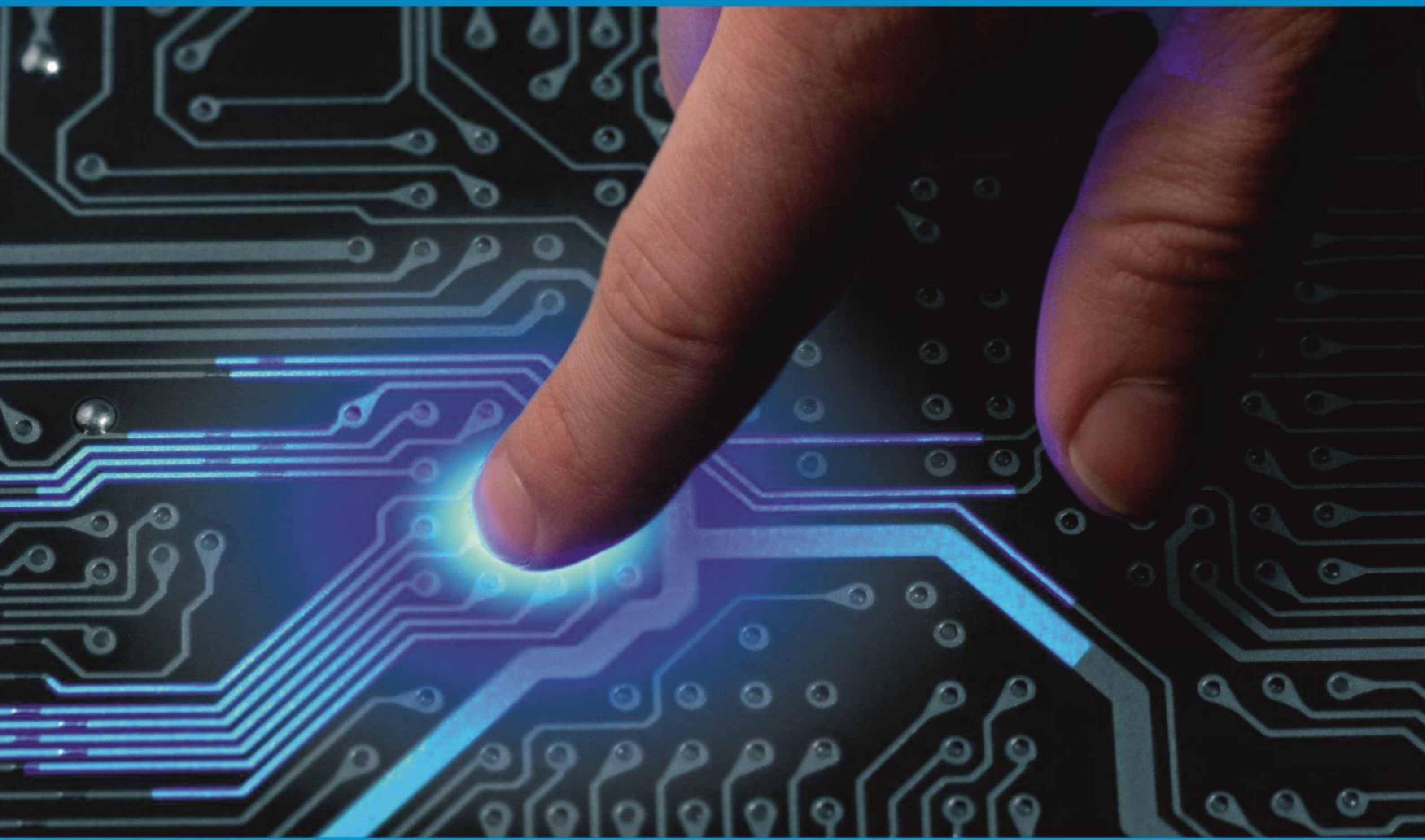
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 3, March 2021

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.488

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.488 |

|| Volume 9, Issue 3, March 2021 ||

| DOI: 10.15680/IJIRCCE.2021. 0903062 |

Reduction of Rumor Impact on Twitter using Greedy Technique

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ABSTRACT: One of the biggest problems in Social Networks is Rumour blocking. The spread of rumors can result in the loss of property and life. An individual tend to spread rumor without deciding the trueness of the information. Since rumors have emerged in the social network and a portion of users have believed it to be true, our aim is to reduce the number of contaminated users by identifying the rumors and removing them from the ultimate data. In this paper, we propose a greedy method for minimization of rumor influence along with User Experience. Likewise, not the same as existing issues of impact minimization, we consider the constraint of user experience utility.

KEYWORDS: Social Media;Rumor transmission; User Experience; Sentiment Classification

I. INTRODUCTION

There has been a significant increase in usage of Social Networks like Twitter, Facebook, WhatsApp, Instagram, etc., over the last 10-12 years. Though they are useful for individuals in connecting with each other and sharing information, managing tasks and events, social media is largely responsible for spreading myths and rumors about the recent Covid-19 pandemic and similar cataclysmic events. Even if a small number of social media users believe the rumor to be true, after sharing the accepted rumor, the ultimate number of users infected by the rumor is large due to the Negative Word of Mouth cascade. Hence it is necessary to design efficient solutions for reducing the rumors spread across social networks and thereby reducing its effects. The Government of India directed telecom operators to force a text messages limit on all cell phone users. The area of Maximizing the spread of information is already researched and well known. Also, its converse problem of reducing the rumor spread which is known by many names such as least cost rumor blocking problem, misinformation containment problem, influence blocking maximization problem is now being researched. Hence developing efficient strategies to reduce the spread of such harmful rumors through any social network is a very important issue. Former works studied various solutions for reducing the spread pace by eliminating the nodes from social networks. The solution in which the nodes are removed in descending order of out-degree is effective. Removal of nodes means just removing the links between the nodes. The task of removing the links is much effective and fundamental than removing nodes since the user of any social network will not be pleased for getting blocked. Recent research results show that the Independent Cascade (IC) Model which is a widely used model of information diffusion is used to solve the Influence Maximization problem on any social network

II. RELATED WORK

Thevast majority of the past works examined augmenting the impact of positive data through social media dependent on the Independent Cascade (IC) model, (Kempe, Kleinberg, and Tardos 2003; Chen, Wang, and Wang 2010; Shirazipourazad et al. 2012). Conversely, the negative impact minimization issue has gained significantly less consideration, yet there have been reliable endeavours in planning successful procedures for impeding pernicious rumors and limiting the negative impact. (Budak, Agrawal, and Abbadi 2011) presented the thought of a "great" crusade in an informal community to check the negative impact of an "awful" one by persuading clients to receive the "great" one. (Kimura, Saito, Motoda 2009) examined limiting the spread of pernicious rumors by impeding a restricted number of connections in an informal organization. They gave two various meanings of defilement degree and proposed comparing enhancement calculations. (Fan et al. 2013) examined the smallest expense rumor impending issue in friendly networks. They presented the idea of "defenders" and attempt to choose a negligible number of them to

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restrict the terrible impact of rumors by setting off an insurance course against the rumor course. There are a couple of impediments in those works. They consider the rumor notoriety as steady during the entire engendering measure, which isn't near the practical situations. Second, in the plan of the rumor hindering systems, either obstructing nodes or connections, they neglect to consider client experience in true interpersonal organizations. We need to try not to impede the clients' records for so long that they may stop grievances or even quit the informal organization. In this way, it is important to think about the effect of hindering time on both the singular nodes and the entire organization.

Client experience is a significant factor for different administrations including social networks. Existing rumor blocking techniques block either nodes(clients) or connections (associations between clients) in interpersonal organizations to keep the gossip from further spread. Nonetheless, none has examined the effect of hindering nodes. As a rule, the more drawn out the client is obstructed, the less palatable the client feels about the informal community. In this manner, if the obstructed time outperforms a specific edge, it is conceivable that the client may stop the interpersonal organization or possibly hold up a grievance to the chairperson. (Bhatti, Bouch, and Kuchinsky 2000) broke down the user-perceived quality in web worker plan and found that clients' capacity to bear dormancy diminishes over the term of association with a webpage.

A utility function was introduced to quantify the consumer satisfaction. Propelled by that, in our work, we apply an altered utility function to quantify client experience in rumor hindering. Rumor impact reduction tends to limit the proliferation impact of unfortunate bits of hearsay in informal organizations. It is inverse to the exemplary impact boost issue (Kempe, Kleinberg, and Tardos 2003). The rumor impact minimization (RIM) issue has been examined in various impact dispersion models in informal organizations. (Fan et al. 2013) considered the smallest expense talk obstructing issue in informal communities and presented the idea of "defenders" to restrict the terrible impact of bits of hearsay by starting a defender course to spread against the rumor course. A greedy algorithm is proposed for both sharp and deterministic course models. (Matoda, Saito, and Kimura) proposed the system of impeding connections rather than hubs in informal organizations to limit the proliferation of malicious rumors.

III. PROPOSED ALGORITHM

Three classical centrality based strategies are utilized as baselines and portrayed:

• Out-Degree. The out-degree d(Ni) of a node Ni is the number of active connections from the node Ni. Kempe et al. showed high degree nodes may outflank other centrality-based heuristics as far as powerful recognizable proof(Kempe, Kleinberg, and Tardos 2003).

• Betweenness Centrality. A node's betweenness is equivalent to the quantity of most brief ways from all nodes to all others that go through that node. As of late, Betweenness centrality has become a significant centrality measure in social networks (Brandes 2008).

• Page Rank. Page Rank technique is an agent eigenvector centrality technique. For its incredible presence in the website page positioning, we additionally use it as a baseline(Page et al. 1999).

Hashtags are an important tool to make posts easier to find and also group with similar posts. Hashtags on Twitter express the emotion of the person posting the tweet. Twitter users retweeting the tweet follow the hashtag to support or oppose the tweet. Hence, hashtags is considered a vital part of this project. A keyword, not essentially a hashtag is given as an input to our system. It then fetches the tweets across the globe containing the keyword passed to the system. Twitter4j, a Twitter API, is used to integrate the system with the Twitter service. The system gets the hashtags from the tweets. For each tweet, there may be zero to many retweets. The retweets play a major role in this system. It takes the hashtags from the retweets similar to how hashtags are taken from tweets. Then the system examines whether the hashtag from tweet changed from tweet and how it changed. It also checks the tone of tweet and their retweets. This way it identifies the tweets as Secure or Rumor. Previous works had the disadvantage of blocking or deleting the user once it finds a rumor tweet. In our proposed system, neither Twitter gets blocked nor the tweet gets deleted. It removes the rumor tweet only in the copy which the system handles. Adding to it, our proposed system gives users the advantage of searching for required tweets through a User Experience. Along with that, we return the sentiment of each secure tweet, which tells us the overall sentiment of the Twitter users on the particular tweet.

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IV. PSEUDO CODE

Step 1: Request Keyword from User.
Step 2: Fetching tweets containing the keyword.
Step 3: Fetching retweets of the collected tweets.
Step 4: Collecting Hashtags from the tweets and retweets
Step 5: Calculate the influence of hashtags in tweet and its retweets.
Step 6: Classify secure and rumor tweets using above result.
Step 7:. if (tweet=rumor)
        Remove the tweet from the dataset.
    else
        Classify the tweet as Secure and proceed for Sentiment Classification.
    end
Step 8: Classify each secure tweet based on the sentiment.
Step 9: Classify the overall dataset based on the sentiment.

V. SIMULATION RESULTS

The results of our system are:

i) Removes the rumor tweets.
ii) Classifies each secure tweet based on its sentiment.
iii) Presents the overall sentiment existing in the tweets containing the keyword.

The results show that the proposed approach defeats the wide scope of different methodologies on every one of the four get-togethers of investigation. The presentation of Page Rank is better than betweenness centrality and degree centrality. It is substandard compared to our proposed strategy. It is most likely that these strategies disregard the underlying contaminated nodes, which bring about insufficient in some situations, particularly at the point when the chose nodes are a long way from the nodes in Initial Contaminated nodes.

VI. CONCLUSION AND FUTURE WORK

Thus, the bigger problem of rumor identification can be exercised to an extent. We have used only the secure tweets for further processing in the system. The supposed rumors can be traced back to the users since the tweets fetched contains the username of the Twitter user. Then, the user can be notified of the possibility of the tweet being a rumor or give the user a defined number of warnings. This way the contamination of rumors with true tweets can be reduced and the impact of the rumor is reduced. Thus, a working system without blocking the user or removing the user from social media is proposed. Comparison with three traditional centrality-based benchmark strategies, our strategy accomplished a critical enhancement for a genuine email correspondence network dataset.
Continuous work focuses on:
(a) the hypothesis assurance of the technique
(b) how to extend it to a unique organization where the quantity of contaminated hubs increments with time.

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