SOME QUESTIONS WE WILL CONSIDER

- Why is it difficult to decide if a particular object belongs to a particular category, such as "chair," by looking up its definition? (247)
- How are the properties of various objects "filed away" in the mind? (256)
- How is information about different categories stored in the brain? (264)

Imagine that you find yourself in an unfamiliar town, where you have never been before. As you walk down the street, you notice that many things are not exactly the same as what you would encounter if you were in your own town. On the other hand, there are many things that seem familiar. Cars pass by, there are buildings on either side of the street and a gas station on the corner, and a cat dashes across the street and makes it safely to the other side. Luckily, you know a lot about cars, buildings, gas stations, and cats, so you have no trouble understanding what is going on.

This chapter is about the kind of knowledge that enables you to recognize and understand the objects in the street scene and the world. This type of knowledge is called **conceptual knowledge**—knowledge that enables us to recognize objects and events and to make inferences about their properties (Rogers & Cox, in press). This knowledge exists in the form of *concepts*. **Concepts** have been defined in a number of ways, including "the mental representation of a class or individual" (Smith, 1989) and "the meaning of objects, events, and abstract ideas" (Kiefer & Pulvermüller, 2012). To express this in concrete terms, we can say that the concept "cat" is the answer to the question "What is a cat?" If your answer is that a cat is an animal that is furry, meows, moves, and eats mice, you will have described your concept of "cat" (Kiefer & Pulvermüller, 2012).

Because we are interested in our knowledge about the world, we need to go beyond cats! When we start expanding our scope to dogs, automobiles, can openers, radishes, and roses, things start to become both more complicated and more interesting, because the question then becomes "How are all of these things organized in the mind?" One way we organize concepts is in terms of *categories*.

A **category** includes all possible examples of a particular concept. Thus, the category "cats" includes tabbies, Siamese cats, Persian cats, wildcats, leopards, and so on. Looked at in this way, concepts provide the rules for creating categories. Thus, the mental representation for "cat" would affect what animals we place in the "cat" category. Because concepts provide rules for sorting objects into categories, concepts and categories are often discussed together, and a great deal of research has focused on the process of **categorization**—the process by which things are placed in categories.

Categorization is something we do every time we place an object into a category, and once we have assigned an object to a category, we know a lot about it. For example, being able to say that the furry animal across the street is a "cat" provides a great deal of information about it (**Figure 9.1**). Categories have therefore been called "pointers to knowledge" (Yamauchi & Markman, 2000). Once you know that something is in a category, whether "cat," "gas station," or "impressionist painting," you can focus your energy on specifying what's special about this particular object (see Solomon et al., 1999).

Being able to place things in categories can also help us understand behaviors that we might otherwise find baffling. For example, if we see a man with the left side of his face painted black and the right side painted gold, we might wonder what is going on. However, once we note that the person is heading toward the football stadium and it is Sunday afternoon, we can categorize the person as a "Pittsburgh Steelers fan." Placing him in that category explains his painted face and perhaps other strange behaviors that happen to be normal on game day in Pittsburgh (Solomon et al., 1999).

These various uses of categories testify to their importance in everyday life. It is no exaggeration to say that if there were no such thing as categories, we would have a very difficult time dealing with the world. Consider what it would mean if every time you saw a different object, you knew nothing about it other than what you could find out by investigating it individually. Clearly, life would become extremely complicated if we weren't able to rely on the knowledge provided to us by categories. Given the importance of categories, cognitive psychologists have been interested in determining the process involved in categorizing objects.

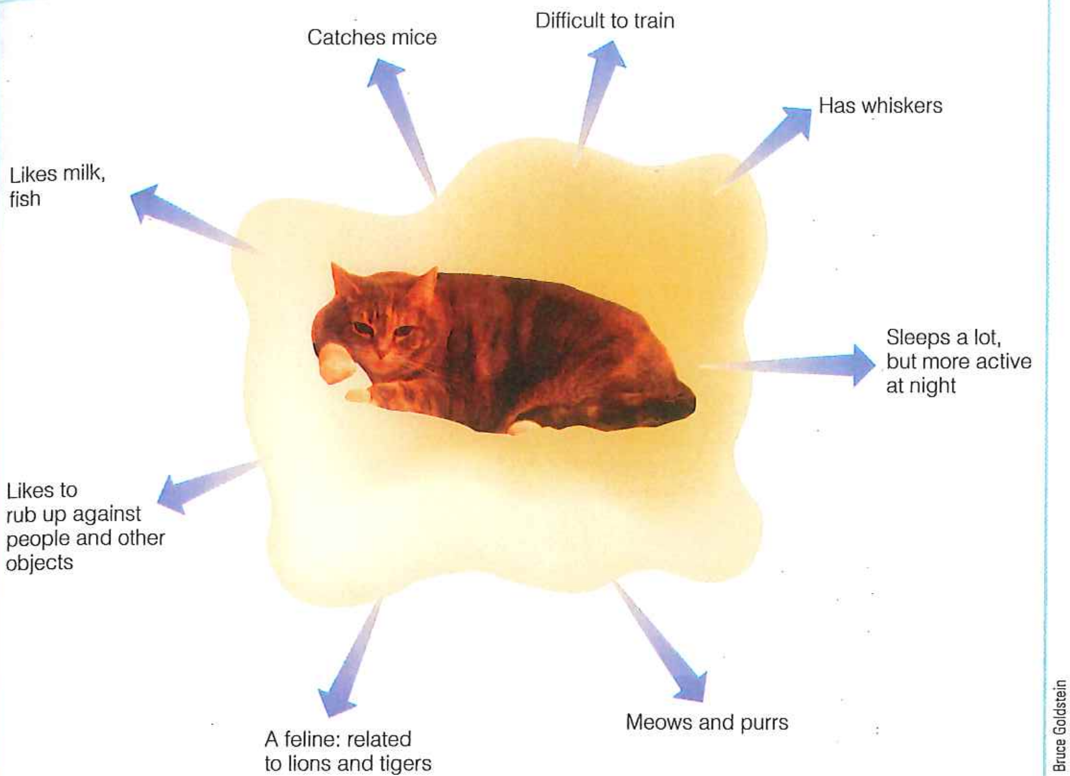


Figure 9.1 Knowing that something is in a category provides a great deal of information about it.

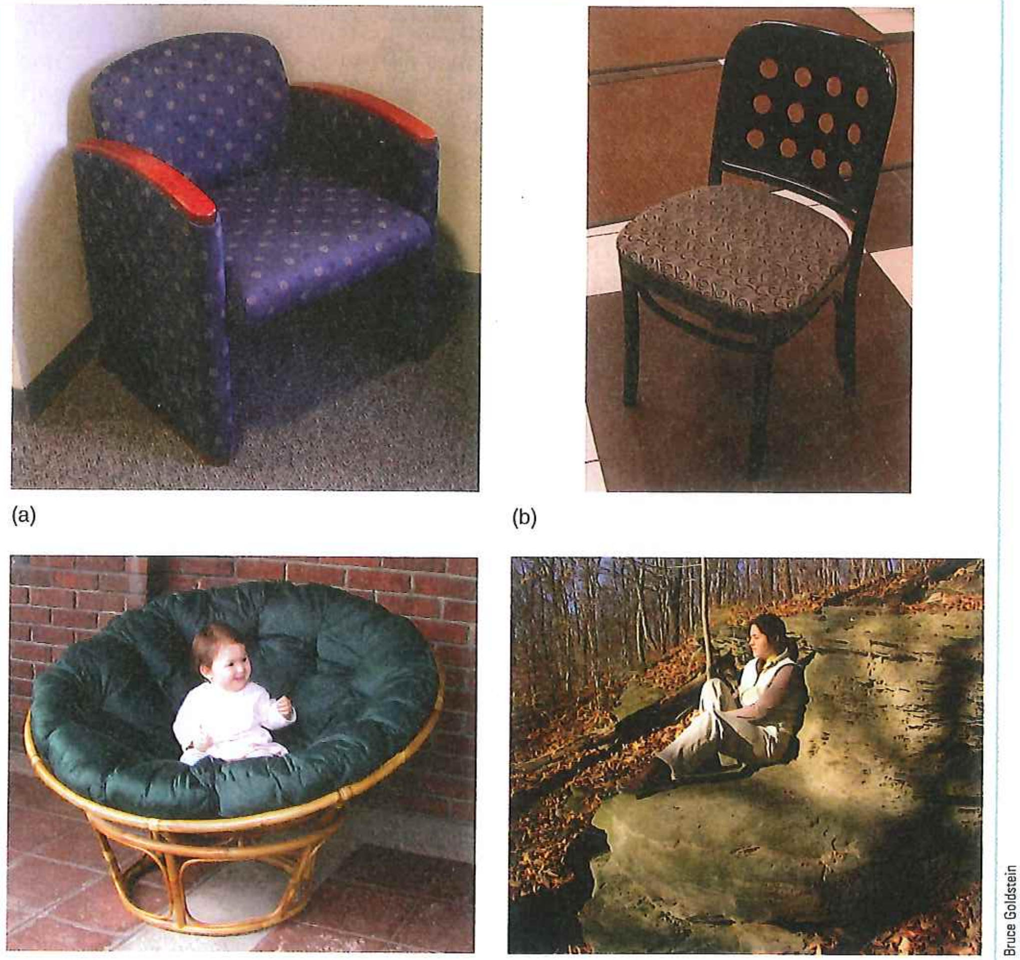
How Are Objects Placed Into Categories?

A time-honored approach to determining the characteristics of an object is to look up its definition. We begin by describing how cognitive psychologists have shown that this "definitional approach" to sorting objects into categories doesn't work. We then consider another approach, which is based on determining how similar an object is to other objects in a category.

WHY DEFINITIONS DON'T WORK FOR CATEGORIES

According to the **definitional approach to categorization**, we can decide whether something is a member of a category by determining whether a particular object meets the definition of the category. Definitions work well for some things, such as geometric objects. Thus, defining a square as "a plane figure having four equal sides, with all internal angles the same" works. However, for most natural objects (such as birds, trees, and plants) and many human-made objects (like chairs), definitions do not work well at all.

The problem is that not all of the members of everyday categories have the same features. So, although the dictionary definition of a chair as "a piece of furniture consisting of a seat, legs, back, and often arms, designed to accommodate one person" may sound reasonable, there are objects we call "chairs" that don't meet that definition. For example, although the objects in **Figures 9.2a** and **9.2b** would be classified as chairs by this definition, the ones in **Figures 9.2c** and **9.2d** would not. Most chairs may have legs and a back, as specified in the definition, but most people would still call the



(a) (b) (c) (d)

Figure 9.2 Different objects, all possible "chairs."

disc-shaped furniture in Figure 9.2c a chair, and might go so far as to say that the rock formation in Figure 9.2d is being used as a chair.

The philosopher Ludwig Wittgenstein (1953) noted this problem with definitions and offered a solution:

> Consider for example the proceedings we call "games." I mean board-games, card-games, ball-games, Olympic games, and so on. For if you look at them you will not see something in common to all, but similarities, relationships, and a whole series of them at that. I can think of no better expression to characterize these similarities than "family resemblances."

Wittgenstein proposed the idea of **family resemblance** to deal with the problem that definitions often do not include all members of a category. Family resemblance refers to the idea that things in a particular category resemble one another in a number of ways. Thus, instead of setting definite criteria that every member of a category must meet, the family resemblance approach allows for some variation within a category. Chairs may come in many different sizes and shapes and be made of different materials, but every chair does resemble other chairs in some way. Looking at category membership in this way, we can see that the chair in Figure 9.2a and the chair in Figure 9.2c do have in common that they offer a place to sit, a way to support a person's back, and perhaps a place to rest the arms while sitting.

The idea of family resemblance has led psychologists to propose that categorization is based on determining how similar an object is to some standard representation of a category. We begin considering the idea of comparison to a standard by introducing the prototype approach to categorization.

THE PROTOTYPE APPROACH: FINDING THE AVERAGE CASE

According to the **prototype approach to categorization**, membership in a category is determined by comparing the object to a prototype that represents the category. A **prototype** is a "typical" member of the category.

What is a typical member of a particular category? Eleanor Rosch (1973) proposed that the "typical" prototype is based on an average of members of a category that are commonly experienced. For example, the prototype for the category "birds" might be based on some of the birds you usually see, such as sparrows, robins, and blue jays, but doesn't necessarily look exactly like any one of them. Thus, the prototype is not an actual member of the category but is an "average" representation of the category (Figure 9.3).

Figure 9.3 Three real birds—a sparrow, a robin, and a blue jay—and a "prototype" bird that is the average representation of the category "birds."

Of course, not all birds are like robins, blue jays, or sparrows. Owls, buzzards, and penguins are also birds. Rosch describes these variations within categories as representing differences in typicality. High typicality means that a category member closely resembles the category prototype (it is like a "typical" member of the category). Low typicality means that the category member does not closely resemble a typical member of the category. Rosch (1975a) quantified this idea by presenting subjects with a category title, such as "bird" or "furniture," and a list of about 50 members of the category. The subjects' task was to rate the extent to which each member represented the category title on a 7-point scale, with a rating of 1 meaning that the member is a very good example of what the category is, and a rating of 7 meaning that the member fits poorly within the category or is not a member at all.

Results for some of the objects in two different categories are shown in Figure 9.4. The 1.18 rating for sparrow reflects the fact that most people consider a sparrow to be a good example of a bird (Figure 9.4a). The 4.53 rating for penguin and 6.15 rating for bat reflect the fact that penguins and bats are not considered good examples of birds. Similarly, chair and sofa (rating = 1.04) are considered very good examples of furniture, but mirror (4.39) and telephone (6.68) are poor examples (Figure 9.4b). The idea that a sparrow is a better example of "bird" than a penguin or a bat is not very surprising. But Rosch went beyond this obvious result by doing a series of experiments that demonstrated differences between good and bad examples of a category.

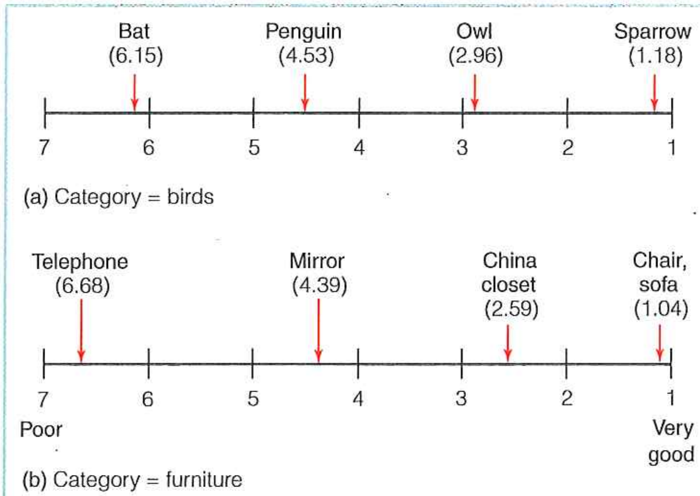


Figure 9.4 Results of Rosch's (1975a) experiment, in which participants judged objects on a scale of 1 (good example of a category) to 7 (poor example): (a) ratings for birds; (b) ratings for furniture. © Cengage Learning

PROTOTYPICAL OBJECTS HAVE HIGH FAMILY RESEMBLANCE How well do good and poor examples of a category compare to other items within the category? The following demonstration is based on an experiment by Rosch and Carolyn Mervis (1975).

DEMONSTRATION
FAMILY RESEMBLANCE

Rosch and Mervis's (1975) instructions were as follows: For each of the following common objects, list as many characteristics and attributes as you can that you feel are common to these objects. For example, common characteristics for bicycles are two wheels, pedals, handlebars, you ride on them, they don't use fuel, and so on. Give yourself about a minute to write down the characteristics for each of the following items:

1. chair
2. sofa
3. mirror
4. telephone

If you responded like Rosch and Mervis's subjects, you assigned many of the same characteristics to chair and sofa. For example, chairs and sofas share the characteristics of having legs, having backs, you sit on them, they can have cushions, and so on. When an item's characteristics have a large amount of overlap with the characteristics of many other items in a category, this means that the family resemblance of these items is high. But when we consider mirror and telephone, we find that there is far less overlap, even though they were both classified by Rosch and Mervis as "furniture" (Figure 9.4b). Little overlap with other members of a category means the family resemblance is low.

Rosch and Mervis concluded from their results that there is a strong relationship between family resemblance and prototypicality. Thus, good examples of the category "furniture," such as chair and sofa, share many attributes with other members of this category; poor examples, like mirror and telephone, do not. In addition to the connection between prototypicality and family resemblance, researchers have determined the following connections between prototypicality and behavior.

STATEMENTS ABOUT PROTOTYPICAL OBJECTS ARE VERIFIED RAPIDLY Edward Smith and coworkers (1974) used a procedure called the **sentence verification technique** to determine how rapidly people could answer questions about an object's category.

METHOD
SENTENCE VERIFICATION TECHNIQUE

The procedure for the sentence verification technique is simple. Subjects are presented with statements and are asked to answer "yes" if they think the statement is true and "no" if they think it isn't. Try this yourself for the following two statements:

An apple is a fruit.

A pomegranate is a fruit.

When Smith and coworkers (1974) used this technique, they found that subjects responded faster for objects that are high in prototypicality (like apple for the category "fruit") than they did for objects that are low in prototypicality (like pomegranate; Figure 9.5). This ability to judge highly prototypical objects more rapidly is called the **typicality effect**.

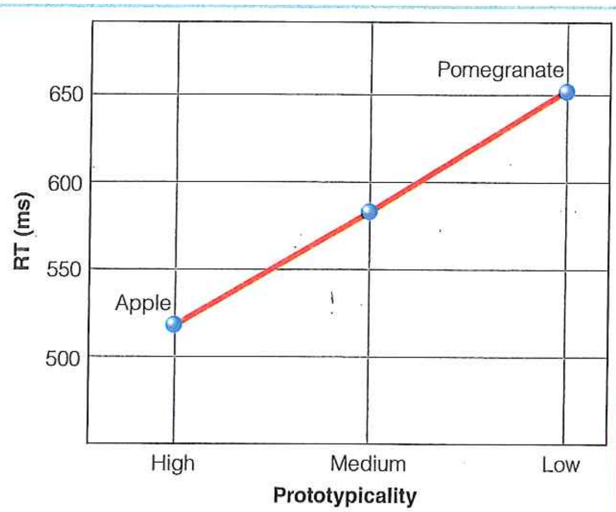


Figure 9.5 Results of E. E. Smith et al.'s (1974) sentence verification experiment. Reaction time (RT) was faster for objects rated higher in prototypicality. © Cengage Learning

PROTOTYPICAL OBJECTS ARE NAMED FIRST When subjects are asked to list as many objects in a category as possible, they tend to list the most prototypical members of the category first (Mervis et al., 1976). Thus, for "birds," sparrow would be named before penguin.

PROTOTYPICAL OBJECTS ARE AFFECTED MORE BY PRIMING Priming occurs when presentation of one stimulus facilitates the response to another stimulus that usually follows closely in time (see Chapter 6, page 170). Rosch (1975b) demonstrated that prototypical members of a category are more affected by a priming stimulus than are nonprototypical members. The procedure for Rosch's experiment is shown in **Figure 9.6**. Subjects first heard the prime, which was the name of a color, such as "green." Two seconds later they saw a pair of colors side by side and indicated, by pressing a key as quickly as possible, whether the two colors were the same or different.

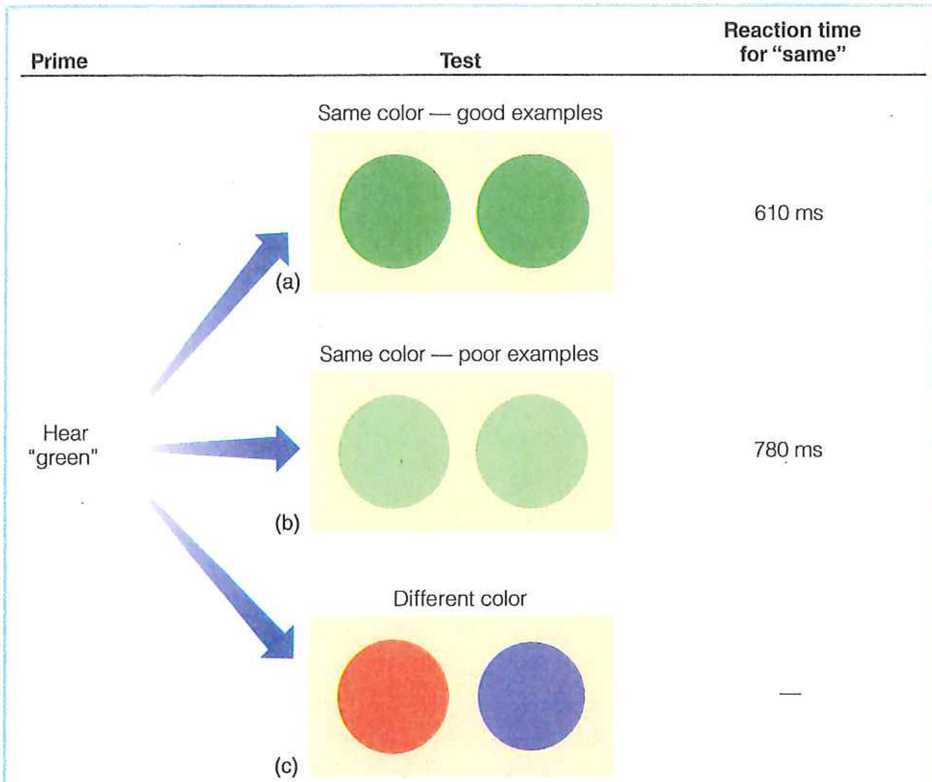


Figure 9.6 Procedure for Rosch's (1975b) priming experiment. Results for the conditions when the test colors were the same are shown on the right. (a) The person's "green" prototype matches the good green but (b) is a poor match for the light green; (c) shows the condition in which colors were different.

The side-by-side colors that subjects saw after hearing the prime were paired in three different ways: (1) colors were the same and were good examples of the category (primary reds, blues, greens, etc.; **Figure 9.6a**); (2) colors were the same but were poor examples of the category (less rich versions of the good colors, such as light blue, light green, etc.; **Figure 9.6b**); (3) colors were different, with the two colors coming from different categories (for example, pairing red with blue; **Figure 9.6c**).

The most important result occurred for the two "same" groups. In this condition, priming resulted in faster "same" judgments for the prototypical (good) colors (reaction time, RT = 610 ms) than for the nonprototypical (poor) colors (RT = 780 ms). Thus, when subjects heard the word *green*, they judged two patches of primary green as being the same more rapidly than two patches of light green.

Rosch explains this result as follows: When subjects hear the word *green*, they imagine a "good" (highly prototypical) green (Figure 9.7a). The principle behind priming is that the prime will facilitate the subjects' response to a stimulus if it contains some of the information needed to respond to the stimulus. This apparently occurs when the good greens are presented in the test (Figure 9.7b), but not when the poor greens are presented (Figure 9.7c). Thus, the results of the priming experiments support the idea that subjects create images of prototypes in response to color names. Table 9.1 summarizes the various ways, previously discussed, that prototypicality affects behavior.

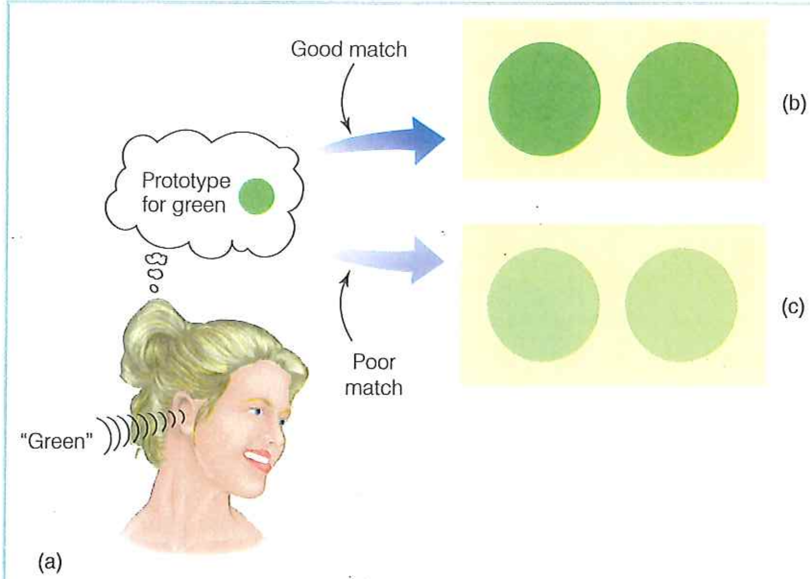


Figure 9.7 How Rosch explains the finding that priming resulted in faster "same" judgments for prototypical colors than for nonprototypical colors.

Table 9.1: Some Effects of Prototypicality

EFFECT	DESCRIPTION	EXPERIMENTAL RESULT
Family resemblance	Things in a category resemble each other in a number of ways.	Higher ratings for high-prototypical items when people rate how "good" a member of the category it is (Rosch, 1975a).
Typicality	People react rapidly to members of a category that are "typical" of the category.	Faster reaction time to statements like "A _______ is a bird" for high-prototypical items (like robin) than for low-prototypical items (like ostrich) (Smith et al., 1974).
Naming	People are more likely to list some objects than others when asked to name objects in a category.	High-prototypical items are named first when people list examples of a category (Mervis et al., 1976).
Priming	Presentation of one stimulus affects responses to a stimulus that follows.	Faster same–different color judgments for high-prototypical items (Rosch, 1975b).

The prototype approach to categorization, and in particular Rosch's pioneering research, represented a great advance over the definitional approach because it provided a wealth of experimental evidence that all items within a category are not the same. Another approach to categorization, called the *exemplar approach,* also takes into account the wide variation among items that belong to a particular category.

THE EXEMPLAR APPROACH: THINKING ABOUT EXAMPLES

The **exemplar approach to categorization**, like the prototype approach, involves determining whether an object is similar to other objects. However, whereas the standard for the prototype approach is a single "average" member of the category, the standard for the exemplar approach involves many examples, each one called an exemplar. **Exemplars** are actual members of the category that a person has encountered in the past. Thus, if a person has encountered sparrows, robins, and blue jays in the past, each of these would be an exemplar for the category "birds."

The exemplar approach can explain many of Rosch's results, which were used to support the prototype approach. For example, the exemplar approach explains the typicality effect (in which reaction times on the sentence verification task are faster for better examples of a category than for poorer examples) by proposing that objects that are like more of the exemplars are classified faster. Thus, a sparrow is similar to many bird exemplars, so it is classified faster than a penguin, which is similar to few bird exemplars. This is basically the same as the idea of family resemblance, described for prototypes, which states that "better" objects will have higher family resemblance.

WHICH APPROACH WORKS BETTER: PROTOTYPES OR EXEMPLARS?

Which approach—prototypes or exemplars—provides a better description of how people use categories? One advantage of the exemplar approach is that by using real examples, it can more easily take into account atypical cases such as flightless birds. Rather than comparing a penguin to an "average" bird, we remember that there are some birds that don't fly. This ability to take into account individual cases means that the exemplar approach doesn't discard information that might be useful later. Thus, penguins, ostriches, and other birds that are not typical can be represented as exemplars, rather than becoming lost in the overall average that creates a prototype. The exemplar approach can also deal more easily with variable categories like games. Although it is difficult to imagine what the prototype might be for a category that contains football, computer games, solitaire, marbles, and golf, the exemplar approach requires only that we remember some of these varying examples.

Based on the results of a number of research studies, some researchers have concluded that people may use both approaches. It has been proposed that as we initially learn about a category, we may average exemplars into a prototype; then, later in learning, some of the exemplar information becomes stronger (Keri et al., 2002; Malt, 1989). Thus, early in learning, we would be poor at taking into account "exceptions" such as ostriches or penguins, but later, exemplars for these cases would be added to the category (Minda & Smith, 2001; Smith & Minda, 2000).

Other research indicates that the exemplar approach may work better for small categories, such as "U.S. presidents" or "mountains taller than 15,000 feet," and the prototype approach may work better for larger categories, such as "birds" or "automobiles." We can describe this blending of prototypes and exemplars in commonsense terms with the following example: We know generally what cats are (the prototype), but we know our own specific cat the best (an exemplar; Minda & Smith, 2001).

Is There a Psychologically "Privileged" Level of Categories?

As we have considered the prototype and exemplar approaches, we have used examples of categories such as "furniture," which contains members such as beds, chairs, and tables. But, as you can see in **Figure 9.8a**, the category "chairs" can contain smaller categories such

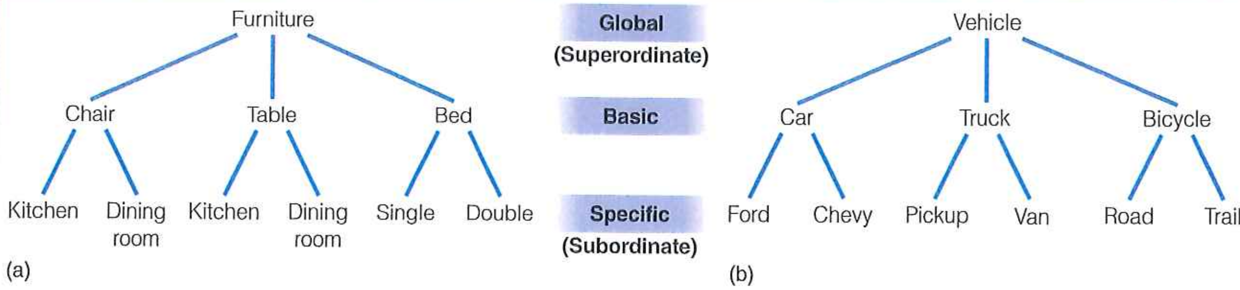


Figure 9.8 Levels of categories for (a) furniture and (b) vehicle. Rosch provided evidence for the idea that the basic level is "psychologically privileged." © Cengage Learning

as kitchen chairs and dining room chairs. This kind of organization, in which larger, more general categories are divided into smaller, more specific categories, creating a number of levels of categories, is called a **hierarchical organization**.

One question cognitive psychologists have asked about this organization is whether there is a "basic" level that is more psychologically important or "privileged" than other levels. The research we will describe indicates that although it is possible to demonstrate that there is a basic level of categories with special psychological properties, the basic level may not be the same for everyone. We begin by describing Rosch's research, in which she introduced the idea of basic level categories.

ROSCH'S APPROACH: WHAT'S SPECIAL ABOUT BASIC LEVEL CATEGORIES?

Rosch's research starts with the observation that there are different levels of categories, ranging from general (like "furniture") to specific (like "kitchen table"), as shown in **Figure 9.8**, and that when people use categories, they tend to focus on one of these levels. She distinguished three levels of categories: the **superordinate level**, which we will call the **global level** (for example, "furniture"); the **basic level** (for example, "table"); and the **subordinate level**, which we will call the **specific level** (for example, "kitchen table"). The following demonstration illustrates some characteristics of the different levels.

DEMONSTRATION
LISTING COMMON FEATURES

This demonstration is a repeat of the task you did in the Family Resemblance demonstration on page 250, but with different categories. For the following categories, list as many features as you can that would be common to all or most of the objects in the category. For example, for "table" you might list "has legs."

1. furniture
2. table
3. kitchen table

If you responded like the subjects in the Rosch and coworkers' (1976) experiment, who were given the same task, you listed only a few features that were common to all furniture, but many features that were shared by all tables and by all kitchen tables. Rosch's subjects listed an average of 3 common features for the global level category "furniture," 9 for basic level categories such as "table," and 10.3 for specific level categories such as "kitchen table" (**Figure 9.9**).

Rosch proposed that the basic level is psychologically special because going above it (to global) results in a large loss of information (9 features at the basic vs. 3 at the global level) and going below it (to specific) results in little gain of information (9 features vs. 10.3). Here is another demonstration that is relevant to the idea of a basic level.

LEVEL	EXAMPLE	NUMBER OF COMMON FEATURES	
Global	Furniture	3	Lose a lot of information.
Basic	Table	9	Gain just a little information.
Specific	Kitchen table	10.3	

Figure 9.9 Category levels, examples of each level, and average number of common features listed by participants in Rosch et al.'s (1976) experiment.

DEMONSTRATION

NAMING THINGS

Look at Figure 9.10 and, as quickly as possible, write down or say a word that identifies each picture.

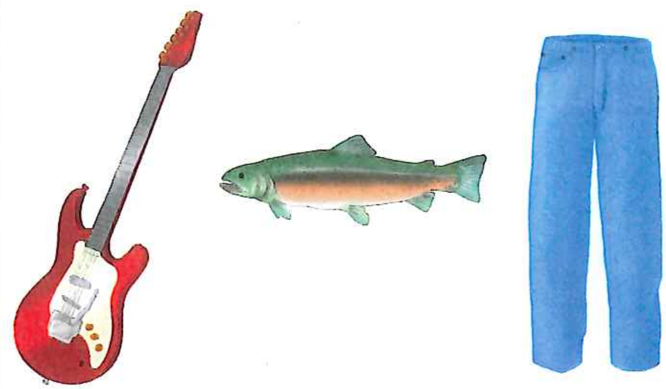


Figure 9.10 Stimuli for the Naming Things demonstration.

What names did you assign to each object? When Rosch and coworkers (1976) did a similar experiment, they found that people tended to pick a basic level name. They said *guitar* (basic level) rather than *musical instrument* (global) or *rock guitar* (specific), *fish* rather than *animal* or *trout*, and *pants* rather than *clothing* or *jeans*.

In another experiment, Rosch and coworkers showed subjects a category label, such as *car* or *vehicle*, and then, after a brief delay, presented a picture. The subjects' task was to indicate, as rapidly as possible, whether the picture was a member of the category. The results showed that they accomplished this task more rapidly for basic level categories (such as car) than for global level categories (such as vehicle). Thus, they would respond "yes" more rapidly when the picture of an automobile was preceded by the word *car* than when the picture was preceded by the word *vehicle*.

HOW KNOWLEDGE CAN AFFECT CATEGORIZATION

Rosch's experiments, which were carried out on college undergraduates, showed that there is a category level, which she called "basic," that reflects college undergraduates' everyday experience. This has been demonstrated by many researchers in addition to Rosch. Thus, when J. D. Coley and coworkers (1997) asked Northwestern University undergraduates to name, as specifically as possible, 44 different plants on a walk around campus, 75 percent of the responses used labels like "tree," rather than more specific labels like "oak."

But instead of asking college undergraduates to name plants, what if Coley had taken a group of horticulturalists around campus? Do you think they would have said "tree" or "oak"? An experiment by James Tanaka and Marjorie Taylor (1991) asked a similar question for birds. They asked bird experts and nonexperts to name pictures of objects. There were objects from many different categories (tools, clothing, flowers, etc.), but Tanaka and Taylor were interested in how the subjects responded to the four bird pictures.

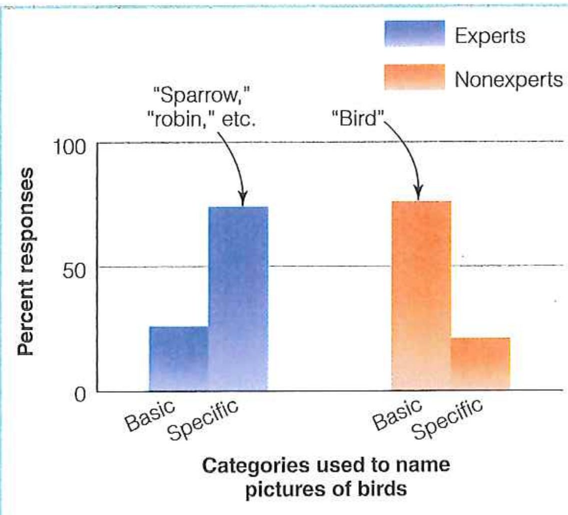


Figure 9.11 Results of Tanaka and Taylor's (1991) "expert" experiment. Experts (left pair of bars) used more specific categories to name birds, whereas nonexperts (right pair of bars) used more basic categories.

The results (Figure 9.11) show that the experts responded by specifying the birds' species (robin, sparrow, jay, or cardinal), but the nonexperts responded by saying "bird." Apparently the experts had learned to pay attention to features of birds that nonexperts were unaware of. Thus, in order to fully understand how people categorize objects, we need to consider not only the properties of the objects but also the learning and experience of the people perceiving those objects (also see Johnson & Mervis, 1997).

From the result of Tanaka's bird experiment, we can guess that a horticulturist walking around campus would be likely to label plants more specifically than people who had little specific knowledge about plants. In fact, members of the Guatemalan Itzaj culture, who live in close contact with their natural environment, call an oak tree an "oak," not a "tree" (Coley et al., 1997).

Thus, the level that is "special"—meaning that people tend to focus on it—is not the same for everyone. Generally, people with more expertise and familiarity with a particular category tend to focus on more specific information that Rosch associated with the specific level. This result isn't surprising, because our ability to categorize is learned from experience; it depends on which objects we typically encounter and what characteristics of objects we pay attention to.

TEST YOURSELF 9.1

1. Why is the use of categories so important for our day-to-day functioning?
2. Describe the definitional approach to categories. Why does it initially seem like a good way of thinking about categories, but then become troublesome when we consider the kinds of objects that can make up a category?
3. What is the prototype approach? What experiments did Rosch do that demonstrated connections between prototypicality and behavior?
4. What is the exemplar approach to categorization? How does it differ from the prototype approach, and how might the two approaches work together?
5. What does it mean to say that there are different levels within a category? What arguments did Rosch present to support the idea that one of these levels is "privileged"? How has research on categorization by experts led to modifications of Rosch's ideas about which category is "basic" or "privileged"?

Representing Relationships Between Categories: Semantic Networks

We have seen that categories can be arranged in a hierarchy of levels, from global (at the top) to specific (at the bottom). In this section, our main concern is to explain an approach to categories that focuses on how categories or concepts are organized in the mind. The approach we will be describing, called the **semantic network approach**, proposes that concepts are arranged in networks.

INTRODUCTION TO SEMANTIC NETWORKS: COLLINS AND QUILLIAN'S HIERARCHICAL MODEL

One of the first semantic network models was based on the pioneering work of Ross Quillian (1967, 1969), whose goal was to develop a computer model of human memory. We will describe Quillian's approach by looking at a simplified version of his model proposed by Allan Collins and Quillian (1969).

Figure 9.12 shows Collins and Quillian's network. The network consists of nodes that are connected by links. Each node represents a category or concept, and concepts are placed in the network so that related concepts are connected. In addition, a number of properties are indicated for each concept.

The links connecting the concepts indicate that they are related to each other in the mind. Thus, the model shown in Figure 9.12 indicates that there is an association in the

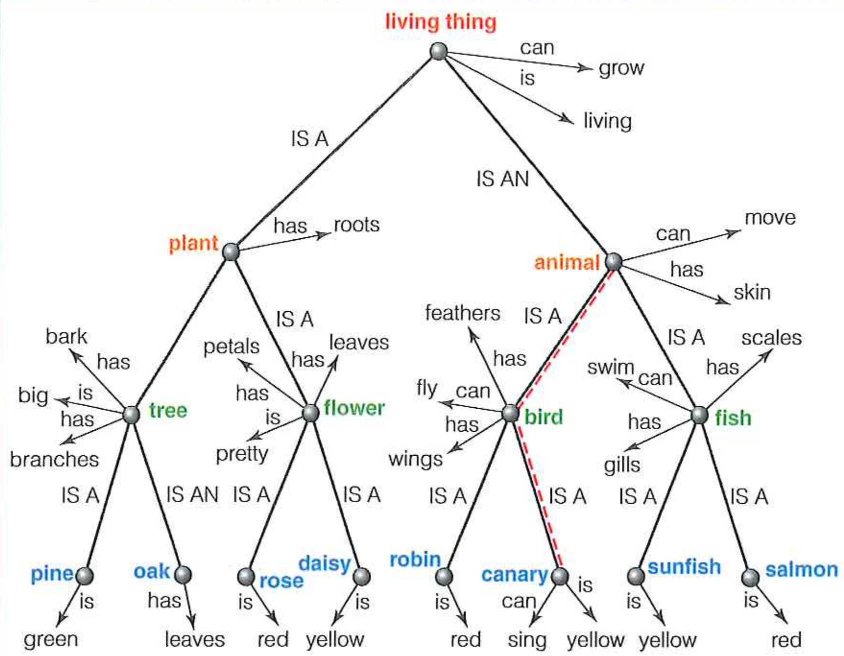


Figure 9.12 Collins and Quillian's (1969) semantic network. Specific concepts are indicated in color. Properties of concepts are indicated at the nodes for each concept. Additional properties of a concept can be determined by moving up the network, along the lines connecting the concepts. For example, moving from "canary" up to "bird" indicates that canaries have feathers and wings and can fly. The dashed lines indicate the distance in the network from canary to bird and from bird to animal. *(Source: Adapted from T. T. Rogers & J. L. McClelland,* Semantic cognition: A parallel distributed processing approach, *Cambridge, MA: MIT Press, 2004.)*

mind between *canary* and *bird*, and between *bird* and *animal* (indicated by the dashes along the links in **Figure 9.12**). It is a **hierarchical model**, because it consists of levels arranged so that more specific concepts, such as "canary" and "salmon," are at the bottom, and more general concepts are at higher levels.

We can illustrate how this network works, and how it proposes that knowledge about concepts is organized in the mind, by considering how we would retrieve the properties of canaries from the network. We start by entering the network at the concept node for "canary." At this node, we obtain the information that a canary can sing and is yellow. To access more information about "canary," we move up the link and learn that a canary is a bird and that a bird has wings, can fly, and has feathers. Moving up another level, we find that a canary is also an animal, which has skin and can move, and finally we reach the level of living things, which tells us it can grow and is living.

You might wonder why we have to travel from "canary" to "bird" to find out that a canary can fly. That information could have been placed at the canary node, and then we would know it right away. But Collins and Quillian proposed that including "can fly" at the node for every bird (canary, robin, vulture, etc.) was inefficient and would use up too much storage space. Thus, instead of indicating the properties "can fly" and "has feathers" for every kind of bird, these properties are placed at the node for "bird" because this property holds for most birds. This way of storing shared properties just once at a higher-level node is called **cognitive economy**.

Although cognitive economy makes the network more efficient, it does create a problem because not all birds fly. To deal with this problem while still achieving the advantages of cognitive economy, Collins and Quillian added exceptions at lower nodes. For example, the node for "ostrich," which is not shown in this network, would indicate the property "can't fly."

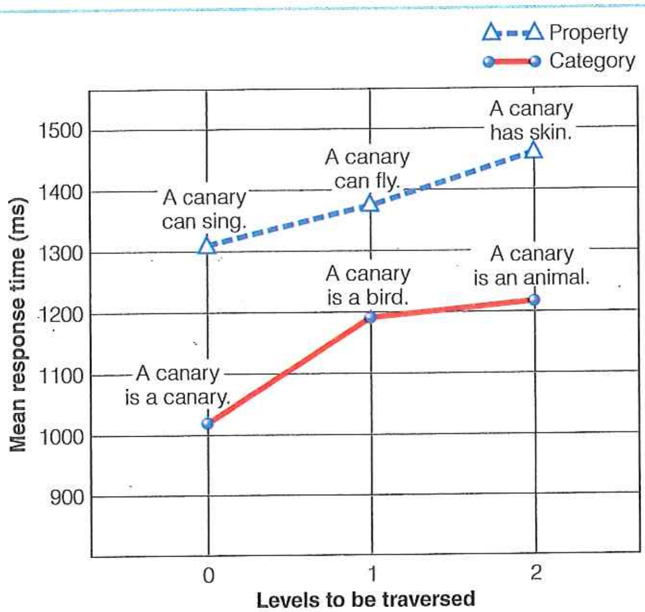


Figure 9.13 Results of Collins and Quillian's (1969) experiment that measured reaction times to statements that involved traversing different distances in the network. Greater distances are associated with longer reaction times, both when verifying statements about properties of canaries (top) and about categories of which the canary is a member (bottom). *(Source: A. M. Collins et al., Retrieval time from semantic memory,* Journal of Verbal Learning and Verbal Behavior, *8, 240–247, Fig. 2, 1969.)*

How do the elements in this semantic network correspond to the actual operation of the brain? Remember from our discussion of models in cognitive psychology in Chapter 1 (page 17) that elements of models do not necessarily correspond to specific structures in the brain. Thus, the links and nodes we have been describing do not necessarily correspond to specific nerve fibers or locations in the brain. This model, and other network models we will be describing, are concerned with how concepts and their properties are associated in the mind. In fact, physiological findings relevant to these models, such as neurons that respond best to specific stimuli (see page 35), were not available until many years after these models were proposed.

Putting aside any possible connection between the network and actual physiology, we can ask how accurately Collins and Quillian's model represents how concepts are organized in the mind. The beauty of the network's hierarchical organization, in which general concepts are at the top and specific ones at the bottom, is that it results in the testable prediction that the time it takes for a person to retrieve information about a concept should be determined by the distance that must be traveled through the network. Thus, the model predicts that when using the sentence verification technique, in which subjects are asked to answer "yes" or "no" to statements about concepts (see Method: Sentence Verification Technique, page 250), it should take longer to answer "yes" to the statement "A canary is an animal" than to "A canary is a bird." This prediction follows from the fact, indicated by the dashed lines in **Figure 9.12**, that it is necessary to travel along two links to get from "canary" to "animal" but only one to get to "bird."

Collins and Quillian (1969) tested this prediction by measuring the reaction time to a number of different statements and obtained the results shown in **Figure 9.13**. As predicted, statements that required further travel from "canary" resulted in longer reaction times.

Another property of the theory, which leads to further predictions, is spreading activation. **Spreading activation** is activity that spreads out along any link that is connected to an activated node. For example, moving through the network from "robin" to "bird" activates the node at "bird" and the link we use to get from robin to bird, as indicated by the colored arrow in **Figure 9.14**. But according to the idea of spreading activation, this activation also spreads to other nodes in the network, as indicated by the dashed lines. Thus, activating the canary-to-bird pathway activates additional concepts that are connected to "bird," such as "animal" and other types of birds. The result of this spreading activation is that the additional concepts that receive this activation become "primed" and so can be retrieved more easily from memory.

The idea that spreading activation can influence priming was studied by David Meyer and Roger Schvaneveldt (1971) in a paper published shortly after Collins and Quillian's model was proposed. They used a method called the *lexical decision task.*

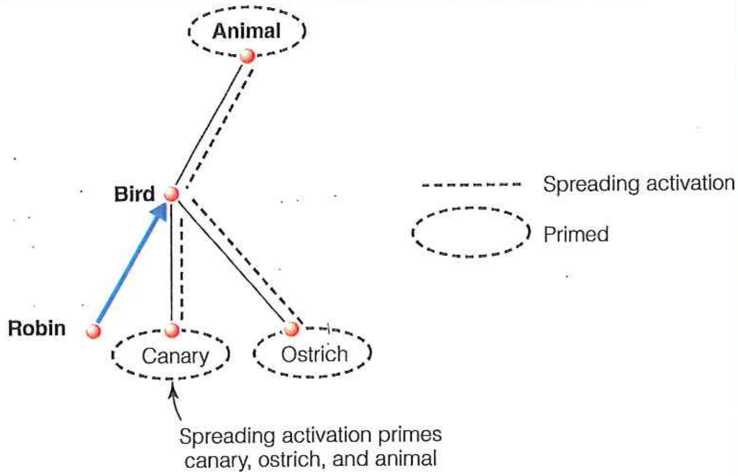


Figure 9.14 How activation can spread through a network as a person searches from "robin" to "bird" (blue arrow). The dashed lines indicate activation that is spreading from the activated bird node. Circled concepts, which have become primed, are easier to retrieve from memory because of the spreading activation.

METHOD
LEXICAL DECISION TASK

In the **lexical decision task**, subjects read stimuli, some of which are words and some of which are not words. Their task is to indicate as quickly as possible whether each entry is a word or a nonword. For example, the correct responses for *bloog* would be "no" and for *bloat* would be "yes."

Meyer and Schvaneveldt used a variation of the lexical decision task by presenting subjects with pairs of words, one above the other, as shown below:

Pair 1:	Pair 2:	Pair 3:	Pair 4:
Fundt	Bleem	Chair	Bread
Glurb	Dress	Money	Wheat

The subjects' task was to press, as quickly as possible, the "yes" key when both items were words or the "no" key when at least one item in the pair was a nonword. Thus, pairs 1 and 2 would require a "no" response, and pairs 3 and 4 would require a "yes" response.

The key variable in this experiment was the association between the pairs of real words. In some trials, the words were closely associated (like bread and wheat), and in some trials they were weakly associated (chair and money). The result, shown in Figure 9.15, was that reaction time was faster when the two words were associated. Meyer and Schvaneveldt proposed that this might have occurred because retrieving one word from memory triggered a spread of activation to other nearby locations in a network. Because more activation would spread to words that were related, the response to the related words was faster than the response to unrelated words.

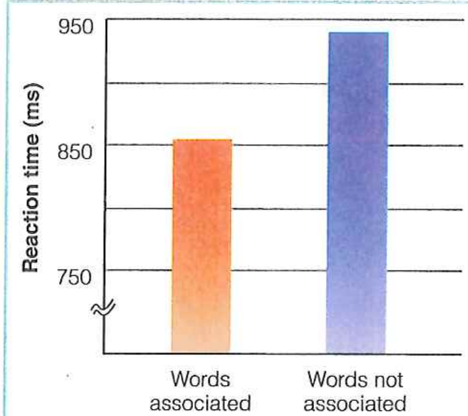


Figure 9.15 Results of Meyer and Schvaneveldt's (1971) experiment. Participants responded faster for words that were more closely associated (left bar). © Cengage Learning

CRITICISM OF THE COLLINS AND QUILLIAN MODEL

Although Collins and Quillian's model was supported by the results of a number of experiments, such as their reaction time experiment (Figure 9.13) and Meyer and Schvaneveldt's priming experiment, it didn't take long for other researchers to call the theory into question. They pointed out that the theory couldn't explain the typicality effect, in which reaction times for statements about an object are faster for more typical members of a category than for less typical members (see page 250; Rips et al., 1973). Thus, the statement "A canary is a bird" is verified more quickly than "An ostrich is a bird," but the model predicts equally fast reaction times because "canary" and "ostrich" are both one node away from "bird."

Researchers also questioned the concept of cognitive economy because of evidence that people may, in fact, store specific properties of concepts (like "has wings" for "canary") right at the node for that concept (Conrad, 1972). In addition, Lance Rips and coworkers (1973) obtained sentence verification results such as the following:

A pig is a mammal. RT = 1,476 ms

A pig is an animal. RT = 1,268 ms

"A pig is an animal" is verified more quickly, but as we can see from the network in Figure 9.16, the Collins and Quillian model predicts that "A pig is a mammal" should be verified more quickly because a link leads directly from "pig" to "mammal," but we need to travel one link past the "mammal" node to get to "animal." Sentence verification results such as these, plus the other criticisms of the theory, led researchers to look for alternative ways to using networks to describe how concepts are organized (Glass & Holyoak, 1975; Murphy et al., 2012) and eventually, in the 1980s, to the proposal of a new approach to networks, called *connectionism*.

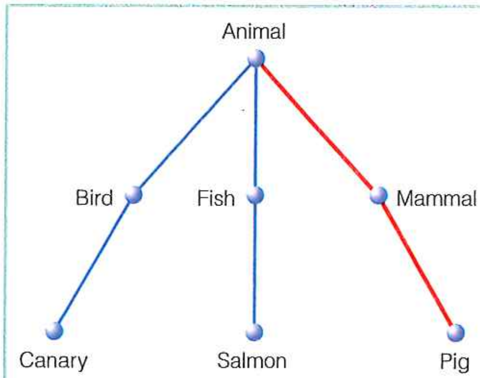


Figure 9.16 Semantic network that shows that "pig" is closer to "mammal" than to "animal." © Cengage Learning

Representing Concepts in Networks: The Connectionist Approach

Criticism of semantic networks, combined with advances in understanding how information is represented in the brain, led to the emergence of a new approach to explaining how knowledge is represented in the mind. In two volumes, both titled *Parallel Distributed Processing: Explorations in the Microstructure of Cognition* (McClelland & Rumelhart, 1986; Rumelhart & McClelland, 1986), James McClelland and David Rumelhart proposed a new approach called *connectionism*. This approach has gained favor among many researchers because (1) it is based on how information is represented in the brain; and (2) it can explain a number of findings, including how concepts are learned and how damage to the brain affects people's knowledge about concepts.

WHAT IS A CONNECTIONIST MODEL?

Connectionism is an approach to creating computer models for representing cognitive processes. We will focus on connectionist models designed to represent concepts. These models are also called **parallel distributed processing (PDP)** models because, as we will see shortly, they propose that concepts are represented by activity that is distributed across a network.

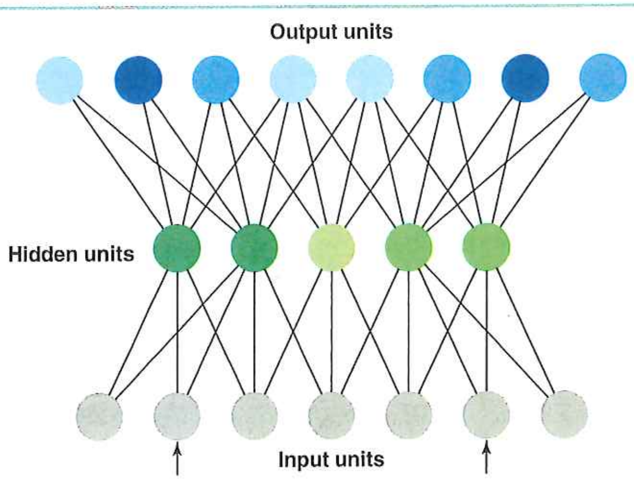


Figure 9.17 A parallel distributed processing (PDP) network showing input units, hidden units, and output units. Incoming stimuli, indicated by the arrows, activate the input units, and signals travel through the network, activating the hidden and output units. Activity of units is indicated by shading, with darker shading indicating more activity. The patterns of activity that occur in the hidden and output units are determined both by the initial activity of the input units and by the connection weights that determine how strongly a unit will be activated by incoming activity. Connection weights are not shown in this figure.

An example of a simple **connectionist network** is shown in Figure 9.17. The circles are **units**. These units are inspired by the neurons found in the brain. As we will see, concepts and their properties are represented in the network by the pattern of activity in these units.

The lines are connections that transfer information between units, and are roughly equivalent to axons in the brain. Like neurons, some units can be activated by stimuli from the environment, and some can be activated by signals received from other units. Units activated by stimuli from the environment (or stimuli presented by the experimenter) are **input units**. In the simple network illustrated here, input units send signals to **hidden units**, which send signals to **output units**.

An additional feature of a connectionist network is connection weights. A **connection weight** determines how signals sent from one unit either increase or decrease the activity of the next unit. These weights correspond to what happens at a synapse that transmits signals from one neuron to another (Figure 2.5, page 30). In Chapter 7 we saw that some synapses can transmit signals more strongly than others and therefore cause a high firing rate in the next neuron (Figure 7.14, page 194). Other synapses can cause a decrease in the firing rate of the next neuron. Connection weights in a connectionist network operate in the same way. High connection weights result in a strong tendency to excite the next unit, lower weights cause less excitation, and negative weights can decrease excitation or inhibit activation of the receiving unit. Activation of units in a network therefore depends on two things: (1) the signal that originates in the input units and (2) the connection weights throughout the network.

In the network of Figure 9.17, two of the input units are receiving stimuli. Activation of each of the hidden and output units is indicated by the shading, with darker shading indicating more activation. These differences in activation, and the pattern of activity they create, are responsible for a basic principle of connectionism: A stimulus presented to the input units is represented by the *pattern of activity* that is *distributed across the other units*. If this sounds familiar, it is because it is similar to the distributed representations in the brain we described

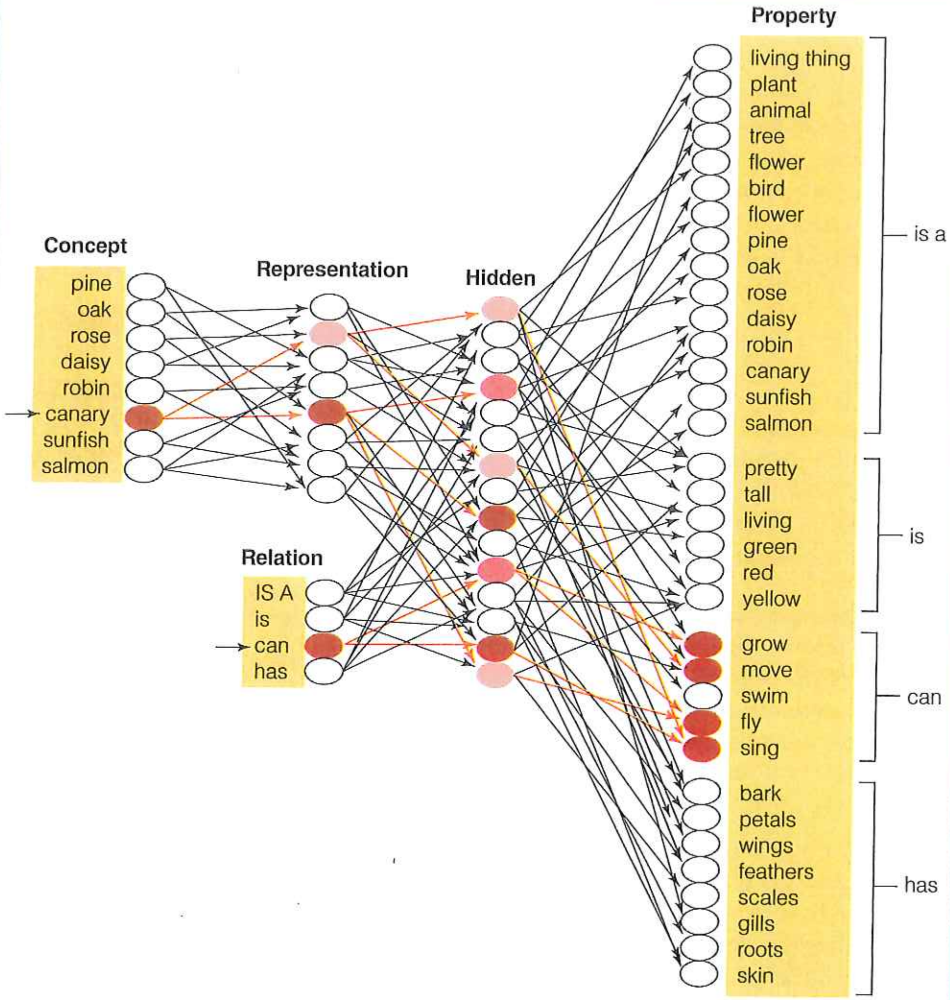


Figure 9.18 A connectionist network. Activation of an item unit ("canary") and a relation unit (*can*) causes activity to travel through the network that eventually results in activation of the property units *grow, move, fly,* and *sing*, associated with "canary can." Shading indicates the activity of the units, with darker shading indicating more activity. Note that only a few of the units and connections that would be activated by "canary" and *can* are shown as being activated. In the actual network, many more units and connections would be activated. *(Source: T. T. Rogers & J. L. McClelland,* Semantic cognition: A parallel distributed processing approach, *p. 56, Figure 2.2. Copyright © 2004 Massachusetts Institute of Technology.)*

in Chapters 2 (page 44), 5 (page 145), and 7 (page 195). Now that we have used the simple network in Figure 9.17 to introduce the basic principles of connectionist networks, we will consider how some specific concepts are represented in the more complex connectionist network shown in Figure 9.18.

HOW ARE CONCEPTS REPRESENTED IN A CONNECTIONIST NETWORK?

The model in Figure 9.18 was described by James McClelland and Timothy Rogers (2003) to show how different concepts and their properties can be represented in a connectionist network. Although this model is more complex than the one in Figure 9.17, it has similar components: units, links, and connection weights (although the connection weights are not shown).

REPRESENTING A CANARY Let's first compare this model to the Collins and Quillian hierarchical model in Figure 9.12. The first thing to notice is that both models are dealing with the same concepts. Specific concepts, such as "canary" and "salmon," shown in blue in Figure 9.12, are represented on the far left as concept items in Figure 9.18. Also notice that the properties of the concepts are indicated in both networks by the following four relation statements: "is a" (A canary is a bird); "is" (A canary is yellow); "can" (A canary can fly); and "has" (A canary has wings). But whereas the hierarchical network in Figure 9.12 represents these properties at the network's nodes, the connectionist network in Figure 9.18 indicates these properties by activity in the attribute units on the far right, and also by the pattern of activity in the representation and hidden units in the middle of the network.

Let's consider what happens when we activate the concept "canary" and a relation unit, *can*. As shown in Figure 9.18, the activation from "canary" and *can* spreads along the connections so that some of the representation units are activated and some of the hidden units are activated. The connection weights, which are not shown, cause some units to be activated strongly and others more weakly, as indicated by the shading of the units. If the network is working properly, this activation in the hidden units activates the *grow, move, fly*, and *sing* property units. What's important about all of this activity is that the concept "canary" is represented by the pattern of activity in all of the units in the network.

TRAINING A NETWORK According to the above description, the answer to "A canary is a . . ." is represented in the network by activation of the property units plus the pattern of activation of the network's representation and hidden units. But according to connectionism, a connectionist network has to be trained in order for this result to occur. This training involves adjusting the network's connection weights. To understand how this happens, let's consider what would happen if we stimulate the units "canary" and *can* before the network in Figure 9.18 has been trained to accurately represent "canary."

In our untrained network, stimulating the "canary" and *can* units sends activity to the representation units and to the hidden units. The effect of this activation on each unit depends on the connection weights between the units. Let's assume that in our untrained network, all of the connection weights are 1.0. If all of the connection weights are the same, then many of the units in the network would be activated by "canary" and *can*, including many incorrect property units like *daisy, tall*, and *green*.

For the network to operate properly, the connection weights have to be adjusted so that activating the concept unit "canary" and the relation unit *can* only activates the property units *grow, move, fly*, and *sing*. This adjustment of weights is achieved by a learning process. The learning process occurs when the erroneous responses in the property units cause an **error signal** to be sent back through the network, by a process called **back propagation** (since the signals are being sent *backward* in the network starting from the property units). The error signals that are sent back to the hidden units and the representation units provide information about how the connection weights should be adjusted so that the correct property units will be activated.

To explain the idea behind activation and back propagation, let's consider a behavioral example. A young child is watching a robin sitting on a branch, when suddenly the robin flies away. This simple observation, which strengthens the association between "robin" and *can fly*, would involve activation. But if the child were to see a canary and say "robin," the child's parent might correct her and say "That is a canary" and "Robins have red breasts." The information provided by the parent is similar to the idea of feedback provided by back propagation.

Thus, a child's learning about concepts begins with little information and some incorrect ideas, which are slowly modified in response both to observation of the environment and to feedback from others. Similarly, the connectionist network's learning about concepts begins with incorrect connection weights, which are slowly modified in response to error signals. In this way, the network slowly learns that things that look like birds can fly, things that look like fish can swim, and things that look like trees are places where robins and other birds might perch.

The connectionist network's learning process therefore consists of initially weak and undifferentiated activation of property units, with many errors (for example, the input "canary" causing activation of the property unit *tall*). Error signals are then sent back through the network, which result in changes in connection weights so the next activation of "canary" results in a new activation pattern. Each learning experience causes only a small change in the connection weights, but after many repetitions, the network assigns the correct properties to "canary."

Although this "educated" network might work well for canaries, what happens when a robin flies by and alights on the branch of a pine tree? To be useful, this network needs to be able to represent not just canaries but also robins and pine trees. Thus, to create a network that can represent many different concepts, the network is not trained just on "canary." Instead, presentations of "canary" are interleaved with presentations of "robin," "pine tree," and so on, with small changes in connection weights made after each presentation.

We can appreciate how this learning process occurs over many trials by looking at the results of a computer simulation (McClelland & Rogers, 2003). The network in **Figure 9.18** was presented with a number of different concepts and relation statements, one after another, and the activity of the units and connection weights between units were calculated by the computer. **Figure 9.19** indicates the activation of the eight representation units in response to the concepts "canary," "rose," and "daisy." At the beginning of the process, the experimenter set the connection weights so that activity was about the same in each unit (Learning trials = 0). This corresponds to the initially weak and undifferentiated activation we discussed earlier.

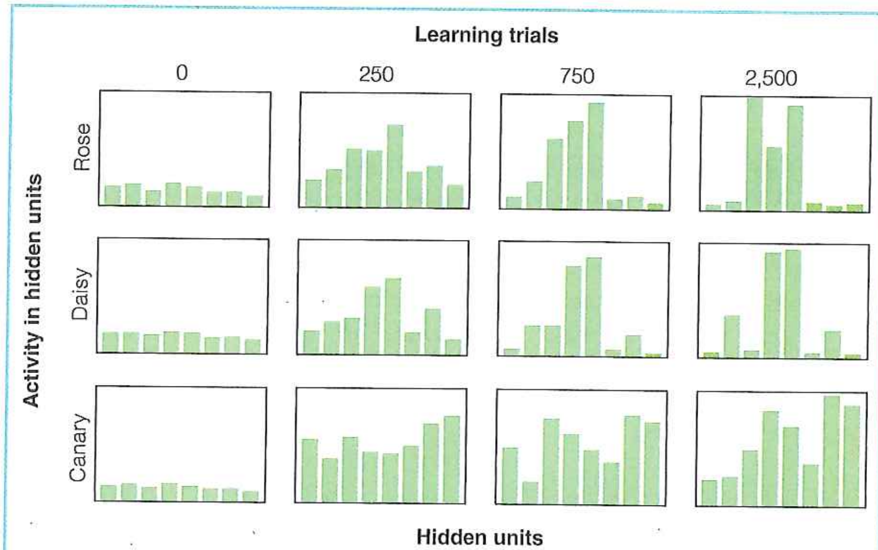


Figure 9.19 Learning in a connectionist network. Bars represent activity in the eight representation units. Notice how the pattern of activation changes as learning progresses. *(Source: Adapted from J. L. McClelland & T. T. Rogers, The parallel-distributed processing approach to semantic cognition,* Nature Reviews Neuroscience, *4, 310–320, 2003.)*

As learning progressed, with each concept being presented one after another and the computer changing the weights just slightly after each trial in response to error signals, the patterns became adjusted, so by Trial 250, the patterns for "canary" and "daisy" begin to look different. By Trial 2,500, it is easy to tell the difference between the patterns for "canary" and "daisy," while the two flowers, "daisy" and "rose," have similar but slightly different patterns.

Although our description has been based on one particular connectionist network, most networks have similar properties. Connectionist networks are created by a learning process that shapes the networks so information about each concept is contained in the distributed pattern of activity across a number of units.

Notice how different this operation of the connectionist network is from the operation of Collins and Quillian's hierarchical network, in which concepts and their properties are represented by activation of different nodes. Representation in a connectionist network is far more complex, involving many more units for each concept, but it is also much more like what happens in the brain.

Because of the resemblance between connectionist networks and the brain, and the fact that connectionist networks have been developed that can simulate normal cognitive functioning for processes such as language processing, memory, and cognitive development (Rogers & McClelland, 2004; Seidenberg & Zevin, 2006), many researchers believe that the idea that knowledge is represented by distributed activity holds great promise. The following results also support the idea of connectionism:

1. *The operation of connectionist networks is not totally disrupted by damage.* Because information in the network is distributed across many units, damage to the system does not completely disrupt its operation. This property, in which disruption of performance occurs only gradually as parts of the system are damaged, is called **graceful degradation**. It is similar to what often happens in actual cases of brain damage, in which damage to the brain causes only a partial loss of functioning. Some researchers have suggested that studying the way networks respond to damage may suggest strategies for rehabilitation of human patients (Farah et al., 1993; Hinton & Shallice, 1991; Olson & Humphreys, 1997; Plaut, 1996).
2. *Connectionist networks can explain generalization of learning.* Because similar concepts have similar patterns, training a system to recognize the properties of one concept (such as "canary") also provides information about other, related concepts (such as "robin" or "sparrow"). This is similar to the way we actually learn about concepts because learning about canaries enables us to predict properties of different types of birds we've never seen (see McClelland et al., 1995).

While active research on connectionism continues in many laboratories, some researchers point out that there are limits to what connectionist networks can explain. Whatever the final verdict on connectionism, this approach has stimulated a great deal of research, some of which has added to our understanding of both normal cognition and how brain damage affects cognition. In the next section we will focus even more directly on the brain by considering neuropsychological and brain imaging research on how concepts are represented in the brain.

The Representation of Concepts in the Brain

We began the chapter by considering some ideas about how categories are represented in the mind, focusing on behavioral experiments testing the ideas of prototypes and exemplars. We then considered two approaches based on the idea of networks: Collins and Quillian's semantic network theory and the connectionist approach.

The idea that concepts can be represented by networks is an approach that takes us closer to our description from Chapter 2 of how representations in the brain are based on activity in areas specialized to process information about specific stimuli such as faces, places, and bodies, and also on activity distributed throughout many interconnected structures in the brain.

We will now introduce some ideas about how concepts are represented in the brain by describing studies of brain-damaged patients and brain imaging experiments on normal subjects. In doing so, we will describe four different proposals for how concepts are represented in the brain.

THE SENSORY-FUNCTIONAL HYPOTHESIS

In one of the classic papers in neuropsychology, Elizabeth Warrington and Tim Shallice (1984) reported on four patients who had suffered memory loss from encephalitis. These patients had a **category-specific memory impairment**—an impairment in which they had lost the ability to identify one type of object but retained the ability to identify other types of objects. Specifically, these patients were able to identify nonanimals, like furniture and tools, as well as fruits and vegetables, but had impaired ability to identify living animals (**Figure 9.20**). (As we discuss various cases below, we will use the term *artifacts* to refer to nonliving things, which would include furniture and tools.)

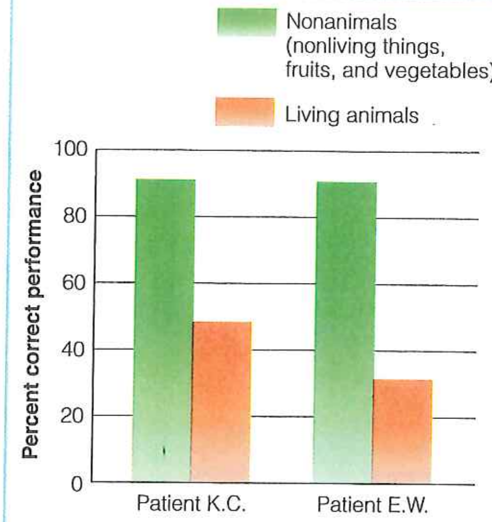


Figure 9.20 Performance on a naming task for patients K.C. and E.W., both of whom had category-specific memory impairment. They were able to correctly name pictures of nonliving things (such as car and table) and fruits and vegetables (such as tomato and pear), but performed poorly when asked to name pictures of animals. *(Source: B. Z. Mahon & A. Caramazza, Concepts and categories: A cognitive neuropsychological perspective,*, Annual Review of Psychology, 60, *27–51, Figure 1, 2009.)*

To explain why this selective impairment occurred, Warrington and Shallice considered properties that people use to distinguish between artifacts and living things. They noted that distinguishing living things depends on perceiving their sensory features. For example, distinguishing between a tiger and a leopard depends on perceiving stripes and spots. Artifacts, in contrast, are more likely to be distinguished by their function. For example, a screwdriver, chisel, and hammer are all tools but are used for different purposes (turning screws, scraping, and pounding nails).

The observation that living things are distinguished by sensory properties and artifacts by functions led to the **sensory-functional (S-F) hypothesis**, which states that our ability to differentiate living things and artifacts depends on a semantic memory system that distinguishes sensory attributes and a system that distinguishes function.

While the S-F hypothesis explained the behavior of Warrington and Shallice's patients, plus dozens of others studied by other researchers, cases were reported that couldn't be explained by this hypothesis. For example, the S-F hypothesis predicts that a patient who can't identify living things should have impaired sensory abilities. However, Caramazza and Shelton (1998) reported a patient who couldn't identify living things and had impaired sensory abilities (as the S-F hypothesis would predict), but who also had impaired functional ability (which the S-F hypothesis wouldn't predict.) The S-F hypothesis also predicts that a person who can't identify artifacts should have impaired functional knowledge. However, Matthew Lambon Ralph and coworkers (1998) reported a patient who couldn't recognize artifacts but who had an impaired sensory ability. Because of cases such as these, most researchers concluded that the S-F hypothesis was too simplified, and they began looking for other attributes that distinguished between living things and artifacts.

THE SEMANTIC CATEGORY APPROACH

The **semantic category approach** proposes that there are specific neural circuits in the brain for some specific categories. According to Bradford Mahon and Alfonso Caramazza (2011), there are a limited number of categories that are innately determined because of their importance for survival. This idea is based on research that we described in Chapter 2, which identified areas of the brain that respond to specific types of stimuli such as faces, places, and bodies (page 42). In addition, we described an experiment by Alex Huth and coworkers (2012) based on brain activity measured as people viewed movies, which resulted in the map in **Figure 2.23**, showing how concepts activated different areas of the brain.

Jeremy Wilmer and coworkers (2010) tested the idea that areas of the brain are innately specialized for specific categories of concepts by measuring face recognition ability in monozygotic (identical) and dizygotic (fraternal) twins. Their finding that the correlation of scores between identical twins was more than twice as high as the correlation for fraternal twins (0.70 vs. 0.29) led them to conclude that there is a genetic basis for the mechanisms that support face recognition (also see Zhu et al., 2010).

While the semantic category approach focuses on areas of the brain that are specialized to respond to specific types of stimuli, it also emphasizes that the brain's response to items from a particular category is distributed over a number of different cortical areas (Mahon et al., 2007; Mahon & Caramazza, 2011). Thus, identifying faces may be based on activity in the face area in the temporal lobe (see Chapter 2, page 42), but it also depends on activity in areas that respond to emotions, facial expressions, where the face is looking, and the face's attractiveness (see page 44).

Similarly, the response to a hammer activates visual areas that respond to the hammer's shape and color, but it also causes activity in areas that respond to how a hammer is used and to a hammer's typical motions. It is important to note that the semantic category approach is not suggesting that there is a place in the brain that is specialized for "hammers." It is saying that evolution has resulted in neural circuits that enable us to efficiently interact with some objects by grasping them and carrying out movements such as swinging that would be important for survival.

THE MULTIPLE-FACTOR APPROACH

The idea of distributed representation is a central feature of the **multiple-factor approach**, but this approach focuses not on brain areas or networks that are specialized for specific concepts but on searching for more factors that determine how concepts are divided up within a category.

We can appreciate this approach by posing the following question: Assume that we start with a large number of items selected from lists of different types of animals, plants, and artifacts. If you wanted to arrange them in terms of how similar they are to each other, how would you do it? You could arrange them by shape, but then items like a pencil, a screwdriver, a person's finger, and a breakfast sausage might be grouped together. Or considering just color, you could end up placing fir trees, leprechauns, and Kermit the Frog together. While it is true that members of specific categories do share similar perceptual attributes, it is also clear that we need to use more than just one or two features when grouping objects in terms of similarity.

Taking this idea as their starting point, researchers picked a number of different features and had subjects rate a large number of items with regard to these features. This was the idea behind an experiment by Paul Hoffman and Matthew Lambon Ralph (2013), who used 160 items like the ones shown in Table 9.2a. The subjects' task was to rate each item on the features shown in Table 9.2b. For example, for the concept "door," the subject would

Table 9.2: Sample Stimuli and Question Used in the Hoffman & Lambon Ralph (2013) Experiment

A. A FEW OF THE 160 ITEMS PRESENTED TO SUBJECTS		
Mammal	Machine	Clothing
Pet	Vehicle	Weapon
Bird	Furniture	Tool
Door	Fish	Fruit

B. QUESTION FOR SUBJECTS	
How much do you associate (insert item from list above) with a particular . . .	
Color	Taste
Visual form	Smell
Motion	Tactile (Touch)
Sound	Performed action (in which you interact with the object)

be asked "How much do you associate door with a particular color (or form, or motion, etc.)?" Subjects assigned a rating of 7 for "very strongly" to 1 for "not at all."

The results, shown in **Figure 9.21**, indicate that animals were more highly associated with motion and color compared to artifacts, and artifacts were more highly associated with performed actions (actions associated with using or interacting with an object). This result conforms to the S-F hypothesis, but Hoffman and Lambon Ralph looked at the groupings more closely, and they found some interesting results. Mechanical devices such as machines, vehicles, and musical instruments overlapped with both artifacts (involving performed actions) and animals (involving sound and motion). For example, musical instruments are associated with specific actions (how you play them), which goes with artifacts, and are also associated with sensory properties (their visual form and the sounds they create), which goes with animals. Thus, mechanical devices have a widely distributed semantic representation that includes regions important for the representation of both living things and artifacts.

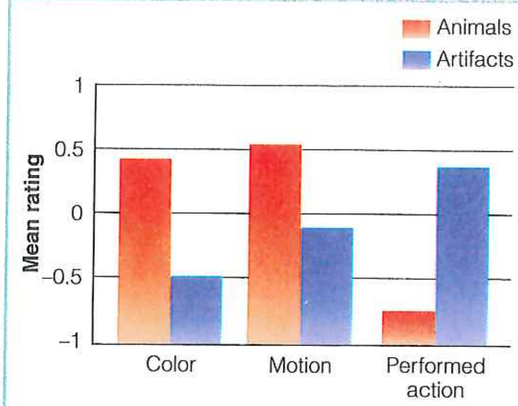
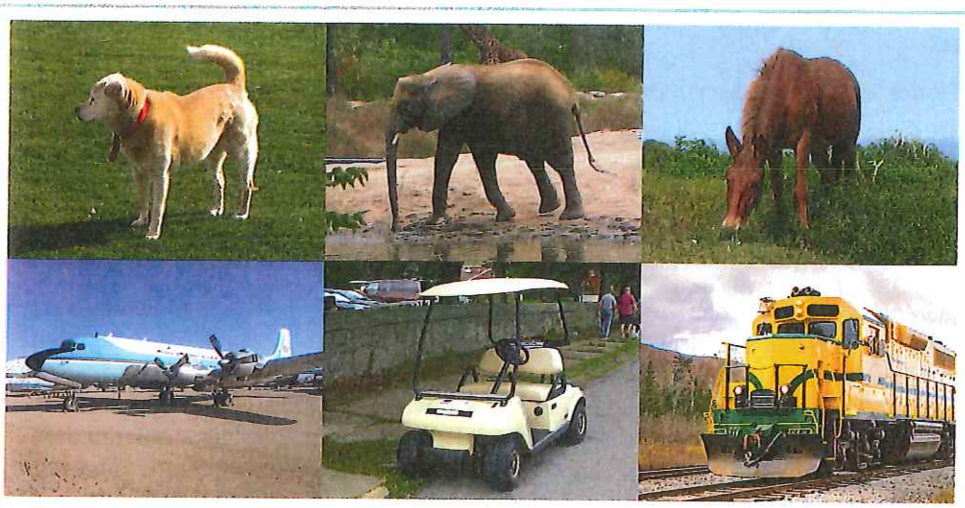


Figure 9.21 How subjects rated animals and artifacts on color, motion, and performed actions. Animals are rated higher on color and motion; artifacts are rated higher on performed actions. *(Source: Based on data in P. Hoffman & M. A. Lambon Ralph, Shapes, scenes and sounds: Quantifying the full multi-sensory basis of conceptual knowledge,* Neuropsychologia, *51, 14–25, 2013.)*

Because of the wide distribution of the representation for mechanical devices, sometimes patients are able to identify mechanical devices even if they perform poorly for other types of artifacts. For example, Hoffman and Lambon Ralph note that there are patients who have poor comprehension of smaller objects but better knowledge of larger artifacts, such as vehicles (Cappa et al., 1998; Hillis et al., 1990; Warrington & McCarthy, 1987).

Another factor that researchers have proposed to differentiate between animals and artifacts is **crowding**, which refers to the fact that animals tend to share many properties (like eyes, legs, and the ability to move). In contrast, artifacts like cars and boats share fewer properties, other than that they are both vehicles (**Figure 9.22**) (Rogers & Cox, in press). This has led some researches to propose that patients who appear to have category-specific impairments, such as difficulty recognizing living things but not artifacts, don't really have a category-specific impairment at all. They propose that these patients have difficulty recognizing living things because they have difficulty distinguishing between items that share similar features. According to this idea, because animals tend to be more similar then artifacts, these patients find animals harder to recognize (Cree & McRae, 2003; Lambon Ralph et al., 2007).

Our final approach also proposes that a number of factors are involved in telling the difference between different objects but proposes that the way we interact with objects is especially important.



Train photo, © Albert Pego/Shutterstock.com; other photos, Bruce Goldstein

Figure 9.22 Some animals and vehicles. Notice that the animals are more similar to each other than are the vehicles. This higher similarity of animals is called crowding.

THE EMBODIED APPROACH

The **embodied approach** states that our knowledge of concepts is based on reactivation of sensory and motor processes that occur when we interact with the object. According to this idea, when a person uses a hammer, sensory areas are activated in response to the hammer's, size, shape, and color, and, in addition, motor areas are activated that are involved in carrying out actions involved in using a hammer. When we see a hammer or read the word *hammer* later, these sensory and motor areas are reactivated, and it is this information that represents the hammer (Barsalou, 2008).

We can understand the basis of the embodied approach by returning to Chapter 3, where we described how perception and taking action interact, as when Crystal reached across the table to pick up a cup of coffee (page 75). The important message behind that example was that even simple actions involve a back-and-forth interaction between pathways in the brain involved in perception and pathways involved in taking action (see Figure 3.33, page 77) (Almeida et al., 2013).

An even more impressive interaction between perception and action occurs when we move higher in the brain to the premotor cortex, where researchers have discovered neurons called **mirror neurons** (Figure 9.23a). Vittorio Gallese and coworkers (1996) were investigating how neurons in the monkey's premotor cortex fired as the monkey performed actions such as picking up a toy or a piece of food. As they were recording from neurons while the monkey carried out specific actions, they observed something they didn't expect: Some neurons in the monkey's premotor cortex fired both when the monkey grasped food on a tray (Figure 9.23b) and when the monkey observed the experimenter grasping food on a tray (Figure 9.23c) (Rizzolatti et al., 1996). These neurons are called mirror neurons because the neuron's response to watching the experimenter grasp an object is similar to the response that occurs when the monkey is performing the action itself (Gallese et al., 1996; Rizzolatti et al., 2000).

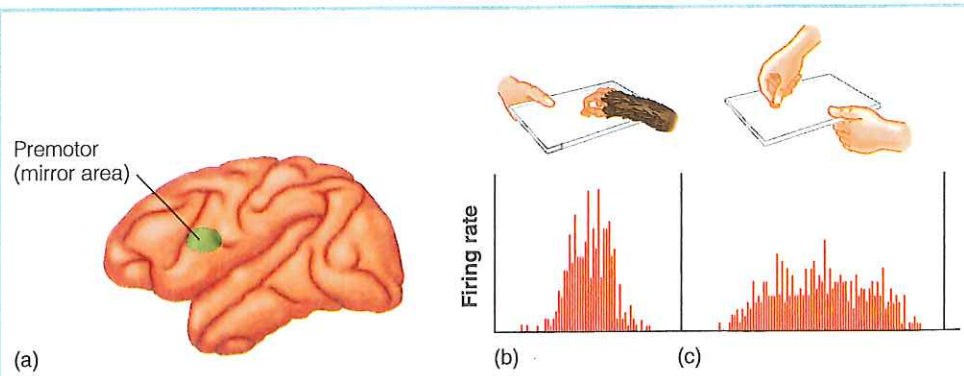


Figure 9.23 (a) Location of the monkey's premotor cortex. (b) Responses of a mirror neuron when the monkey grasps food on a tray and (c) when the monkey watches the experimenter grasp the food. *(Sources: part a, © Cengage Learning; parts b and c, based on G. Rizzolatti et al., Premotor cortex and the recognition of motor actions,* Cognitive Brain Research, 3, *131–141, 2000.)*

Most mirror neurons are specialized to respond to only one type of action, such as grasping or placing an object somewhere. Although you might think that the monkey may have been responding to the anticipation of receiving food, the type of object made little difference. The neurons responded just as well when the monkey observed the experimenter pick up an object that was not food. Evidence has been found for similar neurons in humans (Oosterhof et al., 2013), although some researchers have raised questions regarding the function of these neurons in humans (Dinstein et al., 2008; Hickok, 2009).

What do mirror neurons have to do with concepts? The link between perception (a neuron fires when watching the experimenter pick up the food) and motor responses (the same neuron fires when the monkey picks up the food) is central to the embodied approach's proposal that thinking about concepts causes activation of perceptual and motor areas associated with these concepts. Evidence for this link between perceptual and motor responses in the human brain is provided by an experiment by Olaf Hauk and coworkers (2004), who measured subjects' brain activity using fMRI under two conditions: (1) as subjects moved their right or left foot, left or right index finger, or tongue; (2) as subjects read "action words" such as *kick* (foot action), *pick* (finger or hand action), or *lick* (tongue action).

The results show areas of the cortex activated by the actual movements (**Figure 9.24a**) and by reading the action words (**Figure 9.24b**). The activation is more extensive for actual movements, but the activation caused by reading the words occurs in approximately the same areas of the brain. For example, leg words and leg movements elicit activity near the brain's center line, whereas arm words and finger movements elicit activity farther from the center line. This correspondence between words related to specific parts of the body and the location of brain activity, called **semantic somatotopy**, is also illustrated in **Figure 9.25**, which summarizes the results of a number of experiments. Blue symbols represent locations activated by leg/foot words, red by arm/hand words, and green by face/mouth words (Carota et al., 2012; Pulvermüller, 2013).

Although there is convincing evidence linking concepts and activation of motor areas in the brain, some researchers question whether the embodied approach offers a complete explanation of how the brain processes concepts (Almeida et al., 2013; Chatterjee, 2010; Dravida et al., 2013). For example, Frank Garcea and coworkers (2013) tested patient A.A., who had suffered a stroke that affected his ability to produce actions associated with various objects. Thus, when A.A. was asked to use hand motions to indicate how he would use objects such as a hammer, scissors, and a feather duster, he was impaired compared to normal control subjects in producing these actions. According to the embodied approach, a person who has trouble producing actions associated with objects should have trouble recognizing the objects. A.A. was, however, able to identify pictures of the objects. Garcea and coworkers concluded from this result that the ability to represent motor activity associated with actions is not necessary for recognizing objects, as the embodied approach would predict.

Another criticism of the embodied approach is that it isn't well suited to explaining our knowledge of abstract concepts such as "democracy" or "truth." However, proponents of the embodied approach have offered explanations in response to these criticisms (which we won't go into here; see Barsalou, 2005; Chatterjee, 2010).

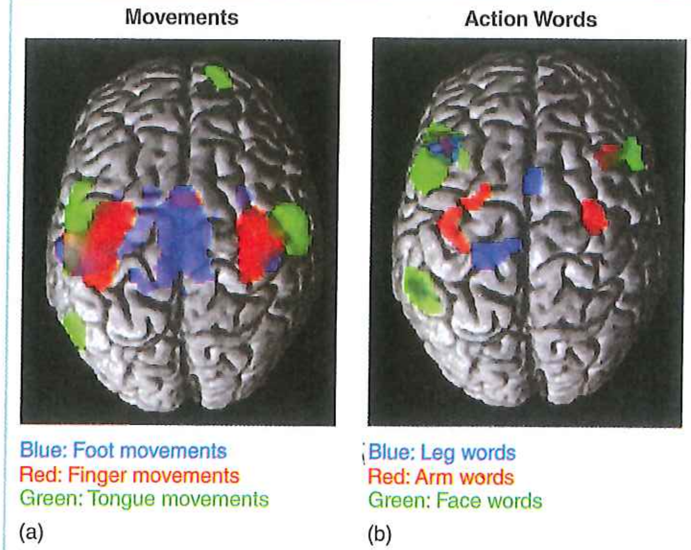


Figure 9.24 Hauk et al. (2004) results. Colored areas indicate the areas of the brain activated by (a) foot, finger, and tongue movements; (b) leg, arm, and face words. *(Source: O. Hauk, I. Johnsrude, & F. Pulvermuller, Somatotopic representation of action words in human motor and premotor cortex,* Neuron, *41, 301–307, 2004, with permission from Elsevier.)*

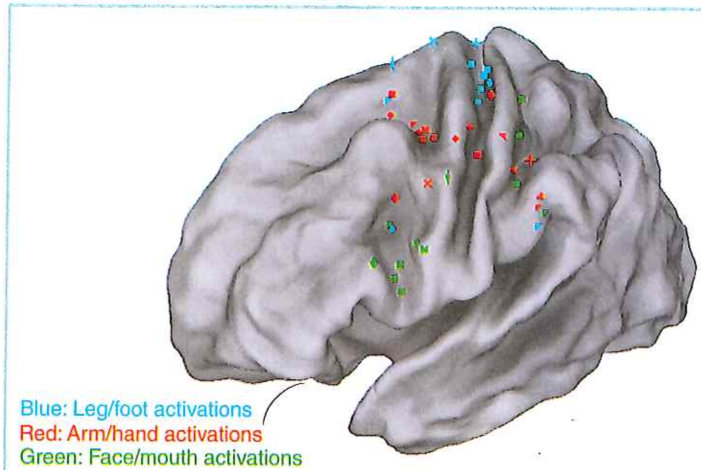


Figure 9.25 Each symbol represents the results of a different experiment that determined where brain activation occurred in response to action words that were related to different parts of the body. *(From F. Carota, R. Moseley, & F. Pulvermuller, Body-part-specific representations of semantic noun categories,* Journal of Cognitive Neuroscience, *24, 1492–1509, Figure 5, 2012. Reprinted by permission of MIT Press.)*

SORTING OUT THE APPROACHES

In Chapter 1 we described research by Sian Beilock and coworkers on what is responsible for "choking under pressure" (see page 16). One of the messages of that discussion was that research involves following a trail from one result to the next. Beilock's research was described because it provided a good example of how research can progress by asking a series of questions that leads eventually to answers about how a process operates.

Applying this idea to the question of how concepts are represented in the brain, we can take the S-F hypothesis as our starting point. However, determining how concepts are represented in the brain is quite a bit more complicated than understanding choking under pressure because of the large number of concepts and the complexity of the brain. Thus, we found that although many researchers took the S-F hypothesis as their starting point, their research led in different directions and resulted in different hypotheses.

I have found that students in my cognitive psychology class are often frustrated by this situation because they want to know what the *answer* is. Which approach is the correct one? Which most accurately describes concepts in the brain? Although the answer to questions such as these may eventually be known, for now we can only say that this area of research is a work in progress and that each of the approaches we have described provides part of the answer to the overall puzzle of how concepts are represented in the brain.

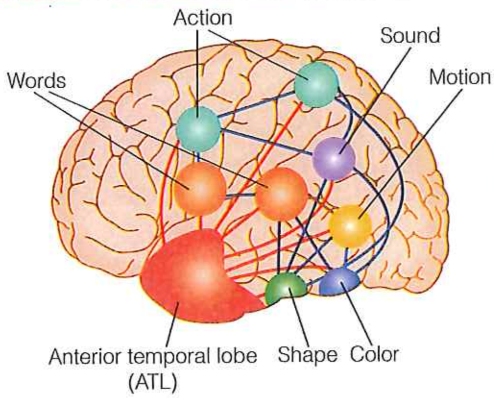


Figure 9.26 The hub and spoke model proposes that areas of the brain specialized for different functions (circles) are linked to the anterior temporal lobe (red), which integrates the information from these areas. *(Source: Adapted from K. Patterson, P. J. Nestor, & T. T. Rogers, Where do you know what you know? The representation of semantic knowledge in the human brain,* Nature Reviews Neuroscience, 8, *976–987, Figure 1, 2007.)*

One thing that all of the approaches agree on is that information about concepts is distributed across many structures in the brain. But the approaches differ in their emphasis on the type of information that is most important. The category-specific approach emphasizes specialized areas of the brain and networks connecting these areas; the multiple-factor approach emphasizes the role of many different features and properties; and the embodied approach emphasizes activity caused by the sensory and motor properties of objects. It is likely that, as research on concepts in the brain continues, the final answer will contain elements of each of these approaches (Goldstone et al., 2012).

Something to Consider

THE HUB AND SPOKE MODEL

The ideas we have been discussing about how concepts are represented in the brain have been based largely on patients with category-specific memory impairments. However, there is another type of problem, called **semantic dementia**, that causes a general loss of knowledge for all concepts. Patients with semantic dementia tend to be equally deficient in identifying living things and artifacts (Patterson et al., 2007).

The generalized nature of the deficits experienced by semantic dementia patients, along with the finding that the **anterior temporal lobe (ATL)** (red area in Figure 9.26) is generally damaged in these patients, has led some researchers to propose the **hub and spoke model** of semantic knowledge. According to this model, areas of the brain that are associated with specific functions are connected to the ATL, which serves as a hub that integrates the information from these areas. Evidence supporting this idea is that damage to one of the specialized brain areas (the spokes) can cause specific deficits, such as an inability to identify artifacts, but damage to the ATL (the hub) causes general deficits, as in semantic dementia (Patterson et al., 2007). This difference between hub and spoke functions has also been demonstrated in non-brain-damaged subjects using a technique called **transcranial magnetic stimulation (TMS)**.

Figure 9.27 TMS coil positioned to present a magnetic field to a person's head. The coil in this position is stimulating the occipital lobe.

METHOD

TRANSCRANIAL MAGNETIC STIMULATION (TMS)

It is possible to temporarily disrupt the functioning of a particular area of the human brain by applying a pulsating magnetic field using a stimulating coil placed over the person's skull (Figure 9.27). A series of pulses presented to a particular area of the brain for seconds or minutes interferes with brain functioning in that area for seconds or minutes. If a particular behavior is disrupted by the pulses, researchers conclude that the disrupted area of the brain is involved in that behavior.

Gorana Pobric and coworkers (2010) presented pictures of living things and artifacts to subjects and measured the response time for naming each picture. They then repeated this procedure while TMS was being applied either to the ATL or to an area in the parietal lobe that is normally activated when a person is manipulating an object (**Figure 9.28**). Red bars indicate response time before TMS stimulation; blue bars are response times during stimulation. They found that stimulating the ATL caused a generalized effect: a slowing in responding to both living things and artifacts (left graph). However, stimulating the parietal area caused a more specific effect: a slowing in responding to artifacts but not to living things (right graph). This result—a general effect of stimulating the "hub" (ATL), but a more specific effect of stimulating an area that would be associated with one of the "spokes" (parietal cortex)—supports the idea of a hub with general functions and spokes with more specific functions (Jefferies, 2013).

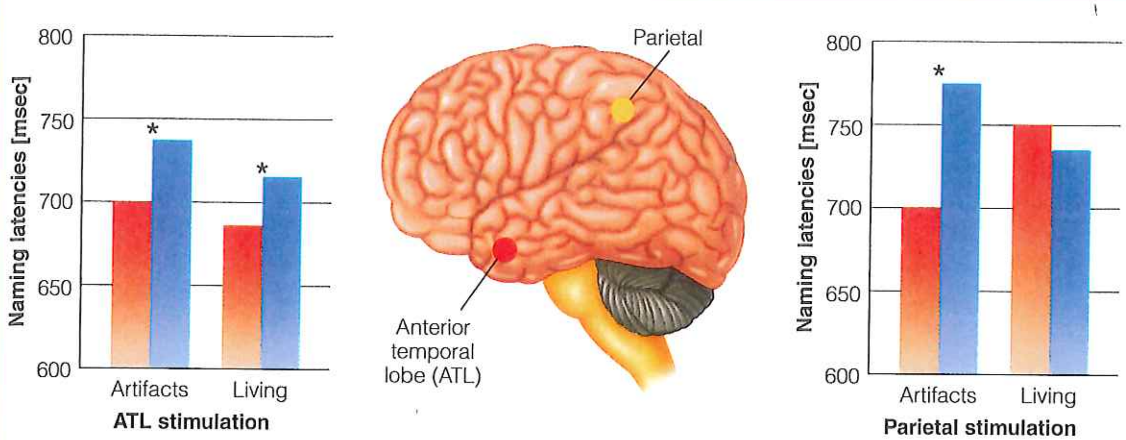


Figure 9.28 Results of Pobric et al.'s (2010) TMS experiment. Red bars indicate response time before TMS stimulation; blue bars are response times during stimulation. Stars above pairs of bars indicate that there is a significant difference between the bars. TMS stimulation of the ATL affected subjects' speed of naming equally for artifacts and living things (left graph). Stimulation of the parietal cortex caused an increase in speed of naming only for artifacts (left pair of bars). *(Source: Adapted from G. Pobric, E. Jefferies, & M. A. Lambon Ralph, Category-specific versus category-general semantic impairment induced by transcranial magnetic stimulation,* Current Biology, *20, 964–968, Figure 1B, 2010.)*

Most researchers agree that the ATL plays a role in integrating information from different areas. But it has also been suggested that other structures may be "hubs," or that the most important way concepts are represented is not by "hubs" but by the pattern of connections formed between the "spokes" (Pulvermüller, 2013). Thus, as we noted at the end of the last section, research on how concepts are represented in the brain is still a "work in progress."

TEST YOURSELF 9.2

1. What is the basic idea behind the semantic network approach? What is the goal of this approach, and how did the network created by Collins and Quillian accomplish this goal? What is the evidence for and against the Collins and Quillian model?
2. What is a connectionist network? Describe how a connectionist network learns, considering specifically how connection weights are adjusted. Also consider how the way information is represented in a connectionist network differs from the way it is represented in a semantic network.
3. Describe the four approaches to explaining how concepts are represented in the brain. Indicate the basic idea behind each hypothesis and the evidence for and against each one.

CHAPTER SUMMARY

1. Semantic memory is our memory for facts and knowledge.
2. Categories are "pointers to knowledge." Once you know something is in a category, you know a lot of general things about it and can focus your energy on specifying what is special about this particular object.
3. The definitional approach to categorization doesn't work because most categories contain members that do not conform to the definition. The philosopher Wittgenstein proposed the idea of family resemblances to deal with the fact that definitions do not include all members of a category.
4. The idea behind the prototypical approach to categorization is that we decide whether an object belongs to a category by deciding whether it is similar to a standard representative of the category, called a prototype. A prototype is formed by averaging category members a person has encountered in the past.
5. *Prototypicality* is a term used to describe how well an object resembles the prototype of a particular category.
6. The following is true of high-prototypical objects: (a) They have high family resemblance; (b) statements about them are verified rapidly; (c) they are named first; and (d) they are affected more by priming.
7. The exemplar approach to categorization involves determining whether an object is similar to an exemplar. An exemplar is an actual member of a category that a person has encountered in the past.
8. An advantage to the exemplar approach is that it doesn't discard information about atypical cases within a category, such as penguin in the "bird" category. The exemplar approach can also deal more easily with categories that contain widely varying members, such as games.
9. Researchers have concluded that people use both approaches to categorization. Prototypes may be more important as people initially learn about categories; later, exemplar information may become more important. Exemplars may work best for small categories (such as U.S. presidents), and prototypes may work best for larger categories (such as birds).
10. The kind of organization in which larger, more general categories are divided into smaller, more specific categories is called hierarchical organization. Experiments by Rosch indicate that a basic level of categories (such as guitar, as opposed to musical instrument or rock guitar) is a "privileged" level of categorization that reflects people's everyday experience.
11. Experiments in which experts were tested show that the basic level of categorization can depend on a person's degree of expertise.
12. The semantic network approach proposes that concepts are arranged in networks that represent the way concepts are organized in the mind. Collins and Quillian's model is a network that consists of nodes connected by links. Concepts and properties of concepts are located at the nodes. Properties that hold for most members of a concept are stored at higher-level nodes. This is called cognitive economy.
13. Collins and Quillian's model is supported by the results of experiments using the sentence verification technique. The spreading activation feature of the model is supported by priming experiments.
14. The Collins and Quillian model has been criticized for several reasons: It can't explain the typicality effect, the idea of cognitive economy doesn't always hold, and it can't explain all results of sentence verification experiments.
15. The connectionist approach proposes that concepts are represented in networks that consist of input units, hidden units, and output units, and that information about concepts is represented in these networks by a distributed activation of these units. This approach is also called the parallel distributed processing (PDP) approach.
16. Connectionist networks learn the correct distributed pattern for a particular concept through a gradual learning process that involves adjusting the weights that determine how activation is transferred from one unit to another.
17. Connectionist networks have a number of features that enable them to reproduce many aspects of human concept formation.
18. Four approaches to explaining how concepts are represented in the brain are the sensory-functional hypothesis, the semantic category approach, the multiple-factor approach, and the embodied approach.
19. The hub and spoke model proposes that different functions in the brain are integrated by the anterior temporal lobe (ATL).

THINK ABOUT IT

1. In this chapter we have seen how networks can be constructed that link different levels of concepts. In Chapter 7 we saw how networks can be constructed that organize knowledge about a particular topic (see Figure 7.5). Create a network that represents the material in this chapter by linking together things that are related. How is this network similar to or different from the semantic network in Figure 9.12? Is your network hierarchical? What information does it contain about each concept?

2. Do a survey to determine people's conception of "typical" members of various categories. For example, ask several people to name, as quickly as possible, three typical "birds" or "vehicles" or "beverages." What do the results of this survey tell you about what level is "basic" for different people? What do the results tell you about the variability of different people's conception of categories?

3. Try asking a number of people to name the objects pictured in Figure 9.10. Rosch, who ran her experiment in the early 1970s, found that the most common responses were guitar, fish, and pants. Notice whether the responses you receive are the same as or different from the responses reported by Rosch. If they are different, explain why you think this might have occurred.

KEY TERMS

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COGLAB EXPERIMENTS Numbers in parentheses refer to the experiment number in CogLab.

Lexical Decision (41)
Absolute Identification (44)
Prototypes (46)