IARNet: An Information Aggregating and Reasoning Network over Heterogeneous Graph for Fake News Detection

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Abstract—Fake News Detection on social network is still a challenging task that requires to integrate different types of information, e.g., source post, comments, and related users to verify the given news. However, previous solutions extract features from different aspects respectively, ignore the inherent relational and logical information among these features. In this paper, we propose IARNet, an Information Aggregating and Reasoning Network over heterogeneous graph for fake news detection, which exploits the interaction between information to aggregate multi-type information and grasps the inherent relationship simultaneously. Firstly, we construct a heterogeneous graph which takes source post, comments, and users as nodes and the interaction between them as edges. Then, a two-level attention mechanism is applied at the node level and type level. Specifically, the node-level attention aims to learn the importance between a node and its specific edge based neighbors, while the type-level attention aims to learn the importance of different types of edges. With the two-level attention mechanism, IARNet can aggregate multi-type information in a hierarchical manner and the information can reason over heterogeneous graph for the facticity of the news. Experimental result shows that our method outperforms the state-of-the-art competitors on real-world datasets with GloVe embeddings. We also demonstrate that using BERT representations further substantially boosts the performance. Our code is available at https://github.com/serryuer/IARNet.

Index Terms—fake news detection, information aggregating, heterogeneous graph

I. Introduction

The widespread of fake news can significantly weaken the public trust in governments and journalism, and change the way people respond to legitimate news [1]. To curtail the spread of fake news on social media and promote trust in the entire news ecosystem, it is crucial to find an effective method for detecting fake news automatically.

Fake news is defined as a story or statement in general circulation without confirmation or certainty to facts [2]. For example, Fig. 1 shows an example of fake news about Malaysia Airlines from Twitter, with a source post and related engagements (i.e., comments and users). Some early works manually design features, e.g., sentiment lexicons and linguistic features, to train classifiers for fake news detection [3]–[6]. Later, various methods based on neural network became popular for this task [7]–[10], as they do not require manual feature engineering. Whereas most of these methods only utilize one type of information, and other types of data cannot be naturally integrated. Recent research [1], [11] thus advancements aggregate news's social engagements with source post to help infer the news is fake or not. They extract information from different aspects respectively, then use simple fusion strategy such as concatenation to obtain the representation of news. However, the rich relationship between different types of data is neglected, which can provide important cues to detect fake news. As shown in Fig. 1, we cannot derive the facticity of the news merely rely on its source post content. Nevertheless, the news can be verified by understanding and reasoning over the multiple engagements.

Fig. 1. An example of fake news on Twitter

Recent studies have shown that graph can provide a general representation to integrate multiple types of data [12]–[14]. Yuan et al. [15] has explored graph neural network for fake news detection. It only focuses on the structure information of propagation tree of news, instead of the aggregation of different types of information. Inspired by the success of graph neural networks in several tasks [16], [17], we expect that they work well to learn news representation from multi-type data. Towards this research gap, we propose to use heterogeneous graph to model the news as shown in Fig. 2, where three kinds of nodes are applied to represent three types of data, i.e., source post, comment, and user respectively and four types of edges are established to represent information interaction between different nodes. One rationality is that the neighbor features could provide valuable clues that are beneficial to infer the facticity of news. For example, users that have higher credibility are likely to post credible content, and if most of the comments on a piece of news are negative, it's probably fake news.

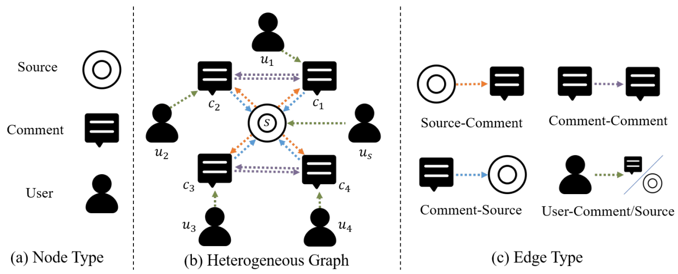


Fig. 2. A heterogeneous graph for modeling social news. (a) Three types of nodes. (b) Social news in heterogenous graph. (c) Four types of edges involved in the graph.

To learn the representation for each entity in the heterogeneous graph, we propose an Information Aggregating and Reasoning Network (IARNet), which considers both node-level and type-level attentions. In particular, given a specific edge type, each node may have lots of edge type based neighbors. In order to distinguish the subtle differences of their neighbors and select some informative neighbors to enrich the representation of themselves, the node-level attention aims to learn the relative importance of edge type based neighbors and assign different attention values to them. Then, the type-level attention will learn the importance of different edge types and assign proper weights to them to aggregate multi-type information. Based on the learned attention values in terms of the two levels, our model can get the optimal combination of edge type based neighbors and multiple edge types in a hierarchical manner, which enables the learned node embeddings to better aggregate multi-type information and sufficiently grasp the inherent relationship among nodes.

To sum up, the main contributions of this paper are as follows:

1) This is the first study that deeply aggregates multi-type information based on heterogeneous graph for detecting fake news.

2) We propose a novel information aggregating and reasoning network (IARNet) over heterogeneous graph, which includes both of the node-level and type-level attentions. Benefitting from such hierarchical attentions, the proposed IARNet can aggregate multi-type information and learn the inherent relationship simultaneously.

3) We apply the proposed method to the real-world dataset and the experiments show that our approach outperforms state-of-the-art methods with GloVe Embeddings [18]. We also demonstrate that using BERT representations [19] further substantially boosts the performance.

II. Related Work

A. Fake News Detection

The task of detecting fake news has undergone a variety of labels, from misinformation, to rumor, to spam [20]. Just as each individual may have their own intuitive definition of such related concepts, each paper adopts its own definition of these words which conflicts or overlaps both with other terms and other papers. For this reason, we specify that the target of our study is detecting news content that is fabricated, that is fake.

There has been a large body of work surrounding text analysis of fake news and similar topics such as rumor or spam. These work focused on mining particular linguistic cues from source contents, such as specific writing styles [6] and sensational emotions [21]. For example, Gupta et al. [8] found that fake news often contain an inflated number of swear words and personal pronouns. Branching off the core linguistic analysis, many have combined the approach with traditional classifiers to label a news as true or false [22]–[24]. In addition, latent textual representations of source contents are modeled using deep neural networks [10], [25], [26] for fake news detection, which has achieved promising results. Besides, the features of visual elements in source contents are extracted to fusion with textual-based features for multimodal fake news detection [27]–[30].

Recently, additional social context features derived from social engagements of news have been exploited for more accurate detection. For example, Natali et al. [20] used a deep hybrid model (CSI) to unify news text, user response, and source users simultaneously for fake news detection. Guo et al. [11] proposed a hierarchical neural network (HPA-BLSTM) to model user engagements with social attention that selects important user comments. Shu et al. [1] employed a sentence-comment co-attention sub-network to exploit both news contents and user comments for fake news detection. Besides, research also focuses on some network-based features, which are extracted by constructing specific networks, such as the propagation networks [9], [31], [32], diffusion networks [33], and interaction networks [34].

However, most of these approaches ignore the interaction between the information or just use simple information combination methods to integrate multi-type data, which unable to grasp sufficient relational and logical information among information.

B. Graph Convolutional Networks

Graph Convolutional Network (GCN) [12] has recently achieved appealing performance in a variety of tasks, such as node classification task [12], recommendation [17], and stock prediction [35]. They can encode both graph structure and features of nodes without the need for designing features of fusion strategy. Besides, attention mechanisms, e.g., self-attention [36], have become one of the most influential mechanisms to deep learning. Graph Attention Network (GAT) [37] introduces the attention mechanisms to learn the importance between nodes and their neighbors and fuse the neighbors to perform node classification.

Recently, there are some preliminary works of applying GCN for fake news detection. Huang et al. [38] proposed a GCN based networks to model user attributes and behaviors for fake news detection. Yuan et al. [15] modelled the global relationships among all source posts, comments, and users to capture the rich structural information of news. They also ignore the interaction between information involved in the news. In this paper, we focus on the aggregating of information extracted from both news contents and social contexts and the interaction between them simultaneously on the heterogeneous graph.

III. Problem Formulation

The purpose of social media fake news detection task is to learn how to detect fake news from social media automatically, which is essentially a binary classification problem. The formal definition of the task is as follows: given the news set $E = \{E_1, E_2, \cdot, E_m\}$ and a label set $L = \{l_1, l_2\}$. E_i represents a event as shown in Fig. 2, which contains a source post s_i and several engagements $\mathcal{E} = \{e_{ijt}\}$. Each engagement $e_{ijt} = \{u_j, c_j, t\}$represents that a user u_j comment source post s_i with c_j at time t. And l_1, l_2represent fake and true news respectively. The task of social media fake news detection is to learn a classification model f, mapping each news E_i to a category label L_j, that is: $E_i \rightarrow L_j$.

IV. The Proposed Model

The proposed fake news detection model consists of four major components: entity encoding, graph constructing, information aggregating and reasoning, and fake news detection. Specifically, the entity encoding module learn the hidden representation for each entity involved in news (e.g., source post, comments, and users); the graph constructing module constructs a heterogeneous graph based on the entities and the interaction between them; the information aggregating module exploits a two-level attention mechanism to aggregate multi-type information over the graph; the fake news detection module learns a classification function to predict the label of given news. For the remainder of this section, we will introduce each of the major steps in detail.

A. Entity Encoding

We divide the entities in the news into two categories according to the content: textual entity and profile entity. For textual entity, which contains source post and comments, we first learn the embeddings of words via a Bidirectional Gated recurrent units (BiGRU) [39] based network, then introduce an attention mechanism to learn the weights measuring word importance, which is used to calculate the final entity representation. For the profile entity, that is user profile, because the features are discrete such as the number of reports, the number of friends and so on, we use one-hot encoding to represent the profile, and feed it into a two-layer fully-connected MLP to get the representation for each user profile entity.

B. Graph Constructing

The heterogeneous graph to model social news $G = (V, E)$ contains one source node $\mathbf{s} \in V$ and several comment nodes $[c_0, c_1, \cdots, c_n] \in V$ with their responding user profile nodes $[u_0, u_1, \cdots, u_n] \in V$ as show in Fig. 2, and four type edges are established in the graph as follows:

Source-Comment(SC): Intuitively, the representation of comment node is based on the information of the source node which describes the whole event. For this reason, we create source-to-comment edge $e_{sc} \in E$ for all comments involved in the given news to enrich their representation.

Comment-Source(CS): The information of comment often expresses doubts or affirmation about the news which can provide import cues to detect fake news. So all comments will be connected to the source node through comment-to-source edge $e_{cs} \in E$ to enrich the representation of source node.

Comment-Comment(CC): If there is a hierarchical relationship between comments, there is also a potential logical relationship between the information they contain, which can be used to enrich the representation of comment node even the source node by information propagation over the graph. So we connect two comments with comment-to-comment edge $e_{cc} \in E$ if they have a superior-subordinate relationship.

User-Comment/Source(UC/US): The credibility of different users on social media is different, which means their comments/source post have a different impact on the authenticity of the news. So we can use the information extracted from the user profile to supplement the representation of the comment/source node. So the edge $e_{uc/us} \in E$ from user profile node to corresponding comment node or source node is established.

C. Information Aggregating and Reasoning

In this part, we present the information aggregating and reasoning part, which is designed to update the representation of nodes by aggregating multi-type information on the heterogeneous graph. As shown in Fig. 4, we apply a two-level attention mechanism to integrate the neighbors' information for the update of source node and comment node. Details are described below.

Due to the heterogeneity of nodes, different types of nodes have different feature spaces. Therefore, we design the type-specific transformation matrix $\mathbf{M}_{\theta_i}$ to project the

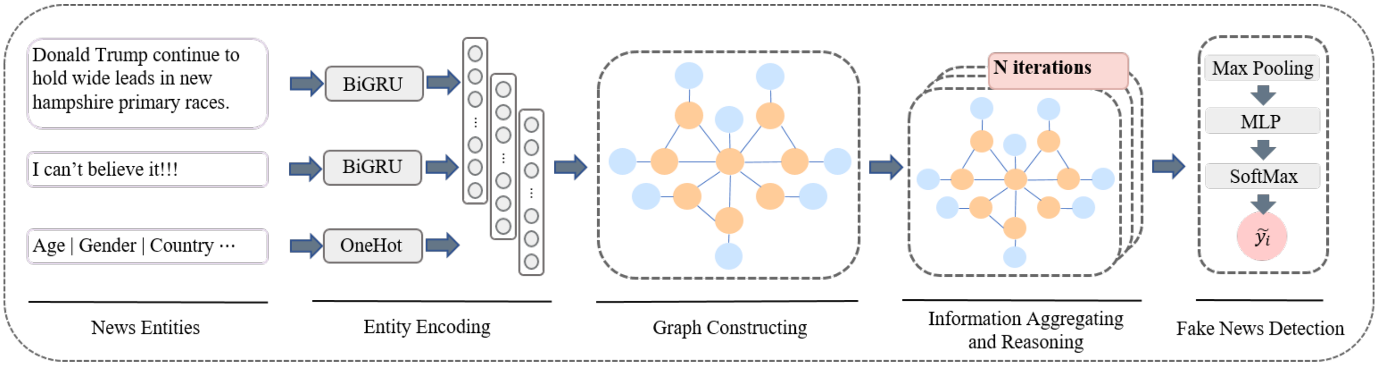
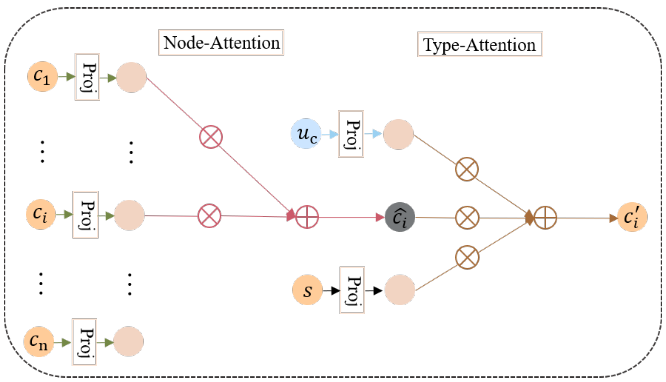
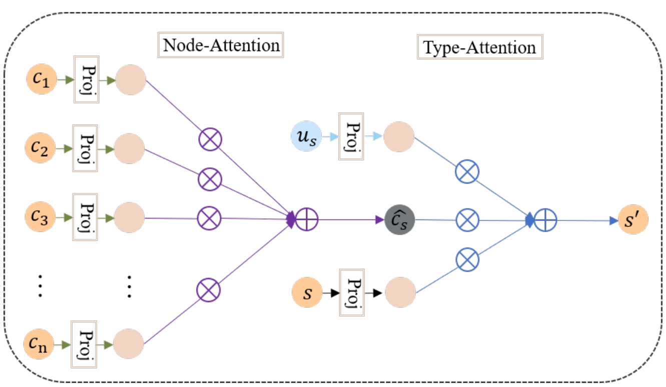


Fig. 3. The architecture of the proposed fake news detection model.



(a) Information Aggregating for Comment Node



(b) Information Aggregating for Source Node

Fig. 4. The information aggregating on the heterogeneous graph.

features of different types of nodes into the same feature space as follows:

$$\mathbf{h}'_{\theta_i} = \mathbf{M}_{\theta_i} \cdot \mathbf{h}_i \tag{1}$$

where θ_i is the type of node, $\mathbf{h}_i$ and $\mathbf{h}'_i$ are the original and projected feature of node i.

Firstly, we show how to aggregate information to update the representation of comment nodes with two-level attention mechanism as shown in Fig. 4(a). Given a comment node c_i, which has related comment nodes $\mathcal{N}_i^c$ as its neighbors across the Comment-Comment edge (include itself). The node-level attention will learn the weight between c_i and its related comment nodes. The importance e_{ij}^c means how important comment j will be for comment i and can be formulated as follows:

$$e_{ij}^c = att_{node}^c(h'_i, h'_j; \theta) \tag{2}$$

where att_{node}^c denotes the deep neural network which performs the node attention for the update of comment node. Next we normalized them to get the weight coefficient α_{ij}^c via softmax function:

$$\alpha_{ij}^c = \operatorname{softmax}_j\left(e_{ij}^c\right) = \frac{\exp\left(e_{ij}^c\right)}{\sum_{k\in\mathcal{N}_i^c}\exp\left(e_{ik}^c\right)} \tag{3}$$

Then, the embedding of c_i's related comment nodes can be aggregated as follows:

$$\hat{\mathbf{c}}_i = \sigma\left(\sum_{j\in\mathcal{N}_i^c} \alpha_{ij}^c \cdot \mathbf{h}'_j\right) \tag{4}$$

Next, the type-level attention will learn the importance of different edge types to aggregate multi-type information, that is related comments, responding user profile, and source post. The detail process is as follows,

$$c'_i = \sigma\left(\sum_{i\in\mathcal{V}} w_i \cdot z_i\right) \tag{5}$$

$$w_i = att_{type}^c(z_i; \theta) \tag{6}$$

where $\mathcal{V}$ represents multi-type information, and z_i is the representation of type i, w_i is the corresponding attention value, att_{type}^c represents the type-level attention.

The information aggregating to update the representation of source node is similar as shown in Fig. 4(b). Firstly, the node-level attention will learn the relative importance for all comment nodes $\mathcal{C} = \{c_1, \cdots, c_n\}$ to source node s as follows,

$$e_{sj}^s = att_{node}^s(h'_s, h'_j; \theta) \tag{7}$$

$$\alpha_{sj}^s = \operatorname{softmax}_j\left(e_{sj}^s\right) = \frac{\exp\left(e_{sj}^s\right)}{\sum_{k\in\mathcal{C}}\exp\left(e_{sk}^s\right)} \tag{8}$$

where att^s_{node} performs the node attention for the update of source node, α^s_{sj} represents the importance of comment node c_j to source node s.

Then, the representation of all comment nodes can be aggregated as follows,

$$\hat{\mathbf{c}_s} = \sigma\left(\sum_{j\in\mathcal{C}} \alpha^s_{sj} \cdot \mathbf{h}'_j\right) \tag{9}$$

Finally, the type-attention of source node will aggregate three types of information, that is source node, aggregated comment nodes, source user node, to update the representation of source node as follows,

$$c'_s = \sigma(\sum_{i\in\mathcal{V}} w_i \cdot z_i) \tag{10}$$

$$w_i = att^s_{type}(z_i;\theta) \tag{11}$$

where c'_s is the new representation of source node s.

To better aggregate the information, we extend all attention to multi-head attention. Specifically, we repeat the attention for K times and concatenate the learned embeddings.

By stacking T layers of IARNet, we assume that the representation of source node and comment node has grasp enough information by aggregating multi-type information. Besides, each textual node in the graph is directly or indirectly connected and transfer information with each other, which means they can reason over the graph to infer the facticity of given news. We feed the final hidden states of all textual nodes $\left\{\mathbf{h}^T_1, \mathbf{h}^T_2, \ldots, \mathbf{h}^T_N\right\}$ into our classifier to make the final classification.

D. Fake News Detection

We employ an max pooling operation to gather information from different textual nodes and obtain the final hidden state o, which is feed into a one-layer MLP to get the final representation o, then, we use $softmax$ function to get the prediction probability l,

$$\mathbf{o} = \text{Max}(\mathbf{h}^T_1, \mathbf{h}^T_1, \cdots, \mathbf{h}^T_N) \tag{12}$$

$$l = softmax(ReLU(\mathbf{Wo} + \mathbf{b})) \tag{13}$$

E. Model Training

Finally, the cross-entropy loss is used as the optimization objective function for fake news detection:

$$L(Y,P) = -\frac{1}{M}\sum_{i=1}^{M}\sum_{k=1}^{K} y_{i,k}\log(p_{i,k}) + \lambda\|\theta\|^2_2 \tag{14}$$

where $y_{i,k}$ is the groun truth of the i_{th} sample in the k_{th} class(1 if $y_{i,k}$ belongs to the k_{th} class, otherwise 0), and $p_{i,k}$ is the probability of prediction that the i_{th} sample belongs to the k_{th} class. M is the number of training data, K is the number of classes, $\|\cdot\|_2$ is the L_2 regularization term for all parameters θ in the model, and λ is the trade-off coefficient.

F. Heterogeneous Graph Sampling

The news in real-world will have many comments while some only have a few comments, the former will introduce some noise to the graph by some weakly correlated comment and the latter will cause the inadequate representation of the graph. They will all weak the performance of the rumor detection method. Traditional graph convolution networks [12] need all the nodes in the graph are present simultaneously during the training procedure, which is not appropriate to be applied in real applications. Some sampling methods were proposed [16], [40] to perform operations on large graphs. However, they are designed for the homogeneous graph.

In this paper, we design a graph sampling strategy based on random walk with restart (RWR) to sample comments. More concretely, we start a random walk from source node s. The walk iteratively travels to the neighbor comment node with a probability p or returns to the source node with a probability $1-p$, and it will automatically return to the source node if it reaches the last level of comments. RWR will runs until it successfully collects a fixed number of comments.

This strategy is able to avoid the aforementioned issues due to the sampled comment size of each source node is fixed, which will enhance the graph representation of less commented news and reduce the impact of noise to the news with more comments.

V. Experiments

A. Data sets

We utilize two real-world datasets to evaluate our method:

Weibo [7]: This dataset includes 2,313 fake news and 2,351 true news. The fake news are verified by Sina community management center, and the true news are gathered by crawling posts in general threads.

Fakeddit [41]: This dataset is the latest fake news detection bench-mark dataset, which was crawled from Reddit [1], and consisting of about 800,000 samples from multiple categories of fake news.

Each sample in two datasets contains news content with labels and social context information. In our experiments, we split each dataset into training set(70%), validating set(20%), and testing set(10%). The more detailed statistics of datasets are shown in Table I.

TABLE I
Statistics of the dataset

Statistic	Weibo	Fakeddit
# of news	4,664	795108
# of fake news	2,313	500,733
# of true news	2,351	294,375
# of posts	1,803,891	11,492,641
# of users	1,422,140	1,670,501

[1] https://www.reddit.com/

B. Baseline Models

We compare our model with five state-of-the-art models that have been used for similar classification tasks and were discussed above as follows:

- DTC [22]: The Model extracts a variety of handcrafted statistical features then use a decisiontree based model to detect fake news.
- SVM-TS [23]: An linear SVM based model which utilizes time-series to model the variation of news characteristics.
- SVM-RBF [42]: An SVM model with RBF kernel that utilize a combination of news characteristics.
- GRU-RNN [7]: A recurrent neural networks based model with GRU units for learning news representations by modeling the sequential structure of relevant posts.
- HPA-BLSTM [11]: A neural network model that learns news representation through a hierarchical attention network on word-level, post-level, and subevent level of user engagements on social media to detect fake news.
- GLAN [15]: A heterogeneous graph network based model which jointly encodes the local semantic and global structural information for fake news detection.
- BERT-AVG: We first use BERT to get the representation for source content and comments content, then use the average of all representations to train a linear classifier.
- BERT-CAT: We concatenate all comments as an all-comment sentence, then construct a text pair formatted as "[CLS]" + source content + "[SEP]" + all-comment sentence + "[SEP]", which is feed into BERT, then we directly use the representation of "[CLS]" as a classification feature to fine-tune the BERT model for fake news detection.

The GLAN model is the state-of-the-art method for fake news detection when submitting this paper.

C. Implementation Details

1) Word Embedding: We try two word embedding strategies for our model. One is 300-dimensional GloVe embeddings [18] for Fakeddit dataset and 300-dimension Chinese word embeddings trained by [43] for Weibo dataset. Another is BERT [19] representations, where we use the base uncased English model with dimension 768 for the Fakeddit dataset and the base Chinese model with dimension 768 for the Weibo dataset.

2) Parameter Settings: For BERT-AVG, the maximum sequence length is 128. And for BERT-CAT, we limit the max length for concatenated comments to 512. In our IARNet, We set the dimension of the hidden state as 300 in our experiments and we map word representations obtained from BERT into 300-dimensional vectors by a linear projection layer. We use 6 attention heads for all multi-head attention in our model. In the Heterogeneous Graph Sampling stage, the number of comments is set as 50 and the probability of restart is set as 0.5.

TABLE II
Experimental Results on Weibo

	Accuracy	F-score
DTC	0.831	0.831
SVM-TS	0.857	0.861
SVM-RBF	0.818	0.819
GRU-RNN	0.910	0.914
HPA-BLSTM	0.943	0.943
GLAN	0.946	0.945
IARNet-GloVe(2)	0.956	0.969
IARNet-GloVe(3)	0.965	0.952
BERT-AVG	0.956	0.956
BERT-CAT	0.952	0.952
IARNet-BERT(2)	0.963	0.970
IARNet-BERT(3)	0.969	0.959

D. Results and Analysis

The experimental results on the Weibo dataset are shown in Table II. For a fair comparison, the experimental results of baseline models are directly cited from previous studies [15], and for our models, we run all models 10 times and report mean results. With GloVe embeddings, our approach IARNet-GloVe(k), where k is the number of layers, beats all baselines on Weibo Dataset. Specifically, our IARNet-GloVe(3) achieves an accuracy of 96.5% on Weibo dataset. This is mainly due to the underlying two-level attention, which enables the model to aggregate multi-type information better and reason over the graph for the facticity of given news.

It is observed that the performance of the first 2 baselines based on handcrafted features (DTC, SVM-TS, SVM-RBF) is obviously poor, indicating that they fail to generalize due to the lack of capacity capturing robust and effective features. SVM-TS performs relatively better because it uses additional temporal and structural features, but it is still clearly worse than the models not relying on feature engineering. For deep learning based methods, GRU-RNN outperforms traditional machine learning based methods, which indicates that the deep neural network can learn deep latent features for rumor detection. Besides, the previous state-of-the-art method GLAN is much more effective than GRU-RNN, which proves the effectiveness of using heterogeneous graph to model social media.

As one direct competitor, HPA-BLSTM uses a hierarchical attention manner to model social news from different aspects, while our model use two-level attention to aggregate information on the heterogeneous graph. Compared to HPA-BLSTM, our model shows superior performance, which directly proves the effectiveness of heterogeneous graph to integrate multi-type information.

Using BERT representation further boosts the performance of our model. BERT-CLS, which uses BERT representations without fine-tuning, achieves surprisingly

TABLE III
Experimental Results on Fakeddit

	Accuracy	F-score
IARNet-GloVe(2)	0.953	0.952
IARNet-GloVe(3)	0.960	0.959
BERT-AVG	0.948	0.949
BERT-CAT	0.939	0.937
IARNet-BERT(2)	0.958	0.958
IARNet-BERT(3)	0.964	0.963

TABLE IV
The ablation analysis on the Weibo and Fakedit Dataset

Models	Weibo Accuracy	Fakeddit Accuracy
IARNet-GloVe-full	0.965	0.960
w/o CS	0.952	0.943
w/o SC	0.957	0.947
w/o CC	0.961	0.949
w/o UC/US	0.962	0.952

excellent performance on this task. After fine-tuning, the performance of BERT-AVG becomes even better. However, we observe that such fine-tuning is quite unstable. The model cannot converge in some trials. Even though the original BERT model already provides strong prediction power, our model consistently improves over them, which indicates that our model provides a better way to aggregate the semantic information and let them to inference over the graph. The accuracy of our model reaches 96.9% and 95.8% on the Weibo and Fakeddit datasets.

E. Ablation Study

In this section, we additionally conduct ablation analysis to show the effects of removing specific type of edge, so that the model cannot capture the relationships between specific types of information.

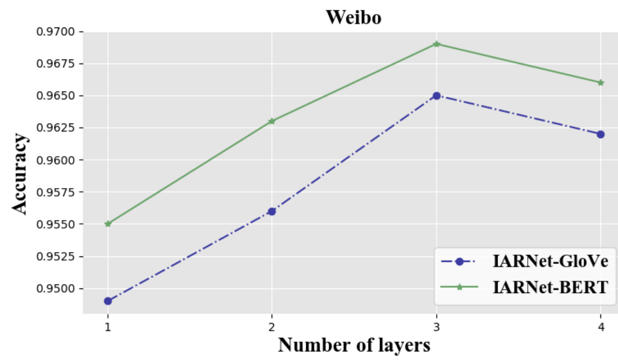
From the results shown in Table IV, we can observe that:

1) Removing the comment-to-source edges has the greatest impact on the performance, and the accuracy drops 1.3% and 1.7% on the Weibo and Fakeddit datasets. It is in line with our intuition because there are many superficial and potential connections between comments and content. Alike, removing the source-to-comment has a similar impact, where we got the accuracy drops 0.8%, 1.3% on two datasets. The edges between source and comment build a path for the information to transfer between each other. Besides, the source node in the middle will acts as a virtual hub to gather and scatter information from and to all connected comment nodes as shown in Fig. 2.

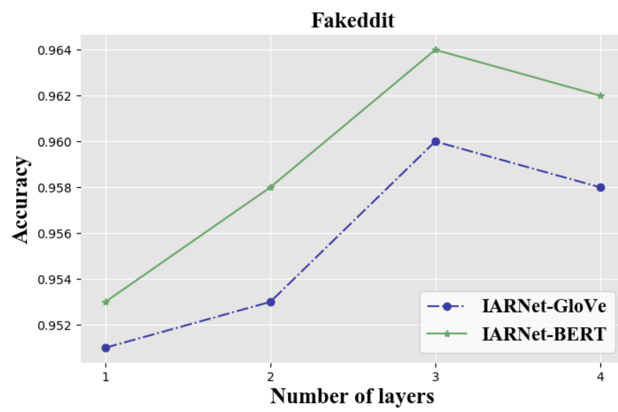
2) Removing the comment-to-comment edges makes the model performs slightly worse because there often has a supplementary relationship between comments with a superior-subordinate relationship, which is helpful to the reasoning over the whole graph for the facticity of the given event.

3) Removing the user-to-comment/source edges results in a 0.3% and 0.8% reduction in accuracy on two datasets. Intuitively speaking, the edge from the user to comment can enrich the representation of comment/source node by introducing user characteristics, and thereby it can improve the performance.

F. Effects of Model Depth



(a) The impact of model depth on Weibo dataset



(b) The impact of model depth on Fakeddit dataset

Fig. 5. The impact of model depth (number of layers).

We explore the impact of model depth (number of layers) in this section. For our IARNet model, we vary its model depth ranging from 1 to 4. As shown in Fig. 5, a one-layer IARNet with GloVe embeddings does not work well, which implies some useful information usually need more than 2-hops reasoning over the graph. Increasing the model depth to 3 would greatly improve the performance. But when model depth larger than 3, the performance will have a little drop, which means the model is too complicated. Our model with BERT representations perform better at every model depth, and our model reaches its optimal performance when model depth is 3.

VI. Conclusion and Future Work

In this paper, we present an information aggregating network over heterogeneous graph to aggregate multi-type information involved in the news, which can also make inference on every piece of information over the graph for the facticity of given news. Compared with previous methods, our approach focuses on the inherent relationships among different information and can leverage information more sufficiently. In our experiments, we demonstrate the effectiveness of our method on Weibo and Fakeddit datasets. Using GloVe embeddings, our approach IARNet-GloVe outperforms the state-of-the-art method. After switching to BERT representations, we show that IARNet-BERT achieves much better performance.

To the best of our knowledge, this paper is the first attempt using heterogeneous graph to aggregate multi-type information of news. Many potential improvements could be made in this direction. For example, we only consider the information involved in given news, future work could further consider other information, such as propagation structure and external knowledge, to improve the performance. Since this work only uses a Graph Sampling Method to sample comments of news and ignores the correlation betwesen comment and source post, we plan to design a more effective sample strategy to sample useful comments for the detecting of fake news.

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