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Introduction

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This special issue demonstrates that a new branch of algorithm research has moved into the scope of *Algorithmica*: the design and analysis of *learning algorithms*. These are algorithms that allow a machine to extract general "knowledge" from concrete instances of a problem, so that it can improve its performance on future instances of the same problem. Learning algorithms have already been investigated in artificial intelligence and neural networks for many decades. Whereas most of this earlier work had focused on experiments with heuristic learning algorithms, the pioneering work of Vapnik, Gold, and Valiant supported the development of rigorous models and concepts for the analysis of learning algorithms. The articles in this special issue show that through intensive work during the last decade the design and analysis of learning algorithms has turned into a mature research area, that builds on concepts, ideas, and tools from a variety of disciplines, such as statistics, information theory, computational complexity theory, optimization, and mathematical logic.

This special issue begins with two articles by Ben-David and Cenzer/Moser that address learning theoretic problems in a rather abstract setting, where one is interested in solving learning problems "in the limit." These articles employ concepts and tools from mathematical logic and topology.

The articles by Blum/Frieze/Kannan/Vempala and Kwek/Pitt are devoted to the design of learning algorithms in Valiant's classical framework of PAC-learning (**p**robably **a**pproximately **c**orrect learning). Here one is interested in learning algorithms for which the required number of examples and computation steps can be bounded by polynomials in terms of the parameters of the learning task.

The articles by Beimel/Kushilevitz and Bshouty/Tamon/Wilson address learning issues within another classical model of computational learning theory: the model for on-line learning. Here the learner (more precisely: the learning algorithm) receives a counterexample to each hypothesis, as long as the current hypothesis disagrees with the target concept of the learning process. The goal is to reach the target concept with a minimum number of counterexamples.

The articles by Cesa-Bianchi/Helmbold/Panizza, Hiraoka/Amari, and Shawe-Taylor explore fruitful combinations of concepts and methods developed for classical models of computational learning theory with new ideas and concepts from probability theory and statistics.

The articles by Kamimura, Rüger, and Smola/Schölkopf address a number of practically relevant algorithmic problems in learning theory, many of them motivated by

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learning problems for neural networks, with advanced methods from pattern recognition, statistics, and information theory.

The quality and breadth of the articles in this special issue demonstrate the vitality of current theoretical work on learning algorithms.

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