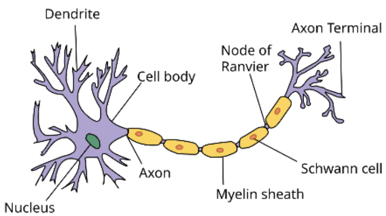
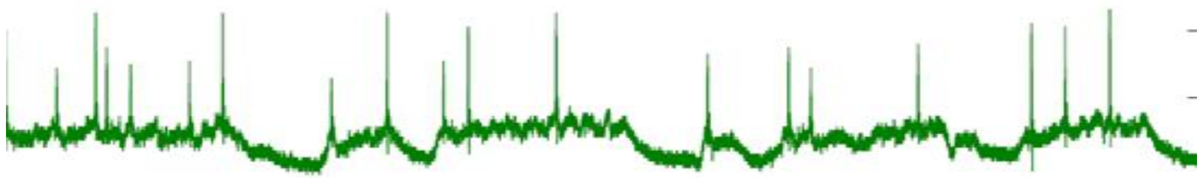




Neural coding of subthreshold sinusoidal inputs into symbolic temporal spike patterns

M. Masoliver, B.R.R. Boaretto, J. Tiana-Alsina, <u>Cristina Masoller</u>

Departament de Física

Universitat Politecnica de Catalunya

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Campus d'Excel·lència Internacional

16th International Workshop on Neural Coding

Monte Verita, Ascona, Switzerland, June 4, 2025

ICREA

AGAUR

GOBIERNO DE ESPAÑA MINISTERIO DE CIENCIA E INNOVACIÓN

I am a physicist, PhD in dynamics of diode lasers (1999)
My first work on neuronal dynamics:

PHYSICAL REVIEW E **70**, 031904 (2004)

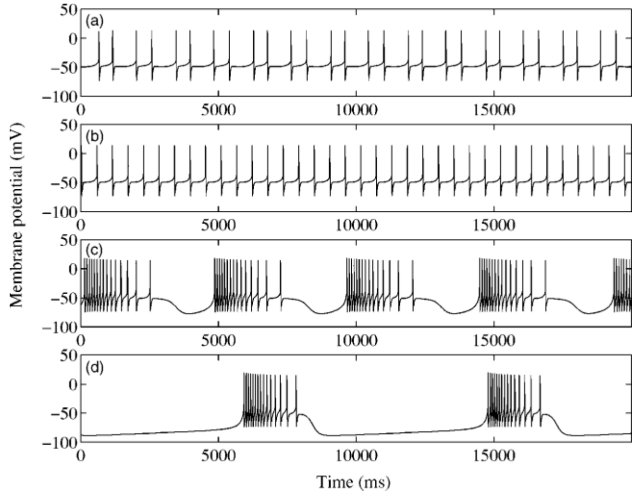
Influence of time-delayed feedback in the firing pattern of thermally sensitive neurons

M. Sainz-Trapága,[1] C. Masoller,[2] H. A. Braun,[3] and M. T. Huber[4]

[1]*Departamento de Física, Facultad de Ciencias Exactas y Naturales, Universidad de Buenos Aires, Buenos Aires, Argentina*
[2]*Instituto de Física, Facultad de Ciencias, Universidad de la República, Igua 4225, Montevideo 11400, Uruguay*
[3]*Institute of Physiology, Deutschhausstrasse 2, D-35037 Marburg, Germany* [4]*Department of Psychiatry, Deutschhausstrasse 2, D-35037 Marburg, Germany* (Received 6 February 2004; published 15 September 2004)

We explore the dynamics of a Hodgkin-Huxley-type model for thermally sensitive neurons that exhibit intrinsic oscillatory activity. The model is modified to include a feedback loop that is represented by two parameters: the synaptic strength and the transmission delay time. We analyze the dynamics of the neuron depending on the temperature, the synaptic strength, and the delay time. We find parameter regions where the effect of the recurrent connexion is excitatory, inducing spikes or trains of spikes, and regions where it is inhibitory, reducing or eliminating completely the spiking behavior. We characterize the complex interplay of the intrinsic dynamics of the neuron with the recurrent feedback input and a noisy input.

DOI: 10.1103/PhysRevE.70.031904 PACS number(s): 87.19.La, 05.45.−a, 05.40.−a, 87.10.+e



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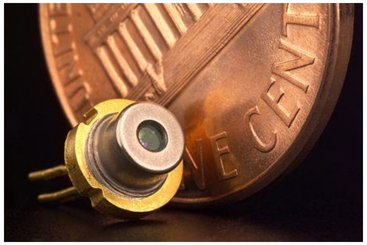
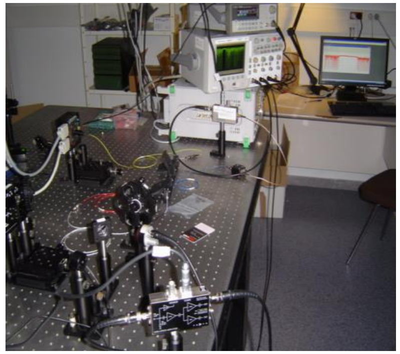
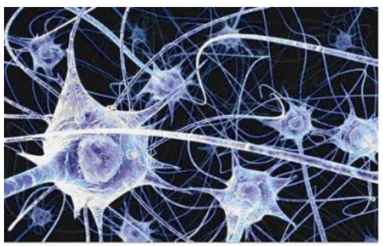
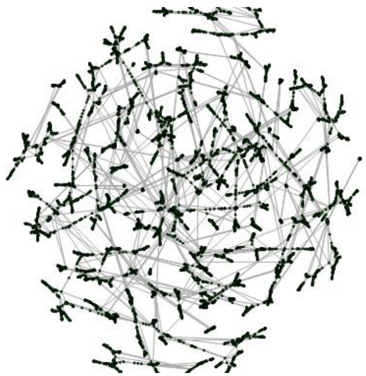
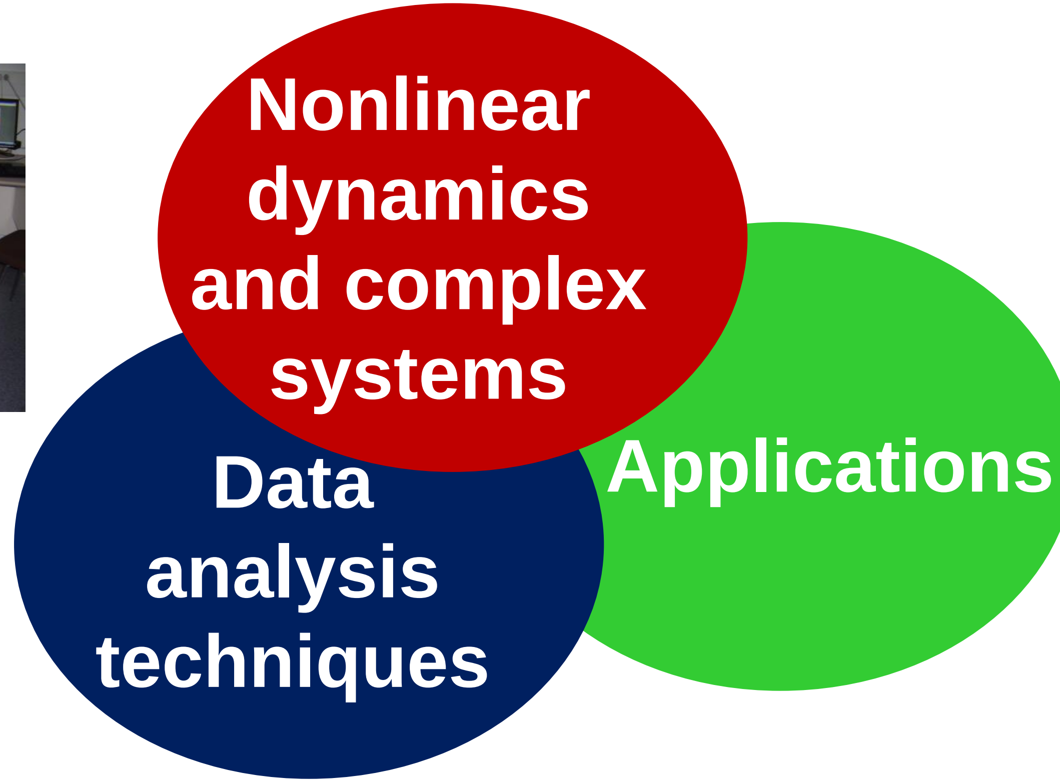
Research lines

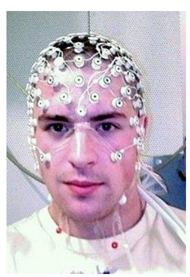


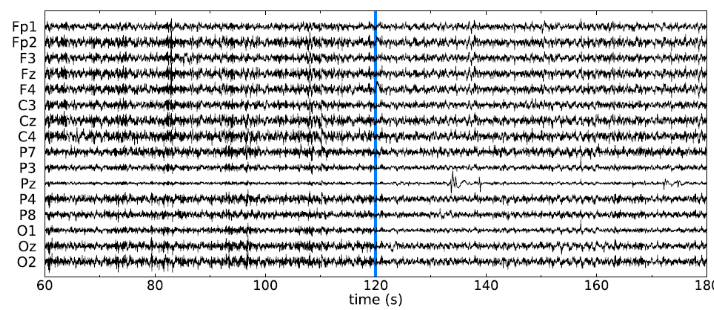


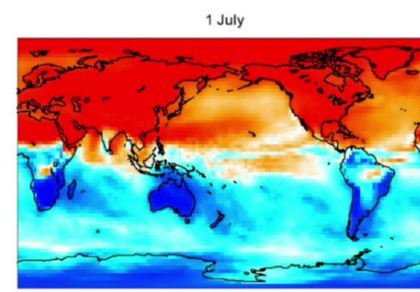












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Outline

- Research objective and motivation
- Symbolic analysis method
- Results
- Discussion

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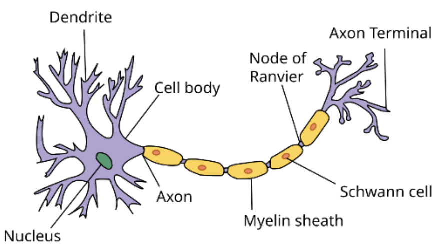
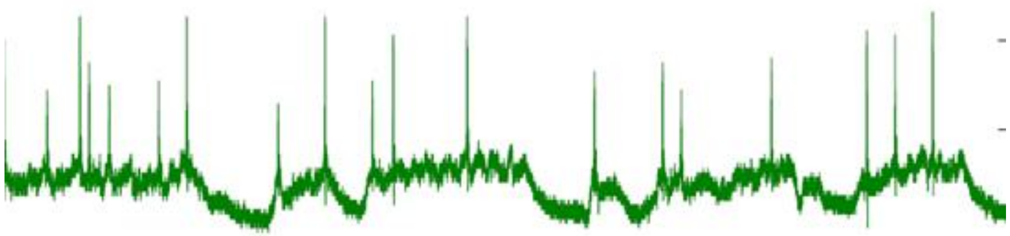
How neurons encode information?





Research goal: Understand how sensory neurons **code** a **subthreshold input**, in the presence of **noise**.

Why do I care?

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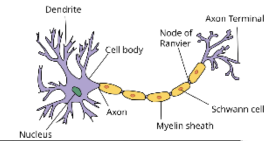
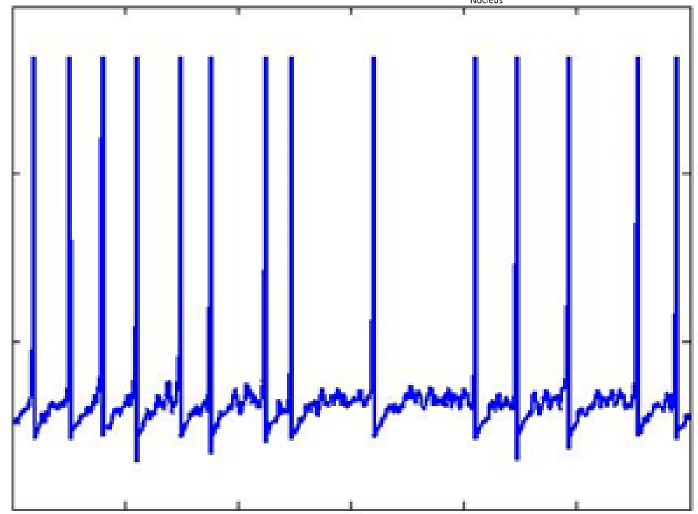
Intensity emitted by a diode laser and simulated spikes

Time 10^{-9} s





Time 10^{-3} s

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Can diode lasers mimic real neurons?

Can the neural code be implemented in diode lasers?

Why do I care?

Uncovering similarities between the "spikes" of neurons and lasers is interesting, but relevant?

At the border of different disciplines you can create new knowledge!

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Motivation

- Data centers, AI systems, HPC systems consume huge amounts of energy.
- Big concern in the context of climate change.
- The human brain processes huge amounts of information using only 19 Watts.
- Uncovering genuine similarities between neurons and lasers will allow to develop **photonic neurons**, able to process information as real neurons do, but
  - much faster,
  - with much lower energy consumption.

European Centre for Medium-Range Weather Forecasts, Reading, UK

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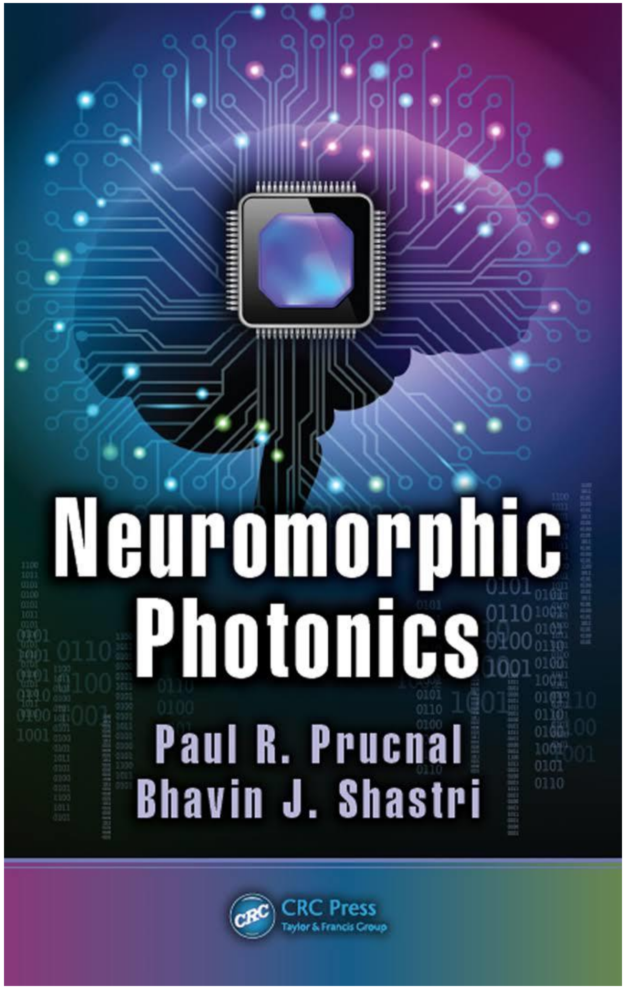
Neuromorphic photonics = Neuromorphic computing with light.

Photonic neuron: optical system that fires a pulse of light when the external stimulation is strong enough.

A photonic neuron that uses the neural code: key to develop energy-efficient neuromorphic computing systems.



Diode lasers are very attractive light sources for photonic neurons.

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Why photonic neurons with Diode Lasers?

- They are inexpensive, compact and energy-efficient.
- They emit a wide range of wavelengths.
- Nanolasers emit ultra low powers; large arrays can be integrated on chips (photonics integrated chips =PICs).
- There are several configurations in which a diode laser emits ("fires") well-defined pulses of light ("optical spikes").

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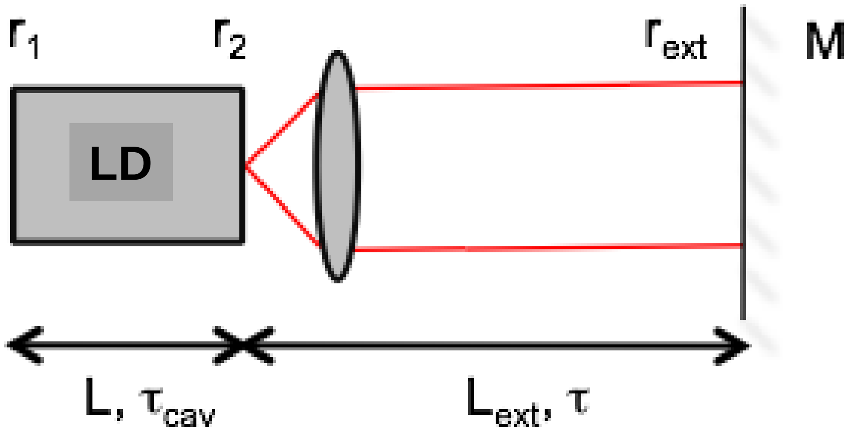
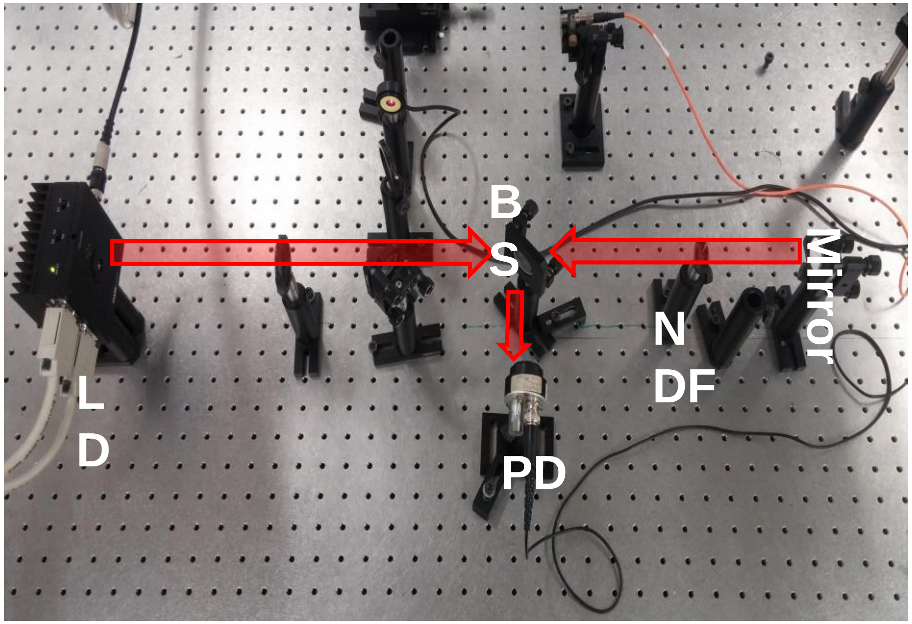
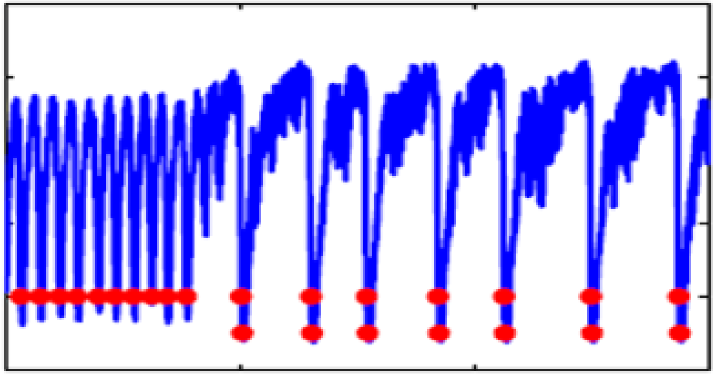
Optical feedback setup

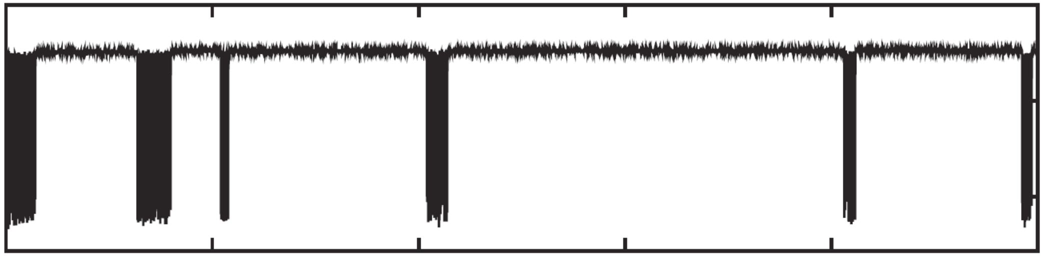


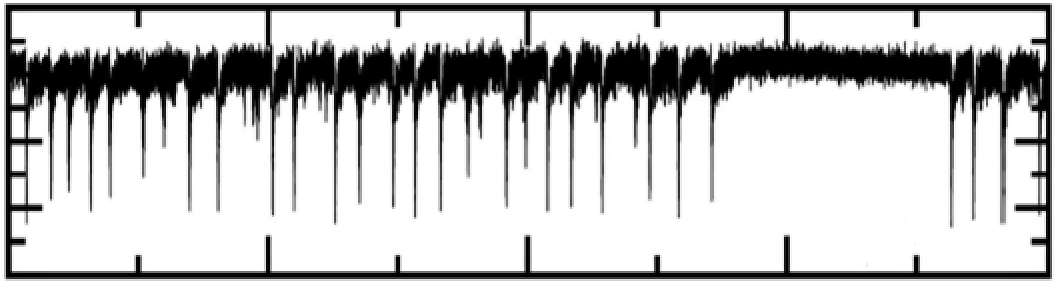


LD: laser diode
BS: beam splitter
PD: Photodetector
NDF: Neutral density filter

The feedback-induced dynamics: excitability, tonic spikes and bursting. Similar to real neurons?







A. Aragoneses, S. Perrone, T. Sorrentino, M. C. Torrent and C. Masoller, "*Unveiling the complex organization of recurrent patterns in spiking dynamical systems*", Sci. Rep. **4**, 4696 (2014).

C. Quintero-Quiroz, J. Tiana-Alsina, J. Roma, M. C. Torrent, and C. Masoller, "*Characterizing how complex optical signals emerge from noisy intensity fluctuations*", Sci. Rep. **6** 37510 (2016).

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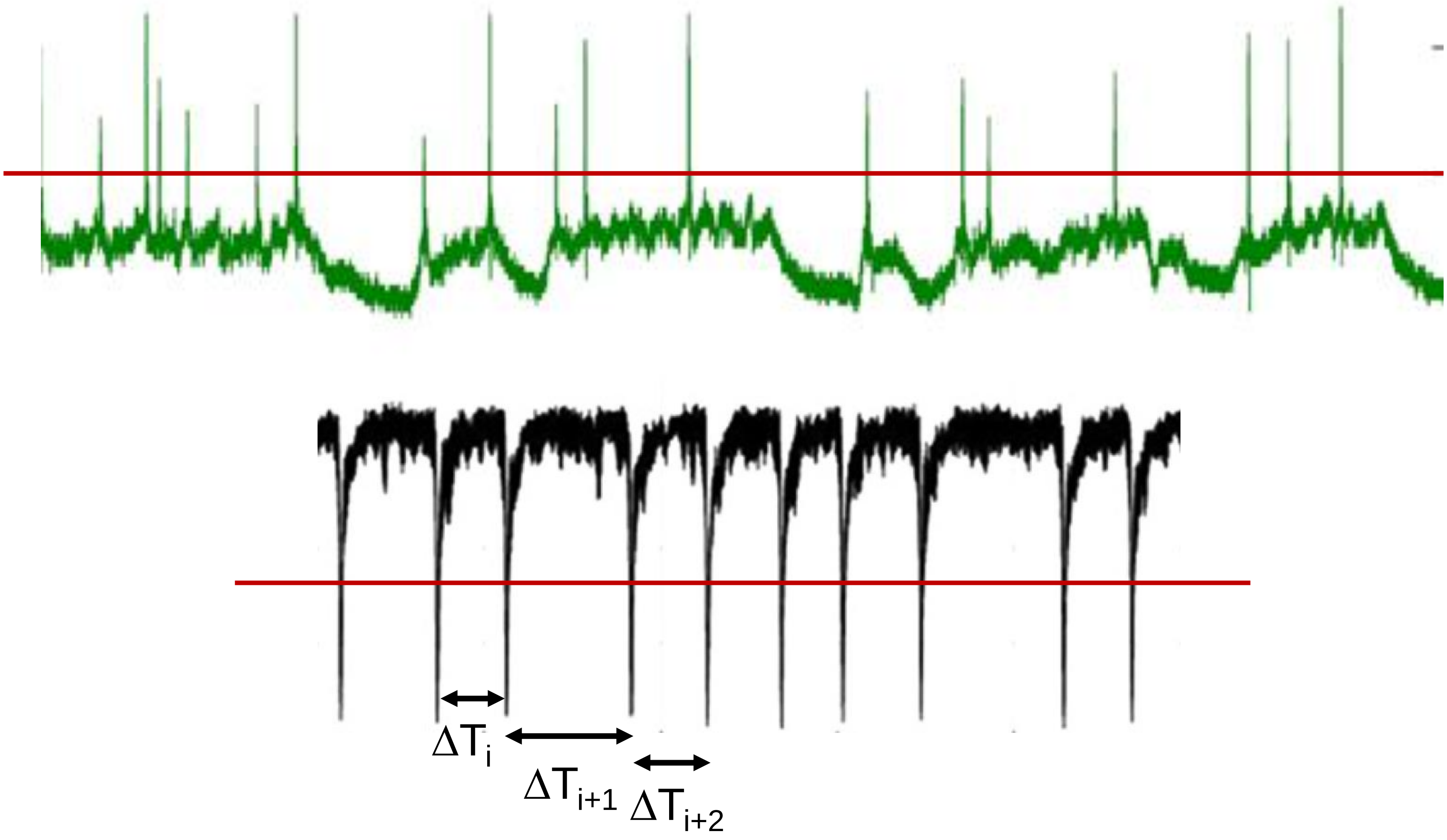
Thresholding detects the spike times ⇒ Point Process ⇒ sequence of inter-spike-intervals (ISIs)



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How to analyze sequences of inter-spike-intervals (ISIs)?

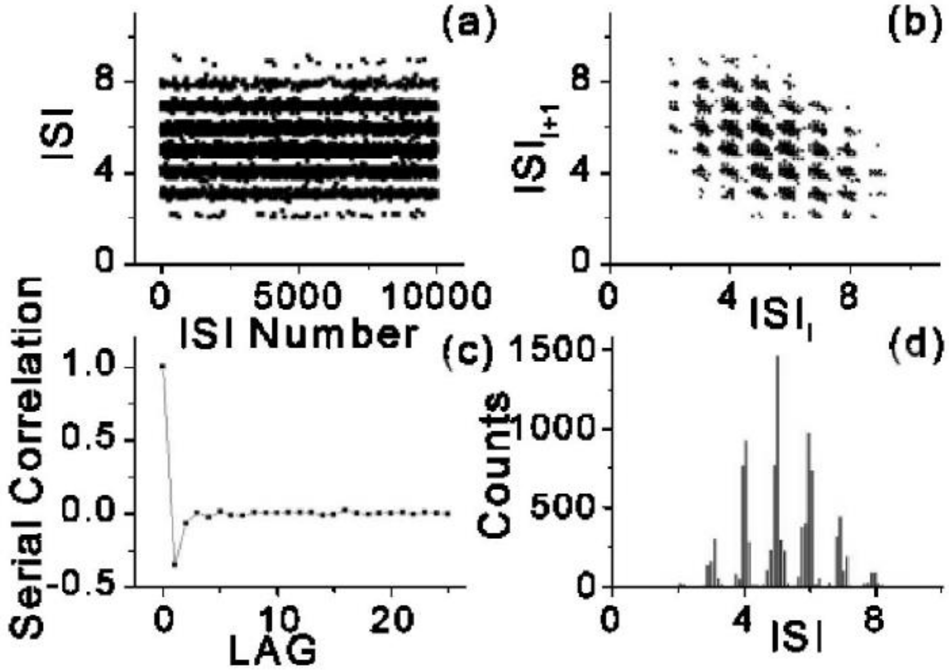

FIG. 1. Analysis of 10 000 consecutive interspike intervals from a P-unit of the weakly electric fish A. Leptorhynchus (data courtesy of Mark Nelson, Beckmann Institute, Illinois, USA; we focus on such "nonbursty" units). Time is in EOD cycles; the EOD frequency is 755 Hz. The firing rate is 145 Hz which corresponds to $P = 0.192$. (a) Raster plot of ISI duration versus ISI number, (b) return map, (c) serial correlation, and (d) histogram.

Chacron, Longtin, et. al, Phys. Rev. Lett. 85, 1576 (2000)

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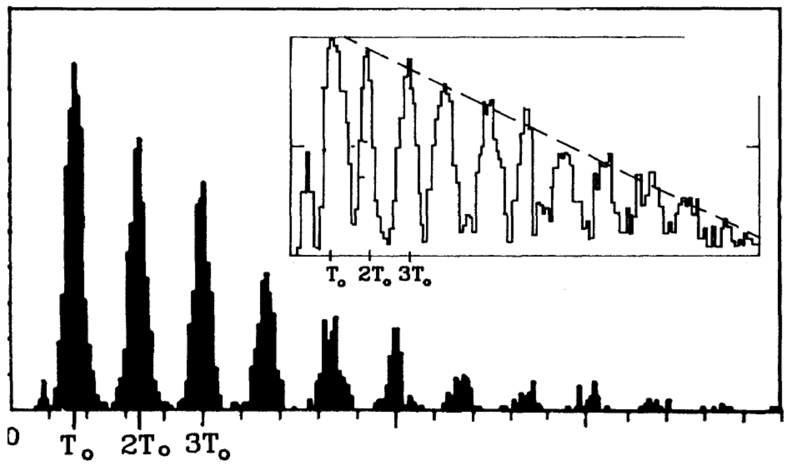
With a small-amplitude sinusoidal input, are the neuronal and laser ISI sequences statistically similar?

Neuronal ISI distribution

(spikes in the auditory nerve of a squirrel monkey with a T_0=1.66 ms, 80 dB sound pure tone sound)

$P(\Delta T_i)$

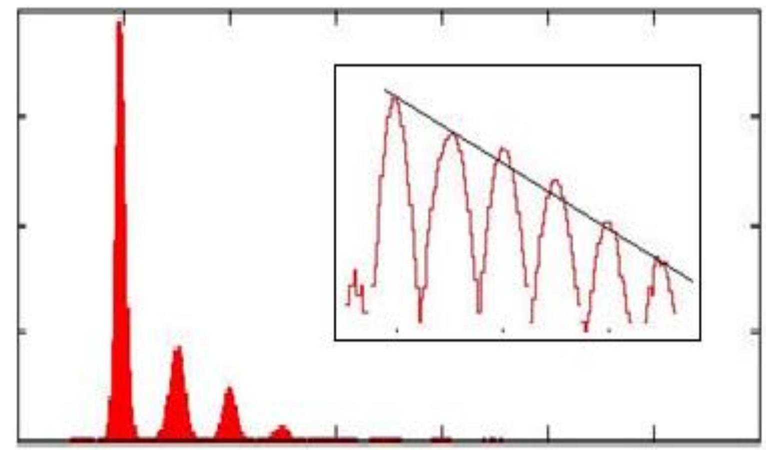


Inter-spike-interval, ΔT_i

A. Longtin et al. PRL (1991)

Diode laser ISI distribution

(the laser current is sinusoidally modulated at 17 MHz, T_0=59 ns).



$2T_0$ $4T_0$

Inter-spike-interval, ΔT_i

A. Aragoneses et al. Optics Express (2014)

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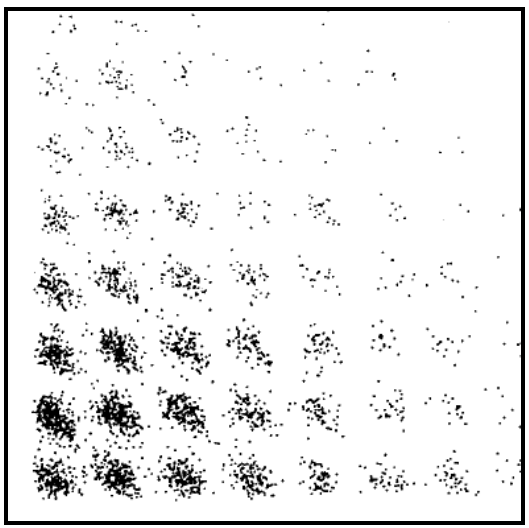
Return maps of inter-spike-intervals: ISI(i) vs. ISI(i+1)

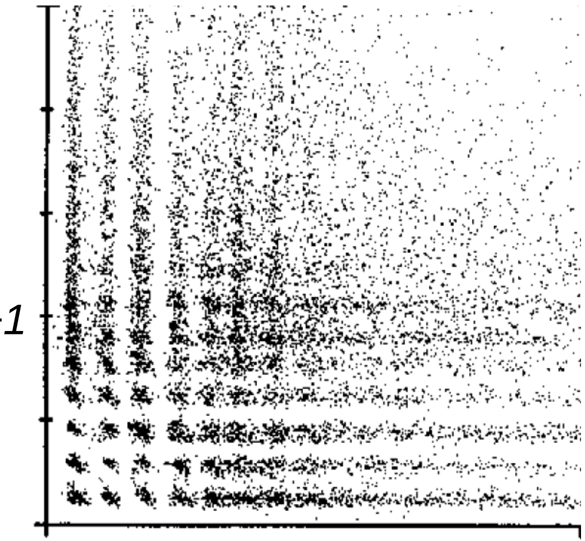
Periodically driven sensory neuron

(cat auditory fiber activity in response to
800 Hz 60 dB sound pressure --pure tone)



A. Longtin, Int. J. Bif. Chaos (1993)

Periodically driven
spiking diode laser



M. Giudici et. al PRE (1997).

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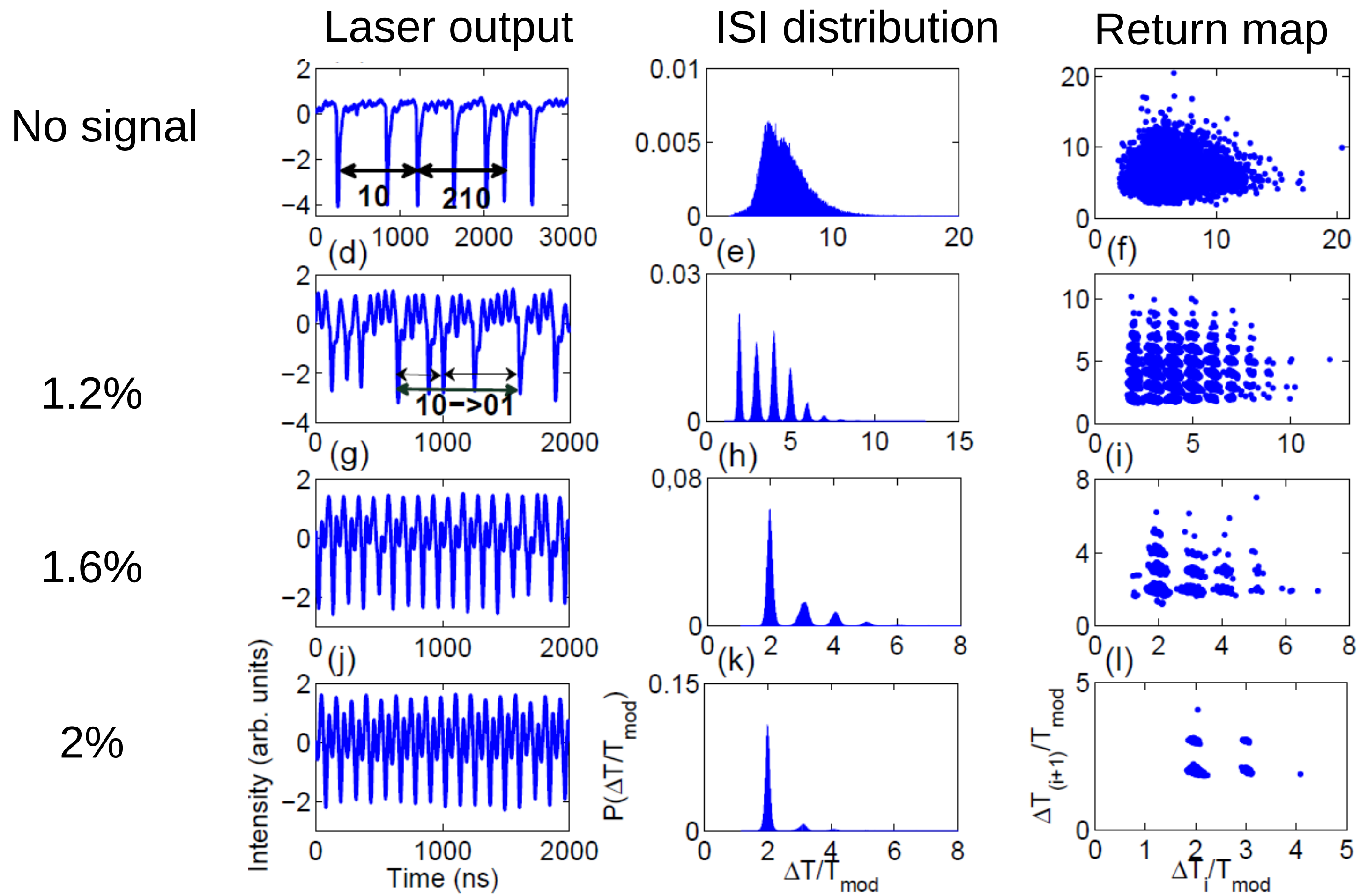
Experiments in our lab with a diode laser with feedback



Aragoneses et al, Optics Express 22, 4705 (2014)

How to identify ISI temporal correlations?

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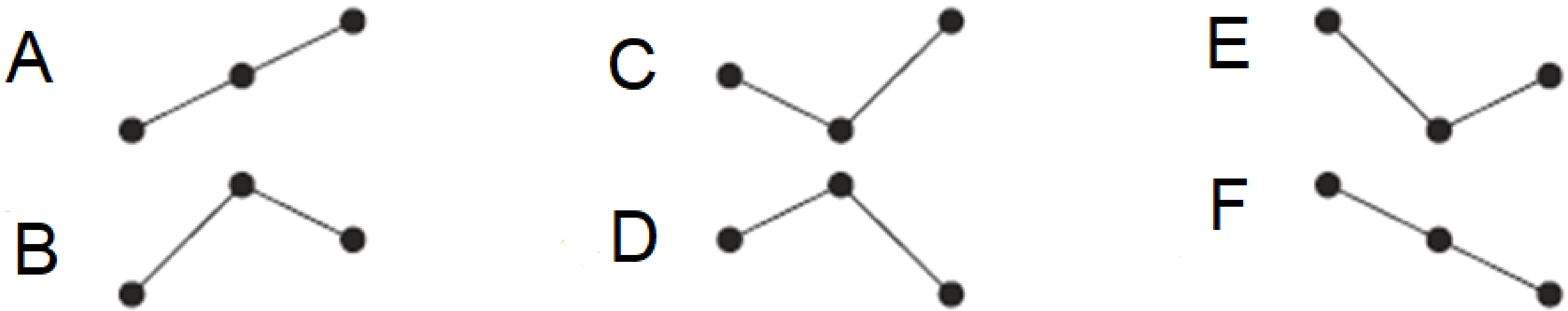
Symbolic analysis method: ordinal analysis

$\{\ldots x_i, x_{i+1}, x_{i+2}, \ldots\}$

Possible order relations among three numbers (e.g., 2, 5, 7)

{…2, 5, 7…} {…5, 2, 7…} {…7, 2, 5 …}



{…2, 7, 5…} {…5, 7, 2…} {…7, 5, 2…}

Drawback! Information about the absolute values is lost.

The sets (5,7,2) and (5,70,2) are represented by the same symbol “D”.

Bandt and Pompe: Phys. Rev. Lett. 2002

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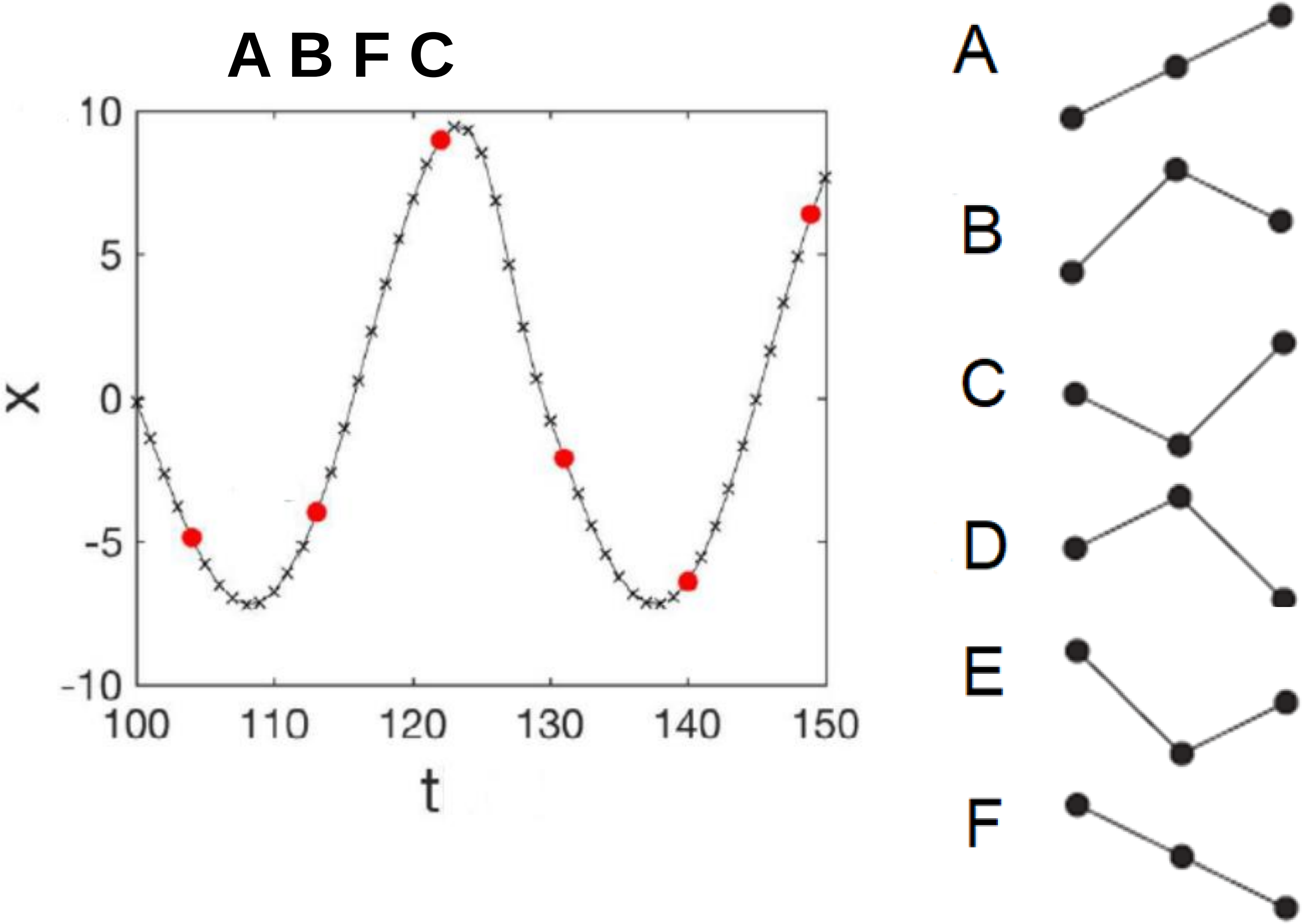
Using the “ordinal code”, which is the message?



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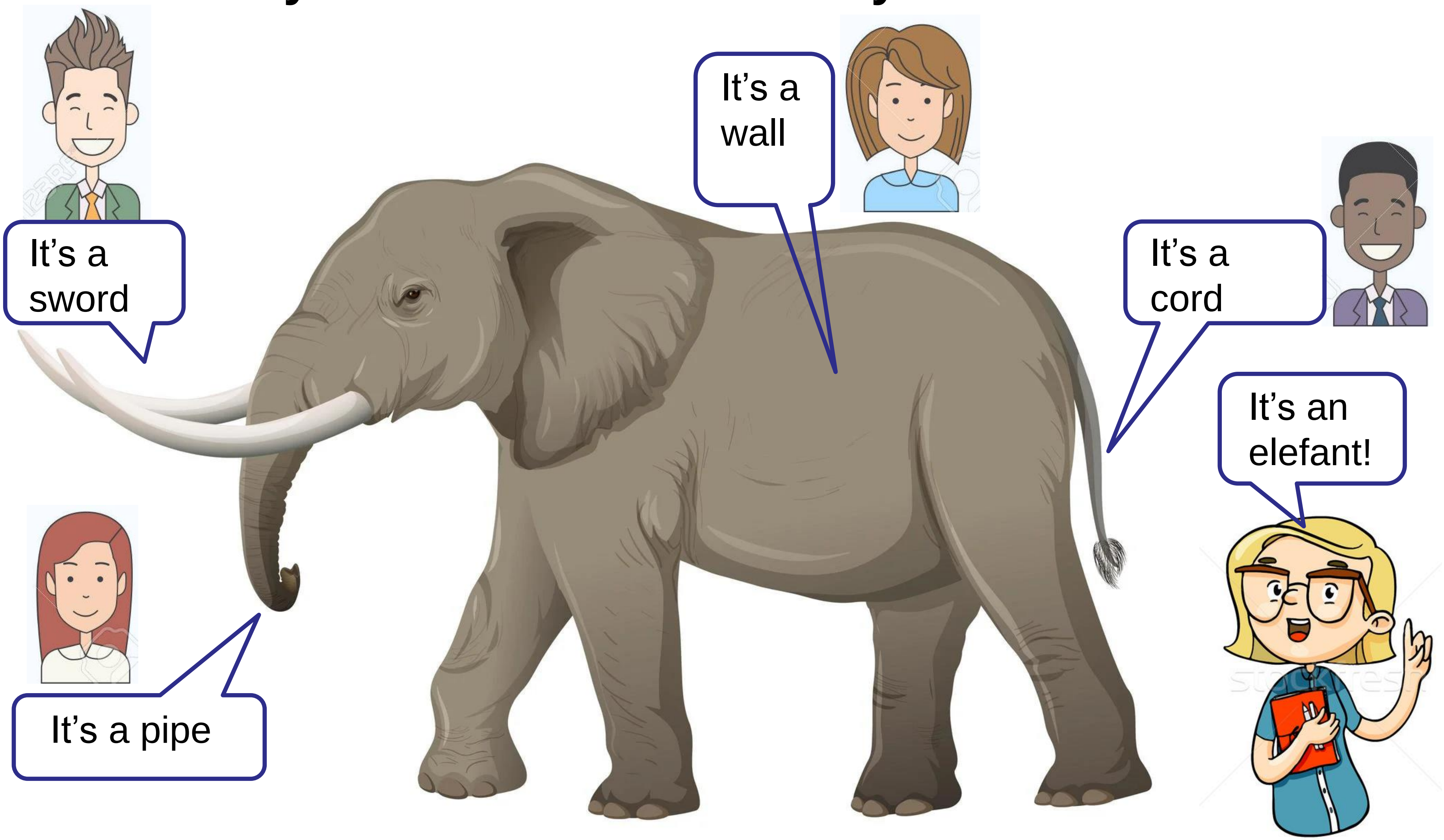
Why to use a nonlinear analysis method?



Nonlinear systems need nonlinear analysis tools

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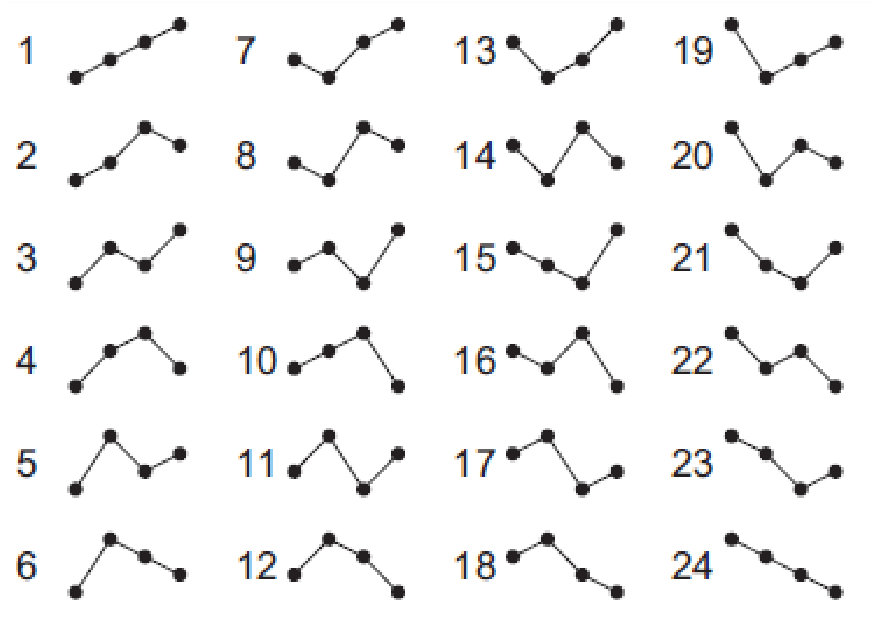
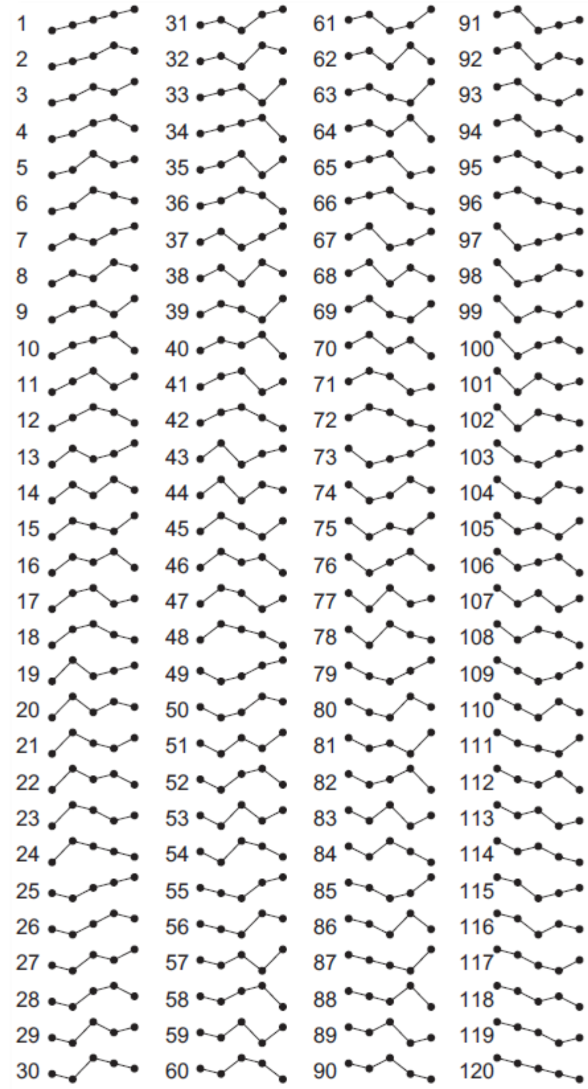
The number of possible patterns increases with the length of the pattern as D!





U. Parlitz et al. / Computers in Biology and Medicine 42 (2012) 319–327

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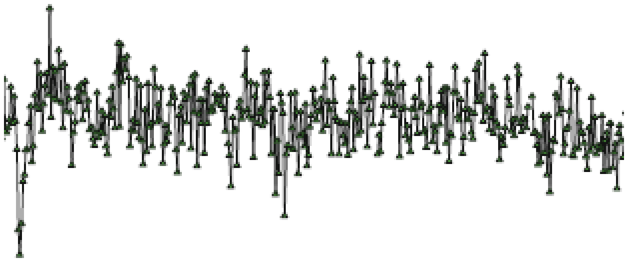
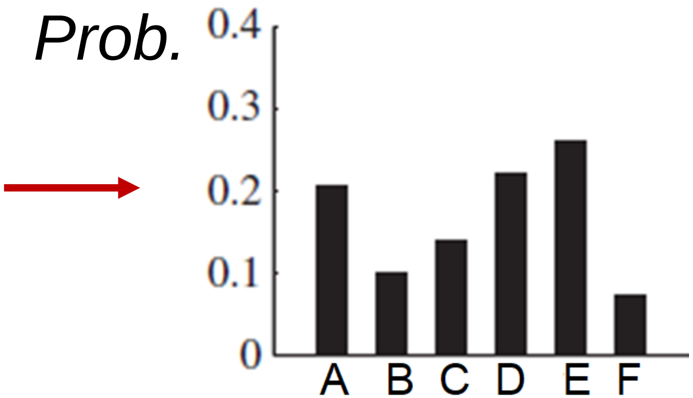
From a sequence of data points, by counting the different patterns, we estimate the "ordinal probabilities"





?

1. Permutation Entropy: $H = -\sum_{i=1}^{N} p_i \ln p_i$ (Nonlinear dimensionality reduction)

$p_i = p_j$ for all $i, j \Rightarrow H$ max

$p_i = 1, p_j = 0$ for all $j \neq i \Rightarrow H=0$

2. Analyze all the probabilities

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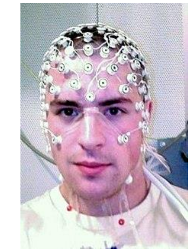
Example of first (entropy) approach: distinguishing eyes-closed and eyes-open states in EEGs of healthy subjects



Eyes closed | Eyes open

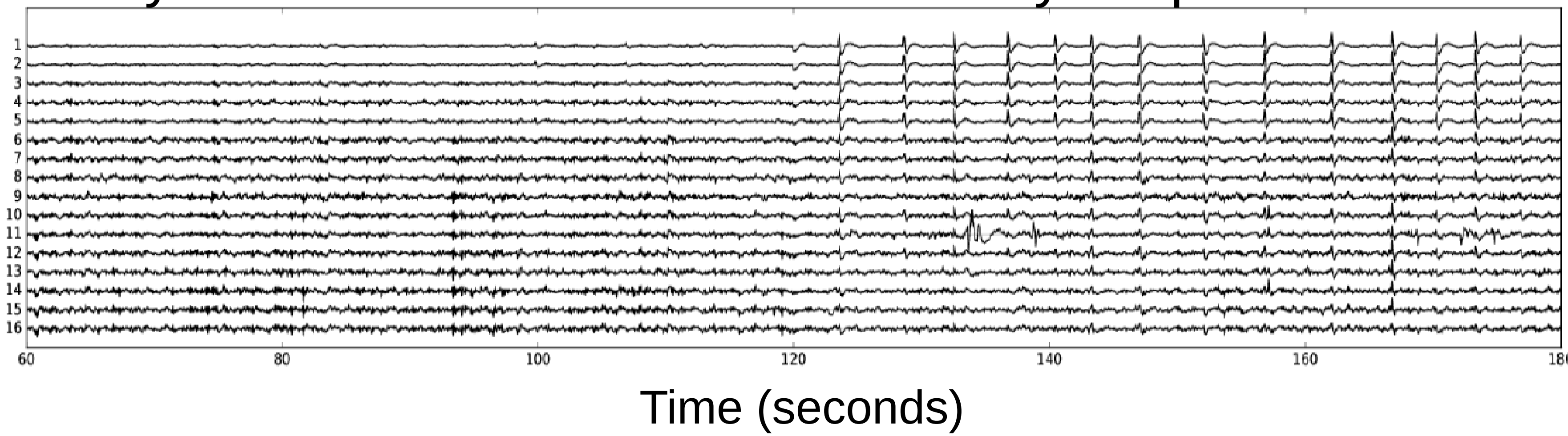


TABLE I. Description of the datasets used.

	DTS1	DTS2
Sampling rate (Hz)	256	160
Time task (seg)	120	60
Total points	30 720	9600
Number of electrodes	16	64
Number of subjects	71	109

DTS1: Bitbrain (Zaragoza)
DTS2: Physionet

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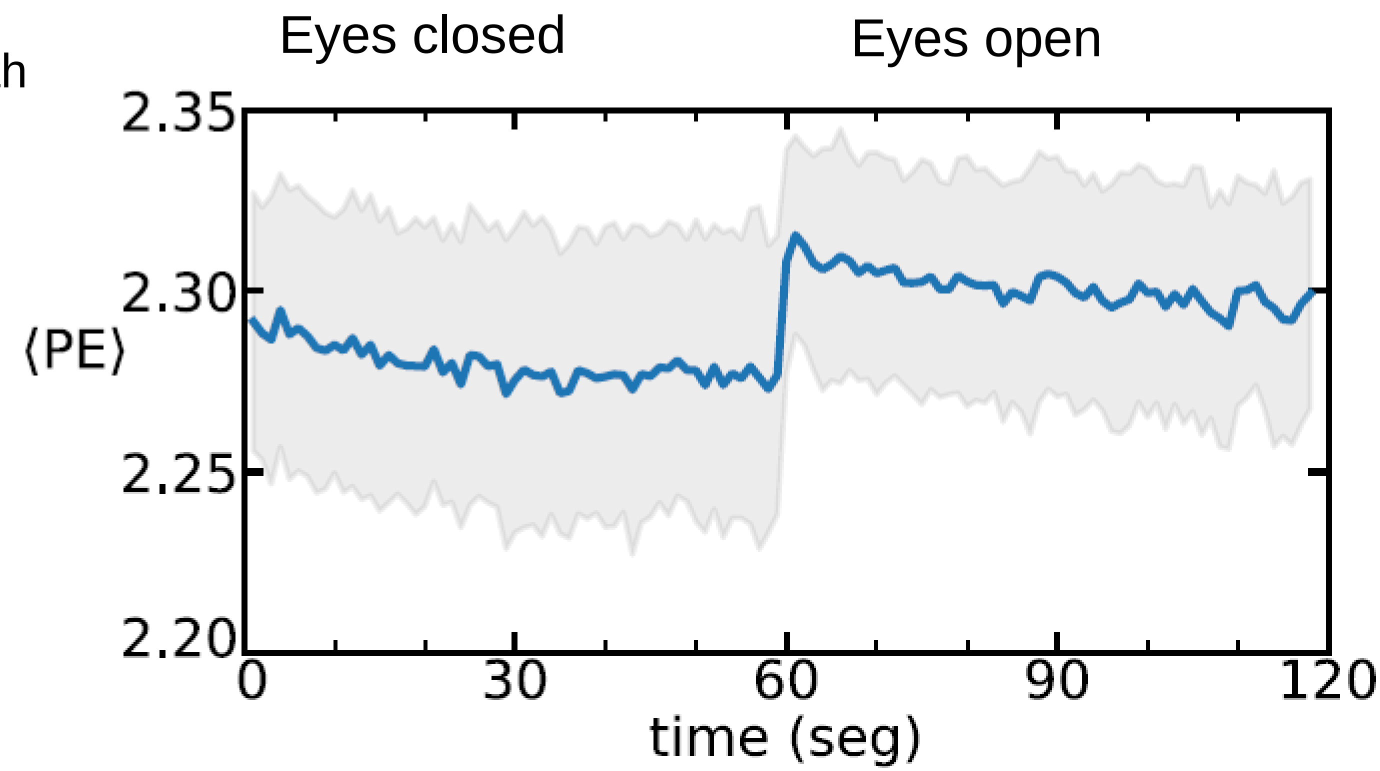
The Permutation Entropy increases in the eyes open state

$$\langle \mathrm{PE} \rangle = \frac{1}{N[\mathrm{electrodes}]} \sum_i \mathrm{PE}^i$$

PE was calculated with patterns of length 4 (# of possible patterns 24) in time windows containing >4000 patterns



Gray region: Standard deviation of ⟨PE⟩ across subjects

C. Quintero-Quiroz, L. Montesano, A. J. Pons, M. C. Torrent, J. García-Ojalvo, C. Masoller, "Differentiating resting brain states using ordinal symbolic analysis", Chaos 28, 106307 (2018).

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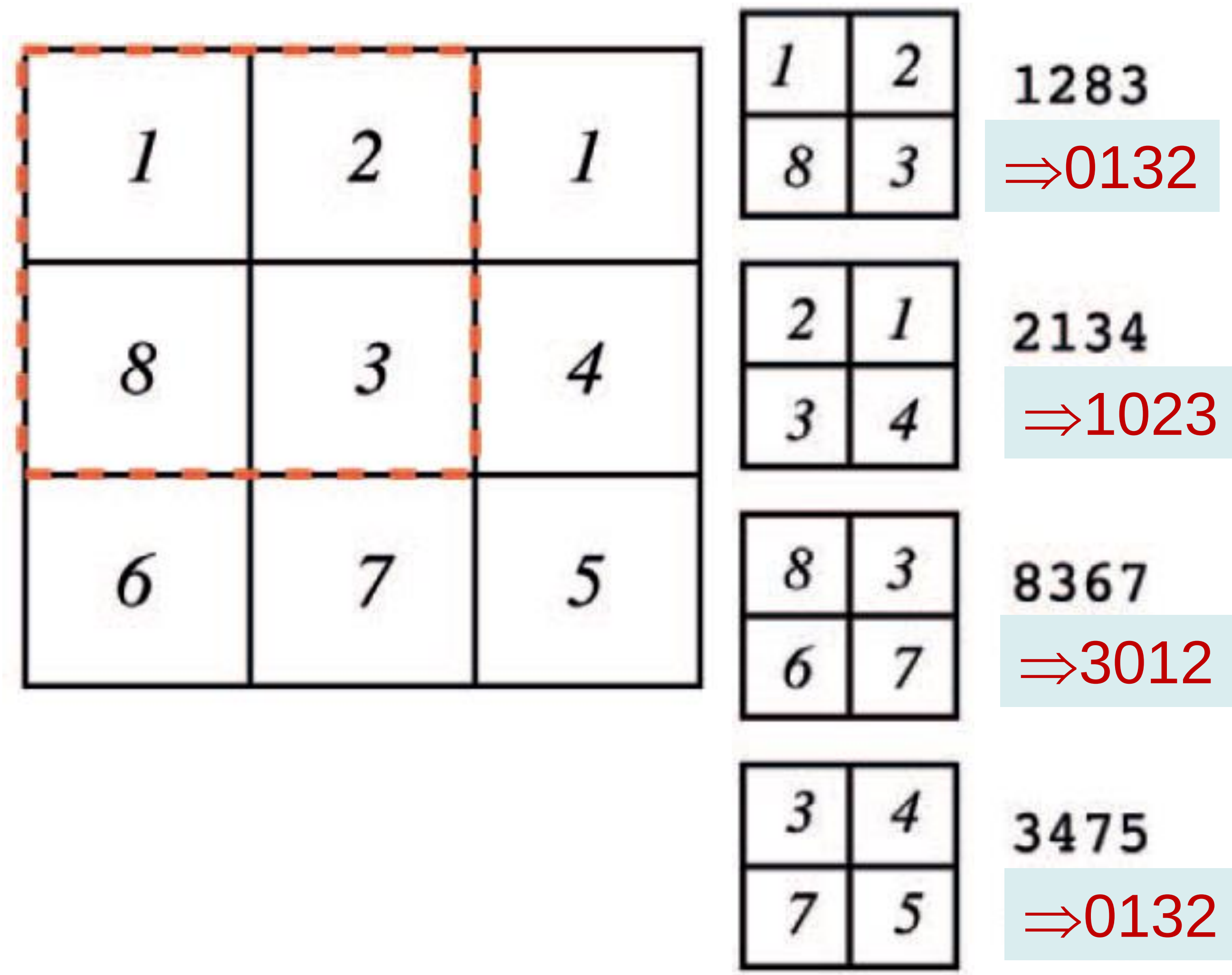
Spatial data ⇒ Spatial Permutation Entropy (SPE)



$$H = -\sum_{i=1}^{N} p_i \ln p_i$$

2x2 pixels:
24 possible
patterns

Haroldo V. Ribeiro and coworkers, PLoS ONE 7, e40689 (2012)

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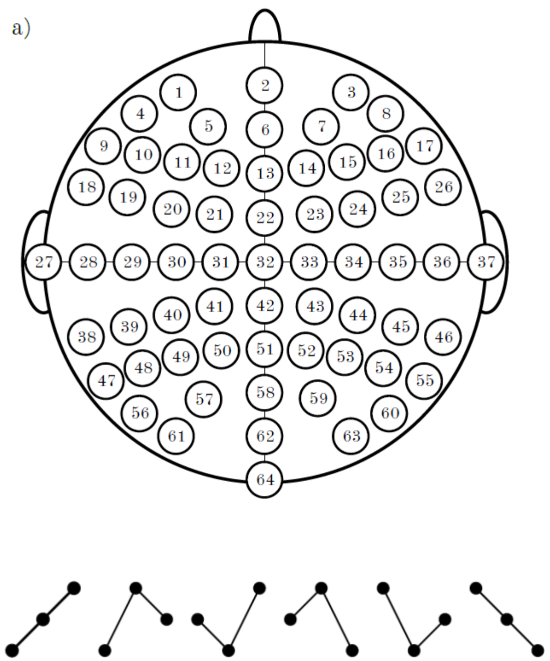
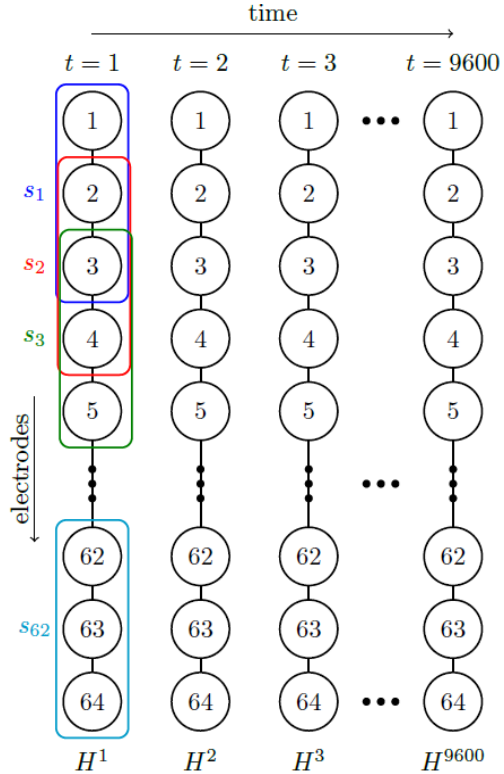
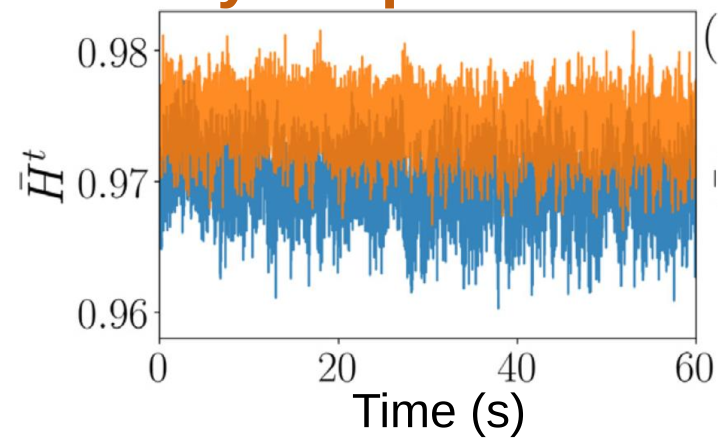
Spatial Permutation Entropy of EEG recordings





Eyes closed
Eyes open



(H_t averaged over subjects)

At each time: 64 channels $\Rightarrow$ 62 patterns to calculate 6 probs.

Bruno Boaretto et al., "Spatial permutation entropy distinguishes resting brain states", Chaos, Solitons & Fractals 171, 113453 (2023).
Juan Gancio et al., "Permutation entropy analysis of EEG signals for distinguishing eyes-open and eyes-closed brain states: comparison of different approaches", Chaos 34, 043130 (2024).

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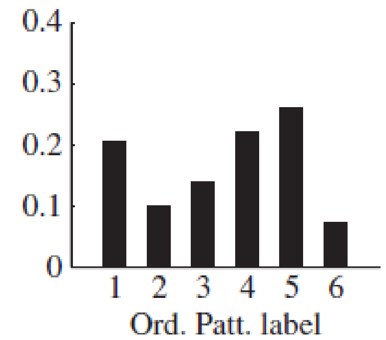
Second option: analyze all the ordinal probabilities

Are the D! ordinal patterns equally probable?



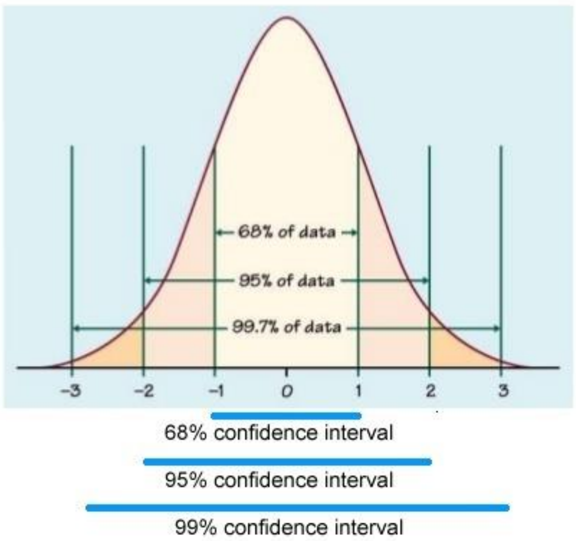
- **Null hypothesis**:

  $p_i = p = 1/D!$ for all $i = 1 \ldots D!$

- If at least one probability **is not** in the interval $p \pm 3\sigma$ with $\sigma = \sqrt{p(1-p)/N}$ and N the number of ordinal patterns:

  We **reject** the NH with 99.74% confidence level.

- Else, we **fail to reject** the NH with 99.74% confidence level.



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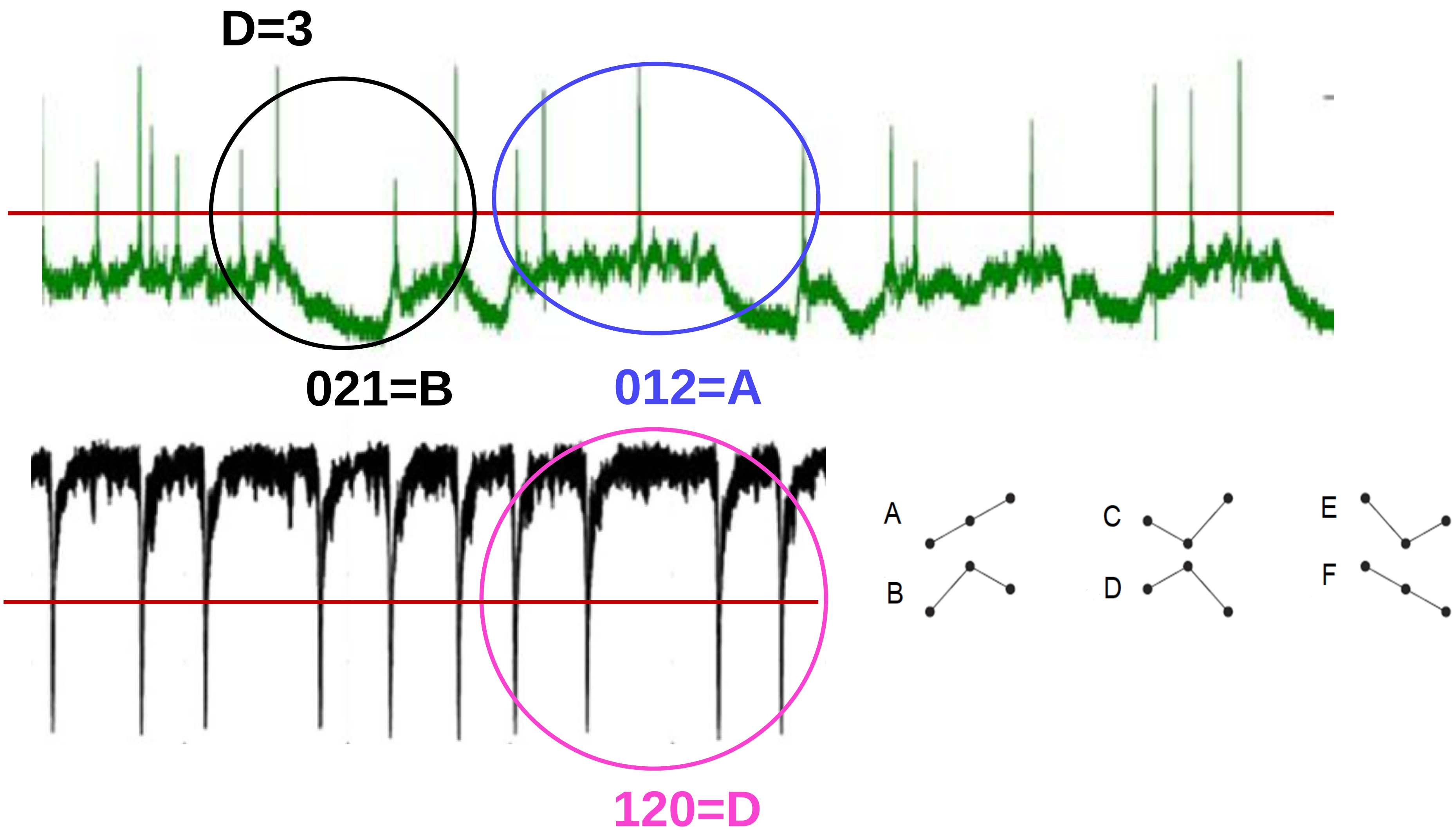
Sequence of inter-spike-intervals (ISIs) ⇒ sequence of ordinal patterns



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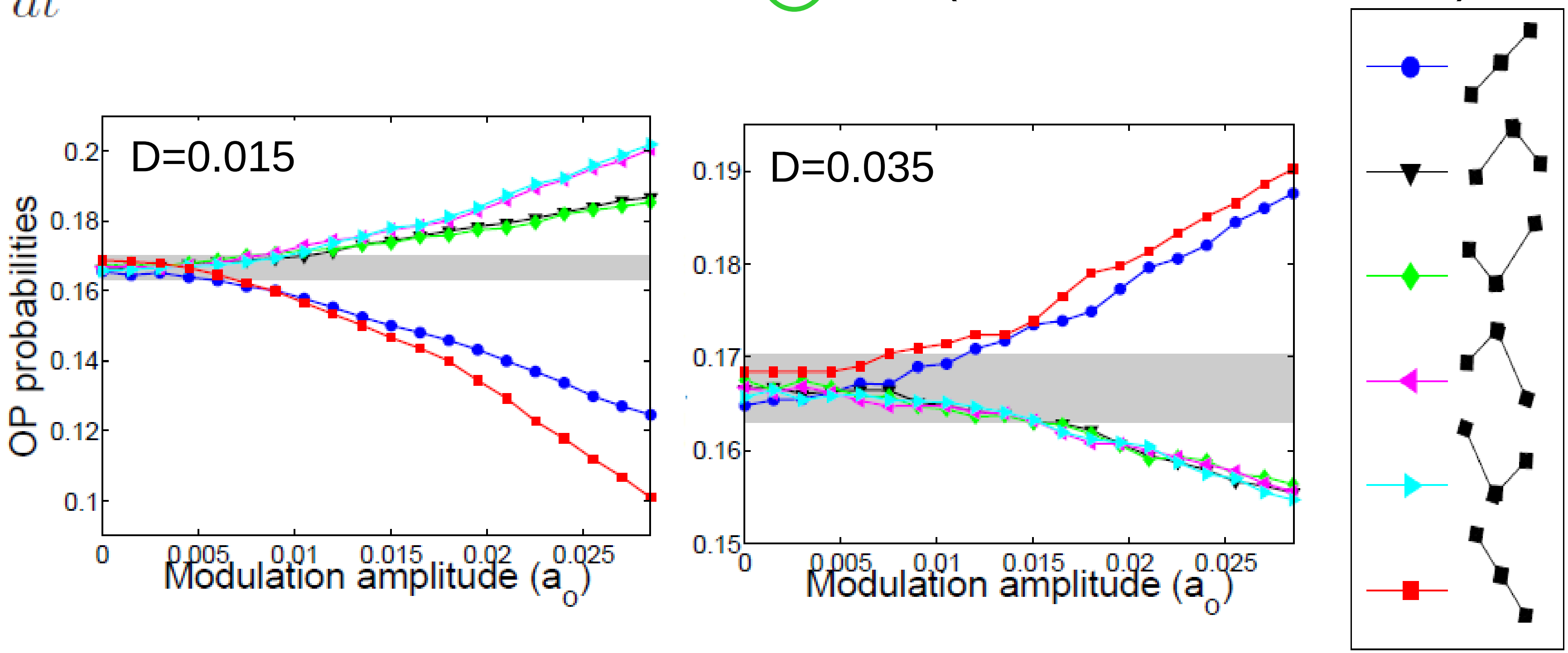
Analysis of spike sequences simulated with a simple neuron model (FitzHugh-Nagumo)

$$\epsilon \frac{dx}{dt} = x - \frac{x^3}{3} - y,$$

$$\frac{dy}{dt} = x + a + \boxed{a_o \cos(2\pi t/T)} + D\xi(t),$$

Weak, **subthreshold** input

Neural noise
(uncorrelated, Gaussian)



Gray region: NH with 99.74% confidence level

J. A. Reinoso, M. C. Torrent, and C. Masoller, Phys. Rev. E. 94, 032218 (2016).

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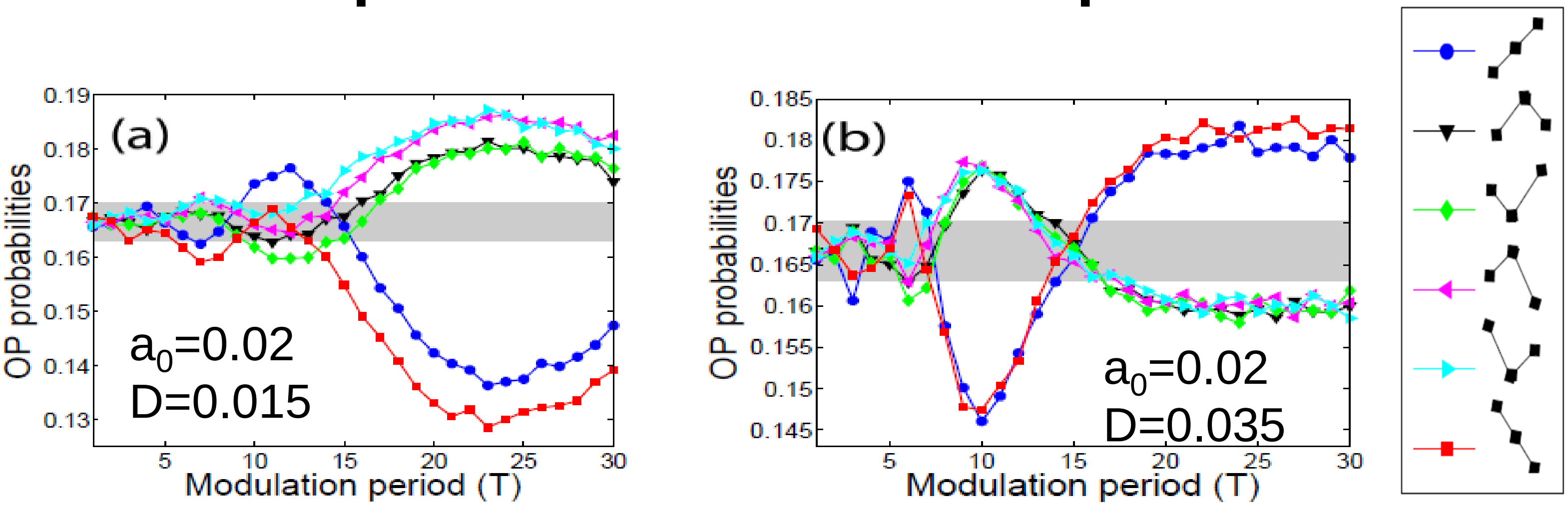
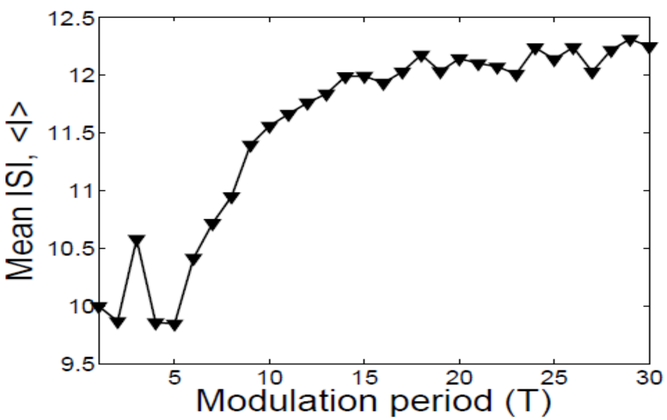
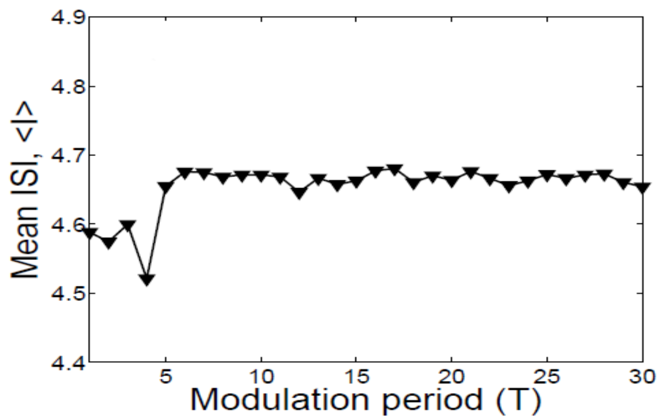
Role of the period of the external input



⇒ More probable patterns depend on period and noise strength.

Which is the underlying mechanism? A change of the spike rate?





⇒ No direct relation.

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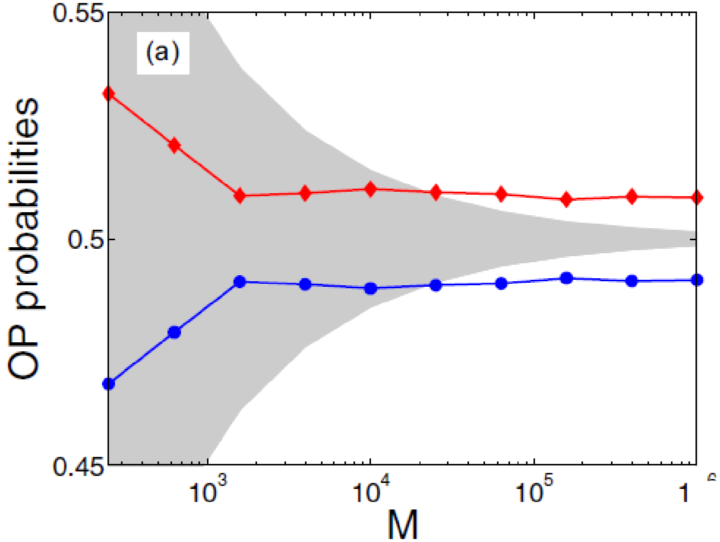
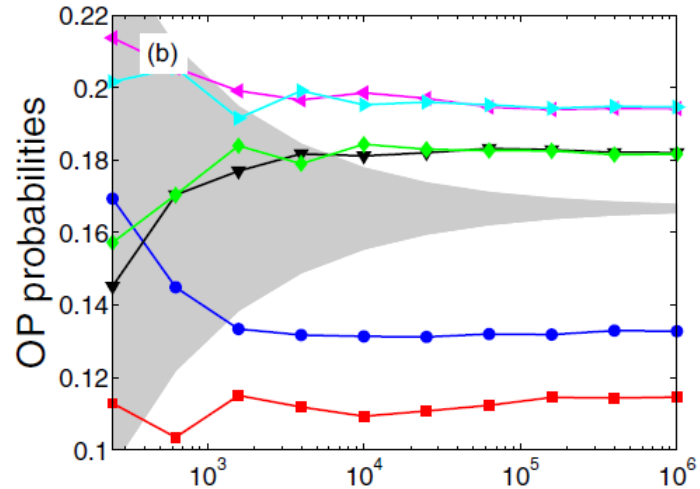
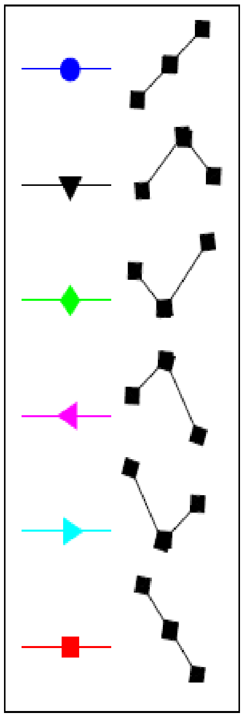
How many spikes do we need to estimate the probabilities?

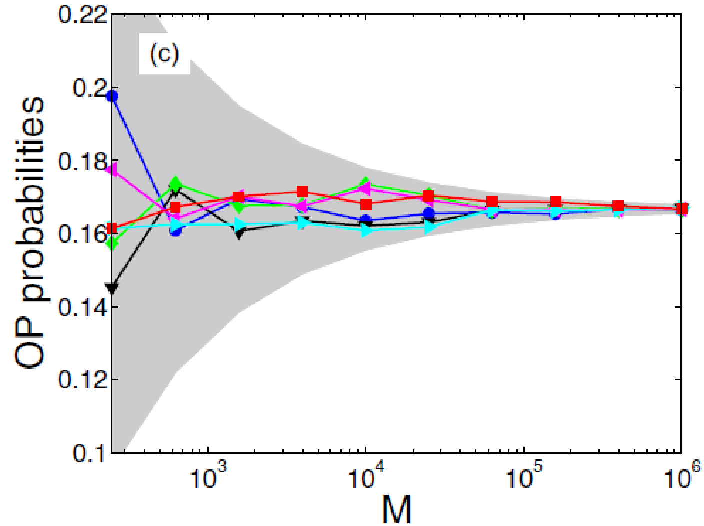
With external signal **01** **10**







Without external signal



Gray region: NH with 99.74% confidence level

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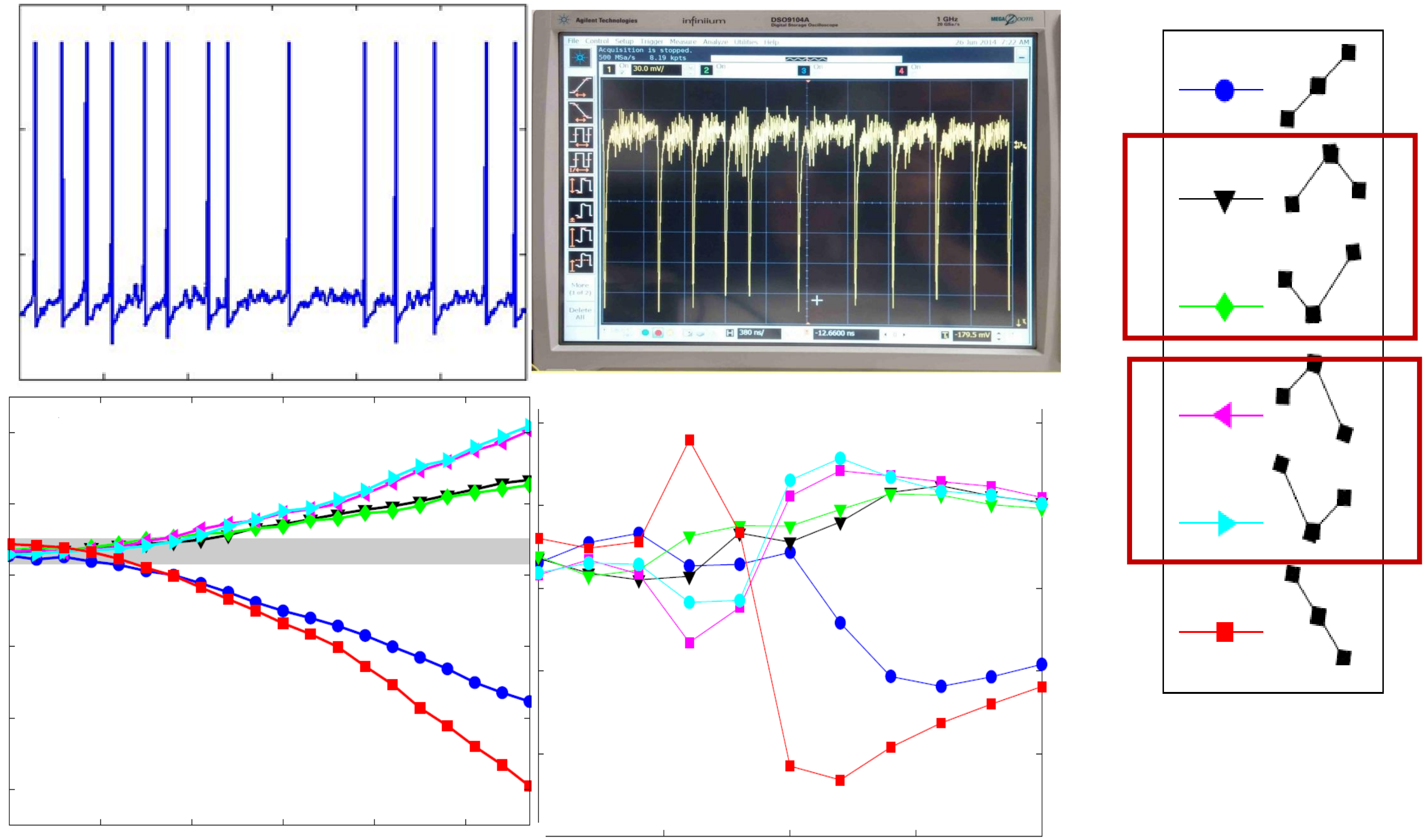
Ordinal probabilities uncover similarities between neuronal spikes and optical spikes

Neuron model **Diode laser**

Ordinal probabilities



Forcing amplitude Forcing amplitude

J. M. Aparicio-Reinoso et al PRE 94, 032218 (2016) A. Aragoneses et al, Sci. Rep. **4**, 4696 (2014)

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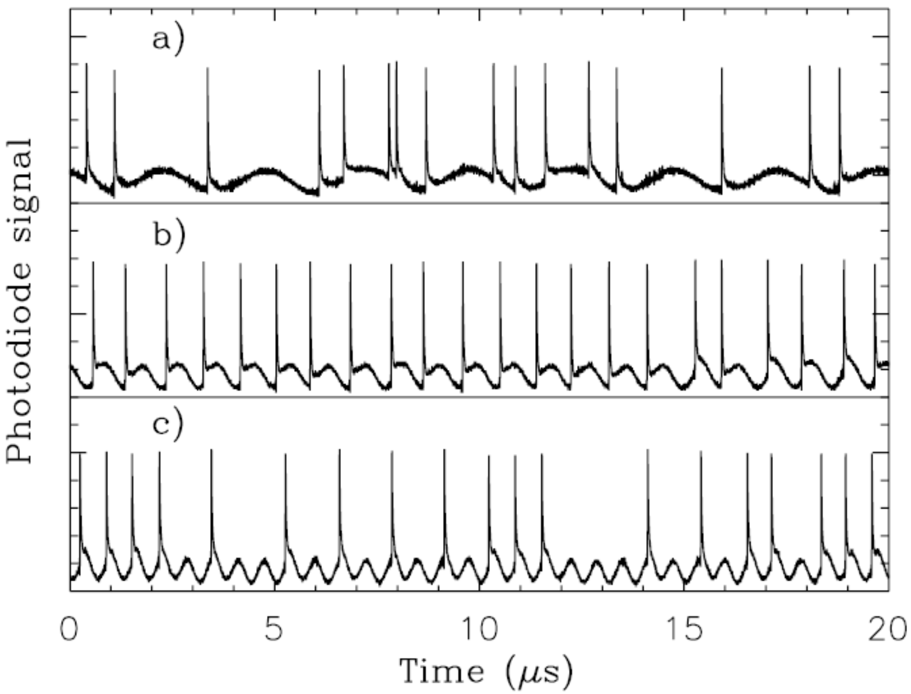
“Stochastic resonance” (SR) has been observed in diode lasers

VOLUME 88, NUMBER 4 PHYSICAL REVIEW LETTERS 28 JANUARY 2002

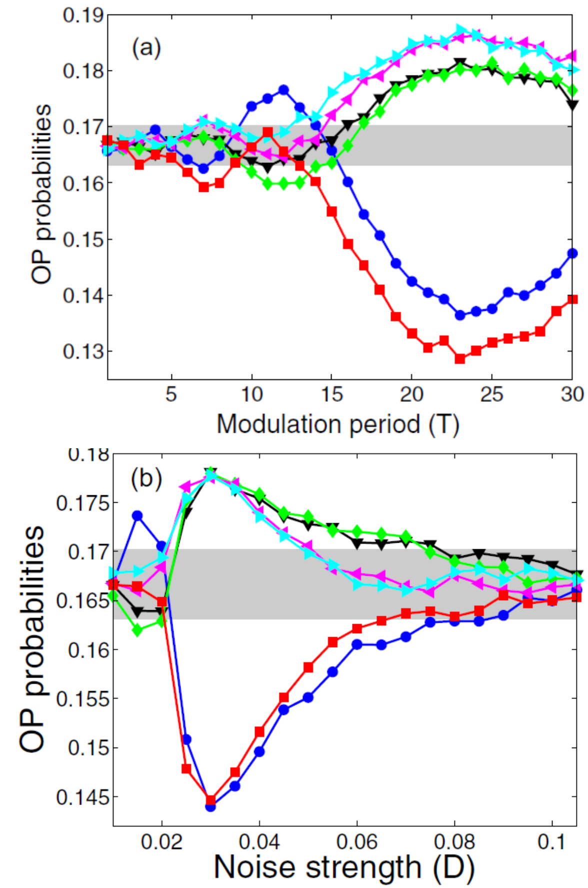
Experimental Evidence of Stochastic Resonance in an Excitable Optical System

Francesco Marino, Massimo Giudici,* Stéphane Barland,† and Salvador Balle
Department de Física Interdisciplinar, Instituto Mediterráneo de Estudios Avanzados (CSIC-UIB), C/ Miquel Marqués 21, E-07190 Esporles, Spain
(Received 1 August 2001; published 10 January 2002)



(varying the frequency of the sinusoidal signal applied to the laser current)

SR also in the neuron model (FitzHugh-Nagumo)



J. M. Aparicio-Reinoso et al. PRE 94, 032218 (2016).

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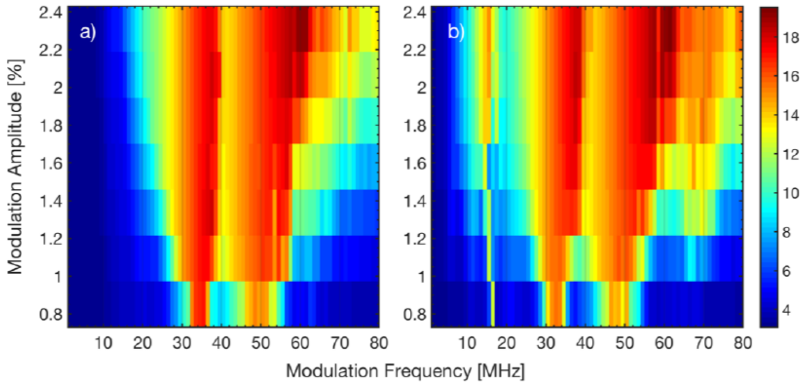
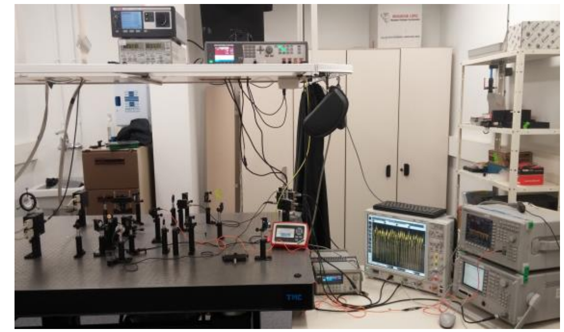
Laser-neuron comparison: a small-amplitude periodic signal encoded in the spike rate

Spike rate in color code

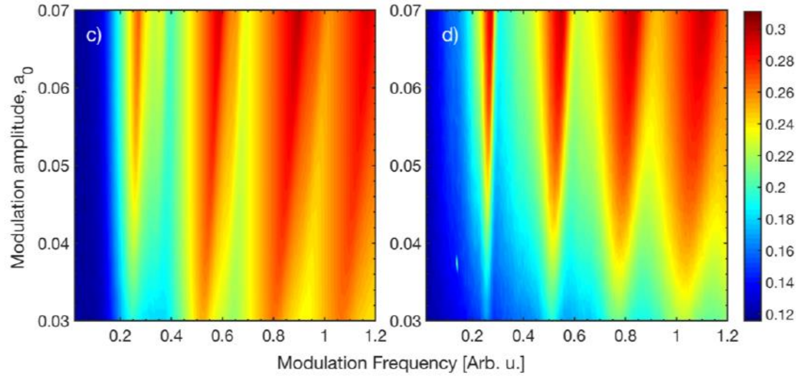
Sinusoidal Pulsed signal

Experiments modulating the laser current





Neuron model with the same input signal



$$\varepsilon \frac{dx}{dt} = x - \frac{x^3}{3} - y\,,$$

$$\frac{dy}{dt} = x + a + D\xi(t)\,.$$

J. Tiana-Alsina, C. Quintero-Quiroz and C. Masoller, "*Comparing the dynamics of periodically forced lasers and neurons*", New J. of Phys. 21, 103039 (2019) (2019).
J. Tiana-Alsina, C. Masoller, "*Time crystal dynamics in a weakly modulated stochastic time delayed system*", Sci. Rep. 12, 4914 (2022).

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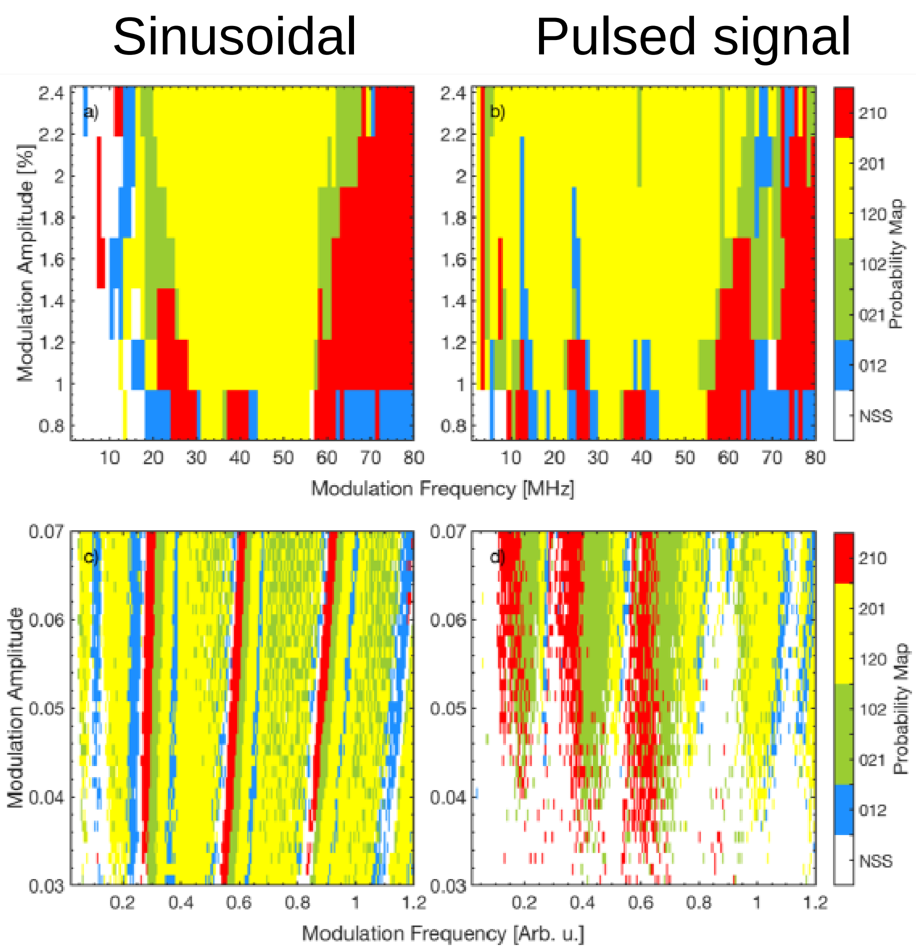
How about the temporal code?

Ordinal analysis uncovers statistical differences in spike timing.

Diode laser with optical feedback

FitzHugh-Nagumo model



Most probable pattern in color code

J. Tiana-Alsina, C. Quintero-Quiroz and C. Masoller, New J. of Phys. 21, 103039 (2019).

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Single-neuron vs ensemble encoding

- Single-neuron encoding: **slow** because long spike sequences are needed to estimate the ordinal probabilities.
- Ensemble encoding: can be much **faster** because, from the ISI sequences of all the neurons, few spikes per neuron can be enough to accurately estimate the probabilities.

subthreshold input

$$\epsilon \dot{u}_i = u_i - \frac{u_i^3}{3} - v_i + a_0 \cos(2\pi t/T) + \frac{\sigma}{k_i}\sum_j^N a_{ij}(u_j - u_i) + \sqrt{2D}\xi_i(t), \qquad i \neq j$$

$$\dot{v}_i = u_i + a.$$

$k_i = \sum_j a_{ij}$

$a_{ij} = a_{ji} = 1$
$a_{ij} = a_{ji} = 0$ Random with prob. ***p***

M. Masoliver and C. Masoller, "*Neuronal coupling benefits the encoding of weak periodic signals in symbolic spike patterns*", Commun. Nonlinear Sci. Numer. Simulat. 88, 105023 (2020).

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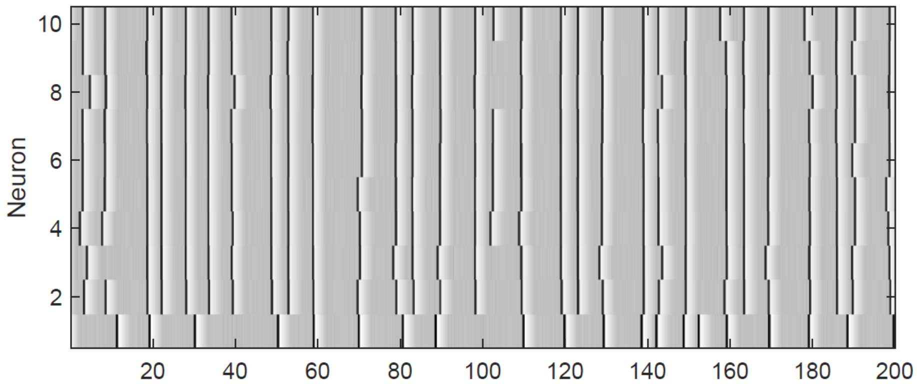
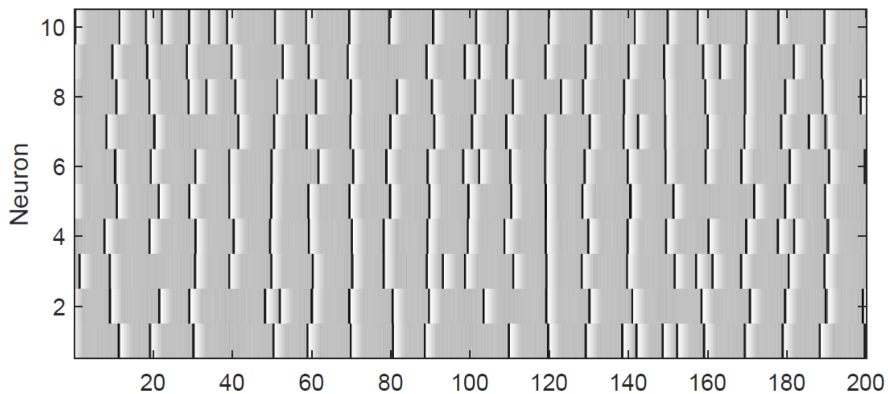
Spiking dynamics with/without coupling, with/without external input

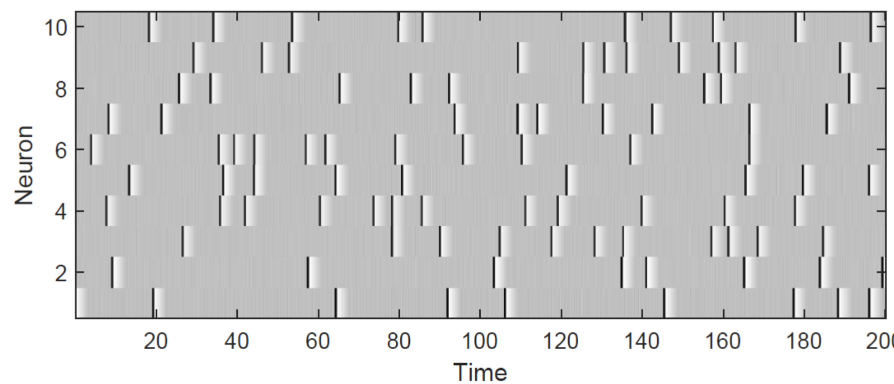
$\sigma \neq 0$
$a \neq 0$



$\sigma = 0$
$a \neq 0$



$\sigma = 0$
$a = 0$



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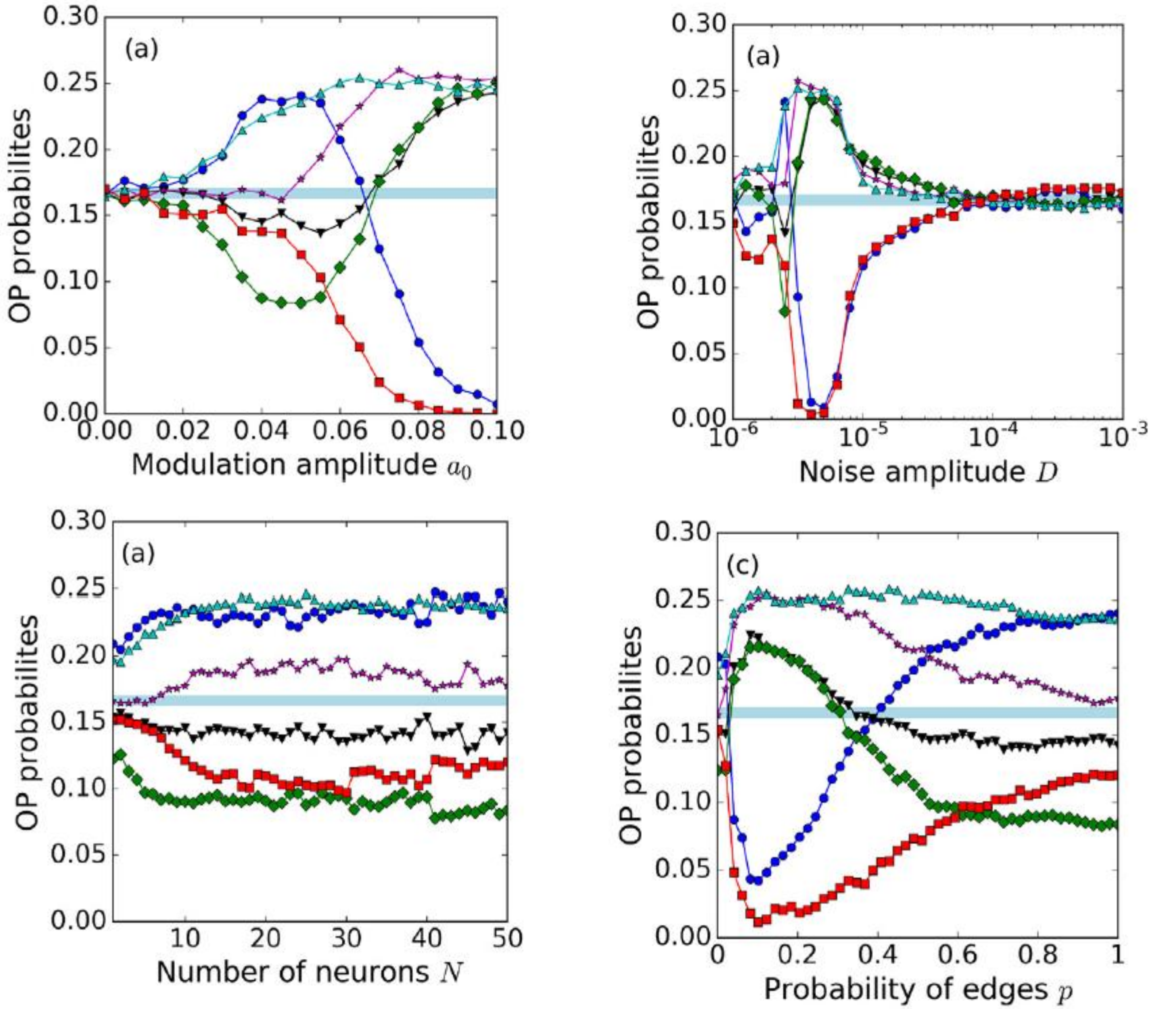
Ensemble encoding of a weak sinusoidal signal in the frequencies of occurrence of ordinal patterns



M. Masoliver and C. Masoller, Commun. Nonlinear Sci. Numer. Simulat. 88, 105023 (2020).

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Take home messages and outlook

- When a neuron perceives a subthreshold sinusoidal input, the ordinal probabilities carry information of the amplitude and period of the input.
- Noise can optimize the encoding of the input.
- The input can not be too slow or too fast.
- A population of neurons can also encode the signal in the probabilities of ordinal patterns.

Ongoing work:

- Can we "decode" the signal's information?

Promising results: B. R. R. Boaretto, E. Macau, C. Masoller, "*Characterizing the spike timing of a chaotic laser by using ordinal analysis and machine learning*", Chaos 34, 043108 (2024)

Thank you for your attention!

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