

Introduction to the chaos focus issue on the dynamics of social systems

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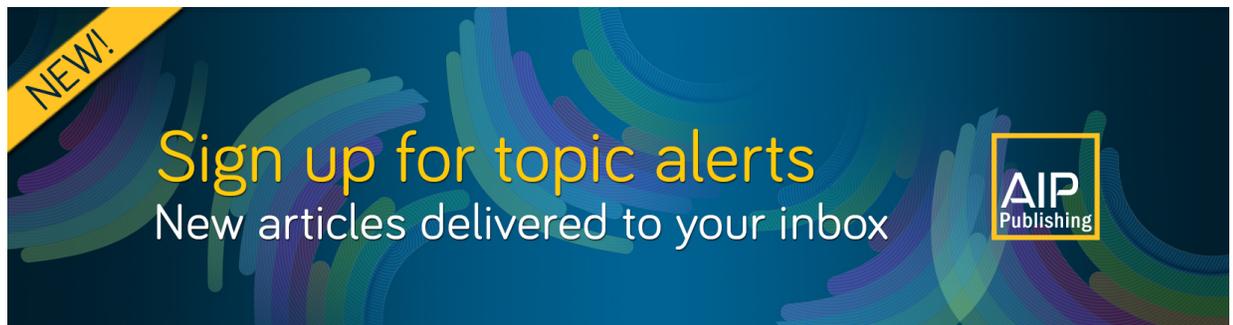
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In social science, we consider systems that consist of an usually large number of individuals whose actions and behaviors are mediated by the interactions among them. After the change in the scientific paradigm brought in by Newton, by which every physical behavior could be predicted from very simple physical laws, people tried to apply the same simplifying principles to other sciences. The apparent similarity of social systems with some problems of interest in the physical sciences became evident quite early. In the same way that a macroscopic body, gas, solid, or liquid, which consists of many interacting units, atoms or molecules, obeys the general laws that rule their behavior, i.e., the law of perfect gases of the Dulong–Petit law for the specific heat of solids, it was naïvely expected that the general laws governing the overall behavior of a social or economical system could arise from very simple general principles. In fact, before the currently accepted name of Sociology for the science describing collective human behavior, Auguste Comte¹ in the first half of the nineteenth century coined for it the term “social physics,” but the term “sociophysics,” or the application of physics concepts and methods to the study of social systems is now quite widespread.^{2–7} In the ultimate goal of deriving the overall, macroscopic behavior from that of the underlying, microscopic constituents, the big revolution initiated in the 1970s by the so-called modern theory of phase transitions and critical phenomena, and the ideas of universality, were an essential ingredients in the emergence of the field of complex systems that has brought new insights into the problem of moving from one scale of reality to the next. An important feature of complex social systems is that the connections between different levels do not only progress from the micro to the macro, but they can also proceed back from the macro to the micro. The introduction of techniques and tools from physics, mathematics, and other disciplines into sociology has led to a fertile area often termed as Computational

Social Sciences.^{8,9} Tools from statistical physics, nonlinear dynamics, agent-based models, game theory, complex networks theory, and big data analysis have been used for problems of opinion formation, cooperation, cultural conflicts, language competition and social learning, wealth distribution, financial markets, socio-technical systems, human mobility, electoral processes, transportation, tourism, city science, epidemics, energy consumption, to give a nonexhaustive list.

Physicists have played a leading role in these new approaches to social science problems. They have typically excelled in two areas: modeling and data analysis. Modeling is the process (or the art) by which we aim at a simplifying description that keeps the essence of the problem under consideration but still advances our understanding and, eventually, it is able to make useful predictions. We hold the point of view that the main use of models is to provide an understanding of the mechanisms beyond the description of collective patterns of behavior. The main goal of modeling is to establish cause–effect relations that go beyond inference from statistical correlations as a necessary step to understand data. Modeling is, hence, about understanding data rather than reproducing data. The theory of epicycles could reproduce (and predict) the movements of planets, but a much deeper understanding came with the advent of the gravitational theory of Newton. Good modeling in the social sciences must serve the following purposes: (i) to be able to pose a well defined question, (ii) to isolate a mechanism of social interaction and determine emergent consequences at the collective level, (iii) to establish cause-effect relations, and (iv) to check common sense wisdom.

There are many examples of models based in interacting agents in this Special Issue, but it is relevant to mention here that many of the models used traditionally to describe collective phenomena in sociophysics are extremely close, if not identical, to well

established models used in statistical physics. As a way of an example, the kinetic Ising model with exchange dynamics and vacancies is isomorphic to the celebrated model of Schelling to study segregation in communities.¹⁰ There are some differences between the physics and sociology contexts. While in physics one is used to routinely taking the thermodynamic limit where the number of interacting particles diverges, it is not the case in social communities where the number of interacting units, or agents, can range from the hundreds to the millions. Another difference is that while in physics, the particles can be classified into a few categories with identical properties in each group (electrons, protons, atoms, or molecules of one type), the heterogeneity in the social sciences is much more evident, with different agents interacting with a different number of other agents (and sometimes the spread in the number of interactions among agents can be very large), or carrying very different intrinsic characteristics, such as the infectiveness of a disease, the charisma, etc. Last, but not least, interactions in social systems are often, but not always, strategic, involving goals and expectations. Beyond that, there are also feelings and, additionally, individuals give different meanings to the same information or fact.

While reliable data from experiments and observations have long been available in the so-called hard sciences (physics, chemistry, etc.), the study of society has suffered a chronic lack of dependable data until very recently.¹¹ The traditional picture in social sciences has been altered dramatically through the advent of information technologies. The introduction of the web in the late 1990s was followed by the development of the blogosphere in the early 2000s and by the foundation of the most popular social networks in the late 2000s and early 2010s. Tools abundantly used in today's societies (such as Twitter or Facebook) are only just over a decade old. In parallel, physical technology has also evolved, making it possible for a large fraction of the population to have access to portable smart devices with continuous online connection. All interactions between users and devices, from person-to-person through devices, and of users with the environment are registered. The analysis of social systems is thus facing a flood of data in marked contrast to the classical drought. Making sense of the abundance of data requires a new conceptual framework toward understanding social systems. Besides, the data are collected to improve services and not to answer scientific questions, making modeling even more relevant. One avenue is to use black-box approaches, such as present routine machine learning or artificial intelligence methods. While valuable in their own right, it is our belief that a deep understanding of social processes requires the development of models that implement mechanisms of social interaction. Building this type of model with explicative and predictive power requires a major paradigm change that should incorporate artificial intelligence technologies to learn about social mechanisms.

This special issue about the dynamics of social systems is a representative set of papers dealing with all issues mentioned above. We have classified them into two categories: modeling and data driven research. In the modeling, the majority of papers use an Individual-based approach, while a few use an approach based on the theory of dynamical systems and stochastic processes. A short summary of each paper and its main results are presented next.

I. MODELING

A. Individual based models (IBM)

- **The impact of malicious nodes on the spreading of false information**, Ruan *et al.*¹²

This is a modeling paper in the general context of Individual Based Models used to understand different mechanisms that act at the micro-level and produce macroscopic social phenomena. The authors address the timely problem of the spread of false information on social media networks. Using a simple information contagion model, they show that there is a critical number of malicious nodes (those that always repost the false message) beyond which the false information breaks out in the network.

- **An agent-based model of multi-dimensional opinion dynamics and opinion alignment**, Schweighofer *et al.*¹³

This is also an Individual Based Model paper on opinion dynamics addressing the question of the emergence of opinion alignment and polarization which is of much relevance in the political context. The paper includes new ingredients not considered in standard opinion formation models, such as multidimensional opinion and change of opinions derived from the cognitive dissonance theory and structural balance theory. Schweitzer and co-workers unveil in this paper basic interaction mechanisms leading to opinion alignment and polarization.

- **Effect of memory, intolerance, and second-order reputation on cooperation**, Xia *et al.*¹⁴

The authors address the question of the emergence of human cooperation through an IBM in which agents interact with different strategies in a theory setup so that, in principle, there is also a goal associated with the individual pay-off. A difference with other IBMs in this Focus Issue is that strategies and interaction rules are not purely theoretical assumptions, but they are based on findings of experimental game theory. The paper describes, using a donation game, different effects of second-order reputation and memory as mechanisms driving cooperation.

- **Phase transition in the Kolkata Paise restaurant problem**, Sinha and Chakrabarti.¹⁵

The Kolkata Paise restaurant problem is an example of a social minority game. In the setup, N agents must choose among N restaurants each one serving a single food. The agents have to decide every evening (on the basis of information about the past evenings, available to everyone) which restaurant to choose and then be able to get the only dish available there. There is an obvious solution to this problem where a dictator forces each consumer to go to a given restaurant, different from the others. The question is whether this dictated solution can be learnt by more "democratic" rules where each agent learns from experience and decides on her own which restaurant to choose every evening. The paper shows that two different stochastic strategies can eventually lead to the most efficient social solution at some limiting control parameter values, corresponding to a phase transition point, thereby implying a very long convergence time (critical slowing down).

- **Polarizing crowds: Consensus and bipolarization in a persuasive arguments model**, Barrera Lemarchand *et al.*¹⁶

There have been many studies on the dynamics of opinion formation in social systems, a topic of relevance in group

decision-making processes, such as political deliberation. This paper introduces a binary-opinion dynamical model where changes of state are due to explicit exchanges of arguments, such that agents decide on one of the two opinions based on the total weights that agents hold for each option. The analysis and results are focused on the total number of accessible arguments, the sizes of the group, and individual memory, and it also considers the influence that bias and homophily in the interactions have on the final collective state. It is found that when interactions are equiprobable and symmetrical, the model only shows consensus solutions. However, when either homophily, confirmation bias, or both are included, the emergence and dominance of bipolarization are observed, which appear due to the fact that individuals are not able to accept the contrary information from their opponents during exchanges of arguments. A relevant parameter is the relation between the number of agents and the number of available arguments in the discussion. Overall, this paper describes the dynamics and shows the conditions wherein deliberative agents are expected to construct polarized societies.

• **I love shopping... but what am I gonna buy? Social interaction and consumption choices**, Caravaggio and Sodini.¹⁷

The study of consumption behavior is a very interesting problem in the dynamics of social systems, as it combines historical, social, and psychological dimensions. This work analyzes the emergence of fashion cycles and other complex phenomena in a discrete-time dynamic model in which agents need to opt between two different goods. The population is divided into two groups, bandwagoners and snobs, that react differently to the aggregate demand for goods in the previous period: while bandwagoners imitate the consumption styles prevailing in society, snobs try to distinguish themselves from them. The preferences for the two groups follow a dynamical map whose behavior, the existence of cyclic or more complex behaviors, is analyzed using tools of dynamical systems. When the structure of the population is fixed, it is possible to observe cyclical behaviors in collective consumption and the onset of chaotic regimes. Moreover, when the agents are able to move from one group to another, the coexistence of different styles may emerge.

• **Competing local and global interactions in social dynamics: How important is the friendship network?**, Jędrzejewski *et al.*¹⁸

It is clear that nowadays people's interactions are not restricted to physical contacts but can extend easily beyond geographical borders. Motivated by a study of social influence in an online movie rating site, in which it is observed that users ratings usually conform to those issued by friends, and anti-conform to those written by strangers, this contribution studies the interplay between local and global interactions in the context of a q -voter model where agents interact with an influence group that can be chosen locally (among adjacent nodes) or globally (randomly on all the networks). An influence group that holds a unanimous opinion can trigger with some probability a conformist or an anti-conformist reaction and make the agent agree or disagree, respectively, with the group opinion. It is considered that conformism/anti-conformism can act at the level of the local and global interactions, leading to four different models whose steady states are computed by using a mathematical simplification known as the pair-approximation. The results are

then compared with numerical simulations of the model rules in different topologies.

• **A model for the competition between political mono-polarization and bi-polarization**, Saintier *et al.*¹⁹

This paper addresses the issue of bi-polarization by considering the dynamics of the propensity to adopt one or two given options. The propensity of an individual varies between 0 and 1 and it evolves by interaction with a neighbor by a mechanism of reinforcement in which individuals with the same opinion orientation become more extreme as they interact, which is known in the literature to induce bi-polarization. The paper then studies the stability of the mono-polarized (all agents with propensity 1 or 0) and bi-polarized states—both analytically and by means of numerical simulations—in an all-to-all coupling scheme. The relative stability of these states depends on a parameter q characterizing the non-linearity of the interaction between agents such that the bi-polarized state is stable when q is smaller than a threshold value q_c , while the mono-polarized state is stable for $q > q_c$. The authors give an intuitive explanation of this behavior.

• **Fake news and rumors: A trigger for proliferation or fading away**, Zehmakan and Galam.²⁰

While a complete understanding and mathematical description of rumor spreading is probably too difficult to achieve, the use of simple models allows us to comprehend its general principles and unveils certain essential aspects. Along these lines, this paper introduces an agent-based-model for the dynamics of rumor opinion. While the opinion is defined as a binary variable (“believer” or “indifferent”), the agents are classified as Seeds (the ones that trigger the rumor), Agnostics (reject any kind of rumor and are always indifferent) or Others (those that can change the state, the majority of the population). The adoption of the rumor by an Other agent occurs by interaction with a group of agents whenever the number of believers of that group is above a threshold m . Furthermore, an Other believer forgets the rumor at a constant rate. Using numerical and analytical methods it is found that the faith of the spreading depends drastically on the value of m in addition to the actual proportions of Seeds and Agnostics. When $m = 1$, even a small group of Believers manages to convince a large part of the community very quickly, but for $m \geq 2$, even a substantial fraction of Believers may not prevent the rumor from dying out after a few update rounds.

• **A two-layer model for coevolving opinion dynamics and collective decision-making in complex social systems**, Zino *et al.*²¹

This paper considers the intertwined coevolution of opinions and decision making in a social system. The authors consider one network representing the communication channel used by the agents to update their opinions, and a different network for the influence channel where they observe others' actions. The model is discussed in the context of the adoption of a novel social norm or innovation. With a single unified modeling framework, and depending on the topology of the interactions and other model parameters, three very different real-world phenomena can be observed: the formation of (i) an unpopular norm, (ii) a popular disadvantageous norm, or (iii) a paradigm shift. It is concluded that when a change of paradigm takes place, the change of opinions precedes that of the actions, as observed in some real-world examples.

- **By force of habit: Self-trapping in a dynamical utility landscape**, Moran *et al.*²²

While most of the above papers consider IBMs in which the actions of the individuals are mechanistically driven by interactions, Moran *et al.* consider individuals with goals: they try to maximize a utility function by changing their choices. The paper considers reinforcement mechanisms such that the utility function depends on past choices. They find a transition between free exploration of the space of choice and self-trapping in a given choice due to memory effects (“by force of habit”).

- **Fear induced explosive transitions in the dynamics of corruption**, Bauzá *et al.*²³

This paper extends a simple compartmental model for corruption dynamics introduced by some of the authors, the so-called HCO for the three main states: Honesty, Corruption, and Ostracism, that agents can hold. Namely, it explores the effect of introducing non-regular topologies governing the evolution of corruption, as a way of introducing social intimidation in the denunciation of corrupt people. The model is analyzed using different connectivity networks by means of Monte Carlo simulations and deterministic microscopic Markov chain equations. When the mechanism of social intimidation is absent or weak, the phase diagram of the model shows three equilibria [(i) full honesty, (ii) full corruption, and (iii) a mixed state] that are connected via smooth transitions. However, when social intimidation is strong, the transitions connecting these states turn explosive leading to a bistable phase in which a stable full corruption phase coexists with either mixed or full honesty stable equilibria.

- **Bird’s-eye view of naming game dynamics: From trait competition to Bayesian inference**, by Marchetti, Patriarca, and Heinsalu.²⁴

The Naming Game was born as a way to understand the spontaneously emerging consensus about the use of one or more words in a group of interacting individuals. With very simple rules it is representative of a class of semiotic dynamics models that describe how a consensus about, e.g., the meaning of a word can emerge from the mutual interactions of a group of individuals, without an external influence. In this contribution, the authors review the field of the Naming Game, from the original version to a recent one introduced by the authors of a cognitive version described in the context of a Bayesian framework.

B. Other mathematical modeling

- **Transport and concentration of wealth: Modeling an amenities-based-theory**, Hasan *et al.*²⁵

This paper relies on a Nonlinear Dynamics approach featuring Reaction-Diffusion equations to study the dynamics of wealth associated with gentrification processes in a city. By means of linear stability analysis and global bifurcation theory the authors identify regimes for which solutions of the RD equations representing wealth and amenity hotspots.

- **Fat tails and black swans: Exact results for multiplicative processes with resets**, Zanette and Manrubia.²⁶

This contribution discusses important aspects of stochastic processes involved in the modeling of social systems. The paper contains a number of exact results for stochastic multiplicative

processes with resets, well known to lead to power-law distributions. These results are discussed in the context of financial markets showing the implications in gain vs. risk investing strategies and the occurrence of extreme events.

- **Rise of nations: Why do empires expand and fall**, Vakulenko *et al.*²⁷

The manuscript presents a modification of the Hopfield model with noise to include two types of nodes: centers and satellites. Super egoistic centers (“empires”) are surrounded by satellites in centralized networks where the evolution of the centers’ activities is slow in comparison with the satellites’ dynamics. In an analogy with the ancient Roman principle, they call their model “divide and conquer” because interactions between satellites are either non-existent or very weak. The authors investigate how the interaction between centers and satellites can lead to different types of dynamics (e.g., chaotic or periodic) and how the number and activity of empires is challenged by fluctuations or by positive or negative weak interactions between satellites. It shows that empires, earlier or later, fall into a control trap: to support the dynamical regime, they should have many satellites, but then their evolution becomes slow. Using an analogy with Bose–Einstein condensation, it is shown that if the noise correlations are negative for each pair of nodes, then the most stable structure with respect to noise is a globally connected network. For positive correlations, the connectivity of centers in an empire should be bounded.

II. DATA DRIVEN RESEARCH

- **Scaling laws and dynamics of hashtags on Twitter**, Chen *et al.*²⁸

Massive Twitter data is freely available and, as a consequence, is widely used by the academic community to study collective phenomena in social networks. In this paper, the authors characterize the statistical properties and dynamics of the frequency of hashtags (message tags). Hashtags are considered as memes subject to evolutionary processes. The paper reports a number of scaling laws that characterize emerging properties of the meme interactions.

- **Dynamics of fintech terms in news and blogs and specialization of companies of the fintech industry**, Ciulla and Mantegna.²⁹

Here, data is collected from news and blogs, as well as professional descriptions of companies. The study focuses on fintech industries, addressing the fast worldwide development of this industrial sector. Data inconsistencies are overcome using methods of complex networks, specifically the methodology of statistically validated networks. The paper reports geographical and economic over-expressions of a set of companies related to the multi-industry, geographically, and economically distributed fintech movement.

- **An urban commuters’ OD hybrid prediction method based on big GPS data**, Wang *et al.*³⁰

The main application of Big Data analysis in social sciences is the study of human mobility. This paper uses GPS data from Chengdu (China) to study the network topology of commuters’ Origin-Destination (OD) paths. The authors propose a hybrid OD prediction method, including a deep learning method,

that captures temporal and spatial dependencies with significant accuracy.

• **Circadian rhythms in temporal-network connectivity,** Alakörkkö and Saramäki.³¹

Circadian patterns in human communication have been widely studied and it is possible to determine, from data recorded with tracking apps, the chronotypes (morningness or eveningness) of individual people. However, much less is known on the variation of the connectivity network itself. Using anonymized data coming from 1.35×10^9 telephone calls and 465×10^6 messages during a 29 week period in a single European country, this paper analyzes the effect that daily patterns of individual activity have on the daily variation of the networks of temporal connectivity, focusing on sequences of communication events that follow one another within a limited time. The findings show that there is indeed a daily cycle in the temporal connectivity where a larger fraction of contacts is associated with such sequences at night and where contacts appear more independent at daytime, a much richer variation in time than what has been known thus far.

In the development of these types of models there are many important open questions. We would like to point out some of those which, in our opinion, could lead to relevant developments. We first note that most of the models for social phenomena are stochastic by nature. On top of the intrinsic stochasticity in individual behaviors, there are other sources that translate into fluctuations of macroscopic variables. One of the most prominent ones is that of heterogeneity in the population. A complete mathematical treatment of stochastic systems that include noise, intrinsic heterogeneity and complex network topologies is not available at the moment. As an example in this direction, it has been found³² that fluctuations at the macroscopic level can bear information about the intrinsic level of heterogeneity, opening the way to quantify the amount of microscopic diversity by looking at aggregate data.

Second, there are important differences between models for social phenomena and in other fields. However, one of the more important discoveries in the field of phase transitions in physical systems has been that of universality classes, by which different physical processes can be classified according to a few relevant variables that determine the same critical behavior. Can we develop a methodology to determine relevant and irrelevant variables in collective social phenomena that allow for a classification scheme of generic social behavior?

Another difference with physical systems is that of individual interpretation of the same fact as a main cause of changing state, action, or strategy. The question is how to incorporate the concept of “meaning” in the different models. Feelings and emotions are also important ingredients that require proper modeling. Another important effect is that of feedback between the emergent behavior and the individual behavior, sometimes called *second order emergence*. This is for instance relevant in epidemic modeling, where a prediction in the media can change individual behaviors. This is certainly different again from physical systems, e.g., a weather prediction for next week does not change the behavior of the system components in the model, but this is not the case for climate change mediated by human activity.³³

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REFERENCES

- ¹A. Comte, *A General View of Positivism* (Trubner and Co., 1865), reissued by Cambridge University Press, 2009.
- ²C. Castellano, S. Fortunato, and V. Loreto, “Statistical physics of social dynamics,” *Rev. Mod. Phys.* **81**, 591 (2009).
- ³S. Fortunato, M. Macy, and S. Redner, “Statistical mechanics and social sciences,” *J. Stat. Phys.* **151**, 1 (2013).
- ⁴P. Sen and B. K. Chakrabarti, *Sociophysics, An Introduction* (Oxford University Press, 2014).
- ⁵See the Special Issue, “From Statistical Physics to Social Sciences,” *Comptes Rendus Physique* **20** (4) (2019), edited by J. P. Bouchaud and J. P. Nadal. <https://www.sciencedirect.com/journal/comptes-rendus-physique/vol/20/issue/4>.
- ⁶F. Schweitzer, “Sociophysics,” *Phys. Today* **71**(2), 40 (2018).
- ⁷P. Ball, *Critical Mass: How One Thing Leads to Another* (Macmillan, 2004).
- ⁸D. Lazer et al., “Life in the network: The coming age of computational social science,” *Science* **323**(5915), 721 (2009).
- ⁹R. Conte et al., “Manifesto of computational social science,” *Eur. Phys. J. Spec. Top.* **214**, 325 (2012).
- ¹⁰T. C. Schelling, “Dynamic models of segregation,” *J. Math. Sociol.* **1**, 143 (1971).
- ¹¹A. Vespignani, “Predicting the behavior of techno-social systems,” *Science* **325**(5939), 425 (2009).
- ¹²Z. Ruan, B. Yu, X. Shu, Q. Zhang, and Q. Xuan, “The impact of malicious nodes on the spreading of false information,” *Chaos* **30**, 083101 (2020).
- ¹³S. Schweighofer, D. Garcia, and F. Schweitzer, “An agent-based model of multi-dimensional opinion dynamics and opinion alignment,” *Chaos* **30**, 093139 (2020).
- ¹⁴C. Xia, C. Gracia-Lázaro, and Y. Moreno, “Effect of memory, intolerance, and second-order reputation on cooperation,” *Chaos* **30**, 063122 (2020).
- ¹⁵A. Sinha and B. K. Chakrabarti, “Phase transition in the Kolkata Paise Restaurant problem,” *Chaos* **30**, 083116 (2020).
- ¹⁶F. B. Lemarchand, V. Semeshenko, J. Navajas, and P. Balenzuela, “Polarizing crowds: Consensus and bipolarization in a persuasive arguments model,” *Chaos* **30**, 063141 (2020).
- ¹⁷A. Caravaggio and M. Sodini, “I love shopping... but what am I going to buy? Social interaction and consumption choices,” *Chaos* **30**, 093133 (2020).
- ¹⁸A. A. Jędrzejewski, B. Nowak, A. Abramiuk, and K. Sznajd-Weron, “Competing local and global interactions in social dynamics: How important is the friendship network?,” *Chaos* **30**, 073105 (2020).
- ¹⁹N. Saintier, J. P. Pinasco, and F. Vazquez, “A model for the competition between political mono-polarization and bi-polarization,” *Chaos* **30**, 063146 (2020).
- ²⁰A. N. Zehmakan and S. Galam, “Rumor spreading: A trigger for proliferation or fading away,” *Chaos* **30**, 073122 (2020).
- ²¹L. Zino, M. Ye, and M. Cao, “A two-layer model for coevolving opinion dynamics and collective decision-making in complex social systems,” *Chaos* **30**, 083107 (2020).

- ²²J. Moran, A. Fosset, D. Luzzati, J.-P. Bouchaud, and M. Benzaquen, "By force of habit: Self-trapping in a dynamical utility landscape," *Chaos* **30**, 053123 (2020).
- ²³F. Bauzá, D. Soriano-Paños, J. Gómez-Gardeñes, and L. M. Floría, "Fear induced explosive transitions in the dynamics of corruption," *Chaos* **30**, 063107 (2020).
- ²⁴G. Marchetti, M. Patriarca, and E. Heinsalu, "A bird's-eye view of naming game dynamics: From trait competition to Bayesian inference," *Chaos* **30**, 063119 (2020).
- ²⁵A. Hasan, N. Rodriguez, and L. Wong, "Transport and concentration of wealth: Modeling an amenities-based-theory," *Chaos* **30**, 053110 (2020).
- ²⁶D. H. Zanette and S. Manrubia, "Fat tails and black swans: Exact results for multiplicative processes with resets," *Chaos* **30**, 033104 (2020).
- ²⁷S. Vakulenko, D. A. Lyakhov, A. G. Weber, D. Lukichev, and D. L. Michels, "Rise of nations: Why do empires expand and fall?," *Chaos* **30**, 093108 (2020).

- ²⁸H. H. Chen, T. J. Alexander, D. F. M. Oliveira, and E. G. Altmann, "Scaling laws and dynamics of hashtags on Twitter," *Chaos* **30**, 063112 (2020).
- ²⁹F. Ciulla and R. N. Mantegna, "Dynamics of fintech terms in news and blogs and specialization of companies of the fintech industry," *Chaos* **30**, 083112 (2020).
- ³⁰Y. Wang, D. Xu, P. Peng, Q. Xuan, and G. Zhang, "An urban commuters' OD hybrid prediction method based on big GPS data," *Chaos* **30**, 093128 (2020).
- ³¹T. Alakörkkö and J. Saramäki, "Circadian rhythms in temporal-network connectivity," *Chaos* **30**, 093115 (2020).
- ³²A. Carro, R. Toral, and M. San Miguel, "The noisy voter model on complex networks," *Sci. Rep.* **6**, 24775 (2016).
- ³³W. Barfuss, J. F. Donges, V. V. Vasconcelos, J. Kurths, and S. A. Levin, "Caring for the future can turn tragedy into comedy for long-term collective action under risk of collapse," *Proc. Natl. Acad. Sci. U.S.A.* **117**, 12915 (2020).