Transformer-Graph Neural Network with Global-Local Attention for Multimodal Rumour Detection with Knowledge Distillation

Tsun-hin Cheung\textsuperscript{1}, Kin-man Lam\textsuperscript{2}

Department of Electronic and Information Engineering
The Hong Kong Polytechnic University

Abstract

Misinformation spreading becomes a critical issue in online conversation. Detecting rumours is an important research topic in social media analysis. Most existing methods, based on Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs), do not make use of the relationship between the global and local information of a conversation for detection. In this paper, we propose a Transformer-Graph Neural Network (TGNN), to fuse the local information with the global representation, through an attention mechanism. Then, we extend the proposed TGNN for multimodal rumour detection, by considering the latent relationship between the multimodal feature and node feature to form a more comprehensive graph representation. To verify the effectiveness of our proposed method for multimodal rumour detection, we extend the existing PHEME-2016, PHEME-2018, and Weibo data sets, by collecting available and relevant images for training the proposal framework. To improve the performance of single-modal rumour detection, i.e., based on text input only, a teacher-student framework is employed to distil the knowledge from the multimodal model to the single-modal model. Experimental results show that our proposed TGNN can achieve state-of-the-art performance and generalization ability evaluated on the PHEME-2016, PHEME-2018, and Weibo data sets.

\textsuperscript{1}Email: tsun-hin.cheung@connect.polyu.hk
\textsuperscript{2}Email: enkmlam@polyu.edu.hk
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1. Introduction

Social media has become a vital way for people to receive information by consuming online news. The rapid spread of social media often leads to unverified or false information, which gives rise to society’s concerns. Rumour, which unconfirmed or unofficial information, are hard for the public to distinguish from the truth. This affects not only general online users, but also journalists, because they may have difficulty in establishing the truth in the context of breaking news [1]. Therefore, automatically detecting rumours has been of great interest to society.

To identify rumours, both the source post and replies in the conversations are important. The replies usually contain opinions and judgements, with regard to the source information. As shown in Fig. 1, the source is a piece of breaking news talking about a hostage in Sydney, being held by Islamic State (ISIS). In fact, there is no direct connection between the hostage and ISIS [2], which is a rumour spreading on the Internet. The replies, which expressed doubt and disagreement about the source information, are very useful indicators of unconfirmed and false information. Therefore, it is important to learn the relationships between the replies to the source information for detecting rumours on social media.

Machine learning-based methods have been the main research focus for rumour detection in recent years [3]. To efficiently identify rumours, the first step is to extract appropriate features from a conversation or message, such as text, images, and propagation patterns. Lexical and statistical features, such as Term Frequency–Inverse Document Frequency (TF-IDF), have been widely used to represent text data for rumour detection [4]. However, these handcrafted representations often lose the dependency of words and the semantic meaning of a sentence. Therefore, deep learning-based methods are used to process the data, so as to learn a more robust representation for classification.
Although deep learning-based methods, such as convolutional neural networks (CNNs) [5,6] and graph convolutional neural networks (GCNNs) [6], have achieved promising performance for rumour detection on social media, there are still some limitations on these network architectures. First, the receptive fields of the convolutional operations in CNNs are localized [7], which is not suitable for modelling the conversations on social media, because a reply does not only depend on the message that it refers to. The global, long-term dependencies of dialogue and other reply chains are equally important for representing a reply in a conversation. Furthermore, even though the family of GNNs [6] can effectively represent the local relationship and connectivity of source-replies in a conversation, existing methods only use a simple maximum pooling operation to aggregate all the node features to form the graph representation. The effectiveness of such a pooling strategy is limited, as it only considers the maximum activation in each feature dimension and neglects all other information during aggregation. Therefore, we aim to build a global-local attention method for a better graph representation, with a hybrid model of transformer and GNN.

In recent years, cross-modal learning has been widely studied in analysing social media content, including sentiment analysis [8], hate-speech [9] and fake-news [10] detection. These studies focus on the design of deep neural networks to learn the cross-modal representation for a pair of text and image. Different from these detection tasks, rumour detection relies more on the information of the replies in a conversation. Therefore, we propose a cross-modal learning module to integrate visual and global textual information to enhance the representational power of the learned features. Then, the relationship of an image and each message reply can be explicitly learnt for detecting rumour.

On social media, not every message is associated with images. Our goal is to enhance the performance of rumour detection, even if only text information is available. Therefore, both text and image information is considered in training our multimodal framework, which can achieve higher accuracy than using text information only. For inference, we also train a rumour detection system with text input only. Our aim is to maintain the performance of this single-modal framework close to the multimodal framework. To achieve this, we apply a teacher-student model to distil knowledge from the cross-modal teacher model to a single-modal student model. This makes the single-
modal student model achieve a similar performance to the cross-modal model, with a simpler architecture.

Fig 1. An Extract of a Conversation on Twitter.
The main contributions of our work are summarized as follows:

- We propose a two-branch transformer-graph neural network (TGNN), to learn both the global and local information of a conversation on social media. We propose a global-local attention module to aggregate the local (node) information to form a graph representation for performing rumour detection.
- We extend the PHEME-2016, PHEME-2018, and Weibo data sets by collecting the images with the Twitter and Weibo APIs for multimodal rumour detection. We make use of the visual features in our proposed TGRNN, by considering the latent relationship of an image and each node feature for classification.
- We employ a teacher-student framework to transfer the knowledge from a multimodal model to a single-modal model. Our experimental results verify the effectiveness and efficiency of our proposed method, across English and Chinese data sets.

2. Related Work

Detecting rumour or misinformation has been an active research area in the last decade. In this section, we first review the related work on rumour detection. Then, we discuss the related studies, including cross-modal learning and knowledge distillation, related to our proposed framework for rumour detection.

The conventional rumour detection approaches are based on statistical analysis. Takahashi et al. [11] were the first to analyse spreading of rumours on Twitter, by considering the word distributions, i.e., the frequently occurred words in data sets. However, the analysing targets are limited to certain events. It is difficult to generalize the models to unseen events. Although this analysis technique achieved limited performance in rumour detection, it motivates the later development of machine learning-based approaches, based on linguistic features.

Machine learning-based methods have shown promising performance in detecting rumours, because of the effective learning of training data. Kwon et al. [12] were the first to utilize machine learning-based methods, including decision tree, random forest,
and support vector machine (SVM), with linguistic features, for rumour detection. Later, propagation-based features [13] and user-based features [14] were used to improve the performance of rumour detection. However, these features are extracted from the source information only. Thus, the generalization ability of these algorithms is weak.

To improve the generalization of rumour detection, the characteristics of a conversation, i.e., the replies to the source information, are considered. Zubiaga et al. [15] constructed the PHEME data set and developed logistics regression with conditional random fields (CRF) for rumour detection. Linguistic features of the source and the replies were used for classification. However, these features are handcrafted and can achieve limited performance only. The aim of this paper is to develop an efficient end-to-end learning algorithm for rumour detection, based on automatic feature extraction and classification.

Neural networks can effectively discover and learn the hidden patterns in a data set. Recurrent Neural Networks (RNNs) [16] and Convolutional Neural Networks (CNNs) [17] can be used to learn the vector representation of a text message. They are often used with pretrained word embedding, such as Glove [18], since the vector representation can represent the semantic meaning of each word. Inspired by neural translation models [19], a pretrained bidirectional transformer (BERT) [20] was proposed for text classification. BERT is composed of several self-attention modules, and represents each word as a linear combination of other word representations in a sentence. BERT has been widely used to encode a sentence into a fixed-length representation [21]. In our work, we leverage the transformer not only for sentence representation, but also for conversation representation.

Apart from sentence representation, neural networks have been utilized to represent conversations on social media. Bai et al. [6] proposed an ensemble graph convolutional neural network (GCNN) to model the source-replies relationships by a two-branch network, containing a graph neural network (GNN) and a convolutional neural network (CNN). The GNN module is used to process the features of a node with its neighbouring nodes. Then, the node features are aggregated with a maximum pooling layer to obtain an overall graph representation. The CNN module is used to obtain a feature representation from the weighted word embedding vectors. Finally, the final feature representation of a conversation is a weighted sum of the features output from the two
modules. A limitation of the method is that the relationship between the global and local information is not fully utilized, since the two branches do not interact with each other. Moreover, the maximum pooling operator only considers the maximum activation value in each dimension of the feature vector and neglect all other values. The resulting features are insufficient to faithfully represent a conversation. Song et al. [22] proposed a recurrent neural network (RNN) to model conversations for rumour detection. However, their proposed method does not consider the relative importance of every message in a conversation, because not every message is essential for rumour detection. Therefore, this brings us to develop a global-local attention module to aggregate the node features of to GNN, so as to achieve an accurate representation of conversations.

Text-based classification has been the most popular technique for social media analysis. As social media content is diverse, visual computing techniques are also useful for the analysis [23]. Recently, multimodal learning, which combines multiple modalities of information, has been applied to social media analysis, such as sentiment analysis, fake-news detection, and hate-speech detection [24]. Deep neural networks, which can automatically learn the deep representation for multimodal classification [25], have been commonly used to fuse the textual and visual information. Most deep neural network-based methods also use an attention mechanism to fuse multiple modalities into a fixed-length representation for classification. Jin et al. [26] proposed a multimodal recurrent neural network to combine the visual features and textual features with an attention mechanism, for rumour detection. However, the work only considers the text in the source message, while those in the replies are ignored. This inspires us to extend multimodal rumour detection to the conversation level. Therefore, our proposed method considers the interactions between messages and replies, from different people. This can make the detection more accurate and robust.

Existing deep cross-modal learning algorithms have been proven to be able to effectively solve detection problems. However, processing and learning multimodal data causes a deep model to have much higher computation and memory requirements. Therefore, knowledge distillation [27] is applied to distil knowledge from a multimodal model to a single-modal model, which has been used in many areas, such as computer vision [28] and speech processing [29]. In knowledge distillation, the pretrained multimodal model is used to learn the deep representations and make soft predictions
of the training data. Then, a single-modal model is trained, based on the deep representations from the multimodal network, so its prediction scores are close to the soft predictions of the multimodal network. In our work, we transfer the knowledge, learned from an image-text model, to a text-only model for rumour detection.

3. The Transformer-Graph Neural Network Framework

In this session, we describe our proposed Transformer-Graph Neural Network (TGNN) for rumour detection. An overview of the proposed model is shown in Fig. 2. The input of TGNN is a conversation, with an image attached, which was posted on social media. It consists of a source post, and a set of replies, each of which is linked to either the source post or another reply. A conversation is expressed as a graph $G$, which consists of a node feature matrix $F$, obtained by the message embedding module, and an edge connectivity matrix $C$, indicating the links of every reply.

3.1 Message Embedding

The goal of the message embedding module is to transform a message, which is either a source or a reply, into a fixed-length representation. Each message is encoded by a pretrained bidirectional transformer (BERT) [20] into a $d$-dimensional vector.
Specifically, we use the hidden representation of the first token, i.e., a special learnable embedding vector added at the beginning of every sentence before sending to the pretrained BERT [20], to form the overall representation of a sentence. For each message $m_i$, we encode it into an embedding vector $f_i \in \mathbb{R}^d$, as follows:

$$f_i = \text{BERT}(m_i). \quad (1)$$

After processing the source post and the replies with sentence embedding, the node features $F = \{f_s, f_1, f_2, \ldots, f_{n-1}\} \in \mathbb{R}^{d \times n}$ are obtained, where the first element in $F$, i.e., $f_s$, is the feature representation of the source information, and the other elements are that of the replies, i.e., $n-1$ replies.

### 3.2 Global branch: Source-Replies Transformer

Global and local features are equally important for representing a conversation. Global features mean the overall context of a conversation, while local features contain the semantic relationship between a reply (or a source) and its linked replies. To extract the global representation from the node features $F$, we use a transformer model, which computes the attention scores among all vectors in the sequence, to learn this representation.

The transformer model consists of several multi-head attention modules. A multi-head attention module consists of $h$ heads of scaled dot-product attention blocks. Each scaled dot-product attention block accepts three inputs, i.e., query $Q$, key $K$, and value $V$. The query matrix $Q$ is used to compute the attention weights by measuring its similarity to the key matrix $K$. Then, the attention weights are multiplied with the value $V$ to obtain the attention vectors. Mathematically, the attention scores $S$ are calculated as follows:

$$S = \text{Softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right), \quad (2)$$

where $d_k$ is the embedding dimension of the key $K$. After calculating the attention scores $S$, the attention value $V'$ can be computed as a linear combination of the attention scores $S$ and key $K$. Therefore, we have
\[ \mathbf{V}' = S \mathbf{V}, \] (3)

The multi-head attention mechanism repeats the scaled dot-product attention \( h \) times, and aggregates the attention value \( \mathbf{V}' \) to obtain a more robust representation of the value \( \mathbf{V} \), as follows:

\[
\text{MultiHead}(Q, K, V) = \text{Concat}(V'_1 W'_1, V'_2 W'_2, ..., V'_h W'_h) W^o,
\] (4)

where \( \text{MultiHead}( ) \) and \( \text{Concat}( ) \) represent the multi-head attention mechanism and the concatenation operation, respectively. It is worth noting that \( W^o \) and \( W'_i \) are trainable parameters to be jointly learned through backpropagation. Finally, the transformer uses a skip connection to add the output of the multi-head attention with the value \( \mathbf{V} \).

Since our goal is to obtain a more comprehensive graph representation, we set the values of query \( Q \), key \( K \), and value \( V \) equal to the node feature \( F \), i.e., \( Q = K = V = F \), in Equation (4), whose output is denoted as \( F_g \in \mathbb{R}^{d \times n} \). As the source post contains the most semantic information of a conversation, we use the hidden representation of the first element in \( F_g \), i.e., the source message representation, to form the global representation of a conversation \( f_g \in \mathbb{R}^{d} \).

### 3.3 Local branch: Source-Replies Graph Attention Network

Given a source tweet and its replies, we use a graph attention network \([30]\) to learn the local node features. The input of the graph attention network is the node feature matrix \( F \) and an edge connectivity matrix \( C \). Our goal is to generate a more comprehensive feature for each node, by considering the relationship between the node and its neighbouring nodes. A shared self-attention layer is applied on every node \( i \) and its neighboring node \( j \).

In the first step, a weight matrix \( W \in \mathbb{R}^{d \times d} \) is shared by every node to compute the attention coefficients, as follows:

\[
e_{ij} = (Wf_i)^T \cdot (Wf_j), \quad j \in \mathcal{N}(i),
\] (5)
where $\mathcal{N}(i)$ represents the neighboring node of node $i$. Then, all the attention coefficients, i.e., $e_{ij}, j \in \mathcal{N}(i)$, are normalized through the Softmax function, as follows:

$$
\alpha_{ij} = \text{softmax}(e_{ij}).
$$

Therefore, the transformed features for every node can be expressed as follows:

$$
f'_i = \frac{1}{K_i} \sum_{j}^{K_i} \alpha_{ij} f_j,
$$

where $K_i$ is the number of neighboring nodes of node $i$.

### 3.4 Visual Global Representation

In a social-media conversation, users may attach an image as supplementary information. In practice, any deep neural network can be employed to extract visual features from the image. In our method, we choose residual network (ResNet), which is commonly used in image classification and recognition. The feature at the last fully connected layer of the pretrained ResNet, whose dimension is denoted as $d_v$, is used as the visual presentation of an image. It is worth noting that not all conversations are associated with images. We input a blank image, i.e., a tensor filled with zero, so that our multimodal model can still be trained, when conversations do not have images attached. For each image $I$, we project the visual representation, extracted by ResNet, and global conversation representation into the same embedding space, as follows:

$$
v = W_v \text{ResNet}(I),
$$

where $v \in \mathbb{R}^d$ is the new global visual representation of an image, and $W_v \in \mathbb{R}^{d \times d_v}$ represents trainable parameters. Then, we combine the visual representation $v$ and global representation of a conversation $f_g$ by element-wise addition, i.e., $f'_g = v + f_g$, to obtain the multimodal global representation of conversation $f'_g$. 


3.5 Global-Local Attention Module

To align the local node features to form the final representation, we compute the correlation, i.e., dot product, between each local representation $f'_i$ and the multimodal global representation $f'_g$ as follows:

$$e'_i = f'_i^T \cdot f'_g$$  \hspace{1cm} (9)

where $i = 1, ..., n - 1$. Then, these attention coefficients are also normalized by using the Softmax function, as follows:

$$a'_i = \text{Softmax}(e'_i).$$  \hspace{1cm} (10)

Thus, we can obtain the final global-local graph representation $f_c$ as follows:

$$f_c = \frac{1}{n} \sum^N_{i=1} a'_i f_i.$$  \hspace{1cm} (11)

Finally, the representation of a conversation $f$ can be expressed as the element-wise addition of features from the local branch and global branch, i.e., $f = f_c + f'_g$.

3.6 Classification and Loss Function

Having obtained the feature representation $f$ of a conversation, we use a Softmax classifier to predict whether it is a rumour or not, as follows:

$$\hat{y} = \text{softmax}(W_c f + b_c),$$  \hspace{1cm} (12)

where $W_c \in \mathbb{R}^{2 \times d}$ and $b_c \in \mathbb{R}^2$ are trainable parameters. We employ the cross-entropy loss as the objective function in our proposed method. Given the predicted label $\hat{y}$ and the ground-truth label $y$, the negative log-likelihood is minimized. Thus, we have

$$\text{loss}_{CE} = -(y \log(\hat{y}) + (1 - y)\log(1 - \hat{y})).$$  \hspace{1cm} (13)
3.7 Knowledge Distillation

To improve the performance of rumour detection with text information only, we perform knowledge distillation with a teacher-student framework. The teacher network is the multimodal model, which has both text and image inputs, while the student network considers text input only. Our goal is to guide the learning of the student network by using the soft labels predicted by the teacher network, so the performance of this network can be enhanced. Given the soft label $\hat{y}_t$ and the predicted label $\hat{y}_s$, our goal is to minimize the distance between the two probability distributions. Therefore, we define the knowledge distillation loss, as follows:

$$\text{loss}_{KD} = \hat{y}_s \log (\hat{y}_s - \hat{y}_t).$$

The total loss of the teacher-student model is computed by:

$$\text{loss}_{total} = \text{loss}_{CE} + \text{loss}_{KD}.$$

4. Experiment and Results

In this section, we first describe the data set used and experimental setup. Then, we evaluate our proposed model and compare the experimental results with existing state-of-the-art methods. Finally, we also show the ablation study of our proposed method for rumour detection.

4.1 Data Sets

In the experiment, the PHEME-2016 [15], PHEME-2018 [31] and Weibo [16] data sets were used to evaluate the methods for rumour detection. The PHEME-2016 data set contains 1972 rumour and 3830 non-rumour English conversations, across five different events, collected on Twitter. The five events include Charlie Hebdo, Ferguson, the Germanwings Crash, the Ottawa Shooting, and the Sydney Siege, which are all real events from 2014 to 2015. The PHEME-2018 data set is an extension of PHEME-2016, by adding the conversations of four more events, including Putin missing, Prince
Toronto, Gurlitt, and Ebola Essien, resulting in a total of 2402 rumour and 4023 non-rumour conversations. The Weibo data set contains 2313 rumour and 2350 non-rumour Chinese conversations. Since the original data sets are not associated with any images, we further collected some relevant images using the Twitter and Weibo APIs. Note that not all posts had images attached by the users, and some of the posts have been removed by the users. The numbers of recovered images for the PHEME-2016 data set are 543 and 1595 for rumours and non-rumours, respectively, while the numbers of recovered images for the PHEME-2018 data set are 733 and 1651 for rumours and non-rumours, respectively. For the Weibo data set, the numbers of recovered images are 1861 and 1982 for rumours and non-rumours, respectively. To evaluate the performance of our model on the PHEME-2016 data set, we adopt cross-validation, across the five events in our experiment. This ensures that there are no overlapping events between the training and testing data sets. Similar to the evaluation on the Weibo data set in the previous work [22], we keep 10% of the samples for tuning parameters. The rest of them are divided by a ratio of 3:1, for training and testing, respectively.

4.2 Experimental Setup

Evaluation Metrics: To evaluate the performance of different classification models, we use the F1 score for positive and negative classes and the accuracy. We also use the macro F1 score, i.e., the unweighted F1 scores for positive and negative classes, to evaluate the different methods for rumour detection.

Hyperparameters: We use the pretrained English and Chinese BERT, for the PHEME and Weibo data sets, respectively. The embedding dimensions of the two BERT models are both 768. To extract visual features, we use the pretrained ResNet with an embedding dimension of 512. For all the experiments, the models were trained with a mini-batch size of 32 for 5 epochs. The Adam optimizer is used with a fixed learning rate of 0.00002. To avoid overfitting, we use the L2 regularization with a rate of 0.0001 and dropout with a rate of 0.3. Our models were implemented in PyTorch. All experiments were conducted on two GeForce RTX 2080 Ti GPUs.
4.3 Comparison with State-of-the-Art Methods

We compare our proposed model, i.e., TGNN, with the following state-of-the-art methods for rumour detection. The qualitative results of the different methods are shown in Table I. The “Average” in Table I is the mean of the evaluation matrices, based on the five events.

**CRF** [15]: This is a traditional machine learning-based method, with context and social features, using conditional random field (CRF) and logistic regression for detecting rumours.

**ARN** [33]: This is an attention-based residual neural network. It uses a CNN with residual connection to combine context features and social features with an attention mechanism, to find out the most important sets of features.

**GCNN** [6]: This is an ensemble graph convolutional neural network, which uses a concatenation operator to combine the features of a conversation generated by CNN and GNN.

**TF-ITF** [22]: This is a traditional machine learning method, which extracts the TF-ITF features with a support vector machine (SVM) for classification.

**ESODE** [34]: This method is based on an ordinary differential equation neural network (ODE-N), which combines statistical features and linguistic features with neural network for rumour detection.

**RNN** [16]: This is a recurrent neural network (RNN) to model the sequential information among messages from a conversation for rumour detection.

**GAN** [32]: This method uses generative adversarial network (GAN) to augment the training samples, by generating harder conversations, in order to force the discriminator to learn more robust rumour indicative features.
Table I. Performances of the Proposed TGNN and Other Methods

| Data sets     | Events         | Methods       | Positive Class | Negative Class | Overall |
|---------------|----------------|---------------|----------------|----------------|---------|
|               |                |               | F1-Score       | F1-Score       | Accuracy| Marco F1 Score |
|               | Charlie Hebdo  | CRF [15]      | 63.60          | 86.92          | 80.76   | 75.26   |
|               |                | ARN [33]      | 53.60          | 84.20          | 76.43   | 65.90   |
|               |                | GCNN [6]      | -              | -              | 84.10   | -       |
|               |                | TGNN w/o image| 67.62          | 89.02          | 83.60   | 78.32   |
|               |                | TGNN          | **68.38**      | **89.83**      | **84.61**| **79.11**|
|               | Ferguson       | CRF [15]      | 46.50          | 85.70          | 77.43   | 66.10   |
|               |                | ARN [33]      | 38.60          | 76.79          | 66.32   | 57.70   |
|               |                | GCNN [6]      | -              | -              | **80.90**| -       |
|               |                | TGNN w/o image| 53.43          | 84.57          | 76.82   | 69.00   |
|               |                | TGNN          | **53.60**      | 85.09          | 77.43   | **69.35**|
| PHEME 2016    | Germanwings    | CRF [15]      | 70.40          | 72.43          | 71.43   | 71.42   |
|               | Crash          | ARN [33]      | 68.75          | 71.43          | 70.15   | 70.09   |
|               |                | GCNN [6]      | -              | -              | 63.80   | -       |
|               |                | TGNN w/o image| 78.09          | 74.77          | 76.55   | 76.43   |
|               |                | TGNN          | **78.75**      | **77.73**      | **78.25**| **78.24**|
|               | Ottawa Shooting| CRF [15]      | 69.00          | 74.87          | 72.25   | 71.94   |
|               |                | ARN [33]      | 65.53          | 70.29          | 68.09   | 67.91   |
|               |                | GCNN [6]      | -              | -              | 68.50   | -       |
|               |                | TGNN w/o image| 75.48          | **75.75**      | 75.62   | 75.62   |
|               |                | TGNN          | **79.51**      | 75.12          | **77.53**| **77.32**|
|               | Sydney Siege   | CRF [15]      | 51.20          | 76.89          | 68.63   | 64.05   |
|               |                | ARN [33]      | 70.19          | 72.40          | 71.33   | 71.30   |
|               |                | GCNN [6]      | -              | -              | 68.30   | -       |
|               |                | TGNN w/o image| 73.86          | 78.78          | 76.58   | 76.32   |
|               |                | TGNN          | **73.32**      | **80.14**      | **77.23**| **76.73**|
|               | Average        | CRF [15]      | 60.14          | 79.36          | 74.10   | 69.75   |
|               |                | ARN [33]      | 59.33          | 75.02          | 70.46   | 67.18   |
|               |                | GCNN [6]      | -              | -              | 73.12   | -       |
|               |                | TGNN w/o image| 69.70          | 80.58          | 77.83   | 75.14   |
|               |                | TGNN          | **70.71**      | **81.58**      | **79.01**| **76.49**|
| PHEME 2018    | N/A            | RNN [16]      | 83.20          | 65.80          | 77.50   | 74.50   |
|               |                | GAN [32]      | 85.70          | 76.00          | 82.10   | 80.90   |
|               |                | TGNN w/o image| 84.44          | 82.94          | 83.69   | 83.75   |
|               |                | TGNN          | **84.74**      | **84.15**      | **84.47**| **84.44**|
| Weibo         | N/A            | TF-ITF [22]   | -              | -              | 85.90   | 86.80   |
|               |                | ESODE [34]    | -              | -              | 92.37   | -       |
|               |                | RNN [16]      | 90.40          | 89.40          | 89.90   | 89.90   |
|               |                | GAN [32]      | 94.40          | 96.00          | 95.20   | 95.20   |
|               |                | TGNN w/o image| 95.31          | 95.54          | 95.43   | 95.43   |
|               |                | TGNN          | **96.33**      | **96.43**      | **96.38**| **96.38**|

Compared with those state-of-the-art methods for rumour detection, our proposed model achieves the best performance, in terms of accuracy and F1 score for rumour detection. On the PHEME-2016 data set, our method can achieve the best performance in most of the events, except for Ferguson. Although the accuracy of GCNN [6] is 3% better than our proposed method in the Ferguson event, the average accuracy of our
method for the five events is 5% better than GCNN. This is because GCNN suffers from the class-imbalance problem, which favours the majority classes. In terms of the overall performance, our proposed method is 1% and 3% better than the state-of-the-art methods, in terms of accuracy and macro F1 score. Different from GCNN, our method utilizes a global-local attention module to aggregate the node features generated by GNN, instead of using the common maximum pooling operation. Our proposed TGNN can automatically select the important node features for rumour detection. Thus, TGNN can obtain a more comprehensive graph representation for a conversation.

For the Weibo data set, our proposed method is much better than TF-ITF [22] and ESODE [34]. This is likely due to the fact that the handcrafted features cannot provide a robust representation for detecting rumours. Comparing with RNN [16] on the Weibo data set, the performance of our proposed TGNN, in terms of both accuracy and F1 Score, is 6% higher than other methods. It is observed that the accuracy and F1 score of our proposed TGNN are also 6% higher than that of RNN on the PHEME-2018 data set. This is due to the fact that the transformer network can capture the global relationship among the messages in a conversation. Compared with GAN [32] on the Weibo data set, our proposed TGNN is 1% better, in terms of both accuracy and F1 Score. Moreover, our TGNN is 1.5% and 2.8%, in terms of accuracy and F1 Score, respectively, better than GAN [32], when evaluated on the PHEME-2018 data set. This is likely because our proposed global-local attention module can successfully attend the important messages for detecting rumours. Moreover, it is shown that the overall performance of a multimodal TGNN, i.e., combining text with images, is better than the model with text only, when evaluated on both the PHEME and Weibo data sets. This implies that visual information is useful for detecting rumours on social media. We will explore the importance of visual information for rumour detection in an example case study session.

4.4 Ablation Study

To verify the effectiveness of the proposed network, we conduct an ablation study on TGNN. We use the transformer-only and GNN-only models to compare with the
For the GNN-only model, maximum pooling is used to form the graph representation of a conversation. The experimental results are shown in Table II.

| Data sets   | Events      | Methods      | Positive Class | Negative Class | Overall |
|-------------|-------------|--------------|----------------|----------------|---------|
| PHEME 2016  | Charlie Hebdo | Transformer-only | 67.83          | 87.79          | 82.30   | 77.81  |
|             | GNN-only    | Transformer-only | 68.37          | 89.75          | 84.51   | 79.06  |
|             | TGNN        | Transformer-only | **68.38**      | **89.83**      | **84.61** | **79.11** |
| Fergus      | Transformer-only | 48.76          | 84.72          | 76.47          | 66.74   |
|             | GNN-only    | Transformer-only | 52.64          | 82.10          | 74.02   | 67.57   |
|             | TGNN        | Transformer-only | **53.60**      | **85.09**      | **77.43** | **69.35** |
| Germanwings | Transformer-only | 75.56          | 73.63          | 74.63          | 74.59   |
| Crash       | GNN-only    | Transformer-only | 77.53          | 74.02          | 75.91   | 75.78   |
|             | TGNN        | Transformer-only | **78.75**      | **77.73**      | **78.25** | **78.24** |
| Ottawa      | Transformer-only | 77.57          | 76.80          | 77.19          | 77.19   |
| Shooting    | GNN-only    | Transformer-only | 77.21          | 72.46          | 75.06   | 73.76   |
|             | TGNN        | Transformer-only | **79.51**      | **75.12**      | **77.53** | **77.32** |
| Sydney      | Transformer-only | 74.77          | 78.98          | 77.07          | 76.88   |
| Siege       | GNN-only    | Transformer-only | 72.77          | 74.12          | 73.46   | 73.45   |
|             | TGNN        | Transformer-only | **73.32**      | **80.14**      | **77.23** | **76.73** |
| Average     | Transformer-only | 68.90          | 80.38          | 77.53          | 74.64   |
|             | GNN-only    | Transformer-only | 69.70          | 78.49          | 76.59   | 73.88   |
|             | TGNN        | Transformer-only | **70.71**      | **81.58**      | **79.01** | **76.15** |
| PHEME 2018  | N/A         | Transformer-only | 83.97          | 83.03          | 83.36   | 83.53   |
|             | GNN-only    | Transformer-only | 81.63          | 79.68          | 80.66   | 80.71   |
|             | TGNN        | Transformer-only | **84.74**      | **84.15**      | **84.47** | **84.44** |
| Weibo       | N/A         | Transformer-only | 94.89          | 94.83          | 94.86   | 94.86   |
|             | GNN-only    | Transformer-only | 93.25          | 92.84          | 93.05   | 93.04   |
|             | TGNN        | Transformer-only | **96.33**      | **96.43**      | **96.38** | **96.38** |

The experimental results show that the performance, using either transformer or GNN, is lower. The accuracy and F1 score are 1% to 3% higher, when the two neural networks are used together, on all PHEME-2016, PHEME-2018, and Weibo data sets. This is likely because the transformer cannot extract local features from messages in a conversation, and the GNN with the maximum pooling operator is limited to form the overall representation of a conversation. By leveraging the powerful representation of these two neural networks and the global-local attention module, the TGNN can achieve the best performance for rumour detection.
4.5 Results of Knowledge Distillation

For the knowledge distillation module, we test the performance of the teacher model, the student model without knowledge distillation, and the student model under the supervision of the teacher network. The qualitative results of the three models are shown in Table III.

| Data sets | Events       | Methods                  | Positive Class | Negative Class | Overall    |
|-----------|--------------|--------------------------|----------------|----------------|------------|
|           |              | Teacher Model            | F1-Score       | F1-Score       | Accuracy   | Marco F1 Score |
|           |              | Student Model w/o KD     | 68.38          | 89.83          | 84.61      | 79.11       |
|           |              | Student Model with KD    | 67.62          | 89.02          | 83.60      | 78.32       |
|           | Charlie Hebdo | Teacher Model            | 53.60          | 85.09          | 77.43      | 69.35       |
|           |              | Student Model w/o KD     | 53.43          | 84.57          | 76.82      | 69.00       |
|           |              | Student Model with KD    | 54.25          | 85.40          | 77.87      | 69.83       |
| Ferguson  | Teacher Model | Student Model            | 78.75          | 77.37          | 78.25      | 78.24       |
|           |              | Model w/o KD             | 78.09          | 74.77          | 76.55      | 76.43       |
|           |              | Student Model with KD    | 80.46          | 74.94          | 78.04      | 76.49       |
|           | Teacher Model | Student Model            | 79.51          | 75.12          | 77.53      | 77.32       |
|           |              | Model w/o KD             | 75.48          | 75.75          | 75.62      | 75.62       |
|           |              | Student Model with KD    | 79.79          | 76.61          | 78.31      | 78.20       |
| Germanwings Crash | Teacher Model | Student Model            | 73.32          | 80.14          | 77.23      | 76.73       |
|           |              | Model w/o KD             | 73.86          | 78.78          | 76.58      | 76.32       |
|           |              | Student Model with KD    | 75.04          | 77.93          | 76.58      | 76.49       |
|           | Teacher Model | Student Model            | 70.71          | 81.58          | 79.01      | 76.15       |
|           |              | Model w/o KD             | 69.70          | 80.58          | 77.83      | 75.14       |
|           |              | Student Model with KD    | 71.39          | 80.88          | 78.99      | 75.89       |
| Sydney Siege | Teacher Model | Student Model            | 84.74          | 84.15          | 84.47      | 84.44       |
|           |              | Model w/o KD             | 84.44          | 82.94          | 83.69      | 83.75       |
|           |              | Student Model with KD    | 84.47          | 83.24          | 83.85      | 83.88       |
| Average   | Teacher Model | Student Model            | 96.33          | 96.43          | 96.38      | 96.38       |
|           |              | Model w/o KD             | 95.31          | 95.54          | 95.43      | 95.43       |
|           |              | Student Model with KD    | 96.21          | 96.36          | 96.29      | 96.29       |

The experimental results show that the overall performance of the single-modal model, in terms of accuracy and F1 scores, is improved, under the supervision of the multimodal model. This is due to the fact that the soft labels, generated by the teacher network, can provide a regularization effect [35] when teaching the student model. Moreover, with the knowledge transferred by the teacher model, the generalization ability of the text-only model is improved, which can be reflected by the test results across the five different events.
4.6 Visualization of Global-Local Attention in Multimodal Conversations

In this section, we demonstrate some qualitative results of multimodal conversations, with the associated global-local attention scores, i.e., the attention weights obtained by Equation (10), so as to understand the importance of visual information and the knowledge distillation framework for rumour detection. We randomly selected some rumour conversations from both the Chinese and English data sets, which can be identified by the multimodal and text-only model with knowledge distillation, but not by the text-only model without knowledge distillation. Fig. 3 shows the source messages and their corresponding images. The associated replies and attention scores are shown in Table IV and Table V for the Chinese and English data sets, respectively.

泰坦尼克号续集《Jack is back》大伙期待吧。
(Translation: Let's look forward to the Titanic sequel "Jack Is Back")

(a)

Altitude & speed chart of 4U9525. Aircraft entered a steep but constant descent.

(b)

Fig 3. The source of Information of Rumours on the (a) Weibo data set (Chinese), and (b) PHEME data set (English)
From Fig. 3(a), we can observe that the associated image is manipulated, such that the digit “2” was added to the movie poster in an unrealistic way. Our multimodal detection model can successfully classify it as a rumour, with the help of a combination of visual and textual information. Moreover, the attention scores in Table IV show that most of the replies express doubts about the source information. However, only the multimodal and text-only model, with knowledge distillation, can pay attention to the important reply, i.e., this is false news, which indicates that the movie poster is fake. This reply is particularly useful for our model to classify the source information as a rumour, but it is ignored in the text-only model without knowledge distillation. This
shows that the knowledge distillation module helps the text-only model to identify the important replies, such that it can achieve a better performance on detecting rumours.

Table V. Visualization of Attention Scores of Multimodal English Conversations.

| Model                      | Ground Truth | Prediction | Conversations (Top 5 Replies)                                                                 | Attention Scores |
|-----------------------------|--------------|------------|------------------------------------------------------------------------------------------------|------------------|
| Multimodal Model           | Rumour       | Rumour     | According graphics the plane entered a decent after 30 minutes, not 5 minutes                   | 0.0752           |
|                            |              |            | The #A320 must have been gliding ie no engine power.                                           | 0.0644           |
|                            |              |            | not the footprints of catastrophic failure ?                                                   | 0.0643           |
|                            |              |            | altitude & speed chart of #4U9525. Plane was in steep descent.                               | 0.0637           |
|                            |              |            | good graphic                                                                                    | 0.0599           |
| Single Modal Model w/o KD  | Rumour       | Non-Rumour | altitude & speed chart of #4U9525. Plane was in steep descent.                               | 0.0823           |
|                            |              |            | the #A320 must have been gliding ie no engine power.                                           | 0.0745           |
|                            |              |            | Not dramatically                                                                                  | 0.0685           |
|                            |              |            | not sure if A320 has ram air turbine and not use AP                                           | 0.0549           |
|                            |              |            | 6 m/s equals jump from a height of 2 meters.                                                    | 0.0467           |
| Single Modal Model with KD | Rumour       | Rumour     | altitude & speed chart of #4U9525. Plane was in steep descent.                               | 0.2212           |
|                            |              |            | the #A320 must have been gliding ie no engine power.                                           | 0.1737           |
|                            |              |            | looks like a cabin depressurisation and emerg descent below MSA unfortunately!                 | 0.0766           |
|                            |              |            | good graphic                                                                                    | 0.0454           |
|                            |              |            | According graphics the plane entered a decent after 30 minutes, not 5 minutes                  | 0.0370           |

Fig 3(b) shows that the post is attached with an image containing the speed chart of an airplane. This image can help the detection pay more attention to those important replies that indicate the wrong information about the curve, i.e., “according to graphics, the plane entered a descent after 30 minutes, not 5 minutes”, as shown in Table V. Thus, this conversation can be successfully detected as a rumour by our multimodal model. With the proposed knowledge distillation framework, these important replies can also be identified by the text-only model, such that it can successfully detect the conversation as a rumour.

5. Conclusion and Future Work

In this paper, we propose a transformer-graph neural network (TGNN), with global-local attention, for modelling a conversation on social media for rumour detection. Our proposed TGNN is composed of a transformer and a graph attention network, to extract global and local information from a conversation, respectively. We extend this model for multimodal input, i.e., text and images, by employing element-wise addition of the
visual representation and the global textual representation. After that, we leverage a teacher-student framework to distillate knowledge from a multimodal model to a single-modal model. This can further improve the performance of the single-modal model. The experimental results have verified the effectiveness of the proposed framework on the PHEME-2016, PHEME-2018, and Weibo data sets for rumour detection, across English and Chinese languages. In this study, we found that rumours spreading on social media can be written in different languages. In our future work, we will employ transfer learning for cross-lingual rumour detection, to identify rumours written in low-resource languages and lack of training samples.

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**Tsun-hin Cheung** received the B.Eng. degree in electronic and information engineering in 2019 from the Hong Kong Polytechnic University, Hong Kong, where he is currently pursuing the Ph.D. degree. His research interests include natural language processing, social media analytics, and multimodal fusion.

**Kin-Man Lam** received his Associateship in Electronic Engineering with distinction from the Hong Kong Polytechnic University (formerly called Hong Kong Polytechnic) in 1986, the M.Sc. degree in communication engineering from the Department of Electrical Engineering, Imperial College of Science, Technology and Medicine, London, U.K., in 1987, and the Ph.D. degree from the Department of Electrical Engineering, University of Sydney, Australia, in 1996. From 1990 to 1993, Prof. Lam was a lecturer at the Department of Electronic Engineering of The Hong Kong Polytechnic University. He joined the Department of Electronic and Information Engineering, The Hong Kong Polytechnic University again as an Assistant Professor in 1996. He became an Associate Professor in 1999, and has been a Professor since 2010. Currently, he is also an Associate Dean of the Faculty of Engineering. He was actively involved in professional activities. He has been a member of the organizing
committee or program committee of many international conferences. Prof. Lam was the Chairman of the IEEE Hong Kong Chapter of Signal Processing between 2006 and 2008. He was a General Co-Chair of the 2012 IEEE International Conference on Signal Processing, Communications & Computing (ICSPCC 2012), APSIPA Annual and Summit 2015, and 2017 IEEE International Conference on Multimedia and Expo (ICME 2017), which were held in Hong Kong, and the Technical Chair of the 2020 IEEE International Conference on Visual Communications and Image Processing. Prof. Lam was the Director Student Services and the Director-Membership Services of the IEEE Signal Processing Society between 2012 and 2014, and between 2015 and 2017, respectively. He was an Associate Editor of IEEE Trans. on Image Processing between 2009 and 2014, and Digital Signal Processing between 2014 and 2018. He was also an Editor of HKIE Transactions between 2013 and 2018, and an Area Editor of the IEEE Signal Processing Magazine between 2015 and 2017. Currently, he is the VP-Publications of the Asia-Pacific Signal and Information Processing Association (APSIPA). Prof. Lam serves as an Associate Editor of APSIPA Trans. on Signal and Information Processing, and EURASIP International Journal on Image and Video Processing. His current research interests include human face recognition, image and video processing, and computer vision.