

Adaptation and Re-description in the Context of Geometric Proportional Analogies

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Abstract

Recent research in analogy, metaphor and retrieval in case-based systems has suggested the need to integrate a re-description capability with the creation of mappings. In this paper, we argue that there is also a need for systems that adapt knowledge for reuse to integrate re-description into the process of adaptation. We describe a system called INA which does this while solving geometric proportional analogies. We then discuss the properties a system must have in order to integrate re-description and adaptation. Finally, we compare our work with some other related approaches.

Introduction

In recent years, several subfields of artificial intelligence have addressed the problem of adapting knowledge for reuse. The field of case-based reasoning (Aamodt & Plaza 1994) is based on the idea that computers can solve problems by storing successful solutions to past problems and then retrieving an old solution previously stored and applying it to some new problem. Typically, the old solution does not fit the new problem exactly and must be adapted to fit the requirements of the new problem. In the related field of analogical reasoning, a similar framework has been worked out (Hall 1989) where, given a target description, a source is retrieved and then a mapping is made from the source to the target possibly extending the target description. The mapping may be thought of as a kind of adaptation where the structure of the source remains invariant and the symbols of the target are substituted for the symbols of the source. In case-based reasoning, adaptation is often characterized as being intra-domain and in analogical reasoning, mapping (a kind of adaptation) is characterized as inter-domain.

Mapping in analogical reasoning has, until recently, been studied with the tacit assumption that there exists a description-building module that somehow creates the descriptions of the source and the target domains and which then remain fixed during the mapping process (Hofstadter 1995, Chap. 4). Let us call this assumption and its variants in other domains: *the description module assumption*. Hofstadter and his col-

leagues have argued that the description module assumption is untenable from a cognitive point of view and has developed the Copycat system with Melanie Mitchell (1993) which integrates description-building with mapping.

Indurkha (1992) has argued that in understanding creative metaphors, the target domain is initially dissimilar to the source domain and must be *re-described* to be like the source domain. Clearly the description module assumption cannot be made in modeling creative metaphor. O'Hara (1992; forthcoming) has been developing a model of re-description in the context of geometric proportional analogies inspired by Indurkha (1989; 1991; 1992). (The solution of geometric proportional analogies were also modeled by Evans (1968). Evans did not attempt to integrate the mapping and description-building processes as we do here.) The description module assumption appears in a slightly different guise in the selection of indices for case-retrieval. We (O'Hara & Indurkha 1994) have argued that a re-description capability was needed in case-based systems to fulfill the promise of flexible case-retrieval.

Systems that adapt knowledge for reuse are also subject to the weakness inherent in the description module assumption. In particular, the kind of adaptations that can be made to an object are restricted by the way the object is described. This is illustrated by the following example. In a relatively recent legal case [CIR v. Soliman, 113 S.Ct. 701 (1993)] involving the home-office tax deduction clause of the IRS code, the plaintiff, an anesthesiologist affiliated with three different hospitals, claimed that his home office, where he kept his patients' records and did administrative tasks like billing was his principal place of business. When this case was decided by the US Supreme Court, in the minority opinion the justices cited a previous case [Texas v. New Jersey et al., 379 U.S. 674 (1965)] where a number of states were involved in a dispute over who gets to escheat the uncollected payments of a corporation. On the surface, and perhaps even after a deeper analysis, the two cases look very different. To see the similarities, one needs to organize the facts of the anes-

thesiologist case into a corporation schema that has an administrative head office and several branch office where services are offered to the clients — a view that was being argued for by the minority opinion. It is only after the facts of the new case are re-described in this way that the cited case can be retrieved and adapted to it.

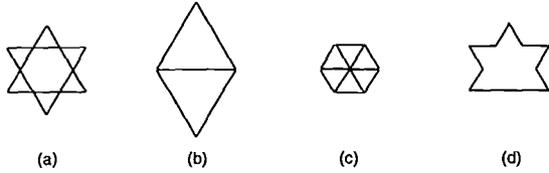


Figure 1: A different description is needed of figure a for each adaptation to figures b, c and d.

The same point can be made in a simpler and more idealized domain. Consider a hypothetical system that adapts one geometric figure (X) to another (Y). Suppose X is the Star-of-David figure shown in Fig. 1(a) and suppose Y is Fig. 1(b). The Star-of-David figure can be adapted to Fig. 1(b) by pulling the two large triangles apart in an up and down direction. The Star-of-David can be adapted to figure Fig. 1(c) by reflecting the six outer triangles inward toward the center. Now, how can the Star-of-David figure be adapted to Fig. 1(d)? Careful examination will reveal that the Star-of-David can be decomposed into a 5-pointed nonagon and a diamond-like pentagon. Fig. 1(d) is created by removing the diamond-shaped pentagon from an overlapping five-pointed nonagon. In each of our examples, the Star-of-David figure must be represented appropriately in order for it to be adapted to the other figure. If the description module of our system has not been able to anticipate a particular description (as certainly might happen in the case of Fig. 1(d)) then related adaptations will be impossible.

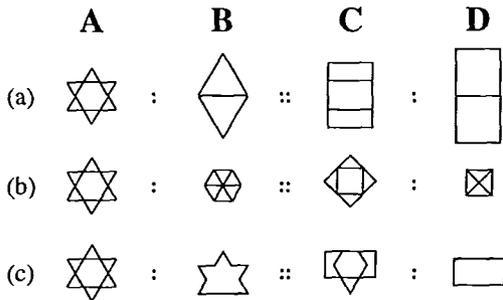


Figure 2: Three proportional analogies formed from geometric figures in Fig. 1.

We are led then, to the view that building and changing descriptions must be integrated with finding an appropriate adaptation. To investigate this integration we have chosen the domain of geometric proportional

analogies i.e., analogies of the form A is to B as C is to D . In proportional analogies, problems involving adaptation and re-description occur in a natural way. Adaptation is simply a part of how a proportional analogy is formed. Fig. 2 shows three proportional analogies with the Star-of-David as figure A and Fig. 1(b), (c) and (d) as figure B respectively. Note that the description of the Star-of-David is different in each case. This should demonstrate to the reader that re-description can be studied in the context of proportional analogies since different proportional analogies can force a figure to have a different description.

In the rest of this paper, we first present some details of a program we are building called INA which solves geometric proportional analogies. Next we discuss how re-description capabilities can be incorporated into systems that adapt knowledge for reuse and finally we briefly compare our work with some other related approaches.

A Blackboard Model of Adaptation and Re-description in Proportional Analogy

INA (for interpretive analogy) is a program that solves geometric proportional analogies such as the ones shown in Fig. 2. While the details of INA are described elsewhere (O'Hara forthcoming), we present some of its key features here.

The Input and Output of INA

The input and output of INA is illustrated in Fig. 3. The input to the program consists of three geometric figures a , b and c each represented as an arbitrary set of line segments, and the output consists of a fourth geometric figure d , four descriptions of figures a , b , c and d , respectively A , B , C and D , plus two transformations T and T' , which respectively transform a 's description into b 's and c 's description into d 's. In addition, the system returns two mappings M , M' which respectively map a 's description to c 's description, b 's description to d 's and a t -mapping TM which maps transformation T to T' .

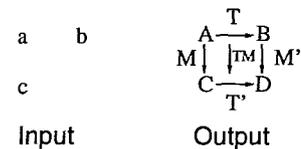


Figure 3: The input and output of INA.

The INA Architecture

INA has a blackboard-style architecture (Engelmore & Morgan 1988) which is illustrated in Fig. 4. The *pre-processor* shown at the bottom of Fig. 4 is invoked once at the beginning of a run and transforms each set of line segments representing figures a , b and c into a new

normalized set of line segments. This new set consists of all vertex-to-vertex line segments in the figure which contain exactly two vertices.

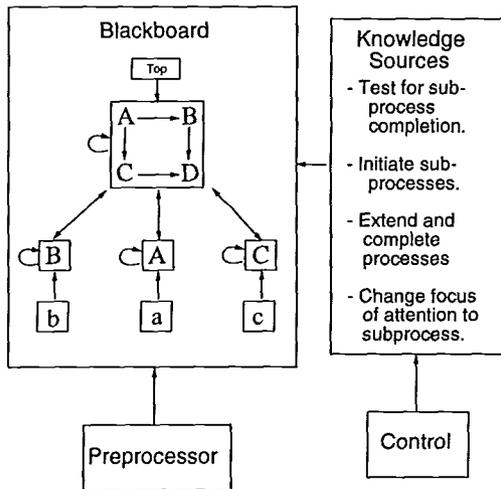


Figure 4: The Architecture of INA.

The knowledge sources (KS's) in Fig 4 are a collection of independent modules which accomplish various subtasks in solving proportional analogies. The four general kinds of tasks which might be performed by an INA KS are listed in the box. KS's and their tasks are best discussed in the context of INA's control structure which we will do below.

The *blackboard* in Fig. 4 is a global data structure in which solutions to proportional analogy problems are built incrementally by the KS's. It is divided into several *sub-blackboards* plus several independent data structures. The boxes labeled a, b, and c represent data structures containing the initial sets of line segments created by the preprocessor. The sub-blackboards labeled A, B and C contain blackboard objects representing various groupings of the input line segments as well as full and partial descriptions of the input figures.

The proportional analogy sub-blackboard is represented by the box labeled with the commutativity diagram. This sub-blackboard contains blackboard objects representing partially and fully constructed proportional analogies. The box labeled *Top* is a data structure containing a single blackboard object called TOP. The KS's associated with TOP makes the top-down decisions about which objects on the proportional analogy blackboard are to be focused on.

Control in INA

Every object on INA's blackboard represents a *process* which is either *completed* or *incomplete*. A completed process is typically used as a component to be added to some other process. An example of a process in INA is a polygon process which is a partially completed poly-

gon, say three sides of a square. When a polygon process is completed, the result may then be *recognized* as a polygon, square, rectangle or what ever is appropriate. A recognized object may then be used to extend another process which includes the object as a component. If a process X produces an object that may be used as a component by some other process Y then X is said to be a *subprocess* of Y. At any given time during the execution of INA, a single incomplete process is the *focus-of-attention* or *FOA* which means that only KS's associated with the FOA may be considered for execution. (Completed processes may not be the FOA since there is nothing left to do.) The relationship of processes to subprocesses in INA is illustrated in Fig. 5.

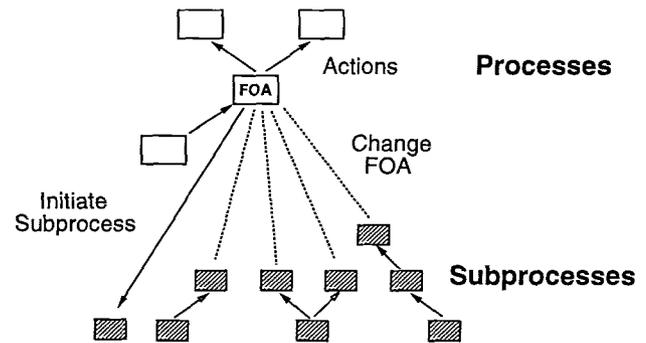


Figure 5: Several tasks may be performed at the focus-of-attention (FOA): initiate subprocesses (solid, downward arrow), change focus-of-attention to subprocesses (dotted lines) and extend the FOA process (upward solid arrows).

As mentioned, a KS may perform four different kinds of tasks: A *cond* task determines whether enough subprocesses of the FOA have been completed so that some action may be taken with respect to the FOA. If not, then more subprocesses are pursued by invoking a *change_foa* subtask (see below). If so, then an *action* task (see below) is invoked on the current FOA.

An *init* task initiates subprocesses for the current FOA. It consists of an *update* procedure that generates subprocess initializations for the current FOA which are then executed immediately.

An *action* task extends or completes a process using the results from its subprocesses. It consists of two components: (1) an *update* procedure which generates new possible actions for the current FOA and adds an *activation record* for each possible action to the *action agenda*; and (2) an *eval* procedure which evaluates the actions on the action agenda. If the *cond* task has been satisfied, the *eval* procedure is used to select the "best" actions to run.

A *change_foa* task changes the focus to some subprocess of the current FOA. It consists of two components: (1) an *update* procedure which generates possible new

foci-of-attention for the current FOA and adds an activation record for each possible new FOA to the *new FOA agenda*; and (2) an *eval* procedure which evaluate the possible FOA's on the new FOA agenda. If the *cond* task has NOT been satisfied, the *eval* procedure is used to select the "best" new FOA's to visit.

Execution in INA always begins with the TOP node as FOA.

Representation on the Figure Blackboards

Three general kinds of objects may appear on a figure blackboard along with their associated processes: *groupings* and *grouping sets*.

A *grouping* is a set of elements perceived by INA to comprise a whole. Groupings may be of different types depending on the kind of elements from which they are built and the sort of configuration they make. An example of a grouping in INA is the *polygon grouping* which is a grouping of line segments forming a closed plane figure. The set of elements from which a grouping is formed is called an *environment*. In INA, the initial environment is the set of all vertex-to-vertex line segments. *Grouping processes* are basically groupings that are "under construction." An example of a polygon grouping process would be three sides of a square. Adding the fourth side would complete the polygon process. Associated with each grouping is a *description*. In INA, descriptions are built from a *description algebra* which consists of a set of *symbols* and a set of *operators* which are functions closed over the set of symbols. A description in INA is a tree where each leaf is labeled by a symbol and each n-ary non-leaf is labeled by an operator. Four examples of descriptions are shown in Fig. 6 in the next section.

A *grouping set* is a set of groupings in a single environment. Together, the union of all groupings in a grouping set must equal the set of elements in the environment. A grouping set may be used as an environment for further grouping. A *grouping set process* is a grouping set in the process of being built. A description of an entire figure is built by repetitively constructing grouping sets where each successive grouping set is the environment for the next. The final grouping set contains a single element: a grouping of the entire figure. The description associated with this grouping is the description of the figure.

Representation on the Proportional Analogy Blackboard

Two kinds of objects appear on the proportional analogy blackboard: proportional analogies and proportional analogy processes. Referring back to Fig. 3, a *proportional analogy* consists of the nine elements described there: descriptions of figures A, B, C and D, transformations T and T', mappings M and M' and t-mapping TM. And in keeping with our notion of complete and incomplete processes, A *proportional analogy*

process is simply a proportional analogy in the process of being built.

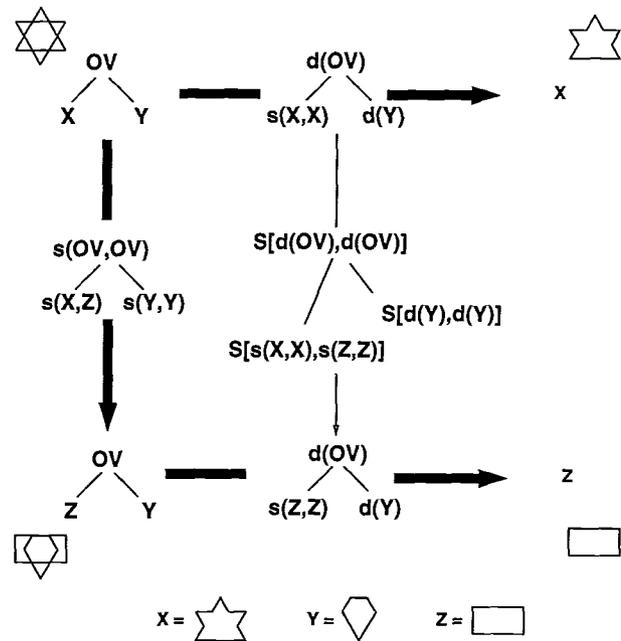


Figure 6: A representation of the proportional analogy from Fig. 2(c).

The various components of a proportional analogy are illustrated in Fig. 6 using the example in Fig. 2(c). X, Y and Z denote the three shapes used: X denotes the five-pointed nonagon, Y the diamond-shaped pentagon and Z denotes a rectangle. OV is the overlap operator. Figure A is described as X overlaps Y and figure C is described as Z overlaps Y. Figure B is described as X and figure D is described as Z. The 'd' symbol denotes the tree-edit operation *delete* and symbol 's' denotes *substitute*. Another tree-edit operation *insert* is not shown. Figure A is transformed to figure B by deleting the operator OV and the symbol Y and substituting X for X. In other words, the pentagon is removed. Figure A is mapped to figure C by substituting OV for OV, Z for X and Y for Y. The 'S' symbol is a *t-substitution* only used in t-mappings. T-mapping TM maps T to T' by substituting: d(OV) for d(OV), s(Z,Z) for s(X,X), and s(Y,Y) for s(Y,Y). We will leave it as an exercise for the reader to determine how figure C is transformed to figure D.

An Example of Top-Down Grouping

The ability to use top-down information to find groupings is the key to re-description. Fig. 7 illustrates how top-down grouping is approached in INA. The diagram shows the state of the Top data structure, the proportional analogy blackboard and the three figure blackboards during the solution of the proportional analogy problem in Fig. 2(c). The proportional analogy

blackboard contains three proportional analogy processes labeled 1, 2 and 3. Figure blackboards B and C each contain a single description of figures B and C respectively and Figure blackboard A contains two descriptions of figure A.

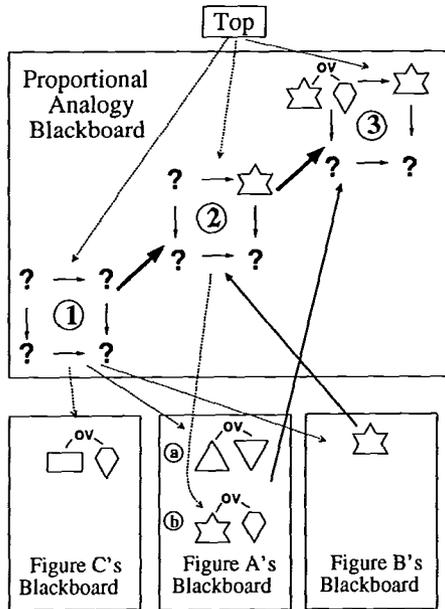


Figure 7: A "snapshot" of the solution of the proportional analogy in Fig. 2(c) shows how the top-down influence of figure C causes the Star-of-David to be re-described as a five-pointed nonagon overlapping a diamond-shaped pentagon.

To get to the state depicted, processing began with the FOA at Top. From Top, the proportional analogy process (PAP) 1 was created and became the FOA. PAP 1 is essentially empty – all structure and no content. PAP 1 passed control successively to objects on the description blackboards A, B, and C. Processing on the description blackboards then produced description a for figure A and the descriptions shown for figures B and C based on gestalt-like criteria. These are descriptions that one might come up with if one looked at the figures independently: for figure A, two overlapping triangles, for figure B, a concave polygon, for figure C a pentagon overlapping a rectangle. (Here, a great amount of detail is suppressed to make our illustration easier. However, the basics mechanisms described are used everywhere on the proportional analogy and description blackboards.) Once, likely components required by PAP 1 are produced, the FOA moves back to it to decide on an action. It chooses to add the description of B to produce PAP 2, since this B's description is in some sense simplest. Top, monitors each step of a solution so, noticing that a new PAP has been created, it now becomes the FOA. This time, Top has two choices for FOA: PAP 1 and PAP 2. Top chooses PAP

2 as FOA since it is the most developed solution. Since PAP 2 already has a description of figure B, it would like to find a description of figure A that is structurally compatible to it. The FOA therefore shifts to the A blackboard and uses the shape of figure B as top-down constraint in creating a new description for A coming up with description b. The FOA returns to PAP 2 and description b is added to create PAP 3.

Incorporating a Re-description Capability in Systems that Adapt Knowledge for Reuse

Implicit in the notion of re-description is that there is more than one description of a given object. Because of this, re-description requires at least two levels of representation. One level is a detailed 'sensory-level' representation and the other is a conceptual-level representation. In INA, the sensory-level representation is the set of vertex-to-vertex line segments created by the pre-processor for each figure. The conceptual-level representation is the system of descriptions, transformations and mappings formed from the description algebra. In the example of legal reasoning presented in the introduction, the sensory-level representation would be the facts of the case and the concept-level representation would be the argument for or against the case involving legal categories. Re-description also requires an interpretation capability that establishes a correspondence between a conceptual-level description and the sensory-level object it represents. In INA, the interpretation of a conceptual-level description is found by recursively evaluating the operators in the description tree. Usually, but not always, two different descriptions represent different decompositions or groupings of an object. In INA, a subtree of a description represents a grouping of the sensory-level representation.

What facilities should a system that adapts knowledge for reuse have in order to incorporate the re-description capability? Let us examine this question from the perspective of a case-based system and look at what additional capabilities are needed with respect to the stored cases and to the input case. First, a *concept-level* language of representation for cases is needed. This, of course, all systems would have. In addition, a *sensory-level* representation language is needed which captures all the low-level detail of the cases. Next, a *description-building system* is required which transforms a sensory-level description into a conceptual one. Finally, a powerful *constraint mechanism* is needed to severely limit the search for alternate descriptions. Without such a mechanism, given a large case-library, the many ways to describe each case, and the fact that the re-description process has a high computational cost, the system would likely be prohibitively inefficient. The constraint mechanism would have to be integrated into the description-building system and linked with the concept-level language. This

would allow the description-building system to either re-describe a retrieved case so that it is adaptable to the input case or, as in the example of legal reasoning mentioned in the introduction, re-describe the input case so that it can be adapted to a stored case.

It turns out that, at least in the domains we have looked at, the goal of the user serves as a very strong top-down constraint to narrow the search space. For instance, in the proportional analogy domain, the goal of having to form a proportional analogy makes the partially completed representations of the three input figures exert top-down influences on each other via the PAP and Top nodes greatly limit the number of options one must consider for each figure. In the domain of legal reasoning, to which we are transporting INA architecture, the goal of the user serves to focus attention on a small set of relevant precedents and suggests ways to re-describe them (or the input case).

Comparison with Related Work

Kedar-Cabelli's (1988) 'purpose-directed analogy' uses the domain theory to develop an explanation for how an object fulfills its function or purpose (e.g. how a styrofoam cup serves to hold a hot drink), and then transfers this explanation to the target object. If we equate 'explanation' with 'description' and 'purpose' with 'goal' we see that in Kedar-Cabelli's approach, given a goal for a base object, its description is created in an EXPLAIN stage followed by a mapping of the base object's description to the target object in the MAP stage. In INA, on the other hand, description-building (EXPLAIN) and mapping (MAP) are integrated. The incremental approach of INA to description-building permits a continual re-evaluation of the "goodness" of the partially built descriptions and the mappings in an analogy.

Branting's (1991) GREBE system uses a fine-grain representation of precedents in that various small inference steps that were made in order to reach an overall conclusion about a case are stored individually. This allows GREBE to generate an explanation for a new case by combining micro-explanations from several different precedents. As explanations can be considered 'representations' in our terminology, Branting's system can be seen as generating an appropriate representation for a new case in terms of the representations of the precedents. However, the representation of precedents are determined a-priori and must be hand-coded in GREBE. Though we have not yet transported our system to the domain of legal reasoning, we expect that in our architecture the system will be able to generate different explanations for precedents also depending on the need (for opinions accompanying the decision on a case often do not explain everything) and thereby exhibit more flexibility.

Shrager's (1987) 'view application' is like applying concept-level representations of the pre-existing views to the sensory-level representation of domain being

learned in order to form a concept-level representation (theory) of it. While this approach is quite close to our work, there are some differences. One is that theory formation is an open-ended process and there are no goal-induced constraints to help with the search. Another is that the domain being learned is not completely available (which requires experimentation) to the learner, whereas in both the proportional analogy and legal domains all the figures and facts are fully accessible.

Hofstadter and his colleagues' (1995) approach comes closest to ours in spirit. Yet, there are some philosophical differences. We believe that the key issue in understanding creative analogies and metaphors is the re-description process. The question that we have focused on is: how can one thing be described in terms of another? Hofstadter and his colleagues have emphasized the notion of an 'active concept', as embodied in the Slipnet, which adjusts itself to new situations. In contrast, we rely on a more conventional approach to concepts, seeing them as static at least over the time of the solution of a proportional analogy. Instead our emphasis is on finding a good "fit" between two descriptions. We believe that human flexibility in creative tasks lies more with the ability to combine concepts in novel ways than in the flexibility of concepts themselves.

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Appendix: Describing the contribution

A. Reasoning framework: The reasoning framework is an algebraic approach to proportional analogies with a focus on the re-description process. No benefits are gained per se by using adaptation. Rather adaptation is simply intrinsic to solving proportional analogy problems. Also, nothing is reused in a proportional analogy. The benefit of our approach lies in combining re-description and adaptation so proportional analogies can be solved that otherwise would not be solvable (see introduction.) The output descriptions of figures A, B and C are constrained to represent figures A, B and C. There are probably other invariants as well.

Knowledge: The knowledge to be adapted are the descriptions and the transformations. Descriptions, transformations, mapping and t-mappings are represented as tree structures. A description describes a geometric figure. Transformations each describe the adaptation of one description to another. Descriptions are built by a set of bottom-up processes that are biased to produce descriptions that satisfy Gestalt-like criteria and a set of top-down processes which are associated with the symbols and operators of the description algebra. The top-down processes associated with

the symbols and operators in the description of one figure are used to induce groupings in other figures so that a transformation or mapping can be made.

Adaptation: A description is adapted to describe another figure. A transformation is adapted to form a new transformation. The resulting descriptions and transformations are used to form a proportional analogy. Transformation and mapping in geometric proportional analogy requires that the descriptions represent the structure of the object so insertions, deletions and substitutions of component figures can be made. The tree structure representations handle this quite nicely.

Reuse: Reuse does not occur in this framework.

Re-description: Figures A, B and/or C may be re-described. Figures A, B and/or C are re-described to form descriptions that are structurally mappable and/or transformable so as to form a proportional analogy. See section on incorporating a re-description capability in a on page 5.

B. Task: The task is to solve proportional analogy problems in the domain of geometric figures. See page 2 for description of task. The output descriptions of A, B and C are constrained bottom-up in that the descriptions must describe the input figures as represented by the set of line segments. From the top-down, the output descriptions must conform to the proportional analogy relation.

C. Evaluation: The INA system is intended as a model of human performance on proportional analogies requiring re-description in one or more of the figures. Our hypothesis is that, on some common level of abstraction, INA does re-description the same way as people do. As the system is not yet completely operational, a full evaluation must wait. Our hypothesis implies that INA should come up with similar answers as people do and should have similar difficulties as people do. How people solve proportional analogies requiring re-description is a question for psychological testing which we are planning to do. INA's performance should be compared and evaluated on proportional analogies that involve adaptations of varying complexity, from no adaptation required to very complex adaptations. Similarly, INA's performance should be compared and evaluated on proportional analogies involving re-description of varying complexity from no re-description required to very complex. Interactions between these two processes should also be studied. We hypothesize that more complex adaptations and re-descriptions should require more computation in INA and in humans and thus should take longer than simpler ones. The primary contribution of our research is to emphasize the need for re-description in the adaptation of knowledge and to suggest the domain of geometric proportional analogies as a framework in which to study the relationship between re-description and adaptation.

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