Community detection and identifying leaders and followers in online social networks

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Abstract— The social networks have become a vital need in this modern era. These networks exhibit modular structure that supports their evolution into highly complex systems. The detection of this modular structure within the social network is known as community detection. It helps to identify closely related nodes and it provides a way to understand the organization of complex systems. There are several algorithms and approaches available to detect communities. A detailed study of those approaches has been made in this review. Leaders are the users having larger influence than others in the network called followers. Identifying leaders and followers in those detected communities found to have wide variety of applications.

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Index Terms— Clustering, Community detection, Followers, Leaders, Modularity.

1 Introduction

Social networks are the well known examples of graphs with communities. The word community refers to a social context. In the area of social network applications, community detection is a growing field of interest. People naturally tend to form groups, within their family, friends and work environment and share their ideas in the form of text. The technology has been extended to share the ideas even through audio and video [18].

The modularity is the most commonly used technique used in earlier days to detect communities. There are several expressions and definitions proposed for modularity. These approaches suffer several disadvantages and there are several algorithms proposed to overcome those disadvantages. The algorithms considered for discussion includes Walktrap2, Markov clusters, random walks and influence dynamics method. In all these algorithm measures are taken to overcome the disadvantages in the modularity based method. A comparative analysis of the steps taken to overcome the modularity based method and complexity of each algorithm has been discussed.

The outline of the paper is as follows. Section II introduces the problem of community detection in social networks. In section III the modularity based method and its disadvantages are discussed. In section IV, the algorithms under consideration are discussed. The comparative analysis is included in section V. Section VI includes the approaches used to detect leaders and followers.

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2 Community Detection

The most important part of a social network is its connections. These connections denote some kind of social relationship between the users. A group of users who are more strongly connected to each other than with other users in the network forms a community. Overlapping communities [12] occurs in some cases of social networks. Detecting such communities is of greater importance in several applications. Clustering is the most general method applied to detect communities. The clustering can be applied on any types of graphs such as large probabilistic graphs [8] and multi-layer graphs [14]. The grouping can also be done using weighted multi-constraints method [15]. The readability of clustered networks can be done using node duplication [17].

Based on clustering, there are several algorithms and approaches available to detect communities. The traditional methods for community detection include graph partitioning, hierarchical clustering, and spectral clustering.

2.1 Graph partitioning method

The problem of graph partitioning involves division of the vertices in to k groups in a way that the number of edges lying between the groups is minimal [5]. Consider a graph G = (V, E), where V is the set of vertices and E is the set of edges. The aim is to partition the graph into k components and minimizing the capacity of the edges between separate components. The k value should be greater than one [5]. The vertices are partitioned into k parts as V_1, V_2,…,V_k such that the parts are disjoint, equal sized, and the number of edges with end-

points in different parts is minimized. A good partition is defined as the one in which the number of edges running between separated components is less. The graph partitioning problems are NP-hard problems. However, uniform graph partitioning can be shown [5] to be NP-complete to approximate within any finite factor.

In this kind of partitioning [5], specifying the number of clusters k has made necessary. Since the number of groups and the size of the group have to be mentioned in prior to the partitioning, this method is not preferred much. Jie Chen and Yousef Saad has proposed extraction of dense sub-graphs which finds huge application in social networking [9].

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2.2 Hierarchical clustering

Hierarchical clustering is the most commonly used clustering technique for social networks. The initial part of any hierarchical clustering method [5] is the definition of a similarity measure between vertices. After a measure is chosen, the computation of the similarity for each pair of vertices has been done without considering whether the vertices are connected or not. The output is a new n x n matrix which is a similarity matrix. This method is classified in two categories. They are agglomerative algorithms and divisive algorithms.

Agglomerative algorithm [5] is a bottom up approach .The clusters are iteratively merged if the similarity of the clusters is sufficiently high. Divisive algorithm is a top down approach. The clusters are split by removing the edges connecting vertices with low similarity.

Hierarchical clustering [5] does not require the knowledge on the number and size of the clusters in advance. This is a great advantage of the hierarchical clustering. Sometimes, the vertices of a community may not be correctly classified, and in many cases, even if some of the vertices have a central role in their clusters, they are missed. This is the worst part of this clustering Another problem is that vertices with just one neighbour are often classified as separated clusters, which does not make sense in most cases.

2.3 Spectral Clustering

The aim of spectral clustering is to cluster the data that is connected with each other. It is not necessary to have compact or clustered data within convex boundaries. The example for compactness includes k-means and mixture models. The connectivity includes spectral clustering as the example [5].

The fundamental idea [5] is explained below:

1. Project the data into R^n

2. Define an A*ffinity* matrix A, using a Gaussian Kernel K or say just an Adjacency matrix (i.e. $A_{i,j}= \delta_{i,j}$)

3. Construct the Graph Laplacian from A (i.e. decide on a normalization)

4. An Eigenvalue problem is solved, such as Lv = λv (or a Generalized Eigenvalue problem is solved Lv = λDv)

5. k eigenvectors $\{v_i, i=1,k\}$ are selected corresponding to the k lowest (or highest) Eigen values $\{\lambda_i, i=1,k\}$, to define a k-dimensional subspace P^tLP

6. By using clustering algorithm like k-means the clusters are formed in the subspace

3 MODUALRITY BASED COMMUNITY DETECTION

Modularity is one of the measures of the structure of networks or graphs [6] .It is used to measure the strength of division of a network into modules. These modules are also called groups, clusters or communities. Dense connections between the nodes are found in networks with high modularity within modules. And sparse connections are found between nodes of different modules in this case. In such cases, many edges found within the communities and only a few edges found between the communities. Modularity works well in those cases.

Modularity has been introduced to measure the quality of community algorithms [6]. Newman provided the following formula for modularity.

$$Q=\sum_i (e_{ij}- a_i^2)$$

where e_{ij}: number of edges having one end in group i and the other end in groupj.$a_i = P_j e_{ij}$: number of edges having one end in group i.

This quantity Q measures difference between the fractions of edges in the network that connect vertices of the same type and the expected value of the same quantity in a network with the same community divisions yet with random connections between vertices.

3.1 Modularity based method using hierarchical agglomeration algorithm

The operation of the algorithm involves finding the changes in the modularity value Q [7]. It results from the amalgamation of each pair of communities, choosing the largest of them, and performing the corresponding amalgamation. The approach of representing the whole community by a vertex, bundles of edges connecting one vertex to another, and edges internal to communities are represented by self-edges is one way to implement this process. This kind of graph is called as multi graph. The adjacency matrix of this multi-graph has elements $A'_{ij} = 2me_{ij}$, and the joining of two communities i and j corresponds to replacing the ith and jth rows and columns by their sum. Unfortunately, calculating ΔQij and finding the pair ij with the largest ΔQij becomes time-consuming.

In this algorithm [7], a matrix of value of ΔQij is maintained and updated instead of maintaining the adjacency matrix and calculating ΔQij. The value of ΔQij need to be stored for those

pairs i and j that are joined by one or more edges as joining two communities with no edge between them can never produce an increase in Q. The matrix will be similarly sparse since this matrix has the same support as the adjacency matrix. So, it should be again represented with efficient data structures. In addition to this [7] , an efficient data structure to keep track of the largest ΔQij has been used. These improvements result in a considerable saving of both memory and time.

A new algorithm [7] for inferring community structure from network topology which works by greedily optimizing the modularity has been described.This algorithm runs in time O(md log n) for a network with n vertices and m edges where d is the depth of the dendrogram. For networks that are hierarchical, which means there are communities at many levels and the dendrogram is roughly balanced, we have d ~ log n. If the network is also sparse, m ~n, then the running time is linear, O (n $\log^2$ n).

3.2 Resolution limit of modularity based method

Though modularity suffers from lot of defects, resolution limit is the most important problem to be addressed. Modularity compares the number of edges inside a cluster with the expected number of edges. It can be found in the cluster if the network were a random network with the same number of nodes and where each node maintains its degree, but edges are randomly attached. The assumption made in the random null model that each node can get attached to any other node of the network. This assumption becomes no reason, if the network is very large, as the horizon of a node includes a small part of the network but ignoring most of it.

Moreover, this implies that the expected number of edges between two groups of nodes decreases if the size of the network increases. So, the expected number of edges between two groups of nodes in modularity's null model may be smaller than one if a network is large enough. If this happens, a single edge between the two clusters would be interpreted by modularity as a sign of a strong correlation between the two clusters. Also the optimizing modularity would lead to the merging of the two clusters of the clusters' features. So, even weakly interconnected graphs which are complete and having the highest possible density of internal edges, and representing the communities that are identifiable, would be merged by modularity optimization if the network were sufficiently large.The optimizing modularity in large networks would fail to resolve small communities for this reason, even when they are well defined. So, modularity is not an efficient method to detect communities in social networks. The algorithms that overcome the defects of modularity based community detection are discussed in the section IV.

4 Approaches Overcoming Defects of Modularity

4.1 Walktrap

The Walktrap algorithm [1] employs the idea of random walks through the network for community detection. This algorithm uses a node-to- node distance measure to identify the communities that are very close to each other. This distance is based on the concept of random-walk. If two nodes belong to the same community, the probability to get to a third node located in the same community with the help of a random walk should not be very different for both of the nodes.

The distance is constructed by adding these differences over all nodes, with a correction for degree. More specifically, anode similarity measure based on short walks has been proposed that it provides sufficient information to be used instead of modularity for community detection via hierarchical agglomeration. However, in this approach [1] modularity is still applied as stopping criterion and metric for comparing their results to other algorithms. Walktrap approach has complexity O(mn^2), which could be O(n^4) in the worst case but behaves as O (n^2 log n) on real-world networks[1].

4.2 Markov clusters

Karsten Steinhaeuser [1] has explained Markov clusters and compared it to the random walker. A random walker placed in a network would spend a longer time walking around the same community before crossing into a different one. Therefore, the probability of nodes i and j belonging to the same community is high if it is assumed that the walk starts at some node i, if another node j has a high probability of being visited during the random walk. Building on these principles, until an equilibrium state is reached, the MCL algorithm uses a series of alternating expansions. The MCL algorithm has complexity O (n^3), but under certain assumptions, can significantly reduce the effective execution time for sparse networks. Recently, a generalized Markov graph model has been proposed by Tian Wang, Hamid Krim and Yannis Viniotis [11].

4.3 Random walks

Dense subgraph of sparse graphs appears in most real-world complex networks. These graphs play an important role in many contexts [16]. Computing those dense sub-graphs is generally expensive. A measure of similarities between vertices based on random walks has been proposed. It has several important advantages: in a network, it captures well the community structure, the computation can be made efficiently, and it can be used in an agglomerative algorithm. By using this, the community structure of a network can be computed efficiently.

Depending on one's objectives [16], one may consider other quality criterion of a partition into communities. The modularity, for instance, is not well suited to find communities at different levels. Another criterion that helps in finding such structures has been provided. When two very different communities are merged, the value

$$\Delta\sigma_k = \sigma_{k+1} - \sigma_k$$

is large. Conversely, if Δk is large then the communities at step k − 1 are relevant for sure. To detect this, the increase ratio ηk has been introduced as shown [16] as

$$\eta k = \Delta\sigma_k / \Delta\sigma_{k-1}$$

Depending on the context in which the algorithm is used, only the best partition i.e. the one for which ηk is maximal is considered or by using another criterion like the size of the communities, the best ones among them are chosen. This is an important advantage of this method. This algorithm has complexity of $O(n^2 \log n)$.

4.4 Influence Dynamics Method

Because of the shortcomings of the function discovered, the focus on the modularity function seems to be lost. Among others limits, the two most important found by Angel Stanoev, Daniel Smilkov and Ljupco Kocarev [2] are the resolution limit of the modularity function and the structural diversity of high-modularity partitions. It is found that border case nodes are another shortcoming of the modularity function [2]. Since all the modularity based methods are driven only by the network topology, they will fail to produce the right partition of the network. There is also an implicit hierarchy in this network [2].

The running times of the first and the last step are of the highest order, with execution times varying from O(n) to $O(n^2)$, depending on the power-law exponent and the number of detected communities, respectively. Thus, the overall complexity varies from O(n) to $O(n^2)$ as well. A distributed framework exists to handle large datasets [13].

The comparative analysis of the algorithms discussed under community detection is shown in the Table I. The defects resolved, methods used to resolve defects, computational complexity and the dataset used are compared in Table I.

5 Leaders And Followers Detection

5.1 Binary Approach

In this approach [3], each user of a social networking site is considered as a node. This approach determines whether a node is leader or not. Social network analysis has been used in order to understand the behavior of the nodes. The centrality measure is used in this approach and it determines whether a node is a follower or a leader. The value of the centrality measure of the leaf nodes is lower than the inner nodes. The leaf nodes are very important especially in terrorist cells as the operations are executed by them. This binary concept [3] is used to highlight the distinctiveness of these nodes.

The three centrality measures considered by D. M. Akbar Hussain [3] are degree, betweenness and closeness. The first measure degree is the number of direct connections to other members of the network.

Other than degree, the well known measures are betweenness and closeness. Betweenness measures the extent to which a node can be an intermediate node in the interaction between the other nodes. Thus, the nodes which are located on many shortest paths between other nodes will have higher betweenness comparing to other nodes. Closeness is the measure of the time taken by the information to spread from a given node to other nodes in the network.

It is clear from the Fig 1 that the nodes 1,5 and 6 can either be a leader or a follower where as other nodes have various positions to be of some importance. From the fig.1 it is difficult to decide the leader. So, binary approach is used. In binary approach, the node with least spill over is considered to be at higher level in the hierarchy. Hence, the node with least spill over is considered to be the leader.

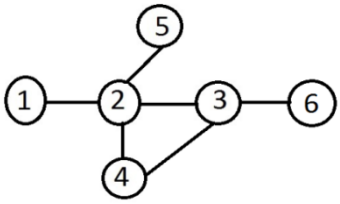

Fig 1. Network of 6 nodes

The main idea behind the binary approach [3] is that the leader is the node that has the lowest or null spill over. The subsequent nodes may have other roles in the network depending on the degree of spill over. The node having the least amount of spill over indicate the node sitting at a higher level, and also having less amount of communication with the rest of the network which is a typical case of a leader in the terrorist network.

The binary approach [3] is discussed mainly based on exploring the terrorist network. Apart from the standard measures like degree, betweenness and closeness several other measures also exists. The process of determining the role of a leader or a follower is hard to determine with standard centrality measures.

5.2 LUCI Model

This approach [4] is used to identify the leaders and followers in online social networks using the Longitudinal User Centered Influence (LUCI) model, which takes input as user interaction information and classifies users into four categories: extrovert leaders, introvert leaders, followers, and neutrals. The interaction information used in this study contains only the timestamp of interaction, the identifier of sender and receiver [4].

The interactions are rarely initiated by the introvert leaders while extrovert leaders frequently initiate the interactions. The followers are the users for whom, the number of interactions initiated by them with their friends depends on how many interactions they received. Neutrals initiate interactions rarely and use the social network very inconsistently [4].

The FJ influence model [4] is considered as the basis for this LUCI model. According to this model, the interaction behavior of a particular user at a time t is a linear function of the interaction behavior and the combined interactions of the neighbors in the previous time period $t - 1$. The model also assigns a weight to the degree to which a user's neighbors' interaction behaviors in the previous time period $t - 1$ influences its interaction behavior in the current time period t. This assigned

weight is called as the network coefficient. The network coefficient of a user is denoted as ρ. The model [4] also assigns a

TABLE I

COMPARATIVE ANALYSIS OF COMMUNITY DETECTION ALGORITHMS

Algorithms	Resolved defects in	Method used	Computational complexity	Dataset
Walktrap	Modularity Approach	Node similarity measure based on short walks	$O(n^2 \log n)$	Zachary karate club
Markov clusters	Walktrap	Alternating expansions and inflations to identify weakly connected components	$O(n^3)$	Network of NCAA Division I Football programs
Random walks	Modularity approach	Introducing the ratio ηk	$O(n^2 \log n)$	A map of the popular board game risk
Influence dynamics method	Modularity approach	Computing membership vectors	varies from O(n) to $O(n^2)$	Zachary karate club

weight to the degree to which a user's interaction behavior in the previous time period t − 1 influences its interaction behavior in the current time period t. This assigned weight is called the ego coefficient. The ego coefficient of a user is denoted as γ. Low ρ, Positive γ: extrovert leaders, Low ρ, Negative γ: introvert leaders, Low ρ, Zero γ: neutrals, high ρ and negligible γ : followers.

5.3 Leader Rank Approach

In many online applications, users are able to select other users to be their sources of information [10]. These user-user relations can be represented by a network with directed links pointing from fans to their leaders. The direction of the link corresponds to votes from fans for their leaders. The popular leaders would have a large number of incoming links which are known as in-links. This is considered as the convention as it matches the direction of random walk in this algorithm, though the flow of the information is in the opposite direction i.e. from leaders to fans. The aim of the approach is to rank all the users based on the network topology.

A network of N nodes and M directed links has been considered by the authors [10]. Nodes correspond to users and links are established according to the relations among leaders and fans. A ground node which connects to every user through bidirectional links has been introduced in order to rank the users. The network thus becomes strongly connected and consists of N + 1 nodes and M + 2N links. One unit of resource is assigned to each node except for the ground node which is then evenly distributed to the node's neighbors through the directed links to initiate the ranking process. The process gets repeated until attaining a steady state. This process is equivalent to random walk on the directed network mathematically.

The stochastic matrix P with elements pij = aij/k_i^{out} represents that, in the next step, the probability that a random walker at i goes to j. If node i points to j, then, aij = 1 and 0 otherwise, while k_i^{out} denotes the out-degree, i.e. the number of leaders, of i. Thus, this probability flow corresponds to the vote from fan i to leader j. By denoting using si(t) [10] the score of node i at time t,

$$si(t+1) = \sum_{j=1}^{N+1} (aji \,/ k_j^{out}) \, s_j(t)$$

The initial scores are si(0) = 1 for all node i and sg(0) = 0 for the ground node. Since the network is strongly connected, the presence of the ground node makes P irreducible. The ground node also ensures the co-existence of loops of size 2 and 3 from any node, which denotes P6 is positive, which means all elements of P6 are greater than zero. Since Pn value is positive for some natural number n, thenon-negative P is primitive.

According to the Perron-Frobeniustheorem [10], P has the eigen value 1 which is maximum limit, with an unique eigenvector. The proof of permittivity and convergence are outlined in Supporting Information (SI). The score $s_i(t)$ for all i thus converges to a unique steady state which is indicated as $s_i(tc)$. Here, the convergence time is tc. At the steady state, distribute the score of the ground node to all other nodes to conserve scores on the nodes of interest are evenly distributed. Thus the final score of a user to be the leadership score S is defined as

$$S_i = s_i(tc) + (s_g(tc)/N)$$

where sg(tc) is the score of the ground node at steady state. There are several advantages of applying Leader Rank in ranking based on the above properties. The advantages include: (i) parameter-freeness, (ii) wide applicability to all kinds of graph, (iii) independence of the initial conditions and (iv) convergence to an unique ranking.

The comparative study of the leaders and followers detection is shown in the Table II. The main idea of the algorithm and the classifications of leaders and followers identification algorithms are compared in Table II.

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TABLE II
COMPARATIVE ANALYSIS OF LEADERS AND FOLLOWERS DETECTION APPROACHES

Algorithms	Main idea	Classified based on	Classifications
Binary approach	Centrality measures	Degree Closeness Betweenness	Leaders Followers
LUCI method	User interaction	Ego coefficient Network coefficient	Extrovert Leaders Introvert leaders Followers Neutrals
Leader rank	User-user relation	Number of in-links	Leaders Ordinary users

6 Current And Future Research Directions

The traditional methods of community detection discussed involve the basic methodologies followed during earlier days for community detection. To detect communities, the modularity based method is the most commonly used one, yet suffers resolution limit problem. Several algorithms emerged to overcome the defects of the modularity based method. Among those algorithms very few has been discussed in this study. Another approach used to detect communities is the correlation based method. In future, the correlation based approach will be employed for community detection. To detect leaders and followers in the detected communities, three different approaches has been discussed. This work can be extended in future by combining the community detection and identification of leaders and followers i.e. in a social networking site, the communities are detected initially. Then, within the detected communities, the leaders and followers can be identified. This work finds huge application in the emerging social networking domain.

7 Conclusion

In this study, the two main aspects of social networking, community detection and leaders and followers identification are considered. The defects found in the modularity based method, a traditional approach is discussed. There are five algorithms considered which overcame the defects found in the modularity based method and a comparative analysis among those algorithms has been done. The leaders and followers detection involves three approaches namely binary approach, user interaction based approach and leader rank method. The functionality of these approaches along with their comparative analysis has been made. This study has provided a clear analysis of the modularity based method, community detection algorithms and leader follower detection approaches.

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