INTRODUCTION

Networks are pervasive in our lives. They are everywhere, from the Internet, to biology, to social relations or economics (M. Newman, Barabasi, & Watts, 2006). The notion of a connected world is one that we assume is prevalent as a foundation. The connectedness of daily things prevails, even when one segments it into sub-networks. Everything seems related, in some sense, to everything else.

In communication, the notion of networks is always present. Formal and informal relations arise from the interplay of actors during communication processes. Traditionally, networks have been categorized into four types, or classes: lattice networks, that are very regular and rigid, where a certain pattern is repeated ad infinitum; random networks, in which every connection is established according to some probability $p$; small-world networks that are somewhat in between random networks and lattice networks, and have high transitivity and short average path lengths; and finally scale-free networks that have the same type of structure at different levels, with a characteristic hub and spoke structure, where every connection is made according to the degree of existing connections. In this scenario, informal communication networks seem to be formed according to other types of rules, as they can’t truly be mapped into one of those four types of networks. These non-trivial networks, arise from the “social” aspect of these kinds of networks and several

DOI: 10.4018/jats.2009071003
authors have discussed the problems of those four types of networks in failing to explain social networks. The problems that informal social communication networks present make them well-suited to be tested under new models of network formation and actor interplay. Multi-agent-based simulation is a popular field where these ideas can be tested and where ideas can be benchmarked.

In the next sections, we discuss the mechanisms presently available for community detection, mainly those developed with networks in mind, and we discuss some application of these algorithms to informal email communication systems through a case study. Also, we present a multi-agent model developed for exploring the influence of using real data in simulation and to test the idea of a “social neighborhood” in the formation of informal assortative communication networks.

Community Detection Algorithms

Community detection can be very useful for performing an exploratory analysis of data, and its usage transverses several domains, from statistics to computer science, biology or psychology. In every science, it is necessary to deal with empirical data, and one of the first classifications that one tries is to group the data according to some property that might manifest itself similarly inside the groups. Several algorithms and techniques have been devised to accomplish this partitioning, but in practice all are faced with situations where a good partitioning isn’t accomplished, and new methods have to be devised. Some methods are robust, and can be used effectively to classify groups with sets of data that are very heterogeneous. On the other hand, some are very specific to certain problems and need initial conditions that are particular to make its results appropriate (Shortreed, 2006).

Looking into more detail at clustering techniques for networks, these can be divided into two main classes, according to the approach they take to the partitioning problem: global or local. In global strategies, the network is taken as a whole and usually a general property is used to divide the network, separating all of its members into clusters. One example of these techniques is hierarchical clustering algorithms like Girvan-Newman (Girvan & Newman, 2001) that use edge betweenness as the property of interest. In local algorithms, the strategy uses some local patterns when considering which points belong to each cluster. Clique percolation (Palla, Derényi, Farkas, & Vicsek, 2005) uses the notion of cliques to identify groups or modules.

Hierarchical Clustering is a type of partitioning strategy that produces a dendrogram from the breaking down of a complete graph. Two sub-classes of this type of partitioning are available, according to the way the dendrogram is built. One is a bottom-up approach, where one starts by considering each node as being a member of its own community, and then the process runs iteratively, merging communities according to some maximal value of a quality function. These are called hierarchical agglomerative methods. In other subclasses, there are the divisive methods of hierarchical clustering, where one considers that all nodes belong to one single initial community and then the process to construct the dendrogram is by breaking the communities iteratively into sub-communities up to the point where all nodes are attributed to communities with one node. The path of divisions is also based on the “optimal” value of some property, usually one that measures the strength of the connections between communities. This sub-class is known as a hierarchical divisive.

Two examples of these methods are the Girvan-Newman (Girvan & Newman, 2001) algorithm (GNA) and the Clauset-Newman-Moore algorithm (CNM) (Clauset, Newman, & Moore, 2004). The former is a hierarchical divisive algorithm, while the latter is agglomerative. GNA uses the edge betweenness to determine which edges can be safely removed from the network and iteratively removes them, splitting the network into sub-networks to construct the final dendrogram. The point in the dendrogram where the “optimal” cut is achieved is then...
Related Content

Evolution of Agents in a Simple Artificial Market
Hiroshi Sato, Masao Kubo and Akira Namatame (2011). Multi-Agent Applications with Evolutionary Computation and Biologically Inspired Technologies: Intelligent Techniques for Ubiquity and Optimization (pp. 118-133).
www.igi-global.com/chapter/evolution-agents-simple-artificial-market/46202?camid=4v1a

Statistical Properties of Community Dynamics in Large Social Networks
www.igi-global.com/article/statistical-properties-community-dynamics-large/37416?camid=4v1a

Hierarchical Multi-Agent Plans Using Model-Based Petri Net
www.igi-global.com/article/hierarchical-multi-agent-plans-using-model-based-petri-net/87147?camid=4v1a
Describing Agent Societies: A Declarative Semantics
www.igi-global.com/chapter/describing-agent-societies/21099?camid=4v1a