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# Machine Learning Techniques For Knowledge-Based Systems

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**Abstract**

This paper provides an overview of recent research in developing machine learning techniques that are relevant to creating knowledge-based systems.

## I. Introduction

The source of power of knowledge-based systems is their domain-specific knowledge. The principal challenge in building a knowledge-based system is the acquisition of this knowledge. Advances in automated knowledge acquisition can be traced to new machine learning methods and to better methods of knowledge organization for knowledge-based systems.

## II. Similarity-Based Learning

*Similarity-based learning* focuses on the induction of knowledge structures from a collection of classified examples. Some of the earliest work in automated knowledge acquisition took this approach, such as Meta-Dendral [Buchanan and Mitchell, 1978] and Induce [Michalski et al., 1983]. These early efforts focused on inducing pattern-action rules for expert systems. Recent research has focused on learning more complex knowledge structures. For instance, Cluster [Stepp and Michalski, 1986] learns classifications of structured objects, and RL [Fu and Buchanan, 1985] learns intermediate concepts, probabilistic domain-level rules, and meta-level rules. There is a growing realization that deleterious interactions between induced rules can significantly reduce problem-solving performance. Two efforts have shown how performance can be improved by deletion of part of the rule set [Michalski et al., 1986,Wilkins et al., 1986].

## III. Explanation-Based Learning

*Explanation-based learning* can be used to improve a knowledge-based system; learning is achieved during the process of constructing explanations of examples [DeJong and Mooney, 1986,Mitchell et al., 1986]. The explanations are constructed using knowledge of the problem domain. This approach represents the major advance in machine learning research in recent years. If a complete domain theory is available, then a deductive approach to explanation-based learning is possible. Excellent examples of a deductive approach are the Leap system in the domain of VLSI circuit design [Mitchell et al., 1985] and the Genesis program in the domain of story understanding [DeJong and Mooney, 1986].

If the domain theory is incomplete, then an inductive approach to explanation-based learning can be taken. The domain theory permits a partial explanation of the example to be constructed. Induction can then be used to complete this partial explanation. A good example of this approach is the Odysseus system in the domain of medical diagnosis [Wilkins et al., 1986,Wilkins et al., 1988].

## IV. Knowledge Representation

It is now widely recognized that the space of expert systems decomposes into a number of generic problem classes, such as diagnosis, design, prediction, and planning [Hayes-Roth et al., 1983]. Construction of an expert system by the use of a shell for the generic problem class has significant consequences for knowledge acquisition. The knowledge of how to do problem solving for a generic class can be manually encoded, and then only the factual domain-specific knowledge needs to be automatically learned. The Odysseus apprentice learning system provides one example of this approach. Odysseus improves an expert system that is implemented using the Heracles expert system shell [Clancey and Bock, 1986], which solves problems using the heuristic classification method. The advantage of a shell derives largely from separation of the declarative knowledge of the application domain from the strategic and procedural knowledge of how problems are to be solved using this knowledge. This procedural knowledge is concentrated in the generic shell.

## IV. Research Directions

We can expect explanation-based learning to be a very active area of research in the next few years. The major open problems relate to dealing with domain theories that are incomplete, inconsistent, or intractable.

Relating machine learning to automatic programming may also turn out to be important. Automatic programming requires three types of knowledge. The first is knowledge of how to program. This is the type of knowledge that was explicitly represented in the PSI system [Green and Barstow, 1978]. The second is knowledge of what the program is supposed to do. The Programmer's Apprentice project focused on the representation of this type of knowledge [Rich et al., 1979]. Lastly, knowledge of the domain in which the program is to operate. This is the type of knowledge that is encoded in knowledge-based expert systems. Past efforts in automatic programming have not involved any significant use of domain knowledge. Knowledge-based expert systems have provided us with an understanding of how to represent and use domain knowledge. Use of this understanding may lead to a renaissance in automatic programming, of which knowledge-based systems are most likely to be the first beneficiary.

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