Contents

1. Introduction

Over the past few years, online social networks (OSNs) have turned out to be the most popular platform for social interactions, viral marketing, exchanging information, reviews, surveys etc. [1]–[5]. Because of the efficiency in spreading information as well as sharing based on the trustworthiness among the users, billions of people in their daily lives use most popular online social media, such as Twitter, Facebook etc., as their primary sources of news and information. For instance, the news on Osama Bin Laden's death first appeared on Twitter and went viral much before its official announcement on public media by the US President [6]. However, the trustworthiness on OSNs may also be exploited to disseminate misinformation as there is very limited scope for validating the genuineness of an information. The spreading of misinformation not only creates public panic, but also leads to economic losses occasionally [7]. In general, it has been seen that in real-world most popular fake news attract more attention than the correct one and disseminate on the social media within a blink of an eye. Recently, a misinformation that went viral on Twitter and created a lot of panic is about Kamala Harris's ineligibility to serve as US vice-president [8] for example. Thus, to enable an OSN to be a trustworthy medium for transmitting correct information, an effective strategy is required to contain the misinformation. In particular, a set of trusted users needs to be found so that spreading correct information from them effectively minimizes the adverse effects of misinformation.

So far, researchers have tried to restrain the misinformation in various ways. The most common technique that is widely used is to block the misinformation sources by selecting the highly influential users as seeds. But, the selection of highly influential users is an NP-Hard problem [9], [10]. Hence, to achieve approximate or near-optimal solutions many computation intensive heuristics have been proposed [6], [11], [12]. Also, there are some game-theoretic based approaches [13], [14] to find the optimal strategies. But, in most of the earlier works, researchers follow a dynamic approach where for a given snapshot of OSN, an optimal set of seed nodes is determined, based on the position of the misinformed nodes, to contain the misinformation faster. Thus, for the same online social network with different instances of misinformation, we need to re-compute the seed set every time which incurs more time. In this paper, for faster restraining and decimation of misinformation a static one-time trust-based seed selection approach is proposed leveraging the topologies of the OSNs. We exploit the community structures[1] of the network to plant the trusted nodes irrespective of the positions of the misinformed nodes, and follow our proposed modified form of LT1DT [15] model for the diffusion of both correct information and misinformation.

Here follows the contribution of our work. We

- model the Misinformation Containment problem as a maximum coverage problem where misinformation as well as correct information propagate in a competitive pattern to maximize their influence on more number of individual.
- follow a proposed modified form of LT1DT [15], considering the trust level of the users to play a role in information diffusion and belief switching.
- propose a fast probabilistic strategy based on trust levels of users to choose a set of trusted seed nodes leveraging the disjoint and overlapping communities of the OSN. Here, the set of trusted seed nodes once gets chosen, will remain invariant unless the community structure changes drastically.
- evaluate the effectiveness of the proposed approach on large-scale real-world OSNs which shows at most 55.61%, 74.58% and 20.87% reductions in *maximum number of misinformed nodes, number of misinformed nodes in steady state and point of decline* respectively, compared to Yang et al.'s algorithm [15].

We organize the rest of the papers as follows. In Section 2, we discuss the related works on misinformation containment. Section 3 introduces the model formation. In Section 4, we present the misinformation containment technique following the proposed trust-based seed selection approach. Section 5 illustrates the experimental results. And finally, we conclude the paper with a scope of future working Section 6.

[1]Community structure in OSN is defined as the decomposition of its users into densely connected subgroups such that connections among these subgroups are sparse [16].

2. Related Works

In last few years, several research studies have been reported in the literature for restraining the misinformation following various competitive information diffusion models.

Tong et al. [17] have proposed a misinformation containment strategy following a multi-cascade diffusion model, where they have introduced the concept of cascade-priority. Ni et al. [18] have proposed a community-based dynamic seed selection strategy to restrict the spread of misinformation following Competitive Independent Cascade Model. Huang et al. [13] have proposed a game-theoretic approach to contain the misinformation following their own proposed individual-based diffusion model. Askarizadeh et al. [14] have proposed a game-theoretic based misinformation containment model in which once a node receives misinformation, it refers to its trusted neighbors or asks the authorized sources to avoid spreading misinformation. Pham et al. [12] have proposed a multi-topic misinformation blocking strategy following Linear Threshold Model. Tripathy et al. [19] have proposed a misinformation containment strategy by diffusing positive information following peer-to-peer Linear Threshold Model. He et al. [20] have proposed a Q-learning based strategy following multi-stage competitive Linear Threshold Model to contain misinformation. In all the prior studies, nodes are never allowed to switch their belief once they adopt either misinformation or correct information.

However, in real-world, people may start to belief in misinformation initially but once they receive correct information either from the authorized sources or their trusted neighbors, they may start to believe in correct information and switch their states. With this trend, Ghoshal et al. [21] have proposed a community-based static seed selection approach to restrain the spread of misinformation following Competitive Independent Cascade Model. In their technique, they have assumed that once a node receives both misinformation and correct information, node will adopt the correct information. Yang et al. [15] have proposed a novel heuristics, called ContrID, for misinformation containment following a modified version of classical Linear Threshold Model, called Linear Threshold Model with One Direction state Transition (LT1DT), that not only considers the influence and decision thresholds for activation of node and convincing a node to believe in either misinformation or correct information respectively, but also allows reconsideration process only for the misinformed nodes. However, the reconsideration process makes their proposed model non-progressive. Hence, by analyzing the steady state, authors have provided the bounds on the number of misinformed nodes and the number of active nodes with correct information. Moreover, authors have used a dynamic truth seed set selection strategy that selects top-k highest contributors based on the diffusion dynamics, to counter the spread of misinformation, which is shown to be an NP-Hard problem.

In majority of previous studies except [20], the aim is to determine a set of positive seeds, based on the positions of the misinformed nodes, to maximize their influence to restrain the spread of misinformation. Hence, it is an influence maximization problem which is known to be NP-Hard [9],[10] and thus, computation intensive. In this paper, for faster containment of misinformation, a static one-time trust-based seed selection approach is proposed leveraging the topologies of the network. We follow the LT1DT [15] information diffusion model only with the decision threshold (a.k.a belief level) and the reconsideration process, to restrain the misinformation. Extensive simulation studies on different real-world OSNs with random distribution of misinformed nodes show that the proposed approach outperforms earlier works in terms of performance metrics, to restrain the misinformation. It is to mention that once the set of trusted seed nodes is computed, it remains invariant and effective to tackle any distribution of misinformed nodes, unless topologies of the network change drastically.

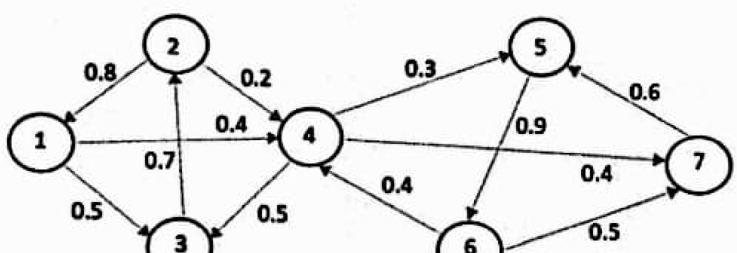
3. Model Formation

Let an Online Social Network (OSN) be represented as a directed graph $G(V, E, W)$, where V is the set of users (*a.k.a.* nodes), E is the set of directed edges that represents the follower-followee relationships between users, i.e., when user i follows user j, we have an edge $(i, j) \in E$, and each ($w_{ij} \in W$) $\in (0, 1]$ represents the trustworthiness of user j on user i. However, in real scenario trustworthiness is not symmetric, i.e, node i trusts its neighbor j does not necessarily imply that node j also trusts its neighbor i. For the directed OSN G, we define the in-neighbor set of a node i as $\Gamma^{in}(i) = \{j \mid (j, i) \in E\}$ and out-neighbor set as $\Gamma^{out}(i) = \{j \mid (i, j) \in E\}$ and we assign the weight $w_{ij} \in (0, 1]$ to each edge $(i, j) \in E$ such that $w_{ij} = 0$ if $(i, j) \notin E$ and for any node $i, \sum_{j \in \Gamma^{in}(i)} w_{ji} = 1$.

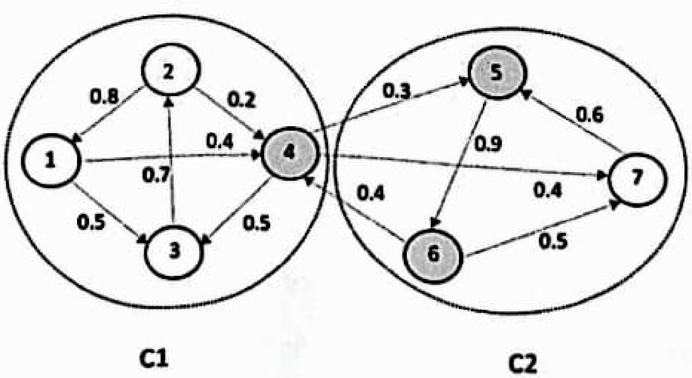
In OSN, community structure is usually defined as the decomposition of users into densely connected subgroups $C = \{c_1, c_2, \ldots, c_k\}$, where each subgroup c_i is a community of G.

Definition 1. For a given set of communities $C = \{c_1, c_2, \ldots, c_k\}$, C is said to be disjoint if for any two sub-groups c_l and c_m, $c_l \cap c_m = \emptyset$, where $l \neq m$,

In this work, we study the impact of the community structure in order to restrain and decimate the misinformation at the earliest.



(a) Online Social Network



(b) Disjoint community

Fig. 1: (a) Trust-based directed online social network; (b) Disjoint community C_D = {(1, 2, 3, 4),(5, 6, 7)}

3.1 Problem Statement

When a misinformation emerges in OSN, it becomes essential to limit the spread of misinformation by diffusing the correct information through some authorized trusted nodes (a.k.a seeds) so that many users primarily accept the correct information, and may influence the misinformed users to switch their belief, to eventually make the OSN free of misinformation. However, it is not possible to decimate the misinformation completely, as we can see in our real-world as well, but our objective is fulfilled when it is at least contained.

Problem Definition : Let $G(V,E,W)$ be a snapshot of an OSN at time t that contains some misinformed users $V_m(t)$. Now, for a given budget B, select a set of trusted seed nodes $V_b(t)$ with correct information such that $V_b(t) \leq B$ and the cardinality of the final misinformed nodes set is minimized after τ time of diffusion.

3.2 System Model

We assume that at each point of time t, a node v may be in either state S_0, S_1 or S_2 where S_0 represents the inactive state of a node, i.e., the node has not yet believed in either misinformation or correct information, S_1 represents an active state of a node where node has been already influenced by misinformation, and S_2 represents an active state of a node where the node has already accepted the correct information and becomes trusted. In most of the studies [15],[21],[22] researchers have proposed a restricted model.However, in reality, it may so happen that an user after believing the correct information may adopt the misinformation again. Hence, to capture the more realistic scenario, in this work, we consider an unrestricted model where a node in S_2 after believing the correct information may adopt the misinformation again in near future. For a clear representation of the scenario, we show the possible state transition of a node in Fig.2

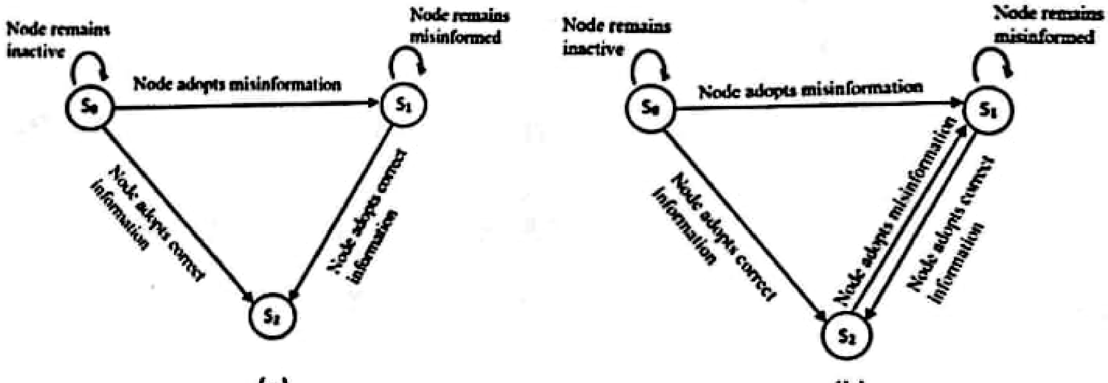


Fig 2 : State transition of a node under a) Restricted ,b) Unrestricted models

It is to be noted that here, a node v in state S_0 changes its state either to S_1 or S_2, depending on whether the sum of trust relationship from its misinformed in-neighbors or from its trusted in-neighbors exceeds the belief threshold λ. Likewise, u in state S_1 changes its state to S_2 if sum of trust relationship from its trusted in-neighbors exceeds λ. And v in state S_2 may only change its state to S_1 if sum of trust relationship from its misinformed in-neighbors exceeds λ.

3.3 Proposed Information Diffusion Model

For the diffusion of both correct and misinformation, in this work, the LT1DT [11] model is considered with a single threshold which we term here as SLT1DT model. Under the SLT1DT model, the network is represented as a tuple $(G(V, E, W), \lambda)$ where λ is the belief threshold of nodes and for any node u the value of $\lambda_u \in$ in (0, 1] [11]. Here, a node will be termed as a M-active node if the node becomes influenced by misinformation. Likewise, the nodes, if influenced by true information, will be termed as T-active nodes.

For Unrestricted model, under SLT1DT, at each time step, a node will accept misinformation if the sum of trust relationship from its M-active in-neighbors is greater than or equal to the belief threshold λ_v i.e.,

$$\sum_{u \in \{\Gamma_v^{in} \cap V_m(t)\}} w_{uv} \geq \lambda_v \qquad \text{-------------(1)}$$

Likewise, v will accept the correct information if the sum of trust relationship from its T-active in-neighbors is greater than or equal to the belief threshold λ_v i.e.,

$$\sum_{u \in \{\Gamma_v^{in} \cap V_b(t)\}} w_{uv} \geq \lambda_v \qquad \text{-------------(2)}$$

However, if at any point of time if both equation (1) and (2) statify, node v will accept the information whose sum of trust relationship has a maximum impact, as has been assumed in [14],[16]. Moreover, if the sum of trust relationship becomes equal for both M-active and T-active neighbors, v will accept either correct or misinformation arbitrarily. The evolution process continues until no more node gets activated or reconsider its decision. In this situation, the system is said to be in steady state.

3.4 Performance Matrix

For a given snapshot of OSN $G(V, E, W)$, performance of the proposed approach is evaluated using the following metrics, as introduced in [23].

- ***Number of M-active Nodes ($|V_m(t)|$):*** It captures the number of misinformed nodes at time t. Mathematically, it is defined as

$$|V_m(t)| = \{i \mid i \in V \text{ and } i \text{ is in } S_1 \text{ at time } t\} \qquad \text{---------- (3)}$$

- ***Number of T-active Nodes ($|V_b(t)|$):*** It captures the number of active nodes with correct information at time t. Mathematically, it is defined as

$$|V_b(t)| = \{i \mid i \in V \text{ and } i \text{ is in } S_2 \text{ at time } t\} \qquad \text{---------- (4)}$$

- ***Point of Inflection P(G):*** In the misinformation growthcurve with time, it refers to the time point at which number of M-active nodes starts decreasing. Mathematically,it is defined as

$$P(G) = \min(t \mid (|V_m(t+1)| - |V_m(t)|) \leq 0) \qquad \text{---------- (5)}$$

4. Misinformation Containment Approach

To restrain the misinformation in OSNs, in most of the earlier works [15], [18], [19], [24], researchers have followed a reactive approach where for the given positions of misinformed nodes, the seed nodes with correct information are planted to maximize their influence [20]. This means, for the same OSN with different instances of misinformation, placement of seed nodes is to be recomputed every time. Since in various forms, the seed selection problem is found to be NP-hard, computation intensive heuristics are applied that requires long time to converge.

However, in this paper, a proactive approach for the placement of seed nodes is followed leveraging the topologies of the OSN, irrespective of the positions of the misinformed nodes. For a given OSN, a set of trusted nodes is computed based on the trustworthiness of nodes by their neighbors. And then, a probabilistic approach is used to select the static set of trusted seed nodes from the set of trusted nodes leveraging the community structure of the network.

Definition 2. A node u is said to be a trusted node if $w_{uv} \geq \delta, \forall v \in \Gamma^{out}(u)$, where δ represents the threshold for trustworthiness.

Example 1. In Fig. 1(a), nodes 3,5 and 7 are the trusted nodes for $\delta \geq 0.6$.

4.1 Selection of Trusted Seed Nodes :

For a given OSN $G(V, E, W)$ with a set of trusted nodes and a budget B, we consider the following seed selection approach to plant the correct information.

1) Disjoint Community Based Approach: As the boundary nodes of the communities play a crucial role in information diffusion [21], [28], this opens up a new idea that placement of trusted seed nodes on the boundary may help significantly to combat the misinformation in OSNs.

Definition 3. For a given disjoint community, Community Boundary Nodes (CBNs) refer to the nodes that contain connecting edges between any two communities [29].

Example 2. In Fig. *1(b)* nodes *4, 5*, and *6* are CBNs.

In this work, we follow a defensive approach that attempts to restrict the misinformation within a community before decontamination by placing trusted nodes on CBNs. Moreover,this placement of trusted seed nodes is independent of the distribution of nodes with misinformation, and remains static unless the community structure of the OSN changes. But for large OSNs, there may be a huge number of CBNs as we observe in our experimental study, and selecting all of them as seed nodes may not be a cost effective procedure. Hence, we use a probabilistic approach to select the static set of trusted seed nodes prioritizing such nodes.

Let the OSN $G(V, E, W)$ has $|V|$ nodes and N_C CBNs, where $N_C << |V|$. Out of $|V|$ nodes and N_C CBNs, say N_S nodes and N_{SC} CBNs are trusted nodes. Now, we randomly select each of the trusted CBN as seed with a probability P_C, so that $\frac{B}{Ns} < P_c < \frac{B}{Nsc}$,whereas we select each of the trusted non-CBN as seed with a probability $P'_C = \frac{B - Pc.Nsc}{Ns - Nsc}$,so that $|V_b(0)| \leq B$.

4.1.1 Algorithm 1 Seed Node Determination leveraging Trust

INPUT: G, set of CBN, I , P_c, P'_c
OUTPUT: $V_b(0)$, S

for each $u \in V$ **do**

if $u \in$ CBN **then**
if $w_{uv} \geq \delta, \forall v \in \Gamma_u^{out}$ **then**
u becomes a trusted seed node with P_c

else
if $w_{uv} \geq \delta, \forall v \in \Gamma_u^{out}$ **then**
u becomes a trusted seed node with P'_c

if success then
$V_b(0) \leftarrow V_b(0) \cup \{u\}$
$S_u \leftarrow 2$

4.1.2 Algorithm 2 Misinformation Containment under unrestricted model following SLT1DT

INPUT: G, $\gamma = |V_m(0)|$,S, λ
OUTPUT: P(G)

for each $u \in V$ **do**
if $u \in V_m(0)$ **then**
$S_u \leftarrow 1$ and $\tau(u) \leftarrow 0$
$T \leftarrow 1$, $T_{min} \leftarrow 1$
repeat
$\gamma_{max} \leftarrow \gamma$
for each $u \in V$ **do**
for each $v \in \Gamma_u^{in}$ **do**
if $S_v = 1$ **then**
$\varepsilon_{mis} \leftarrow \varepsilon_{mis} + w_{uv}$
if $S_v = 2$ **then**
$\varepsilon_{true} \leftarrow \varepsilon_{true} + w_{uv}$
if $\varepsilon_{mis} \geq \lambda_u$ **then**
if $S_u = 0$ **then**

```
        S_u ← 1 and γ ← γ + 1
    if S_u = 2 then
        S_u ← 1 and γ ← γ + 1
else if ε_true ≥ λ_u then
    if S_u = 0 then
        S_u ← 2
    if S_u = 1 then
        S_u ← 2 and γ ← γ − 1
else if ε_mis ≥ λ_u and ε_true ≥ λ_u then
    if ε_mis > ε_true then
        if S_u = 0 then
            S_u ← 1 and γ ← γ + 1
        if S_u = 2 then
            S_u ← 1 and γ ← γ + 1
    else if ε_true > ε_mis then
        if S_u = 1 then
            S_u ← 2 and γ ← γ − 1
        if S_u = 0 then
            S_u ← 2
    else
        r ← randomly choose either 0 or 1
        if r = 0 then
            if S_u = 0 then
                S_u ← 1 and γ ← γ + 1
            if S_u = 2 then
                S_u ← 1 and γ ← γ + 1

        else
            if S_u = 1 then
                S_u ← 2 and γ ← γ − 1
            if S_u = 0 then
                S_u ← 2
if γ < γ_max and T_min ≠ 0 then
    P(G) ← T, T_min ← 0
T ← T + 1

until no more node gets activated or changes its belief
```

4.2 Complexity Analysis

To utilize the memory efficiently, in our approach, we store the OSNs using array based adjacency list (a.k.a Compressed-Sparse-Row (CSR)) [24] representation which takes $O(|V|+|E|)$ amount of space in memory. However, due to the sparse nature of the real world OSNs, $|E| \sim O(|V|)$. In Algorithm 1, for each node in parallel, we explore its out neighbors to check whether the node is trusted, and if so, the node becomes seed with certain probabilities. This takes $O(max(|\Gamma^{out}|))$ time considering the seed selection process as well. To prevent spreading of misinformation in OSNs, each node in parallel explores its in-neighbors in Algorithm 2, which takes $O(max(\Gamma^{in}))$ time. Hence, the total time taken by both Algorithm 1 and 2 is $O(max(|\Gamma^{out}|, |\Gamma^{in}|))$. It is to be noted that the time complexity of the proposed techniques is linear, and hence, suitable for large real-world static OSNs.

5. Experimental Evaluation

To restrain the spread of misinformation in OSNs, thorough simulations have been performed on static real world OSNs to evaluate the efficacy of the proposed technique. We have written the parallel code As the networks don't have edge-weights, we generate the trust values among nodes following the procedure described in Section III. We set the threshold for trustworthiness δ to 0.5 for each OSN, and select k% of total network nodes as budget B, where $0\% < k \leq 1\%$. It is to note that here k is chosen randomly within 0–1% to get a decent value for B. It is evident that larger value of B will not only reduce the number of M-active nodes, but also increase the number of T-active nodes [15], [23]. Even, selecting a large value for B is also not cost-effective. Following [30], the simulation results are averaged over 100 runs. Moreover, we compare the performance of the proposed approach with Yang et al.'s algorithm [15].

5.1 Dataset

Three real-world static directed OSNs, namely, Wikipedia Election [25], soc-Epions [25] and Twitter [26] are considered for the experiment. The details of these datasets are specified in Table I, where Q [16] represents the modularity measure for disjoint community.

TABLE I: Properties of Real-World Directed Online Social Networks

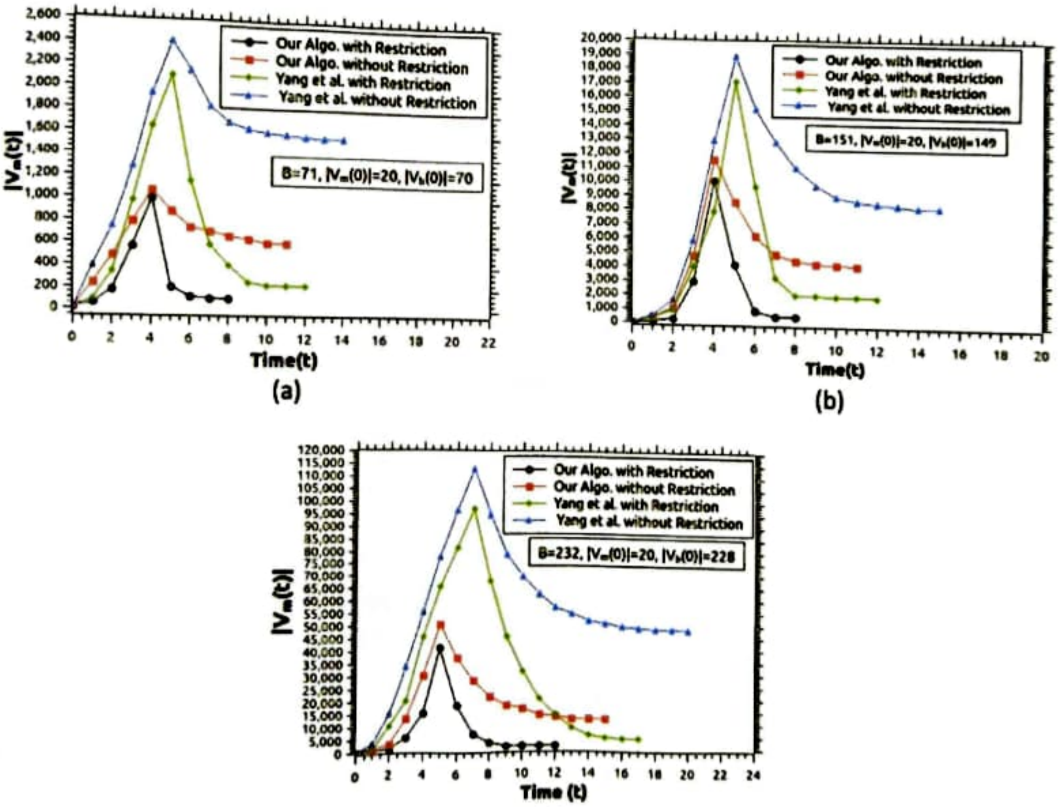
Networks	Nodes	Edges	Q	N_c	δ	N_s	N_{sc}
Wikipedia Election	7115	103689	0.41	3631	0.5	1038	811
soc-Epion	75789	508837	0.45	26647	0.5	18710	1708
Twitter	465017	834797	0.652	75831	0.5	31182	5691

TABLE II: Probabilistic values for selection of Trusted Seed Nodes

Networks	% Node selected $B(0\% < k \leq 1\%)$	B	$\frac{B}{Ns}$	$\frac{B}{Nsc}$	P_C	P'_C	Trusted CBNs	Trusted non-CBNs	$\lvert V_b(0)\rvert$
Wikipedia Election	1	71	0.06840	0.08754	0.0861	0.0006	68	02	70
soc-Epion	0.20	151	0.00807	0.08840	0.0731	0.0006	109	40	149
Twitter	0.05	232	0.00744	0.04076	0.0291	0.0004	103	125	228

5.2 Results

For faster restraining of misinformation, following [20], in Table II we choose P_C close to $\frac{B}{Nsc}$ to select more number of trusted boundary nodes as seeds. Not only that, the probability P_C is chosen in such a way so that same number of trusted CBNs gets selected as seeds. Also, following [27], the misinformation starts spreading from 20 arbitrary nodes.



(a) (b) (c)

Fig. 3 : Spreading Dynamics of misinformation on (a) Wikipedia Election; (b) Soc-Epion; and (c) Twitter Networks

Fig. 3 shows that without posing any restriction on the node state, the misinformation is contained. However, the number of misinformed nodes at the steady state is much higher here compared to the restricted model, which is obvious. The unrestricted model captures the real-world scenario where an user being influenced by the correct information may adopt another misinformation again. From Fig. 3, it is evident that the proposed approach achieves of 38.70–55.61% and 20–20.87% reductions in maximum number of M-active nodes and P(*G*) respectively.

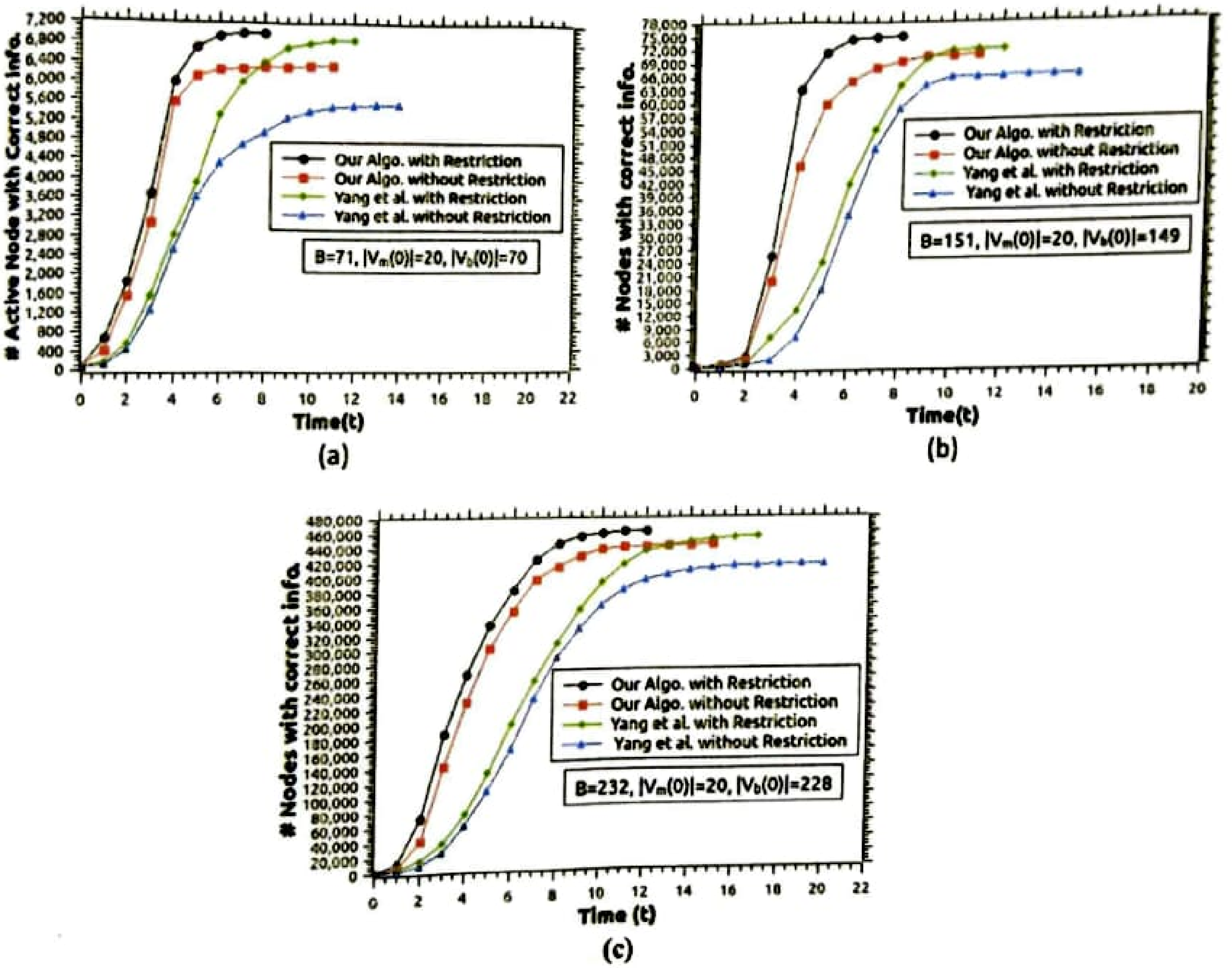


Fig 4: Spreading Dynamics of Correct information on (a) Wikipedia Election; (b) Soc-Epion; and (c) Twitter Networks.

Fig. 4 shows that the number of T-active nodes increases significantly, compared to [15], even if we allow a T-active node to become a M-active node after getting influenced by the misinformation.

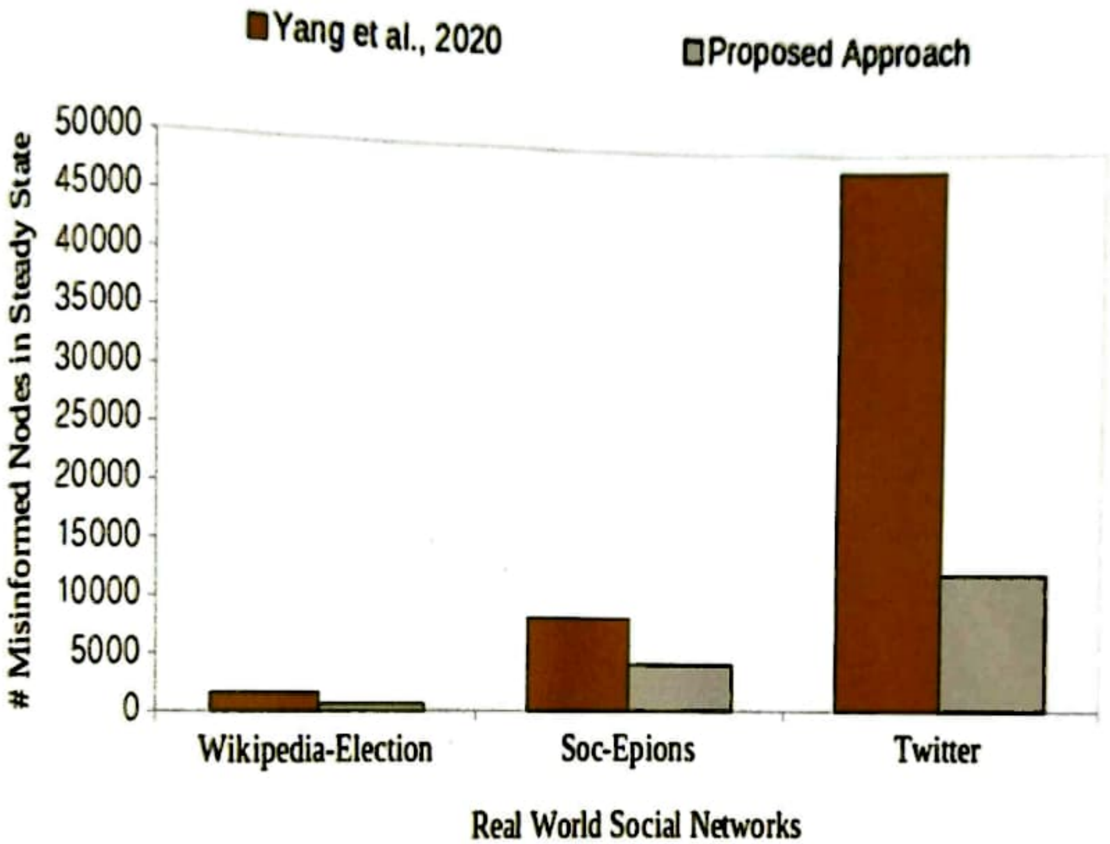


Fig. 5: Number of misinformed nodes in steady state

In Fig. 5, we show the number of M-active nodes in the steady state for the unrestricted model. It is evident that the proposed technique achieves 49.46–74.58% reductions in number of M-active nodes in steady state, compared to [15]. It is to be noted that under this model infected times become insignificant as a misinformed node after adopting the correct information may adopt the misinformation again. Hence we don't include this parameter in the results. In summary, the study shows that the proposed technique contains the misinformation even without posing any restriction on the node states, and hence suitable for real-world practical applications like containing infections, advertisements etc.

6. Conclusion

In this report, a static one-time trust-based seed selection approach is proposed leveraging the topology of the OSNs, to restrain and decimate the misinformation at the earliest. The advantage of the proposed approach is that the seed set remains invariant irrespective of the positions of the misinformed nodes unless the topology of the network varies drastically. Here, a modified version of LT1DT model is followed to diffuse both the correct information and misinformation in OSNs. Extensive simulation studies on three real-world OSNs show that compared to [15], the proposed approach achieves almost 55.61%, 74.58% and 20.87% reductions in maximum number of misinformed nodes, number of misinformed nodes in steady state and P(*G*) respectively, indicating faster containment of misinformation.

As a future direction of work, we need to perform more studies to evaluate the effectiveness of the proposed approach on more real-world OSNs and also, on evolutionary social networks as well. Even, the performance has to be evaluated to show the variation in the number of misinformed nodes with budget in steady state.

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7. References

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