Chapter 5
Theoretical Tools in Modeling Communication and Language Dynamics

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Abstract Statistical physics has proven to be a very fruitful framework to describe phenomena outside the realm of traditional physics. In social phenomena, the basic constituents are not particles but humans and every individual interacts with a limited number of peers, usually negligible compared to the total number of people in the system. In spite of that, human societies are characterized by stunning global regularities that naturally call for a statistical physics approach to social behavior, i.e., the attempt to understand regularities at large scale as collective effects of the interaction among single individuals, considered as relatively simple entities. This is the paradigm of Complex Systems: an assembly of many interacting (and simple) units whose collective behavior is not trivially deducible from the knowledge of the rules governing their mutual interactions. In this chapter we review the main theoretical concepts and tools that physics can borrow to socially-motivated problems. Despite their apparent diversity, most research lines in social dynamics are actually closely connected from the point of view of both the methodologies employed and, more importantly, of the general phenomenological questions, e.g., what are the fundamental interaction mechanisms leading to the emergence of consensus on an issue, a shared culture, a common language or a collective motion?

1 Introduction

One of the first questions the reader could about this chapter is what physics in general, and statistical physics in particular, has to do with the problem of the emergence of language.

Statistical physics has proven to be a very fruitful framework to describe phenomena outside the realm of traditional physics (Loreto and Steels 2007). The last few years have witnessed the attempt by physicists to study collective phenomena emerging from the interactions of individuals as elementary units in social structures (Castellano et al. 2009). In social phenomena, the basic constituents are not

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particles but humans and every individual interacts with a limited number of peers, usually negligible compared to the total number of people in the system. In spite of that, human societies are characterized by stunning global regularities (Buchanan 2007). There are transitions from disorder to order, like the spontaneous formation of a common language/culture or the emergence of consensus about a specific issue. There are examples of scaling and universality. These macroscopic phenomena naturally call for a statistical physics approach to social behavior, i.e., the attempt to understand regularities at large scale as collective effects of the interaction among single individuals, considered as relatively simple entities. This is the paradigm of the Complex Systems science: an assembly of many interacting (and simple) units whose collective (i.e., large scale) behavior is not trivially deducible from the knowledge of the rules that govern their mutual interactions.

Now consider the problem of the emergence of language. It is of course true that if one adopts a static point of view where language is seen as a "system" frozen at a particular point in time with its sound structure, vocabulary and grammar, there is no place for statistical physics oriented studies. But as linguists begin to get access to more and more data from systematic recordings and the massive volume of text appearing on the World Wide Web, and as they look at new language-like communication systems that have emerged recently—such as text messaging protocols for use with mobile phones or social tagging of resources available on the web—doubts arise whether human communication systems can be captured within a static picture or in a clean formal calculus. The static picture is giving way to a view where language is undergoing constant change as speakers and hearers use all their available resources in creative ways to achieve their communicative goals.

This is the point of view of semiotic dynamics (Steels 2000) which looks at language as an adaptive evolving system where new words and grammatical constructions may be invented or acquired, new meanings may arise, the relation between language and meaning may shift (e.g., if a word adopts a new meaning), the relation between meanings and the world may shift (e.g., if new perceptually grounded categories are introduced). All these changes happen both at the individual and the group level, the focus being on the interactions among the individuals as well as on horizontal, i.e., peer-to-peer, communications. Semiotic dynamics is the sub-field of dynamics that studies the properties of such evolving semiotic systems. In this new perspective, complex systems science turns out to be a natural ally in the quest for the general mechanisms underlying the emergence of a shared set of conventions in a population of individuals.

In semiotic dynamics models, assume a population of agents that have only local interactions and carry out some communicative task, such as drawing the attention of another agent to an object in their surroundings by using a name. Typically agents do not start with a given communication system but must build one up from scratch. The communication evolves through successive conversations, i.e., events that involve a certain number of agents (two, in practical implementations) and meanings. It is worth remarking that here conversations are particular cases of language games which, as already pointed out in Wittgenstein (1953a, 1953b), can be used to describe linguistic behavior, even if they can include also non-linguistic behavior, such as pointing.

A conceptual difficulty immediately arises when trying to approach language dynamics, and more generally social dynamics from the point of view of statistical physics. In usual applications, the elementary components of the systems investigated, atoms, and molecules, are relatively simple objects whose behavior is very well known: the macroscopic phenomena are not due to a complex behavior of single entities, rather to nontrivial collective effects resulting from the interaction of a large number of "simple" elements.

Humans are exactly the opposite of such simple entities: the detailed behavior of each of them is already the complex outcome of many physiological and psychological processes, still largely unknown. No one knows precisely the dynamics of a single individual, nor the way he interacts with others. Moreover, even if one knew the very nature of such dynamics and such interactions, they would be much more complicated than, say, the forces that atoms exert on each other. It would be impossible to describe them precisely with simple laws and few parameters. Therefore any modeling of social agents inevitably involves a huge and unwarranted simplification of the real problem. It is then clear that any investigation of models of social dynamics involves two levels of difficulty. The first is in the very definition of sensible and realistic microscopic models; the second is the usual problem of inferring the macroscopic phenomenology out of the microscopic dynamics of such models. Obtaining useful results out of these models may seem a hopeless task.

The critique that models used by physicists to describe social systems are too simplified to describe any real situation is most of the times very well grounded. This applies also to highly acclaimed models introduced by social scientists, such as Schelling's model for urban segregation (Schelling 1971) and Axelrod's model for cultural dissemination (Axelrod 1997). But in this respect, statistical physics brings an important added value. In most situations, qualitative (and even some quantitative) properties of large scale phenomena do not depend on the microscopic details of the process. Only higher-level features, such as symmetries, dimensionality, or conservation laws, are relevant for the global behavior. With this concept of *universality* in mind one can then approach the modelization of social systems, trying to include only the simplest and most important properties of single individuals and looking for qualitative features exhibited by models. A crucial step in this perspective is the comparison with empirical data, which should be primarily intended as an investigation into whether the trends seen in real data are compatible with plausible microscopic modeling of the individuals, are self-consistent, or require additional ingredients.

2 Concepts and Tools

Opinions, cultural, and linguistic traits are always modeled in terms of a small set of variables whose dynamics is determined by the structure of the social interactions. The interpretation of such variables will be different in the various cases: a binary variable will indicate yes/no to a political question in opinion dynamics, two synonyms for a certain object in language evolution or two languages in language competition. Other details may differ, but often results obtained in one case can immediately be translated in the context of other sub-fields. In all cases the dynamics tends to reduce the variability of the initial state and this may lead to consensus (ordered state), where all the agents share the same features (opinion, cultural or linguistic traits) or to a fragmented (disordered) state. The way in which those systems evolve can thus be addressed in a unitary way using well-known tools and concepts from statistical physics. In this spirit some of the relevant general questions we will consider in the review include: What are the fundamental interaction mechanisms that allow for the emergence of consensus on an issue, a shared culture, a common language? What favors the homogenization process? What hinders it?

Generally speaking, the drive toward order is provided by the tendency of interacting agents to become more alike. This effect is often termed "social influence" in the social science literature (Festinger et al. 1950) and can be seen as a counterpart of ferromagnetic interaction in magnets. Couplings of anti-ferromagnetic type, i.e., pushing people to adopt a state different from the state of their neighbors, are also in some cases important and will be considered.

Any modelization of social agents inevitably neglects a huge number of details. One can often take into account in an effective form such unknown additional ingredients assuming the presence of noise. A time-independent noise in the model parameters often represents the variability in the nature of single individuals. On the other hand, a time-dependent noise may generate spontaneous transitions of agents from one state to another. A crucial question then has to do with the stability of the model behavior with respect to such perturbations. Do spontaneous fluctuations slow down or even stop the ordering process? Does diversity of agents' properties strongly affect the model behavior?

An additional relevant feature is the topology of the interaction network. Traditional statistical physics usually deals with structures whose elements are located regularly in space (lattices) or considers the simplifying hypothesis that the interaction pattern is all-to-all, thus guaranteeing that the mean field approximation is correct. This assumption, often also termed homogeneous mixing, generally permits analytical treatment, but it is hardly realistic in a social context. Much more plausible interaction patterns are those denoted as complex networks (see Sect. 2.2). The study of the effect of their nontrivial topological properties on models for social dynamics is a very hot topic.

One concept playing a special role in many social dynamic models and having no equally common counterpart in traditional statistical physics is "bounded confidence," i.e., the idea that in order to interact, two individuals must not be too different. This parallels somewhat the range of interaction in physics: if two particles are too far apart they do not exert any influence on each other. However, let us stress that the distance involved in bounded confidence is not spatial, but rather is defined in a sort of opinion space.

2.1 Order and Disorder: The Ising Paradigm

In the previous section we have seen that the common theme of social dynamics is the understanding of the transition from an initial disordered state to a configuration that displays order (at least partially). Such types of transitions abound in traditional statistical physics (Kubo et al. 1985; Huang 1987). It is worth summarizing some important concepts and tools used in that context as they are relevant also for the investigation of social dynamics. We will illustrate them using a paradigmatic example of order–disorder transitions in physics, the one exhibited by the Ising model for ferromagnets (Binney et al. 1992). Beyond its relevance as a physics model, the Ising ferromagnet can be seen as a very simple model for opinion dynamics, with agents being influenced by the state of the majority of their interacting partners.

Consider a collection of N spins (agents) s_i that can assume two values ± 1. Each spin is energetically pushed to be aligned with its nearest neighbors. The total energy is

$$H = -\frac{1}{2} \sum_{\langle i,j \rangle} s_i s_j, \tag{1}$$

where the sum runs on the pairs of nearest-neighbors spins. Among the possible types of dynamics, the most common (Glauber–Metropolis) (Landau and Binder 2005) takes as elementary move a single spin flip that is accepted with probability $\exp(-\Delta E/k_B T)$, where ΔE is the change in energy and T is the temperature. Ferromagnetic interactions in (1) drive the system toward one of two possible ordered states, with all positive or all negative spins. At the same time, thermal noise injects fluctuations that tend to destroy order. For low temperature T the ordering tendency wins and long-range order is established in the system, while above a critical temperature T_c, the system remains macroscopically disordered. The transition point is characterized by the average magnetization $m = 1/N \sum_i \langle s_i \rangle$ passing from 0 for $T > T_c$ to a value $m(T) > 0$ for $T < T_c$. The brackets denote the average over different realizations of the dynamics. This kind of transition is exhibited by a wealth of systems. Let us simply mention, for its similarity with many of the social dynamic models discussed in the review, the Potts model (Wu 1982), where each spin can assume one out of q values and equal nearest neighbor values are energetically favored. The Ising model corresponds to the special case $q = 2$.

It is important to stress that above T_c no infinite-range order is established, but on short spatial scales, spins are correlated: there are domains of $+1$ spins (and others of -1 spins) extended over regions of finite size. Below T_c instead these ordered regions extend to infinity (they span the whole system), although at finite temperature some disordered fluctuations are present on short scales (Fig. 1).

Not only the equilibrium properties just described, which are attained in the long run, are interesting. A much-investigated and nontrivial issue (Bray 1994) is the way the final ordered state at $T < T_c$ is reached when the system is initially prepared in a fully disordered state. This ordering dynamic is a prototype for the analogous processes occurring in many models of social dynamics. On short time scales, coexisting ordered domains of small size (both positive and negative) are formed. The subsequent evolution occurs through a *coarsening* process of such domains which grows larger and larger while their global statistical features remain unchanged over time. This is the dynamic scaling phenomenon: the morphology remains statistically

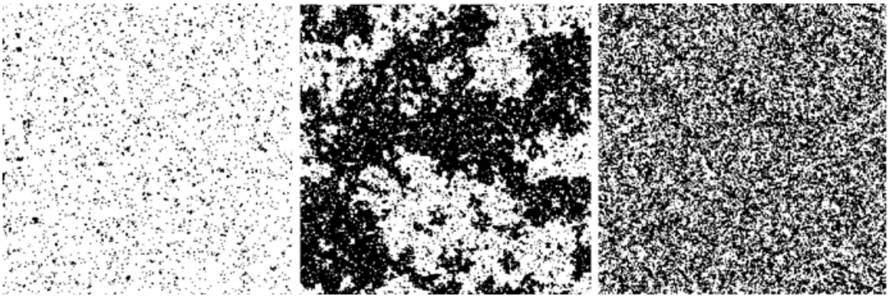

Fig. 1 Snapshots of equilibrium configurations of the Ising model (from *left* to *right*) below, at and above T_c

the same if rescaled by the typical domain size, which is the only relevant length in the system and grows over time as a power-law.

Macroscopically, the dynamic driving force toward order is surface tension. Interfaces between domains of opposite magnetization cost in terms of energy and their contribution can be minimized by making them as straight as possible. This type of ordering is often referred to as curvature-driven and occurs in many of the social systems described in this review. The presence of surface tension is a consequence of the tendency of each spin to become aligned with the majority of its neighbors. When the majority does not play a role, the qualitative features of the ordering process change.

The dynamic aspect of the study of social models requires the monitoring of suitable quantities able to properly identify the buildup of order. The magnetization of the system is not one of such suitable quantities. It is not sensitive to the size of single ordered domains while it measures their cumulative extension, which is more or less the same during most of the evolution. The appropriate quantity to monitor the ordering process is the correlation function between pairs of spins at distance r from each other, $C(r,t) = \langle s_i(t)s_{i+r}(t)\rangle - \langle s_i(t)\rangle^2$, where brackets denote averaging over dynamic realizations and an additional average over i is implicit. The temporal variable t is measured as the average number of attempted updates per spin. The dynamic scaling property implies that $C(r,t)$ is a function only of the ratio between the distance and the typical domain size $L(t)$: $C(r,t) = L(t)^d F[r/L(t)]$. $L(t)$ grows in time as a power-law $t^{1/z}$. The dynamic exponent z is universal, independent of microscopic details, possibly depending only on qualitative features as conservation of the magnetization or space dimensionality. In the Glauber–Metropolis case, $z = 2$ in any dimension. Another quantity often used is the density of interfaces $n_a(t) = N_a(t)/N_p$, where N_p is the total number of nearest neighbor pairs and N_a the number of such pairs where the two neighbors are in different states: $n_a = 1/2$ means that disorder is complete, while $n_a = 0$ indicates full consensus.

Finally, a word about finite size effects. The very concept of order-disorder phase-transitions is rigorously defined only in the limit of a system with an infinite number of components (thermodynamic limit), because only in that limit truly singular behavior can arise. Social systems are generally composed of a large number N of agents, but by far fewer than the number of atoms or molecules in a physical system. The finiteness of N must therefore play a crucial role in the analysis of models of social dynamics (Toral and Tessone 2007). Studying what happens when N changes and even considering the large-N limit is generally very useful, because it helps characterizing well-qualitative behaviors, understanding which features are robust, and filtering out non-universal microscopical details.

2.2 Role of Topology

An important aspect always present in social dynamics is topology, i.e., the structure of the interaction network describing who is interacting with whom, how frequently and with which intensity. Agents are thus supposed to sit on vertices (nodes) of a network, and the edges (links) define the possible interaction patterns.

The prototype of homogeneous networks is the uncorrelated random graph model proposed by Erdös and Rényi (ER model) (Erdös and Rényi 1959, 1960), whose construction consists in drawing an (undirected) edge with a fixed probability p between each possible pair out of N given vertices. The resulting graph shows a binomial degree distribution, the degree of a node being the number of its connections, with average $\langle k \rangle \simeq Np$. The degree distribution converges to a Poissonian for large N. If p is sufficiently small (order $1/N$), the graph is sparse and presents locally tree-like structures. In order to account for degree heterogeneity, other constructions have been proposed for random graphs with arbitrary degree distributions (Molloy and Reed 1995, 1998; Aiello and Lu 2001; Goh et al. 2001; Catanzaro et al. 2005).

A well-known paradigm, especially for social sciences, is that of "small-world" networks in which, on the one hand, the average distance between two agents is small (Milgram 1967), growing only logarithmically with the network size, and, on the other hand, many triangles are present, unlike ER graphs. In order to reconcile both properties, Watts and Strogatz have introduced the small-world network model (Watts and Strogatz 1998) which allows us to interpolate between regular low-dimensional lattices and random networks, by introducing a certain fraction p of random long-range connections into an initially regular lattice (Newman and Watts 1999). In Watts and Strogatz (1998) two main quantities have been considered: the characteristic path length $L(p)$, defined as the number of edges in the shortest path between two vertices, averaged over all pairs of vertices, and the clustering coefficient $C(p)$, defined as follows. If a node i has k connections, then at most $k(k-1)/2$ edges can exist between its neighbors (this occurs when every neighbor of i is connected to every other neighbor of i). The clustering coefficient $C(p)$ denotes the fraction of these allowable edges that actually exist, averaged over all nodes. Small-world networks feature high values of $C(p)$ and low values of $L(p)$.

Since many real networks are not static but evolving, with new nodes entering and establishing connections to already existing nodes, many models of growing networks have also been introduced. The Barabási and Albert model (BA) (Barabási and Albert 1999) has become one of the most famous models for complex heterogeneous networks, and is constructed as follows: starting from a small set of m fully interconnected nodes, new nodes are introduced one by one. Each new node selects m older nodes according to the *preferential attachment* rule, i.e., with probability proportional to their degree, and creates links with them. The procedure stops when the required network size N is reached. The obtained network has average degree $\langle k \rangle = 2m$, small clustering coefficient (of order $1/N$) and a power law degree distribution $P(k) \sim k^{-\gamma}$, with $\gamma = 3$. Graphs with power law degree distributions are referred to as *scale-free networks*.

An extensive analysis of the existing network models is beyond the scope of the present review and we refer the reader to the huge amount of literature on the so-called complex networks (Boccaletti et al. 2006; Albert and Barabási 2002; Dorogovtsev and Mendes 2003; Newman 2003a; Pastor-Satorras and Vespignani 2004; Caldarelli 2007). It is nevertheless important to mention that real networks often differ in many respects from artificial networks. People have used the social network metaphor for over a century to represent complex sets of relationships between members of social systems at all scales, from interpersonal to international. A huge amount of work has been carried out about the so-called social network analysis (SNA), especially in the social science literature (Moreno 1934; Granovetter 1973, 1983; Wasserman and Faust 1994; Scott 2000; Freeman 2004). Recently the interest of physicists triggered the investigation of many different networks: from the network of scientific collaborations (Barabási et al. 2002; Newman 2001a, 2001b, 2004) to that of sexual contacts (Liljeros et al. 2001) and the ongoing social relationships (Holme 2003), from email exchange networks (Ebel et al. 2002; Newman et al. 2002; Eckmann et al. 2004) to the dating community network (Holme et al. 2004) and to mobile communication networks (Onnela et al. 2007; Palla et al. 2007), just to quote a few examples. From this experimental work a set of features characterizing social networks has been identified.

It has been shown (Newman and Park 2003) how social networks differ substantially from other types of networks, namely technological or biological. The origin of the difference is twofold. On the one hand they exhibit a positive correlation between adjacent vertices (also called assortativity), while most non-social networks (Pastor-Satorras et al. 2001; Newman 2003b) are disassortative. A network is said to show assortative mixing if nodes with many connections tend to be linked to other nodes with many connections. On the other hand, social networks show clustering coefficients well above those of the corresponding random models. These results opened the way to a modeling activity aimed at reproducing in an artificial and controlled way the same features observed in real social networks (Jin et al. 2001). We cannot review here all these attempts, but we have quoted some relevant references throughout the review when discussing specific modeling schemes. It is important to keep in mind that future investigations on social dynamics will be forced to take into account, in a more stringent way, structural and dynamic properties of real social networks (Roehner 2007).

When applying models of social dynamics on specific topologies, several nontrivial effects may arise, potentially leading to important biases for the dynamics.

For instance, on a generic uncorrelated network with degree distribution $P(k)$, the degree of the neighbor of a node of degree k is distributed as $kP(k)/\langle k\rangle$ (Pastor-Satorras and Vespignani 2004). This expression can be easily obtained by considering that the required probability distribution for a node neighbor of a given node with degree k is the conditional probability $P(k|k')$, i.e., the probability that a node of degree k' is connected to a node of degree k, for which it holds $\sum_k P(k|k') = 1$. The expression for $P(k|k')$ for an uncorrelated network, can be easily understood if one thinks that the probability that a given node is connected to a node of degree k is proportional to the density of these nodes, $P(k)$, times the number k of emanated edges. As a consequence, the neighbor of a randomly selected node has an expected degree larger than the node itself. For a generic correlated network, the expression for $P(k|k')$ is given by $P(k|k') = (\langle k\rangle P(k,k'))/(k'P(k'))$, where $P(k,k'))$ is the joint probability of having an edge linking two nodes with degrees k and k'. Therefore, on strongly heterogeneous networks, for binary asymmetric interaction rules, i.e., when the two selected agents have different roles, the dynamics could be affected by the order in which the interaction partners are selected (this is the case, for example, in the Naming Game, as seen in Chap. 15).

2.3 Dynamical Systems Approach

One of the early contributions of physicists to the study of social systems has been the introduction of methods and tools coming from the theory of dynamical systems and non-linear dynamics. This development goes by the name *sociodynamics* (Weidlich 2002). The term sociodynamics has been introduced to refer to a systematic approach to mathematical modeling in the framework of social sciences.

Sociodynamics is a branch of synergetics (Haken 1978) devoted to social systems, featuring a few important differences. In synergetics, one typically starts with a large set of microscopic equations for the elementary components and performs a reduction of the degrees of freedom. This is not the case for social systems, for which no equations at the microscopic level are available. In this case one has to identify relevant macro-variables and construct equations directly for them based on reasonable and realistic social hypotheses, i.e., informed by social driving forces. The typical procedure consists of defining probabilistic transition rates per unit of time for the jumps from different configurations of the system corresponding to different values of the macro-variables. The transition rates are used as building blocks for setting up the equation of motion for the probabilistic evolution of the set of macro-variables. The central evolution equation in sociodynamics is the master equation, a phenomenological first-order differential equation describing the time evolution of the probability $P(\mathbf{m},t)$ for a system to occupy each one of a discrete set of states, defined through the set of macro-variables $\mathbf{m}$:

$$\frac{dP(\mathbf{m},t)}{dt} = \sum_{\mathbf{m}'}\big[W_{\mathbf{m}',\mathbf{m}}P(\mathbf{m}',t) - W_{\mathbf{m},\mathbf{m}'}P(\mathbf{m},t)\big], \qquad (2)$$

where $W_{\mathbf{m},\mathbf{m}'}$ represents the transition rate from the state $\mathbf{m}$ to the state $\mathbf{m}'$. The master equation is a gain-loss equation for the probability of each state $\mathbf{m}$. The first term is the gain due to transitions from other states $\mathbf{m}'$, and the second term is the loss due to transitions into other states $\mathbf{m}'$.

While it is relatively easy to write down a master equation, it is quite another matter to solve it. It is usually highly non-linear and some clever simplifications are often needed to extract a solution. In general, only numerical solutions are available. Moreover, typically the master equation contains too much information in comparison to available empirical data. For all these reasons it is highly desirable to derive from the master equation simpler equations of motion for simpler variables. One straightforward possibility is to consider the equations of motion for the average values of the macro-variables $\mathbf{m}$, defined as

$$\overline{m}_k(t) = \sum_{\mathbf{m}} m_k P(\mathbf{m}, t). \tag{3}$$

The exact expression for the equations of motion for $\overline{m}_k(t)$ does not lead to simplifications because one should already know the full probability distribution $P(\mathbf{m}, t)$. On the other hand, under the assumption that the distribution remains unimodal and sharply peaked for the period of time under consideration, one has

$$\overline{P(\mathbf{m}, t)} \simeq P\big(\overline{\mathbf{m}(t)}\big), \tag{4}$$

yielding the approximate equations of motions for $\overline{m}_k(t)$, which are now a closed system of coupled differential equations. We refer to Weidlich (2002) for a complete derivation of these equations as well as for the discussion of several applications. The approach has also been applied to model behavioral changes (Helbing 1993a, 1993b, 1994).

2.4 Agent-Based Modeling

Computer simulations play an important role in the study of social dynamics since they parallel more traditional approaches of theoretical physics aimed at describing a system in terms of a set of equations to be later solved numerically and/or, whenever possible, analytically. One of the most successful methodologies used in social dynamics is *agent-based* modeling. The idea is to construct the computational devices (known as agents with some properties) and then simulate them in parallel to model the real phenomena. The goal is to address the problem of the emergence from the lower (micro) level of the social system to the higher (macro) level. The origin of agent-based modeling can be traced back to the 1940s, to the introduction by Von Neumann and Ulam of the notion of cellular automaton (Neumann 1966; Ulam 1960), e.g., a machine composed of a collection of cells on a grid. Each cell can be found in a discrete set of states and its update occurs on discrete time steps according to the state of the neighboring cells. A well-known example is Conway's

Game of Life, defined in terms of simple rules in a virtual world shaped as a 2-dimensional checkerboard. This kind of algorithms became very popular in population biology (Matsuda et al. 1992).

The notion of agent has been very important in the development of the concept of Artificial Intelligence (McCarthy 1959; Minsky 1961) which traditionally focuses on the individual and on rule-based paradigms inspired by psychology. In this framework, the term *actors* was used to indicate interactive objects characterized by a certain number of internal states, acting in parallel and exchanging messages (Hewitt 1970). In computer science, the notion of actor turned into that of agent and more emphasis has been put on the interaction level instead of autonomous actions.

Agent-based models were primarily used for social systems by Craig Reynolds, who tried to model the reality of living biological agents, known as artificial life, a term coined in Langton (1996). Reynolds introduced the notion of individual-based models in which one investigates the global consequences of local interactions of members of a population (e.g., plants and animals in ecosystems, vehicles in traffic, people in crowds, or autonomous characters in animation and games). In these models, individual agents (possibly heterogeneous) interact in a given environment according to procedural rules tuned by characteristic parameters. One thus focuses on the features of each individual instead of looking at some global quantity averaged over the whole population. In Epstein and Axtell (1996), by focusing on a bottom-up approach, the first large-scale agent model, the Sugarscape, has been introduced to simulate and explore the role of social phenomena such as seasonal migrations, pollution, sexual reproduction, combat, trade and transmission of disease and culture.

The Artificial Life community has been the first in developing agent-based models (Meyer and Wilson 1990; Maes 1991; Varela and Bourgine 1992; Steels 1995; Weiss 1999), but since then, agent-based simulations have become an important tool in other scientific fields and, in particular, in the study of social systems (Conte et al. 1997; Wooldridge 2002; Macy and Willer 2002; Schweitzer 2003; Axelrod 2006). In this context it is worth mentioning the concept of *Brownian agent* (Schweitzer 2003) which generalizes that of Brownian particles from statistical mechanics. A Brownian agent is an active particle which possesses internal states, can store energy and information, and interacts with other agents through the environment. Again, the emphasis is on the parsimony in the agent definition as well as on the interactions, rather than on the autonomous actions. Agents interact either directly or indirectly through the external environment, which provides feedback about the activities of the other agents. Direct interactions are typically local in time and ruled by the underlying topology of the interaction network (see also Sect. 2.2). Populations can be homogeneous (i.e., all agents being identical) or heterogeneous. Differently from physical systems, the interactions are usually asymmetrical since the role of the interacting agents can be different both for the actions performed and for the rules to change their internal states. Agent-based simulations have now acquired a central role in modeling complex systems and a huge amount if literature has been rapidly developing in the last few years about the internal structure of the agents, their activities, and the multi-agent features. An exhaustive discussion of agent-based models is beyond the scope of the present review, but we refer to Schweitzer (2003) where the role of active particles is thoroughly discussed with many examples of applications, ranging from structure formation in biological systems and pedestrian traffic to the simulation of urban aggregation or opinion formation processes.

It is worth mentioning that in this section we mainly discussed simple agent-based models in which the role of the embodiment has been explicitly neglected. In these models the physical interaction of the agents with the environment is highly simplified and at the same time the signals changed with the environment are defined in an abstract way more that in a grounded way, through the sensory motor endowment of the agent. A more realistic use of agent-based schemes will be illustrated in Parts II and III of this book.

3 Conclusions

In this chapter we have illustrated the main statistical tools physicists and mathematicians can bring as a support for the longstanding problem concerning the emergence and evolution of language. We introduced, in particular, the main tools and methods proposed so far for the description of the early stages in the emergence of language: e.g., the formation of a shared lexicon and the establishment of a common set of linguistic categories. Though promising, these studies did not yet face the hardest problems in linguistics, namely the emergence of syntax and grammar. Currently, new studies are ongoing focusing on the emergence of higher forms of agreement, e.g., compositionality, syntactic, or grammatical structures. It is clear how it would be highly important to cast a theoretical framework where all these problems could be defined, formalized, and solved. In this perspective a crucial factor will be most likely represented by the availability of large sets of empirical quantitative data. The joint interdisciplinary activity should then include systematic campaigns of data gathering as well as the devising of new experimental setups for a continuous monitoring of linguistic features. From this point of view, the Web may be of great help, both as a platform to perform controlled online social experiments, and as a repository of empirical data on large-scale phenomena. It is only in this way that a virtuous cycle involving data collection, data analysis, modeling, and predictions could be triggered, giving rise to an ever more rigorous and focused approach to language.

It is worth stressing how the contribution physicists could give should not be considered in any way as alternative to more traditional approaches. We rather think that it would be crucial to foster the interactions across the different disciplines cooperating with linguistics, by promoting scientific activities with concrete mutual exchanges among all the interested scientists. This would help both in identifying the problems and sharpening the focus, as well as in devising the most suitable theoretical concepts and tools to approach the research.

References

Aiello, F. C. W., & Lu, L. (2001). A random graph model for power law graphs. *Experimental Mathematics*, *10*, 53–66.

Albert, R., & Barabási, A.-L. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics*, *74*(1), 47–97.

Axelrod, R. (1997). The dissemination of culture: a model with local convergence and global polarization. *The Journal of Conflict Resolution*, *41*(2), 203–226.

Axelrod, R. (2006). Agent-based modeling as a bridge between disciplines. In L. Tesfatsion & K. L. Judd (Eds.), *Handbook of computational economics* (Vol. 2, pp. 1565–1584). Amsterdam: Elsevier.

Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, *286*, 509.

Barabási, A.-L., Jeong, H., Néda, Z., Ravasz, E., Schubert, A., & Vicsek, T. (2002). Evolution of the social, network of scientific collaborations. *Physica A*, *311*(34), 590–614.

Binney, J., Dowrick, N., Fisher, A., & Newman, M. (1992). *The theory of critical phenomena: an introduction, to the renormalization group*. Oxford: Oxford University Press.

Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., & Hwang, D.-U. (2006). Complex networks: Structure and dynamics. *Physics Reports*, *424*(4–5), 175–308.

Bray, A. (1994). Theory of phase-ordering kinetics. *Advances Physics*, *43*(3), 357–459.

Buchanan, M. (2007). *The social atom*. New York: Bloomsbury.

Caldarelli, G. (2007). *Scale-free networks*. Oxford: Oxford University Press.

Castellano, C., Fortunato, S., & Loreto, V. (2009). Statistical physics of social dynamics. *Revues of Modern Physics*.

Catanzaro, M., Boguñá, M., & Pastor-Satorras, R. (2005). Generation of uncorrelated random scale-free networks. *Physical Revue E*, *71*(2), 027103.

Conte, R., Hegselmann, R., & Terna, P. (1997). *Simulating social phenomena*. Berlin: Springer.

Dorogovtsev, S., & Mendes, J. (2003). *Evolution of networks: from biological nets to the Internet and WWW*. Oxford: Oxford University Press.

Ebel, H., Mielsch, L.-I., & Bornholdt, S. (2002). Scale-free topology of e-mail networks. *Physical Revue E*, *66*(3), 035103.

Eckmann, J., Moses, E., & Sergi, D. (2004). Entropy of dialogues creates coherent structures in e-mail traffic. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(40), 14333–14337.

Epstein, J., & Axtell, R. (1996) *Growing artificial societies: social science from the bottom up*. Washington: The Brookings Institution.

Erdös, P., & Rényi, A. (1959). On random graphs I. *Publications Mathematicae*, *6*, 290.

Erdös, P., & Rényi, A. (1960). On the evolution of random graphs. *Publications of the Mathematical Institute of the Hungarian Academy of Sciences*, *7*, 17.

Festinger, L., Schachter, S., & Back, K. (1950). *Social pressures in informal groups: a study of human factors in housing*. New York: Harper.

Freeman, L. (2004). *The development of social network analysis: a study in the sociology of science*. Vancouver: BookSurge Publishing.

Goh, K.-I., Kahng, B., & Kim, D. (2001). Universal behavior of load distribution in scale-free networks. *Physical Revue Letters*, *87*(27), 278701.

Granovetter, M. (1973). The strength of weak ties. *The American Journal of Sociology*, *78*(6), 1360–1380.

Granovetter, M. (1983). The strength of weak ties: a network theory revisited. *Sociological Theory*, *1*, 201–233.

Haken, H. (1978). *Synergetics; an introduction. Non-equilibrium phase transitions and self-organization in physics, chemistry and biology*. Berlin: Springer.

Helbing, D. (1993a). Boltzmann-like and Boltzmann–Fokker–Planck equations as a foundation of behavioral models. *Physica A*, *196*(2), 546–573.

Helbing, D. (1993b). Stochastic and Boltzmann-like models for behavioral changes, and their relation to game theory. *Physica A*, *193*(2), 241–258.
Helbing, D. (1994). A mathematical model for the behavior of individuals in a social field. *Journal of Mathematical Sociology*, *19*(3), 189–219.
Hewitt, C. (1970). *PLANNER: a language for manipulating models and proving theorems in a robot*. dspace.mit.edu.
Holme, P. (2003). Network dynamics of ongoing social relationships. *Europhysics Letters*, *64*(3), 427–433.
Holme, P., Edling, C. R., & Liljeros, F. (2004). Structure and time-evolution of an Internet dating community. *Social Networks*, *26*, 155.
Huang, K. (1987). *Statistical mechanics*. New York: Wiley.
Jin, E. M., Girvan, M., & Newman, M. E. J. (2001). Structure of growing social networks. *Physical Revue E*, *64*(4), 046132.
Kubo, R., Toda, M., & Hashitsume, N. (1985). *Statistical physics*. Berlin: Springer.
Landau, D., & Binder, K. (2005). *A guide to Monte Carlo simulations in statistical physics*. Cambridge: Cambridge University Press.
Langton, C. (1996). *Artificial life*. Boston: Addison-Wesley Longman.
Liljeros, F., Edling, C., L, A., Stanley, E., & Åberg, Y. (2001). The web of human sexual contacts. *Nature*, *411*, 907–908.
Loreto, V., & Steels, L. (2007). Social dynamics: the emergence of language. *Nature Physics*, *3*, 758–760.
Macy, M., & Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual Revue Sociology*, *28*, 143–166.
Maes, P. (1991). *Designing autonomous agents: theory and practice from biology to engineering and back*. Cambridge: MIT Press.
Matsuda, H., Ogita, N., Sasaki, A., & Sato, K. (1992). Statistical mechanics of population. The lattice Lotka–Volterra model. *Progress of Theoretical Physics*, *88*(6), 1035–1049.
McCarthy, J. (1959). Programs with common sense. In *Proceedings of the Teddington conference on the mechanization of thought processes* (pp. 75–91). London: Her Majesty's Stationary Office.
Meyer, J.-A., & Wilson, S. W. (Eds.) (1990). *From animals to animats: proceedings of the first international conference on simulation of adaptive behavior*. Cambridge: MIT Press.
Milgram, S. (1967). The small world problem. *Psychology Today*, *1*, 60–67.
Minsky, M. (1961). Steps toward artificial intelligence. *Proceedings of the Institute of Radio Engineers*, *49*, 8–30.
Molloy, M., & Reed, B. (1995). A critical point for random graphs with a given degree sequence. *Random Structures & Algorithms*, *6*, 161–179.
Molloy, M., & Reed, B. (1998). The size of the giant component of a random graph with a given degree sequence. *Combinatorics, Probability & Computing*, *7*, 295.
Moreno, J. (1934). *Who shall survive?: a new approach to the problem of human interrelations*. *Nervous and mental disease monograph series* (Vol. 58) Washington: Nervous and Mental Disease Publishing.
Neumann, J. V. (1966). *Theory of self-reproducing automata*. Champaign: University of Illinois Press.
Newman, M. (2001a). Scientific collaboration networks. i. network construction and fundamental results. *Physical Revue E*, *64*(1), 016131.
Newman, M. (2001b). Scientific collaboration networks. ii. shortest paths, weighted networks, and centrality. *Physical Revue E*, *64*(1), 016132.
Newman, M. (2003a). The structure and function of complex networks. *SIAM Review*, *45*(2), 167–256.
Newman, M. E. J. (2003b). Mixing patterns in networks. *Phys. Rev. E*, *67*(2), 026126.
Newman, M. (2004). Coauthorship networks and, patterns of scientific collaboration. *Proceedings of the National Academy of Sciences of the United States of America*, *101*, 5200–5205.
Newman, M., & Park, J. (2003). Why social networks are different from other types of networks. *Phys. Rev. E*, *68*, 036122.

Newman, M., & Watts, D. (1999). Scaling and percolation in the small-world network model. *Phys. Rev. E*, *60*(6), 7332–7342.

Newman, M., Forrest, S., & Balthrop, J. (2002). Email networks and the spread of computer viruses. *Phys. Rev. E*, *66*(3), 035101.

Onnela, J., Saramäki, J., Hyvönen, J., Szabó, G., Lazer, D., Kaski, K., Kertész, J., & Barabási, A. L. (2007). Structure and tie strengths in mobile communication networks. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(18), 7332–7336.

Palla, G., Barabási, A.-L., & Vicsek, T. (2007). Quantifying social group evolution. *Nature*, *446*(7136), 664–667.

Pastor-Satorras, R., & Vespignani, A. (2004). *Evolution and structure of the Internet: a statistical physics approach*. New York: Cambridge University Press.

Pastor-Satorras, R., Vázquez, A., & Vespignani, A. (2001). Dynamical and correlation properties of the Internet. *Physical Revue Letters*, *87*(25), 258701.

Roehner, B. (2007). *Driving forces in physical, biological and socio-economic phenomena*. Cambridge: Cambridge University Press.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, *1*(2), 143–186.

Schweitzer, F. (2003). *Brownian agents and active particles*. Berlin: Springer.

Scott, J. (2000). *Social network analysis: a handbook*. London: Sage.

Steels, L. (1995). A self-organizing spatial vocabulary. *Artificial Life*, *2*(3), 319–332.

Steels, L. (2000). Language as a complex adaptive system. In M. Schoenauer (Ed.), *Lecture notes in computer science*. *Proceedings of PPSN VI*. Berlin: Springer.

Toral, R., & Tessone, C. J. (2007). Finite size effects in the dynamics of opinion formation. *Computer Physics Communications*, *2*(2), 177–195.

Ulam, S. (1960). *A collection of mathematical problems*. New York: Interscience.

Varela, F. J., & Bourgine, P. (Eds.) (1992). *Toward a practice of autonomous systems: proceedings of the first European conference on artificial life*. Cambridge: MIT Press.

Wasserman, S., & Faust, K. (1994). *Social network analysis*. Cambridge: Cambridge University Press.

Watts, D., & Strogatz, S. (1998). Collective dynamics of ‘small-world’ networks. *Nature*, *393*, 440–442.

Weidlich, W. (2002). *Sociodynamics: a systematic approach to mathematical modelling in social sciences*. London: Taylor & Francis.

Weiss, G. (Ed.) (1999). *Multiagent systems: a modern approach to distributed artificial intelligence*. Cambridge: MIT Press.

Wittgenstein, L. (1953a). *Philosophical investigations*. Oxford: Basil Blackwell. (Translated by Anscombe, G.E.M.).

Wittgenstein, L. (1953b) *Philosophische Untersuchungen*. Frankfurt am Main: Suhrkamp.

Wooldridge, M. (2002). *Introduction to multiagent systems*. Chichester: Wiley.

Wu, F. (1982). The Potts model. *Revues of Modern Physics*, *54*(1), 235–268.