New Challenges for Automata Learning

Property-Directed Verification of Recurrent Neural Networks

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CNRS, LSV, ENS Paris-Saclay, Université Paris-Saclay

joint work with LeaRNNify team:

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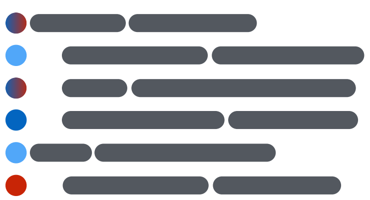
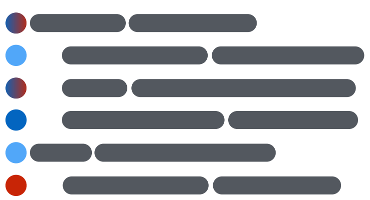
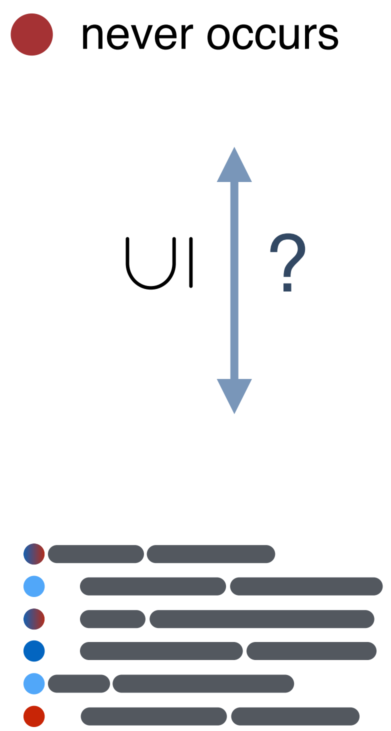
Martin Leucker, Rajarshi Roy, Lina Ye

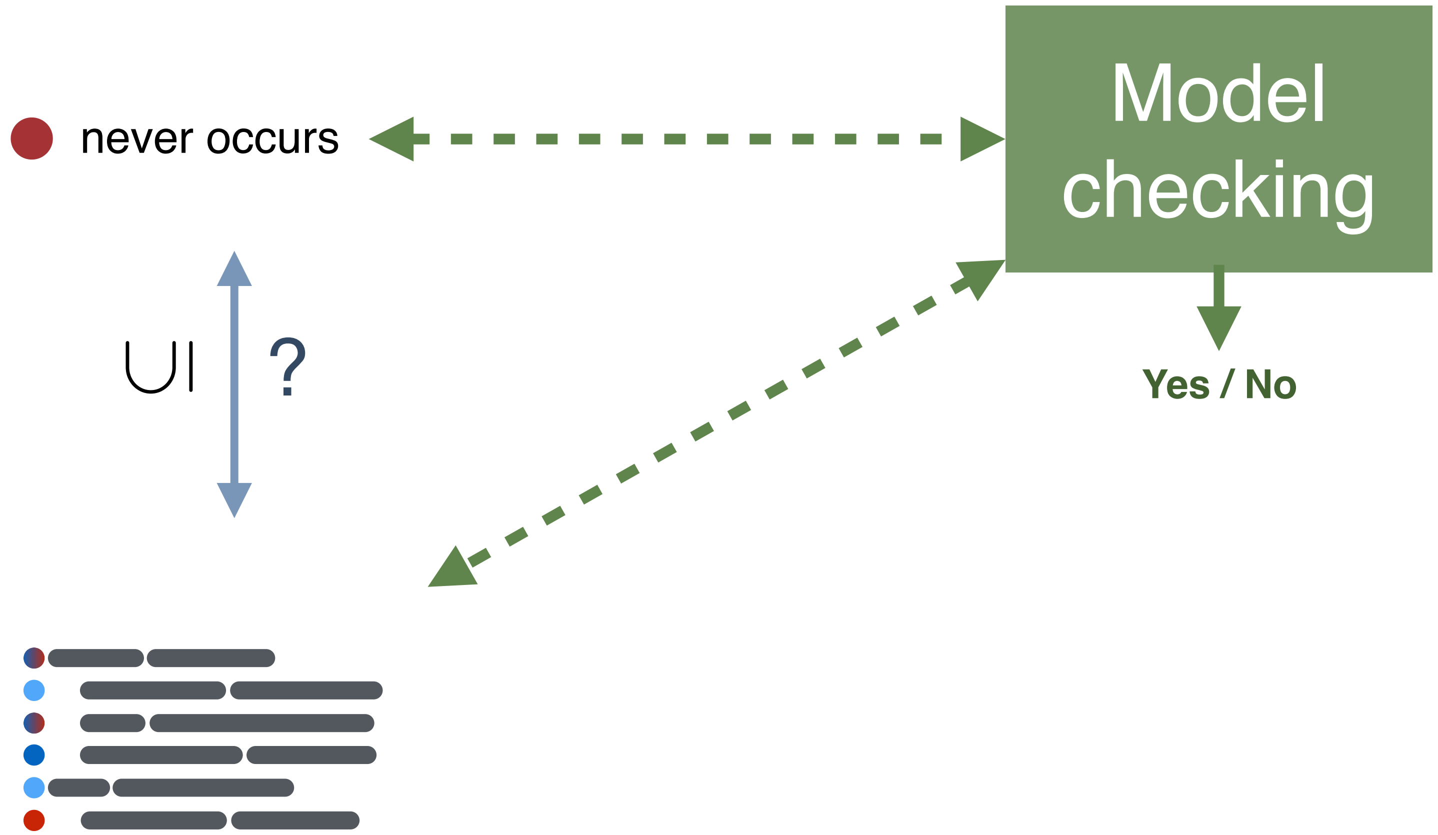
DATAIA Workshop "Safety & AI"
September 23, 2020
CentraleSupélec



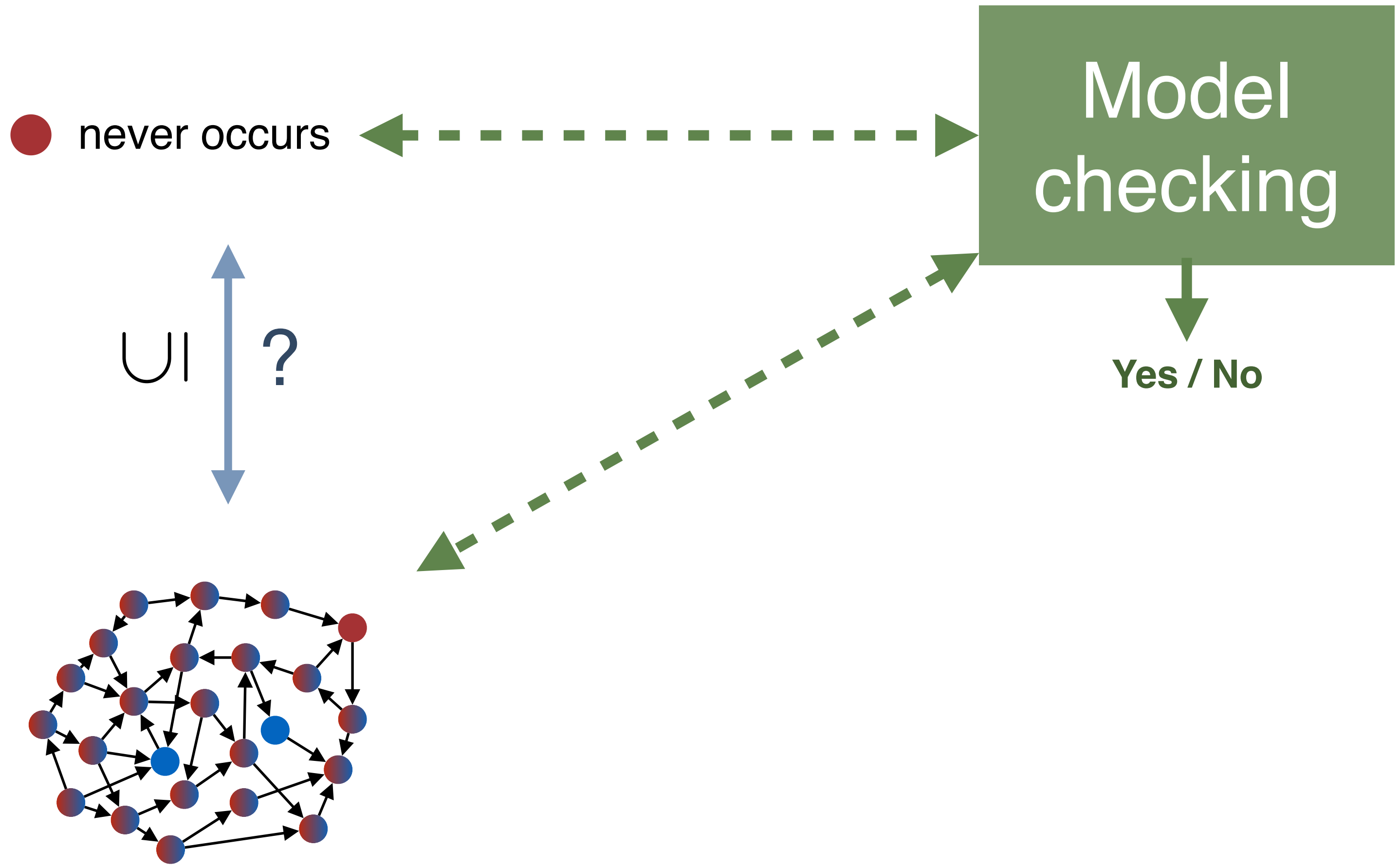
never occurs




never occurs
?



never occurs
Model checking
Yes / No
?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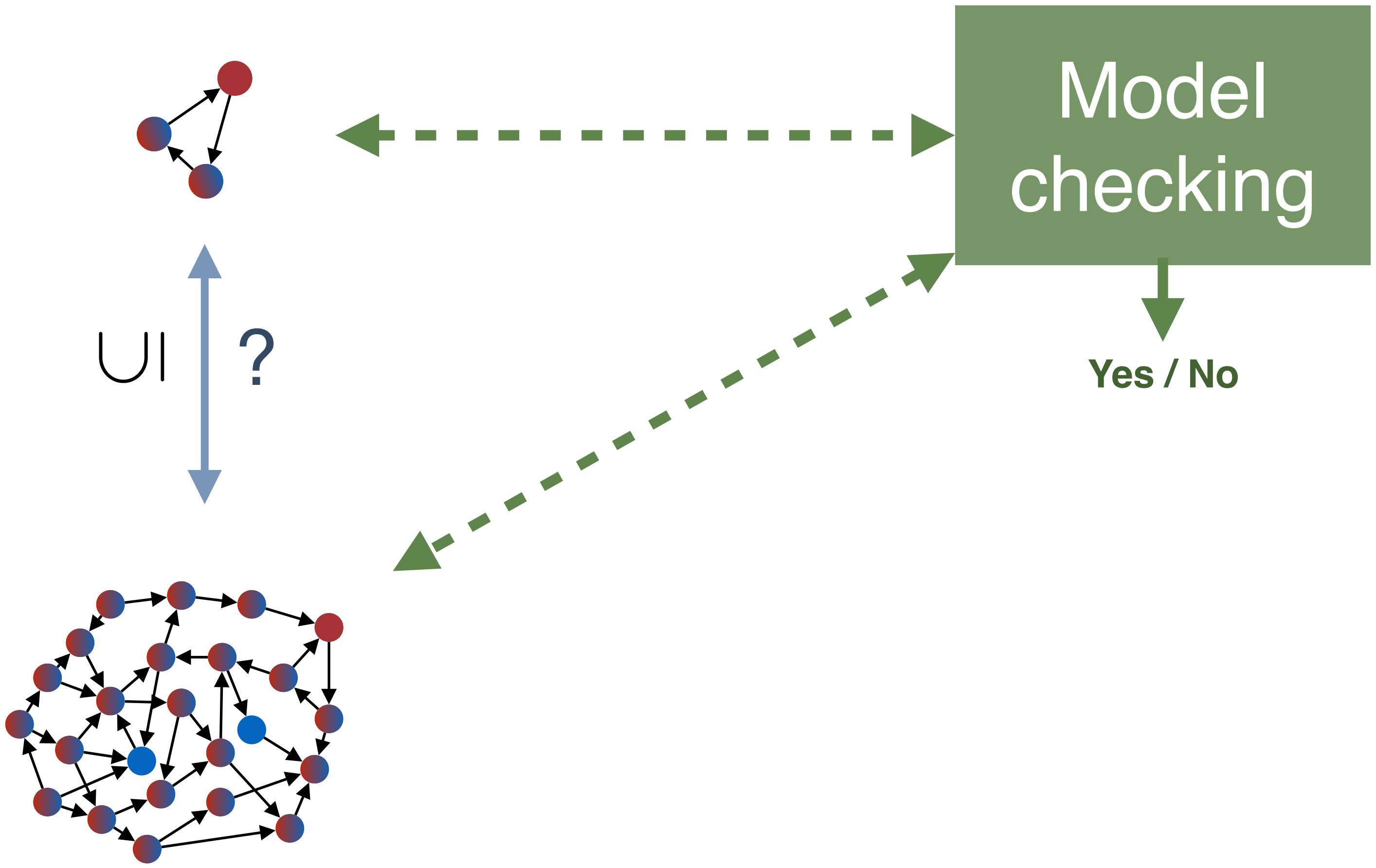
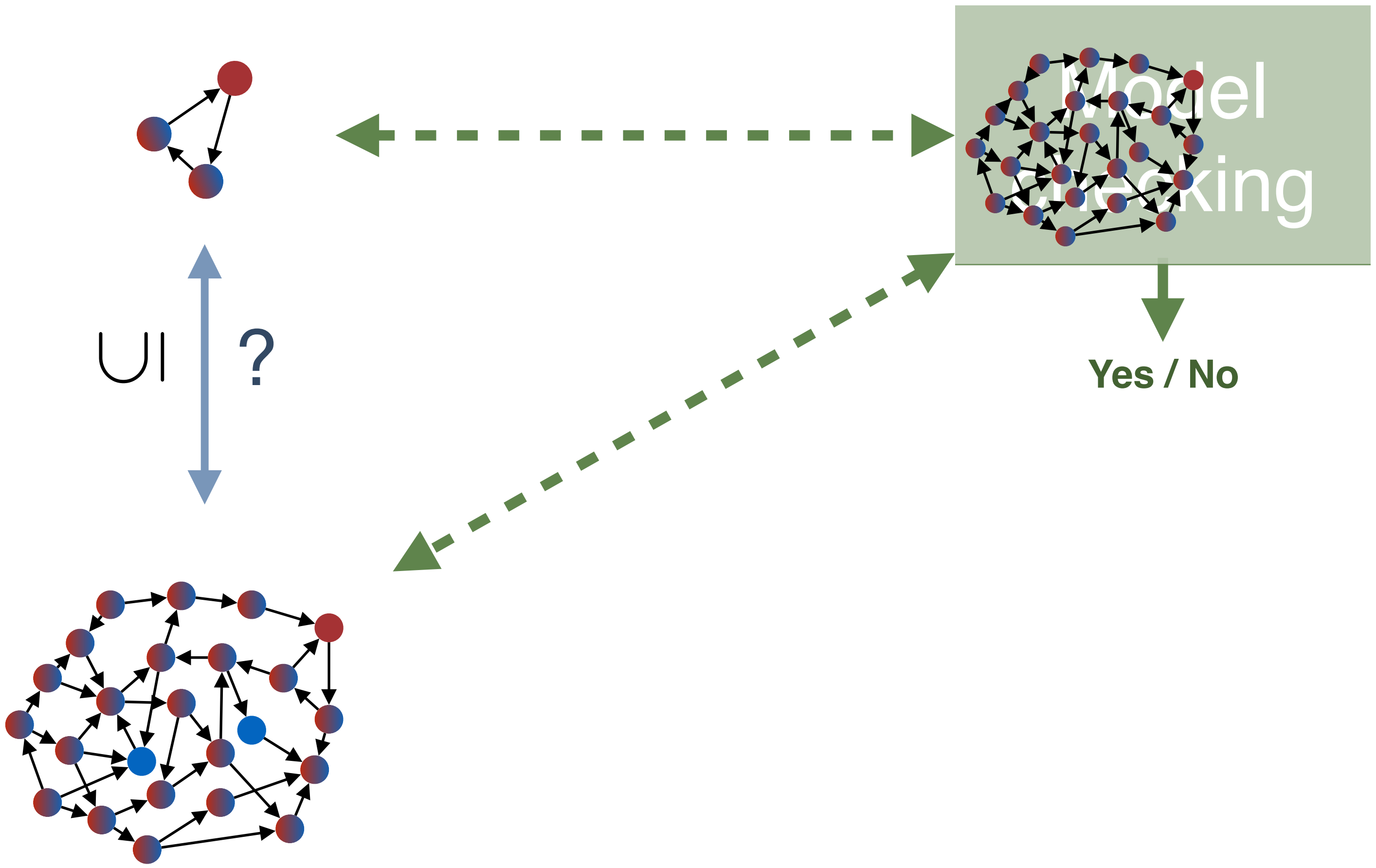
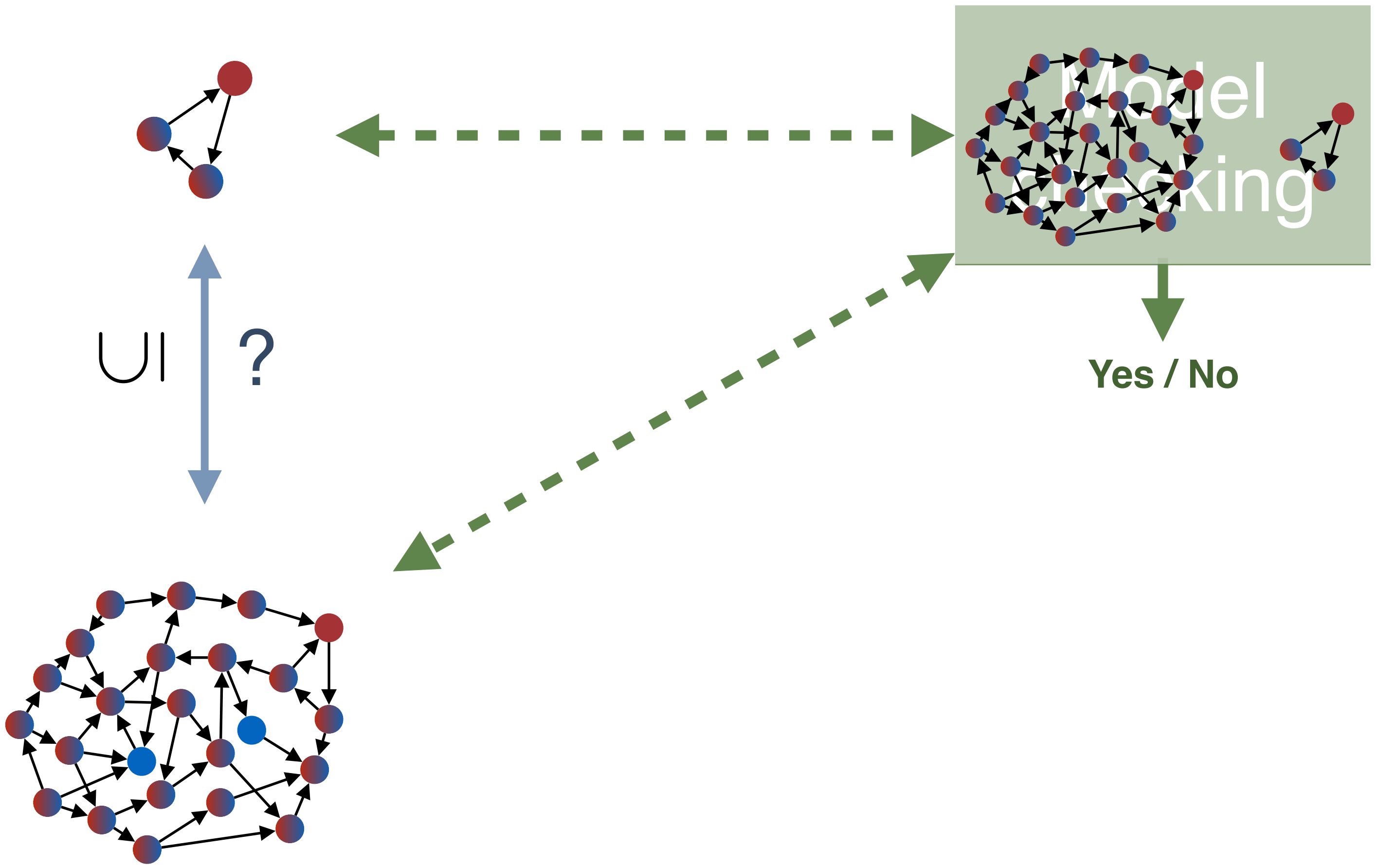
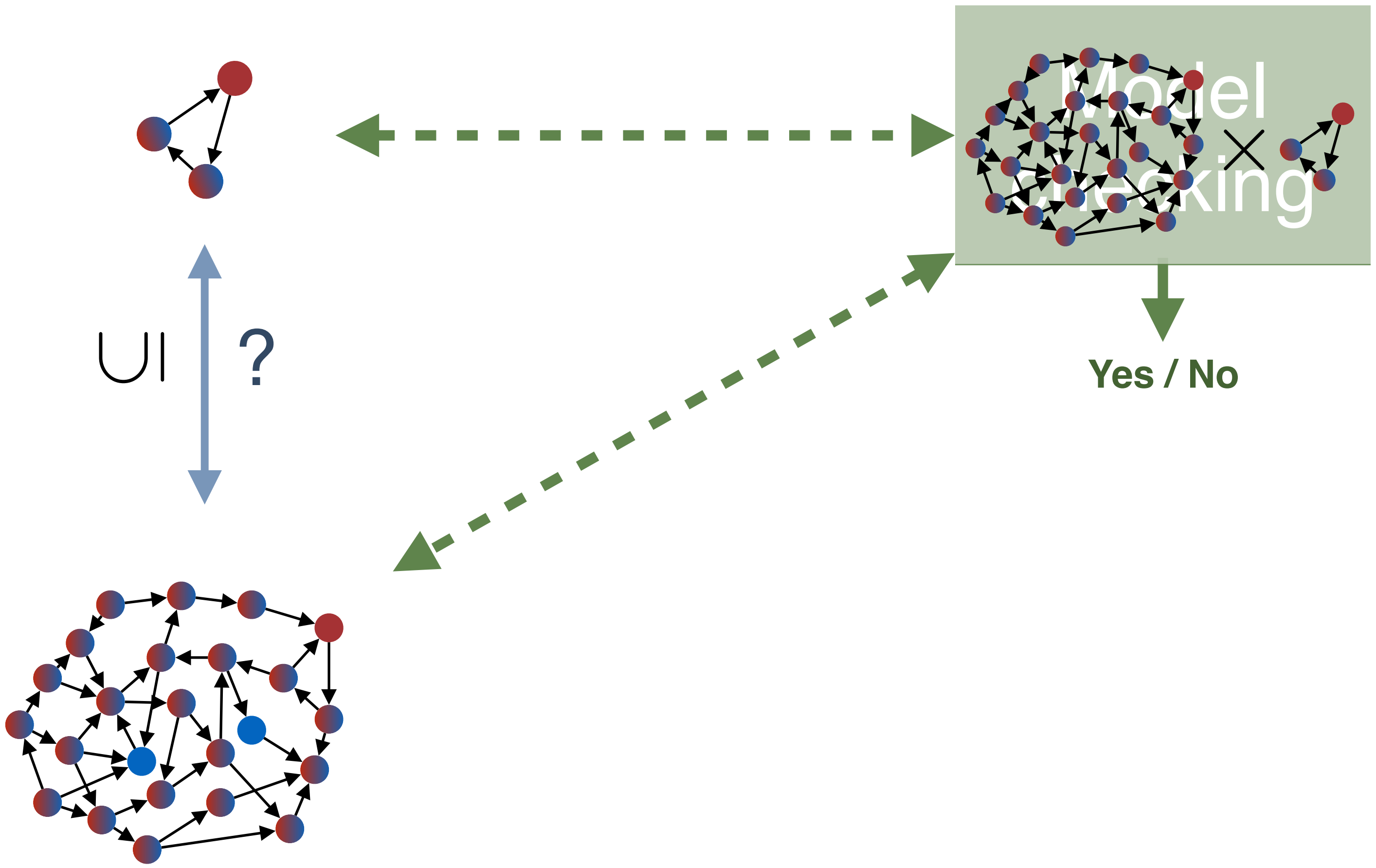


Model checking
Yes / No
?

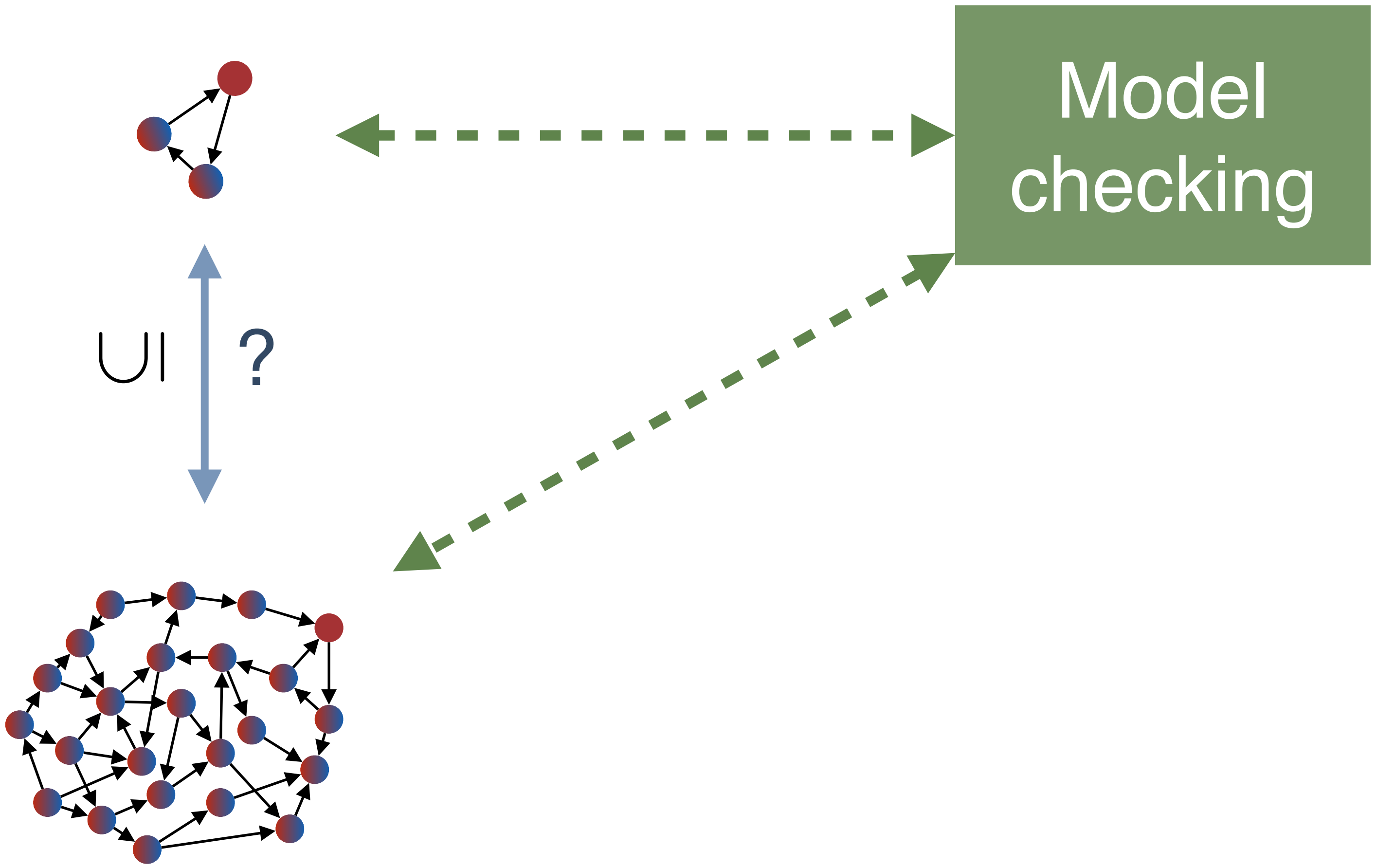


Model Checking
Yes / No
∪I ?


Yes / No

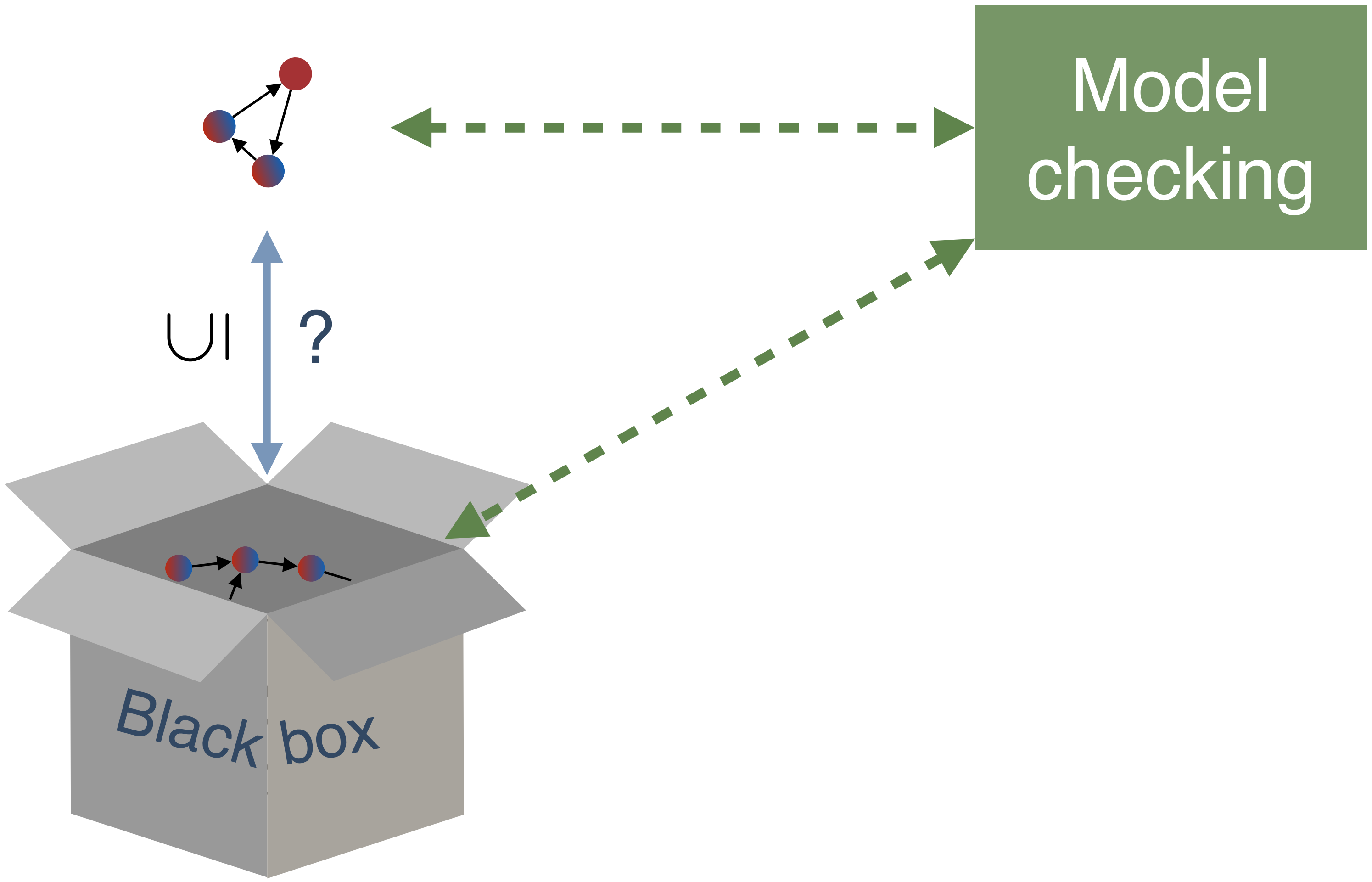


Model
×
?
Yes / No



Model Checking

[Clarke-Emerson, Queille-Sifakis '80s]



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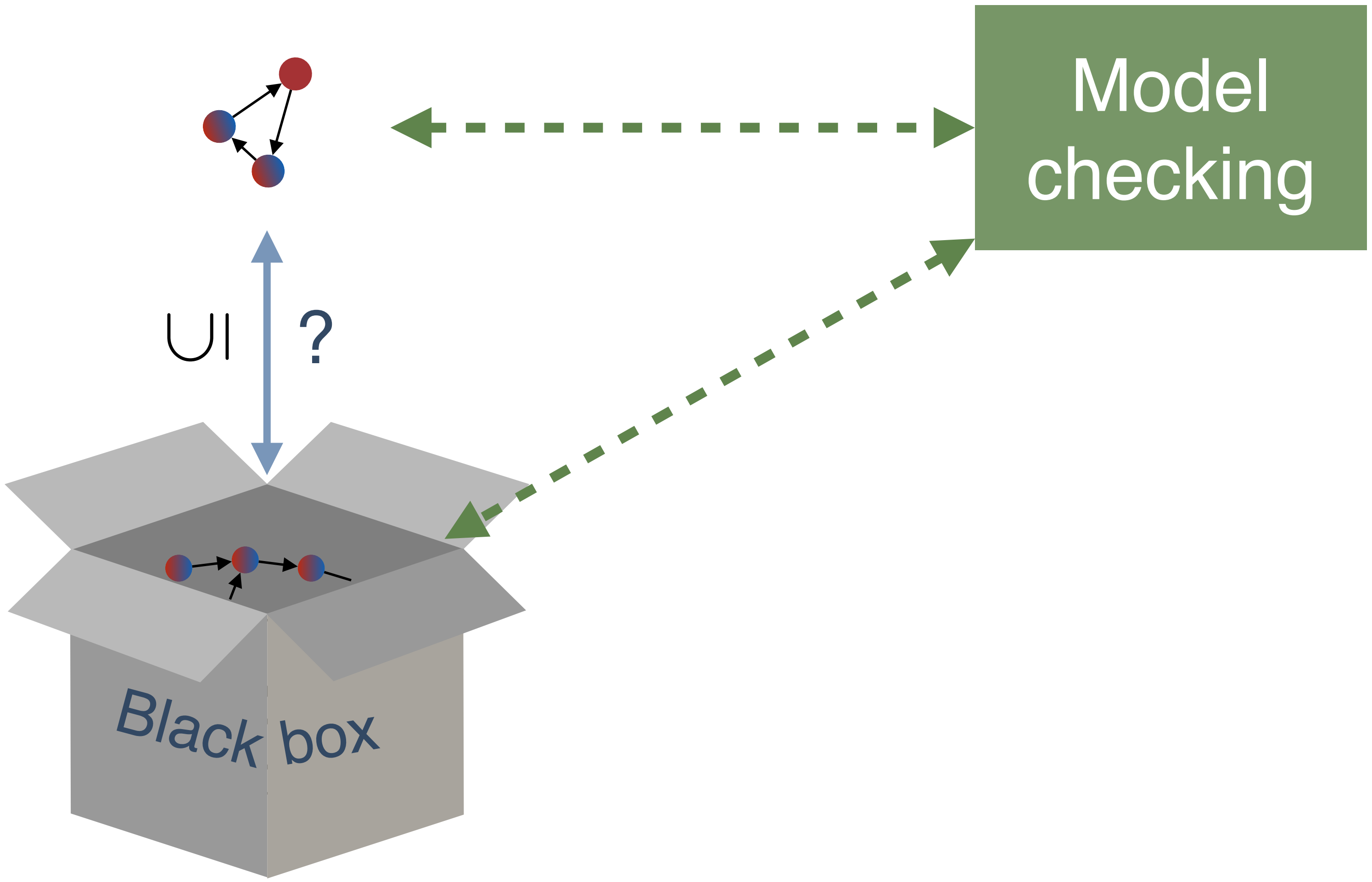
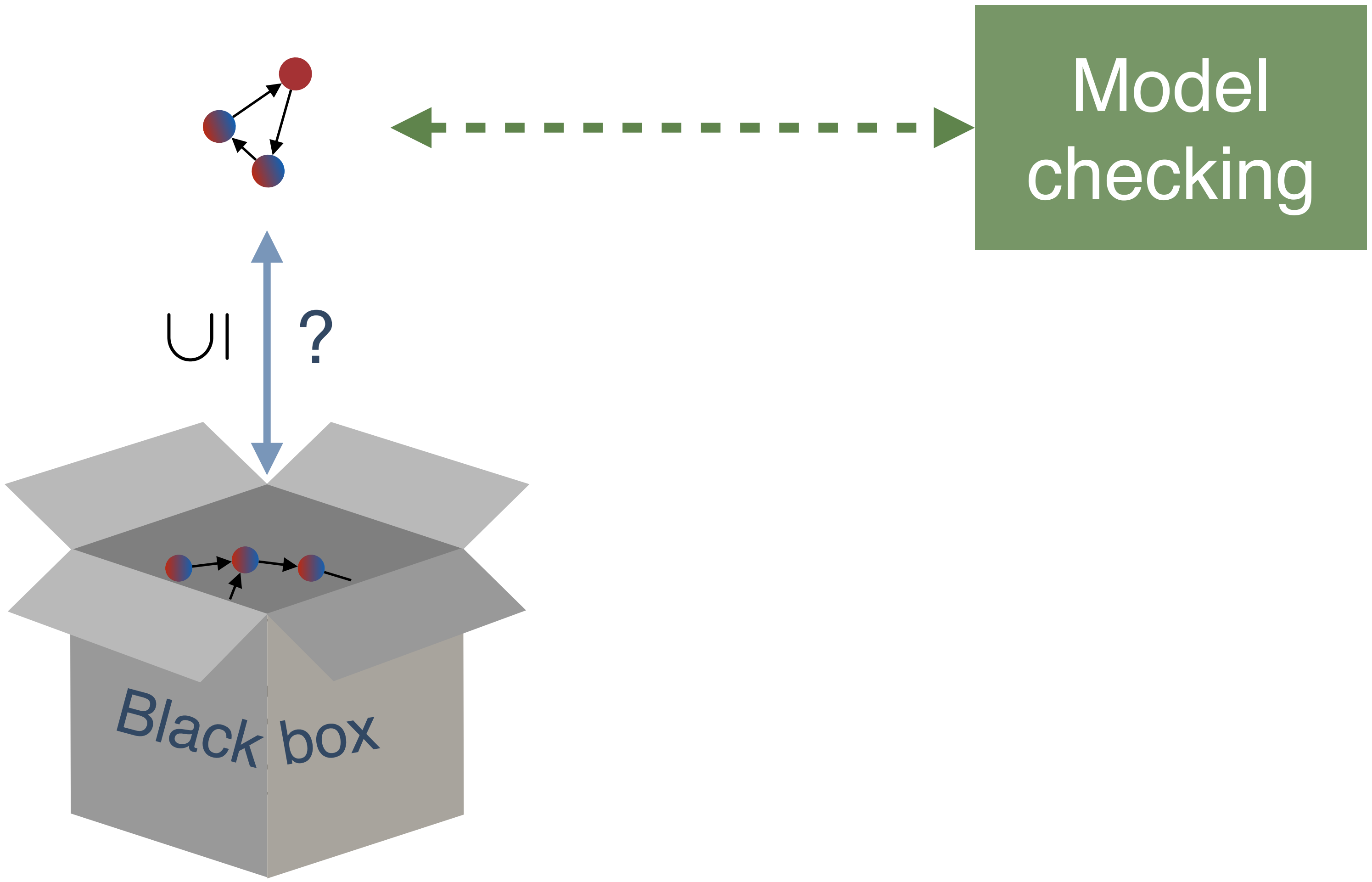


Model Checking

[Clarke-Emerson, Queille-Sifakis '80s]

- legacy software
- code not open source
- third-party software
- embedded systems



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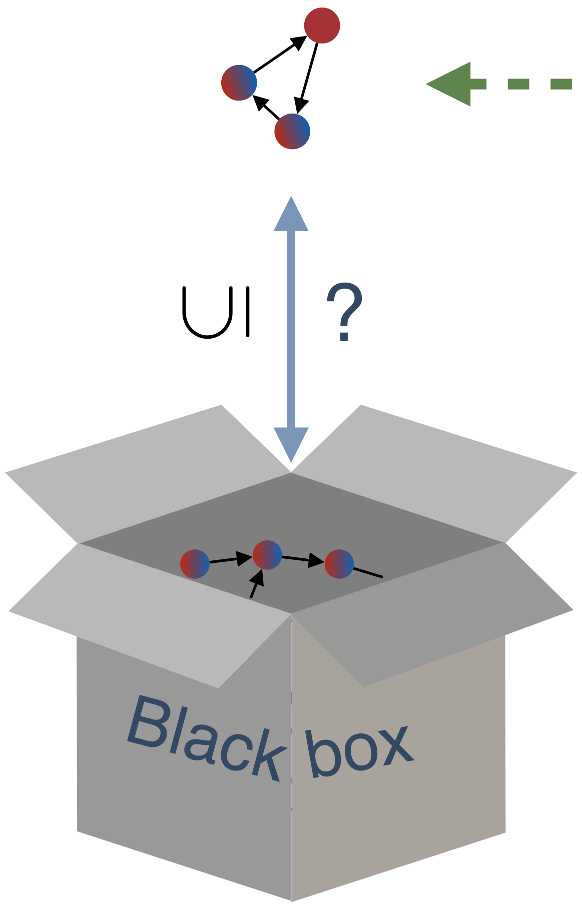

Model checking

Model Checking

[Clarke-Emerson, Queille-Sifakis '80s]

Learner

Learning algorithm

- legacy software
- code not open source
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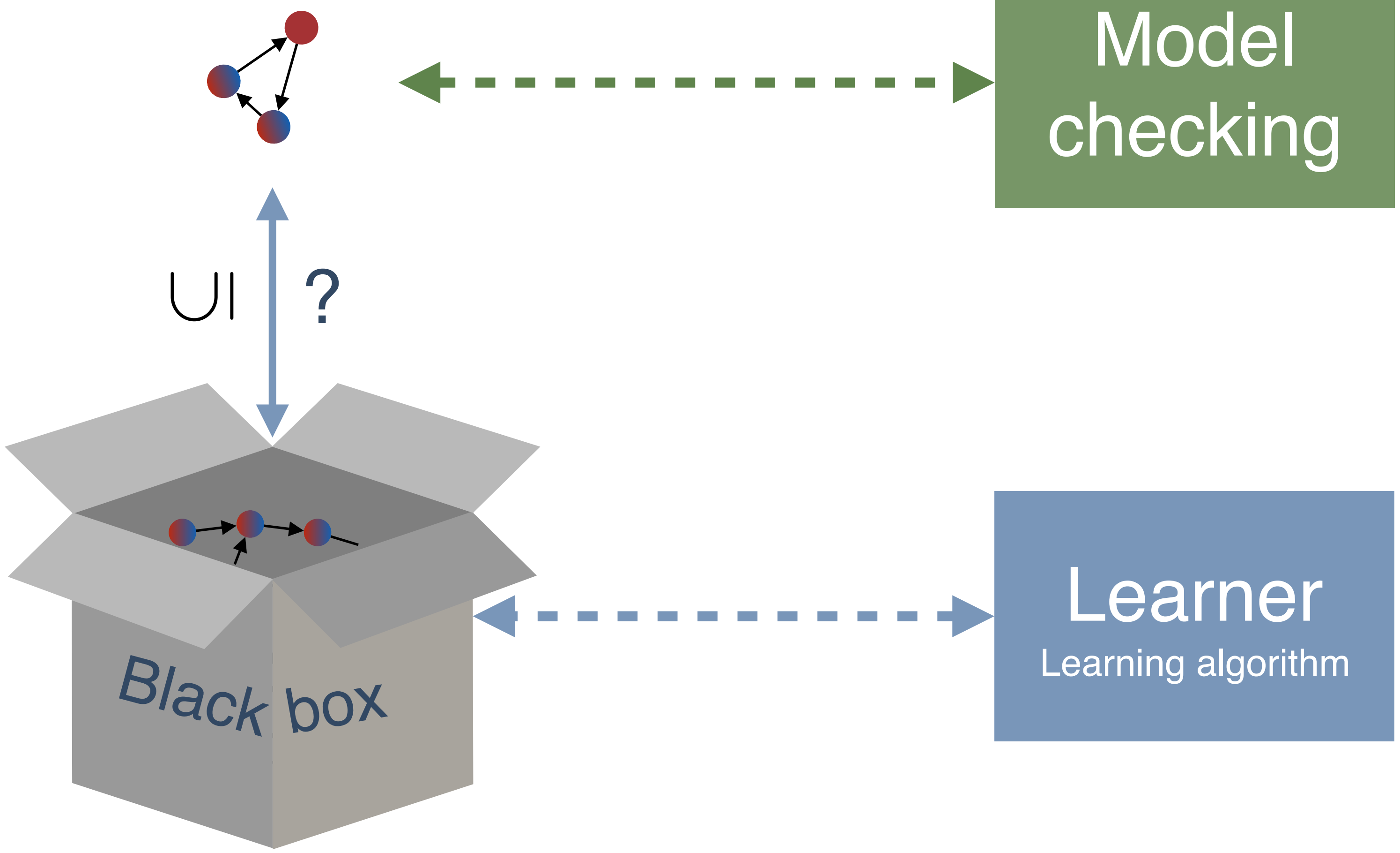

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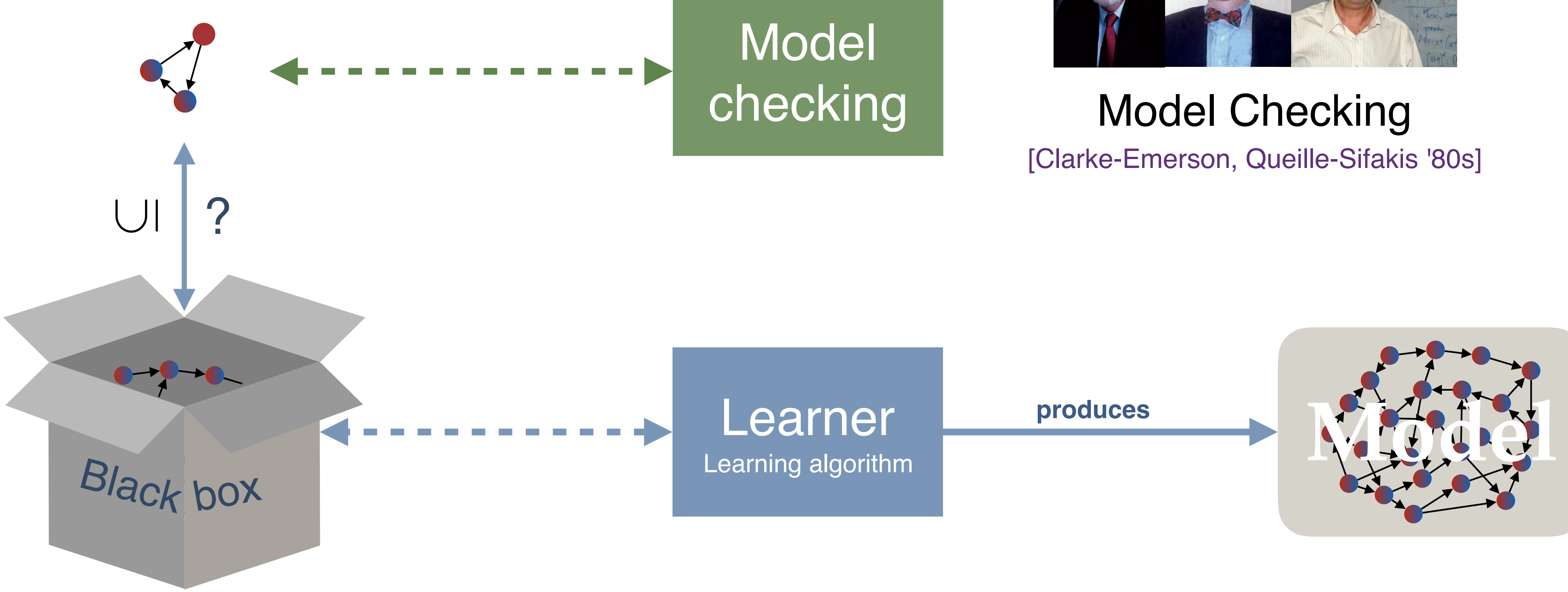

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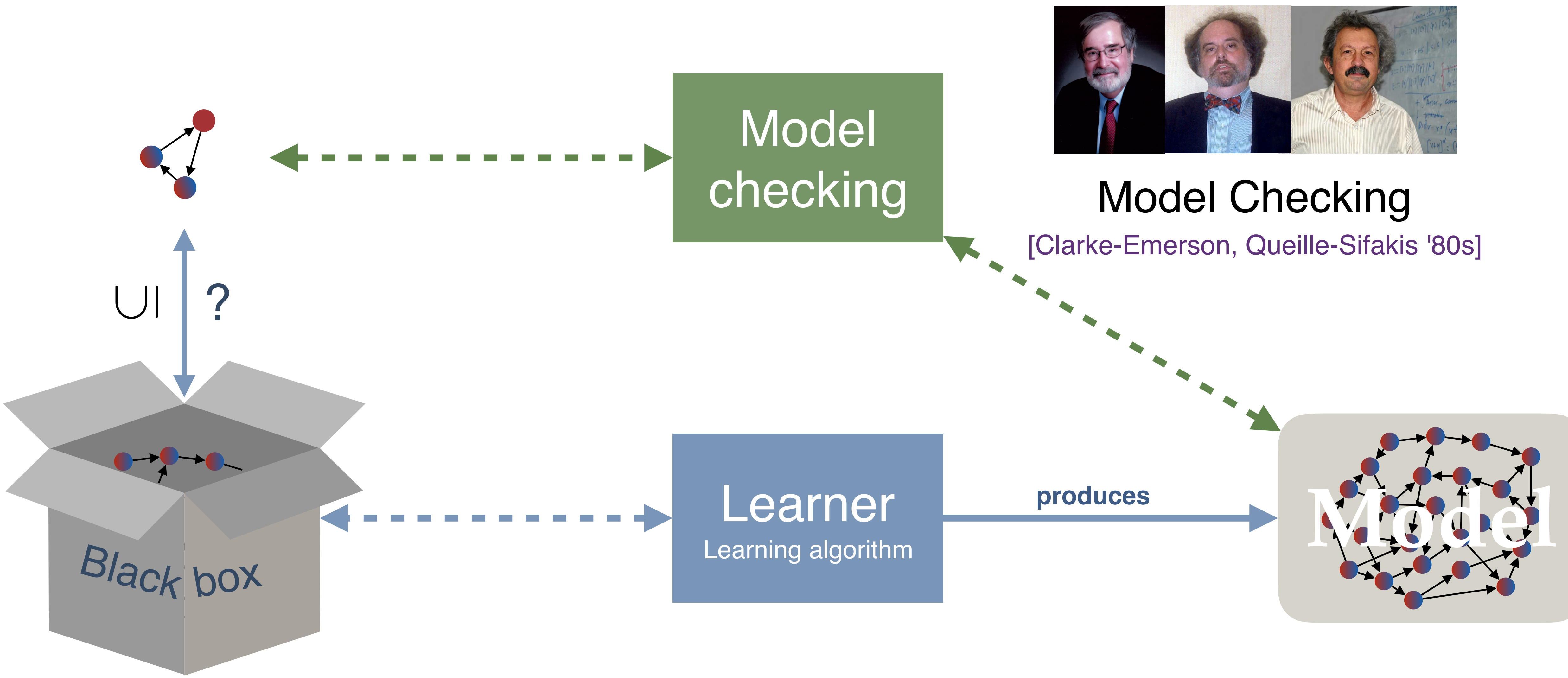

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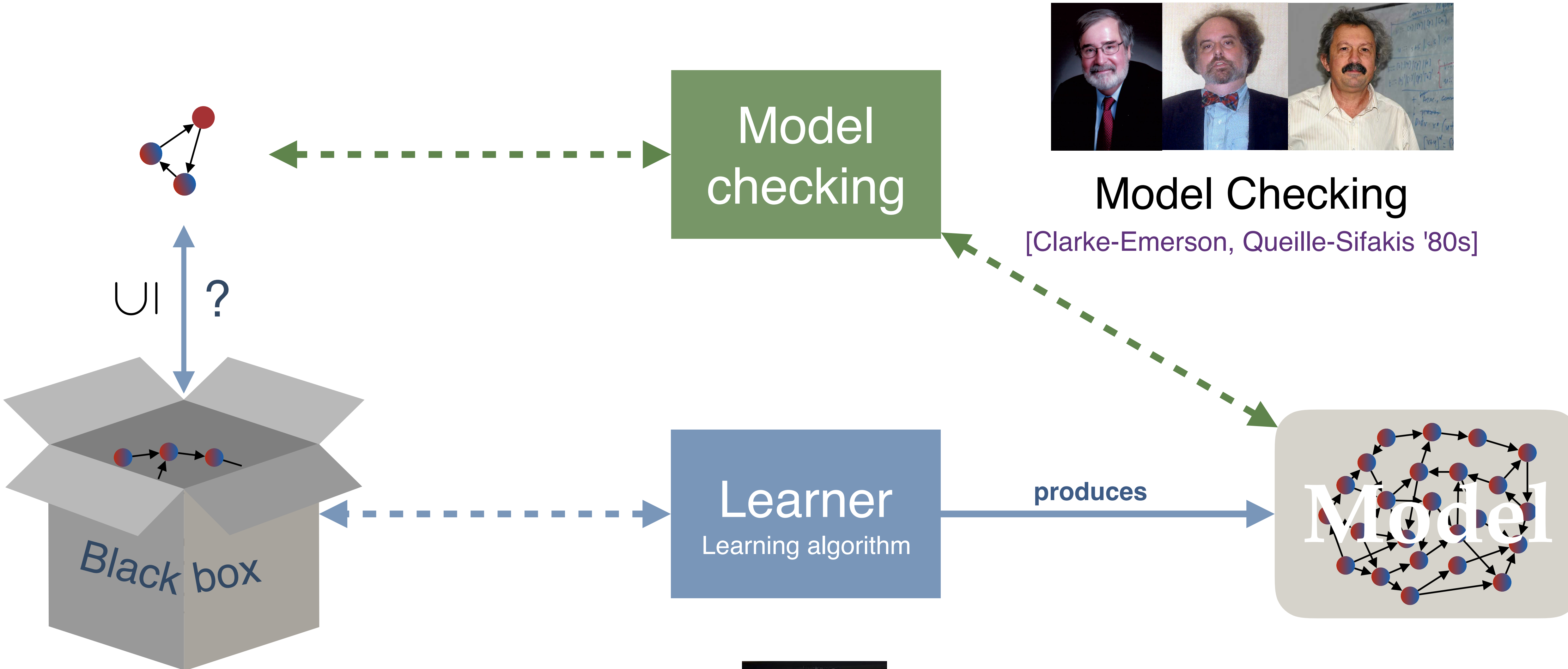

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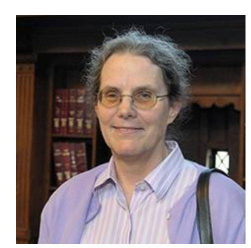

Inference/Model Learning

[Moore '50s, Angluin '80s]

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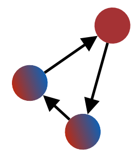
- code not open source
- third-party software
- embedded systems

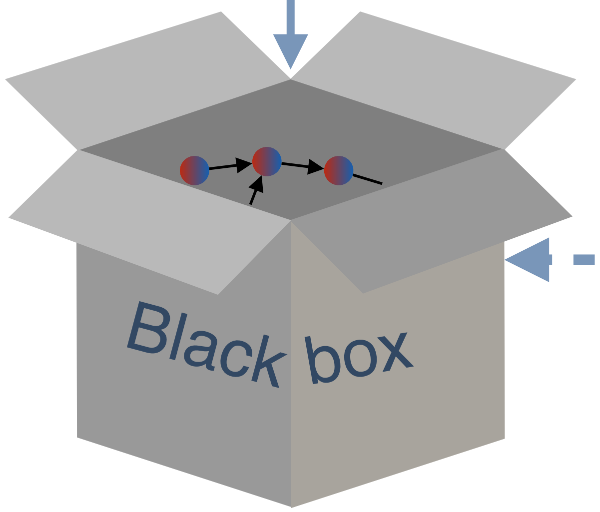


Model
checking

Model Checking

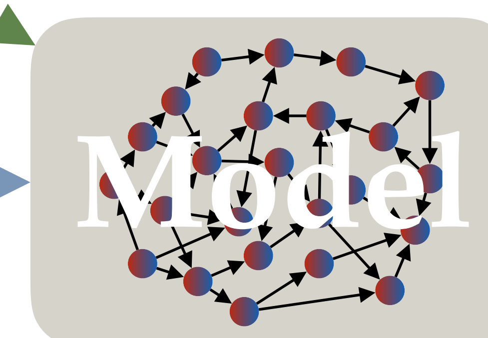
[Clarke-Emerson, Queille-Sifakis '80s]

⊔| ?



Learner
Learning algorithm

produces



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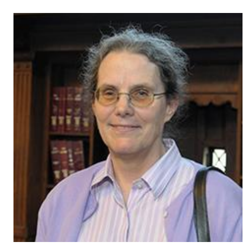

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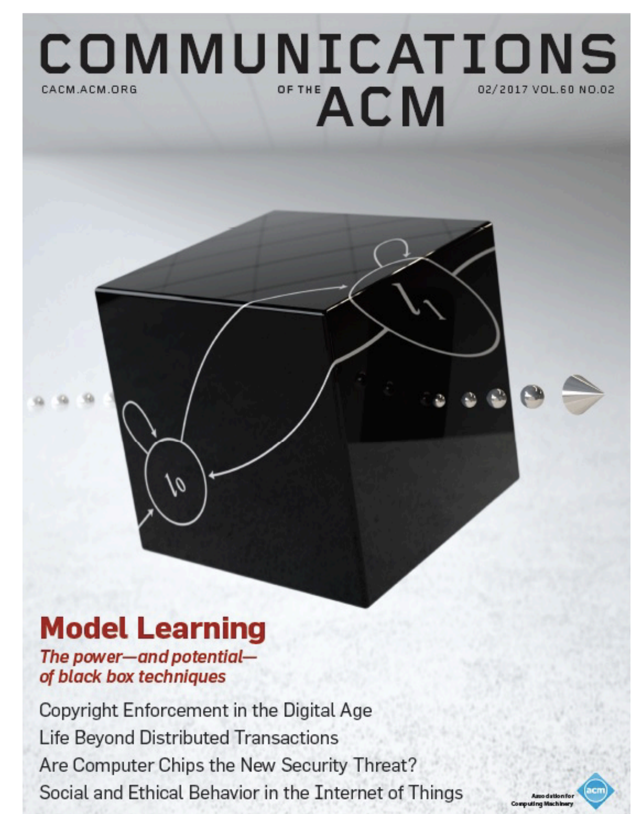
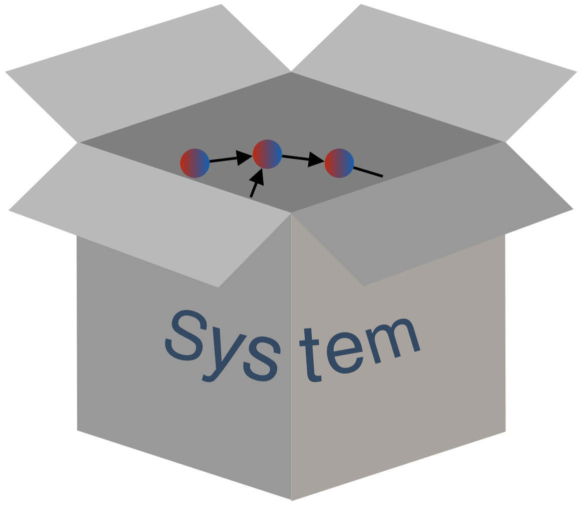


[F. Vaandrager 2017]

Angluin's L* Algorithm

[Angluin 1987]



Angluin's L* Algorithm

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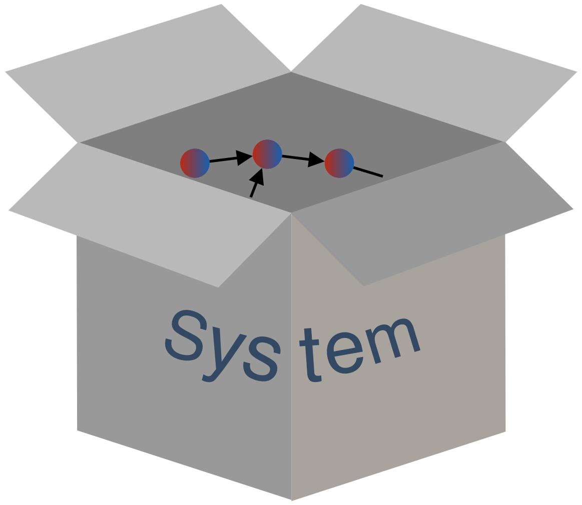
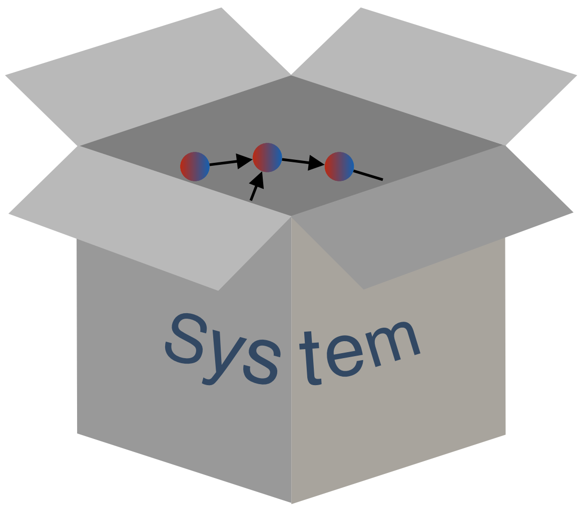


$$L = (a+b)^* b (a+b)$$

[Angluin 1987]



$$L = (a+b)^* b (a+b)$$

$$f_L : \Sigma^* \rightarrow \{0,1\}$$

$$f_L(w) = 1 \text{ iff } w \in L$$

Angluin's L* Algorithm

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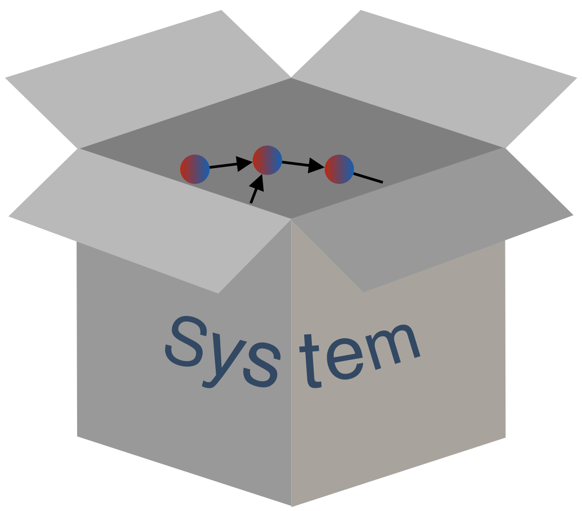

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Learner

Learning algorithm

Angluin's L* Algorithm

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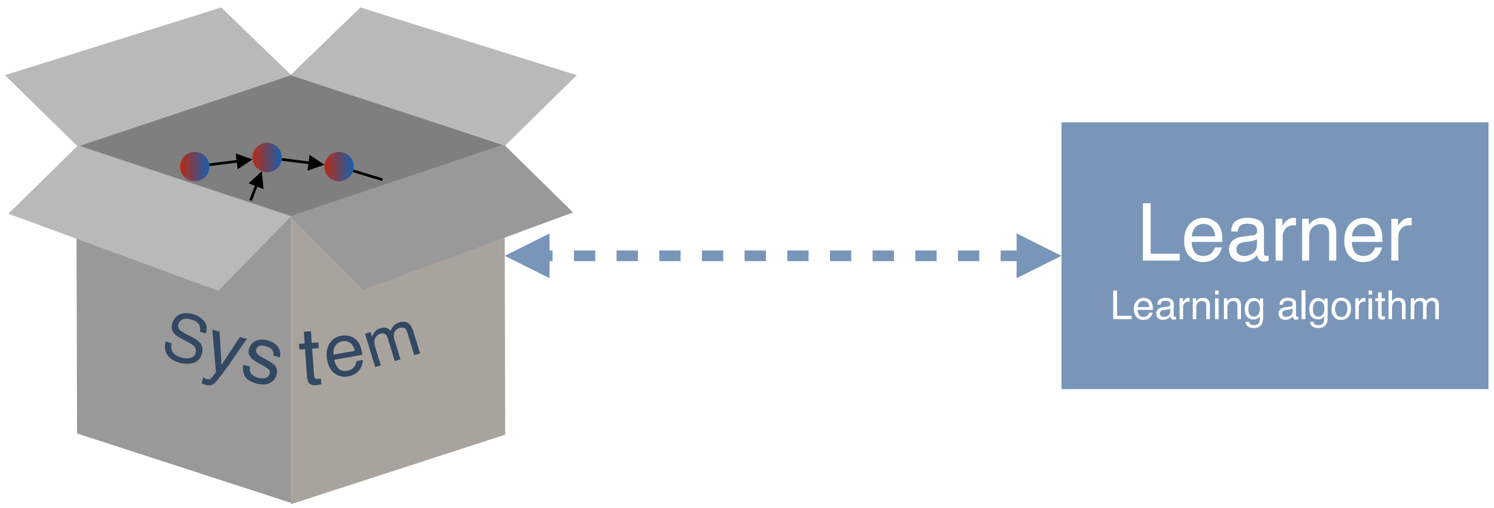

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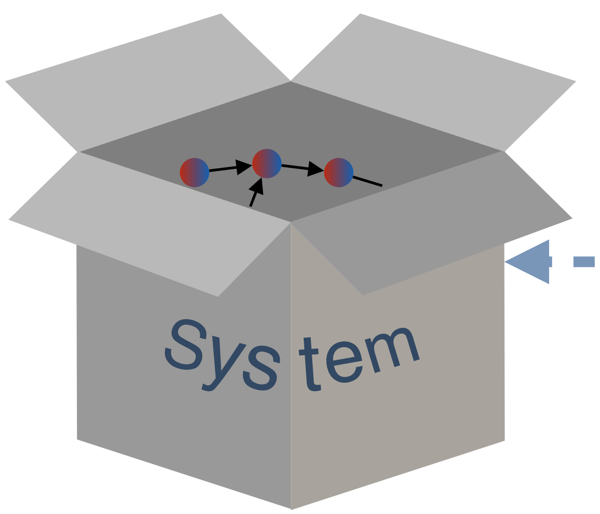

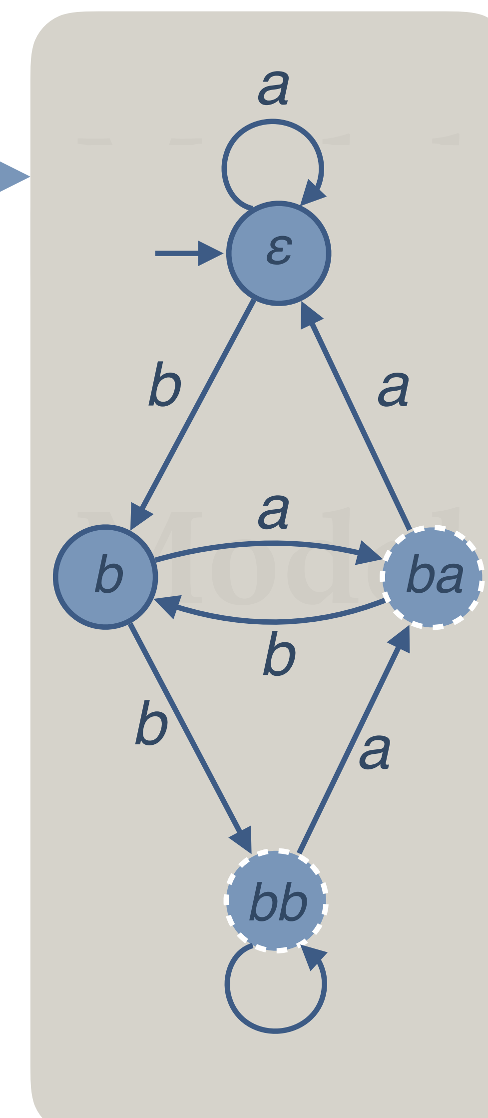

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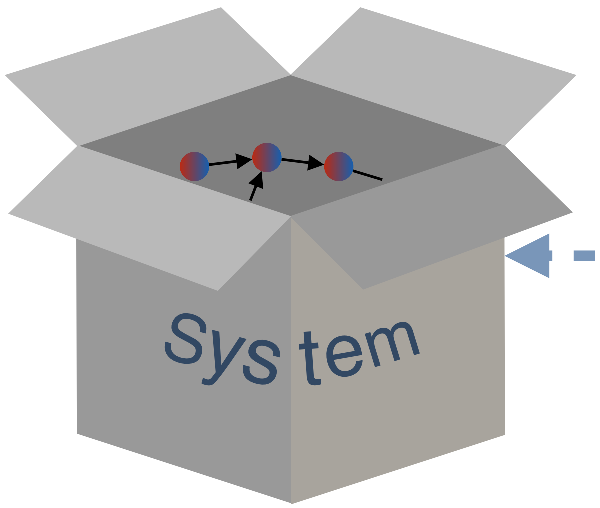

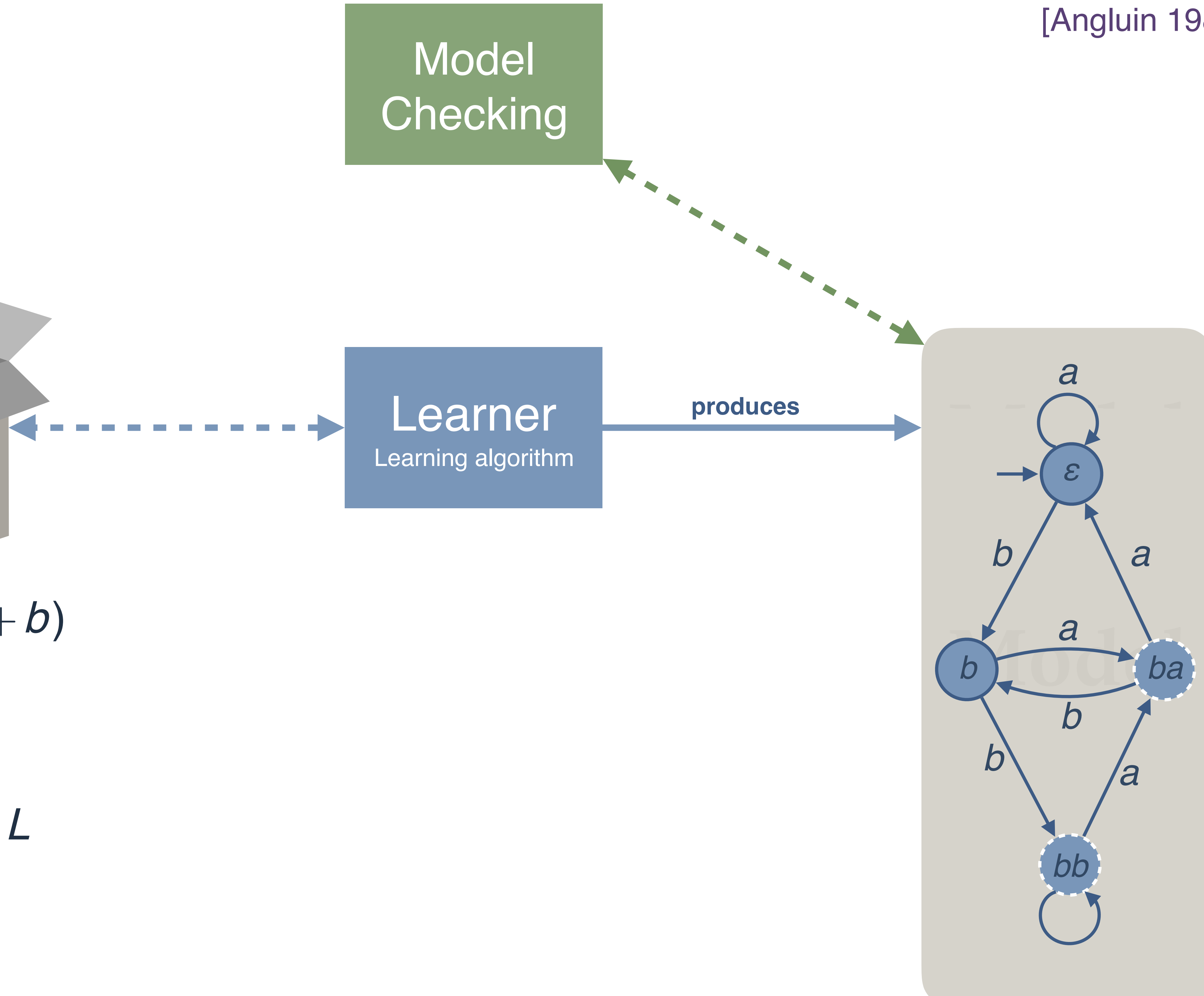

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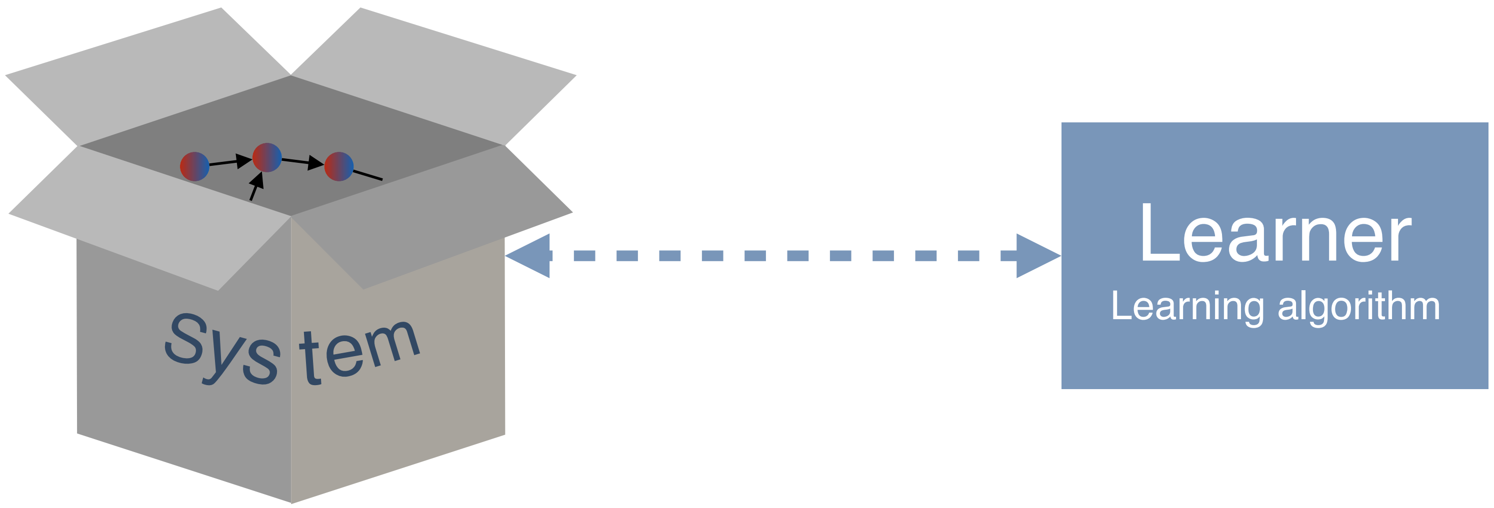

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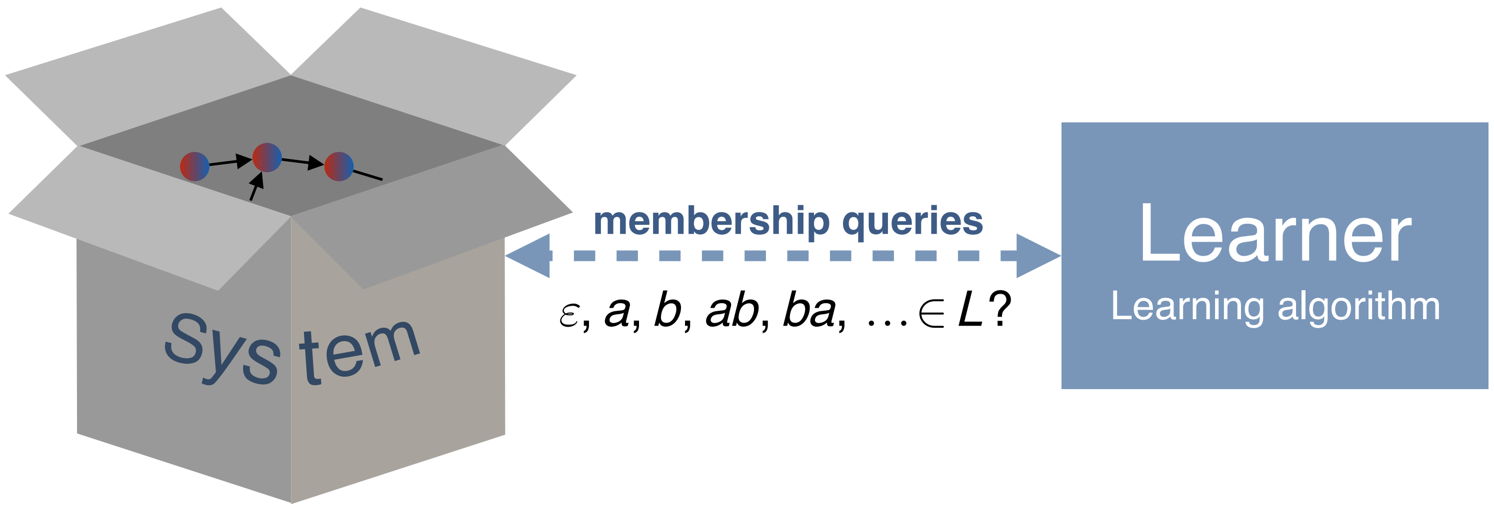

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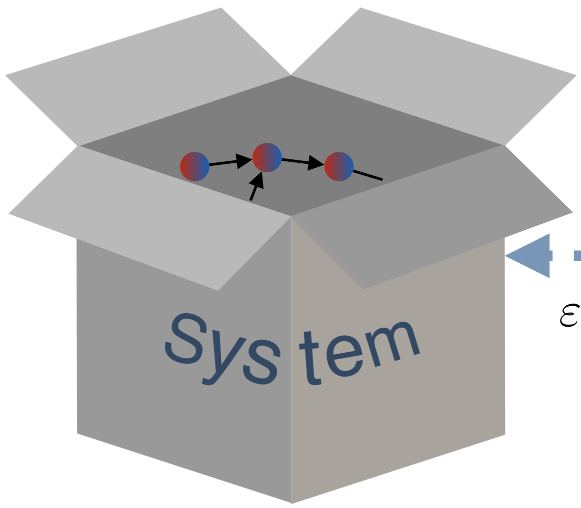

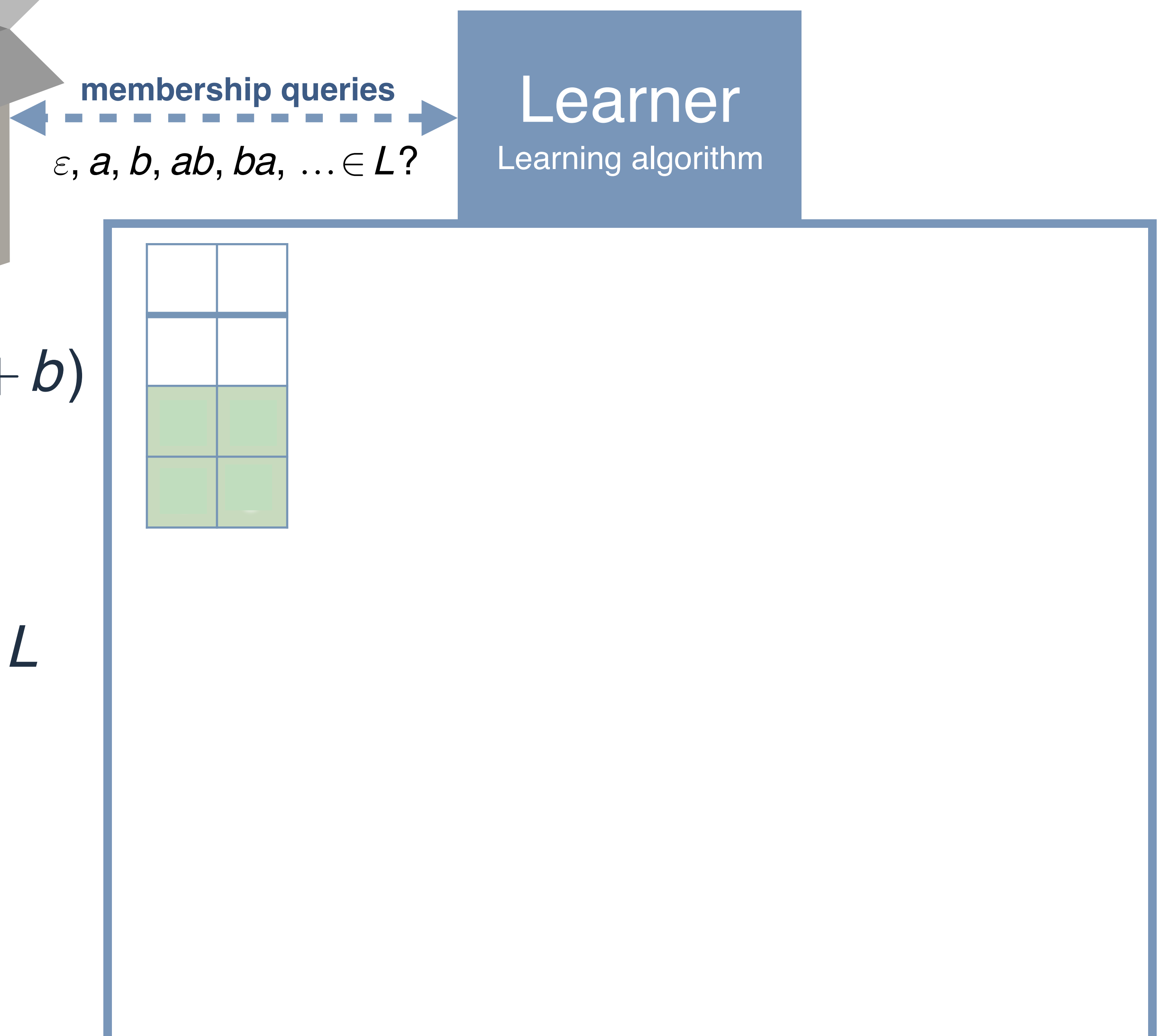

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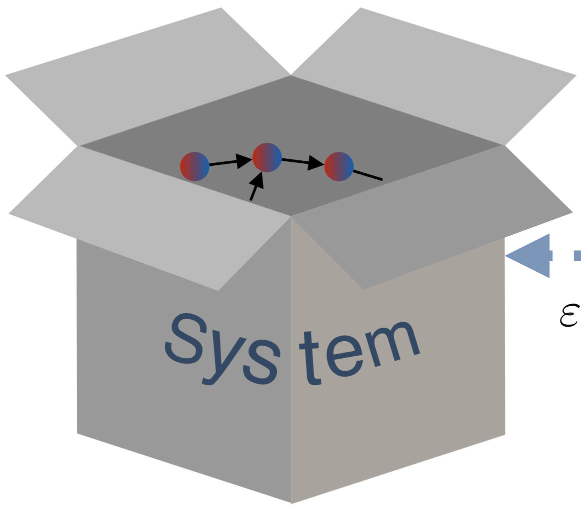

membership queries

ε, a, b, ab, ba, $\ldots \in L$?

Learner

Learning algorithm

	ε
ε	0

$$L = (a+b)^* b (a+b)$$

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Angluin's L* Algorithm

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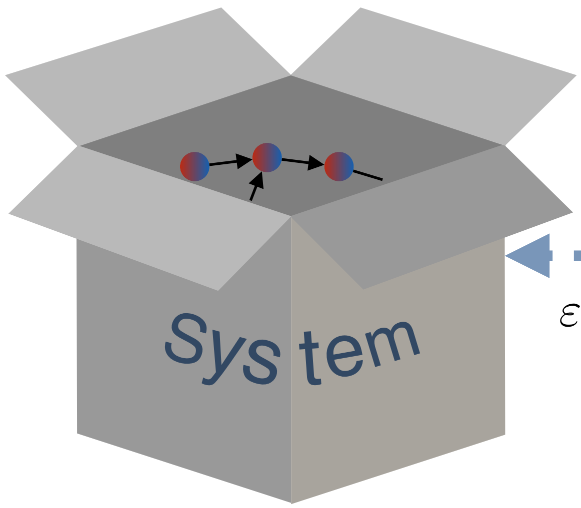

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	ε
ε	0
a	0
b	0

Angluin's L* Algorithm

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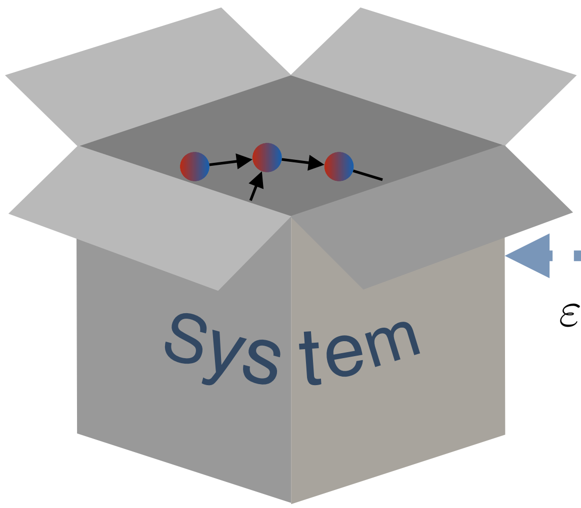


membership queries

ε, a, b, ab, ba, $\ldots \in L$?

Learner

Learning algorithm

$$L = (a+b)^{*} b (a+b)$$

$$f_L : \Sigma^{*} \to \{0,1\}$$

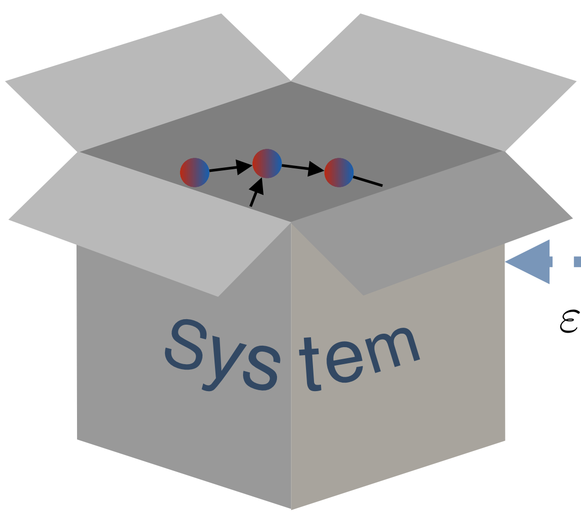
$$f_L(w) = 1 \text{ iff } w \in L$$

	ε
ε	0
a	0
b	0

upper part = states

Angluin's L* Algorithm

[Angluin 1987]



membership queries

$\varepsilon, a, b, ab, ba, \ldots \in L?$

Learner

Learning algorithm

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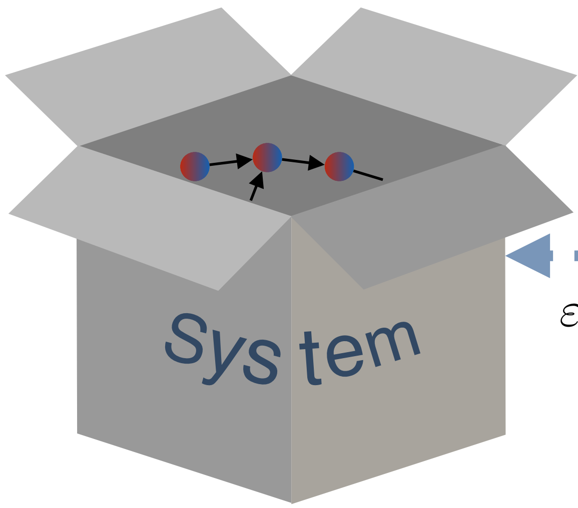
	ε
ε	0
a	0
b	0

upper part = states

lower part = transitions

Angluin's L* Algorithm

[Angluin 1987]



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Learning algorithm

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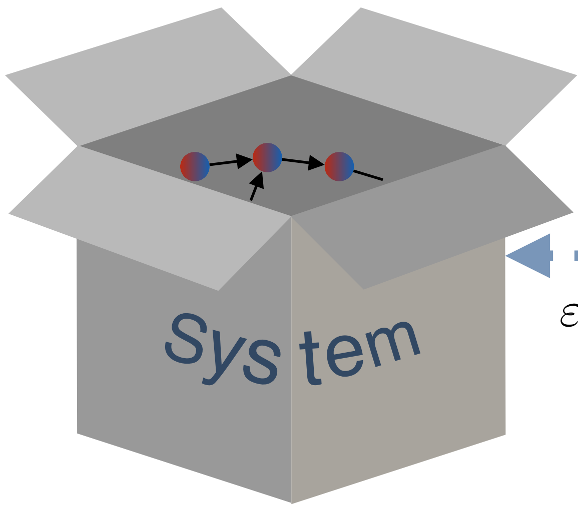

membership queries

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Learner

Learning algorithm

	ε
ε	0
a	0
b	0

coherent ✔

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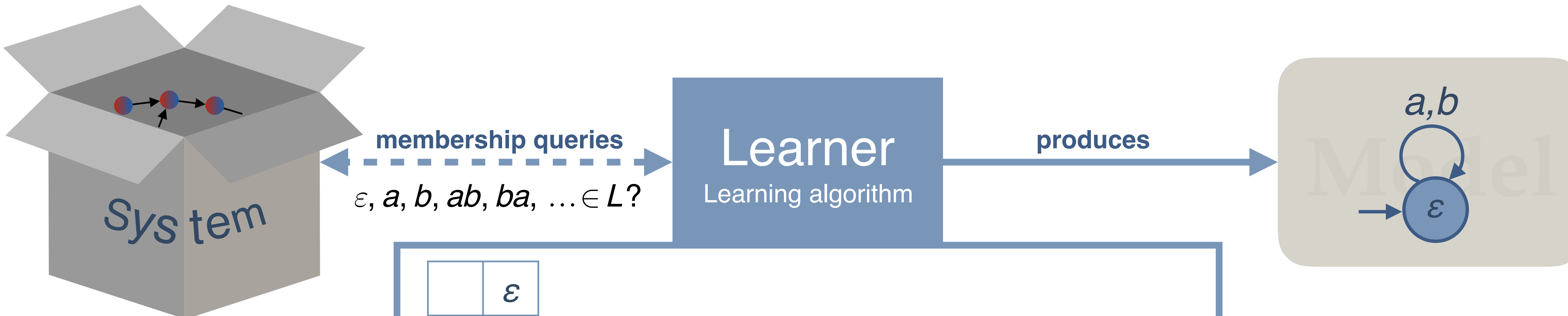

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	ε
ε	0
a	0
b	0

coherent ✔

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Angluin's L* Algorithm

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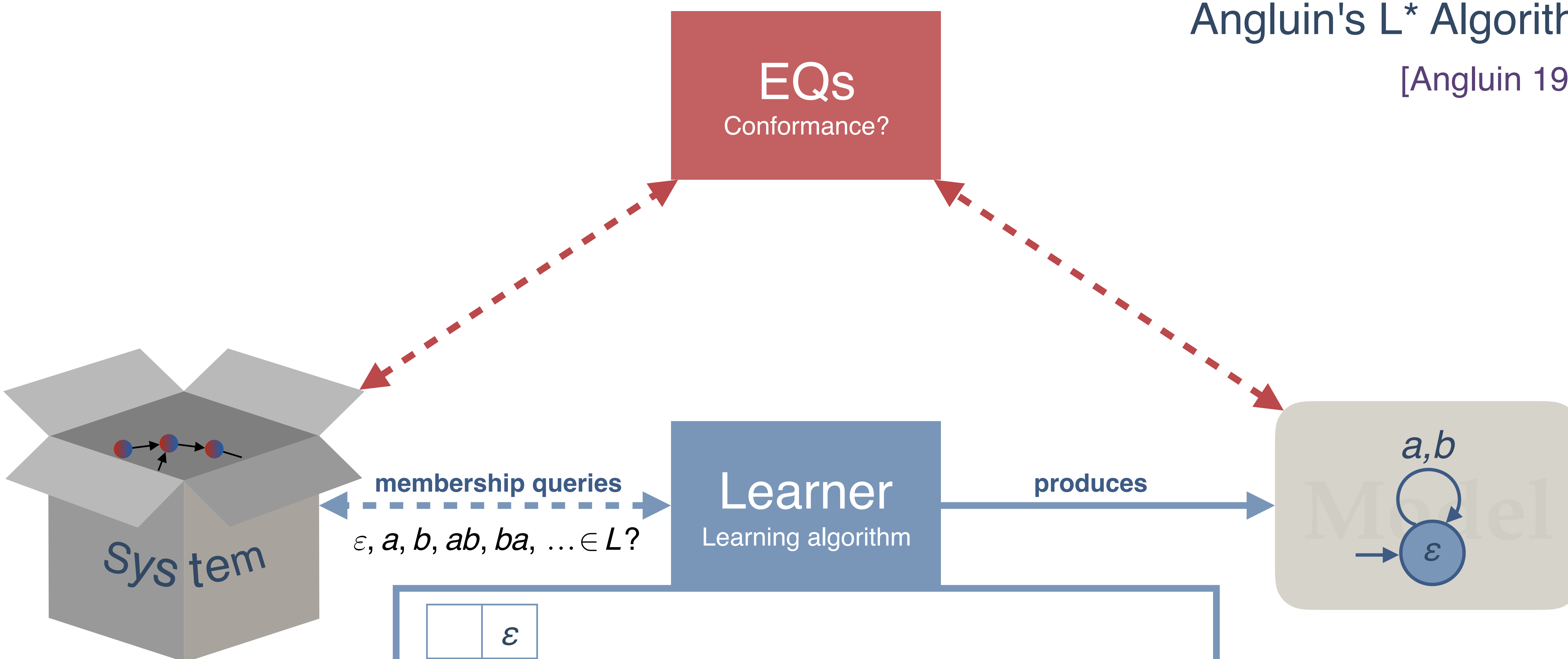

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coherent ✔

Angluin's L* Algorithm

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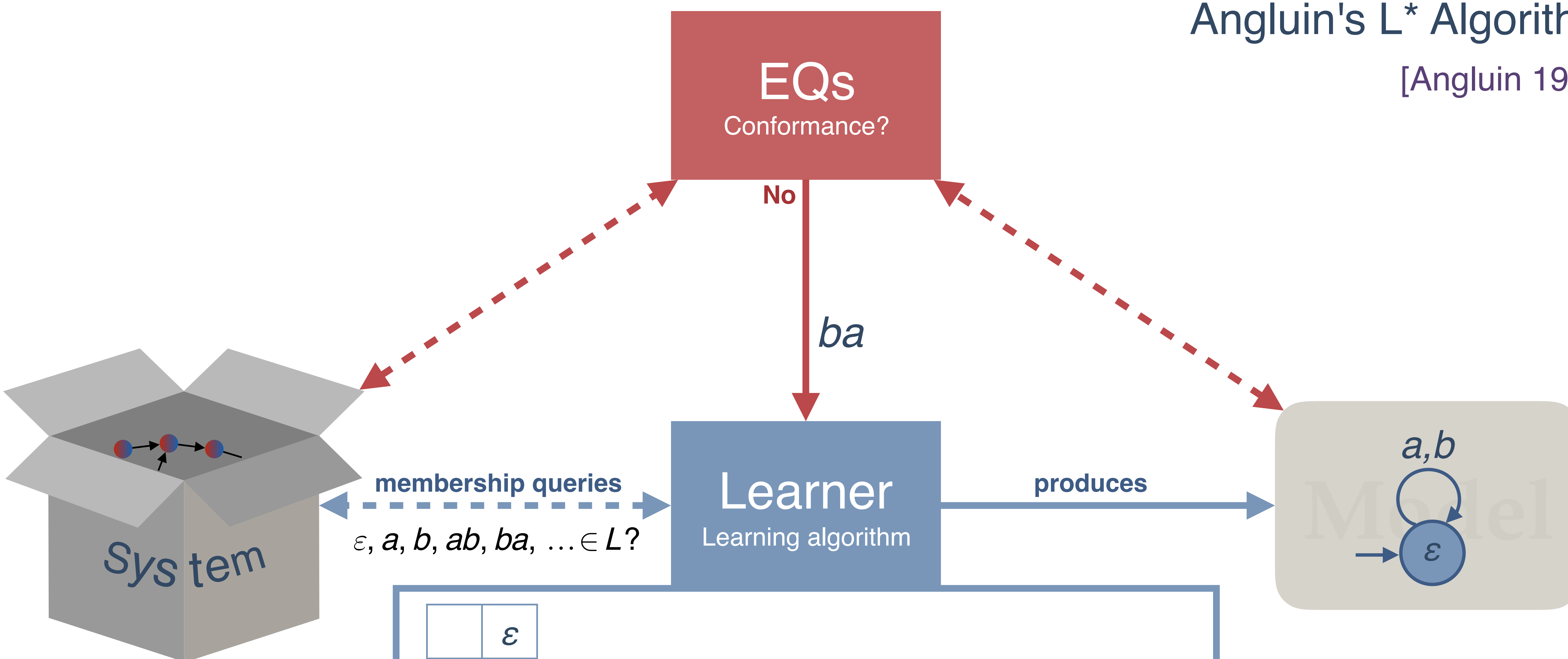

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coherent ✔

Angluin's L* Algorithm

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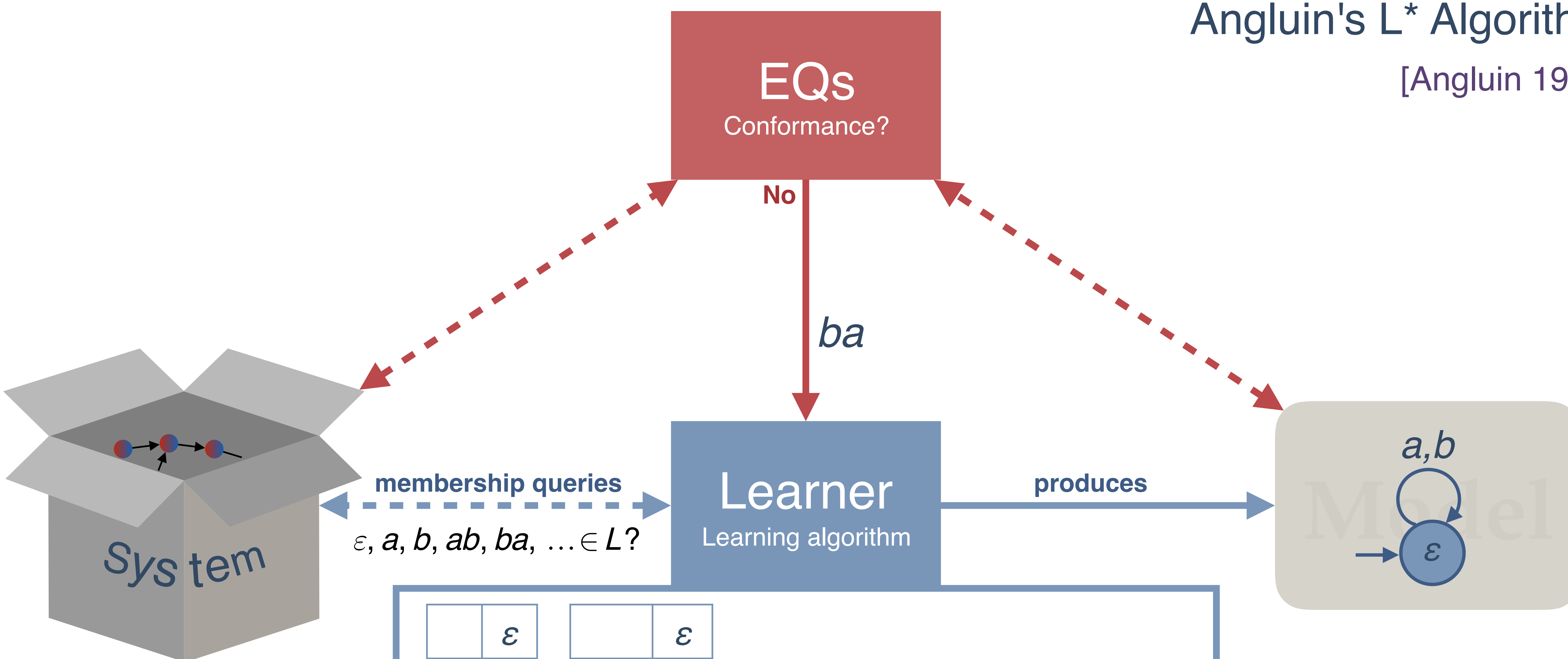

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$$f_L(w) = 1 \text{ iff } w \in L$$

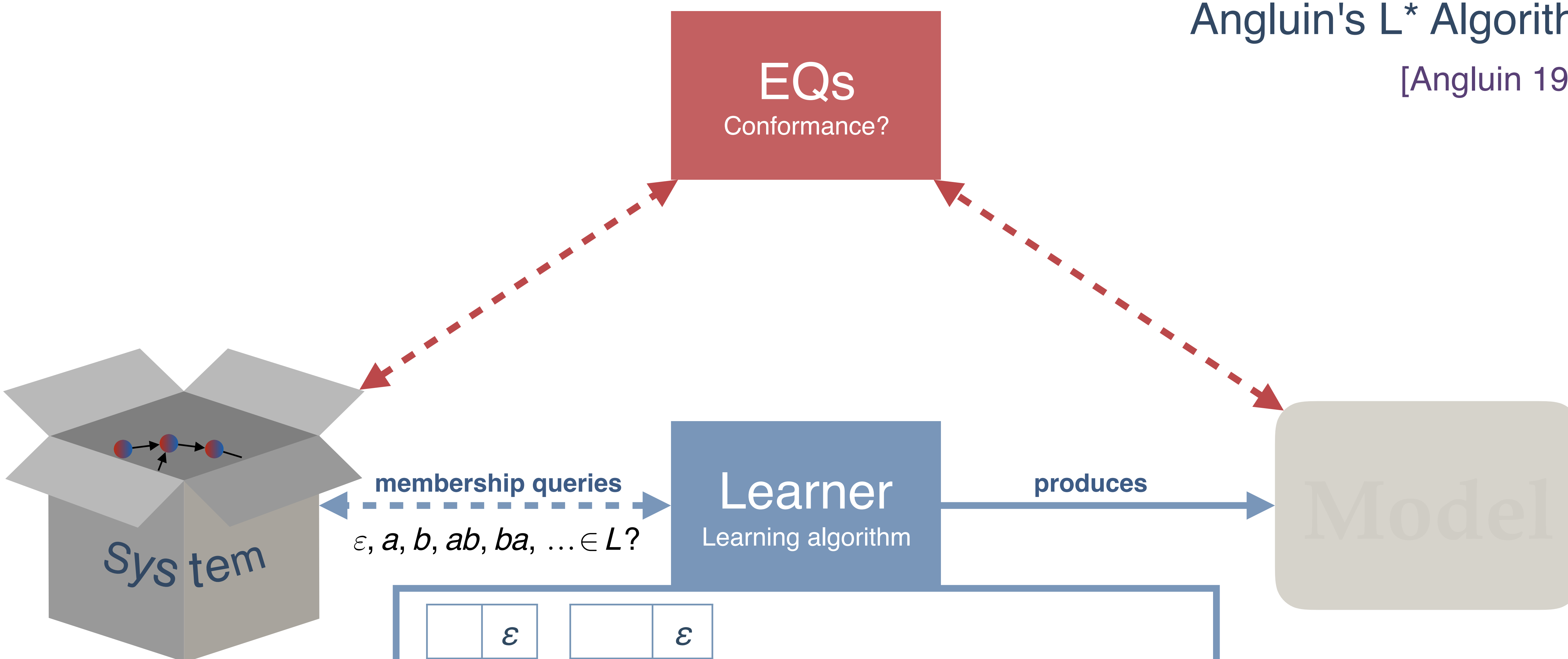
	ε
ε	0
a	0
b	0

coherent ✔

	ε
ε	0
b	0
ba	1
a	0
bb	1
baa	0
bab	0

Angluin's L* Algorithm

[Angluin 1987]



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	ε
ε	0
a	0
b	0

coherent ✔

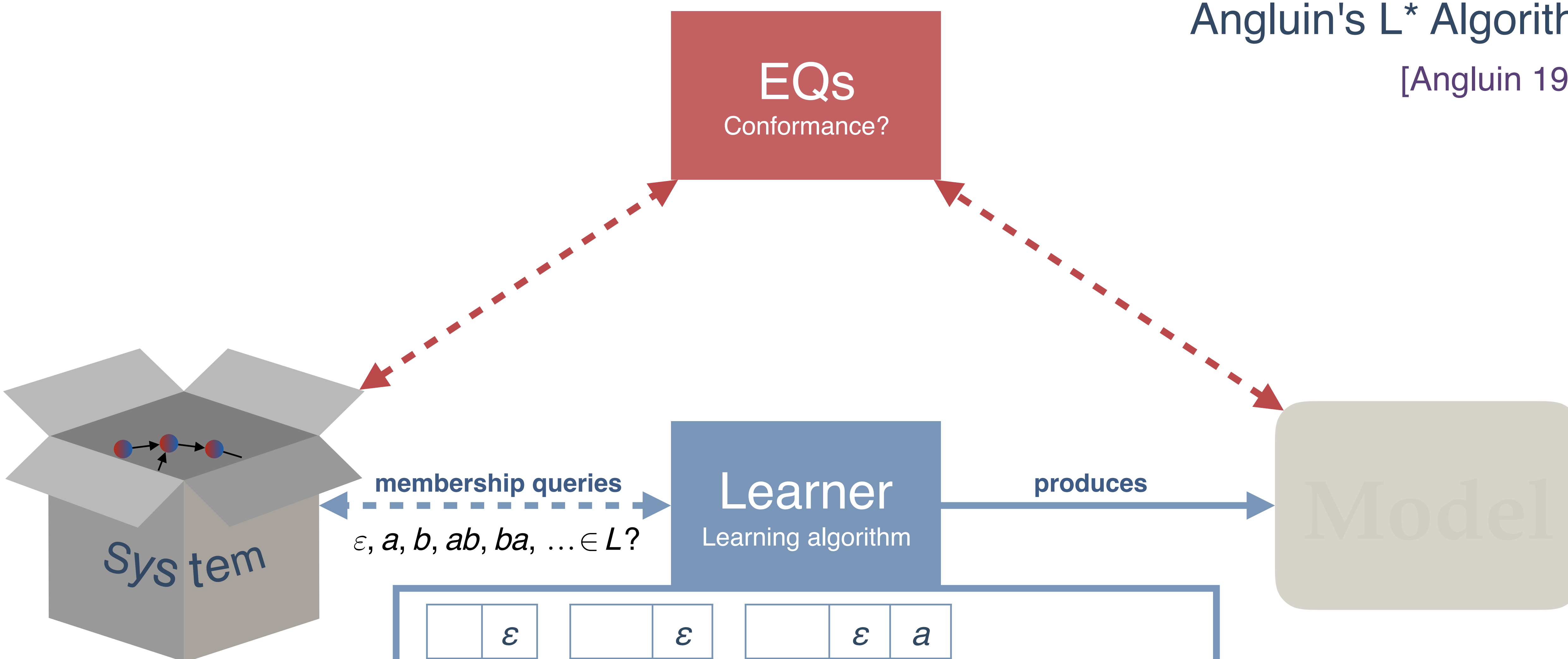
	ε
ε	0
b	0
ba	1
a	0
bb	1
baa	0
bab	0

consistent ✘

a a

Angluin's L* Algorithm

[Angluin 1987]



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	ε
ε	0
a	0
b	0

coherent ✔

	ε
ε	0
b	0
ba	1
a	0
bb	1
baa	0
bab	0

consistent ✘

	ε	a
ε	0	0
b	0	1
ba	1	0
a	0	0
bb	1	1
baa	0	0
bab	0	1

Angluin's L* Algorithm

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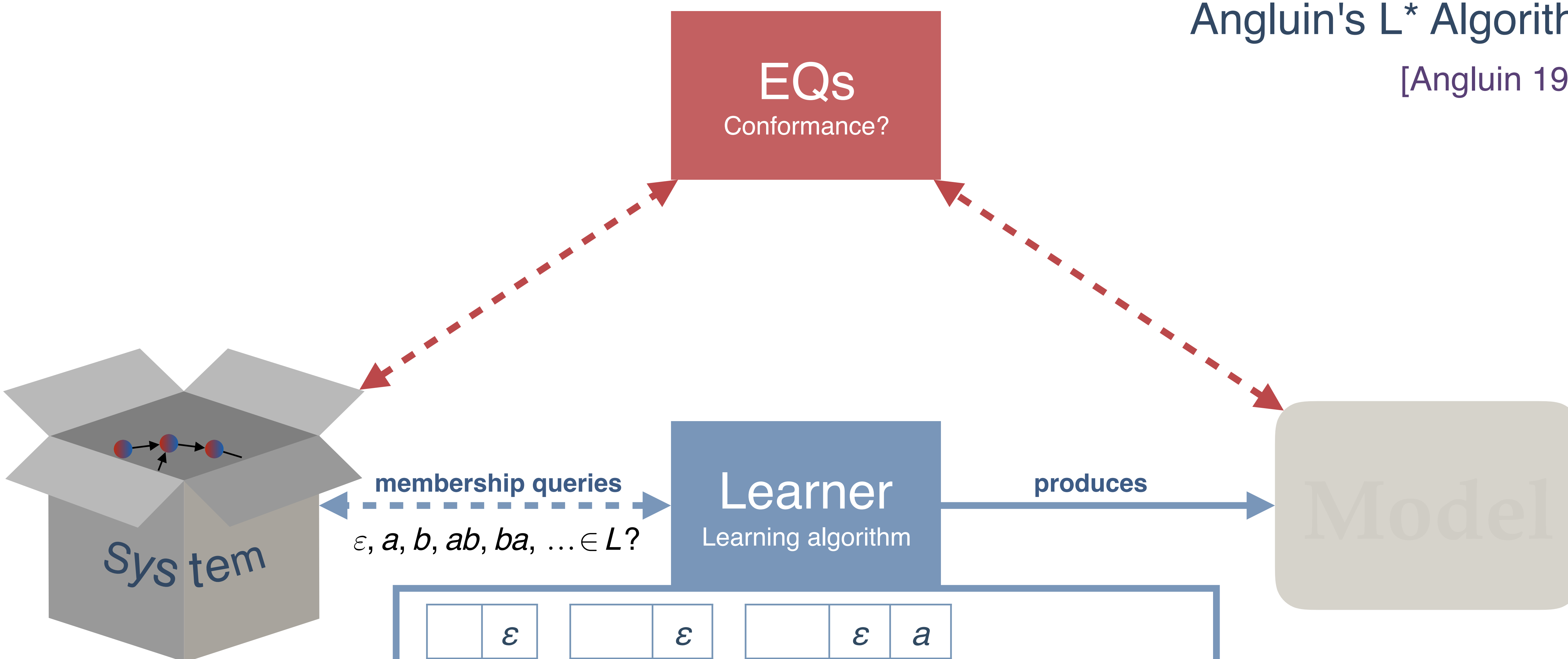

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$$f_L(w) = 1 \text{ iff } w \in L$$

	ε
ε	0
a	0
b	0

coherent ✔

	ε
ε	0
b	0
ba	1
a	0
bb	1
baa	0
bab	0

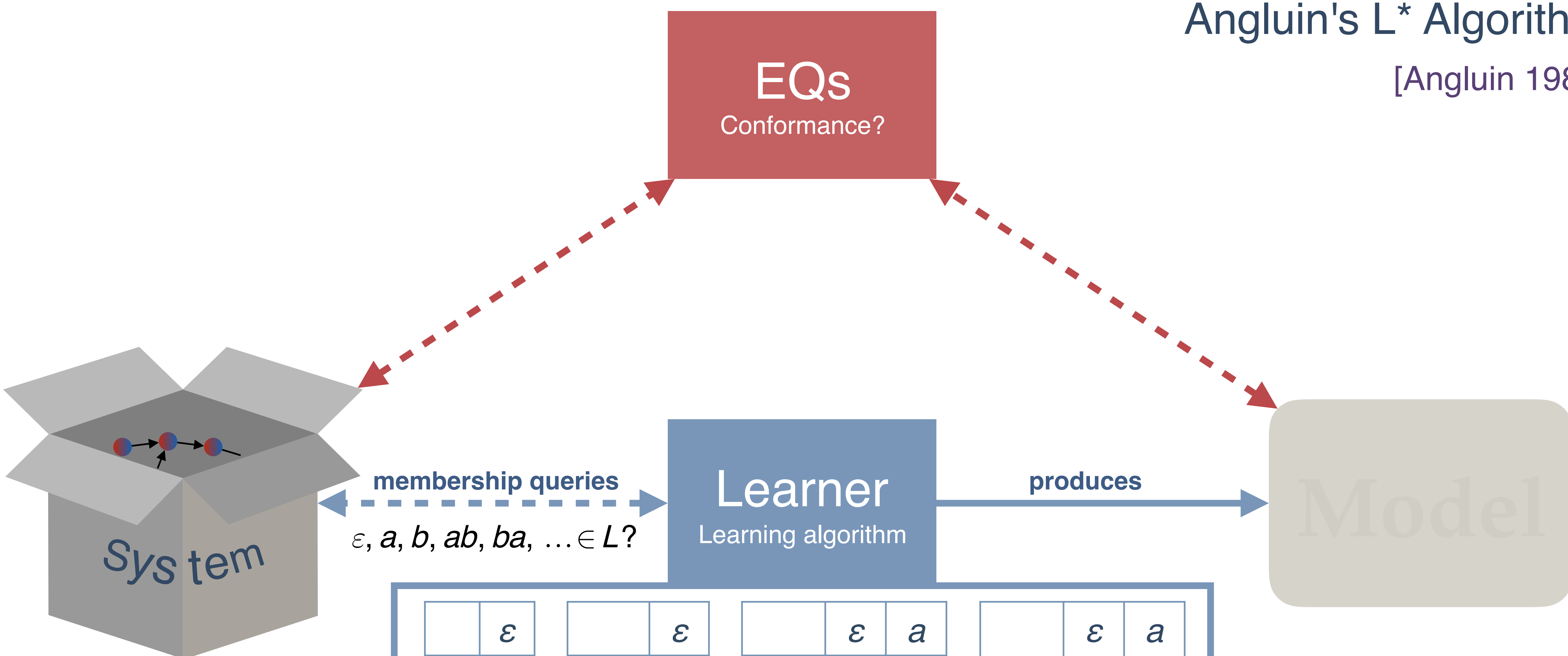
consistent ✘

	ε	a
ε	0	0
b	0	1
ba	1	0
a	0	0
bb	1	1
baa	0	0
bab	0	1

closed ✘

Angluin's L* Algorithm

[Angluin 1987]



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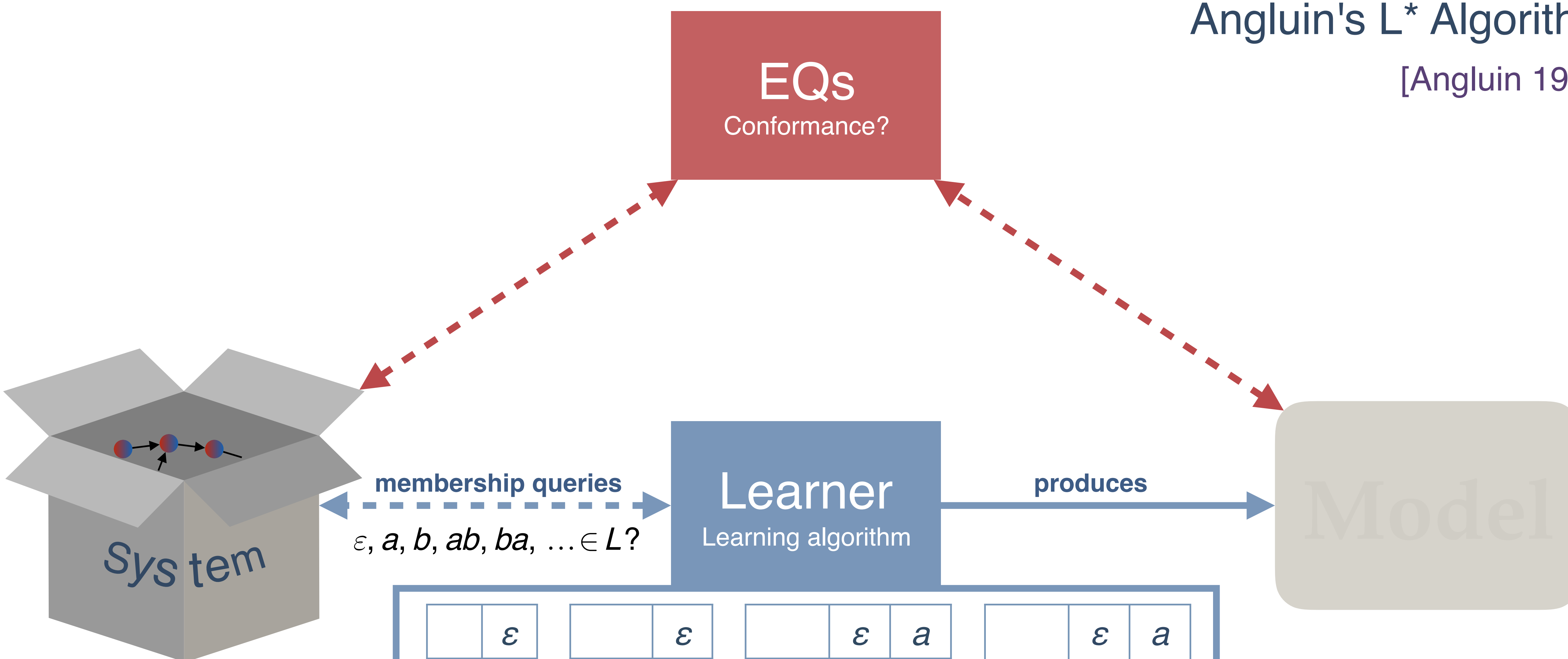

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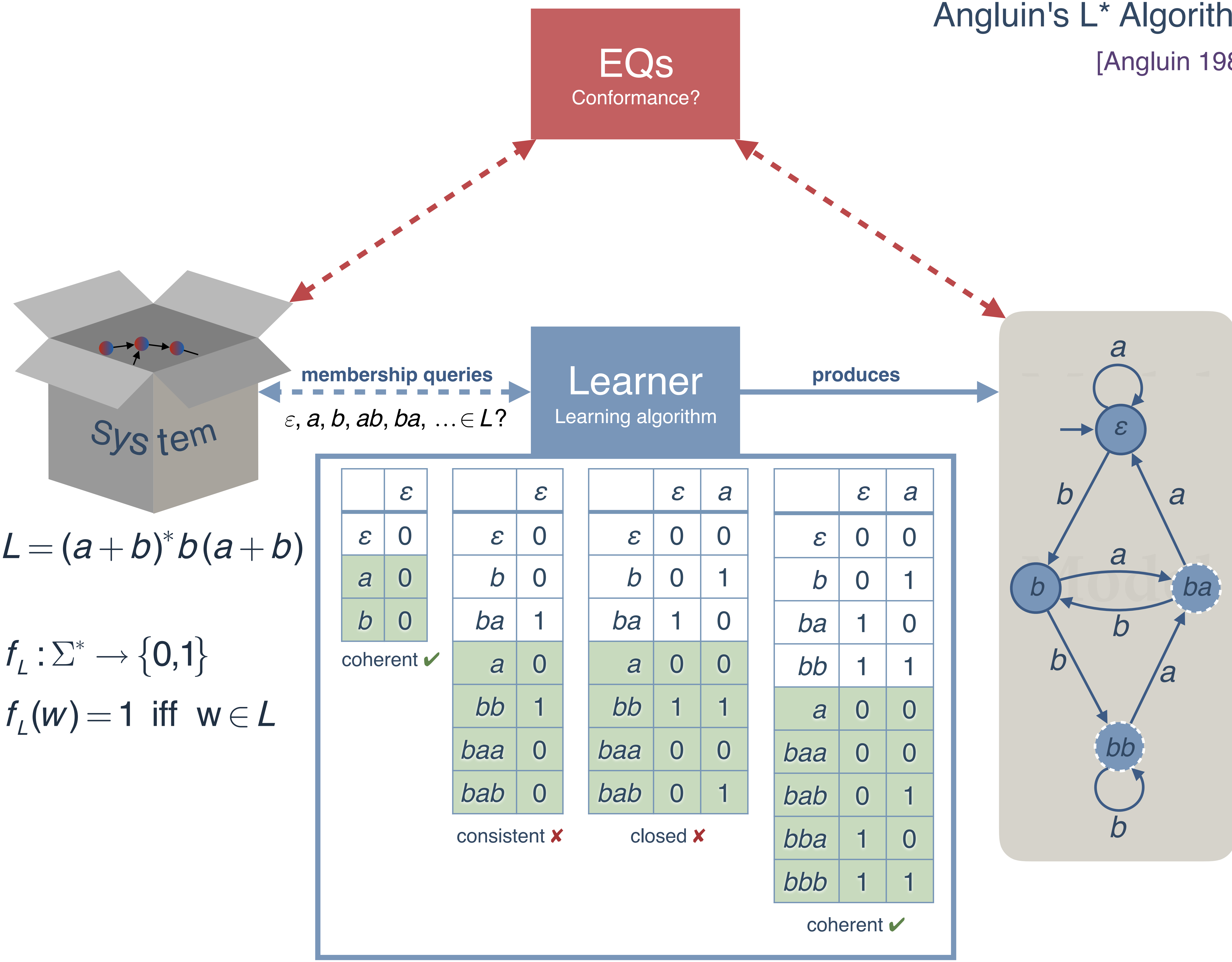

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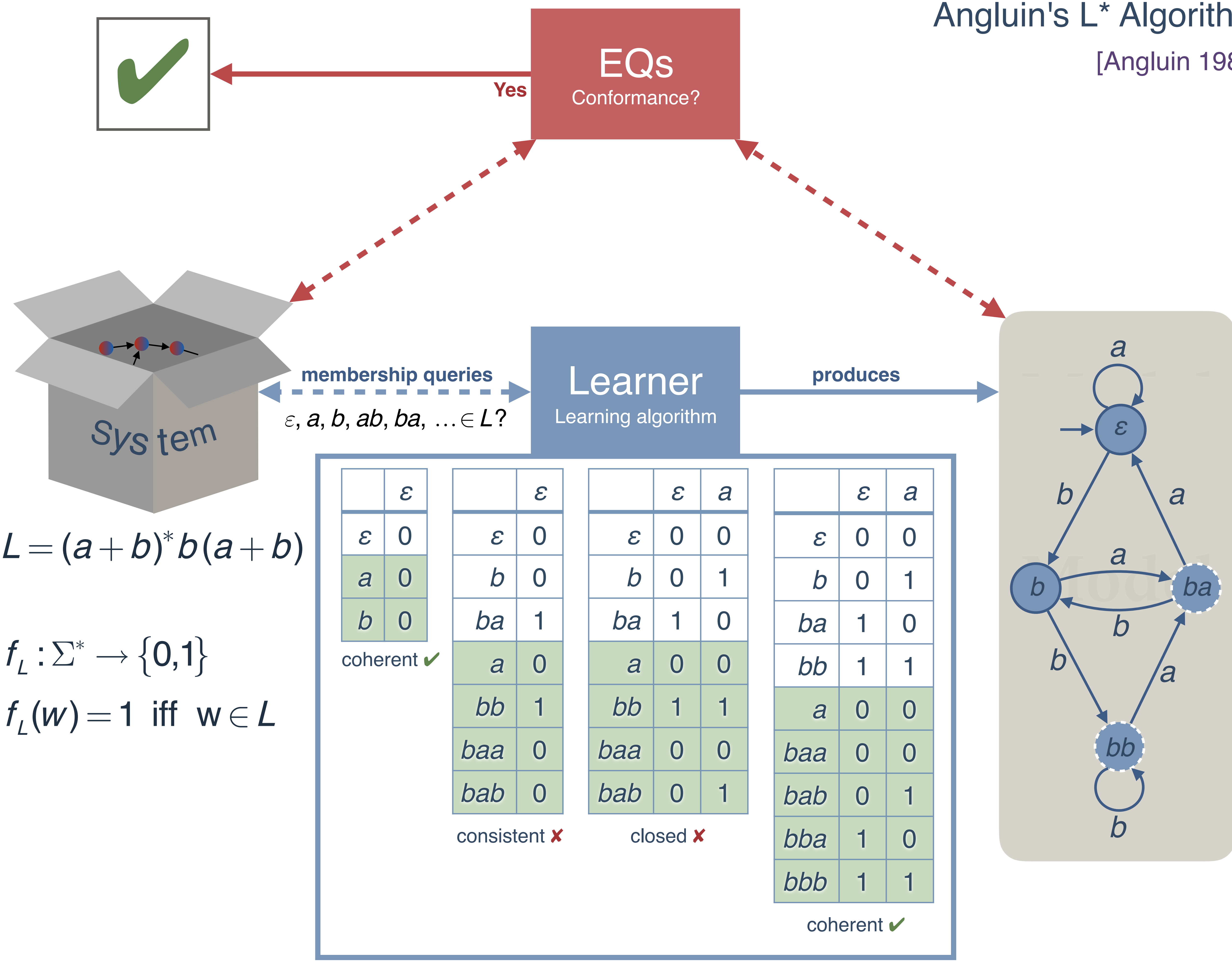

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Angluin's L* Algorithm

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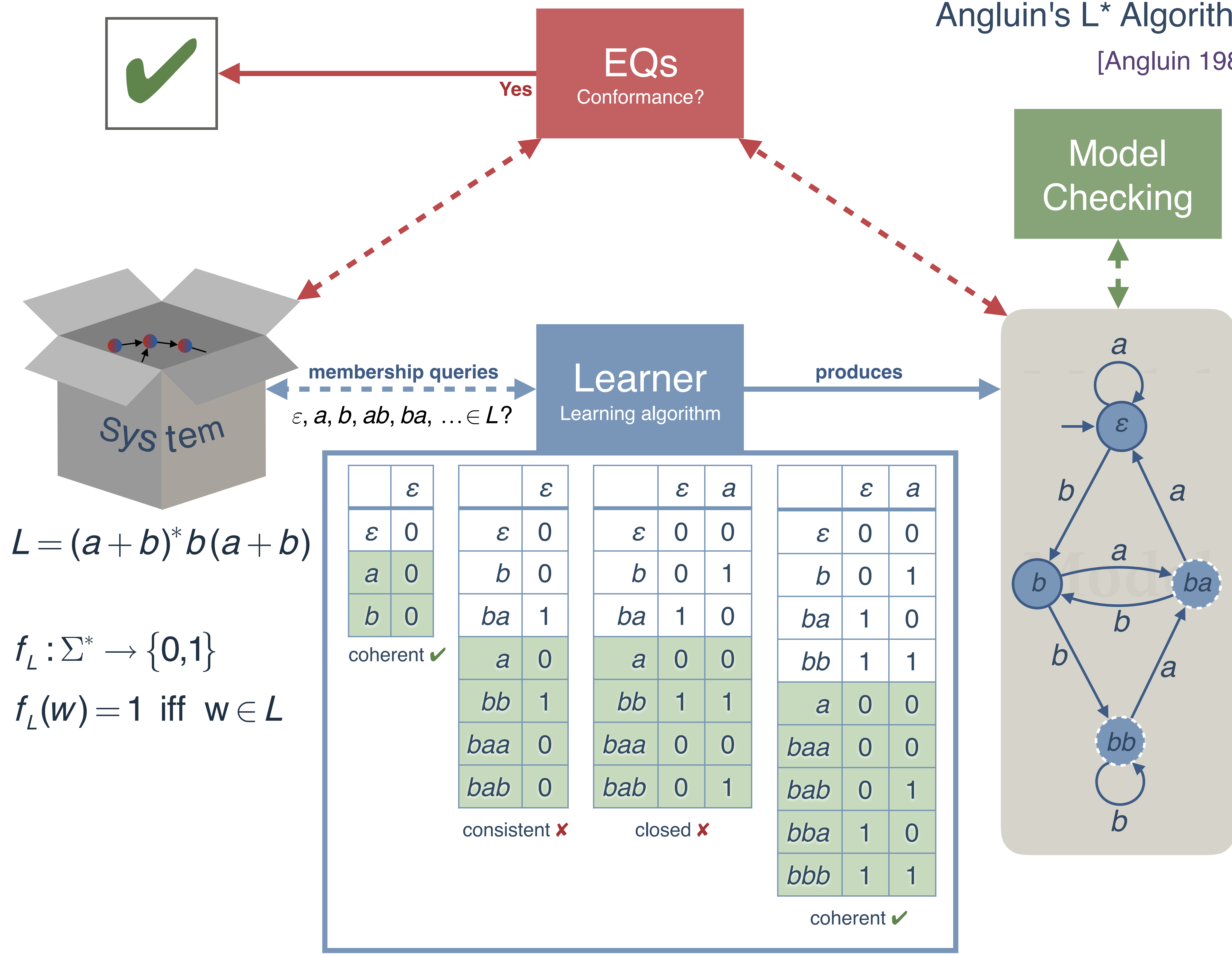

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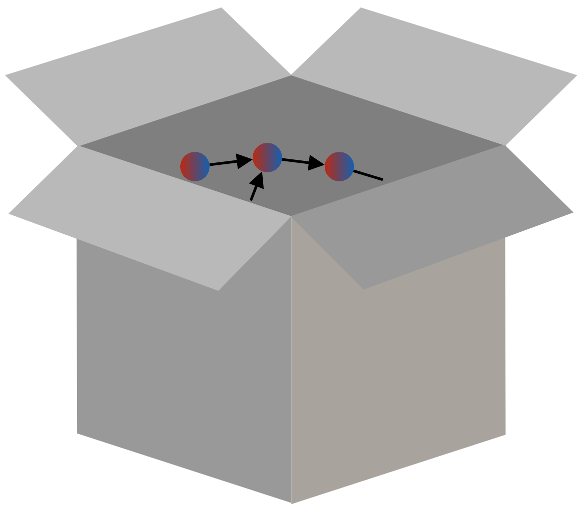
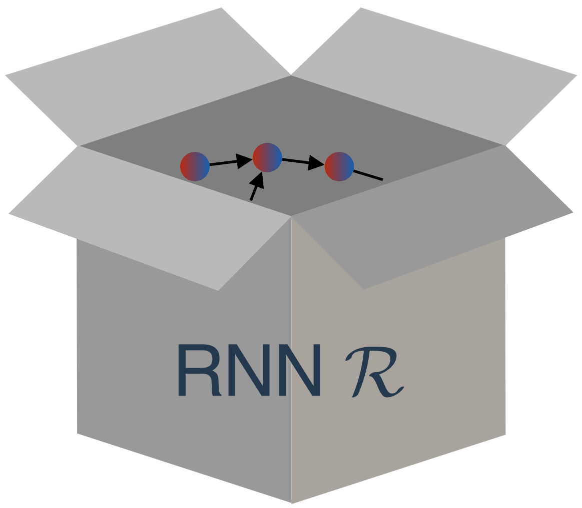


- legacy software
- code not open source
- third-party software
- embedded systems



- legacy software
- code not open source
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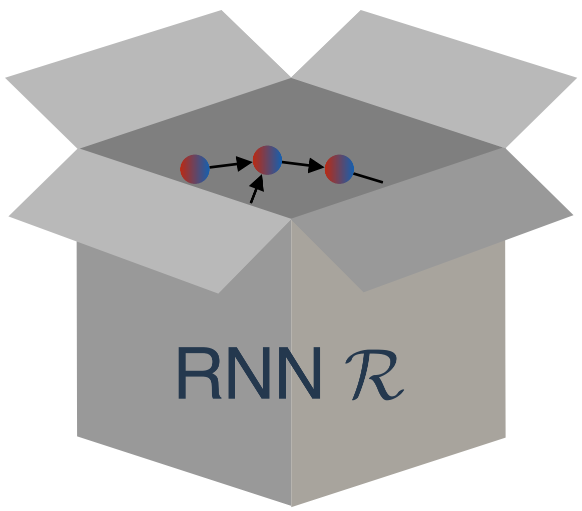
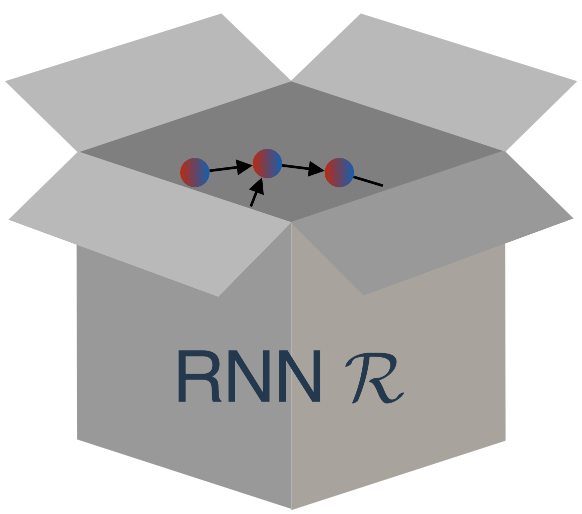
- recurrent neural networks (RNNs)

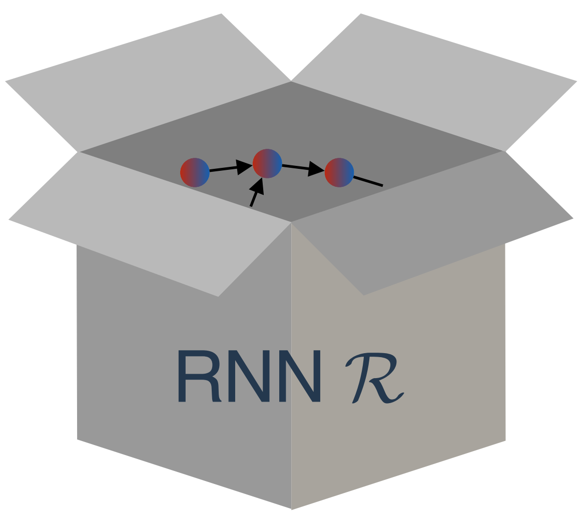


- legacy software
- code not open source
- third-party software
- embedded systems
- recurrent neural networks (RNNs)

(approach works for binary classifiers)



$$f : \underbrace{\mathbb{R}^k}_{\text{state}} \times \underbrace{\mathbb{R}^\ell}_{\text{input}} \longrightarrow \underbrace{\mathbb{R}^k}_{\text{state}}$$



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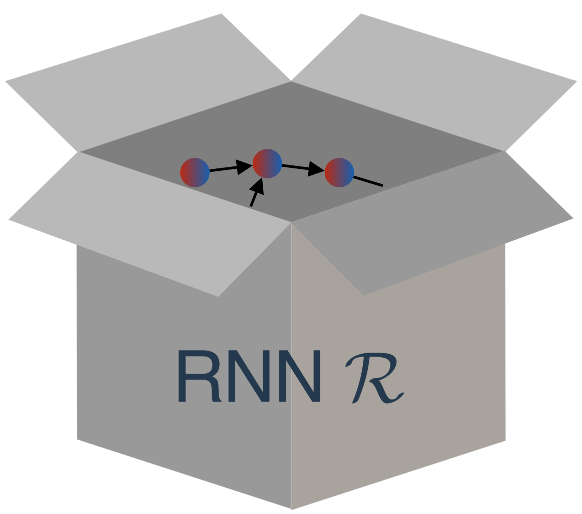

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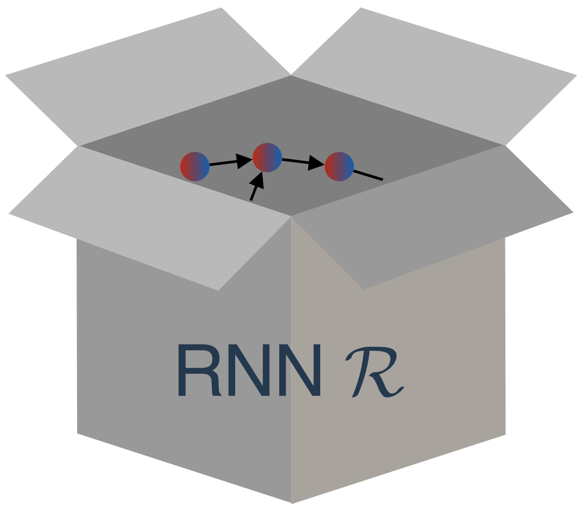

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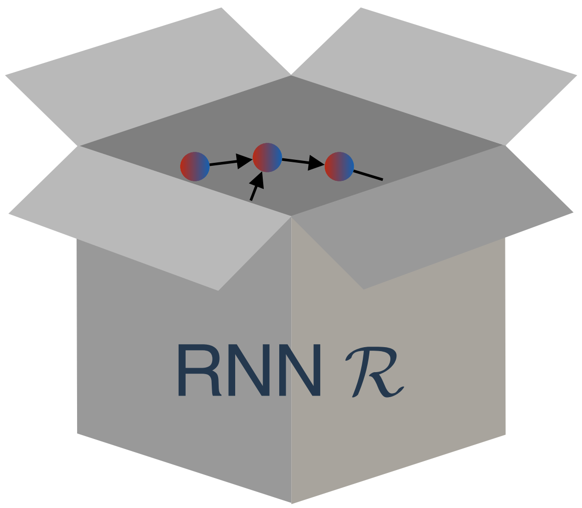

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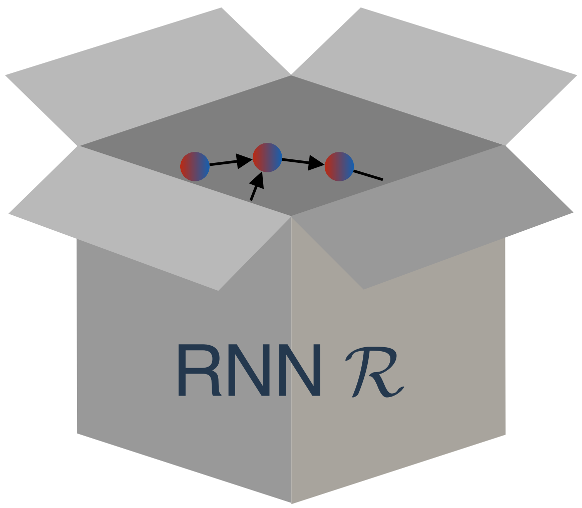
$\rightsquigarrow$ language acceptor

$$L(\mathcal{R}) = \{w \in \Sigma^* \mid g(f(init, w)) = 1\}$$

What does correctness for RNNs mean?



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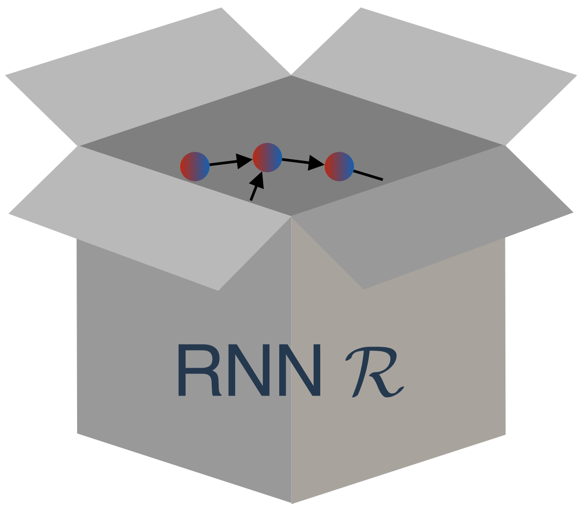
$$L(\mathcal{R}) = \{ w \in \Sigma^* \mid g(f(init, w)) = 1 \}$$

What does correctness for RNNs mean?

Specify correctness using finite automata $\mathcal{E}$ over Σ



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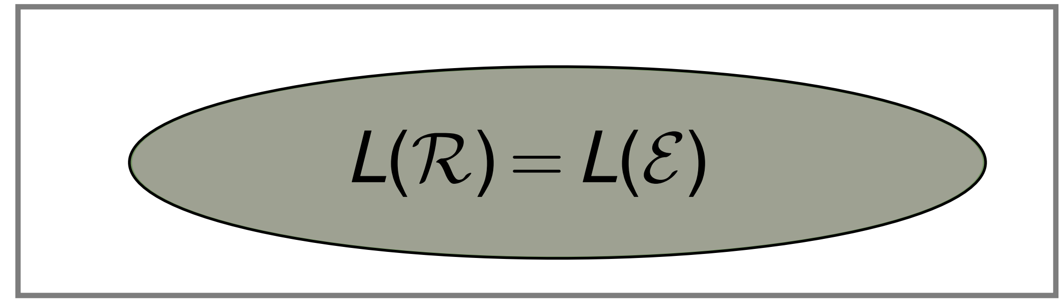
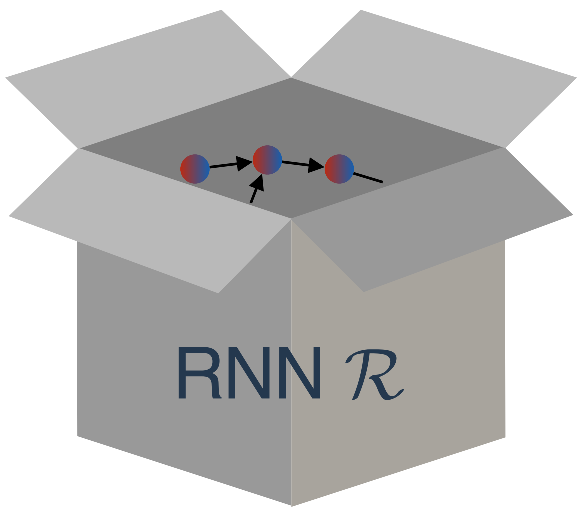
$$L(\mathcal{R}) = \{ w \in \Sigma^* \mid g(f(init, w)) = 1 \}$$

What does correctness for RNNs mean?

Specify correctness using finite automata $\mathcal{E}$ over Σ

$$L(\mathcal{R}) = L(\mathcal{E})$$





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$\rightsquigarrow$ language acceptor

$$L(\mathcal{R}) = \{ w \in \Sigma^* \mid g(f(init, w)) = 1 \}$$

What does correctness for RNNs mean?

Specify correctness using finite automata $\mathcal{E}$ over Σ

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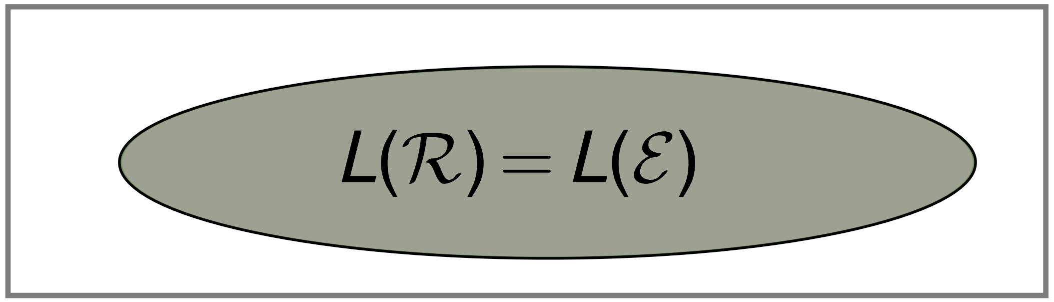
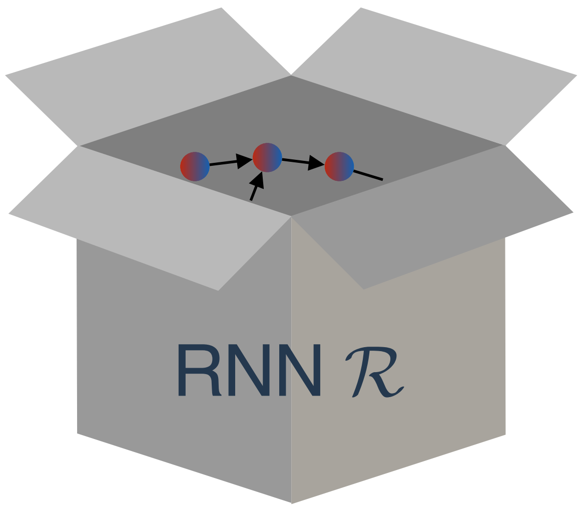


$\rightsquigarrow$ $L(\mathcal{R})$ is a regular language



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$\rightsquigarrow$ language acceptor

$$L(\mathcal{R}) = \{ w \in \Sigma^* \mid g(f(init, w)) = 1 \}$$

What does correctness for RNNs mean?

Specify correctness using finite automata $\mathcal{E}$ over Σ

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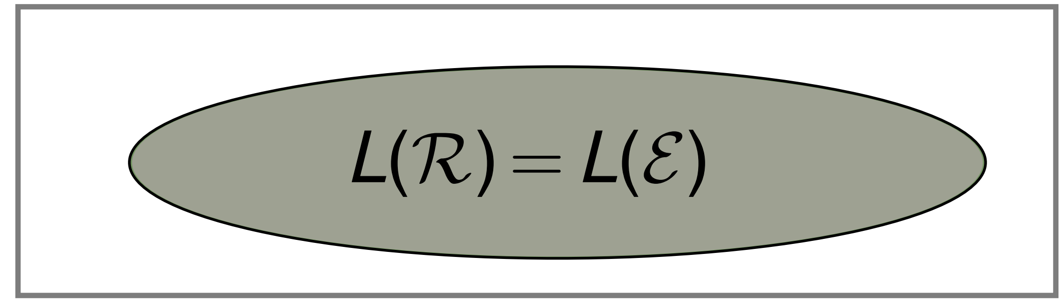
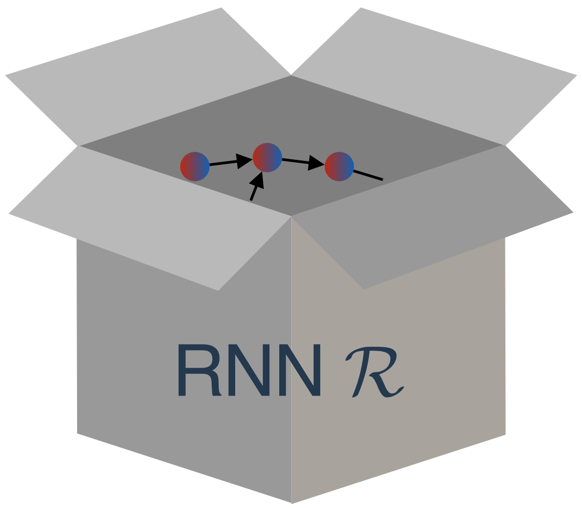


$\rightsquigarrow$ $L(\mathcal{R})$ is a regular language

restrictive: how about RNNs recognizing XML documents?



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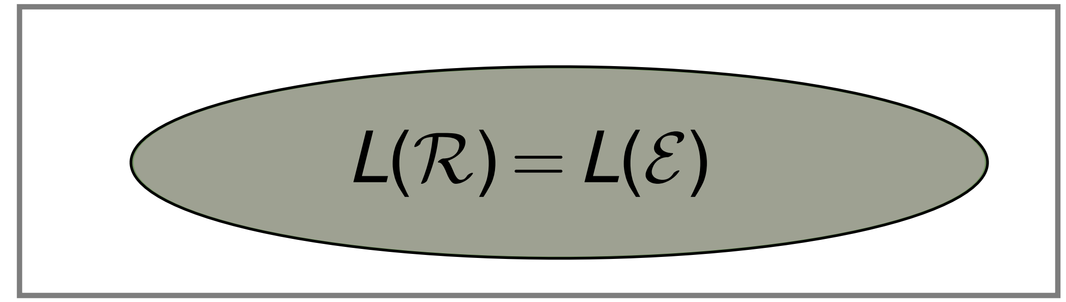
$\rightsquigarrow$ language acceptor

$$L(\mathcal{R}) = \left\{ w \in \Sigma^* \mid g(f(init, w)) = 1 \right\}$$

What does correctness for RNNs mean?

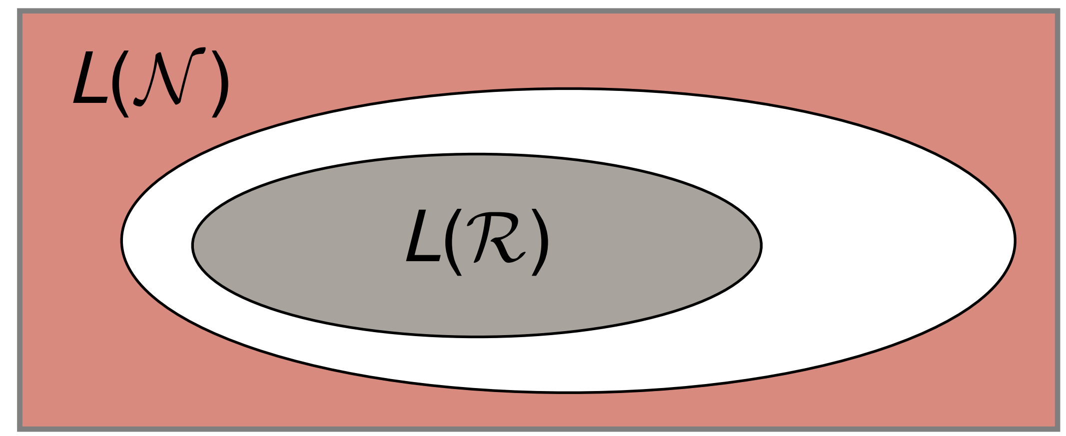
Specify correctness using finite automata $\mathcal{E}$, $\mathcal{N}$ over Σ

$L(\mathcal{R}) = L(\mathcal{E})$



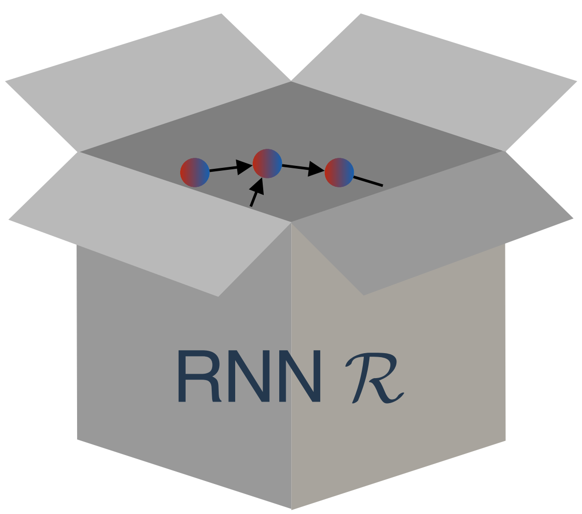
$\leadsto$ $L(\mathcal{R})$ is a regular language

restrictive: how about RNNs recognizing XML documents?



each $w \in L(\mathcal{N})$ must be classified as negative

$\mathcal{R}$ does not produce false positives



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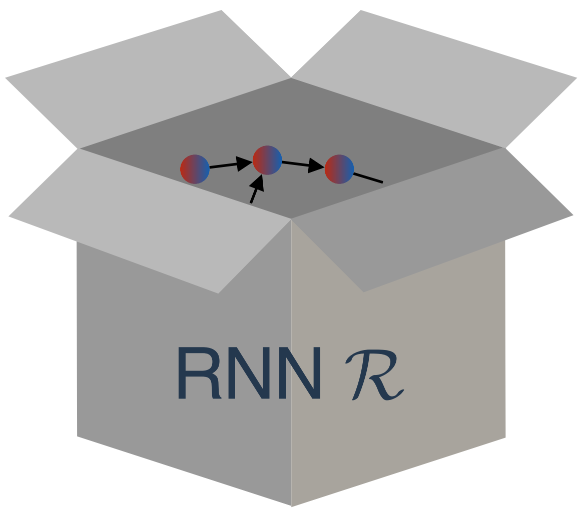
$\leadsto$ language acceptor

$$L(\mathcal{R}) = \{w \in \Sigma^* \mid g(f(init, w)) = 1\}$$

What does correctness for RNNs mean?

Specify correctness using finite automata $\mathcal{E}, \mathcal{N}$ over Σ



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$\rightsquigarrow$ language acceptor

$$L(\mathcal{R}) = \{w \in \Sigma^* \mid g(f(init, w)) = 1\}$$

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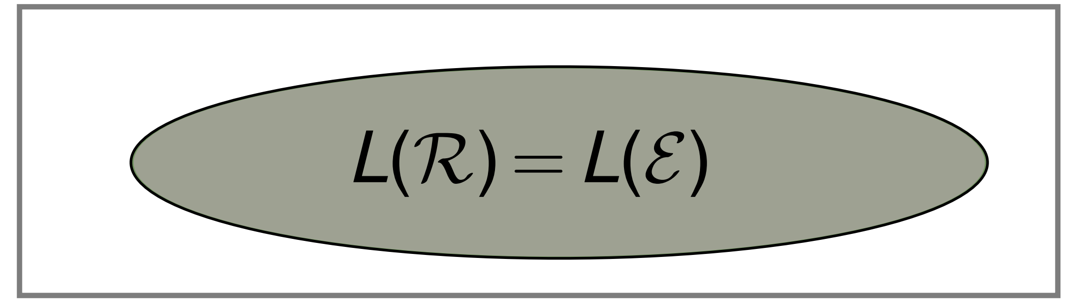
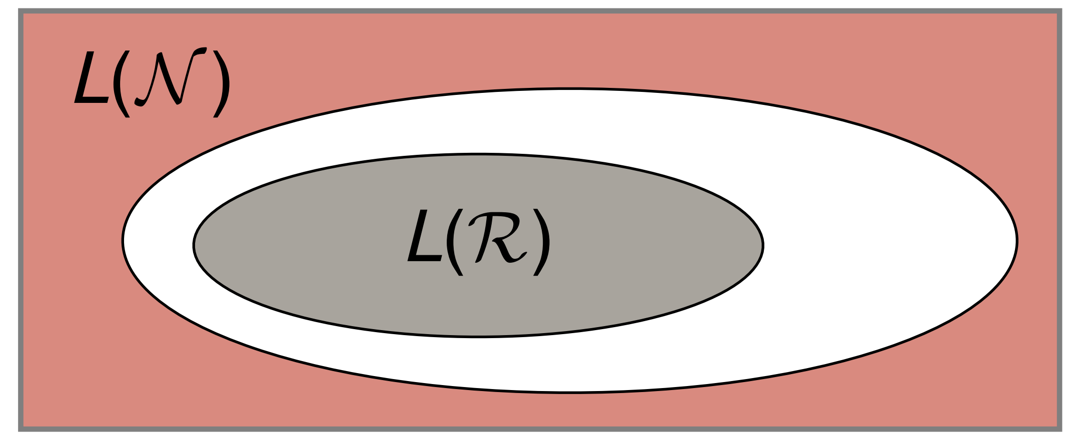


$\rightsquigarrow$ $L(\mathcal{R})$ is a regular language

restrictive: how about RNNs recognizing XML documents?

complement

$$L(\mathcal{R}) \subseteq L(\overline{\mathcal{N}})$$

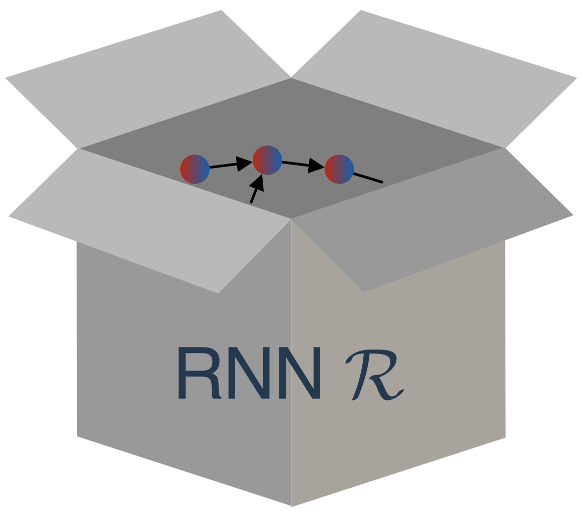


each $w \in L(\mathcal{N})$ must be classified as negative

$\mathcal{R}$ does not produce false positives

What does correctness for RNNs mean?

Specify correctness using finite automata $\mathcal{E}, \mathcal{N}, \mathcal{P}$ over Σ



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$\rightsquigarrow$ language acceptor

$$L(\mathcal{R}) = \{ w \in \Sigma^* \mid g(f(init, w)) = 1 \}$$

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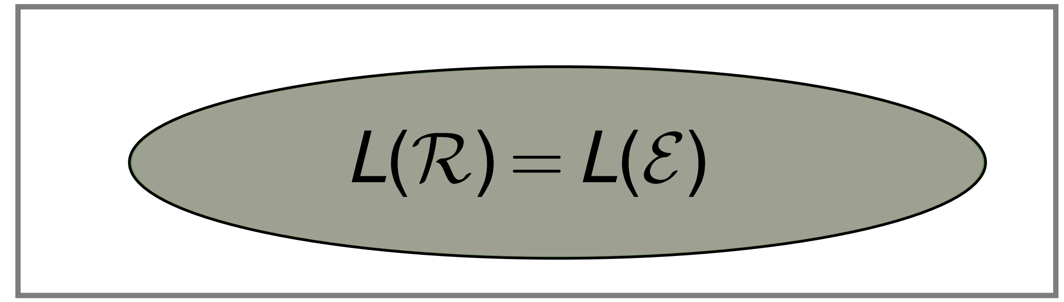

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restrictive: how about RNNs recognizing XML documents?

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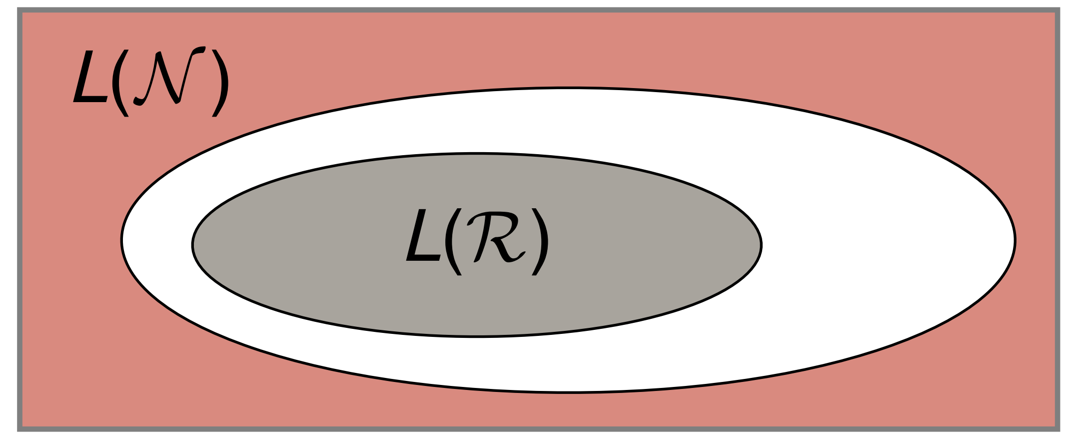
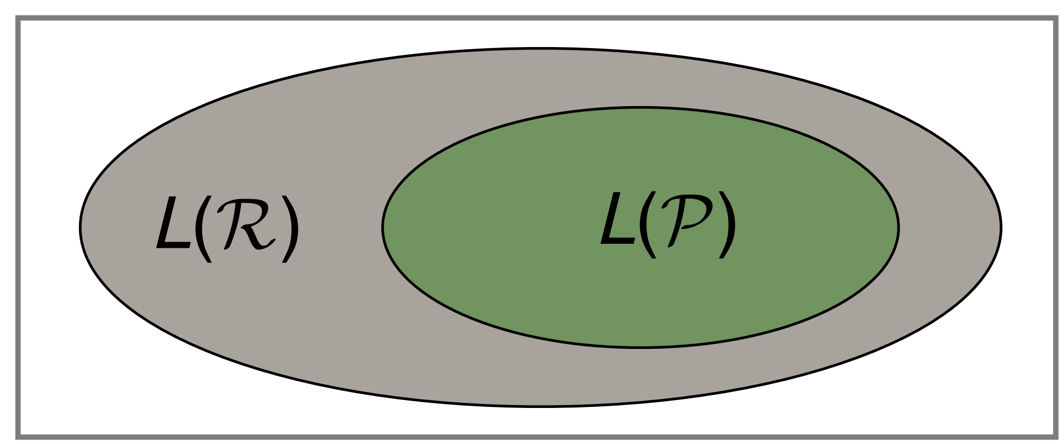


each $w \in L(\mathcal{N})$ must be classified as negative

$\mathcal{R}$ does not produce false positives

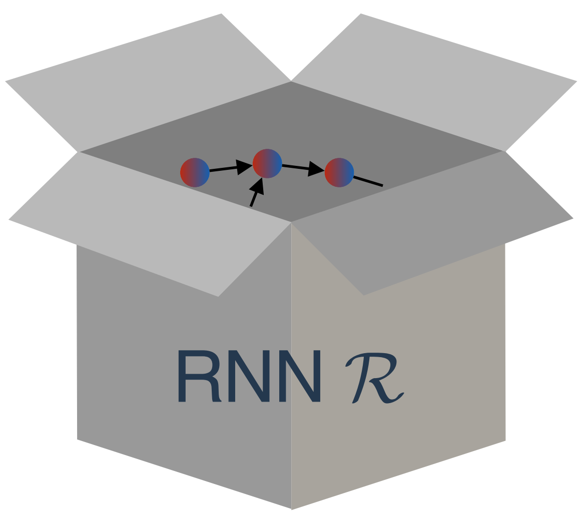


each $w \in L(\mathcal{P})$ must be classified as positive

$\mathcal{R}$ does not produce false negatives

What does correctness for RNNs mean?

Specify correctness using finite automata $\mathcal{E}, \mathcal{N}, \mathcal{P}$ over Σ



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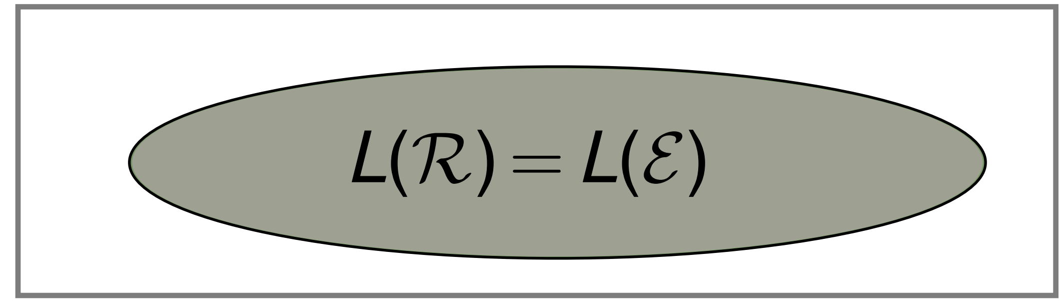
$$g : \underbrace{\mathbb{R}^k}_{\text{state}} \to \{0,1\}$$

$\rightsquigarrow$ language acceptor

$$L(\mathcal{R}) = \{w \in \Sigma^* \mid g(f(init, w)) = 1\}$$

$L(\mathcal{R}) = L(\mathcal{E})$

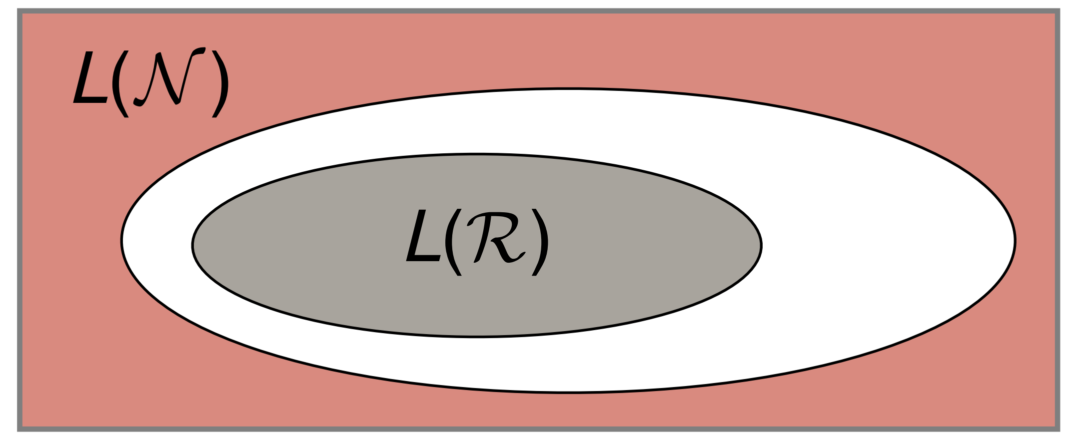


$\rightsquigarrow$ $L(\mathcal{R})$ is a regular language

restrictive: how about RNNs recognizing XML documents?

complement

$L(\mathcal{R}) \subseteq L(\overline{\mathcal{N}})$

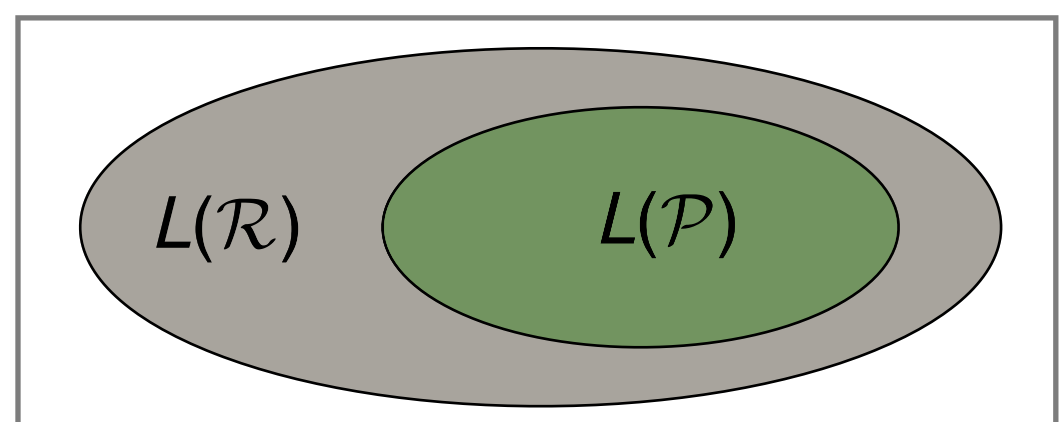


each $w \in L(\mathcal{N})$ must be classified as negative

$\mathcal{R}$ does not produce false positives

$L(\overline{\mathcal{R}}) \subseteq L(\overline{\mathcal{P}})$

complement

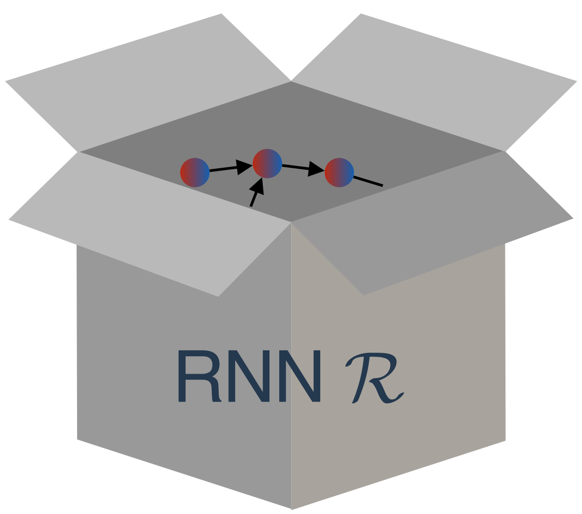


each $w \in L(\mathcal{P})$ must be classified as positive

$\mathcal{R}$ does not produce false negatives

What does correctness for RNNs mean?

Specify correctness using finite automata $\mathcal{E}, \mathcal{N}, \mathcal{P}$ over Σ



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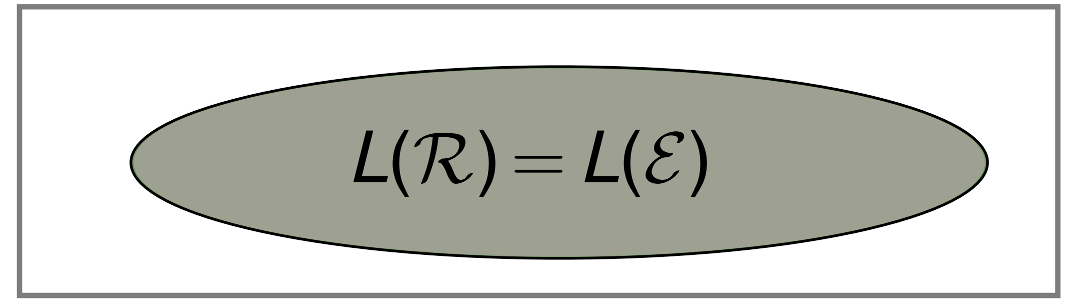
$\rightsquigarrow$ language acceptor

$$L(\mathcal{R}) = \{ w \in \Sigma^* \mid g(f(init, w)) = 1 \}$$

$L(\mathcal{R}) = L(\mathcal{E})$

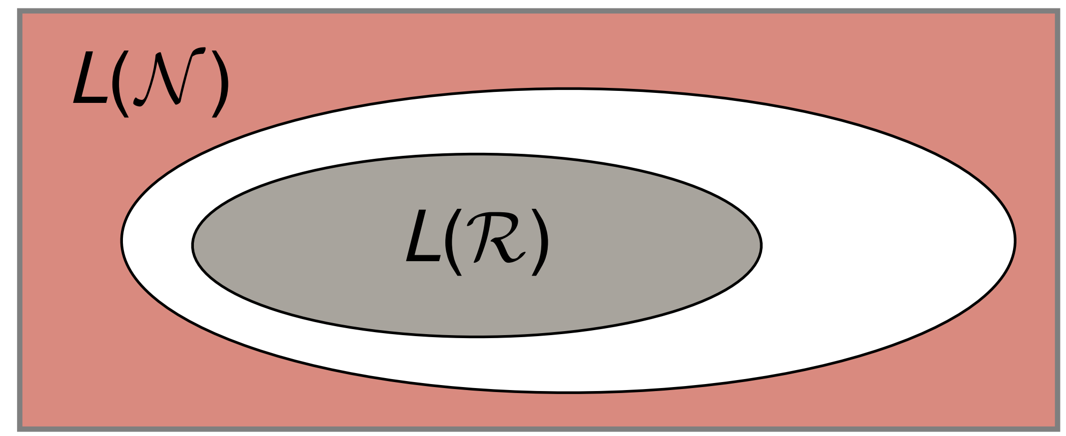


$\rightsquigarrow$ $L(\mathcal{R})$ is a regular language

restrictive: how about RNNs recognizing XML documents?

complement

$L(\mathcal{R}) \subseteq L(\overline{\mathcal{N}})$

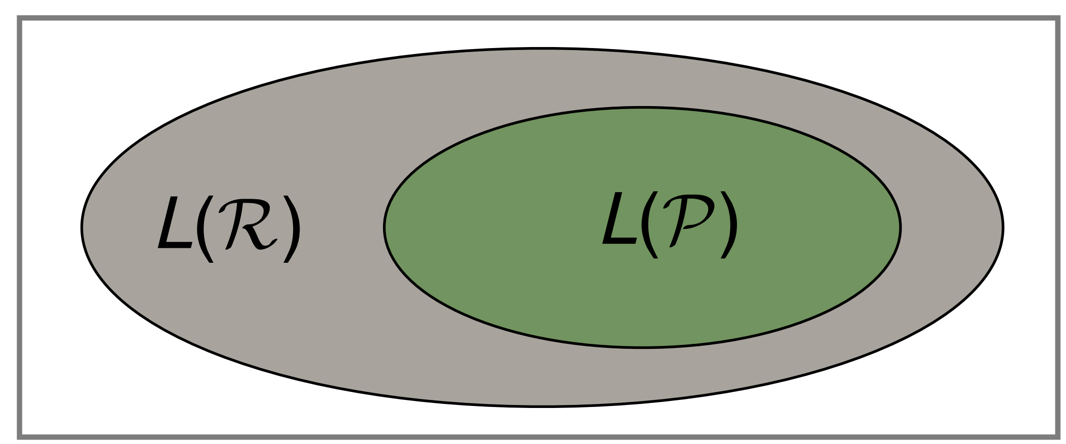


each $w \in L(\mathcal{N})$ must be classified as negative

$\mathcal{R}$ does not produce false positives

inclusion checking

$L(\overline{\mathcal{R}}) \subseteq L(\overline{\mathcal{P}})$



complement

each $w \in L(\mathcal{P})$ must be classified as positive

$\mathcal{R}$ does not produce false negatives

Assume $\mathcal{R}$ is supposed to recognize XML documents over

$$\Sigma = \left\{ \text{<list>, </list>, <item>, </item>} \right\}.$$

```
<list>
    <item>
        <list>
            <item>
            </item>
            <item>
            </item>
        </list>
    </item>
    <item>
    </item>
</list>
```

<list>
<item>
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</item>
</list>

Assume $\mathcal{R}$ is supposed to recognize XML documents over

$$\Sigma = \{ \text{<list>}, \text{</list>}, \text{<item>}, \text{</item>} \}.$$

Regular negative specification $\mathcal{N}$:

<list>
<item>
<list>
<item>
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</list>

Assume $\mathcal{R}$ is supposed to recognize XML documents over

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Regular negative specification $\mathcal{N}$:

"there is an opening tag that is not eventually followed by a corresponding closing tag"

```
<list>
    <item>
        <list>
            <item>
            </item>
            <item>
            </item>
        </list>
    </item>
    <item>
    </item>
</list>
```

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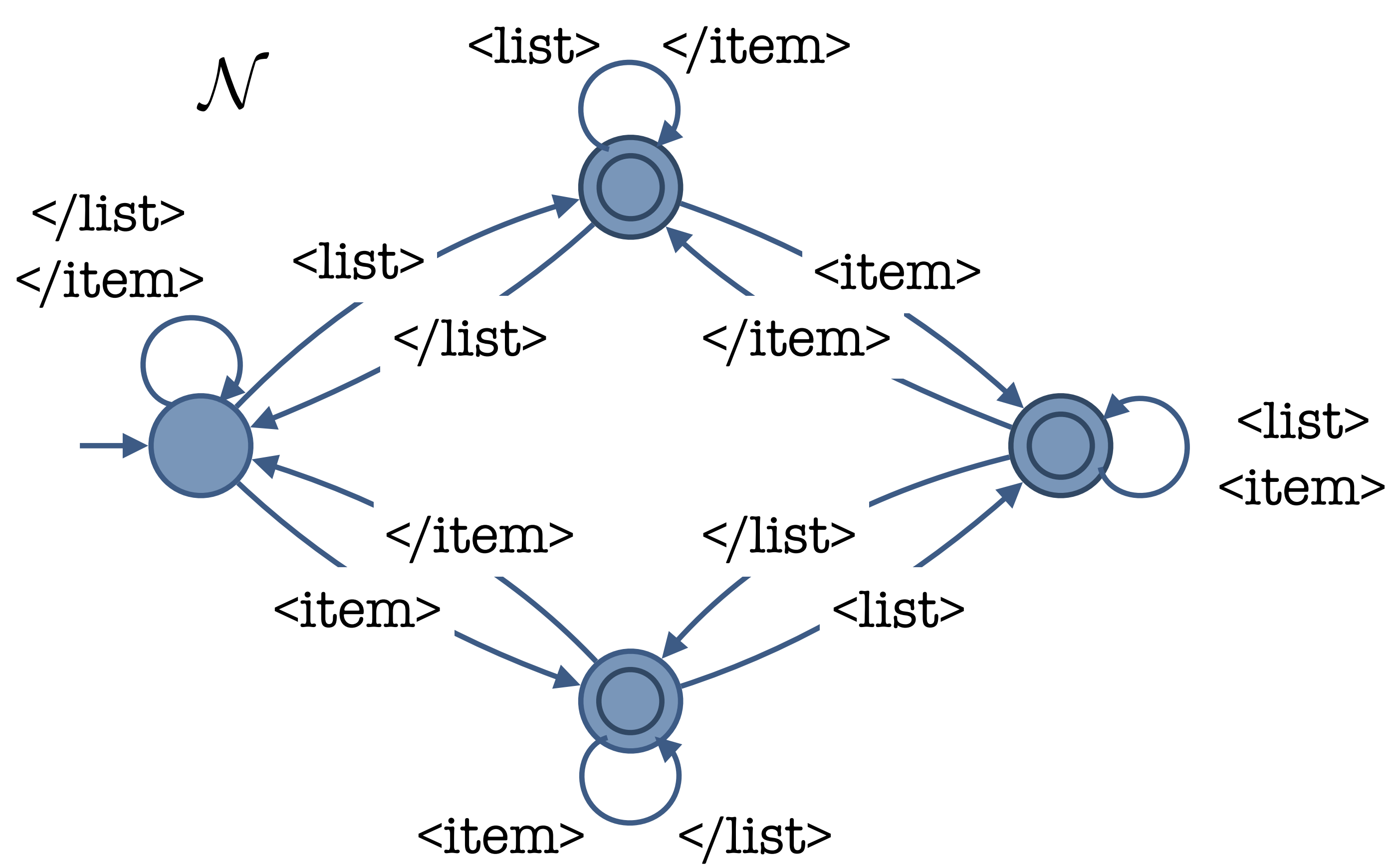

```
<list>
    <item>
        <list>
            <item>
            </item>
            <item>
            </item>
        </list>
    </item>
    <item>
    </item>
</list>
```

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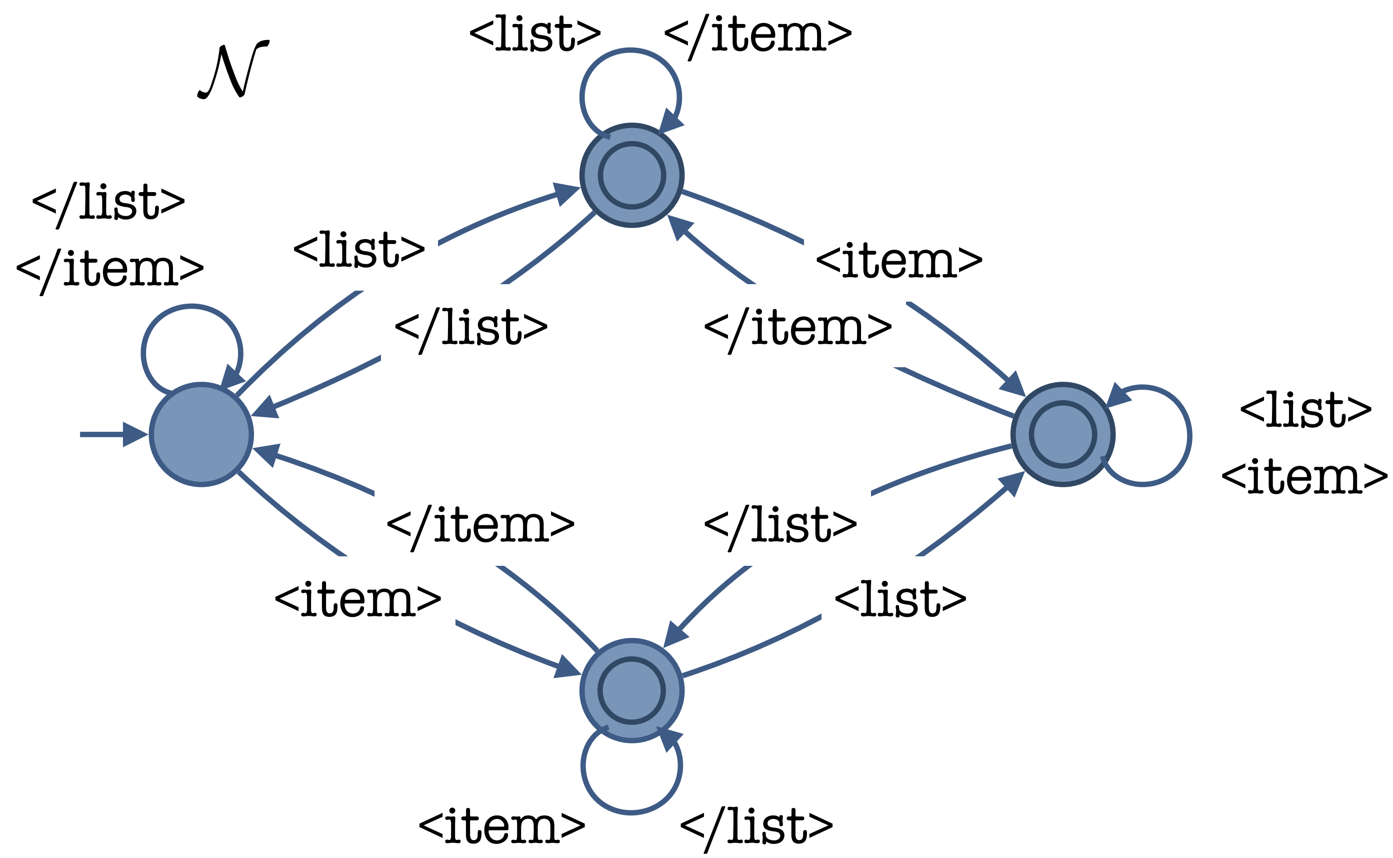

<list> <item> </item> <item> </list> $\in L(\mathcal{N})$

```
<list>
    <item>
        <list>
            <item>
            </item>
            <item>
            </item>
        </list>
    </item>
    <item>
    </item>
</list>
```

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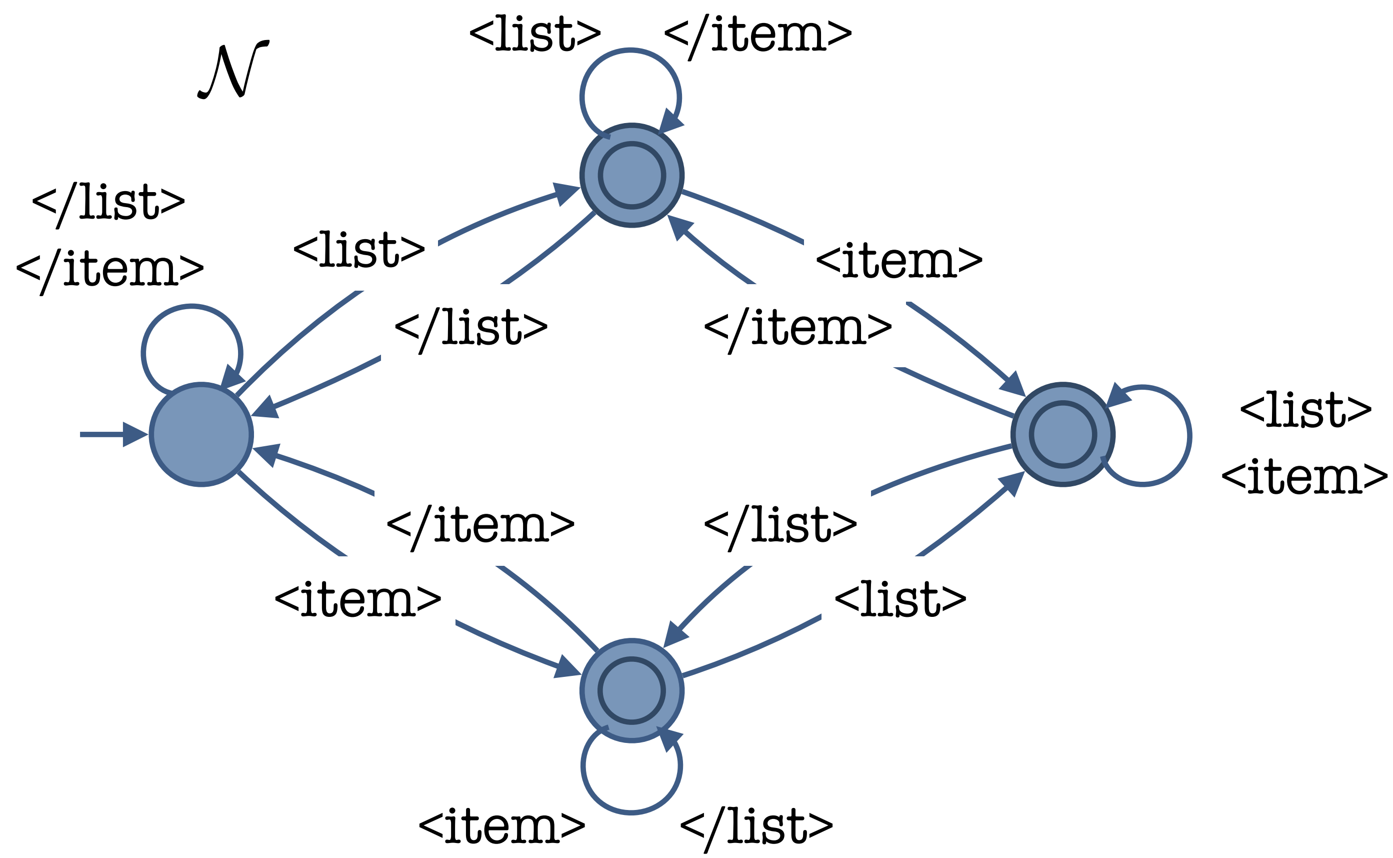

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```
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            </item>
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    <item>
    </item>
</list>
```

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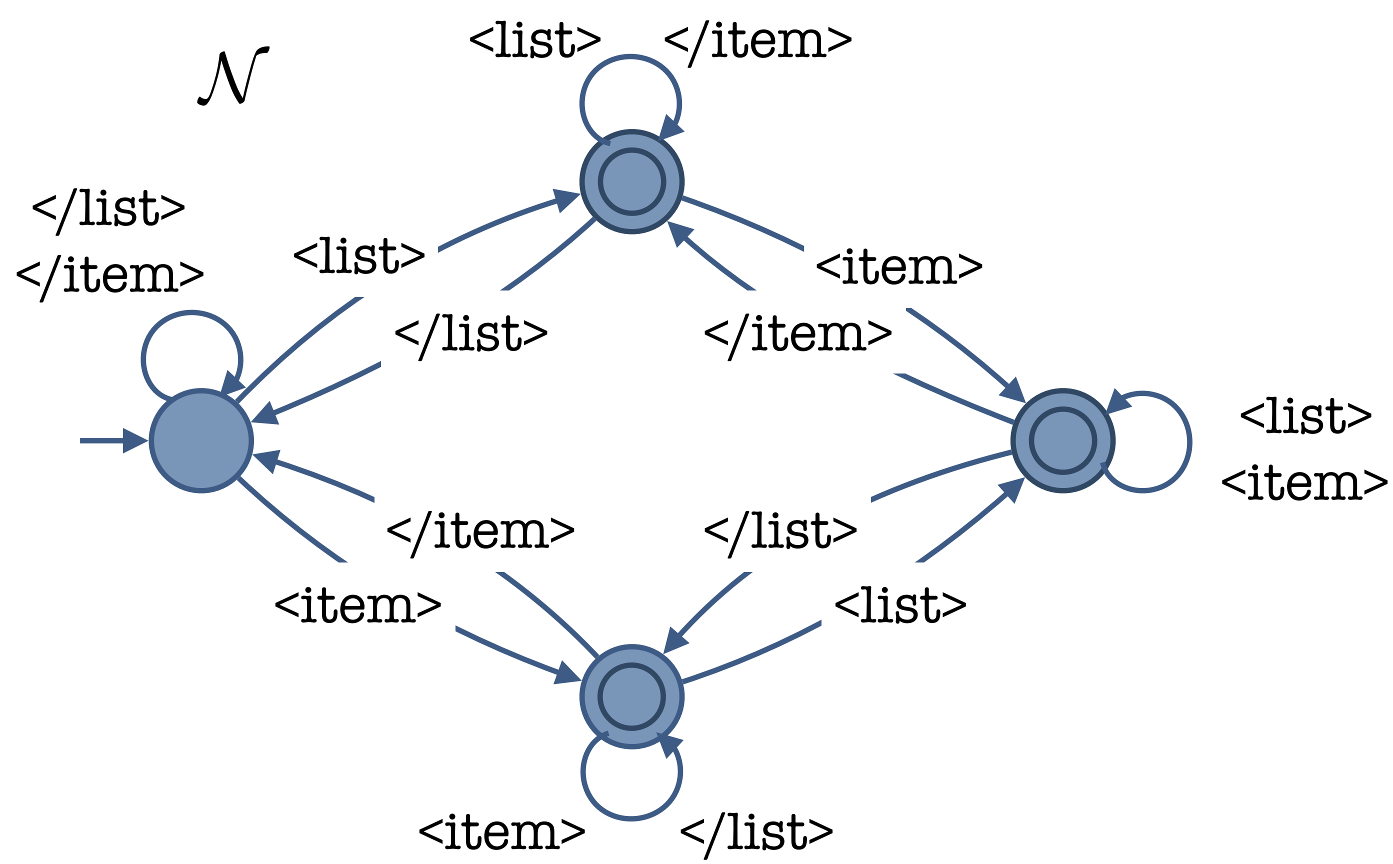

We check $L(\mathcal{R}) \subseteq L(\overline{\mathcal{N}})$.

$\texttt{<list> <item> </item> <item> </list>} \in L(\mathcal{N})$

$\texttt{<list> <item> <item> </item> </list>} \notin L(\mathcal{N})$

```
<list>
    <item>
        <list>
            <item>
            </item>
            <item>
            </item>
        </list>
    </item>
    <item>
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</list>
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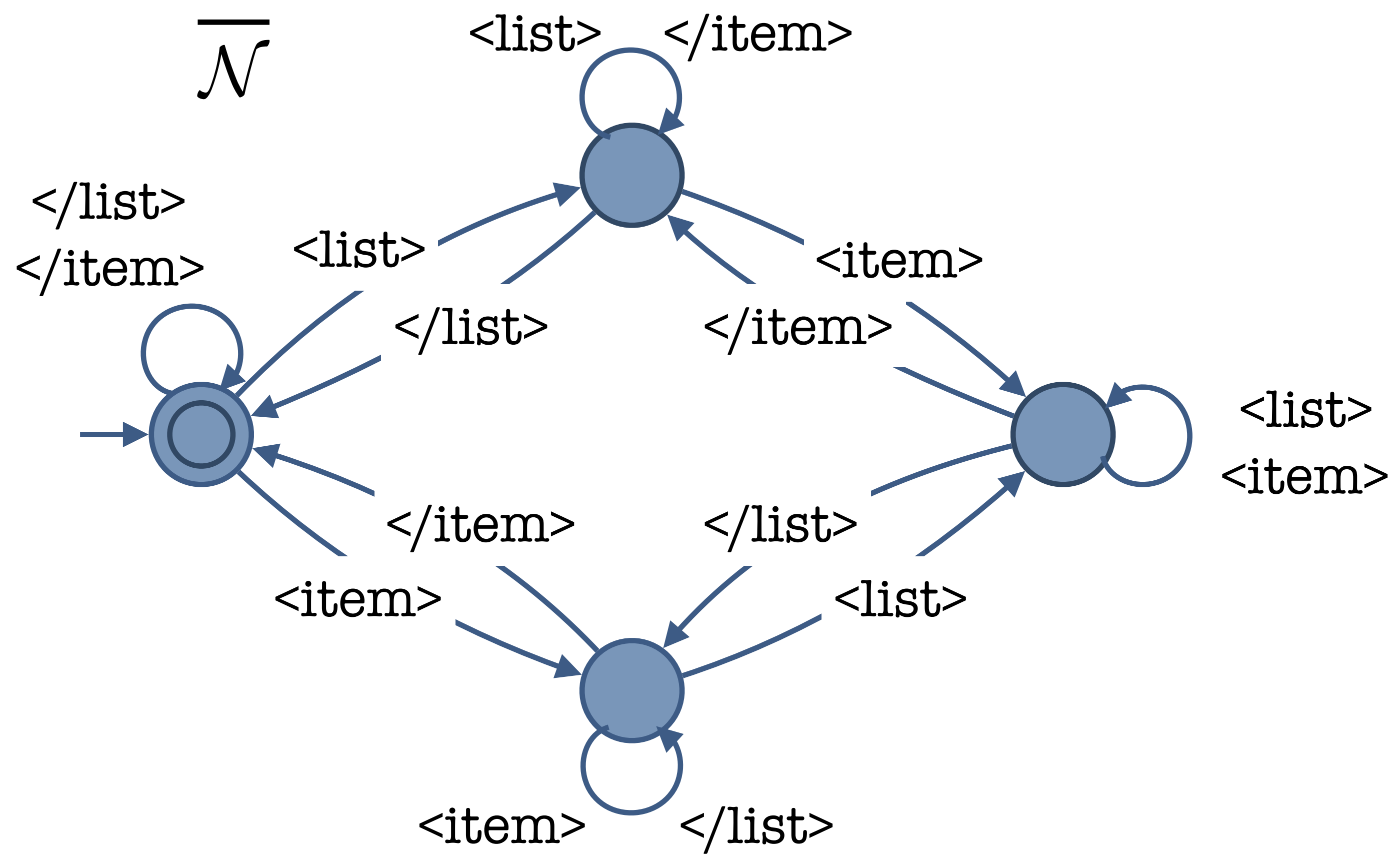

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Checking $L(\mathcal{R}) \subseteq L(\mathcal{A})$ for deterministic finite automaton $\mathcal{A}$

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- Statistical model checking (SMC)
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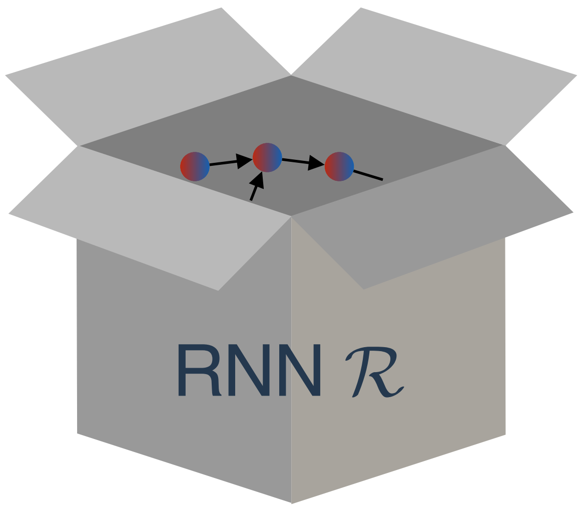
- Property-directed verification (PDV)

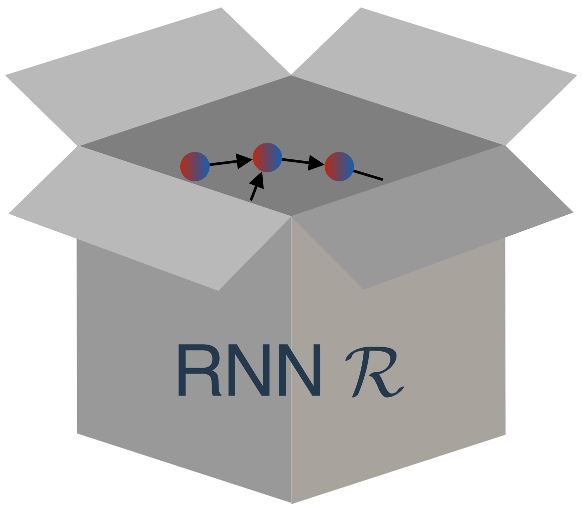
Statistical model checking (SMC)

Fix $\varepsilon, \gamma > 0$.

Sample $\log(2/\varepsilon)/(2\gamma^2)$ words over Σ.



Statistical model checking (SMC)



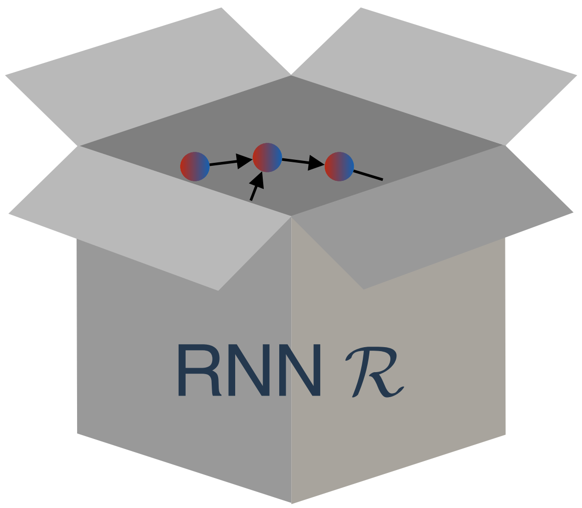
Fix $\varepsilon, \gamma > 0$.

Sample $\log(2/\varepsilon)/(2\gamma^2)$ words over Σ.

If, for some word w, we have $w \in L(\mathcal{R})$ and $w \notin L(\mathcal{A})$:

Property not satisfied.

Statistical model checking (SMC)



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Else, $\mathcal{R}$ is ε-approximately correct with probability at least $1-\gamma$.

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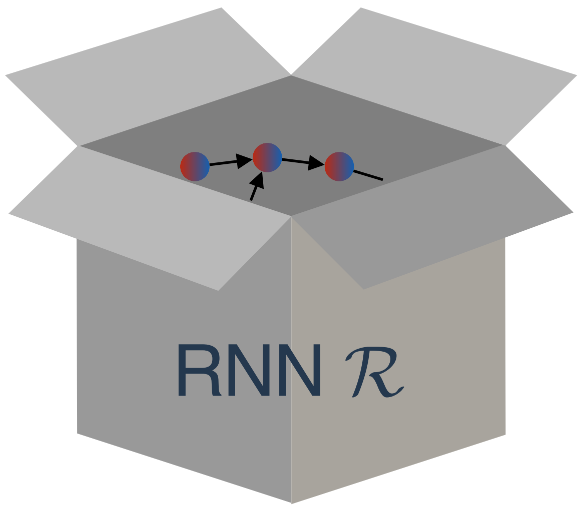

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$$\Pr\left(L(\mathcal{R}) \setminus L(\mathcal{A})\right) < \varepsilon$$

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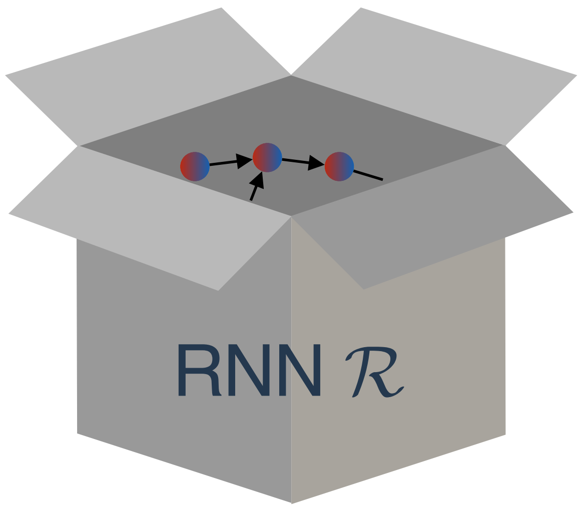

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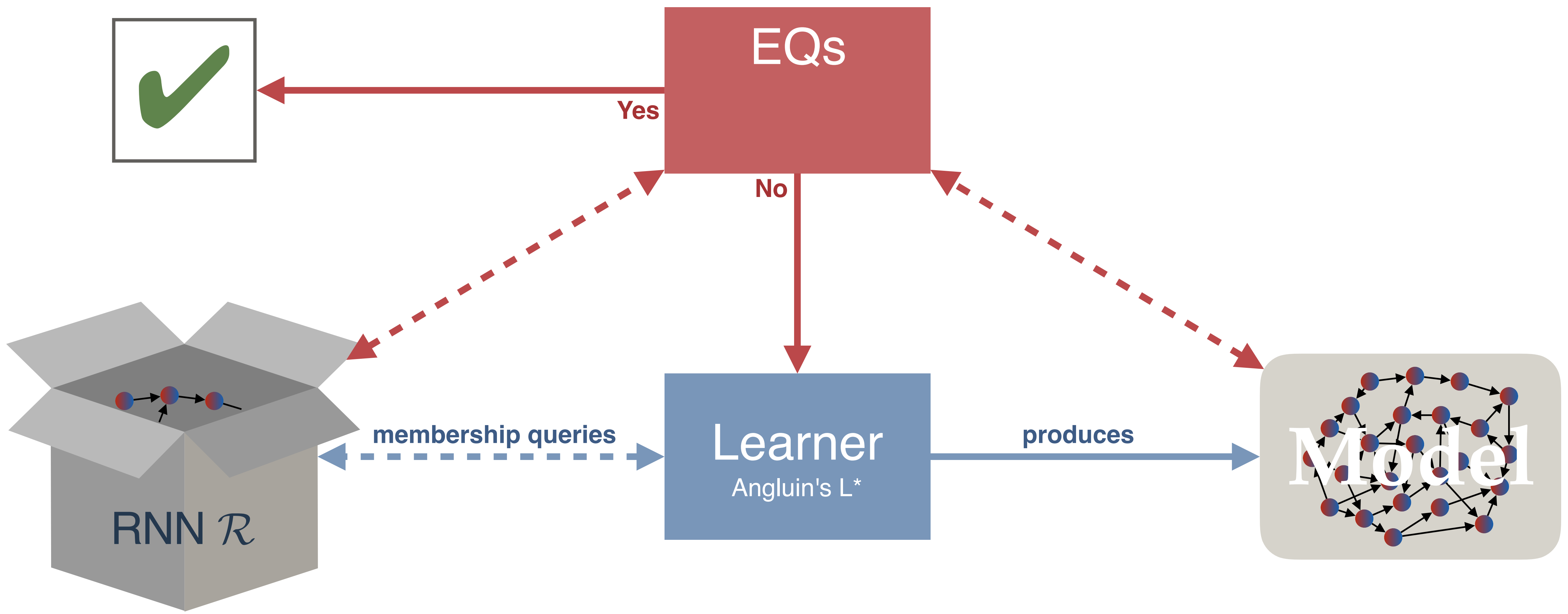
$$\Pr\left(L(\mathcal{R}) \setminus L(\mathcal{A})\right) < \varepsilon$$

- Relies on probability distribution.
- May require many queries.

Automaton abstraction & model checking (AAMC)



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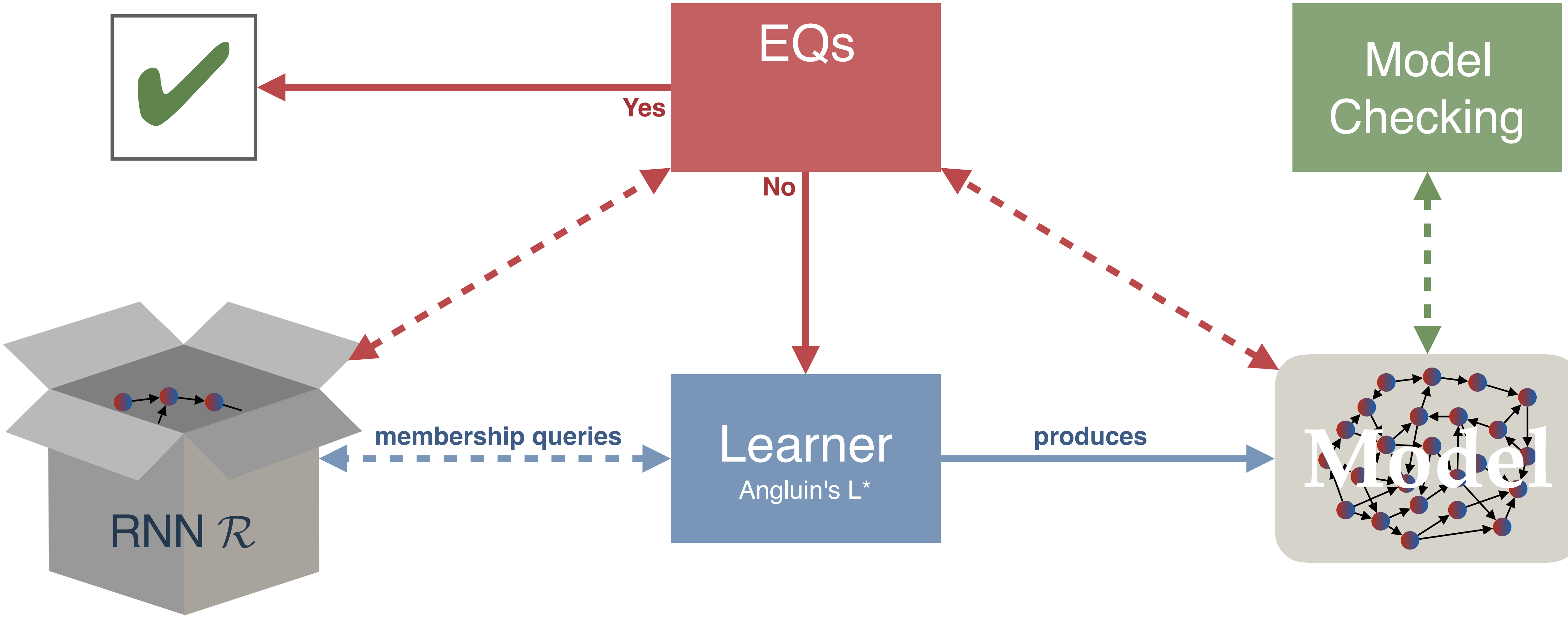

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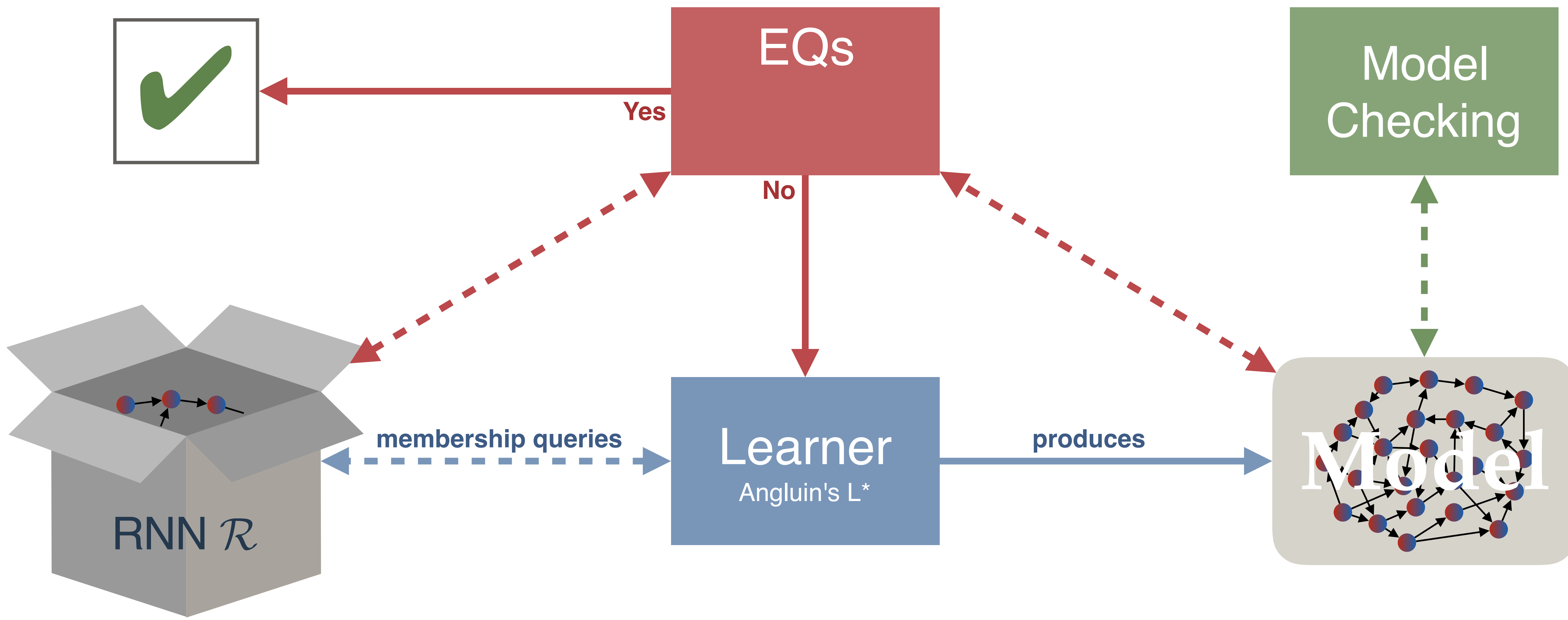
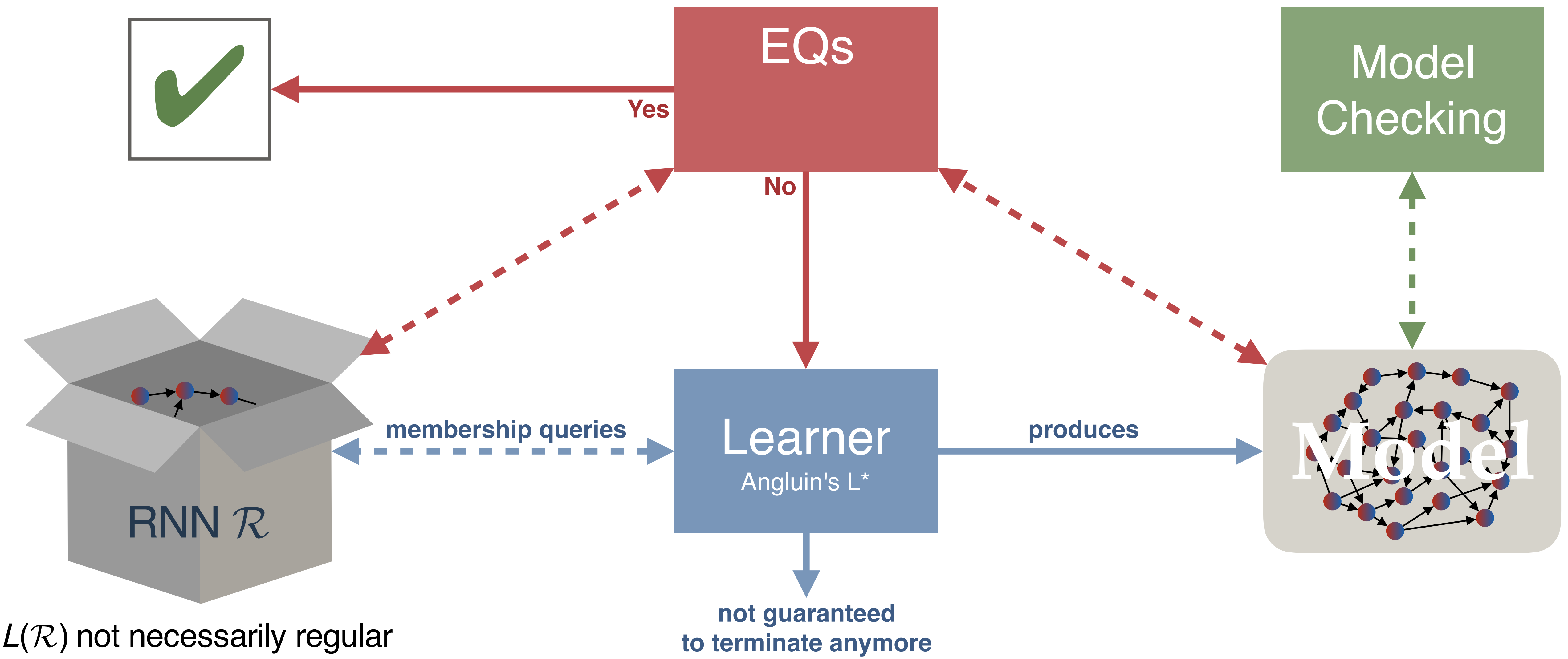


$L(\mathcal{R})$ not necessarily regular

Automaton abstraction & model checking (AAMC)



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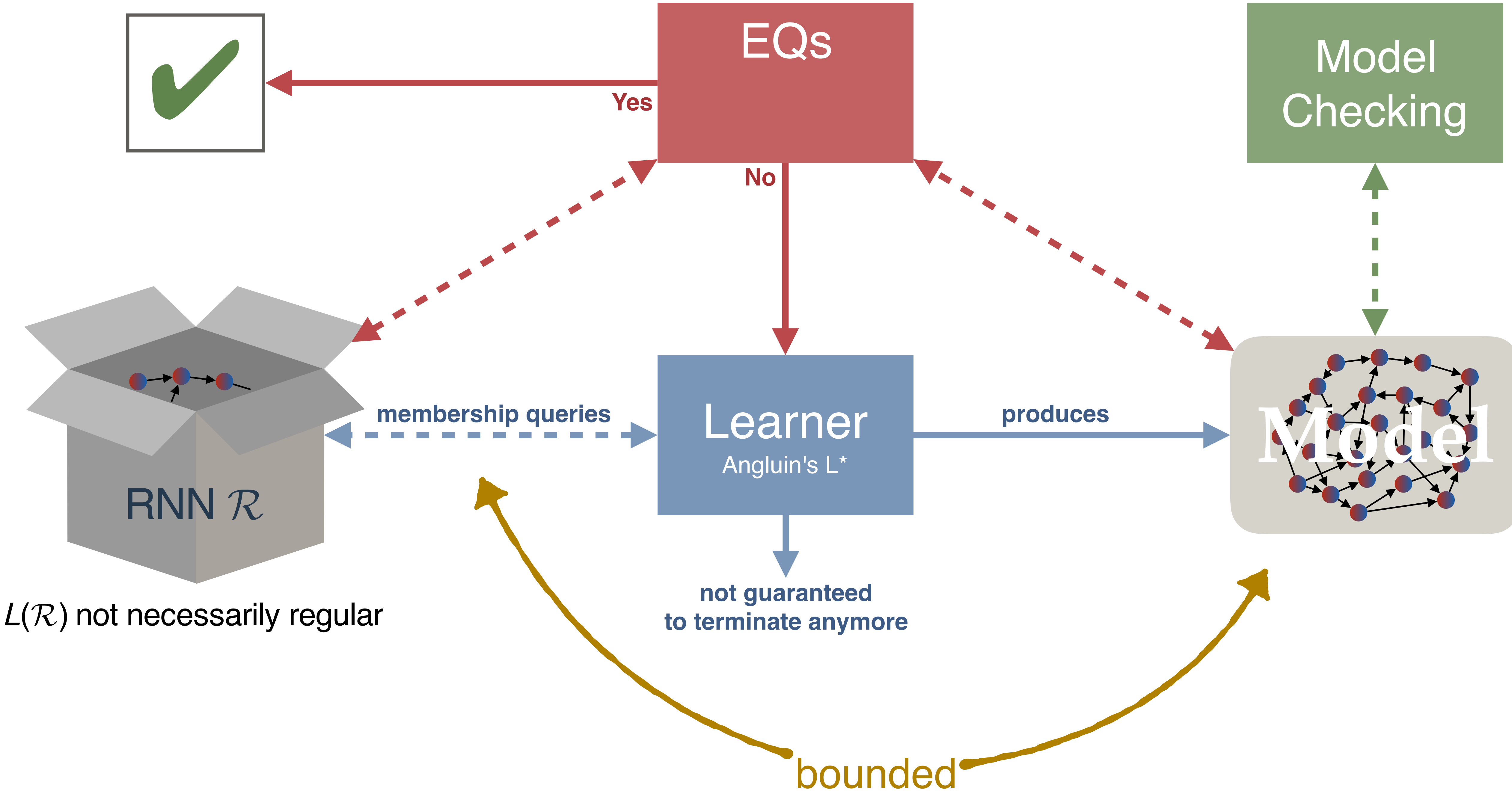

[Mayr, Yovine: Regular inference on artificial neural networks. CD-MAKE 2018]

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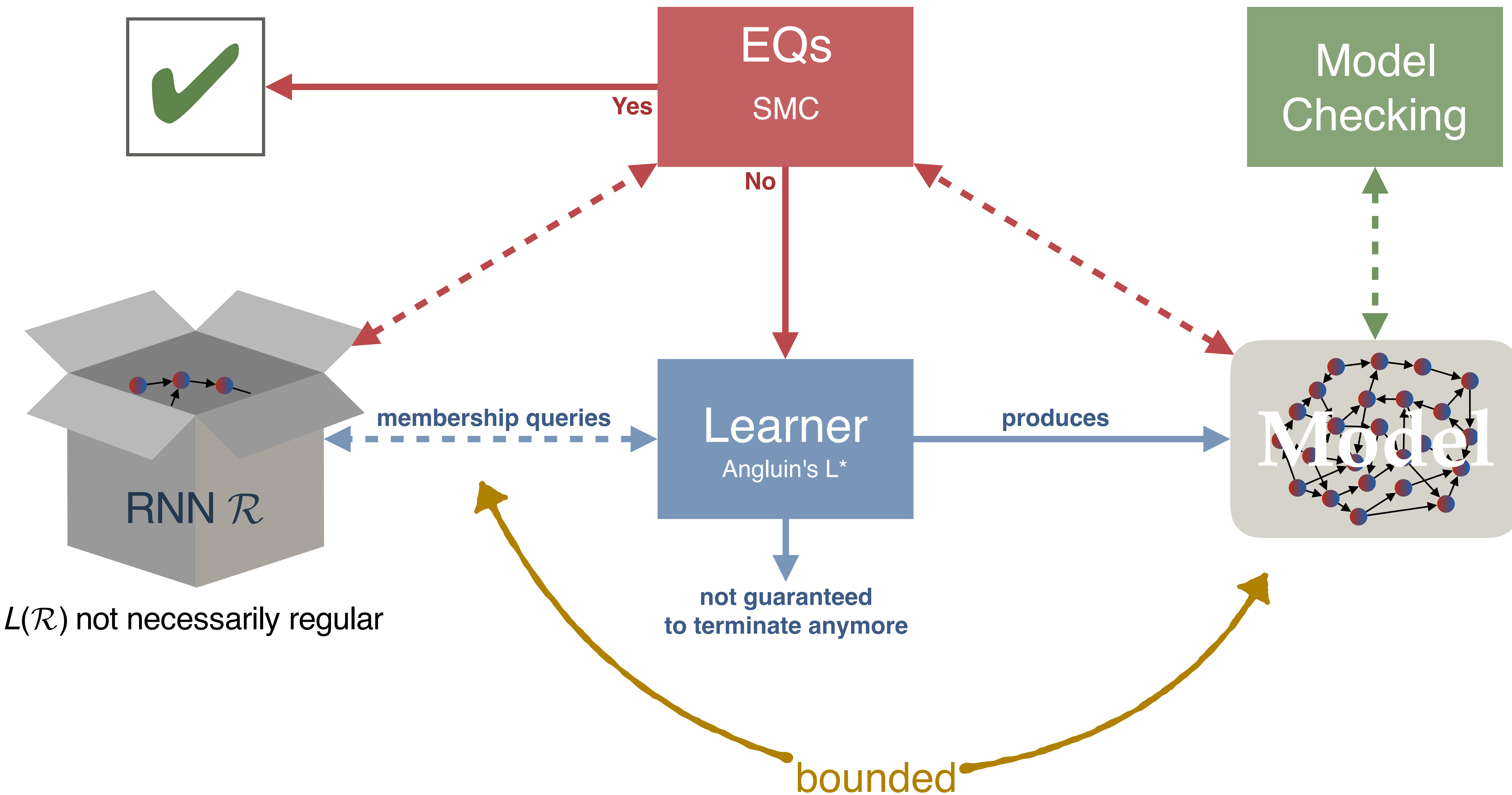

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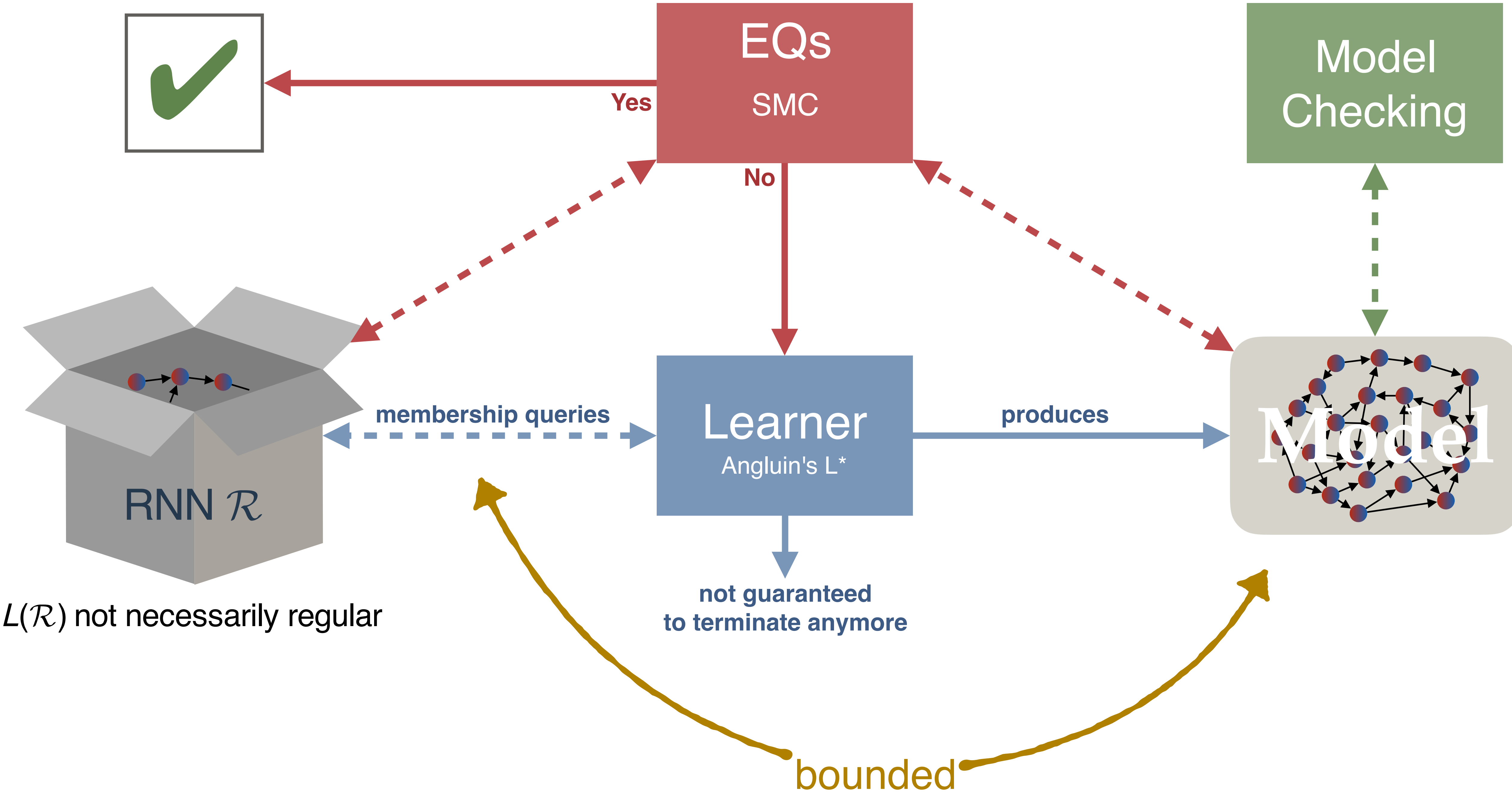

- Relies on probability distribution.

[Mayr, Yovine: Regular inference on artificial neural networks. CD-MAKE 2018]

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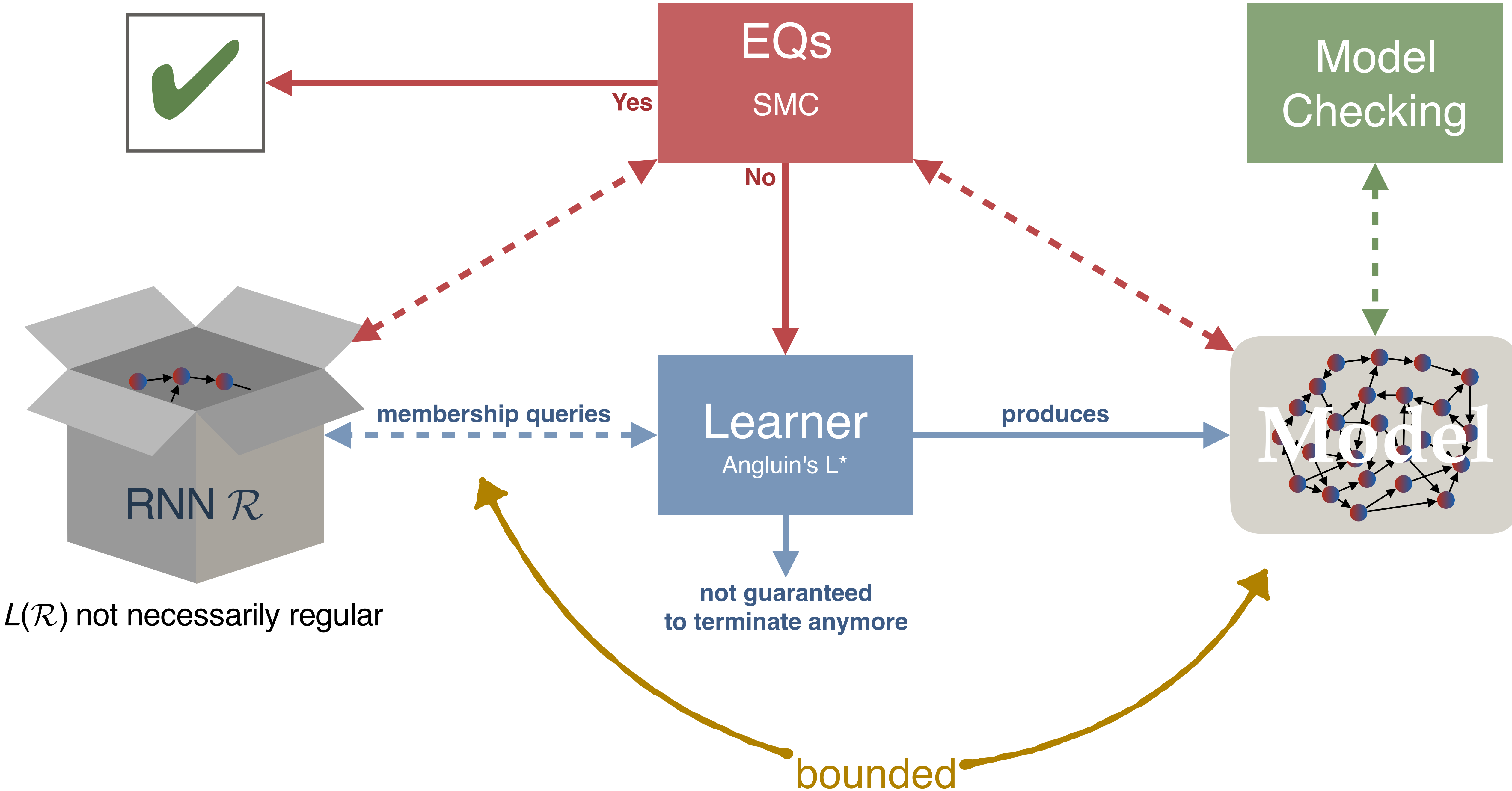
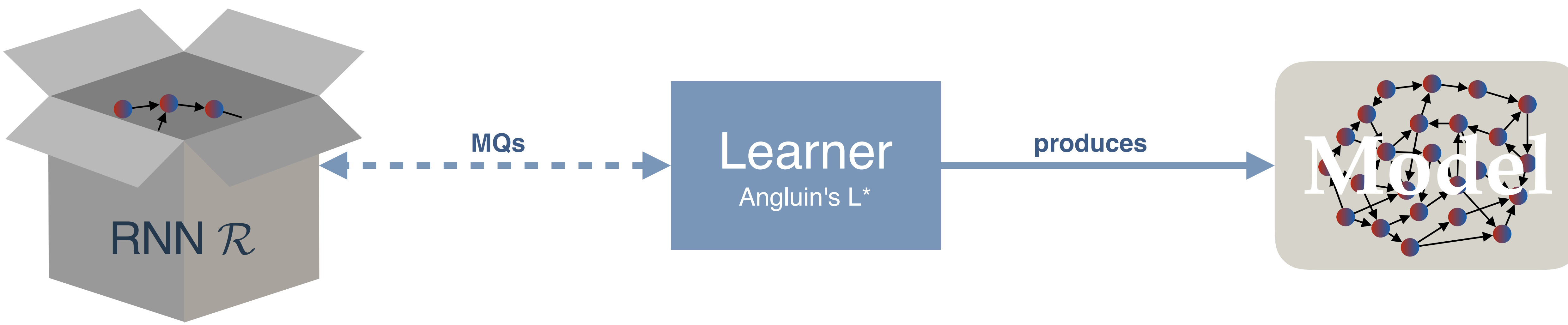


- Relies on probability distribution.
- Counterexample may be spurious.

As EQs are implemented by SMC, a "counterexample" may be classified by RNN as negative.

[Mayr, Yovine: Regular inference on artificial neural networks. CD-MAKE 2018]



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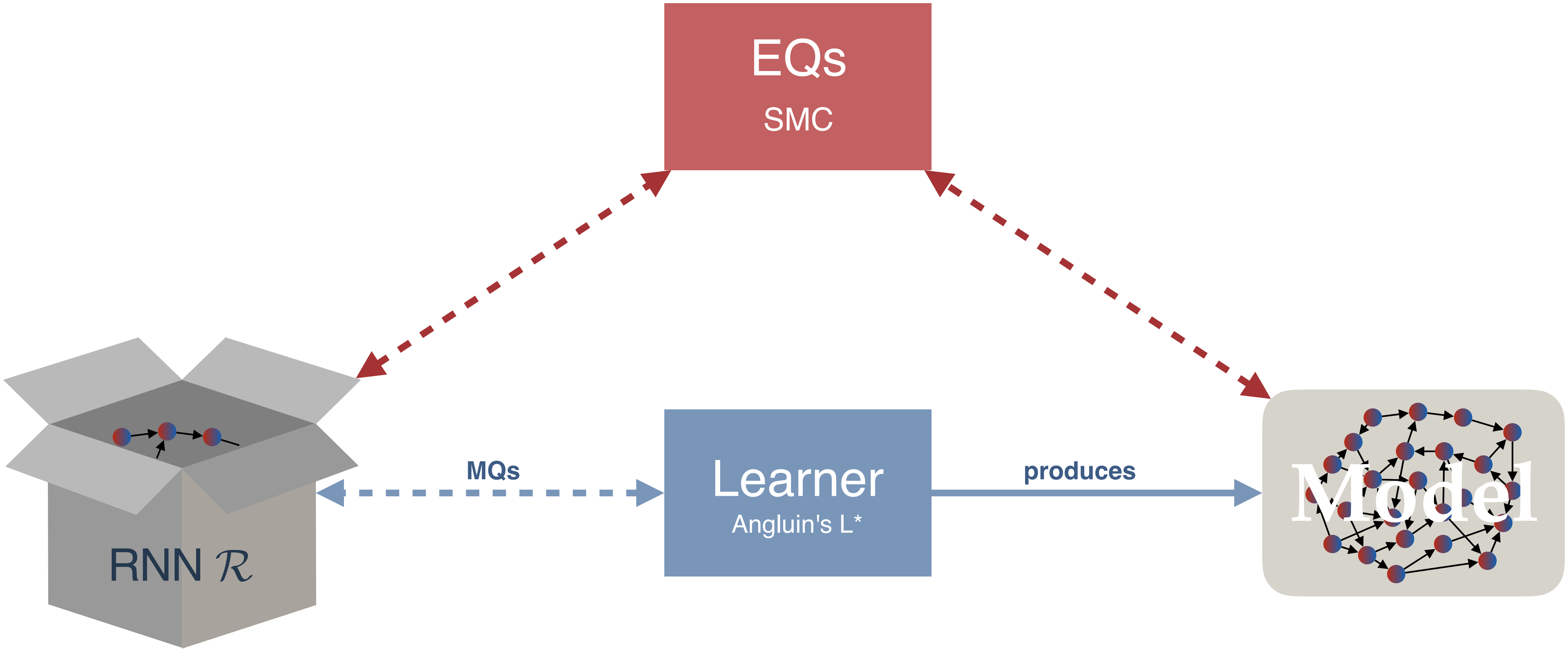

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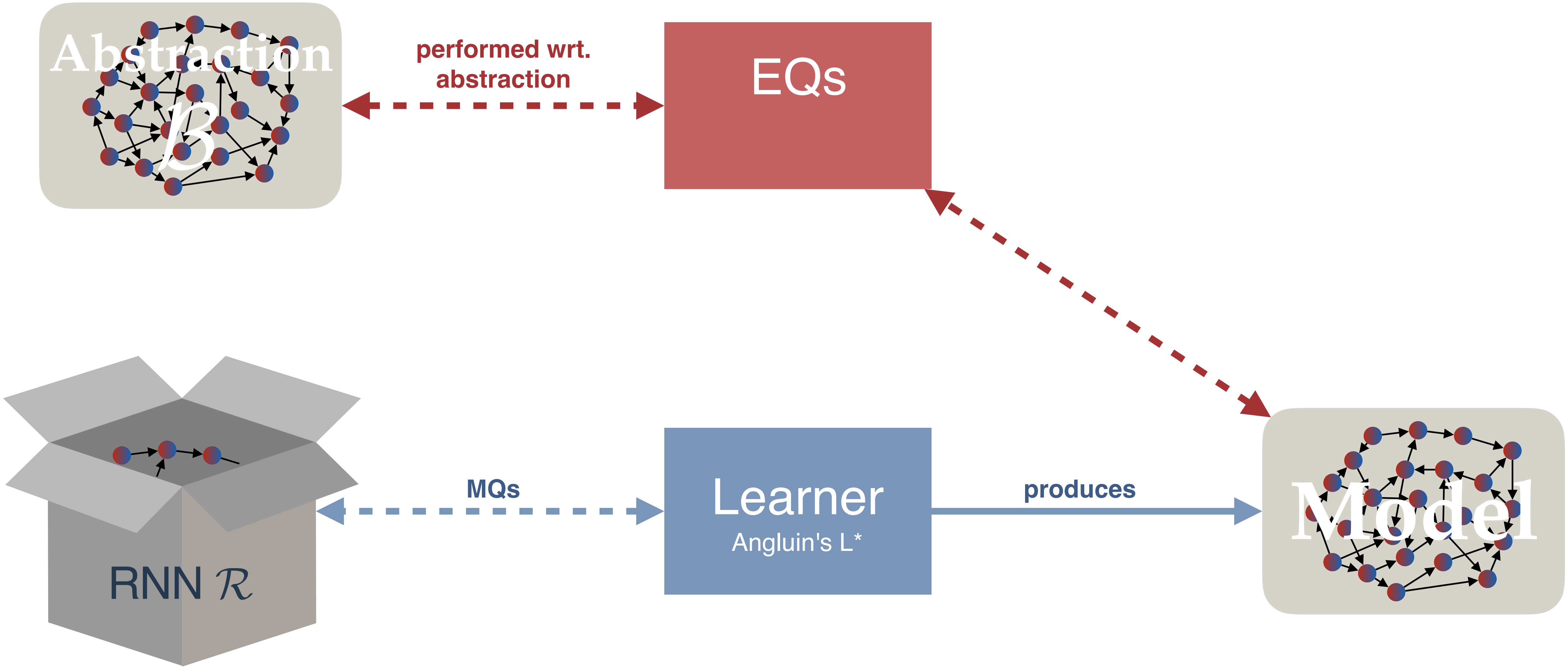

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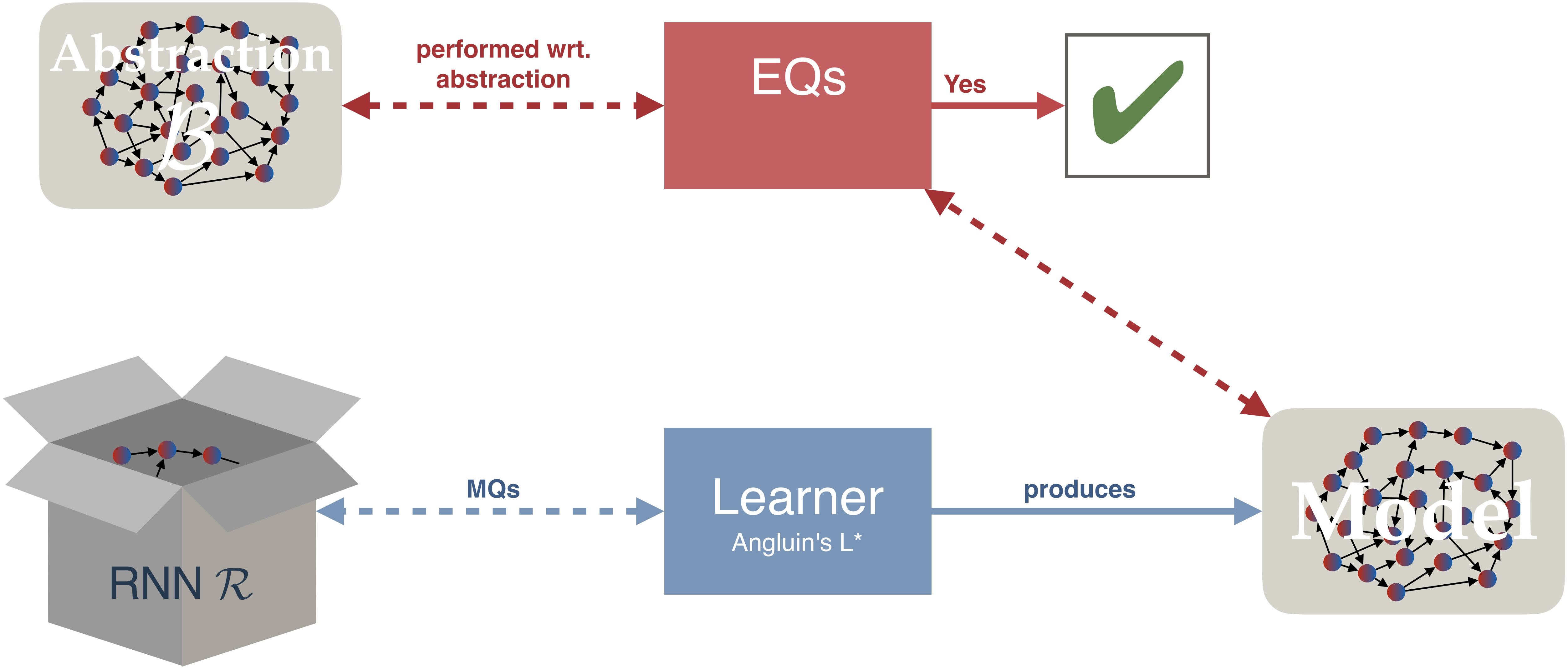

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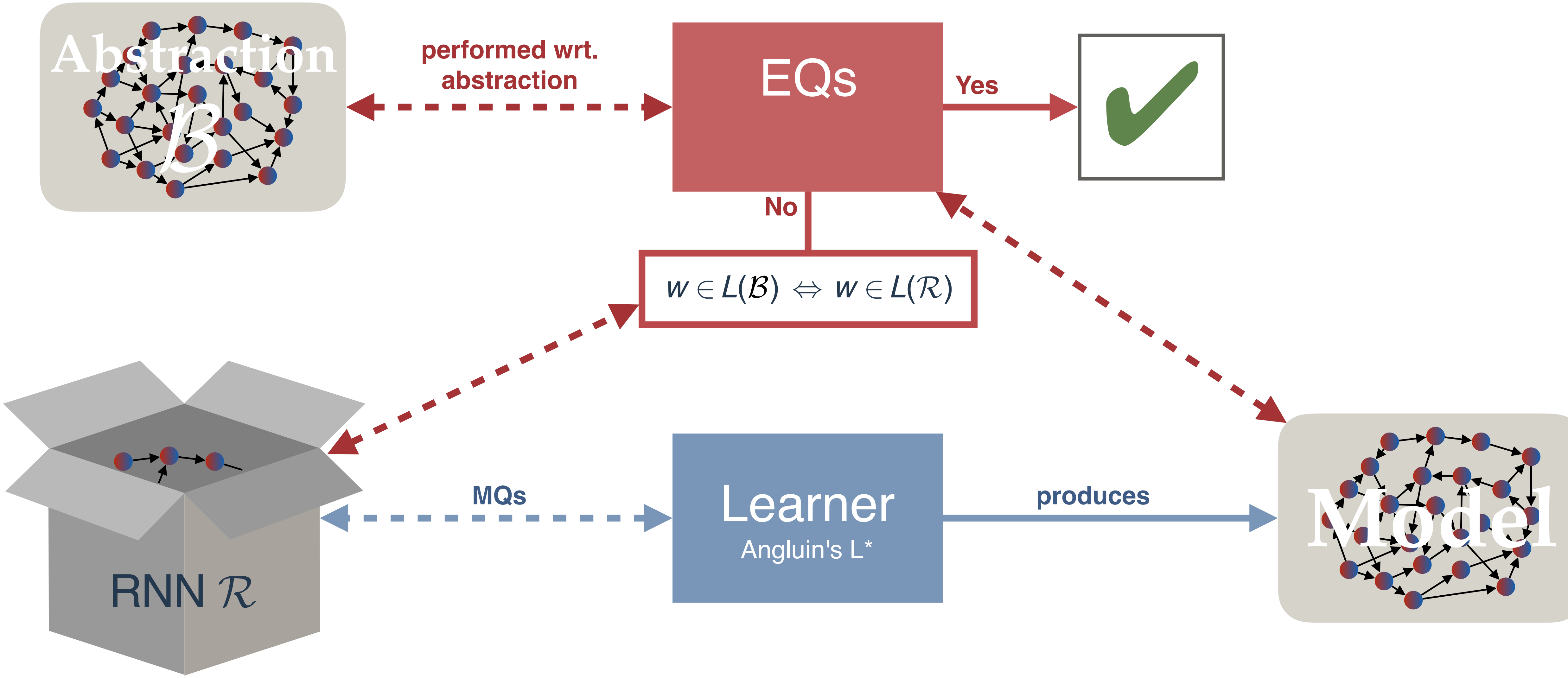

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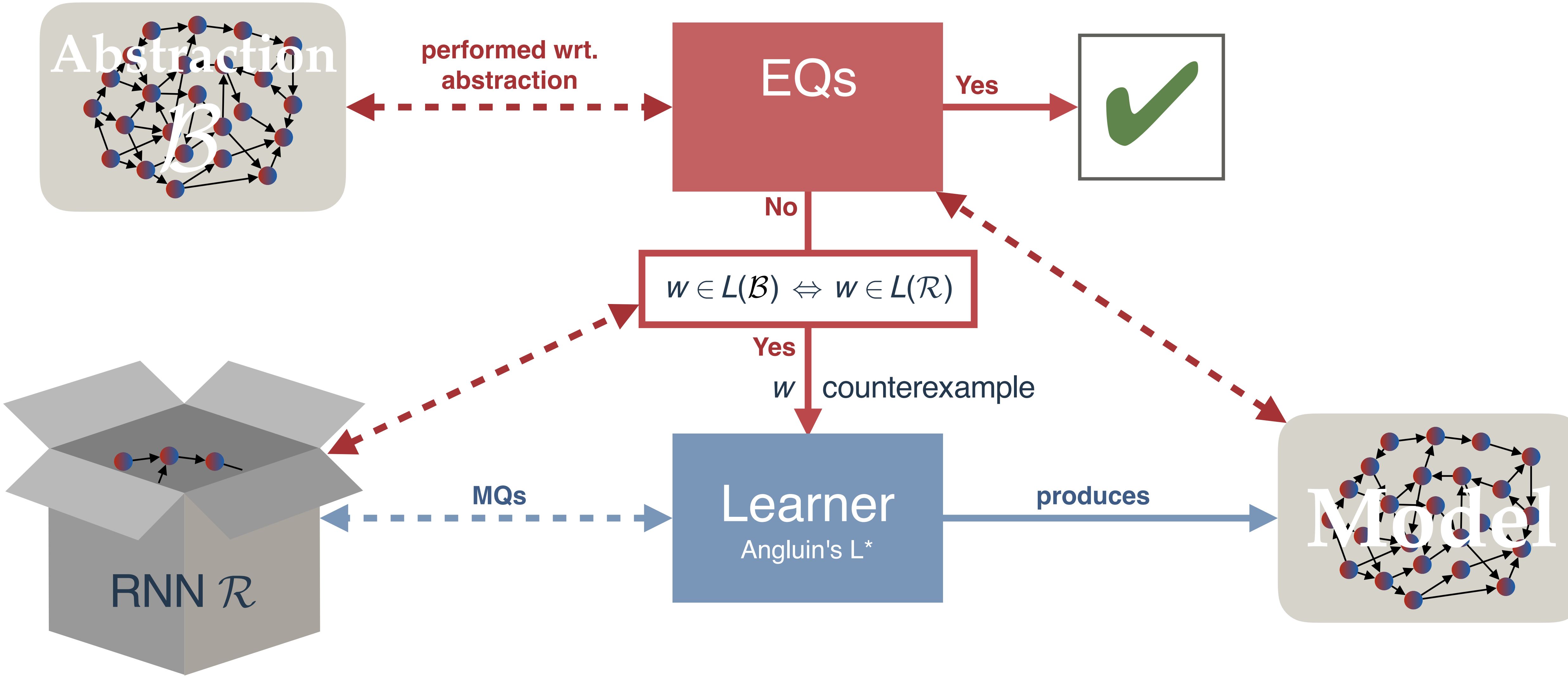

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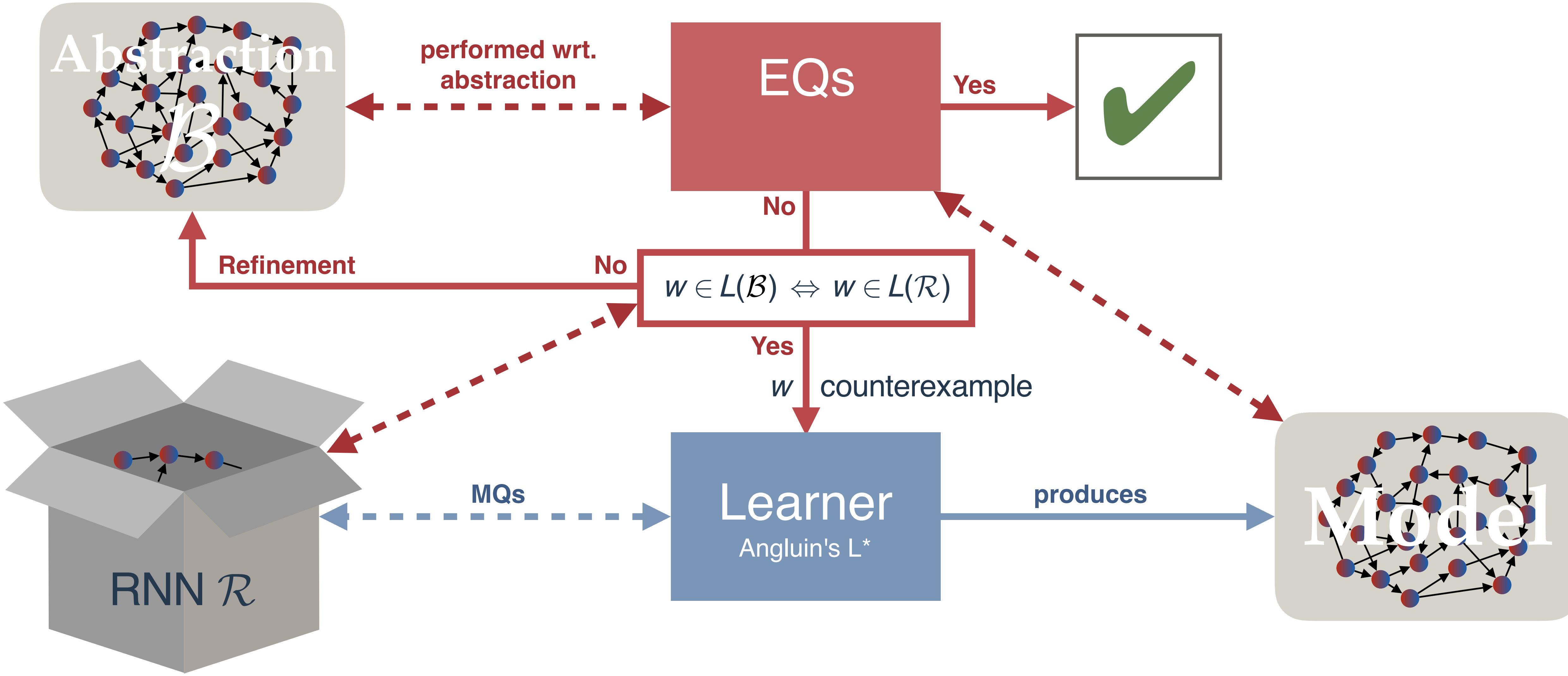

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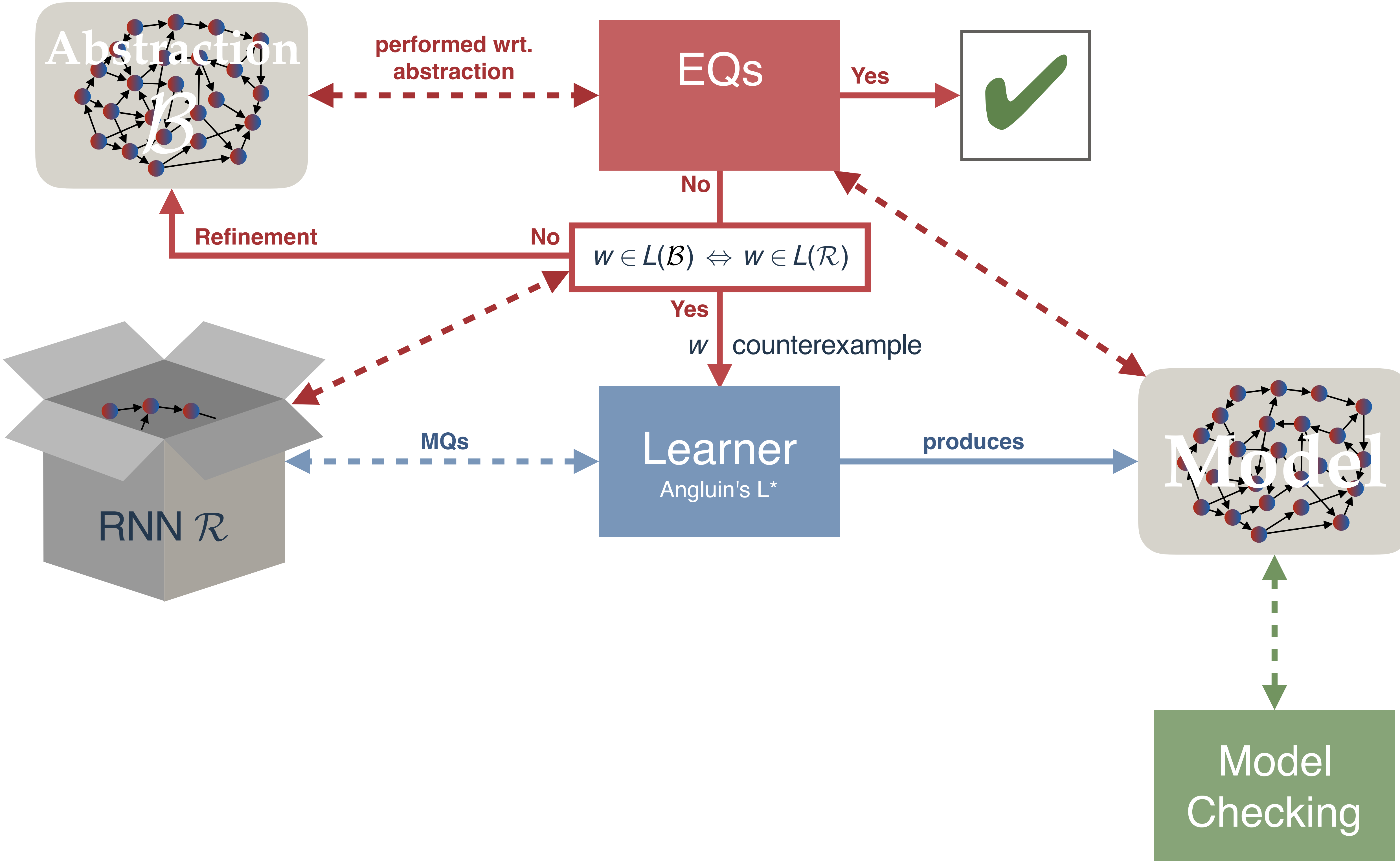

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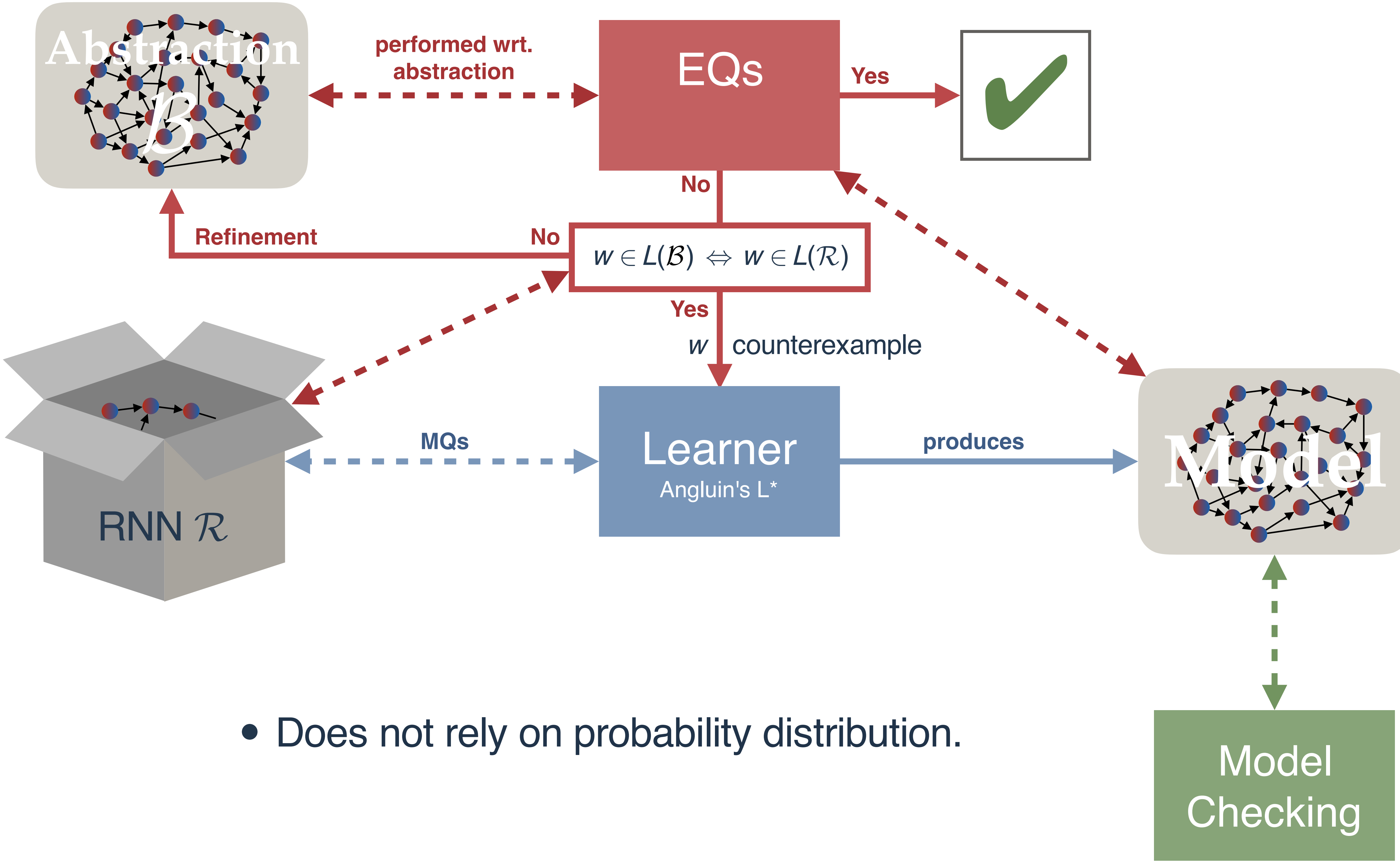

- Does not rely on probability distribution.

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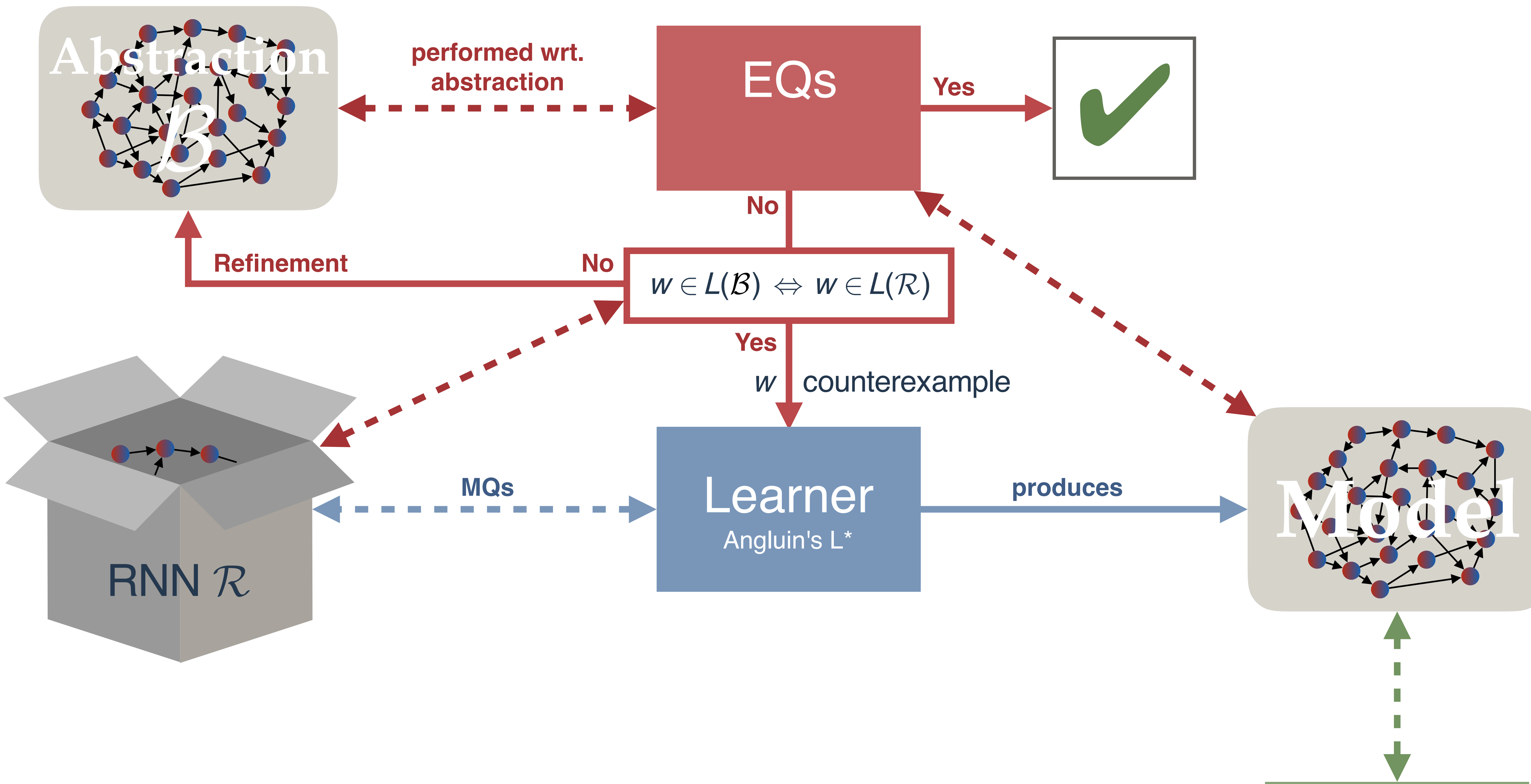
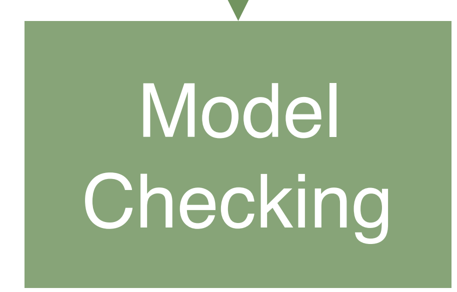


- Does not rely on probability distribution.
- But counterexample may be spurious.

  Depends on the quality of the abstraction.



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Checked on 30 DFAs / RNNs and 138 specifications:

Type	*Avg time* (s)	*Avg len*	*# Mistakes*	*Avg MQs*
SMC	92	111	**122**	286063
AAMC	444	**7**	30	3701916

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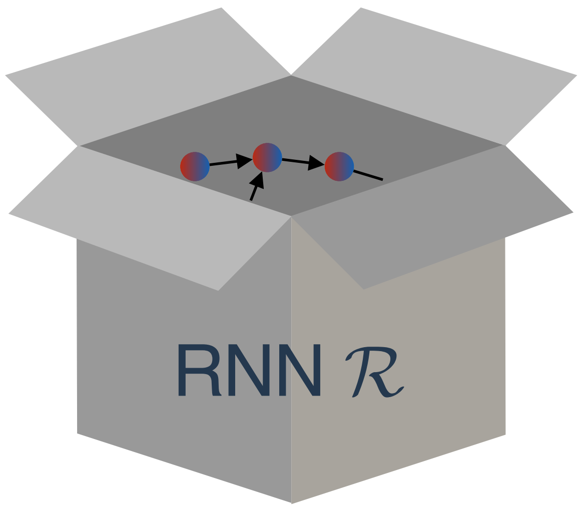
→ Property-directed verification (PDV)



inspired by black-box checking: interweave learning and model checking

[Peled, Vardi, Yannakakis 1999]

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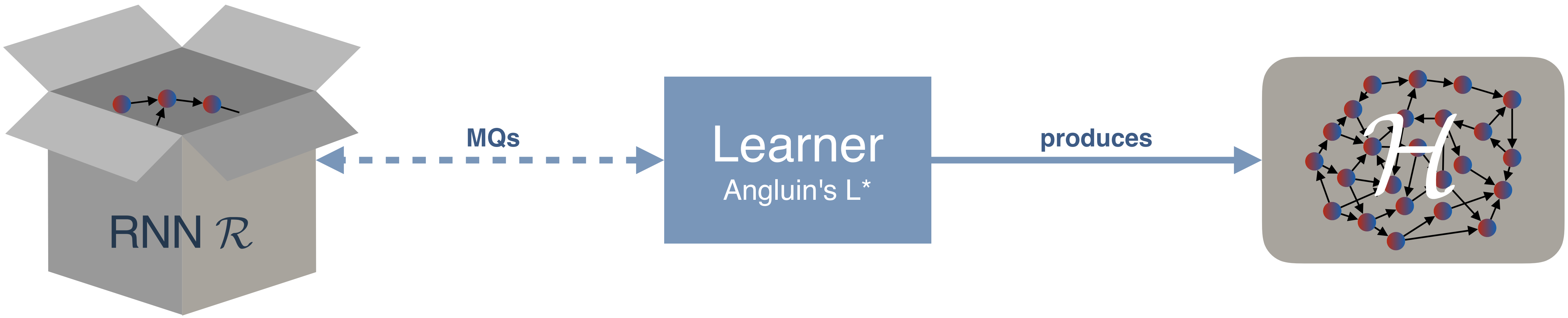

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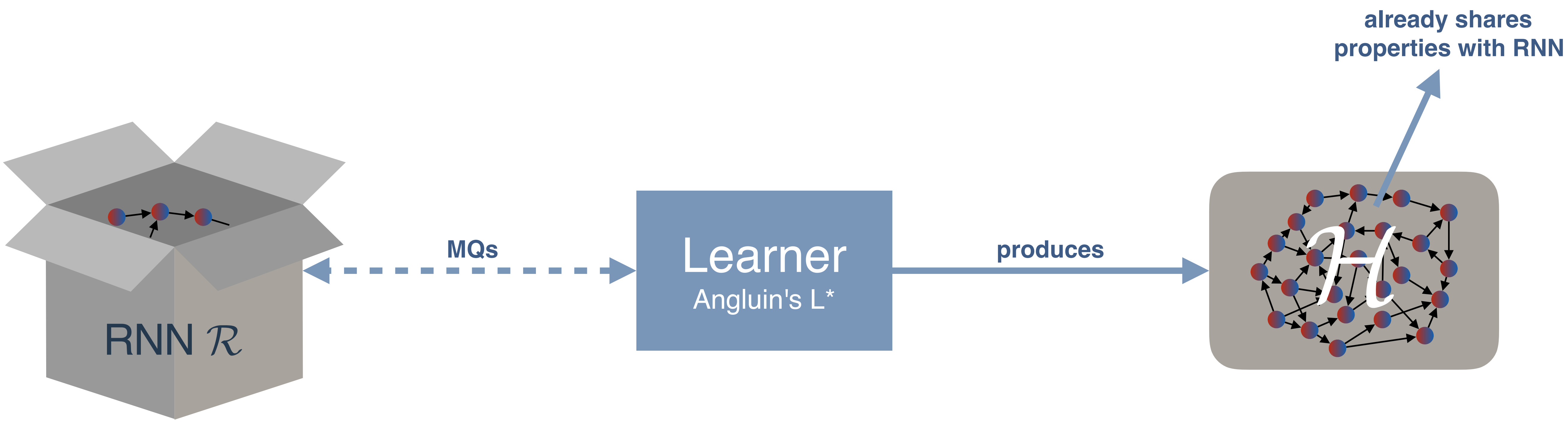

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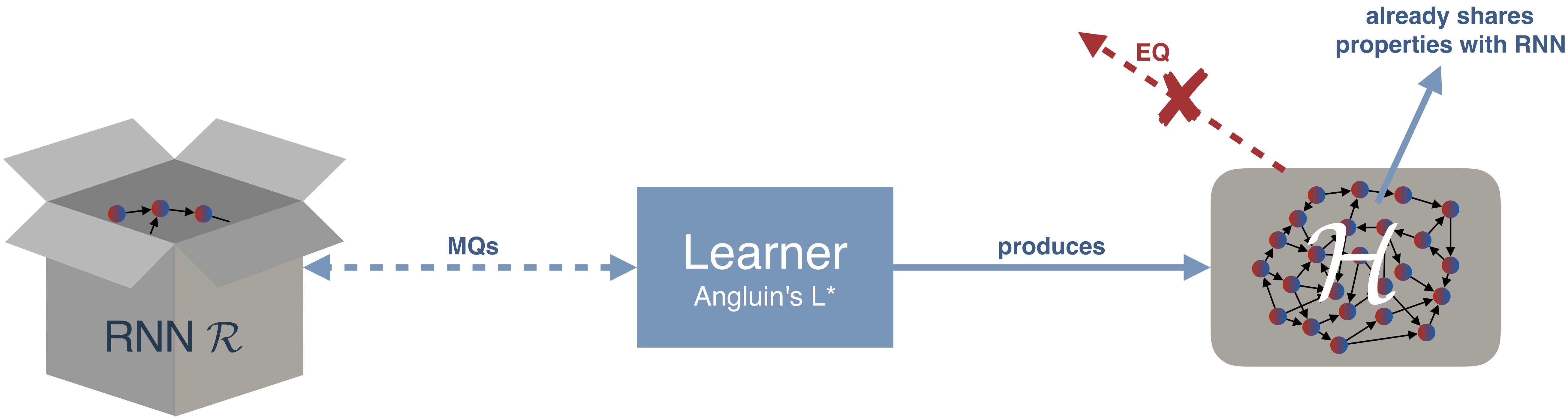

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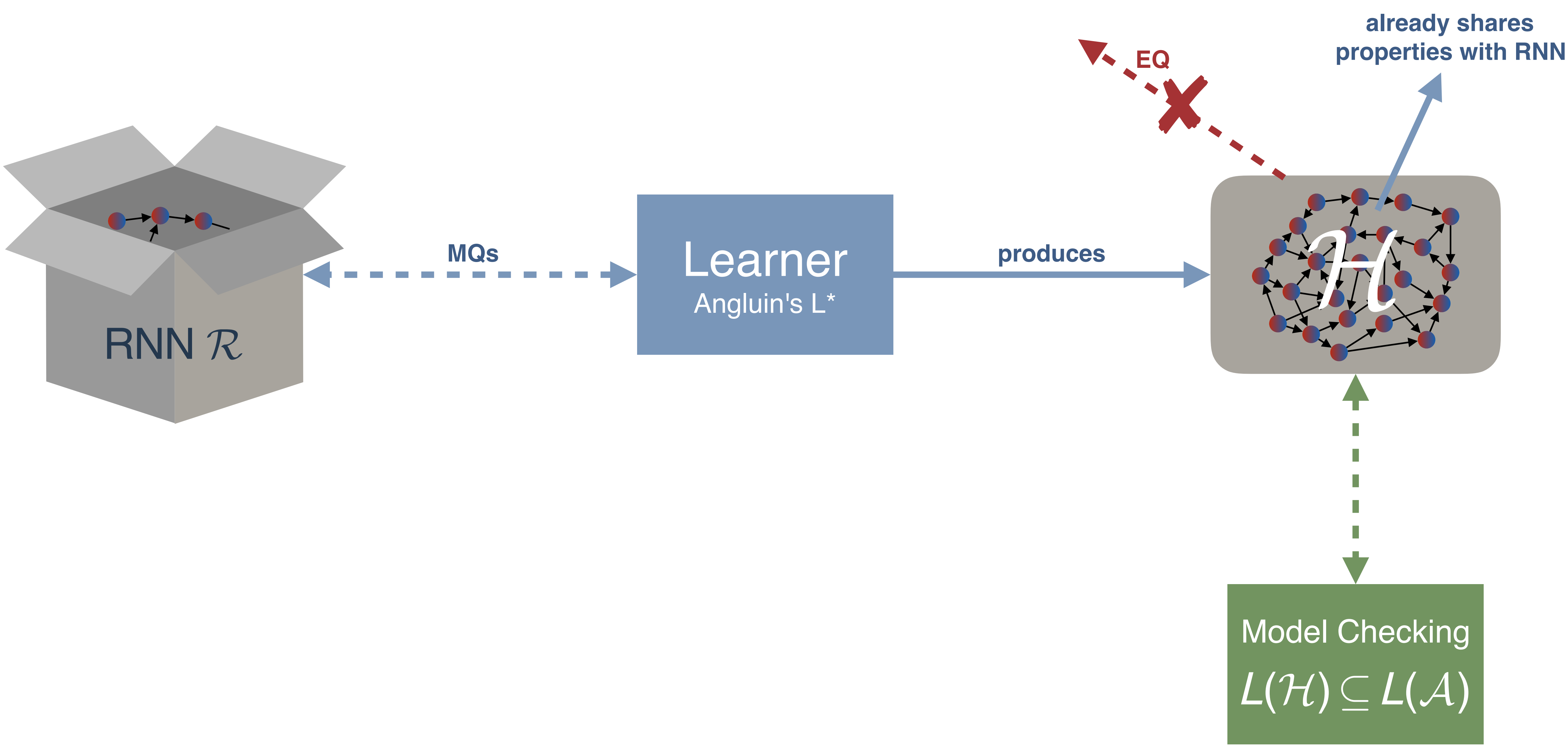

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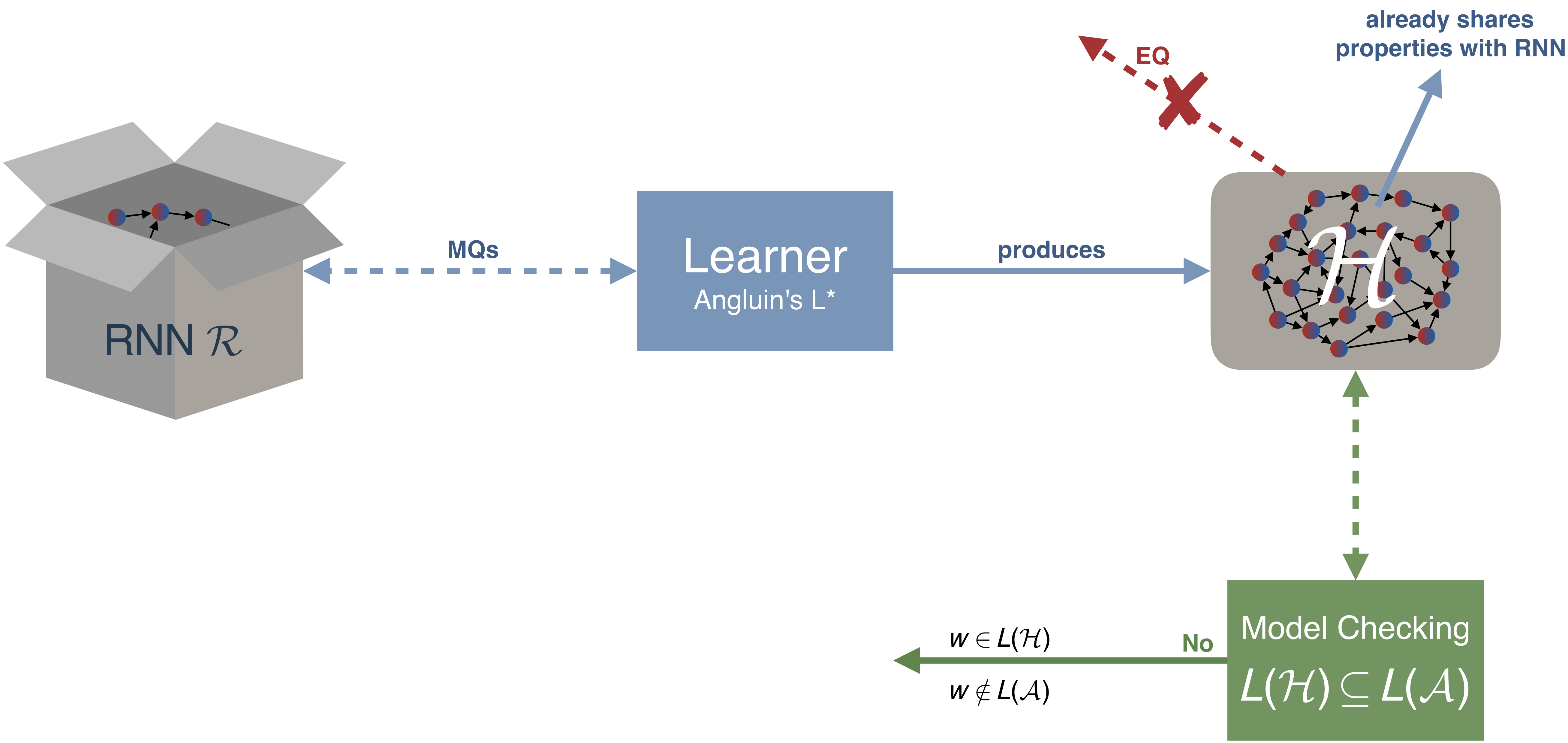

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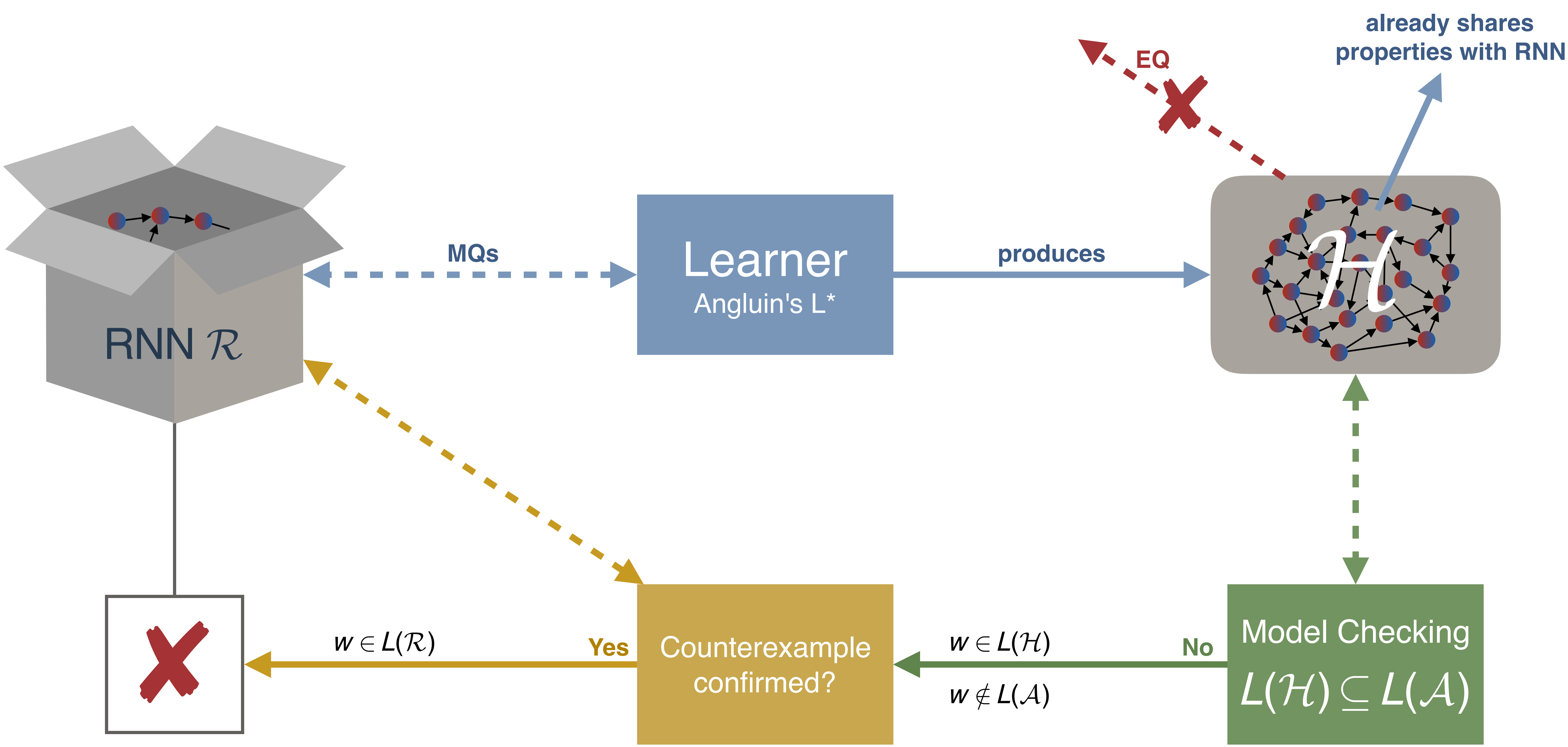

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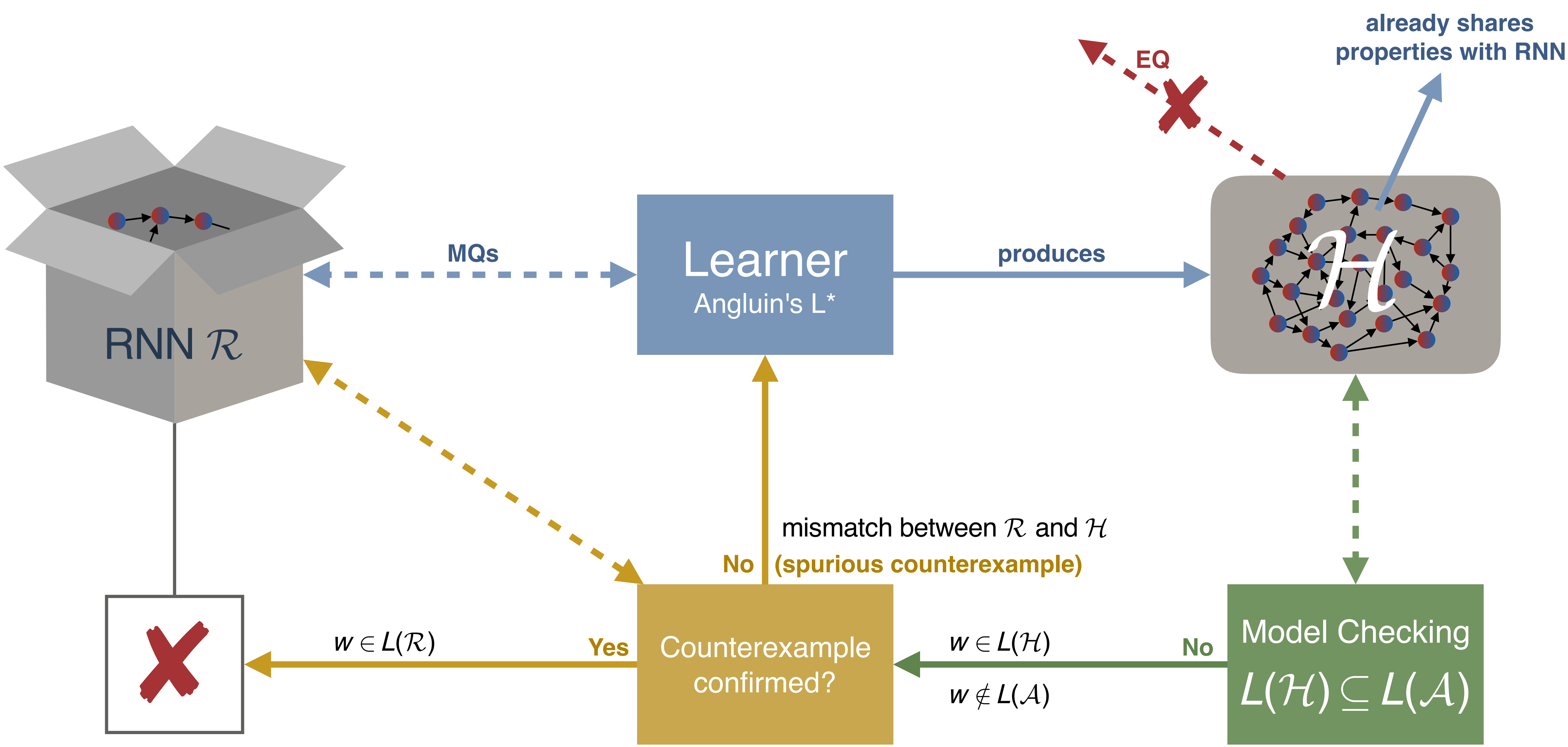

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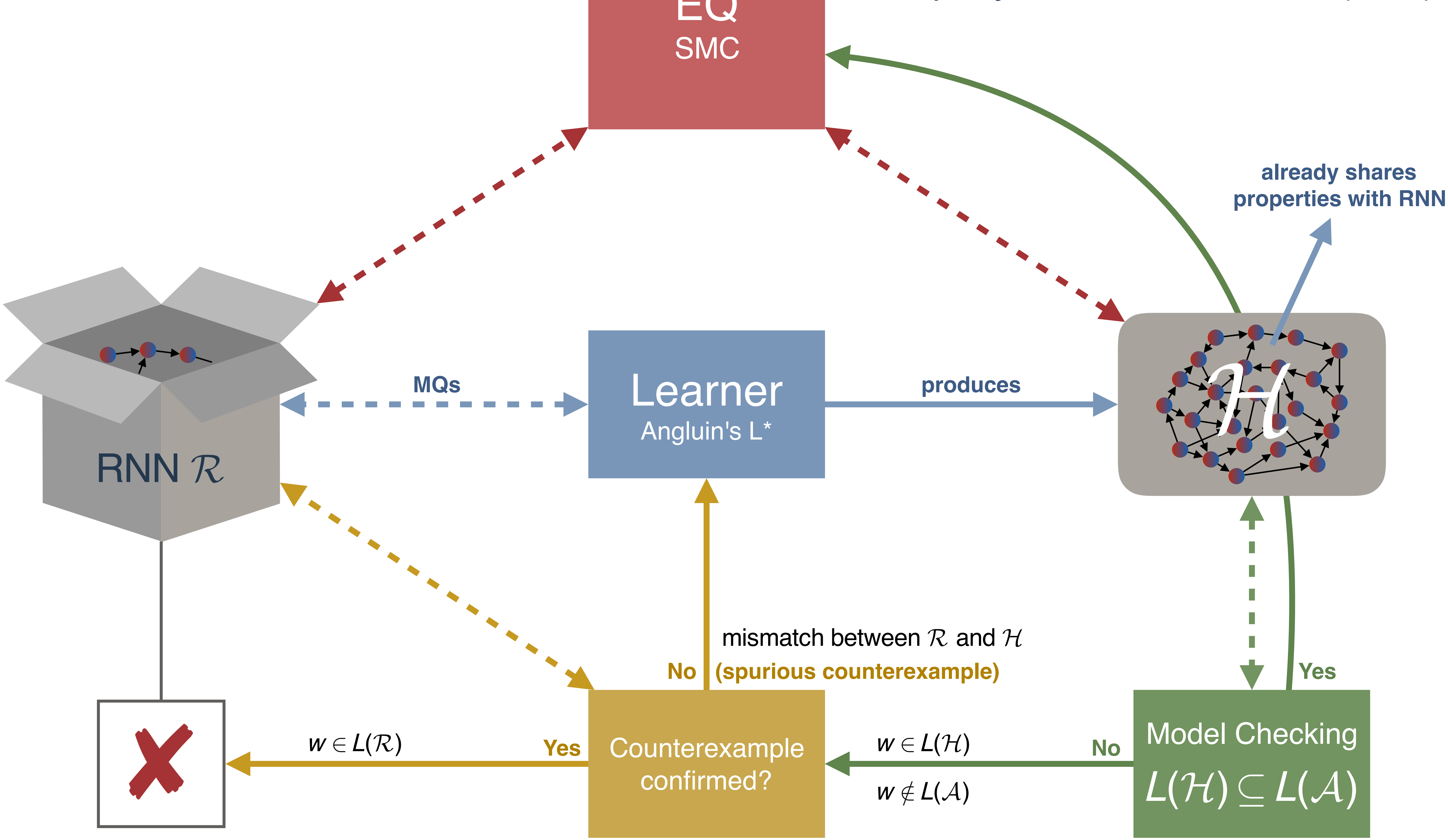

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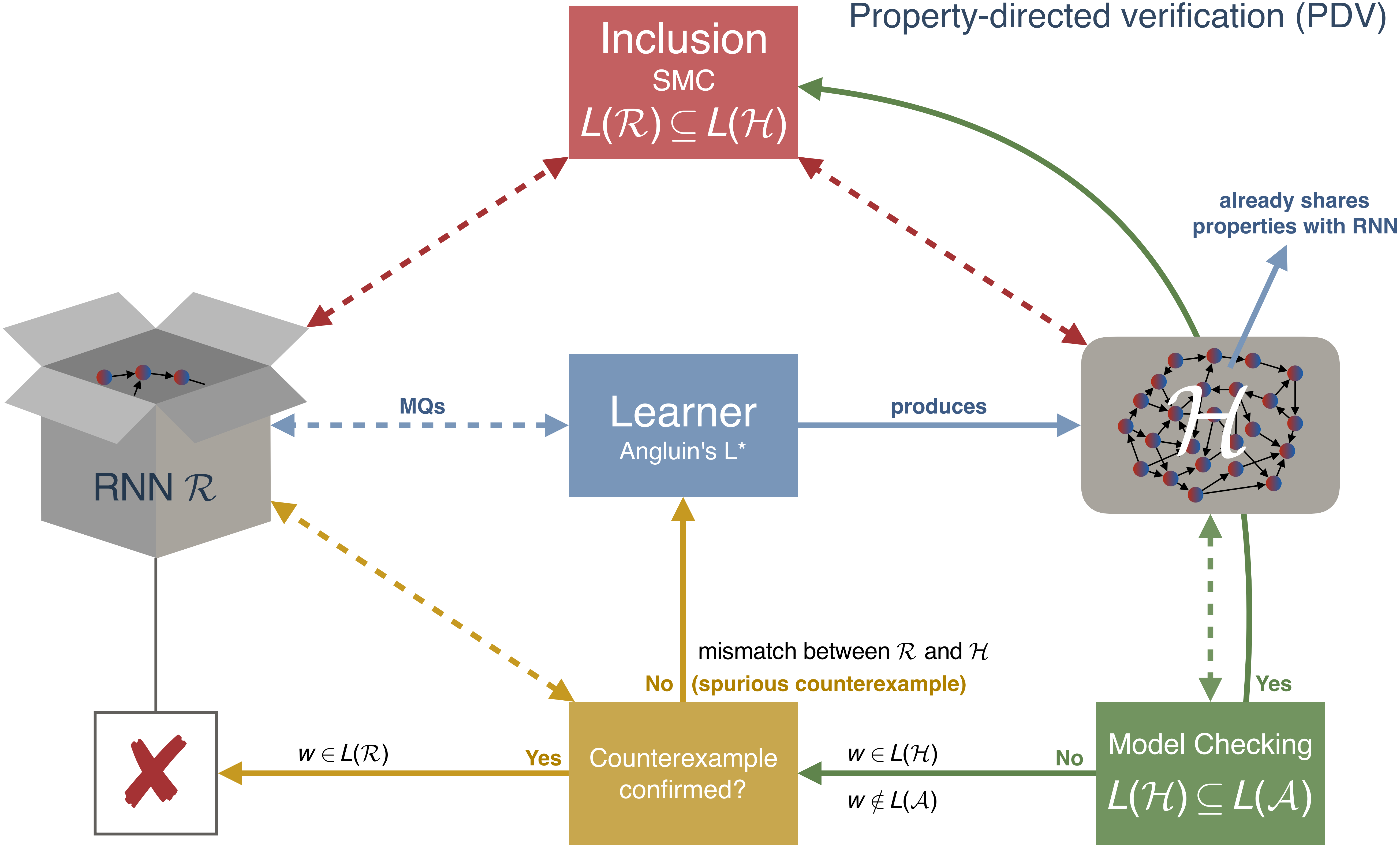

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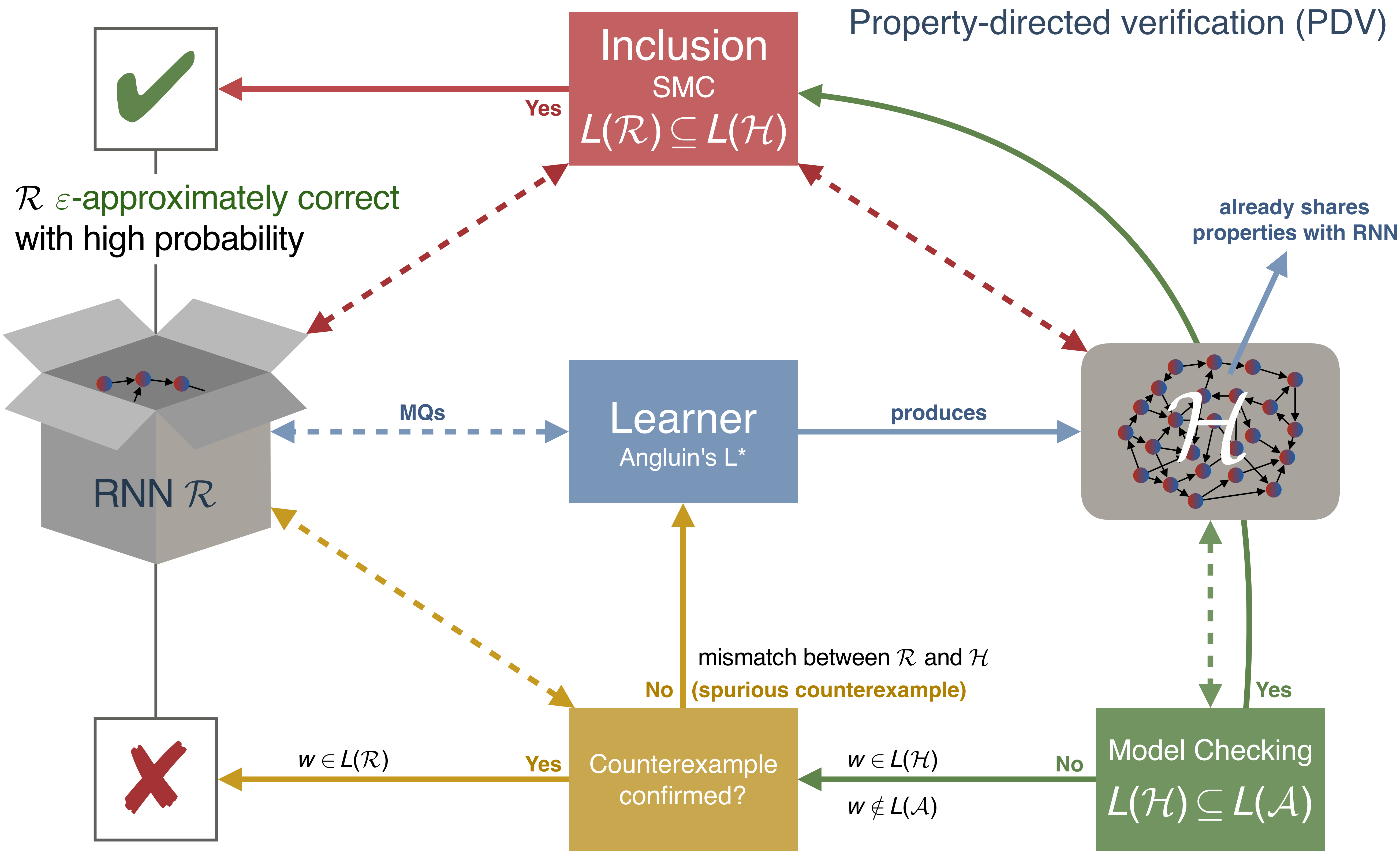

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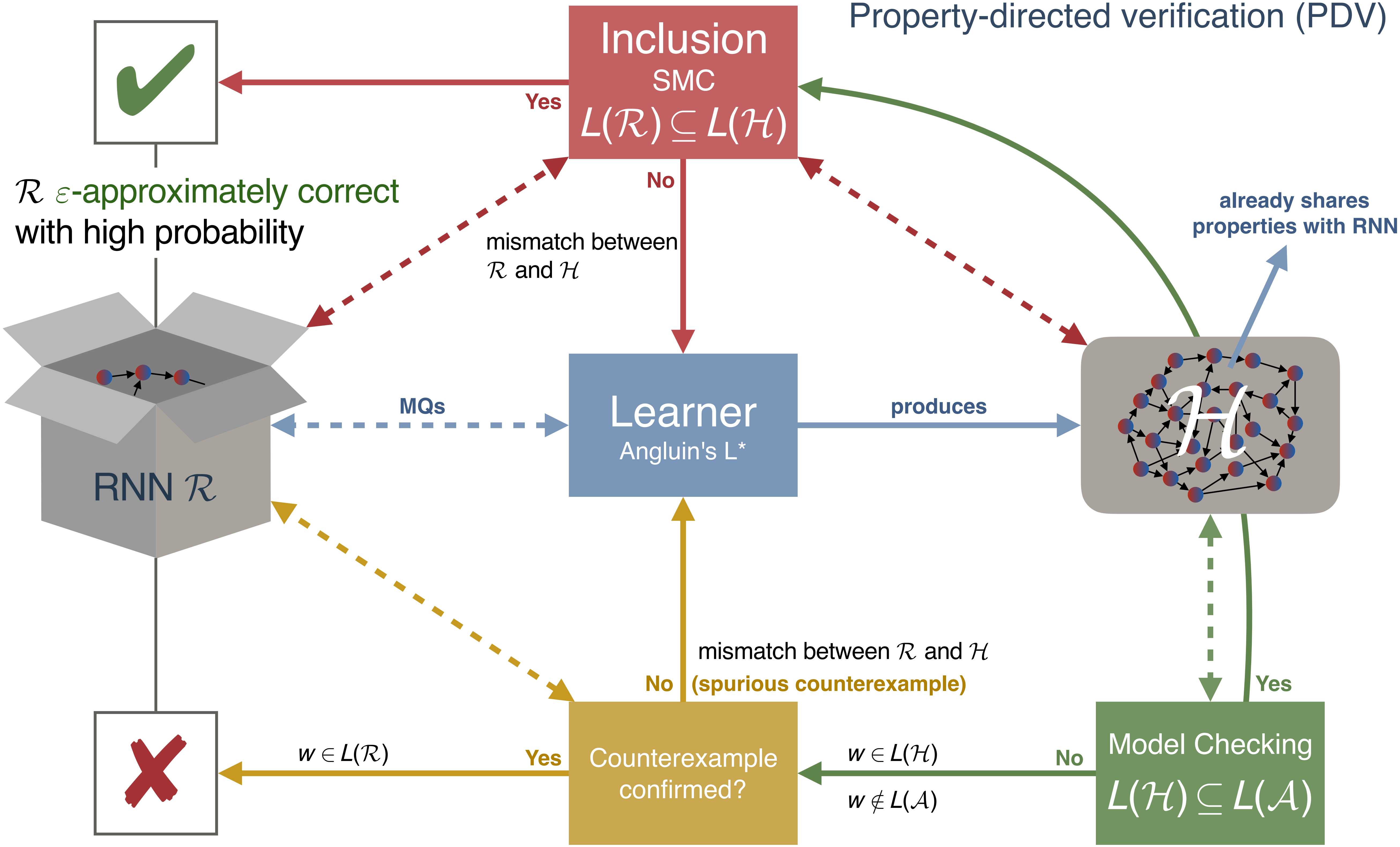

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PDV	**21**	11	109	**28318**

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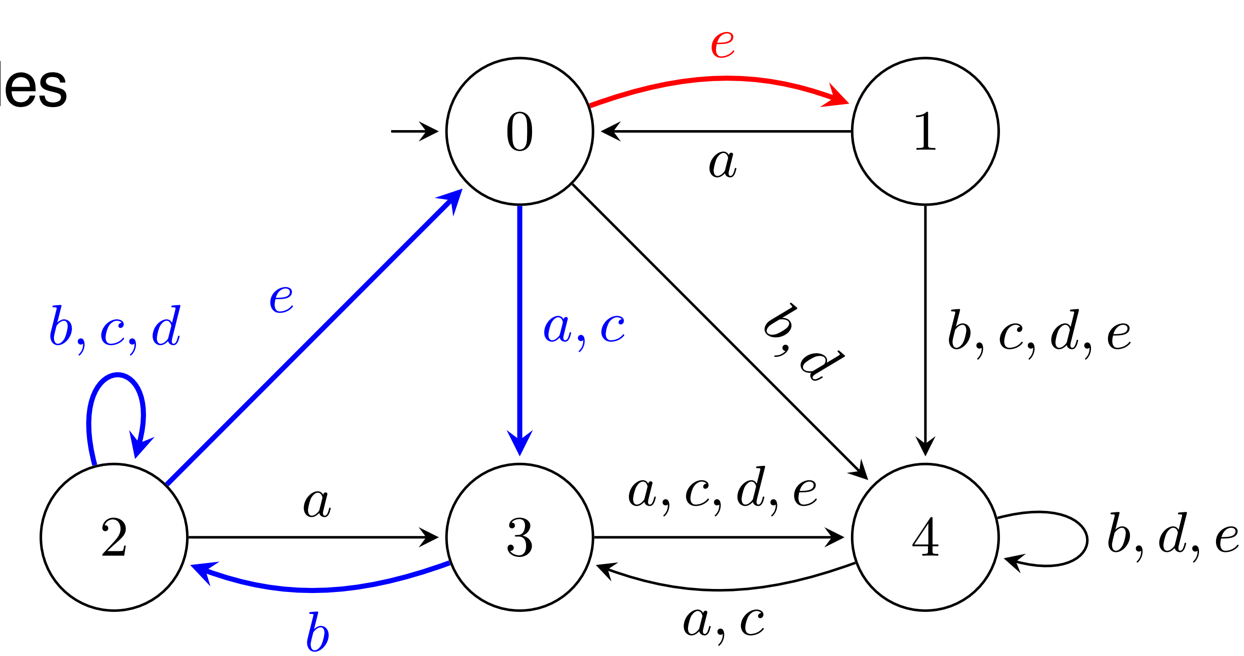
PDV detected "faulty flows"
in 81/ 109 of the counterexamples



Conclusion

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Thank you!