Generalized Statistical Complexity Measure: a new tool for Dynamical Systems.

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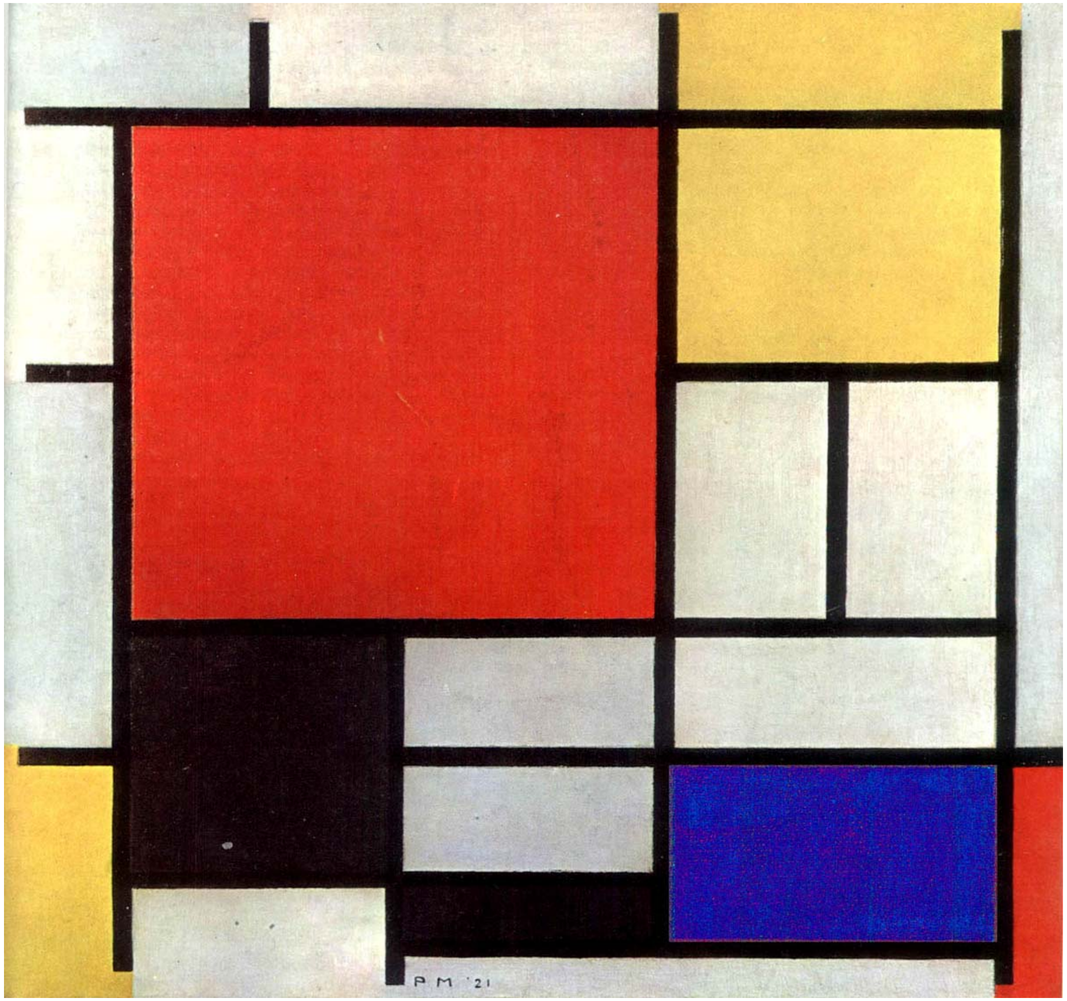
The Simple & The Complex

- **Complexity ?**

The Simple & The Complex



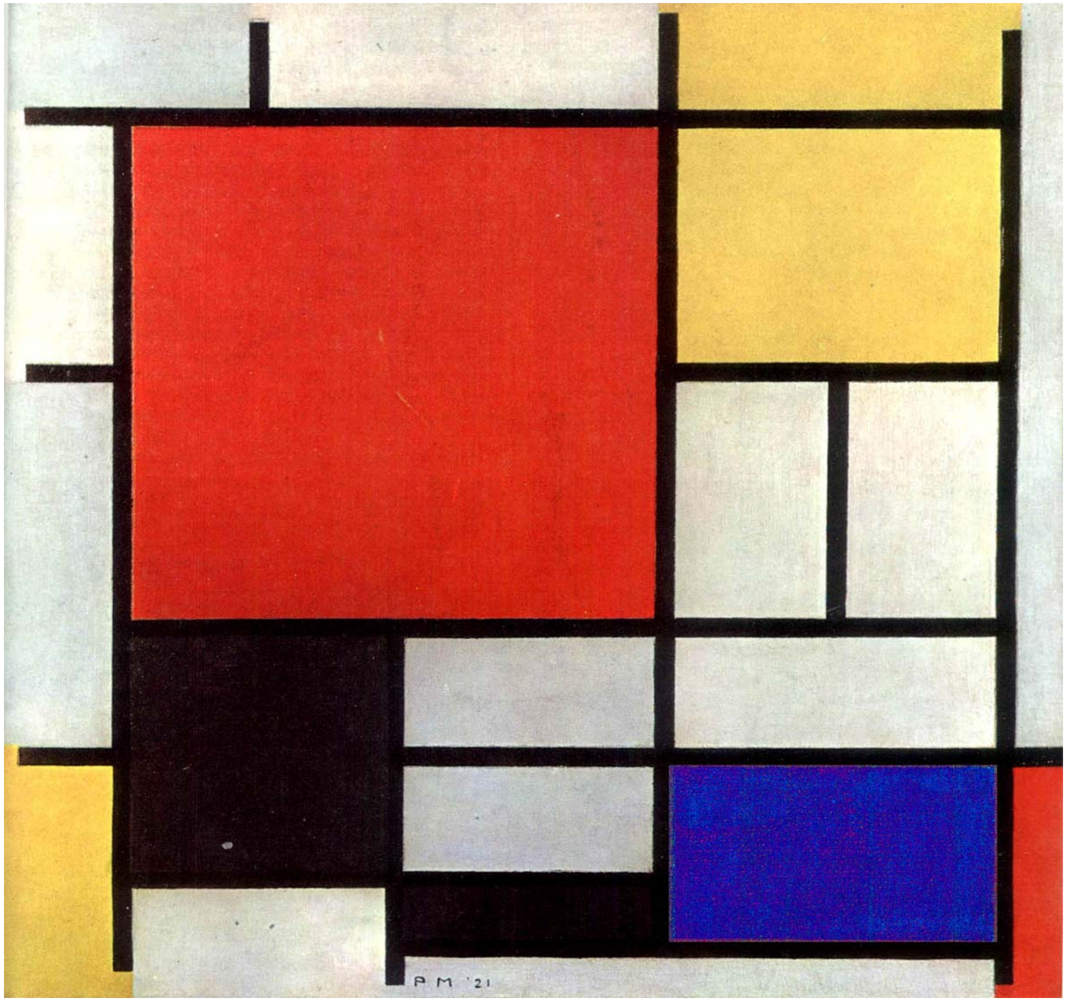
Mondrian

The Simple & The Complex

H = 0

C = 0

Mondrian



The Simple & The Complex

Pollock

The Simple & The Complex

H = 1

C = 0

Pollock

The Simple & The Complex

Bosch

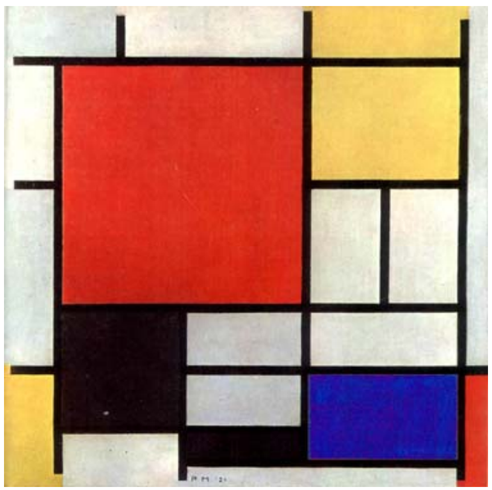
The Simple & The Complex

$H \neq 0$

$C \neq 0$

Bosch

The Simple & The Complex

		
H = 0 C = 0	H ≠ 0 C ≠ 0	H = 1 C = 0

Complexity

The COMPLEXITY has to do with intricate structures hidden in the dynamics, emerging from a system which itself is much simpler than its dynamics. Complexity is characterized by the paradoxical situation of complicated dynamics of simple systems.

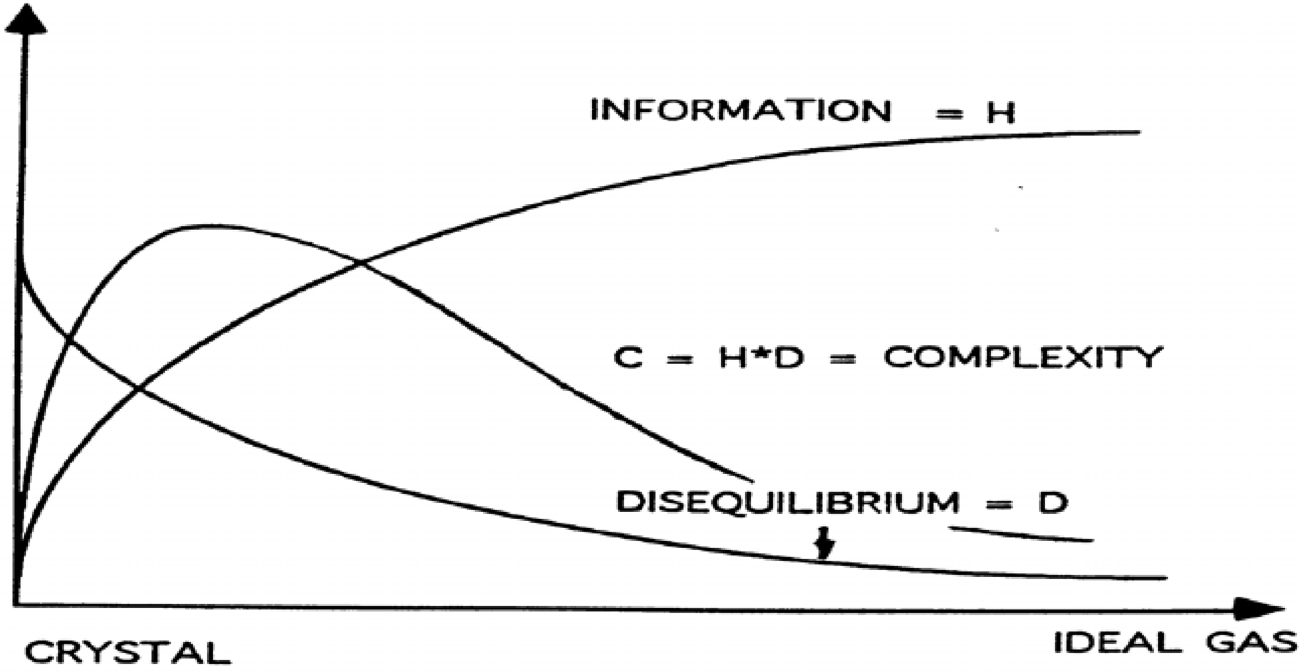
- Periodic motion it is not complex.
- White noise it is not complex.

Crystal & Ideal Gas

Crystal	Ideal Gas
• High ordered system	• Completely disordered system
• Minimal information stored in the system	• Maximal information stored in the system.
• Probability distribution in phase space: $P_j = 1$ for $j = k$; $P_j = 0$ for $j \neq k$	• Probability distribution in phase space: $P_j = 1 / N$ for $j = 1, \ldots, N$
• Maximum Disequilibrium	• Minimum Disequilibrium

Statistical Complexity

COMPLEXITY
$C = H \cdot Q$



Disorder H

- We define for a given probability distribution

$$P = \{p_j,\ j = 1, \cdots, N\} \in \Omega \subset \mathbb{R}^N$$

and its associate information measure $\mathcal{I}[P]$, an amount of "disorder" H in the fashion

$$H[P] = \mathcal{I}[P] \,/\, \mathcal{I}_{max} \ ,$$

where $\mathcal{I}_{max} = \mathcal{I}[P_e]$ and P_e is the probability distribution which maximize the information measure, where P_e is the equilibrium probability distribution. Then $0 \leq H \leq 1$.

Disequilibrium Q

- We define the "disequilibrium" adopting some kind of distance from the equilibrium distribution P_e of the accessible states of the system.

$$Q[P] \;=\; Q_0\, \mathcal{D}[P, P_e] \;,$$

where Q_0 is a normalization constant and $0 \leq Q \leq 1$.
The disequilibrium Q would reflect on the systems's "architecture", being different from zero if there are "privileged", or more likely states among the accessible ones.

Selection of the information measure I

- **Shannon Entropy:**

$$\mathrm{S}_S[\,P\,] \;=\; -\sum_i p_i \cdot \ln[\,p_i\,]\;.$$

- **Tsallis Entropy:**

$$\mathrm{S}_T^{(q)}[\,P\,] \;=\; \frac{1}{q-1}\left[\,1 \;-\; \sum_i \;(\,p_i\,)^q\,\right]\;.$$

- **Escort-Tsallis Entropy:**

$$\mathrm{S}_G^{(q)}[\,P\,] \;=\; \frac{1}{q-1}\left[\,1 \;-\; \left\{\,\sum_i \;(\,p_i\,)^{1/q}\,\right\}^{-q}\,\right]\;.$$

- **Rényi entropy:**

$$\mathrm{S}_R^{(q)}[\,P\,] \;=\; \frac{1}{(1-q)}\ln\left\{\,\sum_{j=1}^{N}(p_j)^q\,\right\}\;.$$

Selection of Distance D

- **Euclidean distance:**

$$\mathcal{D}_E[P, P_e] = \|P - P_e\|_E = \sum_{j=1}^{N} \left\{ p_j - \frac{1}{N} \right\}^2 .$$

- **Wootters distance:**

$$\mathcal{D}_W[P_1, P_2] = \cos^{-1}\left\{ \sum_{j=1}^{N} \left(p_j^{(1)} \right)^{1/2} \cdot \left(p_j^{(2)} \right)^{1/2} \right\} .$$

- **Relative entropy (Kullback relative entropy):**

$$\mathcal{D}_{K_q^\kappa}[P, P_e] = \mathrm{K}_q^{(\kappa)}[P|P_e] = \mathrm{S}_q^{(\kappa)}[P_e] - \mathrm{S}_q^{(\kappa)}[P] .$$

Where $\kappa = S, T, G, R$ – Shannon, Tsallis, Generalized Escort-Tsallis, Rényi, entropic functional forms.

- **Jensen divergence:**

$$\mathcal{D}_{\mathcal{J}_q^\kappa}[P, P_e] = \mathcal{J}_{\mathrm{S}_q^\kappa}^{1/2}[P, P_e] =$$

$$= \frac{1}{2}\,\mathrm{K}_q^{(\kappa)}\left[P \mid \frac{P + P_e}{2}\right] + \frac{1}{2}\,\mathrm{K}_q^{(\kappa)}\left[P_e \mid \frac{P + P_e}{2}\right] .$$

Where $\kappa = S, T, G, R$ – Shannon, Tsallis, Generalized Escort-Tsallis, Rényi, entropic functional forms.

Generalized Statistical Complexity Measures

The family of *Statistical Complexity Measures*, $C_{\nu,q}^{(\kappa)}$, is defined by

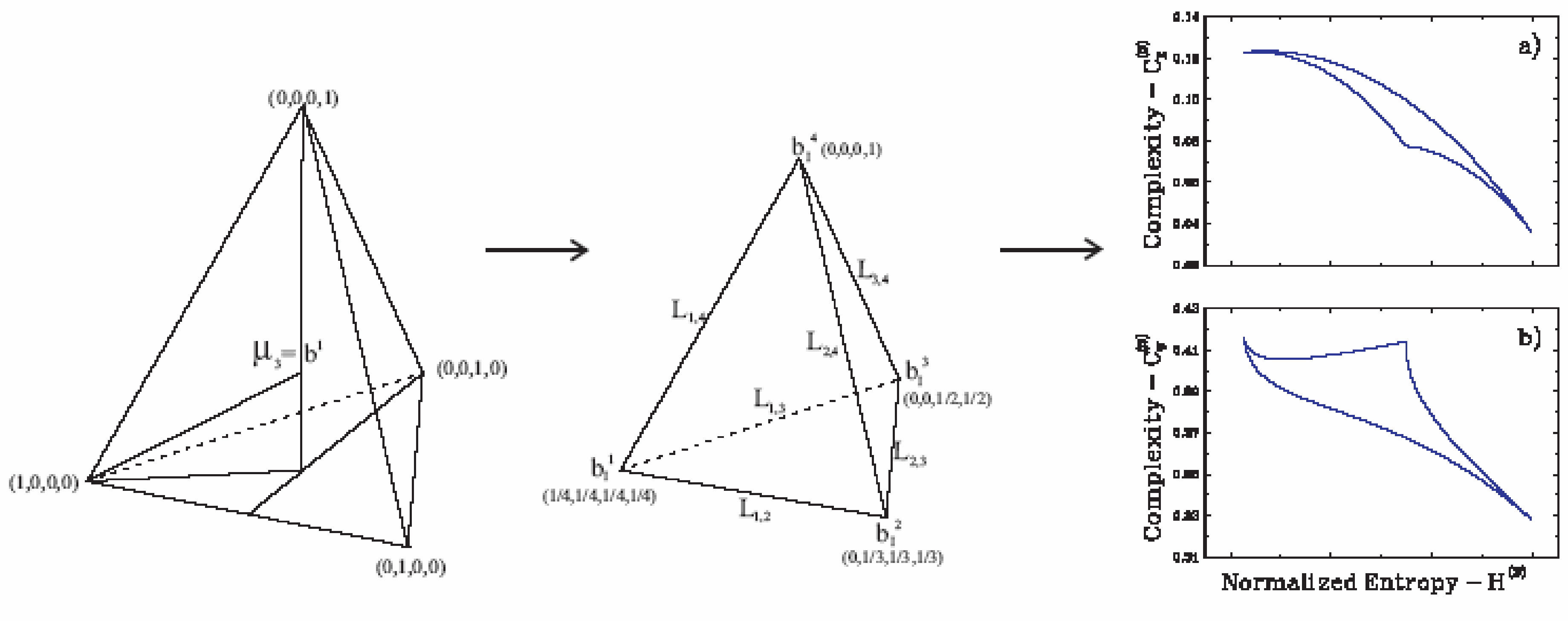
$$\boxed{C_{\nu,q}^{(\kappa)}[P] \;=\; H_q^{(\kappa)}[P] \;\cdot\; Q_q^{(\nu)}[P]}$$

This quantity reflects on the interplay between the amount of information stored in the system and its disequilibrium.

- $\kappa = S,\ T,\ G,\ R$: Shannon, Tsallis, Generalized Escort-Tsallis, Rényi, for a fixed q.

  In Shannons instance $(\kappa = S)$ we have, of course, $q = 1$.
- $\nu = E,\ W,\ K,\ J$: Euclidea, Wootters, Kullback, Jensen.

Maximum and Minimum of Generalized Statistical Complexity Measures



(i) Probability subspace Ω for $N = 4$: $\Omega \equiv \Delta^3$ (3-*simplex*) in an hyperplane of dimension 3. Dotted lines effect the barycentric subdivision with μ_3 the Ω-barycenter.

(ii) Sub-simplex Δ_I^3.

(iii) Maximum and minimum of complexity as function of H obtained by consecutive borders of the sub-simplex Δ_I^3.

Application to Logistic Map

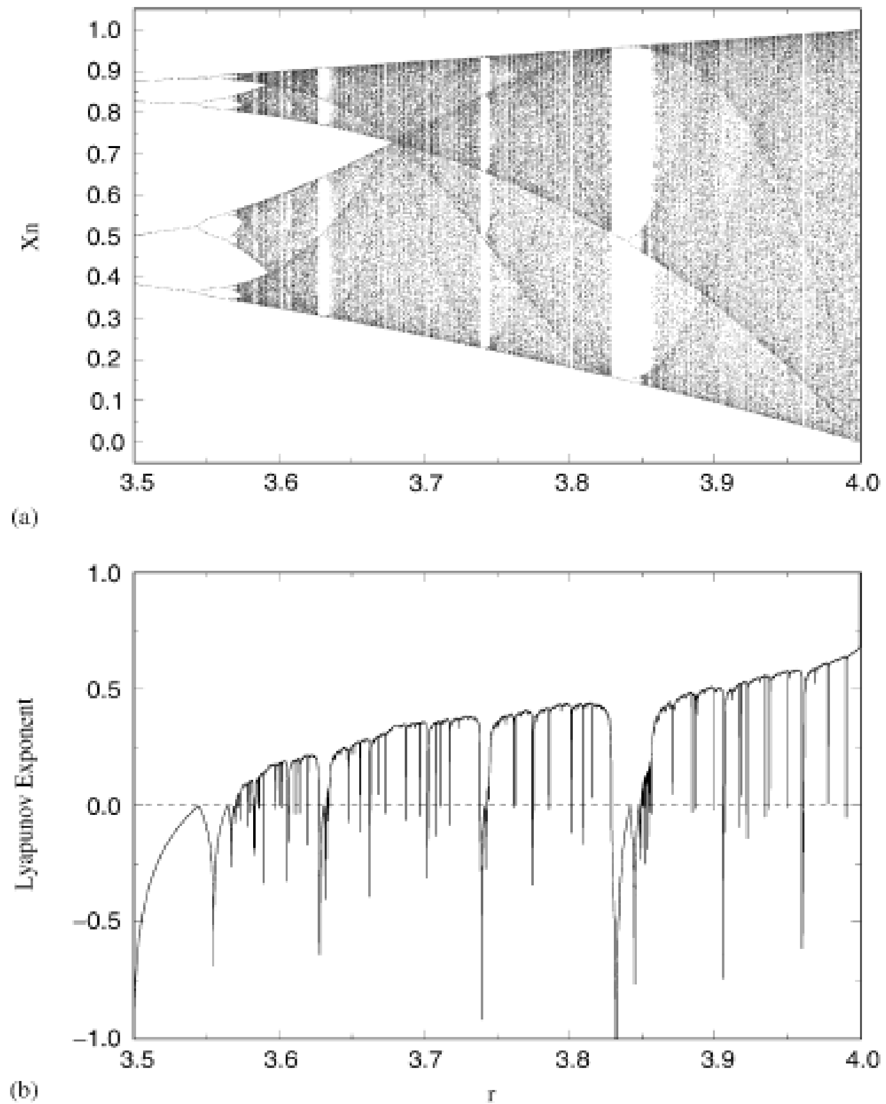
The Logistic Map, $F : x_n \to x_{n+1}$ is described by the ecologically motivated, dissipative system described by the first order difference equation

$$x_{n+1} = r \cdot x_n \cdot (1 - x_n)$$

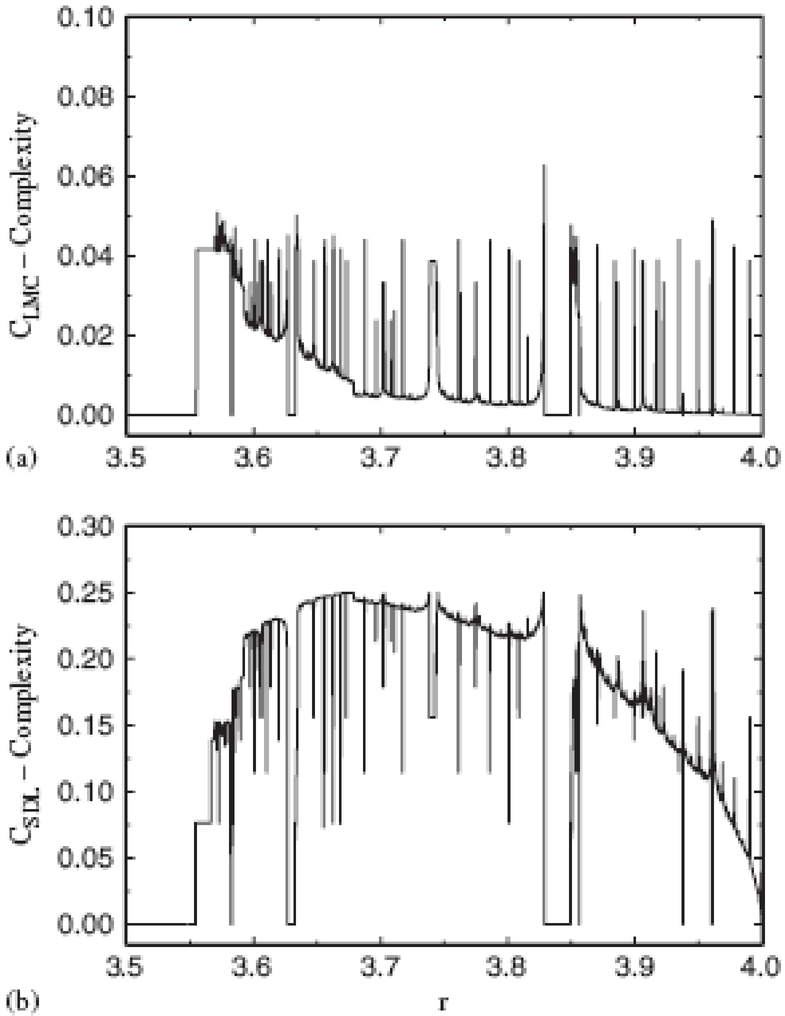
with $0 \leq x_n \leq 1$ and $0 < r \leq 4$.

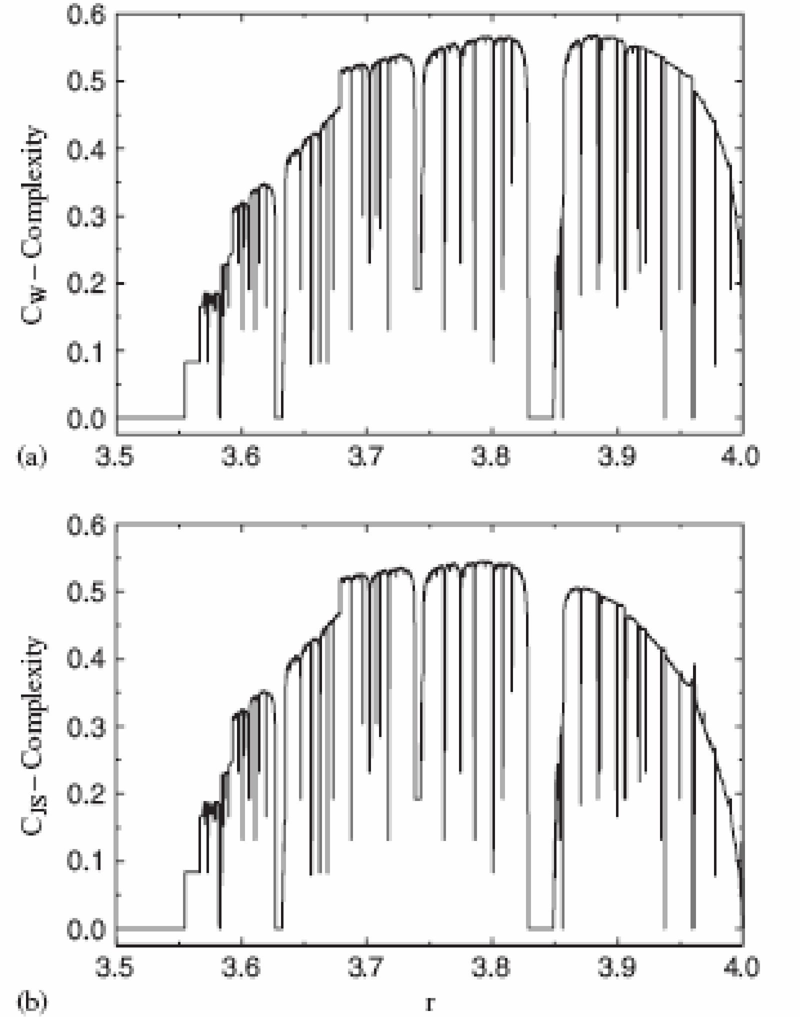
Binary treatment (symbolic dynamics) of the logistic map:

For each parameter value, r, the dynamics of the logistic map was reduced to a binary sequence (0 if $x \leq \frac{1}{2}$; 1 if $x > \frac{1}{2}$) and binary strings of length 12 were considered as states of the system. The concomitant probabilities are assigned according to the frequency of occurrence after running over at least 2^{22} iterations.



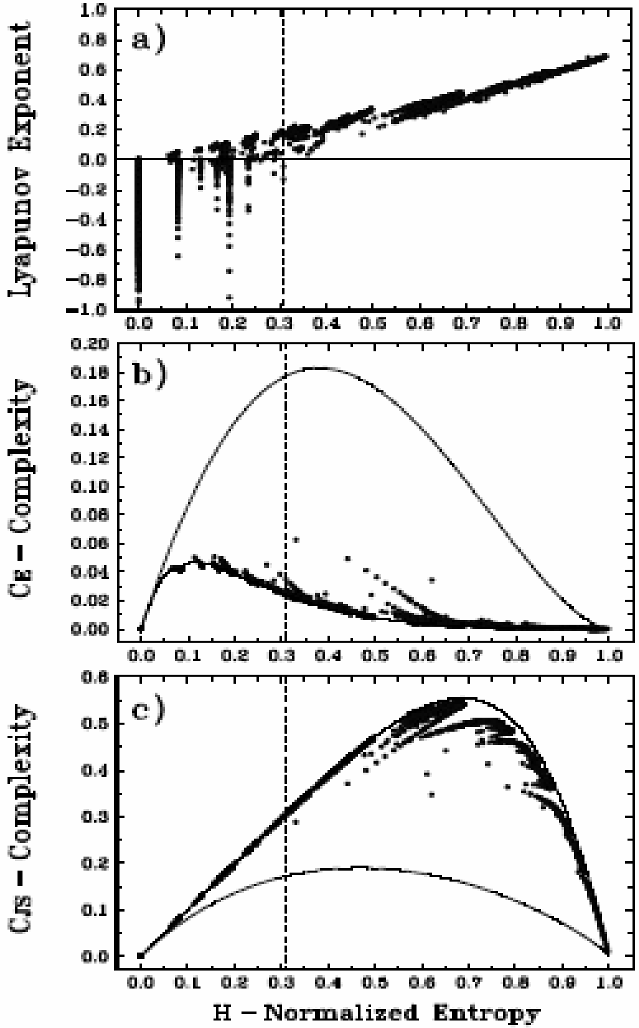
Application to Logistic Map





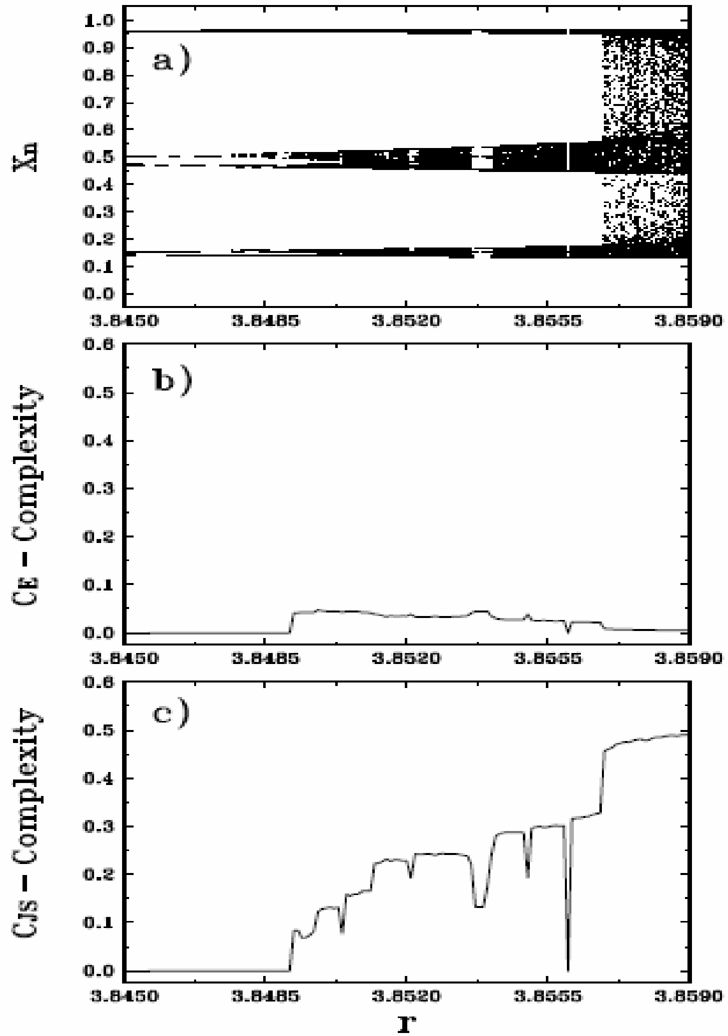
Application to Logistic Map

Notice that, for the case of periodic windows, if $H < \mathcal{H} \approx 0.3$, we can ascertain that $\Lambda < 0$, while for $H > \mathcal{H}$ we see that $\Lambda > 0$, which entails chaotic behavior. The LMC statistical complexity is larger for periodic than for chaotic motion, which is wrong!. The Jensen-Shannon statistical complexity measure, C_{JS}, on the other hand, behaves in opposite manner, and is also different for distinct degrees of periodicity.

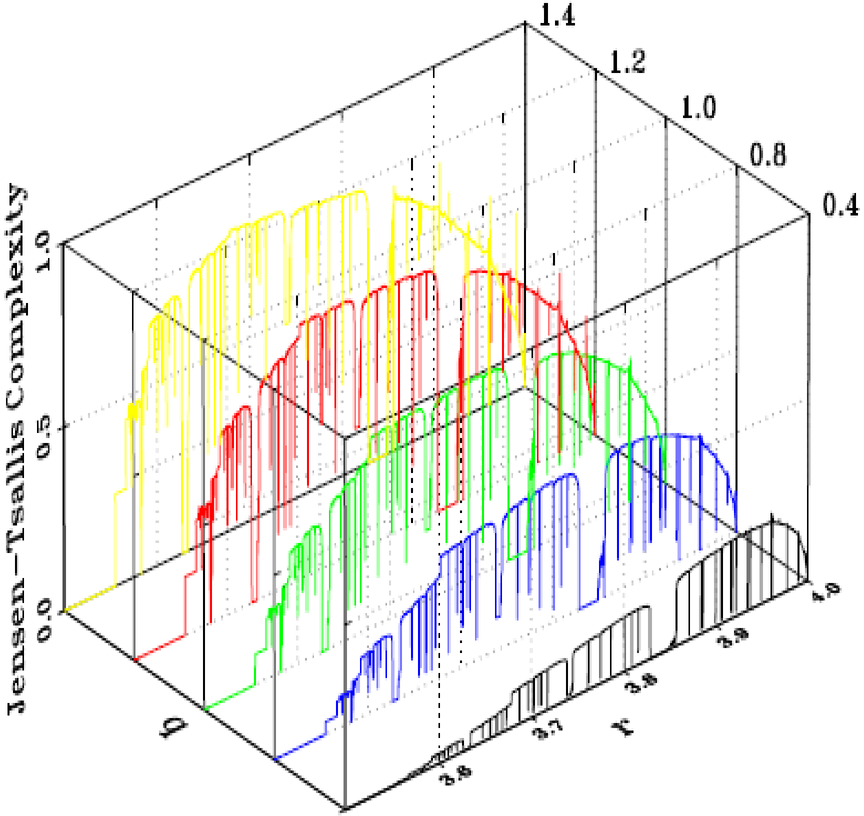


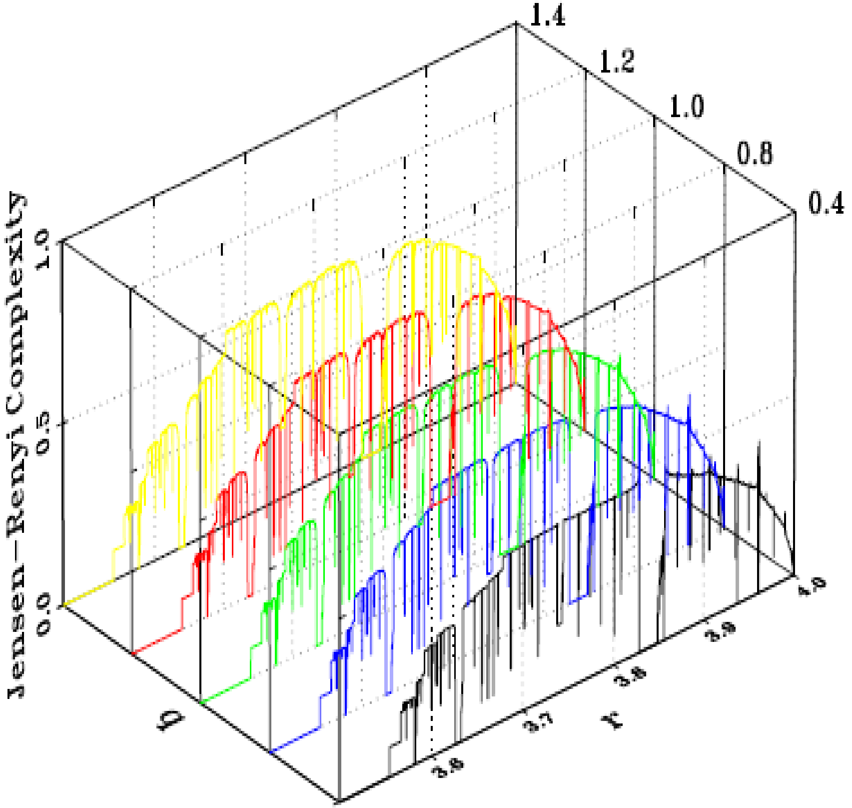
Application to Logistic Map

Summing up: the Jensen-Shannon statistical complexity measure *i)* becomes intensive, *ii)* is able to distinguish among distinct degrees of periodicity, and *iii)* yields a better description of dynamical features (a better grasp of dynamical details).

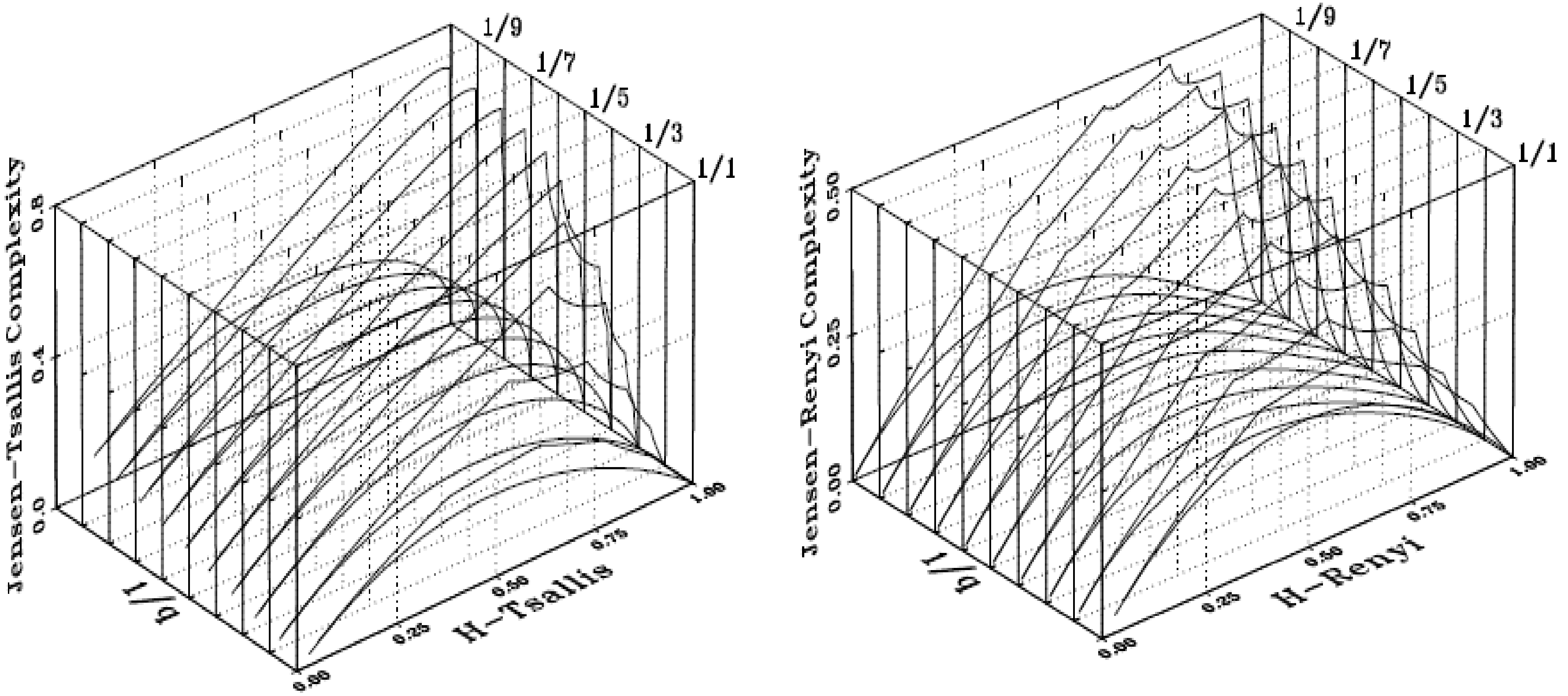


Application to Logistic Map





Application to Logistic Map



N = 6

Probability distribution *P*

Given a time series

$$X = \{x_j,\ j = 1, \cdots, N\} \in \mathbb{R}^N$$

we can define the associate probabily distribution function based on

- Histogram of amplitudes.
- Binary representation.
- Frequency (Fourier Transform).
- Frequency bands (Wavelet Transform).
- Ordinal Patterns (Attractor representation).

Probability distribution

Band-Pompe Methodology:

Given the time-series $\{x_t, t = 1, \cdots, T\}$ and an embedding dimension $d > 1$, we are interested in *ordinal patterns* of order d generated by

$$(s) \mapsto (x_{s-(d-1)}, x_{s-(d-2)}, \cdots, x_{s-1}, x_s)$$

which assign to each time s the d-dimensional vector of values at times $s, s-1, \cdots, s-(d-1)$.

Clearly, the greater the d-value, the more information on the past our vectors are able to yield.

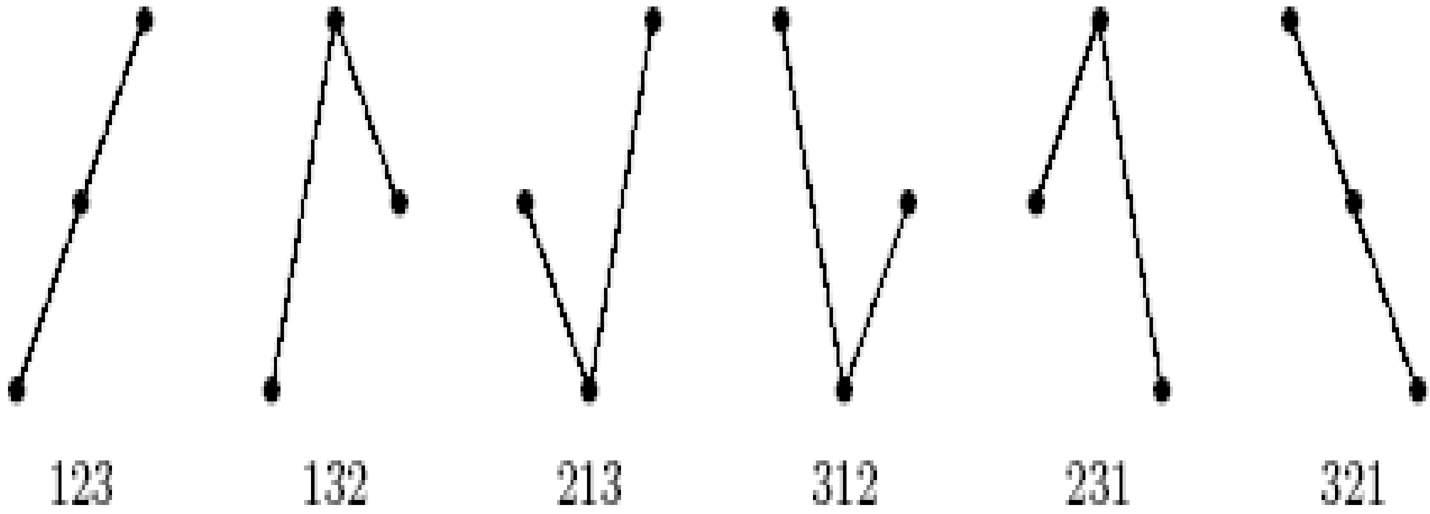
By the *ordinal pattern* related to the time (s) we mean the permutation $\pi = (r_0, r_1, \cdots, r_{d-1})$ of $(0, 1, \cdots, d-1)$ defined by

$$x_{s-r_{d-1}} \leq x_{s-r_{d-2}} \leq \cdots \leq x_{s-r_1} \leq x_{s-r_0}$$

Note that the underlying probability distribution is "extracted" by appropriate consideration regarding causal effects in the system's dynamics.

Probability distribution

Case $D_e = 3$, the number of patterns will be $D_e! = 3! = 6$. Graphically one have:

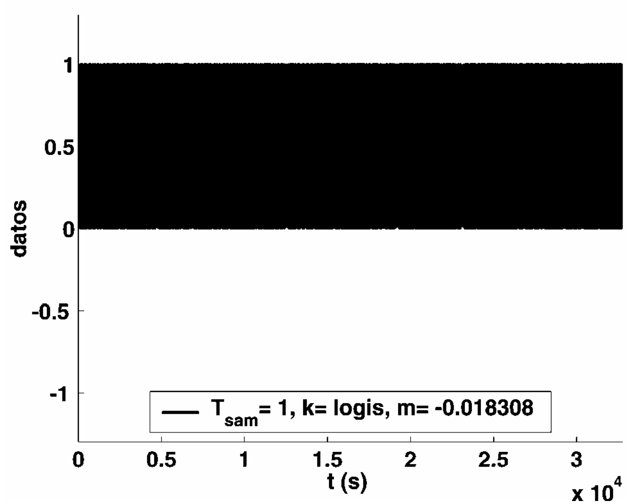


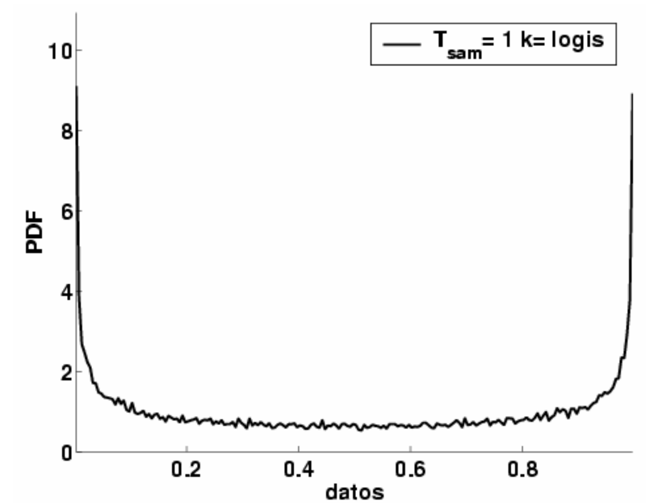
Chaos, Noise & Noise 1 / f*k*

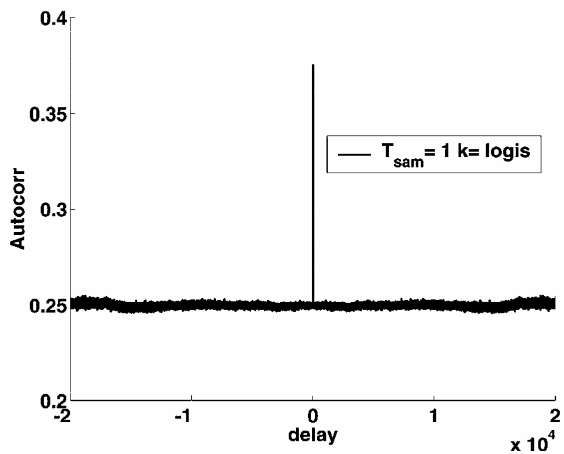
Although being of a quite different physical origin, time series arising from *chaotic systems* share with those generated by *stochastic processes* several properties that make them almost undistinguishable:

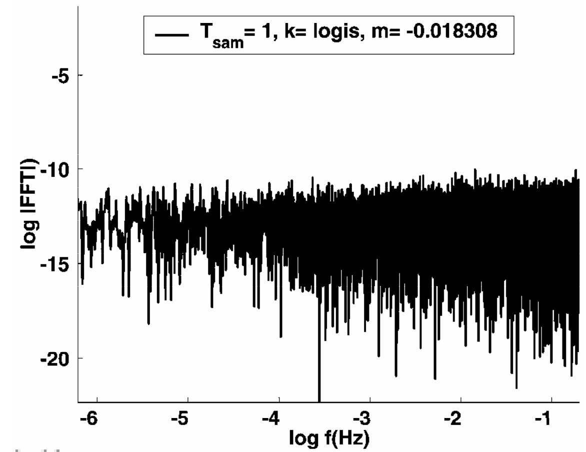
- a wide-band power spectrum,
- power spectrum of type $1/f^k$,
- a delta-like autocorrelation function,
- an irregular behavior of the measured signals, etc.

Chaos, Noise & Noise 1 / f*k*





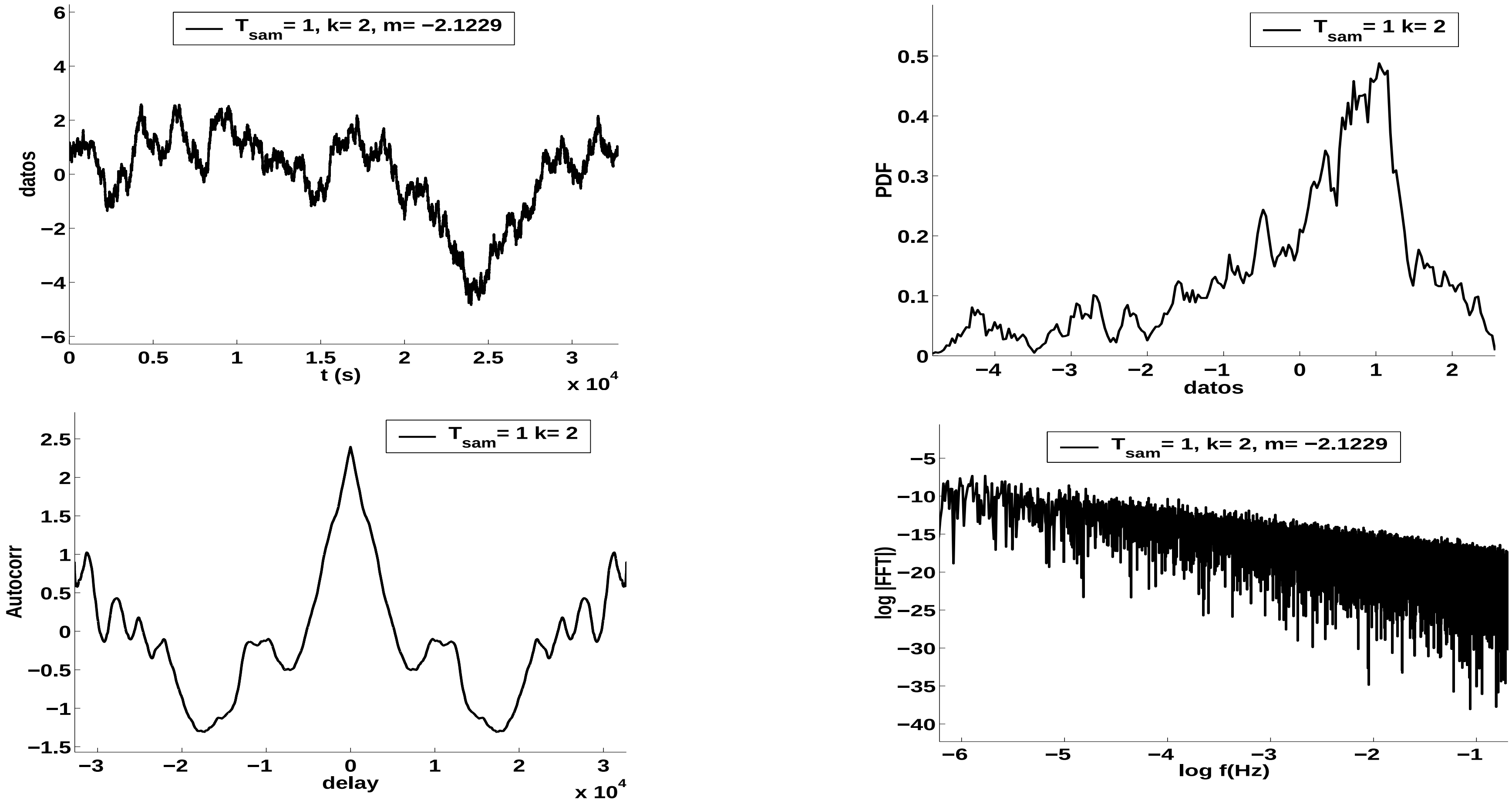




Logistic Map: $X(n+1) \;=\; R\,X(n)\,(1-X(n))\;;\;R=4$

$H_S = 0.638781 \qquad C_{JS}^{(MPR)} = 0.477845$

Chaos, Noise & Noise 1 / f^k



$$\text{Noise } 1/f^k : k = 2$$

$$H_S = 0.858 \qquad C_{JS}^{(MPR)} = 0.232$$

Chaos, Noise & Noise 1 / f^k

Chaotic systems:

- The Logistic Map defined by:

$$x_{n+1} \; = \; r \; x_n \; (1 - x_n) \; .$$

  Note that for $r = 4$ this map has a non uniform natural invariant probability density function (PDF).

- The Skew Tent Map: one has

$$\begin{cases} x/\omega & \text{for } x \in [0, \omega] \\ (1-x)/(1-\omega) & \text{for } x \in [\omega, 1] \end{cases} \; .$$

  For any $\omega-$value this map has a uniform natural invariant PDF ($\omega = 0.1847$ is here considered).

- Henon's Map: it is a $2D$ extension of the Logistic Map given by:

$$\begin{cases} x_{n+1} \; = \; 1 \; - \; a \; x_n^2 \; + \; y_n \\ y_{n+1} \; = \; b \; x_n \end{cases} \; .$$

  The values used here, $a = 1.4$ and $b = 0.3$, correspond to a chaotic attractor with a non-smooth PDF.

Chaos, Noise & Noise 1 / f^k

- The Lorenz Map of Rossler's oscillator: for the $3D$ continuous Rossler oscillator one has

$$\begin{cases} \dot{x} = -y - z \\ \dot{y} = x + a\,y \\ \dot{z} = b + z\,(x - c) \end{cases} .$$

  where $a = 0.2$, $b = 0.2$, and $c = 5.7$ correspond to a chaotic attractor. The Lorenz map is obtained by storing only $x-$minimal values.

- Schuster Maps: Schuster and coworkers introduced a class of maps which generate intermittent signals with chaotic bursts that also display $1/f^z$ noise

$$x_{n+1} = x_n + x_n^z, \qquad \text{Mod } 1.$$

  In particular, results for $z = 5/2$, 2 and $3/2$ are reported.

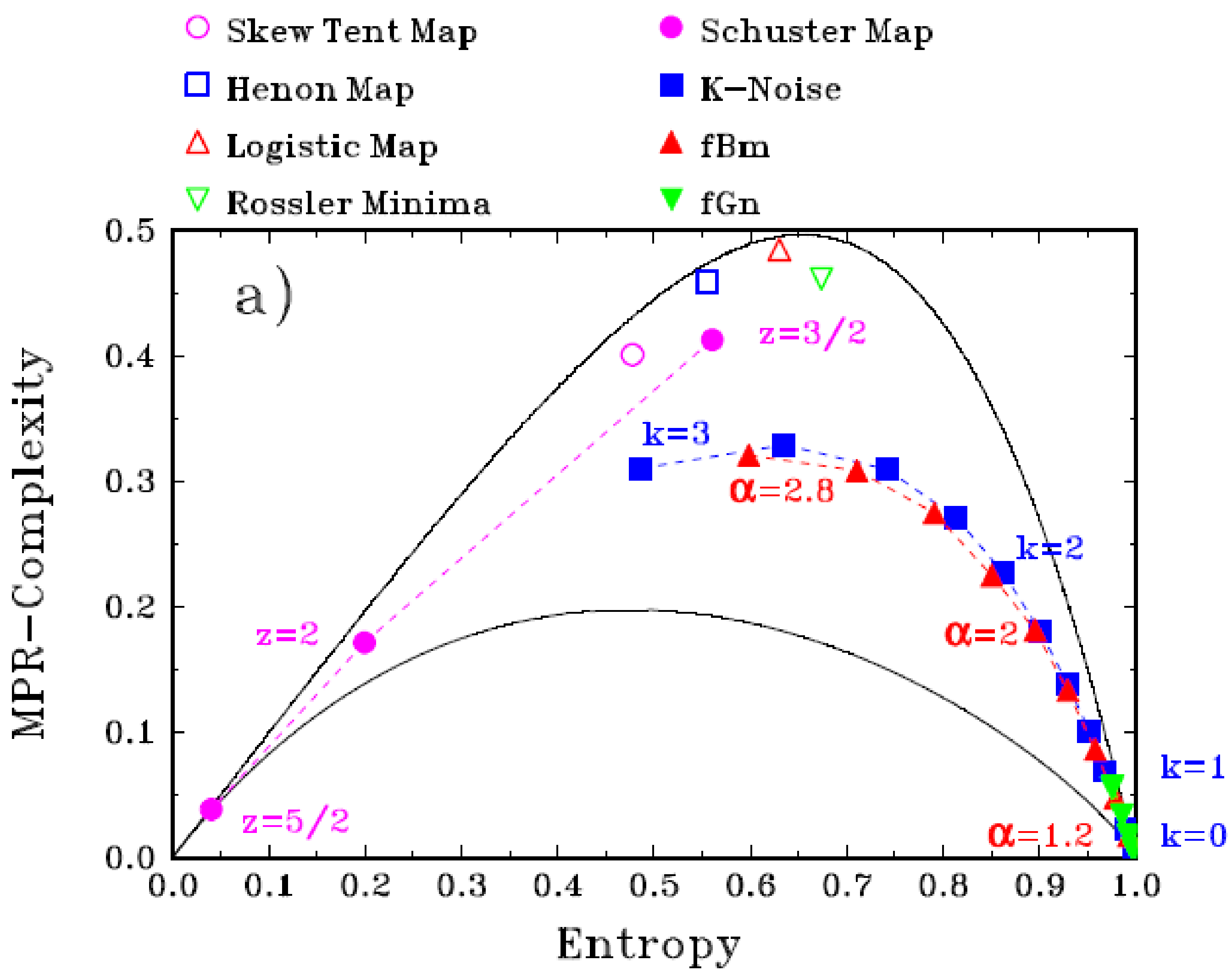
Chaos, Noise & Noise 1 / f^k

Stochastic processes :

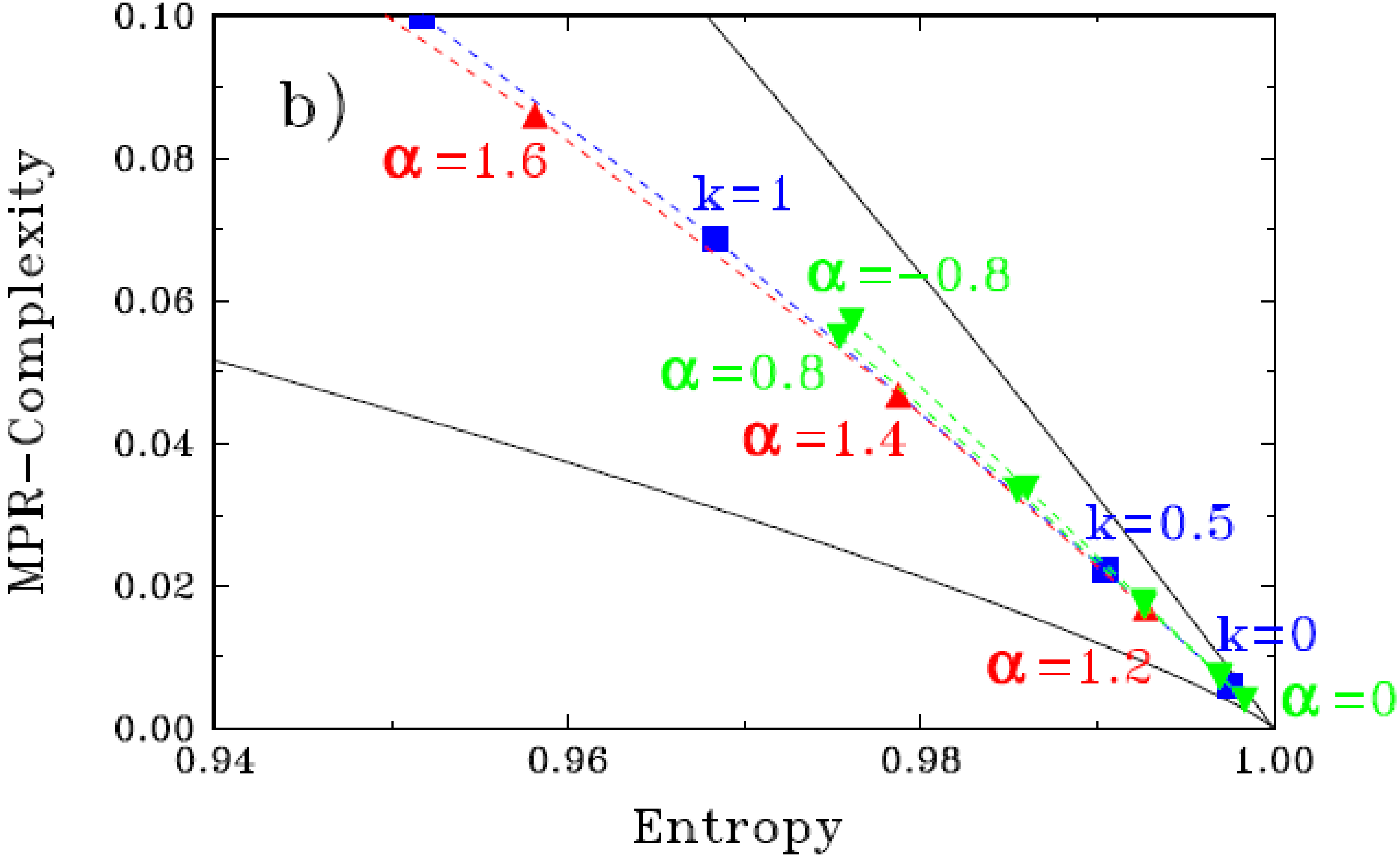
- Noises with f^{-k} Power Spectrum. The ensuing time series x_i has the desired PS and, by construction, is representative of non-Gaussian noises.
- Fractional Brownian motion (fBm) and fractional Gaussian noise (fGn): fBm is the only family of processes which is *(a)* Gaussian, *(b)* self-similar, and *(c)* endowed with stationary increments. The fBm and fGn are continuous but non-differentiable processes (in the classical sense). As a non-stationary process, they do not possess a spectrum defined in the usual sense; however, it is possible to define a *generalized power spectrum* of the form: $\Phi \propto |f|^{-\alpha}$, with $\alpha = 2\mathcal{H} + 1$, $1 < \alpha < 3$ for fBm and, $\alpha = 2\mathcal{H} - 1$, $-1 < \alpha < 1$, for fGn.

  Hurst's $\mathcal{H}$ parameter defines two distinct regions in the interval $(0, 1)$. When $\mathcal{H} > 1/2$, consecutive increments tend to have the same sign so that these processes are *persistent*. For $\mathcal{H} < 1/2$, on the other hand, consecutive increments are more likely to have opposite signs, and we say that they are *anti-persistent*.

Chaos, Noise & Noise 1 / f^k



Chaos, Noise & Noise 1 / f^k



Other Applications

- Characterization of laser propagation through turbulent media.
- Encryption test of pseudo-aleatory messages embedded on chaotic laser signals.
- fBm and fGn dynamics.
- Characterization of Pseudo Random Number Generators and and randomization of chaotic series.
- Stochastic resonance and coherent resonance.
- Analysis of Classical-Quantum transition problem.
- Study of mode and genre of literary texts. Internal chronological development of authorial styles.
- Alterations in the erythrocyte due to different illness.
- Brain electrical activity: EEG background distinction, epileptic activity, sleep, ERP, EP.
- Quantitative brain maturation.
- Identification of biomarkers that correlate with cancer progression.

Thanks !!!!

… and see you in Newcastle, Australia

ENTROPY AND STATISTICAL COMPLEXITY PUBLICATIONS:

Permutation entropy of fractional Brownian motion and fractional Gaussian noise.
L. Zunino, D. G. Pérez, M. T. Martín, M. Garavaglia, A. Plastino, O. A. Rosso.
Physics Letter A 372 (2008) 4768 – 4774

Randomizing nonlinear maps via symbolic dynamics.
L. De Micco, C. M. González, H. A. Larrondo, M. T. Martín, A. Plastino, O. A. Rosso.
Physica A 387 (2008) 3373 – 3383

Encryption test of pseudo-aleatory messages embedded on chaotic laser signals: an Information Theory approach.
O. A. Rosso, R. Vicente, C. Mirasso
Physics Letter A 372 (2008) 1018 – 1023.

Extracting features of Gaussian self-similar stochastic processes via the Bandt and Pompe approach.
O. A. Rosso, L. Zunino, D. G. Pérez, A. Figliola, H. A. Larrondo, M. Garavaglia, M. T. Martín, A. Plastino.
Physical Review E 76 (2007) 061114

Distinguishing noise from chaos.
O. A. Rosso, H. A. Larrondo, M. T. Martin, A. Plastino, M. A. Fuentes
Physical Review Letter 99 (2007) 15102

Bandt-Pompe approach to the classical-quantum transition.
A. M. Kowalski, M. T. Martin, A. Plastino, O. A. Rosso
Physica D 233 (2007) 21 – 31

Characterization of gaussian self-similar stochastic processes using wavelet-based informational tools.
L. Zunino, D. G. Perez, M. T. Martin, A. Plastino, M. Garavaglia, O. A. Rosso
Physical Review E 75 (2007) 021115

Wavelet Jensen-Shannon divergence as a tool for studying the dynamics of frequency band components in EEG epileptic seizures.
M. Pereyra, P. W. Lamberti and O. A. Rosso
Physica A 379 (2007) 122 – 132

Wavelet entropy of stochastic processes.
L. Zunino, D. G. Perez, M. Garavaglia, O. A. Rosso
Physica A 379 (2007) 503 – 512

Model-free stochastic processes studied with *q*-wavelet-based informational tools.
D. G. Perez, L. Zunino, M. T. Martin, M. Garavaglia, A. Plastino, O. A. Rosso
Physics Letter A 364 (2007) 259 – 266

Entropy changes in brain function.
O. A. Rosso
International Journal of Psychophysiology 64 (2007) 75 – 80

Alterations of thalassemic erythrocytes detected by wavelet entropy.
A. M. Korol, M. J. Rasia, O, A, Rosso
Physica A375 (2007) 257 – 264

Random number generators and causality.
H. A. Larrondo, M. T. Martin, C. M Gonzalez, A. Plastino, O. A. Rosso
Physics Letters A, 352 (2006) 421 – 425

EEG analysis using wavelet-based informational tools.
O. A. Rosso, M. T. Martin, A. Figliola, K. Keller, A. Plastino
Journal of Neuroscience Methods 153 (2006) 163 – 182

Generalized statistical complexity measures: geometrical and analytical properties.
M.T. Martin, A. Plastino, O. A. Rosso
Physica A 369 (2006) 439 – 462

Wavelet entropy and fractional Brownian motion time series.
D. G. Perez, L. Zunino, M. Garavaglia, O. A. Rosso
Physica A 365 (2006) 282 – 288.

Characterization of laser propagation through turbulent media by quantifiers based on wavelet transform: dynamical study.
L. Zunino, D. G. Perez, M. Garavaglia, O. A. Rosso
Physica A 364 (2006) 79 – 86.

Entropy and statistical complexity in brain activity.
A. Plastino, O. A. Rosso
European Physical Society - Europhysics News 36 (2005) 224 – 228.
Special Number on: "Nonextensive Statistical Mechanics - Theory and Applications",
J. P. Boon, C. Tsallis (Guest Editors).

Entropic non-triviality, the classical limit, and geometry-dynamics correlations.
A. M. Kowalski, M. T. Martin, A. Plastino, O. A. Rosso
International Journal of Modern Physics B 14 (2005) 2273 – 2285.

Intensive statistical complexity measure of pseudorandom number generators.
H. A. Larrondo, C. M. González, M. T. Martin, A. Plastino, O. A. Rosso
Physica A 356 (2005) 133 – 138.

Quantitative EEG analysis of the maturational changes associated with childhood absence epilepsy.
O. A. Rosso, W. Hyslop, R. Gerlach, R. L. L. Smith, J. Rostas, M. Hunter
Physica A 356 (2005) 184 – 189.

Statistical complexity measure of pseudorandom bit generators.
C. M. González, H. A. Larrondo, O. A. Rosso
Physica A 354 (2005) 281 – 300.

Evidence of self-organization in brain electrical activity using wavelet based informational tools.
O. A. Rosso, M. T. Martin, A. Plastino
Physica A 347 (2005) 444 – 464.

Characterization of laser propagation through turbulent media by quantifiers based on the wavelet transform.
L. Zunnino, D. Pérez, M. Garavaglia, O. A. Rosso
Fractals 12 (2004) 223 – 234.

Order / Disorder in brain electrical activity.
O. A. Rosso, A. Figliola
Revista Mexicana de Física 50 (2004) 149 – 155.

Intensive entropic non-triviality measure.
P. W. Lamberti, M.T. Martin, A. Plastino, O. A. Rosso
Physica A 334 (2004) 119 – 131

Wavelet analysis can sensitively describe dynamics of ethanol evoked spiky local field potential wave of slug (*Limax marginatus*) brain.
A. Schütt, I. Ito, O. A. Rosso, A. Figliola
Journal of Neuroscience Method 129 (2003) 135 – 150

Wavelet statistical complexity analysis of classical limit.
A.M. Kowalski, M.T. Martin, A. Plastino, A. N. Proto, O. A. Rosso
Physics Letter A 311 (2003) 180 – 191

Statistical complexity and disequilibrium.
M.T. Martin, A. Plastino, O. A. Rosso
Physics Letter A 311 (2003) 126 – 132
Elsevier Science, ISSN 0375-9601

Brain electrical activity analysis using wavelet based informational tools (II): Tsallis non-extensivity and complexity measurements.
O. A. Rosso, M. T. Martin, A. Plastino
Physica A 320 (2003) 497 – 511

Wavelet analysis of generalized Tonic-Clonic epileptic seizures.
O. A. Rosso, S. Blanco, A. Rabinowicz
Signal Processing 83 (2003) 1275 – 1289

A transient dominance of theta event-related brain potential component characterizes stimulus processing in auditory oddball task.
J. Yordanova, O. A. Rosso, V. Kolev
Clinical Neurophysiology 114 (2003) 529 – 540

A discovery of new features of gastropod local field potentials by application of wavelet tools.
A.Schüett, O. A. Rosso, A. Figliola
Journal of Neuroscience Method 119 (2002) 89 – 104

Wavelet entropy analysis of event-related potentials indicates modality-independent theta dominance.
J. Yordanova, V. Kolev, O. A. Rosso, M. Schürmann, O. W. Sakowitz, M. Özgören, E. Basar
Journal of Neuroscience Methods 117 (2002) 99 – 109

Brain electrical activity analysis using wavelet based informational tools.
O. A. Rosso, M. T. Martin, A. Plastino
Physica A 313 (2002) 587 – 608

Characterization of time dynamical evolution of electroencephalographic records.
O. A. Rosso, M. L. Mairal
Physica A 312 (2002) 469 – 504

A transient dominance of theta ERP component characterizes passive auditory processing: evidence from developmental study.
V. Kolev, O. A. Rosso, J. Yordanova
Neuroreport 12 (2001) 2791 – 2796

Wavelet entropy: a new tool for the analysis of short duration brain electrical signals.
O. A. Rosso, S. Blanco, J. Yordanova, V. Kolev, A. Figliola, M. Schürmann, E. Basar
Journal of Neuroscience Methods 105 (2001) 65 – 75

Wavelet-entropy in event-related potentials: A new method shows ordering of EEG-oscillations.
R. Quian Quiroga, O. A. Rosso, E. Basar, M. Schürmann
Biological Cybernetic 84 (2001) 291 – 299

Time-Frequency analysis of electroencephalogram series (III): information transfer function and wavelets packets.
S. Blanco, A. Figliola, R. Quian Quiroga, O. A. Rosso, E. Serrano
Physical Review E 57 (1998) 932 – 940

Discrimination measure of correlations in a population of neurons by using the Jensen-Shannon Divergence.
F. Montani, O. A. Rosso, S. R. Schultz
Nonequilibrium Statistical Mechanics and Nonlinear Physics.
XV Conference on Nonequilibrium Statistical Mechanics and Nonlinear Physics.
O. Descalzi, O. A. Rosso, H. A. Larrondo (Editors).
American Institute of Physics, AIP Conference Proceedings 913 (2007) 184 – 189.

Wavelet analysis of spatiotemporal network oscillations evoked in the Incilaria brain.
A. Schütt, O. A. Rosso, Y. Makino, T. Fujie, M. Yano, M. Werner, A. Figliola, U. G. Hofmann
Nonequilibrium Statistical Mechanics and Nonlinear Physics.
XV Conference on Nonequilibrium Statistical Mechanics and Nonlinear Physics.
O. Descalzi, O. A. Rosso, H. A. Larrondo (Editors).

American Institute of Physics, AIP Conference Proceedings 913 (2007) 209 - 214.

Brain maturation changes characterized by Algorithmic Complexity (Lempel and Ziv Complexity).
J. G. Fernández, H. A. Larrondo, A. Figliola, E. Serrano, J. A. P. Rostas, M. Hunter, O. A. Rosso
Nonequilibrium Statistical Mechanics and Nonlinear Physics.
XV Conference on Nonequilibrium Statistical Mechanics and Nonlinear Physics.
O. Descalzi, O. A. Rosso, H. A. Larrondo (Editors).
American Institute of Physics, AIP Conference Proceedings 913 (2007) 196 - 202.

Complexity as a tool for studying neural activity.
O. A. Rosso, M. T. Martin, A. Plastino
Instabilities and Non-equilibrium Structures X. 2005, in press.
Edited by: O. Descalzi, J. Martinez and S. Ricca.
Kluwer Academic Publishes, Dordrecht, Netherlands

A measure of self-organization in neural activity.
O. A. Rosso, M. T. Martin, A. Plastino
Instabilities and Non-equilibrium Structures IX. 2004, pp. 281 – 290
Edited by: O. Descalzi, J. Martinez and S. Ricca.
Kluwer Academic Publishes, Dordrecht, Netherlands.

Generalized information measures and the analysis of brain electrical signals.
A. Plastino, M. T. Martin, O. A. Rosso
Nonextesive Entropy - Interdisciplinary applications. 2004, pp. 261 – 293
Edited by: M. Gell-Mann and C. Tsallis.
Santa Fe Institute Studies in the Sciences of Complexity,
Oxford University Press, New York, USA.

Self-organization in neural matter.
M. T. Martin, A. Plastino, O. A. Rosso
Condensed Matter Theories, Vol. 17,
Proceedings of Workshop on Condensed Matter Theories, Sidney, Australia, 2001.
Edited by M. P. Das and F. Green, 2003, pp. 279 - 291
Nova Science Publishers, New York, US.

Time-frequency analysis of sensorial brain activity.
O. A. Rosso, J. Yordanova, V. Kolev, S. Blanco, A. Figliola, E. Basar, M. Schürmann
Advances in Clinical Neurophysiology,
XV International Congress of Clinical Neurophysiology, Buenos Aires, Argentina.
Supplement to Clinical Neurophysiology Vol.54, 2002, pp. 443 – 450
Edited by: R. C. Reisin, M. R. Nuwer, M. Hallett, C. Medina.
Elsevier Sciences, Amsterdam.

Dynamic characterization of Tonic-Clonic epileptic seizures using wavelet entropy.
O. A. Rosso, S. Blanco, A. Figliola, J. Creso, A. Rabinowicz
Proceedings of the European Medical & Biological Engineering Conference, EMBEC'99
Medical & Biological Engineering & Computing 37, 1999, pp. 1324 - 1325.

Wavelet-Entropy: a measure of order in evoked potentials.
R. Quian Quiroga, O. A. Rosso, E. Basar
Functional Neuroscience: Evoked Potentials and Magentic Fields (EEG Suppl. 49), 1999, pp. 298 – 302
Edited by C. Barber, G. G. Celesia, I. Hashimoto and R. Kakigi
Elseiver Science, London, UK. ISBN 0-444-50062-6

Wavelet-Entropy applied to brain signal analysis.
O. A. Rosso, R. Quian Quiroga, S. Blanco, A. Figliola, E. Basar
Signal Processing IX, Theory and Applications
Proceeding of EUSIPCO'98, Ninth European Signal Processing Conference, Vol. IV, 1998, pp. 2445 – 2248.
Edited by: S. Thodoridis, I. Pitas, A. Stouraitis, N. Kalouptsidis.
Typorama Editions, Athens, Greece.