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Preface

The following six papers are the revised and expanded version of six of the 26 papers presented at the Tenth International Conference on Algorithmic Learning Theory (ALT'99), held at Waseda University International Conference Center, Tokyo, Japan, December 6–8, 1999. The conference proceedings appeared as Lecture Notes in Artificial Intelligence, vol. 1720. All the papers were subjected to the standard refereeing process of this journal.

The field of algorithmic learning theory studies theoretical aspects of machine learning and related topics. In order to formally study various learning mechanisms, many learning frameworks have been proposed and studied. All six papers presented here study properties of learning problems and/or learning algorithms under one or more of these learning frameworks.

The first paper by Balcázar, Castro, Guijarro, and Simon investigates the query complexity in the *query learning* framework. They introduce a new uniform combinatorial characterization for investigating query complexity of learning problems. In query learning, a learning algorithm is expected to produce a hypothesis for an unknown concept by making queries on the concept of certain types. The query complexity is simply the number of queries necessary and sufficient for obtaining a correct hypothesis. Balcázar et al. succeeded in giving a uniform way of characterizing query complexity for some important query types, thereby yielding a uniform perspective to query complexity analysis.

The second and the third papers are about *on-line learning*. In the on-line learning framework, the task of a learning algorithm is to make prediction about some unknown concept based on examples given on-line (almost) as well as the best prediction expert. Takimoto and Warmuth investigate a problem of pruning planar directed acyclic decision graphs which is a generalization of decision tree pruning. Here each pruning is regarded as an expert, and the best expert is the pruning making the most accurate prediction. They show efficient on-line algorithms that can predict nearly as well as the best pruning of a given decision graph. The paper by Goldman and Kwek considers the problem of learning some subclasses of pattern languages. In general, learning pattern languages is very difficult, but due to its importance in various applications, this learning problem has been studied extensively in several learning frameworks. Here they investigate *on-line learning* of pattern languages. By using relationships to "Winnow", a well-known on-line learning algorithm, they discuss the learnability/non-learnability for some subclasses of pattern languages.

In the fourth paper, Bshouty, Eiron, and Kushilevitz introduce a variant of the *PAC learning* framework, for studying and developing learning algorithms robust to noisy

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data. In the PAC learning framework, a learning algorithm is given examples on some unknown concept randomly drawn from the domain under some unknown distribution, and the goal of the algorithm is to make an approximately good prediction hypothesis with high probability. In the original PAC learning framework, it is assumed that given examples are all correct w.r.t. the unknown concept. But for developing learning algorithms robust to noisy data and investigating its difficulty, researchers have introduced some variations of PAC learning. Bshouty et al. generalize the previous notions of noisy data and introduce "nasty noise model" that assumes more general and much worse noisy data. Both positive and negative results are presented.

The situation where given data may contain some errors is also studied in the paper by Lange and Grieser for *inductive inference* algorithms. The task of these algorithms is to come up with a predictive model about some unknown concept whose examples are presented one element at a time. The learning algorithm is required to converge to a predictive model that is always correct from some point onwards. This is essentially the *learning in the limit* framework. In this setting, the learning algorithm, at any given time, has access to all the data seen so far. If the learning algorithm is required to make its conjectures based only on the current data and the previous conjecture, then the framework is referred to as *iterative learning* or *memory limited learning*. For both these frameworks, Lange and Grieser show how the difficulty of learning problems is dependent on the type of given data, such as noise-free vs. noisy data and positive only vs. both positive and negative data. The final paper by Stephan and Zeugmann is also about learning in the limit. They provide an extensive investigation of the learnability of approximations of recursively enumerable (r.e.) sets of recursive functions. They resolve an open question of Blum and Blum and considerably extend the nature of this study by considering more modern learning frameworks like *robust learning*.

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