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Foreword

Forty years after E. Mark Gold's seminal paper *Language Identification in the Limit* (Information and Control 10:447–474, 1967), we can celebrate not only the 40th anniversary of research in the field of *Inductive Inference*, but also the 60th birthday of one of its most influential pioneers, Rolf Wiehagen. This special issue of *Theoretical Computer Science* is dedicated in his honour.

Rolf Wiehagen started his long and outstanding scientific career in Algorithmic Learning Theory, especially in Inductive Inference, as Helmut Thiele's student at Humboldt University in Berlin. As a visiting researcher at the University of Latvia, Riga, as a professor at the Humboldt-University, Berlin, at Darmstadt University of Technology, and now at the University of Kaiserslautern, he has been collaborating with scientists all over the world, most of whom – just like himself – have a remarkable international reputation. Thus he has been one of the leading contributors in the analysis of robust learning, monotonic learning, the complexity of learning, to name just a few lines of research. It has been Rolf Wiehagen's creativity that brought forth formal models of iterative learning, learning with feedback, and learning with additional information – concepts that have had a high impact on research in Inductive Inference. Not less remarkable is his pioneering work on characterisations of learning models which have led to what is known as Rolf Wiehagen's *Thesis in Inductive Inference*, relating search in a hypothesis space to learning in a uniform way.

His commitment is not only visible in the huge number of articles published in highly renowned journals and conference proceedings, but also in his devotion to teaching. Not only his doctoral students have been lucky to learn from a dedicated teacher: every single student that has ever attended his lectures will certainly agree that Rolf Wiehagen is unique in the way he shows his love for Learning Theory and Theoretical Computer Science – and in the way he conveys his seemingly inexhaustible knowledge to others.

Undoubtedly, many colleagues around the world admire and respect Rolf Wiehagen for his numerous valuable contributions to research, for his dedication to his work, but not least, for being an always reliable teacher, colleague, and friend.

This special issue does not only exhibit part of the lines of research influenced by Rolf Wiehagen and his collaborators, but also surveys part of his own work. Here we go back to the time when he, as a young researcher stepping through the snow in Riga, created some of the key techniques that helped him to support his prominent and still living *Thesis in Inductive Inference*.

This keyword leads us to introducing the first article in this issue: Zeugmann and Zilles survey the research on Inductive Inference of recursive functions over the past 40 years, thus giving evidence of the great impact Rolf Wiehagen's work has had and still has. When learning recursive functions, a learning algorithm gets gradually growing subsets of the graph of the target function as input, and is required to eventually come up with a program computing the target function. The survey article focuses mainly on the effect of imposing intuitive constraints on a formal learning model.

Probably the most intuitive of these constraints is consistency, requiring that no intermediate hypothesis a learning algorithm conjectures contradicts the data seen previously. This seemingly trivial requirement is known to affect the capabilities of learning algorithms – a fact that motivates Grieser's research presented in the second article of this special issue. Grieser studies the impact of different variants of consistency constraints in an Inductive Inference framework where learning algorithms can assess their own competence in different situations, i.e., for different input sequences.

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One line of research that was built on Rolf Wiehagen's fundamental definitions is learning with limited memory as opposed to the general Inductive Inference case where it is assumed that a learning algorithm can store arbitrarily large subsets of graphs during the learning process. Such limited memory models are of high practical relevance, and yet their nature is not yet fully explored on a formal level. This line of research is therefore pursued by Freivalds and Bonner, whose article in this issue provides a framework for quantum limited memory learning – combining Inductive Inference and quantum computation in a novel way. One of their main results is that there are classes of recursive functions that can be learned by quantum finite automata-based algorithms with limited memory, but not with any standard Inductive Inference algorithm, not even probabilistically. Freivalds and Bonner demonstrate one way in which Inductive Inference is vital in frameworks in which probably Gold had not yet envisioned his theory 40 years ago.

But more than that, we are lucky to exhibit a wide variety of such examples in this special issue, such as Poland's work on on-line learning. Though today an independent branch of machine learning research, the theory of on-line learning has some roots in common with the theory of Inductive Inference. Poland studies the setting of a (non-stochastic) multi-armed bandit, i.e., a setting in which a learning algorithm, stepwise exploring an unknown environment, can choose between different "experts" (e.g., actions) in every step. Upon every decision step the learner suffers a cost incurred by the chosen expert; however, the cost that other experts have incurred will never be revealed. Significantly extending previous studies, Poland provides an algorithm that achieves costs in an order arbitrarily close to the order of the optimum, in the case of countably many actions. He shows how to adapt his technique to different settings, finally presenting a universal learner whose cost is sublinear compared to any Turing-computable expert.

In most of the aforementioned articles, learning is considered in an adversarial setting, where hardly any prior assumptions are made on the order in which information is presented to the learner. In contrast to that, the results Balbach contributed to this special issue focus on cooperative teaching environments and thus on the problem of how to teach a target function most efficiently to all learners in a given set. Defining two novel variants of classical teaching models, Balbach shows how to obtain results which correct some of the implausibilities observed in the original approach. Here he particularly considers teaching certain classes of Boolean target functions.

Boolean functions, as considered in Balbach's article, can of course be seen as special cases of classifiers. The next contribution in this issue focuses on a different kind of classification task in learning: Jain, Martin, and Stephan consider a logical setting in which, for any structure in a given set of structures over a vocabulary, the aim is to classify closed formulas as to whether or not they are satisfied in that structure. A corresponding classifier has to be learned from all possible information sequences contained in what is called an environment. One of the contributions of this article is to define a new reasonable relaxation of the constraints imposed on learning algorithms. In the model defined and analysed here, one allows the classification to fail on a "small" set of structures, given some environment, i.e., Jain, Martin, and Stephan propose learning with respect to almost all possible "realities", where different probability distributions/measures on the set of possible realities are taken into consideration.

The richness of classes of structured concepts for which learnability studies in the Inductive Inference framework are feasible is further demonstrated by Krishna Rao, who – as opposed to the logical setting studied by Jain, Martin, and Stephan – considers term rewriting systems as possible target concepts for learning. Krishna Rao proves that two very rich, but set-theoretically incomparable classes of term rewriting systems are both learnable in Gold's classical paradigm, if only positive data are presented in the learning process. That means, instead of subsets of the graph of a function, which implicitly provide information about points *not* contained in the graph, here no information about instances which cannot be derived from the target term rewriting system is provided.

Learning from positive data is actually the focus of all further articles in this special issue, since it has to be considered a practically relevant, yet often very difficult task. A significant part of the research here focuses on learning formal languages in the sense that a grammar generating the target language or a decision procedure for testing membership of words in the target language have to be inferred. Very prominent classes of formal languages which have been extensively studied in the framework of Inductive Inference from positive data are the class of non-erasing pattern languages and the class of erasing pattern languages. They have attracted so much attention that it is definitely worth summarizing part of the literature on learning pattern languages in a survey. This is what Ng and Shinohara do in their article which chronologically guides the reader through the history of Inductive Inference of pattern languages from positive data.

Ng and Shinohara's survey is also a nice additional introduction to Reidenbach's article on learning erasing pattern languages. Reidenbach shows how learnability results, and in particular the complexity of their proofs, can depend on the size of the alphabet underlying in the definition of a class of erasing pattern languages. His work significantly extends our knowledge about the learnability of the class of all erasing pattern languages (and a special subclass thereof) from positive data, by providing answers to open questions for certain alphabet sizes. The techniques used by Reidenbach make his work not only interesting for the learning theory community, but provide a major contribution to formal language theory, especially word combinatorics. This is one of several examples showing that research in Inductive Inference is not only relevant for a theoretical foundation of Machine Learning, but is also of impact for other areas in Theoretical Computer Science.

The classes of pattern languages studied by Ng and Shinohara and by Reidenbach have a very useful property: they belong to the type of language classes which are called *indexable classes of recursive languages*. This type of classes does not only contain many classes of practical and theoretical relevance, but is also a basis for a significant line of research in Inductive Inference. Indexable classes of recursive languages have shown to behave differently from more general classes of languages, if questions of learnability are studied. Lange, Zeugmann, and Zilles survey the corresponding line of research in a summary, again with a focus on learning from positive data.

Yet this survey is not meant to suggest that the branch of research on learning formal languages from positive data has been closed. Jain and Kinber, whose article is the last one in this special issue, present some of their recent results on learning formal languages from positive data, covering indexable classes of recursive languages as well as more general types of language classes. They define a novel learning model, by requiring a successful identification of the target language, even if only a part of the instances of the target language can be made available to the learner. Here several relaxations of this model are analysed, particularly also under certain monotonicity constraints.

Of course it is not only the authors whose work has established this special issue in Theoretical Computer Science. We would like to gratefully acknowledge the immense effort with which the referees have supported us. Their thorough and efficient work has been a significant contribution. Our gratitude is also due to Giorgio Aussiello for his support and for providing the opportunity for the publication of this special issue.

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