# Social Networking Analysis: A State of the Art and the Effect of Semantics

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***Abstract*—This paper presents a comprehensive study of the state of the art in Social Networking Analysis and examines the impact of content analysis and the effects of semantics in social networking analysis research. We propose a taxonomy of current approaches, classifying them into the following main categories: 1) graph-theoretic approaches, 2) applications of semantic web technologies and emergent semantics modeling, and 3) data mining and analytics. The purpose is to increase awareness of the social networking analysis community about different ongoing efforts, which not only focus on the network aspect of social networks, shed some light into different approaches and advance the discussion about potential future directions.**

***Keywords*-Social Network Analysis; Semantic Web; Graph Theory;**

## I. Introduction

Online Social Networks mainly aim to promote human interaction on the Web, assist community creation, and facilitate the sharing of ideas, opinions and content. However, Online Social Networks have also become the medium for a plethora of applications such as targeted advertising and recommendation services, collaborative filtering, behavior modeling and prediction, analysis and identification of aggressive behavior, bullying and stalking, cultural trend monitoring, epidemic studies, crowd mood reading and tracking, revelation of terrorist networks, even political deliberation.

Social Networking Analysis Research has lately focused on major Online Social Networks like Facebook, Twitter and Digg. However, research in Social Networks [1] has extracted underlying and often hidden social structures [2] from email communications [3], structural link analysis of web blogs and personal home pages [4] or recently explicit FOAF networks [5], structural link analysis of bookmarks, tags or resources in general [6], co-occurrence of names [7]–[9], and co-authorship in scientific publications references [10], and co-appearance in movies or music productions [11].

Research in Social Networks has in many cases adopted a graph model representation [10], [12], in which nodes represent users and arcs represent explicit links between them. Such research has focused on understanding the structure and evolution of the network [13]. Numerous popular Social Networks such as Facebook and Twitter however have recently released different APIs, exposing more than the superficial structure of social connectedness and creating the so called *Social Graph*. Recent advances in *Semantic Web Technologies*, *Visualization*, and *Data Mining* and *Machine Learning* have lead researchers to analyze social networks from many different angles and perspectives.

In this paper, we present an *extensive overview* of the field of Social Networking Analysis and provide a *taxonomic categorization* of the state of the art. Further, we study the *effects of semantics* in Social Networking Analysis and the *impact of content analysis* in conjunction to the *network aspect* of social networks.

## II. Social Networking Analysis Research

Figure 1 presents a *taxonomy* of different approaches in Social Networking Analysis. The rest of this section provides an overview of such approaches.

### A. Graph Theoretic Social Networking Analysis

Much research on Social Networking Analysis applies graph theory [10], [14] on graph representations so as to unravel certain features of the network, identify the most important actors in a social network and discover community structures. To this end, several centrality measures have been proposed. "*Centrality measures the degree to which network structure contributes to the importance of a node in the network*" [15]. *Betweenness Centrality* measures the fraction of all shortest paths that pass through a given node and is often used to identify nodes that act as boundary spanners between different groups [16]. Studies of human [17] and animal [18] populations suggest that such nodes play a crucial role in the information flow and cohesiveness of the network. *Degree Centrality* measures the number of edges that connect a node to others and is used to identify nodes that have the most connections in the network. However, the centrality of a node also depends on its neighbors' centralities [19]. This measure is captured by the total number of paths linking a node to others in a network. The average length of such paths is measured by *Closeness Centrality*, which indicates the capacity of a node to be reached. "*One such metric, $\alpha$–centrality [19], [20], measures the total number of paths from a node, exponentially attenuated by their length. The*

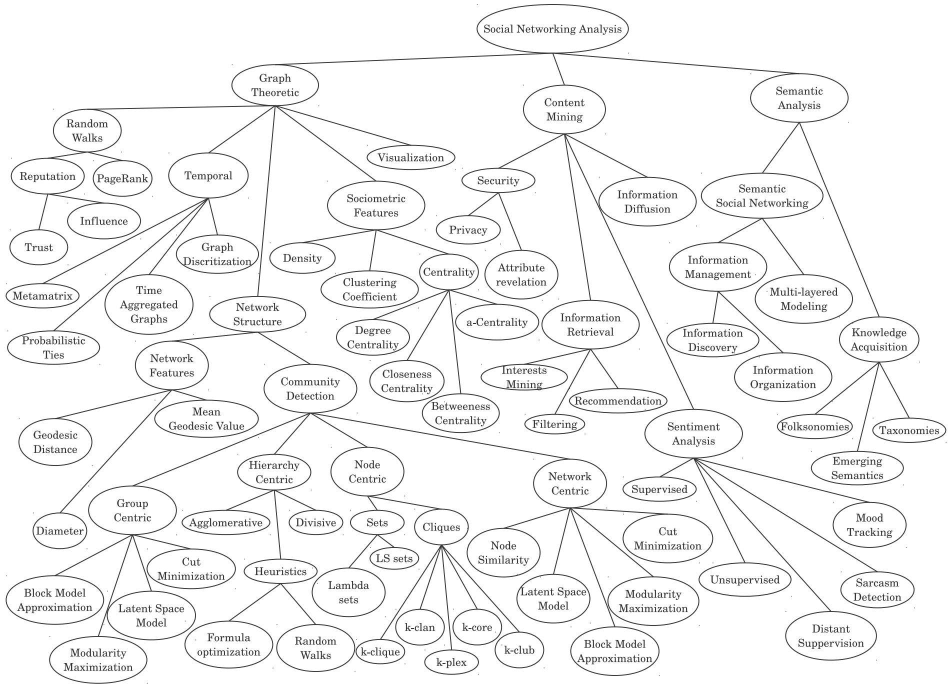


Figure 1. A Taxonomy of Approaches in Social Networking Analysis Research

*attenuation parameter sets the length scale of interactions so as to distinguish between locally and globally connected nodes*" [15]. Other centrality metrics include those based on random walks [21] and path-based metrics. The computation time of centrality measures is computationally expensive, with a minimum time complexity of $O(n \cdot m)$, where $n$ is the number of vertices and $m$ is the number of edges [1]. However, several approximating and parallel algorithms have been proposed for large networks [1].

Closely tied to the concept of nodal degree is *density*, which indicates the percentage of edges that are present in the graph over the total number of plausible edges [22]. The higher the density of a network is, the more nodes in the network are connected to each other. *Clustering Coefficient* measures the likelihood of two nodes connected to a given node being connected themselves. It indicates the degree to which nodes in a network tend to cluster together and it is therefore considered to be a good measure if a network demonstrates "small world" behavior [23]. *Diameter*, on the other hand measures the distance of nodes in a network and is defined as the maximum geodesic distance between any pair of nodes [22]. *Geodesic distance* measures the shortest path between two nodes [22]. Diameter can only be calculated on connected graphs. If the graph is not connected, then diameter is undefined. To overcome this limitation, the *mean geodesic value* is calculated using only reachable pairs of nodes. Intuitively, the higher the diameter of a network is, the more dispersive the graph.

To better understand the network structure and the mechanisms with which this structure affects information spreading as well as to identify sociometric features that influence people behavior, several *community detection algorithms* have been proposed [14]. According to [10] community is a set of actors among whom there are relatively strong, direct, and intense, frequent or positive ties. Some Social Networks like Facebook and Flickr allow or even encourage people to form and join groups. However, in cases where group formation is not supported, network interaction provides sufficient information to infer implicitly formed communities. Community detection algorithms have consistently facilitated *informative visualization* of social networks, and have assisted with the *inference of missing properties* [24].

Community detection criteria may vary, but in general, community detection methods can be divided into four categories [25]. In *node-centric* methods each node in a group must satisfy certain/different properties. Representative measures include *cliques* (complete subgraphs), *k-clique*, *k-clan* and *k-club* (reachability of members), *k-plex* and *k-core* (nodal degrees), and *LS sets* and *Lambda sets* (relative frequency of within-outside ties). In *group-centric* methods each group as a whole has to satisfy certain properties without zooming into node level. In *network-centric* methods the whole network is partitioned into several disjoint sets based on *Node Similarity* (nodes are structurally equivalent if they connect to the same set of nodes), *Latent Space Model* (transform nodes in a lower dimensional space such that the distance measure is kept in the Euclidean Space), *Block Model Approximation* (minimize the difference between an interaction matrix and a block structure), *Cut Minimization* (minimize the cut: the number of edges linking nodes that belong to different groups) and *Modularity Maximization* (measure group interactions compared to the expected random connections in the group). The limitation of network-centric methods is that the number of communities must be known a-priory. In *hierarchy-centric* methods a hierarchical structure of communities is constructed based on network topology. Two strategies are used by hierarchical algorithms. *Divisive hierarchical clustering* partitions the nodes into several sets and each set is iteratively partitioned in smaller subsets [26]. *Agglomerative hierarchical clustering* initializes each node as a community and iteratively merges communities satisfying certain criteria into larger and larger communities [27]. Other algorithms, based on *heuristics* such as random walks or formula optimization are noted in [1].

Due to their computational complexity most of these measures are computed over *static* networks, but their computation may often be accelerated due to specific patterns and laws governing social networks. According to the famous *six degrees of separation* [28], every node is on average approximately six steps away from any other node, while nodes degree distribution follows a power law [29]. "*According to the small world phenomenon [30] the order of the shortest path between any two nodes in a social network of size $n$ is $n \cdot logn$*" [1]. Recently, research over *temporal* analysis of *dynamic social networks* has been conducted. Trends in this field include according to [31] the following approaches: 1) the *meta-matrix*, 2) treating *ties as probabilistic*, and 3) combining social networks with cognitive science and multi-agent systems. *Graph discretization* [32] and *Time-Aggregated Graph* approaches [33] have also been considered.

*Trust* is also important since people tend to trust authorities/experts who have been accredited through their social activity as well as the number of connections they have and their global importance in the social network. [34], [35] exploit trust to perform collaborative filtering by forming bipartite [34] or tripartite [35] models. [35] performs random walks to propagate trust values through the social network, while [36], [37] extend foaf:Person to allow users to indicate trust levels for their connections on a scale of 1-9 (1 = Distrust Absolutely, 9 = Trust Absolutely) in general or for specific topics. *Reputation* [35], [37], [38] may be considered the other side of the same coin since it often serves as a measure of *influence* [39], used to identify and predict the most influential users in a network.

This work has mainly focused on *binary friendship relations*. However, since there is currently no way for users to strictly define friendship levels when they create links to other users, online social networks generally model heterogeneous relationships (e.g. acquaintances and best friends) all the same. In this case, the binary friendship indicator provides only a coarse representation of relationship information. [40] estimates *relationship strength* from interaction activity (e.g. communication, tagging) and users similarity.

### B. Data Mining and Data Analytics in Social Networks

In order to understand the synergy between published text and social structure, graph analysis alone is not sufficient. Analysis of social networking content is also crucial. Content includes but is not limited to microbloging posts as well as social networking users' profiles and web pages. Users' profiles are often used to compute users' similarity for *recommendation* purposes as well as to model *users' interests* [41]. Content analysis may lead to information disclosure [42] and revelation of private information [24].

In order to understand the models that drive information dissemination in social networks research has mainly focus on identifying factors that impact information diffusion [43], [44]. Such factors include the presence of hashtags, mentions and URLs, and ratio between followers and followees.

Hashtags (tags is general), are often used to organize and filter information [45], [46]. Tagging however lacks sentiment expression. Due to the relative importance of social media in advertising and information dissemination and diffusion [47] however, *sentiment analysis* [48] and *sarcasm detection* has recently attracted much attention. Because of the large amount of content being shared in social networks, sentiment analysis is often unsupervised and completely automatic [49]. However, approaches based on distant supervision [50], where labels are implicitly stated with the use of emoticons (e.g. :) for positive and :( for negative) or completely supervised approaches [51] have also been proposed. "*Consumers can use sentiment analysis to research products or services before making a purchase. Marketers can use this to research public opinion of their company and products, or to analyze customer satisfaction. Organizations can also use this to gather critical feedback about problems in newly released products*" [50].

### C. Semantic Social Networking Analysis

Graph representations and analysis performed on top of them share a common limitation. They all have a *poor exploitation of complex relationship types* and most importantly they all *lack semantics*. As an example, information filtering algorithms are either based on graph structure characteristics of social networks [52] or use tagging to organize and filter information but under-exploit relations types, which could enable routing of different messages to different groups of people (e.g. family, friends, co-workers) based on their relationship to the author.

*Tagging*, which has recently become popular, allows users to tag web resources for organizational purposes (e.g. photos in Flickr, bookmarks in Delicious or tweets in Twitter). Twitter users adopted hashtags as an attempt to alleviate the significant *information overload* that the streaming nature of social media impose to users interested in specific topic(s). [45], [46] exploit hashtags for content management, organization and filtering . "*However, hashtags have several limitations such is their lack of organization [53], their ambiguity (e.g. #apple) and heterogeneity (e.g. #realtime, #rt)*" [45] and have to be explicitly included in tweets. By aggregating the set of tags collaboratively used by users, emerging semantics are exploited to generate *folksonomies* and *taxonomies* [6], [54], [55], which are then linked to ontologies [56]. [57] analyses the structure of collaborative tagging systems, as well as their dynamical aspects, uncovers hidden patterns, and proposes a dynamical model of collaborative tagging.

Recently, Online Social Networks started to be modeled with *rich structured data* that incorporate *semantics*. In such models edges between users are split to links that have been weighted based on the communication frequency between users. Further semantics may be imposed using ontologies like FOAF, SIOC, and DC, MOAT, and SKOS to describe users, content and their relationships. FOAF is used for describing people, their relationships and their activity. SIOC specializes FOAF types in order to model interactions between social web applications and resources managed by such applications. Different types of relationships and trust levels may also be utilized to impose a finer grained description using vocabularies like, RELATIONSHIP. RELATIONSHIP specializes the foaf:knows property to specific relationships. A lighter way to add semantics to the representation of persons and web resources is to use microformats.

[1], [58] propose an architecture based on the Semantic Web stack to analyze online social networks while being semantics aware. Its purpose is to explore RDF-based annotated profiles and users' interactions in social networks using background knowledge (domain vocabulary), predefined ontologies and OntoSNA (also encountered as SemSNA), an ontology of Social Network Analysis, which provides a way to compute sociometric features using SPARQL. This work extends classical graph theory algorithms with semantic features, such as types of resources (e.g. foaf:Person) or properties (e.g. foaf:knows or relationship:worksWith) to be considered in the analysis.

While much of the work on semantic microblogging thus far focuses on representing users, microblogs and microblog posts in the Semantic Web, the work described in [59] takes the complementary approach of harvesting semantic data embedded in the content of microblog posts, converting these metadata into RDF and publishing the harvested knowledge base as Linked Open Data. TwitLogic, an open-source semantic data aggregator, which implements the above ideas, provides scoring of microblog content based on recency (time-based significance) and proximity (location-based significance).

Semantic annotation transforms unstructured data into a structured representation that enables applications to better search, analyze, and aggregate information. [45] makes use of annotated microposts together with background knowledge obtained from Linked Open Data to offer advanced search and organizational capabilities. For example, thanks to semantic links between football and sports, all information mapped only to football can be retrieved in queries regarding sports.

*Multilayered models*, which involve the network between people, the network between concepts they use and links to ontologies modeling such concepts have lately been used. [60] proposes the use of such representation so as to extract relationships in one network from relationships in another. [61] on the other hand proposes a multilayered semantic social network model that offers different views of common interests underlying a community of people. Starting from a number of ontology-based user profiles and taking into account their common preferences, the domain concept space is automatically clustered in order to identify similarities among individuals at multiple semantic preference layers and define *emergent*, *layered social networks*.

## III. Conclusion

We presented the state of the art in Social Networking Analysis and proposed a taxonomy of current approaches. We argued that there are three major trends in Social Networking Analysis, namely: 1) Graph Theoretic Analysis, 2) Semantic Social Networking Analysis, and 3) Data Mining and Analytics. Graph theoretic approaches mainly focus on the structure and evolution of the social network as well as the measurement of sociometric features. Such approaches however lack semantics. Data mining techniques on the other hand mainly focus on the content alone, even though some approaches investigate the synergy between content analysis and graph analysis. Semantic Social Networking Analysis is actively trying to address the lack of semantics. However all approaches focus either on the underlying social connectivity graph or the content alone. We feel that an approach which fully exploits both the underlying graph and published content for an enhanced and complex analysis is yet missing.

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