Abstract

Social media rumours, a form of misinformation, can mislead the public and cause significant economic and social disruption. Motivated by the observation that the user network — which captures who engage with a story — and the comment network — which captures how they react to it — provide complementary signals for rumour detection, in this paper, we propose DUCK (rumour detection with user and comment networks) for rumour detection on social media. We study how to leverage transformers and graph attention networks to jointly model the contents and structure of social media conversations, as well as the network of users who engaged in these conversations. Over four widely used benchmark rumour datasets in English and Chinese, we show that DUCK produces superior performance for detecting rumours, creating a new state-of-the-art. Source code for DUCK is available at: ANONYMISED.

1 Introduction

Social media platforms bring easy access to the wealth of information. On the flip side, social media has also accelerated the spread of misinformation (Starbird et al., 2014; Jin et al., 2017). Rumours, a form of misinformation typically defined as stories or statements with unverified truth value (Allport and Postman, 1947), can mislead the public and cause significant economic and social disruption.

Since the seminal work on prediction of information credibility on social media by Castillo et al. (2011), automatic rumour detection on social media has attracted significant research, which aims to detect rumors (in contrast to news articles by credible news sources) or determine the veracity — true, false or unverified — of rumours. Although the task is related to fake news detection, the use of social media for propagation means that various social context features can be leveraged for detection. This is a contrast to FEVER-style fake news detection (Thorne et al., 2018) which relies mainly on a source of world knowledge (e.g. Wikipedia) to fact-check stories.

Early studies of rumour detection focus on supervised learning algorithms incorporating features manually engineered from post contents, user profiles as well as information propagation patterns (Castillo et al., 2011; Liu et al., 2015; Kwon et al., 2013; Ma et al., 2015; Rath et al., 2017). Recent neural approaches typically explore fusing different feature representations for rumour detection. Sequence processing models such as BERT are used to encode the contents of social media conversations, e.g. source posts and the stream of comments (Kochkina et al., 2017; Tian et al., 2020), while graph models have been experimented to model the structure of social media conversations (Bian et al., 2020; Ma et al., 2018; Lu and Li, 2020). Although some approaches use a combination of content and user features for rumour detection, how to leverage pretrained sequence models and graph models to effectively model them remains under-explored.

In this paper we propose DUCK (rumour detection with user and comment networks), a framework that jointly models the user and comment propagation networks. Our study presents an extensive exploration on how we can best model these networks, and compared to previous studies, there are several key differences: (1) we model comments both as a: (i) stream to capture the temporal nature of evolving comments; and (ii) network by following the conversational structure (see Figure 1 for an illustration); (2) our comment network uses sequence model to encode a pair of comments before feeding them to a graph network, allowing our model to capture the nuanced characteristics (e.g. agreement or rebuttal) exhibited by a reply; and (3) when modelling the users who en-
gage with a story via graph networks, we initialise the user nodes with encodings learned from their profiles and characteristics of their “friends” based on their social networks.

We conduct experiments on four widely used benchmark rumour datasets in English and Chinese, and show that DUCK produces superior performance, creating a new state-of-the-art. Although both users and comments provide complementary signals for our task, the comments have a stronger impact. Also, when modelling the network of users who engage with a story, incorporating the social relations of users proves to be very beneficial. Source code for DUCK is available at: ANONYMISED.

2 Related Work

Early studies of rumour detection focus on supervised learning algorithms incorporating engineered features from post contents, user profiles as well as information propagation patterns (Castillo et al., 2011; Liu et al., 2015; Kwon et al., 2013; Ma et al., 2015; Rath et al., 2017).

Recent research focus on neural models to automatically generate various features for rumour detection. Sequence processing models leverage the textual contents from the source posts and user reply comments for rumour detection. Signals such as writing style, stance and opinions as well as emotions are extracted from the text for rumour detection. Shu et al. (2017) introduce linguistic features to represent writing styles and other features based on sensational headlines from Twitter to detect misinformation. To detect rumours as early as possible, Zhou et al. (2019) incorporate reinforcement learning to dynamically decide how many responses are needed to classify a rumour. Tian et al. (2020) explore the relationship between a source tweet and its comments by transferring stance prediction model to classify rumours. Most of these approaches model user comments as a sequence of posts and ignore the conversational structure among the comments.

Graph neural models leverage information propagation patterns for rumour detection. Liu and Wu (2018) experiment with using convolutional and recurrent neural networks to process user features in the retweet propagation path of stories, and Ma et al. (2018) present a tree-structure recursive neural network to model information propagation for rumour detection. Bian et al. (2020) proposed a bi-directional graph network to model the upward and downward information propagation structure among user comments to distinguish false from true rumours.

There are also studies combining signals from contents, users and propagation networks for rumour and fake news detection (Lu and Li, 2020; Nguyen et al., 2020). An ensemble deep learning architecture is presented in Lu and Li (2020), which incorporates source post content and retweet network. Nguyen et al. (2020) propose to learn representations for misinformation detection based on the heterogeneous graph of news, news sources, users and their stances in comments. All these studies largely model the superficial characteristics of comments and users, e.g. comments are represented using static features such as bag-of-words (Bian et al., 2020; Nguyen et al., 2020) and users with simple features extracted from their profiles (Liu and Wu, 2018; Lu and Li, 2020). Deeper interactions, such as the relation between a post and its reply and the social relations (e.g. “following”) of users, remain under-explored. Table 1 summarises the differences between previous studies and our work.

Beyond rumour detection, recent studies explore combining modern pretrained language models and graph models for modelling texts and their interactions. Using the FEVER dataset, Zhong et al. (2020) exploit pretrained models to perform semantic role labelling to understand the relation between clauses in evidence passages and then encode the network with graph models to detect fake news. Liu et al. (2020) use BERT to encode a pair of claim and evidence passage and then propose a kernel graph network to model the fully connected network of evidence passages. Although these two studies combine sequence and graph models, their task has a different data structure and hence their methods cannot be trivially adapted to the rumour detection task.

3 Problem Statement

Let $X = \{x_0, x_1, x_2, \ldots, x_n\}$ be a set of stories, where a story $x_i$ consists of a source post and its reply comments, defined as $x_i = \{(c_0, u_0, p_0, t_0), \ldots, (c_m, u_m, p_m, t_m)\}$, where $c$ refers to the textual content of the post (empty string if it’s a repost/retweet), $u$ the user ID who made the post, $p$ the parent post ID that the current post replies to (null if it’s a source post, e.g. $p_0$ = null), and $t$ the timestamp of the post. Each story
4 Methodology

The overall architecture of our rumour detection approach is presented in Figure 1. It consists of four modules: (1) comment tree: models the comment network by following the reply-to structure using a combination of BERT (Devlin et al., 2019) and graph attentional networks (Veličković et al., 2017); (2) comment chain: models the comments as a stream using transformer-based sequence models; (3) user tree: incorporates social relations to model the user network using graph attentional networks; (4) rumour classifier: combines the output from comment tree, comment chain and user tree to classify the source post. Note that the network structure of the user tree differs from that of the comment tree as the former captures both comments and reposts/retweets but the latter considers only comments (Figure 1).

4.1 Comment Tree

Here we aim to model the conversational structure of the comments that a source post generates. Previous studies typically model this via graph networks, but most use simple features (e.g. bag-of-words) to represent the text (Bian et al., 2020), which fail to capture the nuanced relationships (e.g. agreement) between a parent post and its child/reply post.

To capture the relations of crowd opinions in the comment tree, we propose to use a pretrained language model (BERT; (Devlin et al., 2019)) and graph attention network (GAT; (Vieweg et al., 2010)) to model comment tree; see Figure 2 for an illustration. We first process the set of parent-child posts with BERT (Devlin et al., 2019) before feeding them to a graph network to model the full conversational structure. The self-attention mechanism between the words in the parent and child posts would produce a more fine-grained analysis of their relationship, which representations such as bag-of-words cannot model. Using the comment tree in Figure 2 as an example, this means we would first process the following pairs of posts using BERT: \( \{(0, 0), (0, 1), (0, 2), (2, 6), (2, 7), (6, 9)\} \), where \((0, 0)\) is a pseudo pair created for the source post.
where $c$ represents the text, $\text{emb}()$ the embedding function and $h$ the contextual representation of the $[CLS]$ token produced by BERT.

To model the conversational network structure, we use graph attentional networks (GAT; Veličković et al., 2017). Different to graph convolutional networks (Kipf and Welling, 2016a), GAT iteratively learns node encodings via multi-head attention with neighbouring nodes, and has the advantage to infer encodings for new nodes after it’s trained. To compute $h_i^{(i+1)}$, the encoding for node $i$ at iteration $l + 1$:

$$e_{ij}^{(l)} = LR\left( (a(l) \cdot W(l) h_i^{(l)} ) \right)$$

$$h_i^{(l+1)} = \sigma \left( \sum_{j \in \mathcal{N}(i)} \text{softmax}(e_{ij}^{(l)}) z_j^{(l)} \right)$$

where $LR$ denotes the LeakyReLU activation function, $\oplus$ the concatenation operation, $\mathcal{N}(i)$ the neighbours of node $i$, $e_{ij}^{(l)}$ the unnormalized attention score between node $i$ and $j$, and $a$ and $W$ are learnable parameters. Note that $h_i^{(0)}$ represents the encodings produced by BERT (Equation 1).

To aggregate the node encodings to get a graph representation ($z_{ct}$), we explore four methods:

**root:** Uses the root encoding to represent the graph as the source post is ultimately what we are classifying:

$$z_{ct} = h_0^L$$

where $L$ is the number of GAT iterations.

**¬root:** Mean-pooling over all nodes except the root:

$$z_{ct} = \frac{1}{m} \sum_{i=1}^{m} h_i^L$$

where $m$ is the number of replies/comments.

**△:** Mean-pooling of the root node and its immediate neighbours:

$$z_{ct} = \frac{1}{|\mathcal{N}(0)|} \sum_{i \in \mathcal{N}(0)} h_i^L$$

**all:** Mean-pooling of all nodes:

$$z_{ct} = \frac{1}{m + 1} \sum_{i=0}^{m} h_i^L$$

4.2 Comment Chain

Here we model the posts as a stream in the order they are posted. As such, we have a chain or list structure (rather than a tree structure); see “comment chain” in Figure 1.

We explore three ways to model the comment chain, using: (1) one-tier transformer; (2) longformer (Beltagy et al., 2020); and (3) two-tier transformer.

**One-tier transformer:** Given a source post ($c_0$) and the comments ($\{c_1, \ldots, c_m\}$), we simply concatenate them into a long string and feed it to BERT and use the contextual representation of the $[CLS]$ token as the final representation:

$$z_{cc} = \text{BERT}(\text{emb}([CLS], c_0, [SEP], c_1, \ldots, c_m))$$

where $m'$ ($< m$) is the number of comments we can incorporate without exceeding BERT’s maximum sequence length (384 in our experiments).

**Longformer:** To circumvent the sequence length limit, we experiment with using a longformer, which can process up to 4,096 subwords, allowing us to use most if not all the comments. Longformer has a similar architecture as the one-tier transformer, but uses a sparser attention pattern to process longer sequences more efficiently. We use a pretrained longformer$^2$, and follow the same approach as before for modelling the comment chain:

$$z_{cc} = \text{LF}(\text{emb}([CLS], c_0, [SEP], c_1, \ldots, c_{m''}))$$

where $m'' \approx m$.

**Two-tier transformer:** An alternative approach to tackling the sequence length limit is to model the comment chain using two tiers of transformers: one for processing the posts independently, and another for processing the sequence of posts using representations from the first transformer. Formally:

$$h_i = \text{BERT}(\text{emb}_1([CLS], c_i))$$

$$z_{cc} = \text{transformer}(\text{emb}_2([CLS]), h_0, h_1, \ldots, h_m)$$

\[1\text{Preliminary experiments found that the pseudo pair is important because it allows us to maintain the original network structure.}

\[2\text{https://huggingface.co/transformers/model_doc/longformer.html}]

Figure 2: The architecture of BERT+GAT.
where BERT and transformer denote the first- and second-tier transformers respectively. The second-tier transformer has a similar architecture to BERT, but has only 2 layers and its parameters are initialised randomly.

### 4.3 User Tree

Moving away from the post content, here we model the network of users that interact with a source post (“user tree” in Figure 1). Previous studies found that the user characteristics are different for those that engage with rumours vs. those who don’t (Vosoughi et al., 2018; Shu et al., 2018), motivating us to model the user network. Note that unlike previous studies, our user network captures all users who reply to or repost the source post (previous studies use only the reposts, see Table 1). We explore three methods to model the user network. All methods use a GAT (Veličković et al., 2016b) based on the user features (defined above) and the time difference with the source post.

| Method              | Description                                      |
|---------------------|--------------------------------------------------|
| GAT<sub>prf</sub>  | This is the base method where we initialise the user nodes with random vectors. |
| GAT<sub>prf+rel</sub> | This method initialises the user nodes based on their user profiles: username, user screen name, user description, user account age, number of followers and following users, number of posts and favourite posts, whether the profile is protected, whether the account is GPS-enabled, and the time difference with the source post. |

The main difference between the three methods is in how they initialise the user nodes ($h_i^{(0)}$):

- **GAT<sub>prf</sub>:** Following Liu and Wu (2018), this method initialises the user nodes based on features derived from their user profiles: username, user screen name, user description, user account age, number of followers and following users, number of posts and favourite posts, whether the profile is protected, whether the account is GPS-enabled, and the time difference with the source post.\(^3\)

- **GAT<sub>prf+rel</sub>:** This method initialises the user nodes with representations learned by a variational graph autoencoder (GAE; Kipf and Welling, 2016b) based on the user features (defined above) and their social relations (based on “follow” relations).\(^4\) Intuitively, GAE is an unsupervised learning algorithm that takes in an adjacency matrix as input, and learns node representations that can reconstruct the adjacency matrix in the output.

Note that the network structure of the GAT and GAE is intrinsically different — the former captures the users that engage with a source post while the latter the network of users who follow one another. The idea for using GAE-learned encodings to initialise user nodes is that they are more informative, since they capture information about a user and their peers.

### 4.4 Rumour Classifier

In each module (comment tree, comment chain and user tree), we explore a number of approaches to model its structure (e.g. there are several ways to aggregate the node encodings to produce $z_{ct}$ for the comment tree and 3 different methods to produce $z_{cc}$ for the comment chain). Given an optimal approach for each module (discussed in the Experiments and Results section), DUCK (Figure 1) combines the output from all modules to classify a source post and is trained using standard cross-entropy loss. Formally:

$$
\hat{y} = \text{softmax}(W_c z + b_c) \\
L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i)
$$

where $n$ denotes the number of instances.

### 5 Experiments and Results

#### 5.1 Datasets and models

We evaluate our method on four widely used rumour datasets: Twitter15 (Ma et al., 2017); Twitter16 (Ma et al., 2017); CoAID (Cui and Lee, 2017); and WEIBO (Ma et al., 2017).

| Dataset   | #source nodes | #users | #connections | Avg. time delay/s | Min. # of nodes/s | Max. # of nodes/s | Avg. # of nodes/s |
|-----------|---------------|--------|--------------|-------------------|-------------------|-------------------|-------------------|
| Twitter15 | 1,490         | 276,663| 3,086,741    | 1,337             | 55                | 1,768             | 233,487           |
| Twitter16 | 818           | 19,211 | 1,232,100    | 848               | 81                | 2,765             | 251               |
| WEIBO     | 4,664         | 2,746,818| 2,746,818   | 2,460.7           | 10                | 1,768             | 816               |
| CoAID     | 143,009       | 1,601  | 25,605       | 15.4              | 1                 | 228               | 7                 |

Table 2: Statistics of rumour datasets. “s” denotes an story (source post and its comments).
2020); and WEIBO (Ma et al., 2016). Twitter15 and Twitter16 are Twitter datasets with four rumour classes: true rumour, false rumour, non-rumour and unverified rumour. CoAID (Cui and Lee, 2020) collects a set of COVID-19 news articles shared on Twitter, and they are annotated with two classes (true or fake). WEIBO (Ma et al., 2016) contains a collection of stories from Sina Weibo, a Chinese social media platform, and is annotated with two classes (rumour and non-rumour). Table 2 shows statistics of these datasets. For Twitter-based datasets (Twitter15/16 and CoAID), we crawl the tweets and additional user information (e.g. user profile metadata and followers) via the official Twitter API. For WEIBO, the platform does not provide a means to crawl social relations them and so the user tree uses \( \text{GAT}_{\text{prf}} \).

In terms of data partitioning, for Twitter15 and Twitter16 we follow previous studies (Ma et al., 2015, 2016) and report the average performance based on 5-fold cross-validation. For CoAID and WEIBO, we reserve 20% data as test and split the rest in a ratio of 4:1 for training and development partitions and report the average test performance over 5 runs (initialised with different random seeds). We use the development set of each dataset for tuning hyper-parameters.

Implementation details for all models are given in the Appendix.

5.2 Results

In this section, we first present results for each of the modules (comment tree, comment chain and user tree) separately to understand the best approach for modelling them, and then present the final results where we compare our full model DUCK (Figure 1) to a number of benchmark systems. For the first set of results where we evaluate each module independently, we feed their representations (i.e. \( z_{ct} \), \( z_{cc} \) and \( z_{ut} \)) to an MLP layer to do classification. Specifically, we are interested in the following questions:

- Q1 [Comment tree]: Does incorporating BERT to analyse the relation between parent and child posts help modelling the comment network, and what is the best way to aggregate comment-pair encodings to represent the comment graph?
- Q2 [Comment chain]: Does incorporating more comments help rumour detection when modelling them as a stream of posts?
- Q3 [User tree]: Can social relations help modelling the user network?
- Q4 [Overall performance]: Do the three different components complement each other and how does a combined approach compared to existing rumour detection systems?

For the first three questions, we present development performance using Twitter16 and CoAID as the representative datasets (as the trends are largely the same for the other datasets), while for the final question we report the test performance for all datasets. In terms of evaluation metrics, we present F1 scores for each class and macro-averaged F1 scores as the aggregate performance. All results are an average over 5 runs (5-fold cross-validation for Twitter15/16 and 5 independent runs with different random seeds for WEIBO and CoAID following Ma et al. (2016, 2017); Cui and Lee (2020)).

5.2.1 Comment Tree

To understand the impact of using BERT for processing a pair of parent-child posts, we present an alternative method (“unpaired”) where we use BERT to process each post independently before feeding their \([CLS]\) representation to the GAT. That is, Equation 1 is now modified to:

\[
h_p = \text{BERT}(\text{emb}([CLS], c_p))
\]

where \( h \) will be used as the initial node representation \( h^{(0)} \) in the GAT (Equation 2). We report the performance of this alternative model (“unpaired”)\(^7\) and the different aggregation methods (“root”, “~root”, “▲” and “all”; equations 3, 4, 5 and 6 respectively) in Table 3.

Comparing the aggregation methods, “all” performs the best, followed by “▲” and “root” (0.88 vs. 0.87 vs. 0.86 in Twitter16; 0.87 vs. 0.86 vs. 0.85 in CoAID in terms of Macro-F1). We can see that the root and its immediate neighbours contain most of the information, and not including the root node impacts the performance severely (both Twitter16 and CoAID drops to 0.80 with ~root). Does processing

\(^7\)The “unpaired” approach uses “all” as the aggregation method.
The answer is evidently yes, as we see a substantial
increase and a drop when there are too many com-
ments. Interestingly, even though longformer is
able to include most of the comments, it performs
worse than both one-tier and two-tier transformer,
suggesting that the sparser attention pattern that
longformer introduces has a negative impact. With
these results, we will use the two-tier transformer
to model the comment chain in DUCK.

5.2.3 User Tree
Recall that we use GAT to represent the reply
and repost user network, and we investigate differ-
ent node encodings to initialise GAT: (1) random
initialisation (GAT\textsubscript{rnd}); (2) user profile metadata
(GAT\textsubscript{prf}); and (3) user profile metadata and social
relations (GAT\textsubscript{prf+rel}). Results are shown in Table 4.
Unsurprisingly, random initialisation performs the
worse, and we see a substantial improvement when
user profile information is incorporated, and again
an improvement when we incorporate user social
relations (6% and 5% increase in macro-F1 for
Twitter16 and CoAID). Our results highlight the
importance of incorporating social relations, and
DUCK therefore uses GAT\textsubscript{prf+rel} for modelling
the reply and retweet user network.\footnote{With the exception of WEIBO where we can’t crawl users’
followers, and so it uses GAT\textsubscript{prf}.}

5.2.4 Overall Rumour Detection
Performance
We next compare the rumour detection perfor-
mance of DUCK that combines comment tree, com-
ment chain and user tree models (Figure 1) to the
following state-of-the-art methods: (1) \textsc{RvNN} (Ma
et al., 2018)\footnote{https://github.com/majingCUHK/Rumor_R
\textsc{vNN}}: uses a GRU to process text content
and recursive networks to model the comment net-
work; (2) \textsc{RNN+CNN} (Liu and Wu, 2018): uses
CNN and RNN to model the retweet user network
where user representations are initialised with
user profile features; (3) \textsc{stance-BERT} (Tian et al.,
2018): uses
user profile information is incorporated, and again
an improvement when we incorporate user social
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Twitter16 and CoAID). Our results highlight the
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where user representations are initialised with
user profile features; (3) \textsc{stance-BERT} (Tian et al.,
2018): uses

| Variants | Twitter16 | CoAID |
|----------|----------|-------|
|          | F1 | FR | TR | NR | UR | F1 | T | F |
| unpaired | 0.83 | 0.92 | 0.87 | 0.73 | 0.82 | 0.83 | 0.98 | 0.67 |
| root | 0.86 | 0.85 | 0.92 | 0.85 | 0.83 | 0.85 | 0.98 | 0.71 |
| –root | 0.82 | 0.85 | 0.96 | 0.71 | 0.79 | 0.81 | 0.97 | 0.64 |
| ▲ | 0.87 | 0.89 | 0.95 | 0.74 | 0.88 | 0.86 | 0.99 | 0.74 |
| all | 0.88 | 0.89 | 0.94 | 0.79 | 0.90 | 0.87 | 0.98 | 0.75 |

Table 3: Results for the comment tree. “FR”, “TR”,
“NR” and “UR” in Twitter16 denote false, true, non-
and unveriﬁed rumours respectively; and “T” and “F”
in CoAID means true and fake classes.

Figure 3: Results (macro-F1) for the comment chain
over varying number of comments.
works. For a summary of the different features:

| Model          | Twitter15 F1 | Twitter15 R | Twitter16 F1 | Twitter16 R | CoAID F1 | CoAID R | WEIBO F1 | WEIBO R |
|----------------|--------------|-------------|--------------|-------------|----------|--------|----------|--------|
| RvNN           | 0.72         | 0.76       | 0.82         | 0.68       | 0.65     | 0.74   | 0.74     | 0.84   |
| RNN+CNN        | 0.53         | 0.51       | 0.30         | 0.36       | 0.64     | 0.56   | 0.54     | 0.40   |
| stance-BERT    | 0.82         | 0.82       | 0.85         | 0.87       | 0.71     | 0.83   | 0.82     | 0.88   |
| Bi-GCN         | 0.86         | 0.85       | 0.91         | 0.84       | 0.82     | 0.86   | 0.86     | 0.93   |
| GCAN           | 0.69         | 0.75       | 0.75         | 0.63       | 0.68     | 0.72   | 0.73     | 0.78   |
| DUCK-cc        | 0.30         | 0.81       | 0.88         | 0.81       | 0.84     | 0.88   | 0.88     | 0.79   |
| DUCK-ct        | 0.09         | 0.30       | 0.88         | 0.80       | 0.84     | 0.91   | 0.87     | 0.88   |
| DUCK-ut        | 0.90         | 0.91       | 0.93         | 0.88       | 0.91     | 0.89   | 0.93     | 0.93   |
| DUCK           | 0.90         | 0.91       | 0.93         | 0.88       | 0.91     | 0.91   | 0.93     | 0.91   |

Table 5: Overall rumour detection results. “CT”, “CC” and “UT” denote comment tree, comment chain and user tree respectively, and “R” and “NR” in WEIBO denote rumour and non-rumour.

2020): fine-tunes a BERT pretrained with stance annotations for rumour detection and comments are modelled as a chain (similar to our one-tier transformer model); (4) Bi-GCN (Bian et al., 2020): uses a bidirectional graph convolutional network to model the comment network in a top-down (i.e. nodes are combined starting from the leaf comments) and bottom-up manner (i.e. nodes are combined starting from the root); and (5) GCN (Lu and Li, 2020): uses graph networks to model the retweet user network and a CNN to model the source post with co-attention between the two networks. For a summary of the different features used by these benchmark systems and our model, see Table Table 1.

All benchmark results are produced using the author-provided code, with the exception of RNN+CNN and stance-BERT where we implement ourselves. Note that we only have English results (Twitter15, Twitter16 and CoAID) for stance-BERT as it uses stance annotations from SemEval-2016 (Mohammad et al., 2016), and GCAN and RNN+CNN do not have results for CoAID as it does not contain retweets.

We present the results in Table 5. DUCK (our model) performs very strongly, outperforming all benchmark systems consistently over all datasets, creating a new state-of-the-art for rumour detection. In terms of datasets, WEIBO appears to be the “easier” dataset, where most systems produce a macro-F1 over 90%. We also observe that models that use the comment texts (stance-BERT and Bi-GCN) tend to do better than those that only use the user network (RNN+CNN and GCAN), although the strong performance of DUCK indicates that combining both types of information works best, suggesting that they complement each other. Another thing of note is CoAID, the only dataset where the class distribution is heavily imbalanced. Here we see that most systems struggle with the minority class (“F”), but our combined approach handles this well.

To understand the impact of each module in DUCK, we present variants where we remove one module, e.g. DUCK-ct means comment tree removed. Results suggest that comment tree has the largest impact, followed by comment chain as they produce the largest performance drop when removed. This finding is similar to what we saw earlier, where systems like stance-BERT and Bi-GCN that use comments tend to perform better.

6 Conclusion

We presented DUCK, a social media rumour detection approach that models both the network of users who interact with a story as well as their comments/opinions. Our approach is unique in how we model the comment as a graph (with BERT and GAT) and also as a stream (with transformers) and the user networks together with their peer relations (with GAT and GAE). We conduct extensive experiments over four popular rumour benchmark datasets to evaluate DUCK. We found that the comment network contains the strongest signal for predicting rumours, and social relations are important for modelling the user network. DUCK substantially outperforms all benchmark methods consistently, creating a new state-of-the-art.

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11 https://github.com/TianBian95/BiGCN
12 https://github.com/1852888/GCAN
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A Implementation Details

We implement our models in PyTorch using the HuggingFace library\(^{13}\) and their pretrained BERT\(^{14}\) and Chinese-BERT\(^{15}\). Graph neural networks are implemented with the Geometric\(^{16}\) package.

For the comment tree, we set maximum token length=40 and dropout rate = [0.5, 0.6] for GAT and 0.2 for BERT embeddings. Learning rate is tuned in the range between \([1e^{-5}, 5e^{-5}]\) for BERT and \([1e^{-4}, 5e^{-4}]\) for GAT based on the development set. For comment chain, the learning rate for two-tier transformer (comment chain) is tuned in between \([2e^{-5}, 5e^{-5}]\) with maximum token length as 40. For user tree, we set the dimension of each node hidden features as 256. All models use the Adam optimiser \((\text{Kingma and Ba, 2014})\), and our experiments are run using 4×A100 GPU with 40GB Memory.

\(^{13}\)https://github.com/huggingface

\(^{14}\)https://huggingface.co/bert-base-cased

\(^{15}\)https://huggingface.co/bert-base-chinese

\(^{16}\)https://pytorch-geometric.readthedocs.io/en/latest/