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Editorial

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Statistical physics has proven fruitful for the investigation of the collective dynamics of complex systems, including systems that lie beyond the scope of traditional physics. By leveraging behavioral regularities at the global level, such as averages and distributions, statistical physics can be used to analyze systems with large numbers of components whose individual behavior is highly idiosyncratic. This regularity also occurs when the fundamental constituents are more complex than atoms or molecules. In the XVIIIth century it was first noticed that events such as the number of births, deaths, suicides, etc., tended to be stable in a given geographical area, as long as the observation period is not too long. This stability was surprising because these events are generally unpredictable individually. These empirical regularities motivated Maxwell and Boltzmann to propose a statistical approach to understand the physics of many-particle systems, ultimately leading to the foundations of statistical mechanics [1]. Related observations also convinced scholars of the period that precise quantitative laws, like those of physics, also existed for social phenomena, in spite of the apparently erratic behavior of individuals. For example, Immanuel Kant, in his 1784 essay *On History* refers to universal laws that "*however obscure their causes, [permit] us to hope that if we attend to the play of freedom of human will in the large, we may be able to discern a regular movement in it, and that what seems complex and chaotic in the single individual may be seen from the standpoint of the human race as a whole to be a steady and progressive though slow evolution of its original endowment*".

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This conviction that there should exist a quantitative theory of social phenomena was shared by many noted scholars, such as the Marquis de Condorcet, Auguste Compte (credited as the father of sociology), Adolphe Quetelet, John Stuart Mill, Henry Thomas Buckle, to name a few. Yet more than two centuries after the empirical discovery of the stability of social aggregates, we still lack a social science equivalent of Newton's laws for the motion. There are two main reasons for this shortcoming. The first is the relative dearth of empirical observations compared to those in physics. Robert C. Merton, a Nobel Laureate in Economics, pointed out that Newton's laws were the result of a many-decade process of careful observations by Danish astronomer Tycho Brahe, which were subsequently summarized in mathematical form by Johannes Kepler. The regularity of Kepler's observations inspired Newton's work. Simply put, the absence of a theory of society is not that we are still awaiting the social counterparts of Newton and Einstein, Merton concludes, but rather we have not yet found our Brahe and Kepler.

Additionally, humans are complex, while elementary particles are simple. Since the early experiments by Galileo, physics has focused on elementary objects and their interactions whose simplicity made it possible to derive the basic laws of particle motion, then electromagnetism, and finally the laws of nuclear and subnuclear interactions. By means of powerful mathematical tools, like probability theory, it became possible to recast these laws of elementary interactions in few-particle systems into statistical laws that account for the behavior of many-particle systems.

When we attempt to apply this same minimalist modeling to social phenomena, we face several obstacles:

Heterogeneity. While the constituents of physical systems are *homogeneous*, those of social systems are not. As the Physics Nobel Laureate Wolfgang Pauli said, "*in physics we can assume that every electron is identical, while social scientists do not have this luxury*". While the interactions between electrons under identical conditions are the same, this reproducibility is not true for people, not only because people are unique, but also because humans may *learn* and *adapt* [2]. Thus the same two individuals may react differently in repeated identical situations because of accumulated knowledge. In fact, since history is played only once, we generally have distorted perceptions of social behavior, overemphasizing what actually happened, to the detriment of what could have happened [3].

Emergence. The behavior of a population does not necessarily imply aggregation of individual behaviors. For example, highly segregated residential neighborhoods can emerge in populations of individuals that not only tolerate diversity but even prefer it. Similarly, the properties of a collective can vary over time even if those same properties are constant over time at the individual level.

Reification. Collective decision making does not occur through cognitive processes analogous to decision making by individuals—i.e., there is no "group mind" and properties of individual actors, like intentionality, purpose, regret, or anger, are not properties of collective actors.

Correlation vs. causality. Statistical regularities are useful to identify possible individual-level explanations for population dynamics. However, such correlations do not imply causation. In the absence of general theories, confidence in having identified the underlying causal mechanism usually depends on confirmation based on controlled experiments.

These differences between humans and atoms illustrate the difficulties that confront efforts to create a physics-like science of social life. Even if social scientists had been able to match the successes of physicists in collecting observations of social phenomena, they would have probably failed to extract elementary laws.

However, lessons from critical phenomena give hope that statistical physics can help quantify the dynamics of large groups of individuals. In many phase transitions, the large-scale behavior of a many-particle system is independent of particulate details and their microscopic interactions; only a few basic features are relevant. Thus systems that cannot be fully characterized at the individual level might still display recognizable patterns in the aggregate, if the number of constituents is sufficiently large. This applies not only to the collective behavior of atoms but to human behavior as well.

Building on this analogy, a statistical physics of society, or "sociophysics" [4] seems a feasible goal. In recent years, many simple models, inspired by statistical physics, have been introduced to account for social phenomena such as opinion formation, cultural and language evolution, collective action, crowd behavior, Web user behavior, marketing, financial panics, political polarization, and neighborhood segregation. Although these idealized models have attracted growing interest, their relevance for understanding real-world social dynamics is highly controversial. Models derived from physics are often highly stylized, and are typically based on simplifying assumptions about the mechanisms driving both individual and collective behavior. These simplifications can be useful in thought experiments designed to identify the macro-level implications of a set of behavioral and environmental assumptions but they can also compromise the ability to explain real-world outcomes. And until recently, efforts to introduce more empirically plausible assumptions had to confront the absence of solid empirical data.

This limitation on data is changing rapidly. Social systems with many individuals have now become experimentally observable, due to the rapid increase in computational power to process big data at very low cost, and the growing use of the Web. This is both an increasingly indispensable medium of interaction, as well as a vast repository of the digital traces of those interactions and a platform to carry out controlled experiments involving large numbers of participants. Due to the increasing availability of data, other disciplines, like computer science, have entered this line of endeavor under the rubric of *computational social science* [5, 6]. Sociophysics models cannot avoid validation any more.

This special issue on "The Application of Statistical Mechanics to Social Phenomena" represents our attempt to present and confront several major challenges in sociophysics. Our first goal is very modest—to promote inter-disciplinary cross-fertilization, by making statistical physicists more aware of the perspectives and long-standing contributions of quantitative social scientists and by providing quantitative social scientists a glimpse into the modeling approaches of statistical physics. Both fields can certainly learn from the other and we hope that this issue will help in this endeavor, both in providing exposure to new ideas across fields and also making people aware of some of the active researchers in each field.

A second goal is to expose a representative range of social phenomena that are currently under study by social scientists and by physicists, and to illustrate the perspectives and techniques that are used by current practitioners in their respective subfields. We anticipate that some researchers are only vaguely aware of very relevant investigations that appear in the literature of complementary fields. We therefore hope that this volume helps foster, in some small measure, better communication between the physical and social sciences.

Let us now provide an overview of the contributions to this special issue:

Volume I

In his very entertaining and idiosyncratic style, D. Stauffer begins this volume with a brief review of several classic models of social dynamics that have captured the attention of physicists, including the Schelling model of segregation, idealized models of opinion dynamics, and the dynamics of scientific citations. He also raises the fundamental question—does sociophysics make sense?—that we hope will be partially answered in the positive by this volume.

The following section discusses a variety of stylized models of opinion evolution. For physicists, an important starting point is the voter model, in which each individual is endowed with one of two discrete opinion states. The update step is simplicity itself: a random individual is picked and updates his opinion by adopting the state of one of his neighbors. This update step is repeated until consensus necessarily occurs in a finite system. This description of people as identical atomistic elements is appealing to statistical physicists and has spawned much research. The articles on opinion dynamics in this volume involve atomistic descriptions that incorporate either different modeling perspectives or certain aspects of social reality.

For example the article by Lanchier presents some rigorous results on the evolution of the so-called (Galam) majority-rule model, in which the dynamics operates on all the members of randomly chosen groups. All members of the group adopt the local majority state and repeated updates of this type ultimately lead to consensus. The article by Galam himself discusses new collective features when there are three competing voting states. Some of these features are amplified in the article by Mobilia on the competition between a persuasive majority and a committed minority in a three-state voter model. Another important aspect of opinion dynamics is the very real possibility of disagreement. Some features of this attribute are discussed in the article by Li et al. on the so-called non-consensus model in which the interactions permit the coexistence of two disagreeing states, rather than a monotonic evolution toward consensus. The role of the interaction range in the voter model is explored in the article by Pastor-Satorras et al. Here a voter changes opinion to a given opinion state only if q of its neighbors are in that state. An important aspect of this class of models is that it breaks magnetization conservation (the density difference between voters of opposite states). The distinction between conserved and non-conserved voter models has been an active area of investigation.

Instead of one voter simply adopting the state of another, two individuals may choose to compromise and average their opinions. This appealing model of compromise, first introduced by Deffuant et al. and by Hegselmann and Krause has spawned much research into understanding its rich dynamics. The article by Carro et al. investigates the role of noise and initial conditions on the opinion states of all individuals in the long-time limit. The article by van Brecht et al. explores the compromise model under the combined effects of attractive and repulsive interactions, and with pairwise interactions defined on the Erdös-Rényi random graph. As the density of pairwise interactions is varied the stability of the long-time opinion equilibrium changes drastically. The article by Nyczka and Sznajd-Weron explores the influence of microscopic features of social reality on opinion evolution models, such as the topology of local interaction, the influence of external interactions, the relative role of conformity/anti-conformity, etc. Under the rubric of opinion dynamics, the contribution by Torney et al. introduces a voter-like model that is intended as an idealized model of the movement of individual animals that are part of a large group. This model incorporates the notions of a "correct" choice for one of the two opinion states and "leaders," namely, individuals who "know" the correct choice and cannot be persuaded to move from this opinion state. Loreto et al. explore the interplay between disagreement and external information in opinion dynamics. They find that moderate messages have better success compared to more extreme information. Models of collective action are similar to models of consensus formation in showing how individual behavior can often have surprising consequences for the population dynamics. Centola uses formal models to challenge the widely held assumption that free riding reduces the social efficiency of collective action. On the contrary, self-reinforcing incentives to participate in collective action reduce free riding but make outcomes vulnerable to perturbation. Izquierdo and Izquierdo discuss the applicability of the mean-field approximation to stochastic processes expressable as Markov chains, like many computer models. They derive results from stochastic approximation theory on the relation between computer simulations results for simple stochastic models and their expected deterministic behaviors in the mean-field approximation.

Language dynamics is a subject for which statistical physics ideas seem to be gaining some traction. There are many intriguing regularities in language data, such as word frequencies, the number of distinct words as a function of the corpus size, etc., that are well-suited for statistical analyses. In this vein, the article by Altmann and Motter uses word-frequency dynamics to identify social trends in the dynamics of individuals themselves. The article by Fujie et al. extends the Abrams-Strogatz model for the competition between two languages in a population in which there are more than two languages. In the original Abrams-Strogatz model, the lower-status language always becomes extinct, but language coexistence can arise if more than two languages are in competition.

With the increased availability of pervasive location data that is gleaned from cell phone calls, credit-card transactions, and smart phone applications, the possibility of modeling urban human mobility patterns has moved from being unattainable to reality. The contribution by Hasan et al. investigates the individual mobility patterns from smart subway fare transactions in London and the insights that can be gained from these patterns.

Everyone is interested in popularity. The provocative article by Simkin and Roychowdhury explores the relation between popularity and achievement in data on WWI aces. These authors conclude that there is a power-law distribution for individual fame. This result seems to apply to many other human activities. Another aspect of popularity is the notion of "attention". We are so heavily inundated with information and advertising, that what now matters is how much attention we actually pay to the myriad of sensory inputs that we experience. The article by Huberman explores the relative efficacies of popularity and novelty in determining how to prioritize information. An important measure of popularity in the sciences is scientific citations. We all care about how often our work is cited. The contribution by Golosovsky and Solomon analyzes the citation network of all of *Physical Review* and argues that the citation dynamics is governed by superlinear preferential attachment. They also find evidence of very different citation dynamics of poorly cited papers (which quickly disappear) and highly-cited paper (which seem to be immortal on the time scale of *Physical Review*).

An important aspect of social dynamics is the spreading of a disease or a rumor through a population. The most well-studied epidemic models are the SIS (susceptible-infected-susceptible) and SIR (susceptible-infected-recovered) models. In the former, a susceptible (S) individual is exposed and becomes infected by interacting with an I, but an I eventually recovers and becomes an S again; such a situation describes the common cold, where one can be infected many times. In the SIR model, a recovered individual becomes immune and is given the label R for recovered. The paper by Tunc et al. explores the ramifications of individuals breaking their social contacts in response to an epidemic. In particular, the location of the epidemic threshold was found to depend on the rate at which an individual deactivates links with acquaintances who have fallen ill. The article by Lund et al. investigates the effect of heterogeneous city populations on epidemic spreading within the SIS model. Here, the epidemic dynamics within a city is treated in the mean-field approximation, and travel between cities then couples these dynamical systems.

Classic and well-studied rumor-spreading models have been developed that incorporate three types of individuals: spreaders, stiflers (those that are aware of the rumor but no longer wish to spread it), and those unaware of the rumor. The evolution of these three classes of individuals is reminiscent of the SIR epidemic model. The paper by Borge-Holthoefer et al. exploits currently available online data to expose the inadequacies of this classic model and points the way for more realistic modeling of spreading phenomena.

Volume II

While diffusion and social influence are often assumed to involve processes like persuasion and imitation, influence can also be negative, in which the recipient responds by differentiating from the influencer. The contribution by Johnson et al. explores a simple way in which individual cultural and behavioral traits (e.g., ethnicity) can be incorporated in a model without compromising tractability. This heterogeneous model shows the same power-law distribution of event severity as in models with homogeneous agents, suggesting that this power-law behavior is universal. Another forum for the appearance and resolution of conflict is in Wikipedia. While it is hard to imagine how such an anarchistic and collaborative encyclopedia can work, it has been extraordinarily successful and useful. The contribution of Yasseri and Kertész investigates the dynamics of this collaborative environment and models how conflicts arise as the document develops and how they get resolved.

In the arena of human endeavor, we are (it is hoped) all trying to better ourselves. The contribution of Bardoscia et al. represents an appealing attempt to formalize this improvement process through a "social climbing game". The basic idea is that individuals change their links in a social network to preferentially link to important (high-degree) individuals and to also maximize their number of links. This model undergoes a phase transition to a highly hierarchical state as a social temperature—a measure of the gain in utility in an advantageous update—decreases below a critical value. The recent availability of online sports statistics provide another rich data source with which to apply ideas from statistical physics and quantify social hierarchies. The article by Ben-Naim et al. presents a simple model of competitions in which the only parameter is the probability that the weaker team (as measured by current win/loss records) upsets the stronger team. The model is applied to various sports competitions, where it is shown that single-elimination tournaments are unfair because there is an appreciable probability that a strong team is quickly eliminated or a weak team succeeds. A tournament schedule is devised that is both fair and efficient, in that relatively few games are needed to determine the strongest team.

Economic systems historically have represented one of the main arenas for the application of physics modeling. In the paper by Weisbusch, the author tackles a very important question: will economic growth lead in the future to more or less inequality among world regions? The author uses a spatial model whose basic assumptions are the limitation on resource influx and the tendency to concentrate production on richest producers. The conclusion is that the inequality will persist. Gordon et al. use the Random Field Ising Model and the Schelling model to describe the influence of social interactions in market situations, which often lead to a choice of buying/selling that would not be taken otherwise (bandwagon effect). They find that the price originally posted by the seller is already close to the critical value beyond which there will be little response by other customers, so prices of goods with bandwagon effects do not increase despite their success, as observed in real market scenarios. Koskinen and Lomi find that the standard "gravity" model of international trade describes the network of foreign direct investment relations in the international electricity industry quite well. Toscani et al. adopt Boltzmann-like equations for the evolution in time of the density of wealth in a market composed by many agents. Some of the solutions of these equations develop Pareto tails. Bouchaud shows that the Random Field Ising Model provides a unifying framework to describe the appearance of sudden crises and ruptures in many collective socio-economic systems. Cascades leading to such extreme events are generated either by herding, i.e., reference to peers, or trending, i.e., reference to the past. Time scales are crucial, as they may sometimes be so long that social systems cannot reach optimal equilibria. Rapisarda et al. highlight the importance of random strategies in the social sciences, focusing on the choice of political representatives and financial trading.

Evolutionary game theory, originally developed within biological contexts, has, in recent times, attracted social scientists, economists, and philosophers. In addition to biological evolution it is natural to consider social evolution. In our collection there are four contributions in this area. The paper by Hernandez and Zanette proposes an evolutionary framework for the "Colonel Blotto" Game, a game of how to distribute limited resources among different channels (or battlefields) so as to maximize the probability of long-term success. The authors show that optimal strategies emerge as equilibria of the dynamics, and that this result is robust in generalizations of the model. Fu and Nowak study the influence of migration in the evolution of cooperation within structured populations. In a finite island model, where individuals play games with others on the same site, they find that global migration can lead to stronger spatial effects than local migration for a wide range of the model parameters. Christoforou et al. study the evolution of cooperation by considering the context of crowd computing, which has become very popular in the last few years. They show that the system converges to the exact solution of a given assignment in many cases, even when many participants are defectors. In the paper by Short et al., ties among criminals are introduced in an adversarial evolutionary game in which crimes are perpetrated and criminals may be convicted if enough witnesses testify against them. The presence of these ties (or "sacred values") enhances the persistence of crime even in fairly peaceful communities.

The structure of complex networks and dynamics on these networks have become part of the backbone of complexity science. Social networks in particular have been and are currently being intensely investigated, in large part for their practical importance as communication and information media (e.g., Facebook). Tóth et al. present a study on the detection of communities in networks, a recent and very hot topic, consisting in the identification of cohesive groups of nodes sharing but a few links with the rest of the network. The authors focus on the "clique percolation" method, which is based on exploring the network by following sets of overlapping cliques. The size of the cliques is traditionally chosen such that the system lies just below the critical point for the percolation of the cliques. The paper justifies this assumption by showing that the quality of the partition is higher in this case, according to a quality measure of overlapping community structures. Klemm asks how searchable networks are, i.e., how easily one can reach high centrality nodes by local search. By introducing a measure called smoothness, he shows that many networks have close to optimal searchability for eigenvector centrality, while other measures, like degree and betweenness, are harder to track. Musumeci et al. present a method to reconstruct complex networks starting from a partial information on their structure. Starting from information about some intrinsic fitness of the known nodes, the missing links are detected by calibrating a fitness model on the known links. Tests on synthetic networks and on the World Trade Web show that a faithful reconstruction is possible starting from as little as 10 % of the nodes. Kaski et al. focus on egocentric networks, i.e., the networks of neighbors of a source node (ego). They investigate the difference between the best connection of the ego and the second-best through an analysis of mobile phone communication networks. They find that the ratio of the number of calls of the ego to his most frequent and second most frequent contacts, above a threshold, is a good index for the reliability of the identification of an individual's closest acquaintance. Latora et al. explore the relationship between social capital and structural network measures. In particular, the clustering coefficient and the effective size of the neighborhood of an actor in a social network (the number of its directly-linked contacts), have been both proposed as suitable measures for social capital.

The authors show that these two variables are actually dependent on each other and introduce a new variable that mediates between the two, quantifying the role of bridges that mediate between otherwise disconnected nodes. Schweitzer et al. present an analysis of systemic risk on network systems, determined by cascading failures of macroscopic size. They focus on a system of agents that fail if their load exceeds a given threshold. The authors find that if the threshold distribution is a power law, finite cascades are still possible, while random fluctuations can trigger full cascades. In general, the size of the shock initiating the cascade is not as important as the network topology and the threshold distribution.

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