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Mixed-Initiative Exception-Based Learning for Knowledge Base Refinement

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Introduction

Over the years we have developed the Disciple approach for the rapid development of knowledge bases and knowledge-based agents, by subject matter experts, with limited assistance from knowledge engineers (Tecuci et al, 2000). This approach relies on a Disciple learning agent that can be trained to solve problems by an expert. First, however, a knowledge engineer has to work with the expert to define the object ontology of Disciple. This ontology consists of hierarchical descriptions of objects and features from the application domain. Then, the expert can teach Disciple to solve problems in a way that resembles how the expert would teach a student. For instance, the expert defines a specific problem, helps the agent to understand each reasoning step toward the solution, and supervises and corrects the agent's behavior, when it attempts to solve new problems. During such mixed-initiative interactions, the agent learns general problem solving rules from individual problem solving steps and their explanations of success or failure. A critical role in this multistrategy rule learning process is played by the object ontology, which is used as the generalization hierarchy.

Mixed-Initiative Exception Based Learning

The Disciple approach was successfully used in an agent training experiment at the US Army War College, where experts succeeded to teach personal Disciple agents their own problem solving expertise in military center of gravity (COG) determination (Boicu et al., 2001). This experiment, however, revealed that the rules learned from subject matter experts have a significant number of negative exceptions. A negative exception is a negative example that is covered by the rule, because the current object ontology does not contain any object concept or feature-value pair that distinguishes between all the positive examples of the rule, on one side, and this negative example, on the other side. Therefore, in the context of the current ontology, the rule cannot be specialized to uncover the negative example, which is kept as a negative exception. Such rule exceptions provide valuable information on how the ontology should be extended to represent the subtle distinctions that real experts make in their domain.

We are developing a suite of mixed-initiative multistrategy methods for learning new object concepts and features that extend the object ontology, allowing the elimination of the rule's exceptions. The first type of methods involves only the Disciple agent and the expert, and considers one rule with its exceptions at a time. The second class of methods considers again one rule with its exceptions at a time, but requires also the participation of a knowledge engineer in the mixed-initiative learning process. Finally, the third and most complex type of methods are global, considering all the exceptions from the knowledge base, and involving both the expert and the knowledge engineer. All the methods have four major phases: a candidates discovery phase, a selection phase, an ontology refinement phase, and a rule refinement phase. In the candidates discovery phase, the Disciple agent generates an ordered set of candidates that have the potential of removing the exceptions. Each candidate is a new ontology piece (for instance, a new value of an existing feature, a new object feature, or even new object concept) that has the potential of distinguishing between the positive examples and the negative exceptions. To generate these candidates and to order them by their plausibility, Disciple uses analogical reasoning heuristics, ontology design principles, and hints from the user. In the candidate selection phase, Disciple interacts with the user to test the most plausible candidates, and to select one of them. In the ontology refinement phase Disciple elicits additional knowledge from the expert, related to the selected hypothesis. For instance, if the selected hypothesis is a new type of feature, then Disciple will attempt to elicit from the expert which other objects from the knowledge base have that feature, and will also learn a general definition of the feature. This definition includes a domain concept (which represents the set of objects that can have that feature), and a range concept (which represents the set of possible values of that feature). Finally, in the rule refinement phase, the rule is updated based on the refined ontology. Because of the central role of the object ontology as the generalization hierarchy for learning, an ontology change may potentially affect any rule from the knowledge base, not only those with exceptions. We have therefore developed methods for rapid rule relearning in the context of the updated ontology. These methods maintain the relevant knowledge from which an individual rule was learned, such as generalized explanations and prototypical examples, and automatically regenerate the rule based on the updated ontology.

We will illustrate an example of the first type of exception handling methods, in which the expert collaborates with Disciple to analyze a rule with a negative exception. Figure 1 shows an example of a task reduction step from the Center of Gravity analysis domain (Boicu et al., 2001). It consists of a problem solving task, a question relevant to the reduction of this task, the answer to the question, and the subtask resulted from this answer.

IF the task is
Identify a strategic COG candidate for Japan_1944 with respect to other sources of strength and power
Question: *What is a source of strength and power of Japan_1944?*
Answer: *Concentration_of_naval_assets*
THEN
Concentration_of_naval_assets is a strategic COG candidate for Japan_1944

Figure 1: A problem solving episode

Based on this problem solving episode, Disciple learns a general task reduction rule. This rule, however, generates the wrong solution "Japanese_expectation_for_negotiation is a strategic COG candidate for Japan_1944," which is rejected by the expert. Because the ontology does not contain any element to distinguish between "Japanese_army_forces_on_Luzon" and "Japanese_expectation_for_negotiation," the incorrect reasoning step is kept as a negative exception of the rule. The expert can invoke the Exception Handling tool, attempting to extend the ontology by himself. First Disciple proposes him candidate extensions that have the potential of removing the exception. For instance, Disciple looks for an existing feature that may be associated with "Japanese_army_forces_on_Luzon" (the positive example), without being associated with "Japanese_expectation_for_negotiation" (the negative exception), and finds "is_a_strategically_important_military_capability_for." The domain of this feature is "military_factor", which includes the positive example without including the negative exception. The expert accepts this feature and specifies that its value for the positive example is Japan_1944. Next Disciple guides the expert to also specify this feature for the other instances of military_factor, such as "Japanese_concentration_of_naval_assets." Then it refines the object ontology with this new knowledge acquired from the expert, as shown in Figure 2. Disciple refines also the rule based on this elicited feature value, transforming the negative exception into a negative example that is no longer covered by the rule.

As illustrated above, the first class of methods discovers limited extensions of the ontology (such as an additional feature of an object when the feature definition is already present in the ontology). The second class of methods leads to more complex refinements, such as the definition of new types of objects or the restructuring of the object hierarchy. For instance, Disciple may elicit from the expert an explanation of why the negative exception of a rule is an incorrect problem solving episode, explanation represented by a new type of object that is placed in the object hierarchy. The methods from the third and most complex class first hypothesize knowledge pieces for all the rules with exceptions. Then, they analyze all these hypotheses to define an ordered set of hypotheses, each one eliminating or reducing the number of exceptions from more than one rule.

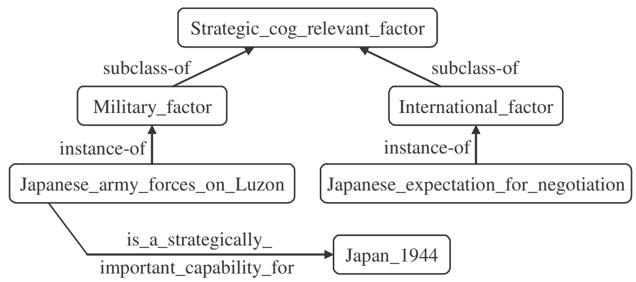

Figure 2: A fragment of the refined object ontology

Conclusions

Some of the above methods are already implemented in the Exception-Based Learning module of Disciple-RKF/COG. With these methods we are proposing a solution to the complex problem of learning with an evolving representation language, as represented by the evolving object ontology.

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