Guest Editors' Introduction

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This special issue of *Machine Learning* presents a small sampling of the recent research in multistrategy learning. Articles included herein are updated and improved versions of the papers presented originally at the Third International Workshop on Multistrategy Learning (MSL-96), held in Harpers Ferry, WV, in May 23-25, 1996. The workshop was organized by George Mason University with the collaboration of International Joint Conferences on Artificial Intelligence, and was sponsored by the National Science Foundation, the Office of Naval Research and the American Association for Artificial Intelligence.

The MSL-96 workshop included many truly excellent contributions to the area of multistrategy learning. It was, therefore, by no means possible to select "best papers"; those selected for this issue are simply a sample illustrating the diversity and the scope of the research in this area. This special issue is the second such issue of *Machine Learning* journal on this topic; the first one included selected papers from the First International Workshop on Multistrategy Learning, held in Harpers Ferry in November 7-9, 1991.

Multistrategy learning is a novel research direction in machine learning, and poses fundamentally new challenges for the field. In contrast to the most work in machine learning so far, which has been primarily concerned with single strategy (or monostrategy) learning, multistrategy learning aims at integrating multiple strategies in a single learning system. To this end, topics of interest in this area include comparative theoretical and experimental studies of *inferential* or *computational* learning strategies, the methods for their integration and the application of such multistrategy or hybrid systems to practical problems. The inferential strategy is defined by the primary inference type employed during the learning process, for example, induction, deduction, or analogy; the computational strategy is defined by the representational system and the computational method used in the learning system, for example, learning decision trees or rules from examples, neural net learning using backpropagation, etc.

Ultimately, research in this area should produce theories and methodologies for development of multistrategy learning systems. The systems may integrate a wide range of inferential and/or computational strategies that draw upon each other in the pursuit of one or more learning goals. Unlike in monostrategy learning systems, in multistrategy learning systems the learning goal, which specifies knowledge or skill that the system desires to acquire, may change from one performance task to another task. The performance task is decided by the performance system in which the learning system is operating.

The study of multistrategy learning systems draws upon the achievements in most subareas of machine learning, as well as related areas of artificial intelligence and cognitive science. As humans are multistrategy learners, multistrategy learning has a natural connection to cognitive studies of learning, and provides an excellent opportunity for cross-fertilization of

research in machine learning and cognitive science. Due to their ability to engage complementary strategies in a learning process, multistrategy learning systems have a potential for solving more complex and versatile learning problems than monostrategy systems. Identifying weaknesses of single strategy methods, finding complementary strategies to maximize learning performance in real-world tasks, and achieving learning synergy in the interaction of strategies are some of the challenging topics in multistrategy learning research.

Earlier efforts in multistrategy learning focused mostly on combining explanation-based learning with empirical learning, and related theoretical and methodological topics (e.g., Michalski and Tecuci, 1991, 1993, 1994; Wnek and Hieb, 1994). Among early systems (sometimes called "integrated learning systems"), one may mention UNIMEM (Lebowitz, 1987), Odysseus (Wilkins, Clancey and Buchanan, 1986), Prodigy (Minton et al., 1987), DISCIPLE (Kodratoff and Tecuci, 1987), OCCAM (Pazzani, 1988), IOE (Dietterich and Flann, 1988), CLINT (De Raedt and Bruynooghe, 1991), Gemini (Danyluk, 1994), KBL (Whitehall and Lu, 1994), and EITHER (Mooney and Ourston, 1994). More recent research involves the integration of a wider range of strategies and puts a much stronger emphasis on practical applications of multistrategy systems (Michalski and Wnek, 1996). This shift can be clearly noticed by comparing the contents of the first and this special issue of *Machine Learning* (as well as the workshop proceedings).

The main focus of the first three articles in this issue concerns new methodologies for multistrategy learning and their experimental applications. The remaining papers address two fundamental application areas for multistrategy systems: one concerned with knowledge discovery in databases and the second with determining desired information in very large information systems such as the world wide web.

The first article, by Giordana, Neri, Saitta and Botta, proposes First Order Logic as a framework for unifying multiple learning strategies. They identify several useful properties of the framework. One such property is the separation between the hypothesis description language and the instance description language. Such a separation provides flexibility in connecting the learning system to various sources of data, for example, relational databases. The second property is the employment of the annotated predicate calculus (Michalski, 1983) for building descriptions with both discrete and continuous attributes. The multistrategy learning is implemented through the integration of several computational strategies, such as decision rule learning, genetic algorithms, and neural nets. The authors' framework assumes limited background knowledge.

The next article, by Sammut, emphasizes the role of background knowledge in multistrategy learning. He points out that the choice of knowledge representation is the central problem in designing a multistrategy learning system. There are two aspects of the representation that are of particular importance. One is the need for uniform representation for both background knowledge and the concept representation language. Second is the need for facilitating the execution of concept descriptions. Both of these aspects are characteristic of the inductive logic programming framework, which he employs in his work. The proposed multistrategy learning system is capable of using several methods for acquiring classification knowledge (ID3-type decision tree learning, Induct-RDR and AQ type rule learning, and the naive Bayes classifier). The system also provides the ability to learn

numerical equations and constructive induction. It assumes a great deal of interaction with the user.

The third article, by Widmer, concerns the problem of incremental learning of context-dependent concepts. Two systems are evaluated: one that combines meta-learning with a Bayesian classifier and the second that combines meta-learning with an instance-based learning. Meta-learning is used for determining contextual attributes. These contextual attributes are then used to properly focus the learned classifier when making predictions. The classifier applies only those hypotheses that were learned in the same context in which the incoming new examples are presented.

The fourth and fifth articles are concerned with applications of multistrategy learning. Morik and Brockhausen's article explores the issues of applying multistrategy learning to knowledge discovery in large databases. Their system combines inductive logic programming with a relational database. It includes a capability for detecting functional dependencies, discretization of numerical attributes, and forming hierarchies.

Pazzani and Billsus present a comparative study of several learning algorithms as applied to the problem of identification of interesting web sites. They studied the applicability of various learning systems to learn and revise web searching user profiles. For this type of task, the learning system is required to be interactive, incremental, and draw from thesaurus-type background knowledge. Out of several learning systems of varied complexity, they selected a naive Bayesian classifier. With the support of a strategy for incrementally revising user profiles, the overall performance of the Bayesian classifier was deemed most satisfactory.

In summary, this special issue presents a selection of articles that cover a range of issues in multistrategy learning—from the development of general methodologies to practical applications. We hope that it will serve as a reference point and a motivator for readers to pursue further this novel, very important, and highly challenging research area of machine learning.

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