Journal of Edge Computing, **2023**, 2(1), pp. 24-36 https://doi.org/10.55056/jec.592

Approach to the fake news detection using the graph neural networks

Ihor A. Pilkevych, *Dmytro L.* Fedorchuk, *Mykola P.* Romanchuk and *Olena M.* Naumchak

[1]*Korolyov Zhytomyr Military Institute, 22 Myru Ave., Zhytomyr, 10004, Ukraine*

Abstract. The experience of Russia's war against Ukraine demonstrates the relevance and necessity of understanding the problems of constant disinformation and propaganda sharing, and the implementation of destructive negative psychological influence. In the article the issue of dissemination in online media informational messages containing negative psychological influence was researched. Ways of improving the system of monitoring online media using the graph neural networks are considered especialy due to automatically fake news detection. The methods of automated fake news detection, based on graph neural networks, were reviewed. The purpose of the article is the analysis of existing approaches that allow identifying destructive signs of influence in text data. It has been found that the best way to automate the process of content analysis is to use the latest machine learning methods. It was determined and substantiated that graph neural networks are the most modern, comfortable, reliable and effective solution for the specified task. An approach to automating this procedure based on graph neural networks has been designed and analyzed, which will allow timely and efficient detection and analysis of fake news in the information space of our country. The main tasks in the course of information space monitoring that can be accomplished with the help of GNNs at the different levels (nodes, edges, graphs) were considered. Most popular and efficient models (Graph Convolution Networks, Graph Attention Network and GraphSAGE) were described and tested. During the research, the process of detecting fake news was simulated. The obtained results showed that the described models of graph neural networks can provide good results in solving the tasks of timely detection and response to threats posed by fake news spread by Russia.

Keywords: graph neural networks, psychological influences, fake news, knowledge graph, information messages, online media, information war

1. Introduction

There is more than one definition of the war waged by Russia against Ukraine, in particular: "hybrid war", "new generation war", "subversive war", "information war". Each of these concepts focuses on the use of non-military means in modern warfare. The importance of the information sphere of confrontation in modern wars has grown significantly in recent years. Information

igor.pilkevich@meta.ua (I. A. Pilkevych); fedor4uk.d@gmail.com (D. L. Fedorchuk); romannik@ukr.net (M. P. Romanchuk); olenanau@gmail.com (O. M. Naumchak)
https://ieeexplore.ieee.org/author/37089181628 (I. A. Pilkevych); https://ieeexplore.ieee.org/author/37089179622 (D. L. Fedorchuk); https://ieeexplore.ieee.org/author/37087013658 (M. P. Romanchuk); https://ieeexplore.ieee.org/author/37089181640 (O. M. Naumchak)
0000-0001-5064-3272 (I. A. Pilkevych); 0000-0003-2896-3522 (D. L. Fedorchuk); 0000-0002-0087-8994 (M. P. Romanchuk); 0000-0003-3336-1032 (O. M. Naumchak)

technologies are becoming one of the most promising types of weapons. Every year, the scope of its application increases primarily due to its ease of use.

The official military doctrine of the Russian federation calls for "simultaneous pressure on the enemy throughout its territory in the global information space". The Internet is used to spread propaganda, misinformation, manipulation of facts, including fake news, etc. The experience of the war of the Russian federation against Ukraine showed that the enemy widely uses the capabilities of the global network to spread negative psychological influences as a means of waging a hybrid war.

From the first day of its independence, our country became the object of Russian propaganda and the direction of concentrated and powerful destructive psychological influences [9]. In particular, Russia's special units widely use the Internet to distribute negative psychological influences to target audiences [7] in distributed special materials of negative psychological influences which have the form of text messages. Therefore, the search for ways to counteract the aggressor's special operations is a relevant research direction.

Special information operations of the Russian federation are aimed at key democratic institutions (in particular, electoral ones), and special services of the aggressor state are trying to intensify internal contradictions in Ukraine and other democratic states. The Russian hybrid warfare technologies against Ukraine, including information intervention models and mechanisms, are spreading to other states, quickly adapting to local contexts and regulatory policies [20]. Restrictive measures (sanctions) and responsibility for their violation and an effective mechanism for monitoring the information space are one of the effective mechanisms for responding to disinformation and propaganda activity in the Russian federation [17].

The availability of online media, the rapidly growing number of sources of information (such as news sites, social networks, blogs, websites, etc.) and the ease with which they can be used to spread information quickly lead to the problem of the viral spread of fake news. The popularization of social networks has exacerbated this long-standing problem [1]. Now, fake news has become a major problem for society and individuals, as well as for organizations and governments fighting disinformation and propaganda [2]. This article is extension of previous research [13] that considers issue dividing the levels of graphs structure on which the problem can be solved.

2. Problem statement

It should be noted that at the current stage, scientific interest is not the amount of information and its constant growth, but the structure of distributed data and their relationship. That is why one of the urgent tasks is the creation of a unique collection of knowledge. For this, first of all, it is necessary to automate the processes of collecting, analyzing, and summarizing data from the network. And the requirements for knowledge will be: the ability to read and understand them both by an automated system and by a person, their structure and sequence.

A modern tool for presenting and preserving knowledge is knowledge graphs (KG). KG is a graph in which vertices are unique entities, and edges are connections between them and their attributes. The advantages of KG include: the ability to model both abstract concepts and real objects; the ability to think about new connections between existing entities; the ability to generate new knowledge based on existing knowledge (creation of new entities).

KG are somewhat similar to relational databases (DBs), but their main difference is semi-structuredness and underlying logical apparatus. (DBs are completely structured and therefore not "flexible" and not suitable for solving a large number of tasks). For example, KG are currently used in such fields as information search, natural language processing; semantic technologies that allow using the semantic load of data in the analysis; machine learning, generation of new knowledge, etc.

The use of KG in the field of processing natural language texts can allow automating the process of monitoring the information space. The purpose of the study is to analyze the approaches and choose the most effective one for building a knowledge graph for detecting fake news (informational messages containing negative psychological influences.

3. Theoretical background

The first knowledge base, on the basis of which the KG was implemented, was DBpedia, which contains about 6 billion related entities, created on the basis of semantic processing of articles from Wikipedia [11]. The most famous example is the Google Knowledge Graph. Other implementations are YAGO [14], WordNet, NELL [4], Freebase (since 2014 as part of Google Knowledge Graph), Wikidata graph [19], LOD Cloud [8] and other.

Wikidata is an open, collaboratively edited knowledge base created to present information in a compatible machine-readable format. The actual information from Wikidata conforms to the RDF data model, where entities are represented as triplets (s, p, o). Other information can be added to the entity description. In [6] other formats were also considered. In particular, they use a variant of the RDF format – named graphs in the form of quads, where a fourth element is added to the usual triplet (s, p, o, i). Where i is additional identifier.

Named graphs extend the RDF ternary model and consider sets of pairs in the form $G(n)$, where G – is RDF-graph, n – IRI or an empty node in some cases, or maybe even for the default graph. We can smooth this representation by concatenating $G \cdot \{n\}$ for each such pair, resulting in fours. Thus, we can encode the quad (s, p, o, i) directly using N-Quads.

KG accumulate knowledge not only in a human-friendly form, like Wikipedia, but also in a machine-intelligible form, creating a basis for machine learning and solving intellectual tasks in various fields.

For the research being conducted, GIS can be an effective tool in solving the task of automating the process of collecting and analyzing data from the information space. Namely, the processing of text data from social Internet services for the purpose of identifying signs of negative psychological influence and, if possible, finding its original source, author, determining the purpose of distribution, target audience, to which the psychological influence is directed, etc.

4. Results

An example of the construction of a KG when solving the problem of analyzing natural language texts.

Having a certain text at the input, the first task is to highlight the named entities and the connections between them, combining the received facts into a graph. For visualization, we will use the metafactory platform, which uses the Wikidata knowledge graph. For example, let's take an article from Wikipedia about Ukraine. Several key points can be identified from the text. For example, language, neighbors, population and start building a graph (figure 1) [13].

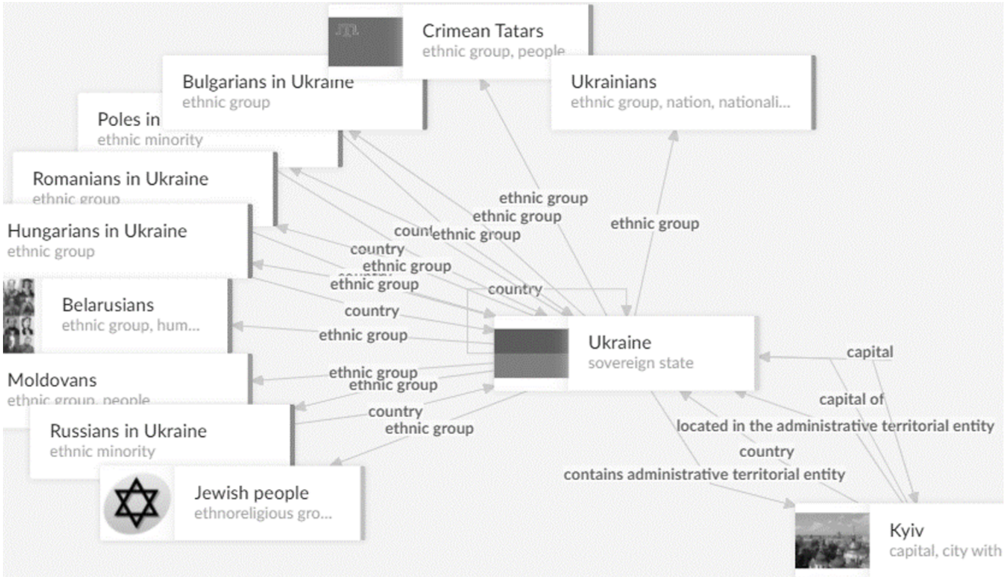

Figure 1: Visualization of the constructed knowledge graph.

We select the predicate "shared border with..." and select the entities corresponding to it. The platform allows you to select all predicates connecting the selected entities for visualization at once. Particular attention is drawn to the size of the graph containing only a few entities and the predicates connecting them.

Therefore, "Ukraine" is the essence of the KG, which is connected with other entities in the form of triplets (s, p, o) or (h, r, t), where s ad o – represent entities, p – connection between them. In the case of a built-in GK, examples of linked triplets for the entity "Ukraine" would be (Ukraine, capital, Kyiv) and (Ukraine, ethnic_groups, Ukrainians), (Ukraine, ethnic_groups, Crimean Tatars), etc.

The use of the KG as a basis for the encoder of entities is effective for several reasons: the distribution of information within the graph allows combining information about the object itself and about its neighbors in the representation of the object; there are several large-scale open source KG.

As mentioned earlier, KG can be presented in two ways. The first is an ontological representation based on formal logic and semantics. The second – vector representation – uses statistical mechanisms to minimize the distances between close entities in multidimensional spaces.

A comparison of the approaches is presented in table 1 [13].

The main difference between the considered approaches is that the symbolic representation implies the recording of facts using symbols (for example, RDF triplets), while in the vector rep-

Table 1
Comparison of the ontological and vector representation of the KG.

Representation	Ontological	Vector
What is it based on?	formal logic (propositional, predicate logic, modal, first-order logic, etc.); semantics	statistics; vector distances
Approaches (standards)	RDF, OWL_1, OWL_2, etc.	GCN, GNN, GAN, TextGCN, etc.
Presentation of data	XML, Turtle, RDFa, JSON-LD, etc	Embeddings
Formal description	$(s, p, o),\ p(s, o),\ s, p, o$	$s, p, o \in \mathbb{R}^d$

resentation the essence and predicates are projected into some d-dimensional space (embedding space).

The main idea of the vector representation is to search for a graph vertices mapping function in a vector space of a certain dimension. That is, a network is taken, fed to the input of a parametric function-encoder, and at the output we get vector representations.

The disadvantage of methods based on shallow learning is transductivity – the model learns vector representations for vertices once and must be retrained every time the graph changes. Also, the disadvantage is that wandering around the graph is random, so the model will produce different results (representations) each time.

Deep models – graph neural networks (GNN) – are free from the mentioned shortcomings. The main idea of which is to build a computational graph for each vertex, the features of which are determined by the features of its neighbors through a non-linear aggregator. GNN are capable of processing graphically structured data. Other types of neural networks work with tabular data, image data (pixel grid), or text data.

GNNs can solve various tasks at the level of graph nodes, including: classification; regression; anomaly detection; clustering; community detection, etc. GNNs can also solve tasks at the edge level. The basic idea is that GNNs model information propagating through the edges of a graph, which allows them to take into account the context and interaction between nodes. Table 2 shows the main tasks in the course of information space monitoring that can be accomplished with the help of GNNs.

There are examples of existing models of graph neural networks and areas (problems) in which they are used are shown in table 3 [13].

The application of GNN allows prediction to be performed both at the level of nodes and at the level of connections (edges). This allows us to predict certain properties of unlabeled nodes based on other nodes and their edges. As for the edges, the prediction of the occurrence of connections between the vertices in the future can be performed. GNNs can classify nodes or predict connections in a network by studying the embedding of nodes. These embeddings are low-dimensional vectors that summarize the positions of nodes in the network as well as the structure of their local neighborhood. It is also possible to perform graph-level prediction based on the structural properties of these graphs when the input data is the complete graph. Such a model can be used, for example, to solve the problem of detecting fake news. Fake news is a phenomenon of modern propaganda and disinformation, which is widely used by the Russian

Table 2
The tasks that conducts using GNNs during information space monitoring.

Level	Tasks	Examples
Nodes	Detecting fake news or disinformation	Identification of deviations from typical patterns during the analysis of the information distribution network;
	Identification of influencers or bots	analyzing the graph of user interactions on a social network to identify influencers or bots which spread propaganda;
	Detecting user groups	identifying groups of users with similar interests that used to personalize content by analyzing interaction;
	Revealing feedback and reactions to information	identifying behavior patterns or sentiment that useful for analyzing public opinion, reactions to news, events etc.;
	Determining popular topic	identifying popular topics, which using for planning content or advertising campaigns by analyzing the discussed topics;
Edges	Predicting the type of interaction between users	identification of atypical connections between users in a social network during content distribution; determining the intensity of communication between users based on their interaction and drawing conclusions about their "naturality"; predicting the presence or absence of interaction between users;
	Detection of anomalies (fake accounts, bots)	identifying unusual ways of spreading information in the graph or fake communication activity; identifying suspicious accounts or bots used to spread propaganda based on their behavior;
	Analysing the spread of propaganda	research the ways in which information is disseminated in the graph and identify patterns that indicate the spread of propaganda;
	Comparison of information sources	analyzing the links between information sources and identifying suspicious ones; identification of networks for spreading negative information (psychological) influence;
Graph	Identifying common propaganda	identification of user groups or information sources that jointly promote a certain ideology or spread false information; analyzing the dynamics of their interactions in the graph; analyzing the connections between the vertices of the graph and identifying subgroups that have similar views and actively cooperate in spreading propaganda content;
	Assessing the impact	measuring the influence of individual graph vertices (key actors) and identifying influential users or sources of false information;
	Identifying patterns of information dissemination	analyzing the ways in which information is disseminated in the graph and identifying patterns that indicate manipulation or propaganda.

Federation in conducting hybrid warfare.

In [10] a three-stage approach to the analysis of fake news using KG is proposed:

Stage 1 – Encoder of news – coding of the title.

Stage 2 – Encoder of entities – identification of named entities, coding of individual objects using KG.

Table 3
Existing models of graph neural networks and areas in which they are applied.

Field of application	Tasks	Algorithm	Model
		GCN	Graph Convolutional Network
		GAT	Graph Attention Network
	Text classification	DGCNN	Graph Convolutional Network
		Text GCN	
		Sentence LSTM	Graph LSTM
		GraphSAGE	GraphSAGE
	Marking sequences	GAT	Graph Attention Network
		Sentence LSTM	Graph LSTM
		Tree LSTM	
	Classification by tonality	GraphSAGE	GraphSAGE
		GAT	Graph Attention Network
	Neural machine translation	Syntatic GCN	Graph Convolutional Network
		GGNN	Gated Graph Neural Network
Text		Tree LSTM	Graph LSTM
	Edge extraction	Graph LSTM	
		GCN	Graph Convolutional Network
		Syntatic GCN	Graph Neural Network
	Event extraction	GraphSAGE	GraphSAGE
		GAT	Graph Attention Network
	Text generation	GGNN	Gated Graph Neural Network
		Sentence LSTM	Graph LSTM
	Reading comprehension	GraphSAGE	GraphSAGE
		GAT	Graph Attention Network
			MLP
	Relational thinking	RNN	Reccurent Neural Network
		GCN	
		DGP	Graph Convolutional Network
	Image classification	GSNN	
		GGNN	Gated Graph Neural Network
	Visual answers to questions		
		GPNN	
Image	Interaction detection	Strucrural-RNN	Graph Neural Network
	Region classification	GNN	
		DGCNN	Graph Convolution Network
	Semantic segmentation	GGNN	Gated Graph Neural Network
		Graph LSTM	Graph LSTM
		3DGNN	Graph Neural Network
Knowledge Graphs	Completed knowledge bases	GNN	Graph Neural Network
	Alignment of knowledge graphs	GCN	Graph Convolutional Network

Stage 3 – Classification of news – final study and classification of news (using, for example, GNN).

Based on this and [12], we have the following steps of the GNN model:

- embedding nodes is done using several rounds of message passing;
- combining node embeddings into a single graph embedding (called a reading layer, for example: global mean pool);
- classifier training based on graph embedding.

The architecture of the GNN model is shown in the figure 2 [13].

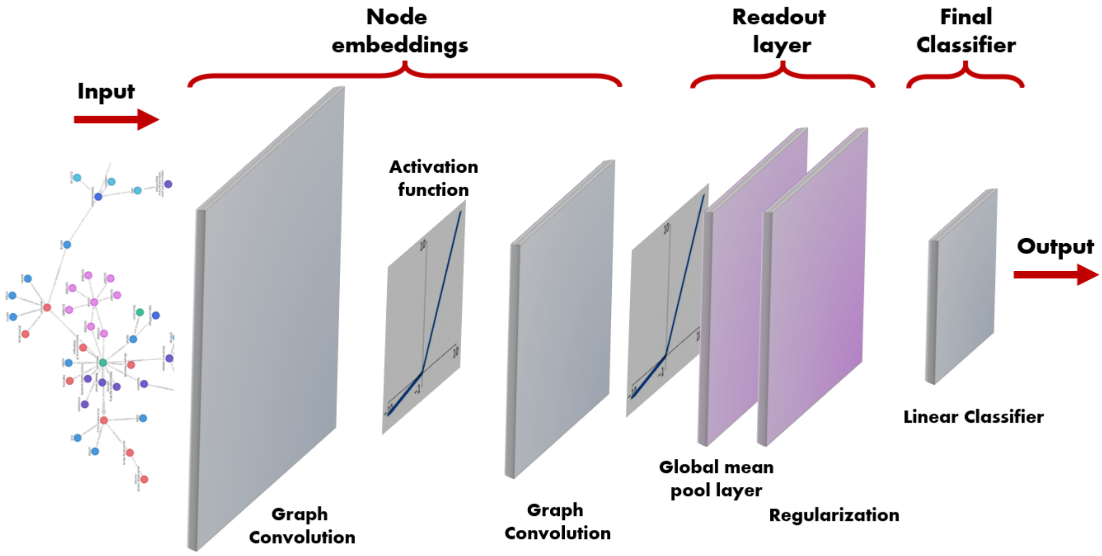

Figure 2: Architecture of the GNN model.

Different types of graph neural networks can be used to solve the problem of detecting propaganda and disinformation in the news based on graph data. The main idea of GNN is to built a computational graph for each node with features $(x_{11}, x_{12}, x_{13}, ..., x_{1m})$ which are determined by the features of its neighbors $(x_{n1}, x_{n2}, x_{n3}, ..., x_{nm})$ through a nonlinear aggregator. This information generalizes in vector $h_i^{(k)}$ (it's a state of node i at step k). It continues to conduct as cycle until all nodes will know the information about each other. The formal definition of a graph neural network can be presented as:

$$h_u^{(k+1)} = UPDATE^{(k)}\left(h_u^{(k)}, AGGREGATE^{(k)}\left(\left\{h_v^{(k)}, \forall v \in \mathcal{N}\left(\mathrm{u}\right)\right\}\right)\right) \tag{1}$$

where $\mathcal{N}(u)$ – set of neighbors for node u. However, the following types of neural networks are better for this task (they can be divided into three groups):

1. Spectral: GCN is one of the most popular types of graph neural networks. A GCN uses filters based on the neighbourhood of nodes in a graph and performs convolution on each node in the graph to obtain the resulting functions. GCNs can be used for node classification,

community detection, and anomaly detection. GCN at general uses the sum of normalized neighbors embeddings:

$$h_v^{(k)} = \sigma\left(w^{(k)} \sum_{v \in \mathcal{N}(\sqcap)\cup\{\sqcap\}} \frac{h_v}{\sqrt{|\mathcal{N}(u)|\,|\mathcal{N}(v)|}}\right) \tag{2}$$

where $w^{(k)}$ is a weight matrix;

$\sigma(\cdot)$ is a non-linear activation function like the ReLU.

GAE [21] – is a type of graph neural network that finds a representation of a graph in a low-dimensional space. A GAE consists of two parts: an encoder and a decoder. The encoder converts the graph into a vector that can be used to classify nodes or find anomalies in the graph. The decoder reconstructs the graph from the resulting representation vector, which allows you to use GAE to generate new graphs.

$$H^{(t)} = \sigma\left(Gconv\left(X^{(t)}, A; W\right) + Gconv\left(H^{(t-1)}, A; U\right) + b\right) \tag{3}$$

where $\sigma(\cdot)$ is a ReLU activation function;

$Gconv$ function is a graph convolutional layer.

The decoder of GAE aims to decode node relational information from their embeddings by reconstructing the graph adjacency matrix, which is defined as:

$$A_{u,v} = dec\left(h_u, h_v\right) \tag{4}$$

2. Based on attention mechanisms: GAT – is a type of graph neural network that uses attention on the nodes of a graph to find meaningful relationships between them. GAT stores information about neighboring nodes and their connections, as well as the weights of the edges between them. This allows GAT to detect complex dependencies between graph nodes and solve problems of node classification or community detection in a graph. Then the final output features of each node can be obtained by (after applying a nonlinearity $\sigma(\cdot)$):

$$h_i^{'} = \sigma\left(\sum_{j \in \mathcal{N}_i} a_{ij} W h_j\right) \tag{5}$$

where a_{ij} – the attention weights that denotes the attention on neighbor $j \in \mathcal{N}$ when we are aggregating information at node i.

Graph Attention Auto-Encoders (GATE) [16] – a neural network architecture for unsupervised representation learning on graph-structured data, which is able to reconstruct graphstructured inputs, including both node attributes and the graph structure, through stacked encoder/decoder layers equipped with self-attention mechanisms.

By considering node features as initial node representations the k encoder layer generates the representation of node i in layer k as follows:

$$h_i^k = \sum_{j \in \mathcal{N}} a_{ij}^k \sigma\left(w^{(k)} h_j^{(k-1)}\right) \tag{6}$$

where a_{ij}^k is attention coefficient indicating the relative relevance of neighboring node j to node i in the k th decoder layer.

3. Non-spectral: Graph Recurrent Neural Networks (GRNN) [15] – is a type of graph neural network that uses recurrent neural networks. As a general learning framework that achieves this goal by leveraging the notion of a recurrent hidden state together with graph signal processing (GSP). In the GRNN, the number of learnable parameters is independent of the length of the sequence and of the size of the graph, guaranteeing scalability.

Given a sequence of graph signal tensors $\{X_t\}$, $X_t \in \mathbb{R}^{N \times F}$, we can update state by parametrizing the linear maps A and B by the graph shift operator S, to obtain H-featured hidden state tensors $Z_t \in \mathbb{R}^{N \times F}$:

$$Z_t = \sigma \left(A_S \left(X_t \right) + B_S \left(Z_{(t-1)} \right) \right) \tag{7}$$

GraphSAGE uses the aggregation of information from neighbouring nodes to calculate the representation of each node in the graph. Different aggregation methods are used for this purpose, such as average, maximum, or concatenation of neighbouring nodes. GraphSAGE does not use a full set of neighbors, but uses a set of neighbors of a fixed size by uniform sampling.

$$h_{\mathcal{N}_{\sqsubseteq}}^t = AGGREGATE_t \left(\left\{ h_u^{t-1}, \forall u \in \mathcal{N}_v \right\} \right) \tag{8}$$

$$h_v^t = \sigma \left(W^t \cdot \left[h_v^{t-1} || h_{\mathcal{N}_v}^t \right] \right) \tag{9}$$

The aggregation of the neighbor representations can be done by a variety of aggregator architectures: MEAN; LSTM; Pooling.

5. Discussion

To investigate the application of the proposed GNN model, we used a dataset consisting of verified facts about fake and real news received and shared on Twitter, verified by both Snopes and Politifact articles. The dataset is split into two subsets called Snopes and Politifact. The messages are characterised by six features: news/fact title; brief public comment; claim; assessment (true, false, erroneous); page content; and summary. The data was divided into two datasets: a training set containing about 70% of the total dataset and a test set containing the remaining data.

The solution was built on the basis of GCN, GAT [18] and GraphSAGE [5] models (one model from each type reviewed earlier), which were pre-trained on The User Preference-aware Fake News Detection (UPFD) data set [3]. The models were trained using cross-entropy loss with class weights. They are evaluated according to the average accuracy measured on the test sets. The choice of hyperparameters consisted of the type and number of GNN convolutions used for node embedding, activation function, and learning rate. The GNN models were trained for 100 epochs. The results of classification accuracy obtained during model training are shown in table 4.

According to the results of model training, the best results were demonstrated by the GraphSAGE model, which outperforms other GNN models due to the use of a fixed-size population

Table 4
The results were obtained during model training.

	GCN	GAT	GraphSAGE
Politifact	Accuracy	Accuracy	Accuracy
content	0.765	0.775	0.797
Snopes	Accuracy	Accuracy	Accuracy
content	0.906	0.927	0.941

formed by a uniform sample for aggregation. Therefore, to solve this problem, it is advisable to use the GraphSAGE model trained on sample text data containing signs of negative psychological influence. Such a model will be able to analyse and detect textual data containing destructive content with signs of negative psychological influence in the process of monitoring online media. An important condition is the availability of a significant amount of training data for model training.

6. Conclusions

Therefore, the issue of analysing online media messages disseminated through social media to identify fake news remains relevant and has become even more acute in the context of a large-scale war. In order to timely detect and respond to the negative impact spread through such messages, it is necessary to improve monitoring systems. The article develops and analyses an approach to automating this process based on graph neural networks, which will allow timely and high-quality detection and analysis of fake news in the information space of our country.

KGs can be used to supplement training samples for machine learning algorithms, which can improve the performance of applications with a limited amount of training data, such as systems for analysing the tone (sentiment analysis) of messages to determine the level of negative influence. Since the CG contains auxiliary factual information about the elements contained in the training samples (entities from the texts in the message and texts in the image on which the model is trained), it helps to extend its functionality. This addition improves the classification accuracy in detecting fake news.

A promising area for further research is to increase the level of automation of content analysis, including textual information, by developing and implementing methods for automatic semantic analysis of texts and determining their content based on neural networks, in particular, using graph classification, regression and clustering.

References

[1] Allcott, H. and Gentzkow, M., 2017. Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives*, 31(2), pp.211–36. Available from: https://doi.org/10.1257/jep.31.2.211.

[2] Berinsky, A.J., 2017. Rumors and Health Care Reform: Experiments in Political Mis-

information. *British Journal of Political Science*, 47(2), p.241–262. Available from: https://doi.org/10.1017/S0007123415000186.

[3] Dou, Y., Shu, K., Xia, C., Yu, P.S. and Sun, L., 2021. User Preference-Aware Fake News Detection. *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. New York, NY, USA: Association for Computing Machinery, SIGIR '21, p.2051–2055. Available from: https://doi.org/10.1145/3404835.3462990.

[4] Giménez-García, J.M., Duarte, M.C., Zimmermann, A., Gravier, C., Jr., E.R.H. and Maret, P., 2018. NELL2RDF: Reading the Web, Tracking the Provenance, and Publishing it as Linked Data. In: S. Capadisli, F. Cotton, J.M. Giménez-García, A. Haller, E. Kalampokis, V. Nguyen, A.P. Sheth and R. Troncy, eds. *Joint Proceedings of the International Workshops on Contextualized Knowledge Graphs, and Semantic Statistics co-located with 17th International Semantic Web Conference (ISWC 2018)*. CEUR-WS.org, *CEUR Workshop Proceedings*, vol. 2317. Available from: https://ceur-ws.org/Vol-2317/article-02.pdf.

[5] Hamilton, W.L., Ying, R. and Leskovec, J., 2017. Inductive Representation Learning on Large Graphs. *Proceedings of the 31st International Conference on Neural Information Processing Systems*. Red Hook, NY, USA: Curran Associates Inc., NIPS'17, p.1025–1035. Available from: https://doi.org/10.5555/3294771.3294869.

[6] Hernández, D., Hogan, A. and Krötzsch, M., 2015. Reifying RDF: What Works Well With Wikidata? In: T. Liebig and A. Fokoue, eds. *Proceedings of the 11th International Workshop on Scalable Semantic Web Knowledge Base Systems co-located with 14th International Semantic Web Conference (ISWC 2015), Bethlehem, PA, USA, October 11, 2015*. CEUR-WS.org, *CEUR Workshop Proceedings*, vol. 1457, pp.32–47. Available from: https://ceur-ws.org/Vol-1457/SSWS2015_paper3.pdf.

[7] Howard, G.E. and Czekaj, M., eds, 2019. *Russia's military strategy and doctrine*. Jamestown Foundation, pp.159–184.

[8] Jentzsch, A., 2014. Linked Open Data Cloud. In: T. Pellegrini, H. Sack and S. Auer, eds. *Linked Enterprise Data: Management und Bewirtschaftung vernetzter Unternehmensdaten mit Semantic Web Technologien*. Berlin, Heidelberg: Springer Berlin Heidelberg, X.media.press, pp.209–219. Available from: https://doi.org/10.1007/978-3-642-30274-9_10.

[9] Levchenko, O.V. and Kosogov, O.M., 2016. Methods of identification of events of negative information influence based on the analysis of open sources. *Systemy obrobky informatsii*, 1, pp.100–102. Available from: http://nbuv.gov.ua/UJRN/soi_2016_1_22.

[10] Mayank, M., Sharma, S. and Sharma, R., 2022. DEAP-FAKED: Knowledge Graph based Approach for Fake News Detection. *2022 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*. pp.47–51. Available from: https://doi.org/10.1109/ASONAM55673.2022.10068653.

[11] Mendes, P.N., Jakob, M., García-Silva, A. and Bizer, C., 2011. DBpedia Spotlight: Shedding Light on the Web of Documents. *Proceedings of the 7th International Conference on Semantic Systems*. New York, NY, USA: Association for Computing Machinery, I-Semantics '11, p.1–8. Available from: https://doi.org/10.1145/2063518.2063519.

[12] Pilkevych, I., Fedorchuk, D., Naumchak, O. and Romanchuk, M., 2021. Fake News Detection in the Framework of Decision-Making System through Graph Neural Network. *2021 IEEE 4th International Conference on Advanced Information and Communication Technologies (AICT)*. pp.153–157. Available from: https://doi.org/10.1109/AICT52120.2021.9628907.

[13] Pilkevych, I., Fedorchuk, D., Romanchuk, M. and Naumchak, O., 2023. An analysis of approach to the fake news assessment based on the graph neural networks. *Proceedings of the 3rd Edge Computing Workshop*. CEUR Workshop Proceedings, doors 2023, pp.56–65. Available from: https://www.ceur-ws.org/Vol-3374/paper04.pdf.

[14] Rebele, T., Suchanek, F., Hoffart, J., Biega, J., Kuzey, E. and Weikum, G., 2016. YAGO: A Multilingual Knowledge Base from Wikipedia, Wordnet, and Geonames. *The Semantic Web – ISWC 2016: 15th International Semantic Web Conference, Kobe, Japan, October 17–21, 2016, Proceedings, Part II*. Berlin, Heidelberg: Springer-Verlag, p.177–185. Available from: https://doi.org/10.1007/978-3-319-46547-0_19.

[15] Ruiz, L., Gama, F. and Ribeiro, A., 2020. Gated graph recurrent neural networks. *IEEE Transactions on Signal Processing*, 68, pp.6303–6318. Available from: https://doi.org/10.1109/tsp.2020.3033962.

[16] Salehi, A. and Davulcu, H., 2020. Graph attention auto-encoders. *2020 IEEE 32nd International Conference on Tools with Artificial Intelligence (ICTAI)*. pp.989–996. Available from: https://doi.org/10.1109/ICTAI50040.2020.00154.

[17] Stratehiia informatsiinoi bezpeky, 2021. Available from: https://www.president.gov.ua/documents/6852021-41069.

[18] Veličković, P., Cucurull, G., Casanova, A., Romero, A., Liò, P. and Bengio, Y., 2018. Graph Attention Networks. 1710.10903.

[19] Waagmeester, A., Stupp, G., Burgstaller-Muehlbacher, S., Good, B.M., Griffith, M., Griffith, O.L., Hanspers, K., Hermjakob, H., Hudson, T.S., Hybiske, K., Keating, S.M., Manske, M., Mayers, M., Mietchen, D., Mitraka, E., Pico, A.R., Putman, T., Riutta, A., Queralt-Rosinach, N., Schriml, L.M., Shafee, T., Slenter, D., Stephan, R., Thornton, K., Tsueng, G., Tu, R., Ul-Hasan, S., Willighagen, E., Wu, C. and Su, A.I., 2020. Science Forum: Wikidata as a knowledge graph for the life sciences. *eLife*, 9, p.e52614. Available from: https://doi.org/10.7554/eLife.52614.

[20] Woolley, S. and Howard, P., 2016. Automation, Algorithms, and Politics| Political Communication, Computational Propaganda, and Autonomous Agents — Introduction. *International Journal of Communication*, 10. Available from: https://ijoc.org/index.php/ijoc/article/view/6298.

[21] Zonghan, W., Shirui, P., Fengwen, C., Guodong, L., Chengqi, Z. and S., Y.P., 2021. A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 32(1), pp.4–24. Available from: https://doi.org/10.1109/TNNLS.2020.2978386.