Neural Computation with Recurrent Neural Networks Composed of Synfire Rings

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Introduction

- We recall important results about the computational power of recurrent neural networks.
- We show that neural networks represent a natural model for oracle-based computation, beyond the Turing limits.
- We introduce a bio-inspired paradigm for neural computation based on the concept of *synfire rings*.

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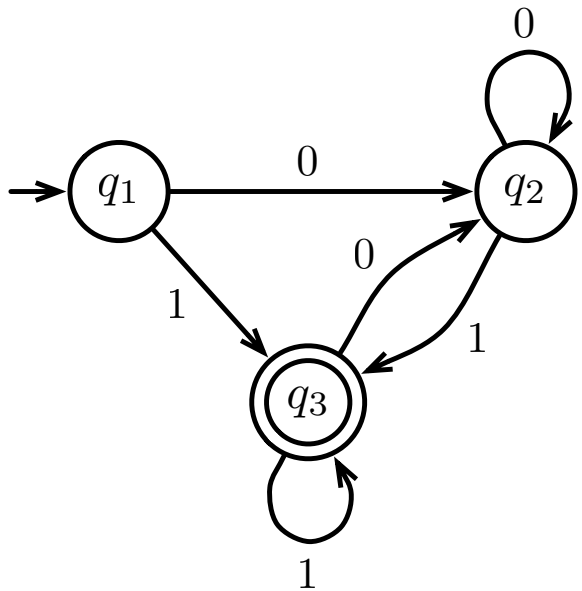
Finite State Automaton

A *finite state automaton* (FSA) can be represented as a graph whose nodes and edges are the computational states and transitions between those.



- input u is *accepted* by $\mathcal{A}$ if $\mathcal{A}(u)$ reaches a final state
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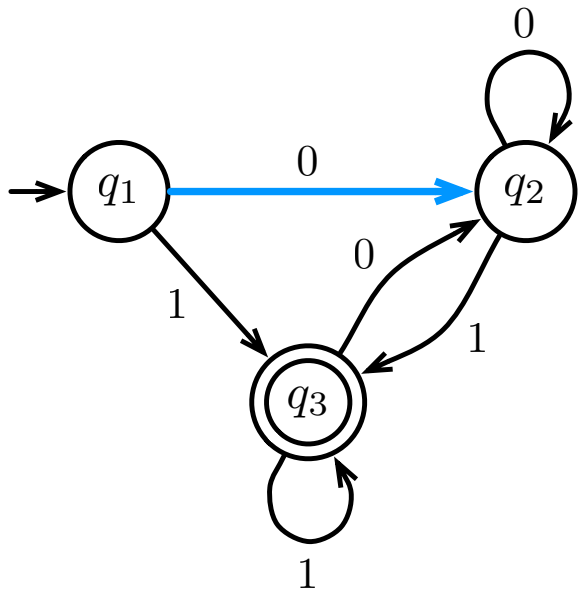

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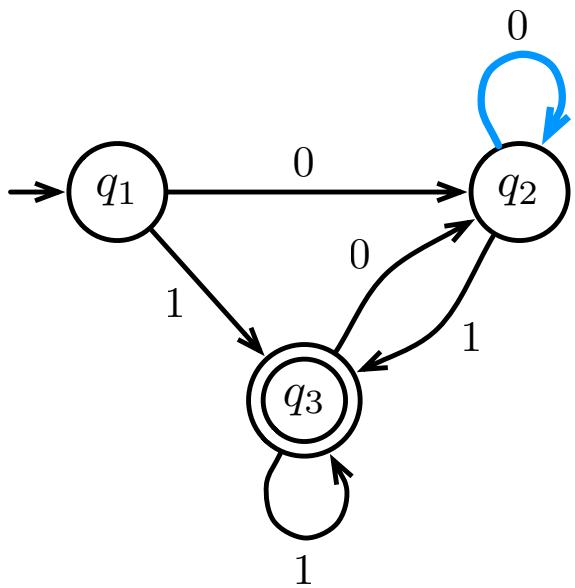

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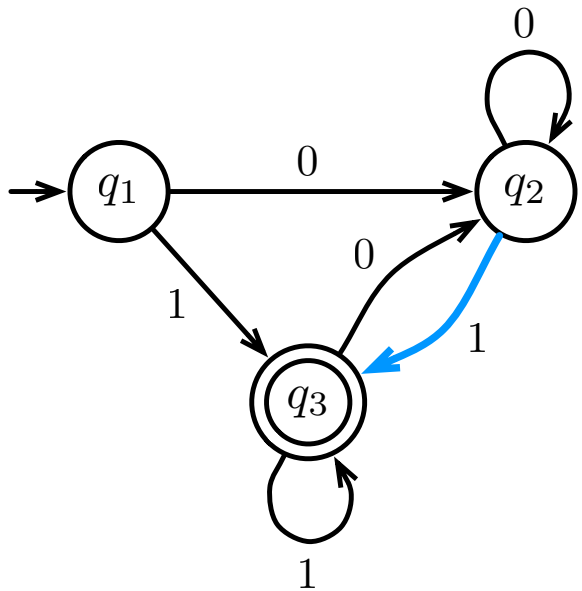

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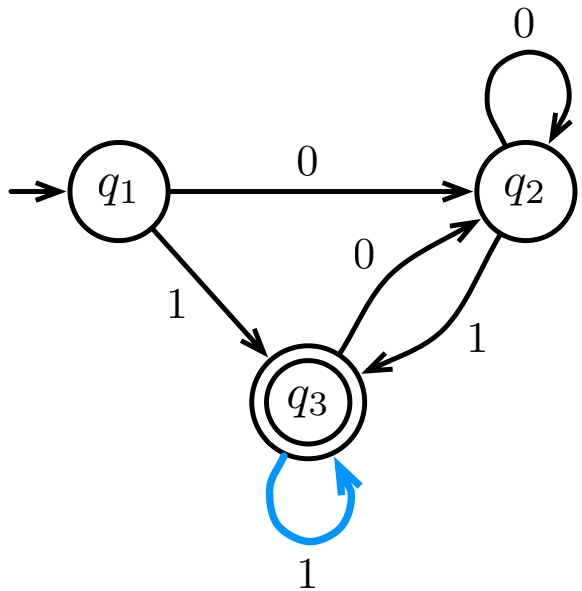

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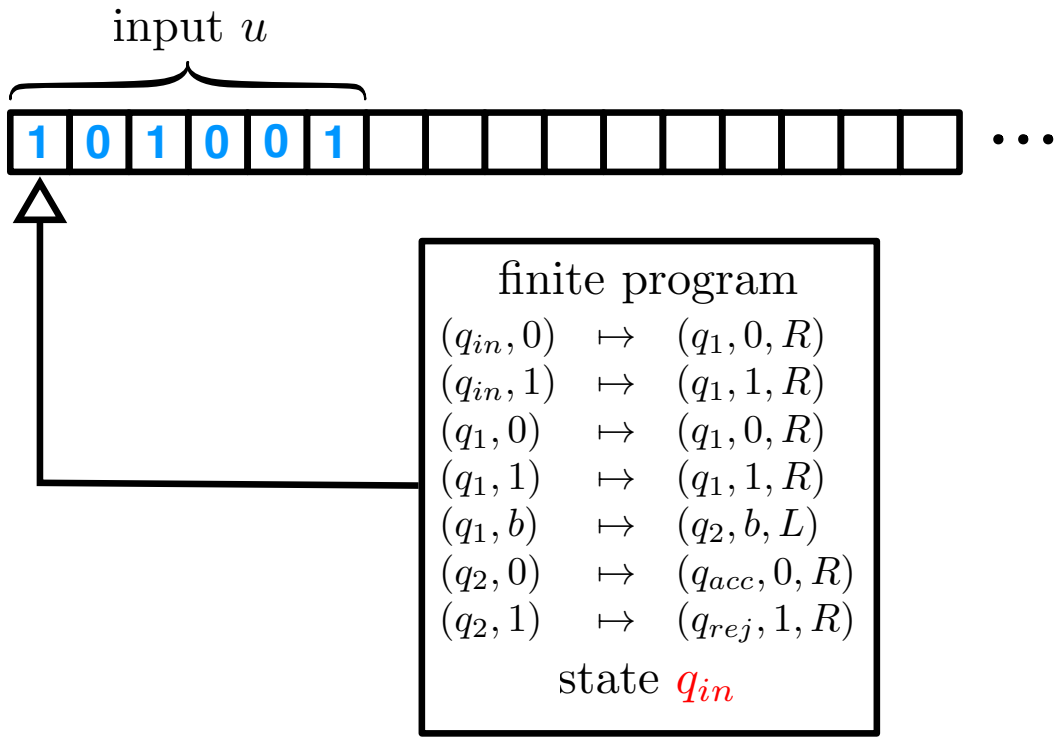

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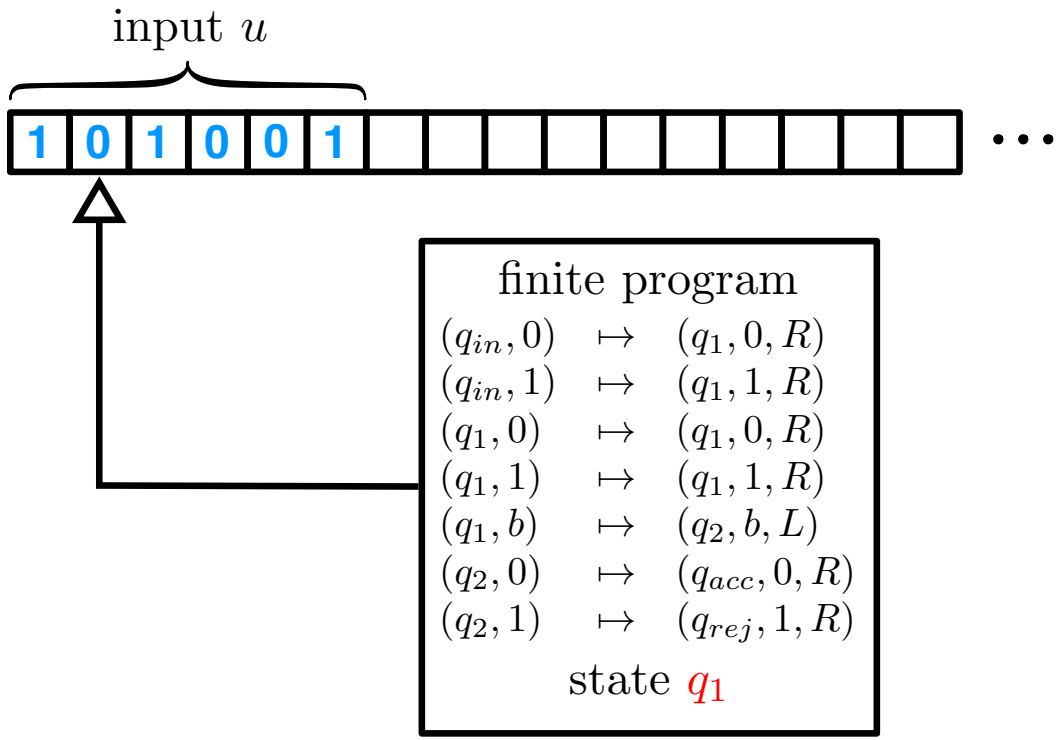

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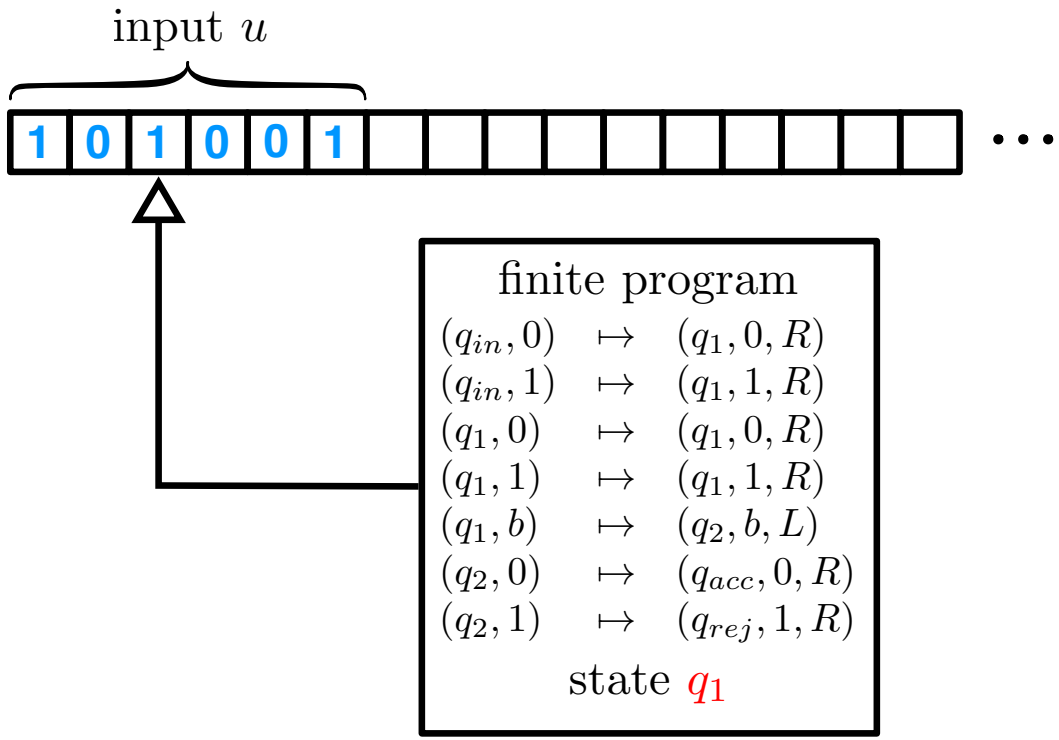

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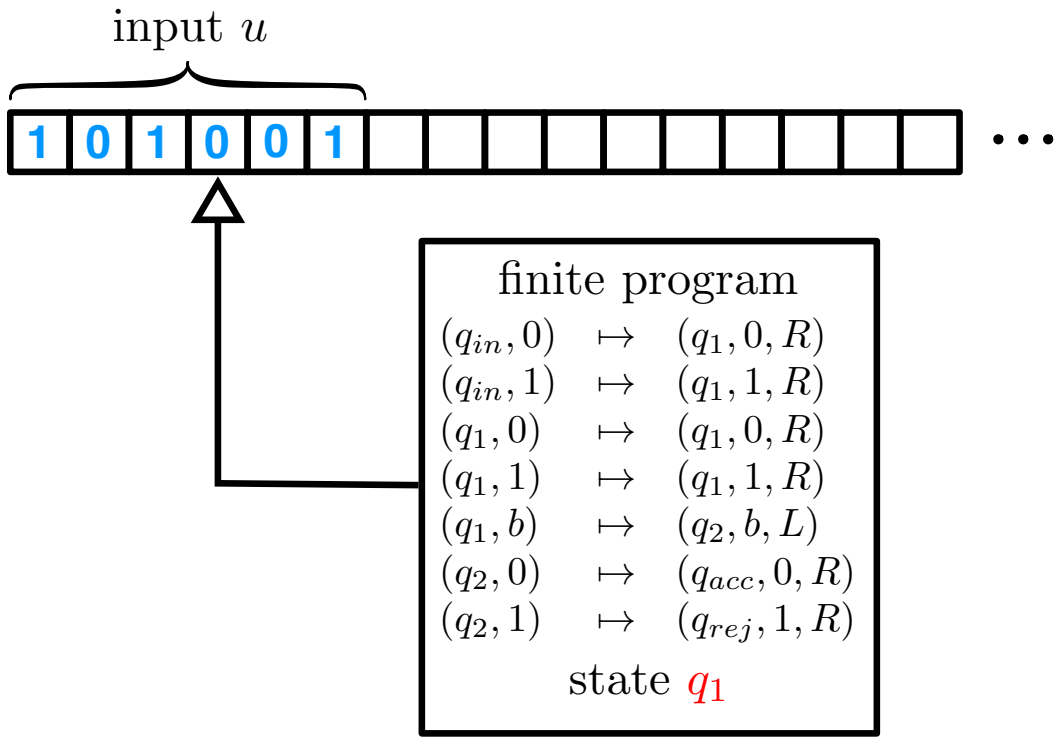

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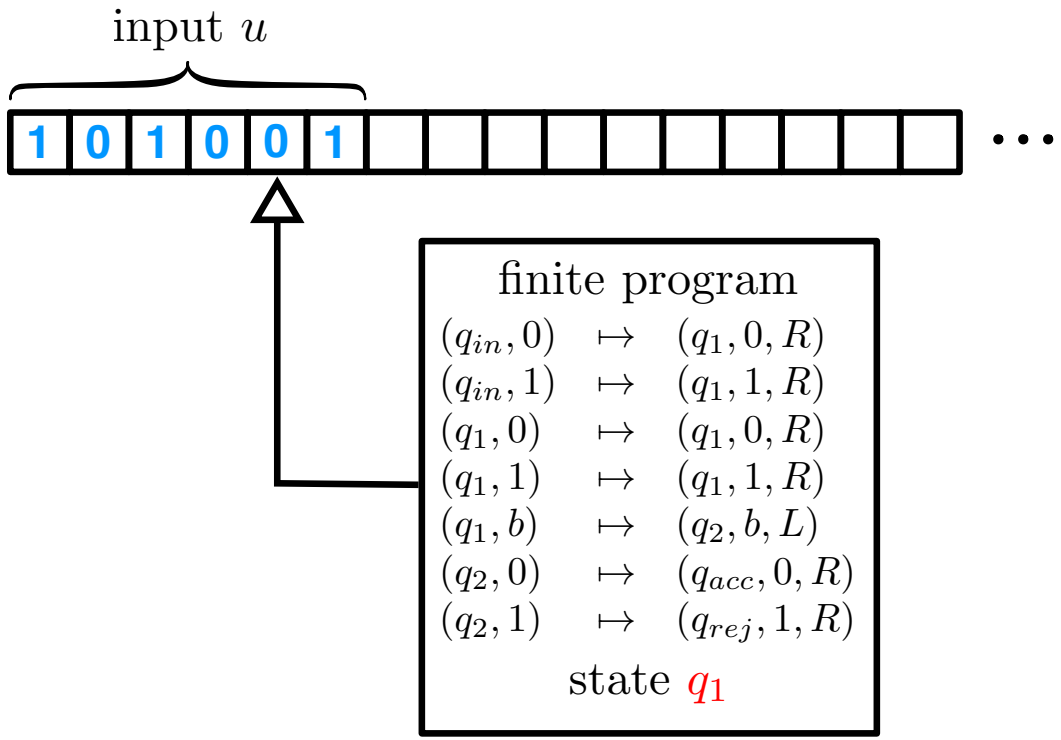

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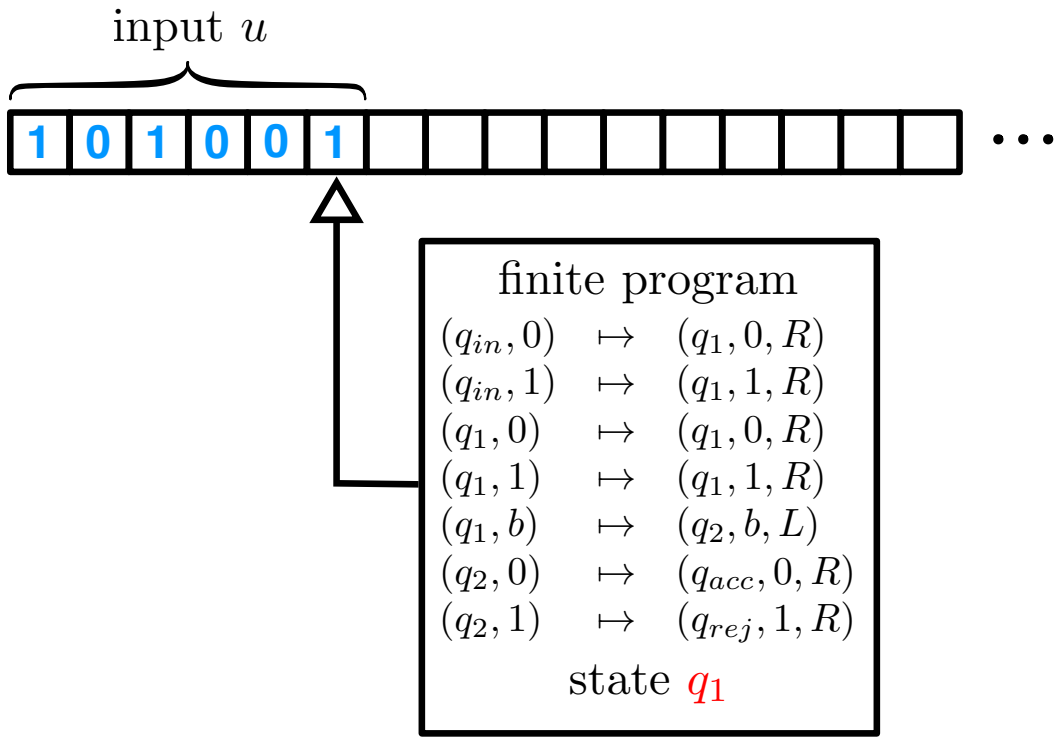

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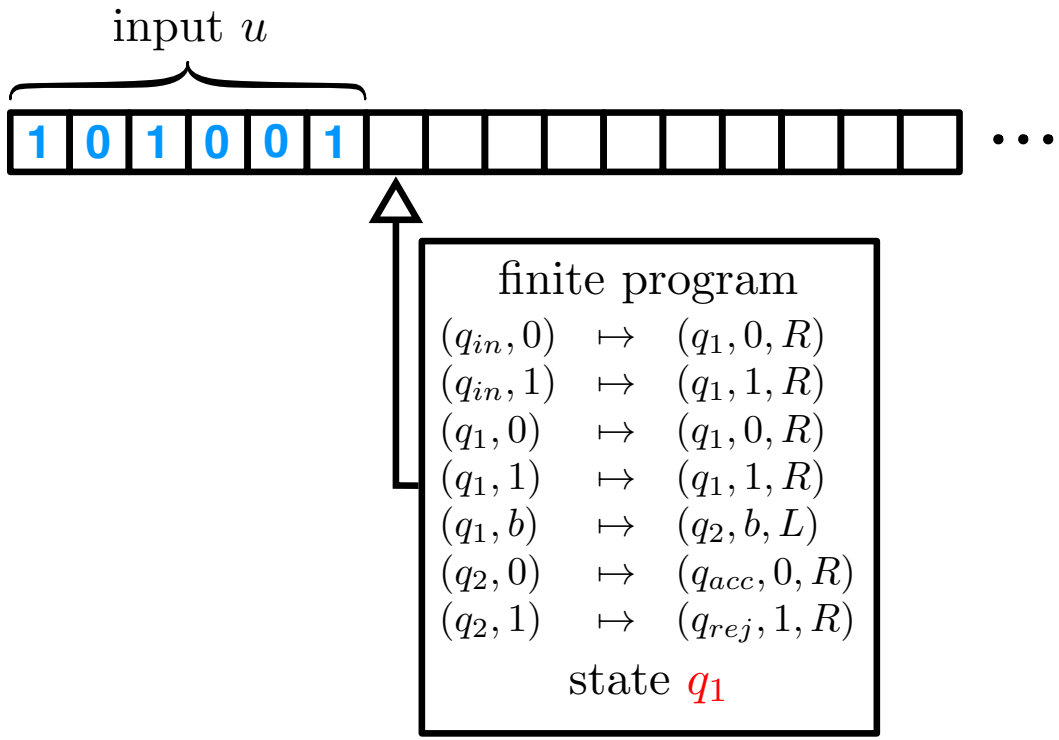

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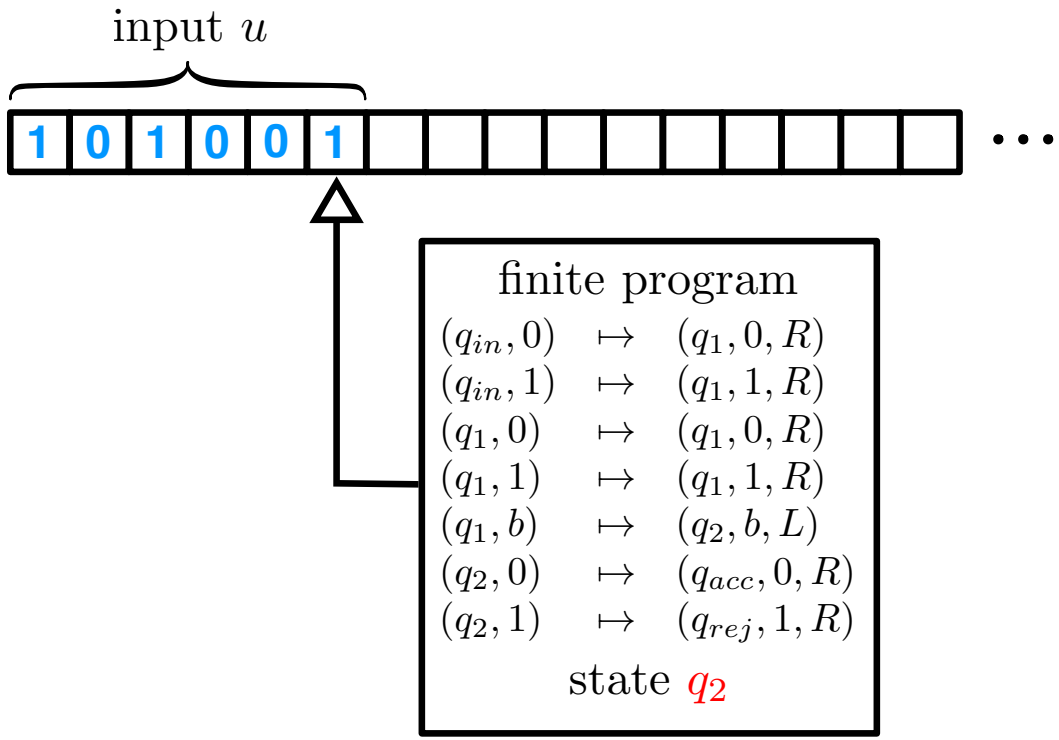

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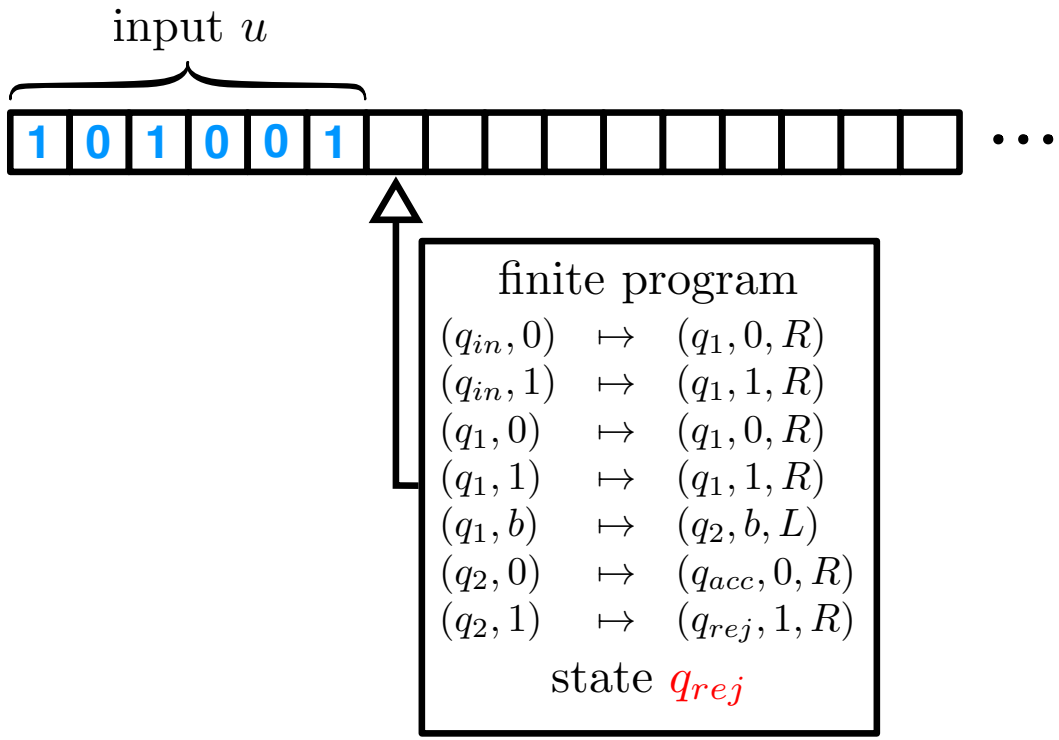

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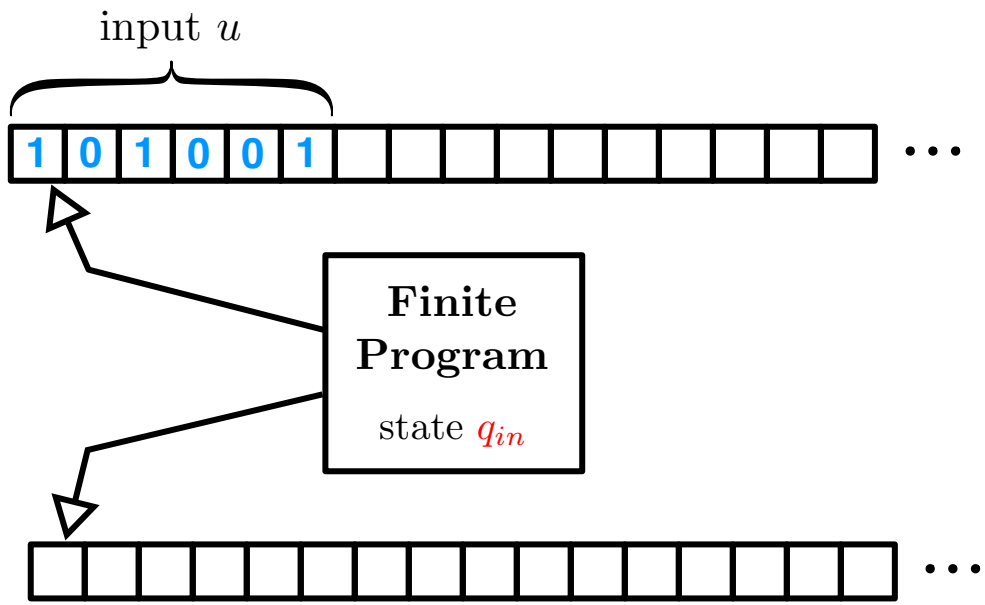
Turing Machine with Advice

A *Turing machine with advice* (TM/A) is a TM provided with an additional advice tape and advice function $\alpha : \mathbb{N} \longrightarrow \{0,1\}^*$.



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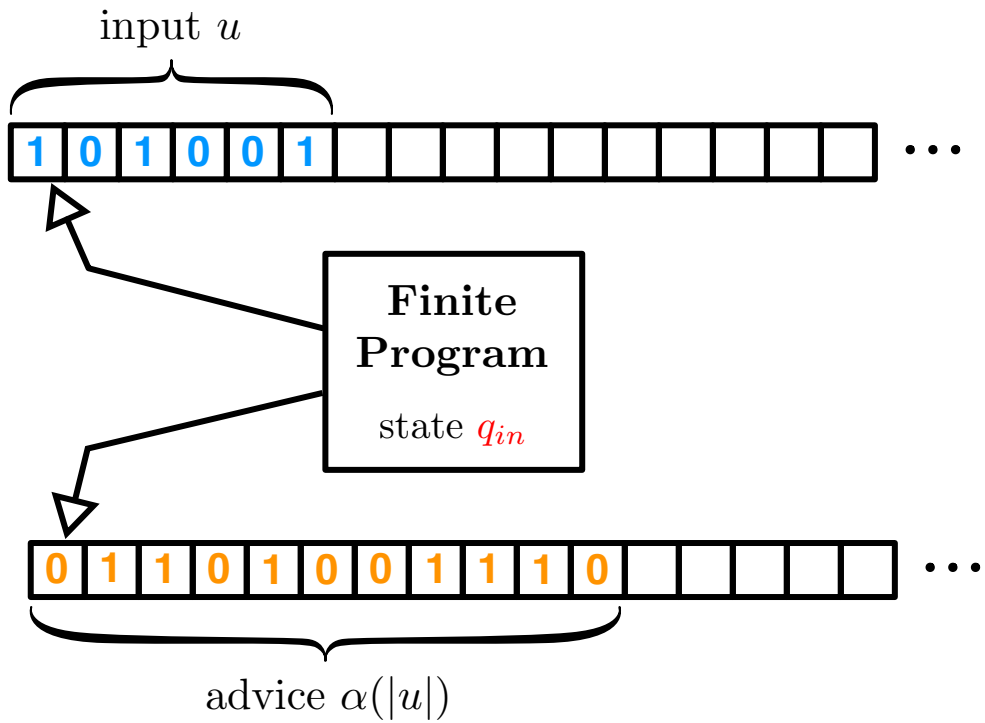

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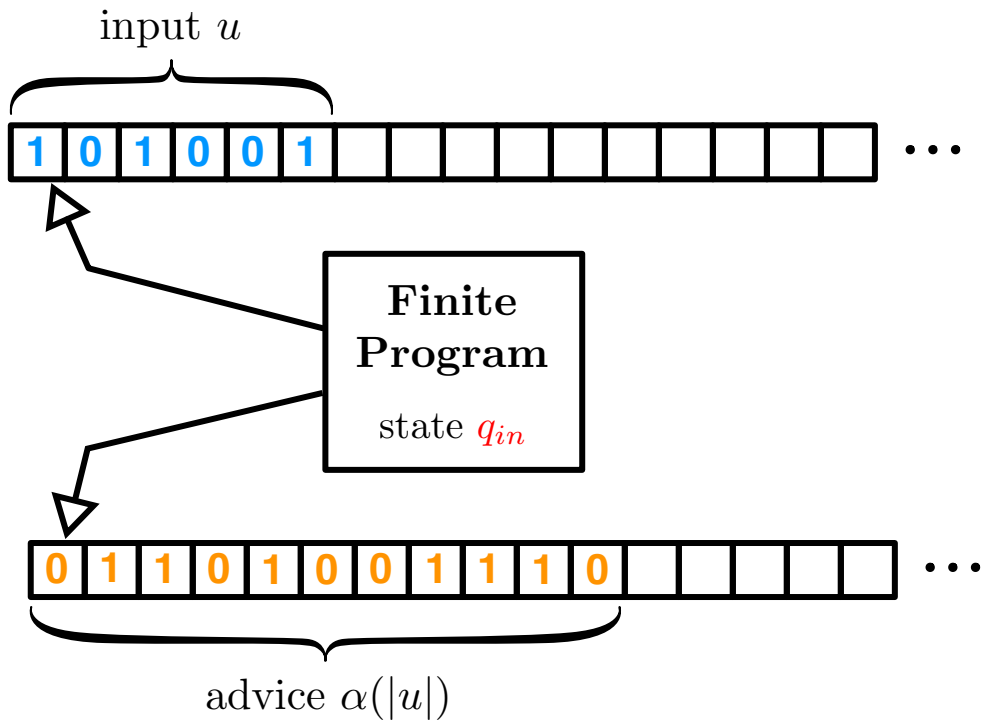

- The class of languages recognized in polynomial time by Turing machines with polynomial advices (TM/poly(A)) is **P/poly**.

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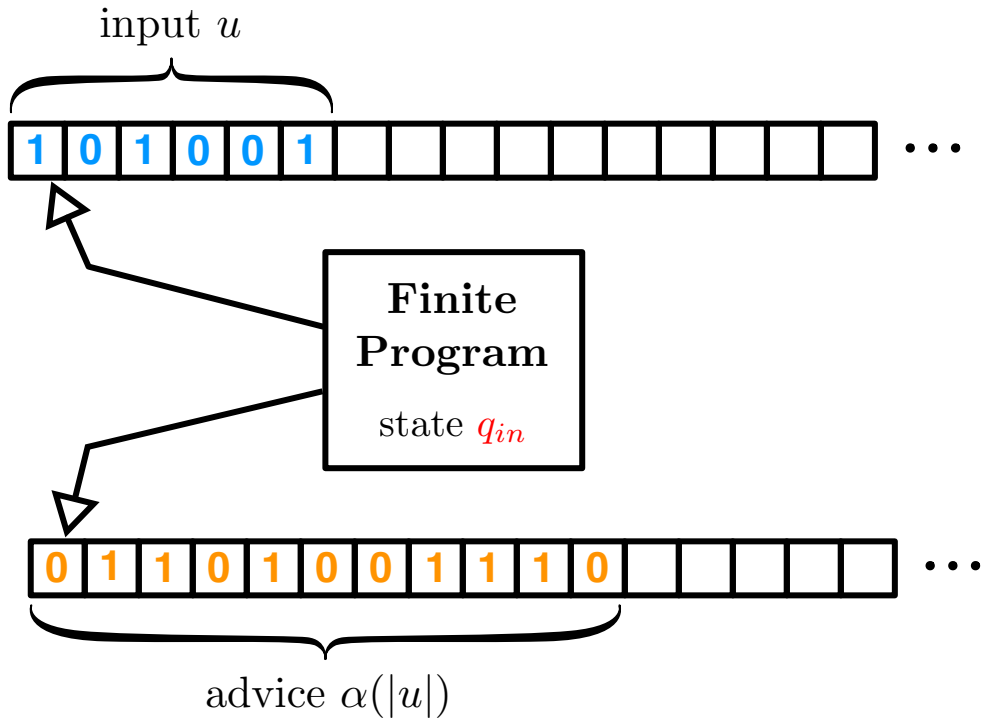
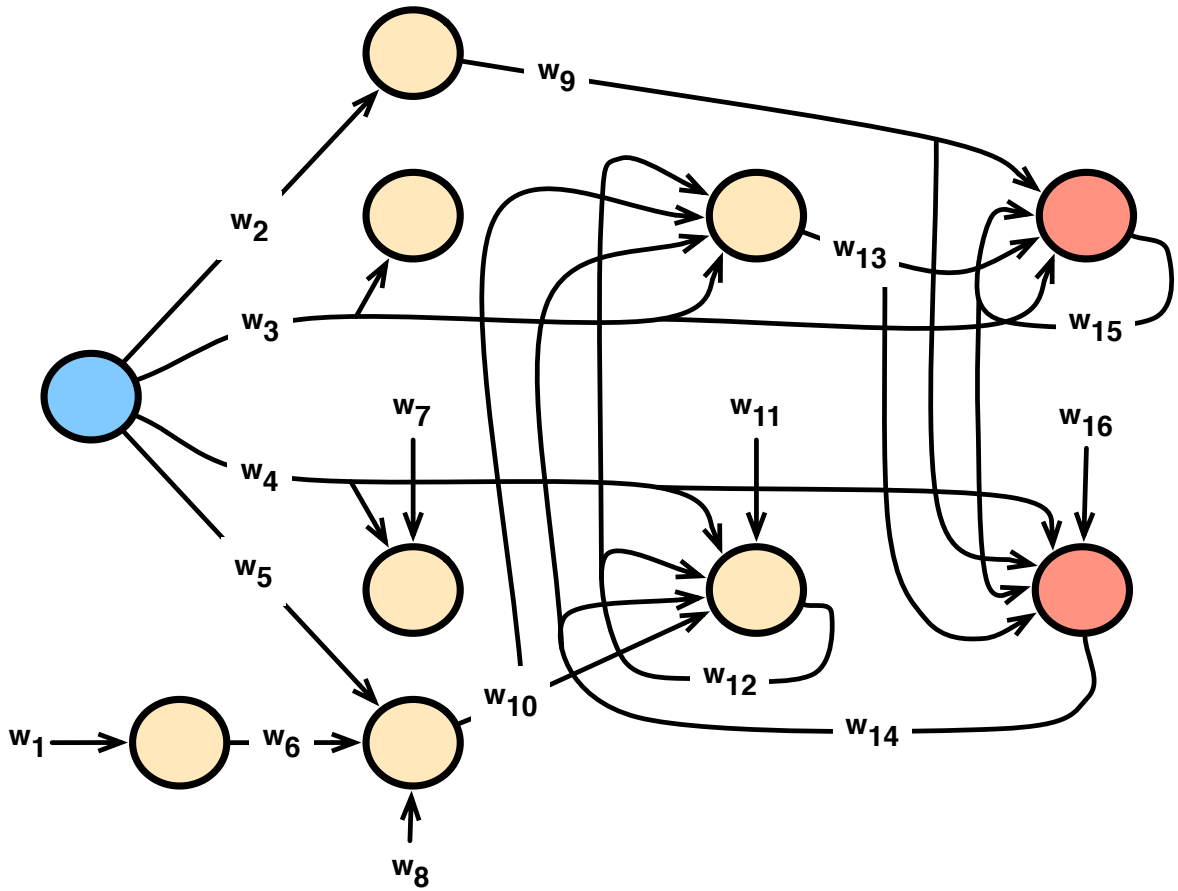
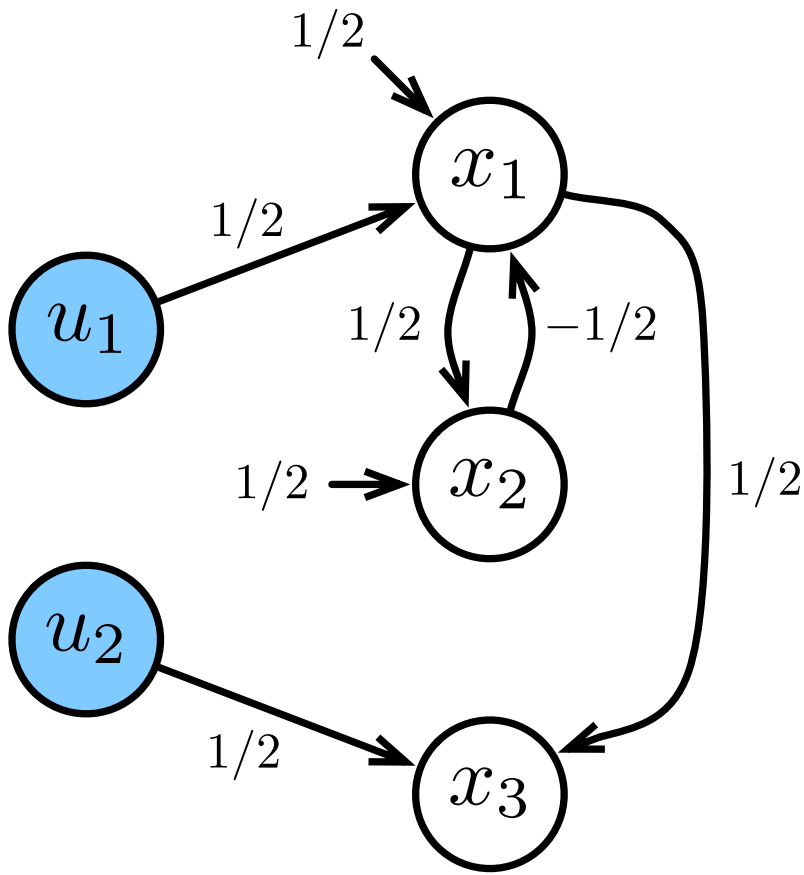


- TM/As are strictly more powerful than TMs: **P/poly** $\supsetneq$ **P**
  They are *super-Turing*...

Recurrent Neural Network



Boolean Recurrent Neural Networks



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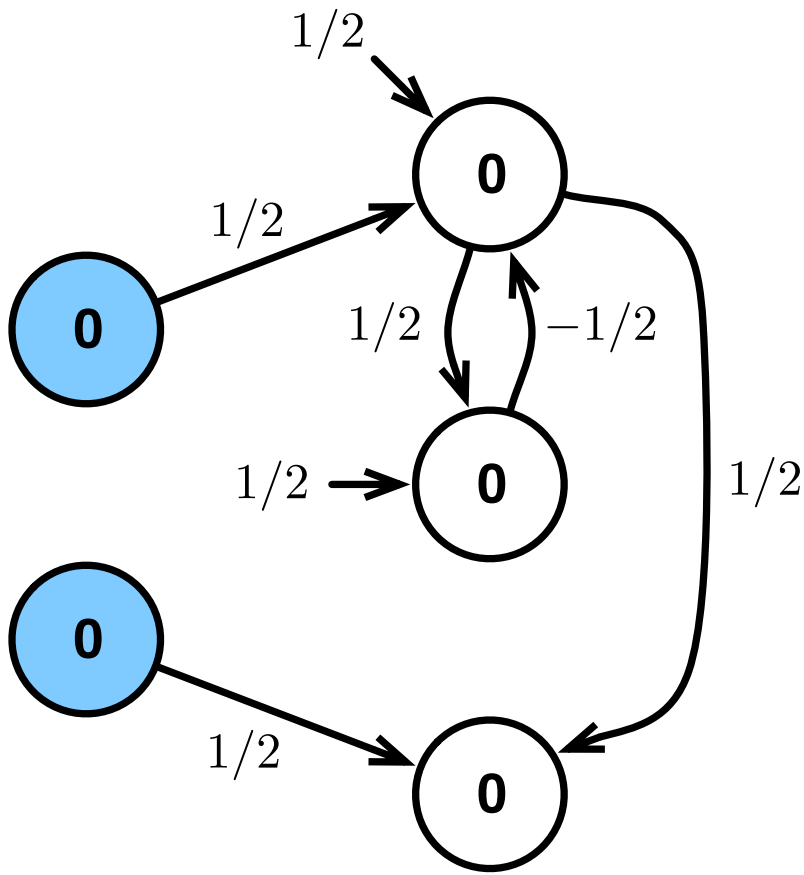

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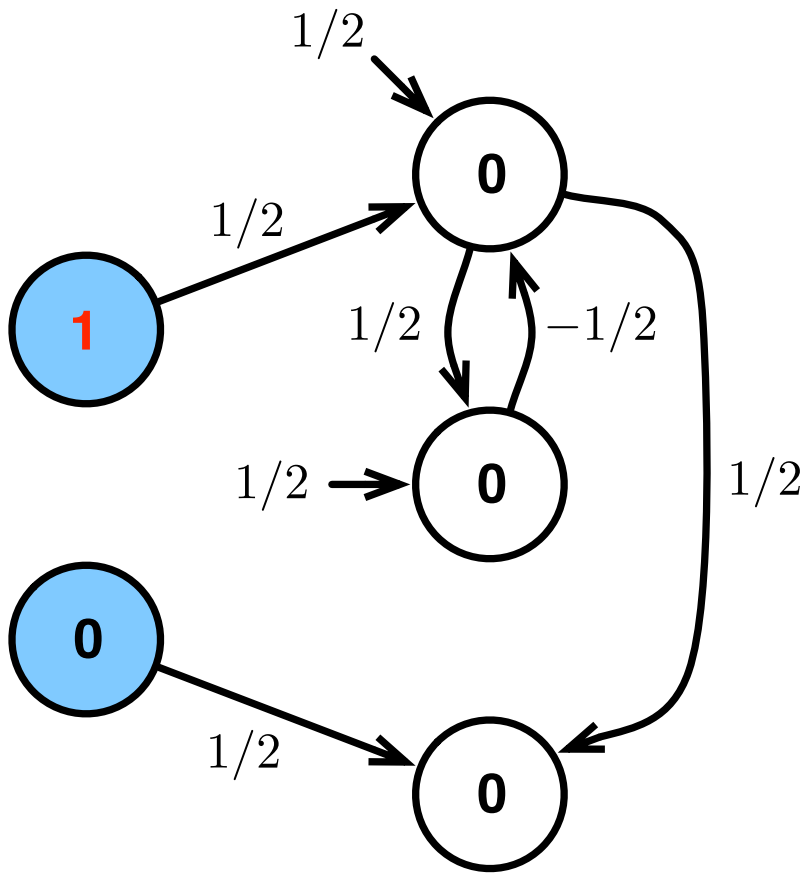

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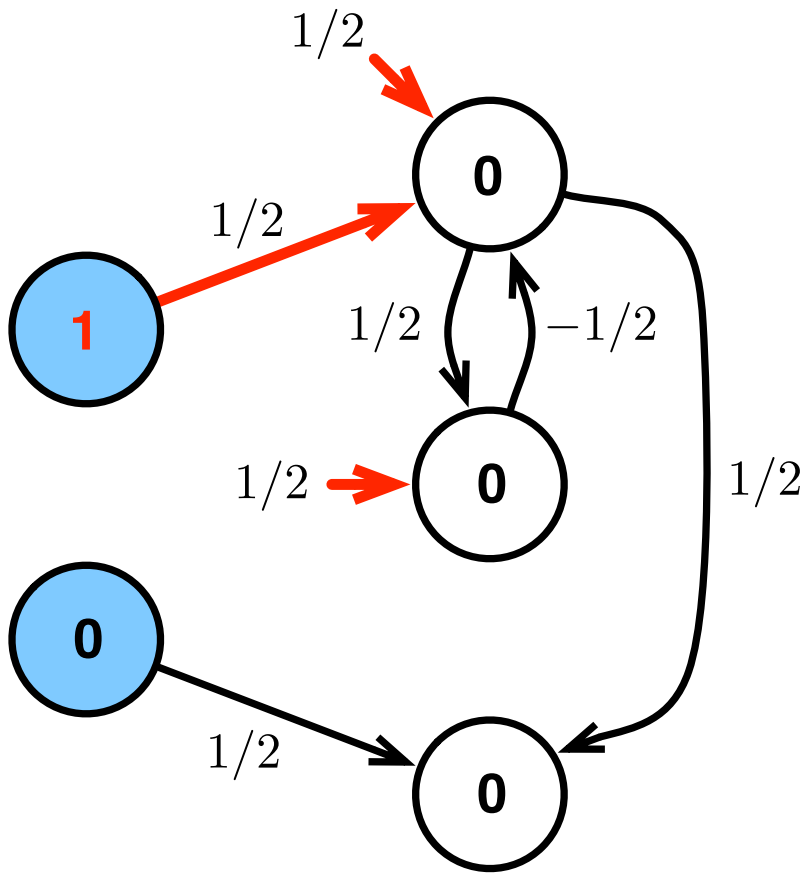

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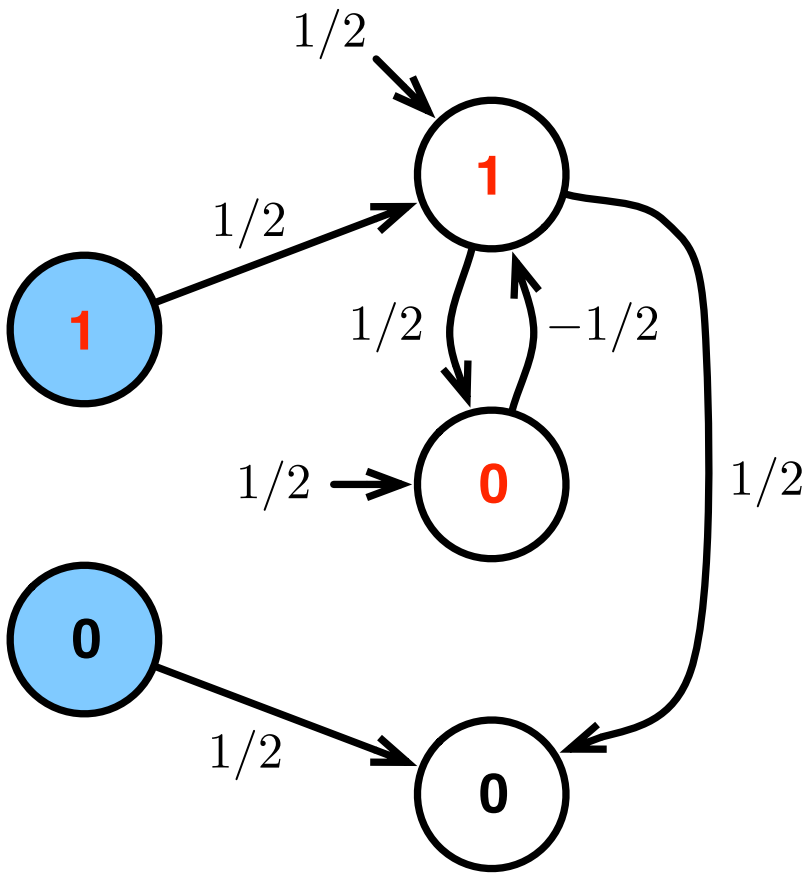

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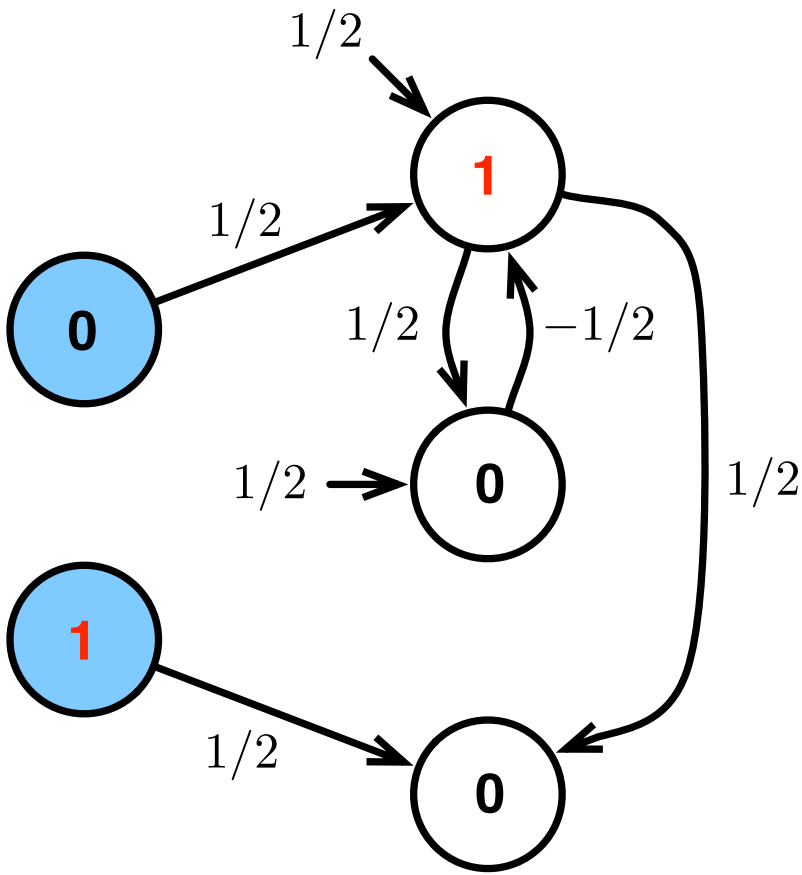

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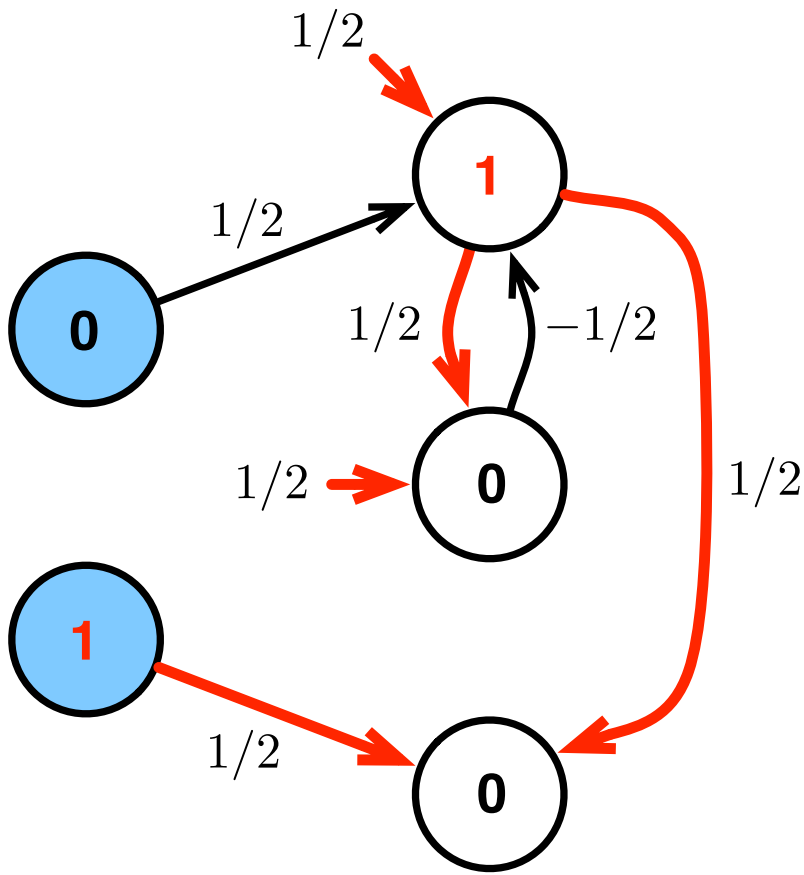

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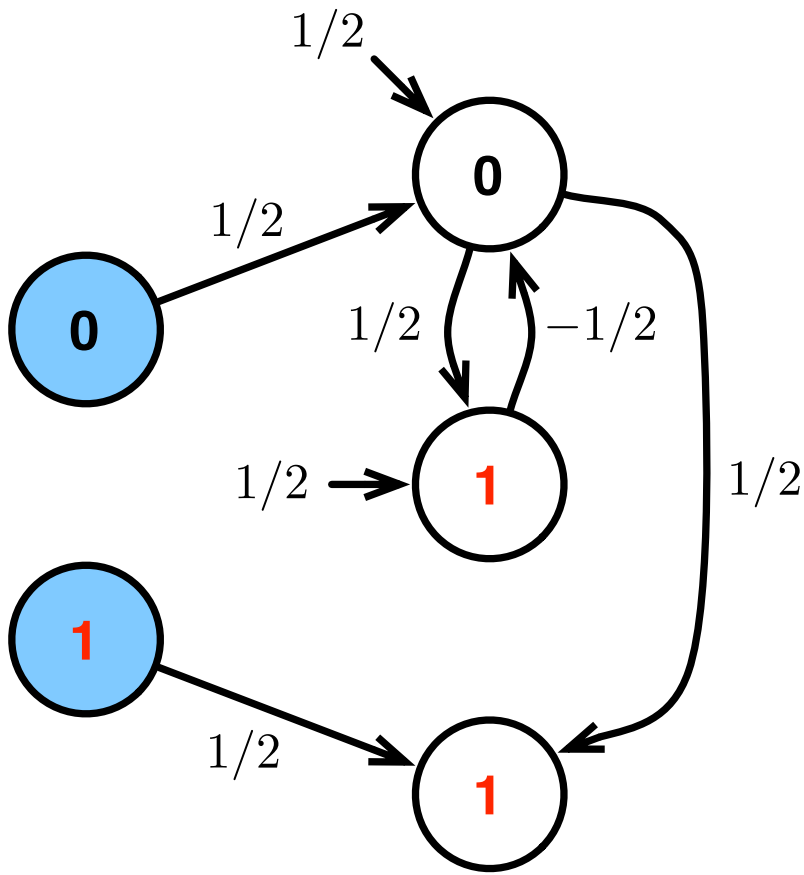

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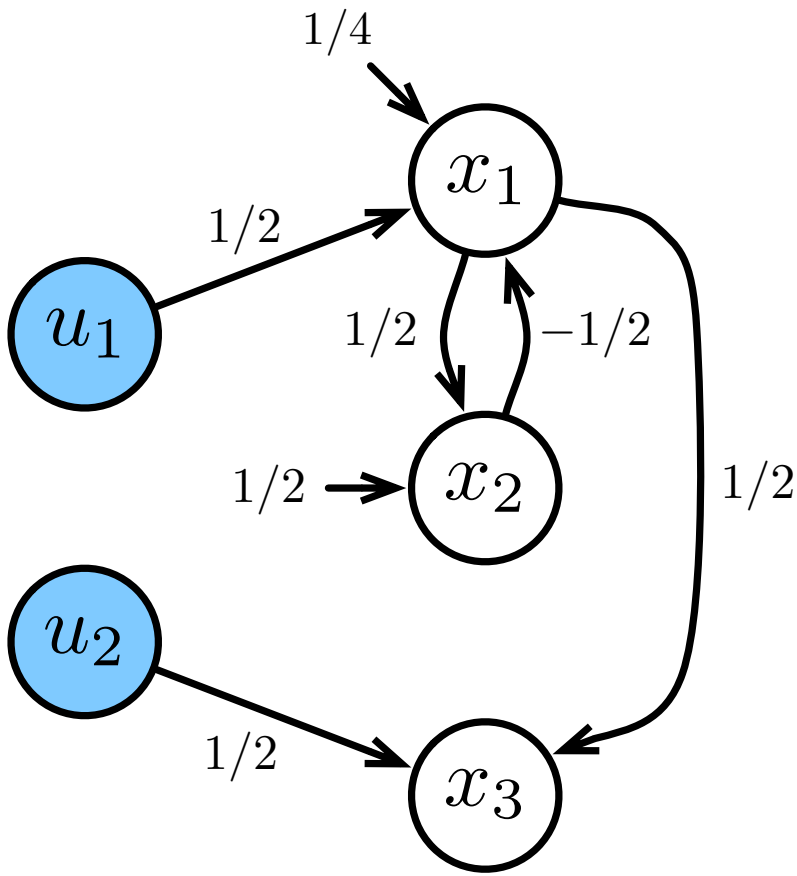

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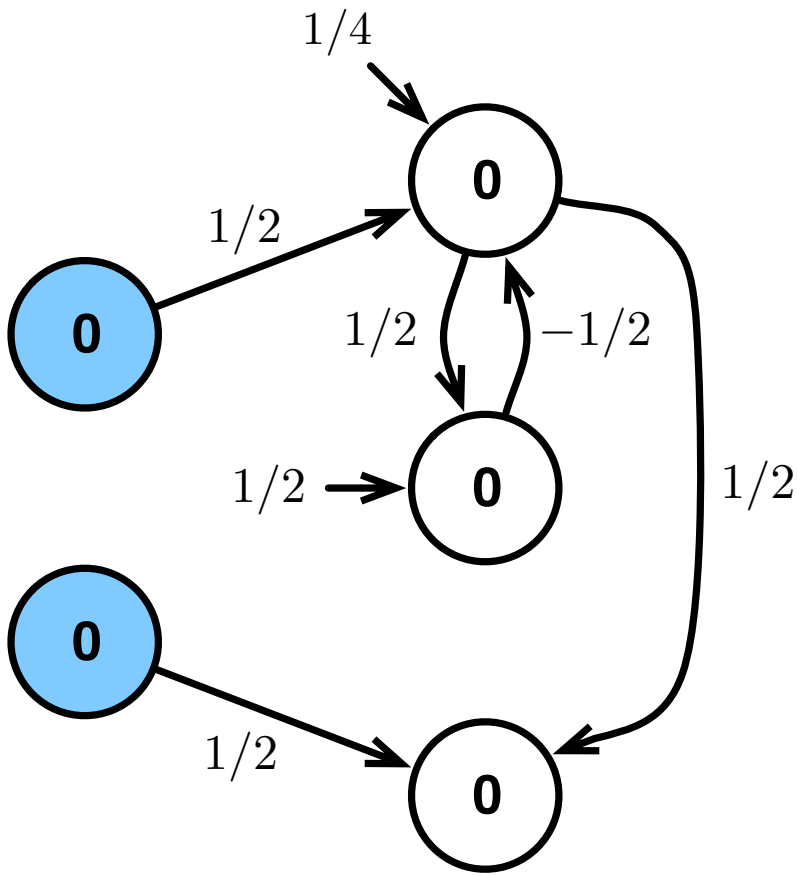

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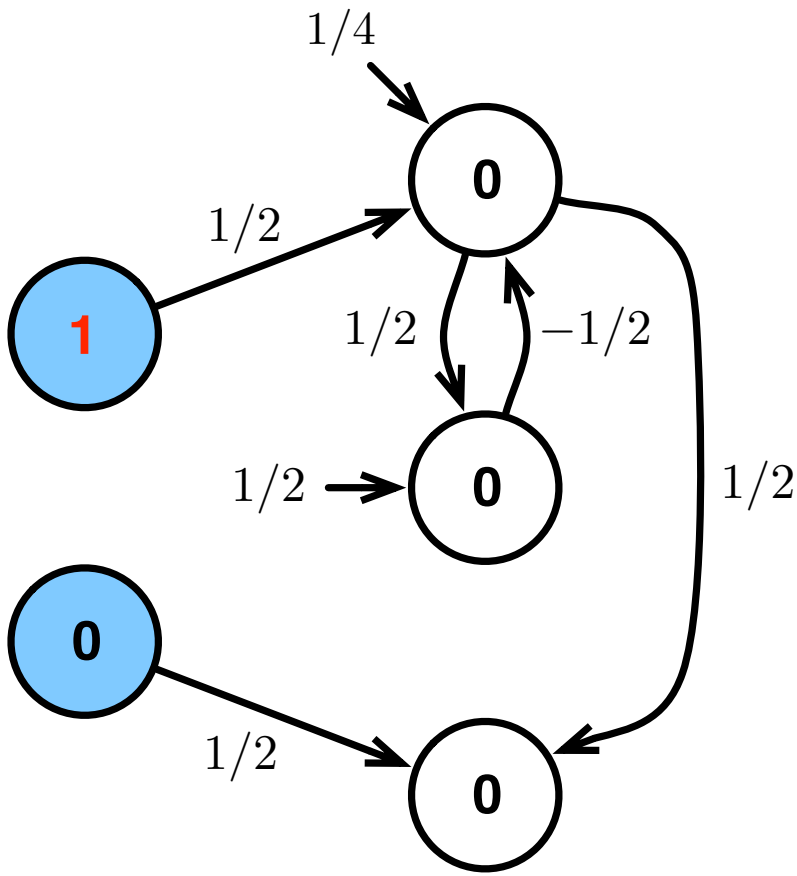

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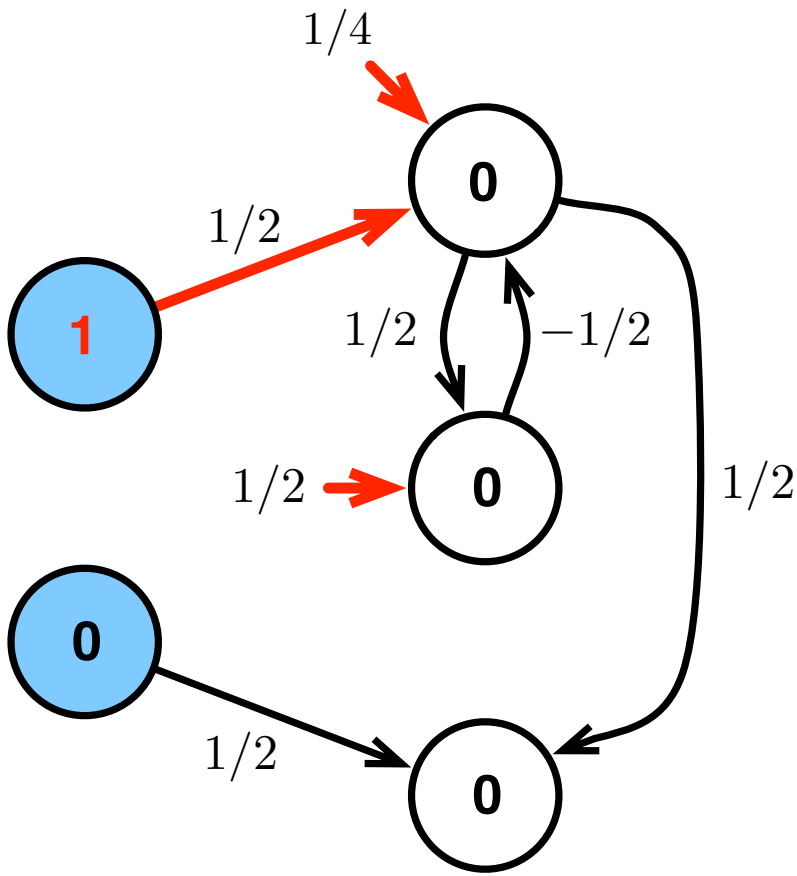

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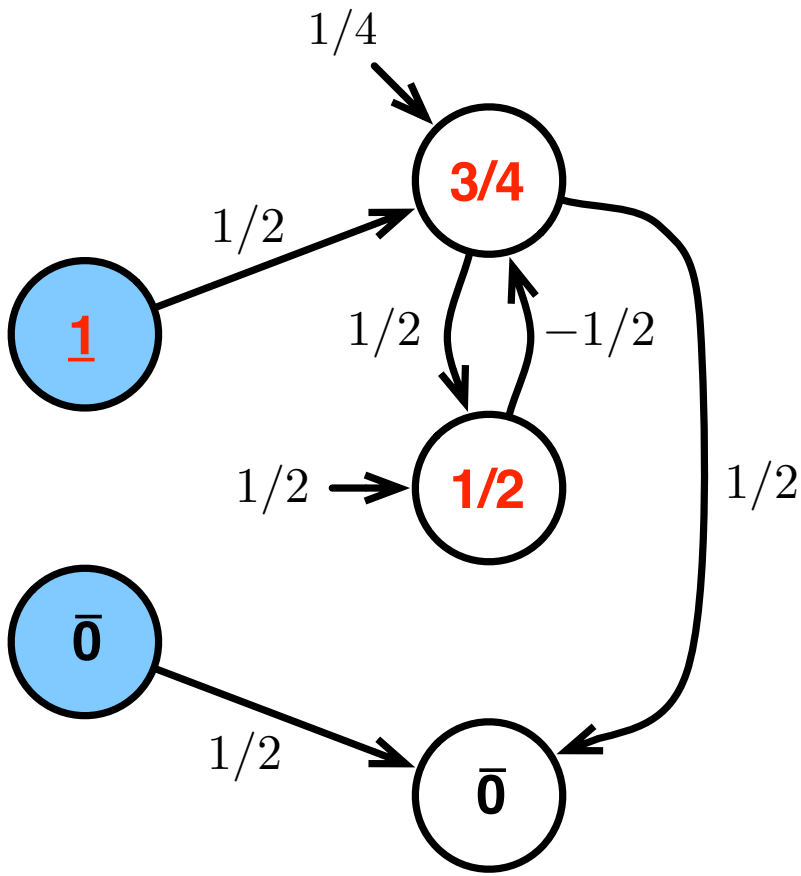

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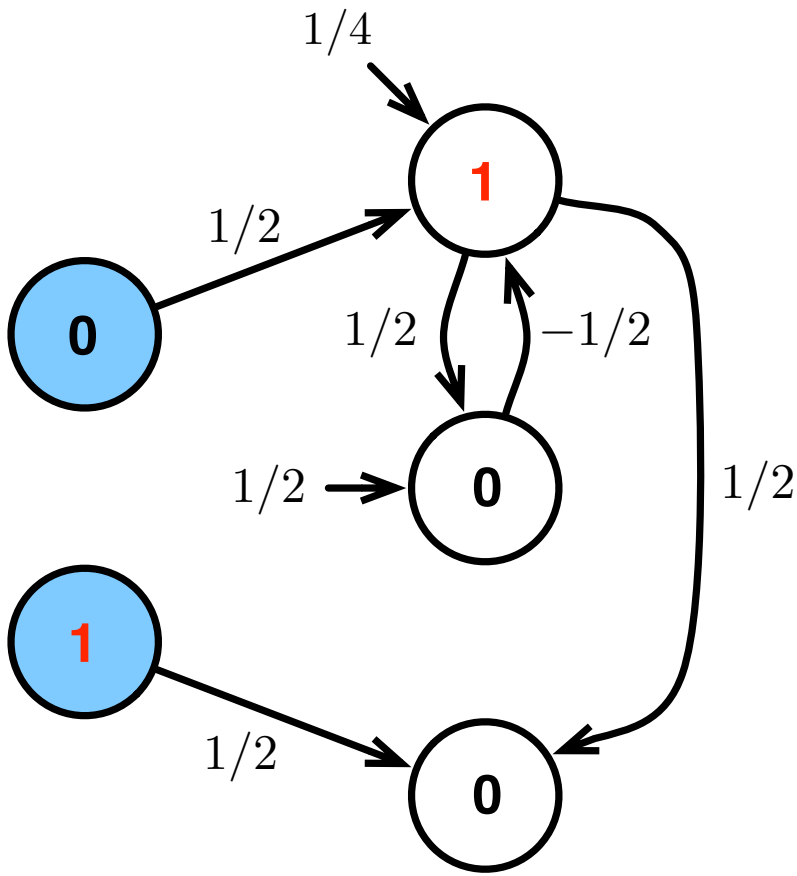

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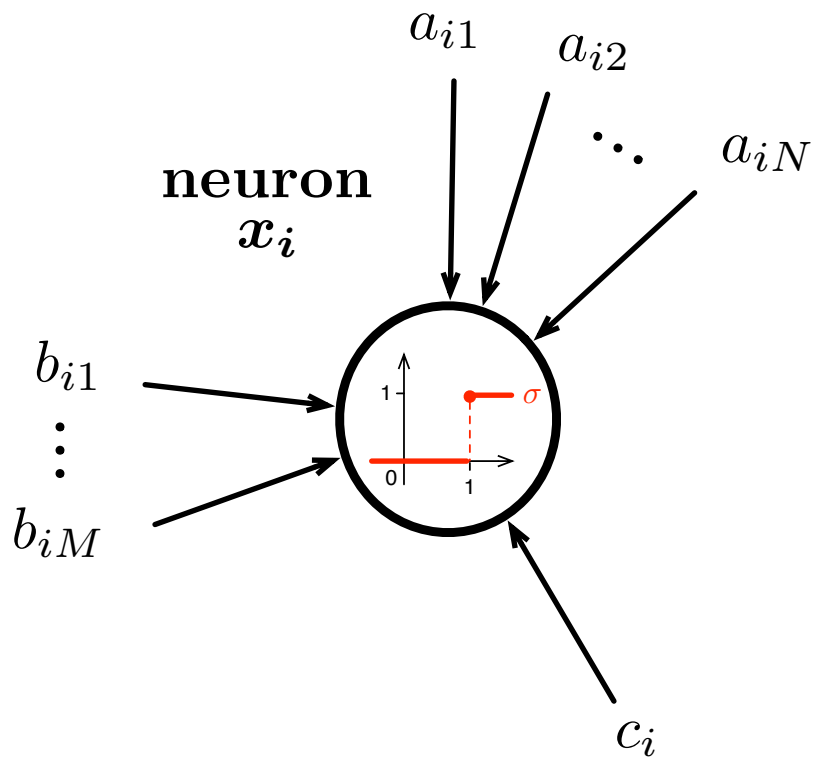

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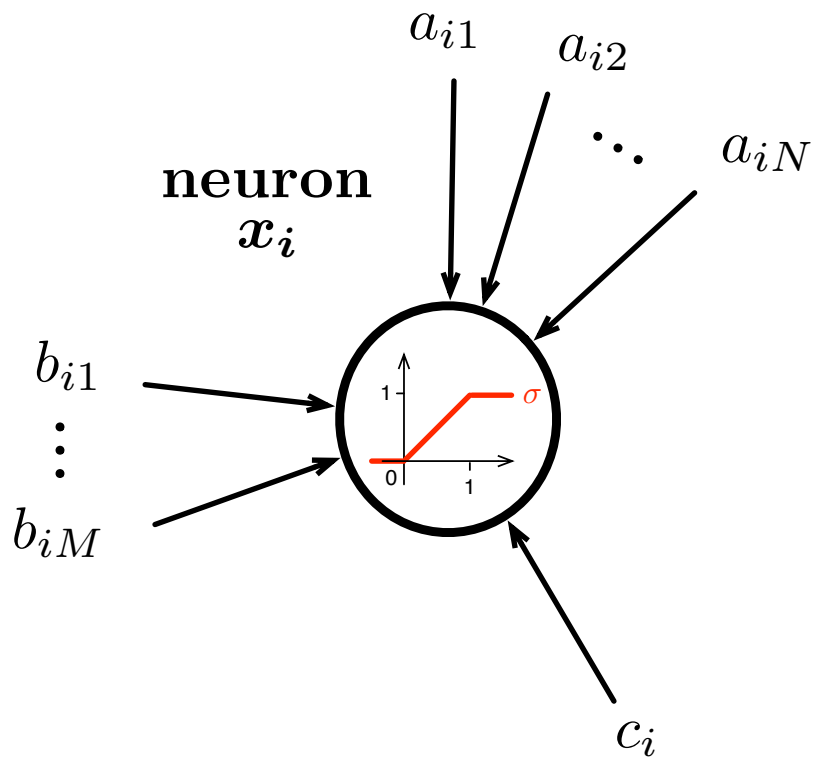

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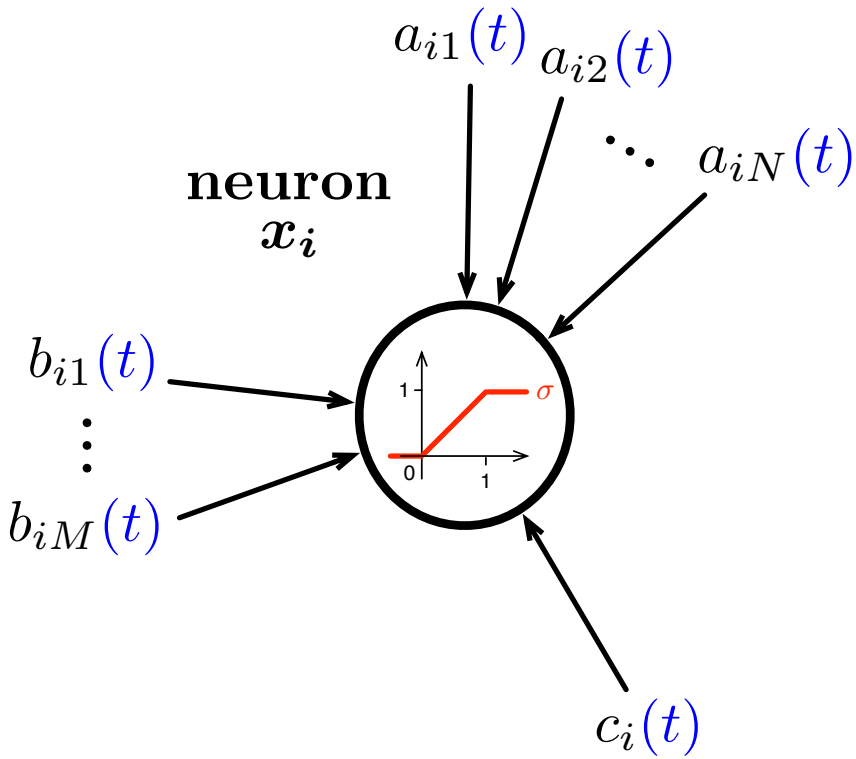

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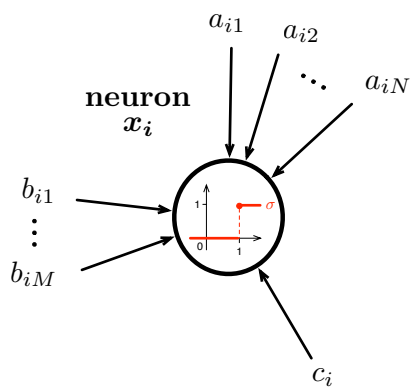

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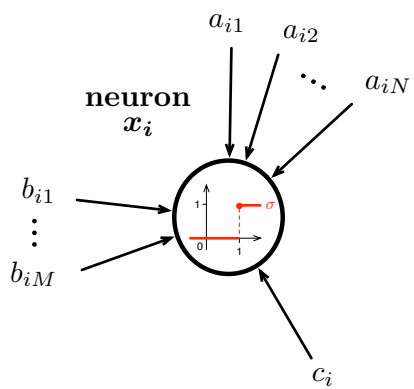

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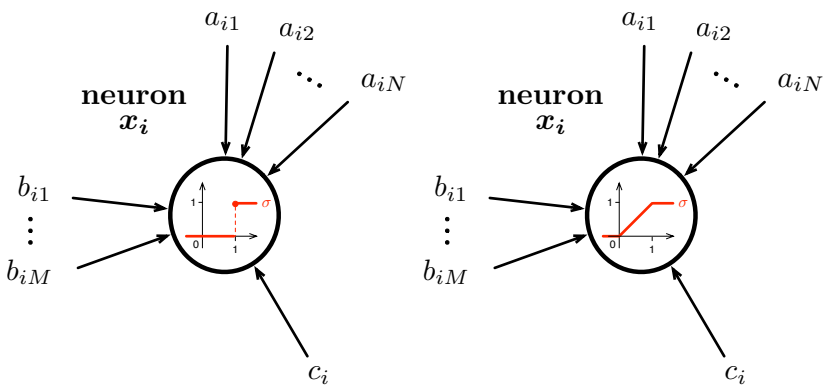

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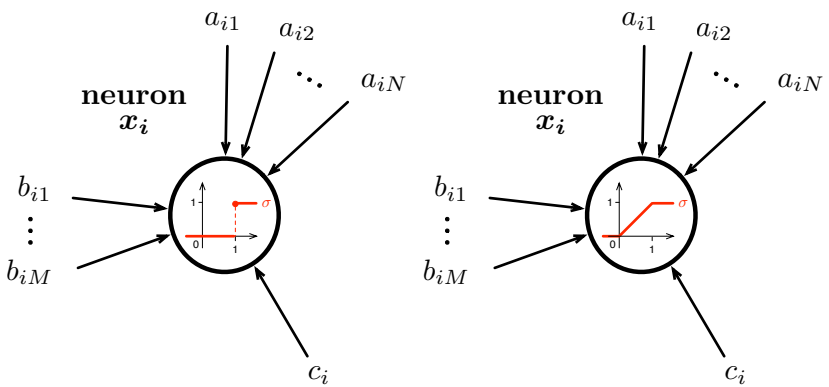

Recurrent Neural Networks

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2. Boolean real RNNs: B-RNN[$\mathbb{R}$]s
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4. Sigmoid static real RNNs: St-RNN[$\mathbb{R}$]s
5. Sigmoid bi-valued evolving rational RNNs: Ev$_2$-RNN[$\mathbb{Q}$]s
6. Sigmoid bi-valued evolving real RNNs: Ev$_2$-RNN[$\mathbb{R}$]s
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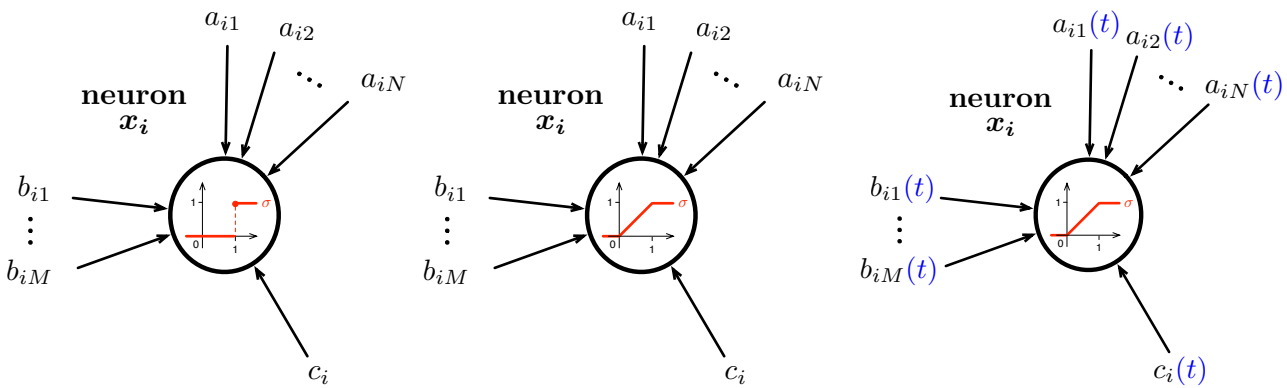
8. Sigmoid general evolving real N-RNNs: Ev-RNN[$\mathbb{R}$]s



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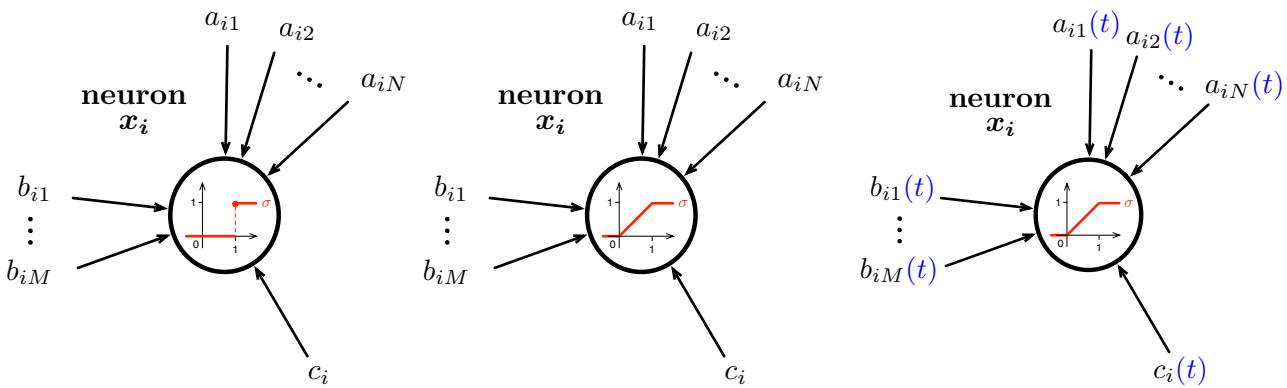

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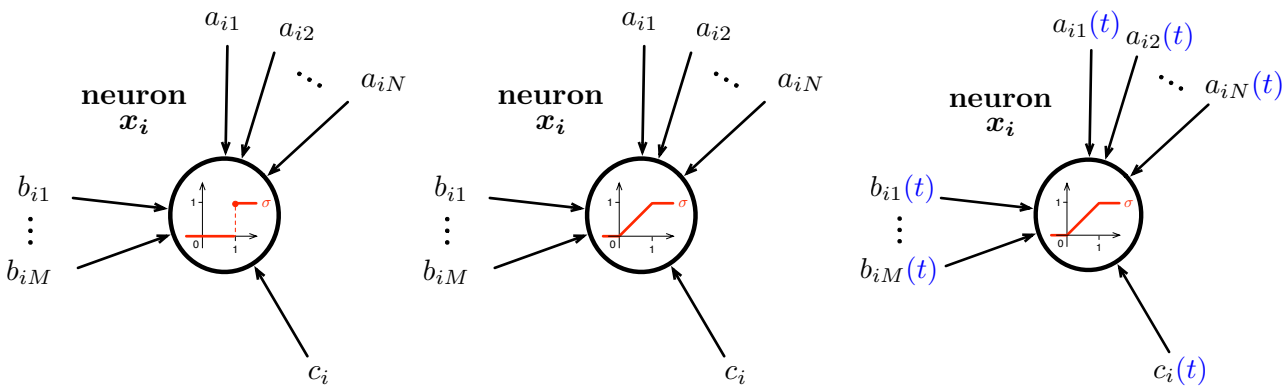

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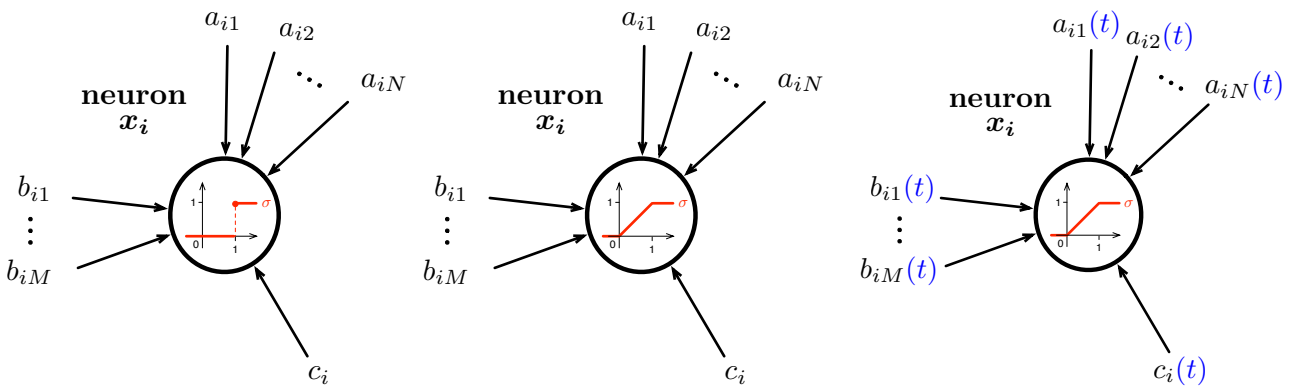

Results: classical computation

	Boolean	Sigmoid		
		Static	Bi-valued Evolving	Evolving
$\mathbb{Q}$	FSA	TM	TM/poly(A)	TM/poly(A)
	REG	**P**	**P/poly**	**P/poly**
	Kl 56, Mi 67	Si & So 95	Ca & Si 11,14	Ca & Si 11,14
$\mathbb{R}$	FSA	TM/poly(A)	TM/poly(A)	TM/poly(A)
	REG	**P/poly**	**P/poly**	**P/poly**
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Infinite Computation

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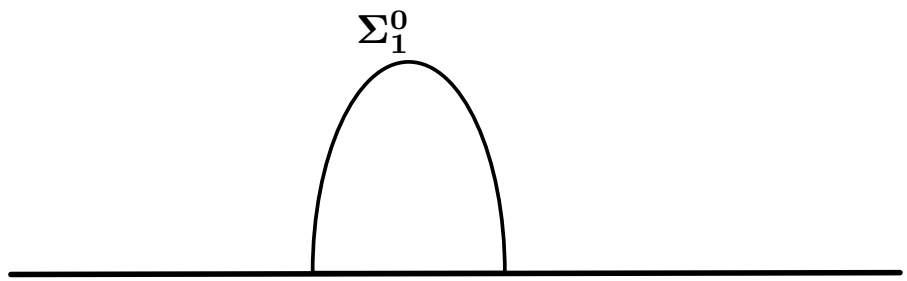

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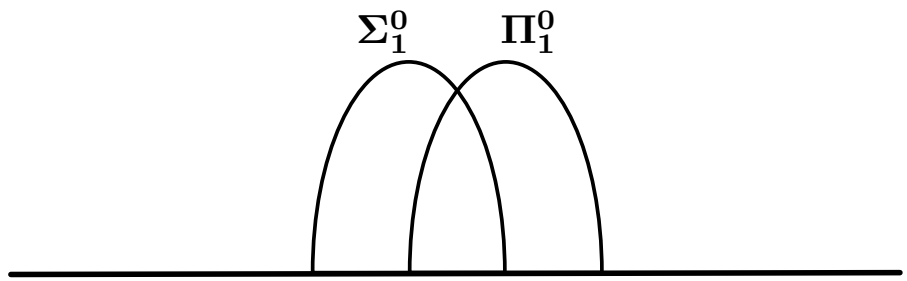

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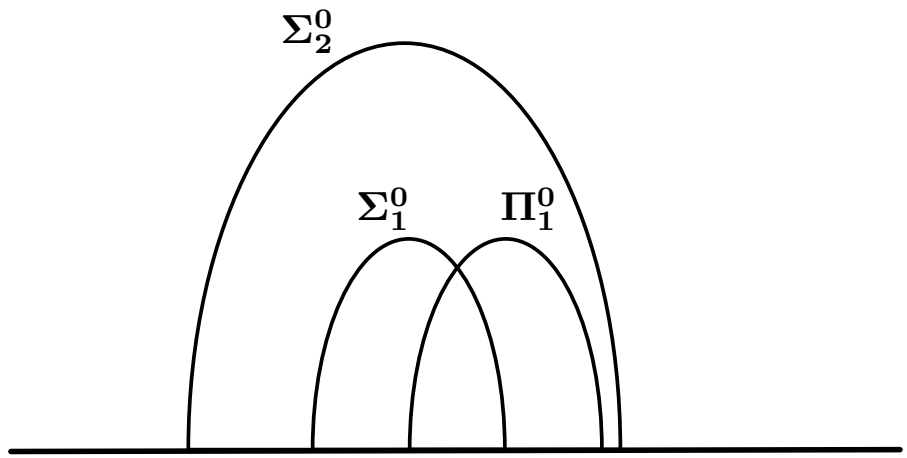

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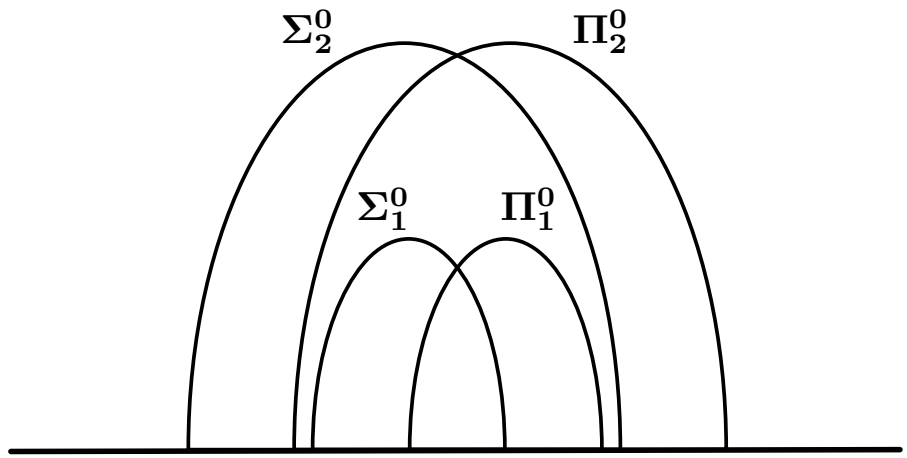

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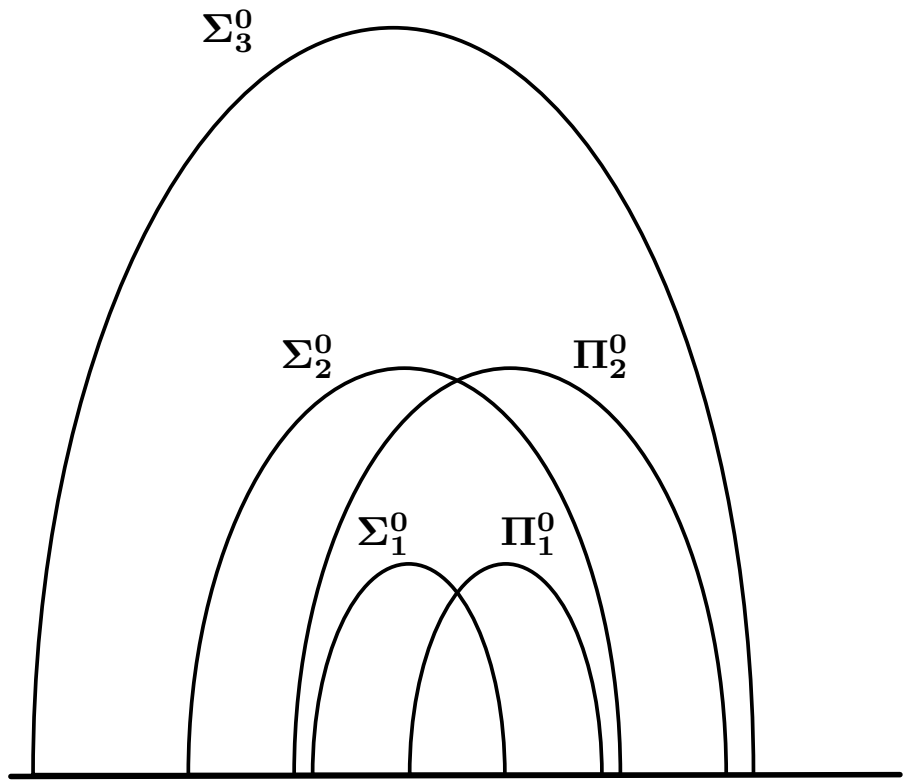

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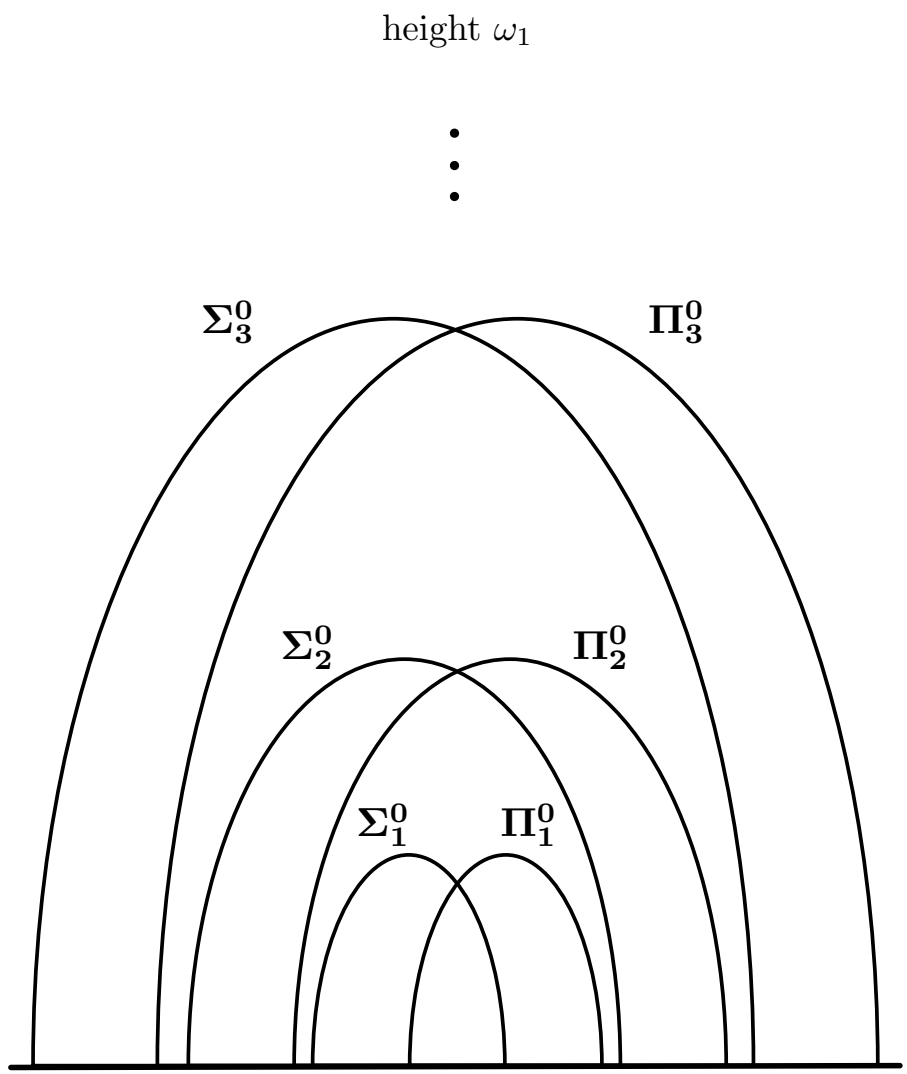

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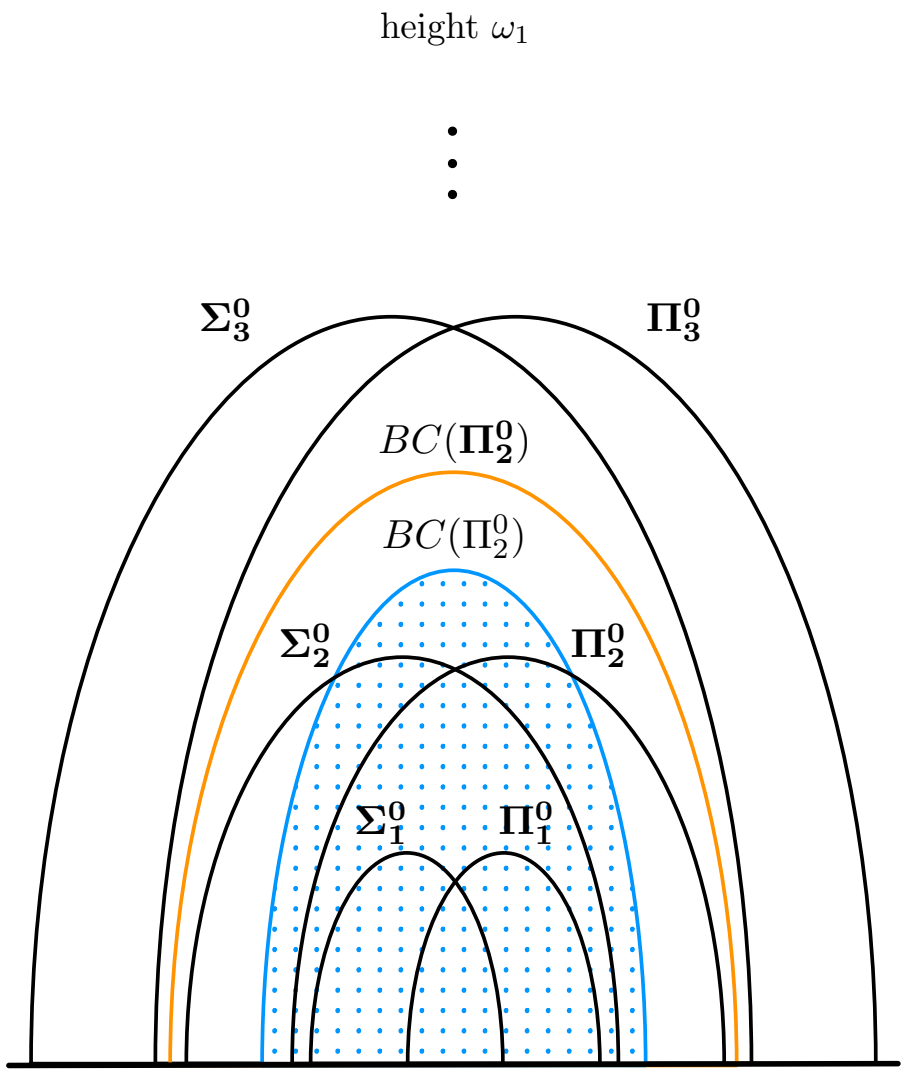

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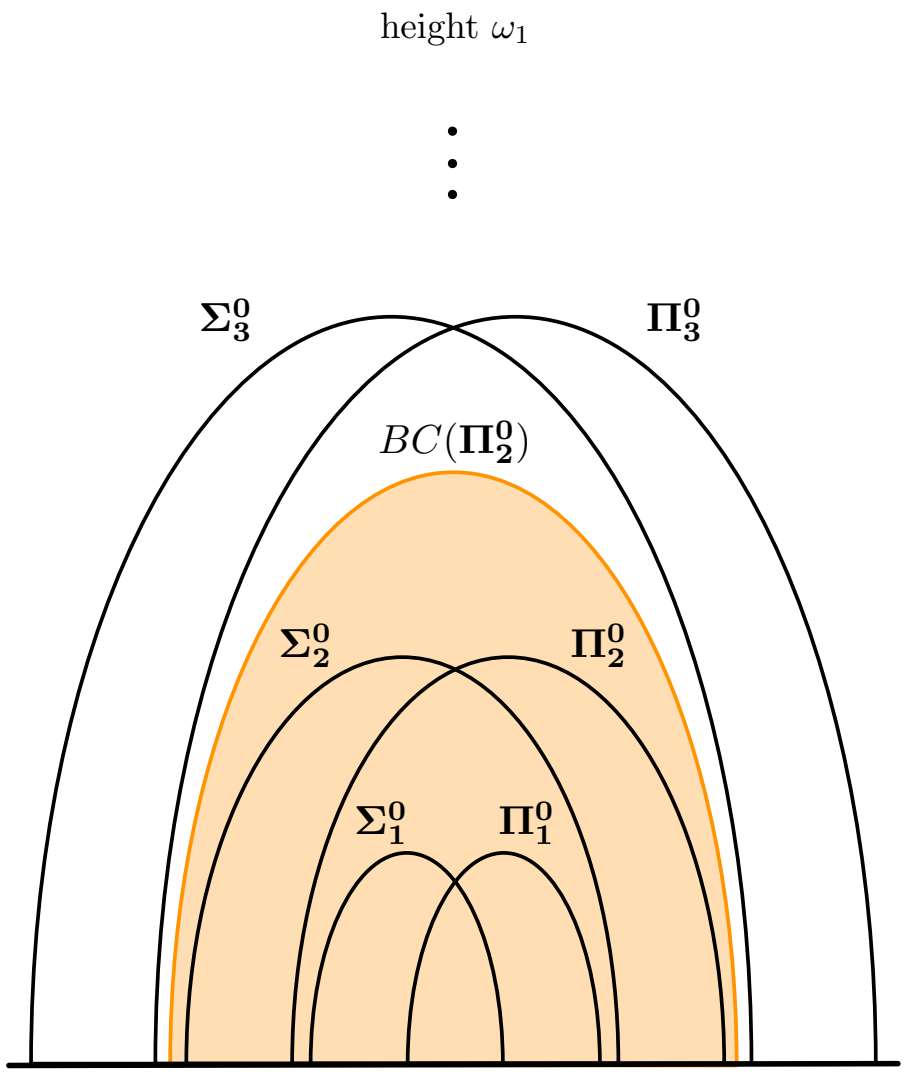

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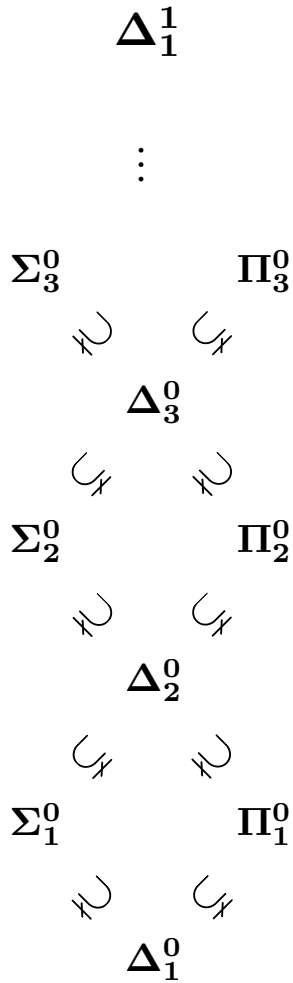

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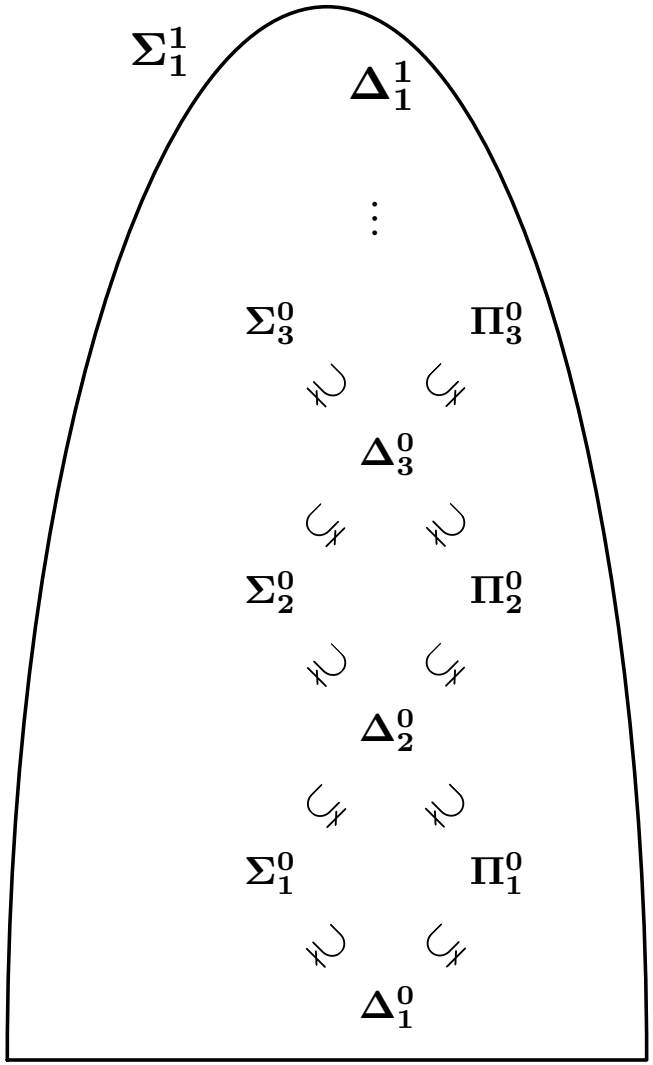

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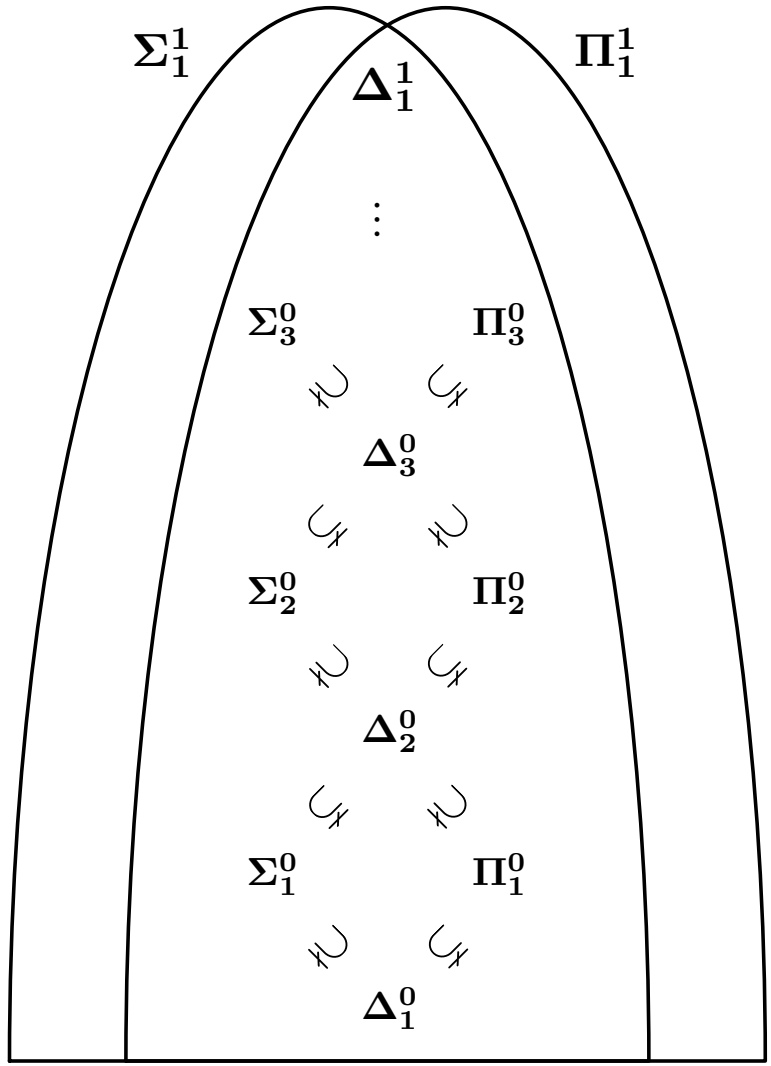

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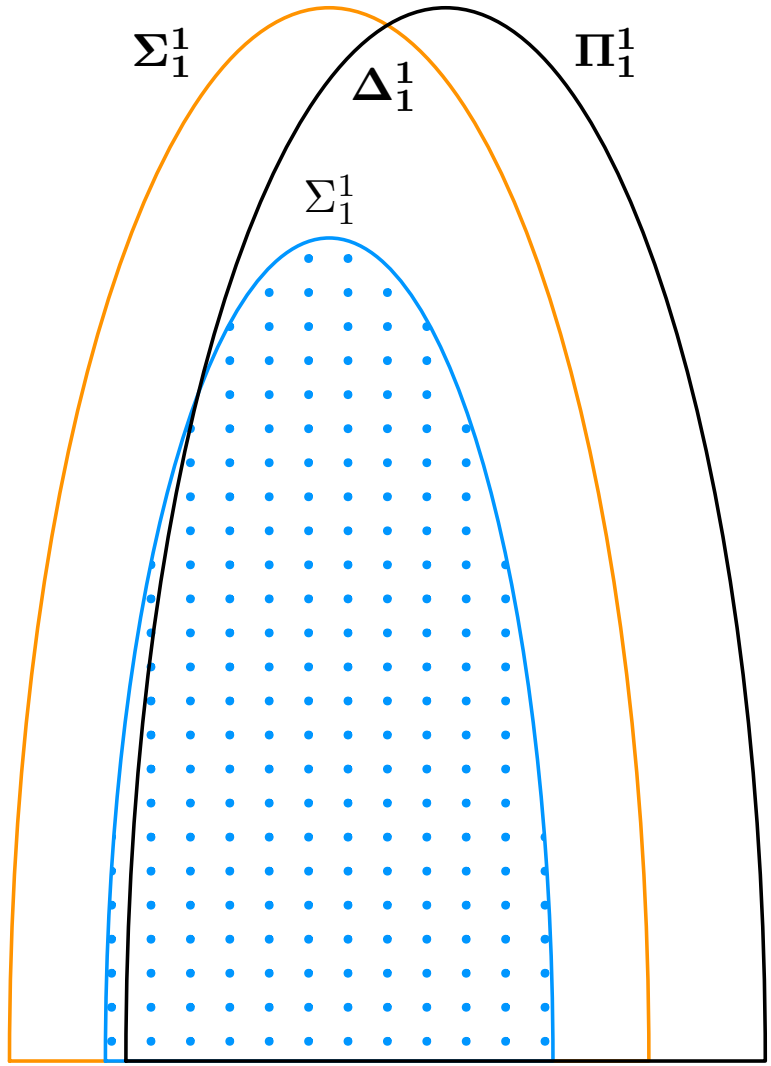

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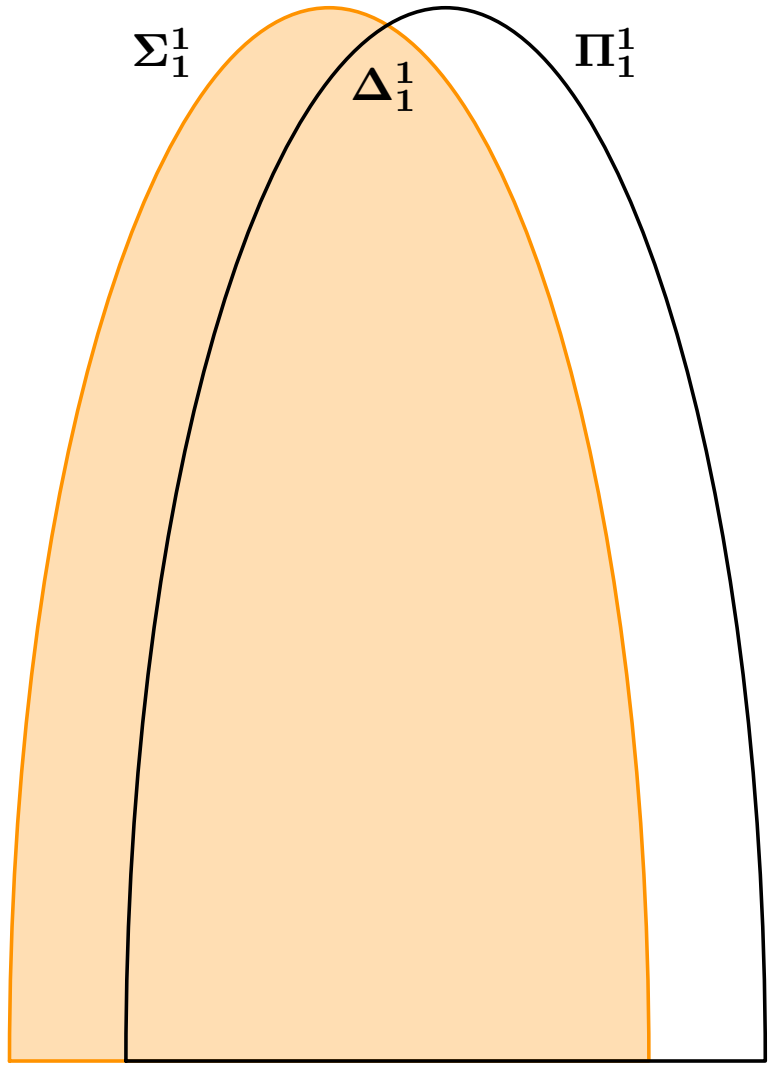

Results: infinite computation / det.

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$\mathbb{Q}$	Muller FSA $\in BC(\Pi_2^0)$ Ca & Vi 10,14	Muller TM $= BC(\Pi_2^0)$ Ca & Vi 15,16	super-Turing $= BC(\mathbf{\Pi_2^0})$ Ca & Vi 15,16	super-Turing $= BC(\mathbf{\Pi_2^0})$ Ca & Vi 15,16
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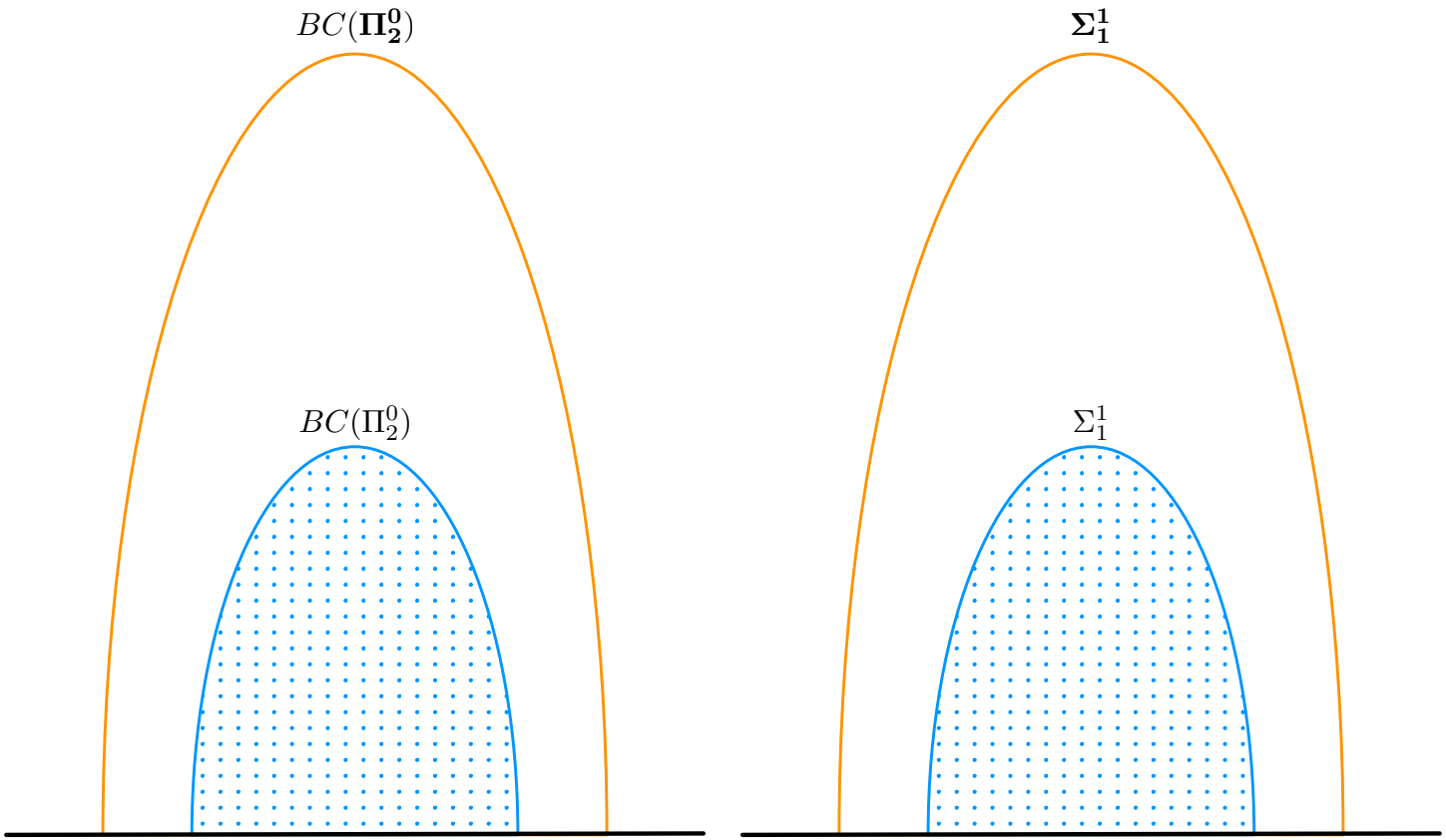
Hierarchy Theorems: stratification of the super-Turing "world"

- We can define infinitely many complexity classes between the Turing and super-Turing levels.



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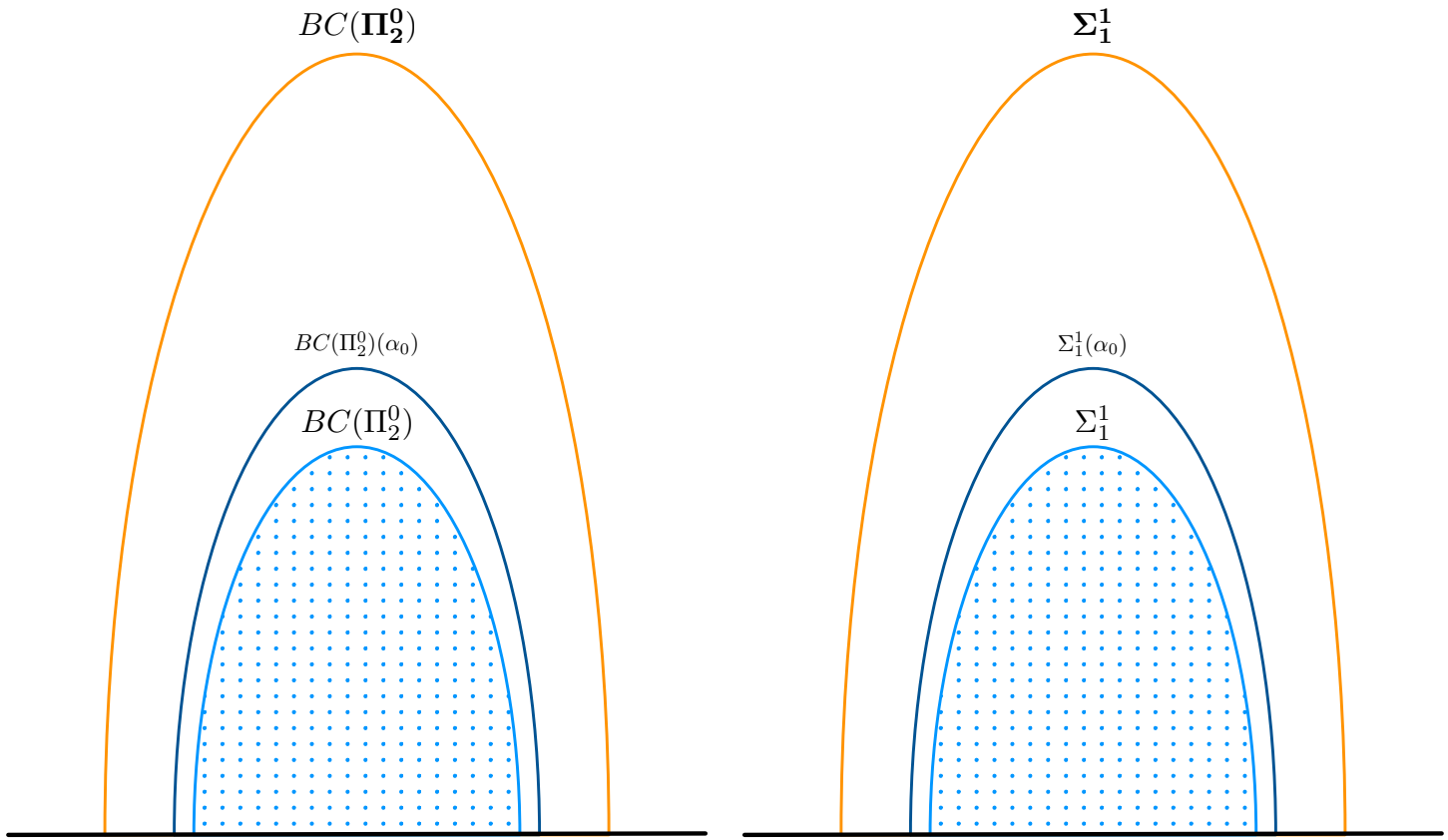

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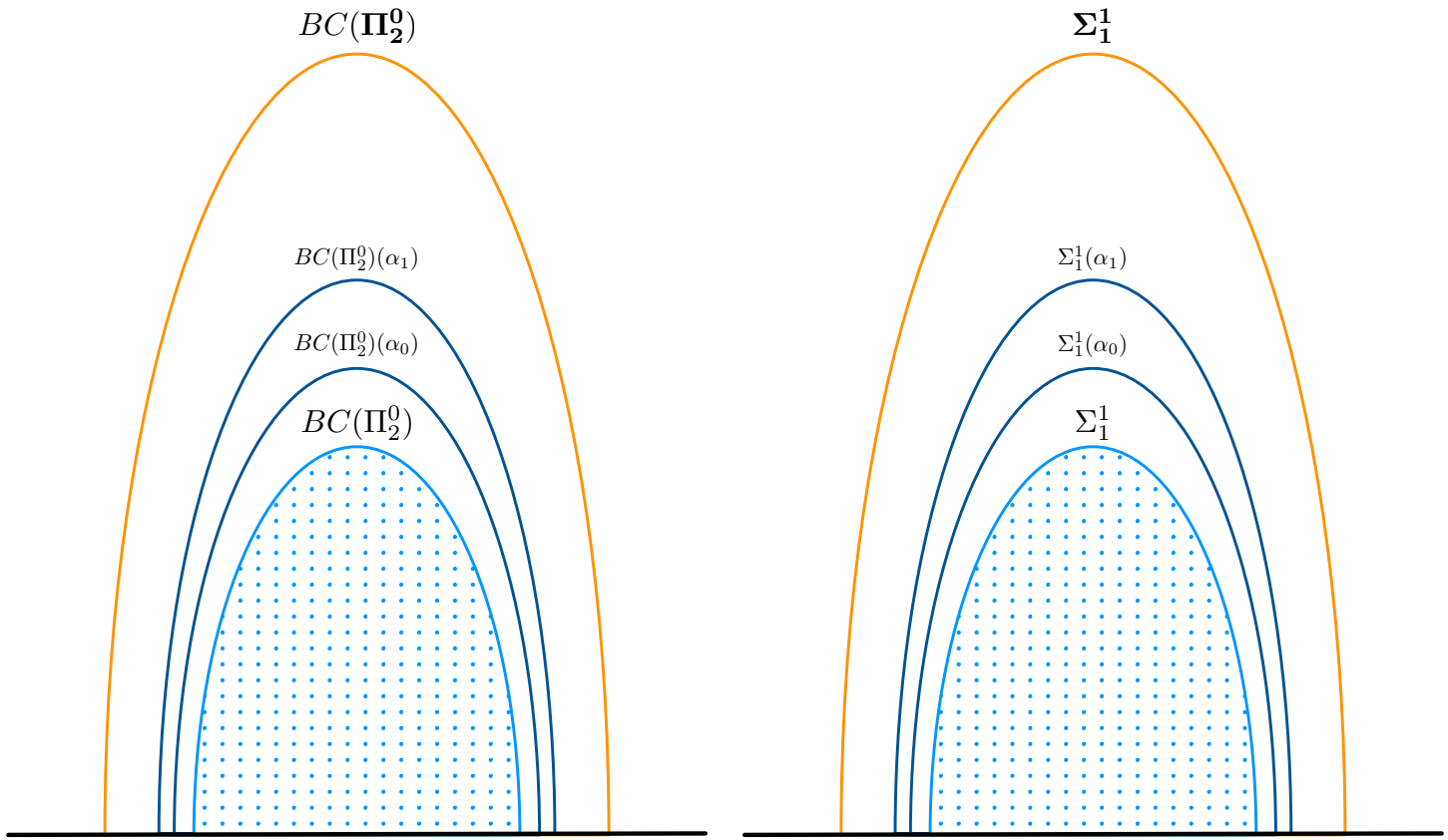

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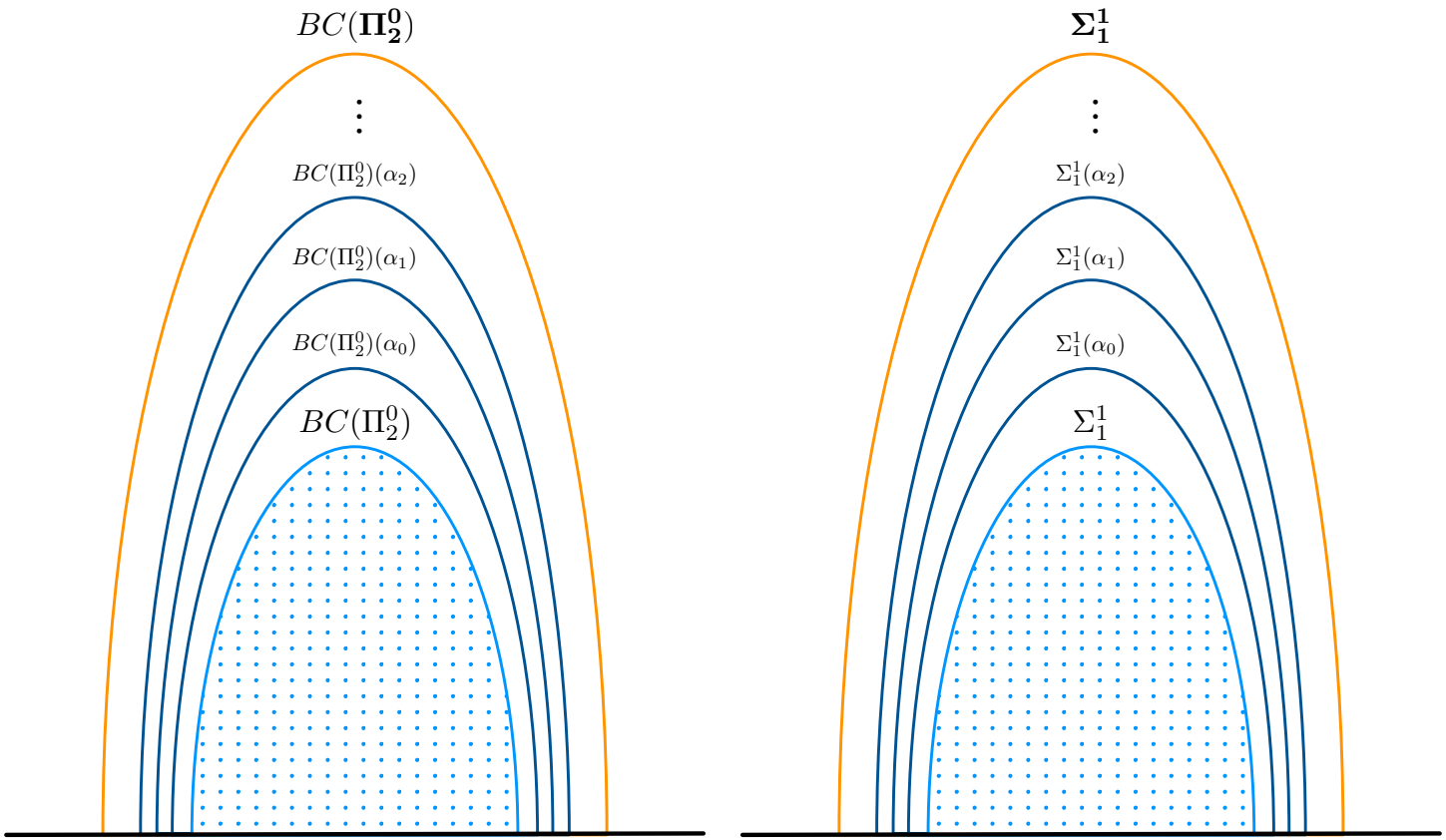

Intermediate Conclusions

- Recurrent neural networks is a natural model for *oracle-based (super-Turing) computation*.
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- We propose a novel paradigm for *abstract neural computation* that takes into account important biological features.

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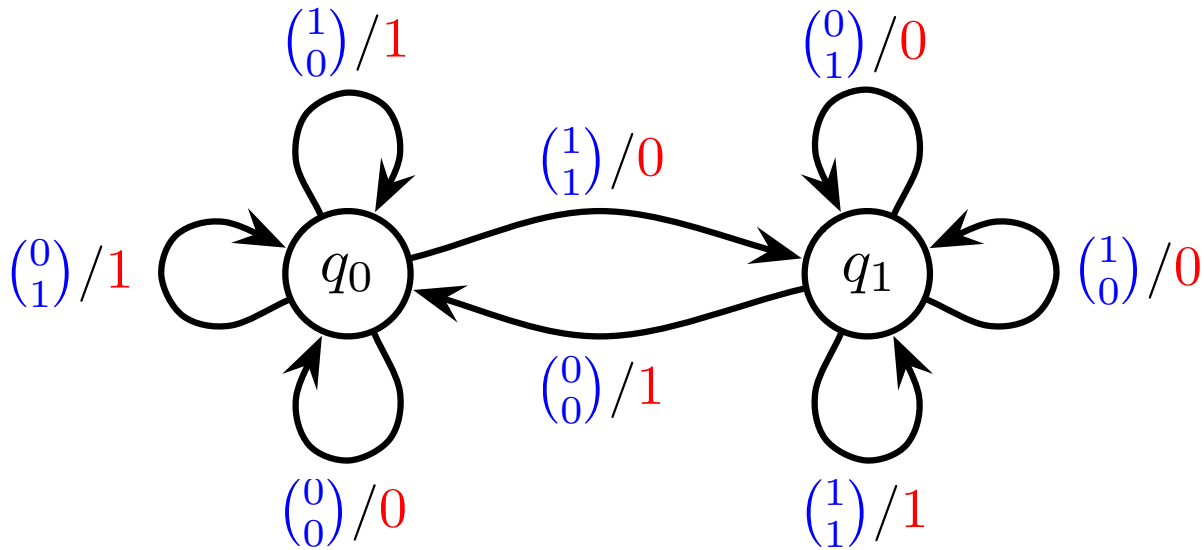
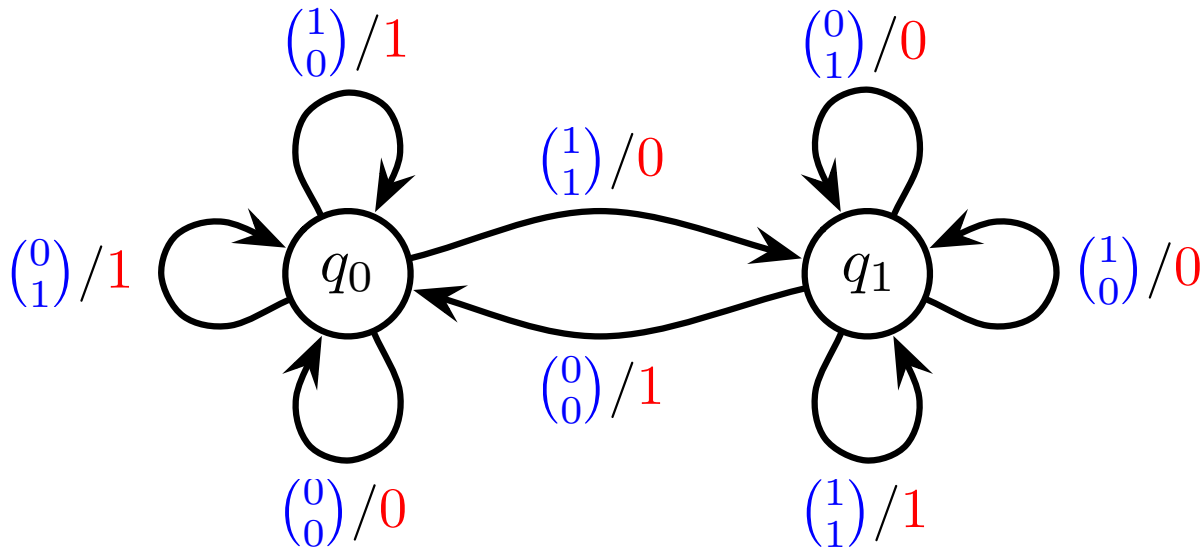
Binary Adder Automaton



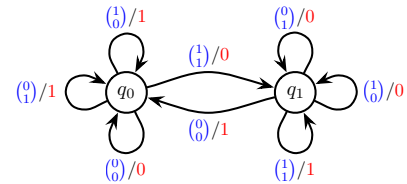
$$\begin{array}{cccccccc} & & 1 & 1^{1} & 0^{1} & 1 & 1 & 0^{1} & 1 \\ + & & & 1 & 1 & 1 & 0 & 0 & 1 \\ \hline & & 1 & 1 & 0 & 0 & 1 & 1 & 0 \end{array}$$

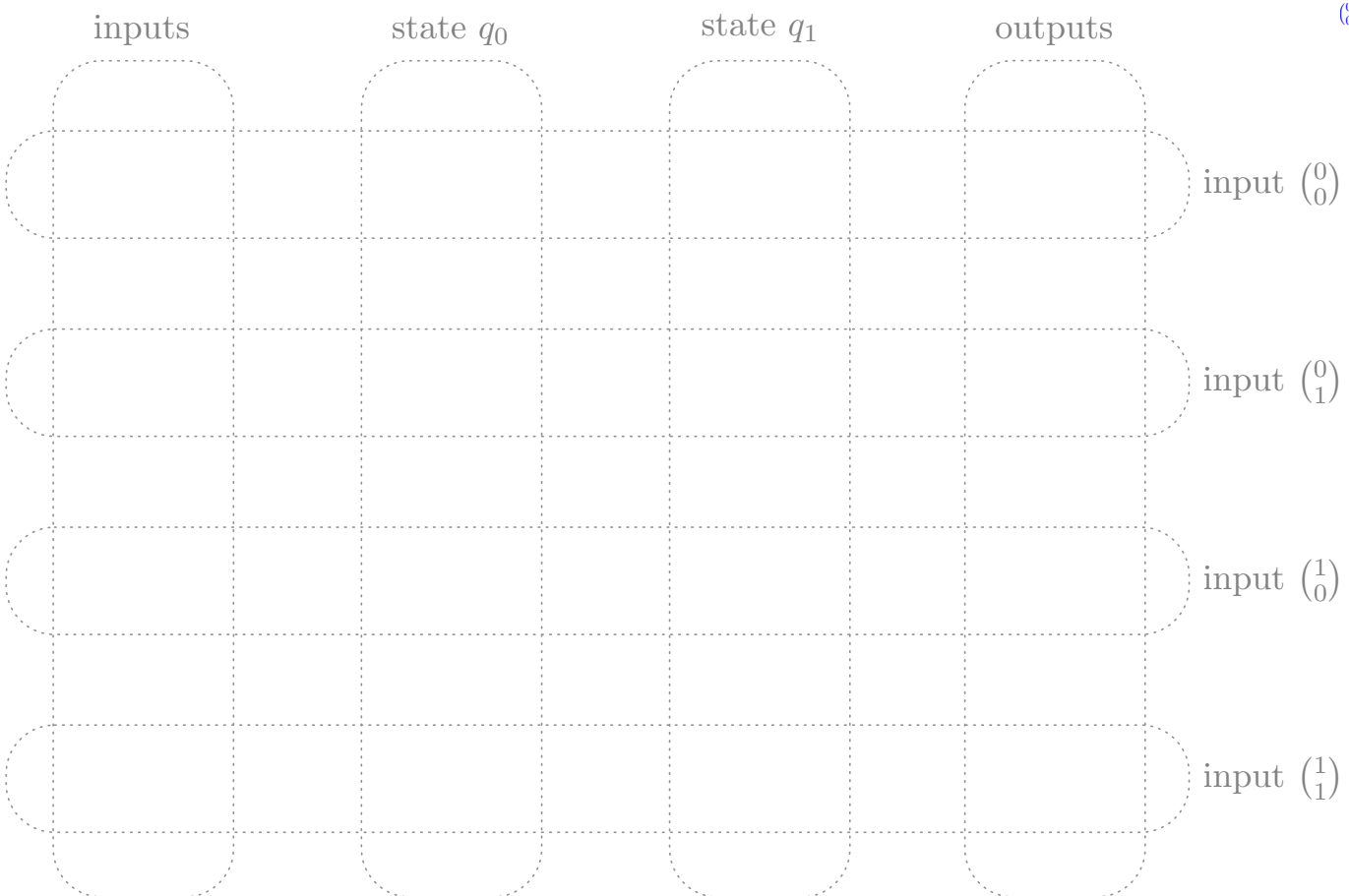
Binary Adder Automaton



$$
\begin{array}{cccccccc}
 & {\scriptstyle 1} & 1^{\scriptstyle 1} & 0^{\scriptstyle 1} & 1 & 1 & 0^{\scriptstyle 1} & 1 \\
+ & & 1 & 1 & 1 & 0 & 0 & 1 \\
\hline
 & 1 & 1 & 0 & 0 & 1 & 1 & 0
\end{array}
$$

Binary Adder Boolean Neural Network





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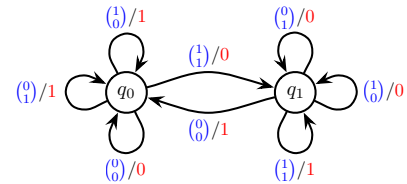

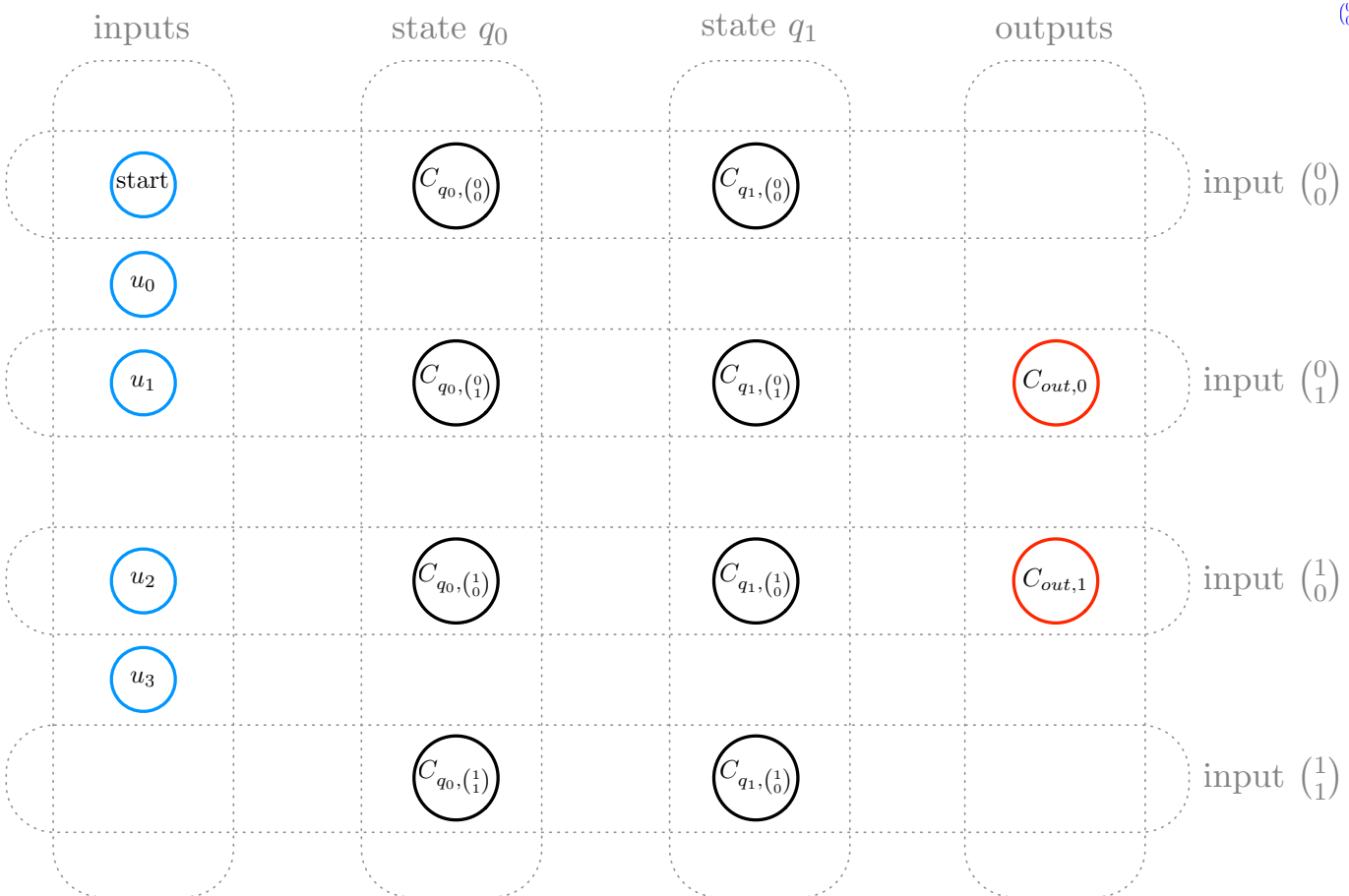

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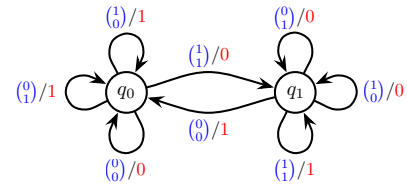

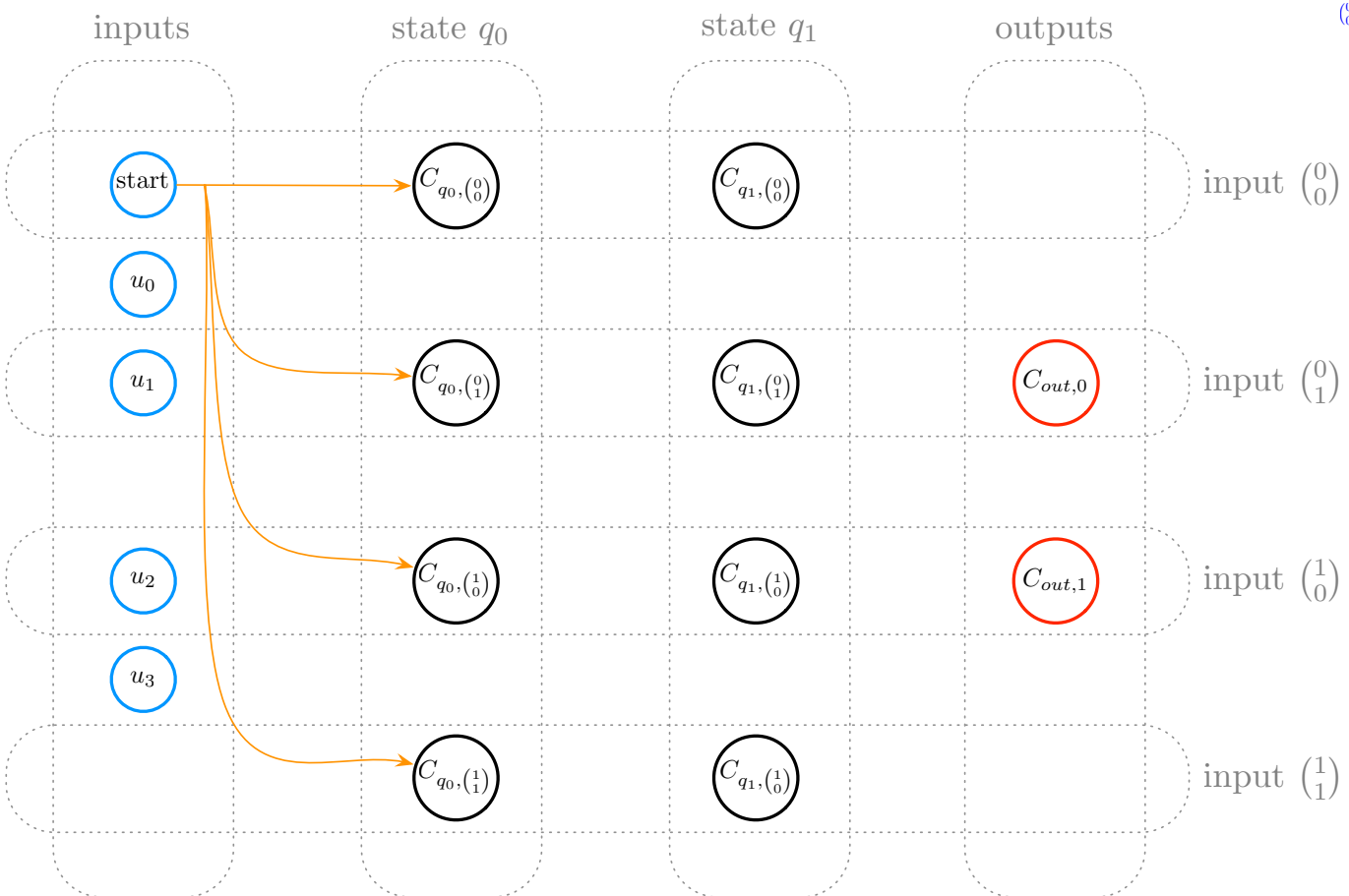

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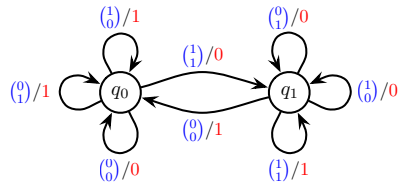

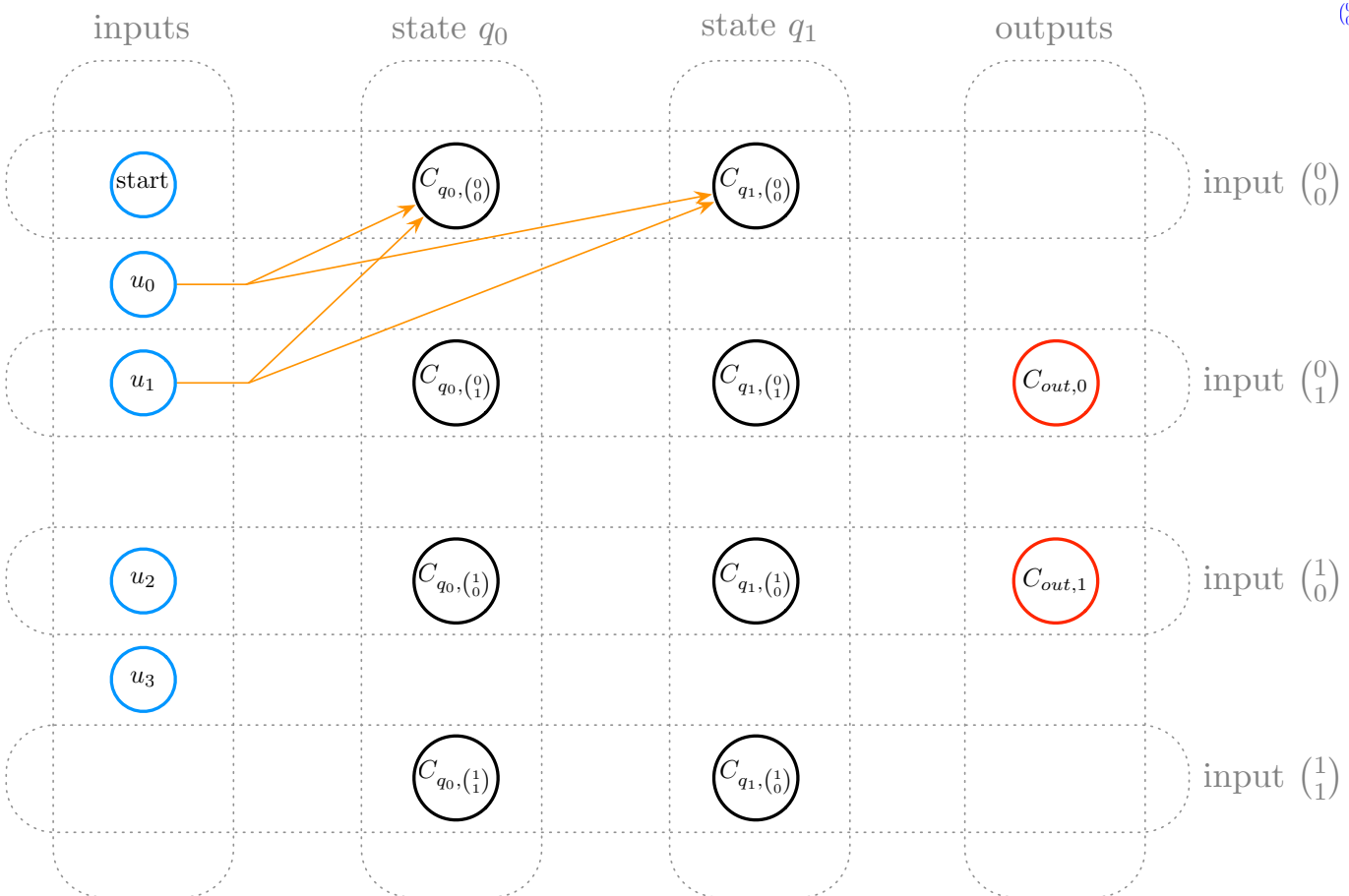

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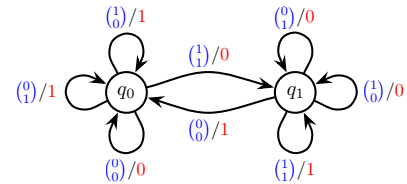

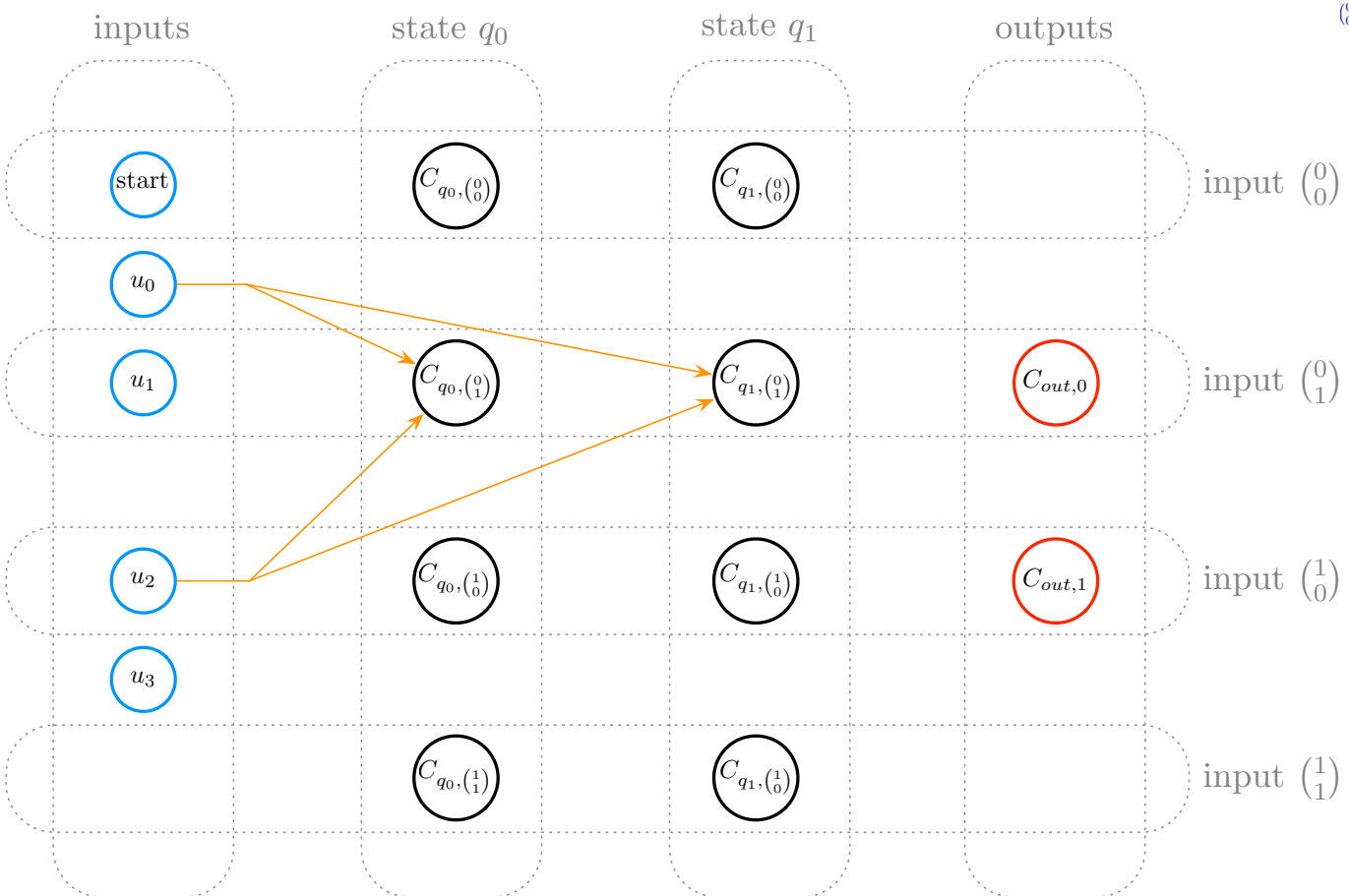

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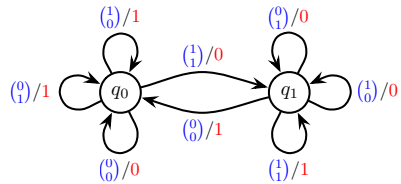

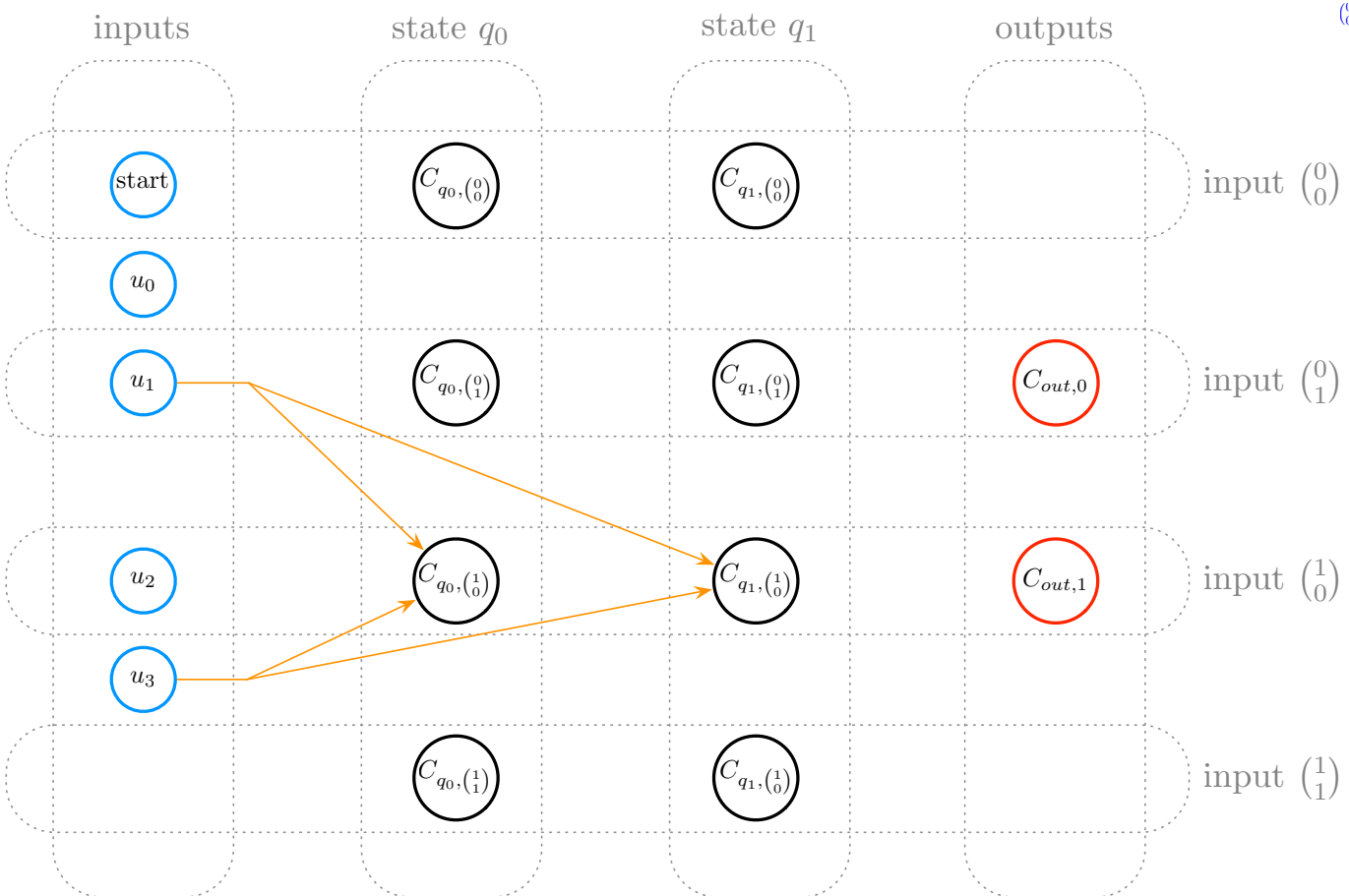

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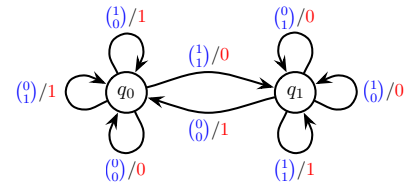

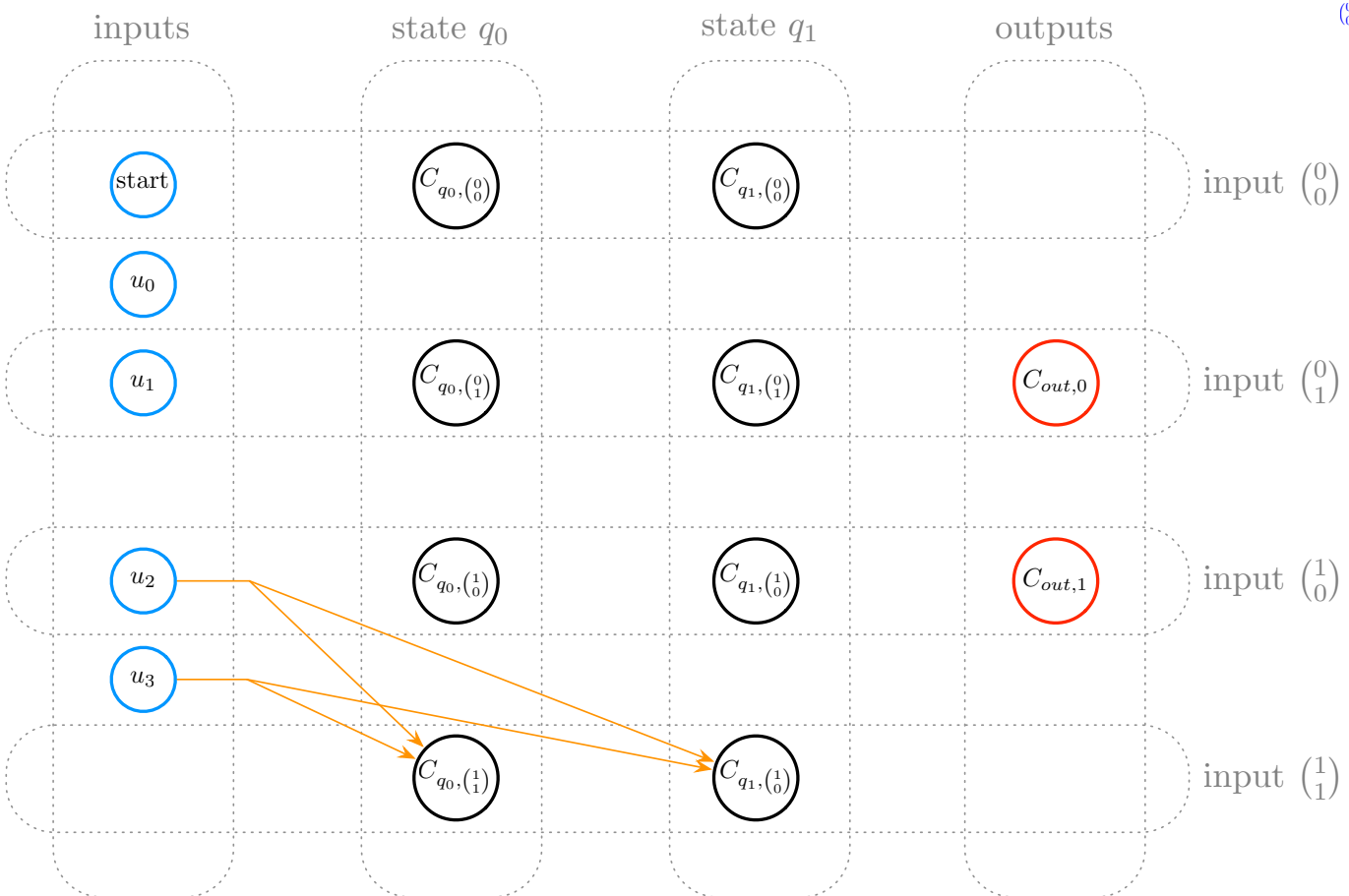

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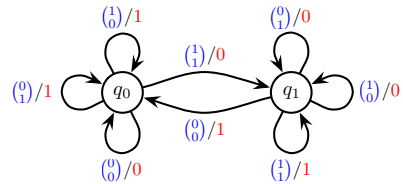
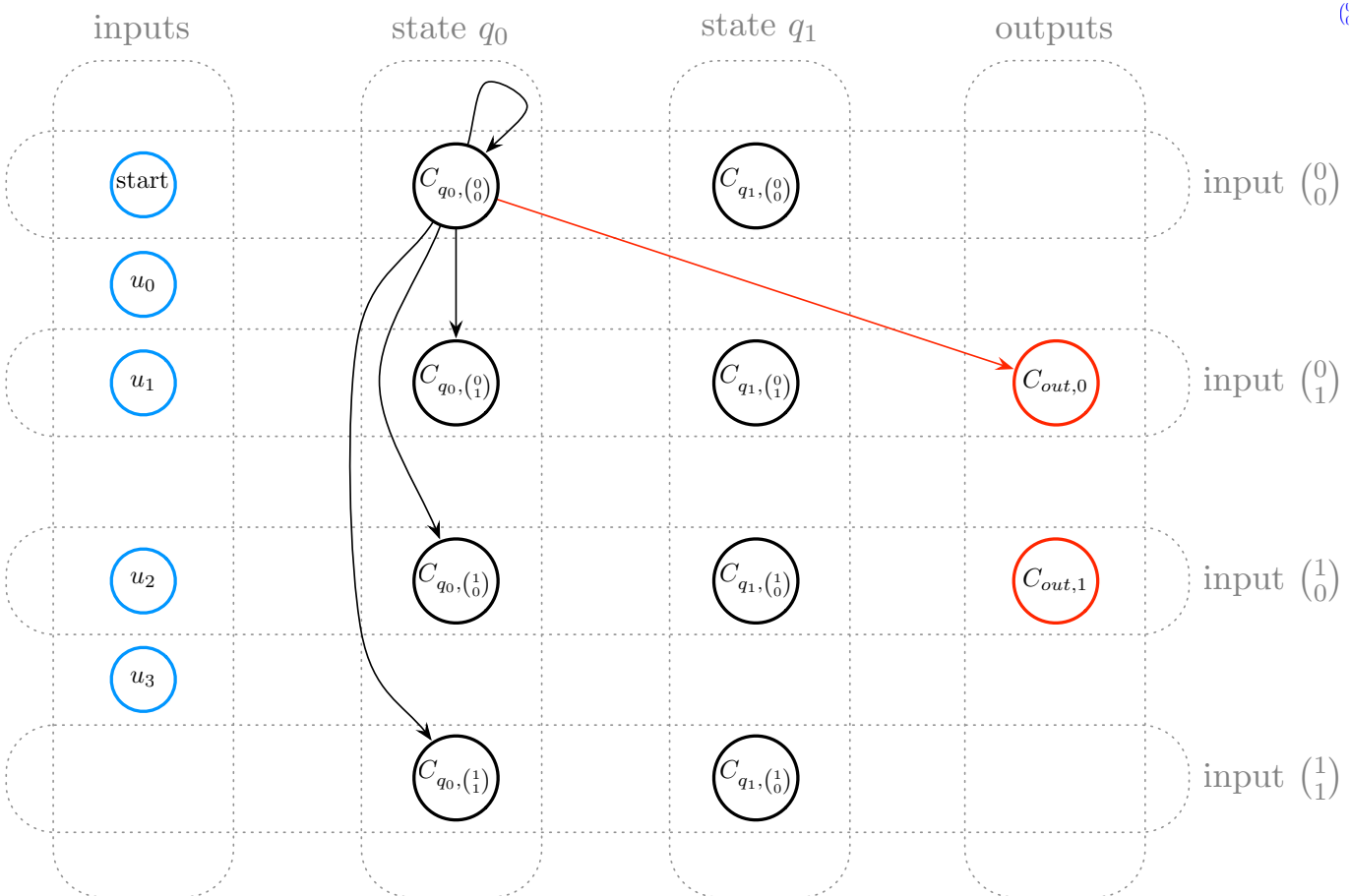
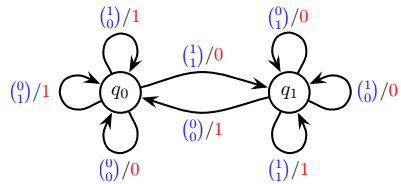
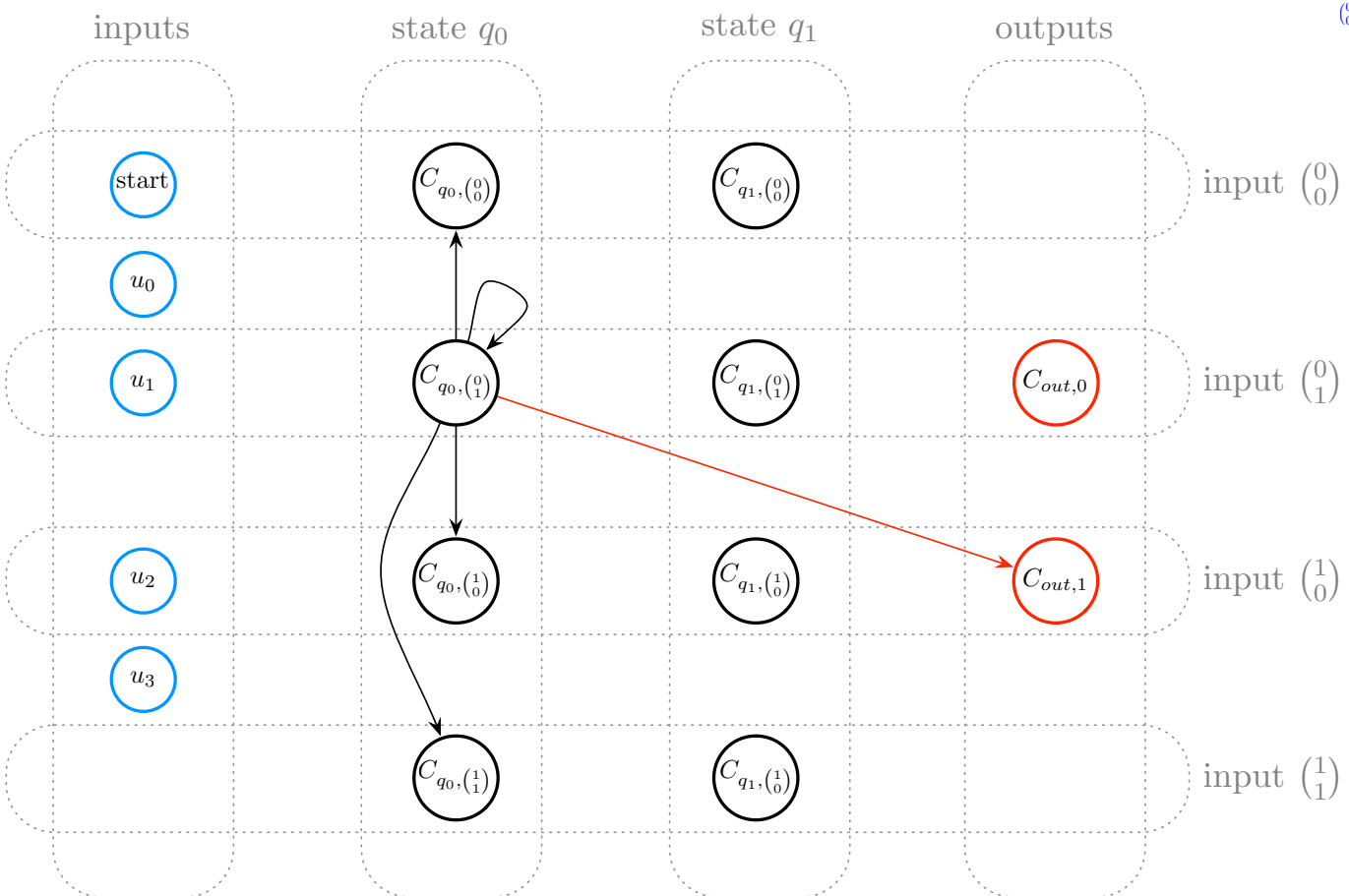




Binary Adder Boolean Neural Network





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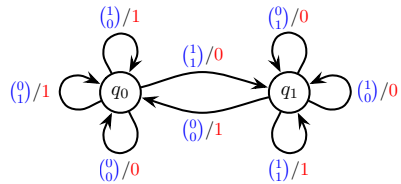

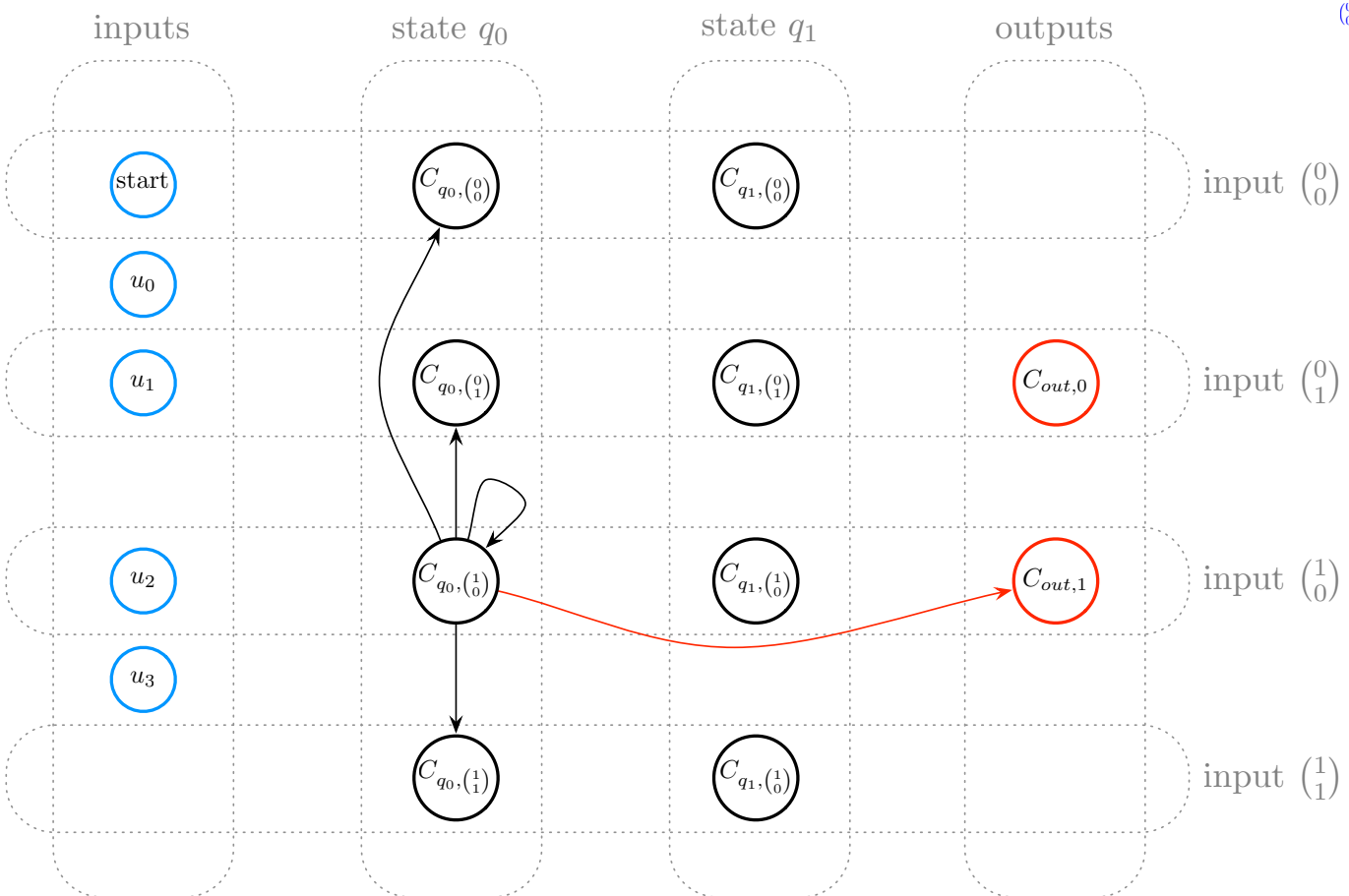

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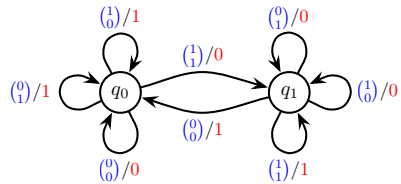

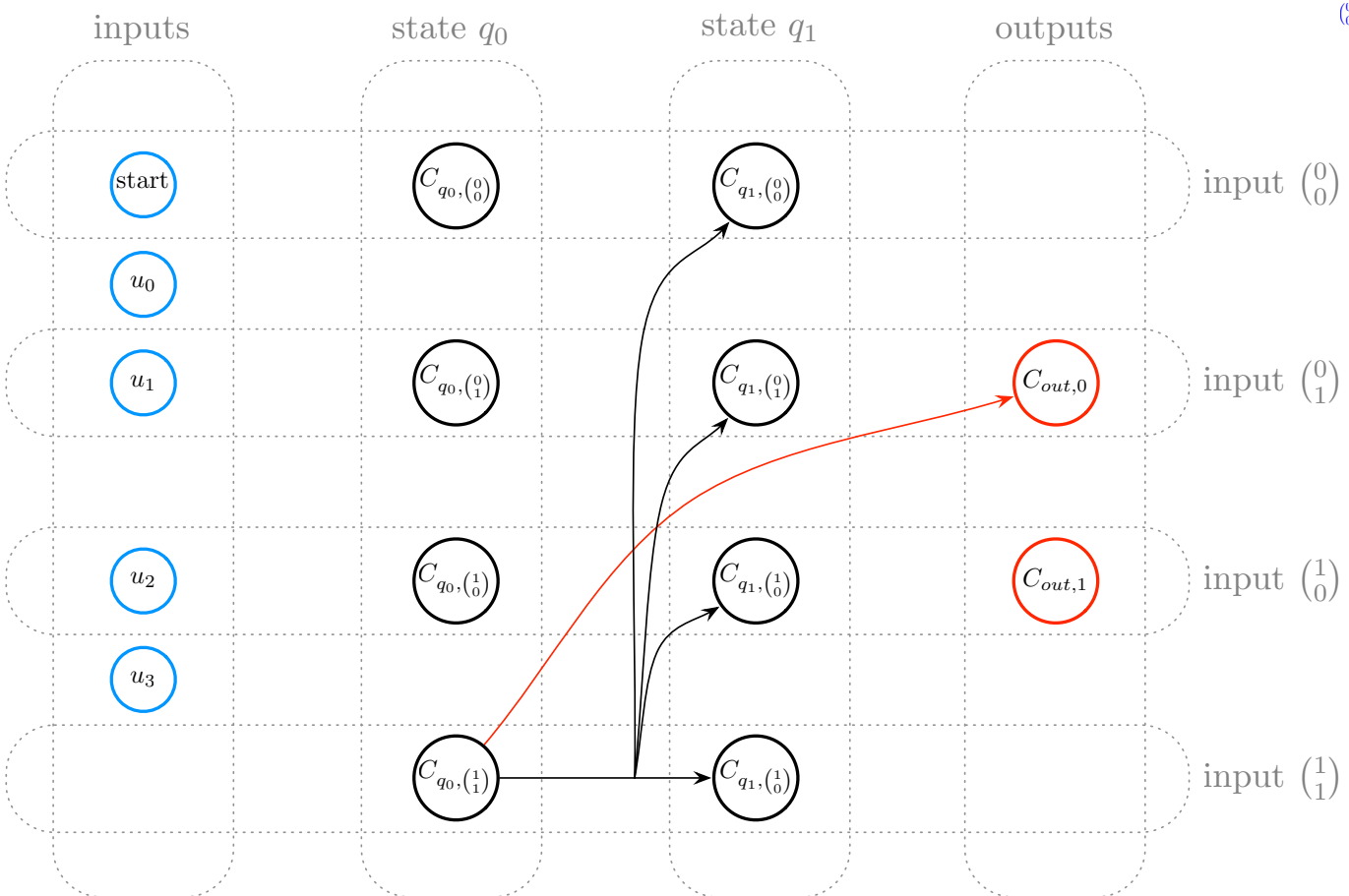

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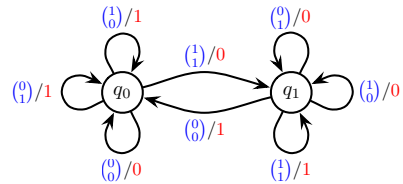

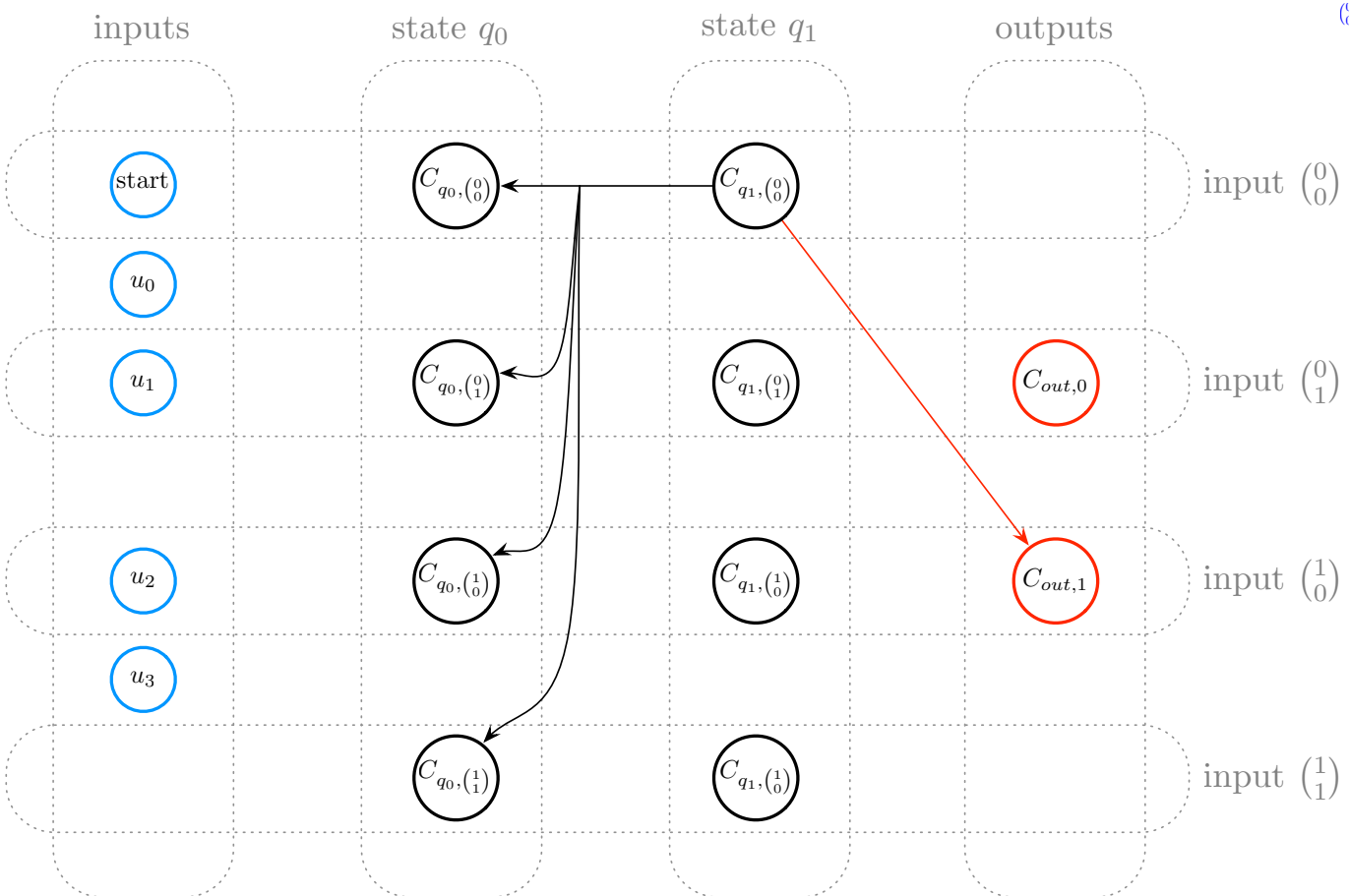

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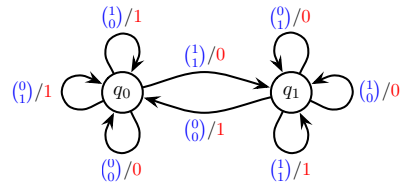

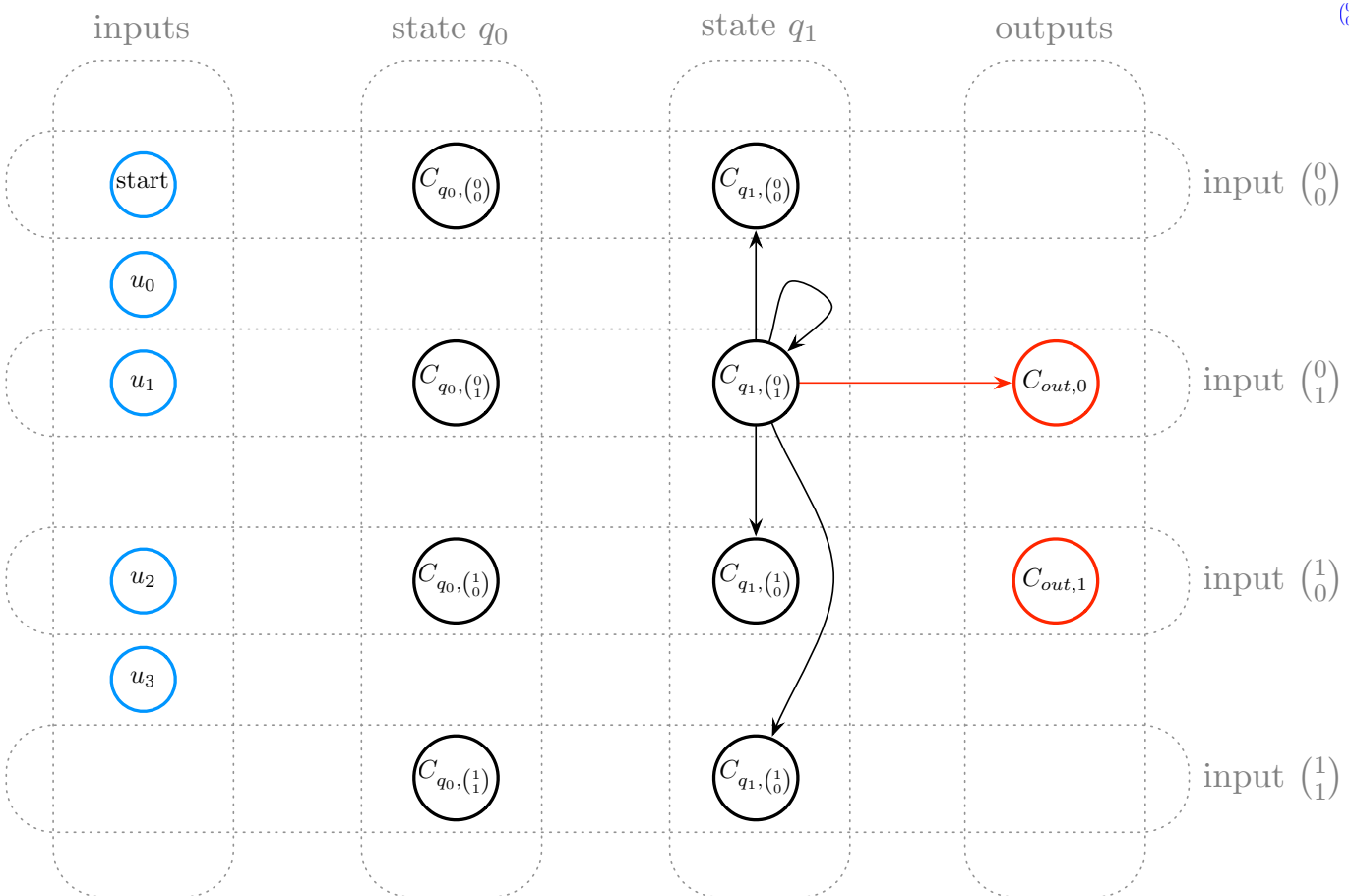

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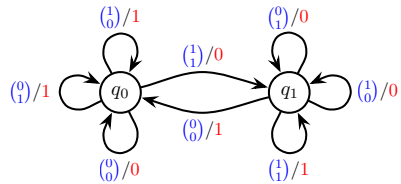

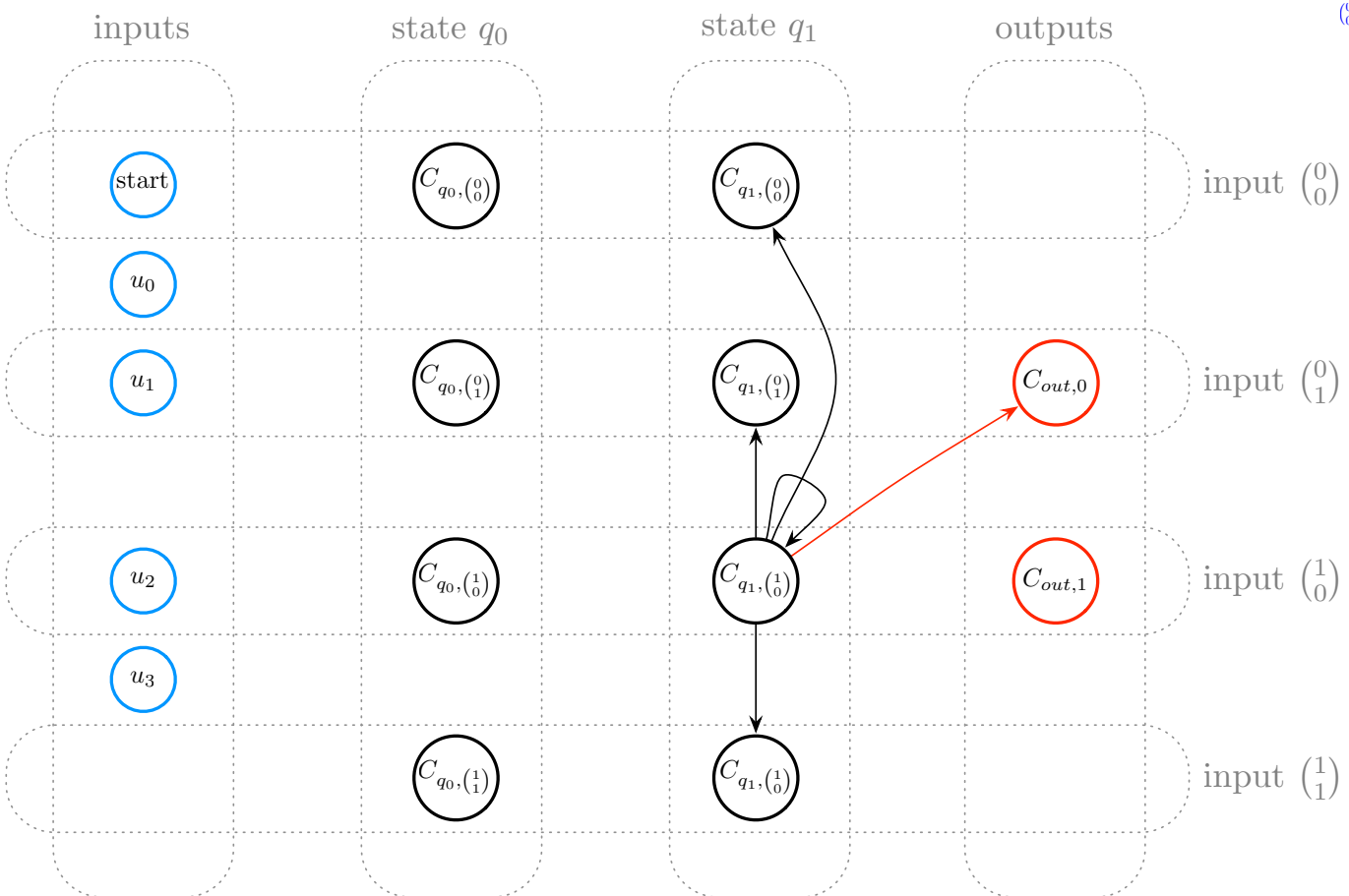

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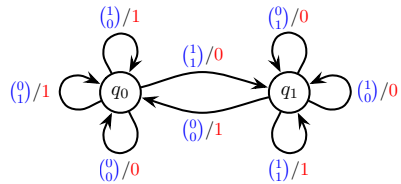

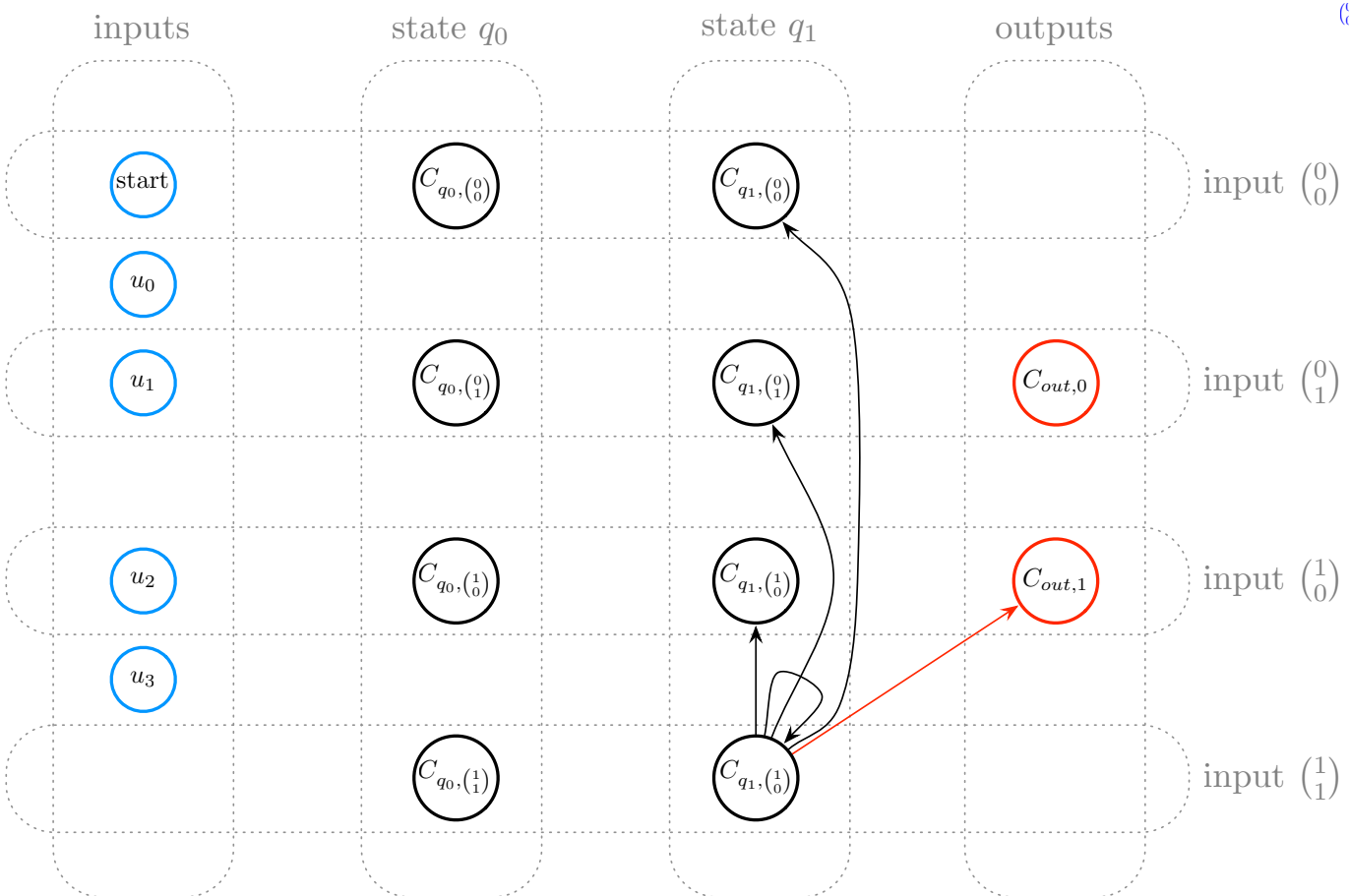

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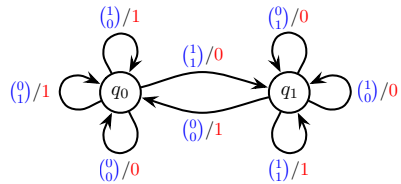
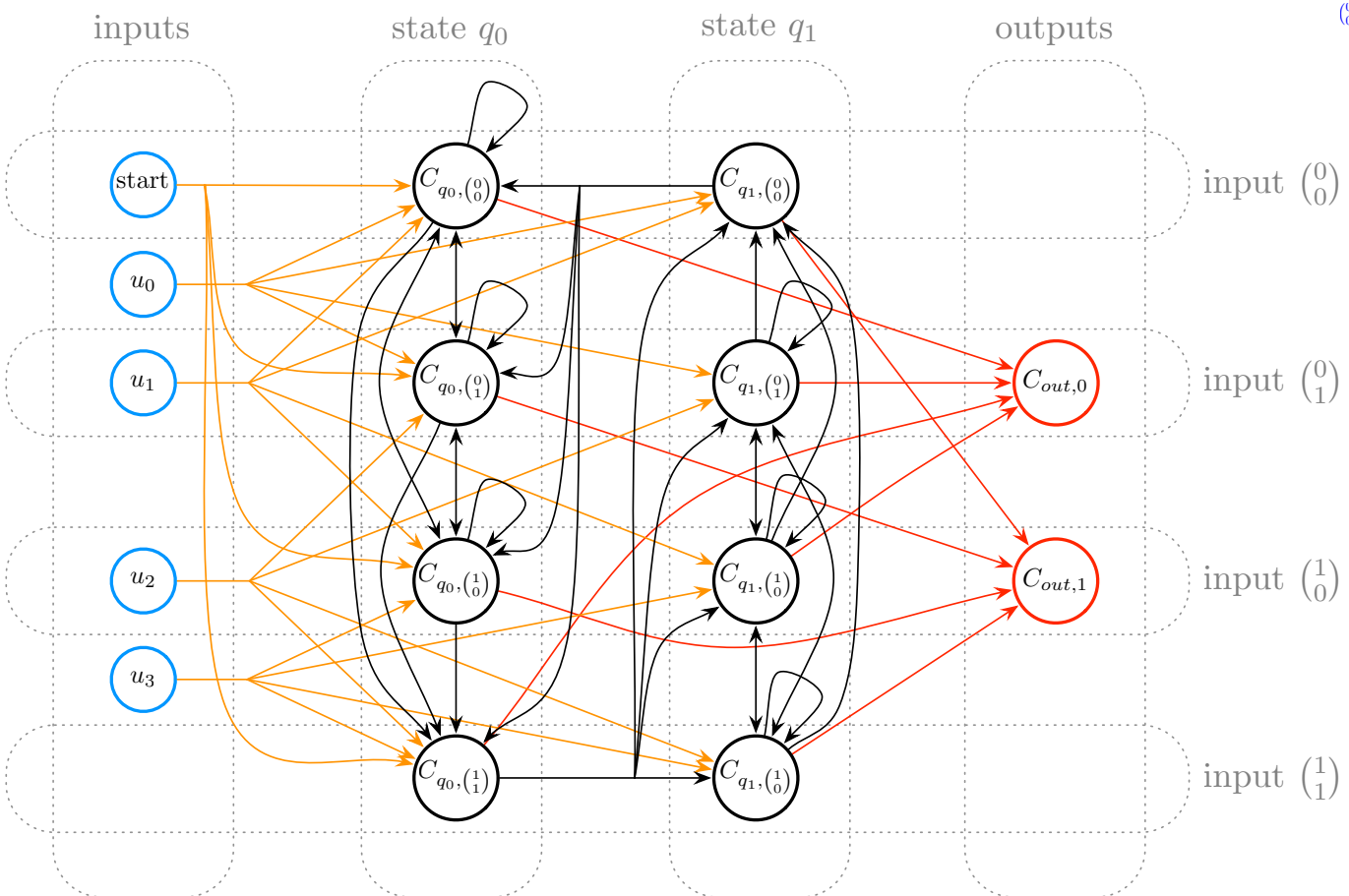
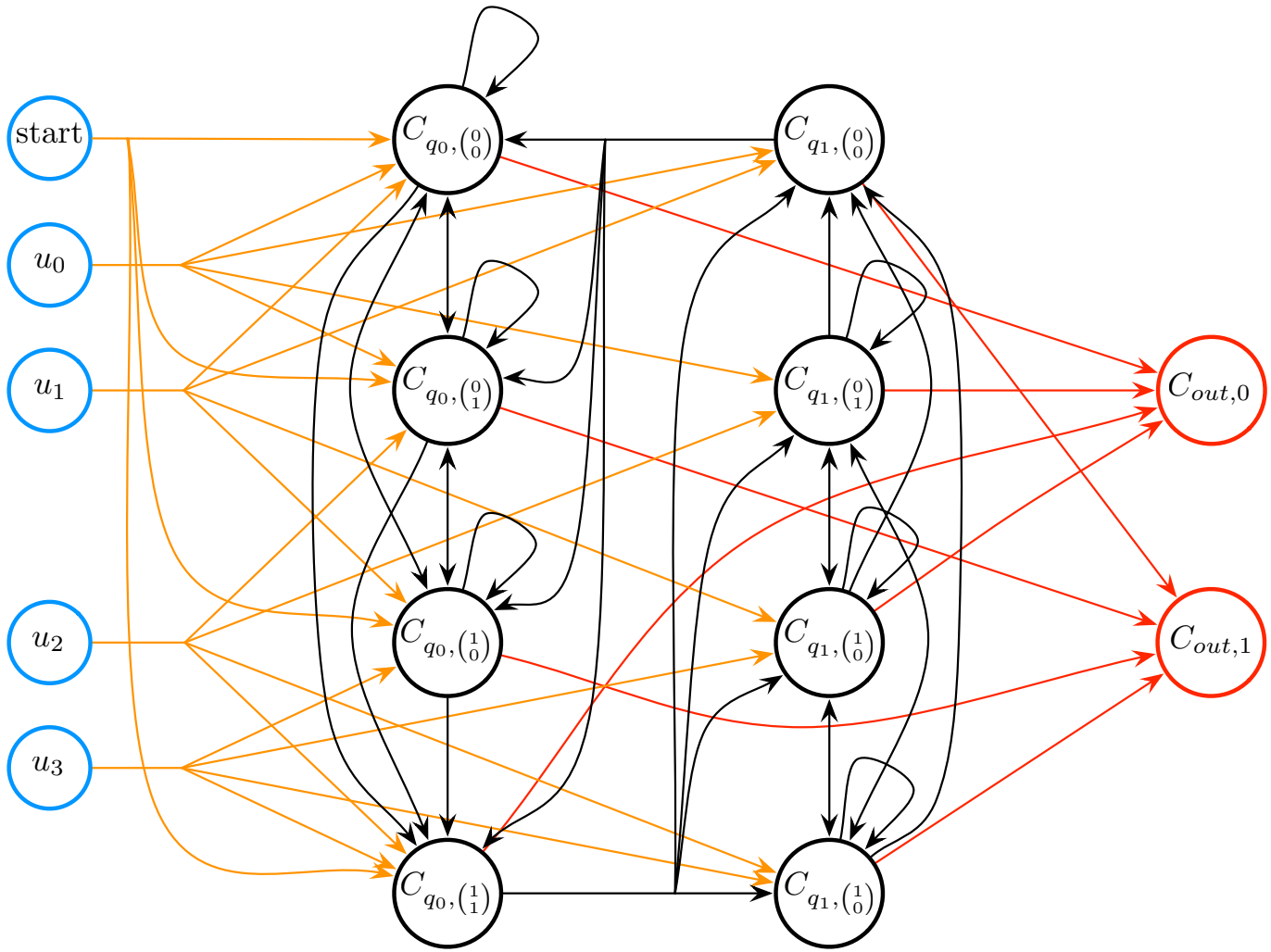




Simulation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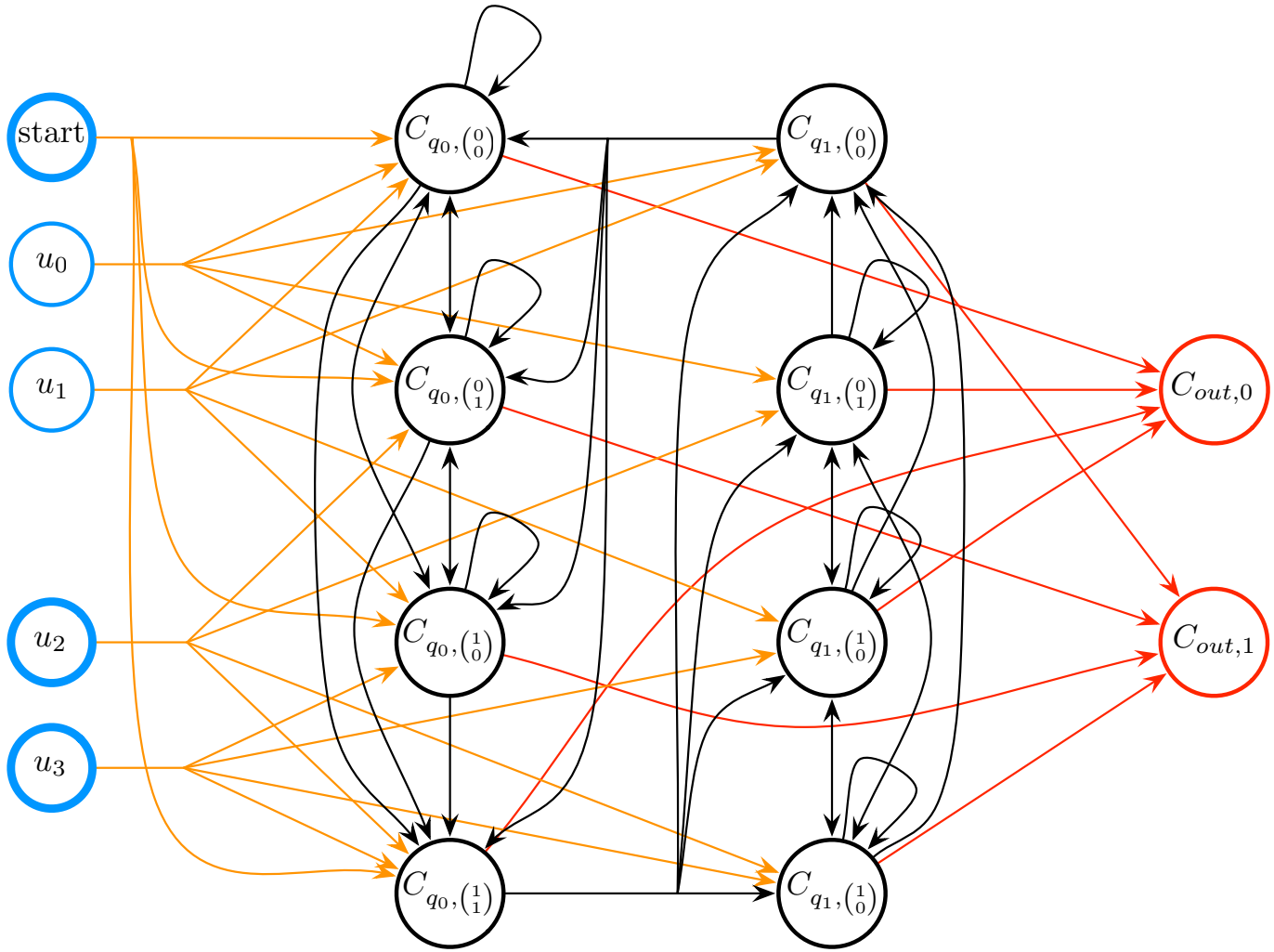
u_0
u_1
u_2
u_3
$C_{q_0,\binom{0}{0}}$
$C_{q_0,\binom{0}{1}}$
$C_{q_0,\binom{1}{0}}$
$C_{q_0,\binom{1}{1}}$
$C_{q_1,\binom{0}{0}}$
$C_{q_1,\binom{0}{1}}$
$C_{q_1,\binom{1}{0}}$
$C_{q_1,\binom{1}{0}}$
$C_{out,0}$
$C_{out,1}$

Simulation


start
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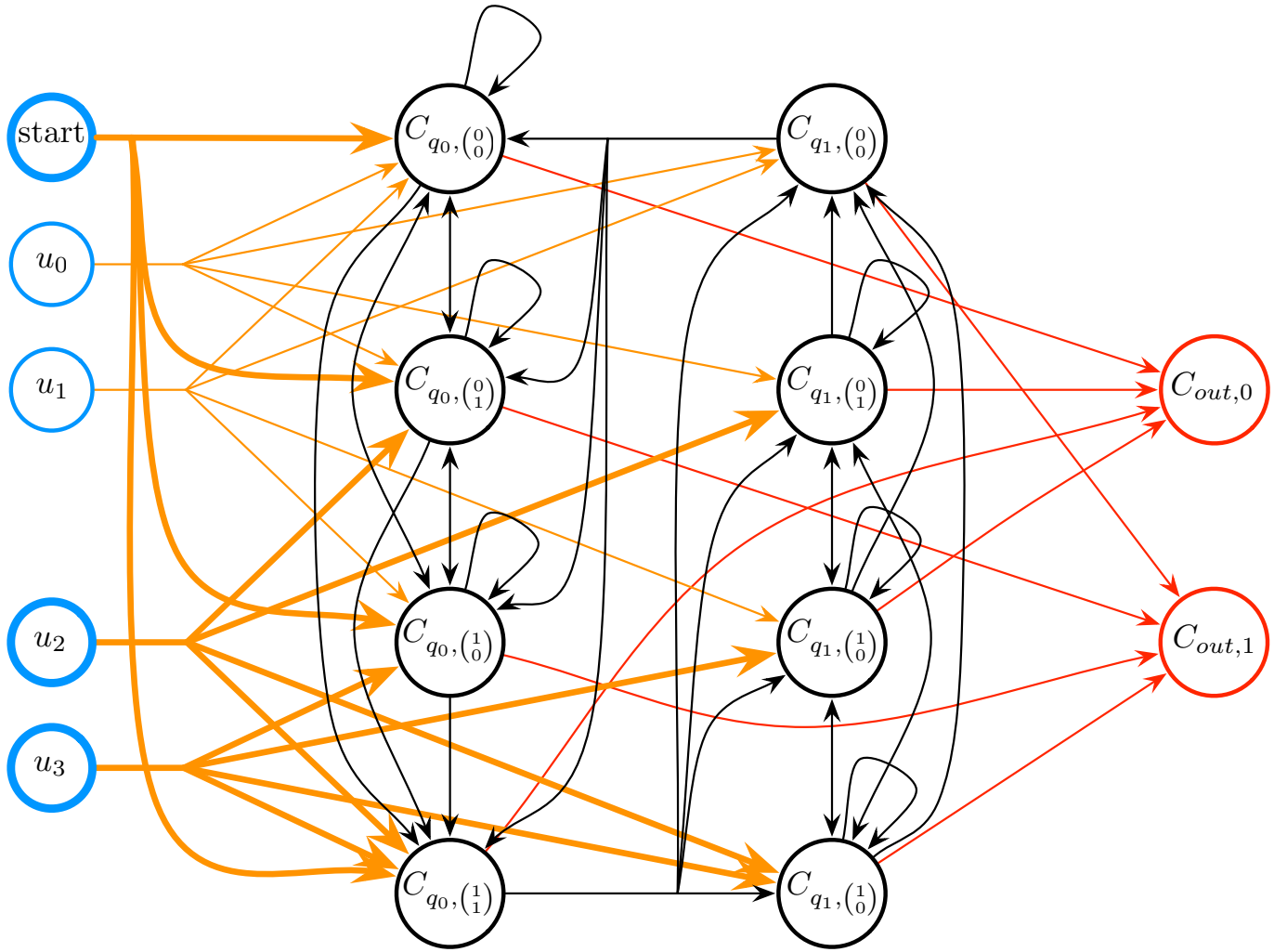
$C_{q_1,\binom{0}{0}}$
$C_{q_1,\binom{0}{1}}$
$C_{q_1,\binom{1}{0}}$
$C_{q_1,\binom{1}{0}}$
$C_{out,0}$
$C_{out,1}$

Simulation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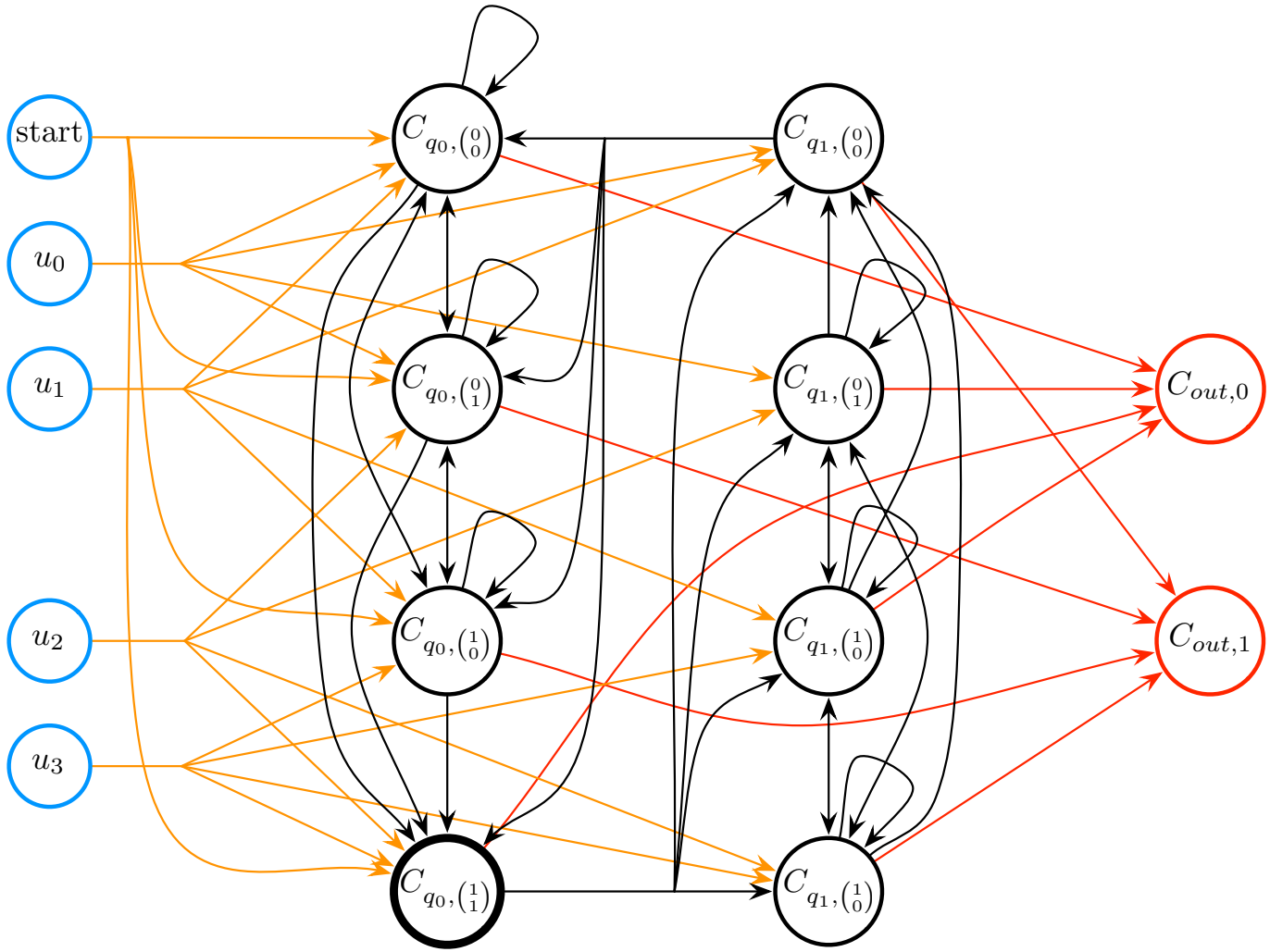
$C_{out,0}$
$C_{out,1}$

Simulation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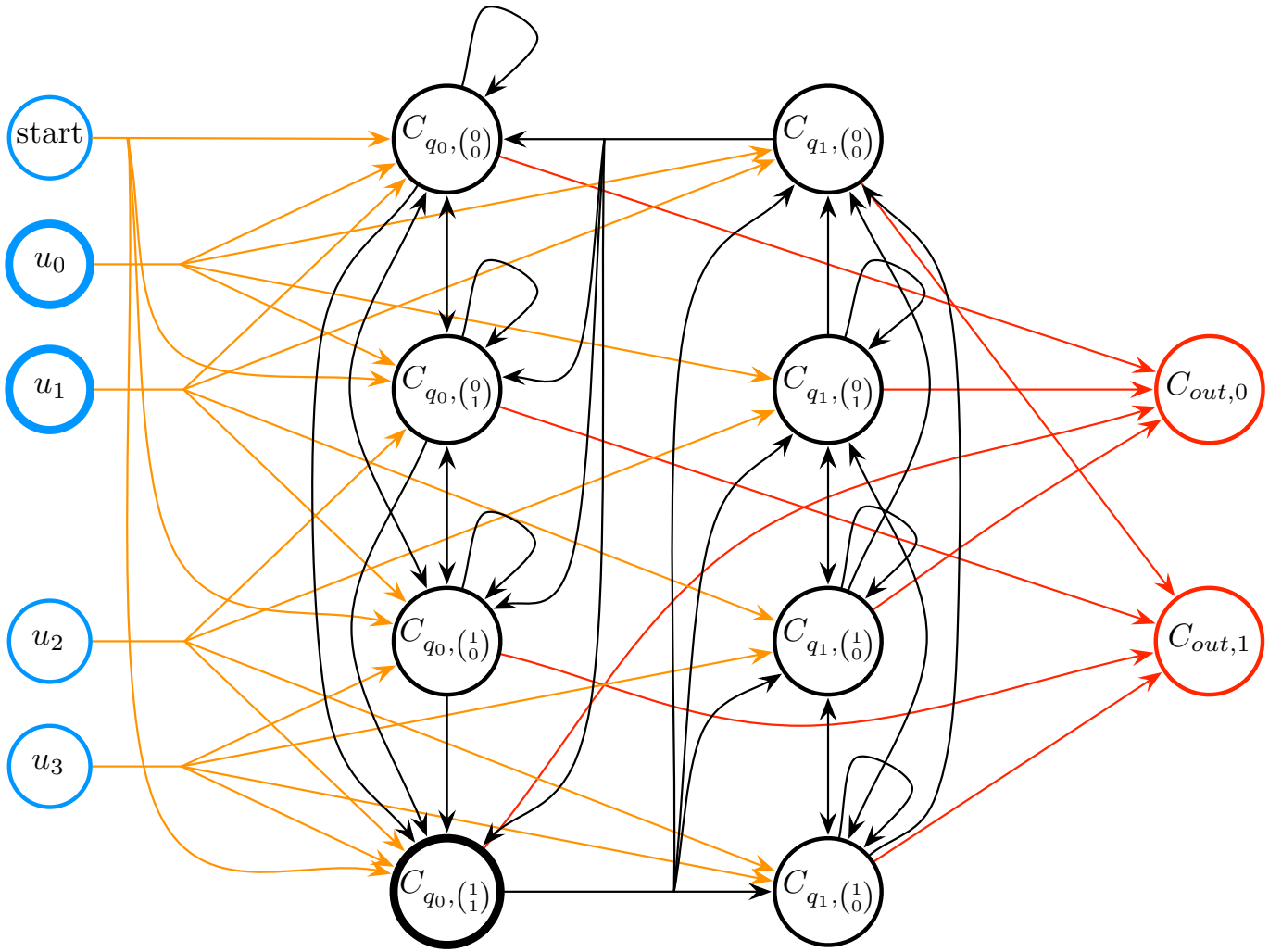
$C_{out,1}$

Simulation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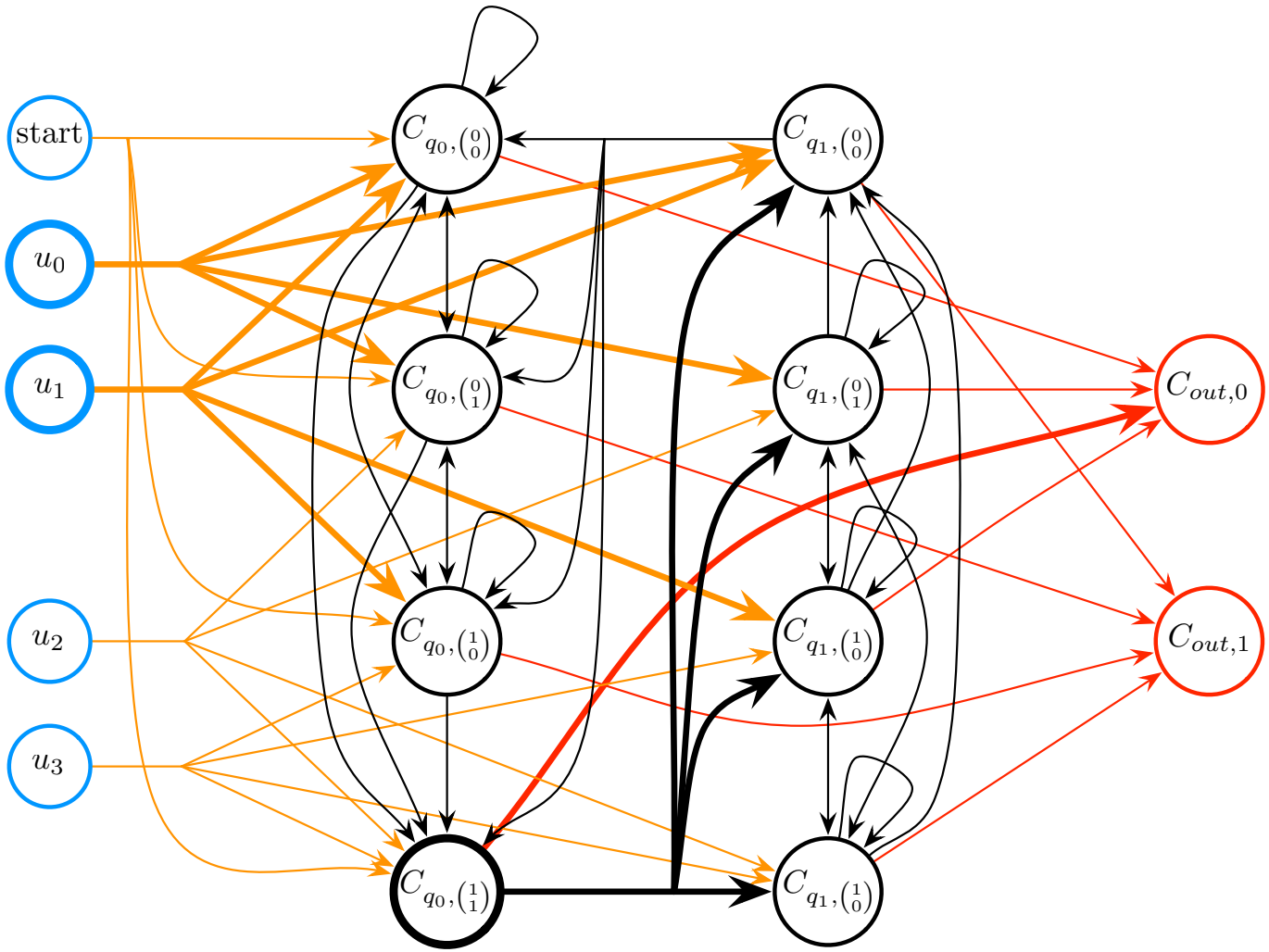
$C_{out,1}$

Simulation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$C_{q_0,\binom{0}{0}}$
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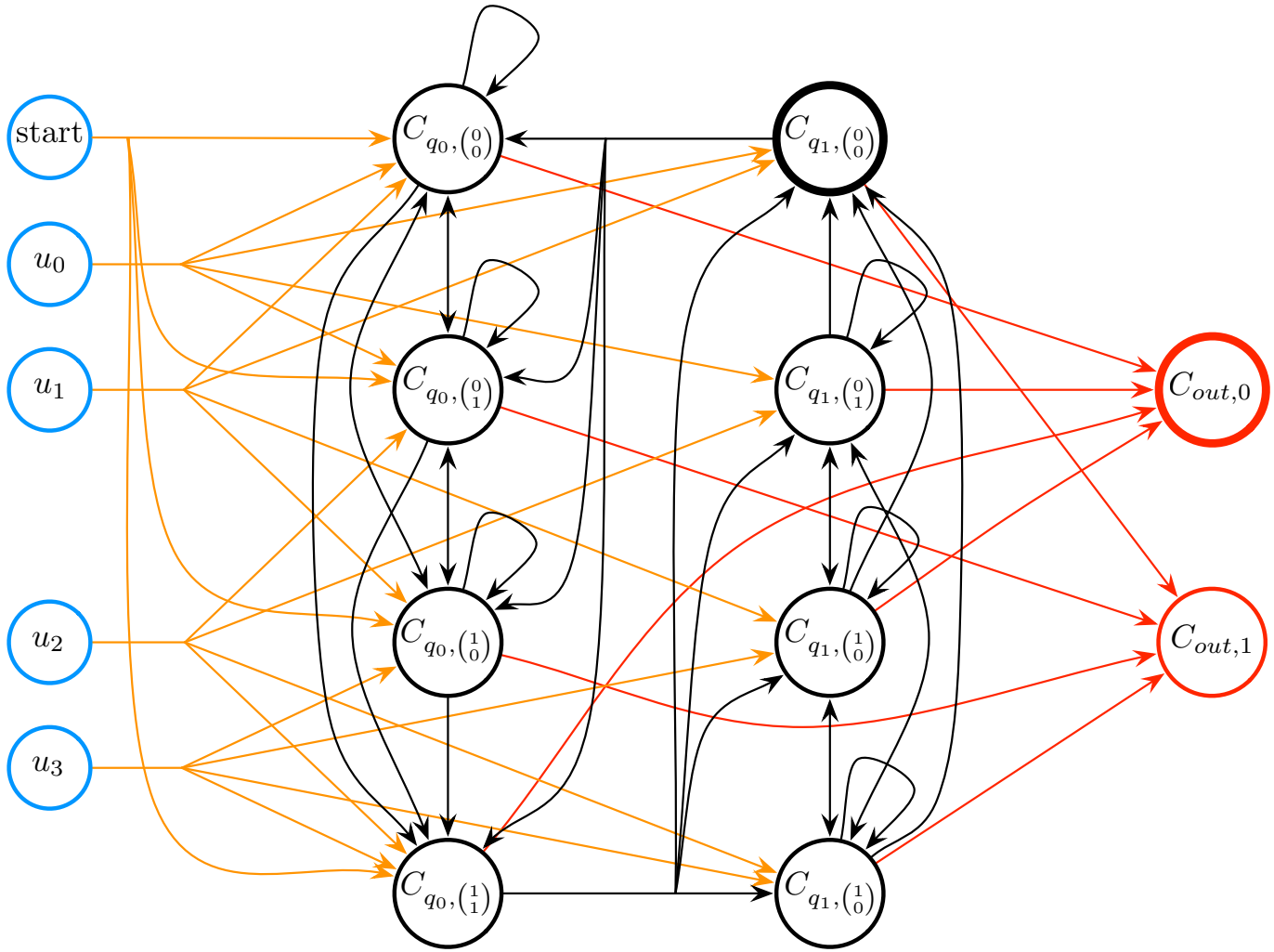
$C_{q_1,\binom{0}{0}}$
$C_{q_1,\binom{0}{1}}$
$C_{q_1,\binom{1}{0}}$
$C_{q_1,\binom{1}{0}}$
$C_{out,0}$
$C_{out,1}$

Simulation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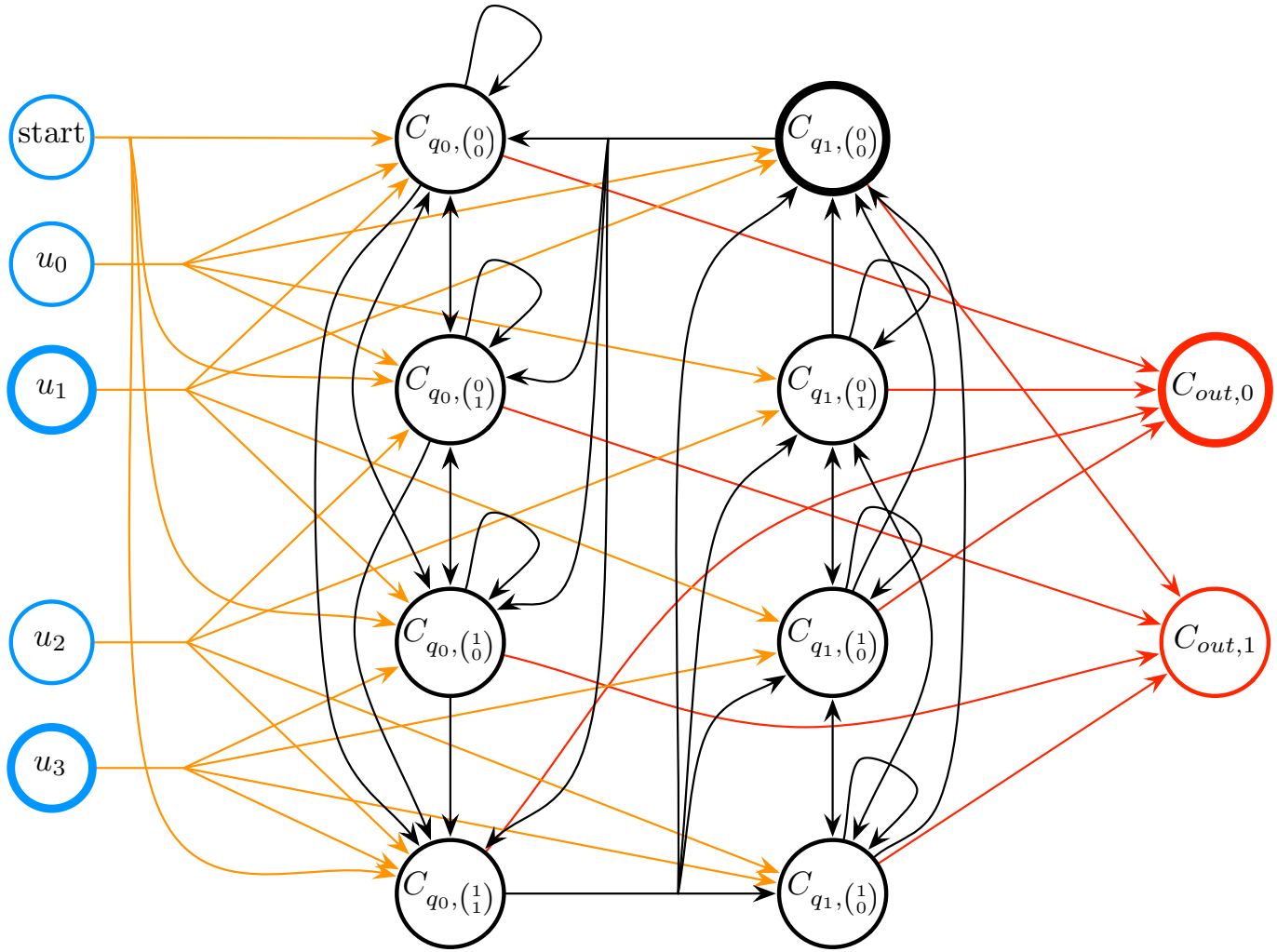
$C_{out,0}$
$C_{out,1}$

Simulation


start
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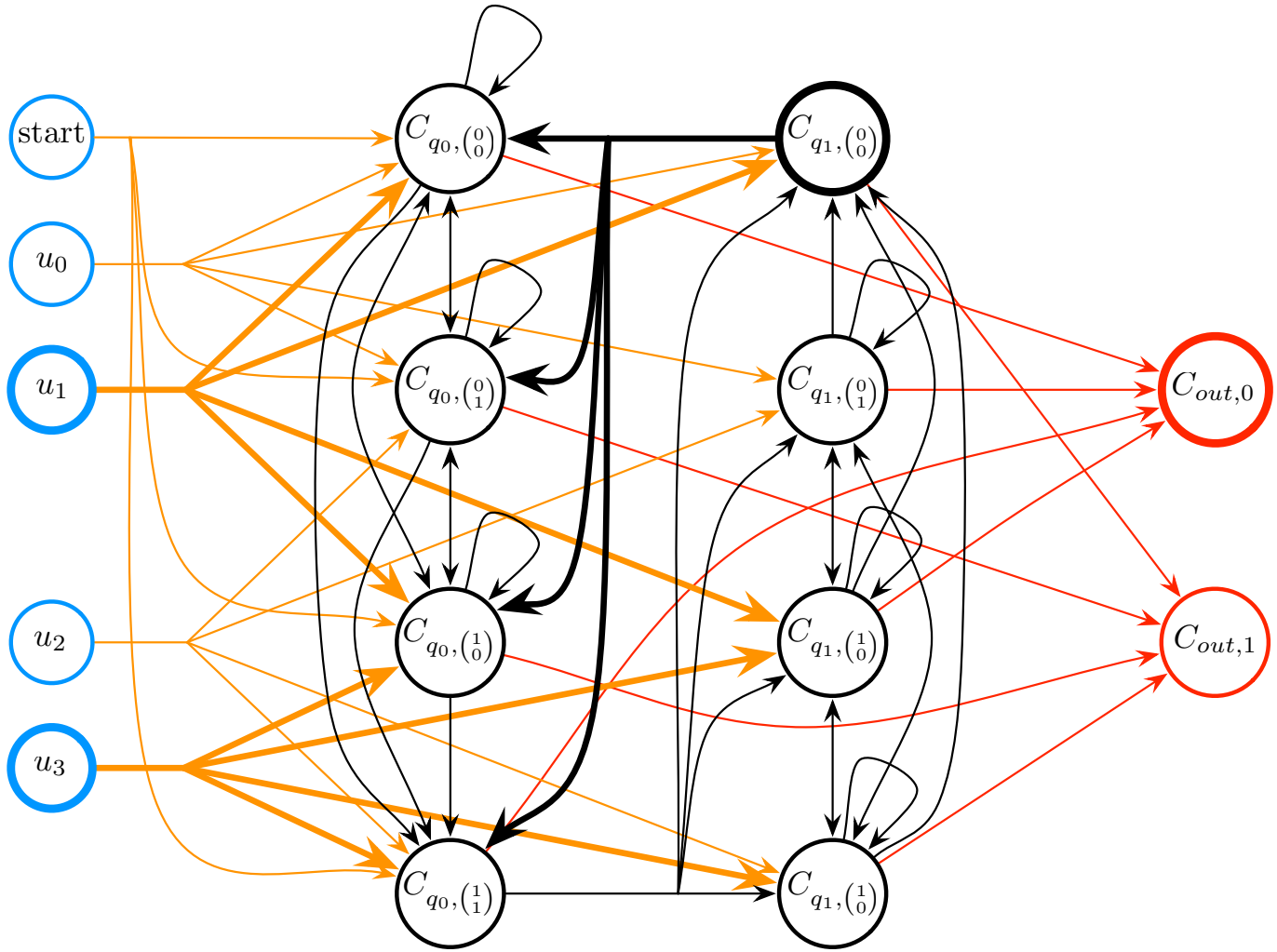
$C_{out,0}$
$C_{out,1}$

Simulation


start
u_0
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u_2
u_3
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$C_{q_1,\binom{0}{0}}$
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$C_{q_1,\binom{1}{0}}$
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$C_{out,0}$
$C_{out,1}$

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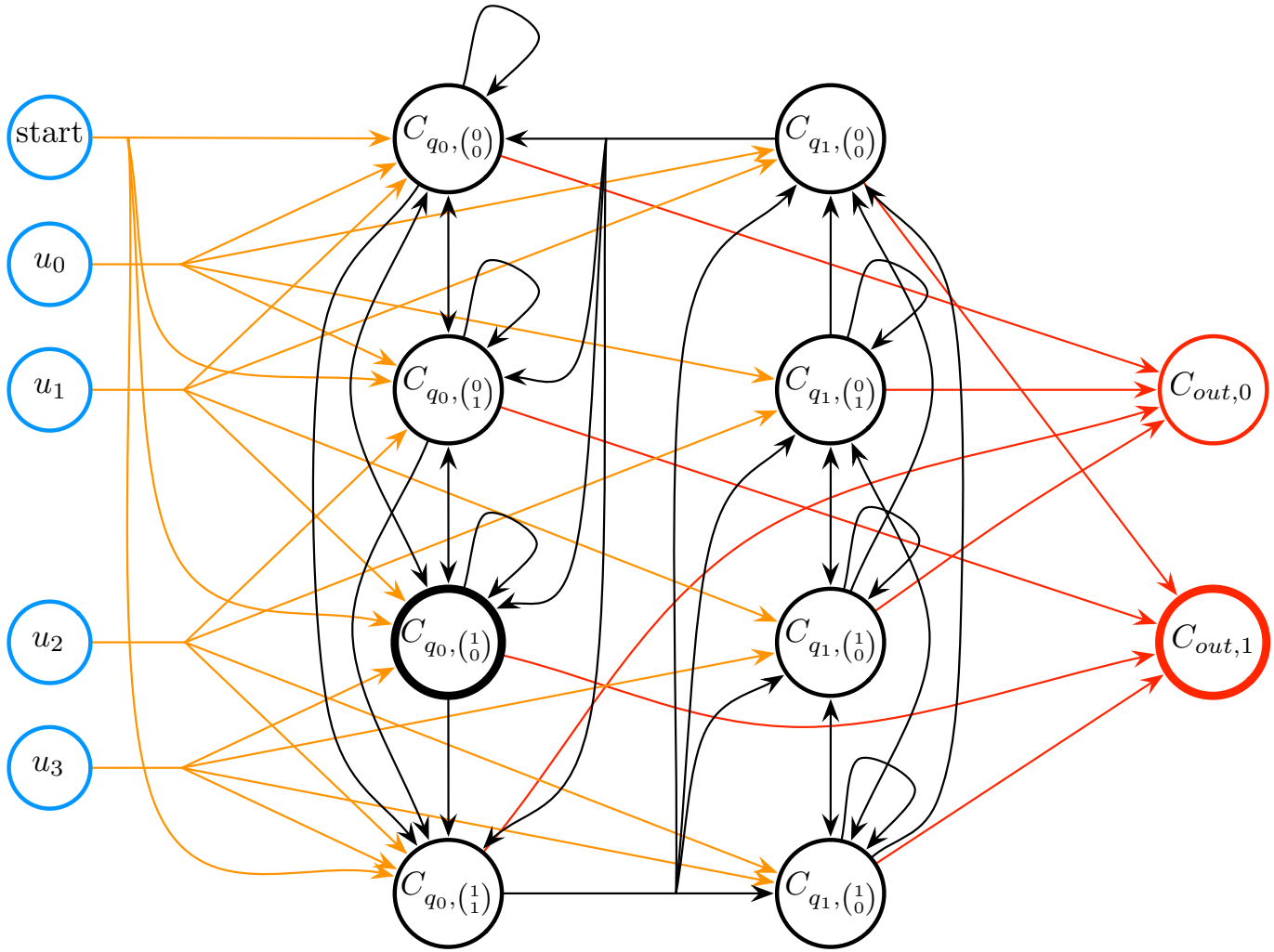
start
u_0
u_1
u_2
u_3
$C_{q_0,\binom{0}{0}}$
$C_{q_0,\binom{0}{1}}$
$C_{q_0,\binom{1}{0}}$
$C_{q_0,\binom{1}{1}}$
$C_{q_1,\binom{0}{0}}$
$C_{q_1,\binom{0}{1}}$
$C_{q_1,\binom{1}{0}}$
$C_{q_1,\binom{1}{0}}$
$C_{out,0}$
$C_{out,1}$

Simulation

time	0	1	2	3	4	5	6	7	8
states	q_0	q_1	q_0	q_0	q_1	q_1	q_1	q_0	–
inputs	$\binom{1}{1}$	$\binom{0}{0}$	$\binom{1}{0}$	$\binom{1}{1}$	$\binom{0}{1}$	$\binom{1}{1}$	$\binom{0}{0}$	–	–
outputs	0	1	1	0	0	1	1	–	–
$start$	1	0	0	0	0	0	0	0	0
u_0	0	1	0	0	1	0	1	0	0
u_1	0	1	1	0	0	0	1	0	0
u_2	1	0	0	1	1	1	0	0	0
u_3	1	0	1	1	0	1	0	0	0
$C_{s,i}$	–	$q_0, \binom{1}{1}$	$q_1, \binom{0}{0}$	$q_0, \binom{1}{0}$	$q_0, \binom{1}{1}$	$q_1, \binom{0}{1}$	$q_1, \binom{1}{1}$	$q_1, \binom{0}{0}$	–
$C_{out,0}$	0	0	1	0	0	1	1	0	0
$C_{out,1}$	0	0	0	1	1	0	0	1	1

Drawbacks of the Construction

- Computational states of the automaton are represented as Boolean states, i.e., spiking configurations of the network.
  - ⋆ Computational states should rather be represented by *sustained activities of neural assemblies*, e.g., by *cyclic attractors*.
- Network is not robust to cell death, synaptic plasticity, architectural plasticity in general.
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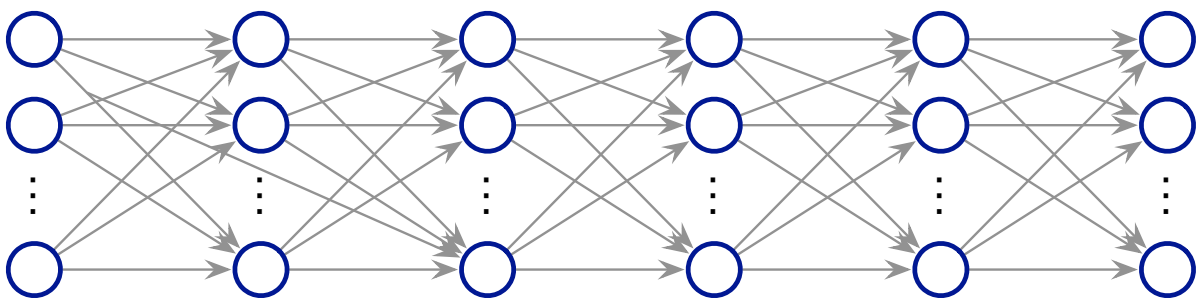
Synfire Chains

- *Synfire chains* allow for robust and highly precise transmission of information in neural networks.
- *Synfire chains* are likely to be crucially involved in the processing and coding of information in neural networks.
- *Synfire chains* have been theorized as fundamental neuronal structures (Abeles 82).



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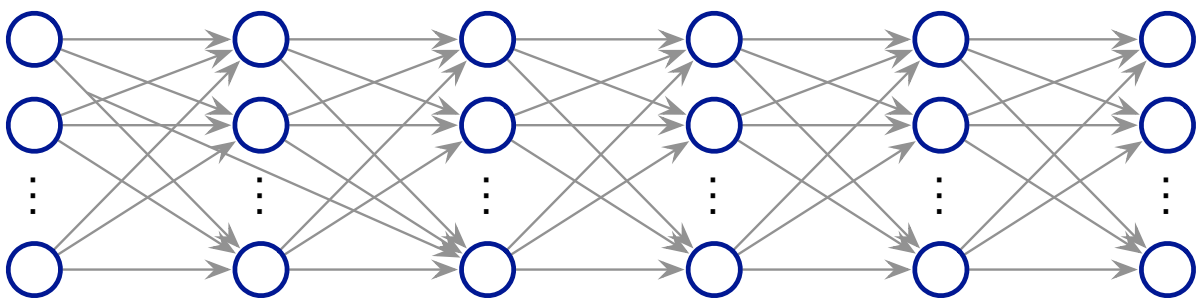

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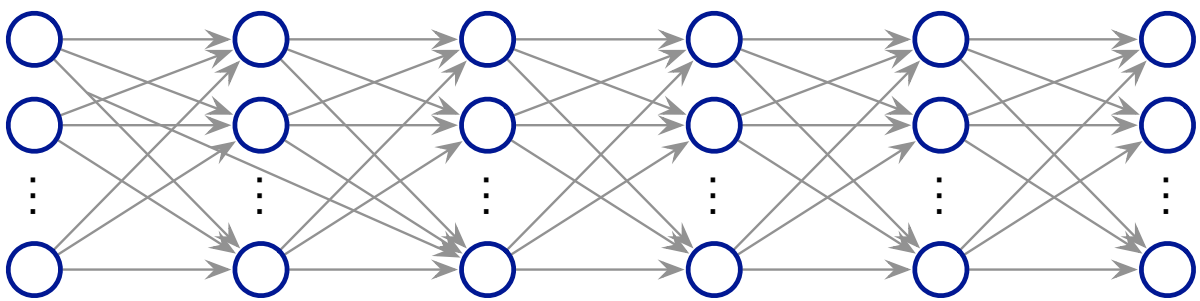

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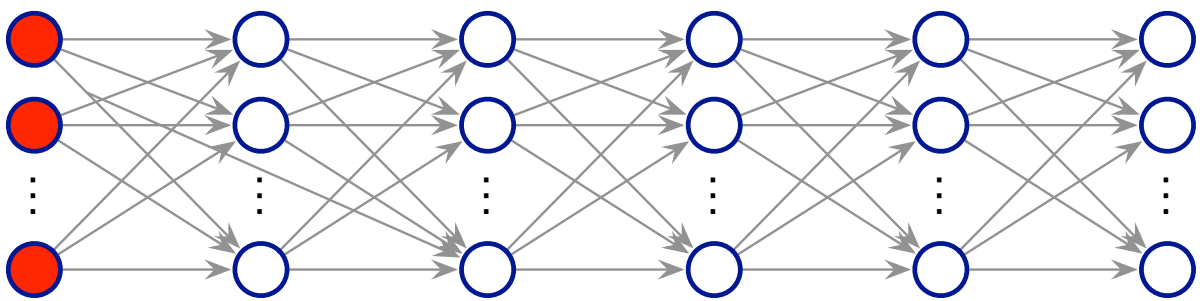

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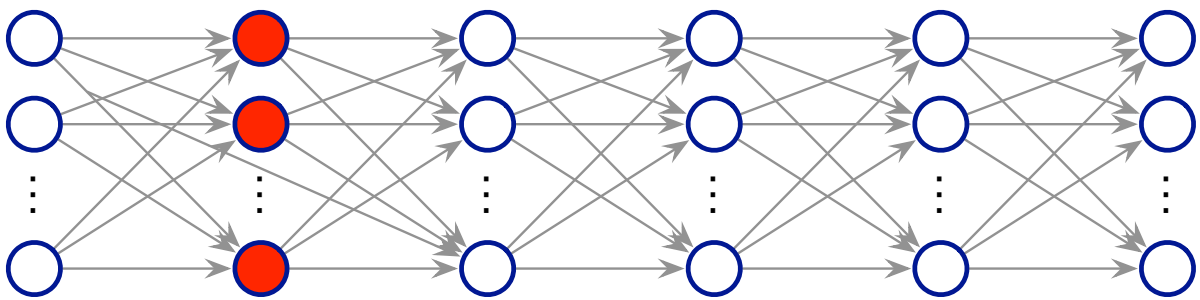

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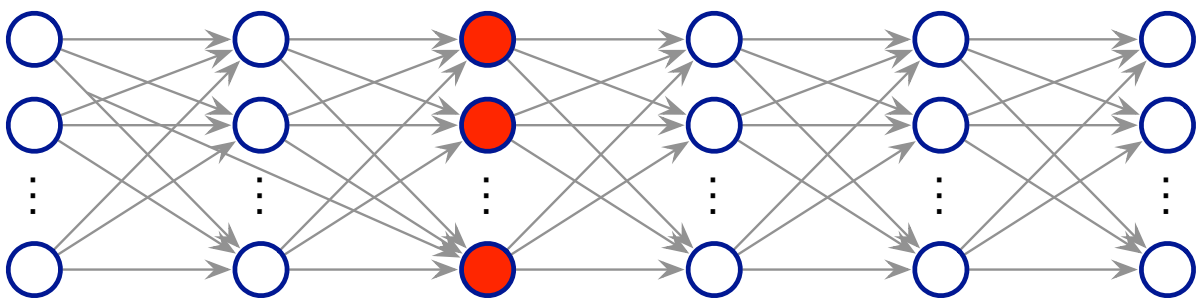

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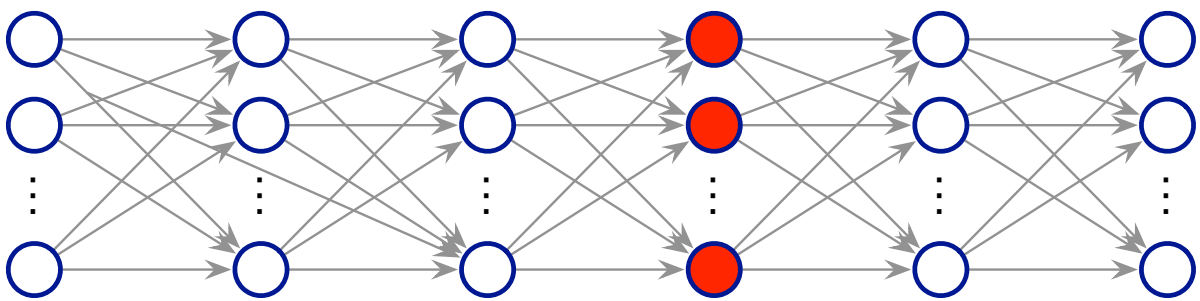

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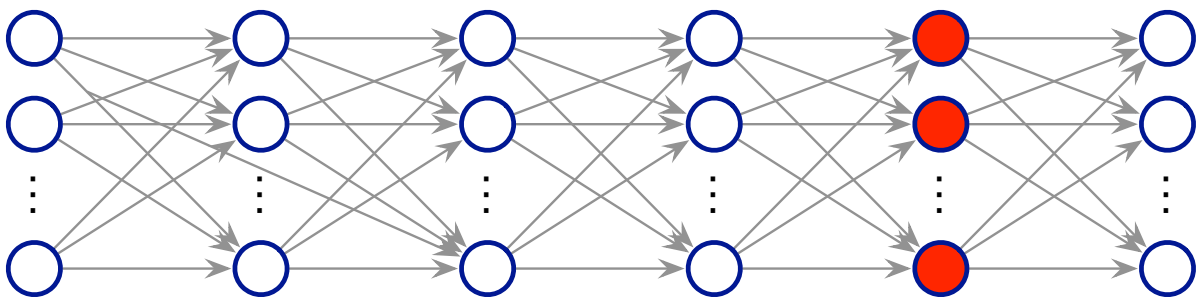

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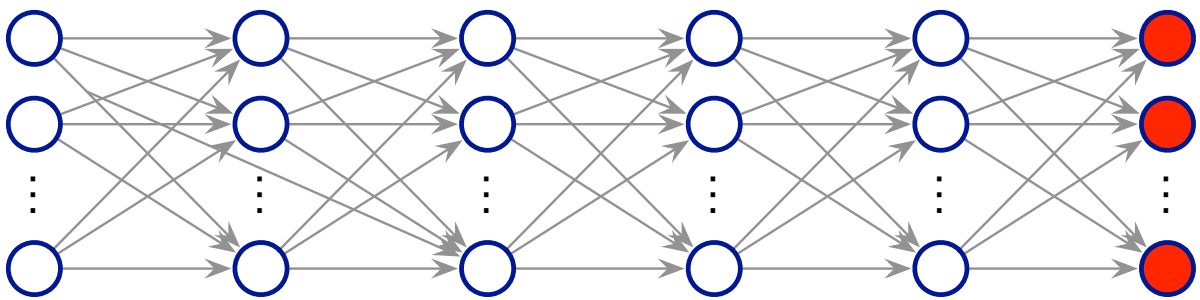

Synfire Rings

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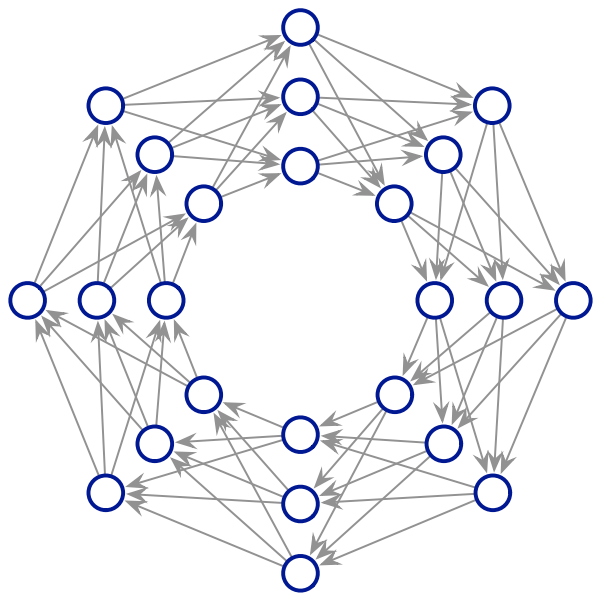

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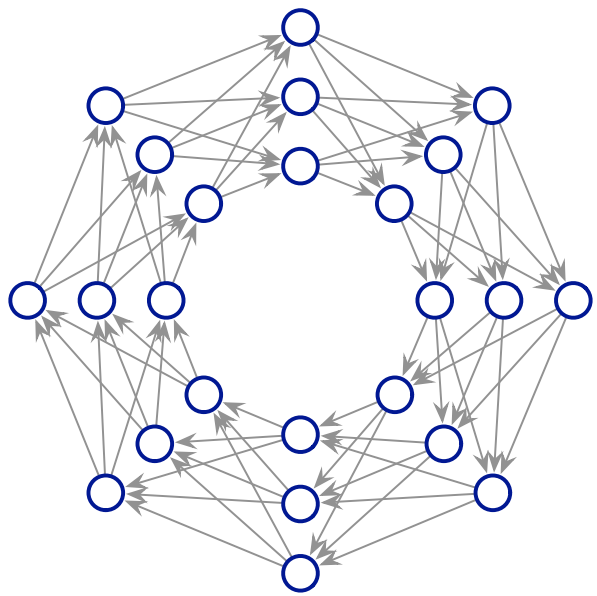

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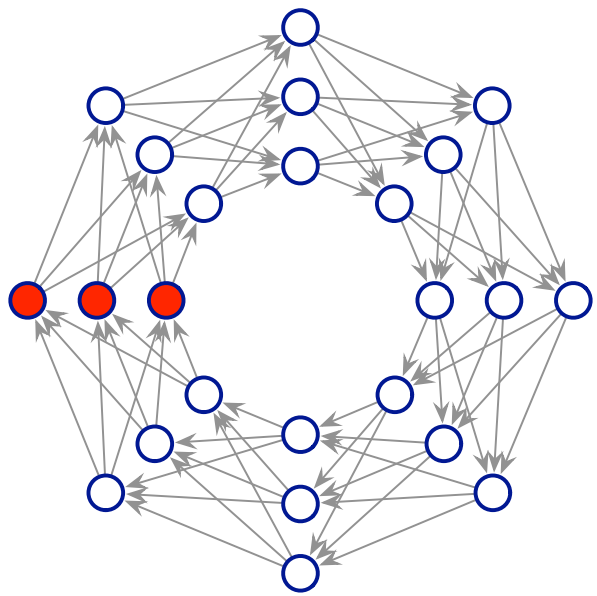

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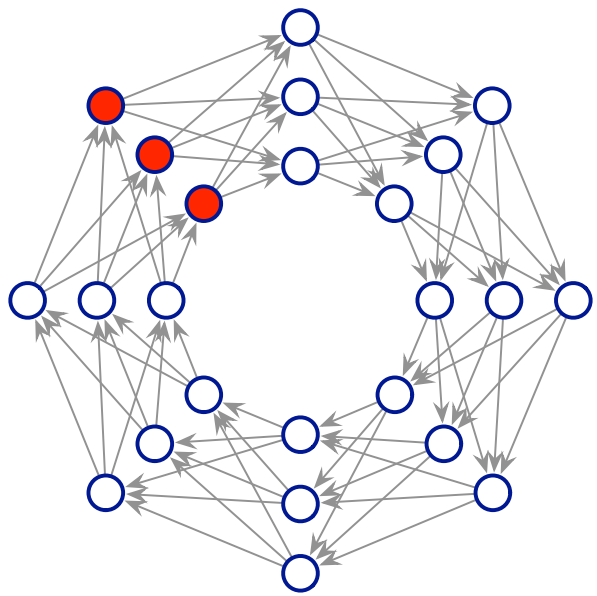

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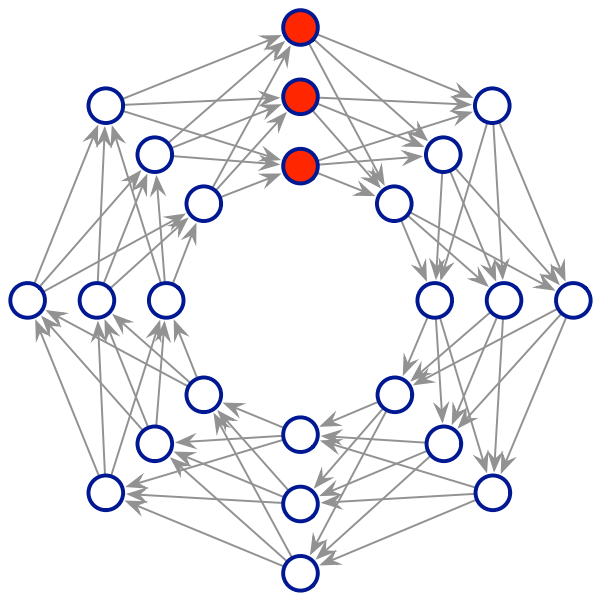

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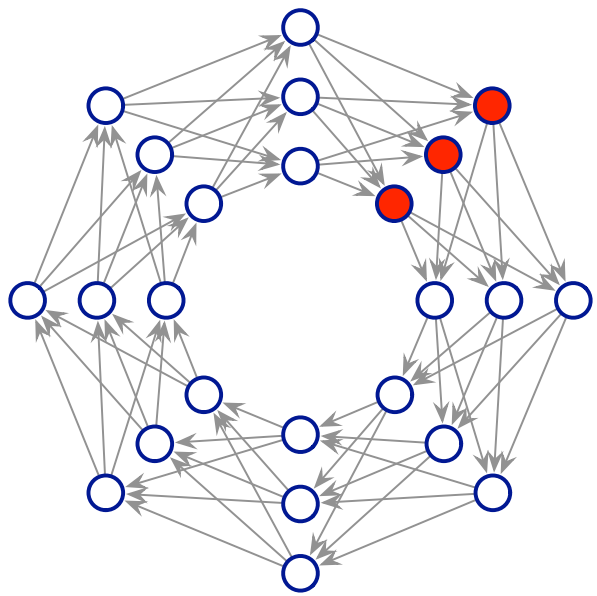

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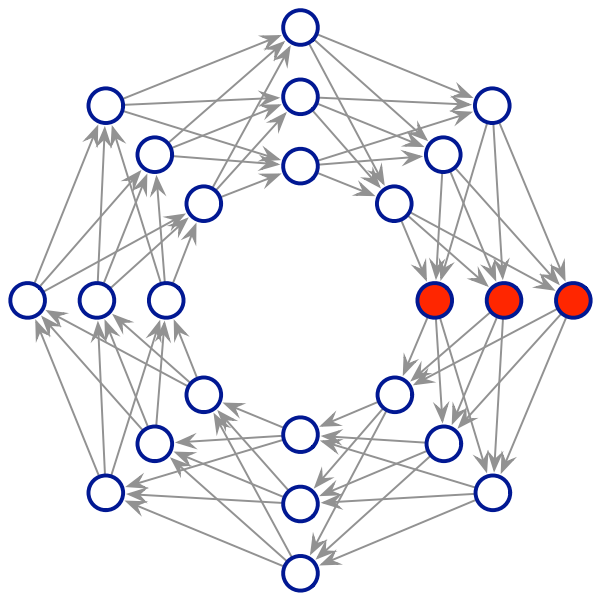

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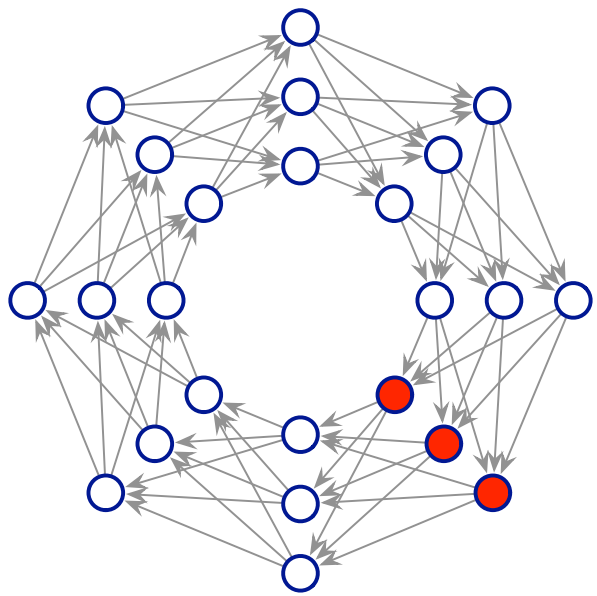

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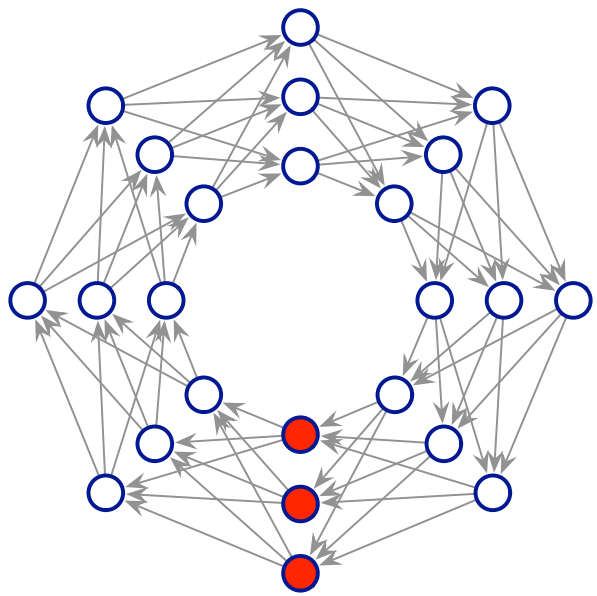

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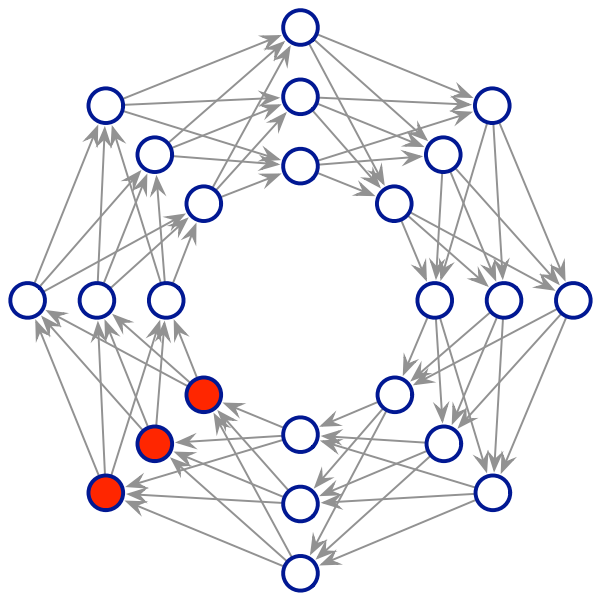

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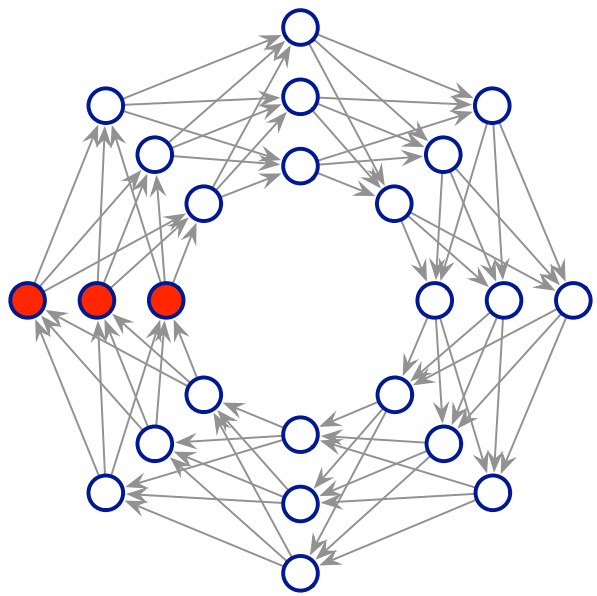

Neural Computation with Synfire Rings

- We introduce a paradigm of neural computation based on *synfire rings*.
- Computational states are represented by sustained activities within synfire rings.
- Hence, the successive computational states are encoded into cyclic attractors.
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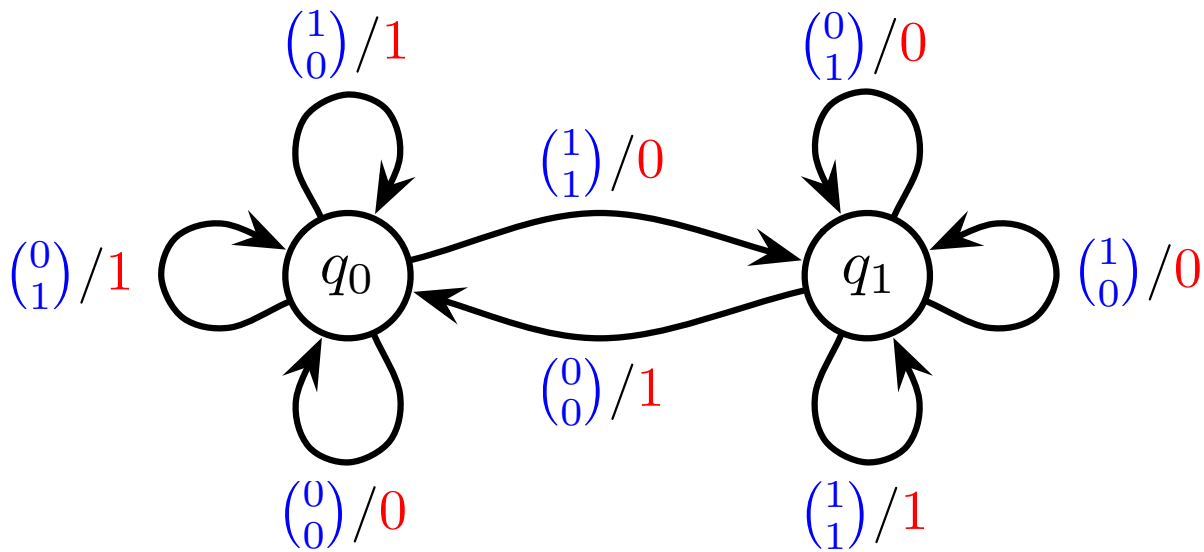

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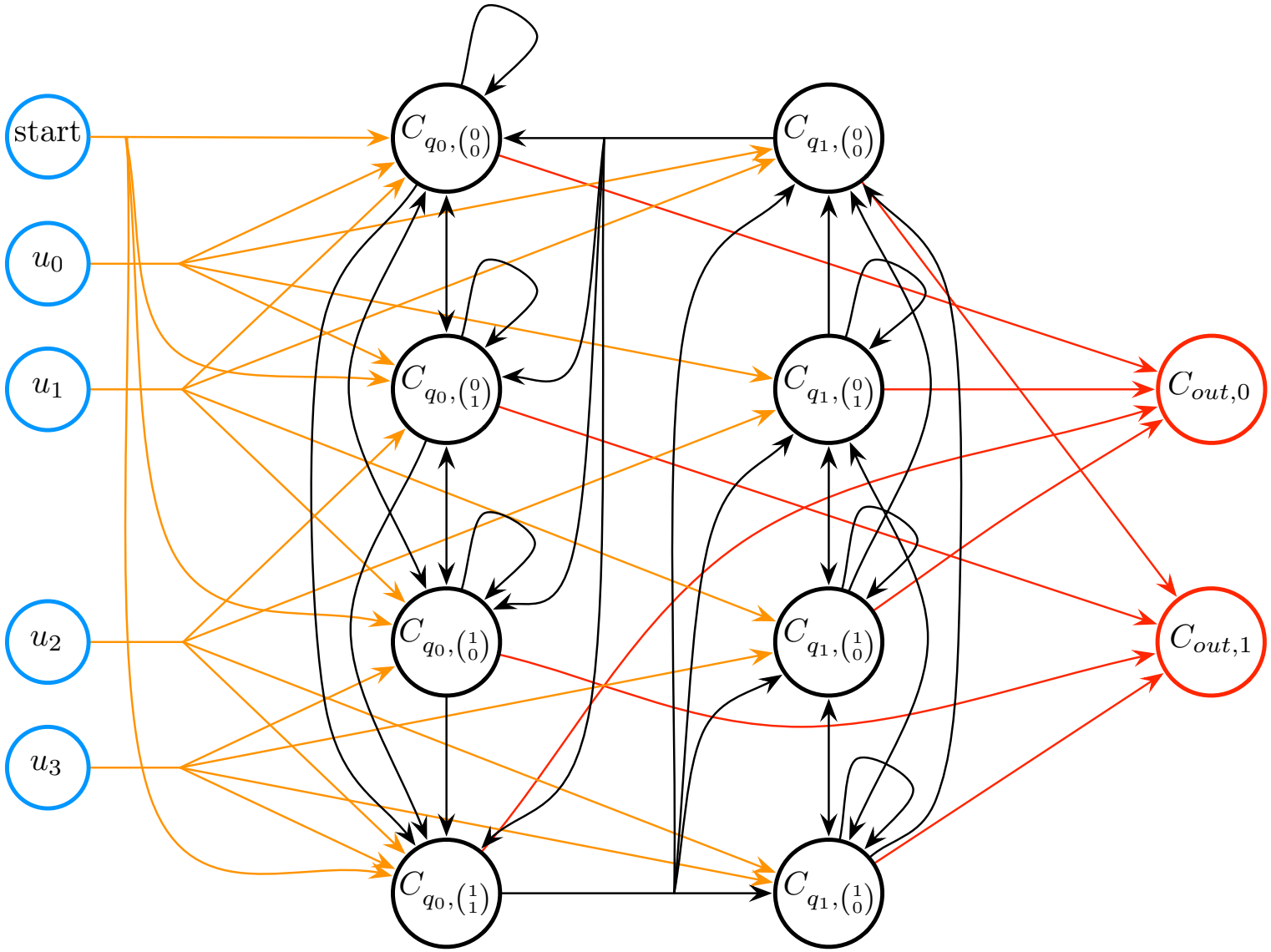

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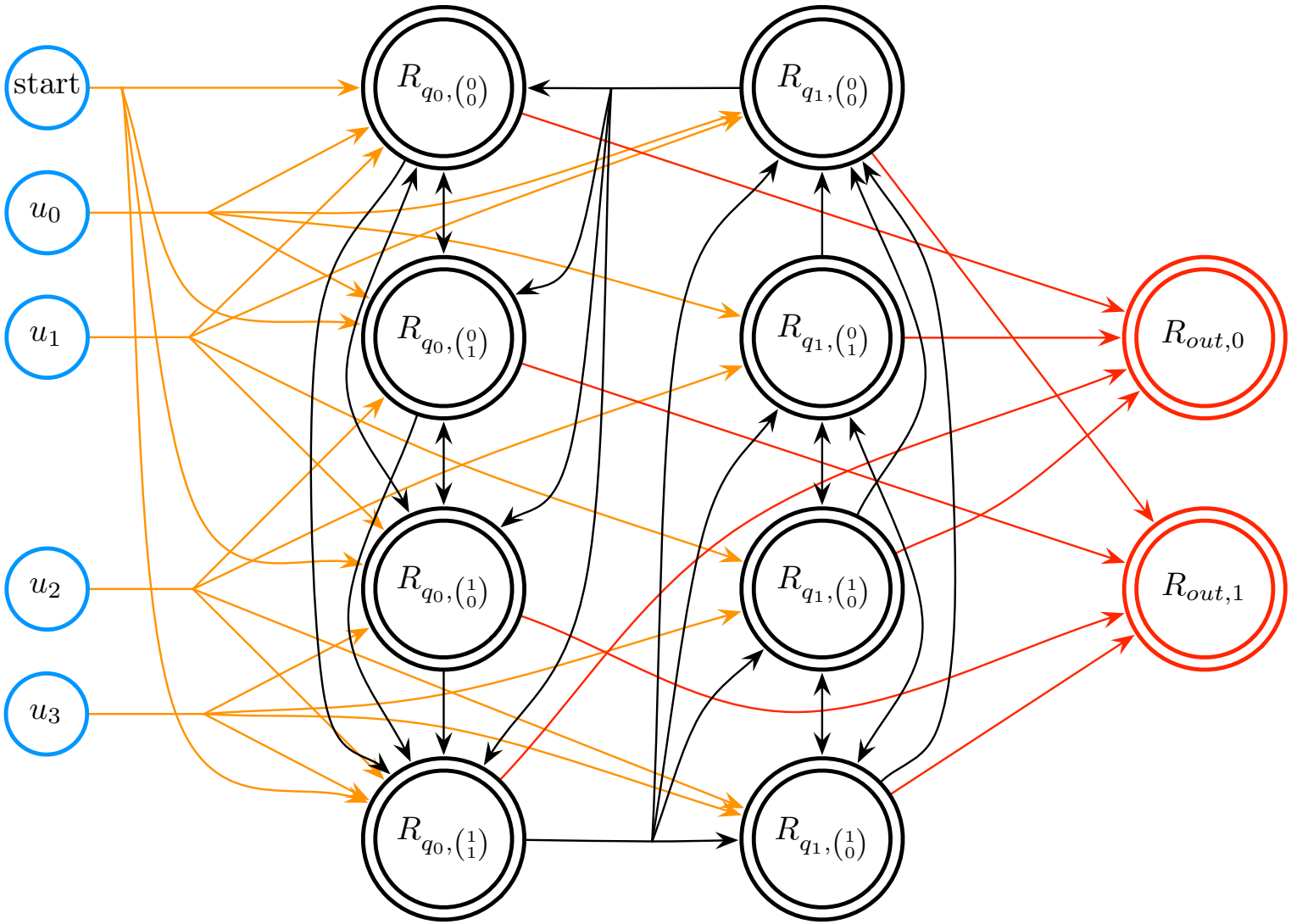
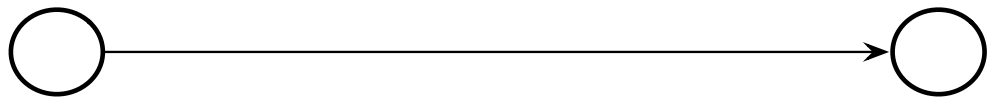


Fibres of connections & Inhibitory System



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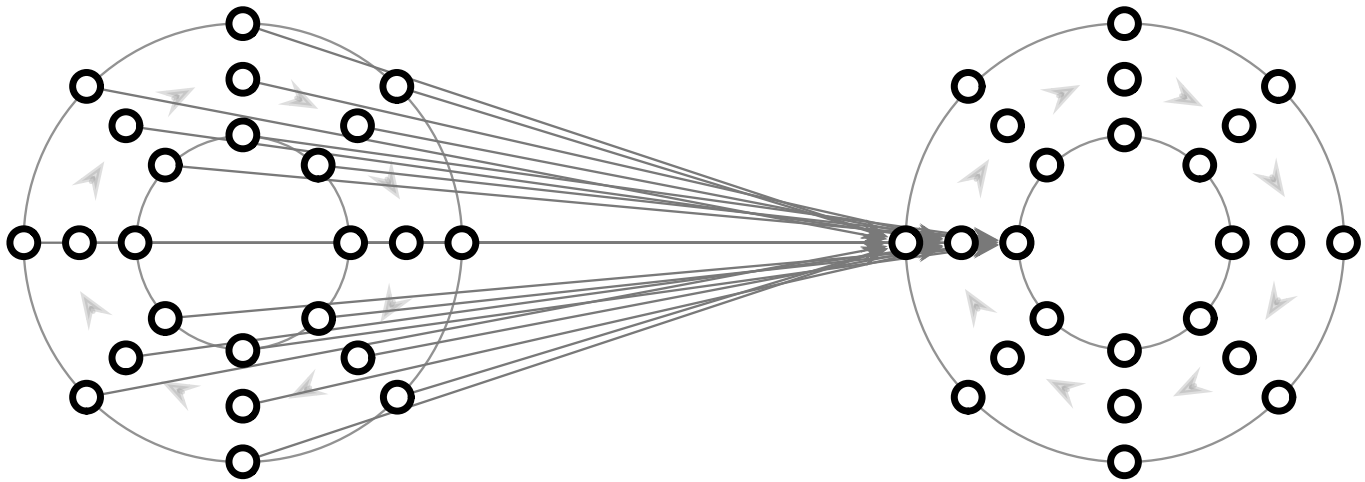

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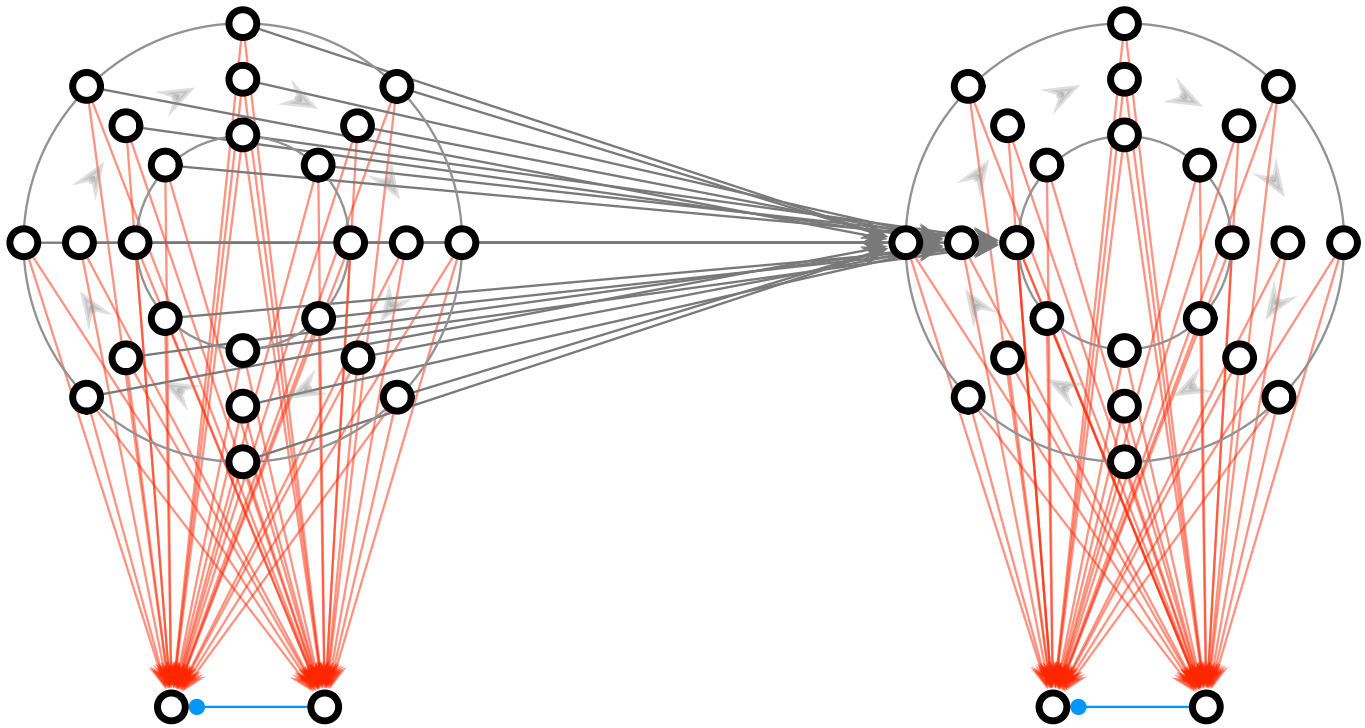

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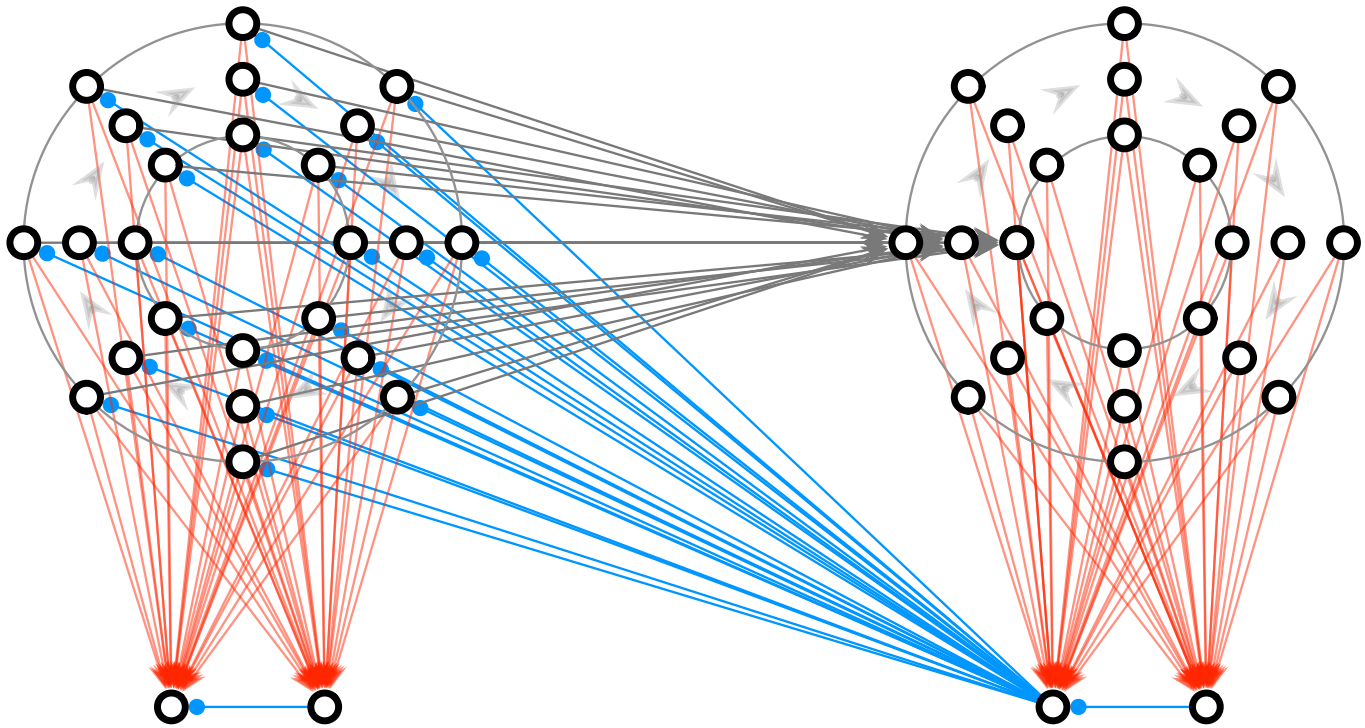

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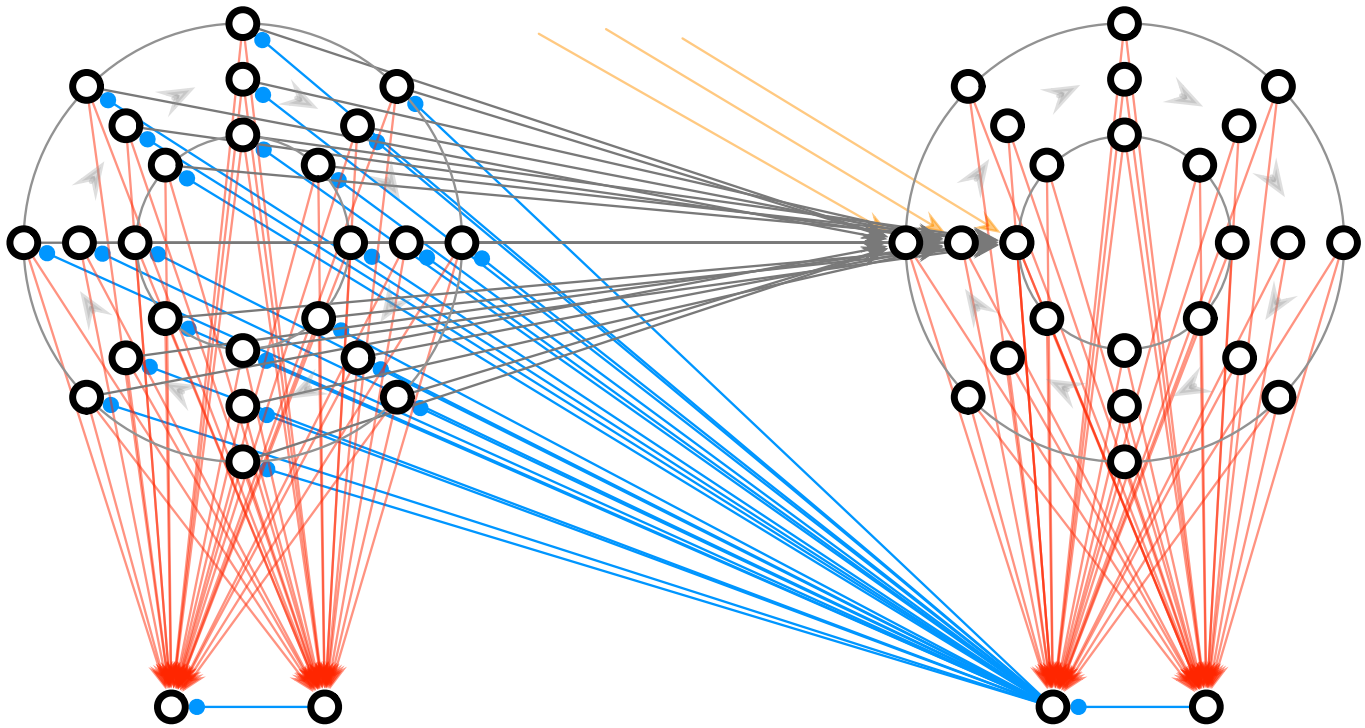

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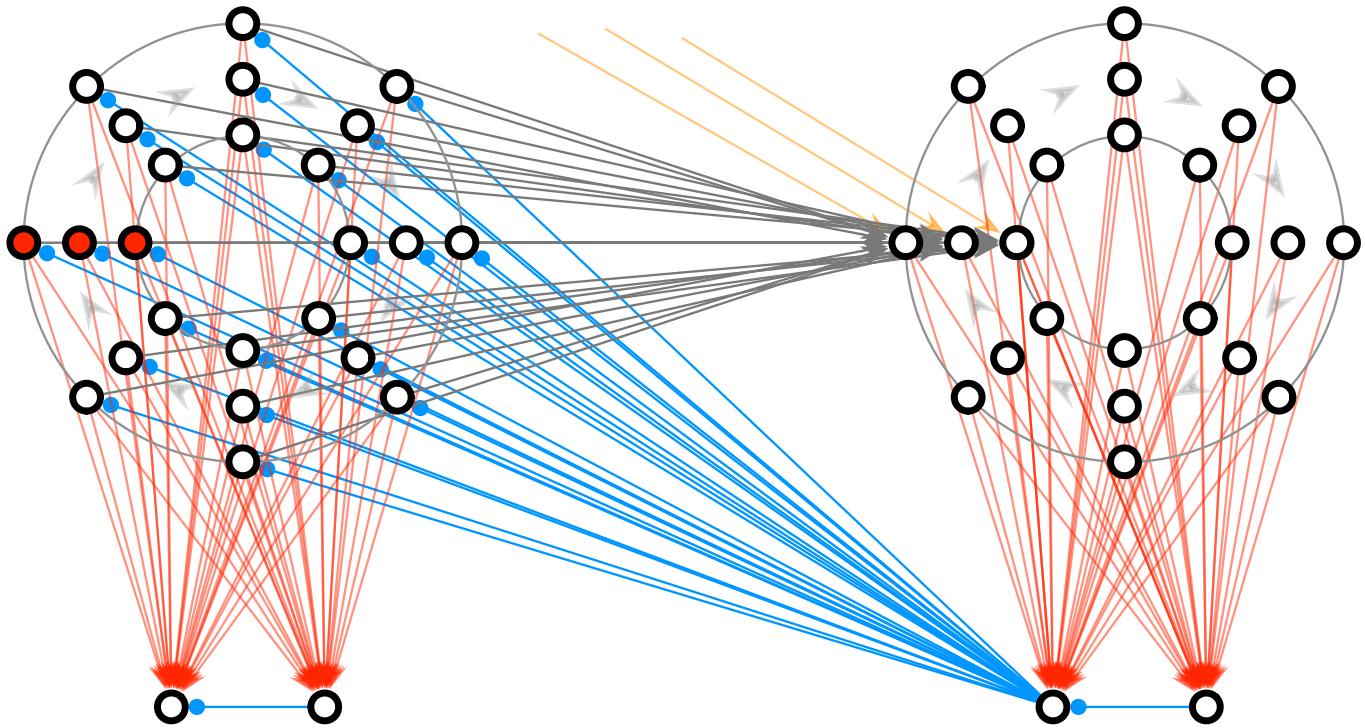

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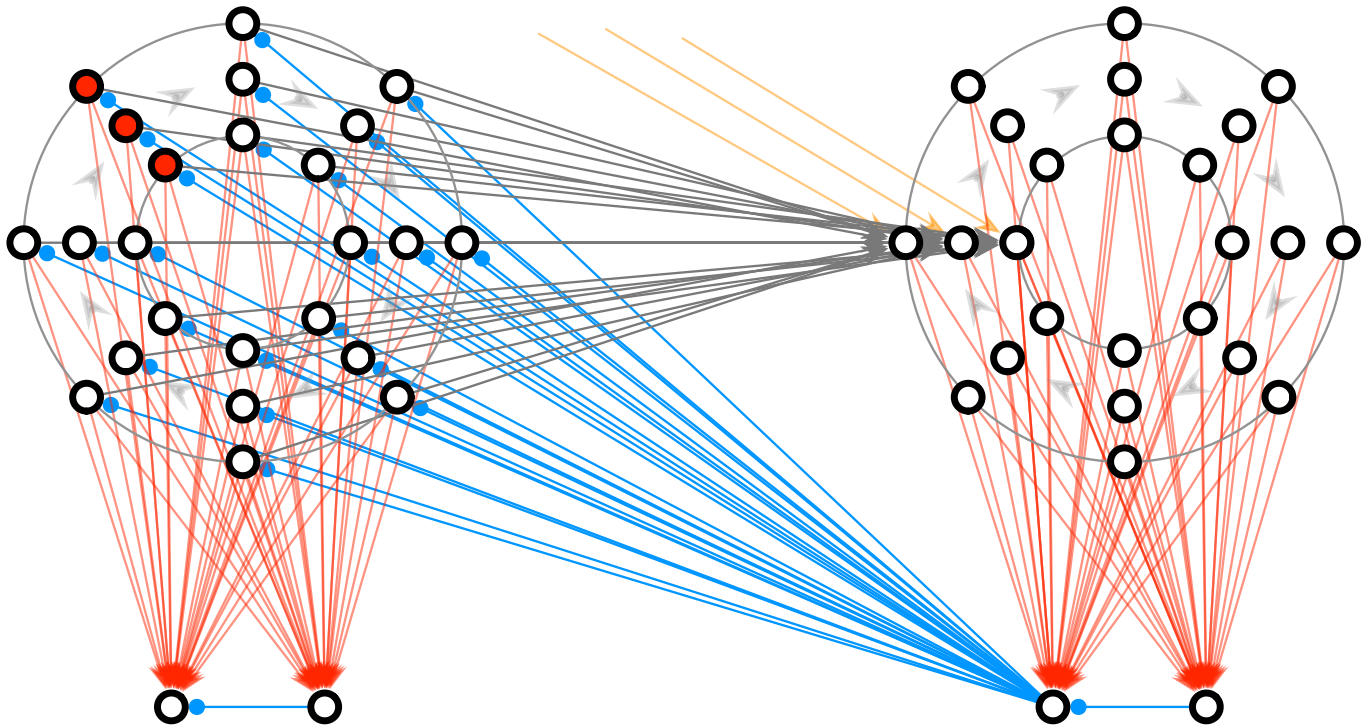

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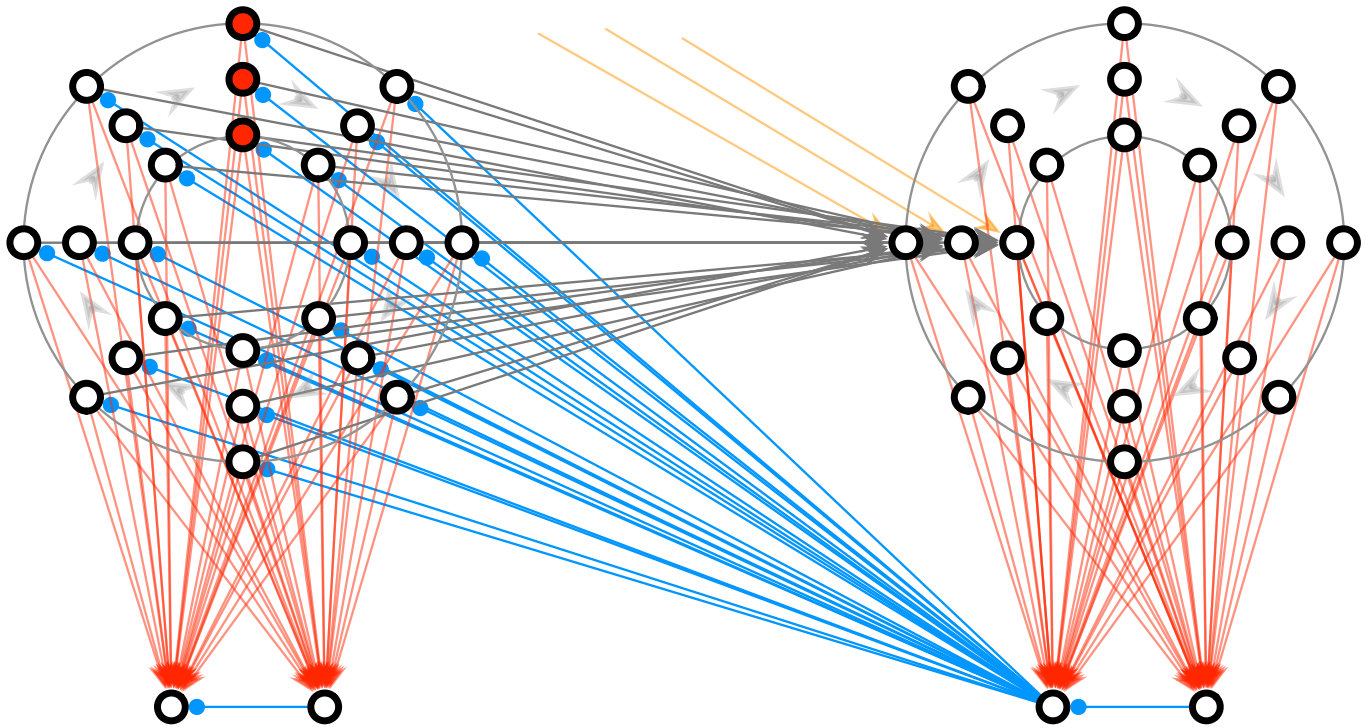

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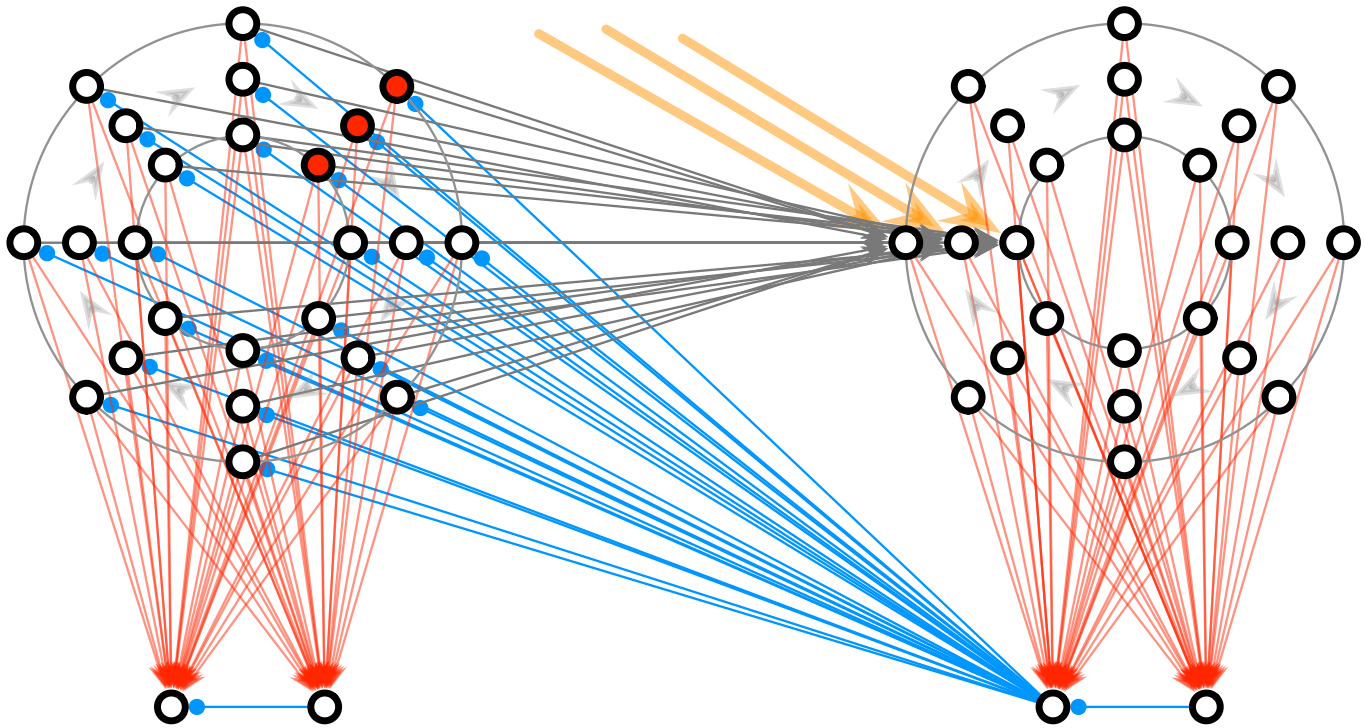

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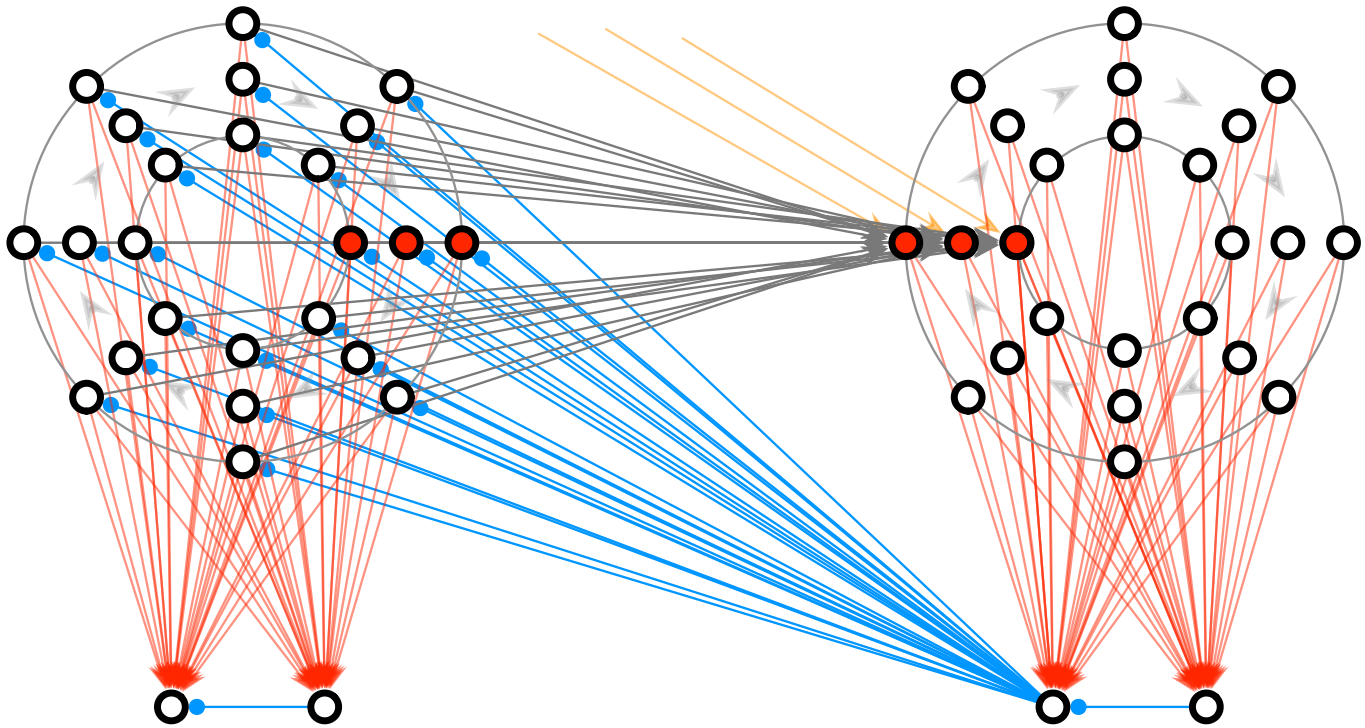

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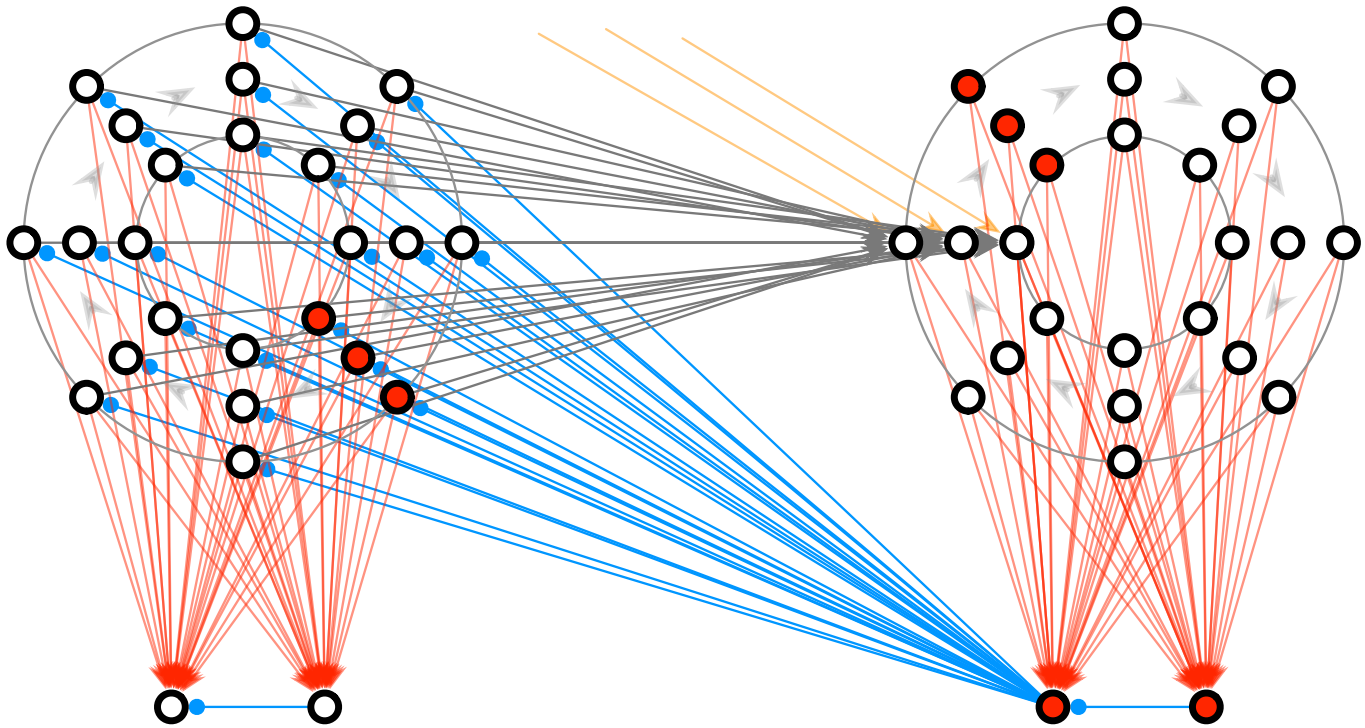

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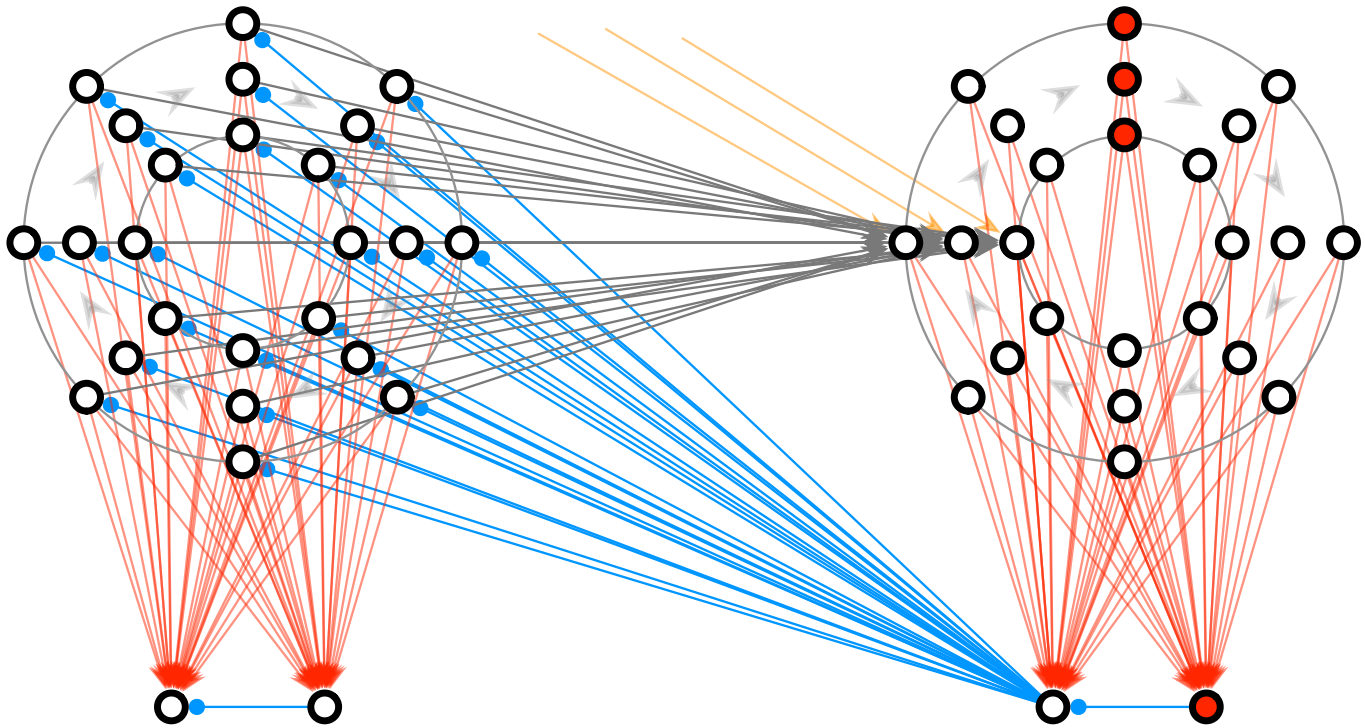

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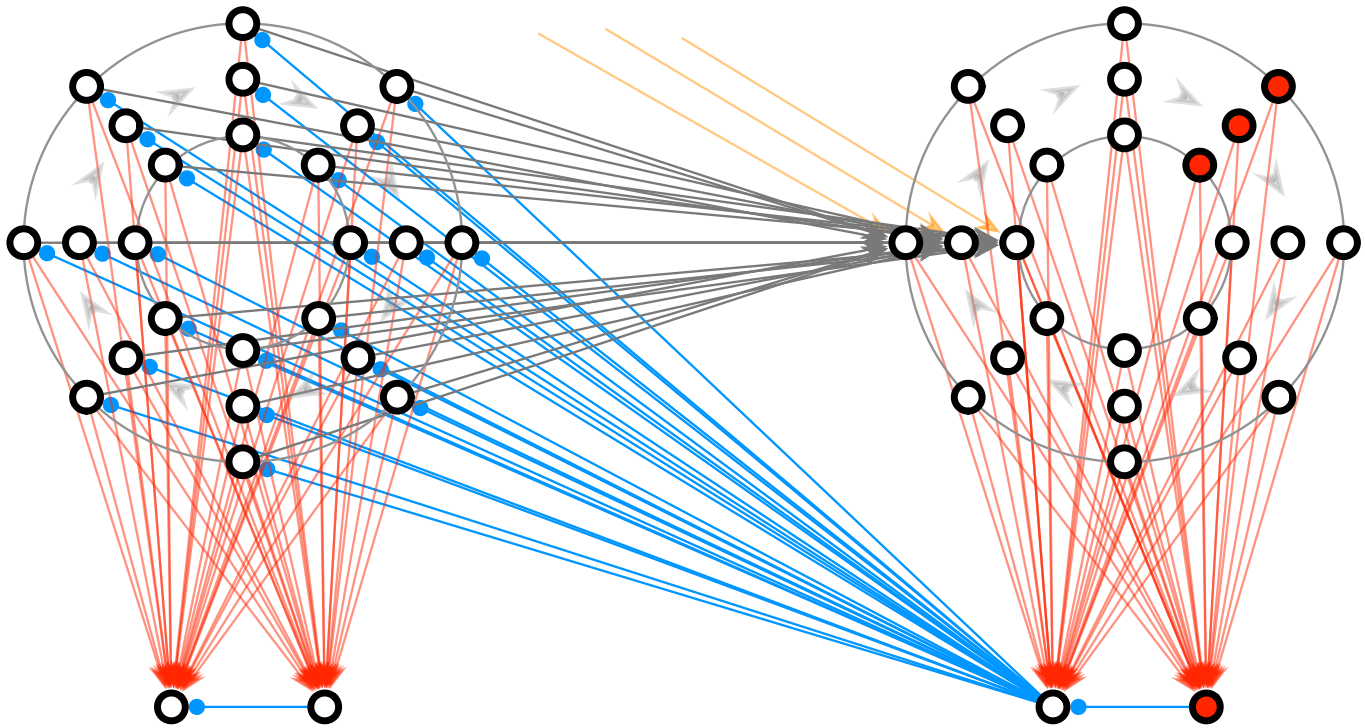

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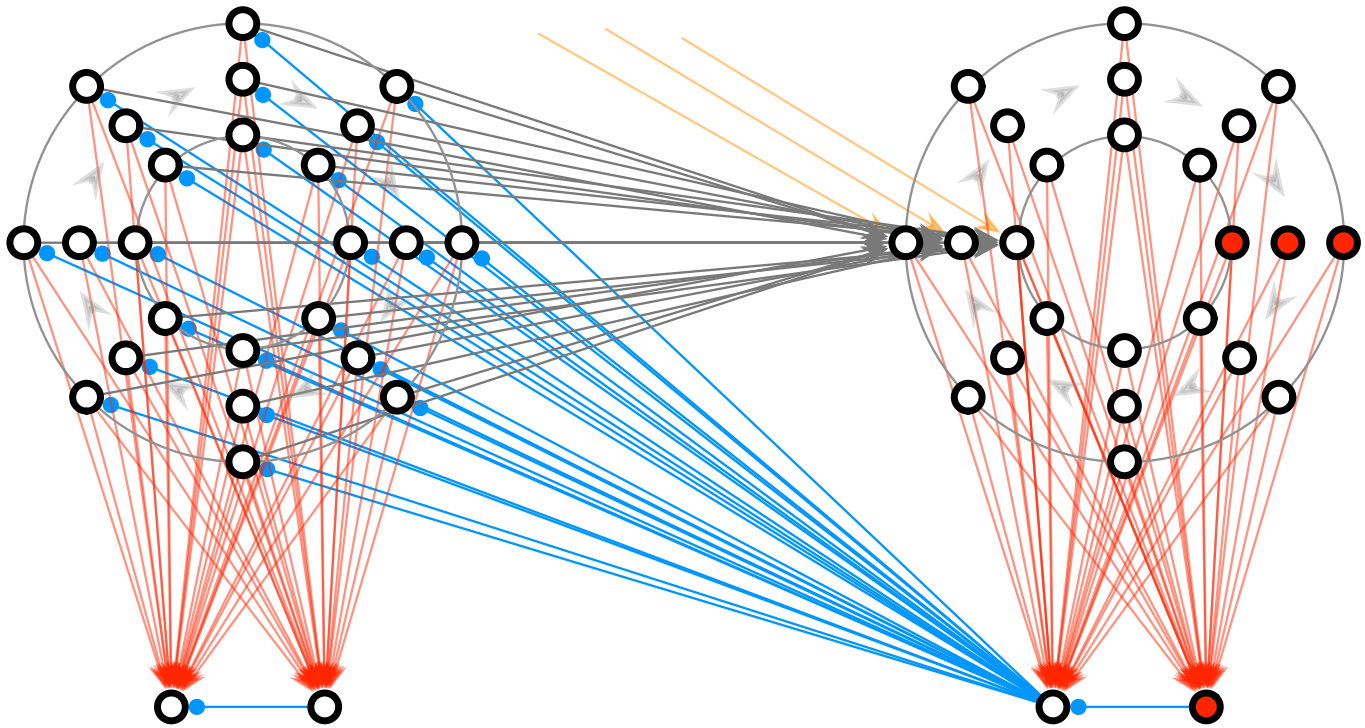
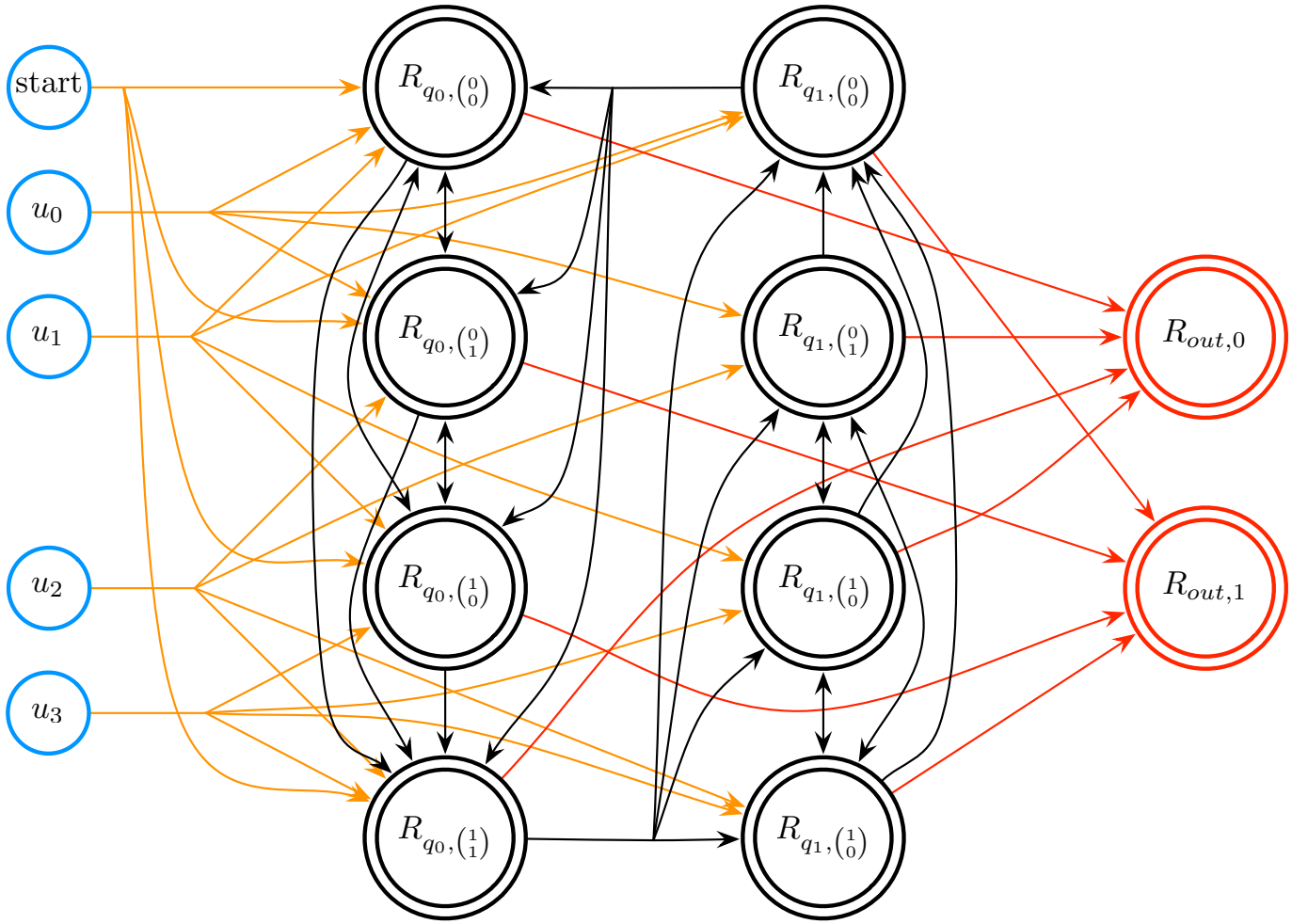


Simulation


start
u_0
u_1
u_2
u_3
$R_{q_0,\binom{0}{0}}$
$R_{q_0,\binom{0}{1}}$
$R_{q_0,\binom{1}{0}}$
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$R_{out,0}$
$R_{out,1}$

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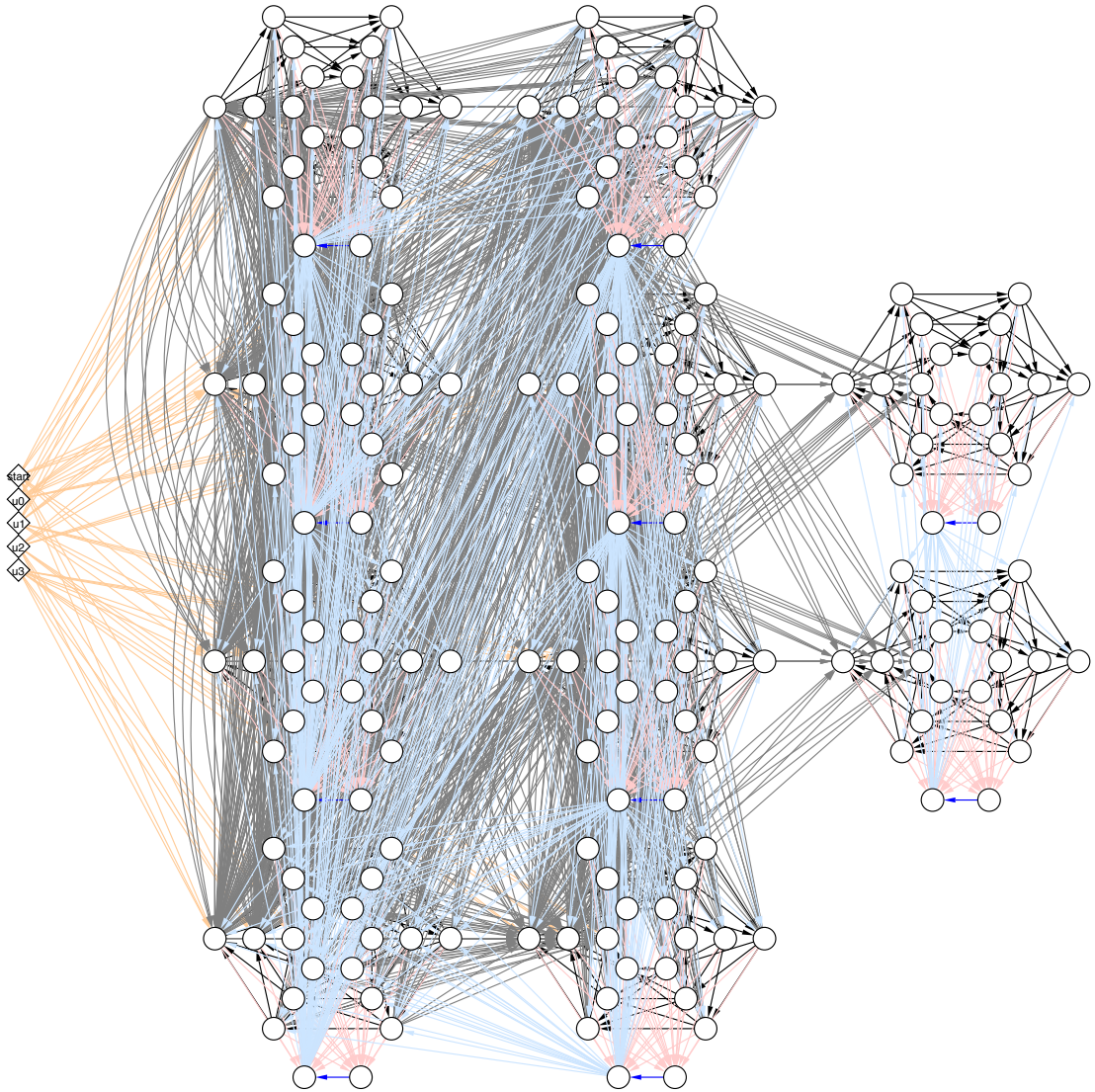

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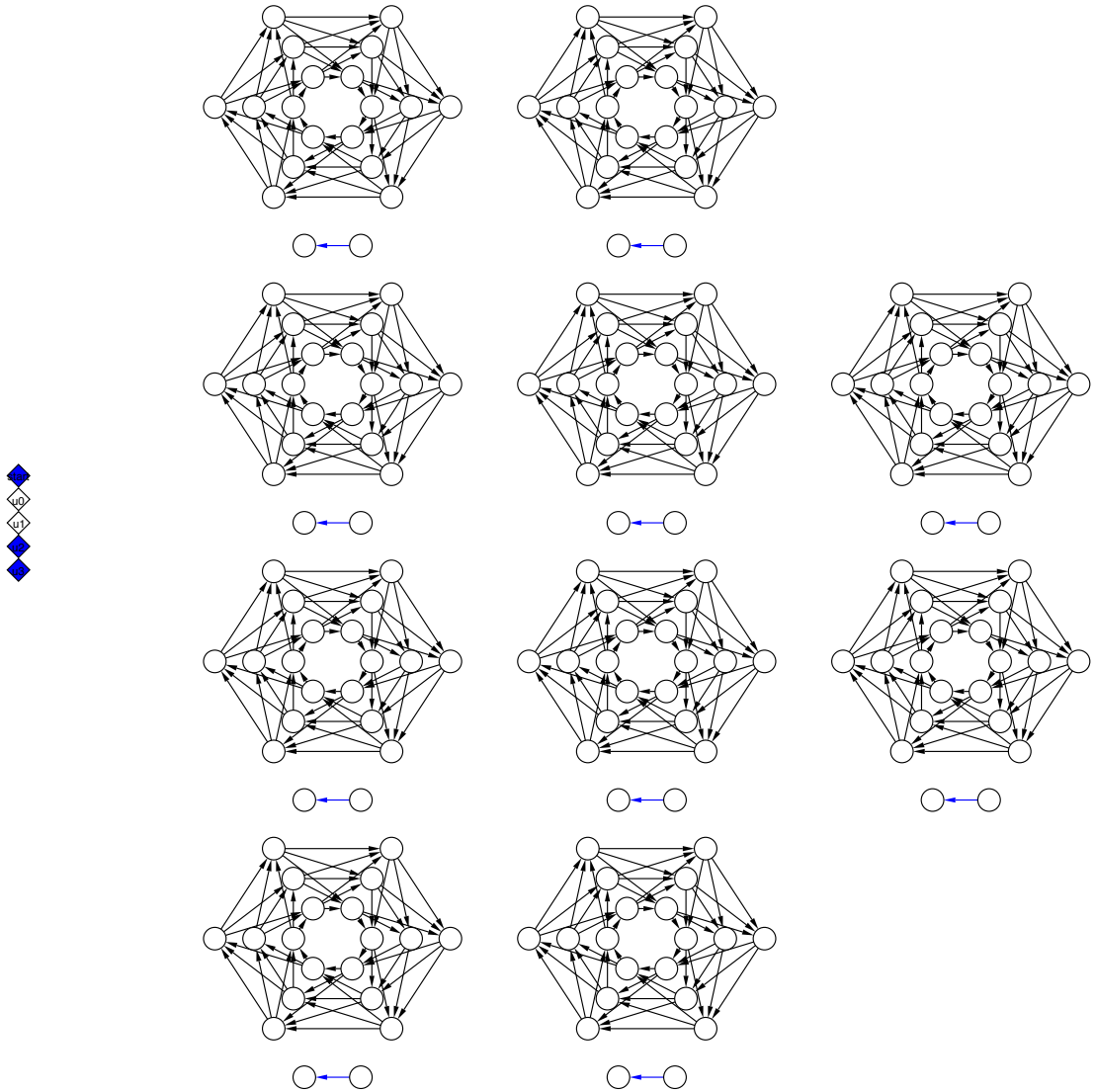

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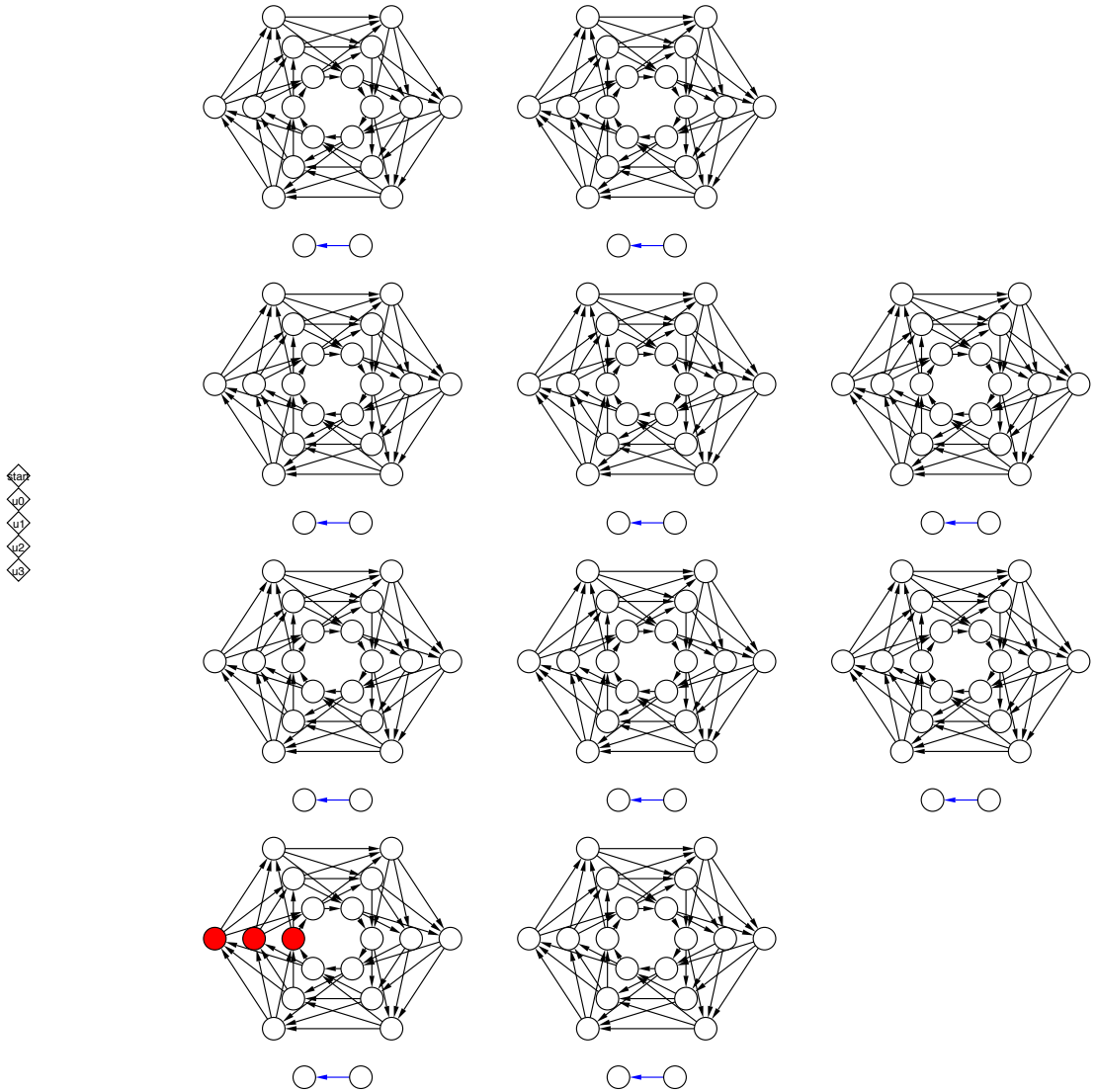

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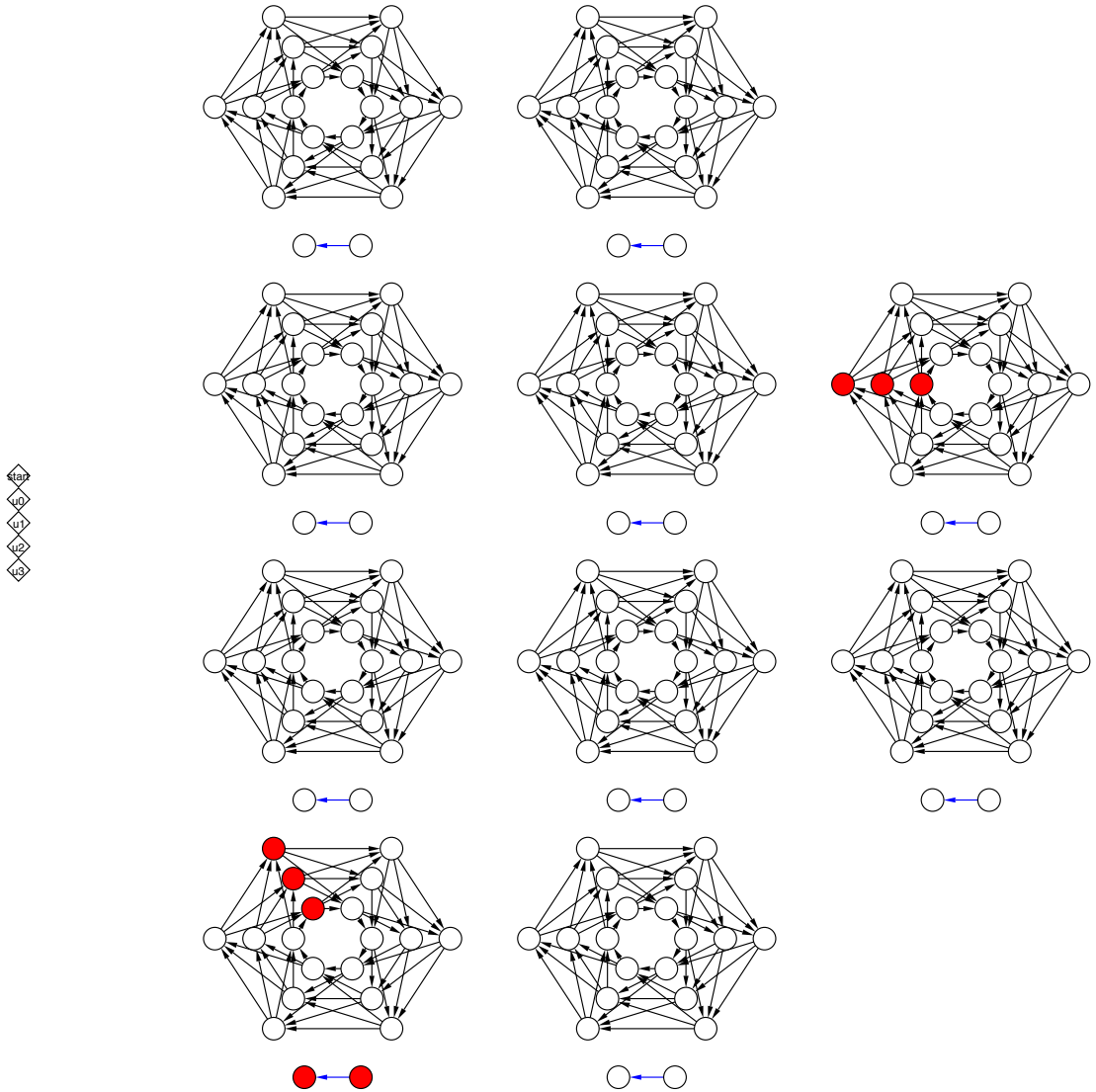

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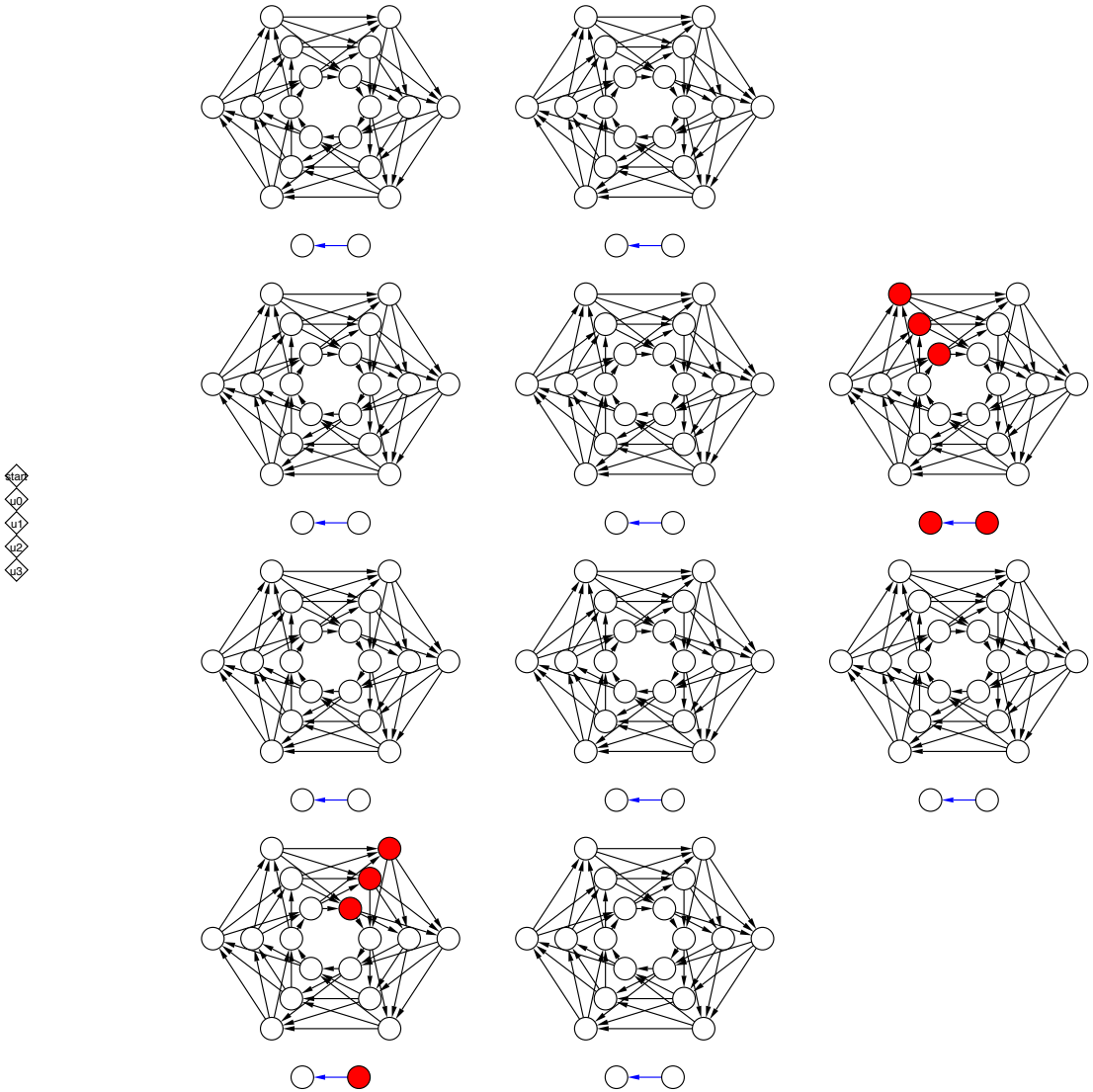

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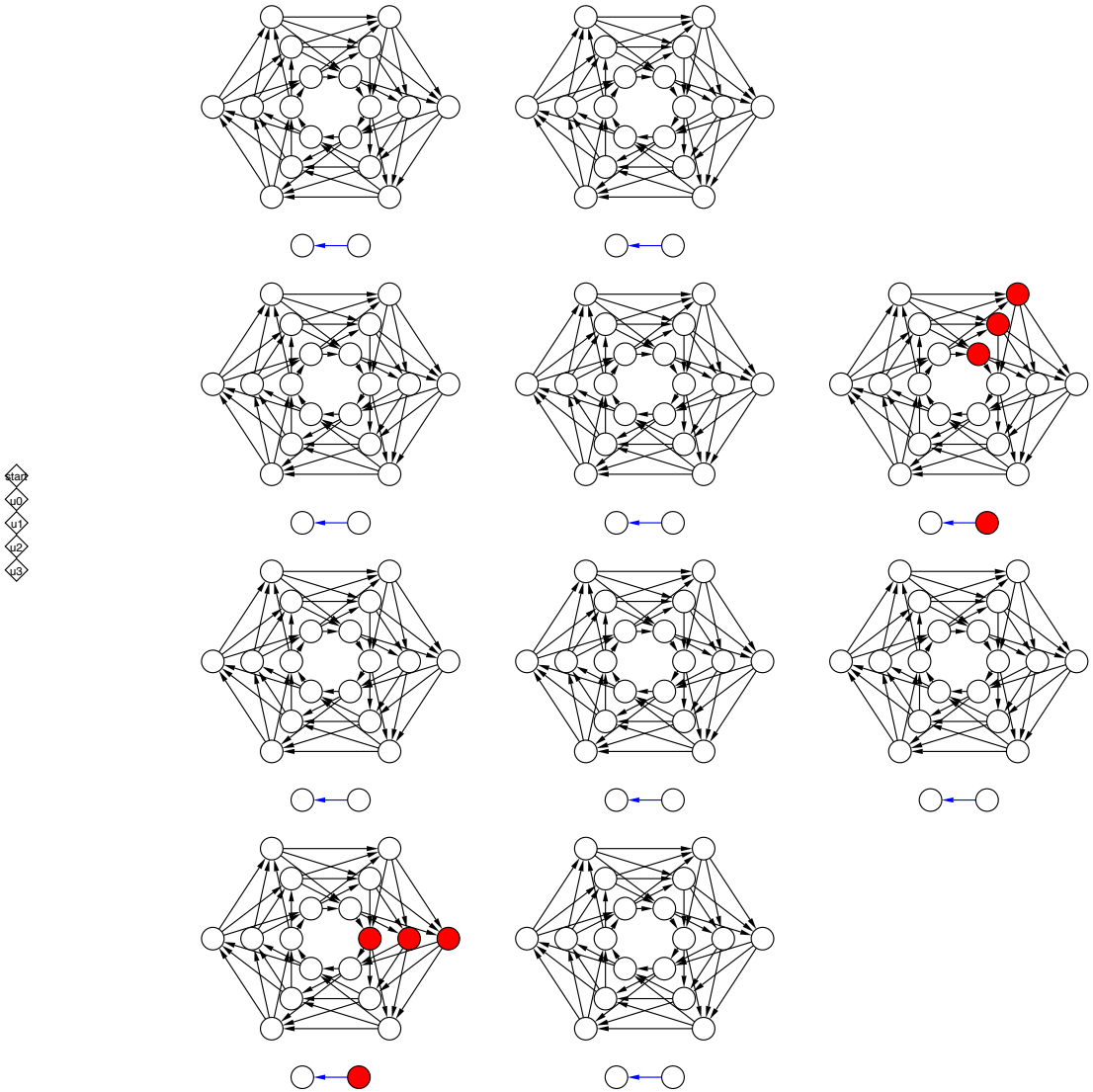

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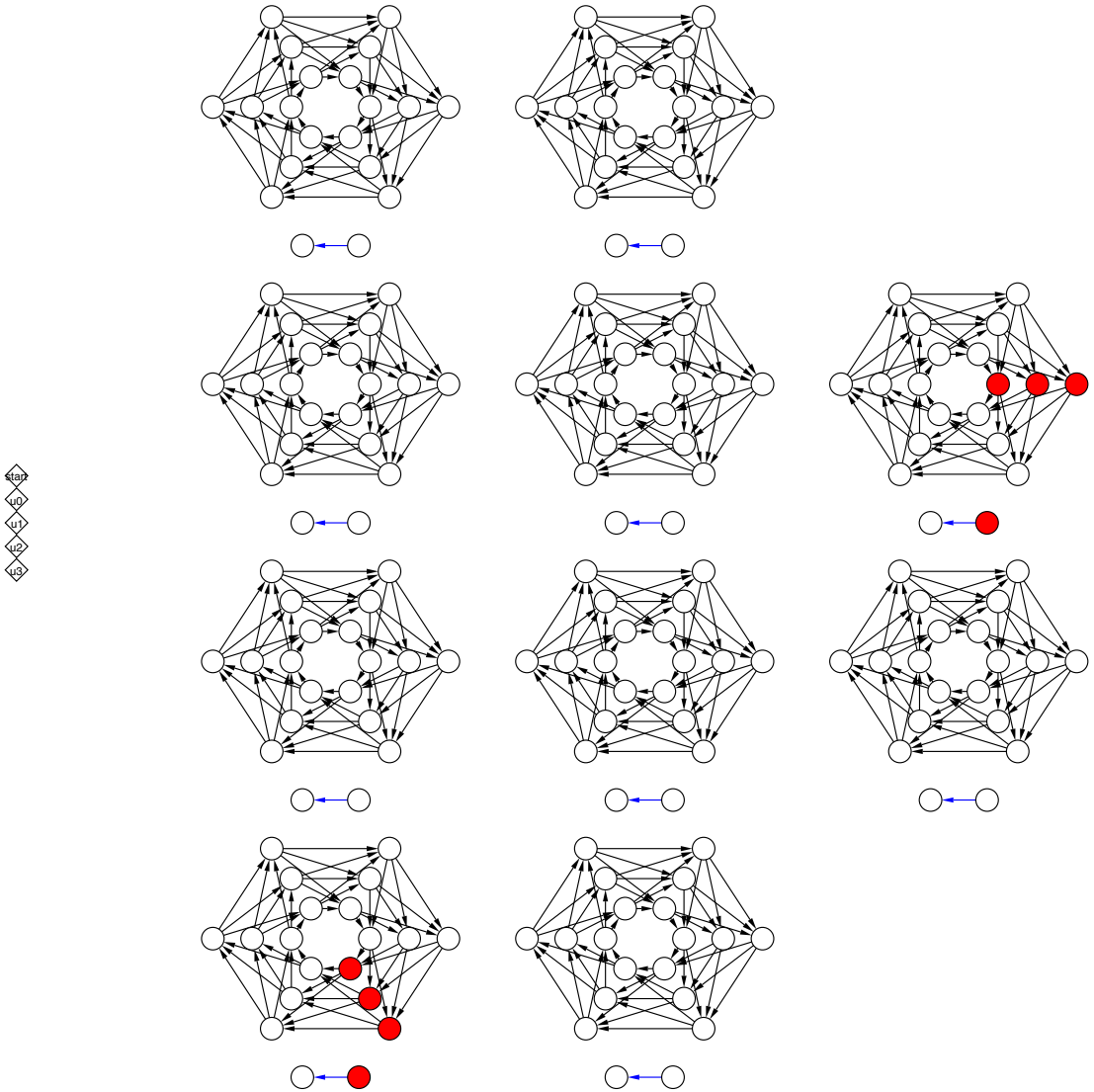

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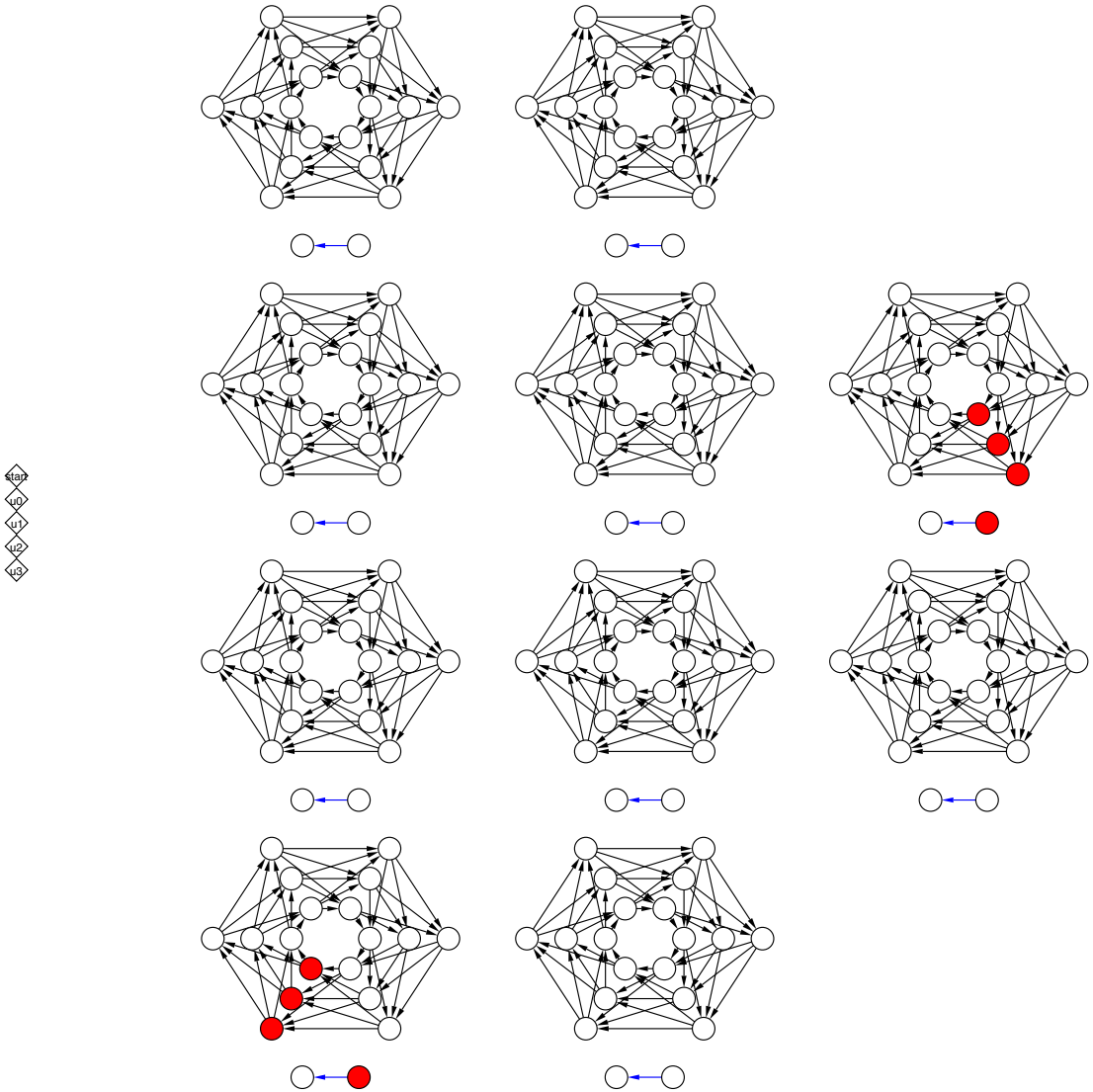

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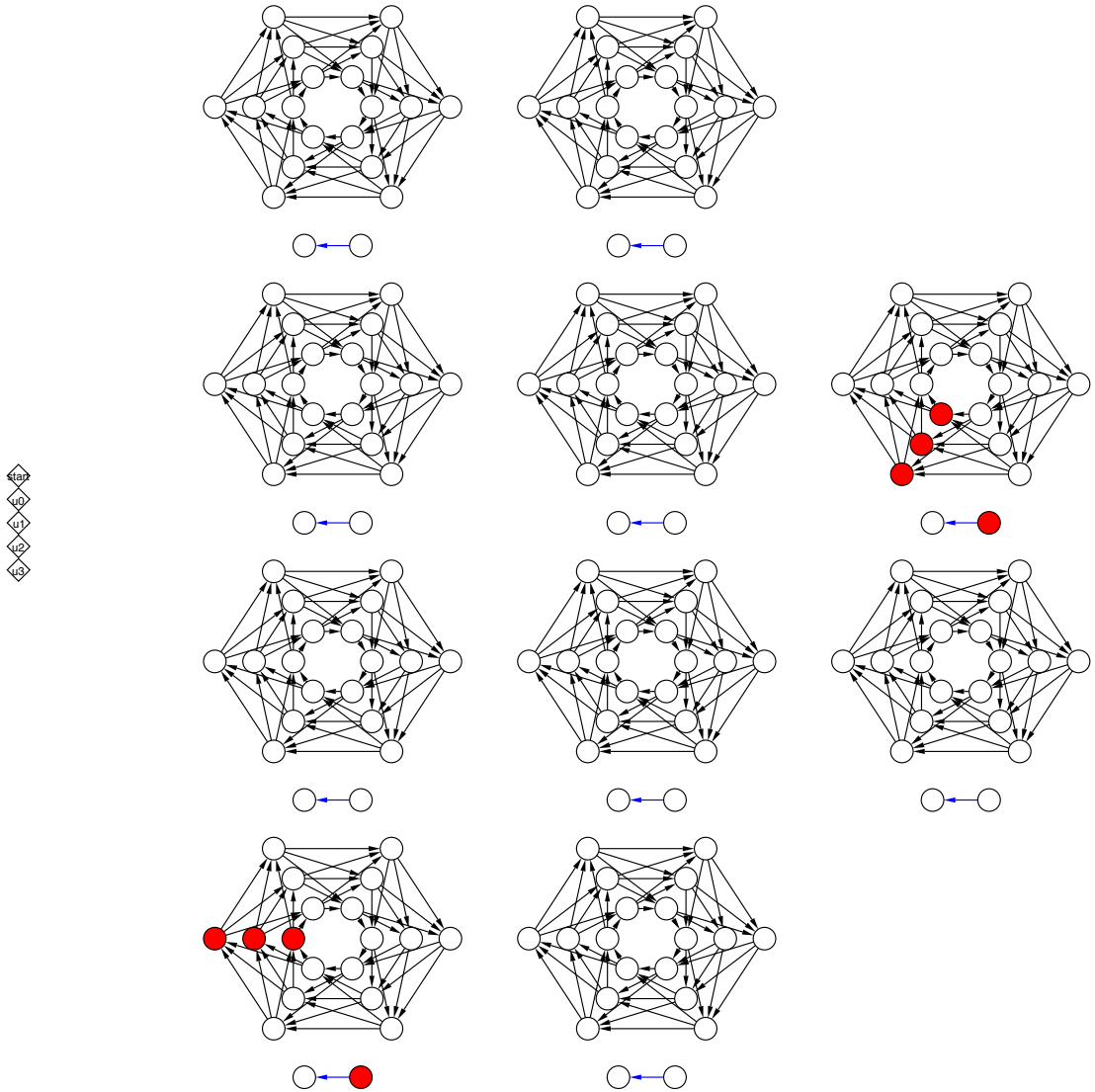

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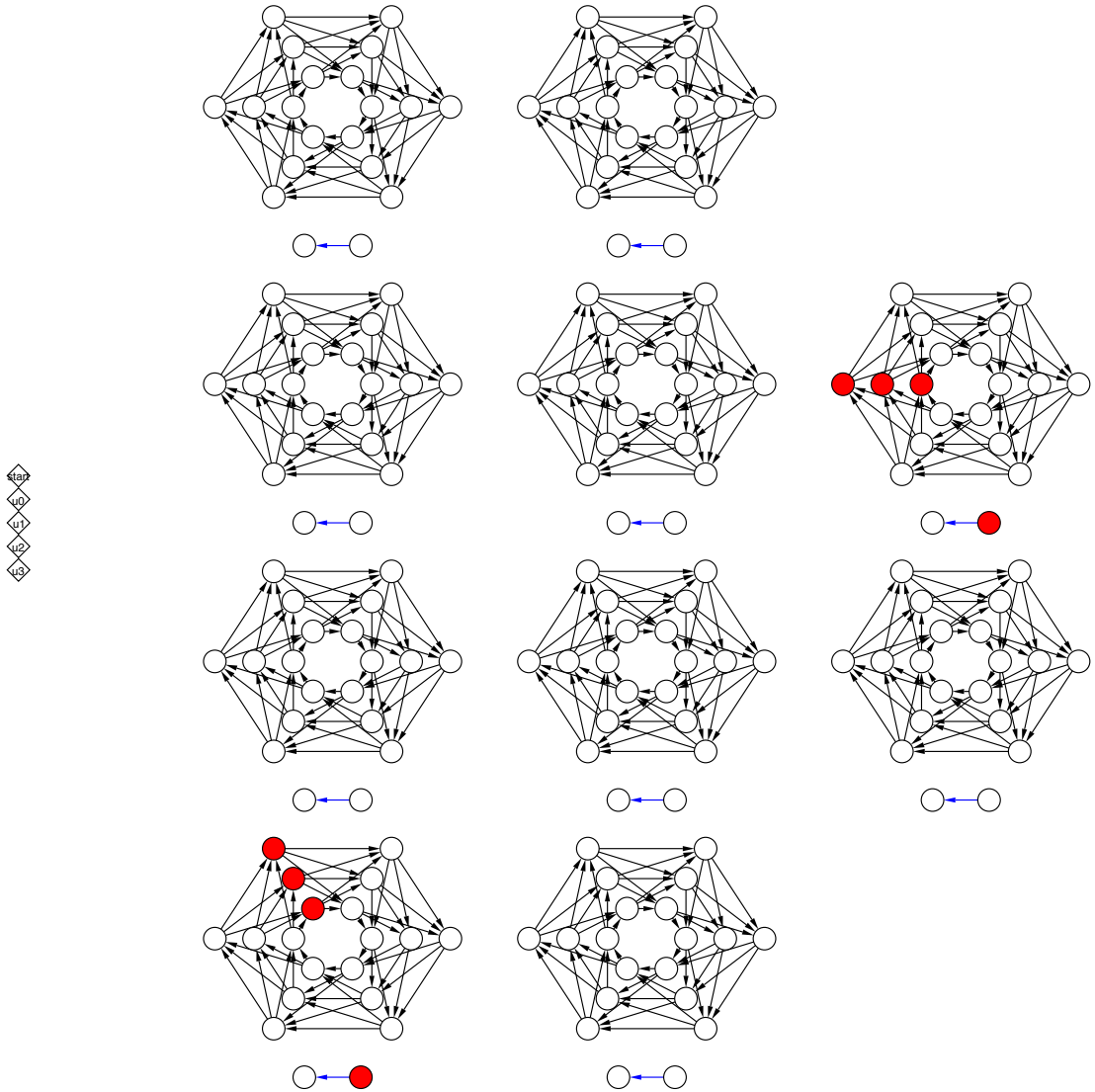

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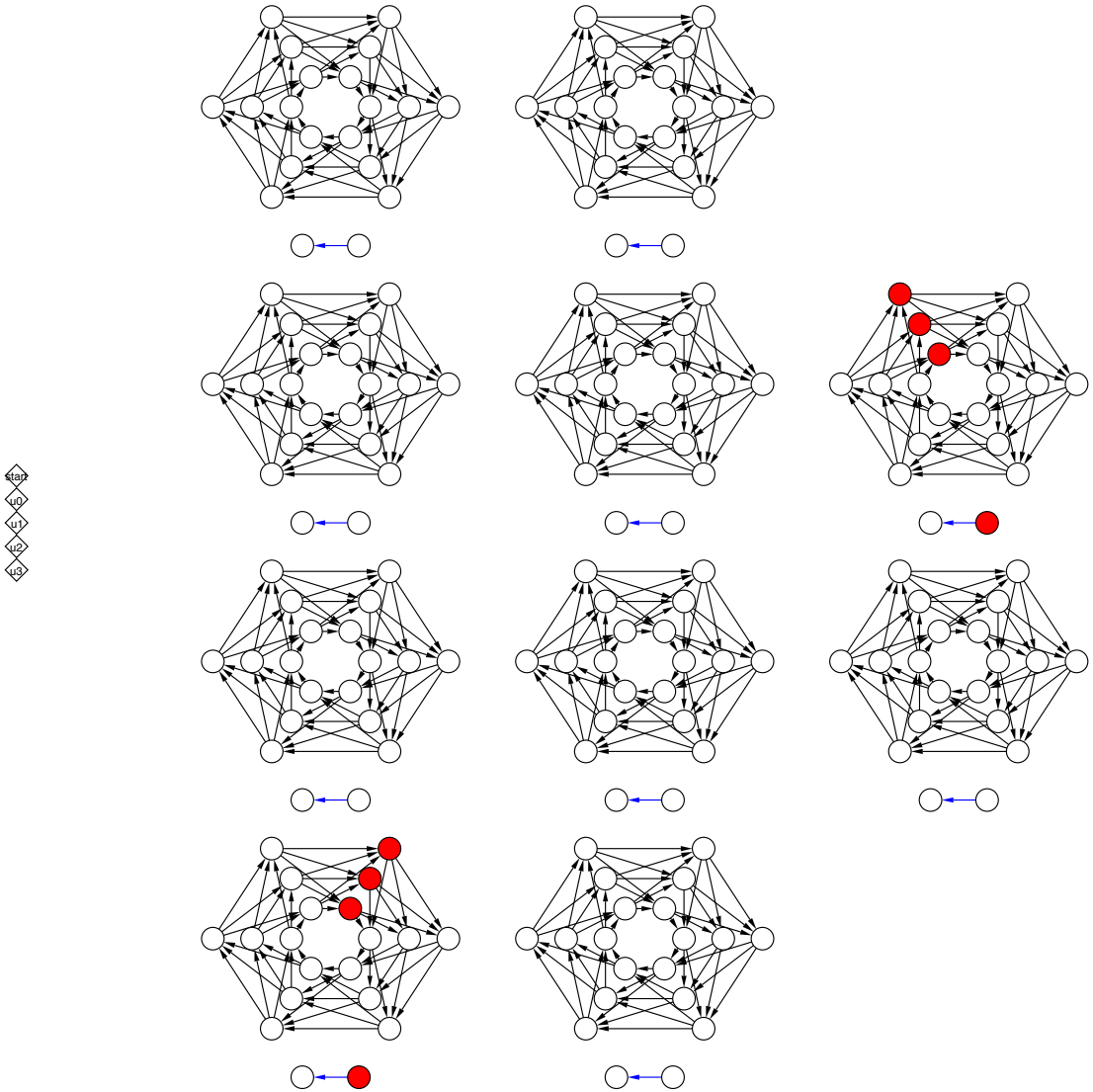

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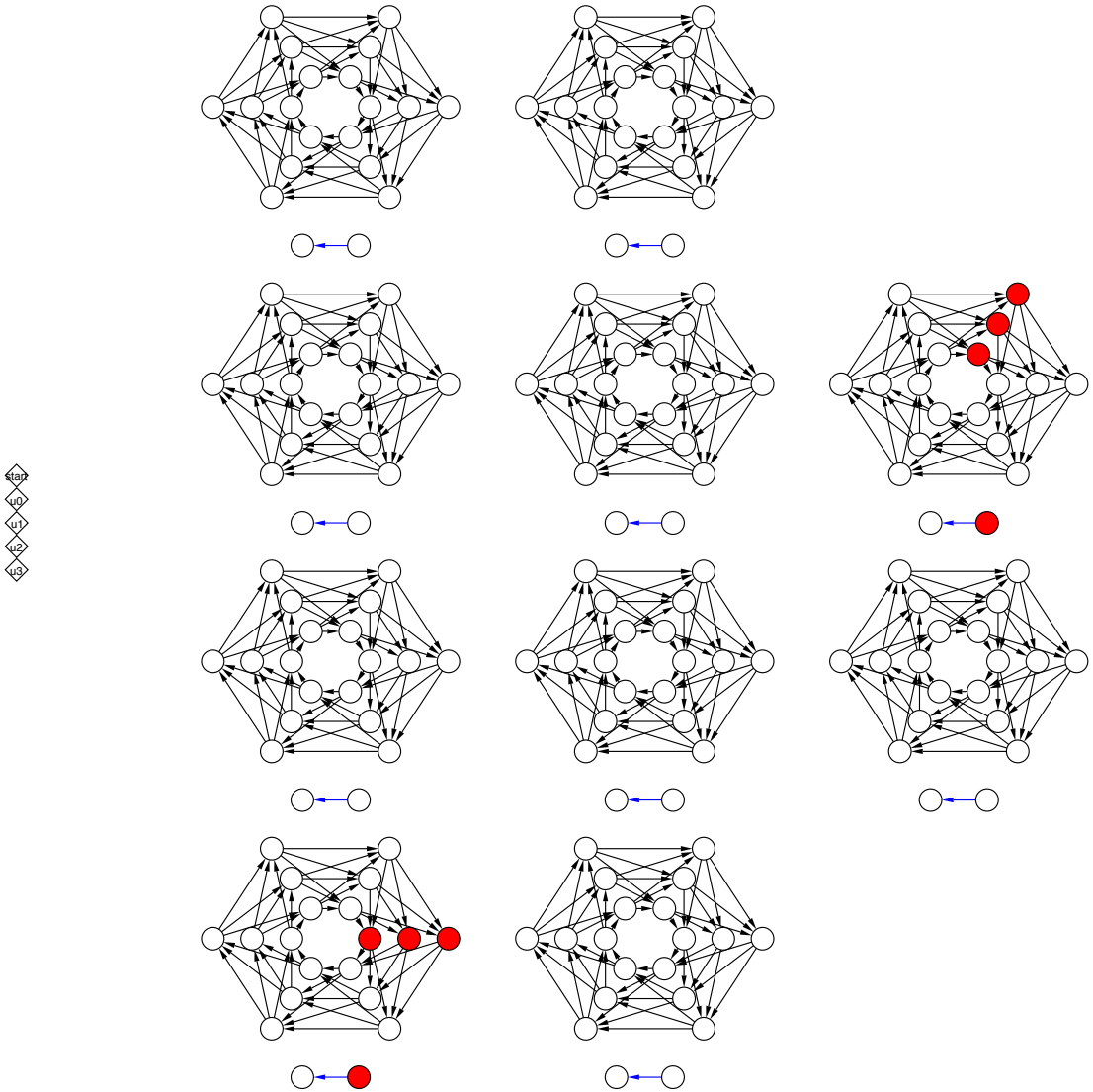

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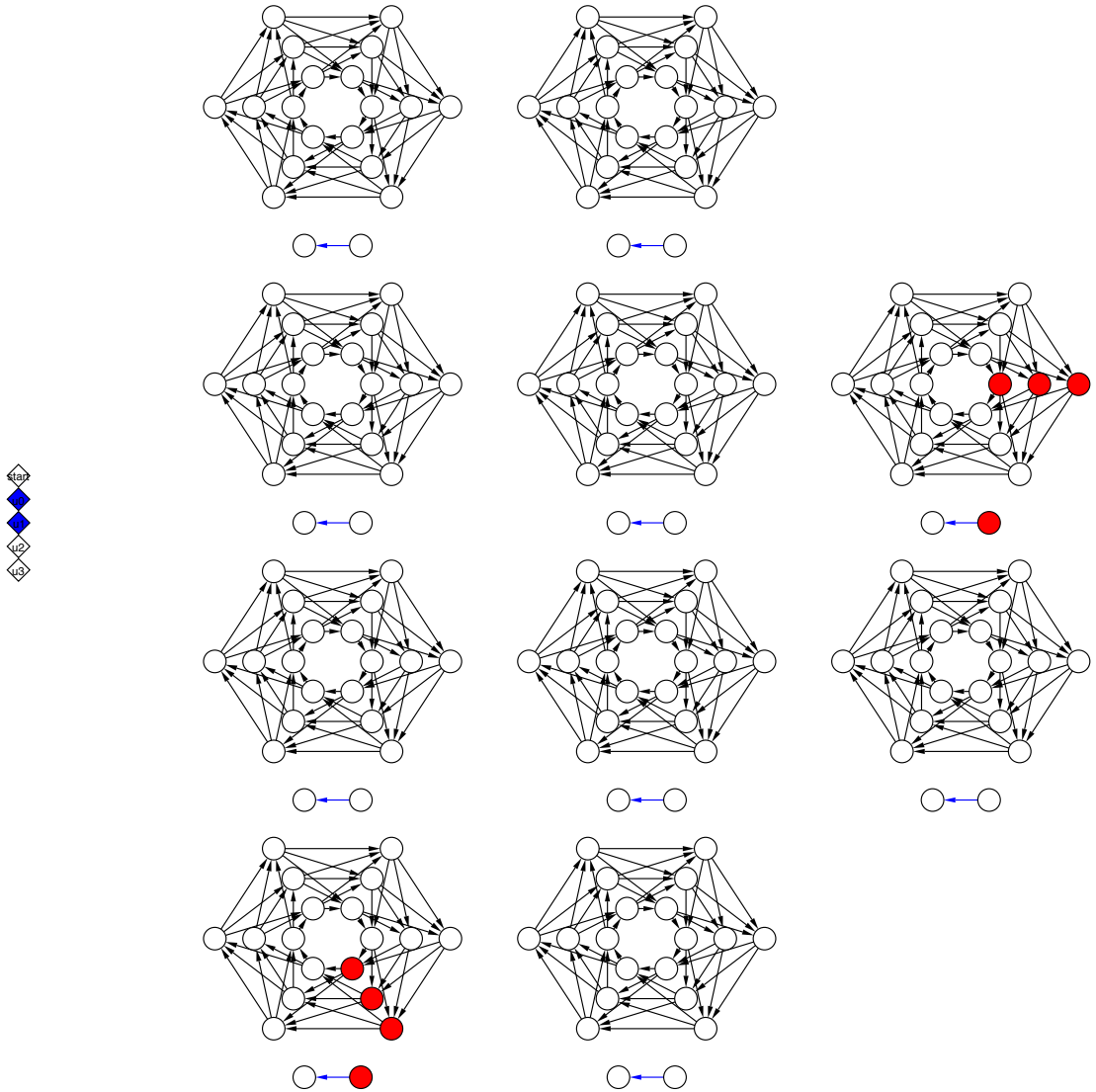

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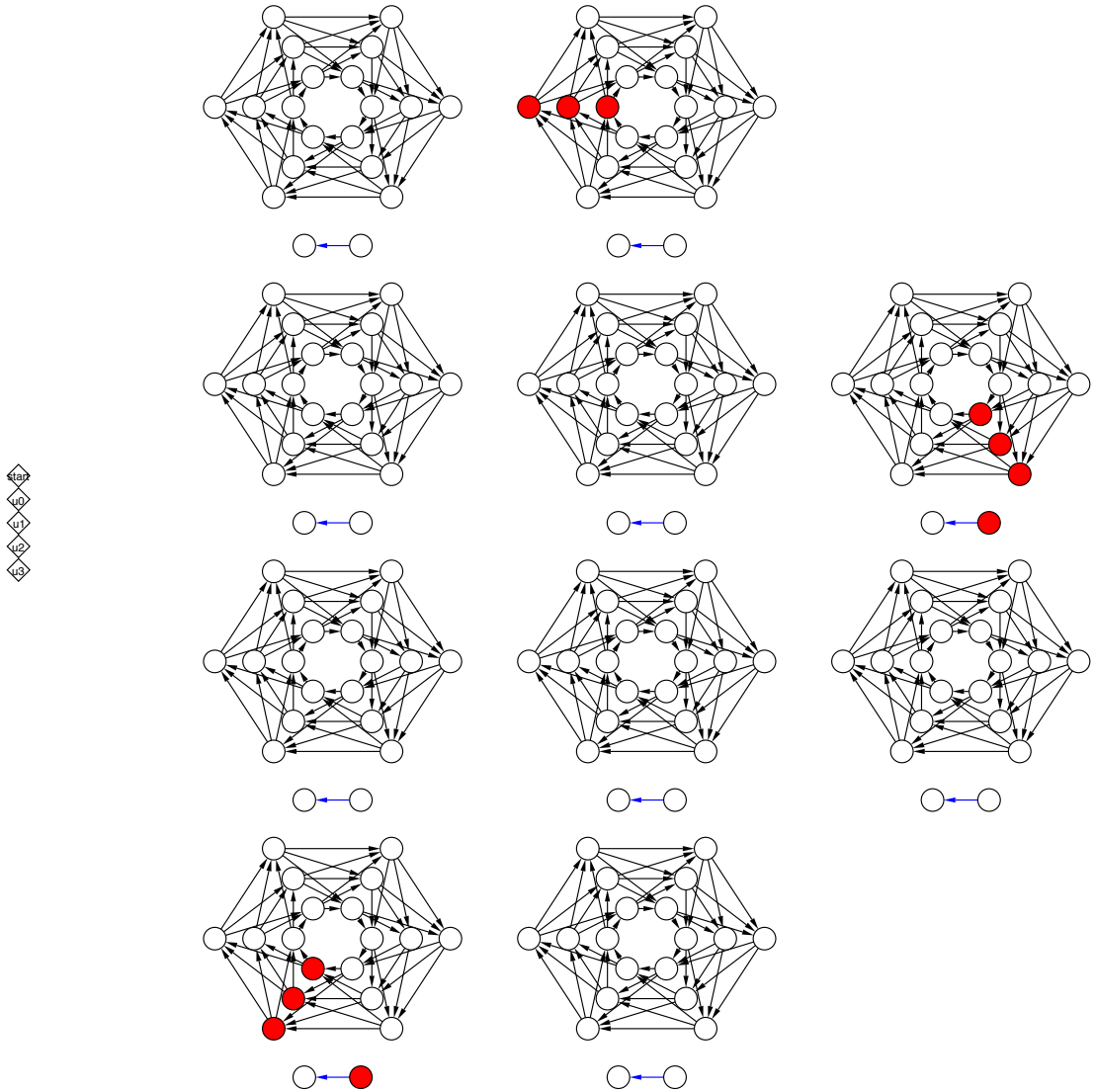

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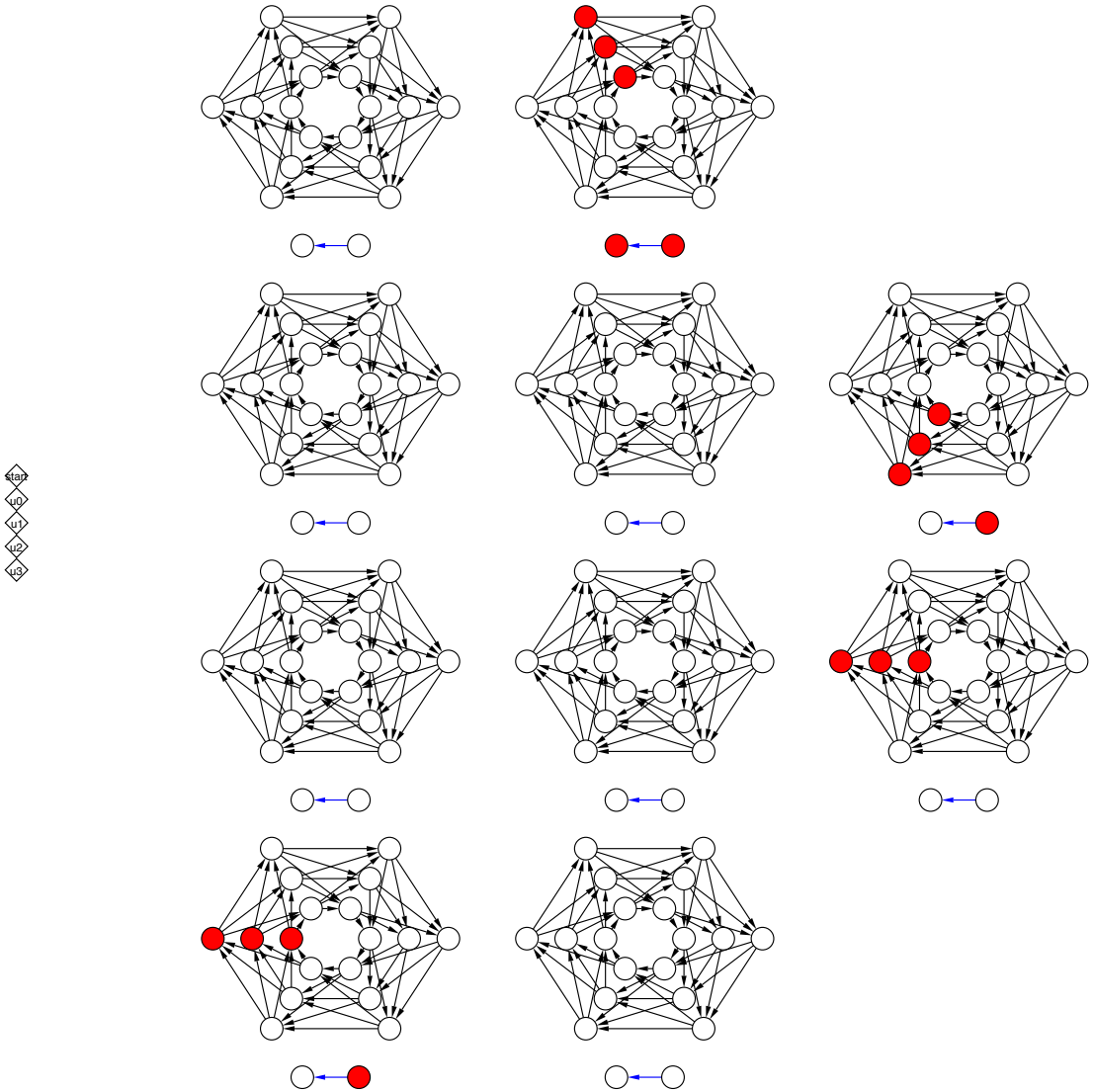

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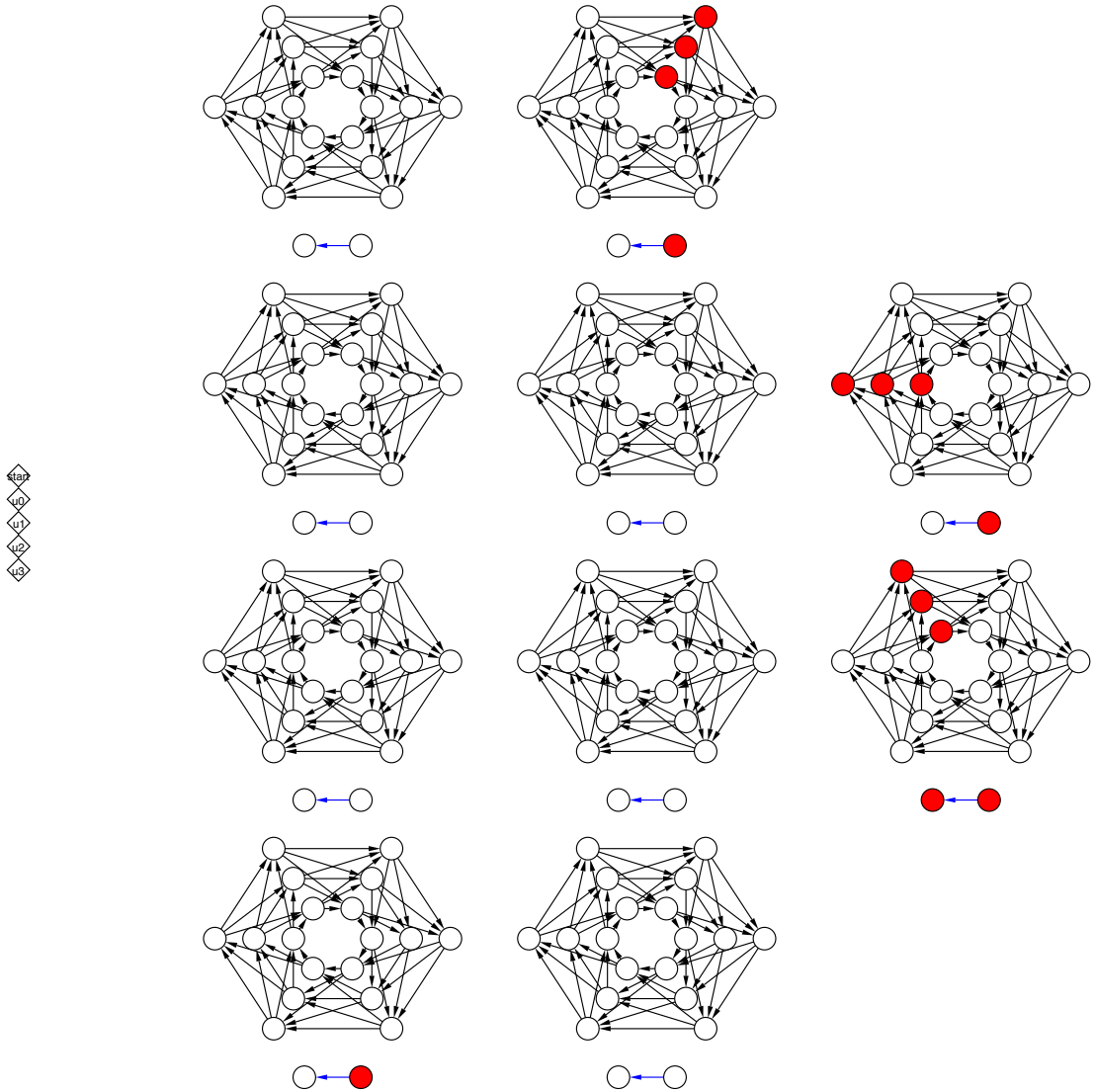

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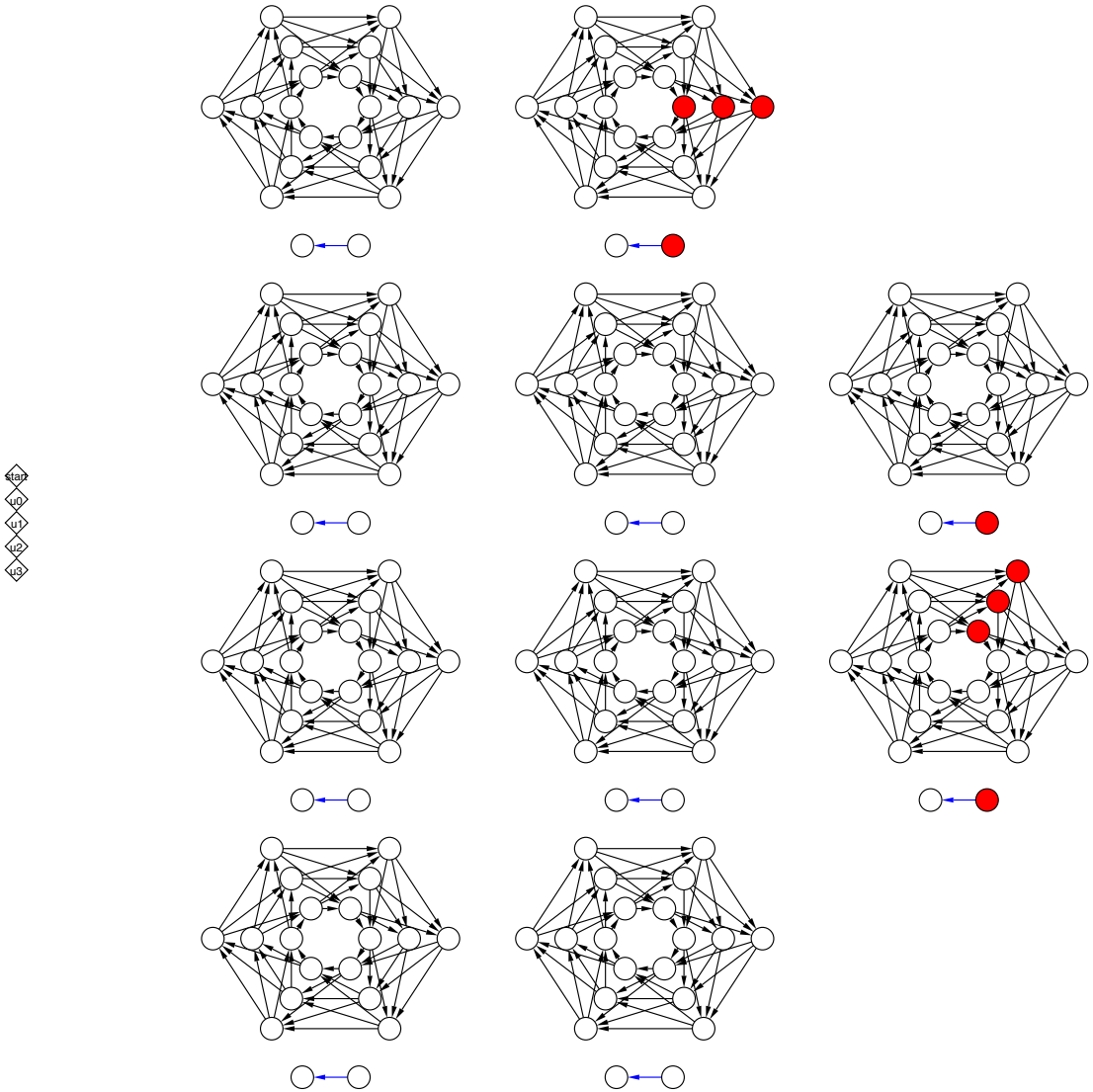

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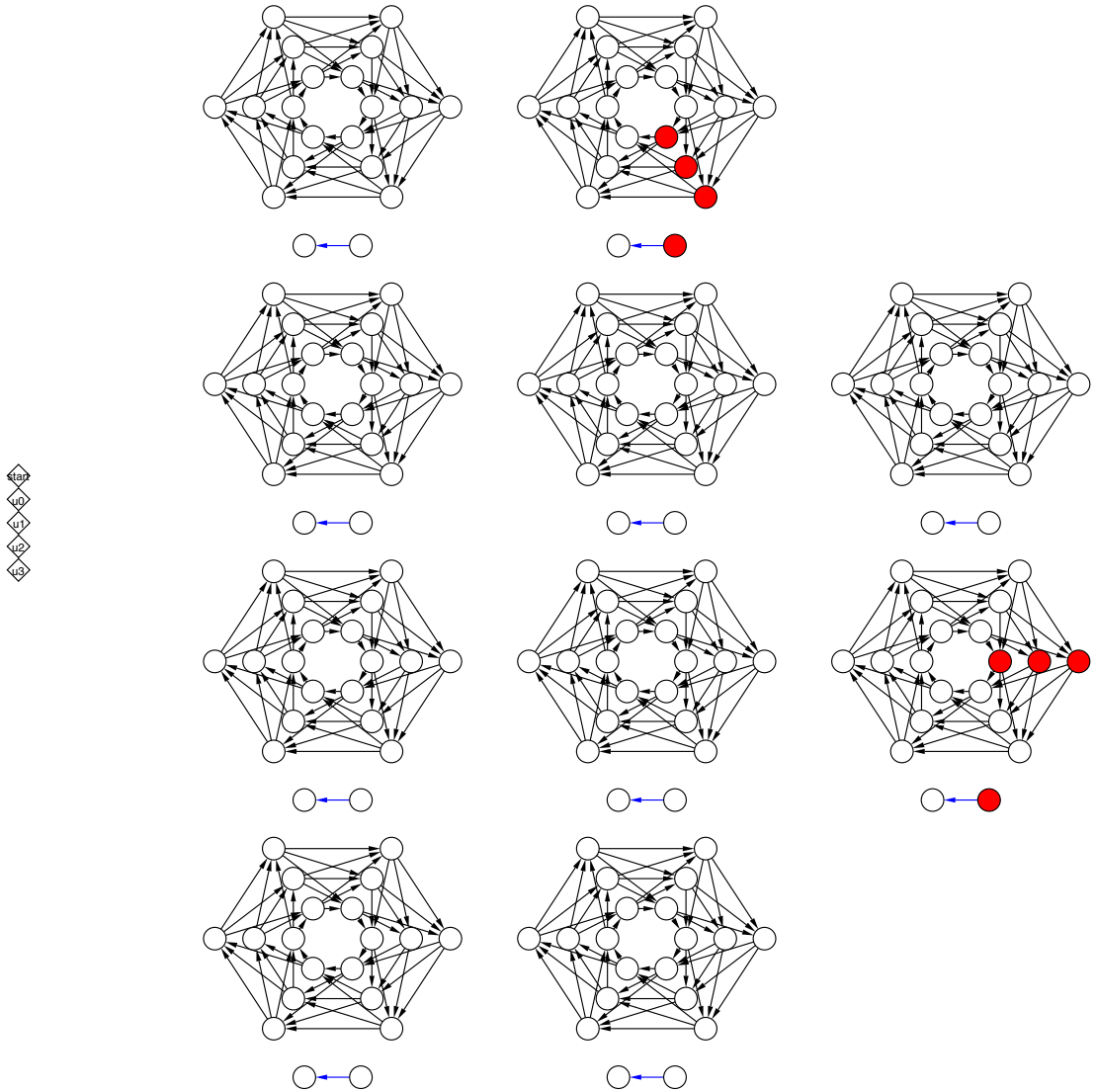

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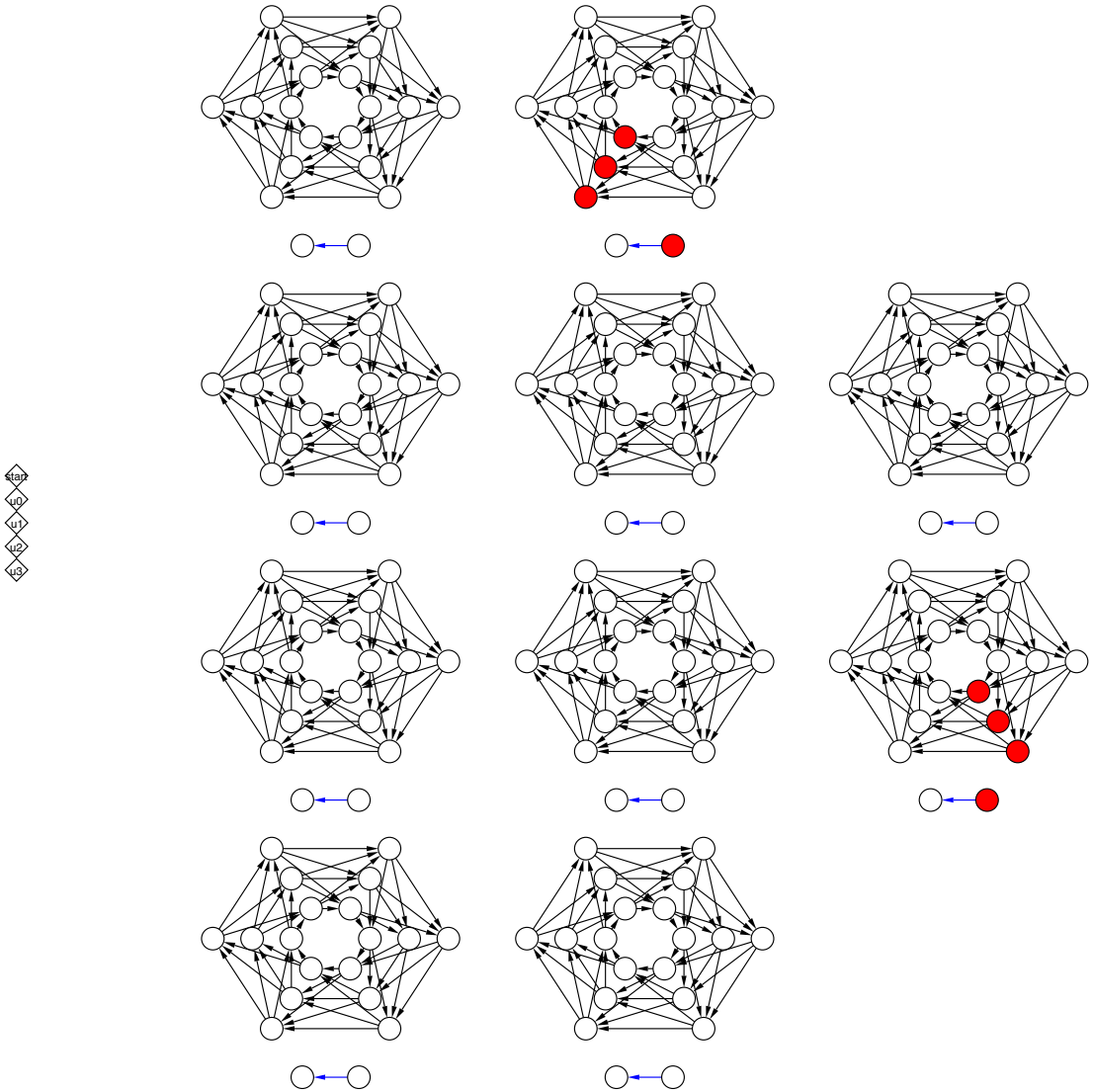

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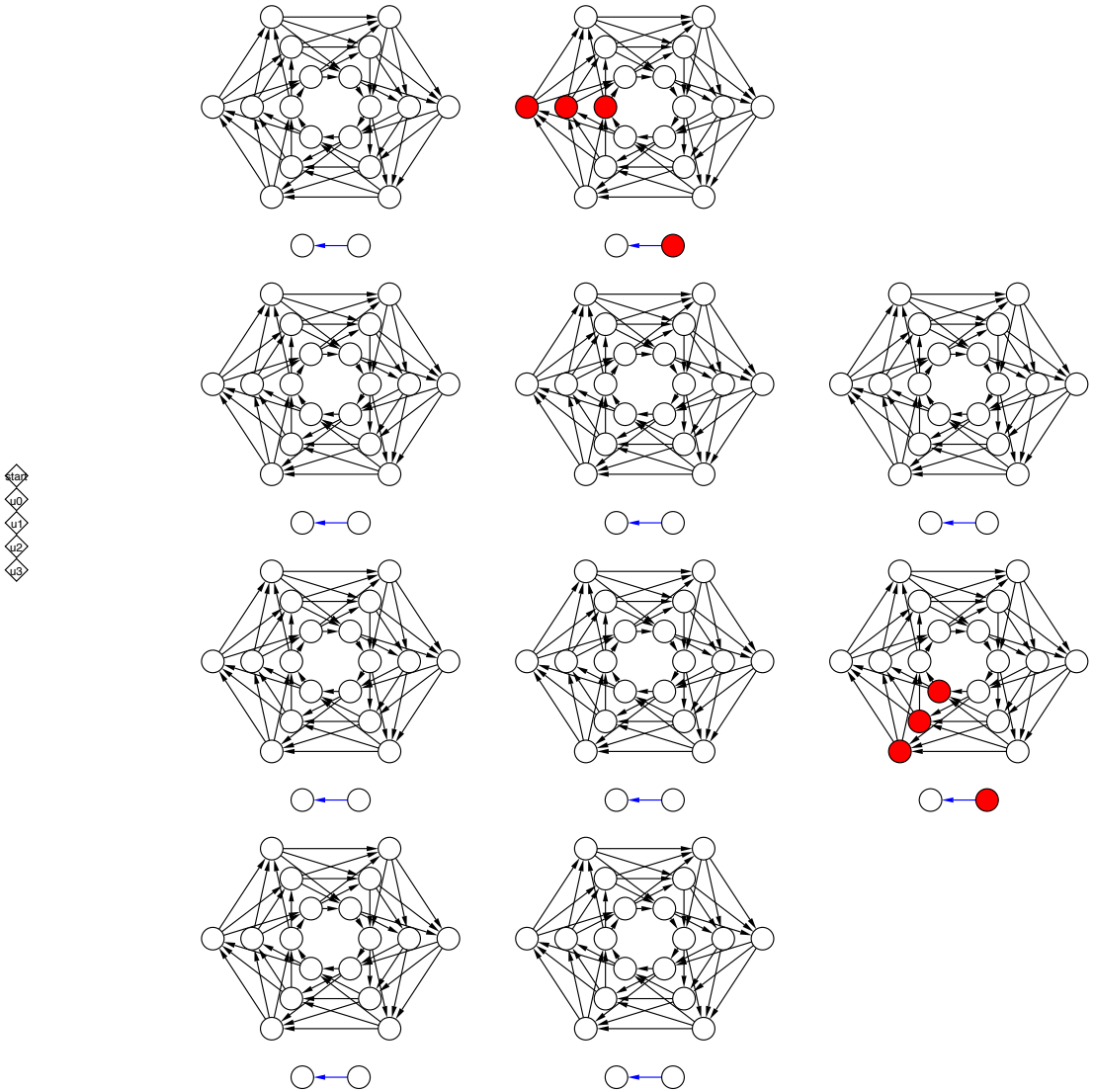

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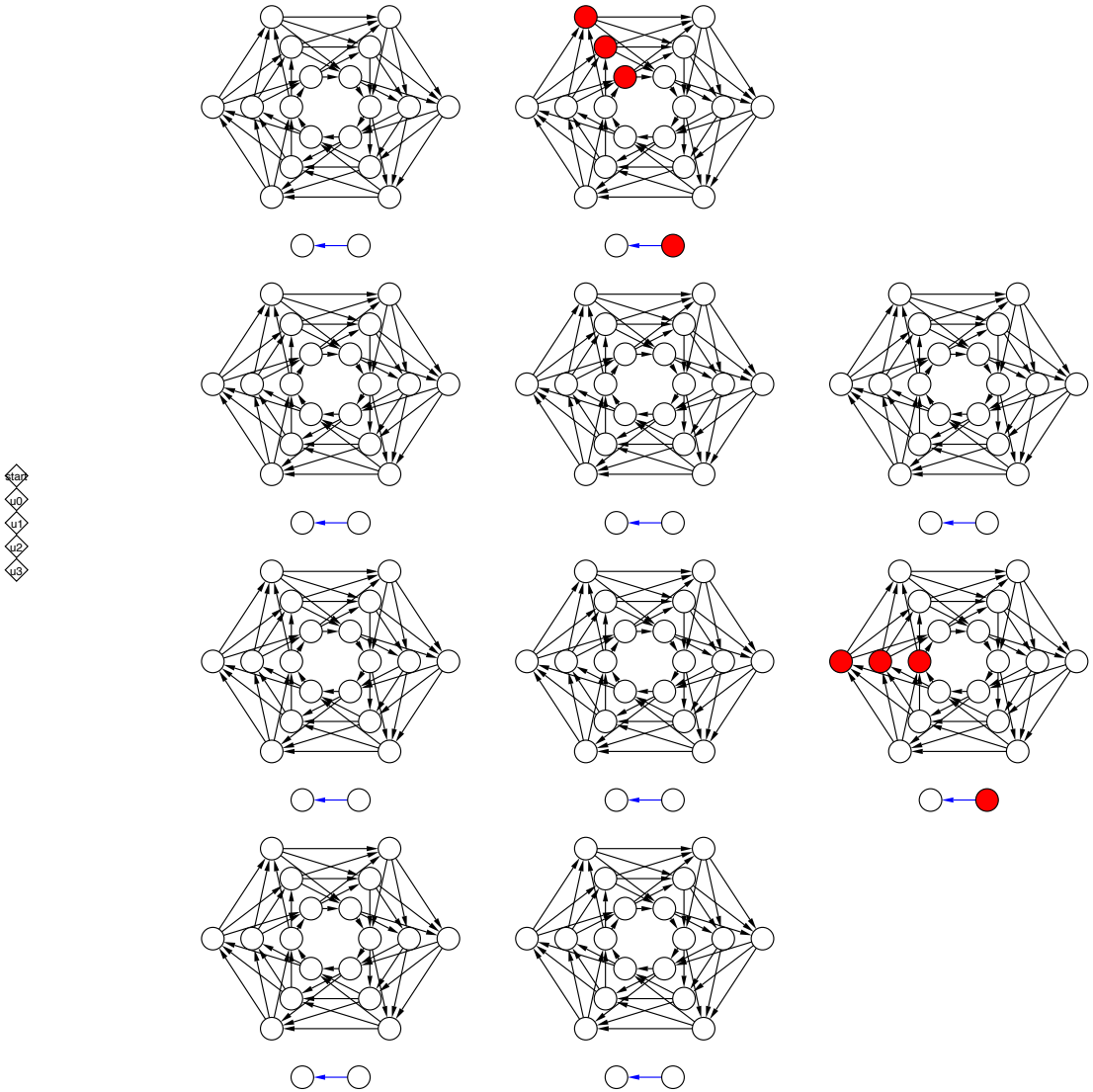

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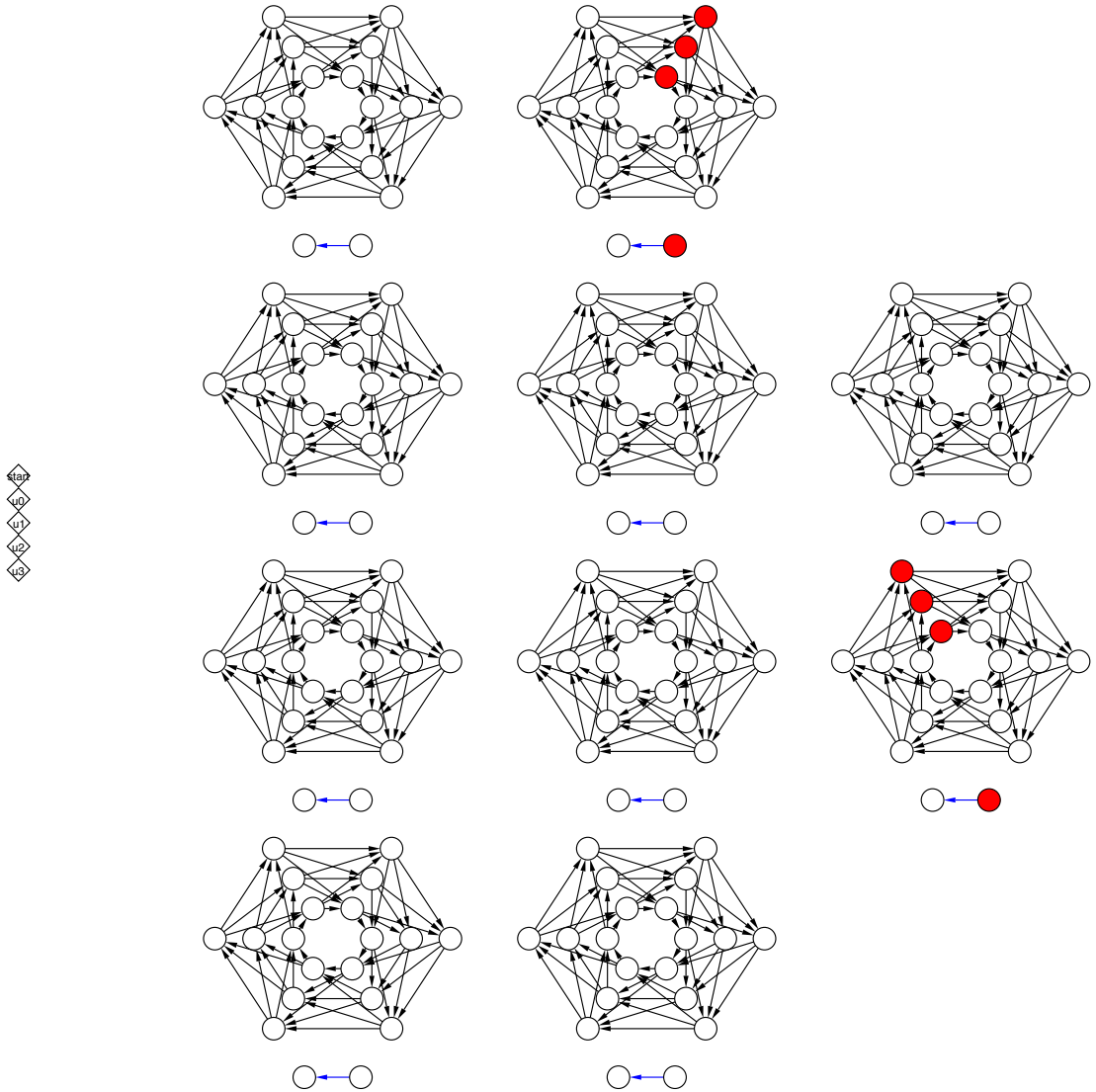
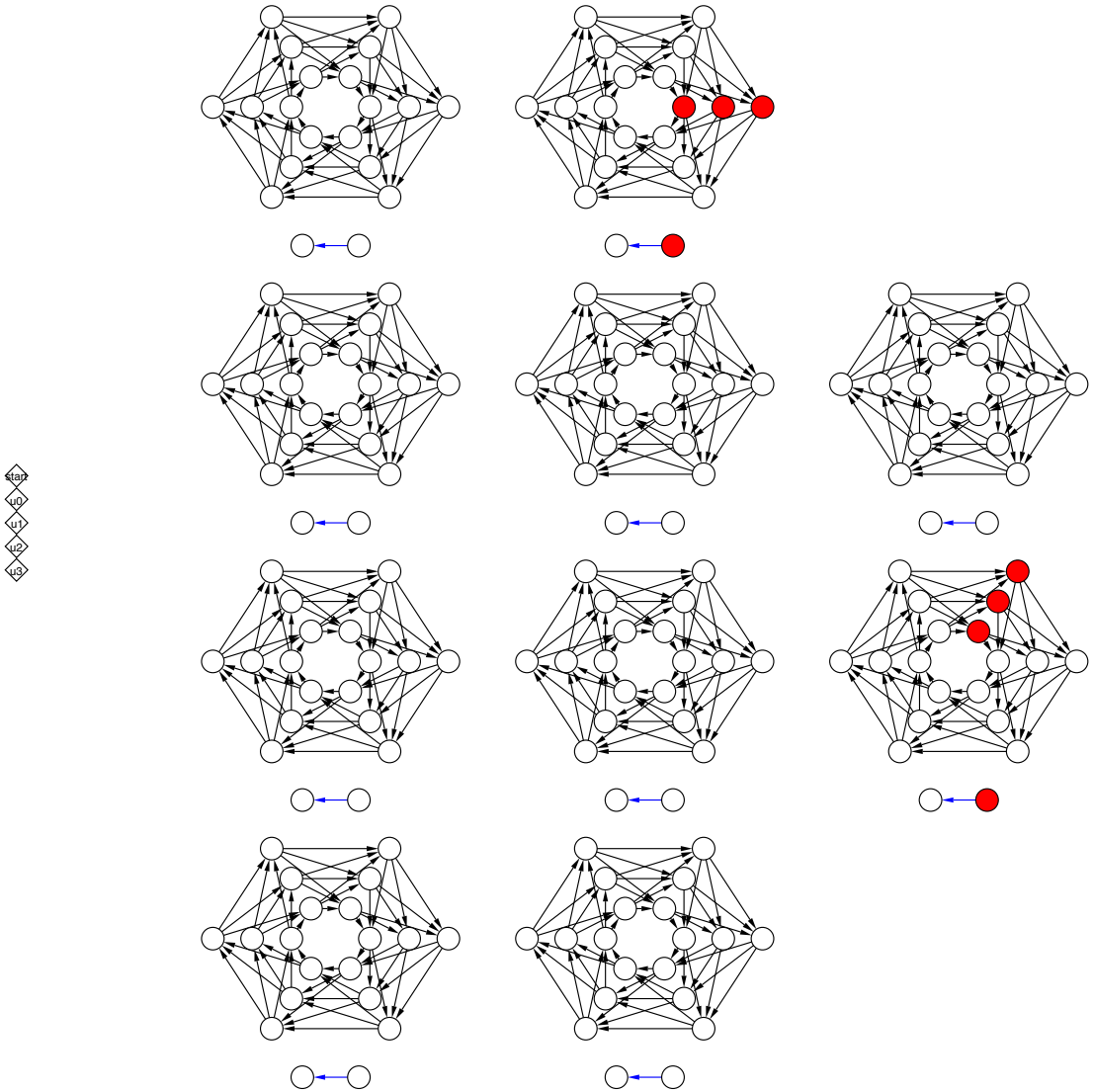
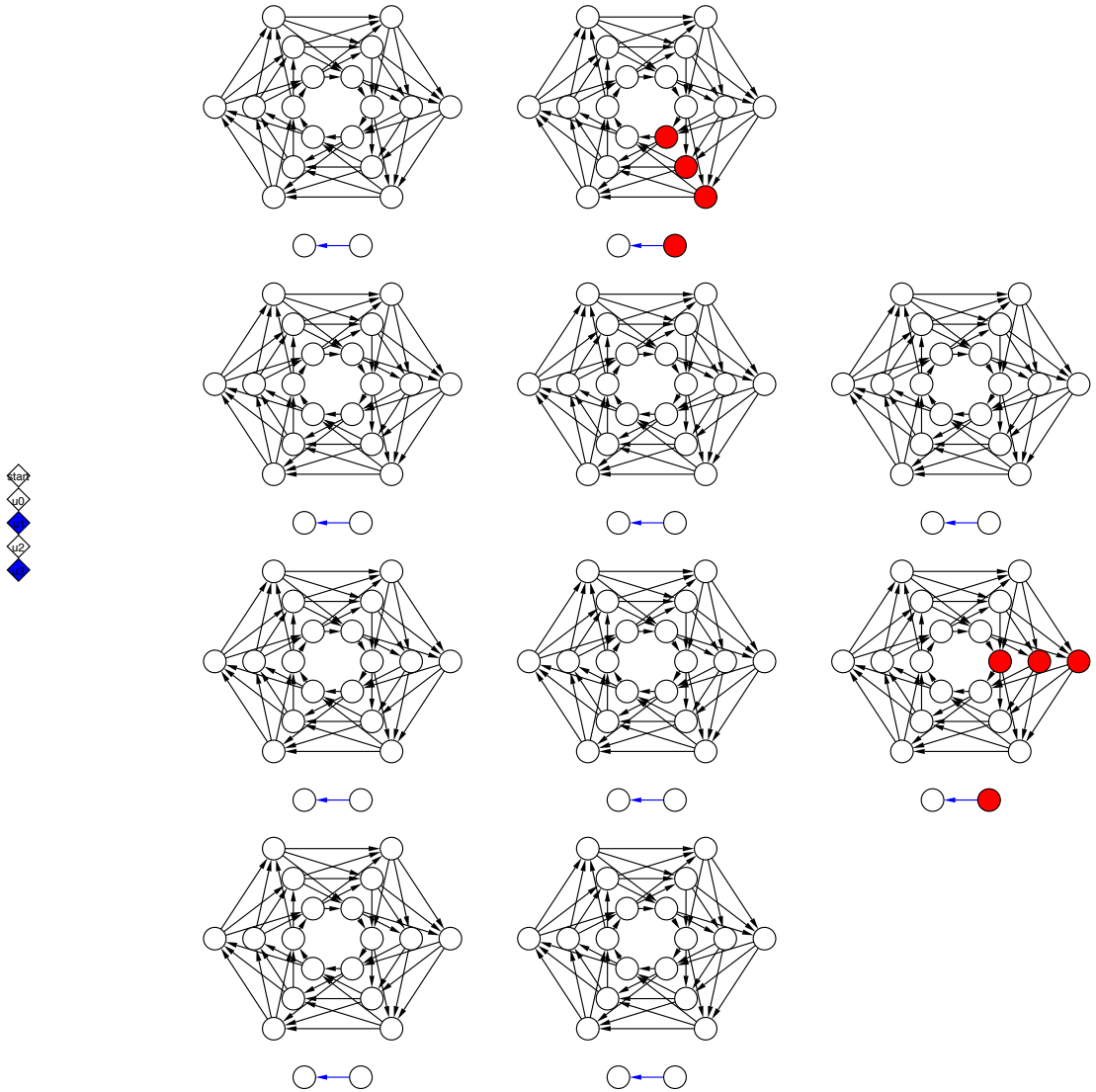


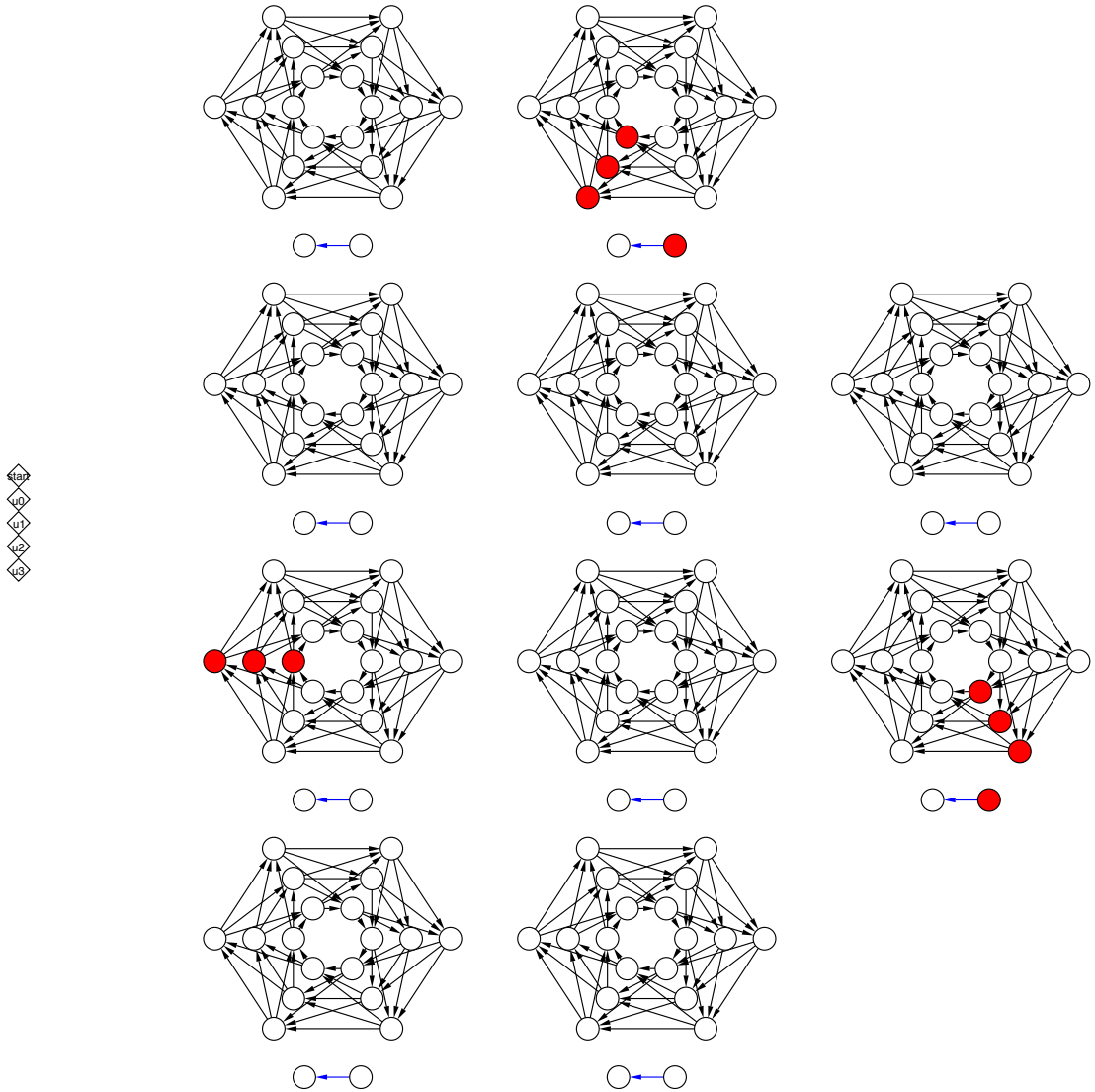
Simulation



Simulation



Simulation



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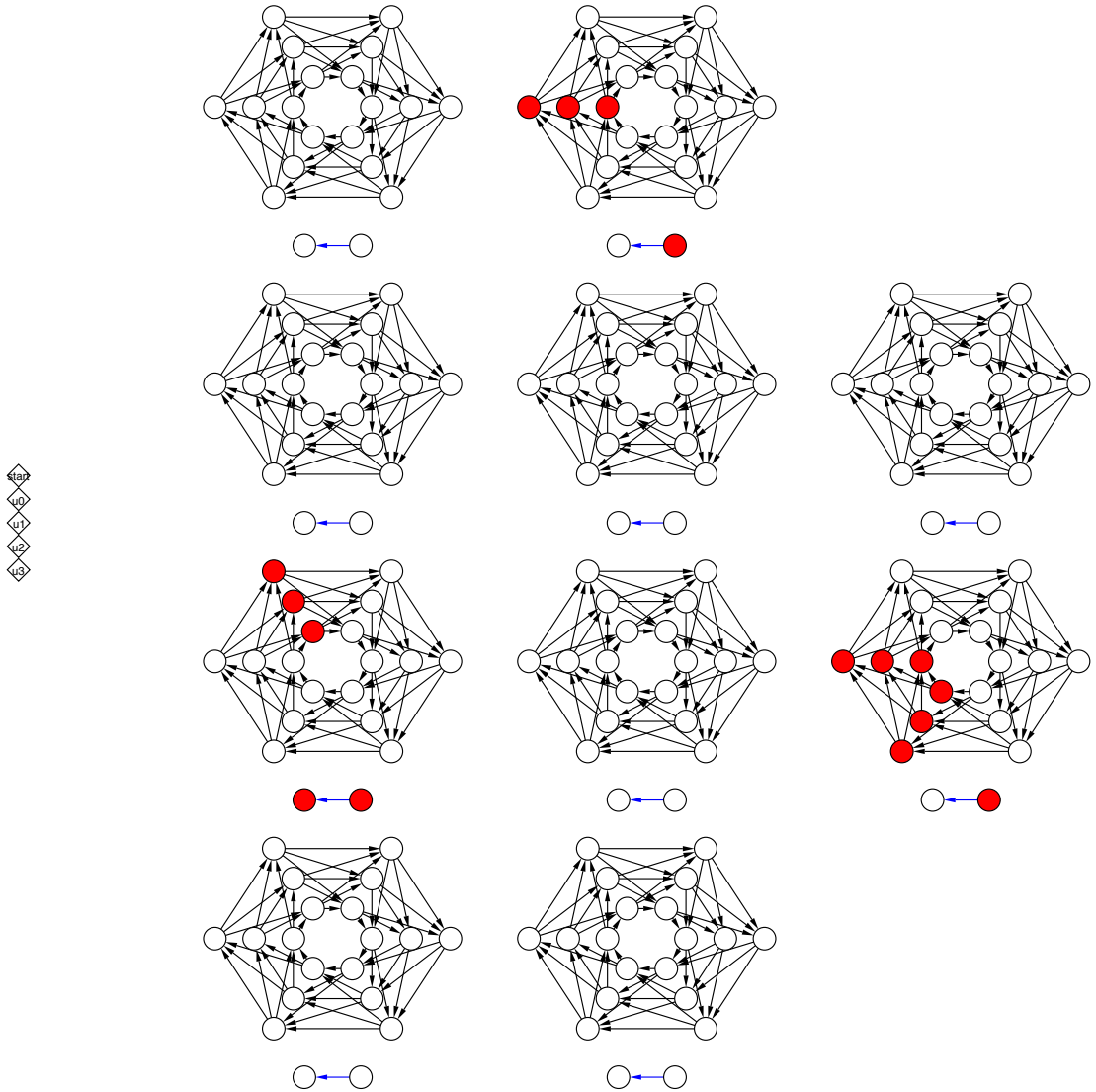

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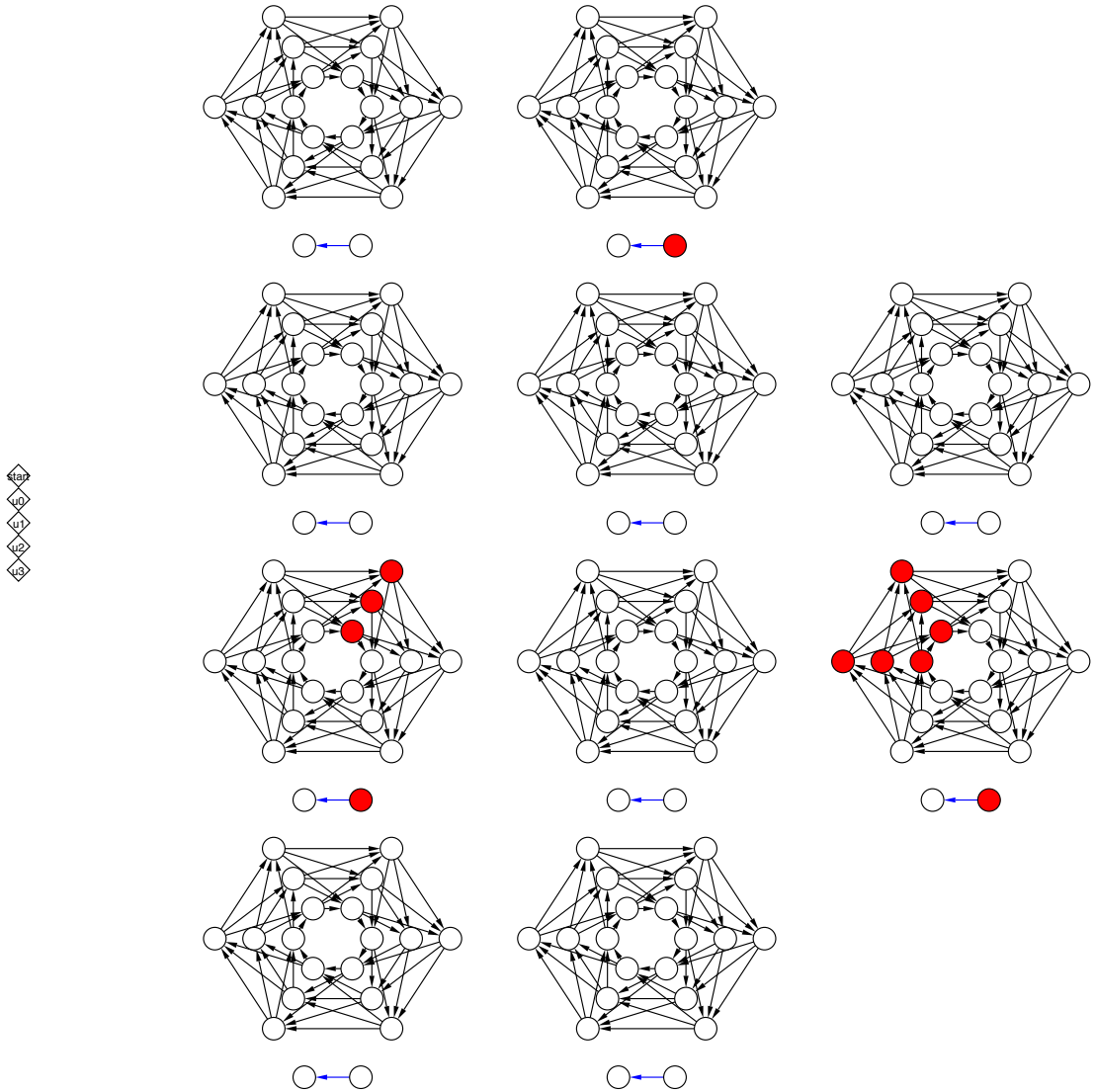

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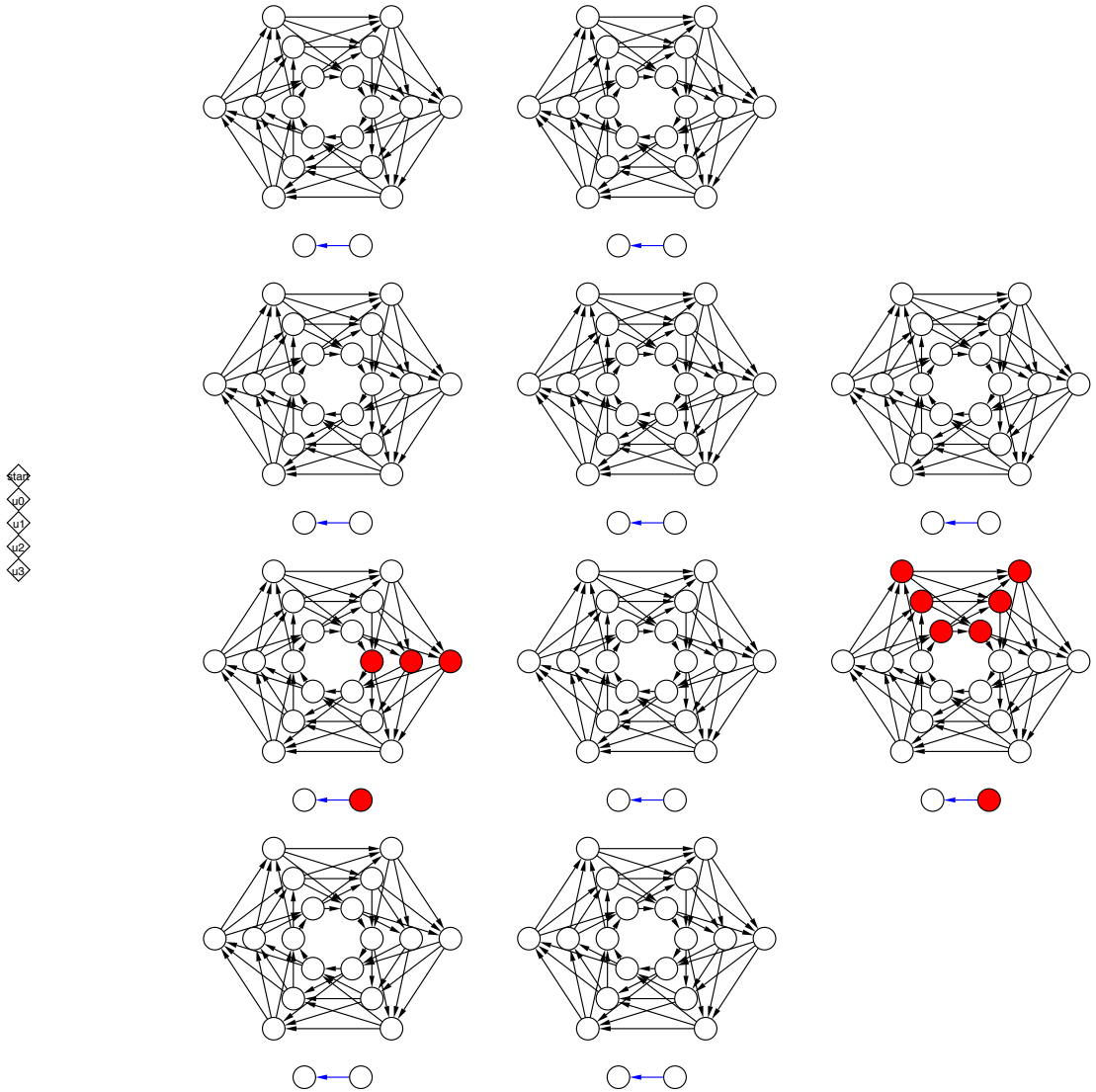

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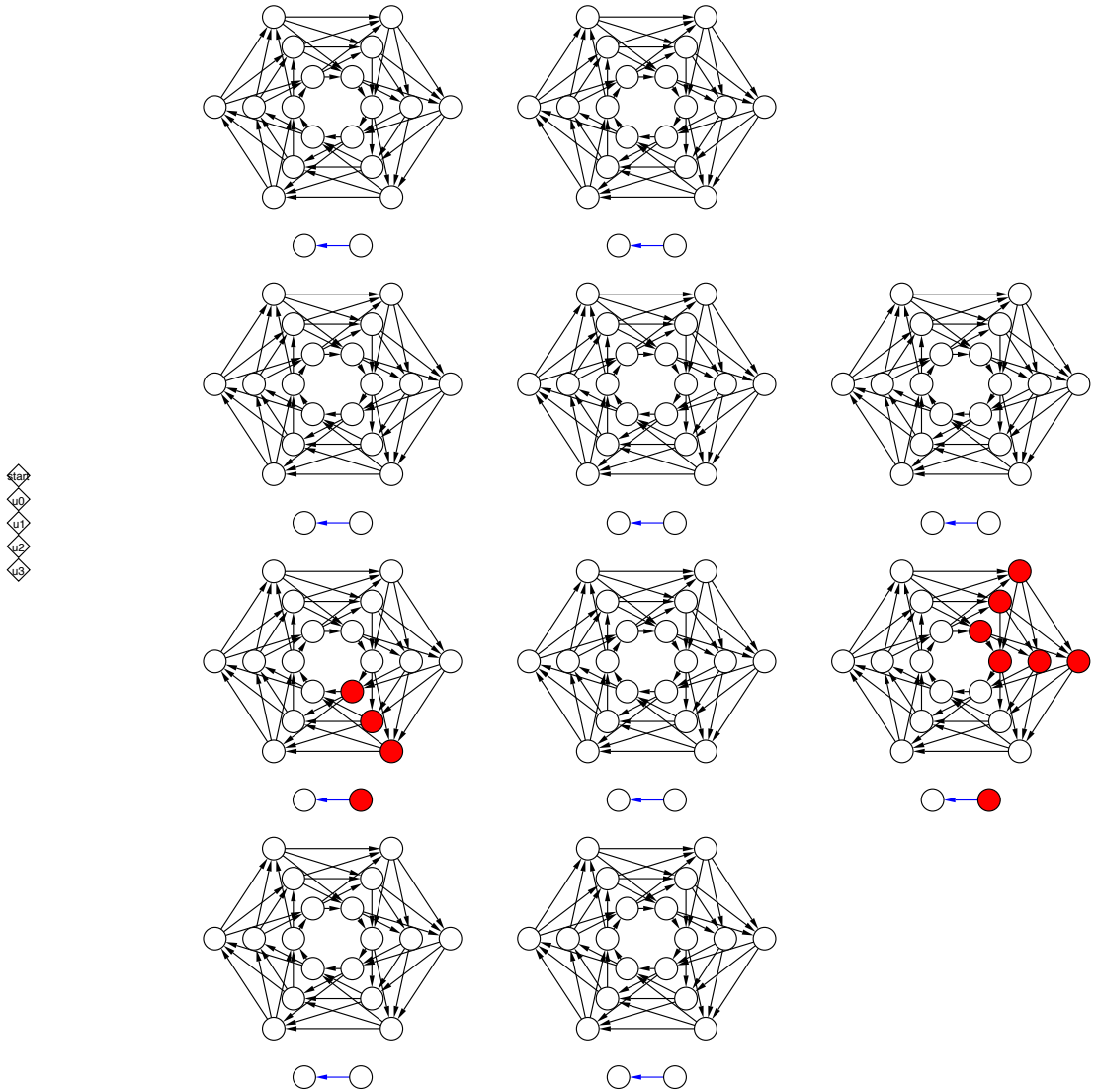
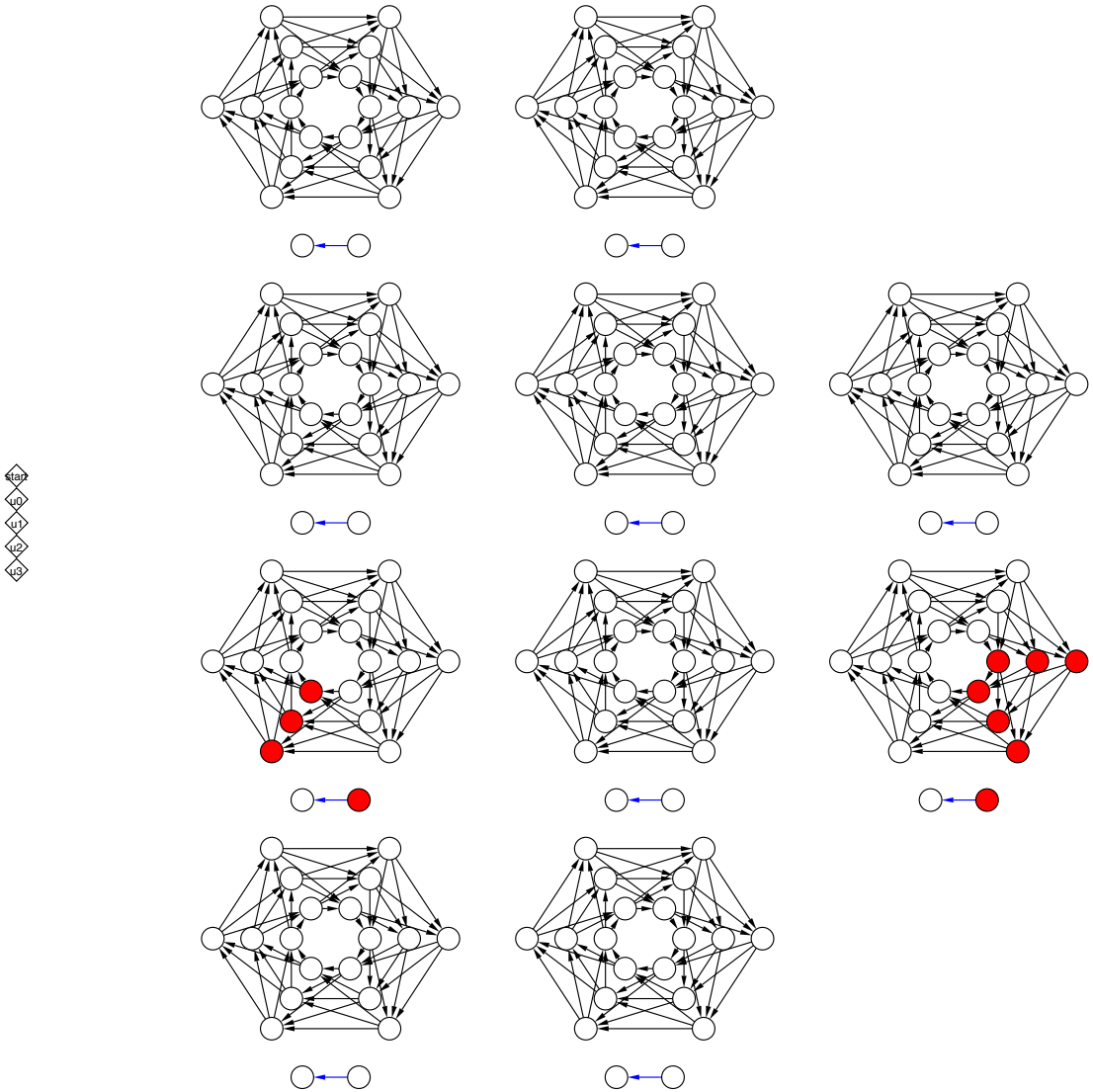
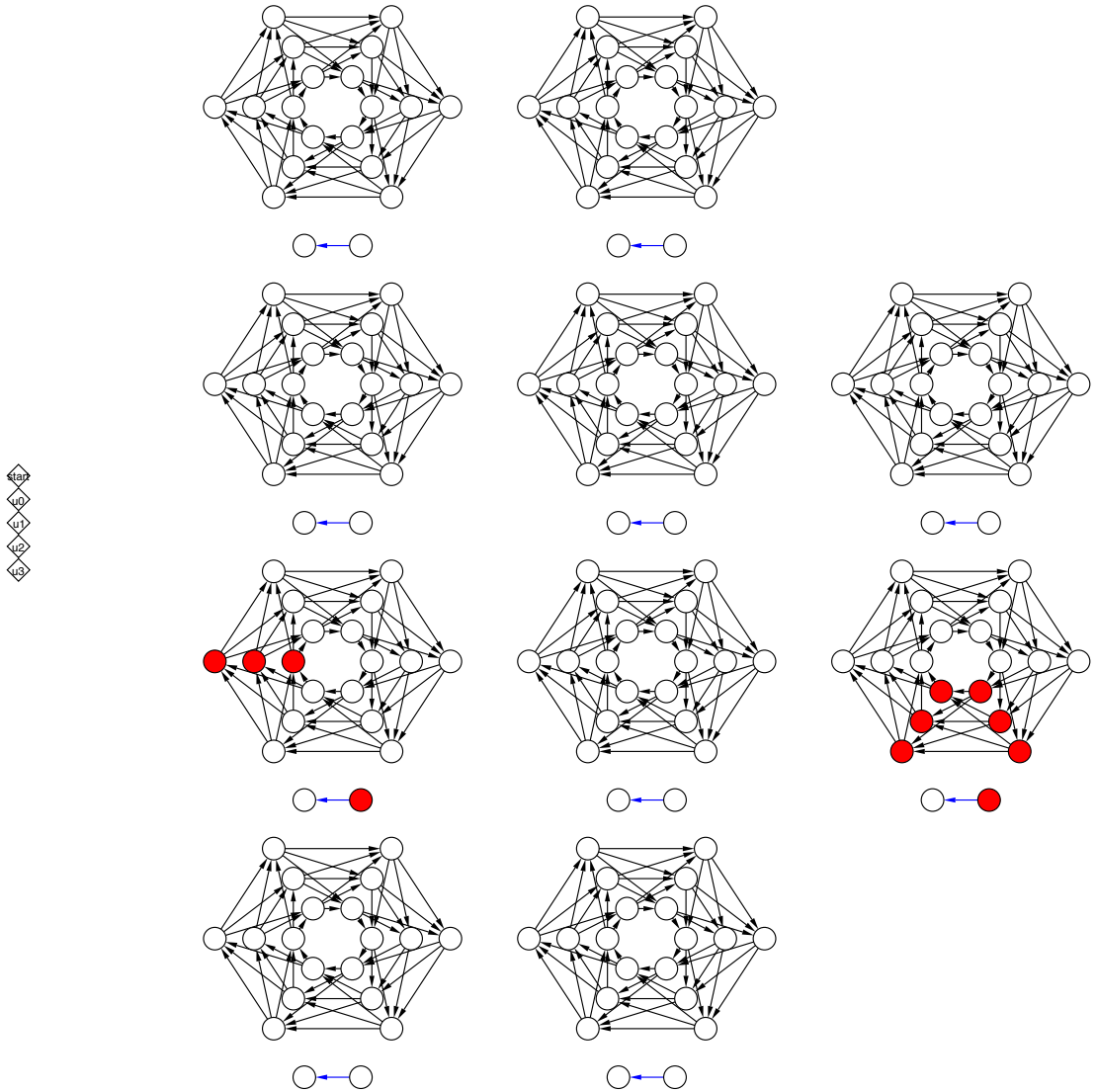


Simulation



Simulation



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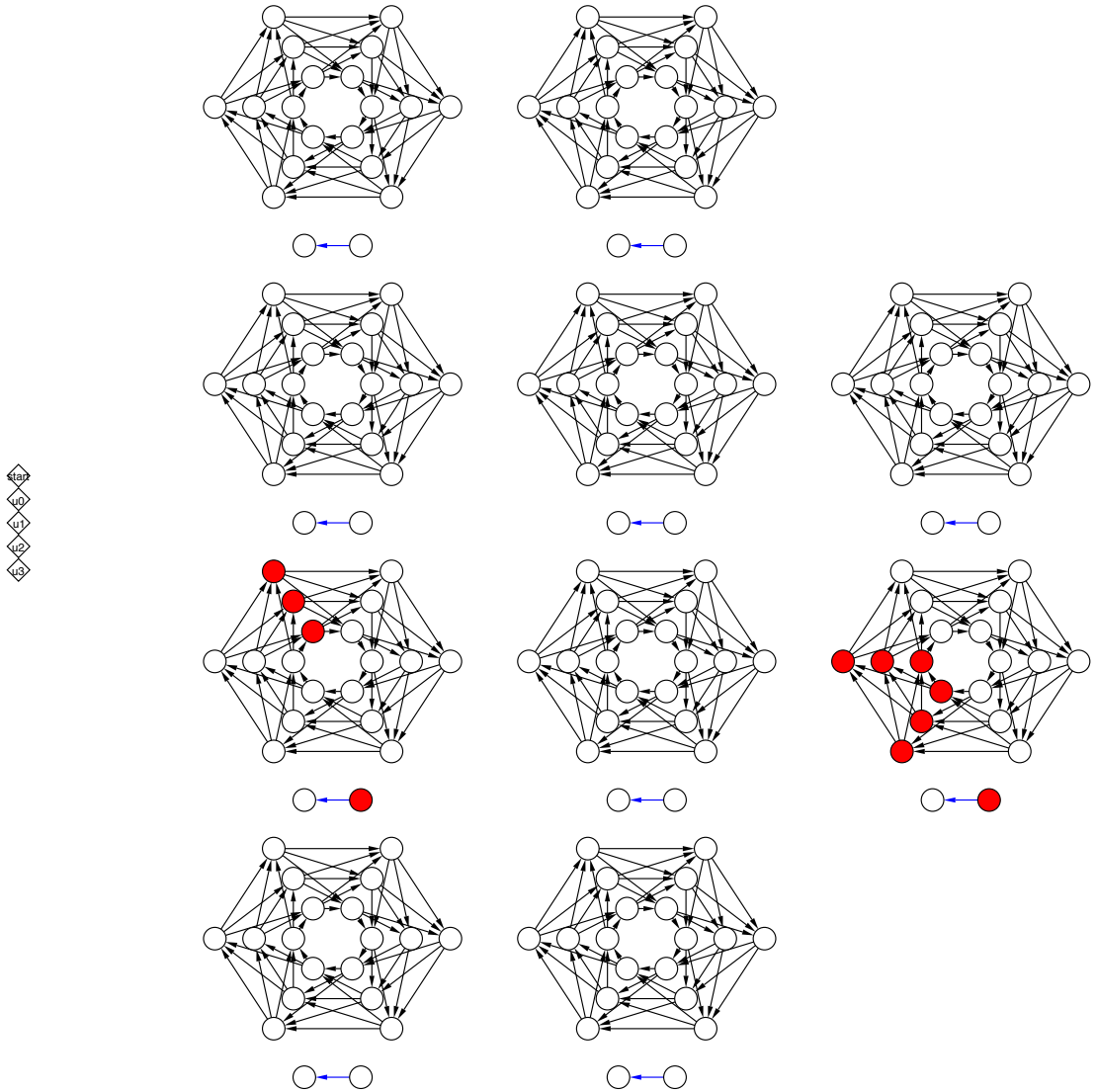
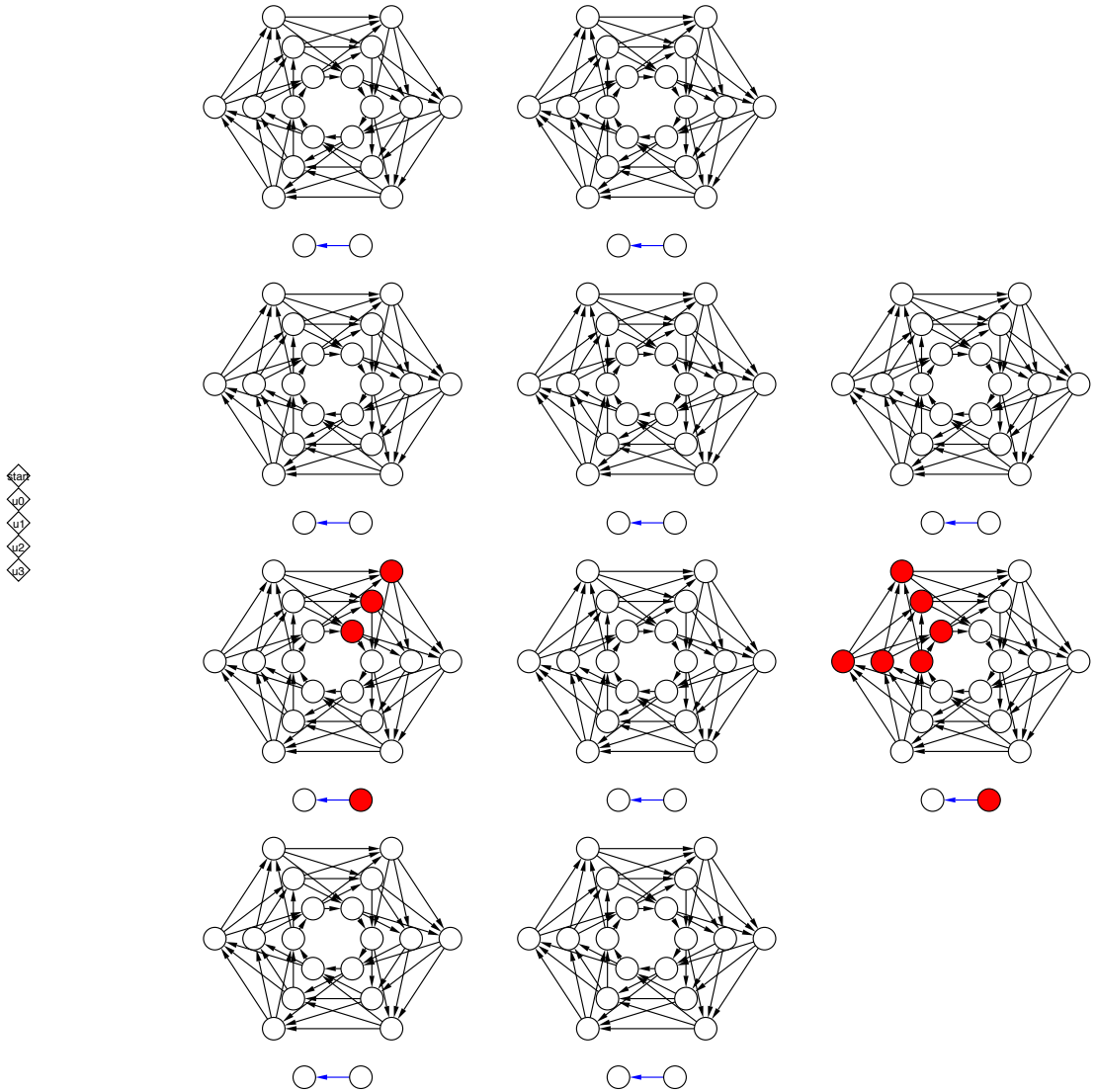


Simulation



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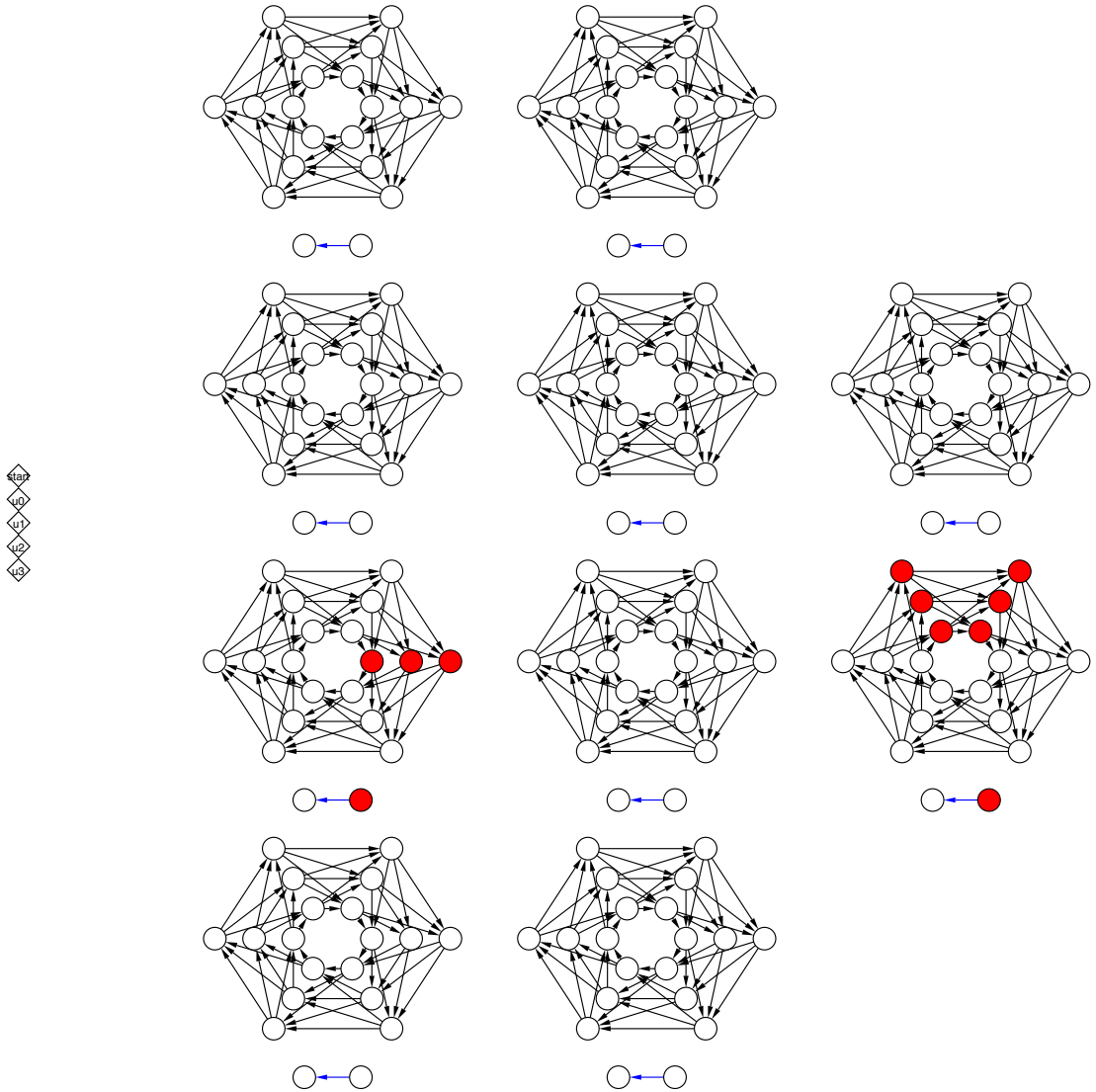
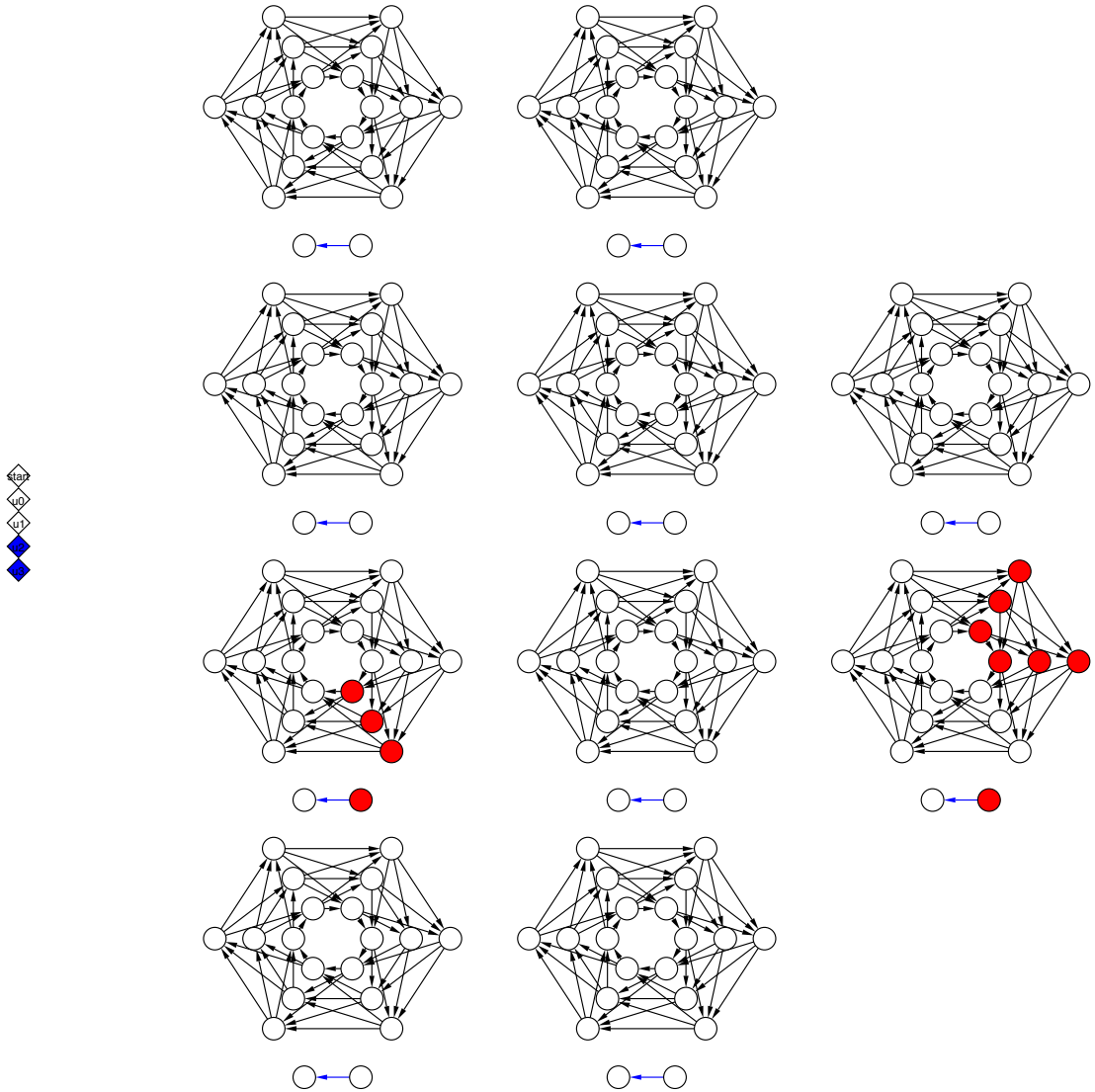


Simulation



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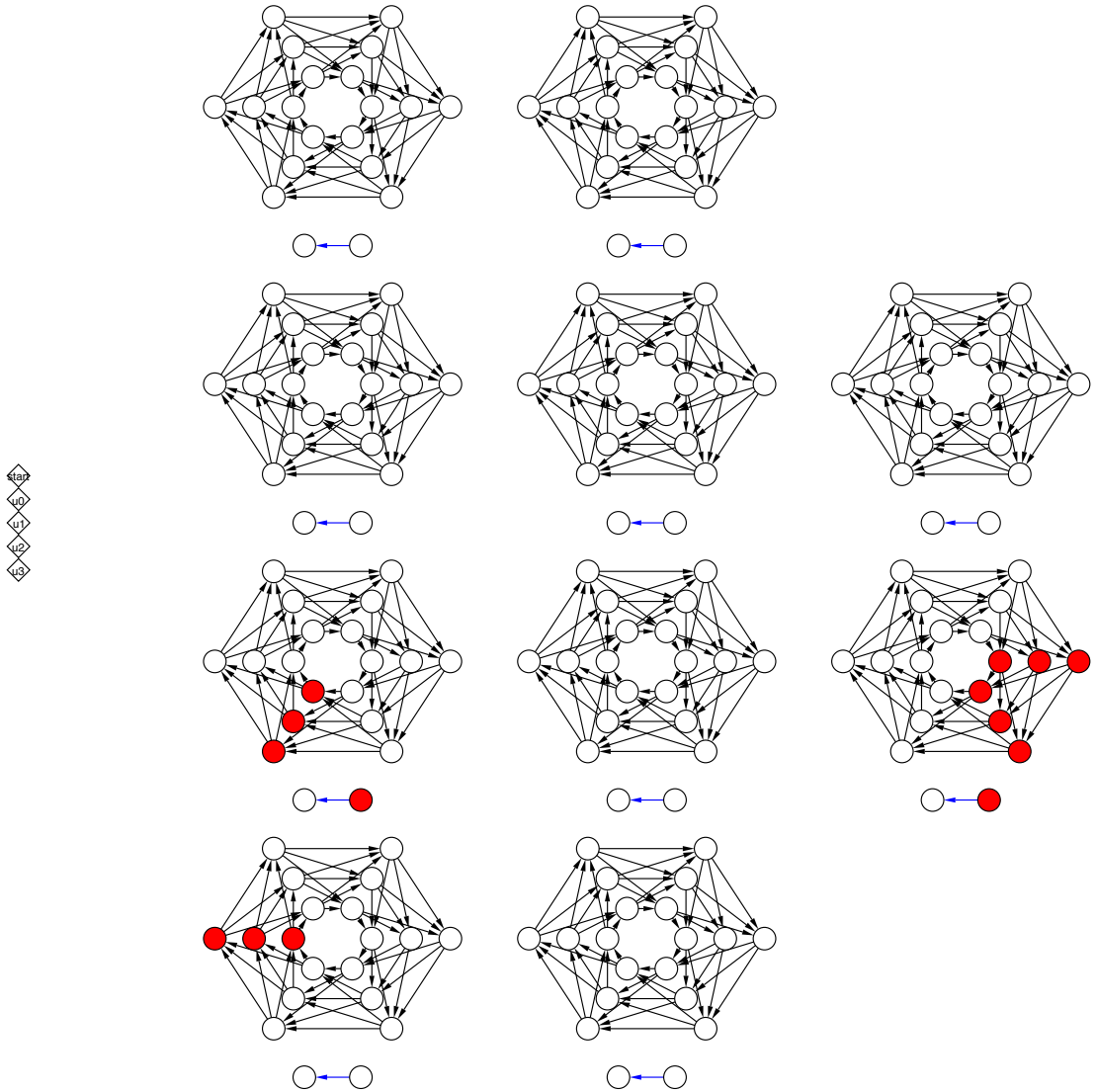

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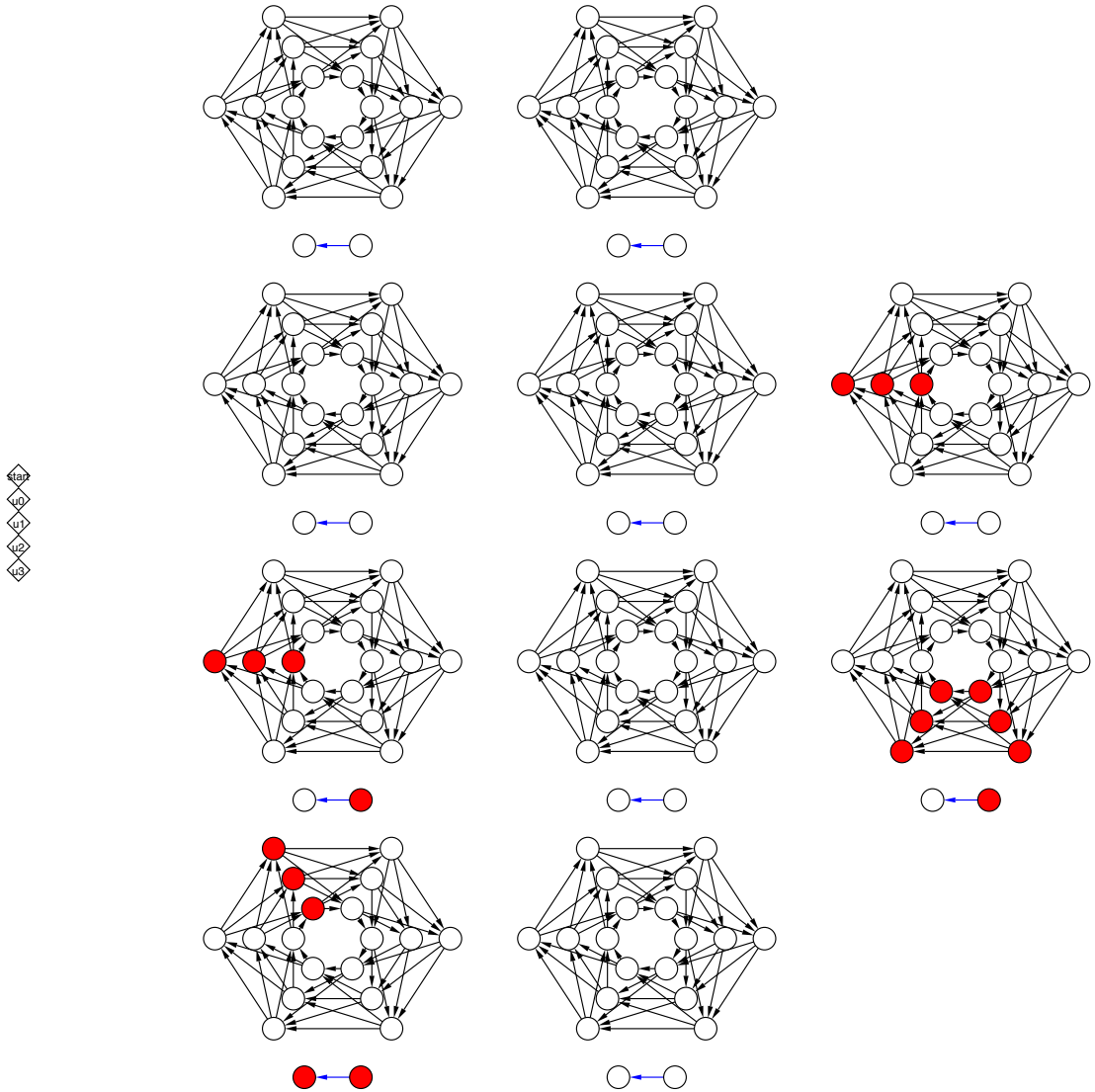

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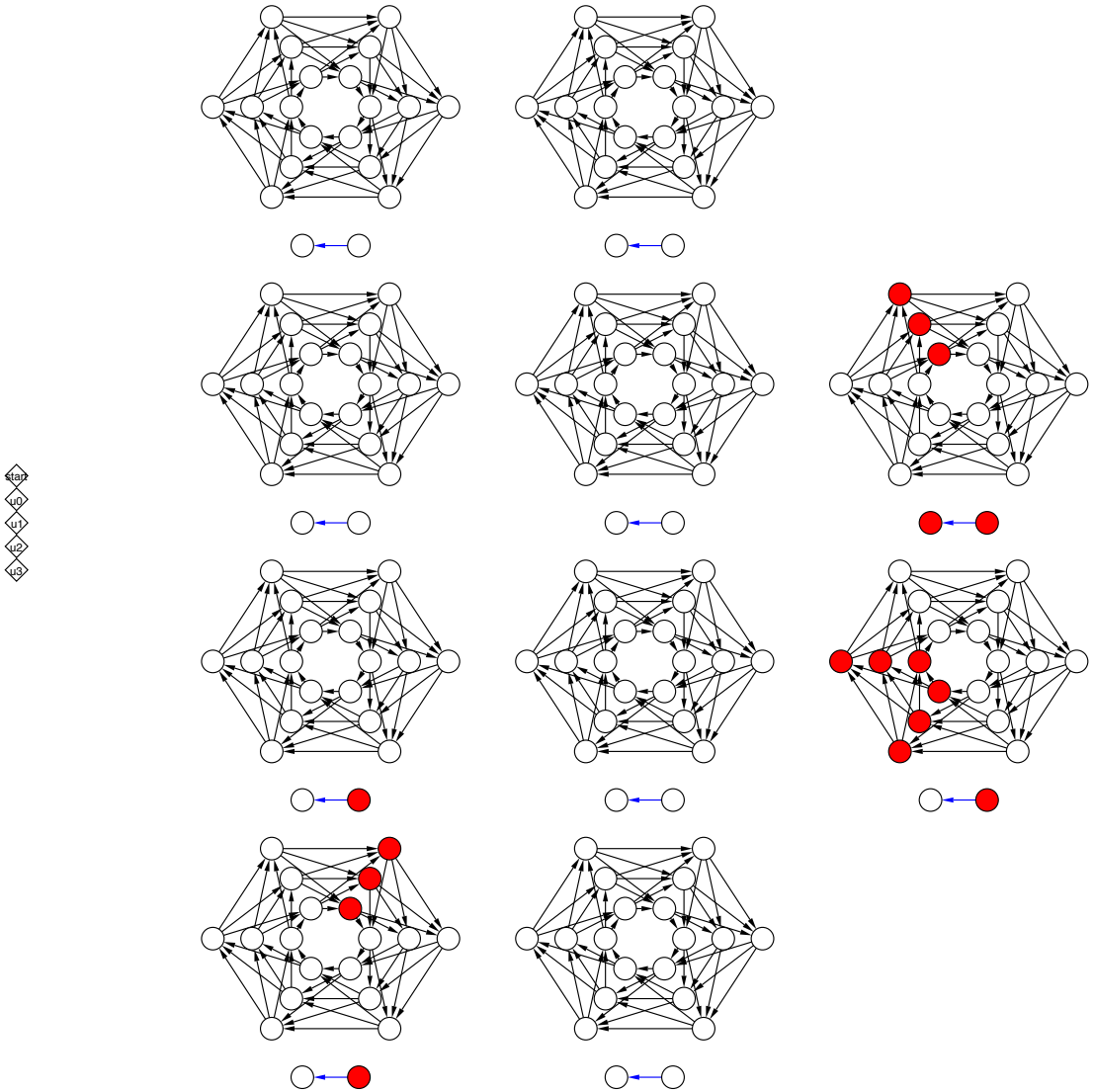
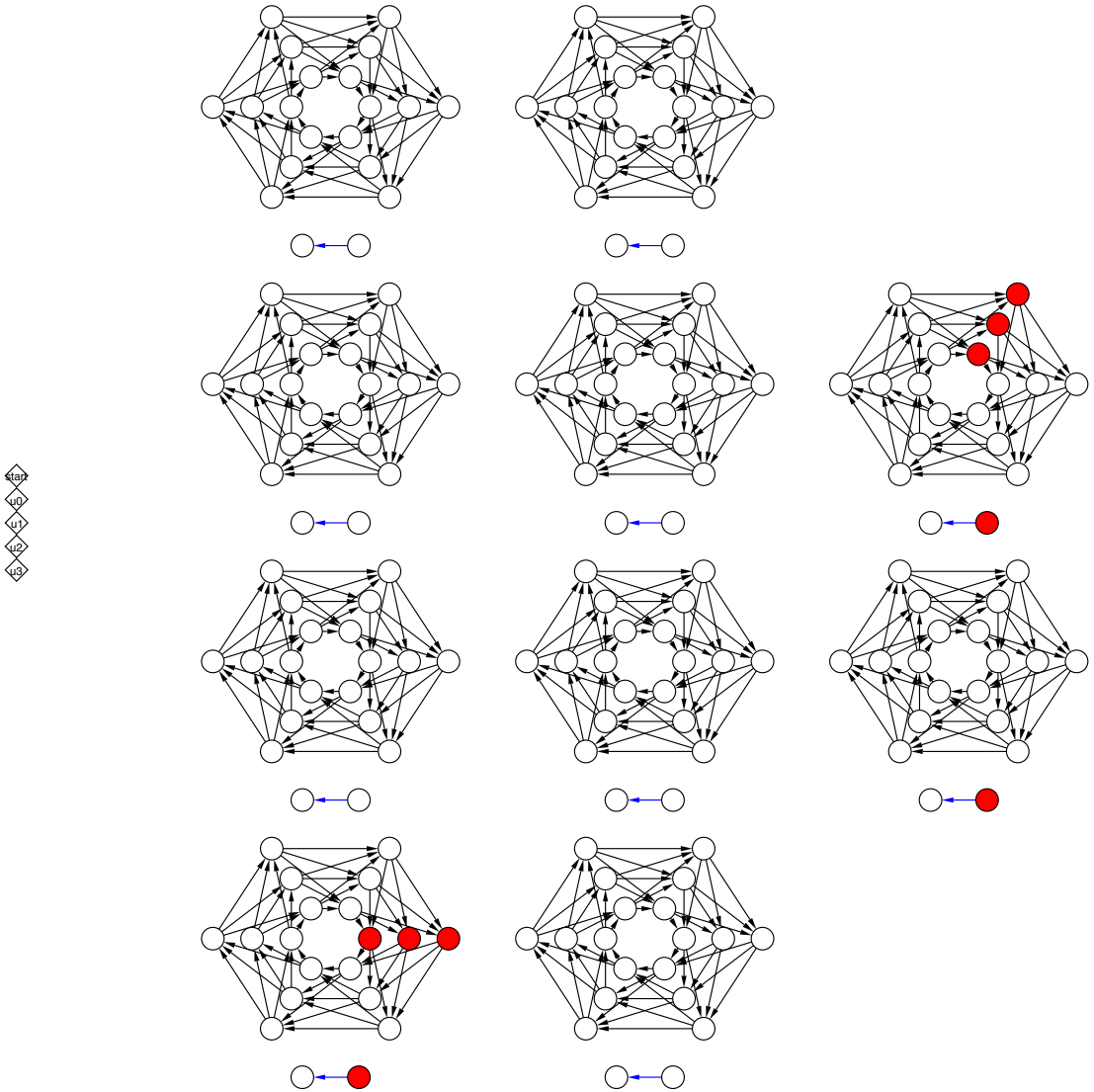
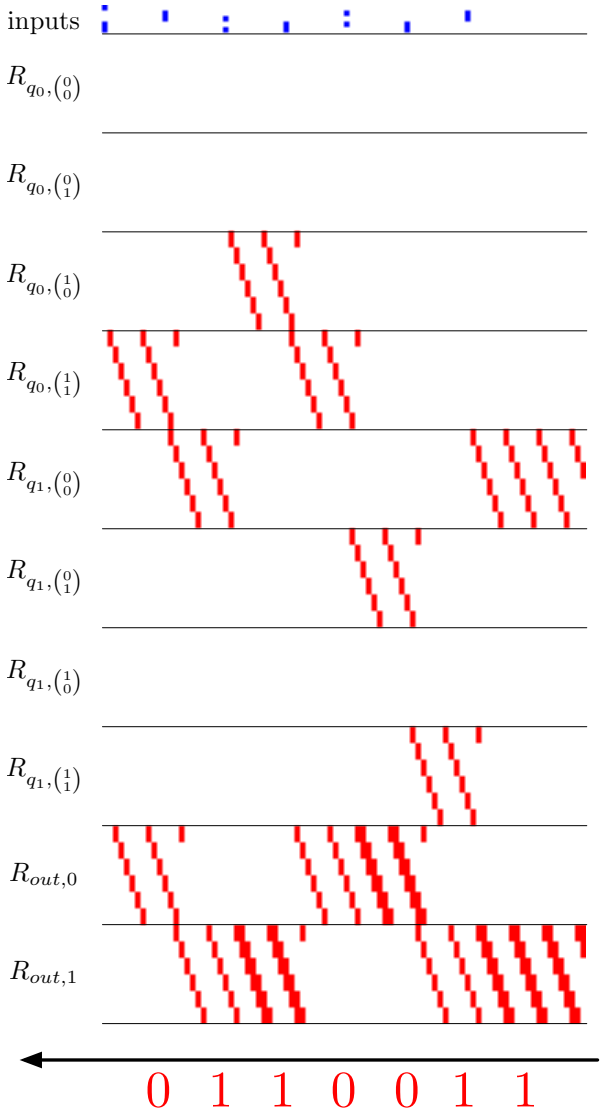


Simulation



Simulation


inputs
$R_{q_0,\binom{0}{0}}$
$R_{q_0,\binom{0}{1}}$
$R_{q_0,\binom{1}{0}}$
$R_{q_0,\binom{1}{1}}$
$R_{q_1,\binom{0}{0}}$
$R_{q_1,\binom{0}{1}}$
$R_{q_1,\binom{1}{0}}$
$R_{q_1,\binom{1}{1}}$
$R_{out,0}$
$R_{out,1}$
0 1 1 0 0 1 1

Automata & Boolean RNNs with Synfire Rings

Since the construction is generic, one has the following result:

Theorem

Any finite state automaton can be simulated by some Boolean neural network composed of synfire rings.

Hodgkin-Huxley Neurons (software demo)

$$\alpha_n(V_m) = \frac{0.01(10 - V_m)}{\exp(\frac{10-V_m}{10}) - 1} \qquad \beta_n(V_m) = 0.125 \exp(\frac{-V_m}{80})$$

$$\alpha_m(V_m) = \frac{0.1(25 - V_m)}{\exp(\frac{25-V_m}{10}) - 1} \qquad \beta_m(V_m) = 4 \exp(\frac{-V_m}{18})$$

$$\alpha_h(V_m) = 0.07 \exp(\frac{-V_m}{20}) \qquad \beta_h(V_m) = \frac{1}{\exp(\frac{30-V_m}{10}) + 1}$$

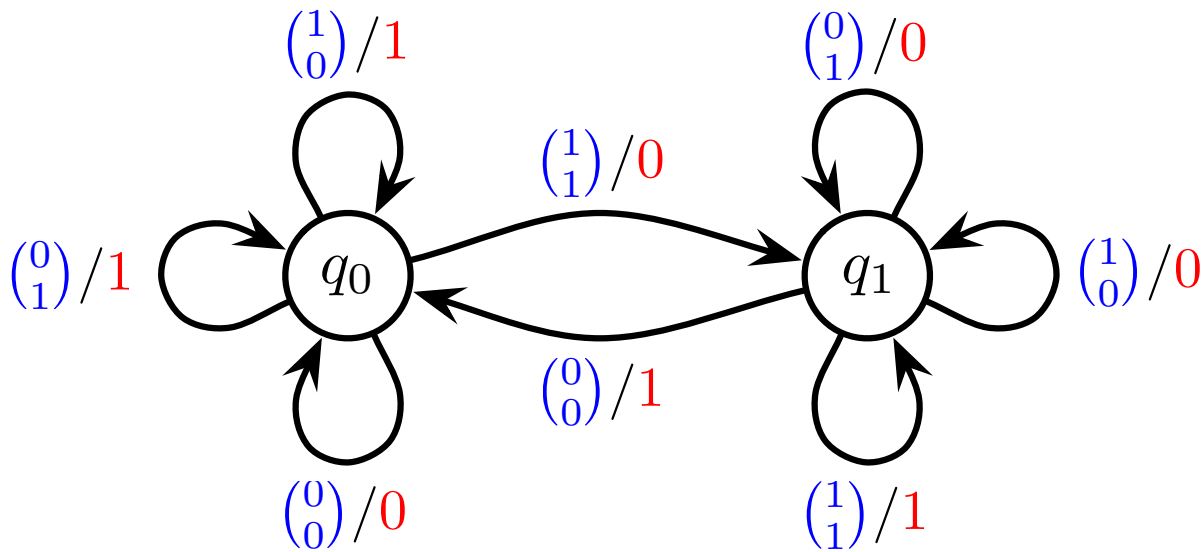
$$\frac{dn}{dt} = \alpha_n(V_m)(1 - n) - \beta_n(V_m)n$$

$$\frac{dm}{dt} = \alpha_m(V_m)(1 - m) - \beta_m(V_m)m$$

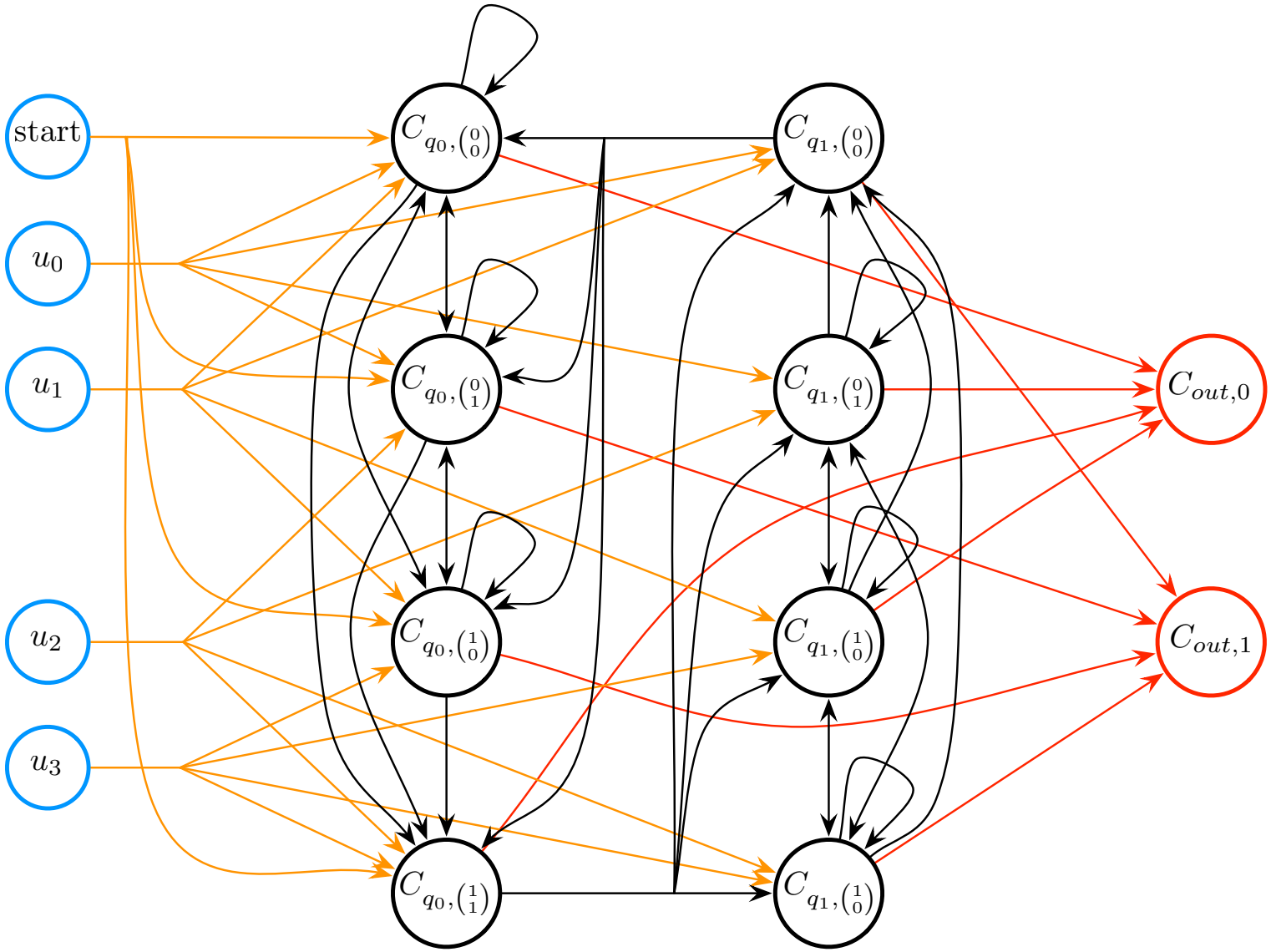
$$\frac{dh}{dt} = \alpha_h(V_m)(1 - h) - \beta_h(V_m)h$$

$$C_m \frac{dV_m}{dt} = I - \bar{g}_{\mathsf{K}} n^4 (V_m - V_K) - \bar{g}_{\mathsf{Na}} m^3 h (V_m - V_{Na}) - \bar{g}_l (V_m - V_l)$$

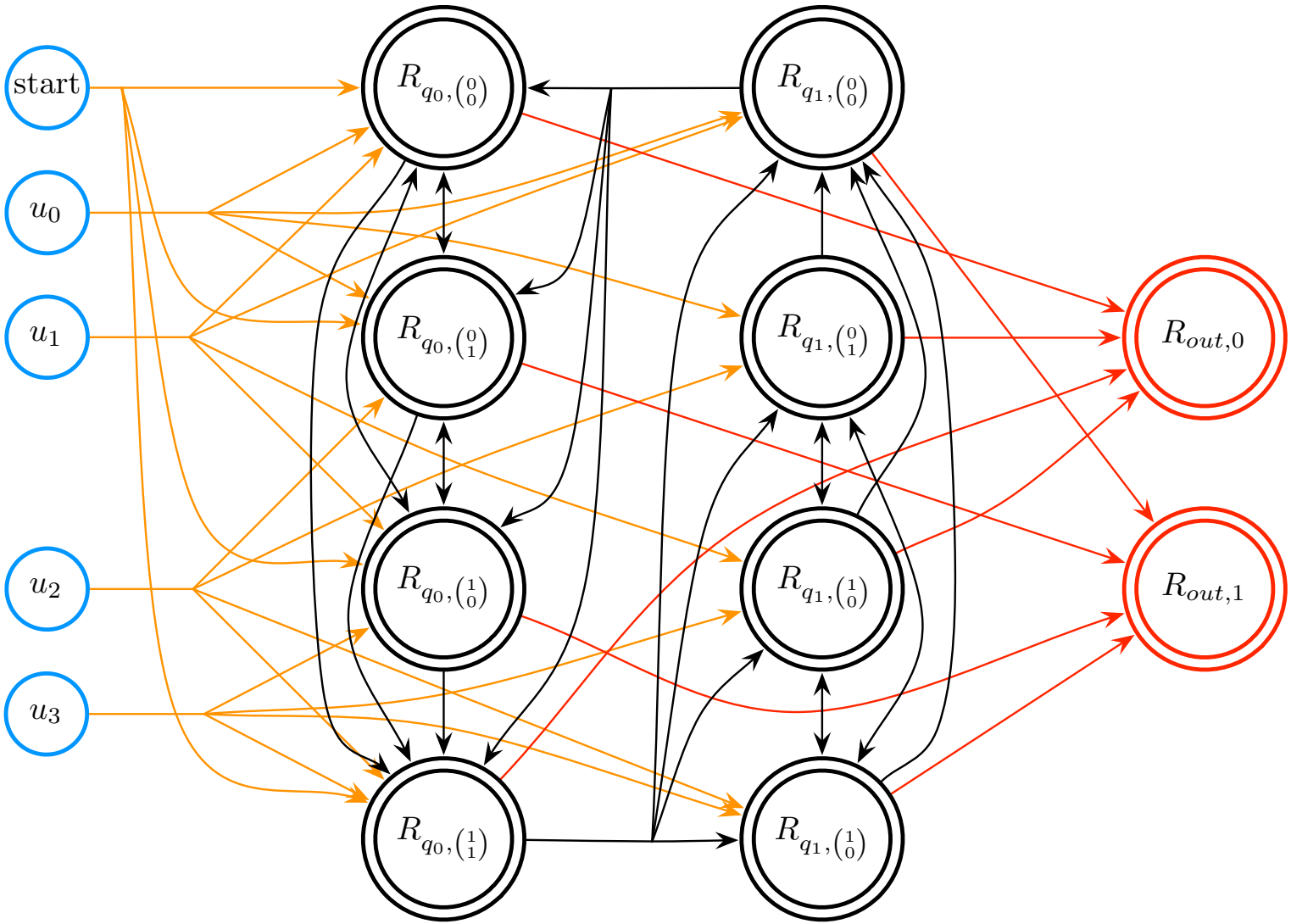
General Construction



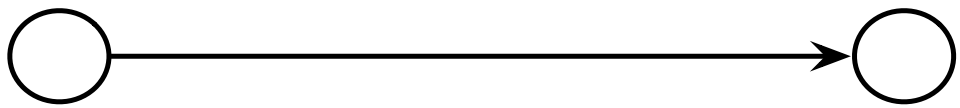
General Construction



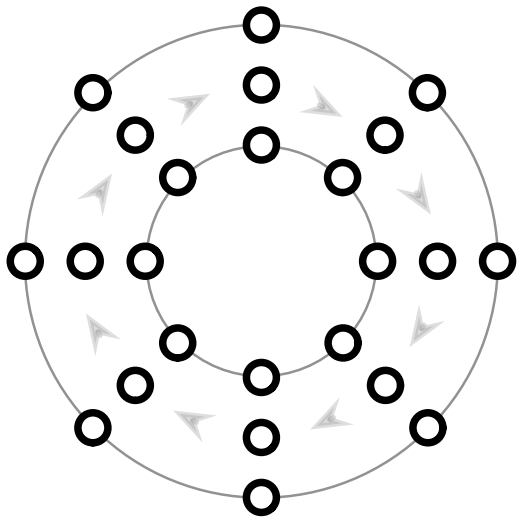
General Construction

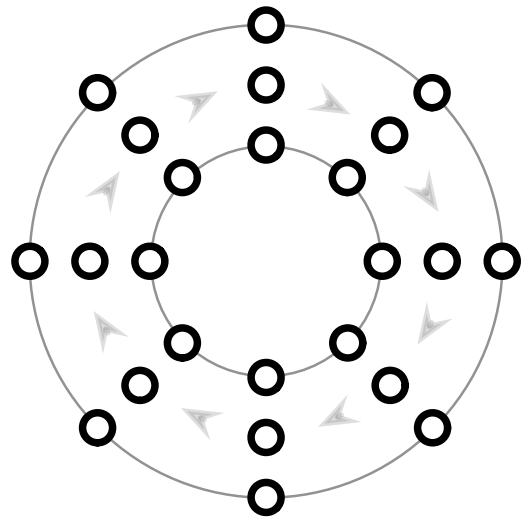


Fibres of connections & Inhibitory System

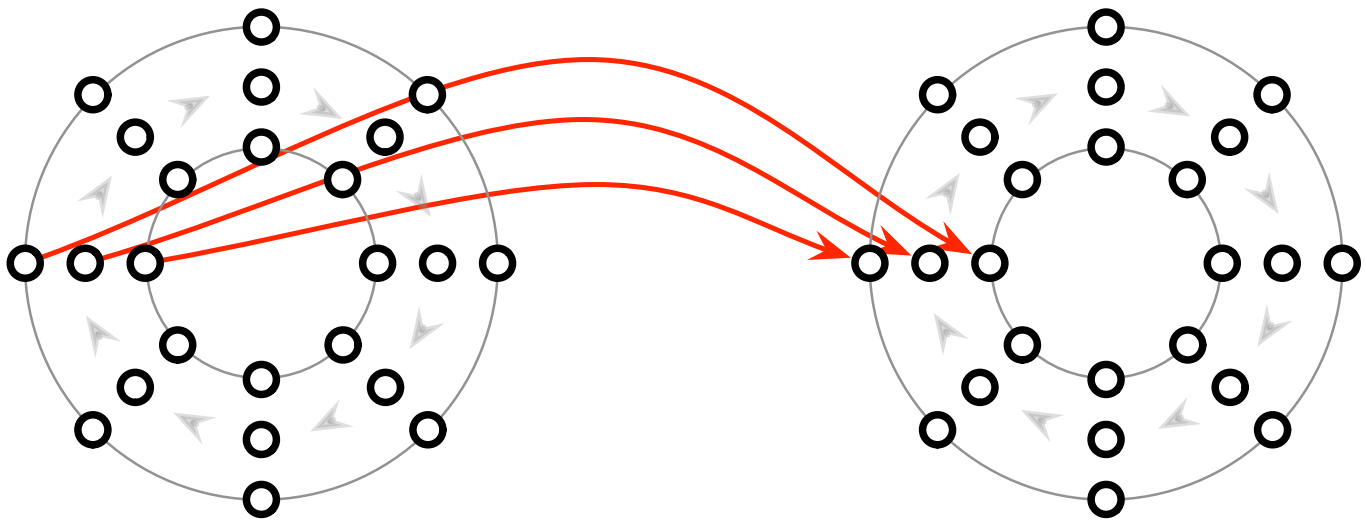


Fibres of connections & Inhibitory System





Fibres of connections & Inhibitory System



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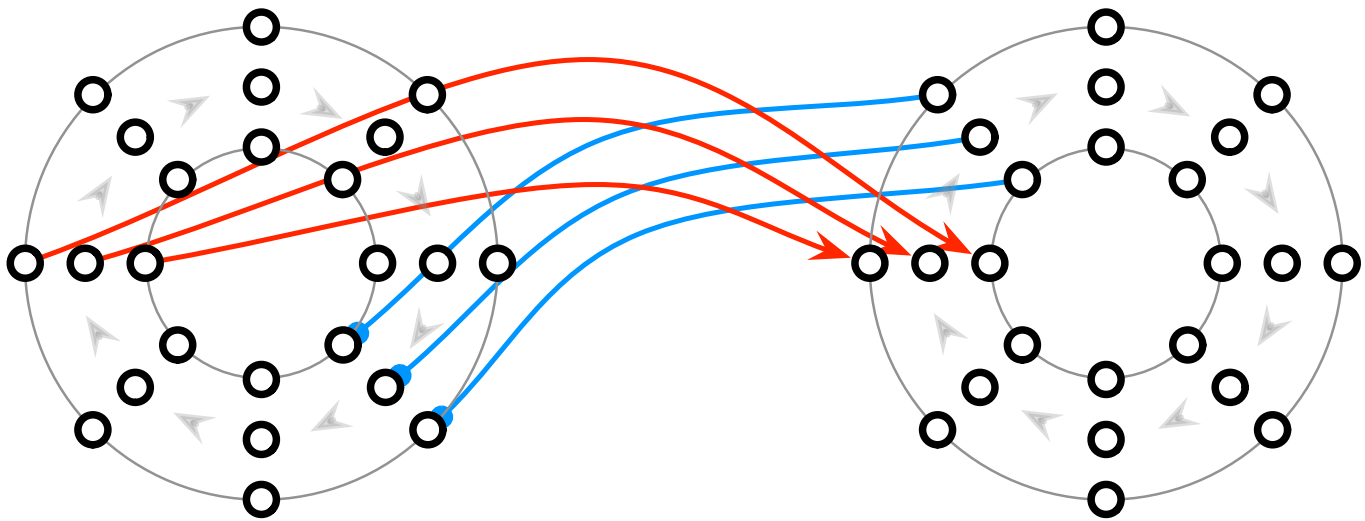
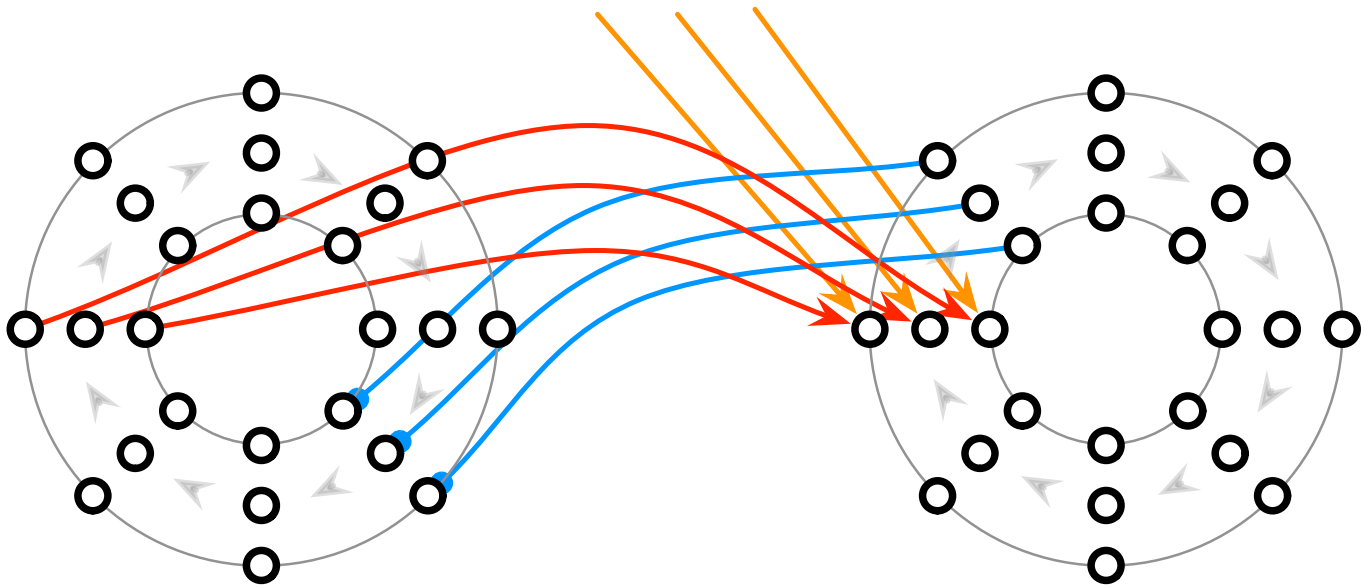
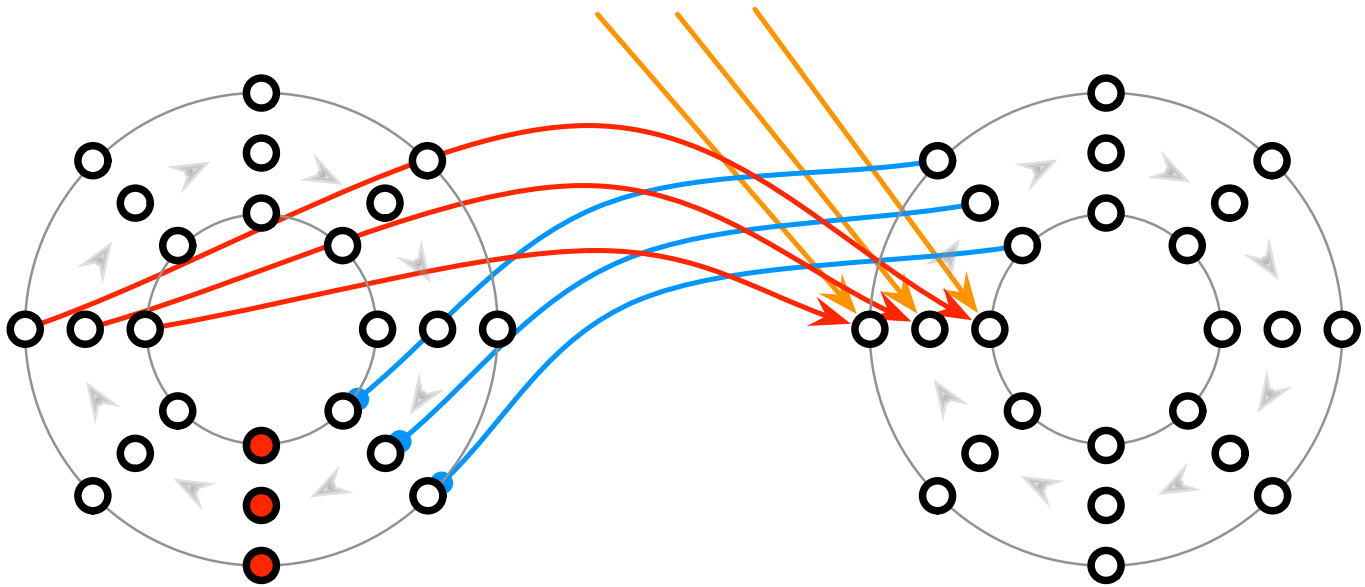


Fibres of connections & Inhibitory System



Fibres of connections & Inhibitory System



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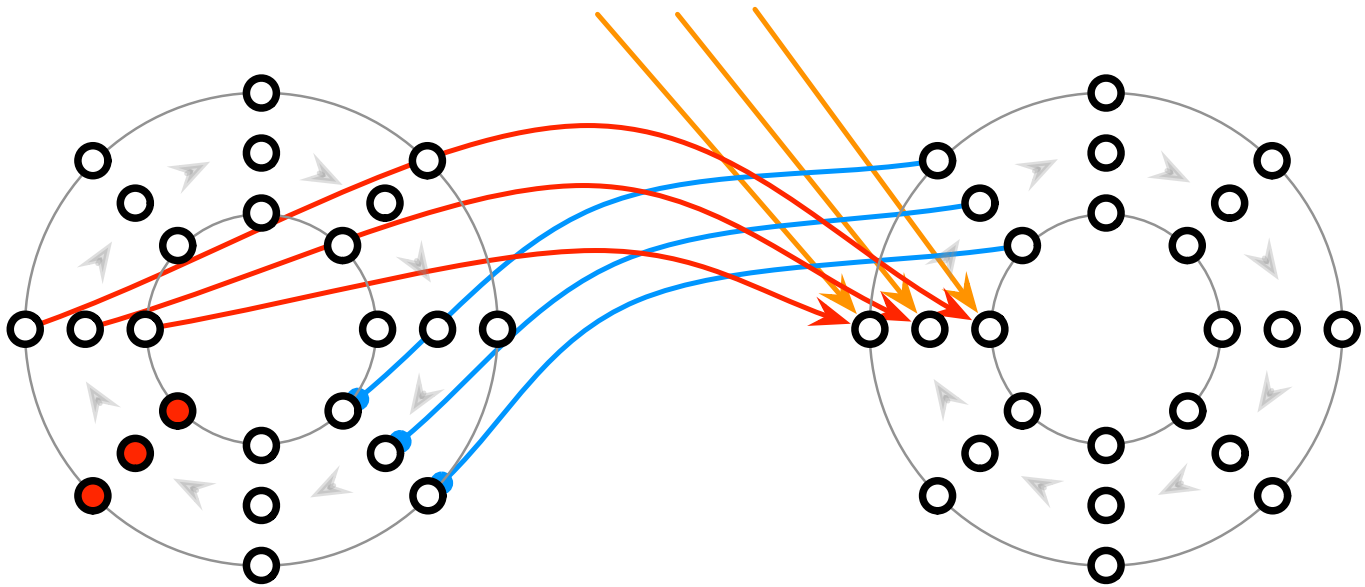
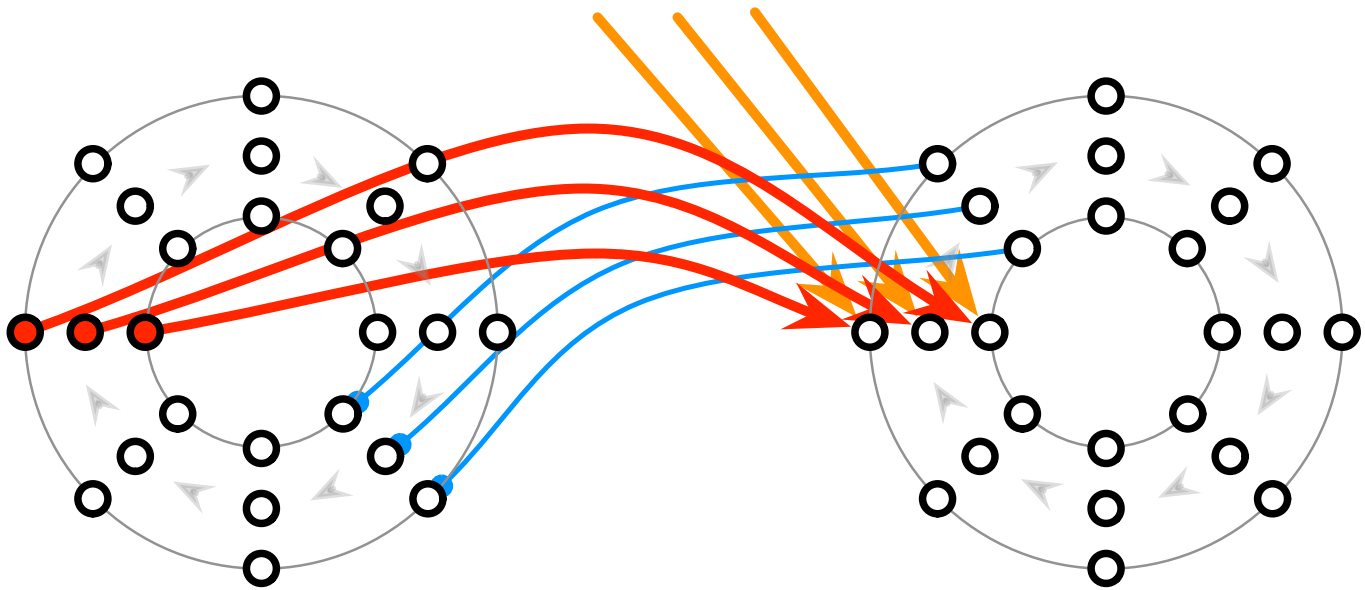
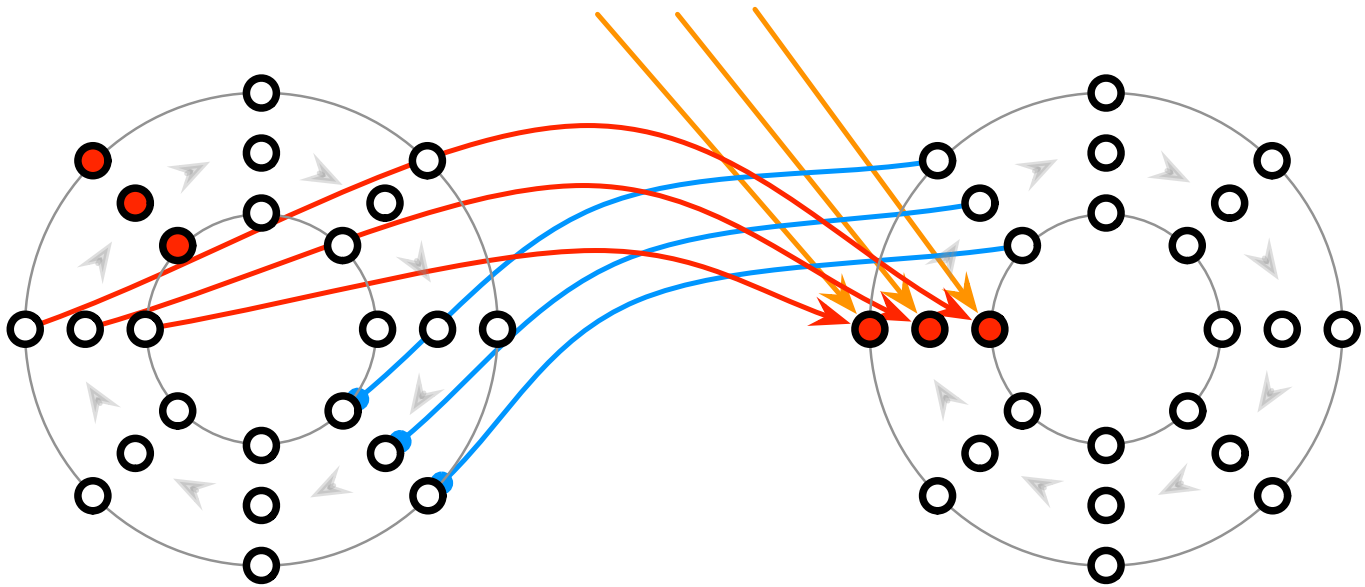


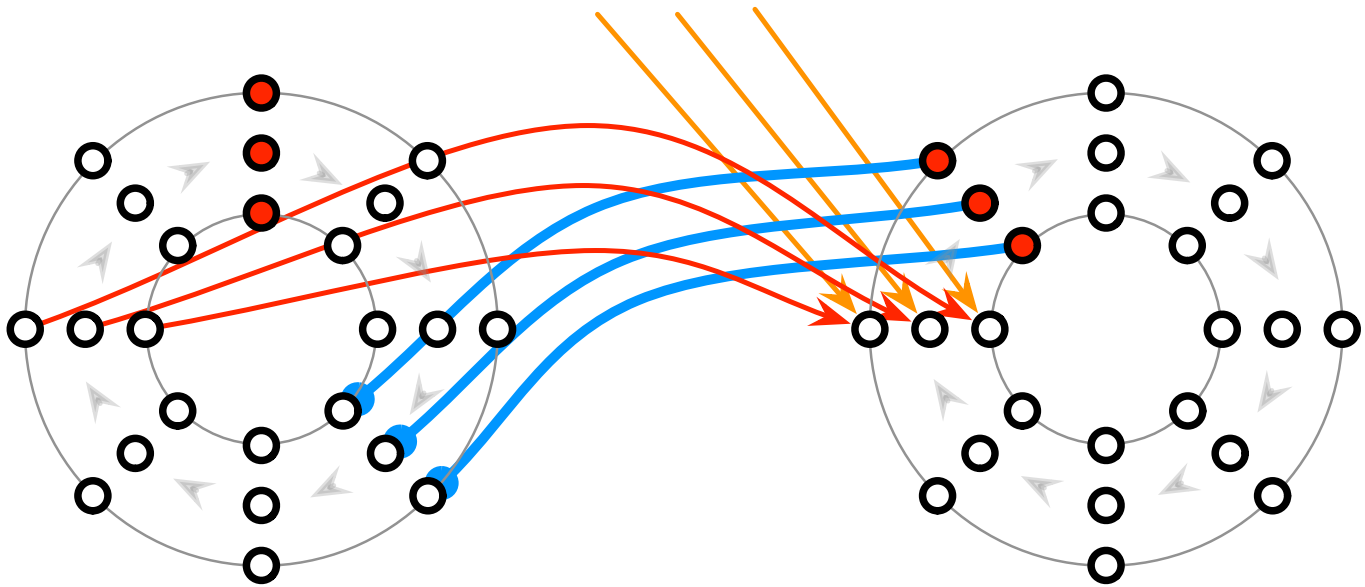
Fibres of connections & Inhibitory System



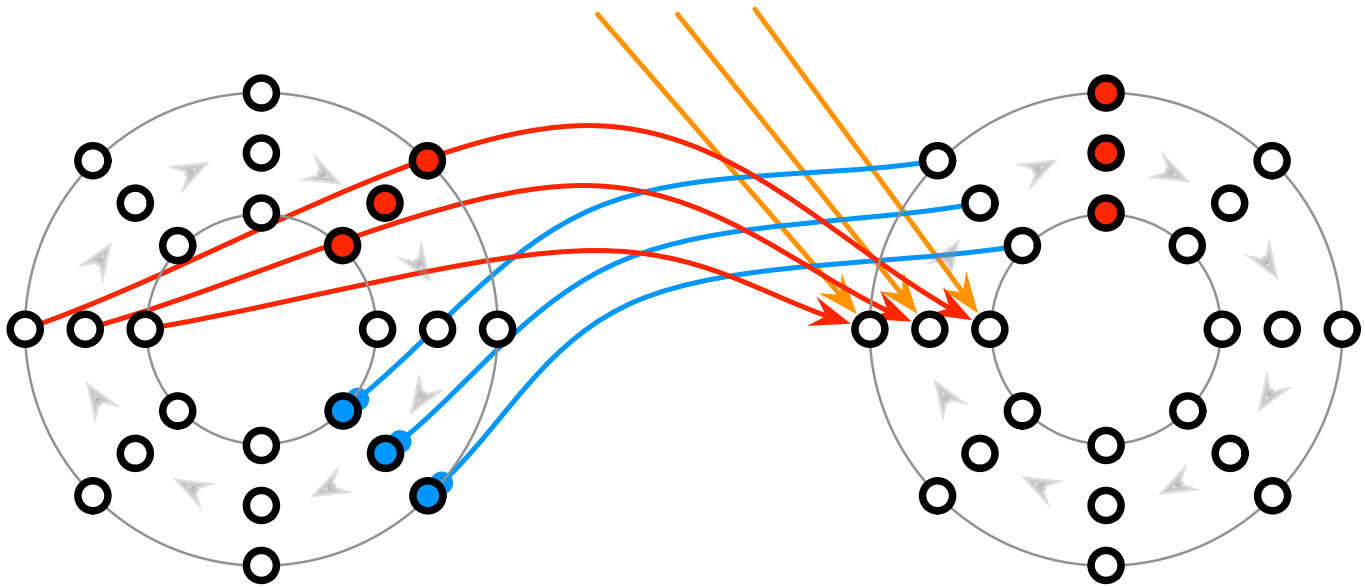
Fibres of connections & Inhibitory System



Fibres of connections & Inhibitory System



Fibres of connections & Inhibitory System



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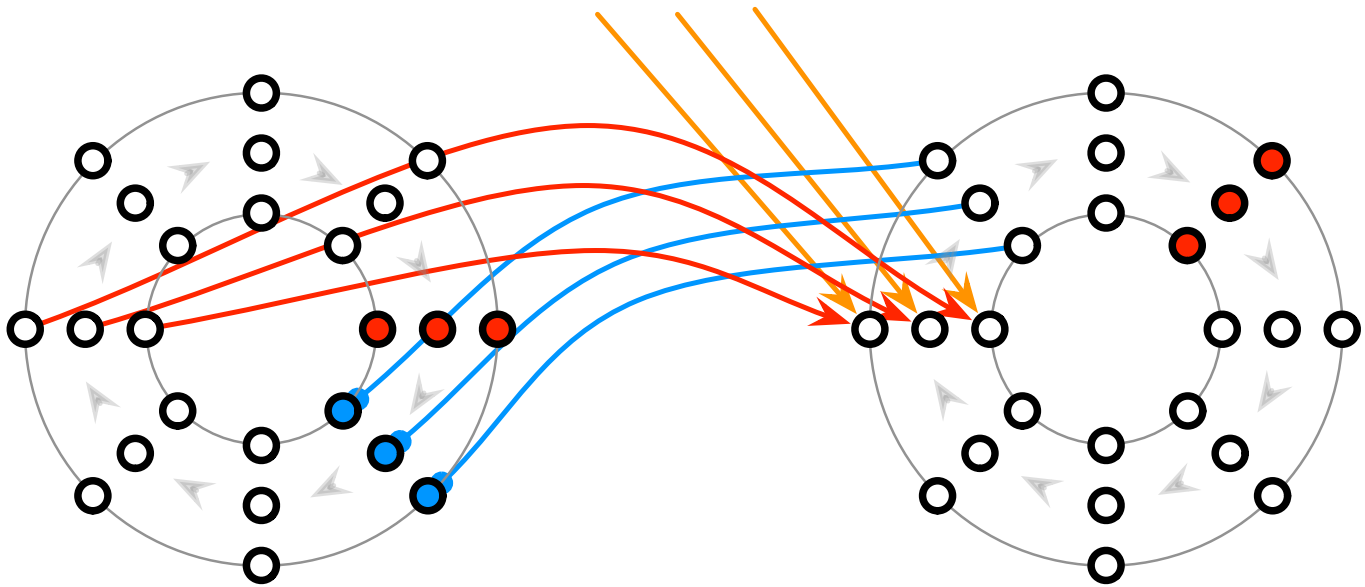

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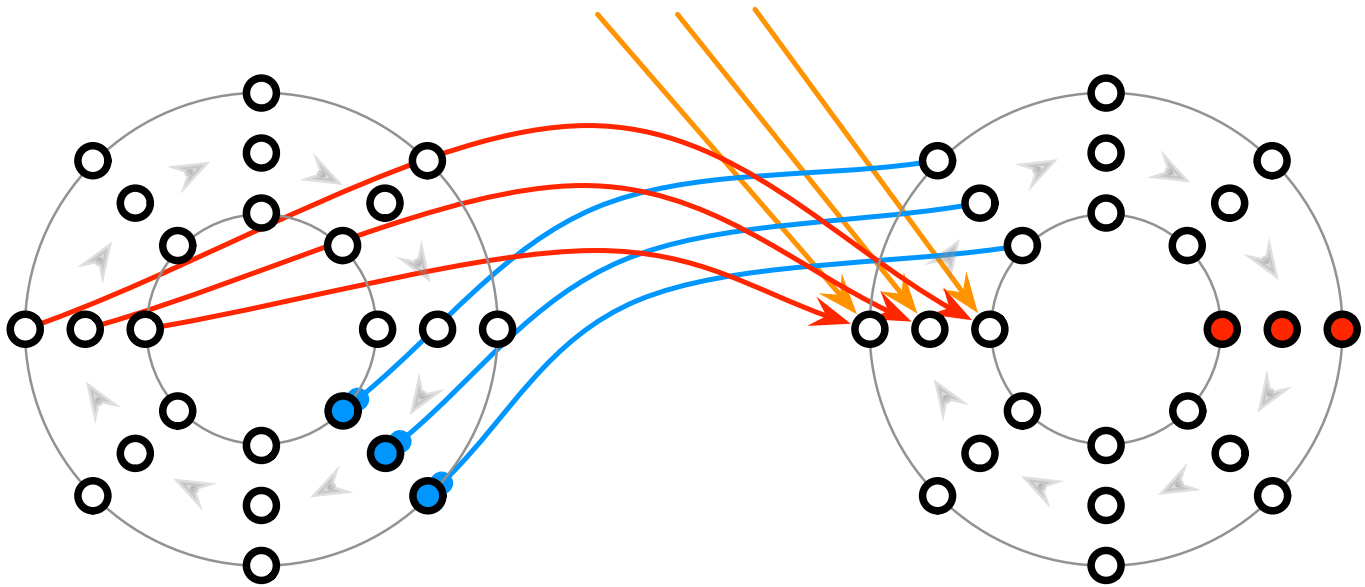

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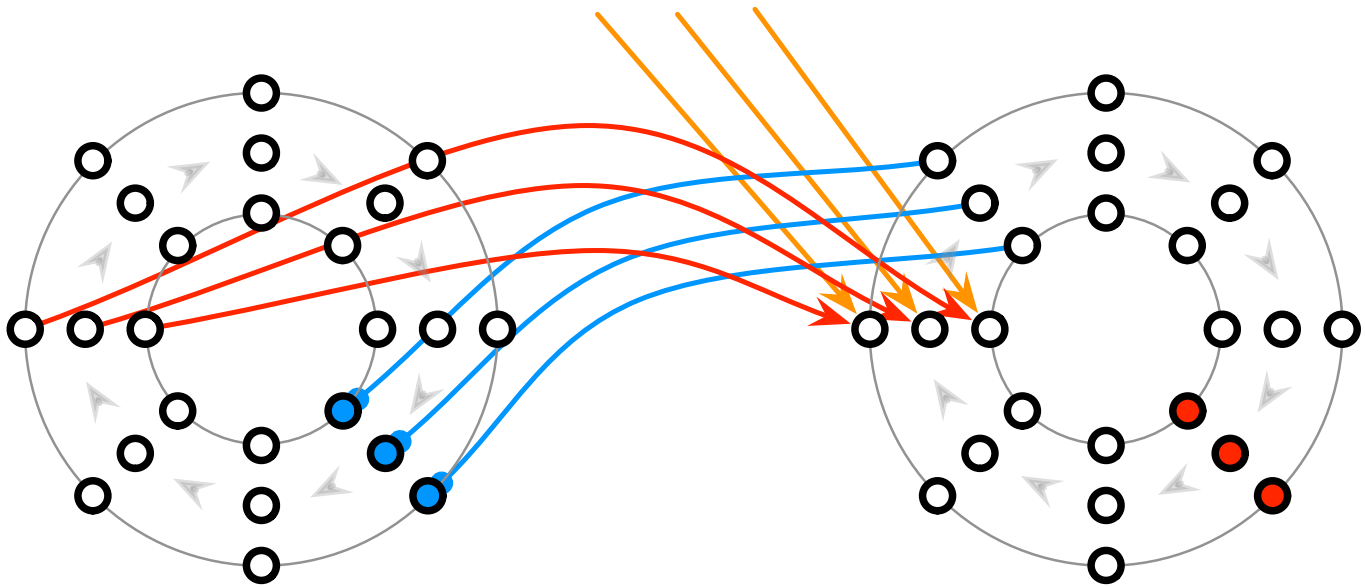

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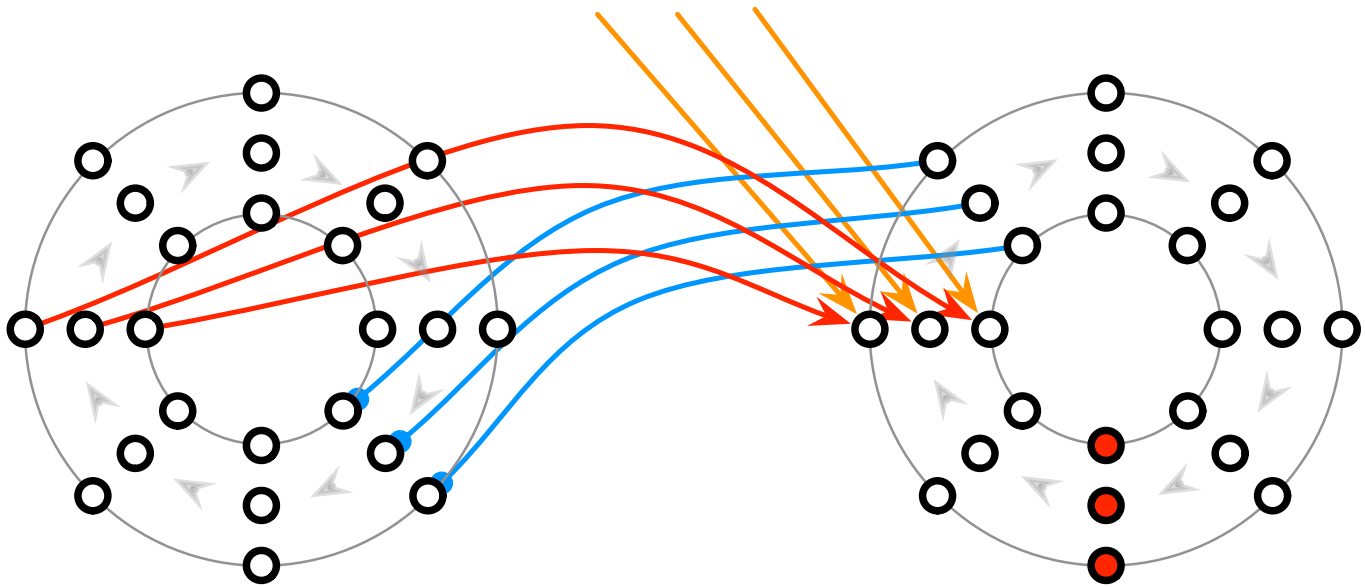
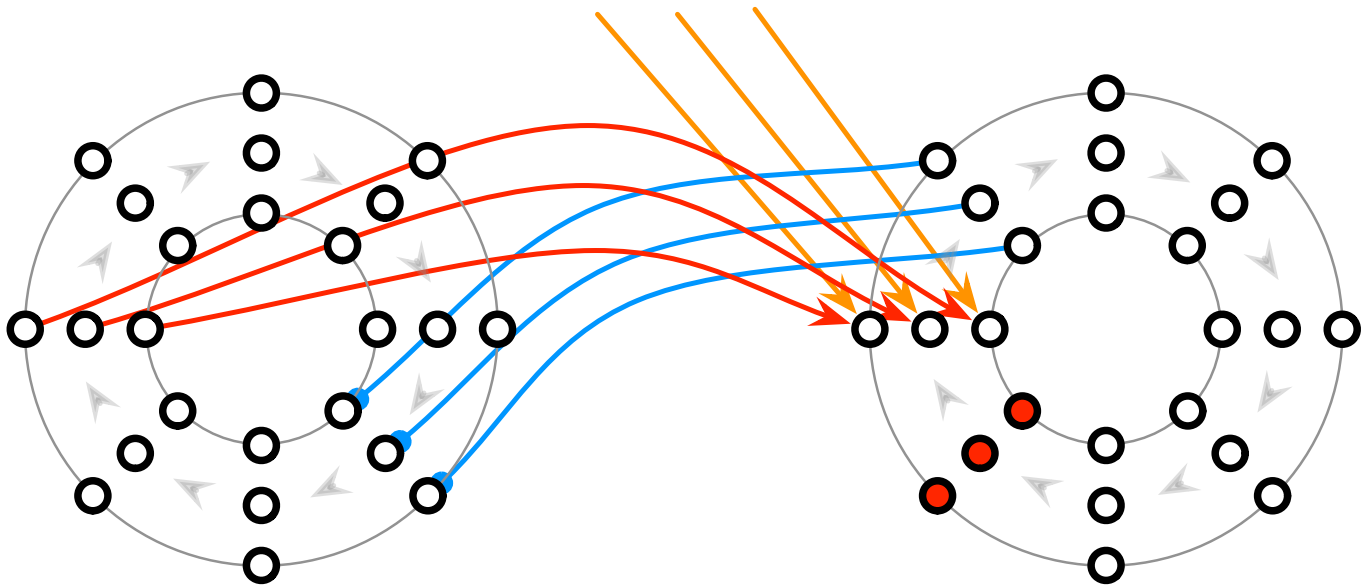


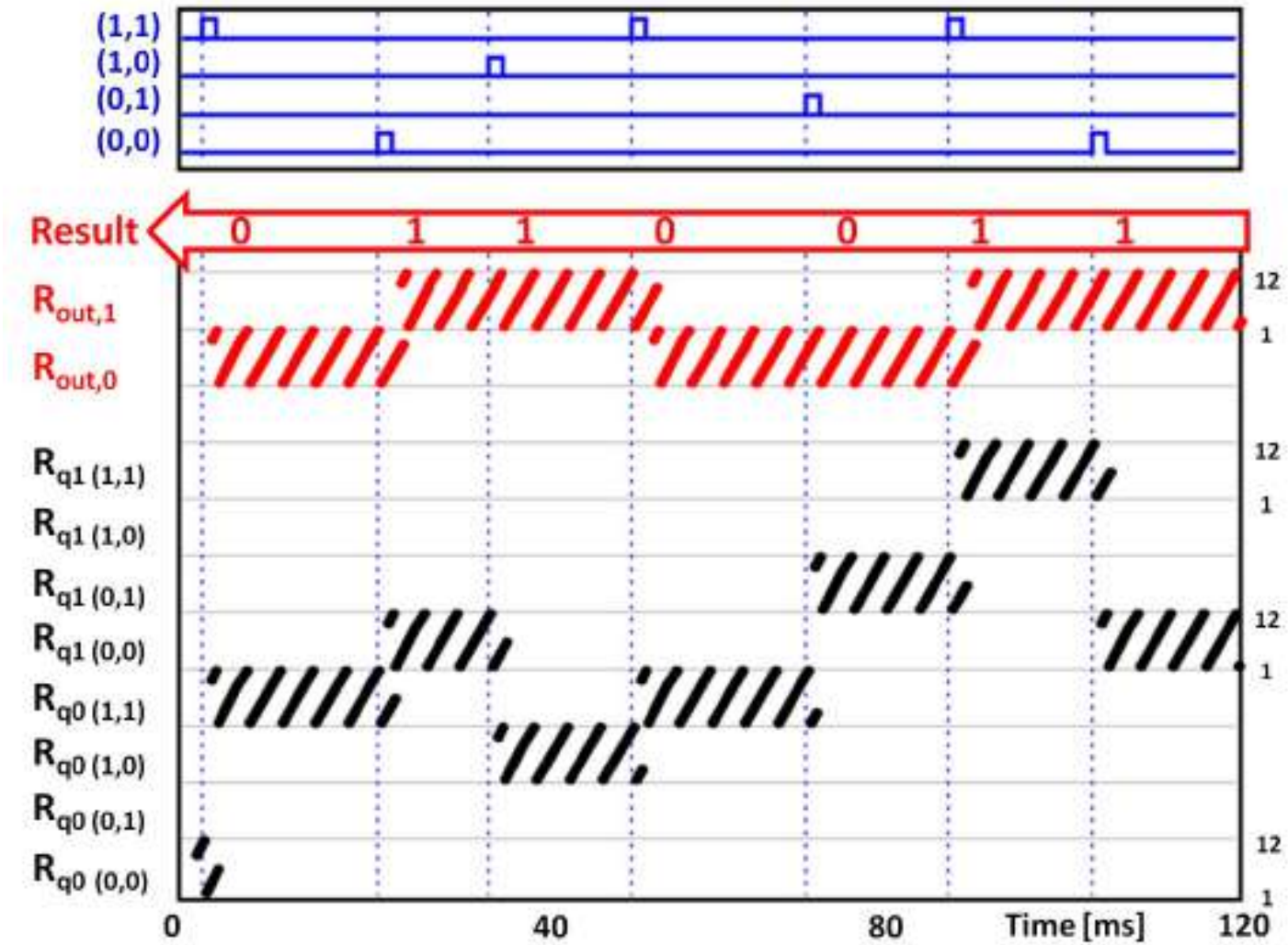
Fibres of connections & Inhibitory System



Simulation

Play movie...

Simulation


(1,1)
(1,0)
(0,1)
(0,0)
Result
0 1 1 0 0 1 1
$R_{out,1}$
$R_{out,0}$
$R_{q1\ (1,1)}$
$R_{q1\ (1,0)}$
$R_{q1\ (0,1)}$
$R_{q1\ (0,0)}$
$R_{q0\ (1,1)}$
$R_{q0\ (1,0)}$
$R_{q0\ (0,1)}$
$R_{q0\ (0,0)}$
12
1
0
40
80
Time [ms]
120

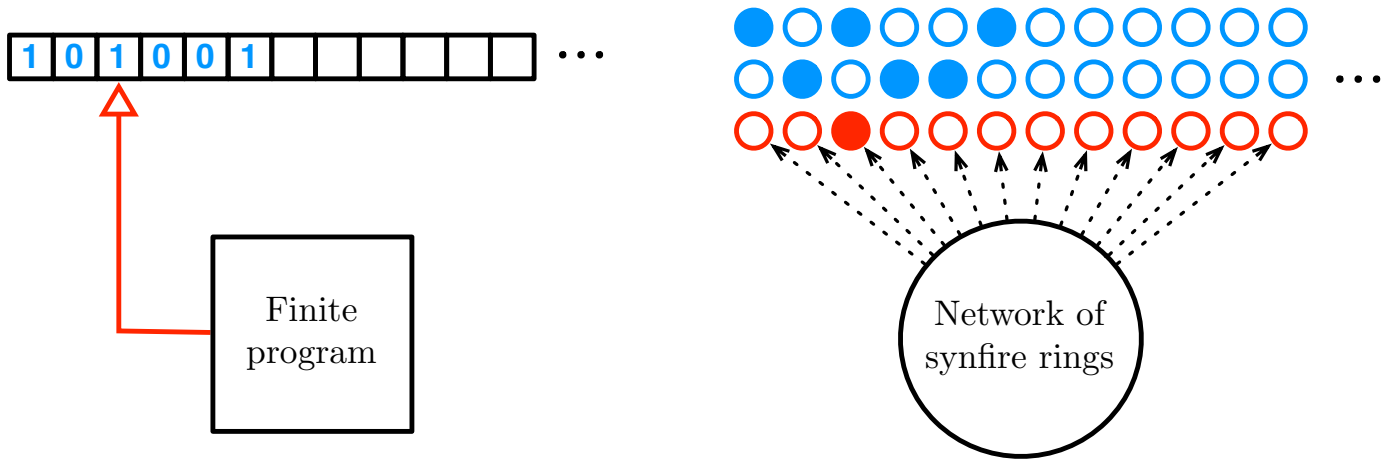
Automata & Hodgkin-Huxley RNNs with Synfire Rings

Theorem

Any finite state automaton can be simulated by some Hodgkin-Huxley based neural network composed of synfire rings.

Future Work: Towards Turing Completeness

We intend to simulate Turing machines with recurrent neural networks composed of synfire rings.



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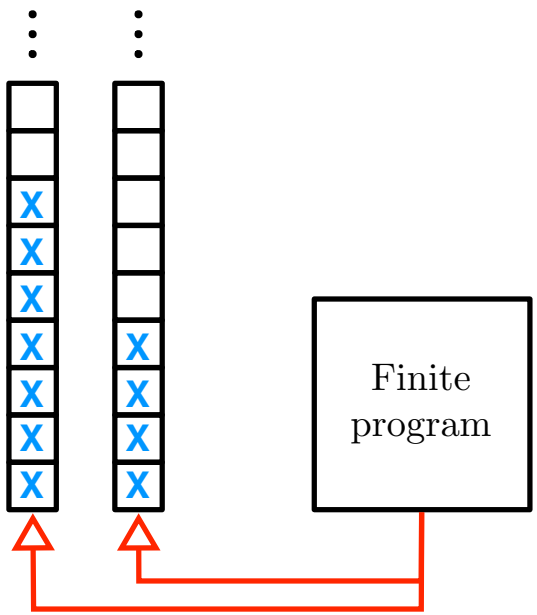
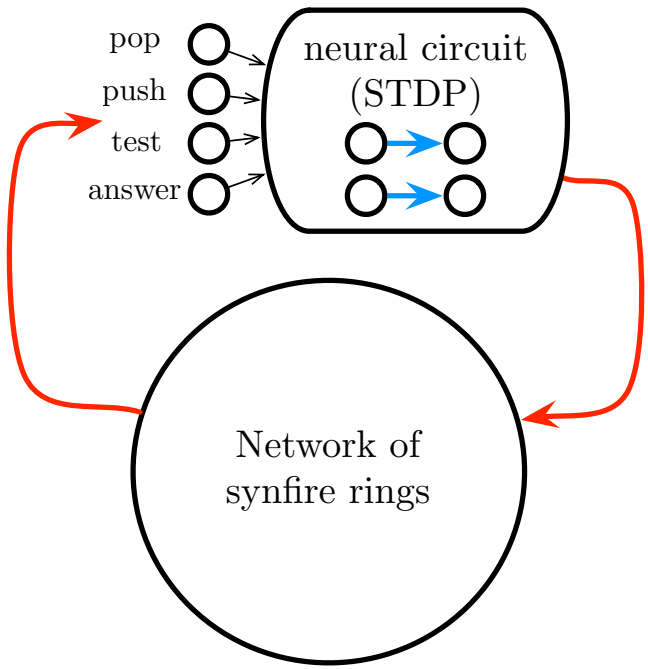
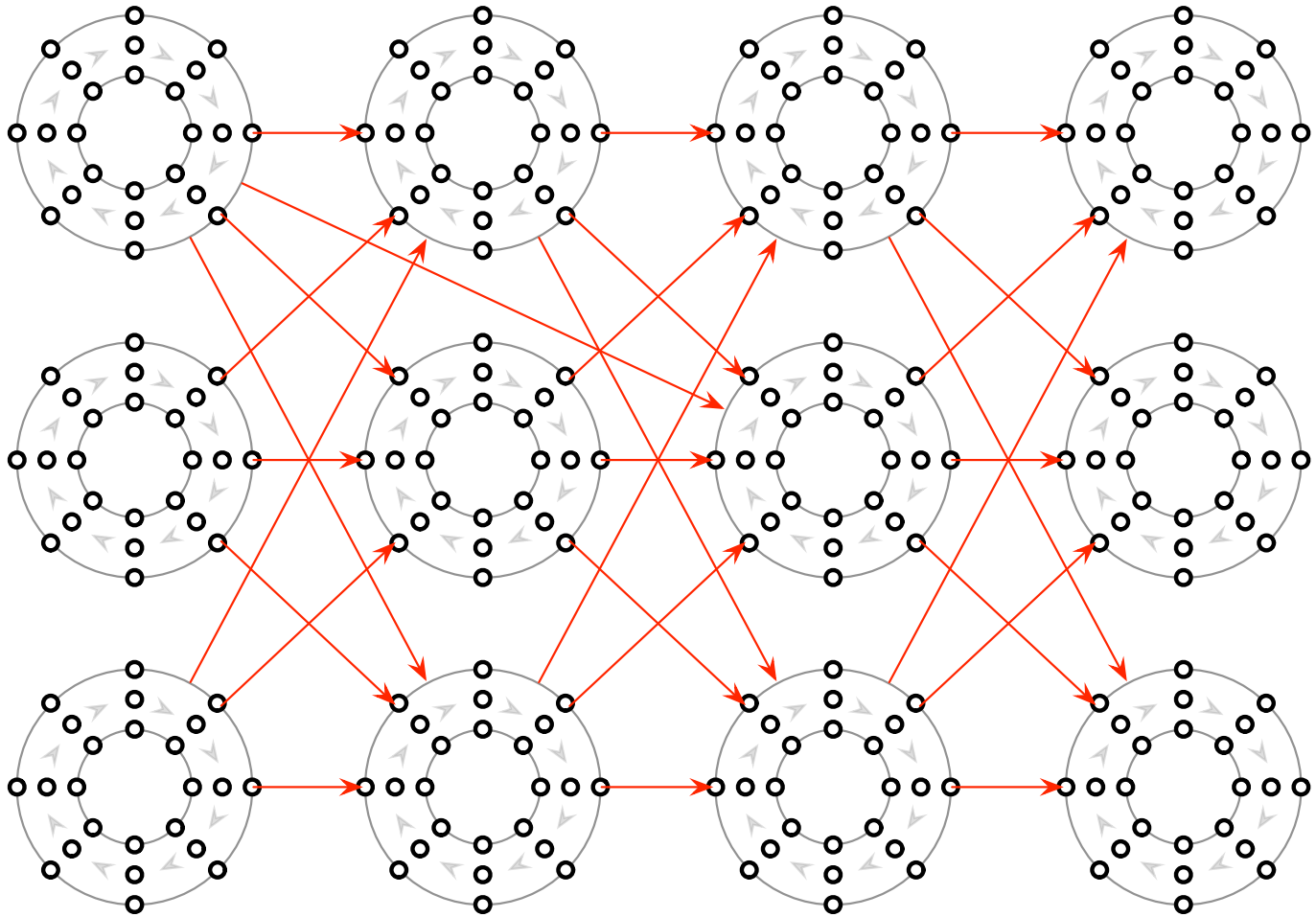




Future Work: Learning within the Synfire Ring Architecture



Conclusions

- Recurrent neural networks represent a natural models for oracle-based computation, beyond the Turing limits.
- We introduced a new paradigm of neural computation based on the concept of synfire rings.
- We intend to study the issue of *learning* within the synfire ring architecture.
- Utopia: achieve the realization of neural computers. By growing cultures of neurons according to the synfire ring architecture, one could in principle realize neural computers.

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