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Inhibitory neurons stabilise the formation of neural assemblies via adaptation and 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 mechanism, few consider the case of **distinct inhibitory units adapting** 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 theta neurons all-to-all connected [2]:

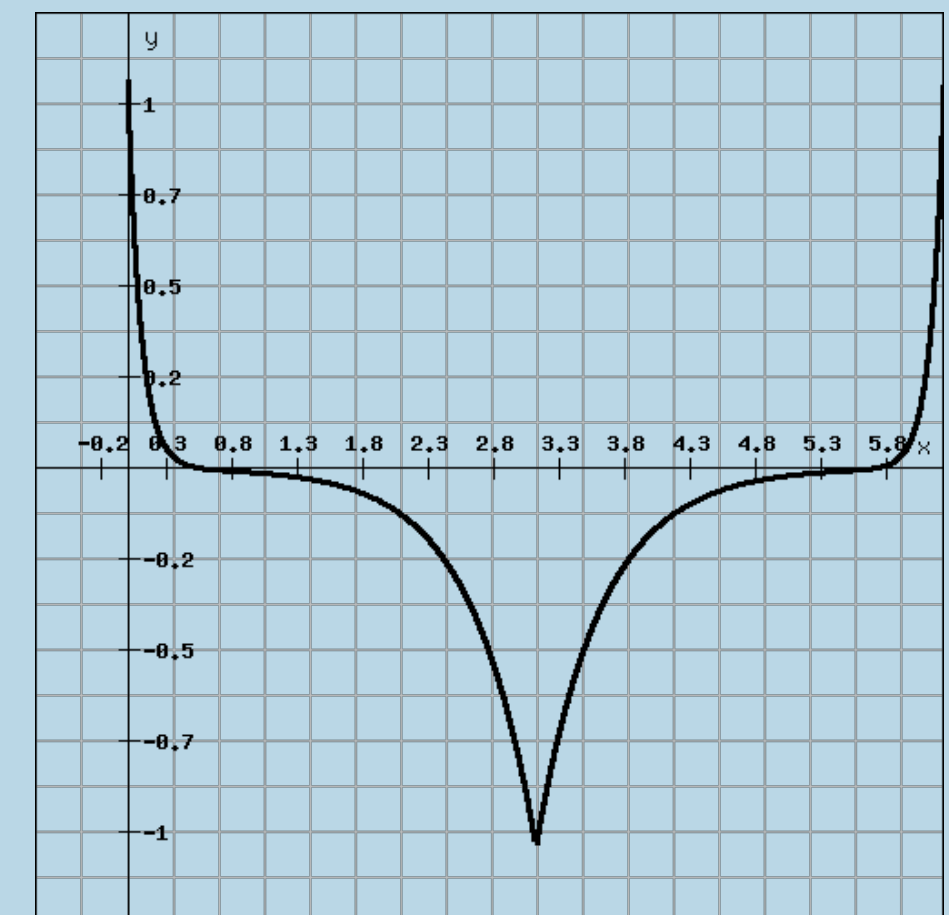
$$\frac{d\theta_i}{dt} = (1 - \cos(\theta_i)) + (1 + \cos(\theta_i))[\eta_i + \frac{g}{N}(\sum_{j=1}^N \kappa_{ij} \sin(\theta_j - \theta_i)) + I_i(t) + \xi_i(t)]$$

Weights adaptation:

$$\begin{aligned} \text{E}_j \rightarrow \text{E}_i & \quad \frac{d\kappa_{ij}}{dt} = [\epsilon_1 + \epsilon_2 H(I_j(t))](\kappa_{ij} - 0) * (1 - \kappa_{ij}) * \Lambda(\Delta\theta) \\ \text{E}_j \rightarrow \text{I}_i & \quad \frac{d\kappa_{ij}}{dt} = \epsilon_1(\kappa_{ij} - 0) * (1 - \kappa_{ij}) * \Lambda(\Delta\theta) \\ \text{I}_j \rightarrow \text{E}_i & \quad \frac{d\kappa_{ij}}{dt} = \epsilon_1(\kappa_{ij} + 1) * (0 - \kappa_{ij}) * \Lambda(\Delta\theta) \\ \text{I}_j \rightarrow \text{I}_i & \quad \frac{d\kappa_{ij}}{dt} = \epsilon_1(\kappa_{ij} + 1) * (0 - \kappa_{ij}) * \Lambda(\Delta\theta) \end{aligned}$$

with $\epsilon_1 \ll \epsilon_2 \ll 1$ the learning rates for slow and fast adaptations

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

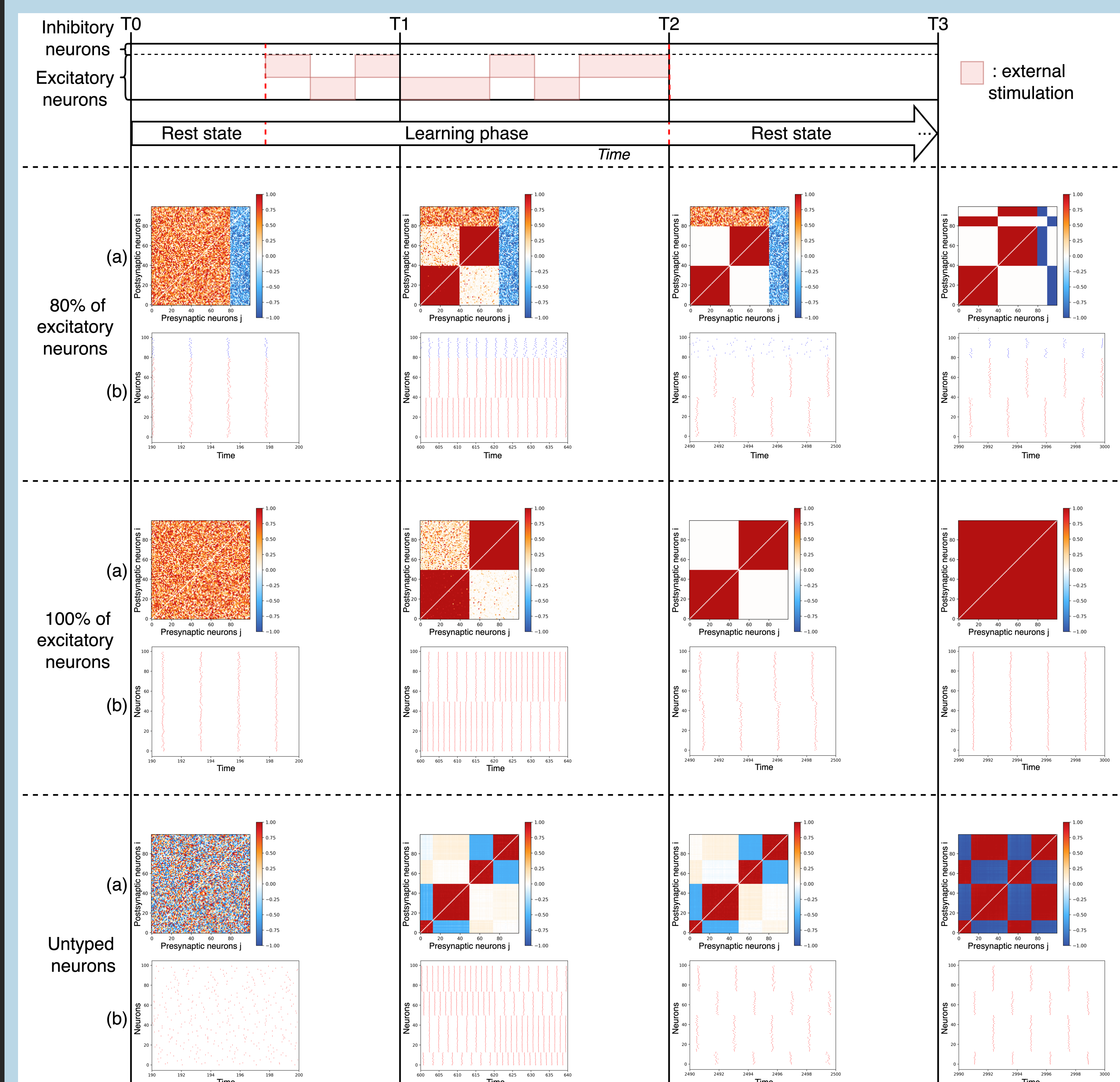


$$\Lambda(\Delta\theta) = \begin{cases} e^{-\frac{\Delta\theta}{0.1}} - e^{-\frac{\Delta\theta - \pi}{0.5}}, & \text{if } 0 \leq \Delta\theta < \pi \\ e^{-\frac{\Delta\theta - 2\pi}{0.1}} - e^{-\frac{\Delta\theta - \pi}{0.5}}, & \text{if } \pi \leq \Delta\theta < 2\pi \end{cases}$$

with $\Delta\theta = |\theta_j - \theta_i|$

Maintaining and consolidating structures

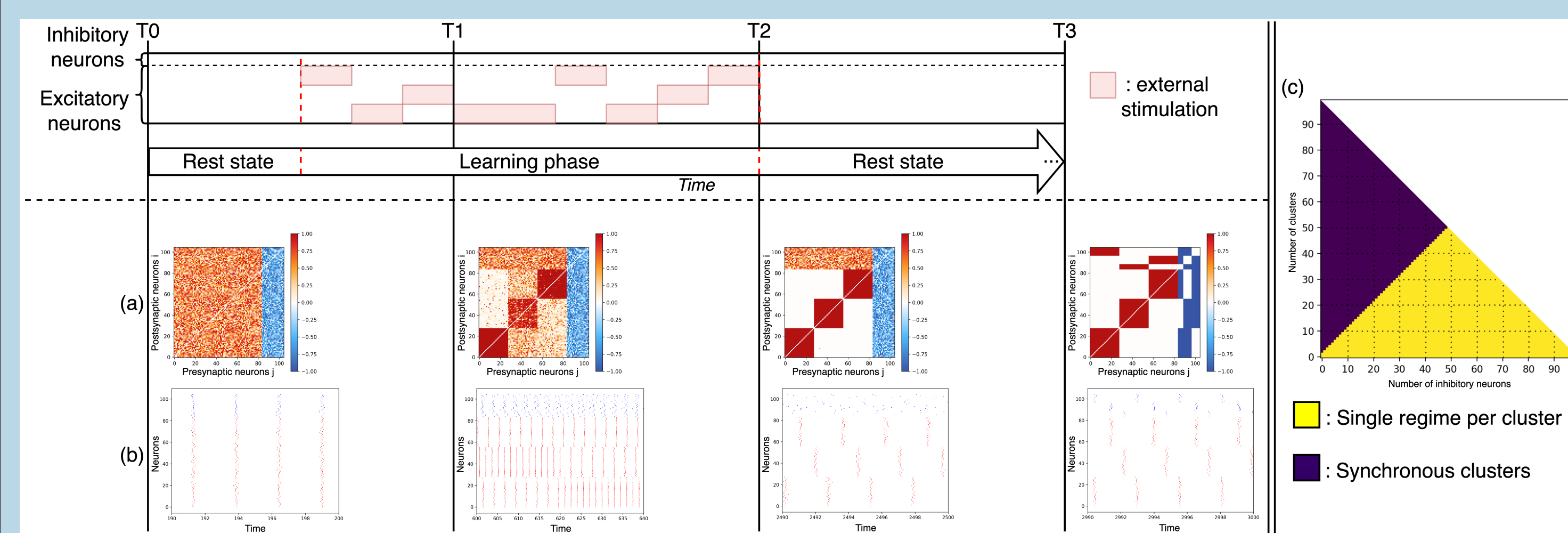
Learning based on the **spatio-temporal correlations** of inputs $I_i(t)$.
Evolution of the network at rest in the **short and long term**.



(a) Weight matrices, (b) Spikes of neurons

Multi-cluster learning

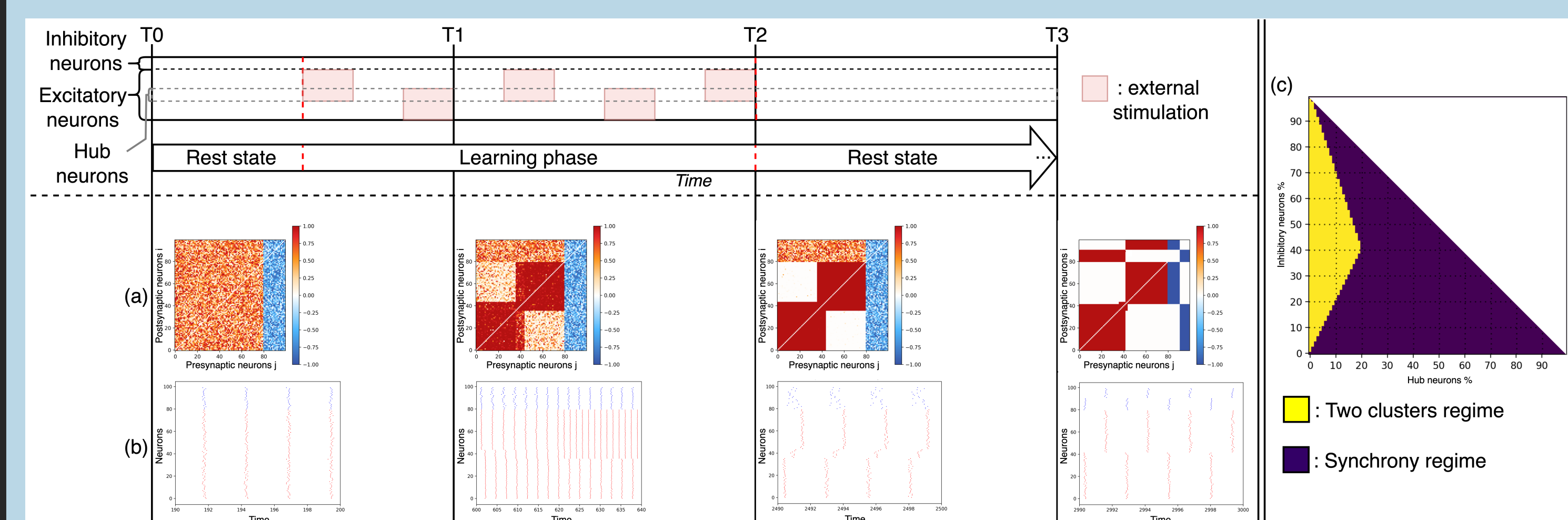
3 clusters = 3 regimes → How many clusters maintained at most?
Theoretical limit: M clusters for $(M - 1)$ inhibitory neurons.



(a) Weight matrices, (b) Spikes of neurons, (c) Generalization to multiple clusters

Overlapping clusters

Creation of hub neurons → How many stable hub neurons at most?
Theoretical limit: M hub neurons for $(2M + 1)$ inhibitory neurons.



(a) Weight matrices, (b) Spikes of neurons, (c) Generalization to multiple hub neurons

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** → memory capacity of the network.

References

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- [4] Jafar Shamsi, Maria José Avedillo, Bernabe Linares-Barranco, and Teresa Serrano-Gotarredona. Oscillatory hebbian rule (ohr): An adaption of the hebbian rule to oscillatory neural networks. In *2020 XXXV Conference on Design of Circuits and Integrated Systems (DCIS)*, pages 1-6. IEEE, 2020.