arXiv:2212.10778v2 [cs.SI] 4 Jan 2023

Mining User-aware Multi-relations for Fake News Detection in Large Scale Online Social Networks

Xing Su, Jian Yang, Jia Wu, Yuchen Zhang
School of Computing, Macquarie University
Sdyney, New South Wales, Australia
{xing.su2,yuchen.zhang3}@students.mq.edu.au
{jian.yang,jia.wu}@mq.edu.au

ABSTRACT

Users' involvement in creating and propagating news is a vital aspect of fake news detection in online social networks. Intuitively, credible users are more likely to share trustworthy news, while untrusted users have a higher probability of spreading untrustworthy news. In this paper, we construct a dual-layer graph (*i.e.*, the news layer and the user layer) to extract multi-relations of news and users in social networks to derive rich information for detecting fake news. Based on the dual-layer graph, we propose a fake news detection model `Us-DeFake`. It learns the propagation features of news in news layer and the interaction features of users in user layer. Through the inter-layer in graph, `Us-DeFake` fuses the user signals that contain credibility information into the news features, to provide distinctive user-aware embeddings of news for fake news detection. The training process conducts on multiple dual-layer subgraphs obtained by a graph sampler to scale `Us-DeFake` in large scale social networks. Extensive experiments on real-world datasets illustrate the superiority of `Us-DeFake` which outperforms all baselines, and the users' credibility signals learned by interaction relation can notably improve the performance of our model [1].

CCS CONCEPTS

• **Information systems** → **Social networks**; • **Computing methodologies** → **Artificial intelligence**.

KEYWORDS

Fake news detection; Multi-relations; Dual-layer graph; Large scale social networks

ACM Reference Format:
Xing Su, Jian Yang, Jia Wu, Yuchen Zhang. 2023. Mining User-aware Multi-relations for Fake News Detection in Large Scale Online Social Networks. In *Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining (WSDM '23), February 27–March 3, 2023, Singapore, Singapore.* ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/XXXXXXX.XXXXXXX

[1]Code is available at https://github.com/xingsumq/Us-DeFake

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
WSDM '23, February 27–March 3, 2023, Singapore, Singapore.
© 2023 Association for Computing Machinery.
ACM ISBN 978-1-4503-9407-9/23/02…$15.00
https://doi.org/10.1145/XXXXXXX.XXXXXXX

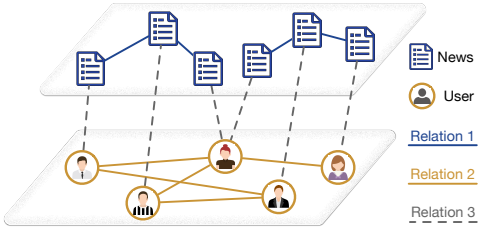


Figure 1: An illustrative example of multiple relations in an online social network for fake news detection. *Relation 1* represents the propagation relation of news, *Relation 2* represents the interaction relation of users, and *Relation 3* represents the posting relation between users and news.

1 INTRODUCTION

Nowadays people are accustomed to obtaining information on online social media, such as Twitter and Facebook. This convenient and quick access to information also brings a negative side, *i.e.*, the brazen spread of fake news. For instance, the spread of COVID-19 fake news that "consuming highly concentrated alcohol could disinfect the body and kill the virus" resulted in more than 5,800 hospitalizations [13]. Fake news has caused severe harm to people's life [34]. Algorithms and mechanisms for fake news detection in online social networks are in urgent need for providing trustworthy information to the public.

In order to detect fake news, the classic text-based methods [24] detect fake news from the perspective of textual content of news, and distinguish linguistic features between real and fake news by capturing different writing styles [8]. Recently, the development of graph neural networks (GNNs) [37] shows promising results in fake news detection. Their capability of handling structural information allows them to explore the logical structure in news sentences or the news property of propagation. For graph-based methods, researchers generally construct graphs of words or sentences to capture textual structure [39], or news propagation graphs to explore the structure of spreading [21]. Furthermore, some graph-based methods consider social contexts, *e.g.*, constructing heterogeneous networks of news and users [12], to provide more information for fake news detection [36].

Although the relation between news and users has been considered in some work, the interaction relation of users that causes fake news spread has not been fully explored [22]. As shown in Figure 1, there are essentially three relations in an online social network, *i.e.*, the propagation relation of news, the interaction relation of users, and the posting relation between users and news. These relations

are interdependent. The interaction patterns between users reflect the credibility of users. Reliable users are unlikely to spread fake news to their friends [18]. Therefore, user credibility reflected in user interaction can provide complementary information for fake news detection. In this space, existing methods still face the following challenges: (1) many methods only model part of relations for fake news detection and ignore the influence of user interaction on fake news spreading; (2) partial relations lead to inadequate information and mediocre performance in fake news detection; and (3) techniques for efficient detection in large scale social networks still require further development and improvement.

To address the aforementioned challenges, we propose a method to capture **U**ser-aware multi-relation**s** for **De**tecting **Fake** news (`Us-DeFake`). As the graph in Figure 1, `Us-DeFake` regards news and users as nodes, constructs an attributed dual-layer network with intra-layers (*i.e.*, news layer, user layer) and inter-layer (*i.e.*, posting layer). This dual-layer graph contains the propagation relation of news, the interaction relation of users, and the posting relations between users and news. To capture information from these multi-relations to assist in fake news detection, the proposed `Us-DeFake` is composed of four components. (1) Subgraph sampling module: it employs a random walk graph sampler to obtain multiple dual-layer subgraphs, to improve the model efficiency and detect fake news in large scale social networks; (2) News propagation module: it utilizes a sampling-based graph learning model, GraphSAINT [42], to learn propagation features of news; (3) User interaction module: it embeds credibility information into user features from user interaction relation; and (4) Fake news detection module: it classifies news into real or fake based on the final user-aware news embeddings. Specifically, the graph sampling module samples multiple independent dual-layer subgraphs, and the subsequent training process of news propagation module and user interaction module is performed in the subgraphs with bias elimination. While training these two modules, `Us-DeFake` fuses the credibility features of users into news features through the inter-layer in the dual graph to update the user-aware news embeddings for the fake news detection module. The main contributions of this work are as follows:

- **Integrality**: We propose a novel model `Us-DeFake` that mines integrated multi-relations in online social networks and learns rich user-aware information of news for accurate fake news detection.
- **Effectiveness**: We illustrate the efficacy of user credibility information in user interaction relation for fake news detection. After considering this relation, the performance of the proposed `Us-DeFake` on two real-world datasets both surpasses the seven state-of-the-art baselines.
- **Efficiency**: Graph sampling procedure in our method enhances its capability of efficient fake news detection in large scale social networks with massive news and users.

2 RELATED WORK

2.1 Text-based Methods

Text-based methods detect fake news through news content. They capture lexical and syntactic features or specific writing styles that are commonly present in fake news content. For example, Pérez-Rosas *et al.* [25] proposed a text-driven method to detect fake news via linguistic features of news. FakeBERT [14] detects fake news by integrating three parallel blocks of 1d-CNN into BERT [3].

To further improve the performance, researchers integrated side textual information into fake news detection. dEFEND [29] exploits news and the relevant comments to jointly capture the explainable sentences for discovering why the news is identified as fake or real. STANKER [26] takes comments as auxiliary features and adopts level-grained attention-masked BERT to distinguish the news. SRLF [41] is a stance-aware reinforcement learning framework that detects fake news by selecting labeled stance data for model training. Zhang *et al.* [43] considered emotional signals in news contents, and proposed dual emotion features to represent dual emotion and the relationship between them for fake news detection.

Albeit these text-based methods also use auxiliary features to detect fake news, they classify each piece of news independently, ignore the inherent spreading mechanism of news, and thus lack the propagation information for detecting fake news. Moreover, without user information, these methods lack the social context in fake news detection, which leads to limited results.

2.2 Graph-based Methods

With the development of graph neural networks (GNNs) [37] which have a strong capability to extract information from structural data, graph learning has attracted considerable attention and has been widely used in many fields, such as community detection in social networks [33]. This technique of mining structural information can be applied to fake news detection as well [7], as it naturally conforms to the property of news propagation. For example, Ma *et al.* [21] built a tree-structured graph of tweets and adopted two recursive neural networks [32] to represent the news propagation tree, which demonstrates high effectiveness for fake news detection at the early stage of propagation. Bi-GCN [1] is a bi-directional graph neural network model for rumor detection, it leverages GCN [16] on directed tweet graph to learn the patterns of news propagation and news dispersion. Moreover, GCN can also capture news-level structural information by constructing graphs for news pieces [4]. Thus, the graph-based method is capable of representing both structural and textural properties for fake news detection.

To provide accurate detection, some researchers incorporated external knowledge to assist in fake news detection. DETERRENT [2] is a graph attention network (GAT) [35] based model that uses additional information from medical knowledge graph to detect health domain misinformation. CompareNet [11] compares the topic-enriched news with the corresponding entities from the knowledge graph to learn semantically adequate features in fake news detection. KAN [6] learns both semantic-level and knowledge-level embeddings through a knowledge-aware attention network. However, it is difficult to obtain the knowledge graph of specific domains involved in some news. Learning entity representations in a large knowledge graph is a time-consuming task as well.

To consider the impact of social context, social engagements have been widely applied in fake news detection. Heterogeneous information networks (HINs) represent diverse connections [28]. Huang *et al.* [12] constructed a HIN by tweets, words and users, and proposed a meta-path based GAT framework to capture misleading news. GLAN [40] integrates heterogeneous information by

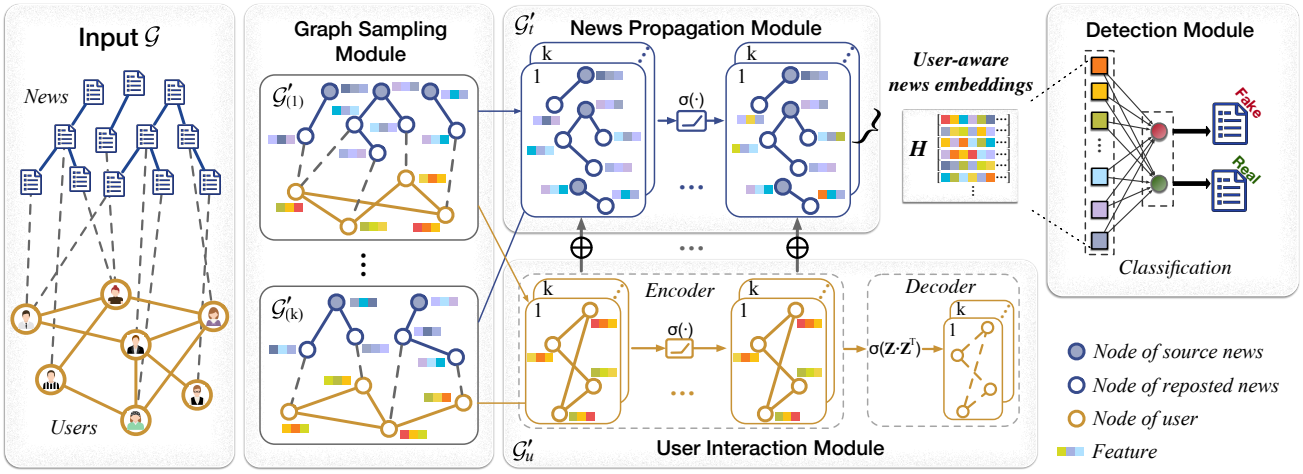


Figure 2: The framework of Us-DeFake for fake news detection. Us-DeFake takes news and users as input in a dual-layer graph, which contains a news propagation graph and a user interaction graph as its two intra-layers, and the posting relation between news and users as its inter-layer (dotted line). Firstly, the graph sampling module samples k dual-layer subgraphs $\mathcal{G}'$ with news layers and user layers. Secondly, for each subgraph, the news layer $\mathcal{G}'_t$ is fed into the news propagation module which adopts GCN to learn news embeddings H in a supervised setting. Meanwhile, the user layer $\mathcal{G}'_u$ is fed into the user interaction module that employs Autoencoder to learn user embeddings Z in an unsupervised setting. Us-DeFake fuses user embeddings to news embeddings through the element-wise addition operation $\oplus$ while training. The user-aware news embeddings H are obtained through the above process. Finally, the detection module regards fake news detection as a binary node classification task, and classifies the nodes of news as real or fake. Since the source news of the datasets in this work comes from fact-checking websites, the nodes of source news have no corresponding user relations.

an attention-based fusion way to preserve structural and semantic features for detecting fake news. HGAT [27] employs a hierarchical attention mechanism in a HIN of news, creators and subjects, and models fake news detection as node classification. However, how to select meaningful meta-paths or execute efficient network schema learning is still the limitation of many HIN-based methods.

Further, to detect cross-domain fake news in online social networks, Silva *et al.* [31] proposed a multimodal model. UPFD [5] utilizes the users' historical posts to summarize user preferences to advance fake news detection. Both methods regard fake news detection as graph classification, that are prone to losing global information. Since graph-level modeling of fake news detection takes each piece of news and its relevant posts or users as a graph, it lacks interaction between users or posts in the entire network.

Hence, our method Us-DeFake is proposed to solve the aforementioned problems under the setting of node classification. Not only does it consider textual information but also structural information in a social context. The multiple relations of news and users are employed to learn the distinctive user-aware representations of news. Compare with the existing methods, Us-DeFake is trained on a series of subgraphs to enhance its adaptability in large scale social networks.

3 DEFINITIONS AND PROBLEM STATEMENT

In this section, we first describe the relevant definitions of graph, and then formulate multiple relations for fake news detection.

DEFINITION 1. **Graph:** Let $G = (\mathcal{V}, \mathcal{E}, \mathcal{X})$ be an attributed graph, where $\mathcal{V}$ is the node set, $\mathcal{E}$ is the edge set, and $\mathcal{X}$ is a set of attributes of the corresponding nodes. $\boldsymbol{A}$ is the adjacent matrix of graph G.

DEFINITION 2. **Subgraph:** $G' = (\mathcal{V}', \mathcal{E}', \mathcal{X}')$, where $\mathcal{V}' \in \mathcal{V}$, $\mathcal{E}' \in \mathcal{E}$, respectively. $\mathcal{X}' \in \mathcal{X}$ is the attribute set of the corresponding nodes in $\mathcal{V}'$.

DEFINITION 3. **Dual-layer Graph:** Let a dual-layer graph be $\mathcal{G} = \{G_1, G_2, \mathcal{E}_{(1,2)}\}$, where G_1 represents the graph of layer 1 and G_2 represents the graph of layer 2. $\mathcal{E}_{(1,2)}$ is the set of inter edges between G_1 and G_2 which donates the relation across the two layers.

In this work, to model multi-relations in online social networks for fake news detection, we use a dual-layer graph to represent news, users, and the relations within or between them. A dual-layer graph with a news propagation graph and a user interaction graph can be defined as: $\mathcal{G} = (G_t, G_u, \mathcal{E}_{(t,u)})$, where $G_t = (\mathcal{V}_t, \mathcal{E}_t, \mathcal{X}_t)$ is the news propagation graph, $G_u = (\mathcal{V}_u, \mathcal{E}_u, \mathcal{X}_u)$ is the user interaction graph, and $\mathcal{E}_{(t,u)}$ represents the posting relation between news and users. Since the proposed method is based on graph sampling, a sampled dual-layer subgraph in our model is denoted as $\mathcal{G}' = (G'_t, G'_u, \mathcal{E}'_{(t,u)})$.

Fake news detection is a binary classification problem. Given a dual-layer graph $\mathcal{G}$, this work models fake news detection as node classification, and aims to detect fake news in the news propagation graph with high accuracy. Each node in the news propagation graph G_t is associated with the binary label $y \in \{0, 1\}$, where 0 denotes that the node is a piece of real news and 1 represents a piece of fake news. The fake news detection graph can be represented as $\mathcal{G} = (G_t, G_u, \mathcal{E}_{(t,u)}, \mathcal{Y})$, where $\mathcal{Y}$ is the label set of news.

4 METHODOLOGY

In this section, we present the proposed Us-DeFake in detail. The fake news detection process of Us-DeFake is conducted in four components: a graph sampling module, a news propagation module, a user interaction module, and a fake news detection module. As shown in Figure 2, the real-world social network data with multi-relations is first constructed as a dual-layer graph to be the input of our model. Then, the graph sampling module samples a series of dual-layer subgraphs for fake news detection in large scale social networks. Subsequently, the news layer and the user layer of each dual-layer subgraph are fed into the news propagation module and the user interaction module, respectively, to learn the news embeddings and user embeddings. To obtain the informative user-aware embeddings of news, user embeddings are fused into the corresponding news embeddings through inter-layer edges during training. Finally, the fake news detection module adopts such distinctive news embeddings to classify fake and real news.

4.1 Graph Sampling Module

The spread of fake news in online social networks often involves a large number of user engagements and intensive news forwarding. This work extracts these multiple relations into a large dual-layer graph with a news layer and a user layer for fake news detection. However, it is inefficient to directly learn graph embeddings in large graphs. Thus, we first employ graph sampling to scale our method to detect fake news in large scale social networks. Through a graph sampler, multiple independent dual-layer subgraphs can be sampled at a small scale to speed up the subsequent training. This graph sampling module can solve the neighbor explosion problem in large scale social networks caused by the explosion of one piece of news, or the excessive interaction of a user.

Algorithm 1: The random walk graph sampler of Us-DeFake

Input: $\mathcal{G} = (G_t, G_u, \mathcal{E}_{(t,u)})$: dual-layer training graph; r: the number of roots; h: the random walk depth.
Output: $\mathcal{G}' = (G'_t, G'_u, \mathcal{E}'_{(t,u)})$: sampled dual-layer graph.

$\mathcal{V}_t^{root}, \mathcal{V}_u^{root} \leftarrow$ Select r root nodes randomly from $\mathcal{V}_t, \mathcal{V}_u$, respectively.
$\mathcal{V}'_t \leftarrow \mathcal{V}_t^{root}, \mathcal{V}'_u \leftarrow \mathcal{V}_u^{root}$
for $i \in \mathcal{V}_t^{root}$ **do**
  $\{p\} \leftarrow$ Sample neighbor nodes of i in depth h.
  $\mathcal{V}'_t \leftarrow \mathcal{V}'_t \cup \{p\}$
end
for $j \in \mathcal{V}_u^{root}$ **do**
  $\{q\} \leftarrow$ Sample neighbor nodes of j in depth h.
  $\mathcal{V}'_u \leftarrow \mathcal{V}'_u \cup \{q\}$
end
$G'_t, G'_u \leftarrow$ Subgraph of $\mathcal{G}$ includes $\mathcal{V}'_t, \mathcal{V}'_u$, respectively.

Random walk as a stochastic process has been employed in many graph samplers [19, 23]. In this work, we employ a random walk-based graph sampler in [42] to obtain subgraphs for data training. To sample a subgraph, we select r root nodes uniformly and randomly on each intra-layer. Each walker walks on an intra-layer in h hops. We sample k subgraphs, where each subgraph is a dual-layer graph. The detailed graph sampling process based on a random walk is described in the Algorithm 1.

4.2 News Propagation Module

News in online social networks contains not only inherent textual information, but structural information due to sending, forwarding, and commenting on related posts. Thus, we take the textual features learned by RoBERTa [20] as attributes to construct an attributed graph of news propagation. To efficiently learn news embeddings in the attributed news propagation graph, the training process conducts on the news subgraphs obtained by the graph sampler. Here we use a sampling based GCN model, *i.e.*, GraphSAINT [42], instead of the vanilla one for scaling Us-DeFake in large social networks. Considering a node i in the ℓ-th embedding layer and a node v in the $(\ell-1)$-th embedding layer. If i is sampled (i.e., $i \in \mathcal{V}'_t$), the aggregated embedding of i can be calculated as:

$$\begin{aligned} \boldsymbol{h}_i^{(\ell)} &= \sum_{v \in \mathcal{V}'_t} \frac{\tilde{\boldsymbol{A}}_{i,v}}{\alpha_{v,i}} \left(\boldsymbol{W}^{(\ell-1)}\right)^T \boldsymbol{h}_v^{(\ell-1)} \mathbb{1}_{v|i} \\ &= \sum_{v \in \mathcal{V}'_t} \frac{\tilde{\boldsymbol{A}}_{i,v}}{\alpha_{v,i}} \tilde{\boldsymbol{h}}_v^{(\ell-1)} \mathbb{1}_{v|i}, \end{aligned} \tag{1}$$

where $\tilde{\boldsymbol{A}}$ is the normalized adjacency matrix, $\boldsymbol{W}$ is the weight matrix. $\boldsymbol{h}_i^{(0)} = \boldsymbol{x}_i$, and $\tilde{\boldsymbol{h}}_v^{(\ell-1)} = \left(\boldsymbol{W}^{(\ell-1)}\right)^T \boldsymbol{h}_v^{(\ell-1)}$. $\mathbb{1}_{v|i} \in \{0,1\}$ is the function to indicate whether the given i is in the news propagation subgraph. $\mathbb{1}_{v|i} = 0$ if $i \in \mathcal{V}'_t \wedge (v,i) \notin \mathcal{E}'_t$; $\mathbb{1}_{v|i} = 1$ if $i \in \mathcal{V}'_t \wedge (v,i) \in \mathcal{E}'_t$; $\mathbb{1}_{v|i}$ is not defined if $i \notin \mathcal{V}'_t$. $\alpha_{v,i} = \frac{p_{v,i}}{p_i}$ is an aggregator normalization, where $p_{v,i} = p_{i,v}$ is the probability of an edge $(v,i) \in \mathcal{E}'_t$ being sampled in a subgraph, and p_i is the probability of a node $i \in \mathcal{V}'_t$ being sampled. This constant can eliminate biases in minibatch estimation for subgraphs. Furthermore, the other constant for bias elimination among subgraphs is loss normalization λ, which is introduced in the loss function by

$$\mathcal{L}_i^t = \sum_{i \in G'_t} \frac{\mathcal{L}_{CE}}{\lambda_i}, \tag{2}$$

where $\lambda_i = |\mathcal{V}_t| \cdot p_i$, $\mathcal{L}_{CE}$ is the cross-entropy loss on node i in the output layer. Thus, the normalized loss function of node i in the news propagation graph is:

$$\mathcal{L}_i^t = \sum_{i \in G'_t} \frac{-y \log \hat{y} - (1-y)\log(1-\hat{y})}{\lambda_i}, \tag{3}$$

where $\hat{y}$ is the predicted value which indicates the probability of news being fake, $y \in \{0,1\}$ is the ground truth label.

4.3 User Interaction Module

The creation and propagation of news are user-initiated. Thus, considering only information of the news itself but ignoring user information can lead to a lack of crucial global information. In general, trustworthy users tend to spread reliable news, while untrustworthy users are prone to propagate fake news. Regarding user credibility, besides user attributes such as verification or the number of issued Tweets, another influencing factor is user topology which reflects the interaction between users. For instance, trusted

normal users commonly follow and share the news with each other, rather than untrusted zombies or virtual users. Therefore, to learn better news embeddings with distinguishing information, this work constructs a user interaction graph to capture user credibility signals, and integrates these signals into news embeddings to enhance their performance in fake news detection.

In this module, the user interaction graph is an attributed graph, in which the learning process is in an unsupervised setting. Hence, we utilize Autoencoder [10], consisting of an encoder and a decoder, to learn the user embeddings. Specifically, we adopt the sampling-based GCN as the encoder to encode the latent features of users, where the aggregation rule is calculated by Eq. (1) as well. To learn credibility information in user interaction from structural perspective, we employ a structural decoder where the learned latent user embeddings Z are decoded as input for the reconstruction of the original user interaction graph:

$$\hat{\boldsymbol{A}} = \text{sigmoid}\left(\boldsymbol{Z}\boldsymbol{Z}^T\right), \tag{4}$$

where $\hat{\boldsymbol{A}}$ is the reconstructed user interaction graph. The learning process is guided by the objective function $\mathcal{L} = \| \boldsymbol{A} - \hat{\boldsymbol{A}} \|^2$. Through the bias estimation for user interaction subgraphs, a user node j's normalized loss becomes

$$\mathcal{L}_j^u = \sum_{j \in G'_u} \frac{\| \boldsymbol{a}_j - \hat{\boldsymbol{a}}_j \|^2}{\lambda_j}, \tag{5}$$

where $\boldsymbol{a}_j \in \boldsymbol{A}$ and $\hat{\boldsymbol{a}}_j \in \hat{\boldsymbol{A}}$ are adjacent vector and reconstructed vector of user j, respectively. λ_j is the loss normalization of user j.

4.4 Fake News Detection Module

In order to learn the user-aware news embeddings with rich multi-relation information for fake news detection, Us-DeFake fuses user embeddings into news embeddings through the inter-layer of the dual-layer graph while training the news propagation module and the user interaction module, to keep finetuning the news embeddings. Suppose the user j published a piece of news i, the updated user-aware news embedding is calculated by

$$\boldsymbol{h}_i = \boldsymbol{h}_i \oplus \boldsymbol{z}_j, \tag{6}$$

where $\oplus$ denotes the element-wise addition operation, the news embedding vector h_i and the user embedding vector z_j require the same dimensions. The detailed training process of Us-DeFake is described in Algorithm 2. Finally, the learned user-aware news embeddings are fed to a softmax layer for fake news detection:

$$\hat{y} = \text{Softmax}\left(\boldsymbol{W}_f \boldsymbol{h}_i + \boldsymbol{b}_f\right), \tag{7}$$

where $\boldsymbol{W}_f$ and $\boldsymbol{b}_f$ are the parameter matrix and vector of a linear transformation. $\hat{y}$ is the predicted value of news i which indicates the probability of news being fake. The total loss function of Us-DeFake to minimize is as follows:

$$\mathcal{L} = \mathcal{L}^t + \mathcal{L}^u. \tag{8}$$

4.5 Time Complexity

In this work, the time complexity of the graph sampler is $O(|\mathcal{V}'_t| + |\mathcal{V}'_u|) < r \cdot h$. For the news propagation module, the time complexity is linear as $O(|\mathcal{E}'_t| d_t d_t^1 \cdots d_t^L)$, where d_t is the dimension of input data in a subgraph and the dimension of each GCN layer is $d_t^1 \cdots d_t^L$. In the user interaction module, the time complexity of Autoencoder is $O(|\mathcal{V}'_u| d_u d_u^1 \cdots d_u^L)$. Thus, the overall time complexity of Us-DeFake is $O(|\mathcal{V}'_t| + |\mathcal{V}'_u| + |\mathcal{E}'_t| d_t d_t^1 \cdots d_t^L + |\mathcal{V}'_u| d_u d_u^1 \cdots d_u^L)$.

Algorithm 2: The training process of Us-DeFake

Input: $\mathcal{G} = (G_t, G_u, \mathcal{E}_{(t,u)})$: dual-layer training graph; $\mathcal{Y}$: labels of nodes in G_t; r, h: parameters of graph sampling.
Output: User-aware embeddings of nodes in G_t.

```
// Initialization: Graph sampling G' = (G'_t, G'_u, E'_(t,u)) according to Algorithm 1; Calculate normalization coefficients α, λ for G'_t, G'_u, respectively.
for each epoch do
    for each minibatch do
        // GCN construction for G'_t = (V'_t, E'_t, X'_t):
        Obtain α–normalized h_i for news node i by Eq. (1);
        // Autoencoder construction for G'_u = (V'_u, E'_u, X'_t):
        Obtain α–normalized z_j for user node j by Eq. (4);
        Update h_i by relation E'_(t,u) as calculated in Eq. (6);
        Backward propagation via the λ-normalized loss L in Eq. (8).
    end
end
return h_i, ∀i ∈ G_t.
```

5 EXPERIMENTS

In this section, we present the experimental results to evaluate the performance of Us-DeFake. Specifically, we aim to investigate the following questions:

- **EQ1** Does Us-DeFake outperform all baseline methods in fake news detection?
- **EQ2** Does Us-DeFake benefit from multiple relations?
- **EQ3** Can user relation explain the results of fake news detection?
- **EQ4** Is Us-DeFake sensitive to the parameters?
- **EQ5** How efficiently does Us-DeFake run on large scale online social networks?

5.1 Experimental Setup

5.1.1 Datasets. To investigate the impact of both news propagation pattern and user interaction pattern on fake news detection, we choose the FakeNewsNet datasets [30] that contain source news fact-checked by PolitiFact[2] or GossipCop[3], relevant tweets, and social engagement of users. For user engagement, we crawled user attributes and user-following relations. The labels are "real" and "fake". Table 1 summarizes the dataset statistics, where the relation "T-T" represents the number of edges in the news propagation graph, "U-U" stands for the edges in the relevant user interaction graph, and "U-T" represents the relation that users post tweets.

[2]https://www.politifact.com/
[3]https://www.gossipcop.com/

Table 1: The Dataset Statistics.

Statistics	Politifact	Gossipcop
Source News	395 (R: 180 / F: 215)	4047 (R: 2444 / F: 1603)
Tweets and Retweets	366,374	378,289
Users	195,389	128,912
Relations	T-T: 370,025 U-T: 328,608 U-U: 16,193,727	T-T: 386,649 U-T: 328,020 U-U: 2,724,896

5.1.2 Baselines. We compare our approach with seven representative baseline algorithms:

- **TextCNN** [15] builds convolutional neural networks (CNNs) on *word2vec* of news contents for sentence classification, it utilizes multiple convolution filters to capture different granularity of text features.
- **HAN** [38] is a hierarchical attention network for document classification. It encodes a two-level attention mechanism for news contents, *i.e.*, sentence-level and word-level attention.
- **BERT** [3] is a pre-trained language model that uses a bidirectional encoder and self-attention heads. For fake news detection, BERT can represent semantic signals in the news.
- **ALBERT** [17] is a lite BERT. It adds a pretraining objective while reducing the number of parameters in BERT for efficient computation on large scale data.
- **TextGCN** [39] extends the semi-supervised model of graph neural networks (GCN [16]) for text classification. In fake news detection, GCN can consider structural information by constructing a word graph of each piece of news.
- **GraphSage** [9] is a classic inductive graph representation method on large networks. In this work, we utilize text embeddings as node attributes and construct a graph of news propagation for detecting fake news.
- **UPFD** [5] is a user preference-aware fake news detection method. It combines users' endogenous preferences by encoding historical posts, and the task of fake news detection is modeled as graph classification.

5.1.3 Experimental Settings and Implementation. For all models, the train-validation-test split of two datasets is 70%-10%-20%. The experimental results are averaged over 5–fold cross validation. We implement our method with Pytorch. All the experiments are conducted by Python 3.6, 1 NVIDIA Volta GPU, and 395G DRAM.

In the experiment of `Us-DeFake`, we set the number of roots to 3000 in the graph sampler module, and the random walk depth to 2, since the news propagation graph is composed of tree structures with a depth of 3. To construct a news propagation graph, ReBERTa [20] is used to learn 768-dimensional embeddings as node attributes. The embedding size in both the news propagation module and the user interaction module is set to 512, and the number of graph convolution layers is set to 2. For model optimization, we adopt the Adam optimizer and set the learning rate to 0.01 for both datasets. We set the number of epoch to 30. For a fair comparison with baselines that do not consider news propagation, we only evaluate the classification results of source news for all methods.

5.1.4 Metrics. To evaluate the performance of approaches in this work, we adopt four commonly used metrics for evaluation, *i.e.*, Accuracy (ACC), Precision (Pre), Recall (Rec), and F1 score (F1).

5.2 Performance Evaluation (EQ1)

To evaluate the overall performance of our method, we compare the proposed `Us-DeFake` with seven popular baselines in two datasets, and measure them by four evaluation metrics. In order to extend our method, we also use GAT [35] in the convolutional layer as a variant of `Us-DeFake`. Table 2 shows the overall experimental results, where "`Us-DeFake-C`" represents our method using GCN and "`Us-DeFake-A`" represents our method using GAT. Bold marks optimal results, underline indicates suboptimal results.

As reflected in Table 2, both our method and its variant achieve optimal or suboptimal results for all metrics on two datasets, which indicates that mining multiple relations in social networks is conducive to fake news detection. Such results reveal that the user-aware news embeddings of `Us-DeFake` indeed learn sufficient information rather than other baseline methods. The reason why `Us-DeFake-A` performs better than `Us-DeFake-C` on Politifact is that users interact more frequently in this dataset. This is illustrated in Table 1, where the number of U-U relations in Politifact is more than in Gossipcop. In `Us-DeFake-A`, the capability of the attention mechanism to capture more information from vital neighbors provides distinctive user signals to user-aware news embeddings, which in return improves the results of fake news detection.

We divide the baselines into two groups, as shown in Table 2, the first four are text-based methods, while the remainders are graph-based methods. The graph-based approaches integrally perform better than the text-based ones, because the graph models consider structural information as well as textual information. Both the inter-sentence or inter-word structure of news and the structure of news propagation can benefit the detection of fake news. ALBERT, as an improved algorithm based on BERT, is expected to perform better. However, as a lite model, parameter reduction affects ALBERT's performance on fake news detection.

Among the graph-based approaches, GraphSage shows a stable performance that surpasses all the text-based methods, because we built the news propagation graph for it. The graph learns the spread property of news. The performance of UPFD comes close to our proposed model. UPFD adapts user information to enhance fake news detection as well, but it utilizes users' historical information, while we consider the users' interaction relationship. However, the gap between UPFD's performance in the two datasets is large, and the performance is not as stable as `Us-DeFake`'s. To sum up, `Us-DeFake` achieves stable and accurate results in fake news detection, and is superior to all baseline methods.

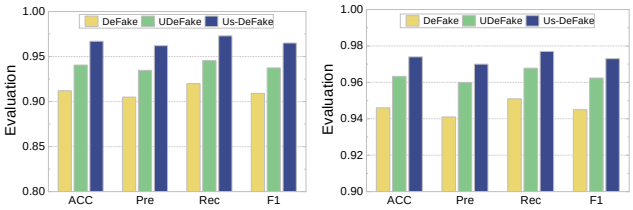
5.3 Ablation Study (EQ2)

To demonstrate the effectiveness of multi-relations in `Us-DeFake` for fake news detection, we conduct ablation experiments to examine the effectiveness of the news propagation relation, the user interaction relation, and the posting relation between users and news. Figure 3 shows the experimental results of the ablation study,

Table 2: Overall performance for fake news detection of different methods.

Methods	Politifact				Gossipcop			
	Acc	Pre	Rec	F1	Acc	Pre	Rec	F1
TextCNN	0.509 ± 0.066	0.518 ± 0.062	0.516 ± 0.062	0.506 ± 0.065	0.442 ± 0.015	0.489 ± 0.012	0.491 ± 0.009	0.432 ± 0.014
HAN	0.491 ± 0.026	0.508 ± 0.03	0.507 ± 0.027	0.484 ± 0.027	0.472 ± 0.027	0.513 ± 0.017	0.512 ± 0.015	0.466 ± 0.03
BERT	0.772 ± 0.042	0.823 ± 0.028	0.783 ± 0.035	0.801 ± 0.026	0.768 ± 0.024	0.767 ± 0.022	0.756 ± 0.021	0.758 ± 0.022
ALBERT	0.585 ± 0.029	0.603 ± 0.166	0.551 ± 0.035	0.502 ± 0.069	0.609 ± 0.024	0.619 ± 0.166	0.539 ± 0.029	0.505 ± 0.075
TextGCN	0.739 ± 0.026	0.742 ± 0.017	0.738 ± 0.025	0.733 ± 0.022	0.75 ± 0.024	0.649 ± 0.122	0.623 ± 0.106	0.627 ± 0.107
GraphSage	0.914 ± 0.025	0.906 ± 0.025	0.927 ± 0.02	0.911 ± 0.025	0.941 ± 0.017	0.934 ± 0.018	0.95 ± 0.014	0.939 ± 0.017
UPFD	0.829 ± 0.006	0.881 ± 0.007	0.767 ± 0.014	0.827 ± 0.006	0.95 ± 0.023	0.947 ± 0.031	0.954 ± 0.016	0.95 ± 0.023
Us-DeFake-A	0.979 **±** 0.011	0.975 **±** 0.013	0.981 **±** 0.011	0.978 **±** 0.012	0.954 ± 0.011	0.951 ± 0.016	0.964 ± 0.009	0.955 ± 0.014
Us-DeFake-C	0.967 ± 0.03	0.962 ± 0.033	0.973 ± 0.024	0.965 ± 0.029	0.974 **±** 0.013	0.97 **±** 0.015	0.977 **±** 0.012	0.973 **±** 0.014

where "DeFake" indicates that the new propagation module is solely used without user-relevant relations. "UDeFake" is the model with the news propagation module and the user interaction module, but it fuses final user embeddings into news embeddings after separate training. "Us-DeFake" integrates user embeddings into news embeddings while training to continuously enhance the distinctiveness of news embeddings by considering the posting relation.



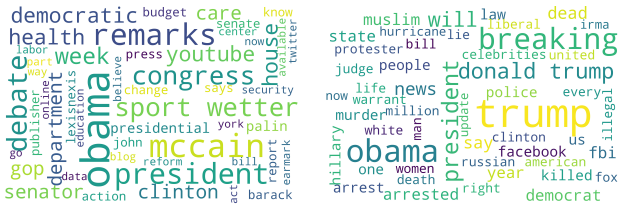
(a) Politifact (b) Gossipcop

Figure 3: Ablation study.

All results in DeFake are greater than 0.9 in both datasets, which indicates that the propagation embeddings with textual features learned by the news propagation module can provide useful information for fake news detection. In UDeFake, after integrating the user interaction module with the news propagation module, all results increase significantly in both datasets. This phenomenon illustrates that considering user interaction relation enriches the information of user-aware news embeddings. The performance of Us-DeFake is further improved, with values of all evaluation metrics above 0.95. This is because fusing the user embeddings into the news embeddings through the posting relation while training can keep finetuning the news embeddings. By capturing three multi-relations, Us-DeFake obtains more enhanced, discriminative, and informative embeddings for fake news detection.

5.4 Case Study (EQ3)

To explore the correlation between news authenticity and user credibility, we conduct a case study on the Politifact dataset about political news. We generate word clouds for real news and fake news, respectively. As shown in Figure 4, the high-frequency words that appear in real news and fake news are different. This confirms the rationality of the news propagation module, which learns the distinguishing news features of real news and fake news in a news propagation graph.



(a) Real News (b) Fake News

Figure 4: Word clouds of news in the Politifact dataset.

Further, to reveal the correlation between news and users, we randomly choose attributes of four relevant users for analysis. The main attributes of these users are shown in Table 3, where User1 and User2 published real news, User3 and User4 published fake news. The columns of "Friends" (*i.e.*, following) and "Followers" represent structural information in the user interaction graph as well. According to Table 3, User1 is a verified public account with lots of followers, so it has a strong influence and is reliable in news spreading. User2 is supposed to be an active normal user with a close number of friends and followers. "Listed" indicates the number of public lists of which this user is a member. Thus, User2 is also trustworthy, because a normal user is not likely to intentionally spread fake news to his or her friends.

Table 3: Part of user attributes of four randomly-selected users for a case study.

User	Friends	Followers	Status	Listed	Verified
User1	870	51,693,630	463,743	213,104	✓
User2	6775	7579	138197	608	×
User3	2388	210	71540	12	×
User4	94	0	327	0	×

User3 and User4 have a low ranking of trust, due to the disproportionate number of friends and followers, or a large amount of

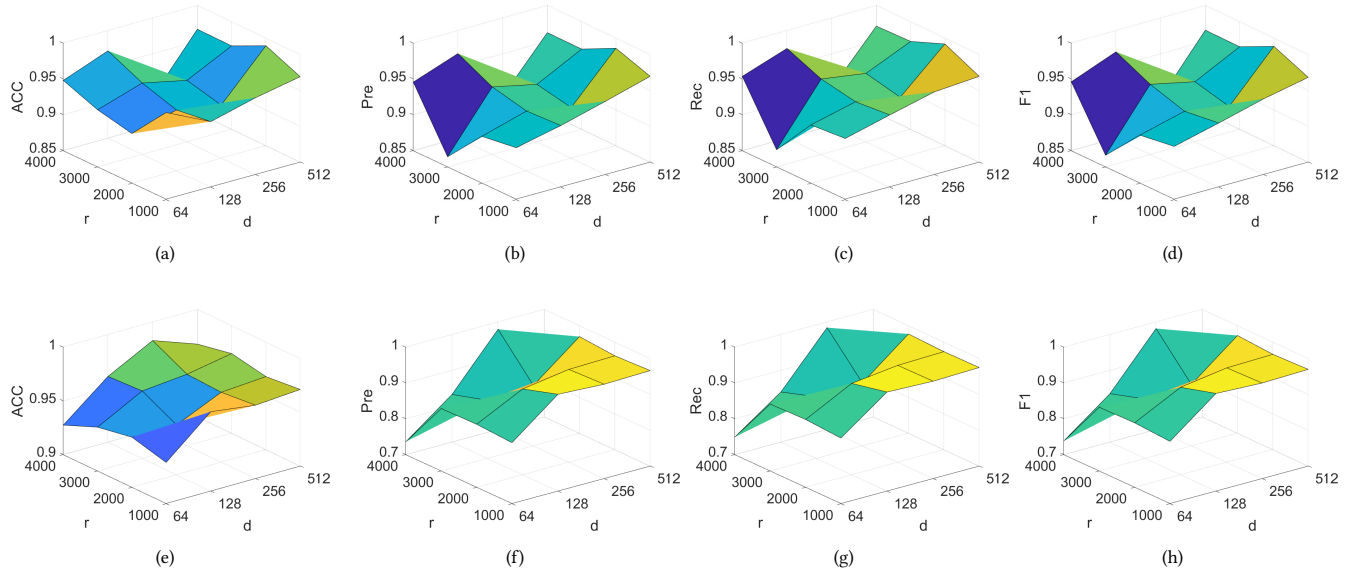


Figure 5: Parameter analysis of the proposed Us-DeFake. (a)–(d) on Politifact dataset, (e)–(h) on Gossipcop dataset.

"Status" with rarely "Listed". These phenomena confirm that news published by reliable users is usually trustworthy, while fake news is generally spread by unreliable users. It is reasonable to employ a user interaction module to assist fake news detection in our method. User reliability can explain why the news is detected as real or fake.

5.5 Parameter Analysis (EQ4)

We also investigated the sensitivity of Us-DeFake to the parameters in regard to the number of roots r when sampling subgraphs and different embedding sizes d in the news propagation module and the user interaction module. Figure 5 shows ACC, Pre, Rec, and F1 results for datasets of Politifact and Gossipcop. The results demonstrate that the number of roots in the graph sampler does not affect results, but the results are unstable when the embedding dimension is set to 64. In general, our method maintains acceptable results in most parameter combinations steadily.

5.6 Time Efficiency (EQ5)

To evaluate Us-DeFake's runtime performance in large scale social networks, we recorded its training time in each epoch. Since the input sizes of the same datasets vary in each method (*e.g.*, the user interaction graph in Us-DeFake is not considered by other baselines), it is unfair to compare the runtime with each other. Figure 6 shows Us-DeFake's average training time of one epoch in the datasets with the 5-fold split. To further speed up the training time and degrade the adverse impact of inveracious interaction between users, we ignore edges between two users whose Jaccard similarity is less than 0.1, so that our model can restore actual user relations and run in less time. The runtime in Figure 6 illustrates that Us-DeFake performs efficiently on both datasets with more than half a million nodes, but the density of the subgraphs obtained by sampling causes fluctuations in runtime.

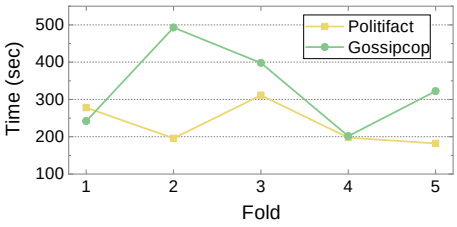


Figure 6: Runtime of Us-DeFake.

6 CONCLUSION

In this work, we propose a user-aware model Us-DeFake to incorporate multi-relations between news and users for fake news detection. We uncover that the interaction relation between users reflects user credibility, and such credibility has a positive correlation with news authenticity. Based on a dual-layer graph construction for multi-relation exhibition, we first adopt a graph sampler to scale fake news detection in large scale social networks. Further, we design the modules of news propagation and user interaction to integrate distinctive user credibility signals into news embeddings for detecting fake news. The extensive experiments on large scale real-world datasets demonstrate the superiority of Us-DeFake, which notably outperforms seven popular baseline methods. In the future, we plan to address the problem of training time instability caused by the graph sampler in Us-DeFake, and explore early detection of fake news in propagation.

ACKNOWLEDGMENTS

This work was supported by the Australian Research Council (ARC) Projects Nos. DE200100964, LP210301259, and DP230100899.

REFERENCES

[1] Tian Bian, Xi Xiao, Tingyang Xu, Peilin Zhao, Wenbing Huang, Yu Rong, and Junzhou Huang. 2020. Rumor Detection on Social Media with Bi-Directional Graph Convolutional Networks. In *AAAI*. 549–556.

[2] Limeng Cui, Haeseung Seo, Maryam Tabar, Fenglong Ma, Suhang Wang, and Dongwon Lee. 2020. DETERRENT: Knowledge Guided Graph Attention Network for Detecting Healthcare Misinformation. In *KDD*. 492–502.

[3] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *NAACL-HLT*. 4171–4186.

[4] Kaize Ding, Jianling Wang, Jundong Li, Dingcheng Li, and Huan Liu. 2020. Be More with Less: Hypergraph Attention Networks for Inductive Text Classification. In *EMNLP*. 4927–4936.

[5] Yingtong Dou, Kai Shu, Congying Xia, Philip S Yu, and Lichao Sun. 2021. User Preference-aware Fake News Detection. In *SIGIR*. 2051–2055.

[6] Yaqian Dun, Kefei Tu, Chen Chen, Chunyan Hou, and Xiaojie Yuan. 2021. KAN: Knowledge-aware Attention Network for Fake News Detection. In *AAAI*. 81–89.

[7] Karish Grover, S M Phaneendra Angara, Md Shad Akhtar, and Tanmoy Chakraborty. 2022. Public Wisdom Matters! Discourse-Aware Hyperbolic Fourier Co-Attention for Social Text Classification. In *NIPS*.

[8] Bin Guo, Yasan Ding, Lina Yao, Yunji Liang, and Zhiwen Yu. 2020. The Future of False Information Detection on Social Media: New Perspectives and Trends. *CSUR* 53, 4 (2020), 1–36.

[9] Will Hamilton, Zhitao Ying, and Jure Leskovec. 2017. Inductive Representation Learning on Large Graphs. In *NIPS*.

[10] Geoffrey E Hinton and Ruslan R Salakhutdinov. 2006. Reducing the Dimensionality of Data with Neural Networks. *Science* 313 (2006), 504–507.

[11] Linmei Hu, Tianchi Yang, Luhao Zhang, Wanjun Zhong, Duyu Tang, Chuan Shi, Nan Duan, and Ming Zhou. 2021. Compare to the Knowledge: Graph Neural Fake News Detection with External Knowledge. In *ACL/IJCNLP*. 754–763.

[12] Qi Huang, Junshuai Yu, Jia Wu, and Bin Wang. 2020. Heterogeneous Graph Attention Networks for Early Detection of Rumors on Twitter. In *IJCNN*. 1–8.

[13] Md Saiful Islam, Tonmoy Sarkar, Sazzad Hossain Khan, Abu-Hena Mostofa Kamal, SM Murshid Hasan, Alamgir Kabir, Dalia Yeasmin, Mohammad Ariful Islam, Kamal Ibne Amin Chowdhury, Kazi Selim Anwar, et al. 2020. COVID-19–Related Infodemic and its Impact on Public Health: A Global Social Media Analysis. *Am. J. Trop. Med.* 103, 4 (2020), 1621.

[14] Rohit Kumar Kaliyar, Anurag Goswami, and Pratik Narang. 2021. FakeBERT: Fake News Detection in Social Media with a BERT-based Deep Learning Approach. *Multimed. Tools. Appl.* 80, 8 (2021), 11765–11788.

[15] Yoon Kim. 2014. Convolutional Neural Networks for Sentence Classification. In *EMNLP*. 1746–1751.

[16] Thomas N. Kipf and Max Welling. 2017. Semi-Supervised Classification with Graph Convolutional Networks. In *ICLR*.

[17] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2020. ALBERT: A Lite BERT for Self-supervised Learning of Language Representations. In *ICLR*.

[18] Peiyao Li, Weiliang Zhao, Jian Yang, Quan Z Sheng, and Jia Wu. 2020. Let's CoRank: Trust of Users and Tweets on Social Networks. *World Wide Web* 23, 5 (2020), 2877–2901.

[19] Rong-Hua Li, Jeffrey Xu Yu, Lu Qin, Rui Mao, and Tan Jin. 2015. On Random Walk based Graph Sampling. In *ICDE*. 927–938.

[20] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A Robustly Optimized BERT Pretraining Approach. *arXiv preprint arXiv:1907.11692* (2019).

[21] Jing Ma, Wei Gao, and Kam-Fai Wong. 2018. Rumor Detection on Twitter with Tree-structured Recursive Neural Networks. In *ACL*. 1980–1989.

[22] Van-Hoang Nguyen, Kazunari Sugiyama, Preslav Nakov, and Min-Yen Kan. 2020. FANG: Leveraging Social Context for Fake News Detection using Graph Representation. In *CIKM*. 1165–1174.

[23] Santosh Pandey, Lingda Li, Adolfy Hoisie, Xiaoye S Li, and Hang Liu. 2020. C-SAW: A Framework for Graph Sampling and Random Walk on GPUs. In *Supercomputing*. 1–15.

[24] Kellin Pelrine, Jacob Danovitch, and Reihaneh Rabbany. 2021. The Surprising Performance of Simple Baselines for Misinformation Detection. In *WWW*. 3432–3441.

[25] Verónica Pérez-Rosas, Bennett Kleinberg, Alexandra Lefevre, and Rada Mihalcea. 2018. Automatic Detection of Fake News. In *COLING*. 3391–3401.

[26] Dongning Rao, Xin Miao, Zhihua Jiang, and Ran Li. 2021. STANKER: Stacking Network based on Level-grained Attention-masked BERT for Rumor Detection on Social Media. In *EMNLP*. 3347–3363.

[27] Yuxiang Ren and Jiawei Zhang. 2021. Fake News Detection on News-Oriented Heterogeneous Information Networks through Hierarchical Graph Attention. In *IJCNN*. 1–8.

[28] Chuan Shi, Yitong Li, Jiawei Zhang, Yizhou Sun, and S Yu Philip. 2016. A Survey of Heterogeneous Information Network Analysis. *IEEE TKDE* 29, 1 (2016), 17–37.

[29] Kai Shu, Limeng Cui, Suhang Wang, Dongwon Lee, and Huan Liu. 2019. dEFEND: Explainable Fake News Detection. In *KDD*. 395–405.

[30] Kai Shu, Deepak Mahudeswaran, Suhang Wang, Dongwon Lee, and Huan Liu. 2020. FakeNewsNet: A Data Repository with News Content, Social Context, and Spatiotemporal Information for Studying Fake News on Social Media. *Big data* 8, 3 (2020), 171–188.

[31] Amila Silva, Ling Luo, Shanika Karunasekera, and Christopher Leckie. 2021. Embracing Domain Differences in Fake News: Cross-domain Fake News Detection using Multi-modal Data. In *AAAI*. 557–565.

[32] Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, and Christopher Potts. 2013. Recursive Deep Models for Semantic Compositionality over a Sentiment Treebank. In *EMNLP*. 1631–1642.

[33] Xing Su, Shan Xue, Fanzhen Liu, Jia Wu, Jian Yang, Chuan Zhou, Wenbin Hu, Cecile Paris, Surya Nepal, Di Jin, et al. 2022. A Comprehensive Survey on Community Detection with Deep Learning. *IEEE TNNLS* (2022).

[34] Sander van Der Linden, Jon Roozenbeek, and Josh Compton. 2020. Inoculating Against Fake News about COVID-19. *Front. Psychol.* 11 (2020), 566790.

[35] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, and Yoshua Bengio. 2018. Graph Attention Networks. In *ICLR*.

[36] Lingwei Wei, Dou Hu, Wei Zhou, Zhaojuan Yue, and Songlin Hu. 2021. Towards Propagation Uncertainty: Edge-enhanced Bayesian Graph Convolutional Networks for Rumor Detection. In *ACL*. 3845–3854.

[37] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and S Yu Philip. 2020. A Comprehensive Survey on Graph Neural Networks. *IEEE TNNLS* 32, 1 (2020), 4–24.

[38] Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alex Smola, and Eduard Hovy. 2016. Hierarchical Attention Networks for Document Classification. In *NAACL-HLT*. 1480–1489.

[39] Liang Yao, Chengsheng Mao, and Yuan Luo. 2019. Graph Convolutional Networks for Text Classification. In *AAAI*. 7370–7377.

[40] Chunyuan Yuan, Qianwen Ma, Wei Zhou, Jizhong Han, and Songlin Hu. 2019. Jointly Embedding the Local and Global Relations of Heterogeneous Graph for Rumor Detection. In *ICDM*. 796–805.

[41] Chunyuan Yuan, Wanhui Qian, Qianwen Ma, Wei Zhou, and Songlin Hu. 2021. SRLF: A Stance-aware Reinforcement Learning Framework for Content-based Rumor Detection on Social Media. *IJCNN* (2021), 1–8.

[42] Hanqing Zeng, Hongkuan Zhou, Ajitesh Srivastava, Rajgopal Kannan, and Viktor Prasanna. 2020. GraphSAINT: Graph Sampling Based Inductive Learning Method. In *ICLR*.

[43] Xueyao Zhang, Juan Cao, Xirong Li, Qiang Sheng, Lei Zhong, and Kai Shu. 2021. Mining Dual Emotion for Fake News Detection. In *WWW*. 3465–3476.