CALF: Categorical Automata Learning Framework

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Abstract. Adaptations of automata learning algorithms for increasingly complex types of automata have to be developed from scratch because there is no abstract theory in place to guide the process. This makes it hard to devise such algorithms, and it obscures their correctness proofs. We introduce CALF, a simple category theoretical framework that provides an appropriately abstract foundation for studying automata learning and furthermore establishes formal relations between algorithms for learning, testing, and minimization.

Context and Talk Overview

Automata learning enables the use of model-based verification methods on black-box systems. The popular $\mathtt{L}^\star$ algorithm [2] has been successfully applied to find bugs in implementations of network protocols [11], to provide defense mechanisms against botnets [9], to rejuvenate legacy software [18], and to learn an automaton describing the errors in a program up to a user-defined abstraction [8].

$\mathtt{L}^\star$ belongs to the class of *active* learning algorithms, which allow for direct interaction with an oracle that can answer different types of queries about the system. This is in contrast with passive learning, where a fixed set of positive and negative examples is provided.

$\mathtt{L}^\star$, originally designed to learn a deterministic automaton, has been adapted for various other types of automata accepting regular languages [5, 3], as well as more expressive automata, including Mealy machines [17], Büchi-style automata [15, 4], and register automata [6, 7]. As the complexity of these automata increases, the respective learning algorithms tend to become more obscure. More worryingly, the correctness proofs become involved and harder to verify.

The goal of the present talk is to introduce an abstract framework for studying automata learning algorithms in which specific instances and correctness proofs can be derived without much effort. The framework can also be used to study related algorithms such as minimization and testing, showing the close connection between the seemingly different algorithms.

First steps towards a categorical understanding of active learning appeared in [14]. Based on their work, Moerman et al. [16] recently derived an adaptation of $\mathtt{L}^\star$ for nominal automata. Nominal automata accept the same kind of languages as register automata, but the simplicity of the derived nominal learning algorithm is in stark contrast with the complexity of the ad hoc algorithms developed for register automata.

In [14] the abstract definitions provided were based on very concrete data structures used in $\mathtt{L}^\star$ which then restricts potential generalization to capture other data structures used by more efficient variations of the $\mathtt{L}^\star$ algorithm. In this talk, we develop a rigorous *categorical automata learning framework* (CALF) that overcomes these limitations and furthermore can be used to study related algorithms such as minimization and testing.

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