Articles

Monster Analogies

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Analogy has a rich history in Western civilization. Over the centuries, it has become reified in that analogical reasoning has sometimes been regarded as a fundamental cognitive process. In addition, it has become identified with a particular expressive format. The limitations of the modern view are illustrated by monster analogies, which show that analogy need not be regarded as something having a single form, format, or semantics. Analogy clearly does depend on the human ability to create and use well-defined or analytic formats for laying out propositions that express or imply meanings and perceptions. Beyond this dependence, research in cognitive science suggests that analogy relies on a number of genuinely fundamental cognitive capabilities, including semantic flexibility, the perception of resemblances and of distinctions, imagination, and metaphor. Extant symbolic models of analogical reasoning have various sorts of limitation, yet each model presents some important insights and plausible mechanisms. I argue that future efforts could be aimed at integration. This aim would include the incorporation of contextual information, the construction of semantic bases that are dynamic and knowledge rich, and the incorporation of multiple approaches to the problems of inference constraint.

> "There is no word which is used more loosely, or in a greater variety of senses, than Analogy." —John Stuart Mill, 1882, p. 393

A nalogical reasoning is a nexus for many issues in AI—how to acquire knowledge, how to represent meaning, how to support creativity and "going beyond the information given," and so on. In many ways, the problem of analogy sets a stage for potential advances in computational logic and machine learning. Existing AI models of analogy are all explicitly based on empirical observations of cognitive phenomena. Thus, the problem of analogy also sets the stage for machine simulation, forcing one to particularize the processes of inference and memory access that are sometimes left underspecified in cognitive theories (Hall 1988).

The purpose of this article is to first describe, then deconstruct, and then reconstruct the concept of analogy as it is conceived in the allied fields of AI and cognitive science. Analysis of the forms and semantics of analogy suggests that the concept can be broadened beyond the common conception. In turn, this suggests ways in which computational approaches might be enhanced, especially by combining the insights from a number of the existing models.

The Focus of This Article

My focus is on verbal-conceptual analogy rather than geometric or pictorial analogies such as those in figure 1. Interesting work has been conducted on geometric analogy and theorem proving by analogy (for example, O'Hara [1992], Kling [1971], and Evans [1968]). Verbal-conceptual analogies are also distinguished from letter-string analogies such as

abc : abd :: iijjkk : iijjll .

Chalmers, French, and Hofstadter (1992) described an interesting system for solving such analogies in which the process of representation building (*perception*) proceeds partly in parallel with the process of analogy construction. I focus on verbal-conceptual analogy because I suspect it is where AI will find much of the beef.

The Scope of This Article

The many AI systems for analogy use a considerable variety of mechanisms (Hall 1988). Some systems begin with elaborate memory representations; others begin impoverished. Some operate on individual analogies; some construct elaborate domain-domain mappings based on experience with multiple Articles



Figure 1. A Simple Geometric Analogy and a Simple Pictorial Analogy.

analogies. Some involve parallel or cyclical processing, and some are more sequential. Most systems use some form of both topdown and bottom-up reasoning, but they do so in different ways. Some models seem passive; that is, they generate all possible mappings or pairings of elements and then evaluate the mappings for coherence. Others some seem more active or selective, say, by restricting mappings to those that satisfy given a priori goals. Some systems place analogical inference into a traditional deductive paradigm; some place it into a traditional productionrule system. Some systems painfully remember all their past failures; other systems attempt to derive generalizable rules. Some check for the adequacy of a solution by soliciting information from the user; some do not. Some systems have been backed up by empirical investigation, and so on.

Detailed analysis of the many AI models (ACME, ANA, ARCS, ARGUS, ARIES, ANALOGY, ASTRA, BORIS, CARE, CARL, ECHO, GRAPES, JULIP, MEDIATOR, PUPS, ZORBA, NLAG, STAR, and so on) is beyond the reach of any article.¹ However, despite details and differences, AI models seem to share a common spirit, which is my level of analysis and the particular topic that will tie things together in the concluding sections of this article.

Related to the focus of this article on verbalconceptual analogy is a focus on symbolic computation. A number of projects have involved connectionist and hybrid architectures for analogy processing (for reviews, see Barnden and Holyoak [1994] and Holyoak and Barnden [1994a]). One motivation for this new work is that analogical reasoning might "bridge the gap between traditional AI and connectionism" (Holyoak and Barnden 1994b, p. 23). Arguably, semantic networks and conceptual graphs are themselves connectionist in spirit. Conversely, some connectionist systems can be regarded as symbolic if they include a mechanism for (1) dynamic binding, (2) symbol passing, or (3) the labeling of links. Perhaps more fundamentally, the connectionist approach might be suited to a certain aspect of analogical reasoning—associative retrieval and mapping based on efficient memory indexing by spreading activation.

From a different perspective, connectionist systems seem to short circuit the problem of specifying a mechanism for conceptual change. That is, they can be models of the results of analogical processing, not the processing itself. Furthermore, some systems do seem blind to the semantics of propositions. (For a discussion of such conundrums, see Barnden and Holyoak [1994]; Holyoak and Barnden [1994a]; Gentner and Markman [1993]; and the Open Commentary, pp. 467–902, accompanying Thagard [1989]).

Symbolic-logical systems for analogy, as defined here, are those that operate by (1) algorithms and heuristics that are dependent on the syntax or semantics of propositions (as well as numeric data) and (2) inference axioms (rules, procedures) that are expressed in terms of propositions and the semantics of their constituent entities, predications, and parameters. (For details, see Hoffman and Gentner [1995], Steinhart [1994], Indurkhya [1992], Martin [1990], Hall [1988], Prieditis [1988], Eliot [1986], Russell [1986], Stelzer [1983], or Bergmann [1979]).

Like most AI systems, many systems for analogy are in a continual process of refinement. Every researcher would acknowledge the gaps between what the systems can do and what humans do. All researchers would acknowledge that their system does not reflect, in all its particulars, the grand theoretical model they hold dear. Nevertheless, at some point, one must examine what programs actually do. The goal in surveying an area is to suggest some possible next steps and open a dialogue. Why really care about this thing called analogy?

The Importance of Verbal-Conceptual Analogy

A great deal of cognitive research has been conducted on analogy. (For reviews, see Hoffman [1995], Holyoak and Thagard [1995], and Gibbs [1994].) Analogy is generally assumed to be a basic process in learning and

Analogy-Metaphor	Key Figure(s)
Physical Science	
Sound moves in waves, like water.	Vitruvius
The Earth is a magnet.	Gilbert
The Earth is like a sailing ship.	Galileo
Light is like sound (that is, waves).	Huygens, Frensel
A planet is a projectile.	Newton
Lightning is a type of electricity.	Franklin
Heat is a fluid, like water.	Carnot
Chemical elements can be arranged according to their	Mendeleeff
properties like the suits in a deck of cards (periodic table).	
Gasses are like a container of billiard balls (kinetic theory).	Boyle ¹
Electromagnetic forces can be conceived in mechanical terms.	Maxwell
Molecules can have shapes, like that of a snake.	Kekule
Atoms are like planetary systems.	Bohr, Rutherford
Division of atomic nucleus is like cell fission.	Frisch, Meitner
The atomic nucleus is like a droplet of fluid.	Bohr
Biological Science	
The heart is a pump.	Harvey ²
Nerves are tubes for conducting animating powers.	Descartes
The eye is a camera.	Keppler, Descartes
Respiration is a type of combustion.	Lavoisier
Species evolution has causes like those governing the growth of	Darwin
human populations.	
Natural evolution is caused by a process parallel to	Darwin
artificial selection (animal breeding).	
Society is like an organism.	le Bon ¹
Organisms are like a society (cell theory).	Virchow ²
Chromosomes are like beads on a string.	Morgan
The body-brain is a machine.	Descartes, de Condillac
Cognitive Science	
The brain is like a telegraph-telephone switchboard.	Helmholtz, Wundt ^{1,2}
The brain is like a network.	Golgi, y Cajal, Lashley, Hebb
The mind-brain is a control mechanism.	de la Mettrie, Wiener
The mind-brain is a connection-making machine.	Locke, James Mill, Hartley
The rational mind-brain is a logical machine.	Pierce, Boole, McCarthy
The rational mind-brain is a computational machine.	von Neumann, Turing
The rational mind-brain is an information processing and communication system	Wiener, Shannon
The rational mind-brain is a symbolic machine	Newell, Simon Feigenbaum Minsky
A computer can be like a neural network	McCulloch Pitts Rosenblatt
r computer cur be like a neural network.	Selfridge Rumelhart
	Sennage, Rumentart

Table 1. Some of the Many Salient Analogies in the History of Some Sciences.

cognitive development and, hence, useful in education (Schumacher and Gentner 1988; Pirolli and Anderson 1985; Brown et al. 1983; Mayer 1980; Ortony 1975; Petrie 1979). For example, it is possible to deliberately design interfaces by taking careful advantage of analogies in the training process (Carroll and Mack 1985).

Likewise, analogy is generally assumed to be critical in problem solving (Mitchell 1993; Chalmers, French, and Hofstadter 1992; Gentner and Gentner 1983; Carbonell 1982; Hofstadter 1981; Verbrugge and McCarrell 1977). Although it can be tricky to induce the spontaneous noticing of analogy in the psychological laboratory (for example, Ross [1987]; Reed, Dempster, and Ettinger [1985]; Gick and Holyoak [1980]; and Hayes and Simon [1977]), a number of experiments have successfully investigated the ways in which analogy serves or disserves reasoning for such things as algebra problems, prose comprehension, and the acquisition of computer programming skill (for example, Ross [1989], Spiro et al. [1989], Holyoak and Koh [1987], and Schustack and Anderson [1979]).

The importance of analogy to mature reasoning and expertise is underscored by numerous studies of creative and scientific problem solving (for example, Clement [1982], Boyd [1979], and Oppenheimer [1956]). "The role of analogy in science can scarcely be overestimated" (Sternberg 1977a, p. 99). It is possible to analyze scientists' entire careers in terms of the analogies in series of projects (see Knorr-Cetina [1981]). Indeed, it is possible to analyze the broad history of science in terms of the major analogies or models.² Leatherdale (1974) and Thagard (1993) listed some important analogies in the histories of biological and physical science. Their lists appear in table 1, with a few examples added.

Although some philosophers of science see analogy as a manifestation of a more general process of induction or generalization, other scholars have seen it the other way around (Indurkhya 1992). In sum, theories of analogy seem to be theories of induction (Mill 1882). "The recognition of similarity" is often regarded as the basic principle underlying inductive arguments of all types (see, for instance, Corbett [1971] and Hesse [1966]). According to this view, analogy might be regarded as merely one source of grist for the inductive mill (Hall 1988). However, some historians and philosophers of science have regarded hypothesis formation, explanation, and the definition of abstract concepts as

critically reliant on analogy in particular (Thagard 1989; Darden and Rada 1988; Leatherdale 1974; and Hesse 1966). Polya (1954), for example, saw analogical thinking as an absolute necessity for mathematical creativity (see also Newell [1983]). As far as I can tell, no modern philosopher or psychologist of science has argued that analogies are not essential to science or not a necessary component in the explanation of scientific creativity (or failure).³

Analogy seems rampant in all domains of human affairs—political and international affairs, psychotherapy, religious writings, legal argument, and so on (see, for instance, Holyoak and Thagard [1995], Hoffman [1992], Klein [1987], Paprotte and Dirven [1987], Honeck and Hoffman [1980], MacCormac [1976], and Pollio et al. [1977]). The importance of analogy is also highlighted by recent research in the paradigm of naturalistic decision making. Expert reasoning sometimes depends on analogies to past cases, so-called case-based reasoning (Hoffman et al. 1995; Veloso and Carbonell 1993; Kolodner 1983). Klein and Weitzenfeld (1982), for example, studied avionics engineers who were analyzing components for new aircraft; their procedure relied explicitly on analogies to functionally similar components of older aircraft.

All this and more serves to justify continuing research by the cognitive scientists; continuing efforts in AI; and continuing collaboration in which cognitive research suggests models for AI, and AI models are empirically compared with human performance.

To launch this exploration, what exactly is this thing we now call analogy?

Forms of Analogy in Modern Psychology and AI

The concept of analogy has a long and rich history (see sidebar). Perhaps the most common modern form is the three-term, multiple-choice, verbal analogy, for example,

Robin : Bird :: Mustang : ? .

Such problems are an important task in many standardized intelligence tests, and the ability to solve them correlates fairly well with overall scores on intelligence tests (Sternberg 1977a, 1977b; Thurstone 1938; Spearman 1923), the correlations ranging from approximately 0.45 to 0.82.

Such problems have been used in the effort to disclose cognitive processes. For example, reaction times and error probabilities in the solving of geometric analogies are a function of the number of transformation operations

A (Very) Brief History of Analogy

nalogies of various forms can be found throughout the history of Western thought. To give just two examples that rely on the comparison of understanding with vision, Plato (The Republic, Book VI, Section XIX) relied on an analogy comparing knowing and seeing to explain the origins of the idea of the "Good" (see Shorey [1946], pp. 101-107), and Dante (The Monarchy, Book III, Section XVI) used a similar analogy ("enlightenment") in his justification of imperial authority in terms of its divine origins (see Hardie [1954], pp. 91-94). The word analogy comes from the Greek term for geometric or numeric proportions, ratios, or symmetries. That is, it referred to the arrangement of two sets of numbers or geometric forms, such that the numbers or forms within each set are related by the same mathematical operator, transformation, or scale (ana logos = "same logic" or "according to a ratio"). Examples would be the geometric analogy presented in figure 1, numeric analogies such as

1:2::2:4

and verbal-geometric analogies such as

Circle : Sphere :: Triangle : Cone . Aristotle, among others, extended the analogy concept to include two additional types of expression: (1) taxonomic relations and (2) perceived resemblances, especially similarities of function. Thus, along with the proportional form, *A* is to *B* as *C* is to *D*, Aristotle included the functional form, *A* is in *B* as *C* is in *D*, where *is in* could refer to categorization, perceived

resemblance, or function. After Aristotle, at least two meaningful paths can be plucked from the history of analogy. One is the path of the Renaissance and Enlightenment scholars who relied on analogy in describing this new thing called science and who debated the place of analogy in rationality. The Aristotelian conception of analogy was used explicitly and productively throughout the Renaissance, for example in Galileo's (1953, orig. 1630) explanation of his observations of the motions of the planets and their moons, Keppler's (early 1600s) astronomical and mathematical investigations, and Boyle's (late 1600s) chemical research. At least because analogical inference was actually used in science, formulators of the concept of scientific method, such as Francis Bacon (1994, orig. 1620), regarded analogy as a respected member of the family of rational modes. In his System

of Logic, John Stuart Mill (1882, p. 393) echoed Aristotle when he defined analogy as "the resemblance of relations. "To the Enlightenment's prophet of automaton theory Etienne de Condillac (1971, orig. 1746), analogy is any relation of similarity.

A second path in the history of analogy was that taken by rhetoric and linguistics. Throughout the Middle Ages, rhetoricians generally regarded analogy as being on par with syllogism-as one of the major forms of proper argumentation. Then, the concept of analogy was broadened, applied by grammarians as an explanation of historical change of word forms and inflections (similar meanings should be represented by similar forms). In addition to such processes as lexical borrowing, analogy as a basic process in language change "was for a thousand years the preoccupation of the clearest heads in Greece and Rome" (Lersch [1838], translated in Esper [1973], p. 2). In contrast to the focus of the ancients on rhetoric (that is, analogies should be correct) and the focus of Renaissance scholars on the separation of logic from rhetoric, when nineteenth-century linguists launched what they regarded as a scientific approach to language (for example, Muller [1862]), the analogy concept became central to explaining language change and the relations of form to function (for example, tense inflections). Analogy was regarded as a basic aspect of all language, including phonetic and syntactic change. Thus, one could refer to

oratorem : orator :: honorem : honor as a proportion (de Saussure 1959, p. 161). As another example, of the five noun declensions in Old English, only the masculine strong declension involved using *s* for pluralization, but by the Middle English period, all the declensions had adopted (by the hypothetical process of analogy) the *s* pluralization. At the word level, the change of verbs from strong to weak and even the creation of new words (*kingdom* and *duke* gave rise to *dukedom*) were also described as change by analogy.

To grammarian Nicholas Beauzee (1767), theoretical psychologist Wilhelm von Humboldt (1960, orig. 1836), and linguist Benjamin Wheeler (1887), analogy governs all human language at the level of syntax and case relations. Following von Humboldt and the rise of empiricism-associationism, linguistic analogy was regarded as a manifestation of the basic psychological process of association (of forms with their significations) (Thumb and Marbe 1901). This view (in conjunction with Francis Galton's pioneering experiments on association) stimulated some of the earliest research, using reaction-time methods in the classification of word-association responses into superordinate, subordinate, and other categorical and semantic relations.

To be sure, from the time of the ancient Greeks through the nineteenth century, the broad use of analogy to explain language was not left unquestioned (see, for instance, Brugmann [1876], pp. 317-320). However, in the mechanistic-behavioristic linguistic theory of Leonard Bloomfield (1933), for example, analogy still played a pivotal role in explaining language change. In Breal's (1964) semantics, analogy is "a primordial condition of all language" (p. 77), and to Charles Hockett (1958), the process of analogy can also explain the formation of new idioms (that is, languages favor certain patterns in their idioms). Both Jackendoff (1983) and Rumelhart and Norman (1981) sought to explain similarity in word meaning (especially classes of verbs) in terms of analogical family resemblances. It appears that Chomskyian linguistics is the only paradigm that has been intent on not using the concept of analogy, let alone regarding it as a basic concept to explain language structure, change, or evolution (Esper 1973).

As an analytic tool, as opposed to a purely rhetorical or pedagogical device, the analogy concept has been expanded greatly over the centuries since the concept was introduced in Western civilization. Indeed, John Stuart Mill's definition—the resemblance of relations—is echoed today by many philosophers, computer scientists, and cognitive scientists.

However, despite the expansions of the concept of analogy and the high praise for its utility in scientific discovery, analogy remains one of the poor boys of logic—analogy is conjectural, or nonmonotonic, as opposed to deductive. Analogy has the status of such modes as inductive reasoning, dialectic reasoning, and rhetorical reasoning.

Overall, the historical legacy has played an important role in determining the shape of modern psychological research and modern computational approaches by delimiting the forms of expression that are to be labeled as analogy. involved (for example, Pellegrino and Glaser [1981] and Mulholland, Pellegrino, and Glaser [1980]). For verbal analogies, the implicit ground or relation is fairly constrained. If the terms in such analogies are rearranged from the expected order, as in

Deep : Costly :: Shallow : ?

or

Humans : Gills :: Fish : Lungs ,

the reordering forces the comprehender to mentally reorder the terms, and the reaction time and error rates increase (Sternberg 1977a) (see also Barnes and Whitely [1981] and Ace and Dawis [1973]).

Much of the psychological research on analogy has involved preformulated problems that are well structured, semantically limited, and largely context free (for example, geometric or letter-string analogies such as those already illustrated). Many of the research findings seem straightforward: It is harder for people to complete three-term analogies than to find a correct alternative in a multiplechoice format (Johnson 1962), people perform better if they are given explicit instruction and feedback (Sternberg 1977a; Inzer 1972); and people do better on verbal analogies if the correct solutions are high-frequency associates of the given terms (Wilner 1964).

Lying perhaps at the other extreme of conceptual difficulty are the analogies of the Miller Analogies Test (MAT) (Psychological Corporation 1993). The MAT is intended to assess scholastic aptitude at the graduate level. It is said to emphasize the recognition of verbal-conceptual semantic relations and fine shades of relational meaning, for example,

Annoy : Enrage :: Enlarge : (a. increase, b. exaggerate, c. augment, d. reduce) .

If one assumes that the first two terms express synonymity, the dilemma is that both a and c would work as answers. The correct solution is b, expressing the relation of *to do X but to a greater degree*. Here are two more examples:

(a. brown, b. pink, c. orange, d. yellow) : Red :: Green : Blue .

The answer is orange (mix of yellow and red, just as green is a mix of yellow and blue).

Induction : (a. confirmation, b. graduation, c. ordination, d. resistance) :: Soldier : Priest.

The answer is ordination.

Scores on the MAT are correlated with the vocabulary subtests in general intelligence tests (Guilford 1967; Meer, Stein, and Geertsma 1955) and are correlated more highly with other tests of verbal analogy reasoning than with tests of pictorial or geometric analogy reasoning (Sternberg 1977a, 1977b), suggesting that to some extent, the MAT does tap into esoteric knowledge of word meanings and facility with semantic relations.

Of all these possibilities—from superficial or literal features to esoteric knowledge—the relations that most commonly underlie the verbal analogies in intelligence tests are similarity, oppositeness, word features (number of letters, sound, spelling), category membership, shared changes of state, functional significance, and quantity (Sternberg 1977a). Some of the many varieties of analogy are presented in table 2. These examples are taken from textbook discussions of intelligence tests, cognitive research, and books on problem solving (for example, Whimbey and Lockhead [1979]).

Having illustrated the modern concept of analogy, I can begin deconstruction.

The Reification of Analogy

The concept of analogy has become ingrained in Western civilization. Indeed, until fairly recently, it has been possible to merely assert without comment that analogizing is a basic cognitive process, much as the rules of logic have been regarded as the rules of thought and not merely rules for proper rhetoric or debate (for example, Halford [1982] and Mill [1882]). This reification has been fairly widespread, as suggested in table 3.

No one is at fault. The reification of analogy has been made all too easy. Reification is also not necessarily a bad thing—certainly not if the reified notion and its conceptual armamentarium afford useful analytic tools or serve a heuristic function. Reification might even lead to analysis or empirical work suggesting that the concept is in need of dismemberment. An example might be the psychological concept of schizophrenia; recent etiological research suggests that there might indeed be more than one underlying disease entity.

Despite the potential heuristic value, reification can lead to confusion between description and explanation. For example, Halford (1992), among many others, asserts that "much of human inference is basically analogical.... Analogy comes naturally to both children and adults" (pp. 193, 211). However, analogy gets defined in such a way that it can embrace diverse forms of inference. This reification is laid out in clearest detail in Sacksteder's (1979) reverie on the question of whether logic justifies analogy or vice versa.

Examples	Expressive Function
Parallelogram : Rhomboid :: Square : Cube	Components
ABC : ABCD :: PQR : PQRS	Sequencing
Pharmacy : Drugs :: Grocery : Food	Containment or location
Steward : Airplane :: Waiter : Restaurant	Location of function
Robin : Bird :: Thoroughbred : Horse	Set-subset-superset
Gills : Fish :: Lungs : Humans	Functions of organic systems
Surgeon : Scalpel :: Writer : Pen	Tools used for jobs
Menu : Restaurant :: Guidebook : City	Navigational tools
Deep : Shallow :: Expensive : Inexpensive	Dimensional polarity
Seed : Tree :: Egg : Bird	Growth transformation
Electron : Nucleus :: Planet : Sun	Shared relation
Loving : Hating :: Admiring : Despising	Oppositional emotions
Thermometer : Temperature :: Clock : Time	Devices and measures
Student : Truant :: Soldier : AWOL	Illegal absence
Dog : Bark :: Cat : Meow	Animal noises
Dam : Flood :: Vaccination : Disease	Prevention
Tennis : Racket :: Baseball : Bat	Equipment used in sports
Kitchen : Eat :: Bedroom : Sleep	Location of household activities
Static : Dynamic :: Structure : Function	Shared relation
Umbrella : Rain :: Galoshes : Puddles	Function in weather apparel
Umbrella : Tree Canopy :: House : Cave	Manufactured versus natural shelter

Table 2. Some of the Countless Relational and Transformational Functions for Analogy.

He began by defining analogy as the postulation of a perceived similarity rather than something justified by logic alone. His second premise was that analogy entails certain inferences based on the similarity of qualities, the similarity of relations, or the similarity of structures. The next premise was that the similarities define transformation rules that make arguments valid or plausible. One could conclude from these premises that analogy underlies logic—because all logic (that is, all hypothetical forms for deductive, inductive, or abductive inference) can be said to rely on structured inference.

To paraphrase Sacksteder (1979), analogy is something we have created by formulating logic such that arrangements are both formed and ruled by the concept. This point deserves emphasis: Given that analogy has become ingrained in Western civilization, it is now possible to claim that analogy is necessary for problem solving precisely because the concept of analogy and the analogy format were invented to label and describe exactly the sorts of phenomena that problem solving involves!

Saying that analogy is basic to logic or cognition is just like saying that "this man behaves crazy *because* he is schizophrenic." This statement is a description, not an explanation.

Analogy seems to be something useful-

the systematic laying out of possible features (relations, and so on) that a comparison entails and the rational or empirical exploration of the relations. However, analogy is not a thing that exists "out there" in either the Platonic realm of mathematics and truth or in the noumenal realm of neurons or in the phenomenal realm of mental representations and processes.

It is granted that so-called analogical reasoning can explicitly or consciously occur in cognition (especially in the cognition of people who think a lot about the concept of analogy). It is granted that explicit analogical reasoning often plays a role in science. It is certainly granted that learning often involves the transfer of old knowledge to support the generation of new knowledge (Brewer 1989). Nevertheless, scientific and creative analogies are usually post hoc; that is, the scientist-reasoner thinks in terms of metaphors and images. (Note that most scientific analogies, such as those in table 1, are usually presented as similes or metaphors.) Only after considerable analysis might the implied relations be fleshed out in an explicit format or realized in a physical model (Hoffman 1995, 1985; Knorr-Cetina 1981; Black 1962).

This perspective suggests that the scope of the modern concept of analogy could be broadened. The next section presents a guiding premise for the reconstruction of analogy.

Author(s)
James (1890, Vol. 2, p. 363)
Hoffding (1904, p. 153)
Breal (1964, p. 77)
Haskell (1978, p. 161)
Rumelhart and Norman (1981, p. 357)
Thagard et al. (1990, p. 259)
Gentner and Jeziorski (1993, p. 447)
Vosniadou and Ortony (1989, p. 1)
Holyoak and Thagard (1995, pp. 4, 67, 72)

For economy of exposition, some entries are partially paraphrased and some are quotations that have been abbreviated without ellipsis.

Table 3. Passages Illustrating the Tendency to Reify Analogy.

The Semantic Flexibility Hypothesis

Hofstadter (1981) argued that analogies arise in unconscious processes in which boundless similarities and resemblances can be perceived. Gentner and Markman (1995) and Vosniadou and Ortony (1989) have made a similar argument, to the effect that the phenomenon called analogy seems to rely on a focal idea in cognitive psychology-similarity. There can be little doubt that the perception of resemblances is critical to learning and language (Verbrugge and McCarrell 1977; Spearman 1923). Research on similarity judgment has converged on the notion that similarity is rarely just a property of things but is a manifestation of an underlying, contextdependent comparison process (Medin, Goldstone, and Gentner 1993).

Furthermore, the research shows that analogy is not just the laying out of similarities based on shared features; for some analogies, what is critical is relations and even higherorder relations. In physics, the analogical mapping of relations (predicates taking two terms), such as dynamics, changes of state, and functions, can be more important than the mapping of literal or superficial features (Gentner 1983; Gentner and Gentner 1983). For example, in an analogy comparing atoms to solar systems, the sun is more massive than a planet; the orbiting relation of a planet with the sun would map to the orbiting relation involving electrons and nuclei. In the analogy comparing electric circuits to fluid flow, voltage across a resistor maps onto pressure across a constriction.

Furthermore, analogy is not just the laying out of similarities; distinctions and differences can also be important. In fact, in ancient Greek thought, analogy was regarded as only one basic style of rhetoric or argumentation. It was mated with *polarity*, the perception of differences or opposites, expressed in the same format as analogy (Lloyd 1966).

The pertinence of semantic flexibility to analogy is highlighted by the academic quandary regarding the relation of analogy to metaphor (Gentner 1982). It is by no means clear that metaphor is an aspect of language and that analogy is a type of reasoning. The metaphor-analogy relation is actually a difficult chicken-egg problem (Hoffman 1995; Holyoak and Thagard 1995). It is sometimes assumed that analogy is a special case of metaphor in which the elements within two domains are explicitly placed in correspondence (Hall 1988). Conversely, some scholars have defined metaphor as a type of analogy (for example, Beck [1978]; for reviews, see Hoffman [1995] and Steinhart [1994]). For example, in his first presentation of an AI system for processing verbal metaphor, Indurkhya (1985) asserted that analogy underlies all metaphors and models, and then later, he (Indurkhya 1988) asserted that analogies and models are special cases of metaphor.

This conundrum reinforces the notion that one really important phenomenon at hand is semantic flexibility: People can relate anything to anything on the basis of anything. Relating can take the form of comparison-the perception of resemblances. It can take the form of contrast-the perception of distinctions. It can take the form of *dependency*—the perception of invariants or relativities. Furthermore, the resemblances, the distinctions, or the invariants can be based on anything (dimensions, attributes, relations, and so on). Hoffman and Honeck (1976) referred to semantic flexibility as the semantic infinity hypothesis, and it is not only pertinent to linguistic generativity (as in Katz and Fodor's [1966] notion of syntactic infinity) but also to reasoning in general and analogy in particular: "To propose an analogy-or simply to understand one-requires taking a kind of mental leap. An idea from the source analog is carried over to the target. The two might initially seem unrelated but the act of making an analogy creates new connections" (Holyoak and Thagard 1995, p. 7). The following examples of semantic flexibility set the stage for the presentation of the monster analogies, which push flexibility to its limit. Once I accomplish the reconstruction, the goal of the last sections is to explore some implications for AI.

Examples of Semantic Flexibility

Semantic flexibility in analogy takes a number of forms.

Multiple Completions

For some analogies, it is easy to assume a single relation, especially if it is a common one. For example, for

Nightingale : ? : : Fox : ? ,

it seems reasonable to infer a type-of relation and complete the analogy with *bird family* and *canine family*. However, an acceptable completion would also be Nightingale : Nursing :: Fox : Anthropology .

Robin Fox happens to be the name of a noted anthropologist.

For many analogies, there is clearly more than one valid interpretation. An easy example would be the numeric analogy

10:1:20:? ,

which could be completed by 2 if one assumes a divide-by-ten relationship or a firstdigit relationship. However, it could be completed by any number less than 20 if one assumes a less-than relationship. The analogy

Washington : Lincoln :: 1 : ?

could be completed by 15 (first and fifteenth presidents) or 5 (portraits on U.S. currency). The analogy

Steward : Airplane :: Waiter : Restaurant

could be based on the places where the jobs are performed or the partial functional similarity of the jobs themselves. The analogy

Warm : Cold :: Approach : Withdraw

could be interpreted as dealing with human emotion or doppler shifting.

For the MAT items, the possibility of multiple completions can never be ignored safely. Look out—Napoleon is a person and a type of brandy...and a type of pastry! Then, an analogy might seem completable based on some semantic gymnastics, when in fact the best (correct) completion is based on the part of speech (nouns versus verbs), the number of letters in the terms, or something equally unobvious. An example from a short course in analytic reasoning (Whimbey and Lockhead 1979) is

Polluted : Pure :: Tainted : ?

Should one look for a completion beginning with the letter t or a completion that means something like undefiled? Analogies that involve multiple completions can take the comprehender down a garden path, depending on the comprehender's ability to psych out the person who concocted the analogy.

Violations of Proportionality

One general form for four-term analogy is expressed in the following equation:

 $<\!\!A,\,R_1,\,B\!\!> \bullet <\!\!C,\,R_2,\,D\!\!> \supset <\!\!R_1,\,R_3,\,R_2\!\!> \ .$

Here, analogy is described in terms of ordered sets and relations, with implication used in a nonmaterial and nontautologous sense. If the *A*, *B*, *C*, and *D* terms refer to word concepts, then they are represented as sets of semantic qualities (features, slot values, and so on); if the terms are conceptual entities or systems (for example, atoms, solar systems), then they

Given that analogy has become *ingrained* in Western civilization, it is now possible to *claim that* analogy is necessary for problem solving precisely because the concept of analogy and the analogy format were invented to label and describe *exactly the* sorts of phenomena that problem solving involves!

are represented as sets of sets, that is, components of superset categories or domains. Taken together, the A and B terms imply the conceptual sets to which they could belong and the relation of these sets. Inferred set and superset membership is coimplicational with candidate relations for the A and B terms and the C and D terms.

Typically, it is assumed that the relation R_1 is identical to the relation R_2 and that the relations are nondirectional. By common definition, a simple or proportional analogy is highly symmetric (see, for instance, Indurkhya [1992]). That is, *A* and *B* can be switched with *C* and *D*, and there will be no alteration of meaning, as in

Gills : Fish :: Lungs : Humans \rightarrow Lungs : Humans :: Gills : Fish .

Similarly, it is believed possible to switch *B* and *C* without changing the meaning:

Gills: Lungs :: Fish : Humans .

However, this switch clearly can involve a change in meaning—surely, R_3 should now make some explicit reference to phylogenetic relations in addition to the functional (respiratory organs) relation.

The identification of R_1 with R_2 is a limiting case, primarily because it gives short shrift to the thinker. For example,

Pine : Wood :: Iron : Metal

could be interpreted according to a simple type-of relation. In this interpretation, R_1 is related to R_2 in that they are identical, and R_3 is interpreted simply as *and* or *as*. However, one can note that iron occurs in semimetallic form in living organisms. In this interpretation, R_3 asserts that R_1 and R_3 are similar, yet different. This flourish added by R_3 would mean that the analogy would perhaps not best be completed with iron. Similarly, the analogy based on a shared functional relation,

Cheeks : Squirrels :: Shopping Bags : Humans,

might not be quite right because cheeks are both living matter and part of the squirrel. As a third example, in the analogy

Umbrella : Mop :: Shell : Watermelon ,

 R_3 can be taken to express the identity of R_1 and R_2 (things that resist versus absorb moisture), but R_3 adds its own flourish—manmade versus organic things.

The flourishes added by R_3 point to the distinctions between the A/B relation and the C/D relation. The flourishes can often safely be ignored, but they are always there. For example, in the analogy

Crow: Bird:: Leopard: Cat,

a simple type-of relation can be assumed for

both R_1 and R_2 . However, both the prototypical crow and the South American leopard have black coverings; so, R_3 involves a potential flourish. As another example,

Falcon : Mustang :: Eagle : Colt

could be interpreted as involving predatory birds and ruminant mammals but also as involving types of Ford and Chrysler automobiles named after animals.

For many intelligence tests, all but one of the potential R_3 flourishes are supposed to be ignored, thus allowing one to assert that an analogy has a best or correct answer or, conversely, to quibble about whether an answer is correct, for example,

Garden : Fence :: Car: (Bumper) .

Although fences can protect gardens, and bumpers can protect cars, bumpers cannot keep trespassers out of cars. Another example is the analogy

Refrigerator : Food :: Wallet : (Money) .

According to my reading, there is more here than the simple relation of containment— wallets do not preserve money in any strong sense. Hence, to me, the correct answer is not thoroughly correct (nor is the analogy an especially good one unless I rely on the cold-cash idiom).

Anomalous Analogies

Johnson (1975) (see also Deese [1974–1975]) had people attempt to solve analogies that were intentionally anomalous, as in

River : Story :: Milk : ? .

If given enough semantic rope, people could come up with solutions and could rationalize the solutions. Independent judges showed high rates of agreement in rating the vast majority of the solutions as justifiable, even though people yielded different solutions. Johnson and Henley (1992) recently extended this finding to multiple-choice anomalous analogies, such as

Horse : Time :: Stone :

(a). king, (b). book, (c). girl, (d). train .

For such analogies, one is effectively blocked from determining any shared literal properties that might suggest a successful completion; relations are about all that are left. In Johnson's experiments, relational solutions were the most frequent, and the independent judges again showed near-perfect agreement in categorizing solutions into relational subtypes.

Analogies can be made difficult by creating the appearance of anomaly. For example,

Drag : Pull :: Travel : Plow

throws the interpreter a curve ball. To *drag* is to pull something behind you, but how does this term fit with the second two terms? To *travel* is not to plow something behind you unless this is a reference to plowing the ocean. However, there is a meaning here: *Drag* is a type of contest involving cars, a *pull* is a type of contest involving tractors, *travel* is an ordinary function of cars, and *plow* is an ordinary function of tractors.

Some of the MAT practice items rely on apparent anomaly, such as in

Speed : Weight :: Knot : Carat

and

Horse : Dolphin :: Camel : Walrus .

Sometimes, apparently anomalous analogies are anything but anomalous as far as their communicative intent. Recall the following popular bumper sticker: "A woman without a man is like a fish without a bicycle."

To embrace the diverse examples that are available, the ontology expressed in column 2 of table 2 is broad enough to include just about anything, even ontological, logical, and linguistic concepts themselves. "The problems with explicating analogical reasoning are legion because virtually anything (from one standpoint or another) can be analogous (on one count or another) to virtually anything else.... There is no such thing as analogy *simpliciter*" (McCauley 1989, p. 482). The stage has been set for presentation of the monsters.

Monster Analogies

As far as I know, God did not set down an Eleventh Commandment concerning the form, format, or content of analogy. A monster analogy has the following characteristics: (1) creating a monster analogy can drive the creator insane, (2) no existing computer system can accept a monster analogy as input without relying on redescription based on some ad hoc criteria, or (3) no existing algorithm can process a monster analogy. However, monster analogies are not necessarily difficult for humans to understand.

Complex Completions

For many of the analogies on the MAT, there is more than one completion. Based on the proportional theory of analogy, the multiple completions of an analogy are generally believed to be somehow separate from one another. There seems to be little reason why we should be constrained to think of it this way. Start with the garden-path analogy:

Tie : Die :: Jail : ? .

Should one opt for a word that rhymes with jail? The analogy could be completed by the word *sell*, the trick being common two-word phrases where the second word is substituted with a heterographic homophone (Dye and Cell). The next step would be analogies such as

Beef: Stake :: Hand : Break .

The relations R_1 and R_2 would both be common two-word phrases with *B* and *D* substituted with heterographic homophones, but R_3 would have to specify that there is a rhyming relation between *B* and *D* as well. In theory, for any three-term analogy having more than one solution, it is possible to concoct an R_3 such that all the multiple solutions are embraced in the single higher-order relation. The analogy

Helicopter : Hummingbird :: Submarine : ?

can be interpreted in at least two ways: (1) man-made versus organic things that fly versus things that swim or (2) things capable of station keeping. For both interpretations, the single term *seahorse* would be a satisfactory completion.

Although some existing AI systems for analogy can generate multiple solutions or mappings, the next processing step is usually to evaluate and select rather than attempt to generate a higher-order relation or integration of the multiple mappings.

Monsters That Necessitate Escape from the Semantic Base

One can easily concoct analogies such as

1: ell :: x : eks.

Because the fourth term is not exx, this monster would be anomalous to systems for processing letter-string analogies (for example, Chalmers, French, and Hofstadter [1992]). The reason is that the semantic base consists initially of information that specifies the partial ordering of characters (for example, it can derive the fact that d comes before p). This monster relies on the fact that letters of the alphabet partially map onto phonemes. Hence, in a notation that uses letters rather than bracketed phonetic symbols, the letter *l* is pronounced *ell*, and the letter x is pronounced eks. One can also rely on the fact that letters of the alphabet contain orthographic information. For this monster-

ijk : ijl :: mno : mnv —

one might assume that the completion should be *mnp* because *p* follows *o* in the alphabet. However, the rule might require the third letter to follow the second letter but not necessarily immediately—it might have to be God set down no "Eleventh Commandment" concerning the form, format, or content of analogy. a letter that consists solely of straight lines. In this case, the correct completion would be *mnv*. Such orthographic information is not contained in AI systems for processing letterstring analogies.

In general, the AI systems for analogy cannot escape their own semantics. A type of verbal monster demonstrates this fact.

Monsters That Seem to Violate Proportionality

As explained previously, it is traditionally assumed that the relation of the *A* and *B* terms is identical to the relation of the *C* and *D* terms— R_1 is identical to R_2 . However, this assumption is purely by convention. One can concoct analogies for which the ordering of the terms is critical in determining the relation of the *A*-*B* and *C*-*D* relations.

A minimal case involves synonymity, as in Naive : Innocent :: Sophisticated : Worldly,

versus antonymity, as in

Naive: Sophisticated : Innocent : Worldly .

However, many other types of contrast are possible. For example,

Circle : Sphere :: Triangle : Cone

relates each of two terms according to a rotational transformation, but the reordering

Circle : Triangle :: Sphere : Cone

relates the terms differently (that is, twodimensional versus three-dimensional forms).

In the case of verbal-semantic analogies, the interpretation of a term is constrained by the term with which it is paired. For example,

Field : Mouse :: Prairie : Dog

involves the relation of common two-word terms for types of rodent, but the reordered analogy—

Dog : Mouse :: Field : Prairie —

involves the relation of domesticated versus undomesticated (*dogs* are domesticated mammals; a *prairie* is an expanse of undomesticated plants).

Semantic monsters such as this are not easy to concoct, even when starting with lists of polysemous words (homophones or homographs), but to make the point, here's another example:

Mount : Horse :: Board : Plane .

One mounts a horse, and one boards a plane. However, in the example

Mount : Board :: Horse : Plane ,

mounts and boards are tools used in advertising, and planes and horses are tools used in carpentry. Monsters of this type could be called *duplex analogies*. The goal in solving a duplex analogy is not just to find the underlying R_1 , R_2 , R_3 solution to the given complete analogy but also to find the reordering of the A, B, C, and D terms that yields a different and coherent R_1 , R_2 , R_3 solution.

The terms in analogy provide context for each other, which can shift subtly or drastically as a function of the ordering of the terms. To paraphrase Holland et al. (1986, p. 302), the relational status of propositions is not defined independently of their participation in an analogy.

Monsters That Violate the *A* : *B* :: *C* : *D* Format

It is easy to construct analogies that have four explicit terms but only three content words. With polysemous nouns (homographic homophones),

Toast : Food :: Toast : Honorific

means that toast is a type of food, and toast is a type of honorific;

Snow : Video :: Snow : Traffic

means that snow is a type of signal disruption, and snow can be a disruption to traffic; and

Belt : Swallow :: Belt : Strike

is again a reference to a type-of relation. It is possible to construct one or more such analogy for every polysemous noun to explicate the ambiguity.

Similarly, it is easy to find analogies with only two or three explicit terms; it can be said that this is the format of many similes and metaphors. For example, the statement *Billboards are warts on the landscape* leaves out the *B* term (faces). The statement *Night's candles are burnt out* leaves out the *B* and *D* terms (stars and something like indoor lighting).

Analogies can also have more than four explicit terms. In using the analogy format to explain language change, linguists of the eighteenth and nineteenth centuries were limited only by the number of languages or the number of inflections being compared, making analogy the expression of any pattern (Bloomfield 1933), as in

Scream : Screams : Screaming : Screamer : Screamed :: Dream : Dreams : Dreaming : Dreamer : ? .

This format is alien to AI and cognitive science and might perhaps be regarded as merely an expression of inflectional patterns. However, remember, there is no Eleventh Commandment. Thus, for example, one could take an analogy such as

Bird : Sparrow :: Mammal : ?

and complete it as

the following characteristics: (1) creating a monster analogy can drive the creator insane, (2) no existing computer *system can* accept a monster analogy as *input without* relying on redescription based on some ad hoc criteria, or (3) no existing algorithm can process a monster analogy.

A monster

analogy has

Bird : Sparrow :: Mammal : Dog : Pig : Rabbit : Platypus ,

expressing the fact that there are a great number of acceptable solutions for a given R_{3} .

Format violation can occur in another way; there is no rule that says that each slot in an analogy has to be occupied by a single word:

Copernicus, Brahe, and Galileo : Astronomy :: Bohr, Heisenberg, and de Broglie : Ouantum mechanics

or

Gun, bullets, retriever : Hunting :: Reel, rod, line, hook : Fishing

Even sentences can appear as components, as in

"The odorless child inspired a chocolate audience" : Semantic anomaly :: "Boy book read the" : Syntactic anomaly .

Thus, although the general form for analogy can be given as A : B :: C : D, each of the components can consist of more than one term, and as many as two of the components can be left implicit. Existing AI models for analogy would have monstrous difficulty with polysemy, ambiguity, and other types of format violation.

Self-Referential Monsters

Why not concoct an analogy that has its own explanation in the second two terms:

Dog : Hound :: Bother : Type .

That is, to *dog* someone is to *hound* (bother) them, with hound also being a type of dog. This example also illustrates another way in which analogies can depend on higher-order relations—the second set of two terms express relations that hold between the first two terms.

One can create analogies that include references to other analogies, as in

Plato's analogies : Philosophy :: Maxwell's analogies : Physics .

In this example, R_3 is something like *seminal for*. Self-referential monsters can involve reference to the concept of analogy itself, as in

This expression : Analogy :: "This sentence is false" : Contradiction .

Here's another such monster:

This Analogy : Tautology :: "Tautology" : ""Tautology"" .

The analogy is tautologous in the sense that it includes a repetition, it is tautologous in that it asserts that it itself is repetitive, and the word *tautology* is tautologous in this analogy because it is itself repeated.

The most extreme case I can imagine is analogies that involve potential self-contradiction or paradox, for example,

This analogy : Ill-formed syntax :: Anomalous sentences : Ill-formed semantics : Horse .

This analogy is self-referential and is ill formed (Why is *Horse* added at the end?), but because it is correct in asserting its own ill formedness, does it really have an anomalous semantics? On the same theme is

"This analogy refers to itself" : Selfreference :: "This analogy does not refer to itself" : Contradiction .

Note that the *C* term satisfies the R_1 and R_2 relation (type of) only by virtue of the presence of the *A* term. As a final example of monster analogies, analogies can be embedded within other analogies, as in

(Feather : Birds :: Hair : Mammals) : Simple :: This analogy : Confusing .

Only in theory could extant models of analogy include *analogy* as a concept-term or as an ontological category in the semantic base. Actually dealing with the semantics of such seemingly paradoxical monsters would fall well beyond the capabilities of any existing AI system.

Monsters That Deny Distinctions of Format Type

It is by no means obvious at the outset that a system for computing analogies must, should, or even could deal with analogies in all their various forms, functional contexts, and monstrous convolutions. However, modelers often claim that their systems are general. And yet, the claim is invariably based on the analysis of a single type of analogy that happens to be especially conducive to the kinds of structural analysis that are engaged (Chalmers, French, and Hofstadter 1992; Russell 1992).

For example, in both AI and cognitive science, verbal analogies are distinguished from geometric or pictorial analogies, but surely this is not just a special but a limiting case. No one would expect that a system for computing verbal analogies or one for computing pictorial analogies would be able to accept as input monsters such as those in figure 2. Humans, of course, can deal with such analogies and fairly easily.

Implications for AI

You are invited to create other monsters. For some of the examples, I might be accused of stretching things, but this is the point. Semantic flexibility confronts both cognitive science and AI with (at least) one significant problem: Articles



Figure 2. Some Mixed-Format Monsters.

[As] with the interpretation of analogy, the ability to produce or interpret a metaphor is limited only by the individual mind's knowledge and the *accessibility of that knowledge to search* (italics added) (Deese 1974–1975, p. 212).

This problem has been discussed in AI in terms of the concept of wanton inference:

[C]reative solutions to problems are often generated by ignoring boundaries between domains of knowledge and making new connections. The major consequence...is that the size of search spaces is greatly increased. Hence, the wanton inference strategy is fundamentally at odds with the received view in AI that the essence of intelligent problem solving is limiting the search for solutions (Dietrich and Fields 1992, p. 92).

How has AI dealt with the phenomena of analogy? One approach to this question would be to launch into an exhaustive analysis of the features of various extant systems and then search for validation and evaluation. An alternative approach begins with recognizing the fact that most extant models for analogy seem to share a common spirit. One way to accommodate monsters might be to combine some of the features and mechanisms of extant models.

The Common Spirit of AI Models

Despite the variety in approaches, goals, and mechanisms, extant systems share many important notions. For example, the theorizing and modeling efforts of a number of modern researchers have begun to evolve beyond the reified notion of analogy. A number of scholars and scientists have argued that both metaphor and analogy are manifestations of (truly?) basic cognitive processes, such as frame transformation and the perception of similarity (for example, Gentner and Jeziorski [1993], Way [1991], Vosniadou and Ortony [1989], Holland et al. [1986], and Knorr-Cetina [1981]).

All the major models are explicitly based on the claim of psychological plausibility or fidelity; that is, models are based on empirical observations of cognitive phenomena or the results of psychological research. Hence, core concepts from cognitive theories have played a major guiding role in system development efforts. Some of the major concepts from cognitive theories of analogy are presented in table 4.

A major commonality consists in the proposed stages for processing (Hall 1988). Nearly all systems involve some sort of incremental or cyclical learning. That is, results from problem-solving episodes can be retained in the form of new stored procedures or rules or changes in the memory representation (for example, Carbonell [1986, 1983], McDermott [1979], and Winston [1978]). Within the problem-solving episode itself, the stages in most models are also shared. All models seem to be a variation on the following theme: (1) meaning analysis (of input problem, of elements within the target); (2) recognition or generation (of candidate bases); (3) mapping, matching, construction, or transfer; and (4) elaboration, evaluation, or justification.

The stages in the earliest models for analogy (for example, Winston [1978]) and also the most recent models (for example, Holyoak and Thagard [1995] and Falkenhainer, Forbus, and Gentner [1990]) mirror the four-stage theme, echoing psychological theories stemming from research on analogy comprehension and problem solving (for example, Clement [1982]; Klein and Weitzenfeld [1982], Grudin [1980], Sternberg [1977a, 1977b], and Winston [1979]).

Given that there is a common spirit to AI models, there seems to be no reason why the advantages and insights of various models could not be combined (Hoffman and Gentner 1995). In terms of their specifics, each of the extant models points in the direction of one or more potentially important, possibly necessary, or certainly useful system feature, outlined in table 5. This is the theme of the remainder of this article.

Cognitive Theory	Focus	Key Ideas
Holland et al. 1986; Clement 1982; Klein and Weitzenfeld 1982; Sternberg 1977a, 1977b	Processing models	There are stages of encoding, inference, generation, and justification.
Katz 1989; Klein and Weitzenfeld 1982; Johnson and Malgady 1980; Nagel 1961	Feature-set theory of the semantic base	Set overlap specifies shared and distinctive features.
Katz 1989; Medin and Ortony 1989; Holland et al. 1986; Tourangeau and Sternberg 1981, 1982; Johnson and Malgady 1980; Ortony 1979a, 1979b	Similarity metrics	Feature-set overlap yields similarity metrics; analogies and metaphors involve salience imbalance; similarity can be between domains as well as concepts.
Verbrugge and McCarrell 1977; Johnson 1975	Interaction and transformation	Analogy comprehension is not a process of comparison based on similarity but the interaction of target and base. The base serves as a filter or framework for restructuring the target in novel yet constrained ways. Meaning is represented in terms of relations (invariants) and context.
Holyoak and Thagard 1989; Holyoak 1984	Schemas	Analogy comprehension is the construction of new schemas.
Gentner and Gentner 1983; Halford 1982	Structure mapping	Mapping involves the establishment of isomorphisms or quasimorphisms between two structures. Mapping of relations is emphasized over attributes or features; mapping of higher-order relations (predicates that take other relations as their arguments) is regarded as especially important. Metrics of mapping structure (that is, clarity, richness, systematicity, and abstractness) can be used to predict comprehension difficulty and recall performance.
Gentner and Markman 1995; Holyoak and Thagard 1995; Holyoak 1984	Fundamental mental operations	Analogy is one of a number of manifestations of more fundamental or basic operations of attention and memory, including the perception of resemblances (features, relations, and high-order relations), the perception of distinctions, and the construction of mental models.
Holyoak 1984; Carbonell 1981	Pragmatics	Analogical reasoning is ill defined in that the initial specification of the target is incomplete. One's purposes and goals help delimit the search space for inductive inference.
Holyoak 1984; Gentner 1983	Evaluation	Analogy-based hypotheses must be verified or validated through the recognition of structure violations. Metrics of mapping structure (that is, clarity, systematicity, richness, and abstraction) can be used to determine the aptness of an analogy.

Table 4. Some of the Major Concepts from Cognitive Theories of Analogy, with Seminal or Representative Citations.

Problems of Representation

Extant systems for computing analogy involve a number of representational schemes frames with slots, conceptual graphs, propositional networks, ordered hierarchies, and so on (Halford 1992). Although formal equivalence is often possible (for example, hierarchies can be tangled, graphs can be latticed), there is usually some motivation for representational choice, either ontological, cognitive, or pragmatic. There are problems across all levels of justification. For example, "Many concepts, psychologically, seem to float back and forth between being objects and attributes" (Chalmers, French, and Hofstadter 1992, p. 197). Formal justification runs up against practical problems (for example,

Model	Innovative or Important Ideas
Burstein 1986	Problem solving includes the use of multiple analogies (base domains). Ana- logical reasoning is seen as a long-term process of elaboration and repair.
Carbonell 1986, 1983, 1981	Inference relies on an ontological hierarchy of goals, plans, and causal rela- tions. The system can retain information about previous successes and fail- ures to generate both domain- or subgoal-specific search heuristics and gen- eral-purpose inductive rules. Analogical mapping is regarded as creating a plan for solving a problem based on transformations of some known proce- dure.
Martin 1990; Greiner 1988;Carbonell 1983, 1981, 1980; Hobbs 1983	The semantic base includes presupplied information in the form of common or conventional metaphors, metaphor themes, or schemas. Pre- supplied information can cover the domains of both the target and base concepts in an analogy.
Chalmers, French, and Hofstadter 1992	After an initial representation is constructed, the processes of representation building and structure mapping proceed in parallel (or as a cycle), with each constraining the other; the semantic base is mutable and dynamic.
Falkenhainer, Forbus, and Gentner 1990	Processing relies on structure mapping, with emphasis on relations. Map- pings are assessed in terms of coherence and consistency. Inference can rely on context and goals. Constraint can come after inference as well as before it. The system can be used as a tool kit for testing algorithms. Mapping is constrained by goal relevance.
Hobbs 1983	Hobbs's recognition of the problem of inference constraint is seminal. Fea- tures within schemas are conceived of as inferences and restrictions on pos- sible inferences. Inference constraint can come from contextual informa- tion.
Holyoak and Thagard 1989;Holland et al. 1986	The model relies on the construction of morphisms or structure mappings. Processing is the construction of new schemas. Schemas can include specification of the exceptions to rules. Nonmappable features generate masks that select trees or subtrees.
Indurkhya, 1992, 1991, 1987, 1985	His model began with a focus on metaphor but emphasized the problem of inference constraint and the coherence of structural mappings. Predictive analogy is said to involve explicit justification and the prediction of new similarities. Poetic metaphor does not entail justification and involves only the noticing of similarities and is called <i>interpretive analogy</i> . Emphasis is on comprehension as a creative process. The system involves two stages of mapping: (1) transfer of conventional features followed by (2) slot filling to construct new tokens or features. The system also includes a mechanism for changing the ontology on which a semantic base relies.
Kedar-Cabelli 1988	The system focuses on explaining why a selected base forms a satisfactory analogy to the target in terms of the problem's goals and purposes, includ- ing the satisfaction of preconditions and the achievement of the functional requirements.
Russell 1986, 1976	The model relies on conceptual dependency theory of relational primitives (after Schank [1975]). Comprehension can induce the generation of new semantic features. Analogies or metaphors can be given multiple interpretations. The system can be used as a tool kit for testing algorithms.
Way 1991	Representation is in terms of conceptual graphs (after Sowa [1984]) arranged in an ontological hierarchy. Semantic features are scaled for salience. New nodes and supertypes can be constructed. Features that do not map induce the creation of masks that select trees and subtrees.
Winston 1979, 1978	Winston's recognition of the problem of inference constraint is seminal. Application of the concept of a frame (after Minsky [1975]) was also semi- nal. In addition, the information within a frame can be indexed according to such features as salience and typicality. In analogy processing, informa- tion is not just mapped, it is transferred. That is, the semantic base can be altered—new frames and slots can be created. Candidate interpretations are assessed in a frame-justification stage.

Table 5. Some of the Major Computer Models for Analogy.

expressing relations as attributes is possible but cumbersome).

The Ontology of Representations

The consensus seems to be that representations cannot define analogy solely on the basis of computations of degrees of similarity or conceptual closeness (that is, the length of paths that connect concepts)—the model of analogy cannot be a mere "counting theory" (as in Rumelhart and Abrahamson [1973]) (Hall 1988; Carroll and Mack 1985). There also seems to be a concensus that representations cannot rely solely on featural similarity; distinctive features are also necessary. Furthermore, relational meaning is just as—or even more—critical to analogy creation and comprehension than (so-called) literal attributes or superficial features.

In the models of Burstein (1986) and Falkenhainer, Forbus, and Gentner (1990), relational meaning is absolutely essential in the semantic base of concepts, and it is prioritized, as well as essential, in the construction of mappings. Relational information is also important in other systems (see, for instance, Chalmers, French, and Hofstadter [1992]). In Russell's (1986, 1976) system, metaphor is said to involve the comparison of semantic features that cross ontological levels. Such level crossing permits nonliteral comparisons of meanings in terms of the primitives of conceptual dependency theory. In this scheme, relational information is present, although it is not explicitly represented as such.

Whatever one's representational choices or ontological commitments, formal schemes for the computational analysis of analogy will be limited (at least) by the depth, breadth, flexibility, and dynamics of the world knowledge that they can represent (Martin 1990; Hall 1988; Burstein 1986).

Canned-in Meaning

One approach is to create systems in which the needed information comes presupplied (Gentner 1983). For example, Greiner's (1988) NLAG system solves problems in hydraulics based on a presupplied analogy—links between domain concepts and principles in hydraulics and domain concepts and principles in electronics. McDermott's (1979) system for manipulating objects in a simulated environment begins with production rules that define objects and goals and with a startup set of actions in an action hierarchy.

For successful application to natural language, a system for processing analogy will probably have to contain a great many canned-in conventional metaphors, as in the models of Carbonell (1981, 1980) and Martin (1990). A system can certainly contain numerous canned-in meaning primitives, as in Russell's (1976, 1986) model. Canned-in memory can also take the form of a corpus of past cases, as in Kolodner and Simpson's (1989) system for mediating economic and political disputes.

The trade-off here is that "if appropriate representations come presupplied, the hard part of the analogy-making task has already been accomplished" (Chalmers, French, and Hofstadter, p. 196).

The Semantic Base Must Be Extensible

Analogies often occur in creative discovery contexts in which all one really has at the start is the topic concept. The challenge of explanation involves missing data and illdefined goals (Klein 1987). Overreliance on preordained meanings might not allow the comprehension task to be accomplished at all. For example, a stored conceptual graph for solar system might work for analysis of the atom-solar system analogy but might fail miserably when confronted with Shakespeare's metaphor Juliet is the sun. "The causal network about the sun which was supplied for the previous analogy is no longer relevant" (Kedar-Cabelli 1988, p. 93). It is clear that analogy and metaphor comprehension are constructive processes-for novel metaphors and analogies, the semantic base must be extensible (Deane 1993; Martin 1990; Katz 1989; Indurkhya 1988; Camac and Glucksberg 1984; Rumelhart and Norman 1981; Ortony, Reynolds, and Arter 1978).

Few AI systems for analogy have been oriented to the problem of creating elaborate causal representations for domains about which little is initially known (but see Burstein [1986]). However, many AI systems for analogy are minimal learning systems in that some information about concepts can be transformed as a result of analogical extension (Holyoak and Barnden 1994c; Hall 1988).

In the models of Holland et al. (1986), Holyoak (1984), and Winston (1979), new schemas (frames and slots) can be constructed. The model of Chalmers, French, and Hofstadter (1992) has a special "radical restructuring" process. In the conceptual graph models of Indurkhya (1992) and Way (1991), new nodes, tokens, and supertypes can be constructed—the semantic base is extendible in both its particulars and its overall structure. In the revised structure mapping engine (SME) of Forbus, Ferguson, and Gentner (1994), mappings can be changed as new information is added to the knowledge base.

Damnably intertwined with questions of representation is the equally ominous problem of how and when to constrain the processes of inference (Hall 1988).

The Mystery of Inference Constraint

How can one determine which rules are revisable? How should one limit a search space? How can one determine which information to transfer or transform? Apart from the particulars of one's answers, many modern analogy researchers would argue that inference constraint cannot be blind. Any workable scheme for constructing analogical mappings cannot operate solely on the basis of a difference-reduction operation (for example, the masking of features or subtrees that do not happen to neatly match, as in the models of Way [1991], Holland et al. [1986], and Carbonell [1983]). Most analogy researchers would probably agree that inference constraint should not be overly impulsive. Like the model of Fass and Wilks (1983), an analogy system can embrace the possibility of explicitly representing ambiguity and conflict and not merely take the occurrence of ambiguity or conflict as a command for immediate resolution.

In analogical reasoning, inference constraint comes in a number of forms serving different functions, both directly and indirectly. One manifestation of constraint is the specification of the scope of a group of inferences, that is, the generation of acceptable candidate base concepts or domains on which a detailed mapping operation might be performed (Thagard et al. 1990). This function is often supported largely by the method used to index memory. A second manifestation of inference constraint is the specification of the conditions under which particular inferences are permissible. For example, in Carbonell's (1981) model, inferencing is constrained in terms of possible sequences or priorities determined by an ontological hierarchy.

Case studies in the history of science, such as the Chalmers, French, and Hofstadter (1992) study of Keppler's reasoning and Gentner and Jeziorski's (1993) and Vickers's (1984) studies of alchemy, show that creative analogical thinking relies on the generation of multiple alternative representational schemes and analogies, which are then pondered and sometimes rejected (and sometimes mistakenly preserved). In such cases, it is clear that constraint comes not only before and during inference but also when processes of evaluation and selection are brought to bear after a mapping operation. A number of systems for processing analogies include criteria for when to reject candidate analogies. Mechanisms include the structure violation process in the theory of Holyoak (1984); the radical restructuring mechanism in the system of Chalmers, French, and Hofstadter (1992); and the coherence evaluation processes in the systems of Indurkhya (1992), Falkenhainer, Forbus, and Gentner (1990), Thagard (1989), Carbonell (1983), and Winston (1979).

A variety of post hoc structural criteria can be used to assess the goodness or validity of completed analogical mappings (for example, complexity, coherence, interconnectedness) (Clement and Gentner 1991). Furthermore, Way (1991) reminds us that psychological criteria can be used to determine the status of elements in a semantic base; for example, in a dynamic semantic hierarchy, frequency of node access could be taken as an index of meaning relevance and could be used to determine the lifetime or accessibility of a node.

The Constraint Flexibility Trade-Off

Processes that constrain inference must be coordinated appropriately with processes that support semantic flexibility and wanton inference (Dietrich and Fields 1992). On the side of semantic flexibility, one can rely on operations such as the insertion of new frames, nodes, slots, operators, parameters, or values; the deletion of operators, parameters, or values; the shifting of levels, subproblems, or procedures; and the substitution of operators or parameters. On the side of constraint, mechanisms take a variety of forms, including the prioritizing of operations, the disabling of transfer for nonmatching features, the use of slot values that explicitly indicate featural salience or importance, the explicit incorporation of information about exceptions to rules, and the numeric analysis of candidate interpretations.

Contextual Constraint

An undercurrent in comparative analyses of analogy models has been the question of whether certain kinds of constraint are arbitrary. To some system developers, constraints that come from problem-solving goals are external to the analogy; hence, such pragmatic accounts are said to rely on arbitrary inferencing (Falkenhainer, Forbus, and Gentner 1990). Some researchers have preferred that constraints on the mapping process come primarily or even exclusively from the syntax and semantics that are internal to an analogy, although allowing pragmatic factors to influence processes that occur before and after mapping (Gentner 1989).

The question of whether pragmatic constraint is arbitrary seems to be becoming a nonissue. Useful sources of constraint include context. Why ignore potentially useful information? Creative metaphors and similes, even apparently anomalous ones, often depend on context. For example, the apparently anomalous simile-a banana is like a *clock*—is made sensible given the story of the elderly man who quipped about his health by saying that he still bought green bananas at the grocery. Psychological research has shown that analogies are not comprehended or analyzed as context-free or isolated expressions. Even when they are presented as such, people create their own contexts, communal or idiosyncratic. To me, the correct solution to

ABC : ABD :: MNO : ?

is the string *MNQ* because Q is the first letter after O that Pat Hayes's granddaddy was really fond of.

Fundamentally, there seems little justification for building separate systems for processing naked analogies and for processing analogies in context (Gentner 1989). Emerging concensus seems to be that analogical reasoning can profitably be integrated into the problem-solving process or planning context (Holyoak and Thagard 1989; Burstein 1986; Carbonell 1986). In the systems of Kedar-Cabelli (1988) and, to a somewhat lesser extent, the model of Carbonell (1981), context in the form of purpose and goal directs the selection of relevant information to be represented. In the system of Chalmers, French, and Hofstadter (1992), context biases both representation and mapping processes. In the recent revision of the SME, Forbus, Ferguson, and Gentner (1994) allow for pragmatic marking of substructures to operate as a filter during inference. Apart from the specifics of the mechanisms, in all these models and those of Hobbs (1983) and Winston (1979) as well, goal-related information is used to guide or constrain inferencing.

Conclusion

Cognitive theories and AI models tend to focus on certain kinds of analogy for certain purposes (for example, multiple-choice–format geometric analogies for use in intelligence tests, incomplete scientific analogies for research on comprehension processes). Analogical thinking clearly depends on the human ability to lay out propositions that express conceptual relations. However, analogy should not be equated with a single form, format, or ontology. Limitations of approaches to analogy are illustrated by monster analogies, analogies that no existing computer system could accept as input, let alone successfully process. Expanding the concept of analogy could broaden the AI approach and enrich cognitive research. That is, the insights from a number of existing models could be combined. Until the scope of systems is broadened, AI might not be able to effectively deal with the fundamental mysteries of perception and cognition, mysteries that not only seem to be the real underpinnings of socalled analogical reasoning but that are also linchpins in strong definitions of AI.

Acknowledgments

I want to thank The Psychological Corporation (1993) for providing a copy of the *Candidate Information Booklet* for the Miller Analogies Test and permitting me to include some of the example items from the booklet. I would like to thank Eric Dietrich, Ken Ford, Pat Hayes, Art Markman, and Dan Wheeler for their critical, encouraging, and helpful comments on the first draft.

The final version of this article was prepared while I was supported by a Fulbright Award from the Council for the International Exchange of Scholars; a contract from Epistemics, Ltd.; and institutional grants from the Office of the President and the Office of the Provost at Adelphi University. I would also like to acknowledge the assistance and support of Professor Shadbolt and the computer support staff of the AI Group in the Department of Psychology at the University of Nottingham.

Table Notes

1. It is not clear who should get credit for first using the analogy in the context of discovery and analysis.

2. Some historical evidence suggests the analogy might actually have been used primarily in the context of justification or pedagogy rather than in the initial discovery context.

Notes

1. Space also does not permit analysis of the many models aimed at the processing of metaphor (for reviews, see Barnden and Holyoak [1994], Indurkhya [1992], Russell [1992], Way [1991], and Martin [1990]).

2. One would have to digress at length to explore the meanings of *model*, let alone the relation of model to metaphor and analogy. See King (1991),

Until the scope of systems is broadened until AI swallows some of the monsters—it *may not be* able to effectively deal with the fundamental mysteries of perception and cognition that are the linchpins in strong definitions of AI.

Holland et al. (1986), Hoffman (1980), Leatherdale (1974), Turbayne (1970), Hesse (1966), Black (1962), Lachman (1960), Hutten (1954), and Rapoport (1953). Some have claimed, flat out, that models *are* analogies *are* metaphors (for example, Indurkhya [1988, 1985] and Chapanis [1961]).

3. For examples, see Boden (1990); Hoffman, Cochran, and Nead (1990); Leary (1990); Gentner and Grudin (1985); MacCormac (1985, 1976); Tweney, Doherty, and Mynatt (1982); Gruber (1980); Nickles (1980); Ricoeur (1975); Harre (1970); Broadbeck (1968); Dreistadt (1968); Koestler (1964); Ramsey (1964); Carnap (1963); Schon (1963); Berggren (1962); Pap (1962); Chapanis (1961); Nagel (1961); Oppenheimer (1956); Hutten (1954); and Campbell (1953). The caution is that the analogy theory of scientific discovery and explanation does not provide a complete picture of the total process, which includes the pragmatics of research effort, innovation, and application (Clement 1982; Knorr-Cetina 1981).

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