

# Persistent activity of neural dynamics on hierarchical networks



Dynamica research group

Edward Laurence<sup>1</sup>, Patrick Desrosiers<sup>1,2</sup>, and Louis J. Dubé<sup>1</sup>

<sup>1</sup> Département de physique, de génie physique, et d'optique, Université Laval, Québec, Canada  
<sup>2</sup> Centre de recherche CERVO, Québec, Canada



## Summary

Hierarchy has been hypothesized to facilitate the emergence of persistent activity [1]. We explore this statement with different hierarchical organizations on a binary neural dynamics. The multiple stable levels of activity, called **persistent activity**, are studied analytically and numerically.

- We analytically bound the number of intermediate states of activity for random, modular and hierarchical directed structures.
- **Hierarchical structures reduce the diversity of activities compared to modular structures.**
- For HPA structures, persistent activity emerges in a narrow window of parameters and shows delayed activation.

## Model

### Binary dynamics with spontaneous activation

Consider a graph composed of  $N$  neurons of binary activity  $X_j(t)$  at time  $t$  and input activity  $m_j(t) = \sum_i w_{ji} X_i(t)$ .

**Rate of activation**

$$F(m) = \begin{cases} 1 + \lambda & m \geq \mu \\ \lambda & \text{otherwise} \end{cases}$$

**Rate of inactivation**

$$R(m) = \nu$$

**Master equation**

$$\mathbb{E}\{X_j(t + \Delta t)\} = \mathbb{E}\left\{[1 - X_j(t)]F(m_j(t))\Delta t + X_j(t)[1 - R(m_j(t))\Delta t]\right\}$$

The master equation for the probability of being active is

$$P_j(t + \Delta t) = [1 - P_j(t)]F(m_j(t))\Delta t + P_j(t)[1 - R(m_j(t))\Delta t]$$

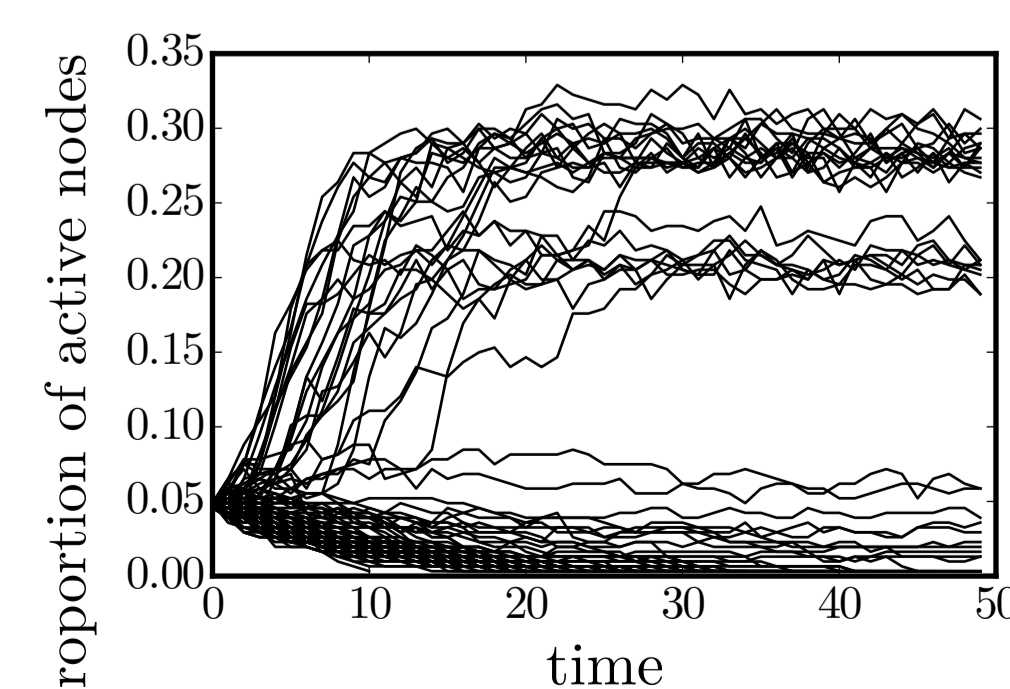
- Each node has at least one and at most two stable steady-states.
- Spontaneous activation enables a minimal level of activity.

## Persistent activity

Persistent activity has been introduced by Kaiser et al. [1], to describe intermediate states of activity detected in neural networks.

- **Persistent activity is an intermediate and stable state of activity.**

In modular networks, we have found that persistent activity emerges from a weak communication between structures.



Example of persistent activity where each line is a single temporal evolution of the proportion of active nodes.

## Bounds on the activity ( $\lambda = 0$ )

### Random network

Let us consider a random network of density  $p$ . To be active, a node must have a number of active neighbors larger than a certain threshold parameter  $\mu$ . A mean-field analysis provides two constraints on the number of active nodes  $r$ .

**Inactive nodes**

$$\frac{pr}{1 + \nu} < \mu$$

**Active nodes**

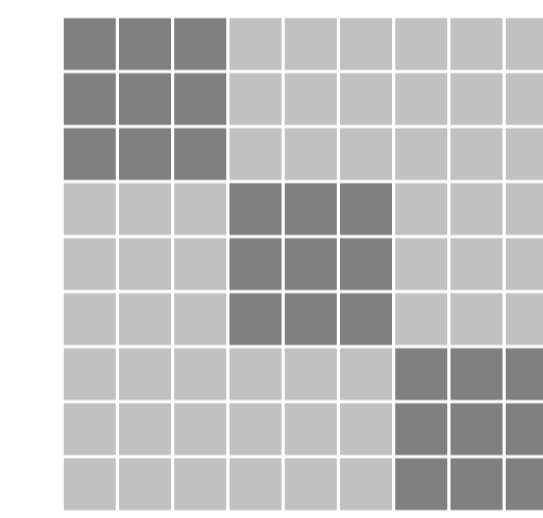
$$\frac{p(r-1)}{1 + \nu} \geq \mu$$

Leading to

$$\frac{\mu(1 + \nu)}{p} + p \leq r < \frac{\mu(1 + \nu)}{p}$$

- **Two stable solutions exist: nodes are either all active or all inactive.**

### Modular network



Adjacency matrix of a planted partition.

Let  $r$  be the number of active nodes from a planted partition of densities  $p_{in}$  and  $p_{out}$  and communities of size  $n$ .

**Inactive nodes**

$$r \frac{p_{out}}{1 + \nu} < \mu$$

**Active nodes**

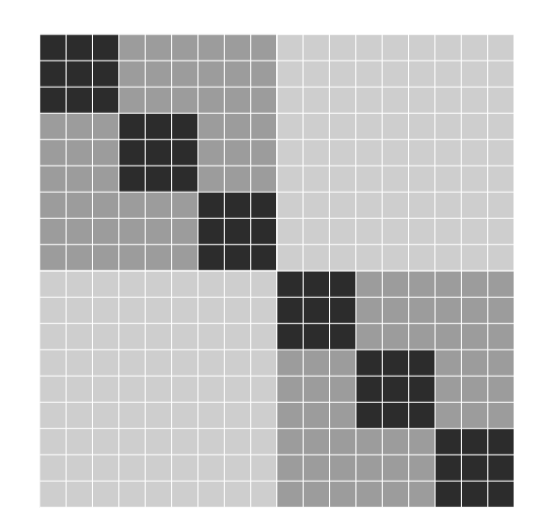
$$\frac{(n-1)p_{in}}{1 + \nu} + \frac{p_{out}}{1 + \nu}(r-n) \geq \mu$$

It leads to boundaries on the number of active nodes.

$$n + \frac{\mu(1 + \nu)}{p_{out}} - \frac{(n-1)p_{in}}{p_{out}} \leq r < \frac{\mu(1 + \nu)}{p_{out}}$$

- The number of active nodes is highly constrained by the dynamics and the densities of the network.
- **Persistent activity of modular networks is bounded.**

### Hierarchical network



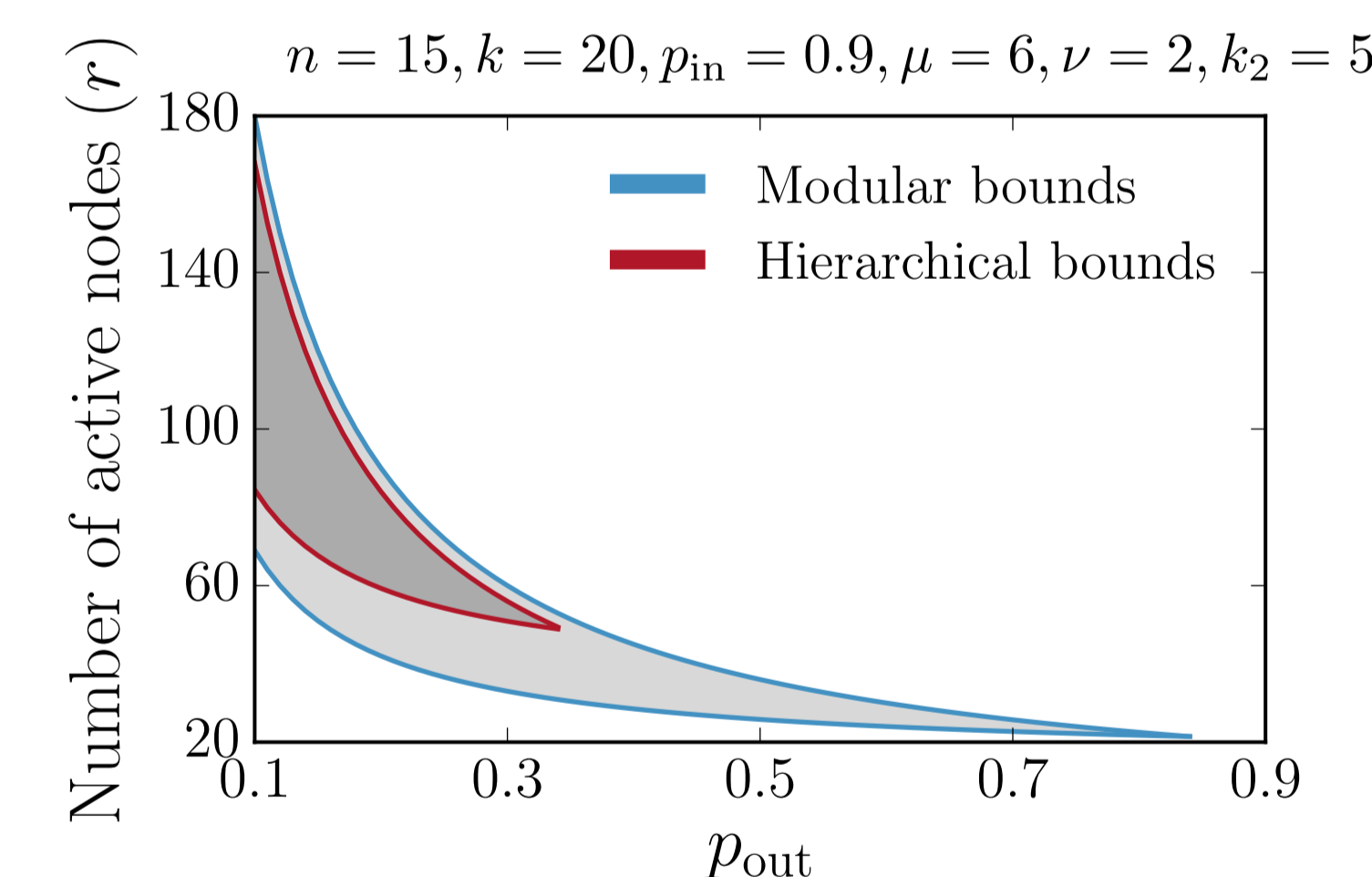
Adjacency matrix of an hierarchical planted partition.

Let us consider a structure of 2 hierarchical levels of organization and  $k_2$  structures at the highest level and  $k_1$  communities of size  $n$  at the lowest level. Densities between structures are  $p_{in}$ ,  $p_1$  and  $p_2$  (see figure on the left). We apply a similar treatment as the modular structure to obtain constraints on the number of active nodes.

$$\left[ \mu(1 + \nu) + p_1 n - p_{in}(n-1) \right] \frac{k_2}{(p_1 - p_2) + k_2 p_2} \leq r < \mu(1 + \nu) \frac{k_2}{(p_1 - p_2) + k_2 p_2}$$

We have compared the hierarchical constraints to the modular constraints for networks of same size and the same number of edges.

- For equivalent networks, hierarchical structures have smaller regions of possible number of active nodes than modular structures.
- **Hierarchy reduces the diversity of persistent activities.**



Example of the bounds for the number of active nodes for modular and hierarchical structures. The gray zones are the bounded regions that contain the admissible values of  $r$  for a given  $p_{out}$ . The parameters  $p_1$  and  $p_2$  are set to obtain the same number of edges and nodes.

## HPA structures

### Hierarchical preferential attachment (HPA)

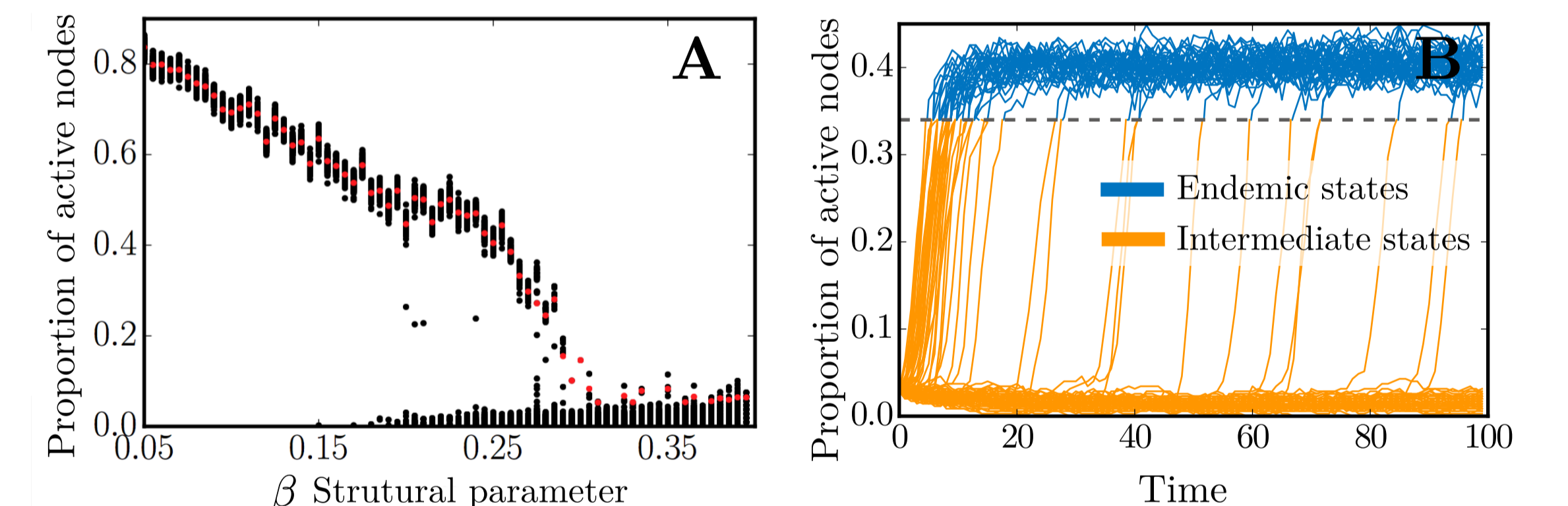
HPA has been introduced in Ref. [2] and is characterised by

- Scale free degree distribution.
- Scale free community size and membership distributions.
- Realistic model for hierarchical structures.

### Observation of persistent activity

We have applied the binary dynamics on HPA networks of four hierarchical levels. We have controlled the structure using a parameter  $\beta$ .

- **Intermediate states of activity emerge close to the critical threshold of activation.**
- **The transition to endemic state is delayed.**



**A:** Single active fraction (black dots) and average active fraction (red dots) of the network as a function of a structural parameter. The binary dynamics is simulated using  $\mu = 3, \nu = 0.1, \lambda = 0.001$

**B:** Active fraction for a given structural parameter  $\beta = 0.25$  close to the threshold as function of time for 100 simulations.

## Bibliography

- [1] KAISER M., GÖRNER M., AND HILGETAG C.C., Criticality of spreading dynamics in hierarchical cluster networks without inhibition, *New J. Phys.*, **9** (2007), p. 110.
- [2] HÉBERT-DUFRESNE L., LAURENCE E., ALLARD A., YOUNG J.-G., AND DUBÉ L.J., Complex networks as an emerging property of hierarchical preferential attachment, *Phys. Rev. E*, **92** (2015), p. 062809.

## Acknowledgements

