The impact of network structure on criticality in cortical circuits

John M. Beggs
Indiana University Physics

Acknowledgements

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Karin Dahmen
Shinya Ito
Nir Friedman
Braden Brinkman
Frances Yeh
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Tom Butler
Masanori Shimono
Lee DeVille
Andrew Lumsdaine

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NIBIB
MIND SCIENCE FOUNDATION
www.mindscience.org
THE NATIONAL ACADEMIES
KECK FUTURES INITIATIVE

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Tom B
Masar
Lee De
Andre

www.mindscience.org

KECK FUTURES INITIATIVE

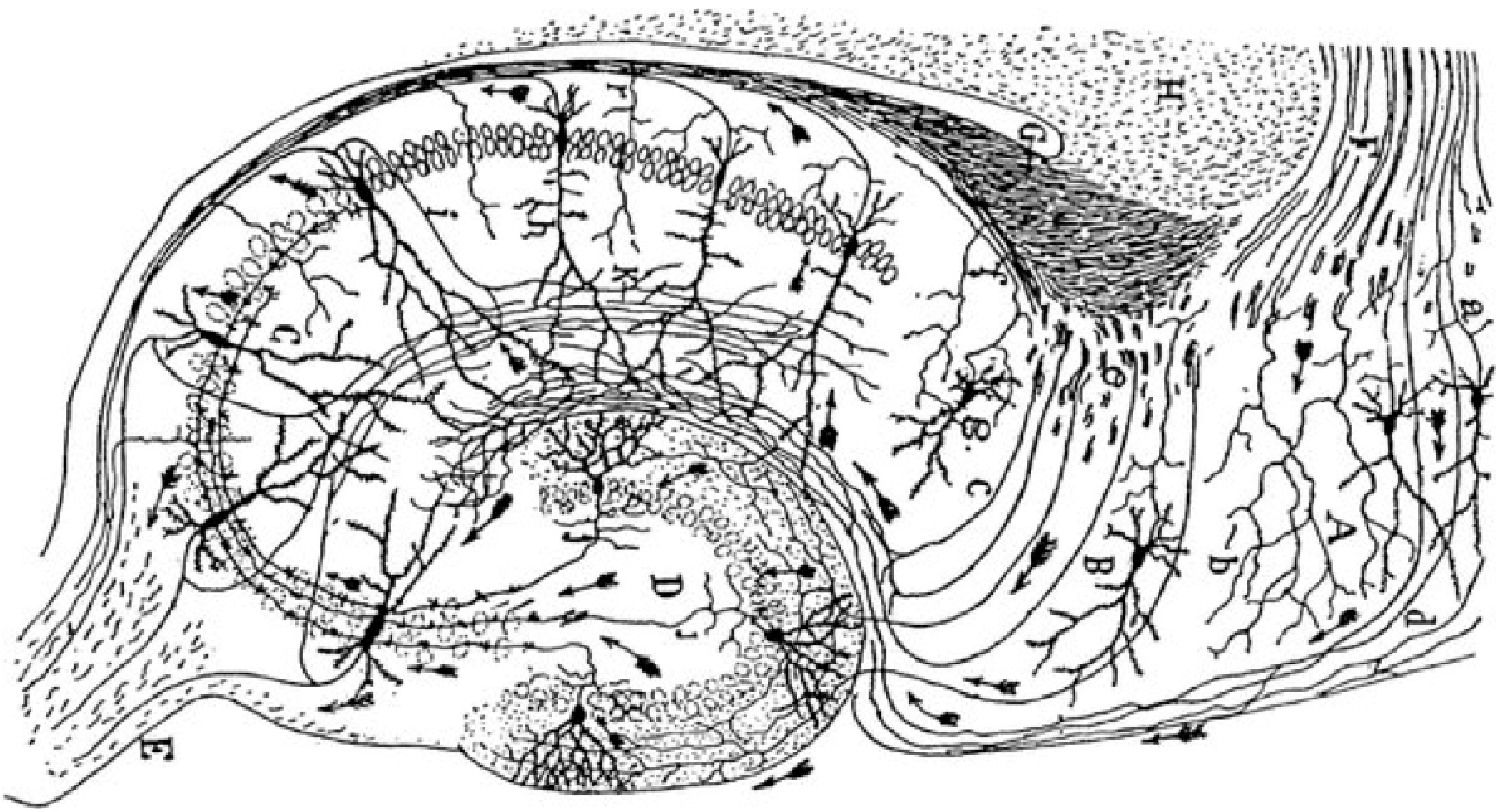
NETWORK STRUCTURE AND CRITICALITY

- Information transfer
- Criticality
- Relating the two

NETWORK STRUCTURE AND CRITICALITY

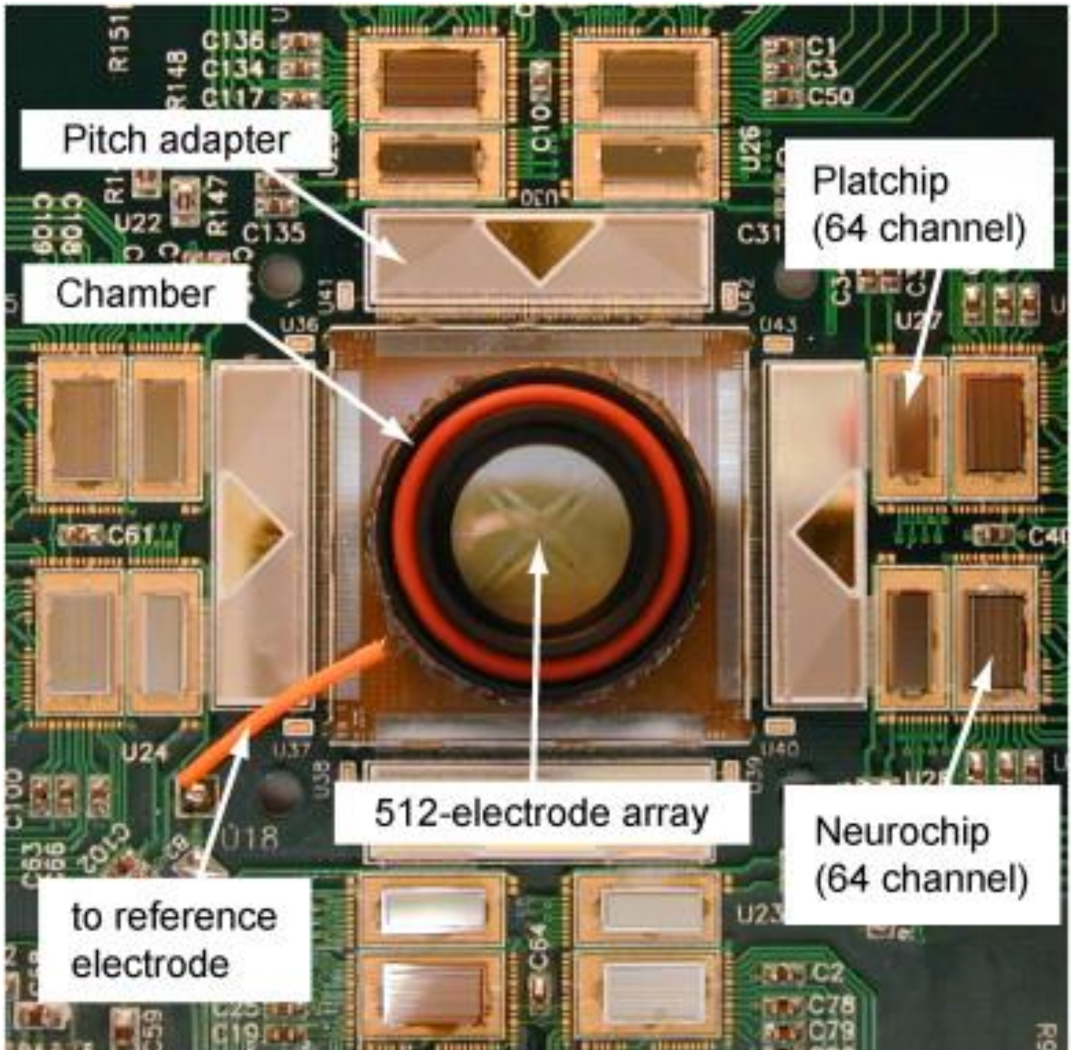
- Information transfer
- Criticality
- Relating the two

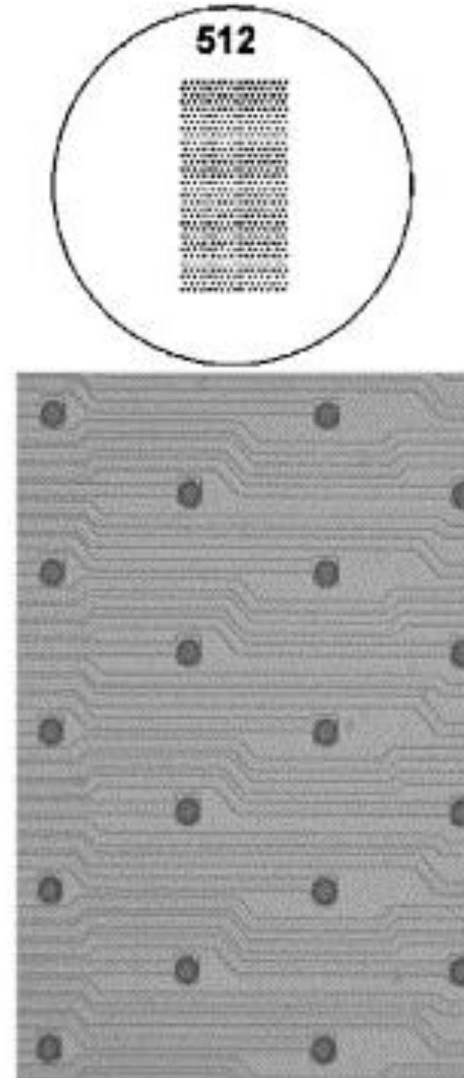
A useful map



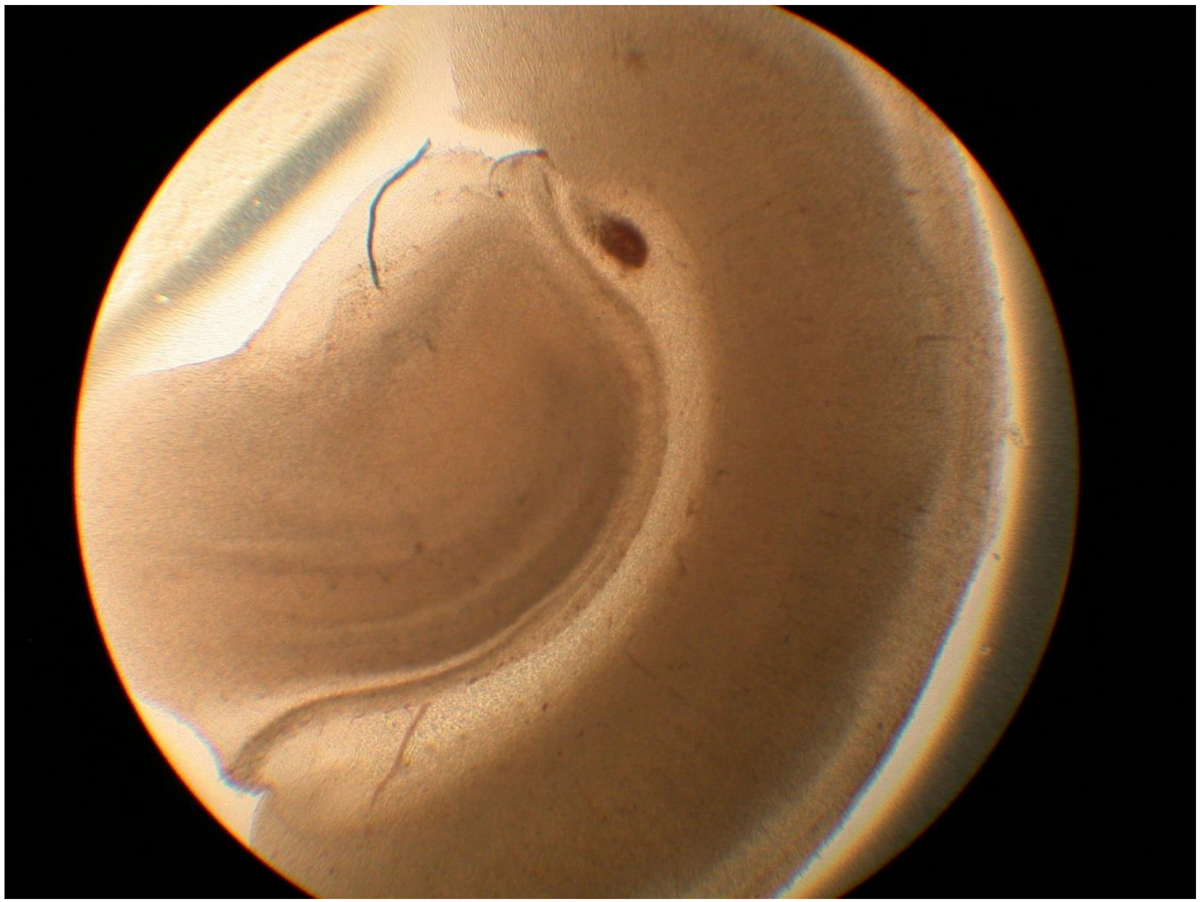
Ramon y Cajal

Good recordings

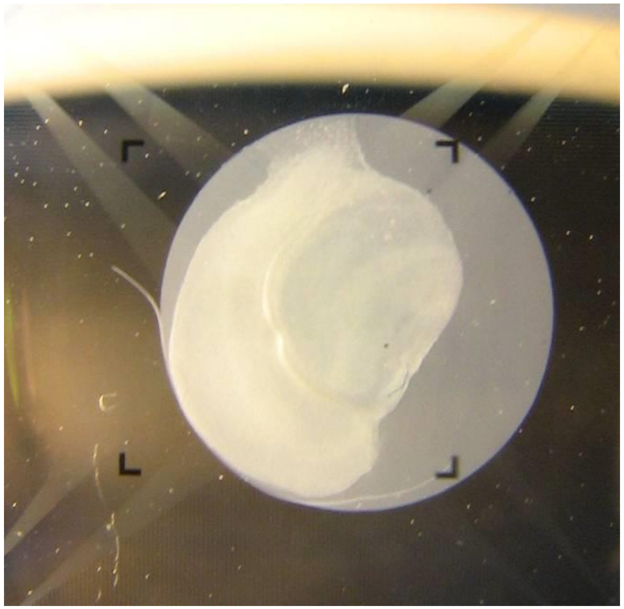


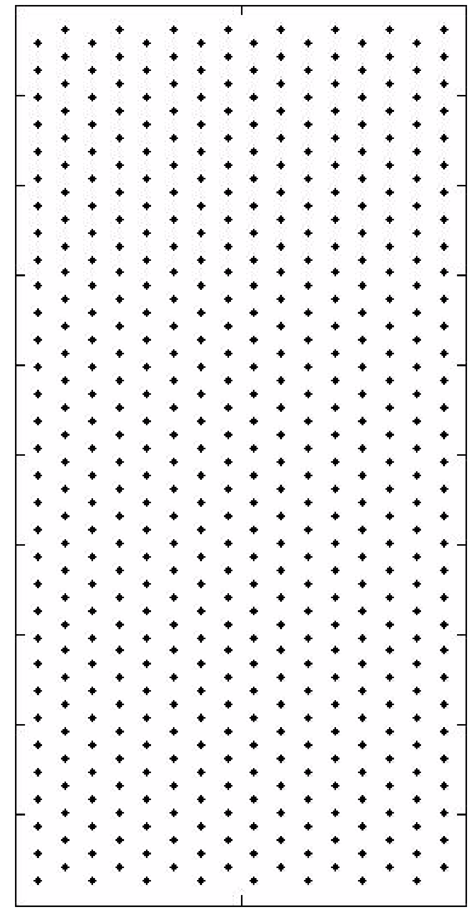


Good recordings



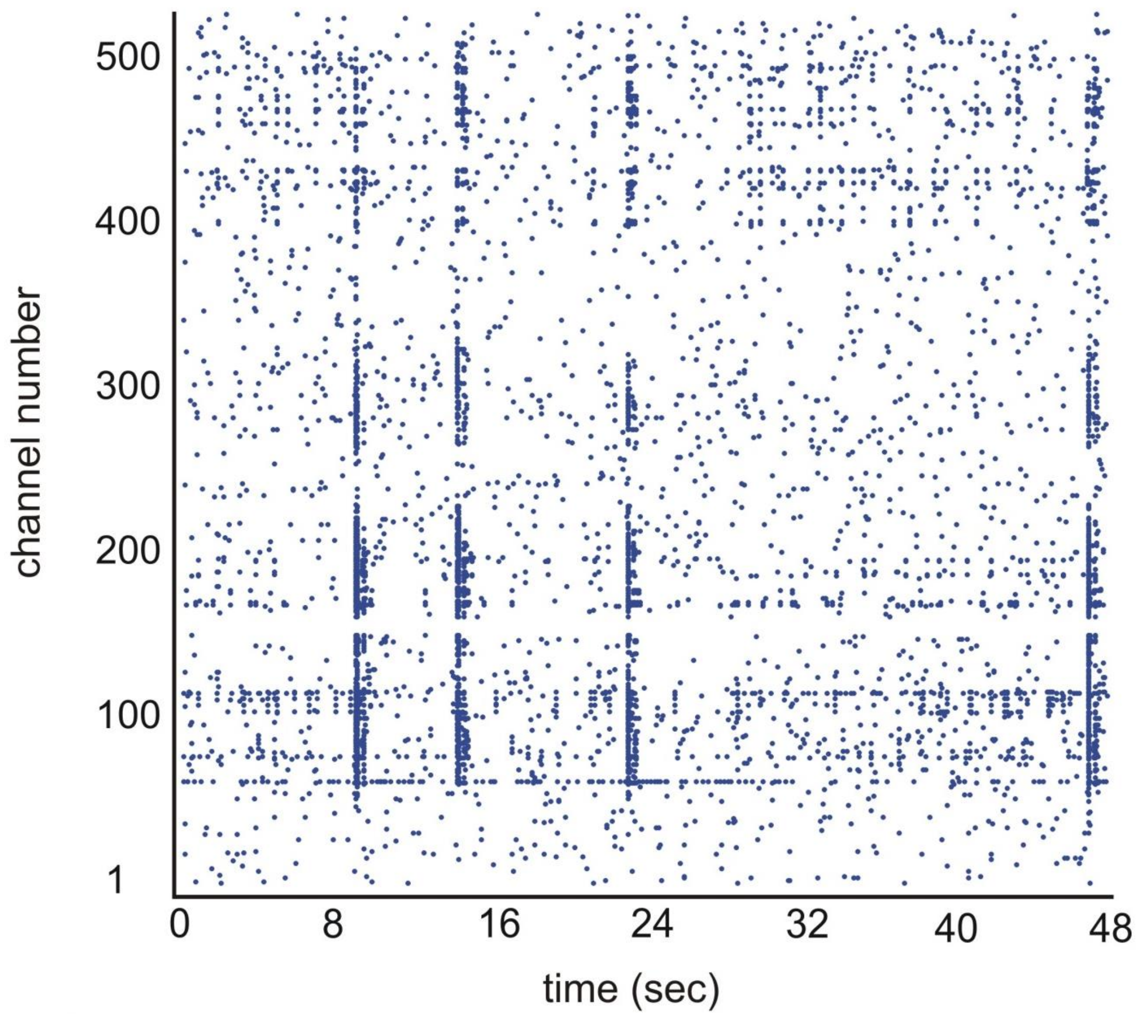
Good recordings





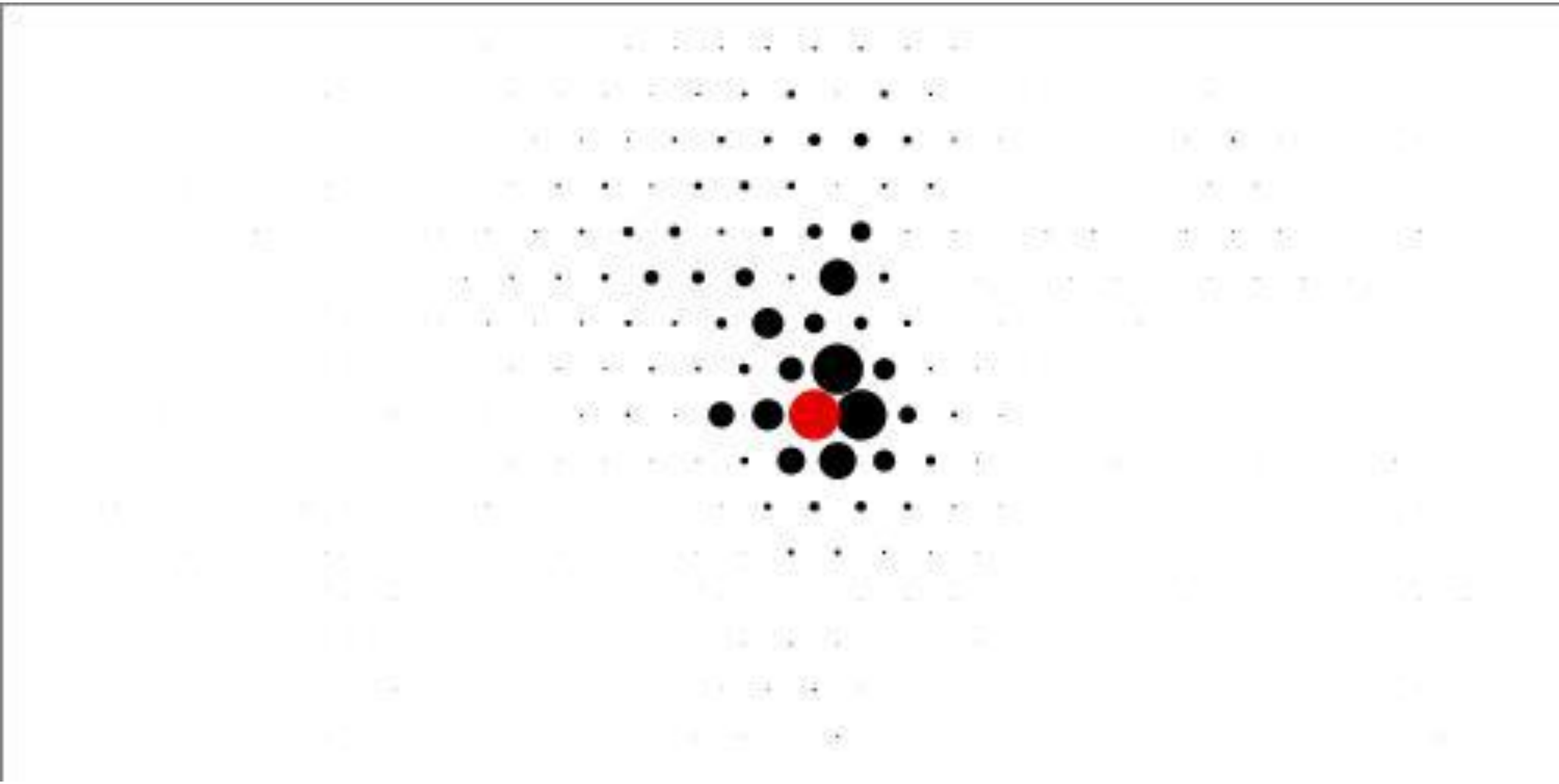
In collaboration with Alan Litke, UC Santa Cruz

Good recordings



…for up to 8 hours

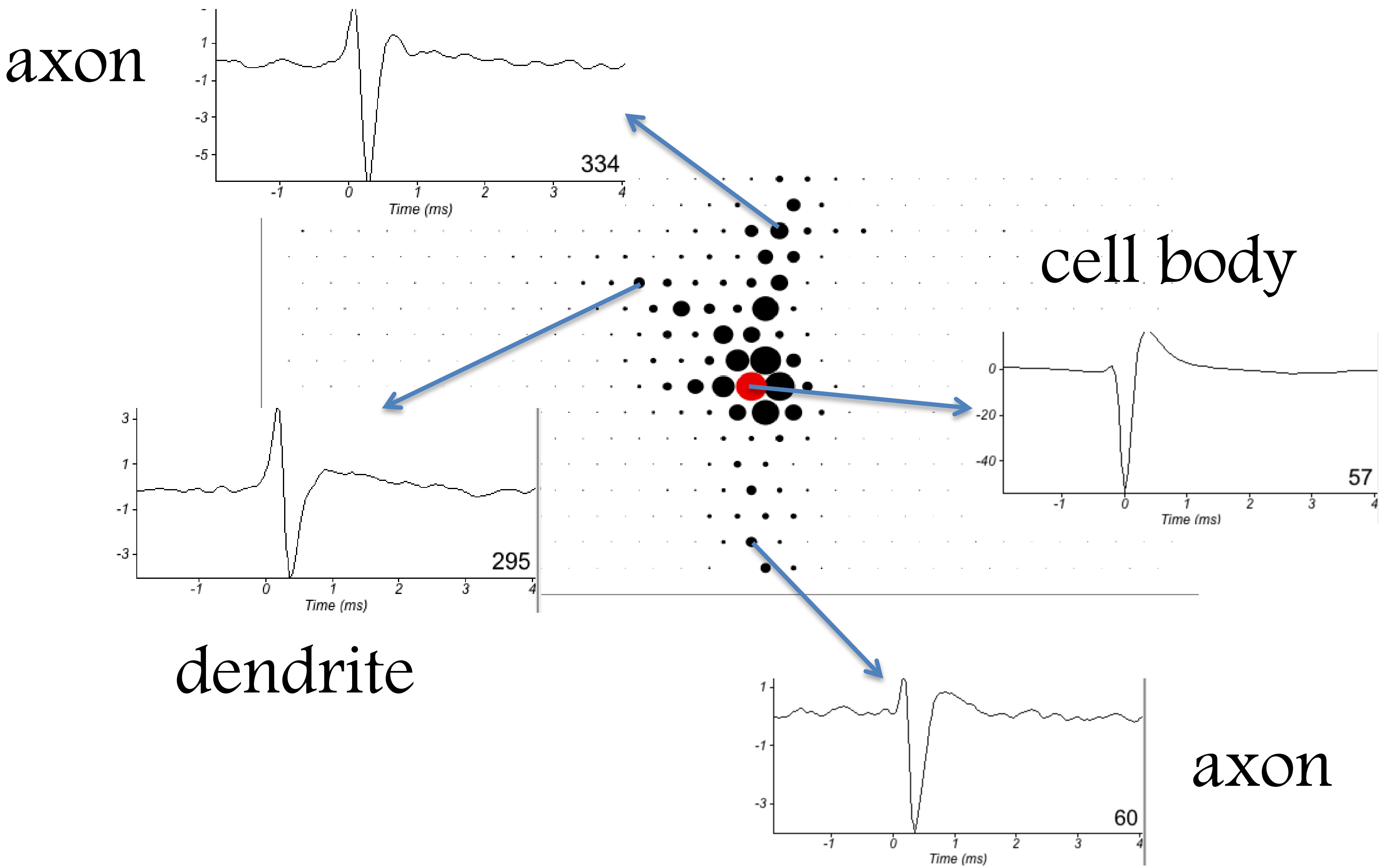
Good recordings



Movie

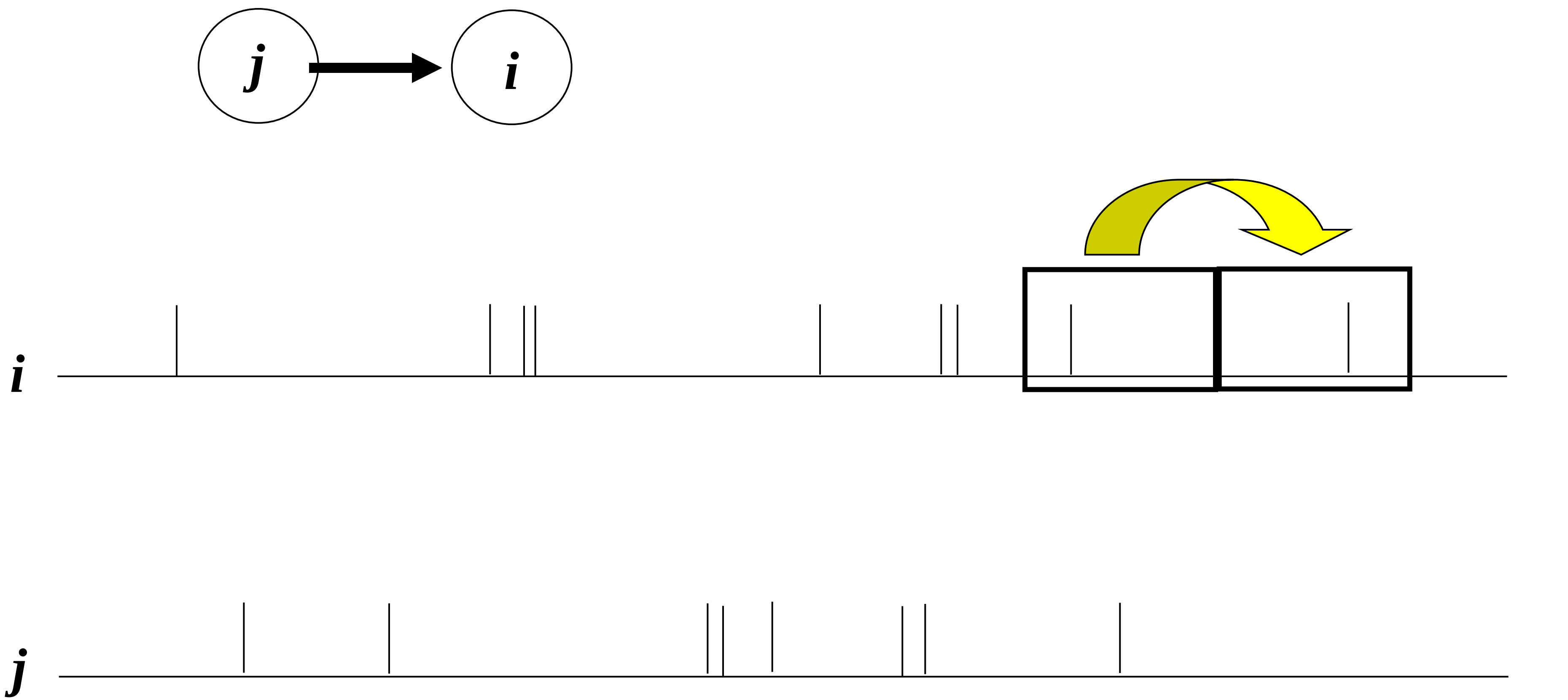
Electrophysiological image of activity propagation along axon: we are probably not undersampling

Good recordings



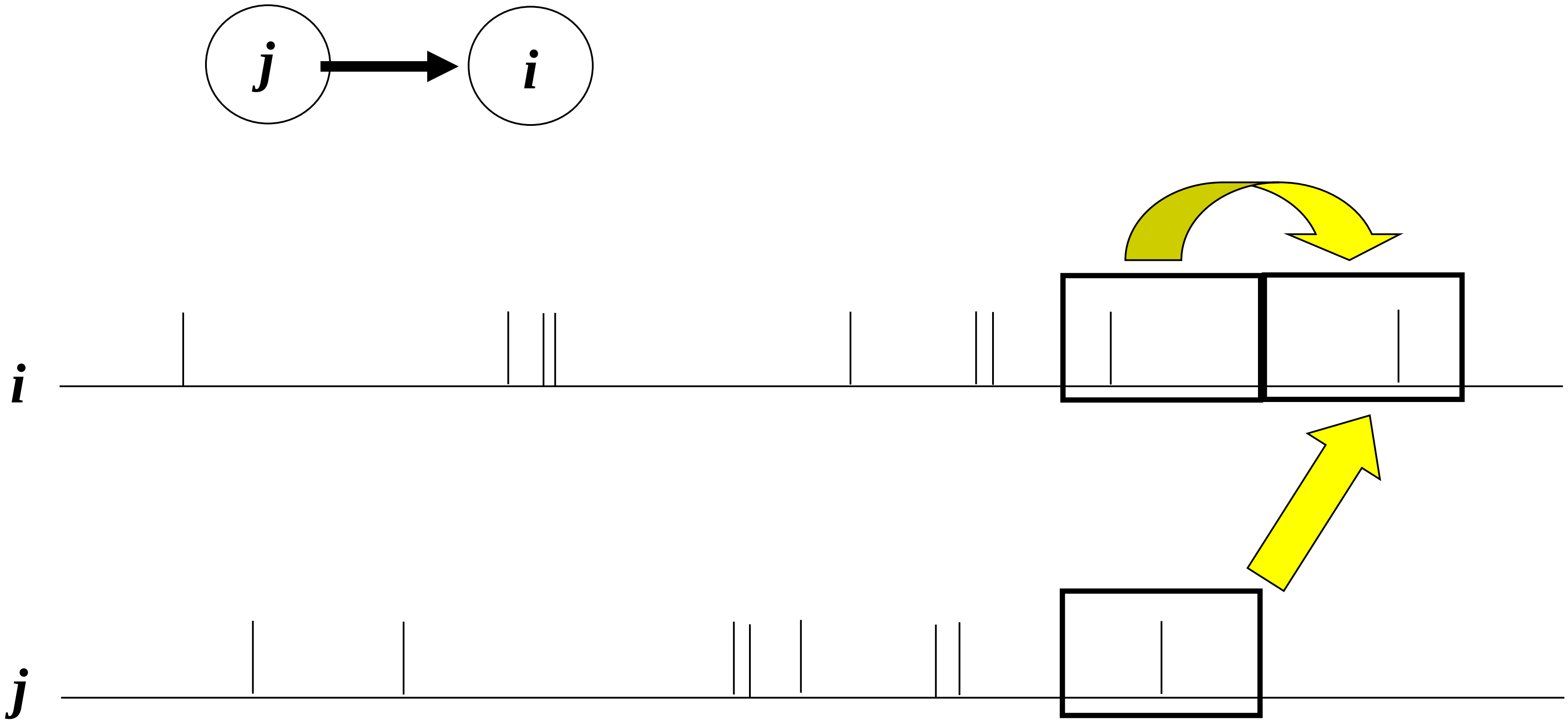
How to measure information transfer?

How well does $\boldsymbol{i_n}$ predict $\boldsymbol{i_{n+1}}$?



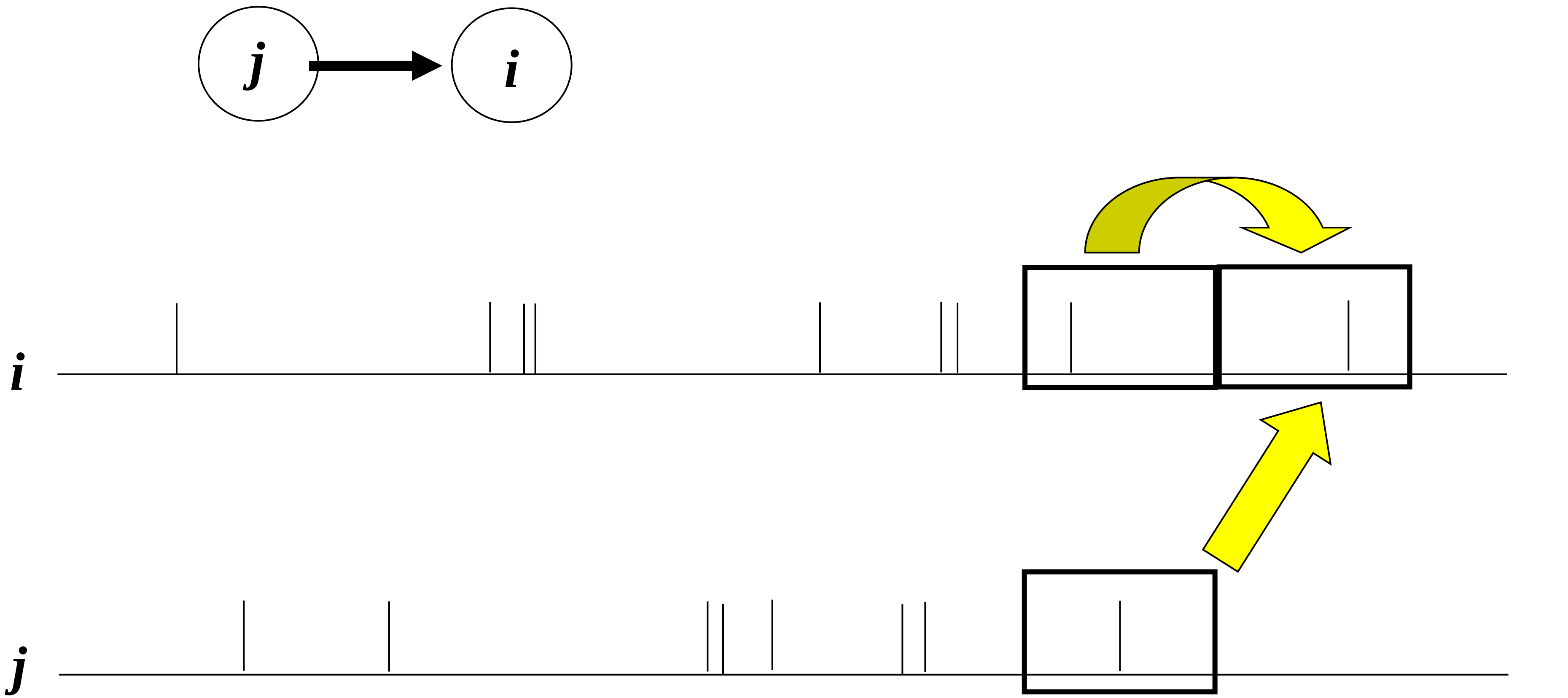
$$Info_{i_n \to i_{n+1}} = S(i_{n+1}) - S(i_{n+1} \mid i_n)$$

How well do $\boldsymbol{i_n}$ and $\boldsymbol{j_n}$ predict $\boldsymbol{i_{n+1}}$?



$$Info_{i_n, j_n \to i_{n+1}} = S(i_{n+1}) - S(i_{n+1} \mid i_n, j_n)$$

If including $\boldsymbol{j_n}$ improves the prediction, then there is effective connectivity



$$Info_{j_n \rightarrow i_{n+1}} = Info_{i_n, j_n \rightarrow i_{n+1}} - Info_{i_n \rightarrow i_{n+1}}$$

"TRANSFER ENTROPY"

VOLUME 85, NUMBER 2 PHYSICAL REVIEW LETTERS 10 JULY 2000

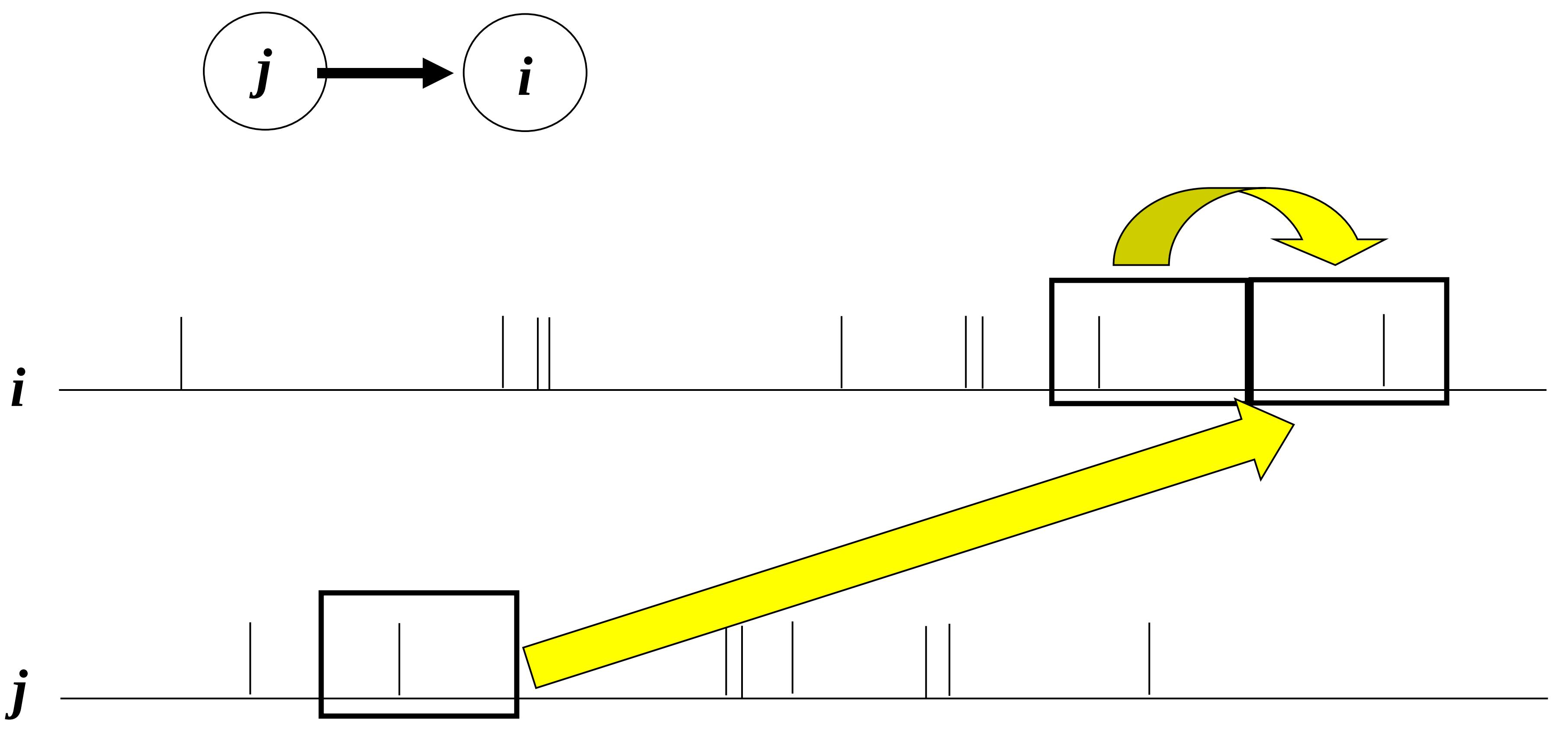
Measuring Information Transfer

Thomas Schreiber
Max Planck Institute for the Physics of Complex Systems, Nöthnitzer Strasse 38, 01187 Dresden, Germany
(Received 19 January 2000)

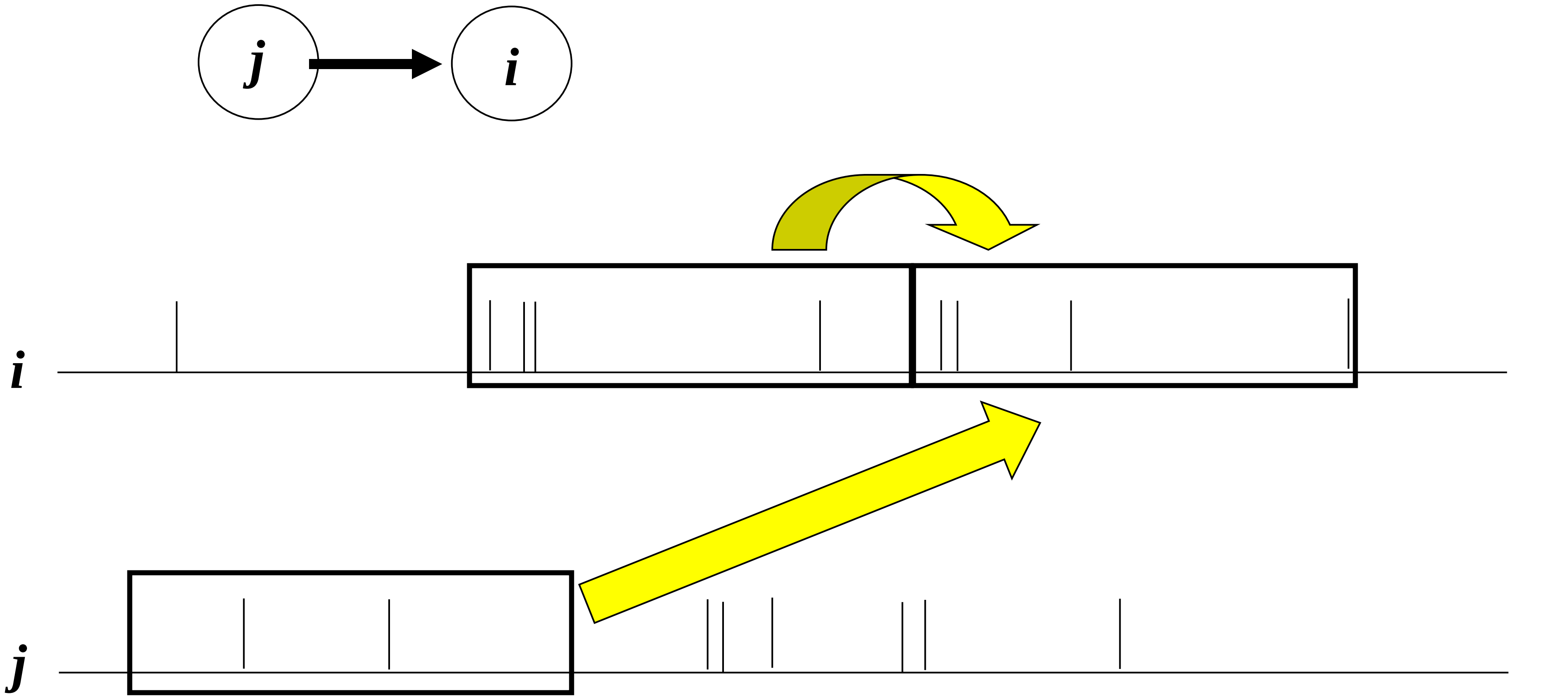
An information theoretic measure is derived that quantifies the statistical coherence between systems evolving in time. The standard time delayed mutual information fails to distinguish information that is actually exchanged from shared information due to common history and input signals. In our new approach, these influences are excluded by appropriate conditioning of transition probabilities. The resulting *transfer entropy* is able to distinguish effectively driving and responding elements and to detect asymmetry in the interaction of subsystems.

$$T_{J\to I} = \sum p(i_{n+1}, i_n^{(k)}, j_n^{(l)}) \log \frac{p(i_{n+1} \mid i_n^{(k)}, j_n^{(l)})}{p(i_{n+1} \mid i_n^{(k)})}$$

Variations of TE - delay



Variations of TE – word length

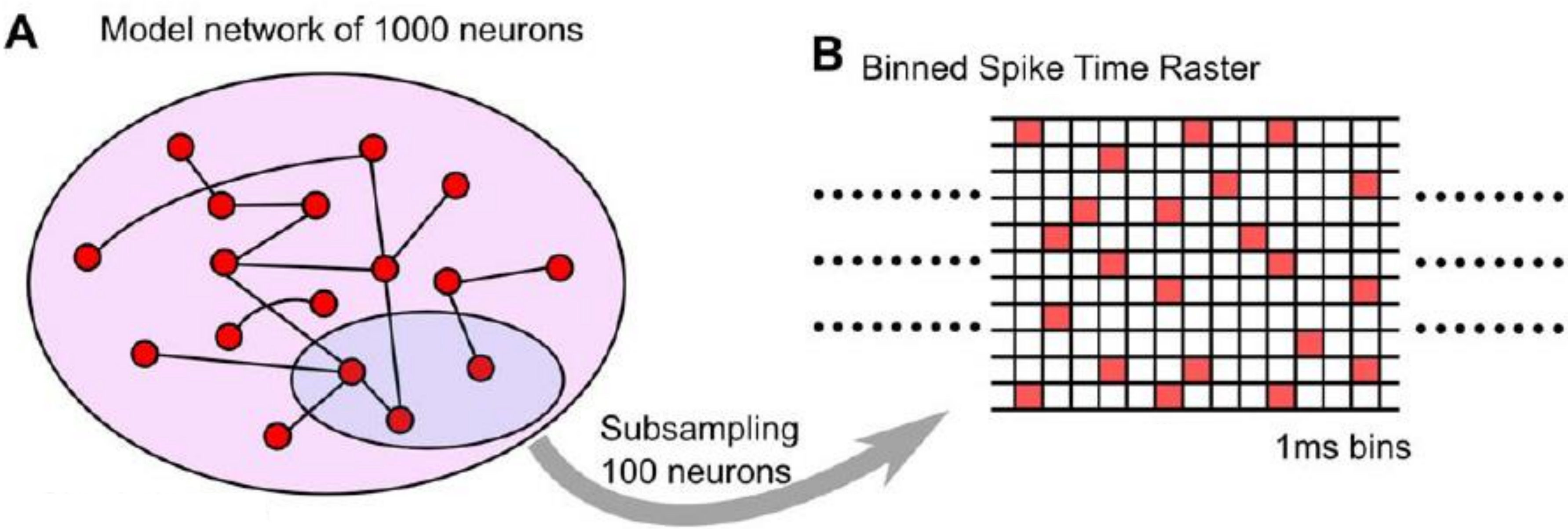


How well can we do?

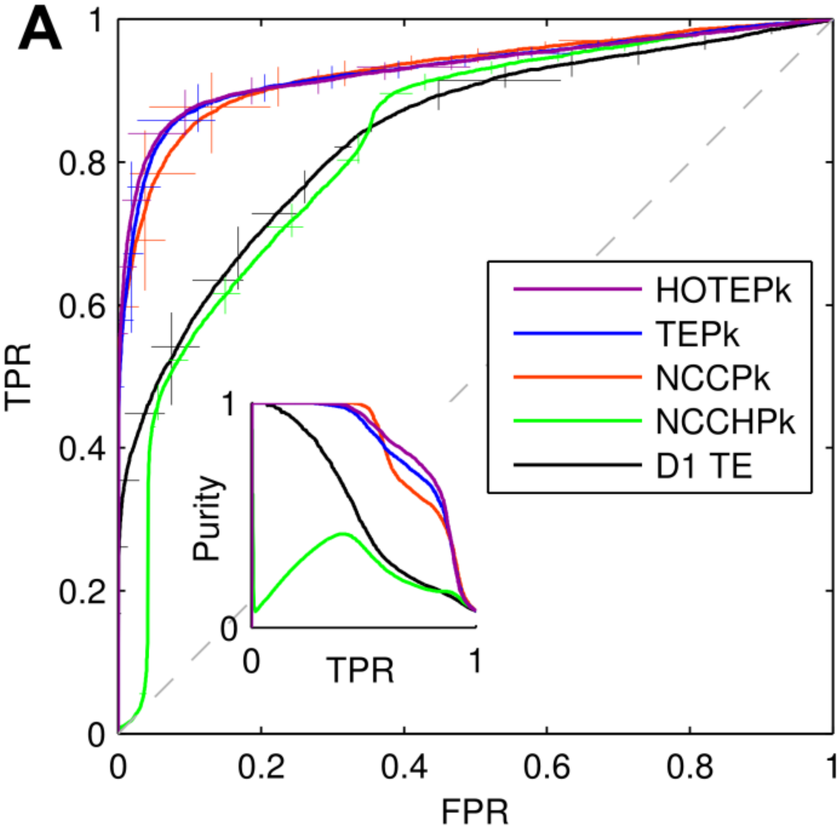
OPEN ACCESS Freely available online
PLoS one

Extending Transfer Entropy Improves Identification of Effective Connectivity in a Spiking Cortical Network Model

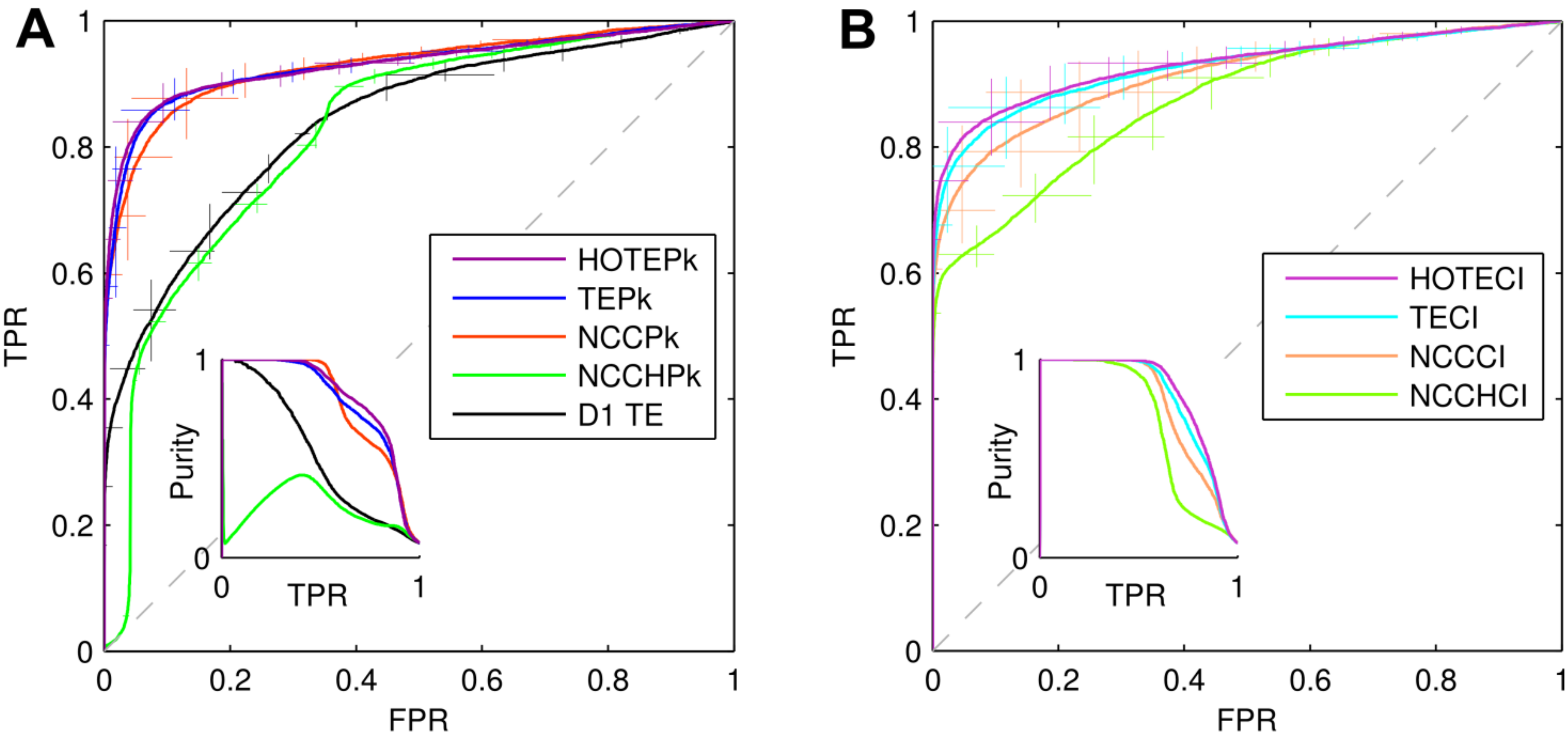
Shinya Ito[1*], Michael E. Hansen[2], Randy Heiland[2], Andrew Lumsdaine[2], Alan M. Litke[3], John M. Beggs[1,4]



How well can we do?



How well can we do?

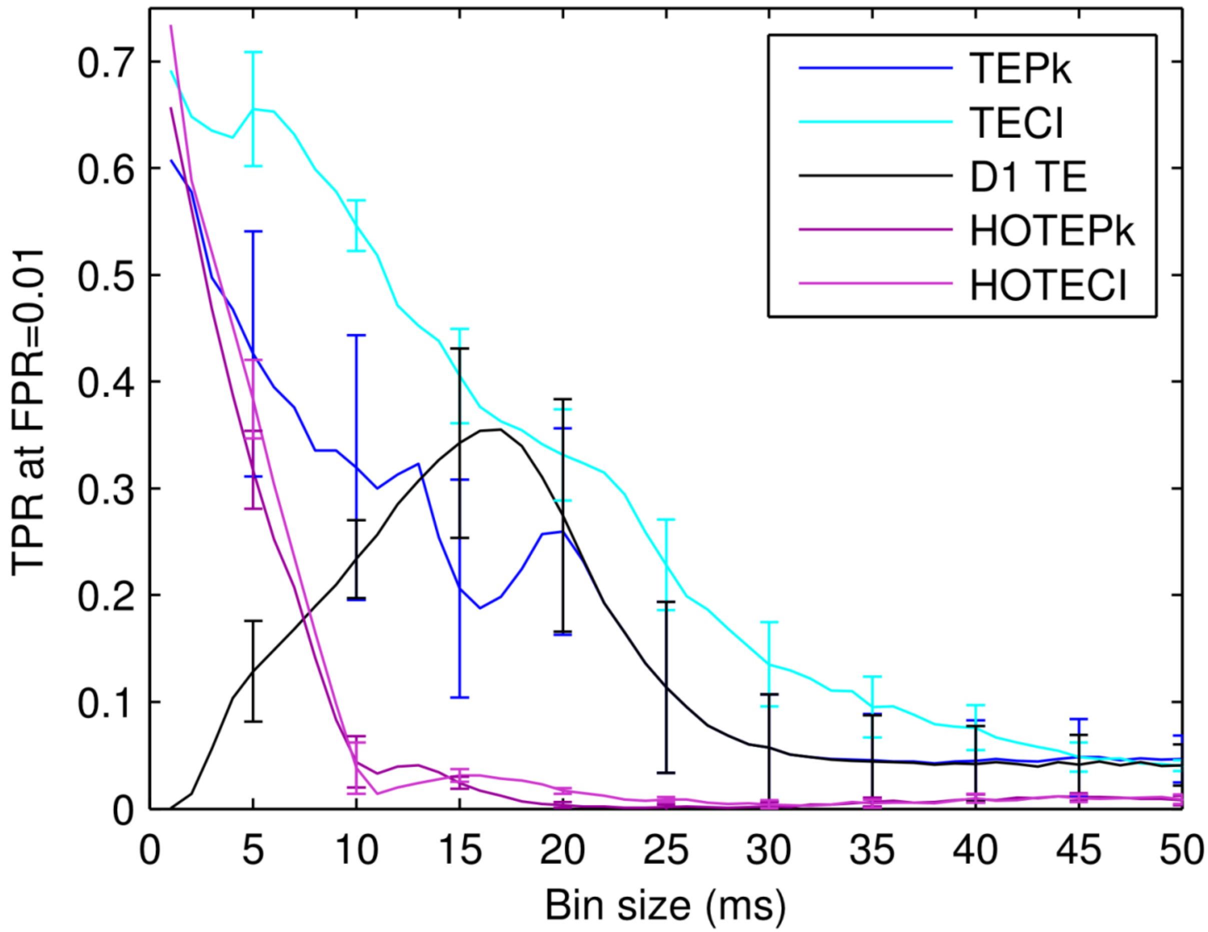


How well can we do?

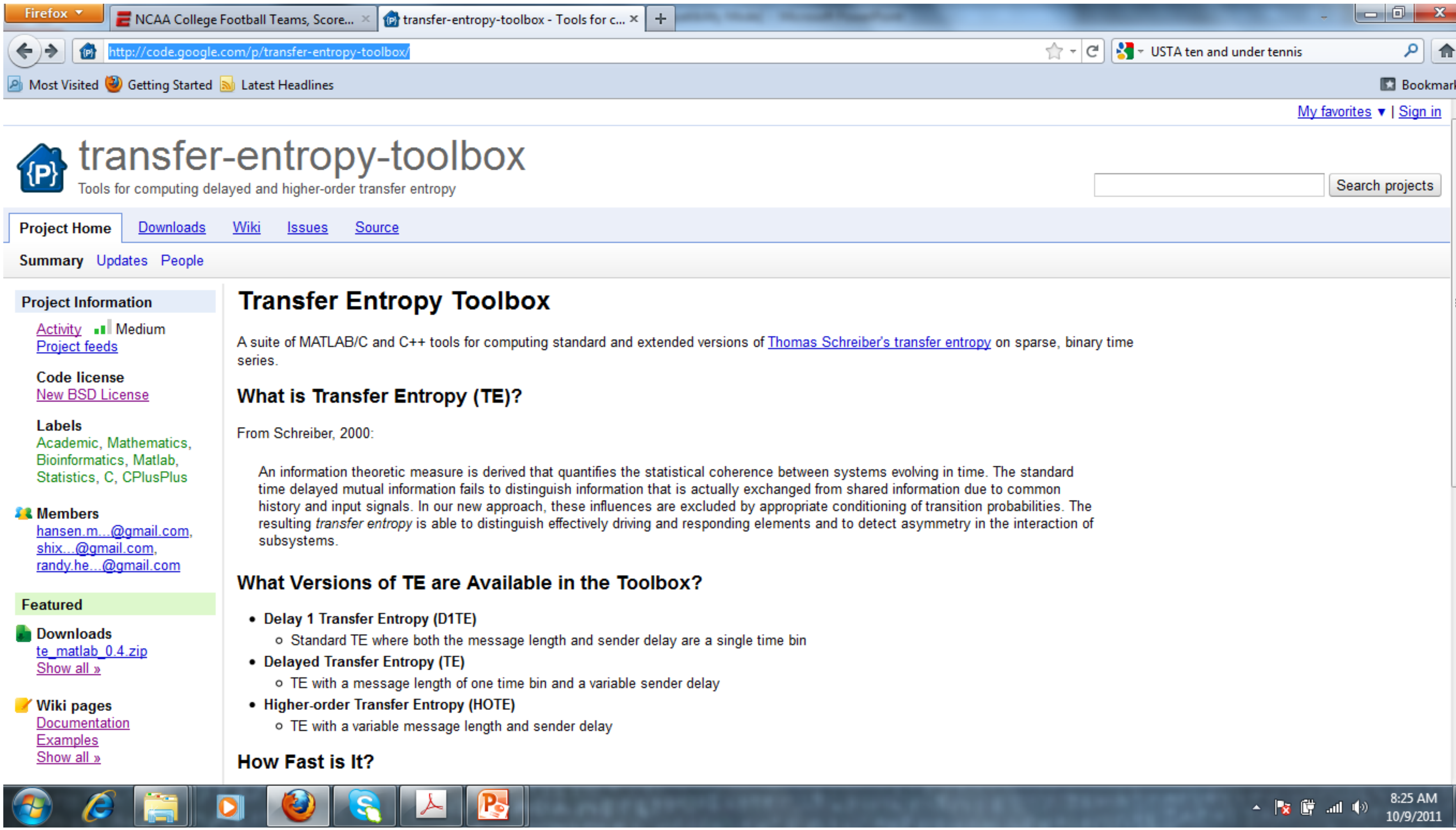
Table 1: Fraction of synaptic weights and TPR at FPR = 0.01

Measure	Fraction synaptic weights	TPR
HOTEPk	0.791 ± 0.102	0.662 ± 0.130
HOTECI	$\boxed{0.851 \pm 0.060}$	$\boxed{0.734 \pm 0.084}$
TEPk	0.750 ± 0.090	0.608 ± 0.108
TECI	0.821 ± 0.055	0.692 ± 0.076
NCCPk	0.763 ± 0.049	0.606 ± 0.062
NCCCI	0.791 ± 0.050	0.649 ± 0.064
D1TE	0.457 ± 0.133	0.355 ± 0.103

Temporal resolution



http://code.google.com/p/transfer-entropy-toolbox/



transfer-entropy-toolbox

Tools for computing delayed and higher-order transfer entropy

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Transfer Entropy Toolbox

A suite of MATLAB/C and C++ tools for computing standard and extended versions of Thomas Schreiber's transfer entropy on sparse, binary time series.

What is Transfer Entropy (TE)?

From Schreiber, 2000:

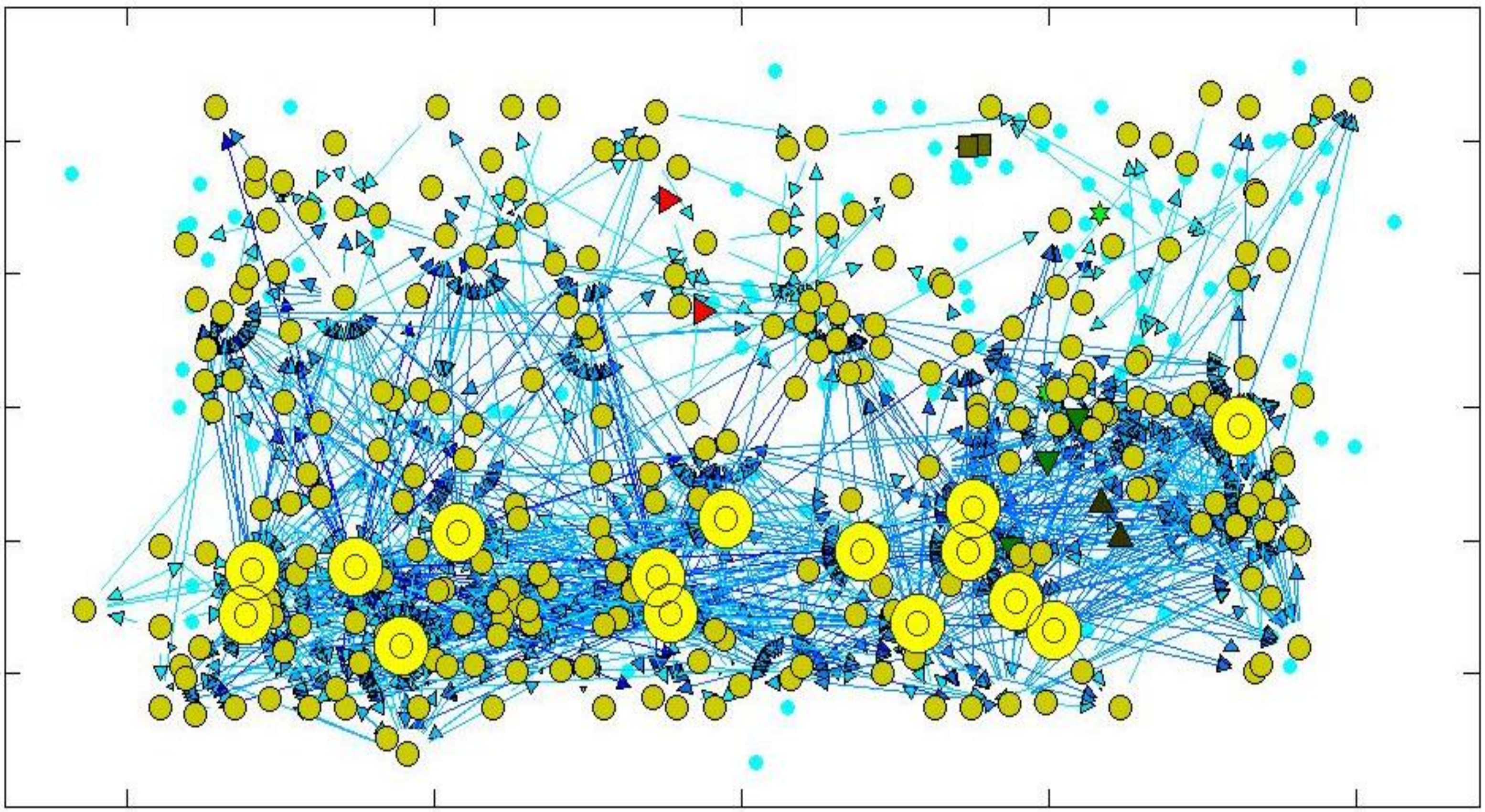
> An information theoretic measure is derived that quantifies the statistical coherence between systems evolving in time. The standard time delayed mutual information fails to distinguish information that is actually exchanged from shared information due to common history and input signals. In our new approach, these influences are excluded by appropriate conditioning of transition probabilities. The resulting *transfer entropy* is able to distinguish effectively driving and responding elements and to detect asymmetry in the interaction of subsystems.

What Versions of TE are Available in the Toolbox?

- **Delay 1 Transfer Entropy (D1TE)**
  - Standard TE where both the message length and sender delay are a single time bin
- **Delayed Transfer Entropy (TE)**
  - TE with a message length of one time bin and a variable sender delay
- **Higher-order Transfer Entropy (HOTE)**
  - TE with a variable message length and sender delay

How Fast is It?

Information transfer map



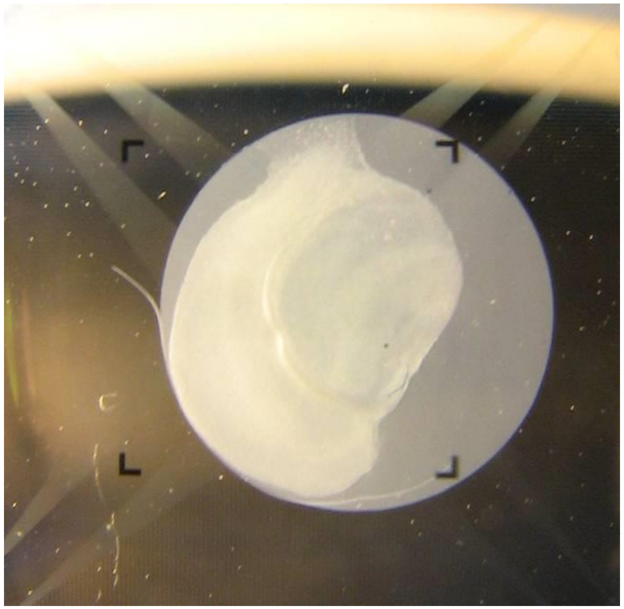
NETWORK STRUCTURE AND CRITICALITY

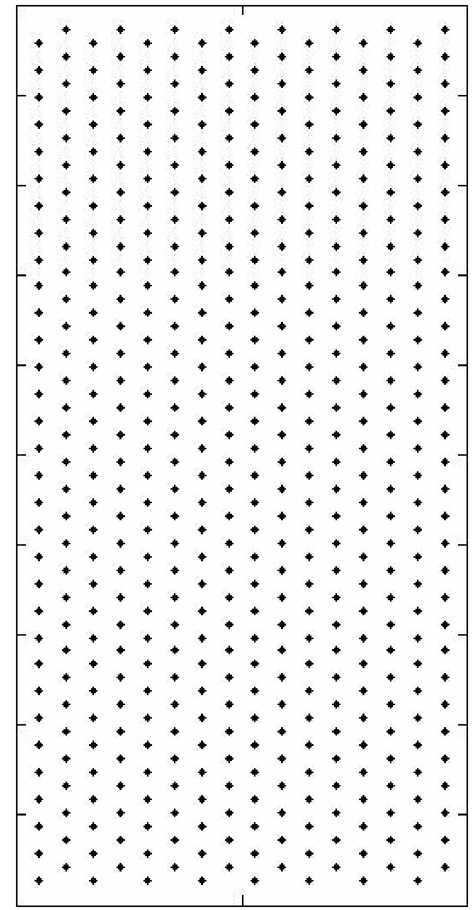
- Information transfer
- Criticality
- Relating the two

Related work

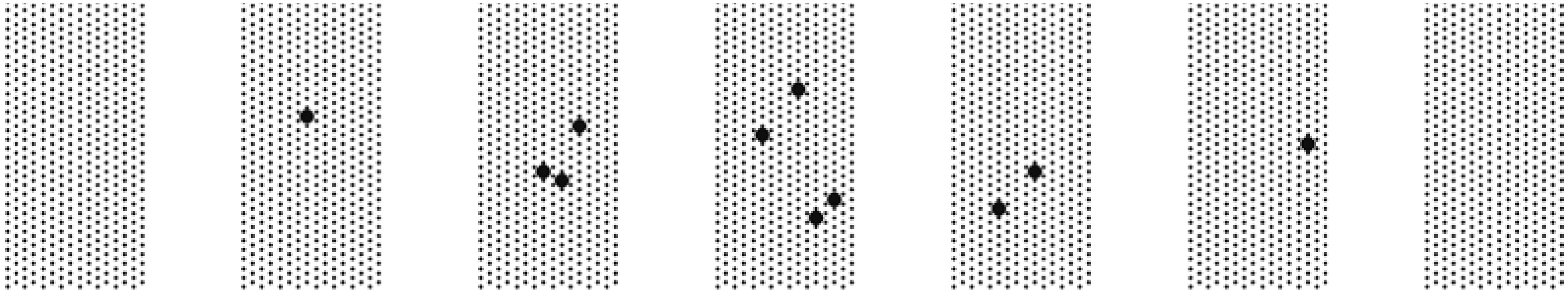
- Per Bak
- Bill Bialek
- Ed Bullmore
- Dante Chialvo
- Mauro Copelli
- Jack Cowan
- Lucia de Arcangelis
- Theo Geisel
- Stuart Kauffman
- J. Scott Kelso
- Chris Langton
- Anna Levina
- Klaus Linkenkaer-Hansen
- Marcelo Magnasco
- Christian Meisel
- Deitmar Plenz
- Viola Priesemann
- Woodrow Shew
- Ralf Wessel
- Greg Worrall

Spontaneous activity



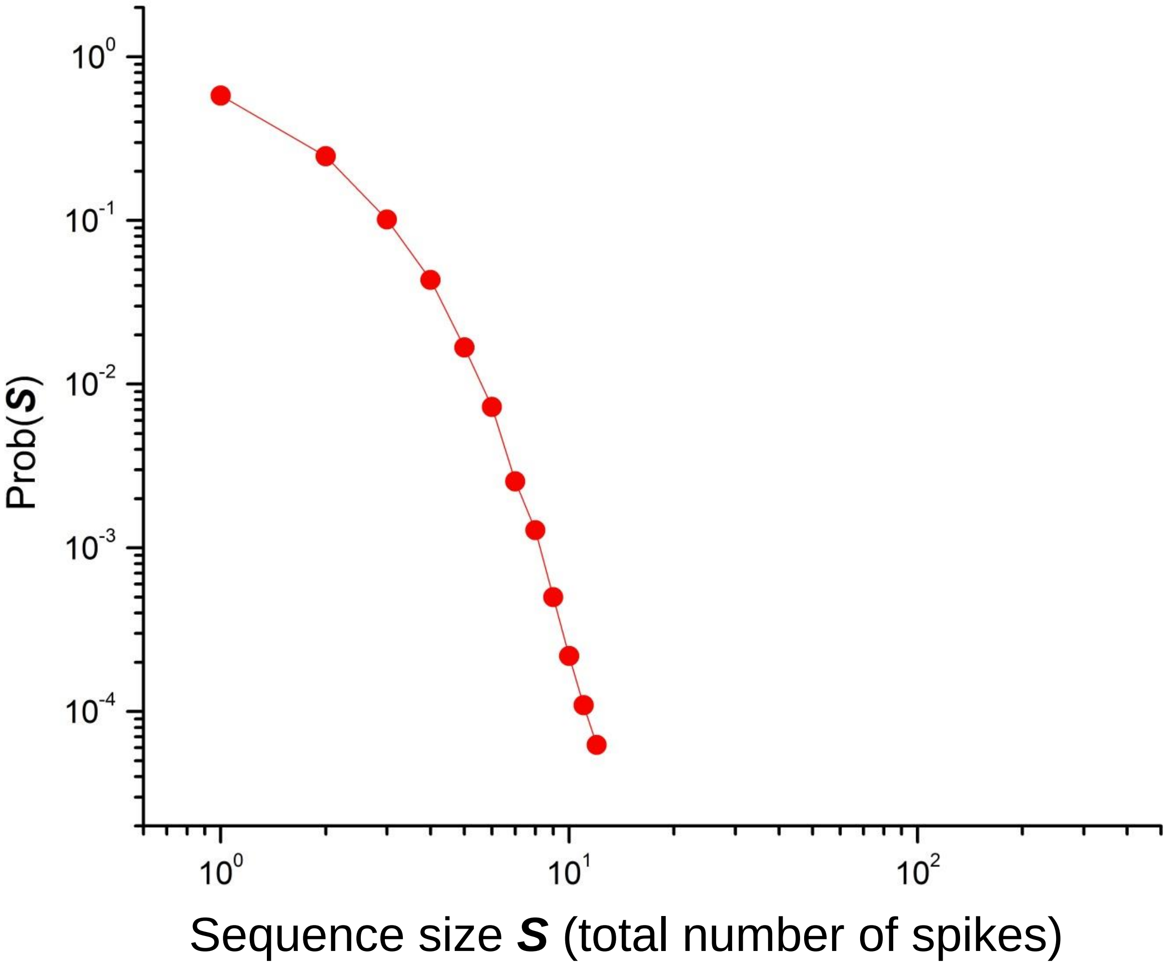


A sequence

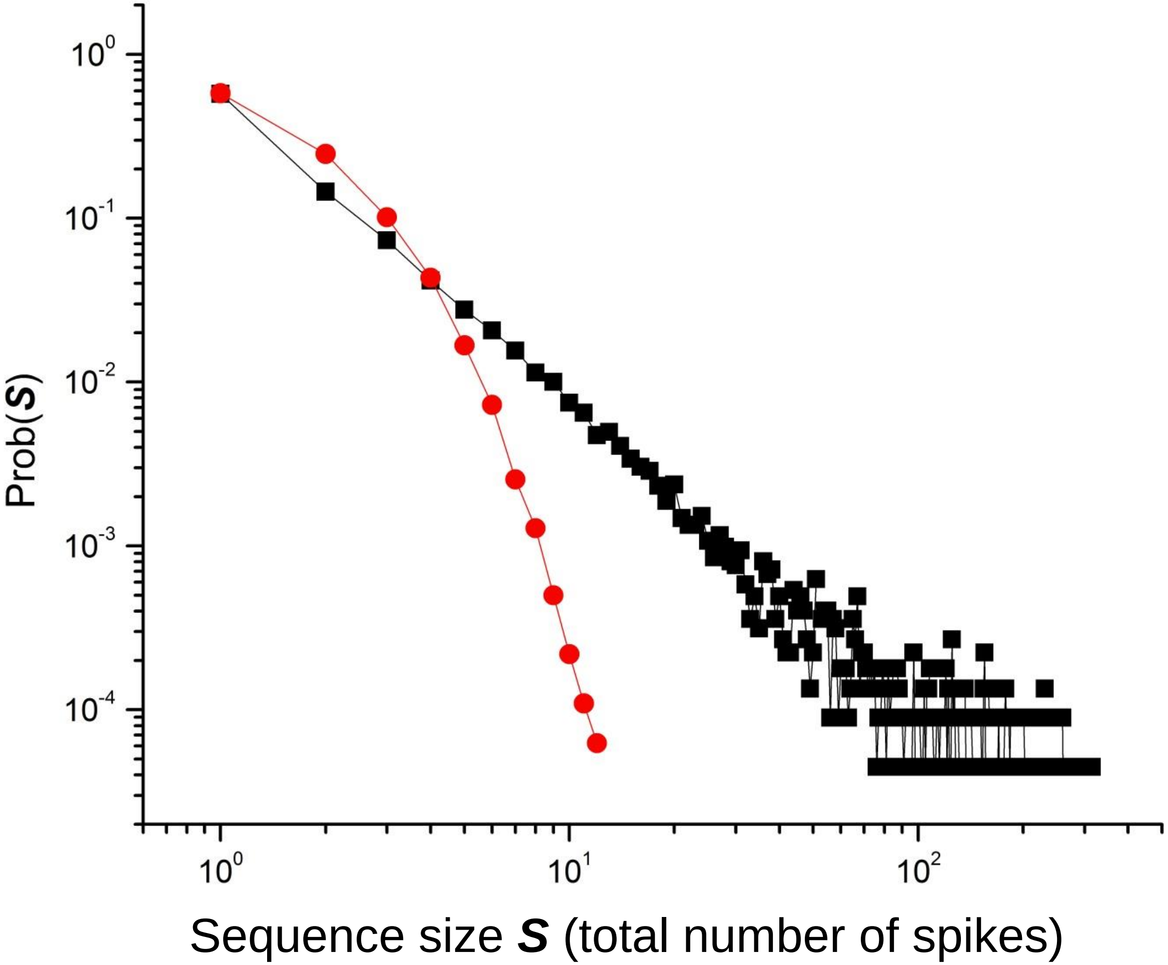


Sequence size = 11

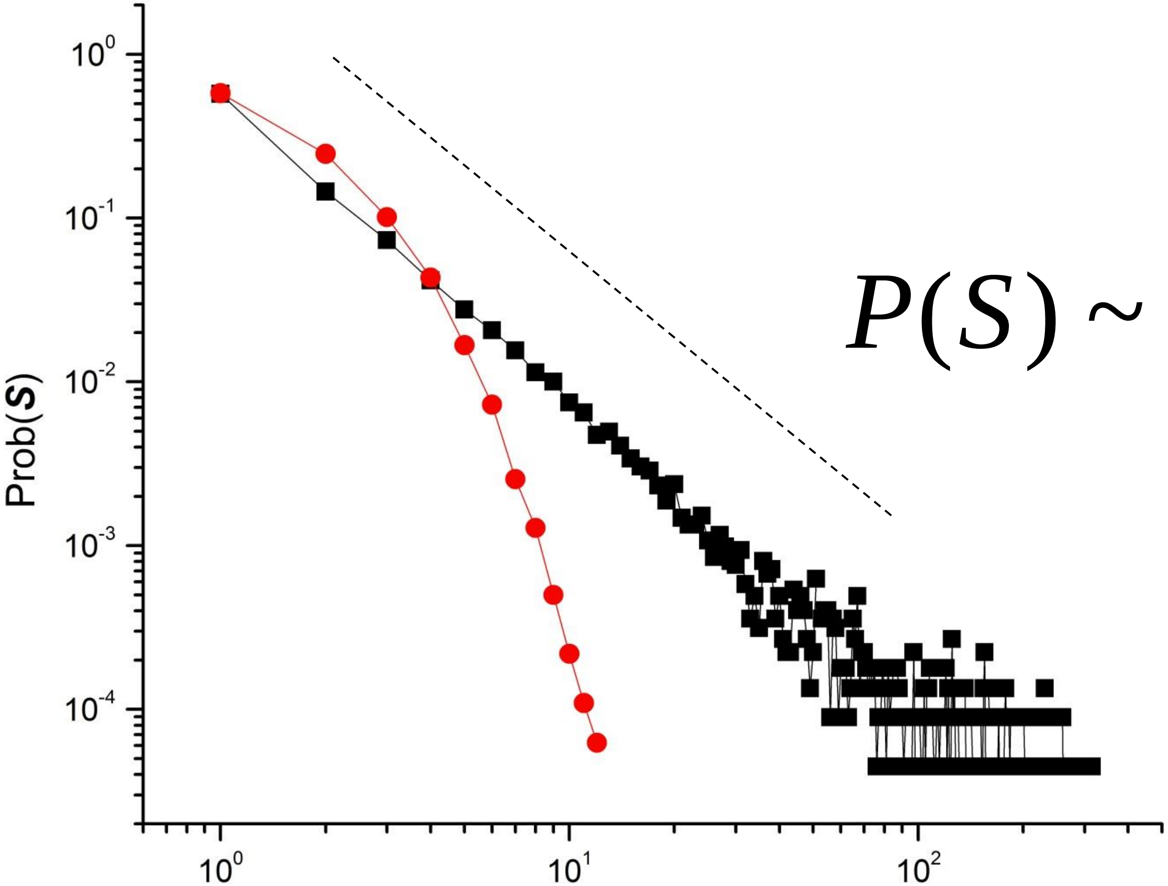
Sequence size distribution



Sequence size distribution



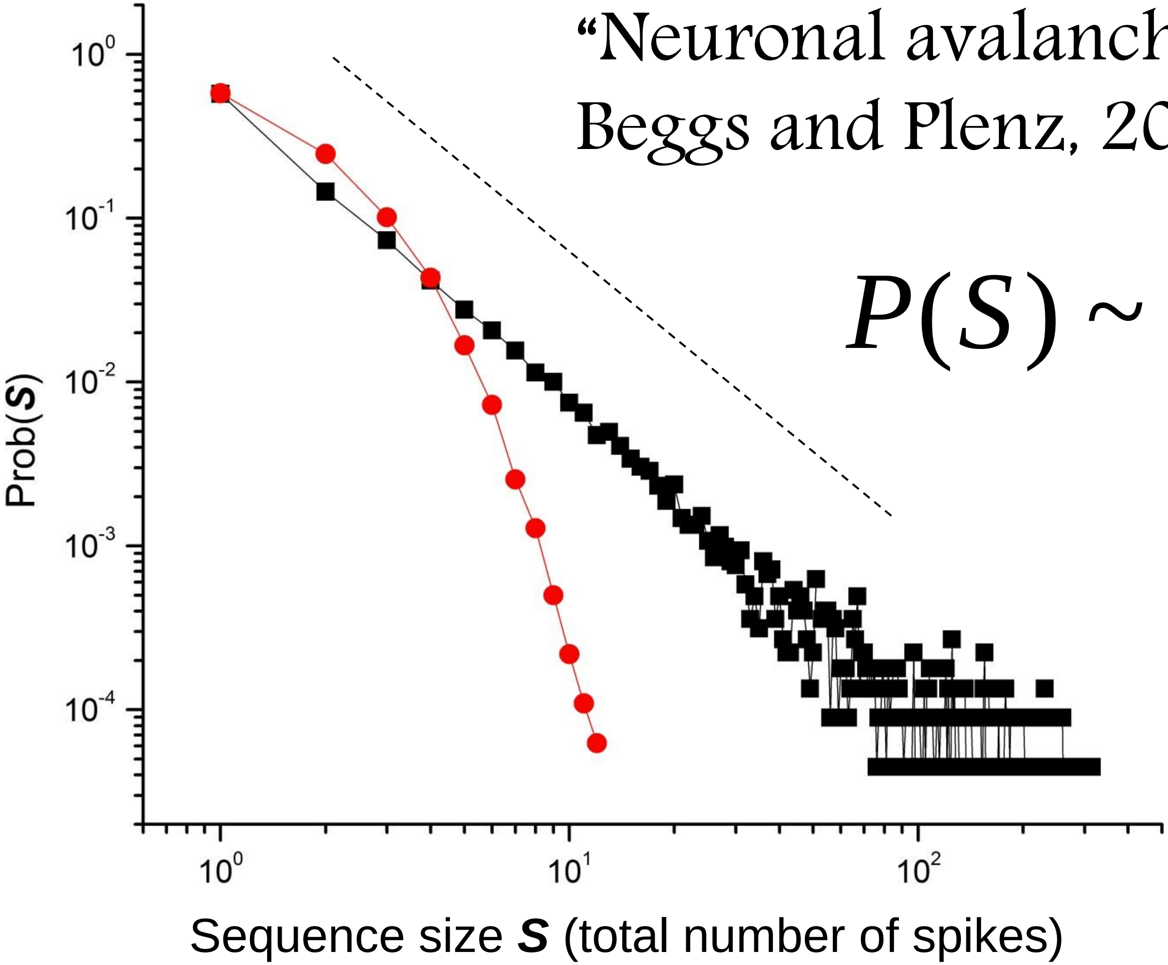
Sequence size distribution



Sequence size ***S*** (total number of spikes)

$$P(S) \sim S^{-\tau}$$

Sequence size distribution



"Neuronal avalanches"
Beggs and Plenz, 2003

$$P(S) \sim S^{-\tau}$$

Maybe critical?

Neuronal avalanches in humans

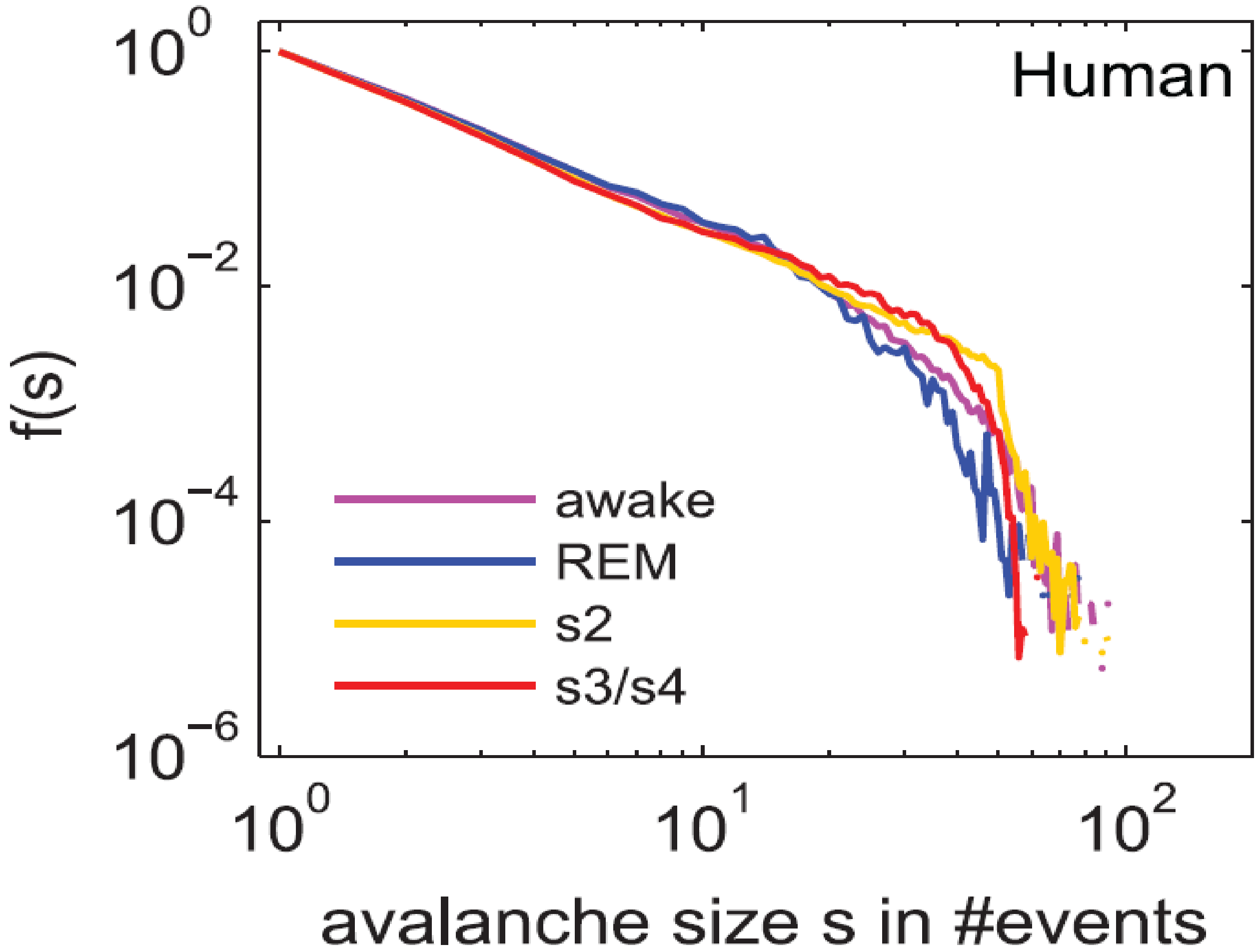
OPEN ACCESS Freely available online PLOS COMPUTATIONAL BIOLOGY

Neuronal Avalanches Differ from Wakefulness to Deep Sleep – Evidence from Intracranial Depth Recordings in Humans

Viola Priesemann[1]*, Mario Valderrama[2], Michael Wibral[3], Michel Le Van Quyen[4]

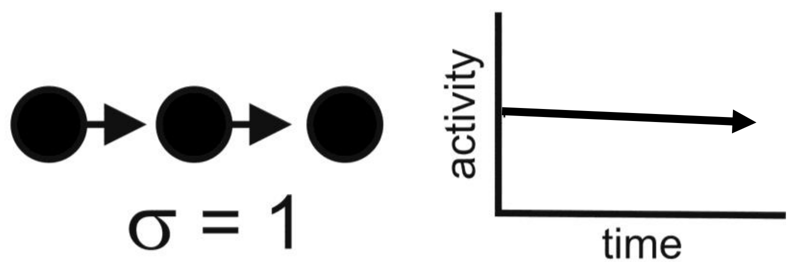
1 Max Planck Institute for Brain Research, Department of Neural Systems and Coding, Frankfurt, Germany, **2** University of Los Andes, Bogotá, Colombia, **3** Johann Wolfgang Goethe University, Magnetoencephalography Unit, Brain Imaging Center, Frankfurt am Main, Germany, **4** Hôpital de la Pitié-Salpêtrière, Centre de Recherche de l'Institut du Cerveau et de la Moelle épinière (CRICM), INSERM UMRS 975 - CNRS UMR 7225-UPMC, Paris, France

Neuronal avalanches in humans

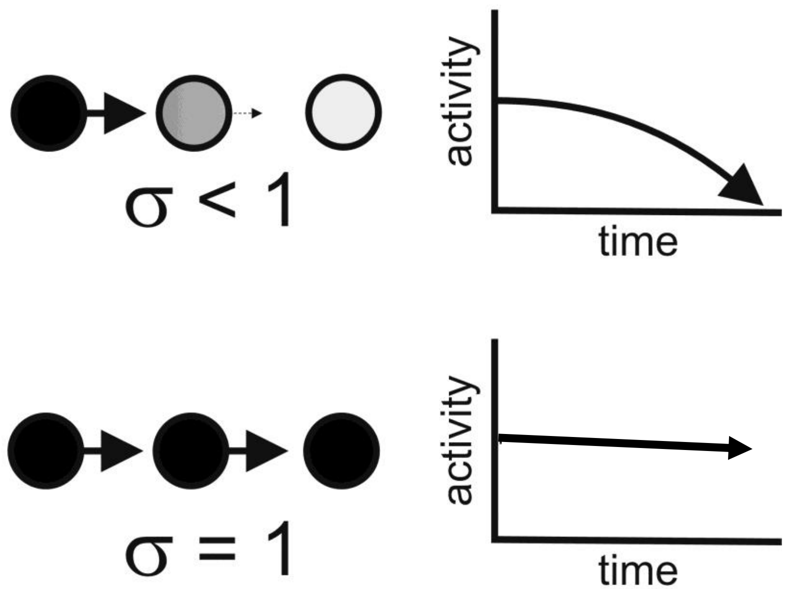


What is criticality good for?

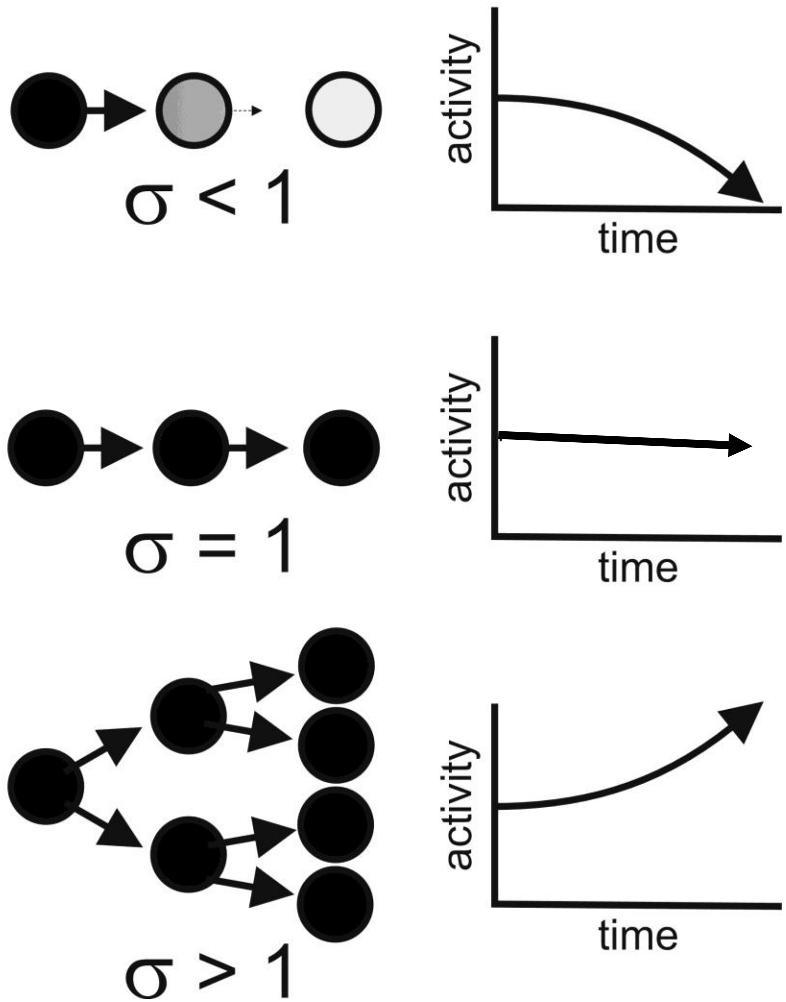
Branching model



Branching model



Branching model

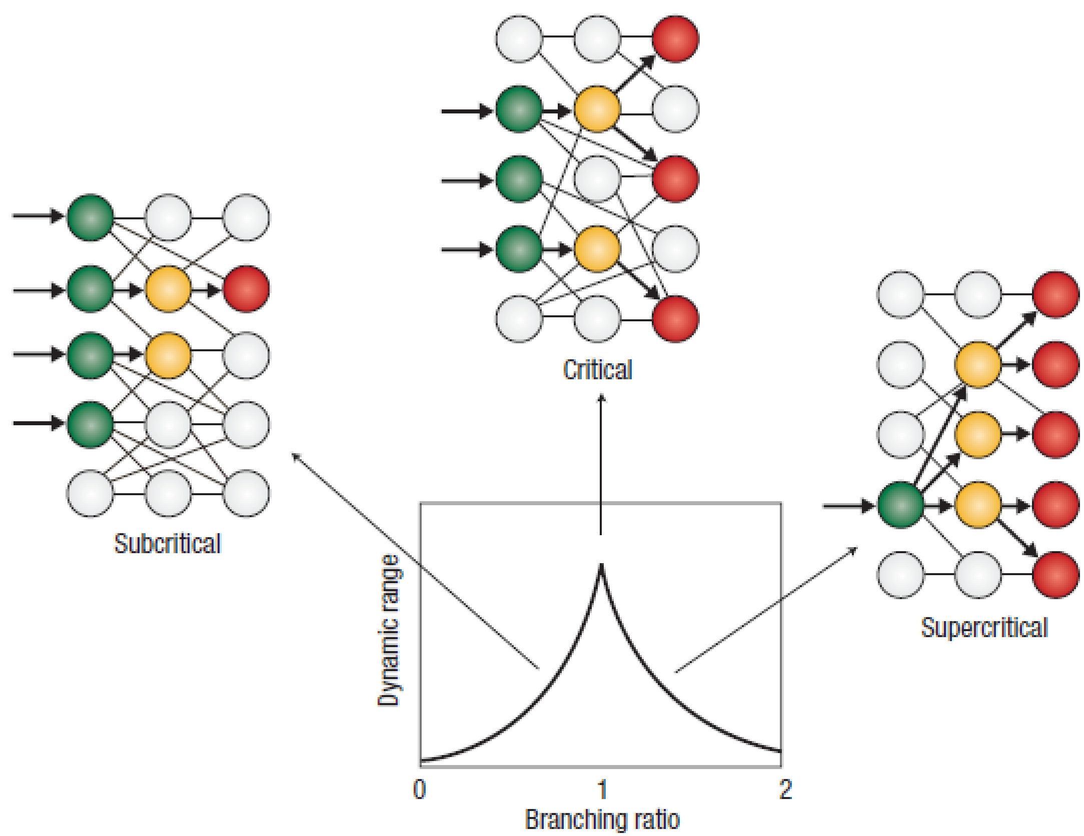


subcritical

critical

supercritical

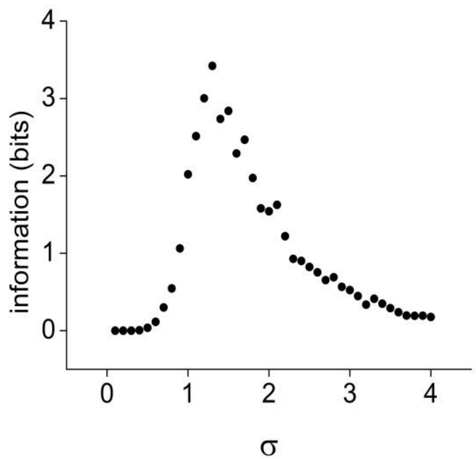
Optimality at criticality



Dante Chialvo, Nature Physics, 2006

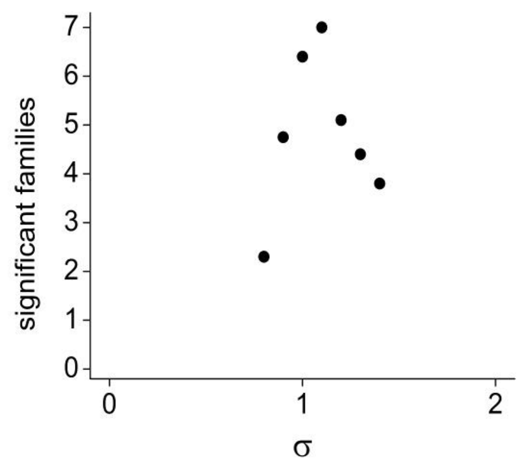
Optimality at criticality

Information transfer



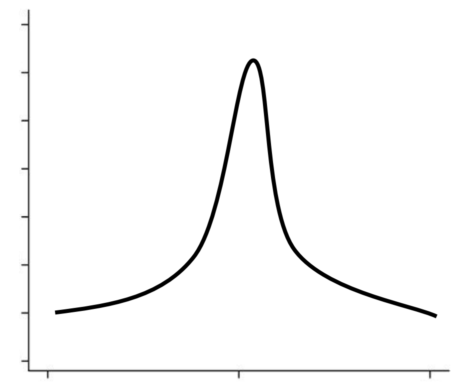
Beggs and Plenz,
J Neurosci 2003; Shew
et al, J Neurosci 2011

Information storage



Haldeman and Beggs,
Phys Rev Lett 2005

Computational power



Bertschinger and Natschlager,
Neural Computation, 2004

Dynamic range: Kinouchi and Copelli, Nature Physics 2006; demonstrated by Shew et al, J Neurosci 2009.

Power laws mean criticality, right?

Near the critical point, only one variable controls the system:

$$\varepsilon \equiv \frac{\sigma - \sigma_c}{\sigma_c}$$

When ε is small, all other terms drop out, leaving a scaling relationship

[Stanley 1971; Goldenfeld 2008].

Near the critical point, only one variable controls the system:

$$\varepsilon \equiv \frac{\sigma - \sigma_c}{\sigma_c}$$

$$f(\varepsilon) = A\varepsilon^x\left(1 + B\varepsilon^y + \ldots\right) \rightarrow f(\varepsilon) \approx A\varepsilon^x$$

When ε is small, all other terms drop out, leaving a scaling relationship

[Stanley 1971; Goldenfeld 2008].

Criticism

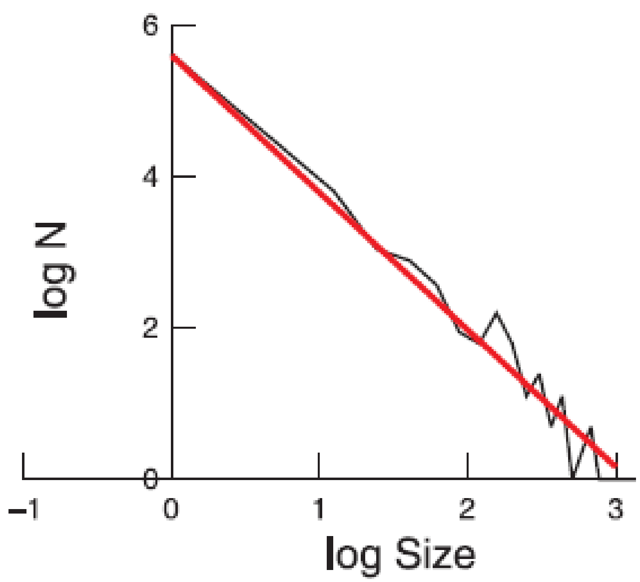
OPEN ACCESS Freely available online

PLoS one

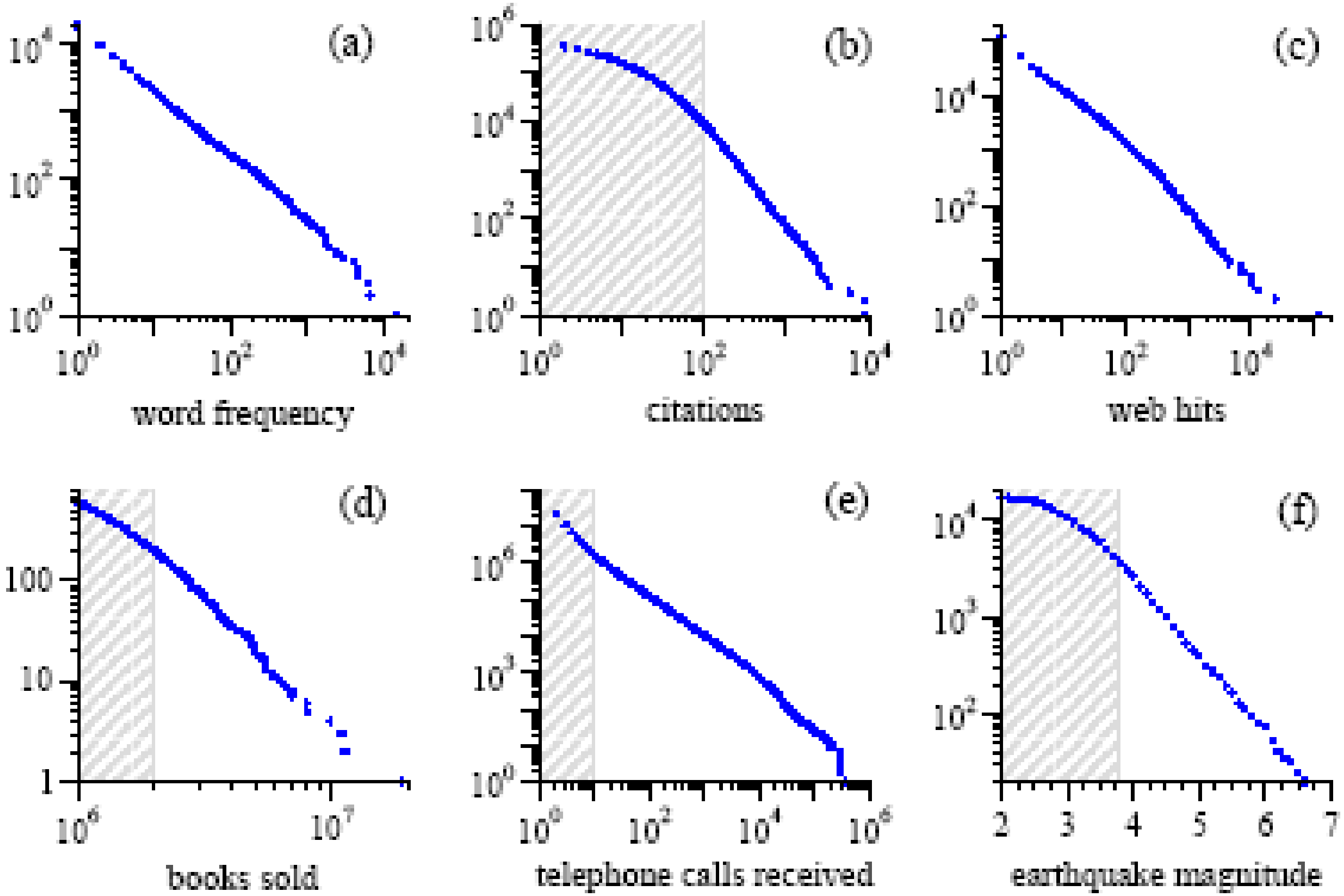
Can Power-Law Scaling and Neuronal Avalanches Arise from Stochastic Dynamics?

Jonathan Touboul[1,2*], **Alain Destexhe**[3]

1 Department of Mathematics, University of Pittsburgh, Pittsburgh, Pennsylvania, United States of America, **2** Laboratory of Mathematical Physics, The Rockefeller University, New York, New York, United States of America, **3** Unité de Neurosciences Intégratives et Computationnelles (UNIC), UPR CNRS 2191, Gif-sur-Yvette, France



Criticism



MEJ Newman, 2005

To demonstrate criticality

To demonstrate criticality

- Multiple power laws

To demonstrate criticality

- Multiple power laws
- Scaling function

To demonstrate criticality

- Multiple power laws
- Scaling function
- Exponent relationship

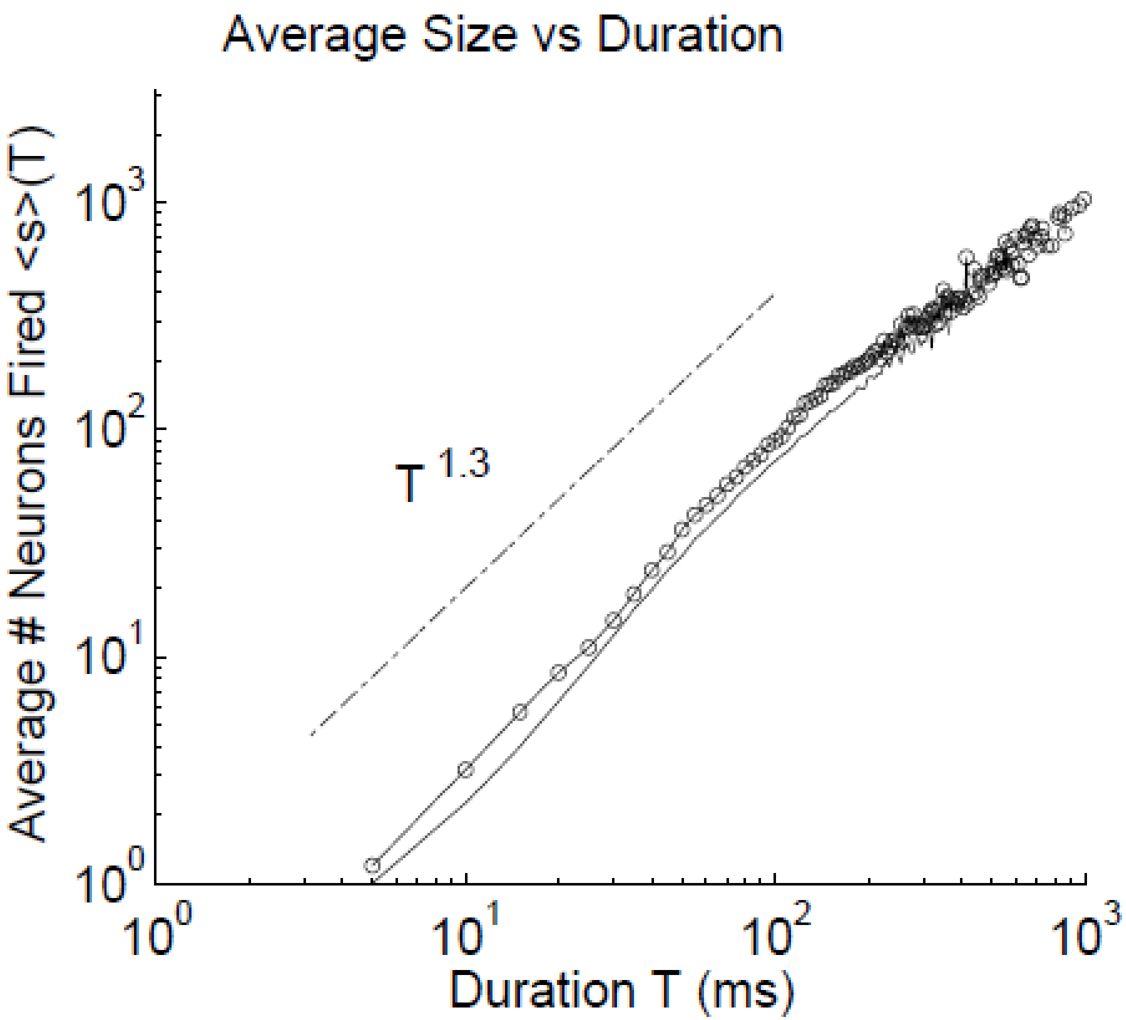
Multiple power laws

$$f(S) \sim S^{-\tau}$$

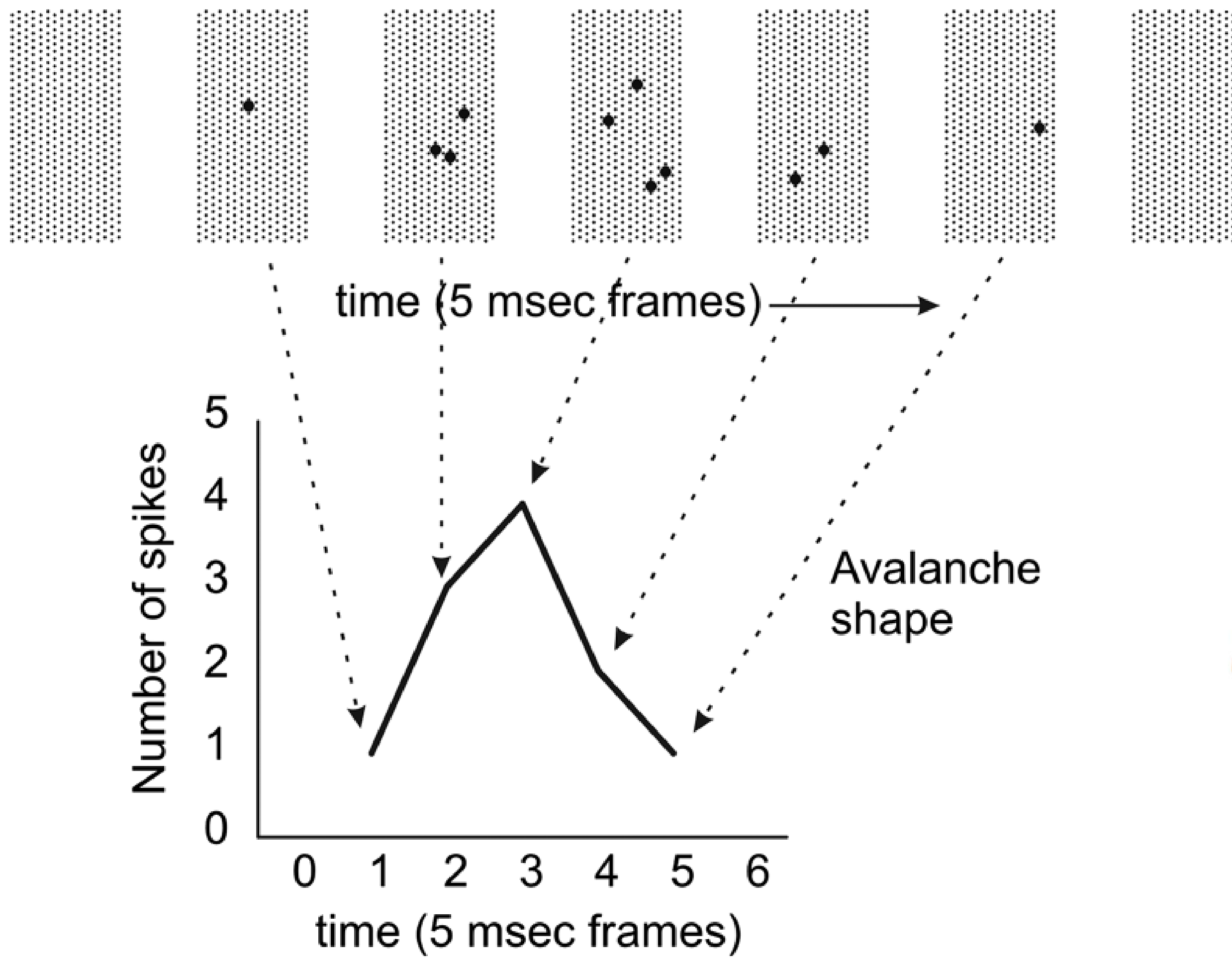
$$f(T) \sim T^{-\alpha}$$

$$\langle S \rangle(T) \sim T^{1/\sigma\nu z}$$

Multiple power laws



Scaling function



$s(t, T)$

Scaling function

$$\langle S\rangle(T) = \int_0^T s(t, T)dt$$

Scaling function

$$\langle S\rangle(T) = \int_0^T s(t,T)dt$$

$$\langle S\rangle(T) \sim T^{1/\sigma\nu z}$$

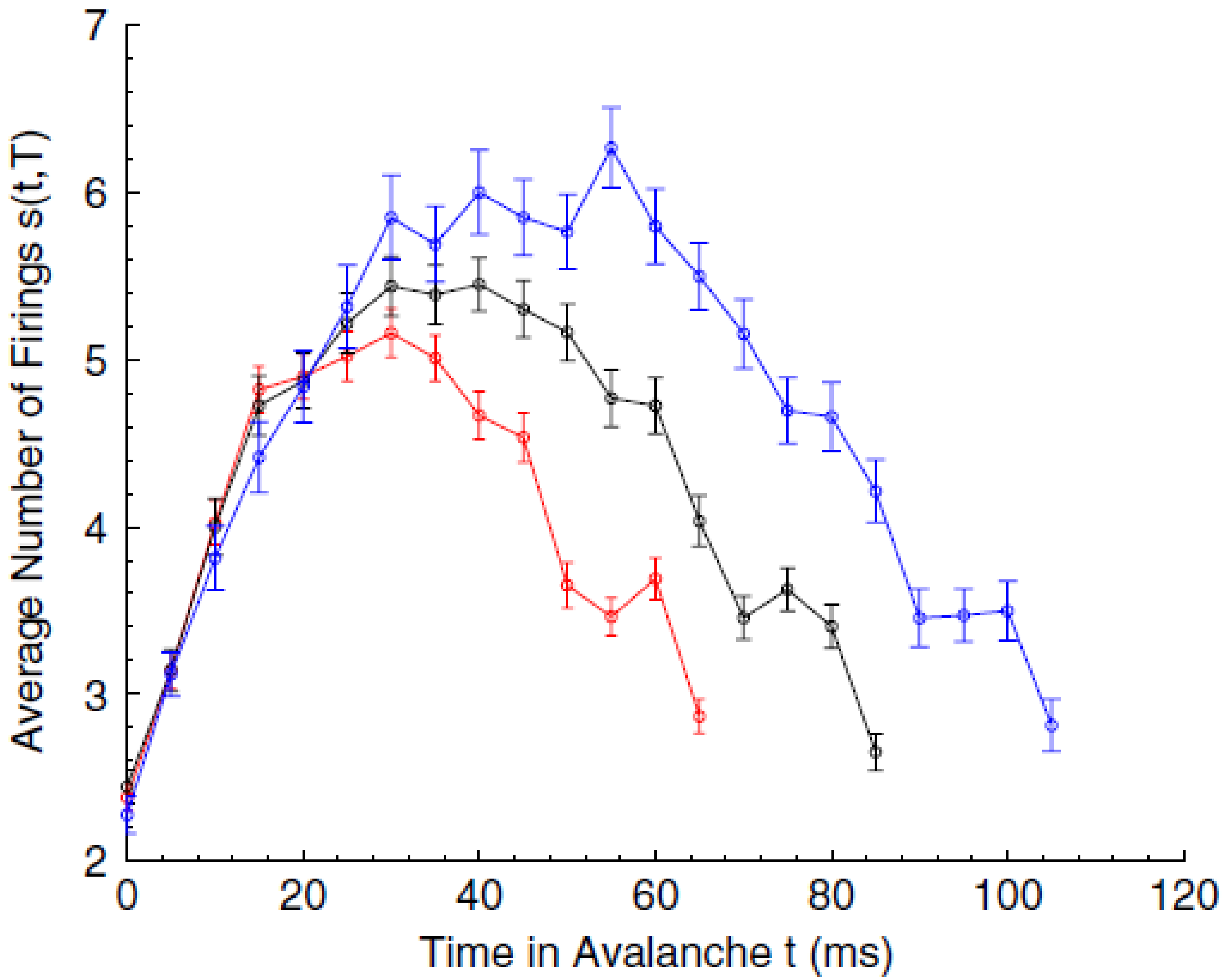
Scaling function

$$\langle S \rangle(T) = \int_0^T s(t, T)dt$$

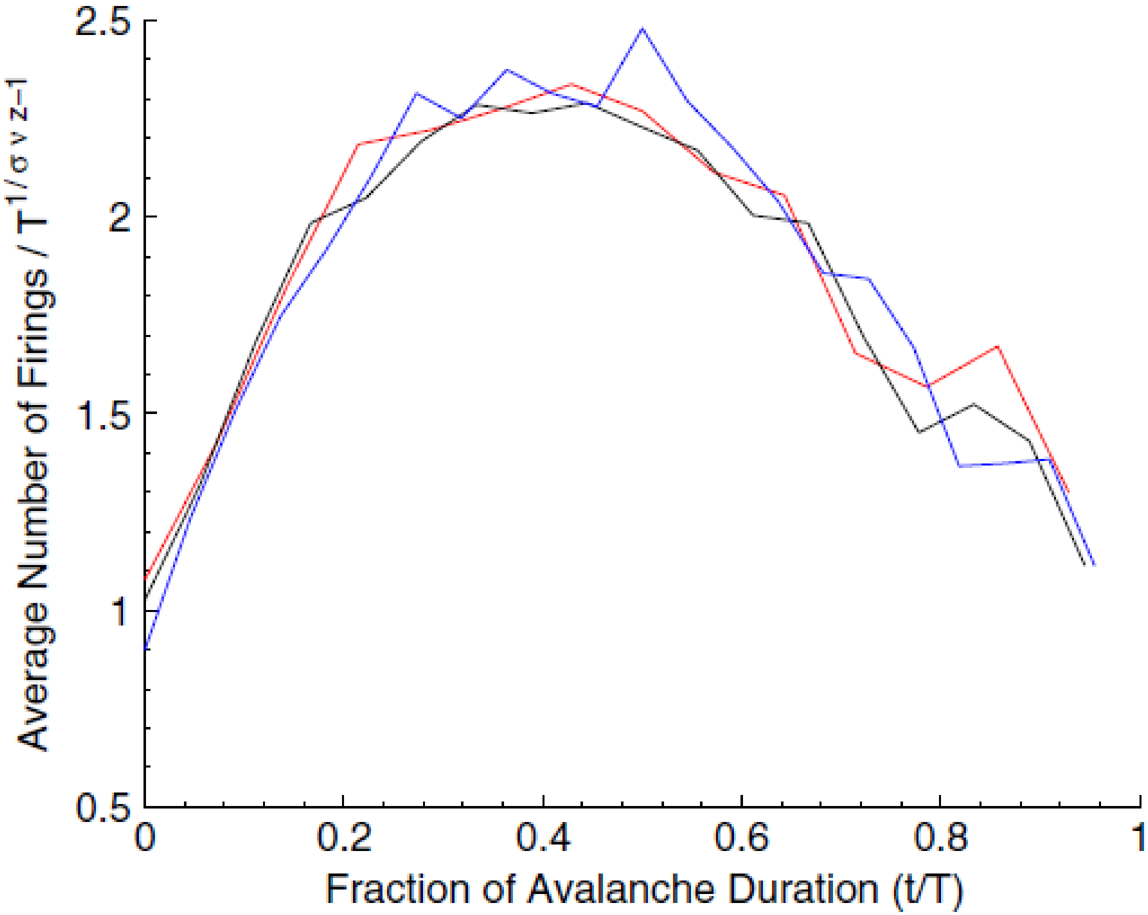
$$\langle S \rangle(T) \sim T^{1/\sigma\nu z}$$

$$s(t, T) \sim T^{1/\sigma\nu z - 1} \mathcal{F}(t/T)$$

Scaling function

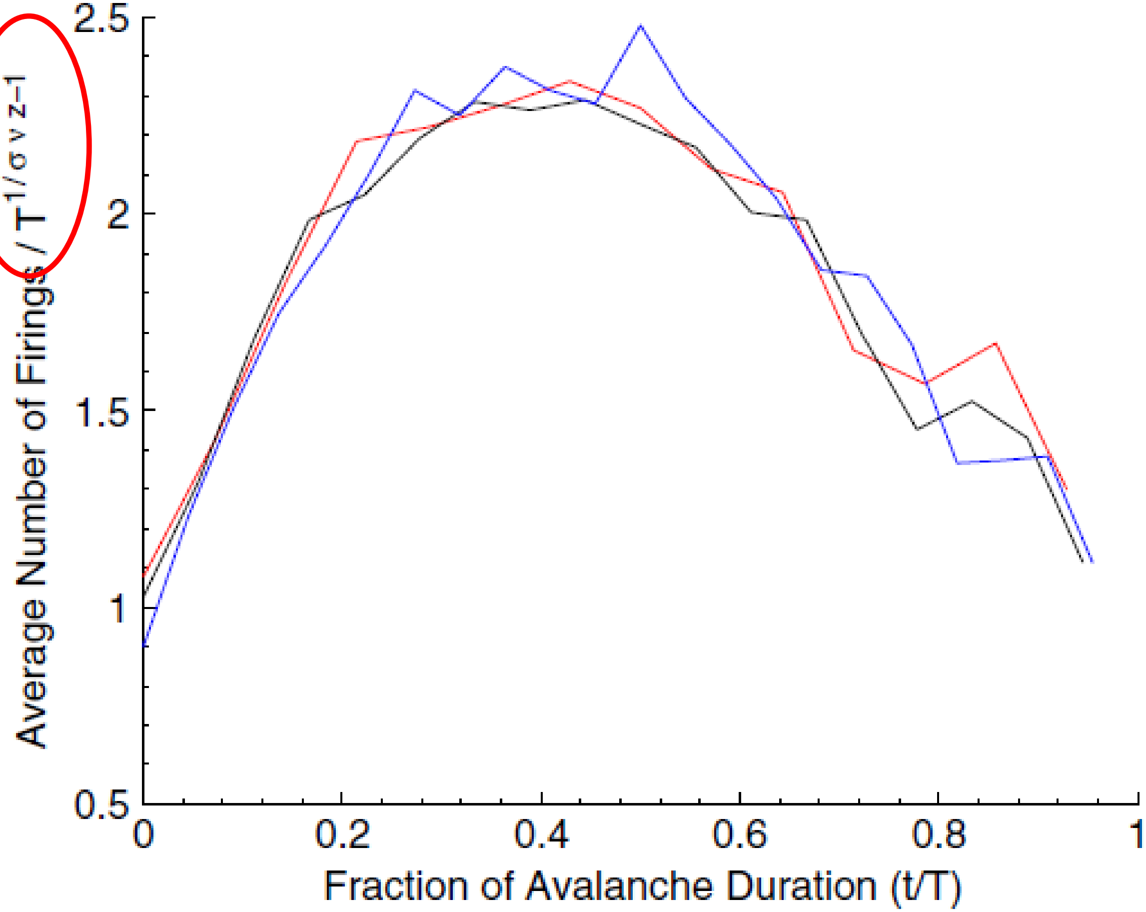


Scaling function



Universal Critical Dynamics in High Resolution Neuronal Avalanche Data

Nir Friedman,[1] Shinya Ito,[2] Braden A. W. Brinkman,[1] Masanori Shimono,[2,5] R. E. Lee DeVille,[3] Karin A. Dahmen,[1] John M. Beggs,[2] and Thomas C. Butler[4,*]

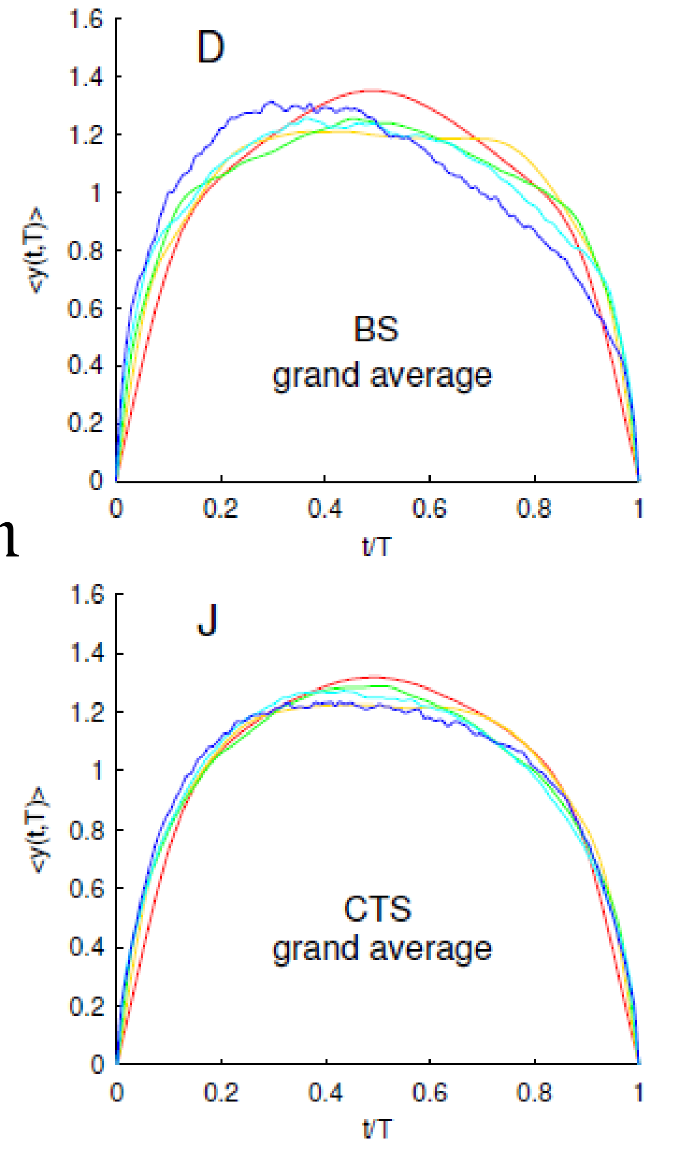


$$\mathcal{F}(t/T)$$

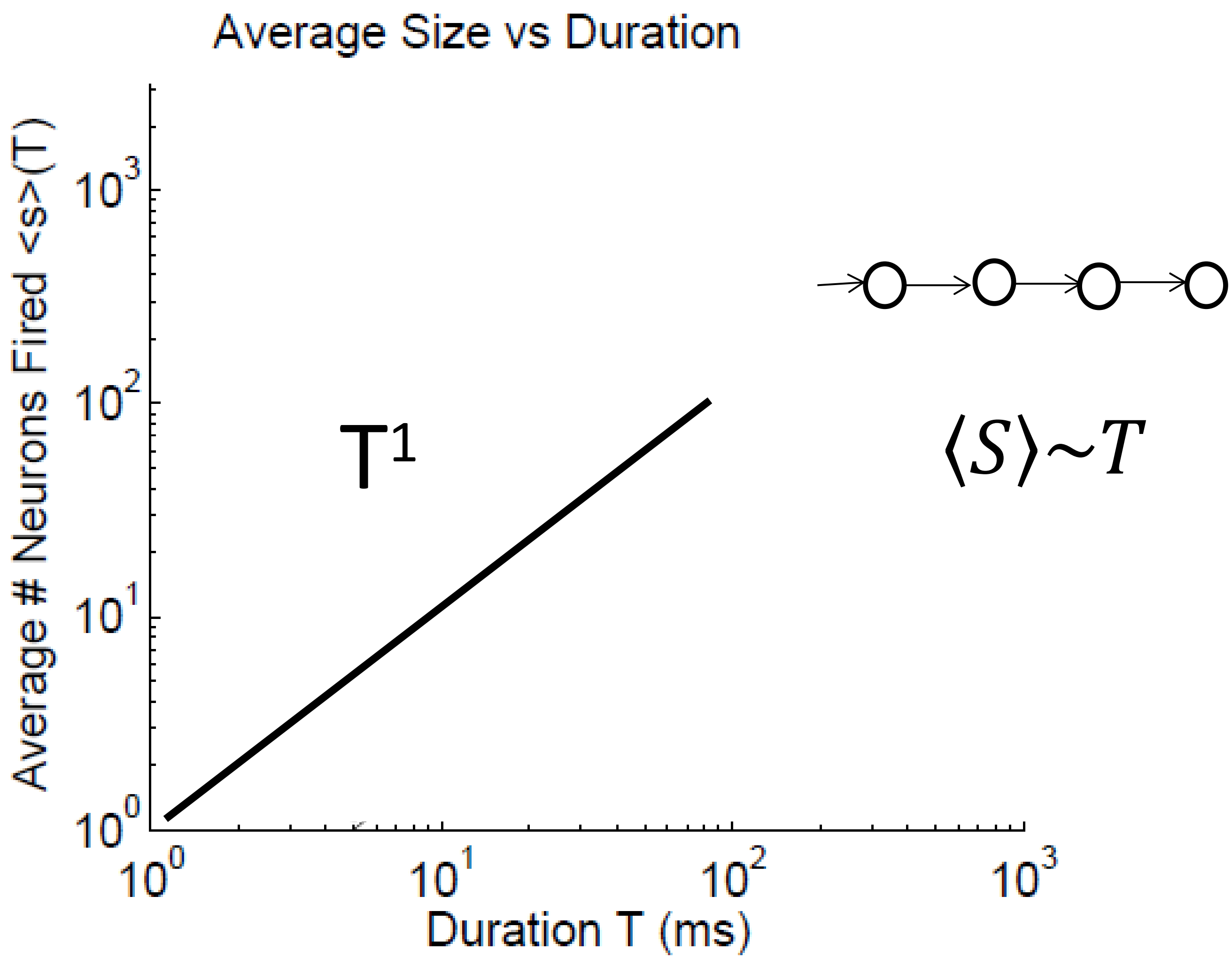
$$s(t,T) \sim T^{1/\sigma\nu z-1}\mathcal{F}(t/T)$$

Roberts et al., Journal of Neuroscience

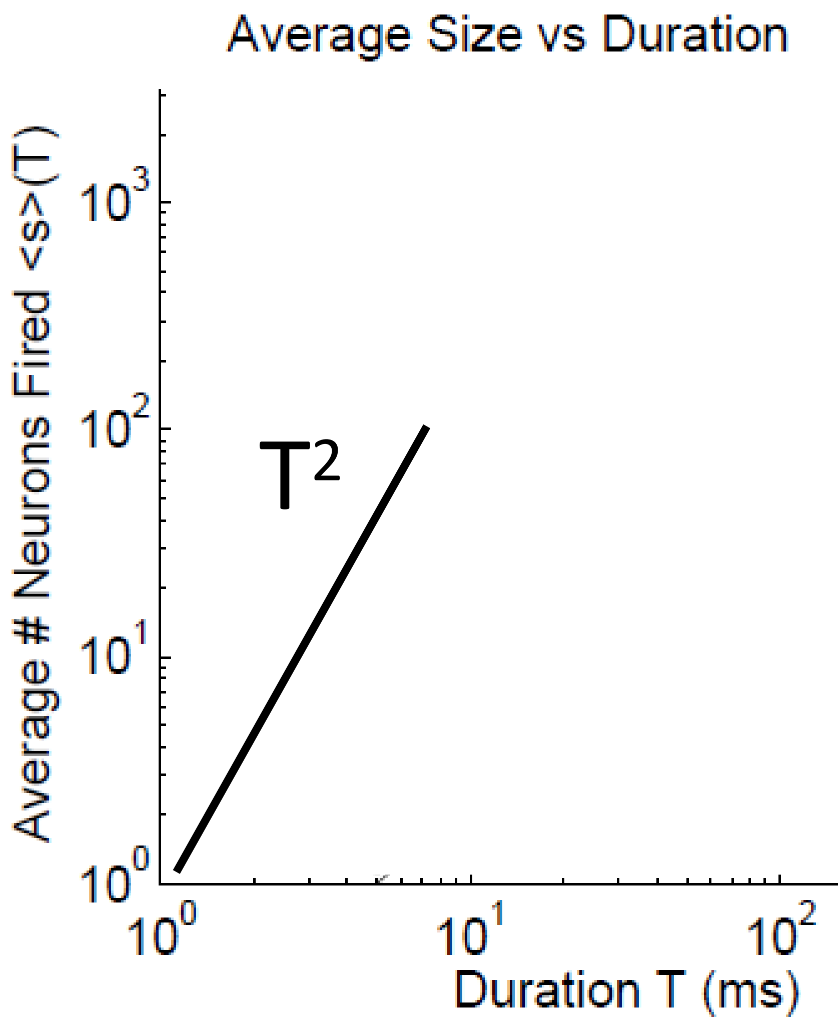
Scale-free bursting in human cortex following hypoxia at birth

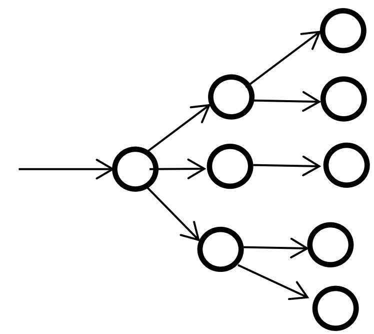


Exponent relationship



Exponent relationship





$$\langle S \rangle \sim T^2$$

Exponent relationship

Avalanche lifetime distribution

$$\frac{\alpha - 1}{\tau - 1} = \frac{1}{\sigma \nu z}$$

Avalanche size distribution

Exponent for height rescaling

Exponent relationship

Avalanche lifetime distribution

$$\frac{1.7 - 1}{1.6 - 1} = \frac{1}{\sigma v z} = 1.3$$

Avalanche size distribution

Exponent for height rescaling

NETWORK STRUCTURE AND CRITICALITY

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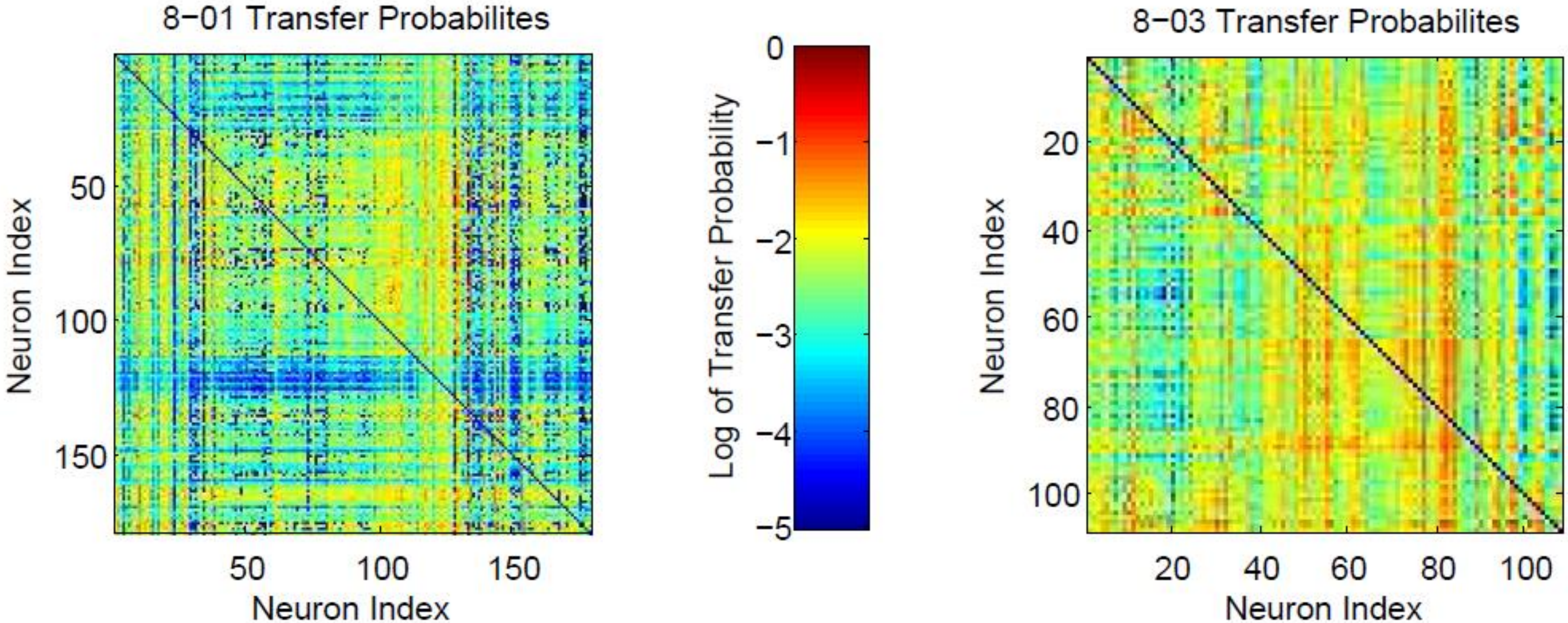
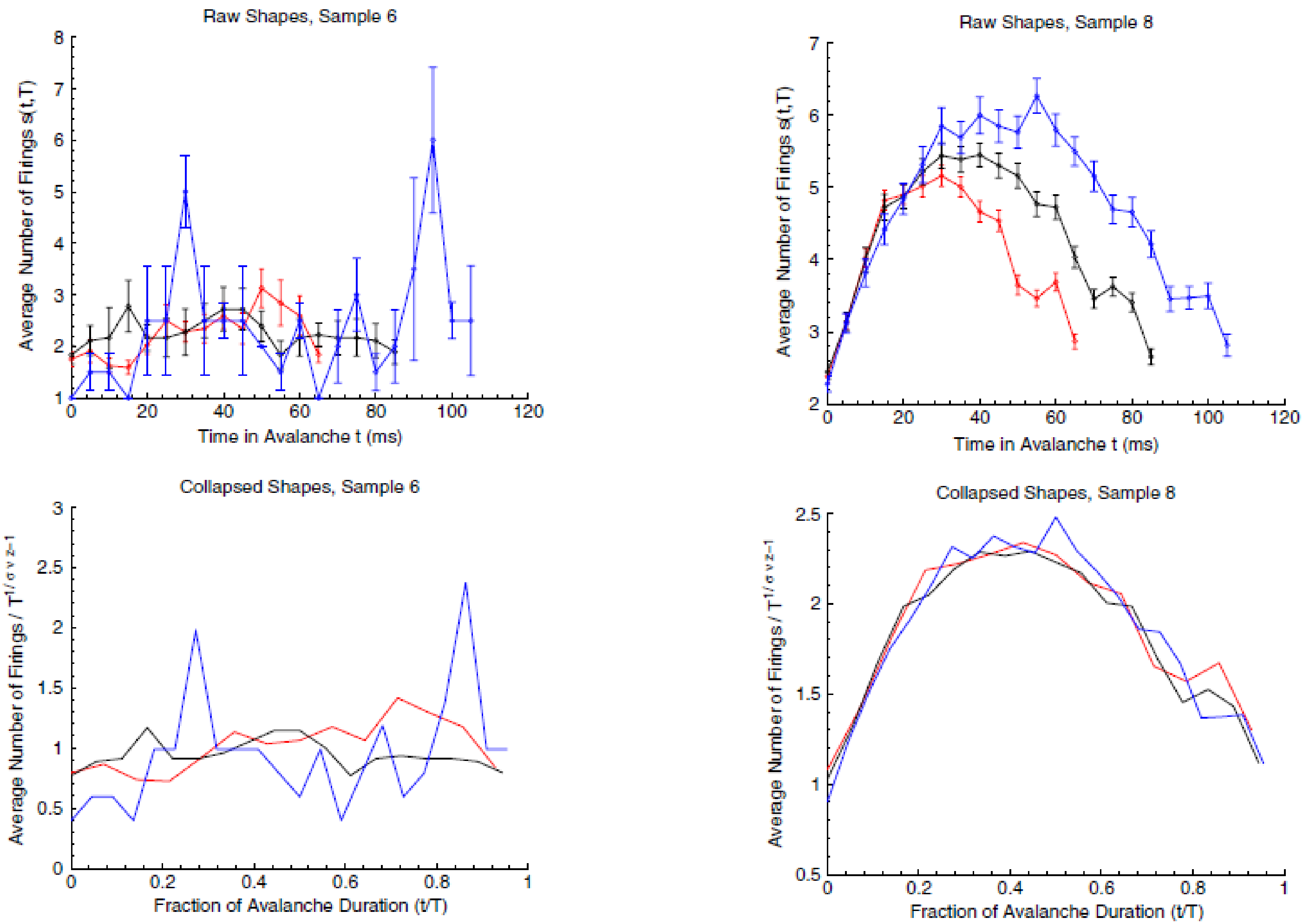
TRANSFER PROBABILITIES...



...AFFECT DATA COLLAPSE

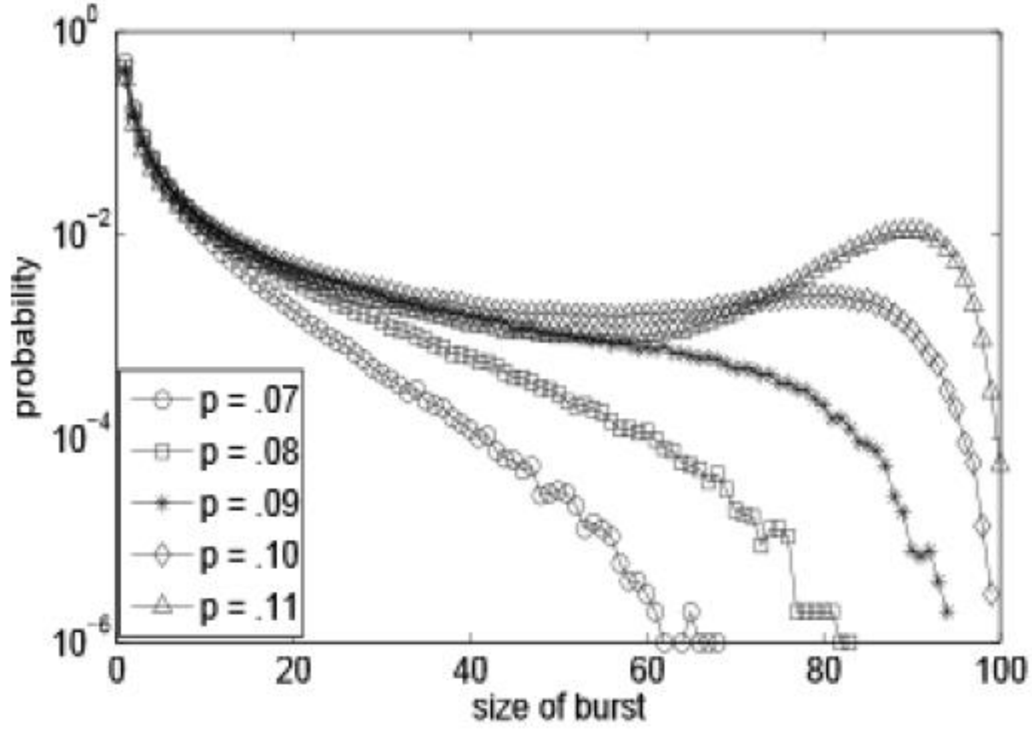


Putting connections into model

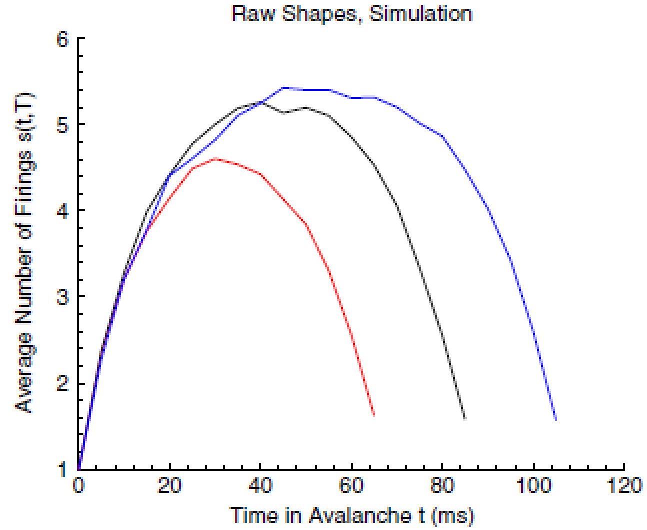
Synchrony and asynchrony in a fully stochastic neural network*

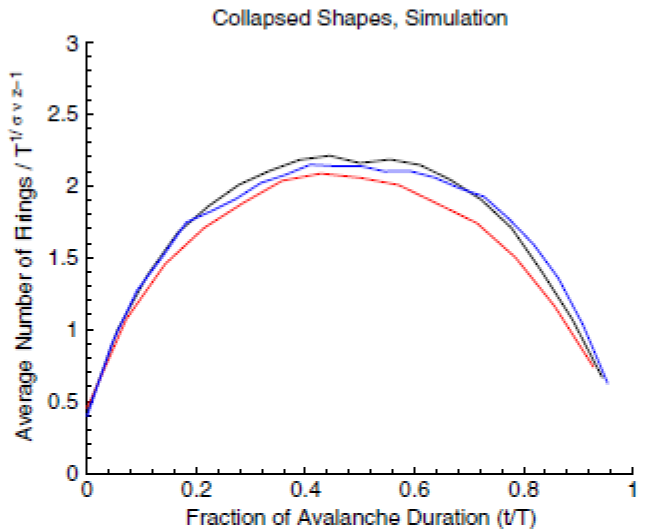
R. E. Lee DeVille† Charles S. Peskin‡

February 14, 2008



Model, with connections from data, gives correct exponents

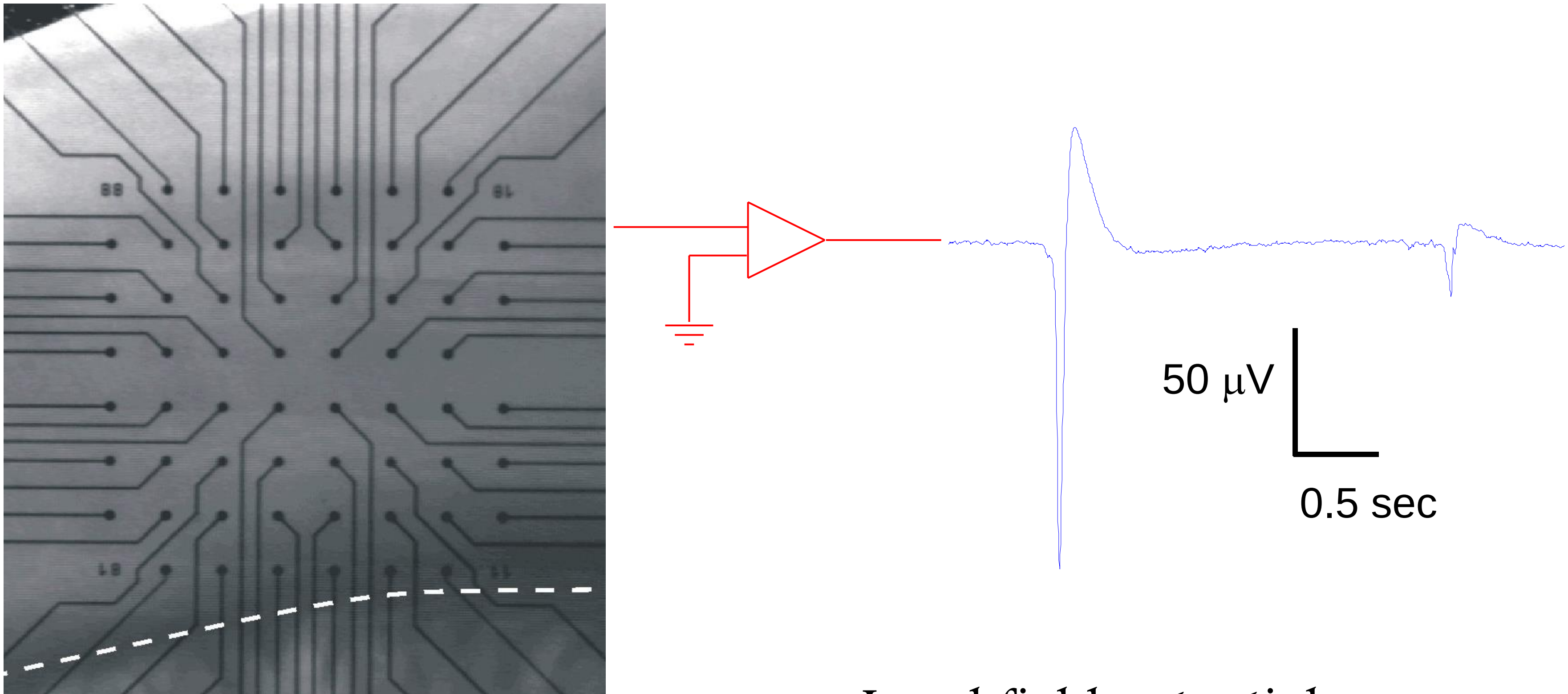




But *all-to-all* connectivity does not give the correct exponents in the spiking model.

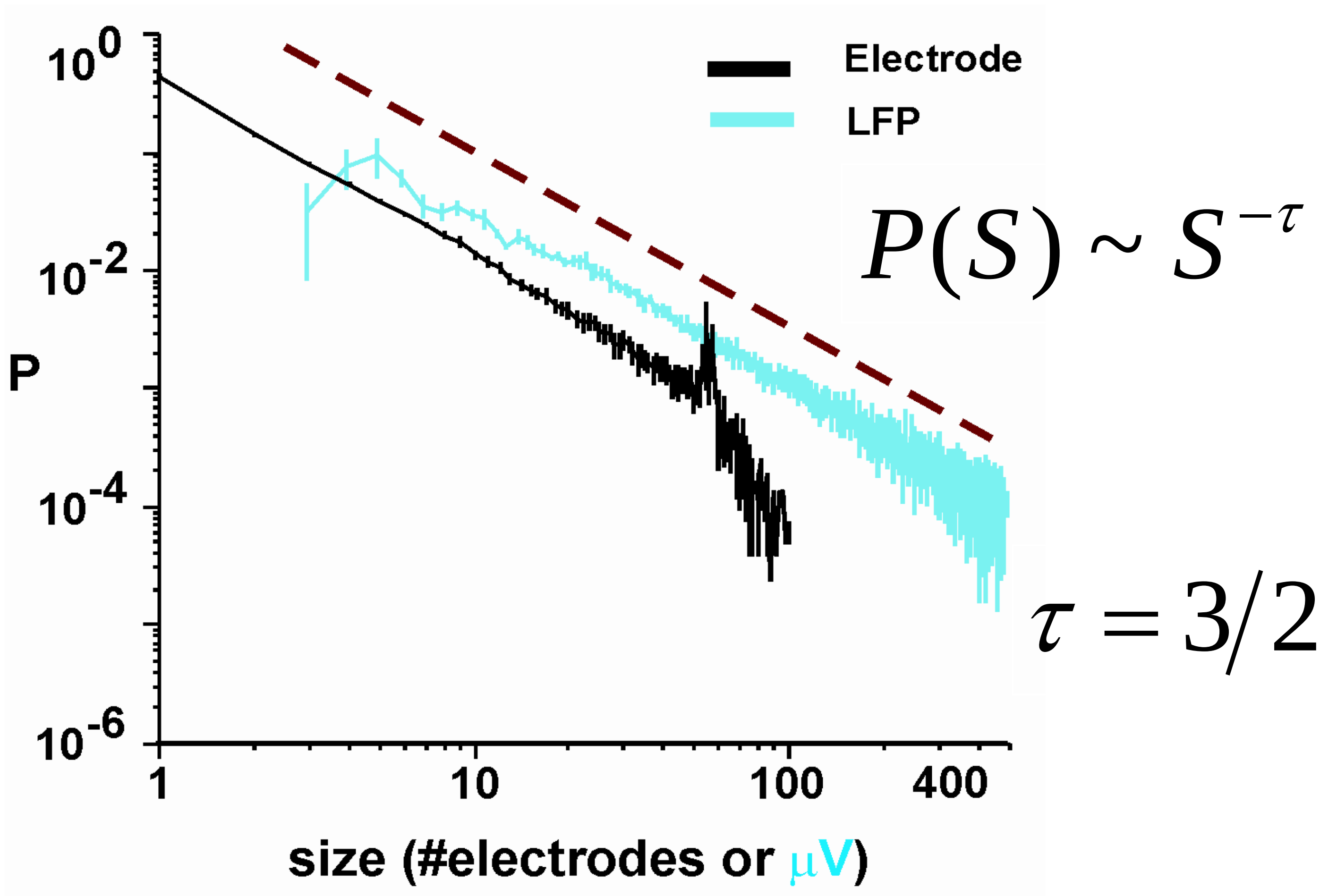
Are there any data that suggest all-to-all connectivity?

Local field potential activity

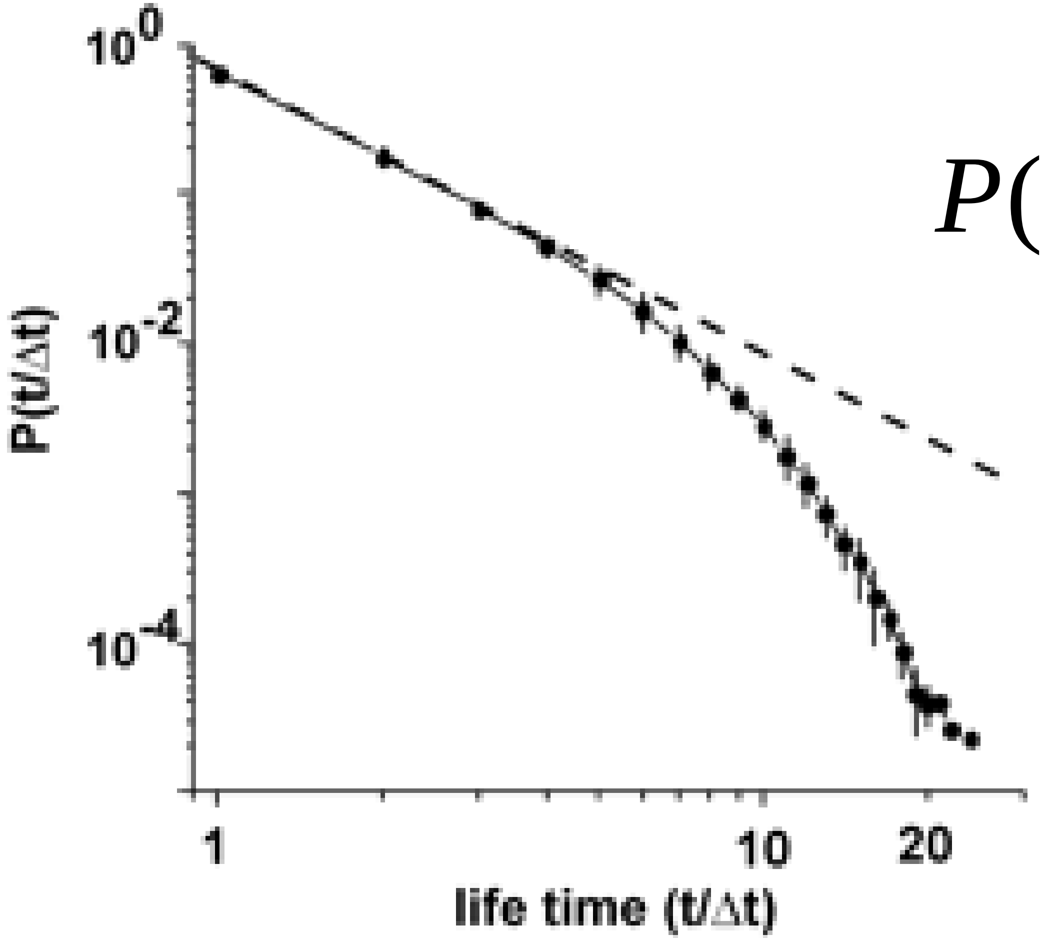


Local field potentials
from one channel

Power law distribution for local field potentials



Power law distribution for local field potentials



$$P(t) \sim t^{-\alpha}$$

$$\alpha = 2$$

Exponent relationship

Avalanche lifetime distribution

$$\frac{\alpha - 1}{\tau - 1} = \frac{1}{\sigma \nu z}$$

Avalanche size distribution

Exponent for height rescaling

Exponent relationship

Avalanche lifetime distribution

$$\frac{2-1}{3/2-1} = \frac{1}{\sigma \nu z} = \frac{2}{1}$$

Avalanche size distribution

Exponent for height rescaling

Suggests all-to-all connectivity

$$\frac{1}{\sigma v z} = 2$$

Exponents indicate structure

$$\frac{1}{\sigma \nu z} = 1.0$$

unconnected

$$\frac{1}{\sigma \nu z} = 1.3$$

spike data

$$\frac{1}{\sigma \nu z} = 2.0$$

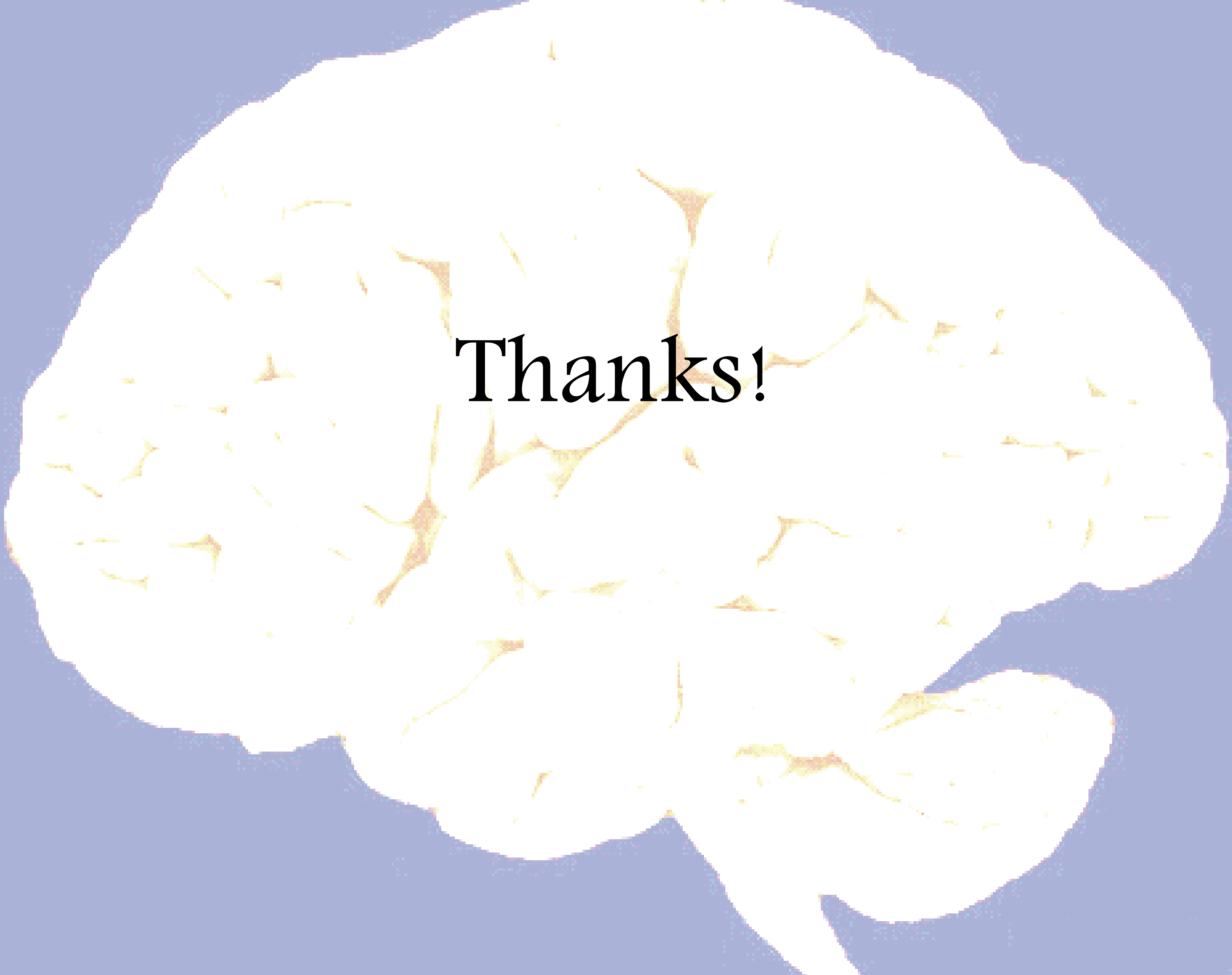
all-to-all connections,
LFP data

NETWORK STRUCTURE AND CRITICALITY

- Information transfer
- Criticality
- Relating the two

NETWORK STRUCTURE AND CRITICALITY

- Information transfer
- Criticality
- Relating the two
- How to maintain old memories, learn new things, and stay critical?


Thanks!