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Assessing Individual and Community Vulnerability to Fake News in Social Networks

Bhavtosh Rath · Wei Gao · Jaideep
Srivastava

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Abstract The plague of false information, popularly called *fake news* has affected lives of news consumers ever since the prevalence of social media. Thus understanding the spread of false information in social networks has gained a lot of attention in the literature. While most proposed models do content analysis of the information, no much work has been done by exploring the community structures that also play an important role in determining how people get exposed to it. In this paper we base our idea on Computational Trust in social networks to propose a novel *Community Health Assessment* model against fake news. Based on the concepts of neighbor, boundary and core nodes of a community, we propose novel evaluation metrics to quantify the vulnerability of nodes (individual-level) and communities (group-level) to spreading false information. Our model hypothesizes that if the boundary nodes trust the neighbor nodes of a community who are spreaders, the densely-connected core nodes of the community are highly likely to become spreaders. We test our model with communities generated using three popular community detection algorithms based on two new datasets of information spreading networks collected from Twitter. Our experimental results show that the proposed metrics perform clearly better on the networks spreading false information than on those spreading true ones, indicating our community health assessment model is effective.

B. Rath and J. Srivastava
Department of Computer Science & Engineering, University of Minnesota, USA
E-mail: {rathx082, srivasta}@umn.edu

W. Gao
School of Information Systems, Singapore Management University
E-mail: weigao@smu.edu.sg

1 Introduction

The use of social media platforms like Facebook, Twitter and Whatsapp is ubiquitous in modern times, making them powerful tools for information propagation and consumption. However, such goodness inevitably gets accompanied by the bad due to the innate vulnerability of human users to misinformation, which can be witnessed with the tremendous problem of *fake news spreading* [16]. *Fake news* is a recently coined term that means fabricated news. *It refers to newsworthy claims that may have no basis in fact, but are presented as being factually truthful.* It gets spread when someone propagates it online via various endorsements such as replying, sharing or re-posting without validating the authenticity of the content.

There is a sheer amount of interest in the research community to understand fake news spreading, as summarized by Sharma et al. [37]. Our approach is orthogonal to these by focusing on *assessing the vulnerability of social networks to false information spreading*. Specifically, our focus is on people and the online communities they create, with the goal of identifying how vulnerable individuals and communities are to believing false information. We propose the Community Health Assessment model that introduces the ideas of neighbor, boundary and core nodes of a community and proposes novel metrics to quantify the vulnerability of an individual and the community itself. *From a public health perspective, determining whether a piece of news is fake or not is akin to determining whether a virus is injurious to health, while our approach is akin to determining whether an individual or community is vulnerable to being infected by the virus.* Thus, the proposed approach provides a complementary perspective, and can be useful in inoculating individuals and communities against spread of fake news.

To assess the vulnerability of users and their communities, we propose methods to quantify the likelihood of a boundary node of a community to believe a news item sent from its immediate neighbors, and also quantify the likelihood of a community's entire boundary node set to believing its neighborhood, i.e., the set of nodes outside the community that are connected to at least one member of the community. Intuitively, if an external node infects a member of a community, the likelihood of the entire community to get infected increases due to high connectivity among community members. Thus, while assessing vulnerability of community, we focus on examining the influence of information propagated from external nodes into the community rather than considering the internal propagation of the news within the community. We evaluate our model on the propagation networks on multiple real-world information spreading networks from Twitter.

In this paper, we make the following three novel contributions:

- We propose the Community Health Assessment model that initiates the ideas of neighbor, boundary and core nodes for a community structure in a social network.
- We propose metrics that are used to quantify the vulnerability of node and community to fake news spreading from outside. Health analogy here

is that fake news is akin to infection, and quantifying vulnerability is akin to assessing immunity to infection spread.

- We present evaluation of the proposed metrics using two datasets based on a set of fact-checked news events, one from snopes.com and the other from a fact-checking website in India. We demonstrate that our proposed metrics can much better assess the vulnerability of social networks to fake news than regular news. To the best our knowledge, this is the first work to systematically quantify the vulnerability to online users and communities to fake news.

The rest of the paper is organized as follows: We first discuss the Related Work, followed by explanation of the Community Health Assessment model and the preliminary ideas that it builds upon. We then explain the algorithm to quantify the vulnerability metrics. Next, in the Experiments and Results section we explain the data collection process, the datasets and the metrics used for evaluation and the results. Finally, we provide concluding remarks and summarize scope of future work.

2 Related Work

We describe briefly prior work in three broadly related domains: *Misinformation Detection*, *Rumor Spreading Models* and *Computational Trust*.

2.1 Misinformation Detection

There has been a surge in interest among researchers over the past few years to build models to detect misinformation. Most approaches in literature model content-based and network-based characteristics of the misinformation. These methods include approaches to capture the style and the language of articles [10], hyperpartisan news content [24] and cues that map language to perceived levels of credibility [20]. Many classification models distinguishing true and false information have also been proposed. Perez-Rosas et al. [23] proposed a fake news detection model using linguistic features. Yang et al. [32] proposed a classification model using client- and location- based features extracted from micro-blogging websites. Network-based approaches that try to model the propagation structures of false information have also been proposed [13, 9, 25, 18]. The use of neural networks has gained strong attention recently. Use of convolution neural networks [3] and recurrent neural networks [17] and numerous variants of these fundamental models have shown promising results. Zhang et al. [42] applied a graph neural network model that aggregates textual information news articles, creators and subjects to identify news veracity. Ma et al. [40] applied generative adversarial networks to counter rumor dissemination by generating confusing training examples to challenge the discriminator of its detection capacity. Shu et al. [41] applies attention mechanism that captures both news contents and user comments to propose

an explainable fake news detection system. Khattar et al. [38] used textual and visual information in a model variational autoencoder coupled with a binary classifier for the task of fake news detection. Lu and Li [39] integrated attention mechanism with graph neural networks using text information and propagation structure to identify whether the source information is fake or not.

2.2 Rumor Spreading Models

Infection spread models from epidemiology, namely SIR (Susceptible, Infected, Recovered) [21], SIS (Susceptible, Infected, Susceptible) [15], SEIZ (susceptible, exposed, infected, skeptic) [44], SIHR (Spreaders, Ignorants, Hibernators, Removed) [33] and their variants [45, 44, 43, 46, 47] have been widely used to model information spreading, including rumors. Modelling rumor spreading as cascade structures in social networks is also well studied [9, 31]. Other models have been proposed to identify the source of rumor spreading [29, 35]. Fan et al. [8] proposed a model to maximize rumor containment within a fixed number of initial protectors and a given time deadline. Social networks are naturally composed of disjoint communities with relations formed within communities stronger than relations formed across communities. Focusing on such communities to understand rumor spread is a domain with a lot of research potential.

Fan et al. [5] proposed an approach to identify a minimal set of boundary nodes that would prevent spread of rumors from neighboring communities. Nguyen et al. [22] proposed a community-based heuristic method to find the smallest set of highly influential nodes whose decontamination with good information would contain rumor spreading. Vosoughi et al. [31] is another closely related work that tried to empirically investigate the spread of true and false news online on a large real-world data repository from Twitter and concluded that false news spreads faster and deeper in networks compared to true news. Susceptibility of users to fake news has also been studied with a content analysis [50] and information diffusion [48] perspective. What makes this work novel is that we propose content-agnostic metrics based on the underlying network structure.

2.3 Computational Trust

Computational social scientists have been interested to quantify the concept of trust in various domains [1] with online social networks being one of them [30]. One of the first works in the area of trust propagation in networks was by Ziegler and Lausen [36]. Some researchers have attempted to understand the role of trust in message propagation during time critical situations [11]. Others have worked to assign scores to nodes in a trust network based on various structural aspects. Kamvar et al. [14] proposed *Eigentrust* to rate trust scores of peers in a P2P network. Mishra and Bhattacharya [19] proposed an iterative

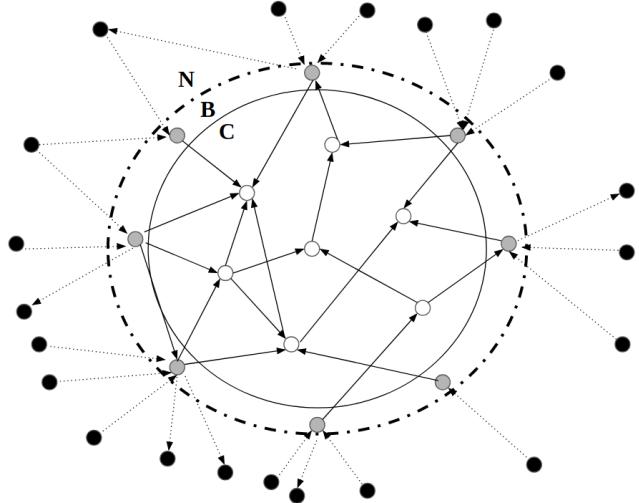


Fig. 1: The three levels of nodes that a piece of information can affect during its propagation. The Neighbor nodes (\mathcal{N}), Boundary nodes (\mathcal{B}) and Core nodes (\mathcal{C}) are represented in black, grey and white, respectively. Boundary edges (connecting neighbor and boundary nodes) are represented by dotted lines.

matrix convergence algorithm to compute the bias and prestige of nodes in a network. Inspired by the HITS algorithm, Roy et al. [27] proposed the Trust in Social Media (TSM) algorithm to compute a pair of complementary trust scores for every node in a social network, on which our vulnerability measures are built upon.

3 Community Health Assessment Model

A social network has the characteristic property to exhibit community structures which are formed based on inter-node interactions. Communities tend to be modular groups where within-group members are highly connected, and across-group members are loosely connected. *Modularity* refers to the ratio of density of edges inside a community to that of the edges outside the community. Thus, based on the edge density, members within a community would tend to have a higher degree of trust among each other than members across different communities. Also, there is variation in the level of inter-member trust across different communities due to varying modularities. If such communities are exposed to false information being propagated from neighboring nodes, the likelihood of the whole community getting infected would be high. Thus it is important to identify vulnerable communities that lie in the path of false information spreading in order to protect them and thus limit the overall influence of false information in the network.

Motivated by this idea we propose the Community Health Assessment model. As part of the modeling, we first propose the ideas of neighbor, boundary and core nodes of a community and then propose metrics to quantify vulnerability of nodes and communities based on the fundamental measures of trust. Figure 1 explains the three groups of nodes with respect to a community which are affected during the process of information spreading, namely:

- *Neighbor nodes*: These nodes are directly connected to at least one node of the community. The set of neighbor nodes is denoted by \mathcal{N} . They are not a part of the community.
- *Boundary nodes*: These are community nodes that are directly connected to at least one neighbor node. The set of boundary nodes is denoted by \mathcal{B} . Edges connecting neighbor nodes to boundary nodes are called boundary edges.
- *Core nodes*: These nodes are only connected to members within the community. The set of core nodes is denoted as \mathcal{C} .

3.1 Preliminaries

3.1.1 Trustingness and Trustworthiness

In social media studies, researchers have used social networks to understand how trust manifests among users. An inspiring work is the Trust in Social Media (TSM) algorithm which assigns a pair of complementary trust scores to each actor, called *Tustingness* and *Trustworthiness* scores [27]. *Tustingness* quantifies the propensity of an actor to trust its neighbors and *Trustworthiness* quantifies the willingness of the neighbors to trust the actor. The TSM algorithm takes a user network, i.e., a directed graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$, as input together with a specified convergence criteria or a maximum permitted number of iterations. In each iteration, for every node in the network trustingness and trustworthiness scores are computed using the equations given below:

$$ti(v) = \sum_{\forall x \in out(v)} \left(\frac{w(v, x)}{1 + (tw(x))^s} \right) \quad (1)$$

$$tw(u) = \sum_{\forall x \in in(u)} \left(\frac{w(x, u)}{1 + (ti(x))^s} \right) \quad (2)$$

where $u, v, x \in \mathcal{V}$ are user nodes, $ti(v)$ and $tw(u)$ are trustingness and trustworthiness scores of v and u , respectively, $w(v, x)$ is the weight of edge from v to x , $out(v)$ is the set of outgoing edges of v , $in(u)$ is the set of incoming edges of u , and s is the involvement score of the network. Involvement is basically the potential risk an actor takes when creating a link in the network, which is set to a constant empirically. Once the trust scores are calculated for each node in the network, TSM normalizes the scores by adhering to the normalization constraint so that both the sum of trustworthiness and the sum of trustingness

of all nodes in the network equals to 1. However, a salient problem of such normalization method lies in that the scale of the scores is dependent on the size of the network. When the network is very large, the resulting scores will become extraordinarily small. To deal with the issue, min-max normalization based on the logarithm of the scores output by TSM can be used to normalize the scores into the range of (0,1]. Details about the TSM algorithm can be found in [26].

3.1.2 Believability

Believability is an edge score derived from the Trustingness and Trustworthiness scores [25]. It helps us to quantify the potential or strength of directed edges to transmit information by capturing the intensity of the connection between the sender and receiver. Believability for a directed edge is computed as a function of the trustworthiness of the sender and the trustingness of the receiver.

More specifically, given users u and v in the context of microblogs such as Twitter, a directed edge from u to v exists if u follows v . The believability quantifies the strength that u trusts on v when u decides to follow v . Therefore, u is very likely to believe in v if:

1. v has a high trustworthiness score, i.e., v is highly likely to be trusted by other users in the network, or
2. u has a high trustingness score, i.e., u is highly likely to trust others.

So, the believability score is supposed to be proportional to the two values above, which can be jointly determined and computed as follow:

$$\text{Believability}(u \rightarrow v) = tw(v) * ti(u) \quad (3)$$

The idea has been previously applied in [25] where a classification model was built to identify rumor spreaders in Twitter user network based on believability measure. Based on [34], *information posted by a person the reader has deliberately selected to follow on Twitter is perceived as useful and trustworthy*, which intuitively implies that follow relation can be considered as proxy for trust.

3.2 Vulnerability Metrics

Motivation: False information generally gets very low coverage from mainstream news platforms (such as press or television), so an important factor contributing to a user's decision to spread a fake news on social media is its inherent trust on its neighbor endorsing it. On the other hand, a user would most likely to endorse a true news since it is typically endorsed by multiple credible news sources. *Thus, we hypothesize that the less credible nature of false information makes it much more reliant on user's trust relationship for spreading further than true news does.* Consequently, we propose our vulnerability

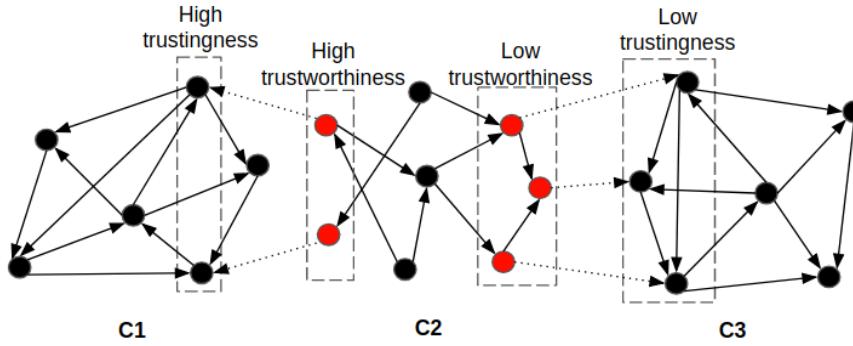


Fig. 2: Illustration of vulnerability to false information spreading. Red nodes are the fake news spreaders and are C1 and C3's neighbor nodes. Dotted lines denote edges connecting C1 and C3's neighbor nodes to boundary nodes.

metrics based upon the idea of computational trust, particularly believability, for assessing the health of individuals and communities encountering false information.

An illustrative Example: We further illustrate the idea of our proposed vulnerability metrics through figure 2. In this example, red nodes in community C2 represent fake news spreaders, and C1 and C3 are two other communities having an identical structure. We see that C3 and C1 have 3 and 2 boundary nodes, respectively, which are directly connected to the fake news spreaders in C2 (with the edges represented through dotted lines). Based on edge count solely, one would think that C3 is more vulnerable to fake news spreading than C1. However, such speculation is not true because the boundary nodes of C3 having low trustingness scores are connected to spreaders in C2 having low trustworthiness scores, while the boundary nodes of C1, which have high trustingness scores, are connected to spreaders in C2 having high trustworthiness scores. Therefore, information are more likely to flow from C2 to C1 than to C3, i.e., C1 is more vulnerable. It is expected that our proposed metric should be able to identify C1 as more vulnerable than C3.

With the believability (Eq. 3) which is defined on top of trustingness and trustworthiness derived from the TSM algorithm, we now derive the metrics to quantify vulnerability of nodes and communities to false information spreading. The proposed vulnerability metrics will help us quantify the likelihood of boundary nodes and communities to believe some information spreading from their neighbors. We assume that the information spreading is widespread outside of the community, i.e., at least some of the neighbor nodes of the community are spreaders. We define the node- and community-level metrics as follows:

1. *Vulnerability of boundary node, $V(b)$:* This metric measures the likelihood of a boundary node b to become a spreader. **It is important to note that the method used to quantify vulnerability of a boundary**

node can be generalized to any node. The metric is derived as follows: The likelihood of node b to believe an immediate neighbor n is a function of the trustworthiness of the neighbor n ($n \in \mathcal{N}_b$, where \mathcal{N}_b is the set of all neighbor nodes of b) and the trustingness of b , and is quantified as $bel_{nb} = tw(n) * ti(b)$, that is, $Believability(n \rightarrow b)$. Thus, the likelihood that b is *not* vulnerable to n can be quantified as $(1 - bel_{nb})$. Generalizing this, the likelihood of b *not* being vulnerable to all of its neighbor nodes is $\prod_{n \in \mathcal{N}_b} (1 - bel_{nb})$. Therefore, the likelihood of b to believe any of its neighbors, i.e. the vulnerability of the boundary node b is computed as:

$$V(b) = 1 - \prod_{n \in \mathcal{N}_b} (1 - bel_{nb}) \quad (4)$$

2. *Vulnerability of community*, $\tilde{V}(C)$: To compute vulnerability of community, we consider the community health perspective, i.e., vulnerability of community to information approaching from neighbor nodes (i.e., outside the community) towards the boundary node (i.e., circumference of the community). As the scenario does not include information diffusion within the community, thus the metric is independent of the core nodes of the community. This metric measures likelihood of the boundary node set of a community C (\mathcal{B}_C) to believe an information from any of its neighbors. The metric is derived as follows: Going forward with the idea in 1), the likelihood that boundary node b is *not* vulnerable to its neighbors can be quantified as $(1 - V(b))$. Generalizing this to all $b \in \mathcal{B}_C$, the likelihood that none of the boundary nodes of a community are vulnerable to their neighbors can be quantified as $\prod_{b \in \mathcal{B}_C} (1 - V(b))$. Thus, the likelihood of community C being vulnerable to any its neighbors, i.e., the vulnerability of the community, is defined as:

$$\tilde{V}(C) = 1 - \prod_{b \in \mathcal{B}_C} (1 - V(b)) \quad (5)$$

The pseudo-code of algorithm to generate the vulnerability metrics is provided in Algorithm 1.

4 Experiments and Results

4.1 Datasets and Setup

We collected two sets of network datasets, namely $DS1$ and $DS2$, summarized in Figure 3 for tweets associated with news articles with confirmed ground truth of veracity from various fact checking websites. $DS1$ contains 12 news networks categorized into three types based on ratings of the news by snopes.com: News $M1$, $M2$, $M3$ and $M4$ are labelled as *Mixture* which indicates that the news has significant elements of both truth and falsity in it, news $F1$, $F2$, $F3$ and $F4$ are labelled as *False* which indicates that the

Algorithm 1: Vulnerability Metrics Computation

Input: $\mathcal{G}(\mathcal{V}, \mathcal{E})$: Spreader's follower-following network;
Output: $V(b)$: Vulnerability of each boundary node, and
 $\tilde{V}(C)$: Vulnerability of each community;

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 $(ti, tw)_{\forall v \in \mathcal{V}} \leftarrow$  Trust scores using  $TSM(\mathcal{G})$ ;  

 $\phi \leftarrow$  Disjoint communities in  $\mathcal{G}$ ;  

 $C \leftarrow$  A community s.t.  $C \in \phi$ ;  

 $\mathcal{B}_C \leftarrow$  Set of Boundary nodes for community  $C$ ;  

 $\mathcal{N}_b \leftarrow$  Set of Neighbor nodes for boundary node  $b$ ;  

for each  $C \in \phi$  do  

  for each  $b \in \mathcal{B}_C$  do  

    for each  $n \in \mathcal{N}_b$  do  

      |  $bel_{nb} = tw(n) * ti(b)$   

    end for  

    |  $V(b) = 1 - \prod_{n \in \mathcal{N}_b} (1 - bel_{nb})$   

  end for  

  |  $\tilde{V}(C) = 1 - \prod_{b \in \mathcal{B}_C} (1 - V(b))$   

end for

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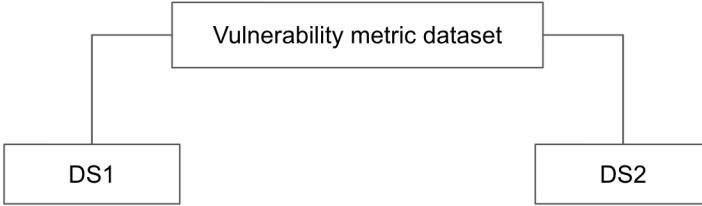
Table 1: Metadata for $DS1$.

Network	ID	No. of nodes	No. of edges	Snopes link
Mixture	$M1$	2,385,188	11,684,879	www.snopes.com/fact-check/nike-workers-pay-kaepernick/
	$M2$	3,669,213	7,054,734	www.snopes.com/fact-check/virginia-prisons-tampons/
	$M3$	6,462,462	10,621,364	www.snopes.com/fact-check/sheriff-nike-shirt-mugshots/
	$M4$	3,512,201	6,108,311	www.snopes.com/fact-check/opportunity-rovers-final-words/
False	$F1$	1,883,329	16,658,841	www.snopes.com/fact-check/were-hate-charges-blm-kidnappers-dropped/
	$F2$	4,981,319	12,625,672	www.snopes.com/fact-check/german-news-trump-nato/
	$F3$	782,209	12,498,122	www.snopes.com/fact-check/jussie-smollett-cnn-job/
	$F4$	503,160	7,797,449	www.snopes.com/fact-check/kamala-harris-jussie-smollett/
True	$T1$	10,929,291	14,933,611	www.snopes.com/fact-check/eva-ramon-gallegos-hpv/
	$T2$	953,040	1,250,463	www.snopes.com/fact-check/nz-prime-minister-massacre-aid/
	$T3$	2,155,927	3,221,985	www.snopes.com/fact-check/betsy-devos-special-olympics/
	$T4$	1,530,958	2,484,553	www.snopes.com/fact-check/texas-governor-tweet-rape/

primary elements of the news are basically false, and news $T1, T2, T3$ and $T4$ are labelled as *True* which indicates that the primary elements of a claim are basically true. $DS2$ contains 10 news events $N1, \dots, N10$ from fact-checking websites based in India with each news event containing a false information network denoted as F_{N1}, \dots, F_{N10} and its corresponding refutation information network denoted as T_{N1}, \dots, T_{N10} . Refutation information can be defined as true information that fact checks a specific item of false information. It is created soon after a false information is debunked and tends to co-exist with the false information. We use $(F \cup T)_{N1}, \dots, (F \cup T)_{N10}$ denotes network obtained by combining false and refutation networks for specific news events. The metadata about news events of $DS1$ and $DS2$ is described in Table 1 and Table 2, respectively.

Table 2: Metadata for DS_2 .

ID	No. of nodes	No. of edges	Link of debunked article
N_1	879,854	2,641,513	www.altnews.in/bjp-mla-raja-singh-plagiarises-pakistan-army-song-dedicates-it-to-indian-army/
N_2	2,900,925	7,882,019	www.altnews.in/amit-malviya-targets-yogendra-yadav-via-edited-video-clip-after-tv-debate-face-off/
N_3	2,449,434	5,691,728	www.altnews.in/shivraj-singh-chouhan-tweets-clipped-video-to-portray-gaffe-by-rahal-gandhi-in-poll-speech/
N_4	2,663,392	4,082,373	www.boonlive.in/pragya-thakur-was-not-4-years-old-at-the-time-of-babri-masjid-demolition/
N_5	757,269	1,880,306	www.altnews.in/2017-video-from-gujarat-shared-as-pm-narendra-modis-rally-in-hyderabad/
N_6	327,794	475,811	www.altnews.in/no-a-bjp-candidate-from-west-bengal-did-not-dress-up-as-hanuman/
N_7	194,075	304,768	www.boonlive.in/did-sp-workers-jump-the-gun-with-a-pm-akhilesh-billboard-not-quite/
N_8	1,600,946	1,731,525	navbharattimes.indiatimes.com/viral-adda/fake-news-buster/news-about-former-srilankan-cricketer-sanath-jayasuriyas-death-is-a-hoax-24858/
N_9	720,303	1,215,479	smhoaxlayer.com/%E2%80%8Bimported-dogs-stone-pelters-for-kasmir-or-imported-entire-video-for-inciting-communal-hatred/
N_{10}	1,197,783	2,036,046	www.altnews.in/hindi/no-mohammad-barkat-ali-is-not-a-regular-audience-of-ndtv/



M (mixture): Network of information having elements of both truth and falsity in it.

F (false): Network of information whose primary elements is false.

T (true): Network of information whose primary elements is true.

F: Network of False information.

T: Network of Refutation information.

FuT: Network obtained by combining **F** and **T**.

Fig. 3: Dataset summary.

We identified the specific source tweet related to each information in question. For evaluation of metrics, we then identified all the spreaders of the source tweet associated with the news, which comprised of the source tweeter (identified using Twitter API) and the list of retweeters (accessible through *twren.ch* or the Twitter search API). We considered the follower-following network of the spreaders obtained from Twitter API, as a proxy for social network. Code implementation and sample dataset is also provided¹.

To evaluate our proposed metrics we used the collection of the twenty two different news spreading networks. We ran the TSM algorithm [27] on follower-following network to compute the trustingness and trustworthiness scores for every node in the network. We then identified disjoint communities by trying three popular community detection algorithms on large networks: Louvain [2] solves an optimization problem that tries to maximize modularity of communities. Infomap [7] algorithm is based on the principles of Information Theory. In contrast to maximizing modularity, the fundamental approach of Infomap

¹<https://github.com/BhavtoshRath/Vulnerability-Metrics>

is to utilize flows in the graph. It uses the map equation framework, which characterizes community detection as a problem of finding a description of minimum information of a random walk process. Label Propagation [6] starts off by assigning a unique label to each node, and then iteratively assigns each node the label most common amongst its neighbors. As a greedy algorithm, Label Propagation is more efficient which is linear to the number of edges in the graph. For each of the communities generated we identified the sets of boundary and neighbor nodes and then computed vulnerability metrics (see Algorithm 1).

The network statistics based on Community Health Assessment model for *DS1* shown in Tables 3, and for false, refutation and the combined network in *DS2* is shown in 4, 5 and 6, respectively. We observe that the datasets contain varying number of communities, ranging from as low as 4/2/7 to as high as 99/2497/1637 with respect to Louvain (L)/Infomap (I)/Label Propagation (LP)². A general observation is that Label Propagation algorithm tends to generate more number of communities while Infomap generates fewer number of communities. Louvain gives more balanced results in terms of size and count of communities.

4.2 Evaluation of Metrics

To measure how good the proposed metrics are able to quantify the vulnerability of nodes and communities, we evaluate the quality of ranking on boundary nodes and communities based on vulnerability scores in comparison with the ground-truth ranking of nodes and communities derived from the news spread in the network. We adopt the ranking evaluation measures widely used in Information Retrieval literature [28].

4.2.1 Evaluate Boundary Node Vulnerability

A vulnerable boundary node is highly likely to have strong believability with its neighbors. We thus consider the ground truth of a vulnerable node as a node which retweets. The ground truth vulnerability of boundary nodes is binary as we only have information of whether the node retweets or not. We thus evaluate this metric using *Average Precision@k* and *Mean Average Precision*.

Average Precision@k (AP@k): We first compute Precision@k (viz. top-k vulnerable boundary nodes based on the metric as a percentage of spreader boundary nodes in a community) and then compute the Average Precision@k ($AP@k$) (viz. the average of Precision@k values over all communities in a network).

Mean Average Precision (MAP): Mean Average Precision is computed as the mean of the average precision scores for the top-k boundary nodes over all communities in a network. The formula to compute MAP is given

²From here on, L: Louvain, I: Infomap, LP: Label Propagation in all tables.

Table 3: Community statistics for *DS1*.

	Information	Community Detection	# of communities (C)	Avg. # of nodes / C	Avg. # of infected nodes / C	Avg. # of \mathcal{B} edges	Avg. # of neighbor nodes	Avg. # of infected \mathcal{B} nodes	Avg. # of infected \mathcal{N} nodes
$M1$	L	54	45,004	53	69,040	7,107	14,401	47	774
	I	36	68,148	81	5,594	1,778	1,408	59	376
	IP	786	3,038	4	603	215	266	3	38
$M2$	L	67	54,764	34	28,250	3,300	13,717	32	494
	I	5	733,843	459	1274	716	453	74	120
	IP	931	3,941	2	1,080	264	620	2	50
$M3$	L	72	89,756	39	20,406	2,878	11,371	36	412
	I	14	461,604	202	49,791	7,848	20,097	186	558
	IP	1,341	4,819	2	1,150	240	702	2	60
$M4$	L	99	35,477	27	10,606	2,285	2,996	23	484
	I	37	94,924	72	16,081	3,933	3,764	66	480
	IP	1,637	2,146	2	709	191	292	2	50
$F1$	L	28	67,262	103	218,939	14,547	34,442	99	1,028
	I	8	235,416	360	1,482	775	616	81	143
	IP	480	3,924	6	933	340	455	5	40
$F2$	L	50	99,626	57	51,664	5,793	21,101	51	660
	I	4	1,245,330	708	1,454	760	637	89	118
	IP	677	7,358	4	2,318	396	1,542	4	84
$F3$	L	15	52,147	31	417,933	16,382	52,259	31	365
	I	133	5,881	3	6,722	1,075	3,225	3	157
	IP	15	52,147	31	5,227	2,285	2,514	24	83
$F4$	L	15	33,544	19	338,248	13,848	56,711	19	246
	I	38	13,241	8	11,255	2,182	5,484	8	171
	IP	7	71,880	41	1,779	992	744	22	64
$T1$	L	47	232,538	59	47,189	2,171	42,783	39	246
	I	34	321,450	82	5,792	1,390	2,261	52	189
	IP	1,283	8,519	2	2,151	202	1,724	2	54
$T2$	L	37	25,758	5	4,150	509	3,095	3	36
	I	9	105,893	22	5,650	1,418	1,777	17	60
	IP	159	5,994	1	1,102	189	752	1	25
$T3$	L	27	79,849	26	10,135	1,942	5,251	18	180
	I	629	3,428	1	1,266	161	641	1	124
	IP	209	10,315	3	1,138	303	584	3	46
$T4$	L	89	17,202	12	4,511	908	1,502	10	205
	I	1,206	1269	1	544	92	271	1	99
	IP	797	1,921	1	723	164	279	1	53

Table 4: Community statistics for false information in *DS2*.

	Information	Community Detection	# of communities (C)	Avg. # of nodes / C	Avg. # of infected nodes / C	Avg. # of \mathcal{B} edges	Avg. # of \mathcal{B}	Avg. # of neighbor nodes	Avg. # of infected \mathcal{B} nodes	Avg. # of infected \mathcal{N} nodes
F_{N1}	L	37	23,935	25	9,654	1,482	3,116	20	163	
	I	3	295,199	314	17,466	4,786	3,224	159	373	
	IP	220	4,025	4	1,299	322	623	4	46	
F_{N2}	L	66	39,510	69	35,877	2,274	16,655	62	562	
	I	6	434,605	759	1	1	1	1	1	
	IP	280	9,313	16	2,148	250	1,571	9	40	
F_{N3}	L	53	44,215	65	23,464	2,774	8,280	59	443	
	I	2497	956	1	926	67	558	1	117	
	IP	313	7,628	11	1,519	347	955	7	40	
F_{N4}	L	37	55,031	24	8,758	1,102	6,539	20	144	
	I	2	1,018,081	447	3,744	1,123	1,959	75	84	
	IP	214	9,515	4	1,918	299	1,356	4	43	
F_{N5}	L	47	11,037	17	10,685	1,617	3,319	17	234	
	I	738	703	1	1,107	107	587	1	155	
	IP	119	4,359	7	1,646	426	848	5	49	
F_{N6}	L	26	10,653	6	2,140	422	1,085	5	50	
	I	4	69,246	40	1,734	584	564	17	64	
	IP	97	2,856	2	768	152	379	2	29	
F_{N7}	L	20	7,230	4	1,261	381	324	3	27	
	I	117	1,236	1	337	74	92	1	29	
	IP	35	4,131	2	724	245	207	2	16	
F_{N8}	L	17	23,188	7	1,479	308	911	5	49	
	I	4	98,551	30	3,439	1,060	1,253	17	60	
	IP	83	4,749	1	494	117	200	1	22	
F_{N9}	L	43	11,092	11	3,673	802	1,219	10	135	
	I	487	979	1	538	77	224	1	90	
	IP	162	2,944	3	830	221	356	3	32	
F_{N10}	L	55	19,506	22	5,681	853	2,455	20	200	
	I	1,045	1,027	1	570	52	281	1	98	
	IP	216	4,967	6	1,066	220	641	5	33	

Table 5: Community statistics for refutation information in $DS2$.

Information		No. of communities (C)	Avg. No. of nodes / C	Avg. No. of infected nodes / C		Avg. No. of \mathcal{B} edges		Avg. No. of neighbor nodes		Avg. No. of infected \mathcal{B} nodes		Avg. No. of infected \mathcal{N} nodes	
T_{N1}	L	40	11,338	10	5,856	856	3,018	8	96	37	58	2	39
	I	2	226,769	200	1,260	606	151	37	96				
	IP	154	2,945	3	1,564	274	1,019	2	96				
T_{N2}	L	47	9,226	10	3,562	540	1,648	9	103	1	80	3	34
	I	472	919	1	581	58	327	1	80				
	IP	167	2,597	3	1,042	169	641	3	80				
T_{N3}	L	15	86,491	32	7,305	987	5,160	10	67	1	80	5	29
	I	457	2,839	1	757	64	437	1	80				
	IP	84	15,445	6	1,497	260	1,032	5	29				
T_{N4}	L	45	23,522	11	5,399	590	3,950	10	102	2	77	1	39
	I	523	2,024	1	740	58	502	1	77				
	IP	214	4,946	2	1,211	167	827	2	39				
T_{N5}	L	15	17,513	6	4,895	305	4,376	2	28	5	45	2	19
	I	2	131,346	46	5,650	936	2,874	5	45				
	IP	40	6,567	2	1,769	159	1,449	2	19				
T_{N6}	L	9	7,458	4	772	220	333	3	10	1	16	1	13
	I	103	652	1	106	25	48	1	16				
	IP	26	2,582	1	376	112	99	1	13				
T_{N7}	L	20	3,067	6	1,280	267	478	5	38	2	22	1	21
	I	2	30,666	57	1,636	871	370	26	22				
	IP	49	1,252	2	648	149	290	2	21				
T_{N8}	L	4	310,826	23	2,152	233	1,723	7	31	15	42	1	21
	I	2	621,653	47	1,968	601	943	15	42				
	IP	64	19,427	1	465	98	208	1	21				
T_{N9}	L	20	13,821	5	1,482	324	836	4	37	9	16	1	28
	I	3	92,143	32	233	81	132	9	16				
	IP	78	3,544	1	564	120	244	1	28				
T_{N10}	L	5	29,757	7	1,098	283	643	5	20	1	14	1	13
	I	49	3,036	1	214	54	84	1	14				
	IP	31	4,800	1	347	119	90	1	13				

Table 6: Community statistics for false and refutation information network combined in $DS2$.

Information	Community Detection	# of communities (C)	Avg. # of nodes / C	Avg. # of infected nodes / C	Avg. # of \mathcal{B} edges	Avg. # of \mathcal{B}	Avg. # of neighbor nodes	Avg. # of infected \mathcal{B} nodes	Avg. # of infected \mathcal{N} nodes
$(F \cup T)_{N1}$	L	40	30,764	33	11,340	2,005	4,302	27	216
	I	5	246,112	267	18,909	4,486	2,997	177	496
	IP	287	4,288	5	1,718	353	982	4	53
$(F \cup T)_{N2}$	L	61	47,556	82	42,135	2,893	18,601	74	603
	I	6	483,488	836	1	1	1	1	1
	IP	321	9,037	16	2,362	284	1,759	10	47
$(F \cup T)_{N3}$	L	48	51,030	79	29,521	3,331	10,170	72	574
	I	2,647	925	1	952	68	549	1	105
	IP	316	7,751	12	1,488	344	929	7	41
$(F \cup T)_{N4}$	L	41	64,961	33	16,483	1,784	10,743	32	230
	I	1,240	2,148	1	964	67	645	1	99
	IP	419	6,357	3	2,044	242	1,387	3	54
$(F \cup T)_{N5}$	L	35	21,636	25	14,600	2,047	4,522	23	219
	I	807	938	1	1,075	105	572	1	148
	IP	142	5,333	6	2,023	418	1,210	5	51
$(F \cup T)_{N6}$	L	31	10,574	6	2,278	398	1,333	5	5
	I	217	1,511	1	545	73	284	1	56
	IP	115	2,850	2	834	150	442	2	31
$(F \cup T)_{N7}$	L	27	7,188	7	1,976	404	664	6	41
	I	3	64,692	61	6,504	1,590	1,535	52	79
	IP	78	2,488	2	882	217	359	2	27
$(F \cup T)_{N8}$	L	14	114,353	15	3,801	371	3,106	5	28
	I	3	533,649	70	9,649	1,620	6,213	33	95
	IP	123	13,016	2	755	122	465	2	26
$(F \cup T)_{N9}$	L	40	18,008	14	4,912	964	2,089	10	109
	I	3	240,101	192	397	174	194	17	27
	IP	192	3,752	3	1,006	237	479	3	39
$(F \cup T)_{N10}$	L	50	23,956	25	6,125	898	2,915	17	161
	I	1,096	1,093	1	576	51	291	1	98
	IP	228	5,253	5	1,152	231	709	5	36

Table 7: Evaluation of vulnerability of boundary nodes for *DS1*.

	AP@1			AP@5			AP@10			AP@15			MAP		
	L	I	LP												
M1	0.759	0.676	0.712	0.736	0.548	0.519	0.606	0.543	0.533	0.661	0.505	0.566	0.672	0.546	0.555
M2	0.818	0.749	0.907	0.769	0.733	0.799	0.821	0.699	0.999	0.733	0.666	0.999	0.785	0.733	0.875
M3	0.805	0.642	0.878	0.567	0.509	0.749	0.590	0.512	0.674	0.524	0.586	0.833	0.596	0.577	0.751
M4	0.468	0.714	0.750	0.366	0.674	0.633	0.323	0.523	0.659	0.325	0.454	0.799	0.350	0.569	0.660
F1	0.892	0.749	0.855	0.824	0.679	0.999	0.922	0.499	0.799	0.899	0.422	0.999	0.876	0.552	0.905
F2	0.819	0.999	0.874	0.727	0.499	0.839	0.741	0.399	0.924	0.706	0.266	0.999	0.714	0.518	0.900
F3	0.933	0.945	0.933	0.955	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.972	0.985	0.995
F4	0.999	0.999	0.999	0.955	0.999	0.999	0.979	0.999	0.999	0.999	0.999	0.999	0.991	0.999	0.999
T1	0.222	0.531	0.868	0.424	0.492	0.716	0.439	0.349	0.479	0.377	0.344	0.533	0.450	0.424	0.644
T2	0.548	0.374	0.482	0.299	0.399	0.999	0.049	0.299	0.699	0.033	0.033	0.466	0.173	0.264	0.726
T3	0.666	0.470	0.913	0.519	0.499	0.999	0.299	0.499	0.899	0.266	0.433	0.799	0.391	0.479	0.900
T4	0.449	0.464	0.699	0.399	0.000	0.479	0.409	0.000	0.499	0.362	0.000	0.366	0.399	0.106	0.500
M_{avg}	0.712	0.695	0.811	0.609	0.616	0.675	0.585	0.569	0.716	0.560	0.552	0.799	0.600	0.606	0.710
F_{avg}	0.910	0.923	0.915	0.865	0.794	0.959	0.901	0.724	0.930	0.900	0.671	0.999	0.888	0.763	0.949
T_{avg}	0.471	0.459	0.740	0.410	0.347	0.798	0.299	0.286	0.644	0.259	0.202	0.541	0.353	0.318	0.692

by $\sum_{k=1}^K AP(k)/K$, where K denotes total number of communities in the network.

4.2.2 Evaluate Community Vulnerability

A community with more number of spreader boundary nodes is more vulnerable to news penetration. As most communities of a network typically have a few spreader boundary nodes, it is not feasible to use node ranking metrics above for evaluating community vulnerability. We thus rank the communities by their vulnerability scores and compare with the ground-truth ranking given by the relative count of spreader boundary nodes in the community. We use Kendall's tau, which is a correlation measure for ordinal data, as evaluation metric. Kendall's tau close to 1 indicates strong agreement, and that close to -1 indicates strong disagreement between evaluated and ground-truth rankings.

Kendall's tau (τ): Let $rel = [rel_1, rel_2, \dots, rel_n]$ represent the ‘relevant’ ranked list of n communities based on ground-truth vulnerability (quantified as the fraction of boundary nodes that are spreaders), and $ret = [ret_1, ret_2, \dots, ret_n]$ represent the ‘retrieved’ ranked list of communities based on our proposed vulnerability metric. Let P represent the # of concordant pairs, Q the # of discordant pairs, T the # of ties only in rel , and U the # of ties only in ret . If a tie occurs for the same pair in both rel and ret , it is not added to either T or U . Then we calculate $\tau = (P - Q)/sqrt((P + Q + T) * (P + Q + U))$.

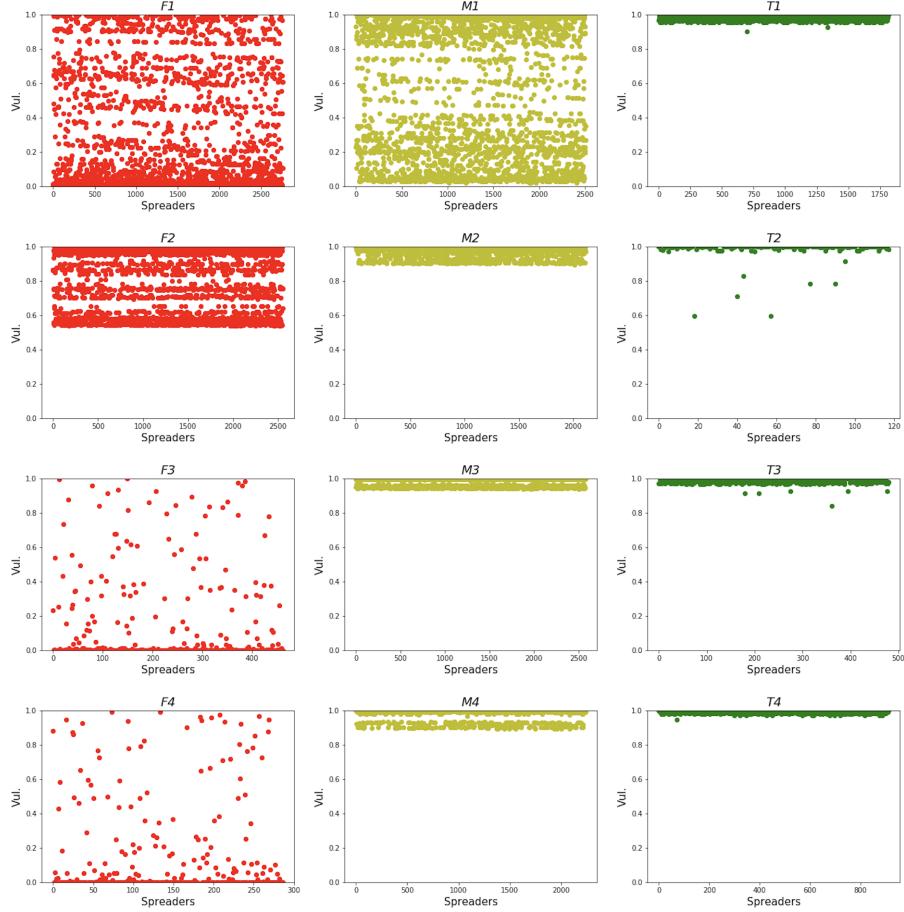
4.3 Results on *DS1*

Table 7 shows the evaluation results for the proposed metric assessing the vulnerability of boundary nodes for *DS1*. For the twelve networks we show the Average Precision for $k = 1, 5, 10$ and 15 and compute the MAP for the top-15 results.

AP@1 shows how well we are able to identify the first spreader boundary node based on our metric. Our metric is able to identify the most vulnerable

Table 8: Evaluation of vulnerability of communities in *DS1*.

	τ_{M1}	τ_{M2}	τ_{M3}	τ_{M4}	τ_{F1}	τ_{F2}	τ_{F3}	τ_{F4}	τ_{T1}	τ_{T2}	τ_{T3}	τ_{T4}
L	-0.027	0.003	-0.149	-0.035	0.050	0.164	0.457	0.161	-0.045	-0.255	-0.090	-0.030
I	0.072	0.000	0.274	0.138	0.642	0.667	0.117	0.146	-0.037	-0.222	-0.025	-0.031
LP	0.039	-0.014	0.019	0.018	0.039	0.029	0.381	0.714	0.003	0.005	-0.110	-0.036

Fig. 4: Distribution of vulnerability score of spreaders in *DS1*.

boundary node in AP of 0.712 averaged over the mixture news networks, 0.91 averaged over the false news networks and 0.471 averaged over the true news networks for Louvain; 0.695 averaged over the mixture news networks, 0.923 averaged over the false news networks and 0.459 averaged over the true news networks for Informap, and 0.811 averaged over the mixture news networks, 0.915 averaged over the false news networks and 0.74 averaged over the true news networks for Label Propagation. Thus, we are able to identify the most

vulnerable boundary node of communities in false news networks with average precision of over 90%. As expected, our metrics show better performance particularly for fake news networks, followed by mixture and then true news networks. Average precision for rest of the k-values also shows similar trend.

Metrics for Louvain-/Infomap-based communities follow a similar trend for the remaining k values. However, Label Propagation communities for k=3 evaluate with AP of 90.25% averaged over the false news networks, which is over 35% and 20% better than the mixture and the true networks, respectively. In this case, true news networks are ranked better than mixture news networks. While k=5 also shows a similar trend, for the rest of the k values Label Propagation-based communities show better performance for the mixture than the true news networks. This insensitivity in evaluation could be attributed to the fact that label propagation algorithm tends to generate more number of communities. Thus, the average community size is much smaller, causing the communities to have sparser boundary and neighbor node sets.

We also observe that the MAP averaged over the false news networks is 47.86% better than the mixture and 150% better than the true news networks for Louvain-based communities; and 25.94% better than the mixture, and 139.9% better than the true news networks for Infomap-based communities; and 33.72% better than the mixture and 37.14% better than the true news networks for Label Propagation-based communities. Therefore, we are able to identify most vulnerable boundary nodes of communities in false news networks with an average MAP of over 75%.

Table 8 shows the evaluation results for proposed metric to compute the vulnerability of a community for *DS1*. For the twelve networks the table shows Kendall's tau value (τ) for communities generated using the three algorithms. We observe that the τ for mixture and true news networks tend to have a negative correlation with the ground truth community ranking. False news networks on the other hand show a positive correlation, with high values of 0.642, 0.667, 0.457 and 0.714 for *F1*, *F2*, *F3* and *F4* respectively. For modular communities generated using Louvain heuristics, our proposed metrics evaluate all false news networks with a positive correlation (average correlation: 0.208) while all true news networks are evaluated with a negative correlation (with average correlation -0.105). Three of the four mixture news networks also have a negative correlation (with average correlation -0.0095). Therefore, our proposed metrics are confirmed to produce better performance on fake news networks, compared to the true and mixture ones.

Figure 4 shows the distribution of vulnerability scores of news spreaders of false, mixture and true news networks as per user IDs. We observe that the scores of spreaders in false news networks have more variance (points are more spread out between 0 and 1) than spreaders in mixture news networks. Mixture news networks (except *M1*) have less variance, while true news spreaders have least variance. Thus we can conclude that trust-based vulnerability metrics are able to distinguish between spreaders with high and low vulnerability better than true news spreaders (where most spreaders are assigned similar scores).

This in turn affects the performance of community vulnerability metrics in a similar way.

4.3.1 Case study of mixture news spreaders

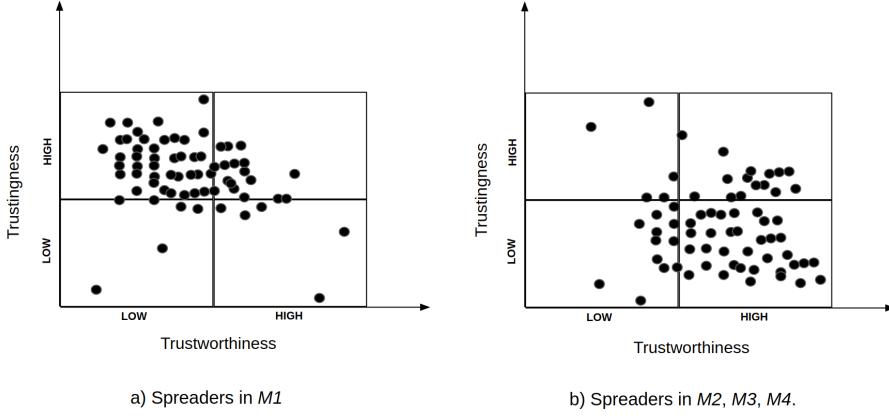


Fig. 5: Case study of spreaders in *Mixture* networks.

On observing the trustingness and trustworthiness scores of the spreaders of mixture news networks as shown in Figure 5 we notice that most spreaders of M_1 have high trustingness and low trustworthiness scores compared to M_2, M_3 and M_4 that have low trustingness and high trustworthiness scores. Source of M_1 was tweeted by a conservative with political undertones and it is known that conservatives are more likely to share fake news [49]. The information shows spreading pattern similar to fake news, as spreaders with high trustingness score shared M_1 without fact checking the claim, unlike the source and spreaders of M_2, M_3 and M_4 who are not political conservatives.

4.4 Results on DS_2

Table 9 shows the evaluation results for vulnerability assessment of boundary nodes for DS_1 . For the thirty networks (three each for the ten news events) we show the Average Precision for $k = 1, 5, 10$ and 15 and compute the MAP for the top-15 results. Based on the AP@1, we show that our metric is able to identify the most vulnerable boundary node with average precision (aggregated over all news events) of $0.735, 0.672, 0.694$ for false, refutation and combined networks respectively when communities are generated using Louvain; $0.705, 0.501, 0.628$ when communities are generated using Infomap and $0.744, 0.501, 0.577$ when communities are generated using Label propagation method. As in DS_1 , we observe that our proposed metrics are able to identify spreaders in false information network with higher precision than spreaders

Table 9: Evaluation of vulnerability of boundary nodes in *DS2*.

	AP@1			AP@5			AP@10			AP@15			MAP			
	L	I	LP													
FN1	0.729	0.999	0.502	0.866	0.533	0.999	0.785	0.333	0.799	0.644	0.222	0.766	0.78	0.48	0.825	
TN1	0.624	0	0.571	0.819	0	0.999	0.766	0	0.999	0.799	0	0.999	0.766	0	0.872	
N1	0.799	0.799	0.577	0.799	0.599	0.899	0.789	0.299	0.899	0.752	0.244	0.999	0.789	0.44	0.897	
FN2	0.728	0.999	0.728	0.599	0	0.933	0.735	0	0.899	0.776	0	0.933	0.711	0.133	0.881	
TN2	0.702	0.314	0.62	0.616	0	0.499	0.516	0	0.999	0.733	0	0.999	0.565	0.079	0.831	
N2	0.745	0.999	0.669	0.614	0	0.699	0.737	0	0.899	0.747	0	0.933	0.697	0.133	0.806	
FN3	0.666	0.49	0.541	0.584	0.799	0.999	0.774	0.899	0.999	0.745	0.733	0.999	0.691	0.808	0.874	
TN3	0.733	0.302	0.607	0.949	0.199	0.999	0.799	0.099	0.999	0.933	0.066	0.999	0.916	0.174	0.973	
N3	0.76	0.532	0.555	0.592	0.879	0.999	0.723	0.849	0.999	0.683	0.866	0.999	0.667	0.846	0.885	
FN4	0.599	0.999	0.556	0.699	0.299	0.999	0.585	0.099	0.899	0.866	0.066	0.999	0.637	0.282	0.878	
TN4	0.622	0.363	0.523	0.516	0	0.699	0.419	0	0.599	0.666	0	0.999	0.531	0.046	0.722	
N4	0.707	0.369	0.579	0.687	0.999	0.799	0.662	0.499	0.966	0.59	0.399	0.866	0.652	0.62	0.786	
FN5	0.914	0.711	0.957	0.899	0.199	0.999	0.924	0.099	0.999	0.895	0.133	0.999	0.907	0.228	0.997	
TN5	0.599	0.999	0.824	0	0.399	0.399	0	0	0	0.199	0	0	0.133	0.073	0.279	0.347
N5	0.857	0.57	0.666	0.89	0.399	0.699	0.957	0.299	0.599	0.893	0.266	0.999	0.911	0.362	0.726	
FN6	0.769	0.499	0.762	0.519	0.533	0.999	0.499	0.599	0.899	0.466	0.533	0.666	0.549	0.581	0.867	
TN6	0.666	0.562	0.923	0	0	0.599	0.099	0	0	0	0	0	0.08	0.037	0.301	
N6	0.612	0.349	0.565	0.599	0	0.699	0.533	0	0.899	0.866	0	0.599	0.599	0.173	0.733	
FN7	0.749	0.499	0.914	0.399	0	0.399	0.099	0	0.199	0.066	0	0.133	0.285	0.033	0.314	
TN7	0.649	0.999	0.833	0.633	0.499	0.999	0.749	0.099	0.899	0.533	0.066	0.666	0.688	0.321	0.836	
N7	0.481	0.999	0.538	0.519	0.733	0.999	0.433	0.749	0.899	0.355	0.533	0.666	0.467	0.74	0.809	
FN8	0.705	0.999	0.724	0.533	0.733	0	0.499	0.566	0	0.333	0.199	0	0.517	0.592	0.097	
TN8	0.499	0.499	0.721	0.499	0.499	0	0	0.349	0	0	0	0	0.218	0.352	0.048	
N8	0.499	0.999	0.442	0.733	0.933	0.199	0.499	0.599	0.099	0.333	0.422	0.066	0.546	0.713	0.2	
FN9	0.72	0.377	0.849	0.672	0	0.999	0.599	0	0.999	0.483	0	0.933	0.582	0.048	0.952	
TN9	0.631	0.666	0.558	0.499	0.199	0.199	0.249	0.099	0.099	0.333	0.066	0	0.409	0.215	0.133	
N9	0.724	0.333	0.526	0.619	0.199	0.899	0.539	0.099	0.699	0.516	0.066	0.999	0.568	0.154	0.817	
FN10	0.773	0.475	0.912	0.576	0.666	0.899	0.622	0.399	0.999	0.552	0.366	0.999	0.605	0.474	0.97	
TN10	0.999	0.31	0.599	0.199	0	0.199	0	0	0.133	0	0	0	0.253	0.02	0.039	
N10	0.759	0.332	0.657	0.599	0.599	0.899	0.614	0.349	0.999	0.599	0.266	0.999	0.627	0.389	0.937	
F_{avg}	0.735	0.705	0.744	0.635	0.376	0.822	0.612	0.299	0.769	0.583	0.225	0.742	0.626	0.366	0.766	
T_{avg}	0.672	0.501	0.678	0.473	0.179	0.539	0.379	0.065	0.479	0.413	0.013	0.479	0.449	0.152	0.51	
M_{avg}	0.694	0.628	0.577	0.665	0.534	0.779	0.649	0.374	0.796	0.633	0.306	0.813	0.652	0.457	0.759	

Table 10: Evaluation of vulnerability of communities in *DS2*.

	τ_F			τ_T			$\tau_{F \cup T}$		
	L	I	LP	L	I	LP	L	I	LP
N1	0.009	0.333	0.075	0.171	1	-0.008	0.128	0	0.027
N2	0.03	0.999	0.044	-0.063	0.015	-0.03	0.066	0.999	0.003
N3	-0.351	-0.001	0.012	0.2	-0.04	0.06	-0.411	-0.012	0.044
N4	0.078	-1	-0.009	-0.222	0.065	-0.011	-0.051	-0.007	-0.022
N5	-0.073	0.003	0.075	-0.238	-1	0.01	-0.055	0.02	0.051
N6	-0.113	1	0.039	-0.055	0.017	0.052	-0.092	0.033	-0.038
N7	-0.284	0.052	0.109	0.157	-1	-0.062	-0.065	0.333	0.066
N8	-0.088	0.333	-0.035	-0.333	-1	-0.089	-0.076	-0.333	0.011
N9	0.08	0.007	0.006	-0.147	0.333	-0.018	0.076	0.333	0.047
N10	-0.019	0.017	0.067	-0.399	-0.022	-0.027	-0.025	-0.028	0.001

in refutation information networks. This can be attributed to the fact that a person's motivation to spread refutation information (whose validity is more certain) is driven more by the nature of the content; unlike false information (whose content is not validated) which is driven less by the content or more by the trust dynamics with the endorser. Metric's performance in identifying false information spreaders in combined network affected slightly due to the

presence of refutation information spreading dynamics, but is still better than only refutation information network.

Trends do not drastically vary for other values of k , with Label Propagation performing slightly better than Louvain while Infomap with lowest performance. Also we observe that certain vulnerability scores are drastically low. This can be attributed to the quality of disjoint communities generated by the community detection algorithm. In scenarios where the number of communities is too low or too large, this causes large variation in the boundary and neighbor node count for the community thus affecting the metric score computation.

Through MAP we aggregate the precision scores for top-15 spreader boundary nodes. We observe precision scores of 0.626/ 0.366, 0.766 for fake information network; 0.449/ 0.152/ 0.51 for refutation information network; 0.652/ 0.457/ 0.759 for combined network using L/ I/ LP.

Table 10 shows the evaluation results for proposed metric to compute the vulnerability of a community for *DS2*. Similar to Table 8, τ for false information networks tend to have more values greater than zero (i.e. positive correlation) compared to refutation information networks.

5 Conclusions and Future Work

We propose novel metrics based on the concept of believability derived from computational trust measures to compute vulnerability of nodes and communities to news spread and show that the metrics is much more sensitive to false information. We confirm our hypothesis that false information have to rely on strong trust among spreaders to propagate while true or refuting information does not. Through experiments on two real-world datasets of large information spreading networks on Twitter we show that our proposed metrics can identify the vulnerable nodes and communities with high precision. While detection of fake news spreading is a widely studied problem, its containment is not. We believe that the proposed model can be used to identify vulnerable individuals and communities to build content-agnostic fake news spread prevention models. We thus propose the *Community Health Assessment* model as a preliminary idea that exploits the structural characteristics of social networks to identify nodes and communities that are most vulnerable to news spreading.

As part of future work we would like to extend the proposed ideas to understand the dynamics of news spreading within a community (i.e. through core nodes). We would also like to include temporal features of news spreading into our model.

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