Annu. Rev. Psychol. 2001. 52:223–47

THINKING

Arthur B. Markman
Department of Psychology, University of Texas, Austin, Texas 78712; e-mail: markman@psy.utexas.edu

Dedre Gentner
Department of Psychology, Northwestern University, Evanston, Illinois 60208; e-mail: gentner@nwu.edu

Key Words reasoning, analogy, domain-specific processes, mental models, learning

■ **Abstract** Reasoning processes allow the human cognitive system to go beyond the information readily available in the environment. This review focuses on the processes of human thinking, including deductive reasoning, induction, mental simulation, and analogy. We survey recent trends across several areas, including categorization, mental models, cognitive development, and decision making. Our chief organizing principle is the contrast between traditional approaches that focus on abstract logical reasoning and a number of current approaches that posit domain-specific, knowledge-intensive cognition. We suggest that some instances of domain-specific cognition result from domain-general processes operating on domain-specific representations. Another theme is the link between reasoning and learning. We suggest that learning typically occurs as a byproduct of reasoning, rather than as an end in itself.

CONTENTS

INTRODUCTION

We have called this chapter "Thinking" rather than using the more traditional title "Reasoning" because we think it important to go beyond the traditional deductive logic focus of the term reasoning and include other ways of arriving at new conclusions, including induction and analogy. In this paper we survey recent trends in the field across several areas, including categorization, mental models, cognitive development, and decision making. A theme that emerges frequently in recent research is an interest in going beyond lab-oriented paradigms to investigations of real-life cognitive activities. A related theme is the relation between abstract logical reasoning and concrete domain-specific reasoning—or to put it another way, between abstract and knowledge-based approaches to reasoning. The idea of reasoning is often equated with the notion of purely logical processes that operate independent of content. In popular imagery, icons such as Mr. Spock and HAL draw their intellectual power from pure logic. Likewise, within psychology the study of reasoning has focused largely on the use of content-independent logical rules (e.g. Johnson-Laird & Byrne 1991, Rips 1994). However, other research shows that the content being reasoned about influences people's reasoning ability, even for tasks to which logical rules are applicable (e.g. Cheng & Holyoak 1985, Cosmides 1989, Wason & Johnson-Laird 1972). Partly because of these findings, there has been considerable recent interest in how people learn and use rich domain representations such as theories and mental models.

As an example of the kinds of phenomena that need explanation, Bassok et al (1998) asked college undergraduates to write addition and division word problems. Presumably, college students are experts at addition and division; it should be straightforward for them to think abstractly about simple arithmetic. However, the content of the problem influenced the form of the word problem written. When asked to write a problem involving two members of the same category (e.g. apples and pears), the students found it easier to write an addition problem than a division problem. In contrast, when given members of thematically related categories (e.g. apples and baskets), they found it easier to write a division problem than an addition problem. Thus, even in the seemingly abstract domain of mathematics, cognitive performance is affected by domain content.

Such effects have led some researchers to suggest that content and context are fundamental to reasoning (Newell & Simon 1972). Some theorists assert that human learning is conservative, with representations that are tied to the initial learning situation (Gentner 1989, Medin & Ross 1989). Indeed, some have taken the extreme opposite of the logicist view, arguing that there is no utility to a general notion of representation or process. One such view is the situated cognition approach that assumes all thinking is fundamentally context-governed (Suchman 1987). A related position is the embodied cognition view, according to which cognitive processes are optimized to mesh with particular sensorimotor activities (Glenberg 1997, Pfeifer & Scheier 1999). For example, Glenberg reviewed evidence that some spatial reasoning tasks are facilitated by specific motor movements consistent with route-following.

Another approach to domain-specific reasoning is modularity theory, which assumes that human learning and development requires innate modules for certain domains such as physical causality or psychology (e.g. Hirschfeld & Gelman 1994). Finally, another approach that postulates domain-specific reasoning is evolutionary psychology, which posits domain-specific modules selected by evolution to solve complex reasoning tasks (Tooby & Cosmides 1989).

These views have had the salutary effect of pointing to phenomena neglected by traditional approaches to cognition. However, in the extreme, the focus on domain-specific modules can lead to abandoning the search for general processes in favor of particularistic descriptions. Our reading of the findings supports a more moderate conclusion. We suggest that both domain-general and domain-specific reasoning have a place in psychology and suggest three lines of reconciliation. First, we invoke a distinction proposed by Newell & Simon (1972) between strong and weak methods of reasoning. Weak methods are general strategies that can operate without special knowledge of a domain, such as means-ends analysis or logical inference rules like modus ponens. Strong methods make intensive use of represented knowledge, as in reasoning by example. Weak methods are valuable because of their generality; they provide a means of operating on novel or knowledge-poor domains. However, Newell and Simon asserted that strong methods are typically superior when the appropriate knowledge is present. Many recent systems have focused on architectures that permit both general and specific knowledge to be used. For example, Sloman (1996) reviewed evidence that people apply specific knowledge to problems in order to answer them quickly, and that this knowledge can even compete with rule-based processes.

The second point of contact is that many instances of domain-specific cognition result from domain-general processes operating on domain-specific representations. Domain specificity can thus be captured without abandoning the idea of domain-general cognitive processes. For example, in cognitive architectures like Anderson's ACT system (Anderson 1993, Anderson & Lebiere 1998), it is assumed that the structure of semantic memory can strongly influence the performance of the model. A third point of connection is that the distinction between abstract and concrete cognition often behaves as a continuum rather than as a dichotomy. Furthermore, the continuum is learning related. As discussed in the next section, alignment and abstraction processes can result in a natural transition from domain-specific to domain-general reasoning (Cheng and Holyoak 1985, Gentner & Medina 1998). This last trend is an instance of another basic theme that emerges from our survey: In many natural contexts, learning occurs as a byproduct of reasoning, rather than as an end in itself. For example, Ross (1997) showed that people's representations of categories are influenced by the way they use the categories in problem solving.

The plan of this chapter is as follows. We first lay out structure mapping, a general process that can capture many domain-specific effects. We then cover research in mental models and theories, traditionally an arena of rich domain-specific cognition. Finally, we survey research in categorization and category-based induction as a case study of the ways domain-general and domain-specific information interact in cognitive processing.

STRUCTURAL ALIGNMENT AND MAPPING

As noted above, we need accounts of reasoning processes that can deal with rich domain-specific knowledge. In each of these cases, we need to find a way to allow information about the new situation to be related to background knowledge.

Comparison is a domain-general process that allows the detection of commonalities and differences in a pair of situations or domains. Many models of similarity have been proposed (e.g. Shepard 1964, Tversky 1977). We focus on recent accounts of similarity that are structurally sensitive, and that allow for complex mental representations and hierarchical relational structures (Falkenhainer et al 1989, Gentner & Markman 1997, Goldstone 1994, Holyoak & Thagard 1989, Hummel & Holyoak 1997, Medin et al 1993). In particular, structure-mapping theory (Gentner 1983) has been used to model analogy, similarity, and metaphor in perceptual and conceptual tasks (Gentner & Markman 1994, 1997; Markman & Gentner 1993a,b, 1996, 1997).

Structure mapping involves two processes: structural alignment and inference projection. The idea behind structural alignment is that comparing structured representations requires a process that is sensitive to similarities, not only between the elements but also between the connections between elements. The structural alignment process matches semantically similar relations, but beyond this it seeks maximal structurally consistent systems of matches. Structural consistency involves two constraints: parallel connectivity and one-to-one correspondence. Parallel connectivity requires that if a pair of predicates is placed in correspondence, then their arguments must also be placed in correspondence, and one-to-one correspondence requires that an element in one representation can match to at most one element in the other representation.

For example, consider the following analogy:

(1) Fred loves Mary,
so Fred bought Mary cookies.

(2) Joyce loves Fred,
so Joyce bought Fred candy.

Fred let Joyce drive his car.

A process that was not sensitive to relational structure would arrive at the correspondences Fred(1)_Fred(2), cookies_candy, and so on. Structural alignment invites the arguments of matching relations to be placed in correspondence. Thus, once the relational correspondence loves(1)_loves(2) is found, Fred(1) is mapped to Joyce and Mary is mapped to Fred(2). Further, by one-to-one correspondence, once the correspondence Fred(1)_Joyce is determined, Fred(1) cannot also match with Fred(2).

A further tenet of structure-mapping is the systematicity principle (Gentner 1983, 1989), which posits that matches between systems of relations connected by higher-order constraining relations are preferred to matches between isolated relations. Such relations include causality or means-end relations in conceptual domains and symmetry or monotonicity in perceptual arenas. This claim is supported by studies that have demonstrated that pairs are seen as more similar when they share systematic relational matches than when they do not (e.g. Gentner et al 1993, Lassaline 1996, Markman & Gentner 1993b) and that matches are seen as more central to an analogy when they are connected to other matching assertions than when they are not (Clement & Gentner 1991).

Systematicity is manifest not only in which commonalities emerge from a comparison but also in which differences are noticed (Markman & Gentner 1993a). In particular, alignable differences tend to be highly salient in similarity comparisons. These are differences that result when nonidentical elements are placed in correspondence by virtue of their connections to the common structure. For example, in the example analogy, cookies and candy will be placed in correspondence, because they fill the same role. Thus, they are an alignable difference. In contrast, Fred's car, which has no correspondence in the first set, is a nonalignable difference—a difference not connected to the common system that has no correspondence in the other domain.

Commonalities are more important in judgments of similarity than are differences (Sjöberg 1972, Tversky 1977). Structural alignment extends this observation to alignable differences, assuming that alignable differences are more prominent than nonalignable differences in similarity tasks. As evidence for this supposition, it has been shown that alignable differences influence similarity comparisons more than do nonalignable differences (Markman & Gentner 1996), are more likely to be listed than nonalignable difference in difference-listing tasks (Markman & Gentner 1993a), are more fluently produced in speeded tasks (Gentner & Markman 1994), and serve as better recall cues for information presented in a comparison than do nonalignable differences (Markman & Gentner 1997).

Systematicity also influences which new inferences are drawn from a comparison (Bowdle & Gentner 1997, Clement & Gentner 1991, Markman 1997, Spellman & Holyoak 1996), thus providing a means of constraining possible inferences. Information that is connected via higher-order constraining relations, such as causality, to the common system is more likely to be projected to the target than is other knowledge about the base. These candidate inferences serve as informed guesses.

Recent research has begun to investigate the real-time processes of comparison. There is evidence for an initial alignment process that is symmetric between base and target, followed by a directional inference process (Falkenhainer et al 1989, Wolff & Gentner 2000). The alignment between two representations is computed via a local-to-global process that begins with individual element matches and then imposes global consistency constraints (Goldstone & Medin 1994).

To summarize, comparison can be viewed as the alignment of structured representations. This process begins with local matches and gradually arrives at the maximal structurally consistent system of correspondences. The comparison process can generate new conclusions in at least four ways: (*a*) it promotes a focus on common connected relational systems that can serve as useful abstractions; (*b*) it highlights alignable differences of a pair, which are likely to be relevant; (*c*) it invites candidate inferences; and (*d*) it sometimes leads to re-representations of one or both domains to increase their similarity (Gentner & Wolff 2000). These processes contribute to learning as well as to online reasoning.

Learning and Reasoning: The Shift from Active Processing to Storage

It is often easier to retrieve something from memory than to derive it by reasoning processes. This idea is evident in many theories of automaticity. For example, Logan (1988, 1996) suggested that in the initial stages of learning a skill, people obtain solutions by carrying out an algorithm. For example, they might learn to add two numbers by starting with the larger one and counting on to add the other. With sufficient practice, they come to be able to retrieve previously stored answers. Siegler & Shipley (1995) observed this progression in children learning to do arithmetic, who shifted from overtly counting on their fingers to retrieving answers from memory.

A similar process of shifting from active computation to memory retrieval can be seen in metaphor comprehension (Bowdle & Gentner 1999; Gentner & Wolff 1997, 2000). When a novel metaphor is presented (e.g. that lawyer is a boa constrictor), an interpretation (e.g. the lawyer is inexorable) is actively computed via alignment processes. However, if the metaphor base is repeatedly used in the same nonliteral way, its metaphorical interpretation may be stored as an alternate word sense. Such stock metaphors can behave like conventional categories (Glucksberg et al 1997) and do not need to be recomputed.

People's propensity to cache frequently encountered solutions can be used to predict their future behavior. In consumer psychology, the single best predictor of a person's purchases in a category is "brand loyalty"—the prior probability distribution of purchases of products in that category (e.g. Guidagni & Little 1983). People tend to buy again what they bought in the past. Our pattern of storing the results of frequently experienced processes is a form of cognitive economy, but it sometimes works against us. In the classic *Einstellung* or "set" effect noted by the Gestaltists, people's continued use of a past successful solution hampers their ability to see a better solution to a problem.

MENTAL MODELS

A mental model is a representation of some domain or situation that supports understanding, reasoning, and prediction. There are two main approaches to the study of mental models. One approach seeks to characterize the knowledge and processes that support understanding and reasoning in knowledge-rich domains. The other approach focuses on mental models as working-memory constructs that support logical reasoning (Johnson-Laird 1983, Johnson-Laird & Byrne 1991). Although we are primarily interested in causal mental models, we first briefly discuss logical mental models.

Logical Mental Models

There is considerable research on how people perform logical reasoning tasks (Evans & Over 1996; Johnson-Laird 1983, 1999; Rips 1994). One prominent explanation for the way people perform logical reasoning is that they form a mental model of the situation (Johnson-Laird 1983). In this view, when faced with a logic problem, the solver imagines a set of tokens organized so as to capture the relevant aspects of the premises. For example, given the premise "all archers are bakers," the solver might imagine a group of people. All those with arrows would also have cakes, but there would be others with cakes and no arrows. With each additional premise, the model is adjusted, and if more than one model is consistent with the premises, then alternate models are constructed. After all the premises have been presented, the resulting model(s) are summarized to give the conclusion. The difficulty of a given problem is determined by the number of different mental models that have to be constructed. This approach has been applied to a variety of logical reasoning situations, including classical syllogisms, multiply quantified statements, and inductive arguments (Johnson-Laird 1983, 1999; Johnson-Laird & Byrne 1991). However, some researchers have argued that logical mental models fail to capture aspects of human processing that are captured in propositional models (Rips 1986, 1994), or that mental models are actually isomorphic to other forms of diagrammatic reasoning in logic (Stenning & Oberlander 1995).

Causal Mental Models

Causal mental models are mental representations that are used in reasoning and that are based on long-term domain knowledge or theories (Gentner & Stevens 1983). They are used to explain reasoning about physical systems and mechanisms (Hegarty & Just 1993, McCloskey 1983) such as spatial representation (Tversky 1991), human-computer interaction (Norman 1988), ecology (Kempton et al 1994), and the development of astronomical knowledge (Vosniadou & Brewer 1992).

Causal mental models differ from logical mental models in two further ways besides their domain of application. First, the elements in a logical mental model are tokens rather like algebraic symbols, whereas the tokens in a causal mental model correspond to elements of causal systems. Second, logical mental models are created on the spot and involve only information currently active in working memory, whereas causal mental models, even those currently active in working memory, are assumed to draw on long-term memory structures.

Causal mental models (hereafter called mental models) are related to several other kinds of representational structures (Markman 1999). Schemas (or schemata) are general belief structures. Scripts are schemas summarizing event sequences and are characterized by a chiefly linear temporal order with limited inferential flexibility. Naive theories or folk theories are global systems of belief, typically encompassing larger domains such as biology. The terms mental models and naive or intuitive theories overlap in their application, though mental models are typically more specific in their application than are theories.

The Use of Mental Models One way people employ their mental models is to perform mental simulations—to imagine the future trajectory of a system given a set of initial conditions. These predictions involve qualitative estimates and often neglect some of the information relevant to the behavior of a system. For example, Gilden & Proffitt (1989) showed people collisions between a moving ball and a stationary ball and asked them which ball was heavier. Making this judgment requires attending both to the velocity of the balls and their trajectories prior to and following the collision. The results showed that people tended to use simple heuristics such as "the ball moving faster after the collision is lighter," or "the ball that ricochets is lighter." Whereas these heuristics are often correct, they do not reflect an integration of the information necessary to answer the question correctly on all trials. A similar analysis of people's predictions about the behavior of rolling wheels suggests that people understand the physics of forward (i.e. translational) motion of rolling wheels, but not the physics of rotational motion (Proffitt et al 1990).

An important aspect of these mental simulations is that they are qualitative (Forbus 1984, Kuipers 1994). That is, people reason about relative properties of physical systems such as direction of motion, relative speed, and relative mass. People do not estimate values of specific quantities, nor do they carry out mathematical simulations of the behavior of a system. These strategies are quite powerful, and have been used as the basis of computational simulations of complex physical systems (e.g. Forbus et al 1991), but they do not require the significant computational machinery that would be necessary to carry out detailed quantitative simulations.

Mental simulation often involves the use of imagery. Schwartz & Black (1996) asked people to solve gear problems such as, "Imagine a pegboard with seven gears on it arranged in a circle so that each gear meshes with one next to it on each side. If you rotate one gear clockwise, in which direction will the gear next to it move?" To answer such questions people often mentally simulate the gears' motions, sometimes with accompanying hand gestures (Hegarty & Just 1993, Metz 1985, Schwartz & J. Black 1996, Schwartz & T. Black 1999). Over time, people gradually learn the parity rule—that every other gear in a sequence turns in the same direction, whereas adjacent gears turn in the opposite direction—and shift from using imagery to solving the problems by rule. (Use of the parity rule reveals that the above problem is a trick. Circuits consisting of an odd number of gears will lock, because two adjacent gears will attempt to move in the same direction.)

Mental simulations may also have a motor component. In one set of studies, Schwartz & Black (1999) showed people a partially filled glass and asked them to predict how far it would have to be tilted in order for the liquid to pour out. People performed poorly, consistent with the Piagetian finding that people have difficulty predicting the level of water in a tilted glass (e.g. Howard 1978). However, when those same people were asked to hold a glass with a line drawn on it at the water level, and to tilt it until the glass would pour (with their eyes closed), they were significantly more accurate than in the explicit prediction task. Thus, it appears that some aspects of mental simulations involve representations that are strongly coupled with motor movements.

To summarize, recent research in mental models suggests that people can use mental simulations to reason about physical events. These simulations incorporate a small number of variables about the event and are often qualitative. Because the simulation process is effortful, with increasing experience people shift to using learned rules or cached results. More generally, this research reveals that people typically possess multiple models of complex systems, some highly context-bound and others more abstract.

Relating Mental Models to Theories

As noted above, there is a close relationship between mental models and intuitive theories. Many researchers have suggested that people's knowledge can be characterized as a theory about the world (Carey 1985, Gopnik & Meltzoff 1997, Keil 1989, Murphy & Medin 1985). The word theory has been used in a number of different ways to describe knowledge. In its loosest form, the term theory is used for the causal knowledge that people use to infer nonobvious properties and to explain observed patterns in the world.

Gopnik & Meltzoff (1997) have explored the possibility that children's knowledge can be characterized in the same terms as scientific theories: as theoretical knowledge that is abstract and coherent, that has explicit causal knowledge, and that makes specific commitments about the ontology of objects. They suggest that children create and use theories much as scientists do to predict and interpret events in the world. This does not, of course, mean that children's understanding is as deep as that of scientists (or even as adults). Preschool children often focus on object properties in their categorizations and explanations and fail to perceive functional or relational commonalities (Gentner & Medina 1998, Halford 1992).

There are some points in favor of the claim that scientific reasoning provides a good model for reasoning in children and adults. First, as Nersessian (1999) notes, scientific reasoning encompasses processes that go beyond hypothesis testing, such as mental simulation and analogy, that are also found in commonsense reasoning. Second, both scientists and nonscientists appear more willing to accept evidence that supports their beliefs than evidence against them. Kuhn (1997) showed this pattern in nonscientists. She first ascertained their views as to which factors matter in a situation and then showed them counterevidence. For example, people who believed that humor increases TV show ratings were shown pairs that differed only in humor, but received identical ratings. People did not change their belief in the importance of humor, but instead constructed other explanations for the finding.

Koehler (1993) found a similar pattern among scientists. Even though scientists state that their prior beliefs should not influence their evaluation of new evidence, they often set a more stringent acceptance criterion for contrary evidence than for consistent evidence. Thus, both scientists and nonscientists appear to resist negative evidence, although possibly to different degrees. Interestingly, there is some divergence of opinion as to the best policy on inconsistencies. Koehler suggests that on Bayesian grounds it is reasonable for scientists to be skeptical of evidence that contradicts their beliefs. However, Dunbar (1995) carried out long-term observations of working microbiology laboratories and concluded that attention to inconsistent findings is a major predictor of success in a laboratory.

There are also differences between scientists and nonscientists. First, scientists possess deeper causal theories than novices. Chi et al (1981) showed that expert physicists sorted physics problems into principle-based categories such as "momentum" and "conservation of energy," whereas novices sorted them into categories with similar diagrams. Second, scientists' knowledge in the domain of expertise is likely to be more explicit than that of novices. This greater degree of explicitness may arise in part from the need for scientists to communicate with other members of the scientific community, and from the specific feedback that scientists get about their ideas. Consistent with this proposal, Chi & VanLehn (1991) found that students learning science benefit significantly from generating explicit explanations for themselves as they study.

Third, although both scientists and nonscientists show resistance to data that are inconsistent with their prior beliefs, scientists are trained to seek such data: e.g. to include in their studies conditions that could disconfirm the hypotheses. In contrast, nonscientists have a strong confirmation bias when testing hypotheses (Evans & Over 1996, Klayman & Ha 1987). The Wason 246 task is a classic demonstration of this confirmation bias. People are told that the sequence 2–4–6 was generated using a rule, and asked to determine the rule by producing further elements. The typical strategy is to guess the rule (such as "increasing by 2") and then test only sequences that satisfy the rule, thereby collecting confirmatory evidence. Most people fail to discover the correct rule ("any increasing sequence"), because they do not test sequences that would disconfirm their hypothesized rule.

In summary, there are commonalities in reasoning styles between scientists and nonscientists, and the differences are often of degree, not kind. However, the combined force of these differences—such as greater explicitness of knowledge and greater commitment to seeking disconfirming evidence—may lead to a substantial overall difference in practice.

The Development of Theories and Mental Models

One route to understanding domain-specific reasoning is to study its development. Developmentalists have explored the way in which domain knowledge is acquired and structured in key domains such as mathematics, physics, and biology. Much of this research is motivated by the question of whether infants are born with domain-specific modular capacities for learning and reasoning. Just as linguistic development has been posited to be the result of an innate language acquisition device, so too might other conceptual abilities reflect an innate endowment for particular domains such as naive physics or a naive biology. For example, Leslie (1991) has proposed a specific theory of mind module and posited that autism is the result of a defective theory of mind module. Some theorists propose a combination of domain-specific and domain-general attentional capacities and learning processes (Baillargeon 1994, Carey 1985). At the other extreme, some theorists argue that purely general learning principles can account for the development of domain-specific modules (Elman et al 1996, Thelen & Smith 1993). According to these theorists, modules are the result of learning. At present, the issue is not resolved. Regardless of the outcome of the debate between nativists and empiricists, however, this body of work is of immense value for understanding how domain knowledge is acquired.

The development of biological knowledge is an arena of intense current interest. Carey (1985) probed children's understanding of the properties of animals (e.g. dogs or worms), plants, and inanimate objects. She asked about biological properties (bones and a heart), biological behaviors (eating, sleeping, and having babies) and psychological properties (thinking). The youngest children (4-year-olds) seemed to take a "man is the measure of all things" approach. They determined the likelihood that an entity had a property based on its similarity to humans. For example, they attributed biological properties to a mechanical monkey—but not to other inanimate objects—over half the time. With increasing age, children came to differentiate based on biological categories—e.g. between mammals and nonmammals. By the age of 10, children correctly treated the mechanical monkey as an inanimate object. Inagaki & Hatano (1987) suggested that the early "personification" responses represent children's productive use of analogy to reason from a well-understood base domain—human beings—to other less familiar species.

Carey's findings suggest that young children's biological theories may not differentiate among animals, or even between animals and plants. Carey further suggested that children's naive biology develops from their naive psychology, which is initially used to predict the actions of the people around them. Other researchers maintain that a naive theory of biology appears early in development. For example, Coley (1995) found that kindergarteners attributed biological properties (e.g. "has blood") according to taxonomic category membership, but attributed psychological properties (e.g. "thinks") according to whether the animal was domesticated. Coley concluded that a distinction between biological and psychological properties is present in young children and becomes more pronounced over development.

Young children reason about animate and inanimate objects in very different ways. Rosengren et al (1991) showed children pictures of animals labeled as "baby animals." When the children were shown new pictures and asked to choose which picture showed the baby as an adult, even preschool children consistently selected the larger animal. They would even accept a shape transformation (e.g. from a caterpillar to a butterfly) rather than choose a smaller "adult." Thus, children expect that animals will get larger, and would rather assume that an animal changed shape than that it got smaller. In contrast, when children were presented with artifacts, they expected them to stay the same size (though possibly to become chipped and broken). Hatano & Inagaki (1999) extended this method to plants and found that children expected both plants and animals to grow rather than to stay the same size. These findings suggest that young children distinguish between living and nonliving things.

However, children's initial understanding of the living-nonliving distinction may not go very deep. Simons & Keil (1995) showed children pairs of pictures of animals or machines with cutaways showing the "insides"—either organs or machinery (e.g. gears and chains)—and asked them to select the right insides for each whole. Only half of the 3- and 4-year-olds associated organs with the insides of animals and machinery with the insides of artifacts. Other children could choose correctly for artifacts but not for animals. Not until 8 years of age could children all select correctly. Simons & Keil suggest a developmental shift from abstract comprehension to specific causal knowledge: Preschool children distinguish between animate and artifact categories, but lack deep causal understanding of these domains. Although this claim that children possess abstract domain theories but lack causal understanding may seem rather tenuous, Keil and his colleagues suggest that adults' mental models of physical systems are similarly incomplete (Wilson & Keil 1998). They find that college students often believe that they know how complex artifacts like car starters and toilets work, but are unable to explain when probed for details. They argue that people are generally unaware of their lack of specific causal information about how common objects work, and call this effect the shallowness of explanation.

Finally, there has been research on how biological information is organized in the brain. Some neuropsychological patients appear to have category-specific impairments for animals; they can name pictures of artifacts but have trouble naming animals (e.g. Caramazza & Shelton 1998, Warrington & Shallice 1984). On the basis of these findings, Caramazza & Shelton (1998) suggest that evolution might have selected for specific mechanisms that facilitate the representation of animate and inanimate objects, and that the observed deficits reflect the breakdown of these systems. Regardless of the resolution of this issue, these findings add weight to the animate/inanimate distinction as an organizing principle for category information.

To summarize, studies of biological knowledge suggest that preschool children can make core distinctions such as the animate/inanimate distinction, but that their understanding deepens with development. Both children and adults have significant gaps in their models and may be unaware of the extent of the missing information. Much remains to be understood. For example, do the various facets of the animate/inanimate distinction—living/nonliving, self-moving/nonself-moving, and so on—reflect unified categories from the start, or are they acquired piecemeal? Is naive biology acquired through general learning processes or through domain-specific processes?

CATEGORIZATION

Categorization research includes both how people classify things into categories and how people draw inferences from known categories. Most research on categorization has focused on domain-general issues such as the role of similarity or the perception of feature centrality. We begin with these approaches and then describe some domain-specific approaches.

Similarity and Categorization

Intuitively, similarity and categorization seem tightly linked. It is not surprising, then, that many studies of categorization have focused on the kinds of similarity relationships between a new exemplar and a stored category representation that allow the new item to be classified as a member of a known category. Prototype models assume that the stored category representation is a summary of the most typical feature values for members of a category, and that new exemplars are classified on the basis of their similarity to these prototypes (e.g. Hampton 1995, Reed 1972, Rosch & Mervis 1975). Exemplar models assume that people store away specific exemplars of the category and classify new items on the basis of their similarity to the stored exemplars (e.g. Kruschke 1992, Medin & Schaffer 1978, Nosofsky 1986).

Most models of similarity are domain general: They assume that some measure of proximity can be calculated for any pair of representations. Two classic influential approaches are the spatial view and the featural view. Spatial models of similarity (e.g. Nosofsky 1986; Shepard 1962, 1964) model individual concepts as points in a multidimensional space and assume that the similarity of a pair of objects is inversely related to the distance between them. Feature-based models of similarity (e.g. Tversky 1977) assume that objects are represented by sets of features, and that the commonalities of a pair are the features in the intersection of the sets representing each object, whereas the differences are just the features not in the intersection. These models have been criticized because they typically assume that a fixed set of dimensions or properties applies to a category (Schank et al 1986), ignoring the role of feature learning during categorization (Schyns et al 1998). Reflecting this perspective, classification experiments typically utilize a fixed set of dimensions, each with a small number of values. Similarity-based models of categorization have also been faulted for ignoring the role of theory in determining the relevance of features to categories (Goldstone 1994, Murphy & Medin 1985).

Current approaches to similarity like the structure-mapping approach described above may better meet some of these requirements. As Goldstone (1994) points out, structural alignment provides constraints on which commonalities among items are relevant for categorizing them. In particular, systematic relational structures are likely to be important for categorization. This point helps to bridge the gap between theory-based and similarity-based categorization. If similarity is computed by a structural alignment process rather than a feature-matching process, then common relational systems will be included in the similarity computation (and even favored, by the systematicity principle); thus, common causal systems will naturally be part of the category representation (Gentner & Medina 1998).

Structural alignment may also influence the way category representations are learned (Lassaline & Murphy 1998). Markman & Wisniewski (1997) asked people to list commonalities and differences of pairs of object categories at different levels of abstraction. People could more easily list commonalities and alignable differences for pairs of categories within a superordinate (e.g. pairs of vehicles or pairs of weapons) than for pairs from different superordinates (e.g. a vehicle and a weapon). This result suggests that object categories are organized around taxonomic clusters whose numbers are readily comparable with other members of the cluster, but not with members of different clusters.

These clusters may develop through reminding-based category learning (Ross et al 1990, Spalding & Ross 1994). In this view, when a new item is presented, it is given an initial representation that serves as a retrieval cue for items in memory. The concepts retrieved serve as a template for constructing the representation of the new item. This process helps create clusters of categories whose members are all comparable. There is some evidence for this reminding-based process. Zhang & Markman (1998) had people learn about a sequence of new brands of microwave popcorn. People first saw a description of the first brand; in a second session, they saw a description of the first brand again followed by descriptions of two more brands whose properties overlapped with those of the first brand. People learned properties of the later brands better if they were alignable differences with the first brand than if they were nonalignable differences, suggesting that they learned the later brands by aligning them to the initial one. These findings suggest that structural alignment influences the representations of new categories.

The studies just described are part of a larger movement that explores the influence of reasoning with categories on what is learned about categories—an instance of the "learning as a byproduct of reasoning" theme mentioned at the beginning of this paper (see Brooks 1978). Ross (1997, 1999) has demonstrated that when features are relevant to a secondary task (either problem solving or a secondary classification) their salience is increased in a primary classification task. Yamauchi & Markman (1998) found that when categories are learned in the process of making feature predictions, their representations focus more on relationships among features than do those of categories learned by classifying new instances.

Finally, the issue of whether language influences category structures has returned to the research foreground. Recent work is exploring whether and how possessing specific semantic categories affects conceptual processing (e.g. Cabrera & Billman 1996, Gentner & Loewenstein 2000, Gumperz & Levinson 1996, Malt et al 1999), as well as how the act of communication affects people's learning and reasoning (Clark 1996, Garrod & Anderson 1987, Markman & Makin 1998).

Inference from Categories

Once categories are established, people can use them to infer features of a new situation. This kind of reasoning is studied using the category-based induction task. In these tasks, people are told that one or more categories has some property and asked how likely it is that some other category has the same property. For example, people might be told that robins have property X and that bluebirds have property X, and asked how likely it is that all birds have property X. The strength of this argument can be compared to that of another argument, such as: "Robins have X, Ostriches have X; how likely are all Birds to have X?"

Many of the central phenomena in category-based induction were mapped out by Osherson et al (1990). According to their similarity-coverage model, the perceived strength of a conclusion increases with the similarity between the premises and the conclusion category. Thus, "robins have X, therefore bluebirds have X" is judged to be a stronger argument than "ostriches have X, therefore bluebirds have X." The similarity-coverage model also predicts a diversity effect in reasoning. Premises from diverse categories lead to stronger arguments than premises that are highly similar to each other. For example, college undergraduates find the argument "robins have X, ostriches have X, therefore all birds have X" to be stronger than the argument "robins have X, bluebirds have X, therefore all birds have X." A related model of induction based on feature overlap was developed by Sloman (1993).

These views of category-based induction rely on overall similarity or feature overlap as a predictor of argument strength. However, recent research suggests that the comparisons involved here may be sensitive to causal alignments. For example, Heit & Rubinstein (1994) showed people arguments in which the properties to be inferred were either behaviors or anatomical properties. People based their judgments of argument strength not on overall similarity, but on similarity with respect to the particular dimension: Thus, whales were considered likely to share a new behavioral property of fish, but a new anatomical property of cattle. Furthermore, it appears that the subjective strength of the induction depends on the causal alignment between premises and conclusion categories (Lassaline 1996).

Category-based induction is also influenced by expertise in a domain. Medin, Atran, and their colleagues (Coley et al 1999, Medin et al 1997) have undertaken a cross-cultural study of biological reasoning. They contrasted category-based induction performance of college undergraduates with that of Itzaj Mayans from Guatemala (who have extensive experience with their native flora), with scientific taxonomists (who study classification of trees), landscape workers (who decide where to plant trees in residential settings), and park maintenance workers (who take care of trees in local parks). One striking difference among these groups arises with diversity-based reasoning. As discussed above, college students consider that a diverse set of premise categories increases the strength of an argument. The taxonomists and landscape workers also preferred diverse arguments. However, both Itzaj Mayans and park maintenance workers showed the opposite effect, preferring arguments with similar categories in the premises to arguments with dissimilar categories in the premises. An analysis of the justifications suggests that the Mayans and landscape workers based their judgments on ecological factors. For example, landscape workers thought that a disease affecting white birches and river birches would affect more trees than a disease affecting white pines and weeping willows (Coley et al 1999). Although the second pair is more diverse than the first, maintenance workers argued that the first pair (the birches) were more likely to cause diseases of all trees, because this pair of trees is more widely planted and more susceptible to disease than pine and willow. Thus, differences in expertise influenced how people evaluated inductive arguments.

To summarize, recent research in category-based induction explores both general processes and specific knowledge structures. People align specific causal systems between the premises and conclusions to guide their inductions. With increasing expertise, people are able to form more elaborate causal explanations.

Feature Centrality

A related area in which domain-general approaches have been applied to categorization is in the determination of the centrality of a feature in a category. The notion of centrality is that some properties of a category are more important than others. For example, for a robin, the property of having wings seems to be more central than the property of having a red breast. It is easier to imagine a robin without a red breast than one without wings. A related point is that some categories seem more cohesive than others. Research has focused on structural properties that may determine cohesiveness and feature centrality.

Gentner (1981) explored the differences between nouns and verbs and suggested that nouns differ from verbs in the relational density of their representations. That is, the semantic components of noun meanings are more strongly interconnected than those of verbs. One consequence of this difference is that the meanings of nouns seem less mutable than the meanings of verbs. For example, people asked to paraphrase a sentence like "the lizard worshipped" are more likely to change the verb's meaning (e.g. "the small gray reptile lay on a hot rock and stared at the sun") than the noun's meaning (e.g. "a man with scaly skin prayed"). In this view, the ease of altering a property of a concept is influenced by the degree to which that property is interconnected with others.

This interconnectivity idea was explored at the level of individual properties by Sloman, Love, and Ahn (Love & Sloman 1995, Sloman et al 1998). They found that the perceived mutability of a feature—that is, how willing people were to accept changes in those features for members of the category—was influenced by its interconnectivity with other features of the category. Features with few interconnections were more mutable than features with many interconnections.

More specifically, there is evidence that an important determinant of feature centrality is whether a property participates in a higher-order constraining structure such as causality. This is consistent with the systematicity principle discussed above. For example, Ahn and colleagues have demonstrated the importance of causally relevant properties (Ahn 1999, Ahn et al 2000). Using sorting tasks, Ahn (1999) demonstrated that people prefer to create categories based on items with a common cause or a common effect, suggesting that they align causal structures across items, and focus on the alignable information. Likewise, Rehder & Hastie (1998) found that common causal relations led items to be placed in the same category. Ramscar & Pain (1996) asked subjects to categorize a set of stories that varied systematically in their similarity relations. Subjects classified the stories by common causal structure rather than by common object features.

Ahn et al (2000) further suggested that causes may be more important than effects. They found that when people categorize new items with missing features, they are more likely to classify an item into a given category when the cause is present and the effect is missing than when the reverse is true (provided the causal relation is plausible). This suggests that the position of a property within a relational structure (as the cause rather than as the effect) influences the importance of that feature in a category.

Similar findings have been shown with temporal relations (Sloman et al 1998). However, we would not expect that just any relation (e.g. taller or darker) or even any relation between relations (e.g. conjunctions) would contribute to centrality. The systematicity effect depends on higher-order constraining relations: relations that bind their relational arguments in informative ways. Future work will have to investigate the effects of content and structure further.

Domain-Specific Approaches to Categorization

Although categorization has traditionally been modeled using domain-general processes, recent research has focused on domain-specific aspects of categorization. First, research in the interface between psychology and anthropology has used cross-cultural similarities and differences in categorization to study the relative contributions of the objective structure of the world and the constraints of the cognitive system to human conceptual structure. Second, as discussed above, research in cognitive development has traced the development knowledge structures that characterize specific domains. One major focus in this work is naive biology: e.g. the distinction between animate and inanimate entities in category acquisition.

Malt (1995) reviewed studies exploring folk biological categories across cultures to examine whether category structure is more strongly influenced by the objective information available in the world or by the structure of the cognitive system. One way to approach this is to compare folk systems with scientific taxonomies, which presumably are designed to capture objective facts about the world. Perhaps unsurprisingly, the evidence that bears on these questions shows a mixture of influences. In general, folk biological (and folk botanical) categories often do bear a strong resemblance to scientific categories, particularly at the genus level (roughly similar to the basic level). This suggests that there are clusters of features in the world, and that people are sensitive to these clusters (Atran 1990, Berlin 1972). However, there are also clear influences of cultural factors on these categories. For example, the folk botanical category "tree" does not pick out a distinct class of plants, and many objects labeled as trees are more closely related in scientific taxonomies to plants we would call bushes than they are to other trees. Instead, categories like tree carry with them certain functional properties such as providing shade.

A second way in which domain-specific information influences categorization is that, as noted above, domain theories can affect the set of features people use to classify an item. This phenomenon can be seen in children as their domain theories develop. Many researchers have found that when children hear a new noun applied to an object, they tend to generalize the word to other objects with the same shape (e.g. Baldwin 1989, Landau et al 1988), but that with increasing knowledge there is a shape-to-taxonomic shift (Imai et al 1994). Children come to use taxonomic information to generalize word meanings (Markman 1989, Waxman 1990).

Consistent with our earlier discussion of the development of domain theories, children appear to consider animacy important in categorization. There is evidence that children are less likely to generalize a new label according to shape when they believe that the object is animate. Jones et al (1991) found that preschool children given labels for a set of novel objects generalized according to shape unless the objects had eyes, in which case they also took into account the texture of the objects. Another early dimension may be whether something is an artifact. Bloom (1998) found that young children pay more attention to the intended function of an item if they are told it is an artifact.

People's knowledge of the functions of categories can also constrain the features they focus on (Heit 1997, Murphy & Allopenna 1994, Spalding & Murphy 1996, Wisniewski & Medin 1994). Wisniewski (1995) had people learn about novel functional categories whose features varied in frequency of association and in functional relevance. For example, if the function of a particular category was to kill bugs, then a functionally relevant feature might be "contains poison," and an irrelevant feature might be "manufactured in Florida." People who were told the functions of the categories prior to learning focused strongly on functionally relevant features, even when these features occurred more rarely than functionally irrelevant features.

These examples illustrate both the importance of specific content and the way in which content interacts with higher-level beliefs. For example, in the developmental studies described here, the importance of a given feature is influenced by children's domain understanding. In cross-cultural research, the content of categories is explored in order to ask fundamental questions about how perceptual experience and cultural conventions interact in cognitive structure.

SUMMARY AND CONCLUSIONS

Human reasoning is characterized by a mix of domain-general and domain-specific aspects. Domain-general processes such as logical deduction operate on the structure of representations, independent of content. Their value is in their wide applicability across domains. At the other extreme are reasoning processes that are specific to particular modalities or content areas. Analogy—structural alignment and mapping—operates at an intermediate level. It has a domain-specific aspect in that it is sensitive to domain content. However, the constraints on these processes (e.g. structural consistency and systematicity) are domain general. Our review suggests that many domain-specific effects can be captured using alignment and mapping processes.

The research reviewed here opens up a number of important avenues for future research. One particularly important area is cross-cultural work. In the section on categorization, we briefly touched on some research with specialized populations including Itzaj Mayans, and groups of American tree experts. This work is part of a growing trend in psychology to move beyond the college undergraduates who typically participate in studies to examine how cultural difference and knowledge difference influence behavior. For example, members of collectivist cultures (like many Asian cultures) may be more willing to take risks than members of individualistic cultures (like the one in the United States), because of a belief that the cultural influences are likely to become an important part of research on reasoning processes.

The role of domain-specific knowledge in reasoning is also central to evolutionary psychology. Cosmides and Tooby (1994) point out that the interests in domain-specific modules in development that we discussed above intersects with work by evolutionary psychologists on mechanisms for solving domain-specific problems. Evolutionary psychology argues that these domain-specific modules evolved to solve problems that were prominent in the environment of early hominids. While it is too early to evaluate the evolutionary perspective, the parallels between this work and research in cognitive development bear further scrutiny.

Domain-specificity has also been explored in cognitive neuroscience. Earlier, we mentioned the proposal by Caramazza and Shelton that there may be specific brain mechanisms to process animate and inanimate objects. There is continued exploration of the way the brain processes information about animate and inanimate objects (as well as faces) in both lesion studies (e.g. Tranel et al 1997) and imaging studies (e.g. Perani et al 1999). At present it is difficult to draw firm conclusions from this work, but significant new research is likely to be done in this area as techniques for brain imaging improve.

The rise of research on imaging heightens the importance of behavioral research on thinking that was the focus of this paper. Current brain imaging techniques are only able to explore tasks that take place in a few seconds. Long complex tasks are difficult to give to patients who may have significant cognitive impairments. Further, complex tasks that take place over a period of minutes or even hours are inappropriate for imaging techniques. However, a better understanding of reasoning behavior will lead to task decompositions that may be more amenable to techniques from cognitive neuroscience.

We are entering an exciting period of research on reasoning. Significant progress have been made on both domain-general and domain-specific processes. This work has opened up new avenues for exploration. The next step in this progression of research will require the development of models that combine domain-general and domain-specific approaches into unified models of reasoning in cognition.

ACKNOWLEDGMENTS

This research was supported by ONR grant N00014-92-J-1098 and NSF-LIS grant SBR-9511757 to DG and by NSF grant SBR-9905013 given to ABM. This chapter was partially prepared while DG was a Fellow at the Center for Advanced Study in the Behavioral Sciences. We are grateful for the financial support provided by the William T. Grant Foundation, award #95167795

LITERATURE CITED

Ahn WK. 1999. Effect of causal structure on category construction. *Mem. Cogn.* 27:1008–23

Ahn WK, Kim NS, Lassaline ME, Dennis MJ. 2000. Causal status as a determinant of feature centrality. *Cogn. Psychol.* In press

Anderson JR. 1993. *Rules of the Mind*. Hillsdale, NJ: Erlbaum

Anderson JR, Lebiere C, eds. 1998. *The Atomic Components of Thought*. Mahwah, NJ: Erlbaum

Atran S. 1990. *Cognitive Foundations of Natural History: Towards an Anthropology of Science*. New York: Cambridge Univ. Press

Baillargeon R. 1994. How do infants learn about the physical world? *Curr. Dir. Psychol. Sci.* 3(5):133–40

Baldwin DA. 1989. Priorities in children's expectations about object label reference: form over color. *Child Dev.* 60:1289–306

Bassok M, Chase VM, Martin SA. 1998. Adding apples and oranges: semantic constraints on application of formal rules. *Cogn. Psychol.* 35:99–134

Berlin B. 1972. Speculations on the growth of ethnobotanical nomenclature. *Lang. Soc.* 1:51–86

Bloom P. 1998. Theories of artifact categorization. *Cognition* 66:87–93

Bowdle B, Gentner D. 1997. Informativity and asymmetry in comparisons. *Cogn. Psychol.* 34(3):244–86

Bowdle B, Gentner D. 1999. Metaphor comprehension: from comparison to categorization. In *Proc. 21st Annu. Conf. Cogn. Sci. Soc.*, pp. 90–95. Vancouver, BC: Erlbaum

Brooks LR. 1978. Non analytic concept formation and memory for instances. In *Cognition and Categorization*, ed. E Rosch, BB Lloyd, pp. 169–211. Hillsdale, NJ: Erlbaum

Cabrera A, Billman D. 1996. Language-driven concept learning: deciphering Jabberwocky. *J. Exp. Psychol.: Learn. Mem. Cogn.* 22(2): 539–55

Caramazza A, Shelton JR. 1998. Domain-specific knowledge systems in the brain: the animate-inanimate distinction. *J. Cogn. Neurosci.* 10:1–34

Carey S. 1985. *Conceptual Change in Childhood*. Cambridge, MA: MIT Press

Cheng PW, Holyoak KJ. 1985. Pragmatic reasoning schemas. *Cogn. Psychol.* 17:391–416

Chi MTH, Feltovich PJ, Glaser R. 1981. Categorization and representation of physics problems by experts and novices. *Cogn. Sci.* 5:121–52

Chi MTH, VanLehn KA. 1991. The content of physics self-explanations. *J. Learn. Sci.* 1:69–105

Clark HH. 1996. *Using Language*. London: Cambridge Univ. Press

Clement CA, Gentner D. 1991. Systematicity as a selection constraint in analogical mapping. *Cogn. Sci.* 15:89–132

Coley JD. 1995. Emerging differentiation of folkbiology and folkpsychology: attributions of biological and psychological properties to living things. *Child Dev.* 66:1856–74

Coley JD, Medin DL, Proffitt JB, Lynch E, Atran S. 1999. Inductive reasoning in folkbiological thought. See Medin & Atran 1999, pp. 205–32

Cosmides L. 1989. The logic of social exchange: Has natural selection shaped how humans reason? Studies with the Wason selection task. *Cognition* 31:187–276

Cosmides L, Tooby J. 1994. Origins of domain specificity: the evolution of functional organization. In *Mapping the Mind*, ed. LA Hirschfeld, SA Gelman, pp. 85–116. New York: Cambridge Univ. Press

Dunbar K. 1995. How scientists really reason: scientific reasoning in real-world laboratories. In *The Nature of Insight*, ed. RJ Sternberg, JE Davidson, pp. 365–95. Cambridge, MA: MIT Press

Elman JL, Bates EA, Johnson MH, Karmiloff-Smith A, Parisi D, Plunkett K. 1996. *Rethinking Innateness: A Connectionist Perspective on Development*. Cambridge, MA: MIT Press

Evans JS, Over DE. 1996. *Rationality and Reasoning*. East Sussex, UK: Psychology Press

Falkenhainer B, Forbus KD, Gentner D. 1989. The structure-mapping engine: algorithm and examples. *Artif. Intell.* 41:1–63

Forbus KD. 1984. Qualitative process theory. *Artif. Intell.* 24:85–168

Forbus KD, Nielsen P, Faltings B. 1991. Qualitative spatial reasoning: The CLOCK project. *Artif. Intell.* 52:417–72

Garrod S, Anderson A. 1987. Saying what you mean in dialogue: a study in conceptual and semantic co-ordination. *Cognition* 27:181–218

Gentner D. 1981. Some interesting differences between nouns and verbs. *Cogn. Brain Theory* 4:161–78

Gentner D. 1983. Structure-mapping: a theoretical framework for analogy. *Cogn. Sci.* 7:155–70

Gentner D. 1989. The mechanism of analogical learning. In *Similarity and Analogical Reasoning*, ed. S Vosnindon, A Ortony, pp. 199–241. New York: Cambridge Univ. Press

Gentner D, Loewenstein J. 2000. Relational language and relational thought. In *Language, Literacy, and Cognitive Development*, ed. J Byrnes, E Amsel. Hillsdale, NJ: Erlbaum. In press

Gentner D, Markman AB. 1994. Structural alignment in comparison: no difference without similarity. *Psychol. Sci.* 5:152–58

Gentner D, Markman AB. 1997. Structural alignment in analogy and similarity. *Am. Psychol.* 52:45–56

Gentner D, Medina J. 1998. Similarity and the development of rules. *Cognition* 65:263–97

Gentner D, Rattermann MJ, Forbus KD. 1993. The roles of similarity in transfer: separating retrievability from inferential soundness. *Cogn. Psychol.* 25:524–75

Gentner D, Stevens AL, eds. 1983. *Mental Models*. Hillsdale, NJ: Erlbaum

Gentner D, Wolff P. 1997. Alignment in the processing of metaphor. *J. Mem. Lang.* 37:331–55

Gentner D, Wolff P. 2000. Metaphor and knowledge change. In *Cognitive Dynamics*, ed. E Dietrich, AB Markman, pp. 295–342. Mahwah, NJ: Erlbaum

Gilden DL, Proffitt DR. 1989. Understanding collision dynamics. *J. Exp. Psychol.: Hum. Percep. Perform.* 15:372–83

Glenberg AM. 1997. What memory is for. *Behav. Brain Sci.* 20(1):1–55

Glucksberg S, McGlone MS, Manfredi D. 1997. Property attribution in metaphor comprehension. *J. Mem. Lang.* 36:50–67

Goldstone RL. 1994. The role of similarity in categorization: providing a groundwork. *Cognition* 52:125–57

Goldstone RL, Medin DL. 1994. The time course of comparison. *J. Exp. Psychol.: Learn. Mem. Cogn.* 20:29–50

Gopnik A, Meltzoff AN. 1997. *Words, Thoughts and Theories*. Cambridge, MA: MIT Press

Guidagni PM, Little JDC. 1983. A logit model of brand choice calibrated on scanner data. *Mark. Sci.* 2:203–38

Gumperz JJ, Levinson SC. 1996. Introduction: linguistic relativity re-examined. In *Rethinking Linguistic Relativity*, ed. JJ Gumperz, SC Levinson, pp. 1–18. Cambridge, MA: Cambridge Univ. Press

Halford GS. 1992. Analogical reasoning and conceptual complexity in cognitive development. *Hum. Dev.* 35(4):193–218

Hampton JA. 1995. Testing the prototype theory of concepts. *J. Mem. Lang.* 34:686–708

Hatano G, Inagaki K. 1999. A developmental perspective on informal biology. See Medin & Atran 1999, pp. 321–54

Hegarty M, Just MA. 1993. Constructing mental models of machines from text and diagrams. *J. Mem. Lang.* 32: 717–42

Heit E. 1997. Knowledge and concept learning. In *Knowledge, Concepts, and Categories*, ed. K Lamberts, D Shanks, pp. 7–41. Cambridge, MA: MIT Press

Heit E, Rubinstein J. 1994. Similarity and property effects in inductive reasoning. *J. Exp. Psychol.: Learn. Mem. Cogn.* 20:411–22

Hirschfeld LA, Gelman SA, eds. 1994. *Mapping the Mind: Domain Specificity in Cognition and Culture*. New York: Cambridge Univ. Press

Holyoak KJ, Thagard P. 1989. Analogical mapping by constraint satisfaction. *Cogn. Sci.* 13:295–355

Howard IP. 1978. Recognition and knowledge of the water-level principle. *Perception* 7:151–60

Hummel JE, Holyoak KJ. 1997. Distributed representations of structure: a theory of analogical access and mapping. *Psychol. Rev.* 104:427–66

Imai M, Gentner D, Uchida N. 1994. Children's theories of word meaning: the role of shape similarity in early acquisition. *Cogn. Dev.* 9:45–75

Inagaki K, Hatano G. 1987. Young children's spontaneous personification as analogy. *Child Dev.* 58:1013–20

Johnson-Laird PN. 1983. *Mental Models*. Cambridge, MA: Harvard Univ. Press

Johnson-Laird PN. 1999. Deductive reasoning. *Annu. Rev. Psychol.* 50:109–35

Johnson-Laird PN, Byrne RMJ. 1991. *Deduction*. Hillsdale, NJ: Erlbaum

Jones SS, Smith LB, Landau B. 1991. Object properties and knowledge in early lexical learning. *Child Dev.* 62:499–516

Keil FC. 1989. *Concepts, Kinds and Cognitive Development*. Cambridge, MA: MIT Press

Kempton W, Boster JS, Hartley J. 1994. *Environmental Values in American Culture*. Cambridge, MA: MIT Press

Klayman J, Ha Y. 1987. Confirmation, disconfirmation and information in hypothesis testing. *Psychol. Rev.* 94:211–28

Koehler JJ. 1993. The influence of prior beliefs on scientific judgments of evidence quality. *Organ. Behav. Hum. Decis. Process.* 56:28–55

Kruschke JK. 1992. ALCOVE: an exemplar-based connectionist model of category learning. *Psychol. Rev.* 99:22–44

Kuhn D. 1997. Is good thinking scientific thinking? In *Modes of Thought: Explorations in Culture and Cognition*, ed. DR Olson, N Torrance, pp. 261–81. New York: Cambridge Univ. Press

Kuipers B. 1994. *Qualitative Reasoning: Modeling and Simulation with Incomplete Knowledge*. Cambridge, MA: MIT Press

Landau B, Smith LB, Jones SS. 1988. The importance of shape in early lexical learning. *Cogn. Dev.* 3:299–321

Lassaline ME. 1996. Structural alignment in induction and similarity. *J. Exp. Psychol.: Learn. Mem. Cogn.* 22:754–70

Lassaline ME, Murphy GL. 1998. Alignment and category learning. *J. Exp. Psychol.: Learn. Mem. Cogn.* 24:144–60

Leslie AM. 1991. The theory of mind impairment in autism: evidence for a modular mechanism of development? In *Natural Theories of Mind: Evolution, Development and Simulation of Everyday Mindreading*, ed. A Whiten. Oxford/Cambridge, MA: Blackwell

Logan GD. 1988. Toward an instance theory of automaticity. *Psychol. Rev.* 95:492–527

Logan GD. 1996. The CODE theory of visual attention: an integration of space-based and object-based attention. *Psychol. Rev.* 103:603–49

Love BC, Sloman SA. 1995. Mutability and the determinants of conceptual transformability. In *Proc. 17th Annu. Conf. Cogn. Sci. Soc.*, pp. 65–59. Pittsburgh, PA: Erlbaum

Malt BC. 1995. Category coherence in cross-cultural perspective. *Cogn. Psychol.* 29:85–148

Malt BC, Sloman SA, Gennari S, Shi M, Wang Y. 1999. Knowing versus naming: similarity and the linguistic categorization of artifacts. *J. Mem. Lang.* 40:230–62

Markman AB. 1997. Constraints on analogical inference. *Cogn. Sci.* 21:373–418

Markman AB. 1999. *Knowledge Representation*. Mahwah, NJ: Erlbaum

Markman AB, Gentner D. 1993a. Splitting the differences: a structural alignment view of similarity. *J. Mem. Lang.* 32:517–35

Markman AB, Gentner D. 1993b. Structural alignment during similarity comparisons. *Cogn. Psychol.* 25:431–67

Markman AB, Gentner D. 1996. Commonalities and differences in similarity comparisons. *Mem. Cogn.* 24:235–49

Markman AB, Gentner D. 1997. The effects of alignability on memory. *Psychol. Sci.* 8:363–67

Markman AB, Makin VS. 1998. Referential communication and category acquisition. *J. Exp. Psychol.: Gen.* 127(4):331–54

Markman AB, Wisniewski EJ. 1997. Similar and different: the differentiation of basic level categories. *J. Exp. Psychol.: Learn. Mem. Cogn.* 23:54–70

Markman EM. 1989. *Categorization and Naming in Children*. Cambridge, MA: MIT Press

McCloskey M. 1983. Naive theories of motion. See Gentner & Stevens 1983, pp. 299–324

Medin DL, Atran S, eds. 1999. *Folkbiology*. Cambridge, MA: MIT Press

Medin DL, Goldstone RL, Gentner D. 1993. Respects for similarity. *Psychol. Rev.* 100(2):254–78

Medin DL, Lynch EB, Coley JD, Atran S. 1997. Categorization and reasoning among tree experts: Do all roads lead to Rome? *Cogn. Psychol.* 32:49–96

Medin DL, Ross BH. 1989. The specific character of abstract thought: categorization, problem solving and induction. In *Advances in the Psychology of Human Intelligence*, ed. RS Sternberg, 5:189–223. Hillsdale, NJ: Erlbaum

Medin DL, Schaffer MM. 1978. Context theory of classification. *Psychol. Rev.* 85:207–38

Metz KE. 1985. The development of children's problem solving in a gears task: a problem space perspective. *Cogn. Sci.* 9:431–71

Murphy GL, Allopenna PD. 1994. The locus of knowledge effects in concept learning. *J. Exp. Psychol.: Learn. Mem. Cogn.* 20:904–19

Murphy GL, Medin DL. 1985. The role of theories in conceptual coherence. *Psychol. Rev.* 92:289–315

Nersessian N. 1999. Model-based reasoning in conceptual change. In *Model-Based Reasoning in Scientific Discovery*, ed. L Magroni, N Nersessian, P Thagard, pp. 5–22. Dordrecht, The Netherlands: Kluwer

Newell A, Simon HA. 1972. *Human Problem Solving*. Englewood Cliffs, NJ: Prentice-Hall

Norman DA. 1988. *The Psychology of Everyday Things*. New York: Basic Books

Nosofsky RM. 1986. Attention, similarity and the identification-categorization relationship. *J. Exp. Psychol.: Gen.* 115:39–57

Osherson DN, Smith EE, Wilkie O, Lopez A, Shafir E. 1990. Category based induction. *Psychol. Rev.* 97:185–200

Perani D, Schnur T, Tettamanti M, Gorno-Tempini M, Cappa S, Fazio F. 1999. Word and picture matching: a PET study of semantic category effects. *Neuropsychologia* 37:293–306

Pfeifer R, Scheier C. 1999. *Understanding Intelligence*. Cambridge, MA: MIT Press

Proffitt DR, Kaiser MK, Whelan SM. 1990. Understanding wheel dynamics. *Cogn. Psychol.* 22:342–73

Ramscar M, Pain H. 1996. Can a real distinction be made between cognitive theories of analogy and categorisation? *Proc. 18th Annu. Conf. Cogn. Sci. Soc.*, pp. 346–51. Hillsdale, NJ: Erlbaum

Reed SK. 1972. Pattern recognition and categorization. *Cogn. Psychol.* 3:382–407

Rehder B, Hastie R. 1998. The differential effects of causes on categorization and similarity. *Proc. 20th Annu. Conf. Cogn. Sci. Soc.*, pp. 893–98. Hillsdale, NJ: Erlbaum

Rips LJ. 1986. Mental muddles. In *The Representation of Knowledge and Belief*, ed. H Brand, RM Harnish. Tucson: Univ. Ariz. Press

Rips LJ. 1994. *The Psychology of Proof: Deductive Reasoning in Human Thinking*. Cambridge, MA: MIT Press

Rosch E, Mervis CB. 1975. Family resemblances: studies in the internal structure of categories. *Cogn. Psychol.* 7:573–605

Rosengren KS, Gelman SA, Kalish CW, McCormick M. 1991. As time goes by: children's early understanding of growth in animals. *Child Dev.* 62:1302–20

Ross BH. 1997. The use of categories affects classification. *J. Mem. Lang.* 37(2):240–67

Ross BH. 1999. Postclassification category use: the effects of learning to use categories after learning to classify. *J. Exp. Psychol.: Learn. Mem. Cogn.* 25(3):743–57

Ross BH, Perkins SJ, Tenpenny PL. 1990. Reminding-based category learning. *Cogn. Psychol.* 22:460–92

Schank RC, Collins GC, Hunter LE. 1986. Transcending inductive category formation in learning. *Behav. Brain Sci.* 9:639–86

Schwartz DL, Black JB. 1996. Shuttling between depictive models and abstract rules: induction and fallback. *Cogn. Sci.* 20:457–98

Schwartz DL, Black T. 1999. Inferences through imagined actions: knowing by simulated doing. *J. Exp. Psychol.: Learn. Mem. Cogn.* 25:116–36

Schyns PG, Goldstone RL, Thibaut JP. 1998. The development of features in object concepts. *Behav. Brain Sci.* 21:1–54

Shepard RN. 1962. The analysis of proximities: multidimensional scaling with an unknown distance function. I. *Psychometrika* 27:125–40

Shepard RN. 1964. Attention and the metric structure of the stimulus space. *J. Math. Psychol.* 1:54–87

Siegler RS, Shipley C. 1995. Variation, selection, and cognitive change. In *Developing Cognitive Competence: New Approaches to Process Modeling*, ed. TJ Simon, GS Halford, pp. 31–76. Hillsdale, NJ: Erlbaum

Simons DJ, Keil FC. 1995. An abstract to concrete shift in the development of biological thought: the insides story. *Cognition* 56:129–63

Sjöberg L. 1972. A cognitive theory of similarity. *Göteborg Psychol. Rep.* 2 (monograph)

Sloman SA. 1993. Feature-based induction. *Cogn. Psychol.* 25:231–80

Sloman SA. 1996. The empirical case for two systems of reasoning. *Psychol. Bull.* 119:3–22

Sloman SA, Love BC, Ahn WK. 1998. Feature centrality and conceptual coherence. *Cogn. Sci.* 22:189–228

Spalding TL, Murphy GL. 1996. Effects of background knowledge on category construction. *J. Exp. Psychol.: Learn. Mem. Cogn.* 22:525–38

Spalding TL, Ross BH. 1994. Comparison-based learning: effects of comparing instances during category learning. *J. Exp. Psychol.: Learn. Mem. Cogn.* 20:1251–63

Spellman BA, Holyoak KJ. 1996. Pragmatics in analogical mapping. *Cogn. Psychol.* 31:307–46

Stenning K, Oberlander J. 1995. A cognitive theory of graphical and linguistic reasoning: logic and implementation. *Cogn. Sci.* 19:97–140

Suchman LA. 1987. *Plans and Situated Actions: The Problem of Human-Machine Communication*. Cambridge, UK: Cambridge Univ. Press

Thelen E, Smith LB. 1993. *A Dynamic Systems Approach to the Development of Cognition and Action*. Cambridge, MA: MIT Press

Tooby J, Cosmides L. 1989. Evolutionary psychology and the generation of culture: I. Theoretical considerations. *Ethol. Sociobiol.* 10(1–3):29–49

Tranel D, Damasio H, Damasio AR. 1997. A neural basis for the retrieval of conceptual knowledge. *Neuropsychologia* 35:1319–27

Tversky A. 1977. Features of similarity. *Psychol. Rev.* 84:327–52

Tversky B. 1991. Distortions in memory for visual displays. In *Spatial Instruments and Spatial Displays*, ed. SR Ellis, M Kaiser, A Grunewald, pp. 61–75. Hillsdale, NJ: Erlbaum

Vosniadou S, Brewer WF. 1992. Mental models of the earth: a study of conceptual change in childhood. *Cogn. Psychol.* 24:535–85

Warrington EK, Shallice T. 1984. Category specific semantic impairments. *Brain* 107:829–54

Wason PC, Johnson-Laird PN. 1972. *Psychology of Reasoning Structure and Content*. London: Routledge

Waxman SR. 1990. Linguistic biases and the establishment of conceptual hierarchies: evidence from preschool children. *Cogn. Dev.* 5:123–50

Wilson RA, Keil F. 1998. The shadows and shallows of explanation. *Minds Mach.* 8:137–59

Wisniewski EJ. 1995. Prior knowledge and functionally relevant features in concept learning. *J. Exp. Psychol.: Learn. Mem. Cogn.* 21:449–68

Wisniewski EJ, Medin DL. 1994. On the interaction of theory and data in concept learning. *Cogn. Sci.* 18:221–82

Wolff P, Gentner D. 2000. Evidence for role-neutral initial processing of metaphors. *J. Exp. Psychol.: Learn. Mem. Cogn.* 26:512–28

Yamauchi T, Markman AB. 1998. Category learning by inference and classification. *J. Mem. Lang.* 39:124–48

Zhang S, Markman AB. 1998. Overcoming the early entrant advantage: the role of alignable and nonalignable differences. *J. Mark. Res.* 35:413–26