is that people use the identification procedure for fast and less reliable categorization, but that they will use the category core for more careful categorization or reasoning (e.g., Armstrong et al. 1983; Smith et al. 1974). Thus, when tasks involve more careful thought, with less time pressure than in many experiments, people might be encouraged to use the category core more. For example, Armstrong et al. (1983) found that people took longer to identify less typical even numbers than more typical ones (e.g., 4 is a more typical even number than 38 is). However, since subjects know the rule involving even numbers and are extremely accurate at this, they may use the category core to ultimately decide the question. Whether this argument can be extended to items that do not have such a clear rule, of course, needs to be considered.

In summary, on this revised view, the effects of typicality result from the identification procedures, whereas certain other behaviors (primarily categorization decisions) depend primarily on the concept core.

I will criticize this theory at the end of the chapter. However, there have been some empirical tests of this proposal as well. First, Hampton's (1979) study mentioned above also included a component in which subjects listed properties of different categories, and he attempted to separate defining from characteristic features. For example, subjects first said what properties they used to decide that something was a fruit. Other subjects then evaluated examples of fruit and similar objects to see which ones had the properties. So, they would have considered whether apple and avocado have properties such as "is from a plant," "is eaten," and "has an outer layer of skin or peel," which were mentioned by other subjects as being critical features. Hampton derived a list of necessary features for each category, by including the listed features that were found in all the category members. For example, all the items that his subjects identified as fruit had the feature "is eaten," and so this

was a necessary feature. The question he next asked was whether these features were defining: If an item had all these features, would it be in the category? The answer is no. He found many cases of items that had all of these necessary features but were not considered to be category members. For example, cucumbers and garlic had all of the necessary features for fruit but were not considered to be category members. This, then, is another failure to find defining features of actual categories. Furthermore, Hampton found that when he simply counted up how many relevant features each item had (not just the necessary features, but all of them), he could predict how likely people were to include the item as a category member. But since all members would be expected to have the defining features (according to the revised classical view), the number of other features should not predict category membership. Thus, nondefining features are important in deciding category membership—not just core features.

In more recent work, Hampton (1988b, 1995) has examined the relationship between typicality measures and category membership judgments. According to the revised classical view, typicality is not truly related to category membership but simply reflects identification procedures. So extremely atypical items like whales or penguins are just as much mammals and birds, respectively, as typical examples are (Armstrong et al. 1983; Osherson and Smith 1981). However, Hampton's results in a number of domains show that typicality ratings are the best predictor of untimed category judgments, the ones that should only involve the core. These results appear to directly contradict the revised classical view.

One reason for the popularity of the classical view has been its ties to traditional logic (Inhelder and Piaget 1964). For example, how does one evaluate sentences of the sort "All dogs are animals" or "Coach is a dog and a pet"? Propositional logic tells us that "Coach is a dog and a pet" is true if "Coach is a dog" and "Coach is a pet" are both true. This can be easily accommodated in the classical view by the argument that "Coach is a dog and a pet" is true if Coach has the necessary and sufficient features of both dogs and pets. Surprisingly, there is empirical evidence suggesting that people do not follow this rule. Hampton (1988b) found that people are willing to call something a member of a conjunctive category (X AND Y) even if it is not in both components (X, Y). For example, subjects believe that chess is in the category sports that are also games, but they do not believe that it is a sport. So, chess seems to fulfill the definition for sport in one context but not in another. He also found (Hampton 1997) that subjects believed that tree houses are in the category of dwellings that are not buildings, but they also believe them to be buildings. So, on different occasions, people say that it does and does not have the defining

features of buildings. Although very troublesome for the classical view, these examples have a very natural explanation on other views, as is explained in chapter 12.

A related advantage that has been proposed for the classical view is that it has a very natural way of explaining how categories can be *hierarchically ordered*. By this I mean that categories can form nested sets in which each category includes the ones "below" it. For example, a single object could be called Coach (his name), a yellow labrador retriever, a labrador retriever, a retriever, a dog, a mammal, a vertebrate, and an animal. These particular categories are significant because *all* yellow labs are dogs, all dogs are mammals, all vertebrates are animals, and so on. As we will see in chapter 7, this aspect of categories has been thought to be quite significant. The classical view points out that if all *X* are *Y*, then the definition of *Y* must be included in the definition of *X*. For example, all red triangles are triangles. Therefore, red triangles must be closed, three-sided figures, because this is the definition of a triangle. Similarly, whatever the definition of labradors is, that must be included in the definition of yellow labs, because all yellow labs are labradors. This rule ensures that category membership is *transitive*. If all *A*s are *B*s, and all *B*s are *C*s, then all *A*s must be *C*s. Since the definition of *C* must be included in *B* (because all *B*s are Cs), and the definition of *B* must be included in *A* (because all *A*s are *B*s), the definition of *C* must thereby be included in *A*. The nesting of definitions provides a way of explaining how categories form hierarchies.

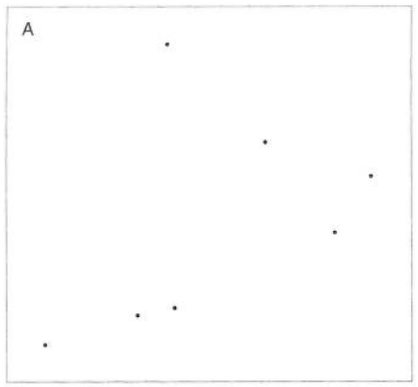
Hampton (1982) suspected that there might be failures of transitivity, which would pose a significant problem for the classical view. He asked subjects to decide whether items were members of two categories—one of them a subset of the other. For example, subjects decided whether an armchair is a chair and whether it is furniture. They also had to judge whether chairs are furniture (they are). Hampton found a number of cases in which an item was judged to be a member of the subset category but not the higher category—that is, examples of chairs that were not thought to be furniture. For instance, subjects judged that chairs were furniture and that a car seat was a chair; however, they usually denied that a car seat was furniture. But if a car seat has the defining features of chairs, and chairs have the defining features of furniture, then car seat must have the defining features of furniture. It should be pointed out that Hampton's task was not a speeded, perceptual judgment, but a more leisurely decision about category membership, which is just the sort of judgment that should involve the concept core. It is puzzling to the revised classical view that even such judgments do not show the use of definitions in the way that is expected. However, we will see later that this kind of intransitivity is easily explained by other views.

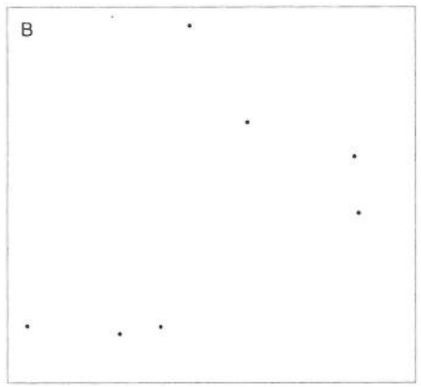
Finally, a theoretical problem with the revised classical view is that the concept core does not in general appear to be an important part of the concept, in spite of its name and theoretical intention as representing the "real" concept. As mentioned earlier, almost every conceptual task has shown that there are unclear examples and variation in typicality of category members. Because the concept core does not allow such variation, all these tasks must be explained primarily by reference to the identification procedure and characteristic features. So, if it takes longer to verify that a chicken is a bird than that a bluejay is a bird, this cannot be explained by the concept core, since chicken and bluejay equally possess the core properties of birds, according to this view. Instead, chicken and bluejays differ in characteristic features, such as their size and ability to fly. Thus, speeded judgments must not be relying on the category core. When this reasoning is applied to all the tasks that show such typicality effects, including category learning, speeded and unspeeded categorization, rating tasks, language production and comprehension, vocabulary learning, and category-based induction, the concept core is simply not explaining most of the data. As a result, most researchers have argued that the concept core can simply be done away with, without any loss in the ability to explain the results (see especially Hampton 1979, 1982, 1995).

Summary of Typicality as a Phenomenon

Before going on to the more recent theoretical accounts of typicality phenomena, it is useful to discuss these phenomena in a theory-neutral way. Somewhat confusingly, the phenomena are often referred to as revealing a *prototype structure* to concepts. (This is confusing, because there is a prototype *theory* that is a particular theory of these results, so sometimes *prototype* refers to the phenomenon and sometimes the specific theory. This is not an isolated case of terminological confusion in the field, as you will see.) A prototype is the best example of a category. One can think of category members, then, arranged in order of "goodness," in which the things that are very similar to the prototype are thought of as being very typical or good members, and things that are not very similar as being less typical or good members (Rosch 1975).

One way to illustrate this concept concretely is by the dot-pattern studies of Posner and Keele (1968, 1970), since it is very clear what the prototype is in their experiments. (Also, these are historically important experiments that are of interest in their own right.) Posner and Keele first generated a pattern of randomly positioned dots (see figure 2.2a) as the category prototype. From this pattern, they made





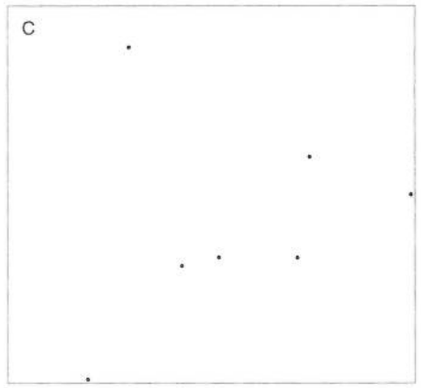


Figure 2.2
Dot patterns of the sort used by Posner and Keele (1968, 1970). 2.2a represents the initial randomly placed dots, the prototype. 2.2b represents a small distortion of the prototype, in which each dot is moved a small distance in a random direction. 2.2c represents a large distortion, in which each dot is moved a large distance. On can make indefinitely many such stimuli by generating a different (random) direction for each dot.

many more patterns of dots, by moving each point in the original pattern in a random direction. In some cases, they moved the points a small amount in that random direction (as in figure 2.2b), and for other items, they moved the points a large amount (as in figure 2.2c). These new patterns were called "distortions" of the original. Here, it is clear that the prototype is the most typical, best member of the category, because it was the basis for making the other patterns. However, it is also the case that the distortions were all somewhat similar to one another by virtue of the fact that they were constructed from the same prototype. Indeed, subjects who viewed only the distortions of four prototypes were able to learn the categories by noticing this similarity (they had no idea how the patterns were made). Furthermore, the prototype itself was identified as a member of the category in test trials, even though subjects had never seen it during learning.[2] Finally, the items that were made from small distortions were learned better than items made from large distortions. And when subjects were tested on new items that they had not specifically been trained on, they were more accurate on the smaller distortions. Figure 2.2 illustrates this nicely: If you had learned that a category looked generally like the pattern in 2.2a (the prototype), you would find it easier to classify 2.2b into that category than you would 2.2c. In summary, the smaller the distortion, the more typical an item was, and the more accurately it was classified.

This example illustrates in a very concrete way how prototypes might be thought of in natural categories. Each category might have a most typical item—not necessarily one that was specifically learned, but perhaps an average or ideal example that people extract from seeing real examples. You might have an idea of the prototypical dog, for example, that is average-sized, dark in color, has medium-length fur, has a pointed nose and floppy ears, is a family pet, barks at strangers, drools unpleasantly, and has other common features of dogs. Yet, this prototype may be something that you have never specifically seen—it is just your abstraction of what dogs are most often like. Other dogs vary in their similarity to this prototype, and so they differ in their typicality. Miniature hairless dogs are not very similar to the prototype, and they are considered atypical; St. Bernards are not very similar, albeit in a different way, and so they are also atypical; a collie is fairly similar to the prototype, so it is considered fairly typical; and so on. As items become less and less similar to the prototype, it is more and more likely that they won't be included in the category. So, if you saw a thing with four legs but a very elongated body, no hair, and whiskers, you might think that it was somewhat similar to a dog, but not similar enough to actually be a dog. However, this is the point at which different people might disagree, and you might change your mind. That is, as similarity gets

lower, there is no clear answer as to whether the item is or isn't in the category. Furthermore, as the item becomes more similar to other categories, the chance increases that it will be seen as an atypical member of that other category. You might decide that your friend's exotic, hairless pet is a weird cat instead of a weird dog.

In short, typicality is a graded phenomenon, in which items can be extremely typical (close to the prototype), moderately typical (fairly close), atypical (not close), and finally borderline category members (things that are about equally distant from two different prototypes). This sort of description summarizes the range of typicality that is often seen in categories. Researchers of all theoretical persuasions talk about category prototypes, borderline cases, and typical and less typical items in this way. However, this way of thinking about typicality should not make us assume that people actually represent the category by a single prototype, like Posner and Keele's original dot pattern, or the best possible dog. There are a number of other ways that they could be representing this information, which I will discuss in the next section and next chapter.

Theoretical Explanations of Prototype Phenomena

What Makes Items Typical and Atypical

What makes something typical or atypical? Why is penguin an atypical bird but sparrow a typical bird? Why should a desk chair be typical but a rocking chair less typical? One possible answer is simple frequency. In North America and Europe (where most of the research on this topic has been done), penguins are seldom if ever seen, whereas sparrows are often seen; there are a lot more desk chairs than rocking chairs, perhaps. This is one part of the answer, but things are not so simple. For example, there are some quite frequent items that are still thought to be atypical of their category. For example, chickens are a very frequently talked-about kind of bird, but they are not considered as typical as some infrequently encountered and discussed birds, such as the oriole or catbird (Rosch 1975) (e.g., I cannot say for certain that I have ever seen an oriole or catbird, but I see chickens fairly often). Similarly, handball is a much more typical sport than car racing (Rosch 1975), even though racing is more popular, is reported in the media, and so on. Mervis et al. (1976) found that simple frequency of an item's name did not predict its typicality. In fact, in the eight common categories they examined (birds, tool, fruit, etc.), none of the correlations of name frequency with typicality was reliably different from 0.

The best answer to the question of what makes something typical is related to the frequency of the item but is a bit more complex: Rosch and Mervis (1975) argued

that items are typical when they have high *family resemblance* with members of the category: "... members of a category come to be viewed as prototypical of the category as a whole in proportion to the extent to which they bear a family resemblance to (have attributes which overlap those of) other members of the category. Conversely, items viewed as most prototypical of one category will be those with least family resemblance to or membership in other categories" (p. 575).[3] That is, typical items (1) tend to have the properties of other category members but (2) tend not to have properties of category nonmembers. For example, an oriole is of the same size as many birds, perches in trees, flies (common bird behaviors), has two wings (universal among birds), and so on. Therefore, even though orioles are not very frequent in my experience, I can recognize them as typical birds because they have frequent bird properties. In contrast, chickens, which I see much more often, are large for birds, white (not a very usual color), do not fly (not common among birds), are eaten (not common), and so on. So, even though chickens themselves are fairly common, their *properties* are not very common as properties for birds, and so they are atypical birds.

Rosch and Mervis (1975) supported this claim in a number of ways. Because their study is so important, I will discuss it in some detail. First, they examined a number of different natural categories[4] to see if they could predict which items would be typical or atypical. Rosch and Mervis selected twenty members of six general categories. Two examples are shown in table 2.1. They had subjects rate each item for how typical it was of its category, and that is reflected in table 2.1 in the order the items are listed (e.g., chair is the most typical furniture, and telephone the least typical). Then Rosch and Mervis had new subjects list the attributes of each of the items. The question was whether typical items would have more of the common attributes than would atypical items. However, there is a problem with just listing attributes, which is that people are not always very good at spontaneously producing attributes for items. If you were to look at such data, you would see that some subjects have produced an attribute for an item, but others have not. Is this because the latter just forgot, or weren't as careful in doing the task? In some cases, that seems likely. Furthermore, it is often the case that attributes listed for one item seem to be equally true for another item, for which it was not listed. For example, people might list "has four legs" for chair but not for bed. Because of this kind of problem (see Tversky and Hemenway 1984 for discussion), Rosch and Mervis asked judges to go through the list of attributes and to decide whether the attributes were true of all the items. So, if some subjects listed "has four legs" for chairs, the judges would decide whether it was also true for the other items of furniture. The judges also eliminated any features that were clearly and obviously incorrect. This *judge-amending process* is now a standard technique for processing attribute-listing data.

Table 2.1.
Examples of items studied by Rosch and Mervis (1975), ordered by typicality.

Furniture	Fruit
chair	orange
sofa	apple
table	banana
dresser	peach
desk	pear
bed	apricot
bookcase	plum
footstool	grapes
lamp	strawberry
piano	grapefruit
cushion	pineapple
mirror	blueberry
rug	lemon
radio	watermelon
stove	honeydew
clock	pomegranate
picture	date
closet	coconut
vase	tomato
telephone	olive

Finally, Rosch and Mervis weighted each attribute by how many items it occurred in. If "has four legs" occurred in ten examples of furniture, it would have a weight of 10; if "is soft" occurred in only two examples, it would receive a weight of 2. Finally, they added up these scores for each feature listed for an item. So, if chair had eighteen features listed, its score would be the sum of the weights of those eighteen features. This technique results in the items with the most common features in the category having the highest scores. Rosch and Mervis found that this feature score was highly predictive of typicality (correlations for individual categories ranged from .84 to .91). That is, the items that were most typical had features that were very common in the category. The less typical items had different features. This result has been replicated by Malt and Smith (1984). Rosch and Mervis illustrated this in a clever way by looking at the five most typical items and five least typical items in each category and counting how many features they each had in common.

They found that the five most typical examples of furniture (chair, sofa, table, dresser, and desk) had thirteen attributes in common. In contrast, the five least typical examples (clock, picture, closet, vase, and telephone) had only two attributes in common. For fruit, the five most typical items had sixteen attributes in common, but the least typical ones had absolutely no attributes in common.

This result gives evidence for the first part of the family-resemblance hypothesis, but what about the second part, that typical items will not have features that are found in other categories? This turns out to be much more difficult to test, because one would have to find out the attributes not just of the target categories (say, fruit and furniture), but also of all other related categories, so that one could see which items have features from those categories. For example, if olives are less typical fruit because they are salty, we need to know if saltiness is a typical attribute of other categories, and so we would need to get feature listings of other categories like vegetables, meats, desserts, grains, and so on, which would be an enormous amount of work. (If I have not made it clear yet, attribute listings are very time-consuming and labor-intensive to collect, as individual subjects can list features of only so many concepts, all of which then must be transcribed, collated, and judge-amended by new subjects.) So, this aspect of the hypothesis is not so easy to test. Nonetheless, Rosch and Mervis were able to test it for two more specific categories (chair and car, Experiment 4), and they found evidence for this hypothesis too. That is, the more often an item had features from a different category, the less typical it was (correlations of $-.67$ and $-.86$).

Both of these studies are correlational. Like most studies of natural categories, the underlying variables that were thought to be responsible for the phenomenon (typicality) were simply observed in the items—the researchers did not manipulate them. As is well known, this leads to the correlation-causation problem, in which there could be some other variable that was not directly measured but was actually responsible for the typicality. Perhaps the most typical items were more familiar, or pleasant, or ... (add your favorite confounding variable). Thus, Rosch and Mervis (1975) also performed experimental studies of family resemblance that were not subject to this problem. They used lists of alphanumeric strings for items, such as GKNTJ and 8SJ3G. Each string was an exemplar, and subjects had to learn to place each exemplar into one of two categories. The exemplars were constructed so that some items had more common features (within the category) than others. Rosch and Mervis found that the items with higher family-resemblance scores were learned sooner and were rated as more typical than were items with lower scores. For these

artificial stimuli, there is little question of other variables that might explain away the results for natural stimuli. In a final experiment, Rosch and Mervis varied the amount of overlap of an item's features with the contrast category. So, one item had only features that occurred in Category 1; another item had four features that occurred in Category 1, and one that occurred in Category 2; a different item had three features that occurred in Category 1, and two that occurred in Category 2; and so on. They found that the items with greater overlap with the other category were harder to learn and were rated as much less typical after the learning phase.

In summary, Rosch and Mervis's (1975) study provided evidence for their family-resemblance hypothesis that items are typical (1) if they have features common in their category and (2) do not have features common to other categories. Unfortunately, there is some confusion in the field over the term "family resemblance." I have been using it here as indicating both parts of Rosch and Mervis's hypothesis. However, other writers sometimes refer to "family resemblance" as being only the within-category component (1 above).[5] In fact, the between-category aspect is often ignored in descriptions of this view. It is important to note, though, that whatever name one uses, it is *both* having features common within a category and the lack of features overlapping other categories that determine typicality according to this view, and Rosch and Mervis provided support for both variables influencing typicality.

This view of what makes items typical has stood the test of time well. The major addition to it was made by Barsalou (1985), who did a more complex study of what determines typicality in natural categories. Using most of the same categories that Rosch and Mervis did, such as vehicles, clothing, birds, and fruit, Barsalou measured three variables. *Central tendency* was, roughly speaking, the family-resemblance idea of Rosch and Mervis, though only including within-category resemblance. The items that were most similar to other items in the category had the highest central tendency scores. *Frequency of instantiation* was the frequency with which an item occurred as a member of the category, as assessed by subjects' ratings. Barsalou felt that the simple frequency of an item (e.g., chicken vs. lark) was probably not as important as how often an item was thought of as being a member of the category, and frequency of instantiation measured this. *Ideals* was the degree to which each item fit the primary goal of each category. Here, Barsalou selected, based on his own intuitions, a dimension that seemed critical to each category. For example, for the category of vehicle, the dimension was how efficient it was for transportation.

Subjects rated the items on these dimensions and also rated the typicality of each item to its category. The results, then, were the correlations between these different measures and each item's typicality.

Barsalou's results provided evidence for all three variables. Indeed, when he statistically controlled for any two of the variables (using a partial correlation), the remaining variable was still significant. Strongest was the central tendency measure. The items that were most similar to other category members were most typical—the partial correlation was .71. This is not surprising, given Rosch and Mervis's results. More surprising was the reliable effect of frequency of instantiation (partial correlation of .36). Consistent with Mervis et al. (1976), Barsalou found that the pure frequency of any item (e.g., the familiarity of chicken and lark) did not predict typicality. However, the frequency with which an item occurred as a category member did predict typicality. This suggests that thinking of an item as being a category member increases its typicality, perhaps through an associative learning process (though see below).

Finally, the effect of ideals was also significant (partial correlation of .45). For example, the most typical vehicles were the ones that were considered efficient means of transportation, and the most typical fruit were those that people liked (to eat). This effect is not very consistent with the Rosch and Mervis proposal, since it does not have to do with the relation of the item to other category members, but with the relation of the item to some more abstract function or goal. Barsalou (1985) presented the results for each category separately, and an examination of the results shows that ideals were quite effective predictors for artifact categories like vehicles, clothing and weapons, but less so for natural kinds like birds, fruit and vegetables.[6] As Barsalou himself notes, since he only used one ideal per category, and since he derived them based on his own intuitions, it is possible that ideals are even more important than his results reveal. If more comprehensive testing for the best ideals had been done, they might have accounted for even more of the typicality ratings. Indeed, a recent study by Lynch, Coley, and Medin (2000) found that tree experts' judgments of typicality were predicted by ideal dimensions of "weediness" and height, but not by the similarity of the trees. Weediness refers to an aesthetic and functional dimension of how useful trees are for landscaping. Strong, healthy, good-looking trees are typical based on this factor. The importance of height is not entirely clear; it may also be aesthetic, or it may be related to family resemblance, in that trees are taller than most plants, and so tall trees are more typical. Surprisingly, the variable of centrality—that is, similarity to other trees (Rosch and Mervis's 1975 first factor)—did not predict typicality above and beyond these two factors.

These results suggest the need for further exploring how important ideals are relative to family resemblance in general.

The importance of ideals in determining typicality is that they suggest that the category's place in some broader knowledge structure could be important. That is, people don't just learn that tools are things like hammers, saws, and planes, but they also use more general knowledge about what tools are used for and why we have them in order to represent the category. Category members that best serve those functions may be seen as more typical, above and beyond the specific features they share with other members.

As mentioned above, correlational studies of this sort, although important to carry out, can have the problem of unclear causal connections. In this case, the frequency of instantiation variable has a problem of interpreting the directionality of the causation. Is it that frequently thinking of something as being a category member makes it more typical? Or is it that more typical things are likely to be thought of as being category members? Indeed, the second possibility seems more likely to me. For example, Barsalou found that typical items are more likely to be generated first when people think of a category. When people think of examples of weapons, for example, they hardly ever start with spears or guard dogs; they are more likely to start with typical items like guns and knives. Frequency of instantiation, then, could well be an effect of the typicality of items, rather than vice versa. Similarly, the effect of ideals might also have come after the category's typicality was determined. That is, perhaps the ideal of vehicles came about (or occurred to Barsalou) as a result of thinking about typical vehicles and what their purposes were. It is not clear which is the chicken and which is the egg.

Barsalou addressed this problem in an experimental study of the importance of ideals. He taught subjects new categories of kinds of people. Subjects in one category tended to jog (though at different frequencies), and subjects in another tended to read the newspaper (at different frequencies). Barsalou told subjects that the two categories were either physical education teachers and current events teachers, or else that they were teachers of computer programming languages Q or Z. His idea was that the joggers would tend to be perceived as fulfilling an ideal dimension (physical fitness) when the category was physical education teachers but not when the category was teachers of language Q; similarly, the newspaper readers would fit an ideal (being informed) when they were current events teachers but not when they were teachers of language Z. And indeed, amount of jogging influenced typicality ratings for the categories described as physical education teachers, but not for the category labeled teachers of language Q even though both categories had the exact

same learning items. That is, the family-resemblance structures of the items were identical—what varied was which ideal was evoked.

This experiment, then, confirms part of the correlational study that Barsalou (1985) reported for natural categories. Ideals are important for determining typicality above and beyond any effects of family resemblance. A number of later studies have replicated this kind of result, and are discussed in chapter 6 (Murphy and Allopenna 1994; Spalding and Murphy 1996; Wattenmaker et al. 1986; Wisniewski 1995). Studies of experts have found even more evidence of the use of ideals (Medin, Lynch, Coley, and Atran 1997; Proffitt, Coley, and Medin 2000).

These studies do not show that family resemblance is not a determinant of typicality, but that there are also other determinants that Rosch and Mervis (1975) would not have predicted. Thus, I am not suggesting that their view is incorrect but that it is only a partial story, for some categories at least. They are clearly correct, however, in saying that frequency in and of itself does not account for typicality to any great degree (see also Malt and Smith 1982). Whether frequency of instantiation is an important variable is less clear. Barsalou's results do give evidence for its being related to typicality. However, since this variable has not been experimentally tested, the result is subject to the counterargument raised above, that it is a function of typicality rather than vice versa. This, therefore, is still an open issue.

End of the Classical View?

The classical view appears only very sporadically after this point in the book. To a considerable degree, it has simply ceased to be a serious contender in the psychology of concepts. The reasons, described at length above, can be summarized as follows. First, it has been extremely difficult to find definitions for most natural categories, and even harder to find definitions that are plausible psychological representations that people of all ages would be likely to use. Second, the phenomena of typicality and unclear membership are both unpredicted by the classical view. It must be augmented with other assumptions—which are exactly the assumptions of the nonclassical theories—to explain these things. Third, the existence of intransitive category decisions (car seats are chairs; chairs are furniture; but car seats are not furniture) is very difficult to explain on the classical view. The classical view has not predicted many other phenomena of considerable interest in the field, which we will be discussing in later chapters, such as exemplar effects, base rate neglect, the existence of a basic level of categorization, the order in which children acquire words, and so on. In some cases, it is very difficult to see how to adapt this view to be consistent with those effects.

In summary, the classical core has very little to do, as most of the interesting and robust effects in the field cannot be explained by cores but must refer to the characteristic features. This is true not only for speeded judgments, but even for careful categorizations done without time constraints.

In spite of all this, there have been a number of attempts to revive the classical view in theoretical articles, sometimes written by philosophers rather than by psychologists (Armstrong et al. 1983; Rey 1983; Sutcliffe 1993). This is a bit difficult to explain, because the view simply does not predict the main phenomena in the field, even if it can be augmented and changed in various ways to be more consistent with them (as discussed in the core-plus-identification procedure idea). Why are writers so interested in saving it? To some degree, I believe that it is for historical reasons. After all, this is a view that has a long history in psychology, and in fact has been part of Western thinking since Aristotle. (Aristotle!) If this were a theory that you or I had made up, it would not have continued to receive this attention after the first 10 or 20 experiments showing it was wrong. But our theory would not have this history behind it. Another reason is that there is a beauty and simplicity in the classical view that succeeding theories do not have. It is consistent with the law of excluded middle and other traditional rules of logic beloved of philosophers. To be able to identify concepts through definitions of sufficient and necessary properties is an elegant way of categorizing the world, and it avoids a lot of sloppiness that comes about through prototype concepts (like the intransitive category decisions, and unclear members). Unfortunately, the world appears to be a sloppy place.

A final reason that these revivals of the classical view are attempted is, I believe, because the proponents usually do not attempt to explain a wide range of empirical data. The emphasis on philosophical concerns is related to this. Most of these writers are not starting from data and trying to explain them but are instead starting from a theoretical position that requires classical concepts and then are trying to address the psychological criticisms of it.[7] In fact, much of the support such writers give *for* the classical view is simply criticism of the evidence *against* it. For example, it has been argued that typicality is not necessarily inconsistent with a classical concept for various reasons, or that our inability to think of definitions is not really a problem. However, even if these arguments were true (and I don't think they are), this is a far cry from actually explaining the evidence. A theory should not be held just because the criticisms of it can be argued against—the theory must itself provide a compelling account of the data. People who held the classical view in 1972 certainly did not predict the results of Rips et al. (1973), Rosch (1975), Rosch and Mervis (1975), Hampton (1979, 1988b, or 1995), or any of the other experiments that helped to

overturn it. It was only after such data were well established that classical theorists proposed reasons for why these results might not pose problems for an updated classical view.

As I mentioned earlier, there is no specific theory of concept representation that is based on the classical view at the time of this writing, even though there are a number of writers who profess to believe in this view. The most popular theories of concepts are based on prototype or exemplar theories that are strongly unclassical. Until there is a more concrete proposal that is "classical" and that can positively explain a wide variety of evidence of typicality effects (rather than simply criticize the arguments against it), we must conclude that this theory is not a contender. Thus, although it pops up again from time to time, I will not be evaluating it in detail in the remainder of this book.

3
Theories

As described in the previous chapter, the classical view has taken a big fall. Into this vacuum other theories developed that did not assume that concepts were represented by definitions and so were not subject to the problems the classical view suffered. This chapter will consider the three main kinds of theories that arose after the downfall of the classical view. The goal here is not to comprehensively evaluate these theories, as that can be done only over the course of the entire book, after the complete range of relevant data has been presented. Instead, this chapter will introduce the three general approaches that are most current in the field and explain how they deal with the typicality phenomena that caused such a problem for the classical view.

The Prototype View

One of the main critics of the classical view of concepts was Eleanor Rosch, who provided much of the crucial evidence that revealed the shortcomings of a definitional approach to concepts. Rosch's writings also provided the basis for a number of the early alternatives to the classical view, all under the rubric of the *prototype view*.

A number of readers interpreted Rosch as suggesting that every category is represented by a single prototype or best example. That is, perhaps your category of dogs is represented by a single ideal dog, which best embodies all the attributes normally found in dogs. I gave such an interpretation in the previous chapter as one way of understanding the existence of typicality. For example, very typical items would be those that are similar to this prototype; borderline items would be only somewhat similar to this prototype and somewhat similar to other prototypes as well. (The dot-pattern experiments of Posner and Keele 1968, 1970, encouraged this interpretation as well, as their categories were constructed from a literal prototype.)

Rosch, however, explicitly denied that this was her proposal (Rosch and Mervis 1975, p. 575), though it must be said that her writing often encouraged this interpretation. She preferred to be open-minded about how exactly typicality structure was represented, focusing instead on documenting that it existed and influenced category learning and judgments in important ways.

The idea that a single prototype could represent a whole category is questionable. For example, is there really an "ideal bird" that could represent all birds, large and small; white, blue, and spotted; flightless and flying; singing, cackling, and silent; carnivorous and herbivorous? What single item could pick out penguins, ostriches, pelicans, hummingbirds, turkeys, parrots, and sparrows? It seems unlikely that a single representation could encompass all of these different possibilities (Medin and Schwanenflugel 1981). Furthermore, a single prototype would give no information about the variability of a category. Perhaps some categories are fairly narrow, allowing only a small amount of variation, whereas others have very large variation (e.g., compare the incredible variety of dogs to the much smaller diversity of cats). If each category were represented by a single "best example," there would be no way to represent this difference (see Posner and Keele 1968, for an experimental demonstration).

In short, the notion of a single prototype as a category representation, which I'll call the *best example* idea, has not been very widely adopted. Instead, the prototype view proposed by Rosch has most often been interpreted as a summary representation that is a description of the category as a whole, rather than describing a single, ideal member. The view I'll discuss was proposed by Hampton (1979) and was fleshed out by Smith and Medin (1981), although its roots lie in Rosch and Mervis (1975).

A critical component of the prototype view is that it is a *summary representation* (just why this is critical will be apparent when the exemplar view is discussed): The entire category is represented by a unified representation rather than separate representations for each member or for different classes of members. This may sound just like the single best example idea that I have just criticized, but you will see that this representation is considerably more complex than that.

The representation itself could be described in terms much like Rosch and Mervis's (1975) family-resemblance view. The concept is represented as features that are usually found in the category members, but some features are more important than others. It is important for weapons that they be able to hurt you, but not so important that they be made of metal, even though many weapons are. Thus, the feature "can do harm" would be highly weighted in the representation, whereas the feature

"made of metal" would not be. Where do these weights come from? One possibility is that they are the family-resemblance scores that Rosch and Mervis derived (see previous chapter). That is, the more often a feature appears in the category and does not appear in other categories, the higher its weight will be. Unlike a best-example representation, this list of features can include contradictory features with their weights. For example, the single best example of a dog might be short-haired. However, people also realize that some dogs have very long hair and a few have short hair. These cannot all be represented in a single best example. The feature list would represent this information, however. It might include "short hair," and give it a high weight; "long hair," with a lower weight; and "hairless" with a very low weight. In this way, the variability in a category is implicitly represented. Dimensions that have low variability might have a single feature with high weight (e.g., "has two ears" might have a high weight, and "has three ears" would presumably not be listed at all). Dimensions with high variability (like the colors of dogs) would have many features listed ("white," "brown," "black," "orange-ish," "spotted"), and each one would have a low weight. Such a pattern would implicitly represent the fact that dogs are rather diverse in their coloring. This system, then, gives much more information than a single best example would.

One aspect of this proposal that is not clearly settled yet is what to do with continuous dimensions that do not have set feature values. So, how does one represent the size of birds, for example: as "small," "medium," and "large," or as some continuous measurement of size? If it is a continuous measurement, then feature counting must be somewhat more sophisticated, since items with tiny differences in size should presumably count as having the same size feature, even if they are not identical. Perhaps for such continuous dimensions, what is remembered is the average rather than the exact features. Another idea is that features that are distinctive are counted, whereas those that are close together are averaged. So, for categories like robins, the size differences are small enough that they are not represented, and we only remember the average size for a robin; but for categories like birds as a whole, we do not average the size of turkeys, hawks, robins, and wrens, which are too diverse. There is some evidence for this notion in category-learning experiments (e.g., Strauss 1979), but it must be said that a detailed model for how to treat such features within prototype theory seems to be lacking.

If this feature list is the concept representation, then how does one categorize new items? Essentially, one calculates the similarity of the item to the feature list. For every feature the item has in common with the representation, it gets "credit" for the feature's weight. When it lacks a feature that is in the representation, or has a

feature that is not in the representation, it loses credit for that feature (see Smith and Osherson 1984; Tversky 1977). After going through the object's features, one adds up all the weights of the present features and subtracts all the weights of its features that are not part of the category.[1] If that number is above some critical value, the *categorization criterion*, the item is judged to be in the category; if not, it is not. Thus, it is important to have the highest weighted features of a category in order to be categorized. For example, an animal that eats meat, wears a collar, and is a pet might possibly be a dog, because these are all features associated with dogs, though not the most highly weighted features. If this creature does not have the shape or head of a dog, does not bark, does not drool, and does not have other highly weighted dog features, one would not categorize it as a dog, even though it wears a collar and eats meat. So, the more highly weighted features an item has, the more likely it is to be identified as a category member.

This view explains the failure of the classical view. First, no particular feature is required to be present in order to categorize the item. The inability to find such defining features does not embarrass prototype theory the way it did the classical view. So long as an item has enough dog features, it can be called a dog—no particular feature is defining. Second, it is perfectly understandable why some items might be borderline cases, about which people disagree. If an item has about equal similarity to two categories (as tomatoes do to fruit and vegetable), then people may well be uncertain and change their mind about it. Or even if the item is only similar to one category, if it is not very similar—in other words, right near the categorization criterion—people will not be sure about it. They may change their mind about it on a different occasion if they think of slightly different features or if there's a small change in a feature's weight. Third, it is understandable that any typical item will be faster to categorize than atypical items. Typical items will have the most highly weighted features (see Barsalou 1985; Rosch and Mervis 1975), and so they will more quickly reach the categorization criterion. If you see a picture of a German shepherd, its face, shape, size, and hair all immediately match highly weighted values of the dog concept, which allow speedy categorization. If you see a picture of a sheepdog, the face, length of hair, and shape are not very typical, and so you may have to consider more features in order to accumulate enough weights to decide that it is a dog.

Recall that Hampton (1982) demonstrated that category membership judgments could be intransitive. For example, people believe that Big Ben is a clock, and they believe that clocks are furniture, but they deny that Big Ben is furniture. How can this happen? On the prototype view, this comes about because the basis of similarity

changes from one judgment to the other. Big Ben is a clock by virtue of telling time; clocks are furniture by virtue of being objects that one puts in the home for decoration and utility (not by virtue of telling time, because watches are not considered furniture). However, Big Ben is not similar to the furniture concept, because it isn't in the home and is far bigger than any furniture. Thus, concept *A* can be similar to concept *B*, and *B* can be similar to *C*, and yet *A* may not be very similar to *C*. This can happen when the features that *A* and *B* share are not the same as the features that *B* and *C* share (see Tversky 1977). On the classical view, this kind of intransitivity is not possible, because any category would have to include all of its superset's definition, and so there is no way that deciding that something is a clock would not also include deciding that it was furniture.

Smith and Medin (1981) discuss other results that can be explained by this feature-listing model. Most prominent among them are the effects of false relatedness: It is more difficult to say "no" to the question "Is a dog a cat?" than to "Is a dog a mountain?" I will leave it as an exercise for the reader to derive this result from the feature list view.

More Recent Developments

Unlike the other views to be discussed in this chapter, the prototype view has not been undergoing much theoretical development. In fact, many statements about prototypes in the literature are somewhat vague, making it unclear exactly what the writer is referring to—a single best example? a feature list? if a feature list, determined how? This lack of specificity in much writing about prototype theory has allowed its critics to make up their own prototype models to some degree. As we shall see in chapter 4, many theorists assume that the prototype is the single best example, rather than a list of features, even though these models have very different properties, for real-life categories, at least.

Feature combinations. The view taken by Rosch and Mervis (1975), Smith and Medin (1981), and Hampton (1979) was that the category representation should keep track of how often features occurred in category members. For example, people would be expected to know that "fur" is a frequent property of bears, "white" is a less frequent property, "has claws" is very frequent, "eats garbage" of only moderate frequency, and so on. A more elaborate proposal is that people keep track not just of individual features but configurations of two or more features. For example, perhaps people notice how often bears have claws AND eat garbage, or have fur AND are white—that is, combinations of two features. And if we propose this, we

might as well also propose that people notice combinations of three features such as having claws AND eating garbage AND being white. So, if you saw a bear with brown fur eating campers' garbage in a national park, you would update your category information about bears by adding 1 to the frequency count for features "brown," "has fur," "eats garbage," "brown and has fur," "brown and eats garbage," "has fur and eats garbage," and "brown and has fur and eats garbage." This proposal was first made by Hayes-Roth and Hayes-Roth (1977) and was made part of a mathematical model (the *configural cue model*) by Gluck and Bower (1988a).

One problem with such a proposal is that it immediately raises the question of a computational explosion. If you know 25 things about bears, say (which by no means is an overestimate), then there would be 300 pairs of features to be encoded. (In general, for N features, the number of pairs would be $N * (N - 1)/2$.) Furthermore, there would be 2,300 triplets of features to encode as well and 12,650 quadruplets. Even if you stopped at triplets of features, you have now kept track of not just 25 properties, but 2,635. For any category that you were extremely familiar with, you might know many more features. So, if you are a bird watcher and know 1,000 properties of birds (this would include shapes, sizes, habitats, behaviors, colors, and patterns), you would also know 499,500 pairs of features and 166,167,000 feature triplets. This is the explosion in "combinatorial explosion." Not only would this take up a considerable amount of memory, it would also require much more processing effort when using the category, since every time you viewed a new category member, you would have to update as many of the pairs, triplets, and quadruplets that were observed. And when making a category decision, you couldn't just consult the 1,000 bird properties that you know about—you would also have to consult the relevant feature pairs, triplets, and so on.

For these reasons, this proposal has not been particularly popular in the field at large. Models that encode feature combinations have been able to explain some data in psychology experiments, but this may in part be due to the fact that there are typically only four or five features in these experiments (Gluck and Bower 1988a, pp. 187–188, limited themselves to cases of no more than three features), and so it is conceivable that subjects could be learning the feature pairs and triplets in these cases. However, when the Gluck and Bower model has been compared systematically with other mathematically specified theories, it has not generally done as well as the others (especially exemplar models), as discussed by Kruschke (1992) and Nosofsky (1992). In short, this way of expanding prototype theory has not caught on more generally. The question of whether people actually do notice certain *pairs* of correlated features is discussed at greater length in chapter 5.

Schemata. One development that is tied to the prototype view is the use of *schemata* (the plural of *schema*) to represent concepts. This form of representation has been taken as an improvement on the feature list idea by a number of concepts researchers (e.g., Cohen and Murphy 1984; Smith and Osherson 1984). To understand why, consider the feature list view described above. In this view, the features are simply an unstructured list, with associated weights. For example, the concept of bird might have a list of features such as wings, beak, flies, gray, eats bugs, migrates in winter, eats seeds, blue, walks, and so on, each with a weight. One concern about such a list is that it does not represent any of the relations between the features. For example, the features describing a bird's color are all related: They are different values on the same dimension. Similarly, the features related to what birds eat are all closely connected. In some cases, these features are mutually exclusive. For example, if a bird has a black head, it presumably does not also have a green head and a blue head and a red head. If a bird has two eyes, it does not have just one eye. In contrast, other features do not seem to be so related. If a bird eats seeds, this does not place any restriction on how many eyes it has or what color its head is, and vice versa.

A schema is a structured representation that divides up the properties of an item into dimensions (usually called *slots*) and values on those dimensions (*fillers* of the slots). (For the original proposal for schemata, see Rumelhart and Ortony 1977. For a general discussion of schemata see A. Markman 1999.) The slots have restrictions on them that say what kinds of fillers they can have. For example, the head-color slot of a bird can only be filled by colors; it can't be filled by sizes or locations, because these would not specify the color of the bird's head. Furthermore, the slot may place constraints on the specific value allowed for that concept. For example, a bird could have two, one or no eyes (presumably through some accident), but could not have more than two eyes. The slot for number of eyes would include this restriction. The fillers of the slot are understood to be competitors. For example, if the head color of birds included colors such as blue, black, and red, this would indicate that the head would be blue OR black OR red. (If the head could be a complex pattern or mixture of colors, that would have to be a separate feature.) Finally, the slots themselves may be connected by relations that restrict their values. For example, if a bird does not fly, then it does not migrate south in winter. This could be represented as a connection between the locomotion slot (which indicates how the bird moves itself around) and the slot that includes the information on migration.

Why do we need all this extra apparatus of a schema? Why not just stick with the simpler feature list? The answer cannot be fully given here, because some of the evidence for schemata comes from the topics of other chapters (most notably chapter

12). However, part of the reason is that the unstructured nature of the feature list could lead to some peculiar concepts or objects being learned. Any features can be added to the list, and there are no restrictions on one feature's weights depending on what other features are. So, if I told you that birds are generally carnivorous, and you read somewhere that birds were generally vegetarian, you could simply list the features in your concept, say, carnivorous, weight = .80; and vegetarian, weight = .80. The fact that these two features both having high weights is contradictory would not prevent a feature list from representing them. Similarly, if I represented both the features "flies" and "doesn't fly" for birds (since some do and some don't), there is nothing to stop me from thinking that specific birds have both these features. The intuition behind schema theory is that people structure the information they learn, which makes it easier to find relevant information and prevents them from forming incoherent concepts of this sort (for evidence from category learning in particular, see Kaplan 1999; Lassaline and Murphy 1998).

Another argument often made about feature lists is that they do not have the kinds of relations that you need to understand an entire object. For example, a pile of bird features does not make a bird—the parts need to be tied together in just the right way. The eyes of a bird are *above* the beak, placed *symmetrically* on the head, *below* the crest. This kind of information is critical to making up a real bird, but it usually does not appear in feature lists, at least as produced by subjects in experiments. Subjects may list "has eyes," but they will not provide much relational information about how the eyes fit with the other properties of birds. Nonetheless, people clearly learn this information, and if you were to see a bird with the beak and eyes on opposite sides of its head, you would be extremely surprised. Schemata can include this information by providing detailed relations among the slots.

In short, a feature list is a good shorthand for noting what people know about a category, but it is only a shorthand, and a schema can provide a much more complete picture of what people know about a concept. For some purposes, this extra information is not very relevant, and so it may be easier simply to talk about features, and indeed, I will do so for just that reason. Furthermore, in some experiments, the concepts have been constructed basically as feature lists, without the additional relational information that a schema would include. In such cases, talking about feature lists is sufficient. However, we should not make the mistake of believing too much in the concepts we make up for experiments, which probably drastically underestimate the complexity and richness of real-world concepts. Schemata may be a better description of the latter, even if they are not required for the former.

The Exemplar View

The theory of concepts first proposed by Medin and Schaffer (1978) is in many respects radically different from prior theories of concepts. In the exemplar view, the idea that people have a representation that somehow encompasses an entire concept is rejected. That is, one's concept of dogs is not a definition that includes all dogs, nor is it a list of features that are found to greater or lesser degrees in dogs. Instead, a person's concept of dogs is the set of dogs that the person remembers. In some sense, there is no real concept (as normally conceived of), because there is no summary representation that stands for all dogs. However, as we shall see, this view can account for behaviors that in the past have been explained by summary representations.

To explain a bit more, your concept of dogs might be a set of a few hundred dog memories that you have. Some memories might be more salient than others, and some might be incomplete and fuzzy due to forgetting. Nonetheless, these are what you consult when you make decisions about dogs in general. Suppose you see a new animal walking around your yard. How would you decide that it is a dog, according to this view? This animal bears a certain similarity to other things you have seen in the past. It might be quite similar to one or two objects that you know about, fairly similar to a few dozen things, and mildly similar to a hundred things. Basically, what you do is (very quickly) consult your memory to see which things it is most similar to. If, roughly speaking, most of the things it is similar to are dogs, then you'll conclude that it is a dog. So, if I see an Irish terrier poking about my garden, this will remind me of other Irish terriers I have seen, which I know are dogs. I would conclude that this is therefore also a dog.

As in the prototype view, there must also be a place for similarity in this theory. The Irish terrier in my yard is extremely similar to some dogs that I have seen, is moderately similar to other dogs, but is mildly similar to long-haired ponies and burros as well. It has the same general shape and size as a goat, though lacking the horns or beard. It is in some respects reminiscent of some wolves in my memory as well. How do I make sense of all these possible categorizations: a bunch of dogs, a few goats, wolves, and the occasional pony or burro? Medin and Schaffer (1978) argued that you should weight these items in your memory by how similar they are to the item. The Irish terrier is extremely similar to some of my remembered dogs, is moderately similar to the wolves, is only slightly similar to the goat, and only barely similar to the ponies and burro. Therefore, when you add up all the similarities, there is considerably more evidence for the object's being a dog than for its being anything else. (I will describe this process in more detail later.) So, it is not just the

number of exemplars that an item reminds you of that determines how you categorize it; just as important is how similar the object is to each memory.

How does this view explain the phenomena that the prototype view explained? First, this theory does not say anything about defining characteristics, so the problems for the classical view are not problems for it. Second, the view has a natural explanation for typicality phenomena. The most typical items are the ones that are highly similar to many category members. So, a German shepherd is extremely similar to many dogs and is not so similar to other animals. A dachshund is not as similar to other dogs, and it bears a certain resemblance to weasels and ferrets, which count against it as a dog. A chihuahua is even less similar to most dogs, and it is somewhat similar to rats and guinea pigs, and so it is even less typical. Basically, the more similar an item is to remembered dogs, and the less similar it is to remembered nondogs, the more typical it will be. Borderline cases are items that are almost equally similar to remembered category members and noncategory members. So, a tomato is similar to some fruit in terms of its having seeds, being round with edible skin, and so forth, but is similar to some vegetables in terms of its taste and how it is normally prepared.

Typical items would be categorized faster than atypical ones, because they are very similar to a large number of category members, and so it is very easy to find evidence for their being members. When you see a German shepherd, you can very quickly think of many dogs you have seen that are similar to it; when you see a chihuahua, there are fewer dogs that are similar to it. Thus, the positive evidence builds up more quickly when an item is typical (Lamberts 1995; Nosofsky and Palmeri 1997). The case of category intransitivity is explained in a way similar to that of the prototype view. For example, Big Ben is similar to examples of clocks you have seen in many respects. Clocks are similar to furniture exemplars in different respects. But Big Ben is not very similar to most furniture exemplars (beds, dressers, couches, etc.), and so it does not reach the categorization criterion. Whenever the basis for similarity changes, the exemplar model can explain this kind of intransitivity.

In short, the exemplar view can explain a number of the major results that led to the downfall of the classical view. For some people, this view is very counterintuitive. For example, many people don't consciously experience recalling exemplars of dogs in deciding whether something is a dog. However, conscious experience of this sort is not in general a reliable guide to cognitive processing. Indeed, one typically does not have conscious experience of a definition or a list of features, either. Access to the concept representation is often very fast and automatic. Second, some people point out that they feel that they know things about dogs, *in general*, not just about

individual exemplars. This is a concern that will come up later as well. However, note that what you know about dogs in general may be precisely what is most common in the remembered exemplars. So, when you think of such exemplars, these general characteristics are the ones that come to mind. Finally, when you first learn a category, exemplar information may be all you encode. For example, if you went to the zoo and saw a llama for the first time, all you know about llamas would be dependent on that one exemplar. There would be no difference between your memory for the whole category and your memory for that one exemplar. If you saw another llama a few months later, you could now form a generalization about llamas as a whole (though the exemplar view is saying that you do not do this). But you would clearly also remember the two llama examples as separate items. When you saw the third llama, you might still remember parts of the first two llamas, and so on. The question is, then, when you have seen a few dozen llamas, are you forming a general description of llamas—as the prototype view says—or are you just getting a better idea of what llamas are like because you have more memories to draw on—as the exemplar view says? But at the very initial stages of learning, it seems that any theory would have to agree that you remember the individual exemplars, or else you would have no basis on which to form generalizations (see Ross, Perkins, and Tenpenny 1990, for a clever twist on this idea).

A final point is that the exemplar model requires that you have specifically categorized these memories. You can easily recognize a German shepherd as a dog because it is similar to other things you have identified as dogs. If you had just seen a lot of other German shepherds without knowing what they were, they couldn't help you classify this similar object. This requirement of explicit encoding will come up again later.

Similarity calculation. Medin and Schaffer (1978) were the first to propose an elaborate exemplar model of concepts. In addition to the exemplar aspect itself, they also introduced a number of other ideas that were taken up by the field. One aspect was the nature of the similarity computation used to identify similar exemplars. In the past, most researchers had considered similarity to be an additive function of matching and mismatching features (Tversky 1977). Medin and Schaffer, however, proposed a *multiplicative* rule, which had a number of important effects on how their model operated.

The first part of this rule (as for additive versions) requires us to identify which aspects of two items are shared and which are different. For example, consider Ronald Reagan and Bill Clinton. They share many aspects: Both are men, are

Americans, were born in the twentieth century, were Presidents of the United States, attended college, are married, and so on. They also differ in a number of aspects: Where they were born, their ages, their political philosophies, their presidential actions, whether they have been divorced, what kinds of clothes they wear, and so on. For each of these matching and mismatching features, we need to decide two things. First, how important is this dimension to determining similarity? So, how important is it for two people to have the same or different sex? How important is age or marital status? How important is political philosophy? We need to decide this so that trivial differences between the two men don't swamp our decision. For example, perhaps neither man has been to Nogales, Arizona, but this should not count as a very important similarity. Perhaps Ronald Reagan has never played bridge, but Bill Clinton has. This does not seem to be an important difference. Second, for the mismatching features, we need to decide just how mismatching they are. For example, the political philosophies of Clinton and Reagan are very different. Their ages are pretty different (Reagan was the oldest president, and Clinton one of the youngest), though both are adults, and so the difference in age is not as large as it could be. However, their typical clothes are not so different. Clinton differs from Reagan a great deal on political beliefs, then, moderately on age, and only a little on clothing.

In order to calculate similarity, we need to quantify both of these factors: the importance of the dimension and the amount of similarity on a given dimension. Medin and Schaffer suggested that the amount of mismatch of each feature should be given a number between 0 and 1. If two items have matching features, they get a 1; if they have mismatching features, they get a number that is lower, with 0 indicating the greatest possible difference on that dimension (this score is typically not given, for reasons that will become apparent). However, the importance of the dimension would be represented by raising or lowering that number. For example, suppose that Reagan's favorite color is yellow, and Clinton's is blue. These are very different colors, but this dimension is not very important. Therefore, Medin and Schaffer (1978, p. 212) suggest that we could still give this item a difference score near to 1. By not paying attention to a difference, you are effectively acting as if the items have the same value on that dimension. So, Medin and Schaffer's rule combines the importance of the dimension and the difference on that dimension in one score.

How similar are Clinton and Reagan, then? If we were to use a similarity rule like the one used by the prototype model described above, we would take the mismatch score of each feature and add it up for all the features (hence, an additive rule). Things that are similar would have many matches and so would have higher scores. Medin and Schaffer, however, suggested that we should multiply together the scores

for each feature. Because the mismatch scores range between 0 and 1, a few mismatches will make overall similarity quite low. For example, suppose that Reagan and Clinton were identical on 25 dimensions but differed on 3 dimensions. And suppose that their differences on those dimensions were moderate, so that they received mismatch scores of .5 each. The overall similarity of Clinton and Reagan would now be only .125 on a 0–1 scale (25 scores of $1 \times .5 \times .5 \times .5$ for the three mismatching dimensions). This does not seem to be a very high number for two items that are identical on 25 out of 28 dimensions. If you work through a few examples, you will see that any mismatching feature has a large effect on diminishing similarity when a multiplicative rule is used. That is, mismatching features actively lower similarity on a multiplicative rule, but they simply do not improve it on an additive view. (You can now see why a similarity score of 0 is seldom given. If a dimension were given a 0, then the entire similarity of the two items is 0, since 0 multiplied by any number is always 0. That single mismatch would result in the two items being as different as possible.)

So far, we have been discussing how to decide the similarity of an item to a single other item. But what if you are comparing an item to a set of exemplars in a category? If you see an animal run across the road, and you want to decide whether to apply the brakes to avoid hitting it with your car, you might first try to identify what kind of animal it is (no point in risking an accident for a squirrel, you might feel) by comparing it to exemplars of other animals you have seen. So, you would compare it to cat exemplars, dog exemplars, raccoon exemplars, skunk exemplars, possum exemplars, and so on. Medin and Schaffer (1978) suggested that you add up the similarity scores for each exemplar in a category. So, if you have 150 exemplars of dogs in memory, you add up the similarities of the observed animal to these 150 items, and this constitutes the evidence for the animal being a dog. If you have 25 possums in memory, you add up the 25 similarity scores to get the evidence for possums, and so on. Loosely speaking, the category with the most similarity to the item will "win" this contest. If the item is similar to a number of categories, then you will choose each category with a probability that is proportional to the amount of similarity it has relative to the others. So, you might decide that such an animal is a raccoon on 60% of such cases but a skunk on 40% of the cases. For mathematical details, see Medin and Schaffer (1978) or Nosofsky (1984).

Because of the multiplicative nature of the similarity score, the Medin and Schaffer rule has an important property: It is best to be *very* similar to a few items, and it is unhelpful to be somewhat similar to many items. Imagine for example, that this animal was extremely similar to two other dogs you have seen, but not at all similar

to any other dogs. The animal will have high similarity to these two items (near to 1.0), which would make the dog category have an overall similarity of almost 2.0. Now imagine that the animal shared three features with every possum you know (25 of them) and was different on three features with every possum. If the three mismatching features each have mismatch values of .25, then the animal would have a similarity of $1 \times 1 \times 1 \times .25 \times .25 \times .25$ to each possum, which is only .015625. When this is added up across all 25 possums, the total similarity for the category is only about .39—considerably less than the 2.0 for the dogs. Perhaps counterintuitively, the two highly similar dogs beat out the 25 somewhat similar possums. This is because the mismatching features result in very low similarities, which cannot easily be made up by having many such examples. In short, *the Medin and Schaffer model says that it is better to have high overlap with a few items than to have moderate overlap with many items*. This property turns out to be a critical one, as the next chapter will reveal.[2]

Prototype advantages. Some empirical results initially discouraged researchers from seriously considering exemplar approaches. One such result was the prototype advantage that was found by Posner and Keele (1968, 1970) and others. When subjects learned categories by viewing distortions of a prototype (see above), they were often better at categorizing the prototype than another new item. (Though they were *not* initially better at identifying the prototype than the old items, as is commonly repeated.) This suggested to many researchers that subjects had actively abstracted the prototype from seeing the distortions. That is, they had learned what the items had in common and stored this as a representation of the whole category. (Because Posner and Keele 1968, actually started with a prototype to make the category members, it is natural to think of subjects who are exposed to the category members doing the same process in reverse.) But from the above discussion, you can see that an exemplar model could easily explain this result. Perhaps the prototype is more similar to the learned exemplars than a new, nonprototypical item is. Since the prototype was the basis for making all the other items, it must be similar to *all* of them to some degree, but this is not true for an arbitrary new item.

Another result was more of a problem for the exemplar view. Posner and Keele (1970) examined categorization for items immediately after category learning and after a one-week delay. When tested immediately, subjects were most accurate for the specific items that they had been trained on (old items), next most accurate for the prototype, and less accurate for new items they had not seen in training. But when tested a week later, memory for the old items declined precipitously, whereas the prototype suffered only a slight decrement. Posner and Keele argued that if the

prototype advantage were due to memory for old exemplars, it should have shown the same kind of decrement after a delay. They concluded that subjects formed a prototype during learning, and this prototype is somehow more insulated against memory loss than are memories for individual exemplars (perhaps because the prototype is based on many presented items, not just one). A similar effect was reported by Strange, Keeney, Kessel, and Jenkins (1970), and Bomba and Siqueland (1983) found the same effect in infants. There are other variables that have similar effects. For example, as more and more exemplars are learned for a category, the memory for old items decreases, but the prototype advantage generally increases (e.g., Knapp and Anderson 1984). If prototype performance is caused by memory for specific exemplars, how could performance on the prototype and old exemplars go in different directions?

An explanation for this kind of result was given by Medin and Schaffer (1978). First, consider why it is that in many cases with immediate testing, old exemplars are remembered best of all. This must be because when the item is presented at test, it results in the retrieval of itself. That is, when item 9 is presented at test, you remember having seen it before, and this makes you particularly fast and accurate at categorizing it. If you forgot this particular item, then it would no longer have this good performance, because it must be less similar to any other item than it is to itself. Over time, however, this loss of memory is just what happens. So, perhaps item 9 was a red circle over a green square. Even though you learned this item during the first part of an experiment, after a week's delay, this memory would be degraded. Perhaps you would only remember that it was a red circle over something green. Now when you get item 9 at test, it is not so very similar to its own memory, because that memory has changed. Similarly, if you learned 25 items as being in category A, your memory for each individual item will not be as good as if you only learned 4 items in this category. As you learn more and more, there is interference among the items which causes the exemplar memory for any one of them to be less accurate. This explains the decrements obtained in performance on old items.

What happens when you present the prototype (which was never seen during learning) at test? If it is an immediate test, the prototype is fairly similar to many items in the category, and so it is easy to categorize. However, it is not identical to any individual item, and so it is still not as fast as the old exemplars are. So, the advantage of old items over prototypes on immediate test is, according to the exemplar model, caused by the fact that the former has a perfect match in memory but the latter does not. (Note that this explanation relies on the exemplar model's weighting close similarity to one item more than moderate similarity to many items.) At delayed testing, the prototype is still very similar to a number of items. In fact,

Calculating Similarity According to the Context Model

Imagine that you have been learning categories made up of geometric figures printed on cards. Each figure is defined by shape, color, size, and position (left or right on the card). After you've learned the categories, suppose you're shown a new item, a large, green triangle on the left of the card. How do you calculate its similarity to the other items in order to decide its membership? The discussion in the main text gives the general outline of how this would be done. This box describes in a bit more detail how this is actually calculated in experiments that attempt to derive exact predictions for the context model.

Given the large green triangle on the left, one would have to compare it to each remembered exemplar. Suppose that you also remember seeing a large blue triangle on the right. We need to decide the matching and mismatching value for each dimension to see how similar it is. The two stimuli match on two dimensions, size and shape, and so these will be given values of 1.0. The two stimuli mismatch on two dimensions, and so these will be given values of s_c (for color) and s_p (for position). The s_c indicates how similar the green of one stimulus is to the blue of the other stimulus. If these are considered fairly similar, the value will be close to 1; if they are considered rather different, then the value would be closer to 0. The s_p correspondingly indicates how similar the left and right positions are. By using the multiplicative rule, we can calculate the entire similarity of these two stimuli as $1 \times 1 \times s_p \times s_c$. The problem is, how do we know exactly what s_p and s_c are so that we can come up with an actual number? In general, the answer is that these numbers will be calculated from the results of the experiment itself. For example, we can see how likely people are to categorize an item that is just like a learned item but differs in color; and we can see how likely people are to categorize an item that is just like a learned item but differs in shape; and so on. By using a mathematical modeling program, researchers in this area can put in the expected formulas for each item (i.e., how similar each test item is to each learned item according to the multiplication rule), and the program will provide the values of s_p, s_c, and the other similarities that make the model perform as well as possible. These are called *free parameters* of a model, because they are estimated from the data, rather than being stated by the theory in advance. (Other theories also have free parameters. For example, I said that prototype theory often has weights on how important each feature is for a category. These could be estimated from the data as free parameters, though they could also be directly measured through means analogous to those described in the next paragraph.)

Unfortunately, this is not entirely the end. Recall that Medin and Schaffer also discussed the possibility that some dimensions might be attended to more than others. Suppose, for example, that subjects never paid attention to the position of the figures for some reason, perhaps not thinking that it was relevant. Now, the value for s_p that we calculate by the above procedure would include *both* the intrinsic similarity of the items and the attention that subjects give to it. If subjects really ignored position, then s_p would equal 1—suggesting that the right and left positions were viewed as identical. That is, there is no way to separate the mismatch score from the amount of attention

continued

that people pay to that dimension, because both are being used by subjects to make categorization decisions. This is not necessarily a problem, but sometimes one does wish to know what the real similarities are, separately from knowing which dimensions subjects paid more attention to.

One way to handle this concern is to choose the stimulus differences so that they are known to be equally different in different dimensions. For example, by asking different subjects to provide similarity ratings, it might be possible to choose a size difference (values for the large and small items) that is psychologically the same size as the color difference (between the particular values of blue and green), which is also equal to the shape difference, and so on. The experimenter can ask subjects to rate the similarity of all the stimuli before doing a categorization experiment. Then he or she can choose stimulus values that are equated, or at least the relative values of s_p, s_c, and the rest can be measured. Unfortunately, this technique cannot tell us how much attention people pay to each dimension during learning—only how similar the stimulus values are perceptually. To discover any attentional differences, one must still estimate the s parameters from the main experiment.

Calculating the exact predictions for these models is not something that can easily be done with paper and pencil, as can be seen by this description. The actual calculations of the s values and therefore the model's precise predictions is almost always done in conjunction with a mathematical modeling program. In other cases, the properties of the models can be illuminated by proofs using the general form of the similarity rule (e.g., Nosofsky 1984; 1992). But these are not tasks for beginners.

because some of the specific information about the old items has been lost, they may now seem even *more* similar to the prototype than they did before. For example, suppose that the prototype was a red circle over a green triangle. This matched item 9 to a large degree, since the two differed only in the shape of the bottom figure. After forgetting, though, the memory for item 9 actually matches the prototype more than before, because there is no longer a conflict between the square in item 9, which has been forgotten, and the triangle in the prototype. In short, the effect of forgetting is to make the old test items less similar to their own memories, but it has less effect (or even the opposite effect) on the prototype.

Hintzman and Ludlam (1980) performed simulations of an exemplar model showing that the above explanation could in fact explain why exemplar memory and prototype memory have separate time courses. They showed that as forgetting occurred, old items became steadily less similar to the remembered exemplars, but prototypes retained their similarity to exemplars for the most part. (See also Hintzman 1986, for a more complete modeling effort.) In short, even if performance is

based only on remembered exemplars, prototype effects will occur because prototypes are quite similar to a number of exemplars. One does not need to propose a summary representation of a category in order to explain prototype effects.

What Is an Exemplar?

For some time now, I have been discussing "exemplars" and the view of concepts based on them. However, I have not yet precisely said what these entities are. To some degree, this question has been left open by the proponents of this view. For example, suppose that I see a squirrel run across a lawn while I walk in to work today. Does this brief glimpse of a squirrel constitute an exemplar, even if I don't pay much attention to it? I have seen hundreds, perhaps thousands of squirrels in this way. Are all these exemplars stored in memory? (And are they stored *as* squirrels? As explained above, encoding the exemplar's category is required for it to influence categorization.) The exemplar view of concepts does not necessarily have an answer to this question, which is in part an issue of memory in general (not just concepts). It would have to say that *if* I did notice and remember that squirrel, then it could have an effect on the way I identify later animals as squirrels. If the squirrel is not encoded into memory or is forgotten, then it clearly can have no effect. But a theory of concepts cannot say exactly what everyone will and will not remember.

There is another, deeper question about exemplars, namely how an exemplar is to be defined. Consider this example. Suppose that I know a bulldog that drools a great deal named Wilbur. In fact, this bulldog lives next door to me, and so I have many opportunities to see him drool. I have seen other bulldogs, some of which appear to be drooling, and some of which do not. How do I decide, now, whether a friend of mine, who is complaining about her new dog's drooling, has a bulldog? According to the exemplar view, I would have to retrieve all the dog exemplars that I know that drool (no small number), and then essentially count up how many of them are bulldogs. But in retrieving these exemplars, how do I count Wilbur? Does he count once, because he is only one dog, or does each *encounter* with Wilbur count separately? Put in more formal terms, do I count types (Wilbur) or tokens (Wilbur-encounters)?

In terms of making an accurate decision, it seems clear that I should only count Wilbur as a type—he should only count as one dog. If I count up every Wilbur encounter as another exemplar, then the fact that a (drooling) bulldog lives next to me is having a large effect on my decision; if a labrador lived next to me, I would have many, many fewer such exemplars. However, which kind of dog happens to be living next door is not relevant to the question of whether a drooling dog is a bulldog. Or, to put it another way, how often I happen to see one particular bulldog should not greatly influence my decisions about bulldogs in general.

Nosofsky (1988) addressed this question in an experiment using colored patches as stimuli. The patches varied in how saturated and bright the colors were: The more saturated and bright colors tended to be in one category, and the less saturated and bright colors in another. He varied the frequency with which items were presented: One of the items was presented five times as often as the other items during learning. If each exemplar is considered as a type, then this frequency manipulation should not influence later category decisions. The fact that one color keeps reappearing would be like the fact that I live next door to Wilbur, not a relevant indication of the category in general. But if exemplars are defined as tokens, then stimuli that were like the more frequent item would be better category examples than stimuli that were like other, less frequent items, because there would be "more exemplars" remembered for the more frequent one. This is exactly what Nosofsky found. After learning, he showed subjects the items and asked them to rate their typicality. The more frequent item and other items that were close to it were rated as being more typical than the less frequent items. By this result, then, an exemplar is not an actual thing but rather the encounter with a thing. So, if I encounter Wilbur a hundred times, this creates 100 exemplars, not just one. Nosofsky also provided a simulation of the exemplar model, showing that it accounted for the results much better if it considered each presentation of the stimulus as an exemplar, rather than each type as being an exemplar.

Barsalou, Huttenlocher, and Lamberts (1998) raised a possible problem with this interpretation of Nosofsky's experiment. They pointed out that we do not know what subjects thought about the reappearing colors. Perhaps they thought that the stimuli were somehow different objects even if they looked identical. (It is difficult to know how to interpret the reappearance of these items, since they were color patches rather than objects.) Furthermore, as color patches are difficult to remember precisely, perhaps people did not realize that exactly the same item was being shown so often. Perhaps they thought that the colors were slightly different. If so, then they would naturally count them as separate exemplars.

Barsalou et al. performed a clever experiment in which they showed two groups of subjects the exact same stimuli during learning, but they varied whether subjects thought that each stimulus was unique, or whether they were seeing some of the items multiple times. Under most conditions, they found that this manipulation had virtually no effect on the concepts people formed; the very frequent exemplar had a strong effect in both conditions. That is, to return to my example, it makes no

difference whether I think I'm seeing 100 different bulldogs or one bulldog 100 times—the effect on my concept of bulldogs is the same.[3] As Barsalou et al. point out, this has implications for prototype models as well as for exemplar models of concepts. In both cases, the theory needs to specify how units are counted up (how many features/exemplars have been viewed), and the empirical results suggest that it is *encounters* with objects that are most important, rather than the objects themselves.

The Knowledge Approach

The discussion of the final major theory is actually a bit premature for the present chapter. The prototype and exemplar models arose from the ashes of the classical view, and they were designed to account for the data that were so problematic for that view. The *knowledge approach* in contrast arose as a reaction to the two other approaches, and it is in some sense built upon them. As a result, we have not yet discussed the experimental results that led to this view, nor are we ready to do so now. A later chapter (chapter 6) provides a more detailed exposition of this account. Nonetheless, it will be useful to have this approach in mind when reading the next few chapters, and so I will give a somewhat brief description of this view now, without providing much of the experimental evidence.

The knowledge approach argues that concepts are part of our general knowledge about the world. We do not learn concepts in isolation from everything else (as is the case in many psychology experiments); rather, we learn them as part of our overall understanding of the world around us. When we learn concepts about animals, this information is integrated with our general knowledge about biology, about behavior, and other relevant domains (perhaps cuisine, ecology, climate, and so on). This relation works both ways: Concepts are influenced by what we already know, but a new concept can also effect a change in our general knowledge. Thus, if you learn a surprising fact about a new kind of animal, this could change what you thought about biology in general (e.g., if you learn that snails are hermaphrodites, your knowledge about sexual reproduction in general could be affected); and if something you learn about a new animal doesn't fit with your general knowledge, you may have cause to question it or to give it less weight. (Could snails *really* be hermaphrodites? Maybe you just misunderstood. Best to say nothing and hope they go away.) In general, then, the knowledge approach emphasizes that concepts are part and parcel of your general knowledge of the world, and so there is pressure for concepts to be consistent with whatever else you know (Keil 1989; Murphy and Medin 1985). In order to maintain such consistency, part of categorization and other conceptual processes may be a reasoning process that infers properties or constructs explanations from general knowledge.

Let me just give a simple example of the kind of knowledge involved here. One area of knowledge that is often studied in research from this perspective is that of biology. We know things about evolution, reproduction, physiology, and ecology, part of which we have just learned "naively" (on our own or informally from parents), and part of which we learned through more formal study. However, even young children seem to have basic ideas about biology (Gelman and Wellman 1991; Keil 1989) that they use in making judgments of the following sort. If a child sees a fuzzy, gray, tiny animal paddling around after a large, white, goose, the child may conclude that the animal must be a goose as well, even though it looks very different from other geese it has seen. Apparently, the child is using the logic: "Babies are smaller than their parents, and they often stick close to their parents. Any baby of a goose must itself be a goose. So, this much smaller animal could well be a baby, even though it looks rather different from the goose, and so it is also a goose." Of course, the child doesn't say this out loud, but there is reason to think that children are sensitive to notions of inheritance and parentage—basic biological properties that then influence their categorizations. In general, this approach says that people use their prior knowledge to reason about an example in order to decide what category it is, or in order to learn a new category.

In one description, this aspect of concepts was referred to as "mental theories about the world" (Murphy and Medin 1985), which is accurate enough if one understands that people's naive theories are incomplete and in some cases contradictory, given our incomplete knowledge and understanding of the things around us. The child in the above example doesn't have a complete theory of biology but does know some basic facts and principles that are partly integrated. Thus, this approach is sometimes called the *theory view* (or even the *theory theory* by those less easily embarrassed than I am). However, the term *theory* suggests to many something more like an official scientific theory, which is probably not an accurate description of people's knowledge (see, e.g., Gentner and Stevens 1983). This has caused some confusion about exactly what the approach is claiming, so I will tend to use the term *knowledge* rather than *theory*, to avoid this potential confusion.

Some of the discussion of schemata discussed in the prototype view is relevant here as well. For example, one reason given for using schemata for representing concepts was that they can represent relations between features and dimensions. This is just one way of representing knowledge about the domain. For example, we may know that animals without wings cannot fly, and so there may be a relation

between the schema slot describing body parts and the slot describing behaviors that manifests this relation.

One of the studies on typicality described in some detail in the previous chapter was also a motivation for the knowledge view, namely, Barsalou (1985). Recall that Barsalou found that *ideals* are important to determining typicality. For example, something might be considered a good example of a weapon to the degree that it was an efficient way to hurt or kill people. This "ideal" weapon is not the average value of all weapons, because most weapons are less than ideal on this account (e.g., a knife requires close distance, accurate handling, and can only cut one person at a time). Barsalou found that items that were closer to the ideal were more typical than items that were farther away, and this was true even when family resemblance was first factored into the typicality judgment. This influence of ideals cannot, then, reflect just pure observation of the category, as a prototype or exemplar approach might claim. If people relied on the weapons they had seen or heard about, they would find only moderately effective devices to be the most typical weapons. Similarly, they would expect only moderately efficient people-movers to be good vehicles, since on average, vehicles are by no means ideal people-movers.

Where do these ideals for categories come from, then? Most likely they come from our knowledge of how each category fits in with other parts of our lives—its place in our greater understanding of the world. We know that vehicles are made *so that* people can be moved from place to place. Therefore, the most typical vehicles would do this in the best possible way. We know that weapons are created in order to hurt (or threaten to hurt) other people. Therefore, the most typical ones are the ones that do this in an effective way. Furthermore, we can apply our general knowledge to evaluate how well different vehicles and weapons actually fulfill these functions.

The importance of such knowledge can be illustrated even more by a kind of category that Barsalou (1985) called *goal-derived categories*. These are categories that are defined solely in terms of how their members fulfill some desired goal or plan, for example, things to eat on a diet, things to take from one's house during a fire, good birthday presents, and so on. For goal-derived categories, very little of the category structure is explained by family resemblance. For example, things to eat on a diet might include celery, sugar-free jello, diet soda, baked potatoes, baked fish, and skim milk. These items differ in many respects. They are much less similar to one another than normal food categories such as dairy products or meats, yet, they are all within the same category by being things that people eat while on a diet. Here, the ideal is something like having the smallest number of calories or the least

fat. So, celery is an excellent example of things to eat on a diet, because it has virtually no fat and is extremely low in calories. Bread is a fairly good example, though it has somewhat more calories and fat. Fruit juice might be a moderate example, since it is low in fat but not particularly low in calories. And ice cream would be a bad example. Barsalou found that the most typical examples of goal-derived categories were the ones that were closest to the ideal. Family resemblance did not explain a significant portion of the variance. This is an extreme case in which an item's place in a larger knowledge structure is perhaps the most important aspect of category membership, and the "average" properties of the category members count for little. For example, the best food to eat on a diet would be a filling food with no calories, fat or other bad ingredients. However, these properties are by no means the most frequent ones of foods that people actually eat while on diets. So, this ideal seems to be imposed by our understanding of what the category is supposed to be, which is in turn driven by our understanding of how it fits into the rest of what we know about foods and their effects on our bodies. The ideal cannot be derived from just observing examples and noting the features that occur most. Although the goal-derived categories are an extreme example of this (because the members have very little in common besides the ideal), Barsalou found evidence for the importance of ideals in common categories as well (see previous chapter). Also, recall that Lynch et al. (2000) found a similar pattern for the category of trees; many other related examples will be described in chapter 6.

One of the themes of the knowledge approach, then, is that people do not rely on simple observation or feature learning in order to learn new concepts. They pay attention to the features that their prior knowledge says are the important ones. They may make inferences and add information that is not actually observed in the item itself. Their knowledge is used in an active way to shape what is learned and how that information is used after learning. This aspect of the theory will be expounded in greater detail in chapter 6.

One clear limitation of the knowledge approach should already be apparent: Much of a concept cannot be based on previous knowledge. For example, you might have previous knowledge that helps you to understand why an airplane has wings, how this relates to its ability to fly, what the jets or propellers do, and so on. However, it is probably only by actual observation of planes that you would learn where propellers are normally located, what shape the windows are, that the seats usually provide no lower back support, and so on, because these things are not predictable from your knowledge before learning the category. Or, in other cases, it is only after observing some category members that you know what knowledge

is relevant and can only then use it to understand the category (see Murphy 2000, for a discussion). So, the knowledge approach does not attempt to explain all of concept acquisition by reference to general knowledge; it must also assume a learning mechanism that is based on experience. However, this approach has not incorporated any empirical learning mechanism. This may be seen as a shortcoming of the knowledge approach, or one can view the empirical learning process as simply being a different problem. That is, proponents of the knowledge approach are pointing out the ways that prior knowledge influences the learning of a new concept, and other aspects of learning are not part of the phenomena they are trying to explain. However, it should be clear that a complete account requires an integrated explanation of all aspects of concept learning. Furthermore, we should not necessarily assume that the empirical and knowledge-based learning components will be easily separable modules. It is possible that the two interact in a complex way so that one must study them together to understand either one (Wisniewski and Medin 1994). However, that discussion must await a later chapter.

Conclusions

It is too early in this book to evaluate these different approaches. However, it is worth emphasizing that none of them suffers from the problems of the classical approach. All of them actively predict that categories will have gradations of typicality and that there will be borderline cases. Unlike the later revisions of the classical model (discussed in the previous chapter; e.g., Armstrong, Gleitman, and Gleitman 1983), these theories claim category fuzziness as an integral part of conceptual processing, rather than an unhappy influence of something that is not the "true" concept. This is because similarity of items is inherently continuous. Category members will be more or less similar to one another and to their prototype, and this gradation of similarity leads to typicality differences, RT differences in judgments, and learning differences. Similarly, whether an item is consistent with one's knowledge in a complex domain is not an all-or-none matter but often a question of relative consistency. Thus, unlike for the classical view, typicality phenomena are not a nuisance to be explained away, but are rather inherent to the working of these approaches.

Another point to be made about each of these approaches is that they are not as entirely self-sufficient as one might like. For example, the prototype view does not deny that people learn and remember exemplars. Clearly, if Wilbur, the bulldog, lives next door to me, and I see him many times per week, I will be able to identify

him and his peculiar attributes. And, as already mentioned, the first time one encounters a category member, the only prototype one can form would be based on that single exemplar. Thus, exemplar knowledge and prototype knowledge must exist side by side to at least some degree, according to prototype theory. The general claim of that theory, however, is that for mature categories, people rely on summary representations of the entire category rather than specific exemplars in making judgments about the concept.

Similarly, I pointed out that the knowledge approach focuses on one important (it claims) aspect of learning and representing concepts. However, it must admit that there is an empirical learning component to concepts, if only to explain the results of psychological experiments that use artificial stimuli that are removed from any knowledge. It is likely, then, that this view will have to be combined with one of the other views in order to form a complete theory of concepts. Finally, exemplar theorists might also agree that there must be a level of general knowledge that is separate from exemplar knowledge and that affects concepts and their use (though in fact most have not addressed this issue). For example, one could argue that facts such as whales being mammals are school-learned general facts, rather than something one learns from seeing many whale exemplars. But of course one does see whale exemplars occasionally too. So, in answering questions about whales, some information might come from the exemplars and some from general knowledge.

This mixture of different kinds of conceptual knowledge makes it difficult to evaluate the different theories. The result in the field has been to focus on certain experimental paradigms in which such mixtures would be expected to be less likely. However, for real-life concepts, we would do best not to assume that a single form of conceptual representation will account for everything.

APPENDIX: THE GENERALIZED CONTEXT MODEL

The body of this chapter has discussed the Context Model, proposed by Medin and Schaffer (1978), as the most influential version of the exemplar approach. However, in more recent times, Robert Nosofsky's enhancement of this, the *Generalized Context Model* or *GCM*, has been more widely cited and tested. This model has a number of different forms, as it has developed over years of investigation. The purpose of this appendix is to describe it in more detail and to give an idea of how it works. For more formal descriptions, see Nosofsky (1992) or Nosofsky and Palmeri (1997).

Overview

Recall that exemplar models argue that you categorize objects by comparing them to remembered exemplars whose categories you have already encoded. The more similar the object is to exemplars in a given category, the more likely it is to be categorized into that category. The categorization process can be thought of as having three parts. First, one must calculate the distance between the exemplar of interest and all the other exemplars. In the Medin and Schaffer (1978) model, this was done by the multiplicative rule described in the main chapter. In the GCM, this is done by a more general distance metric. Second, this distance metric is scaled in a way that has the effect of weighting close similarity much more than moderate similarity. Third, once one has all these similarities of the object to known exemplars, one must decide which category the object is in. This involves a fairly simple comparison of the exemplar similarities of the different categories involved.

The formulas involved in the GCM can be difficult if you aren't familiar with them. I personally am not a math modeling expert, and it has taken me some time to understand them (to the degree that I do). This chapter will help you begin to understand the model. However, to reach a fuller appreciation, I would recommend that when you read individual papers that describe this or other models, you resist the very natural temptation to skip over all the formulas. If you read these formulas and the authors' explanations of them in four or five different papers, you will eventually find (perhaps to your amazement) that you understand what they are talking about. So, don't give up just because it all seems so complicated here. I describe the three parts of the GCM in the following sections.

Distance Calculations

The basic idea of exemplar models is that an object brings to mind other similar exemplars. To measure this, the model calculates the psychological distance between the object to be categorized (usually called *i* below) and all the known exemplars, in order to identify which exemplars are going to be brought to mind.

In order to compare various stimuli, the GCM assumes that they have been broken into dimensions of some kind. This could be because they are items that have been constructed according to certain dimensions (color, size, position on a card, etc.) that subjects would be sensitive to. In other cases, one may have psychological dimensions of the stimuli that are derived from a scaling program, such as multidimensional scaling. For example, using multidimensional scaling, Rips, Shoben, and Smith (1973) discovered that animals were thought to be similar based on their size and predacity. The scaling program provided the values of each item on each dimension, and these would be used to calculate similarity. The distance between any two objects is a function of how far apart they are on each dimension.

Equation (1) shows how the GCM calculates the distance between two items, *i* and *j*, when the dimensions of the objects are known. (Think of *i* as being the object to be categorized, and *j* one of the remembered exemplars.) It is essentially the same as the Euclidean distance between two points in space, from high-school geometry.

$$d_{ij} = \sqrt{\sum_m w_m |x_{im} - x_{jm}|^2} \tag{1}$$

For each dimension m of the items (either a physical dimension or one from a multidimensional scaling solution), you calculate the difference between the items $(x_i - x_j)$ and square it. Then this number is multiplied by the weight for that dimension (w_m). So, important dimensions will be counted more heavily than less important dimensions. (In the original context model, this was reflected in the mismatch values. The GCM more clearly separates psychological similarity from dimensional importance in categorization.) These numbers are added up for all the m dimensions, and the square root is taken. The main difference between this and simple Euclidean distance is the weighting of the dimensions. In calculating real distances, no spatial dimension is weighted more than any other. In the GCM, the w values for each dimension are a free parameter—that is, they are calculated from the data themselves rather than being specified by the model. Kruschke's (1992) influential ALCOVE model (based on the GCM to a large degree) provides a connectionist mechanism that actually learns which dimensions are important.

I should note that this particular form of the distance metric can vary in different studies. (Those who are just trying to get the basic idea of this model should definitely skip this paragraph.) Note that we squared the differences on each dimension and then took the square root of the sum. That is, we raised the distance to the power 2 and then raised the sum to the power 1/2 (that's a square root). Distance metrics in general raise the separation by some power and then the sum to one over that power. The number 2 is only one such number that could be used. We could have used the number 1—that is, raise the distances to the power of 1 (i.e., do nothing) and taken the sum to the power of 1/1 (i.e., do nothing again). This would give us the "city block" metric, in which the distance between two points is the sum of their distances on each dimension. This is called the city block metric, because one does not form hypotenuses for distances—one cannot cut through a city block.

To get from 40th Street and Second Avenue to 43rd Street and Sixth Avenue, one must walk three blocks north and four blocks west, resulting in seven total blocks (let's assume the blocks are squares). By Euclidean distance, the shortest distance connecting these points (cutting across) would be only five blocks. For some stimulus dimensions, the city block metric seems most appropriate, whereas for others, Euclidean distance works best.[4] And for still others, some number in between is most appropriate. Thus, this difference between dimensions can be made into a variable (usually called Minkowski's r), which is altered depending on the nature of the stimuli. So, you may see something like equation (1) with rs and $1/r$s in it.

Turning Distances into Similarity

Unfortunately, we are still not done with deciding the psychological distance between two items. Research has shown that behavioral similarity between items is an exponentially decreasing function of their psychological distance (Shepard 1987). For example, if rats learn to produce a response to a certain colored light, other lights will elicit the same response as a function of the exponential distance between the test light and the original. The exponential function has the effect that things that are extremely close to the object have a large effect, which falls off very quickly as things become moderately and less similar. Recall that Medin and Schaffer (1978) used a multiplicative rule so that objects that are moderately different would have little effect on categorization decisions. The exponential function does the same thing.

As shown in equation (2), the distance scores derived from equation (1) are input to the exponential function, producing a similarity score, s.

$$s_{ij} = \exp(-c \cdot d_{ij}) \tag{2}$$

Note that $\exp(x)$ means to raise e to the xth power, e^x, and that $\exp(-x) = 1/e^x$. Therefore, the bigger x gets, the smaller $\exp(-x)$ gets. In equation (2), this means that the greater the distance between i and j, the smaller the similarity, since the distance is being negated. When distance is 0 (i.e., two stimuli are identical), s would equal 1.0; otherwise, s falls between 0 and 1. The variable c basically determines the spread of similarity by modulating the effect of distance. Sometimes people seem to pay attention to only very close similarity, and other times people take into account even fairly weak similarity. A high value of c corresponds to the former situation, and a low value corresponds to the latter. If c is very high, then the exemplar model is essentially requiring that an item be identical to a known exemplar, because any

distance between i and j would be multiplied by a high number, resulting in a low similarity. If c is very low, then the similarity to all known items is used. Usually, c is a free parameter estimated from the data.

Making the Decision

In order to make a categorization decision, one has to decide which category exemplars are most like the object being categorized, i. If the object is similar to many dogs, a few cats, and one burro, then it is probably a dog. The GCM does this by looking at the object's similarity to *all* objects in every category, and then comparing the similarity of one category to that of all the others. In the previous sections, we calculated the similarity of the object to every other exemplar. If you were to add up all these similarity scores, you would know the total pool of similarity this object has to everything. The GCM uses something called the Luce Choice Axiom to turn this similarity into a response. The Luce Choice Axiom basically asks how much of the total pool of similarity comes from dogs, how much from cats, and how much from burros, and then turns those answers into response probabilities. Equation (3) calculates the probability that the object, i, will be placed into each category, J.

$$P(J \mid i) = \sum_{j \in J} s_{ij} \Big/ \left[\sum_{K} \sum_{k \in K} s_{ik} \right] \tag{3}$$

The numerator is the similarity of i to all the members j of category J (as calculated in equation (2)). The more similar the item is to known exemplars in J, the higher this probability. The denominator is the similarity of i to members of *all* known categories (K), the total pool of similarity mentioned above. In English, then, equation (3) is the ratio of the similarity of i to all the things in J to the total similarity pool.[5] Continuing the previous example, if i is mostly similar to dogs, then perhaps $P(\text{dog} \mid i) = .75$, because dogs have 75% of the total similarity for this object. And perhaps $P(\text{cat} \mid i) = .20$, because the object is similar to a few cats. And because you once saw a very strange burro, $P(\text{burro} \mid i) = .05$. What the Luce Choice Axiom says is that you should call this object a dog 75% of the time, a cat 20% of the time, and a burro 5% of the time.

Note that this formula is probabilistic. It doesn't say that people will always categorize i into the category with the highest score. Instead, it says that their categorization will match the probability score. This behavior is not entirely rational. If it is 75 percent likely that i is a dog, then I should obviously categorize it as a dog

whenever I see it, because it is much more likely to be a dog than a cat or a burro, based on my own experience. Any other response is much less likely. However, people tend to do *probability matching* in these situations, in which they give less likely responses a proportional number of times, rather than always choosing the most likely answer. This behavior is found in many choice tasks in both humans and other animals.

Later versions of the GCM have sometimes incorporated another parameter proposed by Ashby and Maddox (1993), called *gamma*, which relates to the probability matching phenomenon. To do this, the numerator of (3) is raised to the gamma power, and the inside term of the denominator ($\sum_{k \in K} s_{ik}$) is also raised to that power. (The exact value of gamma is usually a free parameter.) That is, once one has calculated the total similarity of i to a category, that similarity is raised to the power gamma. Gamma has the effect of varying the amount of determinacy in subjects' responses. When gamma is 1, the categorization rule has the characteristics mentioned earlier: Subjects respond proportionally to the probability. When gamma is higher, they respond more deterministically: They tend to choose the most likely category more. This is because the similarity values are less than 1, so raising them to a high power tends to decrease the small values almost to 0, thereby benefiting the larger values.

See how simple it all is? No? Well, you are not alone. Although all this may be confusing on first reading, if one simply focuses on one variable or equation at a time, one can usually understand how it works. Attempting to keep the entire GCM in one's head at a time is pretty much impossible, so do not be too discouraged if you don't feel that you get it. Especially at the beginning, you can probably only understand it piece by piece.

Although the GCM has been extremely successful in modeling results of categorization experiments, one criticism of it has been that it is too powerful. The complexity of the model and the number of parameters it has makes it very good at fitting data, even if the data are exactly what would be predicted by a prototype model (Smith and Minda 2000). Perhaps because it is a rather late addition to the model, gamma has struck some in the field as being a dubious construct. Some critics feel that it is simply a free parameter that lets the GCM account for data that could not previously be accounted for, without any clear psychological evidence that determinacy of responding is a variable that changes systematically. However, this level of argument is far beyond that of the present discussion. See the interchange between Smith and Minda (2000) and Nosofsky (2000) for discussion and references.

Whatever the criticisms of it, the GCM has been an extremely influential categorization model. What should now be obvious is that there is a lot more to the GCM than simply saying that people remember exemplars. There are many assumptions about how similarity is calculated, how decisions are made, and what variables affect performance that go far beyond the simple claim of exemplar representations of concepts. Thus, the model's successes and failures cannot be taken as direct evidence for and against exemplars alone.