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A Comprehensive Review on Influence Maximization in Social Networks using Big Data and Cloud Computing

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Abstract- Online social networks have grown in importance as a means of communication, knowledge sharing, and information dissemination. Because social media is so widely used, people's opinions, tastes, and actions are frequently shaped by their friends or peers in the social networks they use. The impact maximization (IM) problem has been widely used to simulate the spread of ideas and inventions throughout the past ten years. The Influence Maximization (IM) challenge is the identification of prominent individuals who can maximize the dissemination of information inside a network. Given the quick expansion of social media platforms like Facebook and Twitter, in this survey, we offer a methodical analysis of the research and potential future paths concerning this issue. We go over the influence maximization, which deals with determining the ideal number of nodes whose combined influence spreads in a social network is maximum information diffusion models and analyzes a variety of algorithms for the traditional IM algorithms, is one of the difficulties of information diffusion on social networks. The primary factors influencing information diffusion, its applications, and the research difficulties in this field are the main topics of this survey article. The fundamental ideas of impact maximization and its various forms are also covered.

Keywords— Influence Maximization, Social Networks, Big Data, Cloud Computing, Information Diffusion, Signed Social Networks

1. INTRODUCTION

Social media platforms like Weibo, Twitter, and YouTube have grown in importance as avenues for gathering and sharing information due to the advancement of internet technology [1]. In contrast to conventional means of exchanging information, users of social applications generate and disseminate information in addition to receiving it, promoting interpersonal communication. This change improves people's capacity to create, obtain, and share information, resulting in swift and extensive information sharing in social networks, particularly when contentious or visually striking news breaks [2-3].

Studying node importance ranking and influence maximization (IM) in social networks is very useful. In terms of public safety identifying influential people can make it possible to monitor criminal activity in real time, hence reducing risks to social security [4]. The collective voice of the masses has become an unavoidable force in the field of public opinion, capable of influencing the emergence of popular themes and the reactions of pertinent authorities [5-6]. In the meantime, social stability and national security are threatened by the network's misleading information and rumors, therefore it's critical to learn how to spot key nodes and promptly change public opinion [7].

The IM challenge in signed social network environments is the main topic of this study. Investigating a group of powerful users in order to optimize the total spread of influence is the problem of instant messaging [8]. Positive linkages and mainly unexplored negative relations are consistent with the majority of traditional IM techniques.

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Nonetheless, some recent IM research has concentrated on signed social networks [9]. In recent years, it has been clear that social media is rife with disputes and controversies. IM on signed social networks leads to some challenges for consideration [10].

Integrating information distribution with stochasticity and polarity of relationships for user acceptance of products is the first difficulty. Positive effect is overestimated when one is unaware of the association's polarity.

Because it creates a new group of active users with each iteration, the computation of influence spread is a spontaneous activity. As a result, accumulating influence under polarity linkages through multiple iterations and looking into a fresh, reliable solution is difficult.

The IM problem is NP-hard under any diffusion mechanism, as demonstrated by the authors of [11]. As a result, it is impossible to develop an accurate solution for large-scale networks. It is a difficult task to compute near-optimal solutions over large-scale signed networks using approximate IM solutions.

I. Contributions

By taking into account both friendly and antagonistic affiliations, this survey primarily focuses on instant messaging algorithms across signed social networks. To the best of our knowledge, this study is the first to survey signed instant messaging algorithms. It offers the principles and methods of the signed social network to address the instant messaging issue. The following is a list of the survey's major contributions:

There has been discussion of the backdrop and information flow deployment on the signed social network using structural information. The study also examines the effects of link polarity and information flow on network characteristics.

When and where knowledge is created explains how it spreads. The evolution of signed social networks and the traditional concepts of information propagation are examined. Additionally, the study focuses on the effects of polarity on the diffusion of knowledge and its traces across social and structural aspects.

The literature presents a variety of instant messaging methods to find influential spreaders under both positive and negative links. As a result, this paper examines and contrasts the most advanced instant messaging algorithms for signed social networks. Additionally, the paper investigates novel avenues for signed social network research.

Lastly, a few research issues in signed social networks are examined along with potential future initiatives. We have also discussed the unresolved problems in the literature. The purpose of this study is to give novice social network analysis researchers a place to start.

II. Applications

In the domains of education, sports, society and culture, media, pattern and knowledge discovery, fake news and misinformation, election campaigns , tourism and hospitality, disaster management, transportation, cyber security, multimedia, and more, signed social networks have enormous application potential [13-15]. Viral marketing, social recommendation, rumor control, epidemiology, link prediction, revenue maximization, profit maximization, behavior analysis, opinion mining, and more are some of the well-known social computing applications of the instant messaging problem in signed networks [16-18].

III. Difference from Existing Surveys

This study is the first to focus solely on the polarity-based IM problem. Negative relationships and over-fitting to positive associations on unsigned networks are ignored in surveys found in the research. The signed social networks and their characteristics are discussed by the authors of [19]. The authors of examine how social influence analysis and instant messaging algorithms have evolved. The authors of [20] go over both the context-aware developments and a thorough examination of traditional IM techniques. Recent advancements and trends in the IM problem are discussed by the authors of [21]. A study of several SNA difficulties, including IM challenges with regard to quantum-based solutions, is presented by the authors of [22]. Developments in signed networks have not been documented by any of the aforementioned surveys, which all concentrate on unsigned social networks. As a result, this study will serve as a foundation for future research on signed social networks. The list of abbreviations used in the article is shown in Table 1.

IV. Organization

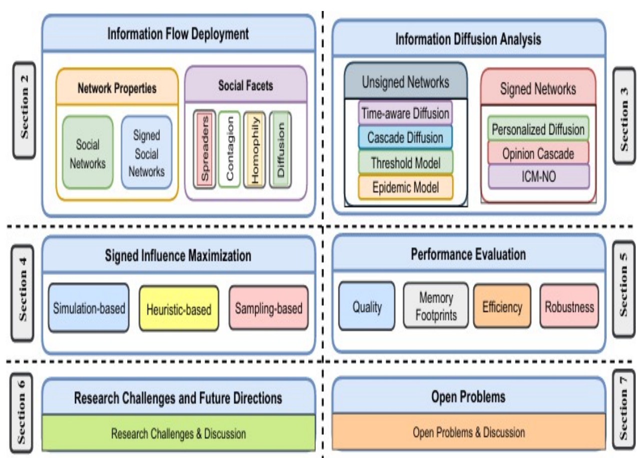

Fig. 1. The survey overview.

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Figure 1 summarizes the full survey. Section 2 discusses the deployment of information flow on signed social networks. In Section 3, we will then go over the information diffusion process on both signed and unsigned social networks. After that, we will explore cutting-edge instant messaging algorithms on the signed social network and present a comparative study in Section 4. Finally, we will discuss future perspectives and research problems related to the instant messaging dilemma on signed social networks. Following that, we covered a few unresolved issues in Section 7. In Section 8, we will wrap up the survey.

I. SIGNED SOCIAL NETWORKS

The principles, information flow, and foundations of polarity-based or signed social networks are covered in this section. First, the qualities of negative linkages and signed social network representation were examined. Both polarity theories' collective characteristics have been examined. Table 2 lists the signed network measurements.

Influence maximization means distributing a message to maximum users through media taking into account that is highly time consuming and impractical. Due to constraints, it is possible to select seed set of influential users than other users can spread the message widely. The IM problem is generally defined as in Eq. (1), where the function (S) defines the influence of a set of seeds S. $S^* = \text{argmax } S \subset V\ \varphi(S)$ subject to some constraints. To select effective seed set, there are three different ways of behavior aware methods:

User's features to determine the relevance of each user to the query.

The characteristics of the relationship to model the probability of spread between users depending on the relevance of the query.

The message (AM) function is targeted to a number of relevant users during the distribution process.

These three types of information encompass the differences between method of behavior agnosticism and method of behavior awareness. The behavioral antiquated method only considers the structure of the graph to determine the influence of the nodes and to identify the number of influential nodes. In other words, behavioral avoidance methods do not take into account specific features of the BV (user behavior capture) and BE (border behavior capture) sets, i.e. different features of the relationship between a user pair. Furthermore, they do not combine different features of the message, as indicated by AM settings in the query message.

In short, the behavioral agnostic method assumes that: (i) all users have the same behavior; (ii) the relationship between the pairs of users is the same; and (iii) the message feature does not affect the propagation process. Some or all of these aspects may be different in behavioral-aware methods. This means that in addition to the structure of graphs, behavioral awareness methods take into account some aspects of behavioral information and propose practical approaches for practical applications in the real world.

Table 1. List of Abbreviations

IM	≜	Influence Maximization
SNA	≜	Social Network Analysis
IDM/DM	≜	Information Diffusion Model
LT	≜	Linear Threshold Model
IC	≜	Independent Cascade Model
PID	≜	Personal Information Diffusion Model
SNIC	≜	Signed Independent Cascade Model
PLID	≜	Polarity-related Linear Influence Diffusion
MC	≜	Monte-Carlo Simulations
SVIM	≜	Signed Influence Maximization under Voter Model
PRIM	≜	Polarity-aware Influence Maximization
IC-P	≜	Polarity-aware Independent Cascade Model
BNINS	≜	Blocking Negative Influential Node Set
RLP	≜	R-Greedy with Live-edge and Propagation-path
TP-IM	≜	Time-sensitive Positive Influence Maximization problem
HDPID	≜	Polarity-based Heat Diffusion Model
EN-IM	≜	Enhanced Negative Opinion Influence Maximization
PIM-SA	≜	Positive Influence Maximizing using Simulated Annealing
SPR	≜	Signed Page Rank
PIM-SN	≜	Positive Influence Maximization Algorithm for Signed Social Networks
AOMF	≜	Activated Opinion Maximization Framework
RR	≜	Reverse Reachable Set
IBM	≜	Influence Blocking Algorithms
DOM	≜	Dynamic Opinion Maximization
QDOM	≜	Q-learning-based DOM Framework
TRM	≜	Triggering Model
TAM	≜	Time-aware Model
GAN	≜	Generative Adversarial Network
MACD-SN	≜	Memetic Algorithm for Community Detection in Signed Networks
MMC	≜	Maximal Multipolarized Clique
MAX-DRQ	≜	Maximal Discrete Rayleigh's Quotient

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This paper focuses on methods of consciousness of behavior. Several surveys extensively discuss the methods of behavioral agnostic.

II. Behaviour-Aware Methods

In the behaviour-aware methods, additional information such as user behaviour, relationship properties, and search content is taken into account to improve the dissemination process in addition to the graph structure. For example, if the request is to advertise a specific product, then all users may not be equally interested in the product. Opinion-aware approaches consider users' opinions about a message in order to identify influential users who have the power to influence other users' attitudes or opinions. These techniques focus on analyzing the sentiment and subjectivity of users in their postings or their comments on messages made by other users in order to ascertain the position and opinion of users toward a message.

The cost and benefit of the spread of advertising queries are considered using money-saving methods. These methods assume that users can estimate their influence on the network and negotiate prices to participate in the distribution process. Consequently, the selection of different users as seed scan involve different costs. In addition, analysis of historical user activities data is used in these methods to estimate the user's valuation of products announced in a spreading process. This can help to bring more value to target users and result in greater benefits in the process.

In physical methods that take into account the geographical location of the user, the query is intended to send a message to the user at a particular location, for example, the query may invite the user to a festival taking location at a particular location. These methods assume that the location of the user can be modeled using historical tracking locations of the user, GPS-enabled technologies, location-based social networks or similar technologies. In the sections that follow, these four categories will be expanded upon and thoroughly examined.

III. Interest-Aware Techniques

These approaches consider the preferences and interests of users. The goal of spreading is to sway users who might be interested in a message. Users' past actions, including posts, likes, ratings, and shopping histories, may be preprocessed to identify their interests. The size of the seed set, $S = k$, is fixed in these approaches and is regarded as a constraint of the IM problem as stated in Eq. (1).

Based on the approach used to determine which users are interested in the query's message, we divide these methods into three kinds. Target nodes are those who are interested in a message. In order to disseminate the message to as many target nodes as possible, instant messaging attempts to choose a seed set. A number of centrality metrics are extended to discourage mining each node's influence in relation to the target nodes. Other nodes have no bearing on the centrality calculation in these metrics; it is solely based on the target nodes. The top-k core nodes are then selected to serve as seeds.

Each node's influence is calculated using the paths connecting it to other nodes in [23-24]. To ascertain the node's region of influence, Suqi Cheng et al. [25] define two sets for each node: followers and influencers. The influential nodes are then greedily chosen to optimize the activation probability of the target nodes in various regions after the nodes are clustered according to their region. An approach based Jae Han Choi et al. [26] maximum effect arborescence method, which ensures a solution within a factor of the ideal solution, is proposed by the authors in [[27-28]

The goal of Susmita Das et al. [29] also message propagation to target nodes. Nevertheless, the diversity of the target nodes that are impacted is also considered in addition to the influence on the target nodes. Jiayi Deng et al. [30] model the challenge as finding a seed set to disseminate the message to target nodes with a variety of attributes, assuming that each target node has a set of attributes. A degree-based approach is then suggested to address the issue.

According to Tyler Derr et al. [31], some silent nodes might be interested in a message but might not have been regarded as target nodes because of their lack of previous activity. Such nodes can be motivated by disseminating the message throughout the network. Consequently, the authors offer a method that chooses a seed set to impact target nodes with structural variety using the reverse influence sampling method [32-33].

According to Linton C. Freeman et al. [34] activating non-target nodes may result in unfavorable expenses and outcomes. In order to increase the number of activated target nodes while concurrently decreasing the number of activated non-target nodes, they address how to choose a set of influential nodes. In Anna Gallo et al. [35] the authors suggest a simulation-based greedy method to find a set of influential nodes that maximizes the number of activated target nodes while keeping the number of non-target activated nodes below a predetermined threshold. They also suggest heuristics for a time-efficient greedy method.

According to Jie Gao et al. [36], the problem's objective function is to maximize the difference between the number of active target nodes and activated non-target nodes. To ascertain each node's influence, the authors provide a centrality metric; influential nodes are chosen iteratively. In conclusion, taking into account a group of nodes as target nodes avoids wasting resources (money or time) and stops a message from spreading to nodes that might not be interested in the message's subject.

The success of the spreading process may be enhanced with additional information regarding the diversity of nodes, such as that found in Heiko Geppert et al. [37]. As demonstrated by Nancy Girdhar et al. [38] considering non-target nodes helps prevent the activation of nodes that could disseminate a negative message and adversely affect the instant messaging process. To find the most influential seeds, a reverse sampling strategy is then suggested.

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The importance of user trust is also considered in Yudong Gong et al. [39], who partition the network into domains according to user trust and common labels. The significant users in each domain are then identified using a degree-based approach. In conclusion, Amit Goyal et al. [40] analyze each user's historical activity to identify a collection of labels that they are interested in.

IV. Topic-Aware Techniques

These techniques start by defining a set of network topics. The behaviour of each user, corresponding to BV, can be modelled using a topic vector; the j-th entry of this vector is a number in [0, 1] and indicates how interested in the j-th topic the user is. Additionally, a topic vector can be used to characterize the behavior of each relationship that corresponds to BE; the j-th entry of this vector is a value in [0, 1] that indicates the spreading (impact) probability on the edge for the j-th topic.

Topic-Aware Online Techniques: There is no preprocessing involved in online topic-aware algorithms; all procedures to find influential seeds are done online when a question arises. In Meng Han et al. [41] the features of the relationship between each pair of nodes are modelled using a topic vector, corresponding to BE. In Qiang He et al. [42], the spreading probability on each edge for the message is computed based on the subject vector of the query, which corresponds to AM, and the topic vector assigned to each edge, which corresponds to BE. Next, a set of influential seeds is identified by extending the IC and LT diffusion models. The authors of Qiang He, et al. [43] consider the function of communities inside the network when choosing a collection of important seeds that span various regions of the network. A number of influential seeds are chosen from each community based on its size after the network is divided into a number of communities.

Each user's behavior is modeled using a topic vector, which corresponds to BV, in Xiaochen He et al. [44]. Xinran He et al. [45] begin by discussing how to ascertain each user's interest in various topics based on their network activities. Then, using the subject vectors of the query and users, they suggest a simulation-based technique to find a collection of influential seeds. In Xinran He et al. [46], entropy divergence notation is used to calculate the similarity between the topic vector of users and the topic vector of the query in order to assign a weight to each node that represents the node's level of interest in the query's message.

Fritz Heider et al. [47] provide a network embedding technique to identify user interests, which is subsequently used to discourage mining each node's influence. An algorithm based on reinforcement learning is used to identify a group of prominent nodes. According to Keke Huang et al. [48], a higher degree of similarity between a user's interests and the query's attributes suggests that the user may be influenced during the spreading phase.

To ascertain the likelihood that each node is impacted throughout the spreading process, they compute the similarity between the topic vector of users and the topic vector of the query. To capture this feature, an independent cascade model is then expanded; a degree-based heuristic is suggested to ascertain each node's influence and choose the seeds iteratively.

V. RESEARCH DIFFICULTIES AND FUTURE PROSPECTS

The instability problem with IM solutions caused by noisy influence and activation probabilities, stochasticity of the diffusion process, and so on was covered by the authors of [49]. There is a greater likelihood that the algorithm will produce distinct seed nodes in each iteration. Consequently, the robustness of IM solutions in signed networks has been the subject of several research. Nevertheless, managing robustness in IM solutions remains a difficult challenge.

Taking Balance and Status Theories into Account: The balanced and imbalanced structure of positive relations in the presence of opposite polarity can be studied using network theories of signed social networks [50]. Even status theory can investigate users' social standing within the network and offer a ranking based on that. As a result, these network theories can be reinterpreted and applied to signed instant messaging, and they may serve as a potential avenue for further research.

Including Incompleteness and Uncertainty: A fixed probability for influence and activation is taken into account in the majority of the literature related to information spread. The results of the diffusion process become unclear and incomplete as a result. The activation history of nodes and user participation in the activation process are not included in these research. Nonetheless, this issue was investigated in certain work in unsigned networks. However, there is still more work to be done in light of opposing influences.

Taking into account the multi-phase diffusion process: With the exception of greedy solutions, the majority of IM techniques choose seed nodes in a single move before initiating the diffusion process. Therefore, the overall influence spread will be decreased if the chosen seeds are not ideal. As a result, choosing seed nodes in several iterations as opposed to a single move will be preferable. The multi-phased diffusion mechanism in unsigned networks was introduced in few recent studies. This could be one approach to successful seed selection.

Thinking About Parallel and Distributed Solutions: The most popular issue with IM methods is scalability. For example, a greedy solution takes more than a week to generate seeds for a few million-node networks. However, in reality, network size is in billions. This happens because these methods serially select seeds. There aren't many studies that address this problem by presenting simultaneous and distributed solutions. For signed instant messaging, more of these frameworks must be suggested.

Adopting Contextual Features: Numerous instant messaging methods have been proposed in the literature by taking into account contextual elements in positive social networks, such as themes, conformity, location, time, competition, and so on. Nevertheless, these investigations have steered clear of detrimental relationships and influences.

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Consequently, it is possible to investigate both contrasting relations and contextual factors.

The Absence of Benchmarking Research: In the past ten years, a lot of research has been conducted in both signed and unregistered networks. Nevertheless, it can be difficult to choose an IM algorithm for a certain situation, dataset, issue, etc. To observe insights regarding these approaches, a thorough and robust empirical investigation under benchmark networks is required. For example, in a benchmarking study of 11 seeding procedures, the authors of found several inconsistencies between these techniques and datasets. For both signed and unsigned network datasets, additional benchmarking analysis is therefore required.

Using Models of Heterogeneous Diffusion: The majority of IM techniques take into account a situation in which a network has only one kind of relationship and diffusion mechanism. In actuality, though, a single network could have multiple relationships. For example, X (previously known as Twitter) networks have numerous relationships, such as retweets, mentions, followers, and so forth, and they have various diffusion methods for these interactions. As a result, heterogeneous diffusion models must be taken into account concurrently. Although some research has attempted to address these situations, much more work remains.

Taking Group Norms into Account: The majority of instant messaging techniques take into account the impact that individuals have on one another while ignoring the impact that communities or groups have on a person. Nonetheless, a group of people who share similar interests, backgrounds, educational backgrounds, preferences, and so forth influence each other's decisions. Group influence has been found in certain research on signed networks and unregistered networks. Therefore, both positive and negative impacts can be used to examine social norms.

Meta-heuristic Solutions' Applicability: Numerous evolutionary techniques, such as genetic algorithms and bioinspired optimizations, have been used to develop IM solutions for unsigned networks. Therefore, polarity-based IM challenges can be used to investigate these nature-inspired methods.

Identifying Network Coupling and Overlapping Users: We need to take into account several networks at once in order to integrate user fluency across the network. In order to incorporate these networks for influence propagation, it is necessary to look into overlapping users. Overlapping users and network coupling techniques in signed networks have been covered in a few research. Thus, it is necessary to investigate multiplex instant messaging in relation to signed networks.

VI. Open Problems

The degree to which information diffusion models are adopted in real-world scenarios is crucial for addressing issues such as boosting voting engagement, event management, viral media, and many more. The diffusion process has been the subject of two different kinds of works: new diffusion models and an extension of the classical model with conflicting relations. The second kind of propagation model must verify its accuracy by gathering information from social media users via surveys and comments.

How may efficiency and efficacy be traded off? The majority of current approaches to the IM problem have either concentrated on efficiency or efficacy. However, because of concerns with cost and scalability, it is essential to address both factors. Few studies have simultaneously examined timeliness and opposing viewpoints. Thus, it is essential to determine whether these models are feasible in order to address opposing viewpoints.

How might generality and opinion change be traded off? The majority of current models are extensions of unsigned diffusion models. Therefore, in order to capture network and user behavior relating to a particular challenge, it is crucial to extend these propagation models and seeding procedures. Effective seeds can be produced by incorporating several relationships, such as positive, negative, neutral, group, and so on. Therefore, it is still possible to investigate the generality of the diffusion process with respect to signed networks.

Finally, we have covered the open issues, future prospects, and research challenges related to signed network settings. We can draw the conclusion that this survey is the first to tackle the instant messaging issue related to signed social networks. We believe that this survey will serve as a foundation for social network researchers and help them grasp the fundamentals.

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