Subthreshold signal encoding by neuronal populations

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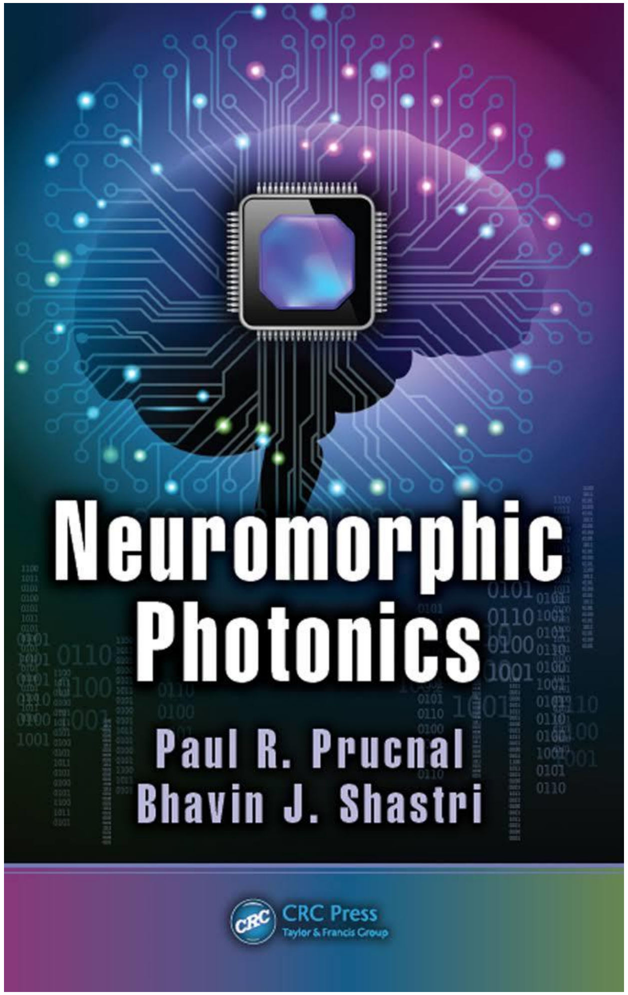
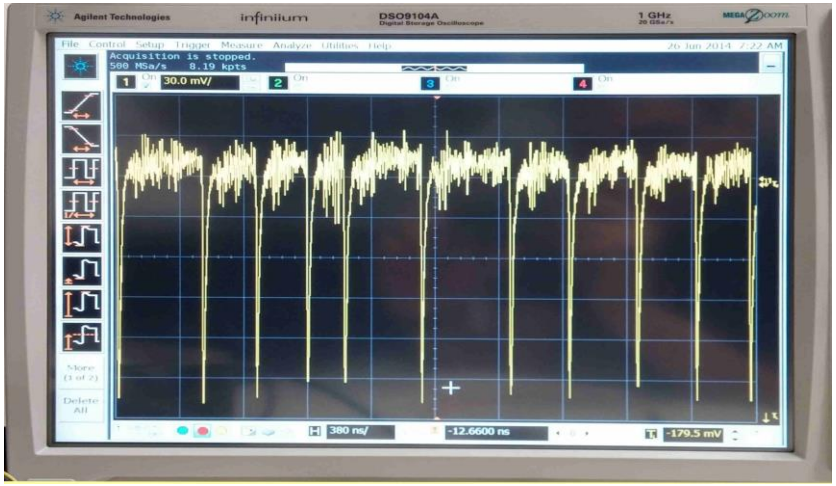
Photonic neurons

Spiking lasers could be the building blocks of ultra-fast, energy-efficient optical information processing systems.



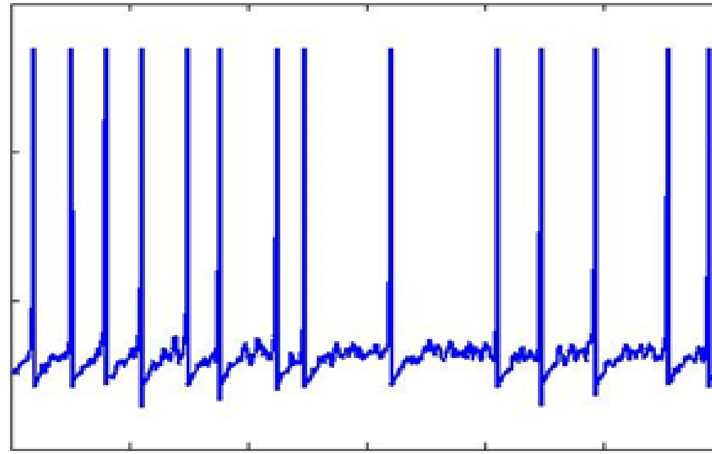
Can lasers mimic real neurons?

Laser spikes



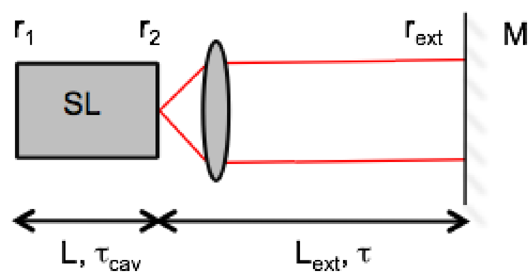
Time (μs)

Neuronal spikes

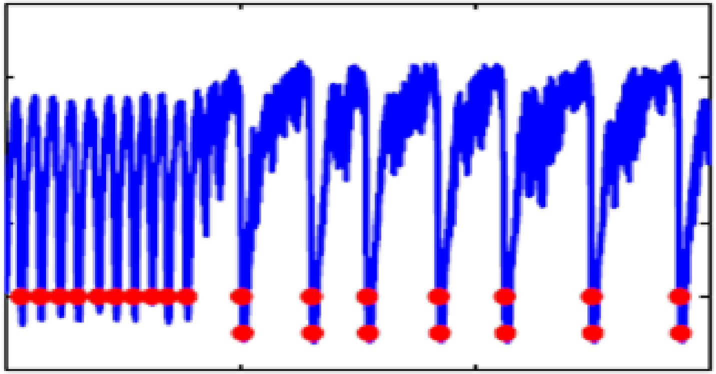


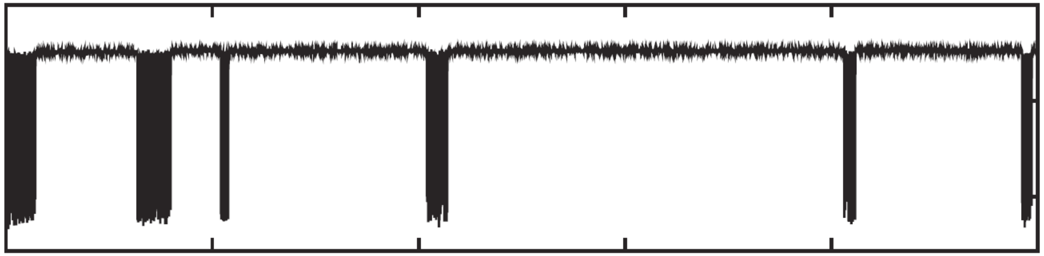
Time (ms)

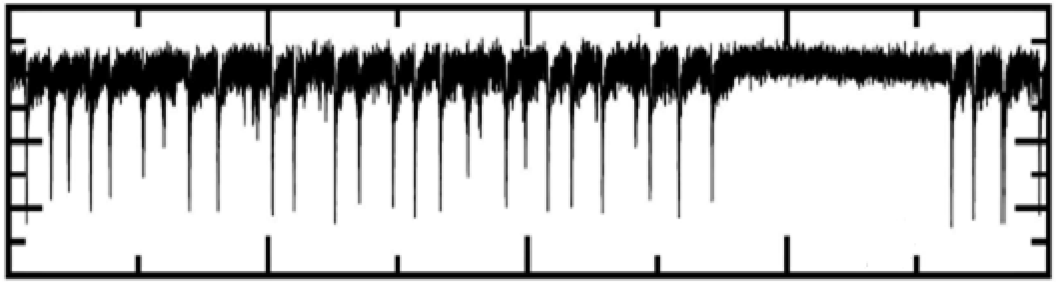
- Inexpensive laser diodes (perturbed by optical feedback).



The laser dynamics: excitability, tonic spikes and bursting. Similar to real neurons?



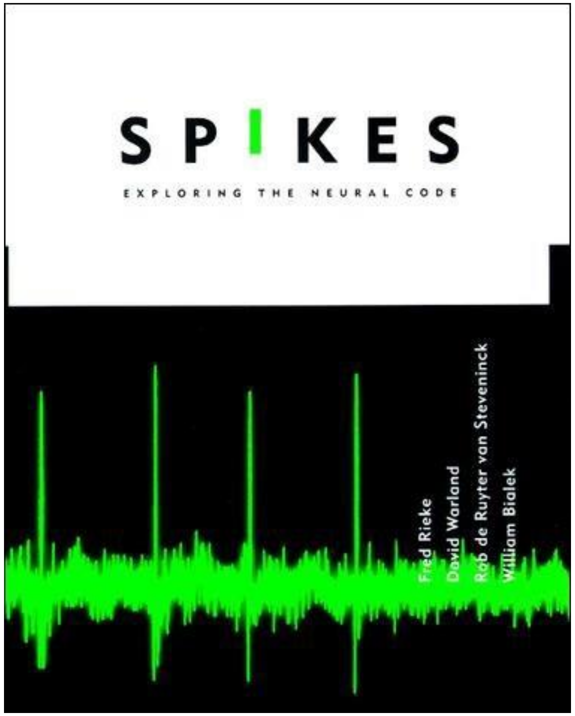




A. Aragoneses, S. Perrone, T. Sorrentino, M. C. Torrent and C. Masoller, "*Unveiling the complex organization of recurrent patterns in spiking dynamical systems*", Sci. Rep. **4**, 4696 (2014).

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).

How neurons encode information?

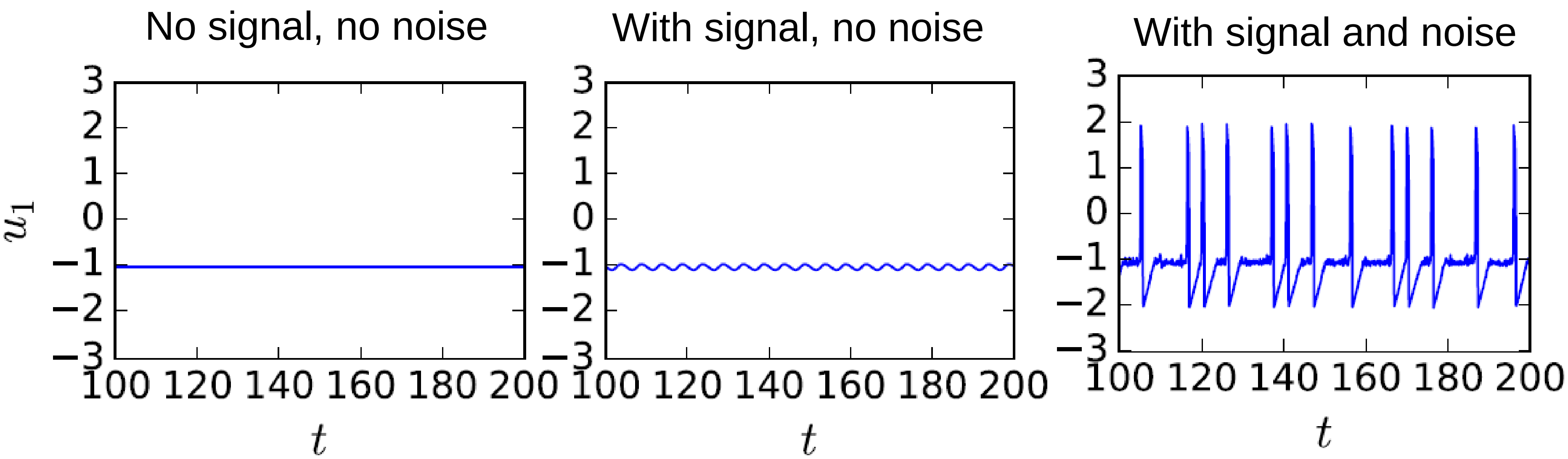


- In the spike **rate**?
- In the relative **timing** of the spikes?
- **Single** neuron encoding or **ensemble** encoding?

- **Cracking (deciphering) the neural code:** important for neuroscience, and also, for building photonic neurons (neuro-inspired optical computing & information processing systems).

Our goal

Try to understand how neurons encode, in sequences of spikes, a weak (subthreshold) signal, in the presence of noise.

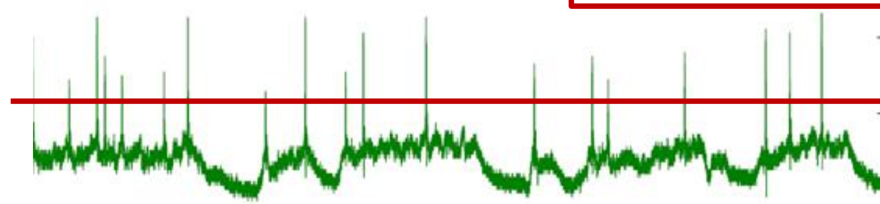


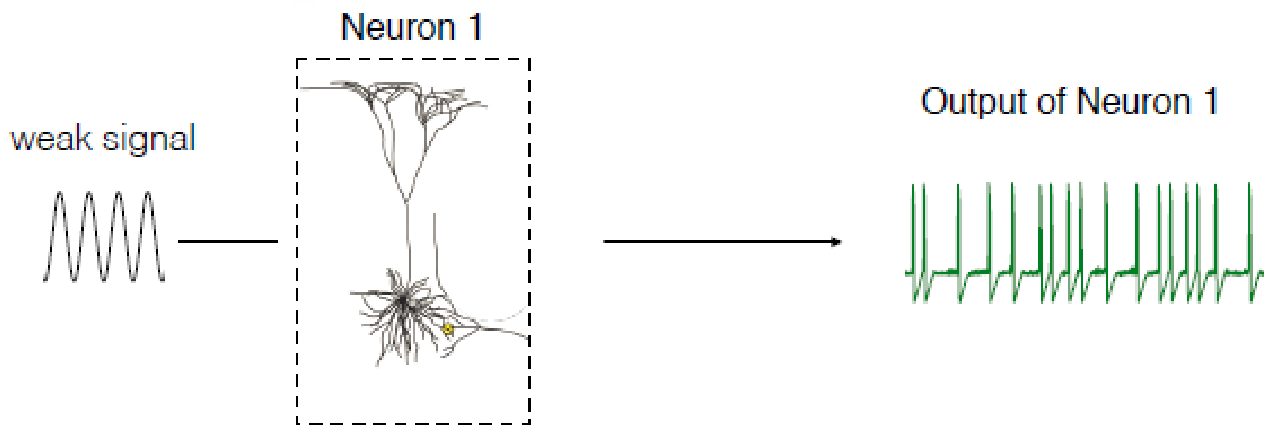
Outline

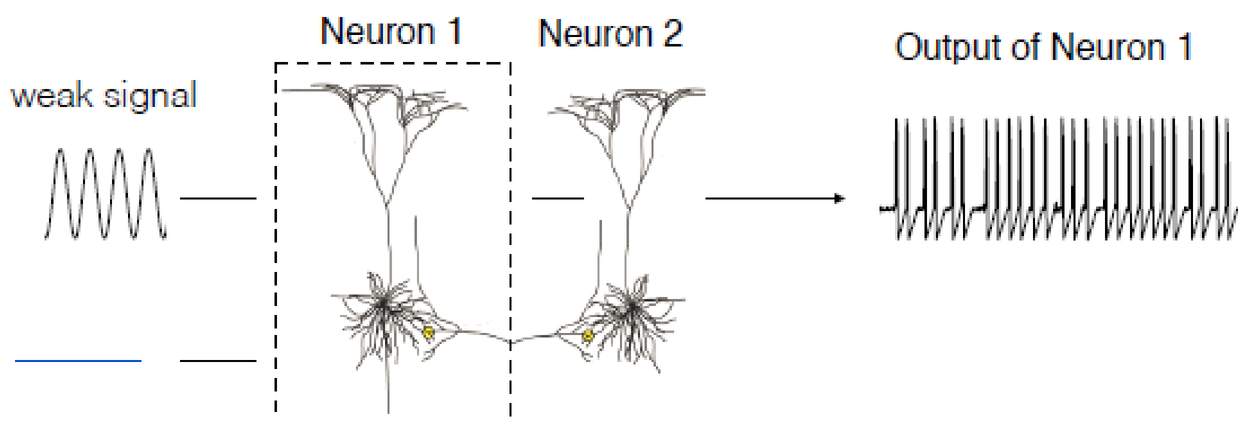
- Symbolic method of analysis of ISI sequences
- Single neuron
- Two coupled neurons
- Neuronal ensemble

$$\{\ldots I_{i-1}, I_i, I_{i+1} \ldots\}$$

inter-spike-intervals $\boxed{I_i = t_{i+1} - t_i}$





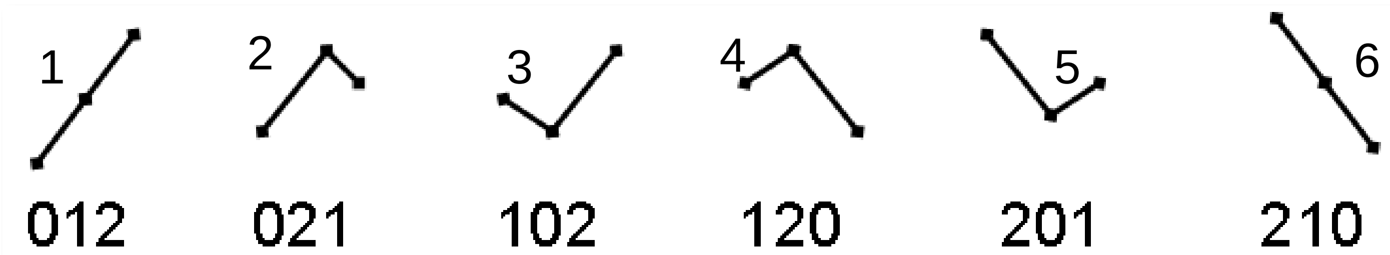


Ordinal time-series analysis

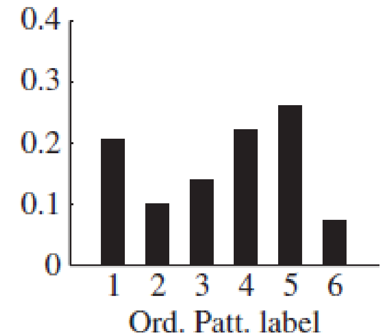
Relative order of three consecutive inter-spike-intervals

$\boxed{I_i = t_{i+1} - t_i}$

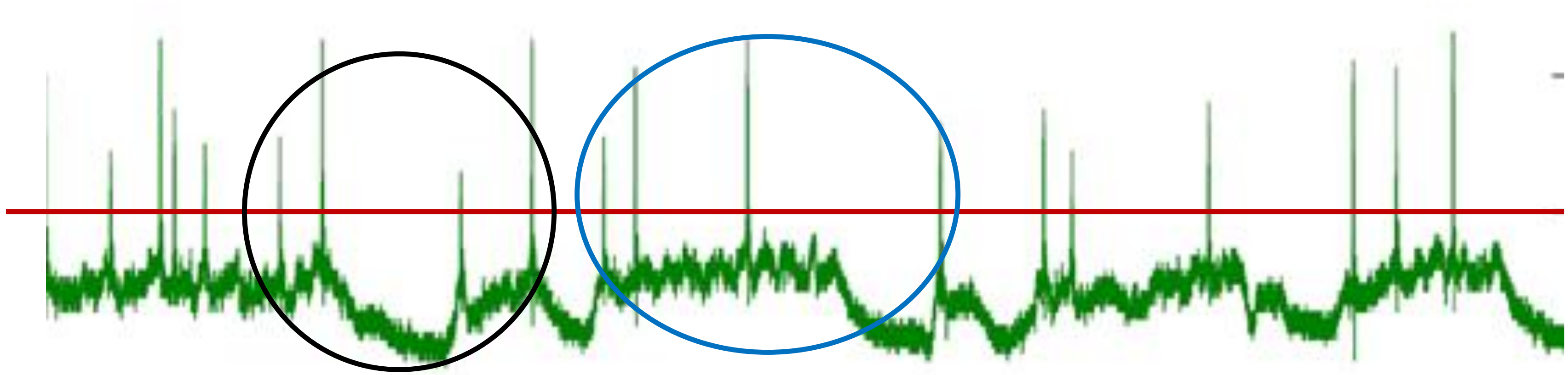
$\{\ldots I_i, I_{i+1}, I_{i+2}, \ldots\}$



Ordinal probabilities



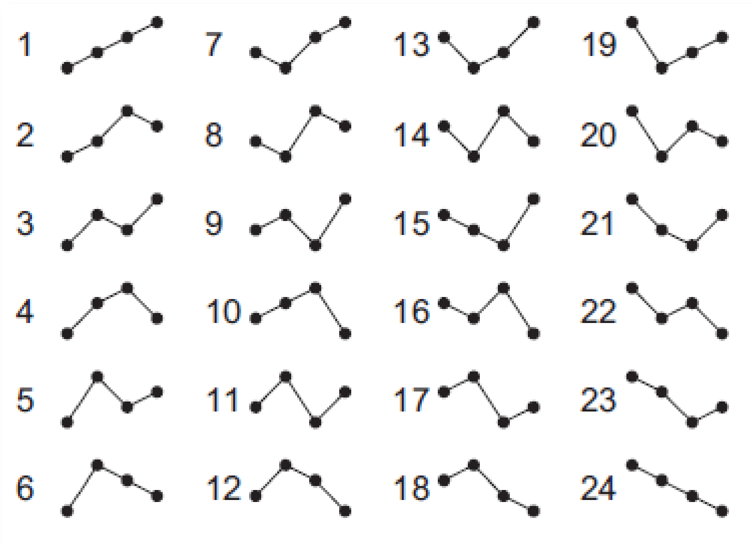
Example: (5, 1, 7) gives “102” because 1 < 5 < 7

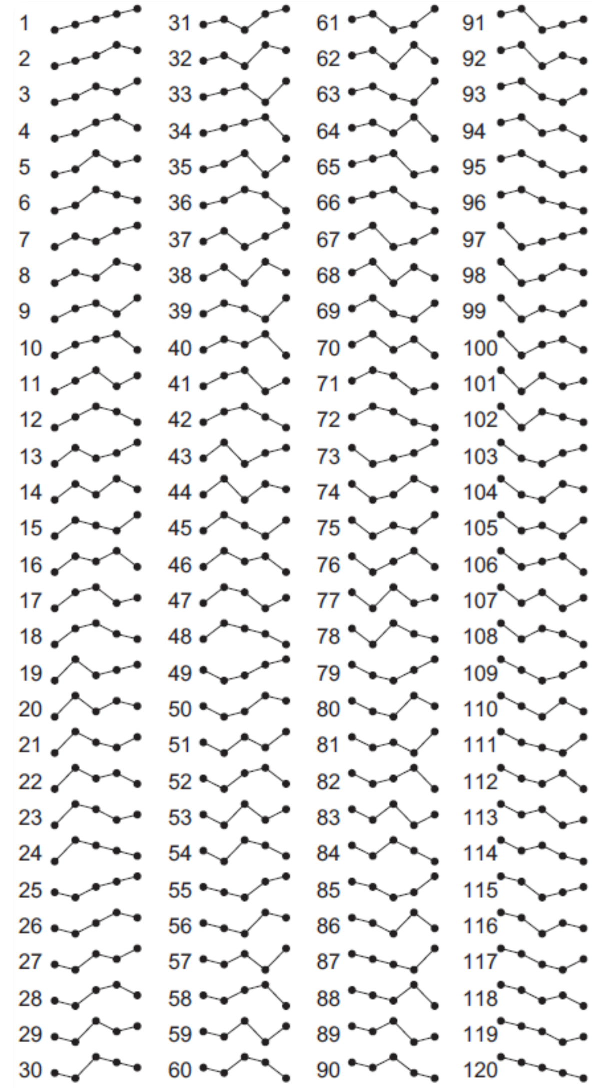


021 **012**

Brandt & Pompe, PRL 88, 174102 (2002)

The number of ordinal patterns increases as D!





- A problem for short datasets
- How to select D? it depends on:
  - The length of the data
  - The length of the correlations
- How to condense the information?

  Permutation entropy: $PE = -\sum_i p_i \ln p_i$

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

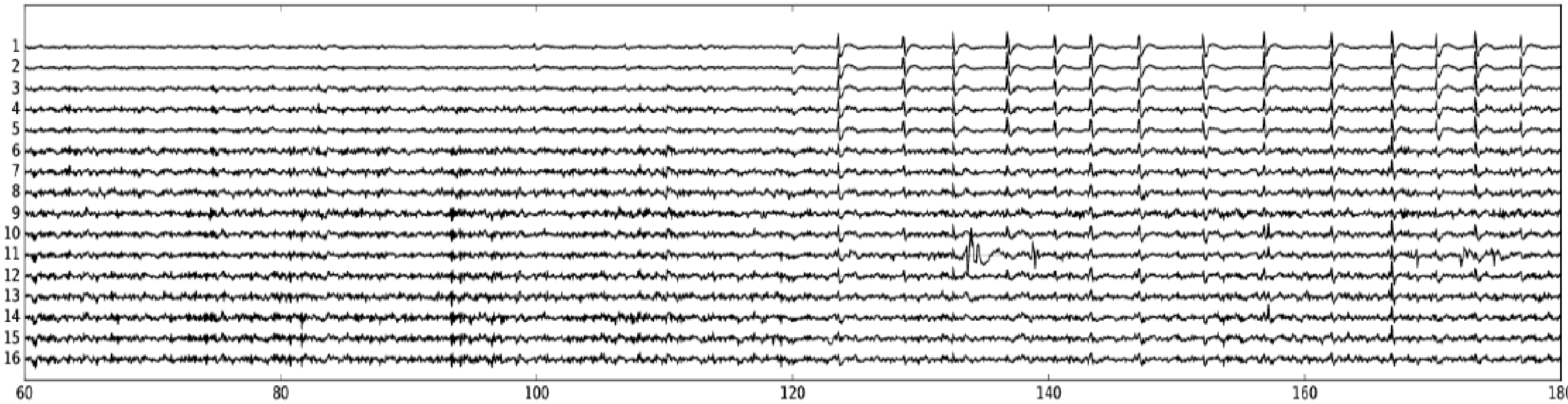
Example of application: distinguishing *eyes closed* and *eyes open* brain states

Analysis of two EEG datasets

	BitBrain DTS1	PhysioNet DTS2
Sampling rate(Hz)	256	160
Time task(seg)	120	60
Total points	30720	9600
Number of electrodes	16	64
Number of subjects	70	109

C. Quintero-Quiroz et al, "*Differentiating resting brain states using ordinal symbolic analysis*", Chaos 28, 106307 (2018)

Eye closed Eye open

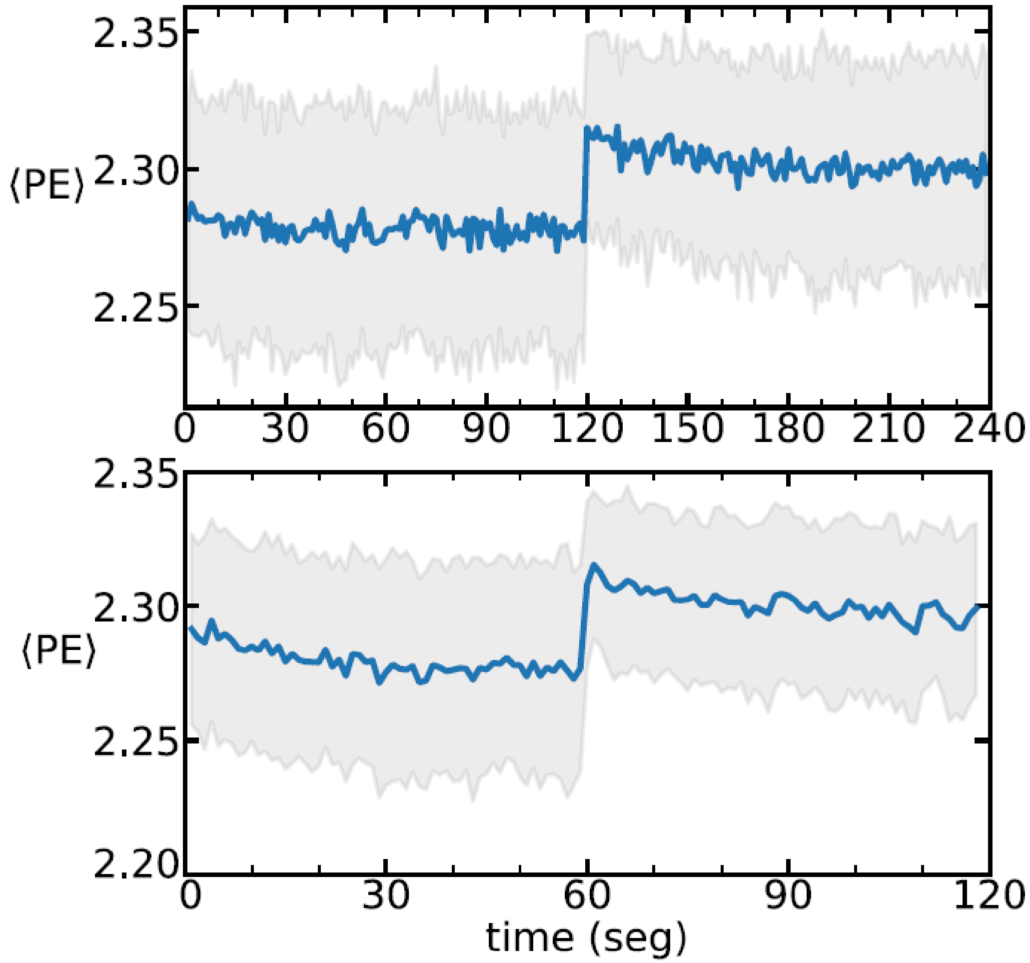


- Ordinal analysis (D=4) was applied to the raw data; no preprocessing needed.

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

- Non-overlapping windows of 1 s $\Rightarrow$ the number of data points in each window is 256 (160) for DTS1 (for DTS2).
- For DTS1 (DTS2), 16 (64) electrodes $\Rightarrow$ in each time window there are 4048 (10048) ordinal patterns.

Results



"Randomization": the entropy tends to increase when the person opens the eyes.

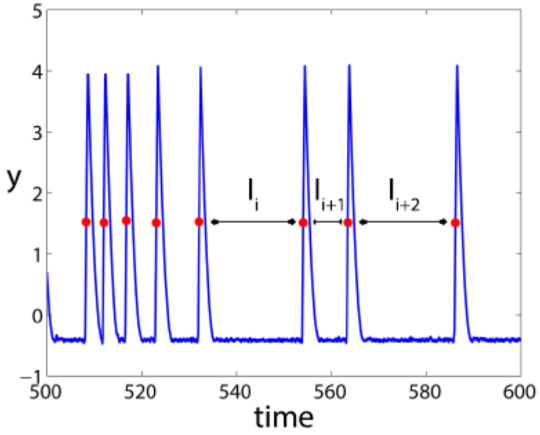
C. Quintero-Quiroz et al, "*Differentiating resting brain states using ordinal symbolic analysis*", Chaos 28, 106307 (2018)

Individual neuron

- more / less expressed patterns in spike sequences encode the information of a subthreshold signal?

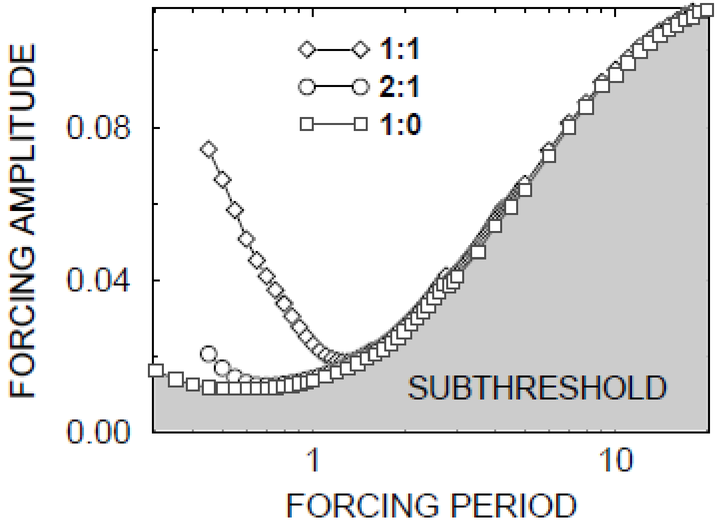
FitzHugh-Nagumo model

$$\epsilon \frac{dx}{dt} = x - \frac{x^3}{3} - y,$$
$$\frac{dy}{dt} = x + a + \boxed{a_o \cos(2\pi t/T)} + D\xi(t),$$



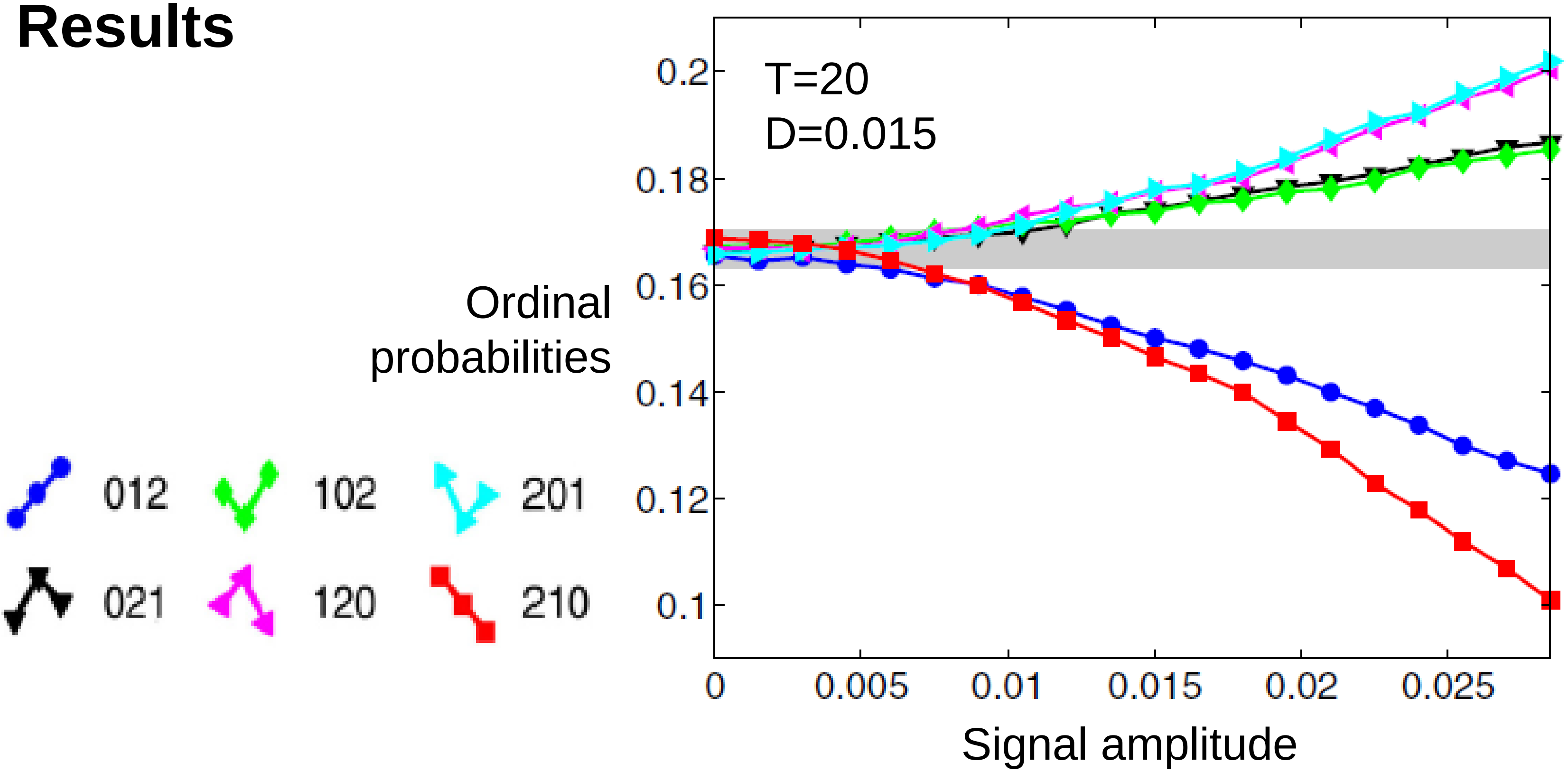
- Gaussian white noise and <u>subthreshold</u> signal: **a_0** and **T** such that spikes are **noise-induced**.

- Time series with M=100,000 spikes simulated (a=1.05, ε=0.01).



Longtin and Chialvo, PRL 1998

Results

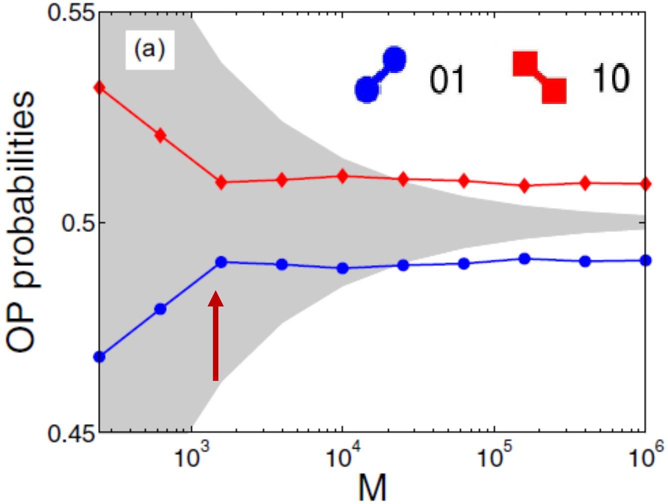


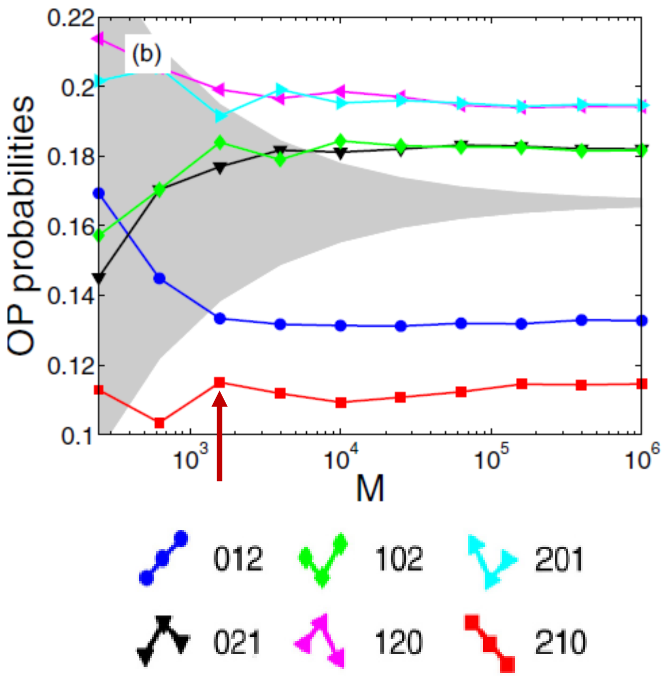
- Gray region: probabilities are consistent with p_i=1/6 i=1…6

J. M. Aparicio-Reinoso, M. C. Torrent and C. Masoller, PRE 94, 032218 (2016)

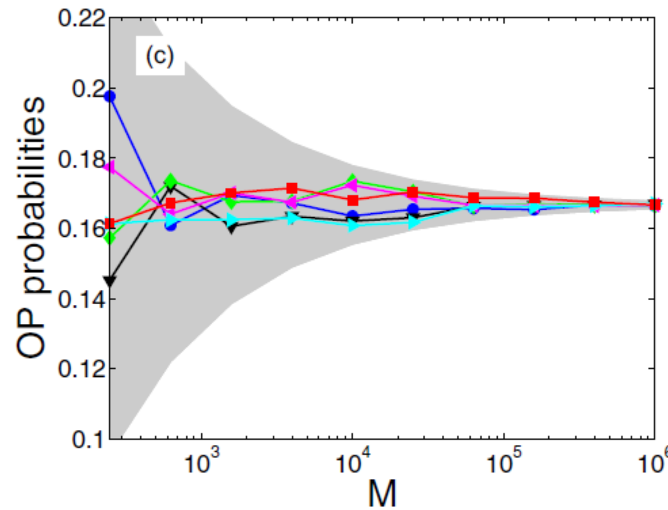
Data requirements

With signal



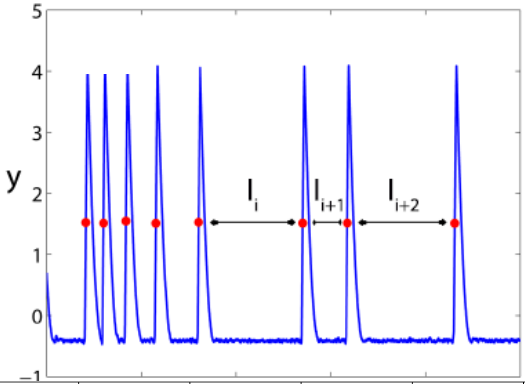


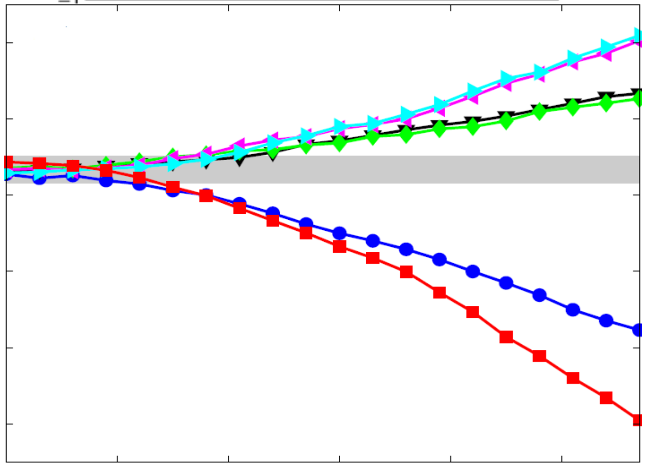
Without signal



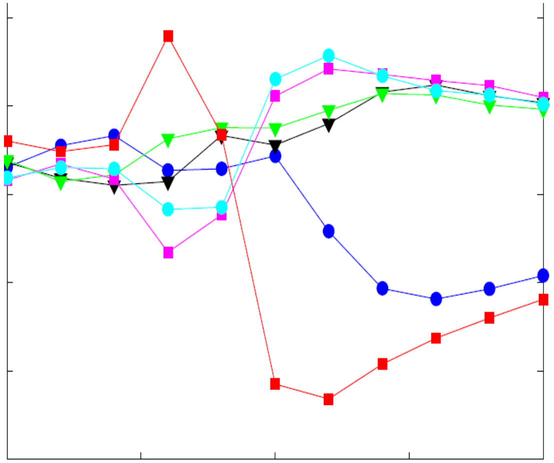
J. M. Aparicio-Reinoso et al PRE 94, 032218 (2016)

Comparison with the laser spikes, when sinusoidal modulation is applied to the laser pump current





Signal amplitude



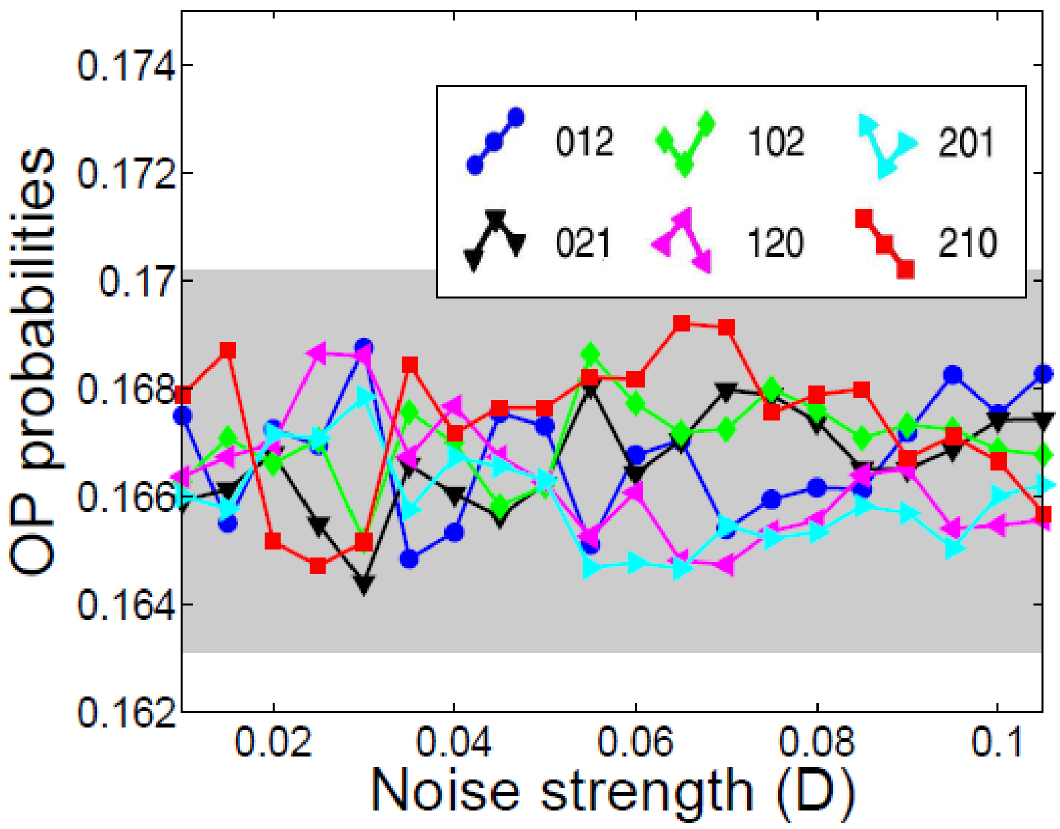
Signal amplitude

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

A. Aragoneses et al, Sci. Rep. **4**, 4696 (2014)

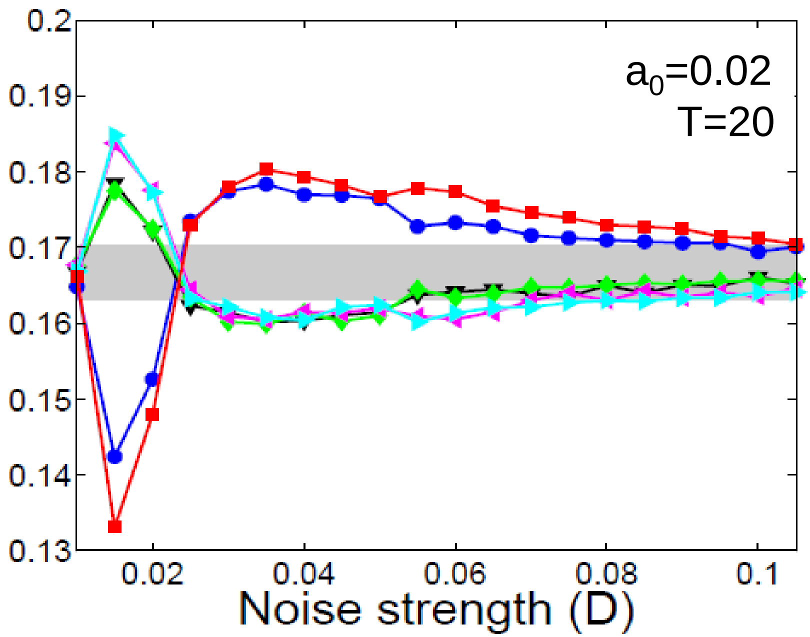
Role of the level of noise

a_0=0



No signal $\Rightarrow$ no temporal ordering in the sequence of spikes

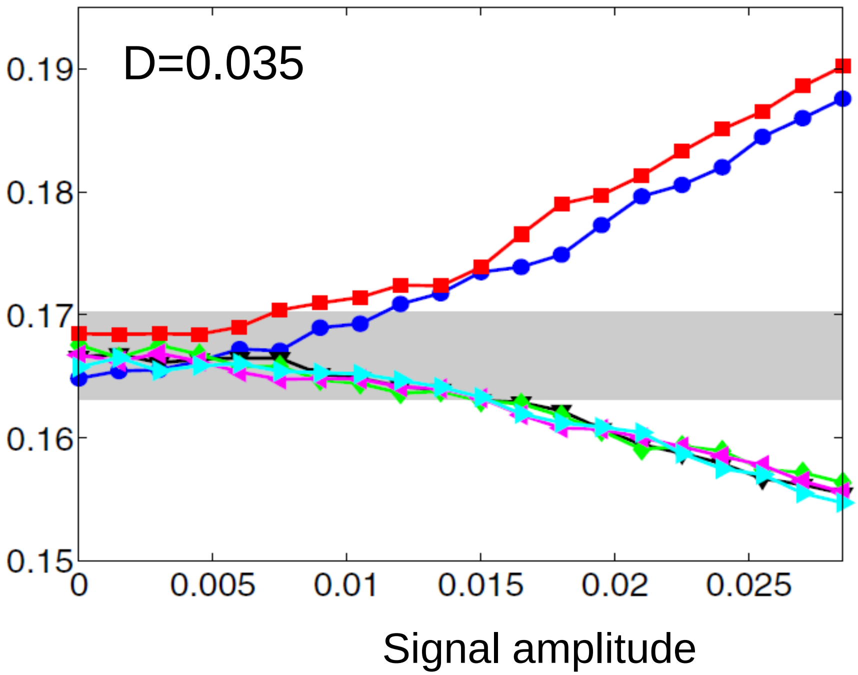
With external signal

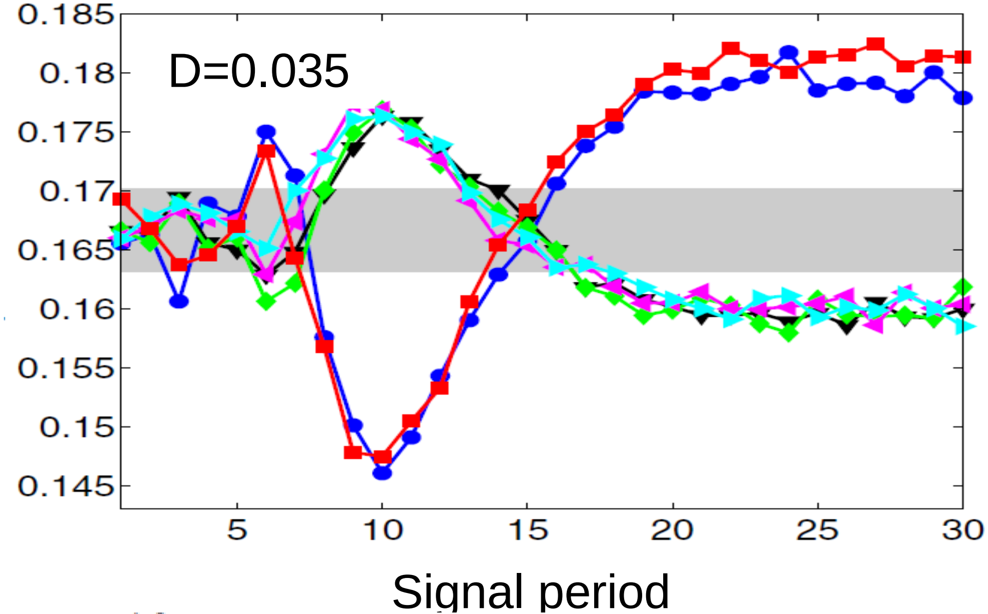


- The signal induces preferred and infrequent patterns.
- Resonant-like behavior.

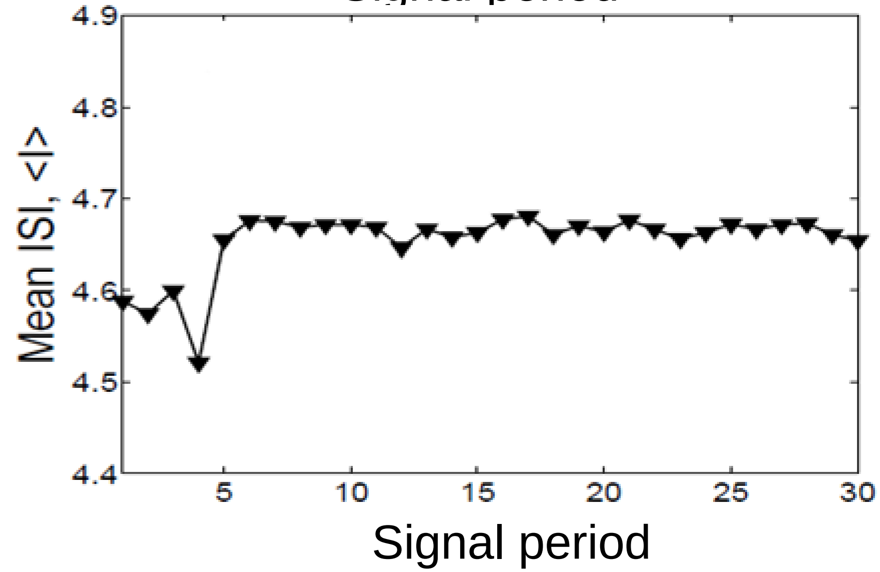
J. M. Aparicio-Reinoso M. C. Torrent and C. Masoller, PRE 94, 032218 (2016).

Probabilities vary linearly with (weak) signal amplitude
More/less expressed patterns depend on the signal period



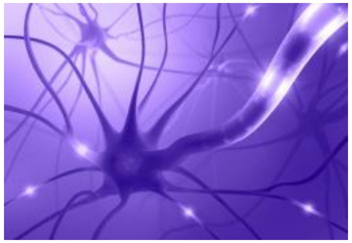
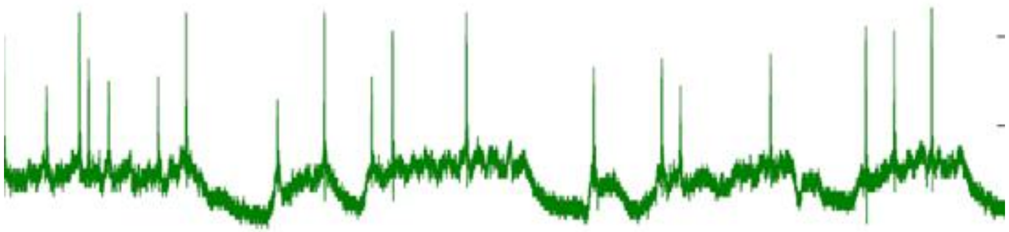


Which is the underlying mechanism?
A change of the mean inter-spike-interval (i.e. spike rate)?

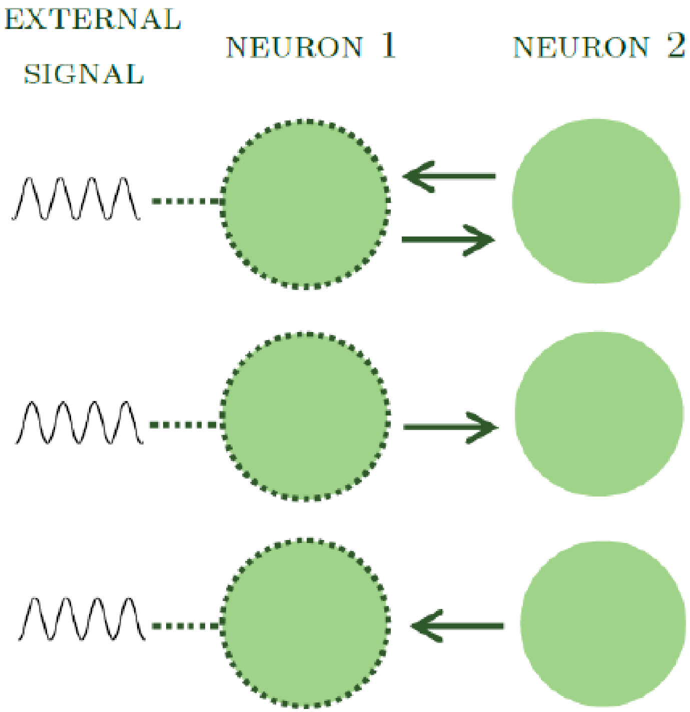


$\Rightarrow$ No direct relation

So… how neurons might encode a weak periodic input?


- The amplitude and the period of the signal might be encoded in more and less expressed patterns.
- <u>Single-neuron encoding</u>: very **slow** because long spike sequences are needed to estimate the probabilities.
- <u>Ensemble encoding</u>: can be **fast** because few spikes per neuron are enough to estimate the probabilities.



Coupling to a second neuron

- how does it affect signal encoding?

Model

$$\epsilon \dot{u}_1 = u_1 - \frac{u_1^3}{3} - v_1 + \boxed{a_0 \cos(2\pi t/T)} + \boxed{\sigma_1 u_2} + \sqrt{2D}\xi_1(t)$$

$$\dot{v}_1 = u_1 + a,$$

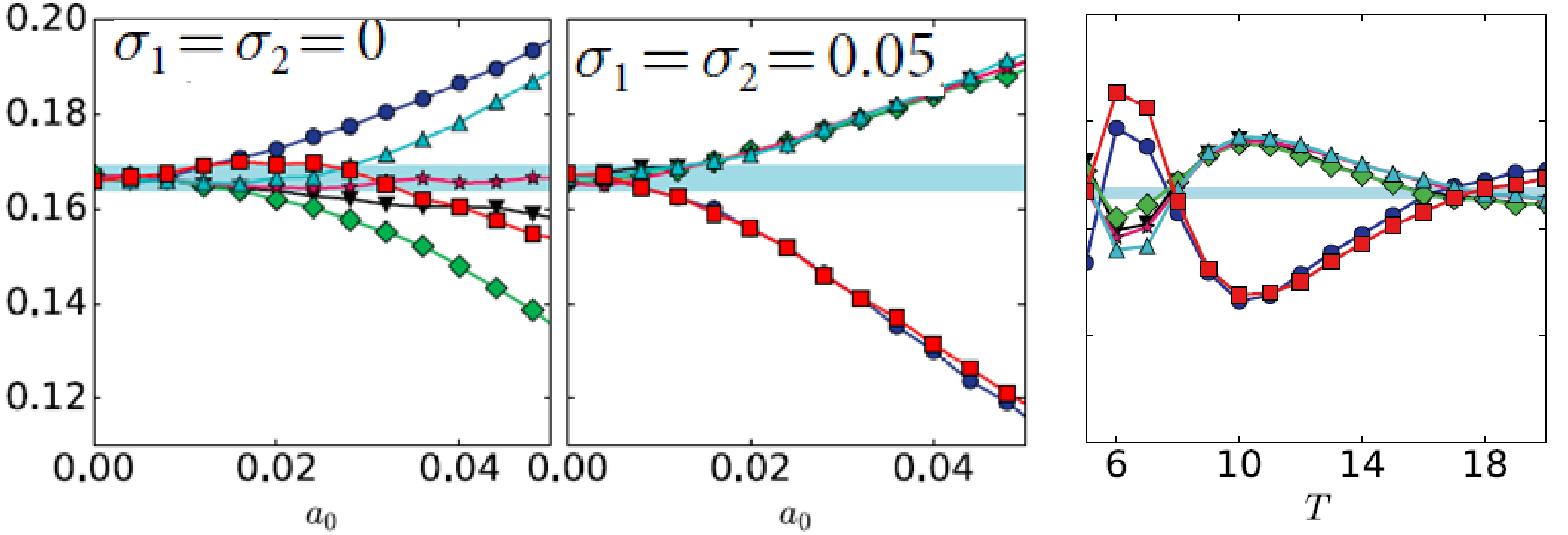
$$\epsilon \dot{u}_2 = u_2 - \frac{u_2^3}{3} - v_2 + \boxed{\sigma_2 u_1} + \sqrt{2D}\xi_2(t)$$

$$\dot{v}_2 = u_2 + a$$

- Identical neurons.
- Linear & instantaneous & asymmetric coupling
- Signal, coupling and noise in the fast variable.
- a=1.05 and ε=0.01; parameters: a_0, T, D, σ_1, σ_2

M. Masoliver and C. Masoller, Scientific Reports 8, 8276 (2018)

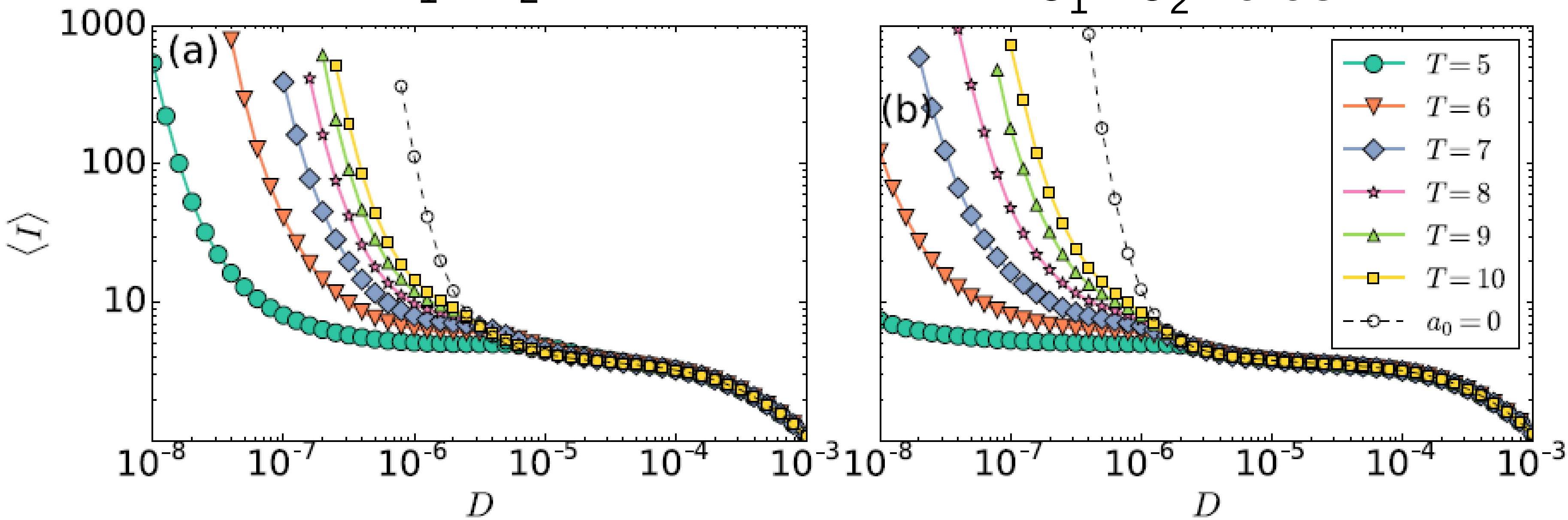
The probabilities depend on the amplitude and on the period of the signal



$\Rightarrow$ Coupling changes the preferred patterns.

Influence of the level of noise

$\sigma_1 = \sigma_2 = 0$ $\sigma_1 = \sigma_2 = 0.05$

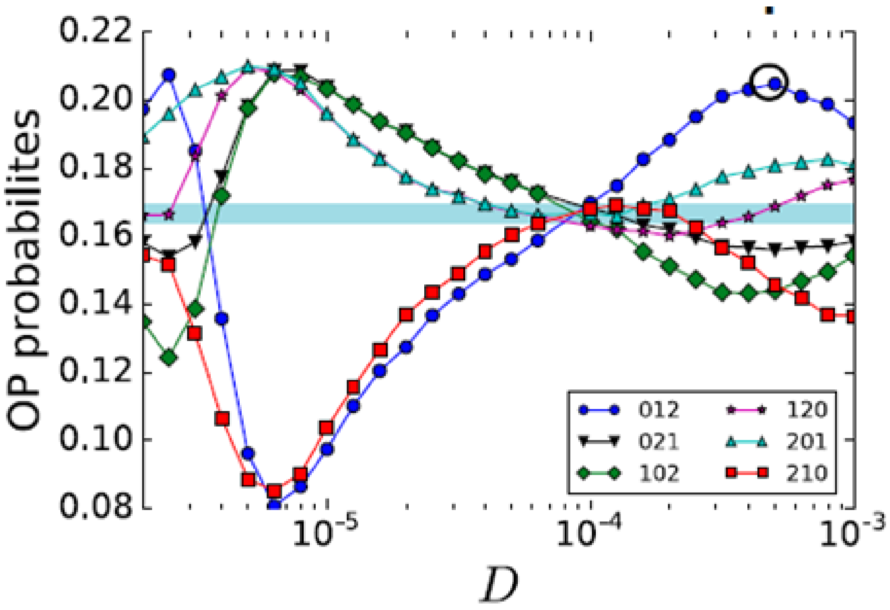


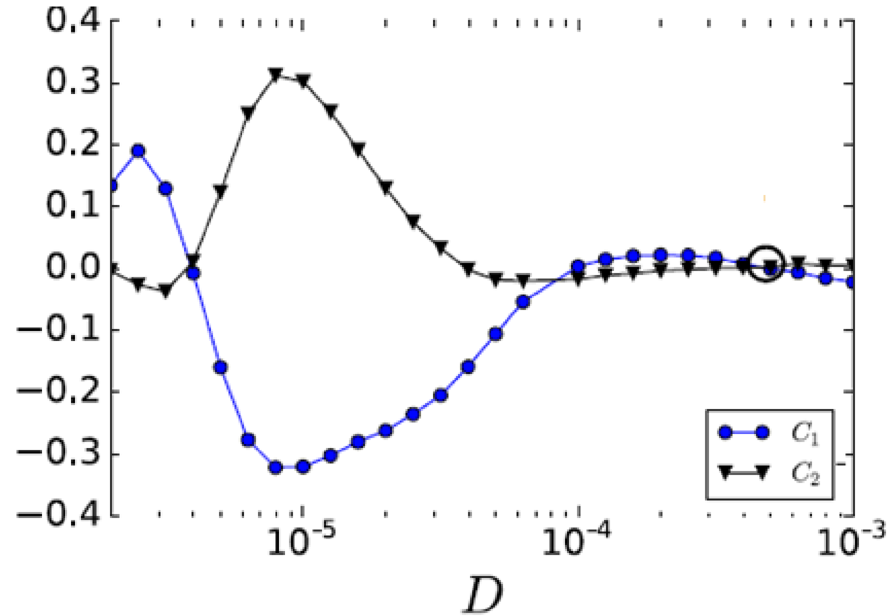
The spike rate (=1/<I>) does not encode the period of the signal.

Are the spike correlations captured by linear analysis?

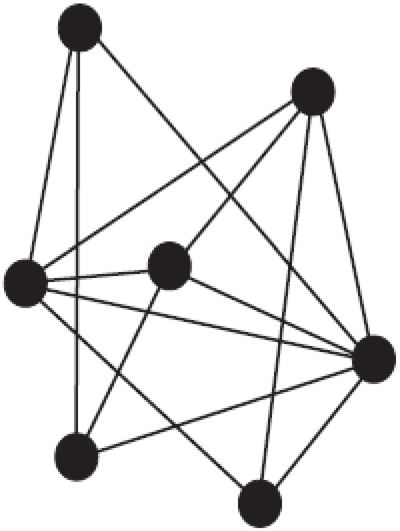
$a_0 = \sigma = 0.05$, T=8

$$C_j = \frac{\langle (I_i - \langle I \rangle)(I_{i-j} - \langle I \rangle) \rangle}{\sigma^2}$$





⇒ For strong noise, correlation coefficients at lag 1 and 2 vanish but ordinal analysis detects more / less expressed patterns.



Neuronal ensemble?

Model

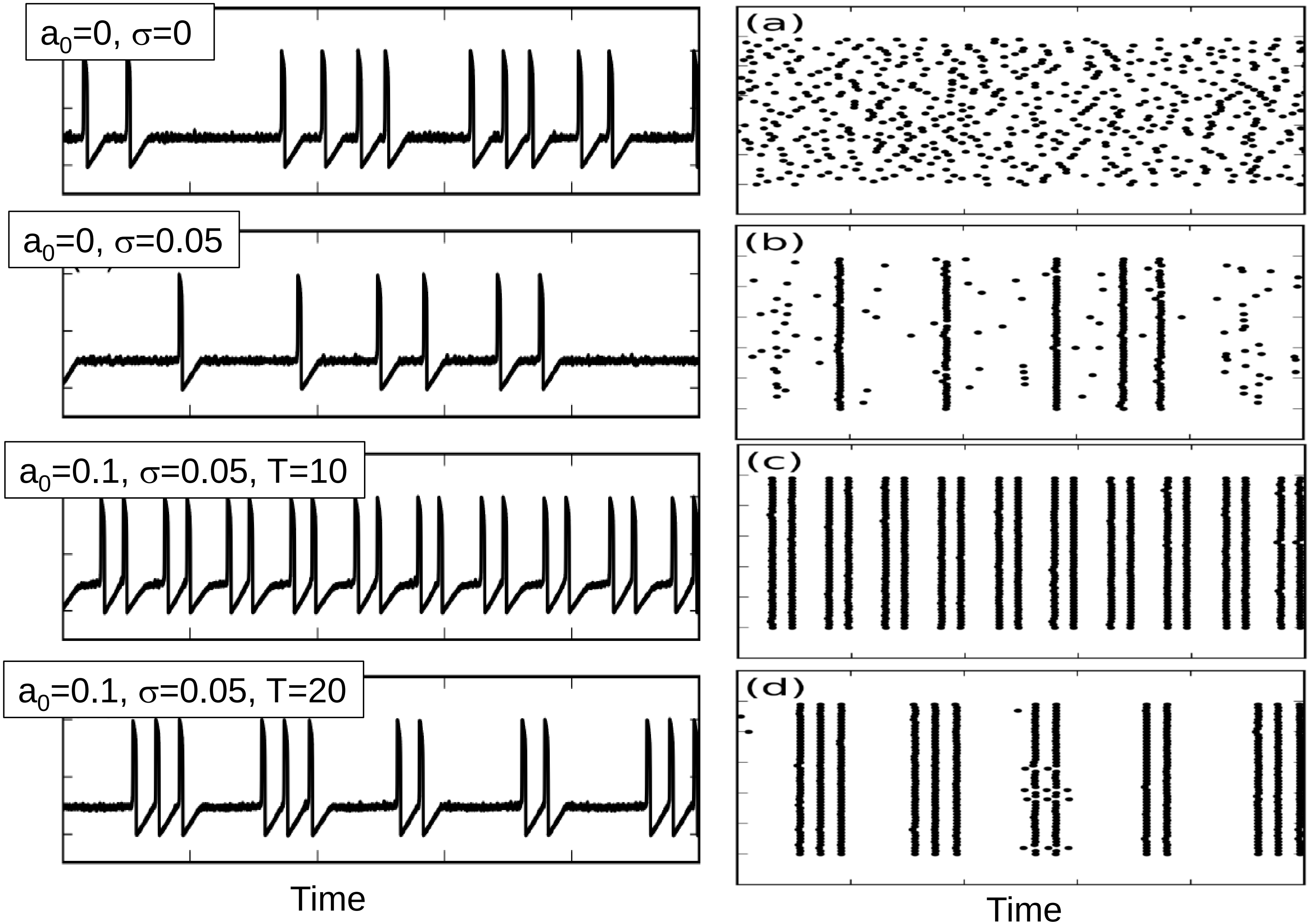
$$\epsilon \dot{u}_i = u_i - \frac{u_i^3}{3} - v_i + \boxed{a_0 \cos(2\pi t/T)} + \boxed{\frac{\sigma}{k_i}} \sum_j^N a_{ij}(u_j - u_i) + \sqrt{2D}\xi_i(t)$$

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

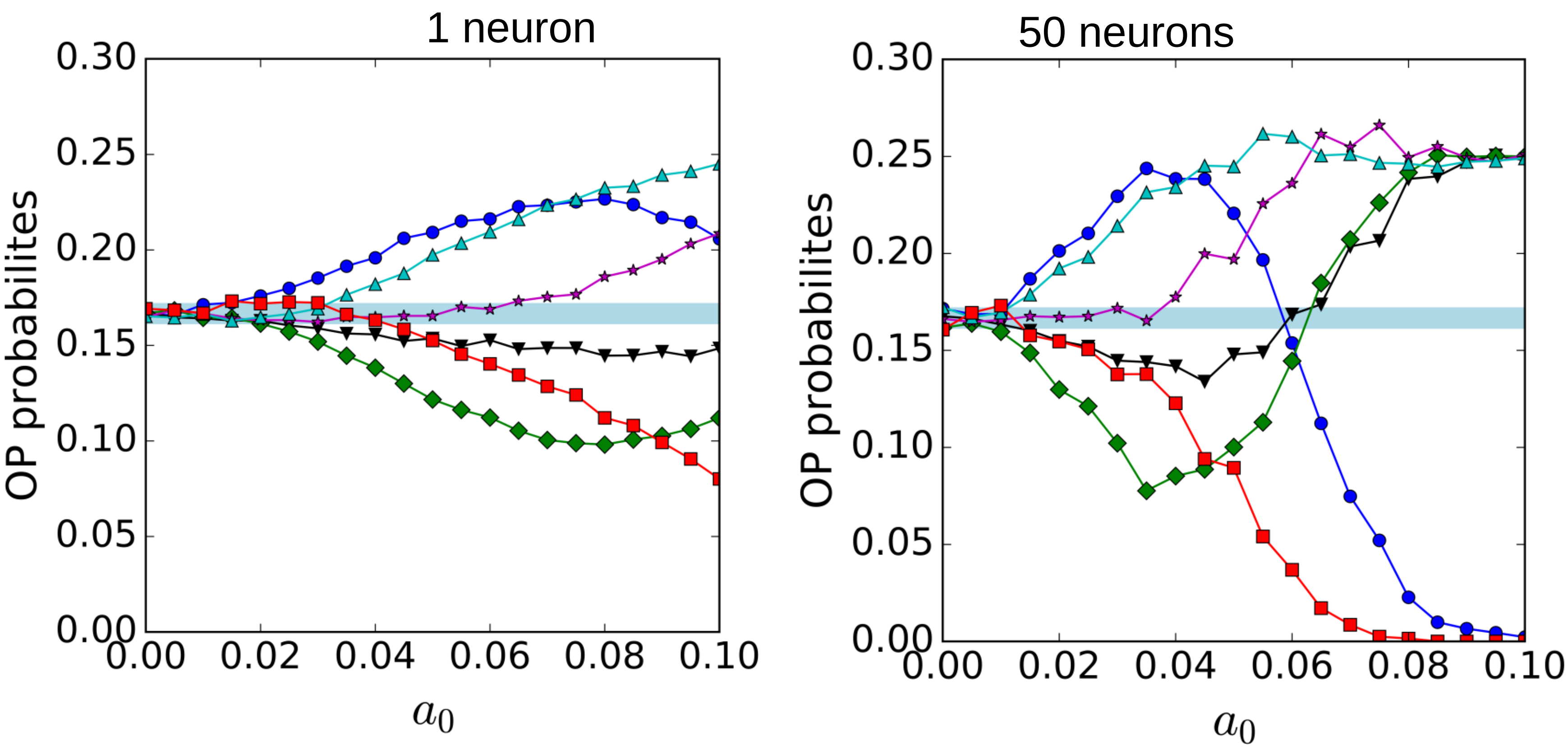
The signal is perceived by each neuron.

The signal is subthreshold for each individual neuron:
with $D = 0$ and $\sigma = 0$, no spikes.

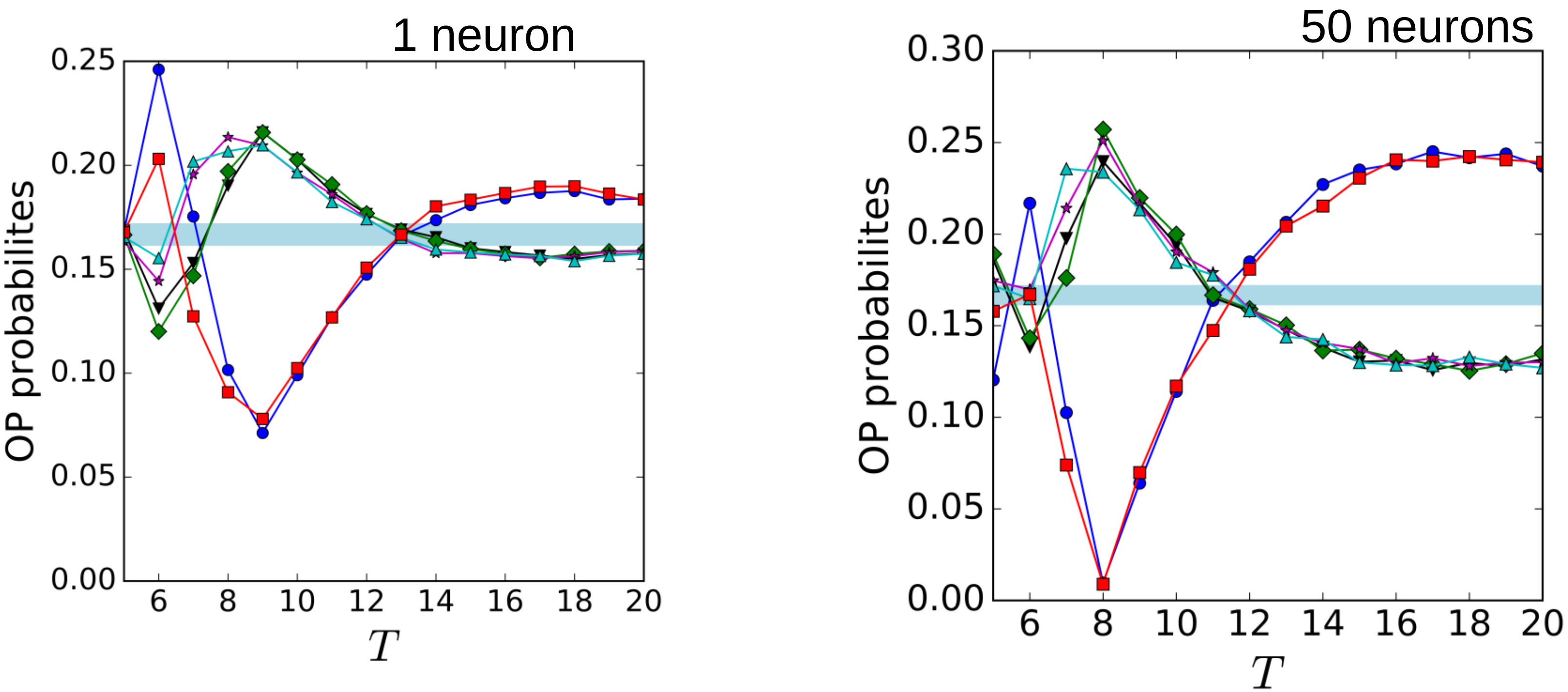
Neuronal activity



Influence of the signal amplitude



Influence of the signal period



Connection to how neurons process information?

A subset of neurons in the human medial temporal lobe are <u>*selectively*</u> activated by pictures of given individuals, landmarks or objects.

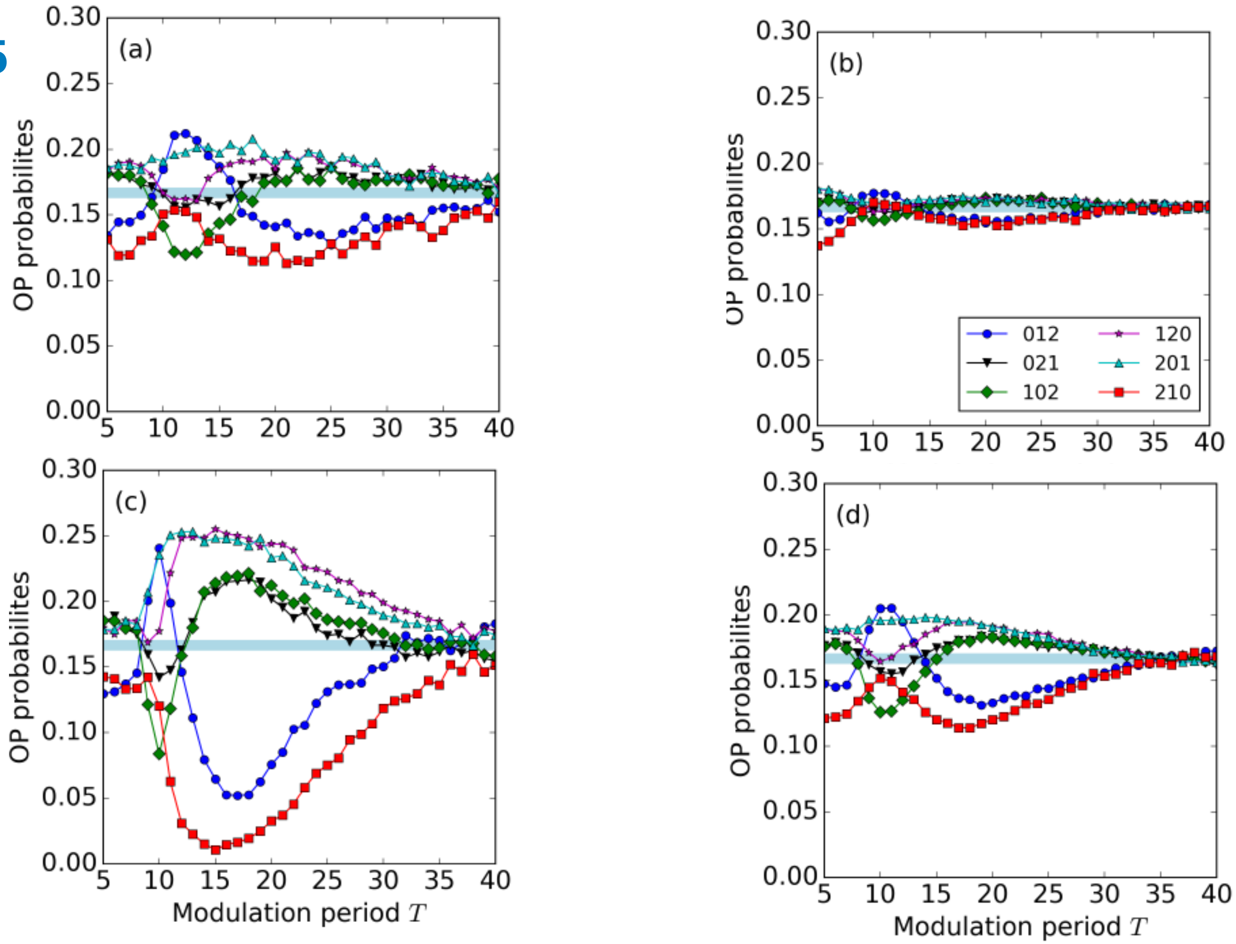
Quian Quiroga et al, Nature 435, 1102 (2005).

Comparison: two vs. 50 coupled neurons

50 neurons | 2 neurons

a_0=0.025

a_0=0.05



Conclusions

- Take home messages:
  - Ordinal time-series analysis uncovers patterns in data.
  - It detects correlations that might not be captured by linear analysis.
- Main conclusions:
  - The ordinal probabilities carry information about the signal (amplitude and period) with or without coupling.
  - Coupling changes the preferred/infrequent patterns.
  - In neuronal ensembles the encoding of the signal can be more pronounced.
- Ongoing work:
  - Similar results with other models and types of coupling.

- To be explored: aperiodic signals, heterogeneities and modular structure.

THANK YOU FOR YOUR ATTENTION !

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http://www.fisica.edu.uy/~cris/

Emergence of spike correlations in periodically forced excitable systems

J. A. Reinoso, M. C. Torrent and C. Masoller, PRE 94, 032218 (2016)

Subthreshold signal encoding in coupled FitzHugh-Nagumo neurons

M. Masoliver and C. Masoller, Scientific Reports 8, 8276 (2018)

Neuronal coupling benefits the encoding of weak periodic signals in symbolic spike patterns

M. Masoliver and C. Masoller, arXiv:1905.01933 (2019)

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