



# Moderate tolerance promotes tag-mediated cooperation in spatial Prisoner's dilemma game



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## HIGHLIGHTS

- Propose an evolutionary prisoner's dilemma game model to study the relation between tag-mediated selective interaction and cooperation.
- Cooperation can be significantly promoted if the tolerance level is moderate.
- High levels of cooperation stem from high cluster heterogeneity and cluster boundaries.
- Cluster heterogeneity can be dynamically generated in the system if the tolerance level and identity mutability are both moderate.

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## ABSTRACT

Humans often behave discriminatorily towards others depending on their group membership. In this work, we establish a spatial Prisoner's dilemma model to investigate the relation between tag-mediated discrimination and cooperation. By introducing tag-mediated selective interaction, we find that if tag length is sufficiently large and individuals have moderate tolerance, cooperation can be promoted. Interestingly, both too high or too low tolerance may inhibit the emergence and maintenance of cooperation, which means that individuals may benefit from moderate tolerance in society. It is also shown that the high levels of cooperation stem from the high heterogeneity and clear boundaries between clusters. Our work should be helpful to understand both the evolution of human cooperation and the science of social identity.

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## 1. Introduction

Human cooperation and its evolution is a challenging problem both in natural science and in social science [1–3]. In a competitive world, the cooperative individuals will reduce their relative fitness because cooperative behavior will provide some benefits to others but impose costs upon the actor. If there are no specific mechanisms in effect, the process of evolution always favors the defectors since cooperators are vulnerable to exploitation by defectors. The evolutionary puzzle of why the large-scale cooperation can emerge and be maintained in human society is attracting widespread interest in many fields such as anthropology [4], biology [5], physics [6], economics [7] and computer science [8]. The paradigm of evolutionary Prisoner's dilemma game (PDG), which could serve as a communication tool to bridge the chasm between various fields, has been proposed to solve this puzzle. In a PDG, two players simultaneously choose between cooperation and defection. Although mutual cooperation leads to the unique Pareto optimal outcome, defection is always a better choice for an individual irrespective of the other's choice. This means that in a well-mixed population where no mechanisms are at work to specify how individuals interact with others or how they compete under natural selection, cooperators cannot prevail.

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In the previous work, in order to investigate how cooperation can be favored over defection in evolutionary PDG, five major mechanisms have been proposed, including kin selection [9], direct reciprocity [10], indirect reciprocity [11], spatial selection [12] and multilevel selection [13]. Generally speaking, these mechanisms may specify how individuals interact with others and how they reproduce under competition [2,3]. The central focus in the investigations of mechanisms is the problem of how assortment among individuals, whereby cooperators can interact more frequently with other cooperators but not defectors, can emerge in the process of evolution [14]. In recent years, a growing body of research has established that cooperation can be significantly promoted under a wide variety of conditions through the interaction structures affected by perceivable, phenotypic tags of individuals [15–21]. As a remarkable example, Riolo et al. [16] showed that even if there is no mechanism of reciprocity or memory, high level cooperation can be attained and maintained. Moreover, the emergence of tag clusters, i.e. the spontaneous group or community formation, can be observed in the simulations of their model. The individuals only cooperate with the members of their own group (on the basis of tag similarity). Although the cooperative clusters are vulnerable when facing the defectors whose tags are similar to those of the cooperators, cooperation can be sustained by newly established tag clusters. Though there are some limitations, Riolo et al.'s work has attracted much attention and generated considerable recent research interest. Some important perspectives of tag-mediated cooperation were investigated and need further discussion, for example, whether the representation of tags (continuous or discrete) can affect the tag mechanism [18,19], whether the use of multiple mechanisms such as the combination of tag mechanism and memory can be more effective for supporting cooperation [22], or how the tag mechanism changes the patterns of spatial segregation in spatial PDG [21,23].

The above studies have revealed the importance of tag mechanism in the emergence and maintenance of cooperation. On the other hand, perceivable tags per se play a significant role in human society, which is why social scientists regard them as an appealing research subject. Some experimental studies in psychology have shown that even originally meaningless distinctions can serve as a clue of group membership and lead to in-group bias or even group conflicts [24–26]; young babies prefer faces of their own race and the language that they have been exposed to Refs. [27,28]. As a famous example in political science, it is generally accepted that high levels of ethnic diversity undermine public goods provision, and numerous mechanisms have been proposed to explain this phenomenon [29,30]. Furthermore, the existence of culture allows humans to have many different types of tags in the forms of language, etiquette, taboo, religion, hairstyle, or ethnicity. Both genetic and cultural tags (often called “identity” in social science) play an important role in the real world. Humans exhibit large-scale cooperation, but the cooperation is often biased towards similar people. Moreover, as tag-based models and some cultural evolution models [31–34] suggested, similarity based interaction can serve as a means of spontaneous community formation. The resulting network structures raise the question of how to analyze and detect communities in these systems [35–40].

The present work will illustrate the relation between tolerance level and cooperation in a tag-mediated selective interaction based evolutionary PDG model. In the conventional selective interaction approach of tag-based models, each individual either interacts with others who have exactly the same tag [18,19], or has a presumed tolerance level to decide how similar the individual and its possible partners are, then stochastically interacts with these partners [15]. To what extent individuals have their tolerance, i.e. how many other individuals will they regard as friends and interact with, is fixed so the relation between tolerance level and cooperation remains unclear in the previous models. Our work relaxes the assumption that individuals only have one possible tolerance level by introducing an exogenous parameter to determine how the individuals treat others with discrimination. If individuals have low tolerance level, they will more frequently avoid interactions with others by regarding more people as out-group members. By changing the tolerance level, we will examine the influence of tolerance, namely the extent that individuals discriminately treat others, on the evolution of cooperation. The present work also relates to the interaction intensity approach of spatial PDG which indicates a best region of interaction intensity for supporting the evolution of cooperation [41,42]. However, in contrast to this interaction stochasticity approach, the occurrence of interactions between individuals is totally deterministic in our model. Nevertheless, an inspection of interaction intensity generated by the tag mechanism may provide a better understanding of our model.

## 2. Method

In order to investigate the role of tolerance in tag-mediated cooperation, we consider a spatial PDG in which space is represented by a  $50 \times 50$  square lattice with periodic boundaries. Our model consists of following parts:

### 2.1. The initialization

Each individual  $i$  is located on one site of the lattice and engages in possible interactions with its Moore neighbors. Each individual has both a tag trait  $t_i$  and a strategy trait  $s_i$ . The tag trait  $t_i$  is represented by a bit sequence of length  $L$  in which each bit has value 0 or 1 ( $t_i \in \{0, 1\}^L$ ). The value of strategy trait  $s_i$  is either  $C$  (Cooperate) or  $D$  (Defect). Initially, both tag and strategy traits are assigned with equivalent probability from the uniform distribution.

### 2.2. The interaction based on dissimilarity perception

Each individual  $i$  decides the group membership of its neighbors by means of dissimilarity perception. The dissimilarity between two individuals is determined by the Hamming distance ( $HD$ ) of their tag bits [43]. If this Hamming distance is

less than a presumed tolerance level  $T$  (i.e. if  $HD_{ij} < T$ ), the neighbor under consideration will be accepted as an in-group member and be allowed to interact with the focal individual. For example, if the Hamming distance between  $i$  and  $j$  is 0 (so  $i$  and  $j$  have the same tag) and tolerance level  $T$  is 1, since  $HD_{ij} < T$  in this case,  $i$  and  $j$  will interact with each other. Based on this assumption and the fact that  $HD_{ij}$  ranges from 0 to  $L$ ,  $T$  can vary from 1 (lowest tolerance) to  $L+1$  (no distinction, because the maximum possible Hamming distance is  $L$ ) as a parameter. In each Monte Carlo step, each pair of interacting individuals will play a PDG and collect their payoffs. Following common practice in tag-based models [16,44,45], cooperative individuals will confer a payoff benefit  $b > 0$  to their partners at a cost of  $c > 0$ , while defectors pay no costs but may benefit from others who cooperate. For example, if one cooperates and the other defects, the defector gets  $b$  and the cooperator loses  $c$ . The resulting game is given by the following payoff matrix:

$$\begin{array}{c} c \\ D \end{array} \begin{array}{cc} c & D \\ \left( \begin{array}{cc} b-c & -c \\ b & 0 \end{array} \right) \end{array}.$$

So long as the benefit-to-cost ratio  $b/c > 1$ , the payoff matrix satisfies the conditions for the PDG. Given the payoff structure, if no additional mechanisms are at work, the dominant strategy for each individual is to defect regardless of what its partner does. Without loss of generality, the value of  $c$  is fixed at 1 in our model so we can study the game as a function of a single benefit-to-cost parameter  $b/c$ .

### 2.3. The updating

For each individual  $i$ , if the richest neighbor's payoff is larger than that of the focal individual, the focal individual copies both the richest neighbor's tag and strategy, otherwise the focal individual's traits remain unchanged. In our model, this updating process is in an asynchronous fashion [46].

### 2.4. The mutation

The two traits of each individual both have a chance to mutate. For the tag trait  $t_i$ , each bit in the tag sequence has a chance to flip to another value (0 to 1, or 1 to 0) with probability  $\mu_t$ . For the strategy trait  $s_i$ , it has a chance to be altered to the opposite strategy (C to D, or D to C) with probability  $\mu_s$ . Thus the population is in a noise environment [47].

The following pseudocode describes the simulation procedure of our model:

```

Initialize
For each Monte Carlo step:
  For each individual:
    Interacts with Moore neighbors on the basis of dissimilarity perception
    and collects payoffs
  End
  For each individual:
    Learns asynchronously by the richest following rule
  End
  For each individual:
    mutates
  End
End

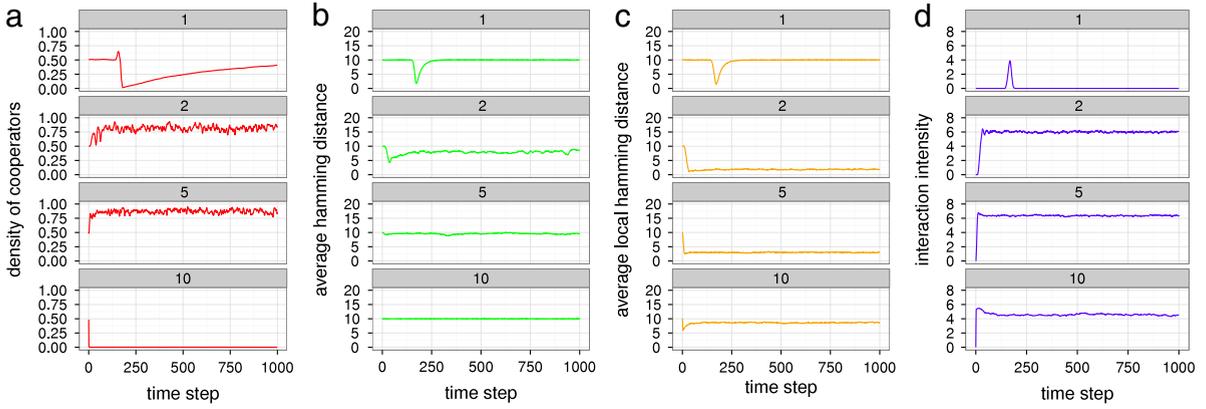
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## 3. Results

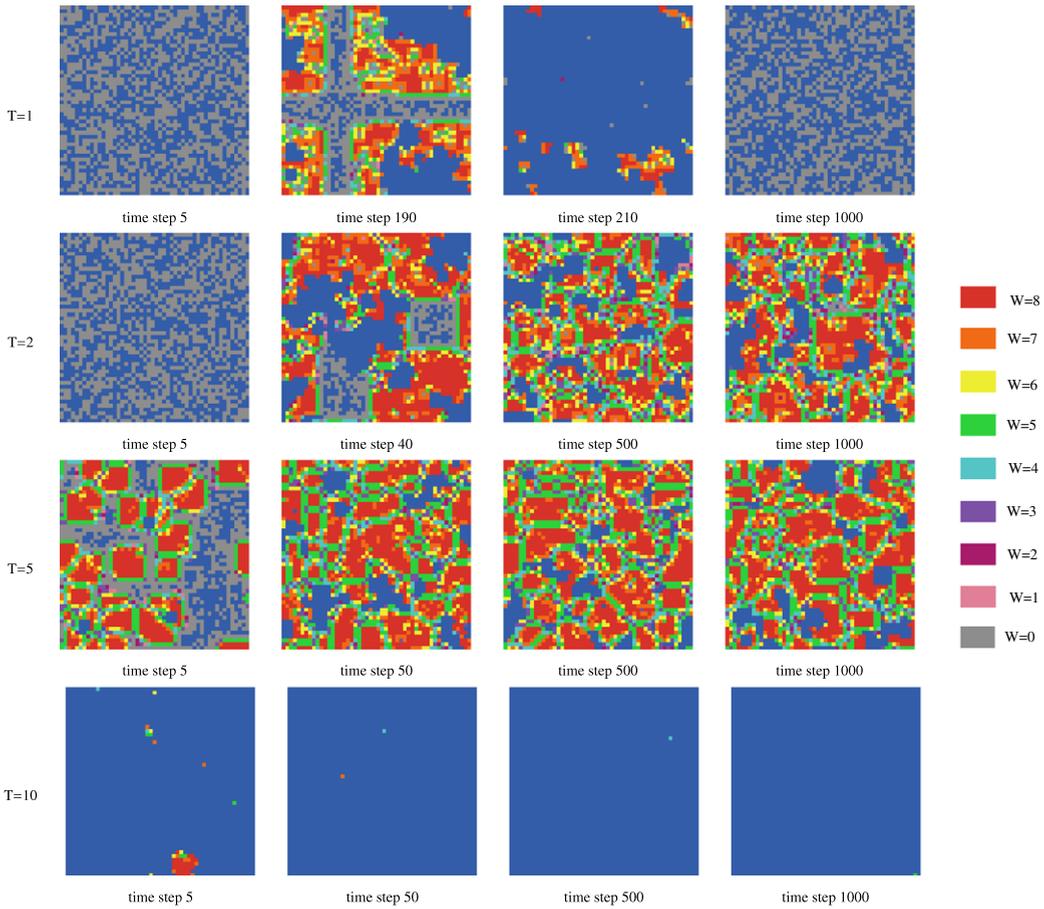
In this section, we will show the results of the above simulation model. The most important quantities for characterizing the system include the following: the density of cooperators,  $f_c$ , which is defined as the fraction of cooperators in the population; global tag heterogeneity,  $h_g$ , which is defined as the average Hamming distance between all individuals; local tag heterogeneity,  $h_l$ , which is defined as the average Hamming distance between direct neighbors; and the interaction intensity of individuals,  $w$ , which is defined as the number of times the focal individual interacts and plays the PDG with its neighbors. We consider both the average interaction intensity,  $\bar{w}$ , and the distribution of  $w$ . Note that in a population with tag heterogeneity, the average interaction intensity may not provide sufficient information about the status of interactions.

### 3.1. The analysis of evolutionary dynamics and spatial patterns

First, we examine the evolutionary dynamics and spatial patterns in some typical simulation runs and find out what can happen under different conditions in the tag-based model.



**Fig. 1.** The evolutionary dynamics of  $f_c$ ,  $h_g$ ,  $h_l$  and  $\bar{w}$  for different values of  $T$  (1, 2, 5, and 10) when  $L = 20$ . Other parameters:  $b/c = 2.0$ ,  $\mu_s = 0.001$ ,  $\mu_t = 0.01$ . (a) Density of cooperators as a function of time step. (b) Global tag heterogeneity  $h_g$  as functions of time step. (c) Local tag heterogeneity  $h_l$  as functions of time step. (d) Average interaction intensity  $\bar{w}$  as a function of time step.



**Fig. 2.** Some typical snapshots for different values of  $T$  (1, 2, 5, and 10). Cooperators are represented by patches with different colors as shown in the legend. Defectors are represented by blue patches. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Figs. 1 and 2 shows the evolutionary process and spatial patterns under different tolerance  $T$  when  $L = 20$ :

If  $T = 1$ , each individual only interacts with its neighbors who have exactly the same tag. It is shown that after some tranquil periods,  $f_c$  suddenly begins to increase slightly, but soon decreases to a very low level near 0. In the meanwhile, both  $h_g$  and  $h_l$  decline to a very low level, but soon they bounce back to the initial levels together. While  $f_c$  is in its takeoff phase,  $w$  also increases, but soon declines to nearly 0. The quick decline of both  $h_l$  and  $h_g$  reflects the fact that a single tag

cluster quickly expands in the whole population, which can also be confirmed by the increase of  $w$ . As shown in the spatial snapshots (first row of Fig. 2), a cooperative cluster emerges and quickly spreads in the population, but it is soon undermined by the mutant defectors within the cluster itself. Once the speed of invasion is sufficiently higher than that of spread of the single cooperative cluster, cooperation cannot be maintained at high level. The reason defectors can successfully invade into the whole population is that the single cluster is full of individuals who have identical or similar tags and therefore the cooperative individuals cannot resist interacting with mutant defectors. Owing to the exploitation by defectors, the cooperators reduce their fitness and then the in-cluster cooperation is soon undermined.

When  $T = 2$ , we see that a significant level of cooperation can be established and maintained. After some tranquil periods,  $f_c$  first exhibits a short term takeoff, then decreases to a moderate level. However, this decrease is much smaller than in the  $T = 1$  case. After a short period of decrease,  $f_c$  quickly bounces to a high level and leads the system into a dynamical equilibrium.  $w$  also exhibits a sharp decrease after its takeoff, but soon it reaches a high level and remains stable. Both  $h_g$  and  $h_l$  decrease while  $f_c$  increases for the first time. However, after the decrease periods,  $h_g$  and  $h_l$  show different dynamics. Though they begin to increase at almost the same time, while  $h_l$  quickly reaches its stable states at a low level,  $h_g$  gradually increases over time and finally reaches a relatively higher level. The disparity between  $h_l$  and  $h_g$  indicates that there are some clusters with high heterogeneity, meaning that individuals in different clusters will have relatively dissimilar tags. The greater this disparity is, the more dissimilar these clusters are. If the clusters have greater heterogeneity, individuals can constantly interact with similar others and avoid interactions with dissimilar others when they are at a boundary between different clusters. The spatial snapshots provide more information about why cooperators could proliferate. As in the  $T = 1$  case, we see a cooperative cluster emerges and quickly spreads as well. However, the impact of invasion of defectors is severely limited in this case because the boundaries between new formed clusters can prevent defectors from invading surrounding clusters. The individuals at the boundaries choose to only interact with similar others thus protect their own clusters from exploitation by the defectors. Remarkably, after the temporary increase of defectors, the whole population is filled with a number of different clusters based on tags, which can be illuminated by the clear boundaries shown in the snapshots.

In the  $T = 5$  case, we see that cooperation can be established and maintained very soon after initialization and finally the system reaches its dynamical equilibrium.  $h_g$  and  $h_l$  exhibit different dynamics in this case. It is shown that  $h_l$  decreases to a low level very soon while  $h_g$  is always in its initial states. From the spatial snapshots, we can find that the initial takeoff of  $f_c$  stems from the simultaneous spread of multiple clusters rather than that of a single cluster in the  $T = 1$  and  $T = 2$  cases. This means that the established clusters have remarkable heterogeneity to avoid interactions between different clusters. As a result,  $f_c$  no longer exhibits any significant decrease after its takeoff because the cluster heterogeneity can effectively help the population to resist the invasion of defectors. Cluster heterogeneity provides clear cluster boundaries so that the impact of invasion is restricted to the clusters which the defectors originally belong to. Defectors cannot spread through the whole population due to the fact that they cannot interact with dissimilar others and hence be replaced by surrounding cooperators.

In the  $T = 10$  case, even individuals with very dissimilar tags will interact with each other. After initialization,  $f_c$  soon decreases to nearly 0 and reaches an equilibrium. As the snapshots show, although a small number of cooperative clusters can emerge, they vanish soon in an environment full of defectors. We can explain this phenomenon by inspecting the dynamics of  $h_g$  and  $h_l$ .  $h_g$  is always in its initial states, while  $h_l$  exhibits some decrease in the beginning, which indicates that some clusters have been successfully established. However, the disparity between  $h_l$  and  $h_g$  decreases over time so that the clusters do not have enough heterogeneity to effectively resist the invasion of defectors. This is because the mutant defectors always have a chance to spread through the whole population in a relatively homogeneous environment. Even though cooperative clusters can exist for a while, they will soon be eliminated under the pressures of selection and mutation.

Fig. 3 shows the typical distributions of  $w$  in the simulation runs described above. We find that if cooperation can be established and maintained (the  $T = 2$  and  $T = 5$  cases),  $w$  has two typical values: 5 and 8. This phenomenon is not surprising if we notice that when there are clear boundaries between clusters, most of the individuals who are at the boundaries have exactly 5 own cluster neighbors. We can regard the individuals who have exactly 5 interacting neighbors as a typical type of boundary individuals. Note that the distribution of  $w$  may lead to a socially efficient outcome in the sense that the boundary individuals need not forgo any benefit from interacting with their own cluster members and the inner members of clusters can receive their maximum possible benefits of cooperation.

For a better understanding of why cluster heterogeneity can serve as a means of resisting the invasion of defectors, we also plot some typical snapshots of consecutive time steps so that we can have a detailed inspection of spatial dynamics. As Fig. 4 shows, some defectors successfully invade into a cooperative cluster, but they soon disappear to be replaced by surrounding cooperators from other clusters. Owing to the dissimilarity between tags, the detrimental interactions carried out by defectors are limited to a very small range within their own clusters (the defectors cannot expand their territory across the boundaries). Therefore, the defectors will be eliminated and replaced by surrounding cooperators due to their low fitness (the territory of defective clusters is gradually reduced by boundary cooperators).

### 3.2. Sensitivity analysis

In the above analysis of evolutionary dynamics and spatial patterns, we have seen that when  $L = 20$ , both too low (the  $T = 1$  case) and too high (the  $T = 10$  case) tolerance levels cannot support high levels of cooperation. The evolutionary success of cooperation can be mostly favored if the tolerance level  $T$  is moderate (the  $T = 2$  and  $T = 5$  cases). Furthermore, we find that the cluster heterogeneity generated by the system may explain why cooperation can be established and

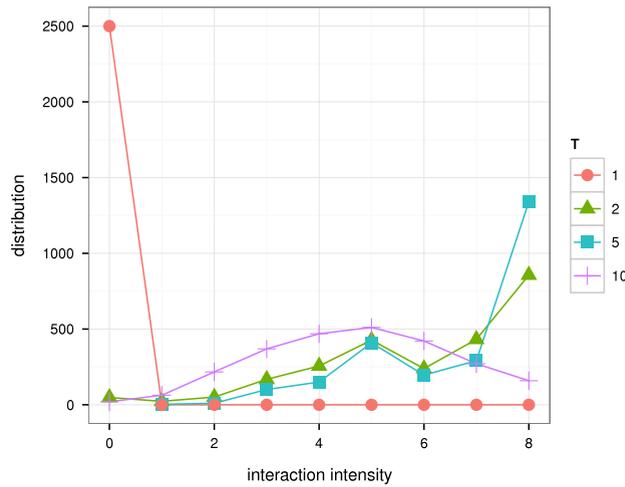


Fig. 3. The distribution of  $w$ . Parameters:  $L = 20, b/c = 2.0, \mu_s = 0.001, \mu_t = 0.01$ .

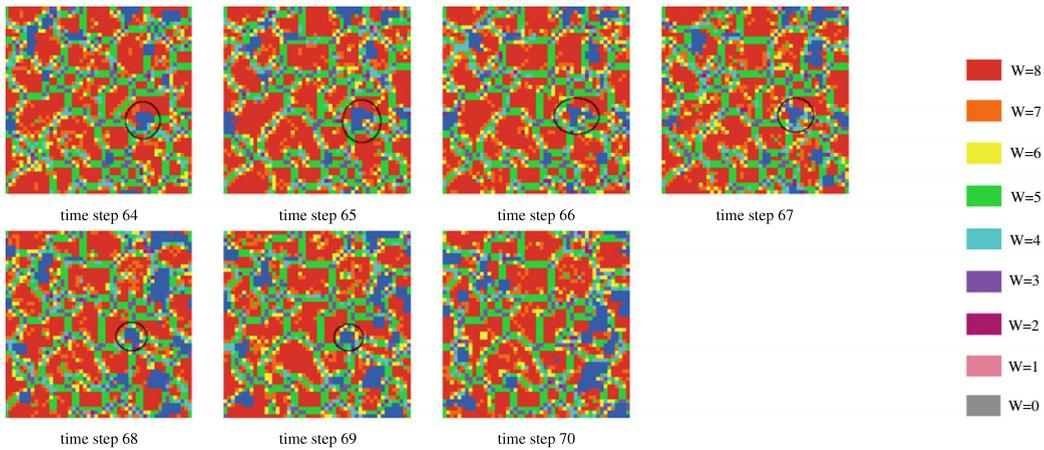
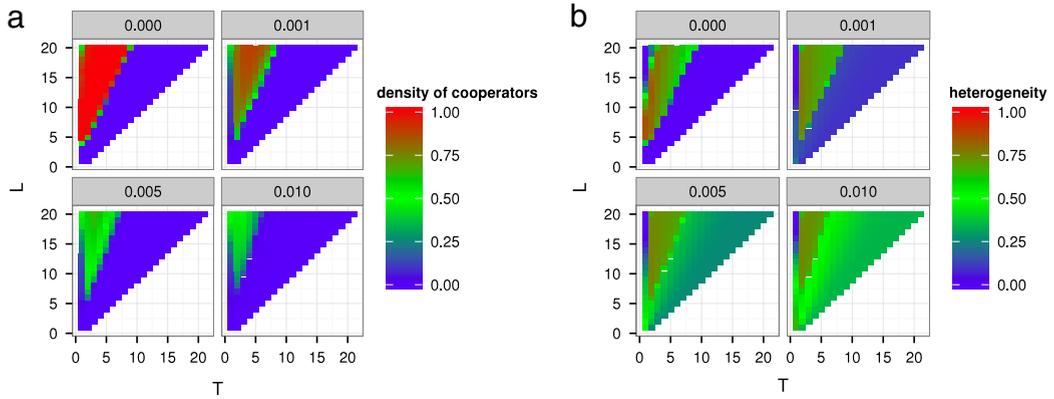


Fig. 4. Some typical snapshots of consecutive time steps (time step 64–70). The black circle in each snapshot denotes invading defectors in a typical cluster. Parameters:  $T = 5, L = 20, b/c = 2.0, \mu_s = 0.001, \mu_t = 0.01$ .

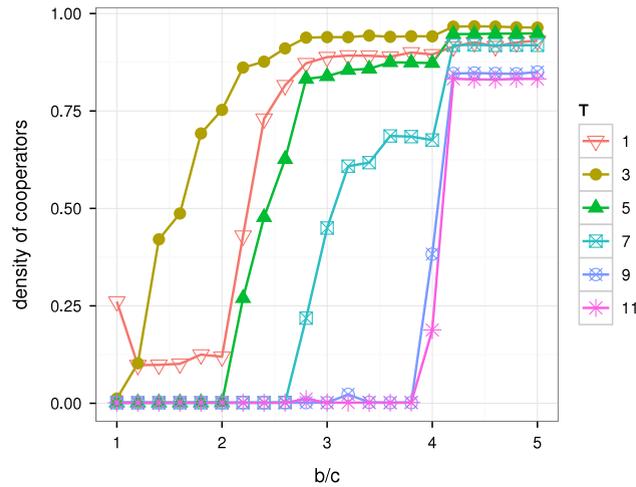
maintained under moderate tolerance levels. In what follows, to further understand these observations, we use sensitivity analysis to find the conditions under which cooperation can be promoted and investigate the effect of the key parameters on the evolution of cooperation. Fig. 5 shows the evolution of cooperation by tuning  $L$  (ranging from 1 to 20) and  $T$  (ranging from 1 to  $L + 1$ ). First, in Fig. 5(a), we note that cooperation can be promoted only if the tag length  $L$  is sufficiently large (for example, for  $\mu_s = 0.001, L$  must be greater than 4). This observation is consistent with some previous studies which argued that tag multiplicity can effectively promote cooperation [8,19,48]. In addition, we find that there are significant differences between environments with and without noise. For  $\mu_s = 0$ , the effects of  $L$  and  $T$  are more dramatic than those in the  $\mu_s \neq 0$  cases. Cooperators will become extinct if  $L$  is too small, but as it exceeds a certain value, cooperation can be established to a very high level. In contrast with the dramatic effect of changing  $L$  in the  $\mu_s = 0$  case,  $f_c$  only increases gradually as  $L$  increases in the  $\mu_s \neq 0$  cases.

The most surprising observation is that when  $\mu_s \neq 0$  and  $L$  is sufficiently large, cooperation can be promoted most effectively if  $T$  is moderate for any given  $L$ . For example, when  $L = 15$ , as the value of  $T$  is increased from 1 to 4,  $f_c$  increases to a high level. However, as  $T$  continues to be increased to higher values,  $f_c$  decreases gradually and eventually the cooperators cannot exist in the systems. This result suggests that if individuals' tolerance is moderate, cooperation can be established and maintained. In other words, neither too high nor too low tolerance level can effectively support cooperation especially in a noise environment.

Fig. 5(b) shows the cluster heterogeneity as a function of  $L$  and  $T$ . We see that the effect of  $T$  on cluster heterogeneity is also not monotonic, and this effect is very similar to that of  $T$  on  $f_c$ . In fact, the regions of high cluster heterogeneity are almost the same as those of high  $f_c$ . This result is not surprising if we remember that in the analysis of evolutionary dynamics we have already shown the relation between cluster heterogeneity and the establishment and maintenance of cooperation. The proposition that cluster heterogeneity may serve as a means of promoting cooperation is further confirmed here by sensitivity analysis.



**Fig. 5.** (a) Density of cooperators  $f_c$  as a function of  $L$  and  $T$  for different values of  $\mu_s$  (shown in the gray rectangles). (b) Cluster heterogeneity, defined as  $1 - h_l/h_g$ , as a function of  $L$  and  $T$  for different values of  $\mu_s$ . Other parameters:  $b/c = 2.0$ ,  $\mu_t = 0.01$ . As in all following figures, results were averaged from 40 independent runs for each set of parameter values.

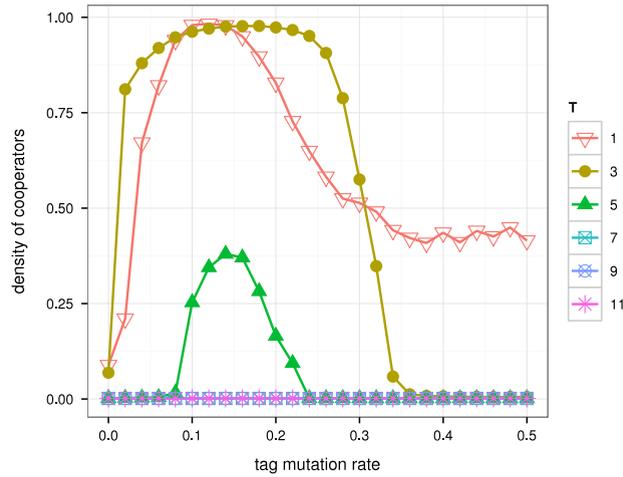


**Fig. 6.** Density of cooperators  $f_c$  as a function of benefit-to-cost ratio  $b/c$  for different tolerance levels  $T$ . Other parameters:  $L = 10$ ,  $\mu_s = 0.001$ ,  $\mu_t = 0.01$ .

Lastly, we would like to investigate how benefit-to-cost ratio  $b/c$  and tag mutation rate  $\mu_t$  affect the evolution of cooperation with tag mechanism. Fig. 6 shows that the effect of  $b/c$  on  $f_c$  exhibits different patterns for different tolerance levels. When  $T$  is too small or too large, as the value of  $b/c$  is increased, there are two regions in which the increase of  $b/c$  will dramatically affect  $f_c$ . In these cases, even a slight change of  $b/c$  may lead to a significant change of  $f_c$ . The most important information shown in Fig. 6 is that when the value of  $T$  is moderate, the evolution of cooperation is most robust in the sense that the region of  $b/c$  resulting in high levels of cooperation is large and the change of  $b/c$  does not affect  $f_c$  too dramatically, which is another benefit of moderate tolerance for promoting cooperation. Fig. 7 shows how  $\mu_t$  affects  $f_c$ . We see that the region of  $\mu_t$  resulting in high levels of cooperation is larger when tolerance level is moderate, which is again a benefit of moderate tolerance for promoting cooperation. Note that the change of  $\mu_t$  also exhibits a non-monotonic effect on  $f_c$ . In order to understand this, we return the proposition that cooperation can be effectively promoted if there is enough cluster heterogeneity. When  $\mu_t$  is very small, tag mutations rarely happen so that new tag clusters cannot be easily formed under the pressure of invasion, which is an observation consistent with some previous studies such as Ref [18]. However, too large  $\mu_t$  also inhibits cooperation in our model, but the reason is different from that in the small  $\mu_t$  cases. If tags are very unstable through mutations, clusters will be undermined soon even though they can be formed. In this situation, cluster heterogeneity can hardly be established and serves as a means of promoting cooperation.

#### 4. Conclusion

In this paper, we established an evolutionary model which consists of tag, tag-based selective interaction and spatial PDG to investigate how tolerance affects the evolution of cooperation. The simulation results of this model show that when individuals have enough tag length and moderate tolerance thus only interact with those who are similar to themselves, a high level of cooperation can be supported, and these results are robust with respect to different values of identity mutability



**Fig. 7.** Density of cooperators  $f_c$  as a function of  $\mu_t$  for different tolerance levels  $T$ . Other parameters:  $L = 10$ ,  $\mu_s = 0.001$ ,  $b/c = 2.0$ .

( $\mu_t$ ) and benefit-to-cost ratio ( $b/c$ ). In the microscope analysis of evolutionary dynamics and spatial patterns, we found that if some tag-based cooperative clusters can be formed in the population, a high level of cooperation can be promoted and maintained due to the cluster heterogeneity and clear boundaries between clusters. Otherwise, when the interaction intensity is too low owing to the low tolerance level (for example, when  $T = 1$ ), cooperation cannot be maintained even though it can be established for a while. This is because the low spread speed of cooperation cannot help the cooperative clusters to overcome the invasion of defectors especially in a noise environment. When tolerance is too high so that individuals interact with more dissimilar others, the defectors can easily invade the nearby clusters across the boundaries without any obstacles, because boundaries between clusters are too vague to avoid frequent interactions between cooperators and defectors.

It is worth noting that some previous studies also introduced some versions of mutually selective interaction mode, such as selective interaction based on reputation [49–51] or payoff inequity [52]. In these models, some properties individuals obtain from the evolutionary process may serve as phenotypic tags to provide information so that individuals can discriminatorily select their partners. For example, Chen et al. introduced conditional interaction into well-mixed PDG and found that moderate tolerance ranges can support cooperation most effectively [50]. In their model, the condition for mutual interaction is based on individuals' reputations. If two individuals have similar reputation, they have more chances to interact with each other. Unlike our model where tags are independent of individuals' behavior, reputation or other properties can provide more information about individuals' past history, generated from either partner selection or strategy. A key feature of these models is that group or kin selection mechanism can emerge as a result so that cooperation can be promoted [49,53]. This feature can also be found in our model. All kinds of tags may provide information of kinship or group membership thus support the emergence of such mechanisms. Unlike previous explorations, our model does not need past history for discriminating individuals, and the results suggest that arbitrary tags may be enough to support cooperation as demonstrated by previous studies [15,17,18]. However, some comparisons between different kinds of tags may be interesting and we still need further modeling for a better understanding of various selective interaction modes.

Our study relates to some important questions in the science of prejudice [54,55]. For example, is a low level of prejudice (high level of tolerance in our model) always better for a society? The results of our study suggest that prejudice is not always a bad thing for social harmony and social efficiency. Moderate levels of prejudice, by which individuals only interact with similar others, can promote human cooperation to some extent as some scholars suggested [56,57]. Under moderate levels of prejudice, various social groups can be formed, thus the generated heterogeneity and group boundaries can prevent the defectors from corroding the whole society. We believe our work may provide a new perspective on the subject of social identity, prejudice and cooperation in humans. The simulation results help us to deepen our understanding of how prejudice based on social identity (represented by tags in our model) affects the emergence and maintenance of cooperation. With evolutionary models and simulation technology, one can further investigate the nature and origin of prejudice and its social function. In particular, if we need to study identity-related policy problem such as how to reduce ethnic conflict and promote cooperation, the simulation model approach may at least provide a new “heuristic” way for policy analysis.

Of course, our results are based on some abstractions and assumptions whose empirical plausibility has not been examined. For example, we assume that each individual in our model has a definite tag which represents its identity, but the identity of a real person is often vague in the sense that others cannot identify his/her identity definitely. In this circumstance, we cannot deterministically tell whether two individuals are in the same group. On the other hand, we also assume that the tolerance level of each individual is homogeneous and is assigned as an exogenous parameter, which is obviously empirically implausible. In the real society, people may have different levels of prejudice and may adjust their prejudice on the basis of the social contexts they are involved in. Both the vagueness of identity and the question of prejudice heterogeneity are important directions for further research. Moreover, the tag mechanism in our model generates additional network struc-

tures onto the lattice. Tag similarity can be seen as weighted link between individuals, and mutual interaction relations also serve as a means of network formation. The overlapping community structures formed in our model are ubiquitous in nature and society [36]. However, although the relation between cluster heterogeneity and cooperation has been investigated, we have not yet discerned the microscopic structures of the clusters to reveal more detailed information about the relation between cooperation and community structures. Some community detecting methods based on maximal sub-graphs [58], seed community [59], core-vertex and intimate degree [60] may provide excellent tools for quantitatively analyzing the microscopic structures and their roles in tag based models. The application of these methods in tag based models is also an important direction for further research and may shed new light on the understanding of human cooperation.

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## References

- [1] S. Bowles, H. Gintis, *A Cooperative Species: Human Reciprocity and its Evolution*, Princeton University Press, 2011.
- [2] D.G. Rand, M.A. Nowak, *Human cooperation*, *Trends Cogn. Sci.* 17 (8) (2013) 413.
- [3] M.A. Nowak, Five rules for the evolution of cooperation, *Science* 314 (5805) (2006) 1560–1563. <http://dx.doi.org/10.1126/science.1133755>.
- [4] E. Cohen, The evolution of tag-based cooperation in humans, *Curr. Anthropol.* 53 (5) (2012) 588–616.
- [5] M.A. Nowak, C.E. Tarnita, T. Antal, Evolutionary dynamics in structured populations, *Philos. Trans. R. Soc. B* 365 (1537) (2010) 19–30.
- [6] C. Hauert, G. Szabó, Game theory and physics, *Amer. J. Phys.* 73 (5) (2005) 405–414.
- [7] L.R. Izquierdo, S.S. Izquierdo, F. Vega-Redondo, Leave and let leave: a sufficient condition to explain the evolutionary emergence of cooperation, *J. Econom. Dynam. Control* 46 (2014) 91–113. <http://dx.doi.org/10.1016/j.jedc.2014.06.007>. URL: <http://www.sciencedirect.com/science/article/pii/S0165188914001456>.
- [8] L. Spector, J. Klein, *Multidimensional Tags, Cooperative Populations, and Genetic Programming*, Genetic and Evolutionary Computation, Springer, US, 2007, pp. 97–112. Book section 7.
- [9] W.D. Hamilton, The genetical evolution of social behaviour. I, *J. Theoret. Biol.* 7 (1) (1964) 1–16.
- [10] R.L. Trivers, The evolution of reciprocal altruism, *Q. Rev. Biol.* (1971) 35–57.
- [11] M.A. Nowak, K. Sigmund, Evolution of indirect reciprocity by image scoring, *Nature* 393 (6685) (1998) 573–577.
- [12] M.A. Nowak, R.M. May, Evolutionary games and spatial chaos, *Nature* 359 (6398) (1992) 826–829.
- [13] D.S. Wilson, A theory of group selection, *Proc. Natl. Acad. Sci.* 72 (1) (1975) 143–146.
- [14] L. Lehmann, L. Keller, The evolution of cooperation and altruism—a general framework and a classification of models, *J. Evol. Biol.* 19 (5) (2006) 1365–1376.
- [15] R.L. Riolo, The effects of tag-mediated selection of partners in evolving populations playing the iterated Prisoner's Dilemma, Report, Santa Fe Institute, 1997.
- [16] R.L. Riolo, M.D. Cohen, R. Axelrod, Evolution of cooperation without reciprocity, *Nature* 414 (6862) (2001) 441–443. <http://dx.doi.org/10.1038/35106555>.
- [17] R. Axelrod, R.A. Hammond, A. Grafen, Altruism via kin-selection strategies that rely on arbitrary tags with which they coevolve, *Evolution* 58 (8) (2004) 1833–1838. <http://dx.doi.org/10.1111/j.0014-3820.2004.tb00465.x>.
- [18] D. Hales, Change your tags fast!—a necessary condition for cooperation? in: P. Davidsson, B. Logan, K. Takadama (Eds.), *Multi-Agent and Multi-Agent-Based Simulation*, in: *Lecture Notes in Computer Science*, vol. 3415, Springer, Berlin, Heidelberg, 2005, pp. 89–98.
- [19] D. Hales, Cooperation without memory or space: tags, groups and the Prisoner's Dilemma, in: S. Moss, P. Davidsson (Eds.), *Multi-Agent-Based Simulation*, in: *Lecture Notes in Computer Science*, vol. 1979, Springer, Berlin Heidelberg, 2001, pp. 157–166.
- [20] A. Traulsen, H.G. Schuster, Minimal model for tag-based cooperation, *Phys. Rev. E* 68 (4) (2003) 046129.
- [21] T. Wu, F. Fu, Y. Zhang, L. Wang, Adaptive tag switching reinforces the coevolution of contingent cooperation and tag diversity, *J. Theoret. Biol.* 330 (2013) 45–55. <http://dx.doi.org/10.1016/j.jtbi.2013.04.007>.
- [22] T. Hadzibeganovic, F.W.S. Lima, D. Stauffer, Benefits of memory for the evolution of tag-based cooperation in structured populations, *Behav. Ecol. Sociobiol.* 68 (7) (2014) 1059–1072. <http://dx.doi.org/10.1007/s00265-014-1718-7>.
- [23] A. Traulsen, J.C. Claussen, Similarity-based cooperation and spatial segregation, *Phys. Rev. E* 70 (4) (2004) 046128.
- [24] H. Tajfel, Social identity and intergroup behaviour, *Soc. Sci. Inform.* /sur les sciences sociales (1974).
- [25] H. Tajfel, J.C. Turner, An integrative theory of intergroup conflict, *Soc. Psychol. Intergr. Relat.* 33 (47) (1979) 74.
- [26] N. Halevy, O. Weisel, G. Bornstein, “In-group love” and “out-group hate” in repeated interaction between groups, *J. Behav. Decis. Mak.* 25 (2) (2012) 188–195. <http://dx.doi.org/10.1002/bdm.726>.
- [27] D.J. Kelly, P.C. Quinn, A.M. Slater, K. Lee, A. Gibson, M. Smith, L. Ge, O. Pascalis, Three-month-olds, but not newborns, prefer own-race faces, *Dev. Sci.* 8 (6) (2005) F31–F36.
- [28] L.S. André, B.-H. Krista, P.-D. Diane, Bilingual and monolingual children prefer native-accented speakers, *Front. Psychol.* 4 (2013). <http://dx.doi.org/10.3389/fpsyg.2013.00953>.
- [29] A. Alesina, R. Baqir, W. Easterly, Public goods and ethnic divisions, Tech. Rep., National Bureau of Economic Research, 1997.
- [30] J. Habyarimana, M. Humphreys, D.N. Posner, J.M. Weinstein, Why does ethnic diversity undermine public goods provision? *Amer. Polit. Sci. Rev.* 101 (04) (2007) 709–725.
- [31] R. Axelrod, The dissemination of culture a model with local convergence and global polarization, *J. Conflict. Resolut.* 41 (2) (1997) 203–226.
- [32] D. Centola, J.C. Gonzalez-Avella, V.M. Eguiluz, M. San Miguel, Homophily, cultural drift, and the co-evolution of cultural groups, *J. Conflict. Resolut.* 51 (6) (2007) 905–929.
- [33] J. Pfau, M. Kirley, Y. Kashima, The co-evolution of cultures, social network communities, and agent locations in an extension of Axelrod's model of cultural dissemination, *Physica A* 392 (2) (2013) 381–391.
- [34] A. Stivala, G. Robins, Y. Kashima, M. Kirley, Ultrametric distribution of culture vectors in an extended Axelrod model of cultural dissemination, *Sci. Rep.* 4 (2014).
- [35] G. Palla, I. Derényi, I. Farkas, T. Vicsek, Uncovering the overlapping community structure of complex networks in nature and society, *Nature* 435 (7043) (2005) 814–818.
- [36] Y. Cui, X. Wang, Uncovering overlapping community structures by the key bi-community and intimate degree in bipartite networks, *Physica A* 407 (2014) 7–14. <http://dx.doi.org/10.1016/j.physa.2014.03.077>. URL: <http://www.sciencedirect.com/science/article/pii/S037843711400288X>.
- [37] Y. Cui, X. Wang, J. Li, Detecting overlapping communities in networks using the maximal sub-graph and the clustering coefficient, *Physica A* 405 (2014) 85–91. <http://dx.doi.org/10.1016/j.physa.2014.03.027>. URL: <http://www.sciencedirect.com/science/article/pii/S0378437114002222>.
- [38] J. Eustace, X. Wang, J. Li, Approximating web communities using subspace decomposition, *Knowl.-Based Syst.* 70 (2014) 118–127. <http://dx.doi.org/10.1016/j.knsys.2014.06.017>. URL: <http://www.sciencedirect.com/science/article/pii/S095070511400238X>.

- [39] J. Li, X. Wang, Y. Cui, Uncovering the overlapping community structure of complex networks by maximal cliques, *Physica A* 415 (0) (2014) 398–406. <http://dx.doi.org/10.1016/j.physa.2014.08.025>. URL: <http://www.sciencedirect.com/science/article/pii/S0378437114007031>.
- [40] A. Lancichinetti, S. Fortunato, J. Kertész, Detecting the overlapping and hierarchical community structure in complex networks, *New J. Phys.* 11 (3) (2009) 033015.
- [41] Z. Li, J. Gao, I.H. Suh, L. Wang, Evolution of cooperation in lattice population with adaptive interaction intensity, *Physica A* 392 (9) (2013) 2046–2051. <http://dx.doi.org/10.1016/j.physa.2012.12.031>. URL: <http://www.sciencedirect.com/science/article/pii/S0378437113000083>.
- [42] X. Chen, F. Fu, L. Wang, Interaction stochasticity supports cooperation in spatial Prisoner's Dilemma, *Phys. Rev. E* 78 (5) (2008) 051120.
- [43] J.W. Kim, A tag-based evolutionary Prisoner's Dilemma game on networks with different topologies, *J. Artif. Soc. Soc. Simul.* (2010).
- [44] R.A. Hammond, R. Axelrod, The evolution of ethnocentrism, *J. Conflict. Resolut.* 50 (6) (2006) 926–936.
- [45] C.E. Tarnita, T. Antal, H. Ohtsuki, M.A. Nowak, Evolutionary dynamics in set structured populations, *Proc. Natl. Acad. Sci.* 106 (21) (2009) 8601–8604.
- [46] B.A. Huberman, N.S. Glance, Evolutionary games and computer simulations, *Proc. Natl. Acad. Sci.* 90 (16) (1993) 7716–7718.
- [47] G. Ren, X. Wang, Robustness of cooperation in memory-based Prisoners' Dilemma game on a square lattice, *Physica A* 408 (2014) 40–46. <http://dx.doi.org/10.1016/j.physa.2014.04.022>. URL: <http://www.sciencedirect.com/science/article/pii/S0378437114003331>.
- [48] J. Tanimoto, Does a tag system effectively support emerging cooperation? *J. Theoret. Biol.* 247 (4) (2007) 756–764.
- [49] X. Chen, L. Wang, Cooperation enhanced by moderate tolerance ranges in myopically selective interactions, *Phys. Rev. E* 80 (4) (2009) 046109.
- [50] X. Chen, A. Schick, M. Doebeli, A. Blachford, L. Wang, Reputation-based conditional interaction supports cooperation in well-mixed Prisoners' Dilemmas, *PLoS One* 7 (5) (2012) e36260.
- [51] X. Wang, X. Chen, J. Gao, L. Wang, Reputation-based mutual selection rule promotes cooperation in spatial threshold public goods games, *Chaos Solitons Fractals* 56 (2013) 181–187. <http://dx.doi.org/10.1016/j.chaos.2013.07.019>. URL: <http://www.sciencedirect.com/science/article/pii/S0960077913001501>.
- [52] A. Ahmed, K. Karlapalem, Inequity aversion and the evolution of cooperation, *Phys. Rev. E* 89 (2) (2014) 022802.
- [53] L. Spector, J. Klein, Genetic stability and territorial structure facilitate the evolution of tag-mediated altruism, *Artif. Life* 12 (4) (2006) 553–560.
- [54] G.W. Allport, *The Nature of Prejudice*, Basic Books, 1979.
- [55] Y. Amir, Contact hypothesis in ethnic relations, *Psychol. Bull.* 71 (5) (1969) 319.
- [56] D. Berreby, *Us and Them: Understanding Your Tribal Mind*, Little, Brown and Company, New York, 2005.
- [57] R. Hardin, *One for All: The Logic of Group Conflict*, Princeton University Press, 1997.
- [58] Y. Cui, X. Wang, J. Eustace, Detecting community structure via the maximal sub-graphs and belonging degrees in complex networks, *Physica A* 416 (2014) 198–207. <http://dx.doi.org/10.1016/j.physa.2014.08.050>. URL: <http://www.sciencedirect.com/science/article/pii/S0378437114007353>.
- [59] J. Li, X. Wang, J. Eustace, Detecting overlapping communities by seed community in weighted complex networks, *Physica A* 392 (23) (2013) 6125–6134. <http://dx.doi.org/10.1016/j.physa.2013.07.066>. URL: <http://www.sciencedirect.com/science/article/pii/S0378437113006973>.
- [60] X. Wang, J. Li, Detecting communities by the core-vertex and intimate degree in complex networks, *Physica A* 392 (10) (2013) 2555–2563. <http://dx.doi.org/10.1016/j.physa.2013.01.039>. URL: <http://www.sciencedirect.com/science/article/pii/S0378437113000915>.