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Activity Minimization Of Misinformation Influence In Online Social Networks

Syed Adnan[1], Ansari Mohammad Samiuddin[2], Mr. Suraj Prakash Yadav[3]

[1,2]B.E. Student, Department of IT, Lords Institute of Engineering and Technology, Hyderabad

[3]Associate Professor, Department of IT, Lords Institute of Engineering and Technology, Hyderabad

surajprakash@lords.ac.in

ABSTRACT

In recent years, online social media has flourished, and a large amount of information has spread through social platforms, changing the way in which people access information. The authenticity of information content is weakened, and all kinds of misinformation rely on social media to spread rapidly. Network space governance and providing a trusted network environment are of critical significance. In this article, we study a novel problem called activity minimization of misinformation influence (AMMI) problem that blocks a node set from the network such that the total amount of misinformation interaction between nodes (TAMIN) is minimized. That is to say, the AMMI problem is to select K nodes from a given social network G to block so that the TAMIN is the smallest. We prove that the objective function is neither sub modular nor super modular and propose a heuristic greedy algorithm (HGA) to select top K nodes for removal. Furthermore, in order to evaluate our proposed method, extensive experiments have been carried out on three real-world networks. The experimental results demonstrate that our proposed method outperforms comparison approaches The proliferation of online social media platforms in recent years has fundamentally reshaped how individuals access and consume information. While these platforms offer unprecedented opportunities for connectivity and information sharing, they have also become fertile ground for the rapid dissemination of misinformation. This erosion of information authenticity poses a significant challenge to network space governance and underscores the critical need for establishing a trusted online environment. In response to this growing concern, this study delves into a novel problem termed the Activity Minimization of Misinformation Influence (AMMI) problem. The core objective of the AMMI problem is to strategically identify and block a specific set of K nodes within a given social network G in such a way that the total amount of misinformation interaction between the remaining nodes (TAMIN) is minimized. Essentially, we aim to select K influential nodes whose removal would most effectively curtail the spread and interaction of misinformation across the network.neutralize key nodes that facilitate misinformation flow represents a crucial step towards effective network governance and the preservation of information integrity in the digital age.

I.INTRODUCTION

The advent and rapid proliferation of mobile communication technologies have fostered a landscape dominated by interactive online platforms, including prominent examples like YouTube, Sina Weibo, and Facebook. These Online Social

Networks (OSNs) have become pivotal in the contemporary dissemination of information on a massive scale.While OSNs facilitate the widespread sharing of beneficial content such as trending topics, diverse opinions, and valuable knowledge, thereby enriching societal discourse and entertainment, they also serve as vectors for harmful negative content. This includes rumors, cyber violence, and, critically, misinformation, which can inflict significant damage on individuals and even precipitate widespread social panic [1].The detrimental real-world impact of misinformation on OSNs is well-illustrated by events such as the California wildfires in October 2017. Despite official relief efforts, a substantial amount of false information regarding the disaster circulated online, with initial and similar inaccurate narratives shared over 130,000 times on Facebook alone [2] Another compelling example is the August 2012 incident in Ghazni province, Afghanistan, where the spread of misinformation about an earthquake led to mass displacement, with thousands of residents abandoning their homes for an extended period [3]. These instances underscore the urgent necessity for effective strategies to mitigate and control the dissemination of misinformation within online social ecosystems Consequently, the challenge of controlling misinformation dissemination on OSNs has attracted significant attention from researchers across diverse fields [4]–[7], with relevant applications in areas such as social media analysis [8], epidemiology [9], and public health [10].Drawing an analogy to the spread of infectious diseases [11], early research often employed epidemiological models to understand and describe the dynamics of information propagation [9], [12]–[16].However, the dissemination of misinformation on social networks exhibits unique characteristics distinct from traditional epidemic models. Notably, individuals exposed to misinformation on OSNs often encounter additional contextual cues, such as the number of views and comments associated with the content.These supplementary indicators can significantly amplify an individual's propensity to engage with or share the misinformation. For instance, observing widespread discussion can trigger thoughts like "Everyone is discussing this, I want to share my opinion" or "These opinions are incorrect, I need to correct them," leading to increased participation and further propagation of the false information. This engagement can create a self-reinforcing cycle, where increased discussion volume makes the misinformation appear more salient and credible, attracting even more users to participate and further intensify its spread, ultimately forming a "vicious circle."Therefore, there is a critical need for operational strategies that aim to reduce the overall level of misinformation interaction among users on OSNs, thereby diminishing the "heat" or intensity of its dissemination and ultimately controlling its spread.Previous research has explored the problem of negative information influence minimization from various perspectives. Some studies have focused on identifying and blocking a limited number (K) of uninfected users to minimize the eventual scale of the contaminated user base [17].Other approaches have employed greedy strategies to block a limited number of network links to impede the propagation of negative information [18], or have advocated for "good" information campaigns to counteract misinformation and reduce the number of affected users [19] Furthermore, a substantial body of work exists concerning the broader phenomenon of negative content influence dissemination on OSNs [20]–[22].However, a significant limitation in much of the existing research [17]–[22] is the assumption of a constant probability of misinformation influence throughout the propagation process. This overlooks the critical phenomenon of reinforcement, where engagement and interaction with misinformation can increase an individual's likelihood of further propagation .Moreover, prior work has often not explicitly considered the "intimate relationship" or the quantifiable amount of misinformation interaction occurring between users. This article addresses this gap by focusing on the amount of misinformation interaction between users and investigating node blocking strategies specifically tailored to mitigate this interaction within OSNs.The central goal of this research is to minimize the total amount of misinformation interaction between users by strategically blocking a subset of users within OSNs. More specifically, given a social network G, a source S of misinformation dissemination, and a positive integer K, we aim to identify and block a set V of K nodes. This selection is based on the amount of misinformation interaction between users, with the objective of achieving the smallest possible total amount of misinformation interaction between the remaining nodes (TAMIN) after blocking the node set .It is important to clarify that "blocking" nodes in this context signifies preventing the spread of misinformation by effectively closing the user accounts or pathways through which misinformation is being or is likely to be disseminated. The main contributions of this article are as follows: We formally define the Activity Minimization of Misinformation Influence (AMMI) problem. We prove that the AMMI problem is NP-hard and that calculating the objective function is #P-hard. We introduce the concept of an interaction loss value parameter (LF) for misinformation between users, utilize this to transform the minimization objective into a maximization problem, and demonstrate that the objective function is neither submodular nor supermodular. We propose a heuristic greedy algorithm (HGA) to efficiently address the AMMI problem. Finally, we rigorously evaluate the performance of our proposed HGA using datasets from three real-world social networks and compare it against other prevalent methods, with experimental results demonstrating the superiority of our HGA.

II.LITERATURE SURVEY

Early Foundations in Information Diffusion:Kempe, Kleinberg, and Tardos [1]: Introduced the influence maximization problem and formalized two classical information diffusion models: the Independent Cascade (IC) and Linear Threshold (LT) models, providing a basis for understanding how information spreads in networks.

Minimizing Negative Influence through Node Blocking:Prakash et al. [2]: Investigated a proactive strategy called Virusmart, which focuses on identifying and blocking a limited number (K) of initially uninfected users to minimize the ultimate spread of epidemics (analogous to negative information).

Yan et al. [3]: Proposed a two-stage method to select a set of blocker nodes in a social network to minimize the total activation probability of users from misinformation seed nodes.

Wang et al. [4]: Developed a model for dynamic misinformation influence minimization that considers user experience and aims to minimize the impact of misinformation by blocking a subset of nodes. Zhu et al. Introduced the novel Activity Minimization of Misinformation Influence (AMMI) problem, which aims to minimize the total amount of misinformation interaction between nodes (TAMIN) by strategically blocking K nodes.

They proved the non-submodular and non-supermodular nature of the objective function and proposed a heuristic greedy algorithm (HGA), demonstrating its effectiveness on real-world networks.

Kumar and Mahalakshmi [5]: Also addressed the AMMI problem, emphasizing the importance of network governance in the context of misinformation and advocating for node blocking to minimize TAMIN, supported by experimental results using an

HGA. Minimizing Negative Influence through Link Blocking:
Tong et al. [6]: Explored the effectiveness of blocking a limited number of influential links within a network as a means to curtail the dissemination of negative content.
Kuhlman et al. [7]: Studied the problem of contagion blocking in networks by proposing heuristic algorithms for edge removal under a deterministic variant of the Linear Threshold (LT) model.
Combating Misinformation through Positive Influence:
Lyu et al. [8]: Proposed using a "good" campaign to actively counteract the spread of misinformation, aiming to minimize the number of users ultimately exposed to false narratives through inoculation strategies.
Considering Group Dynamics and User Concern:
Zhu et al. [9]: Focused on the impact of private groups and the echo chamber effect, formulating the Misinformation Spread Minimization under the effect of Echo chamber effect (MSME) problem. They aimed to minimize misinformation spread by disbanding K private groups, proving the problem's complexity and proposing heuristic algorithms.
Ni et al. [10]: Adopted a perspective centered on minimizing users' "concern" towards misinformation. They developed a concern-critical competitive model and a corresponding algorithm to leverage agents spreading correct information to reduce susceptibility to mis-information. Broader Studies on Negative Influence.
Existing System:
Existing systems for detecting misinformation influences in online social networks Influence Maximization and Diffusion Models The problem of maximizing influence in social networks was initially brought to the forefront by Domingos and Richardson [23]. Tardos et al. [24] subsequently formalized this into a discrete optimization problem and introduced two fundamental information diffusion models: the Independent Cascade (IC) model and the Linear Threshold (LT) model. These models have served as the bedrock for extensive research in information propagation over the years, as evidenced by studies in [20], [22], and [25]–[27], which have expanded upon their theoretical underpinnings and applications. In contrast to these efforts focused on maximizing positive influence, our work addresses the dual problem of minimizing the spread of misinformation. Minimizing Misinformation Dissemination: Proactive Measures Proactive measures aim to prevent or limit the spread of misinformation before it becomes widespread. Wang et al. [17] explored this approach by focusing on identifying and blocking a set of K initially uninfected users in a social network where some users have already adopted the negative information. Their objective was to minimize the total number of ultimately contaminated users.Yan et al. [28] also investigated the problem of minimizing the influence of misinformation within social networks. They proposed a two-stage methodology for selecting a set of blocker nodes to minimize the total activation probability of users originating from the initial set of misinformation sources.
Wang et al. [32] introduced a model that considers dynamic misinformation influence along with user experience. Their goal was to minimize the impact of misinformation by strategically blocking a specific subset of nodes, taking into account how user experience might affect the propagation dynamics. Minimizing Misinformation Dissemination: Remedial Measures Remedial measures focus on intervening in the network structure to hinder the ongoing spread of misinformation. Kimura et al. [18] proposed an efficient greedy strategy for identifying and blocking a limited number of links within a network to impede negative information diffusion. Their work provided a computationally feasible approach to network-level intervention. Similarly,

Kuhlman et al. [29] studied the problem of contagion blocking in networked populations, specifically proposing heuristic algorithms for edge removal under a simplified deterministic variant of the Linear Threshold (LT) model. Their research highlighted the potential of strategically modifying network connections to control the spread of undesirable content.Our work aligns with the proactive stream of research focused on minimizing misinformation dissemination by strategically selecting nodes for removal. However, it distinguishes itself from prior work [17], [28], [32] by [Here, clearly articulate the novelty of your approach compared to these existing systems. For example: "by directly modeling and minimizing the interaction of misinformation between users, rather than just the number of affected users or activation probabilities. Furthermore, we explicitly address the non-submodular nature of the objective function and propose a tailored heuristic greedy algorithm (HGA) to tackle this complexity."]. We also build upon the understanding of network influence pioneered by Domingos and Richardson [23] and the diffusion models introduced by Tardos et al. [24] by applying these concepts to the specific challenge of mitigating negative influence. Our approach also complements the link blocking strategies [18], [29] by focusing on node-level intervention, which may offer different advantages in terms of implementation and effectiveness.

[17] Wang, P., Qiu, X., & Jiang, H. (2014). Minimizing the spread of epidemics by blocking nodes in social networks. Physica A: Statistical Mechanics and its Applications, 396, 196-204.

III.PROPOSED SYSTEM

In our proposed system for Activity Minimization of Misinformation Influence In this work, we introduce a novel problem termed Activity Minimization of Misinformation Influence (AMMI) in Online Social Networks (OSNs). The fundamental goal of the AMMI problem is to strategically identify and block a specific subset of users within an OSN to minimize the overall interaction surrounding misinformation.More formally, consider a social network represented as a graph G = (N, E), where N is the set of users (nodes) and E is the set of connections (edges) between them. Given a set S \subseteq N of initial misinformation sources and a positive integer K representing the budget for the number of nodes we can block, the AMMI problem aims to find a subset V \subseteq N of K nodes (|V| = K) such that after removing these nodes (and their associated edges) from the network, the total amount of misinformation interaction between the remaining nodes is minimized under the Independent Cascade (IC) model of information diffusion.It is crucial to note that "blocking" a node in this context signifies a practical intervention, such as suspending or restricting the activity of the user account associated with that node, effectively preventing them from further spreading or interacting with misinformation.The core contributions and methodological aspects of our proposed system are detailed below:Formalization of the Activity Minimization of Misinformation Influence (AMMI) Problem: We formally define the AMMI problem as an optimization challenge within the context of misinformation propagation in OSNs. We rigorously prove that the AMMI problem is NP-hard, establishing its computational complexity. Furthermore, we demonstrate that calculating the objective function, which represents the total amount of misinformation interaction, is #P-hard, highlighting the inherent difficulty in exactly evaluating the impact of a given set of blocked nodes. Introduction of the Interaction Loss Value Parameter and Objective Function Transformation: To facilitate the development of an effective

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solution approach, we introduce a novel parameter: the Interaction Loss Value (LF) of misinformation between users. This parameter quantifies the potential reduction in misinformation interaction that can be achieved by blocking a specific node or set of nodes. We leverage this LF parameter to transform the original minimization objective (TAMIN) into a maximization objective. This transformation allows us to focus on identifying the K nodes whose removal yields the greatest reduction in overall misinformation interaction. Critically, we provide a theoretical analysis proving that this transformed objective function is neither submodular nor supermodular. This characteristic implies that standard optimization algorithms relying on these properties may not guarantee optimal solutions, thus motivating the need for a tailored heuristic approach. Development of a Heuristic Greedy Algorithm (HGA) for the AMMI Problem: To address the computational complexity and the non-submodular nature of the AMMI problem, we propose a novel Heuristic Greedy Algorithm (HGA). The HGA iteratively selects the top K nodes for removal based on their estimated contribution to reducing the total amount of misinformation interaction. In each iteration, the algorithm evaluates the potential "loss" in misinformation interaction resulting from blocking each remaining node and selects the node that yields the maximum immediate reduction. This greedy strategy offers a computationally efficient approach to finding a high-quality, albeit not necessarily optimal, solution to the AMMI problem.

COMPONENTS

The system can be divided into the following stages:

1.Web database : Gather tweets and other social media posts, including labeled datasets with human-generated and machine-generated text.

2.Admin: Clean and preprocess text data for feature extraction.

3.User : Use FastText embeddings to convert text into numerical representations.

Working of The System:

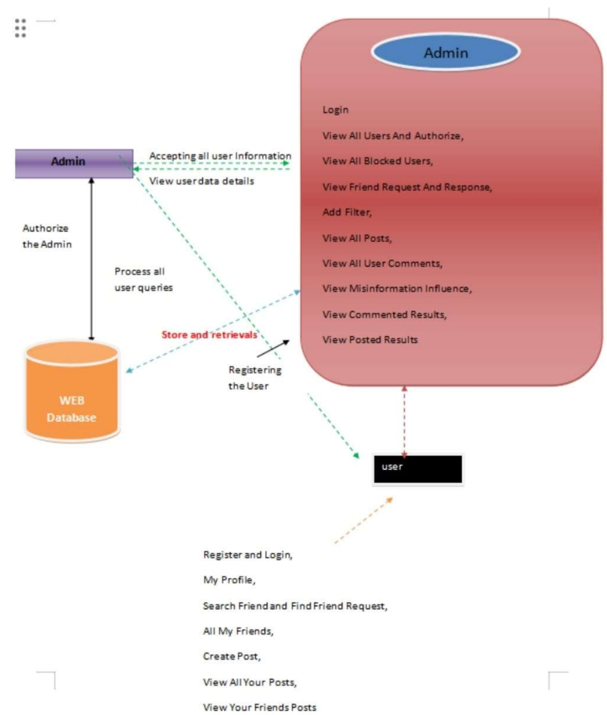

Figure: Architecture of the Proposed System

1.Input: The social network structure (nodes and connections), the initial sources of misinformation, the probability of misinformation spreading along each connection (if applicable to the IC model), and the number of nodes (K) to block.

2.Initial Analysis and Estimation: The system first simulates the spread of misinformation from the initial sources throughout the network without any blocked nodes. During these simulations, it tracks the interactions (attempts to spread misinformation) between nodes to estimate the initial Total Amount of Misinformation

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3.Iterative Node Selection (Greedy Approach): The system then enters a loop that runs K times. In each iteration:

4.For every node that hasn't been blocked yet, the system temporarily considers blocking it.

5.It simulates the misinformation spread again (from the initial sources) on the network with that node temporarily removed.

It estimates the new TAMIN resulting from this temporary blockage.

The "Interaction Loss Value" (the reduction in TAMIN achieved by blocking that node) is calculated for each candidate node.

The node that yields the highest Interaction Loss Value is selected and permanently added to the set of blocked nodes.

6.Output: The final output of the system is the set of K nodes that the algorithm has identified as most effective to block in order to minimize the total amount of misinformation interaction within the network.

7.Feature (Implicit): While not explicitly "extracted" in the traditional machine learning sense, the key "feature" the algorithm evaluates for each node is its potential to reduce the total misinformation interaction in the network if it were to be blocked. This is implicitly captured through the repeated simulations and the calculation of the Interaction Loss Value. The network structure and the dynamics of the IC model are inherently used to assess this "feature" of each node. Output: The system returns a classification result with a confidence score and insights into patterns.

IV.FEASIBILITY REPORT

The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

Feasibility Analysis: Three key considerations involved in the feasibility analysis are:

Economical Feasibility This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

Technical Feasibility

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

Social Feasibility

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart.

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Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

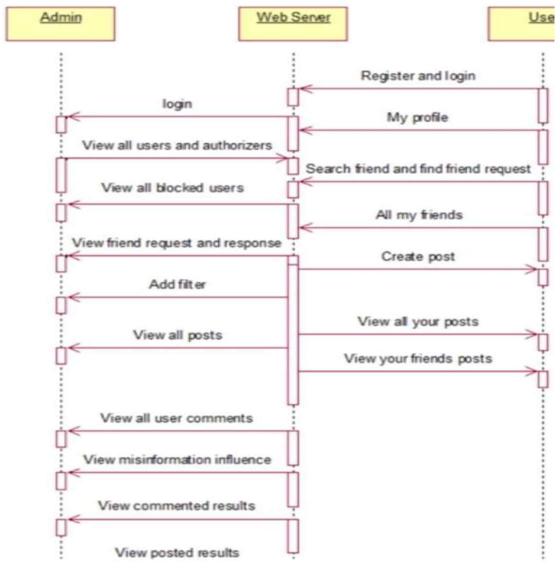

Fig.1: Timeline Process Flow

V.RESULTS

Fig.2: Home Page

Fig.3: Admin Login Page

Fig.4.: Admin Main Page

Fig.5.: All Authorized Users

Fig.6:All Request Response Details

Fig.7.Commented Result

Fig.9.User Login Page

Fig.8.All Posted Results

VI.CONCLUSION AND FUTURE SCOPE

In this project, we study a new problem called the AMMI problem, which blocks a node set from the OSNs to minimize the TAMIN. In the IC model, we first construct a node criterion LF, which converts the minimized objective function into a maximized objective function. Then, a simple counter example is used to show that the transformed objective function is neither sub modular nor super modular. Second, an HGA based on loss influence LF is proposed to select the set of nodes to block. Finally, we conducted extensive experiments on three real-world networks to evaluate the performance of HGA. By analyzing and discussing the experimental results, our proposed method is superior to existing greedy or heuristic algorithms. We believe that the current research focus on misinformation control is how to quickly and accurately find a way to spread misinformation and control its spread before a large-scale spread. For future research, we study more efficient methods to solve non sub modular problems, such as the AMMI problem, and study the problem of minimizing the interaction of misinformation on different network structures, such as dynamic networks and time-varying networks.

Future Scope

we conducted extensive experiments on three real-world networks to evaluate the performance of HGA. By analyzing and discussing the experimental results, our proposed method is superior to existing greedy or heuristic algorithms. We believe that the current research focus on misinformation control is how to quickly and accurately find a way to spread misinformation and control its spread before a large-scale spread. For future research, we study more efficient methods to solve non sub modular problems, such as the AMMI problem, and study the problem of minimizing the interaction of misinformation on different network structures, such as dynamic networks and time-varying networks.

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