Erasmus Mundus Masters in Complex Systems

ENDOGENIZATION OF NETWORK TOPOLOGY IN METAMIMETIC GAMES

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Summary

In this work, we aim to investigate the endogenization of topology parameters in metamimetic games and construct a framework that can be easily adapted for the simulation of this kind of games following any kind of topology.

Metamimetic games are games where the agents follow dynamics of mimesis or imitation as a form of "evolution" of their behaviour. Moreover, their own rules for imitation can be imitated from nearby agents. Up to now, this was always made in a normal grid, that is, agents played a game with their spatial neighbours, evaluated their performance and decided whether to imitate someone else's rules and behaviours or not.

We present a shift in this paradigm by defining neighbourhoods through links, giving more flexibility to the network of agents. Now, instead of being limited to playing with the 8 agents around, the topology can assume any shape, the number of neighbours can vary, and it is even possible to reconstruct the vanilla grid topology by changing some lines of code.

The objective when creating this framework was to investigate if, when putting some topology parameters (such as the likelihood to change a link) as something that could also be copied between agents, the resulting network would somehow resemble a real-life social network. This hypothesis comes from previous work with this class of games, where it was shown that sustained cooperation with a diversity of agents emerges from the model. As it was shown that a metamimetic dynamic could explain a real-life social phenomenon such as sustained cooperation, we decided to investigate whether the real-life clustering of social networks could also be explained via this model.

It turns out that, under a certain range of parameters and starting from either a perfectly ordered network or a so-called small-world network (similar to real social networks), we do get a network with similar coefficients to real life.

However, we were curious to see if we could actually "gain" order, that is, if we could get a small-world network starting out from a completely random network. In this case the gains were very marginal, even at very extreme and unrealistic parameter ranges.

At the end, we are stuck with an answer that is neither "yes" nor "no". The end result is highly dependent on the initial conditions and the range of parameters being used. As this is a very preliminary work, developed in a relatively short timespan, we hope that the created framework will be useful for further investigation on this subject.

Abstract

In this work, we aim to investigate the endogenization of topology parameters in metamimetic games and construct a framework that can be easily adapted for the simulation of this kind of games following any kind of topology. Metamimetic games are games where the agents follow dynamics of mimesis or imitation for their behaviour and rules. Moreover, their own rules for imitation can be imitated from nearby agents. We present a new paradigm for metamimetic games by defining neighbourhoods through links instead of spatial proximity, something that has not been done before. We aim to investigate if, when endogenizing some topology parameters (such as the likelihood to change a link), the resulting network would somehow resemble a real-life social network. This hypothesis comes from previous work with this class of games, where it was shown that sustained cooperation with a diversity of agents emerges from the model. As a result, under a certain range of parameters and starting from either a perfectly ordered network or a small-world network we do get a small-world network. However, if we start out from a completely random network, the gains in clustering were marginal, even at very extreme and unrealistic parameter ranges.

Contents

1 Introduction

The proposition of a metamimetic framework as a model for cultural dynamics appear from a natural challenge faced by traditional game theory: that of modelling agent types as part of the predictive content, as opposed to an explanation to experimental data. It is clear from reality that there is an heterogeneity of preferences and goals between agents, and the standard game-theoretical models tend to propose agent types as an *ex post* explanation for what it is seen in the data, rather than actually integrating agents' types and heterogeneity of preferences into their models. Vernon Smith exposes this in his Nobel Prize Lecture [1]:

> "Technically, the issue can be posed as one of asking how most productively to model "agent types" by extending game theory so that types are an integral part of its predictive content, rather than merely imported as an *ex-post* technical explanation of experimental results. [...] The point that needs emphasis is that it is easy to go from "types" (traditionally utility or beliefs about states) to game theoretic choice; the hard part is to relate "types" to characteristics of the individual's memory-sensory system."

In 2006, Chavalarias introduces the concept of metamimetic games [2], where agent types are a part of the model instead of an explanation to the results. In this model, the distribution of types is a part of the predictive content, and the proportion of agents' types is also data coming from the basic dynamics of the model itself, rather than being an explanation for that.

The interest for heterogeneity of agents that surged recently is due, in a big part, to research in experimental economics. Particularly, research about cooperation have continuously reported heterogeneity in agents' inferred preferences, indicating that we can have robust, stable attractors with a variety of agents' types and preferences sustaining cooperation, and also evidencing the failures of rational choice theory.

We tackle this problem from the side of ecological rationality (as opposed to a more constructivist approach to rationality), from where we observe a cultural co-evolution where trial and error and a more biological-like evolution are paramount, as proposed by Smith [1]. As we have adaptive agents interacting with many different neighbours in their lifespan, the framework of evolutionary game theory seems appropriate.

We can then ask some interesting questions, such as the influence of socio-economical policies in the agents' types distribution and its consequences for the formulation of social welfare policies. We change the problem from assuming that the preferences are fixed, as it is normally done, to a state where the distribution of preferences is itself dependent on the social policies.

Moreover, we introduce the endogenization of the network parameters by enabling agents to change their links to other agents and, therefore, alter their notion of "neighbourhood". We thus address in a new way the trade-off between changing an agent's strategy or changing its environment while coupling it with the fact that both events could lead to a change in the agent's preferences.

In this report, we will discuss the general concept of Metamimetic Games in section 2 and the more specific concept of the Spatial Prisoner's Dilemma in section 3, as they represent, respectively, the dynamics between agents and the game they play with each other. In section 4 we discuss briefly about networks and some of their properties. In section 5 we present the results when network parameters are endogenized. Finally, in section 6, we sumarize the results and discuss their relevance.

2 Metamimetic games

Metamimetic games [2] are designed to account for heterogeneous preferences and cultural co-evolution of different agents with different valuation functions.

In the modelling perspective, types will be defined as rules of behaviour which given some information collected from the environment, the agent's past experience and the agent's utility function, define an action to be taken at every decision step of the model. Utility function, in this work, is the main determinant factor in agent's types.

Chavalarias [3] introduces an agent with meta-cognition and reflexivity capabilities who uses these when imitating other agents' traits. To illustrate this approach, we consider a minimal model which mixes materialistic and non-materialistic individuals playing a game G with two possible moves, C or D (which will stand for cooperation of defection in our case study). In general, agents are inside a population, with a set of neighbours with which they play the game G pairwise and only can learn from agents they interact with. We have two kinds of information that can be processed in terms of an utility function: the agent's payoff and his neighbours' payoffs, and the moves made by both the agent and his neighbours.

We assume that agents have minimal processing capacities on these types of information. For the payoffs, agents are able to compare two figures and take the bigger or the lower. They are, thus, able to process the minimal and maximal payoffs in their neighbourhood. For the distributions of moves in their neighbourhood, they can process frequencies to convert this information into ordinal quantities. Therefore, they are able to know what is the majority of behaviours, for example.

These hypothesis on agents' cognitive capabilities generate four possibilities for the utility functions:

- **Payoffs maximization:** utility is higher when payoffs are higher,
- **Payoffs minimization:** utility is higher when payoffs are lower,
- **Conformism:** utility is higher when agent's strategy is similar to a larger number of neighbors,
- **Anti-conformism:** utility is lower when agent's strategy is similar to a larger number of neighbors.

In the metamimetic framework, we will consider simple mimetic agents like the ones from the work of Nowak and May [4]. Agents measure the performances of their neighbours and their own performance with regards to their utility function; then, they copy the strategy of the most successful agent if they are not themselves one of the best. Agent's types will be named after their underlying utility function, with two payoffs based (or materialistic) types, *maxi*, *mini* and two non-materialistic types *conformist* and *non-conformist*.

In addition to that, we will adopt the framework of metamimetic games [2]. It means that the agent's rules of behaviour are part of the agent's strategy. Agents are considered as reflexive in the sense that they know the criteria or values upon which they base their choice and can take the initiative to change them if necessary. In the proposed model, reflexivity means that agents have the capacity to change their rule of behaviour if they judge that it is not the best rule to achieve their goal. We have then a dynamic relationship between types of types which depends, among other factors, on their relative neighbourhoods.

There are various options for the procedure of types' change. For example, if conformist agents are judged to be the wealthier in terms of payoffs, a maximizer agent could introduce a small proportion of conformism in its strategy, or simply become conformist. Because we want to capture the essence of the consequences of types' endogenization, we will consider the simpler option, which is the latter.

Given all the above, we will consider a metamimetic game where interactions take place as follows for every period of the game:

1. each agent looks at the situation of other agents in its neighbours Γ_A, (payoffs, rules, behaviour);
2. for any agent A, if according to A's utility function there are some agents in Γ_A more successful than A and if all these successful neighbours have a rule of behaviour different from A's, then A copy the rule of an agent taken at random among this set;
3. if according to its (eventually new) rule of behaviour and its associated utility function, A is not among the most successful agents in Γ_A, then A chooses at random one of its neighbours with the better situation and copies its behaviour (C or D);
4. each agent plays the game G with its neighbours using the same behaviour (C or D). Then for each agent, the scores of all its pairwise games are computed and the sum is the new payoff of the agent.

It is important to note that an agent which is the best of its neighbourhood according to its utility function will be satisfied and will not engage in an imitation process at the rule level or at the behavioural level.

The concept of equilibrium associated to this kind of game are metamimetic equilibria, or counterfactually stable states[5]. These are states such that no agent can find itself better when it imagines itself in the place of one of its neighbors. However, since we are considering evolutionary games with potentially noisy dynamics, we will more frequently encounter stable sets of states, *metamimetic attractors*.

3 Spatial prisoner's dilemma

To illustrate the insights brought by metamimetic games to the modelling of agent heterogeneity, we will apply this framework to the modelling of prisoner's dilemma. In the following, we will present a study where the game G is a spatial prisoner's dilemma [4] with the game outcomes described by table 1.

	Cooperate	Defect
Cooperate	$1-p$, $1-p$	0 , 1
Defect	1 , 0	p , p

Table 1: Payoff function of the game played by agents. p represents the strength of dilemma and for $p \in [0, 0.5]$ the game corresponds to a Prisoner's Dilemma.

The results presented by Chavalarias [3] demonstrate that the introduction of reflexivity in mimetic models makes it possible to endogenize agents' types. Their distribution, then, becomes a relevant data generated by the model. Without assuming

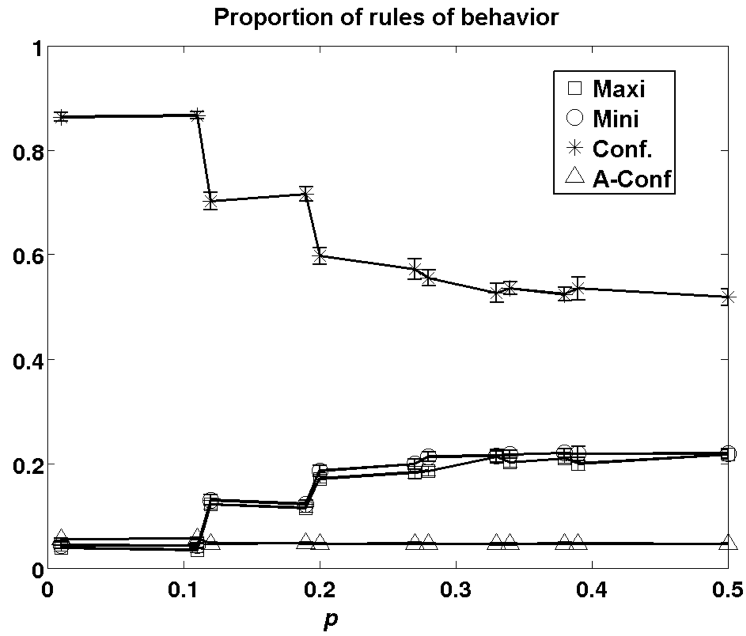

Figure 1: Influence of the strength of the prisoner's dilemma on distribution of rules at attractor for an initial rate of cooperation of 50%. We can observe that environmental factors like the strength of the social dilemma do influence types distribution and that in this example, materialistic types are favoured by strong social dilemma. Discontinuities are due to the discrete character of the neighbourhoods.

any other kind of selection, we can see the emergent processes that can be generated from this simple mimetic dynamic. Also, it shows sustained cooperation being generated from an heterogeneity of agents' types in the attractor, and not by any kind of payoff optimization.

The systems from where these results were obtained can also be seen as Markov processes, with the configuration of rules, behaviours and connections between agents as the states. These are, however, not ergodic, as it can be seen from the influence of initial conditions on the final results of the attractor. Of course in real systems there are all kinds of perturbations and uncertainties, so these models should be made noisy. Therefore, Chavalarias [2] claims that the perturbed Markov processes issued from this model are probably ergodic.

The final results of the attractors will, thus, depend also on the kind of perturbations inserted into the basic models. We discuss some of these options in the Appendix A. For example, one of the natural sources of noise in the modelling of social systems is the lifespan of the agents.

The introduction of ergodicity in the model has two consequences:

- The initial rate of cooperation has no more influence on the attractor,
- The dependence of the systems toward p (see table 1) is similar to what is shown on figure 1 with an increased proportion of payoffs-based types as the strength of the dilemma increases and rate of cooperation oscillating around 50%.

In that case, types distribution does not depend any more on initial conditions, the only parameter being the strength of the social dilemma p. This approach is particularly interesting for modelling situations where p can be interpreted as a political leverage (for example employment legislation or collective agreements could be thought as instruments to modify the employment security, trust, and effort dilemma on the job market [6]). In that case, this approach makes it possible to investigate how political decisions could impact on the evolution of preferences in the population, a phenomenon which importance has been stressed already [7].

4 Networks and their parameters

In a framework where we are using the metamimetic dynamics in a spatial Prisoner's Dilemma, it is clear that the concept of neighbourhood is central and of foremost importance. First, because agents can only "learn", that is, copy strategies from other agents with whom they interact (i.e. their neighbourhood). Second, because the information for their valuation functions (payoffs and strategies) also come from the neighbourhood. Therefore, it is natural to expect different behaviours by changing the way these neighbourhoods are created and interconnected. That brings us to the study of networks and their influences on our model.

There is vast literature about the network effects in game theory. For example, Tang et al [8] show how the average degree of a network can affect both the level of cooperation and the average payoff in a spatial Prisoner's Dilemma. Also, Abramson and Kuperman [9] study the influence of the topology of a network to the cooperation in an evolutionary Prisoner's Dilemma where the agents can copy the behaviour of their neighbours. These are only two of the examples from the many works showing how the way agents are interconnected can be relevant in game-theoretical models.

In this work, we are mostly interested in networks with undirected links between agents, since we are trying somehow to model social interaction (which is normally bidirectional). Furthermore, we are particularly concerned with the concept of small-world networks, as they present characteristics that put them in close relation to social networks in the real world. We briefly discuss this concept and the metrics that were used to classify networks.

4.1 Small-world Networks

Small-world networks are mathematical graphs in which most nodes can be reached from every other by a small number of steps, but where most nodes are not neighbours of one another. This is a model very commonly used for social networks, where we have the existence of "cliques" or clusters but most people are connected via a common acquaintance. They were identified as a class of random graphs by Watts and Strogatz [10], who classified the graphs according to a clustering coefficient and an average node-to-node distance.

4.2 Network Coefficients

In this work, we will concentrate in evaluating network according to two main coefficients, which will now be rigorously defined: Clustering Coefficient and Average Path Length. We use both concepts according to what is presented by Watts, Strogatz [10]

- Clustering Coefficient: Suppose that a vertex v has k_v neighbours; then at most $k_v(kv-1)/2$ edges can exist between them (this occurs when every neighbour of v is connected to every other neighbour of v). Let C_v denote the fraction of these allowable edges that actually exist. Define C as the average of C_v over all v. That will be our Clustering Coefficient.

- Average Path Length: it is defined as the number of edges in the shortest path between two vertices, averaged over all pairs of vertices.

In this context, random graphs would have a small Average Path Length, but also a low Clustering Coefficient, since there is virtually no clustering in the network. On the other hand, regular lattices have high Clustering Coefficient, since most neighbours are also neighbours of your neighbours, but they also present a very high Average Path Length, due to the lack of "shortcuts" in the network. By "rewiring" randomly some links, Watts and Strogatz constructed networks with high Clustering Coefficient and low Average Path Length, where most neighbours are part of a "clique" or a cluster, but any node in the network can be reached in a few hops due to the existence of "shortcuts", nodes that connect faraway cliques. These networks are defined as small-world networks. Small-world networks have been found to model very well the network of social interactions [11].

5 Endogenization of Network Parameters

As an implementation of the metamimetic framework, a program in Netlogo [12] was written, incorporating all the relevant parameters and the introduced settings discussed in appendix A.

The computational simulations were run automatically using the tool OpenMole [13] for sweeping the parameters and sending the computational load to a grid.

The behaviour of the basic metamimetic model under a lattice and a small-world network topology is briefly discussed under the appendix B. Therefore, we will not comment this here.

The basic endogenization made in this model is that of the propensity to rewire. In this, each agent has a given probability to change one of its links when it is not satisfied (i.e. it feels another agent in its neighbourhood is more successful). This probability can also be copied from a more successful neighbour.

We try to identify the importance of this probability to the final configuration of the network on figure 2. Here, we see that even very small probabilities have a huge effect on both average path length and clustering coefficient. We can see that in a small range around 0.05 we get a relatively big gap between both parameters, identifying a small-world network. The same happens for values over 0.2. Please refer to appendix A for the settings on the other parameters.

Next, we try to look whether, for a given configuration of parameters, only changing the initial configuration of the network, by changing the proportion of the links rewired from a lattice, would change the final resulting network. As we can see on figure 3, there is no big influence on the average path length, but the clustering coefficient is slightly affected. Later we will present another result where this influence is clearer.

We then introduce an idea of selective pressure. As our model incorporates a lifespan for agents based on U.S. Census data [14], it was trivial to introduce also a lifespan dependent on the "performance" of the agent. Here, our concept of performance is purely payoff-based, but it can easily be changed, for example, to use the satisfaction function from the work of Batta and Chavalarias [15]. Here, we see some interesting results: in terms of clustering, a very high selective pressure does not yield higher clustering, since the mortality rates becomes too high and agents have no time to change

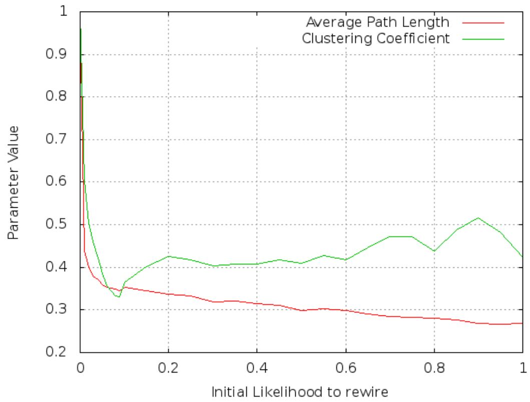

Figure 2: Influence of the rewiring probability to the final resulting network.

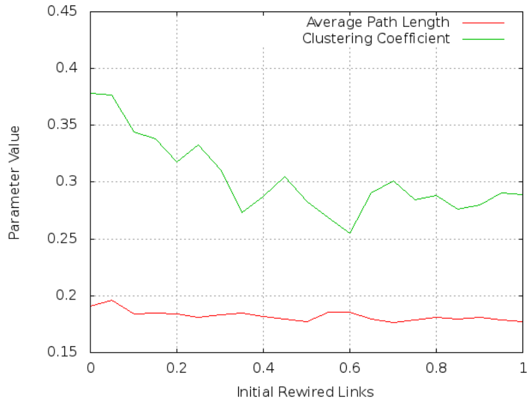

Figure 3: Initial proportion of rewired links versus the parameters of the final one.

their neighbourhoods. The highest clustering coefficient is attained when we have some pressure, but with a value not too high, as it can be seen on figure 4. Also, the dip on cooperation when mild selective pressure is applied is confirmed by a separate, more finely grained simulation, presented here on figure 5.

Moreover, in figure 6, we can see that increasing selective pressure, as expected, favours agents who look to maximize their payoff, since our selection is done purely on a payoff basis. However, a very high selective pressure causes the mortality rate to increase so much that population rates hover close to 25% for each rule, due to the fact that newborn agents are assigned a random rule. Still, maximizers seem to be more favoured in this environment, indicating that they are more likely to survive than other rules.

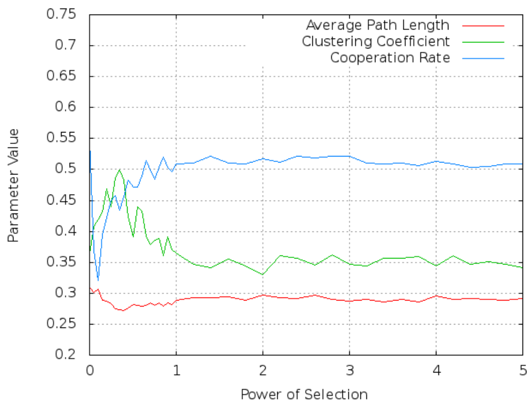

Figure 4: Parameter values for different selective pressure levels.

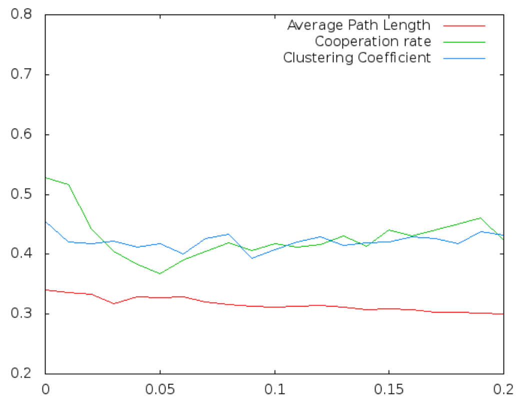

Figure 5: Detail of simulation for very low selective pressure levels.

Finally, we add to the model a preference to make new connections to other agents from which the link-distance is not too big. This way, it is more probable to make a new connection with someone two links away than it is with someone ten links away. We call this a degree of preference, and the strength of this preference can be adjusted (and it can also be copied from successful agents, even though this is not implemented in our model). On figure 7, we verify that any non-zero degree of preference (i.e. anything that

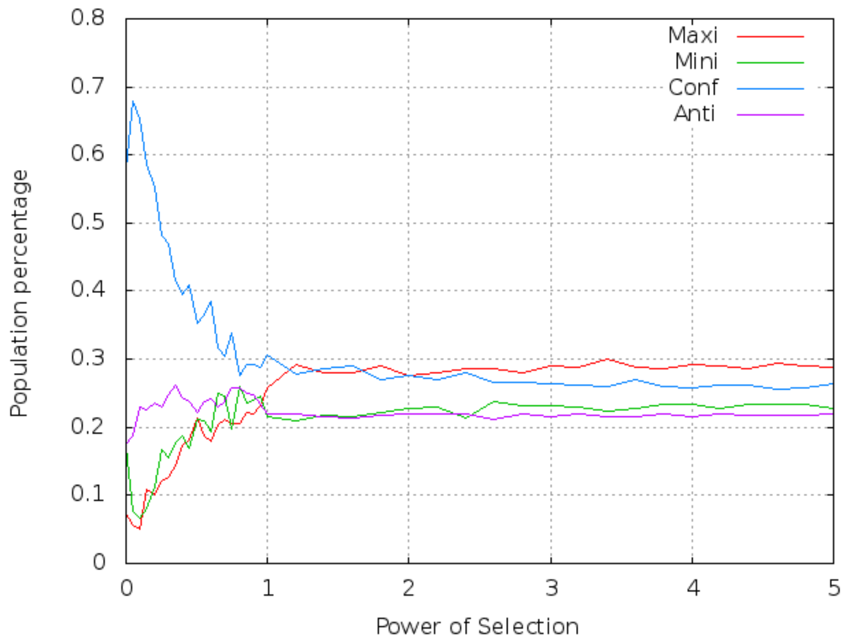

Figure 6: Population fractions using each rule for different selective pressure levels.

is not random rewiring) leads to a very similar value of average path length, no matter what the initial configuration of the network was. However, on figure 8, we see that the degree of preference strongly correlates with the final clustering coefficient (which is to be expected) and that starting from a lattice or a small-world network gives us a considerably bigger clustering than starting from a random network, confirming what we saw on figure 3.

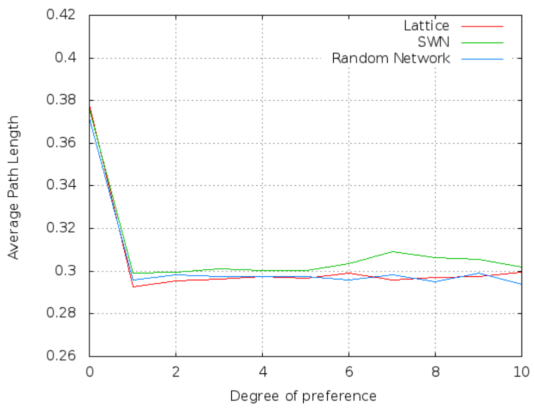

Figure 7: Average path length for different degrees of preference, from different starting configurations

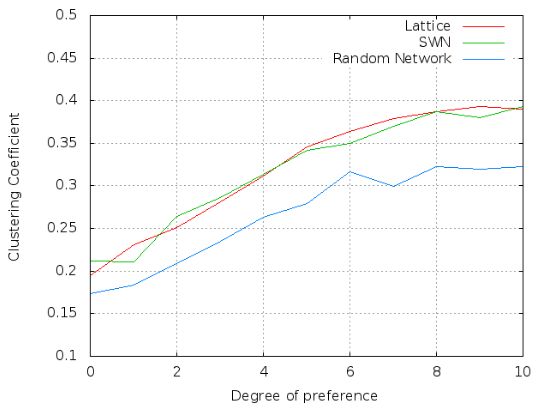

Figure 8: Clustering Coefficient for different degrees of preference, from different starting configurations

6 Conclusions

In this work, we introduce the network component into the realm of metamimetic games. This kind of games have been studied, in general, as being played in a 2D grid. As the notion of "neighbourhood" is essential for these games, we generalize the model to include any kind of neighbourhoods, by making those based on links and not spatial position.

After developing this new framework, we were interested in seeing the results of the endogenization of network parameters. We introduce, initially, the "likelihood to rewire" as a characteristic parameter of each agent. This parameter can, thus, be copied via metamimetic dynamics.

We investigate the effect of different parameters on basically two network coefficients: the average path length and the clustering coefficient. We compare these values with those from a lattice and a random network. By doing that, we can see where the resulting network is more similar to a small-world network.

We see that, under a very strict set of parameter ranges (high degree of preference, starting from a lattice, mild selective power) we get considerable clustering. However, having a random network as a starting point, the gains in clustering are smaller and the network stays in a very disordered way. Also, big gains in clustering only occur when the degree of preference is high enough that rewiring occurs almost exclusively to second-degree neighbours (i.e. the neighbours of an agent's neighbours), which is a very restrictive assumption.

This is still a work in progress - the constructed framework is a building tool upon which much more simulations can be developed. We feel that, for example, the length of the simulations and the number of agents involved might play an interesting role on the final result (more about that on Appendix C).

Acknowledgments

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A Program settings and parameters

Here, we will present all the parameters existent in the Netlogo program that was developed for this work. We also indicate which were the program settings for most of the numerical simulations that were ran for this work.

A.1 Program parameters

A list of all the program parameters, their ranges and a brief explanation about their meaning follows:

- Transcription error: probability to commit an error when copying some parameter from a neighbour (be it rule, behaviour, or any other endogenized parameter). Ranges from 0 to 1.
- Number of nodes: number of agents in the simulation. Ranges from zero to a number compatible with the computational power (400, in our simulations).
- Initial Cooperation: proportion of the agents playing a cooperative behaviour at the beginning. Ranges from 0 to 100 (in percentage).
- Strength of dilemma: indicates how strong the social dilemma is, changing the payoffs of the game. Refer to table 1 for more details. Ranges from 0 to 0.5.
- Initial likelihood to rewire: indicates the initial probability to rewire that the agents have, in the case they are not satisfied with their neighbourhood. Ranges from 0 to 1.
- Initial weight of history: indicates how much agents value their historical payoffs. This value multiples the historical payoff, with the instantaneous payoff composing the rest of the value. 0 indicates they only value instantaneous payoff, 1 they only value their history. Ranges from 0 to 1.
- Maturing period: agents are forbidden to change their rule or behaviour in their first 10 turns of life. This is supposed to model an infancy period, and supposedly favours maxi and mini agents. Boolean.
- Random Initialization: gives random values in all parameters to each agent. Boolean.
- Replacement: turns on or off the lifespan of the agents. Boolean.
- Timescale: consider each turn as a year or a month, in terms of lifespan.
- Degree of Preference: indicates how more likely an agent is to rewire a link to a 2nd degree neighbour to a 3rd degree neighbour, and so on. Ranges from 0 (no preference, random rewiring) to 10 (2nd-degree neighbours have $\frac{10^{10}}{2^{10}}$ more chance to receive a link compared to 10th-degree neighbours).
- Social Threshold: maximum normalized payoff from which selective pressure applies. It means that agents with a normalized payoff above this value will follow the normal lifespan distribution got from the U.S. Census. Ranges from 0 (everyone follows normal lifespan) to 8 (everyone is subject to selective pressure).

- Power of selection: indicates how strongly a payoff indicates the chance of survival. The bigger the value, the less agents survive each turn. Ranges from 0 to 5.
- Initial rewiring probability: indicates the initial stage of the network by indicating the proportion of rewired links from a lattice. Ranges from 0 (lattice) to 1 (random network).

The basic configuration for all simulations is the following (please note that simulations are meant to go over one parameter, so the parameter being evaluated will not follow the value given here):

- Transcription error: 0.05
- Number of nodes: 100
- Initial Cooperation: 50
- Strength of dilemma: 0.5
- Initial likelihood to rewire: 0.5
- Initial weight of history: 0.5
- Maturing period: false
- Random Initialization: false
- Replacement: true
- Timescale: years
- Degree of Preference: 10
- Social Threshold: 8
- Power of selection: 0.1
- Initial rewiring probability: 0

B Behaviour of the basic model in a lattice/SWN

Here, we briefly present the behaviour of the basic model when in a lattice and in a SWN. This is a simulation without rewiring, so the networks are static. There is only the basic metamimetic dynamics between the agents.

As we can see both on figure 9 and figure 10, the behaviour on both situations is similar: for low strength of dilemma, final cooperation follows well the initial one. At higher strengths of dilemma, we see that the picture flattens a little bit, showing that the difference in final cooperation between high and low starting cooperations is quite smaller.

C Behaviour of the model in long-term/large-scale simulations

Here, we present briefly some results obtained when running simulations for longer than normal or with more agents than normal.

First, we ran the simulation presented of figure 3 for 10 times longer than normal (10000 turns instead of 1000). On figures 11 and 12, we can see the results. Both average path length and clustering coefficient presented values smaller than in the short-term simulation, indicating that the network is still changing by the time we stop the simulation.

Finally, we ran the same simulation as that in figure 3 with 1000 agents instead of 100, giving us figure 13. We see that, given that the initial average path length from a lattice depends on the number of agents, the average path length attained is much smaller relatively to that of the lattice. However, also the clustering coefficient seems to be smaller than that of the small-scale simulation.

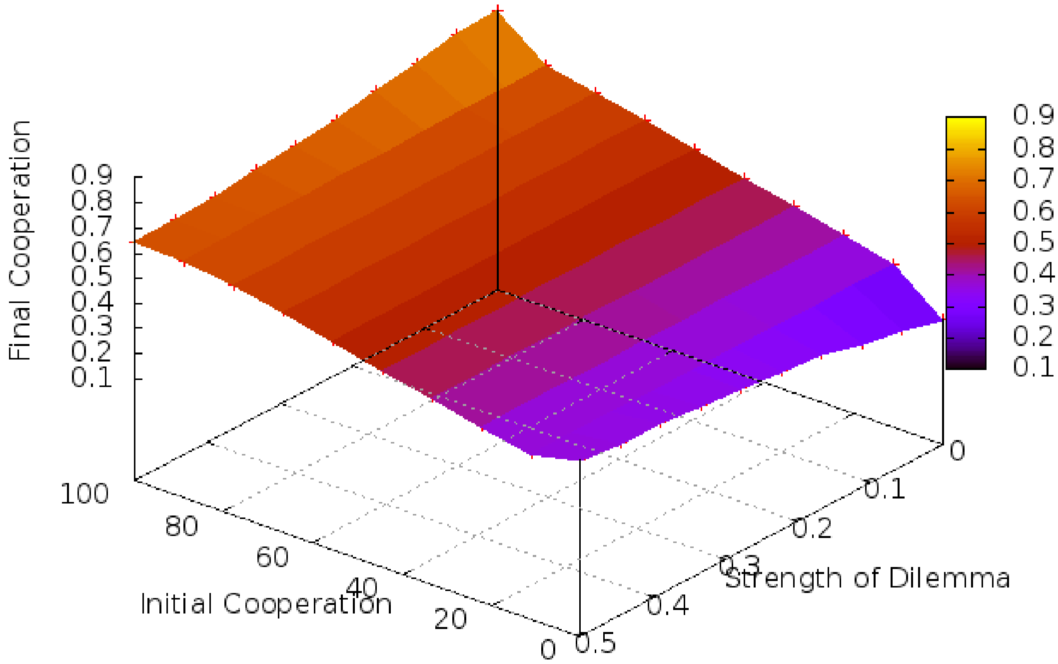

Figure 9: Cooperation for all values of initial cooperation and strength of dilemma in a lattice.

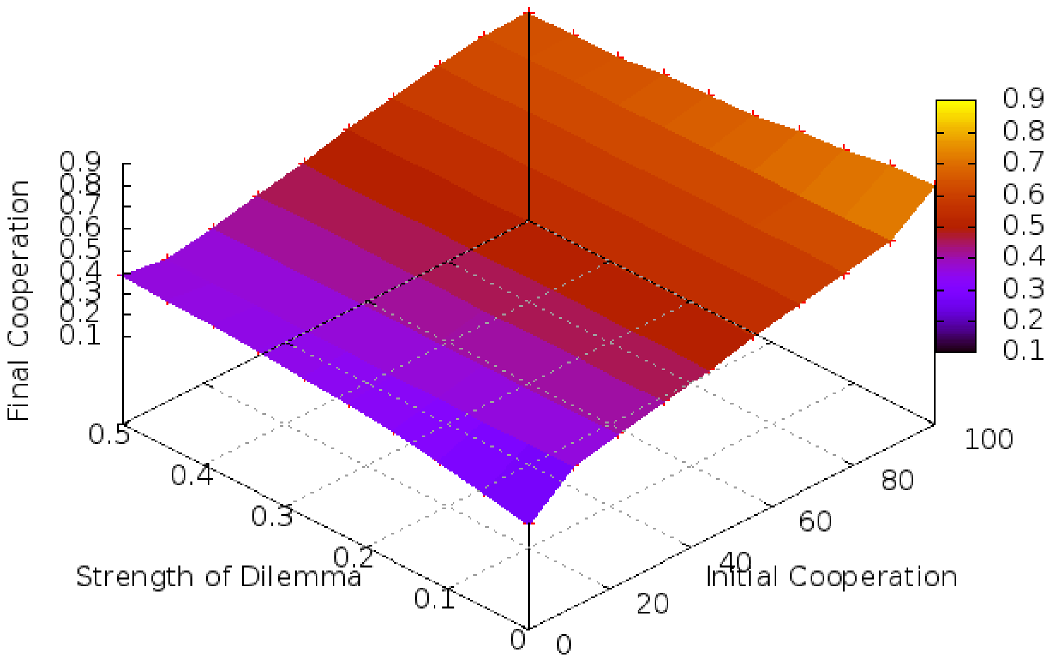

Figure 10: Cooperation for all values of initial cooperation and strength of dilemma in a small-world networks.

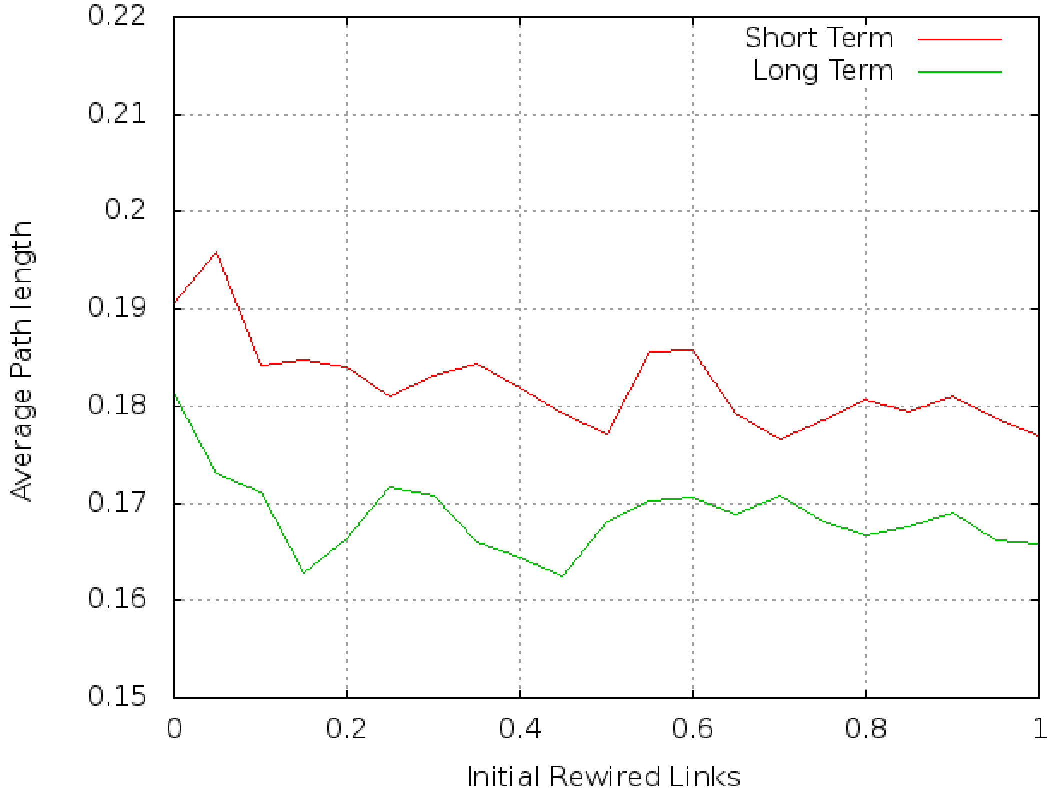

Figure 11: Average path length versus initial state of the network for short and long-term simulations.

Figure 12: Clustering coefficient versus initial state of the network for short and long-term simulations.

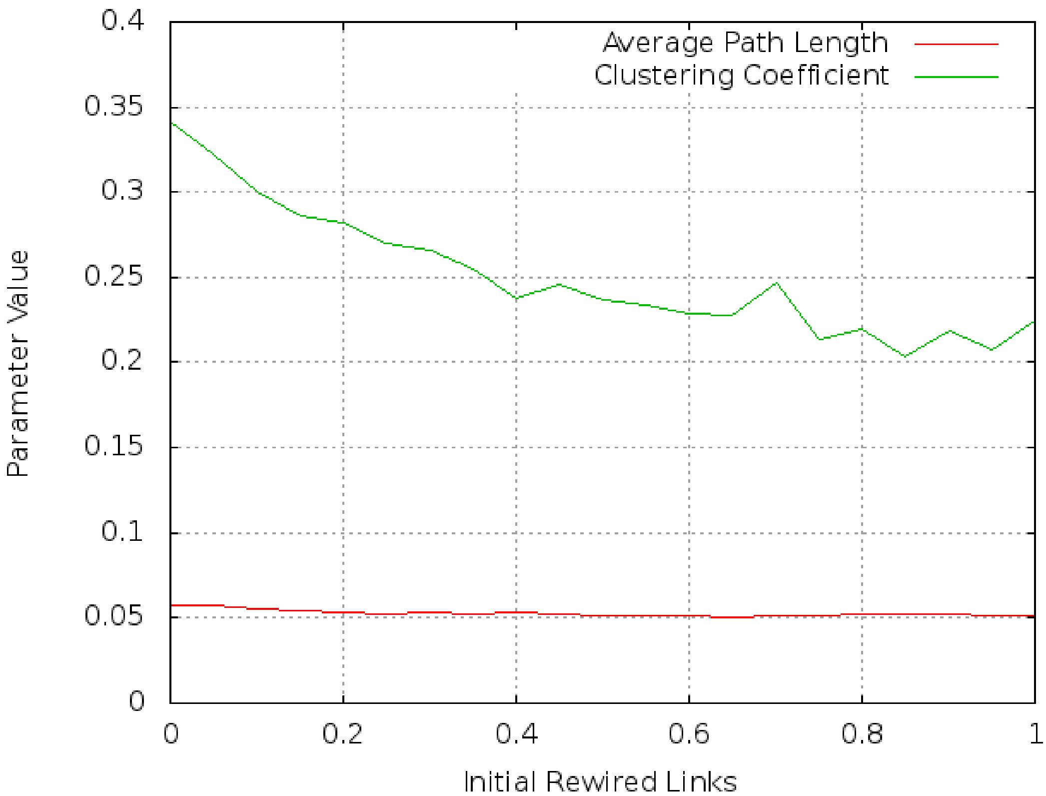

Figure 13: Average path length and clustering coefficient versus initial state of the network for large-scale simulation.