Detection Method of Fake News Spread in Social Network Based on Deep Learning

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Abstract. The current detection of fake news spread in social networks does not consider the correlation between news text and images, resulting in inaccurate detection results. A detection method for fake news spread in social networks based on deep learning is devised. The size of the time period is dynamically adjusted according to the number of news in the time period, and features are extracted uniformly for comments/retweets in the same time period. Preprocess social network news data to ensure that the vast majority of text is covered and controlled within the range of machine computing power. Multi-modal features are mined and constructed from images, texts and user-side information. Modal fusion does not use the addition of residuals, but splices the residuals and attention matrices, and then sends them to the fully connected layer to convert the dimension size, and then Update the modal. The fused feature vector is input into the feedforward network for classification, and the prediction result is obtained. The experimental results show that the design method can improve the detection accuracy, and the deep features it contains can more effectively detect fake media content in social networks.

Keywords: Deep learning · Social network · Fake news · Communication detection · Detection method · News communication

1 Introduction

Mobile information flows at a high speed in today's highly developed Internet, and people are completely accustomed to obtaining required information from major Internet platforms, especially popular domestic social network platforms such as Weibo and Zhihu. The social network platform represented by Sina Weibo attracts hundreds of millions of users to share, interact and disseminate information on its platform by virtue of its openness, flexibility, free, instant and many other features, which accelerates the speed of information exchange between people and depth. While the explosive information and rich content of social network news brings convenience to people, its shortcomings are gradually exposed. Internet users can speak freely on the Internet in real time, and can also adapt news through forwarding or secondary creation. It is an increasingly

W. Fu and L. Yun (Eds.): ADHIP 2022, LNICST 469, pp. 473–488, 2023.
https://doi.org/10.1007/978-3-031-28867-8_35

serious problem to spread information at almost zero cost and to flood the Internet with spam and even fake news. The spread of false rumors will have large-scale negative effects on society and cause social unrest. Online rumors are defined as unsubstantiated explanations that have played a key role in the life cycle of a social networking platform and have caused a certain social impact. At the same time, the diversity of information, the freedom of expression, and the fission of dissemination speed have made false media content and false speeches an excellent opportunity to come to power, and have also made social platforms such as Weibo become the current flood of false information in China. The main source and transmission medium of my country, and the scope of influence is unprecedentedly huge. At the same time, activities such as forwarding and rubbing heat have increased the intensity of short-term outbreaks of false information, and the scope of influence has further expanded. Compared with traditional text information, information with images or videos can not only provide a richer plot to attract more readers, but also often increase the credibility of news, which is often exploited by false rumors. False rumors often use false or fake images and inflammatory language to mislead readers and spread quickly. Such false information not only confuses the public, but also easily arouses bad public sentiment, deepens social conflicts, and affects the prosperity and stability of the country. Fake news that is intentionally or unintentionally reposted not only affects the direction of public opinion, but also violates the people's right to know, and the country's credibility on the Internet will be weakened in the long run. Therefore, research on fake news detection technology is of great significance to help countries and network platforms curb the generation and spread of fake news and maintain social stability [1, 2]. The time period of rumors can be divided into incubation period, outbreak period and settlement period, corresponding to the stage of just release, extensive discussion, verification or no longer having social impact. Generally speaking, rumors should be detected as soon as possible during the incubation period of rumors. Once malicious false rumors reach the outbreak period, they may have a very large negative impact on society. Due to the complexity and variety of media content and its highly confusing nature, it is difficult for humans to achieve a high recognition rate based on experience, which is not conducive to the rapid detection and blocking of false media content. Artificial intelligence technology has been well used with the continuous progress of science and technology and the in-depth exploration of the ancestors, and has achieved very good detection results in text classification tasks. The detection of online rumors can not only purify the ecological environment of the network in today's information overload environment, but also help the public identify effective information, and also improve the credibility and credibility of the platform. Computer technology optimizes the human and material cost of replacing manual review and improves the efficiency of news review. Fake news has the characteristics of frequent occurrence and rapid spread, and it can spread all over the Internet in ten minutes. It is difficult to accurately predict and detect fake news from massive information in a timely manner only by manual screening. This paper proposes a detection method of fake news spread in social networks based on deep learning, which helps to advance the research process of text mining and semantic understanding. It can timely respond to the detection of massive Internet fake news through the more accurate classification algorithm model of fake news prediction, improve the efficiency of news review, optimize the quality of news, and improve the reading experience of users.

2 Detection Method of Fake News Spread in Social Network Based on Deep Learning

2.1 Divide the Social Network News Dissemination Cycle

More and more people begin to use online media to obtain news information with the increasing popularity and simplification of mobile applications [3]. Compared with traditional media, online media has the advantages of quick access to information and easy sharing and communication. Spreading rapidly, these messages may provide ground for reactionary activities, shake people's confidence and cause panic, or increase the unnecessary workload of staff [4]. In the detection of fake news dissemination in social networks, since social networks are a platform with continuous dynamics, if only the performance of features at a certain moment is modeled, the characteristics that the features will change over time are ignored [5]. Since the trend of information dissemination is affected by many aspects, in order to reflect the important influence of the actual characteristics of the network on the dissemination, the method based on the local structural characteristics of the network is firstly proposed, followed by some global roaming counting methods and random block walk models. This paper analyzes the time series propagation mode of information events in order to mine the change mode of features. The practice of dividing the event propagation cycle at equal intervals will cause most of the data to be allocated in the early time interval, and there is little or no available information in the later time interval. For a regular network, since the connections between nodes are regular links based on a known strategy, the path length between any two nodes is longer, but the clustering coefficient between them will be high. Contrary to regular networks, nodes are randomly linked with a certain probability for random networks, so the path length between any two nodes will be shorter, but the clustering coefficient will also be lower. When the propagation cycle is divided at equal intervals because the popularity of events is generally in the early stage, the number of comments/numbers of information events in the middle and late time intervals decreases sharply, and even in many middle and late time intervals there is not a single comment/repost, which leads to the follow-up model. There is no effective information to exploit to extract the temporal variation of features. The social network has the advantages of both the regular network and the random network. The length of the characteristic path between any nodes is small, but the clustering coefficient is quite high. It is more inclined to a certain type (regular or random) network and is controlled by the parameter γ. $\gamma = 0$ represents a regular network, and $\gamma = 1$ represents a random network. The process of converting a regular network into a random network is to reconnect the edges existing in the regular network with γ probability. The dissemination period of information events is no longer divided at equal intervals in this paper, but the size of the time period is dynamically adjusted according to the number of news in the time period, and the features are extracted uniformly for comments/reposts in the same time period. The division process of social network news dissemination cycle is shown in Fig. 1.

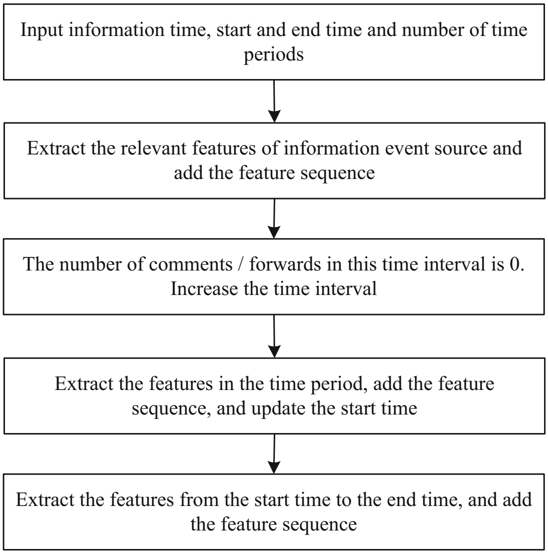

Fig. 1. The division process of social network news dissemination cycle

For information events, the information dissemination period is set, and this time period is divided into M time periods. The information event source is directly divided into a time period in order to highlight the text content characteristics of the information event source in particular, and the number of microblogs and the time interval in this period are initialized to 1. False information on social media seems to be endless, but in fact, a considerable number of events have been judged as rumors. Rumors from many years ago can cause a commotion with a small modification of the place and time. A large amount of similar information often appears in a short period of time after the same false information occurs. If these messages are put into the model indiscriminately, a lot of time will be wasted. Comments/retweets are divided into M-1 time periods. First, the time interval is 1 h. If the number of comments is 0, the time interval is increased, and the time interval is divided into 2 h, and so on. If the number of comments in the current time period is not 0, extract all comment-related features in the current time period. For the last time period, the time interval is no longer cumulative from 1 h, but is set directly to the end time. Information dissemination in online networks is often characterized by high outbreaks, rapid demise, and high anonymity. When tracking the dissemination trajectory of a piece of information, due to various objective reasons, we usually lack information about the underlying dissemination path network, so based on the observed It is a great challenge to reconstruct the hidden propagation paths through the information diffusion process. On social media, the content of fake news is updated and spread quickly, but manual review has the problem of lag and inefficiency. Therefore, it is of great significance to carry out automatic detection of fake news.

2.2 Social Network News Data Preprocessing

We found that there are a lot of invalid data in the data set by observing the original features of the data set, mainly reflected in data duplication and missing attribute values. There are more than 100 occurrences in a concentration, which will undoubtedly affect the subsequent feature extraction and model construction. Therefore, this paper preprocesses the original data to facilitate the subsequent process [6]. Chinese word segmentation is the basis for the text classification of the model constructed in this paper. After successfully segmenting an input Chinese text, the efficiency of computer recognition of words can be greatly improved. Improving the accuracy of Chinese word segmentation can often improve the accuracy of text classification results. Different word segmentation algorithms and thesaurus will affect the final detection effect from the qualitative analysis for text classification tasks. Text preprocessing is required for data that is too long or too short, including removing stop words and data filtering. After the stop words are removed, the overall length of the data is shortened, and words such as “you”, “de”, and “ba” that are common and have no obvious effect on text feature extraction are removed from the content. Similarly, URLs, user nicknames, etc. existing in the data are replaced with spaces through regular expressions. The statistical-based word segmentation method borrows mathematical theory, the most common and relatively mature are Hidden Markov, Maximum Entropy, Conditional Random Field, etc. Given a large number of texts that have been divided into words, divide a sentence, and then formulate different division methods, and calculate the probability of the division results respectively, and take the word segmentation method with the largest division probability. The text content of the news and the user’s personal introduction each have a strong impact on the authenticity of the news, and the connection between the two can also be used as an effective feature for discrimination, such as the possibility of true news when the two are related. Will be significantly improved, and the probability of true news will be greatly reduced when the two are completely unrelated. Since there are many possible combinations of the context of a word, the matrix-based distribution representation usually produces the problem of combinatorial explosion. Furthermore, the sequence of words in the test dataset is likely to be different from the sequence of all words seen in the training set, resulting in poor generalization. Therefore, this article splices the news text with the blogger’s self-introduction, and also splices the blogger’s geographical information and news section categories into the blogger’s introduction. The spliced text is as follows.

$$T = N_T + D_T + C_T + L_T \tag{1}$$

In formula (1), T represents the spliced text; N_T, D_T, C_T, L_T represents news text, user description text, news section category and user geographic location, respectively. Since the statistical based word segmentation method was proposed, the speed of text segmentation and the accuracy of word segmentation have been significantly improved. It is no longer necessary to build a very complete dictionary, and it does not require a deep linguistic knowledge to identify new words and eliminate ambiguity. Using computers to process text classification tasks must represent the word or word after word segmentation into a numerical form that can be recognized by the computer, that is, convert the text into word vectors. It can often be processed manually for data with few missing values, while a large number of missing values will change the distribution of the data, so it is necessary to delete or fill in the missing values. The handling of missing values is shown in Fig. 2.

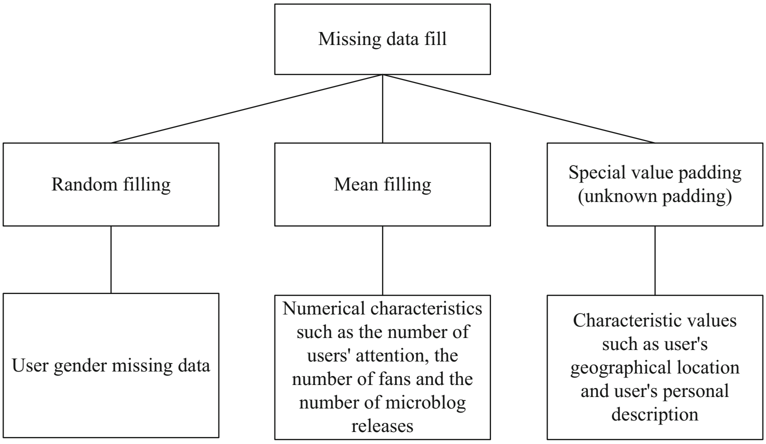

Fig. 2. How to handle missing values

The average special symbols in the text account for 8.3% according to the analysis of the news text content in the dataset, and the text content mainly includes various information such as the body, title, interactive topic, contact information and so on of the news. The neural network-based representation converts sparse word vectors into denser vectors through neural networks rather than statistical matrices. It avoids the curse of dimensionality and can model more complex contextual content. Word2vec generates word vectors by learning the context information of the words, which belongs to the neural network distribution representation. This paper extracts them in a specific format and fixes them at the beginning of the text for the titles and interactive topics in the text, and removes special symbols, http URLs, HTML tags and garbled characters from the news text by regular matching. There is also a type of data in social media, which is characterized by extremely short text length, the main information is reflected in pictures or videos, and the text only contains words such as "view and forwarded video". This type of data text does not contain valid information, temporarily. It is not considered in this article, so it is discarded. Taking into account the problem of machine computing power, the max length of this article is set to 128, which can ensure that most of the text is covered and controlled within the range of machine computing power.

2.3 Fusion of Multimodal News Features

Existing fake news detection often uses single-modal data, such as text, propagation mode or feature engineering, but with the development of the Internet, the ways of presenting news are more and more diverse, and a piece of news usually includes text, images, comments, etc. [7]. Multiple sources of information. This paper will construct multimodal features from images, texts and user-side information to improve fake news detection models. Since the tweets of social networks are mostly short texts, this paper uses LSTM and Text-CNN to extract text features to extract the time-series semantic features and n-gram local features of the text. The pre-trained word vector is used as the input of the model, which is input to LSTM and Text-CNN respectively. The text features are obtained through LSTM, and the hidden layer representation vector is $Z \in SW$, where S is the number of words and W is the feature dimension. The local features of the text are obtained through the Text-CNN module. Images in fake news tend to be of lower quality, clarity and resolution than real news images. The communicator leads to continuous compression of news images through direct copying, multiple forwarding or tampering. Periodic features will be displayed in the frequency domain features for the secondary compression and tampering of images. The DCT algorithm is used to extract the frequency domain features of news images to capture the image structure tampering and compression information in this paper. The extraction process of frequency domain features by discrete cosine transform is shown in Fig. 3.

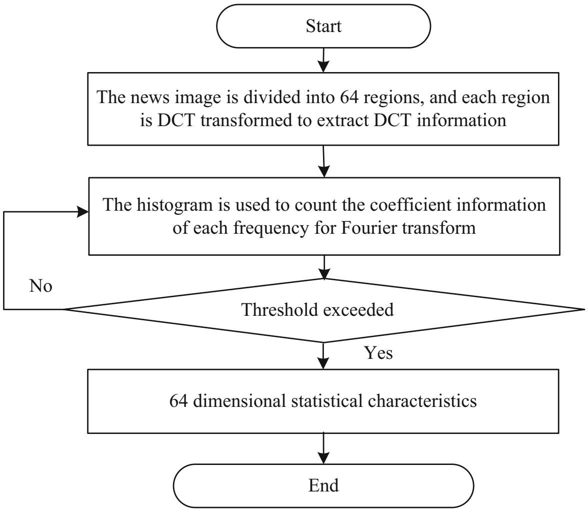

Fig. 3. Extraction process of frequency domain features of news images

User status information includes the user's gender, number of followers, number of followers, location, user description, number of microblogs, news category and other fields. This paper constructs effective features by mining the hidden information of these fields. Taking the number of user followers as an example, fake news is distributed mainly by users with less than 10,000 followers. At the same time, as the number of followers increases, the proportion of fake news in the total number of news releases gradually decreases. The follower growth rate and the follower growth rate in the feature table are the ratio of the number of followers and the number of followers to the registration time, respectively, and the friendly intimacy and the friendly responsiveness are the ratios of the number of mutual followers to the number of followers and the number of fans. Posting activity is the ratio of the number of microblogs to the registration time, and the user reputation value is the ratio of the number of followers to the sum of the number of followers and followers. The features obtained by the above calculations are all continuous values. In light of the actual situation, those with a large number of fans are often certified by Weibo or the official platforms of various media, and the news released is usually true, while those with a small number of fans are often personal bloggers, who publish or forward news to the end. More casual, resulting in the spread of fake news. Modal fusion does not use the addition of residuals, but splices the residuals and attention matrices, and then sends them to the fully connected layer to convert the dimension size, and then update the modality. Convert the text features generated by LSTM into key and value, namely K and V, the calculation process is as follows:

$$\begin{cases} K = f(Z; \varphi_1) \\ V = f(Z; \varphi_2) \end{cases} \tag{2}$$

In formula (2), f represents a fully connected layer without activation function; φ_1 and φ_2 are training parameters. A multi-head attention mechanism is adopted to obtain multi-dimensional attention weights. Propagation features include the number of likes, comments, retweets, and user engagement, where user engagement is the ratio of the number of comments to the sum of the number of comments and retweets. In general, the higher the user engagement, the more attention it can attract, the faster the spread. The above values are continuous values. Multi-head attention is to repeat the attention calculation process many times. The attention weight is calculated by scaling the dot product each time, and the calculation process is shown in formula (3).

$$A = h\left(\frac{f(Z; \varphi_2)\varphi_1}{\sqrt{I}}\right) \tag{3}$$

In formula (3), A represents the attention weight; h represents the activation function; I is the transformed feature dimension. Multiple types of information can complement each other, and it is unreasonable to rely only on a single modality for fake news detection. Statistical features are constructed from three aspects: user information, text statistics and image statistics. These features will be used as user-side contextual features to participate in the construction of the model. The attention weights of each updated modality are computed through a two-layer feed-forward neural network. The updated image features and text features are fused through attention weights.

2.4 Establishment of a Fake News Spread Detection Model in Social Networks Based on Deep Learning

The detection model of fake news dissemination in social networks established in this paper based on deep learning [8] consists of a multimodal feature extraction module, a multimodal feature fusion module [9] and an output module. Traditional machine learning methods require us to construct features by ourselves, but manually constructed features often fail to represent deeper connections between features. Neural networks can automatically capture potential connections in the data, reducing the overhead of manually constructing features for researchers [10]. Among them, the multimodal feature extraction module includes three sub-modules: the text feature extraction module, which uses the BERT model to extract features such as news text semantics and style; the image feature extraction module, which includes the content information and frequency domain information of the image; the contextual feature extraction module, It includes the extraction of user portrait features and statistical features. The event discriminator consists of two fully connected layers. Blog posts in a data set are first labeled with the event to which they belong. Assuming there are k types, the goal of the event discriminator is to correctly assign incoming data to the event to which it belongs. A convolutional filter with window size h takes as input a contiguous sequence of h words in a sentence and outputs a feature. The output vector of the Text-CNN layer is used as the input of the multi-head self-attention layer. By setting the multi-head self-attention, the features between messages in multiple sub-representation spaces can be effectively captured. During training, the feature extractor and false information detector achieve the purpose of improving the detection ability of fake news by reducing the detection loss as much as possible. At the same time, the feature extractor also tries to maximize the loss of event discrimination to achieve the event The discriminator learns the purpose of potentially identical representations between events. The feature vector of text based on the pretrained model can be represented as:

$$\alpha = \tanh[\theta_1 \tanh(\theta_2 + \varepsilon_2) + \varepsilon_1] \tag{4}$$

In formula (4), α is the text feature vector finally obtained in this paper; θ_1 and θ_2 are the weight matrices of the fully connected layer; ε_1 and ε_2 are the corresponding offsets. The idea of the MLM module is to randomly cover the input sentences during training, some words are masked out, and then let the model predict those words by learning the input context. This self-supervised task is similar to cloze. Since Transformer processes a sentence with a distance of 1 for each word, the word prediction mask can take into account the entire sentence. For image data, this paper adds a Batch Normalization layer between the fully connected layer and the activation function in order to speed up network convergence and prevent over-fitting. Finally, after Droupout, the obtained vector is the image content feature vector. Calculated as follows:

$$\begin{cases} \beta = \mathrm{Dr}\tanh\big[B\big(\theta_2\beta' + \varepsilon_2\big)\big] \\ \beta' = \tanh[B(\theta_2\chi + \varepsilon_2)] \end{cases} \tag{5}$$

In formula (5), β is the image content feature vector; β' is the frequency domain feature; Dr is the Dropout processing; B is the Batch Normalization layer; χ is the input image. The task of NSP is to determine whether two sentences are contextual, and to learn the features of sentences through this task. The data used for training are sentence pairs extracted from the corpus. 50% of these sentence pairs are contextually coherent, the other 50% are incoherent, and the second sentence is randomly extracted. This paper uses multiple attentions to calculate the attention weight, and then adds the weighted value to the query value to obtain the potential interaction features between messages. The message features of N intervals can be obtained through the above steps. Single domain features only focus on intra-domain differences, while ignoring the relationship between feature domains. The combination of features also has significance for news judgment. In the above, we obtained the image and text features respectively. The correlation between the text and the image is considered, the consistency between the news text and the image can also be used as the basis for fake news detection. This paper combines text features and image features in order to enhance the feature intersection between image and text. The input required by GraphSAGE is the node feature and the node adjacency matrix. In this model, the node is each blog post, and the feature is the text feature plus the event feature. The text features are extracted by BERT, and the event features are extracted manually. The adjacency matrix is represented by the text similarity between blog posts. The discrete features input from the user side are spliced with numerical features after passing through Dense Embedding, and then 256-dimensional user context features are obtained through two fully connected layers [10]. The multimodal feature vector is obtained by concat splicing, which is expressed as:

$$F = [\alpha, \beta, \alpha \otimes \beta, \eta] \tag{6}$$

In formula (6), F represents the multi-modal feature vector; $\otimes$ is the point multiplication operation; η represents the feature set of the user modality. The feature vector is input into the feedforward network for classification, and the prediction result is obtained. The specific calculation process is as follows:

$$P = \mathrm{sig}[\theta_1 \tanh(F\theta_2 + \varepsilon_2) + \varepsilon_1] \tag{7}$$

In formula (7), P represents the prediction result; sig represents the sigmod activation function. The BLSTM layer uses two unidirectional LSTMs in different directions to memorize the forward propagation information and the backward propagation information respectively. Parent object. The hidden state of forward propagation and the hidden state of backward propagation are concatenated, thereby extending the learning ability of the model for the forward and backward directions. So far, the design of the detection method of fake news spread in social network based on deep learning is completed.

3 Experimental Study

3.1 Experimental Scheme

A comparative analysis experiment is designed In order to verify the overall effectiveness of the detection method of social network false news dissemination based on deep learning. The experimental scheme is as follows:

1) Before the experiment, we prepared for the experiment. The experiment took Weibo as the research object, used the Scrapy Redis framework for parallel crawling, counted the collected data sets, and gave detailed information to explain the experimental environment.
2) Determine the experimental performance indicators, and analyze the performance of the detection method through specific performance indicators, including accuracy, accuracy, recall and F1.
3) After determining the experimental performance indicators, carry out comparative analysis. The comparative methods are detection method of fake news spread in

social network based on deep learning, detection method of fake news spread in social network based on support vector machine and A detection method of fake news spread in social network based on Naive Bayes, Verify the effectiveness and feasibility of this method.

3.2 Experiment Preparation

The training data set used in the experiment in this paper is Weibo blog posts, including text and images. Each blog post has a unique corresponding id and topic field. There are three types of tags: news without judgment, real news and fake news. Due to the limitations of the Weibo API, it is impossible to crawl a large number of unauthorized users' data, and crawling through the API cannot meet the data requirements. Therefore, this article uses website page parsing to obtain Weibo information. The specific method is described as follows. The Weibo page needs to be logged in to view, so this article uses Selenium to simulate login, and saves the cookie information after login to the database to prepare for subsequent crawling. According to the topic area, it is divided into seven major categories: "social life", "medicine and health", "sports and entertainment", "technology", "financial business", "military politics" and "educational examination". In addition to text information, data on social networks also includes external URL links, message prompts (in the form of @ plus username), hashtag tags (indicating the topic to which the text belongs), and emoji pictures. We need to preprocess the original data first for these unconventional data information. This article uses the Scrapy-redis framework for parallel crawling, that is, multiple Scrapy-redis processes run at the same time to crawl, and finally save the data to MongoDB. Hashtag tags and expressions have certain meanings, and no special treatment is performed here. For the URL, replace it with a special link/web page link, and replace it with mention someone/mention someone for the @ plus username. The text is then further processed using word segmentation tools. The quartiles represent the values of the points at the 25th, 50th, and 75th percentiles after sorting, respectively. The maximum length of 1982 is too long, which is an abnormal point. In this experiment, the truncation method is adopted, that is, for all data, the content after the length exceeds a certain closed value max length is deleted. The results of the original data statistics show that 75% of the data length does not exceed 140. The statistical information of the microblog dataset used in the experiment is shown in Table 1.

The data is randomly divided into a training set, a validation set and a test set, to verify the application effect of the detection method of fake news spread in social networks. The deep learning experiments involved in this chapter are all based on the deep learning framework TensorFlow, which has built-in multiple open source software libraries for numerical computing, and supports CPU computing and GPU acceleration.

3.3 Experimental Performance Index

In order to effectively verify the performance of the design method, this paper selects the accuracy rate, precision rate, recall rate and F1 as the evaluation indicators The accuracy rate represents the proportion of correctly classified samples (true TP and true negative TN) to the total number of samples. Precision represents the proportion of predicted

Table 1. Statistics of Weibo dataset

Category	Numerical value	Category	Numerical value
Number of events	40658	Event maximum number of comments	516
False rumor	23612	Event minimum number of comments	3
Real information	22837	Average number of comments on events	22.6
Number of comments	803695	User number	720186

positive samples (true *TP*) that are predicted to be positive (true *TP* and false positive *FP*). The recall rate represents the proportion of predicted positive samples (true *TP*) to actual positive samples (true *TP* and false negative *FN*). F1 is related to its precision and recall, and is equal to the sum of the inverse of precision and the inverse of recall. The larger the F1 value, the more robust the model. The calculation formula is as follows.

The accuracy rate formula:

$$M1 = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

The precision rate formula is:

$$M2 = \frac{TP}{TP + FP} \tag{9}$$

Recall rate formula:

$$M3 = \frac{TP}{TP + FN} \tag{10}$$

F1 formula:

$$F1 = \frac{1}{M2} + \frac{1}{M3} \tag{11}$$

The larger the above experimental performance index value, the better.

3.4 Results and Analysis

The detection method of fake news dissemination in social networks mainly involves classification tasks. The evaluation of the classification effect can be done through a confusion matrix, which is used to compare the predicted results with the actual values. The rows represent the predicted values and the columns represent the actual values. The test results of deep learning-based detection methods for fake news spread in social networks are compared with support vector machine-based and Naive Bayes-based detection methods. Taking all the features involved in this paper as input, the base classifier is trained with 3 detection methods. This paper selects the accuracy rate, precision rate, recall rate and F1 as the evaluation indicators, and uses the pros and cons of the detection effect to verify the effectiveness of the deep learning-based method for the dissemination of fake news in social networks. The experimental comparison results are shown in Table 2–Table 5, respectively.

Table 2. Accuracy comparison

Testing frequency	Detection method of fake news spread in social network based on deep learning	Detection method of fake news spread in social network based on support vector machine	A detection method of fake news spread in social network based on Naive Bayes
1	0.8916	0.8134	0.8307
2	0.8858	0.8168	0.8344
3	0.8925	0.8255	0.8281
4	0.8832	0.8122	0.8325
5	0.8963	0.8086	0.8266
6	0.8858	0.8264	0.8438
7	0.8920	0.8137	0.8352
8	0.9044	0.8322	0.8286
9	0.9027	0.8289	0.8364
10	0.8986	0.8165	0.8251

According to the test results in Table 2, the accuracy of the deep learning-based social network fake news dissemination detection method is 0.8933, which is 0.0739 and 0.0612 higher than that of the support vector machine-based and naive Bayes-based comparative detection methods.

According to the test results in Table 3, the accuracy of the deep learning-based social network fake news dissemination detection method is 0.9177, which is 0.0788 and 0.0669 higher than that of the support vector machine-based and Naive Bayes-based comparative detection methods.

According to the test results in Table 4, the recall rate of the deep learning-based social network fake news dissemination detection method is 0.8767, which is 0.0423 and 0.0576 higher than that of the support vector machine-based and naive Bayes-based comparative detection methods.

According to the test results in Table 5, the F1 value of the deep learning-based social network fake news dissemination detection method is 0.8967, which is 0.0601 and 0.0621 higher than that of the support vector machine-based and naive Bayes-based comparative detection methods. It can be seen from the above classification results that the detection method of fake news dissemination in social networks proposed in this paper integrates various features, which helps to improve the accuracy. The design

Table 3. Accuracy comparison

Testing frequency	Detection method of fake news spread in social network based on deep learning	Detection method of fake news spread in social network based on support vector machine	A detection method of fake news spread in social network based on Naive Bayes
1	0.9208	0.8242	0.8509
2	0.9114	0.8485	0.8658
3	0.9257	0.8268	0.8527
4	0.9225	0.8436	0.8366
5	0.9336	0.8353	0.8433
6	0.9262	0.8525	0.8655
7	0.9152	0.8412	0.8582
8	0.9026	0.8244	0.8378
9	0.9119	0.8377	0.8446
10	0.9074	0.8552	0.8522

Table 4. Comparison of recall rates

Testing frequency	Detection method of fake news spread in social network based on deep learning	Detection method of fake news spread in social network based on support vector machine	A detection method of fake news spread in social network based on Naive Bayes
1	0.8656	0.8309	0.8137
2	0.8828	0.8255	0.8248
3	0.8705	0.8468	0.8019
4	0.8633	0.8236	0.8262
5	0.8966	0.8353	0.8354
6	0.8682	0.8285	0.8185
7	0.8825	0.8296	0.8263
8	0.8757	0.8441	0.8027
9	0.8942	0.8374	0.8135
10	0.8676	0.8422	0.8284

Table 5. Comparison of F1 values

Testing frequency	Detection method of fake news spread in social network based on deep learning	Detection method of fake news spread in social network based on support vector machine	A detection method of fake news spread in social network based on Naive Bayes
1	0.8923	0.8275	0.8319
2	0.8969	0.8368	0.8448
3	0.8973	0.8367	0.8265
4	0.8919	0.8335	0.8314
5	0.9147	0.8353	0.8393
6	0.8963	0.8403	0.8413
7	0.8986	0.8354	0.8419
8	0.8889	0.8341	0.8199
9	0.9030	0.8376	0.8288
10	0.8871	0.8487	0.8401

method has higher mining potential than the comparison method, and the deep features it contains can more effectively detect fake media content in social networks.

4 Concluding Remarks

The advent of the self-media era has given Internet news a richer form of expression, but it has also increased the difficulty of fake news detection. This paper proposes a detection method for fake news dissemination in social networks based on deep learning. This method can effectively improve the detection effect and has effectiveness and advantages. The model in this paper is offline learning, that is the model is trained with the existing data set, and then the model is predicted. If the model is directly used online, the effect may not be very ideal. Everyday information is changing rapidly, how to build a data-driven incremental model is also one of the future research directions.

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