An Examination of the Third Stage in the Analogy Process: Verification-Based Analogical Learning[1]

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Abstract

Many studies of analogy in Artificial Intelligence have focused on analogy as a heuristic mechanism to guide search and simplify problem solving or as a basis for forming generalizations. This paper examines *analogical learning,* where analogy is used to conjecture new knowledge about some domain. A theory of *Verification-Based Analogical Learning* is presented which addresses the tenuous nature of analogically inferred concepts and describes procedures that can be used to increase confidence in the inferred knowledge. The theory describes how analogy may be used to discover and refine scientific models of the physical world. Examples are taken from an implemented system, which discovers qualitative models of processes such as liquid flow and heat flow.

1 Introduction

Analogy is roughly composed of three stages: Access, *Mapping,* and *Evaluation and Use.* Previous work in analogy has focused primarily on how one forms an analogical mapping and how this mapping may be used as a heuristic mechanism to guide search and simplify problem solving. This paper makes a distinction between the different usee of analogy and focuses on *analogical learning,* where analogy is used to conjecture new knowledge about some domain. Since the underlying assumption of *analogical inference* is that certain similarities between two domains imply stronger, relational similarities, the validity of knowledge inferred in this manner is very tenuous. This paper describes some procedures that can be used to increase confidence in the inferred knowledge. Specifically, a theory of *Verification-Based Analogical Learning* is presented which may be used to discover and refine scientific models of the physical world. New models' predictions are compared against observed behavior, enabling the system to test the validity of the analogy and sanction refinements where the analogy is incorrect. The work also addresses another common problem in analogy, that of knowing what relations to map, by showing that the behavioral similarity of two phenomena can be used to initiate and guide the mapping process.

Many scientific theories are postulated as qualitative models of physical phenomena which must be actively confirmed or refuted. This work shows how analogy may be seen as one source of creativity in discovering such models and focuses on how the results of this creativity must be carefully examined. Intuitively, the theory corresponds to how one might construct a wave model of sound from prior knowledge of water wave behavior. Examples are taken from an implemented system to demonstrate how the theory may be used to discover qualitative models of liquid flow and heat flow.

2 The Analogy Process

To understand the possible uses for analogy, one must first have a clear definition of analogy itself. This section serves to clarify common terminology by presenting a breakdown of the analogy process (similar to Gentner, 1986), followed by a discussion of the different uses for analogy.

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Access: The access stage has two purposes. First, it locates a body of prior knowledge (the *base)* which may be analogous to the current situation (the *target).* Second, it should garner out those features of the base which are pertinent to the analogy.

Mapping: The mapping stage consists of finding similarities between the base and target *(matching),* and possibly transferring additional knowledge from the base to the target *(inference).* The work presented in this paper draws from Gentner's (1983) Structure-Mapping theory of analogy and uses a simulation of these principles, the Structure-Mapping Engine (SME) (Falkenhainer, et al, 1986). Mappings constructed by SME consist of the set of base/target correspondences and a potentially empty set of *analogical inferences* - relations that augment the target description by transferring knowledge from the base. SME is guided by a set of *match constructor rules* that specify what items may plausibly match, providing a useful programability option.

Evaluation and Use: Once the correspondences have been found, the quality of the match and its consistency with general domain knowledge should be evaluated before using the proposed analogy. The uses for analogy are discussed in the following section.

2.1 Using an Analogy

Analogy *matches* a base description with a target description of varying levels of completeness. When the target is complete, analogy indicates where the correspondences are and has no predictive power. When the target lacks certain relations, *analogical inference* may occur; relations which hold in the base but are not known to hold in the target are *mapped* into the target domain. Borrowing from Indurkhya (1985), we may formally define two types of analogical inference:

Definition: A set of analogical inferences are *strongly coherent* if every sentence being mapped is logically entailed by the target. The inferences are *weakly coherent* if they are merely consistent with the target, rather than entailed by it.[2]

Thus, some analogical inferences may be seen as knowledge which exists for the target domain, yet is not explicitly stated (i.e., search would be required to retrieve it). Other analogical inferences represent new , knowledge • conjectured facts about the target domain. This is an important distinction for categorising the different uses of analogy:

Analogical Reasoning. Analogical reasoning involves using past experiences as heuristics to guide or assist current reasoning processes, as in recommending promising search paths (e.g. Carbonell (1983), Kedar-Cabelli (1985)). The classification also refers to cases in which analogy is used as a focusing mechanism (e.g., stating an analogy to point out the salient features of the target). It also applies to *case-based reasoning* systems, which draw on previous instances of similar situations for guidance (e.g. Kolodner et al, 1985; Hammond, 1986). Here a strict definition of

[2]Indurkhya (1006) uses *cohersnt* and its subset, strongly *coherent,* to refer to the entire analogical mapping (matches plus inferences). Here we add the term weakly *coherent* and only apply these terms to the inferences.

reasoning by analogy will be employed, in which analogy is used for guidance and those analogical inferences which end up being useful are strongly coherent.

Similarity-Based Generalisation. In analogy, one may use the similarity between two concepts found during the matching stage to form a single, generalised concept. This corresponds closely to many empirical (often called similarity-based) learning methods, some of which use pattern matching techniques to detect similarities in the structural representation of features (e.g., Hayes-Roth & McDermott, 1978; Michalski, 1980).

Analogical Learning. This is a method of learning that is unique to analogy. Roughly, if we know about some base situation and we encounter some target situation which is believed to be similar to the base, perhaps the additional knowledge we have about the base may also hold for the target. Thus, analogical learning uses weakly coherent analogical inferences to posit new knowledge about the target domain.

These uses of analogy may be intermixed. For example, one may use the results of analogical learning to form a more general concept description. Thus, knowledge of the solar system could be used to learn about the Rutherford model of the atom. In turn, these could be used to form a general concept of central-force systems. In addition, the results of analogical reasoning processes may be stored, thus "learning" in the analytical (EBL) sense. This paper focuses on analogical learning. In analogical reasoning, the inferences are used as a heuristic device. Falsely drawn inferences only mean an impact on performance rather than correctness (i.e., they will cause backtracking). In analogical learning, the inferences are accepted as new knowledge which did not exist prior to the analogy. Thus, we must be sure there are sound reasons for believing that the inferences are correct.

The underlying assumption of analogical inference is that surface similarity implies a stronger, relational similarity. Thus, it is a tenuous form of plausible inference. Accepting weakly coherent inferences requires a cautious investigation of the learned concepts. One way to ensure that they make sense is to compare the consequences of these inferences against observed physical behavior - hence, verification-based analogical learning. Theories produced by analogy are evaluated by their ability to predict observed physical phenomena.

3 A Theory Of Model Acquisition

Scientific theories are seldom constructed in a vacuum. They tend to be either refined versions of existing theories or they are transferred theories of similar phenomena. This work addresses both type* of theory construction, using analogical inference as the "inventive" mechanism. Knowledge refinement techniques model the incremental stage of theory construction. By contrast, discovery techniques enable the construction of "first-pass" theories of the world. Analogy offers a method for making large leaps in current knowledge. It allows a reasoning system to come up with an initial theory for some domain which knowledge refinement methods may subsequently adjust.

In general, we know that when two bodies, one hot and one cold, are placed in contact with each other, after a period of time they will reach the same temperature. What happens between the time the two objects are placed in contact and the time the two temperatures equalise? If the notion of water flow suggests itself, we may construct a model for the situation in which heat is seen "flowing" from a higher temperature to a lower temperature. Using the new model shows that it accurately explains the phenomenon. This is called verifying the consistency of the model. The new theory now predicts that certain other events must also be able to happen, such as the bidirectionality of heat flow. We attempt to recollect a prior experience (history) demonstrating this predicted behavior or we conduct simple experiments to explore the space of hypothesized behaviors. This is called venfying the predictions of the model. If we were to extend the analegy further by hypothesising that heat was itself a type of liquid (i.e.. therory of heat) a nmber additional predicational may be-

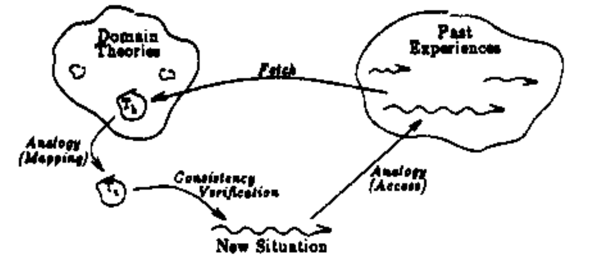

Figure 1: Model construction and consistency verification in VBAL.

made baaed upon the intrinsic properties of liquids and physical objects. For example, conservation of matter would lead to predictions based on conservation of heat. Exploring the consequences of these additional predictions is called verifying the extension of the analogy. This entire process of hypothesis formation, confirmation, refutation, and subsequent refinement is the essence of verification-based analogical learning (VBAL).

In order to learn in this manner, we must be able to reason about scientific theories and the physical situations they describe. This work models the world in terms of qualitative physics, using For bus' Qualitative Process theory (Forbus, 1984).[3] A physics reasoner, QPE (Forbus, 1986b), is employed, which takes qualitative models and produces an envisionment for a given system that describes its possible physical states and the possible transitions between them. A single path through the envisionment (an actual behavior) is called a history. In addition, a physics interpreter, ATMI (Forbus, 1986a), is used to monitor the world and relate observations to known or postulated theories.

The current implementation of VBAL, called Phineas (Figure 2), is designed to operate as a passive observer, relating observed physical phenomena to known theories of the world. When ATMI fails to adequately interpret a new event, the VBAL control module is called upon to construct a potential explanation of the situation (see Figure I) It interacts with SME and a knowledge refinement module to construct a new or revised model:[4]

1. Dynamic Behavior Match. First, a prior situation that appears to exhibit similar behavior is accessed and SME is used to form a match between the behavior of the current and prior situations. This analogy serves to explicitly indicate which aspects of their behavior are the same (e.g., perhaps only some of the prior behavior's states are analogous) and establishes the object and quantity correspondences between the two domains.

2. Relevant Theory Retrieval. Once a satisfactory experience has been retrieved, the domain theories used to explain the matched parts of the prior situation are fetched. These theories are simply a collection of the entity and process definitions that were used by ATMI when it originally encountered the previous behavior. Each state in the history indicates what processes were active during that state. Thus, if the current history only matches a subset of the states in the old history, only the relevant process models are used.

3. Theory Mapping. SME is invoked a second time to map the potentially analogous domain theory to the new domain of interest. This second analogy is generally a pure mapping of structure from one domain to another, appropriately transformed according to the object correspondences provided by the prior analogy

[3]In QP theory, a situation is represented as a collection of objects a set f relationships between them, and a set of processes which account for all changer in ne world (eg, liquid flow). Each object has a set of continuous parameters such as TEMPERATURE and PRESSURE, which are represented as symbolic quanties that have in amount and a denvative Process definitions contain a set r(initial conditions that constriant activation and a set of relations that indicate how the active process would affect the war

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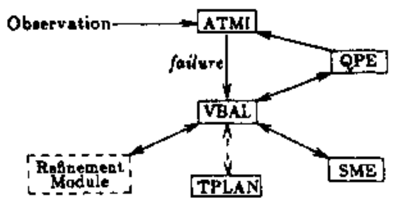

Figure 2: Block diagram of the Phineas system modules.

between the histories. The analogical match is constrained by the object and quantity correspondences established during the dynamic behavior match.

4. Consistency Verification. The correctness of the new model is verified by using it to account for the original situation. QPE takes the model and produces a new envisionment, which ATMI in turn compares to the current situation. If verification fails, model refinement may be used to account for slight imperfections in the analogy, or a different analogy may be tried.

5. Empirical Verification. Given that the new model is consistent with what has been observed, we may now seek further empirical confirmation of its validity through various stages of experimentation. A time-based planner is being used to explore the possibility of constructing simple experiments to perform *prediction verification*. More complex experiments may have to be performed to verify *extensions of the analogy* (Falkenhainer, 1987).

At any time during the verification stages, if the model is found to be flawed, knowledge refinement would be required to make the appropriate adjustments in the model. For example, we could call upon our general physical knowledge to make "common sense" adjustments Alternately, we could resort to directed experimentation to uncover the source of the discrepancy (e.g., Rajamoney, 1985). Finally, we could resort to analogy again, using different situations to fill in and correct the missing theory (e.g., Burstein, 1983).

Phineas' operation will now be reviewed in conjuction with an example of how the system learns a new model of heat flow by drawing an analogy with a similar water flow experience.

3.1 Accessing Analogous Behavior

Suppose the program was given time-ordered measurements of a heat flow situation in which a hot horse shoe has just been thrown into a bucket of cold water. ATMI would translate this sequence into the qualitative history shown in Figure 3 and attempt to explain it in terms of known theories. If the program has no knowledge of heat flow, interpretation will fail. As a result, the analogical learning module will attempt to construct a plausible explanation. First, an analogous history must be located from past experience. Currently, we assume that a suitable situation has been retrieved, leaving the problem of analogical access for separate investigation.[5]

In this case, an analogous water flow history is found (a beaker and a vial attached by a pipe) and SME is invoked to match the current heat flow history to the prior water flow history This establishes which things are behaving in an analogous manner (e.g., which object is the source of flow and which object is the destination). The roles of the beaker water and vial water in the water flow history are found to correspond to the roles of the horse shoe and water in the heat flow history, respectively. Those correspondences which provide a mapping between entities or between their quantities are stored for later reference (the correspondences shown in Figure 3).

[5]The current implementation simply queries the user for the name of the analogous base situation. A number of analogical access mechanisms are being investigated at this time but have yet to be installed and evaluated

Heat Flow History

```
(Decreasing (Temperature (At horse-shoe S0)))
(Increasing (Temperature (At water S0)))
(Greater-Than (Temperature (AT horse-shoe S0))
              (Temperature (AT water S0)))
(Meets S0 S1)
(Constant (Temperature (At horse-shoe S1)))
(Constant (Temperature (At water S1)))
(Equal-To (Temperature (At horse-shoe S1))
          (Temperature (At water S1)))
(Function-Of (Temperature ?x)
             (Heat ?x))
```

Match

```
   Pressure  ↔  Temperature
  Amount-of  ↔  Heat
         S0  ↔  S0
         S1  ↔  S1
  cs-beaker  ↔  horse-shoe
    cs-vial  ↔  water
```

Figure 3: Heat flow history and water flow match.

3.2 Forming a New Model

The program now fetches the relevant domain theory which led to its prior understanding of water flow A second analogical match is performed by SME, this time between the retrieved process model for water flow and the current heat flow situation, producing a new model for heat flow based upon the old water flow model (Figure 4).[6]

The analogy at this stage is highly constrained, due to the set of entity and function correspondences established when the dynamic behaviors were matched. SME's rule-based architecture complements this activity, since the reasoning program may dynamically modify SME's match construction rules to force a match between those entities and quantities that were found to be analogous during the access stage (e.g., Pressure and Temperature) and prevent any alternate matches for these items (e.g., Amount-Of and Temperature).

Notice that the "analogy" here is composed almost entirely of weakly coherent inferences, since the system had no prior model of heat flow. Thus, the model was *constructed* by analogy rather than augmented by analogy. Additionally, this method shows how SME's rule-based architecture supports situations in which entity correspondences are given prior to the match, rather than derived as a result of the match.

In many cases, not enough information is explicitly given for the theory to properly match. In the heat flow example, we need a way of knowing *what* is flowing. This information is not available if the temperature change is all that is known. The domain model for water flow includes an AMOUNT-OF function which corresponds to HEAT in the heat flow domain. However, the quantity HEAT never appeared in the heat flow history as an observable. Without a notion of heat, the program would be forced to either map AMOUNT-OF directly into the new heat flow model or postulate the existence of an unknown aspect of the objects involved which corresponds to an AMOUNT-OF concept for heat flow situations. To avoid this, the world knowledge must include enough information to deduce that temperature and heat possess a relationship similar to the relationship between pressure and amount (mass). In this example, the relation FUNCTION-OF was used to approximate this relationship, enabling the system to match PRESSURE to TEMPERATURE and AMOUNT-OF to HEAT.

The results produced by SME (Figure 4) contain the entity (*skolem* pipe). This indicates that, at the moment, the heat path is

[6]The model shown in the figure was produced by SME. The VBAL control module later translates this into QPE process definition syntax. The figure serves to explicitly show what was produced by analogy.

```
Gmap #1:  { (AMOUNT-OF-S HEAT-WATER) (AMOUNT-OF-S HEAT-HSHOE)
            (PRESS-BEAKER TEMP-HSHOE) (PRESS-VIAL TEMP-WATER) }
  Emaps:    (cs-beaker horse-shoe) (cs-vial water)
  Weight:  2.675
  Candidate Inferences:
       (Implies
          (And (Aligned (*skolem* pipe))
               (Greater-Than (A TEMP-HSHOE) (A TEMP-WATER)))
          (And (Q= (Flow-Rate pi) (- TEMP-HSHOE TEMP-WATER))
               (Greater-Than (A (Flow-Rate pi)) zero)
               (I+ HEAT-WATER (A (Flow-Rate pi)))
               (I- HEAT-HSHOE (A (Flow-Rate pi)))))
```

Figure 4: Analogically inferred model of heat flow.

a conjectured entity. Further experimentation could be used to identify the actual heat path, a knowledge of paths in general could be used to indicate that immersion is a likely path, or the path could be left as a conjectured entity. This last choice correspond? closely to the period in science when a substance, called the *ether,* was believed to exist in order to provide a medium for the flow of light waves. In this example, Phineas concludes that physical contact represents a valid path.

3.3 Consistency Verification

Now that Phineas has a new process model for heat flow, it may repeat its attempt to interpret the original situation. The heat flow process model is given to QPE and ATMI compares QPE's new predictions against the original observations. Since the water flow and heat flow situations are so similar, ATMI finds that the new theory accurately models the heat flow situation. The program has thus verified that the theory is accurate for this and functionally similar instances of heat flow. Experiments may be used to further verify the theory and the new model may be added to the set of known domain theories VBAL takes weakly coherent analogical inferences and adds a new dimension of validity to them, that of empirical validity.

4 Other Examples

Phineas has been used to learn different types of water flow and heat flow models (e.g., an infinite heat source - a stove) and its knowledge representation is being extended to enable learning of oscillation models. A common problem in analogy is knowing what to map. Focusing on the theory that explained the base history indicates which system of relations should be mapped, thus eliminating the need to consider irrelevant relations (e.g., evaporation) in the water - heat analogy. (Falkenhainer, 1986) describes an example in which a model of water flow was learned by drawing upon a two-state heat flow situation (heating up, boiling). It shows how the dynamic behavior match enabled the system to deem the boiling irrelevant to the purpose of the analogy

The examples described above consist of ideal situations; that is, the recalled behavior and corresponding theory were sufficiently similar to analogously explain the observed behavior. Since this will often not be the case, any general theory of analogical learning must include a theory of model refinement. See (Falkenhainer, 1986) for a discussion of refinement in the context of VBAL and how analogy may serve to focus the refinement process.

5 Discussion

Analogy has been shown to be a useful "inventive" mechanism, enabling a reasoning system to construct initial theories of some domain which knowledge refinement methods may subsequently adjust. The current implementation opens the door for a variety of future report h directions. For example, the various access mechanism- urrently being investigated may now be installed and evaluated In addition the system lacks a knowledge refinement module and so is- unable to correctly process the non-ideal situations requiring modification works. in progress to construct a suitable refinement module. This will allow direct testing of the utility of different refinement schemes in the context of analogy. We would also like to test different and more complex domain models to explore the limits of analogy as a learning device.

A key issue in analogical learning concerns the tenuous nature of the inferences made. Given that two domains appear to be similar in a number of ways, how valid are the conjectures made by the matching module about the target domain? One way to ensure they make sense is to compare the consequences of these inferences against observed physical behavior, that is, to establish their *empirical validity.* Similarity-based and explanation-based techniques produce learned concepts that are guaranteed to be correct for the examples used to generate them. In analogical learning, explicit verification and refinement are required in order to learn anything, yet alone refine past knowledge.

This paper has stressed a number of points. First, when discussing analogy, we must draw a clear distinction between reasoning by analogy, similarity-based generalization, and analogical learning. Second, in learning physical models, dynamic behavior may be used to initiate and guide the analogy process. Third, when performing analogical learning, it is important that we ensure there *is* a "causal" argument for believing that surface similarities will lead to meaningful and valid inferences. In addition, we must confirm these inferences by comparing the derived theories against real world behavior. Finally, it has been stressed that any model of analogical learning must necessarily possess a complementary model of knowledge refinement.

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