Design and Implementation of Rumor Refuting and Accountability System Based on Deep Learning and Graphic Database

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Abstract. With the popularity of social networks, online rumors are increasing day by day. Internet rumors are harmful, spread fast, and will cause great loss to personal interests and social interests. In order to suppress the spread of online rumors and hold those who spread rumors accountable, we designed and implemented a system to refute and hold those responsible for online rumors accountable. The system has two major functions. First, with the help of deep learning model, it can automatically detect whether the news reported by users is rumor or not, and push the correct news to all users who have browsed the wrong news, so as to suppress the rumor spread. Second, with the help of graphic database, the whole process of rumor generation and dissemination can be displayed in detail, thus providing strong evidence for relevant departments to investigate the responsibility of those who spread rumors.

Keywords: Deep learning · Graphic databases · Refuting rumors · Accountability system

1 Introduction

With the widespread application of mobile Internet and social networking tools, the network space has gradually become the gathering place of rumors, and in a disguised way, it provides convenient channels for rumors to spread. According to the report, more than one-third of hot events on weibo contained false information [1]. Internet rumors are deceptive, latent and harmful, which will not only damage personal interests, but also interfere with social order, and even affect national image and security. It is urgent to build a accountability mechanism and a rumour refuting platform to control the breeding and spread of rumors. According to the survey, the difficulty of the current online rumor accountability lies in the complexity of the network information, the source of information is difficult to trace, and the low efficiency of the rumor refuting platform

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in reality, which still cannot break through the limitation of manual audit. In addition, it is difficult to trace the source of online rumors, which makes it difficult to accurately refute rumors [2].

In previous work, people focused on how to automatically detect rumors through machine learning, but little attention was paid to the process of refuting rumors and accountability. In this paper, we build an accurate rumor refuting and directional accountability system based on graph database and deep learning model [3]. In this system, the social platform will upload the information reported by users to the system according to the situation reported by users. In order to accurately detect rumors and facilitate subsequent refuting of rumors, the system divides the information into three categories: scientific common sense, current affairs news and opinion output. For scientific and general knowledge and current affairs news, by deep learning models, the system will first find out contrary to the current message semantics, and combining the two news publishers, publishing a variety of factors such as time, confirm one of them as a rumor, the other a message is the rumor message, and to all the users read the rumor to push the rumor message [4]. As for opinion output messages, opinions cannot be simply identified as right or wrong due to their strong subjectivity. Therefore, after finding views that are semantically opposite to them through the neural network model, the views are pushed to users who have browsed the original messages to broaden their horizons. In the accountability stage, the system built a graphic database to more intuitively display the rumor generation and dissemination process, and found the more important nodes through the corresponding algorithm, so as to facilitate the government departments to hold accountable.

2 System Design

2.1 Overall Framework of the System

The accurate rumor refuting and directional accountability system based on deep learning and graphic database is designed and implemented from different perspectives of public social platforms, users of social platforms and governments, focusing on the process of rumor refuting and accountability. As shown in Fig. 1, the system can be divided into two parts: accurate rumor refuting system and rumor oriented accountability system.

In the accurate rumor dispelling system, social platforms are responsible for packaging and uploading to the system the specific content, publisher, release time and release platform of the information reported by users [5]. In the system, the message is divided into three types: opinion output message, scientific common knowledge message and current affairs news message. System for each type of message handling different: to view the output class news, because the social platform user personal point of view it is difficult to make a simple judgment from two dimensions of right and wrong, so the system can through the neural network model to find with the messages of the contrary, and directional pushed to the latter directly to social networking platform, so that social

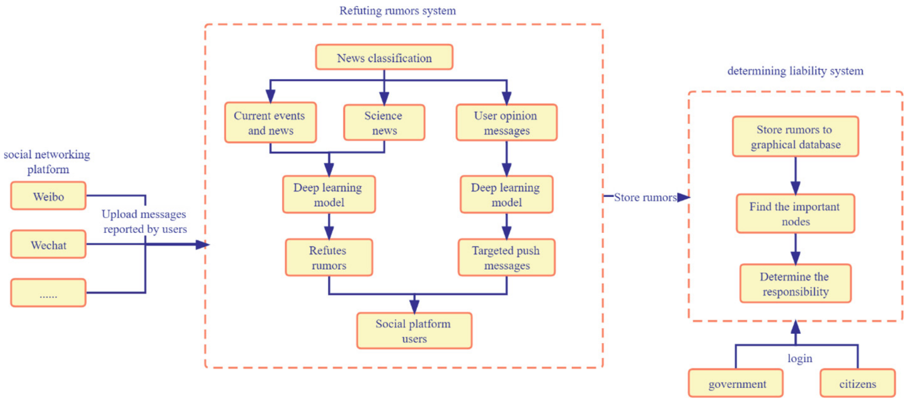

Fig. 1. System framework.

network users open field of vision. For science news, this system will by deep learning model, in the current science news for do not agree with the meaning of the message, and according to the factors such as comprehensive news publishers, publishing time determine the accuracy of the message, if ultimately determine the news as a rumor, will the right to social platform of scientific knowledge push users; For rumors of current affairs news, the system will judge the truth of current affairs news based on a series of factors such as news release time and publisher, and push the truth to social platform users. For users of social platforms, as long as they browse rumors, they will receive the refutation information of the rumors in the system, so as to eliminate the influence of rumors on users of social platforms to the greatest extent [6].

The rumor oriented accountability system will build a graphic database for the rumor data identified in the accurate rumor refuting system, so as to more clearly present the rumor release and forwarding process. Relevant government staff can log in the system to check a series of information such as the specific information of the rumor publisher, rumor content, rumor generation and dissemination process, so as to determine the responsibility of relevant subjects [7]. Users of social platforms can also check the rumor refuting information of all current rumors, relevant information of rumor publishers, rumor spreading process, etc., in order to improve rumor identification ability [8].

2.2 Architecture of the System

As shown in Fig. 2, the accurate rumor refuting and directional accountability system based on deep learning and graphic database includes data acquisition layer, data storage layer, functional module layer and application layer, and provides various business interfaces. In the data collection layer, public social platforms such as Weibo, Zhihu and wechat can package and upload the information of the publisher, content and release time of the reported information to the system. Message data is stored in a combination

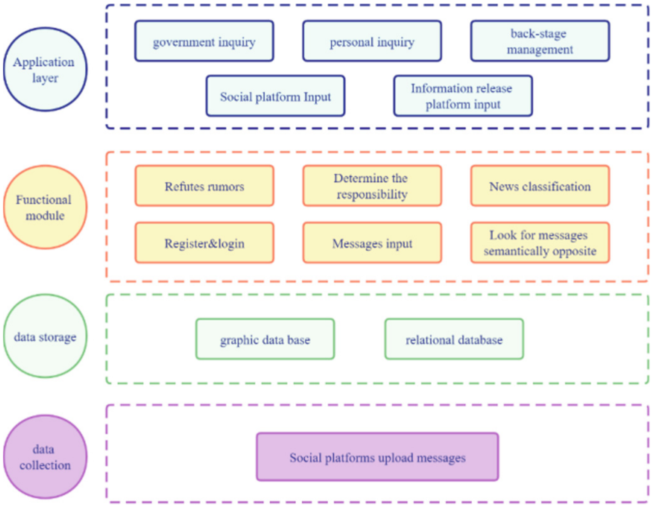

Fig. 2. System hierarchy diagram.

of relational and graphical databases [9]. The graph database stores the id of the rumor publisher, the ID of the "like", the ID of the "forward", the ID of the commenter and the content of the rumor, so as to display the whole process of the rumor generation and dissemination in detail. Relational databases store all the messages uploaded by public social platforms and reported by users for easy searching.

The functional modules of the system include registration and login module, reported message input module, message classification module, message detection module, accurate rumor refuting module and directional accountability module. The application layer provides different business interfaces for different objects, including the input interface of the social platform, the query interface of the government and users of the social platform, and the background management. The system realizes the whole logic function by realizing the interface of each module [10].

3 Implementation of the System

3.1 Messages Classification Model

We extracted some data from weibo, wechat, Zhihu and other social platforms to make a data set for such a three-category task. 1 indicates that the text belongs to current news, 2 indicates that the text belongs to scientific knowledge, and 3 indicates that the text belongs to opinion output. Some data are shown in Table 1.

Table 1. Partial data in the dataset.

The text content	tag
Shanghai: added four medium-risk areas.	1
Eyeball protrusion may be myopia, diplopia is astigmatism, it is recommended to ophthalmology or optician shop to check eyesight, timely correction, prevent more serious vision problems.	2
The CPU can run normally when the temperature is less than 70 °C. The SURFACE temperature of the CPU is between 75 °C and 85 °C, which is the warning temperature, but will not burn the CPU.	2
Seeing the news last night scared me up all night	3

Table 2. Effect comparison of alternative models.

model	acc
BERT	94.83%
ERNIE	94.61%
BERT+CNN	94.44%
BERT+RNN	94.57%
BERT+RCNN	94.51%
BERT+DPCNN	94.47%

During training, we selected many alternative models for effect comparison, and the comparison results are shown in Table 2.

It can be found that only using the original BERT, the effect is already very good, and the accuracy rate reaches 94.83%. The effect of embedding BERT into other models is reduced. Therefore, the BERT model was finally selected, the self-made data set was adopted, the learning rate was set as 5E−5, the Batch size was set as 32, and the epoch was set as 3, and other parameters were set for training.

3.2 Deep Learning Model

In the accurate rumor refuting system, we need to find the information with the opposite semantics to the current information through the deep learning model, which is mainly composed of two modules: the content understanding module and the opposition analysis module. After finding a message whose semantics are contrary to the reported message, we should determine whether the reported message is a rumor by integrating multiple factors, such as the release time and the publisher of the message.

3.2.1 Content Understanding Module

This module realizes two functions, namely, extracting text keywords and generating text summaries. Due to the complex syntactic structure of messages on social platforms, it is difficult to directly calculate the text similarity and the accuracy is not high. Therefore, it is considered to generate text summaries for messages, and the semantics expressed by text summaries are regarded as the semantics of the original text. In addition, considering the huge number of messages on social platforms, semantic comparison between messages on social platforms and reported messages one by one would cost unacceptable time. Therefore, keywords are extracted from the reported messages before semantic comparison. Only messages with the same keywords as the reported messages need to be further generated with text summaries for semantic analysis.

In this module, Textrank algorithm is used to extract text keywords, Transformer is used as the generative summary model, and the text content is taken as the input to analyze and understand the text semantics and generate summary content with a general character. After obtaining the text abstract and keywords, we save them in the relational database, which is convenient for the analysis module to use later.

3.2.2 Oppositional Analysis Module

This module mainly realizes the recognition of opposite semantic sentences. The basic logic to determine whether the message semantics are opposite is as follows: 1) Determine whether two messages describe the same detail of the same event; 2) Judge whether the semantics of the two messages are similar. If the semantics of the two messages are similar, it can be directly considered that there is no possibility of semantic opposites between the two messages; 3) Semantic role analysis and annotation: analyze and compare the subject, predicate, object and other semantic roles of the two messages. Only when the two messages meet the standards set in the system can the two messages be identified as having opposite semantics.

According to the above implementation logic, the system needs to implement syntactically based text similarity calculation, semantically based text similarity calculation, semantic role labeling and set rules that semantic roles should meet. The system calls functions that calculate text similarity in Python's XMNLP library [11] to implement syntactically based text similarity calculation. Then the semantically based text similarity calculation and semantic role annotation are realized by calling functions in Python HanLP library. Finally, after the semantic role annotation is completed, the system sets a series of restriction rules for the semantic role of the message with opposite semantics. Only when the semantic role rules set by the system are satisfied, the two messages can be considered as having opposite semantics [12].

3.3 Accountability System

In precise rumours that the system determines whether by users to report news form after rumors, directional accountability system which forms part of the rumors will be stored in the secondary graphics database, graphic database records the original rumor nodes and forward, reviews, thumb up and it happened relationship of nodes, in order to have more clear the process of the spread of rumors, paint. When implemented, the system synchronizes the graph database to execute a Cypher statement to synchronously increase the message record in the database every time it determines that a message is a rumor. The following is the key code for adding messages to the graph database:

```
public class AddController{
public static void add(Integer userID, string user. string speech, string time){
    Driver driver = GraphDatabase.driver("bolt://lcoalhost:7687",AuthTokens.basic("neo4j","Luhaori8718"));
    Session session = driver.session();
session.run("CREATE (n:origin {UserID:{UserID},user:{user},speech:{speech},time:{time}}) ",paraneters("UserID",UserID,"user",user,"speech",speech,"time",time));
session.close();
driver.close();
}
}
```

To realize the function of the accountability module, it is necessary to find the nodes that play an important role in the rumor spreading process. The system uses PageRank algorithm to calculate the importance of nodes. The more important a node is, it plays an important role in the rumor spreading process. The specific codes are as follows: After obtaining important nodes, the user information corresponding to these nodes will be delivered to social platforms, public security organs and other units with accountability capacity, so as to realize the responsibility tracing for rumors.

```
public class PageRankController{

public static void add(Integer UserID, string user. string speech, string time){

Driver driver = GraphDatabase.driver("bolt://lcoalhost:7687",AuthTokens.basic("neo4j","Luhaori8718));

Session session = driver.session();

session.run("CALL gds.graph.create('myGraph','Origin', 'LINKS',{relationshiproperties:'type'})");

session.run("CALL gds.pageRank.strean('myGraph', {maxIterations:20,dampingFactor:0.85,}) YIELD nodeId, score RETURN gds.util.asNode(nodeId).user As name, score ORDER BY score DESC, name ASC");

session.close();

driver.close();

}

}
```

4 Conclusions

In order to suppress online rumors and govern the network environment, we designed and implemented a refuting and accountability system for online rumors based on deep learning and graphic database. In this system, according to the characteristics of messages, we will be reported by users into three types of messages, each type of message processing methods are different. On this basis, a deep learning model is built to automatically detect messages whose semantics are contrary to the current message, and to determine the rumor according to the rules set by the system. In order to suppress the spread of rumors, the system will push the correct news to users of social media platforms who have viewed the false news. In order to investigate the responsibility of rumor disseminators, the system built a graphic database, which can more intuitively display the whole process of rumor spreading, and determine the responsibility of different subjects through the mining of important nodes. Both the government and citizens can log on to the platform to see the content of rumors and the accountability of publishers.

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