# Learning Realtime One-Counter Automata Submitted at TACAS 2022

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Motivation	DFA Learning	Learning ROCA	Experimental results	References
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- 1. Motivation
- 2. Learning deterministic finite automata
- 3. Learning realtime one-counter automata
- 4. Experimental results

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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#### 1. Motivation

- 2. Learning deterministic finite automata
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Motiva ○●	tion	DFA Learning 000000	Learning ROCA	Experimental results 00	References
1	{				
2		"string": "He	llo, world",		
3		"integer": 42	,		
4		"double": 2.7	18,		
5		"array": ["st	ring"],		
6		"object": {"a	nything": "corr	rect"}	
7	}				

<sup>1</sup>For XML documents, see Chitic and Rosu, "On Validation of XML Streams Using Finite State Machines", 2004

0 0	ition	OFA Learning 000000	Learning ROCA 0000000000000	Experimental results	References
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How to know whether a JSON document satisfies a given set of constraints?

<sup>1</sup>For XML documents, see Chitic and Rosu, "On Validation of XML Streams Using Finite State Machines", 2004

1 {	esults References
<pre>2 "string": "Hello, world",</pre>	
3 "integer": 42,	
4 "double": 2.718,	
5 "array": ["string"],	
<pre>6 "object": {"anything": "correct"}</pre>	
7 }	

How to know whether a JSON document satisfies a given set of constraints?

 $\hookrightarrow$  Automata-based verification<sup>1</sup>.

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What kind of automata can be used? How to construct such an automaton?

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How to know whether a JSON document satisfies a given set of constraints?

 $\hookrightarrow$  Automata-based verification<sup>1</sup>.

What kind of automata can be used? How to construct such an automaton?

 $\hookrightarrow$  Realtime one-counter automata and our learning algorithm!

<sup>1</sup>For XML documents, see Chitic and Rosu, "On Validation of XML Streams Using Finite State Machines", 2004

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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#### 1. Motivation

- 2. Learning deterministic finite automata
  - Deterministic finite automaton
  - Active learning
- 3. Learning realtime one-counter automata
- 4. Experimental results

# A deterministic finite $automaton^2$ (DFA) is a tuple

- $\mathcal{A} = (\mathcal{Q}, \Sigma, \delta, \mathcal{q}_0, \mathcal{F})$  where:
  - Q is the set of states,
  - $\blacktriangleright$   $\Sigma$  is the alphabet,
  - $q_0 \in Q$  is the initial state,
  - $F \subseteq Q$  is the set of accepting states, and
  - ▶  $\delta \subseteq Q \times \Sigma \rightarrow Q$  is the transition function.

<sup>2</sup>Hopcroft and Ullman, *Introduction to Automata Theory, Languages and Computation*, 2000.

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The run for the word  $w = a_1 \dots a_n \in \Sigma^*$   $(n \in \mathbb{N})$  is the sequence of states

$$q_0 \xrightarrow{a_1}{\mathcal{A}} p_1 \xrightarrow{a_2} \dots \xrightarrow{a_n}{\mathcal{A}} p_n.$$

If  $p_n \in F$ , the run is said accepting.

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$$q_0 \xrightarrow{a_1}{\mathcal{A}} p_1 \xrightarrow{a_2} \dots \xrightarrow{a_n}{\mathcal{A}} p_n.$$

If  $p_n \in F$ , the run is said accepting. The language of  $\mathcal{A}$  is the set

$$\mathcal{L}(\mathcal{A}) = \{ w \in \Sigma^* \mid \exists q \in F, q_0 \xrightarrow{w}_{\mathcal{A}} q \}.$$

<sup>2</sup>Hopcroft and Ullman, *Introduction to Automata Theory, Languages and Computation*, 2000.

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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## Let $L \subseteq \Sigma^*$ . We want an algorithm to learn a DFA accepting L.

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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 $\hookrightarrow$  active learning algorithm.

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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# Let $L \subseteq \Sigma^*$ . We want an algorithm to learn a DFA accepting L.

 $\hookrightarrow$  active learning algorithm.

Active because the algorithm queries information during the learning process.

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# Figure 1: Angluin's framework Angluin, "Learning Regular Sets from Queries and Counterexamples", 1987

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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Figure 1: Angluin's framework Angluin, "Learning Regular Sets from Queries and Counterexamples", 1987





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**Algorithm 1** Abstract learner for  $L^*$  [Angluin, "Learning Regular Sets from Queries and Counterexamples", 1987]

Require: The target language L

**Ensure:** A DFA accepting *L* is returned

- 1: Initialize the data structure
- 2: Fill the data structure with membership queries
- 3: while true do

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- 4: Make sure the data structure respects some constraints
- 5: Construct the DFA  $\mathcal{A}$
- 6: Ask an equivalence query over A
- 7: **if** the answer is positive **then**
- 8: return  $\mathcal{A}$
- 9: else
- 10: Given the counterexample *w*, refine the data structure
- 11: Fill the data structure with membership queries

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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Let  $L = \{a^n b (b^* a)^m (a|b)^* \mid n, m \ge 0\}$  over  $\Sigma = \{a, b\}$ .

Let  $u \in \Sigma^*$ . For all  $w \in \Sigma^*$ , we look if  $uw \in L$ . We construct a table where the rows are indexed by the u and the columns by the w. Motivation 00 DFA Learning

Learning ROCA

Experimental results

References

# Let $L = \{a^n b (b^* a)^m (a|b)^* \mid n, m \ge 0\}$ over $\Sigma = \{a, b\}$ .

	ε	а	b	аа	ab	ba	bb	
ε	0	0	1	0	1	1	1	
а	0	0	1	0	1	1	1	
b	1	1	1	1	1	1	1	
аа	0	0	1	0	1	1	1	
ab	1	1	1	1	1	1	1	
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Experimental results

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	ε	а	b	аа	ab	ba	bb	
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b	1	1	1	1	1	1	1	
аа	0	0	1	0	1	1	1	
ab	1	1	1	1	1	1	1	
÷	÷	÷	÷	÷	÷	÷	÷	·

Let  $u, v \in \Sigma^*$  and  $L \subseteq \Sigma^*$ . We say that  $u \sim v$  if and only if<sup>a</sup>

$$\forall w \in \Sigma^*, uw \in L \Leftrightarrow vw \in L.$$

<sup>a</sup>Hopcroft and Ullman, *Introduction to Automata Theory, Languages and Computation*, 2000.

Motivation	
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Learning ROCA

Experimental results

References

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	ε	а	b	аа	ab	ba	bb	
ε	0	0	1	0	1	1	1	
а	0	0	1	0	1	1	1	
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аа	0	0	1	0	1	1	1	
ab	1	1	1	1	1	1	1	
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#### Proposition 1

Let L be a language over  $\Sigma$ . Then, there is a DFA accepting L if and only if the index of  $\sim$  is finite.

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Learning ROCA

Experimental results

References

Let 
$$L = \{a^n b (b^* a)^m (a|b)^* \mid n, m \ge 0\}$$
 over  $\Sigma = \{a, b\}$ .



The Myhill-Nerode congruence encoded in this table has a finite index. We have two equivalence classes:  $[\![\varepsilon]\!]_{\sim}$  and  $[\![b]\!]_{\sim}$ .

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Learning ROCA

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References

## Let $L = \{a^n b (b^* a)^m (a|b)^* \mid n, m \ge 0\}$ over $\Sigma = \{a, b\}$ .



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Motivation	DFA Learning	Learning ROCA	Experimental results	References
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# 1. Motivation

#### 2. Learning deterministic finite automata

- 3. Learning realtime one-counter automata
  - Realtime one-counter automata
  - Behavior graph
  - Learning algorithm

#### 4. Experimental results

Motivation 00 DFA Learning 000000 Learning ROCA

Experimental results

References

A realtime one-counter automaton (ROCA) is a tuple  $\mathcal{A} = (Q, \Sigma, \delta_{=0}, \delta_{>0}, q_0, F)$  where  $Q, q_0$ , and F are defined as before, and the transition functions  $\delta_{=0}$  and  $\delta_{>0}$  are defined as:

$$\begin{split} \delta_{=0} &: Q \times \Sigma \to Q \times \{0, +1\} \\ \delta_{>0} &: Q \times \Sigma \to Q \times \{-1, 0, +1\}. \end{split}$$

Learning ROCA

Experimental results

References

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A configuration is a pair  $(q, n) \in Q \times \mathbb{N}$ .

Learning ROCA

Experimental results

References

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A configuration is a pair  $(q, n) \in Q \times \mathbb{N}$ . The transition relation  $\xrightarrow{\mathcal{A}} \subseteq (Q \times \mathbb{N}) \times \Sigma \times (Q \times \mathbb{N})$  contains  $(q, n) \xrightarrow{a}_{\mathcal{A}} (p, m)$  if and only if  $\begin{cases} \delta_{=0}(q, a) = (p, c) \land m = n + c & \text{if } n = 0 \\ \delta_{>0}(q, a) = (p, c) \land m = n + c & \text{if } n > 0. \end{cases}$ 

Learning ROCA

Experimental results

References

A realtime one-counter automaton (ROCA) is a tuple  $\mathcal{A} = (Q, \Sigma, \delta_{=0}, \delta_{>0}, q_0, F)$  where  $Q, q_0$ , and F are defined as before, and the transition functions  $\delta_{=0}$  and  $\delta_{>0}$  are defined as:

$$\begin{split} \delta_{=0} &: \mathcal{Q} \times \Sigma \to \mathcal{Q} \times \{0, +1\} \\ \delta_{>0} &: \mathcal{Q} \times \Sigma \to \mathcal{Q} \times \{-1, 0, +1\}. \end{split}$$

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Let  $w \in \Sigma^*$ . The counter value of w, according to  $\mathcal{A}$ , is:

$$c_{\mathcal{A}}(w) = n \Leftrightarrow \exists q \in Q, (q_0, 0) \xrightarrow{w}_{\mathcal{A}} (q, n).$$



Figure 2: An ROCA A.



Figure 2: An ROCA A.

$$(q_0,0) \xrightarrow{a}_{\mathcal{A}} (q_0,1) \xrightarrow{a}_{\mathcal{A}} (q_0,2) \xrightarrow{b}_{\mathcal{A}} (q_1,2) \xrightarrow{a}_{\mathcal{A}} (q_1,1) \xrightarrow{a}_{\mathcal{A}} (q_1,0) \xrightarrow{a}_{\mathcal{A}} (q_2,0).$$



Figure 2: An ROCA A.

$$(q_0,0) \xrightarrow{a}_{\mathcal{A}} (q_0,1) \xrightarrow{a}_{\mathcal{A}} (q_0,2) \xrightarrow{b}_{\mathcal{A}} (q_1,2) \xrightarrow{a}_{\mathcal{A}} (q_1,1) \xrightarrow{a}_{\mathcal{A}} (q_1,0) \xrightarrow{a}_{\mathcal{A}} (q_2,0).$$

$$\mathcal{L}(\mathcal{A}) = \{ a^n b (b^* a)^n (a|b)^* \mid n \ge 0 \}.$$

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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# Let $\mathcal{A}$ be an ROCA accepting L. We study the equivalence relation $\equiv$ induced by $\mathcal{A}$ over $\Sigma^*$ .

Let  $u, v \in \Sigma^*$ . We say that  $u \equiv v$  if and only if

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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1.  $\forall w \in \Sigma^*, uw \in L \Leftrightarrow vw \in L$ , and

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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Let  $u, v \in \Sigma^*$ . We say that  $u \equiv v$  if and only if

1.  $\forall w \in \Sigma^*, uw \in L \Leftrightarrow vw \in L$ , and

2.  $\forall w \in \Sigma^*, uw, vw \in Pref(L) \Rightarrow c_{\mathcal{A}}(uw) = c_{\mathcal{A}}(vw).$ 

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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Let  $\mathcal{A}$  be an ROCA accepting L. We study the equivalence relation  $\equiv$  induced by  $\mathcal{A}$  over  $\Sigma^*$ . Let  $u, v \in \Sigma^*$ . We say that  $u \equiv v$  if and only if 1.  $\forall w \in \Sigma^*, uw \in L \Leftrightarrow vw \in L$ , and 2.  $\forall w \in \Sigma^*, uw, vw \in Pref(L) \Rightarrow c_{\mathcal{A}}(uw) = c_{\mathcal{A}}(vw)$ .

For example, let  $L = \{a^n b(b^*a)^n (a|b)^* \mid n \ge 0\}$ . Then,  $b \equiv abba$  but  $ab \not\equiv aab$ .

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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Let  $\mathcal{A}$  be an ROCA accepting L. Using the relation  $\equiv$ , we can construct an infinite deterministic automaton accepting L: the behavior graph of  $\mathcal{A}$   $BG(\mathcal{A}) = (Q_{\equiv}, \Sigma, \delta_{\equiv}, q_{\equiv}^0, F_{\equiv})$  with:

$$Q_{\equiv} = \{ \llbracket u \rrbracket_{\equiv} \mid u \in Pref(L) \},$$

$$\blacktriangleright \ q^0_{\equiv} = \llbracket \varepsilon \rrbracket_{\equiv},$$

• 
$$F_{\equiv} = \{ \llbracket u \rrbracket_{\equiv} \mid u \in L \}$$
, and

►  $\delta_{\equiv} : Q \times \Sigma \to Q$  such that  $\delta(\llbracket u \rrbracket_{\equiv}, a) = \llbracket ua \rrbracket_{\equiv}$  with  $a \in \Sigma$  and  $u, ua \in Pref(L)$ .

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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Figure 3: The behavior graph of A.

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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Figure 3: The behavior graph of A.

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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Let A be an ROCA accepting L and BG(A) be its behavior graph. Then, BG(A) is ultimately periodic.

Motivation	DFA Learning	Learning ROCA	Experimental results	Reference
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Let  $\mathcal{A}$  be an ROCA accepting L and  $BG(\mathcal{A})$  be its behavior graph. Then,  $BG(\mathcal{A})$  is ultimately periodic. Moreover, it is possible to construct an ROCA accepting L from  $BG(\mathcal{A})$ .

Motivation	
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Learning ROCA

Experimental results

References

#### Let $\mathcal{A}$ be an ROCA accepting L.

<sup>3</sup>Based on the algorithm for VCA [Neider and Löding, *Learning visibly one-counter automata in polynomial time*, 2010].

V. Bruyère, G. A. Pérez, G. Staquet Learning ROCA — Learning algorithm

Motivation	DFA Learning	Learning ROCA	Experimental	results
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 Rough idea<sup>3</sup>: learn a sufficiently large initial fragment of BG(A) and construct an ROCA from it.

<sup>3</sup>Based on the algorithm for VCA [Neider and Löding, *Learning visibly one-counter automata in polynomial time*, 2010].

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<b>Notivation</b>	DFA Learning	Learning ROCA	Experimental results	References
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Rough idea<sup>3</sup>: learn a sufficiently large initial fragment of BG(A) and construct an ROCA from it.

What is an initial fragment?
→ BG<sub>ℓ</sub>(A) is a subgraph of BG(A) whose set of states is
{[[u]]<sub>=</sub> ∈ Q<sub>=</sub> | ∀x ∈ Pref(u), 0 ≤ c<sub>A</sub>(x) ≤ ℓ}, with ℓ ∈ N. Let
L<sub>ℓ</sub> = L(BG<sub>ℓ</sub>(A)).

<sup>3</sup>Based on the algorithm for VCA [Neider and Löding, *Learning visibly one-counter automata in polynomial time*, 2010].

lotivation	DFA Learning	Learning ROCA	Experimental results	References
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- Rough idea<sup>3</sup>: learn a sufficiently large initial fragment of BG(A) and construct an ROCA from it.
- ▶ What is an initial fragment?  $\hookrightarrow BG_{\ell}(\mathcal{A})$  is a subgraph of  $BG(\mathcal{A})$  whose set of states is  $\{\llbracket u \rrbracket_{\equiv} \in Q_{\equiv} \mid \forall x \in Pref(u), 0 \le c_{\mathcal{A}}(x) \le \ell\}$ , with  $\ell \in \mathbb{N}$ . Let  $L_{\ell} = \mathcal{L}(BG_{\ell}(\mathcal{A}))$ .
- How to construct an ROCA from BG<sub>ℓ</sub>(A)?
  → Not the focus here but it is possible.

<sup>&</sup>lt;sup>3</sup>Based on the algorithm for VCA [Neider and Löding, *Learning visibly one-counter automata in polynomial time*, 2010].

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- Rough idea<sup>3</sup>: learn a sufficiently large initial fragment of BG(A) and construct an ROCA from it.
- ▶ What is an initial fragment?  $\hookrightarrow BG_{\ell}(\mathcal{A})$  is a subgraph of  $BG(\mathcal{A})$  whose set of states is  $\{\llbracket u \rrbracket_{\equiv} \in Q_{\equiv} \mid \forall x \in Pref(u), 0 \le c_{\mathcal{A}}(x) \le \ell\}$ , with  $\ell \in \mathbb{N}$ . Let  $L_{\ell} = \mathcal{L}(BG_{\ell}(\mathcal{A}))$ .
- How to learn  $BG_{\ell}(\mathcal{A})$ ?  $\hookrightarrow BG_{\ell}(\mathcal{A})$  is actually a DFA.

<sup>3</sup>Based on the algorithm for VCA [Neider and Löding, *Learning visibly one-counter automata in polynomial time*, 2010].

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#### true or a counterexample



#### true or a counterexample





Motivation	
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Learning ROCA

Experimental results

References

#### **Algorithm 2** Adaptation of $L^*$ for ROCAs.

**Require:** A teacher knowing an ROCA  $\mathcal{A}$ 

Ensure: An ROCA accepting the same language is returned

- 1: Initialize the data structure  $\mathcal{D}_\ell$  up to  $\ell=0$
- 2: while true do
- 3: Make  $\mathcal{D}_\ell$  respect the needed constraints and construct  $\mathcal{A}_{\mathcal{D}_\ell}$
- 4: Ask a partial equivalence query over  $\mathcal{A}_{\mathcal{D}_{\ell}}$
- 5: **if** the answer is negative **then**
- 6: Update  $\mathcal{D}_{\ell}$  with the provided counterexample  $\triangleright \ell$  is not modified
- 7: **else**
- 8: Construct all the possible ROCAs  $A_1, \ldots, A_n$  from  $A_{D_\ell}$
- 9: Ask an equivalence query over each  $A_i$
- 10: **if** the answer is true for an  $A_i$  **then return**  $A_i$
- 11: **else** Select one counterexample and update  $\mathcal{D}_{\ell} 
  ightarrow \ell$  is increased

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Let  $\mathcal{A}$  be an ROCA accepting  $L \subseteq \Sigma^*$ . An observation table up to  $\ell$  is a tuple  $\mathscr{O}_{\ell} = (R, S, \widehat{S}, \mathcal{L}_{\ell}, \mathcal{C}_{\ell})$  with:

- $R \subseteq \Sigma^*$  is the prefix-closed set of representatives,
- $S \subseteq \widehat{S} \subseteq \Sigma^*$  are two suffix-closed sets of separators,
- $\mathcal{L}_{\ell}: (\mathcal{R} \cup \mathcal{R}\Sigma)\widehat{\mathcal{S}} \to \{0,1\}$ , and

$$\blacktriangleright \ \mathcal{C}_{\ell}: (\mathbf{R} \cup \mathbf{R}\Sigma) \mathbf{S} \to \{0, \dots, \ell\} \cup \{\bot\}.$$

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- $R \subseteq \Sigma^*$  is the prefix-closed set of representatives,
- $S \subseteq \widehat{S} \subseteq \Sigma^*$  are two suffix-closed sets of separators,
- $\mathcal{L}_{\ell} : (\mathcal{R} \cup \mathcal{R}\Sigma)\widehat{\mathcal{S}} \to \{0,1\}$ , and
- $\blacktriangleright \ \mathcal{C}_{\ell}: (\mathbf{R} \cup \mathbf{R}\Sigma) \mathbf{S} \to \{0, \dots, \ell\} \cup \{\bot\}.$

Let  $Pref(\mathcal{O}_{\ell}) = \{ w \in Pref(us) \mid u \in R \cup R\Sigma, s \in \widehat{S}, \mathcal{L}_{\ell}(us) = 1 \}.$ The following holds for all  $u \in R \cup R\Sigma$ :

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Motivation 00	DFA Learning 000000	Learning ROC	CA 000●0	Experimental results 00	References
			ε		
		ε	0, 0		
		а	0, 1		
		ab	0,1		
		aba	1, 0		
		b	1,0		
		аа	$0, \perp$		
		abb	$0, \perp$		
		abaa	1, 0		
		abab	1, 0		

Motivation 00	DFA Learning 000000	Learning RO	CA 000●0	Experimental results 00	References
			ε		
		ε	0, 0		
		а	0, 1		
		ab	0,1		
		aba	1,0		
		abb	0,1		
		b	1,0		
		аа	$0, \perp$		
		abaa	1, 0		
		abab	1, 0		
		abba	1, 0		
		abbb	$0, \perp$		

Motivation 00	DFA Learning 000000	Learning ROC	:A 00●0	Experimental results 00	References
			ε		
		ε	0,0		
		а	0, 1		
		ab	0, 1		
		aba	1,0		
		abb	0, 1		
		abbb	0, 1		
		Ь	1,0		
		аа	$0, \perp$		
		abaa	1,0		
		abab	1,0		
		abba	1,0		
		abbba	1,0		
		abbbb	$0, \perp$		

$\begin{array}{c c} \varepsilon \\ \hline \varepsilon & 0,0 \\ a & 0,1 \\ ab & 0,1 \\ aba & 1,0 \\ abb & 0,1 \\ \hline abbb & 0,1 \\ \hline b & 1,0 \\ aa & 0, \bot \\ abaa & 1,0 \\ abab & 1,0 \\ abbb & 1,0 \\ abbb & 1,0 \\ abbba & 1,0 \\ abbbb & 0, \bot \end{array}$	Motivation 00	DFA Learning 000000	Learning ROC	A 0000	Experimental results 00	References
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$				ε		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			ε	0,0		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			а	0, 1		
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			ab	0,1		
$ \begin{array}{cccc} abb & 0, 1 \\ abbb & 0, 1 \\ \hline b & 1, 0 \\ aa & 0, \bot \\ abaa & 1, 0 \\ abab & 1, 0 \\ abbb & 1, 0 \\ abbba & 1, 0 \\ abbbb & 0, \bot \end{array} $			aba	1, 0		
$ \begin{array}{c ccc} abbb & 0, 1 \\ \hline b & 1, 0 \\ aa & 0, \bot \\ abaa & 1, 0 \\ abab & 1, 0 \\ abba & 1, 0 \\ abbba & 1, 0 \\ abbbb & 0, \bot \end{array} $			abb	0,1		
$ \begin{array}{cccc} b & 1, 0 \\ aa & 0, \bot \\ abaa & 1, 0 \\ abab & 1, 0 \\ abba & 1, 0 \\ abbba & 1, 0 \\ abbbb & 1, 0 \\ abbbb & 0, \bot \end{array} $			abbb	0,1		
$\begin{array}{c c} aa & 0, \bot \\ abaa & 1, 0 \\ abab & 1, 0 \\ abba & 1, 0 \\ abbba & 1, 0 \\ abbbb & 1, 0 \\ abbbb & 0, \bot \end{array}$			b	1,0		
$\begin{array}{c c} abaa & 1,0 \\ abab & 1,0 \\ abba & 1,0 \\ abbba & 1,0 \\ abbbb & 1,0 \\ abbbb & 0, \bot \end{array}$			аа	$0, \perp$		
$ \begin{array}{c c} abab & 1,0 \\ abba & 1,0 \\ abbba & 1,0 \\ abbbb & 0, \bot \end{array} $			abaa	1, 0		
$\begin{array}{c c} abba & 1,0\\ abbba & 1,0\\ abbbb & 0, \bot \end{array}$			abab	1, 0		
$\begin{array}{c c} \textbf{abbba} & 1,0\\ \textbf{abbbb} & 0, \bot \end{array}$			abba	1, 0		
$abbbb \mid 0, \perp$			abbba	1, 0		
			abbbb	$0, \perp$		

 $\hookrightarrow$  Getting the algorithm to eventually finish is harder than it looks.

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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Let  $\mathcal{A}$  be an ROCA accepting a language  $L \subseteq \Sigma^*$ . Given a teacher for L with an automaton  $\mathcal{A}$ , and t the length of the longest counterexample for (partial) equivalence queries:

Motivation	DFA Learning	Learning ROCA	Experimental results	References
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Let  $\mathcal{A}$  be an ROCA accepting a language  $L \subseteq \Sigma^*$ . Given a teacher for L with an automaton  $\mathcal{A}$ , and t the length of the longest counterexample for (partial) equivalence queries:

An ROCA accepting L can be computed in time and space exponential in |A|, |∑| and t.

Motivation	DFA Learning	Learning ROCA	Experimental results	References
00	000000	00000000000●	00	

Let  $\mathcal{A}$  be an ROCA accepting a language  $L \subseteq \Sigma^*$ . Given a teacher for L with an automaton  $\mathcal{A}$ , and t the length of the longest counterexample for (partial) equivalence queries:

- An ROCA accepting L can be computed in time and space exponential in |A|, |∑| and t.
- The learner asks:
  - $\mathcal{O}(t^3)$  partial equivalence queries
  - $\blacktriangleright$   $\mathcal{O}(|\mathcal{A}|t^2)$  equivalence queries
  - An exponential number of membership (resp. counter value) queries in |A|, |Σ|, and t.

Motivation	DFA Learning	Learning ROCA	Experimental results	References
00	000000	000000000000	•0	

#### 1. Motivation

- 2. Learning deterministic finite automata
- 3. Learning realtime one-counter automata
- 4. Experimental results



# References I

Angluin, Dana. "Learning Regular Sets from Queries and Counterexamples". In: Inf. Comput. 75.2 (1987), pp. 87–106. DOI: 10.1016/0890-5401(87)90052-6. URL: https://doi.org/10.1016/0890-5401(87)90052-6. Chitic, Cristiana and Daniela Rosu, "On Validation of XML Streams Using Finite State Machines". In: Proceedings of the Seventh International Workshop on the Web and Databases, WebDB 2004, June 17-18, 2004, Maison de la Chimie, Paris, France, Colocated with ACM SIGMOD/PODS 2004. Ed. by Sihem Amer-Yahia and Luis Gravano. ACM, 2004, pp. 85–90. DOI: 10.1145/1017074.1017096. URL: https://doi.org/10.1145/1017074.1017096.

Hopcroft, John E. and Jeffrey D. Ullman. Introduction to Automata Theory, Languages and Computation, Second Edition. Addison-Wesley, 2000.

# References II



Neider, Daniel and Christof Löding. Learning visibly one-counter automata in polynomial time. Tech. rep. Technical Report AIB-2010-02, RWTH Aachen (January 2010), 2010.