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Hybrid Community-Driven Influence Maximization in Large Social Networks

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ABSTRACT

Influence maximization in large-scale social networks faces challenges of scalability and community-aware diffusion. As Online social networks (OSNs) are deeply integrated into our daily lives, particularly with the continuous expansion of web services and mobile technologies. The information shared by individuals through social connections directly impacts our beliefs and behaviors. Consequently, identifying influential nodes in complex OSN structure has attracted considerable attention in a wide range of applications such as viral marketing and managing rumors. However, traditional centrality-based methods often fail to achieve optimal influence spread in large-scale, real-world networks due to their high computational complexity and limited consideration of community structures. To address these limitations, in this paper, we propose a novel hybrid approach that combines community detection with influence score calculation. The method evaluates influence within communities (intra-community) using centrality measures, and across communities (inter-community) by identifying bridging nodes, producing a total influence score for each node. We implement the approach using the Louvain algorithm for community detection and a hybrid bridging score to capture inter-community influence. The proposed method is evaluated using the Susceptible-Infected-Recovered (SIR) and Independent Cascade (IC) diffusion models on three real-world datasets. Experimental results demonstrate that our method identifies influential nodes capable of propagating influence more rapidly and effectively compared to existing techniques, demonstrating its scalability and effectiveness for large-scale networks.

1. INTRODUCTION

An online social network (OSN) consists of various social interactions that occur among users. OSNs are web-based platforms that allow users to connect with friends and family, meet new people, join communities, chat, share images, organize events, and build networks with others who share common interests or aspects of daily life [1].

Users of OSNs and their social relationships naturally form a community structure, shaped by shared interests and other factors such as user's activities on the platform. In this structure, individuals with similar traits are closely connected to one another, while having fewer links with users outside their community [2]. Since people naturally belong to and participate in multiple communities simultaneously, the communities actually overlap most of the time. Overlaped nodes (users) who are part of many communities are essential to the spread of information between different communities.

Social network analysis (SNA) leverages graph theory to model a network as a graph composed of nodes and edges, where nodes represent individual actors and edges represent the relationships or interactions between them. One of the important tasks in any SNA is to identify influential nodes in that network and define them as selecting a set of people in the network so that it has the maximum influence over the people of the network and causes a wide spread of the diffusion process [3].

The problem of detecting influential users has attracted considerable attention recently due to its applications in various domains, such as ensuring efficient information dissemination [4], managing the spread and control of rumors [5], recommendation system [6], public health [7], and viral marketing [8]. Furthermore, some nodes have a higher influence on the diffusion process than others, thus influence diffusion in OSN displays specific diffusion patterns. To maximize the effectiveness of information diffusion, influential nodes can serve as the first communicators [9].

One of the most prominent applications of influence maximization is Viral Marketing (VM), which has attracted considerable scholarly attention in recent years. The strong motivation for studying influence and information propagation models with viral marketing is justified by Wang et al. [10].

In other words, when an organization or a company wants to launch a new product in the market using the word of mouth effects within an OSN, the company must identify the influential users on the network and get them to adopt the product with the anticipation that these initial adopters will trigger a large cascade across the network, leading others to adopt. Therefore, diffusion can be understood to be an information transmission process between individuals [11].

Most Existing influence maximization approaches largely focus on individual centrality measures or community detection techniques without effectively leveraging the underlying network structure, particularly the roles of bridging and overlapping nodes. Many methods rely on simplistic single-criterion scoring, which fails to capture the diverse aspects of node influence, and often neglect the importance of inter-community bridge nodes that facilitate influence dissemination across multiple communities.

Additionally, these methods face scalability challenges when applied to large-scale networks, limiting their practical applicability. The limited consideration of overlapping nodes, which can serve as vital connectors among communities, further restricts influence reach. Moreover, much of the existing validation is confined to specific datasets, affecting the generalizability of the results.

Our work bridges these gaps by integrating intra-community centrality, inter community bridging, and overlapping node detection into a unified framework. This comprehensive approach effectively incorporates multiple centrality metrics, overlapping nodes, and accelerates diffusion in large networks. and enhance information diffusion in large-scale networks.

In this paper, we propose a hybrid approach, which integrates community detection with influence measurement-based on centrality measures to enhance accuracy and maximize the influence. This approach ensures that influence is maximized both within and across communities. The proposed method developed from inspiration of previous works [12, 13] in influence maximization that demonstrated the effectiveness of community structure in addressing some problems, such as modeling information spread and marketing applications, additionally, enhances performance in influence maximization [2]. Community detection facilitates the analysis of large-scale OSNs by grouping nodes based on their connectivity patterns or other attributes [14].

This paper incorporates an innovative framework of hybrid multi-criteria influence maximization by utilizing community detection and multi-criteria influence scoring for the purpose of seed selection. The intended identification of seed nodes targets both influencers (nodes that have high influence within the community) and bridge nodes (nodes with the highest potential to bridge communities) to optimize influence maximization.

To summarize, I have developed an approach to improve coverage of influence, produce greater speed of active diffusion, and lower computation costs. Ultimately, the framework has the potential to provide a scalable and holistic approach to maximize influence in large, real-world social networks.

The remainder of this paper is structured as follows: Section 2 provides a literature review, while Section 3 introduces the proposed hybrid method in detail, including the community detection, calculation of node's influence measurement and the selection of the set of influential nodes. Results and discussion are demonstrated in section 4. Finally, this paper is concluded in section 5 with key takeaways, practical implications, and directions for future work, including extensions to dynamic and weighted networks and real-time adaptation.

2. RELATED WORKS

This section presents a focused review of the extensive influential nodes' identification literature from the past five years, with particular emphasis on graph-based and community-based approaches most relevant to our research.

Shi et al. [15] proposed a new optimization framework, CycRak, to maximize influence based on cycles ranking in large undirected networks. Unlike traditional centrality measures such as degree, betweenness and closeness centrality selection methods, the researchers prioritized basic cycles and selected influential nodes from these cycles to maximize information spread for CycRak. The study primarily focused on undirected and unweighted networks. The authors acknowledged this limitation and suggested that extension to other network types was necessary.

In the study [16], authors proposed the Out-degree Effective Link (OEL) algorithm by combining out-degree measure with Effective Link to address the problem of information diffusion maximization in dynamic social networks. By incorporating time-sensitive user interactions, this approach enhanced traditional information maximization procedures. The proposed algorithm extended the Independent Cascade (IC) model work based on local topology and effective links, ensuring that information maximization diffusion aligned with temporal constraints of the real-world. The proposed OEL algorithm, which consisted of two stages, first generated a candidate set of seeds using out-degree centrality measure and metrics of effective links to reduce optimization space and in the second stage; it applied a strategy of greedy selection based on submodular properties to spread maximum influence efficiently. The algorithm primarily considered node degree and effective links, but did not take into account other important network structural properties like clustering coefficient or community structure, which could significantly impact influence propagation.

By integrating information from both the neighboring layers of the node and itself, Zhu and Wang [17] proposed a method for influential node identification in complex networks. Unlike existing approaches like k-shell decomposition and degree centrality, which often failed to differentiate nodes effectively, the proposed method outperformed degree centrality with neighboring layer data to quantify influence more accurately. By repeatedly incorporating nearest neighbor information, the approach enhanced precision in ranking influential nodes. The proposed model was evaluated using the SIR model across multiple real-world networks, and results showed that proposed model outperform compared to seven other centrality measures based methods. The method was primarily tested on unweighted and undirected networks with symmetric adjacency matrices. This limits its applicability to more complex network types, such as weighted or directed networks.

Another study was introduced by Zhu and Huang [18] for influential spreaders identification in complex social networks by leveraging spread centrality and path reachability. SpreadRank dynamically selected influential nodes unlike centrality based tradition methods and it minimized influence overlap by optimizing both suppression effectiveness and information diffusion. On real-world networks using the SIR model, the experimental results demonstrated that SpreadRank outperformed the state of the art approaches in both immunization impact and spreading efficiency. For large-scale networks, the method was computationally efficient but it was not applicable to all network topologies because it assumed a limited number of local pivot nodes.

Both the authors [19, 20] proposed a hybrid model called H-GSM (Hybrid Global Structure Model) for identifying influential nodes in complex networks. In the research [19], the authors integrated the GSM (Global Structure Model) framework with local and global centrality measures, specifically degree and K-shell centrality, to enhance influential node identification. They used three real-world networks (Karate, Netscience1, and Router) to evaluate the performance of the H-GSM model. On the other hand, Mukhtar et al. [20] combined the K-shell decomposition approach and degree centrality in their H-GSM method to incorporate both local and global network information for improved identification of influential nodes. They evaluated the performance of their model using the SIR model to simulate the propagation process on six real-world networks. While both studies applied the same core concept of H-GSM, Mukhtar et al. [19] focused more on integrating the GSM framework with centrality measures, whereas Mukhtar et al. [20] emphasized the use of the SIR model for influence propagation simulation.

Zhao et al. [21] introduced a novel method called KPDN for identifying influential nodes in complex networks. The proposed approach combines the correlation characteristics of both local and global features. For the global perspective, the K-shell decomposition was applied to enhance the discriminative degree of each node. Extensive experiments conducted on multiple real-world networks confirmed that KPDN achieved superior performance compared to traditional algorithms, effectively isolating critical nodes, and rapidly fragmented networks. Overall, the authors' method offers a valuable tool for applications where pinpointing influential nodes was crucial, such as epidemic control, network security, and infrastructure stability.

On the other hand, Alasadi and Arb [22] proposed a solution framework for addressing the influence maximization problem. Their framework involved three main phases: Firstly, the community structure was discovered using the link density-based technique clique percolation (CPM), the set of final seed nodes was chosen after the candidate seeds were created in the second step. The IC diffusion model, which simulates influence diffusion in real world network. Experimental findings demonstrated improvement compared to baseline approaches. The authors highlighted the importance of community detection and overlap in improving influence maximization strategies.

Alasadi et al. [23] proposed a graph-based approach was employed to identify influential nodes, with particular emphasis on overlapping nodes across communities to assess their impact on influencer effectiveness. Empirical analyses and simulation experiments revealed a strong correlation between node centrality score and the properties of overlapping nodes, highlighting their critical role in determining influencer performance. Their findings highlight that leveraging overlapping nodes can significantly enhance influence maximization strategies by reducing computational efforts and focusing on nodes with inherently high influence potential.

While there are many studies on the influence maximization problem in OSN, almost all current approaches have important limitations that make them inapplicable in real-world large-scale networks. The traditional centrality measures and their extensions are global and use the entire network without considering the modular nature of social graphs. Moreover, some methods are based on communities and use a localized approach (these can be referred to as community aware methods), but usually do not include the communities' bridges or ways in which communities interact, which are essential for a large information diffusion.

Additionally, some recent hybrid methods limit themselves to using single dimensional or one-dimensional centrality or they are not large directed networks, especially for networks with overlapping community structures or dynamic connectivity. Very few existing works have developed an explicit way of combining multi-criteria influence scoring in communities with bridge detection between communities, and even fewer works have developed a practical and efficient method that is applicable for complex networks.

Our research contributes to the existing literature to fill the gaps identified above by proposing a hybrid influence maximization method that combines community intra-centrality-based influence with inter-community bridging.

The final method represents a comprehensive and powerful approach to social network analysis especially directed complex networks, as it ensures that selected influencers are both locally highly connected and are positioned to contribute to the acceleration of information propagation across the entire network. The inclusion of intra- and inter-influence expands current research and practice in the area of influence maximization while increasing the efficacy and efficiency of research and practice for communities and the overall influence of large networks.

3. PROPOSED APPROACH

Our paper makes several significant contributions to the field of influence maximization in social networks. It introduces a novel hybrid approach that combines community detection with influence score calculations based on multiple centrality measures, thereby enhancing the accuracy and efficiency of identifying influential nodes.

The approach distinctly targets both intra-community influential nodes and bridging nodes that connect different communities, ensuring a comprehensive influence spread across the entire network. Utilizing the Louvain algorithm for community detection facilitates effective grouping of densely connected nodes, while the hybrid bridging score comprising normalized betweenness centrality and community diversity accurately identifies critical nodes for inter-community information flow.

The proposed approach is validated on three diverse real-world datasets (Soc-Epinions1, Cit-HepTh, ia-digg-reply), demonstrating its robustness, scalability, and superior performance over traditional methods under the most cited diffusion models such as IC and SIR [24]. By emphasizing the role of overlapping nodes and bridge nodes, the approach significantly accelerates influence dissemination and reduces computational complexity. Overall, these contributions provide a practical and scalable solution for influence maximization, applicable to various scenarios like viral marketing and rumor control, by strategically selecting seed nodes for rapid and widespread influence propagation. In this section, we will introduce the detailed process of our proposed hybrid approach.

3.1 Network data preparation

This initial phase involves acquiring and preparing the networks' data for analysis. The process starts with loading the network data. The three datasets used for validating the experiments are detailed in Table 1.

Table 1. Statistical overview of the used datasets

Dataset	|V|	|E|	D_{avg}	Com	CC_{avg}	Type
Cit-HepTh	27,770	352,807	25	≈ 169	0.312	Directed
Soc-Epinions1	75,879	508,837	13	≈ 664	0.137	Directed
Ia-digg-reply	30,400	86,313	5	≈ 424	0.005	Directed

$|V|$ and $|E|$ denote the total numbers of nodes and edges, respectively; D_{avg} indicate the average degree, CC_{avg} corresponds to the mean clustering coefficient, and *Com* represents the community count.

3.1.1 Data preprocessing

Removing self-loops from a network structure is a common practice to ensure a cleaner and more accurate representation of the network. Self-loops are edges that connect a node to itself, and they can cause complications in various network analysis tasks, such as calculating centrality metrics or information flow [25].

In a study on betweenness centrality, it was shown that removing self-loops can lead to a more accurate measure of a node's importance in the large sparse network, the authors specifically note that they consider strongly connected networks with no self-loops, emphasizing that the presence of self-loops is excluded from their analysis and algorithms [26]. Additionally, self-loops can also affect the calculation of other centrality metrics, such as degree centrality and closeness centrality, making it essential to remove them for a more accurate analysis. Another reason for removing self-loops is to ensure accurate information flow [27].

3.1.2 Construct network graph

In this step, the preprocessed data is represented into a formal graph structure to model social relations. Each dataset is represented as directed graph *G(V,E)*, where *V* represent nodes (users) in an OSN, and *E* represent edges (relationships) between users [28]. At the end of this step, three graphs are generated, one from each dataset.

3.2 Community detection

A community or module refers to a group of nodes (users) that are strongly connected and loosely connected to the rest of the nodes of the network. However, in real-world cases, users in OSNs often take part in many communities simultaneously rather than completely disconnected groups. The community structure is a related concept defined as a group of communities within a graph, and is represented as CS={c_1, c_2, c_3, …, c_n}, where CS stands for the community structure and c_i (i = 1 to n) corresponds to the communities.

Community-based influence maximization has been identified as crucial for solving influence maximization problems, demonstrating its potential in large-scale networks [13]. Several studies have emphasized the critical role of community detection in optimizing information diffusion, highlighting its significance in ensuring the effective spread of influence across social networks [29, 30].

In this step communities are uncovered for each graph, to detect network communities, the Louvain algorithm [31] is used because of its demonstrated efficiency, scalability, and ability to detect sub-groups of nodes that are densely connected within large networks. The Louvain method detects community structure using modularity optimization, which is a well known quality function that defines a networks division into communities, comparing the density of intra-community links to what would be expected in a random network. The Louvain method operates in 2 phases in an iterative manner where in the first phase, each node is assigned to the neighbouring community that increases the modularity best, and in the second phase nodes in the same community at the previous iteration are aggregated into super-nodes to create a new smaller graph. The two phases of Louvain are repeated until there is no further improvement in modularity.

3.3 Intra community seed nodes selection

To identify influential nodes within each community, an Intra-community influence selection process is applied, where multiple centrality measures are computed and assigned weighted influence scores. These scores are then normalized to ensure consistency across the network. The selected centrality measures include eigenvector centrality, out-degree centrality [32], PageRank, K-Shell decomposition [15, 33] and Katz centrality [34, 35], as each captures different aspects of node influence. Utilizing multiple centrality metrics ensures that nodes with diverse influence characteristics are considered [12]. The selection steps are as follows:

3.3.1 Graph subsetting and filtering

To ensure reliable analysis, each community is extracted as a subgraph from the original graph G. If a community has fewer than three nodes, it is ignored to avoid unreliable calculations. The subgraph for a given community C_i is defined as:

$$G_{Ci}=(V_{Ci}, E_{Ci}) \quad (1)$$

where V_{Ci} is the set of nodes in community C_i and E_{Ci} is the set of edges connecting them. The condition of filtering communities:

$$\text{I } V_{Ci} \text{ I} < 3 \quad (1)$$

This filtering is necessary because very small communities lack structural complexity, making centrality measures less meaningful. Additionally, skipping such small groups improves computational efficiency by avoiding unnecessary calculations on insignificant clusters. This step ensures that only well-defined communities with sufficient structural information contribute to the selection of influential nodes.

3.3.2 Centrality score calculation

For each community, different centrality measures are calculated to capture different dimensions of user's influence. The out-degree centrality measures the number of direct connections a node has, serving as a basic indicator of local influence [36]. The out-degree centrality of a node refers to the number of edges that originate from the node, indicating the node's ability to reach and influence other nodes in the network.

PageRank centrality assigns influence based on the importance of a node's connections, effectively capturing reputation and authority within the community [37]. In order to rapidly determine the importance of nodes in the network, based on their proximity to the core layers, Xu et al. [38] suggested the global index-based centrality technique known as K-Shell decomposition. This approach is efficient for large-scale networks. with low time complexity. Eigenvector centrality considers not only the number of connections but also the importance of connected nodes, making it useful for detecting structurally significant nodes [39]. Katz centrality extends this by incorporating both direct and indirect connections with a decay factor, allowing for a broader assessment of influence [38].

3.3.3 Normalization of centralities scores

Since each centrality measure operates on different scales, they are normalized to [0, 1] making them comparable, using min-max scaling and is determined by the following equation:

$$\mathrm{Cnorm(v)} = \frac{\mathrm{C(v) - Cmin}}{\mathrm{Cmax - Cmin}} \tag{3}$$

where, C_{min} and C_{max} refer to the minimum and maximum centrality values across all nodes in the community, respectively.

3.3.4 Influence score calculation

To quantitatively assess intra-community influence, a composite influence score is computed for each node using a weighted combination of the centrality measures [40]. The computational formulation is given by:

$$I_{intra}(v)=aC_{out}(v)+bC_{pr}(v)+cC_{ev}(v)+dC_{ks}(v)+eC_{kz}(v) \tag{4}$$

where, $C_{outdg}(v)$, $C_{pr}(v)$, $C_{ev}(v)$, $C_{ks}(v)$ and $C_{kz}(v)$ represent respectively Out-degree centrality, PageRank centrality, Eigenvector centrality, K-Shell centrality and Katz centrality. The coefficients a, b, c, d and e are weights assigned to each centrality measure, ensuring that their sum equals 1.

Using a weighted combination of multiple centrality measures as an approach to capture the influence of nodes is consistent with decision-analysis theory and recent research on influence maximization. In the multi-criteria decision-making (MCDM) literature, the weighted sum model, also called weighted linear combination, is a common method of replacing multiple criteria with the one aggregated score, using normalized weights for comparison and to not allow dominance from any criteria to unduly influence the score [41-47].

In social influence analysis literature, hybrid or combined centrality metrics have been shown to provide a more powerful means at identifying influential nodes than any single metric. For instance, Singh et al. [48] show a combination of degree, closeness, betweenness, and eigenvector centralities as a valued "hybrid-centrality" metric that perform well in various contexts.

Similarly, Şimşek and Meyerhenke [39] demonstrated that a closed-form combination of centralities significantly improves the identification of spreaders under diffusion models, outperforming traditional metrics such as PageRank or betweenness alone. Depending on these theoretical arguments and empirical findings, and supported by our own centrality measures experiments on different directed network structures, we selected the weights (a-e). Our study adopts a weighted combination of out-degree, PageRank, eigenvector, k-shell, and Katz centralities to provide a more comprehensive and balanced assessment of intra-community influence.

3.3.5 Selection of top influencers for each community

Within each community, the top k nodes with the highest $I_{intra}(v)$ values are selected as the most influential nodes, where k is a parameter to be determined depending on the size on the network. In our case within each community, the top 1% of nodes with the highest $I_{intra}(v)$ values are selected as the most influential nodes (k=1% of the total community size). The number of selected nodes for each community is determined as:

$$k=max(1, [0.01 * |V_{ci}|]) \tag{5}$$

where, $|V_{Ci}|$ is the number of nodes in the community. This ensures that even small communities contribute at least one influencer to the final set. The top k nodes are then stored for further analysis. The total number of selected influencers across all communities is computed as:

$$\text{Total seed nodes} = \sum_{\mathrm{Ci}} \mathrm{Sci} \tag{6}$$

where, S_{Ci} is the set of selected seed nodes in community C_i.

3.4 Inter community seed nodes selection

In this step we identify bridging nodes in the network by computing a hybrid bridging score, which integrates betweenness centrality and community diversity [49]. The process involves two main steps: estimating betweenness centrality (B) and computing community diversity (D). Betweenness centrality is a measure that quantifies the number of shortest paths passing through a node, indicating how often a node acts as a bridge between two other nodes [50]. In this work, betweenness centrality is estimated using a sampling approach, which approximates the number of shortest paths passing through a node [51]. The estimated betweenness centrality is then normalized for consistency. This step helps to identify nodes that are crucial for information flow within the network. Community diversity is a measure that counts the number of distinct communities among a node's neighbors, indicating how well a node connects different communities [52]. In this work, community diversity is computed by counting the number of distinct communities among a node's neighbors and then normalizing the value. This step helps to identify nodes that are key influencers for influence diffusion and epidemic control. After estimating betweenness centrality and computing community diversity, a hybrid bridging score is formulated by balancing global network influence and inter-community connectivity. The hybrid bridging score is a weighted sum of the normalized betweenness centrality and community diversity. This score is used to identify bridging nodes in the network. The hybrid bridging score H(v) for node v is represented as a weighted linear combination of normalized betweenness and community diversity:

$$H(v)=\alpha.B(v)+(1-\alpha).D(v) \tag{7}$$

where:

- α=0.6 (importance of betweenness),
- 1-α=0.4 (importance of community diversity)

The value of (α) were chosen based on extensive empirical testing across the datasets used in this study. Through iterative simulations, it was observed that setting (α) to 0.6 and (1-α) to 0.4 consistently resulted in the most effective influence diffusion, balancing local and global influence propagation. Specifically, a higher value of alpha emphasizes intra-community influence, promoting rapid and dense spread within communities. Previous works on influence maximization and bridging node identification has also emphasized the importance of betweenness in connecting communities [53, 54], which supports giving it a slightly higher weight than community diversity. Therefore, we fix (α) to 0.6 and (1-α) to 0.4 in our experiments, as this setting is both empirically validated and theoretically consistent. These parameters were selected because they yielded optimal influence diffusion in our experiments.

3.5 Integration of inter-nodes and intra-nodes

The process involves selecting influential nodes within each community and combining them with nodes that act as bridges between communities. Influential nodes are gathered from different groups, and merged with the set of bridge nodes [55, 56]. This union ensures that all selected nodes are unique, capturing both locally central individuals and those that facilitate connections across the network. The resulting set provides a strategic selection of nodes optimized for influence and connectivity across the entire network.

4. RESULT AND DISCUSSION

The proposed hybrid seed selection method was tested on three different real-world networks of existing social networks (Soc-Epinions1, Cit-HepTh, and ia-digg-reply); we chose these datasets for their differences in size, community structures, and structural complexity. This way we had a good performance testing ground for determining how well and how fast the hybrid influence maximization works in propagating influence and the results validated the method as superior to baseline methods.

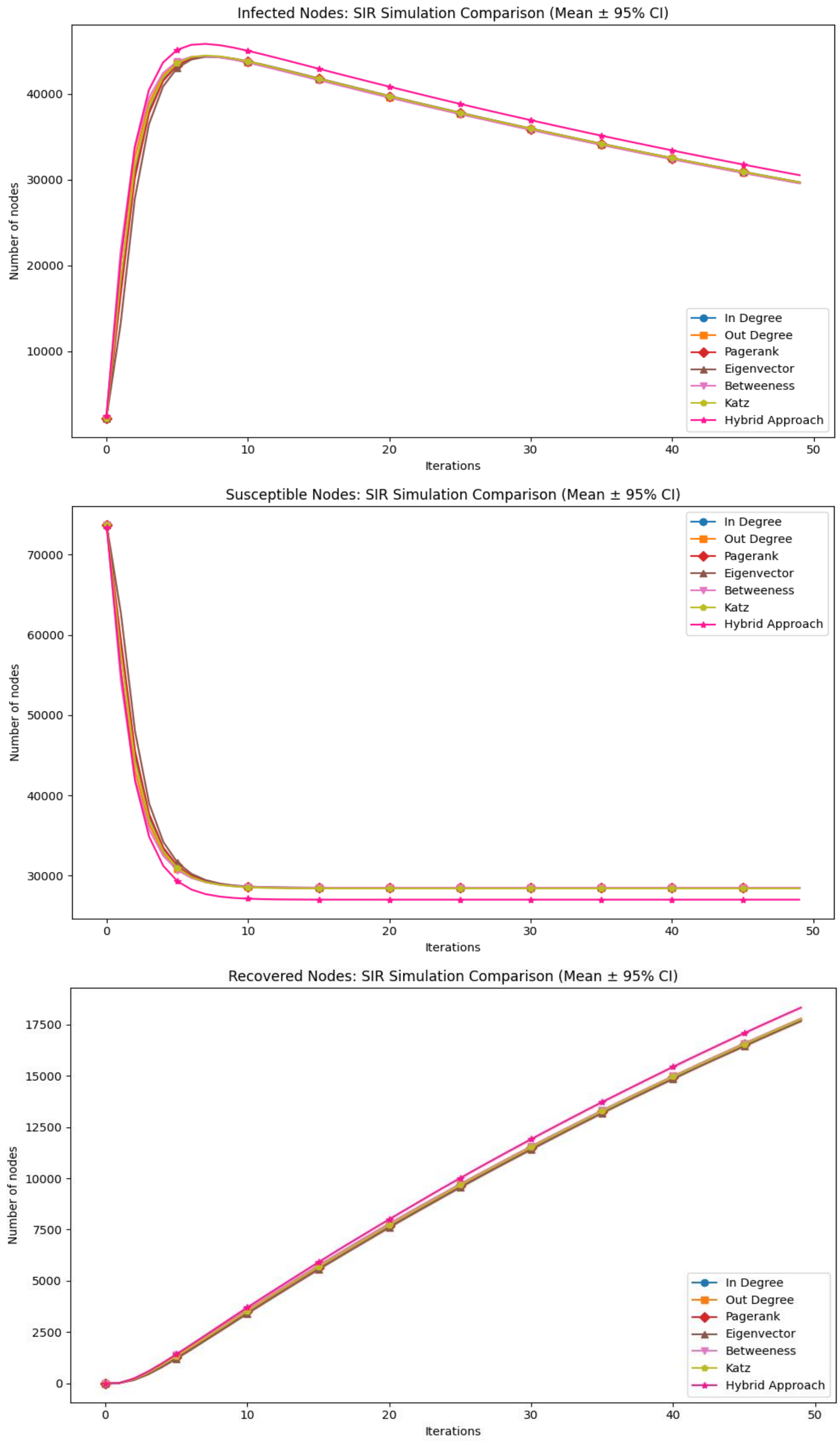
Our experiments across three distinct network datasets showed that the proposed hybrid seed selection model consistently outperformed traditional centrality-based approaches, achieving improvements in influence propagation. The simulation results of the diffusion process under IC and SIR models are presented in Figures 1 and 2, and Tables 2 and 3. We carefully selected parameter values for each model that accurately simulated the flow of information. For the SIR model, we set infection probability (β) to 0.5, and the recovery rate (γ) to 0.01, simulating an epidemic-like diffusion process where nodes stop transmitting influence once they recover [18].

For the IC model, infection probability is determined dynamically based on structural characteristics of the graph [49]. To maintain consistency, we completed 50 iterations for each simulation. Results consistently showed superior performance in networks with overlapping communities due to the integration of intra- and inter-community influence metrics.

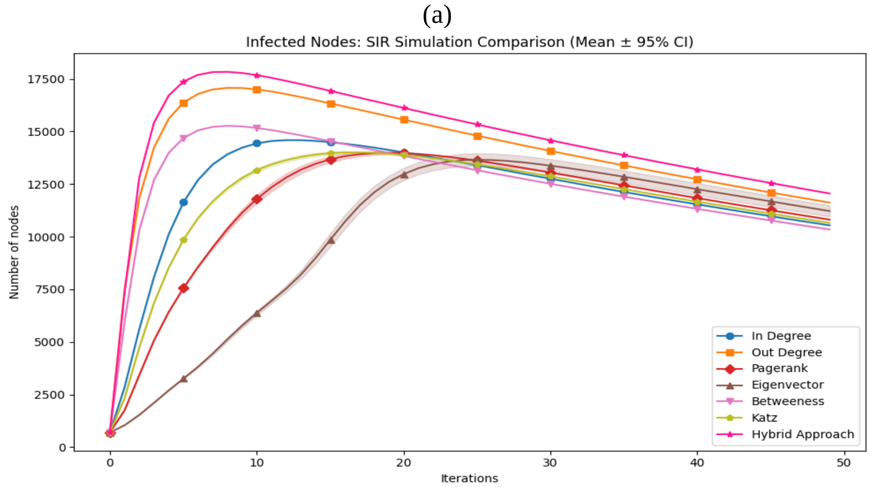
In the Soc-Epinions1 network (75,879 nodes, 508,837 edges), which consisted of complex community structure , the hybrid model achieved approximately 65.62% activated nodes after no more than 10 diffusion steps under the IC model much higher than traditional centrality based methods that achieved 62.7% coverage. This represents a clear gain of almost 3 percentage points (≈2,000 additional activated nodes) compared to the strongest baseline, demonstrating its superior ability to penetrate across communities and trigger larger cascades. More significantly, over 70% of the nodes were activated within 6 steps, meaning that not only did the hybrid model account for greater reach, but also greater speed of diffusion. Under the SIR model, the hybrid method once again performed well and induced around 40 to 41% infected nodes, while standard methods achieved 38 to 39% (around 700 additional infected nodes). In addition, our proposed approach consistently outperform baseline methods in terms of inactivated and susceptible nodes under IC and SIR models respectively. Specifically, it achieves the lowest proportion of inactivated or susceptible nodes, indicating that the influence diffusion not only reaches more users but also leaves fewer nodes unaffected. For instance, on this dataset, our approach leaves only 34% and 36% under IC and SIR respectively, compared to mora than 38 to 39% for the baseline centralities. These results demonstrate that our proposed method can identify influential nodes that are highly influential within-communities, and bridge nodes that allow the diffusion to occur across community structures, allowing for the broad influence to be attained rapidly.

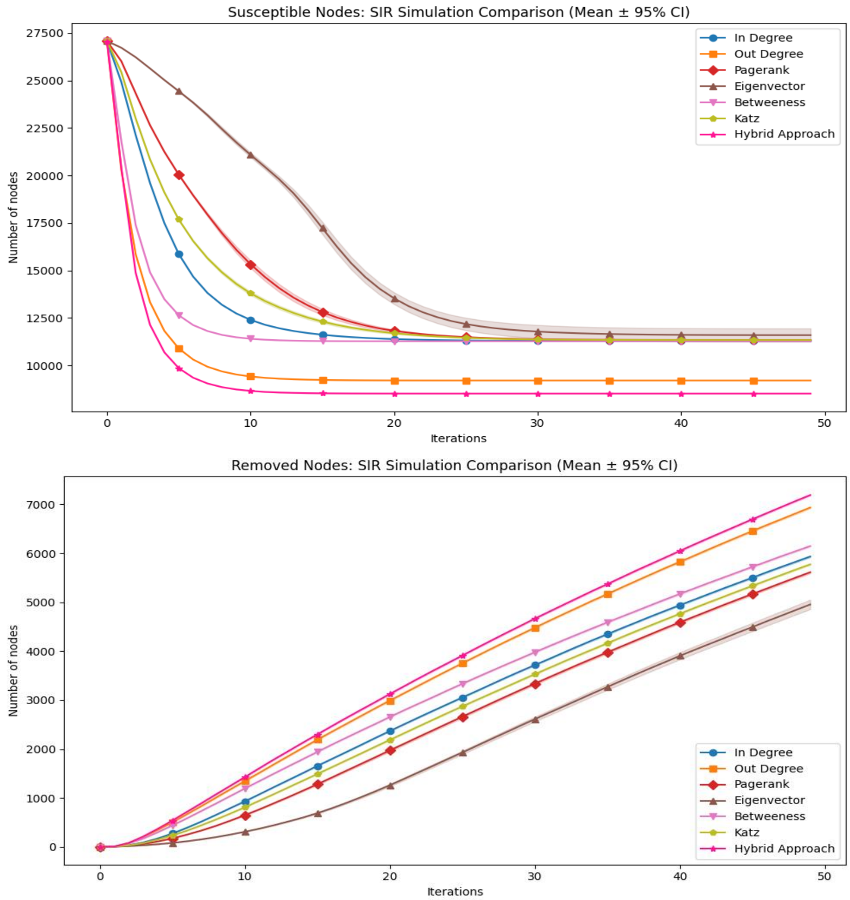
Similarly, in the Cit-HepTh network (27,770 nodes, 352,807 edges), which is a highly hierarchical and dense linking citation network, the hybrid approach achieved over 74.34% activated nodes in 12 iterations under IC model, for the baseline it was 59 to 67% (around 4000 additional infected nodes). This was also the case for the SIR model, which, collectively, covered 44% of infected nodes, for the baselines method it was 39 to 41% (around 1600 infected node), all significantly ahead of other examined methods. The hybrid approach also achieved 80% in only six steps, compared to most of the other traditional approaches, which required 10 or more steps. For instance, on this dataset, our approach leaves only 26.2% and 31.3% under IC and SIR respectively, compared to more than 34 to 41% for the baseline centralities. Further justifying the advantage of bridging capacity in seed selection. These outcomes also imply that global bridging is critical for maximizing influence spread in hierarchical structures.

In the ia-digg-reply dataset (30,400 nodes, 86,313 edges) which contains dense and overlapping community structures, the hybrid method continued to perform well, despite being the only overlapping community structure, covering approximately 99.85% activated nodes under the IC model and 62.3% under SIR after 8 iterations, much higher than traditional centrality based methods that achieved 97.5% and 60.5% under IC and SIR respectively, (around 2,600 additional activated nodes under IC and 700 nodes under SIR model). Moreover, our proposed approach consistently outperform baseline methods in terms of inactivated and susceptible nodes under IC and SIR models respectively. Specifically, it achieves the lowest proportion of inactivated nodes. For instance, on this dataset, our approach leaves only 0.17% and 0.6% under IC and SIR respectively, compared to around 3% for the baseline centralities. Because of the large amount of clustering and overlapping in this network, it was considerably more difficult for traditional methods to find influential nodes.

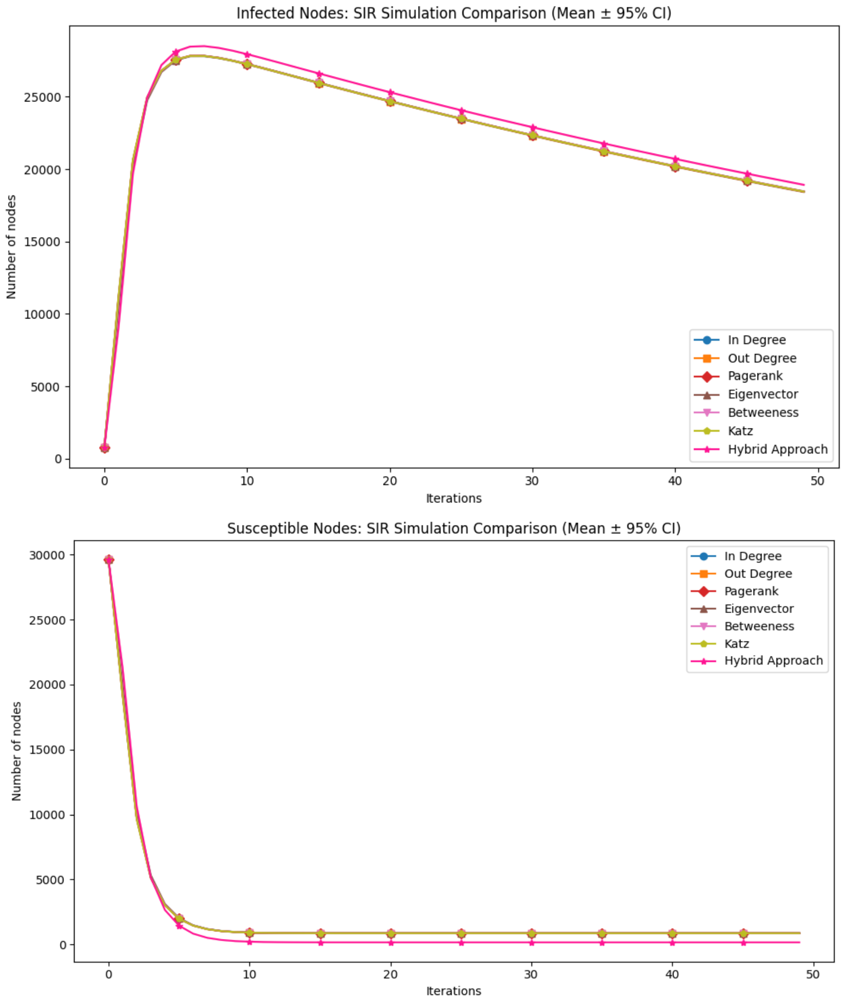

Infected Nodes: SIR Simulation Comparison (Mean ± 95% CI)
Number of nodes
Iterations
In Degree
Out Degree
Pagerank
Eigenvector
Betweeness
Katz
Hybrid Approach
Susceptible Nodes: SIR Simulation Comparison (Mean ± 95% CI)
Number of nodes
Iterations
In Degree
Out Degree
Pagerank
Eigenvector
Betweeness
Katz
Hybrid Approach
Recovered Nodes: SIR Simulation Comparison (Mean ± 95% CI)
Number of nodes
Iterations
In Degree
Out Degree
Pagerank
Eigenvector
Betweeness
Katz
Hybrid Approach

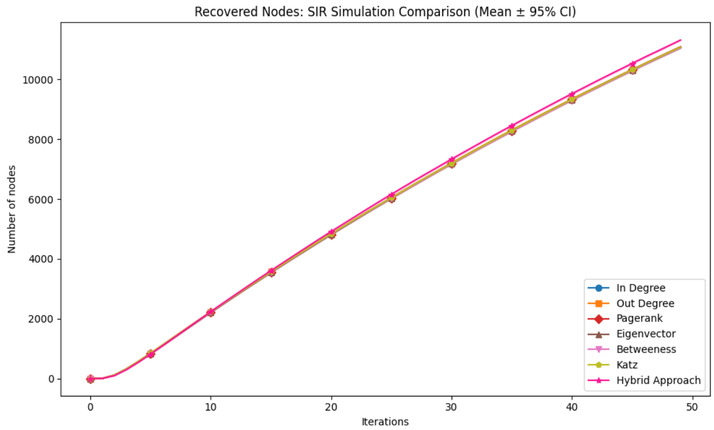
(a)


Infected Nodes: SIR Simulation Comparison (Mean ± 95% CI)
Number of nodes
Iterations
In Degree
Out Degree
Pagerank
Eigenvector
Betweeness
Katz
Hybrid Approach


Susceptible Nodes: SIR Simulation Comparison (Mean ± 95% CI)
Number of nodes
Iterations
In Degree
Out Degree
Pagerank
Eigenvector
Betweeness
Katz
Hybrid Approach
Removed Nodes: SIR Simulation Comparison (Mean ± 95% CI)
Number of nodes
Iterations
In Degree
Out Degree
Pagerank
Eigenvector
Betweeness
Katz
Hybrid Approach

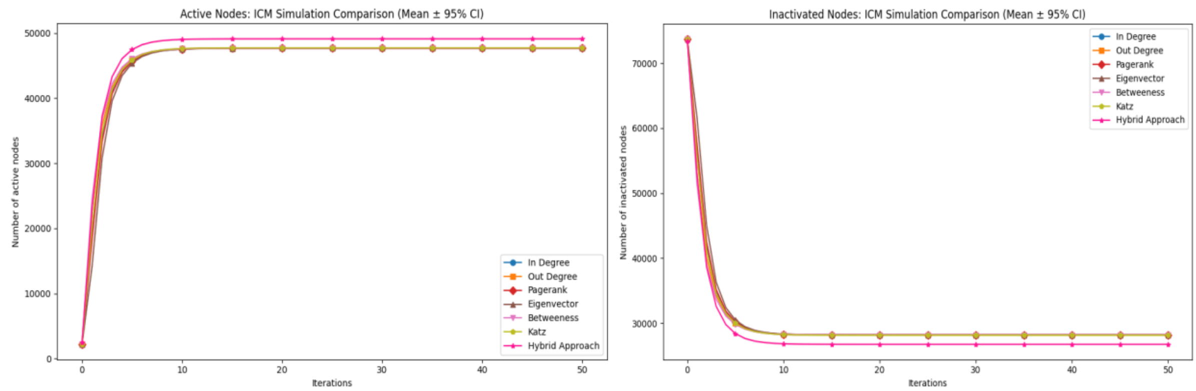
(b)


Infected Nodes: SIR Simulation Comparison (Mean ± 95% CI)
Number of nodes
Iterations
In Degree
Out Degree
Pagerank
Eigenvector
Betweeness
Katz
Hybrid Approach
Susceptible Nodes: SIR Simulation Comparison (Mean ± 95% CI)
Number of nodes
Iterations
In Degree
Out Degree
Pagerank
Eigenvector
Betweeness
Katz
Hybrid Approach

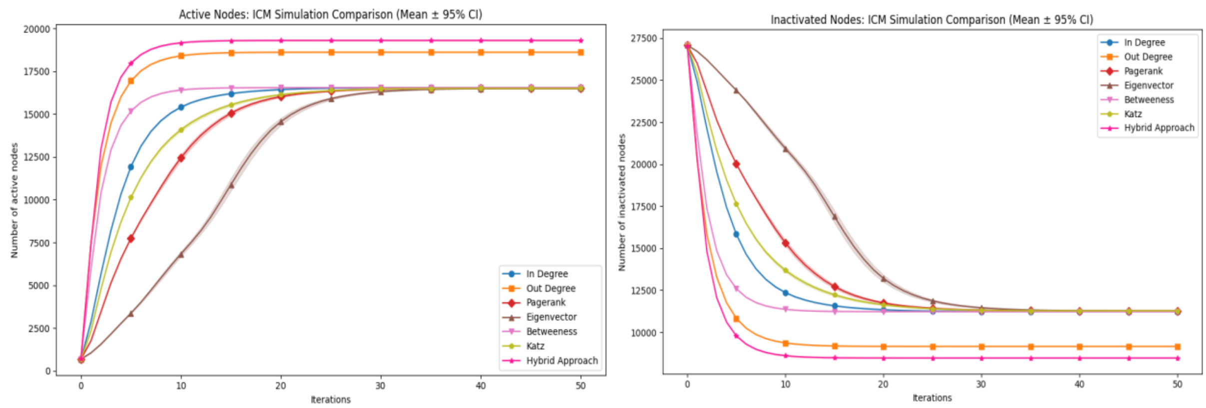


(c)

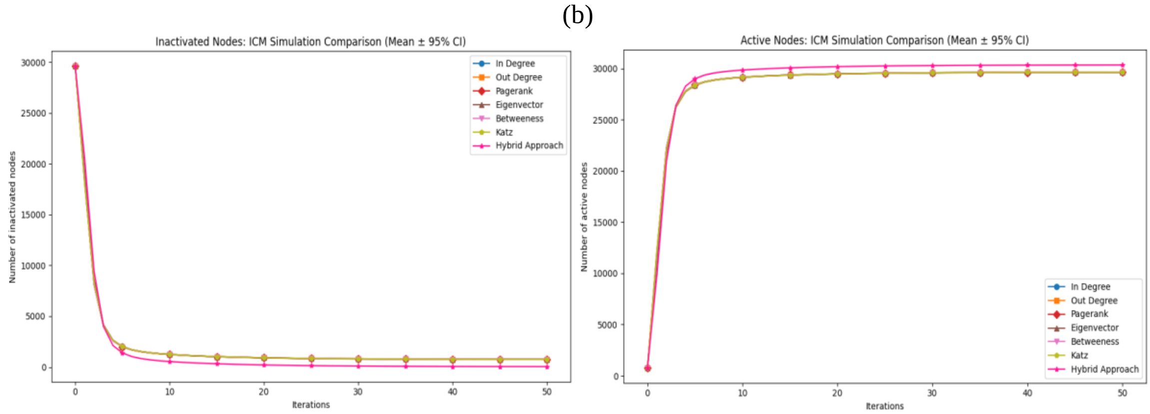
Figure 1. (a) Propagation influence using SIR model, Soc-Epinions1 dataset; (b) Propagation influence using SIR model, Cit-HepTh1 dataset; (c) Propagation influence using SIR model, a-digg-reply dataset



(a)



(b)



(c)

Figure 2. (a) Propagation influence using IC model, Soc-Epinions1 dataset; (b) Propagation influence using IC model, Cit-HepTh1 dataset; (c) Propagation influence using IC model, ia-digg-reply dataset

Table 2. Quantitative comparison of influence diffusion between baseline centrality methods and the proposed approach under IC model

Dataset	Method	Activated Nodes	Inactivated Nodes
	In-degree	16538	11232
	Out-degree	18614	9156
	PageRank	16498	11272
Cit-HepTh	Eigenvector	16498	11272
	Betweenness	16546	11224
	Katz	16498	11272
	Proposed approach	**20645**	**7125**
	In-degree	47676	28203
	Out-degree	47676	28203
	PageRank	47677	28202
Soc-Epinions1	Eigenvector	47676	28203
	Betweenness	47679	28200
	Katz	47728	28145
	Proposed approach	**49799**	**26080**
	In-degree	29644	756
	Out-degree	29647	753
	PageRank	29640	760
Ia-digg-reply	Eigenvector	29637	763
	Betweenness	29644	756
	Katz	29643	757
	Proposed approach	**30357**	**43**

Table 3. Quantitative comparison of influence diffusion between baseline centrality methods and the proposed approach under SIR model

Dataset	Method	Infected Nodes (I)	Susceptible Nodes (S)	Recovered Nodes (R)
	In-degree	10498	11266	6006
	Out-degree	11645	9208	6917
	PageRank	10686	11360	5724
Cit-HepTh	Eigenvector	11552	11319	4899
	Betweenness	10430	11271	6669
	Katz	10544	11336	5890
	Proposed approach	**12088**	**8522**	**7160**
	In-degree	29650	28476	17706
	Out-degree	29702	28482	17790
	PageRank	29767	28476	17526
Soc-Epinions1	Eigenvector	29842	28452	17701
	Betweenness	295601	28492	17859
	Katz	29703	28412	17748
	Proposed approach	**30542**	**27013**	**18324**
	In-degree	18404	870	11026
	Out-degree	18472	896	11032
	PageRank	18448	858	11067
Ia-digg-reply	Eigenvector	18503	865	11032
	Betweenness	18527	858	11015
	Katz	18407	882	11111
	Proposed approach	**19000**	**141**	**12257**

For the recovered (R) state our approach outperform all baseline methods across the three datasets, with higher values on the number of recovered nodes, confirming its effectiveness in maximizing long-term influence coverage.

To support these empirical findings, we further examined the computational time complexity of our proposed approach by analyzing its core components.

First, the community detection step, implemented using the Louvain algorithm, operates with a typical time complexity of O (n log n), where *n* is the number of nodes, making it efficient for large-scale networks [57]. Next, once communities are detected, influence scores within each community are computed using local metrics such as in and out degree, PageRank, k-shell and Katz centrality, the original computations for all the nodes has a time complexity of O(m)per iteration and an overall space complexity of O(n+m), where m is the number of edges. The most expensive component is the bridging score, is a combination of betweenness centrality (which can be computed in O(nm) time using Brandes' algorithm) along with a community diversity metric, but since it only considers community representatives (one per community), the overall cost is still acceptable. Finally, selecting seed nodes involves sorting the top nodes, according to their scores, which can usually be done in O(n log n) time. Our hybrid approach has a time complexity of approximately O(n log n) for large, sparse networks, primarily due to sorting and influence scoring,, and space complexity O(n+m), for the storage of network structures and node metrics. These complexities show the scalability of our method, as well as its practicality for analyzing large social networks.

In this case, the consideration of overlapping community membership and the diversity of nodes influenced greater coverage, the proposed approach outperformed all baseline centrality measures in every experiment in terms of maximizing activations and minimizing uninfluenced nodes. with the hybrid approach achieved a improvements of 2% to +21% percentage point coverage improvement over the baselines. Overall, having community overlap and bridging across communities is important for providing maximal coverage in highly interconnected real-world networks.

Beyond raw coverage, the speeds of influence propagation also showed consistent improvement. For instance, in Cit-HepTh, the hybrid method was at 80% coverage in just six steps, while traditional methods took significantly longer (12 steps). This efficiency is largely due to the hybrid strategy's capacity to prioritize nodes that are either influential within their local clusters or strategically positioned between communities. These nodes accelerate the spread by enabling influence to rapidly disseminate across the network, thereby avoiding the delays seen in locality constrained diffusion.

These differences are not only practically significant but also practically important in environments that have time or urgency concerns such as viral marketing or emergency information sharing. The consistent outperformance of our hybrid approach across diverse network topologies demonstrates that integrating local (intra-community) and global (inter-community) influence factors provides a more comprehensive strategy for influence maximization than methods focusing on isolated centrality measures.

While previous studies such as H-GSM [19, 20] and KPDN [21] incorporated both local and global community information into seed selection, our work extends these approaches by explicitly addressing overlapping community structures and introducing a quantifiable hybrid bridging score that integrates betweenness centrality with community diversity. Similarly, while methods like SpreadRank [18] focus on minimizing redundancy in influence using distance metrics, they overlook the presence and utility of community structures and bridging nodes, limiting their seed selection to local features. OEL [16], although effective in incorporating temporal dynamics, relies solely on local topological features and fails to consider overlapping communities or multi-criteria influence scoring. Our approach improves upon these limitations by combining five normalized centrality measures for intra-community influence and a bridging score for inter-community diffusion, offering a more comprehensive and scalable solution.

In contrast to works like [22, 23], which highlight the importance of overlapping nodes but do not provide strategic integration or quantification of their role, our method not only identifies these nodes but also ensures they actively function as bridges between loosely connected communities. Our findings support the broader understanding that bridge nodes are essential for accelerating information diffusion in complex networks, while challenging the simplifying assumption found in prior work that community boundaries are static or clearly defined.

These results demonstrate that our hybrid method addresses both local and global influence propagation and is adaptable to various network topologies, making it a robust advancement in influence maximization research for time-sensitive and large-scale applications such as viral marketing and emergency communication.

These findings are statistically significant, but they also have practical relevance. It is important when using this type of influential users detection technique in applications such as viral marketing, or public awareness campaigns to influence people rapidly and to as many groups of people as possible. By systematically locating both intra-community influential nodes and cross community connectors, our approach is proven to be a more useful method than those using single topological characteristics. Moreover, the method we presented is inherently flexible and transferable to a range of network topologies, providing similarly strong performance in different network types.

That said, the hybrid model's reliance solely on the network structure presents limitations. The hybrid influence maximization approach effectively identifies influential nodes by analyzing community formations and bridge nodes, which are critical for optimal influence spread. However, the practical issue is that it ignores behavioral factors such as user activity levels, individual user influence style, or content preferences by basing predictions solely on structural properties.

Because of this ineffective influence propagation on relevant behavioral factors (characteristics), the activity may not be reflective of reality, potentially constraining the practical application of study for a wide-range of influences where users behavior plays a major role in diffusion success. I would encourage future research to look at dynamic influence modeling to introduce more realism and applicability to interactions that take place in real-time.

Furthermore, this study focused on snapshots of unweighted and static social networks, when in reality social networks are highly dynamic networks with evolving communities, and users interact with different frequencies. Assuming a simplistic diffusion model will limit the realism of the diffusion simulations because user interaction frequency and edges weights are critical to influence propagation, and the use of structural features in the absence of behavioral factors will pre-dispose to bias of seed selection as we cannot consider the activity or content preference of users. Weighted links or dynamic edges could change which nodes bridge a community, and change the timing and scope of the diffusion of influence.

Addressing these limitations will be a key focus for future work; including strong data extraction procedures to extract the temporal evolution and dynamics of the community, weighted edges and activity-aware influence measurements, including a wider variety of user features and behaviours [58] instead of using only the network structure would effectively allow for the real-time operationalization of the approach and capture more nuanced diffusion patterns, and enhance the applicability of our approach to real-world contexts like emergency information sharing, viral marketing, and rumor control.

In conclusion, the hybrid community-driven influence maximization method represents a significant advancement in the field of influence maximization. By integrating both local (intra-community) and global (inter-community) influence factors into seed selection, and addressing overlapping communities through a multi-criteria strategy, the approach consistently achieves faster and broader diffusion than existing methods. Its ability to adapt across diverse network structures while maintaining superior performance confirms its value for real-world scenarios requiring efficient and scalable influence propagation.

5. CONCLUSIONS

In summary, this work presents a novel hybrid approach for influence maximization in large-scale social networks, integrating community detection with multi-criteria influence scoring. By effectively identifying influential nodes within communities and bridging nodes that connect different communities, the proposed approach ensures a comprehensive and efficient influence diffusion, using of the Louvain algorithm for community detection, with a hybrid bridging score combining betweenness centrality and community diversity, enhances the accuracy and scalability of influence maximization strategies. Empirical validation on three real-world datasets demonstrates that our approach outperforms traditional techniques in speed, influence diffusion, and computational efficiency under multiple diffusion models (SIR and IC). The significance of this work lies in its practical applicability to real-world scenarios such as viral marketing, rumor control, and information dissemination, where rapid and widespread influence is crucial. Overall, this research advances the state-of-the-art by offering a robust, scalable, and effective framework that leverages network structure to optimize influence diffusion, highlighting its importance for both theoretical studies and real-world applications in social network analysis. While our hybrid influence maximization approach offers substantial improvements, it is important to acknowledge certain limitations related to its reliance on structural unweighted networks and exclusion of behavioral factors. Future research will focus on extending the approach to dynamic and weighted networks to further enhance the model's applicability and robustness in real-world scenario.

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