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ARTICLE

Efficient Rumor Control via Disseminating Truthful Information by Influential Nodes

Suqiao Li[1], **Taotao Cai**[2], **Lingling Li**[3,*] **and Xuezhuan Zhao**[4,*]

[1]Library, Zhengzhou University of Aeronautics, Zhengzhou, 450046, China
[2]School of Mathematics, Physics and Computing, University of Southern Queensland, Toowoomba, 4350, Australia
[3]Zhengzhou University of Aeronautics, Zhengzhou, 450046, China
[4]School of Computer Science, Zhengzhou University of Aeronautics, Zhengzhou, 450046, China

*Corresponding Authors: Lingling Li. Email: lilingling@zua.edu.cn; Xuezhuan Zhao. Email: zhaoxuezhuan@zua.edu.cn

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ABSTRACT: Rumor Control (RC), aimed at minimizing the spread of rumors in social networks, is of paramount importance, as the spread of rumors can lead to significant economic losses, societal disruptions, and even widespread panic. The RC problem has garnered extensive research attention, however, most existing solutions for rumor control face a trade-off between efficiency and effectiveness, which limits their practical application in real-world scenarios. In this light, this paper studies the Truth-spreading-based Rumor Control (TRC) problem, and introduces the Subgraph-based Greedy algorithm Optimized with CELF (SGOC), which employs subgraph techniques and the CELF strategy, as the basic solution for the TRC problem. To improve the performance of SGOC, we carefully design a shortest path length dictionary SPR and an Immune Nodes Set (INS), leading to the Shortest Path-Based Rumor Control (SPRC) algorithm. To further enhance the SPRC algorithm, we develop a pruning method that accelerates the construction process of INS, proposing the Improved Shortest Path-Based Rumor Control (ISPRC) algorithm, which demonstrates superior efficiency compared to both SPRC and SGOC. Extensive experiments conducted on five real-world datasets, demonstrate the effectiveness and efficiency of the proposed algorithms.

KEYWORDS: Rumor control; truth spreading; subgraph; shortest path

1 Introduction

The explosion of mobile internet and portable devices has propelled social networks like Facebook, Twitter, and WeChat into indispensable platforms for sharing information and exchanging opinions. Yet, this convenience is a double-edged sword: these platforms have also inadvertently become prime breeding grounds for rumors. Characterized by their rapid spread and misleading nature, unverified rumors can inflict substantial economic losses, trigger societal disruptions, and even spark widespread panic. A striking example of this occurred during the COVID-19 pandemic, when baseless claims about the efficacy of the Chinese herbal remedy Shuanghuanglian liquid against the virus led to a frantic surge in purchases, causing considerable public alarm and market upheaval. The damaging impact of swiftly spreading rumors on society is undeniable, making effective rumor control an urgent and critical challenge.

As previously established, rumor control (RC) is of paramount importance. In recent years, researchers have developed various solutions, broadly categorized into three main approaches: node blocking, edge blocking, and truth-spreading methods [1]. Node blocking methods aim to stop rumor propagation by identifying and removing highly influential nodes within a social network [2,3]. Similarly, edge blocking methods impede rumor transmission by severing connections between key nodes, specifically by identifying and deleting critical edges to minimize misinformation spread [4,5]. While both node and edge blocking can disrupt rumor flow, they inherently alter the network structure, potentially degrading the user experience and unintentionally hindering the spread of legitimate information. In contrast, truth-spreading methods offer a more nuanced solution. This approach identifies influential nodes that act as "seed nodes" to disseminate factual information. Once users receive this accurate information, they become immune to the rumor, effectively curbing its spread [6,7]. A key advantage of this strategy is that it preserves the social network's original structure. Crucially, it blocks the spread of false information without impacting the flow of normal, legitimate communication, aligning well with ethical considerations. This makes it a popular and increasingly favored topic in rumor control research. The methods presented in this paper fall squarely within this paradigm.

While numerous solutions have been proposed to tackle rumor control, most approaches grapple with a fundamental trade-off between quality and efficiency. Algorithms offering strong theoretical quality guarantees often demand significant computation time, whereas faster heuristic algorithms may compromise the effectiveness of rumor control. Given this challenge, our paper presents a detailed study of the rumor control problem and introduces novel methods to address it. First, building upon the multi-campaign independent cascade (MCIC) model, we define the truth-spreading-based rumor control (TRC) problem, which aligns with the truth-spreading methods discussed earlier. To solve this problem, we propose the Subgraph-based Greedy algorithm Optimized with CELF (SGOC), which leverages subgraph techniques and the CELF strategy for improved performance. To further enhance the SGOC algorithm, we then introduce the Shortest Path-Based Rumor Control (SPRC) algorithm, which relies on efficient shortest path calculations. Finally, to boost the efficiency of SPRC, we meticulously designed a pruning method, leading to the Improved Shortest Path-Based Rumor Control (ISPRC) algorithm.

The key contributions of this paper are summarized below:

1. We introduce the SGOC algorithm, which utilizes subgraph techniques and the CELF strategy to tackle the TRC problem under the MCIC model, demonstrating superior efficiency compared to conventional greedy algorithms.
2. To further enhance the SGOC algorithm's performance, we carefully designed the shortest path length dictionary (SPR) and an Immune Nodes Set (INS), leading to the SPRC algorithm, which significantly improves efficiency while maintaining high quality.
3. We developed a novel pruning method to accelerate the INS construction process, resulting in the ISPRC algorithm. This algorithm further boosts efficiency compared to SPRC.
4. We conducted extensive experiments on five real-world datasets, thoroughly demonstrating the effectiveness and efficiency of our proposed algorithms.

The remainder of this paper is organized as follows: Section 2 provides the preliminary background. In Section 3, we introduce SGOC, our foundational solution for the TRC problem. Section 4 describes the proposed SPRC and ISPRC algorithms in detail. Our experiments are presented in Section 5, and finally, Section 6 concludes the paper.

2 Preliminary

2.1 Rumor Blocking

Rumor Control (RC), which aims to minimize the spread of rumors and misinformation in social networks, is a variant of Influence Maximization (IM) [8–10]. Current RC approaches can be categorized into three main types: node blocking methods, edge blocking methods, and truth-spreading methods [1].

Node Blocking Methods focus on reducing rumor spread by targeting and removing key nodes within the social network. For example, Matsuta and Uyematsu [11] developed a tree-structured network to locate the source of a rumor within a specific set of nodes while also estimating the distance between the selected node and the rumor source. Xie et al. [12] utilized a dominant tree structure to evaluate the impact of all candidate blocking nodes, achieving efficient rumor control through their AdvanceGreedy (AG) and GreedyReplace (GR) algorithms. Edge blocking methods identify critical edges whose removal can reduce rumor spread. Khalil et al. [5] investigated the removal of edge sets from the network to address the rumor propagation minimization problem, developing a heuristic algorithm that approximates the objective function and accelerates the rumor control process. Truth-spreading methods involve selecting influential nodes that disseminate truthful information to counteract rumor nodes. Once a node is activated by this truthful information, it becomes immune to rumors, effectively limiting their spread. Yang et al. [13] introduced a heuristic method under the competitive diffusion model, allowing for the simultaneous propagation of truth and rumors within the same network, effectively tackling the challenge of minimizing rumor propagation. Zhong et al. [14] studied the interaction with the anti-rumor mechanisms and designed both deterministic and stochastic control strategies with aperiodically intermittent control timing to minimize rumor spread.

2.2 Diffusion Model

The diffusion model is used to simulate the process of information propagation in networks. In recent years, various models have been developed to simulate this propagation, including the Independent Cascade (IC) model [8], the Linear Threshold (LT) model [8], and the Susceptible-Infected-Recovered (SIR) model [15], etc.

Among these, the IC model is the most classic diffusion model. In the IC model, all participants (nodes in the network) are initially divided into two categories: inactive and activated. In each subsequent round, newly activated nodes have one opportunity to activate their neighboring nodes with a probability of $P(u, v)$, where $P(u, v)$ represents the propagation probability of the edge connecting node u and node v. This process continues until no new nodes are activated. The IC model is widely used because it is easy to implement and close to the actual information propagation process.

However, the original Independent Cascade (IC) model cannot be directly applied to rumor control. In this context, various rumor propagation models have been developed, such as the rumor propagation model in small-world networks [16], the rumor propagation system proposed in [17], and the multi-campaign Independent Cascade (MCIC) model [18], among others. Among these, the MCIC model is more widely adopted. In the MCIC model, all nodes are classified into three states: rumor nodes, truth nodes, and inactive nodes. Both rumor nodes and truth nodes activate their neighbors in accordance with the same rules as in the IC model. When a node is activated simultaneously by both a rumor node and a truth node, it adopts the state of the truth node. Once a node is activated, its state remains unchanged, and the propagation process concludes when no new nodes can be activated. In this paper, we design rumor control algorithms based on the MCIC model, achieving effective results in controlling the spread of rumors.

2.3 Problem Definition

Based on the previously discussed MCIC model, this paper investigates the problem of truth-spreading-based rumor control (TRC), which is defined as follows:

Definition 1: *TRC problem: Given a social network $G = (V, E)$, a set of rumor nodes R and an integer K, the TRC problem aims to identify K influential nodes as a truthful information node set T (where $T \in V \backslash R$), to disseminate truthful information and minimize the spread of rumors R. Based on the MCIC model mentioned above, the spread of R in the presence of T is denoted as $I(R, G)_T$. The TRC problem can be expressed mathematically as follows:*

$$T^* = \underset{T \subseteq V, |T|=k}{\arg\min} \; E(I(R, G)_T) \tag{1}$$

In Formula (1), $E[*]$ represents the expected value and T^* denotes the optimal truthful information node set. According to the work in [18], the TRC problem is NP-hard, indicating that an optimal solution cannot be found in polynomial time. However, reference [18] also demonstrates that the spread function $E(I(R, G)_T)$ in the TRC problem exhibits both submodularity and monotonicity. These properties allow for the application of a greedy algorithm to compute an approximate solution to the optimum with a probability of $(1 - 1/e)$.

3 The Basic Solution for TRC

Based on the definition and analysis in Section 2.3, although the conventional greedy algorithm can provide an approximate solution with theoretical guarantees, it relies on Monte Carlo simulations (often more than 100,000 times simulations) to select truthful information nodes, making it excessively time-consuming and impractical for even medium-sized networks. Inspired by the work in [19], we introduce the Subgraph-based Greedy algorithm Optimized with CELF (SGOC) as the basic solution to tackle the TRC problem. SGOC employs a similar strategy to StaticCELF in [19], originally designed for the Influence Maximization (IM) problem. Specially, SGOC improves efficiency by replacing the Monte Carlo simulation with a subgraph technique and leverages the CELF method [20] to select the node that yields the greatest reduction in rumor spread at each iteration, however, unlike StaticCELF, SGOC calculates the spread of rumors R based on the MCIC diffusion model, rather than the IC model.

In SGOC, each edge in the network $G = (V, E)$ is deleted with a probability of $1 - P_e$ to generate a subgraph SG_i, and this process is repeated θ times to obtain θ subgraphs. For each node $v \in V \backslash R$, we calculate the marginal decrease brought by v in each iteration if necessary, which is determined by the CELF method. The marginal decrease brought by v is calculated based on the MCIC model. The node that results in the greatest reduction in rumor spread is then selected in each round, and this process continues until K truthful information nodes are identified. The detailed pseudo-code for SGOC is provided in Algorithm 1.

Algorithm 1: SGOC

Input: A social network $G = (V, E)$, R (the rumor node set), an integer number K (the size of truthful information node set T), an integer number θ (the number of subgraphs).

Output: The selected truthful information node set T.

1 **for** $i = 1 : \theta$ **do**

2 Generate subgraph SG_i by deleting each edge in network $G = (V, E)$ with a probability of $1 - P_e$;

3 $T \leftarrow \varnothing$;

(Continued)

Algorithm 1 (continued)

4 **for** $i = 1 : K$ **do**
5   **for** $v \in V \backslash (R \cup T)$ **do**
6   **if** *The rumor spread decrease D(v) brought by v needs to be updated, which is determined by CELF strategy* **then**
7             $D(v) \leftarrow Rspread(T, R, SG) - Rspread(T \cup v, R, SG)$;
8   Select node with the largest *D(v)* as the truthful information node v^*;
9     $T \leftarrow T \cup v^*$
10 **return** T
11 **Function** Rspread (T, R, SG)
12     $Spread \leftarrow 0$;
13   **for** $i \in 1 : \theta$ **do**
14         $Rnewa, Ra \leftarrow R, R$;
15         $Snewa, Sa \leftarrow T, T$;
16   **while** $Rnewa \neq \varnothing$ **do**
17             $Tmp \leftarrow \varnothing$;
18   **for** $v \in Snewa$ **do**
19                 $Ntb \leftarrow v's\ children\ in\ SG_i$;
20   **for** $w \in Ntb$ **do**
21   **if** *w have not been infected by R* **then**
22                         $Tmp \leftarrow Tmp \cup w$
23         $Snewa \leftarrow Tmp - Sa$;
24         $Sa \leftarrow Snewa \cup Tmp$;
25         $Tmp \leftarrow \varnothing$;
26   **for** $v \in Rnewa$ **do**
27             $Nrb \leftarrow v's\ children\ in\ SG_i$;
28   **for** $w \in Nrb$ **do**
29   **if** *w have not been infected by T* **then**
30                     $Tmp \leftarrow Tmp \cup w$
31         $Rnewa \leftarrow Tmp - Ra$;
32         $Ra \leftarrow Rnewa \cup Tmp$;
33         $Spread \leftarrow Spread + |Ra|$
34   **return** $Spread/\theta$

In Algorithm 1, we begin by generating θ subgraphs SG (Lines 1–2). Then for each node $v \in V \backslash (R \cup T)$ we update the rumor spread decrease $D(v)$ brought by v using Eq. (2) if necessary, which is determined by CELF strategy (Lines 5–7). In Eq. (2), the subfunction $Rspread(T, R, SG)$ computes the spread of R in the presence of T under MCIC model (Lines 12–34). Next, the node v^* with the largest $D(v)$ is selected as the truthful information node and added into T (Lines 8–9). This process is repeated K times to select K truthful information nodes, forming the truthful information node set T (Lines 4–9).

$$D(v) \leftarrow Rspread(T, R, SG) - Rspread(T \cup v, R, SG) \tag{2}$$

4 The Shortest Path-Based Rumor Control (SPRC) Algorithm

Although the SGOC algorithm described in Section 3 outperforms the conventional greedy algorithm, its computational complexity remains too high for efficient application to real-world networks. To enhance the efficiency of the SGOC algorithm, we propose the Shortest Path-Based Rumor Control (SPRC) algorithm. The SPRC algorithm improves the performance of SGOC by utilizing a carefully designed dictionary data structure, SPR, and an immune nodes set, INS, both of which are derived from shortest path calculations.

4.1 Shortest Path Length Dictionary SPR

In this subsection, we design a dictionary SPR to record the shortest path lengths between rumor node set R and each of R's descendant v_i in each subgraph SG_i. The structure of SPR is shown in Formula 3.

$$SPR = \{v_1 : l_1, v_2 : l_2, v_3 : l_3, ...v_i : l_i\} \tag{3}$$

In Formula 3, $v_1, ...v_i$ represent all descendants of R, and $l_1, ...l_i$ denote the shortest path lengths from each v_i to R. We construct SPR using a Breadth-First Search (BFS) approach. Specifically, in each subgraph SG_i, for each node $Rnode \in R$, we identify its children $Child_{Rnode}$ and record the shortest path length from each $v_i \in Child_{Rnode}$ to R as 1. Then, for each $v_i \in Child_{Rnode}$, we find their children and record their shortest path length to R as 2. This process is repeated until all descendants of R are identified, with their shortest path lengths to R recorded. The procedure for constructing SPR is detailed in Algorithm 2.

Algorithm 2: Obtain SPR for each subgraph

Input: A social network $G = \{V, E\}$, Rumors node set R. The number of subgraphs θ
Output: The shortest path length dictionary SPR for each subgraph
1 $SPRList \leftarrow \varnothing$;
2 **for** $i = 1 : \theta$ **do**
3 Generating the subgraph SG_i by preserving each edge in E with a probability of *P(e)*;
4 $SPL \leftarrow 0$;
5 $SPR \leftarrow \{\}$;
6 **for** $v \in R \cap V_i$ **do**
7 $SPR[v] \leftarrow SPL$;
8 $CS \leftarrow R$;
9 **while** CS **do**
10 $SPL \leftarrow SPL + 1$;
11 $NS \leftarrow \varnothing$;
12 **for** $v \in CS$ **do**
13 $Child_v \leftarrow$ The children of v;
14 **for** $w \in Child_v$ **do**
15 **if** $w \notin SPR.keys()$ **then**
16 Add w into NS;
17 $SPR[w] \leftarrow SPL$;
18 $CS \leftarrow NS$
19 *SPRList.append(SPR)*;
20 **return** *SPRList*

In Algorithm 2, we start by generating θ subgraphs $SG_i = (V_i, E_i), i \in [0, \theta]$, where each edge in E is retained with a probability of $P(e)$ (Line 3). In each subgraph SG_i, for every node $v \in R \cap V_i$, their shortest path length to R is set to be 0, and added to the dictionary SPR (Lines 6–7). Then the children of R are identified, denoted as $Child_v$. For each child node $w \in Child_v$, if w is not already a key in SPR, we set its shortest path length SPL to R as the parent node's length plus 1 and add it to SPR. Next, for the node $w \in Child_v$, we repeat this process, until all the descendants of R and their shortest path lengths are added into SPR (Lines 9–18). Finally, the shortest path length dictionary SPR for SG_i is appended to $SPRList$, which stores SPR for each subgraph SG_i.

4.2 SPRC Algorithm

In this subsection, we provide a detailed explanation of the proposed SPRC algorithm. We start by introducing the carefully designed Immune Node Set (INS), followed by an in-depth description of the SPRC algorithm, which is built on INS.

4.2.1 Immune Nodes Set INS

For each node $v \in V_i \backslash R$, where V_i represents all the nodes in subgraph SG_i, we design an immune node set INS_v to include all nodes that can be protected by v against the rumor. We use a BFS operation to construct INS. Specially, for each node $v \in V_i \backslash R$, we apply the same method as Algorithm 2 to construct a shortest path length dictionary SP_v, which record all v's descendants and their shortest path length to v. Then for each node $w \in SP_v$, if the condition in Expression (4) holds, node w is added into v's immune node set INS_v, The process of constructing INS for each node in every subgraph is outlined in Algorithm 3.

$$(w \in SPRL[i])\&(SP_v[w] \leq SPRL[i][w]) \tag{4}$$

Algorithm 3: Obtain *INS* for each node in every subgraph

Input: Subgraphs SG_i, $i \in [0, \theta]$, SPRList
Output: The immune nodes set *INS* for each node v in every subraph

1 $INSList \leftarrow \varnothing$;
2 **for** $i = 1 : \theta$ **do**
3 $\quad tmpINS \leftarrow \{\}$;
4 $\quad$ **for** $v \in V_i \backslash R$ **do**
5 $\quad\quad$ Construct the shortest path length dictionary SP_v for v;
6 $\quad\quad$ **for** $w \in SP_v.keys()$ **do**
7 $\quad\quad\quad$ **if** $w \in SPRList[i]$ **then**
8 $\quad\quad\quad\quad$ **if** $SP_v[w] \leq SPRList[i][w]$ **then**
9 $\quad\quad\quad\quad\quad$ Add w into *INS*;
10 $\quad\quad tmpINS[v] \leftarrow INS$;
11 $\quad$ *INSList.append(tmpINS)*;
12 **returns** *INSList*

In Algorithm 3, for each node $v \in V_i \backslash R$, we construct its shortest path length dictionary SP_v using the method in Algorithm 2 (Lines 4–5), then for each node $w \in SP_v$, if $w \in SPRList[i]$ and $SP_v[w] \leq SPRList[i][w]$, w is added added to v's *INS* (Lines 6–9). Next, the *INS* for each node $v \in V_i \backslash R$ is stored in $tmpINS$ (Line 10). Finally, $tmpINS$ is added to $INSList$, which stores all the *INS* for each node in every subgraph SG_i.

4.2.2 SPRC Algorithm

In this subsection, we introduce the proposed SPRC algorithm, which is based on the Immune Nodes Set (INS).

In SPRC, nodes are selected as truthful information seed nodes using a greedy strategy. Specifically, in each round, we choose the node that achieves the largest decrease in rumor spread as a truthful information seed node, continuing until K truthful information seed nodes have been selected.

The reduction in rumor spread caused by a particular node v is calculated based on its INS. Specially, we average the size of v's INS in each subgraph to estimate the decrease in rumor spread contributed by v. It's important to note that different nodes may immunize the same target node. Therefore, when calculating the reduction in rumor spread brought by a node v, we should adjust by subtracting the reduction already brought by previously selected seed nodes. The pseudo-code for the SPRC algorithm is provided in Algorithm 4. Additionally, we employ the CELF strategy to accelerate the selection process, which is not displayed in Algorithm 5 due to space limitations.

Algorithm 4: SPRC algorithm

Input: A social network $G = \{v, E\}$, *INSList*, the number of subgraphs θ
Output: Truth information node set *Truth*

1 $T \leftarrow \varnothing$;
2 **for** $j = 1 : K$ **do**
3   **for** $v \in (V \backslash (R \cup T))$ **do**
4         $Dec_v \leftarrow 0$;
5   **for** $i = 1 : \theta$ **do**
6             $tmp \leftarrow \varnothing$;
7   **for** $w \in T$ **do**
8                 $tmp \leftarrow tmp \cup INSList[i][w]$
9             $Dec_v = Dec_v + |INSList[i][v] - tmp|$
10        $Dec_v = Dec_v / \theta$
11    $v^* \leftarrow v$ with the largest Dec_v;
12    $T \leftarrow T \cup v^*$;
13 **return** *Truth*

In Algorithm 4, the truthful information seed node set T is initially empty (Line 1). In each round, we calculate the decrease in rumor spread brought by each node $v \in (V \backslash (R \cup T))$, indicated by Dec_v. Dec_v is initialize as 0 (Line 5). In each subgraph SG_i, for node $v \in (V \backslash (R \cup T))$, we first remove nodes already immunized by T from v's INS (Lines 8–9), then average the size of v's INS in each subgraph as the spread decrease Dec_v brought by v (Lines 5–10). Then node v with the largest Dec_v is selected as the truthful information seed node and added to T (Lines 11–12), until the size of T reaches K.

4.3 Improving SPRC through Pruning Method

Through analysis of the SPRC algorithm, we observed that Algorithm 3, used to obtain INSList, involves a substantial amount of computation and thus is time-consuming. In this section, we introduce a pruning method to reduce the computational burden of Algorithm 3 and present the ISPRC algorithm.

We observe that if node v cannot immunize node w, then v also cannot immunize any of w's descendants. This is because if the shortest path from v to w is longer than the shortest path from the rumor source set R

to w, then the shortest path from v to any descendant of w will likewise be longer than the corresponding path from R. Therefore, when constructing the shortest path length dictionary SP_v in Algorithm 3, we can proactively prune not only node w but also all of its descendants if v cannot immunize w. This strategy is illustrated in Fig. 1. In the figure, the rumor node (node 2) is shown in blue, while node 1, shown in yellow, is attempting to build its shortest path dictionary SP_1. Since the shortest path from node 1 to node 4 is longer than the shortest path from the rumor node to node 4, and the same holds for node 4's descendants (nodes 5, 6, and 7), these nodes are pruned during the BFS traversal and excluded from SP_1. This pruning significantly reduces the computational burden.

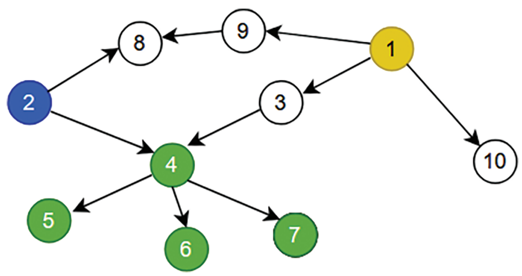


Figure 1: An example of the pruning procedure, node 2 in blue represents the rumor node

Based on the observation above, within each subgraph SG_i, during the construction of the shortest path length dictionary SP_v, we first check if node w exists in the shortest path dictionary $SPRList[i]$. If it does, we then compare the shortest path length from v to w with that from the rumor node set R to w. The condition is expressed in Expression (5).

$$(w \in SPRL[i])\&(SP_v[w] > SPRL[i][w]) \quad (5)$$

If this condition holds, w can be pruned from SP_v, which also implies that all descendants of w are excluded from SP_v. This pruning operation reduces the number of nodes searched during the BFS process when constructing SP_v, and also the size of SP_v, thus greatly lowering the computational load. The pseudo code for constructing SP_v in ISPRC algorithm using pruning method is shown in Algorithm 5.

Algorithm 5: Obtain SPv for each subgraph

Input: Node v, Subgraphs SG_i, $i \in [0, \theta]$, SPRList
Output: The shortest path length dictionary SP_v for each node v in every subgraph SG_i

$SPL \leftarrow 0$;
$SP_v \leftarrow \{\}$;
$CS \leftarrow v$;
while CS **do**
    $SPL \leftarrow SPL + 1$;
    $NS \leftarrow \varnothing$;
    for $v \in CS$ **do**
        $Child_v \leftarrow$ The children of v in SG_i;
        for $w \in Child_v$ **do**
            if $w \notin SP_v$ **then**
                if $(w \in SPRList[i])\&(SPL > SPRList[i][w])$ **then**
                    Continue;

(Continued)

Algorithm 5 (continued)

13 **else**
14 Add w into NS;
15 $SP_v[w] \leftarrow SPL$;
16 $CS \leftarrow NS$
17 **return** SP_v

In Algorithm 5, we follow the same process as in Algorithm 2 to construct the shortest path length dictionary SP_v for node v. The key difference is that before adding a node w to SP_v, we first check whether it satisfies the condition in Expression (5). If the condition holds, node w is excluded from the BFS search and is not added to SP_v (Lines 10–11). This pruning operation reduces the number of descendant nodes of v that need to be searched and decreases the size of SP_v, thereby speeding up the process of constructing INS for v.

4.4 Effectiveness

5 Experiments

In this section, we conduct experiments using five real-world datasets to evaluate the effectiveness and efficiency of our proposed algorithms.

Datasets

For our experiments, we use five real-world datasets: congress-Twitter, ego-Facebook, sx-mathoverflow-c2q, sx-askubuntu-a2q and wiki-talk-temporal. These datasets are available at http://snap.stanford.edu/data/index.html (accessed on 21 July 2025). The congress-Twitter dataset represents the interaction network of the US Congress on Twitter, while the ego-Facebook dataset include connections from $Facebook$. The sx-mathoverflow and sx-askubuntu-a2q datasets include connections from Stack Exchange web site $MathOverflow$ and $AskUbuntu$, respectively. The dataset $wiki-talk-temporal$ captures interactions between Wikipedia users who edit each other's Talk pages. The characteristics of these datasets are detailed in Table 1.

Table 1: Dataset characteristic

Datasets	Type	Nodes	Edges	Degree$_{avg}$
congress-Twitter	Directed	475	13,289	27.98
ego-Facebook	Directed	4039	88,234	21.85
sx-mathoverflow-c2q	Directed, temporal	16,836	101,329	6.02
sx-askubuntu-a2q	Directed, temporal	137,517	262,106	2.59
wiki-talk-temporal	Directed, temporal	1,140,149	3,309,592	2.9

Baselines

Five typical methods are selected as baselines for comparison:

1. Max Degree (MD) method: In this method, the K nodes with the highest out-degree are selected as truthful information node set T.
2. Max Betweenness (MB) method: Here, the K nodes with the largest betweenness centrality are chosen as T.
3. Random (Ran): In this method, K nodes are randomly selected from the network to form T.
4. Max k-core (MC): K nodes with the largest k-core value are selected as T.

5. TIBMM [21]: TIBMM obtains a certain number of Temporal Reverse Reachable Sets using a reverse BFS method. Then, it selects K nodes to form T from these Temporal Reverse Reachable Sets using a Max Cover approach.

Traditional greedy algorithm which is too time-consuming to yield results within an acceptable timeframe was not selected as a baseline due to their high computational cost.

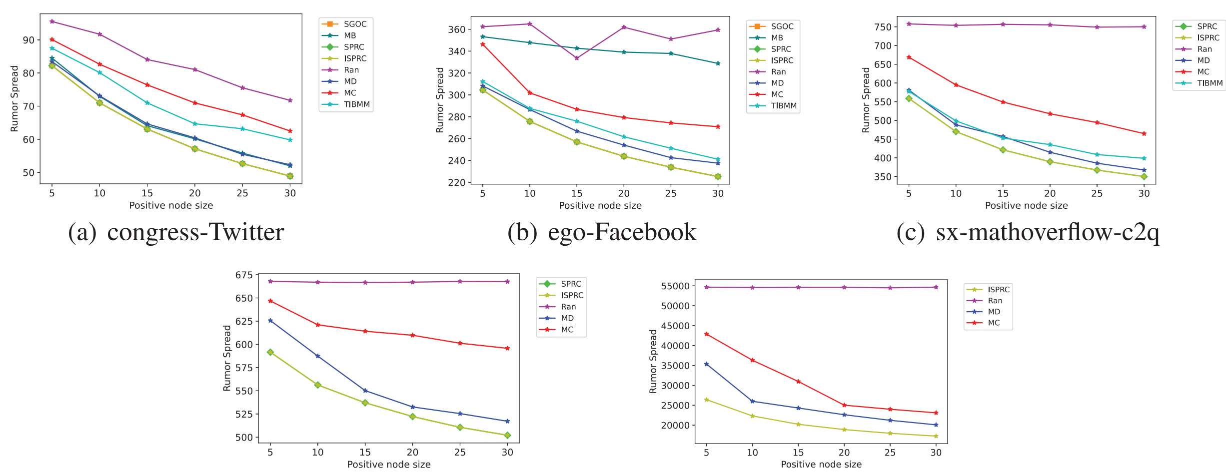
Parameters settings

We conduct our experiments using the MCIC model described in Section 2.2. It is important to note that when both a rumor node and a truthful information node attempt to activate a node simultaneously, the node will be activated by the truthful information node. Additionally, the propagation probability $P(e)$ for each edge e in the network is set using a constant model, in which $P(e)$ is set to a constant number 0.03. The K nodes with the highest out-degree in the network are selected as the rumor node set R. The number of subgraphs θ is set to 200, and the final rumor spread results are calculated based on these 200 subgraphs.

5.1 Effectiveness

In this subsection, we assess the effectiveness of various algorithms by examining the total spread of rumor set R. Specifically, a smaller total spread indicates more effective rumor control by the corresponding algorithm. Figs. 2–4 illustrate the experimental results for eight algorithms across five datasets, with the sizes of R and T varying within the ranges [10, 20, 30] and [5, 10, 15, 20, 25, 30], respectively. Results for some algorithms on sx-mathoverflow-c2q, sx-askubuntu-a2q, and wiki-talk-temporal datasets could not be obtained within a few days, so they are omitted in Figs. 2a–c, 3a–c, 4a–c.

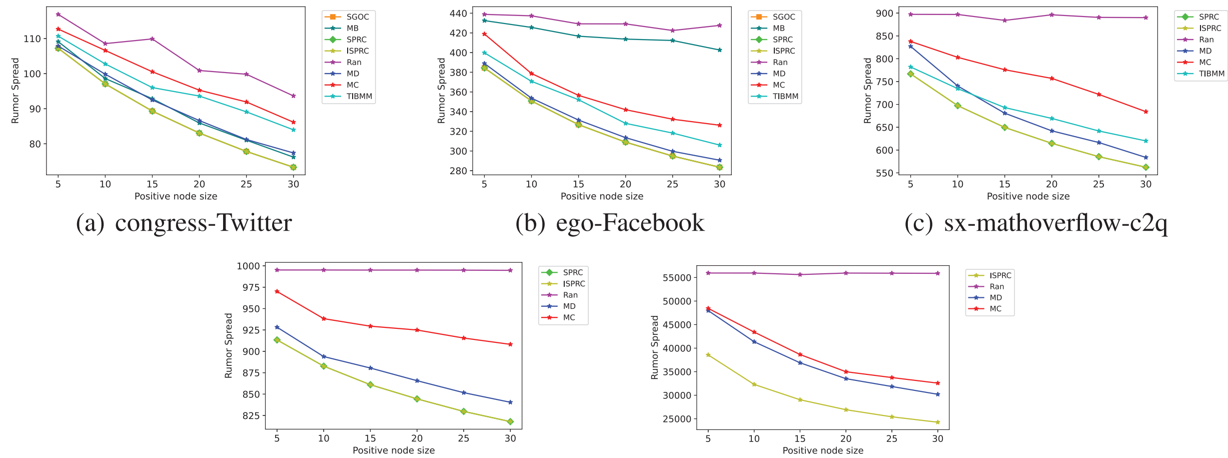
From Figs. 2–4 we observe that the proposed SGOC, SPRC, and ISPRC algorithms consistently achieve the smallest total rumor spread, indicating their superior effectiveness in rumor control. Regarding the MB, MD, MC, and TIBMM algorithms, they show fluctuating performance, but they all underperform compared to SGOC, SPRC, and ISPRC, while the Random algorithm consistently exhibits poor performance across all datasets. This is because the SGOC, SPRC, and ISPRC algorithms proposed in this paper are based on greedy approaches, enabling them to provide approximations to the optimal solutions when solving the TRC problem (whose propagation function is submodular and monotonic), offering theoretical quality assurance in all scenarios.



(a) congress-Twitter (b) ego-Facebook (c) sx-mathoverflow-c2q

(d) sx-askubuntu-a2q (e) wiki-talk-temporal

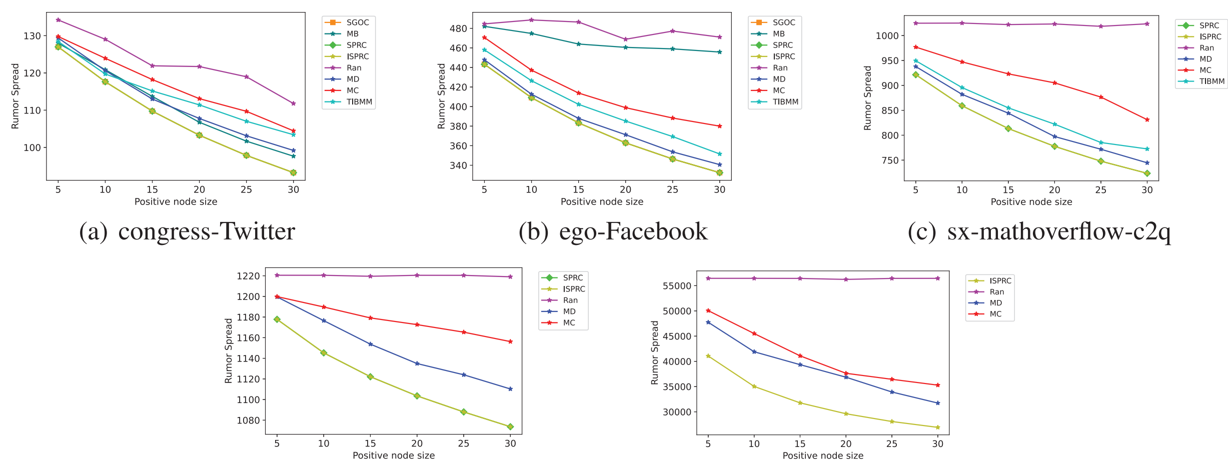
Figure 2: Total rumor spread across different datasets with virous K under constant model when $|R| = 10$



(a) congress-Twitter (b) ego-Facebook (c) sx-mathoverflow-c2q

(d) sx-askubuntu-a2q (e) wiki-talk-temporal

Figure 3: Total rumor spread across different datasets with virous K under constant model when $|R| = 20$



(a) congress-Twitter (b) ego-Facebook (c) sx-mathoverflow-c2q

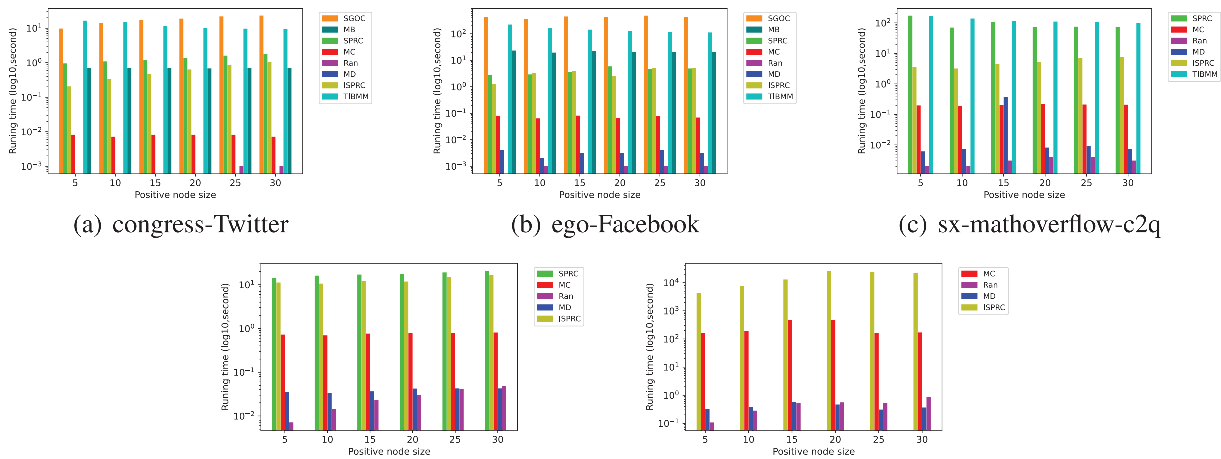
(d) sx-askubuntu-a2q (e) wiki-talk-temporal

Figure 4: Total rumor spread across different datasets with virous K under constant model when $|R| = 30$

5.2 Efficency

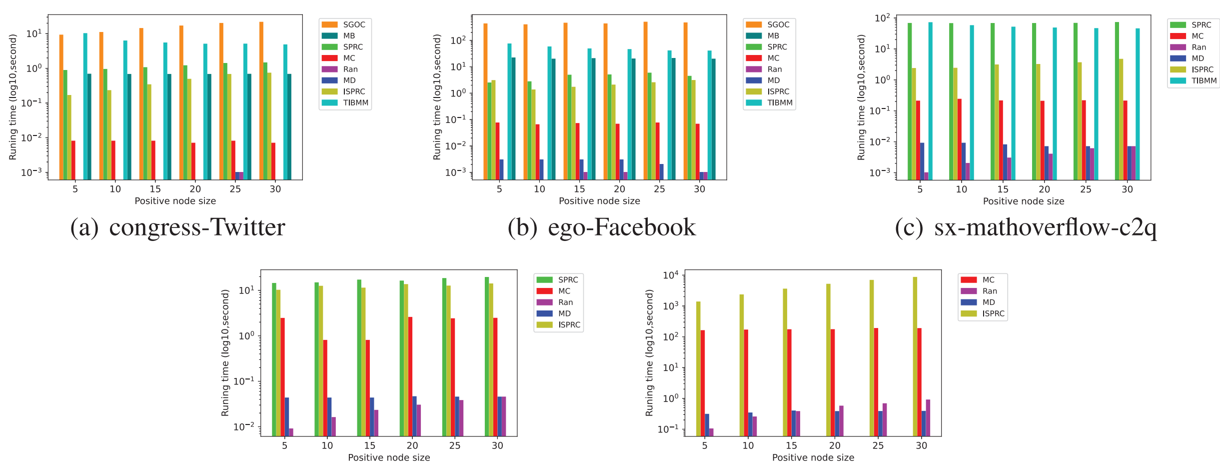
In this subsection, we evaluate the efficiency of various algorithms by comparing their total runtime. Figs. 5–7 show the runtime of different algorithms across five datasets, where $|R|$ ranges between [10, 20, 30] and $|T|$ ranges between [5, 10, 15, 20, 25, 30]. Due to excessive runtime, we do not present the experimental results for some algorithms on the sx-mathoverflow-c2q, sx-askubuntu-a2q, and wiki-talk-temporal datasets.

From Figs. 5–7, we observe that the MD, MB, MC, TIBMM, and Ran algorithms exhibit varying execution times, some longer and some shorter. As discussed in Section 4.4, these algorithms do not perform as well as SGOC, SPRC, and ISPRC.



(a) congress-Twitter (b) ego-Facebook (c) sx-mathoverflow-c2q (d) sx-askubuntu-a2q (e) wiki-talk-temporal

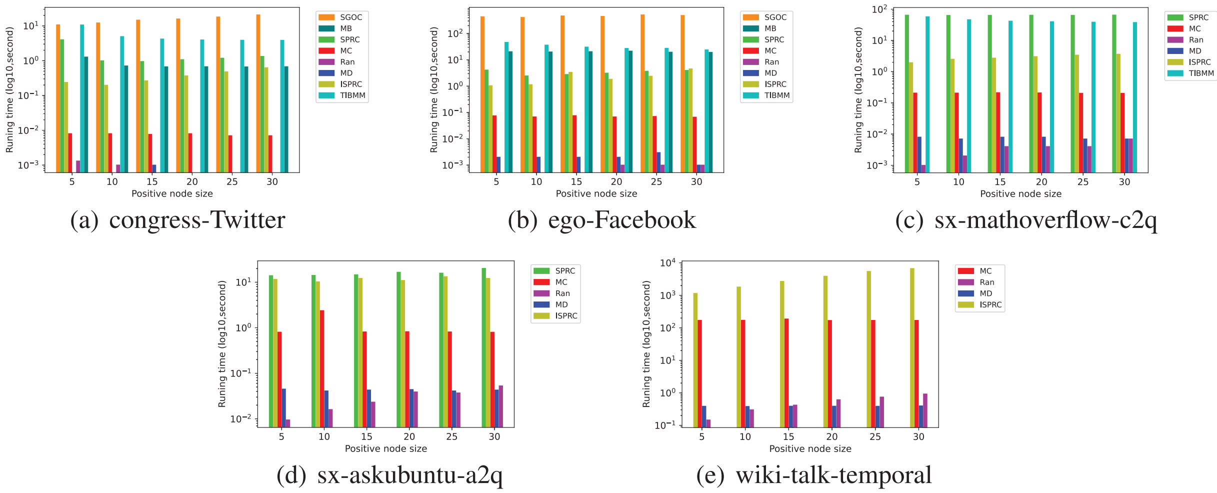
Figure 5: Runtime of eight algorithms across different datasets with varying k under constant model when $|R| = 10$



(a) congress-Twitter (b) ego-Facebook (c) sx-mathoverflow-c2q (d) sx-askubuntu-a2q (e) wiki-talk-temporal

Figure 6: Runtime of eight algorithms across different datasets with varying k under constant model when $|R| = 20$

Among the three algorithms (SGOC, SPRC, and ISPRC) that provide theoretical quality guarantees, ISPRC consistently consumes the shortest runtime, followed by SPRC, with SGOC taking the longest time. This can be attributed to the fact that the SPRC algorithm uses an Immune Nodes Set (INS) data structure which accelerates the execution of the algorithm, while the ISPRC algorithm further speeds up the construction process of INS through a pruning method, thereby decreasing computational complexity and improving the running speed.



(a) congress-Twitter
(b) ego-Facebook
(c) sx-mathoverflow-c2q
(d) sx-askubuntu-a2q
(e) wiki-talk-temporal

Figure 7: Runtime of eight algorithms across different datasets with varying k under constant model when $|R| = 30$

6 Conclusion

In this paper, we study the problem of truth-spreading-based rumor control (TRC), which aims to curb the spread of rumors by disseminating truthful information within a social network. Specifically, we first examine the TRC problem under the MCIC model, then propose the SGOC algorithm as a foundational solution for the TRC problem. To enhance the efficiency of SGOC, we introduce the shortest-path-based rumor control algorithm, SPRC, which leverages a shortest path length dictionary (SPR) and an Immune Nodes Set (INS). To further improve the efficiency of the SPRC algorithm, we employ a pruning method to accelerate the construction of *INS* and propose the ISPRC algorithm. Experiments on five real-world datasets demonstrate the effectiveness and efficiency of the proposed algorithms. In the future, we aim to design diffusion models that more accurately match the rumor propagation process and to develop even more efficient algorithms for rumor control in social networks.

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Author Contributions: Suqiao Li: Writing—original draft, Validation, Methodology, Conceptualization. Taotao Cai: Visualization, Data curation, Software. Lingling Li: Writing—review & editing, Supervision, Funding acquisition. Xuezhuan Zhao: Software, Resources, Writing—review & editing. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: Data will be made available on request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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