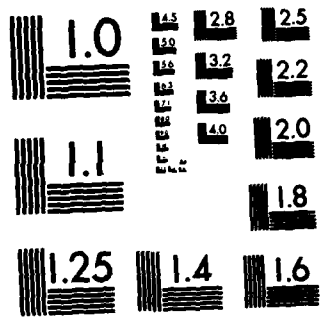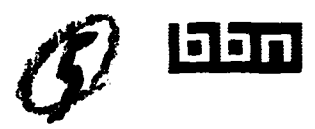END
DATE
FILMED
2 83
DTIC

MICROCOPY RESOLUTION TEST CHART

NATIONAL BUREAU OF STANDARDS-1963-A

Bolt Beranek and Newman Inc.

bbn

Report No. 5192

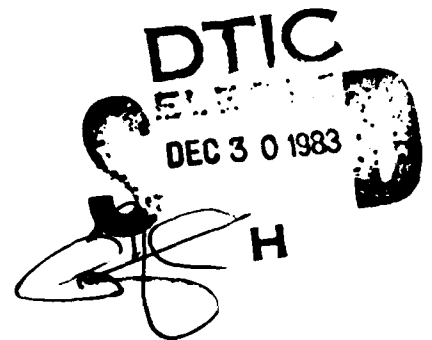# Structure-Mapping: A Theoretical Framework for Analogy

December 1982

DTIC

DEC 3 0 1983

H

FILE COPY

82 12 29 089

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER TR-ONR-6	**2. GOVT ACCESSION NO.** AD-A122 891	**3. RECIPIENT'S CATALOG NUMBER**
4. TITLE (and Subtitle) Structure-Mapping: A Theoretical Framework for Analogy		**5. TYPE OF REPORT & PERIOD COVERED** Technical Report
		6. PERFORMING ORG. REPORT NUMBER BBN Report No. 5192
7. AUTHOR(s) Dedre Gentner		**8. CONTRACT OR GRANT NUMBER(s)** N00014-79-C-0338
9. PERFORMING ORGANIZATION NAME AND ADDRESS Bolt Beranek and Newman Inc. 50 Moulton Street Cambridge, Massachusetts 02238		**10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS** NR 157-428
11. CONTROLLING OFFICE NAME AND ADDRESS Personnel and Training Research Programs Office of Naval Research, Code 458 Arlington, Virginia 22217		**12. REPORT DATE** December 1982
		13. NUMBER OF PAGES 35
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		**15. SECURITY CLASS. (of this report)** UNCLASSIFIED
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

This paper will appear in Cognitive Science, Vol. 7, No. 2, 1983.
A brief version appears in the Proceedings of the IEEE International
Conference on Cybernetics and Society, Seattle, WA, November 1982.

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

analogy; generative models

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

A theory of analogy must describe how the meaning of an analogy is derived
from the meanings of its parts. In the structure-mapping theory, the
interpretation rules are characterized as implicit rules for mapping
knowledge about a base domain into a target domain. Two important features
of the theory are (1) the rules depend only on syntactic properties of
the knowledge representation, and not on the specific content of the
domains; and (2) the theoretical framework allows analogies to be

DD FORM 1473 EDITION OF 1 NOV 65 IS OBSOLETE

distinguished cleanly from literal similarity statements, applications of general laws, and other kinds of comparisons.

Two mapping principles are described: (1) Relations between objects, rather than attributes of objects, are mapped from base to target; and (2) The particular relations mapped are determined by systematicity, as defined by the existence of higher-order relations.

Report No. 5192

STRUCTURE-MAPPING: A THEORETICAL FRAMEWORK FOR ANALOGY

Dedre Gentner

December 1982

Prepared for:
Office of Naval Research
Personnel and Training Research Programs

Abstract

A theory of analogy must describe how the meaning of an analogy
is derived from the meanings of its parts. In the
structure-mapping theory, the interpretation rules are
characterized as implicit rules for mapping knowledge about a
base domain into a target domain. Two important features of the
theory are (1) the rules depend only on syntactic properties of
the knowledge representation, and not on the specific content of
the domains; and (2) the theoretical framework allows analogies
to be distinguished cleanly from literal similarity statements,
applications of general laws, and other kinds of comparisons.

Two mapping principles are described: (1) Relations between
objects, rather than attributes of objects, are mapped from base
to target; and (2) The particular relations mapped are determined
by systematicity, as defined by the existence of higher-order
relations.

Accession For
NTIS GRA&I
DTIC TAB
Unannounced
Justification

By
Distribution/

Availability Codes
Dist   Avail and/or
         Special

A

DTIC
COPY
INSPECTED
3

Structure-Mapping: A Theoretical Framework for Analogy

When people hear an analogy such as "An electric battery is
like a reservoir" how do they derive its meaning?   We might
suppose that they simply apply their knowledge about reservoirs
to batteries; and that the greater the match, the better the
analogy.   Such a "degree of overlap" approach seems reasonably
correct for literal similarity comparisons. In Tversky's (1977)
elegant contrast model, the similarity between A and B is greater
the greater the size of the intersection (A   B) of their feature
sets   and   the less the size of the two complement sets
$(A - B)$ and $(B - A)$.^{2} However, although the degree-of-overlap
model appears to work well for literal similarity comparisons, it
does not provide a good account of analogy. The strength of an
analogical match does not seem to depend on the overall degree of
featural overlap; not all features are equally relevant to the
interpretation.   Only   certain kinds of mismatches count for or
against analogies.   For   example, we could not support the
battery-reservoir analogy by remarking (even if true) that
batteries and reservoirs both tend to be cylindrical; nor does it
weaken the analogy to show that their shapes are different.   The
essence of the analogy between batteries and reservoirs is that
both store potential energy, release that energy to provide power
for systems, etc. We can be quite satisfied with the analogy in
spite of the fact that the average battery differs from the
average reservoir in size, shape, color, and substance.

As another example of the selectiveness of analogical mapping, consider the simple arithmetic analogy 3:6::2:4. We do not care how many features 3 has in common with 2, nor 6 with 4. It is not the overall number of shared versus nonshared features that counts here, but only the relationship "twice as great as" that holds between 3 and 6 and also between 2 and 4. To underscore the implicit selectiveness of the feature match. note that we do not consider the analogy 3:6::2:4 better or more apt than the analogy 3:6::200:400. even though by most accounts 3 has more features in common with 2 than with 200.

A theory based on the mere relative numbers of shared and non-shared predicates cannot provide an adequate account of analogy, nor, therefore. a sufficient basis for a general account of relatedness. In the structure-mapping theory. a simple but powerful distinction is made among predicate types, that allows us to state which ones will be mapped. The basic intuition is that an analogy is fundamentally an assertion that a relational structure that normally applies in one domain can be applied in another domain. Before laying out the theory. a few preliminaries are necessary.

Preliminary Assumptions and Points of Emphasis

1. Domains and situations are psychologically viewed as systems of objects, object-attributes and relations between objects.[3]

2. Knowledge is represented here as propositional networks of nodes and predicates (cf. Miller & Johnson-Laird, 1979; Norman, Rumelhart, & the LNR Group, 1975; Rumelhart & Ortony. 1977; Schank & Abelson, 1977). The nodes represent concepts treated as wholes; the predicates applied to the nodes express propositions about the concepts.

3. Two essentially syntactic distinctions among predicate types will be important. The first distinction is between object attributes and relationships. This distinction can be made explicit in the predicate structure: <u>attributes</u> are predicates taking one argument, and <u>relations</u> are predicates taking two or more arguments. For example, COLLIDE (x,y) is a relation, while LARGE (x) is an attribute.[4]

The second important syntactic distinction is between first-order predicates (taking objects as arguments) and second- and higher-order predicates (taking propositions as arguments). For example, if COLLIDE (x,y) and STRIKE (y,z) are first-order predicates, CAUSE [COLLIDE(x,y), STRIKE (y,z)] is a second-order predicate.

4. These representations, including the distinctions between different kinds of predicates, are intended to reflect the way people construe a situation, rather than what is logically possible.[5]

Structure-mapping: Interpretation Rules

The analogy "A T is (like) a B" conveys that aspects of the hearer's knowledge about B can be applied to T. T will be called the target, since it is the domain being explicated. B will be called the base, since it is the (presumably more familiar) domain that serves as the source of knowledge. Suppose that the hearer's representation of the base domain B can be stated in terms of object nodes b_1, b_2,...,b_n and predicates such as A, R. R'. The hearer knows, or is told, that the target domain has [6] object nodes t_1, t_2,....,t_m. In order to understand the analogy, the hearer must map the object nodes of B onto the object nodes of T:

$$M: \quad b_i \; --> \; t_i$$

Given these object correspondences, the hearer derives inferences about T by applying predicates valid in the base domain B, using the node substitutions dictated by the object mapping:

$$M: \; [R(b_i, b_j)] \quad --> \quad [R(t_i, t_j)]$$

Here $R(b_i, b_j)$ is a relation that holds in the base domain B. [7] Higher-order relations, such as $R'(R_1, R_2)$, can also be mapped:

$$M: \; [R'(R_1(b_i, b_j), R_2(b_k, b_l)] \; -->$$

$$[R'(R_1(t_i, t_j), R_2(t_k, t_l)]$$

Higher-order relations play an important role in analogy, as is discussed below.

Finally, a distinguishing characteristic of analogy is that attributes (one-place predicates) from B tend not to be mapped into T:

$$[A(b_i)] \;-\!\!\!\not\!\!\!-\!\!> \; [A(t_i)].$$

Notice that this discussion has been purely structural; the distinctions invoked rely only on the syntax of the knowledge representation, not on the content. The _content_ of the relations may be static spatial information, as in UNDER(x,y), or FULL(CONTAINER. WATER); or constraint information, as in PROPORTIONAL [(PRESSURE(liquid, source, goal), FLOWRATE(liquid, source, goal)]; or dynamic causal information, as in CAUSE {AND [PUNCTURE(CONTAINER), FULL(CONTAINER. WATER)], FLOW-FROM (WATER. CONTAINER)}.

Kinds of Domain Comparisons

In the structure-mapping framework, the interpretation rules for analogy can be distinguished from those for other kinds of domain comparisons. The syntactic type of the shared versus nonshared predicates determines whether a given comparison is

thought of as analogy, as literal similarity, or as the application of a general law.

In this section, different kinds of domain comparisons are described, using the solar system as a common theme. The top half of Figure 1 shows a partial representation of what might be a person's knowledge of our solar system. (The dotted lines should be ignored for now.) Both object-attributes, such as YELLOW (sun), and relations between objects, such as REVOLVE AROUND (planet, sun) are shown. (The diagram is quite sparse; most of us know much more than is shown here.) Assuming that the hearer has the correct object correspondences, the question is which predicates will be mapped for each type of comparison.

(1) A _literal_ _similarity_ statement is a comparison in which a large number of predicates is mapped from base to target, relative to the number of nonmapped predicates (e.g., Tversky, 1977). The mapped predicates include _both_ object-attributes and relational predicates.

EXAMPLE(1): The X12 star system in the Andromeda nebula is like our solar system.

INTERPRETATION: Intended inferences include both object characteristics--e.g., "The X12 star is YELLOW, MEDIUM-SIZED, etc., like our sun." and relational characteristics, such as "The X12 planets REVOLVE AROUND the X12 star, as in our system."

In a literal similarity comparison, all or most of the predicates
shown would be mapped.

(2) An _analogy_ is a comparison in which relational predicates,
but few or no object attributes, can be mapped from base to
target.

EXAMPLE(2): The hydrogen atom is like our solar system.
(Rutherford, 1906)

INTERPRETATION: Intended inferences concern chiefly the
relational structure: e.g., "The electron REVOLVES AROUND the
nucleus, just as the planets REVOLVE AROUND the sun." but not
"The nucleus is YELLOW, MASSIVE, etc., like the sun." The bottom
half of Figure 1 shows these mapped relations. If higher-order
relations are present in the base, they can be mapped as
well: e.g., The hearer might map "The fact that the nucleus
ATTRACTS the electron CAUSES the electron to REVOLVE around the
nucleus." from "The fact that the sun ATTRACTS the planets CAUSES
the planets to REVOLVE AROUND the sun." (This relation is not
shown in Figure 1.)

(3) A _general law_ is a comparison in which the base domain is an
abstract relational structure. Such a structure would
resemble Figure 1, except that the object nodes would be
generalized physical entities, rather than particular objects
like "sun" and "planet". Predicates from the abstract base
domain are mapped into the target domain; there are no
nonmapped predicates.

8

Figure 1. Structure-mapping for the Rutherford analogy: "The atom is like the solar system."

EXAMPLE(3): The hydrogen atom is a central force system.

INTERPRETATION: Intended   inferences   include   "The   nucleus
ATTRACTS the electron."; "The electron REVOLVES AROUND the
nucleus."   These are mapped from base propositions such as "The
central object ATTRACTS the peripheral object."; or "The less
massive object REVOLVES AROUND the more massive object." These
intended inferences resemble those for the analogy (Example 2).
The   difference   is   that   in   the   analogy   there are other base
predicates that are not mapped, such as "The sun is YELLOW."

All three kinds of comparison involve substantial overlap in
relations, but, except for literal similarity, not in object
attributes.   What happens if there is strong overlap in objects
but not in relations?   Let us leave aside single-component
matches involving only one object out of many, and instead
consider comparisons in which all the objects are shared, but
relations between objects are not. The commonest case in which
this arises is chronology:

(4) A chronology is a comparison between two time-states of the
    same domain. The objects at time 1 map onto the objects at
    time 2. This is the only interesting case in which there are
    shared objects but no shared relations. The two time-states
    share object-attributes, but typically not relational
    predicates.

10

EXAMPLE(4): Two hydrogen atoms and an oxygen atom will combine to form a water molecule.

INTERPRETATION: Although the same objects--two hydrogen atoms and an oxygen atom--are present in both situations, neither configurational relations nor dynamic relations of the initial situation can be mapped into the final situation. Only the independent qualities of the individual atoms (e.g., their atomic weights) are preserved. Note that such overlap among component objects is not sufficient to produce similarity between systems: Two isolated hydrogen atoms and an oxygen atom do not _resemble_ water, either literally or analogically. Chronology will not concern us further; it is included for completeness, as the limiting case of object overlap with no necessary relational overlap.

Table 1 summarizes these distinctions. Overlap in relations is necessary for any strong perception of similarity between two domains. Overlap in _both_ object attributes and inter-object relationships is seen as literal similarity, and overlap in _relationships_ but not objects is seen as analogical relatedness. Overlap in _objects_ but not relationships may be seen as chronology, but not as similarity. Finally, a comparison with neither attribute overlap nor relational overlap is simply an anomaly.

Table 1

Kinds of Predicates Mapped in Different

Types of Domain Comparison

	No. of attributes mapped to target	No. of relations mapped to target	Example
Literal Similarity	Many	Many	The K5 solar system is like our solar system.
Analogy	Few	Many	The atom is like our solar system.
Abstraction	Few[a]	Many	The atom is a central force system.
Anomaly	Few	Few	Coffee is like the solar system

[a] Abstraction differs from analogy and the other comparisons in having few object-attributes in the base domain as well as few object-attributes in the target domain.

According to this analysis, the contrast between analogy and literal similarity is a continuum, not a dichotomy. Given that two domains overlap in relationships, they are more literally similar to the extent that their object-attributes also overlap. A different sort of continuum applies between analogies and general laws: In both cases, a relational structure is mapped from base to target. 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, the comparison is seen as a general law.

Metaphor

A number of different kinds of comparisons go under the term "metaphor." Many (perhaps most) metaphors are predominantly relational comparisons, and are thus essentially analogies. For example, in A. E. Housman's comparison, "I could no more define poetry than a terrier can define a rat.", the object correspondences are terrier--poet and rat--poetry. Clearly, the intended inference is not that the poet is like a terrier, nor certainly that poetry is like a rat, but rather, that the relation between poet and poetry is like the relation between terrier and rat. Again, in Virginia Woolf's simile, "She allowed life to waste like a tap left running." the intent seems to be to convey the relational notion of a person wasting a resource

through neglect, rather than to convey that her life was like running water.

However, not all metaphors are relationally focused; some are predominantly attribute matches. These generally involve shared attributes that are few but striking, and often more salient in the base than in the target (Ortony, 1979): e.g., "She's a giraffe," used to convey that she is tall. Many such metaphors involve conventional vehicles, such as "giraffe" above. or conventional dimensional matches, such as "a deep/shallow idea" (Glucksberg, Gildea & Bookin, 1982; Lakoff & Johnson, 1980). Moreover, metaphors can be mixtures of all of these. Finally, for metaphors that are analyzable as analogies or combinations of analogies, the mapping rules tend to be less regular (Gentner, 1982,a).

Higher-order predicates and systematicity

Relations have priority over object-attributes in analogical matching. However, not all relations are equally likely to be preserved in analogy. For example, in the Rutherford analogy between solar system and atom, the relation MORE MASSIVE THAN (sun, planet) is mapped across to the atom, but the formally similar relation HOTTER THAN (sun, planet) is not. The goal of this section is to characterize this analogical relevance explicitly.

14

Part of our understanding about analogy is that it conveys a system of connected knowledge, not a mere assortment of independent facts. Such a system can be represented by an interconnected predicate structure in which higher-order predicates enforce connections among lower-order predicates.[8] To reflect this tacit preference for coherence in analogy, I propose the systematicity principle: A predicate that belongs to a mappable system of mutually interconnecting relationships is more likely to be imported into the target than is an isolated predicate.

In the Rutherford model, the set of predicates that forms a mappable system includes the following lower-order relations:

(1) DISTANCE (sun, planet),

(2) ATTRACTIVE FORCE (sun, planet)

(3) REVOLVES AROUND (planet, sun), and

(4) MORE MASSIVE THAN (sun, planet).

One symptom of this systematicity is that changing one of these relations affects the others. For example, suppose we decrease the attraction between sun and planet; then the distance between them will increase. all else being equal. Thus relations (1) and (2) are interrelated. Again, suppose we reverse relation (4), to state that the planet is more massive than the sun; then

15

we must also reverse relation (3), for the sun would then revolve around the planet.[9]   One way of expressing these dependencies among the lower-order relations is as a set of simultaneous constraint equations:

$$F_{grav} = \frac{G\, m_p\, m_s}{R^2} = m_p a_p = m_s a_s$$

where F_{grav} is the gravitational force, m_p is the mass of the planet, a_p is the radial acceleration of the planet (and similarly m_s and a_s for the sun), R is the distance between planet and sun, and G is the gravitational constant.

The same interdependencies hold for the atom, if we make the appropriate node substitutions:

(5) DISTANCE (nucleus, electron),

(6) ATTRACTIVE FORCE (nucleus, electron)

(7) REVOLVES AROUND (electron, nucleus), and

(8) MORE MASSIVE THAN (nucleus, electron).

The corresponding equations for the atom are

$$F_{elec} = \frac{-q_e q_n}{R^2} = m_e a_e = m_n a_n$$

where F_{elec} is the electromagnetic force, q_e is the charge on the electron, m_e is the mass of the electron, a_e is the radial acceleration of the electron, R_e is the distance between electron and nucleus, (and similarly for the nucleus), and -1 is the electromagnetic constant.

These equations embody higher-order relations that connect the lower-order relations (1) through (4) into a mutually constraining structure. By the systematicity principle, to the extent that people recognize (however vaguely) that the system of predicates connected with central forces is the deepest, most interconnected mappable system for this analogy, they will favor relations that belong to that system in their interpretations.[10] This is why MORE MASSIVE THAN is preserved while HOTTER THAN is not: Only MORE MASSIVE THAN participates in the central-force system of predicates.

As a final demonstration of the operation of the systematicity principle, consider the analogy "Heat is like water," used to explain heat transfer from a warm house in cold weather. Suppose the hearer's knowledge about water includes two scenarios:

1. AND[CONTAIN(vessel, water), ON-TOP-OF(lid, vessel)]

17

2. CAUSE {AND [PUNCTURE(vessel), CONTAIN(vessel, water)], FLOW-
   FROM (water, vessel)}.

These can be paraphrased roughly as follows: (1) The vessel
contains water and has a lid; (2) if a vessel that contains water
is punctured, water will flow out. Assuming that the hearer has
made   the   obvious   object   correspondences   (water   -->   heat,
vessel --> house and lid --> roof),[11]   which scenario will be
mapped?

Intuitively, the second scenario is more interesting than
the first: (1) conveys merely a static spatial description,
while (2) conveys a dynamic causal description. We would like
chain (2) to be favored over chain (1), so that dynamic causal
knowledge is likely to be present in the candidate set of
attempted predications (to use Ortony's (1979) term).   We could
accomplish this by postulating that analogies select for dynamic
causal   knowledge,   or   more   generally,   for   appropriate
abstractions.   Either of these would be a mistake: The former
course limits the scope of analogy unreasonably, and the latter
course is both vague, in that "appropriateness" is difficult to
define explicitly, and incorrect, in that analogies can also
convey inappropriate abstractions.[12]   We want our rules for
analogical interpretation to choose chain (2) over chain (1), but
we want them to operate, at least initially, without appeal to
specific content or appropriateness. The systematicity principle
offers a way to satisfy both requirements.   Dynamic causal

18

information [e.g., (2)] will usually be represented in a more deeply embedded structure than simple stative information [e.g., (1)]. Thus, by promoting deeply nested relational chains, the systematicity principle operates to promote predicates that participate in causal chains and in other constraint relations. It is a purely syntactic mechanism that 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.

In the next section, empirical support for the structure-mapping theory is briefly discussed. First, however. let us review the performance of the theory against a set of a priori theoretical criteria. The structure-mapping theory satisfies the first requirement of a theory of analogy, that it describe the rules by which the interpretation of an analogy is derived from the meanings of its parts. Further, the rules are such as to distinguish analogy from other kinds of domain comparisons, such as abstraction or literal similarity. Finally, a third feature of the structure-mapping theory is that the interpretation rules are characterizable purely syntactically. That is, the processing mechanism that selects the initial candidate set of predicates to map attends only to the structure of the knowledge representations for the two analogs, and not to the content.

Empirical support

There is research supporting the structure-mapping approach. In one set of studies, subjects wrote out interpretations of analogical comparisons such as "A cigarette is like a time bomb." These interpretations were read to naive judges, who rated each assertion as to whether it was an attribute or a relation. (For a fuller description, see Gentner, 1980b). The results indicated a strong focus on relational information in interpreting analogies. Relational information predominates over attributional information in analogy interpretations, but not in object descriptions generated by the same subjects. Further, a correlation of aptness ratings and relationality ratings revealed that subjects liked the analogies best for which they wrote the greatest degree of relational information.

Other experimental evidence for structure-mapping as part of the psychological process of interpreting complex analogies has included developmental studies (Gentner, 1977a,b; 1980b) and studies of how people use analogies in learning science (Collins & Gentner, in preparation; Gentner, 1980a, 1981; Gentner & Gentner, 1982).

Related research

Complex explanatory analogies have until recently received little attention in psychology, perhaps because such analogies

require fairly elaborate representations of meaning. Studies of analogy in scientific learning and in reasoning have emphasized the importance of shared complex representational structures (Clement, 1981. 1982; Collins & Gentner, in preparation; Gentner, 1980; Gentner & Gentner, 1982; Hesse, 1966; Hobbs, 1979; Hoffman, 1980; Moore & Newell, 1973; Oppenheimer. 1955; Polya, 1973; Riley, 1981; Rumelhart & Norman, 1981; Steels, 1981; Stevens, Collins & Goldin, 1979; VanLehn & Brown, 1980). Although some of this work has been empirically tested, most of it remains in the area of interesting but unvalidated theory. In contrast, much of the psychological experimentation on analogy and metaphor has been either theory-neutral (e.g. Schustack & Anderson, 1979; Verbrugge & McCarrell, 1977) or based on rather simple representations of meaning: e.g., feature-list representations (e.g., Ortony, 1979) or multidimensional space representations (e.g., Rumelhart & Abrahamson, 1973; Tourangeau & Sternberg, 1981). These kinds of representations can deal well with object attributes, but are extremely limited in their ability to express relations between objects, and especially higher-order relations.

Recent work in cognitive science has begun to explore more powerful representational schemes. The Merlin system (Moore & Newell, 1973) featured a mechanism for "viewing x as y" (see also Steels, 1982) which involved explicit comparisons of the shared and nonshared predicates of two situations. Winston (1980, 1981), using a propositional representation system. has simulated

the process of matching a current situation with a previously stored precedent and using the similarity match to justify importing inferences from the precedent to the current situation. Further, in recent work he has investigated importance-dominated matching; here the match between old and new situations is performed by counting only those predicates that occur in causal chains. This requirement is somewhat more restrictive than the structure-mapping principle that participation in any higher-order chain results in preferential mapping. However. it has the similar effect of focussing the matcher on systematic relational structures rather than on haphazard resemblances between situations. One valuable aspect of Winston's work is his modelling of the process of abstracting general rules from the analogical matches. Gick and Holyoak have also emphasized the relationship between analogical matching and the formation of general schemas in an interesting series of studies of transfer in problem-solving (Gick and Holyoak, 1980. in press; Holyoak, in press).

Other researchers have explored specific instances of relational mapping. VanLehn & Brown (1980) have analyzed analogical learning of procedural rules in arithmetic, postulating mapping rules compatible with the rules proposed here. Clement (1981. 1982) has proposed a four-stage series of processes of generating analogical comparisons during problem-solving. Rumelhart & Norman (1981) have used a schema-based

representational system to discuss analogical transfer. Carbonell (1981) has characterized the comprehension of analogy; his approach emphasizes common goals and subgoals as organizing principles. In the main, these accounts are compatible with that given by the structure-mapping theory in each of the problem domains. Relations tend to be preserved across domains with dissimilar object-attributes: e.g., the matching of like procedures that apply to unlike sets of objects (VanLehn and Brown, 1980).

The Analogical Shift Conjecture

Some of the distinctions made here may appear rather academic. To illustrate their potential relevance. let us apply these distinctions to the spontaneous comparisons that people make in the course of learning a domain. An informal observation is that the earliest comparisons are chiefly literal-similarity matches, followed by analogies, followed by general laws. For example, Ken Forbus and I have observed a subject trying to understand the behavior of water flowing through a constricted pipe. His first comparisons were similarity matches, e.g., water coming through a constricted hose. Later, he produced analogies such as a train speeding up or slowing down, and balls banging into the walls and transferring momentum. Finally, he arrived at a general statement of the Bernoulli principle, that velocity increases and pressure decreases in a constriction.

This sequence can be understood in terms of the kinds of differences in predicate overlap discussed in this paper. In the structure-mapping framework, we can suggest reasons that the accessibility and the explanatory usefulness of a match may be negatively related. Literal similarity matches are highly accessible, since they can be indexed by object descriptions, by relational structures, or by both. But they are not very useful in deriving causal principles, precisely because there is too much overlap to know what is crucial. Potential analogies are less likely to be noticed, since they require accessing the data base via relational matches; object matches are of no use. However, once found, an analogy should be more useful in deriving the key principles, since the shared data structure is sparse enough to permit analysis. Moreover, if we assume the systematicity principle, then the set of overlapping predicates is likely to include higher-order relations such as CAUSE and IMPLIES. To state a general law requires another step beyond creating a temporary correspondence between unlike domains: the person must create a new relational structure whose objects are so lacking in specific attributes that the structure can be applied across widely different domains. (See Gick & Holyoak, 1980, in press). One speculation is that such general laws can be discovered by comparing two or more analogies, so that the common subparts of the relational structure can be isolated.

Summary

The **structure-mapping theory** describes the implicit interpretation rules of analogy. The central claims of the theory are that analogy is characterized by the mapping of relations between objects, rather than attributes of objects from base to target; and, further, that the particular relations mapped are those that are dominated by higher-order relations that belong to the mapping (the **systematicity** claim). These rules have the desirable property that they depend only on syntactic properties of the knowledge representation, and not on the specific content of the domain. Further, this theoretical framework allows us to state the differences between analogies and literal similarity statements, abstractions and other kinds of comparisons.

One implication of the theory is that no treatment of domain relatedness can be complete without distinguishing between object features and relational features: that is, between relational predicates and one-place attributive predicates. Careful analysis of the predicate structure is central to modelling the inferences people make in different kinds of comparisons.

References

Carbonell, J. G. Towards a computational model of problem solving and learning by analogy. Unpublished manuscript. Carnegie-Mellon University, Pittsburgh, PA, February 1981.

Clement, J. Analogy generation in scientific problem solving. Proceedings of the Third Annual Meeting of the Cognitive Science Society, 1981.

Clement, J. Spontaneous analogies in problem solving: The progressive construction of mental models. Paper presented at the AERA, New York, 1982.

Collins, A. M. & Gentner, D. Constructing runnable mental models, in preparation.

Gentner, D. Children's performance on a spatial analogies task. Child Development, 1977. 48, 1034-1039. (a)

Gentner, D. If a tree had a knee, where would it be? Children's performance on simple spatial metaphors. Papers and Reports on Child Language Development, 1977. 13, 157-164. (b)

Gentner, D. The structure of analogical models in science (BBN Report No. 4451). Cambridge, Mass.: Bolt Beranek and Newman Inc., 1980. (a)

Gentner, D.   Metaphor as structure-mapping. Paper presented at the meeting of the American Psychological Association, Montreal, September 1980. (b)

Gentner, D.   Generative analogies as mental models. In *Proceedings of the Third Annual Cognitive Science Society*. Berkeley, California. August 1981.

Gentner, D.   Are scientific analogies metaphors? In D. Miall (Ed.), *Metaphor: Problems and perspectives*.   Brighton, England: Harvester Press Ltd., 1982. (a)

Gentner, D.   Structure-mapping: A theoretical framework for analogy and similarity. To appear in *Proceedings of the Fourth Annual Conference of the Cognitive Science Society*. Ann Arbor, Michigan, August 1982. (b)

Gentner, D., & Gentner D. R.   Flowing waters or teeming crowds: Mental models of electricity.   In D. Gentner & A. L. Stevens (Eds.), *Mental models*.   Hillsdale, N.J.: Erlbaum, 1983.

Gentner, D., & Grudin, J. The evolution of mental metaphors in psychology: A ninety-year retrospective.   Unpublished manuscript, April 1982.

Gick, M. L., & Holyoak, K. J. Analogical problem solving. *Cognitive Psychology*, 1980. *12*, 306-355.

Gick, M. L., & Holyoak, K. J. Schema induction and analogical transfer. _Cognitive Psychology_, in press.

Glucksberg, S. Gildea, P. & Bookin, H. B. On understanding nonliteral speech: Can people ignore metaphors? _Journal of Verbal Learning and Verbal Behavior_, 1982, 21. 85-98.

Hesse, M. B. _Models and analogies in science_. Notre Dame, Indiana: University of Notre Dame Press, 1966.

Hoffman, R. R. Metaphor in science. In R. P. Honeck & R. R. Hoffman (Eds.), _The psycholinguistics of figurative language_. Hillsdale, N.J.: Erlbaum, 1980.

Hobbs, J. R. _Metaphor, metaphor schemata, and selective inferencing_ (SRI Technical Note 204). SRI International. Menlo Park, California, Artificial Intelligence Center, December 1979.

Holyoak, K. J. Analogical thinking and human intelligence. To appear in R.J. Sternberg (Ed.), _Advances in the Psychology of Human Intelligence_ (Vol. 2). Hillsdale, N.J.: Erlbaum, in press.

Lakoff, G., & Johnson, M. _Metaphors we live by_. Chicago, Ill.: University of Chicago Press, 1980.

Miller, G. A. Images and models, similes and metaphors. In A. Ortony (Ed.), _Metaphor and thought_. Cambridge: Cambridge University Press, 1979.

Miller, G. A. & Johnson-Laird, P. N. Language and perception. Cambridge, Mass.: Harvard University Press, 1976.

Moore, J., & Newell, A. How can Merlin understand? In L. Gregg (Ed.), Knowledge and Cognition. Potomac, Maryland: Erlbaum, 1973.

Norman, D. A., Rumelhart, D. E. & the LNR Research Group. Explorations in cognition. San Francisco: W. H. Freeman & Co., 1975.

Oppenheimer, R. Analogy in science. Paper presented at the 63rd Annual Meeting of the American Psychological Association, San Francisco, Calif., September 1955.

Ortony, A. Beyond literal similarity. Psychological Review. 1979, 87, 161-180.

Polya, G. Mathematics and plausible reasoning (Volume 1). Princeton, N.J.: Princeton University Press, 1973.

Riley, M. S. Representations and the acquisition of problem-solving skill in basic electricity/electronics. Paper presented at the Computer-based Instructional Systems and Simulation meeting, Carnegie-Mellon University, January 1981.

Rumelhart, D. E., & Abrahamson, A. A. A model for analogical reasoning. Cognitive psychology, 1973. 5. 1-28.

Rumelhart, D. E., & Ortony, A. Representation of knowledge. In
    R. C. Anderson, R. J. Spiro, & W. E. Montague (Eds.),
    Schooling and the acquisition of knowledge. Hillsdale,
    N.J.: Erlbaum, 1977.

Rumelhart, D. E., & Norman, D. A. Analogical processes in
    learning. In J. R. Anderson (Ed.), Cognitive skills and
    their acquisition. Hillsdale, N.J.: Erlbaum, 1981.

Schank, R., & Abelson, R. Scripts, plans, goals, and
    understanding. Hillsdale, N.J.: Erlbaum, 1977.

Schustack, M. W., & Anderson, J. R. Effects of analogy to prior
    knowledge on memory for new information. Journal of Verbal
    Learning and Verbal Behavior, 1979, 18, 565-583.

Steels, L. An applicative view of object oriented programming
    (MIT A.I. Memo No. 15). Massachusetts Institute of
    Technology, Cambridge, Mass., March 1982.

Stevens, A., Collins, A., & Goldin, S. E. Misconceptions in
    student's understanding. Journal of Man-Machine Studies,
    1979, 11. 145-156.

Tourangeau, R., & Sternberg, R.J. Aptness in metaphor.
    Cognitive Psychology, 1981. 13, 27-55.

Tversky, A. Features of similarity. Psychological Review. 1977.
    84, 327-352.

VanLehn, K. & Brown, J. S. Planning nets: A representation for
    formalizing analogies and semantic models of procedural
    skills.   In R. E. Snow, P. A.   Federico & W. E.   Montague
    (Eds.),   Aptitude,   learning and instruction: Cognitive
    process analyses. Hillsdale, N. J.:   Erlbaum, 1980.

Verbrugge,   R. R.,   &   McCarrell,   N. S.   Metaphoric
    comprehension: Studies   in   reminding   and   resembling.
    Cognitive psychology, 1977, 9, 494-533.

Winston, P.   Learning new principles from   precedents   and
    exercises.   MIT Artificial Intelligence Memo No. 632,
    Massachusetts Institute of Technology, Cambridge, Mass., May
    1981.

Footnotes

2

According to Tversky (1977), the negative effects of the two complement sets are not equal: for example, if we are asked "How similar is A to B?", the set (B - A)--features of B not shared by A--counts much more than the set (A - B).

3

These "objects" may be clear entities (e.g. "rabbit"), component parts of a larger object (e.g. "rabbit's ear") or even coherent combinations of smaller units (e.g."herd of rabbits"); the important point is that they function as wholes at a given level of organization.

4

One clarification is important here. Many attributive

predicates implicitly invoke comparisons between the value of their object and some standard value on the dimension. LARGE (x) implicitly means "X is large for its class." For example, a large star is of a different size than a large mouse. But if LARGE (x) is implicitly interpreted as LARGER THAN (X, prototype-x), then this suggests that many surface attributes are implicitly two-place predicates. Does this invalidate the attribute-relation distinction? I will argue that it does not: that only relations that apply within the domain of discourse are psychologically stored and processed as true relations. Thus, a relation such as LARGER THAN (sun, planet), that applies between two objects in the base (or target) domain, is processed as a relation; whereas an implicit attributive comparison, such as LARGER THAN (sun, prototype- star), is processed as an attribute.

5
Logically, a relation R(a,b,c,) can perfectly well be represented as Q(x), where Q(x) is true just in case R(a,b,c) is true. Psychologically, the representation must be chosen to model the way people think.

6
Most explanatory analogies are 1-1 mappings, in which m = n. However, there are exceptions (Gentner, 1982,a).

7
The assumption that predicates are brought across as identical matches is crucial to the clarity of this discussion. The position that predicates need only be similar between the

base and the domain (e.g., Hesse, 1966; Ortony, 1979) leads to a
problem of infinite regress, with similarity of surface concepts
defined in terms of similarity of components, etc,. I will
assume instead that similarity can be restated as identity among
some number of component predicates.

8
  The _order_ of a relation is determined by the order of its
arguments.   A first-order relation takes objects as   its
arguments.   A second-order relation has at least one first-order
relation among its arguments; and in general an nth order
relation has at least one (n-1)th order argument.

9
  This follows from the simultaneous equations below.   The
radial acceleration of either object is given by the force
divided by its own mass; thus the lighter object has the greater
radial acceleration. To maintain separation, it must also have a
tangential velocity sufficient to keep it from falling into the
larger object.

10
  I make the assumption here that partial knowledge of the
system is often sufficient to allow a person to gauge its
interconnectedness.   In the present example, a person may
recognize that force, mass and motion are highly interrelated
without having full knowledge of the governing equations.

11
  In this discussion I have made the simplifying assumption
that, in comprehension of analogy, the hearer starts with the

object correspondences and then maps across the relations. The
actual order of processing is clearly variable.   If the object
assignment is left unspecified, the hearer can use knowledge
about matching relations to decide on the object correspondences.
Therefore, it is more accurate to replace the statement that the
object correspondences are decided before the relational mappings
begin with the weaker statement that the object correspondences
are decided before the relational mappings are finished. This is
largely because in a complex analogy, the number of mappable
relations is large compared to the number of object
correspondences; indeed the number of mappable relations may have
no clear upper bound.

12
    Unless we distinguish the structural rules for generating
the candidate set from other conceptual criteria (such as
appropriateness, insightfulness, or correctness) that can be
applied to the candidate set, we rob analogy of its power to
convey new information. Just as we can perform a syntactic
analysis of what a sentence conveys, even when the information it
conveys is semantically novel or implausible (e.g. "Man bites
dog."), so we must be able to derive a structural analysis of an
analogy that does not depend on a priori conceptual plausibility.
Of course, our ultimate acceptance of the analogy will depend on
whether its candidate set of predicates is plausible; but this is
a separate matter.

Navy

Dr. Ed Aiken
Navy Personnel R&D Center
San Diego, CA 92152

Meryl S. Baker
NPRDC
Code P309
San Diego, CA 92152

1   Dr. Robert Breaux
    Code N-711
    NAVTRAEQUIPCEN
    Orlando, FL 32813

1   CDR Mike Curran
    Office of Naval Research
    800 N. Quincy St.
    Code 270
    Arlington, VA 22217

1   DR. PAT FEDERICO
    NAVY PERSONNEL R&D CENTER
    SAN DIEGO, CA 92152

1   Dr. John Ford
    Navy Personnel R&D Center
    San Diego, CA 92152

1   LT Steven D. Harris, MSC, USN
    Code 6021
    Naval Air Development Center
    Warminster, Pennsylvania 18974

1   Dr. Jim Hollan
    Code 304
    Navy Personnel R & D Center
    San Diego, CA 92152

1   Dr. Norman J. Kerr
    Chief of Naval Technical Training
    Naval Air Station Memphis (75)
    Millington, TN 38054

1   Dr. William L. Maloy
    Principal Civilian Advisor for
        Education and Training
    Naval Training Command, Code 00A
    Pensacola, FL 32508

Navy

1   CAPT Richard L. Martin, USN
    Prospective Commanding Officer
    USS Carl Vinson (CVN-70)
    Newport News Shipbuilding and Drydock Co
    Newport News, VA 23607

1   Dr. James McBride
    Navy Personnel R&D Center
    San Diego, CA 92152

1   Dr William Montague
    Navy Personnel R&D Center.
    San Diego, CA 92152

1   Ted M. I. Yellen
    Technical Information Office, Code 201
    NAVY PERSONNEL R&D CENTER
    SAN DIEGO, CA 92152

1   Library, Code P201L
    Navy Personnel R&D Center
    San Diego, CA 92152

1   Technical Director
    Navy Personnel R&D Center
    San Diego, CA 92152

6   Commanding Officer
    Naval Research Laboratory
    Code 2627
    Washington, DC 20390

1   Psychologist
    ONR Branch Office
    Bldg 114, Section D
    666 Summer Street
    Boston, MA 02210

1   Office of Naval Research
    Code 437
    800 N. Quincy SStreet
    Arlington, VA 22217

5   Personnel & Training Research Programs
        (Code 458)
    Office of Naval Research
    Arlington, VA 22217

Navy

Navy

1   Psychologist
    ONR Branch Office
    1030 East Green Street
    Pasadena, CA 91101

1   Dr. Alfred F. Smode
    Training Analysis & Evaluation Group
        (TAEG)
    Dept. of the Navy
    Orlando, FL 32813

1   Special Asst. for Education and
        Training (OP-01E)
    Rm. 2705 Arlington Annex
    Washington, DC 20370

1   Dr. Richard Sorensen
    Navy Personnel R&D Center
    San Diego, CA 92152

1   Office of the Chief of Naval Operations
    Research Development & Studies Branch
        (OP-115)
    Washington, DC 20350

1   Roger Weissinger-Baylon
    Department of Administrative Sciences
    Naval Postgraduate School
    Monterey, CA 93940

1   LT Frank C. Petho, MSC, USN (Ph.D)
    Selection and Training Research Division
    Human Performance Sciences Dept.
    Naval Aerospace Medical Research Laborat
    Pensacola, FL 32508

1   Dr. Robert Wisher
    Code 309
    Navy Personnel R&D Center
    San Diego, CA 92152

1   Dr. Gary Poock
    Operations Research Department
    Code 55PK
    Naval Postgraduate School
    Monterey, CA 93940

1   Mr John H. Wolfe
    Code P310
    U. S. Navy Personnel Research and
        Development Center
    San Diego, CA 92152

1   Roger W. Remington, Ph.D
    Code L52
    NAMRL
    Pensacola, FL 32508

1   Dr. Bernard Rimland (03B)
    Navy Personnel R&D Center
    San Diego, CA 92152

1   Dr. Worth Scanland, Director
    Research, Development, Test & Evaluation
    N-5
    Naval Education and Training Command
    NAS, Pensacola, FL 32508

1   Dr. Robert G. Smith
    Office of Chief of Naval Operations
    OP-987H
    Washington, DC 20350

Army   Army

Technical Director   1   Dr. Frederick Steinheiser
U. S. Army Research Institute for the   Dept. of Navy
        Behavioral and Social Sciences   Chief of Naval Operations
5001 Eisenhower Avenue   OP-113
Alexandria, VA 22333   Washington, DC 20350

Mr. James Baker   1   Dr. Joseph Ward
Systems Manning Technical Area   U.S. Army Research Institute
Army Research Institute   5001 Eisenhower Avenue
5001 Eisenhower Ave.   Alexandria, VA 22333
Alexandria, VA 22333

Dr. Beatrice J. Farr
U. S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

DR. FRANK J. HARRIS
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

Dr. Michael Kaplan
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

Dr. Milton S. Katz
Training Technical Area
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Harold F. O'Neil, Jr.
Attn: PERI-OK
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Robert Sasmor
U. S. Army Research Institute for the
        Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Air Force   Marines

1   U.S. Air Force Office of Scientific   1   H. William Greenup
        Research   Education Advisor (E031)
    Life Sciences Directorate, NL   Education Center, MCDEC
    Bolling Air Force Pase   Quantico, VA 22134
    Washington, DC 20332
                                             1   Special Assistant for Marine
1   Dr. Genevieve Haddad   Corps Matters
    Program Manager   Code 100M
    Life Sciences Directorate   Office of Naval Research
    AFOSR   800 N. Quincy St.
    Bolling AFB, DC 20332   Arlington, VA 22217

2   3700 TCHTW/TTGH Stop 32   1   DR. A.L. SLAFKOSKY
    Sheppard AFB, TX 76311   SCIENTIFIC ADVISOR (CODE RD-1)
                                               HQ, U.S. MARINE CORPS
                                               WASHINGTON, DC 20380

Coast Guard   Other DoD

Chief, Psychological Reserch Branch   12 Defense Technical Information Center
U. S. Coast Guard (G-P-1/2/TP42)   Cameron Station, Bldg 5
Washington, DC 20593   Alexandria, VA 22314
                                                 Attn: TC

                                              1 Military Assistant for Training and
                                                     Personnel Technology
                                                 Office of the Under Secretary of Defense
                                                     for Research & Engineering
                                                 Room 3D129, The Pentagon
                                                 Washington, DC 20301

                                              1 DARPA
                                                 1400 Wilson Blvd.
                                                 Arlington, VA 22209

Civil Govt   Non Govt

1   Dr. Susan Chipman   1   Dr. John R. Anderson
     Learning and Development   Department of Psychology
     National Institute of Education   Carnegie Mellon University
     1200 19th Street NW   Pittsburgh, PA 15213
     Washington, DC 20208
                                         1   Anderson, Thomas H., Ph.D.
1   Dr. John Mays   Center for the Study of Reading
     National Institute of Education   174 Children's Research Center
     1200 19th Street NW   51 Gerty Drive
     Washington, DC 20208   Champiagn, IL 61820

1   William J. McLaurin   1   Dr. John Annett
     66610 Howie Court   Department of Psychology
     Camp Springs, MD 20031   University of Warwick
                                              Coventry CV4 7AL
1   Dr. Arthur Melmed   ENGLAND
     National Institute of Education
     1200 19th Street NW   1   1 psychological research unit
     Washington, DC 20208   Dept. of Defense (Army Office)
                                              Campbell Park Offices
1   Dr. Andrew R. Molnar   Canberra   ACT 2600, Australia
     Science Education Dev.
         and Research   1   Dr. Alan Baddeley
     National Science Foundation   Medical Research Council
     Washington, DC 20550   Applied Psychology Unit
                                              15 Chaucer Road
1   Dr. Joseph Psotka   Cambridge CB2 2EF
     National Institute of Education   ENGLAND
     1200 19th St. NW
     Washington,DC 20208   1   Dr. Patricia Baggett
                                              Department of Psychology
1   Dr. Frank Withrow   University of Colorado
     U. S. Office of Education   Boulder, CO 80309
     400 Maryland Ave. SW
     Washington, DC 20202   1   Mr Avron Barr
                                              Department of Computer Science
1   Dr. Joseph L. Young, Director   Stanford University
     Memory & Cognitive Processes   Stanford, CA 94305
     National Science Foundation
     Washington, DC 20550   1   Liaison Scientists
                                              Office of Naval Research,
                                              Branch Office , London
                                              Box 39 FPO New York 09510

                                         1   Dr. Lyle Bourne
                                              Department of Psychology
                                              University of Colorado
                                              Boulder, CO 80309

Non Govt   Non Govt

Dr. John S. Brown   1   Dr. Meredith P. Crawford
XEROX Palo Alto Research Center   American Psychological Association
3333 Coyote Road   1200 17th Street, N.W.
Palo Alto, CA 94304   Washington, DC 20036

Dr. Bruce Buchanan   1   Dr. Kenneth R. Cross
Department of Computer Science   Anacapa Sciences, Inc.
Stanford University   P.O. Drawer Q
Stanford, CA 94305   Santa Barbara, CA 93102

DR. C. VICTOR BUNDERSON   1   LCOL J. C. Eggenberger
WICAT INC.   DIRECTORATE OF PERSONNEL APPLIED RESEARC
UNIVERSITY PLAZA, SUITE 10   NATIONAL DEFENCE HQ
1160 SO. STATE ST.   101 COLONEL BY DRIVE
OREM, UT 84057   OTTAWA, CANADA   K1A OK2

1   Dr. Pat Carpenter   1   Dr. Ed Feigenbaum
Department of Psychology   Department of Computer Science
Carnegie-Mellon University   Stanford University
Pittsburgh, PA 15213   Stanford, CA 94305

1   Dr. John B. Carroll   1   Dr. Richard L. Ferguson
Psychometric Lab   The American College Testing Program
Univ. of No. Carolina   P.O. Box 168
Davie Hall 013A   Iowa City, IA 52240
Chapel Hill, NC 27514

                                           1   Mr. Wallace Feurzeig
1   Dr. William Chase   Bolt Beranek & Newman, Inc.
Department of Psychology   50 Moulton St.
Carnegie Mellon University   Cambridge, MA 02138
Pittsburgh, PA 15213

                                           1   Dr. Victor Fields
1   Dr. Micheline Chi   Dept. of Psychology
Learning R & D Center   Montgomery College
University of Pittsburgh   Rockville, MD 20850
3939 O'Hara Street
Pittsburgh, PA 15213   1   Univ. Prof. Dr. Gerhard Fischer
                                                Liebiggasse 5/3
1   Dr. Allan M. Collins   A 1010 Vienna
Bolt Beranek & Newman, Inc.   AUSTRIA
50 Moulton Street
Cambridge, Ma 02138   1   DR. JOHN D. FOLLEY JR.
                                                APPLIED SCIENCES ASSOCIATES INC
1   Dr. Lynn A. Cooper   VALENCIA, PA   16059
LRDC
University of Pittsburgh   1   Dr. John R. Frederiksen
3939 O'Hara Street   Bolt Beranek & Newman
Pittsburgh, PA 15213   50 Moulton Street
                                                Cambridge, MA 02138

Non Govt   Non Govt

1   Dr. Alinda Friedman   1   Dr. James R. Hoffman
    Department of Psychology   Department of Psychology
    University of Alberta   University of Delaware
    Edmonton, Alberta   Newark, DE 19711
    CANADA T6G 2E9
                                            1   Dr. Kristina Hooper
1   DR. ROBERT GLASER   Clark Kerr Hall
    LRDC   University of California
    UNIVERSITY OF PITTSBURGH   Santa Cruz, CA 95060
    3939 O'HARA STREET
    PITTSBURGH, PA 15213   1   Glenda Greenwald, Ed.
                                                "Human Intelligence Newsletter"
1   Dr. Marvin D. Glock   P. O. Box 1163
    217 Stone Hall   Pirmingham, MI 48012
    Cornell University
    Ithaca, NY 14852   1   Dr. Earl Hunt
                                                Dept. of Psychology
1   Dr. Daniel Gopher   University of Washington
    Industrial & Management Engineering   Seattle, WA 98105
    Technion-Israel Institute of Technology
    Haifa   1   Dr. Ed Hutchins
    ISRAEL   Navy Personnel R&D Center
                                                San Diego, CA 92152
    DR. JAMES G. GREENO
    LRDC   1   DR. KAY INABA
    UNIVERSITY OF PITTSBURGH   21116 VANOWEN ST
    3930 O'HARA STREET   CANOGA PARK, CA 91303
    PITTSBURGH, PA   15213
                                            1   Dr. Steven W. Keele
1   Dr. Ron Hambleton   Dept. of Psychology
    School of Education   University of Oregon
    University of Massechusetts   Eugene, OR 97403
    Amherst, MA 01002
                                            1   Dr. Walter Kintsch
1   Dr. Harold Hawkins   Department of Psychology
    Department of Psychology   University of Colorado
    University of Oregon   Boulder, CO 80302
    Eugene OR 97403
                                            1   Dr. David Kieras
1   Dr. Barbara Hayes-Roth   Department of Psychology
    The Rand Corporation   University of Arizona
    1700 Main Street   Tuscon, AZ 85721
    Santa Monica, CA 90406
                                            1   Dr. Stephen Kosslyn
1   Dr. Frederick Hayes-Roth   Harvard University
    The Rand Corporation   Department of Psychology
    1700 Main Street   33 Kirkland Street
    Santa Monica, CA 90406   Cambridge, MA 02138

Non Govt   Non Govt

Dr. Marcy Lansman   1   Committee on Human Factors
Department of Psychology, NT 25   JH 811
University of Washington   2101 Constitution Ave. NW
Seattle, WA 98195   Washington, DC 20418

1   Dr. Jill Larkin   1   Dr. Jesse Orlansky
Department of Psychology   Institute for Defense Analyses
Carnegie Mellon University   400 Army Navy Drive
Pittsburgh, PA 15213   Arlington, VA 22202

Dr. Alan Lesgold   1   Dr. Seymour A. Papert
Learning R&D Center   Massachusetts Institute of Technology
University of Pittsburgh   Artificial Intelligence Lab
Pittsburgh, PA 15260   545 Technology Square
                                           Cambridge, MA 02139

1   Dr. Michael Levine
Department of Educational Psychology 1   Dr. James A. Paulson
210 Education Bldg.   Portland State University
University of Illinois   P.O. Box 751
Champaign, IL 61801   Portland, OR 97207

Dr. Robert Linn   1   Dr. James W. Pellegrino
College of Education   University of California,
University of Illinois   Santa Barbara
Urbana, IL 61801   Dept. of Psychology
                                           Santa Barabara, CA 93106
Dr. Erik McWilliams
Science Education Dev. and Research   1   MR. LUIGI PETRULLO
National Science Foundation   2431 N. EDGEWOOD STREET
Washington, DC 20550   ARLINGTON, VA 22207

Dr. Mark Miller   1   Dr. Martha Polson
TI Computer Science Lab   Department of Psychology
C/O 2824 Winterplace Circle   Campus Box 346
Plano, TX 75075   University of Colorado
                                           Boulder, CO 80309

Dr. Allen Munro
Behavioral Technology Laboratories   1   DR. PETER POLSON
1845 Elena Ave., Fourth Floor   DEPT. OF PSYCHOLOGY
Redondo Beach, CA 90277   UNIVERSITY OF COLORADO
                                           BOULDER, CO 80309

Dr. Donald A Norman
Dept. of Psychology C-009   1   Dr. Steven E. Poltrock
Univ. of California, San Diego   Department of Psychology
La Jolla, CA 92093   University of Denver
                                           Denver, CO 80208

Non Govt   Non Govt

MINRAT M. L. RAUCH   1 DR. ROBERT J. SEIDEL
P II 4   INSTRUCTIONAL TECHNOLOGY GROUP
BUNDESMINISTERIUM DER VERTEIDIGUNG   HUMRRO
POSTFACH 1328   300 N. WASHINGTON ST.
D-53 BONN 1, GERMANY   ALEXANDRIA, VA 22314

Dr. Fred Reif   1 Committee on Cognitive Research
SESAME   % Dr. Lonnie R. Sherrod
c/o Physics Department   Social Science Research Council
University of California   605 Third Avenue
Berkely, CA 94720   New York, NY 10016

Dr. Lauren Resnick   1 Robert S. Siegler
LRDC   Associate Professor
University of Pittsburgh   Carnegie-Mellon University
3939 O'Hara Street   Department of Psychology
Pittsburgh, PA 15213   Schenley Park
                                               Pittsburgh, PA 15213
Mary Riley
LRDC   1 Dr. Edward E. Smith
University of Pittsburgh   Bolt Beranek & Newman, Inc.
3939 O'Hara Street   50 Moulton Street
Pittsburgh, PA 15213   Cambridge, MA 02138

Dr. Andrew M. Rose   1 Dr. Robert Smith
American Institutes for Research   Department of Computer Science
1055 Thomas Jefferson St. NW   Rutgers University
Washington, DC 20007   New Brunswick, NJ 08902

Dr. Ernst Z. Rothkopf   1 Dr. Richard Snow
Bell Laboratories   School of Education
600 Mountain Avenue   Stanford University
Murray Hill, NJ 07974   Stanford, CA 94305

Dr. David Rumelhart   1 Dr. Robert Sternberg
Center for Human Information Processing   Dept. of Psychology
Univ. of California, San Diego   Yale University
La Jolla, CA 92093   Box 11A, Yale Station
                                               New Haven, CT 06520
DR. WALTER SCHNEIDER
DEPT. OF PSYCHOLOGY   1 DR. ALBERT STEVENS
UNIVERSITY OF ILLINOIS   BOLT BERANEK & NEWMAN, INC.
CHAMPAIGN, IL 61820   50 MOULTON STREET
                                               CAMBRIDGE, MA 02138
Dr. Alan Schoenfeld
Department of Mathematics   1 David E. Stone, Ph.D.
Hamilton College   Hazeltine Corporation
Clinton, NY 13323   7680 Old Springhouse Road
                                               McLean, VA 22102

Non Govt   Non Govt

DR. PATRICK SUPPES   1   Dr. Keith T. Wescourt
INSTITUTE FOR MATHEMATICAL STUDIES IN   Information Sciences Dept.
      THE SOCIAL SCIENCES   The Rand Corporation
STANFORD UNIVERSITY   1700 Main St.
STANFORD, CA 94305   Santa Monica, CA 90406

Dr. Kikumi Tatsuoka
Computer Based Education Research
      Laboratory
252 Engineering Research Laboratory
University of Illinois
Urbana, IL 61801

Dr. John Thomas
IPM Thomas J. Watson Research Center
P.O. Box 218
Yorktown Heights, NY 10598

DR. PERRY THORNDYKE
THE RAND CORPORATION
1700 MAIN STREET
SANTA MONICA, CA 90406

Dr. Douglas Towne
Univ. of So. California
Behavioral Technology Labs
1845 S. Elena Ave.
Redondo Beach, CA 90277

Dr. J. Uhlaner
Perceptronics, Inc.
6271 Variel Avenue
Woodland Hills, CA 91364

Dr. Benton J. Underwood
Dept. of Psychology
Northwestern University
Evanston, IL 60201

Dr. David J. Weiss
N660 Elliott Hall
University of Minnesota
75 E. River Road
Minneapolis, MN 55455

DR. GERSHON WELTMAN
PERCEPTRONICS INC.
6271 VARIEL AVE.
WOODLAND HILLS, CA 91367

ME

8