A Complex Systems approach to the emergence of socio-economic phenomena

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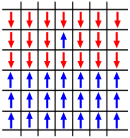
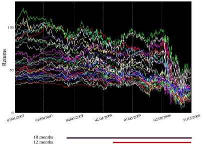
Laboratoire de Physique Théorique et Modélisation, CY Cergy Paris Université, France.

February 3rd, 2022





Scheme

- I. Complex Systems
- II. Social-related Agent-Based Models (ABM's)
- III. Networks Science
- IV. Data Science to understand human nature
- V. Criticality on social-inspired thermodynamic systems and real data
    - Bali's Ancient Terraces
    - Signs of universal patterns in social explosions
- VI. Grants/Projects

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I. Complex system science aims to study...

the phenomena that emerge as a consequence of the interactions between the constituents and, thus, cannot be understood by studying a singular, isolated component.

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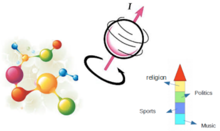
The field has incorporated concepts and methods deriving from many areas, ranging from statistical physics and biology to economics and sociology, which, in a constant process of cross-fertilization, have given rise to new types of questions framed into the field of Complex Systems.

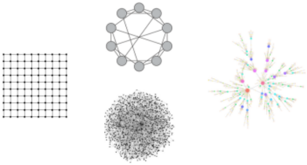
I. Complex systems: 3 main ingredients

- Particles: Internal dimensionality or degree of freedom.



- Dynamics: Interactions (in equilibrium or out-of-equilibrium).

- Connectivity: Dimensionality of the system. Networking Topological properties.



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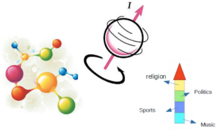

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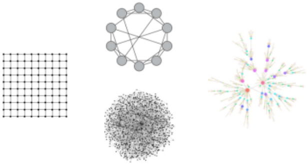

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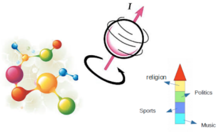

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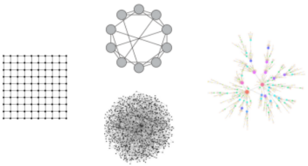

II. Agent-Based Models (ABM's)

Bridge between the **microscopic interactions** among the constituents and the **macroscopic collective behaviour** of the systems

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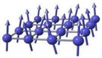
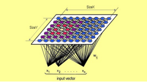
To simulate global **self-organisation**



local interactions



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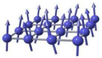

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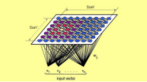

Emergent phenomena as a consequence of well-thought local rules between interacting particles

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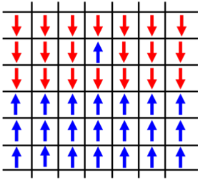
(Physics community) The emergence of macro-behaviour as a consequence of the interactions among the constituents exists in **Statistical Physics**:

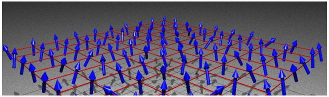
For example, spin models simulate the phase transitions of ferromagnets in thermodynamic equilibrium (Boltzmann distribution).



Ising model (1925)

$$H(\sigma) = -J \sum_{\langle ij \rangle} \sigma_i \sigma_j$$

Each particle can be in only two states



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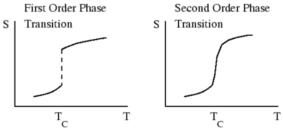

Same ferromagnetic interactions but each particle has access to q states

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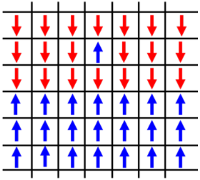

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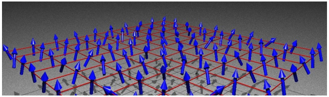

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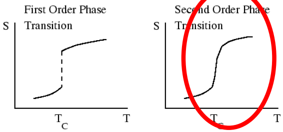
Criticality



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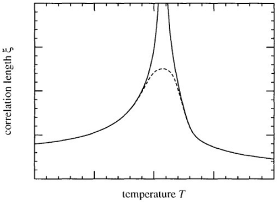
II. Agent-Based Models (ABM's)

Why is criticality so important?

And what is the implication on social systems?



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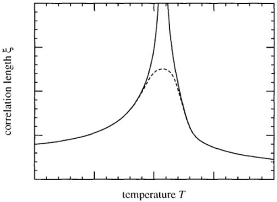

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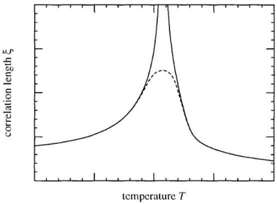

The possibility of finding critical behavior on social-related models is always presents in the physics literature from the Complex Systems community

causes significant simplifications on the thermodynamic functions (power-law shapes)

as they have been found in social-related data

II. Social-related Agent-Based Models (ABM's)

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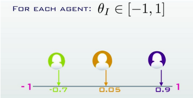
OPINION

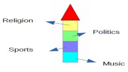
The economy needs agent-based modelling

The leaders of the world are flying the economy by the seat of their pants, say **J. Doyne Farmer** and **Duncan Foley**. There is, however, a better way to help guide financial policies.

Bounded confidence Models



CONFIRMATION BIAS	$if \quad \|\theta_I - \theta_J\| < \varepsilon$
COGNITIVE DISSONANCE	$\langle\theta\rangle_{IJ} = (\theta_i + \theta_J)/2$ $\theta_I = \theta_J = \langle\theta\rangle_{IJ}$



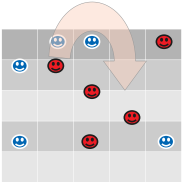
Axelrod Model

(1) Choose randomly two nearest neighbor agents i and j,

(2) calculate the number of shared features (cultural overlap) between the agents ℓ_{ij}.
If $0 < \ell_{ij} < F$:
then (3) with probability ℓ_{ij}/F, set $C_{ik} = C_{jk}$, pick up randomly a feature k such that $C_{ik} = C_{jk}$.

Schelling model

(model for segregation)



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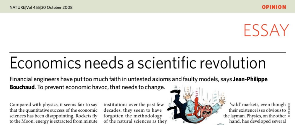
It is about transitions


NATURE|Vol 455|30 October 2008 OPINION

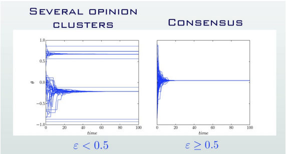
ESSAY

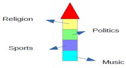
Economics needs a scientific revolution

Financial engineers have put too much faith in untested axioms and faulty models, says **Jean-Philippe Bouchaud**. To prevent economic havoc, that needs to change.

Compared with physics, it seems fair to say that the quantitative success of the economic sciences has been disappointing. Rockets fly to the Moon; energy is extracted from minute institutions over the past few decades, they seem to have forgotten the methodology of the natural sciences as they 'wild' markets, even though their existence is so obvious to the layman. Physics, on the other hand, has developed several

Bounded confidence Models





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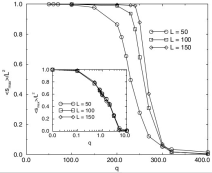

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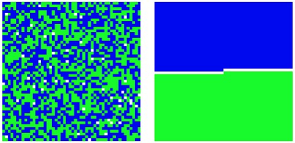
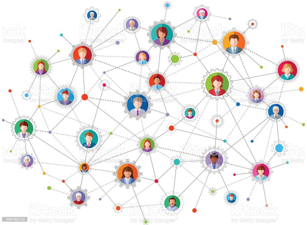


III. The role of topology: Networks Science

Networks Science is the scientific field that studies the pattern of connections among entities. Those entities $\Rightarrow$ nodes or vertices, and links $\Rightarrow$ whenever they interact.

Ex. friendship, social-virtual networks, telephone calls, followers or retweets on Twitter $\rightarrow$ any system able to be represented as an **abstract structure** capturing the patterns of connections.



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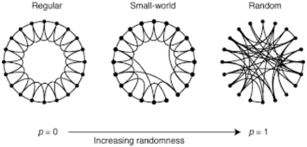
From the physics community:

- Small-world networks (1998).
- Inspired by the small-world experiment by Stanley Milgram.
- The averaged minimal distance between each pair of nodes grows $\propto log(N)$ (as in random networks).
- While the clustering coefficient (# of triangles) remains high (as in regular networks).



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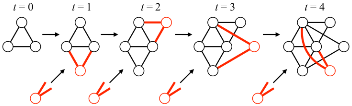

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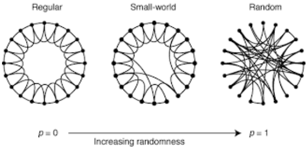

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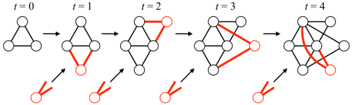

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The representation of the networks can:

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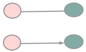
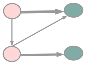
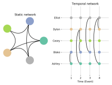


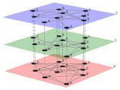
- Also consider the weight to count for the heterogeneity on the frequency of the interactions.



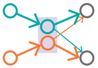
- Examine temporal connectivity, instead of aggregated ones.



- Study high-order interactions, instead of just pair-wise links.



- Be represented as multilayer networks to study multiple subsystems.



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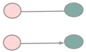

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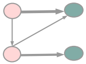

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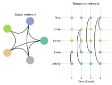

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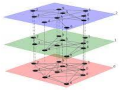

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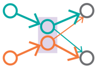

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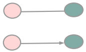

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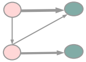

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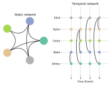

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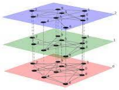

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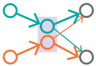

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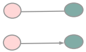

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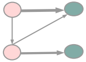

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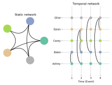

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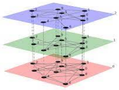
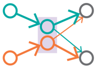


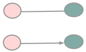
- Be represented as multilayer networks to study multiple subsystems.



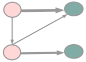
III. The role of topology: Networks Science

The representation of the networks can:

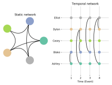
- Be either undirected or consider the direction of the interaction.



- Also consider the weight to count for the heterogeneity on the frequency of the interactions.



- Examine temporal connectivity, instead of aggregated ones.



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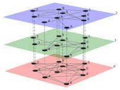

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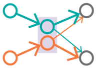


III. Networks Science

RESEARCH ARTICLE

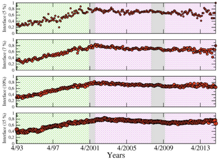
Fragmentation, integration and macroprudential surveillance of the US financial industry: Insights from network science

Yerali Gandica[1,2]*, Marco Valerio Geraci[1,3], Sophie Béreau[1,2,4], Jean-Yves Gnabo[1,2]

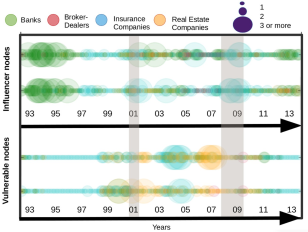
1 CeReFiM (DeFiPP), Université de Namur, Namur, Belgium, 2 Namur Center for Complex Systems - naXys, Université de Namur, Namur, Belgium, 3 ECARES, Université libre de Bruxelles, Brussels, Belgium, 4 CORE, Université catholique de Louvain, Louvain-la-Neuve, Belgium

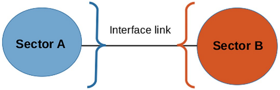
PLOS ONE | https://doi.org/10.1371/journal.pone.0195110 April 25, 2018

Two phases



Proportion of **sector-interface** inside the giant component from April 1993 to November 2014, for different values of the test's cutoff levels for detecting the significant links.





A link is defined as part of the **interface** if its two connecting nodes belong to different sectors.

- We provide new insights on the evolution of the US financial industry over 20 years using network-based metrics.
- Our samples were the 155 financial institutions (banks, broker & dealers, and insurance and real-estate companies) listed in the Standard & Poor's 500 index.
- Dynamic networks were built based a Time- Varying Parameter Vector AutoRegressive (TVP-VAR) approach on stock market returns.
- Our less traditional metrics, such as sectoral interface or measurements based on contagion processes, document the co-existence of both fragmentation and integration phases.

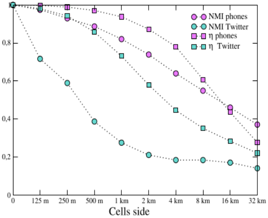
III. Networks Science

RESEARCH

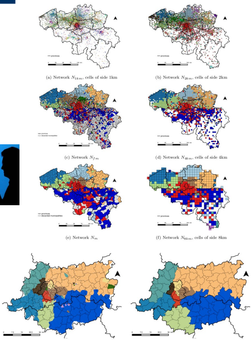
Measuring the effect of node aggregation on community detection

Adeline Decuyper[1], Yérali Gandica[1,2*], Christophe Cloquet[3], Isabelle Thomas[1] and Jean-Charles Delvenne[1,2]

Gandica et al. *EPJ Data Science* (2020) 9:6
https://doi.org/10.1140/epjds/s13688-020-00223-0



Twitter throughout the country of Belgium



Phone calls in the territory of Brabant

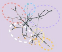
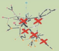
- We identify the class of community detection algorithms most suitable to cope with node aggregation.
- We develop an index for aggregability, capturing to which extent the aggregation preserves the community structure.
- We show results on two real-world examples: mobile phone and Twitter reply-to networks.
- Our main message is that any node-partitioning analysis performed on aggregated networks should be interpreted with caution, as the outcome may be strongly influenced by the level of the aggregation (Modifiable Areal Unit Problem).

III. Networks Science

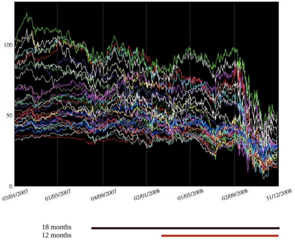
OPEN **A multilevel analysis of financial institutions' systemic exposure from local and system-wide information**

Yérali Gandica[1,2,3,4,5], Sophie Béreau[1,2,3] & Jean-Yves Gnabo[1,2]

Scientific Reports | (2020) 10:17657

Analysis at different scales of inter-dependencies			
Scale	Levels of analysis	Graphical illustration	Network-based metrics
Global topological metric (GT)	Firm topological characteristics computed over the whole system		In-degree centrality Out-degree centrality Betweenness centrality Clustering centrality In-Katz centrality Out-Katz centrality Inverted m-reach M-reach Temporal inverted m-reach * Temporal m-reach *
Aggregated topological metric (AT)	Those characteristics are computed by averaging the relevant topological metrics for all the firms within a community. In turn, all firms from the same community will feature the same values for those AT metrics		In-degree centrality Out-degree centrality Betweenness centrality Clustering centrality Community degree In-Katz centrality Out-Katz centrality Inverted m-reach M-reach Community size Sectoral Entropy * Community inter in–degree Community inter out-degree Inter-Intra Community in-degree Inter-Intra Community out-degree * **F** in-degree / **C** intra-in-degree **F** out–degree / **C** intra-out-degree *
Local topological metric (LT)	Firm topological characteristics computed over the community		In-degree centrality Out-degree centrality Betweenness centrality Clustering centrality Degree centrality Inverted m-reach M-reach In-Katz centrality Out-Katz centrality

Symbols ✕ over links mean those links were eliminated before calculating the measurements



Selected variables	C.R:12 m	C.R:18 m	M.D:12 m	M.D:18 m
Betweenness centrality (GT)	−	−	+	+
Clustering (GT)	−	−	+	+
Inverted 2-reach centrality (GT)	+	+	−	−
Out-Katz centrality (GT)	−	−	+	+
Community size (AT)			+	+
Out-degree centrality (LT)	+	+	−	−
Inverted 2-reach centrality (LT)	+	+	−	
Inter-intra-outdeg (new-AT)	−		+	
Outdeg-intra-outdeg (new GT)	+	+		−
Sectoral-entropy (new-AT)	+		−	
Temporal inverted 2-reach (new GT)				+
Temporal 2-reach (new GT)	−	−	+	+

- We regress measures of vulnerability on three levels of topological measures: global, local and communities ones.
- The sample was the stable (during the crisis) financial institutions (banks, broker & dealers, and insurance and real-estate companies) listed in the Standard & Poor's 500 index.
- Our variables were selected by compromising L2-norm shrinkage (Ridge Regression) and L1-norm penalty (Lasso).
- Our results confirm that the informational content on the different levels is different from that embedded in traditional system-wide topological metrics, and can help predict distress of financial institutions in times of crisis.

IV. Data Science to understand human nature

For a long time, scholars from different backgrounds have been studying

human behaviour

Some fundamental properties had not been found for the lack of reliable data

Digital age

- Is opening up the possibility to uncover some social patterns not so far detected.
- Also pioneering the possibility for the test of models of social patterns as a collective effect of interaction among single individuals.

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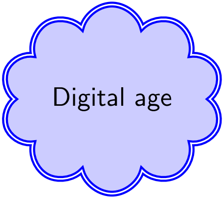

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IV. Data Science to understand human nature

PHYSICAL REVIEW E **91**, 012824 (2015)

Wikipedia editing dynamics

Y. Gandica*
Centre for Computational Physics, Department of Physics, University of Coimbra, 3004-516 Coimbra, Portugal and Department of Mathematics and Namur Center for Complex Systems—naXys, University of Namur, rempart de la Vierge 8, B 5000 Namur, Belgium.

J. Carvalho and F. Sampaio dos Aidos
Centre for Computational Physics, Department of Physics, University of Coimbra, 3004-516 Coimbra, Portugal

(Received 7 November 2014; published 29 January 2015)

- We propose that the probability to edit again WP is proportional to
  - editor's number of previous edits (preferential attachment),
  - the editor's fitness, and
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- We proved that using these simple ingredients, it is possible to reproduce the results obtained for Wikipedia editing dynamics.

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epl A Letters Journal Exploring the Frontiers of Physics

October 2014

EPL, **108** (2014) 18003
www.epljournal.org
doi: 10.1209/0295-5075/108/18003

The dynamic nature of conflict in Wikipedia

Y. Gandica, F. Sampaio dos Aidos and J. Carvalho

Centre for Computational Physics, Department of Physics, University of Coimbra - 3004-516 Coimbra, Portugal

- The level of conflict based on a tolerance parameter (editors' capability to accept different opinions and to change their own opinion).
- We also proposed an improvement in a metric based on double reverts to calculate conflicting pages.

IV. Data Science to understand human nature

PLoS ONE 12(3): e0174509 (2017)

RESEARCH ARTICLE

Stationarity of the inter-event power-law distributions

Yerali Gandica[1]*, João Carvalho[2], Fernando Sampaio dos Aidos[2], Renaud Lambiotte[1], Timoteo Carletti[1]

1 Department of Mathematics and Namur Center for Complex Systems—naXys, University of Namur, Namur, Belgium, **2** Centre for Physics of the University of Coimbra (CFisUC), Department of Physics, Coimbra, Portugal

- A number of human activities exhibit a bursty pattern (very high activity followed by rest periods).
- Their time series of inter-event times follow a power-laws probability distribution with specific exponents.
- What is the intrinsic cause for the robustness of such as exponents?

IV. Data Science to understand human nature

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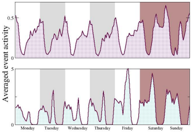
- The first works suggested a decision-based queuing process: the next task to be executed is chosen from a queue with a hierarchy of importance.

- That could explain email sending but not all the online activity where the same exponent power-laws distributions has been found.
- Then, the origin was proposed to be the cyclic constraints in life.
- In a previous work: They removed the circadian patterns from the time series → they found similar inter-event distributions.



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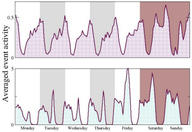

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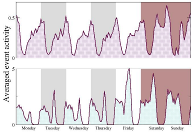

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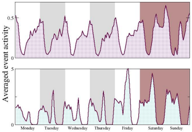
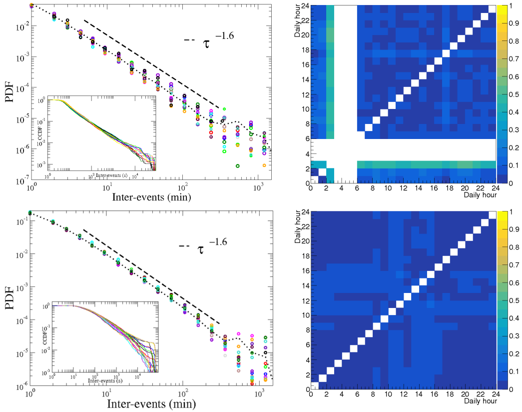


IV. Data Science to understand human nature

We show that similar inter-event distributions take place independently of the hour of the day. $\rightarrow$ by studying Wikipedia editing and Twitter posting.



Left: PDF for the inter-event time of each hour of the day. Dotted lines: PDF using a window of 24 hours (all the data).
Right: K-S distance between the one-hour window CCDFs.

IV. Data Science to understand human nature

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Main conclusion

- Although the probability to start editing is strongly influenced by circadian rhythms $\rightarrow$ the conditional probability distribution for the time between successive edits is independent from the time of day.
- The bursty nature of the process is mostly independent from the circadian patterns.

Take-home message

Before performing an action (make a phone call, send a tweet, edit Wikipedia, etc) we must overcome a "barrier", acting as a cost, which depends, among many other things, on the time of day. However, once that "barrier" has been crossed, there exists a robust distribution of activities **attention**, which no longer depends on the time of day.

IV. Data Science to understand human nature

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IV. Data Science to understand human nature

2018 Fifth International Conference on Social Networks Analysis, Management and Security (SNAMS)

Population Preferences Through Wikipedia Edits

Yérali Gandica
Center for Operations Research and Econometrics (CORE),
Institute of Information and Communication Technologies, Electronics and Applied Mathematics (ICTEAM)
Université catholique de Louvain, Louvain-la-Neuve,
and Center for Research in Finance and Management (CeReFiM), Université de Namur, Namur,
Belgium.
ygandica@gmail.com

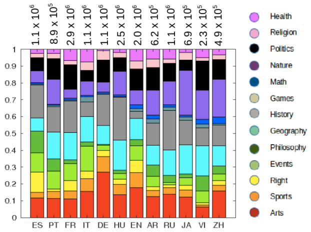


Fig. 2. Distribution of pages for each language. A colour is associated to each category. The colouring of each column gives the proportion of each category with respect to the total number of pages for the given language.

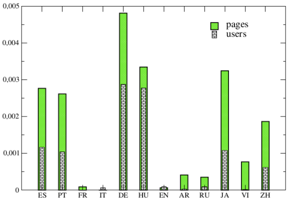


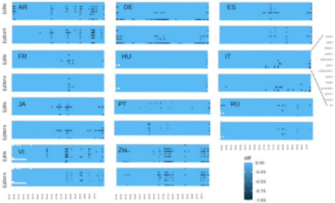
Fig. 4. Degree of homogeneity on the number of pages (in green) and the number of users (in black) among the categories. Calculated by the χ^2-test.

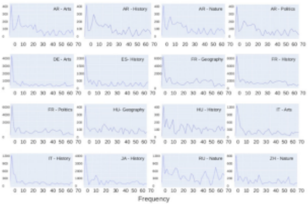
IV. Data Science to understand human nature

The Detection and effect of social events on Wikipedia data-set for studying human preferences

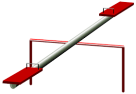
Julien Assuied and Yérali Gandica

January 2022





V. Criticality on social-inspired thermodynamic systems and real data



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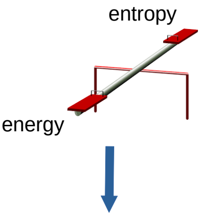

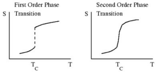

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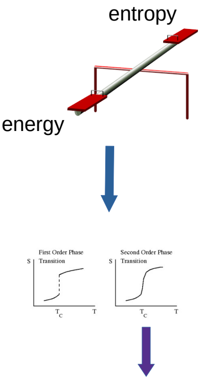
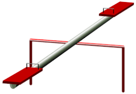


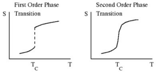
if all the elements are correlated at all scales

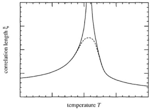
V. Criticality on social-inspired thermodynamic systems and real data

entropy



energy

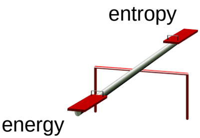


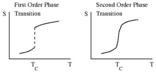


The **divergence on the correlation** causes **important simplifications** on the functions of the systems

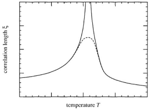
if all the elements are correlated at all scales

V. Criticality on social-inspired thermodynamic systems and real data





Critical Phenomena (in physics)



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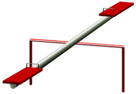
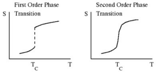
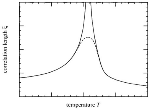




Signs of criticality

Critical Phenomena (in physics)



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V. Criticality on social-inspired thermodynamic systems and real data

Criticality

all the individuals in the systems are highly correlated

V. Criticality on social-inspired thermodynamic systems and real data

Criticality

all the individuals in the systems are highly correlated

Power-law shaped distributions of several metrics with specific values of exponents, have been found in **social systems.**

Critical state:
state characterised by either high **correlations** among the individuals or by the feedback between the individuals and their physical environment (coupled human-environmental interactions)

V. Criticality on social-inspired thermodynamic systems and real data

PHYSICAL REVIEW E **93**, 032132 (2016)

Nature of phase transitions in Axelrod-like coupled Potts models in two dimensions

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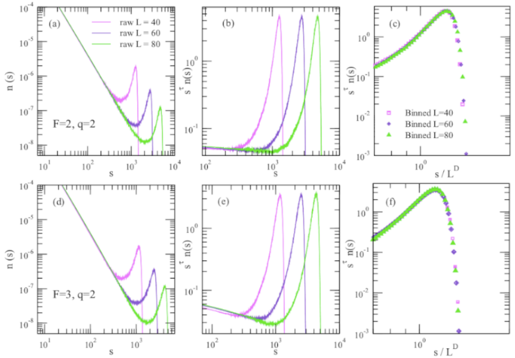
Silvia Chiacchiera†
CFisUC, Department of Physics, University of Coimbra, P-3004-516 Coimbra, Portugal
(Received 20 November 2015; published 17 March 2016)



V. Criticality on social-inspired thermodynamic systems and real data

PHYSICAL REVIEW LETTERS **127**, 168301 (2021)

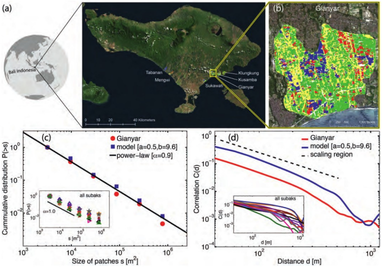
Bali's Ancient Rice Terraces: A Hamiltonian Approach

Yérali Gandica,[1,*] J. Stephen Lansing,[2,3] Ning Ning Chung,[4] Stefan Thurner,[2,5,6] and Lock Yue Chew[7,8]

Adaptive self-organization of Bali's ancient rice terraces

J. Stephen Lansing[a,b,c,e,1], Stefan Thurner[a,b,d,e,f], Ning Ning Chung[b,g], Aurélie Coudurier-Curveur[h], Çağil Karakaş[h], Kurt A. Fesenmyer[i], and Lock Yue Chew[b,g]

www.pnas.org/cgi/doi/10.1073/pnas.1605369114



V. Criticality on social-inspired thermodynamic systems and real data

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The harvest cycle was divided into four stages: grow, harvest, flood, drain.

V. Criticality on social-inspired thermodynamic systems and real data

Mechanisms at work (one thousand years):

Because most rice pests can move, promoting all neighboring farmers to start the cultivation at the same time helps their elimination.

But, if too many fields are flooded at the same time, some fields will experience water stress.

(Promoting farmers to cultivate at different stages).

V. Criticality on social-inspired thermodynamic systems and real data

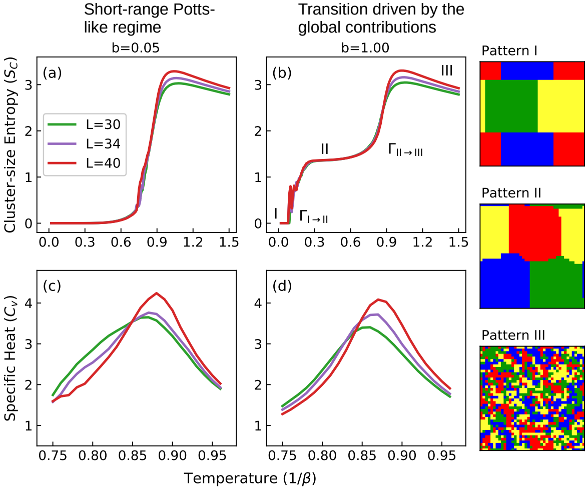
The Subak Hamiltonian

$$H = -a \sum_{\langle i,j \rangle} \delta(\sigma_i, \sigma_j) + \frac{b * k}{N} \sum_{i,j} \delta(\sigma_i, \sigma_j)$$

Local interaction (Potts model) + non-attractive global interaction

- a: Pets Stress, promoting local ordering
- b: Water stress, promoting global disorder

V. Criticality on social-inspired thermodynamic systems and real data



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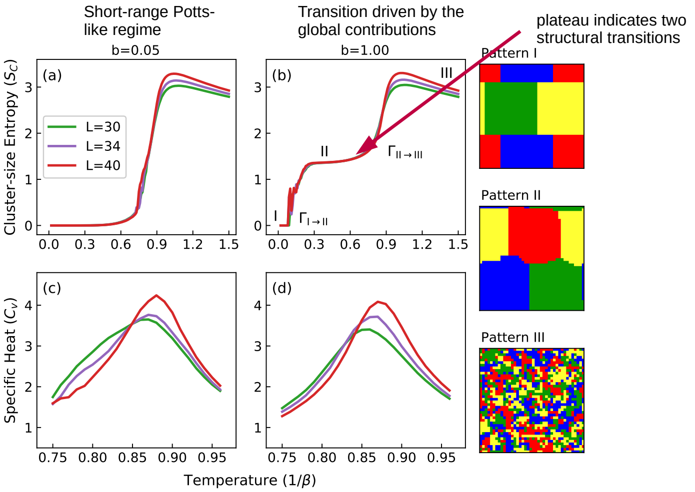

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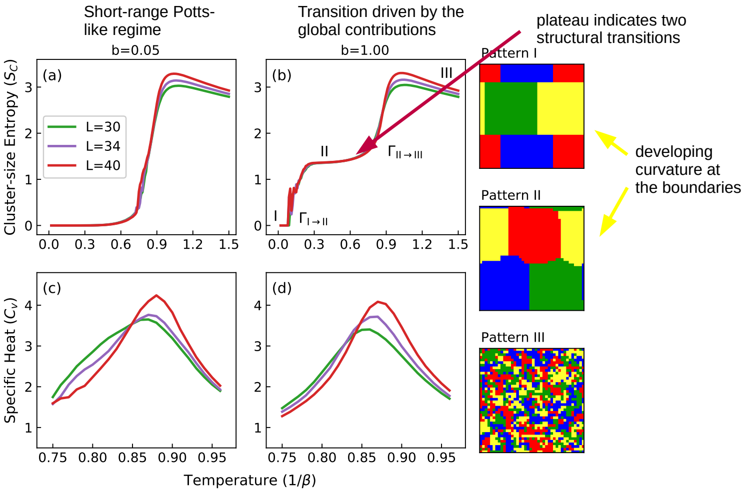

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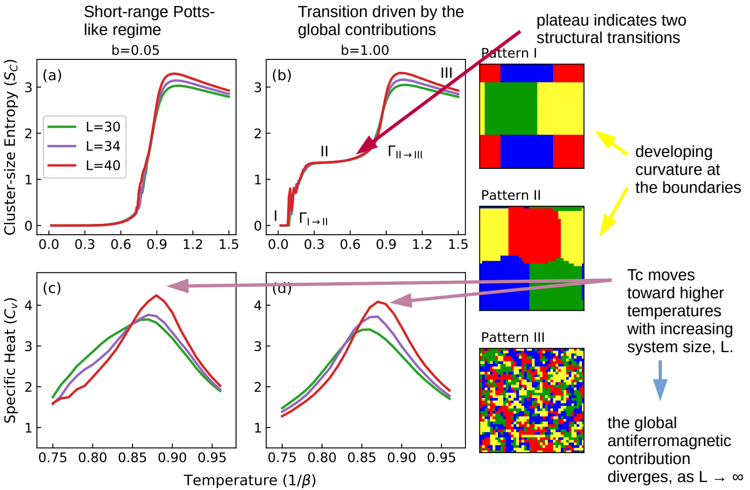

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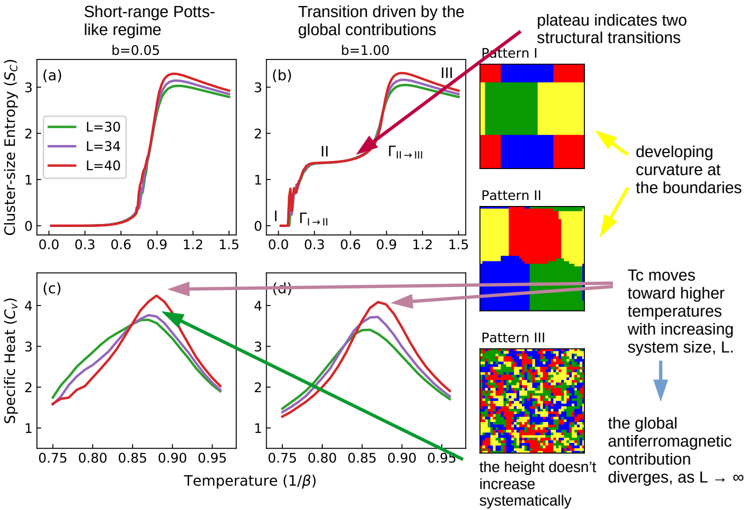
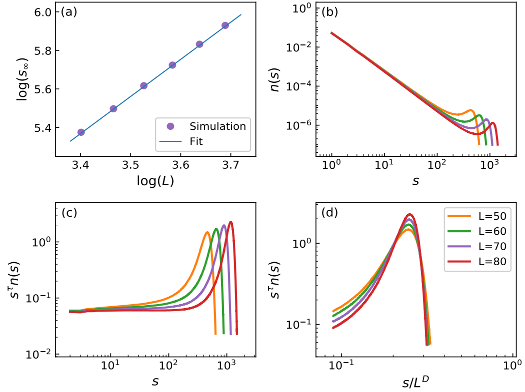


V. Criticality on social-inspired thermodynamic systems and real data

As the apparent transition dominated by the local contributions disappears in $L \to \infty$, we focus on the global antiferromagnetic-driven transition (b=1)

Scaling ansatz

$$T_c(L) = T_c(\infty) + \lambda L^{-1/\nu},$$



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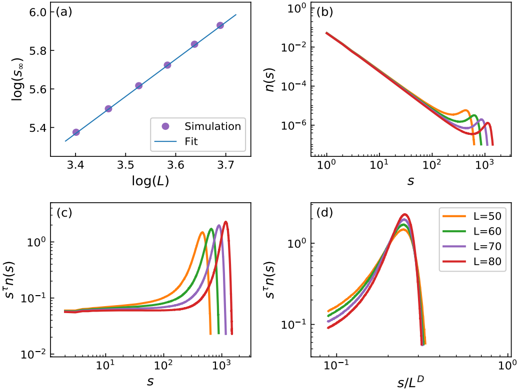

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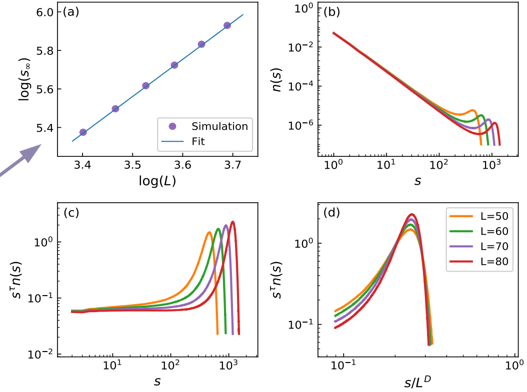

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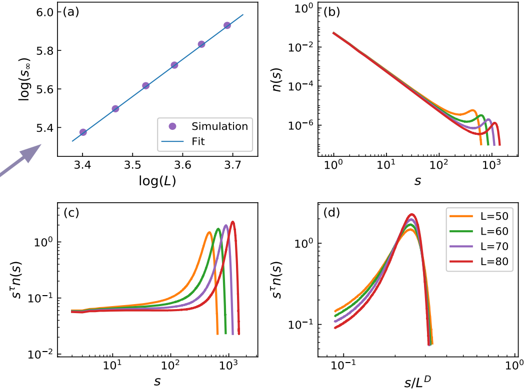
Exponent for cluster-size distribution τ =2.036(1)

D = 1.927(4)



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$$(\tau = d/D + 1)$$

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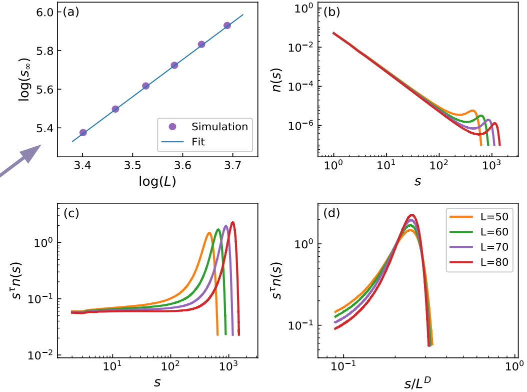

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Although the collapse is not perfect, the system clearly shows signs of criticality. The transition is, if not second order, at least weak first order → The approximate data collapse occurs as a consequence of the increase of the correlation length

Take-home message

**The centuries-old cyclical harvesting patterns:
a critical equilibrium**

- The Green Revolution agriculture reaches Bali in the 1970s.
- The subaks were instructed to cultivate as often as possible (unsynchronized planting schedules).
- By 1977, 70% of southern Balinese rice terraces were planted with Green Revolution rice.
- At first, rice harvests increased. Within 2 years, however, Balinese workers reported "chaos in water scheduling" and "explosions of pest populations".

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V. Criticality on social-inspired thermodynamic systems and real data

Signs of universal patterns in social explosions: An empirical study

'Twitter revolutions'

Are we able to find common patterns?

Collaborators: J. Stephen Lansing (SFI), Ning Ning Chung , Stefan Thurner (SFI), and Lock Yue Chew (NTU)

Some theoretical considerations

- **The success of an on-line movement:** the shift of scale and the later massive off-line protests.

- **The role of the social media:** to facilitate the transformation between small or local feelings of disagreement into large-scale social actions.

- **The way how social media achieves that effect:** growing clusters of people and groups with similar effervescent feelings.

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Some theoretical considerations: why percolating properties?

- **It is natural to think** any macro-social action, as a consequence of spontaneous and massive interactions between all individuals, will have as a consequence the growth and divergence of the correlation between them.

- If the correlation length attains a power-law shape, then power-laws dominance is expected to happen on the cluster's statistics forms.

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The data-sets

Four different large-scale spontaneous manifestations:

- **The Spanish Indignados movement**. The critical point for this data-set was the 15th of May 2011.
- The second and third data sets were taken in Argentina during the year 2019 around two popular movements. A protest against high taxes taking place between January 4th and 6th, and a mobilization asking for justice on November 9th.
- **The Occupy Wall Street** massive demonstrations taking place around May 2012.

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Dataset	Event day/s	Same time		Same nº of hashtag usages	
		N. Tweets	*N. Hashtags*	*N. Tweets*	*N. Hashtags*
noaltarifazo/ruidazonacional	Jan. 4th-6th 2019	81,516	20,059	97,315	22,813
9n/9ngranmarchaporlajusticia	Nov. 9th 2019	136,367	15,266	165,461	18,193
15m	May 15th 2011	39,704	2,991	49,612	3,674
occupy Wall Street	Dec. 5th 2010, Feb. 23th 2011	- (*)	14,788	- (*)	14,787

TABLE I. Datasets composition. (*) For the Occupy Wall Street dataset, tweet ids were not available, but only hashtags usage by users on a daily basis.

- Each data-set has been divided into three periods.
- The period "during" fix the data-windows.
- Then, we divided the analysis in two parts: (a) same amount of time "before" and "after" as "during" the event and, (b) same number of hashtag usages "before" and "after" as "during" the event.

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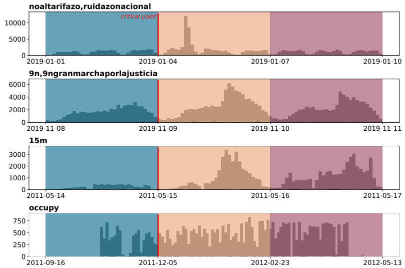
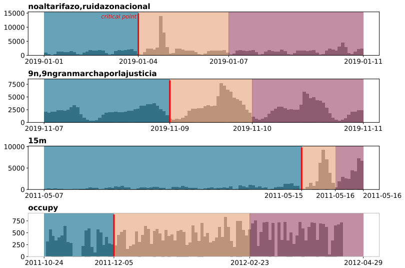
Same number of hashtags Vs. same time





Observation 1:

No similarities seem to appear beyond the highest activity during the event

Hashtag frequency distributions

- For each social movement we fitted a power law distribution for the hashtags' frequencies, for the data-sets "before" and "during".
- As some users might use the same hashtag many times, we consider two different ways of building the hashtag frequency distribution inside each period (second division):
    - **(a)** Counting the number of hashtag usages (Hasht),
    - **(b)** Counting the number of unique users using that hashtag (User).

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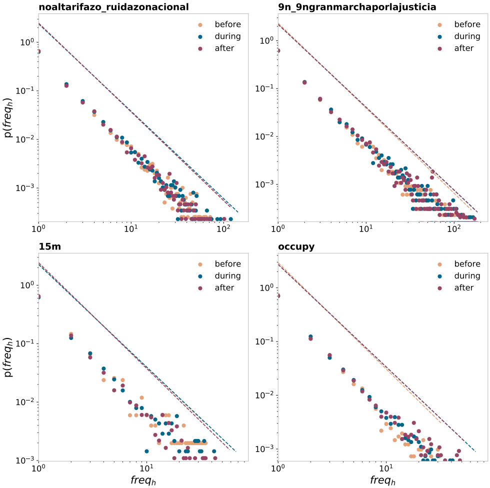

- The power law exponents were fitted by the maximum likelihood method, and all fits passed the Kolmogorov-Smirnov goodness-of-fit test at $p = 0.05$.
- These p-values were computed with the plfit program, following the procedure described in [A. Clauset, C. R. Shalizi, and M. E. Newman, SIAM review51, 661 (2009)].

Hashtag frequency distributions

TABLE II. Discrete power law exponents for the frequency distribution of hashtags, fitted by max-likelihood for each event and time period, when the x_{min} parameter is also fitted by max-likelihood. All fitted x_{min} values lie in the interval [1, 4], and all fits passed the Kolmogorov-Smirnov goodness-of-fit test at p=0.05.

Level	**Dataset**	**Same time**		**Same nº of hashtags**	
		Before	*During*	*Before*	*During*
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	9n/9ngranmarchaporlaj..	1.822(0.011)	1.760(0.010)	1.818(0.009)	1.760(0.010)
	15m	1.960(0.046)	1.825(0.023)	1.793(0.020)	1.825(0.023)
	occupy Wall Street	2.402(0.025)	2.107(0.013)	2.402(0.025)	2.107(0.013)
User	noaltarifazo/ruidazonac..	1.994(0.012)	1.989(0.011)	1.989(0.012)	1.989(0.011)
	9n/9ngranmarchaporlaj..	1.788(0.010)	1.758(0.010)	1.822(0.009)	1.758(0.010)
	15m	2.125(0.054)	1.870(0.024)	1.840(0.020)	1.870(0.024)
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Observation: Lowest values for the exponents on the data-set "during".

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		Before	*During*	*Before*	*During*
Hasht	noaltarifazo/ruidazonac..	1.957(0.011)	1.943(0.011)	1.955(0.011)	1.943(0.011)
	9n/9ngranmarchaporlaj..	1.822(0.011)	1.760(0.010)	1.818(0.009)	1.760(0.010)
	15m	1.960(0.046)	1.825(0.023)	1.793(0.020)	1.825(0.023)
	occupy Wall Street	2.402(0.025)	2.107(0.013)	2.402(0.025)	2.107(0.013)
User	noaltarifazo/ruidazonac..	1.994(0.012)	1.989(0.011)	1.989(0.012)	1.989(0.011)
	9n/9ngranmarchaporlaj..	1.788(0.010)	1.758(0.010)	1.822(0.009)	1.758(0.010)
	15m	2.125(0.054)	1.870(0.024)	1.840(0.020)	1.870(0.024)
	occupy Wall Street	2.074(0.018)	1.959(0.012)	2.074(0.018)	1.959(0.012)

Observation: Also when dividing by the same number of hashtags.

Hashtag frequency distributions

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Observation: Results are robust against counting one or several usages.

Hashtag frequency distributions

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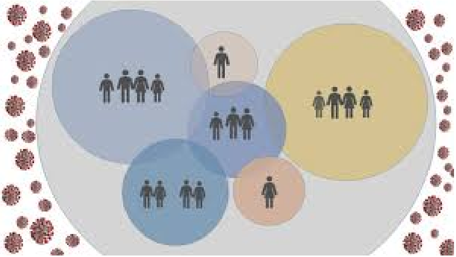
Observation: Power-laws exponents are the same in each social movement

Take-home message

Our only interpretation is that the last phenomenon is a consequence of simplifications thanks to the divergence of the correlation length

VI. Grants/Projects

- Continuing exploring social phenomena through the approach of Complex Systems and Critical Phenomena.
- Can we find the relevant variables, symmetries and conserved quantities in social dynamics?
- **In the age of big data, this approach will reveal which variables to consider, rather than simply organizing all the data to generate outputs.**
- With a broad background in several interdisciplinary fields.



Goal

The development of a theoretical framework to understand criticality in networks and socio-economic systems

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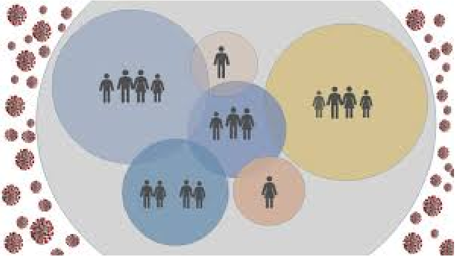

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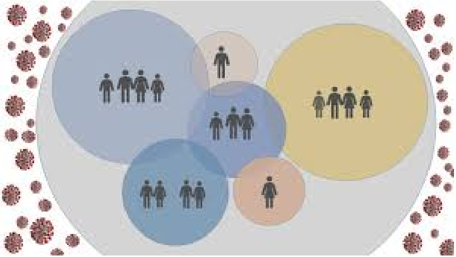

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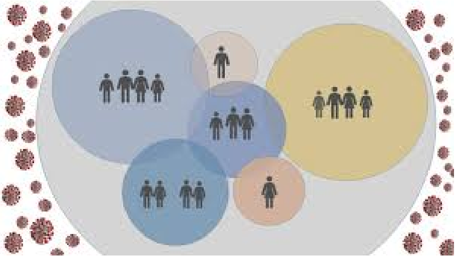

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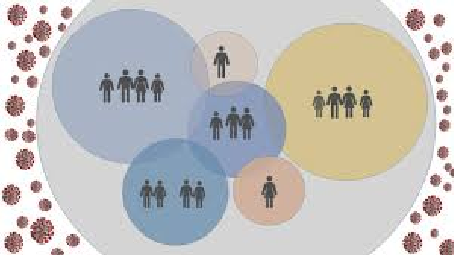

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VI. Grants/Projects

What is the effect of the of firms' heterogeneity on the phase transitions that happened as a consequence of the global financial crisis?

- A first part: MC simulations with heterogeneous spins (to simulate the fact that firms have different capacity to absorb shocks).
- A second part: The design of measurements for studying the absorption of shock by financial firms.

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Grants/Projects

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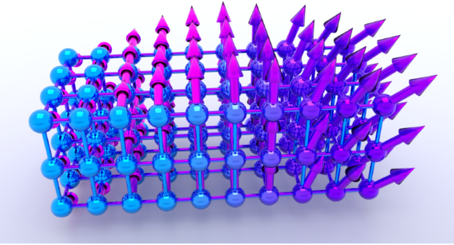

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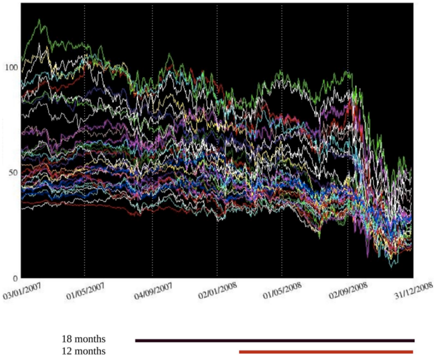
- 2nd part: Measurements to study the absorption of shocks by financial firms: critical slowing down, risk-sharing versus risk spreading, etc.



VI. Grants/Projects

The social temperature of Societies

- The concept of temperature (well-established in thermodynamic equilibrium) has been repeatedly applied to systems that are out-of-equilibrium.
- The temperature measures the amplitude of the noise or of the fluctuations of the physical variables around their average or most probable values.
- This provokes a new question, how can we use real systems observations to understand the role of temperature/noise/fluctuations? pause
- Intiuitively, it seems clear that some societies are more influenced by fluctuations than others.
- How can we quantify it? And more, importantly, is that metric related to some other manifestations on the corresponding society?

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VI. Grants/Projects

Super Statistics approach for human-activity time-scales

- A Poisson process exhibits an exponential inter-event time distribution, where the characteristic decay time is the rate to perform an event.
- While a power-law distribution of the inter-event time is obtained when the rate at which individuals perform their events changes with time. The exponent of the power-law distribution of the inter-event time is a signature of how different rates occur in time.
- The resulting superposition of several different time scales has been previously addressed in super- statistics (SS).
- This "statistics of a statistics" description has successfully been applied to various physical systems such as train delays and turbulence, among others.
- I am interested in applying this approach for the first time to individual human activity to understand the link between the several times involved in one person's activity and the exponent of the power-law distribution of the inter-event times.

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Questions ...(?)