Guest Editors' Introduction

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In 1991, at the First International Workshop on Multistrategy Learning, organized by Ryszard Michalski and Gheorghe Tecuci, a small group of researchers, interested in learning, debated what that prefix “multi” could possibly mean, beyond the folk wisdom that “many is better than one”.

In 1993 and 1996, the second and third editions of the same workshop, organized by Ryszard Michalski and Gheorghe Tecuci, and by Ryszard Michalski and Janusz Wnek, respectively, took place. Even though the definitional debate went on, more concrete instances of “multistrategy” learning were presented and discussed. People agreed on the potential of the approach (or the spectrum of possible approaches), but also recognized that substantial conceptual and methodological advances were required to exploit the whole power hidden in the cooperation of a plurality of components.

In 1998, the Fourth International Workshop on Multistrategy Learning, organized by Floriana Esposito, Ryszard Michalski and Lorenza Saitta, was held in Desenzano del Garda.

Looking back at the four workshops, no precise definition of the field has emerged yet as a universally accepted one. However, a pattern in the frequency of approached themes can be seen. At the beginning, several papers concentrated on the integration of different reasoning mechanisms (such as induction, deduction, abduction, and analogy) into a symbolic learning paradigm. Later, different paradigms were integrated, including symbolic, connectionist and genetic, with almost all the combinations among them. Increasing attention was devoted to handling symbolic and numerical information inside the same system. Starting with the second workshop, new themes appeared, such as boosting, integration of rule-based and instance-based learning, reinforcement learning, learning for planning, constructive induction, knowledge discovery in databases, and ways of exploiting background knowledge.

Two issues persisted over the years: cognitive modeling, which the flexibility of a multistrategy approach seems particularly well suited for, and applications, steadily increasing in complexity, such as the one concerning protocol development and control in a hospital intensive care unit, described by Katharina Morik in her invited talk to the workshop.

The Desenzano workshop was characterized by the ample time allocated for discussion, which allowed all the attendees to actively participate, expressing their agreement or criticisms. The papers in this issue have been collected in the same spirit: they show the diversity spanned by methods inside this Machine Learning subfield, and the efforts in probing new directions.

The nine papers collected are related in various ways. One theme linking the majority of them is the effort to make practical learning and reasoning in subsets of *First Order Logic*. Sebag and Rouveirol present STILL, an any-time learner and reasoner that achieves tractability by exploiting a procedural bias consisting in working on a stochastically sampled subset of the inference space. Esposito et al., on the contrary, aim at the same goal by limiting the explosion of the matching phase through the definition of a θ -subsumption relation restricted by the Object Identity assumption: variables with different names are to be bound to different objects. Finally, extensive use of background knowledge constrains the hypothesis space to be explored by WHY, the learning system presented by Neri. Further aspects of predicate logic representations are dealt with in two more papers: Botta and Piola present a method to learn numerical terms in FOL formulas, evaluated according to a continuous-valued semantics. Lamma, Riguzzi and Pereira extends the classical ILP framework in order to learn concepts and their explicit negations, represented as Extended Logic Programs with an associated three-valued semantics.

Another common theme is *Theory Revision*, the task of Esposito et al.'s system INTHELEX. Botta and Piola's learning of numerical terms can also be seen as a case of theory refinement, as well as Neri's modelling of human conceptual change. Finally, theory revision is discussed and questioned by Burns and Danyluk, who wonder whether accurate feature selection might be a simpler and equally effective alternative to the more extensive types or knowledge refinement proposed in the literature.

Integration of paradigms also appears in more than one paper: Michalski proposes a Learnable Evolution Model methodology, in which the creation of new individuals is yielded by machine learning. He presents experiments in support of the effectiveness, both in terms of knowledge quality and evolutionary speed up, of this type of integration between symbolic learning and Darwinian-type evolutionary competition. Also the systems INDiGENT and TNT-INDiGENT, described by Burns and Danyluk, exploit a genetic search, with the addition of a connectionist component, used to represent knowledge. Botta and Piola's work is a further example of integration between the symbolic and connectionist paradigms.

The common goal of *modeling human learning* relates two of the papers. Sison, Numao and Shimura present a method for discovering and classifying errors made by novice programmers, with the aim of building up a faithful student model. They describe the system MEDD, and present experiments on novice Prolog programs. Neri uses the symbolic system WHY to model the complex knowledge involved in "conceptual change" in young students learning Physics.

Finally, Hsu, Ray and Wilkins propose a different interpretation of multistrategy: their approach to learning from time series envisages the *partition of a complex task* into subtasks, each one possibly involving only a subset of the available descriptors, and then combining the separately obtained results.

Our hope is that readers will find in these papers more questions than answers, feeling thus stimulated to work on multistrategy learning by filling any incompleteness they might spot, by proposing alternative directions they believe are more promising, and by suggesting challenging new applications.

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