Learning Regular Languages via Alternating Automata*

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Abstract

Nearly all algorithms for learning an unknown regular language, in particular the popular \( L^* \) algorithm, yield deterministic finite automata. It was recently shown that the ideas of \( L^* \) can be extended to yield non-deterministic automata, and that the respective learning algorithm, \( NL^* \), outperforms \( L^* \) on randomly generated regular expressions.

We conjectured that this is due to the existential nature of regular expressions, and \( NL^* \) might not outperform \( L^* \) on languages with a universal nature. In this paper we introduce \( UL^* \) — a learning algorithm for universal automata (the dual of non-deterministic automata); and \( AL^* \) — a learning algorithm for alternating automata (which generalize both universal and non-deterministic automata).

Our empirical results illustrate the advantages and trade-offs among \( L^* \), \( NL^* \), \( UL^* \) and \( AL^* \).

1 Introduction

Regular languages are an important class of languages, in that they are simple enough to model many systems/phenomena in real life and enjoy a large variety of theoretical properties, enabling efficient algorithms for many questions involving regular languages. Regular languages can be recognized by many different formalisms, for instance, regular expressions, finite automata, and monadic second order logic of one successor. There are several classes of finite automata, differing in the “branching type”: deterministic finite automata (DFA), non-deterministic finite automata (NFA), universal finite automata (UFA) and alternating finite automata (AFA); and all are equally expressive, and as expressive as the class of regular languages.

A deterministic automaton \( D \) processes a given word \( w = \sigma_1\sigma_2\ldots\sigma_k \) by transitioning from state to state, according to the transition relation. The DFA accepts \( w \) from a given state \( q \), if the state \( q' \) that the automaton arrives at after reading \( \sigma_1 \) accepts the suffix \( v = \sigma_2\ldots\sigma_k \). A non-deterministic automaton \( N \), when in state \( q \) and reading letter \( \sigma \) may transition to one of several states (as determined by its transition relation). The NFA accepts \( w \), from state \( q \) if one of the states \( q_1, \ldots, q_k \)

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the same automaton state.

The $L^*$ algorithm builds a DFA from a given observation table, by associating a state with every distinct row in the table, and determining the transition on letter $\sigma$ from a state corresponding to row $s$ to go to the state that corresponds to the row $s\sigma$. The language accepted from state corresponding to $s$, is therefore indeed the residual of $s$ with respect to $L$ — it consists of all the suffixes $e$ of $s$ for which $se$ is in $L$.

Non-deterministic automata do not, in general, have the residuality property. Suppose an NFA $\mathcal{N}$ recognizing $L$ reads a word $w$ that is in $L$. There is at least one accepting run of $\mathcal{N}$ on $w$, but there may be several non-accepting runs of $\mathcal{N}$ on $w$. Suppose $w = uvv$ (where $u$ and $v$ are words, and $\sigma$ is a letter) and when reading $u$, $\mathcal{N}$ had no non-deterministic choices to make, and it got to state $q$. A choice from state $q$ on $\sigma$ to state $q'$ is "bad" for $w$, if the suffix $v$ is not accepted from $q'$. While this is perfectly fine, and $\mathcal{N}$ still accepts $w$ and correctly recognizes $L$, the state $q'$ does not correspond to a residual language.

[Denis et al., 2001a] have introduced the brilliant notion of non-deterministic residual finite state automata (NRFA) — a special type of NFA, where each state does correspond to a residual language, and intuitively, in the above sense, every choice can be "salvaged". As in the deterministic case, each state $q$ of an NRFA $\mathcal{N}$ recognizing a language $L$ can be associated with a characteristic word $w_q$, such that the words accepted from this state onward, are exactly all the allowed suffixes of $w_q$ in $L$. However, if there are $n$ residual languages for $L$ by the Myhill-Nerode theorem, an NRFA for $L$ may have fewer than $n$ states. If a residual language $L_i$ of $L$ does not correspond to any state of the NRFA then it corresponds to a union of some states of the NRFA.

The residuality property has been shown to be useful for various learning algorithms [Denis et al., 2001b; Esposito et al., 2002; Bollig et al., 2009; Kasprzik, 2010; 2011]. In particular, [Bollig et al., 2009] showed that the ideas of $L^*$ can be generalized to obtain a minimal NRFA rather than the minimal DFA. They name their algorithm NL$^*$. Since the minimal NRFA is at most as large as the minimal DFA and may be exponentially smaller, this approach is very appealing. They further show, that the worst case complexity of NL$^*$ in terms of membership queries and equivalence queries, is slightly worse than that of $L^*$, which makes sense given the obtained succinctness. Nonetheless, they show that on randomly generated regular expressions, NL$^*$ outperforms $L^*$ in both these measures.

Fascinated by these results, in this work we extend the definition of residual automata to universal automata and alternating automata, and the ideas of NL$^*$ to learning algorithms UL$^*$ and AL$^*$ yielding UFAs and AFAs, respectively. A residual NFA for $L$ need not have a state for a residual language of $L$, say $L_i$, if $L_i$ can be obtained by a union of other residual languages. Likewise a residual UFA (URFA) need not have a state for a residual language of $L$, $L_i$, if $L_i$ can be obtained by an intersection of other residual languages. A residual AFA (ARFA) need not have a state for a residual language of $L$, $L_i$,

if $L_i$ can be obtained by a monotone combination of some residual languages $L_{1}, \ldots, L_{k}$ it does have a state for.

[Bollig et al., 2009] have shown that NL$^*$ outperforms $L^*$ on randomly generated regular expressions. Random regular expressions, having an operator for union but not for intersection, are more reminiscent of NFAs, so it is likely that NL$^*$ would outperform $L^*$ on randomly generated NFAs. It is not clear how would $L^*$ and NL$^*$ compare on randomly generated DFAs, UFAs and AFAs. In a preliminary experiment we conducted we compared NL$^*$ and $L^*$ on randomly generated DFAs with up to 100 states, and randomly generated NFAs with 10 states (whose minimal equivalent DFAs yielded up to and more than 150 states). As can be seen in Fig. 1, NL$^*$ indeed outperforms $L^*$ on randomly generated NFAs, but on randomly generated DFAs, $L^*$ outperforms NL$^*$.

Since AFAs generalize both NFAs and UFAs, as well as DFAs, and the ideas of AL$^*$ generalize those of NL$^*$ and $L^*$, we provide our algorithm as a scheme XL$^*$, for $X \in \{D, N, U, A\}$. That is, the algorithms $L^*$, NL$^*$, UL$^*$, AL$^*$ for generating DFAs, NFAs, UFAs, and AFAs, respectively, are obtained from XL$^*$ by calling different sub-procedures, parameterized by the type $X \in \{D, N, U, A\}$.

We tested all four algorithms $L^*$, NL$^*$, UL$^*$ and AL$^*$ on randomly generated DFAs, NFAs, UFAs and AFAs. The results show, that for $X \in \{D, N, U, A\}$, roughly speaking, XL$^*$ out-
recognizing $\Delta$ is a language and $\Delta = (m, v, v, \varepsilon)$ to denote the set of $M$ states for which the smallest $J$ and $L$ or only $AFA$ of states for $w \Delta$ (to use $4$ may be exponentially more succinct $w$ if there exists a string $w$ is $J$. We show that the same holds for their residual $I$ requires $\Delta$ is a residual language of $\Delta$ is a tuple $A = (\Sigma, Q, I, \delta, F)$, and $\Delta$ is a non-deterministic, universal, or deterministic, respectively.

The formal definition of a run tree of an alternating automaton may be found in [Kupferman and Vardi, 1998]. We denote by $[A]$ the set of strings $w$ accepted by $A$. For an automaton $A = (\Sigma, Q, I, \delta, F)$, and state $q \in Q$, we use $A_q$ to denote the automaton obtained from $A$ by making the initial condition $q$, i.e. $A_q = (\Sigma, Q, q, \delta, F)$. Similarly, for a Boolean expression $b \in B_+(Q)$ we use $A_b = (\Sigma, Q, b, \delta, F)$ to denote the automaton obtained from $A$ by making the initial condition $b$.

Residual Automata
If $L$ is a language and $u$ is a string, the residual of $L$ with respect to $L$ is $u^{-1}L = \{v \mid uv \in L\}$. A language $R$ is a residual language of $L$ if there exists a string $u$ such that $R = u^{-1}L$.

**Definition 1.** Let $A$ be an alternating automaton. We say that $A$ is an alternating residual automaton (ARFA) iff $[A_q]$ is a residual language of $[A]$, for every state $q$ of $A$. If $A$ is non-deterministic or universal we say that it is a non-deterministic residual automaton (NRFA) or universal residual automaton (URFA), respectively. We can also use DRFA for deterministic residual automata. By the Myhill-Nerode theorem, for every state $q$ of the minimal DFA $D$ of a language $L$ we have that $[D_q]$ is a residual language of $[D]$. Thus, the minimal DFA is a DRFA, and so is any trimmed DFA.

**Example 1.** Let $\Sigma = \{a, b\}$ and $L = \Sigma^* aa \Sigma^* \cap \Sigma^* bb \Sigma^*$. Fig. 2 shows two ARFAs $A$ and $B$ recognizing $L$. The initial condition of $A$ is $1 \wedge 3$. Since $[A_1] = \Sigma^* aa \Sigma^*$ and $[A_3] = \Sigma^* bb \Sigma^*$, we get $[A] = L$. To see that this is a residual automaton we have to show for each state $i$ a representative word $w_i$, such that $w_i^{-1}L = [A_i]$. We give the following representatives: $w_1 = bb$, $w_2 = bba$, $w_3 = aa$, $w_4 = aab$, $w_5 = aabb$. It is more challenging to see that $B$ correctly recognizes $L$. To get intuition, one can check what states are “active” after reading a certain word, these correspond to splits of a conjunctive part of a transition. All active states need to reach an accepting state for the automaton to accept. After reading $a$, the active set is $\{2, 3, 4\}$, after reading $aa$, it is $\{5, 3, 4\}$ after reading $aabb$ it is $\{5\}$ and after reading $aabb$ it is $\{5\}$. We note that $[A_i] = [B_i]$ for $i \in \{1..5\}$, and $[B_6] = \varepsilon^{-1}L$. Thus $B$ is also a residual automaton.

**Succinctness** It is well known that NFAs and UFAs may be exponentially more succinct than DFAs, and AFAs may be exponentially more succinct than NFAs and UFAs, and doubly-exponentially more succinct than DFAs [Chandra and Stockmeyer, 1976].3 We show that the same holds for their residual counterparts.

**Theorem 1.** NRFA and URFA may be exponentially more succinct than DRFAs. ARFA may be exponentially more succinct than NRFAs and URFAs, and doubly-exponentially more succinct than DRFAs.

The proof is omitted; the method is a general transformation of an automaton for $L$ to a residual automaton for a language $L'$ that is essentially as hard to recognize as $L$.

**3 Learning Alternating Automata**

The $L'$ algorithm makes use of the notion of an observation table. An observation table is a Boolean matrix whose rows and columns are associated with different strings. We define some general notions on Boolean vectors and matrices.

**Boolean vectors and matrices** Let $n$ be a positive integer and $\{0, 1\}^n$ all Boolean vectors of length $n$, also denoted $B^n$. Extend $\wedge$ and $\vee$ to Boolean vectors componentwise. We also define a partial ordering on Boolean vectors: $u \leq v$ if $u[j] \leq v[j]$ for all indices $1 \leq j \leq n$. Let $0$ denote the vector of all 0 entries, and $1$ denote the vector of all 1 entries.

Let $M$ be an $m \times n$ matrix. The $i$-th row of $M$ is denoted $M_i$, and the $i$-th column of $M$ is denoted $M^i$. Note that the rows of $M$ are vectors of size $n$ whereas its columns are vectors of size $m$. For a subset of indices $I \subseteq \{1..m\}$ we use $M_I$ for the $|I| \times n$ matrix obtained from $M$ by deleting the rows $j \notin I$. We can analogously define $M^i$ for $I \subseteq \{1..n\}$.

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3The exact bounds depend on the exact definition of $AFA$. [Kozen, 1976] defined $AFA$s in which the transition relations may also use negation, and showed that there exists an $AFA$ with $n$ states for which the smallest DFA requires $2^{2^n}$ states. We follow the definition of [Chandra and Stockmeyer, 1976], who showed that exists an $AFA$ with $n$ states for which the smallest DFA requires $2^{2^n} / n!$. [Meyer and Fischer, 1971] use $\exists$ and $\forall$ states, and show that a DFA for an $AFA$ with $5n + 2$ states requires at least $2^{2^n}$. 

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row-index of \( M \) is the number of distinct rows of \( M \) and its column-index is the number of distinct columns in \( M \).

An observation table An observation table \( T \) is a tuple \((S, E, M)\) where \( S \) is a list of strings, representing candidate states, \( E \) is a list of strings, representing experiments trying to differentiate the elements of \( S \), and \( M \) is a binary matrix of \(|S| \) rows and \(|E| \) columns. We say that \( T \) is an observation table for \( L \) if \( M_{i,j} = 1 \) iff \( s_i e_j \in L \). By abuse of notation we use \( M_{s,e} \) for \( M_{i,j} \) where \( s \) is the \( i \)-th string of \( S \), and \( e \) the \( j \)-th string of \( E \). Similarly, we use \( M_s \) instead of \( M_i \) and for a subset of strings \( U \subseteq S \) we use \( M_U \) for \( M_{I_U} \) where \( I_U \) is the set of indices of \( U \).

Let \( \Sigma_{<}^* \) be the list of all strings ordered lexicographically. If \( T = (\Sigma_{<}^*, \Sigma_{<}^*, M_L) \) is an observation table for \( L \) then \( T \) is said to be the complete observation table for \( L \). For a language \( L \) we use \( T_L \) to denote the complete observation table for \( L \). By the Myhill-Nerode theorem, if \( L \) is regular then the row-index of \( T_L \) is finite, and the states of the minimal DFA for \( L \) correspond to distinct rows of \( T_L \).

Monotone, union and intersection bases The \( L^* \) algorithm starts with an empty observation table, which it gradually extends and fills using membership queries. In intermediate steps, when the observation tables is closed (defined shortly), it builds a corresponding automaton on which it asks an equivalence query. The definition of closed tables makes use of the following general definitions regarding Boolean vectors.

Let \( V \subseteq \mathbb{B}^n \) be a set of vectors. For a Boolean expression \( b \in \mathbb{B}_+(V) \) we use \([b]\) for the element of \( \mathbb{B}^n \) obtained by applying \( b \) to \( V \). Note that for \( v \in V \), \( v \in \mathbb{B}_+(V) \) and \([v] = v \). For a set of Boolean expressions \( B \) we use \([B]\) for \( \cup_{b \in B} [b] \). A set of vectors \( U \subseteq \mathbb{B}^n \) is said to be

- a monotone basis of \( V \), if \( V \subseteq [\mathbb{B}_+(U)] \),
- an union basis of \( V \), if \( V \subseteq [\mathbb{B}_+(U)] \), and
- an intersection basis of \( V \), if \( V \subseteq [\mathbb{B}_-(U)] \)

If \( U \) is monotone basis for \( V \) and a subset of \( V \) we say it is a subset monotone basis for \( V \), otherwise we may use general monotone basis to emphasize that \( U \) need not be a subset of \( V \). The definitions of subset union basis and subset intersection basis are analogous.

Closed and monotone observation tables Let \( T = (S, E, M) \) be an observation table. The definition of \( T \) being closed is different for \( L^* \), \( \mathcal{N}_L^* \), \( \mathcal{U}_L^* \), and \( \mathcal{A}_L^* \). We thus use \( x \)-closed for \( x \in \{D, N, U, A\} \). The definition of a table being closed is with respect to a set \( P \subseteq S \). The first part is the same for all four: it requires that the empty string \( \epsilon \) is in \( P \) and that for every \( p \in P \), all its one-letter extensions \( \sigma \) for \( \sigma \in \Sigma \) are in \( S \).

As for the second part, intuitively, for \( L^* \), the set \( P \) is the set of distinct rows of the table. For \( \mathcal{N}_L^* \), the set \( P \) is the set of prime rows of the table (that is why we use \( P \) to denote it), i.e., the other rows of the table should be expressible in terms of disjunctions of the prime rows. For \( \mathcal{U}_L^* \), the set \( P \) is the set of prime rows w.r.t conjunction, i.e., the other rows of the table should be expressible in terms of conjunctions of the prime rows. For \( \mathcal{A}_L^* \), the set \( P \) corresponds to a monotone basis for the other distinct rows.

Formally, an observation table \( T = (S, E, M) \) is \( d \)-closed with respect to a subset \( P \) of \( S \), if \( \epsilon \in P \), \( \mathcal{P}_S \subseteq S \) and for every row \( s_i \in S \setminus P \), there exists \( s_j \in P \) such that \( M_i = M_j \). An observation table \( T = (S, E, M) \) is \( \epsilon \)-closed w.r.t. a subset \( P \) of \( S \), if \( \epsilon \in P \), \( \mathcal{P}_S \subseteq S \) and \( M_P \) is a subset monotone basis for \( M_S \). It is \( N \)-closed and \( U \)-closed w.r.t. a subset \( P \) of \( S \), if \( \epsilon \in P \), \( \mathcal{P}_S \subseteq S \) and \( M_P \) is a subset union basis for \( M_S \) or a subset intersection basis for \( M_S \), respectively.

Next we introduce the notion of \( x \)-minimality. Intuitively, being closed with respect to \( P \) guarantees us that all distinct rows are expressible by the allowed combinations of \( P \) rows. A trivial way to achieve this is to include all rows. Since we use \( P \) to derive the set of states of the learned automaton, we want it to be as small as possible. If there is a row in \( P \) that can be expressed by means of the other rows, we can remove it from \( P \). Formally, let \( T \) be \( \epsilon \)-closed w.r.t. \( P \). We say that \( T \) is \( x \)-minimal w.r.t. \( P \) if for every \( p \in P \) and \( P' \subseteq P \setminus p \), \( M_{P'} \notin [\mathbb{B}_+(P')] \). The notions of \( N \)-minimal and \( U \)-minimal observation tables are defined analogously.

From tables to automata Let \( T = (S, E, M) \) be an observation table which is \( \epsilon \)-closed and minimal with respect to \( P \). For \( s \in S \) let \( b_s \in \mathbb{B}_+(P) \) be a Boolean expression over \( P \) satisfying \( M_s = [b_s] \). Then the tuple \((\Sigma, P, \lambda, \delta, F)\) where \( F = \{ p \in P \mid M_{P,\epsilon} = 1 \} \), and \( \delta(p, \sigma) = b_{p\sigma} \), is an AFA, which we denote \( \mathcal{A}_T^P \).

3.1 Finding an Adequate Basis

As mentioned previously, the learning algorithm gradually builds an observation table using membership queries. Two missing ingredients for the learning algorithm are (1) how to find a set \( U \) such that \( T \) is \( x \)-closed and minimal w.r.t it to, and (2) given \( U \) and a string \( s \), how to find, if possible, an expression \( b_s \), in \( \mathbb{B}_+(U) \) such that \( b_s = [b_s] \), where \( \mathbb{B}_A(Q), \mathbb{B}_N(Q), \mathbb{B}_U(Q), \mathbb{B}_D(Q) \) correspond to \( \mathbb{B}_+(Q), \mathbb{B}_+(Q), \mathbb{B}_-(Q) \), and \( Q \), respectively.

Finding a Union/Intersection Basis

Because of the duality of union and intersection we can consider just one of these, and the results follow for the other.

Claim 1. Let \( v \in \mathbb{B}^n \) and \( U \subseteq \mathbb{B}^n \). There is a polynomial time algorithm to determine whether \( v \in \mathbb{B}_+(U) \).

Proof. We compute the union of all vectors \( u \in U \) s.t. \( u \leq v \). Then \( v \) is equal to this union if and only if \( v \in \mathbb{B}_+(U) \). \( \square \)

Given a set of vectors \( U \) and a vector \( u \in U \), we say that \( u \) is union-redundant for \( U \) if \( u \notin \mathbb{B}_+(U - \{u\}) \). We observe that if \( u \in U \) is not union-redundant for \( U \) then it must appear in any subset union basis for \( U \) because it cannot be formed by union using the other elements of \( U \).

Theorem 2. [Bollig et al., 2009] Given a set of vectors \( V \), there is a polynomial time algorithm to find a minimum cardinality subset union basis for \( V \).

\footnote{Note that this question, of finding a subset union basis, is differ-
Note that this shows that there is a unique subset union basis of $V$ of minimum cardinality, and by duality this is true also for intersection.

**Finding a Monotone Basis**

Answering whether a vector $v$ can be expressed as an adequate formula over $U$ is more complicated for the monotone case, but can still be done in polynomial time.

**Claim 2.** Let $v \in B^n$ and $U \subseteq B^n$. There is a polynomial time algorithm to determine whether $v \in B_+(U)$.

**Proof.** If there exists a monotone formula over $U$ representing $v$, then there exists one in DNF form, i.e., in the form $I_1 \cup I_2 \cup \ldots \cup I_k$ where $I_i$ are intersections of subsets of $U$. The following procedure checks if there is a DNF formula over $U$ representing $v$.

Assume $U = \{u_1, \ldots, u_m\}$. A DNF formula over $U$ can be represented by a set of vectors in $B^m$ since a vector in $B^m$ can represent a subset $S$ of $U$, by having index $i$ set to 1 iff the respective vector $v_i \in S$. The given set of vectors $U$ can be represented by an $m \times n$ matrix, whose rows are $U$. In this matrix, a column $M_i$ represents exactly the set of all vectors $v$ in $U$, with $v[i] = 1$. Thus, if $M_i$ is one of the disjuncts of $D$ then $[D[i]] = 1$, unless $M_i = \emptyset$.

Consider the given vector $v$. Let $I_0$ be the set of indices $i$ such that $v[i] = 0$, and likewise $I_1$ be the set of indices $i$ such that $v[i] = 1$. Assume $D$ is a DNF formula for $v$ over $U$. We note that first, for every $i \in I_0$, the column vector $M^i \notin D$, unless $M^i = \emptyset$. As otherwise $[D[i]] = 1$ contradicting it represents $v$ for which $v[i] = 0$. Second, for every $i \in I_1$, either the column vector $M^i \in D$ or some column vector $M^j$ s.t. $0 \neq M^j \leq M^i$ is in $D$, as otherwise none of the disjuncts of $D$ will have 1 in the $i$-th index, contradicting $v[i] = 1$. Thus, to check if such a DNF formula exists it suffices to check that for all pairs of columns $M^j \leq M^k$ we have $v[j] \leq v[k]$. □

Given $v$ can be represented by a formula in $B_+(U)$, there may generall be many different formulas achieving that. Considering both constraints in the proof of Claim 2, for $v \in I_1$, we must include in the DNF formula the smallest $M^j < M^i$. We return the union of the minimal $M^j < M^i$ for all $i \in I_1$. This gives a monotone DNF expression for $v$; a monotone CNF expression can be derived dually.

Unlike the case with union or intersection, finding a monotone subset of minimum cardinality is NP-hard.

**Theorem 3.** Given a set of vectors $V$ and a nonnegative integer $k$, it is NP-complete to determine whether there is a subset monotone basis $U$ for $V$ s.t. $|U| \leq k$.

The proof is omitted; it is a polynomial time reduction from the problem of monotone not-all-equal 3-SAT.

### 3.2 The learning algorithm

From claims 1 and 2 we can extract a procedure $\text{InB}_X(P,s)$ for $X \in \{D,N,U,A\}$ that determines whether $M_x$, the row corresponding to string $s$ in the observation table, can be represented as an adequate combination of $M_P$, the rows corresponding to strings $P$, and returns one such formula if the answer is “yes”.

Since the question of finding a minimum subset monotone basis is NP-hard, the algorithm proceeds greedily, maintaining, in addition to its observation table $T = (S, E, M)$, a subset $P$ of $S$ that is the current candidate for extracting an adequate basis. In each iteration of its main loop, it checks whether $T$ is closed with respect to $P$, by calling procedure $T.\text{IsClosed}(P)$. If the answer is “no”, the procedure returns a string $s_1 \in S \cup P\Sigma$ that cannot be expressed by $B_X(P)$ and the algorithm adds $s_1$ to $P$ and loops. Once $T$ is closed with respect to $P$ the algorithm checks whether $T$ is minimal with respect to $P$, by calling procedure $T.\text{IsMinimal}(P)$. If the answer is “no”, the procedure returns a string $s_2 \in P$ that can be expressed by $B_X(P \setminus \{s_2\})$. The algorithm then removes $s_2$ from $P$, and loops. Once $T$ has been found to be $X$-closed and minimal with respect to $P$, the algorithm calls $X\text{ExtractAut}$ to obtain an $X$-automaton $A$, on which it asks an equivalence query. If the answer is “yes”, the algorithm returns $A$. Otherwise the algorithm uses the counterexample $s_3$ provided by the equivalence oracle to extract experiments to add to $E$.

The procedure $\text{XFind&AddCols}$ examines all suffixes of $s_3$. For each suffix it checks whether it induces a new column, when projected on the strings in $P$ and their one-letter extensions. Formally, let $M_{P\Sigma}$ be the matrix obtained from $M$ by keeping only rows corresponding to strings in $P \cup P\Sigma$. The procedure $\text{XFind&AddCols}(s_3)$ computes for each suffix $e$ of $s_3$ that is not already in $E$, its corresponding column, by calling $\text{MQ}(se)$ for every string $s$ corresponding to a row of $M_{P\Sigma}$. If this column is not a column of $M_{P\Sigma}$ it adds $e$ to $E$.

```algorithm
Algorithm 1: $xL^*$ for $X \in \{D,N,U,A\}$

-oracles: \text{MQ, EQ}
-members: Observation table $T = (S, E, M)$, Candidate states set $P$
-methods: $\text{IsXClosed, IsXMinimal, XFind&AddCols, InB}_X, X\text{ExtractAut}$

$S = \langle e \rangle, E = \langle e \rangle, P = \langle e \rangle$ and $M_{e,e} = \text{MQ}(e)$.

repeat
- $(a_1, s_1) = T.\text{IsClosed}(P)$
- if $a_1 = \text{"no"}$ then
- $P.\text{AddString}(s_1)$
- else
- $(a_2, s_2) = T.\text{IsMinimal}(P)$
- if $a_2 = \text{"no"}$ then
- $P.\text{RemoveString}(s_2)$
- else
- $A = T.\text{XExtractAut}(P)$
- $(a_3, s_3) = \text{EQ}(A)$
- if $a_3 = \text{"no"}$ then
- $\text{XFind&AddCols}(s_3)$
- until $a_3 = \text{"yes"}$

return $A$
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4 Empirical Results

We implemented the algorithmic scheme \(XL^*\) and the sub-procedures \(IsxClosed\), \(IsxMinimal\), \(xFind\&AddCols\), \(InBx\), \(xExtractAut\) for all \(X \in \{D,N,U,A\}\). We have tested the four resulting algorithms \(L^*\), \(NL^*\), \(UL^*\) and \(AL^*\) on four sets of randomly generated automata; in each case the alphabet size was 3 and the number of states was as indicated. The first set consists of randomly generated DFAs of size 1 to 100. The second set consists of randomly generated NFAs of size 10. The third set consists of randomly generated UFAs of size 10. The forth set consists of randomly generated AFAs of size 7.

Equivalence queries were implemented by randomly querying 10,000 membership queries. Lengths were uniformly chosen from 0 to \(t + 2\) where \(t\) is the number of states in the target X-FA. For AFA targets the initial condition and transition relation chose randomly a formula with one alternation of disjunctions and conjunctions.

Figure 3 shows the results of \(L^*\), \(NL^*\), \(UL^*\) and \(AL^*\) on randomly generated AFAs (on the left) and UFAs (on the right). The upper row presents number of states in the learned automaton, the middle row the number of equivalence queries, and the lower row, the number of membership queries. The \(x\)-axis shows the number of states in the minimal DFA of the target language. The results are binned in groups of 10 showing the average value. The error bars correspond to the standard deviations. The blue line is for \(L^*\), the green for \(NL^*\), the purple line for \(UL^*\) and the red line for \(AL^*\). The light grey bars on the background represent the number of experiments in the respective bin, whose scale is on the right.

On AFA targets we can see that the number of states produced by \(AL^*\), is significantly smaller than the others, and the number of states produced by \(NL^*\) and \(UL^*\) is roughly the same. \(AL^*\) also outperforms the others in the number of membership queries, followed by \(UL^*\), \(NL^*\), and \(L^*\), in this order. On the measure of equivalence queries, \(L^*\) uses the fewest equivalence queries, followed by \(UL^*\), \(NL^*\) and \(AL^*\).

On UFA targets, \(UL^*\) comes first in all measures, but the difference in the obtained number of states between \(AL^*\) and \(UL^*\) is negligible. For lack of space we do not include the results on the sets of randomly generated DFAs and NFAs. The latter is, roughly speaking, symmetrical to that of randomly generated UFAs where the blue and purple colors switch. For DFAs, all algorithms produce essentially the same number of states, which is the number of states in the minimal DFA. In this set, \(L^*\), outperforms the others in all parameters, \(NL^*\) and \(UL^*\) perform equally well in all measures, and \(AL^*\) asks more equivalence and membership queries than the other three.
or a learning algorithm for it. However, De Morgan’s Laws show that any Boolean formula has an equivalent formula in which negation is only applied to variables, so it seems reasonable that the ideas of $AL^*$ can be extended to this case by considering for the basis the given set of vectors and their negations.

Our focus in this work was to obtain an $L^*$-style algorithm for AFAs. To this aim, we introduced residual AFAs, a generalization of residual NFAs. However, while we conjecture that $AL^*$ produces ARFAs, and our experiments did not refute this conjecture, we weren’t yet able to prove it. Residual NFAs have been studied from automata theoretic preservative [Denis et al., 2001a] and are now quite well understood. A better understanding of ARFAs, might help us fill in the missing part of the puzzle, and is worthwhile regardless.

5 Discussion

Since the empirical results show that $XL^*$ performs better on randomly generated X-RFAs, it is clear that if one has some knowledge of the target language, classifying it as being of a deterministic, existential, universal or alternating nature, then the corresponding $XL^*$ algorithm is to be preferred. In cases where no such apriori knowledge is available, one might choose the algorithm that has better overall performance on the parameter that is most significant/costly for the application at hand. For instance, if succinctness is crucial one might chose $AL^*$, but if equivalence queries are very expensive one might prefer $L^*$. Since all $XL^*$’s algorithm share the same observation table, one might also consider heuristics where, at different stages of the algorithm, it tries to learn different target types among DRFA, NRFA, URFA and ARFA.

A generalization of alternating automata as defined here (sometimes referred to as Boolean automata [Leiss, 1981]), allows any Boolean formulas, i.e., all formulas over $\lor$, $\land$ and $\neg$, in the initial condition and the transition relations. We have not studied a corresponding definition for the residual case

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References