Similarity-based Qualitative Simulation: A preliminary report

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Abstract

People are remarkably good at using their common sense to predict and explain behavior. Qualitative modeling has provided formalisms that seem to capture many important aspects of human mental models, but standard qualitative simulation algorithms have properties that make them implausible candidates for modeling the flexibility, robustness, and speed of human reasoning. This paper describes work on a different approach, *similarity-based qualitative simulation*, which uses standard QR representations but with analogical processing to predict and explain behaviors. We discuss the motivation and progress towards a theory of similarity-based qualitative simulation, illustrated with examples from the first running prototype.

Introduction

People are capable of using common sense knowledge to explain and predict everyday physical phenomena, such as: filling a cup of tea, boiling a pot of water, kicking a pebble, or throwing a bowling ball. The models people use in reasoning about the physical world are called *mental models* [Gentner & Stevens, 1983]. We need to have a better understanding of mental models if we want to create agents that can operate in unconstrained environments and possess the kinds of common sense reasoning skills people have. Mental models research also provides practical benefits. In an increasingly technological society, understanding the nature of mental models for complex physical systems could help people learn better conceptual models which could reduce accidents and improve productivity [Norman, 1983].

Qualitative reasoning research was originally motivated in part by the goal of creating a computational account of mental models [de Kleer & Brown, 1984; Forbus, 1984; Bredeweg & Schut, 1991; White & Frederiksen, 1990]. Qualitative models do indeed capture several key features of mental model reasoning. These include representing partial and inexact knowledge, reasoning with partial knowledge, and generating multiple predictions at an abstract, conceptual level of representation. We believe that the representations developed by the QR community provide valuable formalisms for expressing the contents of human mental models.

However, we also see significant problems with qualitative simulation, as it has been typically defined in the QR community, when viewed as an account of human mental model reasoning. [Forbus & Gentner, 1997] described three key problems:

1. *Excessive branching*. A huge number of possible behaviors can often be generated even for relatively simple situations, and the number of behaviors tends to grow exponentially with the size of the system simulated [Kuipers, 1994]. This makes standard qualitative simulation algorithms problematic as psychological models in two ways. First, such simulators tend to produce more possible outcomes than people do when making predictions with the same information. Second, human reasoning about mental models is typically quite fast, and seems to scale better.
2. *Spurious behaviors*. Many spurious behaviors tend to be included in predictions of today's qualitative simulators [Kuipers, 1994]. Such behaviors logically follow from the low-resolution input qualitative descriptions but are not physically possible. In no protocol study that we are aware of does one see subjects spontaneously mentioning, for instance, ordinal relationships between higher-order derivatives, even though this information needs to be considered for accurate qualitative reasoning from first principles.
3. *Exclusive reliance on generic domain theories*. Generic domain theories are attractive because they enable a broad range of possible systems to be modeled, for a variety of potential applications [Forbus, 1988]. However, people seem to understand and reason about the physical world by relying more on concrete, specific knowledge [Forbus & Gentner, 1997].

[Forbus & Gentner, 1997] proposed that *hybrid qualitative simulation*, combining similarity-based reasoning with first-principles reasoning, would provide a more plausible psychological account of human mental models reasoning than traditional purely first-principles qualitative simulation. The idea is that most of our predictions are carried out via analogical reasoning, based on experience with similar situations. With enough experience, and accelerated via the use of language, more abstract principles are slowly formed by a conservative generalization process (see Section 2). These principles are also available for something closer to first-principles reasoning in qualitative simulation.

This paper describes our work in progress on creating a hybrid qualitative simulator. Just as many early investigations into qualitative reasoning focused on purely qualitative reasoning, in order to better understand what it could contribute, here we focus exclusively on using analogy for qualitative simulation, what we call *similarity-based qualitative simulation*. Section 2 briefly reviews the analogical processing ideas we are building upon, and Section 3 describes the theory of hybrid qualitative simulation that we have developed. Section 4 illustrates the operation of our first prototype on several examples, analyzing the strengths and weaknesses apparent so far in our approach. Section 5 discussed related work, and Section 6 provides a summary and discussion of future work.

2. Similarity-based reasoning

Human reasoning appears to rely heavily on analogy and similarity [Gentner & Markman, 1997]. In artificial intelligence, this observation has led to important work on *case-based reasoning* (CBR) systems, where reasoning is based on remembering [Leake, 1996]. CBR systems retrieve the most relevant cases from memory and adapt them to meet the new situations instead of using purely first-principles reasoning [Kolodner, 1993; Leake, 1996]. Although CBR systems originally aimed to provide computational mechanisms similar to what people do, most of today's CBR systems tend to rely on feature vectors. Unfortunately, there is ample psychological evidence that human cognition centrally involves similarity computations over structured representations [Gentner & Markman, 1993].

Our theoretical framework of similarity-based reasoning is based on Gentner's [1983] *structure-mapping theory*, and the computational model is based on the Structure-Mapping Engine (SME) for comparison tasks [Falkenhainer *et al*, 1989; Forbus *et al*, 1994] and MAC/FAC [Forbus *et al*, 1995] for retrieval tasks. Given two descriptions, a *base* and a *target*, SME computes one or two *mappings* representing structural alignments between them. Each mapping contains a set of *correspondences* that align particular items in the base with items in the target, and *candidate inferences*, which are statements about the base that are hypothesized to hold in the target by virtue of these correspondences, and a *structural evaluation score,* which provides an indication of the quality of the match, based on structural properties. Candidate inferences can contain *analogy skolems,* entities hypothesized in the target because of statements in the base. (A historical example of such an entity is caloric, a fluid postulated by virtue of an early analogy between heat flow and water flow.) SME has been used to simulate comparison processes and their roles in various cognitive processes. Here, we use SME to match previously stored behaviors to new situations, generating predictions by projecting the correspondences through state transitions predicted via candidate inferences.

MAC/FAC models similarity-based retrieval as a two-stage process. The first stage (MAC) uses a cheap, nonstructural matcher to quickly filter potentially relevant items from a pool of such items. These potential matches are then processed in the FAC stage by a more powerful structural matcher (SME), its output is a set of correspondences between the structural descriptions, a numerical structural evaluation of the overall quality of the match, and a set of candidate inferences representing the surmises about the probe sanctioned by the comparison. Here, we use MAC/FAC to retrieve prior behaviors for generating predictions about a current situation.

In addition to matching and retrieval, we believe that *generalization* over experiences has an important role to play in hybrid simulation. SEQL [Skorstad *et al*, 1988; Kuehne *et al*, 2000] models this generalization process through *progressive alignment*, using SME to compare examples incrementally and build up new generalizations by keeping the overlap when there are very close matches. However, at this stage of our investigation we have not incorporated SEQL into our system, so generalization will get little attention in this paper.

Another key process in analogy is *rerepresentation*, the process of changing the representations in sound ways to improve matching [Yan *et al*, 2003]. There are three aspects to rerepresentation in our model: *detecting opportunities* for rerepresentation, *generating rerepresentation suggestions* based on libraries of general methods, and *strategies* for controlling the rerepresentation process. It works like this:

1. Opportunities for rerepresentation are detected using criteria based on the principles of structure-mapping theory (e.g., a "hole" in an argument, or many to one matches).
2. For each opportunity, *rerepresentation suggestions* that suggest ways to change the descriptions to improve the match are retrieved and tried.
3. One or more suggestions are adopted, causing changes in the base and/or target.
4. The match is re-performed with the updated base and target descriptions.
5. The process continues until the match is suitable, or it fails, as determined by the rerepresentation strategy for the task.

Rerepresentation is important for hybrid qualitative simulation because it expands the space of situations for which each example behavior can be used, thereby improving the amount of coverage provided by each example.

3. Similarity-based Qualitative Simulation

We propose *similarity-based qualitative simulation* as an alternative to the traditional purely first-principles approach typically used in QR. Similarity-based qualitative simulation relies on a library of remembered experiences and generalizations drawn from them and analogical processing to use this experience in new situations. Specifically,

- *Prediction:* Given a new situation, similarity-based retrieval and analogical comparison is used to map a remembered physical behavior onto the situation. The predictions produced by these analogies, we conjecture, correspond to the content of mental simulations.

- *Abduction:* Given a behavior to be explained, an explanation is constructed by mapping explanations for remembered behaviors onto the new behavior.

In both cases, some first-principles reasoning may be used to help check analogical inferences and to filter aspects of the remembered behaviors that do not make sense. But new behaviors are only generated via analogy, rather than sometimes via first-principles reasoning. This is how similarity-based qualitative simulation differs from the hybrid model proposed in the 1997 paper.

The ability for the same analogical reasoning mechanisms to handle both within-domain and cross-domain analogies should provide a flexibility and smoothness to prediction and abduction that is more in accord with human behavior. Since multiple behaviors can be retrieved and applied, branching predictions are possible, just as they are with first-principles qualitative simulation.

Similarity-based qualitative simulation can exploit multiple types of knowledge. Human beings appear to possess a spectrum of knowledge about the physical world (Figure 1), ranging from *concrete memories* to *first principles knowledge*. There are several forms of intermediate knowledge that lie between specific memories and first-principles in terms of their abstractness. Sometimes the integration of multiple types of knowledge can be required to interpret an observation by an SQS system.

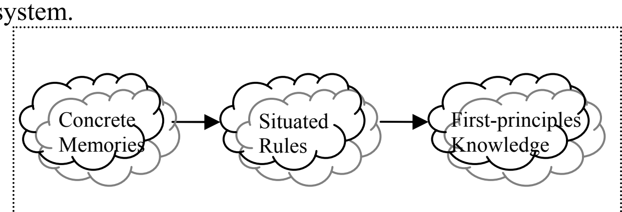


Figure 1. Human beings' knowledge spectrum of the physical world.

Concrete memories represent pure memory of specific circumstances. Such circumstances could be something somebody has experienced only once in his/her whole life (e.g., the moon walking experience for Neil Armstrong), something dramatic (e.g., a car accident), or something interesting just happened recently, and got stored in your memory (e.g., this year's Halloween pumpkin cutting experience). The behavior's description of such circumstances might include many concrete details, such as visual descriptions of the objects and their behaviors [Forbus, & Gentner, 1997].

Situated rules are abstractions of the concrete memories. They are formed by successive comparisons of very concrete situations, conservatively removing details that are not common across otherwise similar situations, and constructing prototypical behaviors [Forbus & Gentner, 1986]. Situated rules are partially abstracted but still partially contextualized. Some accounts of mental schema also appear to have this character.

First-principles knowledge represents the last state of knowledge on the spectrum. It is universal and demonstrative; what we know scientifically is what we can derive, directly or indirectly, from first principles that do not themselves require proof.

One of the consequences of doing reasoning is the slow evolution of mental models, via progressive alignment, that incrementally removes irrelevant aspects of a behavior description in successive comparisons of examples and generates intermediate kinds of knowledge such as situated rules and, ultimately, first-principles knowledge [Forbus & Gentner, 1986]. Rerepresentation also plays an important role in the evolution of mental models, since the process of rerepresentation appears to change memory contents in ways that promote transfer [Gentner *et al*, 2003]. Finally, there is psychological evidence suggesting that language is an important force in rapid learning, in part because it invites appropriate comparisons [Gentner, 2003], which then lead to rerepresentation and/or generalization.

4. A prototype SQS system

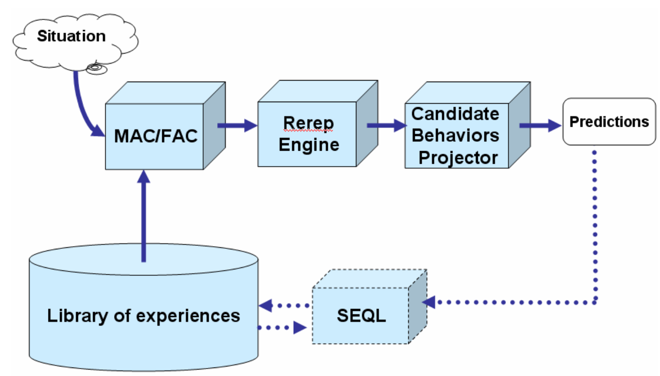


Figure 2. SQS system structure

Figure 2 illustrates the structure of our prototype SQS system. The input is a situation, and the desired output is a prediction of the state (or states) that might happen next. In the first step, processing begins by using MAC/FAC on a library of experiences. MAC/FAC returns between zero and three remindings; if there is no reminding then no prediction is possible. If there are multiple remindings, the reminding with the highest structural evaluation score (i.e., the closest match to the situation) is selected for processing first. In the second step, the match between the retrieved situation and the current situation is scrutinized by the rerepresentation system, and tweaked if necessary. The goal of this rerepresentation process is to ensure that there are candidate inferences concerning state transitions, since these are what will provide predications. Currently, all rerepresentation methods that might increase the structural evaluation score of the match are carried out, exhaustively. If rerepresentation fails, the system returns to the original match.

The third step is to use the correspondences and candidate inferences of the mapping to project possible next states.

This is accomplished by retrieving, for each state transition in the candidate inferences containing the retrieved state as the "before" and an analogy skolem for the "after", the next state from the retrieved state that it predicts. Each transition leads to a new prediction, generated by substituting into the retrieved next state the correspondences found between the retrieved current state and the current situation.

Our current prototype is still missing several important features. For instance, the substitution process for generating new predications is likely to lead to other analogy skolems, and efforts to resolve those skolems by identifying them with entities in the current situation need to be made. We suspect that first-principles reasoning is sometimes used to filter possible candidate behaviors (e.g., continuity violations), but we do not yet filter behaviors in any way. We currently only pick the most similar reminding to generate behaviors from; it seems likely to us that if there were another very close remindings, both might be used to generate behaviors. Currently, we carry out rerepresentation suggestions exhaustively; however, this process should be more selective and be controlled by task specific strategies. Finally, we neither store back into memory the results of rerepresentation, nor do we use SEQL to create generalizations on the fly. Even with these limitations, however, we think that the prototype shows some intriguing behaviors and possibilities.

To test the prototype, we generated a small library of experiences in two ways. First, we used Gizmo Mk2, a descendant of the original QP implementation, to generate envisionments for several classic QR examples (two containers, simple heat flow). We saved with each state information about its individuals, concrete details (e.g., individual appearance and/or surface properties), assumptions, ordinal relations involving both amounts and derivatives, model fragments, and transitions to possible next states, etc. as a single case in MAC/FAC's case library. Second, we generated by hand qualitative descriptions of behavior for a feedback system, to test the system's ability to work with behaviors involving incomplete state descriptions where no first-principles domain theory is available.

We next describe the prototype's operation on several examples, to illustrate its strengths and weaknesses.

Example 1. Two containers liquid flow

Liquid flow is a common phenomenon in physical systems. The prototype's initial knowledge contains behaviors about the classic two container liquid flow system (as shown in Figure 3(a)), in which liquid flows from one container (F) to another (G), through a pipe (P1) connecting them. The two darkened path arrows indicate the qualitative behaviors for the liquid flow model. Initially, if container F's pressure is greater than G's pressure, liquid is flowing from F to G. Eventually, a new state is reached in which their pressures are equal and liquid flow has stopped. If container G had started out with a higher pressure than container F, liquid should flow the other way.

```
State0
↓(AmountOf Water Liquid F)
↑(AmountOf Water Liquid G)
↓(Pressure Wf)
↑(Pressure Wg)
(> (Pressure Wf)
   (Pressure Wg))
(activeMF LiquidFlow)

State1
↑(AmountOf Water Liquid F)
↓(AmountOf Water Liquid G)
↑(Pressure Wf)
↓(Pressure Wg)
(< (Pressure Wf)
   (Pressure Wg))
(activeMF LiquidFlow)

State2
→(AmountOf Water Liquid F)
→(AmountOf Water Liquid G)
→(Pressure Wf)
→(Pressure Wg)
(= (Pressure Wf)
   (Pressure Wg))
(not (activeMF LiquidFlow))
```

Figure 3(a).

Figure 3(b) shows a specific situation given to the prototype, in which a beaker connected to a vial through a pipe and the predictions generated for this configuration by similarity-based reasoning. Drawing from experience, the prototype retrieved `state0` as the closest analogue to the input scenario, inferring the liquid is flowing from the beaker to the vial, and predicted a single next state, based on projecting `state0`'s successive state `state2`, in which the pressure in the beaker and in the vial are equal and the liquid flow has stopped.

```
↓(AmountOf Water Liquid
Beaker)
↑(AmountOf Water Liquid Vial)
↓(Pressure Wb)
↑(Pressure Wv)
(> (Pressure Wb)
   (Pressure Wv))

→(AmountOf Water Liquid
Beaker)
→(AmountOf Water Liquid Vial)
→(Pressure Wb)
→(Pressure Wv)
(= (Pressure Wb)
   (Pressure Wv))
```

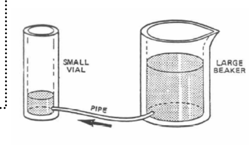
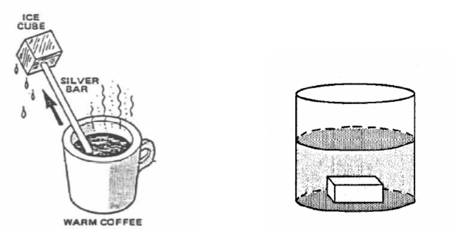


Figure 3(b). Similarity-based qualitative simulation for the beaker-vial liquid flow scenario

Example 2. Heat flow

Figure 4 shows a situation in which a hot brick is immersed in cold water. In order to provide behavioral predictions for this scenario, the prototype begins by searching memory for analogous situations. Only one candidate analogue demonstrates strong similarities with the observed situation – heat flow from hot coffee to ice cube. Figure 3 demonstrates the behaviors of the hot coffee ice cube heat flow scenario, in which heat flows from one finite thermal physical object (hot coffee) to another (ice cube), through a silver bar (bar) connecting them. Eventually a new state is reached in which the hot coffee and the ice cube have the same temperature, and the heat flow process has stopped.



State0

```
↓ (Temperature Coffee)
↑ (Temperature IceCube)
(> (Temperature Coffee)
   (Tempearature IceCube))
(activeMF HeatFlow)
```

State1

```
→ (Temperature Coffee)
→ (Temperature IceCube)
(= (Temperature Coffee)
   (Tempearature IceCube))
(not (activeMF HeatFlow))
```

Input Scenario

```
↓ (Temperature Brick)
↑ (Temperature Water)
(> (Temperature Brick)
   (Tempearature Water))
(activeMF HeatFlow)
```

Behavior Prediction

```
→ (Temperature Brick)
→ (Temperature Water)
(= (Temperature Brick)
   (Tempearature Water))
(not (activeMF HeatFlow))
```

Figure 4. Similarity-based qualitative simulation for the hot brick immersed in cold

The prototype determines that the roles of the hot coffee, ice cube and bar in the heat flow description correspond to the roles of the brick, water and the surface contact between the brick and water in the target situation, respectively. Additionally, it finds that quantities like temperature and heat in the coffee/ice cube situation correspond to the same quantities in the hot brick/cold water situation. It also generates candidate inferences that there should be a heat flow process active in the target input scenario, in which the temperature of the brick is dropping, while the opposite is true for the water. The projected new state for the hot brick cold water scenario is that the brick and the water reach the same temperature eventually, and heat flow process has stopped.

Feedback Control System	Water Level Regulation System
Sensor	Floating ball
Comparator	Pulleys
Temperature set point	Proper water level
Room air	Tank water
Room	Water tank
Oven	Water supply
Heat flow process	Liquid flow process
Furnace on process	Valve open process

Quantities	S1	S2	S3	S4	S5	S6
(Temperature Room) vs. SetPoint	<	=	>	>	=	<
(Ds (Temperature Room))		1			-1	
(activeMF FurnaceOn)		Yes			No	
(activeMF HeatFlow)		Yes			Yes	

Quantities	S1	S2	S3	S4	S5	S6
(Level TankWater) vs. ProperWaterLevel	<	=	>	>	=	<
(Ds (Level TankWater))		1			-1	
(activeMF ValveOpen)		Yes			No	
(activeMF LiquidFlow)		Yes			Yes	

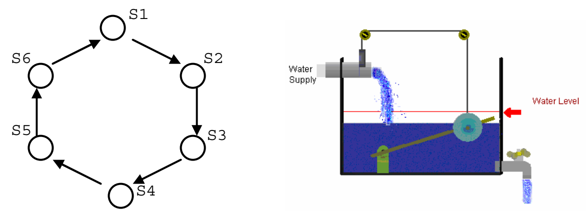


Figure 5. Similarity-based qualitative simulation for the water level regulation system

Example 3. Discrete on/off feedback control system

Consider a simple room heating system. The sensor measures the temperature in the room. The dial on the thermostat allows you to set the temperature you want the room to be at. Two major processes exist in this scenario. When the furnace is on, heat flows from the furnace to the room[1]. The room is also always losing heat to the outside. When the temperature in the room falls below the temperature set point on the dial, the furnace will turn on to heat the room. When the temperature in the house rises above the temperature set point, the furnace will turn off, and the continued heat loss from the room to the outside eventually causes the temperature of the room to drop below the set point. This behavior was encoded by hand, so that we did not have to make any particular commitments to the sources of lag or delay in the system, hysteresis in the set point, or any of a number of factors that would have been required in a correct first principles model of the situation. This enables us to see whether a partially understood situation might still be used for prediction.

Figure 5 chart 2 summarizes the behavior for the heating system. In states S1, S2, and S3 the furnace is on and the temperature of the room is less than, equal to, or greater than the temperature of the set point respectively, with its amount increasing due to the activity of the furnace on process. In state S4, S5, and S6 the furnace is off and the temperature of the room is greater than, equal to, or less than the temperature of the set point respectively, with its amount decreasing due to the heat loss from the room to outside. Starting from any state, the behavior of the home heating system takes the path shown in the six states loop of Figure 5.

Now consider an analogous control system, also shown in Figure 5. The water tank system tries to keep the water level in the tank at a constant value when the faucet is turned on. There is a ball float connected to a stopper valve that moves up and down with the water level. When the ball float moves down, the stopper valve is open. When the ball float moves up, it lowers the stopper, closing the valve. The input scenario given to the prototype is a situation in which the ball float is lower than the proper water level, and the stopper valve is open and letting water into the tank from a

[1] We are ignoring how the furnace is kept hot, something every homeowner with a heating bill would like to do.

larger water supply. The prototype maps the roles of the floating ball, tank water, level of the tank water, the proper water level, pulleys, the water supply, valve open process, and the liquid flow process in the water tank scenario to the sensor, room air, the temperature of the room, the set point, comparator, furnace, furnace on process, and the heat flow process in the home heating system respectively (as shown in the first chart of Figure 5). It retrieves state S1 as the closest reminding for the current situation, and projects the successive five future states the water tank scenario will get to as shown the third chart of Figure 5.

Example 4. Proportional action control system

Proportional action control systems are another kind of feedback control systems. They are different from discrete on/off feedback control systems modeled in example 3 in that such systems set the power supplied to the process proportional to the difference between the temperature and set point in order to provide temperature stability by eliminating fluctuations in temperature. The proportioning action occurs within a "proportional band" around the set point temperature, When the temperature enters the proportional band, the furnace output becomes gradually smaller and the temperature stabilizes somewhere within the proportional band.

Since the closest behavior in the prototype's initial knowledge base is a behavior for discrete on/off feedback control system, given a scenario of a proportional action control system in which the temperature is higher than the set point but smaller than the proportional band and the furnace is on, our prototype predicts the new state for this scenario is that the furnace turns off and that the temperature of the room decreases. This is inconsistent with what the proportional control system actually does. This illustrates that similarity-based qualitative simulation can lead to spurious behaviors, by applying inappropriate analogs. There are two points to make here. First, in a full hybrid simulator first-principles reasoning could be used to do additional testing of predictions, and could in some cases catch spurious behaviors if there is rich enough domain knowledge available. Second, similarity-based qualitative simulation can be improved by remembering the behaviors that it couldn't otherwise explain: A very simple, but we suspect very powerful, learning mechanism.

Example 5. Specific room heating system: a thermostat

This example illustrates how the SQS system applies knowledge from general schemas to make predictions for specific scenarios, and how the rerepresentation engine helps the prototype to achieve flexibility in similarity based qualitative reasoning. As described in example 3 and 4, the prototype's initial knowledge contains behaviors about the general schema for a room heating regulation system. Consider giving a specific room heating system, a thermostat, as the input scenario for the prototype. A small fragment of the representations involved in both situations is:

B:
```
(senses SensorX (Temperature RoomAirX))
(compares ComparatorX (Temperature RoomAirX)
          TemperatureSetpointX)
```

T:
```
(senses ThermostatY (Temperature RoomAirY))
(compares ThermostatY (Temperature RoomAirY)
          TemperatureSetpointY)
```

Our prototype conjectures that the thermostat plays the role of the sensor and comparator in the abstract schema. However, this match cannot be allowed, since it violates the 1:1 constraint of the structure mapping theory, which leads to only one pair of entity alignment (`SensorX` align to `ThermostatY`) being included in the legitimate match between the retrieved situation and the current scenario.

[Yan *et al*, 2003] calls such rerepresentation opportunities *rivals*, which are violations of the 1:1 constraint that lead to structural inconsistency of at least one match hypothesis. It is often caused by the same entity playing multiple roles in the same representation.

Next, our rerepresentation engine takes the reminding match that has the highest structural evaluation score, and refines the description of the thermostat, suggesting that it is the curvature of its bimetallic strip that measures the temperature, and the angular distance between the bimetallic strip and the dial's angle that provides the comparison. This is an example of an *entity splitting* strategy. In general, entity splitting strategies require identifying ways to divide up an entity into distinct parts or aspects, and rewrite its roles in the description to use one or the other of these parts or aspects. After rerepresentation, each of the aspects of the thermostat can match to distinct functional descriptions from the retrieved schema, leading to a much better match. E.g.,

T':
```
(senses (CurvatureFn BimetallicStrip)
        (Temperature RoomAirY))
(compares (AngleFn BimetallicStrip)
          (Temperature RoomAirY)
          TemperatureSetpointY)
```

Finally, the prototype relies on the updated match to project new states for the rerepresented scenario.

5. Related Work

The observation that analogical matching could be used for deduction or abduction depending on the kind of knowledge involved was first made by Falkenhainer [1988]. His PHINEAS system used cross-domain analogies involving behaviors to first retrieve elements of a domain theory used to explain the original behavior, and then modify those domain theory elements to form a partial new domain theory that could explain the new behavior. This new domain theory was tested via first-principles qualitative simulation. While we build on ideas from PHINEAS in several ways, notably the use of the map/analyze cycle and using analogical reasoning for abduction, our MAC/FAC model for retrieval is more psychologically plausible than what was available then, and our focus is on using analogy directly for prediction and explanation, rather than constructing a new first-principles domain theory.

Connectionist simulations of analogical matching and retrieval, such as ACME [Holyoak & Thagard, 1989], LISA [Hummel and Holyoak, 1997] and CAB [Larkey & Love, 2003] are aimed at creating neurally plausible models of analogical processing. Unfortunately, such models so far cannot handle examples as complex as people can, including the examples described in this paper.

The CBR community has created many systems that generate predictions [cf. Kolodner, 1994]. However, CBR systems tend to use matching and retrieval systems that are optimized for each task and each domain. Our system uses psychological models of analogical matching and retrieval that have been used in a variety of domains and tasks [cf. Forbus *et al*, 2002], making it more likely to scale to the wide variety of situations that mental models reasoning is applied in.

6. Discussion & Future Work

We believe that similarity-based qualitative simulation is a plausible model of human reasoning. While our prototype is not yet complete, the examples suggest that the approach has promise. Most of the future work revolves around addressing its limitations:

- The library of experiences needs to be significantly expanded, to stress-test retrieval and rerepresentation.
- Skolem resolution strategies that attempt to identify hypothesized entities in the prediction with unmapped entities in the current situation need to be explored.
- Criteria for using multiple remindings need to be formulated.
- Learning strategies, in the form of storing back the results of rerepresentation and using SEQL to construct generalizations, also need to be explored.

Acknowledgements

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