Information dynamics in the Kinouchi-Copelli model

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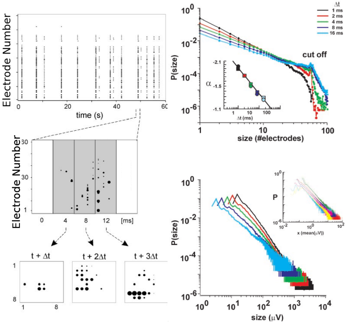
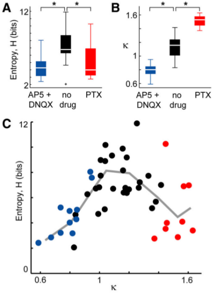
* Experiments revealed **power-law** distributions for both duration and size of bursts of activity.

Beggs and Plenz. J. Neuroscience, v. 23 p. 11167 (2003)

Shew et al. J. Neuroscience, v. 31 p. 55 (2011)

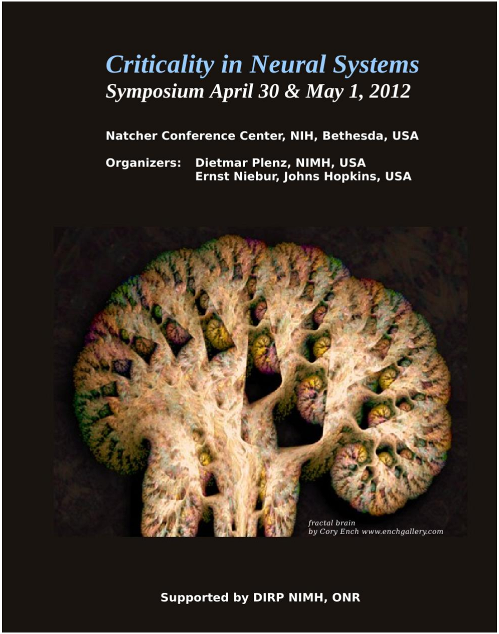




Key questions:

Criticality in neurodynamics?
Critical optimization of information processing?
("Edge of chaos")
Psychophysics?

Criticality in neural systems



Our aim here

- Illustrate connections between neural dynamics and psychophysics
- Argue that information efficiency outperforms information capacity
- Discuss evidence of criticality w/o power-laws
- Preliminary results: quantify information flow leading to psychophysics

Optimal dynamic range $\rightarrow$ **critical optimization**

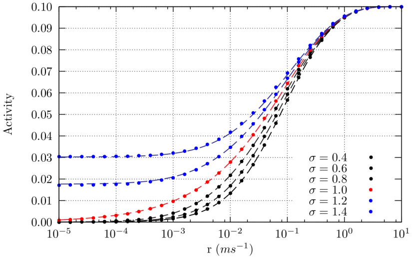
- N **neurons** as nodes of a weighted undirected random graph
- **Weight matrix** A
- **Average connectivity:** K.
- **External stimulus** r**: rate of Poisson process**

Kinouchi and Copelli, Nature Physics, v. 2 p. 348-352 (2006)

* $X_j(t) = 0$: quiescent state
* $X_j(t) = 1$: excited state
* $2 \le X_j(t) \le m-1$: refractory states

- Mean activity = time average of **excited fraction of the network**
- $s_j = \sum_k A_{kj}$: local branching ratio

Average branching ratio: $\sigma := \langle s_j \rangle$



Kinouchi–Copelli model

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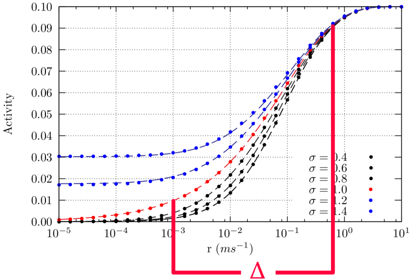
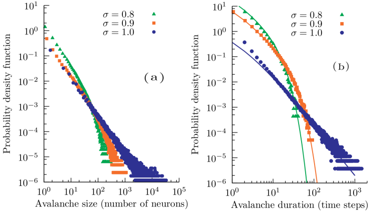


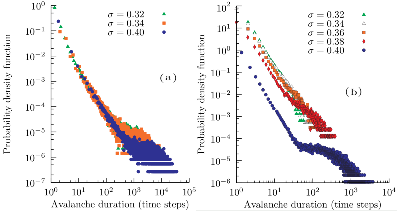
Optimal channel efficiency

Preprint: arXiv:1204.0751v1 [physics.bio-ph]

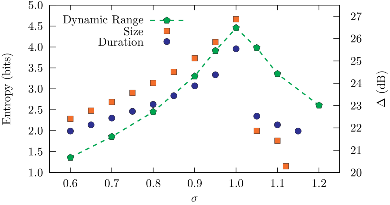
Erdős-Rényi topology

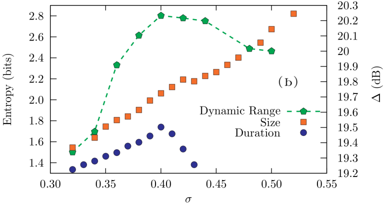


Barabási-Albert topology

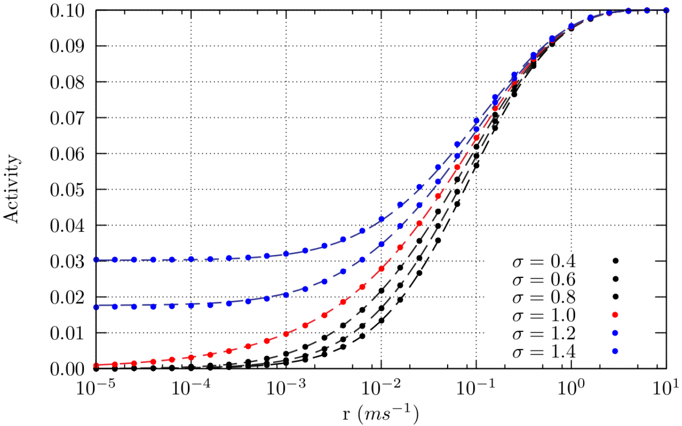


Dynamic range is optimized concomitantly with **information efficiency** encoded in avalanche lifetimes



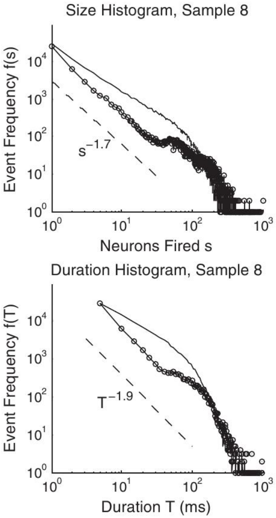


Order parameter: spontaneous activity



No power-laws?

- Dehghani *et al*: arxiv 1203.0738v2
- **Friedman et al: to appear in PRL**



Hamming distance

- Let $\mathcal{A} = (X_1(0), X_2(0), X_3(0), \ldots)$
- Define $\mathcal{B}$ by flipping a randomly chosen node
- $\delta = \frac{1}{N} \sum_{j=1}^{N} |\mathcal{A}_j - \mathcal{B}_j|$

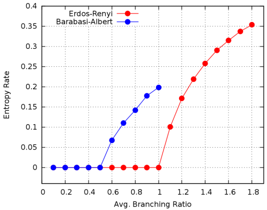
Entropy rate

- Let's define $H_k(X_j) =$

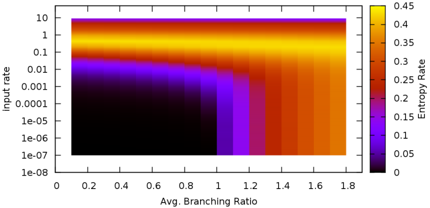
  $\langle -\log \left[P \left\{ X_j(k), X_j(k-1), \ldots, X_j(0) \right\} \right] \rangle$
- $H(X) = \lim_{k \to \infty} \frac{H_k(X)}{k}$

Preliminary reports

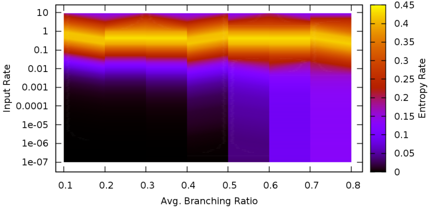
- Performed simulations: $N = 10^4$ and $K = 10$
- **Erdős-Rényi** and **Barabási-Albert** topologies
- **Sampling** $\sim 5 \times 10^3$ events with $k \sim 10$.
- Criticality **vs** Local information dynamics?



Erdős-Rényi topology

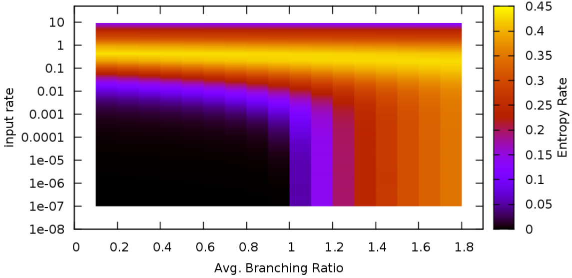


Erdős-Rényi topology

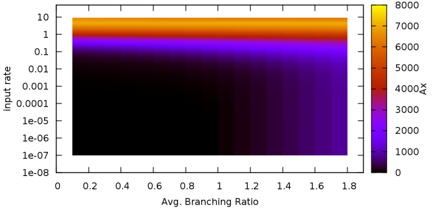


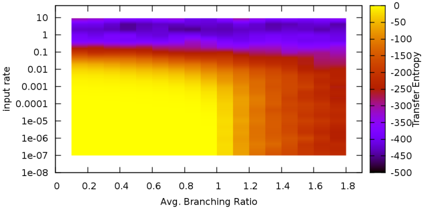
Dynamic range and the entropy rate

Preliminary reports



Reflects somehow the dynamic range optimization

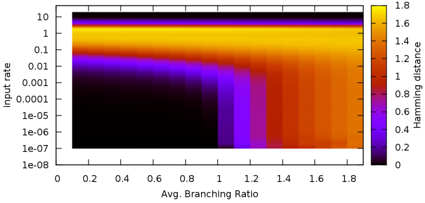




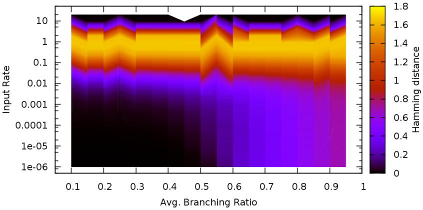
Hamming distance and a transition

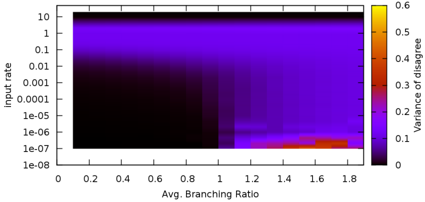
Preliminary reports

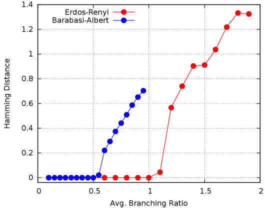
Erdős-Rényi topology



Barabási-Albert topology







The end?

Lots of work to characterize what optimizes information efficiency!

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- Acknowledgements to John Beggs.