

# Twenty projects with Galves-Loecherbach stochastic elements

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# Background: Scientific Reports paper

## SCIENTIFIC REPORTS

OPEN

### Phase transitions and self-organized criticality in networks of stochastic spiking neurons

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Phase transitions and critical behavior are crucial issues both in theoretical and experimental neuroscience. We report analytic and computational results about phase transitions and self-organized criticality (SOC) in networks with general stochastic neurons. The stochastic neuron has a firing probability given by a smooth monotonic function  $\Phi(V)$  of the membrane potential  $V$ , rather than a sharp firing threshold. We find that such networks can operate in several dynamic regimes (phases) depending on the average synaptic weight and the shape of the firing function  $\Phi$ . In particular, we encounter both continuous and discontinuous phase transitions to absorbing states. At the continuous transition critical boundary, neuronal avalanches occur whose distributions of size and duration are given by power laws, as observed in biological neural networks. We also propose and test a new mechanism to produce SOC: the use of dynamic neuronal gains – a form of short-term plasticity probably located at the axon initial segment (AIS) – instead of depressing synapses at the dendrites (as previously studied in the literature). The new self-organization mechanism produces a slightly supercritical state, that we called SOSOC, in accord to some intuitions of Alan Turing.

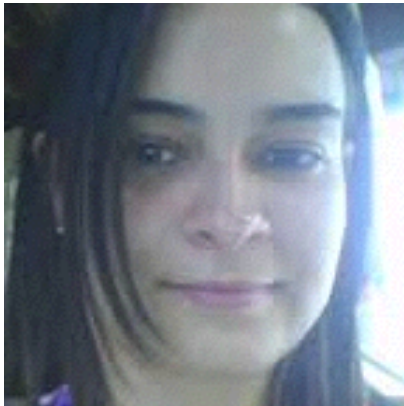
# Collaborators at NEUROMAT



**Ludmila Brochini**



**Jorge Stolfi**



**Ariadne A. Costa**

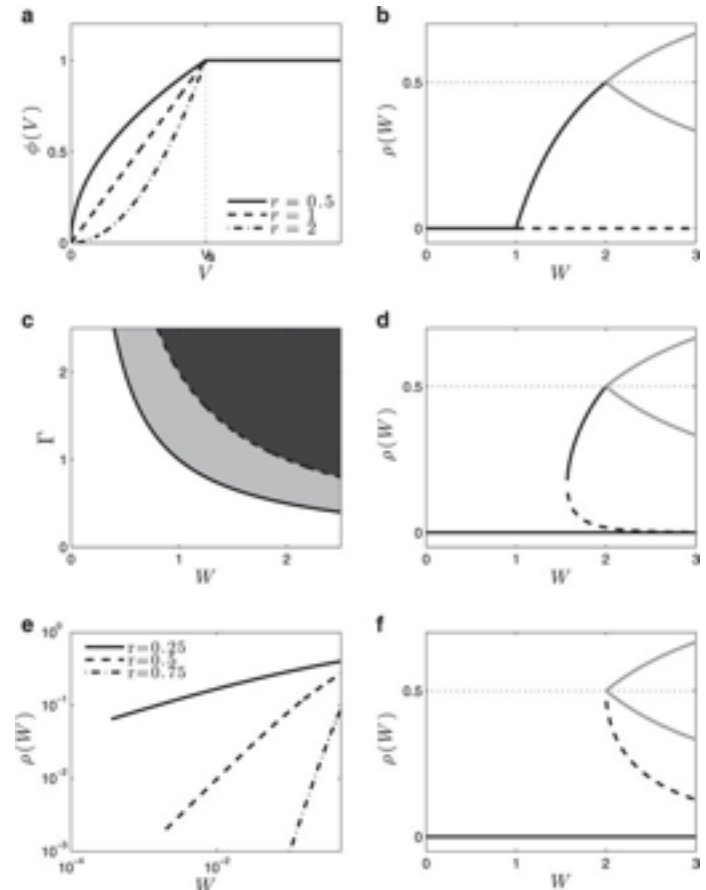


**Antônio C. Roque**

<http://neuromat.numec.prp.usp.br/team>

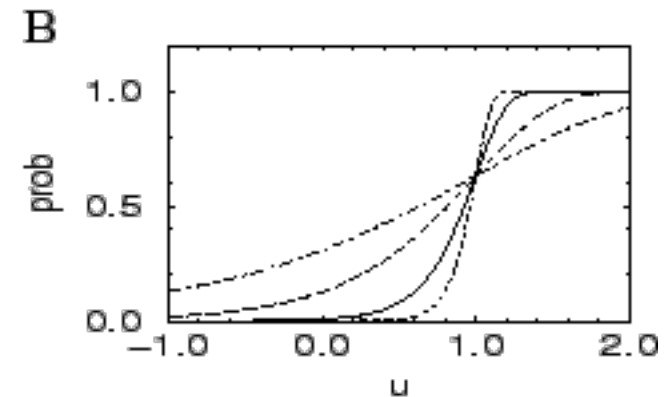
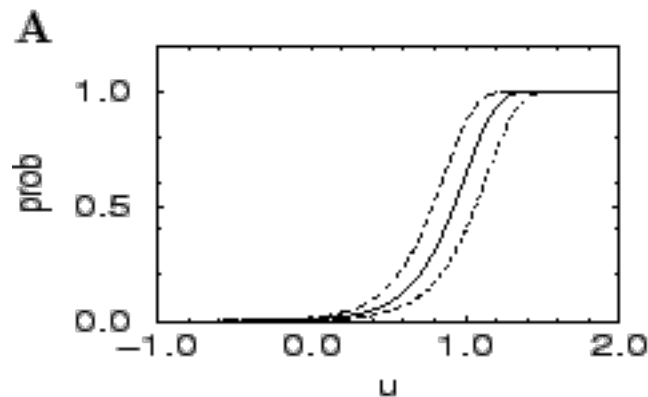
# The GL stochastic element in voltage representation

- $X_i$  = post-synaptic neuron,  $X_j$  = pre-synaptic neuron
- $X_j[t] = 0$  (not firing),  $X_j[t] = 1$  (firing)
- $V_i[t+1] = \mu V_i[t] + I_{\text{ext}} + \sum W_{ij} X_j[t]$  if  $X_j[t] = 0$
- $V_i[t+1] = 0$  if  $X_j[t] = 1$
- $P(X=1|V) = \Phi(V)$



# 1. NEUROSCIENCE: COMPARISON OF GL NEURONS WITH GESTNER'S ESCAPE-NOISE (EN) NEURON

**Novelty:** To relate and compare GL neurons with EN neurons (Gerstner, 2002) [12].



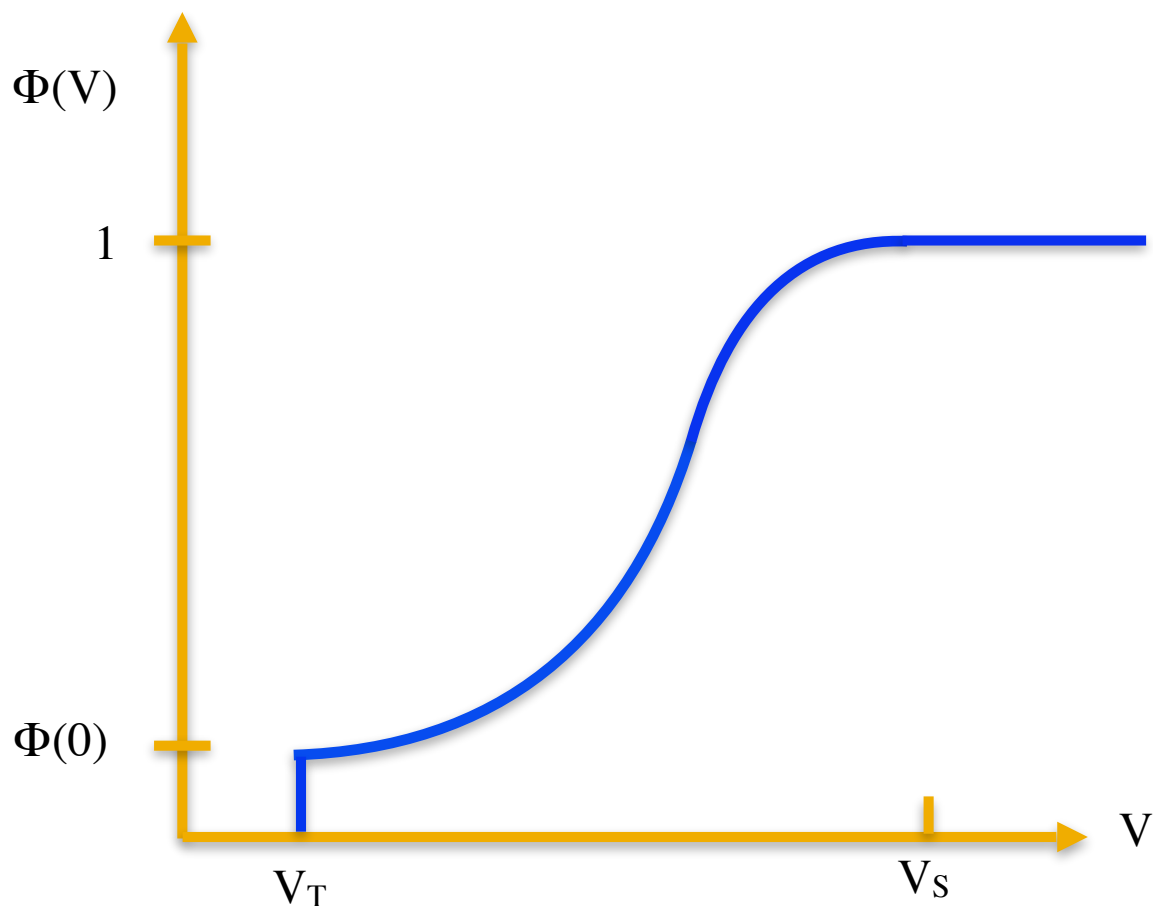
Escape rate model, discrete time version:

$$V[t+1] = \mu V[t] + I_{\text{syn}}[t] + I_{\text{ext}}[t]$$

$$P(X = 1 | V) = \text{sigmoid function}$$

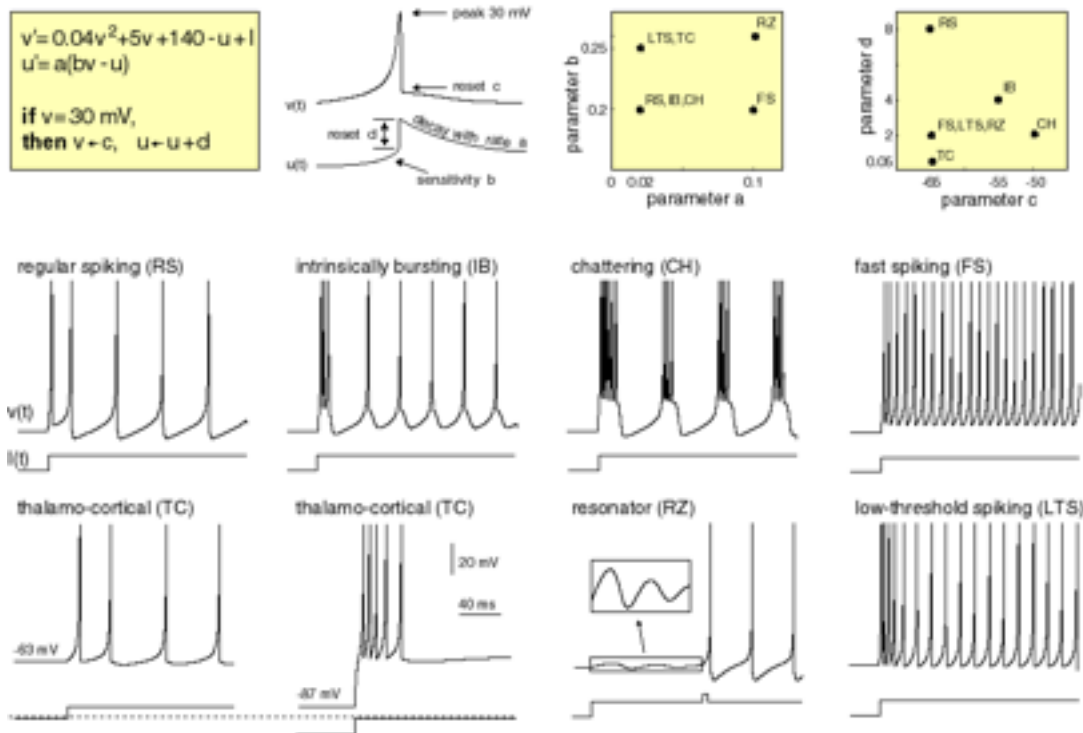
## 2. NEUROSCIENCE: DIFFERENT $\Phi(V)$ FUNCTIONS

**Novelty:** To explore different and more general  $\Phi(V)$  functions.



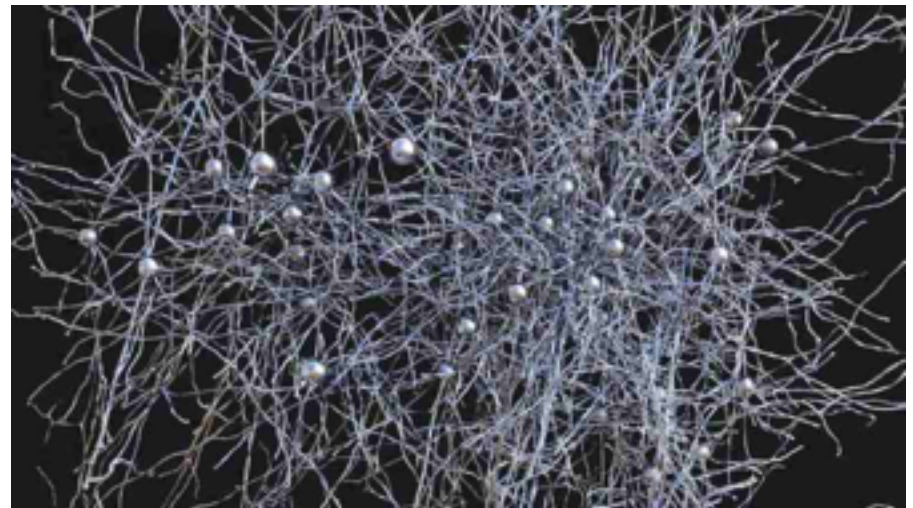
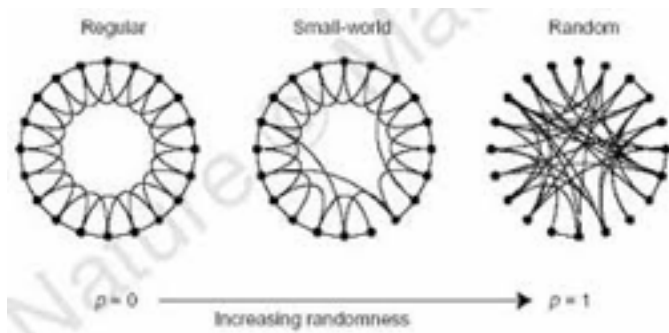
# 3. NEUROSCIENCE: SINGLE NEURONS

**Novelty:** model different types of neurons by using the GL formalism

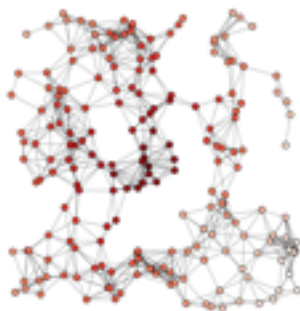


# 4. NEUROSCIENCE: DIFFERENT NETWORK TOPOLOGIES

**Novelty:** To obtain results for GL networks with different topologies that are motivated by biological data and compare them with mean-field solutions obtained by [5].



Scale-free network

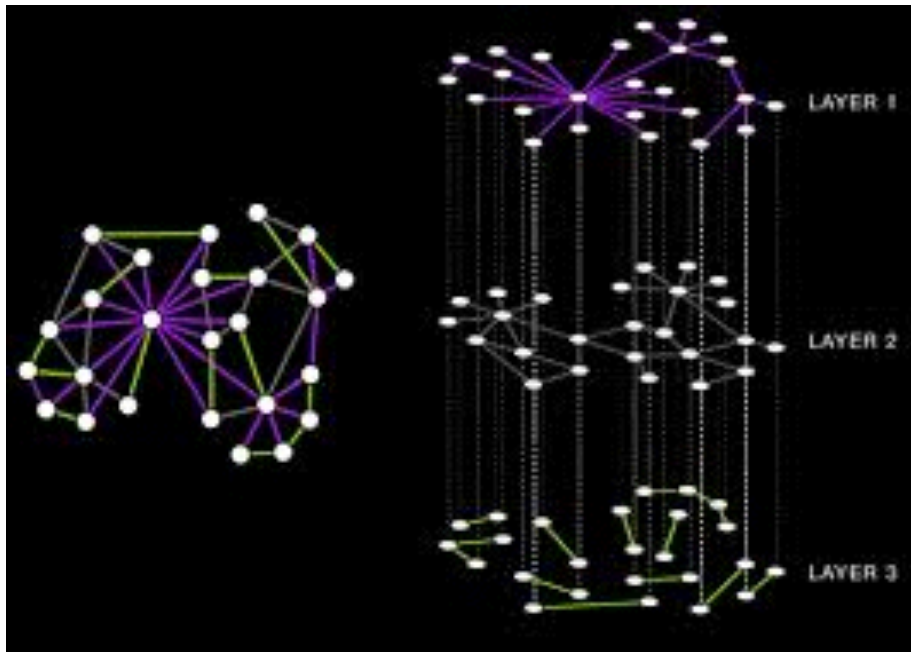


*This is a network of neurons reconstructed with large-scale electron microscopy.  
Credit: Clay Reid, Allen Institute; Wei-Chung Lee, Harvard Medical School; Sam Ingersoll, graphic artist.*



# 5. NEUROSCIENCE: LAYERED NETWORKS

**Novelty:** Architectures with layered networks and possible Psychophysics interpretation.



For a single layer (Kinouchi and Copelli, *Nat. Phys.* **2**, 2006):

Out criticality:  $\rho = c I$

At criticality:  $\rho = c I^m$ ,  $m = 1/2 < 1$

Enlarged dynamic range

$m$  = Stevens Psychophysical Exponent

What occurs if we couple  $n$  layers?

Out of criticality, nothing:

At criticality,  $\rho = c I^{m'}$  ?

$m' = m^n$

New psychophysical exponents?

Larger dynamic range?

# 6. NEUROSCIENCE: DIFFERENT GAINS AND SYNAPTIC DYNAMICS

**Novelty:** Simpler self-organization rules for the synapses and neuronal gains with mean-field analytic results.

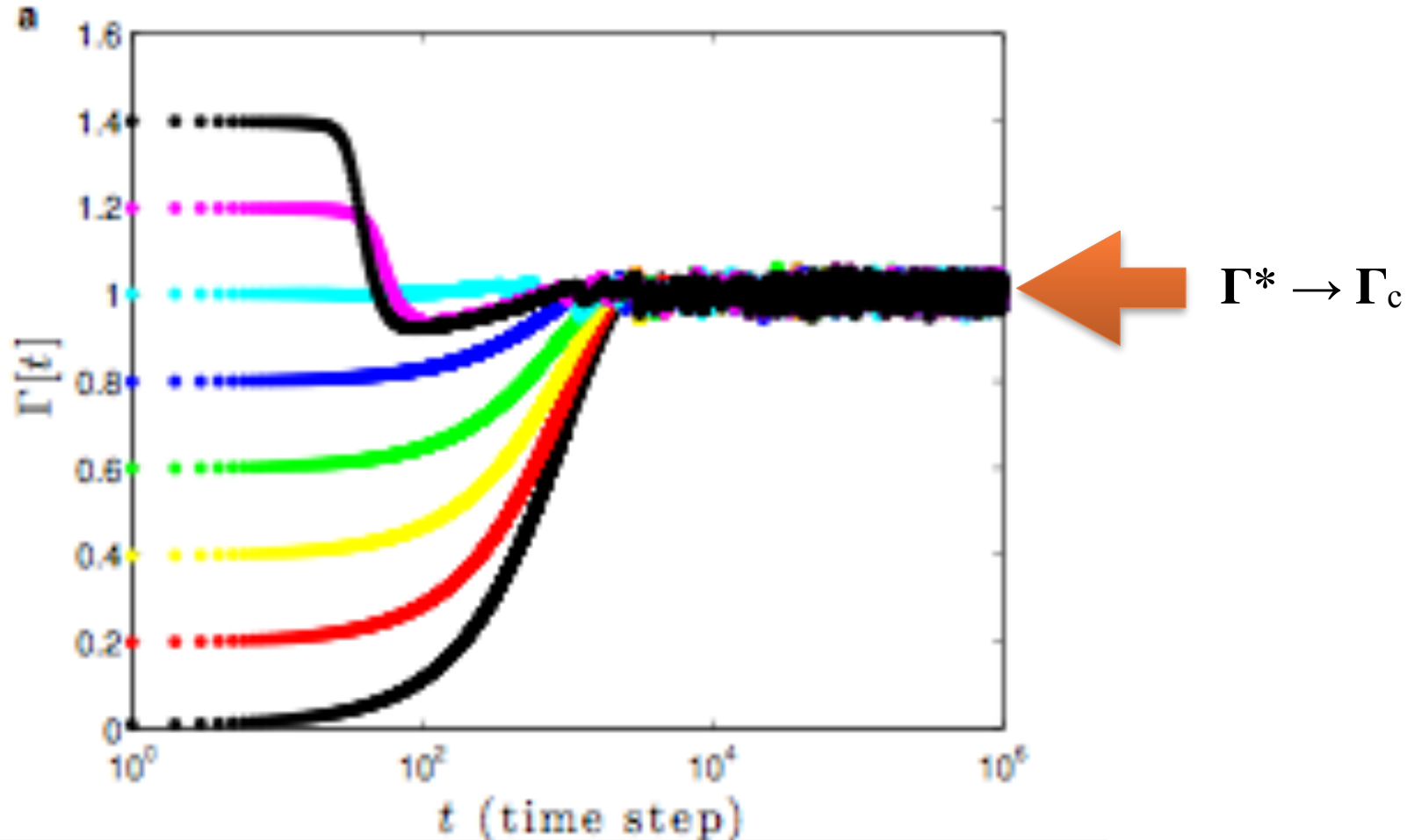
$$\Gamma_i[t+1] = \Gamma_i[t] + \frac{1}{\tau}(A - \Gamma_i[t]) - u\Gamma_i[t]X_i[t]. \quad \text{Brochini } et al., 2016$$

New proposal:

$$\Gamma_i[t+1] = \Gamma_i[t] + \frac{1}{\tau}\Gamma_i[t] - \Gamma_i[t]X_i[t] = \left(1 + \frac{1}{\tau} - X_i[t]\right)\Gamma_i[t]$$

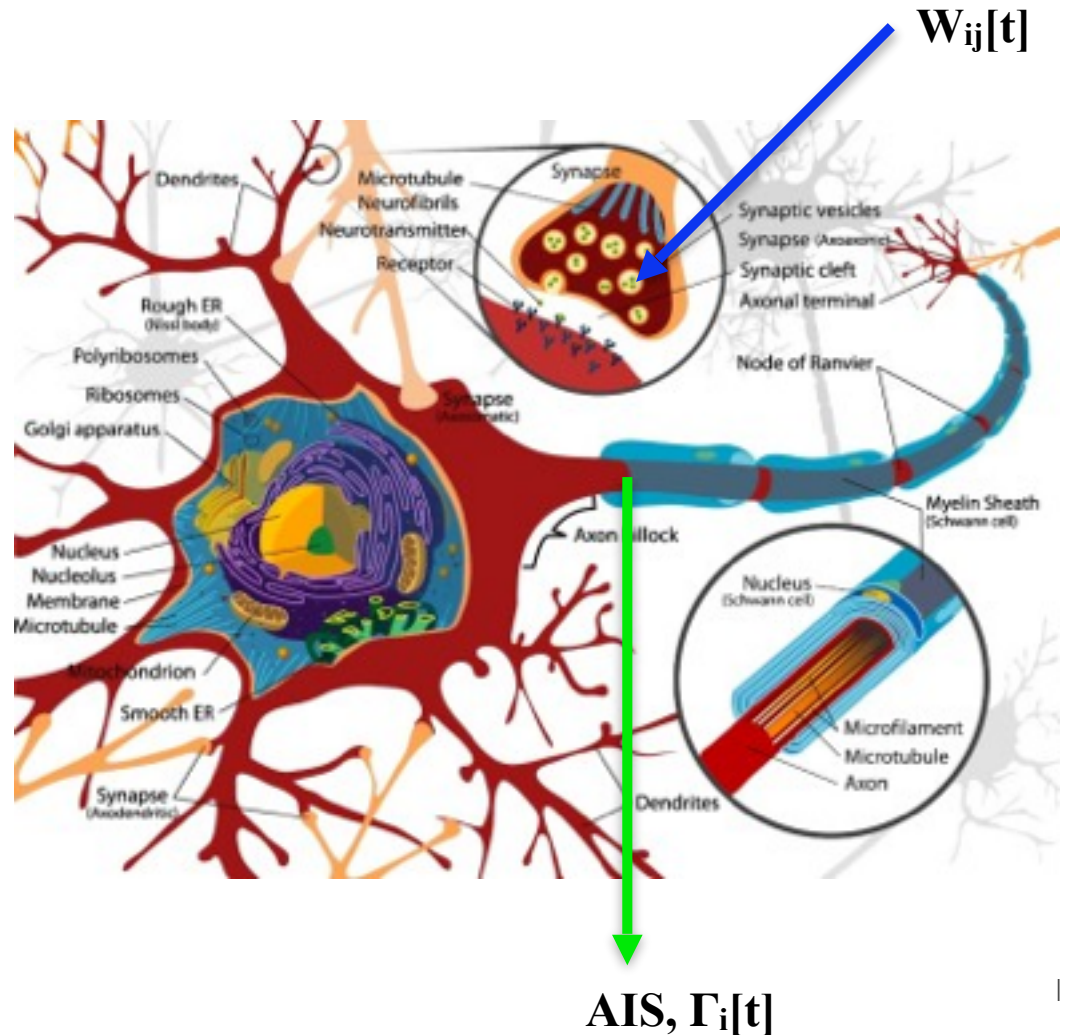
$$\Gamma^* = (1 + 1/\tau)\Gamma_c$$

# Self-organization of the average gain toward the critical region



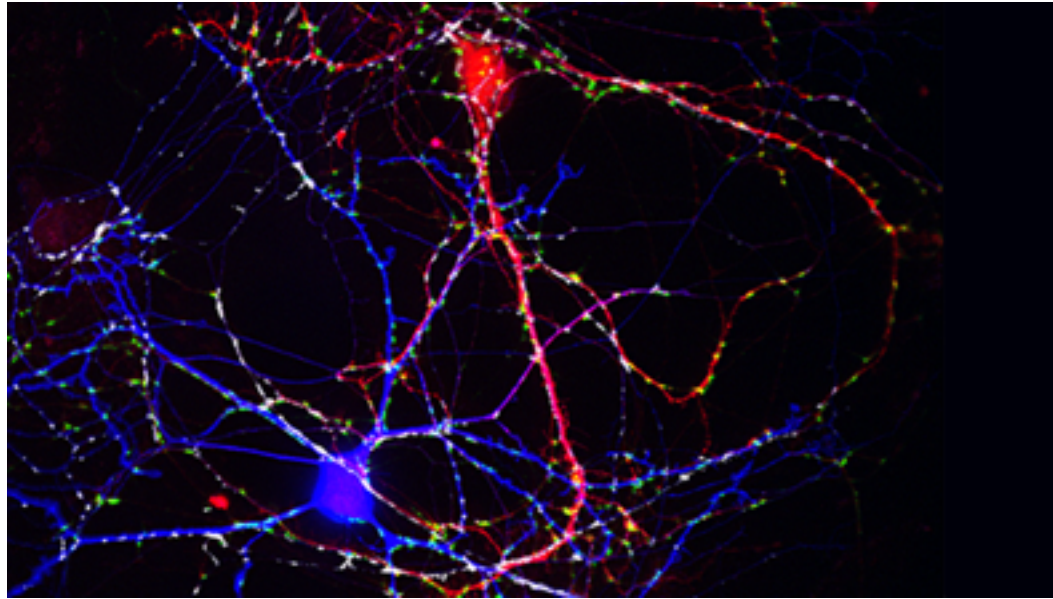
# Why to separate the average gain $\Gamma$ from the average synaptic weight $W$ ?

- In a biological network, each neuron  $i$  has a neuronal gain  $\Gamma_i[t]$  located at the *Axonal Initial Segment* (AIS). Its dynamics is linked to sodium channels.
- The synapses  $W_{ij}[t]$  are located at the dendrites, very far from the axon. Its dynamics is due to neurotransmitter vesicle depletion.
- So, although in our model they appear always together as  $\Gamma W$ , this is due to the use of point like neurons. A neuron with at least two compartments (dendrite + soma) would segregate these variables.



# 7. NEUROSCIENCE: INHIBITORY NEURONS

**Novelty:** Explore the effect of inhibitory neurons in GL networks.

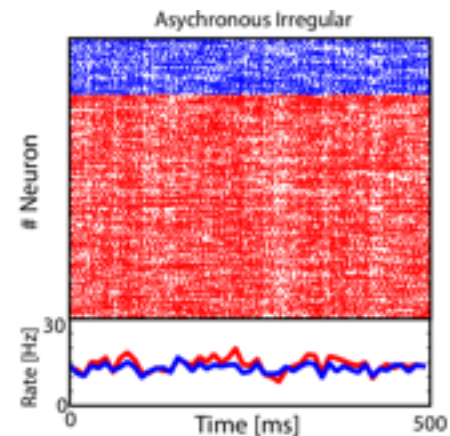
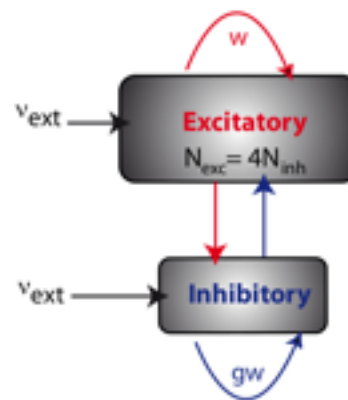


Brain activity is a balancing act — some brain cells are tasked with keeping others in check. This image of brain neurons cultured from a mouse shows this interaction: the “inhibitory” neuron (blue) sends signals that can prevent the “excitatory” neuron (red) from firing. Studying these inhibitory neurons in a dish could reveal important clues about how they regulate the activity of more complex brain circuits. Source: Society for Neuroscience

# 8. NEUROSCIENCE: SELF-ORGANIZED BALANCED NETWORKS

**Novelty:** A mechanism to self-organized GL networks toward the balanced state based in local balance dynamics of the g ratio.

$$g_i = W_I / W_E$$

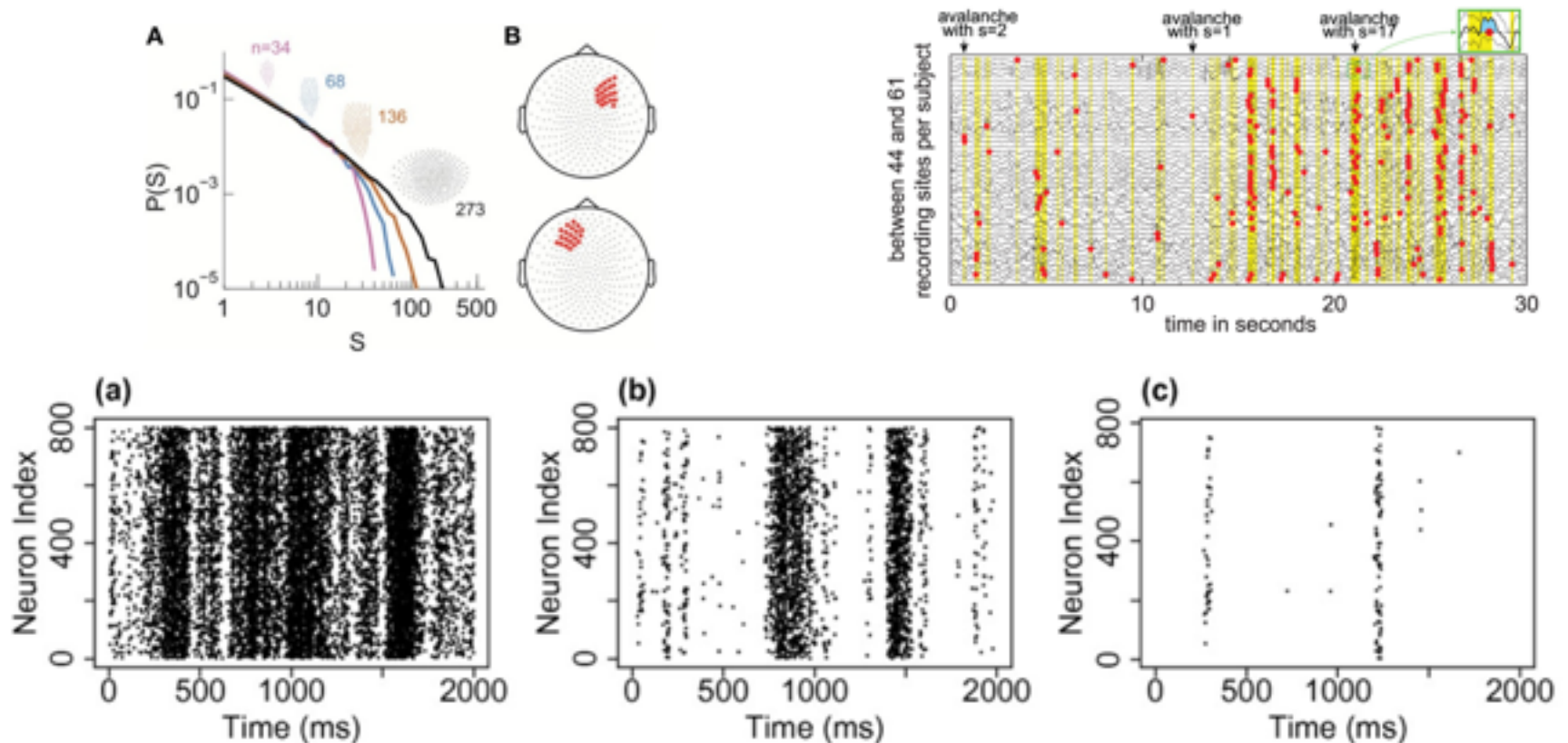


$$g_i[t + 1] = g_i[t] + 1/\tau g_i[t] - X_i[t]$$



# 9. NEUROSCIENCE: SUBSAMPLING IN CRITICAL AND SUPERCRITICAL NETWORKS

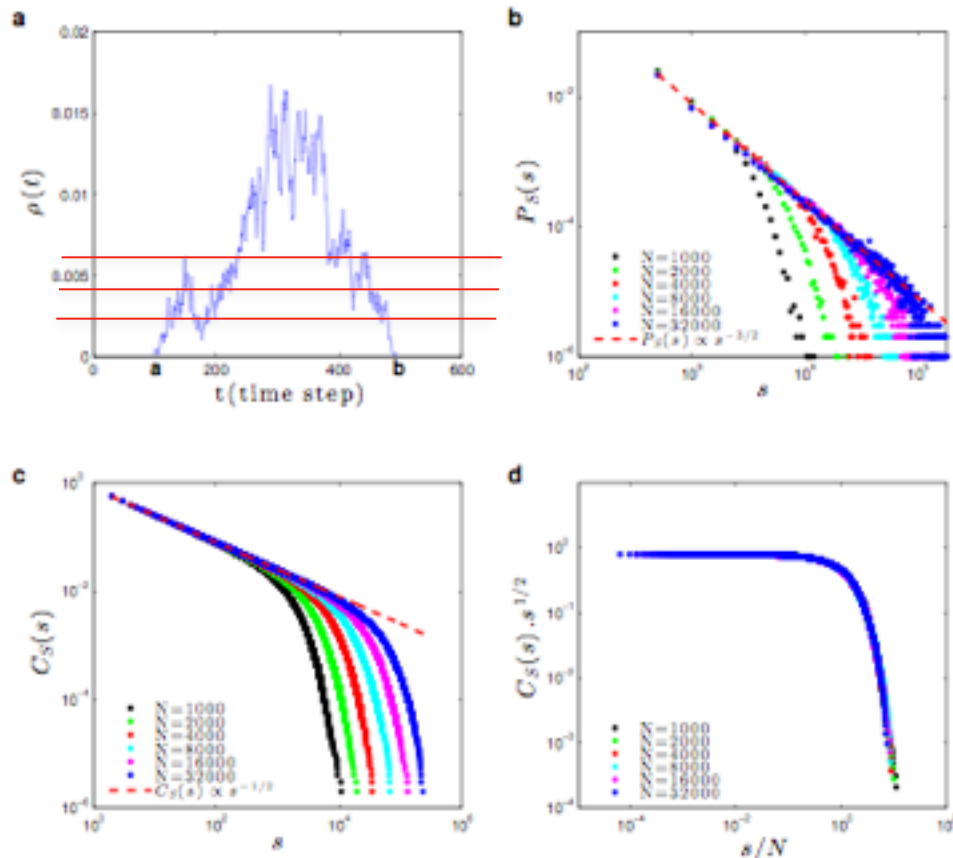
**Novelty:** To examine the effect of subsampling in GL networks.



Effect of input level

# 10. NEUROSCIENCE: EFFECT OF AVALANCHE THRESHOLD DEFINITION IN CRITICAL AND SUPERCRITICAL NETWORKS

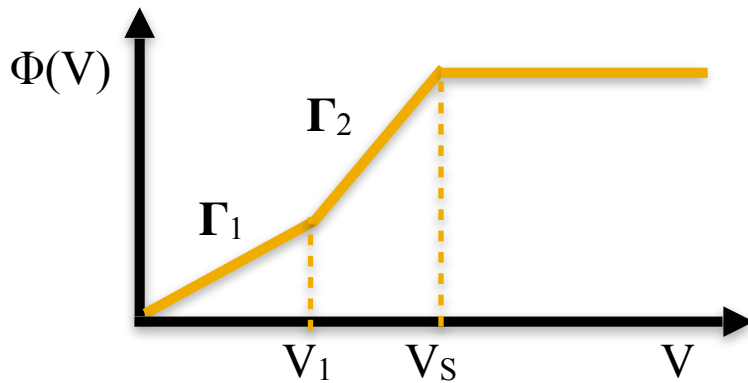
**Novelty:** To examine the effect of a threshold for defining the avalanches sizes and avalanches intervals.



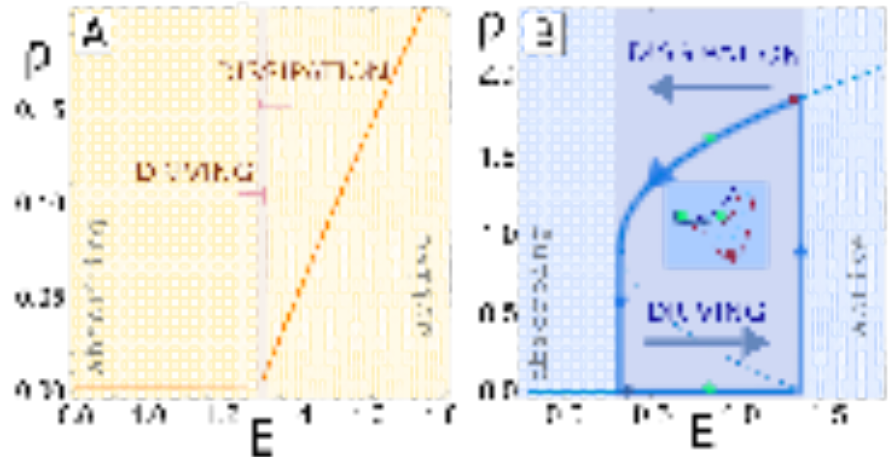
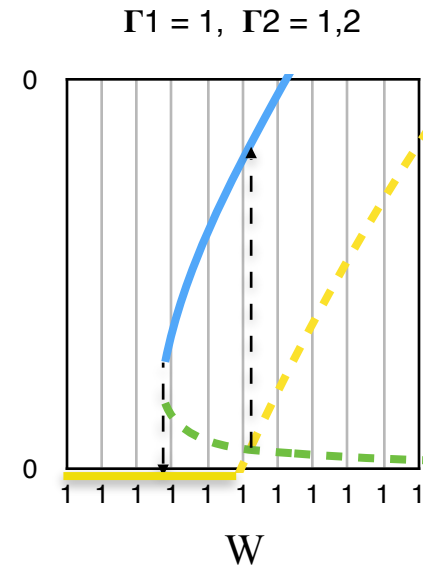


# 11. NEUROSCIENCE: SELF-ORGANIZED BI-STABILITY (SOB)

**Novelty:** Self-organization toward bi-stability region in discontinuous phase transitions.



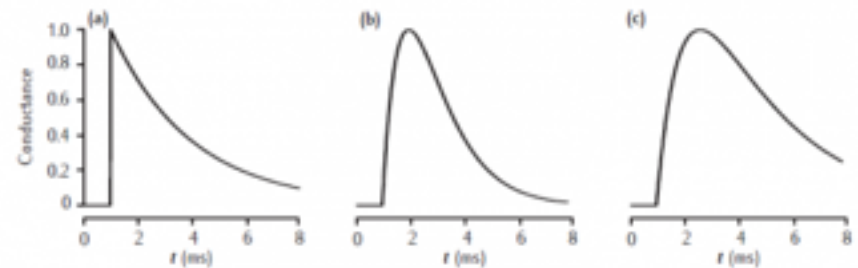
di Santo, S., Burioni, R., Vezzani, A., & Muñoz, M. A. (2016). Self-Organized Bistability Associated with First-Order Phase Transitions. *Physical Review Letters*, 116(24), 240601.



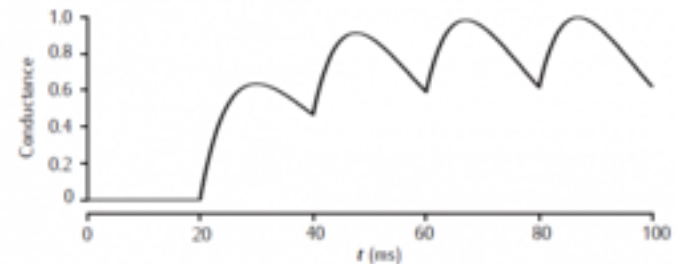
# 12. NEUROSCIENCE: DIFFERENT SYNAPTIC MODELS

**Novelty:** More realistic chemical synaptic coupling between the GL neurons.

$$I_i[t] = \sum_{j=1}^N g_{ij}[t] (V_j[t] - V_i[t])$$

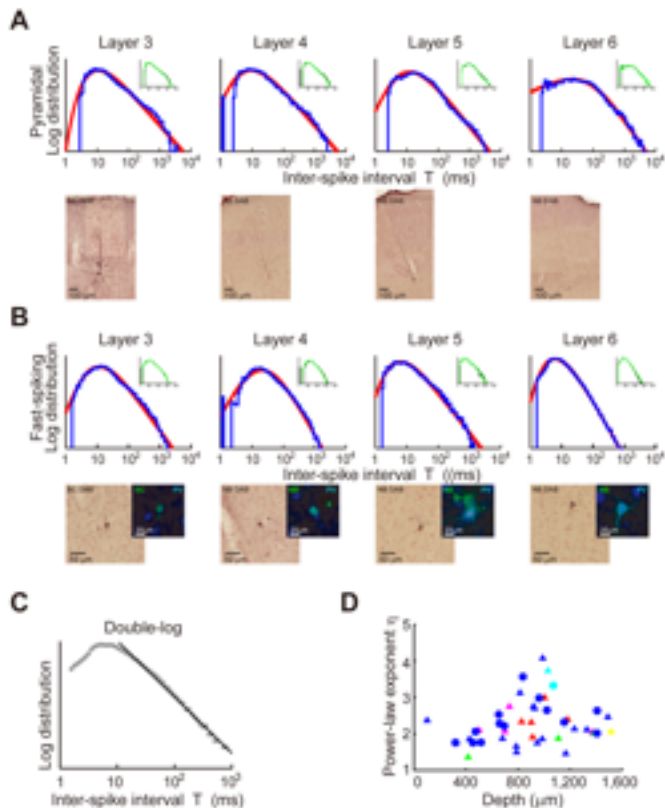


$$g_{ij}[t+1] = \left(1 + \frac{1}{\tau_1}\right) g_{ij}[t] + h_{ij}[t],$$
$$h_{ij}[t+1] = \left(1 + \frac{1}{\tau_2}\right) h_{ij}[t] + J_{ij} X_j[t].$$



# 13. NEUROSCIENCE: INTERSPIKE INTERVALS (ISI) HISTOGRAM FOR GL NEURONS

**Novelty:** Search for ISI histograms with long tails in GL neurons.



PLoS Computational Biology April 12 (2012).  
Power-Law Inter-Spike Interval Distributions Infer a  
Conditional Maximization of Entropy in Cortical Neurons

- Yasuhiro Tsubo ,
- Yoshikazu Isomura,
- Tomoki Fukai

[arXiv.org](http://arXiv.org) [q-bio](http://q-bio)

The emergence of power-law distributions of  
inter-spoke intervals characterizes status epilepticus  
induced by pilocarpine administration in rats

[Massimo Rizzi](#)

(Submitted on 7 Jan 2015)

# 14. PLANT NEUROBIOLOGY: ONE-DIMENSIONAL (OR CAYLEY TREE) NETWORK WITH NEAREST NEIGHBOR INTERACTION

**Novelty:** electric coupling, one dimensional lattice with stochastic excitable waves, possible analytic solutions.

$$V_i[t + 1] = \mu V_i[t](1 - X_i[t]) + g_{i-1,i}(V_{i+1}[t] - V_i[t]) + g_{i,i+1}(V_{i+1}[t] - V_i[t]).$$

## Plants perform complex information processing



- Sensitive exploration of their environment
- Reaction to external stimuli
- Learning and remembering
- Goal seeking
- Error assessment
- Communication with neighbouring plants and other organisms

Plant neurobiology: A paradigm shift in plant sciences; František Baluška, Dieter Volkmann, Peter W. Barlow, Stefano Mancuso



# 15. SOCIOPHYSICS: THE "FENCE BUILDING" ONE DIMENSIONAL MODEL

**Novelty:** New imitation-based sociological problem with possible empirical data, one dimensional lattice with external fields.



$$V_i[t+1] = \mu V_i[t] + h_i + H + \sum_j W_{ij} X_j[t],$$

# 16. GEOPHYSICS: SOC MODELS FOR LIGHTNINGS AND EARTHQUAKES IN A SQUARE LATTICE

**Novelty:** Square lattice and SOC.

$$V_i[t+1] = \mu V_i[t] + \sum_{j \in 2d} W_{ij} X_j[t] \quad \text{if } X_j[t] = 0$$

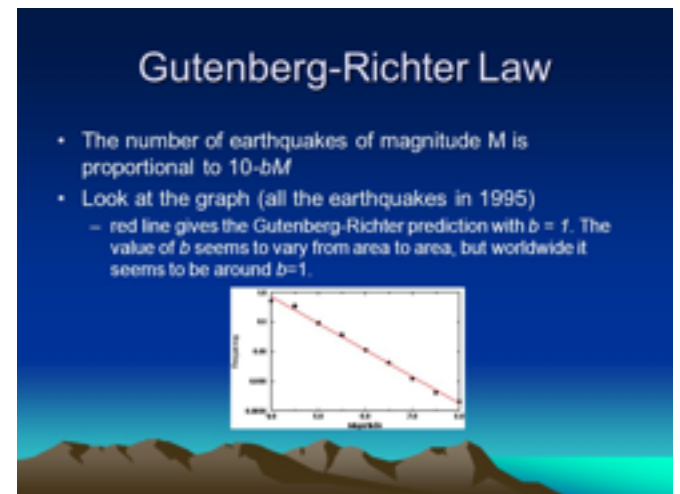
$$V_i[t+1] = 0 \quad \text{if } X_j[t] = 1$$

$$P(X=1 | V) = \Phi(V)$$

Spiking sorting algorithms applied to radio pulses time series from lightnings?

Could we measure the ISI histogram of lightnings?

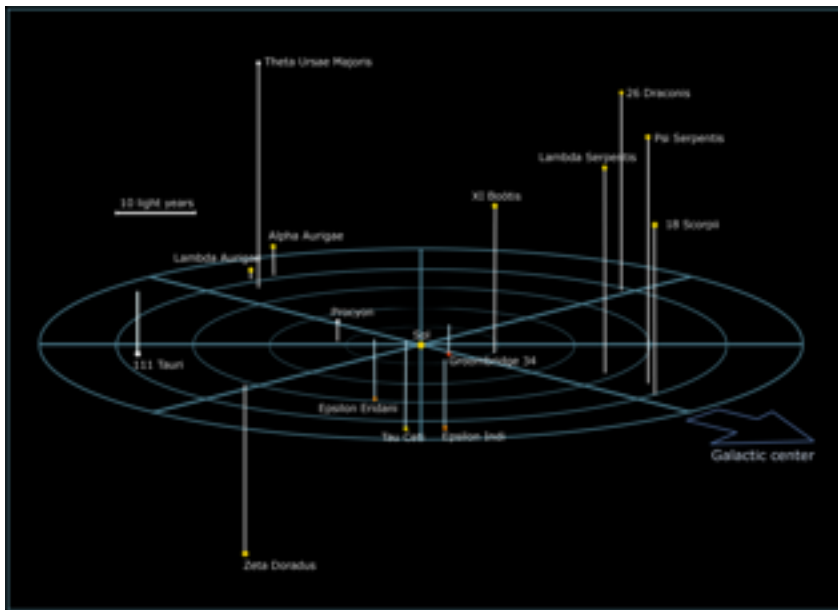
This histogram has a heavy tail?





# 17. COLONIZATION PROCESSES: DIFFUSION MODEL IN A CUBIC LATTICE

**Novelty:** Cubic lattice, different functions  $\Phi_i(V)$  for each site, Invasion Percolation dynamics based in variable thresholds  $V_{Ti}$ .



**Persistence solves Fermi Paradox but challenges SETI projects**

[Osame Kinouchi](#)

Persistence phenomena in colonization processes could explain the negative results of SETI search preserving the possibility of a galactic civilization. However, persistence phenomena also indicates that search of technological civilizations in stars in the neighbourhood of Sun is a misdirected SETI strategy. This last conclusion is also suggested by a weaker form of the Fermi paradox. A simple model for galactic colonization based in a generalized Invasion Percolation dynamics illustrates the Percolation solution for the Fermi Paradox.

$$V_i[t + 1] = \mu V_i[t] + \sum_{j \in \mathcal{N}_i} W_{ij} \delta(X_j[t] - 1)$$

$$\Phi_i(V) = \Gamma(V - V_{Ti}) \Theta(V - V_{Ti}) \Theta(V_{Si} - V) + \Theta(V_{Si} - V)$$

# 18. EPIDEMIOLOGY: STOCHASTIC SIRS MODELS

**Novelty:** large firing state interval, very large refractory period.

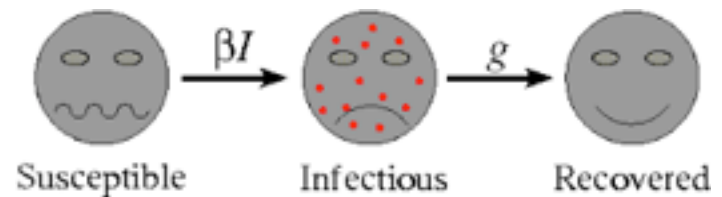
Three state neurons:

$X = 0$  (resting = susceptible)

$X = 1$  (firing = infected)

$X = 2$  (refractory = recovered)

$P(0 \rightarrow 1) = \Phi(V)$ ,  $P(1 \rightarrow 2) < 1$ ,  $P(2 \rightarrow 0) \ll 1$



$$V_i[t + 1] = \mu V_i[t] + \sum_j W_{ij} \delta(X_j[t] - 1)$$



# 19. ECONOPHYSICS: WEALTH DISTRIBUTION MODELS

**Novelty:** negative electrical coupling, complex networks.

$$V_i[t+1] = \mu_i V_i[t] + \sum_i G_{ji} (V_i[t] - V_j[t]) X_i[t] + \sum_j G_{ij} (V_i[t] - V_j[t]) X_j[t],$$



For economy, no reset mechanism  $V[t+1] = 0$  ( $1 - X_i[t]$ )

The ohmic coupling is negative: capital flows from the poor to the rich.

Random factors  $\mu_i$  are individual and can be greater than one, since they represent decay or growth of capital  $V$ .

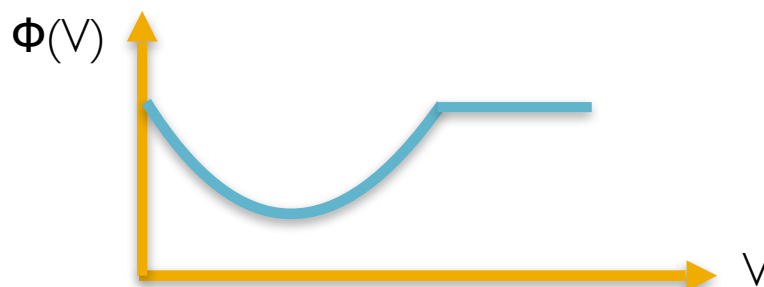
# 20. SOCIOPHYSICS: MODELS OF EMERGENCE OF ALTRUISM

**Novelty:** Non-monotonous functions, diode-like coupling.

$$V_i[t+1] = \mu V_i[t] + \sum_j W_{ij} (V_j[t] - V_i[t]) X_j[t] \Theta(V_j[t] - V_i[t]) - \sum_j W_{ji} (V_i[t] - V_j[t]) X_i[t] \Theta(V_i[t] - V_j[t]).$$

This context of sociological altruism with a  $U$  curve justifies the study of non-monotonous functions for  $\Phi(V)$ . The simplest could be a saturating parabola:

$$\Phi(V) = (aV^2 + bV + c) \Theta(V_S - V) \Theta(V) + \Theta(V - V_S), \quad (38)$$



# Visit us at Ribeirão Preto!



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