

COMP90042 Rumour Detection and Analysis on Twitter

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1 Introduction

With the popularity of the internet and social media in recent years, social media has become an indispensable part of people's lives. More and more people are using social media not only to connect with family and friends, but also to keep up to date with what is currently happening. The role of the user has also changed from that of a receiver of information to that of a creator. Many news outlets publish news on social media, and ordinary users can also express their views and opinions. However, the growth of social media has accelerated the spread of information and has also brought about a proliferation of false rumours. Twitter, one of the most popular social media, has generated a large number of rumours that are difficult to verify and are spreading rapidly among users. Therefore, it is crucial to identify whether a message is a rumour or not.

2 Related Works

The topic of rumour identification and analysis has attracted a great deal of attention in recent years.

Tian et al. (2020) transformed the rumour detection task into a supervised classification problem and trained the model using a set of labelled source tweets and comments. They found that comments responded to different user attitudes towards rumours and non-rumours, and based on this decomposed the problem into rumour detection for detecting positions and tweets from comments. Convolutional neural networks (CNN) and BERT neural network language models were used for the experiments. The article further proposes a rumour detection model based on a combination of these two models with significant advantages for early rumour detection.

Some studies analysed whether a tweet is a rumour by using features other than the content. Kwon et al. (2013) detected rumours by analysing

time, structure and language. They found that non-rumours usually had only one significant spike, while rumours tended to have multiple periodic spikes. They also found that rumours and non-rumours differed significantly in the user diffusion network. A new time series fitting model and network structure are used to train the data. This article shows a more accurate result of identifying rumors from other type of information.

Wu et al. (2015) examined the problem of false rumours on the popular Chinese social network Weibo. In addition to studying traditional semantic features such as topic-based and sentiment-based features, propagation patterns were also investigated through a hybrid Support Vector Machine (SVM) classifier based on a graph-kernel. They found that the false rumor is first posted by a normal user, then reposted and supported by some opinion leaders and finally reposted by a large number of normal users. On the contrary, the normal message is posted by an opinion leader and reposted directly by many normal users. Based on these findings, the model can be used to detect false rumours early, and 90% of rumours can be detected just one day after their initial broadcast.

3 Dataset

This work trains a model based on given training data, optimises the model based on development data, tests the model on test data and ultimately applies it to determine whether tweets related to covid are rumours. The training dataset, the development dataset and the covid dataset are all tweet IDs of source tweets and replies, corresponding to the two sets of tags in separate files. When crawling tweets by tweet IDs, some tweets cannot be retrieved because they have been deleted by the users, so these tweets will be ignored from the data.

Before building the rumour analysis model, the tweet data was analysed.

Dataset	Percentage
train-rumour	0.2216
train-nonrumour	0.7784
dev-rumour	0.2199
dev-nonrumour	0.7801

Table 1: Share of rumours and non-rumours in the dataset

Dataset	Median	Mean
train-rumour	14	30.2
train-nonrumour	5	10.7
dev-rumour	12	26.8
dev-nonrumour	5	12.6

Table 2: Number of replies

4 Task 1

4.1 detection system

introduce our detection system the reason behind the choices

4.2 performance

5 Task 2

5.1 topics

What are the topics of COVID-19 rumours, and how do they differ from the non-rumours?

How do COVID-19 rumour topics or trends evolve over time?

5.2 hashtags

What are the popular hashtags of COVID-19 rumours and non-rumours? How much overlap or difference do they share?

5.3 sentiment

Do rumour source tweets convey a different sentiment/emotion to the non-rumour source tweets? What about their replies?

5.4 users

What are the characteristics of rumour-creating users, and are they different to normal users?

References

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Lin Tian, Xiuzhen Zhang, Yan Wang, and Huan Liu. 2020. Early detection of rumours on twitter via stance transfer learning. In *European Conference on Information Retrieval*, pages 575–588. Springer.

Ke Wu, Song Yang, and Kenny Q Zhu. 2015. False rumors detection on sina weibo by propagation structures. In *2015 IEEE 31st international conference on data engineering*, pages 651–662. IEEE.

A Example Appendix

This is an appendix.