Cost Effective Interventions in Complex Networks Using Agent-Based Modelling and Simulations

Doctoral Consortium

Theodor Cimpeanu
Teesside University
T.Cimpeanu@tees.ac.uk

ABSTRACT

The problem of promoting cooperative behaviour in a complex dynamical network of interacting individuals (e.g. social and epidemic networks or networks of opinion) has been intensely investigated across diverse fields of behavioural, social and computational sciences. In most studies, cooperation is assumed to emerge from the combined actions of participating individuals within the population, without taking into account the possibility of external intervention and how it can be performed in a cost-efficient way. The problem of cost-efficient external intervention is important in a wide range of application domains, ranging from drug prevention programmes and wildlife conservation initiatives to environmental governance or safety compliance in developing technology. International institutions, such as the UN or the EU, also often need to make investments to promote a certain population state such as peace and social diversity, at a minimal cost.

KEYWORDS

Emergent behaviour; Modelling for agent-based simulation; Social simulation

ACM Reference Format:

Theodor Cimpeanu. 2020. Cost Effective Interventions in Complex Networks Using Agent-Based Modelling and Simulations. In *Proc. of the 19th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2020), Auckland, New Zealand, May 9–13, 2020,* IFAAMAS, 3 pages.

1 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 [8]. It can be found in a variety of real-world situations, ranging from ecosystems to human organisations, technological innovations and social networks [6, 16, 17, 20].

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 [15]. 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 towards leveraging cooperation in such hybrid collectives [14]. It may be the case, also, that such incentives would consider polycentric systems [13], where the self-organisation of justice systems is in constant interplay with higher level institutions.

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 ecosystem, 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 ecosystem (i.e., to modify the composition of the population) [10].

Moreover, due to the evolutionary dynamics of the ecosystem (e.g., frequency and structure dependence) [17], 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 ecosystem 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 its total cost.

This question has been studied previously in the context of populations distributed on regular graphs, namely complete or square lattice graphs [5, 7]. 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 [1, 18]. Hence, in my thesis, I aim to study cost-effective interference in various types of networks, among which heterogenous ones, such as different types of scale-free networks, which have been shown to adequately capture real-world networks (such as the World Wide Web [11]).

The main research aims of the project are therefore to generalise intervention models to real-world structures with different levels of heterogeneity in connectivity and connection strengths, as well as dynamical structures with or without mobility, to identify and formalise the presence of exogenous (i.e. institutions) and endogenous (i.e. self-organised) governing mechanisms and finally to apply the developed models to analyse real-world, complex networks (such as Facebook or Twitter).

To achieve the aim and objectives of the project, I have, and continue to, systematically develop a number of computational models based on agent-based simulation techniques and analytical methods from Evolutionary Game Theory. The project aims to contribute novel and fundamental understanding into the literature of AI optimization and decision making in complex systems, providing mechanistic insights about how to achieve high system performance in a cost-effective way.

Proc. of the 19th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2020), B. An, N. Yorke-Smith, A. El Fallah Seghrouchni, G. Sukthankar (eds.), May 9–13, 2020, Auckland, New Zealand.

2 MODELS AND METHODS

2.1 Evolutionary Game Theoretic Models

All the analysis and numerical results obtained, until now, use evolutionary game theoretic methods, using replicator dynamics for infinite populations [9] and agent-based simulation for finite populations [12, 19]. In this setting, the payoff for each agent represents their fitness or social success. Evolutionary dynamics are then shaped by social learning [9, 19], whereby the most successful individuals tend to be imitated more often by others.

In order to simulate evolutionary dynamics, this project will make use of various economic games, with an emphasis on the Prisoner's Dilemma (PD) which I explore using replicator dynamics and simulations. By choosing the most competitive social dilemma [9], the project explores the toughest environment for the emergence of cooperation, therefore increasing the relevance of any observed effects.

Replicator dynamics are used to study the growth of each fraction (of strategies) in the population, as a function of their frequency and relative fitness [9, 19]. According to replicator dynamics, whenever a gradient of selection is positive, the frequency of that particular strategy grows in the population. This method is useful for deriving evolutionarily stable strategies and conditions, mainly on homogenous networks.

In the case of complex networks, I resort to agent-based methods and simulations. Social learning is usually modelled using the pairwise comparison rule [21], a standard approach in studying evolutionary dynamics within the framework of evolutionary game theory. After formalising different models, the evolutionary process is simulated until a stationary state or a cyclic pattern is reached.

2.2 Network Creation

The project has, so far, made use of homogenous (namely complete and structured graphs) and two types of heterogeneous networks, with two different levels of clustering.

For SF networks with low clustering, I adopt the famous Barabási-Albert (BA) model [1]. 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.

To obtain a SF network with high clustering, I resort to the Dorogovtsev-Mendes-Samukhin (DMS) model [4]. Contrary to the BA model, each new node attaches to both ends of a randomly chosen edge. As a result, there is favouritism towards 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.

3 INTERESTING RESULTS SO FAR

In our published output so far, we have shown that network topology plays a very important role when selecting interference strategies, at least in the case of positive incentives towards cooperators [2]. Even in the case of identical connectivity values, the presence

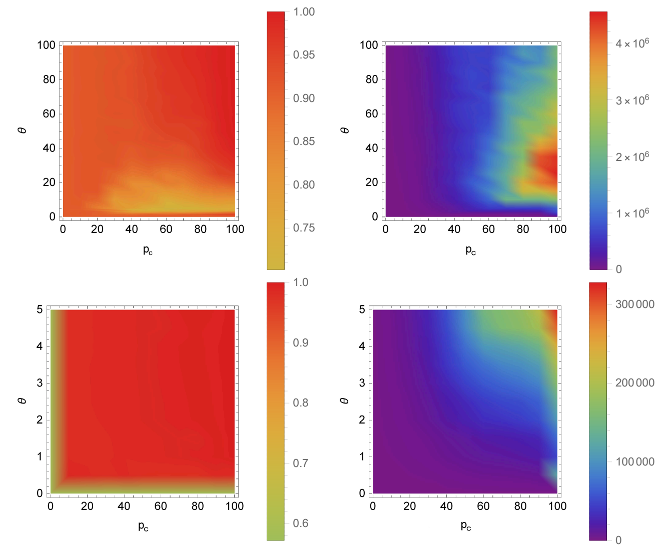

Figure 1: Simple interference based on population composition for BA model (top row) vs DMS model (bottom row), for varying per-individual cost of investment θ, as well as the threshold cooperation in the population p_C. The left column reports the frequency of cooperation while the right one reports the total cost imposed on the institution.

of triangular motifs in the network (i.e. high degree of clustering), greatly influences the effect of exogenous interference. Interestingly and counter-intuitively so, simple incentive mechanisms can sometimes lead to the demotion of cooperators and, implicitly, negatively impacts cooperation levels when compared to control experiments (See Figure 1). By rewarding cooperators in certain network topologies (low clustering with lowly specific candidate selection), this can lead to cyclic behaviours wherein artificially enabling the survival of cooperators in defector neighbourhoods can lead to the exploitation of said cooperators resulting in large defector clusters which cannot self-sustain.

We have also shown how the previously mentioned phenomena can be avoided and why investing in scale-free networks with large degrees of clustering requires less specific information about the network and lessens the burden of continuous investment. In other words, a sufficiently high, initial investment can lead to the emergence of cooperation in highly clustered scale-free networks. These results present us with multiple questions regarding the selection between reward and punishment based not only on initial network conditions or state of cooperation, but also on network structure and topology.

Currently, we are investigating how signalling mechanisms can influence the emergence of peer punishment, and how fear of punishment can be leveraged to promote cooperation and increase social welfare (See Preprint [3]). By gaining further insight into this topic, we could begin exploring interference mechanisms which advertise threat of punishment and/or promise of reward, avoiding the actual act of punishment and therefore reducing the overall cost of interference.

REFERENCES

[1] Réka Albert and Albert-László Barabási. 2002. Statistical mechanics of complex networks. *Reviews of Modern Physics* 74, 1 (2002), 47.

[2] Theodor Cimpeanu, The Anh Han, and Francisco C. Santos. 2019. Exogenous Rewards for Promoting Cooperation in Scale-Free Networks. *Artificial Life Conference Proceedings* 31 (2019), 316–323. https://doi.org/10.1162/isal_a_00181

[3] Theodor Cimpeanu and The Anh Han. 2020. Making an Example: Signalling Threat in the Evolution of Cooperation. arXiv:cs.GT/2001.08245

[4] Sergey N Dorogovtsev, Jos FF Mendes, and Alexander N Samukhin. 2001. Size-dependent degree distribution of a scale-free growing network. *Physical Review E* 63, 6 (2001), 062101.

[5] The Anh Han, Simon Lynch, Long Tran-Thanh, and Francisco C Santos. 2018. Fostering cooperation in structured populations through local and global interference strategies. In *Proc. of the 27th Int. Joint Conf. on Artificial Intelligence '18*. AAAI Press, 289–295.

[6] The Anh Han, Luís Moniz Pereira, and Tom Lenaerts. 2019. Modelling and Influencing the AI Bidding War: A Research Agenda. In *AAAI/ACM conference AI, Ethics and Society*.

[7] The Anh Han and Long Tran-Thanh. 2018. Cost-effective external interference for promoting the evolution of cooperation. *Scientific Reports* 8 (2018), 15997.

[8] J. Hofbauer and K. Sigmund. 1998. *Evolutionary Games and Population Dynamics*. Cambridge University Press.

[9] J Hofbauer and K Sigmund. 1998. *Evolutionary Games and Population Dynamics*. Cambridge University Press.

[10] Simon A Levin. 2000. Multiple scales and the maintenance of biodiversity. *Ecosystems* 3, 6 (2000), 498–506.

[11] Mark Newman. 2018. *Networks, 2nd edition,*. Oxford university press.

[12] M. A. Nowak, A. Sasaki, C. Taylor, and D. Fudenberg. 2004. Emergence of cooperation and evolutionary stability in finite populations. *Nature* 428 (2004), 646–650.

[13] Elinor Ostrom. 2010. Polycentric systems for coping with collective action and global environmental change. *Global Environmental Change* 20, 4 (2010), 550 – 557. https://doi.org/10.1016/j.gloenvcha.2010.07.004 20th Anniversary Special Issue.

[14] Ana Paiva, Fernando P Santos, and Francisco C Santos. 2018. Engineering pro-sociality with autonomous agents. In *Thirty-Second AAAI Conference on Artificial Intelligence*. 7994–7999.

[15] Alexandra S Penn, Richard A Watson, Alexander Kraaijeveld, and Jeremy Webb. 2010. Systems Aikido-A Novel Approach to Managing Natural Systems.. In *in Proc. of the ALIFE XII Conference*. MIT press, 577–580.

[16] M. A. Raghunandan and C. A. Subramanian. 2012. Sustaining cooperation on networks: an analytical study based on evolutionary game theory. In *AAMAS'12*. 913–920.

[17] F. C. Santos, J. M. Pacheco, and T. Lenaerts. 2006. Evolutionary dynamics of social dilemmas in structured heterogeneous populations. *Proceedings of the National Academy of Sciences of the United States of America* 103 (2006), 3490–3494.

[18] Francisco C Santos, Marta D Santos, and Jorge M Pacheco. 2008. Social diversity promotes the emergence of cooperation in public goods games. *Nature* 454, 7201 (2008), 213.

[19] Karl Sigmund. 2010. *The Calculus of Selfishness*. Princeton University Press.

[20] K Sigmund, C Hauert, and M Nowak. 2001. Reward and punishment. *Proceedings of the National Academy of Sciences* 98, 19 (2001), 10757–10762.

[21] A. Traulsen, M. A. Nowak, and J. M. Pacheco. 2006. Stochastic Dynamics of Invasion and Fixation. *Phys. Rev. E* 74 (2006), 11909.