Self-Organized Criticality and Neuronal Avalanches in Networks with Dynamical Synapses

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# Motivation: neuronal avalanches



# Size distribution of neuronal avalanches



 $P(s) = c s^{-3/2}$ 

# Quick historical background of SOC

- Microscopically conservative models with true SOC (Bak, Tang & Wiesenfeld PRL 87, Jensen SOC 98)
- Non-conservative models with afteravalanche (hard) loading, presenting pseudo-SOC (Drossel PRL 92, Kinouchi & Prado, PRE 99)
- Non-conservative models with intraavalanche (soft) loading, presenting SOqC (self-organized quase-criticality) (Levina, Herrmann & Geisel Nat Phys 07, Bonachela et al JSTAT 09, 10)



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### Here:

- Microscopically non-conservative model with "soft" loading, but
- Probabilistic cellular automata (larger system sizes & easier mean field)
- Finite connectivity (random graph)
- Stationary regime: conservative on average
- Fluctuations vanish when  $N \rightarrow \infty$



#### Random network of excitable cellular automata

![](_page_5_Figure_1.jpeg)

Control parameter: Branching ratio:  $\sigma = \langle \sigma_i \rangle = \left\langle \sum_{j}^{K} P_{ij} \right\rangle$ 

Order parameter: Mean firing rate:  $\rho = \lim_{t \to \infty} \rho(t) = \lim_{t \to \infty} \frac{1}{N} \sum_{i=1}^{N} \delta(s_i(t), 1)$ 

![](_page_5_Figure_4.jpeg)

Random graph with K outcoming synapses

![](_page_5_Figure_6.jpeg)

Kinouchi & Copelli, Nat. Phys. 06

#### Directed-percolation phase transition at $\sigma = \sigma_c = 1$

![](_page_6_Figure_1.jpeg)

Chialvo, Nat. Phys. 06

#### Directed-percolation phase transition at $\sigma = \sigma_c = 1$

![](_page_7_Figure_1.jpeg)

Chialvo, Nat. Phys. 2006

### **Synaptic Depression**

# Levina et al, Nat. Phys. 07 (LHG) - Integrate and fire neurons (deterministic) - all-to-all coupling $\dot{h}_i = I_{ext}\delta_{i,\xi_{\tau}} + \frac{1}{N}\sum_{j=1}^N uJ_{ij}\delta\left(t - t_j - \tau_d\right)$ Synaptic depression: slow load $\dot{J}_{ij} = \frac{1}{\tau \nu N} \left( \frac{\alpha}{u} - J_{ij} \right) - u J_{ij} \delta \left( t - t_j \right)$

#### Here

Cellular automata (probabilistic)random graph

$$P\left[s_{j}(t+1)=1\right] = P\left[s_{j}(t)=0\right] \times \left\{1 - \prod_{j}^{K} \left[1 - P_{ij}\delta(S_{i}(t),1)\right]\right\}$$

Synaptic depression: slow load

$$P_{ij}(t+1) = P_{ij}(t) + \frac{\epsilon}{NK} (A - P_{ij}) - \frac{u}{N} P_{ij}(t) \delta(t, t_i)$$

 $0 < \mathbf{A} \le 1$  $0 < \mathbf{u} \le 1$ 

![](_page_9_Figure_0.jpeg)

![](_page_10_Figure_0.jpeg)

# Results

- Analytical (mean-field theory)
- Simulations

# Mean-field theory

$$P[s_j(t+1) = 1] = P[s_j(t) = 0] \times \left\{ 1 - \prod_j^{\mathbf{K}} [1 - P_{ij}\delta(S_i(t), 1)] \right\}$$

![](_page_12_Figure_2.jpeg)

 $\rho^* = \text{stationary density of active sites}$  $\sigma^* = \text{stationary branching ratio}$ 

Kinouchi & Copelli, Nat. Phys. 06

$$\begin{aligned}
P_{ij}(t+1) &= P_{ij}(t) + \frac{\epsilon}{NK}(A - P_{ij}) \\
&- u P_{ij}(t)\delta(t, t_i)
\end{aligned}$$

$$\sigma_{i} = \sum_{j}^{K_{j}} P_{ij}$$
$$\frac{\epsilon}{KN} \left( A - \frac{\sigma^{*}}{K} \right) = \frac{u\sigma^{*}\rho^{*}}{K}$$

Mean-field equation (II)  
$$\sigma^* = \frac{AK\epsilon}{uKN\rho^* + \epsilon}$$

## Mean-field theory

![](_page_13_Figure_1.jpeg)

 $\rho^* = \text{stationary density of active sites}$   $\sigma^* = \text{stationary branching ratio}$ 

![](_page_13_Figure_3.jpeg)

 $\sigma^* \to 1$  when  $N \to \infty$ 

# Results

- Analytical (mean-field theory)
- Simulations

# Branching ratio converges to unity

![](_page_15_Figure_1.jpeg)

 $u = 0.1, A = 1.0, \epsilon = 2.0$ n = 3, K = 10, and N = 30000

# Branching ratio converges to unity

$$\sigma^* - 1 \simeq \frac{(AK - 1)}{1 + \left[\frac{uKN}{(n-1)\epsilon}\right]}$$

$$\sigma^* = \frac{AK\epsilon}{uKN\rho^* + \epsilon}$$

![](_page_16_Figure_3.jpeg)

![](_page_16_Figure_4.jpeg)

Branching ratio converges to unity

# $\sigma \rightarrow 1$

![](_page_17_Picture_2.jpeg)

Is on average good enough?

### Fluctuations decrease with system size

![](_page_18_Figure_1.jpeg)

Bonachela et al., JSTAT 10

$$\sqrt{\langle \sigma^2 \rangle - \langle \sigma \rangle^2} \sim N^{-1/4}$$

$$10^{-1}$$

$$y = 0.1521 x^{-0.256}$$

$$u = 0.1$$

$$A = 0.9$$

$$\epsilon = 0.05$$

SD

Ν

10<sup>4</sup>

 $10^{3}$ 

# Critical ( $\sigma = 1$ ) region enlarges as N increases

![](_page_20_Figure_1.jpeg)

 $(
ho\gtrsim 0)$ 

![](_page_20_Figure_3.jpeg)

![](_page_21_Figure_0.jpeg)

# Critical ( $\sigma = 1$ ) region enlarges as N increases

Critical ( $\sigma = 1$ ) region enlarges as N increases

![](_page_22_Figure_1.jpeg)

Neuronal avalanches for  $\epsilon = \epsilon_0 N^{1/3}$  with cutoff  $s_0 \sim N^{3/4}$ 

![](_page_23_Figure_1.jpeg)

Pruessner-Jensen model:

- Similar parameter dependence
- Different cutoff exponent

(Bonachela & Muñoz, JSTAT 09)

#### Conservative

#### Non-Conservative

![](_page_24_Figure_2.jpeg)

Bonachela & Muñoz, JSTAT 09

![](_page_25_Figure_0.jpeg)

# Conclusions

- $P(\sigma) \xrightarrow{N \to \infty} \delta(\sigma 1)$ , with width decreasing as  $N^{-1/4}$
- Employing  $\epsilon = \epsilon_0 N^{1/3}$ , we have a scaling function for P(s)
- Why does it behave so differently from the LHG model?

Possibility: LHG:  $\mathcal{O}(N^2)$  synapses per time step Here:  $\mathcal{O}(NK)$  synapses per time step

If so, should the LHG yield similar results on a random graph?

• Is it bona fide SOC?

Costa, Copelli and Kinouchi – Can dynamical synapses produce true Self-organized criticality? accepted for publication in *Journal of Statistical Mechanics* (2015)

# Perspectives

 Study of neuronal interspike interval (ISI) probability distribution p(t) in the subcritical, critical and supercritical regime

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Study of neuronal interspike interval (ISI) probability distribution p(t) in the subcritical, critical and supercritical regime

#### PLoS Computational Biology

Power-Law Inter-Spike Interval Distributions Infer a Conditional Maximization of Entropy in Cortical Neurons

•Yasuhiro Tsubo,

- Yoshikazu Isomura,
- Tomoki Fukai

Published: April 12, 2012DOI: 10.1371/journal.pcbi.1002461

#### ISI distributions (log-log graphs)

![](_page_28_Figure_9.jpeg)

# Interspike Intervals (ISI) distributions seems to have long (power laws) tails

![](_page_29_Figure_1.jpeg)

Collaboration with Lézio Soares Bueno Júnior started here!

# Zipf plot for ISIs

![](_page_30_Figure_1.jpeg)

# Thank you

![](_page_31_Picture_1.jpeg)

## Come visit us in Ribeirão Preto!

# Adaptation under constant input

![](_page_32_Figure_1.jpeg)

# Adaptation

![](_page_33_Figure_1.jpeg)

# Adaptation

![](_page_34_Figure_1.jpeg)

# Scaling with system size

![](_page_35_Figure_1.jpeg)

A similar scaling was found for the Pruessner-Jensen model (Bonachela & Muñoz, JSTAT 09)