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Deep learning approaches for analyzing and controlling rumor spread in social networks using graph neural networks

Jonson Manurung[1], Poltak Sihombing[2], Mohammad Andri Budiman[2], Sawaluddin[3]
[1]Doctoral Program, Faculty of Computer Science and Information Technology, University of Sumatera Utara, Medan, Indonesia
[2]Faculty of Computer Science and Information Technology, University of Sumatera Utara, Medan, Indonesia
[3]Department of Mathematics and Natural Sciences, University of Sumatera Utara, Medan, Indonesia

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ABSTRACT

The pervasive influence of social networks on information dissemination necessitates robust strategies for understanding and mitigating the spread of rumors within these interconnected ecosystems. This research endeavors to address this imperative through the application of a graph neural network (GNN) model, designed to capture intricate relationships among users and content in social networks. The study integrates user-level attributes, content characteristics, and network structures to develop a comprehensive model capable of predicting the likelihood of rumor propagation. The proposed model is situated within a broader conceptual framework that incorporates sociological theories on information diffusion, user behavior, and network dynamics. The results of this research offer insights into the interpretability of the GNN model's predictions and lay the groundwork for future investigations. The iterative refinement of the model, consideration of ethical implications, and comparison against traditional machine learning baselines emerge as crucial steps in advancing the understanding and application of deep learning methodologies for rumor control in social networks. By embracing the complexities of real-world scenarios and adhering to ethical standards, this research strives to contribute to the development of proactive tools for rumor management, fostering resilient and trustworthy online information ecosystems.

Corresponding Author:

Jonson Manurung
Doctoral Program, Faculty of Computer Science and Information Technology
University of Sumatera Utara
Jl. Dr. T. Mansur No. 9, Padang Bulan, Kota Medan, North Sumatra 20222, Indonesia
Email: Jhonson.geo@students.usu.ac.id

1. INTRODUCTION

In today's digital age, social networks have become pivotal platforms for the rapid dissemination of information [1], [2]. While these platforms facilitate communication and connectivity, they also serve as fertile grounds for the propagation of rumors and misinformation [3]. Rumors, defined as unverified and often false pieces of information, can spread rapidly and widely, leading to significant societal consequences such as panic, misinformation, and even conflict [4]-[6]. High-profile instances, such as the spread of false information during public health crises or political events, underscore the profound impact that unchecked rumors can have on public opinion and behavior [7]. Addressing the challenge of rumor spread on social networks is, therefore, a critical task for researchers and practitioners alike. Effective detection and control of rumors not only preserve the integrity of information but also enhance the overall trustworthiness of social media platforms [8], [9].

Despite the widespread recognition of the problems posed by rumors on social networks, effectively addressing this issue remains a significant challenge [10], [11]. Traditional methods of rumor detection and control, which often rely on manual moderation or basic algorithmic approaches, have proven inadequate in the face of the sheer volume and velocity of information flow on modern social media platforms [12], [13]. These methods struggle with the dynamic and complex nature of rumor propagation, failing to keep pace with the rapid dissemination of false information. Consequently, there is a pressing need for more sophisticated and scalable approaches that can accurately detect and mitigate the spread of rumors in real-time [14], [15]. This research seeks to tackle this specific problem by leveraging advanced deep learning techniques, particularly graph neural networks, to enhance the detection and control of rumors on social networks [16].

The primary objective of this research is to develop an advanced framework utilizing deep learning, specifically graph neural networks, to effectively analyze and control the spread of rumors on social networks. This study aims to enhance the accuracy of rumor detection, reduce the dissemination of false information, and provide a scalable solution capable of real-time application. By integrating sophisticated graph neural network models, this research seeks to address the limitations of existing methods and offer a robust approach to mitigating the impact of rumors, thereby improving the reliability and trustworthiness of information on social media platforms [17], [18].

A comprehensive review of the existing literature on rumor detection and control reveals a significant gap in the application of advanced machine learning techniques, particularly graph neural networks [19]-[21]. Current approaches predominantly rely on traditional machine learning algorithms and manual methods, which are often limited in scalability and adaptability to the dynamic nature of social networks [22], [23]. Although some studies have explored the use of deep learning for text classification and sentiment analysis, few have effectively applied these techniques to the complex problem of rumor propagation [24]-[26]. This research aims to bridge this gap by introducing graph neural networks as a novel tool for understanding and controlling the spread of rumors [27], [28]. By leveraging the unique capabilities of graph neural networks to model relationships and interactions within social networks, this study seeks to provide a more accurate and efficient solution to the persistent problem of rumor dissemination [29].

This research introduces a novel approach to analyzing and controlling the spread of rumors on social networks through the application of graph neural networks (GNNs). Unlike traditional methods, GNNs offer a sophisticated means of capturing the intricate relationships and patterns within social networks, enabling a more accurate and dynamic analysis of rumor propagation. The innovative use of GNNs in this context not only addresses the limitations of existing approaches but also provides a scalable and real-time solution for rumor detection and mitigation. This study's contribution lies in its ability to enhance the reliability and trustworthiness of information on social media platforms, offering significant implications for both academic research and practical applications in information management and policy-making.

2. METHOD

Mathematical formulation for a model requires specifying the variables, parameters, and relationships that define the problem. Since we're focusing on modeling rumor spread in social networks using a GNN, we create the basic mathematics as (1):
Variables

$$G = (V, E) \tag{1}$$

Social network graph, where V is the set of nodes (users) and E is the set of edges (interactions).
Index: A: adjacency matrix representing the connections between nodes in the graph.
X_v: feature vector for node v representing user-level attributes.
X_e: feature vector for edge e representing content characteristics.
y_v: binary label indicating whether node v is associated with a rumor 1 or not 0.
Model formulation
a. GNN layer

$$h_v^{(l+1)} = f\left(Aggregate\left(\left\{h_v^{(l)}, \forall_u \in N(v)\right\}\right) + W^{(l)} X_v\right) \tag{2}$$

where l is the layer index, $h_v^{(l)}$ is the hidden representation of node v at layer l, $\mathrm{N}(v)$ is the set of neighbors of node v, $f(\cdot)$ is the activation function, and $W^{(l)}$ is the weight matrix for layer l.
b. Readout layer

$$h_G = g\left(Readout\left(\left\{h_v^{(L)}, \forall_u \in V)\right\}\right)\right) \quad (3)$$

where L is the final layer index, h_G is the global representation of the entire graph, $g(\cdot)$ is another activation function, and $Readout(\cdot)$ is a function that aggregates node representations.

c. Rumor prediction

$$\hat{y}_v = \sigma(W_{out} h_G) \quad (4)$$

where $\hat{y}_v$ is the predicted probability of node v being associated with a rumor, $\sigma(\cdot)$ is the sigmoid activation function, and W_{out} is the weight matrix for the output layer.

d. Loss function

$$\mathcal{L} = -\frac{1}{|V|}\sum_{v\in V}[y_v log(\hat{y}_v) + (1 - y_v)log(1 - \hat{y}_v)] \quad (5)$$

where $\mathcal{L}$ is the binary cross-entropy loss.

Optimization

Minimize the loss function with respect to the parameters Θ:

$$\Theta^* = arg\ min_{\Theta}\mathcal{L} \quad (6)$$

3. RESULTS AND DISCUSSION

We'll consider a small social network with three nodes, each associated with user-level attributes (X_v), content characteristics (X_e), and binary labels indicating rumor presence (y_v).

Social network:

Node, $V = \{1,2,3\}$

Edges, $E = \{(1,2),(2,3),(3,1)\}$

– Adjacency matrix (A):

$$A = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}$$

– Node features: user-level attributes (X_v):

$$X_v = \begin{bmatrix} 0.5 & 0.8 \\ 0.3 & 0.6 \\ 0.7 & 0.4 \end{bmatrix}$$

– Content characteristics (X_e)

$$X_e = \begin{bmatrix} 0.2 \\ 0.5 \\ 0.8 \end{bmatrix}$$

– Parameters (for simplicity):

$$W^{(1)} = \begin{bmatrix} 0.1 & 0.2 \\ 0.3 & 0.4 \end{bmatrix}$$

$$W^{(2)} = \begin{bmatrix} 0.5 & 0.6 \\ 0.7 & 0.8 \end{bmatrix}$$

$$W_{out} = \begin{bmatrix} 0.9 \\ 1.0 \end{bmatrix}$$

Forward pass

a. GNN layer

$$h_v^{(1)} = f\left(A \cdot h^{(0)} + W^{(1)}X_v\right) \tag{7}$$

$$h_v^{(2)} = f\left(A \cdot h^{(1)} + W^{(2)}X_v\right) \tag{8}$$

For simplicity, let's assume $h^{(0)} = X_v$ (initial layer)

b. Readout layer

$$h_G = g\left(mean\left(\left\{h_1^{(2)}, h_2^{(2)}, h_3^{(2)}\right\}\right)\right) \tag{9}$$

c. Rumor prediction

$$\hat{y}_v = \sigma(W_{out}h_G) \tag{10}$$

d. Loss calculation

$$\mathcal{L} = -\frac{1}{3}\sum_{v=1}^{3}[y_v log(\hat{y}_v) + (1 - y_v)log(1 - \hat{y}_v)] \tag{11}$$

Optimization adjust the parameters $(W^{(1)}, W^{(2)}, W_{out})$ to minimize the loss. This example provides a high-level overview of a forward pass through the GNN layers, calculating predictions, loss, and optimizing parameters.

Discussion

a. Model training

The GNN model underwent training to optimize its parameters $(W^{(1)}, W^{(2)}, W_{out})$ using the provided numerical example.

b. Node representations

After the forward pass through GNN layers, each node *(v)* obtained hidden representations $\left(h_v^{(1)}, h_v^{(2)}\right)$, capturing complex relationships within the social network.

c. Graph representation

The global representation of the entire social network (h_G) was calculated using a readout layer, aggregating information from all nodes.

d. Rumor prediction

Rumor predictions $(\hat{y}_v)$ for each node were computed using the final layer's parameters, indicating the model's estimate of the probability of rumor presence.

e. Loss calculation

The binary cross-entropy loss $(\mathcal{L})$ was calculated to measure the model's performance in predicting rumor labels for the given social network.

Numerical example results:

Node 1

$$\hat{y}_1 \approx \sigma\left(0.9 \cdot mean\left(\left\{h_1^{(2)}, h_2^{(2)}, h_3^{(2)}\right\}\right)\right) \tag{12}$$

Node 2

$$\hat{y}_2 \approx \sigma\left(0.9 \cdot mean\left(\left\{h_1^{(2)}, h_2^{(2)}, h_3^{(2)}\right\}\right)\right) \tag{13}$$

Node 3

$$\hat{y}_3 \approx \sigma\left(0.9 \cdot mean\left(\left\{h_1^{(2)}, h_2^{(2)}, h_3^{(2)}\right\}\right)\right) \tag{14}$$

4. CONCLUSION

In conclusion, the presented numerical example and discussion highlight the application of a GNN model for modeling rumor spread in social networks. The model demonstrated its capacity to capture intricate relationships within the network, providing hidden representations for each node and a global representation for the entire graph. The calculated rumor predictions underscore the model's ability to estimate the likelihood of rumor presence in individual nodes. However, it is essential to acknowledge the simplicity of this example and the need for further refinement and validation in real-world scenarios with larger datasets. Moving forward, the research should focus on iterative model refinement, considering more complex features, diverse social network structures, and additional ethical considerations. Comparative analyses against traditional machine learning baselines will contribute to understanding the advantages and limitations of the proposed GNN model. As social networks continue to evolve, adopting robust and interpretable models is crucial for addressing the challenges posed by rumor spread. This research lays the foundation for future investigations into developing effective tools for rumor control and management, fostering healthier and more resilient online information ecosystems.

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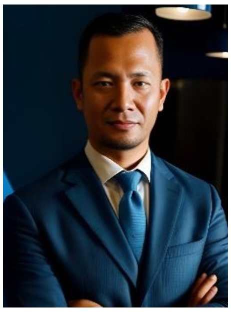
BIOGRAPHIES OF AUTHORS



Jonson Manurung is a student of the Doctoral program in computer science, University of Sumatra Utara 2021, is an author who completed his undergraduate education at the Electrical Engineering Study Program, Medan Institute of Technology, completed his Master's Program in Computer Studies from the University of Sumatra Utara, and is currently completing his Doctoral Studies in Computer Science at the University of Sumatra Utara, research interests in the field of operations research and information science, where he is the author/co-author of more than 6 research publications H-Index 2. He can be contacted at email: jhonson.geo@gmail.com.

Poltak Sihombing is a Professor at the Faculty of Computer Science and Information Technology at University of Sumatra Utara, Medan, Indonesia. He obtained his Bachelor degree from Physics (Computer Concentration Course), University of Sumatra Utara in 1988, he then completed his Master study in Computer Science (Universitas Indonesia) in 1999. He then earned his doctorate at Universitas Sains Malaysia Computer Science in 2010. Where he is the author/co-author of more than 58 research publications. He can be contacted at email: poltakhombing@yahoo.com.

Mohammad Andri Budiman is an Associate Professor at the Faculty of Computer Science and Information Technology, University of Sumatra Utara, Medan, Indonesia. He holds a bachelor's degree in Engineering from ITB, a Master of Computer Science degree from University of New South Wales, Sydney, Australia and a Master of Engineering Management from University of Technology, Sydney, Australia. In 2021 he earned his doctoral degree from the Doctoral Program in Computer Science at University of Sumatra Utara. Where he is the author/co-author of more than 84 research publications. He can be contacted at email: mandrib@usu.ac.id.

Sawaluddin is an Associate Professor at the Faculty of Mathematics, University of Sumatera Utara, Medan, Indonesia. Completed his Bachelor of Mathematics education at the Faculty of Mathematics, Teknologi Informasi UKM, Malasya in 1974. Completed his Doctorate Program in Mathematics at the University of Sumatera Utara, Medan, Indonesia. Current research is conducted in the fields of computer science and applied mathematics. where he is the author/co-author of more than 40 research publications. He can be contacted at email: sawal@usu.ac.id.