Chapter 1
Computational Social Networks: Tools, Perspectives, and Challenges

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Abstract Computational social science is a new emerging field that has overlapping regions from mathematics, psychology, computer sciences, sociology, and management. Social computing is concerned with the intersection of social behavior and computational systems. It supports any sort of social behavior in or through computational systems. It is based on creating or recreating social conventions and social contexts through the use of software and technology. Thus, blogs, email, instant messaging, social network services, wikis, social bookmarking, and other instances of what is often called *social software* illustrate ideas from social computing. Social network analysis is the study of relationships among social entities. It is becoming an important tool for investigators. However all the necessary information is often distributed over a number of websites. Interest in this field is blossoming as traditional practitioners in the social and behavioral sciences are being joined by researchers from statistics, graph theory, machine learning,

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A. Abraham and A.-E. Hassanien (eds.), *Computational Social Networks: Tools, Perspectives and Applications*, DOI 10.1007/978-1-4471-4048-1_1,

and data mining. In this chapter, we illustrate the concept of social networks from a computational point of view, with a focus on practical services, tools, and applications and open avenues for further research. Challenges to be addressed and future directions of research are presented and an extensive bibliography is also included.

Introduction

Internet represents an increasingly important role and gradually comes into play in all walks of our lives because of its rich and varied resources. Currently, social networks provide a powerful abstraction for the structure and dynamics of diverse kinds of people or people-to-technology interaction. Web 2.0 has enabled a new generation of web-based communities, and social networks to facilitate collaboration among different communities. During the last few years, social networking sites have become a de facto part of the Internet and a primary destination for many Internet users. Even though the market seems to be saturated with social networking sites for every type of target group, the concepts driving these sites are incredibly similar in form and execution. More and more people would like to spend their time on the Internet especially in order to build some kind of large social entertainment community and then try to communicate with each other as frequently as practicable so as to see that the relationship between them is getting closer [1].

Social computing supports computations that are carried out by groups of people. Examples of social computing include collaborative filtering, online auctions, prediction markets, reputation systems, computational social choice, tagging, and verification games. Social computing has become more widely known because of its relationship to a number of recent trends. These include the growing popularity of social software and web 2.0, increased academic interest in social network analysis, the rise of open source as a viable method of production, and a growing conviction that all of this can have a profound impact on daily life. Accordingly, social network analysis (SNA) has become a widely applied method in research and business for inquiring the web of relationships on the individual, organizational, and societal level. With ready access to computing power, the popularity of social networking websites such as Facebook, Twitter, and Netlog and automated data collection techniques; the demand for solid expertise in SNA has recently exploded.

Social networking covers a wide range of online environments, with many formal definitions broad enough to encompass almost any web 2.0 collaborative environment [2]. While various public social collaborative environments existed on the Internet as early as the 1980s, the emergence of social networking as it is best understood today arose with the large commercially supported sites such as Friendster (2002), LinkedIn and MySpace (2003), and Facebook (2004), along with content-sharing focused sites with limited social network features such as Flickr (2004) and YouTube (2005). Other social networking sites were developing, which have higher usage outside the USA including Orkut (2005), popular in South America and Asia/Pacific regions, Bebo (2005) in Europe and Australia, and QQ (2006) in China. With the development of Twitter in 2006, social networking took a new twist that increased immediacy and incorporated mobile phones into the social mix [3]. In social media, communities take the form of social networks and the communal groups within them. People establish associations, friendships, and allegiances around content, objects, products, services, and ideas. How they communicate is simply subject to the tools and networks that people adopt based on the influence of their social graph – and the culture within [4]. Many of the social networks are enhanced with multiple collaborative tools that go beyond the personal profile and "friending" links, including the ability to post and share files (text, images, audio, and video), participate in discussions or blogs, co-create and edit content with wiki-like tools, and link in and tag external resources from other websites paralleling social bookmarking. Sites such as Flickr or YouTube are in fact more commonly seen as environments primarily for sharing content, digital pictures, and video [3].

This chapter provides an overview of a number of social network-related concepts from a computational perspective, such as social network analysis, social network services, tools, and applications in addition to exploring main problems facing social networks and addressing challenges, opportunities, and future directions of research. The chapter is organized as follows. Section "Social Network Analysis: Concepts" provides an explanation of the some basic related concepts including social networks versus computer networks and the social network sites. Section "Social Networks: Analysis Metrics and Performance" briefly describing the different performance measures, that have been encountered during any network analysis. Section "Social Network Services and Tools" presents different social networking services and tools. Section "Problems in Social Networks" discusses different problems in social networks including uncertainty, missing data in social network, and finding the shortest path. Finally, opportunities and challenges are discussed in section "Conclusion, Challenges, and Opportunities".

Social Network Analysis: Concepts

Social Network Versus Computer Network

Networks can be categorized according to topology, which is the geometric arrangement of a computer system. Common topologies include a bus, star, and ring, protocol which defines a common set of rules and signals that computers on the network use to follow. Or architecture where networks can be broadly classified as either a peer-to-peer or client/server architecture. Computers on a network are sometimes called nodes. Computers and devices that allocate resources for a network are called servers. It is argued that social networks differ from most other types of networks, including technological and biological networks, in two important ways. First, they have nontrivial clustering or network transitivity and second, they show positive correlations, between the degrees of adjacent vertices. Social networks are often divided into groups or communities, and it has recently been suggested that this division could account for the observed clustering. Further, group structure in networks can also account for degree correlations. Hence, assortative mixing in such networks with a variation in the sizes of the groups provides the predicted level compares well with that observed in real-world networks.

Social Network Sites

Social network sites (SNSs) are websites that allow users to register, create their own profile page containing information about themselves (real or virtual), to establish public “Friend” connections with other members and to communicate with other members [5]. Communication typically takes the form of private emails, public comments written on each others’ profile pages, blog or pictures, or instant messaging. SNSs like Facebook and MySpace are amongst the ten most popular websites in the world. SNSs are very popular in many countries that include Orkut (Brazil), Cyworld (Korea), and Mixi (Japan).

SNS growth seems to have been driven by youth, with Facebook originating as a college site [5] and MySpace having an average age of 21 for members in early 2008 [6]. However, an increasing proportion of older members are also using these sites. The key motivating factor for using SNS is sociability, however, suggesting that some types of people may never use social network sites extensively [7]. Moreover, it seems that extraversion is beneficial in SNSs [8] and that female MySpace users seem to be more extraverted and more willing to self-disclose than male users [9], which hints that they may be more effective communicators in this environment.

SNS are very much interesting because they support relatively public conversations between friends and acquaintances. Walther et al. [10] view that SNS profiles are known as venues for identity expression of members and since public comments appear in these profiles, they may also be composed or interpreted from the perspective of identity expression rather than performing a pure communicative function. At the same time, the public conversations are interesting because the web now contains millions of informal public messages that researchers can access and analyze. The availability of demographic information about the sender and recipient in their profile pages makes it more interesting and useful with an ethical issue arises from its owners that the dataset are explicitly to be used in research (unlike standard interview or questionnaire protocols). However, if the data has been placed in the most public place online as found though Google then its use does not constitute any kind of invasion of privacy [11]. An ethical issue only arises if feedback is given to the text authors or if a contact is established.

The data mining research has been analyzed using MySpace data for commercially oriented purposes rather than social science goals, but then an IBM study demonstrated how to generate rankings of musicians based upon opinions mined from MySpace comments [12] and a Microsoft team developed a league table system for movies by extracting lists from MySpace profiles, without explicit sentiment analysis [13].

Social Networks: Analysis Metrics and Performance

We describe the different performance measures that are encountered during any network analysis in order to understand the fundamental concepts behind the comprehension. The four most important concepts used in network analysis are closeness, network density, centrality, betweenness, and centralization. In addition to these, there are four other measures of network performance that include robustness, efficiency, effectiveness, and diversity. The first set of measures concerns structure, whereas the second set concerns the dynamics and thus depends on a theory explaining why certain agents do certain things in order to access to information [50].

Social Networks Analysis Metrics

Closeness

This refers to the degree with which an individual is nearer to all others in a network either directly or indirectly. Further, it reflects the ability to access information through the "grapevine" of network members. In this way, the closeness is considered to be the inverse of the sum of the shortest distance (sometimes called as geodesic distance) between each individual and all other available in the network. For a network with n number of nodes, the closeness is represented mathematically as

$$c_c(n_j) = \frac{n-1}{\sum_{k=i,j=k}^{n} d(n_i, n_j)} \tag{1.1}$$

Where $C_c n_k$ defines the standardized closeness centrality of node j and $d(n_i, n_j)$ denotes the geodesic distance between j and k.

Network Density

Network density is a measure of the connectedness in a network. Density is defined as the actual number of ties in a network, expressed as a proportion of the maximum possible number of ties. It is a number that varies between 0 and 1.0. When density is close to 1.0, the network is said to be dense; otherwise it is sparse. When dealing with directed ties, the maximum possible number of pairs is used instead.

The problem with the measure of density is that it is sensible to the number of network nodes; therefore, it cannot be used for comparisons across networks that vary significantly in size.

Centrality: Local and Global

The concept of centrality comprises of two levels: local and global. A node is said to have local centrality, when it has the higher number of ties with other nodes or else it is referred to as global centrality. Whereas local centrality considers only direct ties (the ties directly connected to that node), global centrality considers indirect ties also (which are not directly connected to that node). For example, in a network with a “star” structure, in which, all nodes have ties with one central node, local centrality of the central node is equal to 1.0. Whereas local centrality measures are expressed in terms of the number of nodes to which a node is connected, global centrality is expressed in terms of the distances among the various nodes. Two nodes are connected by a path if there is a sequence of distinct ties connecting them, and the length of the path is simply the number of ties that make it up . The shortest distance between two points on the surface of the earth lies along the geodesic that connects them, and, by analogy, the shortest path between any particular pair of nodes in a network is termed a geodesic. A node is globally central if it lies at a short distance from many other nodes. Such node is said to be “close” to many of the other nodes in the network, sometimes global centrality is also called closeness centrality. Local and global centrality depends mostly on the size of the network, and therefore they cannot be compared when networks differ significantly in size.

Betweenness

Betweenness is defined as the extent to which a node lies between other nodes in the network. Here, the connectivity of the node’s neighbors is taken into account in order to provide a higher value for nodes which bridge clusters. This metrics reflects the number of people who are connecting indirectly through direct links. The betweenness of a node measures the extent to which an agent (represented by a node) can play the part of a broker or gatekeeper with a potential for control over others. Methodologically, betweenness is the most complex of the measures of centrality to calculate and also suffers from the same disadvantages as local and global centrality. The betweenness of the nodes in a network can be defined as:

$$c_b(n_j) = \frac{xx}{\frac{(n-2)(n-1)}{2}} \tag{1.2}$$

$$xx = \sum_{k<i, j=k, j=t} \frac{g_{kt}(n_j)}{g_{kt}} \tag{1.3}$$

Where $c_b(n_j)$ denotes the standardized betweenness centrality of node j, $g_{kt}(n_j)$ represents the number of geodesic linking k and I that contains j in between and as the total number of geodesic linking k and i.

Centralization

Centralization is calculated as the ratio between the numbers of links for each node divided by maximum possible sum of differences. Centralization provides a measure on the extent to which a whole network has a centralized structure. Whereas centralization describes the extent to which this connectedness is organized around particular focal nodes, density describes the general level of connectedness in a network. Centralization and density, therefore, are important complementary pair measures. While a centralized network will have many of its links dispersed around one or a few nodes, the decentralized network is one in which there is little variation between the number of links each node possesses. The general procedure involved in any measure of network centralization is to look at the differences between centrality scores of the most central node and those of all other nodes. Basically, centralization can be graphed in three ways: one for each of the three centrality measures: local, global, and betweenness. All three centralization measures vary from 0 to 1.0 where 0 corresponds to a network in which all the nodes are connected to all other nodes whereas a value of 1.0 is achieved on all three measures for "star" networks. However, majority of the real networks lies between these two extremes. Methodologically, the choices of one of these three centralization measures depend on which specific structural features the researcher wants to focus. For example, while a betweenness-based measure is sensitive to the chaining of nodes; a local centrality based measure of network centralization seems to be particularly less sensitive to the local dominance of nodes. It is measured as:

$$R = \frac{\sum_{j=1}^{g} \{\max(D_i) - D_i\}}{(g-1)^2} \tag{1.4}$$

where D_i represents the number of actors in the network that are directly linked to the actor j and g denoted as the total number of actors present in the network.

Social Networks Performance

Once the network analysis is completed, the network dynamics predicts the performance of the network that can be evaluated as a combination of (1) the network's robustness to the removal of ties and/or nodes, (2) network efficiency in terms of the distance to traverse from one node to another and its non-redundant size, (3) effectiveness of the network in terms of information benefits allocated to central nodes, and finally (4) network diversity in terms of the history of each of the nodes [50].

Robustness

Social network analysts have highlighted the importance of network structure in relation to the network's robustness. The robustness can be evaluated based on how it becomes fragmented when an increasing fraction of nodes is removed. Robustness is measured as an estimate of the tendency of individuals in networks to form local groups or clusters of individuals with whom they share similar characteristics, i.e., clustering. For example, if individuals X, Y, and Z are all computer experts and if X knows Y and Y knows Z, then it is highly likely that X knows Z using the so called chain rule. If the measure of the clustering of individuals is high for a given network, then the robustness of that network increases – within a cluster/group.

Efficiency

Network efficiency can be measures by considering the number of nodes that can access instantly a large number of different nodes – sources of knowledge, status, etc., through a relatively small number of ties. These nodes are treated as non-redundant contacts. For example, with two networks of equal size, the one with more non-redundant contacts provides more benefits than the others. Also, it is quite evident that the gain from a new contact redundant with existing contacts will be minimal. However, it is wise to consume time and energy in cultivating a new contact to un-reached people. Hence, social network analysts measure efficiency by the number of non-redundant contacts and the average number of ties an ego has to traverse to reach any alter, this number is referred to as the average path length. The shorter the average path length relative to the size of the network and the lower the number of redundant contacts and the more efficient is the network.

Effectiveness

Effectiveness targets the cluster of nodes that can be reached through non-redundant contacts. In contrast, efficiency aims at the reduction of the time and energy spent on redundant contacts. Each cluster of contacts is an independent source of information. One cluster around this non-redundant node, no matter how numerous its members are, is only one source of information, because people connected to one another tend to know about the same things at about the same time. For example, a network is more effective when the information benefit provided by multiple clusters of contacts is broader, providing better assurance that the central node will be informed. Moreover, because non-redundant contacts are only connected through the central node, the central node is assured of being the first to see new opportunities created by needs in one group that could be served by skills in another group.

Diversity

While efficiency is about getting a large number of (non-redundant) nodes, node's diversity, on the other hand it suggests a critical performance point of view where those nodes are diverse in nature, i.e., the history of each individual node within the network is important. It is particularly this aspect that can be explored through case studies, which is a matter of intense discussion among social network analysts. It seems to suggest that social scientists should prefer and use network analysis according to the first strand of thought developed by social network analysts instead of actor-attribute-oriented accounts based on the diversity of each the nodes.

Social Network Services and Tools

Social Network Services

Currently available social network services have two main formats: (1) sites that are primarily organized around users' profiles *(profile-based social network services)* and (2) those that are organized around collections of content *(content-based social network services)* [14].

Profile-based social network services are primarily organized around members' profile pages – pages which primarily consist of information about an individual member – including their picture, interests, likes and dislikes. Bebo, Facebook and MySpace are all good examples of this. Users develop their space in various ways, and can often contribute to each other's spaces – typically leaving text, embedded content or links to external content through message walls, comment or evaluation tools. Users often include third-party content (in the form of "widgets") in order to enhance their profiles, or as a way of including information from other web services and social networking services.

On the other hand, in *content-based social network services*, the user's profile remains an important way of organizing connections but plays a secondary role to the posting of content. Photo-sharing site Flickr is an example of this type of service. *Shelfari* is one of the current crop of book-focused sites, with the member's "bookshelf" being a focal point of their profile and membership. Other examples of content-based communities include YouTube for video-sharing and last.fm, where the content is arranged by software that monitors and represents the music that users listen to. In this instance, content is generated by the user's activity. The act of listening to audio files creates and updates profile information ("recently listened to"). This in turn generates data about an individual user's neighbors who are people who have recently listened to the same kind of music.

Figures 1.1 and 1.2 from [15] depict visualizations for two examples of music websites, namely; *last.fm*, founded in the United Kingdom in 2002, and *Musicovery*, which is a website letting users discover new music, using the *last.forward* software

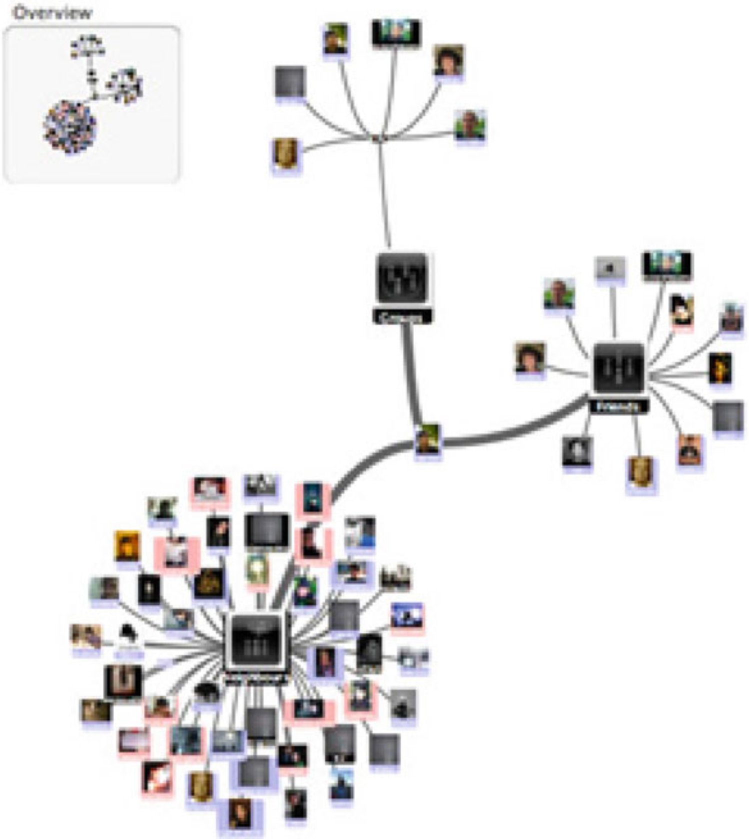

Fig. 1.1 A visualization for *last.fm* music website using *last.forward* software [15]

[15], which is an open source software for analysis and visualization of the social music network of *Last.fm* and *Musicovery*.

Moreover, sites such as Second Life and World of Warcraft represent multi-user online virtual environments in which users to interact with each other's avatars (a virtual representation of the site member). Although the users have profile cards, their functional profiles are the characters they customise or build and control. Friends' lists are usually private and not publicly shared or displayed.

Social Network Tools

Social Bookmarking

Bookmarking is the practice of saving the address of a website users wish to visit in the future on their computer. Social bookmarking, on the other hand, is the practice

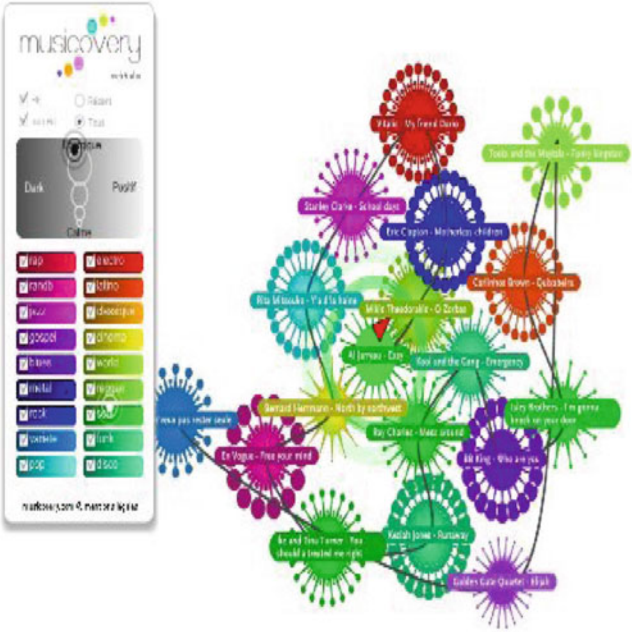

Fig. 1.2 A visualization for *Musicovery* music website using *last.forward* software [15]

of saving bookmarks to a public website and “tagging” them with keywords. Social bookmarking began in unrefined form in the late 1990s. It then fell out of favor online due to changes in the web. It came back in 2005 and has been getting increasingly popular ever since [16].

Social bookmarking is a method for Internet users to organize, store, manages, and search for bookmarks of resources online. In other words, social bookmarking is a user-based online system in which individuals tag their favorite web content and store it in one place, sharing it with others. The favorite content of a person may also be a favorite of another; this will boost the website traffic.

Social Tagging (Social Indexing)

Unlike file sharing, the resources themselves are not shared, but merely bookmarks that reference them. Social tagging – which is also known as collaborative tagging, social classification, and social indexing – allows ordinary users to assign keywords, or tags, to items. It involves linking sites within the various forums, blogs and message boards on social networking websites, blog sites, and content-centric sites and is very useful to share information instantly with other users/friends [16].

Social tagging can be a useful tool for users. Instead of individually saving the site in a variety of folders, just type a few keywords called tags and their sites are organized automatically with sites saved by other users, using those same keywords. All levels of user can benefit from social tagging. Potentially, it is another efficient tool both free and commercially available, which any user can use [17].

Web Syndication

Web syndication is a form of syndication in which website material is made available to multiple other sites. Most commonly, web syndication refers to making web feeds available from a site in order to provide other people with a summary of the website's recently added content (for example, the latest news or forum posts). The term can also be used to describe other kinds of licensing website content so that other websites can use it [18].

Syndication benefits both the websites providing information and the websites displaying it. For the receiving site, content syndication is an effective way of adding greater depth and immediacy of information to its pages, making it more attractive to users. For the transmitting site, syndication drives exposure across numerous online platforms. This generates new traffic for the transmitting site, making syndication a free and easy form of advertisement. Commercial web syndication can be categorized in three ways: (1) by business models, (2) by types of content, or (3) by methods for selecting distribution partners [16]. The term Really Simple Syndication (RSS) is often used to refer to web feeds or web syndication in general, although not all feed formats are RSS-based. A web feed is a data format used for providing users with frequently updated content. Content distributors syndicate a web feed, thereby allowing users to subscribe to it. Making a collection of web feeds accessible in one spot is known as aggregation, which is performed by an aggregator. A web feed is also sometimes referred to as a syndicated feed. RSS is a family of web feed formats used to publish frequently updated works such as blog entries, news headlines, audio, and video in a standardized format. An RSS document includes full or summarized text, plus metadata such as publishing dates and authorship. Web feeds benefit publishers by letting them syndicate content automatically. They benefit readers who want to subscribe to timely updates from favored websites or to aggregate feeds from many sites into one place. RSS feeds can be read using software called an "RSS reader," "feed reader," or "aggregator," which can be web-based, desktop-based, or mobile-device-based.

Knowledge Tagging

Another social networking tool is knowledge tagging. A knowledge tag is a type of meta-information that describes or defines some aspect of an information resource. Knowledge tags are more than traditional nonhierarchical keywords or terms. They are a type of metadata that captures knowledge in the form of descriptions, categorizations, classifications, semantics, comments, notes, annotations, hyperdata, hyperlinks, or references that are collected in tag profiles. These tag profiles reference to an information resource that resides in a distributed, and often heterogeneous, storage repository [19].

Social Search Engines

Social search engines are an important tool that utilize the popularity of social networking services. There are various kinds of social search engines, but sites like Wink and Spokeo generate results by searching across the public profiles of multiple social network sites, allowing the creation of web-based "dossiers" on individuals. This type of people search cuts across the traditional boundaries of social network site membership, although any data retrieved should already be in the public domain.

Mobile Social Networks and Micro-blogging

Many social network sites, for example MySpace and Twitter, offer mobile phone versions of their services, allowing members to interact with their friends via their phones. Increasingly, too, there are mobile-led and mobile-only communities, which include profiles and media-sharing just as with web-based social networking services. MYUBO, for example, allows users to share and view video over mobile networks.

Micro-blogging services such as Twitter and Jaiku allow you to publish short (140 characters, including spaces) messages publicly or within contact groups. They are designed to work as mobile services, but are popularly used and read on the web as well. Many services offer "status updates" – short messages that can be updated to let people know what mood you are in or what you are doing. These can be checked within the site, read as text messages on phones, or exported to be read or displayed elsewhere. They engage users in constantly updated conversation and contact with their online networks.

Social Gaming Applications

A social network game is a type of online game that is played through social networks, and typically features multiplayer and asynchronous gameplay mechanics [20–23]. While they share many aspects of traditional video games, social network games often employ additional ones that make them distinct. Social network games are most often implemented as browser games, but can also be implemented on other platforms such as mobile devices [24]. They are amongst the most popular games played in the world, with several products with tens of millions of players [25]. Green Patch, Happy Farm [26], Farm Town, YoVille, and Mob Wars were some of the first successful games of this genre. Moreover, FrontierVille, CityVille, Gardens of Time, and The Sims Social are more recent examples of very popular social network games. Companies that make social network games include market leader Zynga, 5 min, Playfish, Playdom, Kabam, Crowdstar, RockYou, Booyah, etc.

Social Networking Tools for Distance Learning

Social networking technologies have many positive uses in educational institutions and libraries. They are an ideal environment for youngsters to share what they are learning or to build something together online. The nature of the medium allows students to receive feedback from teachers, peers, parents, and others. Social networking technologies create a sense of community (as do the physical library and school) and in this way are already aligned with the services and programs at the library/school. Schools and libraries are working to integrate positive uses of social networking into their classrooms, programs, and services. By integrating social networking technologies into educational environments, youngsters have the opportunity to learn from adults how to be safe and smart when participating in online social networks [27].

Based on Internet voting, 63% supported the proposition that social networking will bring large, positive changes to educational methods. Similar debates have occurred elsewhere online, in periodicals, and in schools raising issues of affordances versus challenges common to any new technology. Many advocates promote the use of social networking for community building and increasing student engagement in higher education classrooms. Some critics have suggested that the links between computer-mediated discussion (CMD) and learning or engagement are not well documented, proposing that such advocacy is more hype than reality [28]. But recent studies such as [29] indicate that teacher self-disclosure via social networking can increase motivation and improve classroom climate thus impacting student outcomes. In many of these debates, the focus is often limited to the massive and most well known of the social networks, MySpace and Facebook, particularly because media coverage has ensured that even those who have limited familiarity with social networking have heard about these Internet environments. However, social networking tools are more diverse and in fact, some may better fit specific class needs.

Social networking is a tool, with both its advantages and problems for usage in teaching and learning. When used in a learning context where affordances of the technology are carefully evaluated in terms of pedagogical requirements and student learning outcomes, including those elements that result in a supportive and collaborative learning environment, these tools offer significant advantages for distance learning. Among the positive attributes are impacts on student engagement, motivation, personal interaction, and affective aspects of the learning environment. In the case study reported here, specific positive effects included the balancing of individual creativity and personal interactions with the need for structured learning and collaborative course activities. The direct contribution to student achievement remains to be proven, but when technology supports an affirmative, constructivistlearning environment, and contributes to successful pedagogical strategies without distracting from essential objectives for development of knowledge and skills, the result of formative evaluation of social networking potentials for distance learning is positive [3].

Problems in Social Networks

Uncertainty in Social Network

The uncertainty in digital evidence is not being evaluated at present, thus making it difficult to assess the reliability of evidence stored on and transmitted using computer networks [30]. Uncertainty occurs when the actors are confronted with too many interpretations, causing a shock of confusion. In an ambiguous situation there is no lack of information, no gap that could be filled with a better scanning of available information, rather there are at least two (and often more) different interpretations of the situation [31]. Many research works tackled the problem that the data collected through automated sensors, anonymized communication data, and self-reporting logging on Internet-scale networks as a proxy for real relationships and interactions causes some uncertainty.

Alejandro et al. [32] introduced a methodology that incorporates into the social interaction activity records the uncertainty and time sensitiveness of the events through fuzzy social networks analysis (FSNA). Also, they investigated an approach based on the analysis of current flows in electrical networks for the extraction of primary routes of interaction among key actors in a social network. They proposed that the ability to capture the influence of all nodes involved in a network over a particular path represents a promising avenue for the extraction of characteristics of the social network assuming that uncertainty and time sensitiveness are parameters of the information stored on activity logs that cannot be ignored and must be accounted for. Zhong et al. [33] used an adaptive group fuzzy analytic network process group decision support system under uncertainty that makes up for some deficiencies in the conventional analytic network process. Where the first step fuzzy judgments are used when it is difficult to characterize the uncertainty by point-valued judgments due to partially known information, and a bipartite graph is formulated to model the problem of group decision making under uncertainty. Then, a fuzzy prioritization method is proposed to derive the local priorities from missing or inconsistent fuzzy pairwise comparison judgments. As a result of the unlikeliest for all the decision makers to evaluate all elements under uncertainty, an original aggregation method is developed to cope with the situation where some of the local priorities are missing. Hassan et al. [34] observed that the characteristics of social systems are poorly modeled with crisp attributes. A concrete agent-based system illustrates the analysis of the evolution of values in a society enhanced with fuzzy logic to improve agent models that get closer to reality. This has been explored in five aspects: relationships among agents, some variable attributes that determine agent states, functions of similarity, evolution of agent states, and inheritance. Gabriella et al. [35] proposed new approach to combine survey data with multi agent simulation models of consumer behavior to study the diffusion process of organic food consumption. This methodology is based on rough set theory, which is able to translate survey data into behavioral rules. However, the peculiarity of the rough set approach is that the inconsistencies in a data set about consumer behavior are not aggregated or corrected since lower and upper approximations are computed. Also rough set data analysis provides a suitable link between survey data and multi agent models since it is designed to extract decision rules from large quantitative and qualitative data sets.

Missing Data in Social Network

The inherent problem with much of the data is that it is noisy and incomplete, and at the wrong level of fidelity and abstraction for meaningful data analysis. Thus there is a need for methods which extract and infer "clean" annotated networks from noisy observational network data. This involves inferring missing attribute values (attribute prediction), adding missing links and removing spurious links between the nodes (link prediction), and eliminating duplicate nodes (entity resolution).

Moustafa et al. [36] identified a set of primitives to support the extraction and inference of a network from observational data, and describe a framework that enables network analyst to easily implement and combine new extraction and analysis techniques, and efficiently apply them to large observation networks. Perez et al. [36] proposed linguistic decision analysis to solve decision-making problems based on linguistic information by using the ordinal fuzzy linguistic modeling. In such situations, experts are forced to provide incomplete fuzzy linguistic preference relations. So an additive consistency-based estimation process of missing values to deal with incomplete fuzzy linguistic preference relations is developed.

Finding the Shortest Path

The problem of finding the shortest path is finding the path with minimum distance or cost from a starting node to an ending node. It is one of the most fundamental network optimization problems. The shortest path problem also has a deep connection to the minimum cost low problem, which is an abstraction for various shipping and distribution problems, the minimum weight perfect matching, and the minimum mean-cycle problem. Computing shortest paths in graphs is one of the most well-studied problems in combinatorial optimization [37, 38]. Ant colony optimization algorithm is a very initiative machine learning technique in finding the shortest path. The ants, in their necessity to find food and bring it back to the nest, manage not only to explore a vast area, but also to indicate to their peers the location of the food while bringing it back to the nest. Most of the time, they will find the shortest path and adapt to ground changes, hence proving their great efficiency toward this difficult task. Michlmayr [39] proposed SEMANT algorithm based on ant colony optimization. The proposed algorithm finds the shortest path from every querying peer to one or more appropriate answering peers that possess resources for the given query. An unstructured peer-to-peer networks is designed, which consists of carefully selected constituents of the ant algorithms ant colony system, AntNet, and AntHocNet, which were combined and adapted to fit for the application purpose. Lada et al. [40] applied the ant colony optimization system as a messenger distributing its pheromone, the long-link details, in surrounding area. The subsequence forwarding decision has more option to move to, select among local neighbors or send to node has long link closer to its target. They introduced a novel approach for routing in social network. The authors showed that with additional information, the existence of shortcut in surrounding area is able to find a shorter path than using greedy algorithm. Saiteja et al. [41] proposed AntNet algorithm by using ant colony optimization. Kumar and Kumar [42] proposed open shortest path first protocol by using a genetic algorithm. They had implemented a genetic algorithm to find the set of optimal routes to send the traffic from source to destination. Genetic algorithm is well suited for routing problem as it explores solution space in multiple directions at once and less chances to attain local optimum. The proposed algorithm works on initial population created by some other module, access fitness, generate new population using genetic operators and converges after meeting the specified termination condition.

Hybridization between ants algorithm and genetic algorithm was presented by Cauvery et al. [43] for routing in packet switched data networks. Ant algorithm is found to reduce the size of the routing table. A genetic algorithm cannot use global information of the network. Hence the combination of these two algorithms, which makes the packets to explore the network independently, helps in finding path between pair of nodes effectively. White et al. [44] applied ant system with genetic algorithm (ASGA) system to the problem of path finding in networks, demonstrating by experimentation that the hybrid algorithm exhibits improved performance when compared to the basic ant system. They demonstrated that the ant system can be used to solve hard combinatorial optimization problems as represented by Steiner vertex identification and shortest cycle determination. Araujo et al. [45] proposed a new neural network to solve the shortest path problem for Internet work routing. The proposed solution extends the traditional single-layer recurrent HopfIeld architecture introducing a two-layer architecture that automatically guarantees an entire set of constraints held by any valid solution to the shortest path problem. This solution aims to achieve an increased number of succeeded and valid convergences, which is one of the main limitations of previous solutions based on neural networks. Additionally, in general, it requires less neurons. Sangi et al. [46] applied pulse coupled neural network (PCNN) to compute shortest paths. They proposed dual source PCNN (DSPCNN), which can improve the computational efficiency of pulse-coupled neural networks for shortest path problems. Deng et al. [47] proposed a new algorithm by using a particle swarm optimization algorithm with priority-based encoding scheme based on fluid neural network to search for the shortest path in stochastic traffic networks.

Conclusion, Challenges, and Opportunities

This chapter illustrated the field of social networks from a computational point of view, with a focus on practical services, tools, applications, problems, and performance metrics with addition to open avenues for further research. The popularity and ease of use of social networking services have excited institutions with their potential in a variety of areas. However, effective use of social networking services poses a number of challenges for institutions including long-term sustainability of the services; user concerns over use of social tools in a work or study context; a variety of technical issues and legal issues such as copyright, privacy, accessibility, etc. Institutions would be advised to consider carefully the implications before promoting significant use of such services. Clear understanding of these structural properties of a criminal network may help analysts target critical network members for removal or surveillance, and locate network vulnerabilities where disruptive actions can be effective. Appropriate network analysis techniques, therefore, are needed to mine criminal networks and gain insight into these problems.

Another research area is the usage of social networks and their tools for researchers themselves [48, 49]. Social networking tools enable researchers to communicate, network, and share documents with many people regardless of location, and at little or no expense. Researchers can build relationships and keep up to date with people involved in their areas of interest. This encourages discussion, debate, and engagement within their community. Researchers can also discover, filter, and share information using networks of experts in a field to help deal with information overload and find relevant information. While most researchers still favor traditional channels for disseminating research findings (books, journals, conferences, etc.), in some disciplines scholars may want to disseminate protocols or primary data without undergoing unnecessary and lengthy peer review. Social media tools provide a useful platform to do this. Social networking may also provide a publication outlet for researchers who have difficulty getting published in high-ranking journals, or who feel frustrated by the tight controls of senior scholars and publishers over traditional selection and dissemination of research. This may be a risky strategy on one hand, but may assist in raising a scholar's research profile. For example, promoting your research by posting links to your articles on blogs, Twitter, and LinkedIn can drive readers to your article, potentially increasing the number of citations.

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