



## Node Importance Evaluation Algorithm Combining Local and Global Information

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**Abstract:** Node importance evaluation is an important direction of social network research. Ranking influential nodes in social networks is of great theoretical and practical significance to further identify the most influential nodes and understand the network structure. A node importance evaluation algorithm is proposed in this paper, which combines local (degree centrality) and global (position information) information with entropy method. We calculate the distance between nodes and the local core node set as position information. Then, we take into account the influence of the node itself and that of neighbor nodes as the final importance of the node. The results show that the proposed method is effective in comparison experiment in three aspects: monotonicity, correctness and efficiency.

**Keywords:** social networks, node importance, global property, local property

### 1. INTRODUCTION

With the rapid development of Internet information technology, the exchanges between people is increasingly networked. Social networking tools such as Twitter and Facebook penetrate into every aspect of people's lives, outlining social networks of all sizes. In reality, each of us is in one network after another: a circle of friends on social networking sites such as Facebook; research collaboration and paper citation networks in academia; a circle of interests among like-minded friends; and social networks among classmates and friends. With the passage of time, the structure of social networks is becoming more and more complex. There is unknown potential value in the social networks that from these daily communication. The study of social networks has always been an important topic of complex network research. Complex networks have scale-free and small-world characteristics, which also makes some nodes in the network failure may lead to the collapse of the entire network, or even affect the overall situation, we call these nodes as important nodes. Therefore, how to evaluate the importance of nodes in social networks, and how to quickly mine the important nodes in the network has been a hot topic of social network research.

The existing methods for measuring the importance of nodes in social networks can be divided into algorithms based on local attributes, global attributes, random walk and community structure[1]. Degree centrality is the simplest and most common algorithm based on local attributes. The degree of a node represents the number of nodes connected with the node. It can directly reflect the local importance of the node, but it can not well reflect the situation of the node in the whole network. For example, the more fans a Facebook user owns, the more important he or she is in the social circle. Chen et al. put forward the local centrality[2], which considers the degree information of the node itself and its neighbors as the importance of the node. Local clustering coefficient [3] refers to the actual number of edges and neighborhood nodes between neighbors of a node. The ratio of the possible maximum number of edges between points can be used to measure the degree of close ties between neighboring nodes. Many scholars have also improved the clustering coefficient to evaluate the importance of nodes. Measurements based on global attributes include betweenness centrality[4], closeness centrality[5], eigenvector centrality [6], etc. Such algorithms have relatively high time complexity and are not suitable for large-scale networks; Kitsak et al.[7] proposed K-shell

decomposition algorithm, peeling the outer nodes from the edge nodes to the core nodes in turn, and dividing the network nodes into different levels. For the K-shell algorithm can not distinguish the nodes in the same layer, Bea et al. [8], Zeng et al. [9] and Wang et al.[10,11] make corresponding improvements to distinguish the nodes in the same layer. Random walk algorithm mainly includes PageRank [12], HITS [13] and LeaderRank [14]. The algorithm of structural hole properties proposed by Burt et al. [15] is a metric algorithm based on community structure. In recent years, Lü et al. [16] introduced H-index into social networks. A node's H-index means that it has at least h neighbors whose degree is greater than or equal to H. It perfectly proves the delicate relationship among the three node importance metrics (degree, H index and kernel number).

Based on the degree centrality, this paper finds the local core node set in accordance with the degree, then deletes the nodes from the core node in turn until all nodes are deleted, and gets the distance between the nodes to the core node as position information. Through a large number of experiments and comparisons with existing methods, it is easy to see that the proposed method has a significant effect on node importance assessment.

**2. RELATED WORK**

**2.1. Node Importance Assessment**

Node importance assessment is to calculate the importance of all nodes in the network. The research on node importance has been a hot topic in social networks. Early classical sorting algorithms for node importance generally calculate the centrality index of nodes from a single attribute to measure the importance of nodes. In recent years, a lot of methods combining different centrality have been proposed to evaluate the importance of nodes.

**Degree Centrality**

The degree of the node indicates the number of nodes connected with the node, which can directly reflect the local importance of the node, but can not well reflect the situation of the node in the whole network. The degree centrality can directly reflect the direct influence of one node on other nodes of the network.

$$DC_{(i)} = |\Gamma_{(i)}| = \sum_{j \in \Gamma_{(i)}} A_{ij} \tag{1}$$

A is the adjacency matrix of the network G , and  $\Gamma_{(i)}$  is the neighbor node set of node  $v_{(i)}$  .

**Betweenness Centrality**

The betweenness of a node refers to the number of shortest paths through the node in the network. Betweenness centrality[4] defined as follows:

$$BC_{(i)} = \sum_{i \neq s \neq t} \frac{\sigma_{st(i)}}{\sigma_{st}} \tag{2}$$

$\sigma_{st}$  is the number of shortest paths between node  $v_{(s)}$  and node  $v_{(t)}$  , and  $\sigma_{st(i)}$  is the number of shortest paths that pass through the node  $v_{(i)}$  between node  $v_{(s)}$  and node  $v_{(t)}$  .

**Closeness Centrality**

The closeness centrality [5] can be seen as node in the whole network information dissemination to the farthest extent of other nodes, and the greater the node tightness, the closer the node is to the center of the network. The closeness centrality of node  $v_{(i)}$  is calculated as:

$$CC_{(i)} = \frac{n-1}{\sum_{j=1}^n d_{(ij)}} \tag{3}$$

$d_{(ij)}$  is the shortest distance between node  $v_{(i)}$  and node  $v_{(j)}$ , and the time complexity of closeness centrality is  $O(n^3)$ .

**K-shell**

Kitsak et al.[7] proposed a K-shell decomposition algorithm, which removes the outer nodes from the edge nodes to the core nodes, and divides the nodes into different layers. The closer the nodes are to the core, the more important they are. Aiming at the problem that K-shell algorithm cannot distinguish nodes at the same level, Bea et al.[8], Zeng et al. [9] and Wang et al.[10,11]make corresponding improvements to distinguish nodes at the same level.

**Mixed Degree Decomposition (MDD)**

K-shell algorithm only considers the residual degree, but ignores the information of neighbors removed. Zeng et al. [9] proposed a mixed degree decomposition algorithm (MDD) taking into account the residual degree and the information of the removed nodes in each step of K-shell decomposition.

$$MDD_{(i)} = d_r + \lambda d_e \tag{4}$$

$d_r$  is the residual degree of node  $v_{(i)}$ , and  $d_e$  refers to the degree information of the removed node.  $\lambda$  is used to adjust the parameters. When  $\lambda=1$ , it represents the degree of the node. When  $\lambda=0$ , it represents the K-shell value. Zeng and others found that  $\lambda=0.7$  had the best effect.

**Coreness Centrality**

Cnc algorithm regards the sum of K-shell values of neighboring nodes as the importance of nodes, while Cnc+ regards the sum of Cnc values of neighboring nodes as the importance of nodes [17].

$$Cnc_{(i)} = \sum_{j \in \Gamma_{(i)}} KS_{(j)} \tag{5}$$

$$Cnc+_{(i)} = \sum_{j \in \Gamma_{(i)}} Cnc_{(j)} \tag{6}$$

$KS_{(j)}$  represents the K-shell value of node  $v_{(j)}$ , and  $\Gamma_{(i)}$  is the neighbor node set of node  $v_{(i)}$ .

**2.2. Entropy Method**

Entropy method is a method to determine the weights of evaluation indexes according to information entropy. In information theory, entropy represents a measure of the degree of disorder of the system, which is called information entropy. The smaller the information entropy is, the greater the amount of information the index can provide, the higher the importance of the index in the system, and the greater the corresponding weight. When using information entropy to calculate index weight, one of the determinants of correct evaluation is how much information is obtained from the system. Therefore, we can determine the importance of different indicators to the system evaluation by analyzing the entropy weight of different indicators, and obtain an objective and comprehensive evaluation.

If there are  $m$  evaluation index and  $n$  evaluation object, corresponding to the node importance evaluation algorithm namely  $m$  evaluation methods and  $n$  nodes can be constructed, the original evaluation matrix of  $Y$  :

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \tag{7}$$

The information entropy of group  $i$  is  $E_i$  :

$$E_i = -\frac{1}{\ln(n)} \sum_{j=1}^n p_{ij} \ln(p_{ij}) \quad i=1,2,3 \dots m \quad (8)$$

In the formula,  $p_{ij} = y_{ij} / \sum_{j=1}^n y_{ij}$ , if  $p_{ij} = 0$ , then define  $\lim_{p_{ij} \rightarrow 0} p_{ij} \ln p_{ij} = 0$ , The smaller the  $E_i$  is, the greater the weight of the evaluation system will be. Then according to entropy  $E_i$ , we get the weight  $w_i$  of index  $i$ :

$$w_i = \frac{1 - E_i}{m - \sum_{i=1}^m E_i} \quad i=1,2,3 \dots m \quad (9)$$

$$0 \leq w_i \leq 1, \sum_{i=1}^m w_i = 1.$$

### 3. METHODS

Degree centrality is the simplest and most direct evaluation centrality method. The degree of node can be expressed as the number of nodes directly connected with the node, which can directly reflect the influence of a node on neighboring nodes. The importance of a node in a social network depends not only on its own influence, but also on the influence of its neighbors, or the dependence of the neighbors on the node. In this paper, anode importance evaluation algorithm based on local influence and global position information is proposed, which makes up for the defect that degree centrality only has the local influence and improves the discrimination to a certain extent.

**Definition 1** Given a network  $G$ , node  $v_{(i)} \in G$ , the position information of node in the network is defined as  $P$ , and the value of  $P$  represents the distance between the node and the local core node set.

Firstly, according to the degree to find the local core node set, and position information  $P_1=n$  of the core node set is set. The node in the core node set is deleted and the neighbor node (in the remaining nodes) is given  $P_2=P_1-1$ . Then, remove the nodes whose position information is  $P_2$ , until all nodes are deleted. By deleting nodes in this order, we get the distance between all nodes from the local core node set.

**Definition 2** Given a network  $G$ , node  $v_{(i)} \in G$ , in accordance with the degree information and position information of node  $v_{(i)}$  to calculate the  $PD$  by entropy method, and the formula as follows:

$$PD_{(i)} = w_1 \times D_{(i)} + w_2 \times P_{(i)} \quad (10)$$

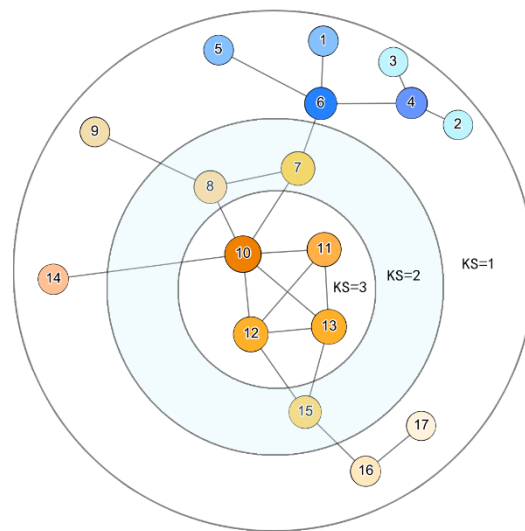
**Definition 3** Given a network  $G$ , node  $v_{(i)} \in G$ , the final importance of node is defined as the sum of its own influence and the indirect influence of neighbor nodes.

$$LG_{(i)} = PD_{(i)} + \sum_{j \in \Gamma_{(i)}} PD_{(j)} \quad (11)$$

In the formula,  $\Gamma_{(i)}$  is the neighbor node set of node  $v_{(i)}$ .  $PD_{(i)}$  is the  $PD$  value of node  $v_{(j)}$ , which is based on degree and position information.  $LG$  is the sum of its own influence and the indirect influence of its neighbor nodes. The degree of a node is the number of nodes connected to the node that takes the influence of neighboring nodes as equal, but the influence of neighboring nodes is different in reality. In this paper, considering the influence of neighboring nodes, the entropy method is used to calculate the sum of local (degree centrality) and global (position information) information as the influence of neighboring nodes, and the sum of the  $PD$  value of neighbor nodes and the  $PD$  value of the node itself as the final importance of the current node, named  $LG$ .

The main idea of the algorithm is as follows:

- 1) Calculate the degree centrality of all nodes.
- 2) Find local core node set based on degree, and set node position information  $P_1=n$ .
- 3) Remove the core node set, and give its neighbor nodes (in the remaining nodes) location information  $P_2=P_1-1$ .
- 4) From the inside to the outside, delete nodes with  $P$  values in the remaining nodes in turn, and give the neighbor nodes (in the remaining nodes) position information  $P$  minus 1,  $P$  minus 1 in each deleted layer until all nodes are deleted.
- 5) Calculate the degree and position information obtained a new evaluation index  $PD$  by entropy method.
- 6) Calculate  $LG$ , the sum of the  $PD$  value of the node and that of its neighbor nodes, as the final importance of the current node.



**Fig1.**The analysis diagram on a schematic network

In order to verify the validity of the  $LG$  algorithm proposed in this paper, a discrimination comparison experiment is conducted on the schematic network shown in Figure1. The network consists of 17 nodes and 21 edges. We use Degree centrality(DC), Betweenness centrality(BC), Closeness centrality(CC), K-shell(KS), Mixed degree decomposition(MDD), Coreness centrality(Cnc+) and our LG algorithm to do the sorting experiments of node importance, and the sorting results are shown in Table 1. As can be seen from Table 1, the proposed algorithm in this paper is slightly superior to MDD, Cnc+ and other algorithms in the classical network.

**Table1.** Ranking of different methods in schematic networks

Rank	KS	DC	BC	CC	MDD	Cnc+	LG
1	10,11,12,13	10	10	10	10	10	10
2	7, 8, 15	6,12,13	6	7	12,13	12,13	12,13
3	others	4,7,8,11,15	7	6,8	11	11	11
4	-	16	4	12,13	6	7,15	7
5	-	others	15	11	7,8,15	8	8
6	-		12,13	14	4	14	15
7	-		8,16	4,15	16	6	6
8	-		others	1,5,9	others	16	4
9	-			16		4	14
10	-			2,3		9	16
11	-			17		1,5	1,5
12	-					2,3,17	2,3,9
13	-						17

## 4. EXPERIMENTAL RESULTS

### 4.1. Evaluation Methods

The ranking results can be evaluated by the monotonicity, which describes the discriminability of a ranking method in the influence capability evaluation. When there are large number of nodes in the network, it is impossible to analyze and compare each node as above, while the monotonicity can be used to calculate the discrimination ability of the algorithm. In the sorting algorithm, an effective sorting method can distinguish all nodes, that is each node can be given different importance. The monotonicity metric  $M$  [6,10] is defined as follows:

$$M_{(R)} = \left( 1 - \frac{\sum_{r \in R} n_r \times (n_r - 1)}{n \times (n - 1)} \right)^2 \tag{12}$$

In the formula,  $n$  is the number of network nodes;  $R$  is the ranking result,  $r$  is the ranking in  $R$ ,  $n_r$  is the number of nodes ranked as  $r$  in the ranking result. The value range of  $M$  is  $M \in [0,1]$ . When  $M=0$ , i. e.  $n_r=n$ , all nodes have the same ranking, and the ranking result is the worst; when  $M=1$ , the ranking of each node is different, and the ranking effect is the best.

In this paper, Susceptible-Infected-Recovered (SIR) mode [9,11] is used to compare the accuracy, we take 20 infection rates  $\beta$  ( $\beta \in [0.01, 0.20]$ ) in the experimental process. In order in the experimental process. In order to reduce the randomness, we calculate the average of each node after 1000 infections (some large network 100 infections) as the value of node propagation influence. The  $\tau$  metric is used to calculate the similarity between the ranking results obtained by the method and those obtained by the SIR model. The experimental elements are the same in different methods, but the sorting results may be different, which meets the requirements of Kendall's tau correlation coefficient [18]. For example, there are two sorting results:  $R_1$  and  $R_2$ ,  $R_1=(x_1, x_2, x_3 \cdots x_n)$ ,  $R_2=(y_1, y_2, y_3 \cdots y_n)$ . For any  $(x_i, x_j)$  and  $(y_i, y_j)$ , if  $x_i > x_j$  and  $y_i > y_j$ , or  $x_i < x_j$  and  $y_i < y_j$ , then the pair is said to be concordant (named  $n_c$ ), otherwise they are discordant node pairs (named  $n_d$ ). The  $\tau$  metric is defined as follows:

$$\tau(R_1, R_2) = \frac{2 \times (n_c - n_d)}{n \times (n - 1)} \tag{13}$$

$n$  is the number of network nodes, using  $\tau$  metric to calculate the correlation coefficient between each sorting method and SIR results to compare the validity and accuracy of the sorting method.

### 4.2. Analysis of Real Network Experiments

Several real networks with different scales are used to evaluate the performance of different ranking methods, including Karate club network (Karate) [19], Dolphin social network (Dolphin), Relationship-patterns (Relationship) [20], Coauthorship network of scientists (Netscience) [21], Jazz musicians network (Jazz), Prison, C. elegans metabolic network (Celegan), E-mail [23], Communication network of Blogs (Blogs) [22], User network of Pretty-Good-Privacy algorithm (PGP) [11]. The comparison algorithm includes Degree centrality (DC), Betweenness centrality (BC), Closeness centrality (CC), K-shell (KS), Mixed degree decomposition (MDD), Coreness centrality (Cnc+) and algorithm based local and global information (LG).

As shown in Table 2, we compare the divisions of different methods in networks of different sizes. As can be seen from the data in the table, the method in this paper has obvious advantages, except Football, Celegan, Power Grid network slightly inferior to other methods. Compared with other methods, the discrimination is greater than or equal to several other methods in most network.

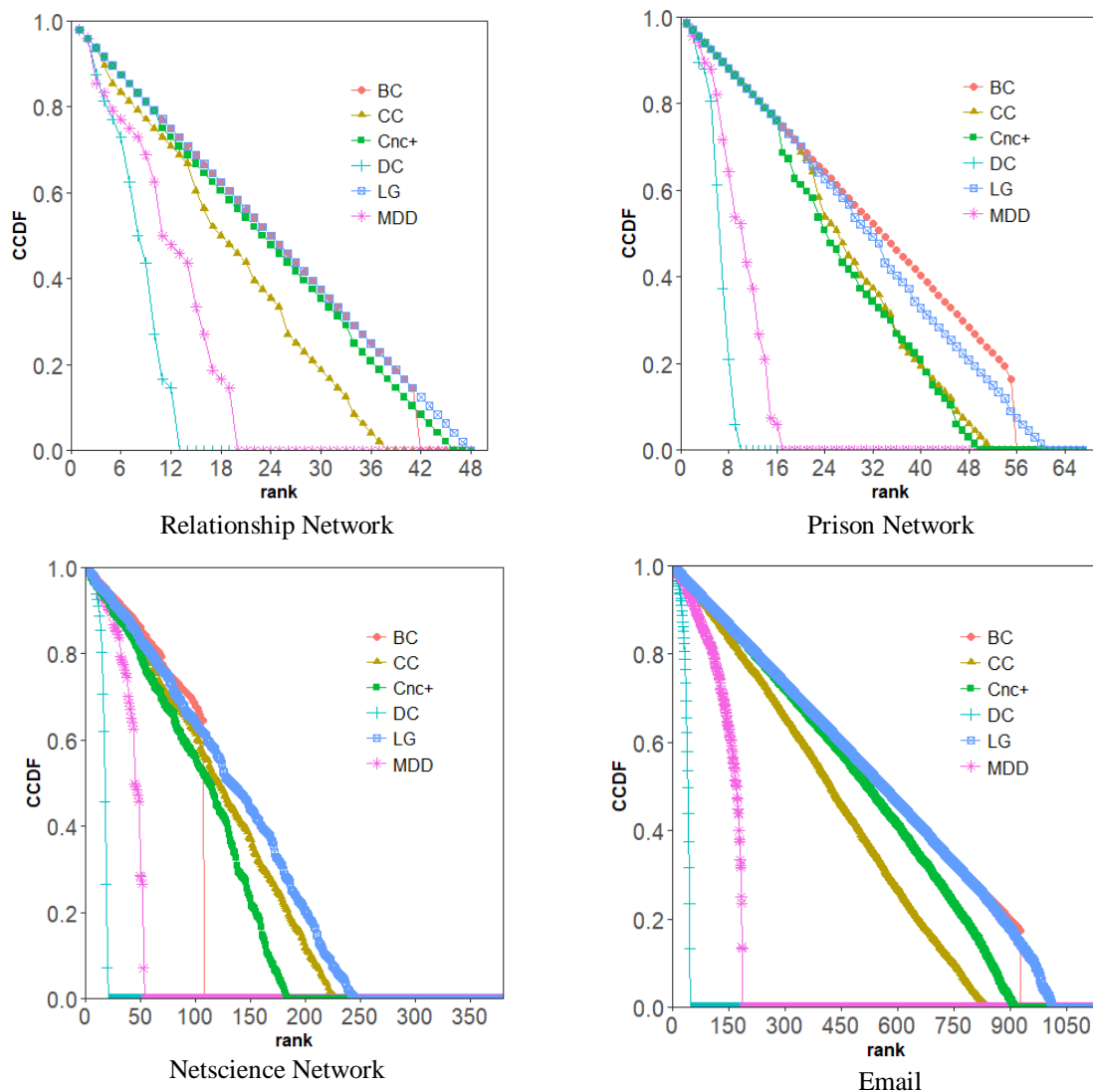
**Table 2.** The monotonicity performance of different ranking methods on real networks

Network	n	m	M(DC)	M(BC)	M(CC)	M(KS)	M(MDD)	M(Cnc+)	M(LG)
<b>Karate Club</b>	34	78	0.7079	0.7723	0.8993	0.4958	0.7536	0.9472	<b>0.9542</b>
<b>Dolphins</b>	62	159	0.8312	0.9623	0.9737	0.3769	0.9041	0.9873	<b>0.9926</b>
<b>Relationship</b>	48	149	0.8338	0.9631	0.9788	0.4794	0.8797	0.9965	<b>1.0000</b>



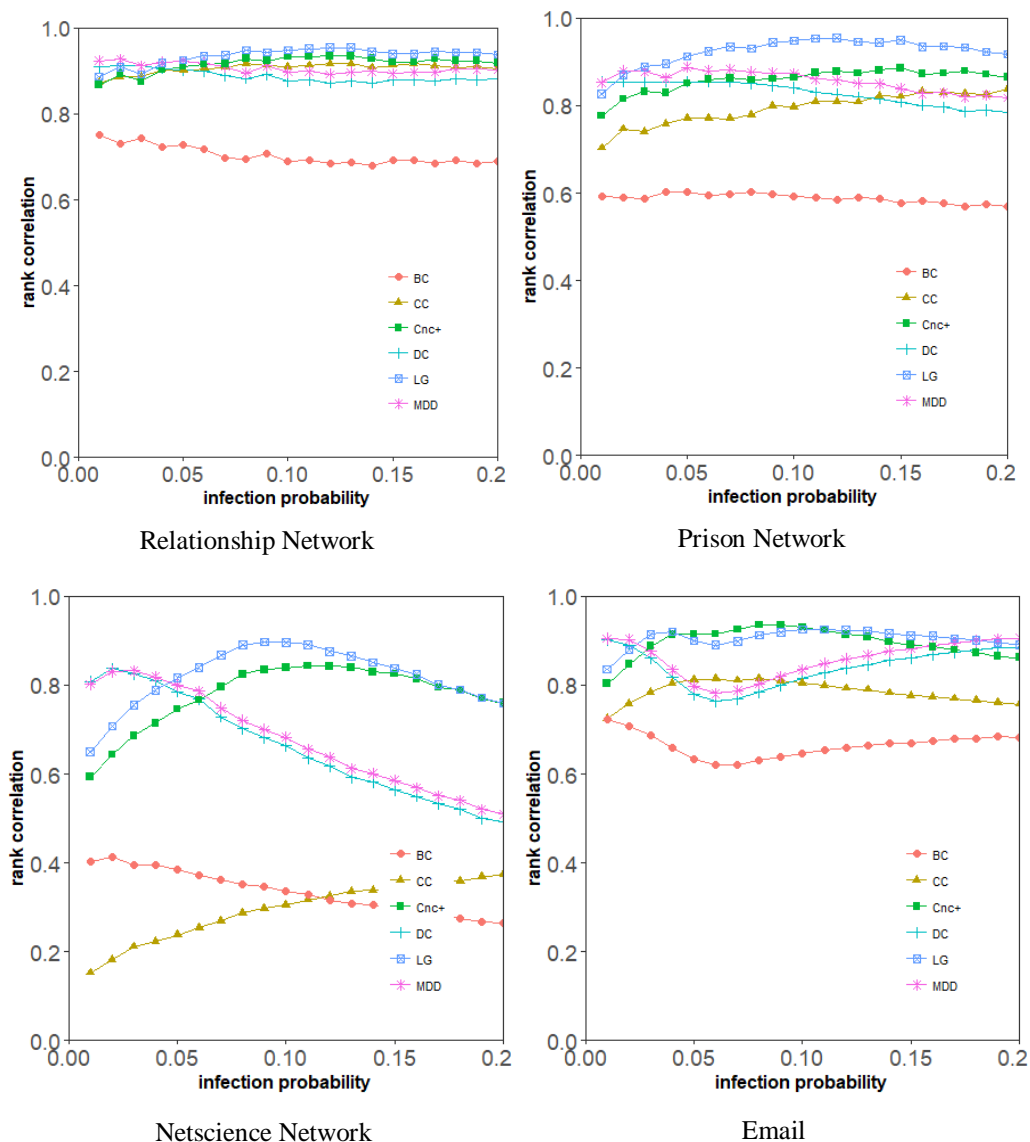
<b>Prison</b>	67	182	0.7307	0.9500	0.9820	0.3070	0.8672	0.9766	<b>0.9919</b>
<b>Book</b>	105	441	0.8252	0.9974	0.9847	0.4949	0.9077	0.9971	<b>0.9996</b>
<b>Football</b>	115	613	0.3637	<b>1.0000</b>	0.9488	0.0003	0.6089	0.9604	<b>0.9848</b>
<b>Jazz</b>	198	2742	0.9659	0.9885	0.9878	0.7944	0.9882	<b>0.9993</b>	<b>0.9993</b>
<b>Celegan</b>	379	914	0.7918	0.8738	0.9900	0.6964	0.8765	<b>0.9975</b>	<b>0.9966</b>
<b>NetScience</b>	453	2025	0.7642	0.3387	<b>0.9928</b>	0.6421	0.8215	0.9893	<b>0.9928</b>
<b>Email</b>	1133	10903	0.8874	0.9400	0.9988	0.8088	0.9229	0.9991	<b>0.9992</b>
<b>Blogs</b>	1490	16718	0.9329	0.9489	0.9980	0.9062	0.9449	<b>0.9992</b>	<b>0.9992</b>
<b>Power Grid</b>	4941	6594	0.5927	0.8313	<b>0.9998</b>	0.2460	0.6928	0.9419	<b>0.9857</b>
<b>PGP</b>	10680	24 316	0.6193	0.5099	<b>0.9996</b>	0.4806	0.6678	0.9851	<b>0.9946</b>

The Complementary Cumulative Distribution Function (CCDF) is plotted based on the Relationship, Prison, Netscience, and Email networks. In Figure 2, the distribution of the ranking results of the methods in different networks is shown. The slower the curve falls in the graph, the better the ranking result is. It can be seen from the figure that the Degree centrality (DC) and MDD methods are the worst in each network, followed by CC, Cnc+, BC. The method LG, proposed in this paper, is effective in distribution, and can distinguish most nodes in the network, especially In the Relationship, Netscience network.



**Fig2.** The Complementary Cumulative Distribution Function (CCDF) plots for ranking list offered by different measures on different networks

The SIR model was used to evaluate the accuracy of node ranking results in the Relationship, Prison, Netscience, and Email networks. In the experiment, the infection rate  $\beta$  ( $\beta \in [0.01, 0.20]$ ) was set to test, and compared the correlation of each method with the SIR model results when the infection rate was different. The result is shown in Figure 3.



**Fig3.** The rank correlation results of different ranking methods on four real networks

As can be seen from Figure 3, the algorithm in this paper is superior to other methods in Relation and Prison networks. On Netscience network, the accuracy is lower than degree centrality and MDD in low infection rate, and superior to all other algorithms in high infection rate stage. On Email networks, the results are basically consistent with the results of Cnc+ algorithm in most of the infection. Therefore, this method is effective in accuracy.

### 4.3. Analysis of Artificial Network Experiments

In this paper, the LFR artificial network generator is used to set parameters to randomly generate networks of different structures, such as the number of nodes  $n = 1000$ , the average degree  $\langle k \rangle = 10$ , the maximum degree  $k_{max} = 50$ , the power-law distribution coefficient  $\lambda = 2$ , and the mixing degree coefficient  $\mu = 0.2$ . As shown in the Figure 4, we change the parameters to compare in this paper. In the respects of discrimination, CC and the method we proposed in this paper are very little affected by the parameters of fluctuation, close to 1, indicating that its ability to distinguish nodes is very good, in



the power-law distribution coefficient is better than other methods. The Degree centrality and the MDD algorithm are not effective and affected by the network structure more easily.

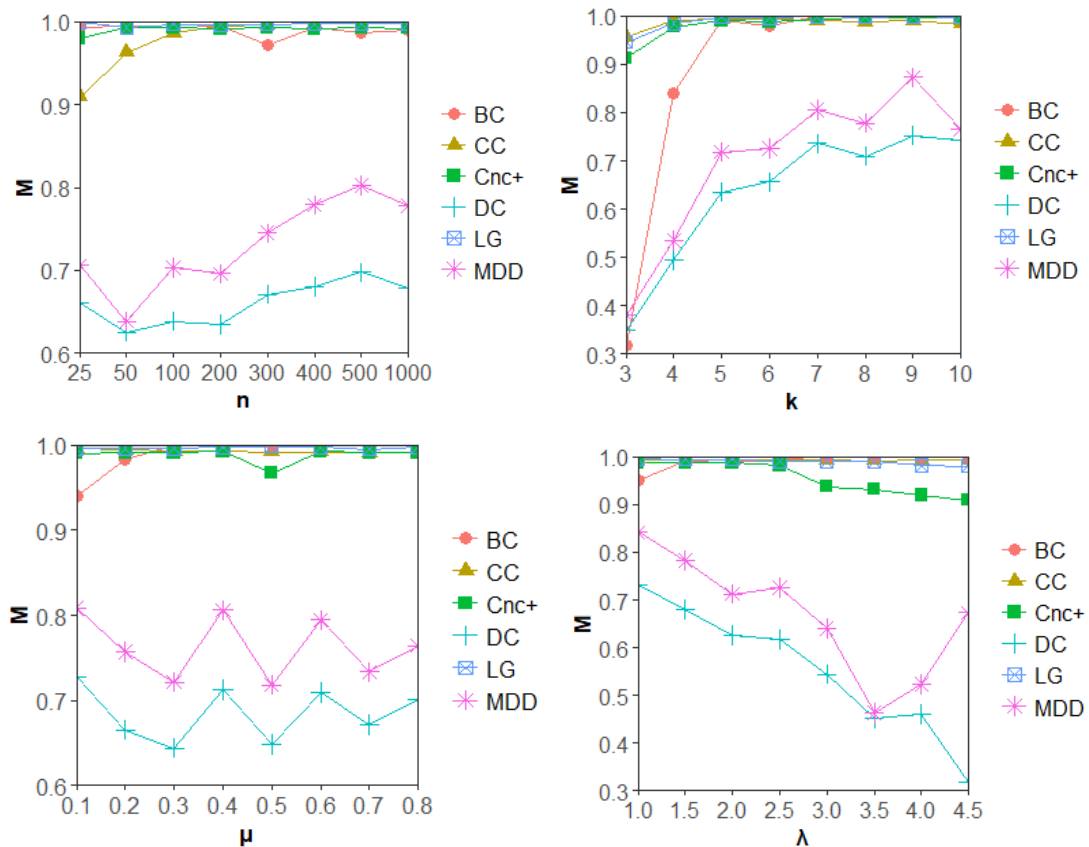


Fig4. The monotonicity of different measures on LFR networks

We compare and analyze the impact of different network structures on algorithm results by changing average degree and power-law distribution coefficient. As shown in Figure 5, with the increase of averaging degree, the change trend of accuracy of our method is the same as that of Cnc+ algorithm. With the increase of average degree, LG algorithm gradually shows advantages. For example, when  $\langle k \rangle = 15$ , this method is superior to that of Cnc+ algorithm.

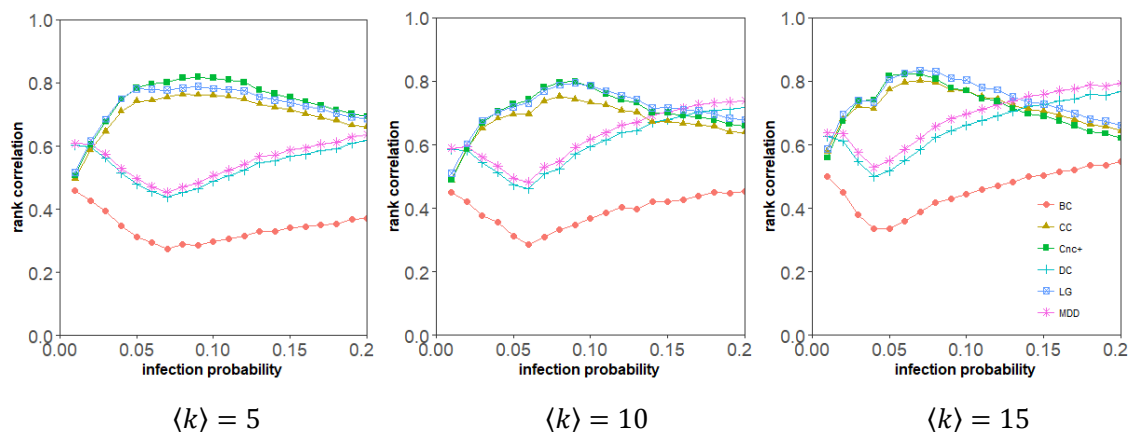
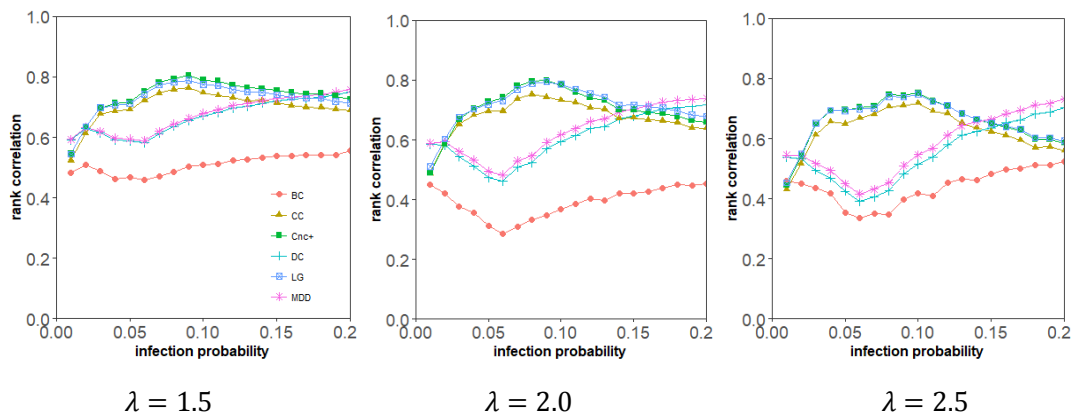


Fig5. The correctness of different measures on LFR networks with different average degree



**Fig6.** The correctness of different measures on LFR networks with different power-law distribution coefficient

As shown in Figure 6, the correctness of each method is compared when the power-law distribution coefficient is changed. With the increase of the power-law distribution coefficient, the accuracy of each method tends to decrease. The general trend of our method does not change much with the increase of the distribution coefficient, indicating that this method is less affected by the power-law distribution coefficient.

#### 4.4. Efficiency and Complexity Analysis

The Programming language and experimental environment of the algorithm will have some influence on the statistics of time efficiency. According to the idea of this algorithm, the time complexity of calculating node degree is  $O(n)$ , the time complexity of searching core node set is  $O(n)$ , and the time complexity of comprehensive index of settlement influence by entropy method is  $O(n)$ . Therefore, the total time complexity of this algorithm is  $O(n)$ . The time complexity of each method is shown in Table 3.

**Table3.** Time complexity of each algorithm

Algorithm	DC	BC	CC	KS	MDD	Cnc+	LG
Time Complexity	$O(n)$	$O(n^3)$	$O(n^3)$	$O(n)$	$O(n)$	$O(n)$	$O(n)$

### 5. CONCLUSIONS

From the experimental results, we can see that in most networks, the method we proposed in this paper is obviously better than other algorithms we compared with. In this paper, degree centrality and position information are combined by entropy method, and we consider not only the local information of the node itself, but also the global attributes such as the distance between the node and the local core node set. Experiments on real networks and artificial networks show that the proposed method has the advantages of distinguishability and accuracy, and is less affected by the variation of network structure.

### REFERENCES

- [1] Han ZM, Chen Y, Liu W, Yuan BH, Li MQ, Duan DG. Research on node influence analysis in social networks. Ruan Jian Xue Bao / Journal of Software, 2017, 28(1):84–104
- [2] Duanbing Chen, Linyuan Lu, Ming-Sheng Shang, Yi-Cheng Zhang, Tao Zhou, Identifying influential nodes in complex networks, Physica A 391(2012) 1777–1787.
- [3] A.L Barabási, H Jeong, Z Néda, et al. Evolution of the social network of scientific collaborations[J]. Physica A Statistical Mechanics & Its Applications, 2015, 311(3):590-614.
- [4] Freeman L C. Centrality in social networks conceptual clarification[J]. Social Networks, 1978, 1(3):215-239.
- [5] Sabidussi G. The centrality index of a graph[J]. Psychometrika, 1966, 31(4):581-603.
- [6] Lü L, Chen D, Ren X L, et al. Vital nodes identification in complex networks[J]. Physics Reports, 2016, 650:1-63.
- [7] Kitsak M, Gallos L K, Havlin S, et al. Identification of influential spreaders in complex networks[J]. Nature Physics, 2011, 6(11):888-893.
- [8] Bae J, Kim S. Identifying and ranking influential spreaders in complex networks by neighborhood coreness[J]. Physica A Statistical Mechanics & Its Applications, 2014, 395(4):549-559.

- [9] Zeng A, Zhang C J. Ranking spreaders by decomposing complex networks[J]. *Physics Letters A*, 2013, 377(14):1031-1035.
- [10] Wang Z, Zhao Y, Xi J, et al. Fast ranking influential nodes in complex networks using a k-shell iteration factor[J]. *Physica A Statistical Mechanics & Its Applications*, 2016, 461:171-181.
- [11] Wang Z, Du C, Fan J, et al. Ranking influential nodes in social networks based on node position and neighborhood[J]. *Neurocomputing*, 2017.
- [12] Brin S, Page L. The anatomy of a large-scale hypertextual Web search engine ☆[C]// *International Conference on World Wide Web*. Elsevier Science Publishers B. V. 1998:107-117.
- [13] Kleinberg J M. Authoritative sources in a hyperlinked environment[J]. *Journal of the Acm*, 1999, 46(5):604-632.
- [14] Lü L, Zhang Y C, Chi H Y, et al. Leaders in Social Networks, the Delicious Case[J]. *Plos One*, 2011, 6(6):e21202.
- [15] Burt R S, Kilduff M, Tasselli S. Social Network Analysis: Foundations and Frontiers on Advantage[J]. *Annual Review of Psychology*, 2013, 64(1):527-547.
- [16] Lü L, Zhou T, Zhang Q M, et al. The H-index of a network node and its relation to degree and coreness[J]. *Nature Communications*, 2016, 7:10168.
- [17] Bae J, Kim S. Identifying and ranking influential spreaders in complex networks by neighborhood coreness[J]. *Physica A Statistical Mechanics & Its Applications*, 2014, 395(4):549-559.
- [18] Knight W R. A Computer Method for Calculating Kendall's Tau with Ungrouped Data[J]. *Publications of the American Statistical Association*, 1966, 61(314):436-439.
- [19] Zachary W W. An Information Flow Model for Conflict and Fission in Small Groups[J]. *Journal of Anthropological Research*, 1977, 33(4):452-473.
- [20] Heidler R, Gamper M, Herz A, et al. Relationship patterns in the 19th century: The friendship network in a German boys' school class from 1880 to 1881 revisited.[J]. *Social Networks*, 2014, 37(37):1-13.
- [21] Newman M E. Finding community structure in networks using the eigenvectors of matrices.[J]. *Physical Review E Statistical Nonlinear & Soft Matter Physics*, 2006, 74(3 Pt 2):036104.
- [22] Guimerà R, Danon L, DãAz-Guilera A, et al. Self-similar community structure in a network of human interactions[J]. *Phys Rev E Stat Nonlin Soft Matter Phys*, 2003, 68(6 Pt 2):065103.
- [23] Glance N, Glance N. The political blogosphere and the 2004 U.S. election: divided they blog[C]// *International Workshop on Link Discovery*. ACM, 2005:36-43.

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