

Article

Mining Algorithm of Relatively Important Nodes Based on Edge Importance Greedy Strategy

Jie Li ^{1,†}, Chunlin Yin ^{1,†}, Hao Wang ², Jian Wang ³ and Na Zhao ^{2,*}

¹ Electric Power Research Institute of Yunnan Power Grid Co., Ltd., Kunming 650217, China; lj1226645407@163.com (J.L.); 18487125168@139.com (C.Y.)

² Key Laboratory in Software Engineering of Yunnan Province, School of Software, Yunnan University, Kunming 650091, China; wang3706@mail.ynu.edu.cn

³ Faculty of Information Engineering and Automation, Kunming University of Science and Technology, Kunming 650504, China; jianwang@kust.edu.cn

* Correspondence: zhaona@ynu.edu.cn

† These authors contributed equally to this work.

Abstract: Relatively important node mining has always been an essential research topic in complex networks. Existing relatively important node mining algorithms suffer from high time complexity and poor accuracy. Therefore, this paper proposes an algorithm for mining relatively important nodes based on the edge importance greedy strategy (EG). This method considers the importance of the edge to represent the degree of association between two connected nodes. Therefore, the greater the value of the connection between a node and a known important node, the more likely it is to be an important node. If the importance of the edges in an undirected network is measured, a greedy strategy can find important nodes. Compared with other relatively important node mining methods on real network data sets, such as SARS and 9/11, the experimental results show that the EG algorithm excels in both accuracy and applicability, which makes it a competitive algorithm in the mining of important nodes in a network.

Keywords: complex network; important nodes; relative importance; important edge



Citation: Li, J.; Yin, C.; Wang, H.; Wang, J.; Zhao, N. Mining Algorithm of Relatively Important Nodes Based on Edge Importance Greedy Strategy. *Appl. Sci.* **2022**, *12*, 6099. <https://doi.org/10.3390/app12126099>

Academic Editors: Pasquale De Meo, Giacomo Fiumara, Xiaoyang Liu and Annamaria Ficara

Received: 19 April 2022

Accepted: 25 May 2022

Published: 15 June 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

With the advances in human scientific cognition and information technology, network science has become a hot topic in academia. As the primary research object of network science, complex networks are gradually emerging in the eyes of scholars [1]. A complex network refers to a network with some or all of the properties of self-organization, self-similarity, attractor, small world, and scale-free. Complex networks can model all aspects of real-life human society, and through the study of these networks abstracted from reality, people can explore the laws of the real world. Therefore, analysis of complex networks and their applications is a crucial issue.

Many research papers on complex networks have been published [2–5]. Early research covered the traditional statistical properties of networks (e.g., the two papers that laid the foundation of complex networks—scale-free networks [6] and small-world networks [7]). Later works described the structural properties of networks (e.g., the exploration of “community phenomena” [8] and “network modalities” [9]). Even later, papers addressed the deeper study of points and lines. The examination of complex networks has undergone tremendous evolution, and the study of the importance of the nodes or edges of complex networks is one of the most important topics.

Nodes and edges are the basic elements of network structure. Studying important nodes or edges helps us protect the system better, but also helps us understand the system better. For example, a disease transmission network can search for known infected people. Then, susceptible people can be searched, treated, and isolated, in order to prevent further

spread of the virus. For another example, Fan et al. collected 20 years of trade data from 232 countries and regions around the world, and then constructed a trade network. In this network, a novel node importance ranking and analysis method was proposed by comprehensively considering factors such as generalized degree, DHC theorem and weight [10]. This method helps the formulation of trade policies in countries around the world, and deepens our understanding of the history of world trade. Xu et al. also pointed out that for traditional information retrieval evaluation metrics based on citation network structure, it is difficult to accurately assess the impact of a particular piece of literature. They experimentally argued that the adapted PageRank and LeaderRank methods are still the most accurate evaluation criteria available [11].

As an interdisciplinary subject, there are examples of applying various computer technologies to the research of complex networks. For example, Liu et al. proposed an artificial neural network-based model for information dissemination and opinion evolution, IPNN (Information propagation and public opinion evolution model based on artificial neural network, IPNN) [12]. Fan et al. proposed a reinforcement learning-based algorithm for node importance identification in complex networks, FINDER. It first learns the exhaustive method in a simulated BA network, continues training the previously trained model in the real network, and evaluates the performance of the model based on the order of node removal [13]. In addition, many excellent improvements to the traditional node importance recognition algorithm have also been proposed. For example, Fan et al. proposed a new node importance ranking metric, the circle ratio, beginning from a circular structure in the network [14]. Traditional methods judge the importance of a node by the contributions of neighboring nodes. However, the circle ratio judges the importance of the current node by the amount of information it brings to its neighbors, which inspires a new research idea [14]. Lu and Liao et al. summarized and sorted out the current node importance identification and ranking methods in various existing networks [15,16].

As we can see, most of the current research on nodes focuses on the mining and discovery of important nodes in a network, but little research exists on the mining of relatively important nodes. The idea of relative node importance considers questions like “which node in a network is the most important relative to a specific node or a specific group of nodes?” Compared with other research fields, the relative or local importance of nodes also has practical implications, especially when the scale of the network grows larger. Some research results on relative node importance mining are available today, but these methods still need improvement. Areas of improvement include whether the time complexity and space complexity can be further reduced, how to further improve the accuracy of existing method, which kind of method performs the best on a specific type of network, and the parameter selection and optimization method, etc.

In this paper, we consider the connection role of important edges in an unweighted network, where the edge importance represents the degree of association between two nodes. The connections between important nodes should be closer, thus we propose a metric to measure edge closeness for important nodes in an unweighted network. It is based on the idea of “the node with the largest edge closeness to a known important node is likely to be an important node” for which an edge importance greedy strategy (EG) is proposed to mine relatively important nodes. Through the comparison experiments with the NN [17] and the RD [18], which originated from protein networks, and the Katz [19], which is based on random wandering, it can be proved that the EG strategy achieves ideal experimental results and shows its application value in identifying the importance level of unprivileged network nodes.

2. Greedy Strategy Based on Edge Importance

The EG algorithm uses greedy strategy that requires an importance measure for the edges in a network before each use. It works by adding known important nodes to a set C that includes all their neighbors, after which one can assign an importance score to the

connected edges of the known important nodes based on the topological information of the network. The importance score can be calculated as follows:

$$SV = \frac{k_j}{k_i} \cdot \frac{1}{d^2} + \frac{1}{cn + 1} \quad (1)$$

where $(k_j/k_i) \cdot (1/d^2)$ is an important component called *NP* value, which measures the importance of a certain node; k_i is the degree of known important node i ; k_j is the degree of known important neighbor node j ; d is the shortest distance between node j and the set of known important nodes; and cn is the number of common neighbors of node j and known important nodes.

The core idea of Equation (1) is actually very straightforward: the larger the k_j is, the greater the importance of node j . On the other hand, since d is the shortest distance between node j and the set of known important nodes, the larger the d is, the smaller the value of $1/d^2$. A small k_j or a large d results in a smaller *NP*, and thus a lower importance score for node j . In other words, nodes with low degree and large distance from known important nodes tend to have lower importance, and vice versa.

In particular, there will be cases where two nodes have the same *NP* value. In order to solve this problem, a bias value $1/(cn + 1)$ is added to Equation (1) to distinguish their importance.

Once the importance score is obtained, the greedy strategy is used to find the node whose edge has the largest score from an edge set that corresponds to known important nodes. The found node will then be added to set C . The edge scores corresponding to each node in set C will be again calculated, and the node will be found by using the same strategy stated previously. This process is repeated until all nodes are added. The order in which nodes are added to set C is exactly the order of their importance.

The pseudo-code for the EG algorithm, also known as Algorithm 1, is as follows:

Algorithm 1: EG Algorithm

Begin

Input Network $G = (V, E)$, the set of known important nodes R ;

Initialization $C = R$; $S = 0$;

1. **While** the number of elements in C is less than $|V|$ **do**:
2. **for** i in C **do**:
3. **for** j in i neighbors **do**:
4. $SV(i, j) = k_j/k_i \cdot 1/d^2 + 1/(cn + 1)$;
5. **end for**
6. $t = \{j | \max(SV)\}$;
7. Place the node t into set C ;
8. **end for**
9. **end while**
10. **return** C

End

The EG algorithm is divided into three parts, which are as follows: computation of the shortest path of a single source; computation of the node importance score; and selection of the greedy policy. The EG algorithm chooses to compute the neighboring nodes of known important nodes. Lines 1–2 of the algorithm are the traversal of the set C , and the nodes in it are computed and analyzed. Lines 3–5 of the algorithm calculate the node importance score by first selecting a node i from among the set of known important nodes, then traversing its neighbor nodes and calculating the importance score of each neighboring node. Lines 6–8 of the algorithm apply a greedy strategy to select nodes, and the node with the highest *SV* is added to set C . The above process is repeated until all nodes are added to set C .

It can be found that the time complexity of the EG algorithm depends mainly on the calculation of the shortest path of a single source and the importance score. It is easy to see

that the calculation of the node importance score is a cumulative process, and depends on the degree of the important nodes. When there is only one element in the set of important nodes, its time complexity is \bar{k} , and \bar{k} is the average degree of the network; when there are two elements, its time complexity is $2\bar{k}$, and so on. The time complexity of this part can be written as $\bar{k} + 2\bar{k} + 3\bar{k} + \dots + n\bar{k}$, which equals to $O(n^2\bar{k})$.

One can also notice that the previously calculated node importance scores are fully reusable when new nodes are added to the set of important nodes. In this case, each time an important node is added, only the neighboring node scores of the newly added node need to be calculated. Based on above analysis, one can conclude that the time complexity actually depends on the number and average degree of nodes in the network, thus the overall time complexity would be $O(n\bar{k})$.

The following section will use the network shown in Figure 1 to illustrate the computation process of the edge greedy strategy.

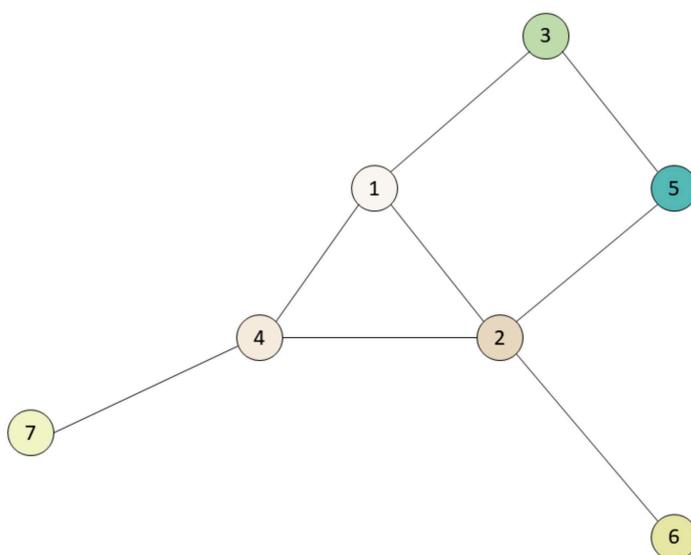


Figure 1. Example network of the edge importance greedy strategy.

Step 1, number the nodes in Figure 1 sequentially are 1, 2, 3, 4, 5, 6 and 7. Let node 1 be a known important node, and add node 1 to set C. Calculate the edge scores first according to the known important node. The edge scores here are (1,2):2.33, (1,3):1.65 and (1,4):2.0. Node 2, which corresponds to edge (1,2), has the largest value of 2.33, and it is added to set C.

Step 2, calculate the edge importance score for nodes 1 and 2 in set C, and one obtains (1,3):1.65, (2,4):1.75, (2,5):1.125, and (2,6):1.0625. Node 4, which corresponds to edge (2,4), has the largest value and is added to set C.

Step 3, calculate the edge importance score for nodes 1, 2 and 4 in set C, and one obtains (1,3):1.65, (2,5):1.125, (2,6):1.0625 and (4,7):1.083. Node 3 has the largest value and is added to set C.

Step 4, calculate the edge importance score for nodes 1, 2, 4 and 3 in set C and obtain (2,5):1.125, (2,6):1.0625 and (4,7):1.083. Node 5 is selected and added to set C.

Step 5, calculate the edge importance score for nodes 1, 2, 4, 3 and 5 in set C and obtain (2,6):1.0625 and (4,7):1.083, and node 7 is added to set C.

Step 6, calculate the edge importance score for nodes 1, 2, 4, 3, 5 and 7 in set C. The edge importance score is (2,6):1.0625 and node 6 is added to set C.

At this point, all nodes are added and the loop ends. For node 1, the order of relatively important nodes possibilities would be 2, 4, 3, 5, 7 and 6.

3. Experiment

The experiments in this paper use four real network data sets.

- (1) The 9/11 criminal relationship network [20]. The nodes represent the terrorists who hijacked the planes and those who had contact with them; the edges represent the interpersonal relationships between them; and the set of important nodes represents the group of terrorists who hijacked the planes on 9/11.
- (2) SARS international aviation network [21]. Each node represents a country; the edge represents the existence of routes between two countries; and the earliest group of countries with the SARS virus is the set of important nodes.
- (3) Mouse protein interaction network [22]. The nodes represent mouse proteins; edges represent the existence of interactions between proteins; and the group of mouse protein kinases is the set of the important nodes.
- (4) Human protein interaction network [22]. The nodes represent human proteins; edges represent the existence of interactions between proteins; and the group of human protein kinases is the set of the important nodes.

The topological information of these network data sets is listed in the following Table 1.

Table 1. Network topology information.

Network	<i>N</i>	<i>N'</i>	<i>M</i>	<i>K</i>	<i>C</i>
9/11	37	19	85	4.59	0.52
SARS	224	18	2247	20.06	0.65
Human	3574	186	6002	3.36	0.15
Mouse	1187	67	1557	2.62	0.09

The table header indicates the topological attributes of a network. *N* is the number of nodes in the network; *N'* is the number of important node sets; *M* is the number of edges; and *K* and *C* are the average degree and clustering coefficient of the entire network, respectively.

In this paper, we use *AUC* (Area Under Curve) to evaluate the overall results of this algorithm for mining relatively important nodes. The *AUC* is calculated as follows.

$$AUC = \frac{0.5n_1 + n_2}{n} \tag{2}$$

where *n*₁ represents the number of times that the importance score of a node selected from the unknown important node set equals that of a node selected from the unimportant node set; *n*₂ represents the number of times that the importance score of a node selected from the unknown important node set is larger than that of a node selected from the unimportant node set. *n* represents the number of comparisons, which is the product of the size of the unknown important node set and the size of the unimportant node set.

In this paper, we conduct nine rounds of experiments for each network, and the ratios (*p*) of known important nodes for each round are set to 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80% and 90%. Each round uses a different algorithm to calculate the relative importance of the nodes, according to which these nodes are ranked. Twenty independent experiments are conducted, and the *AUC* values are calculated for the ranking results.

This paper uses NN [17], RD [18] and Katz [19] for comparison, and the results are as follows.

In Figure 2, the horizontal axis represents the percentage of known important nodes of the set of important nodes, and the vertical axis represents the average *AUC* value. A higher *AUC* value represents a higher effectiveness. It is easy to see that the *AUC* values of most algorithms show an increasing trend as the ratio of important nodes in the network increases. The effect of the EG algorithm is most significant for the 9/11 network, and its *AUC* value remains stable at around 0.8, which is far ahead of other algorithms. In the SARS network and the Human network, our algorithm also achieved satisfactory results.

The *AUC* index maintains its leading position against comparison algorithms, although the margins are not as prominent as those for 911net. One can also note that when the proportion of important nodes exceeds 30%, the *AUC* value of the EG algorithm in the Mouse network is slightly lower than that of the Katz algorithm, which may be due to the fact that the EG algorithm depends on adjacent nodes for judgment.

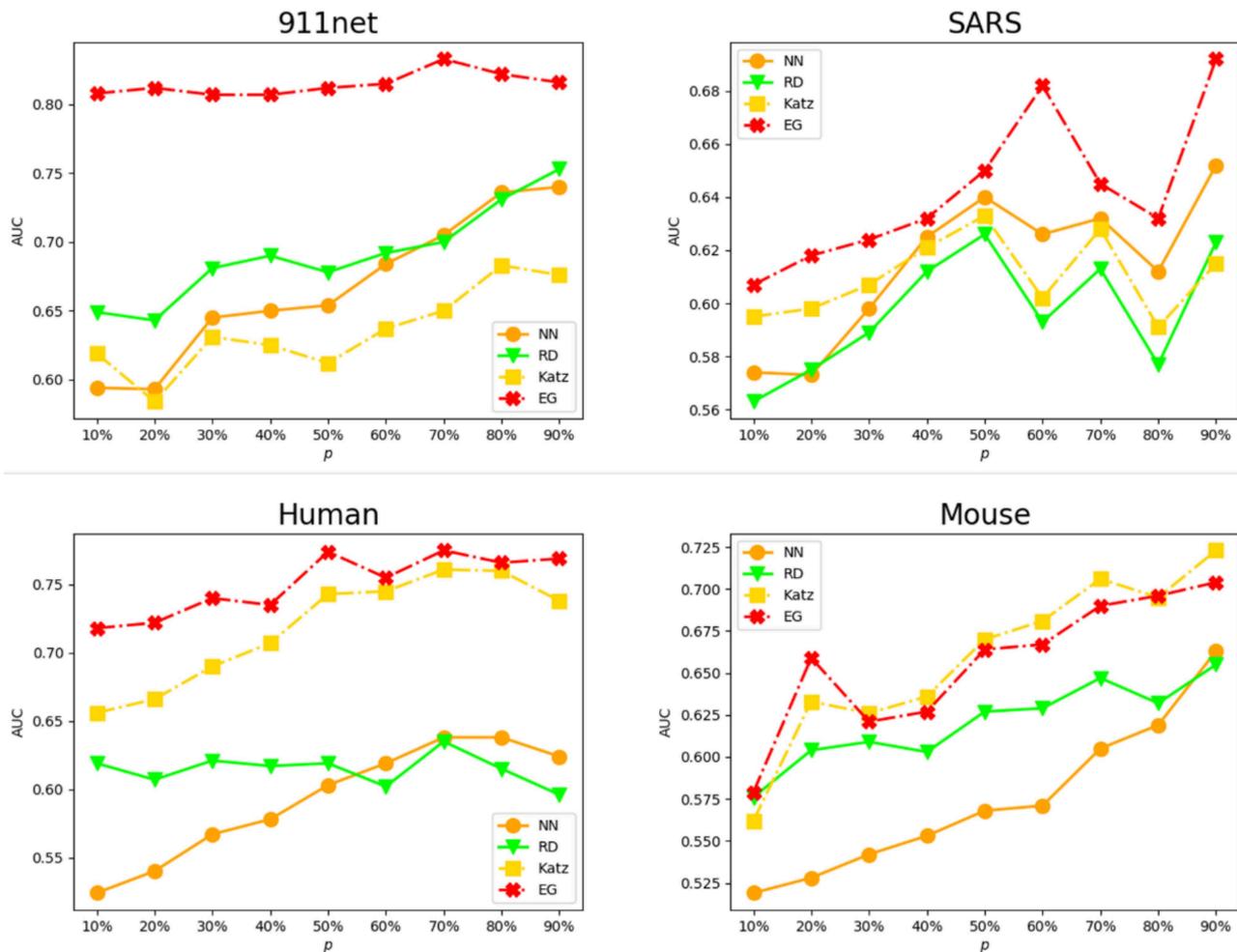


Figure 2. Comparison results from *AUC*s of the edge importance greedy strategy algorithm.

The experiments proved that the EG method performs best on the 9/11, SARS, and Human networks based on the evaluation of the *AUC*, regardless of the ratio of known important nodes. It performs second-best on the Mouse network. From the perspective of network topology, the SARS network is different from other networks and possesses the highest average degree (20). At the same time, both the 911net and SARS networks are with high node aggregation. It can be inferred that the EG algorithm performs the best in those networks that are similar to SARS and 911net. The fluctuation amplitudes of the *AUC*s for the four algorithms at different important node ratios reside in the scope of 0.08~0.12. This indicates that the ratio value in dense graphs has limited effect on these four algorithms. However, the clustering coefficients for both the Human and Mouse networks are smaller compared with those of the SARS and 9/11 networks, and we believe it is this attribute that reduces the advantage of EG over Katz, which performs second best for the Human network.

Further analysis finds that the NN algorithm considers the nodes with more connections to known important nodes as relatively important nodes, so its accuracy decreases when the known important nodes are fewer. On the other hand, when the known important nodes are in large amounts, it is also very challenging for an algorithm like NN

to distinguish important nodes when the number of connected nodes equals that of the known important nodes. The RD method uses the inverse sum of the shortest path lengths with known important nodes to measure relative importance. However, in real networks, the nodes close to known important nodes are not necessarily the nodes we are looking for, and those far from the known important node may actually be the ones we need. The Katz method adopts a random wandering strategy that can better complete the mining task of relatively important nodes in some networks, but it still needs to improve its accuracy for other networks.

4. Discussion and Conclusions

In this paper, we propose the EG method for mining relatively important nodes based on the greedy strategy of edge importance. This method measures the importance of the edges of known important nodes, and uses the most important edges to find nodes that are closely related to the current important nodes. The EG method does not calculate or consider network paths, and thus avoids the limitations of some methods that consider path information only. By comparing with the existing methods of mining relatively important nodes, such as NN, RD and Katz, based on the indicator of *AUC*, we proved the performance and the feasibility of the EG algorithm.

Although the adaptability of our proposed algorithm to different networks has been discussed, we still consider it necessary to further analyze the impact network topology has on an algorithm in a more detailed and systematic way, in order to obtain better guidance for the use of the EG algorithm. The EG method is designed for undirected networks, and does not consider applications in directed or weighted networks. Extending the EG method to directed graphs, weighted graphs, or even time series networks could be another possible future direction. Lastly, it seems that the EG method does not possess a rigorous physical or mathematical meaning; some theoretical work can be carried out surrounding this issue in the future.

Author Contributions: Conceptualization, J.L. and C.Y.; methodology, J.L.; software, J.W.; validation, J.L., C.Y. and H.W.; formal analysis, J.L.; investigation, J.W.; resources, N.Z.; data curation, C.Y.; writing—original draft preparation, J.L. and H.W.; writing—review and editing, J.L. and H.W.; visualization, J.W.; supervision, N.Z.; project administration, N.Z.; funding acquisition, J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Special Plan of Yunnan Province Major Science and Technology Plan (202102AA100021), the National Natural Science Foundation of China (62066048), the Yunnan Natural Science Foundation Project (202101AT070167) and the Open Foundation of Key Laboratory in Software Engineering of Yunnan Province (2020SE311).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Zhou, T.; Bai, W.J.; Wang, B.H.; Liu, Z.J.; Yan, G. Overview of complex network research. *Physics* **2005**, *34*, 6.
2. Xuan, Q.; Wang, J.; Zhao, M.; Yuan, J.; Fu, C.; Ruan, Z.; Chen, G. Subgraph networks with application to structural feature space expansion. *IEEE Trans. Knowl. Data Eng.* **2019**, *33*, 2776–2789. [[CrossRef](#)]
3. Yue, P.; Fan, Y.; Batten, J.A.; Zhou, W.X. Information transfer between stock market sectors: A comparison between the USA and China. *Entropy* **2020**, *22*, 194. [[CrossRef](#)] [[PubMed](#)]
4. Ran, Y.; Liu, T.; Jia, T.; Xu, X.K. A novel similarity measure for mining missing links in long-path networks. *Chin. Phys. B* **2021**, preprint. [[CrossRef](#)]
5. Li, R.; Wang, W.; Di, Z. Effects of human dynamics on epidemic spreading in Côte d’Ivoire. *Phys. A Stat. Mech. Its Appl.* **2017**, *467*, 30–40. [[CrossRef](#)]
6. Barabasi, A.L.; Albert, R. Emergence of scaling in random networks. *Science* **1999**, *286*, 509–512. [[CrossRef](#)] [[PubMed](#)]

7. Watts, D.; Strogatz, S. Collective dynamics of ‘small-world’ networks. *Nature* **1998**, *393*, 440–442. [[CrossRef](#)] [[PubMed](#)]
8. Newman, M.; Girvan, M. Finding and evaluating community structure in networks. *Phys. Rev. E* **2004**, *69*, 026113. [[CrossRef](#)] [[PubMed](#)]
9. Alon, U. Network motifs: Theory and experimental approaches. *Nat. Rev. Genet.* **2007**, *8*, 450–461. [[CrossRef](#)]
10. Fan, T.; Li, H.; Ren, X.L.; Xu, S.; Gou, Y.; Lü, L. The rise and fall of countries on world trade web: A network perspective. *Int. J. Mod. Phys. C* **2021**, *32*, 2150121. [[CrossRef](#)]
11. Shuqi, X.; Msma, B.; Linyuan, L.; Medo, M. Unbiased evaluation of ranking metrics reveals consistent performance in science and technology citation data. *J. Informetr.* **2020**, *14*, 101005.
12. Liu, X.; He, D. Information propagation and public opinion evolution model based on artificial neural network in online social network. *Comput. J.* **2019**, *63*, 1689–1703. [[CrossRef](#)]
13. Fan, C.; Zeng, L.; Sun, Y.; Liu, Y.Y. Finding key players in complex networks through deep reinforcement learning. *Nat. Mach. Intell.* **2020**, *2*, 317–324. [[CrossRef](#)] [[PubMed](#)]
14. Fan, T.; Lü, L.; Shi, D.; Zhou, T. Characterizing cycle structure in complex networks. *Commun. Phys.* **2020**, *4*, 272. [[CrossRef](#)]
15. Lü, L.; Chen, D.; Ren, X.L.; Zhang, Q.M.; Zhang, Y.C.; Zhou, T. Vital nodes identification in complex networks. *Phys. Rep.* **2016**, *650*, 1–63. [[CrossRef](#)]
16. Liao, H.; Mariani, M.S.; Medo, M.; Zhang, Y.C.; Zhou, M.Y. Ranking in evolving complex networks. *Phys. Rep.* **2017**, *689*, 1–54. [[CrossRef](#)]
17. Biagioni, R.; Vandenbussche, P.Y.; Novacek, V. Finding Explanations of Entity Relatedness in Graphs: A Survey. *arXiv* **2018**, arXiv:1809.07685.
18. Wu, X.; Jiang, R.; Zhang, M.Q.; Li, S. Network-based global inference of human disease genes. *Mol. Syst. Biol.* **2008**, *4*, 189. [[CrossRef](#)] [[PubMed](#)]
19. Gori, M.; Pucci, A. Research paper recommender systems: A random-walk based approach. In Proceedings of the 2006 IEEE/WIC/ACM International Conference on Web Intelligence (WI 2006 Main Conference Proceedings) (WI’06), Washington, DC, USA, 18–22 December 2006; pp. 778–781.
20. Krebs, V.E. Mapping networks of terrorist cells. *Connections* **2002**, *24*, 43–52.
21. Airport, Airline and Route Data. Available online: <https://openflights.org/data.html> (accessed on 16 May 2021).
22. Xenarios, I.; Rice, D.W.; Salwinski, L.; Baron, M.K.; Marcotte, E.M.; Eisenberg, D. Dip: The database of interacting proteins. *Nucleic Acids Res.* **2000**, *24*, 289–291. [[CrossRef](#)] [[PubMed](#)]