Automata learning: from probabilistic to quantum

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Summary

This thesis advances automata learning, a fundamental area in computer science that provides structured mathematical frameworks for modeling and analyzing complex systems. Automata learning is of importance for applications like software verification, biological analysis, and autonomous agents' technologies, as it supports both theoretical understanding and practical implementation.

The research addresses three central themes. The first explores the separation of structural and probabilistic information in deterministic models. In this context, a passive learning algorithm is proposed to generate compact probabilistic models from positive samples, demonstrating increased accuracy with larger sample sizes. The second question investigates whether the structural and probabilistic components of non-deterministic probabilistic automata can be learned independently. To tackle this, the thesis introduces an algorithm that uses both positive and negative samples to model complex non-deterministic structures. Optimization techniques are applied to enhance the precision of the probabilistic parameters.

The thesis also examines active learning for automata, focusing on techniques for learning deterministic finite automata and weighted automata. The Hankel matrix plays a crucial role here, a technique that is extended to a new method for learning probabilistic finite automata and later used also in learning quantum automata. The proposed alternative method is still based on the original L* algorithm but separates the learning of the structure from the probability parameters, broadening the scope of active learning approaches to Markov Decision Processes.

The above methods is further explored for quantum automata learning, proposing an active learning algorithm that integrates nonlinear optimization and matrix analysis. This enables efficient language modeling for quantum applications. In fact, the research is concluded with an implementation of quantum automata in quantum optical experiments, overcoming previous limitations by dynamically encoding input lengths without prior knowledge, making quantum finite automata simulations.

Overall, the thesis introduces new algorithms and methodologies that enhance automata learning, particularly for probabilistic and quantum models under uncertain conditions. These contributions lay the foundation for future research, which will focus on new applications

in probabilistic modeling and quantum computing, further expanding the theoretical and practical impact of automata learning.