

ROBUST OPTIMAL-SIZE IMPLEMENTATION OF FINITE STATE AUTOMATA WITH SYNFIRE RING-BASED NEURAL NETWORKS

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INTRODUCTION

- ▶ We introduce a bio-inspired paradigm for neural computation based on the concept of *synfire rings*.
- ▶ Boolean neural networks composed of synfire rings can simulate finite automata and bounded space Turing machines.
- ▶ We provide an **robust and optimal-size implementation** of finite automata by Boolean neural networks partly composed of synfire .

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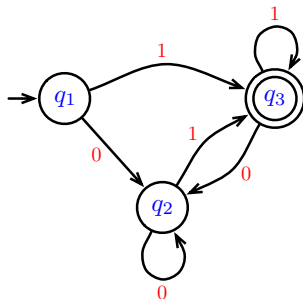
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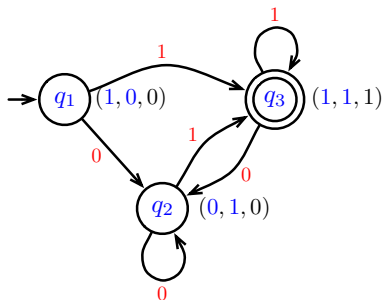
FINITE STATE AUTOMATA & BOOLEAN FUNCTIONS

Automaton



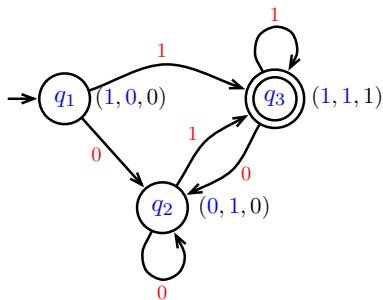
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Boolean function

$$(0, 0, 1, 0) \mapsto (1, 0, 0)$$

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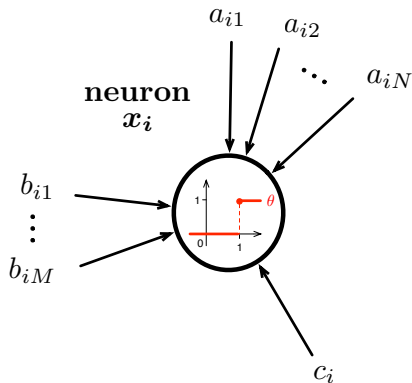
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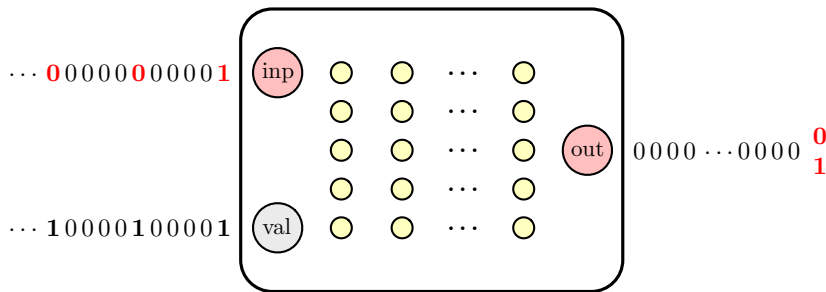
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BOOLEAN NEURAL NETWORKS: DYNAMICS

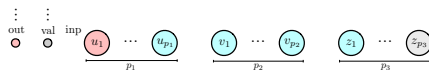


$$x_i(t+1) = \theta \left(\sum_{j=1}^N a_{ij} \cdot x_j(t) + \sum_{j=1}^M b_{ij} \cdot u_j(t) + c_i \right)$$

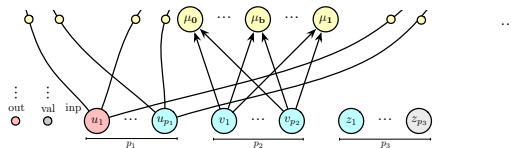
BOOLEAN NEURAL NETWORKS: OFFLINE INPUT / OUTPUT PROTOCOL



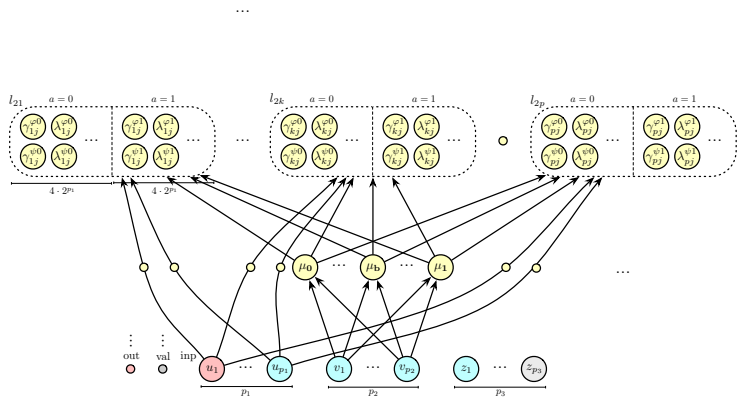
AUTOMATA AND BOOLEAN NEURAL NETS: OPTIMAL-SIZE IMPLEMENTATION



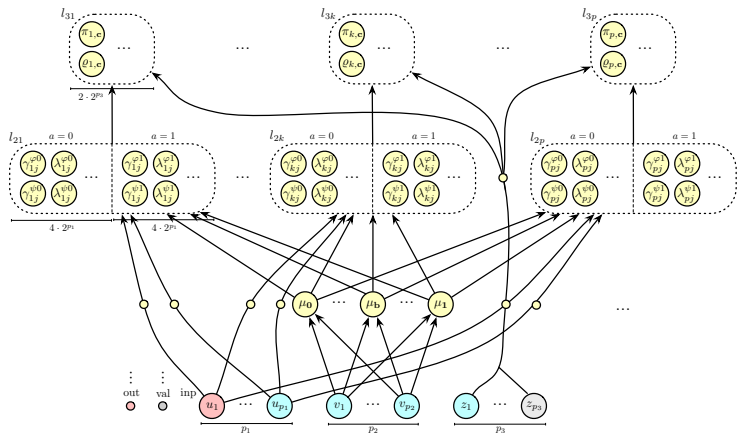
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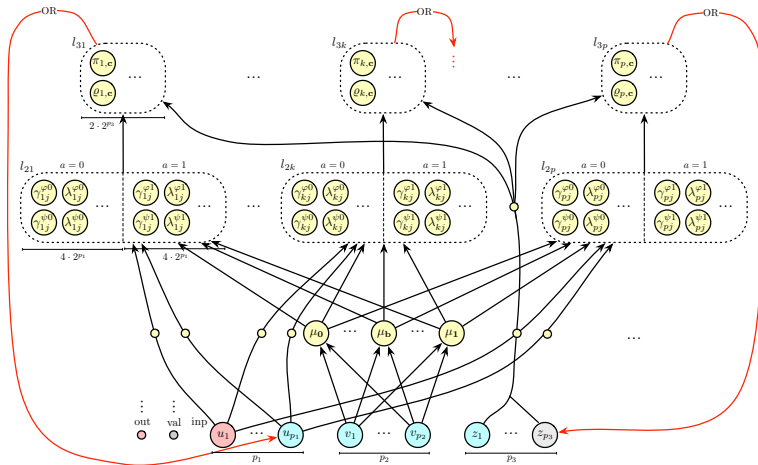
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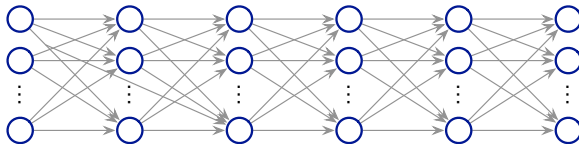
THEOREM (LUPANOV (1973))

Let \mathcal{A} be a finite state automaton with n states¹. Then the four layer Boolean recurrent neural network \mathcal{N} described above simulates \mathcal{A} and has an asymptotical optimal size of $\Theta(\sqrt{n})$.

¹i.e., $p_1 + p_2 + p_3 = \lceil \log(n) \rceil + 2$

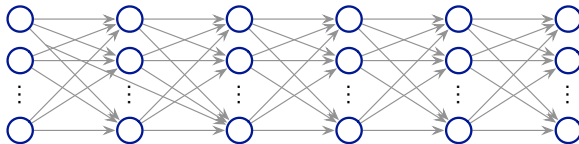
SYNFIRE CHAINS

- ▶ *Synfire chains* allow for robust and highly precise transmission of information in neural networks (ABELES 82).
- ▶ *Synfire chains* are likely to be crucially involved in the processing and coding of information in neural networks.



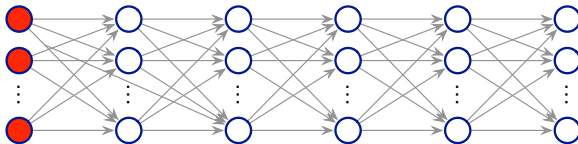
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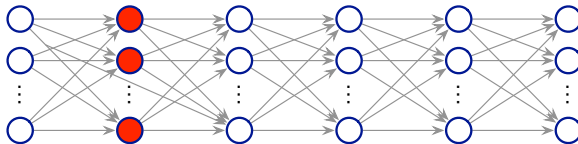
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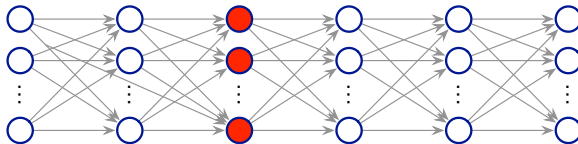
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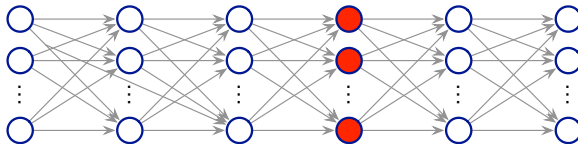
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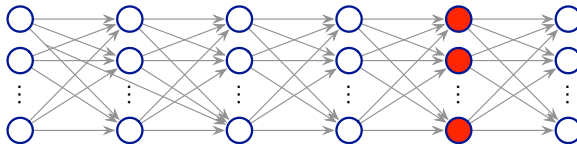
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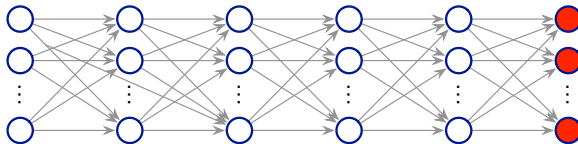
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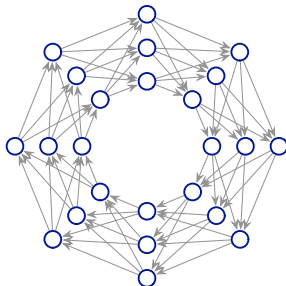
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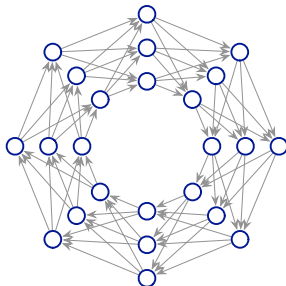
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- ▶ *Synfire rings* allow for robust and temporally precise *self-sustained activities*.



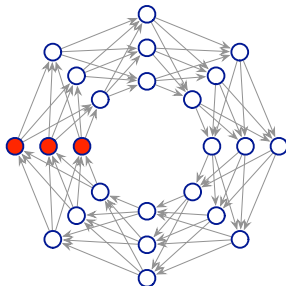
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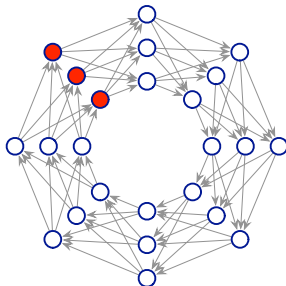
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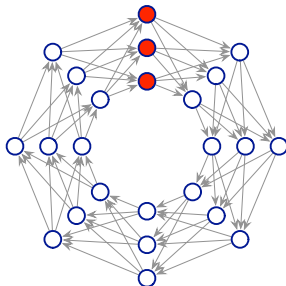
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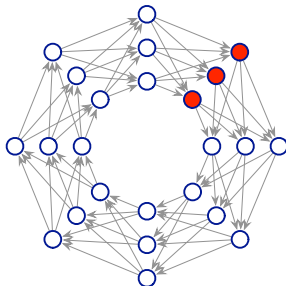
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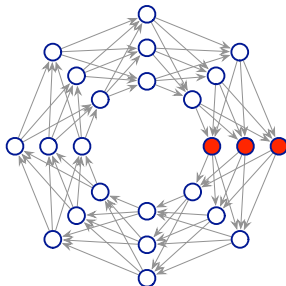
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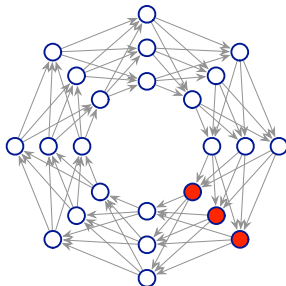
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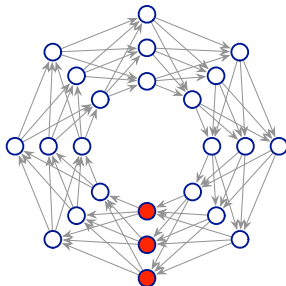
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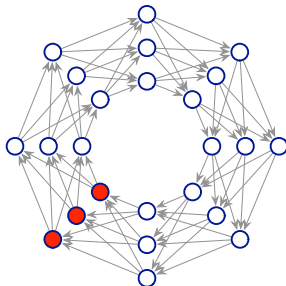
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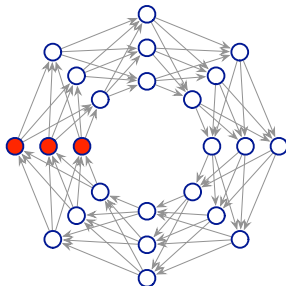
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NEURAL COMPUTATION WITH SYNFIRE RINGS

- ▶ We introduce a paradigm of abstract neural computation based on *synfire rings*.
- ▶ Computational states are represented by sustained activities of synfire rings – i.e., attractors.
- ▶ The global computational process is robust to various kinds of architectural plasticities and synaptic noises.

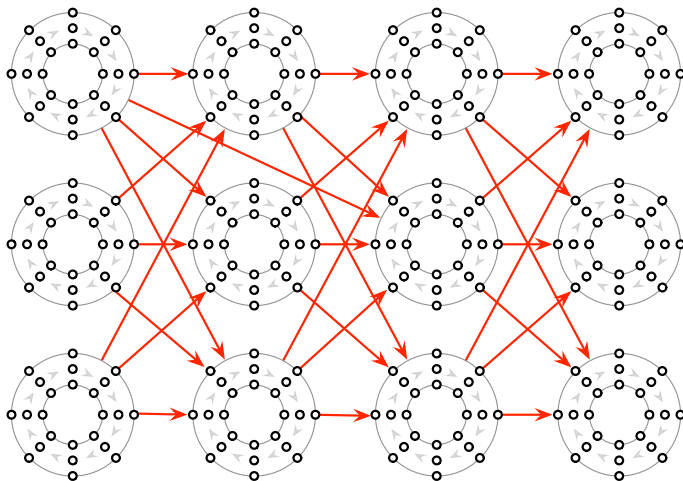
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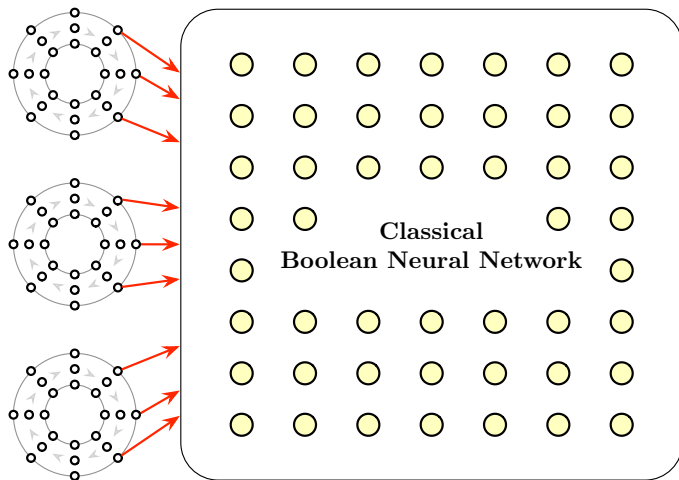
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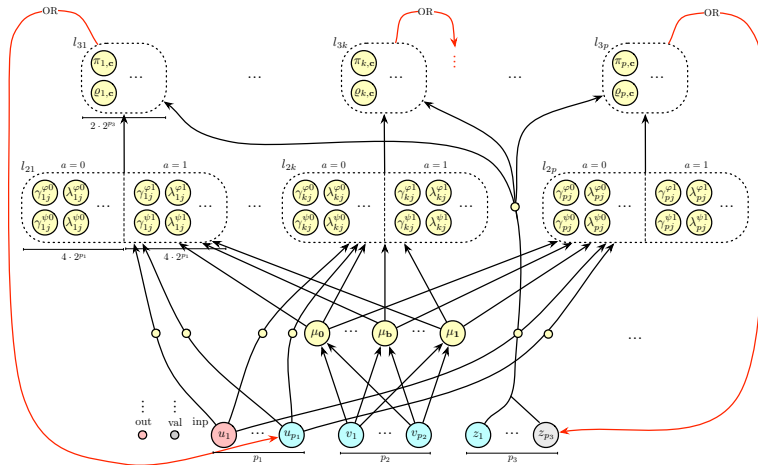
SYNFIRE RINGS: FULL AND HYBRID ARCHITECTURES



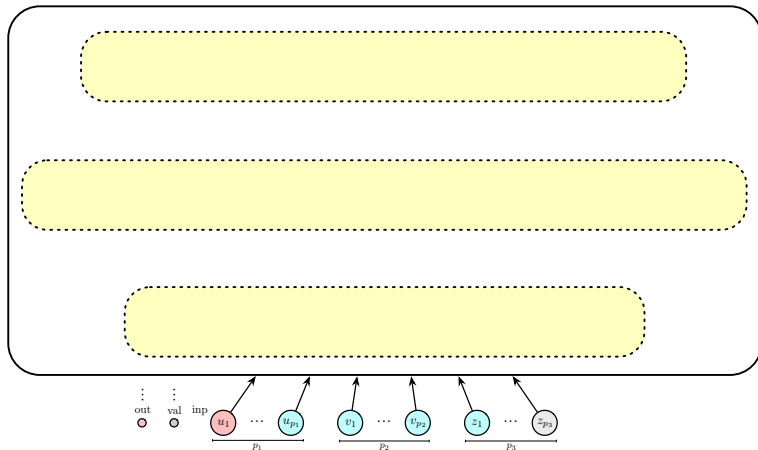
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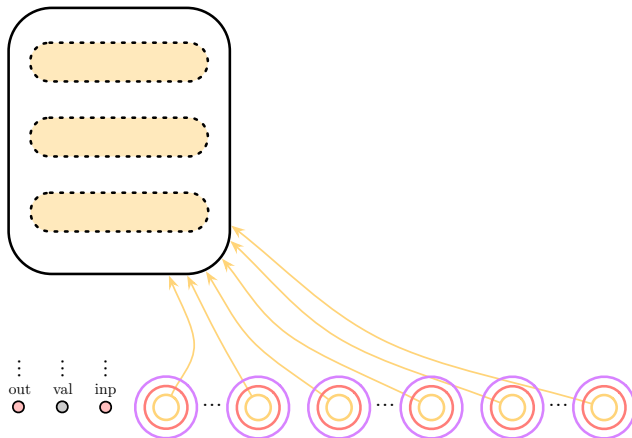
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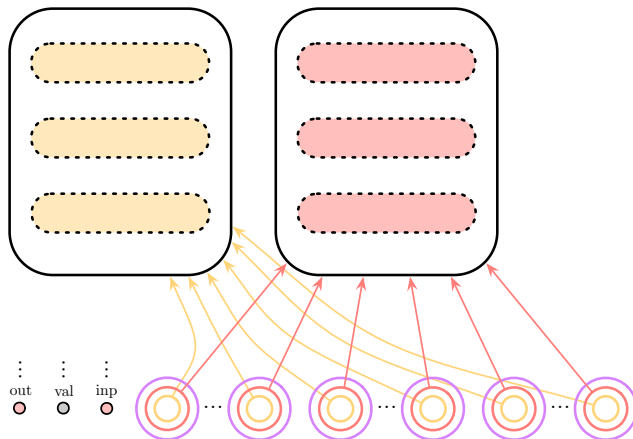
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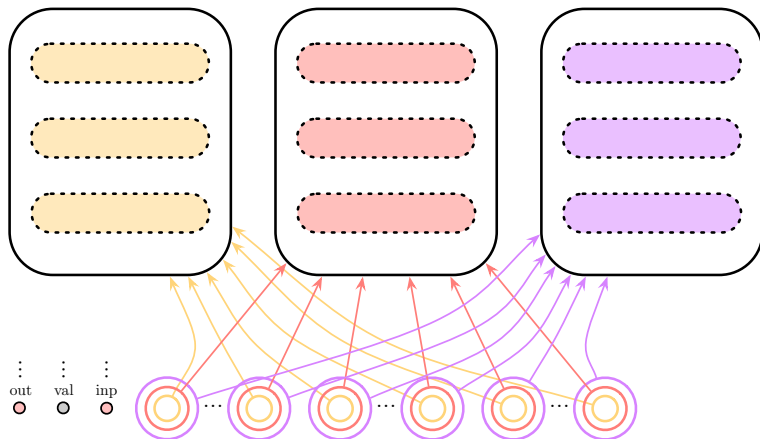
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THEOREM

Let \mathcal{A} be a finite state automaton with n states. Then the synfire ring-based Boolean recurrent neural network \mathcal{N} described above simulates \mathcal{A} and has an asymptotical optimal size of $\Theta(\sqrt{k \cdot n}) = \Theta(\sqrt{n})$ (k is the fixed number of ring's levels).

AUTOMATA / TURING MACHINES AND SYNFIRE RING-BASED BOOLEAN NEURAL NETS

THEOREM

Let \mathcal{A} be a finite state automaton or \mathcal{M} be a bounded space k -tape Turing machine. Then, \mathcal{A} and \mathcal{M} can be simulated by a Boolean neural network \mathcal{N} fully composed of synfire rings.

- ▶ In this case, the construction is not optimal.
- ▶ The architecture is “fully” composed of synfire rings.
- ▶ Play movie...

CONCLUSIONS

- ▶ We presented a new paradigm of neural computation based on **synfire rings**.
- ▶ We provided an **optimal-size implementation** of finite state automata by synfire ring-based neural networks. The construction still needs to be implemented...
- ▶ We intend to study the issue of **learning** within the synfire ring architecture.
- ▶ Towards biological neuronal computers...

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Thank you