

Chapter LXIV

Differential Learning Expert System in Data Management

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INTRODUCTION

Expert systems have been applied to many areas of research to handle problems effectively. Designing and implementing an expert system is a difficult job, and it usually takes experimentation and experience to achieve high performance. The important feature of an expert system is that it should be easy to modify. They evolve gradually. This evolutionary or incremental development technique has to be noticed as the dominant methodology in the expert-system area. The simple evolutionary model of an expert system is provided in B. Tomic, J. Jovanovic, & V. Devedzic, 2006.

Knowledge acquisition for expert systems poses many problems. Expert systems depend on a human expert to formulate knowledge in symbolic rules. The user can handle the expert systems by updating the rules through user interfaces (J. Jovanovic, D. Gasevic, V. Devedzic,

2004). However, it is almost impossible for an expert to describe knowledge entirely in the form of rules. An expert system may therefore not be able to diagnose a case that the expert is able to. The question is how to extract experience from a set of examples for the use of expert systems.

Machine-learning algorithms such as “learning from example” claim that they are able to extract knowledge from experience. Symbolic systems as, for example, ID3 (Quinlan, 1983) and version-space (Mitchell, 1982) are capable of learning from examples. Connectionist systems claim to have advantages over these systems in generalization and in handling noisy and incomplete data. For every data set, the rule-based systems have to find a definite diagnosis. Inconsistent data can force symbolic systems into an indefinite state. In connectionist networks, a distributed representation of concepts is used. The interference of different concepts allows networks to generalize. A network computes for every input the best output.

Due to this, connectionist networks perform well in handling noisy and incomplete data. They are also able to make a plausible statement about missing components. A system that uses a rule-based expert system with an integrated connectionist network could benefit from the described advantages of connectionist systems. Machine-learning helps towards that end.

BACKGROUND

Maintenance of databases in medium-size and large size organizations is quite involved in terms of dynamic reconfiguration, security, and the changing demands of its applications. Here, compact architecture making use of expert systems is explored to crisply update the database. An architecture with a unique combination of digital signal processing/information theory and database technology is tried. Neuro-fuzzy systems are introduced to learn “if-then-else” rules of expert systems.

Kuo, Wu, and Wang (2000) developed a fuzzy neural network with linguistic teaching signals. The novel feature of the expert system is that it makes use of a large number of previous outputs to generate the present output. Such a system is found to be adaptive and reconfigures fast. The expert system makes use of a learning algorithm based on differential feedback.

The differentially fed learning algorithm (Manjunath & Gurumurthy, 2002) is introduced for learning. The learning error is found to be minimal with differential feedback. Here, a portion of the output is fed back to the input to improve the performance. The differential feedback technique is tried at the system level, making the system behave with the same set of learning properties. Thus, control of an expert system controls the entire system

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The expert systems are organized in a hierarchical fashion. Each level controls a unique set of databases. Finally, the different expert systems themselves are controlled by a larger expert system. This ensures security of databases and selective permissions to their access, (i.e., some of the data needs to be public and the rest has to be private and protected; a concept borrowed from object-oriented programming). Thus, the master expert system can have access to public information. The neural networks are integrated with a rule-based expert system. The system realizes the automatic acquisition of knowledge out of a set of examples. It enhances the reasoning capabilities of classical expert systems with the ability to generalize and the handle incomplete cases. It uses neural nets with differential feedback algorithms to extract regularities out of case data. A symbolic-rule generator transforms these regularities into rules governing the expert system. The generated rules and the trained neural nets are embedded into the expert system as knowledge bases. In the system diagnosis phase it is possible to use these knowledge bases together with human experts' knowledge bases in order to diagnose an unknown case. Furthermore, the system is able to diagnose and to complete inconsistent data using the trained neural nets exploiting their ability to generalize.

It is required to describe a possible approach for the optimization of the job scheduling in large distributed systems, based on self-organizing neural networks. This dynamic scheduling system should be seen as adaptive middle-layer software, aware of current available resources and making the scheduling decisions using past experience. It aims to optimize job-specific parameters as well as resource utilization. The scheduling system is able to dynamically learn and cluster information in a large dimensional parameter space and

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