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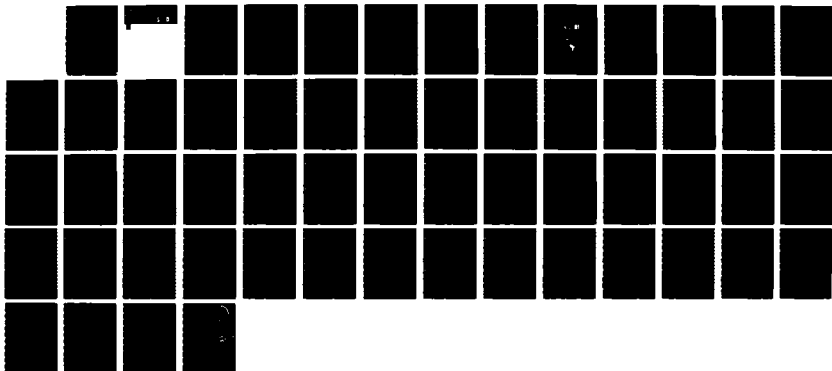
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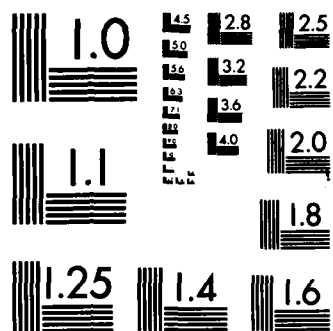
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ANALOGICAL INFERENCE
AND ANALOGICAL ACCESS

by

Dedre Gentner

August 1987

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1a. REPORT SECURITY CLASSIFICATION Unclassified			1b. RESTRICTIVE MARKINGS		
2a. SECURITY CLASSIFICATION AUTHORITY			3. DISTRIBUTION / AVAILABILITY OF REPORT Approved for public release; distribution unlimited		
2b. DECLASSIFICATION / DOWNGRADING SCHEDULE					
4. PERFORMING ORGANIZATION REPORT NUMBER(S) UIUCDCS-R-87-1365			5. MONITORING ORGANIZATION REPORT NUMBER(S)		
6a. NAME OF PERFORMING ORGANIZATION University of Illinois Department of Psychology		6b. OFFICE SYMBOL (if applicable)	7a. NAME OF MONITORING ORGANIZATION Cognitive Sciences (Code 1142CS) Office of Naval Research		
6c. ADDRESS (City, State, and ZIP Code) 603 E. Daniel Champaign, IL 61820			7b. ADDRESS (City, State, and ZIP Code) 800 North Quincy Street Arlington, VA 22217-5000		
8a. NAME OF FUNDING / SPONSORING ORGANIZATION		8b. OFFICE SYMBOL (if applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER N00014-85-K-0559		
8c. ADDRESS (City, State, and ZIP Code)			10. SOURCE OF FUNDING NUMBERS		
			PROGRAM ELEMENT NO. 61153N	PROJECT NO. RR04206	TASK NO. RR04206-0A
					WORK UNIT ACCESSION NO. NR667-551
11. TITLE (Include Security Classification) Analogical Inference and Analogical Access; Unclassified					
12. PERSONAL AUTHOR(S) Dr. Dedre Gentner					
13a. TYPE OF REPORT Technical Report		13b. TIME COVERED FROM 85-9-1 TO 88-8-30		14. DATE OF REPORT (Year, Month, Day) 87-4-8	
				15. PAGE COUNT 48	
16. SUPPLEMENTARY NOTATION					
17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)		
FIELD	GROUP	SUB-GROUP			
05	10		analogy structure-mapping		
			analogical access analogical inference		
			inferential soundness		
19. ABSTRACT (Continue on reverse if necessary and identify by block number) Analogy is a powerful technique in commonsense learning and reasoning. People use analogies in problem solving, in developing mental models of a new domain, and in communicating knowledge. To model these natural uses of analogy, we need to understand the whole process of analogizing from the first, starting with access and ending with drawing inferences or extracting a principle from an analogy. In this paper, I first review the structure-mapping theory of analogical processing and describe a simulation of the theory. I then extend this framework to accessing analogy. I discuss some recent research in our lab that suggests that the accessibility of an analogical match is governed by different factors from its inferential soundness. Finally, I consider some competing theoretical approaches to analogy and suggest an integrated architecture for analogical processing.					
20. DISTRIBUTION / AVAILABILITY OF ABSTRACT ☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT ☐ DTIC USERS			21. ABSTRACT SECURITY CLASSIFICATION Unclassified		
22a. NAME OF RESPONSIBLE INDIVIDUAL Dr. Susan Chipman			22b. TELEPHONE (Include Area Code) 202-696-4318		22c. OFFICE SYMBOL ONR1142PT

**Analogical Inference
and Analogical Access**

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University of Illinois**

This research was sponsored by the Personnel and Training Research Programs, Psychological Sciences Division, Office of Naval Research, under Contract No. N00014-85-K-0559, Contract Authority Number, NR667-551.

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Abstract

Analogy is a powerful technique in commonsense learning and reasoning. People use analogies in problem solving, in developing mental models of a new domain, and in gaining and communicating knowledge. To model natural uses of analogy, we need to understand the whole process of drawing an analogy, beginning with accessing a potential analog and ending with drawing inferences or extracting a principle from the analogy.

In this paper, I first review the structure-mapping theory of analogical mapping and inference and describe a simulation of the theory. I then extend this framework to the issue of how potential analogs are accessed. I discuss recent research that suggests that the accessibility of an analogical match is governed by different factors from its inferential soundness. Finally, I consider some competing theoretical approaches and suggest an integrated architecture for analogical processing.

My goal in this research is to understand how analogy and similarity work in experiential learning and reasoning. To understand analogical learning, we need to know how analogy is accessed and how it is used. In my previous research I focused on how analogy is used in making inferences. More recently I have been investigating access to analogies in long term memory. In this paper I will put these lines together into a cognitive architecture for analogy.

The theoretical framework for this paper is the structure-mapping theory of analogy, which gives the rules for analogical mapping and also functions as a core theory for a broader treatment of analogical learning (Gentner, 1980, 1982, 1983; Gentner & Gentner, 1983). The central intuition is that an analogy is a mapping of knowledge from one domain (the base) into another (the target) which conveys that a system of relations that holds among the base objects also holds among the target objects. In analogy, the target objects do not have to resemble their corresponding base objects. Objects are placed in correspondence by virtue of their like roles in the common relational structure. Thus an analogy is a way of noticing relational commonalities independently of the objects in which those relations are embedded. Central to analogy is the principle of systematicity: people prefer to map systems of predicates, rather than isolated predicates. Analogy conveys a system of connected knowledge, not a mere assortment of independent facts. Preferring systems of predicates that contain higher-order relations with inferential import is a structural expression of this tacit preference for coherence and deductive power in analogy.

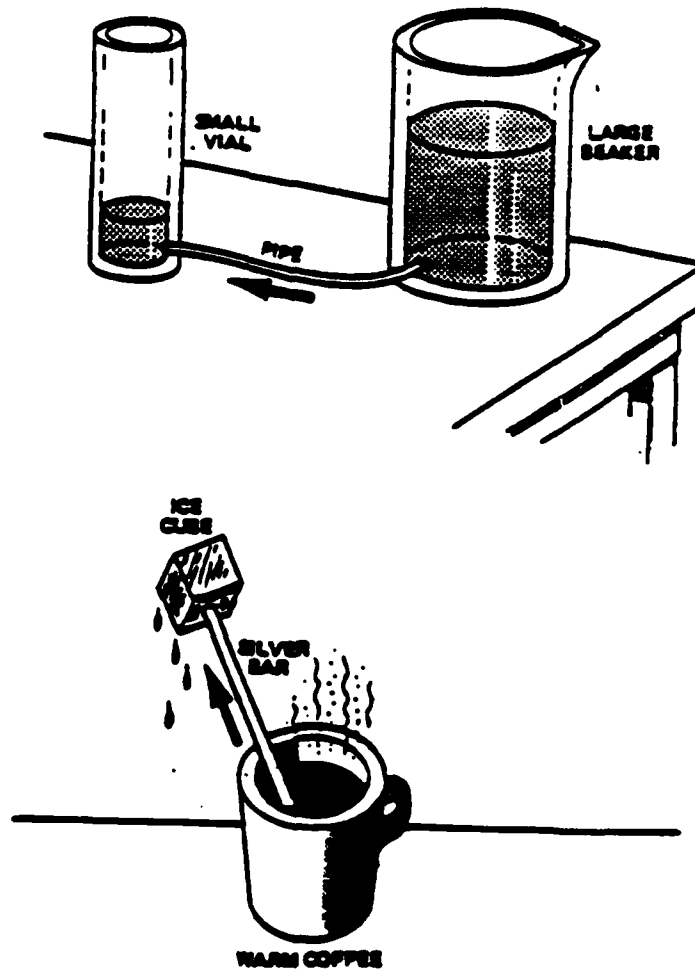
I first describe the basic theory and then discuss the Structure-mapping Engine, a simulation written by Brian Falkenhainer and Ken Forbus

(Falkenhainer, Forbus & Gentner, 1986). In interpreting an analogy, people seek to put the objects of the base in correspondence with the objects in the target so as to obtain maximum structural match. That is, they seek the mapping that maximizes consistency and systematicity. Consistency means that the mapping is 1-1: each object in the base is assigned at most one object in the target. Systematicity refers to the mapping of connected systems of relations, rather than isolated predicates. I will also use the term *systematicity* at times to refer to the presence of a system of relations in a given domain. The systematicity principle states that a base predicate that belongs to a mappable system of mutually interconnecting relations is more likely to be imported into the target than is an isolated predicate. A system of relations refers to an interconnected predicate structure in which higher-order predicates enforce constraints among lower-order predicates. A mappable system in the base is one that can be mapped into the target system without contradiction, and ideally with some partial matching with existing target predicates. The more matches are found between the predicates of the base system and existing predicates in the target, the more support there is for mapping other members of the base system. Thus, in an analogical mapping we are looking for a system of relations that can apply in both base and target. In determining the correspondence between objects in the base and objects in the target, the object descriptions themselves can be arbitrarily different; corresponding objects don't have to resemble each other at all. Instead, the object correspondences are chosen to achieve a consistent and maximally systematic match between predicates in the base and those in the target.

To illustrate the structure-mapping rules, we turn to a specific example: the analogy between heat-flow and water-flow. Figure 1 shows a water-flow situation and an analogous heat-flow situation (adapted from Buckley, 1979, pp

Figure 1

Examples of Physical Situations Involving
Water-flow and Heat-flow



15-25). Figure 2 shows the representation a learner might have of the two situations.

This network¹ represents a portion of what a person might know about the water and heat situations illustrated in the previous figure. These representations are the ones given to the Structure-mapping Engine, as described below. Note that we assume the learner begins with a richer representation of the water situation than of the heat situation.²

In order to comprehend the analogy "Heat is like water." a learner must find the set of object correspondences that allows systematic matching between the two domains. In so doing, the learner must:

- disregard object attributes, such as CYLINDRICAL(beaker)
- map base relations into the target domain
- observe systematicity: i.e., find a system of relations that can apply in both domains. here, the pressure-difference structure in the water domain

CAUSE(GREATER-THAN(PRESSURE(beaker), PRESSURE(vial)),

[FLOW(water, pipe, beaker, vial)])

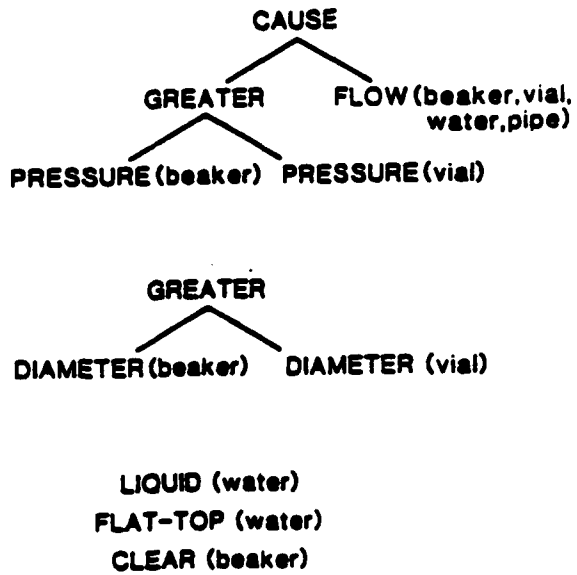
which maps into the temperature-difference structure in the heat domain

1. In this and other figures, predicates, including both relations and functions, are written in upper case and objects are written in lower case. A more detailed representation of the heat/water analogy is given in Forbus & Gentner (1983, 1986).
2. This analogy has been important in the history of theories of heat. It probably underlies the caloric theory of heat, and it was used by Carnot (1824) to illustrate the interrelation between heat and temperature. (See Gentner & Jezewski (in preparation) for a discussion of this history.)

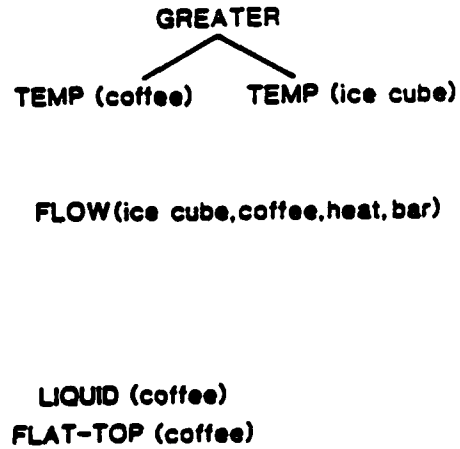
Figure 2

Representations of Water and Heat

WATER FLOW



HEAT FLOW



CAUSE(BREATER-THAN[TEMPERATURE(coffee), TEMPERATURE(ice)],

[FLOW(heat, bar, coffee, ice)]).

- discard isolated relations, such as

BREATER-THAN[DIAMETER(beaker), DIAMETER(vial)]

The object correspondences between the two domains that allow for the best match turn out to be

water --> heat; pipe --> metal bar;

beaker --> coffee; vial --> ice.

As noted earlier, the object correspondences -- water/heat, beaker/coffee, vial/ice, and pipe/bar -- and the function correspondence PRESSURE/TEMPERATURE³ are determined not by any intrinsic similarity between the objects, but by their role in the systematic relational structure. Systematicity also determines which relations get carried across. The reason that

3. In this analogy, the function PRESSURE in the water domain must be matched with TEMPERATURE in the heat domain. Like objects and their attributes, functions on objects in the base can be put in correspondence with different functions in the target in order to permit mapping a larger systematic structure. This is a change from my former position, which only distinguished between object-attributes (one-place predicates), which were allowed to match nonidentically, and relations (2-or-more-place predicates), which had to match identically. I now distinguish functions on objects (including n-place functions) as a separate class, which can match nonidentically. The rationale is that such functions are basically aspects of object descriptions. Like objects and their attributes, they can be put into correspondence with different functions in the target. In other words, the essential distinction is between objects and their descriptions on the one hand and relational structure on the other. My initial formulation in terms of one-place and n-place predicates was too stringent. I thank Ken Forbus, Brian Falkenhainer and Janice Skorstad for discussions on this issue.

GREATER-THAN[PRESSURE(beaker), PRESSURE(vial)]

is preserved is that it is part of a system of higher-order constraining relations -- in this case, the system governed by the higher-order relation CAUSE -- that partially matches a relational system in the target. In contrast, the relation

GREATER-THAN[DIAMETER(beaker), DIAMETER(vial)]

does not belong to a common systematic structure shared by the base and target domains, and so is discarded in the interpretation.

However, it is important to note that which predicates survive in the interpretation depends on the match between the two domains. With a different target domain, the DIAMETER difference will be part of the analogy. For example, suppose that we keep the same base domain -- the water system shown in Figure 2 -- but change the target domain to two objects differing not only in their temperature but also in their specific heat: say, a metal ball-bearing and a marble. Assuming equal mass, they will also have different heat capacities. With this new target, the natural interpretation concerns capacity differences⁴ in the base, as well as level or pressure differences. Now each system involves two interrelated variables: (1) the initial variable of LEVEL (TEMPERATURE) which tells us in which direction water (heat) will flow to achieve equilibrium and (2) a second variable of CAPACITY which determines which vessel will experience the greatest change in LEVEL in achieving

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4. For continuity I have used DIAMETER as the predicate, although CROSS-SECTIONAL AREA would be more accurate. Also, note that there might have been a similar heat-capacity difference between the coffee and ice cube in the original heat figure; but without specifying the masses, this difference could not be assumed.

equilibrium. Now the most systematic relational system that can be mapped to the target is

CAUSE (GREATER-THAN [DIAMETER (beaker), DIAMETER (vial)],

GREATER-THAN [CHANGE-OF-PRESSURE(vial),CHANGE-OF-PRESSURE(beaker)])

This carries over into the target as

CAUSE (GREATER-THAN [HEAT-CAP.(marble), HEAT-CAP.(ball)],

GREATER-THAN [CHANGE-OF-TEMP.(ball), CHANGE-OF-TEMP.(marble)]).

Because the target shares a larger relational system with the base, the natural interpretation of the analogy is now more complex. This illustrates that, for a given base domain, the mapping for a particular target is determined by the best match -- i.e., the most systematic and consistent relational match -- between base and target.⁵ The only case in which the base domain by itself determines the interpretation is that in which nothing is initially known about the target; then matching does not apply and the mapping is one of pure carryover from base to target. In the more normal case when information is known about both base and target, the interpretation is based on both matching between base and target and carryover of predicates from base to target (Gentner, in press).

5. I stress this point because it apparently can be misunderstood; Holyoak (1985) writes that the interpretation of an analogy in structure-mapping depends only on an analysis of the structure of the base domain. To forestall such misconceptions I stress that (as with other kinds of similarity comparisons) the interpretation of an analogy in structure-mapping involves a match -- in this case the most systematic consistent match -- between two domains.

There are a few further points to notice here. First, the order of operations is probably variable. I suspect that often the learner begins with relational matching and mapping and uses the relational matches to determine the object correspondences. (This is the way the simulation performs, as described below.) However, sometimes the object-correspondences are the first step: for example, in cases when the learner is explicitly told the object correspondences. Second, note that the systematicity principle requires a mappable relational system. If the predicates of the base system generate contradictions in the target, then another system must be selected. Third, a member of a base relational system that can successfully be mapped into the target provides support for other members of that system.

Finally, it is useful to distinguish two extremes of analogical processing:

- (1) pure matching: all the predicates of the base system are matched with predicates in the target system. In this case the analogy serves not to communicate new knowledge but to focus attention on a particular common system of predicates.
- (2) pure mapping: the learner is given the object correspondences and simply carries across a system of predicates from the base to the target. This is a case of maximal new knowledge.

These extremes are rare; most analogies involve both matching and mapping. Typically there is a partial match between base and target systems, which then sanctions the mapping of further predicates from the base to the target.

The Structure-Mapping Engine. The Structure-Mapping Engine (SME) is a simulation of the structure-mapping process written by Brian Falkenhainer and Ken Forbus. I describe it briefly here (For a more complete description, see Falkenhainer, Forbus, & Gentner, 1986). Given representations of the base and

target, SME uses systematicity and structural consistency to determine the best mapping(s). When SME is run in its basic analogy mode, only relational structure counts in the match. But SME can also be run with different match rules to simulate mere-appearance matches (only object descriptions count) and literal similarity matches (both object descriptions and relational structure counts in the match). Because literal similarity matches show a broad range of SME's behavior, I will describe the match rules that simulate literal similarity.

SME is given as input structured representations of the water and heat situations, as shown in Figure 2.⁶ The order of events is as follows:

(1) *Local matches.* SME starts by finding potential matches between single items in the base and target. For each entity and predicate in the base, it finds the set of entities or predicates in the target that could plausibly match that item. These potential correspondences (*match hypotheses*) are determined by a set of simple rules: for example,

- (1) if two relations have the same name, create a match hypothesis;
- (2) for every match hypothesis between relations, check their corresponding arguments: if both are entities, or if both are functions, then create a match hypothesis between them.

For example, given the representations in Figure 2, rule (1) creates match hypotheses between the GREATER THAN relations that occur in base and target. Then rule (2) creates match hypotheses between their arguments, since both are -----

6. Note that the representations contain extraneous matches such as LIQUID(water) and LIQUID(coffee). These spurious matches are included to simulate a learner's uncertainty about what matters and to give SME the possibility of making errors.

functions. Note that at this stage the system is entertaining two different -- and inconsistent -- match hypotheses involving GREATER THAN: one in which PRESSURE is matched with TEMPERATURE, and one in which DIAMETER is matched with TEMPERATURE. Thus, at this stage the program will have a large number of local matches.

Another set of rules assigns evidence scores to these local matches: e.g.,

- (1) Increase the evidence for a match if the base and target predicate have the same name.
- (2) Increase the evidence for a given match if there is evidence for a match among the parent relations -- i.e., the immediately governing higher-order relations.

Rule (1) reflects a preference for relational identity and rule (2) reflects a preference for systematicity. It is at this stage that the GREATER-THAN--PRESSURE system in the water domain begins to gain an advantage over the GREATER-THAN--DIAMETER system. This is because the PRESSURE system has more layers of parent predicates that match with the heat system, which leads to higher local evidence scores for PRESSURE than for DIAMETER.

(2) *Constructing global matches.* The next stage is to collect systems of matches that use consistent (i.e., 1-1) entity-pairings. SNE first propagates entity-correspondences up each relational chain to create systems of match hypotheses that use the same entity-pairings. It then combines these into the largest possible systems of predicates with consistent object-mappings. These global matches (called Gmaps) are the possible interpretations of the analogy. Associated with each Gmap is a (possibly empty) set of candidate inferences --

predicates that are part of the base system but were not initially present in the corresponding target system.

(3) *Evaluating global matches.* The global matches are then given a structural evaluation, which depends chiefly on the local match evidence.⁷

An important aspect of SNE is that the global matches (Gmaps) sanction *candidate inferences*: predicates from the base that get mapped into the target domain. These are base predicates that were not originally present in the target, but which can be imported into the target by virtue of belonging to a system that is largely shared by base and target. For example, in the heat/water scenario shown here, the water representation contains the full pressure-difference system, while the heat representation lacks the higher-order CAUSE predicate. That is, it contains only the two first-order predicates

GREATER-THAN[TEMPERATURE(coffee), TEMPERATURE(ice)]

and

[[FLOW(heat, bar, coffee, ice)]]

In this case, the system brings across the higher-order predicate CAUSE from the base domain. In essence, it postulates that there may be more structure in the target than it initially knew about.

SNE's interpretation is based on selecting the most systematic consistent mappable structure. Thus computing systematicity precedes and determines the final selection of object correspondences. Indeed, even in literal similarity

7. SNE also has the capability to consider the number of candidate inferences supported and the graph-theoretic structure in assigning the evaluation, but the ramifications of these options have not yet been explored.

node, as illustrated here, achieving a maximally consistent relational match can outweigh placing similar objects in correspondence.*

SME's matching process is entirely structural. The internal processes of the analogy engine are not directly influenced by the system's problem-solving goals (although, as discussed below, the reasoner's plans and goals can have *indirect* influence since they influence the inputs to the analogy engine). But by promoting deep relational systems, the systematicity principle operates to promote predicates that participate in causal systems and in other constraint relations. Yet this purely structural mechanism guarantees that the set of candidate mappings will be as interesting -- in the sense that a mutually interconnected system of predicates is interesting -- as the knowledge base allows.

Kinds of Similarity. I have claimed that in interpreting analogical matches, only relational predicates count. There is evidence that in judging the aptness of a metaphoric comparison, people do indeed favor such relational mappings (Gentner, 1980, 1986; Gentner & Block, 1983; Gentner & Landers, 1985). But to give a complete psychological account of learning by analogy and similarity, we must also consider other kinds of similarity matches. As was discussed above, not only analogy but also other kinds of similarity can be characterized by the distribution of relational and attributional predicates that are mapped. In *analogy*, only relational predicates are mapped. In *literal similarity*, both relational predicates and object-attributes are mapped. In *mere-appearance* matches, it is chiefly object descriptions that are mapped.

8. This view of literal similarity is a departure from the 'feature-list' view that has been dominant in cognitive psychology (e.g., Tversky, 1977). In ongoing research, Doug Medin, Robert Goldstone and I have found evidence for effects on relational structure on similarity judgements, even with simple geometric figures.

Table 1 shows examples of these different kinds of similarity comparison. The central assumption here is that it is not merely the relative number of shared versus nonshared predicates that matters -- although that is certainly important, as Tversky (1977) has shown -- but also the kinds of predicates that match. For a longer discussion of similarity types see Gentner, 1986).

Table 1
Kinds of Domain Comparison

	ATT	REL	EXAMPLE
Literal Similarity	Many	Many	Milk is like water.
Analogy	Few	Many	Heat is like water.
Abstraction	Few	Many	Heat flow is a through-variable.
Anomaly	Few	Few	Coffee is like the solar system.
Mere Appearance	Many	Few	The glass tabletop gleamed like a pool of water.

To illustrate these distinctions, consider this series of related examples.

(1) *Analogy.* As discussed above, the analogy "Heat is like water." conveys a relational system:

CAUSE(GREATER-THAN(PRESSURE(beaker), PRESSURE(vial)),

[FLOW(water, pipe, beaker, vial)])

is mapped into

CAUSE(GREATER-THAN(TEMPERATURE(coffee), TEMPERATURE(ice)),

[FLOW(heat, bar, coffee, ice)]).

(2) *Literal similarity.* The comparison "Kool-Aid is like water." conveys that most of the water description can be applied to Kool-Aid. In literal similarity, both object descriptions, including attributes like

FLAT-TOP(water) and CYLINDRICAL(beaker)

and relational predicates, such as the systematic structure discussed above, are mapped over.

(3) *Relational abstraction.* The abstract statement "Heat is a through-variable," which might be available to a student who knows some system dynamics, conveys that heat can be thought of as a flow variable that moves across a potential difference. This potential difference requires an across-variable: in this case, temperature. This abstraction, when applied to the heat domain, conveys much the same relational structure as is conveyed by the heat/water analogy (1). The difference is that in the abstract base domain of through-variables and across-variables, there are no concrete properties of objects to be left behind in the mapping.

(4) *Mere-appearance match.* A mere-appearance statement, such as "The table top looked like water," is one with overlap in lower-order predicates -- object-descriptions and some first-order spatial relations -- but not in higher-order relations. Here, the color and texture of the water is mapped onto the table. Although mere-appearance matches are limited in their explanatory utility, they are important in a psychological account of learning, for two reasons: (1) they often occur among novice learners; and (2) in general, mere-appearance matches may be highly accessible in long-term memory.

These contrasts are not dichotomies but continua, . For example, for both analogy and literal similarity, the base and target share relational structure. If that is all they share, then the comparison is an analogy. To the extent that the domains also share common object descriptions, the comparison becomes literal similarity. Another continuum exists between analogy and relational abstraction. In both cases, the base and target share relational structure and do not share object descriptions. Here the continuum is in the nature of the base representation. If the base representation includes concrete objects whose individual attributes must be left behind in the mapping, the comparison is an analogy. As the object nodes of the base domain become more abstract and variable-like, making the comparison becomes more like invoking an abstraction.

Accessing versus Soundness

With these distinctions, we are ready to ask what governs spontaneous access to analogy and similarity. Are the similarities that promote access the same as those that enter into mapping and judging the worth of analogies? To clarify the discussion, let us decompose analogical reasoning into access and

mapping-plus-inference. [For a more detailed treatment of the subprocesses in analogy, see Clement (1981, 1983) and Gentner (1987, in press).] Access is the process of matching a base situation in memory with a given target situation a person is faced with. In other words, it is the process whereby a current target situation reminds a person of a base situation in his memory. Mapping occurs after a base situation has been accessed from memory. In mapping, the predicates of the base are matched with corresponding predicates of the target according to the rules given above, including consistency and systematicity. In cases where a highly systematic relational structure can indeed be mapped into the target domain, structure-mapping predicts that people will consider the analogy sound. Such an analogy can support inferences: because the base and target share systematic relational structure, any additional predicates from the base system can be carried into the target system as candidate inferences. Thus structure-mapping predicts that shared systematicity should be a major determinant of how sound people believe an analogy to be.

Gentner & Landers (1985) investigated the accessibility and subjective soundness of different kinds of similarity matches. The experiment had a two-fold purpose: (1) it tested the prediction that systematicity determines the subjective soundness of a match; and (2) it compared the accessibility of analogy with that of other kinds of similarity matches. This study was designed to create a situation resembling naturalistic long-term memory access. The subjects were 30 students from the MIT Psychology Department. We first gave the subjects a large number (32) of stories to read and remember. One week later, we brought them back, showed them a new set of stories and asked them to tell us if they were reminded of any of the original stories. Finally, they rated the story pairs for their inferential soundness, as explained below. The stories were carefully designed to embody different kinds

of similarity matches. There were three kinds of similarity matches between base and target: mere appearance matches, true analogies and false analogies, as follows:

- mere appearance (MA): first-order relations and object-attributes match
- true analogy (TA): first-order relations and higher-order relations match
- false analogy (FA): only the first-order relations match.

Note that in all three cases, the base and target shared first-order relations. The three similarity conditions differed in which, if any, other commonalities also existed. Table 2 shows an example set of four scenarios: a base scenario plus one example of each of the three kinds of matches.

In the first session, all subjects read the same 18 base stories and 14 filler stories. They were told to read carefully and remember the stories. In the second session, six to eight days later, subjects received a workbook of 18 new target stories: 6 MA targets, 6 TA targets, and 6 FA targets. That is, each target was similar -- in one of the three ways described above -- to one of the 18 base stories the subject had read. The target stories were read in random order. Subjects were divided into 3 groups to counterbalance which type of match occurred in which stories. For each target story read, subjects were instructed to write down any base story they were reminded of, as completely as possible.

The soundness task was given to subjects after they had completed the matching task. In this task, subjects were given workbook showing 18 pairs of stories and asked to rate each pair for the "soundness" of the match between the two stories (explained as "when two situations match well enough to make a strong

TABLE 2

Sample Story Set for the Access and Soundness Experiment

(Gentner & Landers, 1985)

BASE story

Karla, an old hawk, lived at the top of a tall oak tree. One afternoon, she saw a hunter on the ground with a bow with some crude arrows that had no feathers. The hunter took aim and shot at the hawk but missed. Karla knew the hunter wanted her feathers so she glided down to the hunter and offered to give him a few. The hunter was so grateful that he pledged never to shoot at the hawk again. He went off and shot deer instead.

True Analogy TARGET

Once there was a small country called Zerdia that learned to make the world's smartest computer.

One day Zerdia was attacked by its warlike neighbor, Gagrach. But the missiles were badly aimed and the attack failed. The Zerdian government realized that Gagrach wanted Zerdian computers so it offered to sell some of its computers to the country. The government of Gagrach was very pleased. It promised never to attack Zerdia again.

Mere Appearance TARGET

Once there was an eagle named Zerdia who donated a few of her tailfeathers to a sportsman so he would promise never to attack eagles.

One day Zerdia was nesting high on a rocky cliff when she saw the sportsman coming with a crossbow. Zerdia flew down to meet the man, but he attacked and felled her with a single bolt. As she fluttered to the ground Zerdia realized that the bolt had her own tailfeathers on it.

False Analogy TARGET

Once there was a small country called Zerdia that learned to make the world's smartest computer. Zerdia sold one of its supercomputers to its neighbor, Gagrach, so Gagrach would promise never to attack Zerdia.

But one day Zerdia was overwhelmed by a surprise attack from Gagrach. As it capitulated the crippled government of Zerdia realized that the attacker's missiles had been guided by Zerdian supercomputers.

argument from one to the other"). The first story in each pair was one of the base stories from the first session, and the second story was the matching target story the subject had received (whether or not he or she had noticed the match). Thus, each subject rated 1/3 MA, 1/3 TA, and 1/3 FA matches. Subjects used a 1-5 scale, where 5 = highly sound and 1 = spurious.

To score the reminding task, two judges read each of the workbooks and scored the accuracy of the recalled base stories. The judges did not know which experimental condition subjects were in, nor what kind of match they had been given. They used a scale ranging from 5 (excellent recall) to 1 (poor recall), with 0 being used when subjects made no reminding response at all or recalled a different story. * In addition to this overall score, we also computed a flat score. For this score, we counted all recalls with an overall score of 2 or better. This simply measured whether any genuine recall had occurred, without worrying about whether the recall was of high quality.

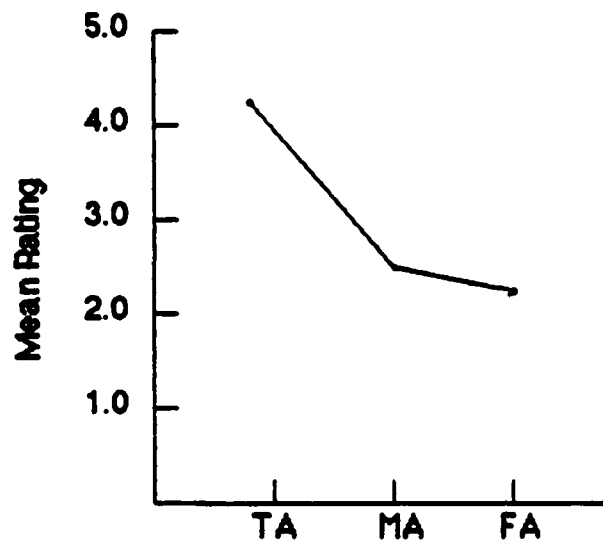
Results of the Soundness Task. Figure 3a shows the results of the soundness-rating task. As predicted by structure-mapping theory, subjects judged the true analogies, the only pairs that shared higher-order structure, to be far more sound than the other two kinds of pairs. The MA and FA pairs, which did not share systematic structure, were judged to be unsound.¹⁰ The difference between false analogies and true analogies is particularly interesting for structure-mapping theory, for these two match types differed only in the presence of higher-order relational structure. The fact that true analogies

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9. There was good agreement among the judges: they were within one point of each other 97% of the time.
 10. These patterns were confirmed by an analysis of variance and by planned-comparison t-tests. The differences between TA and MA and between TA and FA are significant ($p < .001$ in each case), and the difference between MA and FA is not significant ($p = .802$).

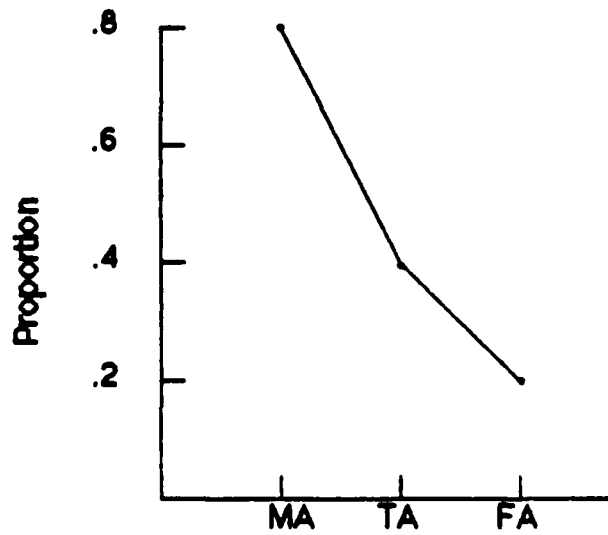
Figure 3

**Results Of The Access Experiment
(Gentner And Landers, 1985)**

a. Mean Rating of Soundness of Match



**b. Proportion of Base Stories Recalled Given
Different Kinds of Matches**



were rated as significantly more sound than false analogies is evidence that it is not just shared relations but shared higher-order relations that determine analogical soundness. These results help confirm the importance of systematicity in human analogical reasoning.

Results of the Reminding Task. The results of the reminding task are quite different. As Figure 3b shows, mere appearance matches are by far the best remembered. This is true for both scoring methods -- overall recall score and flat-match score.¹¹

These results suggest that different kinds of similarity matches are weighted differently in determining the accessibility and the inferential soundness of an analogy. In the reminding task, mere appearance matches were by far the best accessed. True analogies accessed only half as often and false analogies about one third as often. Evidently, access to memory is heavily influenced by surface similarity between the base and target. In contrast, in judging soundness it is systematic structural overlap that counts. Thus, although mere-appearance matches were highly successful at leading subjects to access the base, such matches were nonetheless judged by the same subjects to be spurious comparisons. The matches that people find easiest to make are not the ones they find most valuable in inference.

We have recently replicated these results, adding a literal similarity condition, and the results show the same pattern (Gentner & Rattermann, in preparation). It appears that the subprocesses involved in analogical access

11. Both overall analyses of variance and planned-comparison t-tests indicate that all of the differences --- MA-TA, MA-FA, and TA-FA --- are significant for both overall and flat matching scores ($p < .001$ in all six tests).

and judging analogical soundness may be influenced to different degrees by different kinds of similarity.¹²

- Accessibility is promoted by overall similarity, but perhaps especially by surface similarity.
- Inferential power is governed by similarity of higher-order structures.

These access results accord with other research on access (Bick & Holyoak, 1980, 1983; Reed, 1987; Reed, Ernst & Banerji, 1974; Ross, 1984, 1986; Ross & Sofka, 1986). In this research it has reliably been demonstrated that subjects in a problem-solving task often fail to access prior material that is analogous to their current problem. For example, in Bick and Holyoak's (1980, 1983) studies, subjects were told to solve a problem shortly after hearing a story that was in fact analogous to the problem. A substantial number of subjects failed to access the potential analogy -- and therefore could not solve the problem -- yet, when told that the prior material was relevant, they could solve the problem immediately. This means that their stored information about the prior story formed a good analogy to their current problem; but the analogical commonalities were not sufficient to cause them to spontaneously access this material. Further, the work of Ross (1984, 1986; Ross & Sofka, 1986), Reed (1987) and Novick (1985) indicates that surface commonalties are important in promoting access to prior material. Thus, surface similarity appears to be a major factor in accessing material in long-term memory.

12. Strictly speaking, we cannot compare the importance of surface and structural similarity in a given process, just as we cannot compare the importance of form and color. What we can say is that the relative contribution of surface to structural similarity is greater in access than in inference. I thank Brian Ross for discussion of this point.

These results are problematic for the view that memory is normally indexed by top-level structures such as plans and goals. (Carbonell, 1983; Hammond, 1984). For if access were based on shared plans and goals, the true analogy targets should have been the best cues for the base stories. But this was not the case. Evidently, access to memory is heavily influenced by surface similarity between the base and target, and not merely by similarity in causal structure or in plans and goals. Contrary to the plausible intuition of importance-governed indexing, *analogical access* has a different sensitivity profile from *analogical inference*.

It could be argued that the Bentner & Landers and Bick & Holyoak results are not representative of normal access patterns. As Hammond (personal communication, January, 1986) points out, it may be that a story-reading task is not representative of real-life encoding tasks, in which plans and goals determine how things are indexed (e.g., Burstein, 1983; Carbonell, 1983; Schank, 1982). By this argument, the emphasis on surface information in access in these studies results from the fact that the subjects were not in a goal-driven state at the time of original story encoding. This is a point worth further investigation. There is research suggesting that the amount of relational access depends in part on the nature of the original encoding (Schumacher, 1987). Thus it seems plausible that if the original situation had been more goal-driven, the effects of surface commonalities might have been lower. However, this does not appear to be the whole answer, for there is heavy reliance on surface information in access even in problem-solving contexts, in which the learner should be goal-driven throughout. Subjects who are solving problems both at the time of the original base problem and at the time of the original target problem still show a sizable surface bias in

access (Novick, 1985; Reed, 1987; Reed, Deepster & Ettinger, 1985; Reed, Ernst, & Banerji, 1974; Ross, 1984, 1985, in press).

Clearly, these results cannot be taken to mean that analogical access -- including plan-based access -- never occurs. Such reminders occur at occasionally in commonsense reasoning (e.g., Leake & Owens, 1986; Kass, 1986; Schank, 1982) as well as in expert problem-solving (Clement, 1981, 1983, 1986) and, historically, in scientific discovery (Gentner, 1982; Gentner & Jeziorski, in preparation). Indeed, in the Gentner & Landers study true analogies led to reminders about 40% of the time. A correct model of analogy will have to account both for the fact that analogical reminding is relatively unlikely and for the fact that it does sometimes occur. Further research should clarify the conditions under which analogical access occurs.

From a machine-learning standpoint, it may seem that humans are very badly designed. The human bias for overall-similarity matches rather than analogical reminders must deprive us of countless potential insights. But there may be good reason for this bias. Human data bases are typically very large, orders of magnitude larger than those of any current A.I. systems. An access bias for literal similarity serves to reduce the number of spontaneous matches that have to be checked. If we noticed all the analogical reminders that are inherent in our data bases, the costs of checking potential matches might be prohibitive.

But although this explanation might justify our conservative preference for overall similarity, it does not explain why our access mechanisms also produce mere-appearance matches. At first glance, this seems really dumb. My speculation is that, for beings with good perceptual systems, access on the basis of object descriptions may be a reasonable heuristic for obtaining

literal similarity matches. Surface information is cheap -- that is we seem to process it very easily -- and, at least in concrete physical domains, it is fairly reliable. By and large, what looks like a tiger is a tiger. Thus the cost/reliability tradeoff for humans in use of surface information may be rather reasonable. Whether we should design machines with the same access biases is not clear. If relative costs are different in machine learning systems then a different tradeoff might be preferable. The harder it is to give a machine learning system rich perceptual representations and the easier it is to design efficient methods for checking large numbers of potential similarity matches, the less the payoff for using a human-like access system.

Aside from efficiency of access, it is possible that a bias for literal similarity has subtle but deep advantages in learning very complex systems -- such as language, or the laws of the physical world -- where the appropriate relational structures cannot be predicted in advance. Forbus & Gentner (1983, 1986) have suggested that in such domains initial learning is best described as massive storage of exemplars. Then through similarity matches -- initially literal similarity matches and later analogies -- common relational structure gradually becomes more salient. (It's assumed here that making a similarity match heightens the salience of the matching features in subsequent memory (e.g., Bick & Holyoak, 1983).) Although such a system is initially slow, its advantage is that its eventual abstractions are based on regularities in domain structure rather than on the learner's initial preconceptions.

Related Research:

Pragmatic versus Structural Accounts

Some aspects of structure-mapping have received convergent support in artificial intelligence and psychology. There is widespread agreement on the basic elements of one-to-one mappings of objects with carryover of predicates (Burstein, 1983; Carbonell, 1983; Darden, 1980; Greiner, 1986; Hobbs, 1979; Hofstadter, 1984; Indurkha, 1985; Kedar-Cabelli, 1985; Reed, 1987; Reed, Dempster & Ettinger, 1985; Rumelhart & Norman, 1981; Van Lehn & Brown, 1980; and Winston, 1980, 1982). However, accounts vary in the nature of the selection principle that determines just which predicates come over in analogy. In structure-mapping, the selection rules are structural: namely, a preference for systematic relational matches. Pragmatic and contextual factors influence the matching process only indirectly, by influencing the input to the matcher and by providing pragmatic criteria against which results of the match are judged. (See Figure 4 below.) Although many researchers use systematicity as part of their selection criteria, it is often augmented by specific content knowledge or pragmatic information. For example, an important early system was Winston's (1980, 1982) system, which used a selection criterion based on common object properties and classes but also on specific relational contents: it looked for causal relations in its importance-guided matching algorithm. Other recent accounts have taken a more strongly pragmatic view, emphasizing the central role of plans and goals in the analogical mapping process. For example, Carbonell (1981, 1983) proposed that people comprehend analogies according to an invariance hierarchy -- an ordered sequence of ten interpretation types, starting with shared goal-expectations and continuing through planning strategies, then causal structures and on down to object identities as the last resort. This account focuses on plans and

goals as the most important higher-order relations for analogical mapping. It suggests that a reasoner will always begin by seeking a common goal, then try for a common plan, then a common causal structure, and so on. This is a very different kind of process from the one suggested here, in that the interpretation types are tried in a fixed preset order, rather than (as here) derived by matching structures. As a process model, the invariance hierarchy seems rather implausible. This is especially true for science analogies. In the heat flow/water flow analogy, for example, it seems unlikely that people first try to find a goal-expectation common to heat and water, then try for a common planning strategy, and only then turn to common causal structure. However, Carbonell's hierarchy is a useful start on a taxonomy of the kinds of relational structures that analogies can highlight.

The purest exposition of the pragmatic view is that of Holyoak (1985). He proposes an entirely pragmatic account in which structural principles play no role. In Holyoak's account, there are no independent structural distinctions among predicate types; the only distinction between surface and structural commonalities is that of relevance to the current plan. As Holyoak (1985, p. 81) states:

It is possible, based on the taxonomy of mapping relations discussed earlier, to draw a distinction between surface and structural similarities and dissimilarities. An identity between two problem situations that plays no causal role in determining the possible solutions to one or the other analog constitutes a surface similarity. Similarly, a structure-preserving difference, as defined earlier, constitutes a surface dissimilarity. In contrast, identities that influence goal attainment constitute structural similarities, and structure-violating differences constitute structural dissimilarities. Note that the distinction between surface and structural similarities, as used here, hinges on the relevance of the property in question to attainment of a successful solution. The distinction thus crucially depends on the goal of the problem solver.

Notice that this account is solely pragmatic. Relevance does not suggest considerations of predicate structure, but replaces them. Holyoak argues that systematicity is an epiphenomenon: what passes for structural matching is actually the reasoner's attention to the causal assertions that support current goals. Structural similarities are defined as "identities that influence goal attainment." and surface similarity as "an identity between two problem situations that plays no causal role in determining the possible solutions to one or the other analog." Thus the distinction between surface and structural similarities "hinges on the relevance of the property in question to attainment of a successful solution. The distinction thus crucially depends on the goal of the problem solver."

This view has an immediate appeal: it focuses attention on analogy as an aspect of goal-directed reasoning. Like the work of Burstein (1983), Carbonell (1981) and Kedar-Cabelli (1985), it emphasizes the importance of contextual relevance in analogical processing. These are aspects of analogy that must be taken into consideration; and indeed I will suggest a way to model these factors below (See Figure 4.). However, Holyoak's account goes much further than the others mentioned: it promises to replace structural considerations like systematicity with an ecologically natural notion of the reasoner's goal. But looked at closely, the pragmatic proposal reveals serious problems.

The first disadvantage of the purely pragmatic account is that, because it is a one-factor system, it cannot capture the distinction between soundness and relevance. An analogy can be rejected in a problem-solving situation for two different reasons: it can be judged unsound -- i.e., lacking in sufficient structural overlap to support importing inferences from base to target -- or it can be judged irrelevant -- i.e., as supporting inferences in the target but not the inferences needed at the moment. To capture both these

possibilities, a two-factor theory is necessary: pragmatic criteria, which govern relevance, must be separated from structural criteria, which govern soundness. The purely relevance-based account encounters other serious problems as well: since 'structural identities' (a bit of a misnomer here) are defined as goal-relevant identities, the interpretation mechanism requires that the reasoner have a goal in order to derive an interpretation of an analogy. Outside of a goal-context, there is no basis for choosing which matches to keep. Yet we know that people can comprehend an analogy in isolation.

Finally, it's not clear whether a purely pragmatic account is computationally feasible. Holyoak and Thagard (1986) outline a computer simulation of analogical processing called PI. However, there does not appear to be any published account to date containing enough detail to ascertain whether it operates according to the pragmatic account, whether it runs on more than the single example described, and how sufficient or efficient it is. I will return to these points below, after suggesting what I believe is a better way to model the interaction between structure and context.

Plans and goals in a structural account. Plans, goals and expectations are important throughout cognition (Miller, Gallanter & Pribram, 1960; Schank, 1982; Schank & Abelson, 1977). A complete model of analogical problem solving must take account of the plans and goals of the reasoner (e.g., Burstein, 1983; Holyoak, 1985; Kedar-Cabelli, 1985).¹³ However, the fact that plans and goals are important in analogical reasoning does not mean they should be built into the analogy engine. Analogy occurs in other contexts besides problem-

13. I thank Mark Burstein for many lively and insightful discussions on this point. His arguments have led me to give plans and goals a more explicit role in my account.

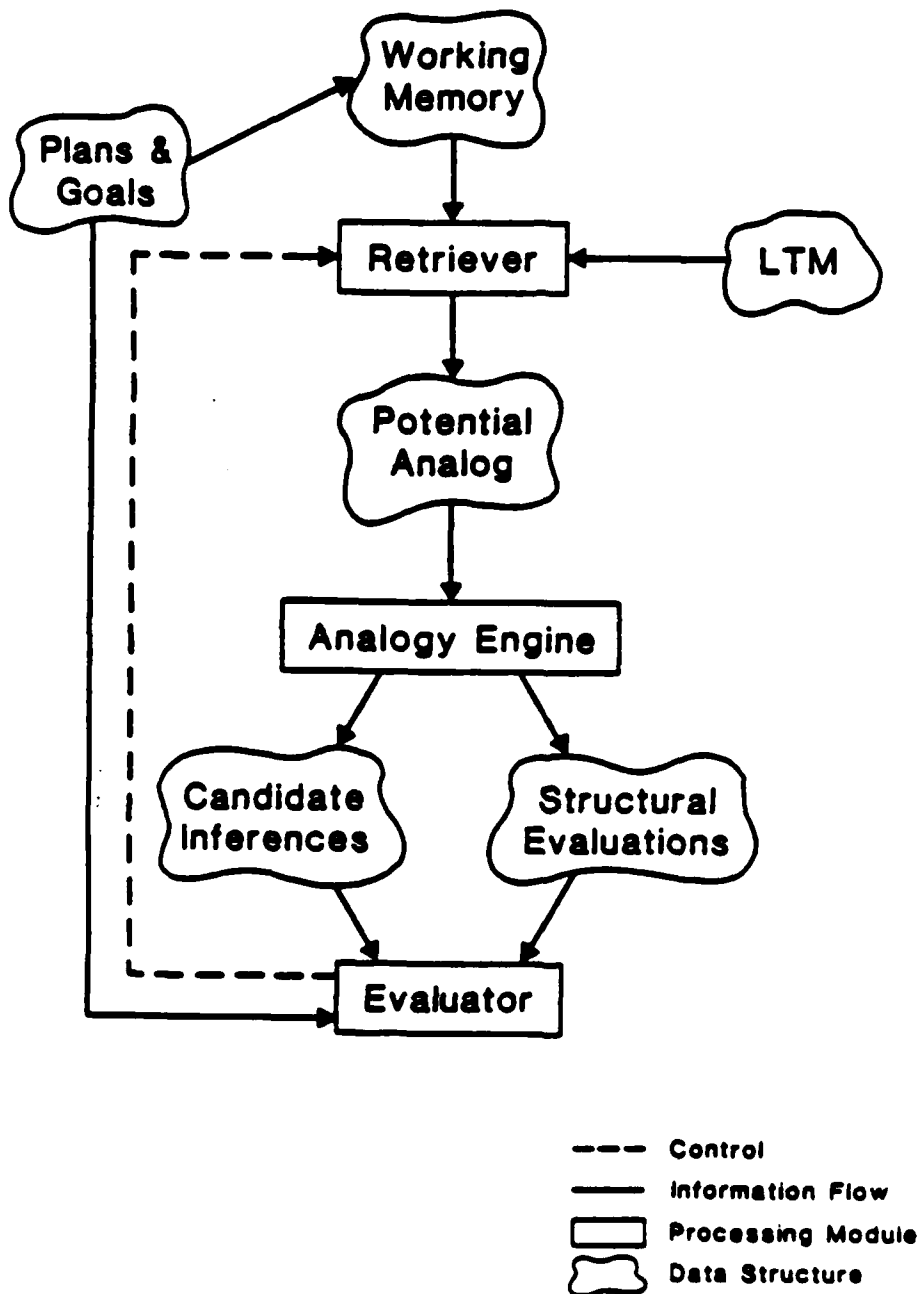
solving. And in the other direction, plans and goals affect many different kinds of human reasoning. In other words, what differentiates analogy from other processes is not the use of plans and goals; it is the nature of the computation performed. What is needed is an account that captures what is specific and essential to analogy, one that is applicable to problem-solving uses of analogy without being restricted to them.

I propose the architecture shown in Figure 4. This architecture provides for a purely structural analogy processor whose input representations and output evaluation are influenced by plans and goals. In a problem-solving situation, the reasoner's goals influence the way the target problem is represented in working memory. This in turn influences what gets accessed. Once the potential base analog is accessed from long-term memory, the analogy engine runs its course. The engine produces an interpretation including candidate inferences and also a structural evaluation. If the structural evaluation is too low -- i.e., if the depth and size of the system of consistently matching predicates is too low -- then the analogy will be rejected on structural grounds. If the analogy passes the structural criterion, then its candidate inferences must be evaluated with respect to the goals of the reasoner. In terms of the computer model, this suggests adding a context-sensitive, expectation-driven module to evaluate the output of SME. Thus, plans and goals influence the process both before and after the analogy engine; but the engine itself is can be run without overt goals. This architecture appears compatible with the combination models proposed by Burstein (1983) and Kedar-Cabelli (1985), which combine structural rules with a pragmatic component so as to choose an interpretation that is both consistent and contextually relevant.

In the model proposed here, both structural properties and contextual-pragmatic considerations enter into analogical problem solving, but they are

Figure 4

A Proposed Cognitive Architecture for Analogical Processing



not equated. Goals are not *required* to define an analogical match. The analogy engine is a well-defined, semi-autonomous system whose results interact with other processes, analogous to the way some natural-language models have postulated semi-autonomous interacting subsystems for syntax, semantics and pragmatics (e.g., Reddy, Erman, Fennell & Neely, 1973). This allows us to capture the fact that analogy must satisfy both a structural and a pragmatic criterion. In addition, any candidate inferences that result from an analogy must be tested for validity in the target domain. At a minimum this means checking whether contradictory information already exists; it may also include conducting experiments to verify the predictions (Bentner, 1982; Breiner, 1986). Thus there are three separate evaluation criteria for analogy: soundness, validity and (when appropriate) relevance.

Separating the pragmatic context from the actual analogy processor has other advantages. Unlike purely pragmatic theories, it captures the fact that people can comprehend an analogy in isolation, with no context at all, and that in so doing they appear to use many of the same processes as they do in a problem-solving context. For example, consider this analogy:

Wit is the salt of conversation, not the food. (Hazlitt)

I suspect that most readers can derive its meaning without prior pragmatic context. Furthermore, if someone tried to use this analogy with the goal of demonstrating that being funny is the most important thing in conversation, you would probably feel that the analogy failed to support the speaker's goal. That is, you would be able to derive an independent structurally-based interpretation of the metaphor, which you could then compare with the speaker's goals to see how effectively it supported them. Of course, as with other kinds of processing, analogical mapping should be faster and easier in the context of pragmatic expectations consistent with a correct structural

interpretation, and harder with inconsistent prior pragmatic expectations. But that is very different from saying that plans and goals are required for analogical processing.

I have occasionally heard people defend the goal-centered approach against examples like the above by arguing that in such analogies "the speaker's plans and goals are derived from the match." Of course, but this is exactly my point: without needing any advance knowledge of the speaker's goals, we can apply our analogy engine to derive a common relational structure which we then infer (in the absence of contradictory information) to be the speaker's goal. Thus structural matches are used to determine goals; this is the opposite of the claim that goal-relevance must drive the matching.

Another advantage of separating pragmatic relevance from structural matching is that it allows a better account of spontaneous generation of analogy. People often generate analogies that have no obvious relevance to plans and goals. For example, Bowerman (personal communication, June, 1985) reports the following analogical reminding. She heard an ambulance approaching and saw the cars pulling over to the side of the road, one after another. She suddenly thought of a sensitive plant -- a mimosa -- which has the characteristic that when touched its leaves shrink in towards the stem in linear succession along the length of the stem. Examples like this are familiar to all of us. They show that, though analogy may be used to serve our plans and goals, its nature does not require a goal-oriented context. The purely pragmatic account of analogy could not handle such examples, since it requires prior plans and goals in order to operate. Holyoak (1985) is aware of this limitation and states that his pragmatic account is meant to apply to analogy in problem-solving. But having to postulate separate processors for analogy in isolation and analogy in problem-solving entails a substantial loss of generality.

One reason for the interest in content-specific or pragmatically driven interpretation processes has been a concern that purely structural information is insufficient to guide analogical mapping. The evidence from the Structure-mapping Engine so far suggests otherwise, since it generates intuitively plausible answers and does so rapidly (Falkenhainer, Forbus & Gentner, 1986). SME is able to reject initially plausible predicate matches like "LIQUID (water) ---> LIQUID (coffee)" purely on the basis of consistency and systematicity. So far SME has performed successfully on over 30 different analogies. Issues of the sufficiency and efficiency this of approach still remain, of course. We are exploring a variety of examples to see where and how the system breaks down. But at present, the structural approach looks quite powerful.

Conclusions

Overall, the advantages of the structure-mapping approach are

- (1) Its rules can be stated precisely.
- (2) Since the rules are statable in terms of the structure of the knowledge representation, we do not have to know in advance which predicates are going to be shared in order to generate or process an analogy.
- (3) Separating structural rules from pragmatics allows us to capture the dual requirements of soundness and relevance; and it allows us to capture the commonalities among analogy interpretation across different pragmatic contexts.
- (4) The distinctions between object descriptions, relations and higher-order relations lead to a similarity space, with distinct subclasses of similarity based not only on how many predicates overlap between base and target, but on what kind of predicates overlap.

The results reviewed here have implications for theories of learning by analogy and similarity. First, they indicate that the analogy process is decomposable into different mechanisms, with very different characteristics. Second, they show that an adequate treatment of similarity must distinguish different subclasses of similarity with different psychological privileges. Third, they provide further evidence for the psychological reality of structure-mapping processes in analogy; it appears that people can carry out rather sophisticated structural matches in the course of comprehending analogy. Finally, these results have implications for the nature of similarity itself. Careful analysis of different kinds of predicate matches may be central to modeling the role of analogy and similarity in learning.

Acknowledgments

This research was supported by the Office of Naval Research under Contract No. N00014-85-K-0559, NR667-551. Preparation of this paper was supported in part by the Max Planck Institute for Psycholinguistic Research, Nijmegen, The Netherlands. I thank Mark Burstein, Cathy Clement, Allan Collins, Judy DeLoache, Brian Falkenhainer, Ken Forbus, Rogers Hall, Doug Medin, Mary Jo Rattermann, Brian Ross, Bob Schumacher, and Janice Skorstad for many helpful discussions and debates on these issues, and for comments on prior drafts of this paper.

A version of this paper will appear in A. Prieditis (Ed.) *Analogical Reasoning: Proceedings of the First Workshop on Analogical Reasoning*. London, England: Pitman Publishing Co.

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