The Open-Source LearnLib

A Framework for Active Automata Learning

Malte Isberner[1], Falk Howar[2], and Bernhard Steffen[1]

[1] TU Dortmund University, D-44221 Dortmund, Germany,
{malte.isberner,steffen}@cs.tu-dortmund.de,
[2] IPSSE / TU Clausthal, D-38678 Clausthal-Zellerfeld, Germany
falk.howar@tu-clausthal.de

Abstract. In this paper, we present *LearnLib*, a library for active automata learning. The current, open-source version of *LearnLib* was completely rewritten from scratch, incorporating the lessons learned from the decade-spanning development process of the previous versions of *LearnLib*. Like its immediate predecessor, the open-source *LearnLib* is written in Java to enable a high degree of flexibility and extensibility, while at the same time providing a performance that allows for large-scale applications. Additionally, *LearnLib* provides facilities for visualizing the progress of learning algorithms in detail, thus complementing its applicability in research and industrial contexts with an educational aspect.

1 Introduction

From the beginning of active automata learning almost thirty years ago [6], it took the software engineering community more than a decade to recognize its value of being able to provide models of black-box systems for the plethora of model-based tools and techniques. More precisely, it was not until the seminal works of Peled *et al.* [35], employing automata learning to model check black-box systems, and Steffen *et al.* [18], who used it to automatically generate test cases for legacy computer-telephony integrated systems, that it gained some interest outside of the purely theoretical spectrum.

Since then, however, active automata learning has enjoyed quite a success story, having been used as a valuable tool in areas as diverse as automated GUI testing [13], fighting bot-nets [12], or typestate analysis [5, 39]. Most of these works, however, used their custom, one-off implementation of the well-known L^* learning algorithm, and hence invested relatively little effort for optimizations, or using a more sophisticated (but harder to implement and lesser-known) algorithm altogether.

We started developing the *LearnLib*[3] library to provide researchers and practitioners with a reusable set of components to facilitate and promote the use of active automata learning, and to enable access to cutting-edge automata learning technology. From the beginnings of the development of *LearnLib*, started in

[3] http://www.learnlib.de

2003, until now, more than a decade has passed. In these years, many lessons were learned on what makes for a usable, efficient and practically feasible product that fulfills this goal (cf. [24, 34, 36]).

This experience forms the basis of the new *LearnLib*, which we present in this paper. The new *LearnLib* is not just an overhaul of the prior version, but completely re-written from scratch. It provides a higher level of abstraction and an increased flexibility, while simultaneously being the fastest version of *LearnLib* to date. As a service to the community and to encourage contributions by and collaborations with other research groups, we decided to make *LearnLib* available under an open-source license (LGPLv3).

This paper gives some insights about the motivation and history of the *LearnLib* project, presents its architecture, and shows in what manners and for which applications *LearnLib* can and has been used. As said above, a number of researches have implemented their custom version of the L^* algorithm, indicating that the implementation of an automata learning algorithm is not a very challenging task. In the following, we state the three main reasons why we believe that using an elaborate framework like *LearnLib* should be preferred, and why it provides a valuable contribution to both the research and industrial community, regardless of the scope or scale at which active automata learning is used in the respective context.

Education and Experimentation. The fact that active automata learning started off as a mainly theoretical enterprise is still reflected in most of the educational material (e.g., textbooks) on this subject. As interesting as the theory behind learning is, an understanding of "how it actually works" is barely conveyed by mathematical formulae and – often trivial – running examples. *LearnLib* provides facilities to visualize the evolution of the internal data structures and the hypothesis step-by-step, allowing users to keep track of the learning process in detail. In conjunction with this, *LearnLib*'s modular architecture allows for quickly exchanging single components or even the whole algorithm, fostering an understanding of how the choice of parameters influences the behavior of an algorithm, or how several algorithms differ from each other.

Performance. The implementation of a learning algorithm comes with many performance pitfalls. Even though in most cases the time taken by the actual learning algorithm is an uncritical aspect (compared to the time spent in executing queries, which may involve, e.g., network communication), it should be kept as low as reasonably possible. Besides, an efficient management of data structures is necessary to enable learning of large-scale systems without running into out-of-memory conditions or experiencing huge performance slumps. In *LearnLib*, considerable effort was spent on ensuring efficient implementations while providing a conveniently high level of abstraction.

Advanced Features. This is what we consider the strongest case for preferring a comprehensive automata learning framework such as *LearnLib* over a custom implementation. While implementing the original version of L^* is not a challenging task, the situation is different for more refined active learning algorithms,

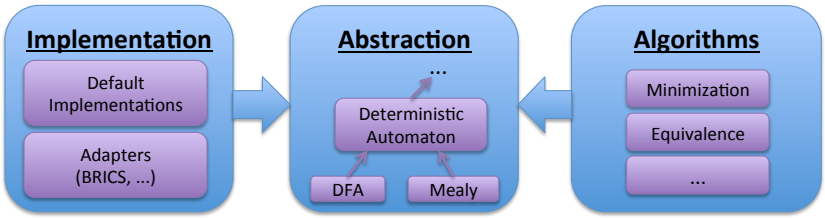


Fig. 1: Architecture of *AutomataLib*

such as Rivest&Schapire's [37], Kearns&Vazirani's [29] or even the very recent TTT algorithm [27]. While we found these algorithms to consistently outperform L^*, the latter remains the most widely used. Also, several other advanced optimizations such as query parallelization or efficient query caches are typically neglected. Even if a lot of effort was spent on optimizing the learning algorithm, for a one-off application it is unlikely that other than the most promising optimizations are pursued. Thus, their impact compared to other alternative approaches remains impossible to assess. Through *LearnLib*'s modular design, changing filters, algorithm parameters or even the whole algorithm is a matter of a few lines of code, yielding valuable insights on how different algorithms perform on certain input data.

Related Work. Despite of the many applications that automata learning has seen, in most of the above-mentioned applications the authors chose to implement their own learning algorithms, mostly slight variants of L^*. We are aware of two other attempts that provide open source libraries of textbook algorithms, complemented by some own developments:

libalf[4] The *Automata Learning Framework* [9], was developed primarily at the RWTH Aachen. It is available under LGPLv3 and written in C++. Its active development seems to have ceased; the last version was released in April 2011.

AIDE[5] The *Automata-Identification Engine*, under active development, is available under the open-source license LGPLv2.1 and written in C#.

The ambitions behind *LearnLib* go further: It is specifically designed to easily compose new custom learning algorithms on the basis of components for counterexample anaylsis, approximations of equivalence queries, as well as connectors to real life systems. Moreover, *LearnLib* provides a variety of underlying data structures, and various means for visualizing the algorithm and its statistics. This does not only facilitate the construction of highly performant custom solutions, but also provides a deeper understanding of the algorithms' characterisitics. The latter has been essential, e.g., for designing the TTT algorithm [27], which almost uniformly outperforms all the previous algorithms.

2 AutomataLib

One of the main architectural changes of the open-source *LearnLib* is that it uses a dedicated, stand-alone library for representing and manipulating automata,

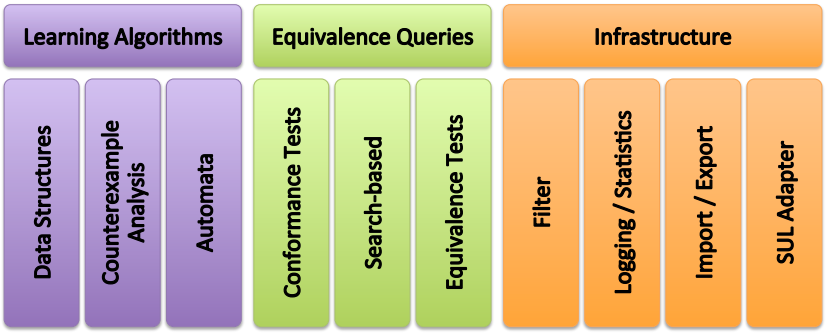


Fig. 2: Architecture of *LearnLib*

called *AutomataLib*.[6] While *AutomataLib* is formally independent of *LearnLib*, its development process is closely intertwined with the one of *LearnLib*. For this reason, *AutomataLib* mainly focuses on deterministic automata, even though selected classes of non-deterministic automata are supported as well (e.g., NFAs).

AutomataLib is divided into an *abstraction layer*, automata *implementations*, and *algorithms* (cf. Fig. 1). The abstraction layer comprises a set of *Java* interfaces to represent various types of automata and graphs, organized in a complex, fine-grained type hierarchy. Furthermore, these interfaces were designed in a generic fashion, to integrate existing, third-party automata implementations into *AutomataLib*'s interface landscape with as little effort and run-time overhead as possible. For instance, a proof-of-concept adapter for the BRICS automaton library[7] could be realized in as little as 20 lines of *Java* code.

Adapters like for the BRICS library form one part of the implementation layer. The other part are generic automaton implementations, e.g., for DFAs or Mealy machines, that provide good defaults for general setups, and are also used by most algorithms in *LearnLib* to store hypotheses.

Sample algorithms shipped with *AutomataLib* include minimization, equivalence testing, or visualization (via *GraphVIZ*'s[8] `dot` tool). The set of functionalities will be continuously extended, with a strong focus on functionality either directly required in *LearnLib*, or desirable in a typical automata learning application context.

An important aspect is that the algorithms operate solely on the abstraction layer, meaning that they are implementation agnostic: they can be used with a (wrapped) BRICS automaton as well as with other automaton implementations. Furthermore, the generic design enables a high degree of code reuse: the minimization (or equivalence checking) algorithm can be used for both DFA and Mealy machines, as it is designed to only require a *deterministic automaton*, instead of a concrete machine type (or even implementation).

[6] http://www.automatalib.net/
[7] http://www.brics.dk/automaton/
[8] http://www.graphviz.org/

3 LearnLib

LearnLib provides a set of components to apply automata learning in practical settings, or to develop or analyze automata learning algorithms. These components can be grouped into three main classes: learning algorithms, methods for finding counterexamples (so-called *Equivalence Queries*), and infrastructure components.

Learning Algorithms. *LearnLib* features a rich set of learning algorithms, covering the majority of algorithms which have been published (and many beyond that). Care was taken to develop the algorithms in a modular and parameterizable fashion, which allows us to use a single "base" algorithm to realize several algorithms described in the literature, e.g., by merely exchanging the involved counterexample analysis strategy. Perhaps the best example for this is the $\mathbf{L}^*$ algorithm [6], which can be configured to pose as **Maler&Pnueli's** [30], **Rivest&Schapire's** [37], or **Shahbaz's** [25] algorithm, **Suffix1by1** [25], or variants thereof. Other base algorithms available in *LearnLib* are the **Observation Pack** [20] algorithm, **Kearns&Vazirani's** [29] algorithm, the **DHC** [33] algorithm, and the **TTT** [27] algorithm. These, too, can be adapted in the way they handle counterexamples, e.g., by linear search, binary search (à la Rivest&Schapire), or exponential search [28]. With the exception of **DHC**, all these algorithms are available in both DFA and Mealy versions. Furthermore, *LearnLib* features the $\mathbf{NL}^*$ algorithm for learning NFAs [8].

Equivalence Tests and Finding Counterexamples. Once a learning algorithm converges to a stable hypothesis, a *counterexample* is needed to ensure further progress. In the context of active learning, the process of searching for a counterexample is also referred to as an *equivalence query*. "Perfect" equivalence queries are possible only when a model of the target system is available. In this case, *LearnLib* uses Hopcroft and Karp's near-linear equivalence checking algorithm [4, 19] available through *AutomataLib*. In black-box scenarios, equivalence queries can be approximated using conformance tests. *AutomataLib* provides implementations of the W-method [14] and the Wp-method [16], two of the few conformance tests that can find missing states. Often, the cheapest and fastest way of approximating equivalence queries is searching for counterexamples directly: *LearnLib* implements a random walk (only for Mealy machines), randomized generation of tests, and exhaustive generation of test inputs (up to a certain depth).

Infrastructure. The third class of components that come with *LearnLib* provide useful infrastructure functionality such as a logging facility, an import/export mechanism to store and load hypotheses, or utilities for gathering statistics. An important component for many practical applications are (optimizing) *filters*, which pre-process the queries posed by the learning algorithm. A universally useful example of such a filter is a *cache filter* [31], eliminating duplicate queries that most algorithms pose. Other examples include a parallelization component that distributes queries across multiple workers [21], a mechanism for reusing system states to reduce the number of resets [7], and for prefix-closed systems [31].

For a learning algorithm to work in practice, some interface to the system under learning (SUL) needs to be available. While this is generally specific to the SUL itself, *LearnLib* provides *SUL adapters* for typical cases, e.g., *Java* classes, web-services, or processes that are interfaced with via standard I/O.

4 Applications

In its ten years of continued development, *LearnLib* has been used in a number of research and industry projects. Here we only very briefly present some of the more recent projects. A more complete list can be found on the *LearnLib* homepage.

Models of Smart Cards. *LearnLib* has been used to infer models of smart card readers [11] and of bank cards [3]. The models were used to verify security properties of these systems.

Models of Network Protocols. In [2, 15], models of communication protocols are inferred using *LearnLib*. The models are used to verify the conformance of protocol implementations to the corresponding specifications.

Continuous Quality Assurance. At TU Dortmund, *LearnLib* has been used in an industry project [38] to generate models of a web application. The models were used to test regressions in the user interface and in the business processes of this application.

FPGA Unit Checking. The authors of [32] propose a method for generating checking circuits for functions implemented in FPGAs. The method uses models of the functions that are inferred with *LearnLib*.

Interface Generation. PSYCO [17, 22] is a tool for generating precise interfaces of software components developed at CMU and NASA Ames. The tool combines concolic execution and active automata learning (i.e., *LearnLib*).

Tomte. Another tool that uses *LearnLib* is **Tomte**, developed at the Radboud University of Nijmegen [1]. It leverages regular inference algorithms provided by *LearnLib* to infer richer classes of models by simultaneously inferring sophisticated abstractions (or "mappers").

5 Conclusion

In this paper we have presented *LearnLib*, a versatile open-source library of active automata learning algorithms. *LearnLib* is unique in its modular design, which has furthered the development of new learning algorithms (e.g., the TTT algorithm [27]) and tools (e.g., Tomte [1] and PSYCO [17, 22]). While in many aspects the open-source *LearnLib* by far surpasses the capabilities of the previous version, there are two major features which have yet to be ported. The first is *LearnLib Studio* (cf. [34]), a graphical user interface for *LearnLib*, and the second is an extension for learning *Register Automata*. An extension for learning Register Automata with the theory of equality only was available upon request for the old *LearnLib* in binary form [23, 26]. We are currently working on a generalized approach [10], which will be included in the open-source release.

References

1. Aarts, F., Heidarian, F., Kuppens, H., Olsen, P., Vaandrager, F.W.: Automata learning through counterexample guided abstraction refinement. In: FM 2012: Formal Methods - 18th International Symposium, Paris, France, August 27-31, 2012. Proceedings. pp. 10–27 (2012)
2. Aarts, F., Jonsson, B., Uijen, J., Vaandrager, F.W.: Generating models of infinite-state communication protocols using regular inference with abstraction. Formal Methods in System Design 46(1), 1–41 (2015)
3. Aarts, F., de Ruiter, J., Poll, E.: Formal models of bank cards for free. In: 2013 IEEE Sixth International Conference on Software Testing, Verification and Validation, Workshops Proceedings, Luxembourg, Luxembourg, March 18-22, 2013. pp. 461–468 (2013)
4. Almeida, M., Moreira, N., Reis, R.: Testing the equivalence of regular languages. In: Proceedings Eleventh International Workshop on Descriptional Complexity of Formal Systems, DCFS 2009, Magdeburg, Germany, July 6-9, 2009. pp. 47–57 (2009), http://dx.doi.org/10.4204/EPTCS.3.4
5. Alur, R., Cerný, P., Madhusudan, P., Nam, W.: Synthesis of interface specifications for java classes. In: Palsberg, J., Abadi, M. (eds.) Proceedings of the 32nd ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages, POPL 2005, Long Beach, California, USA, January 12-14, 2005. pp. 98–109. ACM (2005), http://doi.acm.org/10.1145/1040305.1040314
6. Angluin, D.: Learning Regular Sets from Queries and Counterexamples. Inf. Comput. 75(2), 87–106 (1987)
7. Bauer, O., Neubauer, J., Steffen, B., Howar, F.: Reusing System States by Active Learning Algorithms. In: Moschitti, A., Scandariato, R. (eds.) Eternal Systems, CCSE, vol. 255, pp. 61–78. Springer-Verlag (2012)
8. Bollig, B., Habermehl, P., Kern, C., Leucker, M.: Angluin-style Learning of NFA. In: Proc. IJCAI'09. pp. 1004–1009. IJCAI'09, San Francisco, CA, USA (2009)
9. Bollig, B., Katoen, J.P., Kern, C., Leucker, M., Neider, D., Piegdon, D.R.: libalf: The Automata Learning Framework. In: Touili, T., Cook, B., Jackson, P. (eds.) Computer Aided Verification, Lecture Notes in Computer Science, vol. 6174, pp. 360–364. Springer Berlin Heidelberg (2010), http://dx.doi.org/10.1007/978-3-642-14295-6_32
10. Cassel, S., Howar, F., Jonsson, B., Steffen, B.: Learning extended finite state machines. In: Software Engineering and Formal Methods - 12th International Conference, SEFM 2014, Grenoble, France, September 1-5, 2014. Proceedings. pp. 250–264 (2014)
11. Chalupar, G., Peherstorfer, S., Poll, E., de Ruiter, J.: Automated reverse engineering using lego®. In: 8th USENIX Workshop on Offensive Technologies, WOOT '14, San Diego, CA, USA, August 19, 2014. (2014)
12. Cho, C.Y., Babić, D., Shin, R., Song, D.: Inference and Analysis of Formal Models of Botnet Command and Control Protocols. In: Proc. CCS'10. pp. 426–440. ACM, Chicago, Illinois, USA (2010)
13. Choi, W., Necula, G., Sen, K.: Guided gui testing of android apps with minimal restart and approximate learning. In: Proceedings of the 2013 ACM SIGPLAN International Conference on Object Oriented Programming Systems Languages & Applications. pp. 623–640. OOPSLA '13, ACM, New York, NY, USA (2013), http://doi.acm.org/10.1145/2509136.2509552

14. Chow, T.S.: Testing software design modeled by finite-state machines. IEEE Trans. Software Eng. 4(3), 178–187 (1978)
15. Fiterau-Brostean, P., Janssen, R., Vaandrager, F.W.: Learning fragments of the TCP network protocol. In: Formal Methods for Industrial Critical Systems - 19th International Conference, FMICS 2014, Florence, Italy, September 11-12, 2014. Proceedings. pp. 78–93 (2014)
16. Fujiwara, S., von Bochmann, G., Khendek, F., Amalou, M., Ghedamsi, A.: Test selection based on finite state models. Software Engineering, IEEE Transactions on 17(6), 591–603 (1991)
17. Giannakopoulou, D., Rakamarić, Z., Raman, V.: Symbolic learning of component interfaces. In: Miné, A., Schmidt, D. (eds.) Proceedings of the 19th International Static Analysis Symposium (SAS 2012). Lecture Notes in Computer Science, vol. 7460, pp. 248–264. Springer (2012)
18. Hagerer, A., Hungar, H., Niese, O., Steffen, B.: Model generation by moderated regular extrapolation. In: Proceedings of the 5^{th} Int. Conf. on Fundamental Approaches to Software Engineering, FASE '02. Lecture Notes in Computer Science, vol. 2306, pp. 80–95. Springer Verlag (2002)
19. Hopcroft, J., Karp, R.: A linear algorithm for testing equivalence of finite automata. Tech. Rep. 0, Dept. of Computer Science, Cornell U (December 1971)
20. Howar, F.: Active Learning of Interface Programs. Ph.D. thesis, TU Dortmund University (2012), http://dx.doi.org/2003/29486
21. Howar, F., Bauer, O., Merten, M., Steffen, B., Margaria, T.: The Teachers' Crowd: The Impact of Distributed Oracles on Active Automata Learning. In: Hähnle, R., Knoop, J., Margaria, T., Schreiner, D., Steffen, B. (eds.) Proc. ISoLA 2012, pp. 232–247. CCIS, Springer (2012)
22. Howar, F., Giannakopoulou, D., Rakamarić, Z.: Hybrid learning: Interface generation through static, dynamic, and symbolic analysis. In: Proceedings of the International Symposium on Software Testing and Analysis (ISSTA). pp. 268–279. ACM (2013)
23. Howar, F., Steffen, B., Jonsson, B., Cassel, S.: Inferring Canonical Register Automata. In: Kuncak, V., Rybalchenko, A. (eds.) Proc. VMCAI'12. LNCS, vol. 7148, pp. 251–266. Springer (2012)
24. Hungar, H., Niese, O., Steffen, B.: Domain-Specific Optimization in Automata Learning. In: Proceedings of the 15^{th} Int. Conf. on Computer Aided Verification, CAV'03. Lecture Notes in Computer Science, vol. 2725, pp. 315–327. Springer Verlag (2003)
25. Irfan, M.N., Oriat, C., Groz, R.: Angluin Style Finite State Machine Inference with Non-optimal Counterexamples. In: 1st Int. Workshop on Model Inference In Testing (2010)
26. Isberner, M., Howar, F., Steffen, B.: Learning Register Automata: From Languages to Program Structures. Machine Learning 96(1-2), 65–98 (2014), http://dx.doi.org/10.1007/s10994-013-5419-7
27. Isberner, M., Howar, F., Steffen, B.: The TTT Algorithm: A Redundancy-Free Approach to Active Automata Learning. In: Bonakdarpour, B., Smolka, S. (eds.) Runtime Verification, Lecture Notes in Computer Science, vol. 8734, pp. 307–322. Springer International Publishing (2014), http://dx.doi.org/10.1007/978-3-319-11164-3_26
28. Isberner, M., Steffen, B.: An Abstract Framework for Counterexample Analysis in Active Automata Learning. In: Clark, A., Kanazawa, M., Yoshinaka, R. (eds.) Proceedings of the 12th International Conference on Grammatical Inference, ICGI

2014, Kyoto, Japan, September 17-19, 2014. JMLR Proceedings, vol. 34, pp. 79–93. JMLR.org (2014), http://jmlr.org/proceedings/papers/v34/isberner14a.html
29. Kearns, M.J., Vazirani, U.V.: An Introduction to Computational Learning Theory. MIT Press, Cambridge, MA, USA (1994)
30. Maler, O., Pnueli, A.: On the Learnability of Infinitary Regular Sets. Information and Computation 118(2), 316–326 (1995)
31. Margaria, T., Raffelt, H., Steffen, B.: Knowledge-based Relevance Filtering for Efficient System-level Test-based Model Generation. Innovations in Systems and Software Engineering 1(2), 147–156 (July 2005)
32. Matuova, L., Kastil, J., Kotásek, Z.: Automatic construction of on-line checking circuits based on finite automata. In: 17th Euromicro Conference on Digital System Design, DSD 2014, Verona, Italy, August 27-29, 2014. pp. 326–332 (2014)
33. Merten, M., Howar, F., Steffen, B., Margaria, T.: Automata Learning with On-the-Fly Direct Hypothesis Construction. In: Hähnle, R., Knoop, J., Margaria, T., Schreiner, D., Steffen, B. (eds.) Leveraging Applications of Formal Methods, Verification, and Validation, pp. 248–260. Communications in Computer and Information Science, Springer Berlin Heidelberg (2012), http://dx.doi.org/10.1007/978-3-642-34781-8_19
34. Merten, M., Steffen, B., Howar, F., Margaria, T.: Next Generation LearnLib. In: Proceedings of the 17^{th} Int. Conf. on Tools and algorithms for the construction and analysis of systems, TACAS'11. Lecture Notes in Computer Science, vol. 6605, pp. 220–223. Springer Verlag (2011)
35. Peled, D., Vardi, M.Y., Yannakakis, M.: Black Box Checking. In: Wu, J., Chanson, S.T., Gao, Q. (eds.) Proc. FORTE '99. pp. 225–240. Kluwer Academic (1999)
36. Raffelt, H., Steffen, B., Berg, T., Margaria, T.: LearnLib: a framework for extrapolating behavioral models. Int. J. Softw. Tools Technol. Transf. 11(5), 393–407 (2009)
37. Rivest, R.L., Schapire, R.E.: Inference of Finite Futomata Using Homing Sequences. Inf. Comput. 103(2), 299–347 (1993)
38. Windmüller, S., Neubauer, J., Steffen, B., Howar, F., Bauer, O.: Active continuous quality control. In: CBSE. pp. 111–120 (2013)
39. Xiao, H., Sun, J., Liu, Y., Lin, S., Sun, C.: Tzuyu: Learning stateful typestates. In: Denney, E., Bultan, T., Zeller, A. (eds.) 2013 28th IEEE/ACM International Conference on Automated Software Engineering, ASE 2013, Silicon Valley, CA, USA, November 11-15, 2013. pp. 432–442. IEEE (2013), http://dx.doi.org/10.1109/ASE.2013.6693101

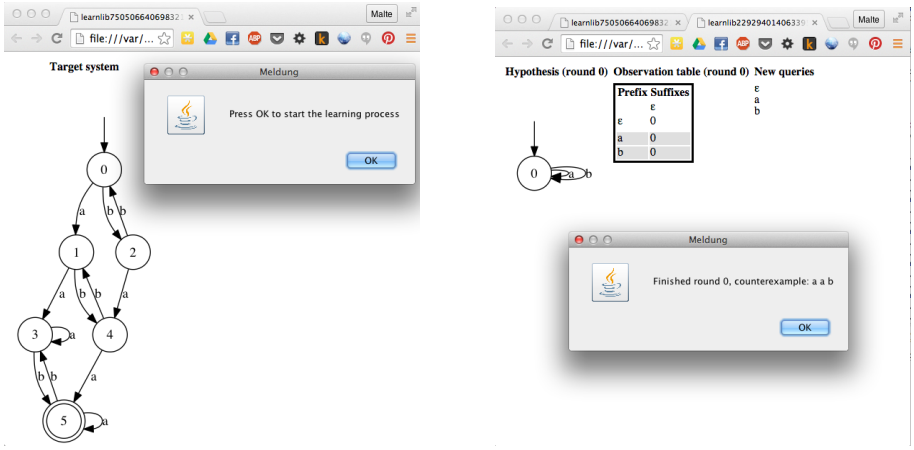
A A Short, Visual Demonstration of *LearnLib*

As the name suggests, *LearnLib* is primarily a library that can be used programmatically via its API. However, *LearnLib* also provides visualization capabilities that facilitate the understanding of learning algorithms. The following is a demonstration of these capabilities that have been used successfully during a tutorial at ISoLA 2014, and received very positive feedback.

The aim of the following is to foster an understanding of the role of counterexample analysis, in particular how long counterexamples negatively affect the performance of the L* algorithm, and how the TTT algorithm avoids these effects.

A.1 The L* algorithm

In a first step, the L* algorithm is applied to a simple target system (Fig. 3a). The user is explicitly prompted to start the learning process. Automata are rendered using the *GraphVIZ* `dot` tool and displayed in a browser, which enables the user to easily jump back to previous intermediate steps.



(a) (b)

Fig. 3: (a) Target system to be learned; (b) initial L* hypothesis

The L* algorithm starts with an initial one-state hypothesis (Fig. 3b), constructed from an observation table. A counterexample is obtained by a simulated equivalence test (as the target system is known). After a few more steps, the L* algorithm has inferred the final hypothesis (Fig. 4).

In a second step, the effect of (unnecessarily) long counterexamples is demonstrated. In this scenario, the user is prompted to enter a counterexample after

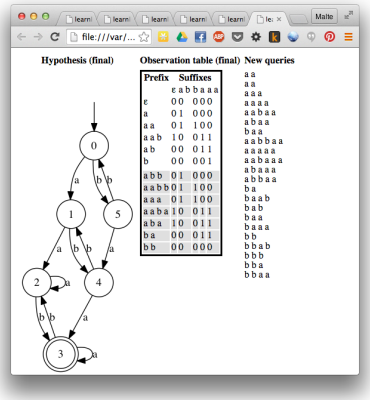


Fig. 4: Final L* hypothesis

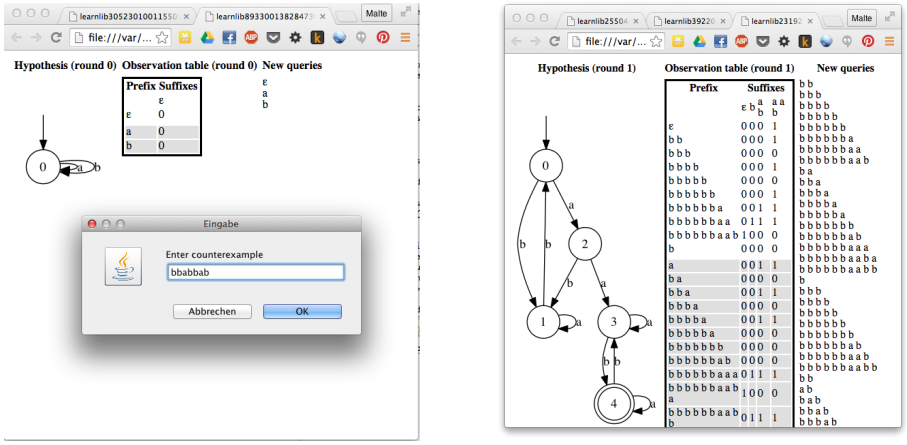
each stable hypothesis (Fig. 5a). Then, the resulting (considerably larger) observation table and hypothesis are shown (Fig. 5b).

A.2 The TTT Algorithm

The TTT algorithm was designed to mitigate the effects of excessively long counterexamples. In particular, it ensures that at the end of each intermediate steps, the length of all suffixes is linearly bounded. Furthermore, it replaces the observation table data structure with a binary decision tree (called discrimination tree).

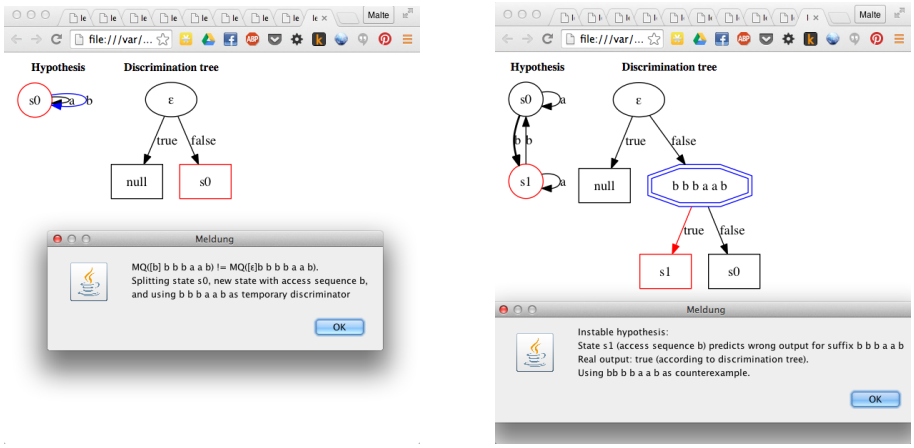
The TTT algorithm analyzes counterexamples by applying prefix transformations (Fig. 6a). The hypothesis resulting from the first step, however, sometimes contradicts the observations stored in the discrimination tree (Fig. 6b), referred to as an *instable hypothesis*. Furthermore, while the discrimination tree contains long suffixes (*bbbaab* in this case), these are marked as temporary (octagon shape) and will be replaced later.

An instable hypothesis gives rise to a new counterexample, which TTT handles in the ordinary fashion (Fig. 7). After a few more iterations of counterexample analysis and hypothesis stabilization, the (long) suffix *bbbaab* can be *finalized* (Fig. 8), replacing it with a shorter suffix (*b*). Message boxes inform the user about the progress in detail, and colored nodes in the data structure draw the attention to the important and changing parts.



(a) (b)

Fig. 5: (a) Prompt for entering a counterexample; (b) resulting observation table and hypothesis



(a) (b)

Fig. 6: (a) First counterexample analysis in the TTT algorithm; (b) detection of instable hypothesis

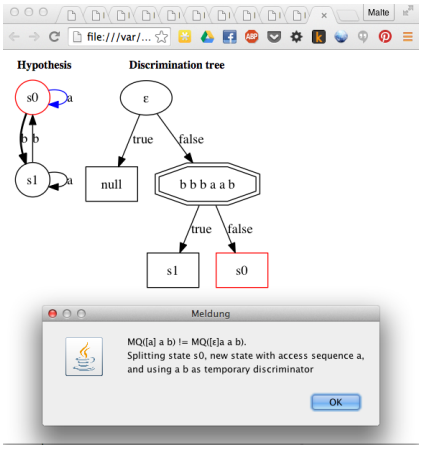


Fig. 7: Counterexample analysis step resulting from an instable hypothesis

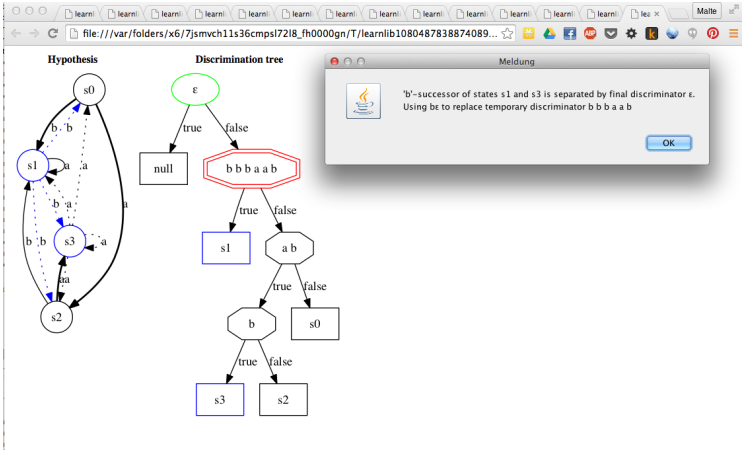


Fig. 8: Finalization step in the TTT algorithm