A Myhill-Nerode Theorem for Register Automata and Symbolic Trace Languages

Frits Vaandrager Abhisek Midya

Radboud University Nijmegen

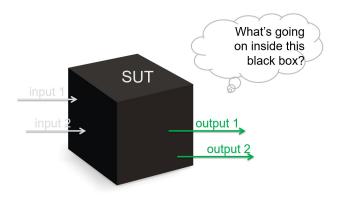
ICTAC, December 3, 2020



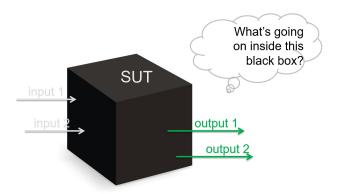
Outline

- 1 Introduction and Motivation
- 2 Our Myhill-Nerode Theorem
- 3 Conclusions and Future Work

Black-box Automata Learning



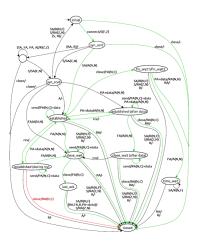
Black-box Automata Learning



System Under Test (SUT) behaves like deterministic state machine



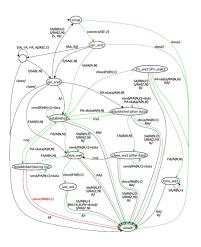
Success Stories Automata Learning



Standard violations found in implementations of major protocols:

- TLS (Usenix Security'15)
- TCP (CAV'16)
- SSH (Spin'17)

Success Stories Automata Learning



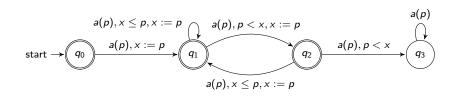
Standard violations found in implementations of major protocols:

- TLS (Usenix Security'15)
- TCP (CAV'16)
- SSH (Spin'17)

These findings led to bug fixes in implementations.

Register Automata

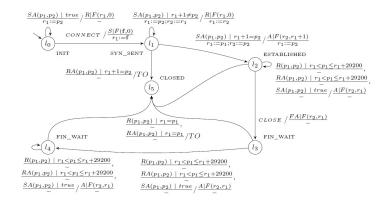
In applications inputs and outputs carry data parameters. State-of-the-art learning techniques either manually construct mappers to abstract from data parameters, or infer register automata (RAs) from black-box observations.



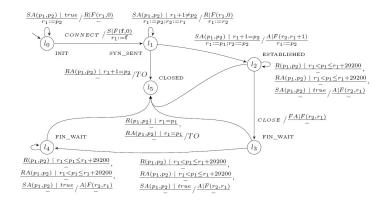
Learning Tools for Register Automata

- Tomte, Radboud University, only handles equality predicates
- LearnLib, TU Dortmund, only handles equality predicates
- RALib, Uppsala/Dortmund, handles a few other predicates

RALib TCP Case Study (FMICS-AVoCS'17)



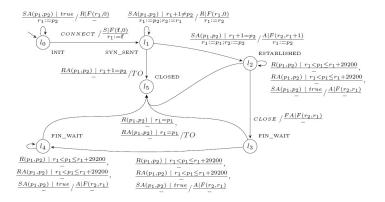
RALib TCP Case Study (FMICS-AVoCS'17)



These findings led to bug fix in Linux TCP implementation!



RALib TCP Case Study (FMICS-AVoCS'17)



These findings led to bug fix in Linux TCP implementation! ... but > 200.000 inputs were needed to learn model



Limits of Black-box Learning?

Black-box learning is highly effective bug finding technique

Limits of Black-box Learning?

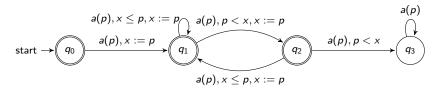
- Black-box learning is highly effective bug finding technique
- ... but it has scalability problems

Limits of Black-box Learning?

- Black-box learning is highly effective bug finding technique
- ... but it has scalability problems
- ... and fundamental restrictions on supported data types
- Challenge: use white-box information while preserving extensionality of black-box models

Data Words

In black-box learning, we observe (accepted) data words.

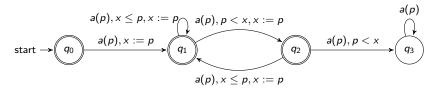


Register automaton accepts data word a(1)a(4)a(0)a(7) via run

$$(q_0,[]) \xrightarrow{a(1)} (q_1,[x \mapsto 1]) \xrightarrow{a(4)} (q_1,[x \mapsto 4]) \xrightarrow{a(0)} (q_2,[x \mapsto 0]) \xrightarrow{a(7)} (q_1,[x \mapsto 7])$$

Symbolic Words

Symbolic words record constraints on data parameters encountered during a run, using variable v_i as a marker for the i-th input value.



RA accepts symbolic word a \top a $v_1 \le v_2$ a $v_3 < v_2$ a $v_3 \le v_4$ via symbolic run

$$\begin{array}{c} (q_0,[]) \xrightarrow{a,\top,x:=p} (q_1,[x\mapsto v_1]) \xrightarrow{a,x\leq p,x:=p} (q_1,[x\mapsto v_2]) \\ \\ \xrightarrow{a,p< x,x:=p} (q_2,[x\mapsto v_3]) \xrightarrow{a,x\leq p,x:=p} (q_1,[x\mapsto v_4]) \end{array}$$

Symbolic Languages

- Symbolic words can be observed using white-box techniques like tainting, symbolic execution and concolic execution
- Can we adapt learning algorithms to this grey-box setting?

Symbolic Languages

- Symbolic words can be observed using white-box techniques like tainting, symbolic execution and concolic execution
- Can we adapt learning algorithms to this grey-box setting?
- Yes, see our iFM'20 paper! Approach effective, but ad hoc and limited to predicates like = and <
- Can we do better?

A Classic Result

Definition (Nerode equivalence)

The equivalence relation \sim_L on Σ^* induced by a language $L \subseteq \Sigma^*$:

$$u \sim_L v$$
 iff $\forall w \in \Sigma^* : u \cdot w \in L \Leftrightarrow v \cdot w \in L$

Theorem (Myhill-Nerode, 1958)

Language L is regular iff \sim_L has finitely equivalence classes. Moreover, the number of states in the smallest deterministic finite automaton (DFA) recognizing L is equal to the number of equivalence classes (index) of \sim_L .

Importance of Myhill-Nerode

Myhill-Nerode Theorems (MNTs) are crucial for model learning:

- Angluin's classical L* algorithm for learning regular languages is based on MNT and approximates Nerode congruence
- Maler & Steiger establish MNT for ω -languages that serves as basis for learning algorithm
- SL* learning algorithm of Cassel et al based on MNT for data languages and register automata
- Francez & Kaminski, Benedikt et al, and Bojańczyk et al present MNTs for data languages

Importance of Myhill-Nerode

Myhill-Nerode Theorems (MNTs) are crucial for model learning:

- Angluin's classical L* algorithm for learning regular languages is based on MNT and approximates Nerode congruence
- Maler & Steiger establish MNT for ω -languages that serves as basis for learning algorithm
- SL* learning algorithm of Cassel et al based on MNT for data languages and register automata
- Francez & Kaminski, Benedikt et al, and Bojańczyk et al present MNTs for data languages

Can we come up with MNT for symbolic languages?

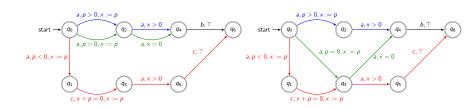


No Unique Minimal Register Automaton

Consider symbolic language L with 3 symbolic words and their prefixes:

$$w = a v_1 > 0 \ a v_1 > 0 \ b \ \top$$
 $u = a v_1 = 0 \ a v_1 = 0 \ b \ \top$
 $z = a v_1 < 0 \ c \ v_1 + v_2 = 0 \ a v_2 > 0 \ c \ \top$

Both register automata below accept *L*:



Nerode Relations

We look for symbolic versions of what Kozen calls Nerode relations:

Definition

A relation \equiv_I on Σ^* is a Nerode relation if it satisfies the following three conditions, for $u, v \in \Sigma^*$ and $\alpha \in \Sigma$,

```
u \equiv_{l} v \Rightarrow (u \in L \Leftrightarrow v \in L)
u \equiv_{l} v \Rightarrow u\alpha \equiv_{l} v\alpha ("right invariance")
\equiv_{l} has finite index
```

Symbolic Languages

Definition (Feasible)

Let $w = \alpha_1 G_1 \cdots \alpha_n G_n$ be a symbolic word. Then w is feasible if

- $guard(w) = G_1 \wedge \cdots \wedge G_n$ is satisfiable, and

A symbolic language is feasible if it is prefix closed and consists of feasible symbolic words.

Regular Symbolic Languages

Definition (Regularity)

A feasible symbolic language *L* is regular iff there exist three relations:

- an equivalence \equiv_I on L, called location equivalence,
- an equivalence \equiv_t on $L \setminus \{\epsilon\}$, called transition equivalence,
- a partial equivalence \equiv_r on $\{(w, v_i) \in L \times \mathcal{V} \mid i \leq length(w)\}$, called register equivalence; w stores v if $(w, v) \equiv_r (w, v)$.

We require \equiv_l and \equiv_t , as well as the equivalence induced by \equiv_t to have finite index. Furthermore, we require ...

Regular Symbolic Languages (cnt)

$$(w, v) \equiv_{r} (w, v') \Rightarrow v = v'$$

$$w\alpha G \equiv_{t} w' \alpha' G' \Rightarrow w \equiv_{t} w'$$

$$(2)$$

$$w\alpha G \equiv_{t} w' \alpha' G' \Rightarrow \alpha = \alpha'$$

$$(3)$$

$$w\alpha G \equiv_{t} w' \alpha G' \wedge \sigma = matching(w, w') \Rightarrow G[\sigma] \equiv G'$$

$$(4)$$

$$w \equiv_{t} w' \Rightarrow w \equiv_{t} w'$$

$$(5)$$

$$w \equiv_{t} w' \wedge w \text{ stores } v_{m} \Rightarrow (w, v_{m}) \equiv_{r} (w', v_{n})$$

$$(6)$$

$$u \equiv_{t} u' \wedge u = w\alpha G \wedge u' = w' \alpha G' \wedge (w, v) \equiv_{r} (w', v') \wedge u \text{ stores } v$$

$$\Rightarrow (u, v) \equiv_{r} (u', v')$$

$$(7)$$

$$u \equiv_{t} u' \wedge u = w\alpha G \wedge u' = w' \alpha G' \wedge (u, v) \equiv_{r} (u', v') \wedge v \neq v_{m+1}$$

$$\Rightarrow (w, v) \equiv_{r} (w', v')$$

$$w \equiv_{t} w' \wedge w\alpha G \in L \wedge v \in Var(G) \setminus \{v_{m+1}\} \Rightarrow \exists v' : (w, v) \equiv_{r} (w', v')$$

$$\wedge Sat(guard(w') \wedge G[\sigma]) \Rightarrow w' \alpha G[\sigma] \in L$$
"right invariance" (10)
$$w \equiv_{t} w' \wedge w\alpha G \in L \wedge w' \alpha G' \in L \wedge \sigma = matching(w, w')$$

$$\wedge Sat(G[\sigma] \wedge G') \Rightarrow w\alpha G \equiv_{t} w' \alpha G'$$
"determinism" (11)

Regular Symbolic Languages (cnt)

Definition (Matching)

We define matching(w, w') as the variable renaming σ that maps each marker of w to the marker of w' stored in the same register (if any):

$$\sigma(v) = \begin{cases} v' & \text{if } (w, v) \equiv_r (w', v') \\ v_{n+1} & \text{if } v = v_{m+1} \\ \text{undefined otherwise} \end{cases}$$

Here m and n denote number of inputs in w and w', respectively.

Main Result

Theorem (Soundness)

Suppose A is a register automaton. Then $L_s(A)$ is regular.

$\mathsf{Theorem}\;(\mathsf{Completeness})$

Suppose L is a regular symbolic language over Σ . Then there exists a register automaton \mathcal{A} such that $L = L_s(\mathcal{A})$.

Conclusions and Future Work

- **1** Register automata can be defined directly from a regular symbolic language, with locations materializing as equivalence classes of \equiv_I , transitions as equivalence classes of \equiv_t , and registers as equivalences classes of \equiv_r
- 2 No restrictions on allowed data types!
- Challenge: develop learning algorithm based on our result
- Refactoring of legacy software excellent application domain

Example

Consider symbolic language with following symbolic words (plus prefixes):

$$w = a v_1 > 0 \ a v_1 > 0 \ b \ \top$$
 $u = a v_1 = 0 \ a v_1 = 0 \ b \ \top$
 $z = a v_1 < 0 \ c \ v_1 + v_2 = 0 \ a v_2 > 0 \ c \ \top$

Words are \equiv_l equivalent if they lead to same location in RA below, \equiv_t equivalent if they share final transition, and $(y,v)\equiv_r (y',v')$ if symbolic values v and v' are stored in same register after words y and y', resp.

