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## Role of inhibition for the formation of neural assemblies in plastic neural networks subject to selective stimuli

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## Context

**Inhibition** has a determining role in the dynamics and in the adaptation capacity of the brain. Although many studies with **coupled oscillator** models attempt to simulate this process, few consider the case of **distinct inhibitory and excitatory** units having an **adaptation mechanism** on their synaptic weights and thus impacting the network state. Therefore, this work aims at studying the impact of **inhibition** on the **synchronization** and the **structure** of **coupled oscillator networks** under the influence of **adaptation**.

## Model

Network of  $N$  theta neurons all-to-all connected [2]:

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

With the phase  $\theta_i \in [-\pi, \pi]$ , the excitability parameter  $\eta_i$ , the global coupling  $g$ , the coupling weight from presynaptic neuron  $j$  to postsynaptic neuron  $i$   $\kappa_{ij}$ , the external inputs  $I_i(t)$  and the additive Gaussian noise  $\xi_i(t)$ .

Weights adaptation:

$$\begin{matrix} \text{E}_j & \xrightarrow{\kappa_{ij}} & \text{E}_i \\ \text{E}_j & \xrightarrow{\kappa_{ij}} & \text{I}_i \end{matrix} \quad \frac{d\kappa_{ij}}{dt} = [\epsilon_1 + \epsilon_2 H(I_j(t))] \kappa_{ij} (1 - \kappa_{ij}) \Lambda(\Delta\theta)$$

$$\begin{matrix} \text{E}_j & \xrightarrow{\kappa_{ij}} & \text{I}_i \\ \text{I}_j & \xrightarrow{\kappa_{ij}} & \text{E}_i \end{matrix} \quad \frac{d\kappa_{ij}}{dt} = \epsilon_1 \kappa_{ij} (1 - \kappa_{ij}) \Lambda(\Delta\theta)$$

$$\begin{matrix} \text{I}_j & \xrightarrow{\kappa_{ij}} & \text{E}_i \\ \text{I}_j & \xrightarrow{\kappa_{ij}} & \text{I}_i \end{matrix} \quad \frac{d\kappa_{ij}}{dt} = \epsilon_1 (\kappa_{ij} + 1) (-\kappa_{ij}) \Lambda(\Delta\theta)$$

With  $\epsilon_1 \ll \epsilon_2 \ll 1$  the learning rates for slow and fast adaptations and  $H(x)$  the Heaviside function.

Symmetric phase difference-dependent plasticity rule [1, 3, 4]:

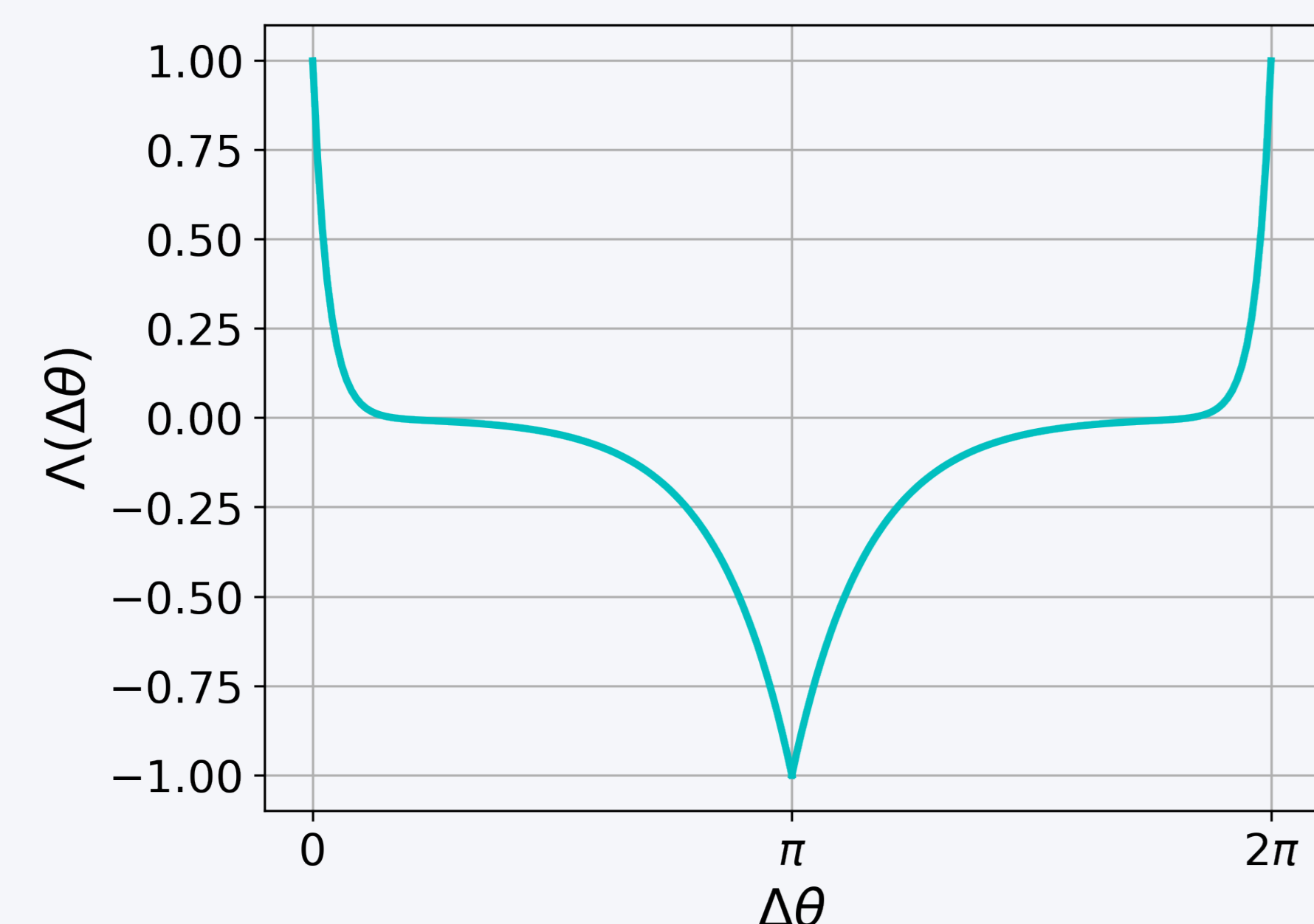


Figure 1. Hebbian plasticity function with a larger time window for depression than for potentiation.

## Discussion

- The creation of **clusters** is induced by the **spatio-temporal correlations** of the stimuli applied to the network and by the resulting **adaptation** mechanism, thus maintaining a certain **synchrony** in them.
- By preserving a specific dynamics to each cluster, **inhibitory** neurons allow to **maintain** and **reinforce** the learned structure over the **long term** → memory consolidation.
- The amount of **inhibitory** neurons is related to the quantity of **clusters/informations** possible to **retain** and to the number of **hub neurons** for **integration** [5] → memory capacity of the network.
- The **proportion of inhibitory** neurons in a network should be a compromise between the **number of informations** possible to retain and their **complexity** (cluster size) → 20% of inhibitory neurons in the biological cortex.

## Maintaining and consolidating structures

- Learning based on the **spatio-temporal correlations** of inputs  $I_i(t)$  applied to 2 different areas of the network.
- We observe the evolution of the network at rest over the **short and long term** in networks of **excitatory and inhibitory** neurons, then with only **excitatory** neurons and finally with **unlabelled** neurons (both excitatory and inhibitory).
- Without distinct inhibitory units, the 2 clusters created **synchronize** at rest and consequently are **forgotten** in the long term.
- The presence of inhibition also allows the **structure** to **consolidate** where each inhibitory neuron associates with a cluster.

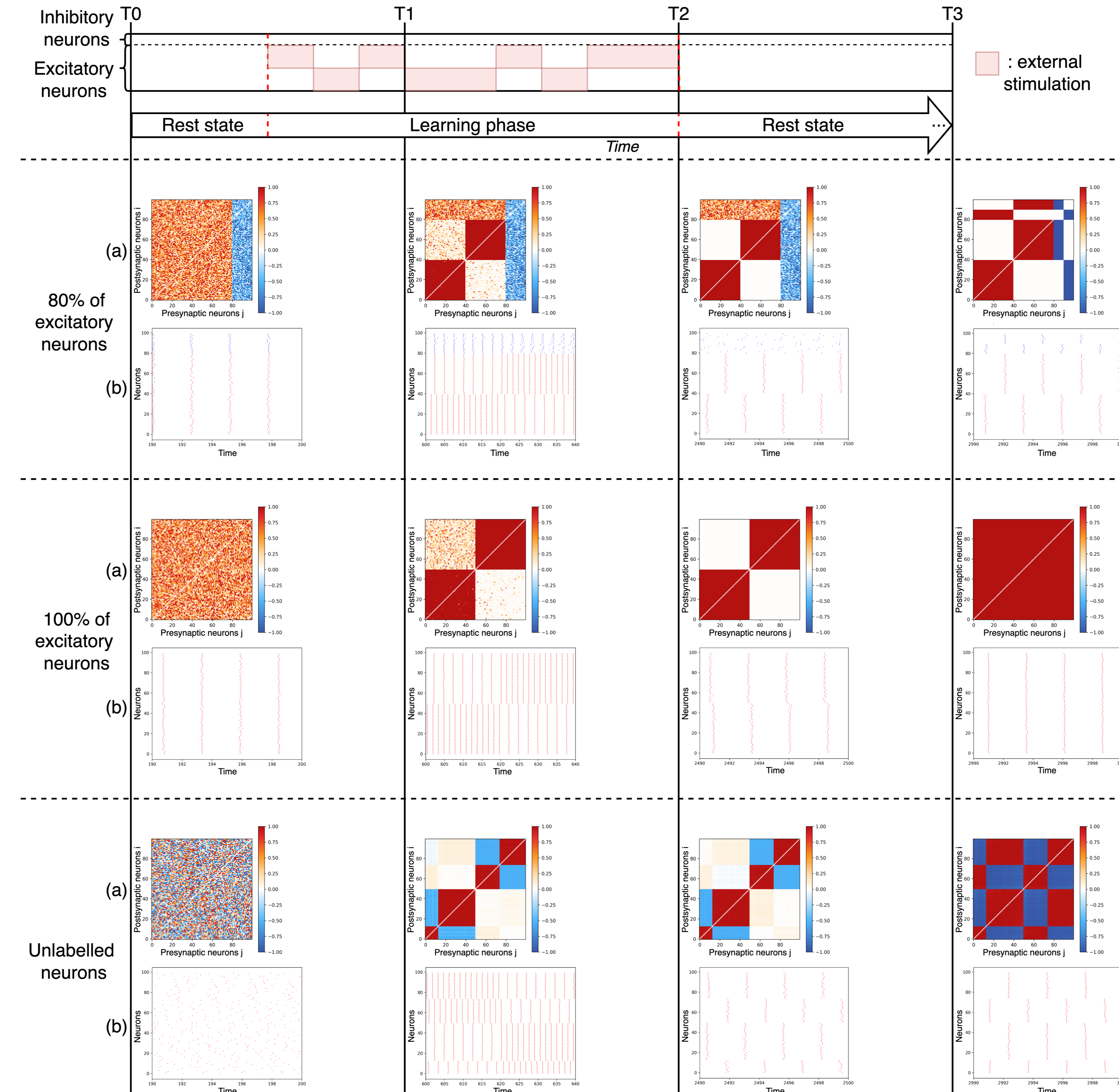


Figure 2. Experiment with 2 clusters. Graphs (a) represent the weight matrices at times T0, T1, T2 and T3: the color denotes if the connection is excitatory (red) or inhibitory (blue) or absent (white). Graphs (b) are raster plots at times T0, T1, T2 and T3, displaying the firing times of excitatory (red dots) and inhibitory (blue dots) neurons. Note that the inhibitory neurons are sorted by phases at time T3 in our model to better visualize clusters, otherwise the associations with each group are random. The neurons are also sorted by phases in each cluster for the last model.

## Multi-cluster learning

- By creating 3 clusters, we obtain 3 different regimes → How many clusters can we maintain at most in the long term?
- Generalizing we get the following limit: for  $M$  clusters we need at least  $(M - 1)$  **inhibitory** neurons to avoid synchrony between clusters.

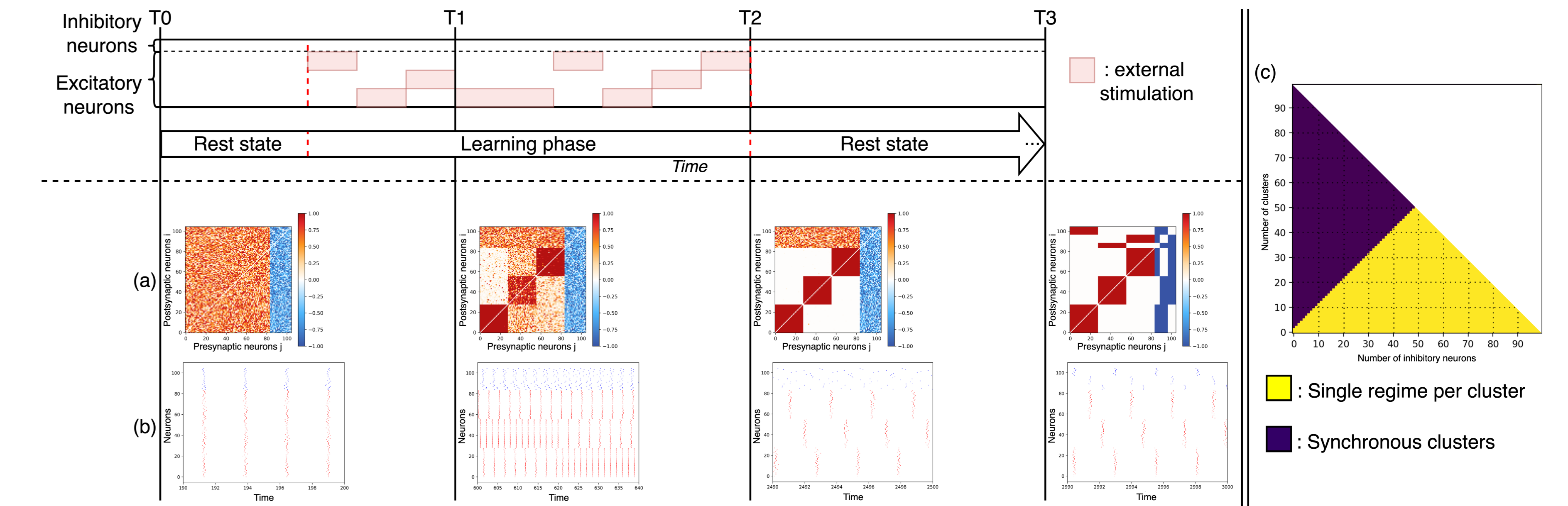


Figure 3. Experiment with 3 or more clusters. Graphs (a) represent the weight matrices at times T0, T1, T2 and T3: the color denotes if the connection is excitatory (red) or inhibitory (blue) or absent (white). Graphs (b) are raster plots at times T0, T1, T2 and T3, displaying the firing times of excitatory (red dots) and inhibitory (blue dots) neurons. Note that the inhibitory neurons are sorted by phases at time T3 to better visualize clusters, otherwise the associations with each group are random. Graph (c) presents the limit for cases with a single regime per cluster (in yellow) and cases where some clusters synchronize (in dark blue) according to the number of clusters in the network (groups of positively coupled neurons) and the number of inhibitory neurons in the network. Note that this graph corresponds to a network of 100 neurons (explaining the white area), but it can be generalized to a larger network.

## Overlapping clusters

- Overlapping inputs cause the creation of **hub neurons** → How many hub neurons can we stabilize at most?
- Generalizing we get the following limit: for  $M$  **hub** neurons we need at least  $(2M + 1)$  **inhibitory** neurons to avoid synchrony between the 2 clusters.

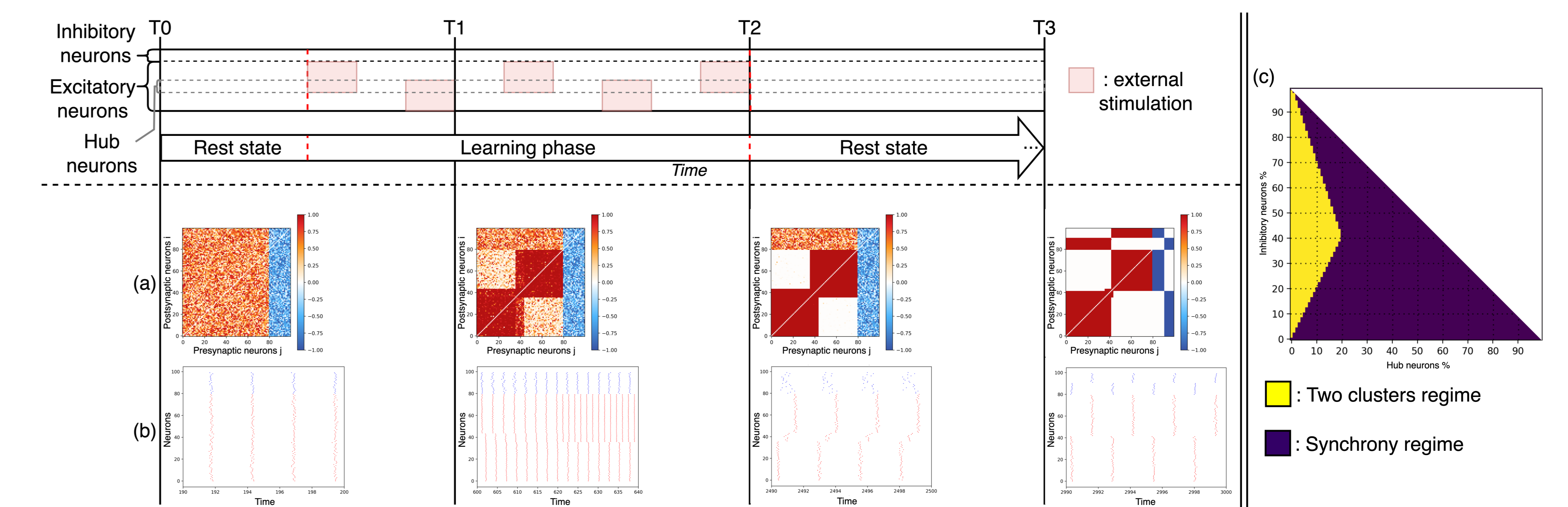


Figure 4. Experiment with 2 overlapping clusters (8 or more neurons in common). Graphs (a) represent the weight matrices at times T0, T1, T2 and T3: the color denotes if the connection is excitatory (red) or inhibitory (blue) or absent (white). Graphs (b) are raster plots at times T0, T1, T2 and T3, displaying the firing times of excitatory (red dots) and inhibitory (blue dots) neurons. Note that the inhibitory neurons and the hub neurons are sorted by phases at time T3 to better visualize clusters, otherwise the associations with each group are random. Graph (c) presents the limit of a two clusters regime (in yellow) to a synchrony regime (in dark blue) between two groups of neurons according to the proportion in the network of overlapping neurons between them and the proportion of inhibitory neurons in the network. Note that the percentage of remaining neurons corresponds to the neurons of the two separate clusters.

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