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► **To cite this version:**

Mengji Yang, Aicha Seklouli-Sekhri, Haiqing Zhang, Lijuan Ren, Xi Yu, et al.. A Review on Influence Dissemination in Social Networks. 2023 The 3rd International Conference on Big Data Engineering and Education (BDEE 2023), chengdu university, Aug 2023, Chengdu, China. hal-04188160

HAL Id: hal-04188160

<https://hal.science/hal-04188160>

Submitted on 25 Aug 2023

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A Review on Influence Dissemination in Social Networks

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Abstract—Influence dissemination research is a key issue in information dissemination in social networks. Due to the practical significance of influence analysis in marketing, advertising, personalized recommendation, and public opinion monitoring, researchers have investigated the problem from different perspectives and proposed solutions. In this paper, we review the influence propagation in social networks and conclude that the existing research uses three main approaches, network topology analysis, greedy algorithms, and heuristic algorithms. Also, according to the purpose of the research, we divided the existing literature into three categories, individual influence analysis, community mining, and influence maximization. Finally, based on state-of-the-art research, we unveil current weaknesses and future research directions.

Keywords—social networks, influence dissemination, individual influence, community mining, influence maximization

I. INTRODUCTION

Over the past decade, information dissemination in social networks has received much attention from researchers. These researchers have focused on how information spreads, what factors influence the spread of information, and what kinds of information lead to faster spread [1] [2] [3]. Social influence occurs when others influence a person's opinions, emotions or behavior while disseminating information [4]. With the further deepening of the research, influence dissemination has become a key area in information dissemination with significant practical value [5]. Key concerns in this area include: who influences whom, who are the most influential users, how influence spreads, and more. Influence analysis can be beneficial in many areas, such as viral marketing [6], product recommendations or advertising [7] [8], while the government can be used for public opinion analysis [9].

This paper provides an overview and comparison of research on influence dissemination in recent years. Network topology

analysis, greedy and heuristic algorithms are mainly used as problem solutions. From our perspective, most of these studies can be divided into three categories: the first category is individual influence analysis. This field focuses on how to find the most influential nodes. The second category is community mining, which focuses on how to mine a class of nodes with common attributes in online social networks. The third category is influence maximization, selecting the seed set V of nodes to influence as many uninfluenced users as possible, based on a specific propagation model and node set K .

The rest of this paper is organized as follows. The second section introduces the basic methods commonly used in influence dissemination. In Section III, we present some representative studies of individual influence. In Section IV, we compare community mining algorithms. Then, in Section V, we discuss the progress of influence maximization. At the end of each section, we provide comments on the literature. Finally, we conclude the paper and discuss future directions for influence analysis. The symbols and notations that have been used in the subsequent sections of this paper are given in TABLE I.

II. BASIC METHODS OF INFLUENCE RESEARCH

In the field of influence propagation research, most researchers' study is based on three aspects, the first is network topology, the second is greedy algorithms, and the third is heuristic algorithms. These three aspects can be independent of each other or can be combined to optimize the algorithm further and improve scalability.

A. Network Topology

Many studies consider network topology. In general, nodes with better connectivity (measured from metrics such as the centralities of a node) often contribute to the propagation of influence. However, only considering the topological structure of the network will lead to an extensive range of duplication of

influence propagation. Researchers often consider combining other algorithms or user factors to avoid this problem.

B. Greedy Algorithms

The greedy algorithm is mainly used in influence maximization problems. The greedy algorithm selects the node with the maximum marginal gain to the seeds in each iteration. Kempe et al. [10] systematically discuss that the influence maximization problem is NP-hard and the greedy algorithm can find the local optimal solution in polynomial time. But the computation is too expensive for real social networks.

Therefore, many researchers have proposed a series of improved algorithms. Leskovec et al. [11] proposed the CELF

(Cost-Effective Lazy Forward) algorithm, which is based on a submodel of the influence function and effectively reduces the time complexity. Goyal et al. [12] proposed CELF++ based on the CELF algorithm, which further reduces the number of Monte Carlo simulations [13], thus reducing the time complexity.

In addition, Wang et al. [14] proposed the CGA (Community-Based Greedy Algorithm) by combining the network topology. They detected the community first and then selected seed nodes to limit the node influence within the community. Although the time complexity is reduced in the influence maximization stage, detecting communities is time-consuming and the global influence is ignored simultaneously. A comparison of these algorithms is shown in the TABLE II.

TABLE I. SYMBOLS AND NOTATIONS

Symbols	Interpretation
O	Time complexity
k	Maximum allowable cardinality for the seed set
m	Number of edges of the network
n	Number of users of the network
R	number of Monte Carlo simulation
$t(\epsilon)$	Number of iterations

TABLE II. COMPARISON OF THE GREEDY ALGORITHM AND ITS VARIANTS

Algorithm	Time Complexity	Advantages	Disadvantages
Basic Greedy [10]	$O(kmnR)$	Approximation guarantee	High time consumption and low scalability
CELF [11]	$O(kmnR)$	Approximation guarantee and easy to implement	Scalability is still very poor
CELF++ [12]	$O(kmnR)$	Approximation guarantee	Not applicable to practical situations
CGA [14]	$O(E + (Z - M)NTp + MKTp + K Cp Tp)$	Reduced calculation time for influence maximization stage	High time complexity overall

TABLE III. COMPARISON OF THE HEURISTIC ALGORITHM AND ITS VARIANTS

Algorithm	Time Complexity	Advantages	Disadvantages
PageRank [15]	$O(t(\epsilon)n^2)$	Reduced computation time	Poor solution quality
LeaderRank [16]	$O((m + 1)l + n)$	Improved the convergence speed and robustness of PageRank	Not suitable for dynamic networks
PMIA [17]	$O(d_n \log_n)$	Available for real network computing	Does not provide approximation guarantee
LDAG [18]	$O(n^2 + kn^2 \log n)$	Scalability has been improved	Not enough accuracy
SimpPath [21]	$O(kmnR)$	Scalability has been improved	Accuracy is not guaranteed

Although the greedy algorithm has a very high time complexity, due to its strong interpretability, many researchers have subsequently proposed improved algorithms to reduce the time complexity and make the greedy algorithm more practical.

C. Heuristic Algorithms

Due to the time-consuming nature of greedy algorithms, a series of heuristic algorithms are used to avoid this problem, such as PageRank [15], and LeaderRank [16]. These algorithms are used to discover high-influence nodes in the network.

Chen et al. [17] [18] proposed the PMIA method and the LDAG method, which are based on the IC (Independent Cascade) model [19] and the LT (Linear Threshold) model [20], respectively. They select local seed nodes by iteration, and although they can obtain a better solution set, the time complexity is still more expensive. Based on the LDAG algorithm, Goyal et al. [21] proposed the Simpath algorithm. The algorithm computes propagation by searching nearby simple paths, using the parameter n to control the balance between running time and seed quality. As the research progresses, some user factors are also considered. Such as user interaction [22] and psychology [23]. A comparison of these algorithms is shown in TABLE III.

Compared with the greedy algorithm, the heuristic algorithm has been greatly improved in time complexity, and the scalability is better than the greedy algorithm. The heuristic algorithm also has some disadvantages, such as the accuracy cannot be guaranteed and the lack of a unified and complete theoretical system. However, it still does not prevent researchers from further extending it.

III. INDIVIDUAL INFLUENCE

Research on individual influence focuses on identifying influential users in social networks who play a crucial role in information dissemination. A representative area of research is opinion leader mining. The study of individual influence can be approached from different perspectives, such as network topology, the information shared by users [24], and the influence of user behavior [25]. Next, we review some of the research in this field and then compare them.

A Şimşek [26] combined several centrality calculation methods (Degree Centrality [27], Eigenvector Centrality [28], Closeness Centrality [29]) to propose a new method called Lexical Sorting Centrality (LSC). The sorting mechanism of this method is similar to lexical sorting. Compared to a single centrality measure, LSC can more quickly and accurately distinguish the propagation ability of nodes and identify the node with the most robust propagation ability.

G Sun et al. [30] proposed a complex model of multi-subnet combination. The model extracts sub-networks from the original social network from multiple perspectives, such as sentiment or comments, and can more accurately detect opinion leaders through multi-subnet synthesis.

L Jain et al. [31] proposed an improved algorithm for detecting local or global opinion leaders in a community or social network. The article uses an improved Leuven method to

identify community structures in social networks and then applies the Firefly algorithm to identify opinion leaders and global opinion leaders. Compared to traditional algorithms such as Betweenness Centrality [32], Degree Centrality, and PR (PageRank) algorithm, the proposed algorithm achieved better accuracy, precision, recall, and F1-score results.

F Riquelme et al. [33] proposed a parameterizable influence spread-based centrality measure for detecting influential users in social networks called General Influence Spread Rank (GISR). GISR is a generalized and parameterizable centrality measure based on two well-known influence spread models: the IC and LT models. This measure allows for adjusting depth levels, probability, and directionality of initial neighbor activation to study how these parameters affect actors' centrality. Experiments validate the importance of neighborhood depth levels and reveal that other connectivity aspects are also relevant to the centrality problem.

U Ishfaq et al. [34] proposed a new method for evaluating the importance of nodes, called HCURank (Hybrid Centrality Users Rank), which is based on existing centrality measures and uses the entropy weight technique to assign objective weights to each criterion. The TOPSIS method ranks the importance of nodes in the network. The study assessed the validity of the proposed model using four real-world social networks. The results showed that, compared to a single centrality criterion, the proposed model is superior and effective in ranking the importance of network nodes.

A Pellicani et al. [35] proposed a new system called SAIRUS to automatically identify at-risk users on social networks. This system solves the task of node classification in social networks by combining three perspectives: the semantics of user-generated text content, the user relationship network, and spatial user proximity. Unlike existing methods, SAIRUS learns three independent models, each taking advantage of the characteristics of each data type, and then uses a stack generalization approach to learn a model to merge their contributions. Extensive experimental evaluation on variants of two real-world Twitter datasets demonstrated the proposed approach's superiority over 15 competitors based on a single or combined perspective. The applicability of SAIRUS to real-world social networks, which can be affected by noisy data, is also evident when focusing specifically on marginal users.

Most research on individual influence focuses on the most influential users, such as opinion leaders. The literature shows that researchers approach this topic from three angles: network topology [26] [30] [31] [33] [34] [35], user interaction [30] [31] [33] [34] [35] (such as content sharing and forwarding) and user attributes [30] [33] [35] (such as interests and emotions). In network topology analysis, centrality analysis is an effective method. By considering user interaction and attributes, researchers can more accurately identify a group of influential users in social networks. However, screening users for influence based on network structure is a good choice. In recent years, increasing attention has been paid to studying individual influence. When influential users are identified, companies or governments can use this group to disseminate information to most users [36] quickly. A comparison of the literature is shown in TABLE IV.

IV. COMMUNITY MINING

As a phenomenon of social influence, people with common values form communities. Community structures are common in social networks. The entire network can be divided into different communities based on user behavior, attributes, and other factors [37]. The connections between nodes within these communities are relatively dense, while links outside the community are sparse. Detecting communities in real-world social networks can help us better understand social structures. Research on community-based influence has a variety of applications, such as viral marketing for various products and targeted recommendation systems. Effectively dividing communities in social networks is a crucial research problem in community influence diffusion. We present some of them in the following.

J J Whang et al. [38] proposed an overlapping community detection method called NISE (Neighborhood-Inflated Seed Expansion). The algorithm is divided into four stages: filtering, seeding, expansion, and propagation. The algorithm first filters the overlapped graph region, finds seeds in the biconnected core graph in the filtered graph, and expands the seeds into seed

clusters using PageRank clustering. The community is then extended to the area removed in the filtering stage. The algorithm can effectively detect overlapping communities and handle large-scale datasets.

I Koc [39] used the Coot bird metaheuristic optimizer to detect communities. The article also compared six metaheuristic methods and proposed a CommunityID approach to speed up Modularity calculations. As a result, the combination of the Coot bird and CommunityID could detect communities in less time.

X Li et al. [40] proposed a community detection algorithm called SICD (Social Influence Based Community Detection) based on network topology and the social influence of user behavior. The algorithm is used in event-based social networks and combines two types of social influence using a weight function to achieve a unified social influence. The k-means algorithm is then used for community detection. The algorithm considers the network's topology and users' behavior to measure user relationships better. It also demonstrates its validity on real datasets.

TABLE IV. COMPARISON BETWEEN DIFFERENT MODELS IN INDIVIDUAL INFLUENCE

Author	User Interaction	User Behavior	Based on Network Structure	Method	Evaluation Criteria	Application
A Şimşek [26]	-	-	✓	Centrality analysis	Accuracy, calculation time	Degree centrality sorting
G Sun [30]	✓	✓	✓	A multi-subnet composited complex network	Accuracy, calculation time	Opinion leader detection
L Jain [31]	✓	-	✓	Leuven and Firefly method	Accuracy, precision, recall and F1-score	Opinion leader detection
F Riquelme [33]	✓	-	✓	Influence diffusion model	Centralities, execution time	Influential user detection
U Ishfaq [34]	✓	-	✓	Centrality model	Jaccard similarity, ability of influence spread	Ranking the importance of network nodes
A Pellicani [35]	✓	✓	✓	Semantic content, relationships and spatial analysis	Accuracy, precision, recall, F1-score	Risk user identification

TABLE V. COMPARISON OF COMMUNITY DETECTION METHODS

Author	Seeds or Links	User Attributes	Text Content	Method	Evaluation Criteria	Application
J J Whang [38]	✓	-	-	PageRank	Calculation time, accuracy	Overlapping community detection
I Koc [39]	-	-	-	Metaheuristic algorithms	Modularity, Calculation time	Fast community detection
X Li [40]	✓	✓	✓	Influence analysis, K-means	Modularity, normalized mutual information	Community detection, social recommendations
Y Wang [41]	✓	-	-	Proximity-based group formation game	F1-score, normalized mutual information	Community detection
H Fani [42]	✓	✓	✓	Linear interpolation	Precision, recall and F-measure	Community detection, news recommendations

Y Wang et al. [41] used the proximity group formation game model to detect communities in social networks. This method constructs a probabilistic generation model to reconstruct the topology of a given graph, preserving the first- and second-order proximity between vertex pairs. Then, the evolution of community structure is described using game theory. Finally, the community interaction probability matrix is used to detect communities.

H Fani et al. [42] proposed a multi-modal feature learning method for identifying user communities from a time-evolution perspective, combining content and network structure analysis. The primary strategy of this algorithm is linear interpolation, such as neural embedding based on user time-content similarity and time-content embedding in social links. This method can achieve more accurate community identification than social links and content analysis alone.

The above literature shows that effective community detection is the first step in studying influence diffusion. Earlier studies focused on network topology [38], but considering only the connections between nodes does not accurately reflect the real community and can be disrupted by user attributes or content. As a result, more recent studies have considered these factors for improving accuracy [40] [42]. Community detection is an NP-hard problem and some researchers have chosen non-traditional methods to solve it. For example, I Koc [40] uses meta-heuristics for community detection, while H Fani [42] employs multi-modal embedding, innovatively considering the time dimension. As the number of factors considered increases, so does computational complexity; these studies also propose methods for reducing time complexity. A comparison of the above literature is presented in TABLE V.

TABLE VI. COMPARISON OF INFLUENCE MAXIMIZATION METHODS

Author	Find Seeds	Network Topology	Greedy Algorithm	Heuristics Algorithms	Evaluation Criteria	Application
W Li [48]	✓	✓	-	-	Calculation time, accuracy	Influence maximization
J Ding [49]	✓	✓	✓	-	Time complexity, fitting with real data	Influence maximization
S Kumar [50]	✓	✓	-	-	Degree of fitting with real data	Influence maximization
Z Liang [51]	✓	✓	✓	-	Calculation time, influence diffusion, competition coefficient	Competitive influence maximization
A K Singh [52]	✓	✓	✓	✓	Influence coverage, influence spread time	Find high-influence user set

V. INFLUENCE MAXIMIZATION RESEARCH

Influence maximization is a hot topic in social network analysis research, attracting attention in academia and business. For companies, social networking is not just a tool for disseminating information, but also a marketing platform [43], [44]. Some studies have shown that friend recommendations receive more attention [45]. With a limited budget, companies aim to select as few people as possible on the social platform as seed nodes [46], so their product can receive more attention and promotion, encouraging purchases. As a result, the key problem in influence maximization is identifying the most suitable nodes to maximize the influence of other nodes on the social network [47]. Some recent literature on this topic is discussed below.

W Li et al. [48] studied the influence of group emotion on information transmission and proposed a corresponding influence maximization algorithm. Two algorithms are proposed based on the definition of emotional power and group credibility: PUEA (Potential User Discovery based on Emotion Aggregation), which is based on emotion aggregation, and TFIP (Two-Factor Information Propagation model). The PUEA algorithm is used to identify influential users, while the TFIP algorithm identifies influential users based on their emotional and structural characteristics. The time performance of the algorithm is better than that of the greedy algorithm, and its performance is superior to that of PageRank and other heuristic algorithms.

J Ding et al. [49] proposed a new seed selection strategy, R-greedy, based on the RIC (Realistic Independent Cascade) model and taking into account the probability of node reception. They also proposed an M-greedy algorithm to reduce the time complexity of R-greedy. Finally, a D-greedy algorithm was proposed that combines the advantages of the two algorithms. These algorithms were compared with CELF-Greedy, Static Greedy, and BKRIS algorithms on different datasets. Experimental results show that the proposed algorithms (R-greedy, M-greedy, D-greedy) outperform these state-of-the-art algorithms.

S Kumar et al. [50] proposed SGNN (Struc2vec Graph Neural Network) for identifying influential users in complex networks, based on graph embedding and graph neural networks. This study transforms the influence maximization problem into a regression problem. First, a feature vector is generated for each node in the network using struc2vec node embedding, and these feature vectors are then input into a graph neural network (GNN)-based regressor for processing. Seed nodes are ranked according to their predicted influence, and the top-ranked K nodes are selected as the final seed nodes. Additionally, the method can capture the nodes' structural identity and the network's topological characteristics.

Z Liang et al. [51] proposed the RRT (Reachable set-based Greedy) algorithm, based on the greedy algorithm. When constructing the model, the algorithm incorporates target nodes and competition relationships into the independent cascade

model. It uses the greedy algorithm to select as many nodes as possible to cover the reverse reachability set. And a pruning strategy is also designed to improve the algorithm's performance.

A K Singh et al. [52] proposed a new Link Prediction-based Influential Node Tracking framework (LPINT) that considers the factors of social network evolution over time. Using the greedy algorithm, the algorithm first identifies the seed set in a snapshot, then uses link prediction to predict the following graph snapshot. Next, a heuristic algorithm is used to find the seed set in the predicted snapshot, and finally, the prediction results are used to assess the influence spread. Compared to other algorithms, such as PageRank and DegreeDiscount, LPINT achieves better performance in terms of network impact coverage and impact propagation time.

The above research indicates that studies on influence maximization are primarily based on network topology, greedy algorithms [49] [51] and heuristic algorithms [52]. A comparison of the above literature is presented in TABLE VI. Early research focused on network topology, identifying high-influence nodes based on node centrality and other indicators. However, selecting seed nodes based solely on node topology can result in a large overlap in the influence coverage of nodes. Due to the limitations of topology-based research, researchers have used greedy algorithms to obtain better solution sets than those based on topology. Nevertheless, greedy algorithms have high time complexity, limiting their scalability. Subsequently, researchers proposed a series of heuristic algorithms, such as PageRank and LeaderRank, to address the time complexity issue. At the same time, researchers have considered additional factors that affect communication, such as user emotions [48], dynamic changes in the network [52], and other characteristics. The inclusion of these factors increases the accuracy of the propagation model.

VI. CONCLUSIONS

This paper illustrates the basic methods commonly used to influence propagation in social networks. We then present the latest status of influence research in social networks regarding individual influence, community mining, and influence maximization. We compare the proposed methods. At the same time, some directions of influence propagation research need to be further strengthened.

is based on static networks. Therefore, the dynamic evolution of communities is the focus of future research.

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