

A novel framework in complex network analysis: Considering both structure of relations and individual characteristics in closeness centrality computation

F.Barzinpour* and B. H. Ali Ahmadi

Department of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran

CHRONICLE

Article history:

Received October252012
Received in revised format
December 28 2012
Accepted January30 2013
Available online
1February2013

Keywords:

Complex networks
Social network
Community structure
Spectral clustering
Closeness centrality
Node attribute

ABSTRACT

In this paper, we develop a novel framework for defining radial measures of centrality in complex networks. This framework is based on the combination of two approaches: social network analysis and traditional social science approach by considering both structure of relations and individual characteristics. It is always an important issue to detect communities in complex networks as efficiently as possible to understand both the structure and function of the networks and to interpret radial centrality measures. Therefore, we propose spectral clustering by determining the best number of communities as a prerequisite stage before finding radial measures. Based on the proposed framework, an algorithm to compute the closeness centrality in complex networks is developed. We test the proposed algorithm on Zachary's karate club network, which is considerably used as a benchmark for community detection in a network. The preliminary results indicate that the new method is efficient at detecting both good inter-cluster closeness centrality and the appropriate number of clusters.

© 2013 Growing Science Ltd. All rights reserved.

1. Introduction

The recent advances on complex networks represent an essential area of multidisciplinary research including physics, mathematics, chemistry, biology, social sciences, and information sciences, among others. These systems are commonly represented by (un)directed graphs techniques, which consist of sets of nodes representing the objects under investigation such as people or groups of people, molecular entities, computers, etc., joined together in pairs by links, showing the corresponding nodes are related by some kind of relationship. These networks include the Internet, World Wide Web, social networks, information networks, neural networks, food webs, reaction and metabolic networks, and protein–protein interaction networks (Estrada & Rodríguez-Velázquez, 2006; Mello et al., 2009).

Centrality is a fundamental concept in network analysis and it has been used to investigate (potential for) autonomy, control, risk, exposure, influence, belongingness, brokerage, independence, power and so on. In addition, many other studies use well-known measures of centrality but do not identify them as such. For example, researchers working with ego-networks use the term “network size” to refer to a variable that in another context we would recognize as degree centrality (Borgatti & Everett, 2006;

* Corresponding author. Tel: +98217724-5063.
E-mail: barzinpour@iust.ac.ir (F. Barzinpour)

Agarwal et al., 2011). One of the key problems in complex networks is how to detect community structures, which have dense internal links and a lower density of external links. Many studies have verified the community structure in various complex networks (for review papers see Newman(2004) and Fortunato(2010), and a comparison paper see Danon et al.(2005)). For example, in protein-protein interaction networks, communities are likely to group proteins having the same specific function within the cell, in the graph of the World Wide Web they may correspond to groups of pages dealing with the same or related topics. In metabolic networks they may be associated with functional modules such as cycles and pathways, in food webs they may identify compartments, in economy they may represent a set of tightly coupled stocks or industrial sectors, and so on (Niu et al., 2008; Pollner et al., 2008; Zhang et al., 2007; Ghosh et al., 2011).

Clearly, the ability to detect community structure in a network has important practical applications. For instance, it can help us reduce complex networks to much simpler systems, since there is a growing need to deal with huge real-world networks and few of the existing methods scale up to large graphs (Liu & Liu, 2010). It gives us insights into the structure-functionality relationship (Ma et al., 2010) and can help us understand the network system, well.

Community detection plays an important role for interpreting centrality measures; because identifying clusters and their boundaries allow for a classification of vertices based on their structural position in the modules. Therefore, vertices with a central position in their clusters, i.e. sharing a large number of edges with other group partners, may have an important function of control and stability within the group. In addition, vertices lying at the boundaries among modules play an important role of mediation and lead the relationships and exchanges among different communities (Fortunato, 2010). On the other hand, some measures of centrality assign correct centrality scores only if the network has a core-periphery structure in which all nodes revolve more or less closely around a single core. Therefore, without such a cluster analysis, we cannot proceed with developing these kinds of centrality measures.

An individual's propensity to make new connections may influence the extent and value of his or her social network. The effect of individual characteristics on social networks is important because empirical studies of the consequences of networks have discovered associations among the number, structure, strength and content of network ties and a range of individual and organizational outcomes, including personal influence, job performance, innovation, career success, satisfaction and affect (Bidart & Lavenue, 2005; Hu & Wang, 2012; Lippert & Spagnolo, 2011; Liu, 2011; Louch, 2000; Reagans, 1998; Simon & Tellier, 2011; Totterdell et al., 2008; Valente & Foreman, 1998).

Although social network research has examined the influence of observable individual attributes, such as gender, it has largely ignored the individual psychological characteristics that may shape personal networks. This is due, in part, to the fact that social network research has been principally concerned with the structure and effects of relations among people, groups or organizations, rather than on psychological attributes of the individuals. Nevertheless, such attributes are likely to contribute to the formation and maintenance of ties among people within networks. It will thereby impact the behavior of those networks (Borgatti & Everett, 1999). This conception, in which both individual agency and social structure determine action, offers an alternative to a strict structural perspective in which action derives solely from the structure of social networks.

As mentioned earlier, this work makes a novel framework on complex networks analysis by considering individual characteristics as well as structure of relations and it introduces an extended and improved algorithm to find closeness centrality that has five valuable advantages at the same time:

- The algorithm is suitable for (un)weighted, (un)directed graphs.
- It tackles the core-periphery assumption problem with clustering as a preprocessing stage.

- It maps graph to separate nodes clustered via data clustering techniques and does not need clustering methods in graphs.
- Its dimensionality reduction (from $n \times n$ matrix to $n \times k$ matrix, ($k < n$)) makes computations much simpler.
- It converts person-to-person data to person-to-attribute and provides the opportunity to consider individual's characteristics beside relations structure.

The present paper also validates the proposed algorithm on a real-world social network, Zachary's karate club, which is by far the most investigated system used as a benchmark to test community detection algorithms. This network was the only standard network in Social Network Analysis (SNA) context we could find which has some information about vertices' individual characteristics.

The remainder of the paper is organized as follows: The subsequent part, Section 2, introduces the necessary background and notations. Then, in Section 3, three main problems in this context, which are derived from reviewing the related literature, are discussed and, their solutions introduced. The proposed framework and algorithm based on these solutions is then represented. Furthermore, section 4 applies the proposed algorithm to a commonly used benchmark for community-finding and compares the results to various state-of-the-art techniques. Finally, in section 5, conclusions and remarks as well as further works are presented.

2. Basic concepts

2.1. Centrality

Social Network Analysis (SNA) focuses on depicting the structure of the group, the most important members in it and the influence of the structure on individuals (Wasserman&Faust, 1994). Based on this, there are several measures, which help to identify key members or the most important members in the network as well as the underlying structure of the network itself. Among all introduced measures, four measures stand out as foundational in our field: degree, closeness, betweenness, and eigenvector centralities. Their prominence within the field of network analysis stems from the fact that they all have strong yet distinct theoretical underpinnings and that they are frequently applied for empirical analysis of social systems (Borgatti et al., 2006; Kuhnert et al., 2012). For these reasons, we will restrict the present paper to these four measures and introduce them as Guzman (2008) suggested:

- *Degree Centrality* (introduced by Nieminen (1974)): considers the number of connections at a specific node (in directed graphs it is measured using the in-degree and out-degree as measures). This attribute is used as a surrogate for a measure of the level of potential communication activity from a specific node. The easier it is for an individual to communicate directly with others, the more degree centrality that individual has.
- *Closeness Centrality* (proposed by Sabidussi (1966)): represents a measure of the sum of the geodesic distances between a specific node and the remaining nodes in the network. The lower the sum, the greater the centrality. A node is more "central" if it is closer to many more nodes than any other node. It also stands for a level of independence for a given node. When a specific node has the ability to communicate with many other nodes and has a minimum number of intermediaries, it is more autonomous and thus has higher independence.
- *Betweenness Centrality* (developed by Freeman (1979)): focuses on the ability to communicate with other nodes. This attribute is obtained by counting the number of possible geodesic paths among pairs of nodes. It means that the most "central" node lies among the most pairs of nodes. It can also be measured by analyzing the node that, which falls between any other two nodes on the shortest path between them.

- *Eigenvector centrality* (presented by Bonacich (1987)): is based on the largest characteristic eigenvalue of the adjacency matrix. In other words, it assesses a person's centrality as a function of the centrality of the people, which is associated. This means that rather than measuring the extent in which a given actor "knows everybody", it measures the extent to which the actor "knows everybody who is anybody" (Borgatti & Everett, 2006).

Some centrality measures such as all degree-like, closeness-like and eigenvector-like measures evaluate volume or length of the walks (A walk from node u to node v is a sequence of adjacent nodes which begins with u and ends with v and may have repeated nodes or edges) that emanate from or terminate with a given node. Social network researchers refer to these as radial measures. Another kind of centrality measures which assess the number of walks that pass through a given node, are called medial measures, including all betweenness-like measures. The distinction between radial and medial measures is called Walk Position, which determines type of nodal participation (Borgatti & Everett, 2006). It is obvious that all centrality indices evaluate an overall summary of a node's involvement in the walk structure of the network. It is a measure of how much of the walk structure is dependent on a given node but one may raise the question: under what conditions is it reasonable to summarize, with a single value, a node's cohesion with all others? Consider the mean of any list of numbers. It can always be computed, but only serves as a summary when the distribution of the numbers is unimodal. Therefore, if the list is known to be normally distributed, one can produce the entire distribution by the mean and standard deviation. However, if the shape of the distribution is bimodal, the mean is a very poor summary. For example, imagine the ideal serving temperature of milk is in the range of 30–45° for much of the population (because they like iced milk), and the ideal serving temperature for the other half of the population is in the range of 120–150° (because they like hot milk). Now, does the average of the ideal temperatures identify a good assessment of the population's tastes? In other words, does a luke-warm temperature of 86.25° provide a right picture of what the people's tastes are? Apparently not. According to Borgatti and Everett (2006) a radial centrality measure is unmistakably interpretable in a network which has unimodal dyadic cohesion, but not in one which has multimodal type. Namely, radial centrality makes sense in networks, which have, at most, one center and would not be partitioned in two or more components.

If a network contains more than one subgroup, eigenvector centrality will specify zeros to all nodes not in the largest subgroup, even if they are highly central in their own subgroup. Rather, those nodes load highly on the remaining eigenvectors. That is to say, the eigenvectors of a cohesion matrix measure strength of involvement of each node to each major component (subgroup).

A usual image in SNA and other fields is that of the core/periphery structure. Given its wide currency, it comes as a gap in related literature that the notion of a core/periphery structure is not often tested before computing a radial measure of centrality. It should be mentioned that medial centrality measures do not make the same one-group assumption. These measures correctly determine high centrality scores to nodes serving as bridges among components. Nevertheless, it is still the case that it is difficult to interpret a given value of medial centrality without specifying the group's cohesive structure.

2.2. *Spectral clustering approaches*

Graph nodes clustering and "community detection" are important subjects that have been the content of much recent studies in various fields of science: physics, applied mathematics, computer science, social science, pattern recognition (see for instance Fortunato, 2010; Donetti & Muñoz, 2004; Jabal-Ameli et al., 2011). There is also a vast literature on spectral graph theory. As Yen et al. (2009) mentioned, spectral techniques have been applied in a wide variety of contexts including high performance computing, image segmentation, web pages ranking, information retrieval, data clustering, and dimensionality reduction.

In this section, we shall follow the nice tutorial by Fortunato (2010), with the focus on spectral clustering. Spectral clustering is made up of a change of representation of the initial set of objects into a set of points in space, whose coordinates are elements of eigenvectors: the obtained set of points is then clustered via standard techniques, like k -means clustering. Here a question is when one can directly cluster the initial set of objects by applying the similarity matrix and why it is required to cluster the points resulting from the eigenvectors. The underlying fact is that the transformation induced by the eigenvectors makes the cluster properties of the initial data set much more obvious. In this way, spectral clustering is able to resolve data points, which could not be separated by applying direct k -means clustering, for example one reason is that the latter tends to deliver convex sets of points. The Laplacian, which is by far the most used matrix in spectral clustering, is given by

$$L = D - A, \quad (1)$$

where A is the adjacency matrix and D is the diagonal matrix whose elements are the vertex degrees. In general, using the eigenvectors of the Laplacian, L , in spectral clustering is more promising and applying A (or of its weighted counterpart W) is not reliable. In this way, from the components of the eigenvectors one can identify the components of the graph. If a graph consists of k components, which are disconnected from each other, its Laplacian has k zero eigenvalues. Otherwise, if the graph is connected, but has k sub graphs which are weakly linked to each other, the spectrum of the Laplacian will have one zero eigenvalue, with all others being positive. However, the lowest $k-1$ non-vanishing eigenvalues are still close to zero. For instance, let us consider the $n \times k$ matrix, V , whose columns are the k eigenvectors above mentioned. The n rows of V are used to represent the graph vertices in a k -dimensional Euclidean space, through a Cartesian system of coordinates. Therefore, techniques like k -means clustering can clearly distinguish k groups of points, with the points of each group localized close to each other and far from the other groups.

By reversing this argument, the number of clusters of a graph which has to be given as input, could be derived by checking whether there is an integer k such that the first k eigenvalues are small and the $(k+1)$ -th is relatively large. However, when the clusters are very mixed with each other, it may be hard to identify significant gaps between the eigenvalues.

2.3. Considering nodes attributes

According to Borgatti and Everett (1999), social network analysis differs from traditional social science in that traditional social science studies attributes of individuals (which is called monadic attributes) whereas network analysis studies social relations i.e. attributes of pairs of individuals (which is called dyadic attributes). By concentrating on different monadic and dyadic attributes, traditional social science and network analysis have various canonical data sets. In traditional social science, the people are considered as cases and the monadic attributes are observed as variables, therefore, the canonical data set can be considered as a person-by-attribute matrix. In the network case, the canonical data set can also be considered as a person-by-person matrix, which is conceived of as considering a single social relationship (or other dyadic attribute) among a set of actors. In such circumstance, the cases are the (ordered or unordered) pairs of actors, and the entire relation or dyadic attribute is considered as a single variable. In spite of this, the difference between traditional social science and network analysis is not practically so neat. One explanation is that there are methods of converting 2-mode data sets into 1-mode matrices, in which the techniques of network analysis can be applied, consequently. Another reason is that some 2-mode data are evidently relational in spirit and come up as expected in network research. For instance, the assignment of workers to projects may be seen as relationships among the set of workers and the set of projects. Another reason is that some data can be collected and preserved either as 1-mode or 2-mode, at the ease of the researcher. For example, if two different related sets such as students and teachers are regarded as separate sets of entities, the data are 2-mode, but if they are seen as a single set of entities (persons), the data are 1-mode.

Nowadays, even traditional social scientists are concerned with the structure and effects of relations among people, groups or organizations. People normally deal with networks more than individuals do, so in this paper we choose the network analysis paradigm but we also consider individuals attributes since such attributes influence the formation and maintenance of relationships among people within networks, and will thereby impact the behavior of those networks. This idea, in which both individual agency and social structure give direction to action, presents an alternative to a narrow structural perspective in which action originates exclusively from the structure of social networks or from the personal characteristics.

3. Closeness centrality in complex network by considering both structure of relations and industrial characteristics

3.1. General framework for computing closeness centrality in complex networks

The resulting structure shown in Fig.1 is based on points mentioned in previous sections, classifies a series of problems, their casual factors and proposals for solutions and specifies the general framework in which every radial measures of centrality can be assessed and interpreted, properly.

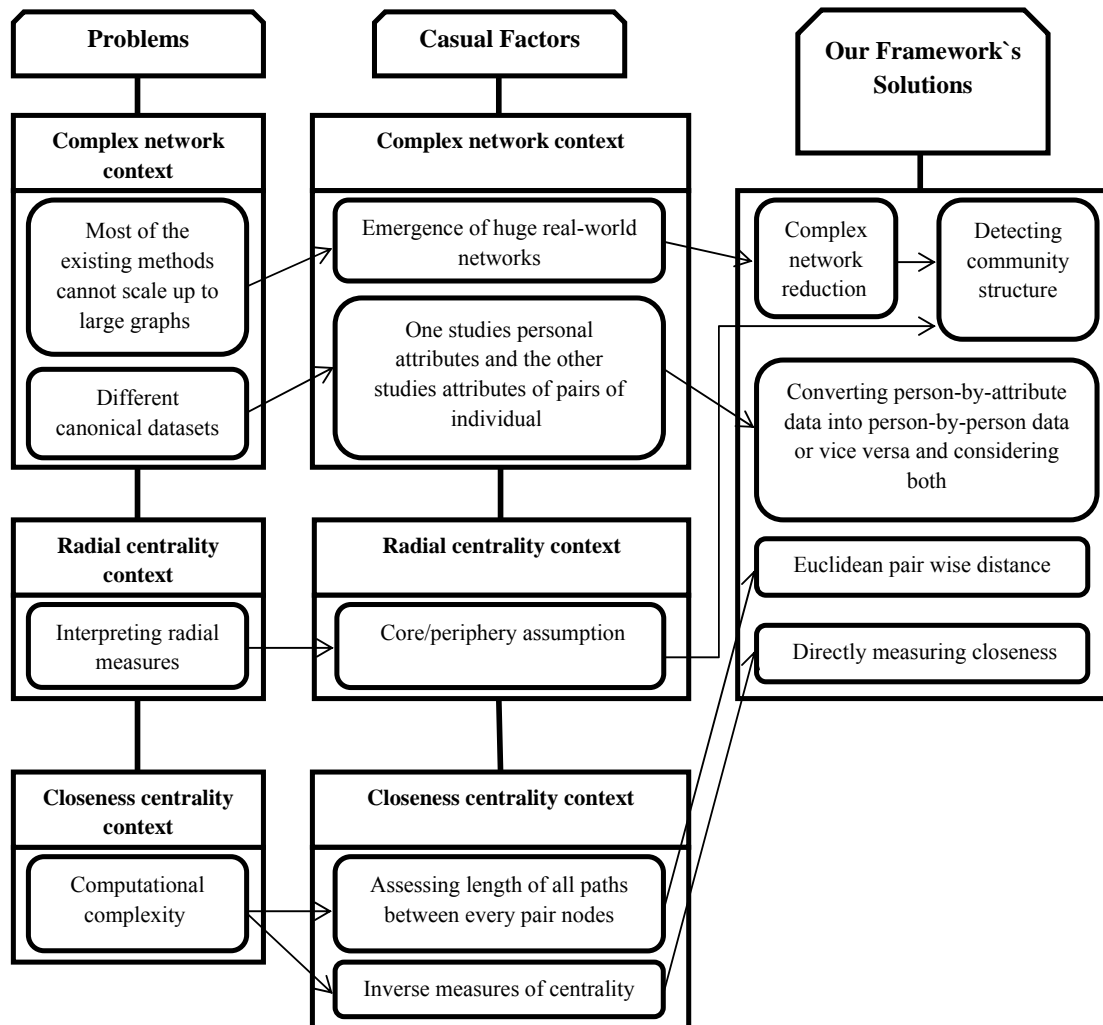


Fig. 1 General framework for computing closeness centrality in complex networks

Our proposed solutions are then applied for the algorithm offered for computing closeness centrality in complex networks. The resulted framework indicates three main challenges; the first challenge in

complex network context is that in latest years we have encountered an unpredictable growth of interest and activity, which regards the structure and dynamics of complex networks. This is as a result of the appearance of motivating and challenging new cases of complex networks such as the internet and wireless communication networks.

Moreover, network models have become standard tools in social science, economics, the design of communication and transportation systems, banking systems, etc. In view of the fact that these networks are in general very complex and not many of the methods upgrade to large graphs, it is advantageous to see whether they can be cut down to much simpler systems. Particularly, much effort has gone into splitting networks into small numbers of communities. On the other hand, differential focus in traditional social science (which studies personal attributes) and social network analysis (studies attributes of pairs of individuals) is a considerable challenge too. Converting person-by-attribute data into person-by-person data or vice versa and considering both individual agency and social structure is our proposed solution to this challenge. In the second challenge, which occurs in radial centrality context, as a result of core/periphery assumption, radial measures may be assigned and interpreted, improperly. Therefore, determining whether the network satisfies the one-group requirement must be accomplished first and if the network contains more than one component, subgraph radial indices should be assigned. The last challenge is the computational complexity in closeness centrality context, which is detailed in section 3.3.

3.2. The proposed algorithm

Based on the framework presented in Section 3.1, we propose an algorithm (Fig.2) consisting of the following steps:

- Form the input datasets according to the spectral analysis
 - Given the input datasets. (For complex networks, these datasets is described by the adjacency matrix such that $A_{ij}=1$ if node i and j are connected by an edge and $A_{ij}=0$ otherwise.)
 - Define D to be the diagonal matrix whose (i, i) -element is the sum of A 's i -th row, which represents the degree of the node i . Then construct the normalized Laplacian, which is defined as follows,

$$L_{rw} = D^{-1}L \quad (2)$$
 - Find k nontrivial eigenvalues of the normalized Laplacian, L_{rw} , such that the first k eigenvalues of L_{rw} are small and the $(k+1)$ -th is relatively large; where k is the number of clusters.
- Preparing a matrix as an input for clustering
 - If $k=1$, then network has core-periphery structure; Compute closeness centrality via usual techniques.
 - If $k>1$, then Computing a $n \times k$ matrix, V , whose columns are eigenvectors of L_{rw} .
 - Adding l attributes of individuals nodes to have a $n \times (k+l)$ matrix Q as an input for clustering.
- Given the input matrix, Q and number of clusters, k , cluster the nodes using usual techniques like k -means.
- Determine center of clusters (Closeness centrality within clusters).
- Finally, compute graph's closeness centrality (Closeness centrality between centers of clusters).

3.3. Computational complexity

Let us accomplish the presentation of our proposed algorithm with a brief discussion on computational complexity. The two critical computational components of the approach are the spectral mapping and

pairwise distances. The other steps of the framework, like computing the Laplacian matrix have insignificant computational cost compared with the computation of those mentioned above. All closeness centralities need computing distance matrix D (Borgatti& Everett, 2006).

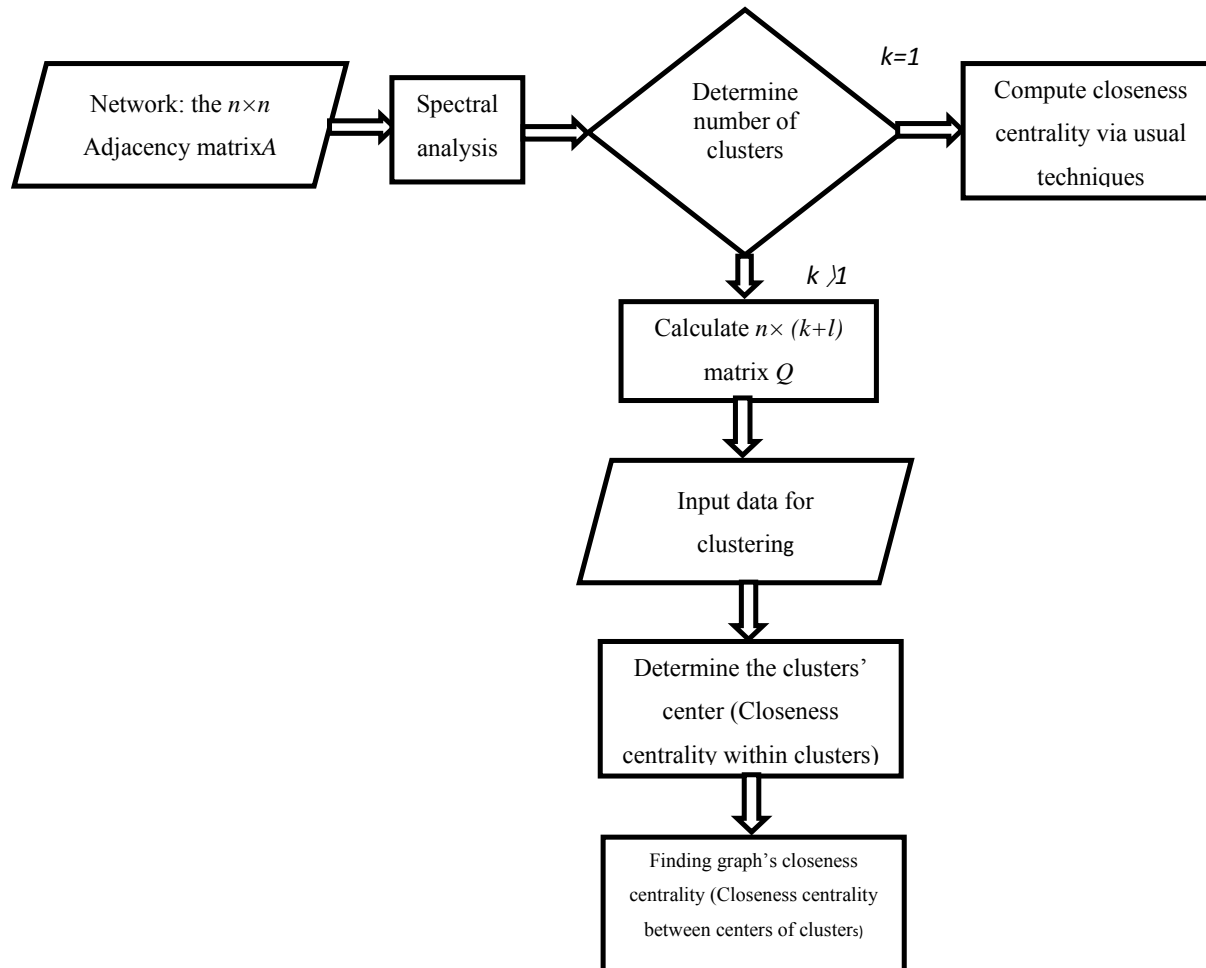


Fig. 2 Data flow of the proposed algorithm

Freeman's measure, closeness depends on geodesic distances where each d_{ij} entry in the geodesic distance matrix can be viewed as the minimum of the vector of lengths of all paths from i to j . In spite of this, if we do not suppose that a given substantive observable fact, such as diffusion of information, always makes use of the shortest paths, it implies to take into account all paths from i to j , perhaps by choosing the median or mean length of all paths. The hardship in all this, is that they oblige defining all walks among every pair of nodes and assessing their length. However, our proposed measure uses the adjacency matrix A , and pairwise Euclidean distance which makes the computation much faster than that of the pairwise geodesic distances. In spite of this, other variants of closeness are inverse measures of centrality, because larger values specify less centrality. As a result, they technically measure farness rather than closeness (Borgatti& Everett, 2006) but our index is a direct measure of closeness (rather than farness) and does not need any transformation.

The spectral mapping necessitates computing the eigenvectors of potentially very large matrices. Though this may be computationally cost-effective, some concepts make this step actually faster. Primarily, in spectral mapping, approximating all the eigenvectors is not necessary, and in such circumstances, the classical speed-up techniques can be used for finding only the eigenvectors corresponding to the top eigenvalues. If further speed-up is required, classical techniques from Kernel

methods can be applied, where the eigenvectors are determined for a subset of the surface points, and then interpolated to the rest (Mahmoudi&Sapiro, 2009).

4. Experimental results

4.1. Dataset description

Testing an algorithm implies applying it to a particular problem whose solution is identified and comparing such solution with that provided by the algorithm. In order to test our method on such networks, we have a big limitation, finding a standard dataset in which there are some precise information about the vertices and their properties as well as the relationships and edges among them. Since, as mentioned before, almost all network analysts focus on attributes of edges in a network, while on the other hand, social science researchers are interested in individual characteristics of vertices in a network.

Finally, we consider the well-known karate club friendship network studied by Zachary (1977), which has grown to be a commonly used benchmark for testing community-finding algorithms (Arenas et al., 2008; Duch& Arenas, 2005; E et al., 2008; Estrada, 2011; Fortunato et al., 2004; Girvan & Newman, 2002; Li et al., 2009; Newman, 2004, 2006a, 2006b; Newman & Girvan, 2004; Radicchi et al., 2004; Reichardt&Bornholdt, 2004; Wu &Huberman, 2004; Zhang et al., 2008; Zhang et al., 2011; Zhou, 2003). It is composed of 34 vertices, the members of a karate club in the United States, who were studied during a period of three years. Some individuals who were detected to interact outside the activities of the club are connected by edges. Sometime later, a conflict between the club president and the instructor causes the fission of the club into two separate factions, supporting the instructor and the president, respectively. Here, the question is whether the real partition in two social groups could be calculated from the graph topology.

4.2. Experimental settings and parameter tuning

We use the ‘faction’ feature in Zachary’s work (1977) as a node attribute which is added to edge attributes after mapping them in spectral space. ‘Faction’ gives the factional affiliation of the individual, either with that of John A. (the officer), or that of Mr. Hi (the instructor), or none. The strong/weak designations in this feature indicate whether the individual was a strong or a weak supporter of the faction's ideological position. We deal with this feature as an ordinal variable that varies from 1(John strong) to 5(Hi strong).

The other issue is the choice of the Laplacian matrix to use in this application; because the graph vertices do not have the same or similar degrees, the choice of the Laplacian significantly influences the results. Since in most cases, normalized Laplacians are more promising and of the normalized Laplacians, L_{rw} is more reliable, we choose L_{rw} as our Laplacian matrix.

Main computational stages of our algorithm are performed by using appropriate software; we use MATLAB for computing eigenvalues and vectors, SPSS Clementine for clustering, and UCINET for assessing centralities.

4.3. Results and discussions

Based on our algorithm, we find eigenvalues of the normalized Laplacian, L_{rw} ; Because first three nontrivial eigenvalues were still close to zero, and that the fourth was clearly different from zero, the vertex vectors of the first three nontrivial eigenvectors should still enable us to clearly distinguish the clusters in a 3-dimensional space and 4 communities would be the best partitioning of the network. Fig.3 shows the size of the eigen-gap between pairs of consecutive eigenvalues of the matrix L_{rw} , as a function of k , number of clusters. As mentioned before, clustered data have four features, three

correspond to elements of first three nontrivial eigenvectors, which is obtained from relationships among nodes (edges), and one feature corresponds to nodes ‘faction’ attributes. Results of our clustering with different community numbers done by SPSS Clementine software confirm this, i.e. four communities made less Sum of Squared Error (SSE).

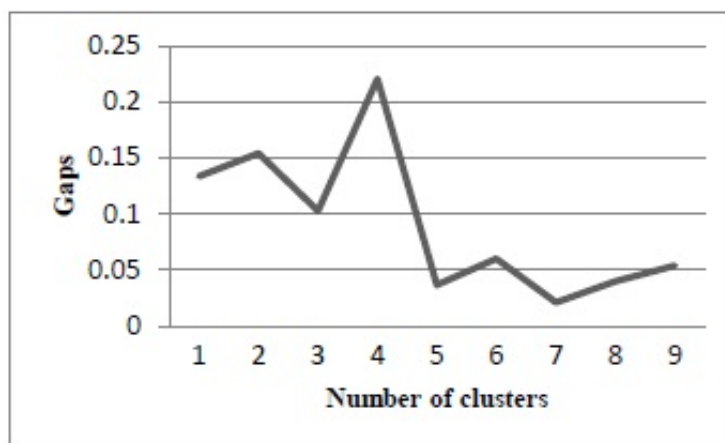


Fig. 3. Functional representation of the gaps between pairs of consecutive eigenvalues of the matrix and number of clusters

However, different clustering methods based on optimizing various modularity functions have proposed the same cluster numbers. For example, Fortunato (2010) proposed four clusters based on the best partition found by optimizing the modularity of Newman and Girvan (2004), and based on multi-resolution method by Arenas et al. (2008) indicated the most stable partition was two clusters. However, the partition obtained with straight modularity optimization consists of four clusters, which is less stable, Liu and Liu (2010) showed the community structure obtains the greatest modularity could be of four clusters, etc.

Fig.4 and Table 1 show results of applying our method on Zachary’s karate club network. In Table 1, the column named ‘Node with highest closeness centrality within each cluster’ determines the closest node to the cluster center, which is determined by *k*-means clustering technique. Since node 34 has less ‘Sum of proximities with other cluster centers’, it is obvious that node 34 has the greatest closeness centrality among these four central nodes and, thus, it is the whole network’s closeness centrality. In this case, our data were partitioned into two clusters via proposed method. The results obtained exactly match the social fission observed by Zachary (1977).

In order to examine the effect of considering individual node attributes on the results, we clustered 3 field data (removing ‘faction’ attribute) by our proposed method in two communities; which leads to 12 nodes misclassified as compared to the real fission in the karate club.

For comparing results with the case when closeness centrality is computed without clustering as a preprocessing stage and via usual techniques, we determine closeness scores of network’s node by UCINET software. According to Table 2, node 2, which in our method obtains the second score in closeness centrality, is 7th in the analysis by UCINET; Node 11 is third in our method and 15th in the UCINET analysis, and finally node 26, which is fourth in our method, is 16th. Therefore, the preprocessing proposed considerably affects the results and could not be removed.

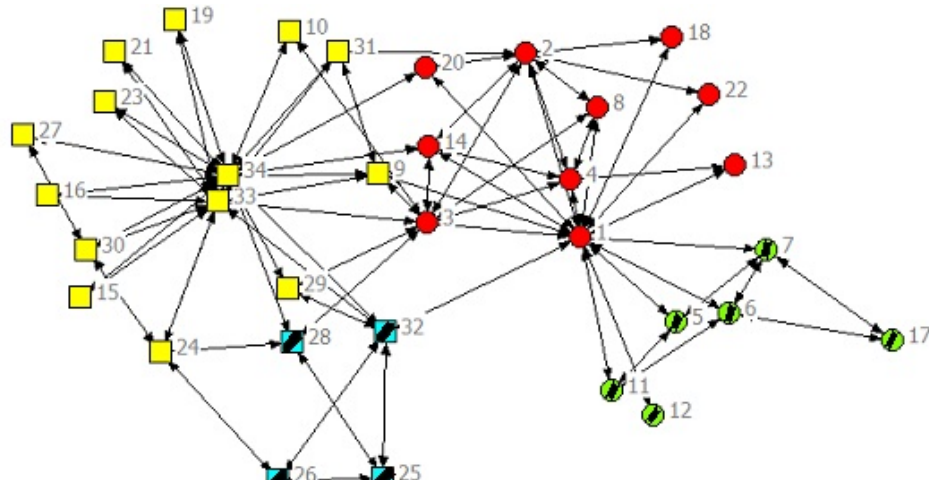


Fig. 4. Zachary's karate club network. Squares and circles indicate the two communities observed by Zachary, colors denote the subdivision found by our algorithm.

Table 1
Results of applying the proposed method on Zachary's karate club network

Cluster	Number of nodes	Nodes	Cluster center	Node with highest closeness centrality within cluster	Sum of proximities with other cluster centers
1	10	N1, N2, N3, N4, N8, N13, N14, N18, N20, N22	(-0.082, 0.184, 0.026, 0.0875)	N2	2.82
2	4	N25, N26, N28, N32	(0.138, -0.129, -0.376, 0.062)	N26	3.07
3	6	N5, N6, N7, N11, N12, N17	(-0.3, -0.268, -0.011, 0.917)	N11	2.95
4	14	N9, N10, N15, N16, N19, N21, N23, N24, N27, N29, N30, N31, N33, N34	(0.132, -0.051, 0.117, 0.125)	N34	2.77

Table 2
Closeness centrality analysis without clustering as a preprocessing stage, done by UCINET software

Node	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Closeness centrality	56	48	55	46	37.9	38	38	44	51	43	37.9	36.6	37	51	37	37	28
Rank	1	7	2	8	15	14	14	11	4	12	15	18	17	4	17	17	20
Node	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
Closeness centrality	37.5	37	49	37	37.5	37	39	37.5	37.5	36.2	45.8	45.2	38	45.8	54	50	54
Rank	16	17	6	17	16	17	13	16	16	19	9	10	14	9	3	5	3

According to Zachary (1977), an edge connects the individuals who are said to be friends outside the club activities. During the factional conflict in the club, which led to the fission, the club meeting kept on the setting for decision making. If, at a specified meeting, one faction had a majority, it would try to pass resolutions and decisions beneficial to its ideological position. The other faction would then get revenge at a future meeting when it held the majority, by canceling the unfavorable decisions and replacing with ones favorable to itself. Therefore, the result of any crisis was identified by which faction was able to "stack" the meetings most successfully. The information (the calling of a meeting) usually began with one of the factional leaders, Mr. Hi or John A. Considering the course of political conflict in the club; it would be beneficial to the source if members of the opposing faction did not get this information. So in such network the closest person to members of his group is important not to all members of the network, and therefore clustering before determining the closeness centrality is necessary. On the other hand nodes which are center of clusters, indicate persons that are the closest one to members of their community, i.e. they attend in more number of contexts outside the club in

which interaction took place between the two individuals involved and can call group members for meeting faster than others. This means they are not necessarily faction's leader.

5. Conclusions and future works

We have introduced a new algorithm based on a general framework aimed at computing closeness centrality in complex networks in an efficient and systematic way. The method combines spectral techniques, considering individual node attributes, and cluster analysis as preprocessing stages.

The nodes of the network are projected into a D -dimensional space, where D is a number of first nontrivial eigenvectors of the Laplacian matrix; their coordinates are the node-projections on each eigenvector. Then nodes attributes are added and by computing Euclidean distance in such an eigenvector space, k -means clustering technique are employed to generate network's partition in communities. The number of clusters giving the maximum modularity is taken as the output of the algorithm for a fixed D . It has also been discussed that in conditions where the clusters are not very mixed with each other, D can be determined by assessing gaps between eigenvalues, providing a way to avoid computing all or large number of eigenvalues, which significantly reduces computational complexity, and maximizes the modularity by defining the best number of communities as an input of clustering and thus enhance the performance of the method. The best results are obtained using both edge structure and node attributes.

Even if assessing closeness centrality have been profusely discussed before, we believe that our algorithm represents a step forward in studying complex networks, as it combines spectral techniques with (i) the novel concept of considering both node and edge attributes, which provide a link between traditional social studies and modern network research and (ii) a way to optimize the number of eigenvalues taken into consideration.

An interesting result we can see in this experiment is that by clustering the network as a preprocessing stage, the picture of the network after fission which happened later, is obvious. This again confirms that individual characteristics effect networks future status. Challenges in SNA can be classified into three broad areas: instance modeling, evolution modeling, and predictive modeling (Kaza, 2008). Instance modeling concentrates on the study of static network properties, evolution modeling investigates factors behind network growth, and predictive modeling looks at recognition of hidden and future network links. This essay focuses on instance modeling and examines the role of node status in network's centrality. It is found that centrality indices as measured by both considering edge and node attributes can help us in evolution and predictive modeling.

Further work will be devoted to the extension and to the study of other centrality measures that lie in our proposed framework as well as the development of new clustering algorithms dealing, for instance, with other dissimilarity measures (for instance weighted distance, parametric Pearson product moment correlation, or angular distance (Yen et al., 2009)). We will also investigate the possibility of adapting multiple contexts (layers). Moreover, it would be interesting to study the behavior of the proposed algorithm in other real complex networks of larger size.

References

- Agarwal, P., Sahai, M., Mishra, V., Bag, M., & Singh, V. (2011). A review of multi-criteria decision making techniques for supplier evaluation and selection. *International Journal of Industrial Engineering Computations*, 2, 801-810.
- Arenas, A., Fernández, A., & Gómez, S. (2008). Analysis of the structure of complex networks at different resolution levels. *New Journal of Physics*, 10 (5), 053039.

- Bidart, C., & Lavenue, D. (2005). Evolutions of personal networks and life events. *Social Networks*, 27, 359-376.
- Bonacich, P. (1987). Power and centrality: a family of measures. *American Journal of Sociology*, 92, 1170-1182.
- Borgatti, S. P., & Everett, M. G. (1999). Network Analysis of 2-Mode Data. *Social Networks*, 19, 243-269.
- Borgatti, S. P., & Everett, M. G. (2006). A Graph-theoretic perspective on centrality. *Social Networks*, 28, 466-484.
- Borgatti, S. P., Carley, K. M., & Krackhardt, D. (2006). On the robustness of centrality measures under conditions of imperfect data. *Social Networks*, 28, 124-136.
- Danon, L., Duch, J., Diaz-Guilera, A., & Arenas, A. (2005). Comparing community structure identification. *Journal of Statistical Mechanics*, 09008.
- Donetti, L., & Muñoz, M.A. (2004). Detecting network communities: a new systematic and efficient algorithm. *Journal of Statistical Mechanics*, 10012.
- Duch, J., & Arenas, A. (2005). Community detection in complex networks using external optimization. *Physics Review E*, 72, 027104.
- E, W., Li, T., & Vanden-Eijnden, E. (2008). Optimal partition and effective dynamics of complex networks. *Proceeding of the National Academy of Sciences USA*, 105 (23), 7907-7912.
- Estrada, E. (2011). Community detection based on network communicability. *Chaos*, 21, 016103.
- Estrada, E., & Rodríguez-Velázquez, J. A. (2006). Subgraph centrality and clustering in complex hyper-networks. *Physica A*, 364, 581-594.
- Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, 486, 75-174.
- Fortunato, S., Latora, V., & Marchiori, M. (2004). Method to find community structures based on information centrality. *Physics Review E*, 70, 056104.
- Freeman, L. (1979). Centrality in social networks: Conceptual clarification. *Social Networks*, 1, 215-239.
- Ghosh, T., Sengupta, S., Chattopadhyay, M., & Dan, P. K. (2010). Meta-heuristics in cellular manufacturing: A state-of-the-art review. *International Journal of Industrial Engineering Computations*.
- Girvan, M., & Newman, M. (2002). Community structure in social and biological networks. *Proceeding of the National Academy of Sciences USA*, 99 (12), 7821-7826.
- Guzman, M. (2008). *A probabilistic programming approach in the analysis of social networks*, Master thesis, University of Arkansas, Arkansas.
- Hu, H., & Wang, X. (2012). How people make friends in social networking sites—A microscopic Perspective. *Physica A*, 391, 1877.
- Jabal-Ameli, M. S., Aryanezhad, M. B., & Ghaffari-Nasab, N. (2011). A variable neighborhood descent based heuristic to solve the capacitated location-routing problem. *International Journal of Industrial Engineering Computations*, 2(1), 141-154.
- Kaza, S. (2008). *Instance, evolution, and predictive modeling of social networks*, PhD thesis, The University of Arizona.
- Kuhnert, M. T., Geier, C., & Elger, C. E. (2012). Identifying important nodes in weighted functional brain networks: A comparison of different centrality approaches. *Chaos*, 22, 023142.
- Li, T., Liu, J., & E., W. (2009). Probabilistic framework for network partition. *Physics Review E*, 80, 026106.
- Lippert, S., Spagnolo, G. (2011). Networks of relations and Word-of-Mouth Communication. *Games and Economic Behavior*, 72, 202-217.
- Liu, C. (2011). The effects of innovation alliance on network structure and density of cluster. *Expert Systems with Applications*, 38, 299-305.
- Liu, J., & Liu, T. (2010). Detecting community structure in complex networks using simulated annealing with k-means algorithms. *Physica A*, 389, 2300-2309.
- Louch, H. (2000). Personal network integration: transitivity and homophily in strong-tie relations. *Social Networks*, 22, 45-64.

- Ma, X., Gao, L., Yong, X., &Fu,L. (2010).Semi-supervised clustering algorithm for community structure detection in complex networks. *Physica A*, 389, 187-197.
- Mahmoudi,M., &Sapiro,G. (2009).Three-dimensional point cloud recognition via distributions of geometric distances.*Graphical Models*, 71, 22–31.
- Mello, B.A., Batistuta, L.H., Boueri,R., &Cajueiro, D.O. (2009).Measuring the flow of information among cities using the diffusion power.*Physics Letters A*, 374, 126-130.
- Newman,M. (2004).Detecting community structure in networks.*European Physical Journal B*, 38, 321-330.
- Newman, M., &Girvan, M. (2004).Finding and evaluating community structure in networks. *Physics Review E*, 69 (2), 026113.
- Newman,M. (2006a). Finding community structure in networks using the eigenvectors of matrices.*Physics Review E*, 74, 036104.
- Newman, M. (2006b).Modularity and community structure in networks. *Proceeding of the National Academy of Sciences USA*, 103 (23), 8577-8582.
- Nieminen, J. (1974). On centrality in a graph.*Scandinavian Journal of Psychology*, 15, 322-336.
- Niu, Y. Q., Hu, B. Q., Zhang, W., & Wang, M. (2008).Detecting the community structure in complex networks based on quantum mechanics. *Physica A*, 387, 6215-6224.
- Pollner, P., Palla, G., Ábel, D., Vicsek, A., Farkas, I. J., Derényi, I., &Vicsek,T. (2008).Centrality properties of directed module members in social networks. *Physica A*, 387, 4959-4966.
- Radicchi, F., Castellano, C., Cecconi, F.,Loreto, V.&Parisi, D. (2004).*Proceeding of the National Academy of Sciences USA*, 101, 2658-2663.
- Reagans,R. (1998). Differences in social difference: examining third party effects on relational stability.*Social Networks*, 20, 143-157.
- Reichardt, J.,&Bornholdt,S. (2004).Detecting fuzzy community structures in complex networks with a Potts model.*Physical Review Letters*, 93, 218701.
- Sabidussi, G. (1966). The centrality index of a graph.*Psychometrika*, 31, 581-603.
- Simon, F., &Tellier, A. (2011). How do actors shape social networks during the process of new product development? *European Management Journal*, 29, 414-430.
- Totterdell,P., Holman, D., &Hukin, A. (2008).Social networkers: Measuring and examining individual differences in propensity to connect with others. *Social Networks*, 30, 283-296.
- Valente, T. W.,& Foreman, R. K.(1998).Integration and radiality: measuring the extent of an individual's connectedness and reachability in a network. *Social Networks*, 20, 89-105.
- Wasserman, S.,& Faust, K. (1994).*Social Network Analysis: Methods and Applications*. Cambridge:Cambridge University Press.
- Wu,F., &Huberman, B.A. (2004).Finding communities in linear time: a physics approach.*European Physical Journal B*, 38, 331-338.
- Yen, L., Fouss, F., Decaestecker, C., Francq, P.,&Saerens, M. (2009). Graph nodes clustering with the sigmoid commute-time kernel: A comparative study.*Data and Knowledge Engineering*, 68, 338-361.
- Zachary,W. (1977).An information flow model for conflict and fission in small groups, *Journal of Anthropological Research* 33 (4), 452-473.
- Zhang, S., Wang, R., & Zhang, X. (2007). Identification of overlapping community structure in complex networks using fuzzy c-means clustering. *Physica A*, 374, 483-490.
- Zhang, J., Zhang, S.,& Zhang, X. (2008). Detecting community structure in complex networks based on a measure of information discrepancy. *Physica A*, 387, 1675-1682.
- Zhang, J., Xu, X., Li, P., Zhang, K., & Small, M. (2011). Node importance for dynamical process on networks: A multiscale Characterization. *Chaos*, 21, 016107.
- Zhou, H. (2003). Distance, dissimilarity index, and network community structure, *Physics Review E*, 67 (6), 061901.