Collective Social Dynamics and Social Norms

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1 Introduction

How individual behaviour is determined or at least influenced by social norms is one of the classic questions of social theory. Here we consider a norm as a rule guiding individual decisions concerning rituals, beliefs, traditions, and routines. Populations of individuals or sometimes even companies or nations often exhibit a remarkable degree of coordinated behaviour helping to prevent or govern conflicts. When this coordination is enforced without the help of a central authority, the coordinated behaviour and the arising regulation of conflict may be due to the existence of norms. What distinguishes a norm from other cultural products like values or habbits is the fact that adherence to a social norm is enforced by sanctions.

> A norm exists in a given social setting to the extent that individuals usually act in a certain way and are often punished when seen not to be acting in this way (Axelrod, 1986).

Therefore, the existence of a norm is not a matter of yes or no but a matter of degree. In turn, how often a certain action is taken or how often an actor is punished for not taking that action determines the growth or decay of a norm.

A social norm can persist although the initial rational origin changes or even vanishes over time. Actions that were originally performed because they were necessary to survive under certain environmental conditions may continue to persist as a social norm although the current circumstances do not require them anymore. Thus, a norm may or may not have a rational foundation. Norms are sometimes unwritten and unspoken rules that become

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apparent only when they are violated. Nevertheless, in some societies norms are clearly defined rules.

Adherence to norms is enforced by sanctions which may be formal or informal. For instance, in politics, civil rights and civil liberties are not only supported by the power of the formal legal system but as well by informal norms determining what is acceptable (Axelrod, 1986). Then again, violation of a norm may be punished on a purely informal level in such a way like stigmatising or ignoring the violator. Typical sanction mechanisms used in real life are ostracism, physical retaliation, refusal of social approval, gossip, etc. (Diekmann and Voss, 2003). In the course of development of a society it may happen that norms become internalised such that violation of norms is psychologically painful for the deviator even when the sanction mechanism is not active anymore (Scott, 1971). If a norm is internalised by every member of a society the norm remains stable even without performing any sanction. Another possibility of enforcing a social norm is given by considering one special type of behaviour to be the "normal" situation, e.g. in a certain society a leading position can only be assigned to a man, people above a certain age are assumed to be married and the like. Consequently, the existence of a social network is a prerequisite for successful implementation of social norms.

Although norms determine individual behaviour they must be negotiated on the macro level (Haferkamp, 1976). Different subgroups of a society possess different abilities to transfer their local guidelines to other groups. Basically, the more resourceful groups may allocate resources to less resourceful groups who will support the institutionalisation of a certain norm. In the sequel both groups internalise the norm. The resourceful also have the power to sanction deviation which stabilizes the norm and further increases the power of the resourceful. However, not all groups within a society will adopt a certain norm. Individuals may consider themselves associated with an inclusive group (in–group) but also have the desire to dissociate from certain other groups of individuals, the out–groups. This interplay of association and dissociation on one hand strengthens solidarity within in–groups, but on the other hand allows for coexistence of contradicting norms within a society. Consequently, in one and the same situation, the expectations regarding a certain desired behaviour differs among members of different groups (Saam and Harrer, 1999).

Axelrod (1986) investigates the emergence and stability of behavioural norms within an n–person game. The players can choose to defect and receive a payoff for defection. In the next step, those players who catch the defector out have the opportunity to impose a punishment but have to bear the enforcement costs. However, if this punishment is costly, a norm to cooperate will not necessarily be established. Each strategy has two dimensions determining the players propensity to defect and the probability to punish deviant behaviour. The actors are endowed with limited rationality and apply an evolutionary approach to choose their strategy. They observe each other and the more successful strategies are more likely being imitated. Numerical simulations reveal that this setup basically does not support the emergence and stability of a norm suggesting cooperative behaviour. Since no one has any incentive to punish a defection, the question arises how a norm can ever get established. Therefore, Axelrod employs a metanorm ensuring that agents must punish those whom they dected not punishing observed deviant behaviour. With this extension a norm against defection is established and stable once it is established.

Diekmann and Voss (2003) showed that rational actors in a one–shot situation are able to enforce social norms with sanctions even when the punishment is costly. Many papers address the presence of such social norms. For instance Palivos (2001) observes the effects of a presence of family–size norms which indicate that an agent's fertility behaviour depends on prices and income as well as on the fertility rate of the cohorts. Lindbeck et al. (1999) investigate the interplay between social norms and economic incentives. They consider a continuum of individuals facing the decision to work or to live off public transfers. Those individuals who refuse to work receive a transfer but also suffer from embarrassment due to social stigma. This disutility increases as the share of people refusing to work decreases. Thus, the strength of the social norm that the source of an individuals means of subsistence should be the individuals own work is determined endogenously within the modelling framework. The model investigated by Lindbeck allows for two possible outcomes: a low–tax society determined by a majority of taxpayers or a high–tax society carried by a majority of transfer recepients. Cole et al. (1992) analysed a multi–generation model in which parents can improve their childrens' matching prospects by increasing savings. If all families do that the offsprings' advantage vanishes since their parents activities offset each other. Nevertheless, the system is not in an equlibrium if all families abandon this effort since in such a situation it would be advantageous for any single family to deviate. Cole et al. (1992) showed that there equist equilibria where over–saving takes place as well as equilibria where it is supressed. In an extended version of this model Cole et al. (1998) include a *wealth–is–status social norm*, which means that a woman receiving multiple proposals accepts the one from the wealthies candidate, and an *aristocratic social norm* where a man's status is inherited. While the former social norm leads to over–saving and deadweight losses the latter allows to supress over–saving within families belonging to the upper class.

Another promising field of application of social norms is the investigation of life course events. Certainly, the timing and sequencing of major events of an individuals life course, such as the first sexual relationship, union formation, leaving parental home, marriage, and first birth is determined by decisions which are in priciple taken by the individual. Nevertheless, the individuals' environment has an influence on these decisons. This influence may take place through normative guidelines providing some rules of thumb generated by the society as a whole but also through imitation of the behaviour of the individuals who are closely connected — the relevant others. Neglecting these influence mechanisms, that is, not to behave according to the rules may incur some costs for the individual such as the exclusion from a group or the loss of reputation. Therefore, the normative rules guiding the timing of major life course events are enforced by formal and informal sanctions. This qualifies the guidelines to serve as perceived social norms shaping individuals' lives. Billari and Mencarini (2004) did an empirical in–depth analysis of perceived norms regarding lower and upper limits on sexual debut and marriage.

Billari et al. (2003) introduce an agent–based one–sex non–overlapping–generations model to understand the dynamics of the intergenerational transmission of age–at–marriage norms. The social norms at first influence the agents mate search decisions. In case of a successful search resulting in a marriage the norms of the partners are transmitted to their offsprings by means of a certain combiner creating a new norm for the child based on the parents' norms. Aparicio Diaz and Fent (2006) investigate whether these results also hold in a more complex setup where heterogeneity with respect to age and sex is explicitly taken into account. Moreover, they also include the timing of union formation and fertility into the model. To create a more realistic model of the evolution of age norms the characteristics of the agents are extended and the social norms are split into two sex-specific norms.

The age–at–marriage norms serve as guidelines for individuals to make decisions about the right point in time to get married. Normative guidelines generally are a decision guidance whenever an individual has to decide about something important. Thus certain actions are influenced by social norms or social rules that state how individuals ought to behave in certain circumstances.

The individual being in the situation of taking a decision at the micro level is guided by social norms imposed at the macro level. Moreover, the set of all micro level decisions within a certain society generates the macro level behaviour of the system which may either strengthen the existing social norms or weaken them if there is a collective trend to deviate. Thus, the long run development of social norms is the result of collective dynamics within a social network. The society is a system containing a large number of individuals interacting through their social networks to serve their own needs. Granovetter (1973, 1983, 1985) provides a theory of embeddedness suggesting that all economic action accomplished either by individuals or by organisations is enabled, constrained, and shaped by social ties among individuals. The number of connections may vary among individuals but we may assume that there is no completely unconnected individual (except the man in the moon) and no one is connected to all others. The impact of different types of connectivity, i.e. the influence of the network structure under consideration has been extensively studied (see for instance Barabasi and Albert (1999), Collins and Chow (1998), Rahmandad and Sterman (2004), and Watts and Strogatz (1998)).

Ehrlich and Levin (2005) emphasise that human beings are not only the result of biological evolution but also of a process of cultural evolution. In opposite to genes which can only pass unidirectionally from one generation to the next, norms, ideas, conventions, and customs can pass between individuals distant from each other and even from the childrens to their parents. Ehrlich and Levin postulate that a clear understanding of the interactions between cultural changes and individual actions is crucial to the success of efforts to influence cultural evolution. Cooperation in human societies relies essentially on social norms even in modern societies, where cooperation substantially hinges on the legal enforcement of rules. A theory of social norms should help to explain how norms emerge, how they are maintained, and how one norm replaces another. Moreover, we do not only want to discuss individual behaviour in the presence of norms but also how norms change over time.

The remainder of this paper is organised as follows. Section 2 explains in detail the simulation model we developed to investigate the evolution of norms within a population of artificial agents. In section 3 we present and discuss the results obtained in various runs of numerical simulations and in section 4 we summarise and interpret these results.

2 The model

We consider an artificial population featuring N agents. Each agent $i \in \{1, \ldots, N\}$ of our artificial population is linked to all agents $j \in I(i)$ and $j \in O(i)$ where $I(i)$ denotes the agents in–group and $O(i)$ represents the agents out–group. The number of agents in $I(i)$ is given by $k_i := \|I(i)\|$ and the size of $O(i)$ is $l_i := \|O(i)\|$. The behaviour of agent i at time t is denoted by $x_i^t \in [0, 1]$ and the current behaviour of all agents within an in–group determines the groups social norm. We assume that the in–group relationship is symmetric, thus, $j \in I(i) \iff i \in I(j)$. If agents i and j belong to the same in–group but deviate from each other they receive (and impose) a punishment proportional to $(x_i^t - x_j^t)^2$. Consequently, agent i receives a disutility for deviating from the social norm of his in–group which is proportional to $\sum_{j \in I(i)}(x_i^t - x_j^t)^2$. Moreover, the agents are reluctant to change their own behaviour, which is characterised by a disutility proportional to $(x_i^{t+1} - x_i^t)^2$. Finally, each group of the population has the desire to express its own idendity. Therefore, agents obtain a positive utility by differing from the out–group proportional to $\sum_{j \in O(i)}(x_i^t - x_j^t)^2$. We assume that agent i can only observe the current behaviour within the population but does not have the ability to anticipate future movements of other agents. Introducing the parameters $\alpha, \beta \in [0,1]$ to adjust the weight of the utilities and disutilities, the utility function which agent i wants to maximize becomes

$$\begin{aligned} U(x_i^{t+1}) &= -\beta \left[\alpha (x_i^{t+1} - x_i^t)^2 + (1-\alpha) \sum_{j \in I(i)} (x_i^{t+1} - x_j^t)^2 \right] \\ &\quad + (1-\beta) \sum_{j \in O(i)} (x_i^{t+1} - x_j^t)^2. \end{aligned} \tag{1}$$

Utility maximising solution

Assuming that an agent cannot foresee the impact of his own decision on the other agents' behaviour, the partial derivatives of (1) become

$$\begin{aligned} \frac{\partial U(x_i^{t+1})}{\partial x_i^{t+1}} &= -2\beta \left[\alpha (x_i^{t+1} - x_i^t) + (1-\alpha) \sum_{j \in I(i)} (x_i^{t+1} - x_j^t) \right] \\ &\quad + 2(1-\beta) \sum_{j \in O(i)} (x_i^{t+1} - x_j^t) \qquad (2) \\ \frac{\partial^2 U(x_i^{t+1})}{\partial (x_i^{t+1})^2} &= -2\{\beta[\alpha + (1-\alpha)k_i] - (1-\beta) l_i\}. \end{aligned}$$

If $\beta \leq l_i/[\alpha + (1-\alpha)k_i + l_i]$ the utility function is linear or convex. In that case the optimal x_i^{t+1} is either zero or one. Assigning $x_i^{t+1} := 0$ and $x_i^{t+1} := 1$ in equation (1) reveals that the agent chooses zero (one) if

$$-\beta \left[\alpha(1 - 2x_i^t) + (1-\alpha) \sum_{j \in I(i)} (1 - 2x_j^t) \right] + (1-\beta) \sum_{j \in O(i)} (1 - 2x_j^t) < (>) 0.$$

From that it follows immediately that if at a certain time t all agents have either the same norm $x_i^t = 0$ or $x_i^t = 1$ and $\beta \leq l_i/[\alpha + (1-\alpha)k_i + l_i]$ the whole population switches between zero and one. If the above expression is equal to zero, the agent is indifferent among $x_i^{t+1} = 0$ and $x_i^{t+1} = 1$. If

$$\beta > \frac{l_i}{\alpha + (1-\alpha)k_i + l_i} \tag{3}$$

the utility function is concave and the utility maximizing x_i^{t+1} becomes

$$x_i^{t+1} = \frac{\beta[\alpha x_i^t + (1-\alpha)\sum_{j\in I(i)} x_j^t] - (1-\beta)\sum_{j\in O(i)} x_j^t}{\beta[\alpha + (1-\alpha)k_i] - (1-\beta)l_i}. \tag{4}$$

The agents decision is a weighted sum of the agents current behaviour x_i^t, and the behaviour of the agents in his in–group $I(i)$ and in his out–group $O(i)$, where the weights are proportional to the respective marginal utilities. The above solution (4) is only feasible if it holds $0 \le x_i^{t+1} \le 1$. The constraint $0 \le x_i^{t+1}$ requires

$$\beta \ge \frac{\sum_{j\in O(i)} x_j^t}{\alpha x_i^{t+1} + (1-\alpha)\sum_{j\in I(i)} x_j^t + \sum_{j\in O(i)} x_j^t} \tag{5}$$

and $x_i^{t+1} \le 1$ is fulfilled if

$$\beta \ge \frac{\sum_{j\in O(i)}(1-x_j^t)}{\alpha x_i^{t+1} + (1-\alpha)\sum_{j\in I(i)}(1-x_j^t) + \sum_{j\in O(i)}(1-x_j^t)}. \tag{6}$$

Otherwise the agent again chooses either zero or one.

In the homogenous case $k_i = k$ and $l_i = l\ \forall i$ the critical parameters are the same for all agents. Figure 1 depicts the different regions in the α–β plane resulting from the numerical parameters $k = 20$, $l = 40$.

If there is an in–group of agents at the extreme values zero (one), such that $x_i^t = 0(1)$, $x_j^t = 0(1)\,\forall j \in I(i)$ and $x_j^t > 0(< 1)$ for at lest one $j \in O(i)$ then (4) results in $x_i^{t+1} < 0(> 1)$ which means the agent will stay at the respective end of the interval. Therefore, clusters of agents at the interval ends are stable provided there is a force of repulsion from an out–group of agents with a different social norm.

An interior solution $x_i^t \in (0,1)$ can only be stable if $x_i^{t+1} = x_i^t$, from (4) we conclude that this holds if

$$x_i^t = \frac{\beta(1-\alpha)\sum_{j\in I(i)} x_j(t) - (1-\beta)\sum_{j\in O(i)} x_j(t)}{\beta(1-\alpha)k_i - (1-\beta)l_i}. \tag{7}$$

Again the conditions (5) and (6) must be fulfilled to ensure that the above stationary solution lies in the interval $(0,1)$.

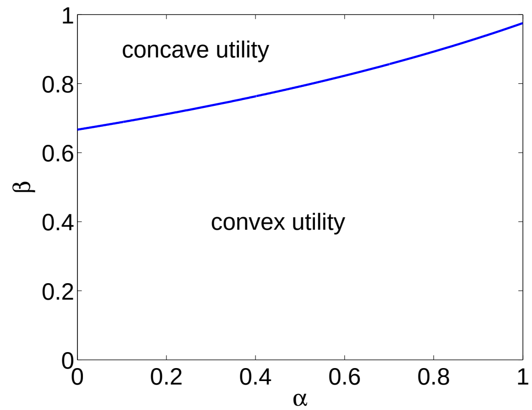


Figure 1: The α–β plane for $k_i = 20$, $l_i = 40$

Costs of sanctions

Now we will have a look at the costs of being punished and at the costs of imposing a punishment. Recall that in the simple version of the (Axelrod, 1986) simulation model the agents are reluctant to impose a punishment since there is no economic incentive to punish and it even incurs costs. However, as (Fehr and Fischbacher, 2004a) pointed out, sanctions are the decisive factor for norm enforcement. Anyhow, in the real world individuals are willing to impose a punishment even if this is disadvantageous in economic terms as long as the costs of imposing a sanction are not very high. In an experimental setup deployed by Fehr and Fischbacher (2004b) a third party observes test persons in a prisoners' dilemma and has the option to punish players for defecting. Although disadvantageous from a purely profit–maximising point of view third parties are willing to punish defection particularly when the opponent cooperated. Thus, the enforcement of norms is largely driven by nonselfish motives. These findings may empirically justify Axelrod's approach to include a metanorm. Here, we exercise a similar approach by just taking it for granted that people are punished and impose a punishment, respectively, if agents deviate from the behaviour of their in–group (recall equation 1). Nevertheless, a social norm will only be enforced by sanctions if the costs of punishing are much lower than the costs of being punished. Let us assume a fully connected group of individuals with agent 1 deviating from the rest of the group. Thus we have the two types of behaviour x_1 and x_j for $j \in \{2, \ldots, n\}$. For simplicity we assume that the members of this group have no links to agents outside the group. Moreover, since we are only looking at the sanction but not at the desire to deviate from the out–group we assume $\beta = 1$. If agent 1 refuses to converge toward the other agents (i.e. $x_1^t = x_1 \forall t$) and the other agents refuse to converge as well, he receives a disutility

$$U(x_1) = -(1-\alpha)(n-1)(x_1 - x_j)^2$$

from being punished while the other agents have to bear the costs

$$U(x_j) = -(1-\alpha)(x_1 - x_j)^2$$

for imposing the punishment. Therefore, the disadvantage of being punished is $(n-1)$ times higher than the enforcement costs. If the agents maximize their utility, we can conclude from equation (4) that their behaviour in the next time step becomes

$$\begin{aligned} x_1^{t+1} &= \frac{\alpha x_1^t + (1-\alpha)(n-1)x_j^t}{\alpha + (1-\alpha)(n-1)} \\ x_j^{t+1} &= \frac{(1-\alpha)x_1^t + [\alpha + (1-\alpha)(n-2)]x_j^t}{\alpha + (1-\alpha)(n-1)}. \end{aligned}$$

From that it follows that the deviator (agent 1) makes a bigger movement than the other group members if $\alpha < \frac{n-1}{n}$. For $\alpha = 1/2$ the agents converge to a common behaviour already after one iteration and for $\alpha < 1/2$ overshooting takes place.

Status within a group

In real populations the status of an individual determines his power and influence and also his propensity to adhere to social norms. Individuals with a higher status gain more from community membership which also increases the threat of ostracism. If an individual gains little or nothing from community membership the threat of ostracism is of little importance (Cole et al., 1998). In this simulation the number of links an agent posseses represents his status within the population. The number of connections determines the influence of the individual on the behaviour of the population but also the number of people who can punish an agent for deviating from their own behaviour. Consequently, agents with a higher status are more interested in corresponding to their relevant others than those with a low status.

Consider a group of n agents with agent 1 having $k_1 = n-1$ links to all other members of the group who all exhibit the current behaviour x_j^t, while agents $j \in \{2, \ldots, n\}$ have only $k_j = 1$ link to agent 1 and no other links (see figure 2a). Assuming again $\beta = 1$ the optimal behaviour in period $t+1$ (4)

is given as

$$\begin{aligned} x_1^{t+1} &= \frac{\alpha x_1^t + (1-\alpha)k_1 x_j^t}{\alpha + (1-\alpha)(n-1)} \\ x_j^{t+1} &= \alpha x_j^t + (1-\alpha)x_1^t \end{aligned}$$

The weight of agent 1 on the behaviour of agent j is $(1-\alpha)$, while the weight of agent j on the behaviour of agent 1 is $(1-\alpha)/(\alpha+(1-\alpha)(n-1))$. (**Remark:** In the last expression the denominator is greater than one for $n > 2$). This means, agent 1 is $(\alpha+(1-\alpha)(n-1))$ times more powerful than the other agents. As a consequence, the long run equilibrium $\mathbf{x}$ becomes

$$\mathbf{x} = \frac{\alpha + (1-\alpha)(n-1)}{\alpha + (2-\alpha)(n-1)}\, x_1^0 + \sum_{i=2}^{n} \frac{1}{\alpha + (2-\alpha)(n-1)}\, x_i^0. \tag{8}$$

Example 1 *To illustrate the power of an agent with higher capital we consider a population of* $n = 12$ *agents linked like in figure 2a. The initial social norms are* $x_1^0 = 0$ *and* $x_i^0 = 1 \forall i \in \{2, \ldots, 12\}$*. Applying the numerical parameters* $\alpha = 0.9$ *and* $\beta = 1$*, it follows from equation (8) that the population converges toward the equilibrium* $\mathbf{x} = 0.846$*. In figure 2b the dashed red line illustrates the development of agent 1 and the solid blue line illustrates the development of agents 2 to 12.*

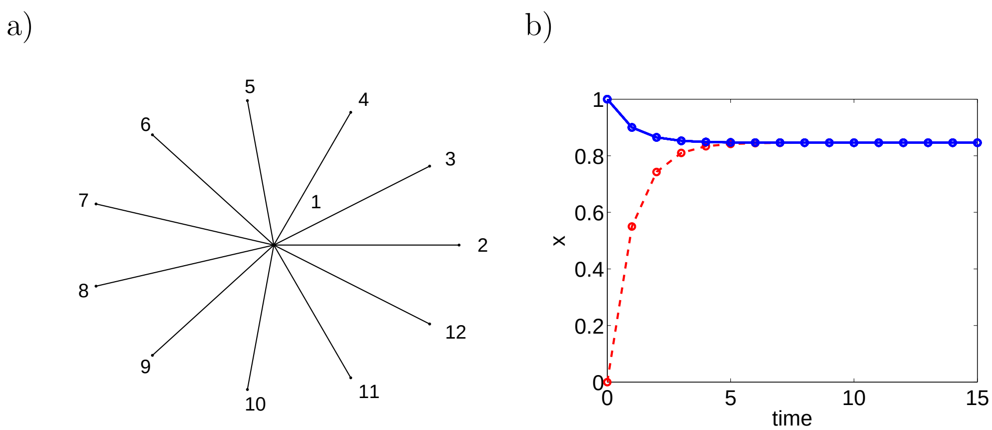


Figure 2: Status of an agent within a group

As noted above, the number of links not only determines the influence on others but also the temptation to deviate. Suppose agent 1 is linked to k_1 agents who all have the same current behaviour $\tilde{x}$. Then (1) becomes

$$U(x_1^{t+1}) = -\beta[\alpha(x_1^{t+1} - x_1^t)^2 + (1-\alpha)k_1(x_1^{t+1} - \tilde{x})^2] + (1-\beta) \sum_{j \in O(i)} (x_1^{t+1} - x_j^t)^2.$$

If the number of links fulfils

$$k_1 < \frac{(1-\beta)\sum_{j\in O(i)}(x_1^{t+1} - x_j^t)^2 - \beta\alpha(x_1^{t+1} - x_1^t)^2}{\beta(1-\alpha)(x_1^{t+1} - \tilde{x})^2} \tag{9}$$

the utility gained from deviating from the out–group is higher than the disutility of deviating from the in–group. Thus, if the weight $(1-\beta)$ is sufficiently high, agents with a low status within the cummunity fulfiling (9) are tempted to violate the social norm. Since in our model the number of links represents the status, this feature perfectly corresponds with (Cole et al., 1998) postulating that low status families gain little from adhering to the social norm.

Dominance of groups

The support of a certain behavioural norm depends on the groups who support that norms. Those groups who are in the majority or have greater economic and political power can more easily establish and enforce their rules as a general norm which has to be obeyed by the whole population (Axelrod, 1986). To show how this effect comes into play in our formal model we consider two groups exhibiting different behaviour x_i^t and x_j^t. The first group consists of n_i and the second group of n_j members. The two agents i and j belonging to these different groups are linked to each other and with each member of their group resulting in $k_i = n_i - 1$ and $k_j = n_j - 1$ (see figure 3a).

Assuming $\beta = 1$ we can conclude from (4) that the weight of agent j of the behaviour of agent i in period $t+1$ is $\frac{\alpha+(1-\alpha(n_i-1)}{\alpha+(1-\alpha(n_j-1)}$ times the weight of agent i on the behaviour of agent j in period $t+1$. Hence, the long run equilibrium becomes

$$\mathbf{x} = \frac{\alpha + (1-\alpha)(n_i - 1)}{2\alpha + (1-\alpha)(n_i + n_j - 2)}\, x_i^0 + \frac{\alpha + (1-\alpha)(n_j - 1)}{2\alpha + (1-\alpha)(n_i + n_j - 2)}\, x_j^0 \tag{10}$$

This illustrates that a bigger group with more links — representing economic and political power in our model — will make smaller movements to achieve a compromise but can force the other agents to adopt to their norms.

Example 2 *Figure 3b illustrates the convergence toward a global social norm obtained from a simulation with 21 agents. The dominant group i consists of* $n_i = 14$ *and the dominated group consists of* $n_j = 7$ *agents. The dominant group starts with the social norm* $x_i^0 = 0$ *and the dominated group is endowed with the initial norm* $x_j^0 = 1$. *The only connection between the two groups is the link between agent* $i = 14$ *and agent* $j = 15$. *Since agents i and j are* *linked to all members of their respective groups, the dominance of group i does not only originate from the superior group size but also from the higher number of links of agent i compared to agent j. Figure 3b shows the time development of norms within the agent population unsing parameters $\alpha = 0.5$ and $\beta = 1$. The dashed red trajectories illustrate the dynamics of agent i and its respective group and the solid blue line represents the dynamics of agent j and its group. The graphic shows that the dominated group makes*

a) b)

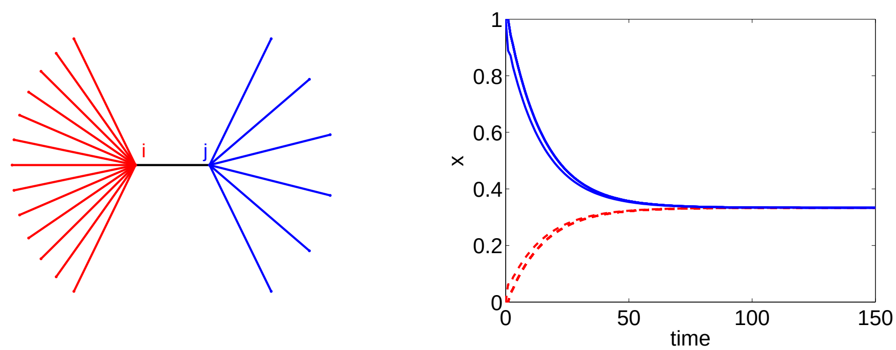


Figure 3: Dominance of groups

bigger moves in each time step and the whole population converges toward the equilibrium $\mathbf{x} = 1/3$ determined by equation 10.

In reality it is not only the size but also economic and political power, which makes a group dominant (Axelrod, 1986). In this model power is represented by the number of links an individual possesses. In the next example we consider two groups of equal size ($n_1 = n_2$) but with different numbers of links between group members ($k_1 > k_2$). Since a higher number of links means more power, the first group dominates the second group despite the equal size of the two groups. Again there is only one pair of agents linking these two groups together (see figure 4a).

Example 3 *To illustrate the dominance resulting from a higher number of links we run simulations with the numerical parameters $n_1 = n_2 = 10$, $k_1 = 6$, $k_2 = 2$, $\alpha = 0.5$, and $\beta = 1$. For the initial social norm we choose $x_i^0 = 0 \ \forall i \in \{1, \ldots, n_1\}$ and $x_j^0 = 1 \ \forall j \in \{n_1 + 1, \ldots, n_1 + n_2\}$ The red dashed lines represent agents 1 to n_1 and the solid blue lines represent agents $n_1 + 1$ to $n_1 + n_2$. The social norm within the agent population develops like shown in figure 4b. The social norm converges toward 0.3039 which means that the dominance of group one in this example is even stronger than in the previous*

a) b)

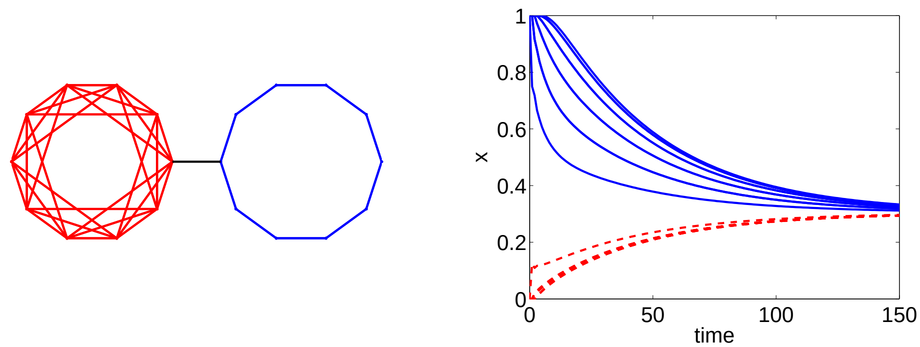


Figure 4: Dominance of groups due to economic and political power

one. Moreover, it is also possible that a minority rules the majority due to a higher number of links.

3 Simulation Results

In the following we will discuss results obtained from numerical simulations with $N = 200$ agents on a one–dimensional regular lattice network and with $N = 900$ agents on a two–dimensional regular lattice network. In both cases we apply periodic boundary conditions.

In the one–dimensional case we choose $k_i = k = 20$ (i.e. each agents in–group contains the ten nearest neighbours on the left and the ten nearest neighbours on the right), the out–group consists of $l_i = l = 40$ neighbouring agents, and the intersection of In– and out–group is empty. The initial values x_i^0 are uniformly distributed in the interval (0,1). Each set of numerical parameters α, β is simulated with ten different initial distributions. Figures 5 to 10 are obtained with $\alpha = 0.3$. Consequently, the critical value for parameter β (see equation 3) becomes approximately 0.7117.

We start with those dynamics related to the region below the solid blue line in the α–β plane in figure 1. Figures 5 to 8 show simulation results obtained with $\beta = 0.3$. The graph in figure 5a depicts the trajectories of the agents behaviour versus time. It can be seen clearly that they never stabilise but fluctuate between the interval ends and some intermediate levels because the dominant repulsion motivates the agents to leave. The bar charts in figures 5b) and 6 illustrate the distribution of behaviours among the agent population at a certain time t. The horizontal axis represents the 200 agents and the length of the bars indicate the respective social norms. In 5b) we see the initial random distribution which does not exhibit any specific patterns. Figure 6 depicts the social norms from time step 69 to time step 74. The

a) b)

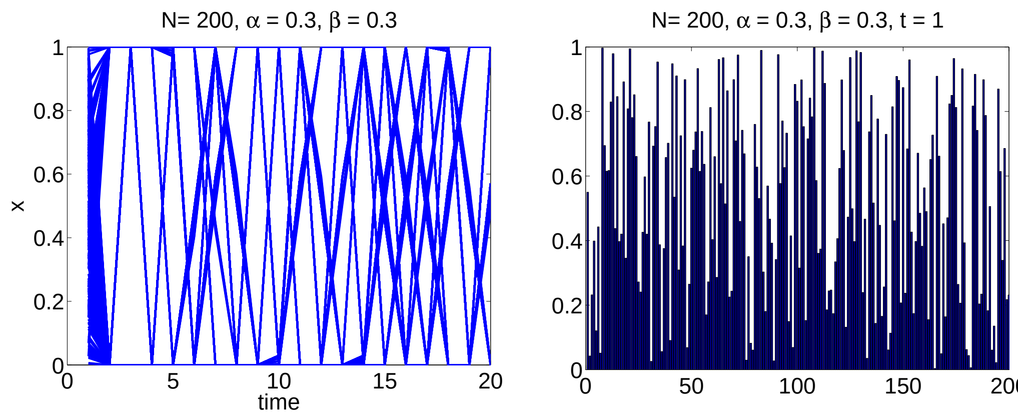


Figure 5: Simulation Results — one–dimensional regular lattice

situation at $t = 69$ exhibits practically polarisation, i.e. there are eight separated groups of agents, four of them at $x_i^t = 0$ and four at $x_i^t = 1$. In the next time step ($t = 70$) there are only four groups left, and one of them chooses a social norm somewhere between the interval ends. It is remarkable that the two small groups of agents at the right–hand side of the diagram choosing $x_i^{69} = 1$ keep their norm for the next time step, while all the other agents switch to a different norm. Nevertheless, these coexisting social norms are not sustained since the agents continue to switch in the following time steps. Another feature of these dynamics is that they are periodic with a period length of 11 time steps. Thus, plotting the distribution from $t = 80$ to $t = 85$ would result in exactly the same graphs like in figure 6. At the beginning of the simulation the agents need a certain transient phase and reach the cylce at $t = 69$. Figures 7 and 8 are related to the same set of numerical parameters like figures 5 and 6 but to another initial distribution. The graphs in 7 a) and b) show the trajectories over time and the initial distribution, respectively. Figure 8 reveals that the patterns reached after the transient phase are the same like before but with this initialisation the system arrives on the cycle already at $t = 24$.

In the context of social norms the dynamics discussed above, characterized by individuals who completely change their behaviour from period to period do not seem to be realistic. Therefore, we increase the parameter β to modify the dynamics of our system such that the agents slightly adopt their behaviour at each time step. Crossing the borderline in figure 1 means

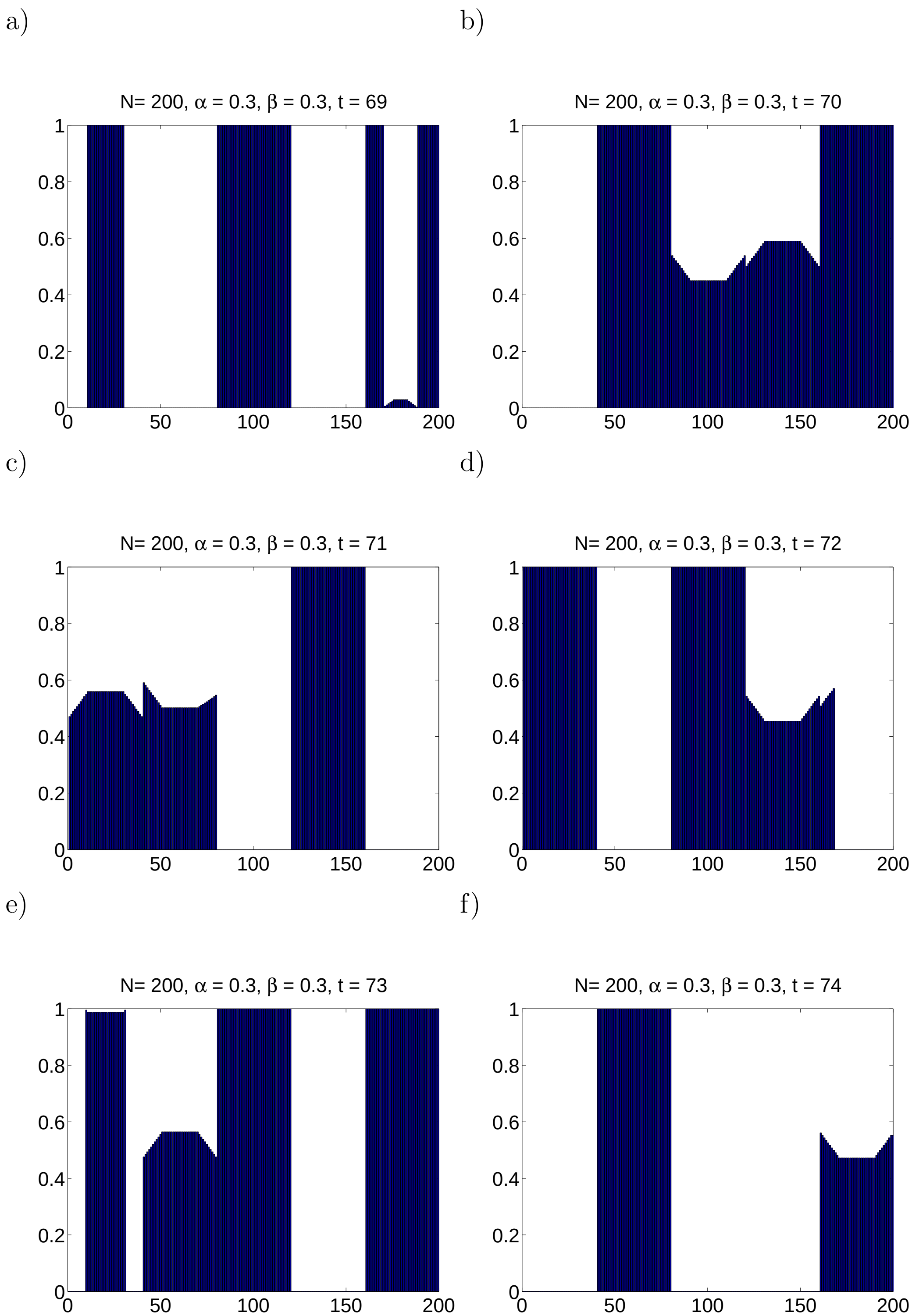


Figure 6: Simulation Results — one–dimensional regular lattice

a) b)

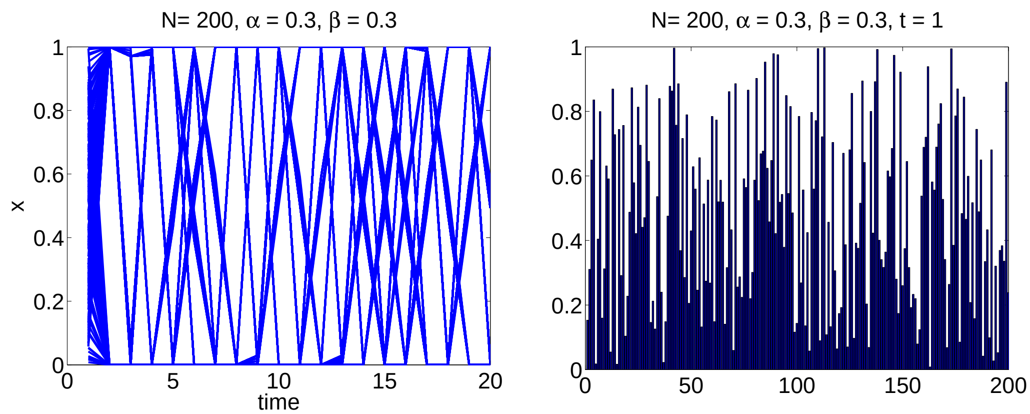


Figure 7: Simulation Results — one–dimensional regular lattice

that the utility function (1) becomes concave and in equation (4) the positive weight an agent assigns to his own and his in–groups behaviour exceeds the negative weigth assigned to the out–groups behaviour. Applying the parameters $\alpha = 0.3$ and $\beta = 0.95$ we obtain the results depicted in figures 9, 10, and 11. Figure 9a) depicts the trajectories during the transient phase and figure 9b) shows the trajectories from $t = 270$ to $t = 300$. Starting from a random initial distribution the agents' norms temporarily converge toward the center due to the dominance of the force of attraction. After a few time steps there is a notable consensus within the population and a global social norm gets established. As soon as the population is crowded close to the center the sanction mechanism becomes very weak because of the small deviation. This makes the repulsion dominant and groups of connected agents move toward the edges of the interval. Consequently, at the beginning of the simulation diversity among the population decreases but later on increases. Figure 9b) shows that the agents persist to oscillate between the interval ends but only make moderate steps at each period of time. However, an agent who arrives at one interval end is not repeled from the border immediately but stays there for a certain time before he starts to move back to the other interval end.

The next figure 10 illustrates the distribution of norms among the population from $t = 200$ to $t = 230$. In each graph we see one big group of agents exhibting $x_i^t = 0$, another big group with $x_i^t = 1$ and a few agents bridging the gaps between these two groups. The clusters at zero and one are not stable but move slowly through the agent population. The agents stay at the interval ends between 50 and 60 time steps and the journey to the other

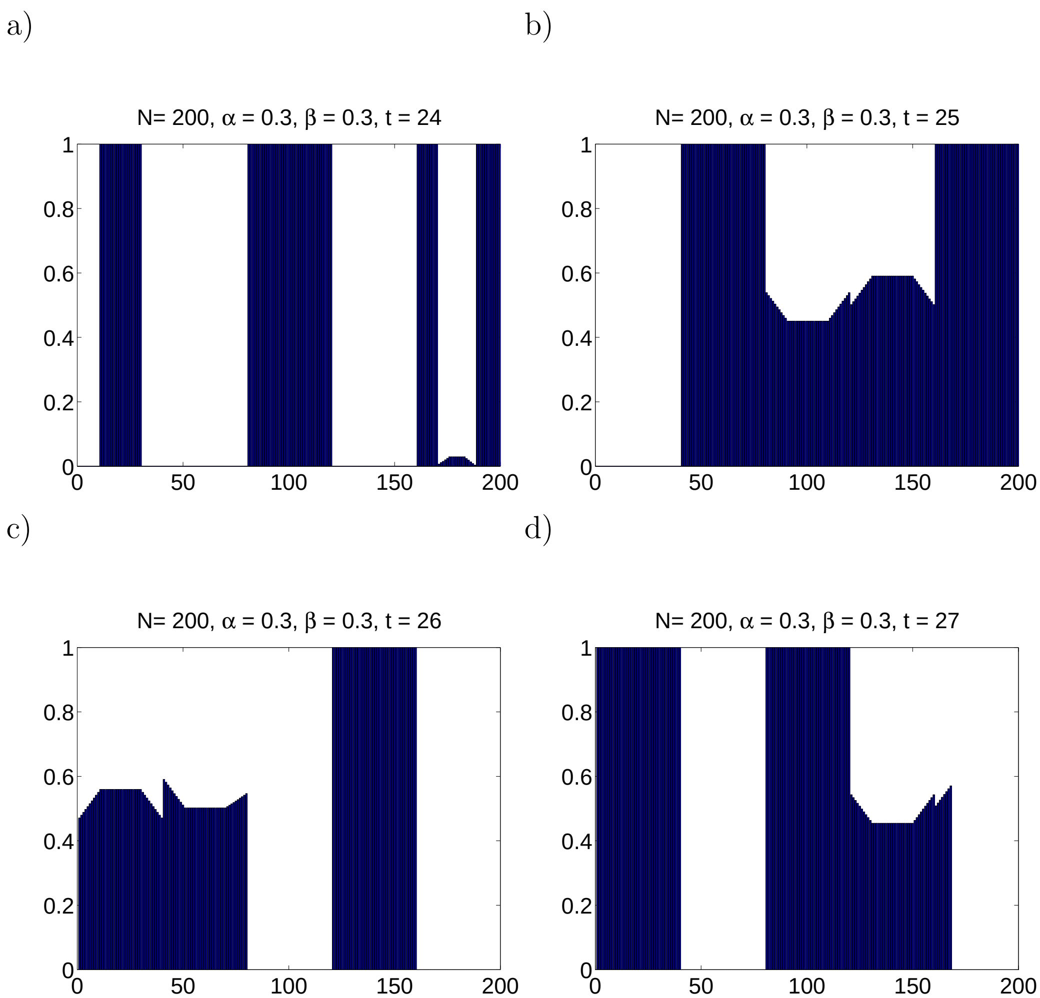


Figure 8: Simulation Results — one–dimensional regular lattice

a) b)

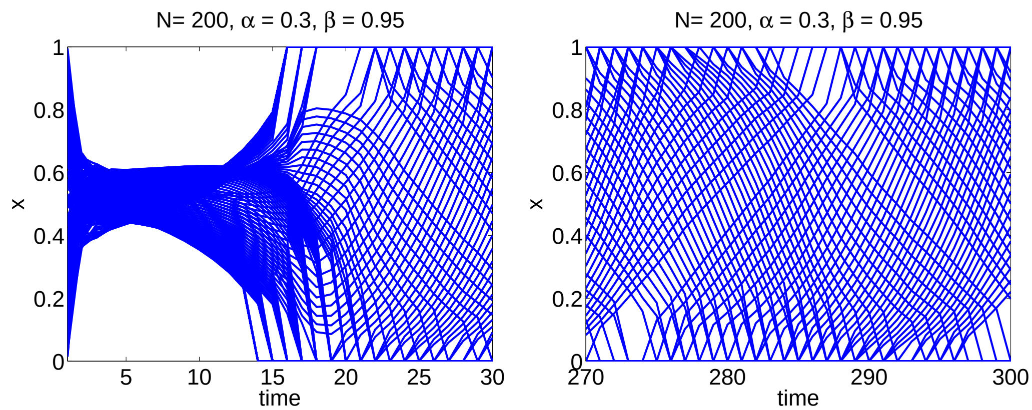


Figure 9: Simulation Results — one–dimensional regular lattice

interval end takes 10 to 15 time steps. Because of these variations it takes 400 time steps until the agent population as a whole comes back to a pattern already observed previously.

Figure 11 shows histograms of the distribution of norms within the population at time $t = 1, 2, 5, 10, 15$, and 20. While in the initial state at $t = 1$ the whole range of possible norms is applied with virtually the same frequency, already at $t = 2$ distinct clusters become apparent. Compared to the initial distribution the number of actually existent norms becomes small during the simulation. From that we can conclude that there are two groups of agents diverging into opposite directions that cause the extinction of the previously established global norm. Since groups of connected agents diverge together (see figure 10), local norms within the groups persist but the global norm vanishes. Since the agents' trajectories never stabilise, the clusters at the interval ends are not stable either but continue to move through the agent population.

In the two–dimensional case the 900 agents are located on a quadratic grid with side length 30 and periodic boundary conditions. For the in–group we choose an extended Moore neighbourhood with radius 3 which leads to $k_i = k = 48$ and for the out–group we choose a quadratic area with side length 9 (i.e. $l_i = l = 81$) which does not intersect with the agents in–group. Again, the initial values x_i^0 are uniformly distributed in the interval (0,1) and each set of numerical parameters α, β is simulated with ten different initial distributions. Figures 12 to 16 are obtained with $\alpha = 0.3$, (i.e. the critical value for parameter β (see equation 3) is approximately 0.70496) and $\beta = 0.95$ which is above the critical value. Therefore, the agents consider

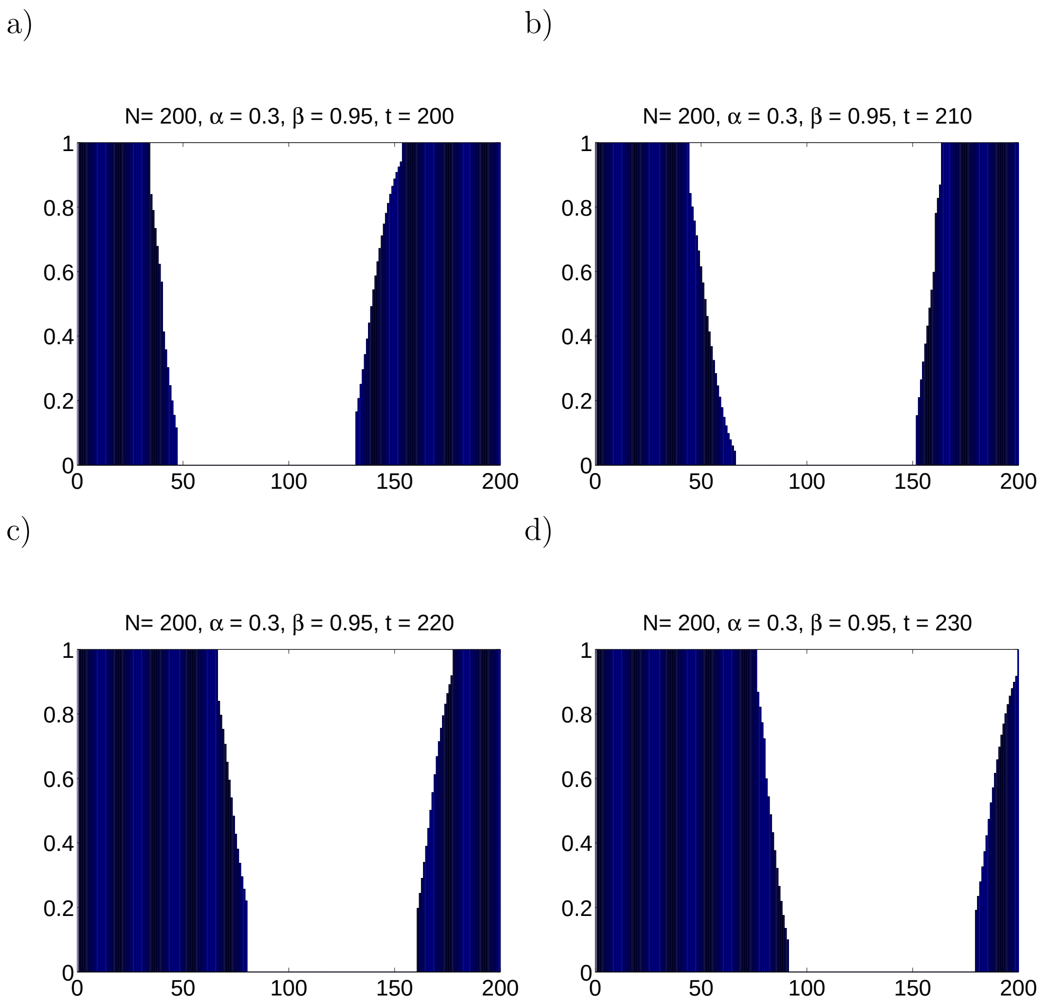


Figure 10: Simulation Results — one–dimensional regular lattice

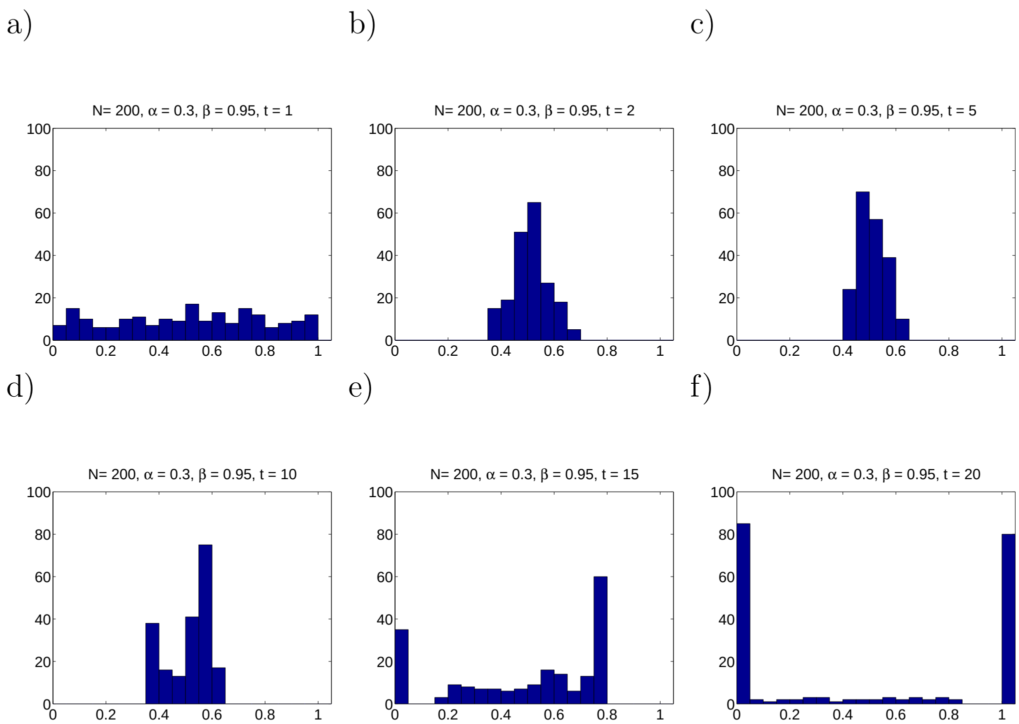


Figure 11: Distribution of norms — one–dimensional regular lattice

compliance within the in–group to be more important than distinction from the out–group.

Figures 12a) and b) depict the trajectories during the transient phase and figures 12c) and d) display the trajectories from $t = 2300$ to $t = 2500$. Figures 12a) and c) contain the trajectories of all 900 agents while figures 12b) and d) exhibit the trajectories of 100 agents which are distributed over the whole lattice. Like in the one–dimensional case the agents' norms temporarily converge toward the center due to the dominance of attraction and global consensus arises. A few time steps later repulsion dominates and groups of connected agents move toward the edges of the interval. Figures 12c) and d) show that the agents persist to oscillate between the interval ends. Agents arriving at one interval end stay there for 164 to 235 time steps before moving back to the other interval end. The journey between the two interval ends takes 60 to 131 time steps.

Figures 13 to 15 illustrate the distribution of social norms at a certain time among the two–dimensional lattice. The colours indicate a certain value x_i^t. In order to allow for a distinction of different behaviour even during the period determined by temporary consensus the scaling of colours is adapted to the current diversity at each time step. Thus, the meaning of blue and

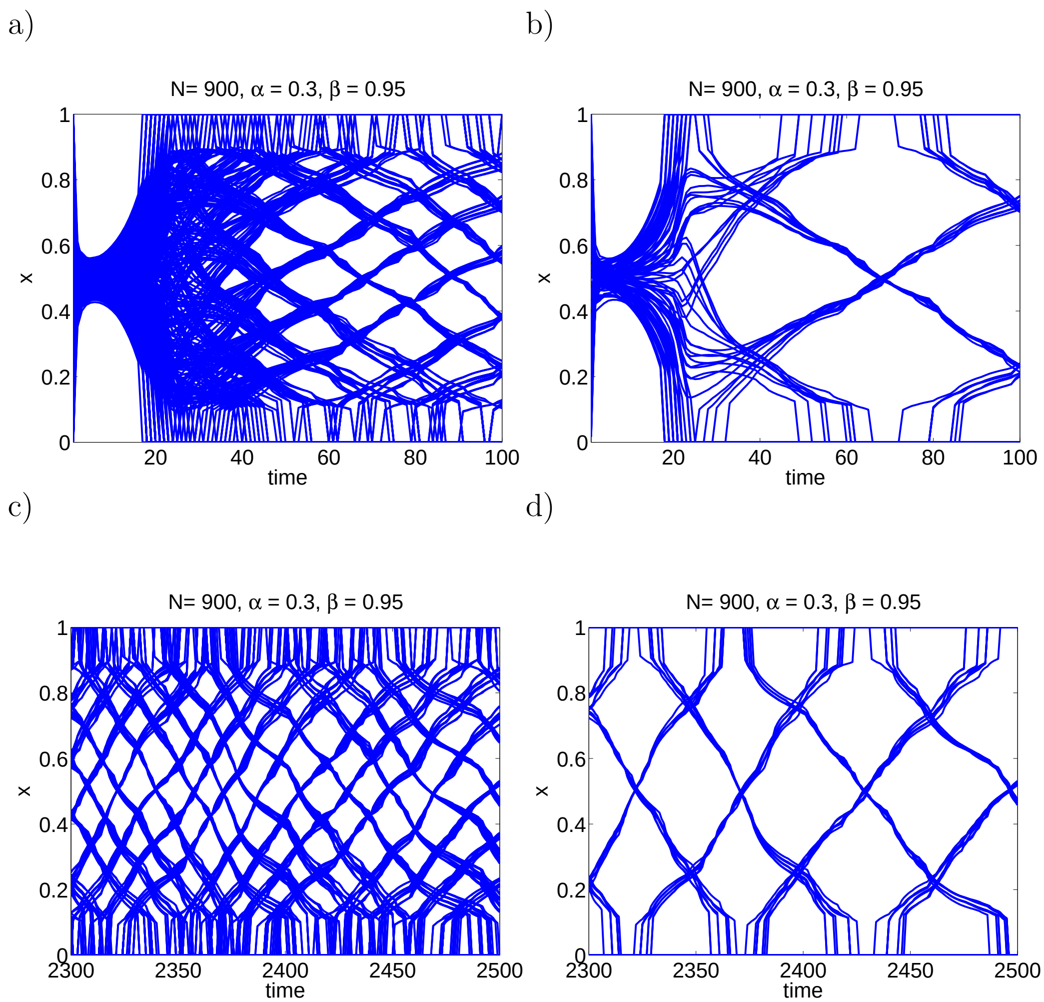


Figure 12: Simulation Results — two–dimensional regular lattice

red for instance in figures 13a) and c) is not the same. However, the colour bars indicate the level of diversity at each time step under consideration. Figure 13 a) illustrates the dynamics during the transient phase. Starting with a maximum diversity at $t = 1$ the agents form up groups characterised by similar behaviour while they converge toward the center. These groups become even more pronounced in the following when the agents leave the center and diverge toward the interval ends. Since the deviation within in–groups is small the agents only experience a small disutility for deviation while they move outwards.

In figure 14 we see that the shape of groups with similar behaviour changes to horizontal bars. Thus, although the simulation is run on a two–dimensional lattice the dynamics actually only varies along one dimension. However, depending on the initial random distribution the groups sometimes evolve into horizontal bars and sometimes into vertical ones.

Figure 15 displays the behavioural dynamics from $t = 500$ to $t = 1090$. Although the previously observed horizontal bars remain the system is not in an equilibrium and the bars slowly move upwards. After the initial transient phase every state of the system is exactly replicated after 590 iterations. This period length is insensitive to different initial distributions.

Figure 16 again sketches the actual distribution of norms from time $t = 1$ to $t = 150$. The series of graphs clearly indicates convergence toward a global consensus during the transient phase followed by a gradual divergence toward two big clusters at the interval ends and several smaller clusters in between containing those agents moving between the interval ends.

4 Summary

We study the emergence, stability and replacement of social norms to allow for a better understanding of the self–organised development of cooperation in human societies. We deploy a numerical simulation model incorporating persistence, i.e. the individuals' reluctance to alter their behaviour, solidarity, the desire to be associated with a certain group (the in–group), and the desire to differ from some individuals belonging to the out–group. These three components constitute the agents' utility function to be maximised. Within this framework the network topology is crucial for the agents propensity to adhere or deviate from a social norm. While some literature on social norms suggest that norm enforcement is driven by nonselfish motives (e.g. Fehr and Fischbacher, 2004b) we consider profit maximising agents but explicitely define a disutility obtained from deviations within the in–group. Thus, instead of inserting a metanorm like Axelrod (1986), the agents in our model are

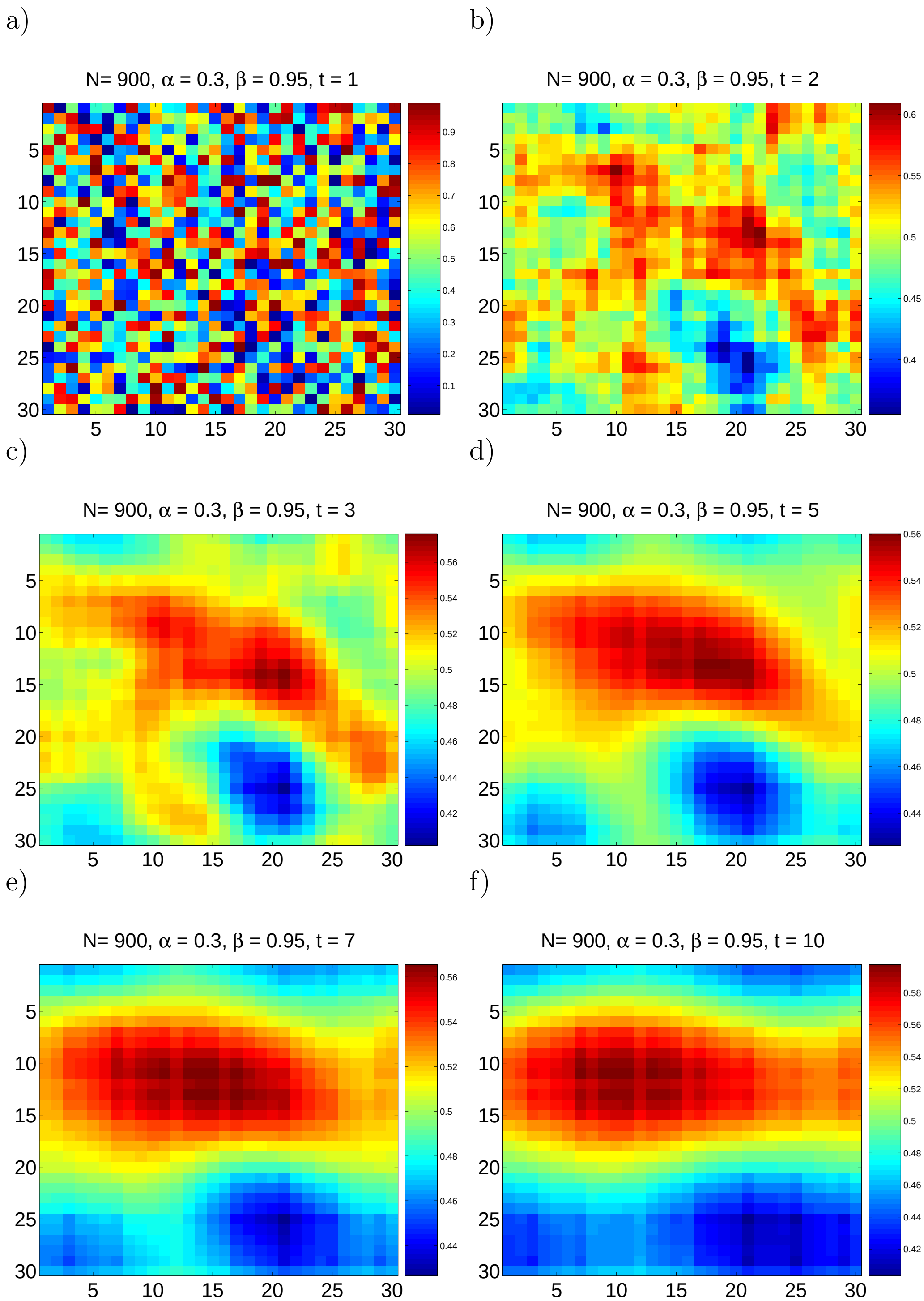


Figure 13: Simulation Results — two–dimensional regular lattice

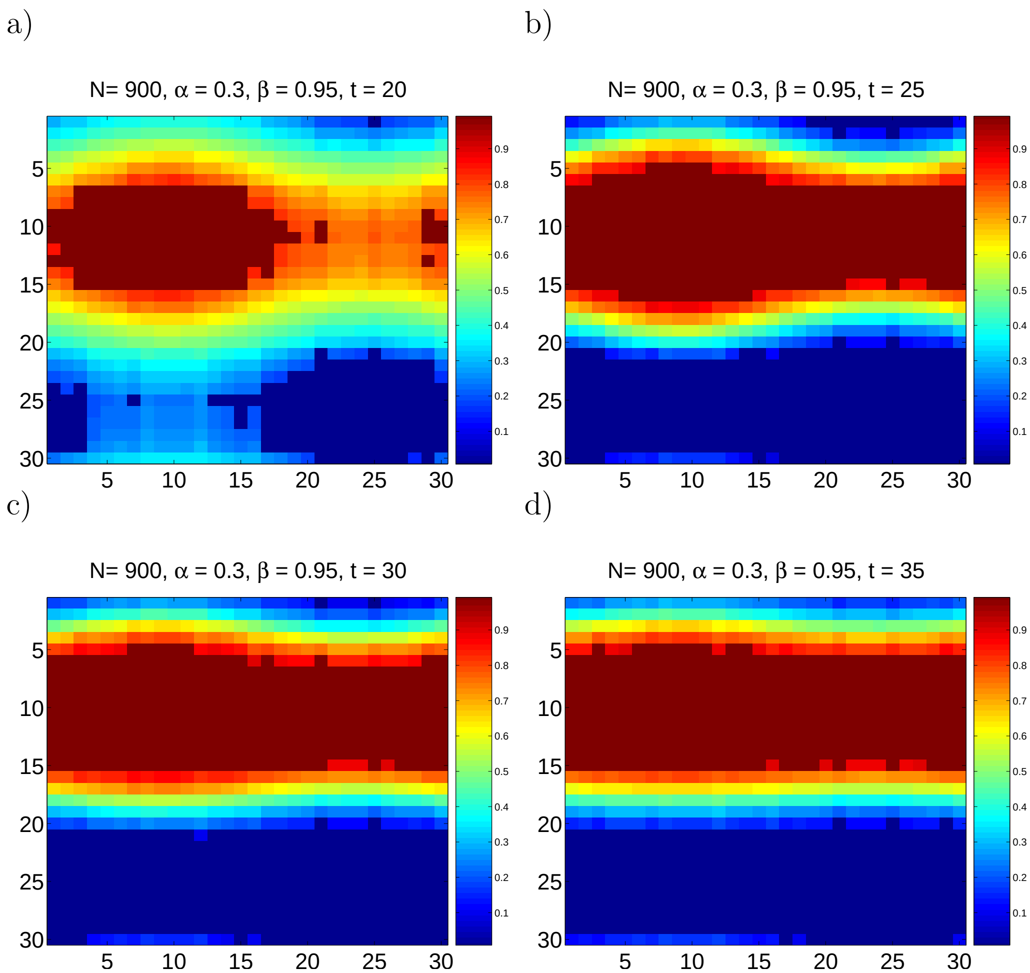
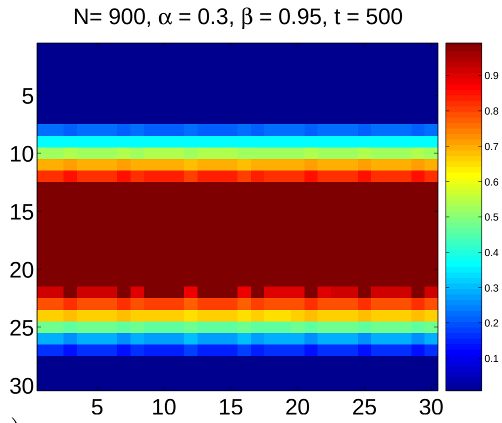
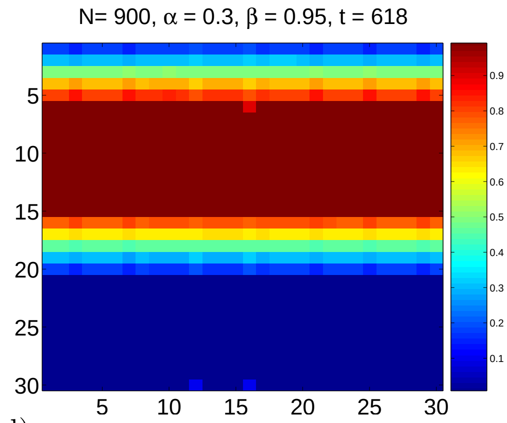


Figure 14: Simulation Results — two–dimensional regular lattice

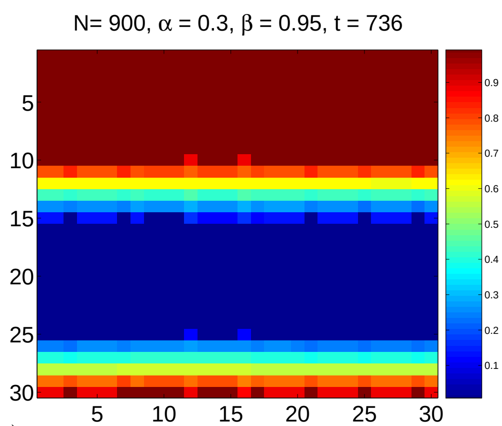
a)



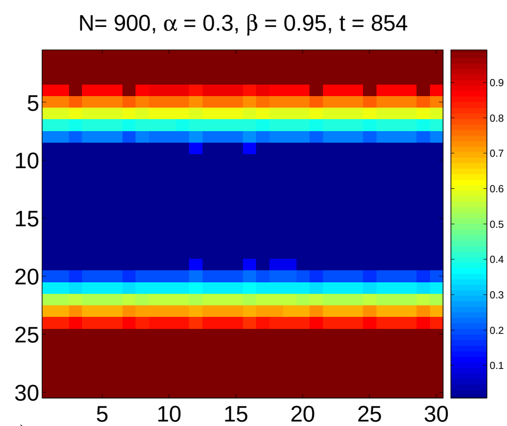
b)



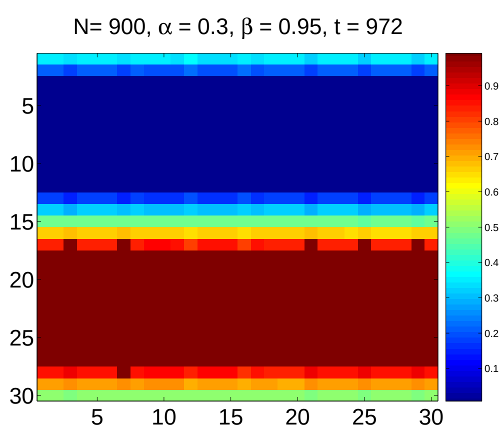
c)



d)



c)



d)

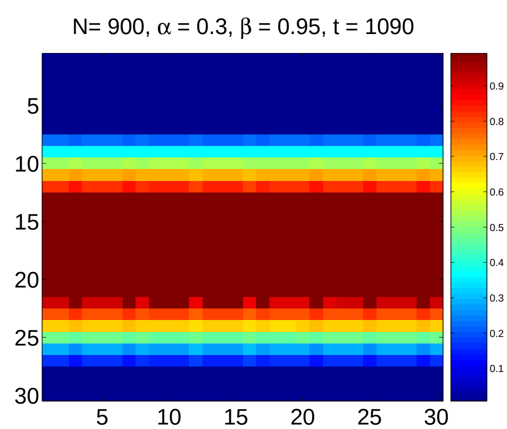


Figure 15: Simulation Results — two–dimensional regular lattice

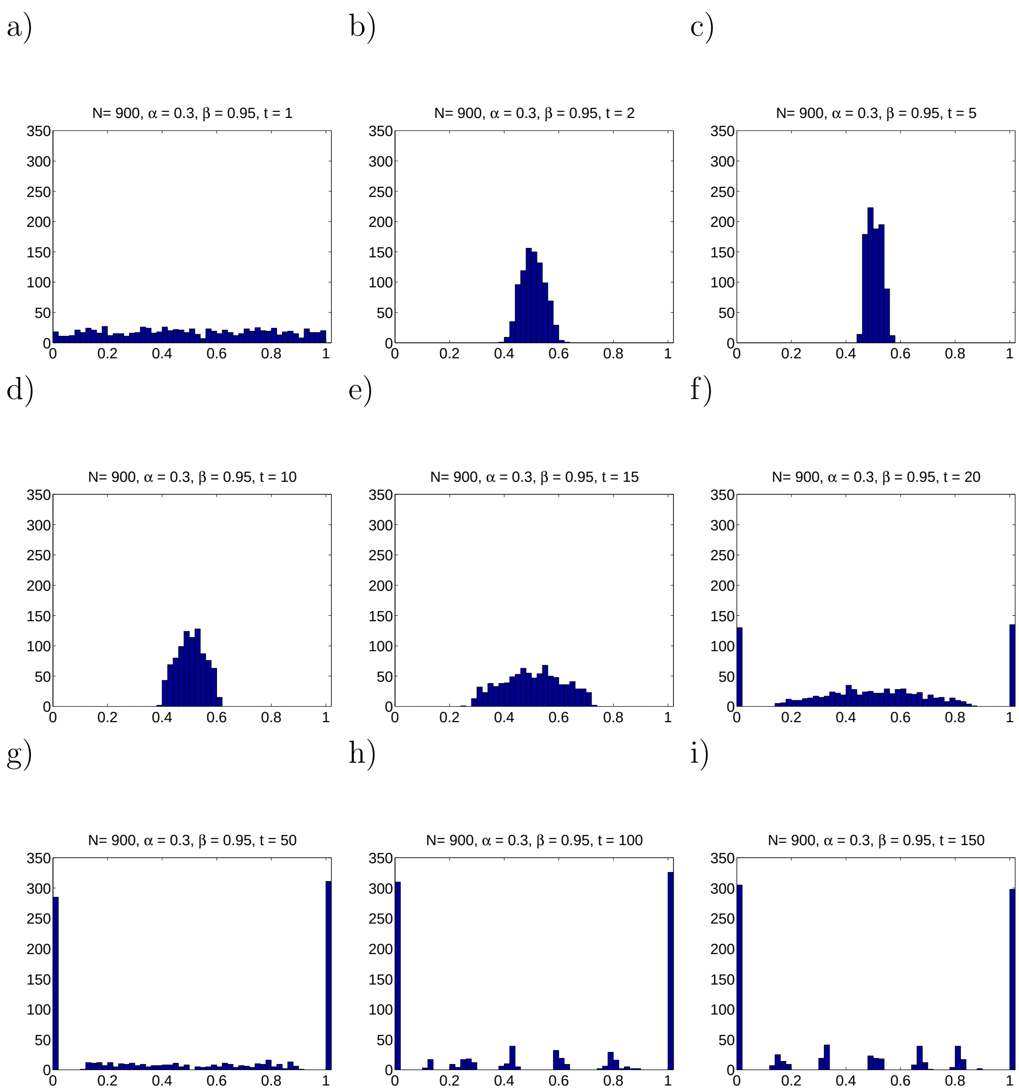


Figure 16: Distribution of norms — two–dimensional regular lattice

just assumed to experience a disutility from deviation or bear the costs of imposing a sanction, respectively.

We carry out numerical simulations with $N = 200$ agents arranged on a one–dimensional regular lattice and with $N = 900$ agents arranged on a two–dimensional regular lattice and make use of periodic boundary conditions in both cases. In those parameter settings where the desire to deviate from the out–group outweighs the desire to agree to the in–group, the time development of the agents' behaviour exhibits coexistence of several local norms but is rather erratic which means that agents change their behaviour significantly from one period to another. Since this seems not to be realistic in the context of modelling social norms those sets of numerical parameters where solidarity is stronger are more interesting. In that case the system is capable to arrive in a state of global consensus due to the force of attraction. This consensus is not stable in the long–run but is replaced by a regime where groups of agents persist at one end of the behaviour spave for a certain time, then they move at moderate speed through the whole space, and finally, persist at the other end of the space, before they again conduct a tour to the other end. Moreover, after the transient phase not only the movements of individual agents exhibit periodic dynamics but also each state of the system as a whole, i.e. the set of actions of the whole population, is repeated with a constant period length. This period length depends on the numerical parameters and the network topology but not on the random intialisation. These results possess some similarities with those obtained by (Weidlich and Brenner, 1995; Brenner et al., 2002) in the context of fashion cycles but the underlying mechanism is different.

The model under consideration is appropriate to explain the emergence of temporary social norms prevalent in certain subgroups of the society. Moreover, it motivates what may be the reason for the adjustment of existing norms in the course of time. The underlying mechanisms are persistence, solidarity, differentiation, and an exogenously given connectivity. Since in reality an individuals social network is not static, a promising advancement of this model would be to investigate the validity of our results in case of a network topoloty which changes endogenously.

Acknowledgements

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