Knowledge Enhanced Multi-modal Fake News Detection

Yi Han, Amila Silva, Ling Luo, Shanika Karunasekera, Christopher Leckie
{yi.han@,amila.silva@student.,ling.luo@,karus@,caleckie@}unimelb.edu.au
School of Computing and Information Systems
The University of Melbourne

ABSTRACT
Recent years have witnessed the significant damage caused by various types of fake news. Although considerable effort has been applied to address this issue and much progress has been made on detecting fake news, most existing approaches mainly rely on the textual content and/or social context, while knowledge-level information—entities extracted from the news content and the relations between them—is much less explored. Within the limited work on knowledge-based fake news detection, an external knowledge graph is often required, which may introduce additional problems: it is quite common for entities and relations, especially with respect to new concepts, to be missing in existing knowledge graphs, and both entity prediction and link prediction are open research questions themselves. Therefore, in this work, we investigate knowledge-based fake news detection that does not require any external knowledge graph. Specifically, our contributions include: (1) transforming the problem of detecting fake news into a subgraph classification task—entities and relations are extracted from each news item to form a single knowledge graph, where a news item is represented by a subgraph. Then a graph neural network (GNN) model is trained to classify each subgraph/news item. (2) Further improving the performance of this model through a simple but effective multi-modal technique that combines extracted knowledge, textual content and social context. Experiments on multiple datasets with thousands of labelled news items demonstrate that our knowledge-based algorithm outperforms existing counterpart methods, and its performance can be further boosted by the multi-modal approach.

CCS CONCEPTS
• Computing methodologies → Supervised learning by classification: Neural networks.

KEYWORDS
fake news detection, knowledge graph, graph neural networks, social media

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1\(^{1}\)Here we use the definition in [59]: fake news is intentionally and verifiably false news published by a news outlet.

1 INTRODUCTION
The prevalence of fake news\(^{1}\) on social media has serious repercussions on our society. Especially when equipped with big data analysis, it can accurately reach specific target audiences to spread fear, aggravate hatred, and cause riots and violence.

While significant efforts have been made on fake news detection, most existing work focuses on the textual content and social context, where textual content includes the news headline and body, and social context means user interactions over social media. For example, once a news item is published online, it may be tweeted by multiple users. Each of these tweets and its retweets form a separate cascade [42], and all the cascades form the propagation pattern/network (we use these two terms interchangeably in this work) of a news item.

Knowledge-level information, on the other hand, has been much less explored. Here knowledge refers to the entities in the news content and the relations between them. Typically, it can be represented in the format of a triple: (Subject, Predicate, Object), i.e., SPO triple [1]. Within the limited work on knowledge-based fake news detection, an external knowledge graph is often required. For example, Cui et al. [8] incorporate an article-entity bipartite graph and a medical knowledge graph to better capture the important entities and guide the embedding of news articles to detect healthcare misinformation. However, it is unlikely for any knowledge graph to contain all possible entities and relations, and it is not a trivial task to accurately predict missing ones. To overcome this issue, in this work, we investigate knowledge-based fake news detection that does not require any external knowledge graph.

Pan et al. [24] approach this problem by constructing two knowledge graphs, with one on real news (KG\(_T\)) and one on fake news (KG\(_F\)). Each of these two knowledge graphs is then used to train a TransE [6] model, and a news item is verified by comparing the average or maximum bias of the two models over the extracted relations, where the bias of a triple \((s, p, o)\) is defined as \(||s + p - o||^2\). A news item is classified as "Real" if the bias of the model trained on KG\(_T\) is smaller, and "Fake" otherwise.

In our work, by contrast, we look at the problem from a different perspective: given the recent development on graph neural networks (GNNs) and their superior performance on non-Euclidean data, we investigate whether it is possible to transform fake news detection into a knowledge graph classification problem.

Initially, we test a method that constructs a separate knowledge graph for each news item, and then applies GNNs for graph-level classification. However, our preliminary experiments suggest that this method does not achieve satisfactory results, with an average accuracy only around 73%. A key reason is that normally a very
limited number of relations/triples can be extracted from each news item, which means that the constructed knowledge graph is too small to accurately verify the veracity of a news item.

Therefore, we propose a new approach and transform the problem of fake news detection into a subgraph classification task. Specifically, our contributions include:

- Inspired by the work of [2], which designs a GNN model called SubGNN for subgraph classification, we propose to extract entities and relations from each news item, all of which form a single knowledge graph where a news item is represented by a subgraph (Fig. 1a), and then all subgraphs with their corresponding news labels (fake/real) are used to train a SubGNN model, so that the obtained model can classify each subgraph/news item. As demonstrated by the experimental results in Section 6, this method can achieve much better performance.

- To further improve the performance of the above model, we develop a simple but effective multi-modal fake news detection algorithm. In addition to extracted knowledge, other forms of information, such as the textual content and propagation network, can also contribute to detecting fake news. Specifically, as can be seen from Fig. 1b, in our proposed method three models are first trained separately: (1) a propagation-based model [12] that verifies a news item purely on its propagation pattern; (2) a document classification model using hierarchical attention networks [50] that operates directly on the news content; and (3) a knowledge-based model proposed in this work. We demonstrate that by concatenating the generated embeddings of these three models to train a multilayer perceptron (MLP), this seemingly simple approach can outperform each individual model by a clear margin.

The remainder of this paper is organised as follows: Section 2 defines the research problem; Sections 3 and 4 present our knowledge-based fake news detection algorithm which does not require any external knowledge graph; Section 5 introduces an architecture that combines knowledge-, text- and propagation-based models to facilitate multi-modal fake news detection; Section 6 provides experimental results to demonstrate the effectiveness of our proposed methods; Section 7 reviews previous work related to fake news detection on social media; and finally Section 8 concludes the paper and offers directions for future work.

2 PROBLEM DEFINITION

Originally, the fake news detection problem can be defined as: given a set of labelled news items $D = \{(W_i, y_i) \mid i = 1, 2, \ldots\}$, where $W_i \in \mathcal{W}$ is the textual content for news item $i$ (i.e., a sequence of
words), and \( y_i \in Y = \{0 \text{ (Real)}, 1 \text{ (Fake)}\} \) is the label of \( W_i \), the goal is to learn a mapping \( g : W \rightarrow Y \) that classifies each news item.

In this work, we take a knowledge-based approach and break down the above formulation into the following two sub-problems:

**Knowledge graph construction.** The aim of the first step is to extract information from each news item to construct a knowledge graph. Conventionally, this involves named entity recognition and relation extraction, which have been extensively studied. However, we have tested several existing named entity-based relation extraction techniques, and our results suggest that when applied to news items, these methods normally generate a relatively small number of relations, which may lead to substantial information loss. Therefore, in the first sub-problem we design a new relation extraction algorithm that extracts a set of relations/triples \( R_i = \{(e_{ij}, r_{ij}, e'_{ij}) | i = 1, 2, \ldots\} \) from news content \( W_i \), where \( e_{ij}, r_{ij}, e'_{ij} \) contain one or multiple words in \( W_i \). Each of these triples means that \( e_{ij} \) and \( e'_{ij} \) has the relation of \( r_{ij} \). For example, a triple (David Warner, troll, Virat Kohli) can be extracted from the sentence "David Warner trolls Virat Kohli on Instagram over his grey beard" (Fig. 2). Note that here we do not pre-define any relation type or named entity.

**Subgraph classification.** Once all the relations are extracted from news items, and a single knowledge graph is constructed (in the case where a part of the graph is isolated from the rest, we only keep the largest connected component), each news item is assigned to a subgraph based on its extracted relations. Therefore, the original fake news detection problem is transformed into a subgraph classification task formulated as follows: given a set of labelled sub-knowledge graphs \( \{(SG_i, y_i) | i = 1, 2, \ldots\} \), where \( SG_i \in SG \) represents the sub-knowledge graph that corresponds to news item \( i \), and \( y_i \in Y = \{0 \text{ (Real)}, 1 \text{ (Fake)}\} \) is the label of \( SG_i \), then the goal is to learn a classifier \( f : SG \rightarrow Y \) that labels each subgraph. Note that here different subgraphs are not necessarily mutually exclusive and may contain common nodes.

In the following two sections, we explain in detail our solution to the above two problems.

### 3 KNOWLEDGE GRAPH CONSTRUCTION

In order to extract relations from news items to build a knowledge graph, we have first tested the following options: (1) an OpenNRE [11] model trained on the Wiki80 dataset\(^3\) with a BERT encoder, (2) an OpenNRE model trained on the Wiki80 dataset with a CNN encoder, (3) an OpenNRE model trained on the TACRED dataset\(^4\) [54] with a BERT encoder, (4) an ATLOP [55] model trained on the DocRED dataset [51]. The first three models are for sentence-level relation extraction, while the last one is for document-level relation extraction—hence it can extract more accurate relations than the other three models in our case.

Our experimental results suggest that all these models extract a relatively small number of relations from each news item, which may lead to substantial information loss. In addition, it is also unlikely for all the extracted relations to form a single graph. A main reason is that the relation types are pre-defined in these three datasets: Wiki80/TACRED/DocRED contains 80/41/96 relations, which cannot cover all the scenarios. As a result, in many cases even though a certain type of relation does exist, "no_relation" is returned instead.

One option is to create our own dataset from the collected news items with a larger number of pre-defined relations, and then retrain an OpenNRE or ATLOP model. However, in order to significantly increase the number of pre-defined relations, we also need a considerably larger number of relation instances for training. Considering that DocRED already has a total number of 1,508,320 instances, it is unlikely to obtain a much larger quantity from the thousands of collected news items.

Therefore, we design a new technique that can expand the number of extracted relations. Specifically, we do not pre-define any relation type, and instead focus on the verbs in each sentence, since there is a verb that has the relation of \( r_{ij} \). For example, "David Warner trolls Virat Kohli on Instagram over his grey beard" (Fig. 2). Note that here we do not pre-define any relation type or named entity.

### Algorithm 1: Relation Extraction

| Input: | The textual content \( W = \{w_0, w_1, \ldots\} \) of a news record |
|---|---|
| Output: | The list of relations \( L \) |
| \( L \leftarrow \emptyset \); | |
| \( W \leftarrow \text{coreference_resolution}(W) \); | |
| \( \{D_0, D_1, \ldots\} \leftarrow \text{dependency_parsing}(W) \); | |
| \( \{p_0, p_1, \ldots\} \leftarrow \text{pos_tagging}(W) \); | |
| \( \{l_0, l_1, \ldots\} \leftarrow \text{lemmatization}(W) \); | |
| for \( i \in \{0, 1, 2, \ldots, |W| - 1\} \) do | |
| if \( p_i \) is a verb then | |
| \{left_nodes, right_nodes\} \leftarrow \{0, 0\}; | |
| edge_type \leftarrow l_i; | |
| for \( (w_{ij}, r, w_{ij}) \) in \( D_i \) do | |
| if \( l_i \) is "not" then | |
| edge_type \leftarrow \text{"not_"} + edge_type; | |
| else if \( r \) in \( \{\text{subj}, \text{attr}, \text{xcomp}\} \) then | |
| left_nodes \leftarrow left_nodes \cup \{l_k\}; | |
| right_nodes \leftarrow right_nodes \cup \{l_k\}; | |
| else if \( r \) in \( \{\text{dobj}, \text{obj}, \text{attribution}\} \) then | |
| left_nodes \leftarrow left_nodes \cup \{l_k\}; | |
| right_nodes \leftarrow right_nodes \cup \{l_k\}; | |
| for left_node in left_nodes do | |
| for right_node in right_nodes do | |
| | |
| return \( L \leftarrow L \cup \{\text{left_node, edge_type, right_node}\}; | |

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\(^3\)https://github.com/thunlp/OpenNRE/blob/master/benchmark/download_wiki80.sh

\(^4\)https://nlp.stanford.edu/projects/tacred/
The grammatical structure of each sentence in $W$ is extracted using the dependency parser available in Spacy\(^3\) (Line 3). This step returns a set of tuples $D_i$ for each word $w_i$. Each entry in $D_i$ is a tuple $(w_k, r, w_j)$, where $w_k$ is another word in the same sentence of $w_i$ that is related to word $w_j$ from the relation type $r$, e.g., nominal subject (nsubj), direct object (dobj), open clausal complement (xcomp), as shown in the third box in Fig. 2. Note that the relation here has different meaning from the relation between entities mentioned above in the problem definition.

- The Part-of-Speech (POS) tags \{p0, p1, ...\} and the base-forms \{l0, l1, ...\} of the words in $W$ are recovered using the POS tagger\(^4\) and the lemmatizer\(^5\) in Spacy (Line 4-5).
- The verbs in $W$ are identified by looping through POS tags of the words in $W$ (Line 6-7).
- For each identified verb $w_i$, the connected words in the dependency parse tree $D_i$ are analysed. If a negation, i.e., words that reverse the meaning of a word, is found to be attached to $w_i$, $w_i$ is updated as "not_" + $w_i$, e.g., "care" becomes "not_care" in the given example (Line 11-12).
- Then, the connected nodes are categorised as either left_nodes or right_nodes based on their relation to $w_i$. If the relation type of a connected word is nominal subject (nsubj), it is added to left_nodes (Line 13-14).
- Otherwise, if the relation to $w_i$ belongs to one of the following types: direct object (dobj), indirect object (iobj), attribute (attr), and open clausal complement (xcomp), it is added to right_nodes (Line 15-16). In the example of Fig. 2, for the verb "troll", "David Warner"/"Virat Kohli" is categorised as left_nodes/right_nodes, respectively. In addition, even though "respond" is a verb in the second sentence, it will be extracted as a possible object of "not_care" by our algorithm due to the xcomp connection between them.
- In the end, the relation set is constructed by connecting each item in left_nodes with each item in right_nodes using the corresponding verb, i.e., $w_j$ in the above example (Line 17-19).

Our experimental results show that by applying the above approach, substantially more (over 10 times) number of relations can be extracted from the news items in total. For example, as shown in Fig. 3, in the left text box is the snippet of a news item\(^8\), and the relations extracted by our method are listed in the middle text box. As a comparison, the relations extracted by the ATLOP model are given on the right.

We have compared the cases where the knowledge graph is built using the relations extracted by (1) Algorithm 1, (2) an ATLOP model trained on the DocRED dataset (since DocRED is especially collected for document-level relation extraction), (3) both (1) and (2). Our experiment suggests that the best result is achieved when only the relations extracted by Algorithm 1 are used.

Note that we are not proposing a general method for relation extraction, since it is unlikely for the defined rules to work for all cases, and Algorithm 1 is only for our knowledge-based fake news detection technique.

After all the relations are extracted from news items, we add them one by one to form a single knowledge graph. Then each news item can be represented by a subgraph, based on the relations extracted from it. Therefore, the original problem of detecting fake

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\(^3\)https://spacy.io/usage/linguistic-features#dependency-parse
\(^4\)https://spacy.io/usage/linguistic-features#pos-tagging
\(^5\)https://spacy.io/usage/linguistic-features#lemmatization
\(^8\)https://www.politifact.com/factchecks/2010/feb/04/paul-krugman/krugman-calls-senate-health-care-bill-similar-law/
Krugman calls Senate health care bill similar to law in Massachusetts

The recent Massachusetts Senate election captivated Americans far beyond the Bay State. In that contest, Republican Scott Brown picked up a seat formerly held by the late Democratic giant Edward Kennedy. Brown’s upset victory was aided by a wave of frustration over how Congress and President Barack Obama have been handling health care reform legislation.

During the campaign, Brown said that if he was elected, he would become the 41st Republican senator, enabling the GOP to block the Democratic majority from reaching the 60-vote threshold required to pass key legislation, including a health care bill. The Senate has already passed a version of health care, but it needs to be reconciled with a different bill passed by the House and then signed by the president before it becomes law.

Subject: Senate
Object: Massachusetts
Predicate: locate

Subject: Massachusetts
Object: Senate
Predicate: located in the administrative territorial entity

Subject: Massachusetts Senate
Object: Massachusetts
Predicate: applies to jurisdiction

Figure 3: An example that compares the extracted relations using Algorithm 1 and by an ATLOP model. Left text box: the snippet of a news item. Middle text box: relations extracted by Algorithm 1. Right text box: relations extracted by an ATLOP model trained on the dataset of DocRED.

news now transforms into classifying each of the subgraphs, as explained in the next section.

4 SUBGRAPH CLASSIFICATION

In this section, we first give a brief introduction to graph neural networks and SubGNN, and then explain how a sub-knowledge graph is classified in our case.

4.1 Background on Graph Neural Networks

Given a graph \( G = (V, E) \), with vertex/node set \( V \), edge set \( E \), and node feature set \( X \in \mathbb{R}^{|V| \times d} \) (i.e., each node has \( d \) features), many GNN models can be formulated as a message passing framework [3, 47] in which information is propagated from one node to another along edges.

During each message-passing iteration \( k \), the embedding for node \( v \in V \) is updated according to the information aggregated from \( v \)'s neighbourhood \( N(v) \), which can be expressed as follows:

\[
h^{(k+1)}_v = \text{UPDATE}\left(h^{(k)}_v, \text{AGGREGATE}\left(h^{(k)}_u \mid u \in N(v) \right)\right),
\]

where \( h^{(0)}_v = x_v \in X \). The update step is often omitted by adding self-loops to the input graph, and the node embedding becomes:

\[
h^{(k+1)}_v = \text{AGGREGATE}\left(h^{(k)}_u \mid u \in N(v) \right).
\]

Take a basic GNN for example [10], the model can be defined as:

\[
H^{(k+1)} = \sigma(A + 1) H^{(k)} M^{(k+1)},
\]

where (1) \( H \) is the matrix of node embeddings/representations; (2) \( \sigma \) is a non-linear activation function, e.g., the rectified linear unit (ReLU) function; (3) \( A \in \{0, 1\}^{|V| \times |V|} \) is the adjacency matrix: \( A_{i,j} = 1 \) if there is an edge from node \( i \) to node \( j \), and \( A_{i,j} = 0 \) otherwise; and (4) \( M \) is the weight matrix to be learned.

4.2 Background on SubGNN

Most existing work on GNN focuses on node- and graph-level prediction tasks, while subgraphs are much less studied. To bridge this research gap, Alsentzer et al. [2] propose SubGNN that learns an embedding function \( F : SG \rightarrow \mathbb{R}^d \) to map each subgraph into a lower-dimensional representation.

Specifically, the embedding function \( F \) captures features from three channels—position, neighbourhood and structure, each of which has two subchannels—internal and border:

- Position. The internal position of subgraph \( SG_i \) is defined as the distance between \( SG_i \)'s components—\( SG_i \) may contain a single connected component or multiple isolated components. The border position is defined as the distance between \( SG_i \) and rest of \( G \).

- Neighborhood. The internal neighborhood and border neighborhood are defined as the identity of \( SG_i \)'s internal nodes and border nodes, respectively, where border nodes refer to nodes within the \( k \)-hop neighborhood of internal nodes.

- Structure. The internal structure is defined as the internal connectivity of \( SG_i \), while the border structure is defined by edges connecting \( SG_i \)'s internal nodes to the border neighborhood.

4.3 Classify Sub-Knowledge Graphs

Each of the above channels can be used separately or together. We have tested multiple SubGNN models with different combinations of the three channels, and find that models that rely only on the structure channel gives the best result. This is because in our case, the internal and border structures, i.e., how nodes are connected with each other within a subgraph and with the rest of the graph, are more informative for determining whether a news item is fake or not. Interestingly, the neighborhood channel does not perform
as well as the other two, but this is consistent with the ablation study in the original work [2].

In order to facilitate subgraph-level message passing for the structure channel, a number of connected components (each subgraph may contain single or multiple components) are randomly sampled via triangular random walks [5]—they are called anchor patches $\mathcal{A} = \{A_i | i = 1, 2, ..., n_A\}$. The embedding of a subgraph component (SC) is then represented in the following form:

$$h^{(k+1)}_{SC} = \sigma\left(M^{(k+1)} \cdot h^{(k)}_{SC}, AGG\left(\{y(S, A_i) \cdot a_i | i = 1, ..., n_A\}\right)\right),$$

where $y$ is a pre-defined similarity function, $a_i$ is the learned representation of $A_i$, $AGG$ is an aggregation function, e.g., the sum operator, and $M$ is a layer-wise trainable weight matrix.

If a subgraph contains multiple isolated connected components, its embedding is generated by concatenating the embeddings of all components.

5 KNOWLEDGE ENHANCED MULTI-MODAL FAKE NEWS DETECTION

In addition to the extracted knowledge, the textual content itself and how the news item propagates through the social network also provide valuable information for detecting fake news. Therefore, in this section we study how to combine our knowledge-based approach with existing content- and propagation-based methods for more accurate detection.

Formally, given a set of labelled news items $(SG_i, W_i, P_i, y_i) | i = 1, 2, ..., n_SG$ is the sub-knowledge graph, $W_i \in \mathcal{W}$ is the textual content, $P_i \in \mathcal{P}$ is the propagation network, and $y_i \in \mathcal{Y} = \{0\text{ (Real)}, 1\text{ (Fake)}\}$ is the label of the corresponding news, the goal is to learn a classifier $f : \mathcal{S}_G \times \mathcal{W} \times \mathcal{P} \rightarrow \mathcal{Y}$ that can label each news item.

As shown in Fig. 1b, we first train three knowledge-, text- and propagation-based models separately on the same training dataset. Then for each training instance, we feed its $SG_i, W_i$ and $P_i$ into the obtained models to generate three separate embeddings $h_{ik}, h_{ir}, h_{ip}$, all of which are concatenated to form the final embedding $h_i = h_{ik} @ h_{ir} @ h_{ip}$. In the end, an MLP is trained on the set of embeddings $\{h_i | i = 1, 2, ..., n_SG\}$.

Our experimental results in Section 6 demonstrate that this seemingly simple method outperforms each individual model by a clear margin. Specifically, in this work we choose the following two as the text- and propagation-based models:

- A document classification model using hierarchical attention networks [50]. The overall architecture of this model consists of four components: (1) a word encoder where words are embedded with a GRU-based sequence encoder; (2) a word-level attention layer where the importance of a word is measured by its similarity with a word-level context vector, which is jointly learned during the training process; (3) a sentence encoder that is also based on bidirectional GRU; and (4) a sentence-level attention layer that calculates the weight of a sentence in a similar way to (2). The reason why we choose this model is that previous work has shown that it performs better than other text-based models for fake news detection [33], such as LIWC [25], text-CNN [17].

- A propagation-based algorithm [12] that applies the GNN model of DiffPool [52] (built on top of GraphSage [9]) to verify a news item purely on its propagation pattern (as explained in the introduction) and the features of the corresponding Twitter users, including (1) whether the user is verified, (2) the timestamp when the user was created, (3) the number of followers, (4) the number of friends, (5) the number of lists, (6) the number of favourites; (7) the number of statuses, (8) the timestamp of the tweet. The adjacency matrix corresponding to the propagation pattern of a news item and the node feature matrix are fed as input for graph-level classification. We choose this model due to its simplicity and efficiency.

Note that (1) although the experimental results in the next section suggest that our knowledge-based model works well together with the above two models, especially the propagation-based model, they can be replaced by other options too; (2) in addition to text content and propagation network, there are other useful forms of information as well, including user replies, images and external knowledge graphs, especially domain-specific knowledge graphs. We leave more sophisticated fusion techniques for future work.

6 EXPERIMENTAL VERIFICATION

In this section, we empirically verify the effectiveness of our proposed knowledge-based and multi-modal fake news detection algorithms over two datasets with thousands of labelled news items.

6.1 Datasets

While there are a number of public datasets on fake news detection covering different domains, we choose the dataset of FakeNewsNet [34] in our work. FakeNewsNet contains labelled news from two websites: politifact.com and gossipcop.com—我们 call them Politifact and GossipCOp hereafter. For each news item, the dataset provides both linguistic and visual information, all the tweets and retweets, as well as the information of the corresponding Twitter users. For more details please refer to [34].

The reasons why we choose Politifact and GossipCOp over other options include: (1) they align with the our definition of fake news—fake news is intentionally and verifiably false news published by a news outlet. Some public datasets on fake news detection, e.g., Twitter16 [22], Weibo [21], Pheme [18] are intended for detecting rumours, satires, misinformation, etc. (2) They provide accurate ground truth labels, which are collected using fact-checking websites. As a result, they are more accurate than those datasets where news items are weakly labelled by applying distant supervision techniques. For example, the datasets of ReCOVery [57] and CoAID [7] label news records based on the reliability of the source. (3) They provide social context data, which is missing in datasets such as BuzzFeedNews [32], Ma-Twitter [21] and LIAR [43]. This type of information is required by the chosen propagation-based approach to construct the propagation network for each news item.

Table 1: Sstatistics of the PolitiFact and GossipCop datasets.

| Dataset    | No. of Fake News | No. of Real News |
|------------|------------------|------------------|
| PolitiFact | 185              | 225              |
| GossipCop  | 4942             | 2520             |

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3https://www.politifact.com/

4https://www.gossipcop.com/
Table 2: Performance comparison of fake news detection on the dataset of PolitiFact

| K1 | T1 | P1 | Accuracy | Precision | Recall | F1   |
|----|----|----|----------|-----------|--------|------|
| ✓  |    |    | 0.837    | 0.844     | 0.801  | 0.836 |
| ✓  | ✓  |    | 0.829    | 0.838     | 0.824  | 0.826 |
| ✓  | ✓  | ✓  | 0.854    | 0.855     | 0.852  | 0.852 |
| ✓  | ✓  | ✓  | 0.858    | 0.853     | 0.842  | 0.857 |
| ✓  | ✓  | ✓  | 0.884    | 0.922     | 0.829  | 0.883 |
| ✓  | ✓  | ✓  | 0.876    | 0.862     | 0.877  | 0.876 |
| ✓  | ✓  | ✓  | 0.919    | 0.913     | 0.913  | 0.919 |

Avg bias [24] 0.752 0.725 0.776 0.729
Max bias [24] 0.662 0.617 0.638 0.618

1 K: knowledge-based, T: text-based [50], P: propagation-based [12]

Table 3: Performance comparison of fake news detection on the dataset of GossipCop

| K1 | T1 | P1 | Accuracy | Precision | Recall | F1   |
|----|----|----|----------|-----------|--------|------|
| ✓  |    |    | 0.783    | 0.813     | 0.870  | 0.750 |
| ✓  | ✓  |    | 0.788    | 0.767     | 0.747  | 0.754 |
| ✓  | ✓  | ✓  | 0.872    | 0.855     | 0.860  | 0.858 |
| ✓  | ✓  | ✓  | 0.800    | 0.823     | 0.888  | 0.768 |
| ✓  | ✓  | ✓  | 0.861    | 0.882     | 0.910  | 0.843 |
| ✓  | ✓  | ✓  | 0.879    | 0.916     | 0.899  | 0.866 |
| ✓  | ✓  | ✓  | 0.871    | 0.903     | 0.900  | 0.856 |

Avg bias [24] 0.749 0.646 0.621 0.629
Max bias [24] 0.723 0.625 0.627 0.626

1 K: knowledge-based, T: text-based [50], P: propagation-based [12]

The statistics of the dataset are listed in Table 1. Note that the values are smaller than those reported in [34] because (1) many news items, especially fake news, have already been removed, (2) some tweets and retweets of a news item are no longer retrievable, and we cannot build the corresponding propagation pattern. Therefore, those news items are also excluded from our experiments.

6.2 Baselines

Three baselines are considered: in addition to the two models chosen in Section 5, i.e., test-based [50] and propagation-based [12], we also implement the knowledge-based method [24] described in the introduction.

In order to compare these models, the datasets are split as follows: 70% of the data are used for training, 15% are for validation, and the remaining 15% are for test. In addition, all models are evaluated with the following commonly used metrics: accuracy, precision, recall and F1 score.

Model hyper-parameters. (1) For the text-based model, both the word embedding dimension and the GRU dimension are set to 100, the learning rate is 0.003, and the batch size is 32 for PolitiFact and 128 for GossipCop. (2) For the propagation-based model, the hyper-parameters for the DiffPool algorithm are: 2 pooling layers, 64 hidden dimensions and 64 embedding dimensions. In addition, the learning rate is 0.001, and the batch size is 128. (3) For our knowledge-based model, the hyper-parameters for SubGNN are selected from the following ranges: batch size $\in [64, 128]$, learning rate $\in [3e-5, 1e-3]$, number of layers $\in [1, 4]$, number of structure anchor patches $|A_0| \in [15, 45]$, and feed forward hidden dimension sizes $\in [32, 64]$ with dropout $\in [0.0, 0.4]$. (4) For our multi-modal approach, number of feed forward layers $\in [2, 4]$ with hidden dimension sizes $\in [8, 64]$ and dropout $\in [0.0, 0.2]$. (5) For the baseline of [24], the embedding dimensions of $K_{GF}$ and $K_{TG}$ are in the range of $[30, 50]$ for PolitiFact, and $[50, 100]$ for GossipCop.

6.3 Performance Comparison of Fake News Detection

Tables 2 and 3 show the performance comparison on the two datasets of PolitiFact and GossipCop (results in bold correspond to the best values or values less than 0.01 below the best values). The results suggest that:

- Our knowledge-based model outperforms the baseline of [24] on both datasets.
- In terms of each single model of $K$, $T$ and $P$, the difference among their performances on the dataset of PolitiFact is not significant, but the propagation-based model achieves the best performance on the dataset of GossipCop, while the other two perform similarly again.
- In terms of the multi-modal approach, the performance of any combination of two models is almost always better than each individual model.
- If we compare the different combinations, $K + T < T + P \approx K + P \leq K + T + P$: (1) since the knowledge- and text-based models rely on the same source of information—the news content, the combination of these two performs the worst. (2) When the knowledge- or text-based model is combined with the propagation-based model, they perform similarly and both better than (1). (3) The combination of all three models performs the best overall.

The above results suggest that while our knowledge-based approach that does not require any external knowledge graph is effective, combining it with other sources of information can further boost its performance.

6.4 Time sensitivity analysis

In addition to the metrics of accuracy, precision, recall and F1 score, it is important to understand how the performance of a model changes over time, since in real cases a deployed fake news detection system is likely to face highly dynamic and volatile data.

We run time sensitivity analysis over a period of 26 weeks (half a year) on the dataset of GossipCop (the dataset of PolitiFact contains only around 400 news items spread over a number of months, which are insufficient to run the analysis): all news items are sorted by their timestamp, and the first 70% are used for training while the last 30% are for testing. During test time the data are divided into separate groups based on the number of weeks from the test news item to the last training item, then the four metrics are calculated over each group, i.e., the model performance is measured weekly. Fig. 4 shows how different models perform over time.
Figure 4: Time sensitivity analysis for the dataset of GossipCop. The x-axis is the number of weeks from the test item to the last training item.

We can see that (1) the multi-modal approach performs the best in most cases. (2) In the first few weeks, the performance drop of the text-based and the knowledge-based approaches is more obvious than that of the multi-modal and the propagation-based approaches. (3) All four models are relatively stable between Week 5 and Week 25. The results further confirm the effectiveness of the multi-modal approach that combines extracted knowledge, text content and propagation network.

7 RELATED WORK

In this section, we provide a brief review of the related work on fake news detection, which has become a popular research problem over recent years. Specifically, following a similar taxonomy in [26, 36], we classify existing work into three categories: content-based approaches, context-based approaches and mixed approaches, which mainly rely on news content, social context, and a mix of both for detection, respectively. In addition, we also summarise prior work on fake news early detection and explainability.

7.1 Content-based Approaches

The most straightforward content-based approach is to consider fake news detection as a text classification problem, and apply techniques such as RST [30], LIWC [25] and text-CNN [17] to identify fake news. These algorithms often serve as baselines. In addition to the knowledge-based detection methods discussed in this paper, another line of research studies fake news from a style-based perspective.

7.1.1 Style-based Detection. Since the purpose of fake news is to mislead the public, they should exhibit unique writing styles that are rarely seen in real news. This is supported by forensic psychological studies [40], which have shown that statements based on factual experiences differ from those derived from fabrication or fiction in both content and quality.

Therefore, style-based methods aim to identify the different content style, which can be represented by quantifiable features, including attribute-based language features or structure-based language features. For example, Perez-Rosas et al. [29] train linear SVMs on the following linguistic features to detect fake news: unigrams, bigrams, punctuation, psycholinguistic, readability and syntax features. Other methods that fall into this category include [13, 28, 41, 43].

In addition to textual information, images posted in social media have also been investigated to facilitate the detection of fake news [15, 44, 49, 58].

7.2 Context-based Approaches

Social context here refers to the interactions between users, including tweet, retweet, reply, mention and follow. As mentioned in the introduction, these engagements can form the propagation pattern for a news item, and a number of studies have used various types of models to identify the difference in the propagation pattern between real and fake news: Wu et al. [45] use a hybrid SVM; Ma et al. [22] use Propagation Tree Kernel; Wu et al. [46] incorporate LSTM cells into the RNN model; Liu et al. [19] use both RNNs and CNNs; Shu et al. [35] and Zhou et al. [60] propose different types of
features and compare multiple commonly used machine learning models; Monti et al. [23], Lu et al. [20] and Bian et al. [4] apply GNNs to study propagation patterns.

In addition to the propagation network, other types of graphs can also be built from social context. For example, Jin et al. [14] build a stance network where the weight of an edge represents how much each pair of posts support or deny each other. Then the credibility of all the posts related to a news item is estimated to decide whether the news is fake or real, which can be formalised as a graph optimisation problem.

In another example, Tacchini et al. [39] propose to detect fake news based on users who liked them on Facebook. They tested logistic regression-based and harmonic Boolean label crowdsourcing-based methods, and their results suggest that both methods can achieve high accuracy.

While all the above methods are supervised, an unsupervised approach is proposed by Yang et al. [48], which builds a probability graphical model to capture the generative process among the validity of news, user opinions and user credibility.

### 7.3 Mixed Approaches

Since both news content and social context can provide valuable evidence, mixed approaches use these two sources of information to differentiate between fake news and real news.

Ruchansky et al. [31] design a three-module architecture that combines the text of a news article, the received user response and the source of the news: (1) in order to capture temporal representations of articles, the first module trains a RNN that takes the user response, news content and user features as input; (2) the second module generates for each user a score and a low-dimensional representation based on user features; (3) the third module takes the output of the first two modules and trains a neural network to label the news item.

A pre-extracted word set is used in [53] to construct explicit features from the news content, user profile and news subject description. Meanwhile, RNNs are applied to learn latent features, such as news article content information inconsistency and profile latent patterns. Once the features are obtained, a diffusive network is built to learn the representations of news articles, creators and subjects.

Shu et al. [37] propose to use the tri-relationship among publishers, news articles and users to detect fake news. Specifically, the latent representations for news content and users are learned with non-negative matrix factorization, and the problem is formalised as an optimisation over the linear combination of each relation. They compare a number of machine learning algorithms to solve the optimisation problem in their experiments.

### 7.4 Explainability

In addition to the above work, a few recent papers have started to work on explainability, which provides evidence to support why their model labels certain news items as fake/real [20, 27, 33].

For example, Lu et al. [20] propose a novel attention mechanism for fake news detection which jointly considers news textual content, retweet sequences in propagation networks, and user co-occurrence networks.

### 7.5 Fake News Early Detection

Considering that it is difficult to correct people’s perception towards an issue, even if the previous impression is inaccurate [16], it is more crucial to detect fake news at an early stage before it becomes widespread. Therefore, another line of research works on early detection of fake news [19, 38, 56]. Shu et al. [38] study multiple weak signals of user sentiment, bias and credibility, and then combine weakly labelled data with a small amount of manually labelled data to train a fake news detection model.

### 8 CONCLUSIONS AND FUTURE WORK

A series of incidents over recent years have demonstrated the significant damage that fake news can cause to society. In this work, we investigate knowledge-enhanced multi-modal techniques for fake news detection. Specifically, we transform the problem of detecting fake news into a subgraph classification task, and design a knowledge-based algorithm that does not require any external knowledge graph. In addition, we propose a multi-modal detection algorithm that combines extracted knowledge, textual content and social context. Experimental results on two datasets with thousands of labelled news items demonstrate the effectiveness of our approaches.

For future work, we will further explore more sophisticated methods rather than simple concatenation to combine different sources of information. Moreover, in addition to news content and propagation networks, we intend to exploit other modalities as well, including images and external knowledge graphs.

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