An STDP Rule for the Improvement and Stabilization of the Attractor Dynamics of the Basal Ganglia-Thalamocortical Network

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Introduction

- We consider a simplified Boolean model of the basal ganglia-thalamocortical network (case study).
- The Boolean context, although relatively simple, allows for a complete analysis of the attractor dynamics of the networks.
- We show that both local and global variations of the synaptic weights significantly influence the attractor dynamics of the network.
- We introduce an *adaptive Spike Timing-Dependent Plasticity rule (STDP)* which improves and stabilizes the attractor dynamics of the network.

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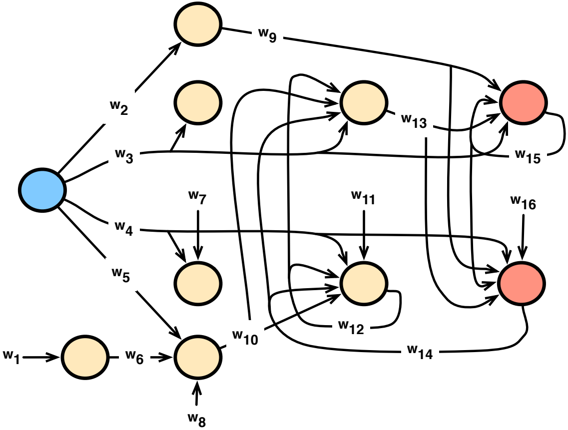
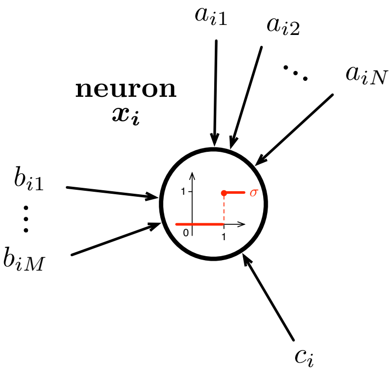
Recurrent Neural Network



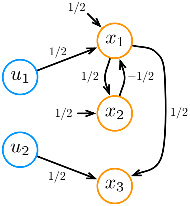
Boolean Recurrent Neural Network



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

Attractors and Cycles

Boolean Neural Network **Finite State Automaton**



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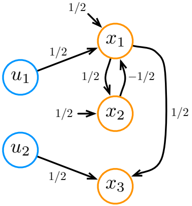
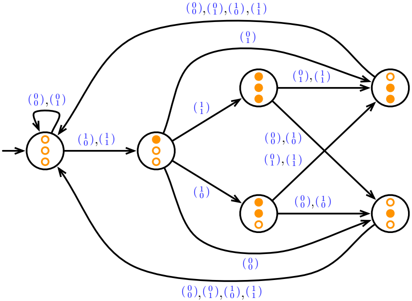


Finite State Automaton



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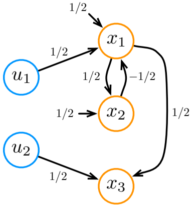

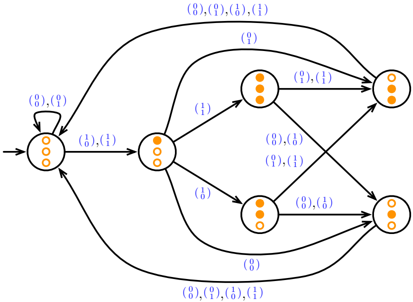

Input stream  ...

Attractors and Cycles

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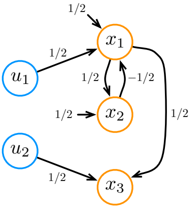

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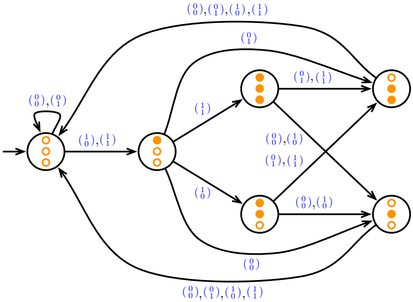
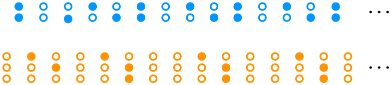


Input stream

Sequence of states



Attractors and Cycles

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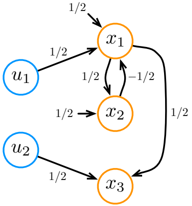

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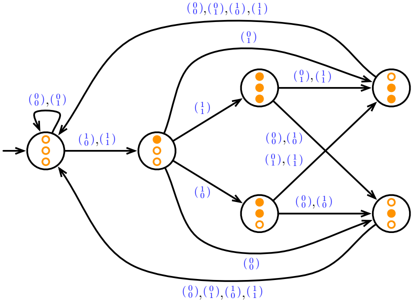
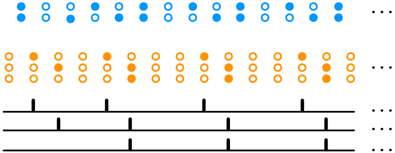


Input stream

Sequence of states

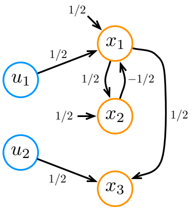
Raster plot

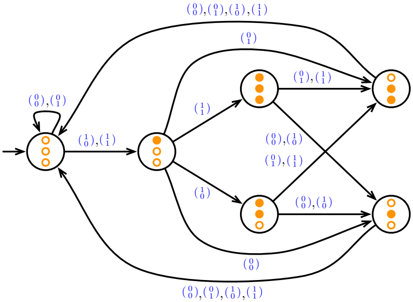


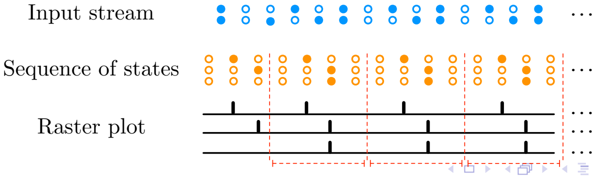
Attractors and Cycles

Boolean Neural Network **Finite State Automaton**

ATTRACTOR



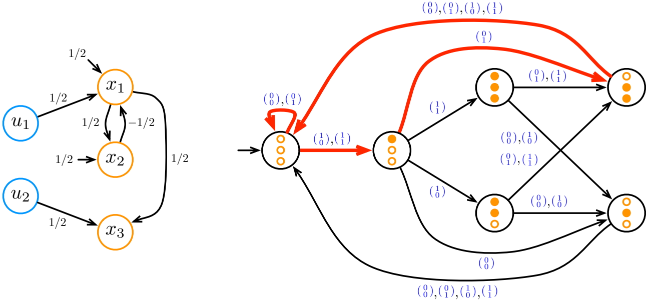




Attractors and Cycles

Boolean Neural Network **Finite State Automaton**

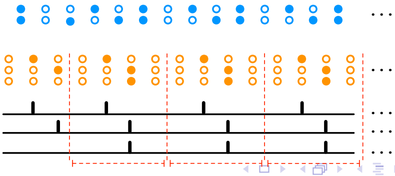
ATTRACTOR ⟺ **CYCLE**



Input stream

Sequence of states

Raster plot



Attractors and Cycles

Boolean Neural Network **Finite State Automaton**

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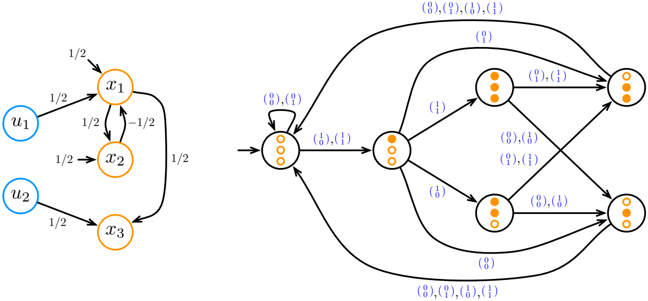
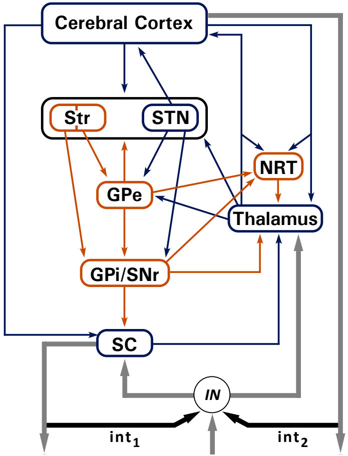


7 attractors **7 simple cycles**

Boolean Model of the Basal Ganglia-Thalamocortical Network



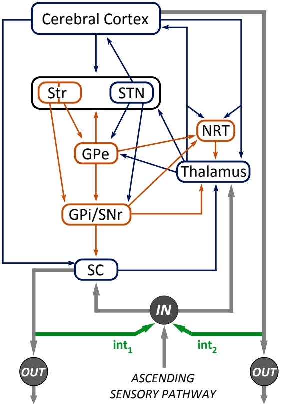
IN	input node
SC	superior colliculus
GPi/SNr	output nuclei of the basal ganglia formed by the GABAergic projection neurons of the intermediate part of the pallidum and of the substantia nigra pars reticulata
Thalamus	thalamus
GPe	external part of the pallidum
NRT	thalamic reticular nucleus
Str-D1	striatopallidal component of the striatum
Str-D2	striatonigral component of the striatum
STN	subthalamic nucleus
Cerebral Cortex	cerebral cortex

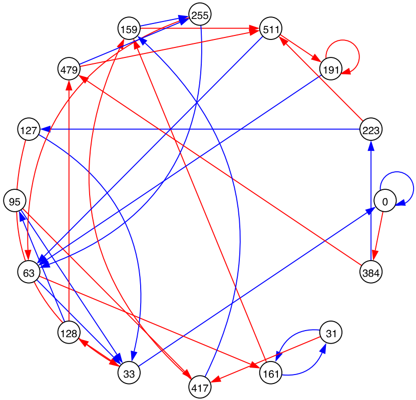
Boolean Model of the Basal Ganglia-Thalamocortical Network

Source	**Target (Node #)**									
Node # (Name)	0	1	2	3	4	5	6	7	8	9
0 (IN)	·	1	1	·	·	·	·	·	·	·
1 (SC)	int_1	·	1	·	·	·	·	·	·	·
2 (Thalamus)	·	·	·	1	·	1	1	1	1	1
3 (RTN)	·	·	-1	·	·	·	·	·	·	·
4 (GPi/SNr)	·	-1	-1	-1	·	·	·	·	·	·
5 (STN)	·	·	·	·	2	·	2	·	·	2
6 (GPe)	·	·	·	-1/2	-1/2	-1/2	·	-1/2	-1/2	·
7 (Str-D2)	·	·	·	·	·	·	-1	·	·	·
8 (Str-D1)	·	·	·	·	-1/2	·	-1/2	·	·	·
9 (CCortex)	int_2	1/2	1/2	1/2	·	1/2	·	1/2	1/2	·

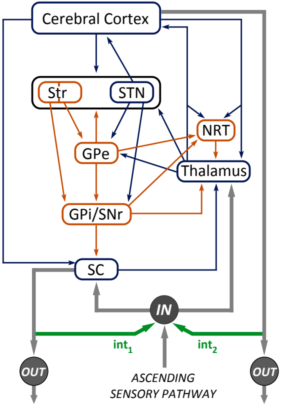
Table: Adjancency matrix

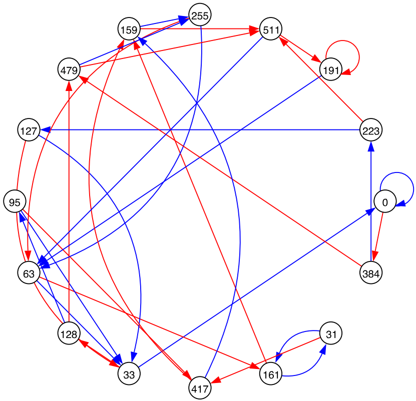
BGT Network and Corresponding FSA





Synaptic Weights and Attractor Dynamics





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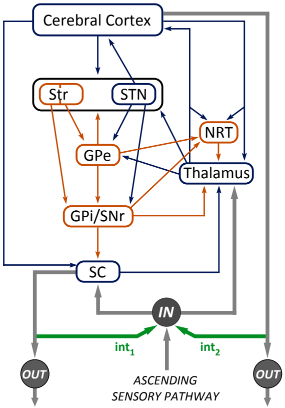
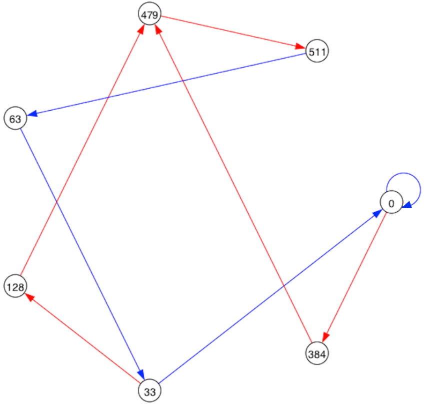
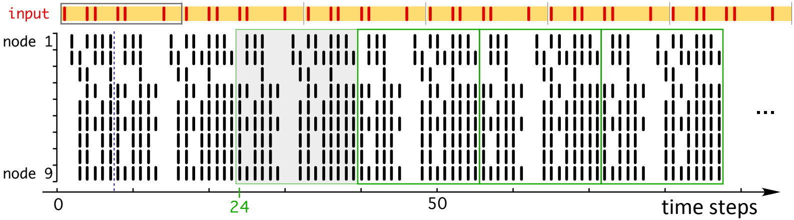




Synaptic Weights and Attractor Dynamics

- Both global and local variations of the synaptic weights significantly influence the attractor dynamics of the network

threshold $\theta = 0.5$



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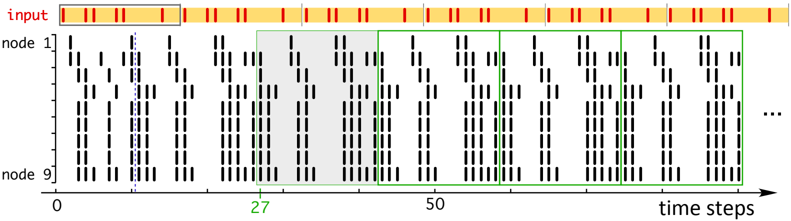
threshold $\theta = 0.6$



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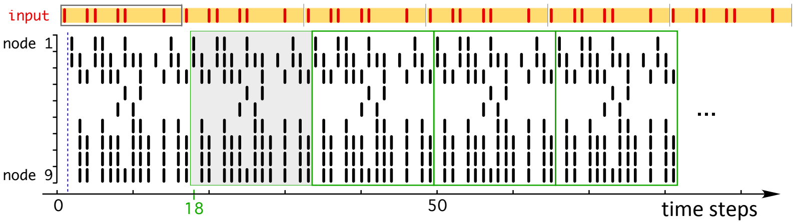
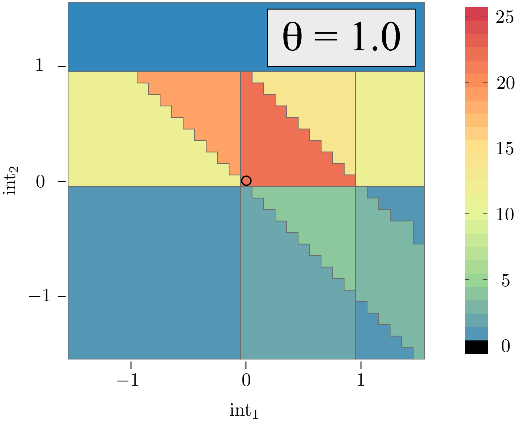
- Both global and local variations of the synaptic weights significantly influence the attractor dynamics of the network

threshold $\theta = 0.6$ and weight "Thala $\to$ STN" $w_{2,5} = 0.9$

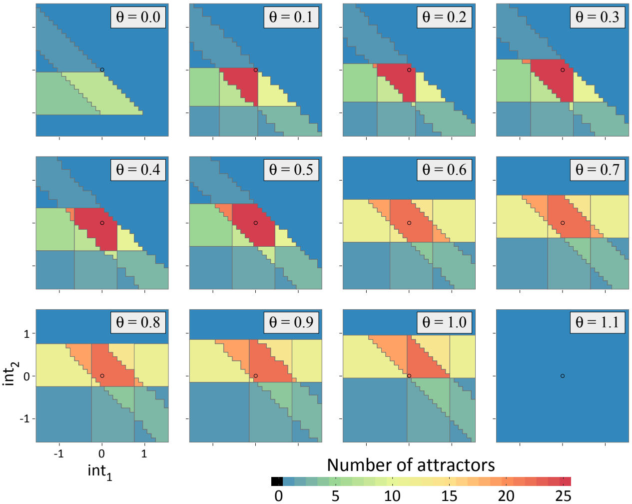


Interactivity and Attractor Dynamics

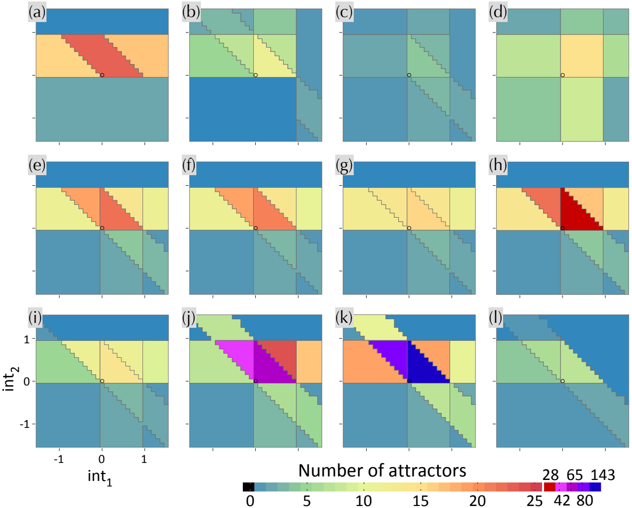
- A key feature to neural networks' information processing is the "circular causal relationships" (Wiener 48) – i.e., *feedback loop* or *interactivity* – between the system and its environment.



Global Weights' Change vs Interactivity



Local Weights' Change vs Interactivity



Adaptive STDP Rule

- Can we improve the attractor dynamics of the network by means of a spike-timing dependent plasticity (STDP) rule?
- Yes. We consider an *adaptive* STDP rule.
- *Adaptive:* the learning rate of the rule evolves over time.
- The application of the rule improves the attractor complexity of the BGT network throughout its computational process.

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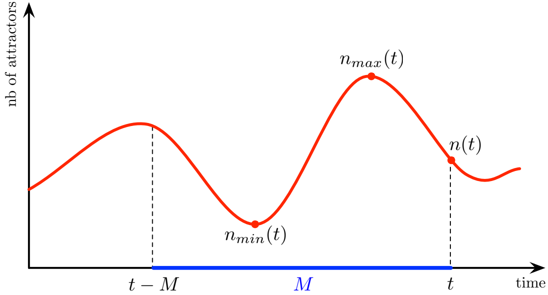
Adaptive STDP Rule: memory

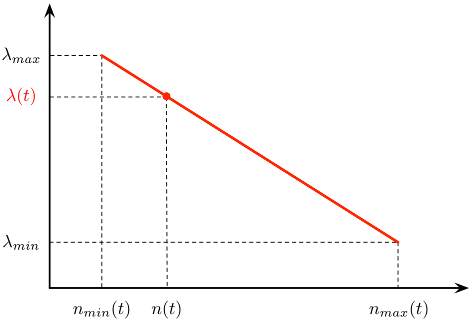
$$\begin{aligned} \color{blue}{M} &= \textit{memory} \text{ of the network} \\ n(t) &= \text{number of attractors of the network at time } t \\ n_{min}(t) &= \min\{n(t') : \max(0, t-M) < t' \leq t\} \\ n_{max}(t) &= \max\{n(t') : \max(0, t-M) < t' \leq t\}. \end{aligned}$$



Adaptive STDP Rule: learning rate

- The *learning rate* $\lambda(t)$ depends on the current, min and max number of attractors seen during the last M time steps.

$$\lambda(t) = \begin{cases} \lambda_{max} + \dfrac{(n(t) - n_{min}(t))(\lambda_{min} - \lambda_{max})}{n_{max}(t) - n_{min}(t)} & \text{if } n_{min}(t) \neq n_{max}(t) \\ \lambda_{max} & \text{otherwise} \end{cases}$$



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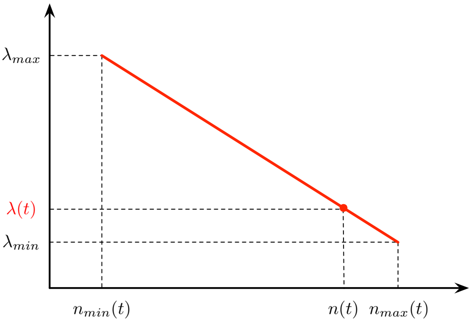

Adaptive STDP Rule

- $a_{ji}(t)$: synaptic weight between x_i and x_j at time t

$$a_{ji}(t+1) = a_{ji}(t) + \lambda(t)\Big[x_i(t)x_j(t+1) - Cx_j(t)x_i(t+1)\Big]$$

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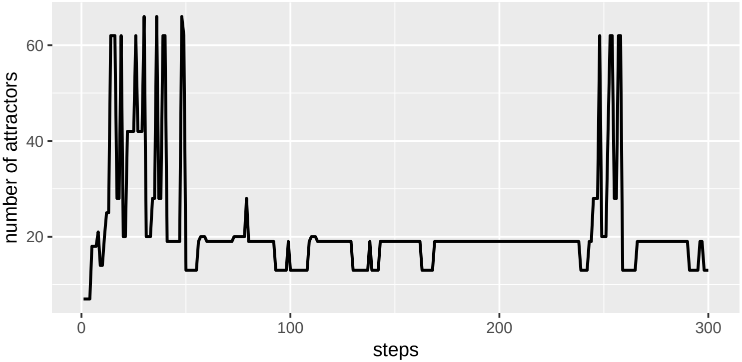

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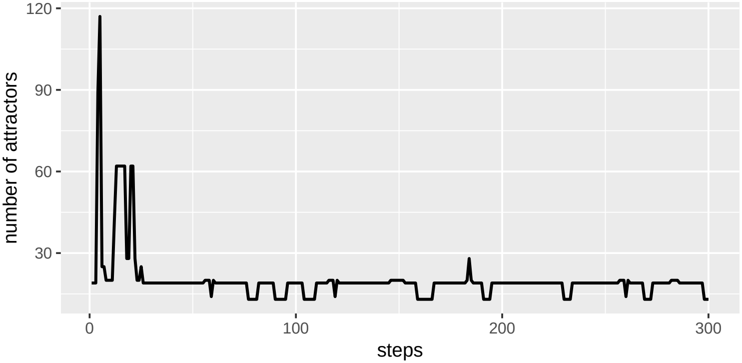

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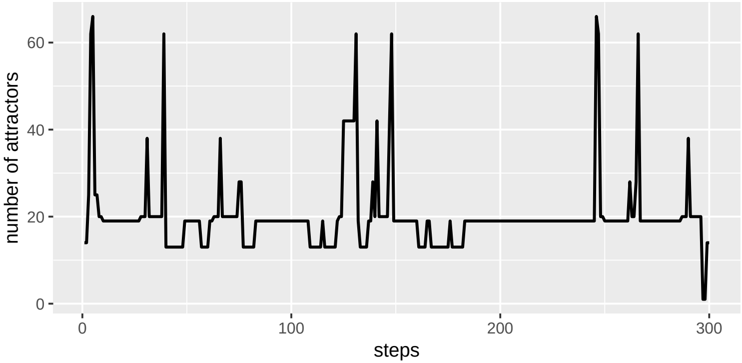

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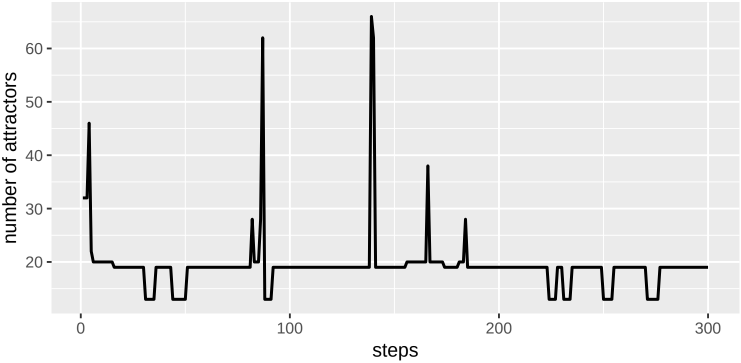

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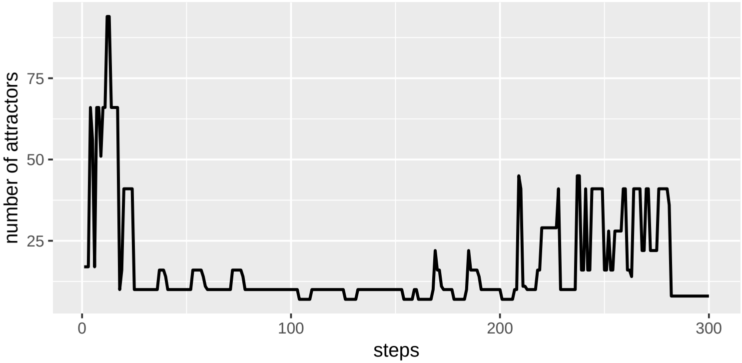

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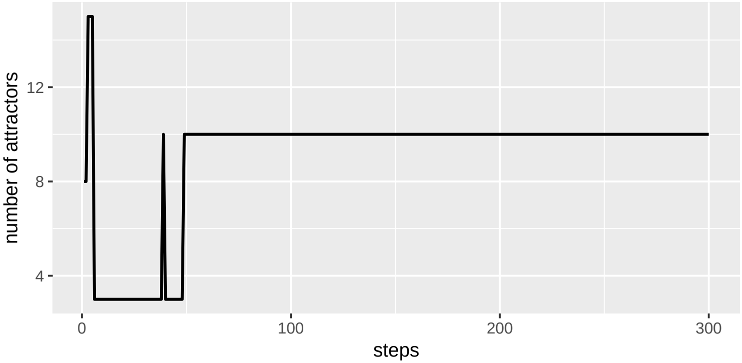

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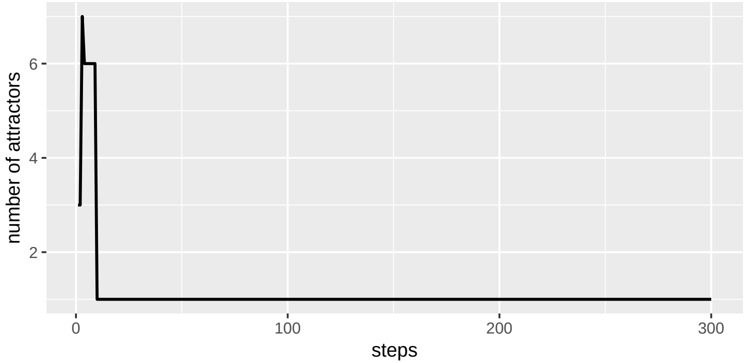

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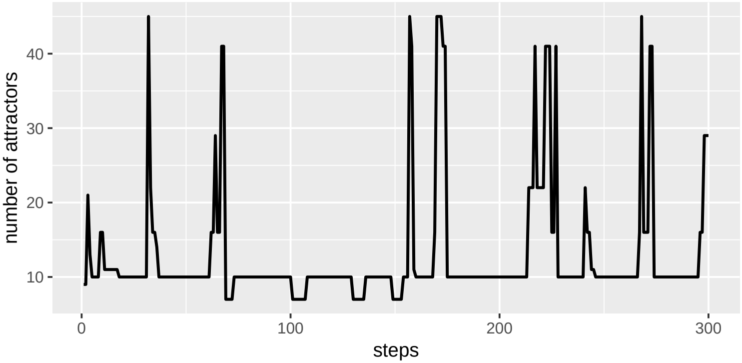

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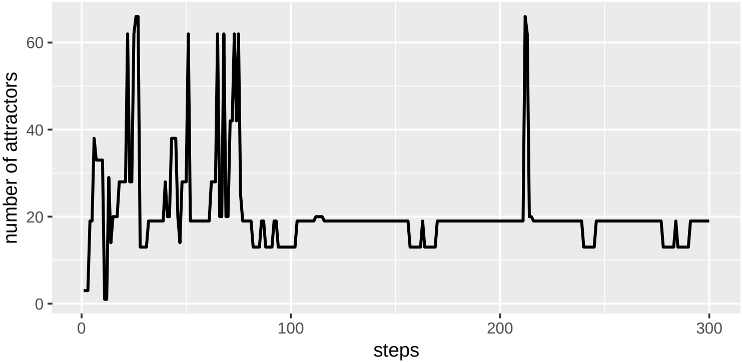

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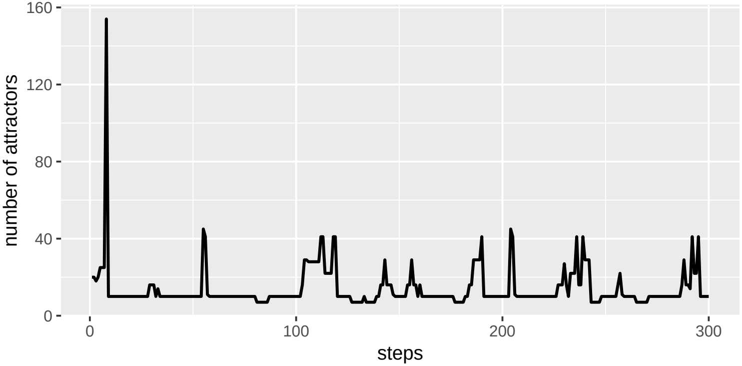
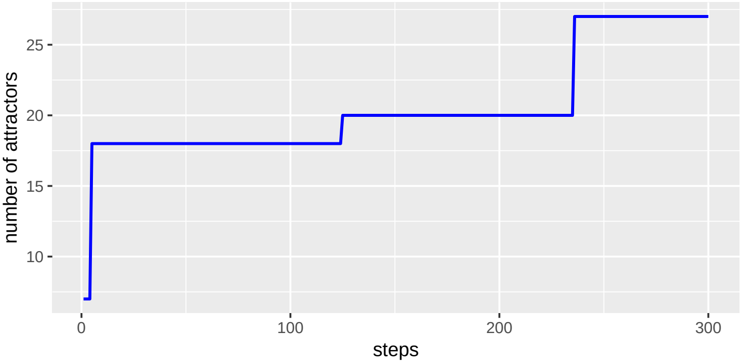


Simulations: M = 120 (larger memory)



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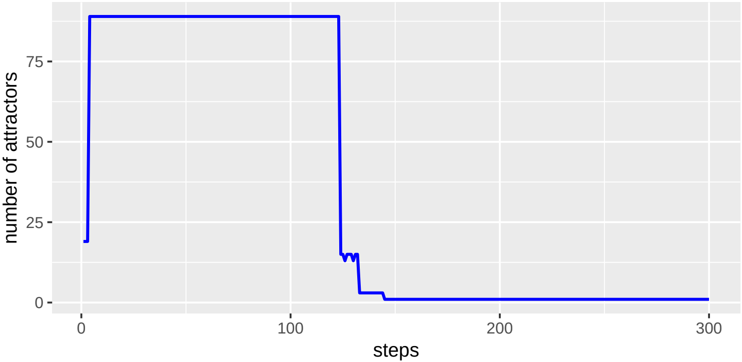

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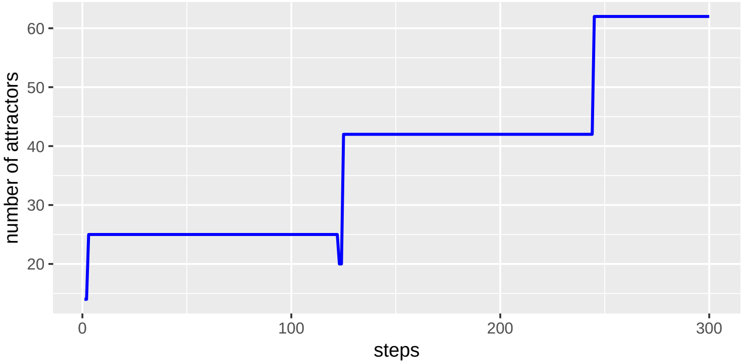
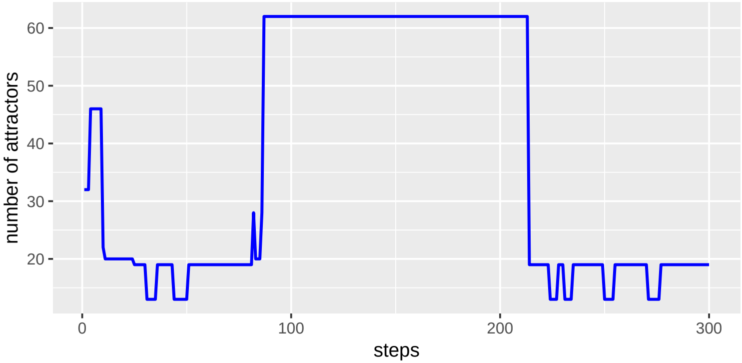
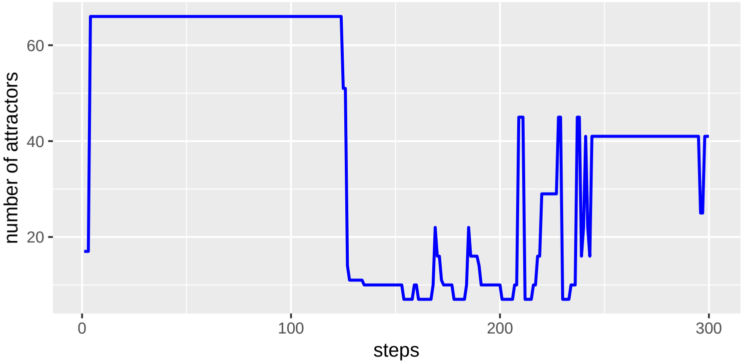


Simulations: $M = 120$ (larger memory)



Simulations: M = 120 (larger memory)



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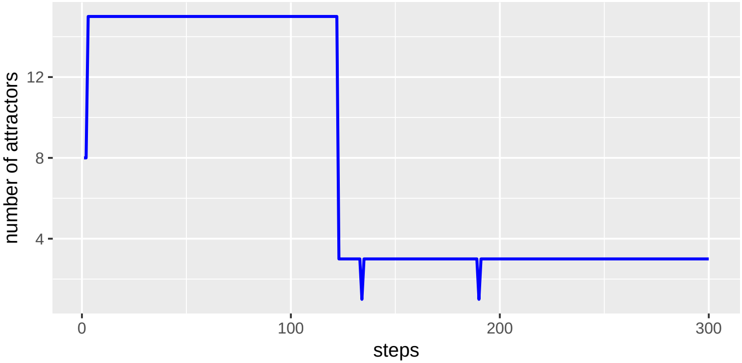

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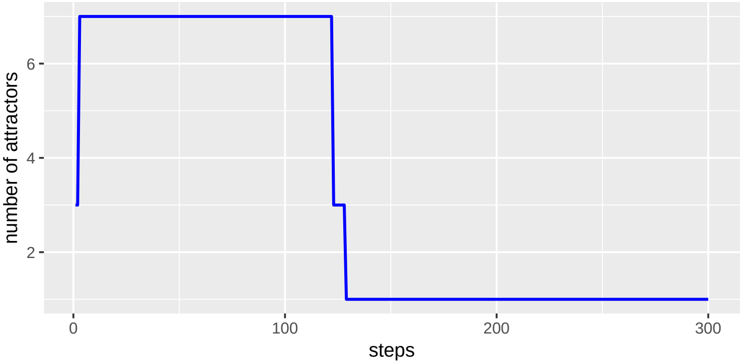

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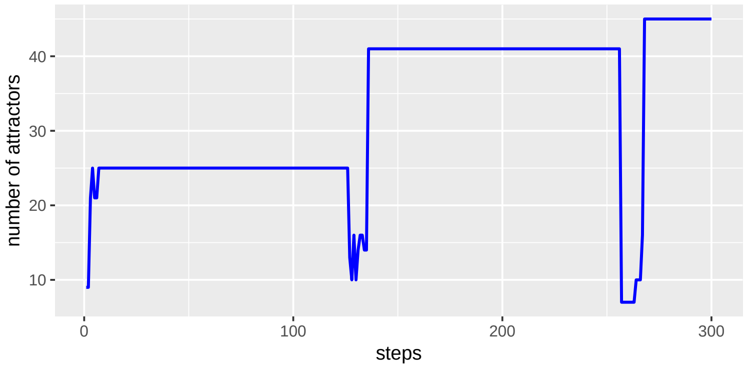

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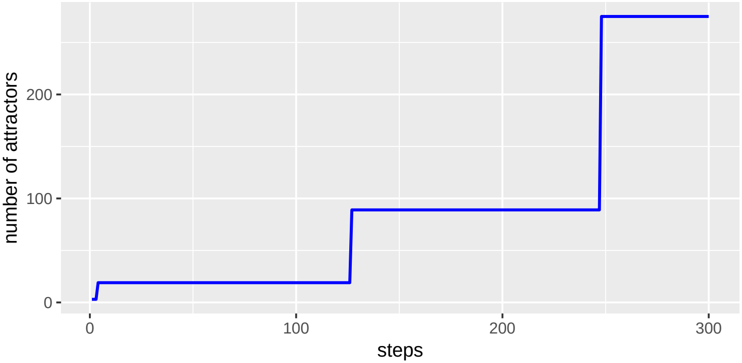

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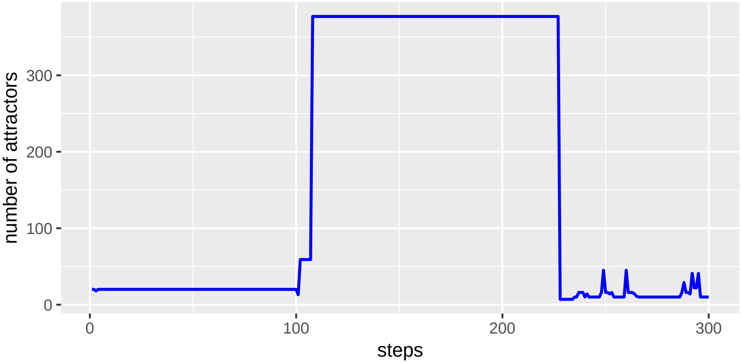
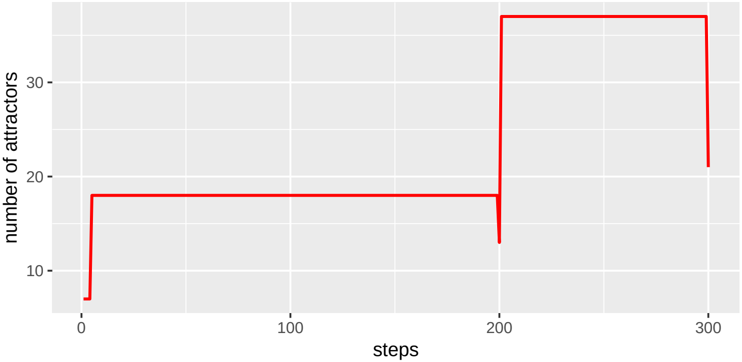
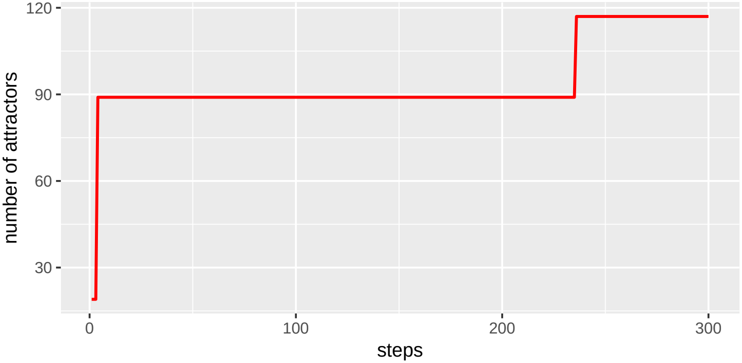


Simulations: M = 240 (larger memory)



Simulations: M = 240 (larger memory)



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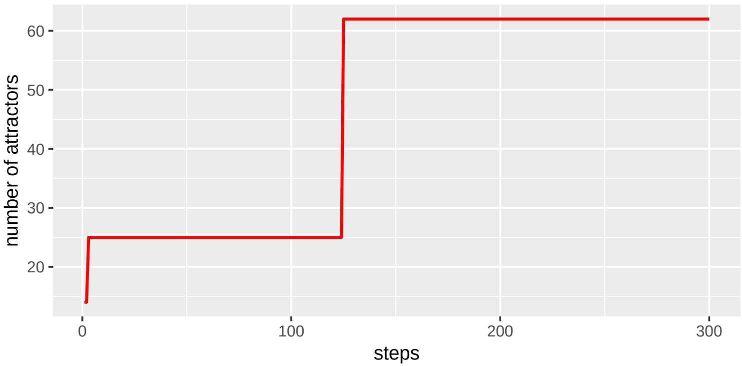

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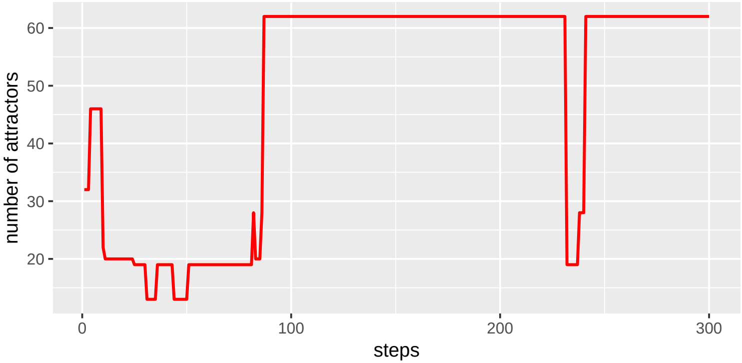

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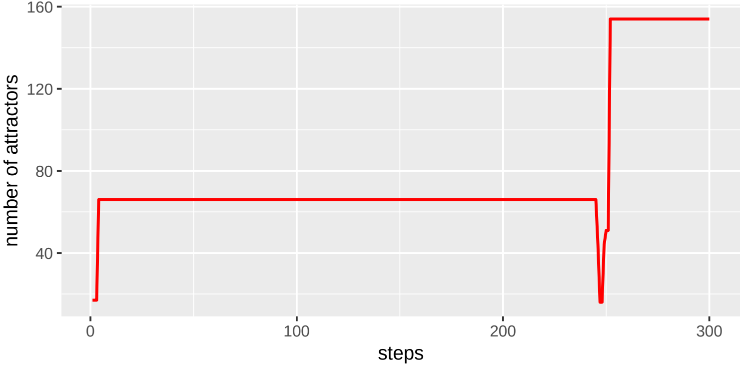

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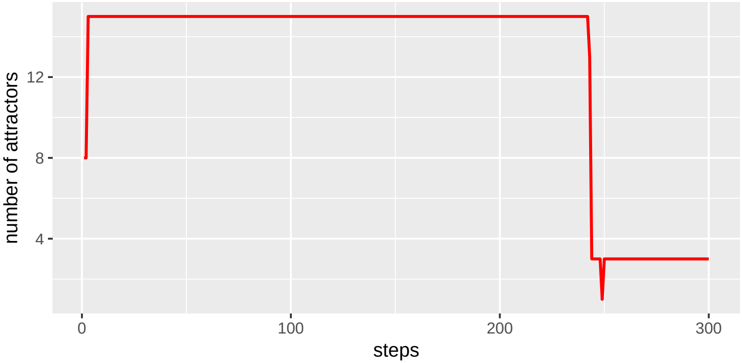

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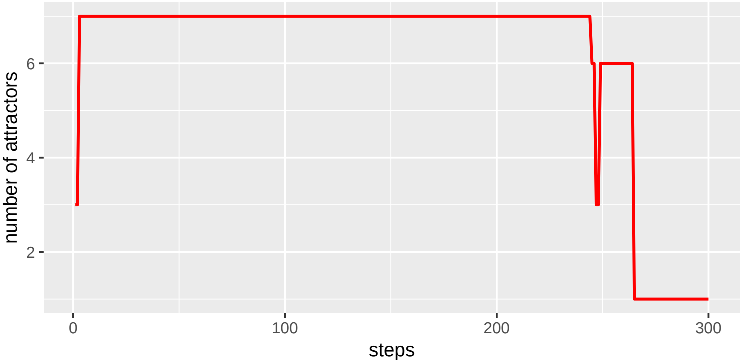

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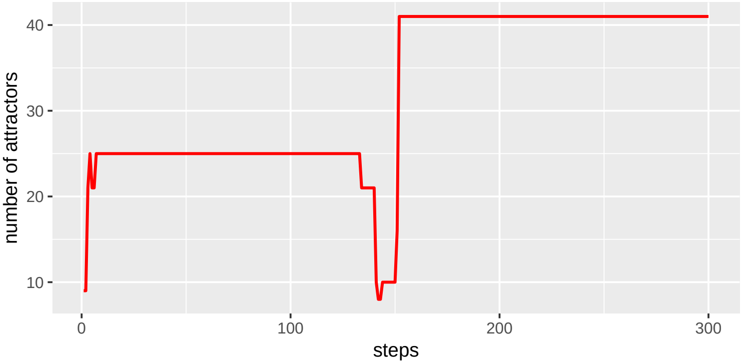

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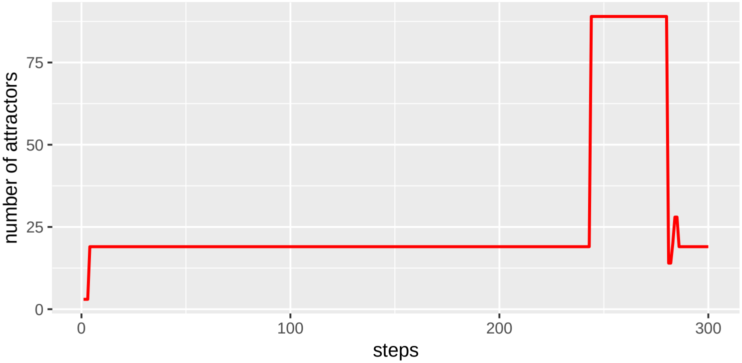

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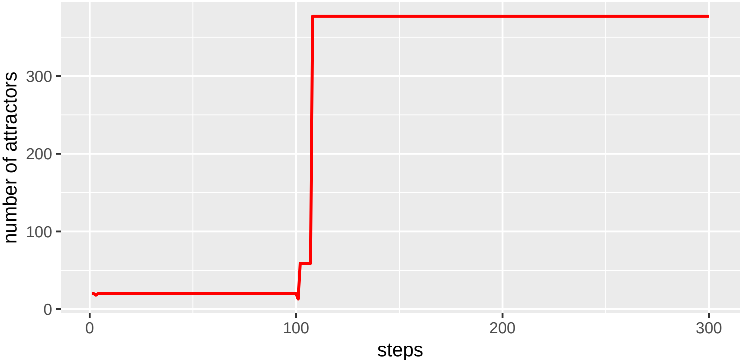

Conclusions

- Feedback – or interactivity – regulation as well as global and local variations of the synaptic weights significantly influence the attractor dynamics of the BGT network.
- These processes can be combined with each other to stabilize and/or improve the attractor dynamics of the network.
- It is possible to improve the attractor dynamics of the BGT network by means of an *adaptive STDP rule*.
- The adaptive STDP rule implements a *twofold evolving process*: the synaptic weights evolve according to the STDP rule, and the STDP rule also evolves due to its adaptive learning rate.
- These considerations support the rationale that *synaptic plasticity* might be crucially involved in the computational capabilities of neural networks.

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Thank you