VIIIA FORMA

Universidade Federal do Ceará Departamento de Física



A Maximum Entropy Model for the Network of Commercial Transactions between Cities based on Data from Electronic Invoices

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## It started with disordered superconductors...

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### **Flux Front Penetration in Disordered Superconductors**

Stefano Zapperi,<sup>1</sup> André A. Moreira,<sup>2</sup> and José S. Andrade, Jr.<sup>2</sup> <sup>1</sup>INFM sezione di Roma 1, Dipartimento di Fisica, Università "La Sapienza," P.le A. Moro 2, 00185 Roma, Italy <sup>2</sup>Departamento de Física, Universidade Federal do Ceará, 60451-970 Fortaleza, Ceará, Brazil (Received 7 November 2000)

We investigate flux front penetration in a disordered type-II superconductor by molecular dynamics simulations of interacting vortices and find scaling laws for the front position and the density profile. The scaling can be understood by performing a coarse graining of the system and writing a disordered nonlinear diffusion equation. Integrating numerically the equation, we observe a crossover from flat to fractal front penetration as the system parameters are varied. The value of the fractal dimension indicates that the invasion process is described by gradient percolation.

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PACS numbers: 74.60.Ge, 05.45.-a, 47.55.Mh

Collecting all the terms, we finally obtain a disordered nonlinear diffusion equation for the density of flux lines

$$\Gamma \,\frac{\partial \rho}{\partial t} = \vec{\nabla} (a\rho \,\vec{\nabla} \rho \,-\,\rho \,\vec{F}_c) \,+\,k_B T \nabla^2 \rho \,. \tag{5}$$

## And the Tsallis thermostatistics was there!

PRL 105, 260601 (2010)

PHYSICAL REVIEW LETTERS

week ending 31 DECEMBER 2010

#### **Thermostatistics of Overdamped Motion of Interacting Particles**

J. S. Andrade, Jr.,<sup>1,3</sup> G. F. T. da Silva,<sup>1</sup> A. A. Moreira,<sup>1</sup> F. D. Nobre,<sup>2,3</sup> and E. M. F. Curado<sup>2,3</sup>

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> We show through a nonlinear Fokker-Planck formalism, and confirm by molecular dynamics simulations, that the overdamped motion of interacting particles at T = 0, where T is the temperature of a thermal bath connected to the system, can be directly associated with Tsallis thermostatistics. For sufficiently high values of T, the distribution of particles becomes Gaussian, so that the classical Boltzmann-Gibbs behavior is recovered. For intermediate temperatures of the thermal bath, the system displays a mixed behavior that follows a novel type of thermostatistics, where the entropy is given by a linear combination of Tsallis and Boltzmann-Gibbs entropies.

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PACS numbers: 05.10.Gg, 05.20.-y, 05.40.Fb, 05.45.-a

is a conveniently rescaled variable. This functional leads to the following entropic form:

$$S[P] = \frac{D}{\bar{\gamma}} \left[ 1 - \int_{-\infty}^{\infty} dx P^2(x, t) \right] - \frac{k_B T}{\bar{\gamma}} \int_{-\infty}^{\infty} dx P(x, t)$$
$$\times \ln P(x, t). \tag{17}$$

Equation (17) is precisely the sum of Tsallis entropy with  $\nu = 2$ , which appears as a consequence of many-body

 $k_BT \gg a$ , i.e.,  $\langle x^2 \rangle \propto t$ . In the presence of a restoring external force and for T > 0, a stationary-state analytical solution for Eq. (13) can still be obtained,

$$\rho(x) = \frac{k_B T}{a} W \left\{ \frac{a\rho(0)}{k_B T} \exp\left[\frac{a\rho(0)}{k_B T} - \frac{\alpha x^2}{2k_B T}\right] \right\}, \quad (15)$$

where the *W*-Lambert function is defined implicitly through the equation  $W(z)e^{W(z)} = z$  (see [22] and references therein). In order to test this prediction, extensive MD

#### **Thermostatistics of Overdamped Motion of Interacting Particles**

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# **Nonextensive Statistics and Complex Networks**

## ✓ Dynamical and Growth Models:

- D. Soares, C. Tsallis, A. Mariz, and L. da Silva, Preferential attachment growth model and nonextensive statistical mechanics, Europhys. Lett. 70, 70 (2005).
- S. Brito, L. da Silva, and C. Tsallis, Role of dimensionality in complex networks, Sci. Rep. 6, 27992 (2016).
- S. Brito, T. C. Nunes, L. R. da Silva, and C. Tsallis, Scaling properties of *d*-dimensional complex networks, Phys. Rev. E 99, 012305 (2019).



Prof. Luciano da Silva A Real Force of Nature!

## ✓ Random Network Models:

### PHYSICAL REVIEW RESEARCH 5, 033088 (2023)

### Random networks with q-exponential degree distribution

Cesar I. N. Sampaio Filho<sup>®</sup>,<sup>1</sup> Marcio M. Bastos<sup>®</sup>, Hans J. Herrmann<sup>®</sup>,<sup>1,2</sup> André A. Moreira,<sup>1</sup> and José S. Andrade, Jr.<sup>®</sup><sup>1</sup> <sup>1</sup>Departamento de Física, Universidade Federal do Ceará, 60451-970 Fortaleza, Brazil <sup>2</sup>PMMH, ESPCI, CNRS UMR 7636, 7 quai St. Bernard, 75005 Paris, France

1) Using the Configurational Model, we can generate random unbiased complex networks exhibiting *q*-exponential degree distributions with arbitrary parameter values.

2) With an additional degree of freedom, these networks generalize the scale-free ones, therefore having great flexibility with respect to topological and transport properties, like assortativity, small-world behavior, and resilience to random and malicious attacks.

# Projeto Cientista Chefe de Dados – Economia Nota Fiscal Eletrônica





# Generalized Modularity Algorithm Stochastic Block Model [Peixoto, PRE (2018)]

The algorithm identifies modules based on the correlations between pairs of sites and on the network generation process.





## Infomap Algorithm Rosvall & Bergstrom, PNAS (2008)

- The algorithm finds modules in a network by minimizing the lengths of a random walker's movements.
- The network will be compacted if regions are identified where the walker tends to remain for a long time.
- It captures the network's optimal community structure in terms of its associated flow dynamics.









**Matrix of Commercial Transactions** 



strong correlations within the communities!

## Bipartite Networks of Cities and Traded Products Revealed Comparative Advantage (RCA) Index Hidalgo *et al.*, *Science* (2007)

 $q_m^p \rightarrow$  monetary value traded by the city *m* of the product *p*.  $RCA_{m}^{p} =$ Selling **Buying** FORTALEZ Municipalities Municipalities JUAZEIRO DO NORTI UAZEIRO DO NORTI SOBRA SOBRA > III > | | | CRATEÚS CRATEÚS ≻ IV IV ACARA ACARA Products Products



## From Correlations to "Interactions" Maximum-Entropy Model for Cities and their Traded Products

> Assuming that  $\beta = 1$  and rewriting the equations as,

$$P(\vec{\sigma}) = Z^{-1} \exp(\sum_{m} h_m \sigma_m + \sum_{m < n} J_{mn} \sigma_m \sigma_n) \text{ and } Z = \sum_{\{\vec{\sigma}\}} \exp(\sum_{m} h_m \sigma_m + \sum_{m < n} J_{mn} \sigma_m \sigma_n)$$

the fields  $\{h_m\}$  and couplings  $\{J_{mn}\}$  can be obtained by solving,

$$\langle \sigma_m \rangle = \frac{\partial}{\partial h_m} \ln Z = \sum_{\{\vec{\sigma}\}} \sigma_m P(\vec{\sigma}) \quad \text{and} \quad \langle \sigma_m \sigma_n \rangle = \frac{\partial}{\partial J_{mn}} \ln Z = \sum_{\{\vec{\sigma}\}} \sigma_m \sigma_n P(\vec{\sigma})$$
  
Boltzmann Machine Learning

In practical terms, we search for a solution of this inverse-Ising problem using a Monte Carlo (MC) algorithm as a core solver with the following updating rules:

$$h_m(l+1) = h_m(l) - \eta(l)[\langle \sigma_m \rangle_{MC} - \langle \sigma_m \rangle_{obs}]$$
 (1)

$$J_{mn}(l+1) = J_{mn}(l) - \eta(l) [\langle \sigma_m \sigma_n \rangle_{MC} - \langle \sigma_m \sigma_n \rangle_{obs}]$$
 (2)

Once we infer all the parameters  $\{h_m\}$  and  $\{J_{mn}\}$  that better reproduce the sets  $\{\langle \sigma_m \rangle_{obs}\}\$  and  $\{\langle \sigma_m \sigma_n \rangle_{obs}\}\$ , while maximizing the entropy, the Boltzmann distribution characterizes the statistics of the product activities of the cities composing a given community.

From Correlations to "Interactions"

**Boltzmann Machine applied to the Microdynamics of Ceará's Economy** 



Muito obrigado!