In relazione alla visita del sottoscritto presso il Departamento de Matemáticas dell'Universidad Carlos III de Madrid (UC3M), dal 31/10/2016 al 21/11/2016, nell'ambito del Programma Short-Term Mobility, anno 2016) - titolo del progetto: "EFFECT OF GOSSIP AND SOCIAL INFLUENCE ON THE EVOLUTION OF COOPERATION", l'attività svolta durante il soggiorno presso il laboratorio ospitante ha incluso i seguenti punti:

- Analisi dati e interpretazione dei risultati di un esperimento con soggetti umani sul ruolo del gossip (scambio di informazioni privato) nelle dinamiche comportamentali di individui che interagiscono mediante Public Goods Game; sia l'esperimento che l'analisi e l'interpretazione dei risultati sono stati fatti in stretta collaborazione con il Prof. Angel Sánchez della UC3M. L'articolo scientifico sui risultati ottenuti è attualmente in corso di scrittura, e sarà presto inviato a rivista.

- Studio teorico e simulativo dell'influenza della vigilanza degli altri sul comportamento degli individui, per capire sotto quali condizioni ambientali il controllo (reale o percepito) dei pari favorisce l'affermarsi di strategie e comportamenti prosociali. Il lavoro è stato fatto in collaborazione con la Dr. María Pereda della UC3M, e l'articolo relativo è già stato scritto e inviato alla rivista "Games" (copia allegata a questo documento).

- Progettazione di nuovi esperimenti e simulazioni con l'UC3M sempre nell'ambito dello studio della cooperazione nelle comunità umane.

- Pianificazione di future collaborazioni tra il LABSS-ISTC e l'UC3M per eventuali prossimi progetti europei.

Roma, 12 dicembre 2016

Il fruitore: Dott. Daniele Vilone

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Article

Social pressure and environmental effects on networks: a path to cooperation

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Abstract: In this paper we study how the pro-social impact due to the vigilance by other individuals is conditioned by both environmental and evolutionary effects. To this aim, we consider a known model where agents play a Prisoner's Dilemma Game among themselves and the pay-off matrix of an individual changes according the number of neighbors which are "vigilant", *i.e*, how many neighbors watch out for her behavior. In particular, the temptation to defect decreases linearly with the number of vigilant neighbors. This model proved to support cooperation in specific conditions, and here we check its robustness with different topologies, microscopical update rules and initial conditions. By means of many numerical simulations and few theoretical considerations, we find in which situations the vigilance by the others is more effective in favoring cooperative behaviors and when its influence is weaker.

Keywords: Cooperation; Prisoner's Dilemma; Evolutionary Dynamics; Monitoring Hypothesis.

1. Introduction

The emergence and surviving of cooperative and, more in general, pro-social behaviors in nature and human societies has been one of the most debated issues in natural and social sciences since a long time [1–3]. Indeed, there is an apparent, yet paradoxical, contrast between the advantages of selfish strategies at level of individuals, which should be expected to be mostly preferred by natural selection, and the ubiquitous presence of cooperation and altruism at level of communities (not necessarily in humans) [4]. In order to solve this problem, in the last decades many different mechanisms have been proposed [5–7]. What emerges from all this great deal of studies is that there is not a single universal mechanism which enhances cooperation against defection, but that different phenomena have a different explanation. In particular, if we limit our discussion to the pro-social behaviors in human communities, it has been demonstrated how indirect reciprocity [8], partner selection and punishment [9,10] or gossip [11] can foster cooperative strategies in various situations.

Another factor which has been found at work in favoring human cooperation is the vigilance by others: more precisely, people tend to adopt more altruistic behaviors when they are observed by peers [12,13], or even when they simply feel they are watched [14–16] (*Monitoring Hypothesis*). In Ref. [17], a game-theoretical model able to describe this effect was presented. In particular, the effect of the vigilance was considered as a reduction of the temptation to defect in a Prisoner's Dilemma Game played in complex networks. As a result, the higher was the level of vigilance, the higher was the final degree of cooperation throughout a population. In that work, the behavior of the model was tested only in a few kinds of complex networks (essentially random and scale-free), with just one evolutionary rule (replicator) and always with the same initial conditions (completely random). Anyway, as we have stressed above, the effect of the various mechanisms which determine the dynamics of these phenomena generally is not universal: for instance, the same topological structure can in some cases foster cooperation, or hinder it in different situations [7]. Therefore, in this paper we aim to deepen and further clarify the results reported in Ref. [17], testing the robustness of its results by changing different aspects and parameters of the original model. In practice, we will focus on three factors: the topology (that is, the network on which the population evolves), the evolutionary algorithm (the rule following which the individuals adapt their strategies), the initial conditions. This is important because in the real world communities live in different environments and evolve in different ways, so that a test of this type allows to evaluate better the reliability of the model and the entirety of its results.

The paper is organized as follows: in the next section we will define the model, then in Sec. 3 we will present the results of the simulations and, where possible, of some theoretical analysis. Finally, in Sec. 4 we will discuss such results and sketch some perspectives.

2. Model

We consider a population of N individuals interacting through an evolutionary Prisoner's Dilemma Game (PDG) under vigilance pressure. The population is set on a given network, which is equivalent to assign links between the individuals which can interact directly: according to the distribution of links, the topology of the system will be different. Every player is characterized by a strategy, C (cooperation) or D (defection), and at each elementary time step plays a round of the PDG with her neighbors, and her neighbors do the same on their turn. After each interaction, an individual i gets a payoff according to her payoff matrix:

	$\mathbf{C}_j$	$\mathbf{D}_j$
$\mathbf{C}_i$	1	0
$\mathbf{D}_i$	T_i	P

(1)

where C_i, D_i are the strategies adopted by the player herself, and C_j, D_j the strategies utilized by the neighbor j; the total payoff collected by i in a single step of the dynamics will be the sum over all the payoffs collected with each neighbor. Of course, to have a PDG it must be $T_i > 1 \ \forall i$; furthermore, we restrict to the weak Prisoner's Dilemma (wPDG), that is the case $P = 0$ [5].

Moreover, every player can be either in a vigilant state, that is, controlling her neighbors' strategy, or not. Defining the variable V_i which is equal to 0 if player i is not vigilant, and equal to 1 if she is, a non vigilant individual can become vigilant following a Watts' threshold rule [17,18]:

$$V_i^{0\to 1}(m_i, k_i) = \begin{cases} 1 \quad if \quad m_i/k_i > \theta_i, \\ \\ 0 \quad if \quad m_i/k_i \leq \theta_i \ , \end{cases} \tag{2}$$

where m_i is the number of neighbors of the node i that are already vigilant, k_i is the degree of node i, and $\theta_i \in [0, 1]$ the personal threshold of node i above which she becomes vigilant. In this work we consider this threshold constant and equal for every player: $\theta_i = \theta \ \forall i$.

The pressure due to the vigilance makes the temptation to defect effectively lower than in absence of any external control: actually, it has already been demonstrated that people feel uncomfortable if they adopt anti-social behaviors being just feeling observed [15,16]. In terms of the payoff matrix, we can model this phenomenon linking the temptation entry in the matrix (1) to the number of vigilant neighbors:

$$T_i = b - \frac{m_i}{k_i}(b-1)\,, \tag{3}$$

where b is the value of the temptation in absence of vigilance.

Evolutionary rules

After all the individuals have played a round of the game, they update their strategies synchronously, according to a given rule. In this work we have studied three different update algorithms: replicator (REP), unconditional imitation (UI), or a mixed update rule (MUR), inspired by reference [19].

Replicator — With REP we proceed as follows. Let s_i be the strategy the individual i is playing, and π_i her payoff. With the proportional imitation rule, each individual i randomly choose one from her k_i neighbors (individual j) and adopts her strategy with probability:

$$p_{ij}^t \equiv P\left\{s_j^t \to s_i^{t+1}\right\} = \begin{cases} (\pi_j^t - \pi_i^t)/\Phi & if \quad \pi_j^t > \pi_i^t, \\ 0 & if \quad \pi_j^t \leq \pi_i^t, \end{cases} \tag{4}$$

where $\Phi = max(k_i, k_j)[max(1,T) - min(0,S)]$ so that $p_{ij}^t \in [0,1]$.

Unconditional Imitation — With UI rule, in order to evolve her strategy every player imitates the one adopted by the neighbor that has obtained the best payoff, provided it is larger than her own (otherwise, nothing happens).

Mixed update rule — In this case, with probability q the player simply imitates the strategy of one of her neighbor picked up at random, and with probability $1-q$ evolves according the UI rule described above. While REP rule is more representative of evolutionary phenomena in biology, this one describes better the dynamics underlying the decision making processes of human beings: therefore, it depicts more realistically social phenomena [19,20].

In any case, whatever the update rule is, the strategies of the individuals are updated synchronously. Finally, after revising their strategies, players update their vigilance status, according to the rule given in Eq. (2).

3. Results

We accomplished many simulations of the model defined in the previous section, with different parameter values, topology, and update rules, in order to generalize the results presented in Ref. [17]. In order to characterize and analyze the behavior of the model, we will consider the quantity $\langle \rho \rangle$, that is, the final average cooperator density. In this way, it will be easy to discern when the cooperation finally invades the system, or is removed, or possible intermediate configurations.

All the simulations presented here have been carried out with $N = 1000$ individuals. In case of monoplex networks, the topologies utilized in this paper are i) Erdös-Rényi (ER) random networks [21], ii) Barabasi-Albert (BA) scale-free networks [22], iii) regular two-dimensional lattices (with absorbing boundary conditions), iv) link-added small-world (LASW) random networks [23,24]. Unless explicitly indicated, the initial conditions are totally random, so that at the initial stage of the dynamics, on average there are 50% of cooperators; analogously, also the initial vigilant players are picked up at random: therefore, if only cooperators can be vigilant, we will have at the beginning the 25% of vigilant cooperators, otherwise, in Subsec. 3.4 the initial vigilant individuals will be the 50% of the population, equally distributed among cooperators and defectors.

3.1. Influence of the update rule

Here we consider monoplex and duplex networks, and check how the behavior of the system changes by varying the way the individuals evolve their strategies.

3.1.1. Unconditional Imitation

Let us consider an ER and a BA networks, with average degree $z = 4$ and $z = 16$. In Fig. (1) the final average cooperation density as a function of the temptation b is shown for different values of the threshold θ in the ER case, while in Fig. (2) we report the same results for a BA network.

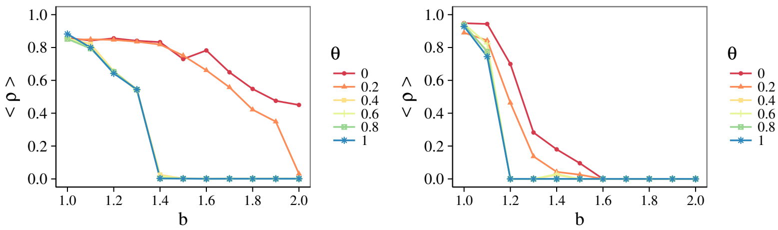

Figure 1. ER network. $z = 4$ left, $z = 16$ right. Average final fractions of cooperators ρ as a function of b for different values of θ.

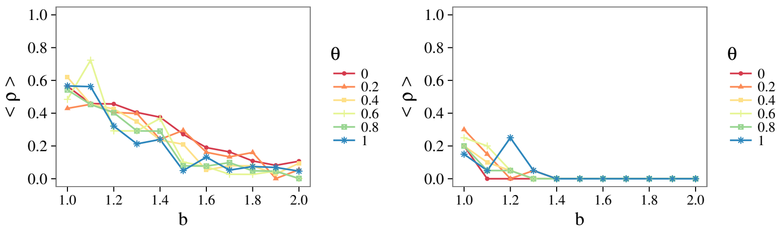

Figure 2. BA network. $z = 4$ left, $z = 16$ right. Average final fractions of cooperators ρ as a function of b for different values of θ.

As it is easy to see, the cooperation is much more supported in ER topology than in BA. Comparing such results with the ones presented in Ref. [17], we notice that with REP rule the cooperation is favored both in ER and BA networks. Therefore, we can conclude that the presence of hubs hinders the emergence of cooperative behaviors with a purely deterministic evolution algorithm, *i.e.*, a small amount of noise is necessary for cooperation to overcome this barrier. This is further confirmed by taking into consideration a duplex BA-BA network, that is when the network of game dynamics and the one of vigilance dynamics are separated [17], and both are BA networks with the same average degree. As shown in Fig. 3, the final level of cooperation remains as low as in the BA monoplex case.

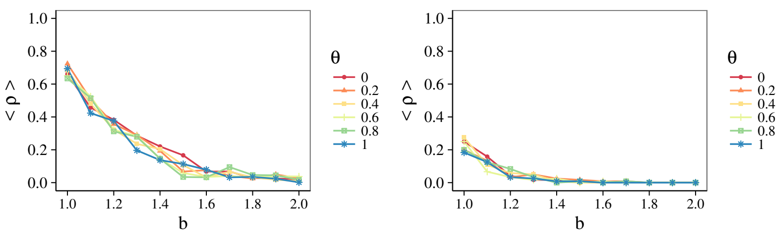

Figure 3. BA-BA duplex network. $z = 4$ left, $z = 16$ right. Average final fractions of cooperators ρ as a function of b for different values of θ.

3.1.2. Mixed update rule

We want now to check the robustness of the model with respect to the MUR rule, which is more realistic in the human interactions [20]. As shown in Figs. 4 and 5, θ (vigilance) has no effect on cooperation, but update rule does. When the probability of following the non-strategic imitation rule is low ($q = 0.3$), we can find some levels of cooperation, but with higher values (i.e. $q = 0.5$) cooperation is hindered as it happened in subsection 3.1.1.

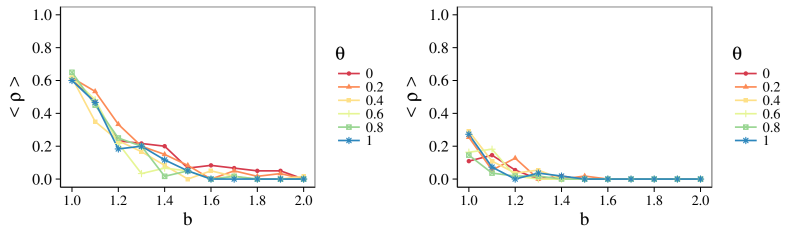

Figure 4. Mixed update rule with $q = 0.3$. BA-BA duplex network. $z = 4$ left, $z = 16$ right. Average final fractions of cooperators ρ as a function of b for different values of θ.

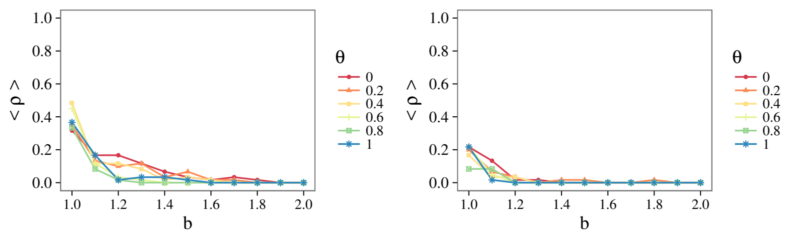

Figure 5. Mixed update rule with $q = 0.5$. BA-BA duplex network. $z = 4$ left, $z = 16$ right. Average final fractions of cooperators ρ as a function of b for different values of θ.

It is worth to stress the fact that increasing the weight of the non-strategic imitation hinders the cooperation. This could be explained by considering that, by UI rule, cooperators connected with other cooperators have a very high fitness and are surely imitated by a linked defector. To clarify this idea, let us consider a defector j with four neighbors, among which there is only one cooperator i. Since cooperators tend to cluster, it is likely that the three defectors are connected to other defectors, getting in a single game round a fitness equal to 4, whilst i will be probably linked to three cooperators, gaining $3b$ (for seek of simplicity, we assume that every individual has exactly 4 links). So, if $b > 4/3$, player j will definitely turn herself cooperator if evolves by UI rule, while will remain a defector with probability $3/4$ following the non-strategic update algorithm. Indeed, in Figs. 4 and 5, we see clearly that the final cooperator density practically vanishes just around $b \approx 1.3$, coherently with the above considerations.

3.2. Other topologies

Up to now, we have considered the most classical examples of complex topologies, that is, ER and BA networks. Here we aim to check the behavior of the model on topological structures with different features. In particular, ER and BA networks differ mainly for the fact that in the former there are no hubs (nodes with much more connections with respect to the average), contrarily to what happens in scale-free BA networks [25]. Anyway, both have a small diameter (*i.e.*, the average distance between two nodes picked up at random scales as the logarithm of the system size), and a small clustering coefficient (*i.e.*, the probability that two neighbors of a third node are also neighbors is much smaller than 1). Therefore, it is worth to consider networks with one or both diameter and clustering coefficient different from ER and BA networks.

For this purpose, we took into consideration a Watts-Strogatz Small-World topology, which has the property to behave locally as a regular lattice-like network (*i.e.*, high clustering coefficient), but as a random network globally (small diameter). Moreover, we built such network following a different procedure from the one presented in Refs. [23,26]: starting from a regular square lattice of $N = 1000$ nodes each one with $z = 4$ neighbors, we added links between non connected nodes with a probability p, as in the LASW model defined in Ref. [24]. In this way, by tuning the parameter p we can explore the lattice ($p = 0$), and small-world ($0 < p \lesssim 2z/N$) topologies. Now, as illustrated in Fig. 6, we see how in lattice the system cannot sustain cooperation (left graph), but increasing the density of short-cuts, the cooperation is mostly enhanced, even better than in ER topology (middle and right graphs). Interestingly, the results do not depend on θ, apart the fact that defection easily overcomes cooperation when $\theta = 1$ already for small values of b.

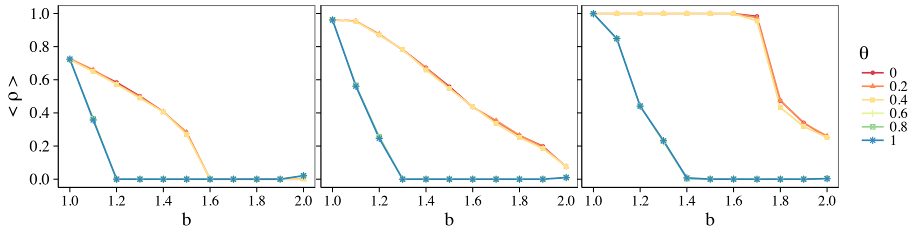

Figure 6. LASW network. Pure lattice (left), lattice with 10% of pure lattice number of links added (middle), lattice with 30% of pure lattice number of links added (right). Average final fractions of cooperators ρ as a function of b for different values of θ.

3.3. Different initial conditions

A simple mean-field analysis of the model suggests that the outcome of the dynamics should depend also on the initial conditions, in particular on the initial distribution of the vigilant players. Actually, the vigilance can have an effective influence on the evolution of the system only if the vigilant individuals are enough to make the others vigilant too, following Eq. (2). Now, considering a mean-field approach, the probability that an individual with k connections has initially m vigilant neighbors is

$$P(m;k) = \binom{k}{m} a_0^m (1 - a_0)^{k-m} \,, \tag{5}$$

where a_0 is the initial density of the vigilant individuals. Then, it can be easily computed the average density of vigilant neighbors at the beginning of the dynamics:

$$\left\langle \frac{m}{k} \right\rangle = \sum_{m=0}^{k} \frac{m}{k} P(m;k) = a_0 \,. \tag{6}$$

Therefore, the effect of vigilance should become noticeable for $\theta < a_0$: since we usually set that initially half of cooperators are also vigilant, we expect a transition from high cooperation to defection for θ larger than a critical θ^* such that

$$\theta^* \approx \frac{\rho_0}{2} \tag{7}$$

where $\rho_0 = 0.5$ is the initial cooperator density. Of course, we also expect that the network structure changes at least partially this picture. In fact, the influence of the initial conditions is almost completely removed in non-trivial topologies, as we are going to show in the following.

In Fig. 7 we present the final cooperator distribution for a system on a square lattice evolving by the REP rule. As it is easy to realize, if the number and distribution of initial vigilant individuals is such that no other player can be activated, then there will be no effect of the vigilance and the cooperation vanishes already for small values of the temptation b. On the contrary, as the initial distribution allows, even through statistical fluctuations, that some inactive player can have enough vigilant neighbors to get activated, then the number of vigilant individuals soon increases and the system ends up in a configuration with a higher level of cooperation, independently from the initial number of vigilant agents.

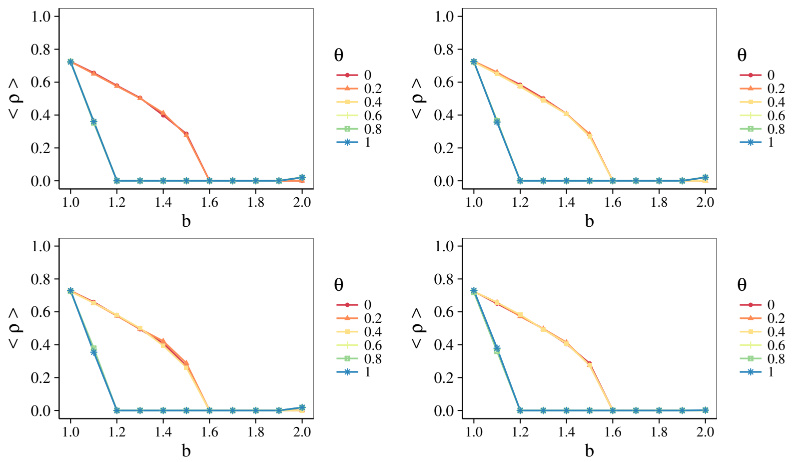

Figure 7. Square lattice, different initial vigilant densities. Upper left: only one initial vigilant put in the middle of the lattice. Upper right: initial probability for each cooperator to be vigilant equal to 0.001. Lower left: initial probability to be vigilant equal to 0.05. Lower right: initial probability to be vigilant equal to 0.45. Average final fractions of cooperators ρ as a function of b for different values of θ.

This is true also on ER random networks, as shown in Fig. 8: in the end, there is practically no effect of the initial vigilant density on the final fate of the dynamics. Indeed, as can be proven by comparing these results with the Fig. 1(a) of the Ref. [17], $\langle\rho\rangle$ is always very close to the value of the case $a_0 = 0.25$, apart some slight differences. This same picture holds for BA networks as well: also with this topology the final level of cooperation does not depend on the initial distribution of the activated players, as reported in Fig. 9.

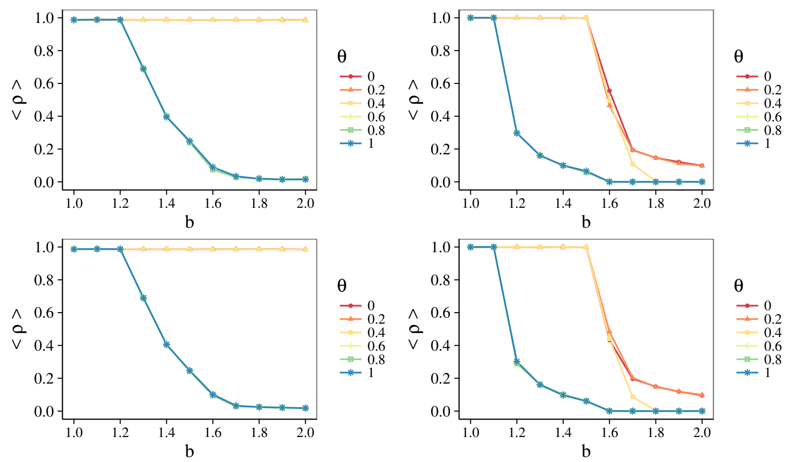

Figure 8. ER network, different initial vigilant densities. Left graphs: $z = 4$; right graphs: $z = 16$. Upper figures: initial probability to be vigilant 0.05; lower figures: initial probability to be vigilant 0.45. Average final fractions of cooperators ρ as a function of b for different values of θ.

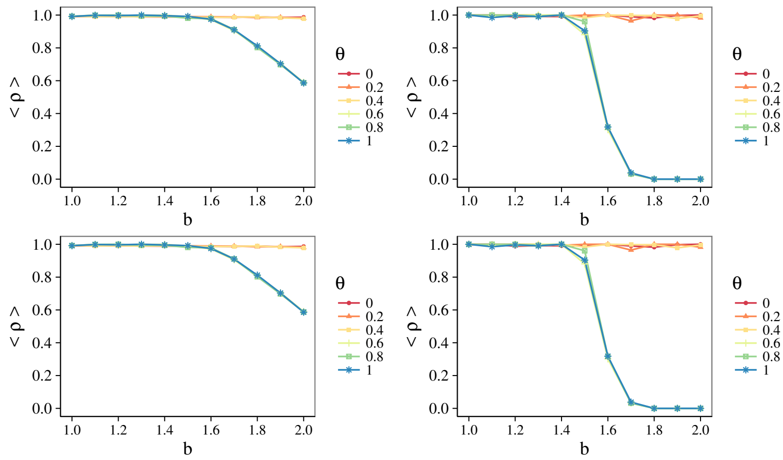

Figure 9. BA network, different initial vigilant densities. Left graphs: $z = 4$; right graphs: $z = 16$. Upper figures: initial probability to be vigilant 0.05; lower figures: initial probability to be vigilant 0.45. Average final fractions of cooperators ρ as a function of b for different values of θ.

Therefore, we can finally state that the dynamics turns out to be robust with respect to varying the initial conditions, so that what has been presented in the previous subsections can be considered as general results with respect to the initial configuration of the system.

3.4. *Case of vigilant defectors*

Until now, we have set that only cooperators can be also vigilant players. In fact, in a PDG also defectors have interest to be connected with cooperators, so it is plausible to consider a situation where also who is not a cooperator can be vigilant. In practice, in human interactions also who adopts anti-social behaviors can force the others to behave fairly [11,27,28].

Therefore, we considered the case in which every player, independently from the fact that she is either a cooperator or a defector, can be a vigilant one. We show the results for this case only on square lattice, because here the effect is magnified with respect to the remaining topologies. Actually, as shown in Fig. 6(left), in this topology cooperation is mostly hindered.

In Fig. 10 we see that already a very small probability ϱ_0 to be an initial vigilant (upper left graph) helps cooperation to invade the population already for not-too-high vigilance $\theta \lesssim 0.5$, and, from $\varrho_0 \gtrsim 0.05$ on (upper right and lower graphs), also for $\theta = 0.6$ the final cooperator density does not vanishes even at higher values of b. This is of course an expected result, since allowing more individuals to activate as vigilant ones decreases much more the average temptation of every player, according to the Eq. (2). This outcome holds also in different topologies.

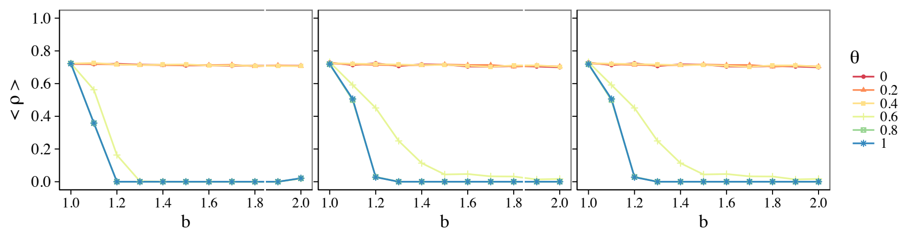

Figure 10. Lattice, vigilance independent from strategy. Left: initial probability to be vigilant 0.001; middle: initial probability to be vigilant 0.05; right: initial probability to be vigilant 0.45. Average final fractions of cooperators ρ as a function of b for different values of θ.

4. Discussion and Conclusions

The model of vigilance firstly presented in Ref. [17], and further developed here, treats the pro-social effect due to the control (be it real or just perceived) by peers as a decreasing of the temptation to defect: the more neighbors watch out for the behavior of a subject, the less is the probability that the latter adopts a selfish strategy. Even though the preliminary results of this approach turned out to be promising, before considering it a viable way to describe this phenomenon it was necessary to test its full validity. Therefore, in this paper we have aimed to ascertain that the main features of the model are basically robust: that is, we verified that, through the mechanism of vigilance proposed here, cooperation is actually fostered for a broad values of the parameters at stake and in different environmental configurations. In particular, we showed that the beneficial influence of the vigilance works in more realistic configurations, allowing us to hypothesize that what has been repeatedly observed in experiments and field observations can be actually explained as a smaller temptation to defect in presence of controllers.

The results which in our opinion allow us to consider the model realistic are the following:

- vigilance needs the small-world effect (the presence of short-cuts connecting individuals physically far away from each other) to be efficient in fostering cooperation (in regular lattices, Fig. 6, it does not help), and the small-world property is ubiquitous in most real social systems;
- vigilance works not only when the individuals update their strategy by means of an essentially evolutionary rule (REP), but also when they evolve through more typically "social" mechanisms as pure imitation (at least on ER networks); moreover, considering the mixed rule, which takes into account the intrinsic non-strategic component of humans' decision making processes, we found that the cooperation can tolerate the influence of irrationality only when this is low ($q < 0.5$), coherently with the results of Ref. [20];
- the results do not depend sensitively on the initial conditions (at least on complex topologies): this is a fundamental feature of the model since it is usually hard to determine the initial conditions for real social systems; on the other hand, in complete graphs (*i.e.* in mean-field approximation), this is not true, but only small human communities can be described in this way, and in such cases different dynamical mechanisms are at work [29].

Of course, further investigations are needed to validate definitively the model, in particular experiments explicitly aimed to check if this peculiar kind of phenomenon (decreased temptation in a PDG) takes actually place when subjects play in the laboratory. This kind of studies are already planned for the next future.

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Author Contributions: M. P. created the original model and accomplished the simulations. D. V. conceived the model generalizations and accomplished the theoretical analysis. Both authors wrote and revised the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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