A Swarm Simulation Platform for Agent-Based Social Simulations

Raul Cajias, Antonio González-Pardo, and David Camacho

Abstract. The social sciences have long employed simulations and statistical models in their research methodology as testing and validation tools. Recent advances in complex networks have produced a set of new graph-based tools with which to study and characterize larges-scale, complex social data. We propose a swarm simulation platform that allows quick prototyping of agent-based social models, using an iterative simulation development cycle. This platform is designed to provide meaningful graph-based metrics of the social ties formed. A description of the system is given, as well as experimental results obtained from sample models.

Keywords: Agent-Based Social Simulation, Swarm computing, Graph Theory.

1 Introduction

The current boom in social-oriented online technologies has generated a wealth of social data. As a consequence, social computing now attracts increasing attention from a number of different fields ranging from the social sciences and social simulation, to statistical physics and computer science. Specialty journals like *Social Networks* and several conferences (e.g the International Sunbelt Social Network Conference) have helped bring attention to the field [9].

One major computational approach to social simulation is the field of agent-based social computing (ABSS). Complex systems like social interactions may be too difficult to understand using regular statistical and mathematical tools. ABSS borrows

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from agent-based computing, computer simulation and social sciences to provide a framework of social simulation based on agent-based modeling and artificial intelligence. The result is a methodological approach to the testing, refinement and extension of theories [19]. Agent-based models are characterized by their flexibility, allowing to incorporate a wide variety of actor-driven micro-mechanisms influencing the formation of ties , as well as permitting social influences to be controlled to assess its effect on the network as a whole [17, 7]. While social sciences have a long history of employing computer simulations, agents-based simulations have only been partially developed [4]. On the other hand, great strides have been made in the field of complex networks—again, spurred by the growing popularity of online social networks. These works tend to focus on the use of graph topology to extract patterns that may be used in the mining of knowledge. In the past, the topological characteristics of a social graph have been used to generate dynamic models [1, 6, 2]. Other node-centric models have been developed to explore how assortivity influences graph evolution [11, 12].

In social graphs, some nodes tend to group together in highly-connected clusters, known as communities. In social graphs, it has been observed that the stability, age and size of communities found in social and non-social relationship graphs over time, had a particular signature that could help in differentiating them [20]. Building on the swarm agent platform MASON [10], we have developed a swarm ABSS platform designed to explore different social models using graph-mining tools. As a first contribution, we present the platform, and provide a baseline test to determine whether a given model present the same high-order characteristics.

This article is structured as follows: the next section will give a description of the simulation platform . Section 3 gives an overview of the simulation design process, while section 4 provides a detailed description of three sample social models implemented with the platform. Finally chapter 5 draws out our conclusions and ongoing efforts.

2 Description of the Simulation Platform

The platform is comprised of two main components—a simulation engine and a graph-mining toolkit. Together, they allow social models to be quickly implemented, meassured and compared. A simulation consists of a static number of swarm agents navigating a terrain, where they interact with each other and choose to establish or sever social ties. Arbitrary proximity constraints can be placed in the interaction of agents as it has special significance to social interactions [3, 7, 16].

To run a simulation, agents are given movement, and interaction patterns. Movement dictates how agents navigate their environment—random, follow-the-leader, etc—while interaction determines the tie formation protocol each agent abides by. Likewise, environment size, simulation duration, and other external attributes are defined prior to the simulation. During the simulation, snapshots of the social ties formed are taken in the form of an undirected graph, where nodes represent agents, and edges the existence of social ties between them. Once the simulation ends, a list of such snapshots in chronological order is returned. At this point, the simulation may be analyzed from a dynamic networks perspective, using the graph-based toolbox provided by the platform.

A main concern in the network analysis step is to determined whether the model implemented presents basic social networks properties. Indeed, in social networks, the age of a community seems to be positively correlated to its size—bigger communities tend to last longer—while its member stability is negatively correlated to its lifespan—communities that last longer have a very active membership. Non-social networks, like router networks or the world wide web, on the other hand present negative size/age correlations and positive member stability/lifespan correlation [20].

In order to study the evolution of simulated social models, a number of graph metrics are provided. After each simulation cycle, the graph cluster index, average path length and node degree distribution are calculated from the social graph. These metrics allow the model to be weighted against known small-world and free-scale graphs topologies [1], both of which are known to be characteristic of real social networks.

The work by [18] suggests that these metrics may not be enough to fully characterize real-world social networks, and instead advocates the use of *high-order* structures, so two community detection algorithms are used: Girvan-Newman algorithm and the Cluster Percolation Method (CPM). Non-overlapping communities can be detected using the Girvan-Newman algorithm[5], which has a long track in the social sciences field, while overlapping communities can be detected with CPM [14]. Tracking community evolution can be done by either monitoring community overlaps across time-steps with *CPM*—see [8], or with the *CommTec* algorithm proposed by [20], which identifies core community nodes and follows their community membership through time.

As proposed in [20], tracing of communities over time can yield two important metrics: the correlation between the size and age of communities, or *growth* and the correlation between member stability and lifespan of communities, or *metabolism*. Size of a community at a given time $C^{(t)}$ refers to the number of members it has, while age refers to how long the community has existed. The lifespan of a community is the number of future communities that can trace their origin to it. Member stability (MS) is an index referring to how much a community changes over time, calculated with the following formula:

$$MS(C^{(t)}) = \frac{C^{(t)} \cap (C_1^{(t+1)} \cup C_2^{(t+1)} \ldots \cup C_n^{(t+1)})}{C^{(t)} \cup (C_1^{(t+1)} \cup C_2^{(t+1)} \ldots \cup C_n^{(t+1)})}$$

Where $C_1^{(t+1)} \cup C_2^{(t+1)} \ldots \cup C_n^{(t+1)}$ is the union of all communities in the next time-step that can trace their origin to $C^{(t)}$

3 Experimental Results

3.1 Random Model

To establish a baseline for models, we first implement a swarm model to produce an Erdös-Rényi random graph[15]. Whereas the former presents each agent with an uniform connection probability p over $n-1$ other agents, this model works on the subset of n agents within a predefined range.The model is implemented as follows: a number of swarm agents are created and scattered in a finite plane, which they navigate in random trajectory. Agents come in contact with one another by getting within a predefined range. At each simulation time-step, agents scan their surrounding and create or drops ties with agents found, with a probability p.

Figures 1(a), 1(b) displays the growth and metabolism graphs from a sample run. In this case, both graphs present a positive correlation, a behavior not observed in social or non-social graphs. The model was implemented using 100 agents which ran for 300 steps. From trial runs, the majority of results did not conform to social or non-social behavior—76% of the simulations rans

3.2 Christakis-Fowler Model

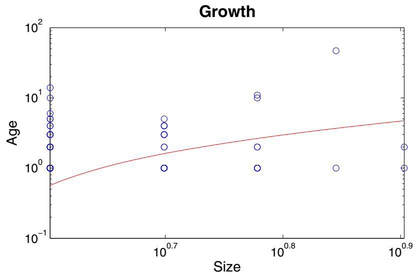
The *Christakis-Fowler* model (CF) is a parametrized social network model that takes into account individual personality traits, as well as peer influence when forming social ties. A thorough study of the effect each parameter has on the model, from a statistical perspective, can be found in [13].

The model was implemented with parameters from [13] for validation purposes, and simulations were run using 1000 agents moving randomly on a finite plane for 300 steps. Figure 1(c) displays the age/size graph taken from a sample run, while figure 1(d), the stability/trace span of the same run. As observed in social graphs, the growth of this model positive, while metabolism negative. This behavior was observed in 90% of the simulation ran.

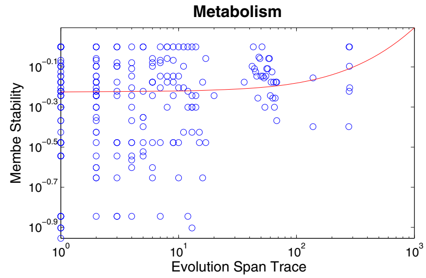
We have observed how higher-order topological characteristics from a graph can be used to characterize social ties. Furthermore these experiments have helped us validate our social model implementation, as well provided a common ground on which to compare different models.

4 Conclusions and Further Work

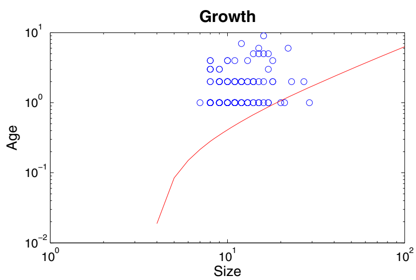
Social network analysis is currently a booming field of research attracting talent from areas like the social sciences, computer science, statistical physics and many others. Recent advances in the field of complex networks have helped understand the mechanics of social networks, offering new ways of measuring and modeling them. To take advantage of these tools, we have developed a new agent-based social simulation platform that incorporates graph-based metrics to the evaluation of their models.



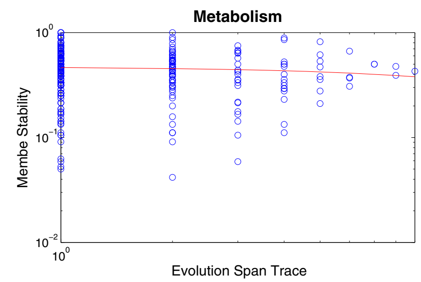
(a) Random Model. Size and age



(b) Random Model. Stability and evolution trace span



(c) CF Model. Size and age.



(d) CF Model. Stability and evolution trace span

Fig. 1 Growth and metabolism of the CF and random models.

Using this new platform, we have simulated two swarm models. In these models, communities and their evolution have been tracked over time to test for graph topologies typically found in social networks. We found that these metrics where able to correctly differentiate a social model from a non-social. future work, we plan to extend the metrics used to provide a more robust baseline social test, as well as the ability to compare models by low- and high-order characteristics. We believe this new platform will become very valuable in understanding complex dynamic models.

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