Performance Comparison of Fake News Detection on Social Networks

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Abstract

Fake news has been around for centuries, but with the advent of social media and digital technology, it has become more widespread and pervasive. Detecting fake news is a challenging task as it often involves a complex combination of text analysis, fact-checking, and source verification. Traditional fake news detection is more focused on text analysis, extracting certain words associated with fake news from the text as a basis for judgment, but when the text data is too large, or the text avoids using obvious fake news words when conveying false information will lead to difficulty in detecting fake news.

However, using graph networks can circumvent this defect. We map the real and fake news labels in the dataset to the users and focus more on a user and his neighbor nodes who prefer to retweet real news or fake news, through the analysis of user behavior for fake news detection. Based on Twitter datasets, we implement a GCN model as the baseline for the benchmark. Also, we utilize different algorithms, such as GAT, Graph-MLP, and Graph-SAGE, to measure the impact on the accuracy of fake news detection.

Keywords: GCN, GAT, Graph-SAGE, Graph-MLP

1 Introduction

The widespread circulation of false information in the digital era, particularly through the internet and social media, has posed a significant obstacle for journalists, scholars, and the general public. The detection of fake news involves the validation and confirmation of the veracity of news and other forms of media content that are deliberately deceptive, false, or unreliable. Currently, there are two common methods for detecting fake news. One is text-based, which involves using natural language processing (NLP) [6]. The other is based on social networks which could be used in graphs and node classification for detection.

Our idea is to apply a non-GNN model called Decision Tree [7] and multiple traditional node classification algorithms, such as Graph Convolutional Network(GCN) [2], Graph Attention Networks (GAT) [11], Graph Sample and Aggregated (Graph-SAGE) [1] and Graph Multi-layer Perceptrons (Graph-MLP) [3], to social networks. We use a labeled Twitter dataset where each tweet is marked as true or false and includes the associated user vectors. Each node classification algorithm is used for cross-validation to classify these tweets and provides their respective accuracy. We will compare the performance of these algorithms and analyze which one is most suitable for this problem.

2 Background and related work

2.1 Background

In recent years, the proliferation of social networks has brought about rapid dissemination of information and news on a global scale. While this connectivity has numerous advantages, it has also led to the widespread circulation of fake news. Fake news refers to deliberately fabricated or misleading information presented as factual news, often with the intention to deceive or manipulate public opinion. The impact of fake news on social networks has been significant, with instances of false information influencing elections, spreading harmful rumors, and even inciting violence in some cases. Recognizing the potential dangers associated with the spread of fake news, researchers, technologists, and social media platforms have undertaken efforts to develop mechanisms to detect and mitigate its effects. Fake news detection on social networks involves the application of various techniques, including natural language processing, machine learning, data mining, and network analysis. These techniques aim to analyze the content, context, and sources of news articles or posts to identify potential instances of misinformation or disinformation. Machine learning algorithms play a crucial role in fake news detection. These algorithms are trained on large datasets of reliable and fake news articles, learning to distinguish between the two based on patterns and features extracted from the text. These features may include lexical, syntactic, and semantic attributes that capture the distinctive characteristics of fake news. By leveraging these learned patterns, machine learning models can classify new articles or posts as either reliable or potentially fake.

Social network analysis is another key component of fake news detection. It involves analyzing the propagation patterns of news articles or posts across social networks. By examining the structure of the network and the behavior of users, researchers can identify suspicious patterns, such as coordinated efforts to spread misinformation or the presence of bot accounts amplifying fake news content.

2.2 Related work

The detection of fake news on social networks has garnered significant attention from researchers, technologists, and organizations worldwide. Over the years, several studies and approaches have been proposed to tackle this problem. Here are some notable areas of related work in the field of fake news detection:

Singh, Vivek, et al's work [10] introduces a novel method for automated fake news detection using linguistic analysis and machine learning. The approach involves extracting linguistic features from news articles and employing various machine learning algorithms for classification. The proposed system outperforms existing methods, demonstrating high accuracy in detecting fake news. The study's findings contribute to combating misinformation and improving the credibility of news sources.

Jin et al's work [4] investigates the effectiveness of BERT, a pre-trained language model, for fake news detection. It compares BERT with traditional machine learning models and demonstrates that BERT achieves superior performance by capturing complex semantic relationships and contextual information in the text.

Shu et al's work [8] investigates the role of social network analysis in fake news detection. It explores the characteristics of social networks, including network structures, user behaviors, and information propagation, to identify features and patterns associated with the spread of fake news.

2.3 Datasets

In this project, we will use KaiDMML/FakeNewsNet K. Shu et al.(2019)'s dataset [9]. Their dataset was collected from Twitter by following the method proposed in Fakenewsnet [9]. Specifically, FakeNewsNet uses information from two third-party fake news detection websites, Politifact and Gossipcop, to label some Tweet IDs. K. Shu et al. used these IDs to crawl the original tweets and related user data on Twitter. The node information in the dataset is shown in Figure 1.

Dataset	#Graphs (#Fake)	#Total Nodes	#Total Edges	#Avg. Nodes per Graph
Politifact (POL)	314 (157)	41,054	40,740	131
Gossipcop (GOS)	5464 (2732)	314,262	308,798	58

Figure 1. Dataset and graph statistics

In our project, we utilize two datasets: Gossipcop and Politifact. These datasets consist of both fake and real news information sourced from two fact-checking websites, along with the associated social engagement data from Twitter.

The Politifact dataset comprises a total of 314 graphs, out of which 157 are classified as fake graphs. It contains a combined total of 41,054 nodes and 40,740 edges. On average, each graph in this dataset consists of approximately 131 nodes.

The Gossipcop dataset, on the other hand, consists of 5,464 graphs, with 2,732 identified as fake graphs. This dataset contains a total of 314,262 nodes and 308,798 edges. The average number of nodes per graph in this dataset is approximately 58.

These datasets provide valuable resources for studying fake and real news propagation networks on Twitter, based on fact-checking information from Politifact and Gossipcop.

3 Methods

In order to detect fake news in this dataset, a simple idea is to use node classification algorithms. We plan to use multiple classical algorithms, including Graph Convolutional Networks (GCN) [5], GAT [11], Graph-MLP [3], and GraphSAGE [12]. Additionally, we still want to set up a Decision Tree model [7] as the baseline for the benchmark. As the latest and most advanced method for fake news network detection, GCN may have significant performance advantages over our node classification algorithms. This could help us determine which algorithm is more suitable for solving this problem.

Our approach involves applying traditional node classification algorithms, such as Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), Graph Sample and Aggregated (SAGE), and Graph Multi-layer Perceptrons (Graph-MLP), to social networks. And we compare them with a non-GNN model, Decision Tree. To evaluate their performance, we utilize a labeled Twitter dataset where each tweet is categorized as true or false, and corresponding user vectors are included. Through cross-validation, we employ each node classification algorithm to classify these tweets and measure their accuracy. By comparing the performance of these algorithms, we aim to analyze and determine the most suitable approach for the problem of fake news detection on social networks. In our project, we employed four different graph neural network (GNN) models and one non-GNN model for automatic fake news detection on the Twitter social network and compare the performance of these models.

3.1 GCN

The first model, GCN (Graph Convolutional Network), is a geometric deep learning algorithm that extends classical convolutional neural networks to graphs. It allows for the fusion of heterogeneous data, including content, user profiles and activities, social graphs, and news dissemination.

3.2 GAT

Building upon GCN, our second model, GAT (Graph Attention Network), incorporates a novel mechanism for aggregating features from neighboring vertices to the central vertex.

It leverages the attention mechanism to effectively integrate the correlation between vertex features into the model. We expect GAT to achieve improved accuracy performance in fake news determination through vertex classification.

3.3 Graph-MLP

The third model, Graph-MLP (Graph Multi-Layer Perceptron), aims to automatically identify fake news within a dataset consisting of both real and fake news propagation networks on Twitter. The model's architecture follows a typical design, consisting of linear layers followed by activation, normalization, and dropout layers. We utilize a block structure that includes linear-activation-layer normalization-dropout, with two additional linear layers for prediction. Activation is performed using the Gelu function, and Layer normalization is employed for enhanced training stability instead of batch normalization. Dropout is included to prevent overfitting. The second-to-last linear layer is supervised for feature transformation using our proposed NContrast loss, while the last linear layer is specifically designed for learning node classification.

3.4 Graph-SAGE

Our fourth model, Graph-SAGE (Graph Sample and Aggregated), is applied to a dataset comprising real and fake news propagation networks on Twitter, constructed using fact-check information from Politifact and Gossipcop. Graph-SAGE aggregates feature information from nearby nodes to generate node embeddings using a forward propagation algorithm. The model parameters are assumed to be already learned, and the embeddings are used to learn the Graph-SAGE model parameters through standard stochastic gradient descent and backpropagation techniques.

Overall, these models offer different approaches to fake news detection, leveraging the power of graph neural networks and incorporating various techniques such as attention mechanisms and embedding aggregation.

4 Experiment and Results

4.1 Experiment setting

In our experiment, we have implemented all models using the PyTorch framework, with the GNN models built using the PyTorch-Geometric package. For the dataset Politifact, We have set a unified graph embedding size of 128, a batch size of 128, learning rate of 0.001, and utilized the Adam optimizer. L2 regularization with a weight of 0.001 is applied to all models. For the dataset Gossipcop, We have set a unified graph embedding size of 128, a batch size of 128, learning rate of 0.0001, and utilized the Adam optimizer. L2 regularization with a weight of 0.001 is applied to all models.

For the datasets, we have employed a train-validation-test split of 70%-10%-20% across all models, ensuring consistent evaluation. This means that 70% of the data is used for training, 10% for validation, and 20% for final testing.

By following this experimental setup, we have obtained results that provide valuable insights and performance evaluations for our project.

4.2 Results and Analysis

According to the validation assessment metrics presented in Table 1, for the Politifact dataset, the GraphSAGE model demonstrates the highest accuracy, the lowest loss, and a high precision compared to other models. Similarly, for the Gossipcop dataset, the GraphSAGE model exhibits the highest accuracy, the highest precision, and a low loss. Based on these observations, it can be concluded from the table that the GraphSAGE model performs the best in terms of fake news detection on social networks.

Table 1. Validation Assessment Metrics

Dataset	Model	Accuracy	Precision	Loss
Politifact	Baseline	0.74	0.77	9.39
	GCN	0.79	0.84	**0.96**
	GAT	0.80	0.83	0.97
	SAGE	**0.81**	**0.86**	0.98
	MLP	0.76	0.80	1.07
Gossipcop	Baseline	0.86	0.80	5.11
	GCN	0.86	0.91	10.15
	GAT	0.92	0.90	6.61
	SAGE	0.92	0.89	6.38
	MLP	**0.95**	**0.95**	**4.49**

Figure 2 illustrates the comparative performance of different models on the Politifact dataset. The graph depicts the performance trends over various epochs. From the figure, it is evident that the GraphSAGE model consistently achieves the highest accuracy across different time periods. Notably, GraphSAGE outperforms the GAT model, which in turn surpasses the Graph-MLP model in terms of accuracy. Similarly, the Graph-MLP model demonstrates higher accuracy compared to the GCN model, which outperforms the Decision Tree model. These results indicate that GraphSAGE possesses superior classification capabilities for distinguishing between true and false news instances within the Politifact dataset. The model's effective information aggregation and utilization from neighboring nodes contribute to its accuracy surpassing other models.

Furthermore, the precision analysis reveals a similar trend. GraphSAGE exhibits higher precision than the GAT, Graph-MLP, GCN, and Decision Tree models. Precision emphasizes the model's ability to accurately classify instances as fake news, minimizing false positives. The superior precision of the GraphSAGE model demonstrates its strong capability to correctly identify fake news instances. Additionally, the GraphSAGE model exhibits the lowest loss compared to other models, indicating its effectiveness in minimizing classification errors.

In summary, the results from the performance analysis highlight the consistent superiority of the GraphSAGE model in terms of accuracy, precision, and loss when applied to the Politifact dataset. The model's capacity to aggregate features from neighboring nodes and capture complex relationships within the graph structure contributes to its exceptional performance in accurately detecting fake news instances.

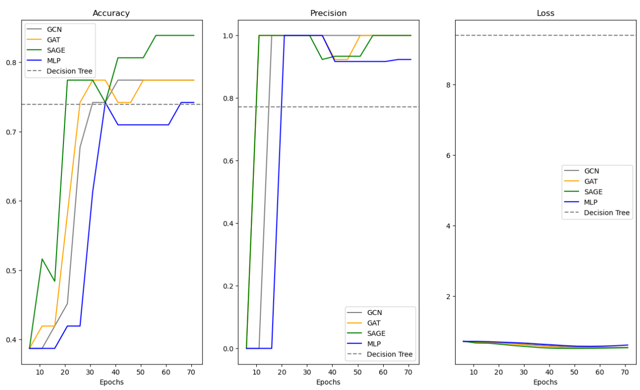

Figure 2. Performance comparison on Politifact

In Figure 3, the performance of different models on the Gossipcop dataset is compared, providing valuable insights into their effectiveness. GraphSAGE stands out as the top performer across multiple metrics, including accuracy, precision, and loss. The accuracy of GraphSAGE surpasses that of the Decision Tree model, which, in turn, outperforms the MLP model. Additionally, the MLP model exhibits better accuracy than the GCN model, while the accuracy of GCN surpasses that of GAT. Moreover, GraphSAGE achieves the highest precision among all the models, followed by MLP, GAT, and GCN. This indicates the model's superior ability to correctly classify instances as fake news, minimizing false positives. In terms of loss, GraphSAGE demonstrates the smallest value, followed by GAT, MLP, GCN and Decision Tree. The low loss value of GraphSAGE highlights its strong optimization capabilities and its ability to effectively reduce errors.Overall, the results underscore the superiority of GraphSAGE in accurately detecting fake news instances in the Gossipcop dataset. Its exceptional accuracy, precision, and minimized loss demonstrate its efficacy in capturing relevant features and relationships within the dataset. GraphSAGE outperforms other models, showcasing its potential for effectively identifying and distinguishing fake news instances in the Gossipcop dataset.

5 Conclusion

In our project, we compare the performance of a non-GNN model and four GNN models in automatically detecting fake

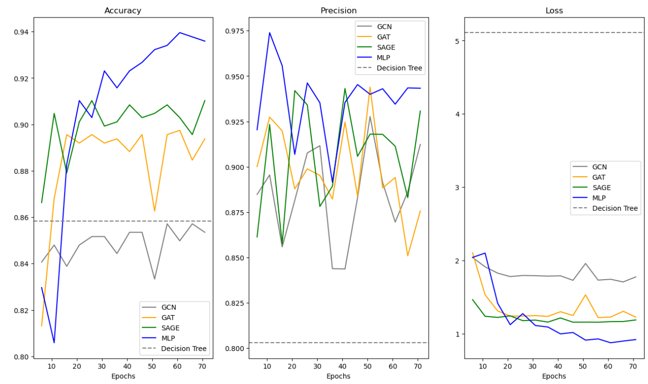

Figure 3. Performance comparison on Gossipcop

news on the Twitter social network. We utilize a non-GNN model: Decision Tree and four different GNN models: GCN, GAT, Graph-MLP, and Graph-SAGE. Each model is applied to the datasets containing both real and fake news propagation networks constructed from fact-check information obtained from Politifact and Gossipcop. Our objective is to achieve accurate and robust fake news detection by leveraging heterogeneous data encompassing user profiles and activities, social network structure, news dissemination patterns, and content. As the results show, Graph-SAGE has the best performance in the detection of fake news. In terms of future work, there are several promising directions to explore. Firstly, more advanced GNN architectures and variations could be investigated to further enhance the detection performance. Techniques like graph attention mechanisms, graph transformers, or graph reinforcement learning can be integrated to capture more nuanced relationships and improve model interpretability.

Secondly, incorporating additional data sources and features could augment the effectiveness of fake news detection. For example, sentiment analysis, user engagement patterns, or external knowledge graphs could provide valuable insights into the authenticity of the news.

Finally, considering the temporal dynamics of fake news dissemination and evolution is an important avenue for future research. Models that can capture the evolving nature of fake news and adapt over time could be developed to improve detection accuracy.

Overall, our work contributes novel approaches to fake news detection using GNN models and geometric deep learning techniques. By achieving high accuracy and demonstrating robust behavior, we strive to make a significant impact in combating the spread of misinformation on social media.

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A Experiment

A.1 Source code

Codes are available on *Google Drive*.

A.2 Hyper parameters

Table 2. Suggested Hyperparameters

Parameters	Epoch	Learning Rate	Batch Size
Politifact	70	0.001	128
Gossipcop	100	0.0001	128