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Preface

This special issue of Theoretical Computer Science consists of seven papers selected from the papers presented at the 11th International Conference, Algorithmic Learning Theory, held in Sydney, Australia, December 2000. Preliminary version of the papers appeared in Lecture Notes in Artificial Intelligence, vol. 1968. Following the conference, authors were invited to submit full versions of their papers to the special issue. All the papers were subjected to the standard refereeing procedure of Theoretical Computer Science.

Algorithmic learning theory aims at theoretical study of learning problems and algorithms by providing formal models of learning and analyzing complexity of learning problems and performance of learning algorithms. It provides foundations for such varied branches of artificial intelligence as machine learning, inductive logic programming, data mining, and others.

The first paper, an invited paper by Watanabe, deals with sequential sampling algorithms for algorithmic learning theory. In algorithmic learning theory, random sampling is a basic mean to estimate the proportion of instances with a certain property, and the estimation of the appropriate sample size is often essential to achieve efficient learning. Sequential sampling is a useful technique for designing adoptive sampling algorithms, which obtains instances one by one and determines from these instances whether or not it has already seen enough number of examples for a given task. Watanabe shows two typical sequential sampling algorithms for simple estimation problems, and explains when and how such sequential sampling algorithms are used for designing learning algorithms with theoretically guaranteed performance.

The next paper by Lange, Grieser and Zeugmann falls under the area of inductive inference and gives a systematic study of learning of indexable concept classes in which the final hypothesis describes a finite variant of the target hypothesis. Various models are studied: learning in the limit, finite identification, set-driven learning, conservative inference and behaviourally correct learning. For unbounded, but finite, number of errors, results shown include the equivalence of set-driven, conservative and limit learning and behaviourally correct learning being strictly more powerful than limit learning. This contrasts with the non-error case where limit learning and behaviourally correct learning coincide, and limit and conservative learning separate for learning indexed families. The authors also establish nice characterizations of the criteria of learning with unbounded (but finite) number of errors in terms of finite tell-tale sets.

The next paper by Nessel and Lange deals with the learnability of erasing pattern languages within Angluin's model of learning with queries. The type of queries considered include membership, subset, superset and equivalence queries (along with their restricted forms). The authors study, to what extent, the results for non-erasing pattern languages and the subclass of (non-erasing) regular pattern languages carry over to the setting of erasing pattern languages. The authors also consider the situation in which additional information (in the form of a string from the target language) is available to the learner before starting the process of asking queries. It is shown that most of the results about learnability of regular pattern languages carry over to the case of erasing regular pattern languages. However, when the full class of erasing pattern languages is considered, some query types (membership/restricted superset queries) are not sufficient for learning.

The next paper by Satoh considers learning of taxonomic relations, where a taxonomy is represented by a tree-structured concept hierarchy. Formalizing this problem as case-based reasoning problem with a taxonomy, the author first analyzes the representability of the case-based reasoning framework by showing upperbounds of necessary postive and negative examples in the framework of PAC learning. Using the approximation method of finding a critical case-base, the author presents an efficient algorithm that learns a minimal case-base from polynomially many random cases

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using polynomially many membership queries in terms of the DNS size and CNF size of a target relation. This result solves an open problem on the learning complexity of case-based reasoning with taxonomic information.

The next paper by Denis, Gilleron and Letouzey considers learning from positive and unlabeled examples. In many machine learning settings, getting labeled examples are difficult, however unlabeled data is abundant. Also for some classification problems positive data are available. Many machine learning algorithms, such as decision tree induction algorithms and naïve Bayes algorithms use examples only to evaluate statistical queries. Kearns designed the Statistical Query learning model in order to describe such algorithms. In this paper authors design a scheme which transforms any SQ-like algorithm into an algorithm based on positive statistical queries and instance statistical queries. The authors show that any class learnable in the Statistical Query model is learnable from positive statistical queries and instance statistical queries only if a lower bound on the weight of any target concept f can be estimated in polynomial time. Then this result is used to design a decision tree induction algorithm based on C4.5 that uses only positive and unlabeled examples.

The final two papers study the hardness of learning from examples. The paper by Hirata considers a learning problem for acyclic conjunctive queries over relational databases from instances within the inductive logic programming framework. Acyclicity is a natural concept in hypergraph theory, and proved to be effective to restrict the computational complexity of many combinatorial problems in database area. This paper presents prediction hardness results for fragments of acyclic conjunctive queries with the model of PAC learning. First, the author shows under a standard cryptographic assumption that acyclic conjunctive queries are not polynomial time predictable even if the maximum arity of the predicates in a database is bounded by constant. Furthermore, it is shown that acyclic conjunctive queries are as hard to predict as DNF formulas when the maximum arity is bounded by two. These results show a gap between reasoning and learning of conjunctive queries in relational databases.

The paper by Dasgupta and Hammer considers efficient learning of feedforward neural networks. The authors consider the objective of maximizing the ratio of correctly classified points compared to the size of the training set. They show that it is NP-hard to approximate the ratio within some constant relative error if architecture with varying input dimension, one hidden layer and two hidden neurons are considered under some assumptions about the activation function. For single hidden layer threshold networks with varying input dimension and n hidden neurons, approximation within a relative error depending on n is NP-hard even if restricted to situations where the number of examples is limited with respect to n. Also, the objective of minimizing the failure ratio in the presence of misclassification errors is considered, and some NP-hardness results have been obtained.

Due to unexpected problems this special issue appears with an unusual delay with respect to the event to which it is devoted. We apologize to the authors and to TCS readers for this inconvenience but we are nevertheless pleased that the excellent papers selected for this issue are finally appearing. We would like to express our immense gratitude to all the members of the ALT 2000 program committee for their careful selection of these papers, the anonymous referees for their quick and constructive reviews, and the authors for their effort in improving the papers. Moreover, we are very grateful to Giorgio Ausiello, the Editor-in-Chief of Theoretical Computer Science, for giving us a chance to edit this special issue.

H. Arimura, S. Jain
Hokkaido University, Japan
E-mail addresses: arim@ist.hokudai.ac.jp (H. Arimura), sanjay@comp.nus.edu.sg (S. Jain)