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Combining evolutionary game theory and network theory to analyze human cooperation patterns

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ABSTRACT

As natural systems continuously evolve, the human cooperation dilemma represents an increasingly more challenging question. Humans cooperate in natural and social systems, but how it happens and what are the mechanisms which rule the emergence of cooperation, represent an open and fascinating issue. In this work, we investigate the evolution of cooperation through the analysis of the evolutionary dynamics of behaviours within the social network, where nodes can choose to cooperate or defect following the classical social dilemmas represented by Prisoner's Dilemma and Snowdrift games. To this aim, we introduce a sociological concept and statistical estimator, “Critical Mass”, to detect the minimum initial seed of cooperators able to trigger the diffusion process, and the centrality measure to select within the social network. Selecting different spatial configurations of the Critical Mass nodes, we highlight how the emergence of cooperation can be influenced by this spatial choice of the initial core in the network. Moreover, we target to shed light how the concept of homophily, a social shaping factor for which “birds of a feather flock together”, can affect the evolutionary process. Our findings show that homophily allows speeding up the diffusion process and make quicker the convergence towards human cooperation, while centrality measure and thus the Critical Mass selection, play a key role in the evolution showing how the spatial configurations can create some hidden patterns, partially counterbalancing the impact of homophily.

1. Introduction

In such a variety of systems, from biology to social networks, we can observe the emergence and the maintenance of a phenomenon, difficult to investigate and explain: cooperation. Humans cooperate building complex societies as well as predators hunt in groups in order to become stronger. “Cooperate” means to produce a benefit for a group sacrificing (with a cost) that one of the single individuals. Therefore, one of the most difficult challenges is to explain how an individual should choose the group benefit rather than a selfish behavior, which could be a more profitable choice considering his own perspective. Evolutionary Game Theory (EGT) [1,2] constitutes the theoretical framework for investigating the evolution of cooperation in social dilemmas within a population of nodes [3–5]. It combines the notions of game theory and evolutionary dynamics, taking into account the dynamics of strategies of a population of agents, each of them with its own strategy, interacting with each other and earning payoffs [6]. Evolutionary dynamics represents the mathematical tool to formalize the evolutionary process where the strategies change over time, making the higher fitness strategy more common and spreading them over the population. Therefore, EGT allows us to consider a dynamical context, in which the single actions and strategies represent the result of the evolutionary process. The persistent strategies will be the most successful ones in terms of payoff, that is, the strategies which will produce higher payoffs over time. It is more likely that these strategies with a high fitness (in EGT, payoff is translated into fitness, and the frequency of strategies in the population changes over time accordingly) proliferate and they will be imitated by the other players, while strategies who do not reproduce will be driven out through natural selection. The question in social dilemmas is that if, from one hand, the strategy with the highest individual fitness is defection, from the other hand the overall society would benefit more from cooperation. Thus, cooperation should not evolve under these conditions, but in the reality we can observe how the cooperation in nature does exist. This seems in contrast with the Darwin's principle of natural selection, then the

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challenge is to understand how does the cooperation evolve, explaining why and what are the hidden mechanism leading to this evolutionary process. To explore the evolutionary process, we consider the two most common used social dilemmas represented by the Prisoner's Dilemma Game (PDG) and the Snowdrift Game (SG) [7].

Cooperation constitutes a crucial aspect in the study of social evolution, where interactions among individuals influence the success of the community [8–11] . As underlined in [12], the structure of the network, its properties, the dynamics and the interactions among individuals affect the emergence of cooperation and its evolutionary dynamics. Social interactions depend on the structure and properties of the network, thus the structural characterization of the networks where evolutionary process takes place allows shedding light on the mechanisms by which cooperative behavior emerges and eventually overcomes the natural temptation to defect. For this reason, it becomes essential to exploit social network analysis, which is one of the most used paradigms in behavioral sciences [13]. Social relationships and networking are the key components of the human life and they have been historically bound to time and space constraints. These restrictions have been partially removed due to the increase of social connectedness. Users are increasingly keen to interact, cooperate and collaborate, share contents, and to participate through social media. In [14], the authors have formalized the problem of collective action of large groups towards cooperative and defective behaviors. The role of a single actor or a group of people, community or coalition, could contribute to trigger a dynamic action inside population, which could represent a social contagion process [15]. Collective behavior means the spontaneous emergence of different phenomena without a central regulation mechanism, such as "birds of a feather flock together" [16–20]. Centrality measure is a fundamental concept in social network analysis [13,21]. It allows to measure the importance of the various nodes in the social network, so that the more a node is central, the more it is able to influence the other nodes in the network [22–24]. Centrality assumes a key role in the selection of nodes belonging to the Critical Mass (CM), where Critical Mass (in analogy with the physical concept) is defined sociodynamically as the minimum coalition, able to trigger a behavior within a population [14,25,26]. Therefore, centrality measure constitutes a way to weigh the various nodes of the network, measuring their impact on the evolutionary process.

Nodes interact in the social network in several ways and with a variable rate which depends on various factors. Among these factors, the phenomenon that "birds of a feather flock together", also referred as homophily, is surely one of the most interesting and influential in the formation of social ties, by ruling cooperative interactions in human societies. In fact, humans tend to associate to and cooperate with someone else who has similar characteristics. Some authors have defined homophily as the principle that "similarity breeds connection" [16], used to explain how social ties are forged and cut off over time. Other authors have underlined how homophily is one of the most striking sociological regularities of social life [27,28]. From an "individualistic" point of view, homophily can be explained in terms of similarity of individual and psychological preferences, referred also as "choice homophily". Instead, from a "structuralist" perspective, homophily is also the result of the same shared environments (workplaces, neighborhood, etc.) which create an homogeneity in tastes and behaviors, generating strong patterns of homophily. This kind of homophily is also called "induced homophily" [29]. The concept of homophily is important in the dynamics of collective action and Critical Mass mobilization. Humans tend to interact and create groups with other humans who have similar features or interests [30]. Therefore, homophily represents the similarity between connected nodes, in terms of demographic, behavioral and biological features. Nodes actions will be correlated because of their higher homophily rather than their interactions [19]. The family, the organizations to which we belong and the geographic proximity to our position in the social system, create "contexts" in which homophilic relationships are formed. Homophily can be defined as the principle whereby a contact between persons similar occurs at a high rate compared to that which occurs between different people. The most pervasive and widespread feature of homophily is that the cultural, behavioral and genetic information traveling through the network, will tend to be understood and localized within groups and communities that are shaped by the action of the same homophily. This implies that the distance, in terms of social characteristics, results in a network distance, that is, the number of relationships through which an information must travel to connect two individuals. Thus, from a social network point of view, homophily can be seen as an organizing principle. The analytical strategies used to analyze the homophily can vary widely according to the types of bonds. Homophily could be a bias that leads people to associate more often than one might expect, given a relative number of opportunities [27,31]. Other studies focus on the homogeneity of a network or the similarity of a dyad measured only on some features, without clarifying whether this uniformity is an opportunity created by demographic or by a process of selection in the opportunities [32]. The heterogeneity and similarity dyadic measures are often not highly correlated. By analyzing all these variants we can distinguish between the effects of homophily created by the demographics of potential links, named as the "Baseline Homophily", and homophily measured explicitly regardless of any opportunity sets, referred as "Inbreeding Homophily". Homophily is the result of a wide variety of dimensions regarding age, gender, race and ethnicity, socioeconomic status, and education, etc. This work aims at analyzing how homophily can impact the diffusion of a social behavior within a social network. Homophily, acting through its different dimensions, can produce a change in behaviors, unexpected if considering only the social influence and contagion. Beyond varying the homophily level in the network, our goal is also to choose different spatial configurations of the Critical Mass, that is, the initial seed of adopters (e.g., cooperators) who start the diffusion process. Then, we explore the evolution of cooperation within a social network, using the framework of EGT, identifying the conditions under which a behavior diffuses and becomes persistent in the population. As we will see in the simulation results, these conditions are related to the homophily level in the social network, and to the CM nodes selection depending on the structural properties of the social network.

2. Methods

2.1. Critical mass and centrality

Space, time and infrastructure play a fundamental role in enabling social interactions to form and evolve, and in allowing them to become sustainable from the point of view of energy use and human effort [33]. In [14] Critical Mass is defined as the minimum coalition n, such that if actors organize into coalitions of size n, at least n people will prefer mutual cooperation to unilateral defection, and it is calculated as follows:

$$min(n) \; s.t. \left\{ \sum_{i=1}^{N} H(R_i - T_i) \right\} \geq n \tag{1}$$

where N is the overall population and $min(n)$ is the minimum coalition size. The latter depends on the Heaviside function of the difference between Reward and Temptation payoffs, R_i and T_i respectively. These payoffs are evaluated considering different types of games, in which a player is a randomly selected node from the

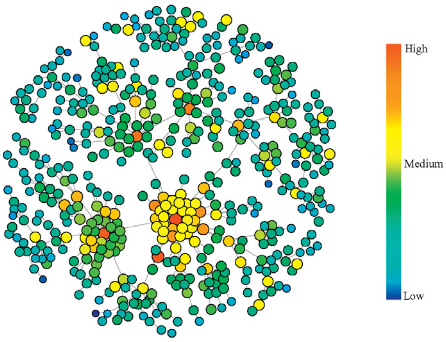


Fig. 1. Centrality measures in the network. Based on a quantitave analysis, we illustrate qualitatively centrality distribution in the scale-free network: as showed in the color bar, colors range from 'blue' to 'red', where 'blue' indicates the lowest centrality measure, while 'red' corresponds to the highest values. Centrality is calculated using the eigenvector centrality, which allows including the concept of influence, considering not only the number of links of each node, but also the quality of these connections. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

population, and it is asked him to choose to cooperate or defect, while the other "player" is a collective player representing the interest of the other coalition's members. Then Critical Mass could be represented as the minimum value of people which actively participate to social networks and cooperate in order to influence collective participation and the spread of a human behavior. The Critical Mass is able to trigger an evolutionary dynamics, and evolves independently in the network through cooperation emerging both from social interactions and homophily, thus the network evolves according to cooperation strategies, in order to strengthen the influence and spread of a human behavior. The eigenvector centrality [34] allows to include the concept of influence in our analysis; it can also be seen as a weighted sum of not only direct connections but indirect connections of every length [35]. Eigenvector centrality, starting from the spectral properties of the adjacency matrix, considers not only the number of links of each node, but also the quality of such connections. Central nodes are the most influential nodes which can condition the behaviors of their neighboring nodes. Fig. 1 shows the distribution of the eigenvector centrality in the social network, modeled as a Scale-Free (SF) [36].

Fig. 2 illustrates the spatial configurations of CM chosen according to the centrality value in the social network. The target is to investigate the role of the selection of the CM nodes in the evolution of cooperation, as we will see in 3.

Considering a large group problem and the diffusion of a collective action in a population of nodes, in 2.2 we introduce a novel approach and a model which allows to evaluate the evolutionary dynamics of human behaviors. Thus, we propose a model to analyze the evolutionary dynamics of the diffusion of behaviors through social network analysis and exploiting the framework of evolutionary game theory.

2.2. Evolutionary dynamics of cooperation

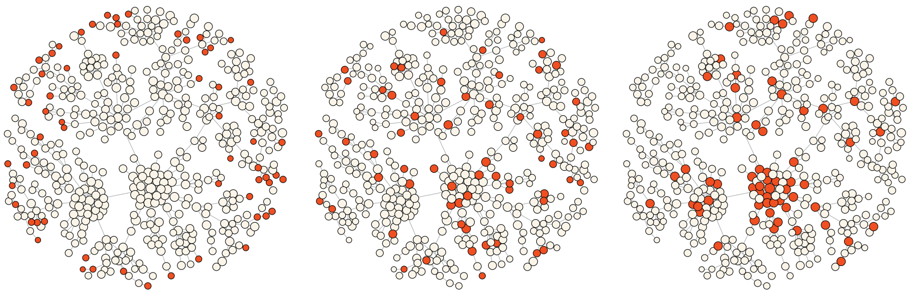
The study of evolutionary games on networks allows to understand the emergence of cooperation in different contexts [37]. The emergence of such a collective phenomenon, cooperation, is a key issue that arises when studying seemingly diverse evolutionary puzzles, such as the origin of multicellular organisms, the altruistic behavior of humans and primates, or the way advanced animal societies, such as ant colonies, work, among others. Understanding the emergence of cooperation in the context of Darwinian evolution remains a challenge to date, met by scientists from many different fields of natural and social sciences [38].

Table 1
Payoff matrices of PDG (a) and SG (b).

(a) Prisoner's dilemma			(b) Snowdrift		
	C	D		C	D
Payoff to C	b - c	-c	Payoff to C	b - c/2	b-c
Payoff to D	b	0	Payoff to D	b	0

In order to address this problem we exploit the mathematical framework provided by EGT, and in particular the two social dilemmas represented by the Prisoner's Dilemma (PD) and the Snowdrift Game (SG) as metaphors for studying cooperation between unrelated individuals. In both these pairwise social dilemmas, nodes/agents can take one of two strategies: Cooperation (C) and Defection (D) [7]. The payoff matrices of the two games are illustrated in Tables 1(a) and (b):

In the PD game, cooperation results in a benefit b to the opposing player, but incurs a cost c to the cooperator (where $b > c > 0$); defection has no costs or benefits. In both cases, independently of whether the opponent plays C or D, it is, therefore, better to play D. In evolutionary settings, payoffs determine reproductive fitness, and it follows that D is the Evolutionarily Stable Strategy (ESS). This can be formalized using replicator dynamics [39], which admits pure defection as the only stable equilibrium. The social dilemma is thus established, since mutual cooperation yields both an individual and total benefit higher than that of mutual defection. The social dilemma of the PD can be relaxed by assuming that cooperation yields a benefit accessible to both interacting players, while costs are shared between cooperators. This results in the so-called Snowdrift Game (also known as the *Hawk-Dove Game*, or the *Chicken Game*). In the SG, the order of P and S is exchanged, such that $T > R > S > P$, therefore cooperation yields a benefit b to the cooperator as well as to the opposing player, and incurs a cost c if the opponent defects, but only a cost $c/2$ if the opponent cooperates. Thus, both strategies can invade when rare, resulting in a mixed evolutionarily stable state at which the proportion of cooperators is $1 - c/(2b - c)$. It is important to note that in this state the population payoff is smaller than it would be if everybody played C, hence the SG still represents a social dilemma [40]. Its essential ingredient is that, in contrast to the PD, cooperation has an advantage when rare, which implies that the replicator dynamics [39] of the SG converges to a mixed stable equilibrium at which both C and D strategies are present. The PD game is in fact the most stringent cooperative dilemma, where for cooperation to arise a mechanism for the evolution of cooperation is needed [41]. The pairwise nature of the game is translated to a population scale by making the agents/nodes playing with each other, and accumulating the payoff obtained from each interaction. After each round of the game, the strategies of the agents are updated so that those agents with less payoff are tempted to copy the strategy of those fittest individuals. In unstructured populations, in which players are well-mixed, evolutionary dynamics leads all the individuals to defection [39]. However, the existence of a network of interactions, so that each agent can only play with those directly connected to it, the population can sometimes promote the emergence of cooperation. This mechanism promoting cooperation was coined as network reciprocity [42], and it was observed to be substantially enhanced when the network substrate is a scale-free network [38], a real-world network, with a power law dependence of the degree distribution, $P(k) \sim k^{\gamma}$, with the exponent γ typically satisfying $2 < \gamma < 3$. For this reason, we decide to adopt a scale-free as network substrate (see 3). Indeed Nowak and May discovered how the spatial structure can promote the evolution of cooperation through the network reciprocity, which relies on the fact that cooperators do best if they are surrounded by other cooperators [42]. If



(a) Edge Nodes (EN) (b) Random Nodes (RN) (c) Central Nodes (CN)

Fig. 2. Spatial configurations of Critical Mass. Nodes of Critical Mass, indicated with ‘red’ color, are chosen according to their centrality value in the social network: in (a) Critical Mass is selected from the less central nodes or Edge Nodes (EN); in (b) Critical Mass is randomly selected (RN); in (c) Critical Mass is chosen considering the more Central Nodes (CN). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

interactions among players are structured rather than well mixed, the clustering of cooperators is more likely to be stable since defectors have limited opportunities for exploiting those that are located in the interior of cooperative clusters. Furthermore, the network reciprocity is increasingly promoted by heterogeneity of the interacting social networks. It has been found that scale-free networks provide a unifying framework for the evolution of cooperation, therefore methods of statistical physics can be used successfully to study collective phenomena in social systems, and in particular in evolutionary games [41]. The choice of a heterogeneous interacting network, such as the scale-free network, is related to two key aspects. First, as we know, real populations are heterogeneous [43], in fact there are some individuals “richer” than others in terms of connections, or in other words individuals exhibit a different number of average neighbors whom they interact with [38], and heterogeneity arises naturally whenever people make decisions and some individuals may impose their preferences according to their social connections [44]. The so-called “preferential attachment” rule, which represents the basic foundation of scale-free network modeling, together with the characteristic power law degree distribution, makes the heterogeneity extremely large. Second, a vast literature has underlined the important role of heterogeneous social influence on the emergence of cooperation in social networks [38,45,46]. In contrast, using an homogeneous network in the evolutionary dynamics of cooperation, where the connectivity is represented by a single-scale graph with a gaussian degree distribution [44,47], would produce a low heterogeneity and, as underlined in [48], this will result in a long-term noncooperative behaviour, since cooperators are not able to resist to noncooperative invaders and eventually there will be the rapid extinction of all cooperators for all the values of b employed. In addition, homogeneity would produce an even more challenging scenario in an extremely noncooperative game, such as Prisoner’s Dilemma game. Moreover, other authors have highlighted microscopically in terms of clusters, how a cooperative behavior is more successful in scale-free network than in homogeneous graph [49]. Thus, as the main aim of this work is to investigate the evolutionary dynamics of cooperation considering social dilemmas and different spatial configurations of “Critical Mass”, we consider the heterogeneous ansatz.

In this work, as explained before, we merged the concept of Critical Mass and the concept of eigenvector centrality in the selection of the CM nodes. Once CM has been calculated, we consider an evolutionary game theoretic approach to study the emergence of cooperation within nodes which can adopt one of two different strategies, cooperation or defection, taking into account the two social dilemmas represented by the Prisoner’s Dilemma Game and the Snowdrift Game. After having defined analytically the model we present the results obtained from simulations. As we will see in the Section 3, we simulate the evolutionary process in accordance with the standard Monte Carlo simulation procedure, composed of elementary steps; including the distribution of competing strategies, which is an elementary step entails randomly selecting a player and one of its neighbors, calculating the payoffs of both players, and finally attempting strategy adoption. First, a randomly selected player x acquires its payoff P_x by playing the game with all its neighbors on network. Next, player x randomly chooses one neighbor y on the updating network, who then also acquires its payoff P_y on the interaction network in the same way as previously did player x. Lastly, player x adopts the strategy S_y from player y with a probability determined by the Fermi function [50]. The strategy adoption depends on the payoff difference, along with some uncertainty in the decision making to account noise level K and homophily factor δ_{xy}:

$$W(S_y \to S_x) = \frac{1}{1 + \exp \frac{(P_x - P_y)}{\delta_{xy} K}} \tag{2}$$

The temperature K represents a noise level (or selection intensity) and quantifies the uncertainty related to the strategy adoption process, it can vary in the range $]0, +\infty[$. The selected value of K is a traditional and frequently employed choice that does not qualitatively affect the evolutionary outcomes, as shown in many preceding works and reviewed comprehensively in [51]. In the $K \to 0$ limit, the adoption of a successful strategy is deterministic, while in the $K \to +\infty$, the strategy learning is blind. Each Monte Carlo step gives a chance for every player to change its strategy once on average.

The homophily factor $\delta_{xy} = \delta_{yx}$ we introduced, measures the homophily difference between two players, so that more they have a high homophily level, more one player tends to imitate the strategy of the other one at each round. δ_{xy} is a simulation parameter which allows to take into account the genotypic-phenotypic traits of the individuals, it can vary in the range $]0, +\infty[$, in particular for $\delta_{xy} \to 0$, the two nodes present a high homophily value, while in the $\delta_{xy} \to +\infty$ limit, there is no homophily.

It is crucial to observe that the homophily value in Eq. (2), is an overall value taking into account the different dimensions related to homophily, such as age, gender, race and ethnicity, socioeconomic status, and education [16]. The various dimensions are represented by a different homophily values, each one with its own weight. The weight could be influenced by a huge variety of factors, depending on the context and social environment. In our model, we chose static weights for all the nodes of the network. δ_{xy}, given by the following Eq. (3), is an equivalent homophily value, indicating an equilibrium value of the different dimensional aspects of homophily:

$$\delta_{xy} = \frac{\sum_{i=1}^{F} w_i \delta_{xy_i}}{\sum_{i=1}^{F} w_i} \tag{3}$$

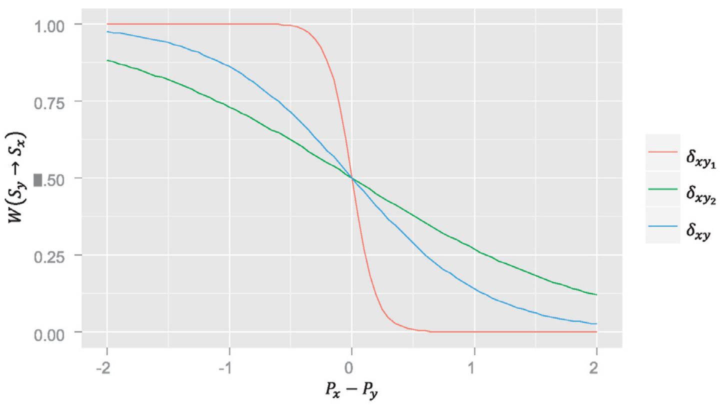


Fig. 3. Fermi distribution according to the payoff difference between the two players x and y (in this example we have chosen $\delta_{xy_1} = 0.1$, $\delta_{xy_2} = 1$, $w_1 = w_2 = 1$ and $K = 1$). In particular, the ‘red’ curve corresponds to dimension δ_{xy_1}, while the ‘green’ curve corresponds to the dimension δ_{xy_2}, and the ‘blue’ curve represents the equivalent homophily value δ_{xy}, evaluated according to Eq. (3). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

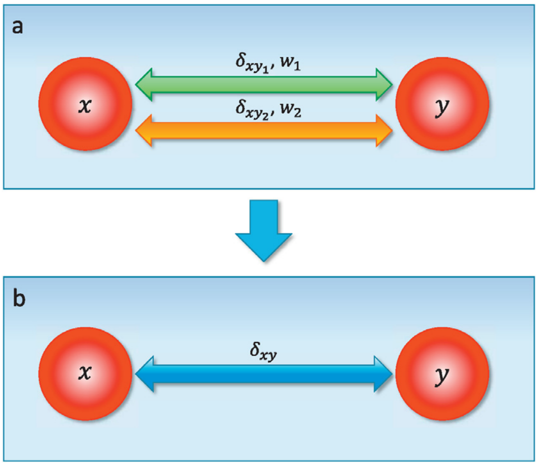
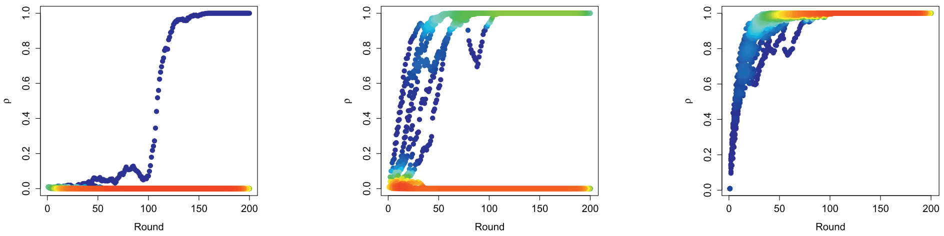


Fig. 4. Equivalent homophily value. In the figure, we show how to represent different weighted features with an equivalent homophily value, in order to enclose several traits, corresponding for instance to two or more different kind of homophily among two nodes. In (a) we show two different features, respectively δ_{xy_1} with weight w_1 and δ_{xy_2} with weight w_2, of the nodes x and y. In (b) we represent the two previous features between the same nodes using an overall measure δ_{xy}.

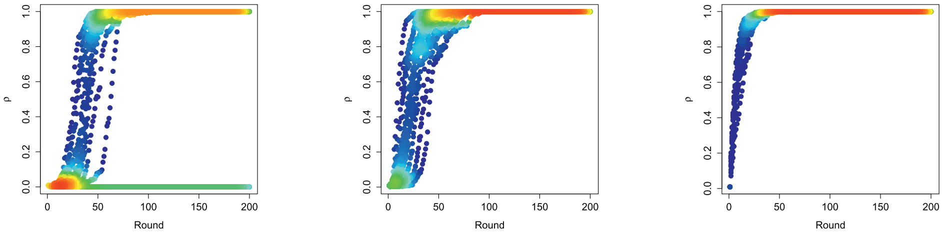
where F is the number of dimensions, each one with a weight w_i; δ_{xy_i} indicates the homophily difference between x and y with regards to the ith dimension. The considered homophily values resemble temperatures in the thermal equilibrium relation of n bodies, which gives the equivalent temperature at equilibrium. Thus, the equivalent homophily δ_{xy}, evaluated according to Eq. (3), represents a “homophilic” equilibrium. Fig. 3 qualitatively illustrates the Fermi distribution according to the payoff difference accumulated by the two players x and y. Fig. 4 illustrates how the two different features δ_{xy_i} may be represented through an overall homophily value.

3. Results

The simulations have been conducted choosing a scale-free network with $N = 10^3$ nodes. The homophily level δ_{xy} is evaluated considering each couple of neighboring nodes; in particular, σ represents the standard deviation of the genotypic-phenotypic traits assigned to the population of nodes, normally distributed around a mean value. Figs. 5 and 6 show the fraction of cooperative nodes ρ against the rounds or time steps. ρ varies in the range [0, 1], where 0 corresponds to the global defection, while 1 means a global cooperation of the population. We have simulated the evolutionary dynamics for a fixed number of simulations, and the color corresponds to the population’s density, so ‘red’ indicates the highest density, while ‘blue’ means the lowest density. In particular, we show the evolution of cooperation until 200 rounds as, in correspondence of that value, the convergence has already been reached. In Fig. 5 the PD game is played between the interacting nodes, while in Fig. 6 the SG game is played, in order to address the case of a less stringent cooperative dilemma. For each game and for each value of σ, fixed a CM value (which represents the chosen number of initially cooperative nodes), we have considered three different spatial configurations of CM nodes selection: in Edge Nodes (EN), in Random Nodes (RN), and in Central Nodes (CN). In particular, $\sigma = 8$ means a low homophily level, while $\sigma = 1$ means a higher homophily level. In the CN case, the CM is chosen considering the more central nodes; in the EN case, the Critical Mass is selected from the less central nodes and, finally, the RN case corresponds to a mixed configuration, where CM nodes are selected in random way. In both games, PD (Fig. 5) and SG (Fig. 6), we observe that the more central is CM and the higher is the homophily level, the more quickly nodes converge to cooperation and the frequency of successful ($\rho = 1$) tends to the maximum value. In other words, increasing the centrality of the CM nodes and the homophily level, we note a faster emergence of cooperation. Instead, for the lower homophily levels and considering the CM distributed in the edge nodes, we have the lowest frequency of successful, that means a global tendency to defect. In the SG game (Fig. 6), as we expected, since the payoff’s difference between cooperation and defection is less than PD game, the evolution of cooperation is slower than PD game. This results in a major number of oscillations and a lower frequency of successful, so a major number of rounds is needed until reaching the cooperation, and the evolution is not guaranteed even if a higher homophily level and a central CM is selected. The variation in the selection of the Critical Mass nodes, chosen according to their centrality value in the social network, creates different evolutions of cooperation, due to the various impact of the CM on the population. Comparing Fig. 5C with Fig. 5D in the Prisoner’s Dilemma game, and comparing Fig. 6C with Fig. 6D in the Snowdrift game, we can see the relation between the impact of this CM nodes selection and homophily in the evolution of cooperation. The evidence suggests how the effect of the selection of CM nodes is partially counterbalanced by homophily, as the latter is able to make stronger the relationships between connected nodes, and thus pushing nodes towards a strategy adoption which is ruled by the similarity, even if those connected nodes have a low value in terms of eigenvector

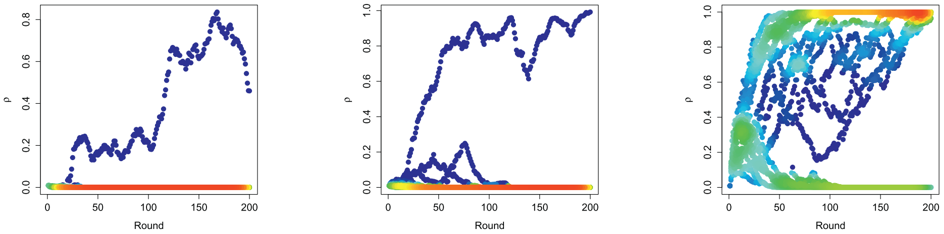


(a) EN, $\sigma = 8$ (b) RN, $\sigma = 8$ (c) CN, $\sigma = 8$

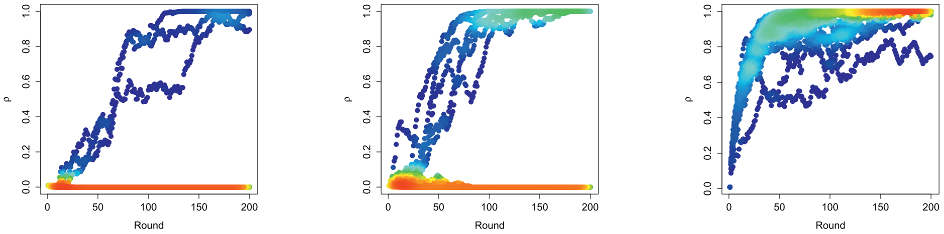


(d) EN, $\sigma = 1$ (e) RN, $\sigma = 1$ (f) CN, $\sigma = 1$

Fig. 5. Evolution of cooperation in the Prisoner's dilemma. We show the fraction (or density) of cooperators against the rounds in evolutionary dynamics for Critical Mass distributed in edge nodes (EN) in (a)(d), random nodes (RN) in (b)(e), central nodes (CN) in (c)(f), with $\sigma = 8$ in (a)(b)(c), and $\sigma = 1$ in (d)(e)(f). The fraction of cooperative nodes ρ varies in the range [0, 1], where 0 corresponds to the global defection, while 1 means a global cooperation of the population. The color corresponds to the population's density, where 'red' indicates the highest density, while 'blue' means the lowest density. In particular, we show the evolution of cooperation until 200 rounds as, in correspondence of that value, the convergence has already been reached. In particular, $\sigma = 8$ means a low homophily level, while $\sigma = 1$ means a higher homophily level. We can see that the more central is CM and the higher is the homophily level, the more quickly nodes converge to cooperation and the frequency of successful ($\rho = 1$) tends to the maximum value, that is we note a faster emergence of cooperation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



(a) EN, $\sigma = 8$ (b) RN, $\sigma = 8$ (c) CN, $\sigma = 8$



(d) EN, $\sigma = 1$ (e) RN, $\sigma = 1$ (f) CN, $\sigma = 1$

Fig. 6. Evolution of cooperation in the snowdrift game. We show the fraction (or density) of cooperators in evolutionary dynamics for Critical Mass distributed in edge nodes (EN) in (a)(d), random nodes (RN) in (b)(e), central nodes (CN) in (c)(f), with $\sigma = 8$ in (a)(b)(c), and $\sigma = 1$ in (d)(e)(f). As in Fig. 5, we show the evolution of cooperation until 200 rounds as, in correspondence of that value, the convergence has already been reached. In the SG game, since the payoff's difference between cooperation and defection is less than PD game, the evolution of cooperation is slower than PD game. This results in a major number of oscillations and a lower frequency of successful, so a major number of rounds is needed until reaching the cooperation, and the evolution is not guaranteed even if a higher homophily level and a central CM is selected. As observed in the PD game, also in the SG game, the more central is CM and the higher is the homophily level, the more quickly nodes converge to cooperation and we note a faster emergence of cooperation.

centrality. In other words, if from one hand these Edge Nodes (EN) play apparently a minor role in the diffusion of a behavior within the overall population because of their low centrality value, from the other hand, interestingly, they can strongly impact on their homophilic contacts, generating a group able to conduct the overall population, except in some cases, towards a cooperative behavior, even though it takes more time steps to reach the evolution of cooperation with respect to the CN case. From a microscopic point of view, simulation results suggest how the edge nodes act as a small community with a high cohesion force due to homophily. This generates some hidden dynamic patterns among nodes, making them able to diffuse a behavior more than expected if we would consider only the macroscopic structural properties of the social network.

4. Discussion

Our work was intended to explore human cooperation and its evolution in a social network. We exploited the concept of Critical Mass, and its role in the dynamics of the evolutionary process. Furthermore, we considered different spatial configurations of the CM nodes to understand how and to what extent the CM selection would affect the diffusion of behaviors. To characterize this CM nodes selection, we chose CM using different centrality values, calculated taking into account the eigenvector centrality defined by [35]. We chose the eigenvector centrality since it allows us to evaluate the influence of nodes on their neighborhood, assigning a high value to the more influential nodes. To investigate the evolutionary dynamics, we exploited the framework of EGT using the two social dilemmas represented by the Prisoners Dilemma Game and Snowdrift Game. The PDG and SG are probably the most common dilemmas used to investigate the evolution of cooperation [52–54]: the PDG is more strictly non-cooperative game than SG but, evolutionarily, it can lead to the evolution of cooperation, if it is played iteratively among nodes of a population and considering some additional features of nodes, going beyond the classical network connections. For this reason, in our model, we considered similarity among nodes, referred as homophily, and we stressed its role together with centrality and the selection of CM nodes in the evolutionary dynamics of human cooperation. In the evolutionary model, we inserted a new term, δ_{xy}, which represents the homophily distribution level among nodes in the social network. It is normally distributed and weighted considering the various dimensions of homophily using an equivalent homophily value derived from a relation analogous to the “thermal equilibrium” equation. Thus, at the end of each round of the game, each node updates its strategy not only according to the payoff difference experimented in the previous round but also considering the homophily value. To investigate the evolution of cooperation, we compared the more natural choice, consisting of selecting the more central nodes as CM nodes, with other CM nodes configurations, where the CM nodes are selected randomly (RN case) and among the less central nodes (EN case). Simulation results shed light on some hidden dynamics patterns due to the microscopic effect of homophily. In fact, even though we chose the CM nodes considering EN, a high homophily value is able to reinforce the links among nodes creating a major effort to cooperate. Thus, even considering “weak” groups communities, in terms of centrality and influence, homophily acts as a cohesion force which is able to push nodes towards cooperation (even if it takes more steps to reach it). In [45] and [55] the authors have demonstrated the role of heterogeneity in evolutionary dynamics of cooperation, introduced considering a scale-free network, thus a heterogeneous populations makes the sustainability of cooperation easier to get than in homogeneous populations, despite of the adopted social dilemma.

In this work, starting from heterogeneity and a scale-free network, we have also investigated the emergence of cooperation considering other two key parameters. The first is a statistical estimator, “Critical Mass”, used to evaluate the importance of the selection of a particular spatial configuration of initial critical nodes, chosen according to the eigenvector centrality value, which allows weighing the influence of nodes on neighborhood. The second is the introduction of a shaping factor of social relationships, represented by homophily, which explains how social ties are forged and cut off over time, able to enclose various features, the cultural, behavioral and genetic information traveling through the network, creating a weight impacting the emergence of cooperation. Therefore in our study, evaluating the joined role of these two aspects, it emerges an important difference with [45], related to the initial condition, since we do not consider an equal percentage of strategies (cooperators and defectors) randomly distributed among the population but, as one of our targets has been to explore the evolution considering different initial spatial configurations, we have placed the “Critical Mass” of initial cooperative nodes in different spatial configurations in order to see their effects on evolutionary dynamics.

Therefore, coherently with [56], we showed how homophily can facilitate diffusion from a small initial set of CM nodes.Therefore, these results could help developing collective awareness platforms towards the user empowerment through the acquisition by the user of more control, sharpening his critical awareness of social situation and environment and the stimulation of participation inside society [57,58]. Furthermore, as underlined in [59], it could be relevant to study the evolutionary effect of environmental fluctuations on homophily, evalutating how these fluctuations may change population dynamics creating different evolutionary trajectories of human cooperation over time.

Coherently with [8,60,61], another key aspect to be more explored is the evolutionary dynamics of human cooperation in multilayer networks [62,63], considering also what may be the role of introducing an extra dimension of analysis, stressing the importance of the coupling between the network layers [64] and allowing us to unveil the hidden emergent dynamics and observing nontrivial patterns within a population across network layers.

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