

Inhibitory neurons control the consolidation of neural assemblies via adaptation to selective stimuli

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Mathias Quoy, Gorka Zamora-López

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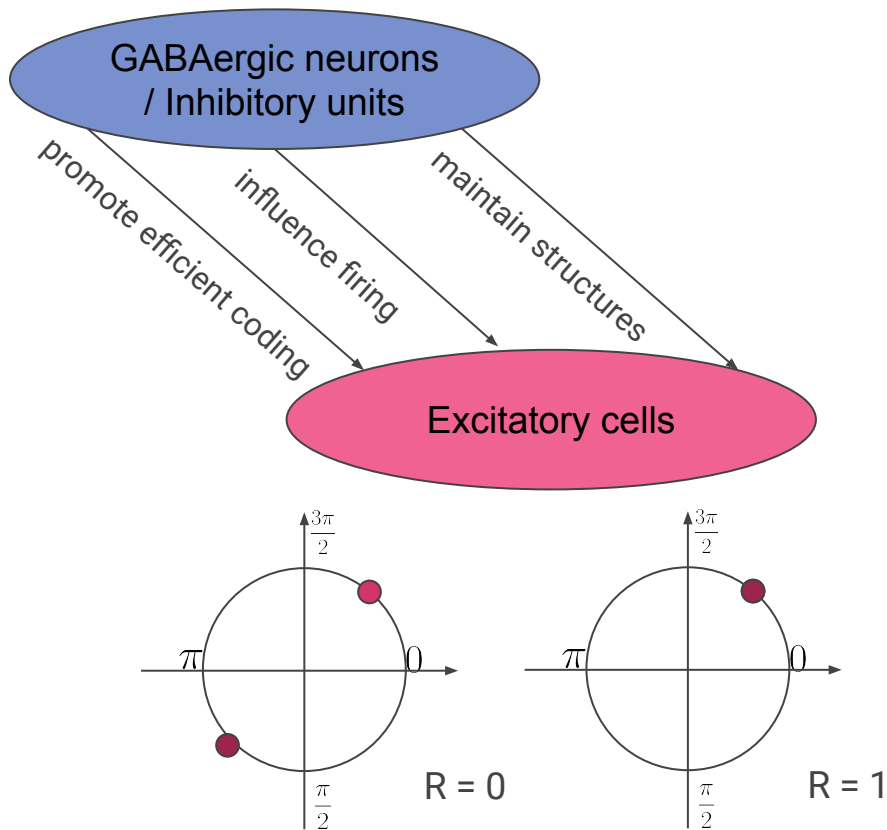
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Introduction: Context and problems

Context :

- **Inhibition** plays a key role in the **learning** and the **dynamics** of the brain
- These aspects are also found in **neural network models**
- **Oscillator models** are well suited for highlighting the **synchronization** degree of a network according to inhibition and excitation



Introduction: Context and problems

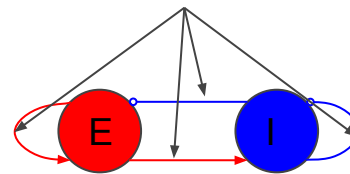
Problems:

In coupled oscillator models

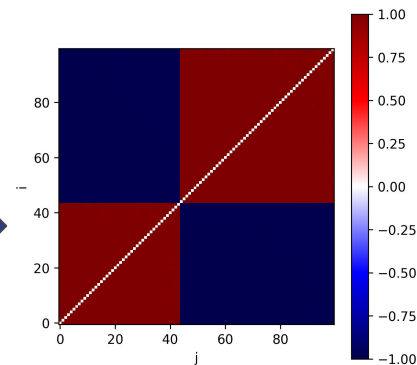
- Too few experiments associate **inhibition** with an **adaptation** mechanism



Fixed couplings between oscillators



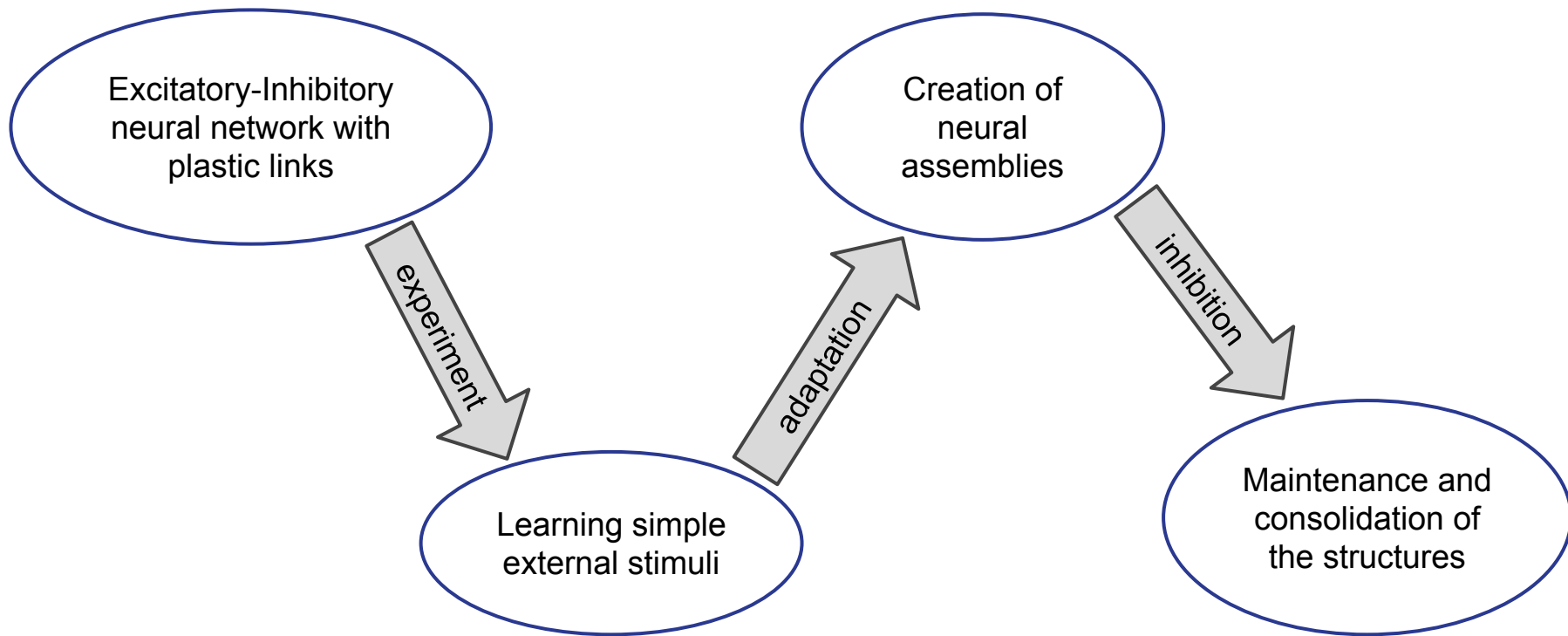
- No **distinction** made in general between excitatory and inhibitory neurons, **Dale's principle** not respected



Coupling weight matrix of Kuramoto-like oscillators (Berner 2021)

Introduction: Objectives

What is the role of **inhibitory** neurons in the **emergence** and **consolidation** of **neural assemblies** due to stimulus-driven plasticity?



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Methods: Model - Neurons dynamics

Network of N **θ -neurons** (Ermentrout & Kopell 1986) all-to-all connected described by:

Neuron phase

Global coupling

External input

$$\frac{d\theta_i}{dt} = (1 - \cos(\theta_i)) + (1 + \cos(\theta_i))[\eta_i + \frac{g}{N} (\sum_{j=1}^N \kappa_{ij} \sin(\theta_j - \theta_i)) + I_i(t) + \xi_i(t)]$$

Excitability parameter

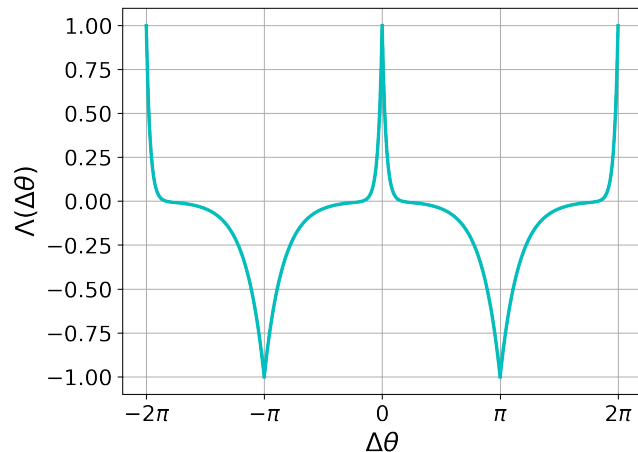
Coupling weight from presynaptic neuron j to postsynaptic neuron i

Additive Gaussian noise

Methods: Model - Plasticity function

The **symmetric phase difference-dependent plasticity** rule (Lücken et al. 2016, Shamsi et al. 2020) is described by:

$$\Lambda(\Delta\theta) = \begin{cases} e^{-\frac{\Delta\theta}{0.1}} - e^{\frac{\Delta\theta-\pi}{0.5}}, & \text{if } 0 \leq \Delta\theta < \pi \\ e^{\frac{\Delta\theta-2\pi}{0.1}} - e^{-\frac{\Delta\theta-\pi}{0.5}}, & \text{if } \pi \leq \Delta\theta < 2\pi \end{cases}$$



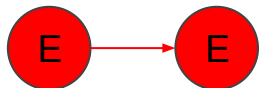
The Hebbian plasticity function

With the phase difference: $\Delta\theta = |\theta_j - \theta_i|$

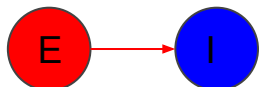
Methods: Model - Weights adaptation

The dynamic of the **coupling weight** κ_{ij} from presynaptic neuron j to postsynaptic neuron i is given by the following equations, with $H(x)$ the Heaviside function, $\epsilon_1 \ll \epsilon_2 \ll 1$ the learning rates for the slow and the fast adaptation respectively.

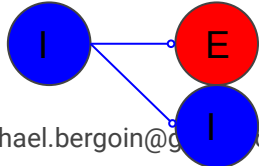
- If the neurons i and j are **excitatory** the dynamic of the coupling weights is given by :


$$\frac{d\kappa_{ij}}{dt} = [\epsilon_1 + \epsilon_2 H(I_j(t))] \kappa_{ij} (1 - \kappa_{ij}) \Lambda(\Delta\theta)$$

- If only the neuron j is **excitatory** the dynamic of the coupling weights is given by :


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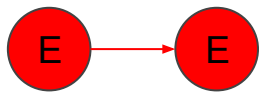
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Methods: Model - Weights adaptation

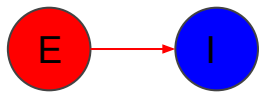
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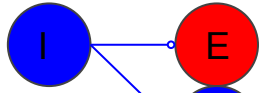
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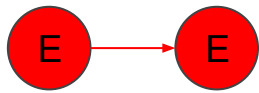
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Plasticity function

Methods: Model - Weights adaptation

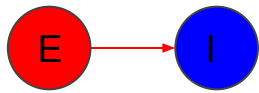
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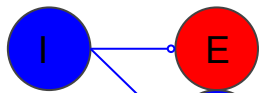
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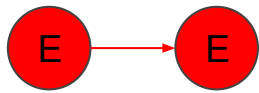
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Soft bounds

Methods: Model - Weights adaptation

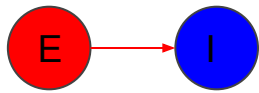
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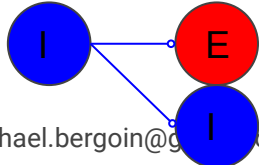
$$\frac{d\kappa_{ij}}{dt} = [\underbrace{\epsilon_1 + \epsilon_2 H(I_j(t))}_{\text{Slow adaptation}}] \kappa_{ij} (1 - \kappa_{ij}) \Lambda(\Delta\theta)$$

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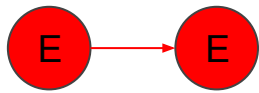
$$\frac{d\kappa_{ij}}{dt} = \underbrace{\epsilon_1}_{\text{Slow adaptation}} (\kappa_{ij} + 1) (-\kappa_{ij}) \Lambda(\Delta\theta)$$

Slow adaptation

Methods: Model - Weights adaptation

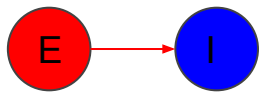
The dynamic of the **coupling weight** κ_{ij} from presynaptic neuron j to postsynaptic neuron i is given by the following equations, with $H(x)$ the Heaviside function, $\epsilon_1 \ll \epsilon_2 \ll 1$ the learning rates for the slow and the fast adaptation respectively.

- If the neurons i and j are **excitatory** the dynamic of the coupling weights is given by :



$$\frac{d\kappa_{ij}}{dt} = [\epsilon_1 + \underbrace{\epsilon_2 H(I_j(t))}_{\text{Fast adaptation}}] \kappa_{ij} (1 - \kappa_{ij}) \Lambda(\Delta\theta)$$

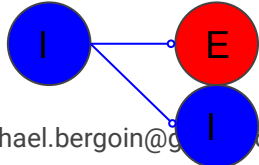
- If only the neuron j is **excitatory** the dynamic of the coupling weights is given by :



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Fast adaptation

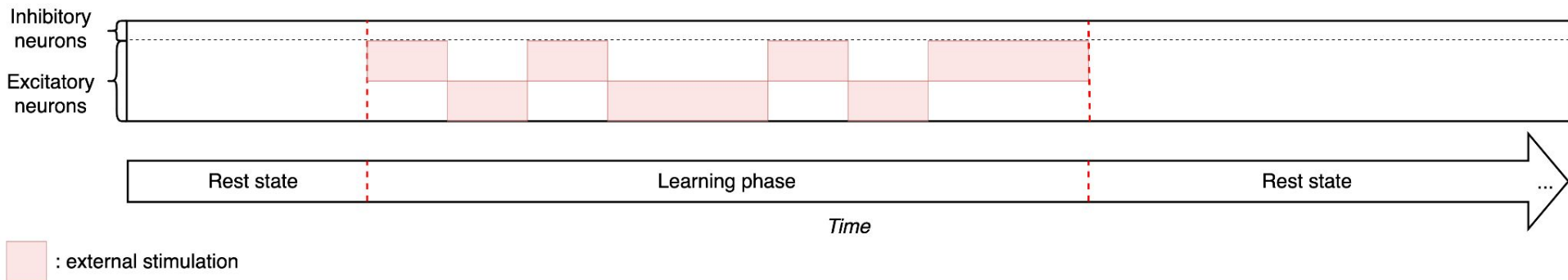
- If the neuron j is **inhibitory** the dynamic of the coupling weights is given by :



$$\frac{d\kappa_{ij}}{dt} = \epsilon_1 (\kappa_{ij} + 1) (-\kappa_{ij}) \Lambda(\Delta\theta)$$

Methods: Experimental protocol

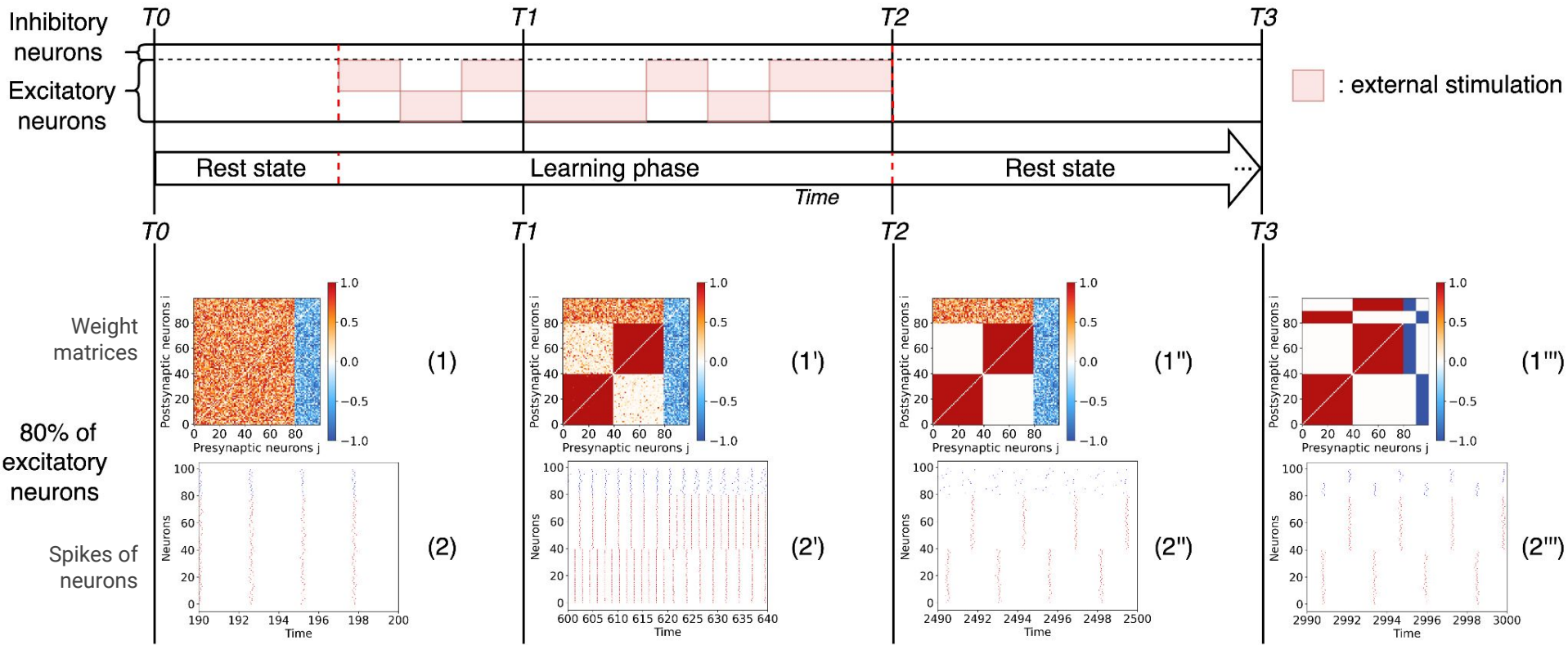
- A first phase of spontaneous activity
- Stimulate **2 different areas** (i.e., groups of excitatory neurons) alternatively and randomly with binary values (constant input)
- Create particular (modular) **structures**
- Observe the **dynamics** obtained during the rest state and the action of **inhibition** on it over the **short and long term**



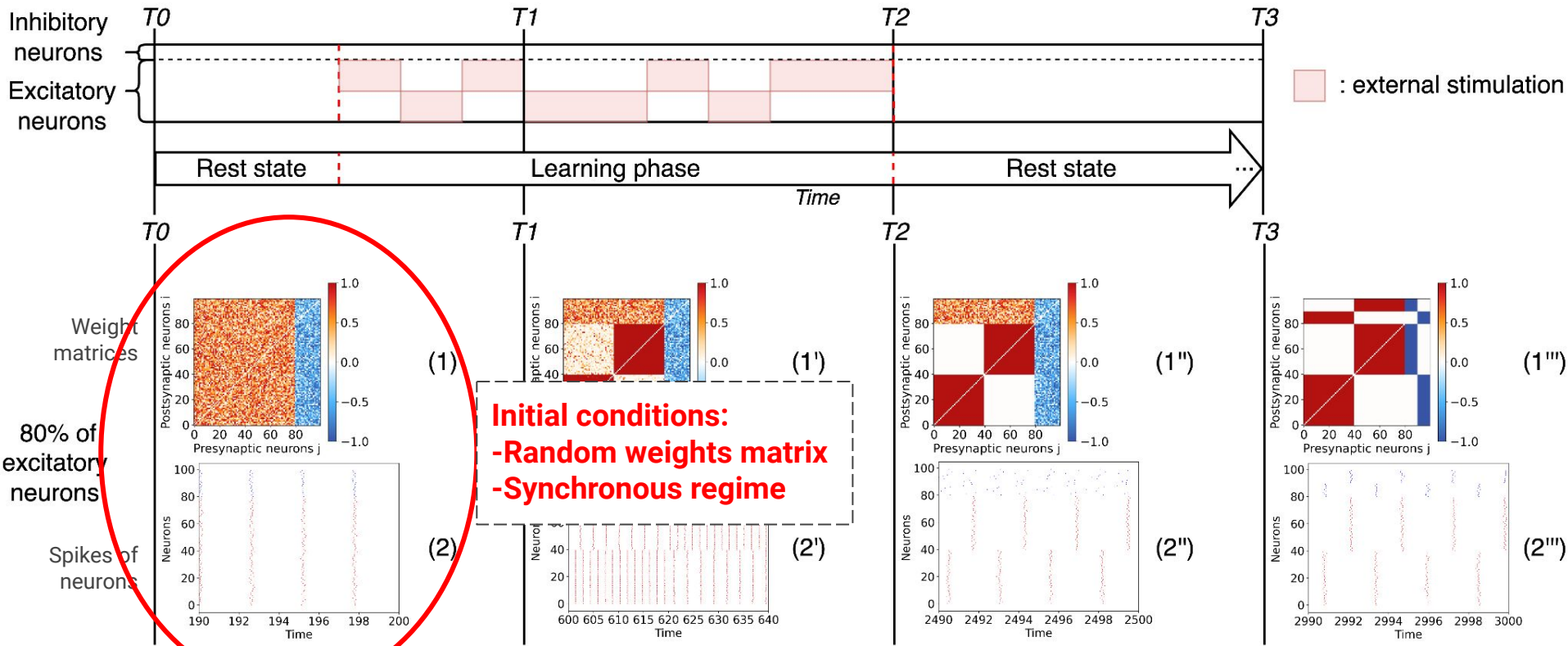
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Results: Maintain and consolidate structures

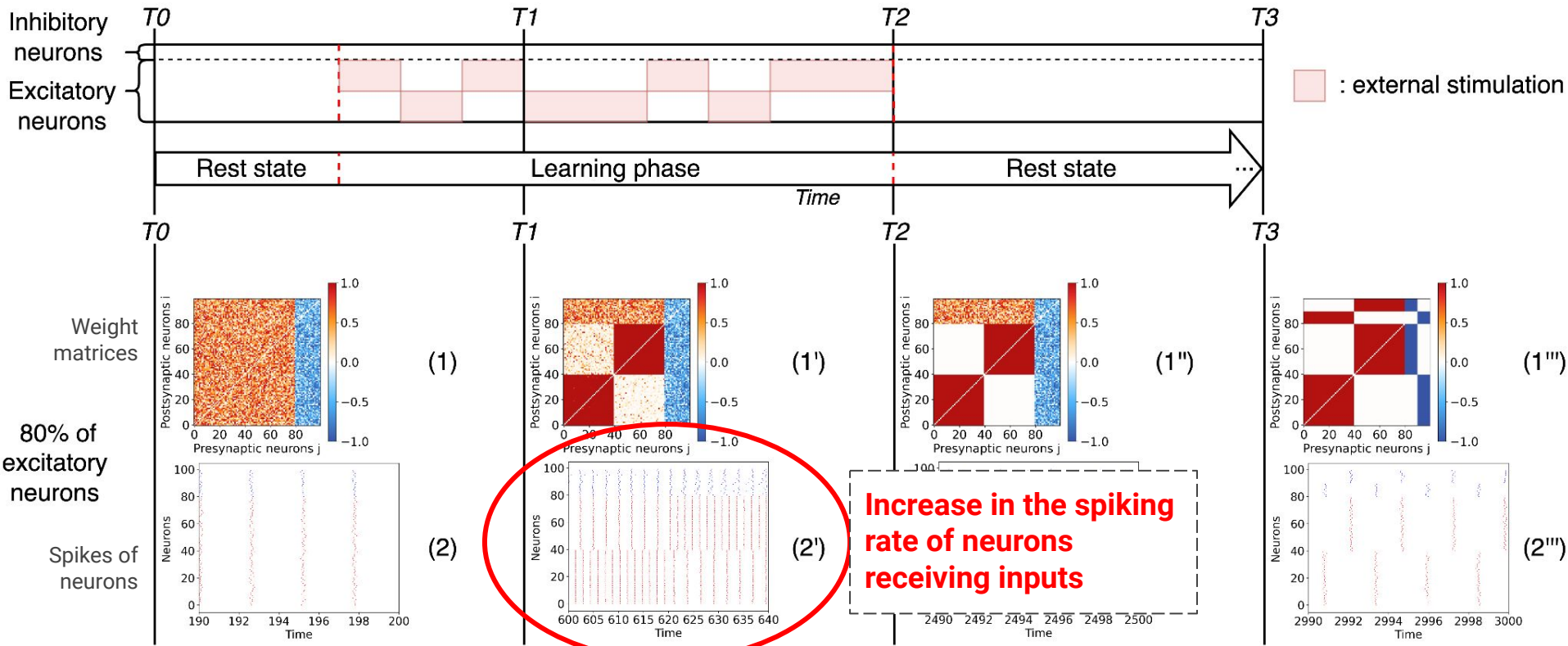


Results: Maintain and consolidate structures

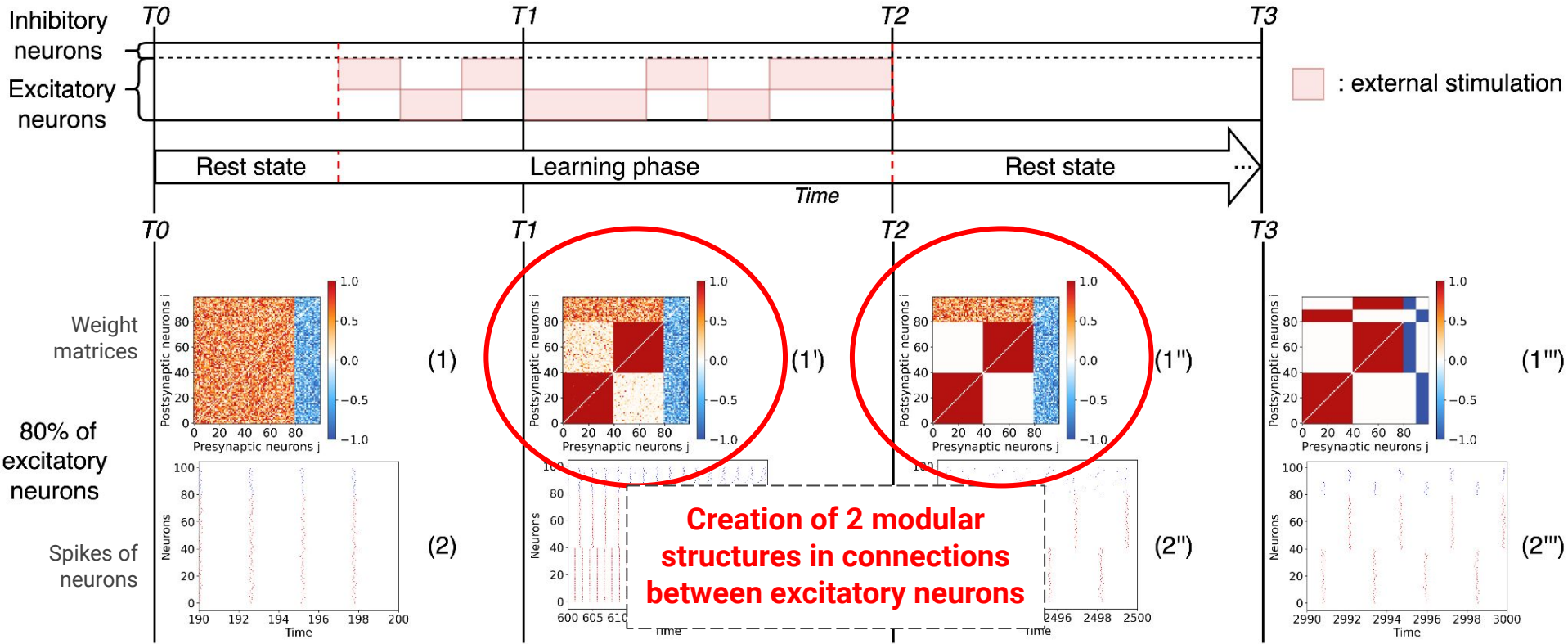


(Bergoin, et al. 2023)

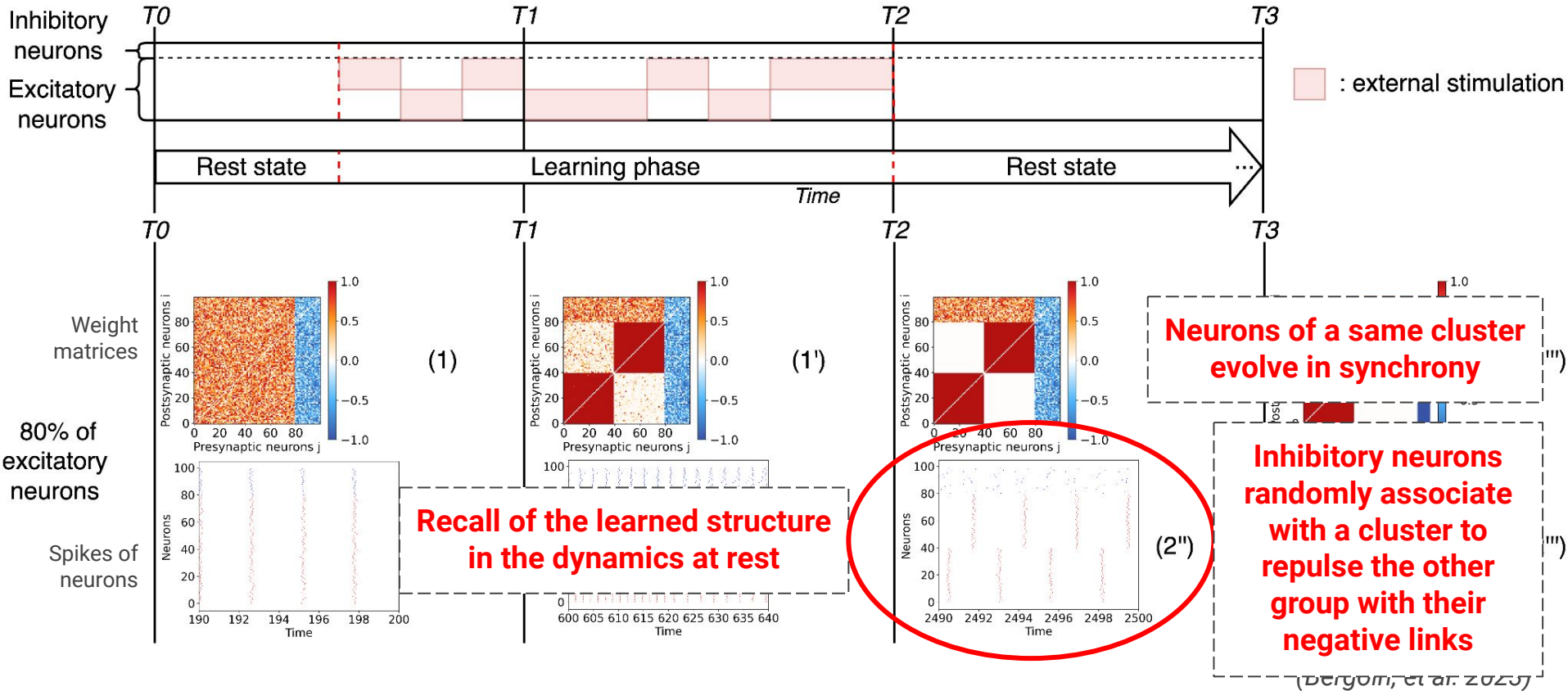
Results: Maintain and consolidate structures



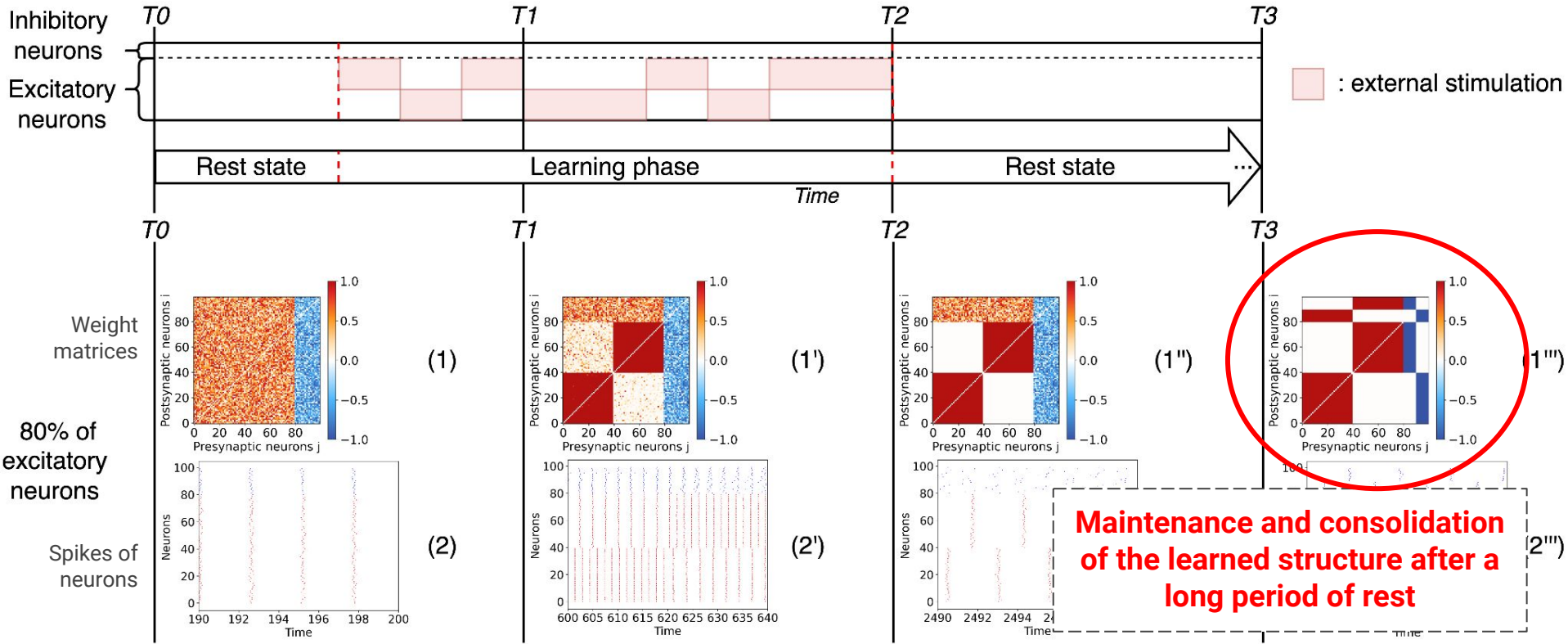
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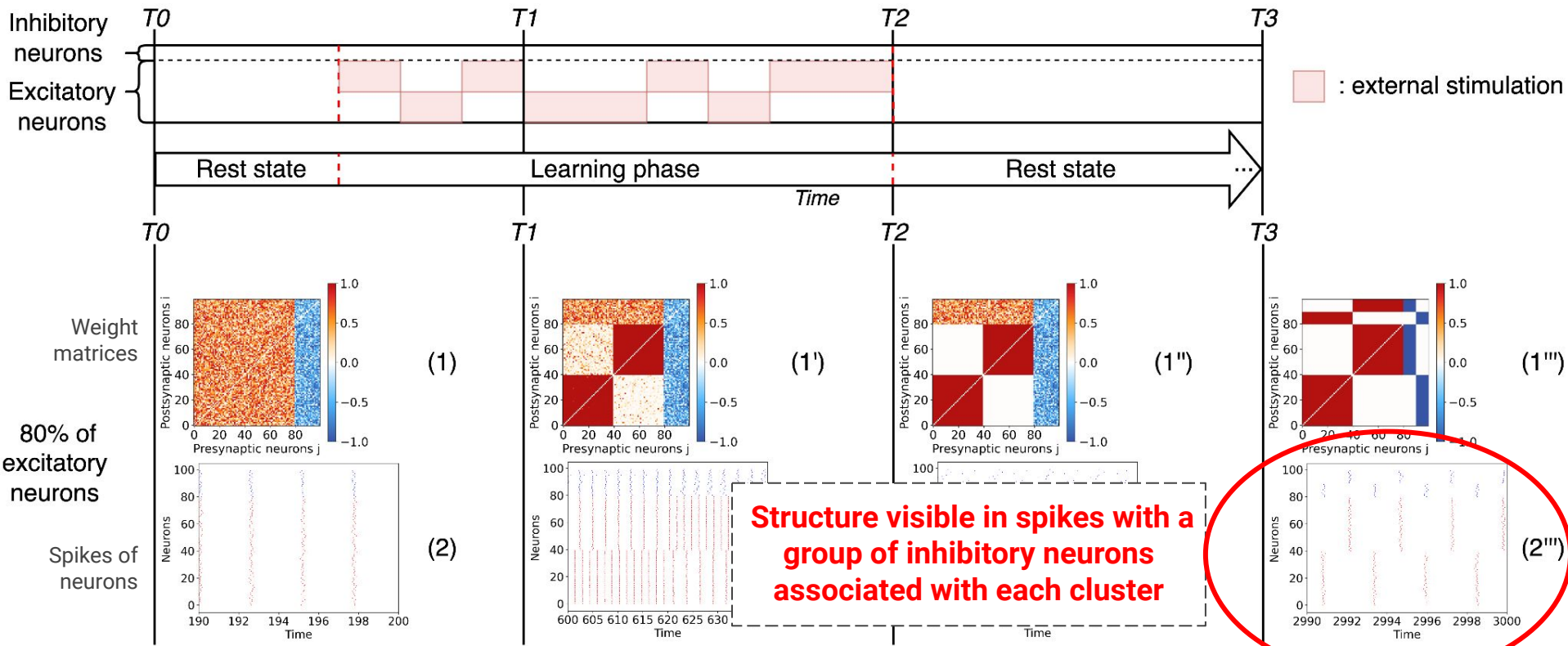


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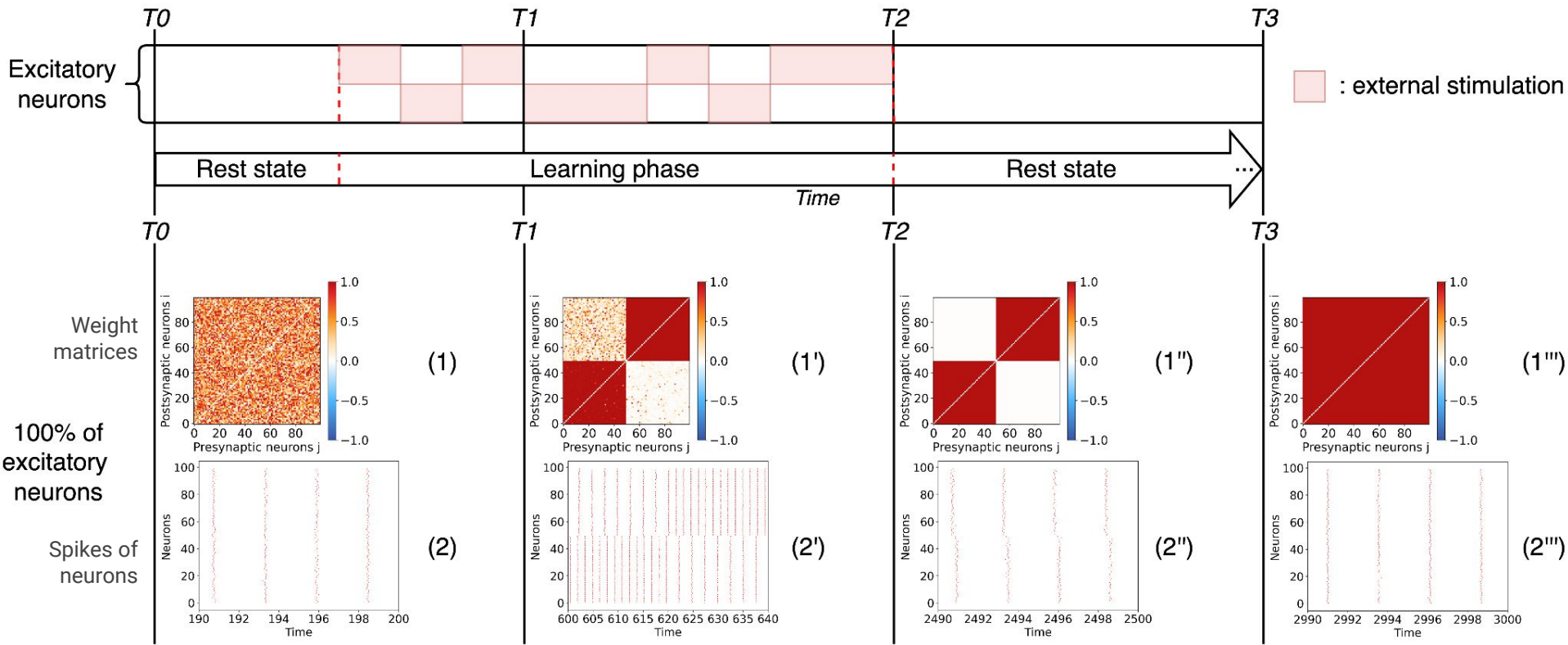


(Bergoin, et al. 2023)

Results: Maintain and consolidate structures

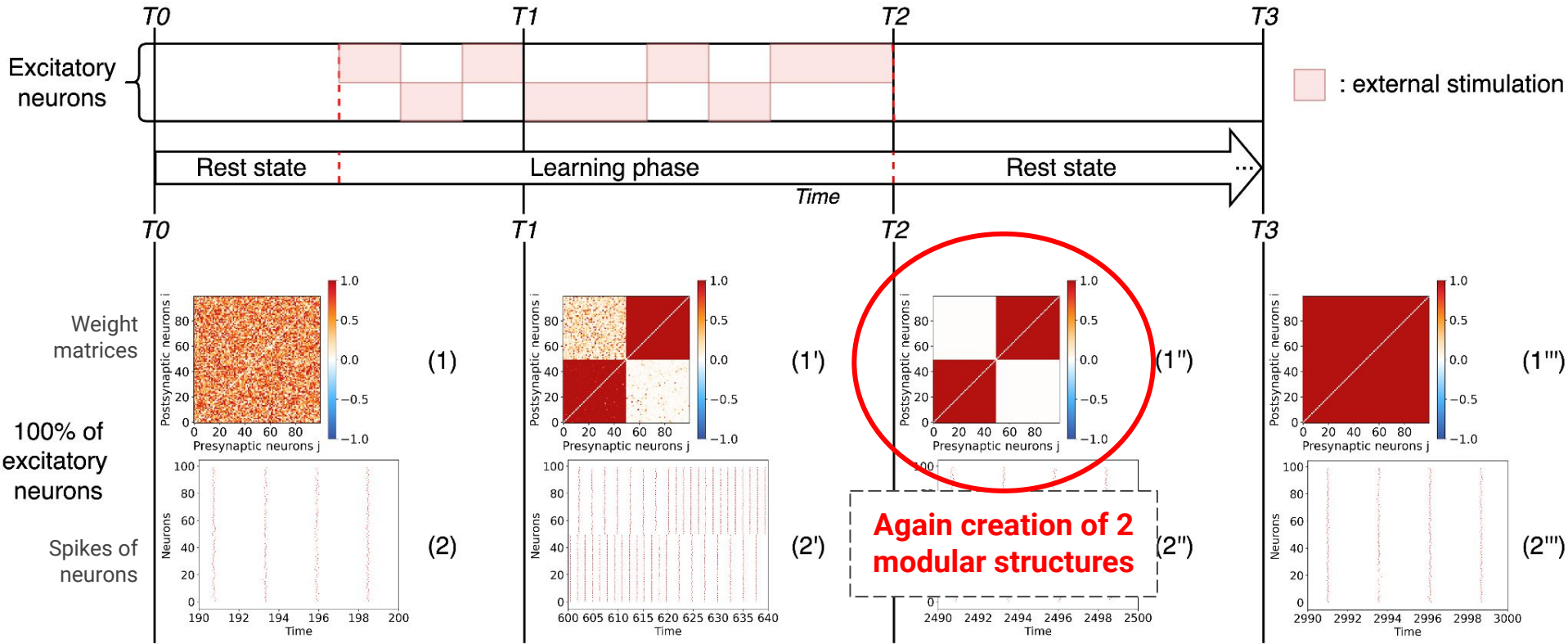


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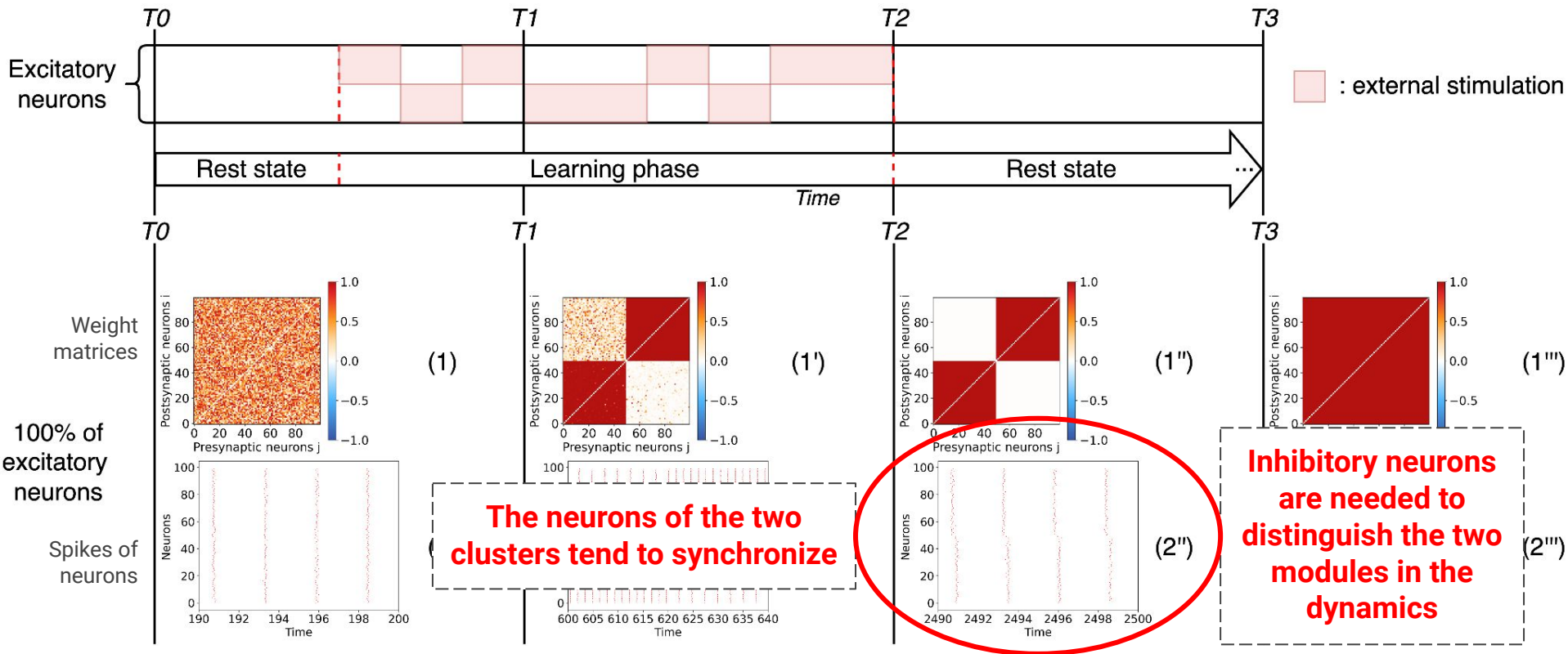
(Bergoin, et al. 2023)

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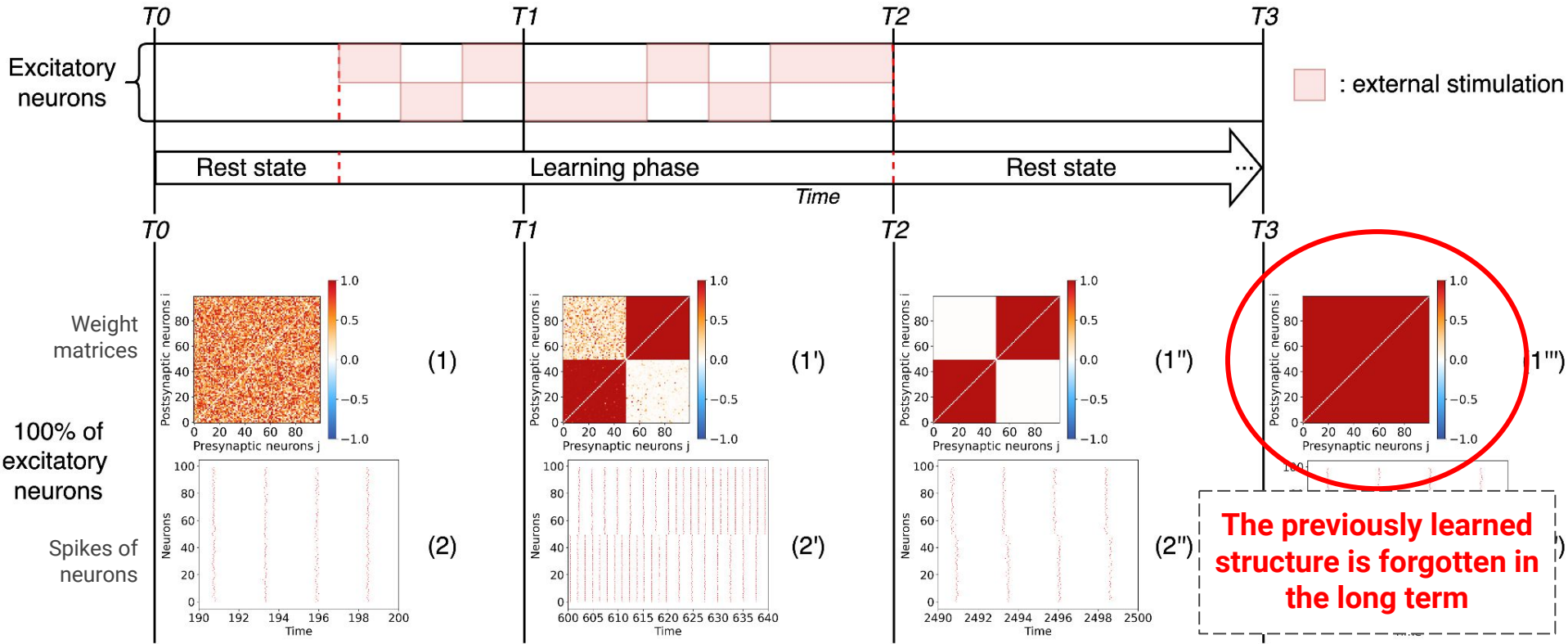
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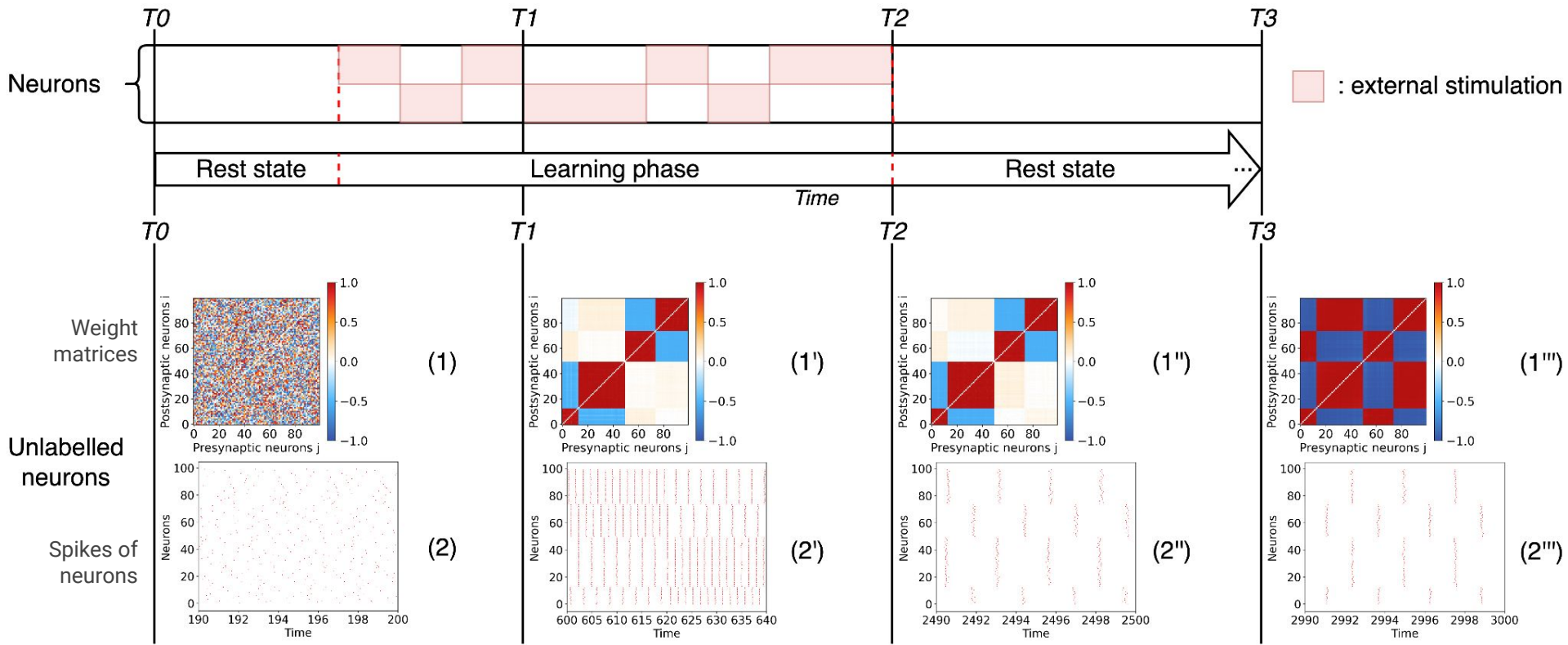
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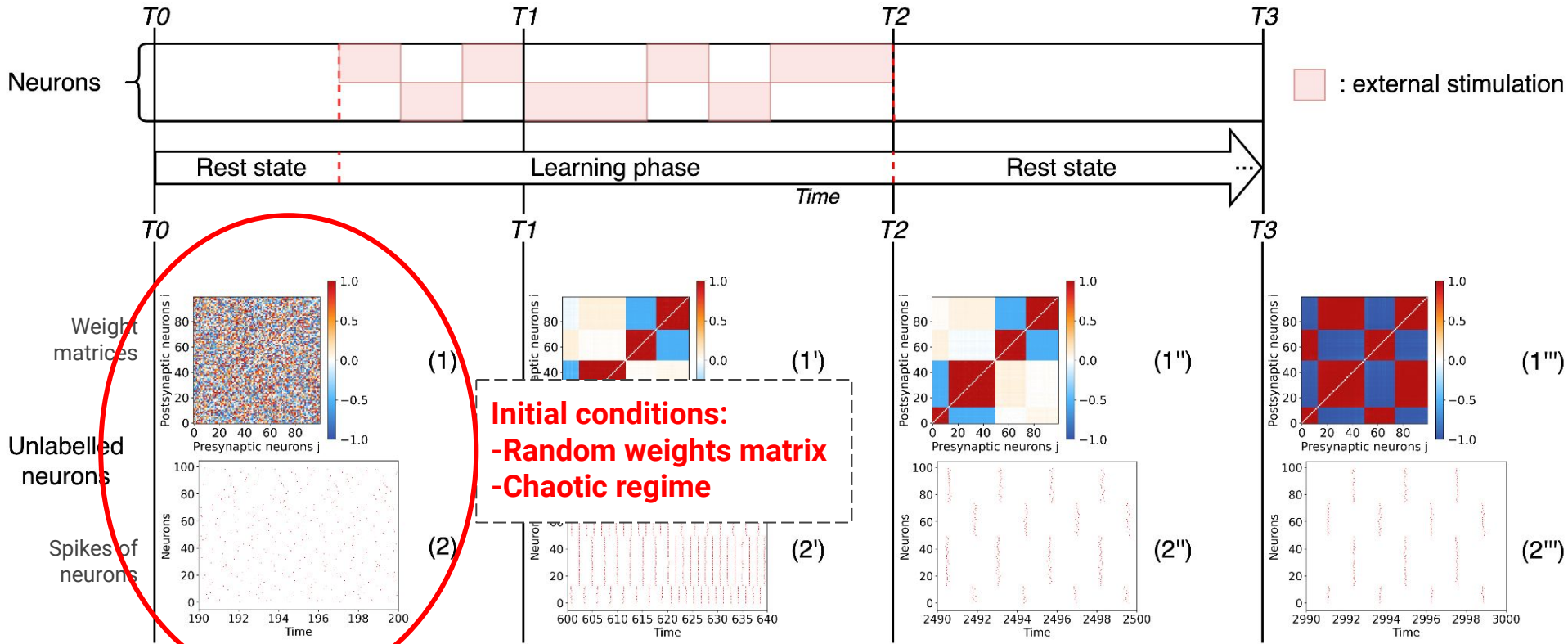
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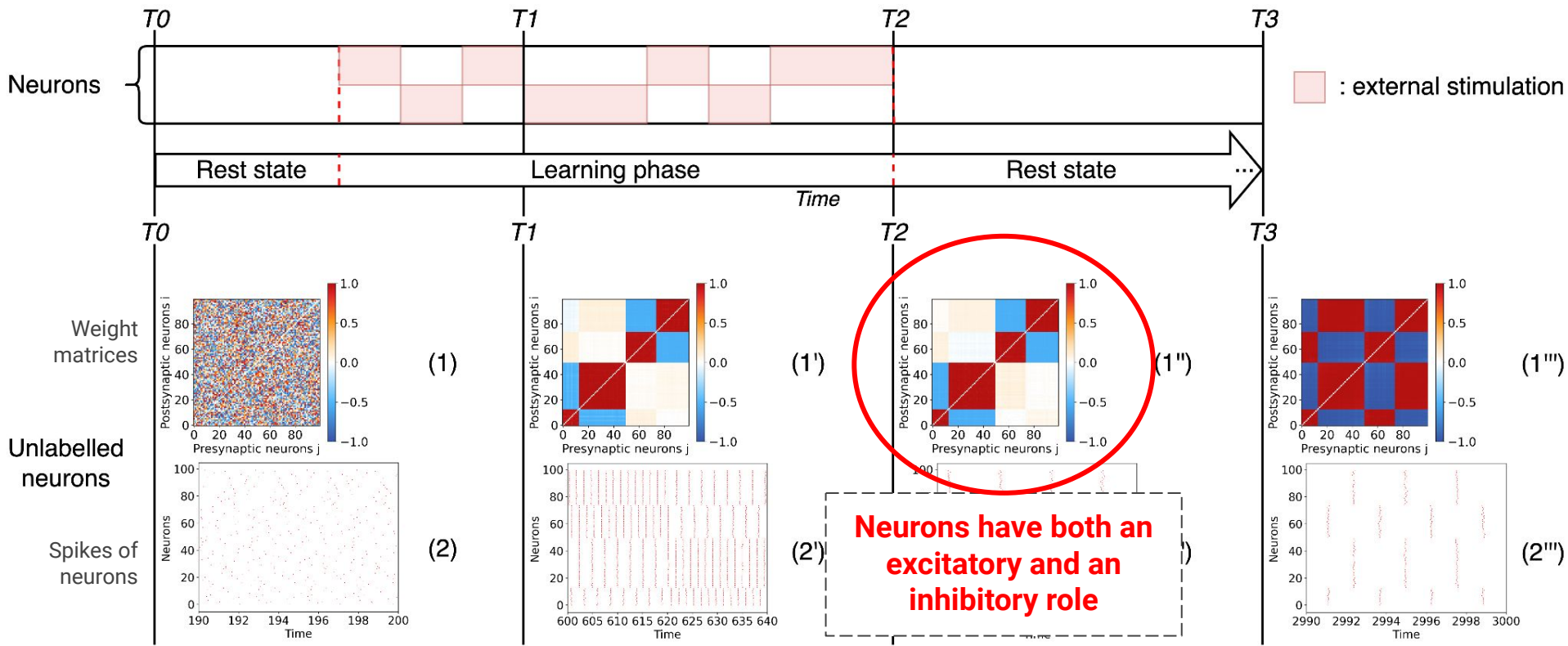
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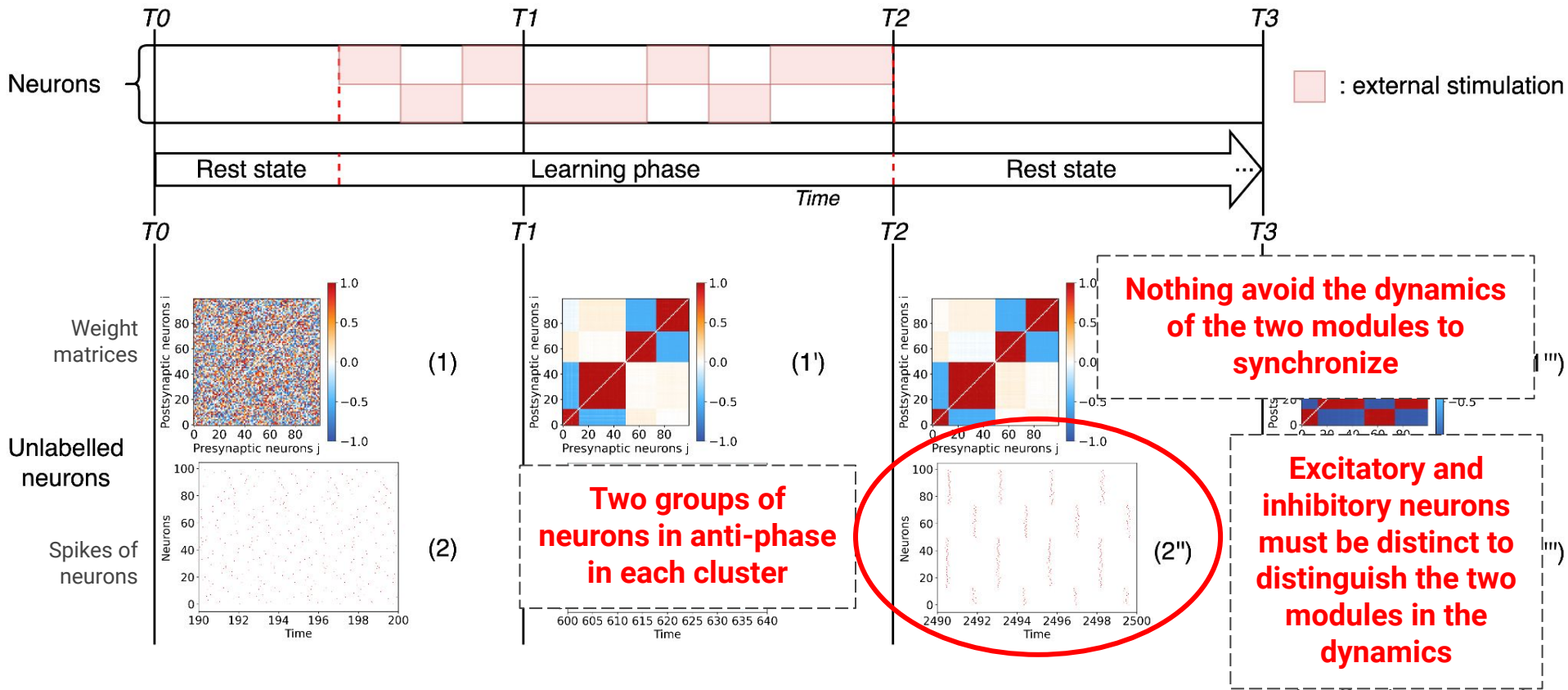
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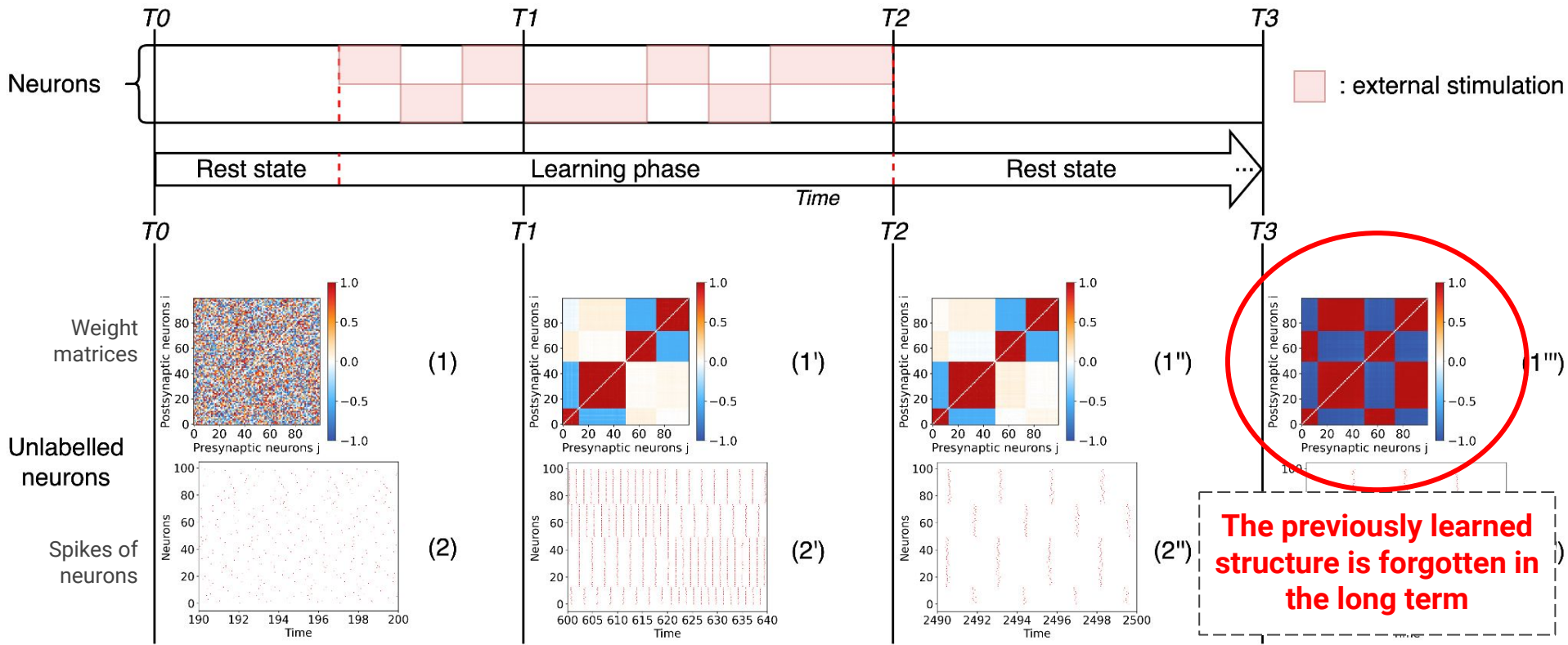


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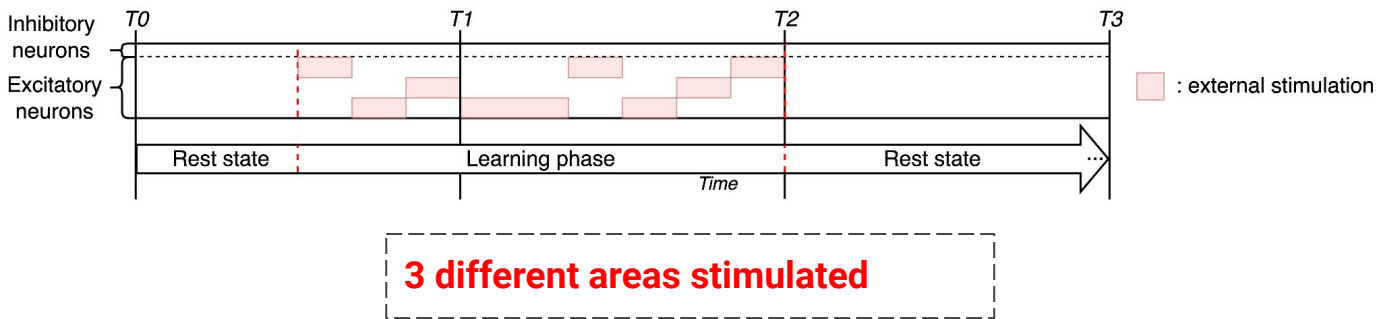
Results: Maintain and consolidate structures



How much inhibition is needed?

Results: Learning capacity according to inhibition

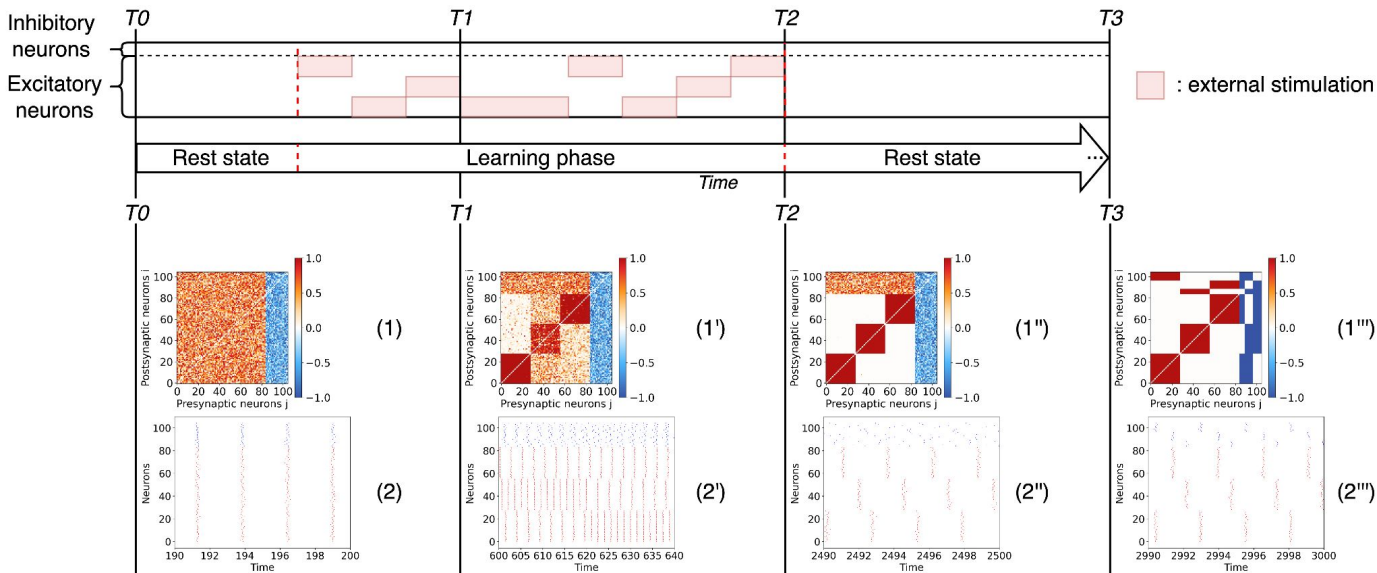
1) Learning multiple clusters



(Bergoin, et al. 2023)

Results: Learning capacity according to inhibition

1) Learning multiple clusters



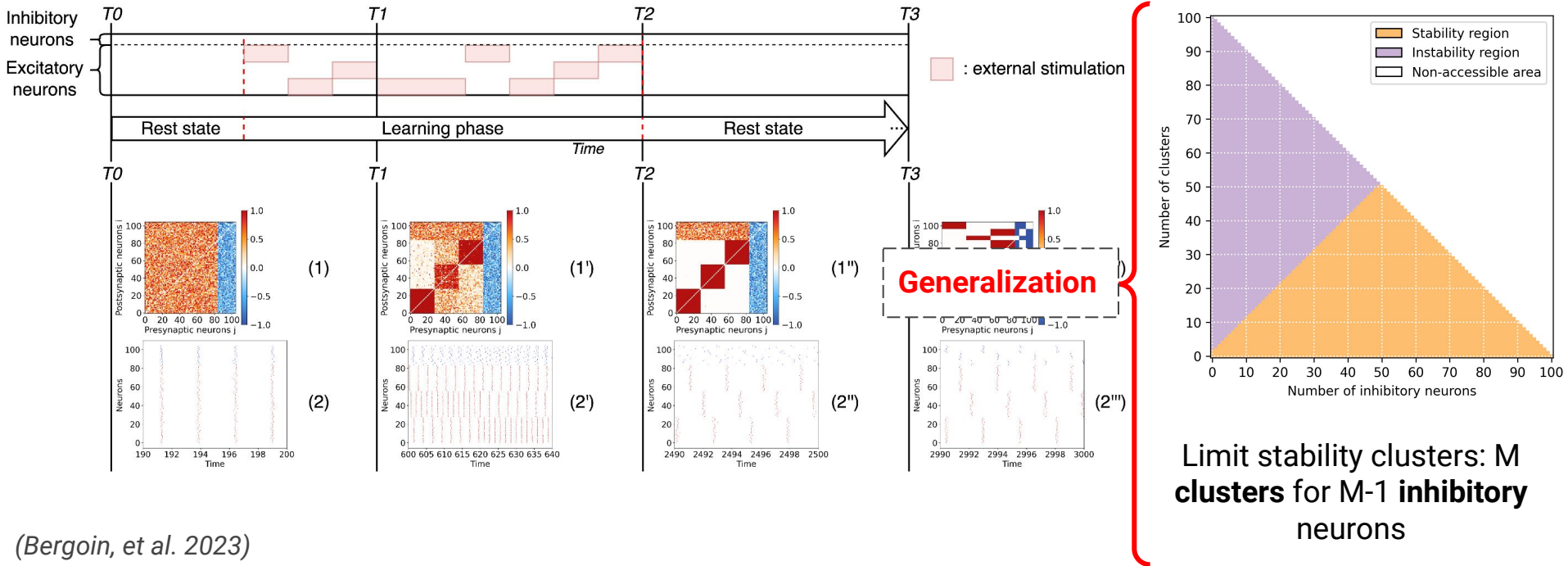
- 3 clusters in weights connectivity
- 3 dynamics temporally separated by a same interval

→ How many clusters maintained maximum?

(Bergoin, et al. 2023)

Results: Learning capacity according to inhibition

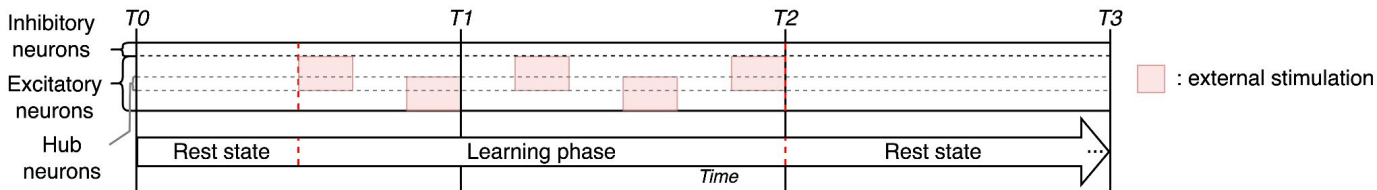
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(Bergoin, et al. 2023)

Results: Learning capacity according to inhibition

2) Overlapping clusters

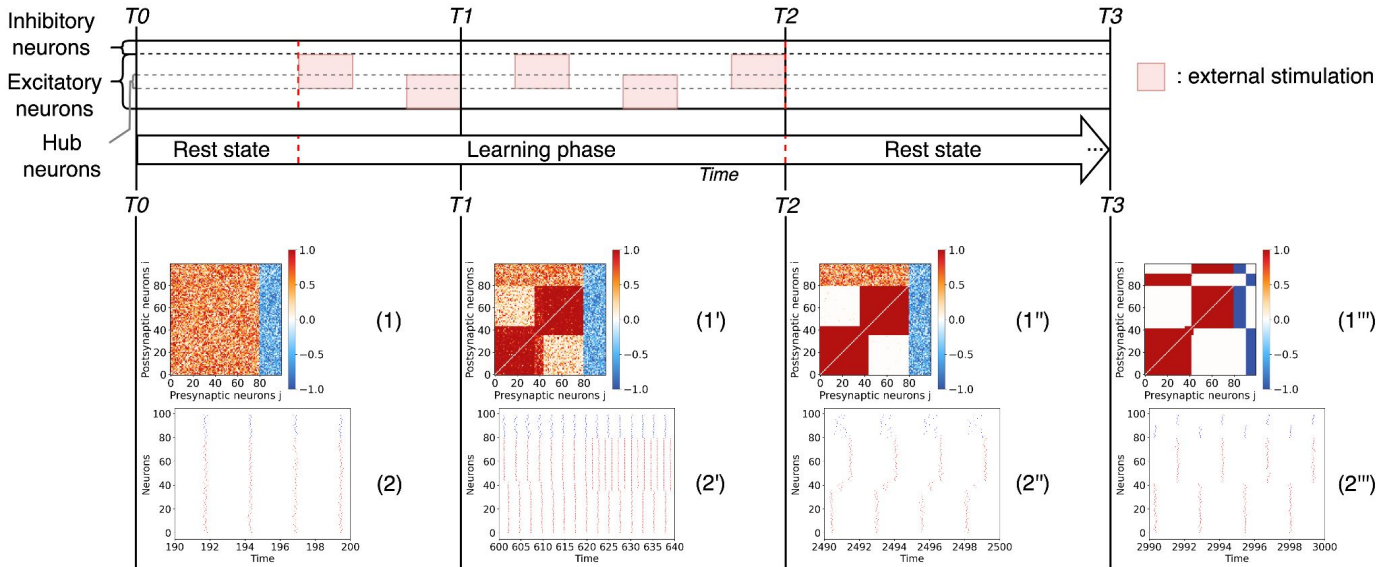


Neurons in common in the two stimulated areas

(Bergoin, et al. 2023)

Results: Learning capacity according to inhibition

2) Overlapping clusters



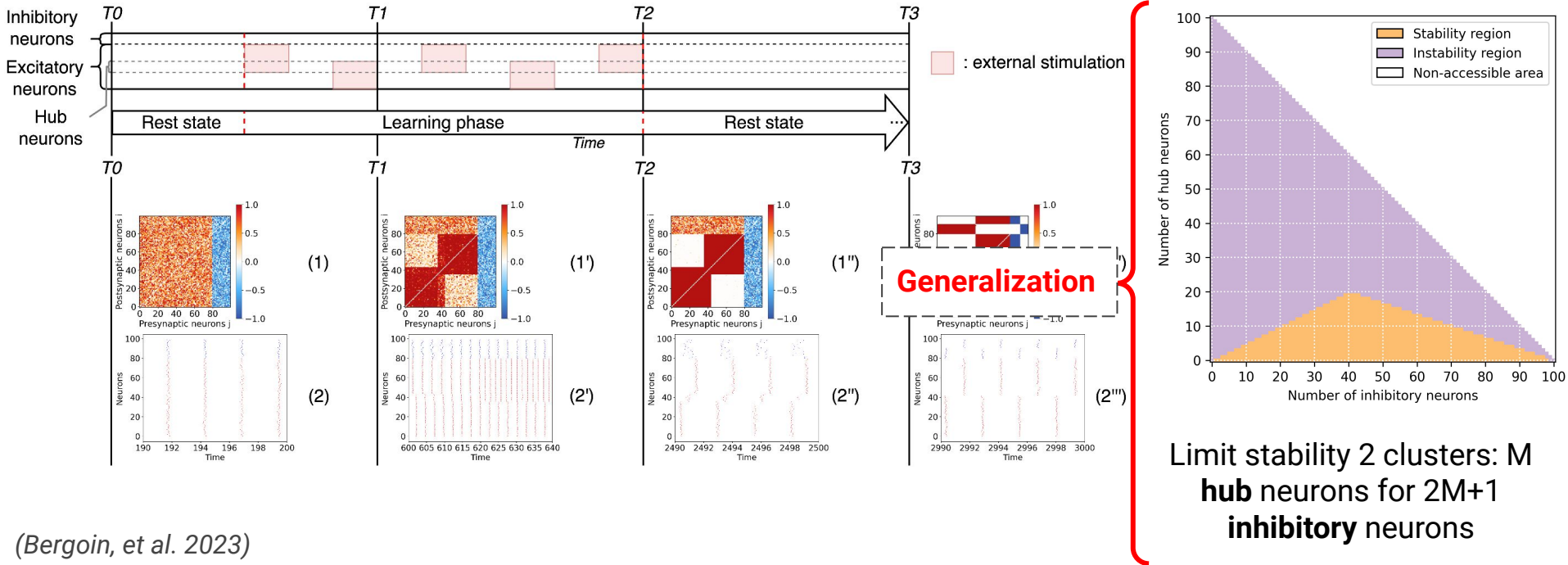
- **“Hub neurons”** connected to the two clusters admitting an intermediate regime
- **Overlap neurons too numerous = the clusters synchronize**

→ **How many overlap neurons maximum?**

(Bergoin, et al. 2023)

Results: Learning capacity according to inhibition

2) Overlapping clusters



(Bergoin, et al. 2023)

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Discussion

Modulation of synchronization:

- **Learning** allows correlated neurons to maintain some degree of **synchrony** with each other
- Each group **repulses** each other thanks to the **inhibitory** neurons constituting them
- It's necessary to have a **balance** between the **inhibitory** and **excitatory** forces working on the different (sub)clusters with a small advantage for inhibition

Creation and maintenance of modular structures:

- The **creation** of clusters is induced by the **spatio-temporal correlations** of the stimuli applied to the network and therefore by the resulting **adaptation** mechanism
- **Inhibitory neurons** make it possible to **maintain** the learned structure and thus to **reinforce** it for the **long term** → memory consolidation (recall in rest to consolidate)
- The **amount of inhibitory** neurons is related to:
 - Quantity of clusters/**informations** possible to retain
 - Number of overlapping/**hub** neurons for transmission/integration

} **Memory capacity
of the network**

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} **Memory capacity
of the network**

Discussion

Modulation of synchronization:

- Learning allows correlated activity to emerge and synchrony with each other
 - Each group repulses each other by inhibiting them
 - It's necessary to have a balance between excitatory and inhibitory forces working on the different (sub)clusters within the network
- **Proportion of inhibitory neurons: compromise between the number of information possible to retain and their complexity (cluster size)**

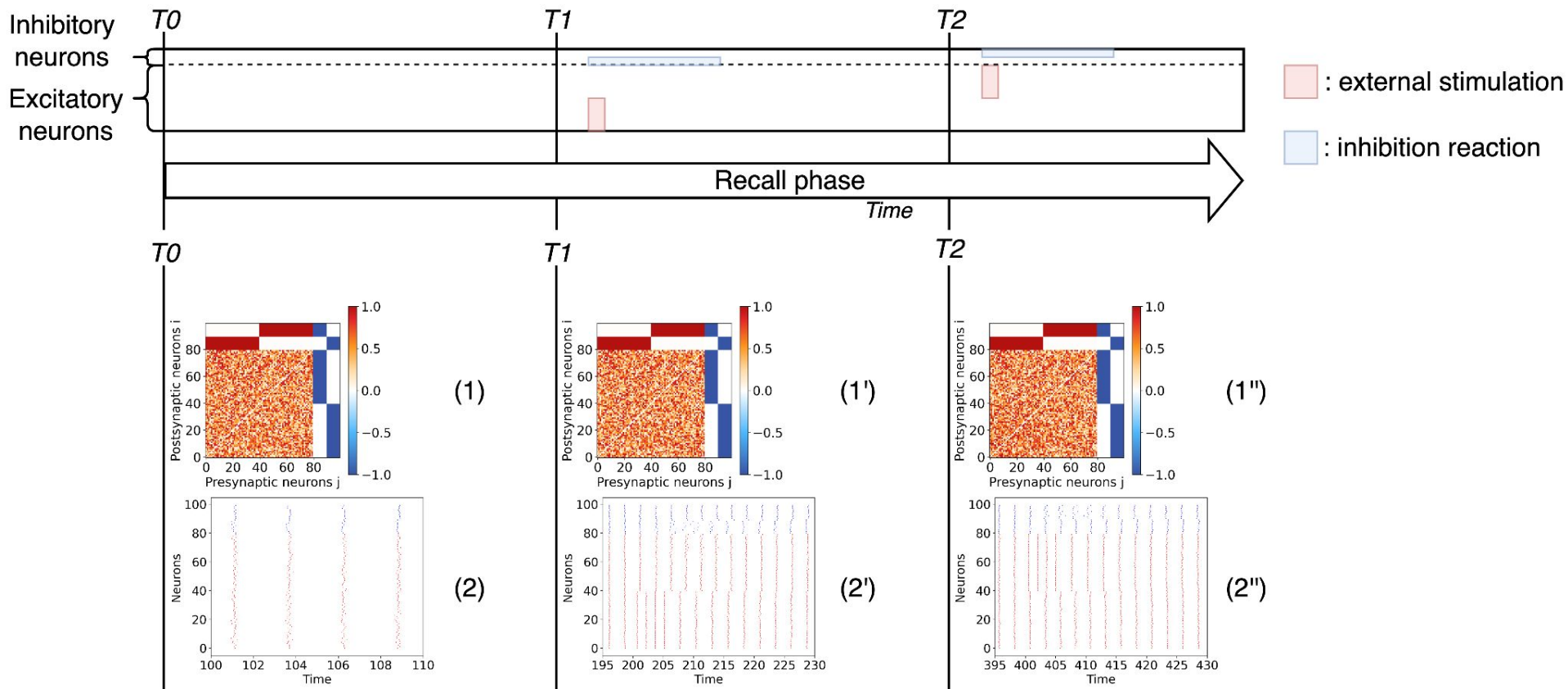
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} **Memory capacity of the network**

Thank you
for
your attention

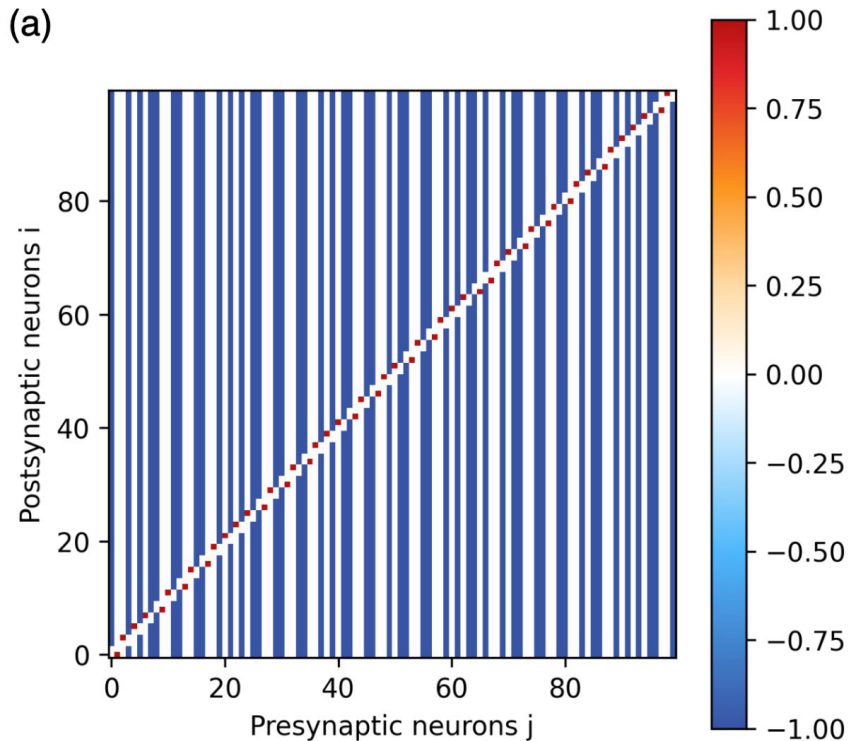
Supplementary results: pattern recall



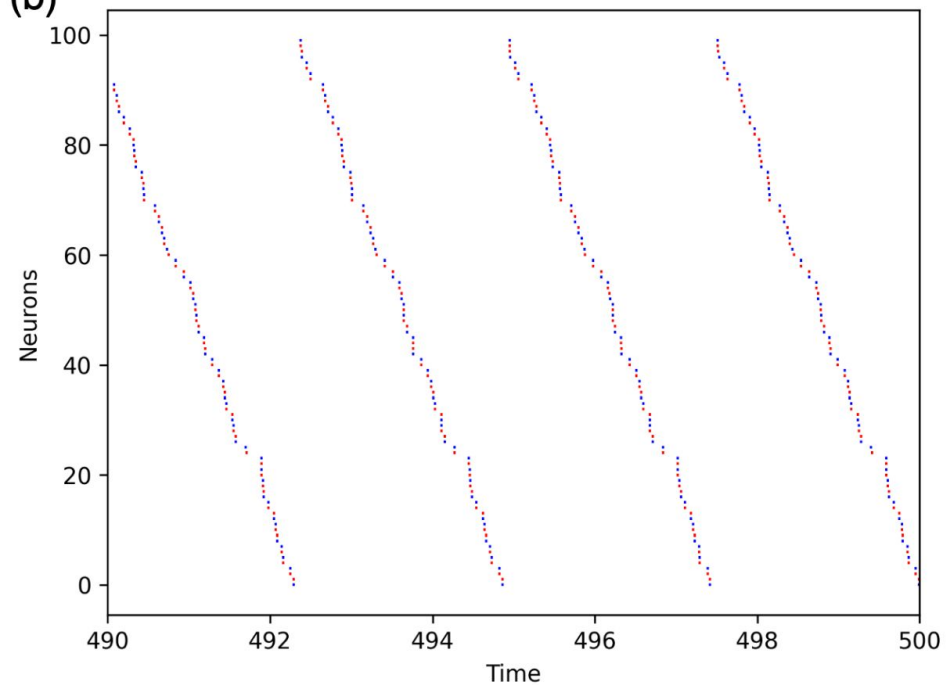
(Bergoin, et al. 2023)

Supplementary results: splay state

(a)



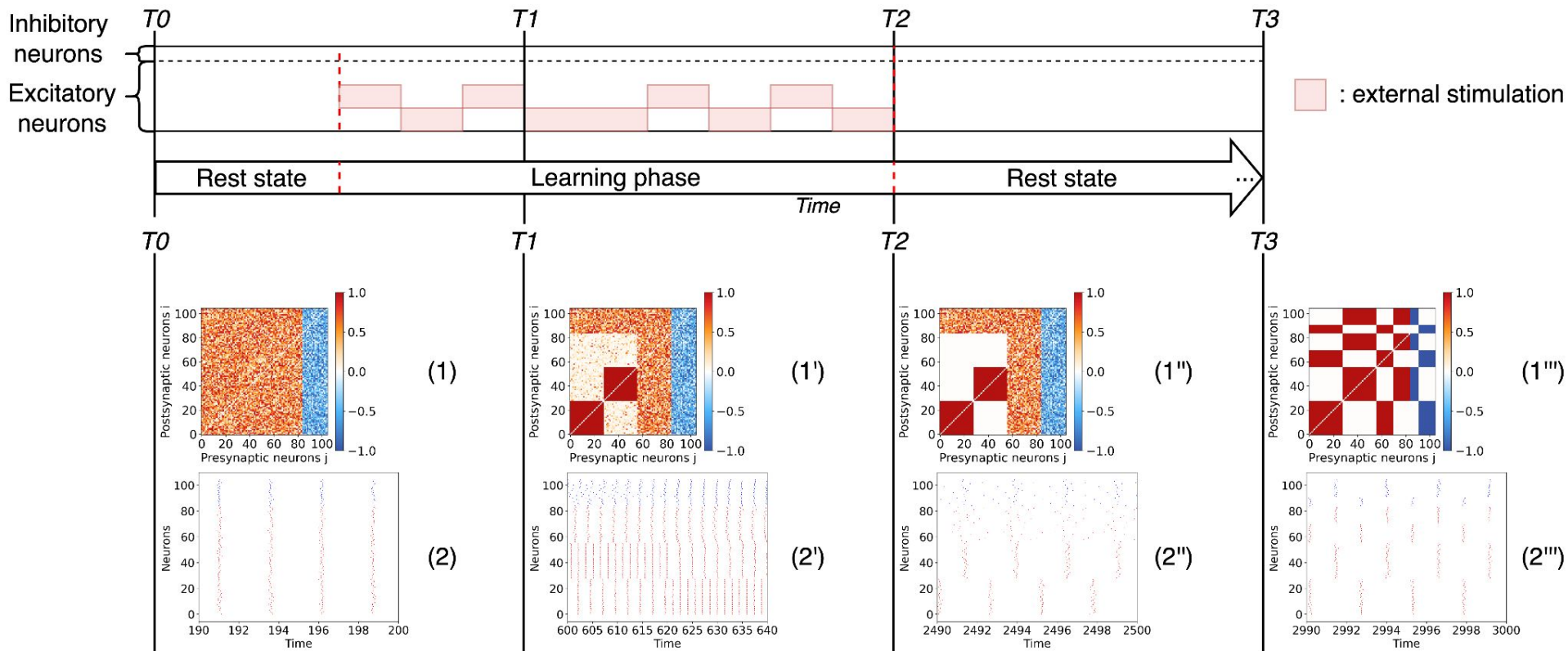
(b)



(Bergoin, et al. 2023)

Supplementary results: 2 clusters and one area not stimulated

(Bergoin, et al. 2023)



Supplementary results: 2 clusters randomly stimulated

(Bergoin, et al. 2023)

