Learning Effective Search Control Knowledge: An Explanation-Based Approach

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Abstract

In order to solve problems more effectively with accumulating experience, a problem solver must be able to learn and exploit search control knowledge. Although previous research has demonstrated that Explanation-Based Learning (EBL) is a viable approach for acquiring control knowledge, in practice the learned control knowledge may not be useful. For control knowledge to be effective, the cumulative benefits of applying the knowledge must outweigh the cumulative costs of testing whether the knowledge is applicable. Previous research in EBL has ignored this issue, which I refer to as the *utility* problem. Most researchers have simply demonstrated that EBL can improve performance on particular examples without analyzing exactly when performance improvement will occur. In practice, it is much more difficult improve performance over a population of examples than it is to improve performance on isolated examples.

One answer to the utility problem is to search for "good" explanations -- explanations that can be profitably employed to control problem solving. Instead of simply adding control knowledge haphazardly, a learning system must be sensitive to the problem solver's computational architecture and the potential costs and benefits of adding knowledge. This thesis analyzes the utility of EBL, and describes a method for searching for good explanations. The method, implemented in the PRODIGY/EBL system, consists of a three-stage heuristic search. Given a problem solving trace, PRODIGY first selects what to learn. The system chooses from a variety of target concepts, each representing a different strategy for optimizing performance. Secondly, after creating an initial explanation from the trace, PRODIGY searches for a representation of the explanation that is efficient to match. Finally the system empirically tests the effectiveness of the learned control knowledge to determine whether it is actually worth keeping.

The thesis includes a set of comprehensive experiments testing the performance of the PRODIGY/EBL system and its components in several domains. In addition, a formal description of EBL is presented, together with a correctness proof for PRODIGY's generalization method.