**Fraud News Detection using GNN**

**Project report in partial fulfillment of the requirement for the award of the degree of**

**Bachelor of Technology**

**In**

**Computer Science and Technology**

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**CERTIFICATE**

This is to certify that the project titled **Fraud news Detection using GNN** submitted by **Yash Shankar Tiwary(University Roll No. 12019009022091), Subhimal Sahu (University Roll No. 12019009001190)**, **Sushant Kumar Suman ( University Roll No. 12019009022213), Malayban Ganguly(University Roll No. 12019009022051)**, **and Sanjeet Kumar(University Roll No. 12019009005039)** students of UNIVERSITY OF ENGINEERING & MANAGEMENT, KOLKATA, in partial fulfillment of requirement for the degree of Bachelor of Computer Science and Technology, is a bonafide work carried out by them under the supervision and guidance of Prof. Nilanjan Chatterjee & Prof. Arnab Chatterjee during 7th Semester of academic session of 2022 - 23. The content of this report has not been submitted to any other university or institute. I am glad to inform that the work is entirely original and its performance is found to be quite satisfactory.

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**TABLE OF CONTENTS**

**ABSTRACT........................................................................ 5**

**CHAPTER – 1: INTRODUCTION............................................... 6**

**CHAPTER – 2: LITERATURE SURVEY**

**2.1 A Literature Review of NLP Approaches to Fake News Detection and Their Applicability to Romanian Language News Analysis.....................................................................7**

**2.2 Fake News Detection via NLP is Vulnerable to Adversarial Attacks.....................................................................7**

**CHAPTER – 3: PROBLEM STATEMENT.....................................................................9**

**CHAPTER – 4: PROPOSED SOLUTION**

**4.1 Endogenous Preference Encoding.....................................................................10**

**4.2 Exogenous Context Extraction.....................................................................11**

**4.3 Information Fusion.....................................................................11**

**CHAPTER – 5 : EXPERIMENTAL SETUP AND RESULT ANALYSIS**

**5.1 Experimental Setup .....................................................................13**

**5.2 RQ1: Performance Evaluation.....................................................................13**

**CHAPTER – 6 : CONCLUSION .....................................................................15**

**BIBLIOGRAPHY ..........................................................................16**

**ABSTRACT**

**Disinformation and fake news have posed detrimental effects on individuals and society in recent years, attracting broad attention to fake news detection. The majority of existing fake news detection algorithms focus on mining news content and/or the surrounding exogenous context for discovering deceptive signals; while the endogenous preference of a user when he/she decides to spread a piece of fake news or not is ignored. The confirmation bias theory has indicated that a user is more likely to spread a piece of fake news when it confirms his/her existing beliefs/preferences. Users’ historical, social engagements such as posts provide rich information about users’ preferences toward news and have great potentials to advance fake news detection. However, the work on exploring user preference for fake news detection is somewhat limited. Therefore, in this paper, we study the novel problem of exploiting user preference for fake news detection. We propose a new framework, UPFD, which simultaneously captures various signals from user preferences by joint content and graph modeling. Experimental results on real-world datasets demonstrate the effectiveness of the proposed framework. We release our code and data as a benchmark for GNN-based fake news detection:**

**https://github.com/safe-graph/GNN-FakeNews.**

**CHAPTER – 1:**

**INTRODUCTION**

In recent years, social media has enabled the wide dissemination of disinformation and fake news– false or misleading information disguised in news articles to mislead consumers [27, 37]. Disinformation has resulted in deleterious effects and raised serious concerns, demanding novel approaches for fake news detection. Among various fake news detection techniques, fact-checking is the most straightforward approach; however, it is usually laborintensive to acquire evidence from domain experts [9]. In addition, computational approaches using feature engineering or deep learning have shown many promising results [3, 12, 23, 31]. For example, SAFE [36] and FakeBERT [11] used the TextCNN [35] and BERT [5, 28, 29] to encode the news textual information, respectively; GCNFN [17] and GNN-CL [8] leveraged the GCN [14] to encode the news propagation patterns on social media (e.g., news sharing cascading among social media accounts). However, these methods focus on modeling news content and its user exogenous context and ignore the user endogenous preferences. Sociological and psychological studies on journalism have theorized the correlation between user preferences and their online news consumption behaviors [24]. For example, Naíve Realism [22] indicates that consumers tend to believe that their perceptions of reality are the only accurate views, while others who disagree are regarded as uninformed, irrational, or biased; and Confirmation Bias theory [18] reveals that consumers prefer to receive information that confirms their existing views. For instance, a user believes the election fraud would probably share similar news with a supportive stance, and the news asserting election is stolen would attract users with similar beliefs [1]. To model user endogenous preferences, existing works have attempted to utilize historical posts as a proxy and have shown promising performance to detect sarcasm [13], hate speech [20], and fake news spreaders [21] on social media. In this paper, we consider the historical posts of social media users as their endogenous preference in news consumption. We propose an end-to-end fake news detection framework named User Preference-aware Fake Detection (UPFD) to model endogenous preference and exogenous context jointly (as shown in Figure 1). Specifically, UPFD consists of the following major components: (1) To model the user endogenous preference, we encode news content and user historical posts using various text representation learning approaches. (2) To obtain the user exogenous context, we build a tree-structured propagation graph for each news based on its sharing cascading on social media. The news post is regarded as the root node, and other nodes represent the users who shared the same news posts. (3) To integrate the endogenous and exogenous information, we take the vector representations of news and users as their node features and employ Graph Neural Networks (GNNs) [7, 17] to learn a joint user engagement embedding. The user engagement embedding and news textual embedding are used to train a neural classifier to detect fake news. Our major contributions can be summarized as follows:

• We study a novel problem of user preference-aware fake news detection on social media;

• We propose a principled way to exploit both endogenous preference and exogenous context jointly to detect fake news; and

• We conduct extensive experiments on real-world datasets to demonstrate the effectiveness of UPFD for detecting fake news.

**CHAPTER – 2:**

**LITERATURE SURVEY**

**2.1 A Literature Review of NLP Approaches to Fake News Detection and Their Applicability to Romanian Language News Analysis**

Against the changes the world is currently facing, an increasing number of daily tasks are moving online, including reading the news and being informed about relevant topics. The increase in the volume of information made available led, in turn, to fake news dissemination becoming a trending topic on the Internet. Recent events such as the COVID-19 pandemic have shown that fake news exerts a significant negative influence on societies by highlighting stories that do not necessarily report on facts.1 Moreover, fake news serves to misinform people and manipulate their opinions for several reasons.2 Research communities expressed concern about this flood of misinformation and introduced automated fake news identification solutions based on Natural Language Processing (NLP) techniques. In this study, we reference existing datasets and related work in the analysis of English fake news, discuss potential detection techniques for Romanian fake news, as well as establish future work plans for this research initiative. Literature Review In this section, we discuss frequently employed methods for compiling fake news corpora, alongside the machine learning solutions developed to analyze data and build classifiers capable of distinguishing between fake and true news.

**2.2 Fake News Detection via NLP is Vulnerable to Adversarial Attacks**

Fake news is an increasingly common feature of today’s political landscape. To help address this issue, researchers and media experts have proposed fake news detectors adopting natural language processing (NLP) to analyze word patterns and statistical correlations of news articles. While these detectors achieve impressive accuracy on existing examples of manipulated news, the analysis is typically quite shallow— roughly, models check whether news articles conform to standard norms and styles used by professional journalists. This leads to two drawbacks. First, these models can detect fake news only when they are under-written, for instance when the content is totally unrelated to the headline (so-called “clickbait”) or when the article includes words considered to be biased or inflammatory. While this criteria suffices to detect many existing examples of fake news, more sophisticated rumor disseminators can craft more subtle attacks, for instance taking a well-written real news article and tampering the article in a targeted way. By preserving the original subject matter and relating the content tightly to the headline without using biased phrases, an adversarial article can easily evade detection. To demonstrate this kind of attack, we evaluate a state-of-the-art model called Fakebox. We introduce three classes of attacks: fact distortion, subject-object exchange and cause confounding. We generate adversarial versions of real news from a dataset by McIntire (2018), and show that Fakebox achieves low accuracy when classifying these examples. At the same time, requirements posed by current detectors are often too strict. Real news which is under-written or talks about certain political and religious topics is likely to be mistakenly rejected, regardless of its accuracy. This is a particularly serious problem for open platforms, such as Twitter in the United States and TouTiao in China, where much of the news is contributed by users with diverse backgrounds. To prevent frustrating false positives, platforms are still heavily relying on manual work for separating fake news from real news. We provide experimental evidence for Fakebox’s potential of misclassifying real news. Taken together, our experiments highlight vulnerable aspects of fake news detection methods based purely on NLP. Without deeper semantic knowledge, such detectors are easily fooled by fact-tampering attacks and can suffer from a high rate of false positives, mistakenly classifying under-written yet real news which may not be written in a journalistic style. To address these problems, we argue that some form of fact-based knowledge must be adopted alongside NLP-based models. What this knowledge is remains to be seen, but we consider a straw man solution: a crowdsourced knowledge graph that aggregates information about news events and helps judge whether information extracted from news articles is reliable. The rest of our paper is organized as follows. In Section 2, we introduce three kinds of attacks targeting fake news detectors. Section 3 introduces the dataset from which we generate adversarial examples and our target model Fakebox. We evaluate Fakebox’s performance under attacks in Section 4. In Section 5, we discuss weaknesses of NLP-based detectors and propose augmenting detectors with knowledge information, such as a crowdsourced knowledge graph, as a step towards making fake news detection more robust

**CHAPTER – 3:**

**PROBLEM STATEMENT**

Among various fake news detection techniques, fact-checking is the most straightforward approach; however, it is usually laborintensive to acquire evidence from domain experts. In addition, computational approaches using feature engineering or deep learning have shown many promising results. For example, SAFE and FakeBERT used the TextCNN and BERT to encode the news textual information, respectively; GCNFN and GNN-CL leveraged the GCN to encode the news propagation patterns on social media (e.g., news sharing cascading among social media accounts). However, these methods focus on modeling news content and its user exogenous context and ignore the user endogenous preferences. Sociological and psychological studies on journalism have theorized the correlation between user preferences and their online news consumption behaviors . For example, Naíve Realism indicates that consumers tend to believe that their perceptions of reality are the only accurate views, while others who disagree are regarded as uninformed, irrational, or biased; and Confirmation Bias theory reveals that consumers prefer to receive information that confirms their existing views. For instance, a user believes the election fraud would probably share similar news with a supportive stance, and the news asserting election is stolen would attract users with similar beliefs . To model user endogenous preferences, existing works have attempted to utilize historical posts as a proxy and have shown promising performance to detect sarcasm , hate speech , and fake news spreaders on social media.

**CHAPTER – 4:**

**PROPOSED SOLUTION**

In this section, we present the details of the proposed framework for fake news detection named UPFD (User Preference-aware Fake News Detection). As shown in Figure 1, our framework has three major components. First, given a news piece, we crawl the historical posts of the users engaged in the news to learn user endogenous preference. We implicitly extract the preferences of engaged users by encoding historical posts using text representation learning techniques (e.g., word2vec [16], BERT [5]). The news textual data is encoded using the same approach. Second, to leverage user exogenous context, we build the news propagation graph according to its engagement information on social media platforms (e.g., retweets on Twitter). Third, we devise a hierarchical information fusion process to fuse the user endogenous preference and exogenous context. Specifically, we obtain the user engagement embedding using GNN as the graph encoder, where the news and user embeddings encoded by the text encoder are used as their corresponding node features in the news propagation graph. The final news embeddings are composed by the concatenation of user engagement embedding and news textual embedding. Next, we will introduce how we encode endogenous preference, extract the exogenous context, and fuse both information.

**4.1 Endogenous Preference Encoding**

It is non-trivial to explicitly model the endogenous preference of a user only using his/her social network information. Similar to [2, 13, 20] which model the users’ personality, sentiment and stance using their historical posts, we leverage the historical posts of a user to encode his/her preference implicitly. However, none of the previous fake news datasets contain such information. In this paper, we select the FakeNewsNet dataset [25] which contains news content and its social engagement information on Twitter. Then we use the Twitter Developer API [4] to crawl historical tweets of all accounts that retweeted the news in FakeNewsNet. To obtain rich historical information for user preference modeling, we crawl the recent two hundred tweets for each account, so as to near 20 million tweets being crawled in total. For inaccessible users whose accounts are suspended or deleted, we use randomly sampled tweets from accessible users engaging the same news as its corresponding historical posts. Because deleting the inaccessible users will break the intact news propagation cascading and results in a less effective exogenous context encoder. We also remove the special characters, e.g., “@” characters and URLs, before applying text representation learning methods. To encode the news textual information and user preferences, we employ two types of text representation learning approaches based on language pretraining. Instead of training on the local corpus, the word embeddings pretrained on a large corpus are supposed to encode more semantic similarities between different words and sentences. For pretrained word2vec vectors, we choose the 680k 300-dimensional vectors pretrained by spaCy [10]. We also employ pretrained BERT embeddings to encode the historical tweets and news content as a sequence [5] using bert-as-a-service [32]. Next, we elaborate the details of applying the above text representation learning models. spaCy includes pretrained vectors for 680k words, and we average the vectors of existing words in combined recent 200 tweets to get user preference representation. The news textual embedding is obtained similarly. For the BERT model, we use the cased BERT-Large model to encode the news and user information. The news content is encoded using BERT with maximum input sequence length (i.e., 512 tokens). Due to BERT’s input sequence length limitation, we could not use BERT to encode 200 tweets as one sequence, so we resort to encode each tweet separately and average them afterward to obtain a user’s preference representation. Generally, the tweet text is way shorter than the news text, we empirically set the max input sequence length of BERT as 16 tokens to accelerate the tweets encoding time.

**4.2 Exogenous Context Extraction**

Given a news piece on social media, the user exogenous context is composed of all users that engaged with the news. We utilize the retweet information of news pieces to build a news propagation graph. As the toy example of the news propagation graph shown in Figure 1, it is a tree-structured graph where the root node represents the news piece, and other nodes represent users who share the root news. In this paper, we investigate the fake news propagation on Twitter as a proof-of-concept use case. To build propagation networks in Twitter, we follow a similar strategy used in [8, 17, 26]. Specifically, we define a new piece as 𝑣1, and {𝑣2, . . . , 𝑣𝑛} as a list of users that retweeted 𝑣1 ordered by time. We define two following rules to determine the news propagation path: • For any account 𝑣𝑖 , if 𝑣𝑖 retweets the same news later than at least one following accounts in {𝑣1, . . . , 𝑣𝑛}, we estimate the news spreads from the account with the latest timestamp to account 𝑣𝑖 . Since the latest tweets are first presented in the timeline of the Twitter app, and thus have higher probabilities to be retweeted. • If account 𝑣𝑖 does not follow any accounts in the retweet sequences including the source account, we conservatively estimate the news spreads from the accounts with the most number of followers. Because tweets from accounts with more followers have a higher chance to be viewed/retweeted by other users according to the Twitter content distributing rules. Based on the above rules, we can build the news propagation graphs on Twitter. Note that this approach can be applied to other social media platforms like Facebook as well

**4.3 Information Fusion**

Previous works have demonstrated that fusing the user features with a news propagation graph could boost the fake news detection performance. Since the GNN can encode both node feature and graph structure in an end-to-end manner, it is a good fit for our task. Specifically, we propose a hierarchical information fusion approach. We first fuse the endogenous and exogenous information using the GNN. With a GNN, the news textual embedding and user preference embedding can be taken as node features. Given the news propagation graph, most GNNs aggregate the features of its adjacent nodes to learn the embedding of a node. Like previous GNN-based graph classification models [33, 34], we apply a readout function over all node embeddings to obtain the embedding of a news propagation graph. The readout function makes the mean pooling operation over all node embeddings to get the graph embedding (i.e., user engagement embedding). Second, since the news content usually contains more explicit signals regarding the news’ credibility [3]. We fuse the news textual embedding and user engagement embedding by concatenation as the ultimate news embedding to enrich the news embedding information. The fused news embedding is finally fed into a two-layer Multilayer Perceptron (MLP) with two output neurons representing the predicted probabilities for fake and real news. The model is trained using a binary cross-entropy loss function and is updated with SGD.

**CHAPTER – 5 :**

**EXPERIMENTAL SETUP AND RESULT ANALYSIS**

**5.1 Experimental Setup**

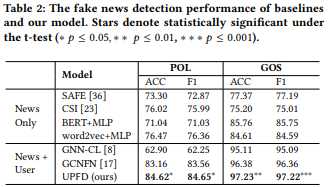
**5.1.1 Dataset**. Previous works have proposed a couple of fake news datasets with news pieces from different websites and their fact-checking information [19, 30]. To investigate both the user preference and propagation pattern of fake news, we choose the FakeNewsNet dataset [25]. It contains fake and real news information from two fact-checking websites and the related social engagement from Twitter. The dataset statistics are shown in Table 1.

**5.1.2 Baselines**. We compare the UPFD with fake news detection models that utilize different information. Many baseline methods leverage extra information like image information which is not included in the FakeNewsNet [25]. To ensure a fair comparison, we implement the baselines only with the parts for encoding the news content, user comments, and news propagation graph. CSI [23] employs an LSTM to encode the news content information to detect fake news. SAFE [36] uses the TextCNN [35] to encode the news textual information. GCNFN [17] is the first fake news detection framework to encode the news propagation graph using GCN [14]. It takes the profile information and comment textual embeddings as the user feature. GNN-CL [8] encodes the news propagation graph using DiffPool [34], a GNN designed for graph classification. The node features are extracted from user profile attributes on Twitter. The list of ten profile feature names can be found in [8, 15] We also add two baselines that apply MLP directly on news textual embeddings encoded by word2vec and BERT.

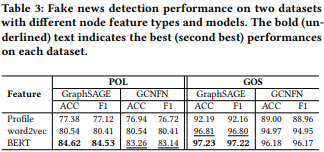
**5.1.3 Experimental Settings**. We implement all models using PyTorch, and all GNN models are implemented with PyTorch-Geometric package [6]. We use unified graph embedding size (128), batch size (128), optimizer (Adam), and L2 regularization weight (0.001), trainval-test split (20%-10%-70%) for all models. The experimental results are averaged over five different runnings. Other hyper-parameters for each model are reported with the code.

**5.2 RQ1: Performance Evaluation**

Table 2 shows the fake news detection performance of UPFD and six baselines. First, we can observe that UPFD has the best performance comparing to all baselines. UPFD outperforms the best baseline GCNFN around 1% on both datasets with statistical significance. The experimental results of UPFD and GCNFN demonstrate that the user comments (used by GCNFN) are also beneficial to fake news detection; and the user endogenous preference could impose additional information when user comment information is limited.



Second, since all baselines either encode the news content or user comments without considering the historical posts, we can tell that leveraging the historical posts as user endogenous preferences could improve the fake news detection performance. Note that the UPFD with the best performance on the both datasets uses BERT as the text encoder and GraphSAGE as the graph encoder.



**CHAPTER – 6 :**

**CONCLUSION**

In this paper, we argues that user endogenous news consumption preference plays a vital role in the fake news detection problem. To verify this argument, we collect the user historical posts to implicitly model the user endogenous preference and leverage the news propagation graph on social media as the exogenous social context of users. An end-to-end fake news detection framework named UPFD is proposed to fuse the endogenous and exogenous information and predict the news’ credibility on social media. Experimental results demonstrate the advantage of modeling the user endogenous preference

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