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TWITTER FAKE NEWS DETECTION USING GRAPH NEURAL NETWORKS

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Abstract**—***This article is devoted to the intellectual processing of text information for the purpose of detecting rail news. To solve the given task, the use of deep graph neural networks is proposed. Fake news detection based on user preferences is augmented with deeper graph neural network topologies, including Hierarchical Graph Pooling with Structure Learning, to improve the graph convolution operation and capture richer contextual relationships in news graphs. The paper presents the possibilities of extending the framework of fake news detection based on user preferences using deep graph neural networks to improve fake news recognition. Evaluation on the FakeNewsNet dataset (a subset of Gossipcop) using the PyTorch Geometric and PyTorch Lightning frameworks demonstrates that the developed deep graph neural network model achieves 94% accuracy in fake news classification. The results show that deeper graph neural networks with integrated text and graph features offer promising options for reliable and accurate fake news detection, paving the way for improved information quality in social networks and beyond.*

Index Terms—Fake news detection; graph neural networks; Twitter; binary classification; graph pooling.

I. INTRODUCTION

Social networks have become an integral part of modern life. There are approximately 4.9 billion social media users worldwide, about 60% of the world's population. It is predicted that by 2027, the number of people using social media will grow by half a billion to reach 5.4 billion users. Eighty-five percent of mobile phone owners are social media users. This is a direct consequence of the development of smartphones, affordable high-speed Internet and, in fact, social networks such as Twitter and TikTok.

The high penetration of social media facilitates the rapid transfer of information between people and communities. About half of the users of online platforms use them to keep in touch with friends or to find entertainment content. Despite this, the online space has become a platform for the dissemination of various opinions and news. Recent studies [1] show that twenty percent of adults in the United States receive political news through social media. This situation is not unique to the states; examples can be found in the Ukrainian political sphere: some MPs use TikTok to broadcast live from the Verkhovna Rada of Ukraine, and various figures create their own pages or channels to support their own narratives.

Social media also has a similar impact on society as a whole, not just the political part of it. People of all views now have the opportunity to create online communities to share their opinions or encourage people to take action. Positive examples of such communities include Ukrainian NGOs and charitable foundations: 'Superhumans', which rehabilitates soldiers who have lost limbs, and 'Come Back Alive', which is the largest military charity in Ukraine. The communities built on social media around the above-mentioned initiatives work for a common goal and systemic change for the better in our society.

Unfortunately, in addition to the many positive examples of the impact of social media, there are also negative ones. Social platforms also facilitate the rapid spread of fake news and rumors. Fake news is news articles that are intentionally false [2]. Maliciously created fake news can have a significant negative impact on society, particularly during major events such as national elections or pandemics.

During the global COVID-19 pandemic, various conspiracy theories, rumors, and harmful disinformation gained millions of views on social media, which had negative consequences for people's health. Under the influence of unverified information, people were less willing to follow medical standards and recommendations (wearing masks, seeking medical attention in a timely manner, etc.). Another example of the destructive use of social media is the large-scale disinformation campaigns conducted by the russian federation to sow panic in Ukrainian society, which have been conducted since the beginning of the full-scale invasion of Ukraine.

The problem of detecting fake news is complex, as it requires large human and time resources to process and verify information. In order to combat fake news and reduce its harmful impact, researchers are developing various methods based on artificial intelligence, including graphs.

II. PROBLEM STATEMENT

Although automated news retrieval from the Internet is quite easy nowadays, fake news detection methods still do not reach the required levels of accuracy and the desired level of generality. The reasons for this are the high diversity of news and the large number of factors that need to be taken into account during the detection process.

On the other hand, the development of artificial intelligence has provided tools for the development of automated fake news classification and detection systems that can process more information than experts.

In general, the task of detecting fake news is to determine the veracity of a news item based on certain information. Such information can include both textual and visual data of the news itself and related contextual information: similar news, comments on social media, data about users involved in the distribution process. It can be formalized as follows: for each set of posts $A=\{a_m\}$ $m=1,...,M$ there is a corresponding label $y_m \in \{0,1\}$, denoting its truthfulness. Thus, we have a set of pairs $(a_1, y_1)...(a_m, y_m)$, which are independent random copies $(A,Y) \in Ax\{0,1\}$. The goal of classification is to build a rule for predicting Y based on the data A. Such a rule is the function $h: X \rightarrow \{0, 1\}$, called a classifier.

The purpose of developing fake news detection algorithms is to create a classifier that can reliably determine the veracity of a news publication. The following metrics are used to assess the quality of such an algorithm:

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN},$$

$$precision = \frac{TP}{TP+FP},$$

$$recall = \frac{TP}{TP+FN},$$

$$F1 = \frac{2TP}{2TP+FP+FN},$$

where TP is true positive; TN is true negative; FP is false positive; FN is false negative. This set of metrics is standard for classification tasks and can accurately show the quality of the developed model.

III. RELATED WORKS

A. *Graph neural networks*

There are various studies devoted to building models for recognizing and classifying fake news. An important place among them is occupied by machine learning methods: classical and deep.

More classical machine and deep learning methods such as SVM, logistic regression, recurrent neural networks, and convolutional neural networks usually rely on the content of the news and conduct textual analysis for classification. The use of contextual information is less common in combination with the above methods, because taking into account complex non-Euclidean relationships is not a trivial task. It can be solved with the help of graph modeling techniques. For example, the BiGCN method [3] collects all the comments under a publication and builds a news distribution graph based on them.

The last decade has seen a leap in the development and practical application of geometric deep learning methods. Many concepts of this field were described in the paper Geometric Deep Learning: Grids, Groups, Graphs, Geodesics, and Gauges [4]. One of the most important achievements of the researchers was the definition of a graph neural network. In the broadest sense, a graph neural network is an artificial neural network created to process input data in the form of a graph. In general, graph neural networks are a certain generalization of the usual convolutional networks. In the context of computer vision, a convolutional layer applied to an image can be represented as a graph layer applied to a graph whose vertices are pixels and whose relationships (edges) exist only between neighbors.

A key element in graph neural networks is the transmission of messages between neighbors. This process iteratively changes the representation of the graph by exchanging information between connected vertices. Throughout the development of the field of graph neural networks, many variants of network architectures have been proposed, each of which has its own characteristics [5], [6], [7], [8], [9], [10].

The Graph Convolutional Network (GCN), which was proposed in 2016 in [5], is one of the most well-known graph neural network architectures. Its main advantage is the simplicity of the algorithm and implementation. Its essence lies in the aggregation of data between neighboring nodes by averaging. This algorithm is very similar to the classical convolution used for images, with the difference that instead of pixels, the nodes are graphs. The disadvantages of GCN are computational complexity, as the process of iteration and aggregation can take a long time, especially when working with large graphs, and an excessive level of smoothing of the original features, which leads to a deterioration in the quality of classification.

Graph Attention Network (GAT) [6] is an architecture similar to GCN, but still has its own feature, namely an integrated attention mechanism [11]. This allows the network to learn the importance of edges between nodes and adjust the weights used during aggregation accordingly. This approach is especially often used in language-related tasks. GAT solves the problem of excessive smoothing, but also increases the computational complexity compared to GCN.

An important step in the development of graph neural networks was the invention of the GraphSAGE method [7]. This architecture overcame the problem of using deep networks on large graphs. Instead of performing iterations on all nodes of the graph. GraphSAGE selects a certain subset whose values are aggregated. Thus, the network can learn the representation of even graphs containing hundreds of thousands of nodes much faster. GraphSAGE has found application in all types of graph problems and has outperformed the classic GCN and GAT.

An interesting architecture is the Graph Isomorphism Network (GIN) [8]. This graph network is specially designed to solve the problem of graph classification. The key novelty of this approach is that it allows distinguishing between graphs that are not isomorphic to each other. Simply put, graph isomorphism is an equivalent relation for "similar" structures. This distinction is based primarily on the structure of the graph, not on the features contained in the nodes. GIN has found application in the field of bioinformatics, as graph distinction and prediction of their properties is a necessary part of modern biological research.

In general, there is a lot of research focusing on building new methods for convolutional operations on graphs. Although such methods give excellent results on graph-related problems, there are other tools that can be used in graph networks.

B. Hierarchical Graph Pooling with Structure Learning

Modern convolutional neural network architectures cannot do without pooling layers. Their purpose is to reduce the dimensionality of features. This allows to increase the computational efficiency of the model by reducing the number of its parameters, and also forces the model to learn higher-level features. Two common fusion methods are mean fusion and maximum fusion, which respectively combine image pixels or elements of a representation vector. Similar methods have been adapted for graphs and graph neural networks [12].

Since graphs have a more complex structure than images, pooling methods become more complex accordingly. Hierarchical Graph Pooling with Structure Learning (HGP-SL) [13] is a pooling operator that combines graph pooling and structure learning methods. The method adaptively selects a subset of graph nodes that will move to the next layers. In general, if the information in a node can be represented by its neighbors, then such a node can be removed. This process can lead to the disconnection of connected graph nodes, which will worsen the completeness. To preserve the structural information of the graph, a mechanism for learning the graph structure is introduced. The topology of the network including HPG-SL proposed in [13] is shown in Fig. 1.

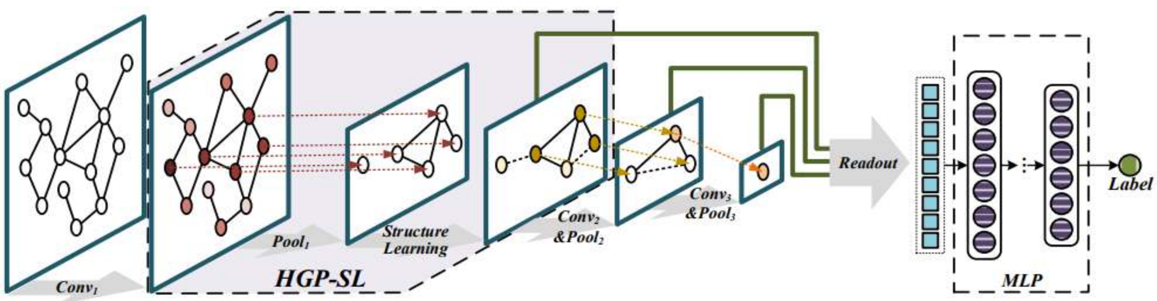

Fig. 1. Graph model with HGP-SL

C. Fake news detection using graph neural networks

Here are three main conceptual approaches to solving the problem of fake news detection using graph neural networks.

1) Knowledge-based methods evaluate the veracity of a news story based on a constructed knowledge graph. Such a graph is mainly built on the basis of data (textual and visual) obtained from the publication itself. In methods that involve external knowledge, this graph is also supplemented with facts from some external repository.

2) Propagation-based methods assess the veracity of a news item based on a graph representing the process of its spreading through social networks. This graph contains entities that symbolize the interaction between the user and the news: reposts, comments.

3) Methods based on a heterogeneous social context involve a wider range of available information. The graph constructed by such methods can cover several news items and the set of relevant users who interacted with them. Due to the large number of entities that fill the graph, there are many approaches to its construction.

In general, the process of detecting fake news using graph networks can be divided into the following steps.

- *Gathering the necessary data.* At this stage, information is collected from social media. There are many technologies and approaches for Web Scraping, such as using the BeautifulSoup library for the Python programming language. The collected data is also processed: a vector representation is obtained from the textual data, which can be used to train neural networks. Graph construction. Creating relationships between the collected pieces of information is a very important part of using graph algorithms. While in the case of distribution-based methods, the connections are obvious (activity in a social network), for knowledge-based methods, other approaches need to be used. The PMI method [14] is one of them, it builds a fully connected graph and assigns weights to the edges corresponding to the similarity of the nodes.
- *Graph encoding*. The next step is to encode the constructed graph using a deep graph network. GCN [5] is a very common approach, and the other methods mentioned [6], [7], [8] are also frequently used.
- *Classification*. The last step in this process is to actually get a prediction of the truthfulness of the news based on the coded graph.

D. Using Semantics to Understand Fake News

An example of a knowledge-based approach is the method described in a 2019 publication [26]. It solves the problem of not just recognizing fake news, but classifying it.

The described method distinguishes between the following types of publications: satire, propaganda, deception, and verified articles. Deceptive articles aim to convince the reader of the truthfulness of a certain far-fetched story, while propaganda articles aim to convince the reader of the correctness of a particular political or social agenda. Satirical posts, in turn, deliberately expose real people, organizations or events to ridicule [15]. As noted in [16], previous approaches rely on a certain set of artificial features to distinguish between news. The researchers contrasted this approach with their observations of the patterns of interaction between sentences in different types of news articles and proposed a model based on graph neural networks to model these interactions.

The developed model has the following structure: the input graph is built on the basis of the news, where the nodes are sentences and the edges are built on the basis of their semantic similarity; LSTM is used to obtain sentence embedding; two types of graph architectures (GCN [5], GAT [6]) are used in the experiments to obtain graph embedding.

The topology of such a network is shown in Fig. 2. This classifier outperformed the classical convolutional and recurrent networks in the task of multi-class fake news classification. This result showed the prospects of using graph networks to solve the problem of fake news detection. The next step in the development of approaches to solving the problem of fake news recognition was the involvement of contextual information related to the news.

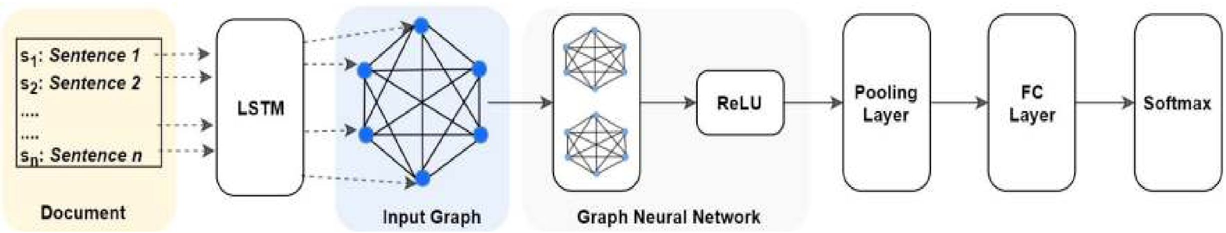

Fig. 2. GCN-Text classifier architecture

E. User Preference-aware Fake News Detection

An approach that fits more organically into the concept of using graph neural networks is methods based on the spread of fake news.

Obtaining information about the spread of news on social media is a painstaking task that requires a proper approach to downloading data from the network. It is also worth noting that when solving tasks related to the social context, the relevance of the data used plays an important role, as it is impossible to develop a model based on 2005 data that will be able to adequately perform the tasks in 2023.

FakeNewsNet [17] has become a classic dataset for solving the problem of detecting fake news based on social media data. The original paper containing all the details of the dataset was published in 2018. The dataset itself includes textual information about the news and social context in the form of the news distribution network on Twitter. Information about the truthfulness or falsity of news was taken from two online resources dedicated to verifying news on various topics: Politifact and Gossipcop. This dataset became the basis for the development of the User Preference Aware Fake News Detection (UPFD) [18].

This approach uses the FakeNewsNet data, supplementing it with historical information of users who participated in the spread of the news. The 200 most recent posts in the Twitter profile are used as historical data. To process textual information about users, representation learning methods are used: Word2Vec [19] and BERT [20]. The same models are used to encode the news text itself. After text processing, a graph with a tree structure is built. The root node of the graph is the news itself, and the leaves are users. The data stored in the nodes are the corresponding representations of the original textual information. A graph neural network is used to obtain a vector representation of the graph. The last step before the direct news classification is to combine the features of users and news articles. In this way, information received from users is more explicitly involved, which improves classification results. The entire framework is shown in Fig. 3.

The described approach has shown good results and effectiveness of combining features of historical user preferences and textual information from the news. At the same time, only single-layer graph networks GCN, GAT and GraphSAGE were used in the experiments. This leaves room for improvement by using more advanced graph approaches.

IV. PROPOSED APPROACH

A. Proposed model

In this paper, the architecture of the UPFD framework is used as a basis for the fake news recognition method.

The data processing process remains identical to the original: based on the FakeNewsNet dataset, graphs of news distribution in social networks are built, and the BERT model is used to obtain vector representations of the text. 200 historical tweets of users are encoded separately and then weighted. The resulting feature vectors have a dimension of 768.

We used deep topologies augmented with HGP-SL layers to perform the fusion operation. The topology proposed in [13] and shown in Fig. 1 will be used as a basis. GCNs will be used as the graph convolution operation. This model will take an appropriate place in the UPFD architecture shown in Fig. 3. Also, as part of the experiments, it was decided to discard the process of combining the representations obtained from the graph with the news representation. The neural classifier at the end of the model has a fairly simple topology of several linear layers and Dropout layers for regularization. The topology of the classifier is shown in Fig. 4.

B. Implementation details

As mentioned earlier, we use the FakeNewsNet dataset.

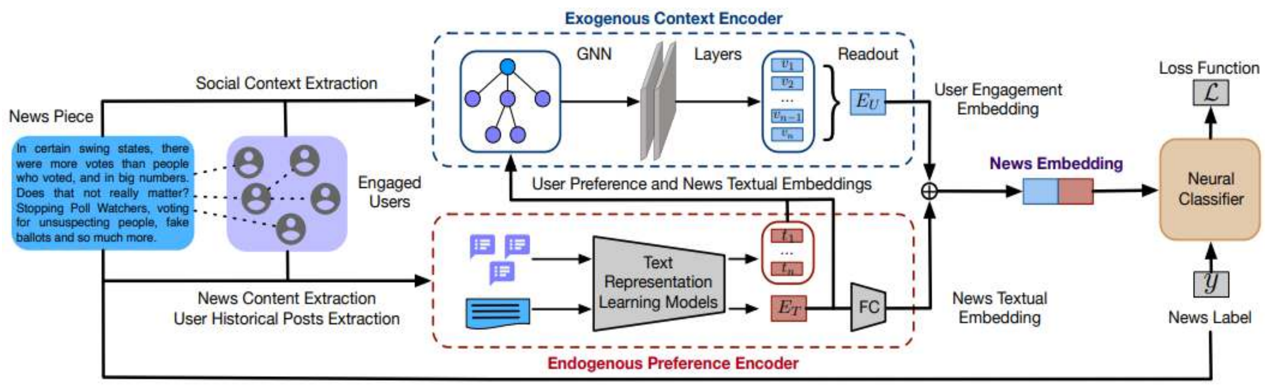

Fig. 3. Demonstration of UPFD framework

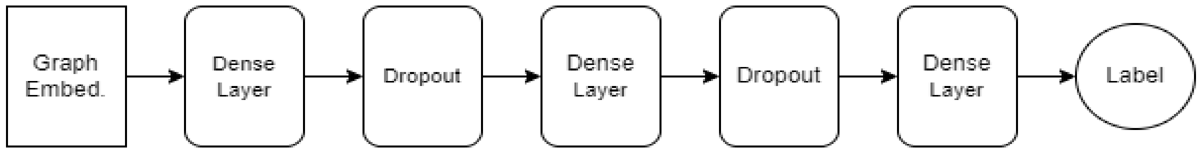

Fig. 4. Classifier head of the model

The part based on Gossipcop was included in the experiments. Table I shows the statistics of the data.

TABLE I. DATASET STATISTICS

Graphs overall	Fake Graphs	Nodes	Edges	Avg. edges per graph
5464	2732	314.262	308.798	58

Figure 5 shows an example of a graph taken from the selected data set.

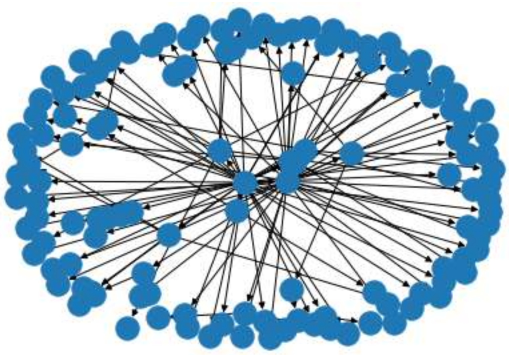

Fig. 5. Example of a data graph

As you can see, the graph does have a tree structure, and the root node is clearly visible. It is also worth paying attention to the presence of second – and sometimes third-order links. Such links appear when users repost posts that contain links to the original news.

The dataset was split into training, validation, and test samples in the proportion of 20% – 10% – 70%. The models were implemented on the basis of the Pytorch Geometric framework, which contains tools for developing your own deep graph learning modules and the ability to use already implemented popular methods. Training was performed using the Adam method with a training speed of 1e-3. L2 regularization with a parameter of 0.001 was also used.

C. *Experimental results*

The model was trained for a maximum of 300 epochs. An early stopping strategy was used if there was no improvement in the results on the validation set over the last 30 epochs.

Figures 6–8 show the results of the model during training and validation.

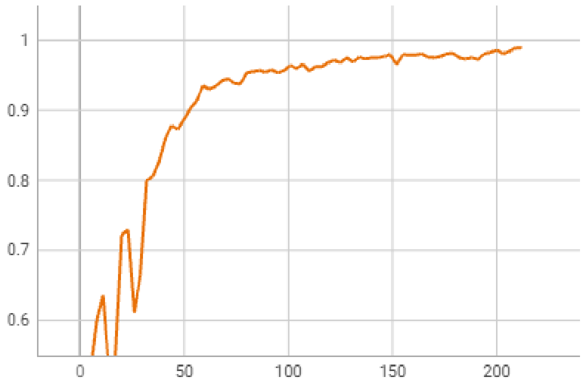

Fig. 6. Train accuracy

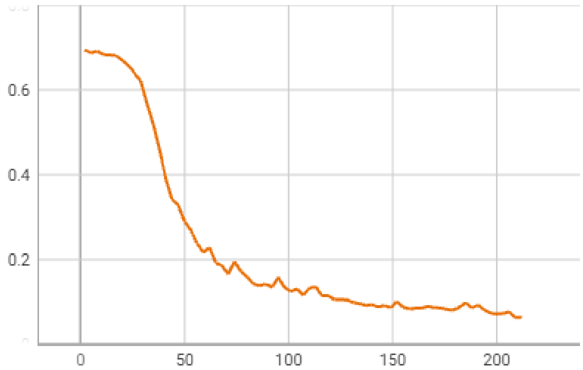

Fig. 7. Train loss

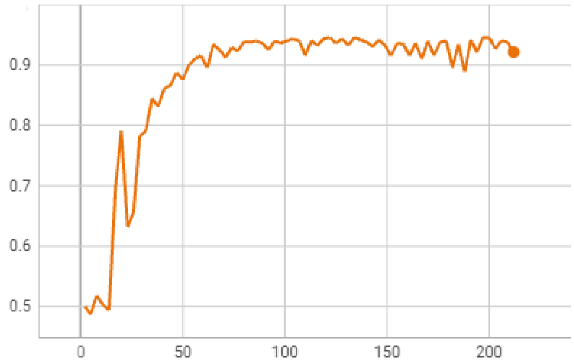

Fig. 8. Validation accuracy

It can be seen that the model showed good results. No overfitting was detected, as evidenced by the validation values. Next, we checked the results on the test sample. Table II shows the results of the model on the test sample.

TABLE II. MODEL RESULTS ON TEST SET

Method	Acc	F1	Prec	Rec
UPFD + HGP-SL	0.94	0.94	0.93	0.95

V. CONCLUSION

In this paper, we extended the UPFD framework with a developed deep model that utilizes HGP-SL layers for the fusion operation. The developed model has shown good generalization results as evidenced by the high metrics performance on the test set.

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В. М. Синєглазов, К. І. Билим. Розпізнавання фейкових новин у Twitter за допомогою графових нейронних мереж

Цю статтю присвячено інтелектуальному обробленню текстової інформації з метою виявлення рейкових новин. Для розв’язання поставленого завдання запропоновано використання глибоких графових нейронних мереж. Виявлення фейкових новин з урахуванням уподобань користувачів доповнено більш глибокими топологіями графових нейронних мереж, що включають в себе Hierarchical Graph Pooling with Structure Learning, для покращення операції згортки графа і захоплення більш багатих контекстних зв'язків у графах новин. У статті представлено можливості розширення фреймворку виявлення фейкових новин з урахуванням уподобань користувачів за допомогою глибоких графових нейронних мереж для покращення розпізнавання фейкових новин. Оцінка на наборі даних FakeNewsNet (підмножина Gossipcop) з використанням фреймворків PyTorch Geometric і PyTorch Lightning демонструє, що розроблена глибока модель графової нейронної мережі досягає 94% точності в класифікації фейкових новин. Результати показують, що більш глибокі графові нейронні мережі з інтегрованими текстовими та графовими функціями пропонують перспективні варіанти для надійного і точного виявлення фейкових новин, прокладаючи шлях до підвищення якості інформації в соціальних мережах та за їх межами.

Ключові слова: розпізнавання фейкових новин; графові нейронні мережі; Twitter; бінарна класифікація; об’єднання графів.

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