Topology imbalance and Relation inauthenticity aware Hierarchical Graph Attention Networks for Fake News Detection

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Abstract

Fake news detection is a challenging problem due to its tremendous real-world political and social impacts. Recent fake news detection works focus on learning news features from News Propagation Graph (NPG). However, little attention is paid to the issues of both authenticity of the relationships and topology imbalance in the structure of NPG, which trick existing methods and thus lead to incorrect prediction results. To tackle these issues, in this paper, we propose a novel Topology imbalance and Relation inauthenticity aware Hierarchical Graph Attention Networks (TR-HGAN) to identify fake news on social media. Specifically, we design a new topology imbalance smoothing strategy to measure the topology weight of each node. Besides, we adopt a hierarchical-level attention mechanism for graph convolutional learning, which can adaptively identify the authenticity of relationships by assigning appropriate weights to each of them. Experiments on real-world datasets demonstrate that TR-HGAN significantly outperforms state-of-the-art methods.

1 Introduction

Fake news is a news article that is intentionally and verifiably false and could mislead readers (Rashkin et al., 2017; Zhou and Zafarani, 2020). The widespread of fake news can immensely affect cyberspace security and even social stability (Lazer et al., 2018). For example, fake news “all of Walmart’s e-commerce stores would include a pay with litecoin option beginning October 1”\(^1\) causes Litecoin’s prices surged by over 37% to $236 and Bitcoin’s prices fell below $44,000 (Kogan et al., 2021), resulting in huge losses for many investors.

Various fake news detection methods are developed to classify whether the news is fake or not, which can be roughly divided into news content-based methods and social context-based methods. Existing news content-based methods (Qazvinian et al., 2011; Maddock et al., 2015; Jin et al., 2013; Wu et al., 2015; Ma et al., 2017) typically focus on mining lexical and syntactic features (Feng et al., 2012; Potthast et al., 2017; Conroy et al., 2015) from news contents, ignoring the rich structural information of news propagation. To address this limitation, social context-based methods (Yuan et al., 2019; Yang et al., 2021; Shu et al., 2019; Yuan et al., 2020) tend to learn the feature representations by the structure information of News Propagation Graph (NPG), where NPG consists of multiple types of nodes (e.g., news, comments and users) and relationships (e.g., follower, retweet and friendship).

![Figure 1: Three types of unauthentic relation scenarios on news propagation graphs (NPG). Nodes representing fake objects (e.g., news or comments) and abnormal users are highlighted in red, while the unauthentic relations are represented by dotted lines. (a) An abnormal user User\(_1\) forwards a true news News\(_3\), and he manipulates or tricks a normal user User\(_2\) to create a fake supporting comment on a fake news News\(_1\), or he hacks a normal user User\(_3\) to forward a fake news News\(_2\). (b) A fake news producer User\(_1\) deletes real opposing comments produced by normal users. (c) An abnormal user User\(_1\) follows many normal users to disguise himself.](https://genesisblockhk.com/fake-news-litecoin-and-walmart-are-not-partnering-in-payments/)

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\(^{1}\)https://genesisblockhk.com/fake-news-litecoin-and-walmart-are-not-partnering-in-payments/
Although these social context-based methods achieve promising performance, they have an ill-advised assumption that impair the performance of fake news detection. Specifically, they assume a piece of news connecting with a trustworthy user should also have high credit. However, in many cases, the relationships in NPG can be manipulated by users and thus are unauthentic. For example, we present several types of unauthentic relations in Figure 1, where a fake news creator could manipulate other users to create fake comments to support the fake news, or delete real comments opposing the fake news. This leads to inaccurate NPG with unauthentic propagation structure, which confuses existing social context-based methods to make an incorrect prediction.

Besides, NPG usually has the problem of topology imbalance: the imbalance caused by the asymmetric and uneven topology of labeled nodes, where the decision boundaries are driven by the labeled nodes close to the topological class boundaries thus interfering with the model learning (Chen et al., 2021). Ideally, the influence from labeled nodes should decay with the topology distance and also the node influence boundaries should be consistent with the true class boundaries. But the topology imbalance issue would cause the node influence boundaries to deviate from the true class boundaries, resulting in inaccurate results. Nevertheless, most approaches neglect this issue in NPG, interfering with the detection results.

To tackle these issues, we propose a novel Topology imbalance and Relation inauthenticity aware Hierarchical Graph Attention Networks (TR-HGAN) for fake news detection. We firstly design a topology smoothing strategy to measure the weights of labeled nodes to alleviate the topology imbalance issue. Then we propose a hierarchical-level attention mechanism to identify the authenticity of relations by measuring the appropriate weights to each of them, which can effectively reduce the influence of the inauthentic relationships in NPG. The main contributions of this paper are as follows:

- We study a novel topology smoothing strategy to address the problem of topology imbalance of NPG. To the best of our knowledge, this is the first attempt to solve the topology imbalance issue of the NPG during fake news detection.

2 Related Work

Fake news detection challenges the usage of related information (such as text content, comments, propagation patterns, etc.) to distinguish whether a news article is fake or not. Related works can be divided into two perspectives: i) News content-based methods; ii) Social context-based methods.

2.1 News Content-based Methods

News content-based methods concentrate on designing some textual features such as content writing styles (Shu et al., 2017), lexical and syntactic features (Feng et al., 2012; Potthast et al., 2017; Conroy et al., 2015) to detect the truthfulness of news articles. For instance, Potthast et al. (Potthast et al., 2017) extracts various style features from news contents and predict fake news and media bias. Ma et al. (Ma et al., 2016; Yu et al., 2017) captures news features from low-level to high-level with deep neural networks. Although these approaches achieve good performance on fake news detection, they focus on learning text features alone, rarely considering whether the features can be captured by utilizing the news propagation structure.

2.2 Social Context-based Methods

Social context-based methods principally learn social interactions or information propagation structures through neural networks for further detection. Specifically, Wu et al. (Wu et al., 2015) propose a graph kernel-based SVM classifier that aims to learn high-order news propagation patterns of news articles. RvNN (Ma et al., 2018) and BiGCN (Bian et al., 2020) are developed based on bottom-up and top-down propagation trees for learning the embedding of fake news propagation structure. However, these tree-structured based studies don’t utilize the social network structure information, neglecting the fact that the information dissemination on social media is essentially spread in the form of heterogeneous graph.

To tackle these issues, (Lu and Li, 2020) constructs an user interaction graph to model the potential interactions between users, and then develop a dual co-attention mechanism to learn the
co-influence features. Recent studies (Yang et al., 2021; Yuan et al., 2019; Nguyen et al., 2020) formulate the news propagation structure as a heterogeneous news propagation graph with various types of nodes (e.g., news, comments, and users), and then apply GNNs model to capture the structure features for fake news detection. However, they don’t consider the unauthentic relations and inherent topology imbalance problem in the graph, and thus may fail to detect the intentional fake news.

3 Proposed Model

The overall architecture of TR-HGAN is shown in Figure 2, which involves four main components: i) NPG Construction; ii) Text Embedding; iii) Hierarchical Graph Attention Network that consists of topology imbalance smoothing strategy and hierarchical-level attention strategy; and iv) Fake news classification. Next, we describe each part of TR-HGAN in detail.

3.1 NPG Construction

Let $\mathcal{M} = \{m_1, m_2, ..., m_{|\mathcal{M}|}\}$ be a set of news articles on social media, where $m_i$ is the $i$-th news articles and $|\mathcal{M}|$ is the number of news. Let $\mathcal{C}(m_i) = \{c_1, c_2, ..., c_n\}$ be a set of comments of $m_i$, $\mathcal{U} = \{u_1, u_2, ..., u_{|\mathcal{U}|}\}$ be a set of users who create news or comments. To illustrate our motivation, we construct a heterogeneous news propagation graph (NPG) denoted as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \mathcal{M} \cup \mathcal{U} \cup \mathcal{C}$ covers the sets of news articles, users and comments, $\mathcal{E}$ involves different relationships between nodes. An example of the NPG is shown in the left of Figure 2, where two nodes are connected if they have posting/commenting relationships. Specially, there would be an edge between two news nodes if they share similar neighbors but irrelevant content. Users are connected if they have follower/comment the same news/followee relationships.

3.2 Text Embedding

To obtain the text representation for each news article, we apply CNN (Chen, 2015; Grefenstette et al., 2014) and multi-head self-attention (Vaswani et al., 2017) to obtain the text representation for each text, which is the same as the existing state-of-the-art fake news detection approaches, i.e. GLAN (Yuan et al., 2019) and CGAT (Yang et al., 2021).

Given a source news $m_i$ and its comments $C = \{c_1, c_2, ..., c_n\}$. Firstly, we capture initial sequence feature $f_{m_i} \in \mathbb{R}^d$ of news $m_i$ with CNN. By the same way, the feature $f_{c_j} \in \mathbb{R}^d$ of each comment $c_j$ can be extracted. Then we refine the coherence semantic representation between comments and source news by using multi-head self-attention to capture dependencies across news content and comments. From the above operation, the final text feature $\hat{f}_{m_i}$ for each news and $\hat{f}_{c_j}$ for each comment can be extracted. The initial feature $\hat{f}_{u_k}$ of user node $u_k$ can be calculated by the user profile data (such as friends count, followers count, status count, etc.).

3.3 Hierarchical Graph Attention Network

3.3.1 Topology Imbalance Smoothing Strategy

To tackle the topology imbalance problem in NPG, we propose a strategy of smoothing the topology structure to alleviate the resulting problems. We assume that if a labeled news node $m_i \in \mathcal{V}$ encounters strong influence from the other labeled neighbor nodes, the node $m_i$ owns great influence and is close to topological class boundaries. In other words, the influence of labeled nodes should decay with the topology distance. To measure how topologically close node $m_i$ is to the center of the class it belongs to, we calculate the topology location value $T_m$ by measuring the expectation of message-passing probability between the node $m_i$ and its neighbors when node $m_i$ randomly walks across the entire graph:

$$T_m = \mathbb{E}_{x \sim P_m} \left[ \sum_{j \in [1, s], j \neq y_m} \frac{1}{|S_j|} \sum_{i \in S_j} P_{i,x} \right], \quad (1)$$

where $y_m$ is the ground-truth label of node $m_i$, $P_m$ indicates the personalized PageRank probability (Page et al., 1999) vector for the node $m_i$, which can be viewed as the distribution of influence exerted outward from each $m_i$. $P_{i,x}$ indicates the probability from $m_i$ to $m_x$. $S_j$ represents the training sets for different classes, where $s$ is the number of classes. The normalization item $\frac{1}{|S_j|}$ is added to make the influence from the different classes comparable when computing conflict.

The larger the topology location value $T_m$ of $m_i$, the more topologically closer to class boundaries the node $m_i$. Figure 2.(A) apparently shows that it can decrease the training weights of labeled nodes $c_2$ and increase the weights of labeled nodes $c_4$ close to the fake news $m_3$, thus relieving the topology-imbalance issue. Inspired by the study
(Chen et al., 2021), in order to promote the training weights of nodes for effective model learning, we also train node weights based on their topology location values by:

\[
\begin{align*}
    w_m &= w_{\text{min}} + \frac{w_{\text{max}} - w_{\text{min}}}{2} (1 + \cos \frac{\text{Rank}(T_m)}{Y} \tau),
\end{align*}
\]

where \( w_m \) is the modified training weight for \( m \), \( w_{\text{min}}, w_{\text{max}} \) indicates the lower bound and upper bound of the weight correction factor, \( Y \) is the set of labeled news article nodes, \( \text{Rank}(T_m) \) is the ranking order of \( T_m \) from the smallest to the largest.

3.3.2 Hierarchical-level Attention Strategy

Considering nodes \( u, m, c \) are three different types of nodes belong to the different semantic spaces, the GCN (Kipf and Welling, 2016) cannot be directly applied to the NPG due to the node heterogeneity issue. Surprised by the recent work on heterogeneous graph convolution (Linmei et al., 2019), we employ a hierarchical attention mechanism to learn the representation of each node. Specifically, to alleviate the negative effects of those unauthentic relations, we adjust the weights between two nodes by type-level attention and node-level attention learning.

1) Node-level attention. For each type of nodes (e.g., node with type \( \tau \), where \( \tau \in \{u, m, c\} \)), we firstly design the type-specific transformation matrix \( M_{\tau} \) to project the features of different types of nodes into the same feature space. Take the news article node \( m_i \) as an example, given the input feature vectors \( \hat{f}_{m_i} \), the projection process can be shown as:

\[
\begin{align*}
    h'_{m_i} &= M_{\tau} \cdot \hat{f}_{m_i}.
\end{align*}
\]

Similarly, the initial features of each comment and each user can be projected as \( h'_{c_j}, h'_{u_k}, h'_{m_i} \), respectively. Thus, the initial input features of the node-level attention layer are the \( h'_{c_j}, h'_{u_k}, h'_{m_i} \).

In the face of fake news detection, the target node is the news article node \( m_i \in \mathcal{M} \) with the type \( \tau \). The neighbors of it belong to \( V \in \{ \mathcal{M}, \mathcal{U}, \mathcal{C} \} \) with...
the type \( \tau' \). Given a node pair \((m_i, v_j)\), where \( v_j \in V \), we design the node-level attention to get the weight coefficient different neighboring nodes via:

\[
\alpha_{ij}^\tau = softmax\left(\sigma(\mu_\tau[h_{m_i} || h'_{v_j}])\right), \tag{4}
\]

where \( \mu_\tau \) is the attention parameter for the type \( \tau \), \( || \) means concatenation operation, \( \sigma(\cdot) \) denotes LeakyReLU function. Then, the type-level node \( \mathcal{V}_m^\tau \) on graph can be aggregated by the neighbor’s projected features with the corresponding weights as follows:

\[
\mathcal{V}_m^\tau = \sigma\left(\sum_{v_j \in V} \alpha_{ij}^\tau \cdot h'_{v_j}\right). \tag{5}
\]

2) Type-level attention. Through the node-level attention, we fuse information from neighbor nodes with the same type into the representation of a type-level node. Different types of nodes contain type-specific information, which requires us to learn the importance of different node types. Thus, we adopt the type-level attention to learn the weights of news article nodes \( m_i \) from all types of nodes by:

\[
\beta_{m_i}^\tau = softmax\left(\sigma(W[\mathcal{V}_m^\tau || \mathcal{M}_{m_i}])\right), \tag{6}
\]

where \( W \) is the weight matrix. Finally, we incorporate all type-level nodes to get the final representation \( h_{m_i} \) of the target news node \( m_i \):

\[
h_{m_i} = \sum_{\tau} \beta_{m_i}^\tau \cdot \mathcal{V}_m^\tau. \tag{7}
\]

### 3.4 Fake News Classification

For the target news \( m_i \), we aim at learning an inference function \( f : \mathcal{G} \to \mathcal{Y} \) to predict whether it is fake or not. After the above procedures, we get the structure features \( h_{m_i} \), as well as its coherence-based sentence representation \( \hat{f}_{m_i} \), and then concatenate them as final features. Then the final representations of news are fed to softmax classifier based on fully-connected layers to obtain category probability \( \hat{y}_{m_i} \):

\[
\hat{y}_{m_i} = softmax(W[h_{m_i}; \hat{f}_{m_i}] + b). \tag{8}
\]

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

\[
\mathcal{L}(\Theta) = -\frac{1}{|Y|} \sum_{m \in Y} w_m \sum_{j=1}^{s} y_{m}^{j} \log \hat{y}_{m_i}^{j}, \tag{9}
\]

where \( y_{m}^{j} \) is the gold probability of fake news class, \( s \) is the number of classes and \( \Theta \) represents all parameters of the model.

### 4 Results and Discussion

#### 4.1 Datasets

In order to evaluate the performance of TR-HGAN, we conduct experiments on three benchmark datasets: Weibo (Ma et al., 2016), Twitter15 (Liu et al., 2015) and Twitter16 (Ma et al., 2017). Table 1 gives statistics of the three datasets. The Weibo dataset contains binary labels, i.e., fake news (FR) and non-fake news (NR), whereas Twitter15 and Twitter16 datasets have four types of labels, i.e., fake news (FR), non-fake news (NR), unverified news (UR), and true news (TR), where the label true news denotes a news article that debunks the fake news. For a fair comparison, for each dataset, we randomly select 10% of the dataset as the validation subset, and divide the rest data into training and testing subsets with a ratio of 3:1.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Weibo</th>
<th>Twitter15</th>
<th>Twitter16</th>
</tr>
</thead>
<tbody>
<tr>
<td>source news</td>
<td>4664</td>
<td>1490</td>
<td>818</td>
</tr>
<tr>
<td>fake news</td>
<td>2313</td>
<td>370</td>
<td>205</td>
</tr>
<tr>
<td>non-fake news</td>
<td>2351</td>
<td>374</td>
<td>205</td>
</tr>
<tr>
<td>unverified news</td>
<td>0</td>
<td>374</td>
<td>203</td>
</tr>
<tr>
<td>true news</td>
<td>0</td>
<td>372</td>
<td>205</td>
</tr>
<tr>
<td>users</td>
<td>2,746,818</td>
<td>276,663</td>
<td>173,487</td>
</tr>
<tr>
<td>comments</td>
<td>3,805,656</td>
<td>331,612</td>
<td>204,820</td>
</tr>
</tbody>
</table>

Table 1: Dataset statistics.

#### 4.2 Baselines

To highlight performance superiority of the proposed TR-HGAN, we select a series of state-of-the-art methods as baselines. The first two methods try to capture fake news features by using content-based structure. The next six methods extract fake news features through social contexts-based structure, among which, the first four methods are tree-structured models and the last two models are pure heterogeneous graph-based approaches. They are described as follows:

- **SVM-TS** (Ma et al., 2015): An SVM model that utilizes time-series to model the variation of hand-crafted features of news.
- **GRU** (Ma et al., 2016): A RNN-based model that captures the temporal contextual information of relevant retweets or comments.
- **RvNN** (Ma et al., 2018): A tree-structured recursive neural method that learns fake news features via the news propagation structure.
• **PPC** (Liu and Wu, 2018): A propagation-based approach that detects fake news with a combination of recurrent and convolutional networks.

• **Bi-GCN** (Bian et al., 2020): A novel bi-directional model that explores fake news characteristics by operating on both top-down and bottom-up propagation of fake news.

• **EBGCN** (Wei et al., 2021): A propagation-based method that adaptively rethinks the reliability of latent edge-wise relations.

• **CGAT** (Yang et al., 2021): An end-to-end graph-based framework that jointly exploits text and structure information by using graph adversarial learning framework.

• **GLAN** (Yuan et al., 2019): A graph-based method that encodes contextual information and global structural information by adopting a global-local attention network.

4.3 Experimental Setup

For fair comparison, we adopt the same evaluation metrics used in the prior studies (Yuan et al., 2019; Bian et al., 2020; Wei et al., 2021). We also add accuracy (Acc.), precision (Prec.), recall (Rec.) and $F_1$ score as the evaluation metrics.

For text embedding step, for each source news $m_i$, we truncate the text if its length is larger than 150 words and pad zero if the length is smaller than 150. All word embeddings of the model are initialized with the 300-dimensional word vectors, which is released by (Yuan et al., 2019). The convolutional kernel size $k$ is set to (4, 5, 6) with 100 kernels for each kind of size. Therefore, the final text representation $f_{m_i} \in \mathbb{R}^d$ of news $m_i$ are concatenated by all feature vectors $f^k_{m_i}$ obtained by different filters. Besides, the parameters $w_{min}$, $w_{max}$ at topology imbalance smoothing strategy is set to [0.25, 0.5, 0.75], [1.25, 1.5, 1.75], respectively.

4.4 Performance Efficiency

Table 2 and Table 3 show the results of fake news detection on Weibo, Twitter15 and Twitter16 datasets. We bold the best performance of each column in tables, from where we can observe social context-based methods outperform those news content-based methods using only textual features, which reveals the superiority of learning high-level representations for detecting fake news.

<table>
<thead>
<tr>
<th>Method</th>
<th>Class</th>
<th>Acc.</th>
<th>Prec.</th>
<th>Rec.</th>
<th>$F_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM-TS</td>
<td>NR</td>
<td>0.857</td>
<td>0.878</td>
<td>0.830</td>
<td>0.857</td>
</tr>
<tr>
<td></td>
<td>FR</td>
<td>0.839</td>
<td>0.885</td>
<td>0.861</td>
<td></td>
</tr>
<tr>
<td>GRU</td>
<td>NR</td>
<td>0.910</td>
<td>0.952</td>
<td>0.864</td>
<td>0.906</td>
</tr>
<tr>
<td></td>
<td>FR</td>
<td>0.876</td>
<td>0.956</td>
<td>0.914</td>
<td></td>
</tr>
<tr>
<td>RvNN</td>
<td>NR</td>
<td>0.908</td>
<td>0.912</td>
<td>0.897</td>
<td>0.905</td>
</tr>
<tr>
<td></td>
<td>FR</td>
<td>0.904</td>
<td>0.918</td>
<td>0.911</td>
<td></td>
</tr>
<tr>
<td>PPC</td>
<td>NR</td>
<td>0.921</td>
<td>0.949</td>
<td>0.889</td>
<td>0.915</td>
</tr>
<tr>
<td></td>
<td>FR</td>
<td>0.896</td>
<td>0.962</td>
<td>0.923</td>
<td></td>
</tr>
<tr>
<td>BiGCN</td>
<td>NR</td>
<td>0.935</td>
<td>0.925</td>
<td>0.943</td>
<td>0.933</td>
</tr>
<tr>
<td></td>
<td>FR</td>
<td>0.951</td>
<td>0.887</td>
<td>0.917</td>
<td></td>
</tr>
<tr>
<td>CGAT</td>
<td>NR</td>
<td>0.939</td>
<td>0.938</td>
<td>0.942</td>
<td>0.941</td>
</tr>
<tr>
<td></td>
<td>FR</td>
<td>0.939</td>
<td>0.938</td>
<td>0.938</td>
<td>0.935</td>
</tr>
<tr>
<td>GLAN</td>
<td>NR</td>
<td>0.948</td>
<td>0.937</td>
<td>0.957</td>
<td>0.947</td>
</tr>
<tr>
<td></td>
<td>FR</td>
<td>0.967</td>
<td>0.934</td>
<td>0.950</td>
<td></td>
</tr>
<tr>
<td>TR-HGAN</td>
<td>NR</td>
<td>0.963</td>
<td>0.957</td>
<td>0.964</td>
<td>0.960</td>
</tr>
<tr>
<td></td>
<td>FR</td>
<td>0.962</td>
<td>0.961</td>
<td>0.960</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Fake news detection results on Weibo dataset.

In addition, TR-HGAN performs better than the tree-structured based methods (e.g., RvNN, PPC, BiGCN, EBGCN). It can attribute that tree-structured methods neglect the messages are spread by a graph structure (i.e., constructed with source news, comments and users) rather than a tree structure (i.e., only constructed with source news and retweets), which limit the learning of high-level features.

Moreover, the proposed TR-HGAN outperforms state-of-the-art graph-based GLAN on three datasets. Specifically, as Table 2 shows, TR-HGAN achieves improvement of 1.5% on Weibo, comparing with the best baseline GLAN in terms of accuracy. We can also find TR-HGAN obtains 2.5% and 1.7% improvements than the best model on accuracy over all metrics across Twitter15 and Twitter16, respectively. We discuss the fact for two main reasons. First, TR-HGAN considers the inherent unauthentic relations and rich structural features in the news propagation graph. Second, unlike CGAT and GLAN, TR-HGAN pays more attention to the node topology imbalance problem on NPG, which helps improve our models much more.

4.5 Ablation Study

In this part, we test the performance of TR-HGAN variants with different configurations, including:

- **TR-HGAN w/o Text**: it only uses source news texts for fake news classification.

- **TR-HGAN w/o C**: it removes the news com-
Table 3: Fake news detection results on Twitter15 and Twitter16 datasets.

<table>
<thead>
<tr>
<th>Method</th>
<th>Acc.</th>
<th>NR</th>
<th>FR</th>
<th>TR</th>
<th>UR</th>
<th>Acc.</th>
<th>NR</th>
<th>FR</th>
<th>TR</th>
<th>UR</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM-TS</td>
<td>0.544</td>
<td>0.796</td>
<td>0.472</td>
<td>0.404</td>
<td>0.483</td>
<td>0.574</td>
<td>0.755</td>
<td>0.420</td>
<td>0.571</td>
<td>0.526</td>
</tr>
<tr>
<td>GRU</td>
<td>0.646</td>
<td>0.792</td>
<td>0.574</td>
<td>0.608</td>
<td>0.592</td>
<td>0.633</td>
<td>0.772</td>
<td>0.489</td>
<td>0.686</td>
<td>0.593</td>
</tr>
<tr>
<td>RvNN</td>
<td>0.723</td>
<td>0.682</td>
<td>0.758</td>
<td>0.821</td>
<td>0.654</td>
<td>0.737</td>
<td>0.662</td>
<td>0.743</td>
<td>0.835</td>
<td>0.708</td>
</tr>
<tr>
<td>PPC</td>
<td>0.842</td>
<td>0.811</td>
<td>0.875</td>
<td>0.818</td>
<td>0.790</td>
<td>0.863</td>
<td>0.820</td>
<td>0.898</td>
<td>0.843</td>
<td>0.837</td>
</tr>
<tr>
<td>BiGCN</td>
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<td>0.891</td>
<td>0.860</td>
<td>0.930</td>
<td>0.864</td>
<td>0.880</td>
<td>0.847</td>
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<td>EBGCN</td>
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<td>0.901</td>
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<tr>
<td>GLAN</td>
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<td>0.923</td>
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<td>0.875</td>
<td>0.851</td>
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<tr>
<td>TR-HGAN</td>
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<td>0.925</td>
<td>0.935</td>
<td>0.932</td>
<td>0.923</td>
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<td>0.932</td>
<td>0.949</td>
</tr>
</tbody>
</table>

Figure 3: TR-HGAN ablation analysis results on three datasets in terms of Accuracy and $F_1$.
Measuring the importance between different nodes. Besides, TR-HGAN consistently achieves relatively high accuracy score on all datasets than other models at each deadline. This is because TR-HGAN considers the problem of topology imbalance and unauthentic relations in NPG. In the model, the importance of each node can be measured by topology imbalance smoothing strategy, which boosts the performance of detecting results. Second, the unauthentic relations can be refined by the hierarchical attention mechanism, which helps identify unreliable relationships and reduce the noisy of problem nodes in time, so as to detect the authenticity of news as soon as possible.

4.7 Case Study
To further illustrate why our model outperforms state-of-the-art baseline GLAN (Yuan et al., 2019), we randomly sample two fake news from Twitter15 dataset. As depicted in Figure 5, the news, comments and corresponding users are formulated as nodes and relations are modeled as edges in NPG. As shown in the left of Figure 5, we observe that comment $c_3$ is irrelevant with news $m_1$ although replying, which reveals the ubiquity of unauthentic relations among news in the NPG and it is necessary to consider the inauthenticity caused by these unauthentic relations.

The right of Figure 5 indicates the constructed weighted NPG. For a target node $m_1$, existing graph-based models (e.g., GLAN, CGAT) always generate the feature representation of $m_1$ by aggregating the information of its all neighbors according to seemingly authentic edges. However, edge between node $m_1$ and $c_3$ would bring noise features and limit the learning of useful features for fake news detection. The proposed TR-HGAN can successfully weaken the negative effect of this unauthentic edge by hierarchical-level attention network. Besides, the target fake news node $m_1$ will affect the class boundary shift of its neighbors due to the topology imbalance of NPG. Thus, the topology imbalance smoothing strategy is adopted to decrease the weights of those useless nodes and strengthen the weights of important nodes close to target node. Accordingly, the TR-HGAN is capable of learning more conducive features and can enhance the robustness of results.

5 Conclusion
In this paper, we have studied the unauthentic relations and topology imbalance issue in the news propagation structure from a weight learning perspective on fake news detection. We propose a topology imbalance and relation inauthenticity aware hierarchical graph attention networks (TR-HGAN) to capture robust structural features. Specifically, we design a topology imbalance smoothing strategy to address the problem of topology imbalance in NPG by increasing the weight of nodes with great influence and decreasing the weight of nodes with weak influence. Besides, we develop a hierarchical graph attention mechanism for graph convolutional learning, which can adaptively measure the authenticity of the relationships by assigning appropriate weight to each relationship.
thus effectively reduce the influence of the unauthentic relations. Extensive experiments conducted on three commonly benchmark datasets demonstrate that our model can significantly surpass the state-of-the-art baselines on both fake news classification and early detection tasks.

Acknowledgements

The research is supported by the National Key Research and Development Program of China under Grant 2020AAA0108504, National Nature Science Foundation of China under Grant Nos.62102321, Fundamental Research Funds for the Central Universities under Grant No. D5000200146.

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