Stimulus-Driven Unsupervised Synaptic Pruning in Large Neural Networks

J. Iglesias[1,3,4], J. Eriksson[3], B. Pardo[2], M. Tomassini[1], A.E.P. Villa[1,3,4]

1st Brain, Vision and Artificial Intelligence Symposium
Napoli, 2005-10-20

[1] Information Systems Department, University of Lausanne, Switzerland

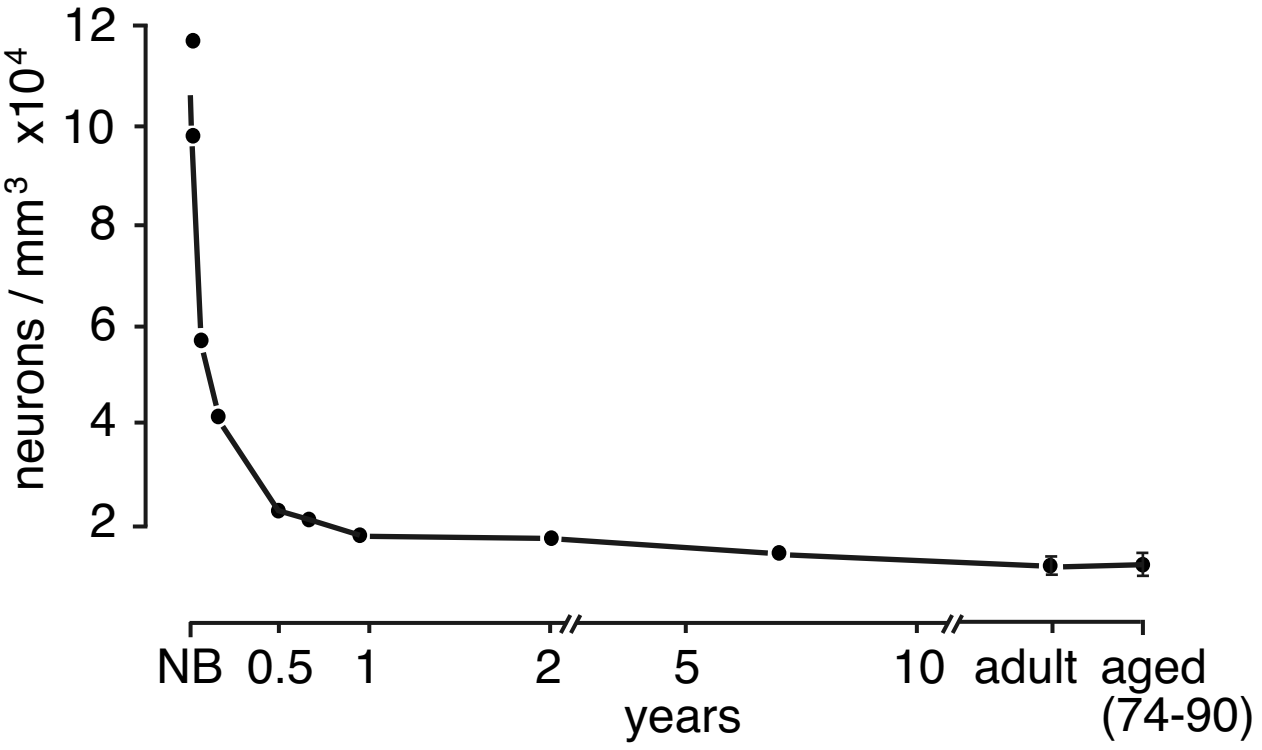
[2] Centro de Biologia Molecular Severo Ochoa, Universidad Autonoma de Madrid, Spain

[3] Laboratory of Neuroheuristics, University of Lausanne, Switzerland

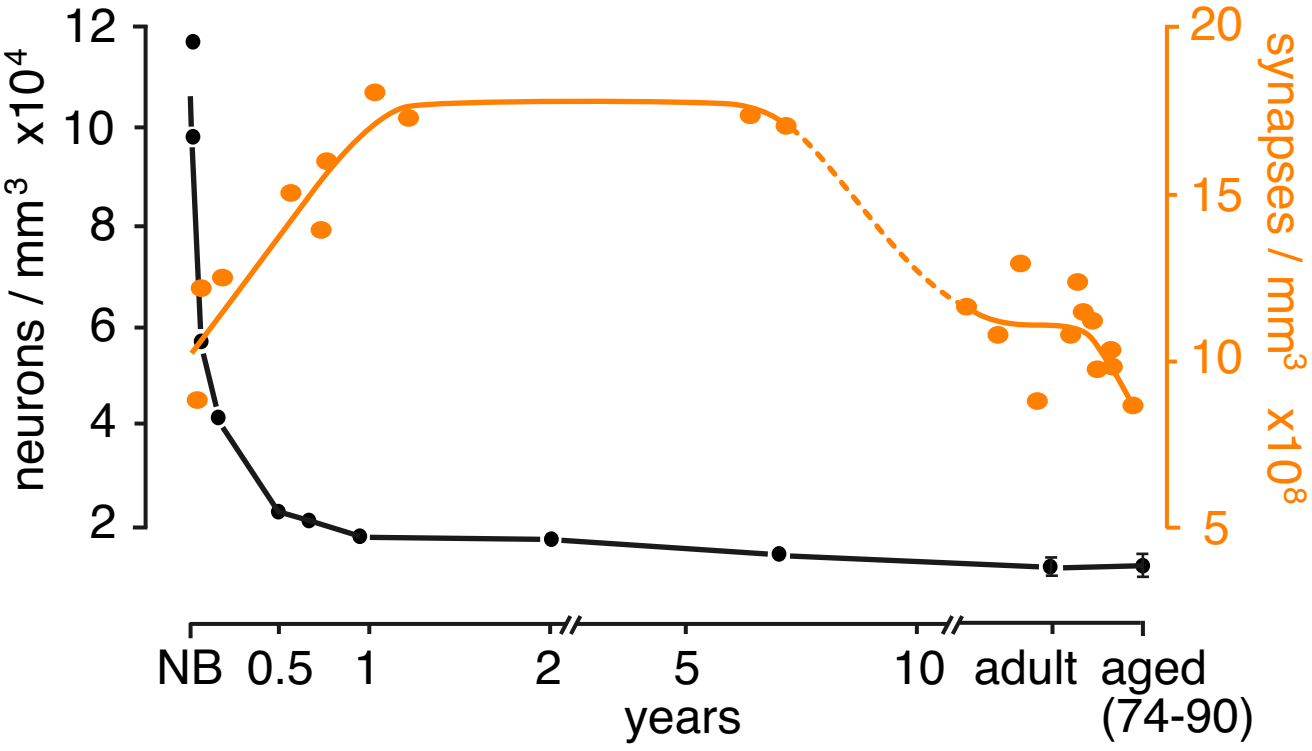
[4] Laboratory of Neurobiophysics, University Joseph-Fourier, France

<javier.iglesias@unil.ch>

introduction: synaptogenesis and synaptic pruning



introduction: synaptogenesis and synaptic pruning



modified from Huttenlocher, *Synaptic density in human frontal cortex – developmental changes and effects of aging*, Brain Research, 163:195–205, 1979

- The memory performance of a network is optimally maximized if, under limited metabolic energy resources restricting their number and strength, synapses are first overgrown and then pruned.

Chechik *et al.*, *Synaptic pruning in development: A computational account*, Neural Computation, 10(7):1759–77, 1998

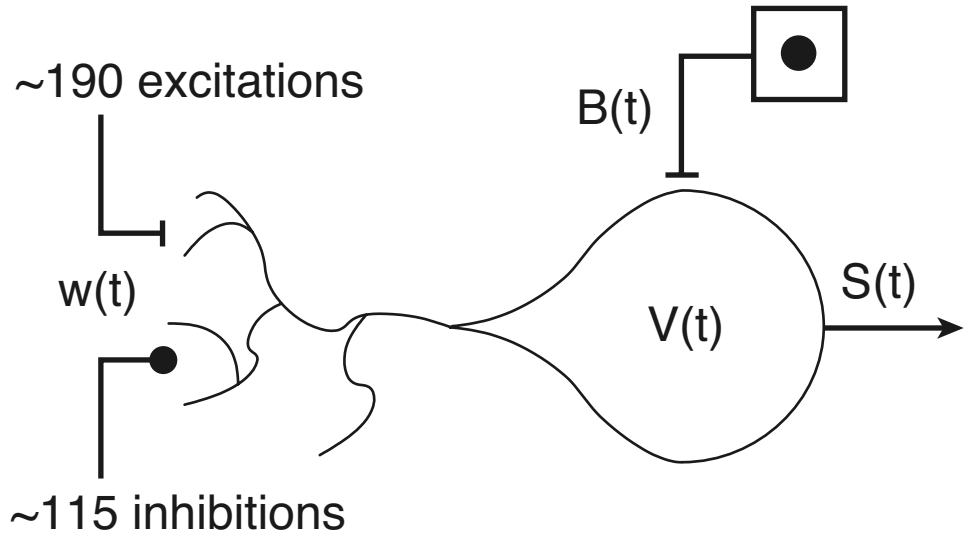
- Neuronal regulation might maintain the memory performance of networks undergoing synaptic degradation.

Horn *et al.*, *Memory maintenance via neuronal regulation*
Neural Computation, 10(1):1–18, 1998

- STDP has been shown to maintain the postsynaptic input field.

Abbott *et al.*, *Synaptic plasticity: taming the beast*
Nature Neuroscience, 3:1178–83, 2000

introduction: leaky integrate and fire neuromimetic model



Type I	=	excitatory 80%	
Type II	=	inhibitory 20%	
V_{rest}	=	-76	[mV]
θ_i	=	-40	[mV]
τ_{mem}	=	8	[ms]
t_{refract}	=	1	[ms]
λ_i	=	10	[spikes/s]
n	=	50	

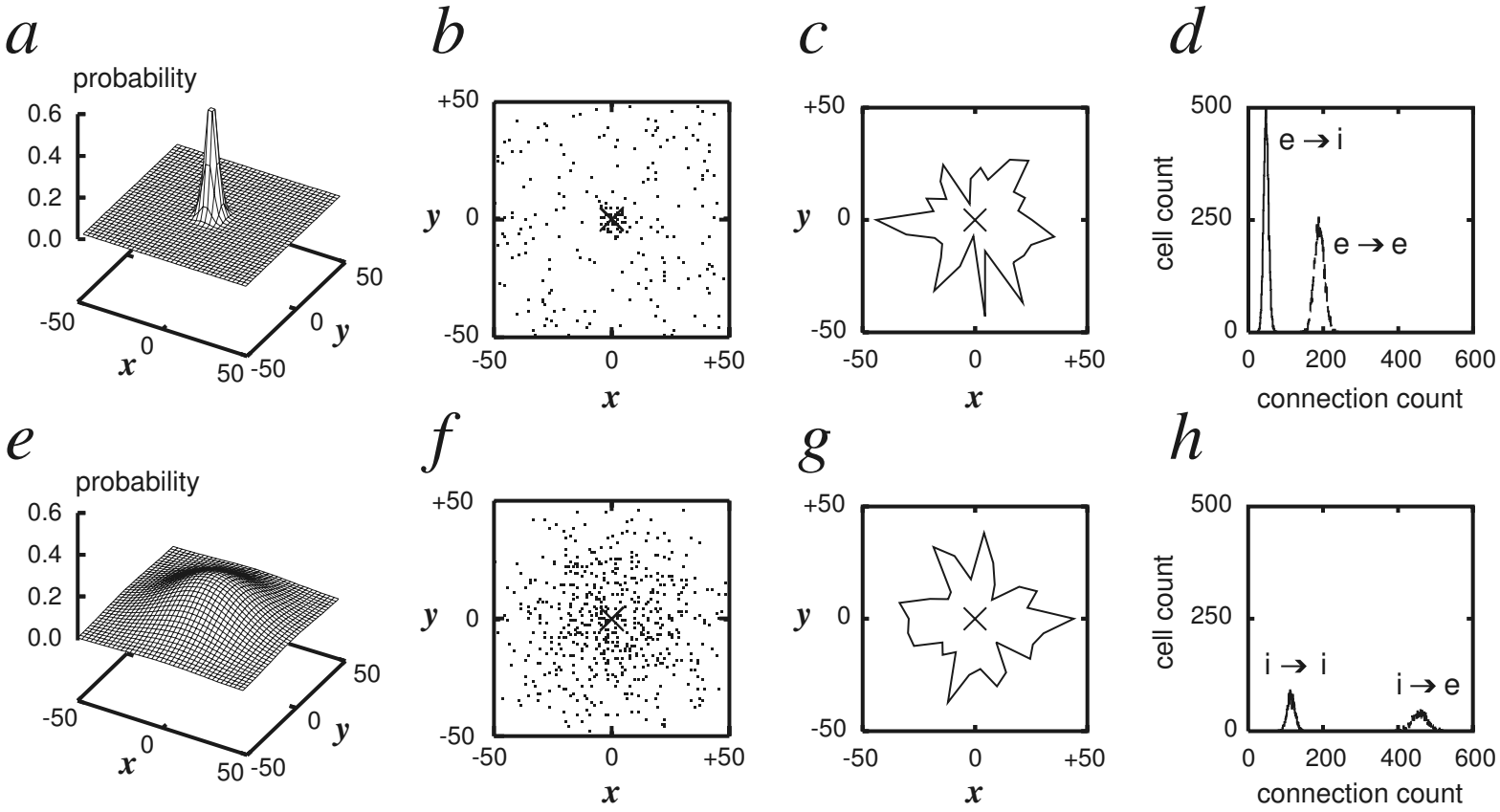
$$V_i(t+1) = V_{\text{rest}[q]} + (1 - S_i(t)) \cdot ((V_i(t) - V_{\text{rest}[q]}) \cdot k_{\text{mem}[q]}) + \sum_j w_{ji}(t) + B_i(t)$$

$$S_i(t) = \mathcal{H}(V_i(t) - \theta_{q_i})$$

$$w_{ji}(t+1) = S_j(t) \cdot A_{ji}(t) \cdot P_{[q_j, q_i]}$$

$$B_i(t+1) = \mathcal{P}_{reject}(\lambda_{q_i}) \cdot n \cdot P_{[q_1, q_i]}$$

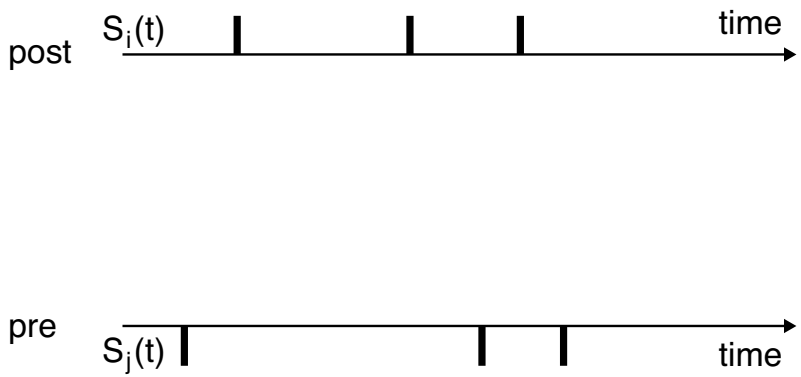
model: network



Iglesias *et al.*, *Dynamics of Pruning in Simulated Large-Scale Spiking Neural Networks*, Biosystems, 79(1-3):11-20, 2005

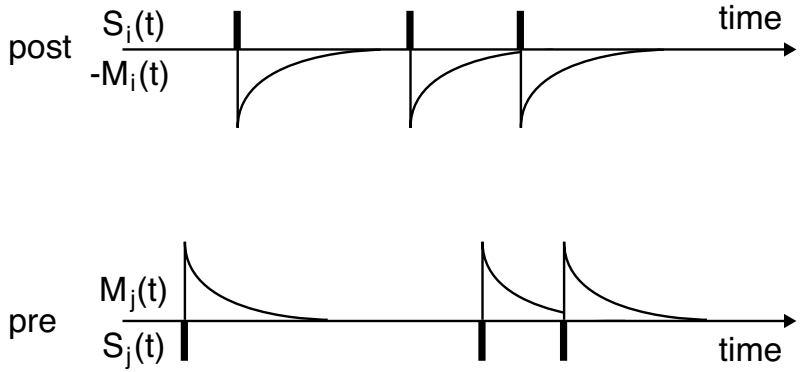
model: STDP and pruning

$$L_{ji}(t+1) = \begin{array}{l} L_{ji}(t) \cdot k_{\mathrm{act}[q_j,q_i]} \\ +(S_i(t) \cdot M_j(t)) \\ -(S_j(t) \cdot M_i(t)) \end{array}$$



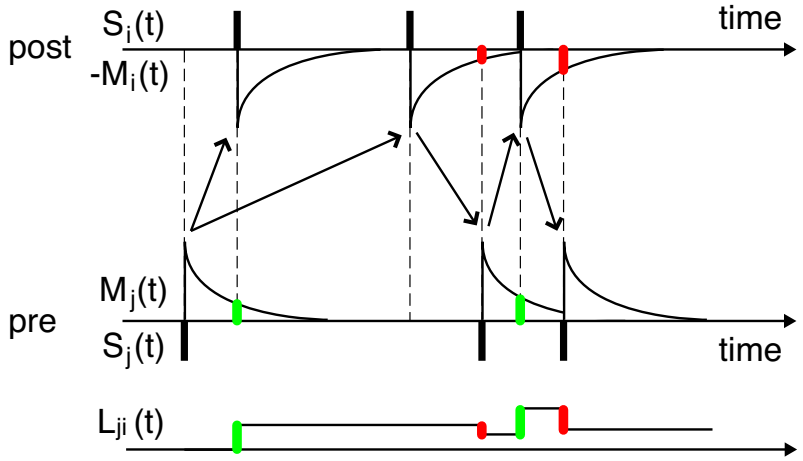
model: STDP and pruning

$$L_{ji}(t+1) = \quad L_{ji}(t) \cdot k_{\mathrm{act}[q_j,q_i]} + (S_i(t) \cdot M_j(t)) - (S_j(t) \cdot M_i(t))$$



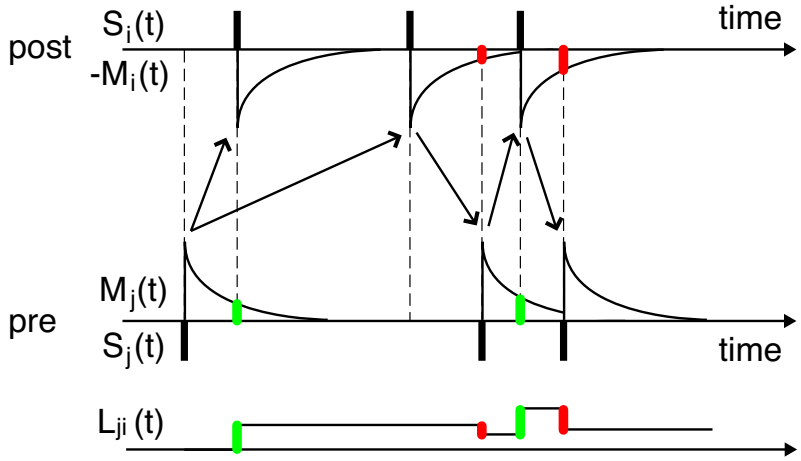
model: STDP and pruning

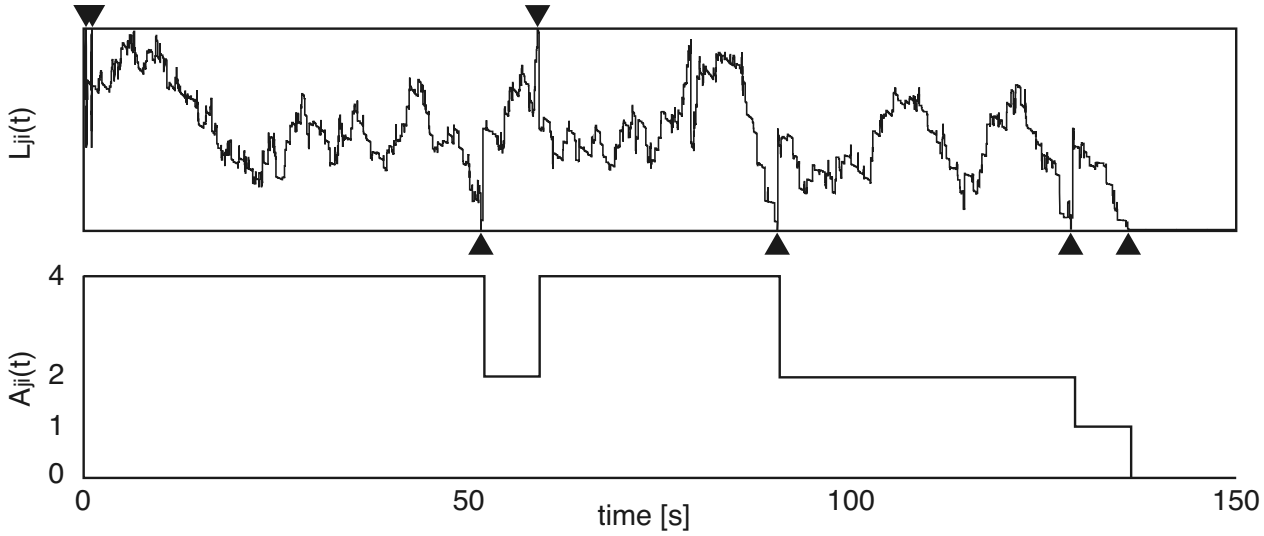
$$L_{ji}(t+1) = \quad L_{ji}(t) \cdot k_{\mathrm{act}[q_j,q_i]} + (S_i(t) \cdot M_j(t)) - (S_j(t) \cdot M_i(t))$$



model: STDP and pruning

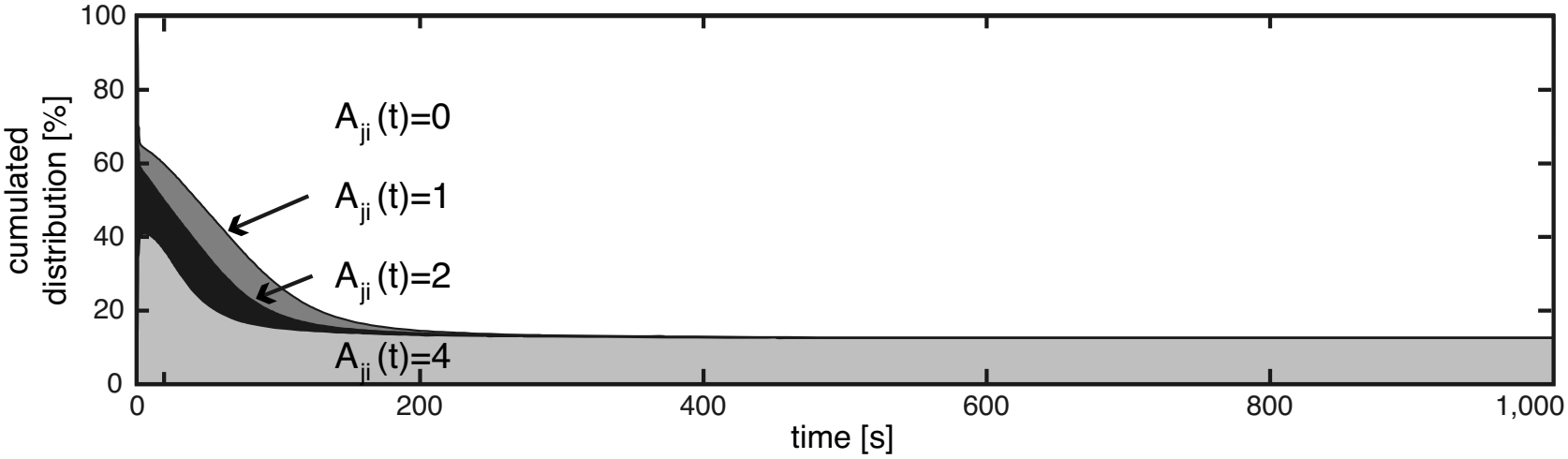
$$L_{ji}(t+1) = L_{ji}(t) \cdot k_{\mathrm{act}[q_j,q_i]} + (S_i(t) \cdot M_j(t)) - (S_j(t) \cdot M_i(t))$$

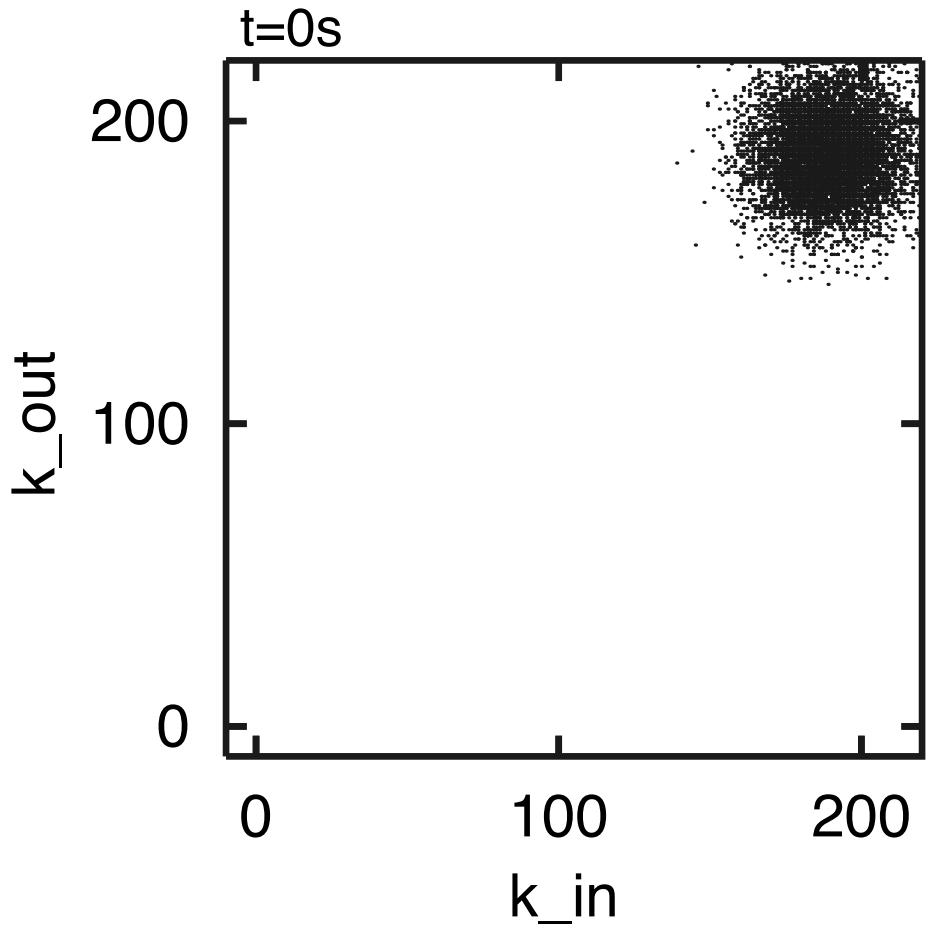


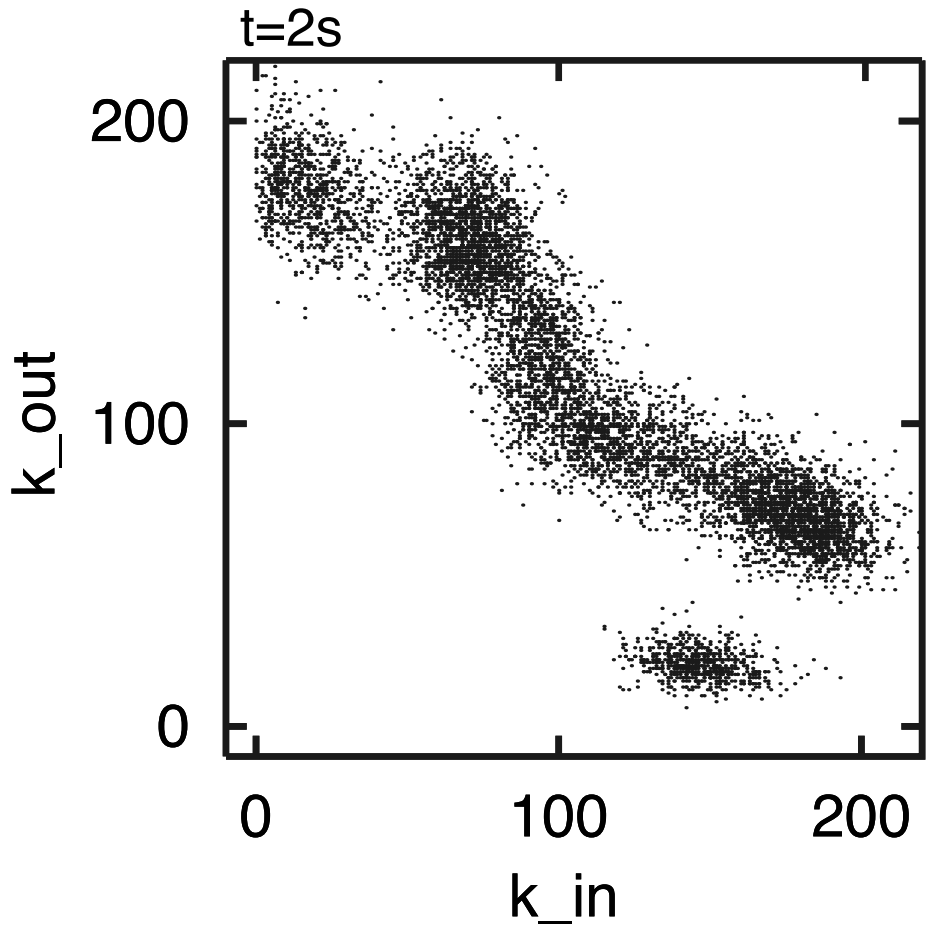


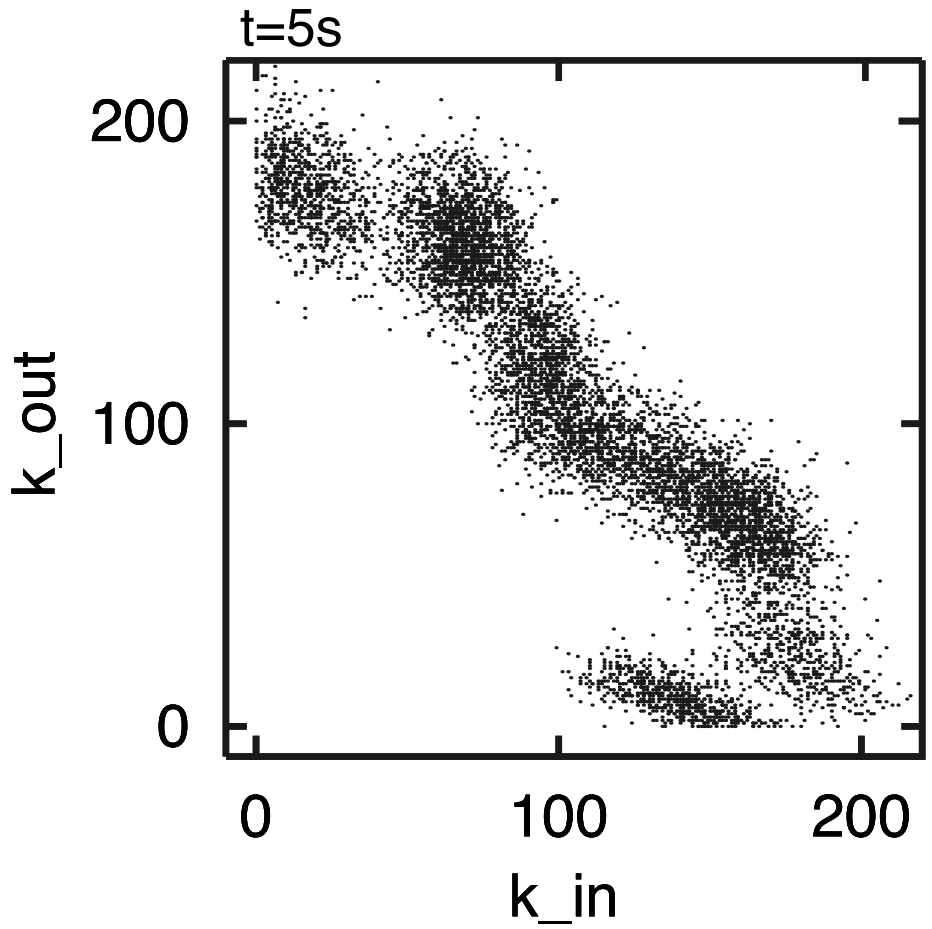
$$w_{ji}(t+1) = S_j(t) \cdot A_{ji}(t) \cdot P_{[q_j,q_i]}$$

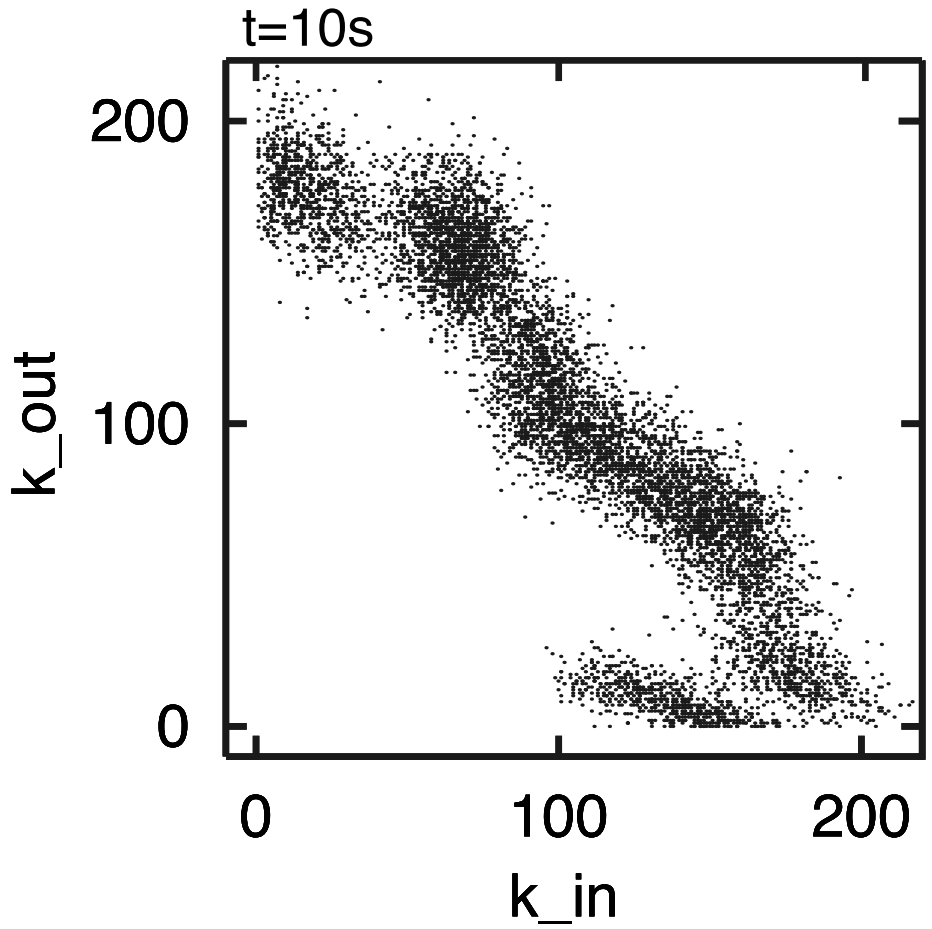
results: simulation evolution

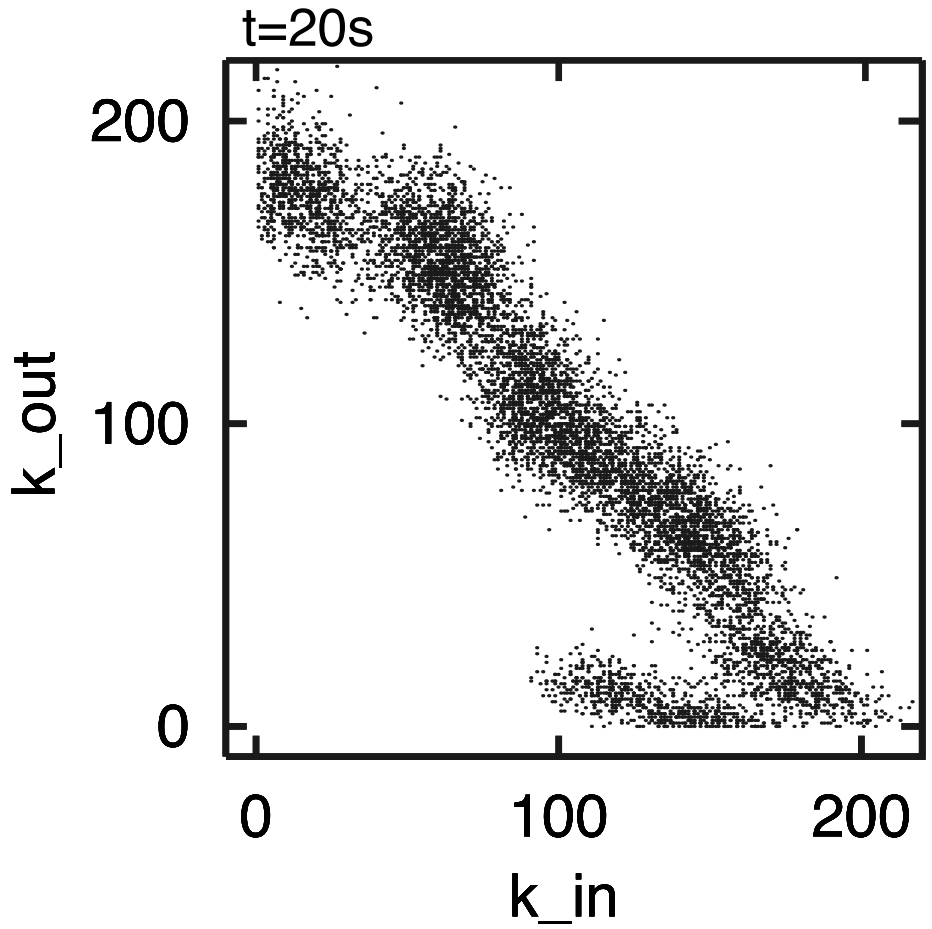


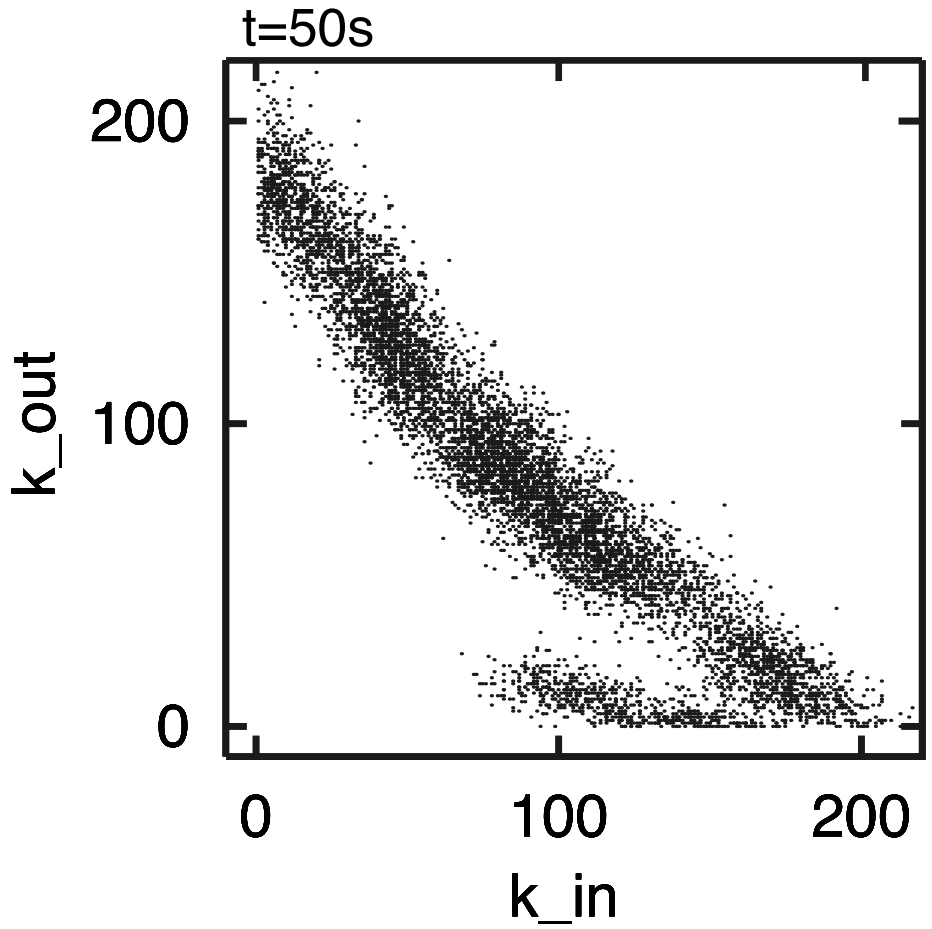

t=0s
200
100
0
k_out
0
100
200
k_in

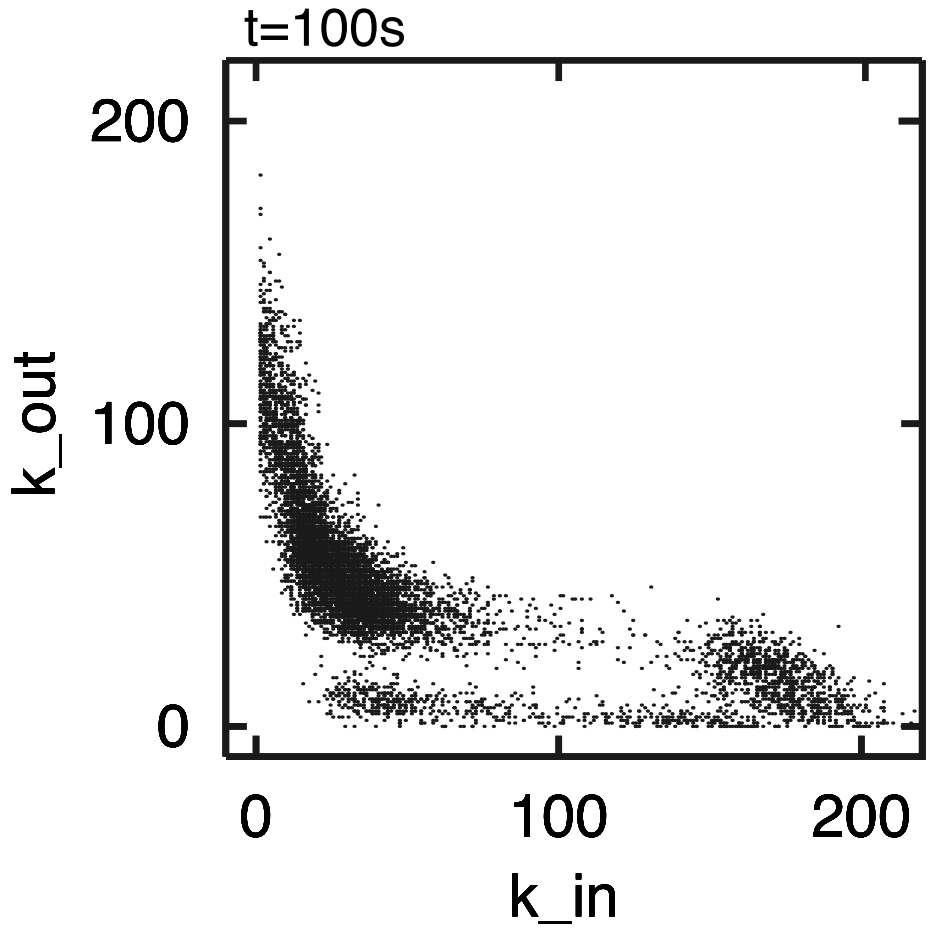

t=2s
200
100
0
k_out
0
100
200
k_in

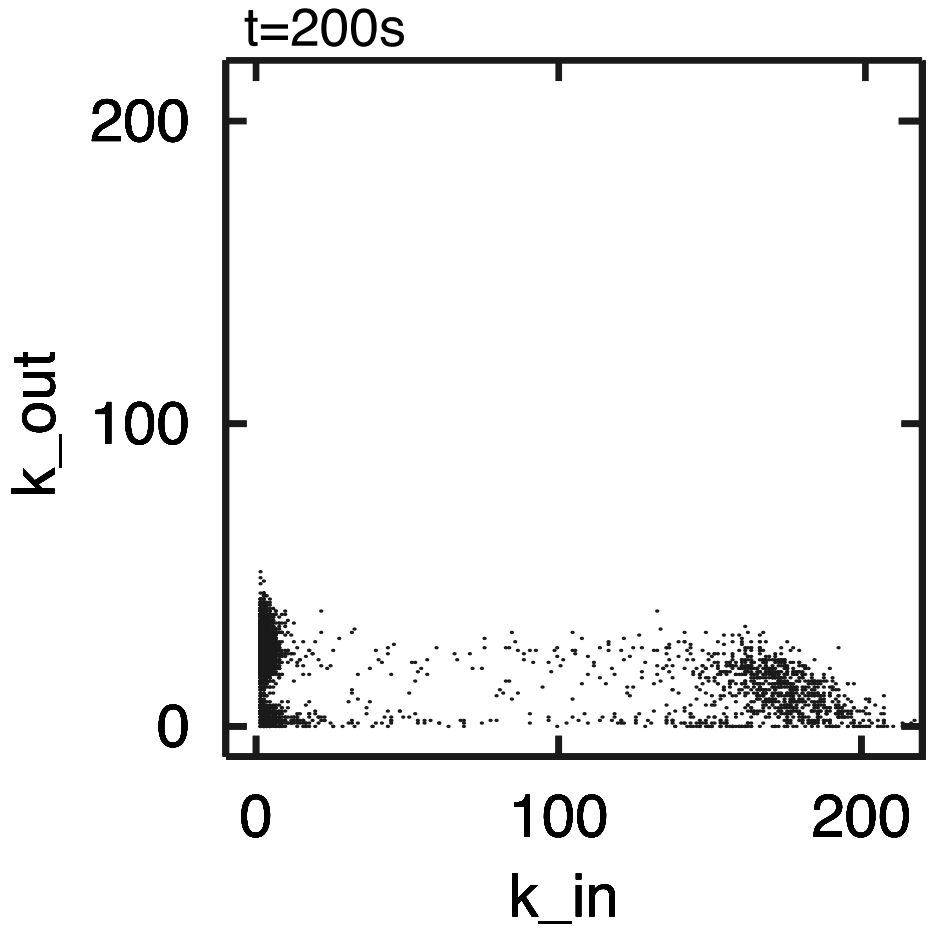

t=5s
200
100
0
k_out
0
100
200
k_in

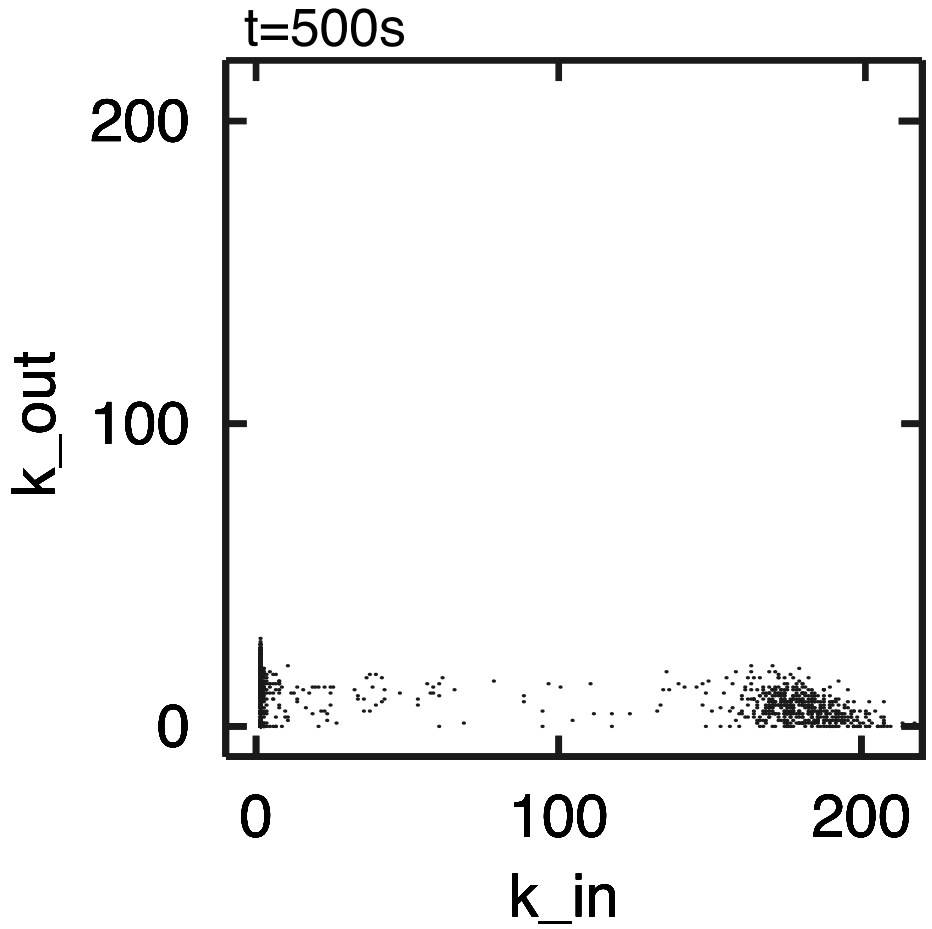

t=10s
200
100
0
k_out
0
100
200
k_in


t=20s
200
100
0
k_out
0
100
200
k_in

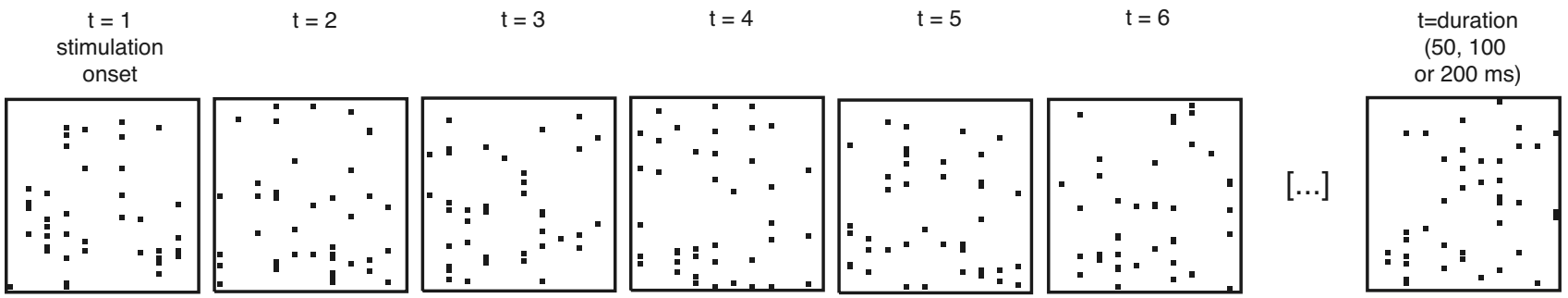

t=50s
200
100
0
k_out
0
100
200
k_in


t=100s
200
100
0
k_out
0
100
200
k_in


t=200s
200
100
0
k_out
0
100
200
k_in


t=500s
200
100
0
k_out
0
100
200
k_in

model: simple stimulus

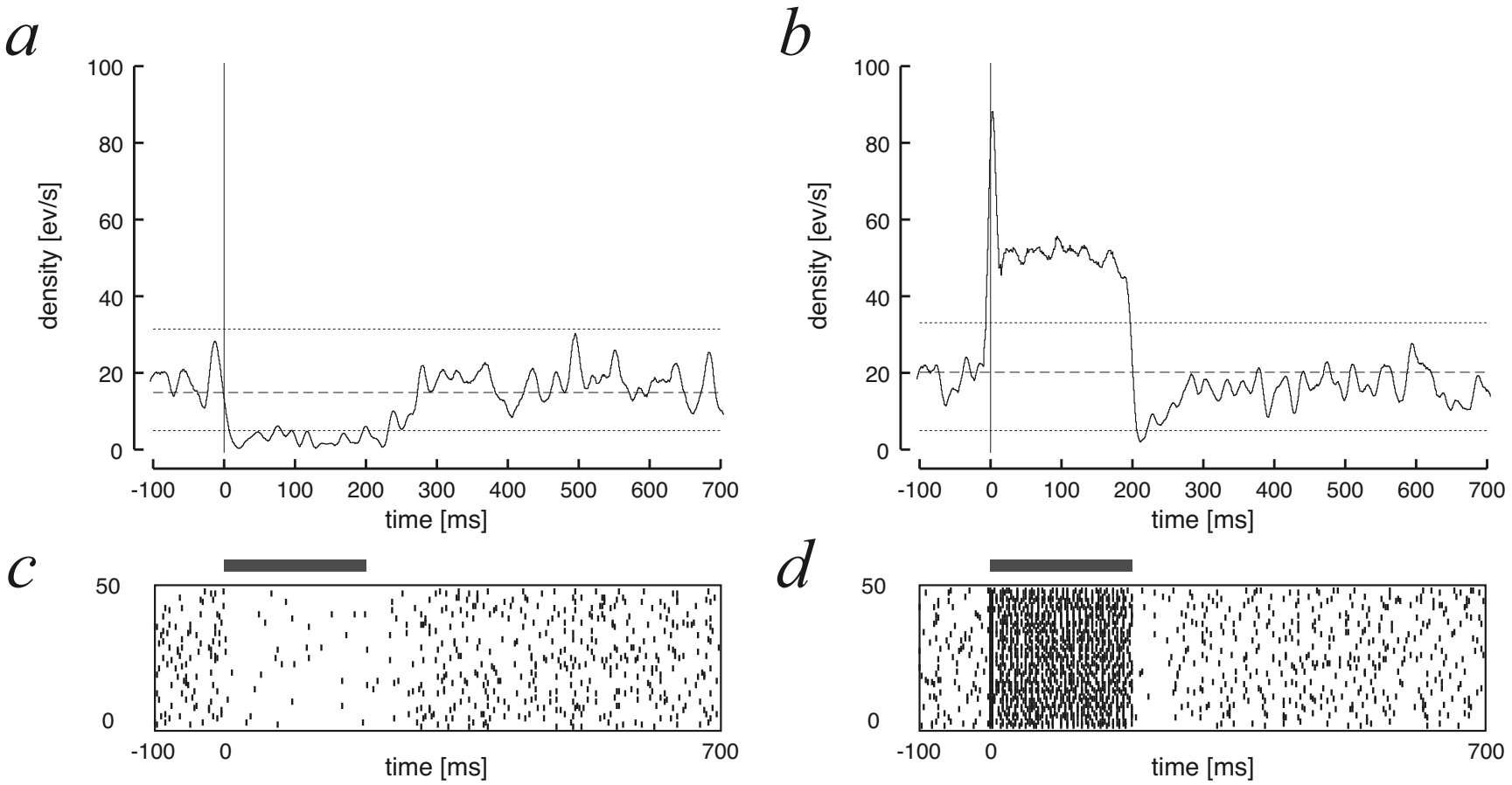


every 2 seconds
10 vertical bars moving to the right
during 200 time steps.

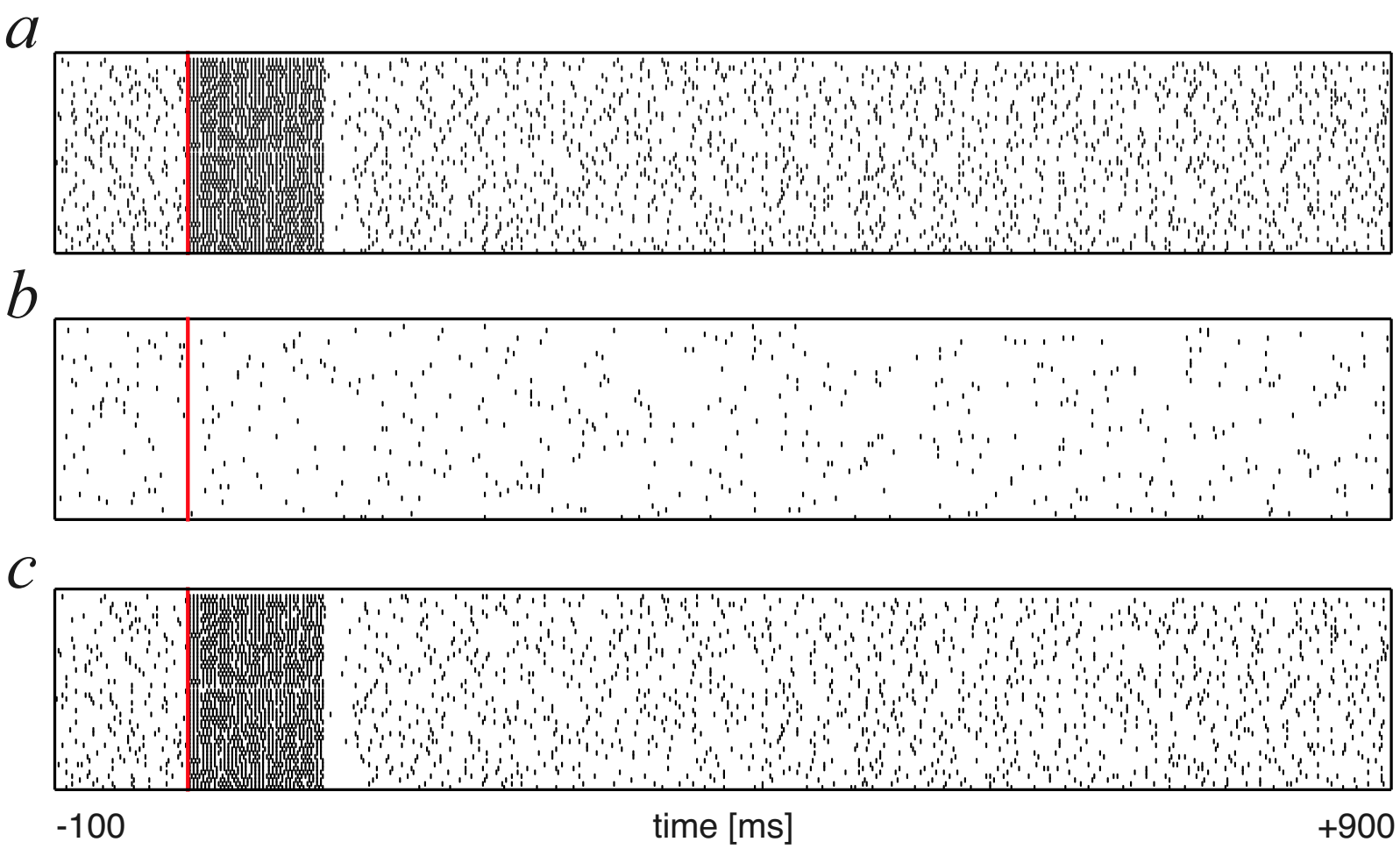
input units ratio: 10% excitatory units.
randomly selected before stimulation or in the beginning

See an animated sequence.

results: unit response to stimuli



results: differential rasters



Strongly Interconnected (SI) units

at the end of the simulation
set of cells (discarding input units)
maintaining $k_{out} \geq 3$ and $k_{in} \geq 3$
with strongest activation level ($A_{ji}(t) = 4$)
with units with the same properties.

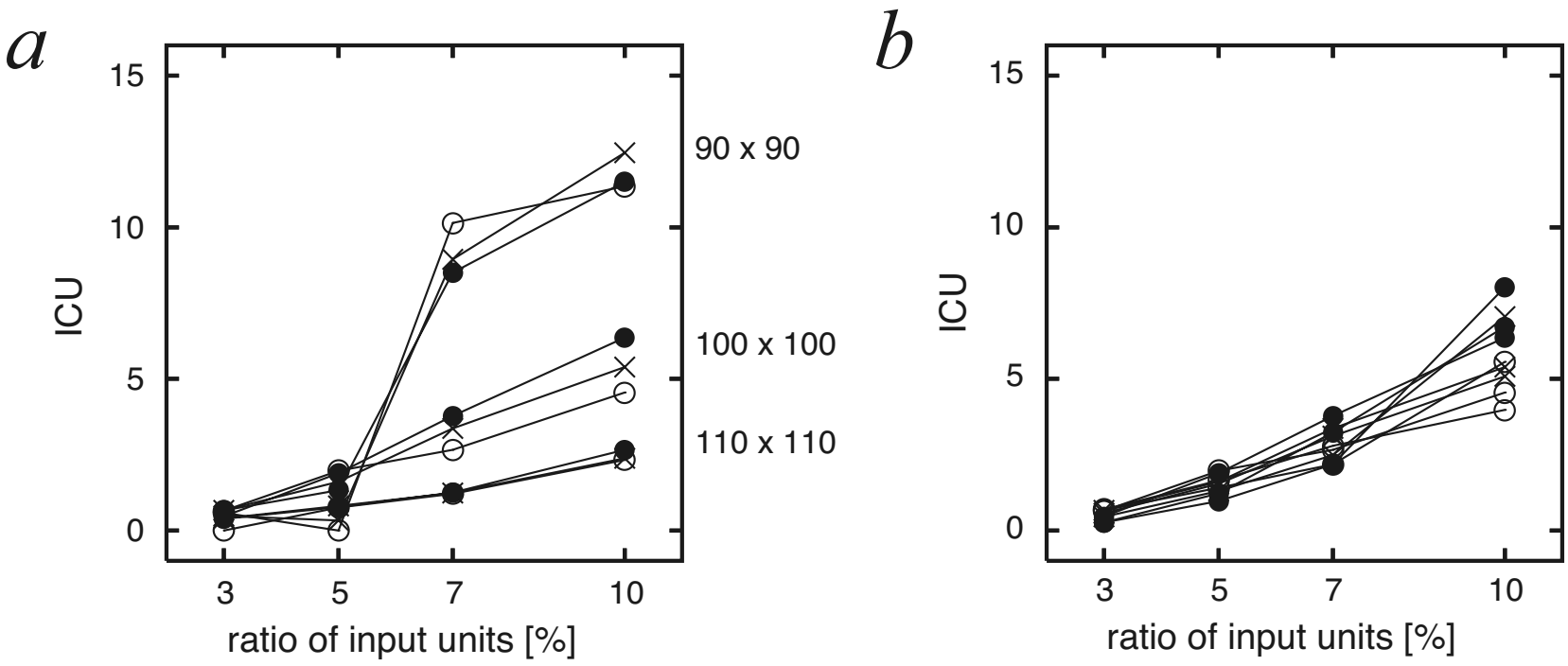
Neighbourhood

all excitatory units (including input units)
with at least one projection to or from SI-units.

Index of Connected Units (ICU)

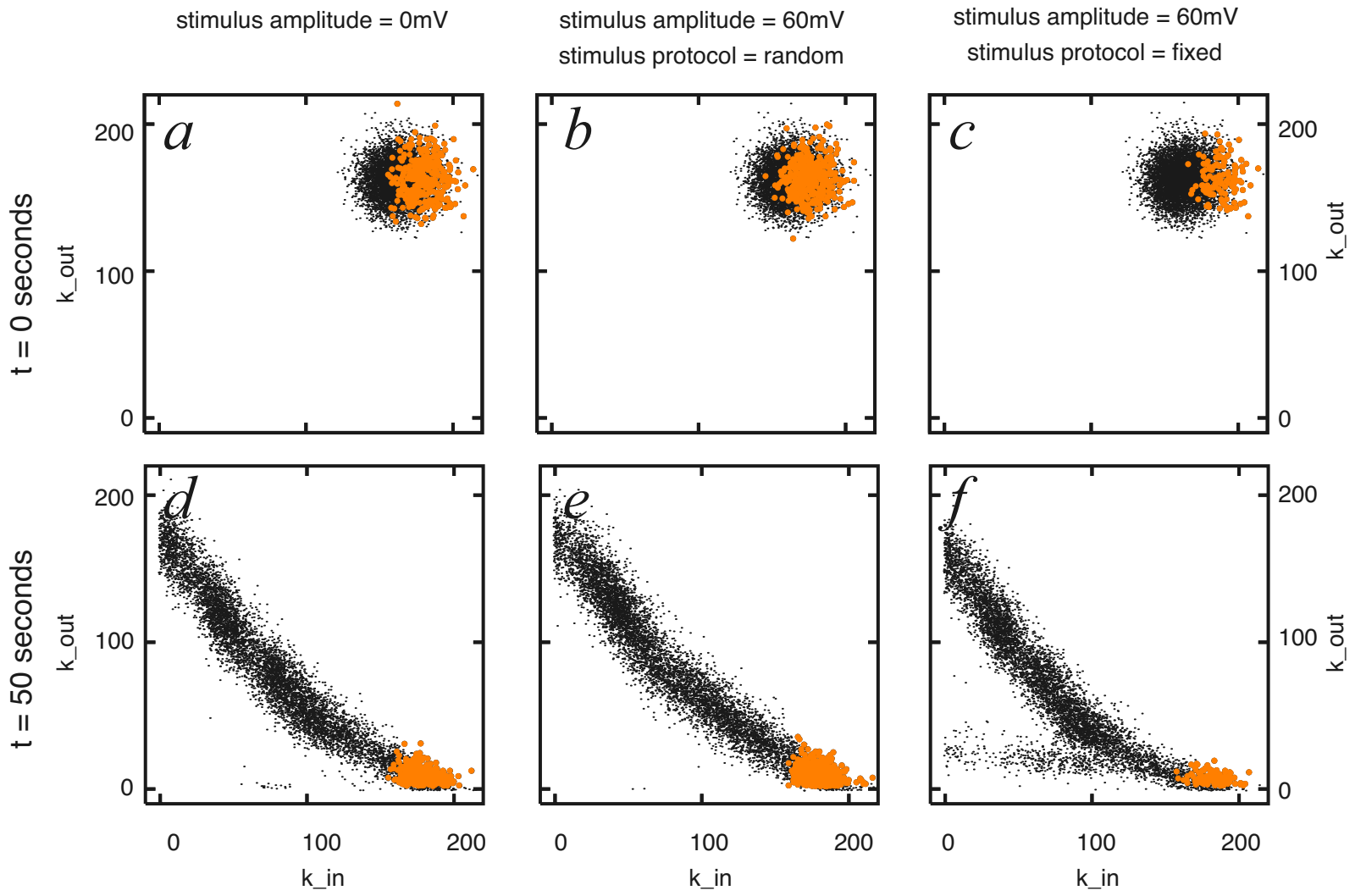
ratio between the number of input units
and the number of SI-units.

results: scaling factor

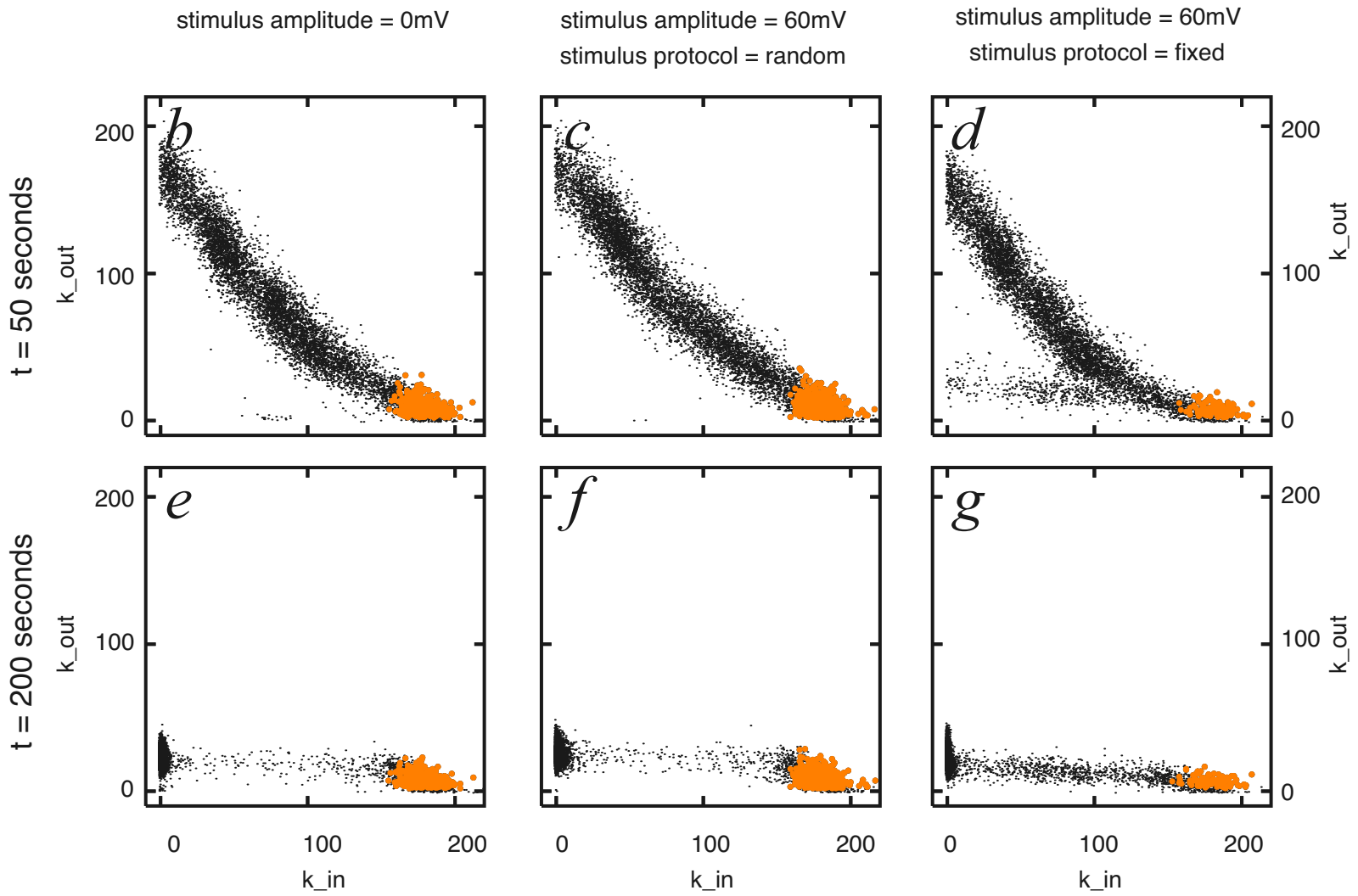


Iglesias *et al.*, *Dynamics of Pruning in Simulated Large-Scale Spiking Neural Networks*, Biosystems, 79(1-3):11-20, 2005

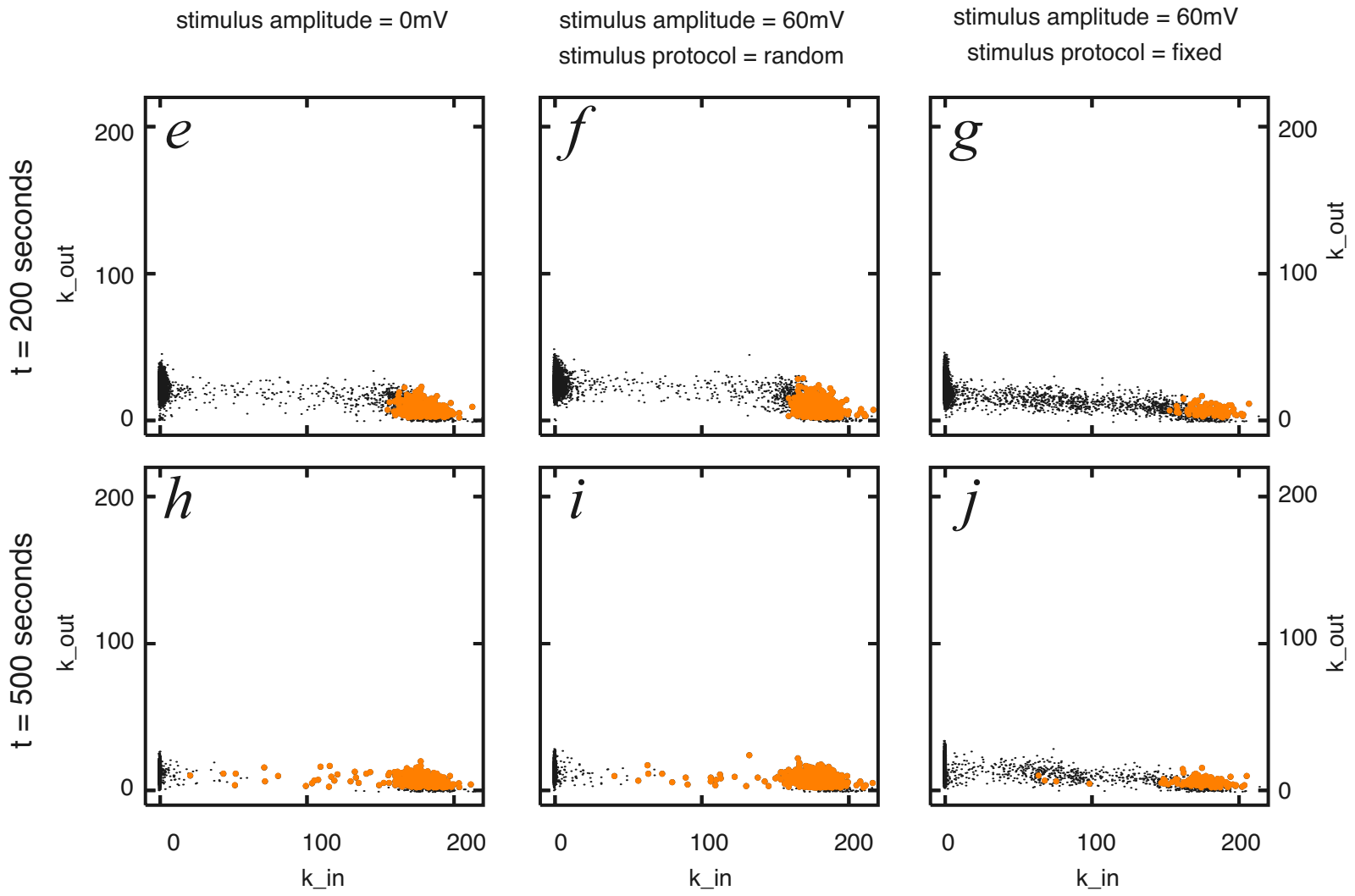
results: emergence of circuits from t=0 to t=50s



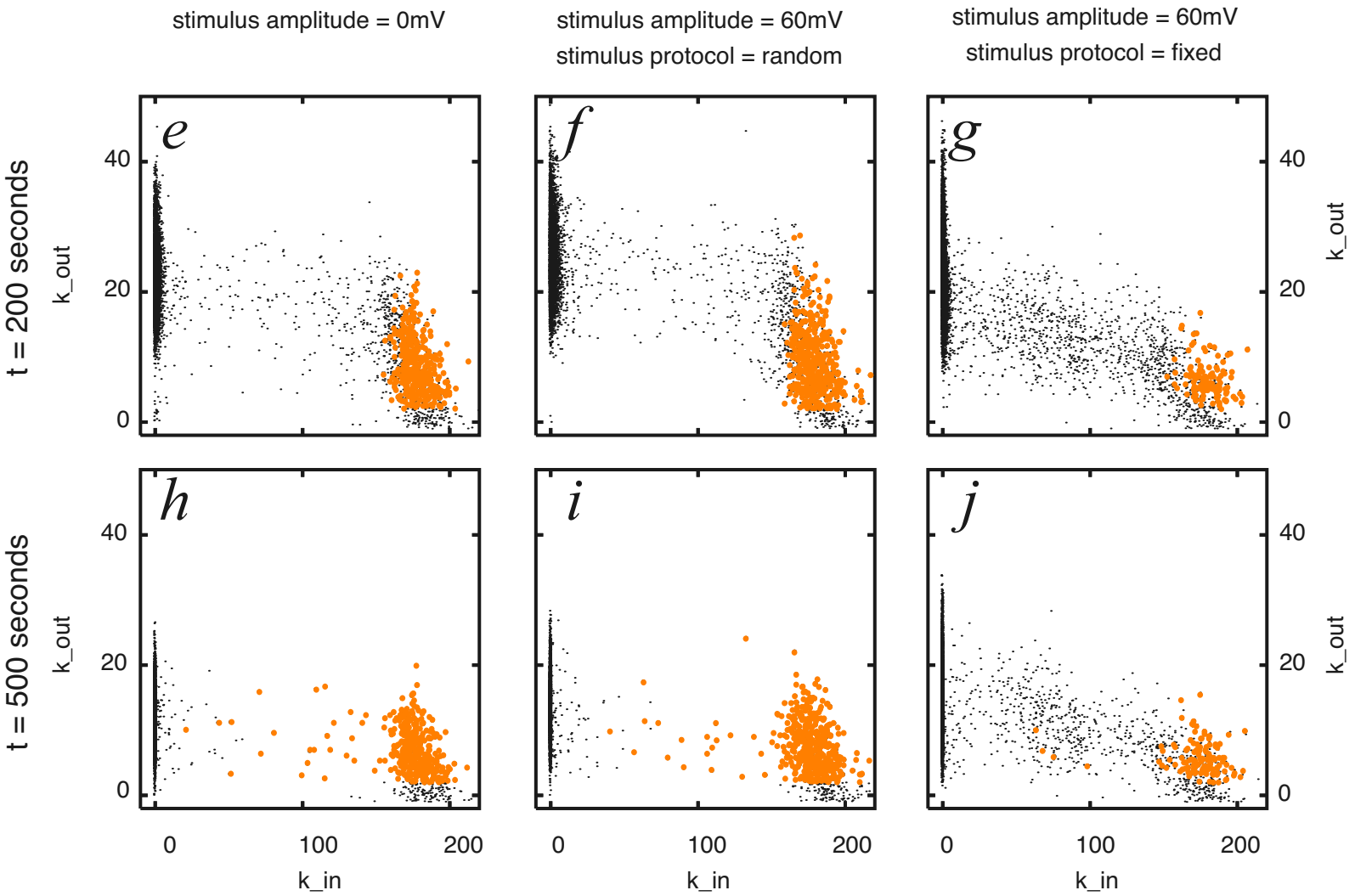
results: emergence of circuits from t=50 to t=200s



results: emergence of circuits from t=200 to t=500s

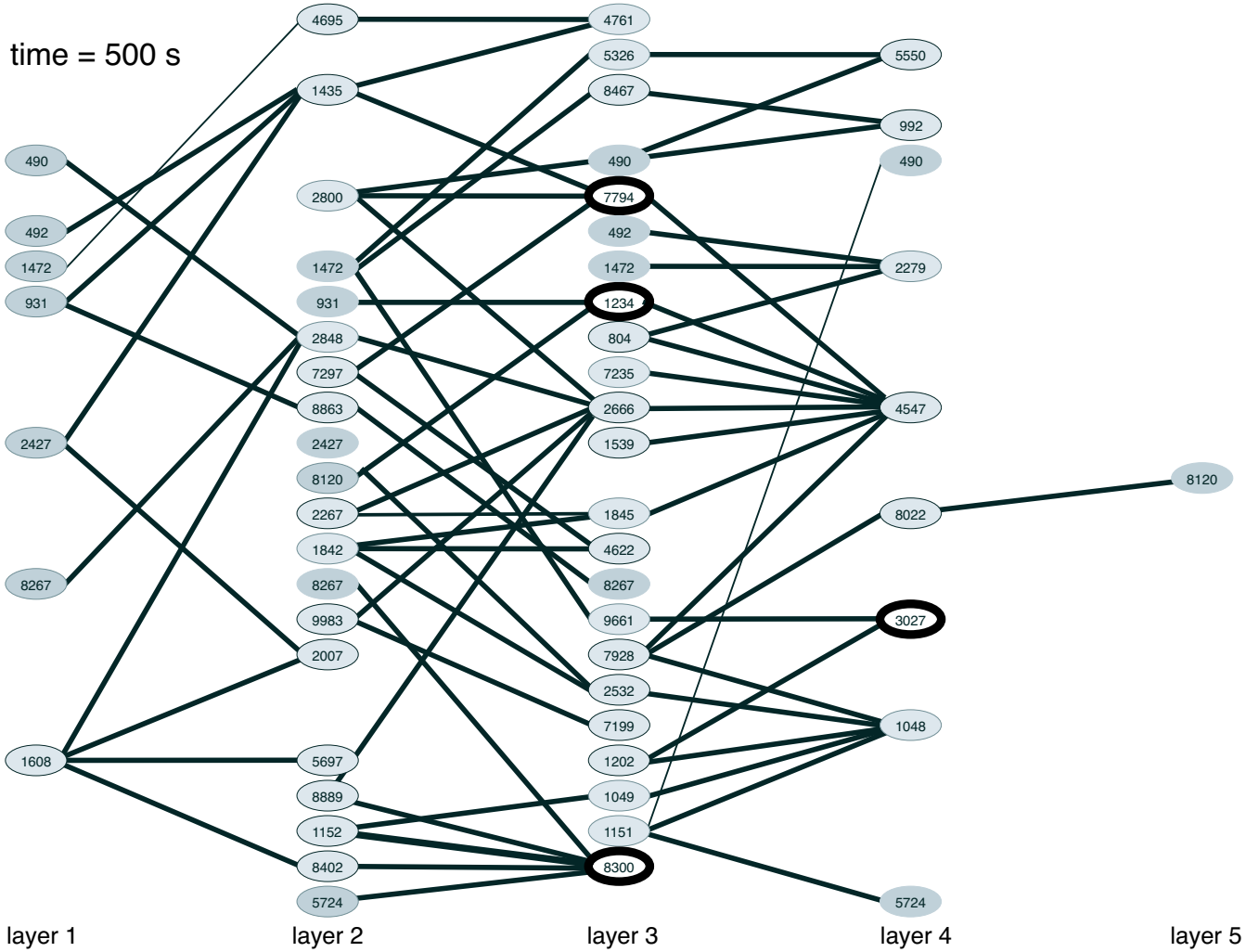


results: emergence of circuits from t=200 to t=500s (cont.)



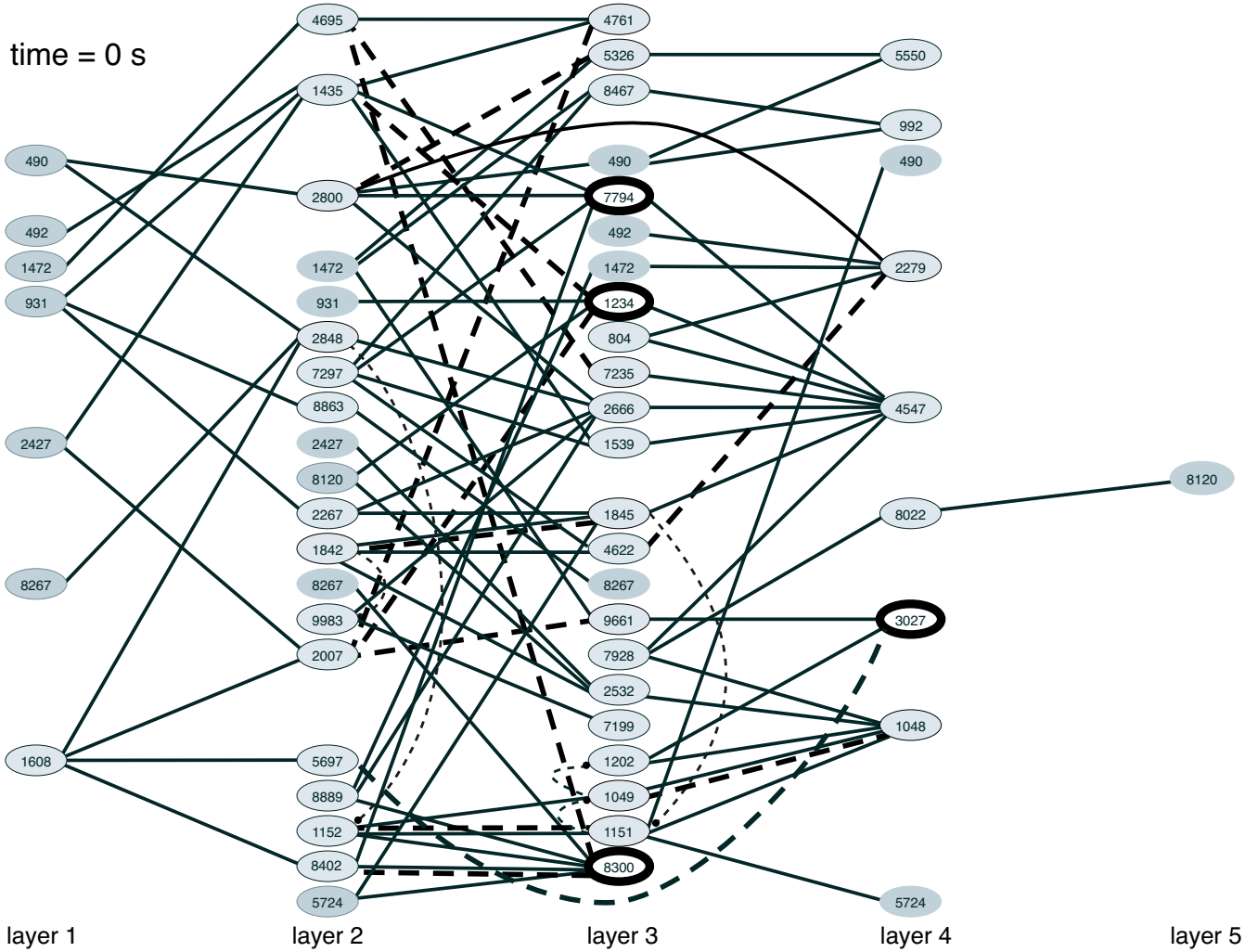
results: circuit

Iglesias *et al.*, *Emergence of Oriented Cell Assemblies Associated with Spike-Timing-Dependent Plasticity*, LNCS 3696:127-132, 2005

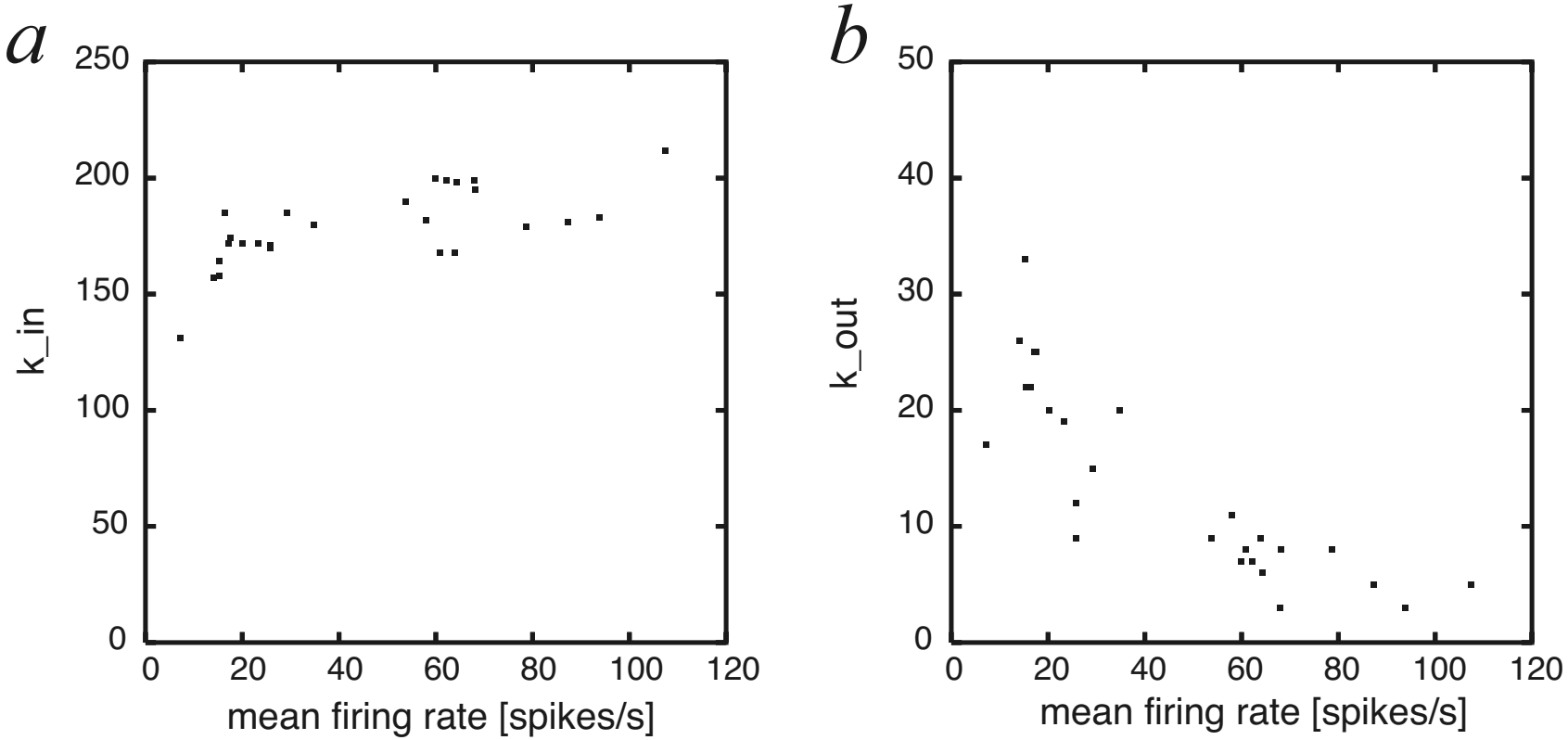


results: circuit

Iglesias *et al.*, *Emergence of Oriented Cell Assemblies Associated with Spike-Timing-Dependent Plasticity*, LNCS 3696:127-132, 2005

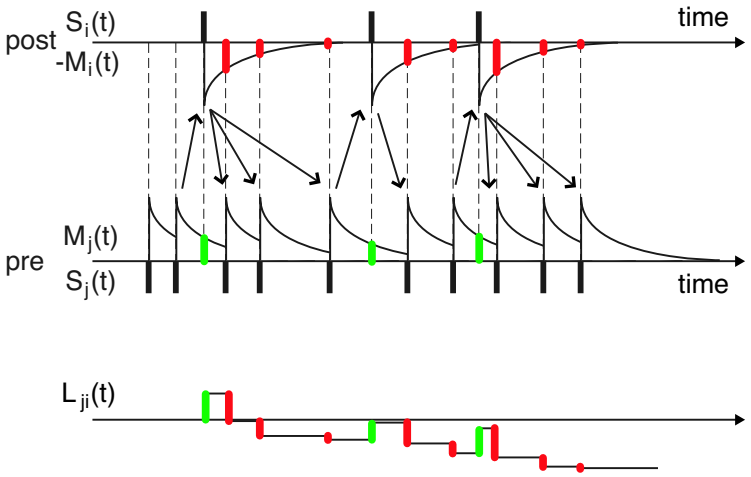


results: firing rates *vs.* connection degrees

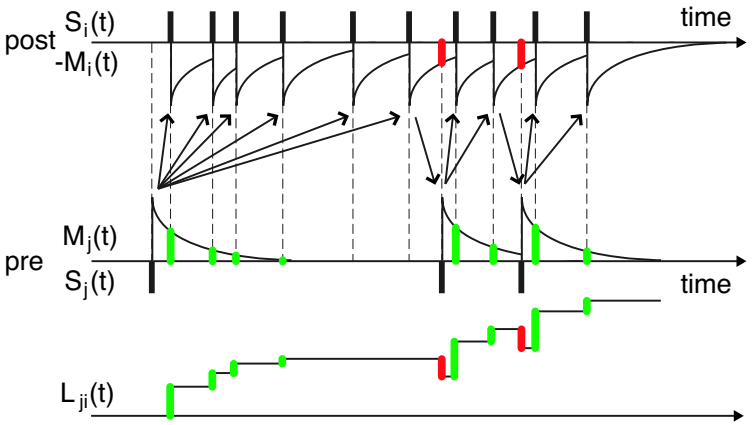


discussion: firing rates *vs.* connection degrees (cont.)

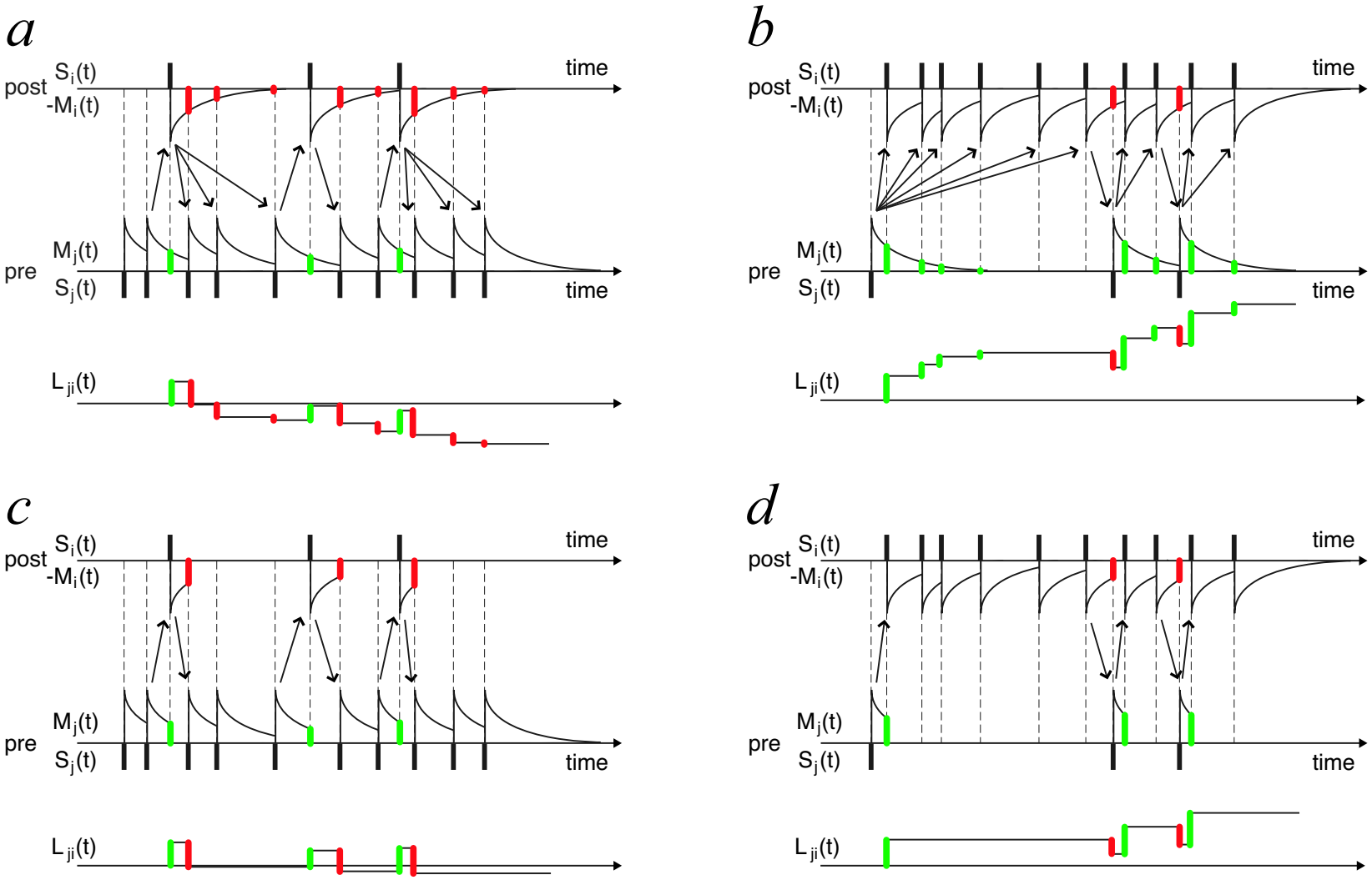
a



b



discussion: firing rates *vs.* connection degrees (cont.)



Froemke and Dan, *Spike-timing-dependent synaptic modification induced by natural spike trains*, Nature, 416:433–8, 2002

- emergence of oriented circuits
  by synaptic pruning associated with STDP

- introduction of a scaling factor
  to maintain properties of the emergence
  across different network sizes

- role of pre– vs. postsynaptic firing rate difference
  on STDP synaptic modification rule