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Rumor Detection of Covid-19 Related Microblogs on Sina Weibo

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Abstract

Since the outbreak of COVID-19 in Wuhan in 2019, Sina Weibo has become a platform for rumors to spread rapidly with more than 200 million daily active users. Based on this, we focus on the epidemic-related rumors on Sina Weibo during the epidemic. By summarizing the features extracted by feature engineering in the research of rumor detection from 2011 to now, we find that the existing features have low utilization rate of the user's geographical location property. Although the public display of the user's IP geographical location in Sina Weibo since April 28, 2022 has greatly improved the authenticity of this property, its utilization is still limited to extracting the explicit feature of IP geographical location. Moreover, the existing research has not paid attention to the filtering mechanism of the platform when extracting features, and has taken advantage of this phenomenon.

According to the shortcomings of the existing research, we put forward two new indicators based on the filtering mechanism of Sina Weibo, the available comments and the first-class available comments. The available comments represent comments in the comment area of each microblog that have not been filtered by the filtering mechanism. The first-class available comments represent available comments that directly reply to the original microblog. Based on the new indicator of first-class available comments and users' IP geographical location property, we further put forward 10 new features. Finally, we train seven classifiers, including logistic regression, SVM based on linear kernel, SVM based on RBF kernel, Naive Bayes, random forest, DNN and CNN. By comparing the prediction effects of each classifier and the prediction effects of the classifier before and after adding new features, it is concluded that the random forest classifier performed best in this application scenario, and the new features can improve the accuracy of random forest classifier by 1.33%, the precision rate of positive cases by 2%, the precision rate of negative cases by 5%, the recall rate of positive cases unchanged and the recall rate of negative cases by 14%.

Keywords: rumor detection; social media; available comments; first-class available comments; Sina Weibo

1. Introduction

The emergence of Web2.0 has accelerated the rise and expansion of social media. In online social networks, users are not only browsers of network information, but also producers and disseminators of network information [1]. Because of its openness and publicity, social media has become an important information dissemination channel in public health emergencies [2]. Since the outbreak of COVID-19 in Wuhan in 2019, the topics and contents related to the COVID-19 epidemic have attracted close attention from all walks of life and spread rapidly

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and widely on social media. Social media has become a ”hotbed” and ”infection chain” of social media rumors, which has had a negative impact on network order, people’s health and social stability [3].

Since its launch in 2009, Sina Weibo has become the largest social media platform in China. According to the financial report of Sina Weibo in the second quarter of 2022, the monthly active users in Sina Weibo in June 2022 were 852 million and the daily active users were 252 million [4]. With the huge scale of social networks and users in Sina Weibo, the problem of social media rumors on Sina Weibo has become increasingly prominent. According to the annual report on development of new media in china (2015) released by the Chinese Academy of Social Sciences in 2015, the survey shows that nearly 60% of fake news first appeared in Sina Weibo [5]. The annual report on development of new media in china (2017) pointed out that rumor information in social media caused network information pollution and affected the normal development of social relations [6]. There are also many articles in the annual report on development of new media in china (2021) that mentioned online rumors [7]. Up to now, led by Sina Weibo rumors, social media rumors in China are still very prominent. Based on this, it is of great significance to dig deep into the characteristics of rumor data and detect rumors automatically and efficiently.

Our work contributes to the rumor detection of Covid-19 related microblogs on Sina Weibo in the following four aspects.

- We summarize features extracted by feature engineering in the feature extraction part of rumor detection field from 2011 to now, and get 272 existing features, including 72 existing features based on messages, 40 existing features based on users, 66 existing features based on clusters and 94 existing features based on propagation.
- we put forward two new indicators based on the filtering mechanism of Sina Weibo, the ”available comments” and the ”first-class available comments”. The ”available comments” represent comments in the comment area of each microblog that have not been filtered by the filtering mechanism. The ”first-class available comments” represent available comments that directly reply to the original microblog.
- Based on the new indicator of ”first-class available comments” and users’ IP geographical location property, we further put forward 10 new features, i.e., the average emotional score of the first-class available comments in each microblog, the positive proportion of the emotional score of the first-class available comments in each microblog, the number of ”@” in the first-class available comments in each microblog, the number of question marks in the first-class available comments in each microblog, the number of first-person pronouns in the first-class available comments in each microblog, the average length of the first-class available comments in each microblog, the proportion of the first-class available comments to the total comments in each microblog, the proportion of the first-class available comments having same IP geographical location with the publisher to the total first-class available comments in each microblog, the average emotional score of the first-class available comments having same IP geographical location with the publisher, and the proportion of the first-class available comments having same IP geographical location with the publisher and having question marks in it to the total first-class comments. Experiments show that the new indicators and features proposed in this paper can effectively improve the performance of the classifier.
- We establish seven classifiers, including logistic regression, SVM based on linear kernel, SVM based on RBF kernel, Naive Bayes, Random Forest, DNN and CNN, and get the conclusion that Random Forest classifier is the best classifier in this application scenario.

The remainder of this paper is organized as follows. Section 2 reviews the existing research on rumor detection, and combs the existing feature extraction work from two directions, i.e., feature extraction using feature engineering methods and feature extraction using representation learning methods. Section 3 proposes our rumor detection method based on the first-class available comments on Sina Weibo. We introduce the data used in this paper and the 28 existing features we extracted at first, and then the two new indicators for rumor detection and ten new features based on communication and their construction ideas. Section 4 reports the prediction effects of seven classifiers before and after adding new features and draws the experimental conclusion. Section 5 summarizes this paper, points out the shortcomings of this paper, and looks forward to the future.

2. Literature Review

In 2011, Castillo et al. published the first paper on automatic rumor detection using computer technology, which proved the effectiveness of computers in the field of rumor detection, and put forward the research pattern that rumor detection features are extracted and then input into a classifier for classification [8]. Since other layers of the deep neural network can be regarded as providing representations for the classifier of the last layer, rumor detection using a single deep learning model can also be regarded as the pattern of feature extraction and classifier. Therefore, the existing research on rumor detection can all be regarded as this pattern, in which the feature extraction part can be divided into feature engineering and representation learning, and the classifier part can be divided into traditional machine learning classifier and deep learning classifier.

At present, the research focus of rumor detection lies in feature engineering and representation learning. The core of feature engineering is the extraction of new features. New features are extracted through feature engineering to improve the accuracy of rumor detection. The core of representation learning is representation learning network structure and algorithm. A good representation learning method can get good representation and improve the accuracy of rumor detection. the reminder of this section will introduce the existing rumor detection research from two angles, i.e., feature extraction using feature engineering methods and feature extraction using representation learning methods.

2.1. Feature Extraction Using Feature Engineering Methods

We classify the features extracted by feature engineering in the existing research into four categories, i.e., features based on messages, features based on users, features based on clusters and features based on propagation. Features based on messages pay attention to contents of tweets or microblogs. Features based on users describe the user identity information of tweets or microblogs publishers. Features based on clusters study the overall characteristics of its cluster by taking a topic or community as the cluster. Features based on propagation mainly focus on information dissemination and user interaction, such as communication network structure and comments and forwarding generated by user interaction. In this paper, we summarize a total of 272 existing features extracted by feature engineering method in the feature extraction of rumor detection in existing research work, including 72 existing features based on messages, 37 existing features based on users, 69 existing features based on clusters and 94 existing features based on propagation.

Scholars have done a lot of work in feature extraction using feature engineering methods. We can see that the process of feature extraction using feature engineering methods shifts from explicit features to implicit features, from single features to composite features. This reflects the continuous refinement and deepening of feature extraction using feature engineering methods. However, rumor detection needs to bring forth new ideas and propose new adaptive features with the continuous updating of social media functions. Due to the user's geographical location feature extracted from the existing work can be selected by the user himself, the credibility of geographical location feature is poor and it has not been paid enough attention by scholars. The situation has changed since April 28th, 2022. Under the requirements of the National Regulations on the Management of Internet User Account Information, Sina Weibo has started to display the real-time IP geographic location of commentators in the comment area and the real-time IP geographic location of users' personal homepages. As a result, the authenticity of geographic location feature and the geographical attribute of events make IP geographic location a promising feature, but the existing work has not paid enough attention to it.

In addition, only Alzanin et al. put forward a feature about sensitive content [9], however, their focus is on whether the external link is sensitive rather than whether the message itself and the comment information generated by the message are sensitive. Sina Weibo has its own blocking mechanism and will block illegal or sensitive content as well as bad comments. Therefore, although scholars can not directly get sensitive texts and comments themselves, they can explore whether the blocked content is beneficial to rumor detection through the number of comments blocked by Sina Weibo. At present, the work on blocked information is still in a blank state.

2.2. Feature Extraction Using Representation learning Methods

With the continuous development of research on social media rumor detection based on feature engineering, scholars have put forward more and more features, and social media rumor detection based on traditional machine learning needs to deal with a lot of feature extraction and selection work. Since the deep learning algorithm emerged in the field of image recognition in 2012, the academic circles have rapidly applied the deep learning algorithm to various fields, especially those that need a lot of feature extraction work, such as image recognition and text analysis. Because deep learning has strong learning ability and can automatically extract features, it has also been widely concerned in the field of rumor recognition [10].

In 2016, Ma et al. applied deep learning algorithm to the field of rumor detection for the first time, using RNN to realize representation learning and classification [11]. Ajao et al. put forward the LSTM-CNN model in their work in 2018, which can automatically learn and classify rumors without manually extracting any features [12]. In the same year, Chen et al. used automatic encoder to detect social media rumors for the first time, and proposed an unsupervised learning model combining RNN and automatic encoder [13]. Ma et al. proposed two recursive neural network models based on tree structure to learn representation and rumor detection [14]. In 2020, Bian et al. proposed a two-layer graph convolution neural network for representation learning [15]. Asghar et al. applied BiLSTM-CNN model based on word embedding to the field of rumor detection for the first time in 2021, and used BiLSTM model for representation learning and CNN classification [16].

Although these rumor detection method based on representation learning can get rid of the difficulty of manual feature extraction, or can effectively combine manual feature extraction with automatic feature extraction, the natural end-to-end structure of deep learning leads to the lack of controllability in model training, which makes it difficult to grasp the key components in rumor information, and the training time is long and the model is complex [17]. Therefore, attention mechanism is introduced to improve it. Jin et al. proposed RNN with an attention mechanism in 2017 [18]. Chen et al. proposed a CNN model based on attention mechanism in 2019, combining attention mechanism with residual network for the first time to detect rumors [19]. However, there is a black box when using representation learning methods, and the features obtained have no actual meaning, such as ”feature001” and ”feature002”. As a result, it is impossible to interpret the meaning of the features, so that Sina Weibo can not use the features obtained by representation learning to directly block or reduce the generation and spread of rumors through the screening mechanism.

3. Proposed Method

Due to the black box when using representation learning methods, we utilize feature engineering methods to extract features, and propose our rumor detection method based on first-class available comments, according to the deficiency of feature extraction in existing research.

3.1. Dataset Description

We crawl microblogs with #epidemic# tag from April 28th, 2022 to October 31st, 2022, and manually marked rumors and non-rumors. Because the dataset is extremely unbalanced, we screen and crawl microblogs which was reported as false information in the false information plate in Sina Weibo, and finally got 12,274 microblog data, 8,732 user data and 18,367 comment data. Among them, microblog data can be directly obtained from the main page of microblogs, including user name, Weibo text content, number of forwards, comments, and likes, etc. User data can be directly obtained from the homepage of Weibo users, including user name, personal profile, authentication information, IP location, Weibo registration time, credit rating, historical blog posts, number of fans and followers, etc. Comment data is the data crawled from the comment area of each microblog, including the commenter name, text content, and IP location of each commenter, etc.

3.2. Existing Feature selection

We have constructed 28 existing features by referring to the effective features pointed out in existing researches and the features of actual data. The 28 existing features we extract including 16 existing features based on messages as shown in Table 1, 9 existing features based on users as shown in Table 2 and 3 existing features based on communication as shown in Table 3. For the selected 16 existing features based on messages, we use jieba word segmentation tool to segment words and mark parts of speech, and then use SnowNLP method based on emotional dictionary to calculate the emotional score. SnowNLP is a class library written in python language, which can handle Chinese text content conveniently [20].

Table 1. The existing features based on messages extracted in this paper.

index	feature	Literature source
1	number of characters in microblog	[8]
2	whether microblog contain first-person pronouns or not	[8]
3	whether microblog contain second-person pronouns or not	[8]
4	whether microblog contain third-person pronouns or not	[8]
5	number of URLs in microblog	[8]
6	number of words expressing positive feelings in microblog	[8]
7	number of words expressing negative feelings in microblog	[8]
8	emotional score of microblog	[8]
9	whether microblog contain pictures or not	[21]
10	whether microblog contain videos or not	[21]
11	number of event verbs in microblog	[22]
12	number of "@" in microblog	[23]
13	number of tags in microblog	[23]
14	number of smiley face expressions in microblog	[23]
15	total number of question marks and exclamation marks in microblog	[23]
16	month of microblog publishing	[24]

For the selected 9 existing features based on users, it should be noted that user accounts can be divided into official accounts and personal accounts, in which official accounts have official authentication, and personal accounts can apply for personal authentication. For the feature "whether the location of user and topic are near or not", we modify it to "whether the user's IP geographical location appears in the message text or not". In addition, we set 15th, 2023 as current time to calculate the time-related features.

Table 2. The existing features based on users extracted in this paper.

index	feature	Literature source
1	user's registered duration	[8]
2	number of user's historical microblogs	[8]
3	number of user's fans	[8]
4	number of user's attention	[8]
5	whether the user is authenticated or not	[8]
6	whether the user profile is empty or not	[8]
7	whether the user's IP geographical location appears in the message text or not	[25]
8	user's IP geographical location	[25]
9	user's credit	[26]

For the selected 3 existing features based on propagation, it should be noted that the comment number of microblog crawled here is the number displayed on the main page of the microblog. Because of the filtering mechanism that will block bad information and illegal content in Sina Weibo, the comment number of microblog is not equal to the number of comments in the comment area.

Table 3. The existing features based on propagation extracted in this paper.

index	feature	Literature source
1	comment number of microblog	[21]
2	forward number of microblog	[21]
3	like number of microblog	[23]

3.3. New Indicators and New Features

By summarizing the features extracted by feature engineering in the research of rumor detection from 2011 to now, we find that the existing features have low utilization rate of the user's geographical location property. Although the public display of the user's IP geographical location in Sina Weibo since April 28, 2022 has greatly improved the authenticity of this property, its utilization is still limited to extracting the explicit feature of IP geographical location. Moreover, the existing research has not paid attention to the filtering mechanism of the platform when extracting features, and has taken advantage of this phenomenon.

According to the shortcomings of the existing research, we put forward two new indicators based on the filtering mechanism of Sina Weibo, i.e., the available comments and the first-class available comments, as shown in Table 4. The available comments represent comments in the comment area of each microblog that have not been filtered by the filtering mechanism. This indicator can reflect the information that comments of a microblog can actually convey to readers, and can measure the sensitivity of comments in the comment area, which has practical significance. The first-class available comments represent available comments that directly reply to the original microblog. This indicator can measure the sensitivity of comments that directly comment on the original microblog, and can reflect the information in the comments that is really transmitted to the publisher, and it also has practical significance.

Table 4. Two new indicators extracted in this paper: available comments and first-class available comments.

index	new indicator	meaning
1	available comments	comments in the comment area that have not been filtered by the filtering mechanism
2	first-class available comments	available comments that directly reply to the original microblog

Based on the new indicator of first-class available comments and users' IP geographical location property, we further put forward 10 new features as shown in Table 5, i.e., the average emotional score of the first-class available comments in each microblog, the positive proportion of the emotional score of the first-class available comments in each microblog, the number of "@" in the first-class available comments in each microblog, the number of question marks in the first-class available comments in each microblog, the number of first-person pronouns in the first-class available comments in each microblog, the average length of the first-class available comments in each microblog, the proportion of the first-class available comments to the total comments in each microblog, the proportion of the first-class available comments having same IP geographical location with the publisher to the total first-class available comments in each microblog, the average emotional score of the first-class available comments having same IP geographical location with the publisher, and the proportion of the first-class available comments having same IP geographical location with the publisher and having question marks in it to the total first-class comments.

Table 5. Ten new features based on propagation extracted in this paper.

index	new feature
1	average emotional score of the first-class available comments in each microblog
2	positive proportion of the emotional score of the first-class available comments in each microblog
3	number of "@" in the first-class available comments in each microblog
4	number of question marks in the first-class available comments in each microblog
5	number of first-person pronouns in the first-class available comments in each microblog
6	average length of the first-class available comments in each microblog
7	proportion of the first-class available comments to the total comments in each microblog
8	proportion of the first-class available comments having same IP geographical location with the publisher to the total first-class available comments in each microblog
9	average emotional score of the first-class available comments having same IP geographical location with the publisher
10	proportion of the first-class available comments having same IP geographical location with the publisher and having question marks in it to the total first-class comments

4. Results

The classifiers we select include logistic regression, SVM based on linear kernel, SVM based on RBF kernel, Naive Bayes, Random Forest, DNN and CNN. In order to evaluate the model results, we choose the evaluation indicators of accuracy, positive case precision, negative case precision, positive case recall and negative case recall. To explore whether the two new indicators and the 10 new features based on the new indicator contribute to rumor detection, and to explore which of the seven classifiers performs best in the scene of social media rumor detection under epidemic situation, we input the data before and after adding new features to the classifiers respectively. The classification effect of each classifier before and after adding new features is shown in Table 6, where $precision_p$ indicates positive case precision, $precision_n$ indicates negative case precision, $recall_p$ indicates positive case recall, and $recall_n$ indicates negative case recall. In addition, model-28 means modeling 28 existing features, and model-38 means modeling 28 existing features together with 10 new features.

Table 6. The classification effect of each classifier before and after adding new features.

model	*accuracy*	$precision_p$	$precision_n$	$recall_p$	*recalln*
logistic-28	0.9490	0.95	0.88	1.00	0.30
logistic-38	0.9596	0.96	0.88	1.00	0.42
linear SVM-28	0.7020	0.95	0.10	0.72	0.46
linear SVM-38	0.8146	0.95	0.15	0.84	0.41
RBF SVM-28	0.9322	0.93	0.75	1.00	0.02
RBF SVM-38	0.9379	0.94	0.75	1.00	0.02
NB-28	0.9215	0.94	0.31	0.98	0.12
NB-38	0.9268	0.95	0.37	0.97	0.23
RF-28	0.9641	0.96	0.95	1.00	0.50
RF-38	0.9774	0.98	1.00	1.00	0.64
DNN-28	0.1929	0.05	0.86	0.66	0.16
DNN-38	0.7118	0.11	0.95	0.49	0.73
CNN-28	0.9215	0.04	0.93	0.01	0.99
CNN-38	0.8838	0.21	0.95	0.30	0.92

According to the performance of the seven classifier models before and after adding new features, we can get the first conclusion of this paper: after adding new features, the the rumor detection ability of the seven classifiers are improved as a whole. This proves that the new indicators and 10 new features proposed in this paper are helpful to detect social media rumors related to the epidemic. In addition, by comparing the performance of seven kinds of classifiers on five indicators, we can see that the random forest model is the best model in accuracy, positive case precision, negative case precision and positive case recall, whether before or after adding new features. In negative case recall, this index measures the proportion of negative cases that are correctly predicted as negative cases, that is, the ability to identify non-rumors. However, DNN-38 model and CNN model, which perform better than random forest model in this index, have significantly lower positive recall, that is, the model's ability to identify rumors. Therefore, it can be inferred that DNN and CNN models greatly sacrifice the ability to identify rumors in order to obtain the ability to identify non-rumors, having a tendency to predict rumors as non-rumors. In the scene of rumor detection under epidemic, this tendency of DNN and CNN makes them unsuitable as classifiers. Therefore, we regard the random forest model as the model with the best performance in this rumor detection scenario, perhaps for the following reason. Random forest model combines the predictions of multiple decision trees into a model. The modeling logic is that a model composed of many mediocre models, which will still be better than a single good model. Therefore, random forest is not easy to produce over-fitting, which is extremely important for the unbalanced data used in our experiment.

5. Conclusion

In this study, we put forward two new indicators, i.e., available comments and first-class available comments. Based on the new indicator of first-class available comments and users' IP geographical location property, we further put forward 10 new features. To find out the best classifier and the effect of new features, we train seven classifiers and compare the prediction effects of the classifier before and after adding new features. It is concluded that the random forest classifier performed best in this application scenario, and the new features can improve the accuracy of random forest classifier by 1.33%, the precision rate of positive cases by 2%, the precision rate of negative cases by 5%, the recall rate of positive cases unchanged and the recall rate of negative cases by 14%.

Our work has the following shortcomings. First, the amount of data in this paper is relatively small, and there is a problem of data imbalance. Secondly, we only crawl the content of a microblog in text format, and do not extract multi-modal data, so it fails to extract all the information contained in a microblog. Thirdly, this we do not extract the characteristics based on clusters. Therefore, we will enrich our data volume as well as data types, balance our dataset, and extract features more comprehensively in the future work.

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