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A Survey on Recent Methods of Finding Influential Nodes in Complex Networks

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ABSTRACT

Influential nodes refer to the ability of a node to spread information in complex networks. Identifying influential nodes is an important problem in complex networks which plays a key role in many applications such as rumor controlling, virus spreading, viral market advertising, research paper views, and citations. Basic measures like degree centrality, betweenness centrality, closeness centrality are identifying influential nodes but they are incapable of large-scale networks due to time complexity issues. Chen et al. [1] proposed semi-local centrality, which is reducing computation complexity and finding influential nodes in the network. Recently Yang et al. 2020 [2] proposed a novel centrality measure based on degree and clustering coefficient for identifying the influential nodes. Sanjay et al. 2020 [3] gave voterank and neighborhood coreness-based algorithms for finding the influenced nodes in the network. Zhiwei et al. 2019 [4] considered the average shortest path to discover the influenced node in the network. These are the few recent local,global and mixed centralities. In this paper, we show a broad view of recent methods for finding influential nodes in complex networks. It also analyzes the new challenges and limitations for a better understanding of each method in detail. The experimental results based on these methods show better performance compared with existing basic centrality measures.

Key words: Complex networks, Centrality measures, Influential nodes, SIR model.

1. INTRODUCTION

In recent years, the research on complex networks has gained attention in various fields such as social networks, collaboration networks, email network, biological science, brain networks, railway networks, climate networks, international trade networks and technological networks [5,6,7,8,9,11]. Understanding dynamics of information spreading processes in a complex networks is an important topic with many diverse applications, such as information dissemination, information propagation, viral marketing, controlling rumors and opinion monitoring. With the evolution of social networks there are more new platforms such as Orkut, Facebook and Flickr in 2004, Twitter in 2006, Whatsapp and Instagram in 2009 [12]. The ways in which people get information have changed. A part of information propagate from one individual or community to another in a network which is also known as information spread or information propagation [13]. During this process, social influence occurs when a person's opinions, emotions, or behaviors are affected by other people [14]. Most of the studies investigating which factors affect information propagation and which factor plays an essential role in understanding the diffusion phenomenon. Mainly, the interactions among persons are responsible for the propagate of information in the network, their position and topological properties have direct effect to the diffusion phenomena causes in the network. So that, a fundamental aspect on understanding and controlling the spreading dynamics is the identification of influential spreaders that can diffuse information to a large portion of the network [15]. It is important to find a set of seed nodes in complex network such that it can propagate information to a large portion of the network.

Understanding dynamics of information spreading processes in a complex networks is an important subject area with many different applications.

Viral marketing: It is the word-of-mouth effect. The goal is to promote an idea or a product in a large fraction of individuals in the network. In the network, individuals that have already adopted the product, recommend it to their friends who in turn do the same to their own social circle. The simple question here is how to target a few initial individuals such that by give free samples of the product to them or explaining the idea to them. So that can maximize the spread of influence in the network [16].

Controlling rumors: The rumors spread rapidly and broadly, and they have huge disastrous power. In many emergencies situations, rumors can not only cause social panic but also may cause mass unpredicted incidents and affect social stability. Therefore, for stopping and controlling the rumor transmission, it has great theoretical and practical significance to determine if there is an influential spreader and identify who is the influential spreader in rumor propagation process.

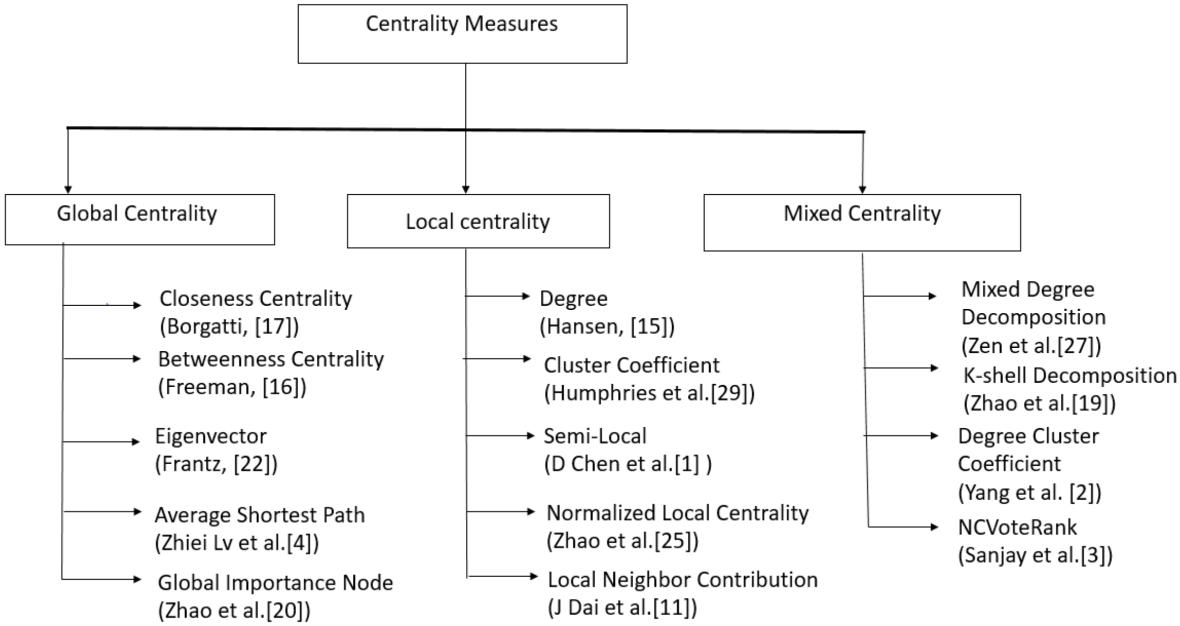

Figure 1: Categories of Centrality measures

Opinion monitoring: In a network, individual influence refers to opinion leaders-related research. They have a certain influence on other users in a social network. The influence of opinion leaders cannot be neglect in information diffusion research [3].

However, discovering influential nodes has remarkable practical value in many other applications such as predict information propagation, behavior analysis, gauging public opinion, the study of psychological phenomena, and for resource allocation in public health care systems [14]. Influential nodes refer to the ability of a node to spread information in complex networks. It is important to find a set of seed nodes in complex network such that it can propagate information to a large portion of the network. In recent years, many methods have been discovered to find seed nodes or influential nodes in complex networks.

On one hand by using the influential nodes, we can give advertisements for products, detecting drug target persons [17], finding social leaders [18]. In recent years, several methods have been discovered to find seed nodes in complex networks by using degree centrality [19], between centrality [20], closeness centrality [21], eigenvector centrality, semi-local centrality[22], k-shell centrality [23], local structure centrality, and global structure centrality [24]. By identifying influential nodes in complex networks, the following advantages can be obtained: 1) in terms of rumor control, it is helpful to stop the rumors for not spreading needless information; 2) in terms of virus spreading, it is thoughtful to controlling the diseases; 3) in terms of fraud detection, it is considerate to avoid harmful nodes.

The network topology plays a crucial role in network behavior and functioning. Ranking the nodes based on position of a node in the network and capability of spreading. The basic measure of a node's influence can be the number of neighbors it has, which is called degree of the node. But it is distinguished that all nodes having the same node degree may not have the same spreading range in some situations. Furthermore moving towards betweenness centrality[20], closeness centrality[21], semi-local centrality[1], k-shell decomposition [23], clustering coefficient [25], and global perspective. Centralities are categorized into three categories shows in the figure 1.

Some centrality measure of node defined based on local information of a node such a measures call it as local centrality measures. For example degree centrality, clustering coefficient, semi-local centrality and local neighbor contribution. Some centrality measure of node defined based on global information such a measures call it as global centrality measures. For example, closeness, betweenness and eigenvector centralities. Recently few methods are focused on the local and as well as global structure of the network, such as mixed degree decomposition, k-shell decomposition and degree cluster coefficient. Some ranking methods based on the shortest path, betweenness centrality, and closeness centralities are used. Furthermore, eigenvectors[26] and PageRank [27] are representative methods based on eigenvectors.

During the last decade many centralities based on many ideas and different techniques have defined. Although there exist partial overviews of centralities, a recent survey is essential for finding influential nodes in networks. In this paper, we aim at outlining and helpful the overall situation in the field of identifying most influential nodes. We not only give a description of each method but also provide new challenges and limitations of each method. Based on the collection of information, we give conclusions on the recent field and disclose several problems that seem important to be resolved in future.

The rest of the paper is organized as follows: In section II describes different type study on global, local and mixed centrality measures and their results. We study SIR model which is one of the diffusion method used for finding influential nodes in Section III. Conclusions and the discussions in Section IV.

2. RECENT CENTRALITY MEASURES

In this section, for the motive of perfectness of the present work, we briefly summaries different type of centralities used by researchers to find the influential nodes in different ways, including our main focus of this paper.

2.1 Global Centrality Measures

Finding influential nodes in complex networks is a key point. Using basic degree centrality we can find important nodes but in the aspect of large-scale networks it is difficult to conclude influential nodes. Furthermore many types of centralities are used for finding influential nodes. Those global centralities like eigenvector, betweenness centrality[20], and closeness centrality [21] can be used for better identifying influential nodes. Closeness centrality[21] is considered as an average distance from one node to all other nodes in a network. Betweenness centrality defined as number of times a node act as a bridge along the shortest path between any two other nodes. Eigenvector[26] is a measure of the influence a node in complex networks. If a node is pointed to by many nodes then that node will have high eigenvector centrality. These centralities are basic and global centrality measures.

Zhiwei [4]proposed an average shortest path centrality to rank the spreaders, in which the relative change of the average shortest path (ASP) of the whole network is taken into account. The ASP method considers the relative change of the average shortest path of the whole network after removing every node. Especially, it is measuring the effect of the information diffusion between all pair of nodes if you remove a node in the network. ASP centrality produced good results compared to degree, betweenness, and closeness centralities. It measures to information diffusion efficiently with in the nodes in the network (see Table 1 S.NO 1).

Zhao et al. [24] proposed a novel method called Global importance of each node (GIN), which takes into account not only the importance of node itself but also the influence of all other nodes in the network into consideration. The influence of the node consists of two parts, one is self-importance and other one is global importance. Self-importance measures the influence of the node exerting on the other node. Global importance based on the influence of the nodes linked to it. GIN measure depends on the self-importance and global importance. The experiment results shows this method outperforms with other method global centrality methods in terms of the spreading information. It is also shows similar to closeness centrality. This approach has superiority in identifying nodes that seem unimportant but are important in the complex networks (see Table 1 S.NO 2).

The global centrality measures have some limitations which is computing these measures in large scale network takes time. So researchers also look at the local centrality measures which we are going to discuss in next sub section.

2.2 Local Centrality Measures

Some of the local centrality measures defined based on local behavior of node such as degree centrality[19], semi-local centrality[22] and cluster coefficient[28]. k-shell and degree centralities are two methods based on neighbors for finding influential nodes. Global centralities take a long time and increase the computational complexity.

Chen et al. [1] proposed semi-local centrality, which is reducing computation complexity. Semi-local centrality measure defined based on neighbors and next nearest neighbors up to four level from a node with in the network. Semi-local centrality is compared with the degree, betweenness, and closeness centralities and gives better results with lower computational complexity. In some cases closeness centrality gives almost as good as semi-local centrality for better identifying influential nodes(see Table 1 S.NO 3).

Dai et al. [11] proposed the local neighbor contribution (LNC) method which combined the influence of the nodes with the contribution of the nearest and next-nearest neighbor nodes. Node contraction defines the influence of a node to be equivalent to the destructiveness of the network after the node is removed. This method mainly focus on the node's own influence and support of nearest and next-nearest neighbor nodes. Moreover, the LNC method is used to calculate the influence of each node in the network by using four steps. In the first step, the sum of neighbor node degrees is computed. The influence of the nearest and next-nearest neighbor node degrees is calculated in the second step. In the third step, calculate the own influence of each node in the network. Finally in the fourth step, calculate the influence of the nodes in the network which tells the contribution of the nearest and next-nearest neighbor nodes. This new method capturing the node influence accurately and gives more reasonable results compared with other measures (see Table 1 S.NO 4).

Berahmand [28] defined a new semi-local and free-parameter centrality measure by applying the natural features of complex networks for identifying nodes. The proposed centrality combines the degree, negative effects of

S.NO	Name of Measure	Formulas	Author and year/ Category
1	Relative change in average shortest path	$AC[k]=\frac{\lvert ASP[G_k^{'}]-ASP[G]\rvert}{ASP[G]}$ Where ASP[G] is average shortest path and $G_k^{'}$ is the node k is removed from G.	Zhiwei Lv et al. (2019)[4] Global Centrality
2	Global Importance of a node	$GIN_i=e^{\frac{1}{n}\times d_i}\times\sum_{i\neq j}\frac{d_j}{dis_{ij}}$ where d_i is the degree of ith vertex and dis_{ij} is the distance between vertex i and j.	Zhao et al. (2020)[24] Global Centrality
3	Local Centrality	$C_L(v)=\sum_{u\in\Gamma(v)}Q(u)$ where Q(u) is sum of all nearest neighbours of vertex u and $\Gamma(v)$ is neighbours of vertex v	Chen et al. (2012)[1] Local Centrality
4	Local Neighbour Contribution (LNC)	$Inf(v)=NeiCon(v)\times OwnCon(v)$ Where $NeiCon(v)$ is contribution of nearest and the nest nearest neighbour nodes of node v. $OwnCon(v)$ is contribution ability of node v.	Dai et al. (2019)[11] Local Centrality
5	Centrality measure based on of clustering coefficient	$C[i]=d_i\times\frac{1}{cc(i)+\frac{1}{d_i}}+\sum_{j\in N_2}cc(j)$ Where d_i is the degree of ith vertex, cc (i) local clustering coefficient.	Berahmand et al. (2018)[28] Local Centrality
6	Normalized local centrality (NLC)	$NLC(v)=\sum_{u\in\Gamma_1(v)}\left(\sum_{w\in\Gamma_2(u)}\left(\frac{\Gamma_1(w)}{\sqrt{\sum_{i\in\Gamma_2(u)}\Gamma_1(i)^2}}+\frac{c(w)}{\sqrt{\sum_{i\in\Gamma_2(u)}c(i)^2}}\right)\right)$ Where $\Gamma_n(v)$ is number of n-order neighbourhood of node v and c (i) local clustering coefficient.	Zhao et al. (2018)[29] Local Centrality
7	Local Centrality with coefficient (CLC)	$CLC(v)=f(C(v))\times C_L(v)$ Where $f(C(v))$ is effect of clustering coefficient of vertex v and $C_L(v)$ is local centrality measure.	Zhao et al. (2017) [33] Local Centrality
8	DCC (Degree and clustering coefficient)	$DCC(i)=\alpha I_D(i)+\beta I_C(i)$ where $I_D(i)$ is the effect of degree and neighbour's degree of node i, $I_C(i)$ effect of clustering coefficient of node i.	Yang et al. (2020)[2] Mixed Centrality
9	NCVoteRank Centrality	$NCV(v)=\sum_{i\in N(v)}(Va_i\times NC(i)\times(1-\theta)+Va_i\times\theta)$ where Va_i voting ability of node i, NC(i) normalized neighbourhood coreness and θ is the controlling parameters	Sanjay et al. (2020)[3] Mixed Centrality

TABLE I. RECENTDIFFERENT TYPE OF CENTRALITY MEASURES.

the node's clustering coefficient and positive effects of the second-level neighbor's clustering coefficient of a node. It is new centrality measures based on the local properties of a node to find out seed nodes. The advantage of this measure is time complexity which is near linear time complexity even for large scale networks. The proposed method shows better results compared to the other local and semi-local measures (see Table 1 S.NO 5).

Zhao et al. [29] proposed a normalized local centrality(NLC) measure based on two types of information, one is the influence feedback of the nearest neighbor nodes and other one is information about the nearest neighbor nodes. NLC is also focused on the calculation of the local clustering coefficient of nodes and influence of nearest neighbors. This measure captures the local centrality of a node and its local clustering coefficient. Based on the NLC, top 100 influential nodes considered as a seed nodes and compared their results with different basic centrality measures (see Table 1 S.NO 6). Zhao et al. [29] also proposed new local centrality measure based on a local centrality with coefficient which depend on topological connections between neighbors and information on neighbors. The experimental results shows that local centrality with coefficient gives better than various local centrality measures (see Table 1 S.NO 7).

2.3 Mixed Centrality Measures

If we defining local centrality measure then global behavior is ignored similarly vice versa. So recently many researcher showing an interest towards the defining the mixed centrality measures which mix up with local and global information of a node. Mixed centrality measures are defined as the combination of local and global centralities. Some of the mixed centrality measures studied which are mixed degree decomposition (MDD), k-shell decomposition and degree cluster coefficient etc.[28,31]. The mixed degree decomposition (MDD) method defined by Zeng et al.[31] to increase the exactness of k-shell.

Yang et al.[2], presented a novel mixed centrality measure which is consider as degree and clustering coefficient (DCC).DCC is defines based on four parts: effect of degree, neighbor's degree, clustering coefficient, and next level neighbor's clustering coefficient. The advantage of this mixed centrality measure is less time complexity which is O (nk^2) where n is number of node in the network and k is average degree. The simulation results shows DCC performs better (see Table 1 S.NO 8).

Sanjay et al. [3] proposed a coreness-based VoteRank method. It is called the NCVoteRank. To find spreaders by considering the coreness value of neighbors for the voting. Zhang et al.[32] introduced VoteRank centrality measure to find the seed nodes. It determines spreaders based on a voting scheme where the voting ability of each node is the same and each node gets the vote from its neighbors. But in NCVoteRank, the voting ability of each node should be different and depends on its topological position in the networks. The NCVoteRank centrality to find spreaders in four steps such as initialization phase, voting phase, update phase, and iteration phase. Time complexity for find the centrality measure for each node is linear time. They showed significant improvement compared to other centrality measured by setting the spreader nodes (see Table 1 S.NO 9).

Jinfang Sheng et al. [30] proposed a new method, called global and local structure (GLS), to find influential nodes. This method considers both local and global structures of the network. The local structures only focus on the nearest neighbor nodes but whereas the global structure is measured by its closeness to all nodes in the network. GLS can be divided into four steps. The first step belongs to constructing a network. In second step, whereas calculating the common nodes later calculate the number of the common nodes and then calculate the global influence. In third step, first, calculate the average degree of all neighbor nodes, next calculate the contribution probability of the neighbor node, and finally determine the local influence. Finally, the influence of each node on the whole network is calculated. The time complexity of the finding this measure is $O(n^2)$ where n is number nodes in the network. By using this measure, identifying the influential nodes more efficiently and accurately if it compared with closeness and betweenness centrality measures.

3. SIR MODEL

There are many explanatory models exists to study the information diffusion. These explanatory models aim is to examine the information diffusion process and discover the factors that affect it in an attempt to explain information diffusion. The information diffusion process can be considered in the same way as an epidemic spread process. In the compartment model of epidemics, the basic models are SI (Susceptible Infected) model, SIS (Susceptible Infected Susceptible) model, SIR (Susceptible Infected Recovered) model and SIRS (Susceptible Infected recovered Susceptible) models [13]. Information diffusion mainly depends on individual influence, community influence, and influence maximization. Recently many researchers have been investigated this information diffusion with these three type [35, 36, 37]. In predictive models, being able to accurately predict that information will be useful. In a social network, when a part of important information is circulated by an individual, the information will be spread quickly throughout the social network. Predictive models are used to find the future information diffusion process in social networks based on certain factors. These models are also used for influence maximization. They are the independent Cascade [38], the linear threshold model [39], and the game theory model [40].

Information diffusion has been an important subject area in social networks research in recent years. Although there have been many innovatory studies in this field, there are still some issues that need to be resolved. Some of those are competitive influence maximization, finding weak nodes, information diffusion based on sentiment or emotion and prediction of information diffusion for dynamic networks. SIR (susceptible-infected-recovered) model is a kind of compartmental model which is describing the dynamics of infectious disease. The SIR model is used to simulate not only spread of the virus but also information process. The SIR model [34] categorized the network nodes into susceptible nodes have no immunity from the disease. Infected nodes, which have the disease and can spread it to others and recovered nodes which have recovered from the disease and are immune to further infection. Figure 2 shows that three compartments.

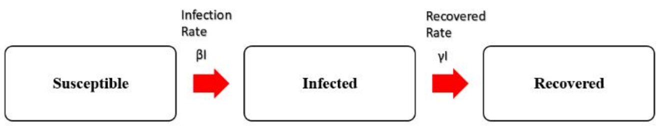

Figure 2. SIR (Susceptible-Infected-Recovered) Model

For evaluating the performance, the SIR model is using. By using the SIR model we can examine the spreading information and the number of infected nodes. Four real networks such as Romania, LastFM, Facebook and Email datasets are used to evaluate the performance by using SIR model. Initially a random node is taken to be infected node (influential node) by averaging over 100 implementations. The information propagation within the network according to SIR model shown in Figure 3.

We accessed four datasets from https://snap.stanford.edu/data/. Many researchers used this SIR model for testing the information diffusion by giving the initial seed nodes as top ranked nodes based their new centrality measures.

4. CONCLUSIONS AND DISCUSSIONS

Although no efficient algorithm for detecting influential nodes in the network, many researchers focused on different centrality measures to discover the influential nodes in the network. There are many approaches towards finding effective spreading influenced nodes bylocal, global and mixed centrality measures. These centrality measures mainly focused on how the node involved in connecting neighbors, distance from all other nodes, participation in shortest paths. There scope to focus on the new centrality measure or decomposition which concentrate on good connectivity with neighbors and good strength in the community so that it maximize the influence in the network. It is still open problem to give efficient algorithm to find this centrality measure. By using this centrality measure we can predict the influence of the network.

Many researchers focused on different centrality measures and decomposition methods to detect the influential nodes on static networks only. Many of the real world networks are dynamic networks it means network changes over time. Very few people have been working on this direction because finding centrality measure for every time stamp is an expensive. There is scope to work on dynamic networks with existing centrality measure or our new centrality measure. So that we can predict the influence maximization in the dynamic network [41].

This paper concentrated on some of the local centralities, global centralities and mixed centralities. Compare to degree, betweenness and closeness centralities, semi-local central performed better way. Local centralities are better than global centralities and mixed centralities combination of local and global centralities. In this paper from all of centralities, average shortest path performed well. The future work would focus on finding new centrality and combination of local and global structure. While reviewing literature we found many important papers and surveying the many important aspects of social networks. We survey recent methods for detecting influential nodes in network. SIR epidemic model is used for simulating the infection spreading process.

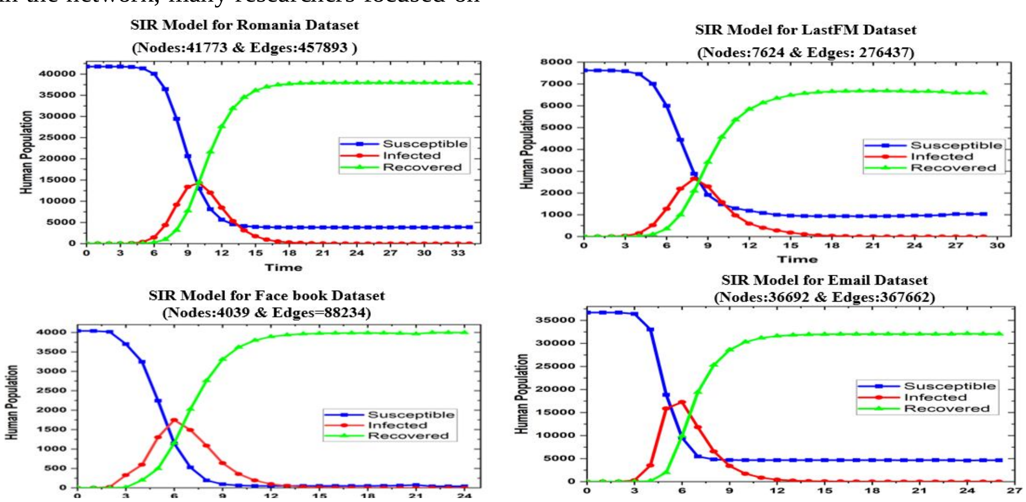

Figure 3: The cumulative number of infected nodes as a function of time by averaging over 100 simulations

REFERENCES

1. D. Chen, L. Lü, M. S. Shang, Y. C. Zhang, and T. Zhou, ***Identifying influential nodes in complex networks,*** *Phys. A Stat. Mech. its Appl.*, vol. 391, no. 4, pp. 1777–1787, 2012, doi: 10.1016/j.physa.2011.09.017.
2. Y. Yang, X. Wang, Y. Chen, M. Hu, and C. Ruan, ***A Novel Centrality of Influential Nodes Identification in Complex Networks,****IEEE Access*, vol. 8, pp. 58742–58751, 2020, doi: 10.1109/ACCESS.2020.2983053.
3. S. Kumar and B. S. Panda, ***Identifying influential nodes in Social Networks: Neighborhood Coreness based voting approach,****Phys. A Stat. Mech. its Appl.*, vol. 553, Sep. 2020, doi: 10.1016/j.physa.2020.124215.
4. Z. Lv, N. Zhao, F. Xiong, and N. Chen, ***A novel measure of identifying influential nodes in complex networks,*** *Phys. A Stat. Mech. its Appl.*, vol. 523, pp. 488–497, 2019, doi: 10.1016/j.physa.2019.01.136.
5. K. Musial, P. Bródka, and P. De Meo, ***Analysis and Applications of Complex Social Networks 2018,****Complexity*, vol. 2019, no. i, pp. 2–4, 2019, doi: 10.1155/2019/9082573.
6. X. Fu and K. Xu, ***Visualization and Analysis of Small-World Email Networks,*** pp. 2–3, 2007.
7. L. da F. Costa, F. A. Rodrigues, and A. S. Cristino, ***Complex networks: The key to systems biology,"****Genet. Mol. Biol.*, vol. 31, no.3, pp. 591–601, 2008, doi: 10.1590/S1415-47572008000400001.
8. Q. K. Telesford, S. L. Simpson, J. H. Burdette, S. Hayasaka, and P. J. Laurienti, ***The Brain as a Complex System: Using Network Science as a Tool for Understanding the Brain,****Brain Connect.*, vol. 1, no. 4, pp. 295–308, 2011, doi: 10.1089/brain.2011.0055.
9. W. Wang *et al.*, ***Analysis of the Chinese railway system as a complex network,*** *Chaos, Solitons and Fractals*, vol. 130, p. 109408, 2020, doi: 10.1016/j.chaos.2019.109408.
10. J. F. Donges, Y. Zou, N. Marwan, and J. Kurths, ***Complex networks in climate dynamics: Comparing linear and nonlinear network construction methods,****Eur. Phys. J. Spec. Top.*, vol. 174, no. 1, pp. 157–179, 2009, doi: 10.1140/epjst/e2009-01098-2.
11. J. Dai *et al.*, ***Identifying Influential Nodes in Complex Networks Based on Local Neighbor Contribution,****IEEE Access*, vol. 7, pp. 131719–131731, 2019, doi: 10.1109/ACCESS.2019.2939804.
12. Chang, Yi, Jiliang Tang, Dawei Yin, Makoto Yamada, and Yan Liu. ***Timeline Summarization from Social Media with Life Cycle Models.*** In IJCAI, pp. 3698-3704. 2016.
13. Guille, Adrien, Hakim Hacid, Cecile Favre, and Djamel A. Zighed. ***Information diffusion in online social networks: A survey.*** ACM Sigmod Record 42, no. 2 (2013): 17-28.
14. Milgram, Stanley. ***The small world problem."***Psychology today 2, no. 1 (1967): 60-67.
15. Malliaros, Fragkiskos D., Maria-Evgenia G. Rossi, and Michalis Vazirgiannis. ***Locating influential nodes in complex networks.*** Scientific reports 6, no. 1 (2016): 1-10.
16. S. Bhattacharya, K. Gaurav, and S. Ghosh, ***Viral marketing on social networks: An epidemiological perspective,****Phys. A Stat. Mech. its Appl.*, vol. 525, pp. 478–490, 2019, doi: 10.1016/j.physa.2019.03.008.
17. L. Udrescu *et al.*, ***Clustering drug-drug interaction networks with energy model layouts: Community analysis and drug repurposing,****Sci. Rep.*, vol. 6, no. August, pp. 1–10, 2016, doi: 10.1038/srep32745.
18. S. Ahajjam, M. El Haddad, and H. Badir, ***LeadersRank: Towards a new approach for community detection in social networks,*** in *Proceedings of IEEE/ACS International Conference on Computer Systems and Applications, AICCSA*, 2016, vol. 2016-July, doi: 10.1109/AICCSA.2015.7507215.
19. D. L. Hansen, B. Shneiderman, and M. A. Smith, ***Calculating and Visualizing Network Metrics,****Anal. Soc. Media Networks with NodeXL*,pp.69–78, 2011,doi:10.1016/b978-0-12-382229-1.00005-9.
20. L. C. Freeman, ***A Set of Measures of Centrality Based on Betweenness,****Sociometry*, vol. 40, no. 1, p. 35, 1977, doi: 10.2307/3033543.
21. S. P. Borgatti, ***Centrality and network flow,Soc. Networks,*** vol. 27, no. 1, pp. 55–71, 2005, doi: 10.1016/j.socnet.2004.11.008
22. J. Dong, F. Ye, W. Chen, and J. Wu, ***Identifying Influential Nodes in Complex Networks via Semi-Local Centrality,****Proc. - IEEE Int. Symp. Circuits Syst.*, vol. 2018-May, no. 978, 2018, doi: 10.1109/ISCAS.2018.8351889.
23. P. Cimiano, F. Frasincar, G. J. Houben, and D. Schwabe, Engineering the Web in the Big Data Era: 15th International Conference, ICWE 2015 Rotterdam, The Netherlands, June 23-26, 2015 Proceedings,*Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 9114, pp. 269–283, 2015, doi: 10.1007/978-3-319-19890-3.
24. J. Zhao, Y. Wang, and Y. Deng, ***Identifying influential nodes in complex networks from global perspective,****Chaos, Solitons and Fractals*, vol. 133, 2020, doi: 10.1016/j.chaos.2020.109637.
25. M. D. Humphries and K. Gurney, ***Network 'small-world-ness': A quantitative method for determining canonical network equivalence,****PLoS One*, vol. 3, no. 4, 2008, doi: 10.1371/journal.pone.0002051.
26. T. L. Frantz, M. Cataldo, and K. M. Carley, ***Robustness of centrality measures under uncertainty: Examining the role of network***

topology,*Comput. Math. Organ. Theory*, vol. 15, no. 4, pp. 303–328, 2009, doi: 10.1007/s10588-009-9063-5.

27. S. Kumar, ***Analyzing the Facebook workload,****Proc. - 2012 IEEE Int. Symp. Workload Charact. IISWC 2012*, pp. 111–112, 2012, doi: 10.1109/IISWC.2012.6402911.
28. K. Berahmand, A. Bouyer, and N. Samadi, ***A new centrality measure based on the negative and positive effects of clustering coefficient for identifying influential spreaders in complex networks,****Chaos, Solitons and Fractals*, vol. 110, pp. 41–54, 2018, doi: 10.1016/j.chaos.2018.03.014.
29. X. Zhao, F. Liu, S. Xing, and Q. Wang, ***Identifying influential spreaders in social networks via normalized local structure attributes,*** *IEEE Access*, vol. 6, pp. 66095–66104, 2018, doi: 10.1109/ACCESS.2018.2879116.
30. J. Sheng *et al.*, ***Identifying influential nodes in complex networks based on global and local structure,****Phys. A Stat. Mech. its Appl.*, vol. 541, no. xxxx, p. 123262, 2020, doi: 10.1016/j.physa.2019.123262.
31. A. Zeng and C. J. Zhang, ***Ranking spreaders by decomposing complex networks,*** *Phys. Lett. Sect. A Gen. At. Solid State Phys.*, vol. 377, no. 14, pp. 1031–1035, 2013, doi: 10.1016/j.physleta.2013.02.039.
32. J. X. Zhang, D. B. Chen, Q. Dong, and Z. D. Zhao, ***Identifying a set of influential spreaders in complex networks,*** *Sci. Rep.*, vol. 6, no. May, pp. 1–10, 2016, doi: 10.1038/srep27823.
33. [33] X. Zhao, F. Liu, J. Wang, and T. Li, ***Evaluating influential nodes in social networks by local centrality with a coefficient,****ISPRS Int. J. Geo-Information*, vol. 6, no. 2, 2017, doi: 10.3390/ijgi6020035.
34. C. Xia, Z. Liu, S. Sun, L. Wang, and Z. Chen, ***An sir epidemic model with cleared state in complex networks,*** *ICIC Express Lett.*, vol. 5, no. 9 A, 2011.
35. Ullah, Farman, and Sungchang Lee. ***Identification of influential nodes based on temporal-aware modeling of multi-hop neighbor interactions for influence spread maximization.*** Physica A: Statistical Mechanics and its Applications 486 (2017): 968-985.
36. Sheikhahmadi, Amir, Mohammad Ali Nematbakhsh, and Ahmad Zareie. ***Identification of influential users by neighbors in online social networks.***Physica A: Statistical Mechanics and its Applications 486 (2017): 517-534.
37. Li, Hui, Sourav S. Bhowmick, Jiangtao Cui, Yunjun Gao, and Jianfeng Ma. ***Getreal: Towards realistic selection of influence maximization strategies in competitive networks.***In Proceedings of the 2015 ACM SIGMOD international conference on management of data, pp. 1525-1537. 2015.
38. Zhu, Tian, Bai Wang, Bin Wu, and Chuanxi Zhu. ***Maximizing the spread of influence ranking in social networks.*** Information Sciences 278 (2014): 535-544.
39. Hao, Chen, and Wang Yitong. ***Threshold-based heuristic algorithm for influence maximization.*** Journal of Computer Research and Development 49, no. 10 (2012): 2181.
40. Wang, Y. Z., Jian-Ye Yu, W. Qu, H. Shen, X. Cheng, and C. Lin. ***Evolutionary game model and analysis methods for network group behavior.***Chinese Journal of Computers 38, no. 2 (2015): 282-300.
41. Taj, R. Moulay, Z. Ait El Mouden, AbdeslamJakimi, and MohaHajar. ***Towards Using Recurrent Neural Network for Predicting Influenza-Like Illness: Case Study of Covid-19 in Morocco.*** International Journal of Advanced Trends in Computer Science and Engineering 9, no. 5 (2020).