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Guest editors' foreword

This special issue of *Theoretical Computer Science* is dedicated to the Nineteenth International Conference on Algorithmic Learning Theory (ALT 2008) held at Budapest, Hungary, October 13–16, 2008. It contains nine articles that were among the best in the conference.[1] The authors of these papers have been invited by the Special Issue Editors to submit completed versions of their work for this Special Issue. Once received, these papers underwent the usual refereeing process of *Theoretical Computer Science*. In the following, we shortly introduce each of the papers.

In algorithmic learning theory mathematics is used to model and to understand how computer programs may learn from experience. Depending on the learning task considered, a considerable interaction between various mathematical theories including statistics, probability theory, combinatorics, linguistics, and theory of computation is required. Moreover, we see also a fruitful interaction with the practical, empirical fields of machine and statistical learning.

Vovk and Shen study Dawid's prequential framework from the viewpoint of the algorithmic theory of randomness. They consider the on-line learning protocol, where one has to forecast probabilities of binary observations. They then compare two notions of randomness of a sequence of forecasts and observations. One is game-theoretic (martingale-based) due to Schnorr and Levin and the other is measure-theoretic randomness due to Martin–Löf. The main result shows that in such a framework measure-theoretic and game-theoretic randomness do actually coincide. The authors then turn their attention to game-theoretic and measure-theoretic probability and show that they coincide on the open sets. Having this result, it is only natural to ask whether or not game-theoretic and measure-theoretic probability do also coincide for wider classes of sets. This is answered affirmatively by showing that they indeed coincide on the Borel, and even analytic, sets.

Chernov, Kalnishkan, Zhdanov, and Vovk study the problem of forecasting when no probability assumptions can be made. Here, a sequence $\gamma_1, \omega_1, \gamma_2, \omega_2, \ldots$ is generated and the forecaster makes decision γ_t after having seen the outcomes $\omega_1, \ldots, \omega_{t-1}$. Then a penalty $\lambda(\omega_t, \gamma_t)$ is paid. The assumption is then that there is a set of experts, each of which makes its own decision. The forecaster is informed about these decisions to date and the goal of the forecaster is to make decisions that are not much worse than any of the experts.

In an earlier paper, Vovk has presented a forecaster algorithm which is called the Aggregating Algorithm. The Aggregating Algorithm is applicable provided that the loss function satisfies a certain exponential convexity property.

Defensive Forecasting was also proposed by Vovk and his collaborators. It is based on a representation of losses with the help of supermartingales. So far, only special versions of the Defensive Forecasting algorithm have been related to the Aggregating Algorithm. The main contribution of the present paper is that the Aggregating Algorithm and Defensive Forecasting are equivalent in the traditional setting of a countable number of experts and a finite number of outcomes. Surprisingly, not only the performance guarantees are the same but also the predictions. Also, more general settings are considered. While the Defensive Forecasting algorithm works also in the more general settings more or less directly, the Aggregating Algorithm requires substantial modifications.

Mukherjee and Schapire consider the problem of learning to predict as well as the best in a group of experts making continuous predictions. So the expert predictions lie in the interval $[-1, 1]$, the observations are in the set $\{-1, 1\}$ and the predictions made lie in the set $\{-1, 0, 1\}$. The loss function is the number of mistakes made. The authors present an algorithm for prediction with expert advice under the assumption that the best expert has loss k or less. The algorithm presented is based on drifting games which have been considered previously by Schapire.

Lower and upper bounds are shown which match up to an additive factor of $O(\log k)$. Furthermore, the paper provides a lower bound on the loss of any weighted majority algorithm. Finally, it turns out that continuous experts are only as powerful as experts making binary or no prediction in each round.

Reinforcement learning in a Markov decision process with deterministic transitions and random rewards is studied by Ortner. In this setting, both the transition rule and the reward distributions are unknown and must be learned. Learning

[1] The conference proceedings, including preliminary versions of these papers, appeared as Lecture Notes in Artificial Intelligence, vol. 5254, Springer, 2008.

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the transition rule is done by a deterministic exploration procedure. The remaining problem is then to deal with the exploitation–exploration problem concerning the rewards. An upper confidence bound strategy is applied to solve this problem.

The author proposes a new algorithm called UCycle and proves an upper bound on its expected regret. This bound is non-asymptotic and thus better than results obtained previously. On the other hand, the new bounds require the assumption that the Markov decision process is deterministic. Finally, an interesting application of the results to bandits with switching costs is provided.

The Information Bottleneck method was introduced by Tishby, Pereira, and Bialek. This is an information theoretic framework for extracting relevant components of an input random variable X with respect to an output random variable Y. Intuitively, one has to find a compressed, non-parametric and model-independent representation T of X that is most informative about Y.

Shamir, Sabato, and Tishby deal with the learning theoretic justification of the Information Bottleneck method, which has remained unclear by two main reasons. In contrast to most finite-sample based machine learning methods, the joint distribution between X and Y is assumed to be known and explicitly used by the Information Bottleneck method. And second, it remained unclear why maximizing mutual information about Y is useful for learning in a natural setting.

The paper addresses these problems and discusses approximations by empirical distributions, how the Information Bottleneck method trades off generalization and accuracy (regularization), and how it generalizes the notion of (minimal) sufficient statistics.

Antos, Grover, and Szepesvári study a learning problem that is connected with the quality control problem. That is, one has to estimate the means of k distributions when the sample size for each estimator is to be allocated to the different distributions in an on-line fashion. The authors then show that the optimal allocation rule assigns sample sizes proportional to the variances of the distributions. However, in the setup considered the variances are not known, and thus a new approach is needed. The authors design an allocation rule that has a loss, measured as the worst mean squared error, as small as that of the optimum plus a regret of the order of $n^{-3/2}$. This bound is conjectured to be optimal. Furthermore, it is proved that the algorithm asymptotically performs similarly to the ideal algorithm knowing the correct variances.

Angluin, Aspnes, and Reyzin also consider an active learning problem, where the learner is allowed to ask queries. The objects to be learned are a special kind of social networks which are called *hidden independent cascade networks*. Such networks are digraphs whose nodes represent agents. Any possible activation of agent k by agent j is represented by a directed edge from node j to k. Furthermore, activation probabilities are associated with the edges and there is a distinguished node called the output node. Once a node is activated, it can influence its neighbors with the probability that is associated with the corresponding edge. The problem is then to learn the influence probability of the edges. The queries the learner is allowed to ask are so-called exact value injection queries. The exact value injection query returns the expected value of the activation of a designated output node when a set of nodes is set to some fixed value and the rest of the free nodes takes random values. Of course, such queries are expensive and the authors show how to minimize the number of queries necessary.

It is shown that every social network of size n can be learned efficiently by using $O(n^2)$ injection queries. This matches the information theoretic lower bound shown by the authors for this problem. A second important result is obtained for networks that form a tree rooted at the output node. These networks can be learned by using $\Theta(n \log n)$ injection queries.

Inductive inference of formal languages from positive data has attracted considerable attention for more than 40 years. The basic scenario is that the learner receives more and more strings from the target language and outputs a sequence of hypotheses which has to stabilize eventually. The hypotheses output are grammars and the final grammar is required to correctly generate the target language. The interesting question is, of course, which language classes are learnable in this model under some realistic assumptions.

Becerra-Bonache, Case, Jain, and Stephan investigate the iterative learnability of simple external contextual languages (abbr. SEC). The interest in these languages is derived from linguistics, where contextual grammars were introduced to model certain aspects of natural languages. Requiring a learner to be iterative means that it has to compute its actual hypothesis from its previous hypothesis and the new string coming in. This demand takes into account that it is not realistic to allow the learner to store all strings presented. Furthermore, the SEC languages are parameterized resulting in classes $\mathrm{SEC}_{p,q}$. Intuitively, the parameter q refers to the number of contexts and p to the number of positions, where additions to a sentence can be made.

The results obtained are both positive and negative depending on whether or not additional (natural) requirements are made.

The paper by Jain, Lange, Moelius III, and Zilles also studies inductive inference of formal languages from positive data. The problem considered is a modification of iterative learning. Now, the learner is additionally allowed to store an *a priorily fixed* number of examples resulting in bounded example memory learning which was introduced by Lange and Zeugmann. So the learner computes its current hypothesis from its previous hypothesis, the new string coming in, and the examples memorized.

Jain, Lange, Moelius III, and Zilles consider a variation of the bounded example memory learning model in which the learner's memory is not only constrained in how much data may be stored, but also in *how long* an example may be memorized without being refreshed. So, if a string s is stored but not presented to the learner again thereafter, then the learner must forget the string *s*. This new model is called *temporary example memory* learning, and many interesting results are presented. The discussion focuses on the comparison of bounded example memory and temporary example memory.

We would like to thank all the referees for their fine reports and their efficient work. Special thanks go to the members of the program committee of ALT 2008 for selecting the papers. We are very grateful to all authors for submitting their papers and for all their efforts to improve and to polish their articles. Finally, we are particularly thankful to Giorgio Ausiello for the opportunity to compile this special issue.

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