Self-Organization and Emergence in Social Systems: Modeling the Coevolution of Social Environments and Cooperative Behavior

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Self-organization and emergence in social systems. Modeling the coevolution of social environments and cooperative behavior

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Abstract

We demonstrate with computational simulation scenarios how social environment and individual behavior coevolve and how fundamentally different macro-effects emerge, when separate micro-mechanisms are combined. Our framework considers social interactions in prisoner's dilemmas, stag hunt, chicken or coordination games among agents on a spatial grid. Neither imitation of more successful strategies nor the migration to more favorable locations can promote cooperation in prisoner's dilemmas. However, when both microscopic mechanisms are combined, they cause the segregation of cooperators and defectors, and the self-organization of cooperative clusters on the macro-level. These are robust to randomness, while cooperation may break down in a "globalized society". Results are discussed regarding their implications for the evolution of norms and institutions.

Keywords: Spatial games; mobility and migration; spatio-temporal pattern formation; agent-based simulation; social dilemmas; cooperation; self-organization

and emergence; representative agent models; randomness and noise; replicator equation; social learning and imitation

The questions why individuals agglomerate in cities, groups or networks and why people show "social" and other-regarding behavior are among the most fundamental questions of sociology and other behavioral sciences (Hobbes, [1651] 1984; Park, 1925; Parsons, 1937; Schelling, 1971, 1978; Granovetter, 1973; Axelrod, 1984; Coleman, 1990). These two questions are mutually interrelated, as social interactions require a certain degree of adaptiveness and coordination to enable cooperation. Otherwise many interactions would fail or end up in conflict (Axelrod, 1997; Henrich et al., 2004; Winter et al., 2009; Rauhut and Winter, 2009).

Cooperation is crucial for societies, since it allows the creation of common goods that no single individual could establish alone. These common goods reach from shared infrastructures to social institutions (Olson, 1965; Taylor, 1976; Ostrom et al., 1994; Skyrms, 2005; Young, 2008). However, it has been identified early on that the contribution to public goods establishes a dilemma, sometimes phrased as "the tragedy of the commons" (Hardin, 1968). As the creation of these goods requires an individual effort and the result is shared by everybody, there is a temptation to make the own contribution as little as possible and receive as much of the result as one can. Consequently, we face the problem of over-fishing, the pollution and exploitation of our environment, and the problem of sustainable social benefit systems (such as an affordable health insurance), to mention only a few examples (Ellickson, 1991; Hardin, 1995; Raub and Buskens, 2004; Milinski et al., 2008; Diekmann, 2009).

When addressing the question of the inter-relatedness between social influence and cooperative behavior, a substantive theory of decision-making on the micro-level has to be assumed to enable the explanation of such macro-effects. Approaches like Skinner's behaviorism (Skinner, 1938), proposing that individual behaviors would be like reflexes that could and would be "programmed", turned out to be too mechanical. As a consequence, social scientists have promoted the idea of *cultural inheritance* (Boyd and Richerson, 1985; Barkow, 1992; Skyrms, 2005), according to which certain behaviors would spread by social *learning*. Social learning is of major importance for the development of humans, as the complexity of our social environment implies that we cannot learn everything by trial and error. Learning by observation, i.e. imitation, facilitates a much quicker spreading of successful behaviors in social neighborhoods (Coleman et al., 1957; Mahajan and Peterson, 1985; Rogers, 2003; Lane et al., 2009), even beyond the limits of family relationships.

Furthermore, the micro-level theory of individual decision-making has to take into account a considerable level of unpredictability and randomness. This is

supported by social learning theories. Everybody is exposed to a large variety of different influences superimposing each other. As a consequence, one cannot hope to describe human behavior by a deterministic model. For example, the multinomial logit model (McFadden, 1974; Manski and McFadden, 1981) is *one* such model, considering probabilistic behavior.

In addition, the understanding of micro-macro relationships in social systems such as the coevolution of social influence and cooperation requires a dynamical mechanism, relating micro-motives with macro-patterns over time. Evolutionary theory has been recently applied to understand what are the behaviors which actually spread and what are the ones which disappear. Here, the assumption of natural selection and competition, together with a faster reproduction of more successful individuals eventually leads to a selection of the more successful behaviors (Samuelson, 1997; Nowak, 2006a). This spreading mechanisms, based on genetic reproduction, can be described by *replicator equations*, while the imitation of behaviors is reflected by *game-dynamical equations*, which formally look the same (see Appendix A). Assuming that more successful behaviors are imitated more frequently than less successful ones, this also implies a spreading of behaviors, which are more successful than average (in terms of providing a higher "payoff"). The other behaviors should eventually disappear (Hofbauer and Sigmund, 2002; Helbing, 1992; Young, 1993).

Finally, the explanation of cooperation should account for recent empirical findings of moral behavior, such as "fairness" (Fischbacher et al., 2001; Camerer, 2003; Fehr and Gintis, 2007). However, it appears desirable to develop models that do not assume *per se* an *inclination* towards cooperative or defective behavior. Therefore, we assume that the behavior of individuals may change from cooperative to defective and vice versa, depending on the conditions. When proposing such a model in the following, we will address several puzzles and reveal their surprising mutual interconnections:

1. How does the social environment influence the individual behavior, and how does it in turn determine the environment?
2. Which micro-mechanisms can explain the widespread *clustering* of social activities in social systems like the formation of groups or settlements?
3. Does *mobility* of individuals influence the aggregate level of cooperation?
4. What is the importance of *local interactions* in a globalized world?

Our model will reproduce the following stylized facts of social systems, without putting them into the underlying model assumptions:

- Individuals with similar behavioral strategies tend to agglomerate (form groups, cities, etc.).

- Individuals with different behavioral strategies tend to segregate.
- Individual behaviors are partially determined by the social environment they are contributing to—a fact, that is often explained by assuming social norms.
- A social environment persist longer than individuals contribute to it on average—something which is well-known from many social institutions, considering their considerable inertia.

The remainder of this manuscript is organized in three major parts: Section 1 introduces the game-theoretical framework of modeling social interactions in space and time. Here, the role of local interactions, migration and randomness is analyzed in separation. We equip the agents with two (bounded) rational micro-motives: (1) imitation of successful strategies and (2) migration to locations with higher payoffs. Subsequently, we study the importance of the agents' interaction range for maintaining cooperation. We also demonstrate that migration motives induce structural effects and the emergence of patterns such as clusters of similar strategies and the segregation of different ones.

In section 2, the interaction of the model ingredients is evaluated, yielding astonishing and sometimes counter-intuitive results: Imitation and success-driven migration alone cannot enhance cooperation. However, when taken together, these two mechanisms show surprising interaction effects in the sense that cooperation is promoted and maintained at high levels. This effect can be understood as a "side-effect" of the combination of migration and imitation motives, resulting in cooperative clusters. Finally, we show that our findings are robust to different kinds of randomness.

In section 3, our results are discussed and related to some of the challenging methodological and theoretical problems in sociology. More specifically, we discuss the relevance of complexity in social systems in the sense that non-linear interactions on the micro-level of social systems can cause the emergence of fundamentally different and sometimes counter-intuitive properties at the system level. Moreover, our simulation results are related to social norms and applied to the study of possible effects of globalization on the level of cooperation in social systems. Finally, we discuss the possibility of empirical tests with a particular emphasis on behavioral laboratory experiments.

1 Formulating a Model of Success-Oriented Behavior in Space and Time

In the following, we will outline the underlying microscopic assumptions of our model of success-driven behavior and study their implications separately and to-

gether. We have decided for a game-theoretical framework, as game theory is currently one of the most developed mathematical theories of social interactions (Samuelson, 1997; Gintis, 2000; Camerer, 2003; Raub and Buskens, 2004; Voss, 2006; Fehr and Gintis, 2007; Diekmann, 2009). Specifically, our model belongs to the area of spatial evolutionary games, and it builds upon a seminal paper of Nowak and May (1992). It also relates to earlier work by Schelling (1971).

1.1 Social Interactions in a Game-Theoretical Modeling Framework

Following the KISS principle of keeping models simple in order to be able to identify the underlying mechanisms creating certain results, Nowak and May (1992) came up with a simple, but powerful approach: In their world, individuals are distributed in a two-dimensional space. While this space can reflect geographical space (assuming interactions on a plaza or in an urban neighborhood), it could also be viewed as an abstract representation of a social space, e.g. when processes of opinion formation are studied (Hegselmann and Krause, 2002; Deffuant et al., 2005). In their model, Nowak and May discretize space into a chess-board-like square grid of $L \times L$ equally sized cells, which are assumed to be occupied by one individual each. That is, the computer simulation involves $N = L^2$ individuals altogether. These individuals have two behavioral alternatives $i \in \{1, 2\}$ (often called "strategies"), which are updated in parallel every time step Δt. Therefore, Nowak and May's agent-based model can be viewed as cellular automaton model (Heckathorn, 1996; Macy and Willer, 2002; Macy and Flache, 2002; Gilbert and Troitzsch, 2005; Hegselmann, 2009). In each round (time step, iteration), individuals in the model (the "agents") are assumed to have binary (dyadic) interactions with each of their m nearest neighbors. Each binary interaction results in a certain "payoff" P_{ij}, which depends on the behavior i of the focal individual and the behavior j of the respective interaction partner (neighbor). This payoff reflects the degree of success of the interaction in a quantitative way. The payoffs of *all* binary interactions with the m neighbors is then added up to determine the overall payoff $P_i(t) = \sum_j P_{ij}$ of the focal individual, showing behavior i in time step t. The procedure for the other individuals is the same.

After all individuals had social interactions (in parallel), it is assumed that they find out what the overall payoffs of their m neighbors were. To reflect social learning, the strategy applied by the most successful neighbor is then copied ("imitated"), if this neighbor was more successful than the respective focal individual. Otherwise the individual sticks to the previous behavior in the next time step. Note, however, that not only the *focal* individual may change the behavior. The imitated individual may do so as well, since it has a different set of neighbors. As a consequence, the behaviors of the individuals in this model can strongly change in space and time. In fact, the outcome of such interactions tends to be

non-stationary, i.e. the individual behaviors keep changing. In other words, the resulting social interaction patterns do not persist over longer time periods—in contrast to what we will find in the model proposed below.

1.1.1 Discussion

The model of Nowak and May described above assumes boundedly rational agents (cf. Simon, 1982; Gigerenzer and Goldstein, 1996; Sober and Wilson, 2003; Gintis, 2009). Their agents do not try to anticipate all future actions and reactions of all interaction partners (the m neighbors), as a professional chess player would try. Agents only try to improve their situation in the next iteration as compared to their current situation. Specifically, they unconditionally imitate more successful interaction partners without trying to anticipate their future behavior or future interactions. In particular, no shadow of the future (Taylor, 1976; Axelrod and Hamilton, 1981; Axelrod, 1984; Fudenberg and Maskin, 1986) is assumed to influence the individual decisions. Consequently, there are many ways to modify the model. For example, one can study the different kinds of games: In this article, we focus on the coordination game, the prisoner's dilemma, the stag hunt game (also called assurance game), and the snowdrift game (also called chicken or hawk-dove game).

Unconditional imitation can be replaced by stochastic imitation rules (Szabó and Hauert, 2002; Hauert and Doebeli, 2004), by a best response rule (Young, 2001), or by a win-stay-lose-shift rule (Macy, 1991; Macy and Flache, 2002). Furthermore, one could consider indirect reciprocity in repeated interactions (considering a shadow of the future), signalling and reputation effects, network interactions, group competition, etc. Some of these can be taken into account by effective payoffs, which are different from the original payoffs P_{ij} (Nowak, 2006b; Helbing and Lozano, 2009). This transformation of payoffs is a very practical way of studying the impact of certain interaction mechanisms (Helbing and Lozano, 2009). It is also interesting to study effects of multi-stage strategies like, for example, tit for tat (Axelrod, 1984). Finally, it is worthwhile to study effects of a partial occupation of the grid (i.e. the existence of empty cells) (Vainstein et al., 2007), of irregular grids with varying numbers of neighbors (Hegselmann and Flache, 1998), and of different update rules (Rajewsky et al., 1998). The simulation results shown in this paper, for example, assume a random sequential update (Glance and Huberman, 1993), as people usually do not change their behaviors in a synchronized way.

1.2 The Role of Local Interactions

Our first computational results demonstrating the great relevance of microscopic assumptions for the macroscopic outcome will study the effect of neighborhood

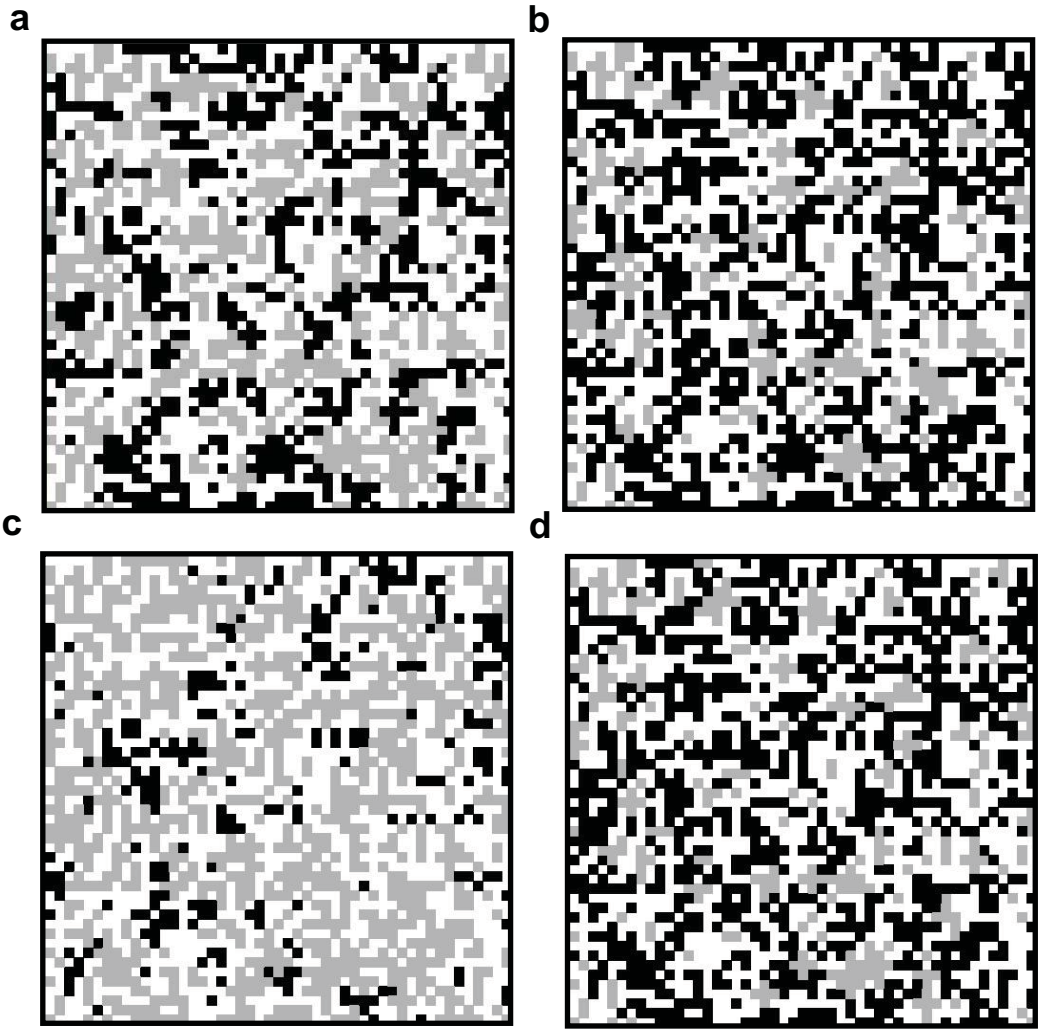


Figure 1. Representative simulation results of spatial games without mobility, when individuals unconditionally imitate the best strategy among their $m = 4$ neighbors, given the own payoff is lower. The simulations are conducted on a 49×49 spatial grid with 50 % empty sites (black = defector or strategy 1; grey = cooperator or strategy 2; white = empty site). For comparison, all simulations were performed with identical initial conditions, and snapshots were taken after $t = 50$ iterations. The payoffs are denoted by $P_{11} = R$, $P_{12} = S$, $P_{21} = T$, and $P_{22} = P$. (a) Coordination game with $R = P = 1$ and $T = S = 0$. (b) Prisoner's dilemma with $T = 1.3$, $R = 1$, $P = 0.1$ and $S = 0$. (c) Assurance game (stag hunt game) with $T = 1$, $R = 1.3$, $P = 0.1$, $S = 0$. (d) Chicken game (also called snowdrift or hawk-dove game) with $T = 1.3$, $R = 1$, $P = 0$, $S = 0.1$.

size m. Figure 2 shows results for the prisoner's dilemma game, where behavior $i = 1$ shall correspond to cooperation and $i = 2$ to defection (i.e. cheating or free-riding). For the payoffs, we have $P_{11} = R$, $P_{12} = S$, $P_{21} = T$, and $P_{22} = P$ with $T > R > P > S$. Accordingly, mutual cooperation gives a higher payoff (the "reward" R) than defection on both sides (which comes with the "punishment" P). However, the highest payoff results for unilateral defection (the "temptation" T), and the unilateral cooperator ends up with the poorest possible result (the "sucker's payoff" S). Due to $T > R$, there is a temptation for defection, and $P > S$ implies a risk of cooperation. Taken together, no matter what the interaction partner does, defection is always the better choice. As a consequence, even when we start with a high fraction of cooperators in the beginning (here: 90%), we will end up with predominant defection. In fact, if everybody interacts with everybody else (corresponding to $m = L^2$), nobody will cooperate anymore after a couple of iterations (see Fig. 2a). This also corresponds to the outcome of the replicator equation or game-dynamical equation (see Appendix A), which assumes that interaction partners are "well mixed". Such an assumption leads to results that are independent of the spatial configuration. It allows one to apply a "mean-field approximation", which assumes that the dynamics can be determined by studying interactions with an *average* interaction partner. In economics, the mean-field approach corresponds to the representative agent concept.

However, when considering *local* interactions (i.e., when $m \ll L^2$), the computational results may significantly deviate from what the mean-field approximation (and, therefore, the representative agent concept) predicts (see Fig. 1b). Interactions with small neighborhoods allow for the existence of local differences, and surprisingly, this prevents the complete extinction of cooperators. When there is a local cluster of cooperators, cooperators in the cluster reach a high payoff, which may cause defectors to imitate cooperators (if $T - R$ and $P - S$ are not too large). Therefore, if the percentage of defectors is high, the number of defectors imitating cooperators may reach the same level as the number of cooperators becoming defectors, particularly as there are not so many cooperators left to be converted. This is somewhat comparable to the hawk-dove game, where too many hawks as compared to doves will also prevent their further spreading (Hofbauer and Sigmund, 2002). In fact, as defectors are imitated by cooperators, they destroy their cooperative neighborhood, which results in a low payoff of P per interaction as compared to the high payoff T per interaction in a neighborhood of cooperators. Nevertheless, when starting with a high percentage of cooperators, the level of cooperation will fall dramatically, before it stabilizes at a finite value at the end.

1.3 Considering Mobility in Space

Humans usually do not stay their entire life in the same location, and their position in social space (e.g. their status and the social connections they maintain)

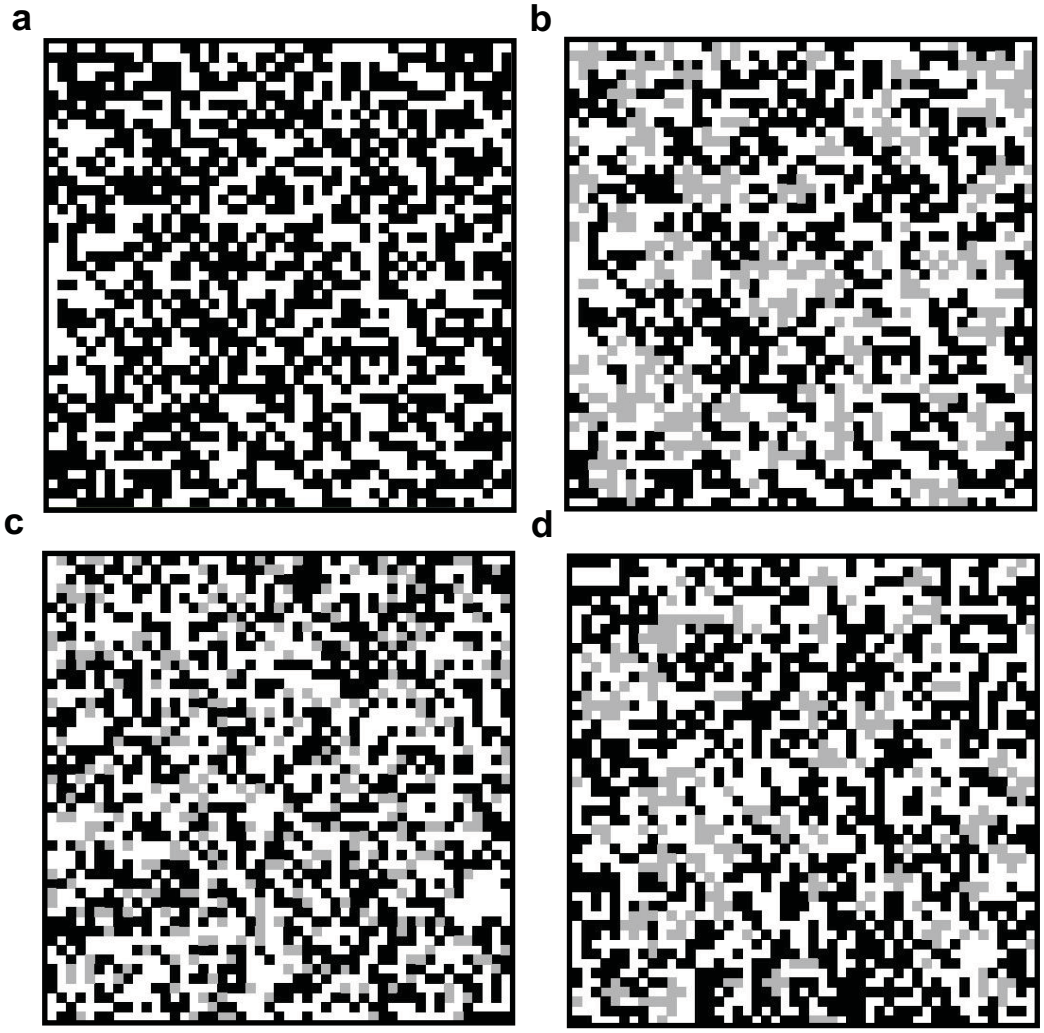


Figure 2. Representative simulation results of spatial games, when individuals imitate better perfoming strategies within their interaction neighborhood of size m. Left: "Global" interactions, where everybody interacts with everybody else. Right: Local interactions with the $m = 4$ nearest neighbors only. Top: In the spatial prisoner's dilemma with "global" interactions, cooperation disappears completely (see a), while a moderate level of cooperation can be maintained in the case of local interactions (see b). Bottom: In the snowdrift game, cooperation is possible even for global interactions (see c), but the level of cooperation is higher, when individuals interact locally (see d).

changes as well. Therefore, it is an interesting question, what will happen when integrating game-theoretical models and models of mobility. Will the resulting individual-based models produce new kinds of spatial-temporal self-organization? Can we easily understand why phenomena like group formation, agglomeration, and segregation are so widespread in social, economic, and biological systems, although one often tries do counteract these phenomena (e.g. by certain political interventions)? What is the role of mobility for social cooperation? Does leaving the birth place necessarily reduce cooperation by cutting social ties, as one may think? And is migration a "bad thing", as many people seem to feel? The models studied below give some interesting answers, but of course, further studies are in place.

1.3.1 Classification of Mobility Models

Mobility can be modeled in different ways, and it makes sense to give the corresponding models different names. First, one can distinguish models with continuous motion ("motion games" such as the social force model (Helbing and Molnar, 1995; Hoogendoorn and HL Bovy, 2003)) from models with discrete motion, which are characterized by occasional jumps from one location to another ("migratory games") (Helbing and Yu, 2009). Furthermore, one needs to separate models with random motion ("diffusion games") from models with directed motion ("driven games"). One can further differentiate between cases of externally driven mobility (based on environmental influences) and self-driven mobility (based on individual decisions). In case of goal-driven mobility, an individual tries to increase or optimize some target function. This case applies, for example, when an individual tries to reach a certain location (which is a "pull effect") rather just getting away from a certain place (which would be a "push effect"). If the direction and size or speed of mobility are determined by the overall payoff expected in a certain location, one speaks of "success-driven" or "success-oriented mobility". Then, mobility is determined by the same payoffs that determine the results of the game-theoretical interactions discussed above. Such a specification keeps the model simple, as it requires only two new model parameters (the mobility range M and density ρ of individuals). Conceptually, success-driven migration follows the same approach in which the imitation of better performing neighbors was modeled. Therefore, the following discussion particularly focuses on this case of mobility.

1.3.2 Success-Driven Migration

Let us come back to the previously studied spatial game, which assumes a grid-like structure of the underlying (geographical or social) space, and updates the individual behaviors at discrete time steps. We will now extend this game by "success-driven migration", according to which individuals try to improve their expected

overall payoff by occasional moves to other places. The underlying assumption is that a higher expected payoff, for example a higher level of cooperation, makes a neighborhood more attractive.

In the following, we will assume that each cell ("site") of the grid is occupied only once, or it is empty. This corresponds to a flat space (without more frequent interactions in high-rise buildings) and to the existence of territorial effects, as multiple occupancies are not considered. While these assumptions are obviously simplifications, it is easy to generalize the model. We will focus on the case where the fraction $\rho = N/L^2$ of occupied cells (the "population density") is given, i.e. it is not changing by birth-and-death processes, which may be taken into account as well (Epstein, 2007). Individuals can move to empty sites within a certain migration range M. Within this range, each individual is assumed to perform a "test interaction" in order to determine the fictitious overall payoff that would result when moving to this location ("neighborhood testing"). The individual moves to the tested location with the highest payoff, and in case of several equivalent locations, to the closest of them. We assume a random sequential update and periodic boundary conditions (i.e. the square grid is updated as if it were a torus).

1.3.3 Spatio-Temporal Self-Organization

The computer simulations depicted in Fig. 3 start with a random distribution of individuals in space. The initial distribution of the two behaviors $i \in \{1, 2\}$ considered is random as well. 50% of them show behavior 1, and 50% behavior 2. In this section, we will not consider imitation processes, i.e. behavioral changes. Therefore, the fractions of both behaviors stay the same, but their distribution in space may change. In fact, for many specifications of the payoff matrix P_{ij}, we find an interesting dynamics and the emergence of typical patterns in space. These are characteristic for the respective game (e.g. the prisoner's dilemma or the coordination game). Conditions for the occurrence of pattern formation can be analytically determined and understood in terms of attractive or repulsive social forces (Helbing and Vicsek, 1999; Helbing and Platkowski, 2002; Helbing, 2009). These depend on the payoffs and local distribution of the different behaviors in space. One can also determine payoff combinations, for which pattern formation does not occur (Helbing and Yu, 2008; Helbing, 2009). This basically means that both behaviors will remain uniformly distributed.

Figure 3a illustrates pattern formation in the coordination game, prisoner's dilemma, stag hunt game, and chicken game, when the mechanism of imitation is replaced by success-driven migration. In all cases, we assume a density of $\rho = 0.5$ (i.e. 50% occupied cells) and a migration range of $M = 5$. Note that the results of figure 3a remind of the segregation patterns studied by Schelling (1971).

For comparison, when agents move to a randomly chosen new location, if their

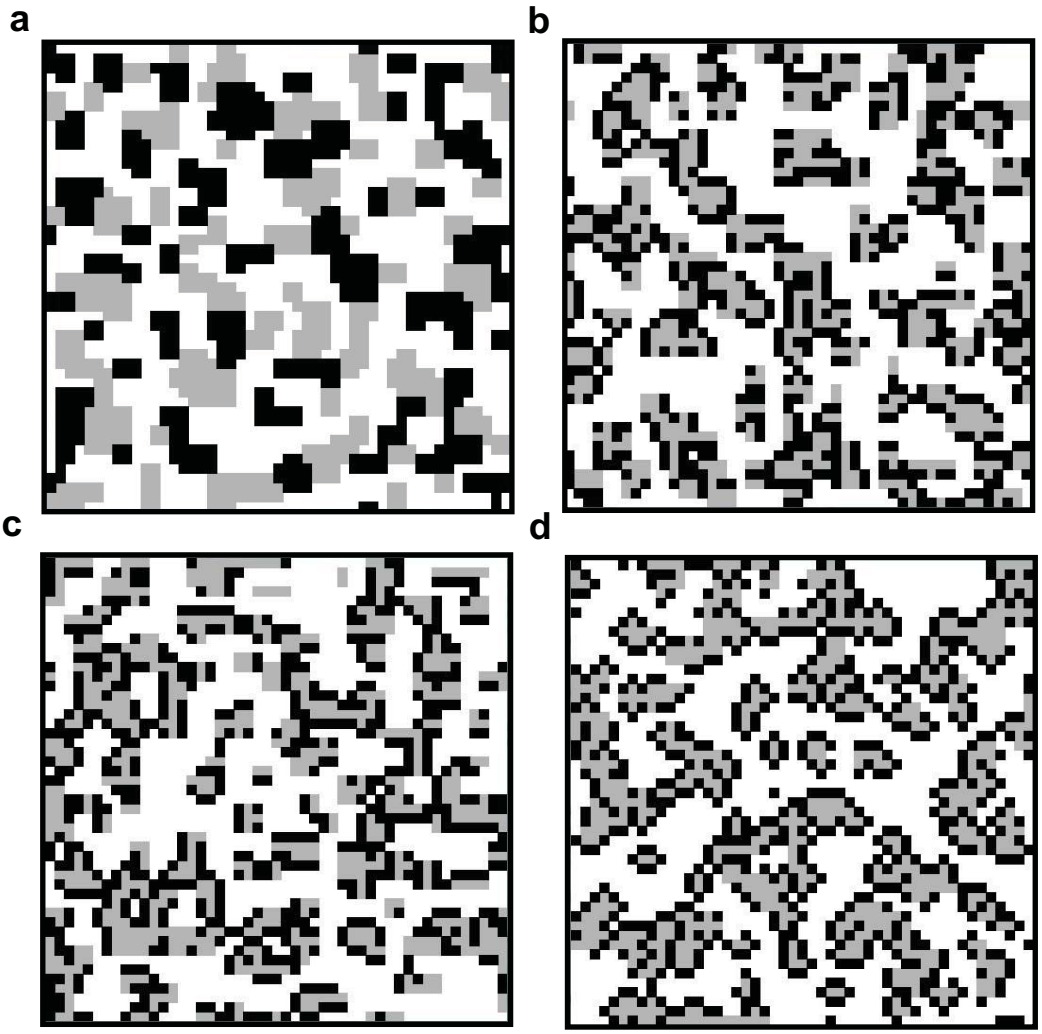


Figure 3. Success-driven migration (here with a migration range of $M = 5$) promotes pattern formation, as compared to the case where individuals imitate superior strategies in their neighborhood, but do not move (see Fig. 1). Grey cells represent "cooperators" or strategy 1, black ones "defectors" or strategy 2. Parameters are chosen as in Fig. 1. (a) In the coordination game, intra-group interactions are structurally more stable than inter-group interactions, leading to the emergence of residential segregation (compare to Schelling, 1971). (b) In the prisoner's dilemma, cooperators form clusters more efficiently than defectors. Consequently, defectors end up at the boundaries of cooperative clusters. (c) In the assurance game (or stag hunt game), agents with strategy 1 benefit more from intra-group interactions, which successfully excludes agents with strategy 2; although these have strong incentives to enter clusters of strategy 1. (d) In the chicken game (or snow-drift game), defectors have no incentive for cluster formation due to $P = 0$, so that only a few clusters of defectors can be found.

payoff is below the average of their neighbors, no spatio-temporal pattern formation occurs. This *diffusive* kind of migration rather leads to a uniform distribution of strategies in space (not shown). Therefore, different kinds of mobility have different macroscopic effects.

1.3.4 Discussion

Phenomena like agglomeration and segregation are wide-spread in social and economic systems. Examples for agglomeration reach from the creation of settlements and cities (Weidlich, 2003) over the formation of groups (Homans, 1950; Sherif, 1966; Tajfel, 1982; Yamagishi and Kiyonari, 2000; Hegselmann and Krause, 2002; Takacs, 2002; Kerr and Tindale, 2004; Friedkin, 2004) up to the agglomeration of wealth (Orbell and Dawes, 1993; Gould, 2002; Fujita and Thisse, 2002). This applies as well to segregation, which is often (but not necessarily) found to come along with social status, income, religion, race, language, age, gender or other characteristics, even though this is politically discouraged. Schelling has shown that already small differences in preferences may be sufficient to create segregation (Schelling, 1971). The approach presented here allows one to put his line of thought into a unified and general game-theoretical framework.

In order to understand the spatio-temporal dynamics resulting from success-driven migration, it is useful to translate the underlying interactions into social forces (Helbing, 2009). On the one hand, repulsive forces result, when it is profitable to move away from a given location ("push effect"). It is very intuitive that this can cause segregation. On the other hand, attractive forces result, when it is profitable to move to another location ("pull effect"). This can cause agglomeration. For example, if the payoff in interactions with other individuals is positive (which requires a sufficient control of aggressiveness), individuals will try to increase the number of interactions.[1] This will cause people to move together, i.e. to agglomerate in settlements. This tendency of agglomeration was probably a precondition for the development of further factors supporting social behavior: For example, repeated interactions have facilitated the evolution of direct reciprocity,

[1]Note that an eventual reduction of the level of aggression among humans is likely (Santos et al., 2008), for example when considering group competition: A less aggressive group can reach cooperative goals, while separated individuals or small groups are much more limited in what they can reach. It also makes reproduction less efficient when people often kill each other. Consequently, individuals who get along well ("social beings") are expected to win through when competing with tribes with less aggression control. A similar phenomenon is known from virus epidemics: Viruses tend to become less deadly over time, as those variants who do not kill their host are able to spread more efficiently. It would be interesting to explore whether the different developments in the funding situations of different scientific disciplines correlate with the degree of individualism or cooperation in these fields (which may be measured by rejection rates or the average number of people involved in collaborative projects, publications, or the research fields themselves).

based on a "shadow of the future" (Gouldner, 1960; Taylor, 1976; Axelrod, 1984; Fudenberg and Maskin, 1986; Falk and Fischbacher, 2006). Also indirect reciprocity, which is based on reputation effects, requires people to frequently interact with each other. Both, direct and indirect reciprocity are known to promote the cooperation of individuals (Nowak, 2006b). Taken together, this may be viewed as an explanation of "homophily", which is again used as a concept to explain a variety of human behaviors (Lazarsfeld and Merton, 1954; McPherson et al., 2001; Flache and Mäs, 2008).

Spatial games with mobility have been investigated in other publications before (Vainstein et al., 2007; van de Rijt et al., 2009; Sicardi et al., 2009), but did not generally show a cooperation-promoting effect, in particular not a resistance to targeted invasion attempts by defectors. In fact, it was believed for some time that mobility would undermine cooperation (Vainstein et al., 2007). Compared to diffusive kinds of mobility, however, success-driven migration seems to be more efficient in supporting cooperation than many other kinds of mobility (Helbing and Yu, 2008, 2009; Roca, 2009; Meloni et al., 2009). This is probably because it does not only avoid bad neighborhoods, but also searches for better ones in an active way.

The above proposed model can obviously be extended in various ways, and the following section mentions only a few of them. It is possible, for example, to allow for multiple occupancy, but pattern formation phenomena like agglomeration and segregation have been found under such conditions as well (Helbing and Vicsek, 1999; Helbing and Platkowski, 2002). One can also introduce moving costs (i.e. transaction costs) and costs for neighborhood testing, but the latter are normally much lower than the former and, therefore, negligible in relation. Furthermore, relocations to other places can be implemented in a probabilistic way (see Sec. 1.4). An interesting extension would be the consideration of friendship networks (Szabó and Fath, 2007; Lozano et al., 2008; Corten, 2009). The mechanism of cutting links, when interactions are not profitable, and of strengthening links, when interactions are favorable, is comparable to the effect of relocating. The difference, however, is that one has to live with his/her neighbors and colleagues, i.e. interactions cannot always be avoided, even when dissatisfactory. Moreover, the number of friends may vary considerably, creating situations in which some people are "hubs" of the social network. It would be interesting to see what happens, if relocations and social networks would be considered at the same time, particular as people may keep interacting with old friends, even over very long distances.

Furthermore, the mechanism of neighborhood testing may be replaced by other mechanisms. For example, when identifying better locations, one may orient at the cumulative payoff of individuals, which is somehow reflected by how wealthy a certain neighborhood appears ("neighborhood tagging"). As not everybody can afford to move to a wealthy neighborhood, however, relocation costs (transaction costs) should be considered here. In social space, "entrance fees" to certain exclu-

sive social circles (e.g. golf clubs) would have similar effects. Of course, finding good neighborhoods would be more difficult, if we would not allow agents to previously identify how profitable interactions in a new neighborhood might be. Such situations of bad orientation can be modeled by replacing the mechanisms of neighborhood testing or neighborhood tagging by something like a win-stay-lose-shift rule (Macy and Flache, 2002). Furthermore, the frequency of relocations could be varied as compared to the number of interaction steps. The model can also be extended by the considering of birth-and-death processes, as is done in demographic games (Epstein, 2007).

We are fully aware that the individual motives for migration may be quite different, which deserves to be studied by more detailed and more differentiated models. In fact, the subject of migration is an own research field (Hotelling, 1978; Weidlich and Haag, 1988; Mueller et al., 2000; Plane et al., 2005; Kalter, 2008) with its own set of models. Our model is not aimed at competing with these models. Rather we want to understand what the fundamental effects of mobility are, when combined with social interactions and social learning. In this connection, it is favorable to have a simple model with a few parameters only. This largely simplifies the identification of the reasons underlying certain outcomes of the model (see below).

1.4 Noise

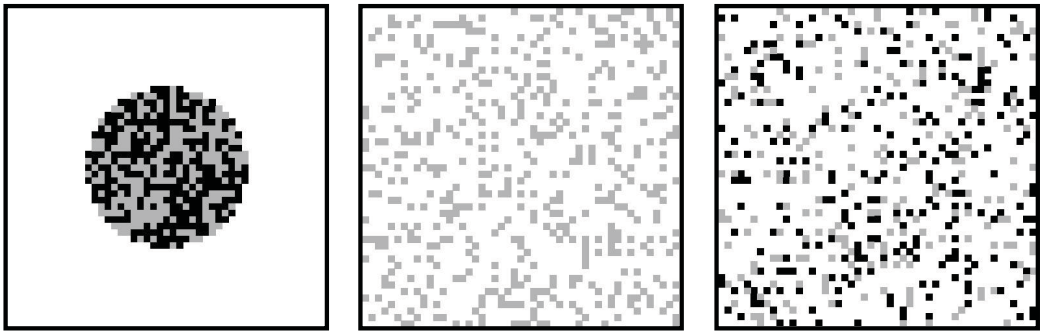
As discussed briefly in the beginning of this article, individual decisions are normally not well predictable. This discourages the use of deterministic ("mechanistic") models assuming a unique stimulus-response relationship. In fact, decision-making may depend on a large number of factors which hardly accessible to scientific analysis. Furthermore, decision-making may be probabilistic by nature, as it is assumed by the multinomial logit model, for example (McFadden, 1974; Manski and McFadden, 1981). Therefore, it makes sense to use stochastic update rules such as the Fermi update rule (Szabó and Hauert, 2002) or the Moran rule (Traulsen and Nowak, 2006). Here, we will use an even simpler approach by assuming that, with a certain probability, individuals do something which is not in accordance with the previously discussed update rules of imitation or success-driven migration. Specifically, we will consider three kinds of "noise", i.e. three kinds of randomness:

1. **Noise 1** delineates *strategy mutations*, assuming that an individual spontaneously chooses (with probability q) the *other* behavior of what the imitation rule would predict (i.e. the behavior is "flipped" as compared to the usual one). This reflects that people change their mind or explore alternatives from time to time ("trial-and-error behavior").

2. **Noise 2** describes *random relocations*, assuming that an individual spontaneously (with probability q) will move to a randomly chosen free site, which may be inside or outside the migration range M. Such noise allows to consider random (i.e. diffusive) relocations over potentially long distances. For example, imagine a job offer by an internationally oriented university or a love affair during the holidays.

3. **Noise 3** combines noise 1 with noise 2 and assumes for simplicity that a fraction of $q/2$ individuals perform strategy mutations and, independently of this, a fraction $q/2$ relocates randomly.

One may think that the above noises will mainly cause more fuzzy results, i.e. reduce the level of order and organization in the system. And in fact, when starting with a circular cluster of people showing behavior 1 (e.g. cooperation) and when studying noise effects in the absence of imitation or success-driven relocations, our intuition is confirmed: In the presence of noise 1, both possible behaviors occur in the circular cluster of people, and eventually they are equally and uniformly distributed over the cluster (see Fig. 4a). Noise 2 implies that people will eventually spread all over the grid, i.e. the cluster of people is dissolved (see Fig. 4b).



(a) **(b)** **(c)**

Figure 4. The impact of different kinds of randomness on the emergence of pattern formation and cooperation in the prisoner's dilemma. (a) *Random strategy mutations* make the final fraction of cooperators independent of the initial ones. (b) *Random relocations* make the final location independent of the initial ones. (c) The *combination* of the two kinds of randomness make the final results independent of both, the initial fraction of cooperators and their initial locations.

Finally, noise 3 destroys the spatial structure and creates a uniform, random mixture of behaviors in space (Fig. 4). In other words, noise 1 tends to make the finally resulting fractions of both behaviors independent of the *initial* fractions. Noise 2 tends to make the final distribution of individuals in space independent of the initial distribution. And noise 3 tends to make the outcome independent of both, the initial fraction of behaviors and their distribution in space. However, when combining noise with imitation or relocations, some counter-intuitive effects occur, as we will see in the next section.

2 Interaction of the Microscopic Model Ingredients

In the following subsections, we will perform the update steps in a random sequential way and in the following order: First, people relocate, keeping their previous behavior, then they have social interactions, afterwards they imitate better performing neighbors, and finally, noise is applied. We will turn off one or several of these update steps to study the combination of certain mechanisms in separation. The only update step that will always be switched on is the game-theoretical interaction determining the payoffs. All computer simulations below are for a density of $\rho = 0.5$ (i.e. 50% empty sites). For a study of density-dependent effects in a similar model without noise, see Helbing and Yu (2008).[2]

2.1 Imitation and Noise

We will now come back to the games studied in Figs. 1, but with the addition of noise 1 and noise 2, assuming a noise level of $q = 0.05$, corresponding to 5% individuals performing random strategy changes or relocations in each time step. Overall, one can see in Fig. 5 that noise 1 and noise 2 increase the disorder in the system as compared to Fig. 3. In the presence of random relocations (noise 2), cooperation in the prisoner's dilemma disappears completely in the course of time, i.e. the result is the same as for well-mixed populations (see Fig. 5a).

When noise 1 is considered, random strategy changes will always lead to a certain level of cooperation, which is usually small (see Fig. 5b).[3] Moreover, the finally resulting fractions of both behaviors become independent of peculiarities of the initial conditions, no matter how small the noise level q is. As long as $q \neq 0$, it is irrelevant for the final outcome, whether the initial level of cooperation is 90% or only 10%. This is demonstrated in Fig. 6 for the prisoner's dilemma with $q = 0.001$ (i.e. 1 out of 1000 people showing a random strategy change in each time step).

In contrast, when the noise is turned off completely, corresponding to $q = 0$, the finally resulting level of cooperation depends very much on the initial condition, i.e. everything is largely history-dependent (see Fig. 6). Due to the principal difference between the case of no noise with $q = 0$ and a system with little noise (e.g. $q = 0.000001$), the system behavior in the model without noise is rather pathological, although social systems often behave in a history-dependent way. This observed

[2]Note that changing the order of the update steps does not question our main conclusions. Nevertheless, it changes the appearance of the resulting spatio-temporal patterns and the sensitivity to noise. For a discussion see (Yu and Helbing, 2009) and http://www.soms.ethz.ch/migrationgames.

[3]If q has the maximum value of 1, it is still below 50%.

Figure 5. (a) In the presence of random relocations (noise 2), cooperation in the spatial prisoner's dilemma disappears, when individuals imitate more successful individuals in their local neighborhood (cf. Fig. 1b). (b) Random strategy mutations (noise 1) can maintain a small fraction of cooperators, which is, however, only due to "mistakes" in the imitation or trial-and-error behavior.

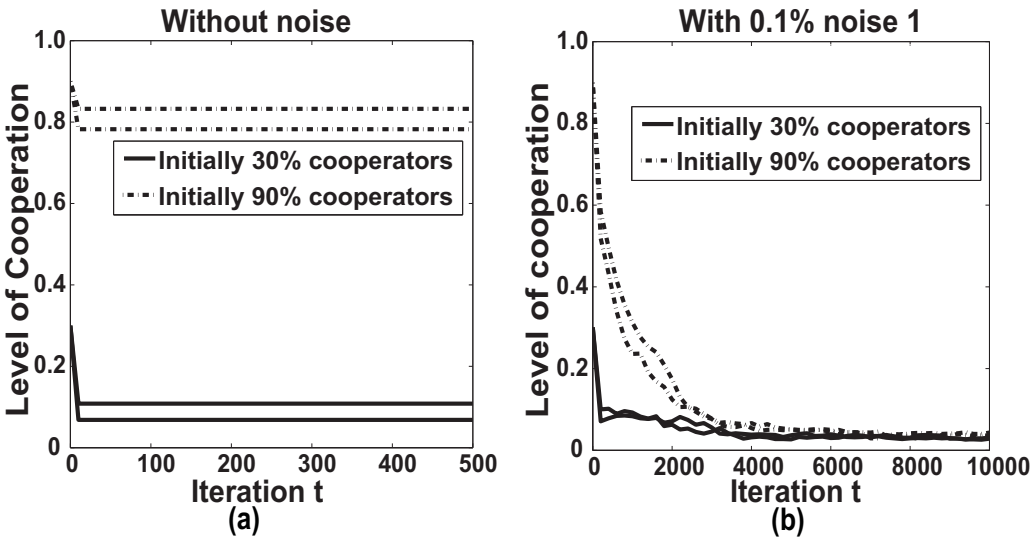


Figure 6. Simulation of social systems can show strong history dependence and sensitivity to initial conditions without noise. Simulations show results for spatial prisoner's dilemmas with imitation only. (a) Without noise, the level of cooperation decreases, but stays constant after some time, as the spatial configuration is "frozen" (i.e. it becomes stationary). The result is very sensitive to the initial level of cooperation and even to the initial configuration in space. (b) Introducing a small degree of randomness (only one strategy mutation among 1000 agents) demonstrates that "artificially" high initial levels of cooperation decrease quickly. The eventually resulting level of cooperation fluctuates around a typical value, which depends on the noise level, but is independent of the initial conditions. Nevertheless, each system takes its own path.

history-dependence, however, refers to the fact that a social system takes a unique path,[4] which is also true for noisy systems: Each realization in the presence of noise is different, i.e. each run of the computer simulation takes a different historical path. Nevertheless, the statistical features of the finally resulting system are pretty much the same, i.e. each noisy system sooner or later has the same fate in terms of the fraction of cooperators the system finally fluctuates around.

2.2 Success-Driven Migration and Noise

When we study the four games featured by Fig. 3 in the presence of noise with $q = 0.05$ (i.e. 5% of the individuals perform strategy mutations or random relocations in each time step), we find the following: While noise 1 tends to cause some unspectacular changes in the strategy distribution (not shown), noise 2 tends to reduce the level of agglomeration and segregation (see Fig. 7). In fact, similar to Fig. 4b, large enough relocation rates $q \approx 1$ can destroy *any* spatial structures, as they imply a random distribution of people in space.

2.3 Imitation and Success-Driven Migration

So far, we have seen that imitation tends to drive the level of cooperation in the prisoner's dilemma towards very low levels (see Fig. 3b). Furthermore, success-driven migration as well can not increase the level of cooperation (i.e. the percentage of cooperators)—it just stays the same (see Fig. 3. Therefore, it is very intriguing that we find a *growth* in the level of cooperation, when imitation and success-driven migration are *combined* with each other.

Figure 8 shows the outcome for the four previously considered games, assuming a migration range of $M = 5$ (i.e. neighborhood testing is performed in a Moore neighborhood of range $M = 5$. Comparing Fig. 8 with Fig. 3, we can see that the combination of imitation with success-driven migration leads to a coevolution of spatial organization and behavior. The interaction between imitation and migration can actually change the outcome dramatically. Let us discuss this particularly for the case of the prisoner's dilemma. Here, we find a much higher-than-expected level of cooperation, if the temptation $T - R$ and $P - S$ are not too big.[5]. The explanation of this is not at all trivial, but requires to consider the combination and interaction of different effects:

[4]Another kind of history-dependence occurs, when we have an equilibrium selection problem, and the system evolves towards one of several qualitatively different states, depending on the initial condition. Such a behavior is, for example, displayed by the snowdrift (chicken) game in well-mixed populations, see Appendix A.

[5]See Fig. 2 in (Helbing and Yu, 2008) and Fig. 6 in (Helbing and Yu, 2009) for detailed dependencies on payoff parameters

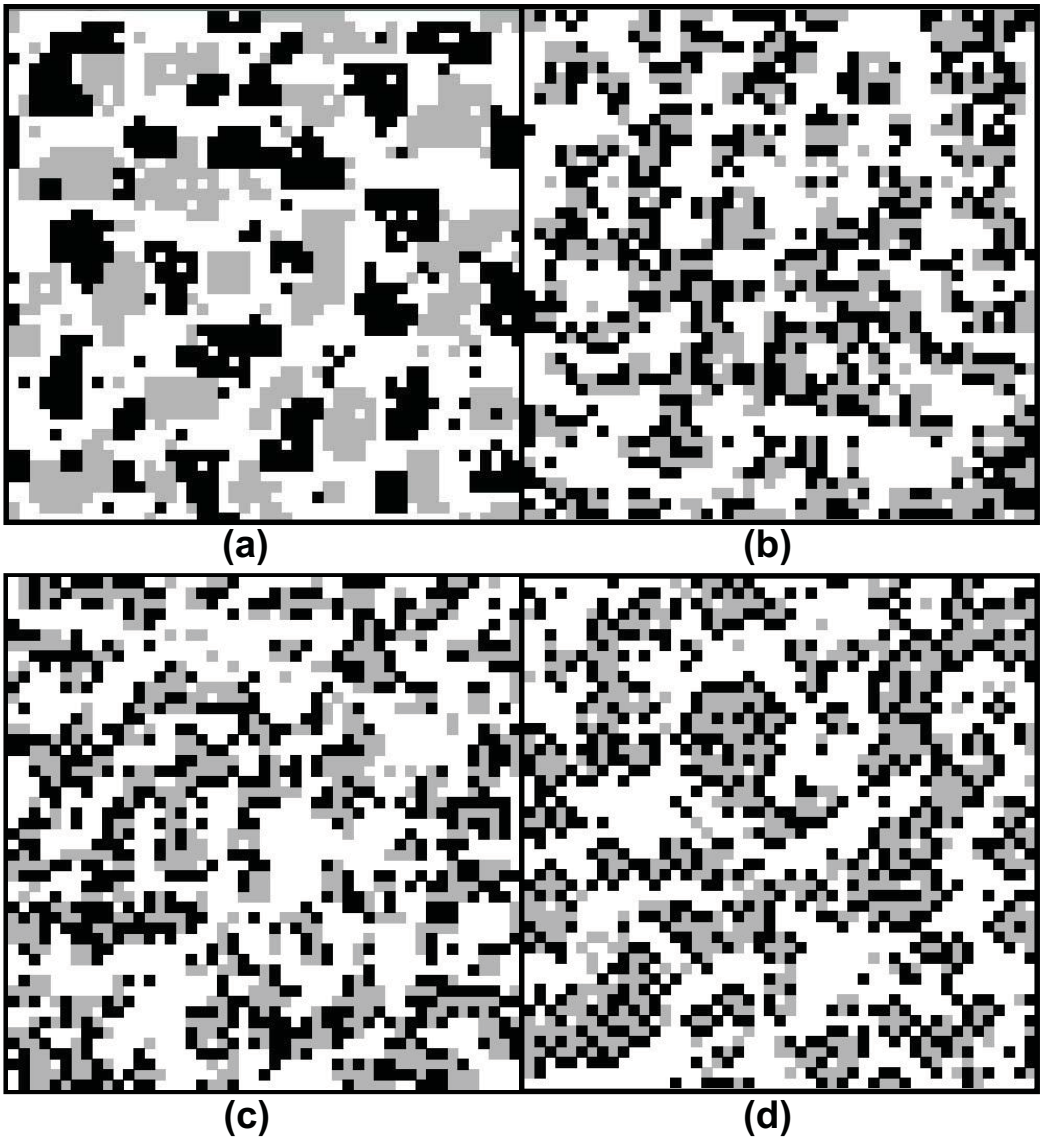


Figure 7. Success-driven migration (here with $M = 5$) promotes pattern formation, even when considering random relocations of 5% of all individuals in each time step (noise 2 with $q = 0.05$). Compared to Fig. 3, random relocations disturb the spatial patterns formed by the migration of individuals, but the residential segregation and agglomeration is maintained. The displayed results are (a) for the coordination game, (b) for the prisoner's dilemma, (c) for the assurance game and (d) for the chicken game (see caption of Fig. 1 for parameters).

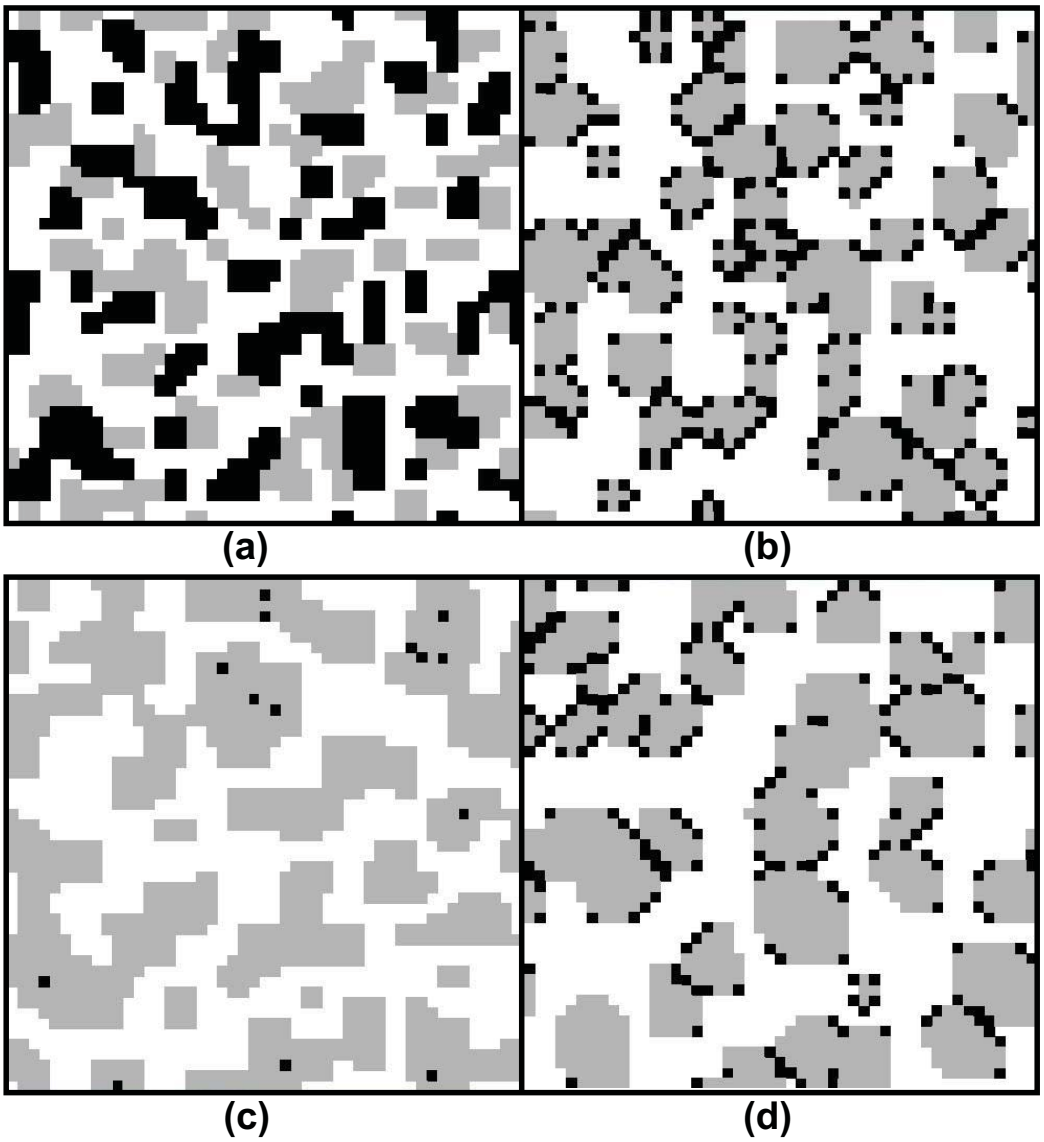


Figure 8. The combination of success-driven migration with imitation can considerably promote the spreading of cooperation by means of pattern formation (compare with Figs. 1+3). (a) In the coordination game, strategy 1 and 2 strongly segregate in space. (b) In the prisoner's dilemma, high levels of cooperation result thanks to the mobility of cooperators, allowing them to form clusters efficiently and to exclude defectors. Defectors, ending up at the borders of cooperative clusters, tend to imitate cooperative strategies in order to reach higher payoffs. (c) In the assurance (stag hunt) game, one of the strategies wins through and the other one disappears in the course of time. (d) In the chicken (snowdrift) game, cooperation can reach high levels, and defectors stay at the borders of cooperative clusters.

1. First of all, success-driven migration lets cooperative individuals evade defectors, if they can, and lets them seek a cooperative neighborhood, which promises a higher payoff.

2. If cooperators cannot evade defectors, because there are no better free sites available, cooperators tend to turn into defectors by imitation as well.

3. Both effects imply that defectors tend to quickly destroy a cooperative environment, which decreases their overall payoff.

4. In contrast, cooperators are happy staying together over a long time, which yields a high overall payoff.

5. Therefore, clusters of cooperators have a tendency to persists, while neighborhoods of defectors are not stable, but rather short-lived.

6. Of course, once the overall payoff of defectors goes down, they try to find new cooperative neighborhoods for exploitation, but they respond to the evasion of cooperators with a delay.

7. Cooperators are usually quicker than defectors to fill empty sites in a cooperative cluster, because there are more cooperators than defectors close-by. Hence, it is likely that a cooperator will be first to fill the gap.

8. As a consequence, defectors tend to end up at the boundaries of a cooperative cluster. There, however, they are often turned into cooperators, as cooperators in a cooperative cluster tend to earn more payoff than defectors at the boundary of a cluster.

9. This tends to increase the fraction of cooperators, and the level of cooperation can become very high.

10. Usually, one ends up with a situation in which defectors keep chasing cooperators, but these can successfully evade such invasion attempts and reconfigure. This continuous adaptation eventually leads to a great majority of cooperators under conditions, where defectors would prevail without success-driven migration.

2.3.1 Discussion

Formulating our discovery in somewhat different words, the combination of imitation with success-driven motion creates correlations in the behavior of individuals. In particular, a cooperative environment makes individuals more cooperative, which creates a reinforcement effect and self-stabilization. Such an environment creates conditions, under which it is likely that individuals will cooperate again in the next time step. Moreover, the probability is high that close-by individuals

cooperate as well. This circumstance makes it profitable on average to cooperate. This tendency would be even more pronounced, if the agents in our computer simulation were oriented at increasing *future* payoffs, i.e. if our model would consider a "shadow of the future", which can be done by transformations of the payoffs (Helbing and Lozano, 2009).

If the imitation rule would be replaced by a one-stage best response rule, individuals in a cooperative cluster may trust on the cooperation in the neighborhood in the next time step and decide to defect. However, if everybody would behave this way, the resulting payoff would be just mS rather than mT, i.e. quite poor. Therefore, an argument along the line of group selection would suggest that communities with a best response behavior (pursuing a short-sighted profit maximization) should die out in the course of time when competing with communities following an imitation behavior as assumed in our model.

2.4 Imitation, Migration and Noise

One open question is; "What will happen in the presence of noise?" Will noise always reduce the level of cooperation or even destroy cooperation, as it used to be in the imitation-only and in the success-driven migration-only case? Of course, large levels of noise ($q \approx 1$) can destroy clusters and cooperation, but our findings for reasonable noise levels are very striking. One surprising observation is that, when starting with defectors only, we observe a sudden outbreak of predominant cooperation.

Figure 9 compares computer simulations with imitation and success-driven migration, but no noise, with the situation in the presence of randomness, namely noise 1, when 5% of the individuals randomly flip their behavior as compared to the usual update rules, for noise 2, when 5% individuals randomly relocate, and noise 3, when 2.5% of the individuals perform random relocations and another 2.5% flip their behavior randomly in each time step. Surprisingly, moderate noise levels do not destroy cooperation—they may in fact *promote* it. Furthermore, it is intriguing that, in a scenario starting with defectors only, noises 1 and 3 can even give *birth* to cooperation. This is actually *not* because noise will create a configuration with an unexpectedly high level of cooperation after sufficiently many time steps. Such an outlier would occur after an astronomically long time period only. It actually turns out to be sufficient that, by random coincidence, only a few neighboring individuals happen to cooperate in the same time step. Once a small cooperative cluster of over-critical size has occurred, cooperation spreads according to the mechanism described in Sec. 2.3. In fact, our previous discovery that noise, in the long run, makes the statistical behavior of the system independent of the initial conditions, *requires* that the system finally ends up with a high level of cooperation, even when starting with no cooperators at all. But this statistical independence says

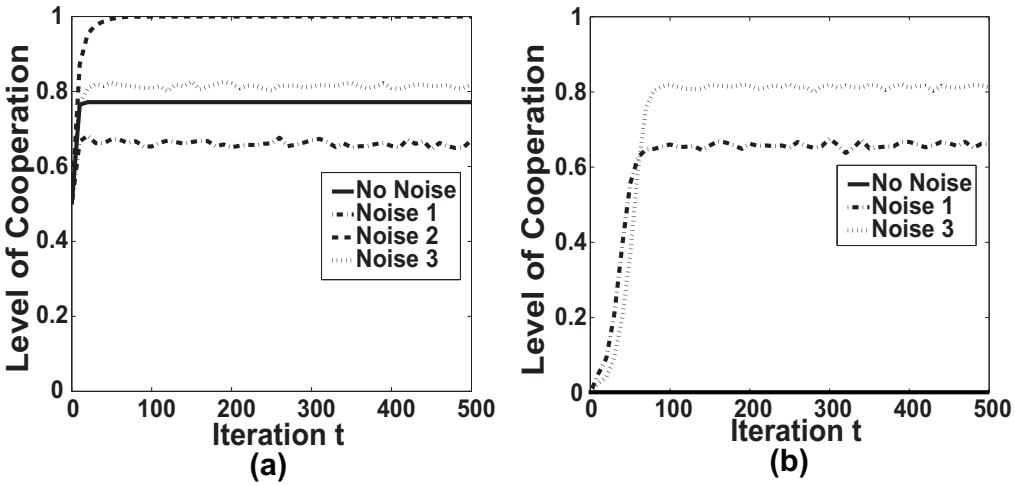


Figure 9. In simulation scenarios with imitation and success-driven migration, high levels of cooperation are robust to the presence of randomness (noise 1, 2, or 3). Moderate degrees of randomness (here: $q = 0.05$) can even increase the level of cooperation in the prisoner's dilemma by overcoming suboptimal spatial configurations ("frustrated states") (Yu and Helbing, 2009). (a) When starting with 50% cooperators, random relocations (noise 2) and the combination of random relocations with random strategy mutations (noise 3) can enhance cooperation, compared to simulations without noise. (b) Outbreak of cooperation in a world of defection (i.e. 100% defectors at time $t = 0$). Random strategy mutations (noise 1) and their combination with random relocations (noise 3) enable the formation of critical clusters of cooperators after some time. These clusters trigger the outbreak of cooperation as cooperators spread via the mechanism discussed in Sec. 2.3. It is noteworthy that the required time for the occurrence of critical clusters is comparably short, suggesting that the outbreak of cooperation should be observable in reality (and therewith measurable with laboratory experiments). However, the random occurrence of critical clusters of cooperators is not possible without random strategy mutations, i.e. the level of cooperation stays zero in the case of noise 2 (random relocations only), as in the case of no noise.

nothing about the underlying dynamics. In fact, it matters a lot how quickly cooperators can build up cooperative clusters as compared to the rate at which they are destroyed by defector invasion and by noise effects.

3 Conclusions

3.1 Summary

In our manuscript, we have addressed the way in which individual behavior determines the social environments and this in turn affects behaviors of people. Furthermore, we have shown the importance of such feedback loops for the spreading of cooperation in social dilemma situations. Our method is based on agent-based modeling, combining game theory with properties of a Schelling-like segregation model. Specifically, we have demonstrated the emergence of aggregation and segregation patterns in space when individuals select their neighborhood in a success-driven way. When, in addition, individuals imitate more successful neighbors, cooperation can efficiently spread throughout the population, while defectors spread in case of no mobility. Therefore, the combination of social learning with mobility promotes cooperation under conditions, when none of the two mechanisms alone can do so. In the presence of random strategy and location changes, there may even be an outbreak of predominating cooperation, when there are defectors only in the beginning. Therefore, mobility may have played a major role in the evolution of social behavior.

In order to understand the interdependence of micro-motives and macro-behavior, we have varied the following aspects of the interactions on the micro-level: 1. The payoff matrix, including the kind of game (e.g. prisoner's dilemma, snow-drift game, or coordination game), 2. the range of mobility, 3. the initial level of cooperation and initial configuration, 4. the consideration or omission of different kinds of randomness ("noise"). We demonstrated the respective differences in the resulting macroscopic outcomes, particularly on the level of cooperation, the spatial organization (mixed or segregated behaviors), and the spatio-temporal dynamics. It is noteworthy that the spatio-temporal distribution of behaviors in space is characterized by macroscopic patterns, whose properties are distinctly different from the characteristics of individual behavior on the microscopic level. Among the patterns formed by success-driven migration are agglomeration patterns on the one hand (reflecting phenomena such as settlement or group formation) and segregation patterns on the other hand (reflecting the tendency of people with different behaviors to separate from each other).

It is demonstrated that the complex interplay of micro-motives and macro-behavior can generate widespread cooperation in social systems. The level of cooperation tends to increase and to create a majority of cooperators, if migration

is allowed, in contrast to the prevalence of defectors in the case of no mobility. The mechanism relies on the cooperators' tendency to form clusters, while defectors end up at the *boundaries*. The superiority of cooperation in the case of mobile individuals results from the different time periods over which the neighborhoods of cooperators and defectors change. More specifically, the unexpected promotion of cooperation by considering mobility is due to spatio-temporal pattern formation. Success-driven migration, assuming that individuals try to move to more favorable places within a certain migration range, can destabilize a uniform distribution of behaviors and produce adaptive, self-stabilizing patterns, which are surprisingly resistent against moderate noise levels, and allow cooperators to evade invasion attempts of defectors. This can "invert" the resulting system behavior, when compared to systems without mobility, or when interaction partners are random (corresponding to a "well-mixed" population, see Appendix A). As a consequence, one can end up with a majority of cooperators in the prisoner's dilemma rather than with defection by everybody.

3.2 Conclusions

One advantage of agent-based computer models of this kind is the possibility to analyze all model components separately and in combination—something which is much more difficult with other kinds of analyses such as experimental or survey methods. This approach has revealed a variety of interesting and sometimes counter-intuitive effects:

1. **The combination of several failing mechanisms can be successful.** Specifically, neither imitation of better performing behaviors nor success-driven migration could increase the level of cooperation in the prisoner's dilemma, but their combination could. This is a good demonstration that social systems (and complex systems with non-linear interactions between their system components in general) cannot be understood by superimposing their elementary properties. Non-linear interactions often show the emergence of new and fundamentally different system properties (such as spatio-temporal pattern formation or the outbreak of prevalent cooperation in this paper).

2. **Randomness ("noise") does not necessarily cause unpredictability and disorder in social systems.** In fact, when moderate in size and combined with imitation and success-driven migration, it can increase the level of cooperation and allow the system to overcome suboptimal ("frustrated") states. It may also lead to more predictable statistical features of the system (see Fig. 6). In contrast, neglecting noise in models of social systems may generate unrealistic history-dependencies (i.e. artificial dependencies of the system behavior on the initial conditions).

3. **The restriction to local interactions can result in opposite effects compared to representative agent models.** Specifically, we may find the outbreak of cooperation in the prisoner's dilemma under conditions, where defection by everyone would result in the case of well-mixed populations (see Appendix A, Fig. 2a and Fig. 2b).

4. **Cooperative clusters share some typical features of social institutions such as path dependence.** Both, the spatial scale of cooperative clusters and the time period between their occurrence and disappearance are large as compared to the space occupied by individuals and the time scale of their strategy or location changes. That is, the macroscopic structures persist longer than the individuals participate in them.

5. **The spatio-temporal interaction patterns display features related to social roles and norms**. The social environment influences the behavior of individuals, which is at the same time created by it. First, individuals tend to agglomerate in order to increase the number of neighbors they can profitably interact with. Where sufficiently many cooperators happen to be next to each other, they earn a high payoff, which causes neighboring individuals to imitate cooperation. The formation of cooperative clusters in turn stabilizes the cooperative behavior. Thanks to this feedback loop, the interaction between the microscopic level of individual behavior and the macroscopic level of the social environment (neighborhood) has a self-reinforcing character. It establishes a coevolution of spatial interactions and social interaction patterns, which loosely reminds of the way how the execution of certain behavioral roles establishes norms, which in turn stabilize the compliance with them (Elster, 1989; Opp, 2001; Voss, 2001; Ostrom, 2000; Bendor and Swistak, 2001; Bicchieri, 2006; Horne, 2008; Rauhut and Krumpal, 2008).

3.3 Discussion

Social systems are extremely rich. They possess a lot of interesting properties, which are difficult to understand. As we have shown, explanations of such properties may be unexpected, even when based on simple mechanisms. We believe that this is actually *typical* for social systems. When many people interact, this is likely to result in self-organization phenomena, which may be compared with what Adam Smith imagined as the result of an "invisible hand" (in contrast to external regulation). A well studied example is the segregation of oppositely moving pedestrians in bidirectional pedestrian crowds and the preference of pedestrians for *one* side constituting a behavioral convention (Helbing, 1992; Moussaïd et al., 2009), which is the right-hand side in continental Europe and the left-hand side in Japan.

It is interesting to note that emergent phenomena (i.e. fundamentally new and qualitatively different system properties) can be explained by *non-linear* models only, where effects are not just cumulative and not proportional to causes. (In *linear* models, all system properties can be derived by adding up the properties of its elements, which is more intuitive.)

Besides this more theoretical insight, it is interesting to wonder about empirical evidence. Experiments of migratory spatial games appear to be possible, but have not been performed yet. We are currently preparing for them. Nevertheless, some insights have already been gained in an iterated game addressing the so-called route choice dilemma (Helbing et al., 2005). Here, two individuals have to repeatedly decide to either choose the freeway or an alternative road, which is slower. However, the average travel time becomes smallest, if one individual takes the freeway and the other one the alternative road. In the experiment, after a considerable number of iterations, individuals normally start choosing the freeway and the other road in an oscillatory and anticorrelated way. Typically, the transition to coordinated oscillatory behavior ("alternating cooperation") occurs out of a sudden, similar to the outbreak of cooperation in our computer simulations. This transition can be qualitatively well explained by a reinforcement learning model (Helbing et al., 2005). Therefore, we expect that also the results of the computer simulations in this paper will eventually be verified by game-theoretical experiments.

One may also ask for practical implications of our computer simulation model. In some sense, one could say that segregation patterns constitute a social coordinate system in geographical space, which creates local cultures and serves as a basis of trust. It has been argued recently that the recent financial crisis has resulted in part from the breakdown of the network of trust. Therefore, it is interesting to speculate whether this may be a side effect of globalization itself. If the world became a "global village" and conditions were the same everywhere (which can be simulated by increasing the interaction neighborhood m), people could not improve their situation anymore by moving to other places. As a consequence, the basis for maintaining cooperation would be lost, and the expected outcome would be defection (see Fig. 10). In other words, social differentiation is a success principle promoting cooperation, which is surprising in some sense.

It is clear that these thoughts need further verification, before final conclusions can be drawn, but it is evident that the seriousness of these implications call for further studies of the possible impact of globalization, as it progresses. The hypothesis to be tested is that local cultures are beneficial for the level of cooperation in a social system and that increasing spatial homogeneity would destroy the natural forces keeping a social system together. This would require to strengthen other cooperation-enhancing mechanisms in order to stabilize the system. It is certainly worth asking, whether more surveillance and stronger punishment institutions, as they are currently established all over the world, are the best possible

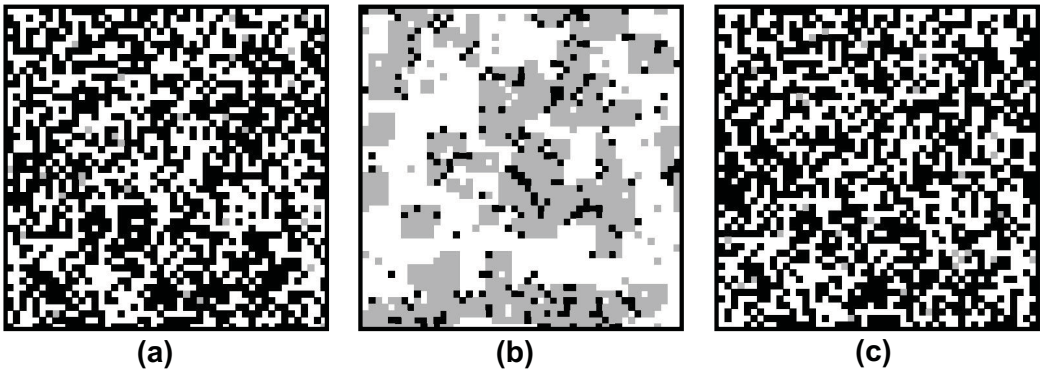


Figure 10. Impact of "globalization" on cooperation in the migratory prisoner's dilemma with imitation and noise 3 (with $q = 0.05$). (a) If the interaction neighborhood m is large and the migration range is small ($M = 5$), cooperation breaks down. The reason is that, when everybody interacts with everybody else, there is no gain by migrating to other locations, and the situation is the same as in the scenario of Fig. 2a (with imitation, but no success-driven migration). (b) When the migration neighborhood M is large, but individuals interact locally (here: $m = 4$), the mechanism of success-driven migration still supports the formation of cooperative clusters. (c) For a large migration range and a large interaction neighborhood, the situation is as in scenario (a), and cooperation breaks down, as the mechanism of success-driven migration becomes useless.

solution, or whether there are more favorable ones to solve the cooperation problem in social dilemma situations.[6] One other solution would be reputation-based social networks. Considering the rapid development of the Web2.0, it seems that such a mechanism is currently being established (particularly among the younger generation), and that it may replace local interactions one day. In view of the unexpected practical importance of these developments for the level of cooperation in our society, we propose that these questions should be paid more scientific attention to in the future.

A Game-Dynamical and Replicator Equations

In the limit of large neighborhoods m, we have the situation that everybody interacts with everybody else, and we do not have any difference between spatial locations. In this case, the situation is the same as if everybody would interact with a randomly chosen individual, and the game-dynamical or replicator equations should apply.

Let us shortly discuss this equation, here. If $p(1,t)$ denotes the probability that individuals show behavior 1 and $p(2,t)$ is the probability to show behavior 2, the normalization condition for a game with two alternative behaviors implies

[6]for related discussions on punishment and surveillance institutions along with experimental data see Gürerk et al. (2006); Rauhut (2009); Rauhut and Junker (2009).

$p(2,t) = 1 - p(1,t)$. We assume that the payoff when behavior i meets strategy j is P_{ij}. The expected payoff $E(i,t)$ for behavior i (its "success") can then be determined by multiplying the respective payoffs with the probabilities of meeting an interaction partner with behavior j, i.e. $E(i,t) = \sum_j P_{ij} p(j,t)$. That is, the success of a strategy is given by the average payoff, when weighted with the occurrence frequencies $p(j,t)$ of the behaviors j of the interaction partner. Let us furthermore assume that the increase in the relative frequency $p(i,t)$ of a behavior i increases proportionally to the fraction $p(i,t)$ of individuals showing that behavior (who can spread it), and that the growth (or decay) rate is proportional to the difference between the success $E(i,t)$ of behavior i and the average success $A(t) = \sum_i E(i,t)p(i,t)$ of all behaviors. Then, for $i = 1$, the change of relative frequency $p(i,t)$ of behavior i with time is given by

$$\frac{dp(1,t)}{dt} = p(1,t)[E(1,t) - A(t)] = p(1,t)[1 - p(1,t)][E(1,t) - E(2,t)]\,. \qquad (1)$$

The equation for $i = 2$ is obtained by interchanging 1 and 2, but it is easier to use the relation $p(2,t) = 1 - p(1,t)$. Equation (1) is known as replicator equation, particularly when a behavioral trait spreads by genetic inheritance of "fitter" (more successful) individuals (Gintis, 2000). If a behavior spreads through imitation, we obtain the same equation, when a proportional imitation rule is assumed (Helbing, 1992). In that case, one often calls it the game-dynamical equation. Let us shortly discuss this equation in more detail. One can show that $E(1,t) - E(2,t) = (P_{11} - P_{21})p(1,0) + (P_{12} - P_{22})[1 - p(1,t)]$. With this, the game-dynamical equations become

$$\frac{dp(1,t)}{dt} = p(1,t)[1 - p(1,t)][B + (C - B)p(1,t)] \qquad (2)$$

with $B = (P_{12} - P_{22})$ and $C = (P_{11} - P_{21})$. The time-independent ("stationary") solutions of this equation can be determined by setting $dp(1,t)/dt = 0$. Correspondingly, we find the stationary solutions $p(1,t) = p_1 = 0$, $p(1,t) = p_2 = 1$, and $p(1,t) = p_3 = |B|/(|B|+|C|)$, given that $0 \leq p_3 \leq 1$ (otherwise the third stationary solution would violate the normalization condition and would, therefore, not exist). The stability of these stationary solutions p_k it given by the so-called "eigenvalues" λ_k. They can be calculated as $\lambda_1 = B$, $\lambda_2 = -C$, and $\lambda_3 = -B(1 - p_3)$ (Helbing and Lozano, 2009). An eigenvalue $\lambda_k < 0$ means that a stationary solution is stable with respect to sufficiently small variations, i.e. the system would go back to the stationary solution. In contrast, an eigenvalue $\lambda_k > 0$ corresponds to an unstable stationary solution, i.e. any small variation would drive the system away from the stationary state. Correspondingly, the system will end up in one of the stable stationary states.

For the coordination game with $P_{11} = P_{22} = P$ and $P_{12} = P_{21} = 0$, we have the two stationary solutions $p(1,t) = 0$ and $p(1,t) = 1$, while $p(1,t) = 1/2$ is unstable. Therefore, we will end up with 0% or 100% individuals using behavior 1. Considering trial-and-error behavior (noise 1), the majorities will be

less extreme, but a behavioral convention will still evolve, when the mutation rate is not too high (Helbing, 1992). One good example for such a behavioral convention is the preference of pedestrians for one side (for example the right-hand side in continental Europa, the left-hand one in Japan). Similar considerations were carried out by Peyton Young (1993).

Let us now use the abbreviations $P_{11} = R$, $P_{22} = P$, $P_{12} = S$, and $P_{21} = T$. For the prisoner's dilemma with $T > R > P > S$ (i.e. $B = S - P < 0$ and $C = R - T < 0$), the only stationary solution is $p(1,t) = p_1 = 0$, corresponding to defection by everybody. In the snowdrift (chicken) game with $T > R > S > P$ (i.e. $B > 0$ and $C < 0$), the only stable stationary solution is $p(1,t) = p_3$, i.e. we will have a coexistence of a finite fraction p_3 of cooperators with a fraction $1 - p_3$ of defectors. Finally, in the stag hunt (assurance) game with $R > T > P > S$ (i.e. $B < 0$, $C > 0$), we have the stable stationary solutions $p(1,t) = p_1 = 0$ and $p(1,t) = p_2 = 1$. As in the coordination game, the finally resulting solution depends on the initial condition $p(1,0)$, i.e. it is history-dependent. If $p(1,0) < p_3$, then the system ends up with $p(1,0) = p_1 = 0$. In contrast, if $p(1,0) > p_3$, the system will evolve in time towards the stationary solution $p(1,t) = p_2 = 1$. It is very interesting to see, how the results for the spatial games and migratory games with local interactions differ from these results for well-mixed populations (see the discussion in the main text). Finally, we would like to mention that the instability analysis can be extended to game-dynamical equations with spatial interactions, but the calculations become quite cumbersome then (Helbing, 2009).

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