

Exogenous Rewards for Promoting Cooperation in Scale-Free Networks

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Abstract

The design of mechanisms that encourage pro-social behaviours in populations of self-regarding agents is recognised as a major theoretical challenge within several areas of social, life and engineering sciences. When interference from external parties is considered, several heuristics have been identified as capable of engineering a desired collective behaviour at a minimal cost. However, these studies neglect the diverse nature of contexts and social structures that characterise real-world populations. Here we analyse the impact of diversity by means of scale-free interaction networks with high and low levels of clustering, and test various interference mechanisms using simulations of agents facing a cooperative dilemma. Our results show that interference on scale-free networks is not trivial and that distinct levels of clustering react differently to each interference mechanism. As such, we argue that no tailored response fits all scale-free networks and present which mechanisms are more efficient at fostering cooperation in both types of networks. Finally, we discuss the pitfalls of considering reckless interference mechanisms.

Introduction

The problem of explaining collective behaviours among self-interested individuals in evolving dynamical systems has fascinated researchers from many fields, and is a well studied research topic in evolutionary game theory (Hofbauer and Sigmund, 1998). It can be found in a variety of real-world situations, ranging from ecosystems to human organisations and technological innovations and social networks (Santos et al., 2006; Sigmund et al., 2001; Raghunandan and Subramanian, 2012; Han et al., 2019). It has been also investigated in various Artificial Life systems such as swarm-based systems and biologically inspired artificial social systems (Nitschke, 2005; Bonabeau et al., 1999).

In this context, cooperation is typically assumed to emerge from the combined actions of individuals within the system. However, in many scenarios, such behaviours are advocated and promoted by an external party, which is not part of the system, calling for a new set of heuristics capable of *engineering* a desired collective behaviour in a self-organised complex system Penn et al. (2010). For instance, if one considers a near future, where hybrid societies comprising humans and machines shall prevail, it is important to

identify the most effective incentives to be included to leveraging cooperation in such hybrid collectives (Paiva et al., 2018). In a different context, let us consider a wildlife management organisation (e.g., the WWF) that aims to maintain a desired level of biodiversity in a particular region. In order to do that, the organisation, not being part of the region's eco-system, has to decide whether to modify the current population of some species, and if so, then when, and in what degree to *interfere* in the eco-system (i.e., to modify the composition of the population) (Levin, 2000). Since a more impactful intervention typically implies larger costs in terms of human resources and equipment, the organisation has to achieve a balance between pregnant wildlife management and a low total investment cost. Moreover, due to the evolutionary dynamics of the eco-system (e.g., frequency and structure dependence) (Santos et al., 2006), undesired behaviours can reoccur over time, for example when the interference was not sufficiently strong in the past. Given this, the decision-maker also has to take into account the fact that it will have to repeatedly interfere in the eco-system in order to sustain the level of biodiversity over time. That is, it has to find an efficient interference mechanism that leads to its desired goals, while also minimising the its total cost.

This question has been studied previously in the context of populations distributed on regular graphs, namely the complete and the square lattice graphs (Han and Tran-Thanh, 2018; Han et al., 2018). In this type of network, every individual has the same degree of connectivity (i.e. the number of neighbours). However, in social graphs and real-world populations, individuals typically have a diverse social connectivity (Albert and Barabási, 2002; Santos et al., 2008). Hence, in this paper, we study cost-effective interference in heterogeneous networks, namely different types of scale-free networks, which have been shown to well capture real-world networks (such as the World Wide Web) (Newman, 2018). In particular, we consider populations of individuals distributed in a scale-free network, who interact with their neighbours via the one-shot Prisoner's Dilemma (PD), where uncooperative behaviour is preferred over cooperation (Sigmund et al., 2001; Santos et al., 2006). As an

outsider decision-maker, we aim to promote cooperation by interfering in the system, rewarding particular agents in the population at specific moments.

The research question here is to identify when and how much to invest (on individuals distributed in a network) at each time step, in order to achieve our desired ratio of cooperation within the system such that the total cost of interference is minimised, taking into account the fact that individuals might have different levels of social connectivity. For instance, we might wonder whether it is sufficient to focus the investment only on highly connected cooperators since they are more influential, thereby leading to cost-efficiency? Do we need to take into account a neighbourhood's cooperativeness level which was shown to play an important role in square lattice networks (Han et al., 2018)? Also, when local information is not available and only global statistics can be used in the decision making process, how different are the results in heterogeneous networks, in comparison to regular graphs?

To answer these questions, this paper will systematically investigate different general classes or approaches of interference mechanisms, which are based *i)* on the global population statistics such as its current composition, *ii)* a node's social connectivity in the network and *iii)* the neighbourhood properties such as the local cooperativeness level.

Our results show that interference in a heterogeneous network exhibits a significantly more complex challenge (to be cost-effective while ensuring high levels of cooperation) and much richer nonlinear dynamic behaviours, compared to regular graphs. For instance, in both well-mixed and square lattice graphs, a greater per-individual investment cost would ensure at least the same level of cooperation since it gives each cooperator a better fighting chance for survival against defectors. However, this is not the case in the context of heterogeneous networks as increasing the per-individual investment cost could actually be detrimental for cooperation.

The rest of the paper is structured as follows: the next section provides a brief overview of the related work, which is followed by a detailed description of our model, methods and its results. The paper ends with a final discussion.

Related Work

The problem of explaining the emergence and stability of cooperative behaviour has been studied intensively in many fields, from Social Sciences, Economics, Physics to Multi-agent Systems and Artificial Life (Hofbauer and Sigmund, 1998; Nowak, 2006; Han et al., 2012; Nitschke, 2005). Several mechanisms responsible for the evolution of cooperation have been identified, including direct and indirect reciprocity (Nowak and Sigmund, 2005), kin and group selections (Traulsen and Nowak, 2006), network reciprocity (Santos and Pacheco, 2005; Santos et al., 2006), punishment and rewarding (Sigmund et al., 2001), and cognitive mecha-

nisms (Han et al., 2011, 2012). However, these mechanisms do not consider how cooperation can be promoted by an external party. Instead, they are incorporated as part of individual strategic behaviours, in order to study how they evolve and whether their evolution promotes a better outcome for cooperative behaviour. In contrast, our interference mechanisms are external, i.e. they are not incorporated into the individual strategy.

In addition, the aim of our mechanisms is to minimise the cost of interference while guaranteeing high levels of cooperation, contrary to past literature where the cost optimisation is often omitted. In this respect, our work is also different from the modelling works of institutional incentives to encourage cooperation through costly reward and punishment (Sigmund et al., 2010; Vasconcelos et al., 2013) as well as through enforcing agreements (Han et al., 2017).

Similarly, our work also differs from EGT literature on optimal control in networked populations (Riehl and Cao, 2017; Ramazi and Cao, 2015), where cost-efficiency is not considered. Instead, these works on controllability focus on identifying which individuals or nodes are the most important to control (i.e. where individuals can be assigned strategies as control inputs), for different population structures.

Closely related to the current work are the analyses on well-mixed populations (i.e. having a fully connected graph structure) (Han and Tran-Thanh, 2018) and on square-lattice structured populations (Han et al., 2018), which study cost-efficient interference on the aforementioned types of networks, respectively. Moving to the more complex scenario of heterogeneous networks where individuals might have different degrees of connectivity (i.e. the number of neighbours), an interference mechanism might need to take this new dimension into account to be cost-efficient. As shown below, cost-efficient interference mechanisms that incorporate this information can outperform those who only consider global population statistics and neighbourhood cooperative properties as in previous works.

Also related to current work is the research of cooperation in social networks where changes are initiated from inside the system (Raghunandan and Subramanian, 2012; Franks et al., 2013, 2014). Among them, more relevant to our paper is the recent work by Franks *et al.* (Franks et al., 2014), which has explored the use of influencers on complex networks. However, these influencers are also part of the system and thus, similar to the cases mentioned above, this work does not consider external interference mechanisms. Given this, it does not address similar decision-making problems that we examine here.

Models and Methods

Prisoner's Dilemma on Scale Free Networks

We consider a population of agents on scale-free networks of contacts (SF NOCs)— a widely adopted heterogeneous population structure in population dynamics and evolutionary

games (for a survey, see (Szabó and Fath, 2007)). We focus our analysis on the efficiency of various interference mechanisms in spatial settings, adopting an agent-based model directly comparable with the setup of recent lab experiments on cooperation (Rand et al., 2014).

Initially each agent is designated either as a cooperator (C) or defector (D) with equal probability. Agents' interaction is modelled using the one-shot Prisoner's Dilemma game, where mutual cooperation (mutual defection) yields the reward R (penalty P) and unilateral cooperation gives the cooperator the sucker's payoff S and the defector the temptation T . As a popular interaction model of structured populations (Szabó and Fath, 2007), we adopt the following scaled payoff matrix of the PD: $T = b$, $R = 1$, $P = S = 0$. (with $1 < b \leq 2$). We adopt a weak version of the Prisoner's Dilemma in spite of cooperator prevalence shown in previous works on scale-free networks of contacts (Santos et al., 2008), so as to have a direct link of comparison with studies on the effects of rewarding mechanisms in different types of networks (Han et al., 2018).

For SF networks with low clustering we adopt the famous Barabási-Albert (BA) model (Albert and Barabási, 2002). Starting from a complete graph of m_0 nodes, at every time-step one adds new node with $m \leq m_0$ edges linking to existing nodes, which are chosen with a probability that is proportional to the number of links that the existing nodes already have. The new node always connects to m distinct nodes, and duplicate connections at each time step are not allowed. The average connectivity of the network is $z = 2m$.

To obtain a SF network with high clustering, we resort to the Dorogovtsev-Mendes-Samukhin (DMS) model (Dorogovtsev et al., 2001). Similarly to the BA model, we also have growth, yet each new node attaches to both ends of a randomly chosen edge. As a result, we favor the creation of triangular relations between individuals, thereby greatly enhancing the clustering coefficient of the final network. As in the BA model, the process of choosing the edge implicitly promotes the preferential choice of highly connected nodes, leading to the same degree distribution. The edges chosen at each time step are distinct and multiple connections between the same two nodes are not allowed. This network also has an average connectivity of $z = 2m$. Both types of SF NOCs are pre-generated, before the strategies of players are designated and before the first generation commences playing.

At each time step or generation, each agent plays the PD with its immediate neighbours. The score for each agent is the sum of the payoffs in these encounters. Before the start of the next generation, the conditions of interference are checked for each agent and, if they qualify, the external decision maker increases their payoff. Multiple mechanisms (i.e. multiple conditions) can be active at once. At the start of the next generation, each agent's strategy is changed to that of its highest scored neighbour (Nowak and May, 1992; Szabó and Fath, 2007). Our analysis will be primarily based

on this deterministic, standard evolutionary process in order to focus on understanding the cost-efficiency of different interference mechanisms.

We simulate this evolutionary process until a stationary state or a cyclic pattern is reached. The simulations converge quickly, with the exception of some cyclic patterns which do eventually reach a stationary state. Because this work studies cost effective intervention, these rarely-occurring patterns which inherently invite very large total costs are escaped early by running simulations for only 75 generations, at which point the accumulated costs are excessive enough for this mechanism to not be of interest. Moreover, the results are averaged for the last 25 generations of the simulations for a clear and fair comparison (e.g. due to cyclic patterns). In order to improve accuracy related to the randomness of network topology in scale-free networks, each set of parameter values is ran on 10 different graphs for both types of SF NOCs. Furthermore, the results for each combination of network and parameter values are obtained from averaging 30 independent realisations. It is important to note that the distribution of cooperators and defectors on the network is different for every realisation.

Note that we do not consider mutations or random explorations in this work. Thus, whenever the population reaches a homogeneous state (i.e. when the population consists of 100% of agents adopting the same strategy), it will remain in that state regardless of interference. Hence, whenever detecting such a state, no further interference will be made.

Cost-Efficient Interference in Networks

As already stated, we aim to study how one can efficiently interfere in a structured population to achieve high levels of cooperation while minimising the cost of interference. An investment in a cooperator consists of a cost $\theta > 0$ (to the external decision-maker/investor). This investment is added to the payoff of an agent if certain conditions are met. Each mechanism has different conditions for investment. In particular, we investigate whether global interference mechanisms (where investments are triggered based on network level information) or their local counterparts (where investments are based on local neighbourhood information) lead to successful behaviour with better cost efficiency. To do so, we consider three main classes of interference mechanisms based *i)* on the global composition of the population, *ii)* the node's connectivity in the network and *iii)* the neighbourhood cooperation level.

1. Population composition based (POP): In this class of mechanisms the decision to interfere (i.e. to invest on all cooperators in the population) is based on the current composition of the population (we denote x_C the number of cooperators currently in the population). Namely, they invest when the number of cooperators in the population is below a certain threshold, p_C (i.e. $x_C \leq p_C$), for $1 \leq p_C \leq z$. They do not invest otherwise ($x_C > p_C$). The value p_C describes

how widespread the defection strategy should be to trigger the support of cooperators' survival against defectors.

2. Node Influence (NI): For this mechanism, the decision to invest in a given cooperator is dependent on how influential its node is (i.e. how many connections end in that node). Whereas POP considered the composition of the population, NI looks at how connected a node is in the network. That is to say, the decision-maker invests in a cooperator node C when the number of its immediate neighbours ($|k_C|$) divided by the maximum connectivity ($\max |k_i|$) is above a threshold of influence c_I , for $0 \leq c_I \leq 1$. Otherwise, i.e. when $0 \leq c_I \leq \frac{|k_C|}{\max |k_i|}$, no investment is made. The value c_I describes how influential a cooperator node should be to trigger an investment into its survival.

3. Local cooperation based (LC): In this class of mechanisms, the decision to invest in a given cooperator is based on the cooperativeness level in that cooperator's neighbourhood. Namely, the decision-maker invests in a cooperator when the number of its cooperative neighbours is below a certain threshold, n_C , for $0 \leq n_C \leq |k_C|$; otherwise, no investment is made. By varying the local cooperation threshold n_C , we aim to provide an answer to the important question of how much cooperation is required in a neighbourhood before the investor can choose to withhold the intervention and save the interference cost and under which conditions this can happen. For instance, one can ask whether it is safe to withdraw action in a neighbourhood without affecting the outcome, therefore eliminating unnecessary interference.

Interestingly, these mechanisms require different levels of information which may or may not be readily available in the given network. In some cases, such as social networks, the connectivity (i.e. the number of friends) of a node is virtually free information which requires no effort on the part of the external decision maker to discern. On the other hand, other mechanisms such as POP, inherently require more information about the population and the level of cooperativeness in different parts of the network. POP is a broad mechanism which only requires knowledge about overall cooperativeness, but LC invites even more detailed observations, in order to determine the cooperativeness in each neighbourhood. Combining NI with LC generally does not require any more observation than LC by itself. Our study of neighbourhood based interference does not take into account the cost of gathering information, it is a direct comparison between perceived gains in cooperation and the associated per-individual cost of interference set out in the interference mechanisms.

Results

In contrast to the study on square lattice networks (Han et al., 2018), as detailed below for each interference mechanism, we found that performing cost-effective interventions

on SF NOCs presents multiple concerns. In a square lattice population, more detailed observations resulted in more effective intervention with a better outcome. On the other hand, more knowledge about the population in SF NOCs simply reduces the risk of interfering to the detriment of cooperators. In other words, interfering in SF NOCs without adequate knowledge should be approached cautiously or it could act to the benefit of defectors. This issue is prevalent in the BA model and is not representative of the DMS model.

Positive interference in BA models broadly requires very high θ values (often orders of magnitude higher than similar mechanisms performed on square lattice populations) or a blanketing mechanism that targets all or almost all cooperators, even those which are not necessarily in danger of converting to D. Converging to 100% C is very difficult unless both of these conditions are met and this introduces multiple concerns in the role of an exogenous interfering party. We avoid focusing on solutions where the per-generation cost is excessive, as it is unlikely for any institution to be able to produce such exorbitant sums in one generation, as required by these heterogeneous networks, instead we focus on effective intervention with manageable amounts of per-generation cost. In the following subsections we detail the results obtained for each interference mechanism.

Population Based

We compare population-based interference mechanisms, i.e. POP, on the two different types of SF NOCs, the BA model and the DMS model, namely how efficient the mechanisms are at promoting cooperation with minimal total cost (See Figure 1).

For SF NOCs with a large clustering coefficient, we found that it is very easy to escape cyclic patterns and a minimal amount of interference, enabling the population to quickly converge to 100% cooperation. Without any interference, the frequency of Cs is greatly dependent on the initial distribution of strategies in the network and there is a large probability that Ds will quickly overtake the Cs, if the oldest (i.e. the most connected) nodes are initially Ds. Conversely, applying even a minimal amount of interference to Cs, at any point in the rapid decline of C population, helps Cs in converging to 100% of cooperation. Because of this, investing any more than minimal amounts of ($\approx \theta$), as well as interfering when the average cooperation is above 50%, increases the total cost with little to no benefit to the frequency of Cs. Note that the results are consistent for a larger cost θ . We plot up to $\theta \leq 5$ just for the sake of clear presentation.

In direct contrast with our findings for the DMS model, an external decision maker should only interfere in BA models with great care, as investing without discrimination could lead to a lower cooperation frequency when compared to no interference (See Figure 1). We observe that using certain values of θ negatively impacts average cooperation levels across a wide range of p_C values. For these undesired val-

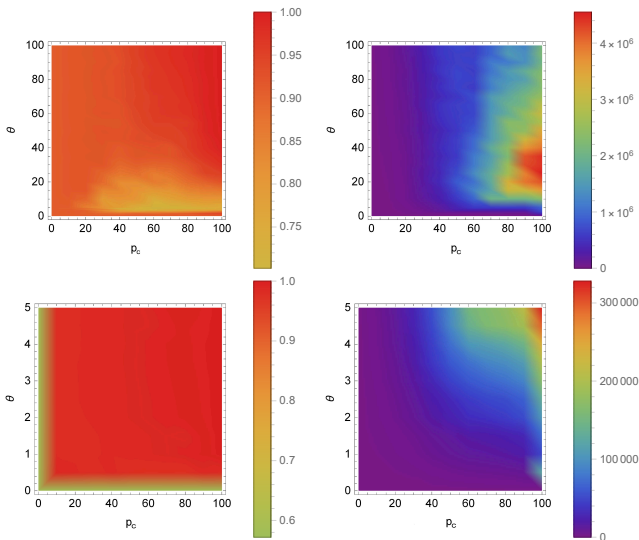


Figure 1: **Population-based (POP) interference for BA model (top row) vs DMS model (bottom row)**, for varying per-individual cost of investment θ , as well as the threshold of population cooperation p_C . The left column reports the frequency of cooperation while the right one reports the total cost required. We note in particular, the significant difference in total cost between the two models. Parameters: $b = 1.8$; $n = 5000$; $z = 4$ (average node connectivity).

ues of θ , cyclic patterns would form which ultimately help Ds by maintaining C players in clusters dominated by Ds (see Figure 2). This type of negative impact occurs when the θ value is not high enough for Cs to be able to convert a cluster to cooperation, but not low enough as to let the Ds converge to 100% D in that cluster. Many of these cyclic patterns eventually settle to 100% C if the simulation is ran for a sufficient number of generations (≈ 250). We note that the accumulated cost of interference at the end of the long-lasting cyclic patterns is prohibitively large, which make such values of θ undesirable for an external decision maker with limited resources.

Positive interference in BA models can be achieved by selecting very low or extremely high values for θ , with a high value for p_C . BA models converge to a high C frequency even without interference, so it is important to select a value for p_C that will allow interference after the system has reached a stable state (typically $p_C > 90$). In terms of total cost, it is more efficient to select very low values of θ , but the overall benefit to cooperation levels is much lower than with very high values of θ . Therefore, it is up to the external decision maker to decide if the increase in cooperation is worth the higher cost in resources.

Node Influence

When an exogenous decision maker takes into account only how connected a node is, see Figure 3, i.e. how influential it is in the network, it becomes very unlikely for interference to provide a meaningful improvement to levels of C in BA

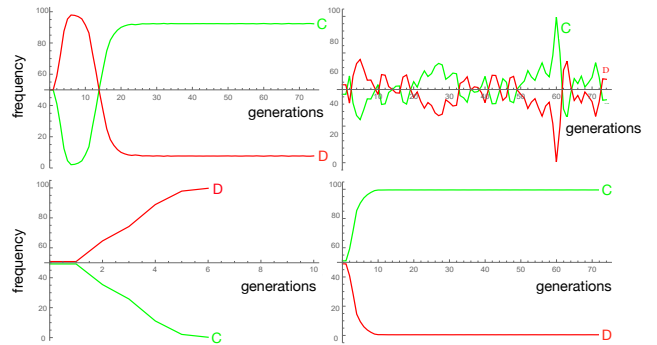


Figure 2: **Evolution of cooperation: BA Model (top) vs DMS model (bottom)**, for $\theta = 5$, $p_C = 80$. C and D frequencies are shown in green and red, respectively. The left column shows the network without interference, while the right one shows the same network after population-based (POP) interference. Other parameters: $b = 1.8$; $n = 5000$; $z = 4$ (average node connectivity).

models. Very low values of c_I (≈ 0.1), coupled with small to intermediate values of θ can cause a decrease in the average cooperation, forming previously discussed cyclic patterns (See Figure 2). For all other values, cooperation seems to be very inert. This phenomenon can be explained by the fact that clusters have already been decided in favour of cooperators and all that remains of defectors survives in a stable state around non-influential nodes. By targeting only the most influential cooperators, the external decision maker can have no impact on the less connected nodes, which enable the survival of defectors. Therefore, only a blanketing mechanism at very low c_I can reach the lowly connected cooperators and produce an increase in the average cooperation. This type of blanketing mechanism with low c_I quickly accumulates large amounts of total investment cost.

In SF networks with a high clustering coefficient, on the other hand, one can ensure convergence to 100% C in a cost effective way by selecting intermediary values of c_I (typically $\approx c_I = 0.6$) and low values for θ . An interesting observation is that contrary to POP, interference does not mean that the system will converge to 100% C. Anything more than minimal amounts of c_I show no increase to average of cooperation except at extremely high θ values. In other words, it appears that D clusters are very difficult to shift after the initial distribution of strategies on the network and the amounts of fitness they acquire are almost impossible to match except for a very large individual investment into the oldest and, implicitly, most influential, nodes. Similarly to the effect of NI on the BA model, a blanketing mechanism encourages the formation of C dominated neighbourhoods, which in turn generates a greater fitness than anything but very large values of individual investment θ . Interestingly, increasing individual investment at anything but low values of the influence threshold c_I actually promotes defection by enabling the temporary survival of cooperators connected to defectors which are centers of hubs. This, in turn, allows de-

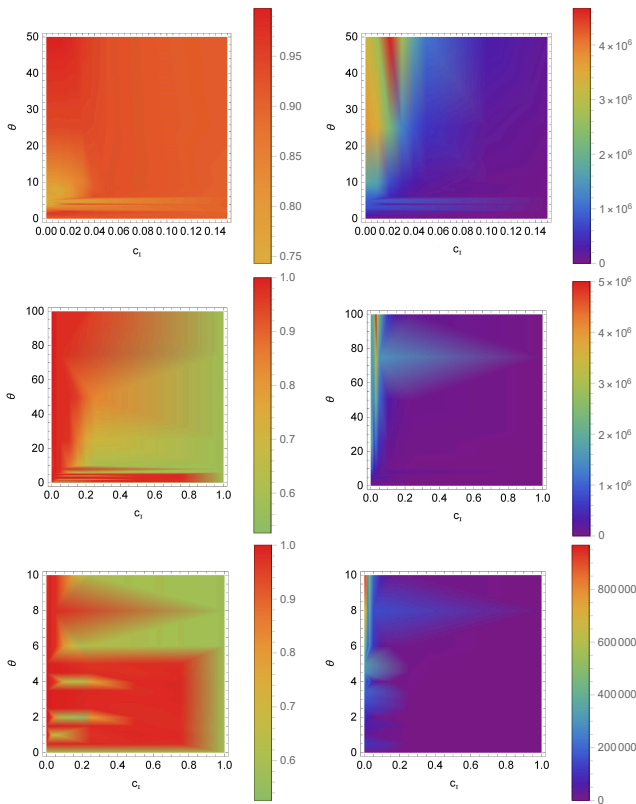


Figure 3: **Node influence based (NI) interference for BA model (top row) vs DMS model (middle row) and detailed view of DMS model (bottom row)**, for varying per-individual cost of investment θ , as well as the threshold for cooperator influence c_I . The left column reports the frequency of cooperation while the right one reports the total cost required. The ranges for θ and c_I are scaled for clear presentation. Parameters: $b = 1.8$; $n = 5000$; $z = 4$ (average node connectivity).

factor hubs to convert any remaining cooperator hubs. It is important to note that the initial distribution of players in the hubs is ultimately what determines which way the network will converge, so this type of interference does not produce any decrease in cooperation, as is the case of the BA model.

Local Cooperation

By the same token as earlier observations, interference on the BA model comes with the risk of reducing overall cooperation. What is more, LC based interference produces negative results for a wider range of parameters than any other mechanism (See Figure 4). That notwithstanding, investing smartly using the LC mechanism can lead to 100% cooperation, whereas the other mechanisms struggle. The key to such smart investments is in choosing a value for the threshold of local cooperation n_C which approaches the upper limit ($n_C \rightarrow 1$), with individual investment θ values high enough to convert defectors situated in cooperator clusters. As the value of n_C approaches 1, redundant investment decreases. With higher values of θ , the network converges

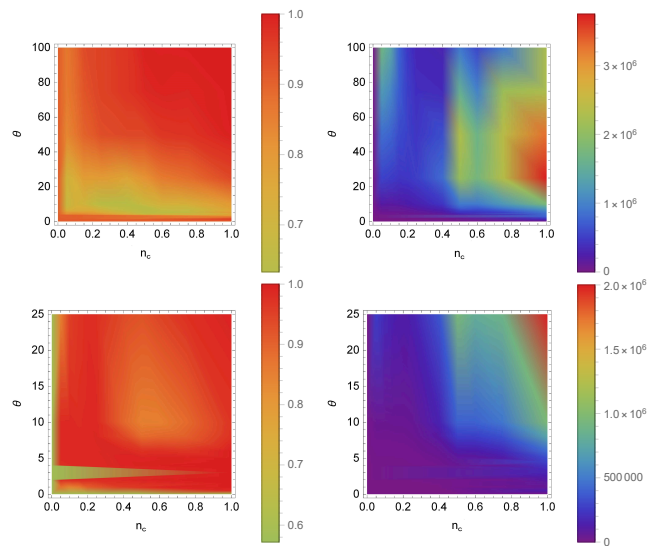


Figure 4: **Local cooperation based interference for BA model (top row) vs DMS model (bottom row)**, for varying per-individual cost of investment θ , scaled for clear presentation, as well as the threshold of neighbourhood cooperation n_C . The left column reports the frequency of cooperation while the right one reports the total cost required. Parameters: $b = 1.8$; $n = 5000$; $z = 4$ (average node connectivity).

more rapidly and therefore overall cost is reduced. Therefore, LC based interference can be regarded as the least risk averse, but potentially the most impactful given realistic values of per-individual investment θ .

With the exception of a small range of values for per-individual investment θ , the LC interference mechanism achieves a very high average cooperation for the clustering network. This reinforces the assumption that interference at any point in the decline of cooperation is enough to shift the scales and enables cooperators to overtake the defectors. On the basis thereof, an external decision maker can reduce the costs of interference by selecting very low values for n_C in combination with a high enough individual investment θ . For intermediate values of the local cooperation threshold n_C in combination with not high enough θ values, an interesting phenomenon is observed: the promotion of the survival of defectors by enabling the survival of cooperator nodes without actually giving them a chance of converting defectors in their neighbourhood, thereby allowing the defectors to exploit those cooperators.

Combining Node Influence and Local Cooperation

Due to the ease of acquiring information related to node connectivity in some types of networks, we test a combination of the two mechanisms where a cooperator node receives the individual investment only if both thresholds, local cooperation n_C and node influence c_I are met. Our results show that this is a risk-averse interference mechanism for low values of c_I (See Figure 5).

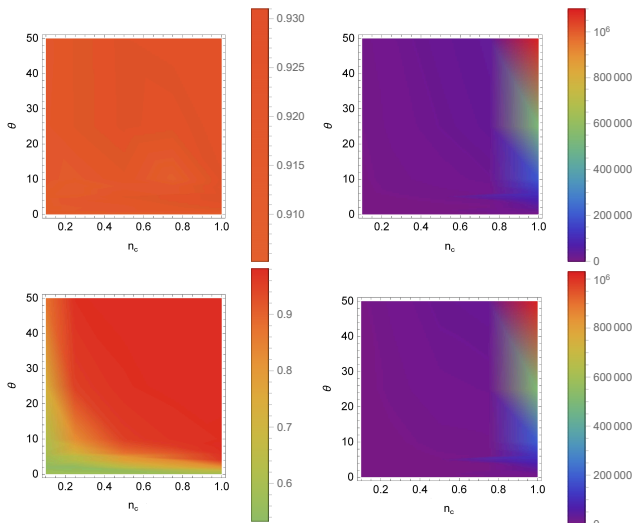


Figure 5: **Combination between node influence and local cooperation based interference for BA model (top row) vs DMS model (bottom row)**, for varying per-individual cost of investment θ and threshold of neighbourhood cooperation n_C , for $c_I = 0.05$. The left column reports the frequency of cooperation while the right one reports the total cost required. Parameters: $b = 1.8$; $n = 5000$; $z = 4$ (average node connectivity).

For the BA model, the possibility of inappropriate interference which leads to cyclic patterns is virtually eliminated even for very low values of c_I . We note that for very high values of per-individual investment θ , there is a marked increase in levels of cooperation while maintaining cost efficiency, if a high enough value for n_C is selected, similarly to our results for the LC-based mechanism. In that case, introducing the added parameter of node influence serves no purpose and reduces perceived gains to cooperation.

In the case of the SF NOC with a high prevalence of triangular motifs (DMS), the combination mechanism produces similar results to the ones observed for solely LC-based interference, but with slightly reduced costs across the range of parameter values and with a more predictable correlation between threshold values, per-individual investment cost and gains in cooperation. The maximum gains to levels of cooperation are reduced slightly when compared to the single two mechanisms, with the exception of very high θ .

Following these findings, we have shown that an integrated approach to interference would work best when the nature of the network is ambiguous. In that case, this type of interference would promote converge to cooperation in the case of the DMS model, without risking the decrease in cooperation seen in the BA Model for the two interference mechanisms applied independently.

Conclusions and Future Work

In summary, this paper aims to determine how best an external decision maker could incentivise a population of autonomous agents facing a cooperative dilemma to fulfil a

coveted collective state. We build on a previous account which identified the most effective mechanisms to foster cooperative scenarios in spatially distributed systems in regular graph structured populations of agents, but instead we consider two popular models of scale-free networks of contacts. In particular, we try to understand if the insights set out in the context of regular graphs remain applicable to heterogeneous models, as well as exploring an additional avenue of interference enabled by the variance in node connectivity. To address these issues, we have combined an evolutionary game theoretic model with several incentive mechanisms in two types of pre-generated networks characterised by preferential attachment, with different clustering coefficients. We argue that this problem cannot be solved trivially and we show that transitivity (i.e. the global clustering coefficient) should be the driving force behind the choice of an interference mechanism in promoting cooperation in heterogeneous network structures, as well as its application.

Our comparison between the two types of SF networks provides valuable insights regarding the importance of clustering in the outcome of cooperation. We found that a large clustering coefficient allows for successful, cost-effective interference, indeed even when disregarding a full comprehension of the population and its tendencies. These results are of particular interest, given that most SF networks portray high clustering, such as in the case of social ties where friends are likely to be friends of each other (Newman, 2018). Moreover, heterogeneous scenarios inhibited by spatial constraints (e.g. in highly urbanised areas or even the allotment of rangelands such as pastures) also impose some measure of clustering.

In the absence of clustering, we found that impetuously rewarding cooperators can lead to cyclic patterns which damage cooperation in the long run, and we show how this can be avoided when a decision maker lacks information about the level of clustering of the network. We observe a large negative impact on the cost of rewarding cooperators in the case of a low clustering coefficient, and provide insights on how it can be reduced. Moreover, we show that ignoring lowly connected individuals leads to unprofitable and even futile intervention irrespective of network transitivity.

Our future work aims to provide a comprehensive exploration of external interference on multiple types of networks while adopting different strategy update forms, such as stochastic learning (Szabó and Fath, 2007). We envisage that stochasticity will increase the overall cooperation and reduce the occurrence of cyclic patterns due to reckless interference, or eliminate them altogether. Furthermore, we plan to examine spatially-motivated interference mechanisms for heterogeneous networks, encouraging the formation of links between nodes or on the contrary, cutting off said links. The inherently high levels of cooperation in heterogeneous networks motivate us to experiment with a higher bias towards defection or mechanisms specifically

aimed at lowly connected nodes.

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