Analogy Tutor: A Tutoring System for Promoting Conceptual Learning via Comparison

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Abstract

A major challenge in artificial intelligence is building intelligent, interactive learning environments that can support students in human-like ways. Analogical reasoning can be a catalyst for conceptual learning, yet very few systems support analogical reasoning as an instructional activity. In my thesis, I plan to demonstrate that an analogy tutor can assist conceptual learning by guiding students through instructional comparisons.

Introduction

Artificial intelligence in education has grown into an entire subfield aimed at developing intelligent systems that use AI techniques to adaptively and dynamically help students learn (VanLehn 2011). Today's state of the art intelligent learning environments support students as they navigate well-defined problems (e.g. algebra problem solving). However, misconceptions are often resistant to instruction in procedural problem solving (Hestenes, Wells & Swackhamer 1992). It is therefore important to explore new approaches for supporting conceptual learning in more domains, using instructional techniques that are new to tutoring systems.

Instructional comparison (i.e. comparing two scenarios to promote learning) is a technique that is pervasive classrooms and in textbooks but has yet to be adequately explored in intelligent tutoring systems. Cognitive science research indicates that analogical comparison can help individuals learn abstract concepts and apply those concepts to new scenarios (Gick & Holyoak 1983; Loewenstein, Thompson & Gentner 1999). In my thesis, I plan to demonstrate that an analogy tutor can assist conceptual learning by guiding students through instructional comparisons.

Related Work

To characterize instructional comparison, I will draw upon research on a*nalogical reasoning,* which refers to the processes that occur when people compare things to each other. Analogical reasoning has been described by *Structure-Mapping Theory (SMT)* (Gentner, 1983) and instantiated with the *Structure Mapping Engine (SME)* (Falkenhainer, Forbus & Gentner 1989). SME takes two structured descriptions, a base and a target, and computes *correspondences*, which indicate how items match to each other and may also compute *candidate inferences*, which are things that are true in the base and hypothesized to be true in the target (black nodes in Figure 1).

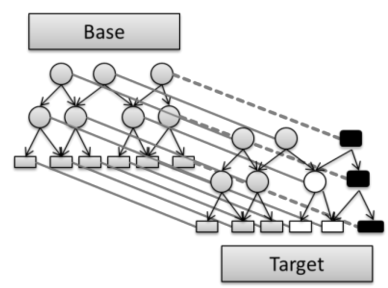

Figure 1: Two structured descriptions and the analogical mapping between them. The lines connecting the base to the target are correspondences. Black nodes are introduced via candidate inference and white nodes are candidate inference support.

To characterize the qualitative nature of conceptual knowledge, I will use related work on *qualitative reasoning* (Forbus, 1984), which enables reasoning about processes and quantities without numerical values, and *model formulation* (Friedman & Forbus, 2011), which enables a system to formulate partial causal models about a scenario. The use of qualitative representations is important because qualitative problem solving has been shown to be an excellent probe for conceptual knowledge (Hestenes, Wells & Swackhamer 1992).

Many tutoring systems have used qualitative representation and reasoning, but to the best of my knowledge, there have only been two intelligent tutoring systems that use analogy. The bridging analogies tutor (Murray et al. 1990) uses intuitive physical scenarios to help students understand less intuitive physical scenarios. This system, however, did not provide students with feedback about their inferences or comparisons. Another system modeled analogies used by expert human tutors (Lulis 2005), and while the system modeled complex dialogue for each analogy, the representations were not extendable to new analogies or different domains.

Planned Approach

To support my thesis, I will develop an analogy tutor that guides students through comparisons of scenarios in physics and biology. Structure-mapping will be used as the basis of the task model to provide the student with detailed feedback. This tutoring system will be built on the Companions Cognitive Architecture (Forbus & Hinrichs, 2006) which has qualitative reasoning capabilities and uses analogy as a central reasoning mechanism.

During a single iteration of a comparison, the student will be asked to sketch two scenarios into CogSketch (Forbus et al., 2011), an existing sketch understanding system that automatically generates structured representations that can be input to SME. Model formulation will be used to identify a causal model for the student's scenario. The student will be asked to interactively compare the scenarios to each other. I will build feedback strategies into a *structure-mapping task model* to provide the student with fine-grained feedback on their comparison. For instance, given two scenarios where the student fails to infer an important candidate inference, the tutor can use candidate inference support (white nodes, Figure 1) to automatically generate hints to the student. The content of the candidate inference support and the hints will be domain specific (e.g. causal antecedents to the qualitative causal model). However, the mechanism for retrieving those hints will be based on structure-mapping theory, and will therefore be domain-independent.

As of this writing, I have developed a subset of the qualitative causal models that will be needed to represent the conceptual physics scenarios. All other aspects of the tutor are currently under development.

Evaluation and Contribution

My evaluations will test two main hypotheses. The first is that the system can use the same reasoning mechanisms to understand sketched analogies in multiple domains. I will test this by evaluating the system's interpretations of sketched analogies (e.g. precision and recall of candidate inferences) in physics and biology (Harrison & Cole, 2007). The second hypothesis is that the system's interpretation of analogies and strategies for providing feedback can help individuals learn in a conceptual domain. I will conduct a controlled study measuring the learning effects of the analogy tutor versus a learning activity that does not use instructional comparison. With these evaluations, the main contribution of my thesis will be a framework for developing analogy-based tutoring systems for conceptual knowledge with domain-independent feedback strategies.

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