On Automata Learning and Conformance Testing Bengt Jonsson

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Acknowledgments

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Outline

- Motivation
- Automata Learning
- Conformance Testing, Model Checking
- Extensions to richer Automata Models
- Applications in Protocol Model Generation

Modeling in System Development



Model BasedTest Generation



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Modeling Gap

- Typically, models are not available
- Modeling SUT [system under test] is among biggest obstacles in Model Based Testing [A. Hartman]
- What to do if there is no model? (the norm in practice)

Supporting Model Generation



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How to support generation of models?

- Model Behavior of existing implementation
 - By observations gained during extensive testing
- Potential Applications:
 - Regression testing
 - Migrating from manual to model-based testing
 - Modeling environment of SUT, libraries
- Problem: Constructing State Machines from traces/executions/words
 - Has been studied in Automata Learning

Simplest form of Automata Learning

- From sample of words
- find simple(st) state machine that explains them

Requirements Capture

 Generate State Machine Specification from set of allowed (and disallowed) scenarios:



Compositional Verification[Giannakopoulou, Pasareanu et al]

Complex Model Checking Problem:



If

Checking E || M |= φ too complex: Find abstraction A of E, s.t.:

```
E refines A
Α || Μ |= φ
-----
Ε || Μ |= φ
```

Building A using Learning ASSUME: $w \parallel M \parallel = \varphi$ can be checked for single behavior w Check $w \parallel M \parallel = \varphi$ for many w, Construct A from these checks Check whether A satisfies premises

Specification Mining[Ammons, Bodik, Larus]



Problem: Find restrictions on how API calls may be ordered
Assume we have well-tested programs that use the API
Analyze executions of such programs.
Form an Automaton that summarize these executions.

API:



Learning





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Some Terminology

Given an Instance space X

- Concept is a subset of X
- Concept Class is a class of Concepts
- Sample is a (finite) set of labeled examples
 - x+ where $x \in C$
 - x- where x∉C
- Learner produces Hypothesis (in Concept Class) from Sample
- Teacher knows Concept, produces Sample
 - Can also, e.g., answer queries
- Hypothesis H is correct if H = C
- Hypothesis H is consistent with sample if
 - if x+ in sample then $x \in H$
 - if x- in sample then $x \notin H$
- Concepts have Representations
 - size of Concept C = size of its Representation

Automata learning

- Assume finite set Σ of symbols
- Instance space: Σ^*
- Concept Class: Regular languages
- Representation of Concept: DFA
- Sample is a (finite) set of labeled words
 - w+ where $w \in L$
 - w- where w∉L

Deterministic Finite Automata (DFA)



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Deterministic Finite Automata (DFA)

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Finite State Machines accepting sequences of input symbols

Σ symbols

		Myhill-Nerode:
Q $\delta: Q \times \Sigma \to Q$ $F \subseteq Q$	states transition function accepting states	Given language L For prefix u , define $L_u = \{v \mid uv \in L\}$ Nerode congruence: $u \approx u'$ iff $L_u = L_{u'}$
Assumptions:		Unique Minimal DFA accepts regular L
•Deterministic		Q: equivalence classes [u],
 Completely specified 		δ ([u] _* ,a) = [ua] _* transition function
		$F : \{[u]_{\approx} \mid u \in L\}$ accepting states
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Automata Learning: Frameworks

Construct DFA from sample of accepted and rejected words. Passive learning: sample given

Only accepted words
 (positive sample)
 Accepted and rejected words
 Observing SUT/test suites



Active learning: Learner chooses words, teacher classifies

Testing SUT



Mealy Machines

Finite State Machines w. input & output

- I input symbols
- O output symbols
- Q states
- $\delta : \mathbf{Q} \times \mathbf{I} \to \mathbf{Q}$ transition function
- $\lambda: \mathbf{Q} \times \mathbf{I} \to \mathbf{O}$ output function
- •Often used for protocol modeling, for protocol testing techniques,
- Assumptions:
- Deterministic
- •Completely specified



Passive Learning:

Construct DFA from sample of accepted and rejected words.

- Which DFA?
- The most succinct one!
 - which conforms to sample,
 - and has fewest states



- Finding smallest DFA is NP-hard [Gold 78]
- Can be found by constraint solving (Biermann's algorithm)

Biermann's Algorithm

Is there a conformant DFA with n states?

Encode this as a CSP problem

- Map each prefix **u** in tree to some state $q_u \in \{1 ... n\}$
- Subject to constraints:
 - $q_u \neq q_v$ if u accepted, v rejected
 - if ua va are prefixes, then $q_u = q_v$ implies $q_{ua} = q_{va}$

Try example for n = 3



Biermann's Algorithm

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Try example for n = 3

Check

Accepted: a b aaa aabb bba

Rejected: A aa aab

Discussion

- Problem w. Biermanns algorithm: Exponential
- Q: Is there a setting to learn automata polynomially in some way?
- By Gold's result, we cannot hope to learn minimal DFA from arbitrary sample.



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Identification in the Limit





- Assume Teacher incrementally enumerates all words (classified) in Σ^{\star}
- After each word, Learner can use previous words to form hypothesis H

Learner identifies L in the limit,

if H converges to correct hypothesis after finitely many words

Still, (exponentially) much data may be needed

Learner

Efficient Identification in the Limit



Concept Class is efficiently identifiable in the limit if \exists polynomials p,q, s.t. for any concept C in concept class

- Learner can produce H in time O(p(|seen sample|))
- Exists sample S of size O(q(|C|)) s.t. Learner produces correct H whenever seen sample contains S
- S called "characteristic sample" for C
- S can depend on Learner

Observations

- if Concept class is efficiently identifiable in the limit, then
- Learner needs polynomial time to produce hypothesis
- Concepts characterized by polynomial-size characteristic sets
- With "helpful" Teacher, the Learner needs only polynomially much data to infer C
- With "unhelpful" Teacher, the Learner may need a lot of data to infer C
- Learner should work well for characteristic sets, should make "reasonable" hypotheses otherwise. MOVEP '10 on Automata Learning 30

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Characteristic Samples

- A characteristic sample S for C should uniquely characterize C in the following sense:
- Learner should produce hypothesis C from any sample that contains S and is consistent with C

Implies that if

- S is characteristic sample for C and
- S' is characteristic sample for C' then either
- C is inconsistent with S' or
- C' is inconsistent with S
- (otherwise what to do with $S \cup S'$?)

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Characteristic Samples for DFAs

A characteristic sample for L should identify its DFA. This can be done by

- Demonstrating that there are n states
 - Each state represented by access string u

u represents $\delta(q_0, \mathbf{u})$

• For each state q and symbol a, uniquely identify $\delta(q,a)$

Separating Sequences A separating sequence for q and q' is a suffix v such that $\delta(q,v)$ is accepting and $\delta(q',v)$ is rejecting (or vice versa)



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Separating Sequences

A separating sequence for q and q' is a suffix v such that

 $\delta(q, \mathbf{v})$ is accepting and $\delta(q', \mathbf{v})$ is rejecting (or vice versa)

A separating family of DFA is a family of sets $\{Z_q \mid q \text{ is a state of DFA}\}$

s.t. $Z_q \cap Z_{q'}$ contains separating sequence for q and q'

1 : Λ b 2 : Λ 3 : Λ b



Separating Sequences

A separating family of DFA is a family of sets $\{Z_q \mid q \text{ is a state of DFA}\}$

s.t. $Z_q \cap Z_{q'}$ contains separating sequence for q and q'

If all Z_q are equal (to W), then W is a **characterizing** set





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Separating Sequences

A separating family of DFA is a family of sets $\{ Z_a \mid q \text{ is a state of DFA} \}$

- s.t. $Z_a \cap Z_{a'}$ contains separating sequence for q and q'
- If all Z_a are equal (to W), then W is a characterizing set



W : **A** b

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Characteristic Sample

Let Sp(L) be prefixes in minimal spanning tree of DFA(L) Let K(L) be { ua | $u \in Sp(L) \quad a \in \Sigma$ } Let Characteristic Sample be Sp(L) \cup { $uv \mid u \in Sp(L) \cup K(L) \quad v \in Z_{au}$ }



Why characteristic sample?

When forming DFA from prefix tree:

- The states $\{q_u \mid u \in Sp(L)\}$ cannot be merged
 - since they are separated by suffixes
- Each state in $\{q_u \mid u \in K(L)\}$ can be merged with at most one state in $\{q_u \mid u \in Sp(L)\}$
- Easy to construct minimal DFA from sample



State Merging Algorithms

- Traverse the prefix tree from root
- For each new state
 - if possible, merge it with some seen state
 - Otherwise, promote it to a new state in the resulting DFA
- Red states are determined to become DFA states
- Blue states (frontier) are the successors of red states, waiting to be candidates for merging with red states.
- Repeatedly
- Merge blue with red if no inconsistency results
- "Unmergeable" blue state becomes red



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What if we change order?



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About State Merging

- Order in which blue states are considered matters.
- If considered states stay within {q_u | u ∈ K(L) } a minimal DFA will be constructed
- Otherwise, "suboptimal" merges may result
- Remedy: Teacher and Learner agree on a fixed technique to construct Sp(L)
 - e.g., to consider strings in lexicographic order
 - RPNI algorithm. [Oncina, Garcia]
- Otherwise: use heuristics for choosing "best merge",
 - e.g., to select states with "largest" subtrees.

About State Merging

- Time Complexity (in size of sample):
 - At most a quadratic number of candidate merges \bullet considered.
 - Each merge takes linear time to check
 - I.e., time complexity is polynomial.

Active Learning

Learner actively constructs the characteristic sample,



Ideas

- Maintain candidates for Sp(L) K(L) W where W is a distinguishing set
- Ask membership queries for $\{ uv \mid u \in Sp(L) \cup K(L) \mid v \in W \}$
- If u in K(L) is separated from all prefixes in Sp(L) by separating suffix, move u to Sp(L) and extend K(L)
- For new u' in K(L) let W be large enough to separate u' from all but (at most) one prefix in Sp(L)



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About L* [Angluin]

- DFA with n states can be learned using
 - <n equivalence queries
 - $O(|\Sigma|n^2 + n \log m)$ membership queries
 - m is size of longest counterexample
- Produced hypothesis is always minimal DFA which is consistent with seen membership queries
 - These are a characteristic set for hypothesis
- Equivalence query idealizes (possibly) exponential search for deviations from model
- The setup with Membership and Equivalence queries makes it possible to formulate polymial-complexity algorithm.

Mealy Machines

•Finite State Machines w. input & output

- I input symbols
- O output symbols
- Q states
- $\delta: \mathbf{Q} \times \mathbf{I} \to \mathbf{Q} \quad \text{transition function}$
- $\lambda : \mathbf{Q} \times \mathbf{I} \to \mathbf{O} \quad \text{output function}$
- •Often used for protocol modeling, for protocol testing techniques,
- Assumptions:
- •Deterministic
- •Completely specified



Conformance Testing

- Given MM A, construct a sample (i.e., a test suite) S such that A is "best fit" to explain S
 - Typically: A is the only MM with < |A| states, which is consistent with S

W-method

Let Sp(L) be prefixes in minimal spanning tree of MM Let K(L) be { $ua \mid u \in Sp(L) \quad a \in I$ }



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W-method



Z-method



Learning vs. Conformance Testing

- Learning: Find Concept A which is "best fit" to explain a \bullet given sample S
- Conformance Testing: Given Concept A, construct a sample S such that A is "best fit" to explain S
- For automata learning: A characteristic sample for A is also a conformance test suite for A

L* vs. W-method

- A sample generated by L* is also a conformance test suite generated by the W-method
- A conformance test suite generated by the W-method is a characteristic sample
- A is the only MM of size $\leq |A|$ which is consistent with S
- Q: Can we check whether A is the only automaton of size $\leq |A| + k$ which is consistent with S

Vasilevski-Chow test suite

- Let k = 2
- Test suite should allow non-minimised MM



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Vasilevski-Chow test suite

- Let k = 2
- Test suite should allow non-minimised MM
- Must cope with anomaly



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Resulting test suite

- Let W be a characterizing set for A
- VC-test suite has form

 $S = \{ uxv \mid u \in Sp(L) \cup K(L) \mid x \in I^{\leq k} \mid v \in W \}$

- A is only MM of size $\leq |A| + k$ which is consistent with S
- Size of sample: $O(|\Sigma|^{k+1} n^2)$

Adaptive Model Checking [Peled Yannakakis 02]



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LearnLib: a Tool for Inferring Models

- Developed at Dortmund Univ. [Steffen, Raffelt, Howar, Merten]
- Central Idea: use domain-specific knowledge to reduce the number of queries:
 - Prefix-closure
 - Independence between symbols (e.g., in parallel components)
 - Symmetries
- These properties correspond to "filters" between observation table and SUT



Whata about Extensions of Automata?

- Input and output symbols parameterized by data values. •
- State variables remember parameters in received input
- Types of parameters could be, .e.,g
 - Identifiers of connections, sessions, users
 - Sequence numbers
 - Time values

Timed Automata

- Based on standard automata
- Clocks give upper and lower bounds on distance in time between occurrences of symbols.
- Temporal properties of Timed Automata (reachability, LTL, ...) can be model-checked
- Implemented in tools (UPPAAL, IF/Kronos)



Timed words: (get, 14.4) (put, 16.4) (get, 29.34) (put, 30.3) ...

Event-Recording Automata

- Timed Automata can not be determinized in general
- Event-Recording Automata (ERA): One clock for each symbol, which is reset on that symbol.
- ERA can be determinized

Assumption:

Inference algorithm can precisely control and record timing of symbols.

> Timed words: (get, 14.4) (put, 16.4) (get, 29.34) (put, 30.3) ...

Clocked words: (get, [14.4,14.4]) (put, [2.0,14.4]) (get, [14.94,12.94]) (get, [0.96,13.9]) ... MOVEP '10 on Automata Learning

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Event-Recording Automata

- Σ (symbols) {put, get}
- L (locations) $\{I_{0}, I_1\}$
- I_0 (initial location)
- E (edges) \subseteq L x Σ x Guards x L
- **F** (accepting locations) \subseteq L



Event-Recording Automata



Non-Unique Representation

• Deterministic ERAs do not have unique representations



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Learning DERAs by Quotienting [Grinchtein, Leucker, al.]

- Find equivalence relation \approx on symbols and states, s.t.
 - ~ respects accepting/non-accepting states
 - $q \approx q'$ $a \approx a'$ implies $\delta(q,a) \approx \delta(q',a')$
- Learn the Quotient DFA

 $\Sigma / \approx Q / \approx \delta^{\approx} (\delta([q]_{\approx}, [a]_{\approx}) = [\delta(q, a)]_{\approx}) F / \approx$ For DERAs

- Equivalence on states based on region equivalence
- Assume largest constant K_a in constraints on x_a

• <a , $[x_a, x_b]$ > << <a , $[y_a, y_b]$ > iff for all $k \leq K_a$ - $x_a \leq k$ iff $y_a \leq k$ and $x_a \geq k$ iff $y_a \geq k$

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Regions: From infinite to finite

Concrete State (I, [2.2, 1.5]) Symbolic state (region) (I,)



Abstraction of symbols



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We need only initial regions

Concrete State (I, [0.7, 0]) Symbolic state (region) (I, _____)



Regions preserved by transitions

Concrete State (I, [0.7, 0]) Symbolic state (region) (I, _____)



Simple DERAs

• DERA with "small guards"



Modifying Setup

The following setup does not work



Adding Assistant

Learner actively constructs the characteristic sample,



Query Complexity

- Size of Region graph is roughly
 O(|L| K^{|Σ|})
- Number of Membership Queries is about cubic in this number

Single-Clock Automata [Verwer et al. 09]

Consider Deterministic Timed Automata with one clock

- Still, no unique minimal representation
- But, there is a variant of Nerode Congruence
 - if we know where resets occur



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Single-Clock Automata [Verwer et al. 09]

The timed language can be formed from a finite number of Congruence classes Only, it must be determined when to reset? Define canonical form by prioritizing conflicts



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Refining Guards [Verwer et al. 09]

• Guards can be refined by counterexamples

0

get;

put ;

Guards refined from counterexamples

- get @0 put @2 accepted
- get @3 put @7 rejected

Determine the reason for difference by investigating other traces

- (binary) search procedure
- Finds "explaining pair", e.g.,
 - get @2.2 put @4.2 accepted
 - get @2.2 put @4.7 rejected
- Suggests reset at get and guard x ≤ 2 on put transition

Single-Clock Automata [Verwer et al. 09]



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Applications to Realistic Procotols

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SIP Protocol [Aarts, Jonsson, Uijen]

From RFC 3261:

- SIP is an application-layer control protocol that can •
 - establish, modify, and terminate multimedia sessions (conferences) such as Internet telephony calls.
 - invite participants to already existing sessions, such as multicast conferences.

Structure of SIP packets

Method(From; To; Contact; CallId; CSeq; Via), where

- Method: type of request, either INVITE, PRACK, or ACK.
- From and To: addresses of the originator and receiver
- CallId: unique session identier.
- Cseq: sequence number that orders transactions in a session. IGNORE THE BELOW
- Contact: address where the Client wants to receive input
- Via: transport path for the transaction.

part of SIP Server



Finding an Abstraction

- Abstraction of Concrete Message PRACK(558,1) depends on internal state of SUT previous history
- Assistant must maintain relevant parts of history: e.g., local copies of CurId, CurSeq



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Possibly Infinite State Mealy Machine

input symbols Ι output symbols 0 Q states initial state **q**₀ $\delta: \mathbf{Q} \times \mathbf{I} \to \mathbf{Q}$ transition function $\lambda: \mathbb{Q} \times \mathbb{I} \to \mathbb{O}$ output function



Possibly Infinite State Mealy Machine		Abstraction	
I	input symbols	IA	abstract input symbols
0	output symbols	O ^A	abstract output symbols
Q	states	R	states
q ₀	initial state	r ₀	initial state
$\delta: \mathbf{Q} \times \mathbf{I} \to \mathbf{Q}$	transition function	$\delta^{R}: R \times (I \cup O)$) → R update
$\lambda: \mathbb{Q} \times \mathbb{I} \to \mathbb{O}$	output function	$\alpha_{I}: R \times I \to I$	A input abstraction
		α_{O} : R x $O \rightarrow O$	O ^A output abstraction

Possibly Infinite State Mealy Machine		Abstraction	
I , O	symbols	I ^A , O ^A	abstract symbols
Q , q ₀	states , initial state	R,r ₀	states , initial state
$\delta: \mathbf{Q} \times \mathbf{I} \to \mathbf{Q}$	transition function	δ ^ℝ : R x (I∪O) –	R update
$\lambda: \mathbf{Q} \times \mathbf{I} \to \mathbf{O}$	output function	$\alpha_{I}: R \times I \to I^{\scriptscriptstyle A}$	input abstraction
		α_{O} : R x $O \rightarrow O^{A}$	output abstraction



Abstracted Mealy Machine $I^{A} , O^{A} \qquad abstract symbols$ $Q \times R , \langle q_{0}, r_{0} \rangle \qquad states , initial state$ $\delta^{A}: Q \times R \times I^{A} \rightarrow Q \times R \text{ transition function:}$ $\delta^{A}(\langle q, r \rangle, a^{A}) = \{ \langle \delta(q, a), \delta^{R}(r, a) \rangle \mid \alpha_{I}(r, a) = a^{A} \}$ $\lambda^{A}: Q \times R \times I^{A} \rightarrow O^{A} \quad output \text{ function:}$ $\lambda^{A}(\langle q, r \rangle, a^{A}) = \{ \alpha_{O} (\delta^{R}(r, a), \lambda(q, a)) \mid \alpha_{I}(r, a) = a^{A} \}$

Exists equivalence \approx on $Q \times R$ s.t.

- $\langle q,r \rangle \approx \langle q',r' \rangle$ and $\alpha_{I}(r,a) = \alpha_{I}(r',a')$ implies
 - $\langle \delta(q, a), \delta^{\mathsf{R}}(r, a) \rangle \approx \langle \delta(q', a'), \delta^{\mathsf{R}}(r', a') \rangle$ $\alpha \left(\delta^{\mathsf{R}}(r, a), \lambda(q, a) \right) = \alpha \left(\delta^{\mathsf{R}}(r', a'), \lambda(q', a') \right)$
 - $\alpha_O \left(\delta^{\mathsf{R}}(\mathsf{r}, \mathsf{a}), \lambda \left(\mathsf{q}, \mathsf{a} \right) \right) = \alpha_O \left(\delta^{\mathsf{R}}(\mathsf{r}', \mathsf{a}'), \lambda \left(\mathsf{q}', \mathsf{a}' \right) \right)$
Modified Criterion

Exists equivalence ~ on Q x R s.t.

- <q,r> \approx <q',r'> and $\alpha_{I}(r,a) = \alpha_{I}(r',a')$ implies
 - $\langle \delta(q, a), \delta^{\mathsf{R}}(r, a) \rangle \approx \langle \delta(q', a'), \delta^{\mathsf{R}}(r', a') \rangle$
 - $\alpha_{O} \left(\delta^{\mathsf{R}}(\mathsf{r}, \mathfrak{a}), \lambda \left(q, \mathfrak{a} \right) \right) = \alpha_{O} \left(\delta^{\mathsf{R}}(\mathsf{r}', \mathfrak{a}'), \lambda \left(q', \mathfrak{a}' \right) \right)$

Can happen, e.g., if Q can be written $L \times R$, and

- if $\delta(\langle l,r \rangle, a) = \langle l',r' \rangle$ then
 - $\mathbf{r}' = \delta^{\mathsf{R}}(\mathbf{r}, \mathbf{a})$
 - I' depends only on $\alpha_{I}(r, a)$
- if λ (<1,r>, a) = b then
 - α_{O} ($\delta^{R}(r, a)$, b) depends only on $\alpha_{I}(r, a)$

Mapping parameters of input messages

	first	next	last
cid	CurId = ⊥ and Method = INVITE or cid = CurId	cseq = CurSeq+1	<otherwise></otherwise>
cseq	CurSeq = ⊥ and Method = INVITE or cseq = CurSeq		<otherwise></otherwise>

Maintaining auxiliary variables

	first	last	next
CurId	:= cid	<unchanged></unchanged>	
CurId	:= cseq	<unchanged></unchanged>	<unchanged></unchanged>

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Abstraction Mappings



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Abstraction Mappings



Output-abstr

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Model inferred by Learner (part)



What the SUT must have done:

Variables: CurId, CurSeq



Experiments

- Learner: the LearnLib tool (developed at TU Dortmund)
 - Efficient implementation of L*
 - Several equivalence oracles, e.g., controllable-size random test suite.
- SUT: ns-2 protocol simulator
 - Provides implementations of many standard protocols
 - Rather convenient C++ interface (no packet analyzer necessary)
- Assistant
 - Bridges asynchronous interface of LearnLib w. synchronous interface of ns-2
 - Implements instantiation of input symbols, and abstraction of output symbols

Learning SIP in ns-2

- Inference: about 1 thousand membership queries one equivalence query
- Model w. 10 locations and 70 transitions
- ns-2 implementation does not check incoming cseq parameter, just returns it.

Resulting Model



Fig. 3. Full SIP model

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Transport Control Protocol (TCP)

- Only connection establishment and termination
- SUT is ns-2 implementation of TCP
- Consider 2 sequence number parameters
- Similar type of abstraction

TCP

- Model of behavior of TCP in ns-2
- Only transitions with "accepted" values of input parameters are shown.
- Values of parameters not displayed



Conclusions

- Basic Principles of Automata Learning for Finite-State systems understood
- Learning and Conformance Testing:
 - Two sides of the same coin.
- Learning for extended automata models largely unexplored

Some Future work

- Techniques for handling common forms of data
- Dynamically refining abstractions
- Learning nondeterministic models
- Learning timed models in practice
- Learning under assumptions on module usage
- Efficient search for counterexamples
- Efficient construction of test harnesses
- Some references can be found at http://leo.cs.tu-dortmund.de:8100/