

A Review on Online Social Network: Issues & Challenges

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Received 15 January 2016; accepted 12 April 2016; published 15 April 2016

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Abstract

The Usage of Online social network is increasing day by day where a large number of users publicly access their friend's link and post any message on the wall. OSN enables different user's to use the services with a security of using these messages on the user's wall. Hence various techniques are implemented for the filtering of these wall messages, but there are still various issues and challenges found during the usage of these techniques used in OSN. Here in this paper various issues and challenges from various techniques are discussed and hence on the basis of various issues a new and efficient technique is implemented in future.

Keywords

OSN, Community Kernel

1. Introduction

A social network can be explained as a social structure consisting of individuals or organizations. These are related each other by some means. The social network perspective provides a set of methods for analyzing the structure of social entities and the theories thereby explaining the patterns in the structures. These structures use social network analysis and identify local and global patterns, locate influential entities and examine network dynamics. The approaches used in social networks enable to know social interaction being visualized first and investigated with the help of properties of relations between the units and not the unit's properties itself. The network configurations and network analytics are formed by singular or combination relations in social networks. Social networking service basically provides platform for edifice of social networks or social relations between users sharing interests, activities, backgrounds etc. Social network service provider enables the user to maintain profile containing his or her social links and other add ons.

Therefore with the help of social networks, users are able to build a public profile and maintain list of users for sharing connections and can cross and view the connections in the system. Social network services are generally web based, facilitating the users or the clients to interact over the Internet that can be in the form of e-mail,

instant message etc. Social network provides and allows using multiple information and communication tools in the form of mobile connectivity, photo, video, sharing etc.

Community services provided by social networks are group centered and sometimes even social networks are termed as individual centered service. Social networks are generally divided into communities and groups which consist of users having same likes, features, dislikes, interests etc. The main types of social networking services are those which are categorized or divided in groups or communities of users like schoolmates, politicians, celebrities etc. and a giving a recommendation system linked with the trust of users. The widely used Social networks are Facebook, Google+, YouTube, LinkedIn, Instagram, Pinterest, Tumblr and Twitter.

Each user maintains its own social network that may be online or offline and contains friends, families and people whom they are acquainted with. The fundamental aim lying behind online social networking services is to make users' social networks visible to others who are not connected to his/her immediate network. Social network held people together by friendship, classmates, colleagues, business partners, etc. having pre-established interpersonal relationships. The connections between the users are generally formed one at a time. The primary reason that lies behind the people is to join a social networking site for maintaining old relationships with others and making new ones for expanding their network.

Social networks act as unique service in which the users can collectively recognize others if they are fake. The users also generally do not compartmentalize their life *i.e.* they don't have only one social network.

Communities in the social network are held together by common interest among the users. The users may possess common hobby for which the other community members may be passionate, may have a common goal, similar lifestyle, geographical location etc. Thereby in social networks users exhibit different influence and different behavior [1].

Internet contains information of various types and kinds. For gaining knowledge from these data, various users exist on internet and continue to use it. The users generally share, disseminate and communicate multiple type of information between them. The information is in the form of texts, audio, video, images etc. [2]. These users may belong to multiple communities consisting of similar type of users in behavior influencing each other for sharing various types of data.

Social Networks is visualized in the form of internet service helping the user to build a networks over the internet which is social in nature and builds relations with other users for sharing of interests and participate in multiple activities with the users who are characterized by communities.

Communities over the social networks discover groups of interacting objects in the form of nodes formalizing the relations between them. For example a community in a social network can be defined as groups of friends attending the same school or people of the same home town etc. [3]. The communities correspond to users having similar scientific disciplines, family, friends, similar interests etc.

Network community's helps in study of functionally related objects for analysis and for studying interactions between the modules, predict unobserved connections etc. A community structure property is contained by social networks which is explained in the form of groups of vertices having denser connections inside each group are divided and the fewer connections which crosses groups division where vertices and connections represent network users and social interactions respectively.

Members of communities of a social network *i.e.* nodes share things between them in common like interests in the field of photography, movies, music or political topics thereby interacting more frequently with each other as compared with the members outside of their community structure. Community detection therefore in a network is explained on the basis of gathering of network vertices into groups in which nodes in each group connect densely on the inner side and sparsely on outer side [4] [5].

Community kernel detection problem has practical applications like representative user finding, friend recommendation, network visualization, marketing etc. The problem being considered as non-trivial in nature has a set of challenges in which true influential user's identification is hard. The number of followers of the individual is used as indicator but its count contains no information about who follows them in return. Influential users interacting with each other is slightly non clear process and its process of taking place can be explained with the example like there is half probability of an actress or any other type of user to follow another actress or a sports person or politician etc.

Basically in real world social networks with thousands of millions of nodes are increasing with rapid growth. That's why we need an algorithm with high scalability to resolve the dilemma of community. For this, method kernel detection is required with subtasks so that it can identify influential (kernel) members and detecting the formation of community kernels.

The nodes (or vertices) in social Networks are the typical systems which represent entities that have some relationships. Web graphs, telecommunication networks, genetic networks, trade networks etc. are examples of such systems other than social networks. Generally the recognition of cluster of vertices within which the connections (or edges) are numerous and between which they are rare are symbolized by community detection or clustering.

The methods like Spectral clustering are used for clustering which are basically based on the eigen decomposition of a Laplacian matrix that is derived from the data. This gave us an idea of being expansion of the clustering model to out of sample nodes. Thus on a small subset of whole graph the clustering model can be trained and visualized and so while dealing with huge and complex networks the method could be applied to the rest of the network in a learning agenda platform. The problem of online clustering of huge and raising networks can be easily resolved with out-of-sample extension in the community detection field algorithm. Thus when every new vertex is arriving in a data stream, it doesn't have to run on a new graph on the application of the above process [6].

Social influence affects the social networks governing the dynamics of social networks. Users gets influenced by other users when sharing information, exchanging data, messaging etc. and forms communities in which users are influenced by similarities.

Social network analysis focuses upon macro level models in the form of degree distributions, clustering coefficient, communities, small world effect etc. Social influences usually defines that a user may have higher influence over field or a topic than other user and the other may higher influence with completely different field, topic or interest. This arises a fact that users are needed to be analyzed based on influences for forming community. Social influence does not explains the global measure of importance of nodes or users and it only defines the measure on the links in between nodes.

2. Literature Survey

Authors & Year	Chaotic map used	Ref. no.	Description
Liaoruo Wang, Tiancheng Lou, Jie Tang and John E. Hopcroft	Community Kernel Detection, WEBA, GREEDY	[1]	The problem of community kernel detection in large social networks is described as recognizing kernel members and distinguishing the structure of community kernels. They proposed two algorithms for overcoming the issues in one approach. Greedy algorithm which is based on maximum cardinality search. The algorithm efficiently obtains an approximate solution without having a bounded error. Whereas in WEBA they defined and optimized an objective function that is capable of explicitly quantifying the detected community kernels. The algorithm efficiently obtains an approximate solution having a small error bound.
Jaewon Yang, Julian McAuley and Jure Leskovec	Communities from Edge Structure and Node Attributes (CESNA)	[7]	While identifying network communities clustering a set of nodes into communities in which a node belongs to multiple communities simultaneously arises a problem. This is due to the fact that nodes in communities possess common properties and attributes having multiple relationships among themselves. They remarked that with the help of two sources of data the clustering task can be performed. They developed an accurate and scalable overlapping community detection method for networks consisting of node attribute information thus providing high performance. They presented Communities from Edge Structure and Node Attributes (CESNA). CESNA is based on a general model for networks with node attributes. Their scheme detected overlapping communities through hard node community memberships. They assumed that communities generate both the network and attributes. Thereby dependency between the network and attributes is possible. For discovering communities they developed a block coordinate ascent method in which all model parameters can be updated in time linear with the number of edges inside the network
Jure Leskovec, Kevin J. Lang and Michael W. Mahoney	Graph partitioning, Conductance, Flow based methods.	[8]	They explored various community detection methods in for resolving issues related to the performance and biases of different network community detection algorithms on multiple kinds of networks. They focused on understanding the structural properties of clusters by various methods and then enabling the user to use particular application which would be the most suitable clustering method. They described various classes of empirical evaluations of methods for community detection in networks demonstrating the artifactual properties and systematic biases of community detection objective functions and multiple approximation algorithms.

Continued				
Kevin S. Xu, Mark Kliger, and Alfred O. Hero III	Adaptive evolutionary clustering	[9]	They recognized the problem of detecting communities in static networks explaining that various community detection methods derived from the methods of graph partitioning and data clustering which are modularity maximization and spectral clustering. They addressed the extension of community detection to dynamic networks and called it as community tracking. They proposed performing of community tracking by an adaptive evolutionary clustering framework. The adaptive Evolutionary clustering combines data from several time steps for computing the clustering results on single time step allowing the clustering results varying smoothly over time.	
Nam P. Nguyen, Thang N. Dinh, Ying Xuan and My T. Thai	Quick Community Adaptation	[10]	They explained that nodes mobility and unstable links properties of the network efficient routing scheme design is a difficult issue. Due to the natural tendency of forming groups of communication a groups of nodes are densely connected inside the network than outside. They gave MANET forming community structure. They proposed QCA which is a fast and adaptive algorithm that identifies efficiently the community structure of a dynamic social network. Their approach reduced the computational cost and processing time. QCA is used to develop community identification core deploying routing strategies in MANETs. The simulation results of QCA enables applicability their proposed method in mobile computing	
Andrea Lancichinetti and Santo Fortunato	Girvan and Newman (GN benchmark), LFR	[11]	They formalized the problem of using the type of algorithms which are reliable for the applications. They proposed and explained the LFR benchmark and compared partitions quantitatively. They presented analysis of the algorithms and performance on GN benchmark and then on the LFR benchmark for various versions which includes weighted and directed graphs and the graphs of overlapping communities. They explained the issue of algorithms giving a null result and how they handle networks without predictable community structure like random graphs.	
Nina Mishra, Robert Schreiber, Isabelle Stanton and Robert E. Tarjan	Graph Clustering	[12]	They formulated the discovery of close-knit clusters in the networks. The clusters are important and should be deployed. The clusters that typically do not overlap have all vertices are clustered ignoring external sparsity thereby limiting to the clustering criteria. They introduced a new measure for overcoming the limitations by naturally combining internal density with external sparsity. Their proposed scheme explored combinatorial properties of internally dense and externally sparse clusters giving an algorithm for provably finding such clusters and assuming that a large gap between internal density and external sparsity is present. But still the components like external sparsity, overlapping clusters in which not every vertex is clustered and internal density lacks. They generated a new graph clustering criterion which perfectly suits for social networks.	
Jie Tang, Jimeng Sun, Chi Wang and Zi Yang	Topical Affinity Propagation (TAP)	[13]	They suggested the need of methods to analyze and quantify the social influences for quantitatively measuring the strength of topic level social influence. They explained the representative nodes on a given topic, identified topic level experts and their social influence on a particular node and quick connection to a particular node via tough social ties. For performing topic level influence propagation TAP is able to accept results of any topic modeling and the existing network structure.	

3. Conclusion

Since online Social Network enables various users to interact easily and quickly. Although there are various techniques implemented for the community detection and message filtering but the techniques implemented contain various issues and problems due to that it's efficient and accuracy decreases. Here in this paper a complete survey of all such techniques is discussed and analyzed, hence on the basis of various issue a new and efficient technique is implemented.

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