



Active Learning of Symbolic Mealy Automata

Kengo Irie¹, Masaki Waga^{1,2}, and Kohei Suenaga¹

Kyoto University¹, National Institute of Informatics²

2025 November 27th, ICTAC 2025



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Active DFA Learning

[Angluin, Inf. Comput.'87]

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Learner



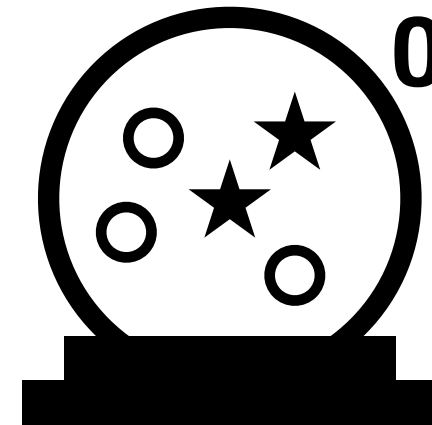
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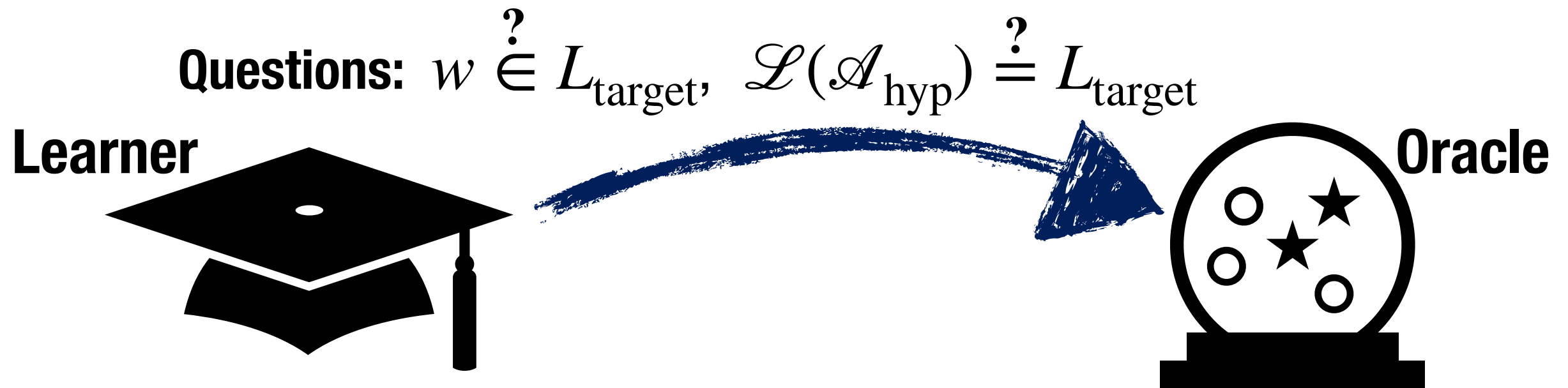


Oracle



Active DFA Learning

[Angluin, Inf. Comput.'87]



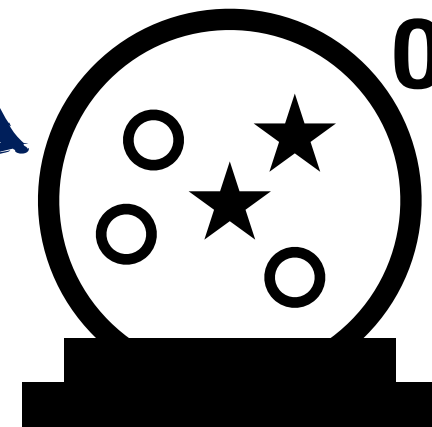
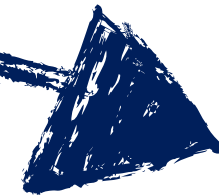
Active DFA Learning

[Angluin, Inf. Comput.'87]

Membership

Questions: $w \stackrel{?}{\in} L_{\text{target}}, \mathcal{L}(\mathcal{A}_{\text{hyp}}) \stackrel{?}{=} L_{\text{target}}$

Learner



Oracle

Active DFA Learning

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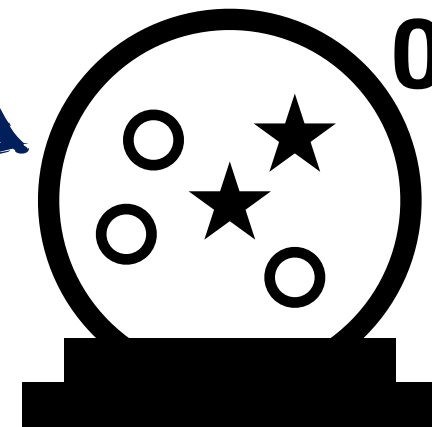
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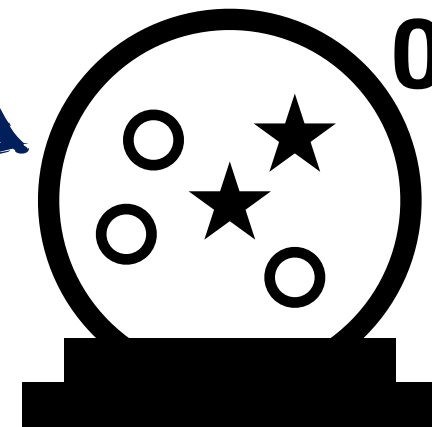
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Oracle



Answers: Yes, No, Evidence $w \in \mathcal{L}(\mathcal{A}_{\text{hyp}}) \triangle L_{\text{target}}$

Active DFA Learning

[Angluin, Inf. Comput.'87]

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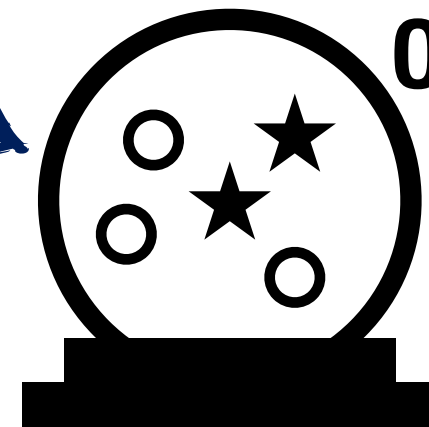
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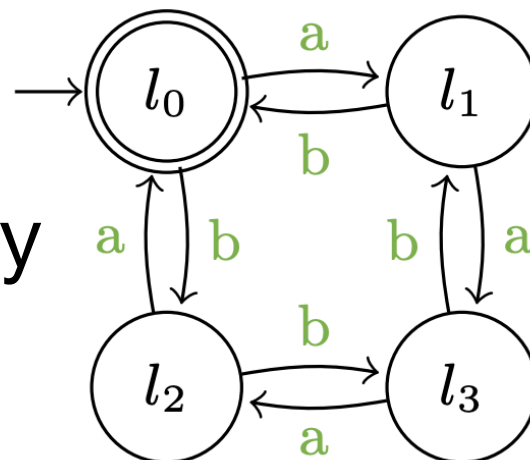


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Answers: Yes, No, Evidence $w \in \mathcal{L}(\mathcal{A}_{\text{hyp}}) \triangle L_{\text{target}}$

L_{target} is recognized by



Active DFA Learning

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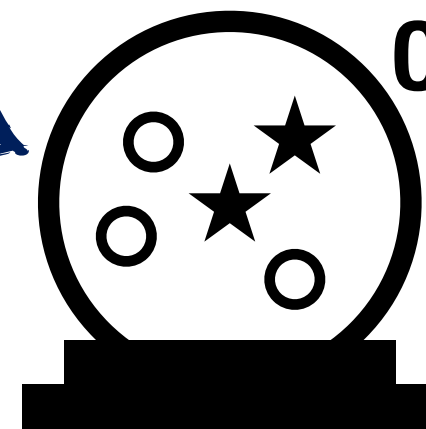
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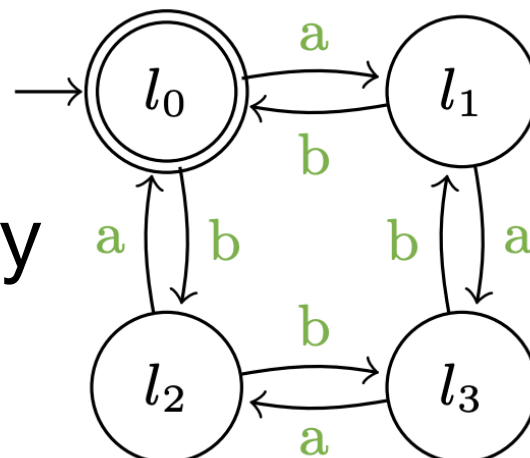


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Answers: Yes, No, Evidence $w \in \mathcal{L}(\mathcal{A}_{\text{hyp}}) \triangle L_{\text{target}}$

L_{target} is recognized by



Studied from both AI/ML
and FM/SE/PL

Extensions of Active Automata Learning

- Learning with fewer queries in practice/theory
 - e.g. better analysis of counterexamples, better data structures, ...
- Learning automata with multiple outputs
 - e.g. Mealy/Moore machines
- Learning automata over infinite alphabets
 - e.g. symbolic automata, nominal automata, ...
- ...

Extensions of Active Automata Learning

- Learning with fewer queries in practice/theory
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- Learning automata with multiple outputs
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- Learning automata over infinite alphabets
 - e.g. symbolic automata, nominal automata, ...
- ...

e.g. Approx. black-box
systems as automata

Learning Symbolic Automata

[Drews & D'Antoni, TACAS'17]

Automata w/ predicates on trans.
for infinite/huge alphabets, e.g. $\mathbb{N}$

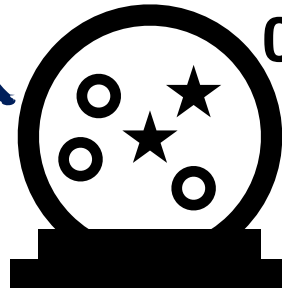
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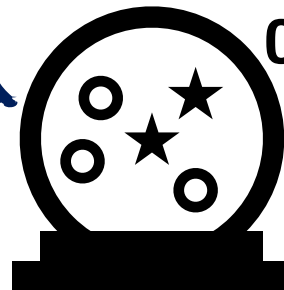
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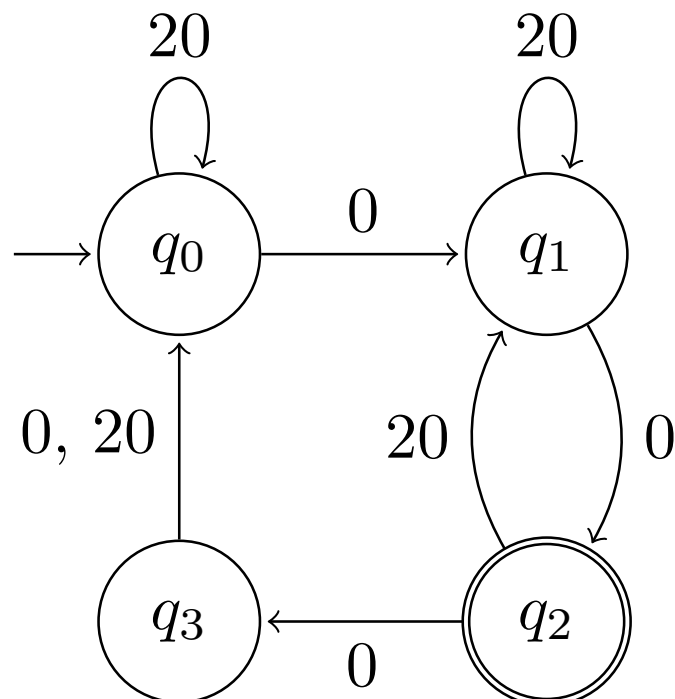


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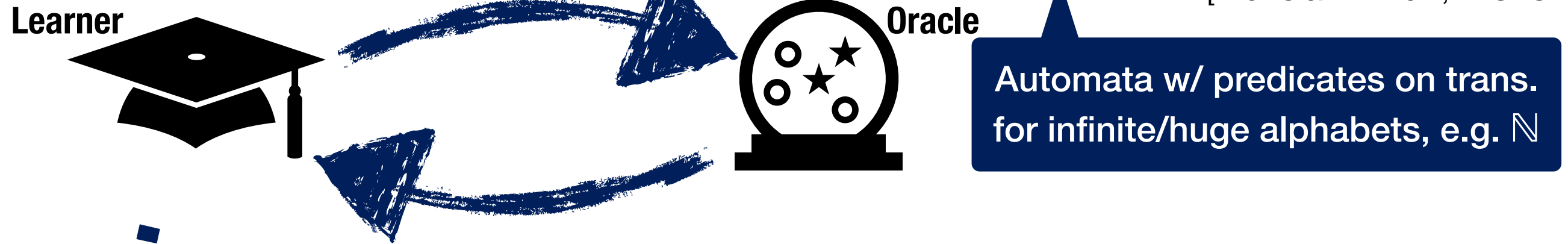
Automata w/ predicates on trans.
for infinite/huge alphabets, e.g. $\mathbb{N}$

Learn a DFA over
a part of the alphabet
e.g. $\subseteq \mathbb{N}$

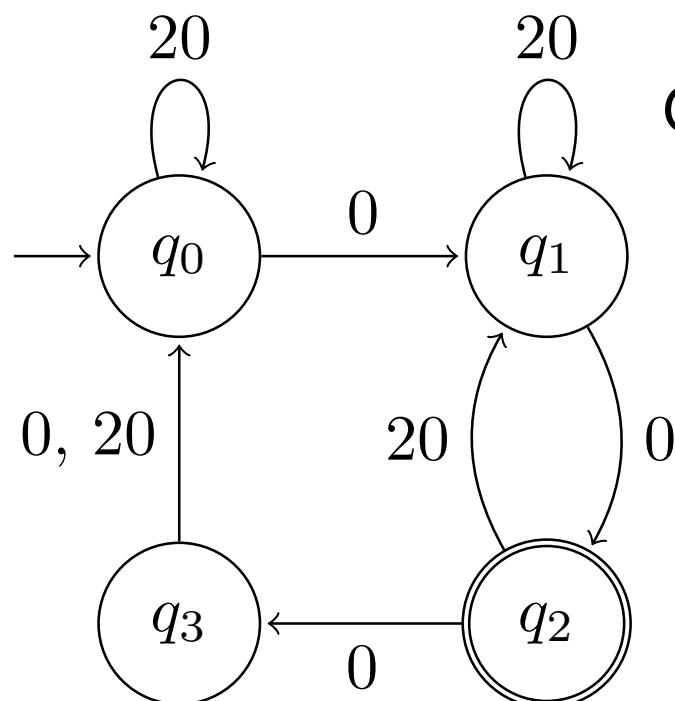


Learning Symbolic Automata

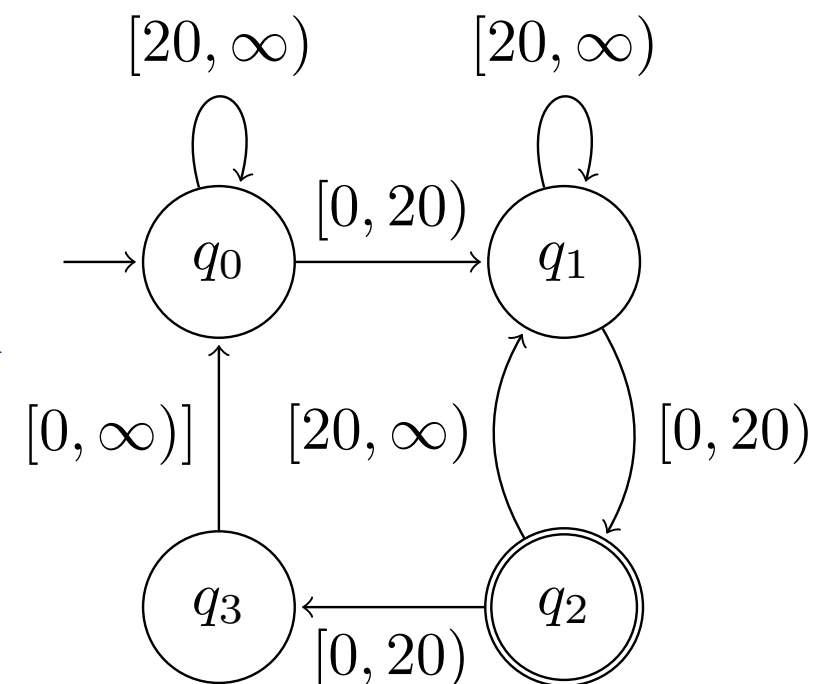
[Drews & D'Antoni, TACAS'17]



Learn a DFA over
a part of the alphabet
e.g. $\subsetneq \mathbb{N}$

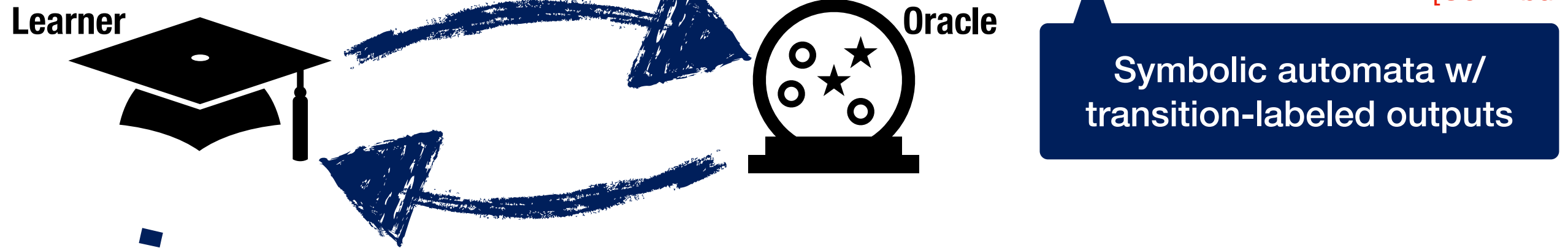


Generalize concrete characters
into predicates
e.g. intervals over $\mathbb{N}$

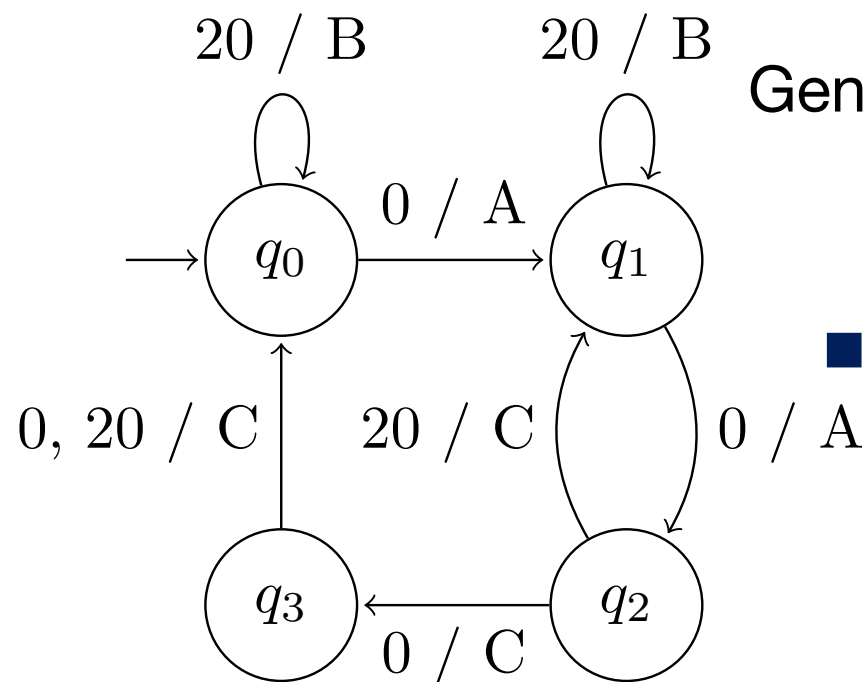


Learning Symbolic Mealy Automata

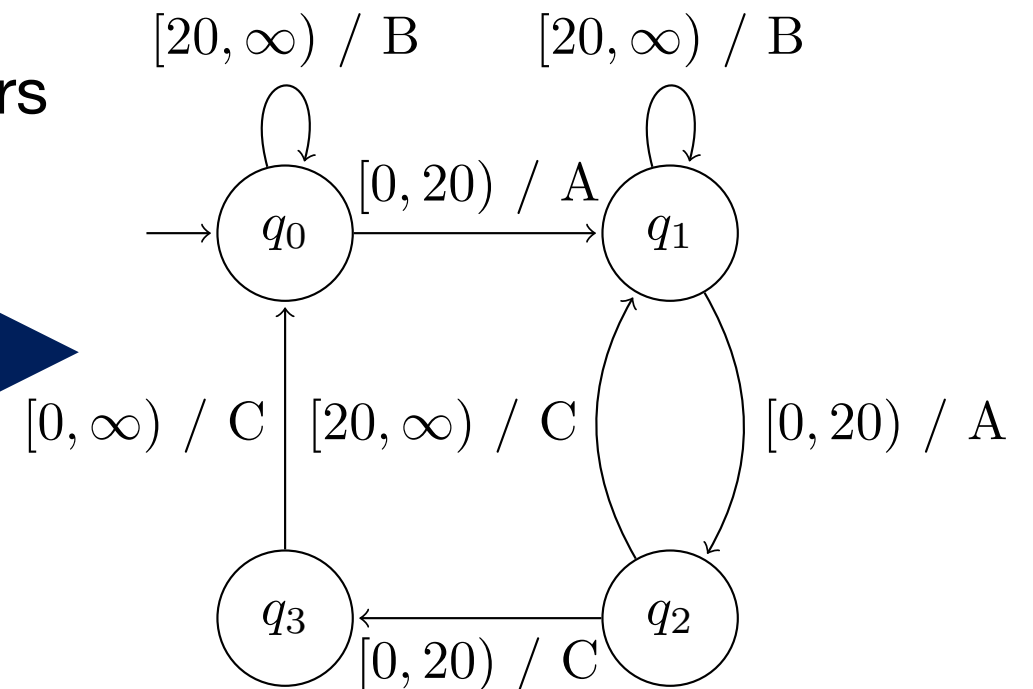
[Contributions]



Learn a *Mealy machine* over
a part of the alphabet
e.g. $\subseteq \mathbb{N}$



Generalize concrete characters
into predicates
e.g. intervals over $\mathbb{N}$



Learning Symbolic Mealy Automata

[Contributions]

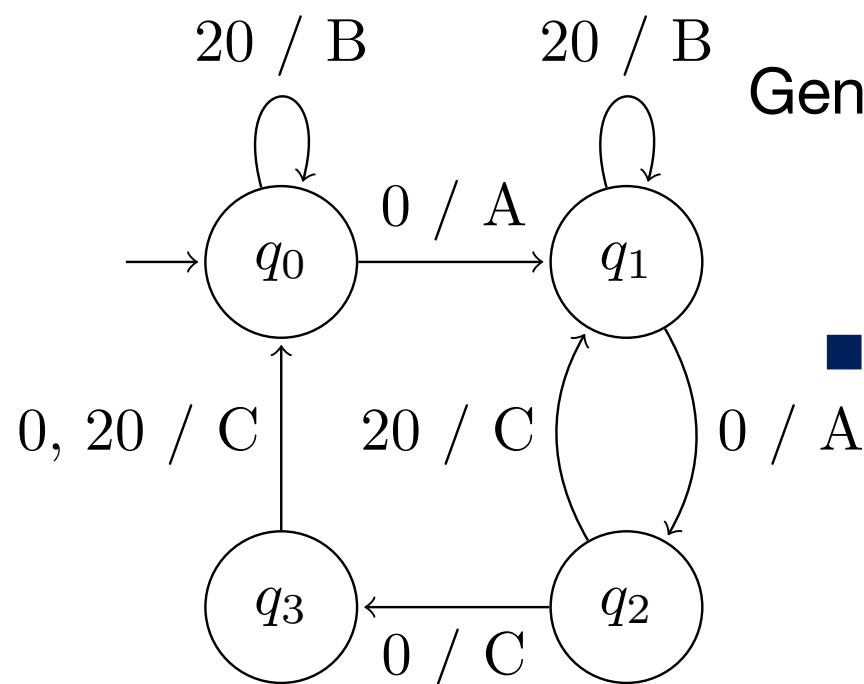
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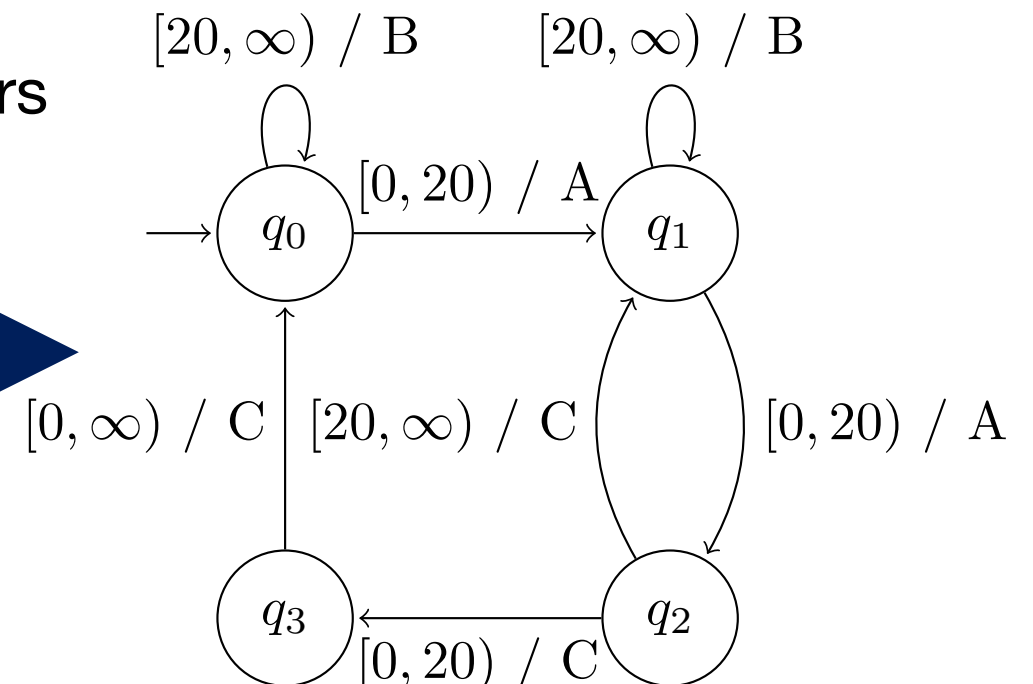
Symbolic automata w/
transition-labeled outputs

Learn a *Mealy machine* over
a part of the alphabet
e.g. $\subseteq \mathbb{N}$

Naively, chars on learned transition/output
functions may be different
→ Successor/output of some “transitions”
may be undefined!!



Generalize concrete characters
into predicates
e.g. intervals over $\mathbb{N}$



Idea: Explicitly Learn “Essential” Characters

Σ_E : Finite set of current essential characters

- Σ_E incrementally increases
- New characters are found via equivalence queries

1. Learn a Mealy machine $\mathcal{M}^e$ over Σ_E ($\subsetneq \Sigma$)
2. Generalize the characters in $\mathcal{M}^e$ to predicates to obtain a symbolic Mealy automaton $\mathcal{M}$

Contributions

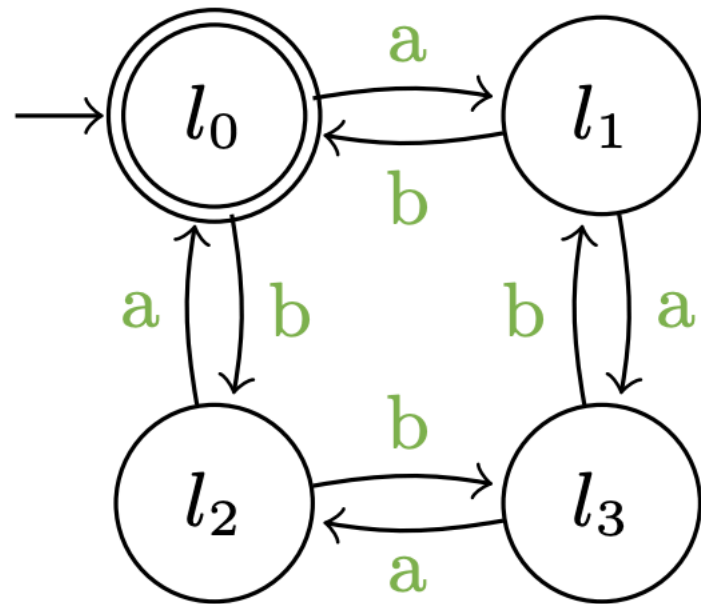
- Learning algorithm for symbolic Mealy automata
 - Idea: Explicitly learn “essential” characters Σ_E
- Complexity analysis of our algorithm
 - Worst case query complexity
 - An example to demonstrate the tightness
- Implementation + Experiments
 - Typically much more efficient than theoretical bound

Outline

- Preliminaries: Algorithms for active automata learning
 - Idea: Identify good prefixes/suffixes
 - Data structure: observation table
 - Learning algorithm for symbolic automata
- Our learning algorithm: Learning symbolic Mealy automata
 - Idea: Explicitly learn “essential” characters
- Experiments

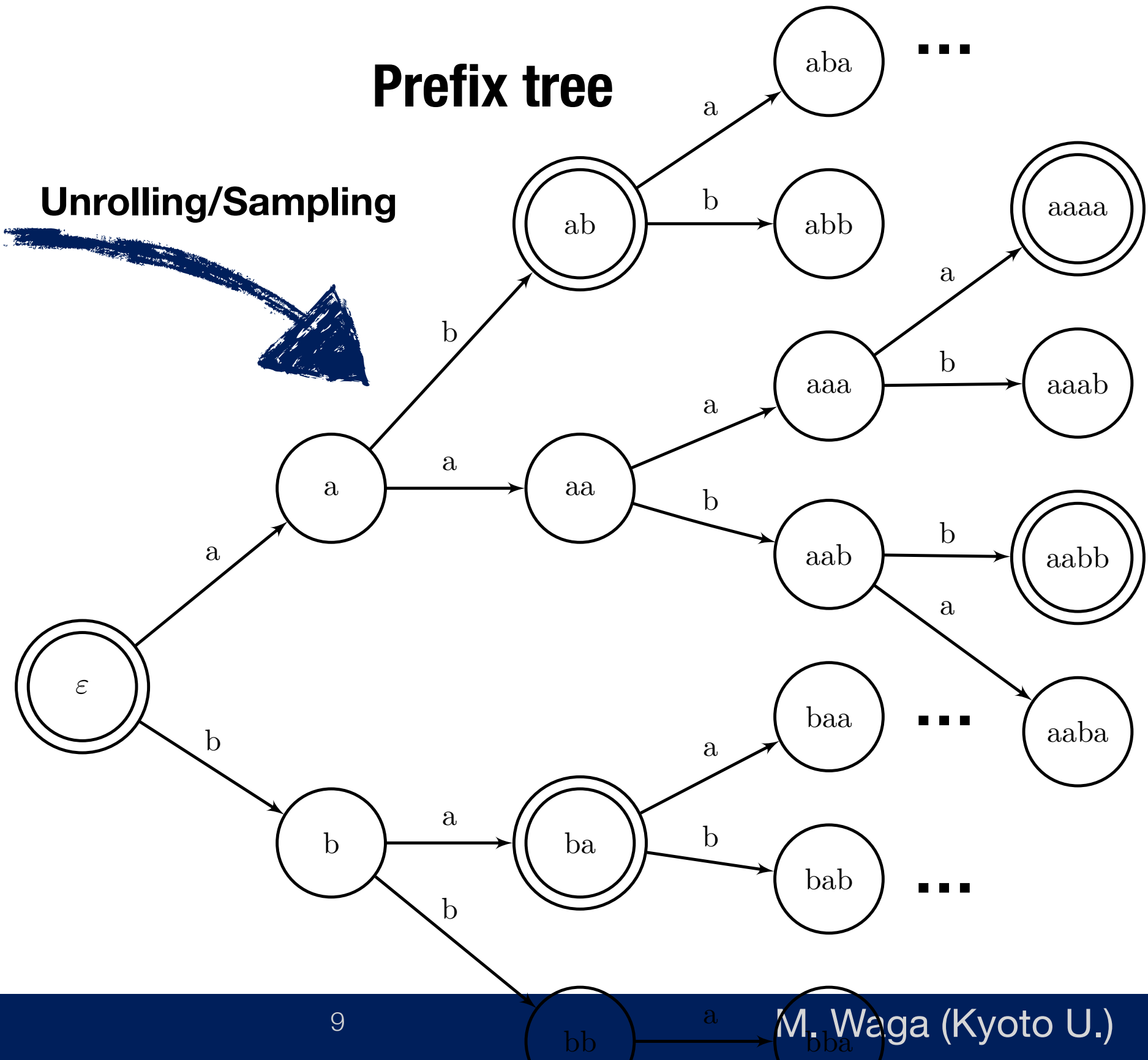
Idea: Find Good Prefixes/Suffixes

Target DFA



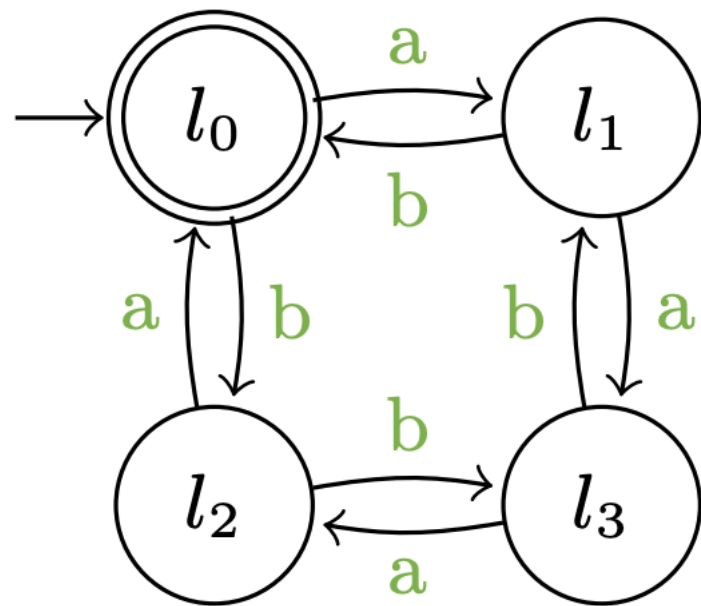
Unrolling/Sampling

Prefix tree



Idea: Find Good Prefixes/Suffixes

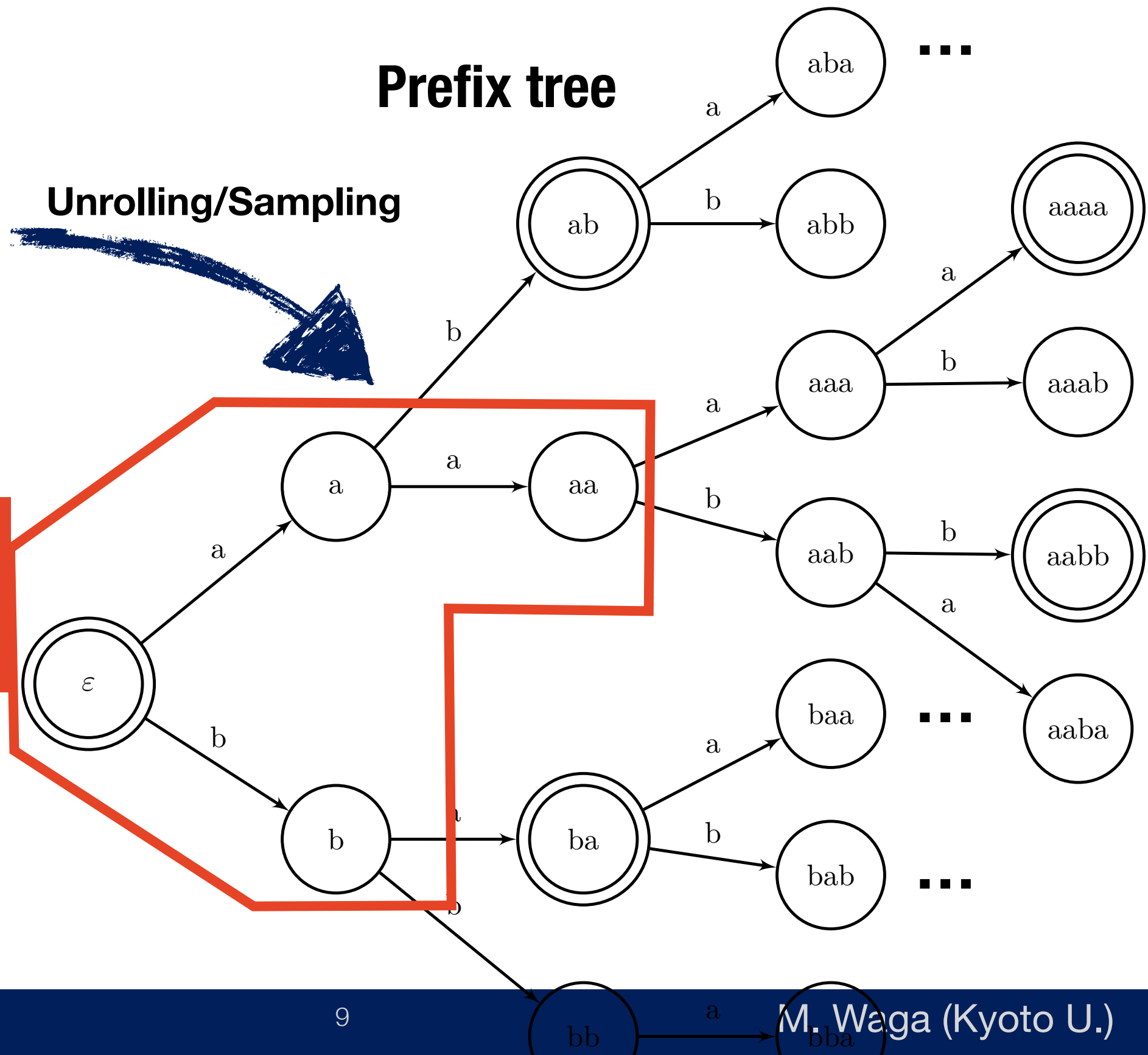
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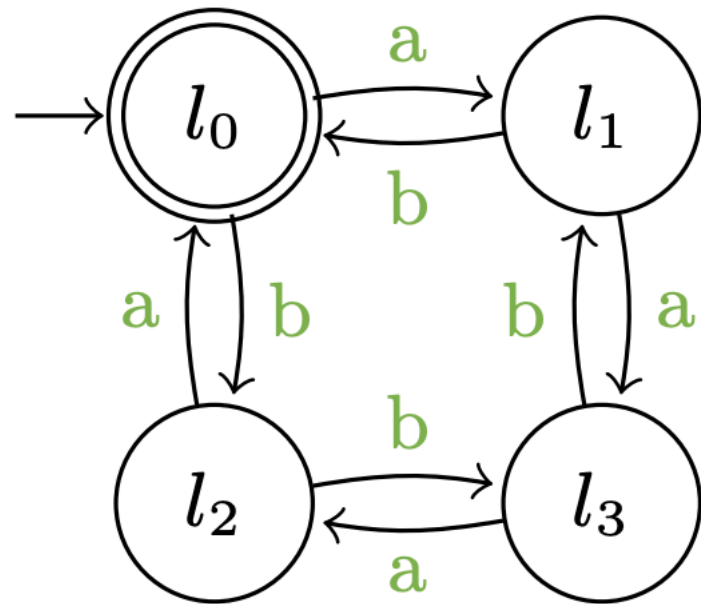
Unrolling/Sampling

Prefixes S to cover states



Idea: Find Good Prefixes/Suffixes

Target DFA



Prefix tree

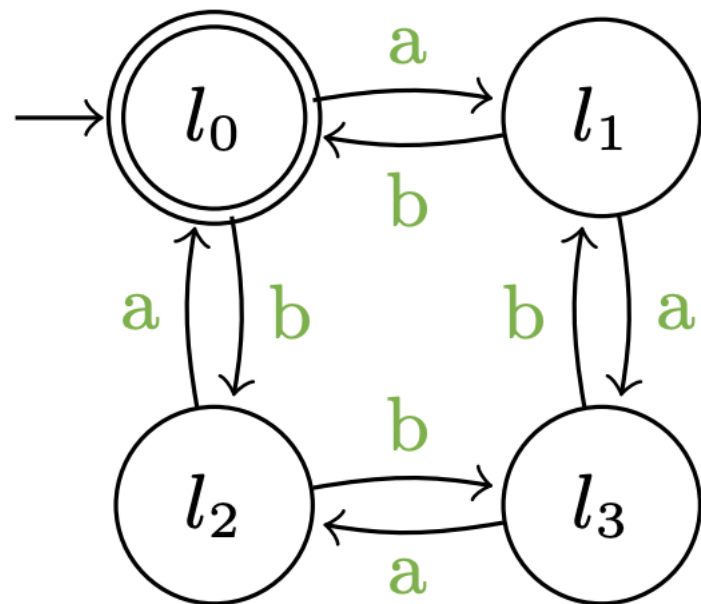
Unrolling/Sampling

Prefixes S to cover states

Suffixes E to distinguish prefixes

Idea: Find Good Prefixes/Suffixes

Target DFA



Prefix tree

Unrolling/Sampling

Prefixes S to cover states

Inequivalent wrt. Nerode's congruence, i.e., $s \cdot w \in L$ and $s' \cdot w \notin L$ for some $w \in \Sigma^*$

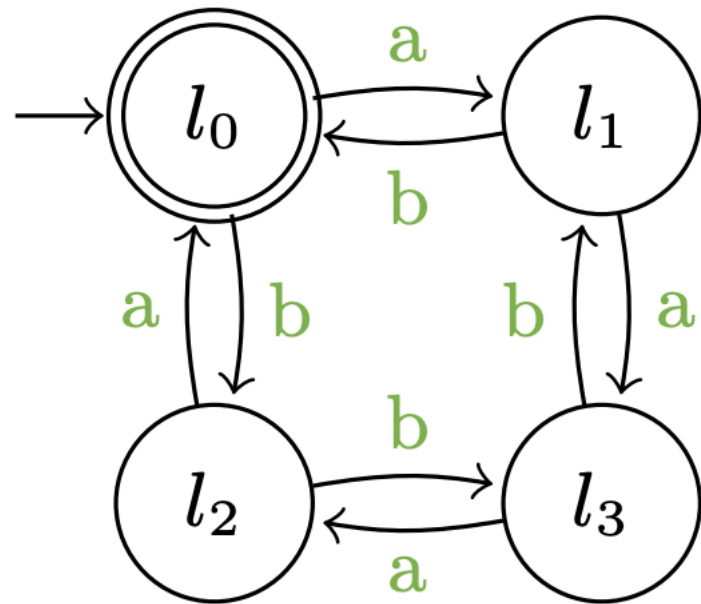
Suffixes E to distinguish prefixes

Idea:

Test Nerode-equivalence, i.e.,
deem w and w' are Nerode-equivalent if
 $w \cdot e \in L \iff w' \cdot e \in L$ for any $e \in E$

Suffixes

Target DFA



Prefix tree

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Suffixes E to
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Observation Table for DFA Learning

[Angluin, Inf. Comput.'87]

Table showing the membership of concatenated words

Shows if $s \cdot e \in L$
e.g. if $a \cdot \varepsilon = a \in L$

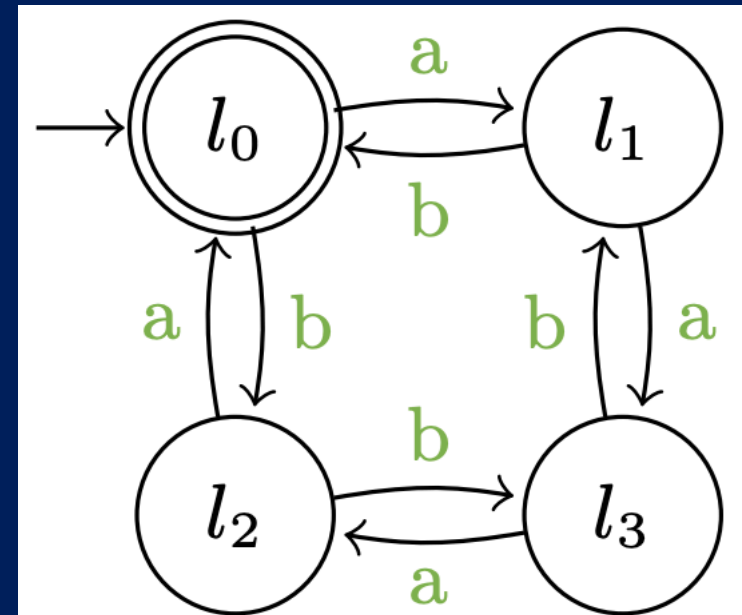
Suffixes E to
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Prefixes S to
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$S \cdot \Sigma \setminus S$

	ε	a	b
ε	T	$\perp$	$\perp$
a	$\perp$	$\perp$	T
b	$\perp$	T	$\perp$
aa	$\perp$	$\perp$	$\perp$
ab	T	$\perp$	$\perp$
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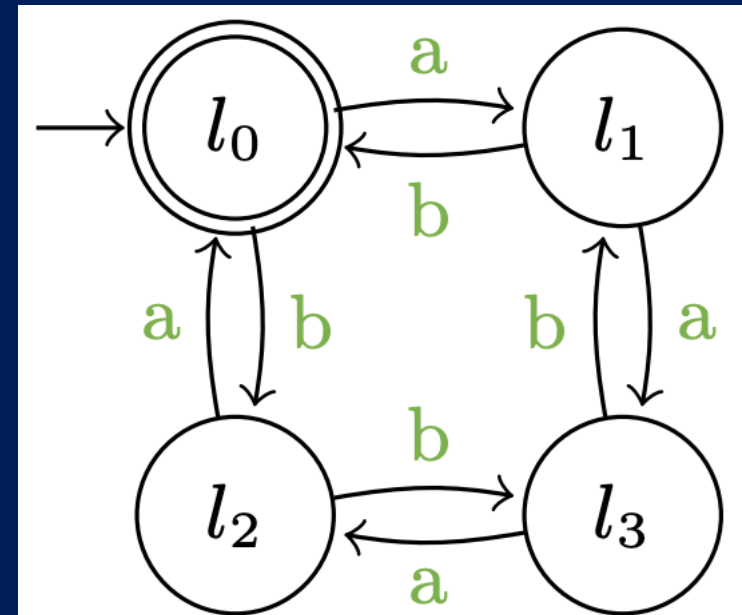
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Table for



Each $s \in S$ corresponds
to one state

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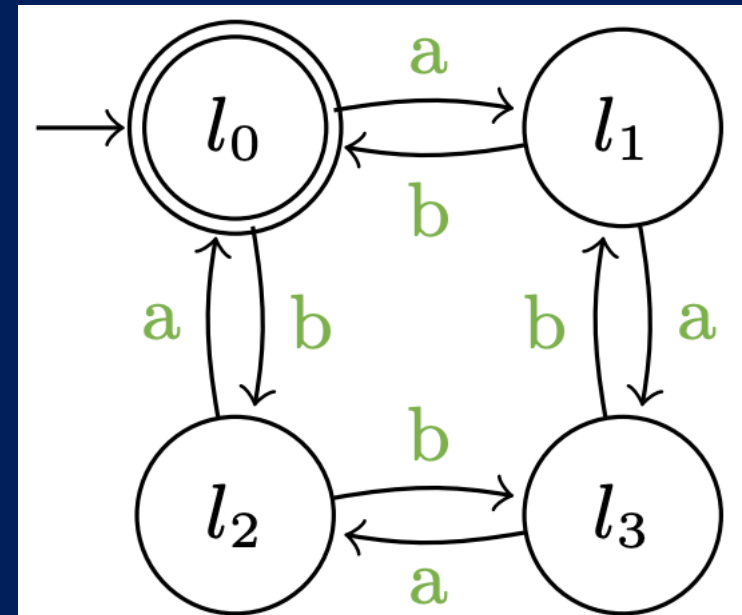
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Used to define
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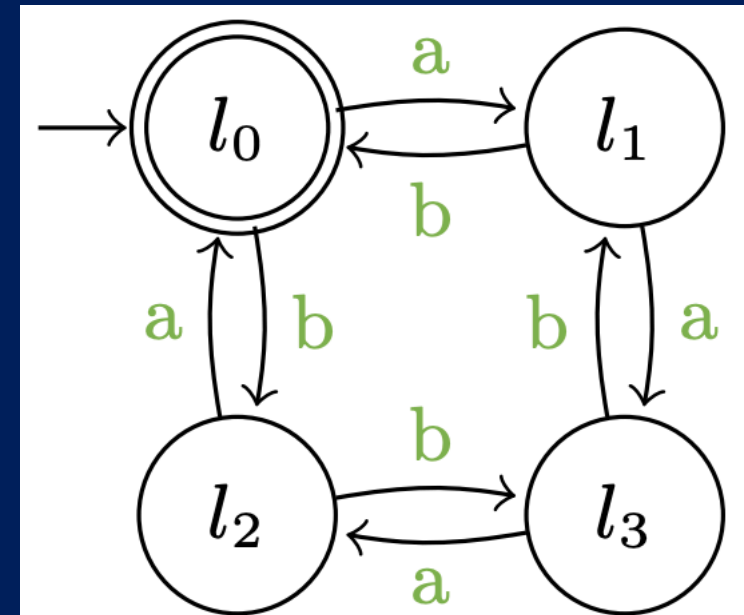
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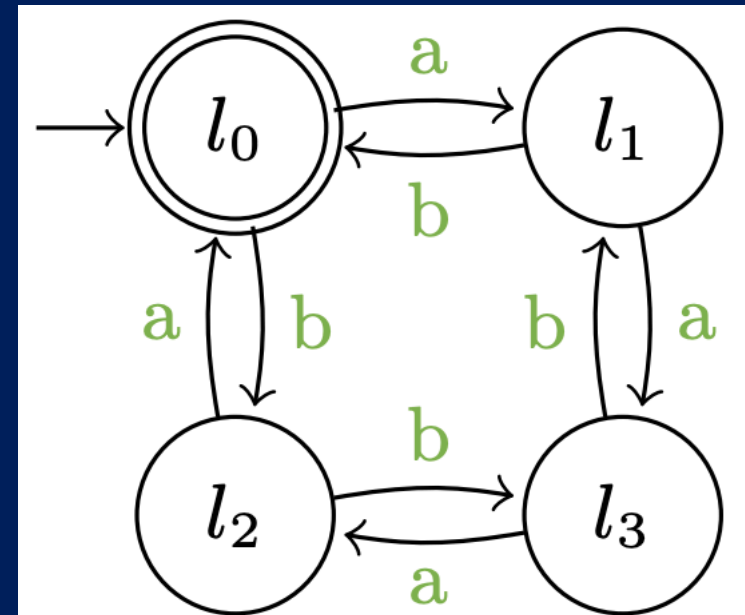
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Successor
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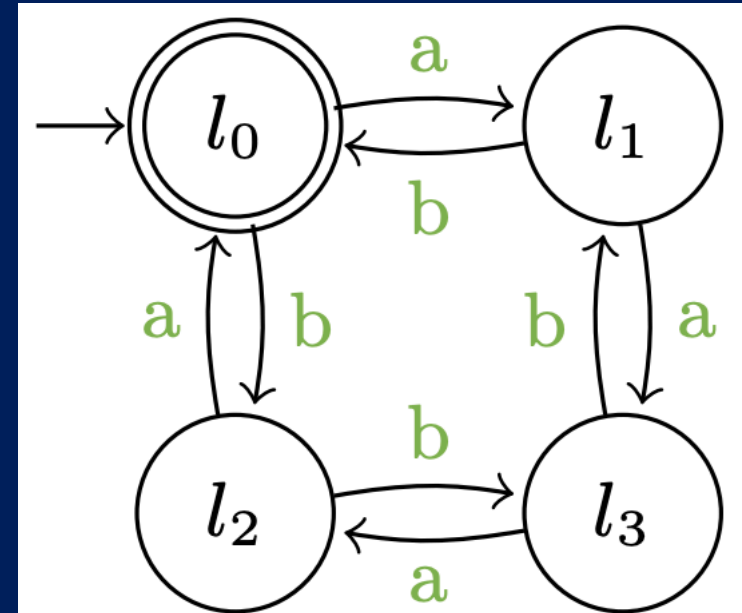
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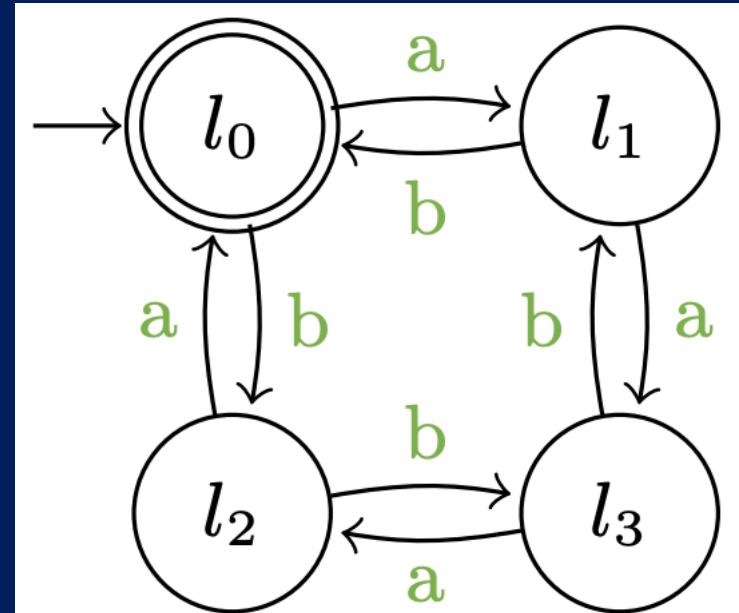
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Table for



Equivalent!

Each $s \in S$ corresponds
to one state

Used to define
successors

Observation Table for Mealy Machines

[Niese, 2003]

Idea: Require $E \supseteq \Sigma$ to learn output function for each state

Output of $s \cdot e$
e.g. $\mathcal{M}(a \cdot \varepsilon) = \mathcal{M}(a)$

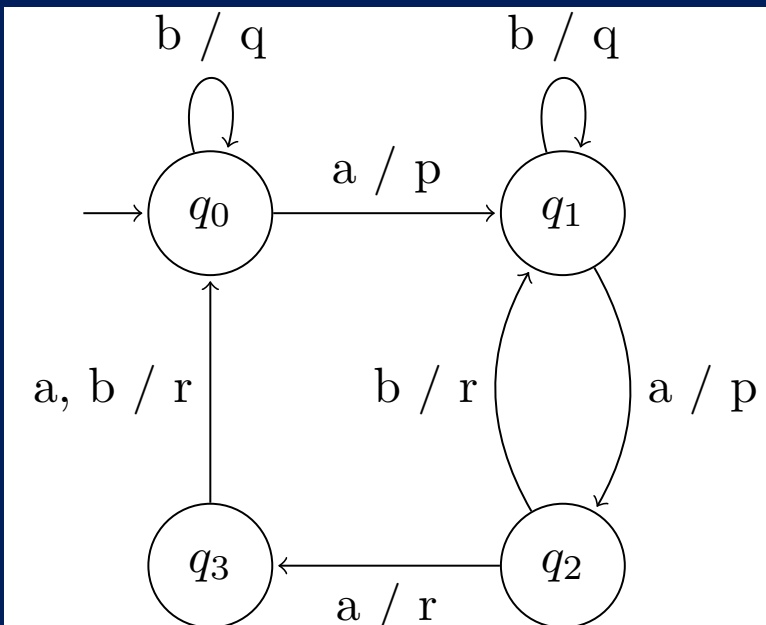
Prefixes S to
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$S \cdot \Sigma \setminus S$

Suffixes E to
distinguish
prefixes

	a	b	aa
ε	p	q	p
a	p	q	r
aa	r	r	r
aaa	r	r	p
b	p	q	p
ab	p	q	r
aab	p	q	r
aaaa	p	q	p
aaab	p	q	p

Table for



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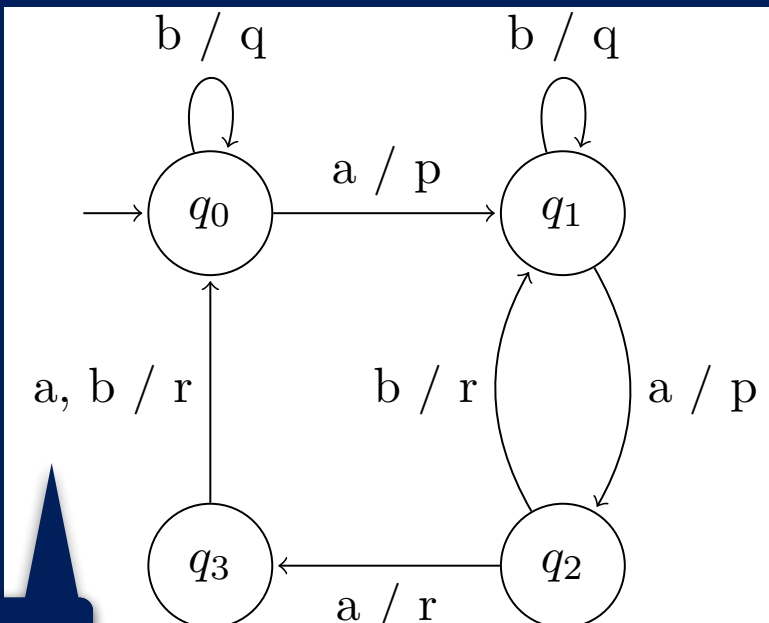
$S \cdot \Sigma \setminus S$

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a	p	q	r
aa	r	r	r
aaa	r	r	p
b	p	q	p
ab	p	q	r
aab	p	q	r
aaaa	p	q	p
aaab	p	q	p

Table for

Output fun.
for q_3



Observation Table for Symbolic Automata

[Drews & D'Antoni, TACAS'17]

Use finite R containing some of $S \cdot \Sigma$ to learn partial successors

Shows if $s \cdot e \in L$
e.g. if $0 \cdot \varepsilon = 0 \in L$

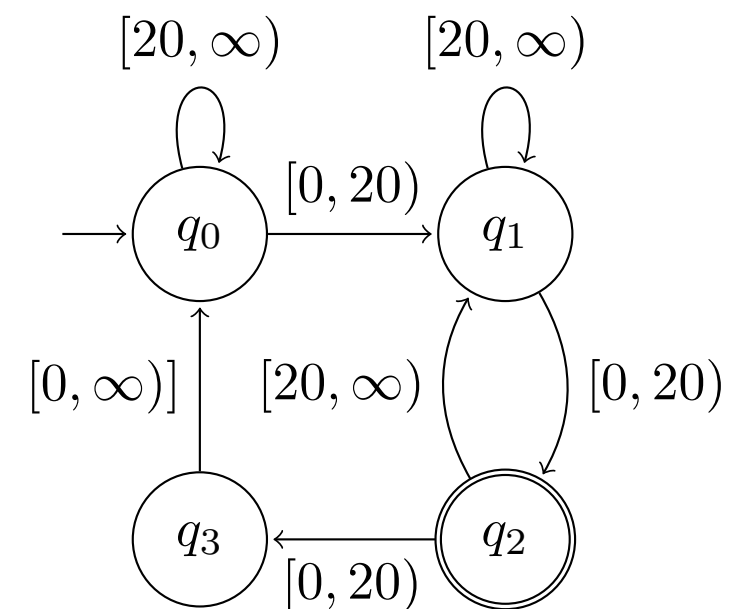
Suffixes E to
distinguish
prefixes

Prefixes S to
cover states

R contains
some of $S \cdot \Sigma \setminus S$

	ε	0	20
ε	$\top$	$\perp$	$\perp$
0	$\perp$	$\perp$	$\top$
20	$\perp$	$\top$	$\perp$
0,0	$\perp$	$\perp$	$\perp$
0,20	$\top$	$\perp$	$\perp$
20,0	$\top$	$\perp$	$\perp$
20,20	$\perp$	$\perp$	$\perp$
0,0,0	$\perp$	$\top$	$\perp$
0,0,20	$\perp$	$\perp$	$\top$

Table for



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[Drews & D'Antoni, TACAS'17]

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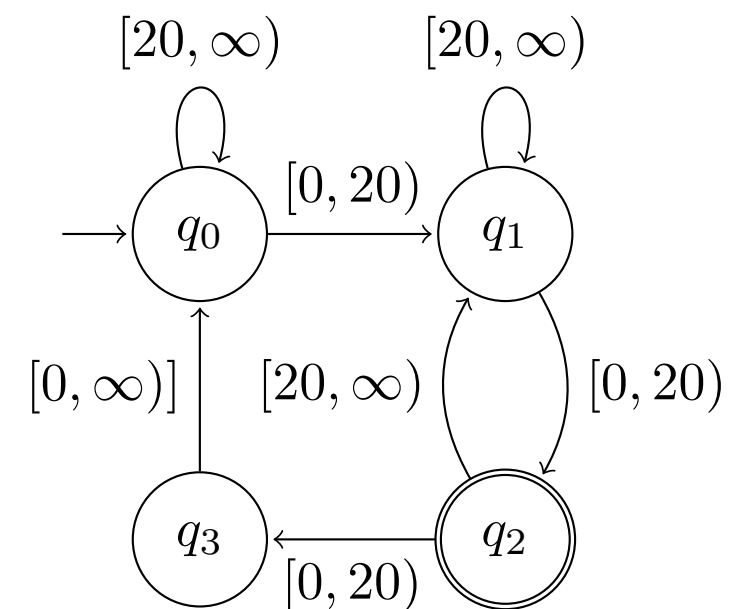
Prefixes S to
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R contains
some of $S \cdot \Sigma \setminus S$

Construct a partial
transition function

	ε	0	20
ε	$\top$	$\perp$	$\perp$
0	$\perp$	$\perp$	$\top$
20	$\perp$	$\top$	$\perp$
0,0	$\perp$	$\perp$	$\perp$
0,20	$\top$	$\perp$	$\perp$
20,0	$\top$	$\perp$	$\perp$
20,20	$\perp$	$\perp$	$\perp$
0,0,0	$\perp$	$\top$	$\perp$
0,0,20	$\perp$	$\perp$	$\top$

Table for



Summary so far...

- Learn automata by identifying “essential” prefixes/suffixes
 - Data structure: observation table
- For Mealy machines:
 - Successors: Ensure row indices include $S \cdot \Sigma$
 - Outputs: Ensure column indices include Σ
- For symbolic automata, relax requirements on totality to
 1. learn a partial transition function
 2. generalize characters to predicates

Outline

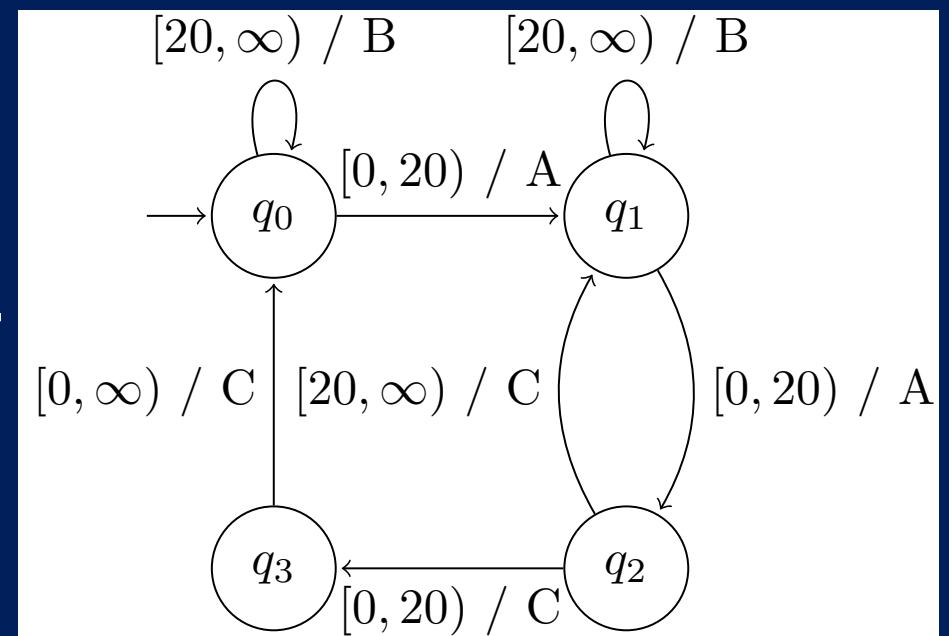
- Preliminaries: Algorithms for active automata learning
 - Idea: Identify good prefixes/suffixes
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 - Learning algorithm for symbolic automata
- Our learning algorithm: Learning symbolic Mealy automata
 - Idea: Explicitly learn “essential” characters
- Experiments

Constructing Symbolic Mealy Automata from Observation Tables

Issue: Successors/outputs may be undefined

	0	0,0
ε	A	A
0	A	C
0,0	C	C
0,0,0	C	A
20	A	A
0,20	A	C
0,0,20	A	C
0,0,0,0	A	A
0,0,0,20	A	A

Table for

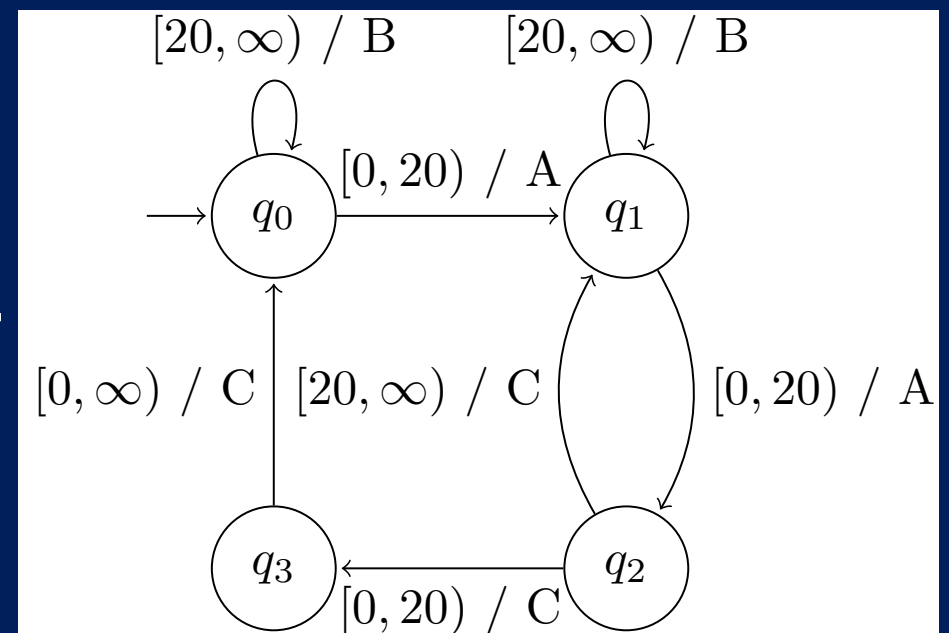


Constructing Symbolic Mealy Automata from Observation Tables

Issue: Successors/outputs may be undefined

	0	0,0
ε	A	A
0	A	C
0,0	C	C
0,0,0	C	A
20	A	A
0,20	A	C
0,0,20	A	C
0,0,0,0	A	A
0,0,0,20	A	A

Table for



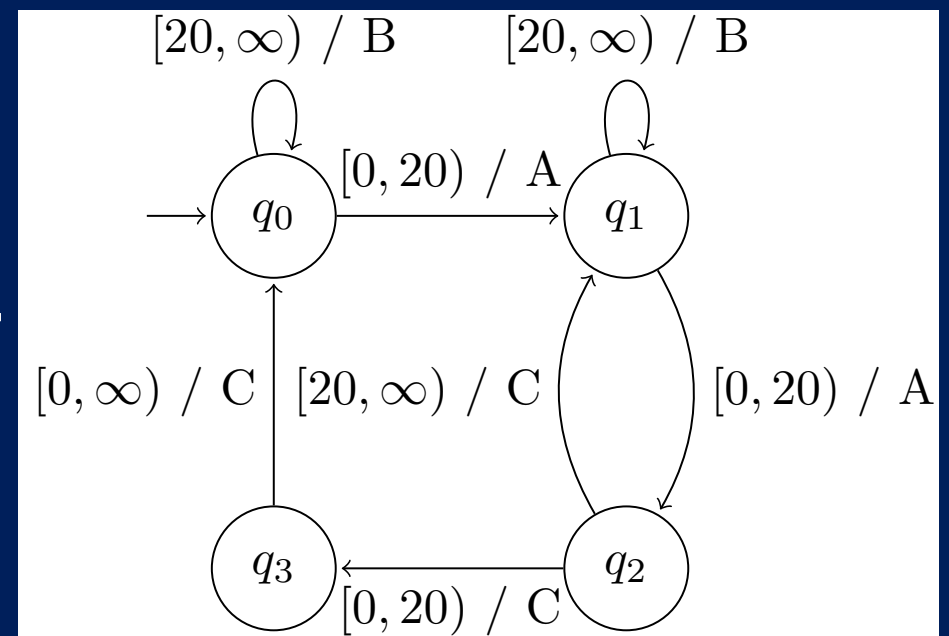
Constructing Symbolic Mealy Automata from Observation Tables

Issue: Successors/outputs may be undefined

Successor
with 20

	0	0,0
ε	A	A
0	A	C
0,0	C	C
0,0,0	C	A
20	A	A
0,20	A	C
0,0,20	A	C
0,0,0,0	A	A
0,0,0,20	A	A

Table for



Constructing Symbolic Mealy Automata from Observation Tables

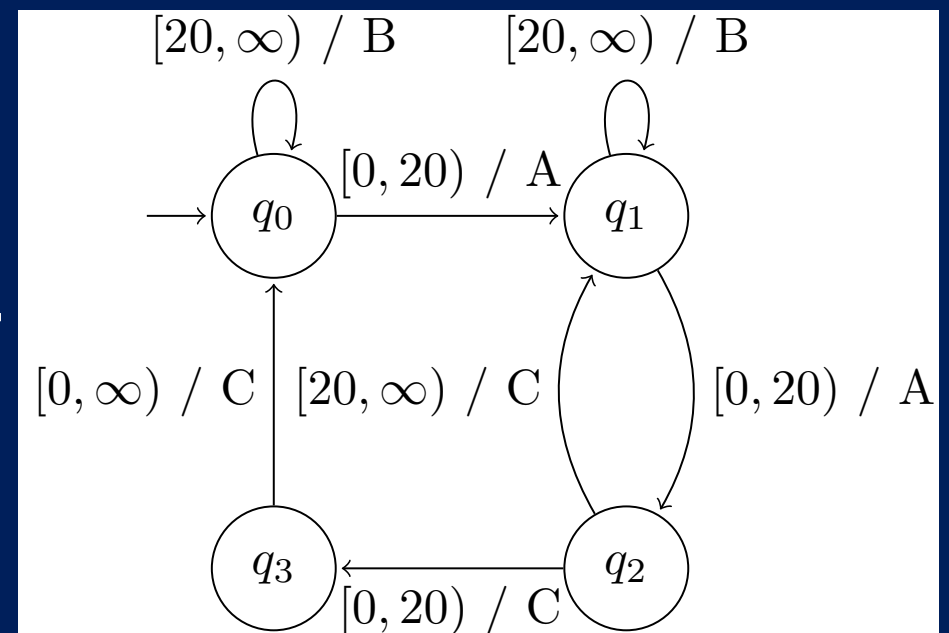
Issue: Successors/outputs may be undefined

Output for 20 is undefined

Successor
with 20

	0	0,0
ε	A	A
0	A	C
0,0	C	C
0,0,0	C	A
20	A	A
0,20	A	C
0,0,20	A	C
0,0,0,0	A	A
0,0,0,20	A	A

Table for



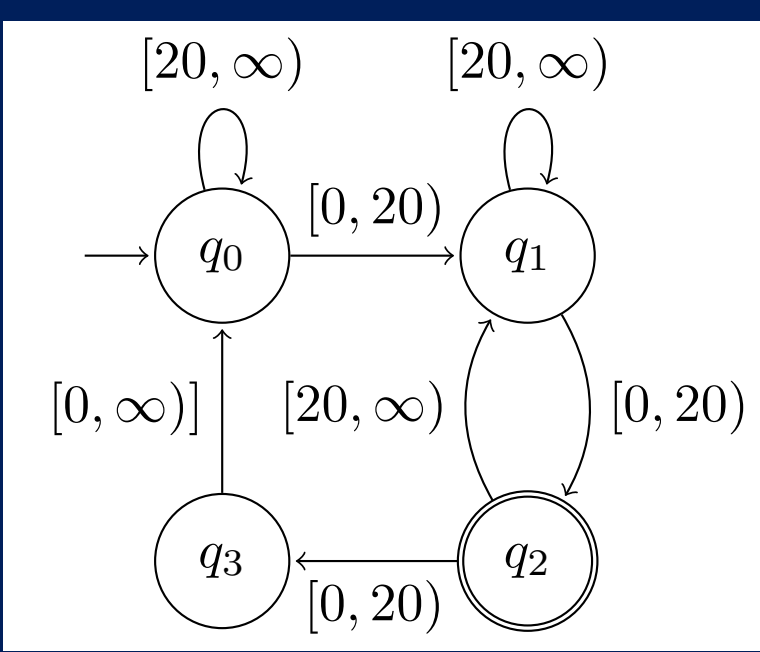
Observation Table for Symbolic Mealy Autom.

[Contributions]

Idea: Explicitly identify essential characters Σ_E

		Essential characters Σ_E		Suffixes E to distinguish prefixes
		0	20	0,0
Prefixes S to cover states	ε	A	B	A
	0	A	B	C
	0,0	C	C	C
	0,0,0	C	C	A
R contains some of $S \cdot \Sigma \setminus S$	20	A	B	A
	0,20	A	B	C
	0,0,20	A	B	C
	0,0,0,0	A	B	A
	0,0,0,20	A	B	A

Table for



Output Closedness

[Contributions]

Definition

An observation table for symbolic Mealy automata is output-closed if for any $s, s \cdot a \in S \cup R, a \in \Sigma_E$ holds

Observation table can be made
output-closed by increasing Σ_E

Lemma

If the successor from $s \in S$ with $a \in \Sigma$ is defined in an output-closed observation table, the output from s with a is also defined

→ We can construct a Mealy machine over Σ_E

Outline of Symbolic Mealy Learning

1. Initialize observation table
2. Make observation table satisfy certain properties, including output closedness
3. Construct a Mealy machine $\mathcal{M}^e$ over Σ_E
4. Generalize characters into predicates to construct a symbolic Mealy automaton $\mathcal{M}$
5. Ask equivalence query with $\mathcal{M}$
 - If $\mathcal{M}$ is equivalent to target, return $\mathcal{M}$
 - Otherwise, add prefixes of the counterexample to R
→ Go back to Step 2

Correctness of Our Algorithm

[Contributions]

Theorem

If our algorithm for learning symbolic Mealy automata terminates, the returned symbolic Mealy automaton represents the same function as the target one.

The proof is immediate because the algorithm terminates only if the equivalence oracle returns “Yes”.

Complexity Analysis with Σ_E^{final}

- Σ_E^{final} : Σ_E at the end of learning
- New characters in Σ_E are found by equiv. queries
→ Σ_E^{final} depends on the “smartness” of the oracle

Note: Σ_E^{final} may not be finite in general, i.e., the learning algorithm may not terminate

- Example: for $\Sigma = \mathbb{Q}$, oracle can keep returning a new character that is closer to the actual threshold

Upper Bound of # of Queries

Theorem

The number of queries in our algorithms is bounded by

- $(|\Sigma_E^{final}| + m + 1) \times n^2 + (2m + |\Sigma_E^{final}| + 1) \times |\Sigma_E^{final}| \times n + m \times |\Sigma_E^{final}|^2$ for membership queries

- $n + |\Sigma_E^{final}|$ for equivalence queries

Polynomial queries
(similar to classical results)

where

Complexity in state space and characters can independently make learning difficult

- m : maximum length of the counterexample in equiv. query
- n : number of states of the target symbolic Mealy automata

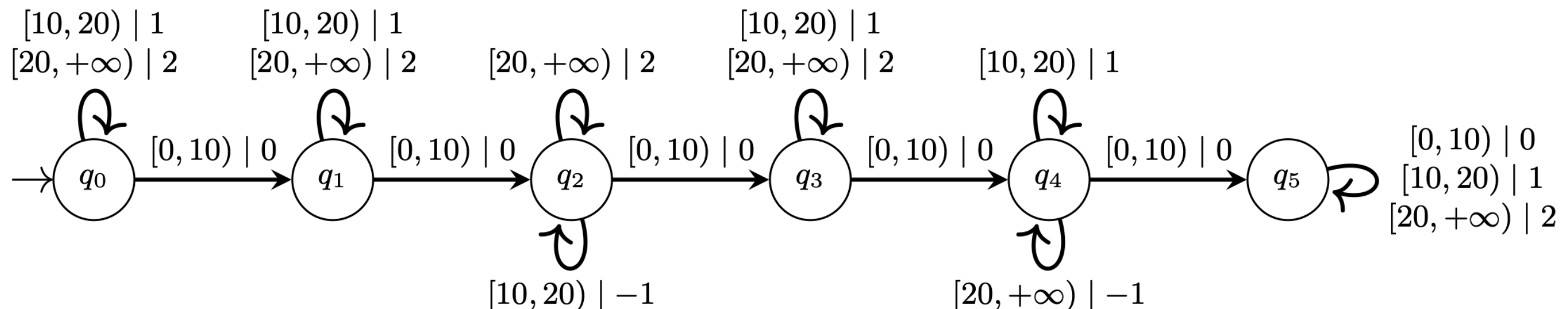
A Lower Bound of # of Queries

Theorem

For any $n, k \in \mathbb{N}$ s.t. $k \geq n \geq 2$, there is a target symbolic Mealy automaton with $2n$ such that $|\Sigma_E^{final}| = k$ and our algorithm requires at least $n + k$ equivalence queries.

Concrete example of the independent contribution of state space and characters to the learning complexity

Example ($n = k = 3$)



Outline

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Implementation & Experiments

- Implemented our learning algorithm in Java
 - <https://github.com/SoftwareFoundationGroupAtKyotoU/learningsma>
- Two kinds of benchmarks
 - Random examples to observe the scalability
 - Generated 10 examples for each configuration
 - “Practical” examples from MATLAB/Simulink models
 - Mars Helicopter (MH) and Automatic Transmission Gear System (ATGS)
- Intel Xeon E5-2687W v3, 251 GiB RAM, with Ubuntu 22.04.4 LTS

Scalability wrt Number of States

of output queries scales almost linearly wrt # of states

← $|E|$ is almost 0 and quadratic term is ≈ 0

of states = 10 # of states = 20 # of states = 40 # of states = 80

	10	10	10	10
$ \Sigma_E^{final} $	10	10	10	10
# of output queries	1015.6	2035.95	4010.9	8186.59
# of eq. queries	10	10.1	10	10.18
$ R $	91.56	181.57	361.09	722.55
$ E $	0.0	0.1	0.0	0.2

Words of length 1 are typically enough to distinguish states
→ E is not used

Scalability wrt $|\Sigma_E^{final}|$

of output queries scales almost linearly wrt $|\Sigma_E^{final}|$

← $|E|$ is almost 0 and quadratic term is ≈ 0

	$ \Sigma_E^{final} = 10$	$ \Sigma_E^{final} = 20$	$ \Sigma_E^{final} = 40$	$ \Sigma_E^{final} = 80$
# of states	10	10	10	10
# of output queries	1015.6	4075.6	9104.7	16161.6
# of eq. queries	10	20	29.99	40
$ R $	91.56	193.78	293.49	394.04
$ E $	0.0	0.0	0.0	0.0

“Practical” Examples

Query complexity seems better than the worst-case bound, also for “practical” examples.

	Mars Helicopter	Automatic Transmission Gear System
# of output queries	6516	86446.8
# of equivalence queries	36	66
$ \Sigma_E^{final} $	36	68
# of states	5	16
Max. length of cex.	4	12
$ E $	0	6
Boolean dimensions in Σ	1	0
Numeric dimensions in Σ	3	2

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$|E|$ is small

“Practical” Examples

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	Mars Helicopter	Automatic Transmission Gear System
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Less than half of the upper bound (14,309 and 177,408)

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# of output queries	6516	86446.8
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$ \Sigma_E^{final} $	36	68
# of states	5	16
Max. length of cex.	4	12
$ E $	0	6
Boolean dimensions in Σ	1	0
Numeric dimensions in Σ	3	2

Much better than the worst case
(# eq. $\leq |\Sigma_E^{final}| + \text{\# of states}$)

Conclusions

- Learning algorithm for symbolic Mealy automata
 - Idea: Explicitly learn “essential” characters Σ_E
- Complexity analysis of our algorithm
 - Worst case query complexity
 - An example to demonstrate the tightness
- Implementation + Experiments
 - Typically much more efficient than theoretical bound

Future Directions

- Better handling of counterexamples based on [Rivest & Schapire, '93]
- Learning symbolic Mealy automata based on active learning of predicates, e.g., [Argyros & D'Antoni, CAV'18]
- Testing black-box systems by combining with model checking, e.g., [Peled+, FORTE'99]

Appendix

Nerode's congruence

Nerode's congruence ($\equiv_L$): For

- language: $L \subseteq \Sigma^*$
- prefixes: $s, s' \in \Sigma^*$

$$s \equiv_L s' \text{ iff. } \forall e \in \Sigma^* . s \cdot e \in L \iff s' \cdot e \in L$$

e.g. for $L = (ab)^*$, $\varepsilon \equiv_L ab$, $a \equiv_L aba$, ...

Accepted iff $s \in (ab)^*$

Accepted iff $s \in b(ab)^*$

✓: Easy to construct $\mathcal{A}$ s.t. $\mathcal{L}(\mathcal{A}) = L$ from $\equiv_L$

- **Idea:** Use $\Sigma^* / \equiv_L$ as the state space

✗: Requires *infinite* comparison to check if $s \equiv_L s'$

Other Requirements for Making Mealy Machines

Definition (closedness)

An observation table for symbolic Mealy automata is closed if for any $r \in R$ there is $s \in S$ with the same row

Definition (consistency)

An observation table for symbolic Mealy automata is consistent if for any $s, s' \in S \cup R$ and $s \cdot a, s' \cdot a \in S \cup R$, $row(s) = row(s')$ implies $row(s \cdot a) = row(s' \cdot a)$

Other Requirements for Making Mealy Machines

Definition (evidence-closedness)

An observation table for symbolic Mealy automata is evidence-closed if for any $s \in S$ and $e \in \Sigma_E$,
 $s \cdot e \in S \cup R$ holds