

# EXPRESSIVE POWER OF RECURRENT NEURAL NETWORKS OVER INFINITE INPUT STREAMS

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Joint work with Olivier Finkel

Laboratoire d'Économie Mathématique  
Université Paris 2

13 April 2017

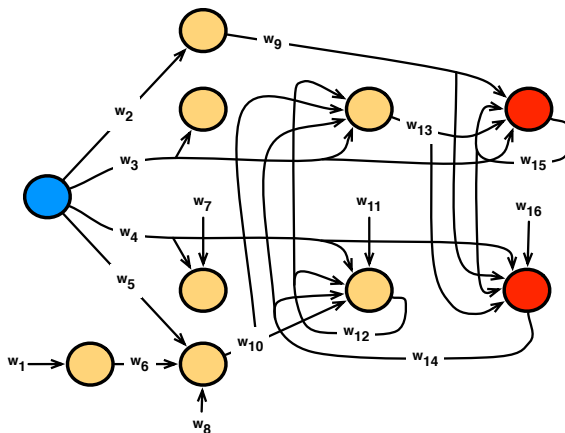
# INTRODUCTION

- ▶ The computational capabilities of recurrent neural networks have mainly been studied in the context of classical computation: McCulloch & Pitts, Turing, Kleene, von Neumann, Minsky, Papert, . . . , Siegelmann & Sontag, . . .
- ▶ We provide a characterization of the computational power of recurrent neural networks in terms of their attractor dynamics, i.e., in the context of infinite input stream computation.

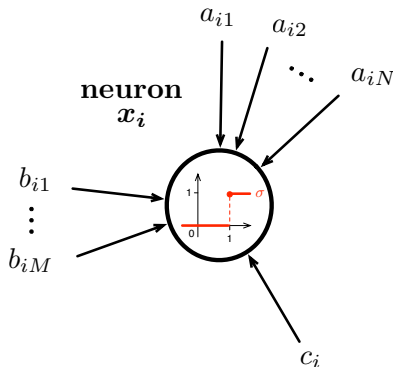
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# RECURRENT NEURAL NETWORK

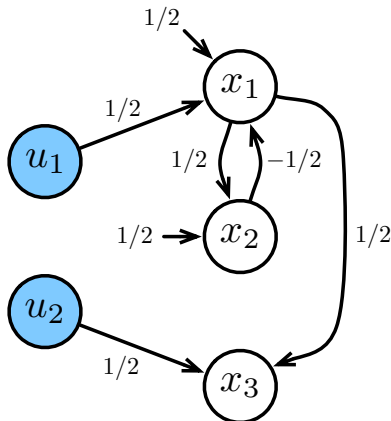


# BOOLEAN RECURRENT NEURAL NETWORKS

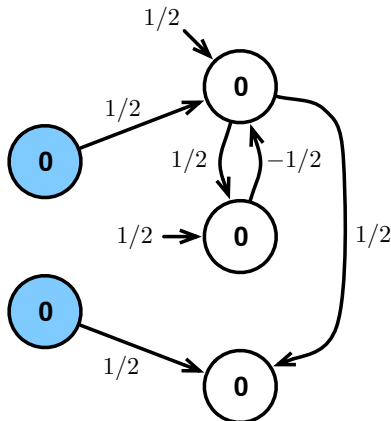


$$x_i(t+1) = \theta \left( \sum_{j=1}^N a_{ij} \cdot x_j(t) + \sum_{j=1}^M b_{ij} \cdot u_j(t) + c_i \right)$$

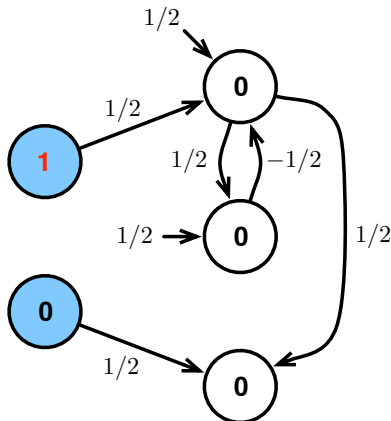
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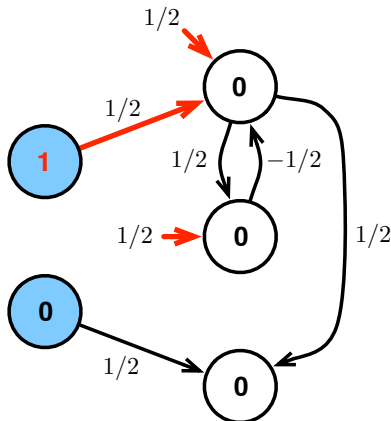


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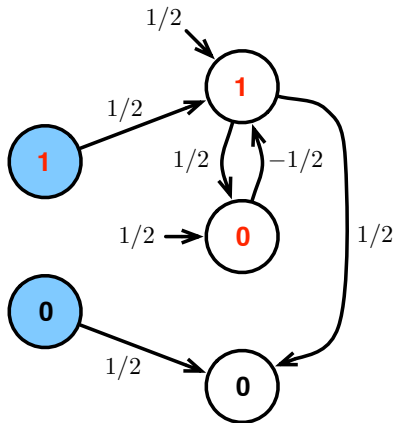




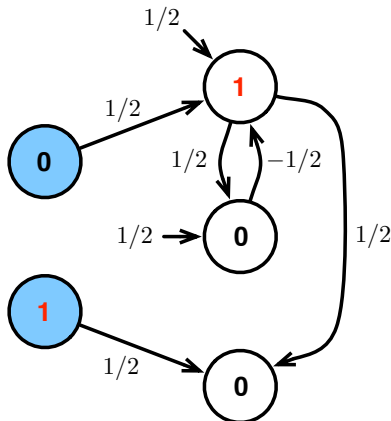
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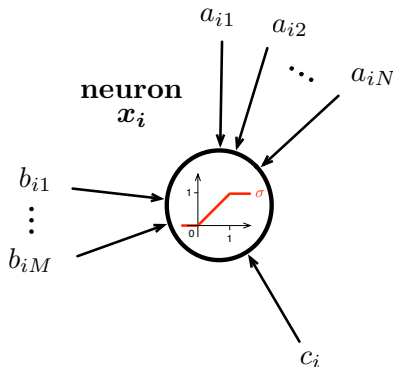
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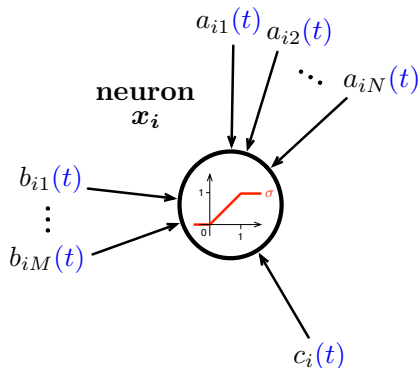


# SIGMOIDAL RECURRENT NEURAL NETWORKS



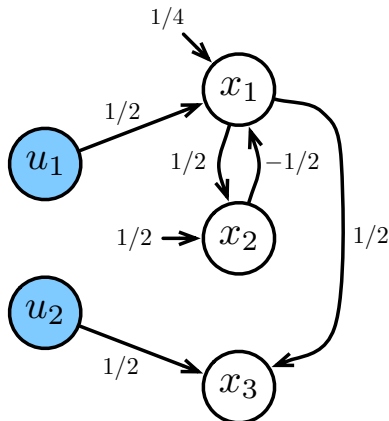
$$x_i(t+1) = \sigma \left( \sum_{j=1}^N a_{ij} \cdot x_j(t) + \sum_{j=1}^M b_{ij} \cdot u_j(t) + c_i \right)$$

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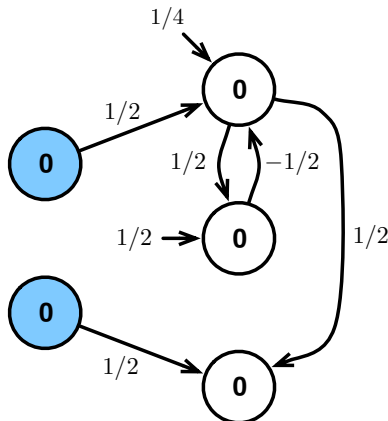


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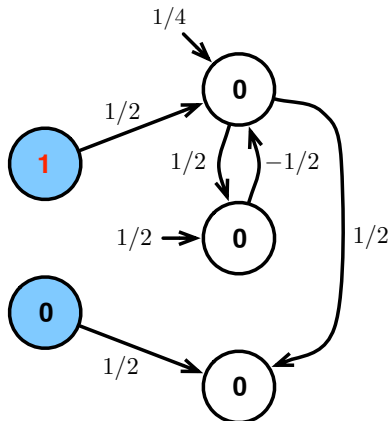
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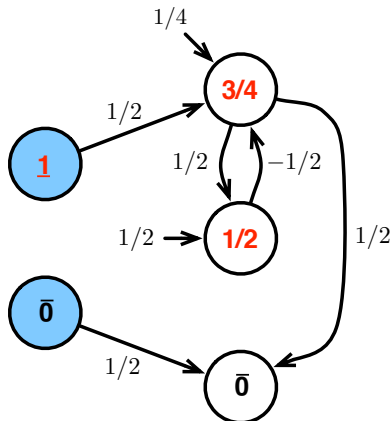
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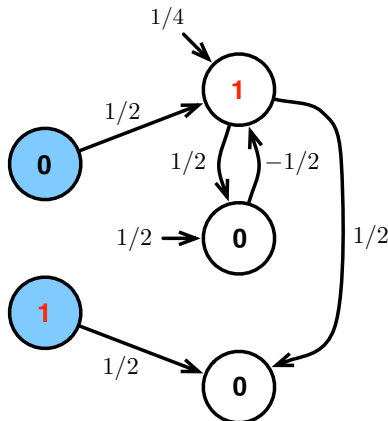




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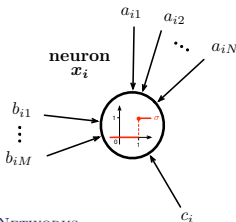
We consider eight models of RNNs:

1. Boolean rational RNNs: B-RNN[ $\mathbb{Q}$ ]s
2. Boolean real RNNs: B-RNN[ $\mathbb{R}$ ]s
3. Symbolic state rational RNNs: SL-RNN[ $\mathbb{Q}$ ]s
4. Symbolic state real RNNs: SL-RNN[ $\mathbb{R}$ ]s
5. Symbolic rational vector RNNs: SV-RNN[ $\mathbb{Q}$ ]s
6. Symbolic rational vector real RNNs: SV-RNN[ $\mathbb{R}$ ]s
7. Symbolic rational vector rational RNNs: EV-RNN[ $\mathbb{Q}$ ]s
8. Symbolic rational vector real RNNs: EV-RNN[ $\mathbb{R}$ ]s

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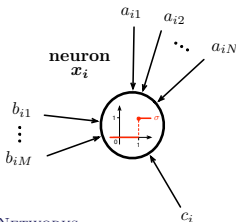
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| 5. Sigmoidal bi-valued evolving rational RNNs: | Ev <sub>2</sub> -RNN[ $\mathbb{Q}$ ]s |
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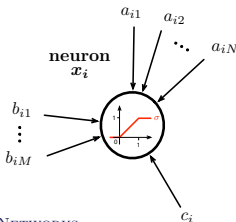
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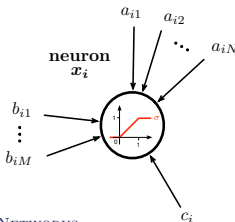
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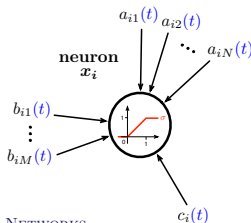




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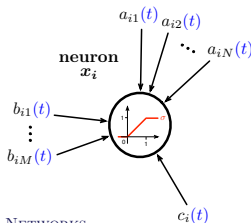
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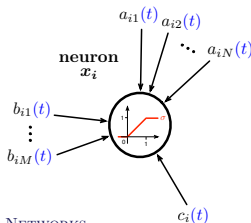
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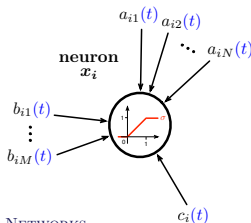
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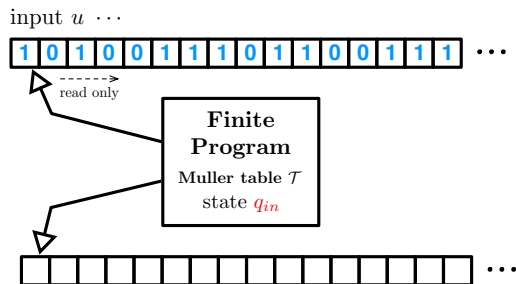


# RESULTS (CLASSICAL COMPUTATION)

	BOOLEAN	STATIC	BI-VALUED	EVOLVING	EVOLVING
Q	<b>FSA</b>	<b>TM</b>	<b>TM/poly(A)</b>	<b>TM/poly(A)</b>	
	<b>REG</b>	<b>P</b>	<b>P/poly</b>	<b>P/poly</b>	
	KI 56, Mi 67	Si & So 95	Ca & Si 11,14	Ca & Si 11,14	
R	<b>FSA</b>	<b>TM/poly(A)</b>	<b>TM/poly(A)</b>	<b>TM/poly(A)</b>	
	<b>REG</b>	<b>P/poly</b>	<b>P/poly</b>	<b>P/poly</b>	
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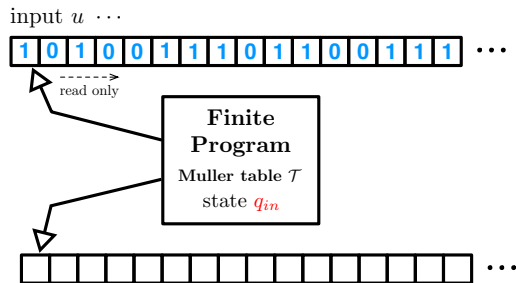
# MULLER TURING MACHINE

A *Muller Turing machine* consists of a classical TM with Muller acceptance condition. Muller table  $\mathcal{T}$ : collection of sets of states.



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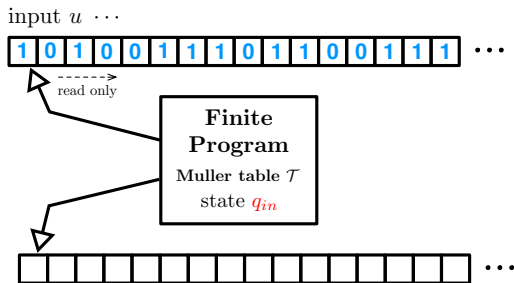
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- The  $\omega$ -word  $u$  is *accepted* by  $\mathcal{M}$  if  $\inf(\rho_u) \in \mathcal{T}$ .

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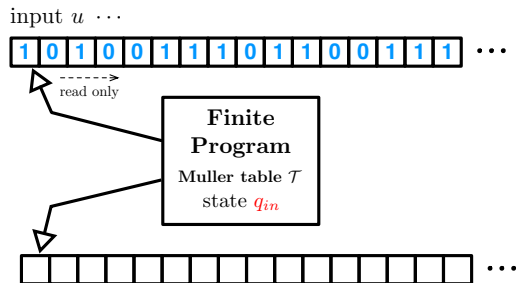


- The  $\omega$ -word  $u$  is *rejected* by  $\mathcal{M}$  if  $\inf(\rho_u) \notin \mathcal{T}$ .



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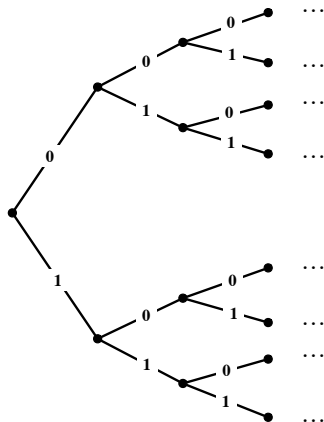
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- Set of  $\omega$ -words accepted is the  $\omega$ -language *recognized* by  $\mathcal{M}$ .

# TOPOLOGY

The Cantor space  $\{0, 1\}^\omega$   
the set of infinite sequences of bits

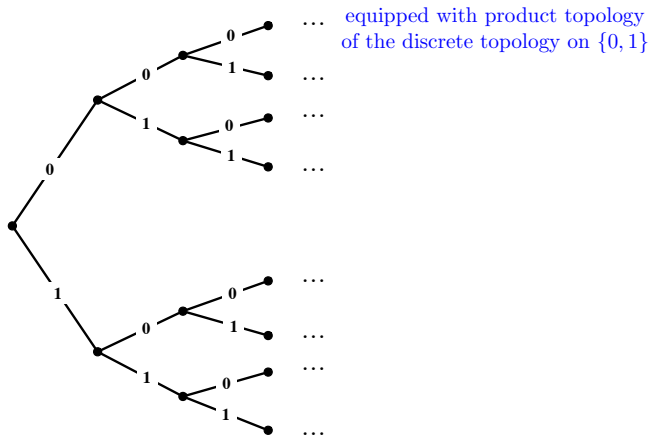






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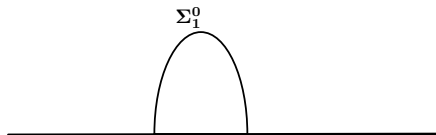
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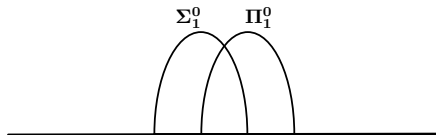
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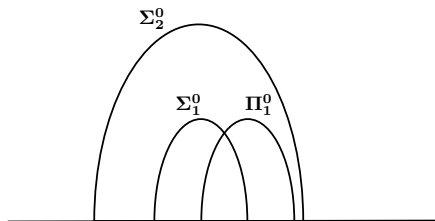


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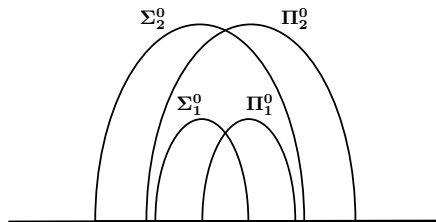




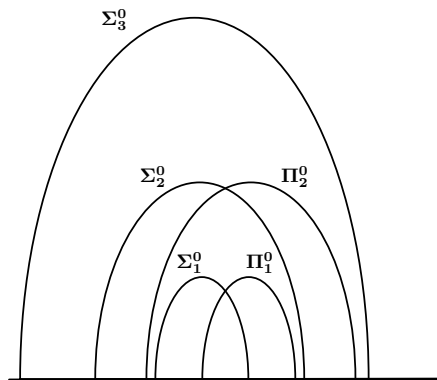
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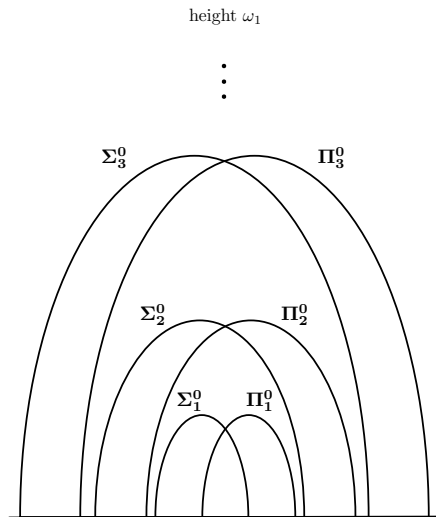
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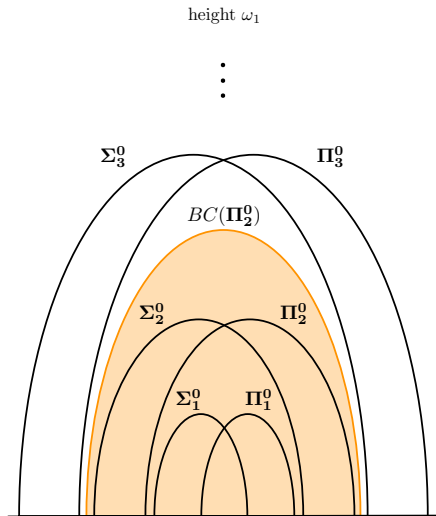
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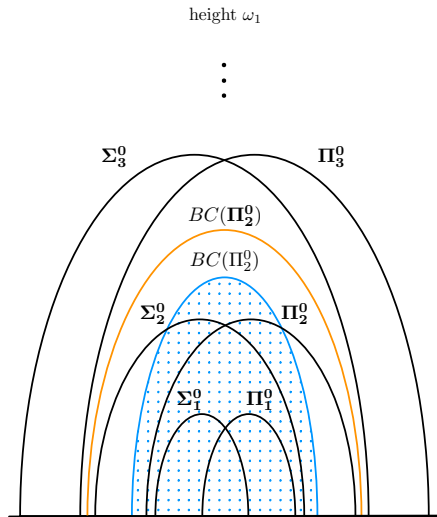
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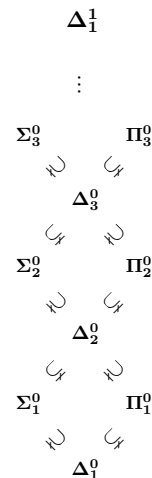
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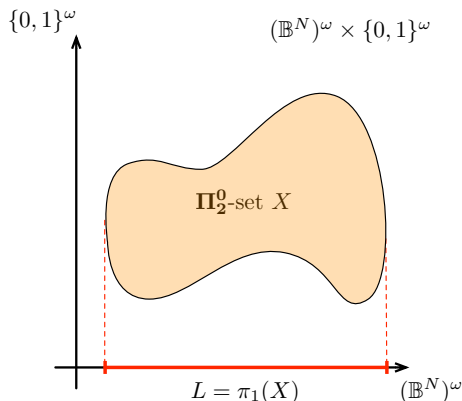


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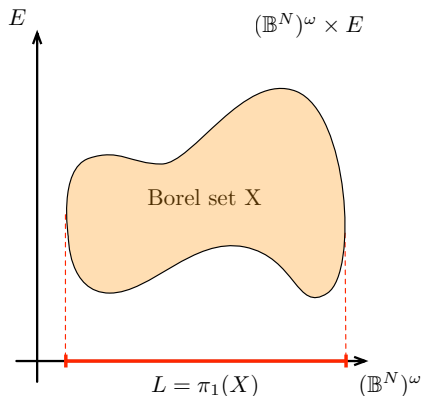
- An  $\omega$ -language  $L \subseteq (\mathbb{B}^N)^\omega$  is *analytic* ( $\Sigma_1^1$ ) iff it is the first projection of some  $\Pi_2^0$ -set  $X \subseteq (\mathbb{B}^N)^\omega \times \{0, 1\}^\omega$ .



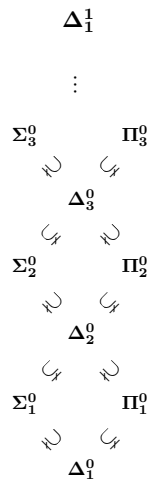


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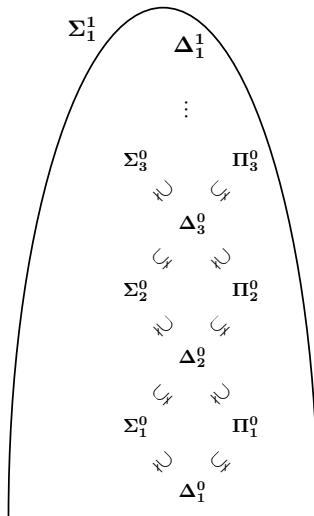
- An  $\omega$ -language  $L \subseteq (\mathbb{B}^N)^\omega$  is *analytic* ( $\Sigma_1^1$ ) iff it is the first projection of some Borel set  $X \subseteq (\mathbb{B}^N)^\omega \times E$ , where  $E$  is a Polish space.



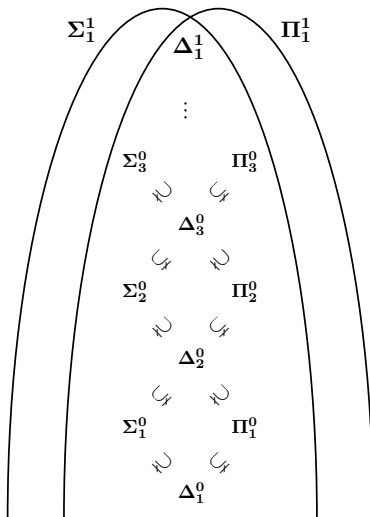
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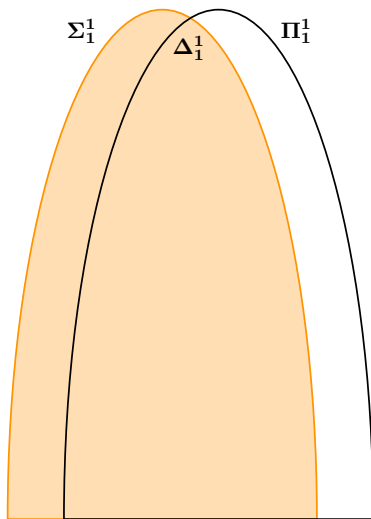
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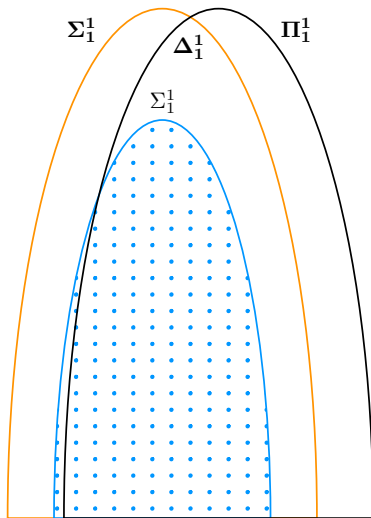
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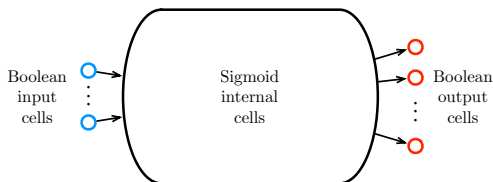


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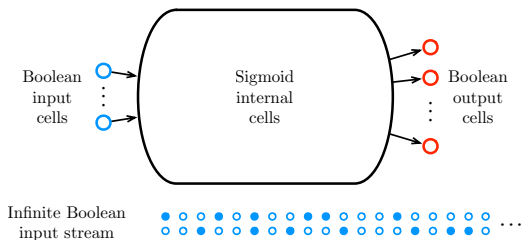
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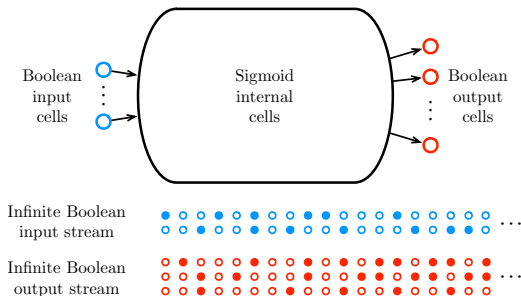
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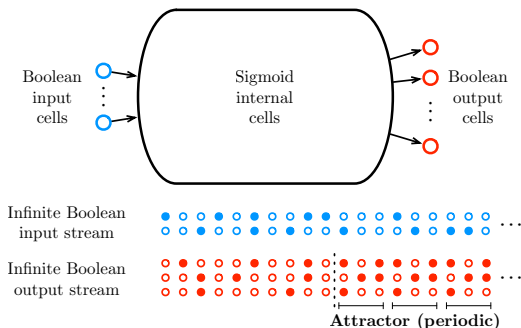
# DETERMINISTIC $\omega$ -RNNs

We consider RNNs with Boolean input and output cells, sigmoidal internal cells, and working on infinite input streams.



# DETERMINISTIC $\omega$ -RNNs

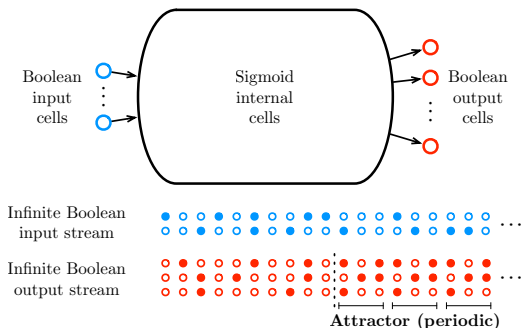
We consider RNNs with Boolean input and output cells, sigmoidal internal cells, and working on infinite input streams.



- The attractors are assumed to be classified into two possible kinds: *accepting* or *rejecting*.

# DETERMINISTIC $\omega$ -RNNs

We consider RNNs with Boolean input and output cells, sigmoidal internal cells, and working on infinite input streams.



- An infinite Boolean input stream is *accepted* by  $\mathcal{N}$  if the corresponding Boolean output stream visits a *accepting* attractor.





# DETERMINISTIC $\omega$ -RNNs

We consider six models of deterministic RNNs:

1. static rational RNNs: D-St-RNN[ $\mathbb{Q}$ ]s
2. static real RNNs: D-St-RNN[ $\mathbb{R}$ ]s
3. bounded evolving rational RNNs: D-E<sub>b</sub>-RNN[ $\mathbb{Q}$ ]s
4. bounded evolving real RNNs: D-E<sub>b</sub>-RNN[ $\mathbb{R}$ ]s
5. unbounded evolving rational RNNs: D-E<sub>u</sub>-RNN[ $\mathbb{Q}$ ]s
6. unbounded evolving real RNNs: D-E<sub>u</sub>-RNN[ $\mathbb{R}$ ]s

# DETERMINISTIC $\omega$ -RNNs

We consider six models of deterministic RNNs:

1. static rational RNNs:

2. static real RNNs:

3. bi-valued evolving rational RNNs:

4. bi-valued evolving real RNNs:

5. general evolving rational RNNs:

6. general evolving real N-RNNs:

D-St-RNN[ $\mathbb{Q}$ ]s

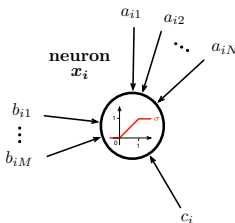
D-St-RNN[ $\mathbb{R}$ ]s

D-Ev<sub>2</sub>-RNN[ $\mathbb{Q}$ ]s

D-Ev<sub>2</sub>-RNN[ $\mathbb{R}$ ]s

D-Ev-RNN[ $\mathbb{Q}$ ]s

D-Ev-RNN[ $\mathbb{R}$ ]s



# DETERMINISTIC $\omega$ -RNNs

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D-St-RNN[ $\mathbb{Q}$ ]s

2. static real RNNs:

D-St-RNN[ $\mathbb{R}$ ]s

3. bi-valued evolving rational RNNs:

D-Ev<sub>2</sub>-RNN[ $\mathbb{Q}$ ]s

4. bi-valued evolving real RNNs:

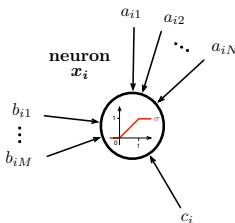
D-Ev<sub>2</sub>-RNN[ $\mathbb{R}$ ]s

5. general evolving rational RNNs:

D-Ev-RNN[ $\mathbb{Q}$ ]s

6. general evolving real N-RNNs:

D-Ev-RNN[ $\mathbb{R}$ ]s

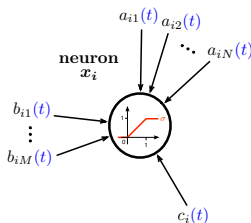




# DETERMINISTIC $\omega$ -RNNs

We consider six models of deterministic RNNs:

- |                                      |   |
|--------------------------------------|---|
| 1. static rational RNNs:             | D-St-RNN[ $\mathbb{Q}$ ]s               |
| 2. static real RNNs:                 | D-St-RNN[ $\mathbb{R}$ ]s               |
| 3. bi-valued evolving rational RNNs: | D-Ev <sub>2</sub> -RNN[ $\mathbb{Q}$ ]s |
| 4. bi-valued evolving real RNNs:     | D-Ev <sub>2</sub> -RNN[ $\mathbb{R}$ ]s |
| 5. general evolving rational RNNs:   | D-Ev-RNN[ $\mathbb{Q}$ ]s               |
| 6. general evolving real N-RNNs:     | D-Ev-RNN[ $\mathbb{R}$ ]s               |



# DETERMINISTIC $\omega$ -RNNs

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D-St-RNN[ $\mathbb{Q}$ ]s

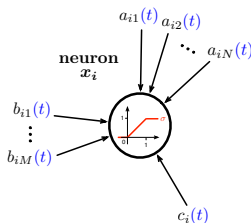
D-St-RNN[ $\mathbb{R}$ ]s

D-Ev<sub>2</sub>-RNN[ $\mathbb{Q}$ ]s

D-Ev<sub>2</sub>-RNN[ $\mathbb{R}$ ]s

D-Ev-RNN[ $\mathbb{Q}$ ]s

D-Ev-RNN[ $\mathbb{R}$ ]s



# DETERMINISTIC $\omega$ -RNNs

We consider six models of deterministic RNNs:

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4. bi-valued evolving real RNNs:
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D-St-RNN[ $\mathbb{Q}$ ]s

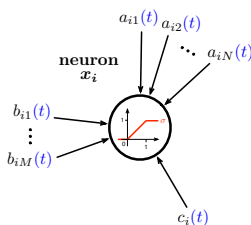
D-St-RNN[ $\mathbb{R}$ ]s

D-Ev<sub>2</sub>-RNN[ $\mathbb{Q}$ ]s

D-Ev<sub>2</sub>-RNN[ $\mathbb{R}$ ]s

D-Ev-RNN[ $\mathbb{Q}$ ]s

D-Ev-RNN[ $\mathbb{R}$ ]s



# DETERMINISTIC $\omega$ -RNNs

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4. bi-valued evolving real RNNs:
5. general evolving rational RNNs:
6. general evolving real N-RNNs:

D-St-RNN[ $\mathbb{Q}$ ]s

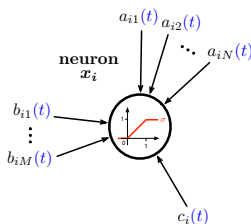
D-St-RNN[ $\mathbb{R}$ ]s

D-Ev<sub>2</sub>-RNN[ $\mathbb{Q}$ ]s

D-Ev<sub>2</sub>-RNN[ $\mathbb{R}$ ]s

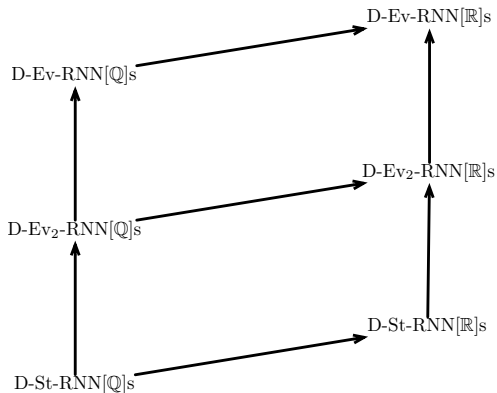
D-Ev-RNN[ $\mathbb{Q}$ ]s

D-Ev-RNN[ $\mathbb{R}$ ]s



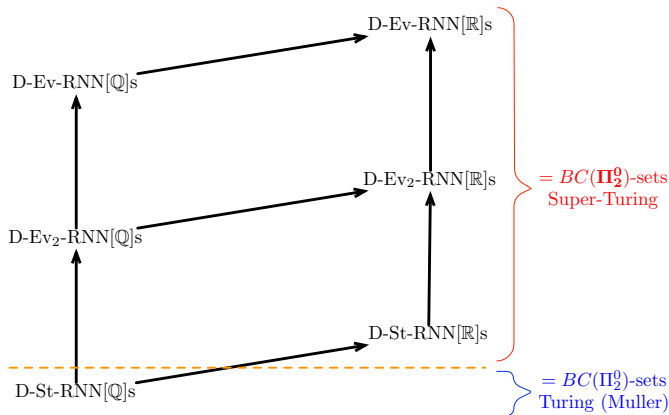
# RESULTS

Relationship between the models:



# RESULTS

Relationship between the models:



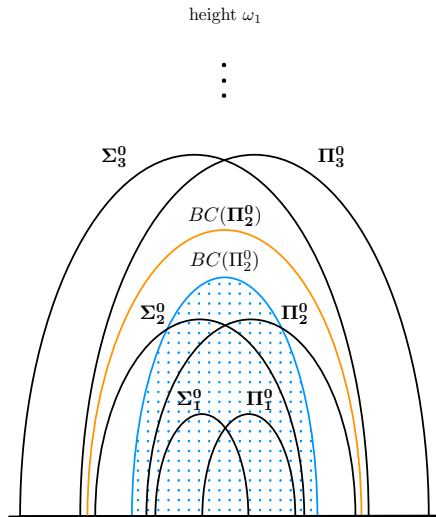
# RESULTS

## THEOREM

*Let  $L \subseteq (\mathbb{B}^M)^\omega$ . The following conditions are equivalent.*

- ▶  $L \in BC(\Pi_2^0)$
- ▶  $L$  is recognizable by some deterministic Muller TM
- ▶  $L$  is recognizable by some D-St-RNN[ $\mathbb{Q}$ ]

## RESULTS





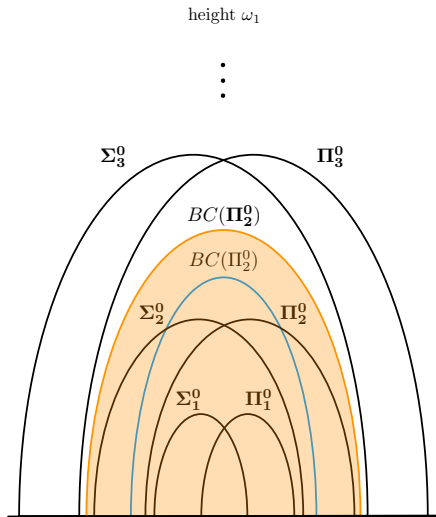
# RESULTS

## THEOREM

Let  $L \subseteq (\mathbb{B}^M)^\omega$ . The following conditions are equivalent.

- ▶  $L \in BC(\Pi_2^0)$ ;
- ▶  $L$  is recognizable by some  $D\text{-St-RNN}[\mathbb{R}]$ ;
- ▶  $L$  is recognizable by some  $D\text{-Ev}_2\text{-RNN}[\mathbb{Q}]$ ;
- ▶  $L$  is recognizable by some  $D\text{-Ev-RNN}[\mathbb{Q}]$ ;
- ▶  $L$  is recognizable by some  $D\text{-Ev}_2\text{-RNN}[\mathbb{R}]$ ;
- ▶  $L$  is recognizable by some  $D\text{-Ev-RNN}[\mathbb{R}]$ .

## RESULTS



# RESULTS – SUMMARY

DET.	STATIC	BI-VALUED EVOLVING	GENERAL EVOLVING
$\mathbb{Q}$	D-St-RNN[ $\mathbb{Q}$ ]s $= BC(\Pi_2^0)$ Turing (Muller)	D-Ev <sub>2</sub> -RNN[ $\mathbb{Q}$ ]s $= BC(\Pi_2^0)$ super-Turing	D-Ev-RNN[ $\mathbb{Q}$ ]s $= BC(\Pi_2^0)$ super-Turing
$\mathbb{R}$	D-St-RNN[ $\mathbb{R}$ ]s $= BC(\Pi_2^0)$ super-Turing	D-Ev <sub>2</sub> -RNN[ $\mathbb{R}$ ]s $= BC(\Pi_2^0)$ super-Turing	D-Ev-RNN[ $\mathbb{R}$ ]s $= BC(\Pi_2^0)$ super-Turing

# DETERMINISTIC $\omega$ -RNNs

We consider two other models of deterministic RNNs:

1. static real RNNs with only one real weight:

D-St-RNN[ $\mathbb{Q}, \ulcorner \alpha \urcorner$ ]s, where  $\ulcorner \alpha \urcorner \in \mathbb{R}$  encoding of  $\alpha \in \{0, 1\}^\omega$

2. bi-valued evolving rational RNNs with only one evolving weight:

D-Ev<sub>2</sub>-RNN[ $\mathbb{Q}, \alpha$ ]s, where  $\alpha \in \{0, 1\}^\omega$

## DETERMINISTIC $\omega$ -RNNs

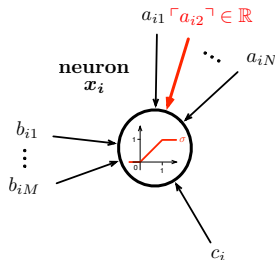
We consider two other models of deterministic RNNs:

1. static real RNNs with only one real weight:

D-St-RNN[ $\mathbb{Q}, \lceil \alpha \rceil$ ]s, where  $\lceil \alpha \rceil \in \mathbb{R}$  encoding of  $\alpha \in \{0, 1\}^\omega$

2. bi-valued evolving rational RNNs with only one evolving weight:

D-Ev<sub>2</sub>-RNN[ $\mathbb{Q}, \alpha$ ]s, where  $\alpha \in \{0, 1\}^\omega$



## DETERMINISTIC $\omega$ -RNNs

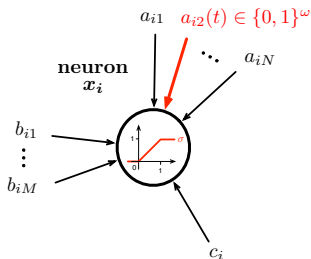
We consider two other models of deterministic RNNs:

1. static real RNNs with only one real weight:

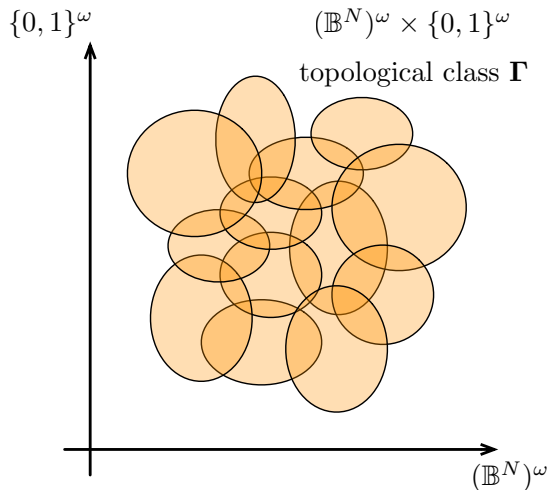
D-St-RNN[ $\mathbb{Q}, \lceil \alpha \rceil$ ]s, where  $\lceil \alpha \rceil \in \mathbb{R}$  encoding of  $\alpha \in \{0, 1\}^\omega$

2. bi-valued evolving rational RNNs with only one evolving weight:

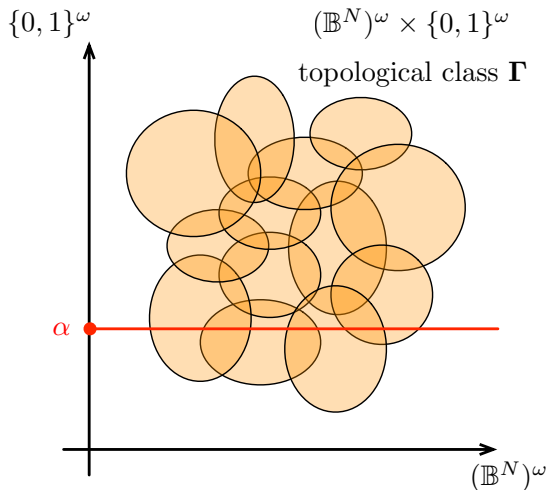
D-Ev<sub>2</sub>-RNN[ $\mathbb{Q}, \alpha$ ]s, where  $\alpha \in \{0, 1\}^\omega$



# TOPOLOGY

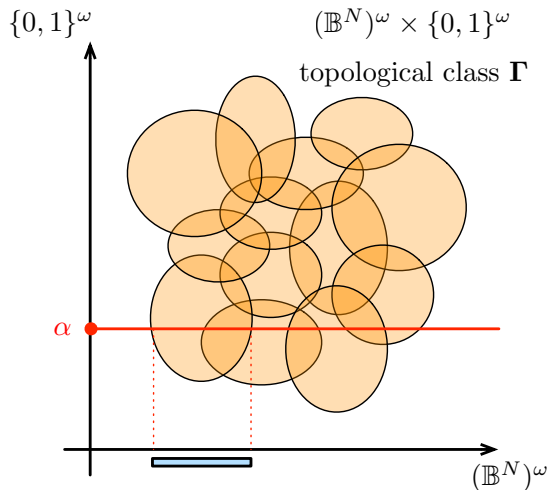


# TOPOLOGY

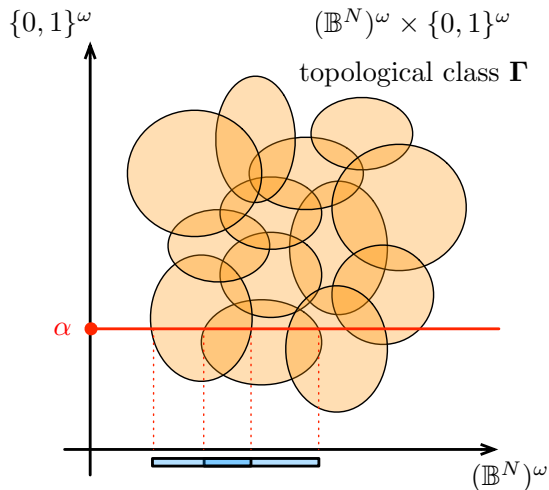




# TOPOLOGY

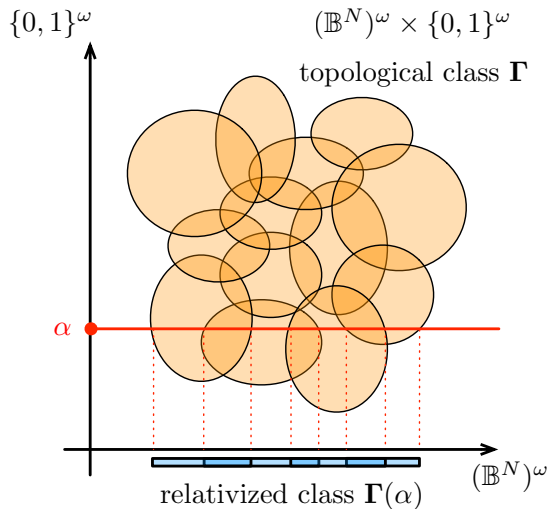


# TOPOLOGY





# TOPOLOGY

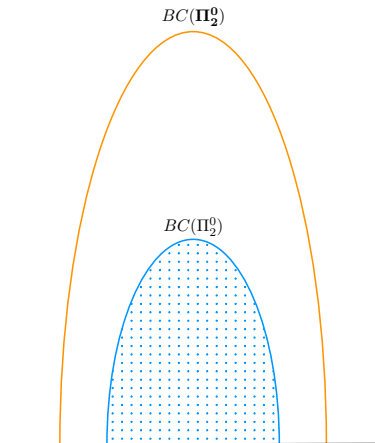


# RESULTS

## THEOREM

Let  $L \subseteq (\mathbb{B}^M)^\omega$ . The following conditions are equivalent.

- ▶  $L \in BC(\Pi_2^0)(\alpha)$ , for some  $\alpha \in \{0, 1\}^\omega$
- ▶  $L$  is recognizable by some  $D\text{-St-RNN}[\mathbb{Q}, \lceil \alpha \rceil]$
- ▶  $L$  is recognizable by some  $D\text{-Ev}_2\text{-RNN}[\mathbb{Q}, \alpha]$

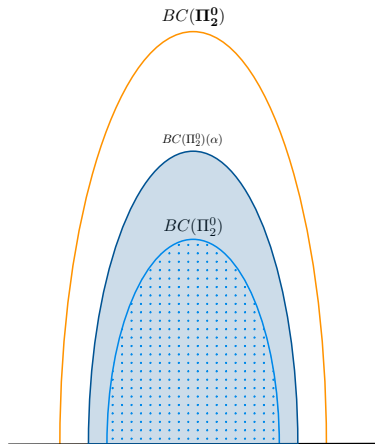


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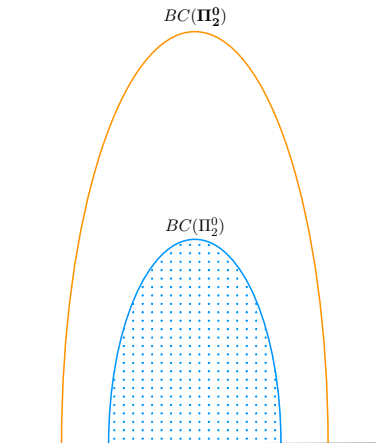
# RESULTS

## PROPOSITION

*There exist some infinite sequence  $(\alpha_k)_{k < \omega_1}$ , where each  $\alpha_i \in \{0, 1\}^\omega$ , such that*

$$BC(\Pi_2^0)(\alpha_i) \subsetneq BC(\Pi_2^0)(\alpha_j)$$

*for all  $i < j < \omega_1$ .*



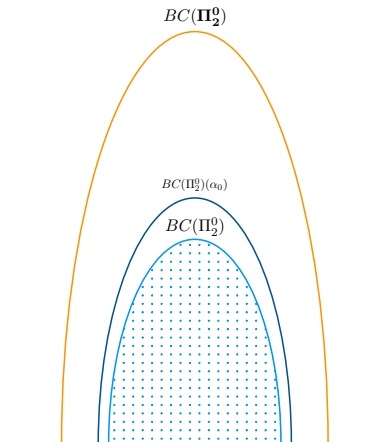
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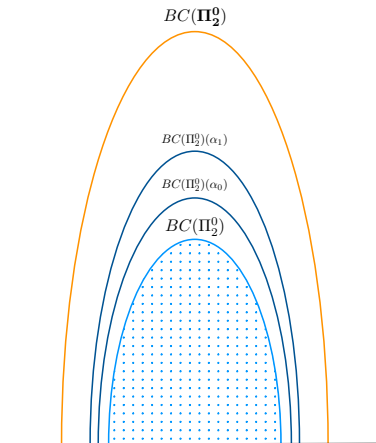
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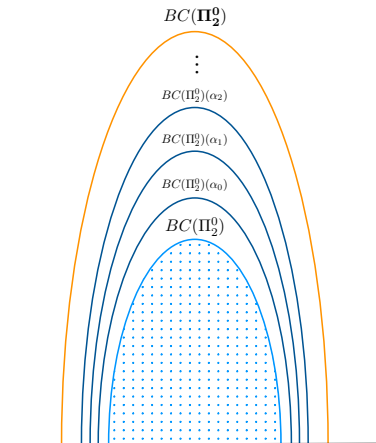
# RESULTS

## PROPOSITION

*There exist some infinite sequence  $(\alpha_k)_{k < \omega_1}$ , where each  $\alpha_i \in \{0, 1\}^\omega$ , such that*

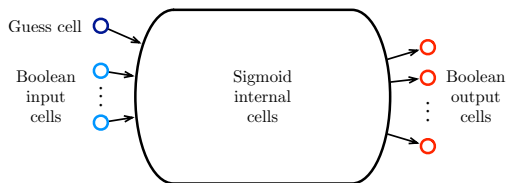
$$BC(\Pi_2^0)(\alpha_i) \subsetneq BC(\Pi_2^0)(\alpha_j)$$

*for all  $i < j < \omega_1$ .*



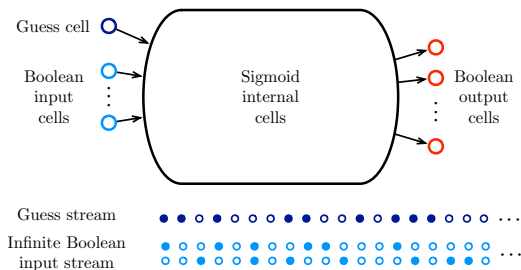
# NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

The RNNs are provided with an additional Boolean guess cell.



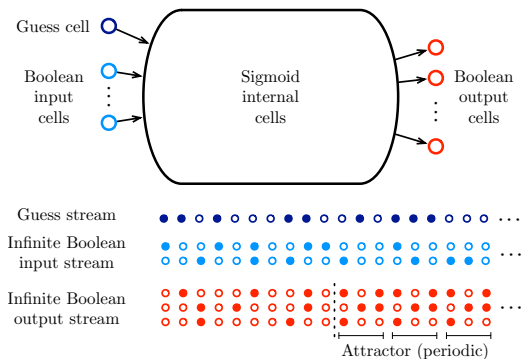
# NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

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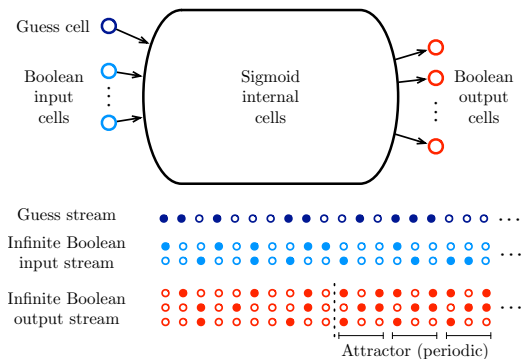
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# NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

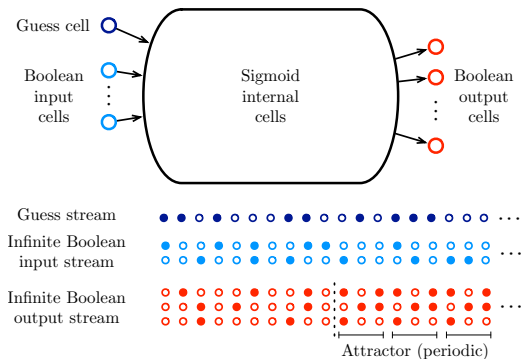
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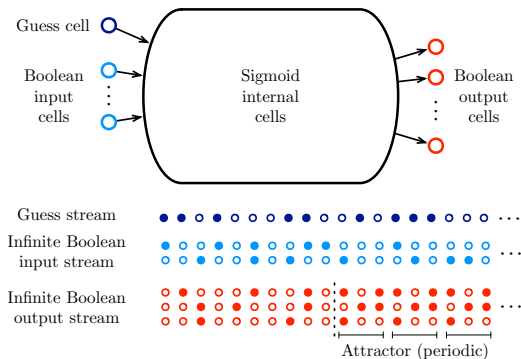
The RNNs are provided with an additional Boolean guess cell.



- Input stream  $s \in (\mathbb{B}^M)^\omega$  *accepted* by  $\mathcal{N}$  iff there exists some guess  $g \in \mathbb{B}^\omega$  s.t.  $\mathcal{N}(s, g)$  enters an accepting attractor.

# NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

The RNNs are provided with an additional Boolean guess cell.



- Input stream  $s \in (\mathbb{B}^M)^\omega$  *rejected* by  $\mathcal{N}$  iff for all guess  $g \in \mathbb{B}^\omega$ ,  $\mathcal{N}(s, g)$  enters an accepting attractor.



# NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

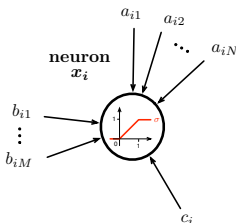
We consider six models of nondeterministic RNNs (of type I):

1. static rational RNNs:  $N\text{-St-RNN}[\mathbb{Q}]_s$
2. static real RNNs:  $N\text{-St-RNN}[\mathbb{R}]_s$
3. bounded evolving rational RNNs:  $N\text{-Evo-RNN}[\mathbb{Q}]_b$
4. bounded evolving real RNNs:  $N\text{-Evo-RNN}[\mathbb{R}]_b$
5. unbounded evolving rational RNNs:  $N\text{-Evo-RNN}[\mathbb{Q}]_u$
6. unbounded evolving real RNNs:  $N\text{-Evo-RNN}[\mathbb{R}]_u$

# NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

We consider six models of nondeterministic RNNs (of type I):

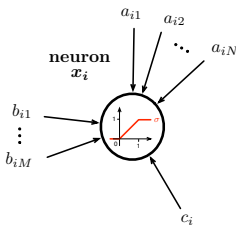
- |                                      |   |
|--------------------------------------|---|
| 1. static rational RNNs:             | N-St-RNN[ $\mathbb{Q}$ ]s               |
| 2. static real RNNs:                 | N-St-RNN[ $\mathbb{R}$ ]s               |
| 3. bi-valued evolving rational RNNs: | N-Ev <sub>2</sub> -RNN[ $\mathbb{Q}$ ]s |
| 4. bi-valued evolving real RNNs:     | N-Ev <sub>2</sub> -RNN[ $\mathbb{R}$ ]s |
| 5. general evolving rational RNNs:   | N-Ev-RNN[ $\mathbb{Q}$ ]s               |
| 6. general evolving real N-RNNs:     | N-Ev-RNN[ $\mathbb{R}$ ]s               |



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We consider six models of nondeterministic RNNs (of type I):

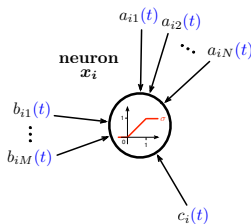
- |                                      |   |
|--------------------------------------|---|
| 1. static rational RNNs:             | N-St-RNN[ $\mathbb{Q}$ ]s               |
| 2. static real RNNs:                 | N-St-RNN[ $\mathbb{R}$ ]s               |
| 3. bi-valued evolving rational RNNs: | N-Ev <sub>2</sub> -RNN[ $\mathbb{Q}$ ]s |
| 4. bi-valued evolving real RNNs:     | N-Ev <sub>2</sub> -RNN[ $\mathbb{R}$ ]s |
| 5. general evolving rational RNNs:   | N-Ev-RNN[ $\mathbb{Q}$ ]s               |
| 6. general evolving real N-RNNs:     | N-Ev-RNN[ $\mathbb{R}$ ]s               |



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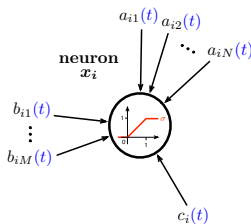
- |                                      |   |
|--------------------------------------|---|
| 1. static rational RNNs:             | N-St-RNN[ $\mathbb{Q}$ ]s               |
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| 4. bi-valued evolving real RNNs:     | N-Ev <sub>2</sub> -RNN[ $\mathbb{R}$ ]s |
| 5. general evolving rational RNNs:   | N-Ev-RNN[ $\mathbb{Q}$ ]s               |
| 6. general evolving real N-RNNs:     | N-Ev-RNN[ $\mathbb{R}$ ]s               |



## NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

We consider six models of nondeterministic RNNs (of type I):

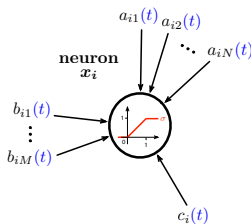
- |                                      |   |
|--------------------------------------|---|
| 1. static rational RNNs:             | N-St-RNN[ $\mathbb{Q}$ ]s               |
| 2. static real RNNs:                 | N-St-RNN[ $\mathbb{R}$ ]s               |
| 3. bi-valued evolving rational RNNs: | N-Ev <sub>2</sub> -RNN[ $\mathbb{Q}$ ]s |
| 4. bi-valued evolving real RNNs:     | N-Ev <sub>2</sub> -RNN[ $\mathbb{R}$ ]s |
| 5. general evolving rational RNNs:   | N-Ev-RNN[ $\mathbb{Q}$ ]s               |
| 6. general evolving real N-RNNs:     | N-Ev-RNN[ $\mathbb{R}$ ]s               |



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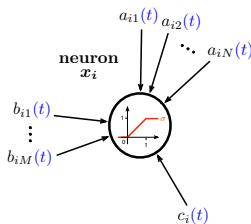
- |                                      |   |
|--------------------------------------|---|
| 1. static rational RNNs:             | N-St-RNN[ $\mathbb{Q}$ ]s               |
| 2. static real RNNs:                 | N-St-RNN[ $\mathbb{R}$ ]s               |
| 3. bi-valued evolving rational RNNs: | N-Ev <sub>2</sub> -RNN[ $\mathbb{Q}$ ]s |
| 4. bi-valued evolving real RNNs:     | N-Ev <sub>2</sub> -RNN[ $\mathbb{R}$ ]s |
| 5. general evolving rational RNNs:   | N-Ev-RNN[ $\mathbb{Q}$ ]s               |
| 6. general evolving real N-RNNs:     | N-Ev-RNN[ $\mathbb{R}$ ]s               |



## NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

We consider six models of nondeterministic RNNs (of type I):

- |                                      |  |
|--------------------------------------|--|
| 1. static rational RNNs:             | $\text{N-St-RNN}[\mathbb{Q}]_s$          |
| 2. static real RNNs:                 | $\text{N-St-RNN}[\mathbb{R}]_s$          |
| 3. bi-valued evolving rational RNNs: | $\text{N-Ev}_2\text{-RNN}[\mathbb{Q}]_s$ |
| 4. bi-valued evolving real RNNs:     | $\text{N-Ev}_2\text{-RNN}[\mathbb{R}]_s$ |
| 5. general evolving rational RNNs:   | $\text{N-Ev-RNN}[\mathbb{Q}]_s$          |
| 6. general evolving real N-RNNs:     | $\text{N-Ev-RNN}[\mathbb{R}]_s$          |

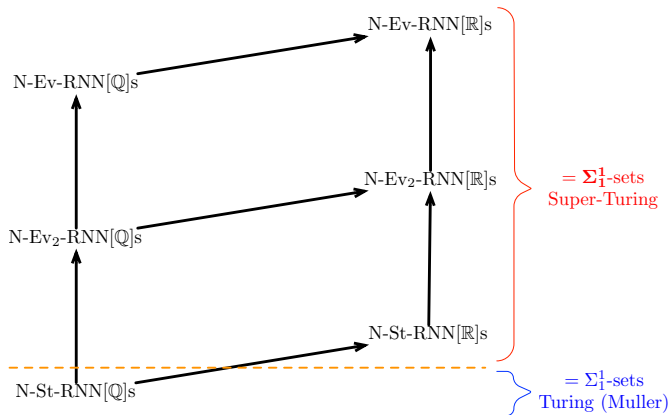






# RESULTS

Relationship between the models:



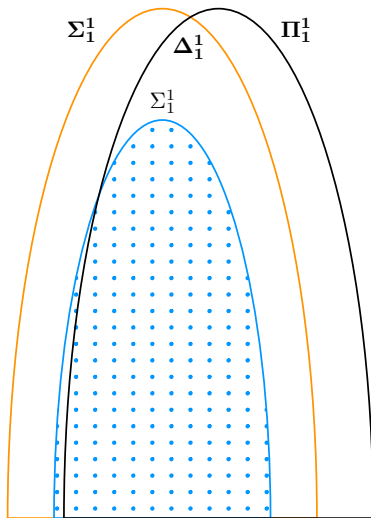
# RESULTS

## THEOREM

*Let  $L \subseteq (\mathbb{B}^M)^\omega$ . The following conditions are equivalent.*

- ▶  $L \in \Sigma_1^1$
- ▶  $L$  is recognizable by some nondeterministic Muller TM
- ▶  $L$  is recognizable by some N-St-RNN[ $\mathbb{Q}$ ]

## RESULTS



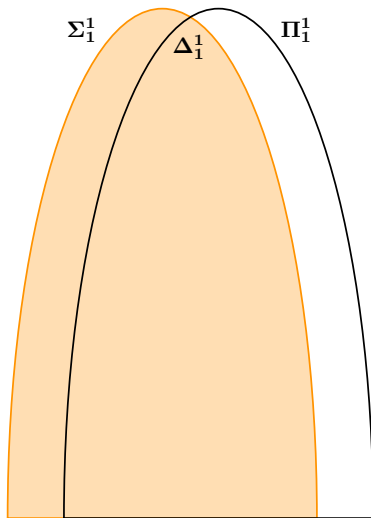
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Let  $L \subseteq (\mathbb{B}^M)^\omega$ . The following conditions are equivalent.

- ▶  $L \in \Sigma_1^1$ ;
- ▶  $L$  is recognizable by some  $N\text{-St-RNN}[\mathbb{R}]$ ;
- ▶  $L$  is recognizable by some  $N\text{-Ev}_2\text{-RNN}[\mathbb{Q}]$ ;
- ▶  $L$  is recognizable by some  $N\text{-Ev-RNN}[\mathbb{Q}]$ ;
- ▶  $L$  is recognizable by some  $N\text{-Ev}_2\text{-RNN}[\mathbb{R}]$ ;
- ▶  $L$  is recognizable by some  $N\text{-Ev-RNN}[\mathbb{R}]$ .

## RESULTS



# RESULTS – SUMMARY

NONDET.	STATIC	BI-VALUED EVOLVING	GENERAL EVOLVING
$\mathbb{Q}$	N-St-RNN[ $\mathbb{Q}$ ]s $= \Sigma_1^1$ Turing (Muller)	N-Ev <sub>2</sub> -RNN[ $\mathbb{Q}$ ]s $= \Sigma_1^1$ super-Turing	N-Ev-RNN[ $\mathbb{Q}$ ]s $= \Sigma_1^1$ super-Turing
$\mathbb{R}$	N-St-RNN[ $\mathbb{R}$ ]s $= \Sigma_1^1$ super-Turing	N-Ev <sub>2</sub> -RNN[ $\mathbb{R}$ ]s $= \Sigma_1^1$ super-Turing	N-Ev-RNN[ $\mathbb{R}$ ]s $= \Sigma_1^1$ super-Turing

# NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

We consider two other models of nondeterministic RNNs (type I):

1. static real RNNs with only one real weight:

$N\text{-St-RNN}[\mathbb{Q}, \ulcorner \alpha \urcorner]s$ , where  $\ulcorner \alpha \urcorner \in \mathbb{R}$  encoding of  $\alpha \in \{0, 1\}^\omega$

2. bi-valued evolving rational RNNs with only one evolving weight:

$N\text{-Ev}_2\text{-RNN}[\mathbb{Q}, \alpha]s$ , where  $\alpha \in \{0, 1\}^\omega$

# NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

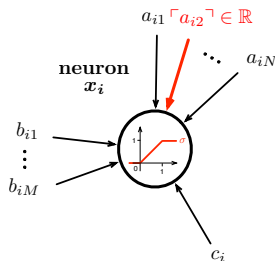
We consider two other models of nondeterministic RNNs (type I):

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2. bi-valued evolving rational RNNs with only one evolving weight:

N-Ev<sub>2</sub>-RNN[ $\mathbb{Q}, \alpha$ ]s, where  $\alpha \in \{0, 1\}^\omega$





# NONDETERMINISTIC $\omega$ -RNNs (TYPE I)

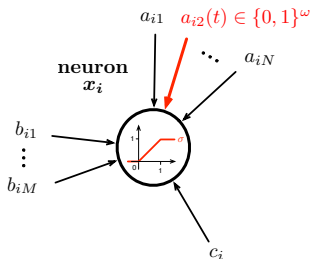
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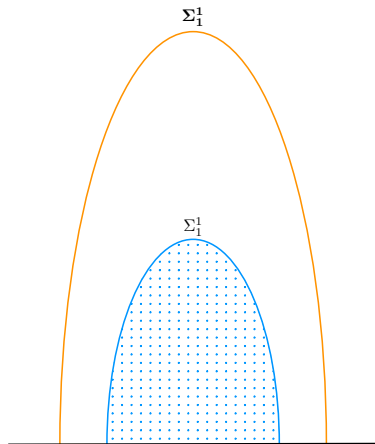


## RESULTS

## THEOREM

Let  $L \subseteq (\mathbb{B}^M)^\omega$ . The following conditions are equivalent.

- ▶  $L \in \Sigma_1^1(\alpha)$ , for some  $\alpha \in \{0, 1\}^\omega$
- ▶  $L$  is recognizable by some  $N\text{-St-RNN}[\mathbb{Q}, \ulcorner \alpha \urcorner]$
- ▶  $L$  is recognizable by some  $N\text{-Ev}_2\text{-RNN}[\mathbb{Q}, \alpha]$

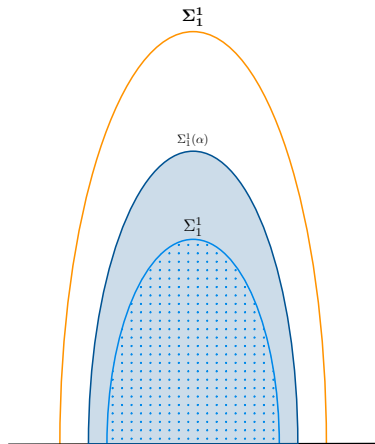


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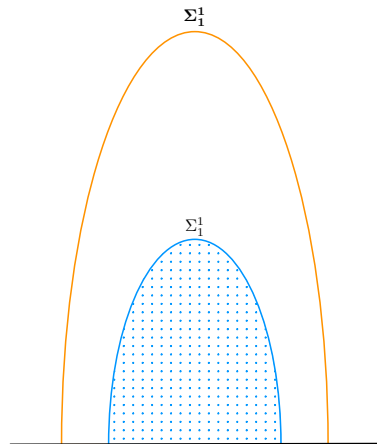
# RESULTS

## PROPOSITION

*There exist some infinite sequence  $(\alpha_k)_{k < \omega_1}$ , where each  $\alpha_i \in \{0, 1\}^\omega$ , such that*

$$\Sigma_1^1(\alpha_i) \subsetneq \Sigma_1^1(\alpha_j)$$

*for all  $i < j < \omega_1$ .*



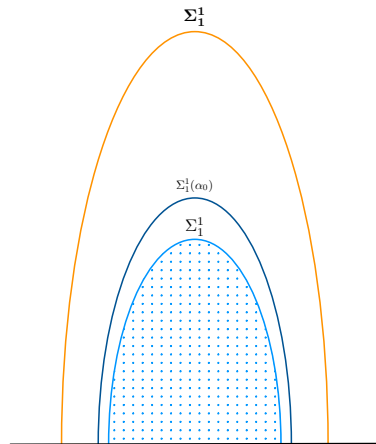
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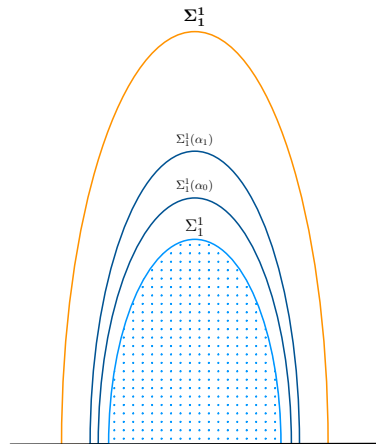
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## EXPRESSIVE POWER OF RECURRENT NEURAL NETWORKS

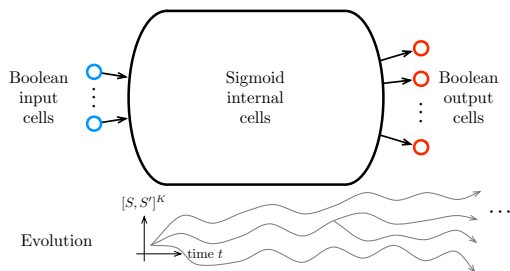
## JÉRÉMIE CABESSA

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# NONDETERMINISTIC $\omega$ -RNNs (TYPE II)

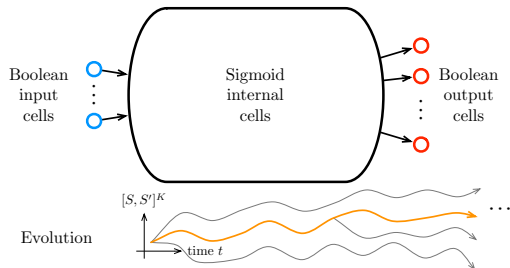
The RNNs are provided with an additional evolution set.





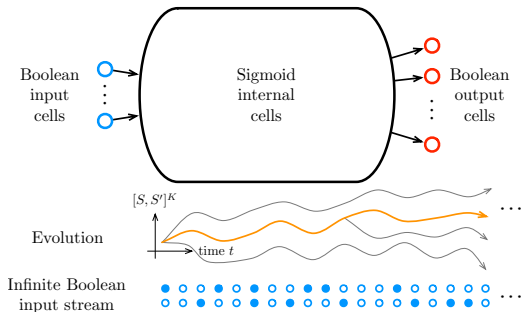
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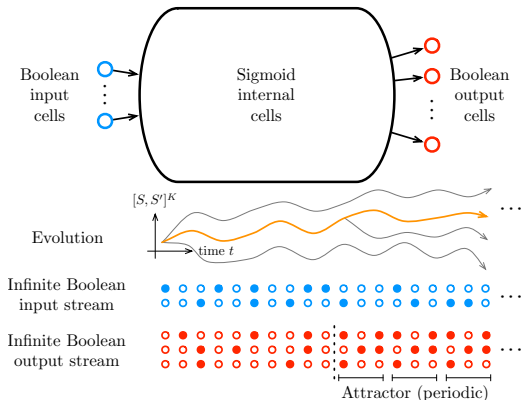
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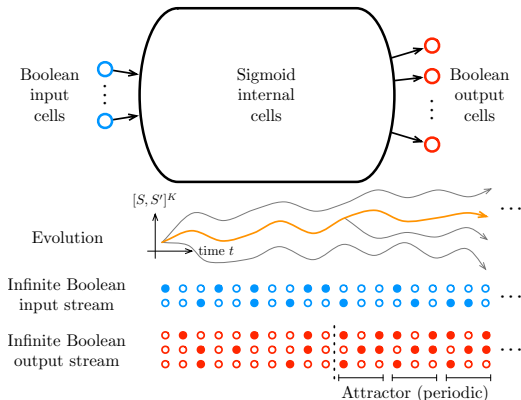
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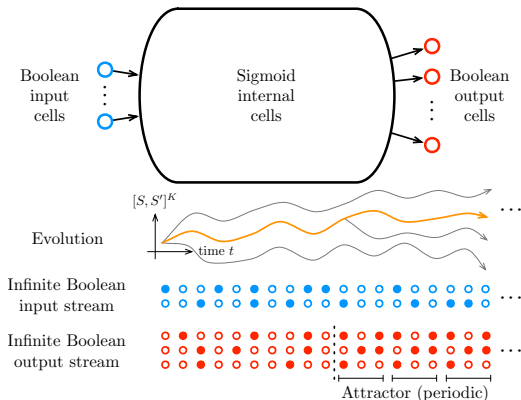


- The attractors are assumed to be classified into two possible kinds: *accepting* or *rejecting*.



# NONDETERMINISTIC $\omega$ -RNNs (TYPE II)

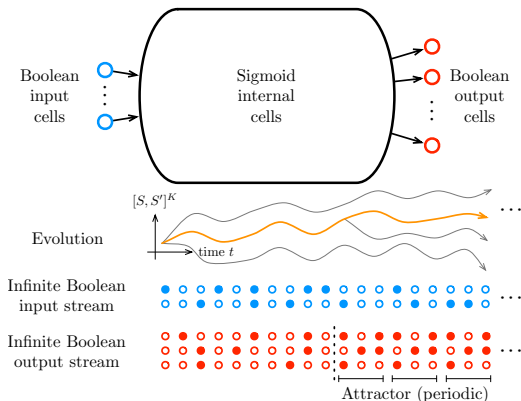
The RNNs are provided with an additional evolution set.



- Input stream  $s \in (\mathbb{B}^M)^\omega$  *rejected* by  $\mathcal{N}$  iff for all evolutions  $e \in E$ ,  $\mathcal{N}(s, e)$  enters an rejecting attractor.

# NONDETERMINISTIC $\omega$ -RNNs (TYPE II)

The RNNs are provided with an additional evolution set.



- We have more results in this context also...

# CONCLUSION

- ▶ We provided a characterization of the expressive power of recurrent neural networks in terms of their attractor dynamics.
- ▶ The super-Turing computational capabilities of neural models is related to the issue of *hypercomputation*.
- ▶ Current physical theories are consistent with the possibility of hypercomputational systems (quantum, relativistic, etc.). No such systems are currently feasible or harnessable.



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