Learning Discrete Timed Automata

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Chennai Mathematical Institute

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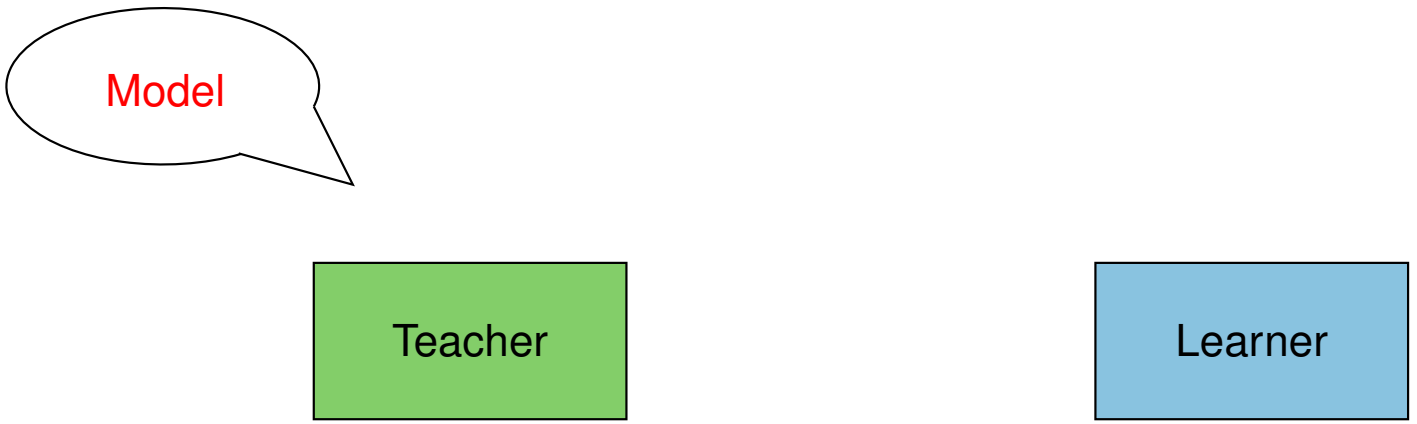
Schedule

Learning

Learning Problem

Learning Problem



Learning Problem

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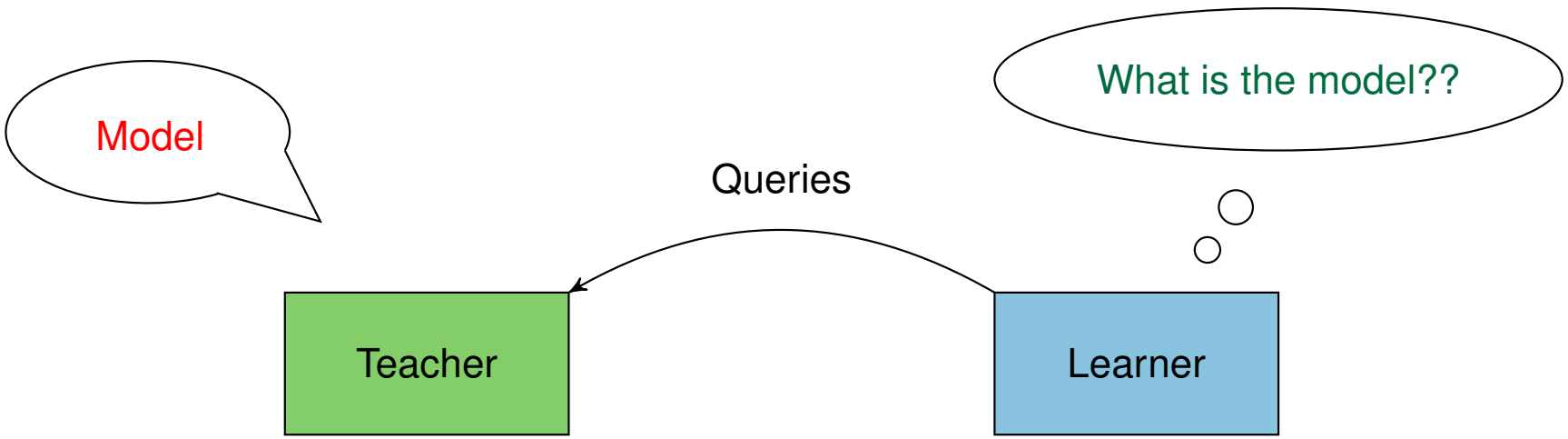
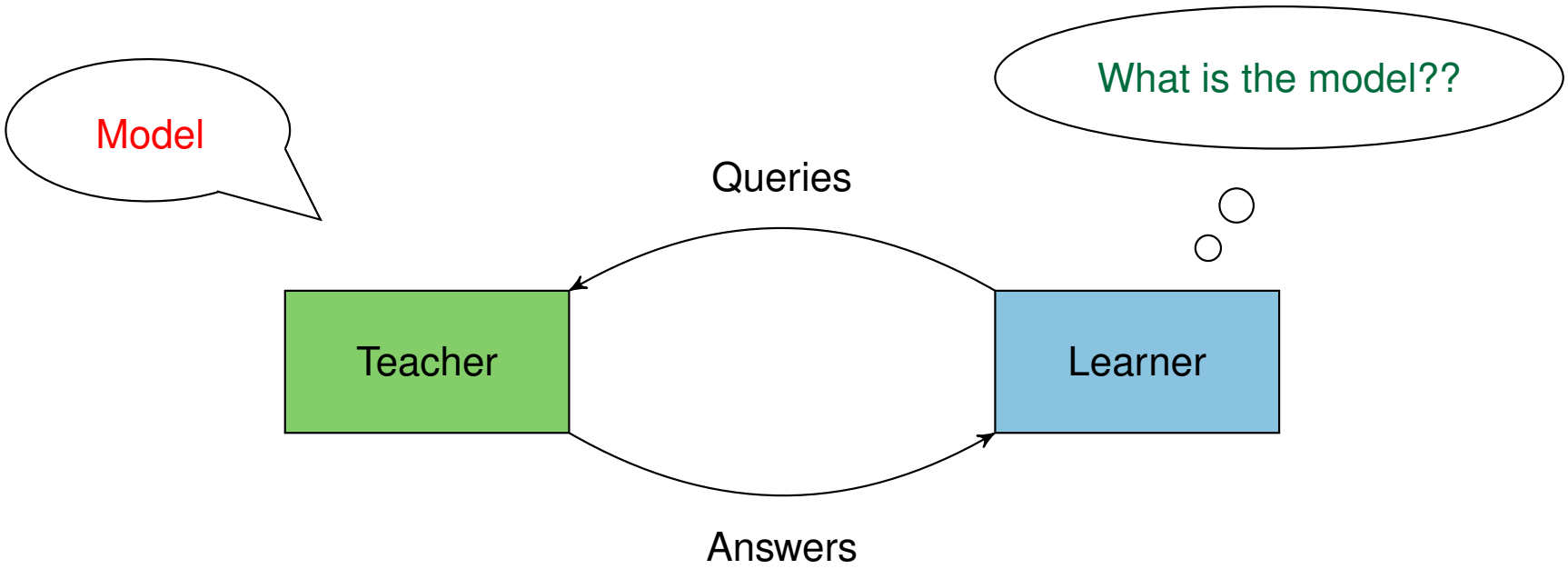
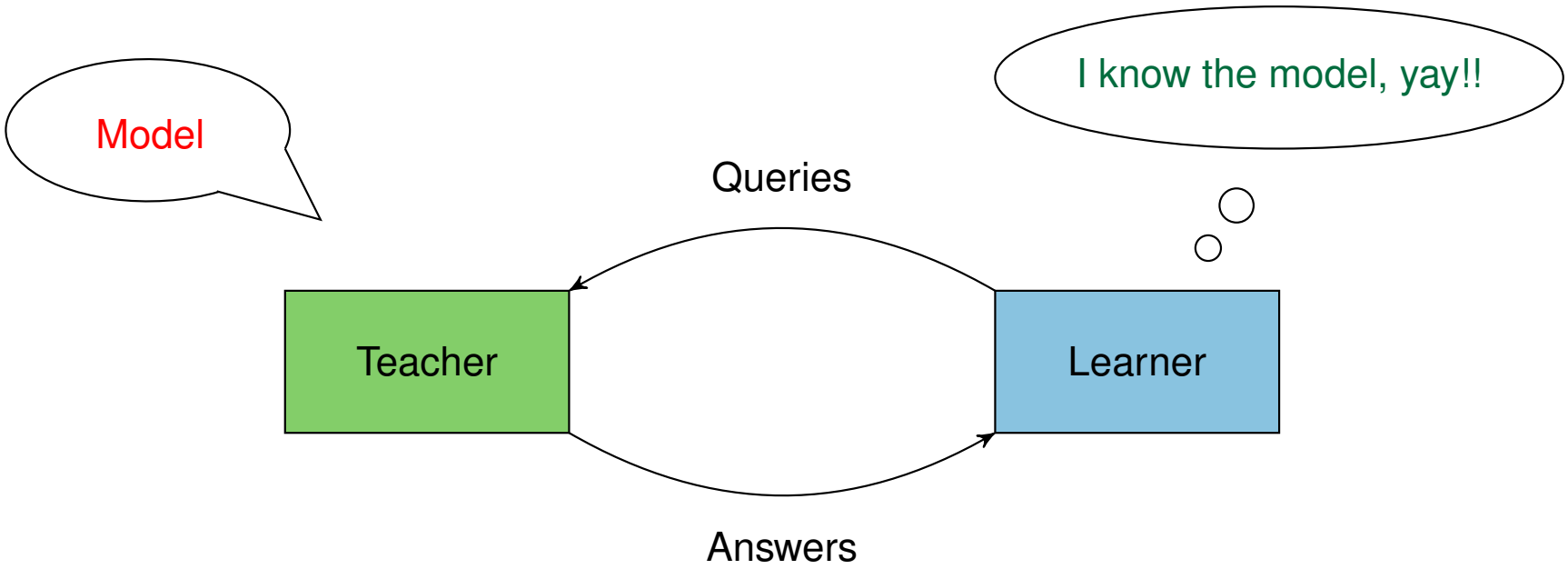


Learning Problem



Learning Problem

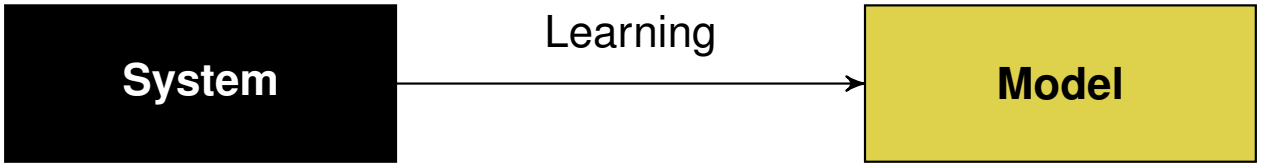


Motivation

System

[1] Peled D., Vardi M.Y., Yannakakis M. (1999) Black Box Checking. Formal Methods for Protocol Engineering and Distributed Systems. PSTV 1999, FORTE 1999.

Motivation



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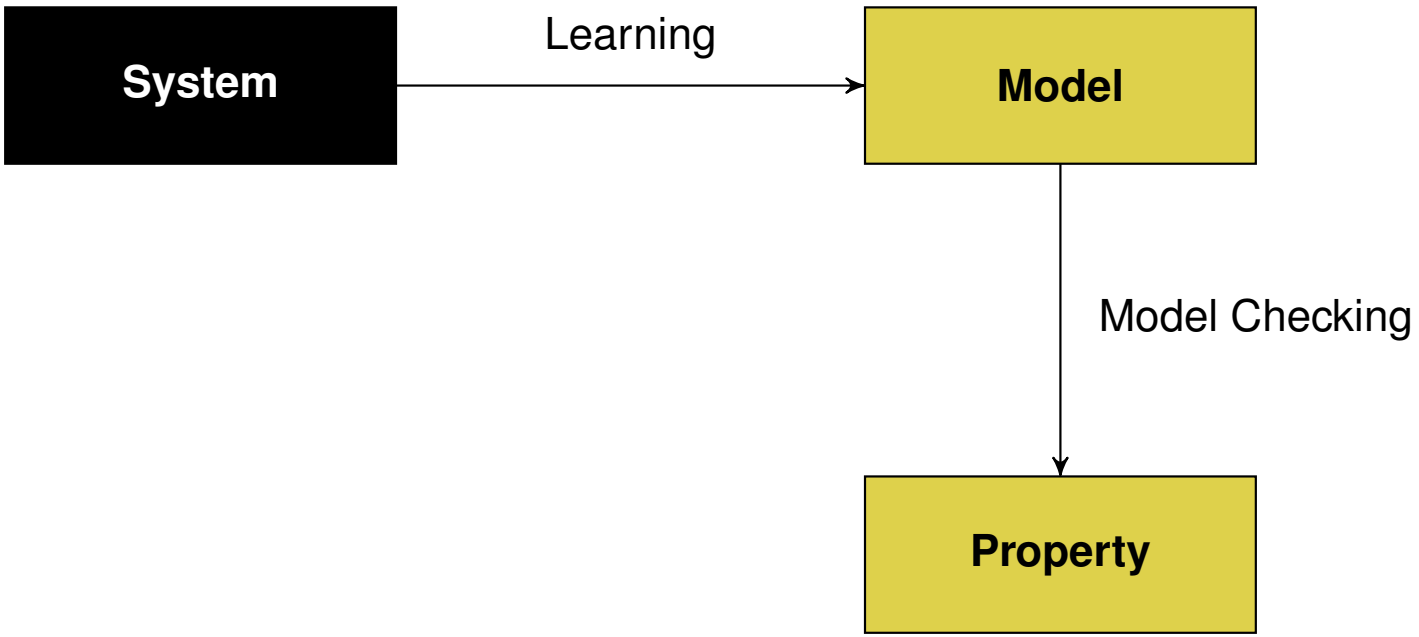

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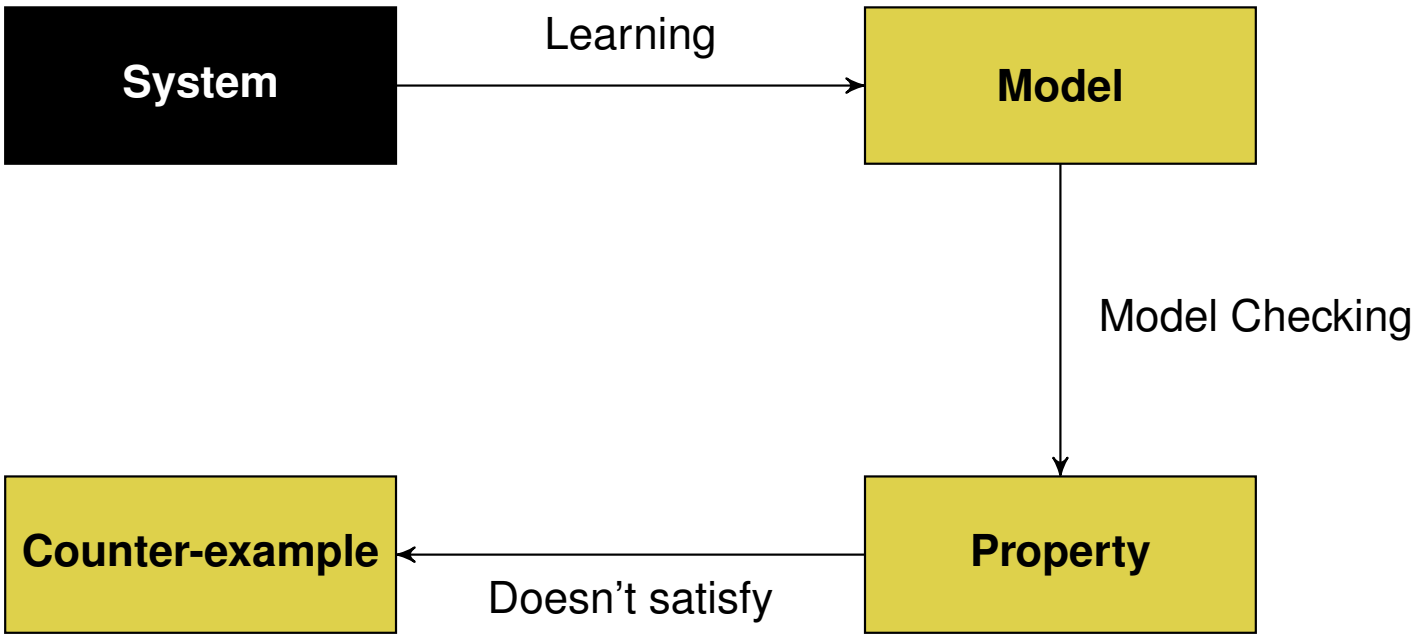
Motivation



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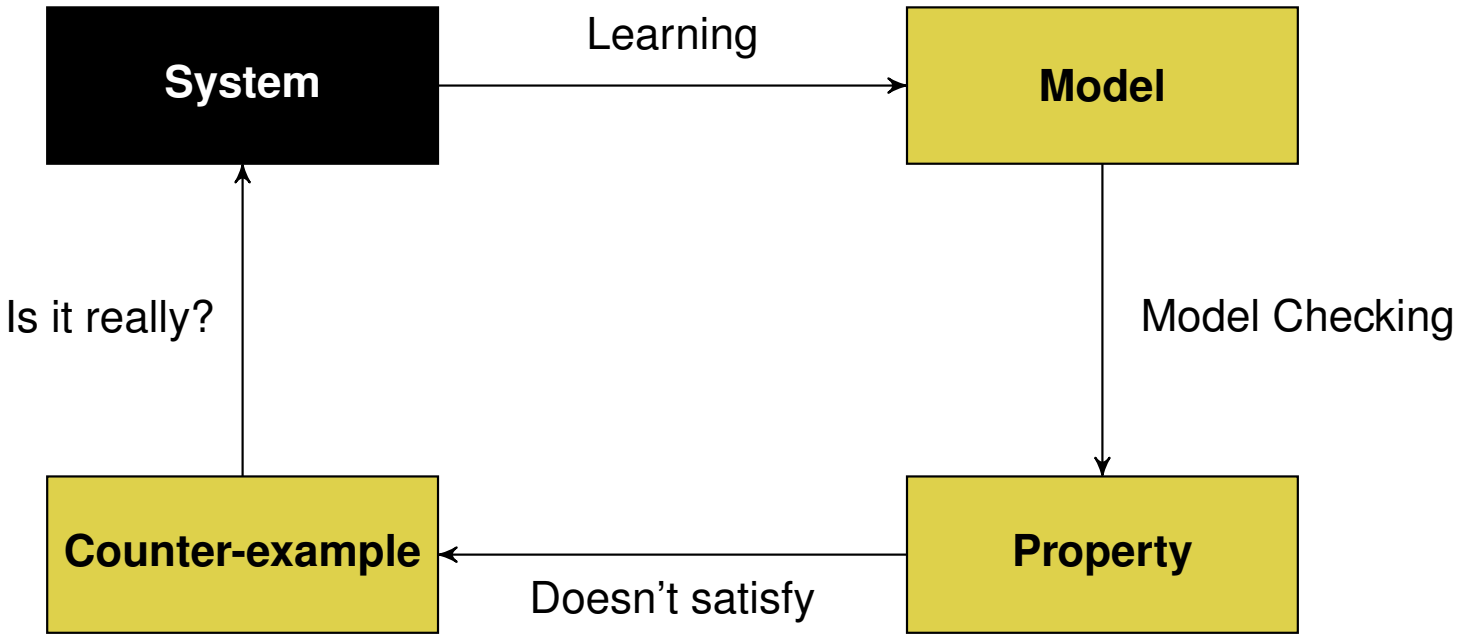
Motivation



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Types of learning

Two types of learning:

Active Learning

Passive Learning

Types of learning

Two types of learning:

Active Learning

Learner asks if some instance satisfies the model on the fly.

Passive Learning

Sets $\mathcal{P}$ and $\mathcal{Q}$ of positive and negative instances are known to the learner.

Automata Learning

Learning DFA

$\mathbf{L}^*$: an active learning algorithm by D. Angluin[1987].

Learning DFA

L*: an active learning algorithm by D. Angluin[1987].

Two types of queries learner can ask:

Learning DFA

L*: an active learning algorithm by D. Angluin[1987].

Two types of queries learner can ask:

- **Membership queries**: ask if some string is accepted by the target automaton.

Learning DFA

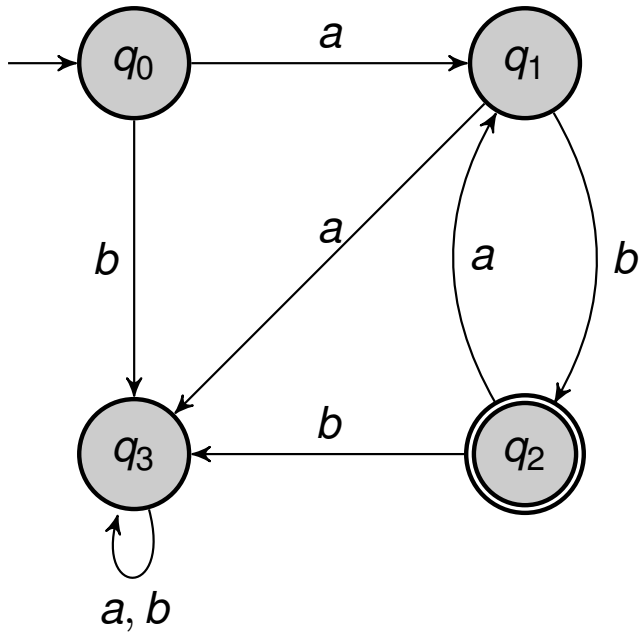
L*: an active learning algorithm by D. Angluin[1987].

Two types of queries learner can ask:

- **Membership queries**: ask if some string is accepted by the target automaton.
- **Equivalence queries**: give a hypothesis automaton to the teacher and ask if it is equal to the target automaton. If not, teacher returns a counter-example.

Learning DFAs

$$\mathcal{L}(D) = (ab)^+$$

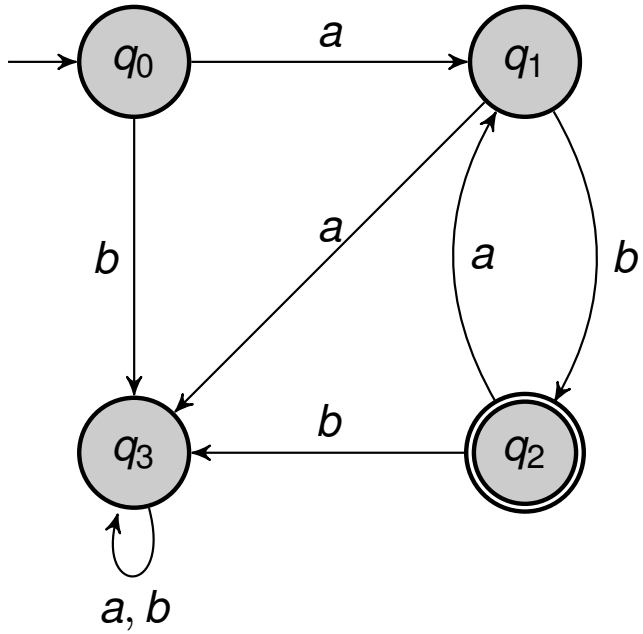


Deterministic Finite Automaton D

Learning DFAs

$\mathcal{L}(D) = (ab)^+$

Run L^* on this.

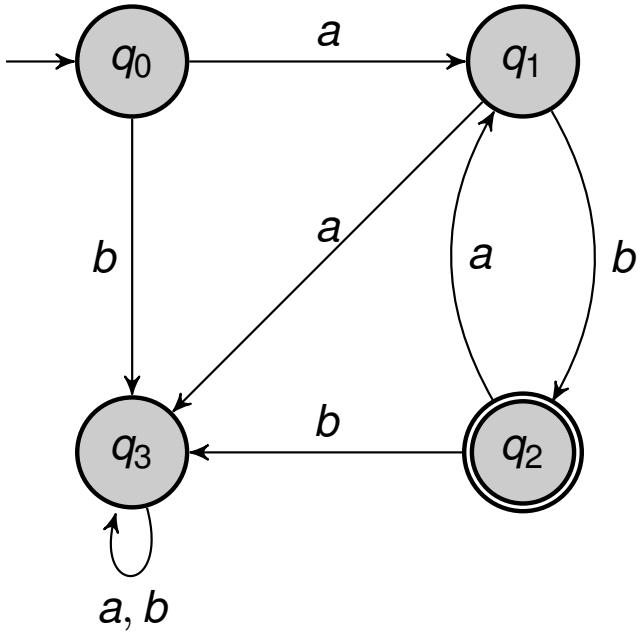


Learning DFAs

Observation Table	
T	E
S	$-/+$
R	$-/+$

$T = (\Sigma, S, R, E, f)$

- Σ is a finite alphabet,
- $S, R, E \subseteq \Sigma^*$ and $R = S \cdot \Sigma$,
- $f(u) = +$ if $u \in \mathcal{L}(D)$ and $f(u) = -$ otherwise.

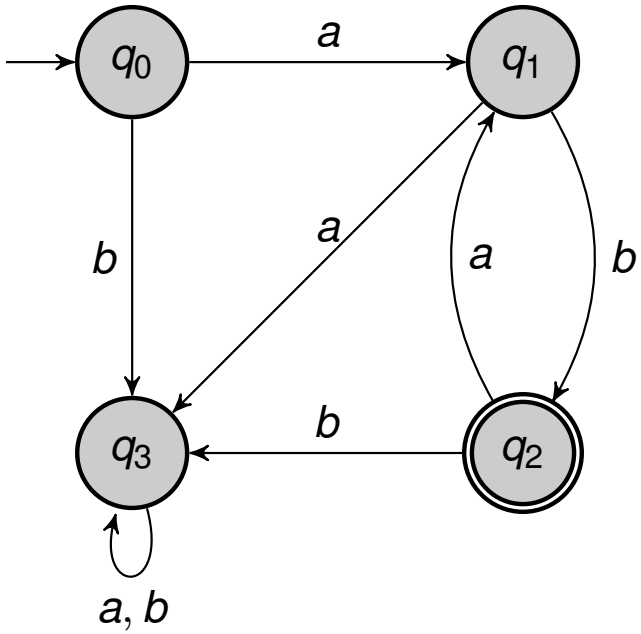


Learning DFAs

Observation Table	
T_0	ϵ
ϵ	–
a	–
b	–

Initially

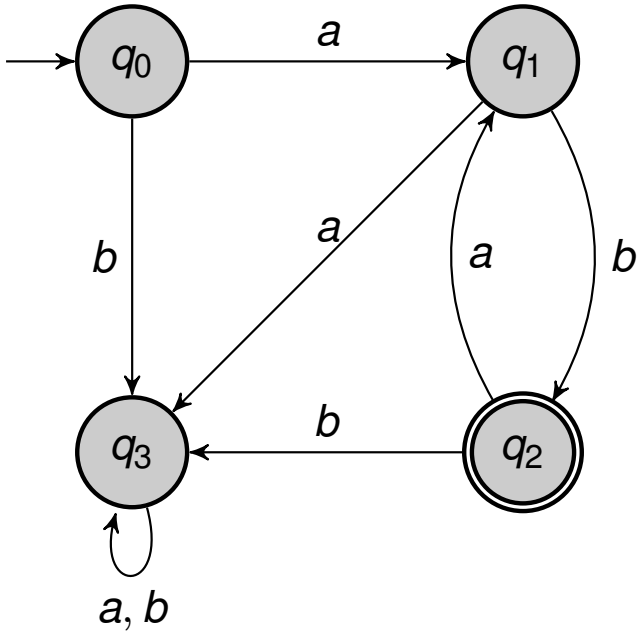
- $S = E = \{\epsilon\}$
- $R = \{a, b\}$
- $f(\epsilon) = f(a) = f(b) = -$



Learning DFAs

Observation Table	
T_0	ϵ
ϵ	–
a	–
b	–

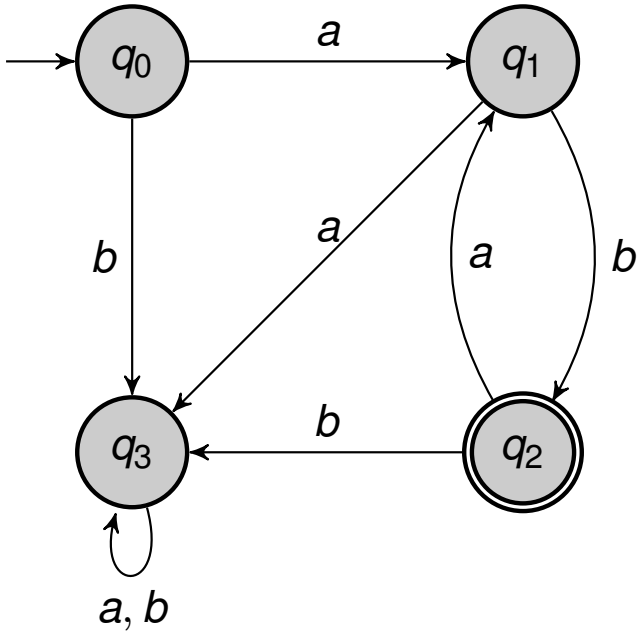
Check if it is { ***closed*** ***consistent***



Learning DFAs

Observation Table	
T_0	ϵ
ϵ	–
a	–
b	–

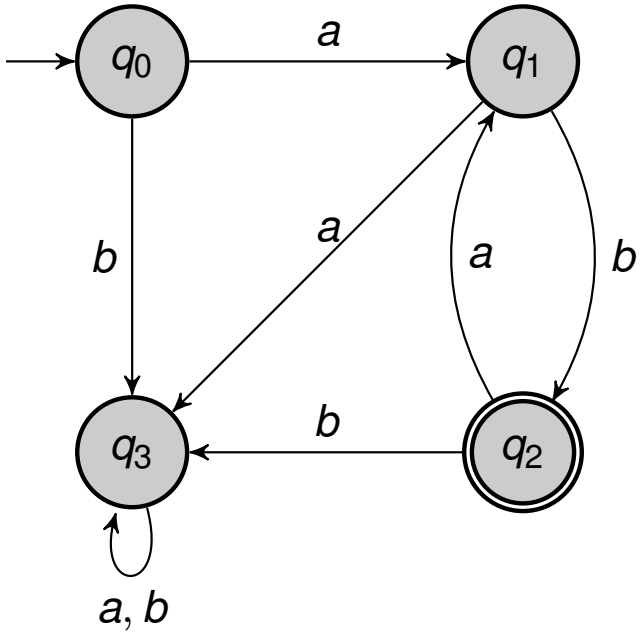
Check if it is { ***closed*** ✓ ***consistent***



Learning DFAs

Observation Table	
T_0	ϵ
ϵ	–
a	–
b	–

Check if it is { ***closed*** ✓ ***consistent*** ✓

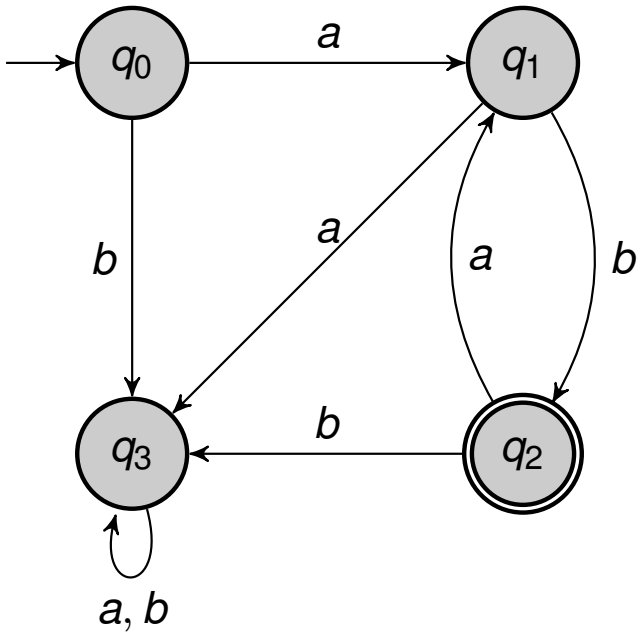


Learning DFAs

Observation Table	
T_0	ϵ
ϵ	–
a	–
b	–

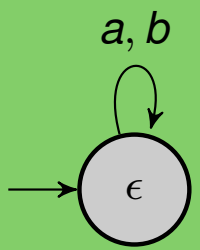
Construct a hypothesis automaton $M(T)$ from the table.

- S is the set of states
- R represents the transitions
- ϵ is the initial state
- $s \in S$ is final if first entry of $row(s)$ is $+$

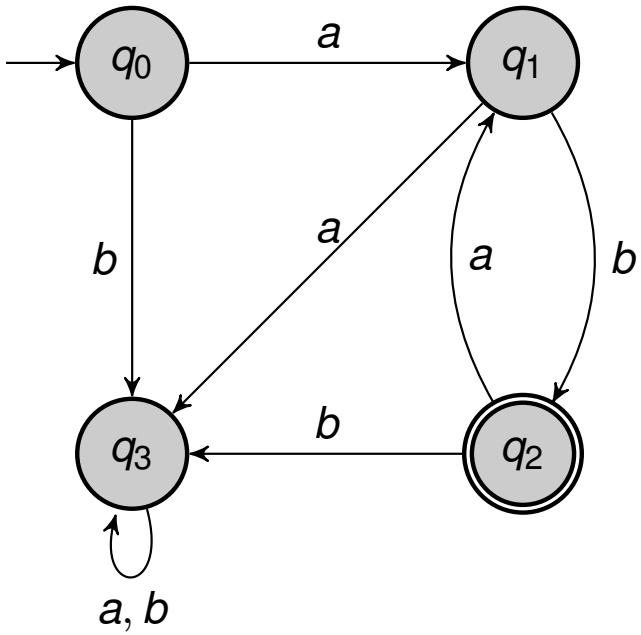


Learning DFAs

Observation Table	
T_0	ϵ
ϵ	–
a	–
b	–

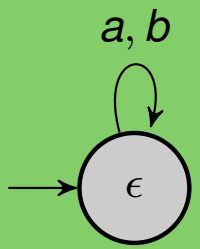


Hypothesis automaton $H_0 = M(T_0)$



Learning DFAs

Observation Table	
T_0	ϵ
ϵ	–
a	–
b	–



Hypothesis automaton $H_0 = M(T_0)$

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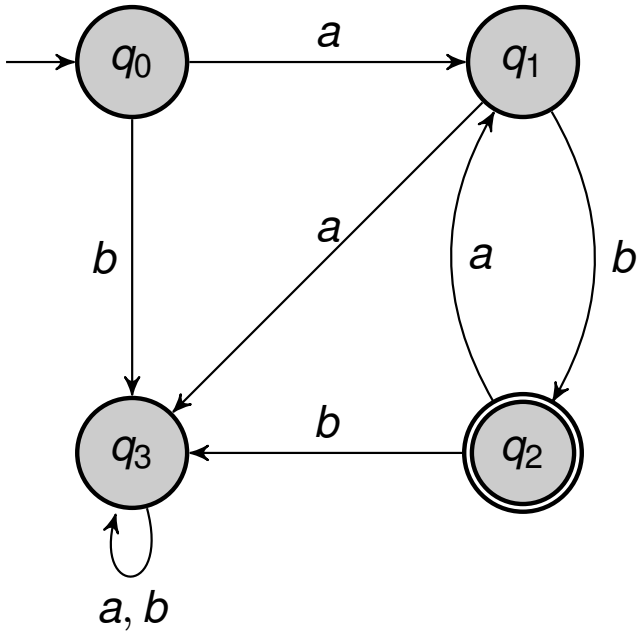
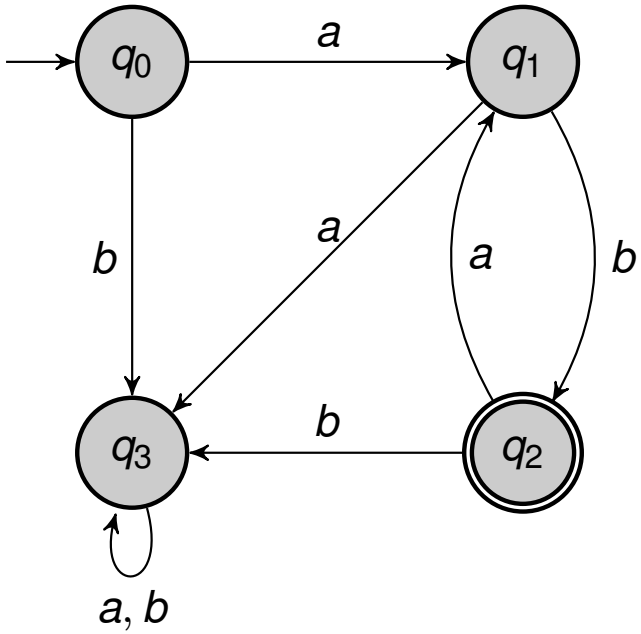


Learning DFAs

Teacher returns a counter-example

$w = ab$

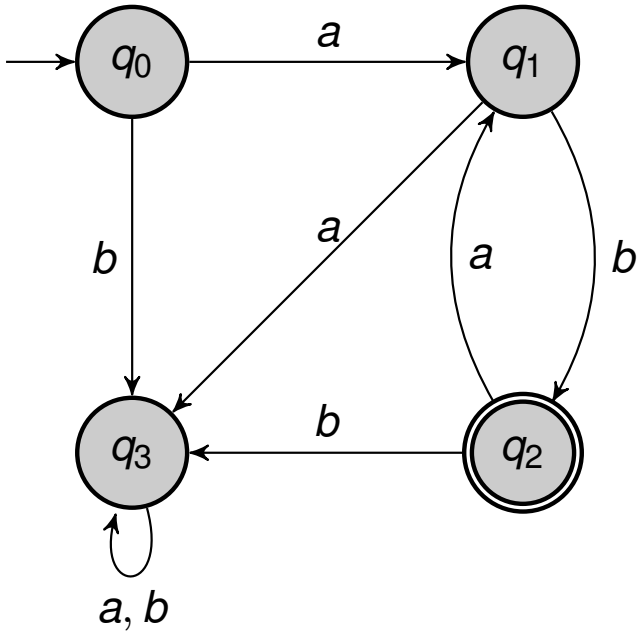


Learning DFAs

Teacher returns a counter-example

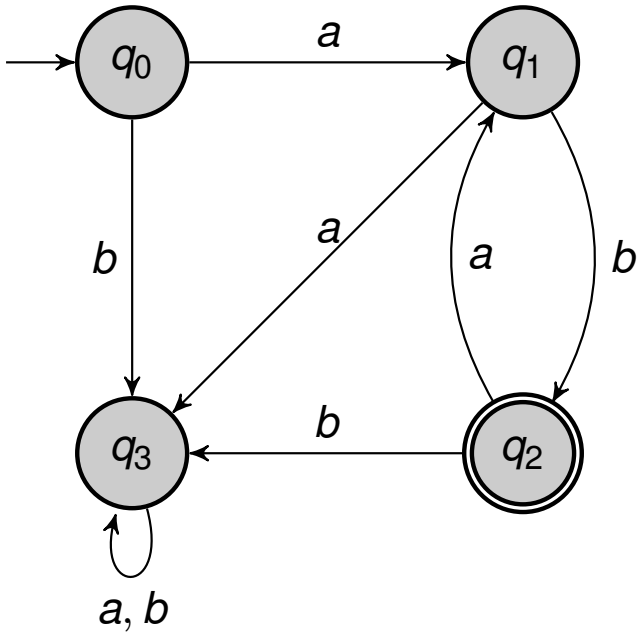
$w = ab$

Add all prefixes of w to S.



Learning DFAs

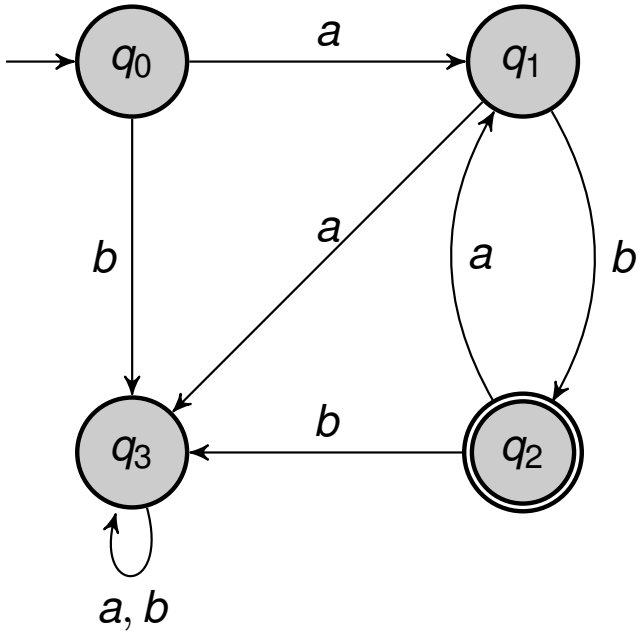
Observation Table	
T_1	ϵ
ϵ	$-$
a	$-$
ab	$+$
b	$-$
aa	$-$
aba	$-$
abb	$-$



Learning DFAs

Observation Table	
T_1	ϵ
ϵ	$-$
a	$-$
ab	$+$
b	$-$
aa	$-$
aba	$-$
abb	$-$

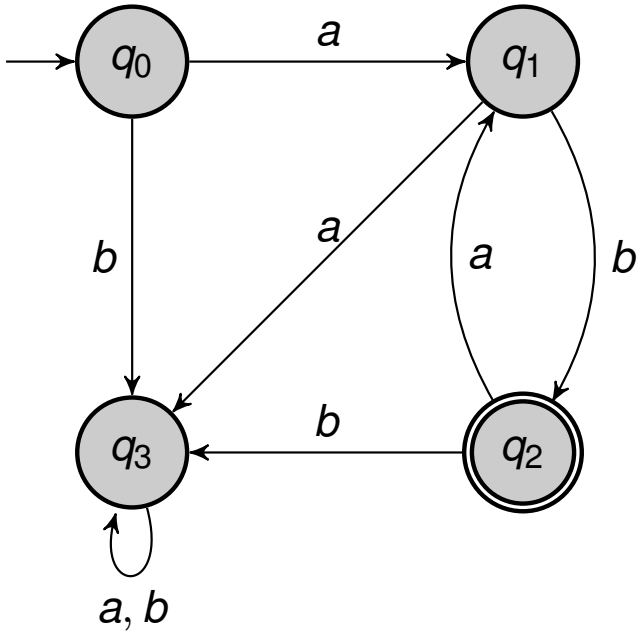
Check if it is { ***closed*** ***consistent***



Learning DFAs

Observation Table	
T_1	ϵ
ϵ	$-$
a	$-$
ab	$+$
b	$-$
aa	$-$
aba	$-$
abb	$-$

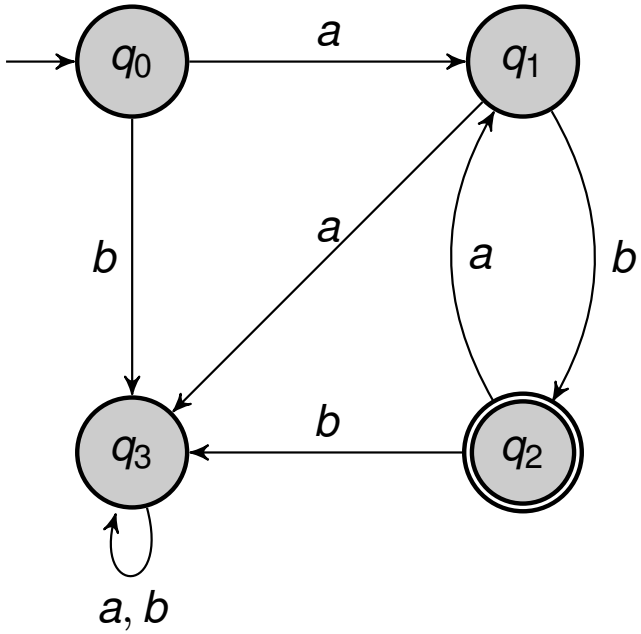
Check if it is { ***closed*** ✓ ***consistent***



Learning DFAs

Observation Table	
T_1	ϵ
ϵ	$-$
a	$-$
ab	$+$
b	$-$
aa	$-$
aba	$-$
abb	$-$

Check if it is { ***closed*** ✓ ***consistent*** ✗

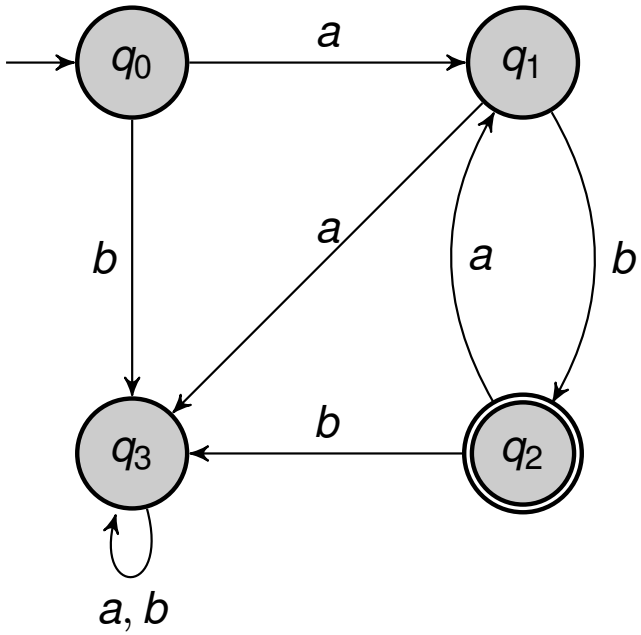


Learning DFAs

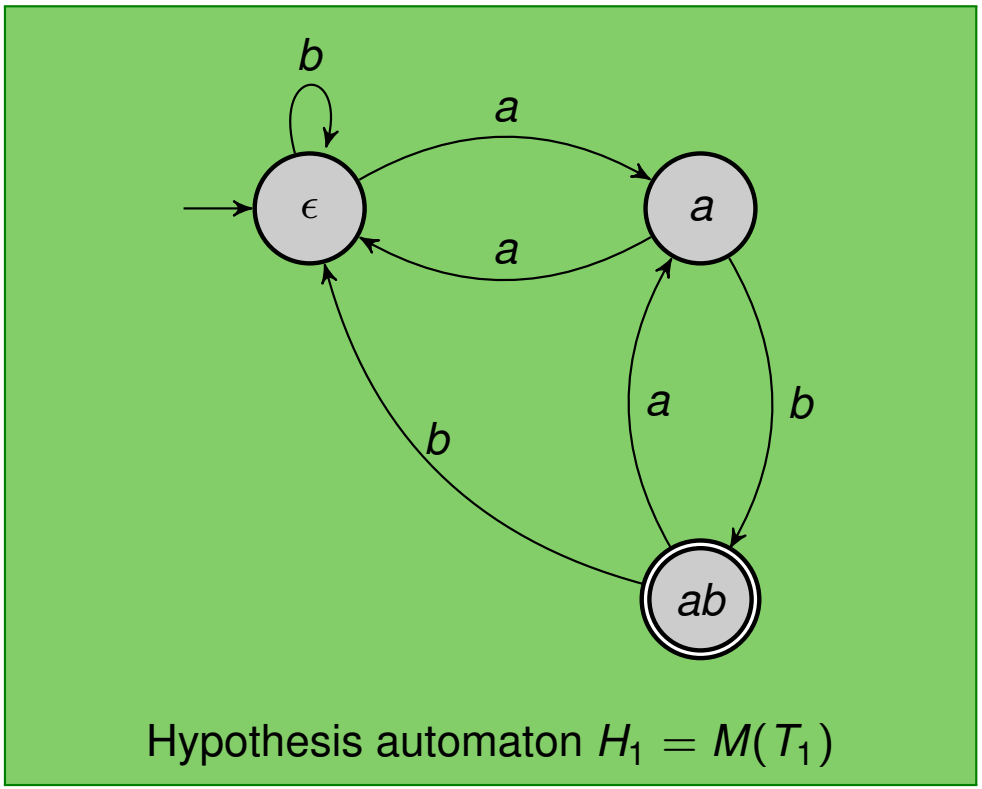
Observation Table

T_1	ϵ	b
ϵ	$-$	$-$
a	$-$	$+$
ab	$+$	$-$
b	$-$	$-$
aa	$-$	$-$
aba	$-$	$+$
abb	$-$	$-$

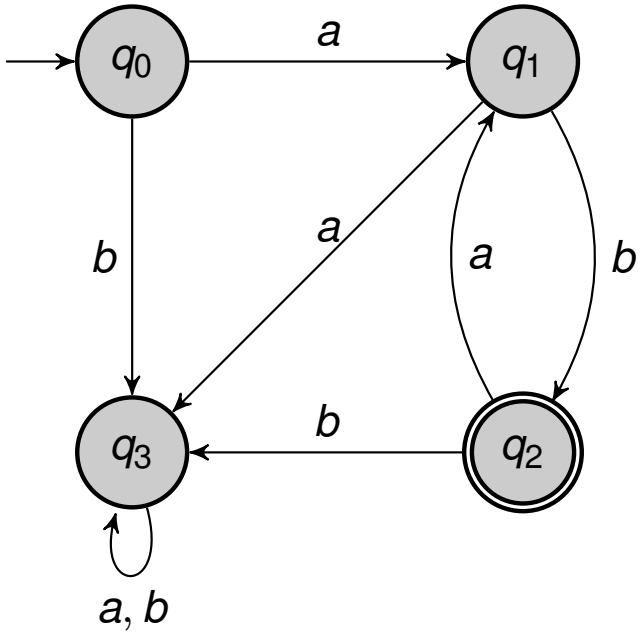
Add b to **E**



Learning DFAs



Hypothesis automaton $H_1 = M(T_1)$



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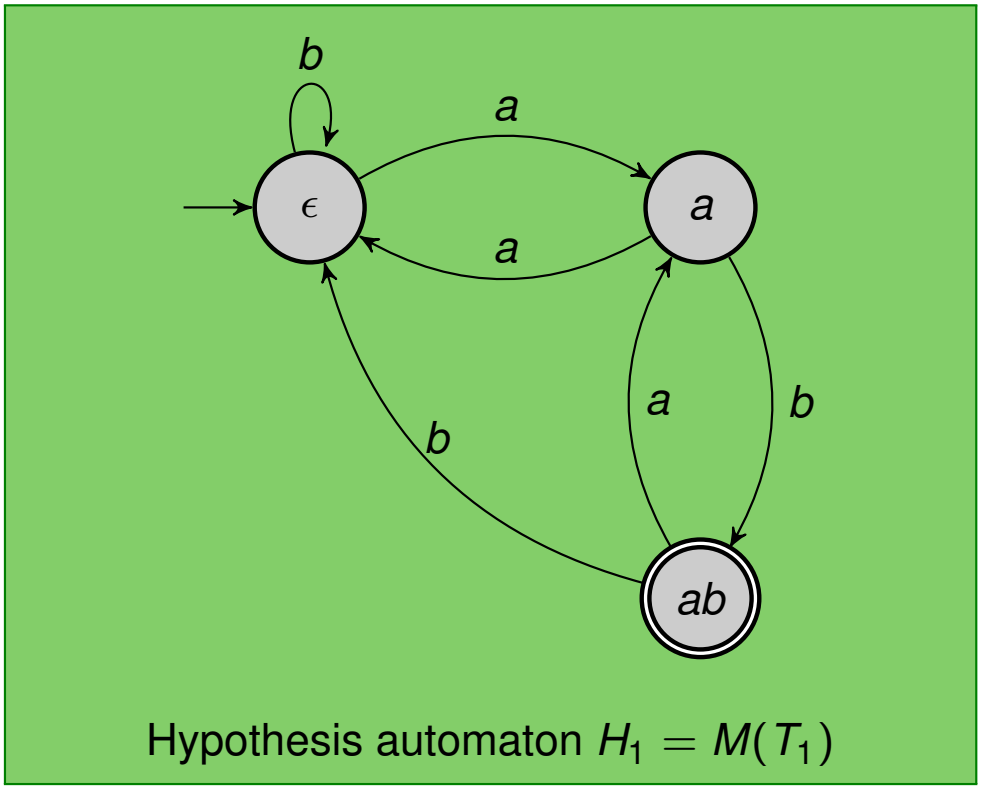

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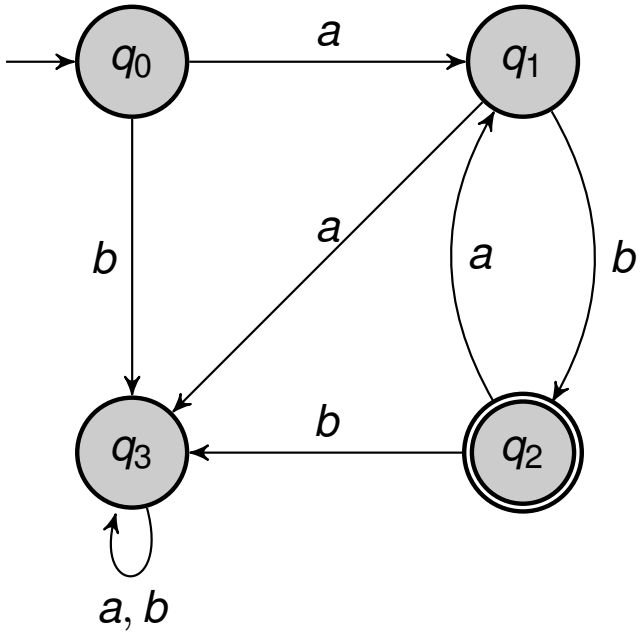
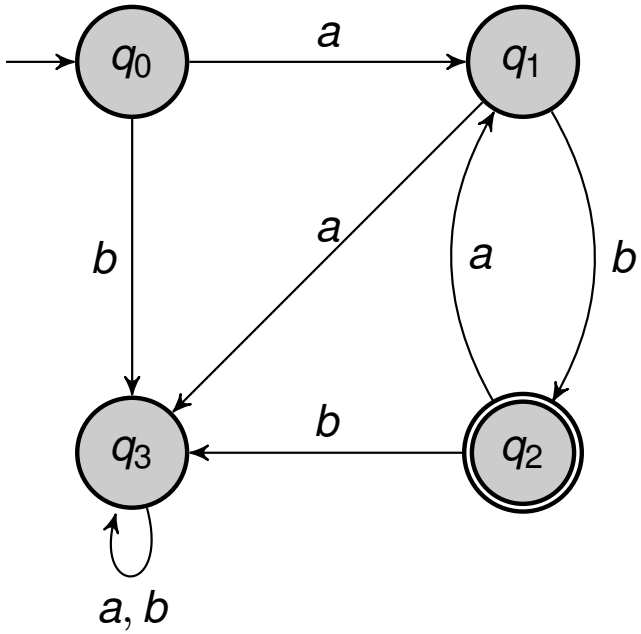


✗

Learning DFAs

Get a counter-example

$w' = bab$

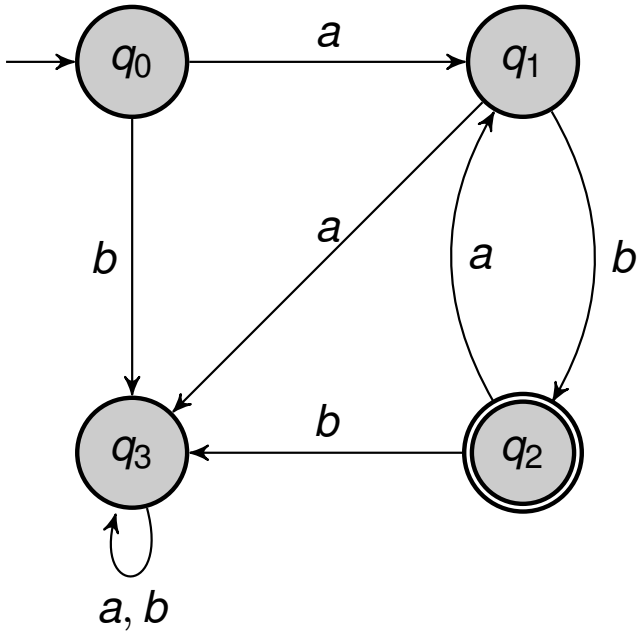


Learning DFAs

Get a counter-example

$w' = bab$

Add all prefixes to S.



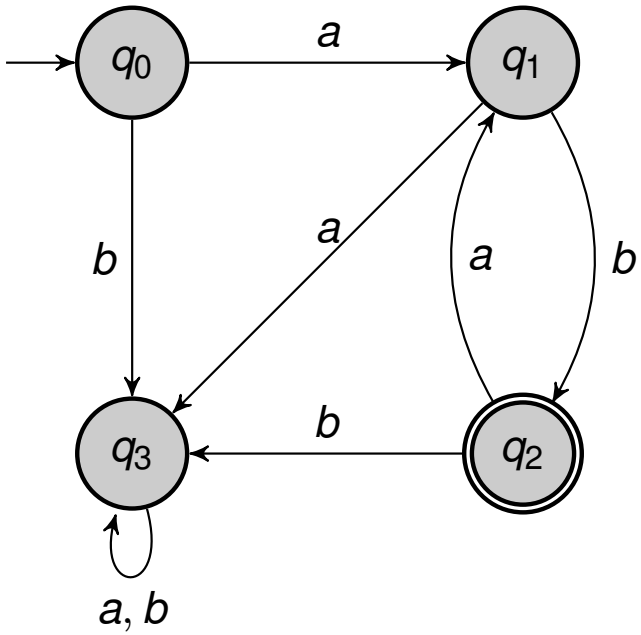
Learning DFAs

Observation Table		
T_1	ϵ	b
ϵ	−	−
a	−	+
b	−	−
ab	+	−
ba	−	−
bab	−	−

bb	−	−
aa	−	−
aba	−	+
abb	−	−
baa	−	−
bab	−	−
$baba$	−	−
$babb$	−	−

closed ✓

consistent ✗



Learning DFAs

Observation Table

T_1	ϵ	b
ϵ	−	−
a	−	+
b	−	−
ab	+	−
ba	−	−
bab	−	−

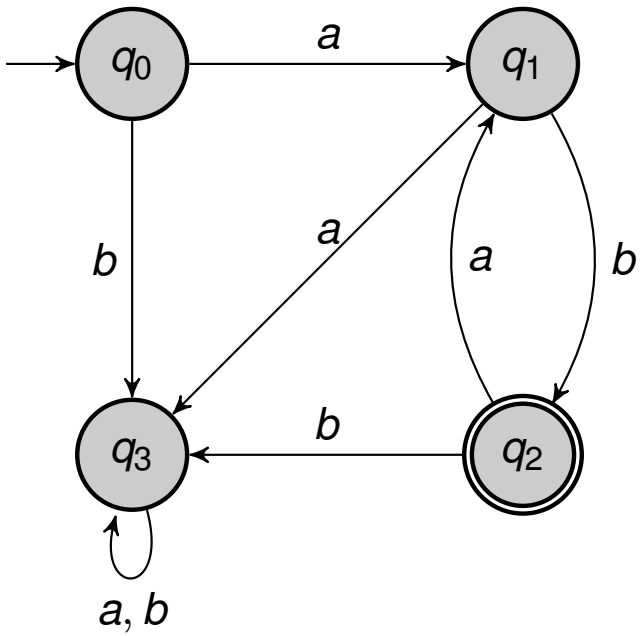
bb	−	−
aa	−	−
aba	−	+
abb	−	−
baa	−	−
bab	−	−
$baba$	−	−
$babb$	−	−

closed ✓

consistent ✗

Consider ϵ and b

$$f(\epsilon \cdot a \cdot b) \neq f(b \cdot a \cdot b)$$

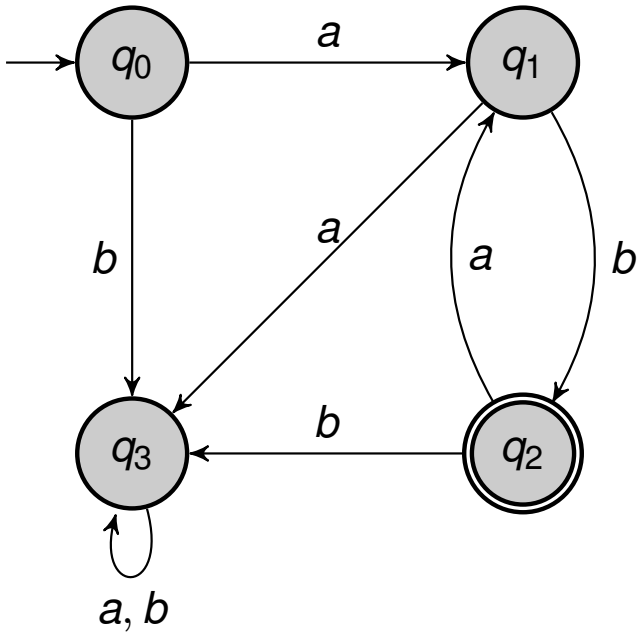


Learning DFAs

Observation Table

T_1	ϵ	b
ϵ	−	−
a	−	+
b	−	−
ab	+	−
ba	−	−
bab	−	−

bb	−	−
aa	−	−
aba	−	+
abb	−	−
baa	−	−
bab	−	−
$baba$	−	−
$babb$	−	−



closed ✓

consistent ✗

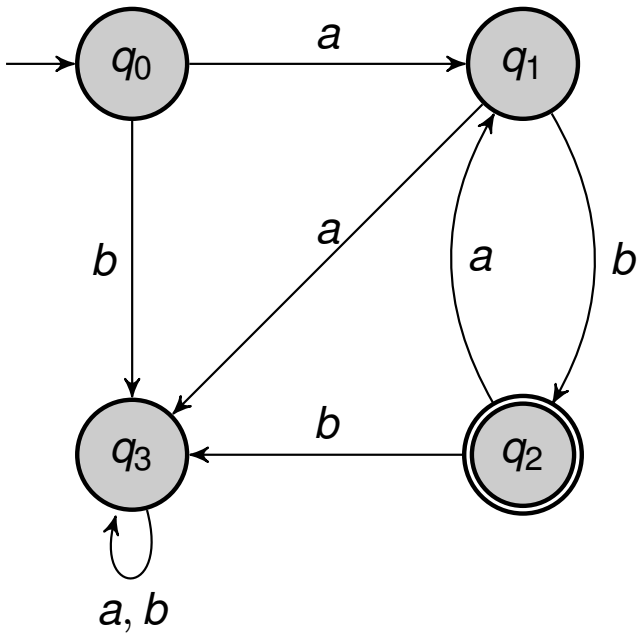
Consider ϵ and b

$$f(\epsilon \cdot a \cdot b) \neq f(b \cdot a \cdot b)$$

Add all suffixes of $a \cdot b$ to E.

Learning DFAs

Observation Table			
T_2	ϵ	b	ab
ϵ	−	−	+
a	−	+	−
b	−	−	−
ab	+	−	+
ba	−	−	−
bab	−	−	−
bb	−	−	−
aa	−	−	−
aba	−	+	−
abb	−	−	−
baa	−	−	−
bab	−	−	−
$baba$	−	−	−
$babb$	−	−	−



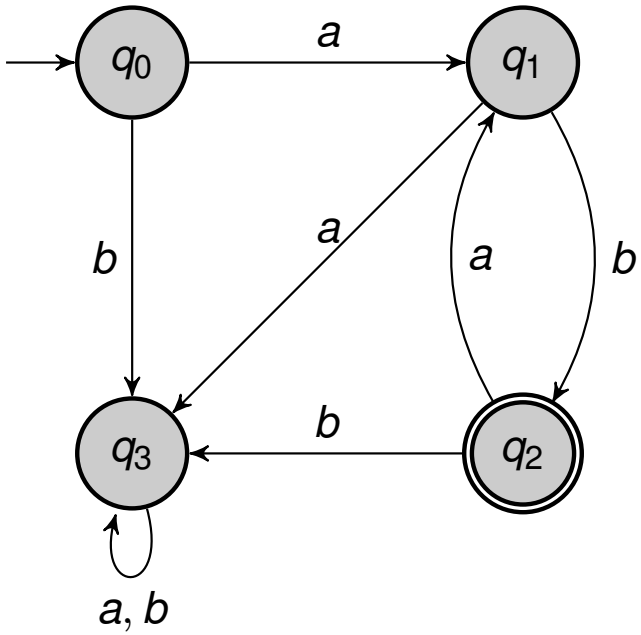
Learning DFAs

Observation Table

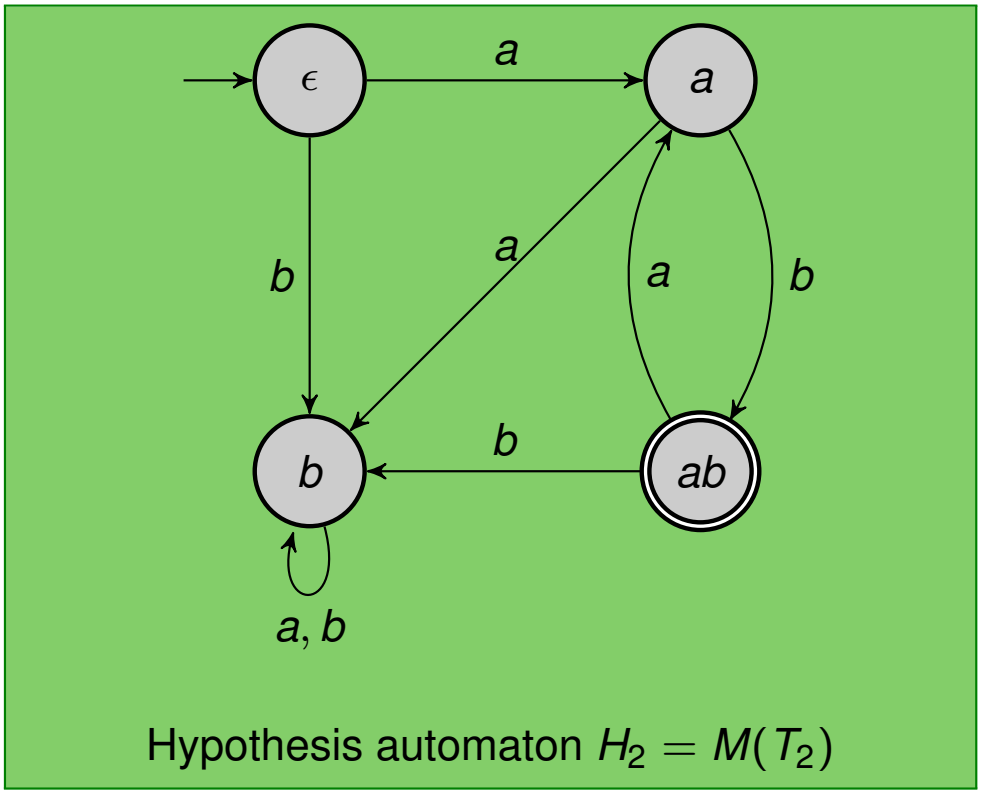
T_2	ϵ	b	ab
ϵ	−	−	+
a	−	+	−
b	−	−	−
ab	+	−	+
ba	−	−	−
bab	−	−	−
bb	−	−	−
aa	−	−	−
aba	−	+	−
abb	−	−	−
baa	−	−	−
bab	−	−	−
$baba$	−	−	−
$babb$	−	−	−

closed ✓

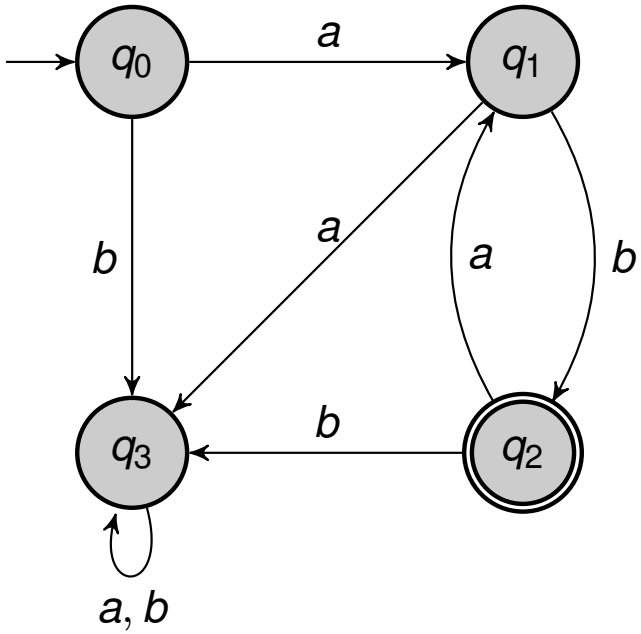
consistent ✓



Learning DFAs



Hypothesis automaton $H_2 = M(T_2)$



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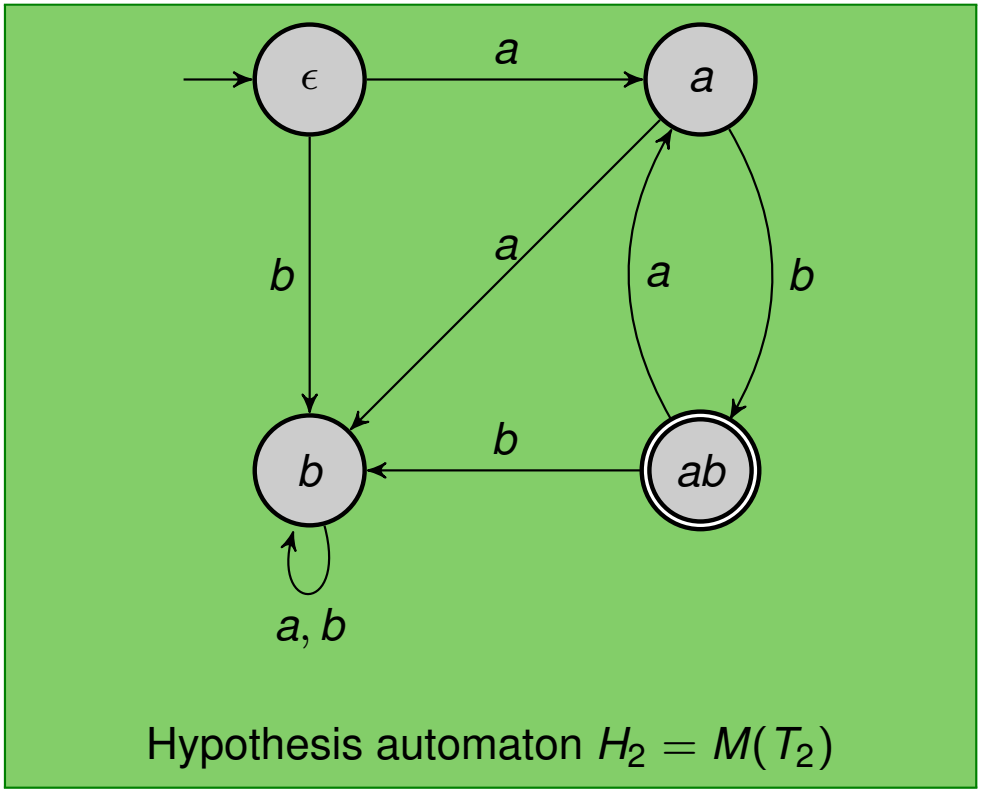

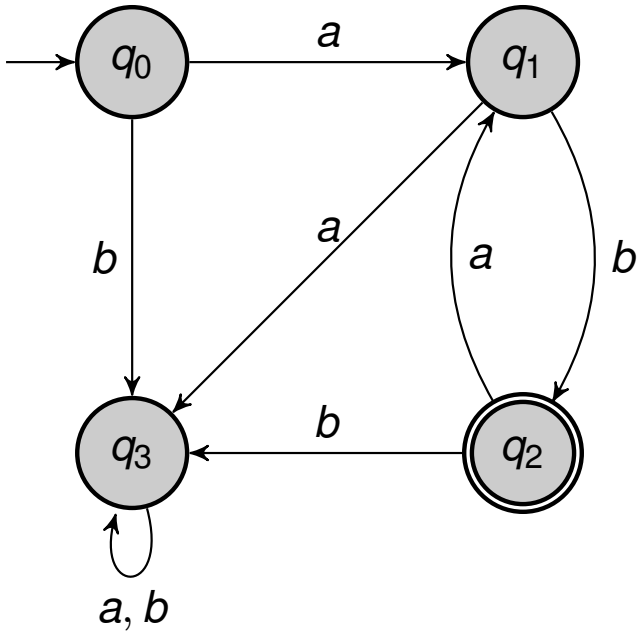

✓

Implementation

There have been several **implementations** of learning algorithms, some notable ones are:

Implementation

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- **libalf**: The Automata Learning Framework
  Bollig B., Katoen JP., Kern C., Leucker M., Neider D., Piegdon D.R. (2010) libalf: The Automata Learning Framework. CAV 2010.

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There have been several **implementations** of learning algorithms, some notable ones are:

- **libalf**: The Automata Learning Framework
  Bollig B., Katoen JP., Kern C., Leucker M., Neider D., Piegdon D.R. (2010) libalf: The Automata Learning Framework. CAV 2010.
- The Open-Source **LearnLib**
  Isberner M., Howar F., Steffen B. (2015) The Open-Source LearnLib. CAV 2015.
- **Symbolic Automata**
  Drews S., D'Antoni L. (2017) Learning Symbolic Automata. TACAS 2017.

Learning

Learning Automata

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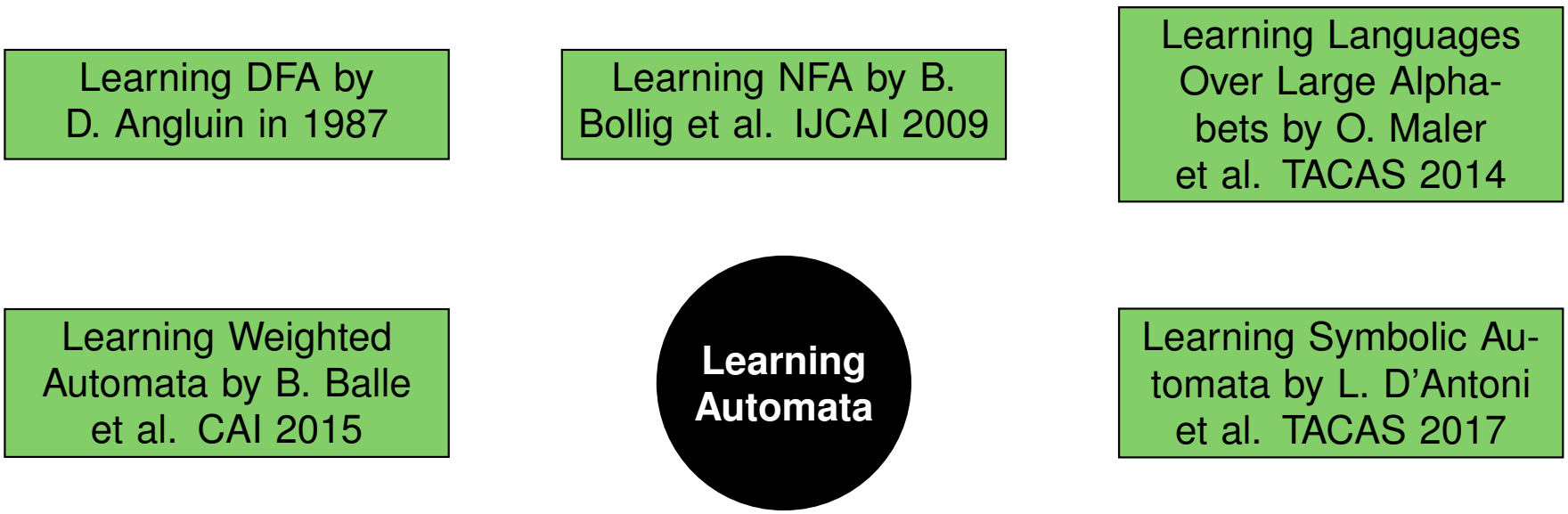
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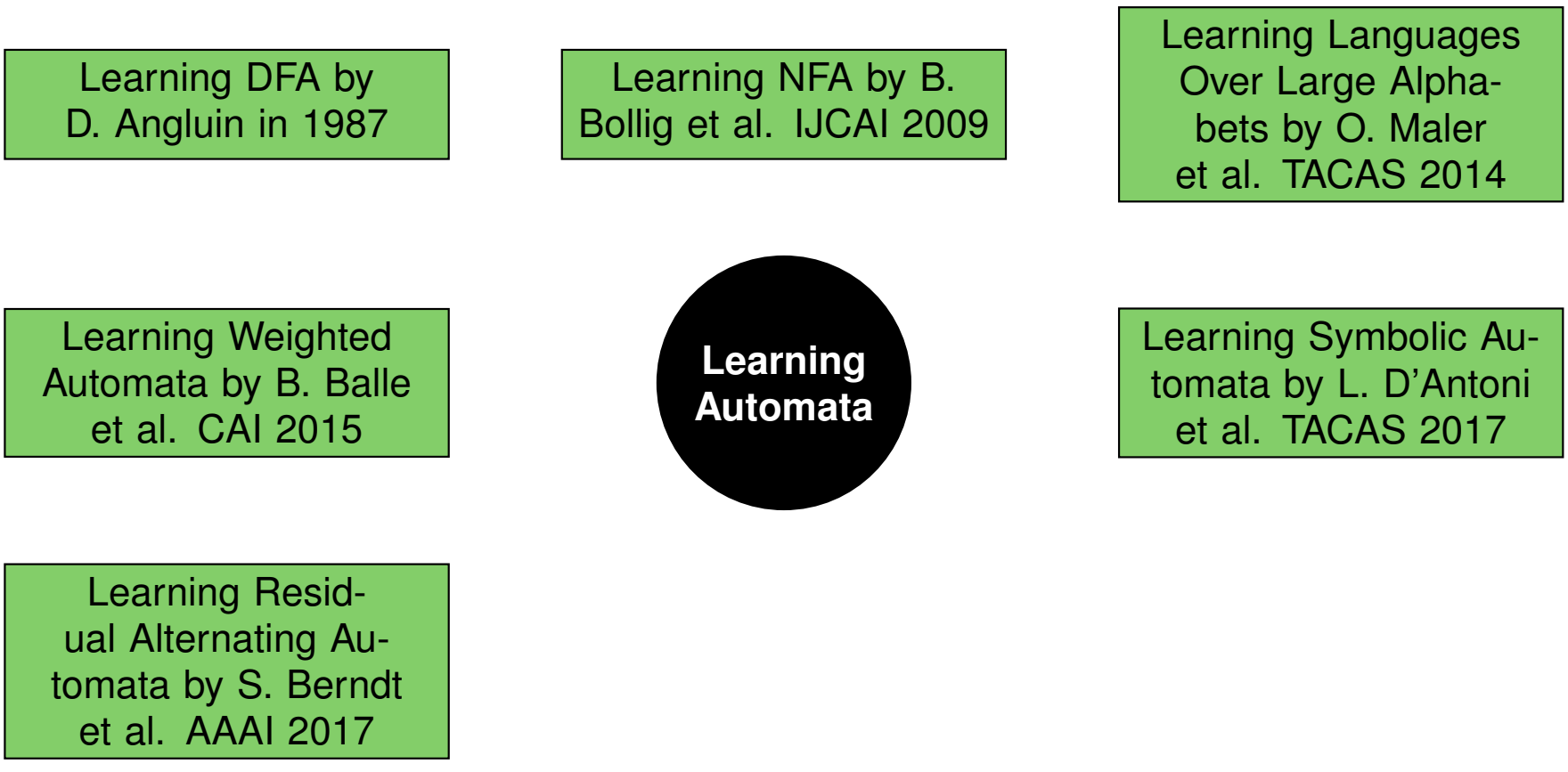
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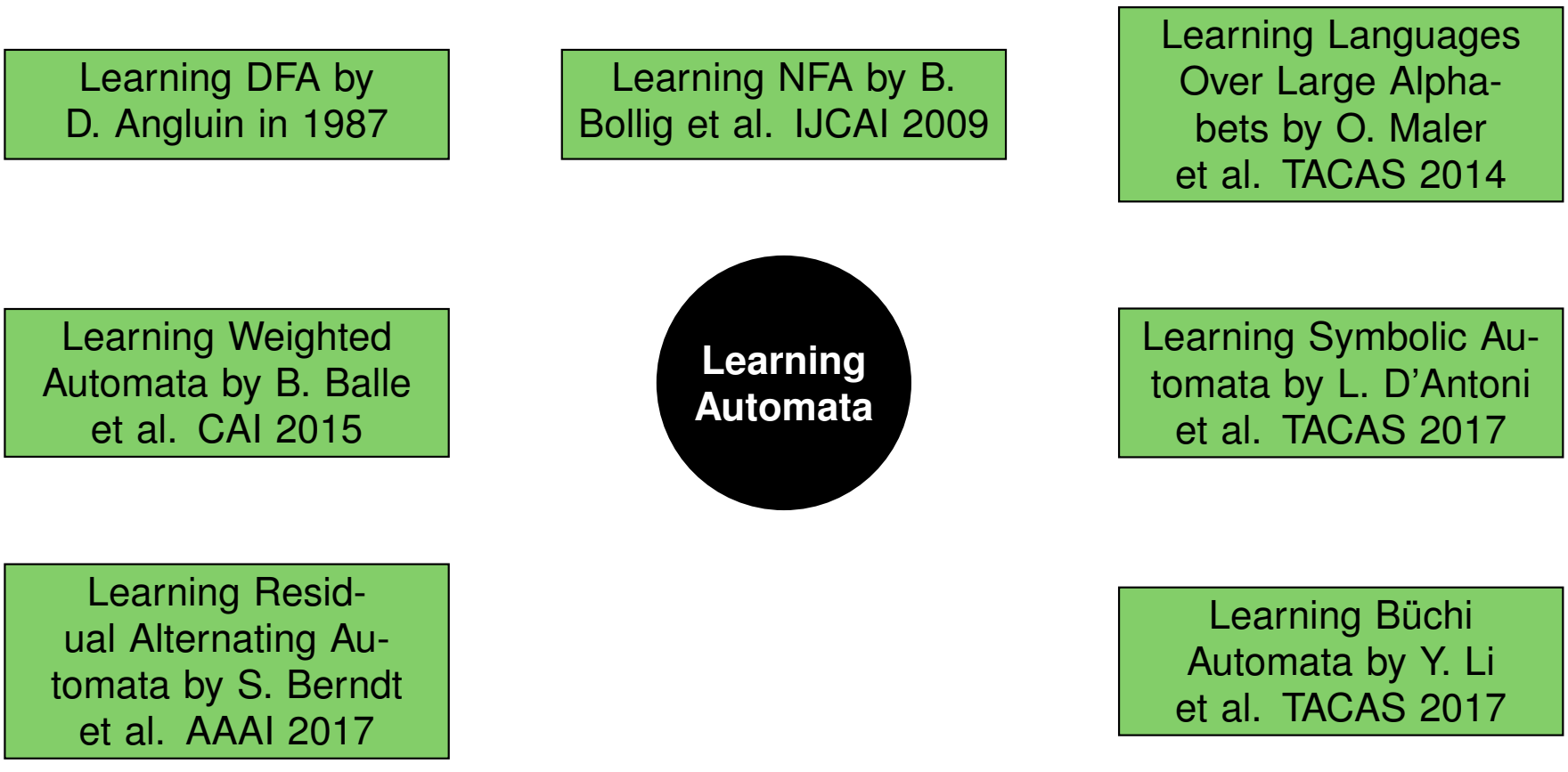
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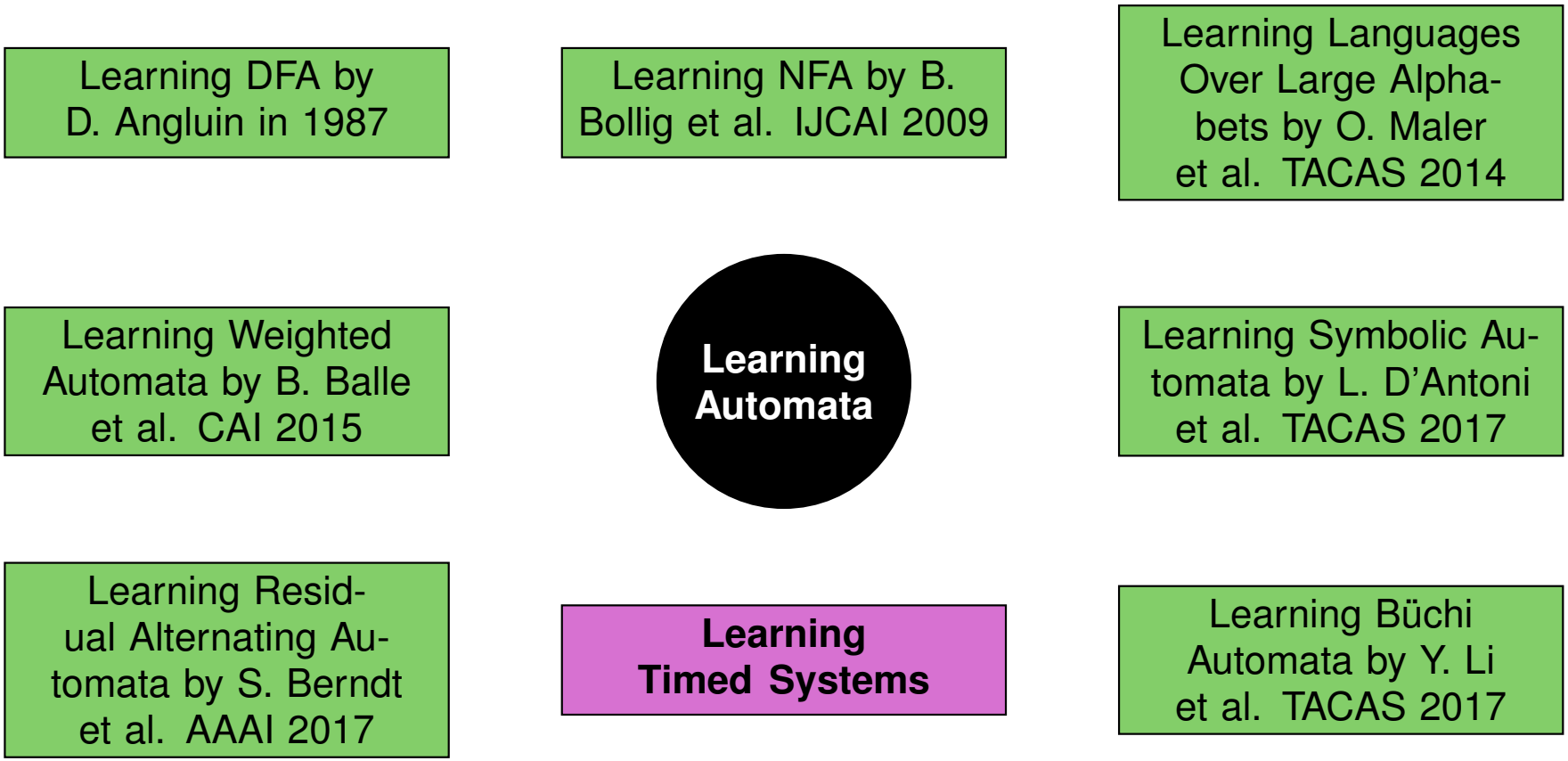
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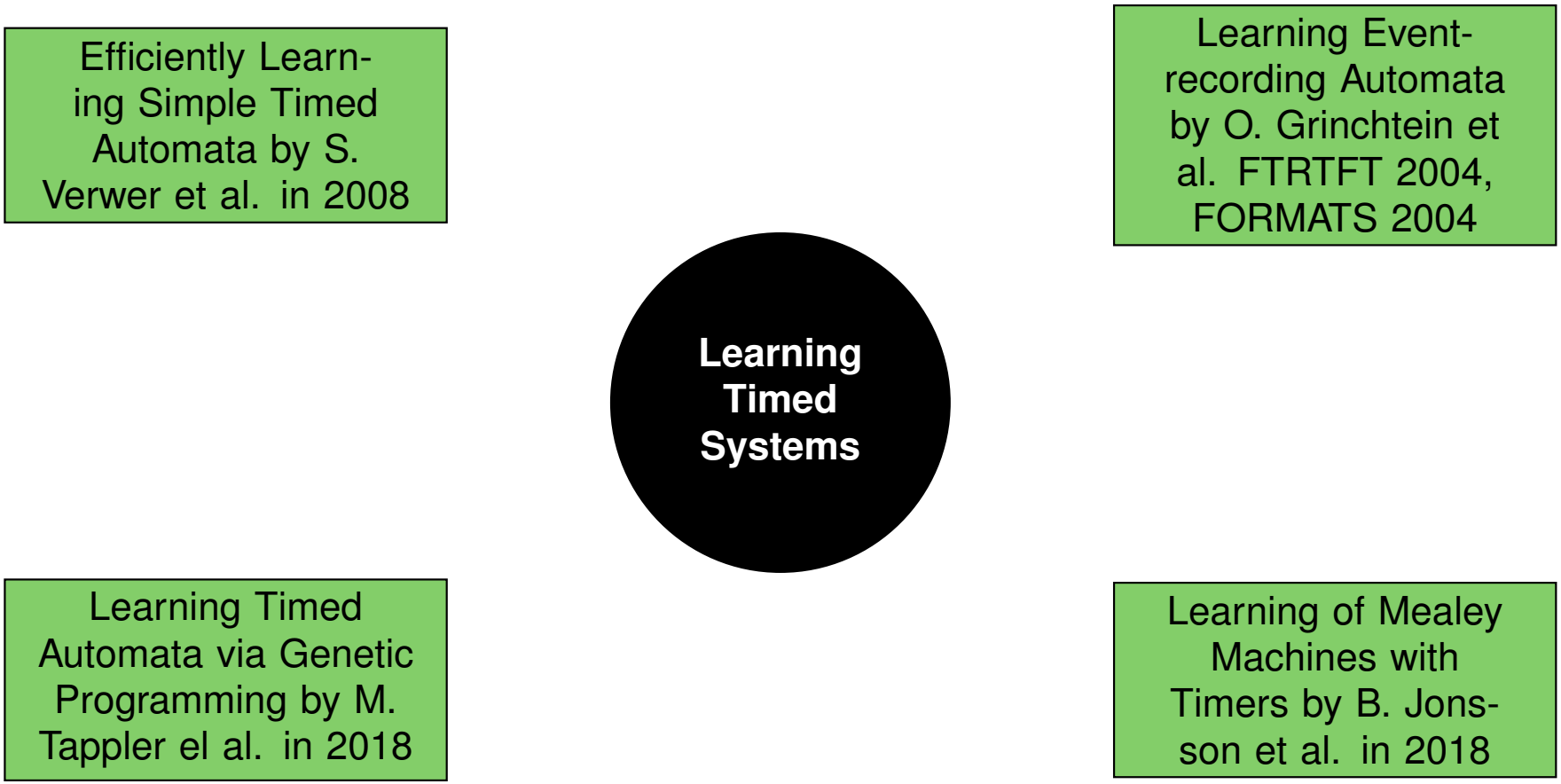
Learning Timed Automata via Genetic Programming by M. Tappler el al. in 2018

Learning Timed Systems



What we want to do and why?

Find an active learning algorithm for a subclass of timed automata.

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- A lot of other examples are given in 'The Unmet Challenge of Timed Systems' by O. Maler.

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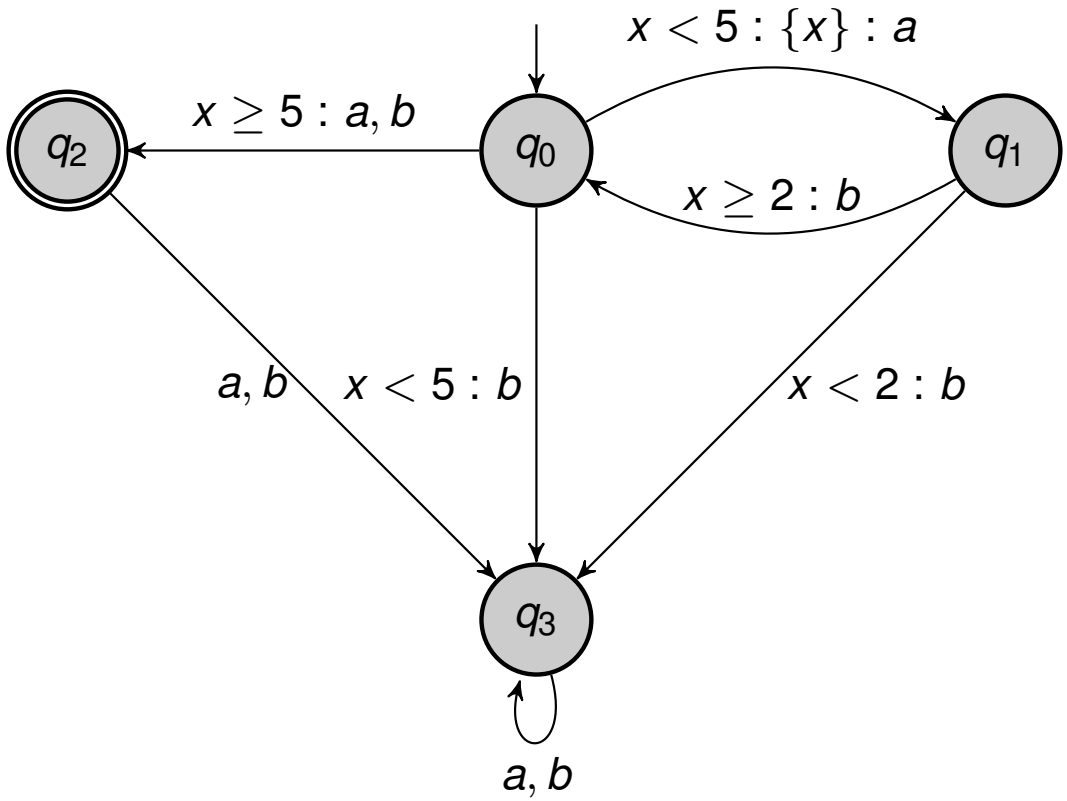
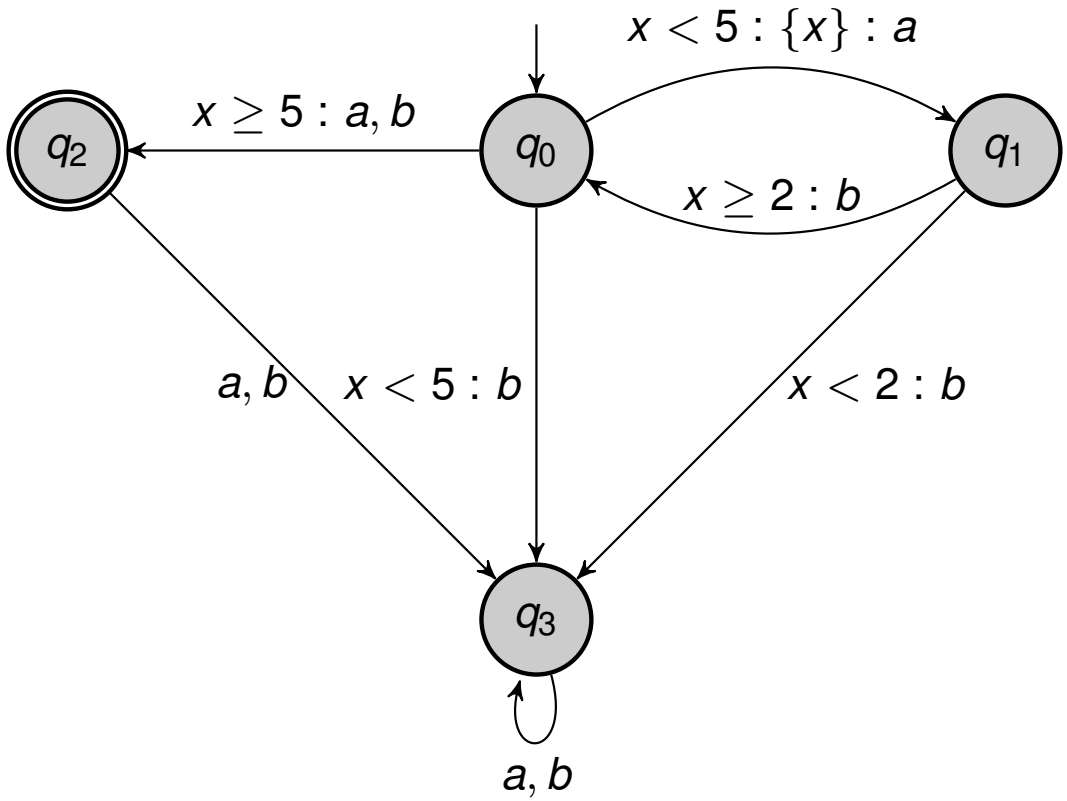
Discrete Timed Automata

Timed Automata



Example of a **timed automaton**.

Timed Automata



Example of a **timed automaton**. $q_0 \overset{a}{\underset{2.5}{\longrightarrow}} q_1 \overset{b}{\underset{4.7}{\longrightarrow}} q_0 \overset{a}{\underset{6.3}{\longrightarrow}} q_1 \overset{b}{\underset{10.1}{\longrightarrow}} q_0 \overset{a}{\underset{12.0}{\longrightarrow}} q_2$

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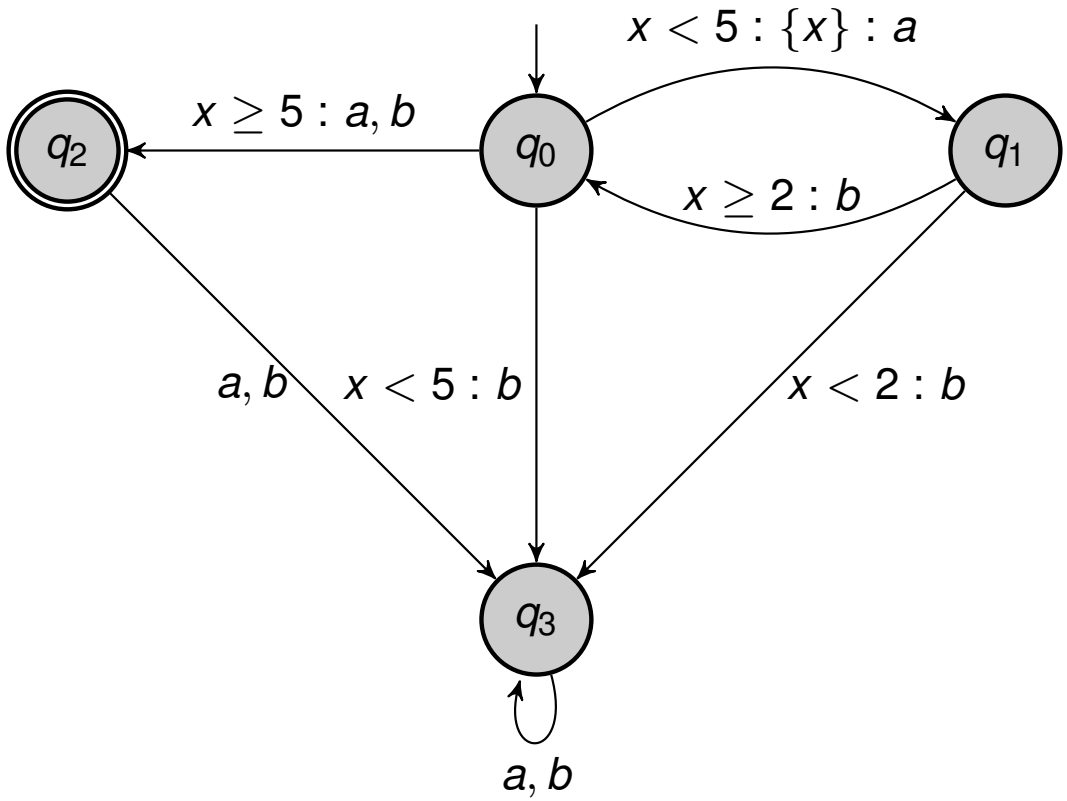

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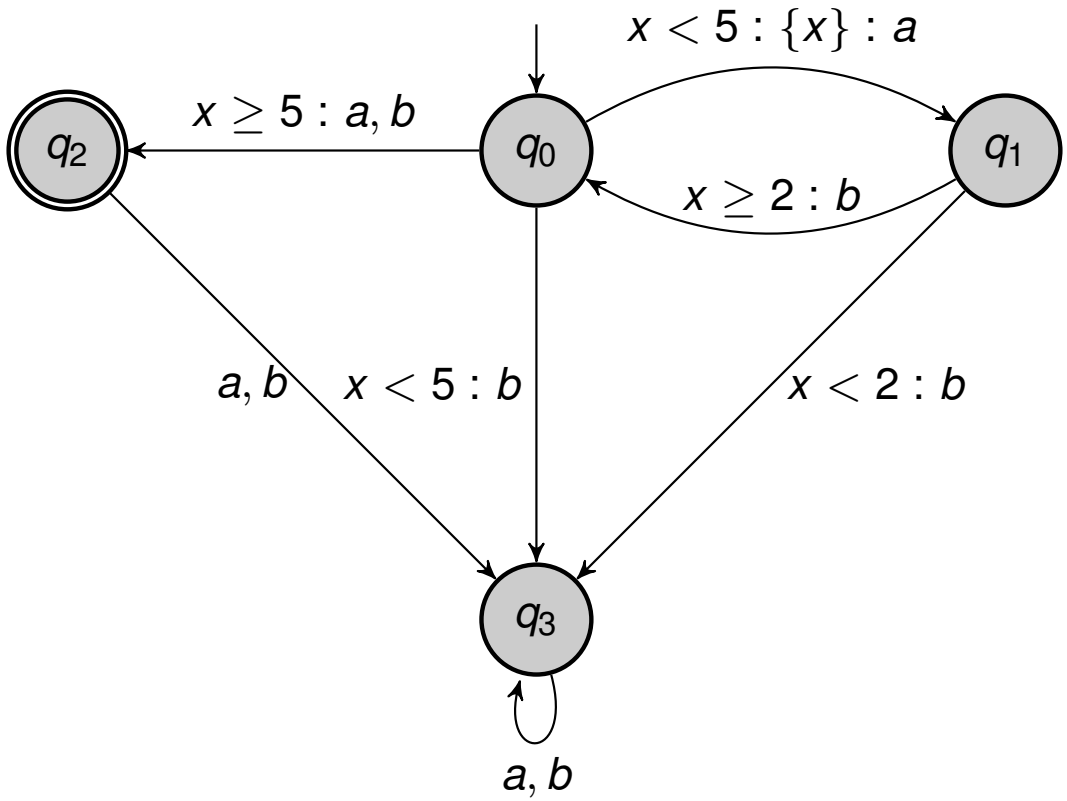

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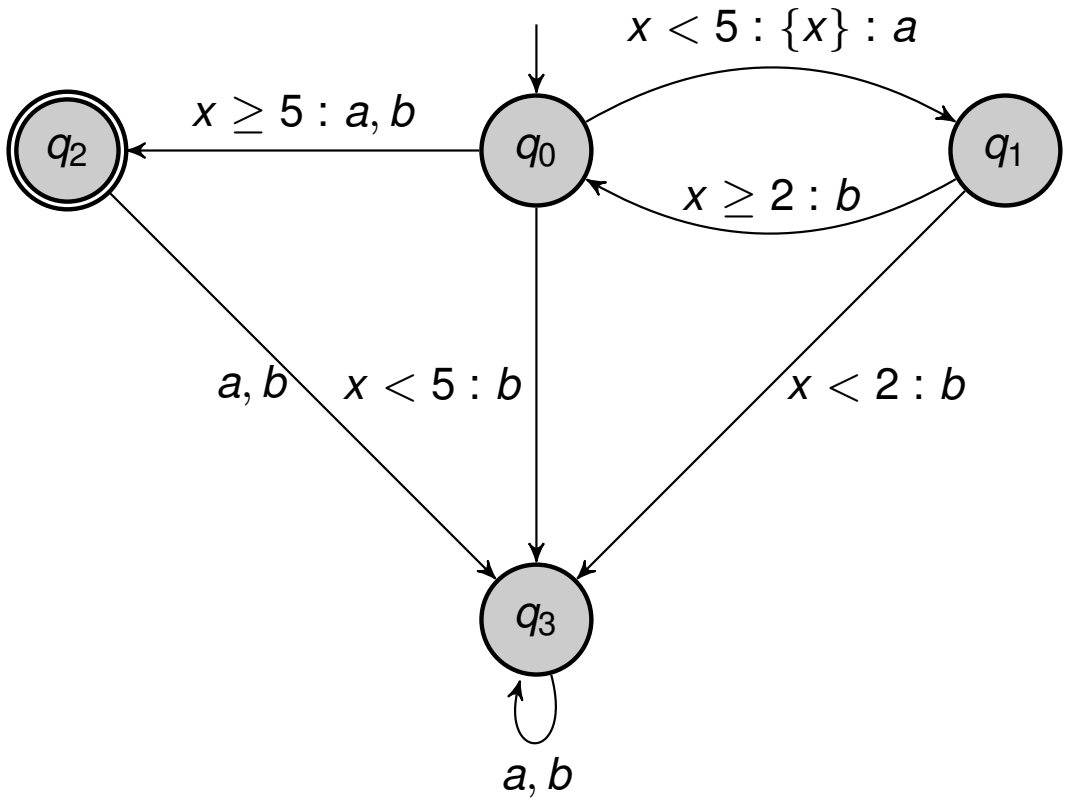
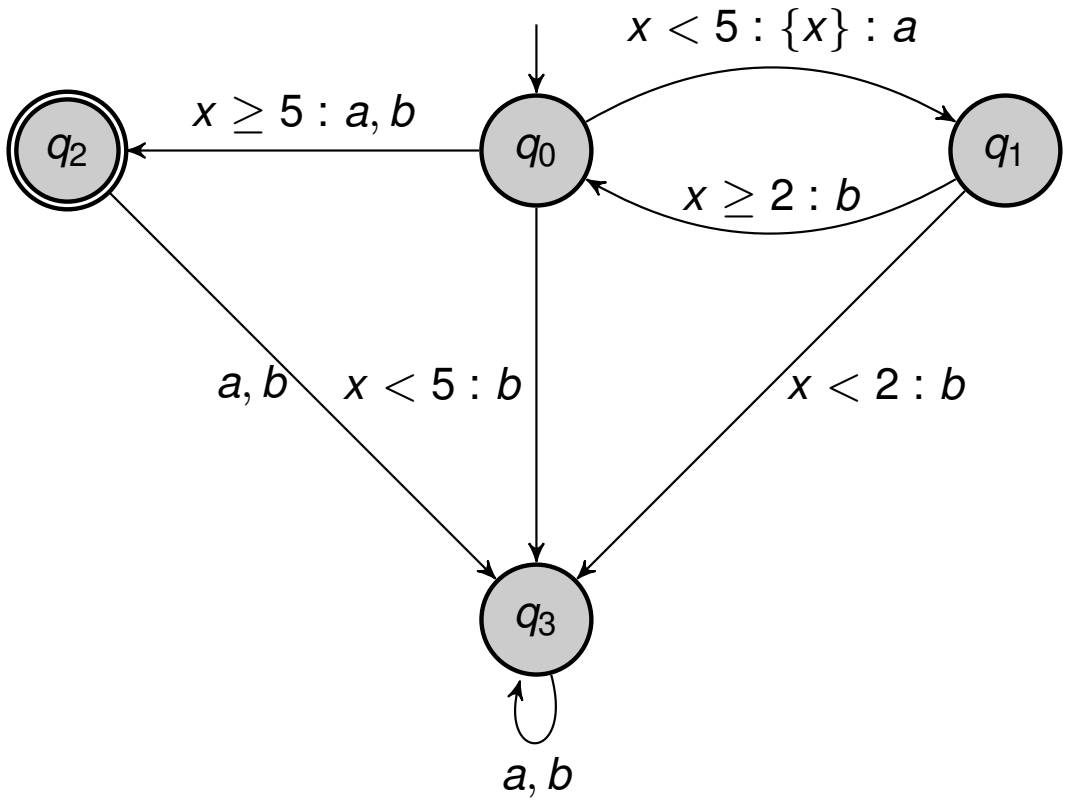


This is a **discrete timed automaton** also.

$$q_0 \xrightarrow[3]{a} q_1 \xrightarrow[6]{b} q_0 \xrightarrow[6]{a} q_1 \xrightarrow[8]{b} q_0 \xrightarrow[12]{a} q_2$$

Discrete Timed Automata



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Learning Discrete Timed Automata

Why learn discrete timed automata

- Discrete time is easier to handle than dense time.
- Expressive enough.
- Can be applied to real world systems.

Learning Discrete Timed Automata Using L^*

Learn *discrete timed automata* as a **DFA**.

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Each tick represents one time unit.

For a timed language $L \subseteq (\mathbb{N} \times \Sigma)^*$, we can convert it into a regular language $L' \subseteq (\Sigma \cup \{✓\})^*$

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Size of this automaton will be **HUGE**.

But, can be learned using $\mathbf{L}^*$.

A better approach

If we can group the *ticks* together, we can get a smaller automaton.

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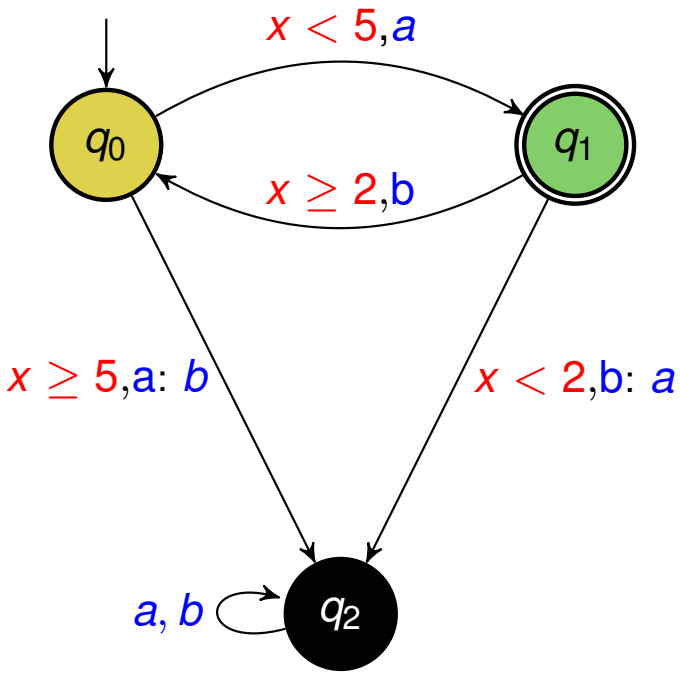

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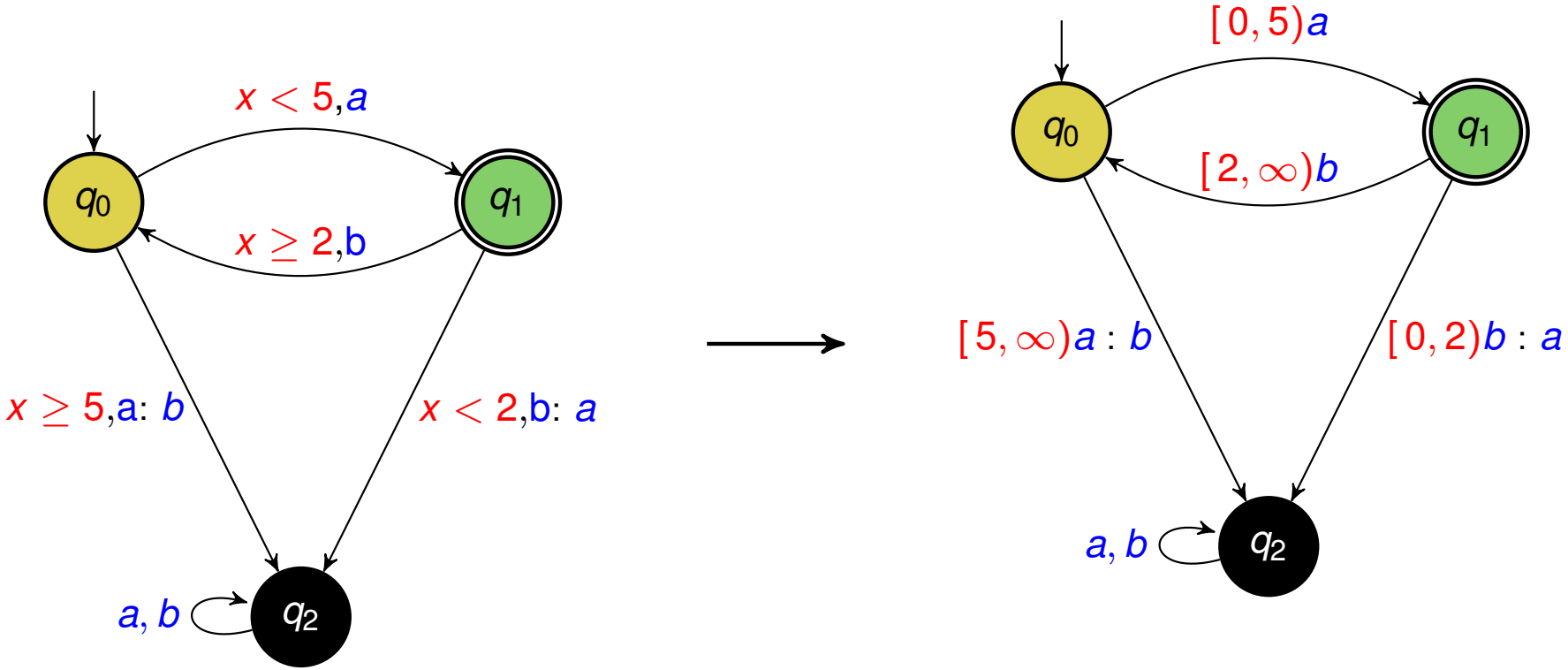
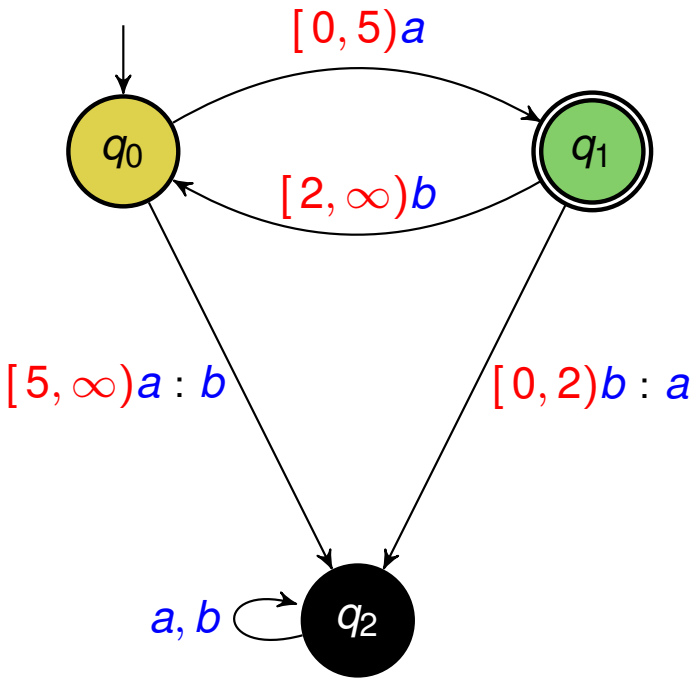


This looks like a **symbolic automata**.

A better approach



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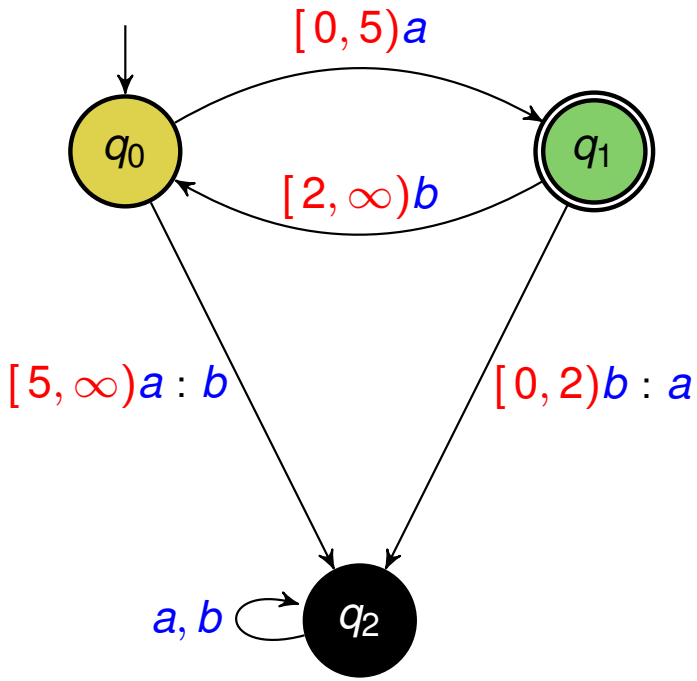

Intervals at each transition represents the value of clock for which transition is valid.

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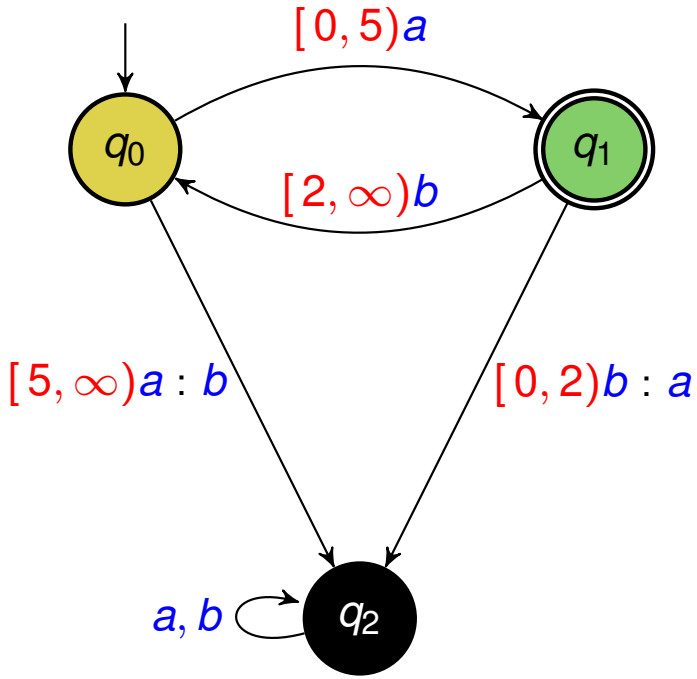

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Consider this transformation:

$$(2,a)(3,b)(6,b)(6,a) \longrightarrow (2,a)(1,b)(3,b)(0,a)$$

Equivalence of DiTA and r-DDTA

DiTA := class of discrete timed automata.

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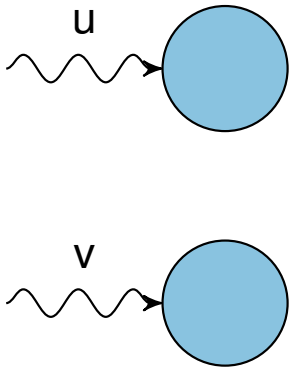
Learn a r-DDTA for a given DiTA.

Why reset on every transition?



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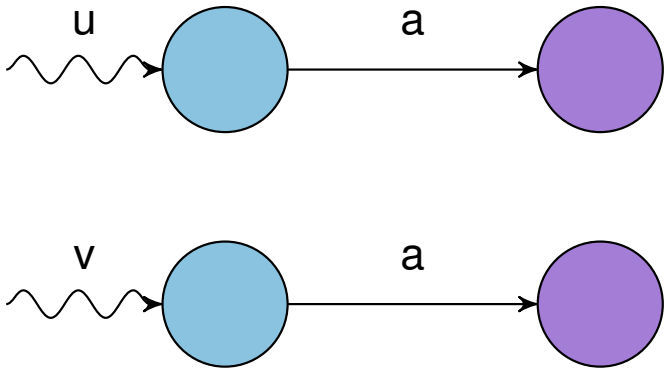

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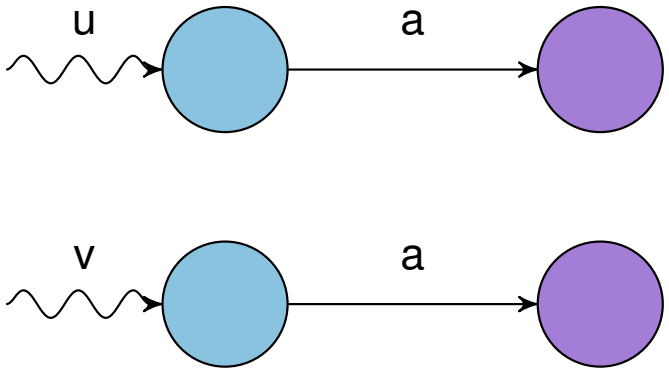

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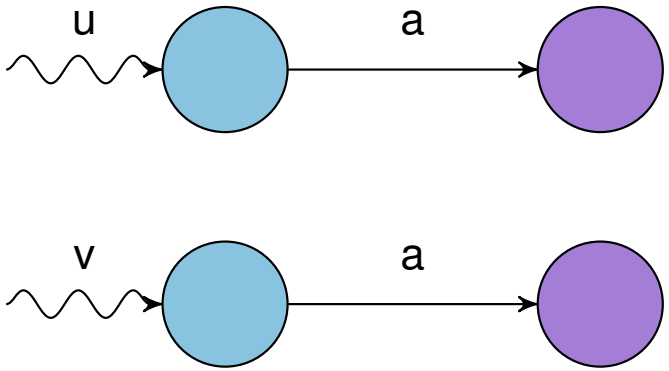

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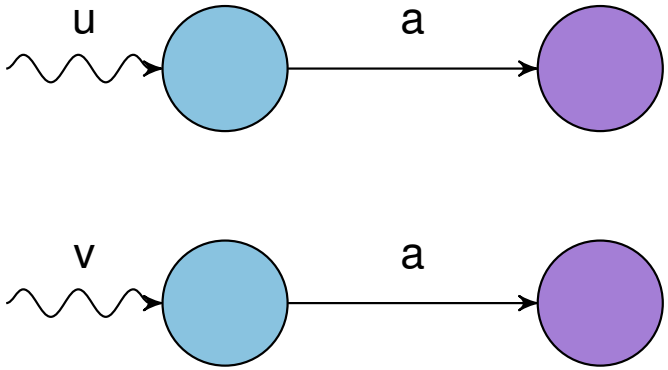

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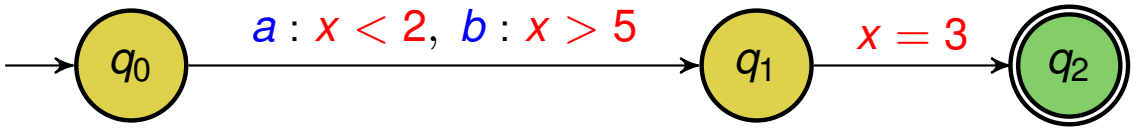

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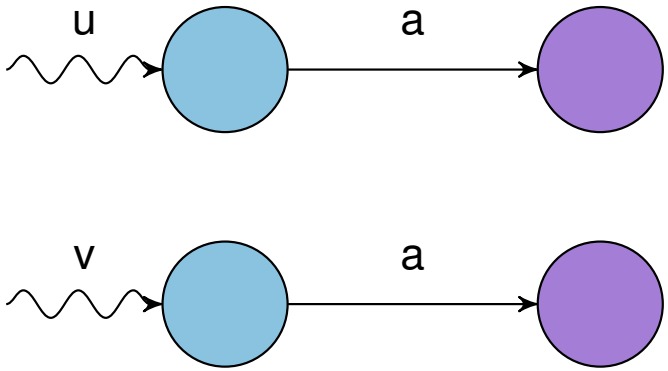

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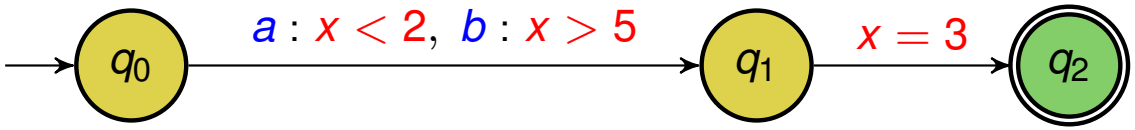
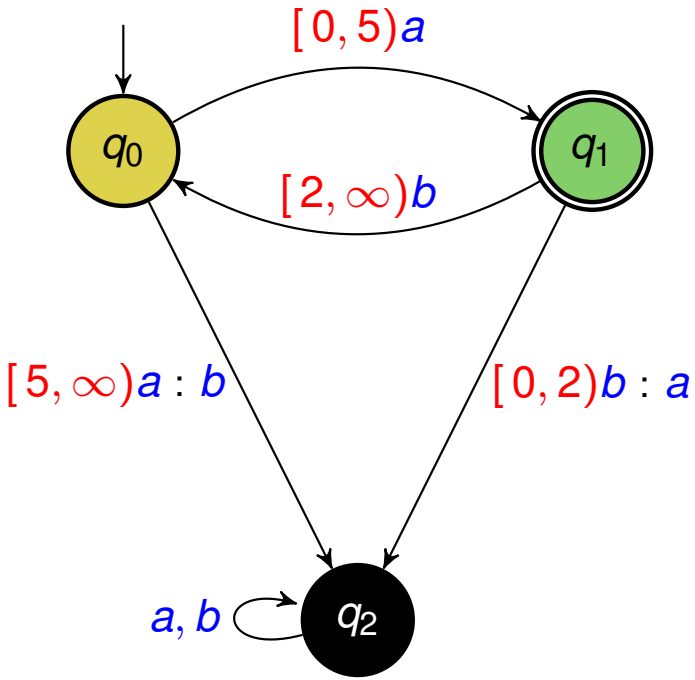


On reading $(1, a)$ and $(6, b)$, automaton is in q_1 state but $(6, b)$ cannot take transition to the accepting state.

Learning r-DDTA

Learning r-DDTA



Learning r-DDTA

Observation Table	
T_0	ϵ
ϵ	
$[0, \infty)a$	
$[0, \infty)b$	

μ: **evidence function** (for each entry in the table there are some evidences)

$$\mu([0, \infty)a) = (0, a)$$
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Add $[0,\infty)a$ to S and its continuations to R

and set $\mu([0,\infty)a[0,\infty)a) = (0,a)(0,a)$
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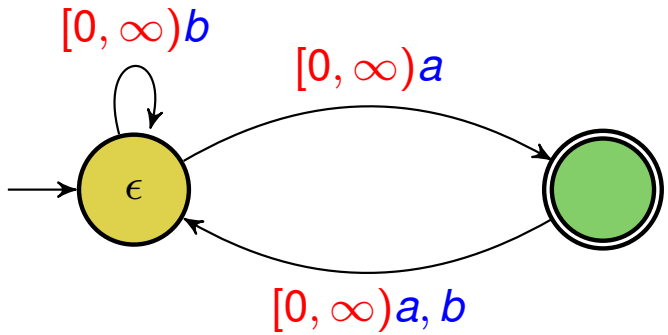

Hypothesis automaton: H_0

Learning r-DDTA

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μ: **evidence function** (for each entry in the table there are some evidences)

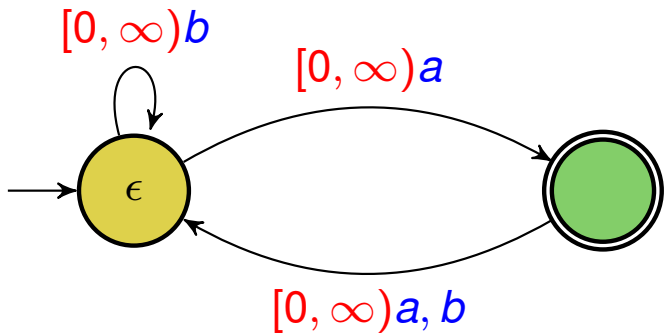
$$\mu([0,\infty)a) = (0,a)$$
$$\mu([0,\infty)b) = (0,b)$$

Fill the table by asking **membership queries** only for the evidences of an element of the table.

Check if the table is **closed** ✓

Add $[0,\infty)a$ to S and its continuations to R

and set $\mu([0,\infty)a[0,\infty)a) = (0,a)(0,a)$
$\mu([0,\infty)a[0,\infty)b) = (0,a)(0,b)$



Hypothesis automaton: H_0

✗

Learning r-DDTA

Teacher returns a minimal counter-example
$w = (5, a)$

Find factorization of $w = u \cdot b \cdot v$
such that $u \in \mu(s)$ for some $s \in S \cup R$ and $u \cdot b \notin \mu(s')$ for any $s' \in S \cup R$.

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For $w = (5, a)$: $u = \epsilon$, $b = (5, a)$ and $v = \epsilon$.

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Therefore $s \in S$, which represents that u is already a state in the hypothesis but b indicates that partition boundary is not correctly defined.

Learning r-DDTA

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such that $u \in \mu(s)$ for some $s \in S \cup R$ and $u \cdot b \notin \mu(s')$ for any $s' \in S \cup R$.

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For $w = (5, a)$: $u = \epsilon$, $b = (5, a)$ and $v = \epsilon$.

Therefore $s \in S$, which represents that u is already a state in the hypothesis but b indicates that partition boundary is not correctly defined.

Hence, replace $[0, \infty)a$ with $[0, 5)a$ in the table and add $[5, \infty)a$ to R.

Learning r-DDTA

Observation Table	
T_1	ϵ
ϵ	$-$
$[0,5)a$	$+$
$[5,\infty)a$	$-$
$[0,\infty)b$	$-$
$[0,5)a([0,\infty)a$	$-$
$[0,5)a([0,\infty)b$	$-$

Is it **closed**?

Learning r-DDTA

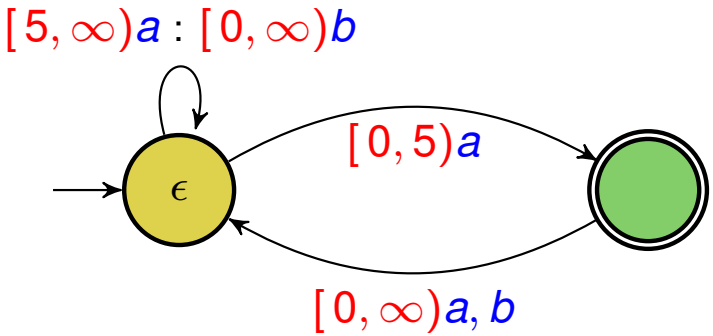
Observation Table	
T_1	ϵ
ϵ	$-$
$[0,5)a$	$+$
$[5,\infty)a$	$-$
$[0,\infty)b$	$-$
$[0,5)a([0,\infty)a$	$-$
$[0,5)a([0,\infty)b$	$-$

Is it **closed**? ✓

Learning r-DDTA

Observation Table	
T_1	ϵ
ϵ	$-$
$[0,5)a$	$+$
$[5,\infty)a$	$-$
$[0,\infty)b$	$-$
$[0,5)a([0,\infty)a$	$-$
$[0,5)a([0,\infty)b$	$-$

Is it **closed**? ✓

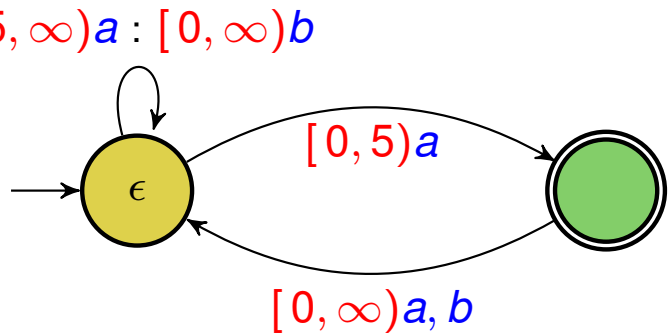


Hypothesis automaton: H_1

Learning r-DDTA

Observation Table	
T_1	ϵ
ϵ	$-$
$[0,5)a$	$+$
$[5,\infty)a$	$-$
$[0,\infty)b$	$-$
$[0,5)a([0,\infty)a$	$-$
$[0,5)a([0,\infty)b$	$-$

Is it **closed**? ✓



Hypothesis automaton: H_1

✗

Learning r-DDTA

Get a **minimal counter-example** $(w = 5, a)(0, a)$

Learning r-DDTA

Get a **minimal counter-example** $(w = 5, a)(0, a)$

$$w = u \cdot b \cdot v$$

$$u = (5, a),\ b = (0, a) \text{ and } v = \epsilon$$

$$\text{and } u = \mu([5, \infty)a)$$

Learning r-DDTA

Get a **minimal counter-example** $(w = 5, a)(0, a)$

$$w = u \cdot b \cdot v$$

$$u = (5, a),\ b = (0, a) \text{ and } v = \epsilon$$

$$\text{and } u = \mu([5, \infty)a)$$

This time we have the second case i.e. $s \in R$

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This time we have the second case i.e. $s \in R$

This means that s is not equivalent to any state in the hypothesis automata and should form a new state.

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This time we have the second case i.e. $s \in R$

This means that s is not equivalent to any state in the hypothesis automata and should form a new state.

Find $s' \in S$ such that $row(s) = row(s')$ Add $s \in S$ and add $b \cdot v$ and all of its suffixes to E to distinguish between s and s'.

Learning r-DDTA

Get a **minimal counter-example** $(w = 5, a)(0, a)$

$$w = u \cdot b \cdot v$$

$$u = (5, a),\ b = (0, a) \text{ and } v = \epsilon$$

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This time we have the second case i.e. $s \in R$

This means that s is not equivalent to any state in the hypothesis automata and should form a new state.

Find $s' \in S$ such that $row(s) = row(s')$ Add $s \in S$ and add $b \cdot v$ and all of its suffixes to E to distinguish between s and s'.

Add $[5, \infty)a[0, \infty)a$ and $[5, \infty)a[0, \infty)b$ to R.

Learning r-DDTA

Observation Table		
T_2	ϵ	$(0, a)$
ϵ	$-$	$+$
$[0,5)a$	$+$	$-$
$[5,\infty)a$	$-$	$-$
$[0,\infty)b$	$-$	$-$
$[0,5)a[0,\infty)a$	$-$	$-$
$[0,5)a[0,\infty)b$	$-$	$-$
$[5,\infty)a[0,\infty)a$	$-$	$-$
$[5,\infty)a[0,\infty)b$	$-$	$-$

Is it **closed**?

Learning r-DDTA

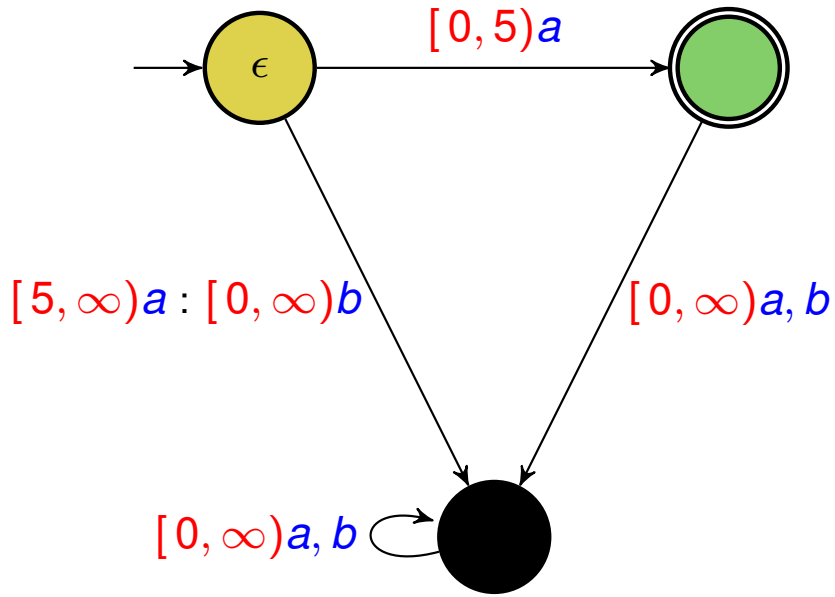
Observation Table		
T_2	ϵ	$(0, a)$
ϵ	$-$	$+$
$[0,5)a$	$+$	$-$
$[5,\infty)a$	$-$	$-$
$[0,\infty)b$	$-$	$-$
$[0,5)a[0,\infty)a$	$-$	$-$
$[0,5)a[0,\infty)b$	$-$	$-$
$[5,\infty)a[0,\infty)a$	$-$	$-$
$[5,\infty)a[0,\infty)b$	$-$	$-$

Is it **closed**? ✓

Learning r-DDTA

Observation Table		
T_2	ϵ	$(0, a)$
ϵ	$-$	$+$
$[0, 5)a$	$+$	$-$
$[5, \infty)a$	$-$	$-$
$[0, \infty)b$	$-$	$-$
$[0, 5)a[0, \infty)a$	$-$	$-$
$[0, 5)a[0, \infty)b$	$-$	$-$
$[5, \infty)a[0, \infty)a$	$-$	$-$
$[5, \infty)a[0, \infty)b$	$-$	$-$

Is it **closed**? ✓

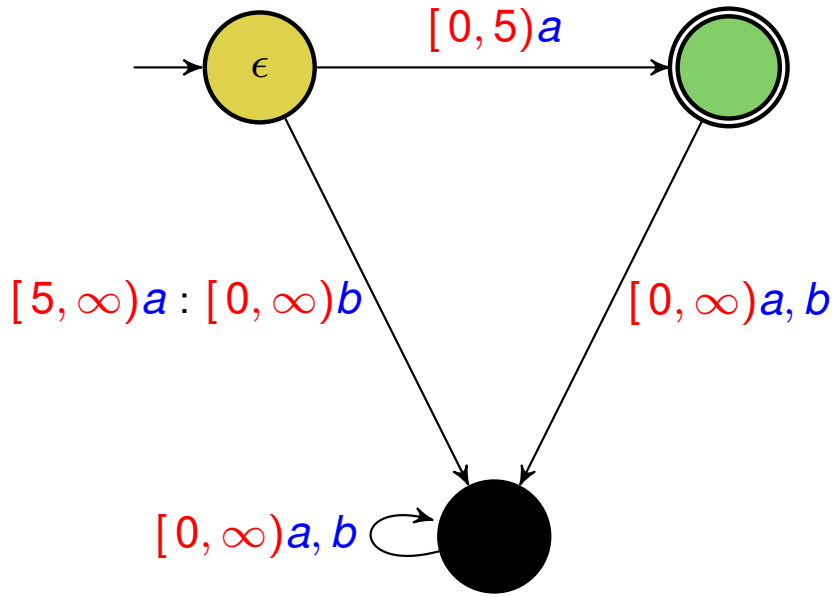


Hypothesis automaton: H_2

Learning r-DDTA

Observation Table		
T_2	ϵ	$(0, a)$
ϵ	$-$	$+$
$[0,5)a$	$+$	$-$
$[5,\infty)a$	$-$	$-$
$[0,\infty)b$	$-$	$-$
$[0,5)a[0,\infty)a$	$-$	$-$
$[0,5)a[0,\infty)b$	$-$	$-$
$[5,\infty)a[0,\infty)a$	$-$	$-$
$[5,\infty)a[0,\infty)b$	$-$	$-$

Is it **closed**? ✓



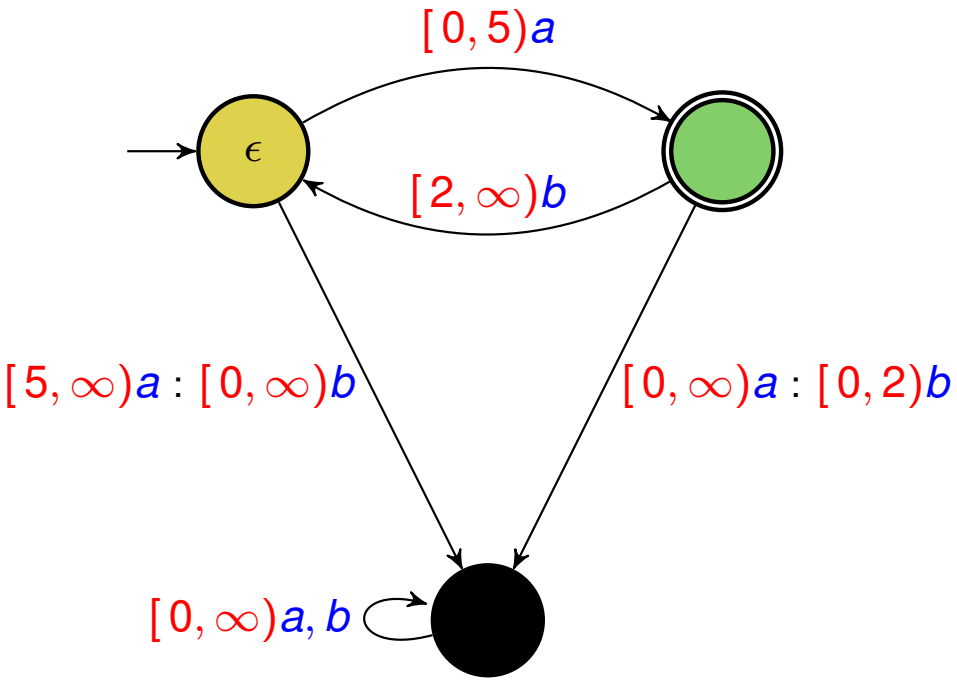
Hypothesis automaton: H_2

✗

Learning r-DDTA

In the next iteration

Observation Table		
T_3	ϵ	$(0, a)$
ϵ	$-$	$+$
$[0,5)a$	$+$	$-$
$[5,\infty)a$	$-$	$-$
$[0,\infty)b$	$-$	$-$
$[0,5)a[0,\infty)a$	$-$	$-$
$[0,5)a[0,2)b$	$-$	$-$
$[0,5)a[2,\infty)b$	$-$	$+$
$[5,\infty)a[0,\infty)a$	$-$	$-$
$[5,\infty)a[0,\infty)b$	$-$	$-$



Hypothesis automaton: H_3

✓

Canonical Automaton

Theorem. *The automaton we get from this algorithm is minimal and unique up to the renaming of states and the clock*.

Canonical Automaton

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Summary:

- A learning algorithm for discrete timed automata.
- Assumption on the teacher is not drastically different from L^*.

Future work and Conclusion

Conclusion

- Learning problem and why it is useful.

Conclusion

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- L^* with an example.

Conclusion

- Learning problem and why it is useful.
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- Discrete timed automaton.

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- Learning problem and why it is useful.
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- Learning DiTA is equivalent to learning r-DDTA.

Conclusion

- Learning problem and why it is useful.
- L^* with an example.
- Discrete timed automaton.
- Learning DiTA is equivalent to learning r-DDTA.
- Algorithm to learn r-DDTA.

Future Work

- Implement this algorithm and run it on some examples and compare them with S. Verwer's tool.

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- Implement this algorithm and run it on some examples and compare them with S. Verwer's tool.
- Learn some real system using this algorithm.
- Generate minimal DiTA from r-DDTA.

Thank You


WHAT YOU BROUGHT TO SEMINAR AND WHAT IT SAYS ABOUT YOU:
Stuff to take notes: First year. Foolishly thinks he'll ever need notes again.
Reading material: Third year. Just here for show.
Didn't bring anything: ABD/Postdoc. Has nothing better to do.
Laptop: Young Assistant Professor. Working on three proposals at the same time.
Playing with latest Gadget/Gizmo: Full Professor. Loooves new toys.
tap tap
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