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Detecting Fake News Using Emotion Vectors

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Abstract

With the recent development of social media, information can now be communicated more easily and efficiently than previously thought possible. Although the easy transmission of information tends to generate considerable information, it also results in considerable wrong information being broadcast. As a result, the recipients and readers of information are now required to select the necessary information and judge the authenticity of the information obtained. In recent years, fake news, which is news generated from false information, has become a topic of considerable interest and is recognized as an issue that has tremendous influence on social behavior.

In this paper, we focus on emotions in fake news that activates the emotions of readers, and show the usefulness of emotion vectors in detecting fake news using emotion-learned embedding vectors.

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Fake News, Classification, Emotion Vector, CNN, Bi-LSTM, GloVe

Introduction

With the spread of social media in recent years, fake news has become a social problem. According to Dictionary.com[1], which provides English dictionaries on the Internet, fake news is an inflammatory false news story created to be widely shared for the purpose of generating revenue or promoting or discrediting a public figure, political campaign, or company. One of the characteristics of fake news is the incitement of people, which is the incitement is the stimulation of people's emotions to encourage them to take a particular action. Therefore, for the detection of fake news, it is important to consider the emotions contained in the news, such as malice, incitement, etc. that stimulate people's emotions. However, traditional fake news detection methods compare the content with other sources to scrutinize the target news for inconsistencies, and do not take emotions into account.

Therefore, in this paper, we propose a method for detecting fake news using emotion vectors in the sentence.

Related Works

Word embedding with emotion learning

Seyeditabari et al. proposed a method [1] to incorporate emotions into word embedding using emotion models, lexicons and NRC emotion lexicons [2] by Prutik's Circle of Emotions [3]. This method reduces the angular distance among words with similar emotions and increases the angular distance among words with opposite emotions to maintain the shape of the original vector space and reduce information loss. By learning the word embedding space for these two purposes, we incorporate emotions into word embedding.

Fake news detection using emotions of news sender and reader

Zhang et al. proposed a method [4] to detect fake news using the emotions contained in the news itself written the sender and the emotions of the readers in the news comments. The semantic and emotional features of the sentences were extracted from the news, and the emotional features were extracted from the comments to detect fake news. For datasets, we used RumourEval-19 [5] for English and Weibo-16 and Weibo-20, which are created from Weibo[2] posts for Chinese, and as well as social media posts and comments as input.

Positioning of this study

In this study, we used Seyeditabari et al. [1] to obtain an emotion-learned embedding. Moreover, the objectives of this study and Zhang et al.'s study [4] are different. In this study, only the emotions contained in the news are used to detect fake news. However, Zhang et al.'s study focuses on social media and used the emotions of the news sender and reader to detect fake news.

Proposed Method and Experiments

Overview

In this study, we focus on the emotions in fake news that activates readers' emotions, and detect fake news using embedding vectors that learn emotions. We implemented following logistic regression models: Convolutional neural network (CNN) [6], and bi-directional long short term memory (Bi-LSTM)[7]. To demonstrate the superiority and versatility of emotion vectors in detecting fake news, we performed embedding on each neural network structure using three methods: the existing method GloVe [8], GloVe that learns emotions using Seyeditabari et al.'s method [1], and a method that concatenates the aforementioned two methods. We then conducted an experiment to compare the detection accuracy of fake news obtained by the models.

Embedding

In this study, embedding is performed using GloVe. The emotion vector is obtained by Seyeditabari et al.'s method [1]. We used GloVe in this study because Seyeditabari et al.'s method succeeded in improving the accuracy of the original GloVe by 29% in an emotionally adapted vector space. In the following, the mechanism to obtain embedding using GloVe is described as the GloVe model; Seyeditabari et al.'s mechanism to obtain embedding using GloVe is called the

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emotional GloVe model, and the mechanism to obtain embedding by concatenating the features obtained by the GloVe model and the emotional GloVe model is called the concatenation model.

Dataset and label

LIAR[9], a manually labeled dataset with 10 years of data from PolitiFact[3] was used in this study. PoltiFact is a website that verifies the authenticity of statements related to politics, in a variety of contexts. It has reporters and editors from the Tampa Bay Times that conduct the fact-checking. Authenticity-verified statements and statements are labeled in 6 levels (Table 1).

Label	Description
True	Accurate
Mostly-true	Accurate, but lacking information
Half-true	Important information missing or distorted
Barely-true	Little accurate information and manipulated impressions
False	Inaccurate
Pants-fire	Flat-out lie (pants-on-fire)

Table 1: LIAR labeling.

LIAR is also divided into training data, which is used to update the weights of the model, validation data, which is used to tune the hyperparameters of the model, and test data, which is used to check the generalization performance of the model after training (Table 2).

Data type	Quantity
Learning data	10240
Verification data	1284
Test data	1267

Table 2: Quantity of data in LIAR.

The following three types of correct answer labels were used (Table 3).

Binary classification	6 valued classification	False 4 valued classification
True	True	
	Mostly-true	
	Half-true	Half-true
False	Barely-true	Barely-true
	False	False
	Pants-fire	Pants-fire

Table 3: Details of the labels

For the binary classification labels, the correct labels for the data that are true, mostly-true, and half-true were set to true, and the correct labels for barely-true, false, and pants-fire were set to false. The labels for the 6 valued are shown in Table 1. For the purpose of classifying the degree of fake news, false 4 valued classifications was performed using the following labels: half-true, barely-true, false, and pants-fire. The LIAR contains the following information.

- Insistence
- Speaker
- Party affiliation of the speaker
- Speaker's occupation
- Location of the speaker's home
- Circumstances under which the claim was made
- Quantity of incorrect claims (pants-fire, false, barely-true, half-true, mostly-true) that the
- speaker made before making the claim

In this study, we used only "Insistence" to detect fake news from the text of news articles.

Models Used in the Study

The models used in this study are explained in this section. They were trained for a sufficient amount of time, and the weights at the point in time when they showed the highest rate of correct answers on the validation data were used as the final weights. The parameters common to all models are shown in Table 4.

Output dimension of embedding layer	300
Batch size	16
Activation function of the output layer	Softmax
Loss function	Cross-entropy loss

Table 4: Parameters common to all models.

Logistic regression model

The structure of the logistic regression model using the GloVe model or the emotional GloVe model is shown in Figure 1.

The structure of the logistic regression model with the concatenation model is shown in Figure 2.

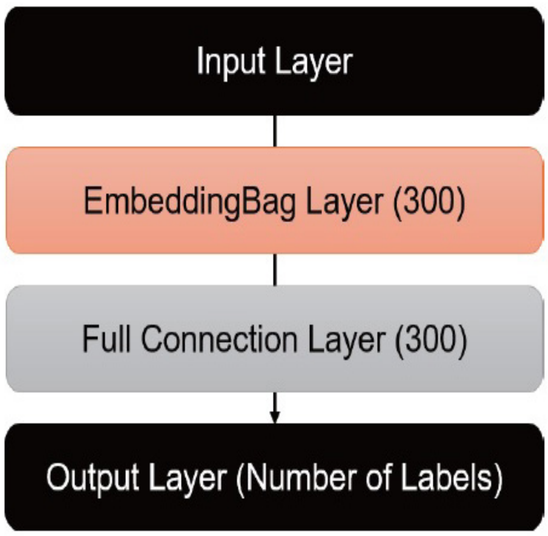

Figure 1: Structure of logistic regression model with the GloVe model or the emotional GloVe model.

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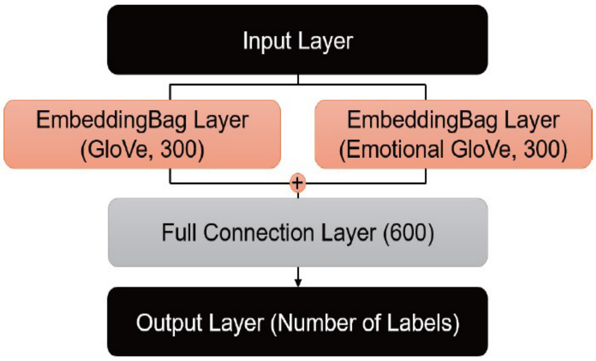

Figure 2: Structure of the logistic regression model with the concatenation model.

Table 5: shows the parameters of the logistic regression model when binary classification was performed.

Quantity of epoch	200
Learning rate of the *n* th epoch	$1.0 \times 0.75^{[\frac{1}{5}n]}$

Table 5: Parameters of the logistic regression model for binary lassification.

Table 6 shows the parameters of the logistic regression model using the GloVe model or the emotional GloVe model when 6 valued or false 4 valued classification was performed.

Quantity of epoch	500
Learning rate of the *n* th epoch	$2.0 \times 0.85^{[\frac{1}{5}n]}$

Table 6: Parameters of the logistic regression model using the GloVe model or the emotional GloVe model for 6 valued, false 4 valued classification.

Table 7 shows the parameters of the logistic regression model using the linkage model when 6 valued and false 4 valued classifications were performed.

Quantity of epoch	400
Learning rate of the *n* th epoch	$1.5 \times 0.85^{[\frac{1}{5}n]}$

Table 7: Parameters of the logistic regression model with the linkage model for 6 valued and false 4 valued classifications.

The structure of CNN using the GloVe model or the sentiment GloVe model is shown in Figure 3.

The parameters of the CNN using the GloVe model or the emotional GloVe model are shown in Table 8.

Quantity of epoch	10
Learning rate of the *n* th epoch	$5.0 \times 10^{-4} \times 0.10^{[\frac{1}{2}n]}$
Activation function of each convolutional layer	ReLU[10]
Stride	2
Dropout rate for each pooling layer output after consolidation	0.20

Table 8: Parameters of CNN with GloVe model or emotional GloVe model.

The structure of the CNN using the concatenation model is shown in Figure 4.

The parameters of the CNN with the concatenated model are shown in Table 9.

Quantity of epoch	10
Learning rate of the *n* th epoch	$5.0 \times 10^{-4} \times 0.10^{[\frac{1}{2}n]}$
Activation function of each convolutional layer	ReLU
Stride	2
Dropout rate for each pooling layer output after consolidation	0.25

Table 9: Parameters of CNN with concatenated model.

Bi-LSTM

The structure of the Bi-LSTM with the GloVe model or the emotional GloVe model is shown in Figure 5.

Figure 6 shows the structure of Bi-LSTM using the concatenation model.

The parameters of Bi-LSTM are shown in Table 10.

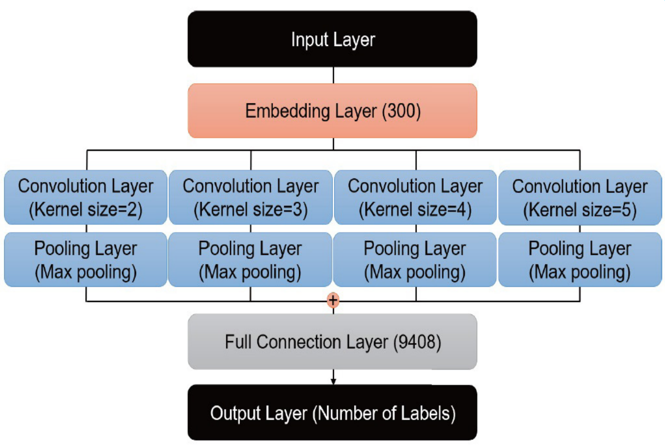

Figure 3: Structure of a CNN using the GloVe model or the sentiment GloVe model.

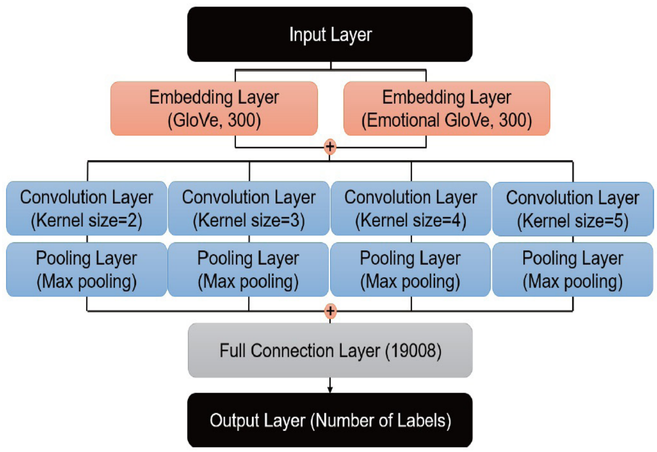

Figure 4: Structure of the CNN using the concatenation model.

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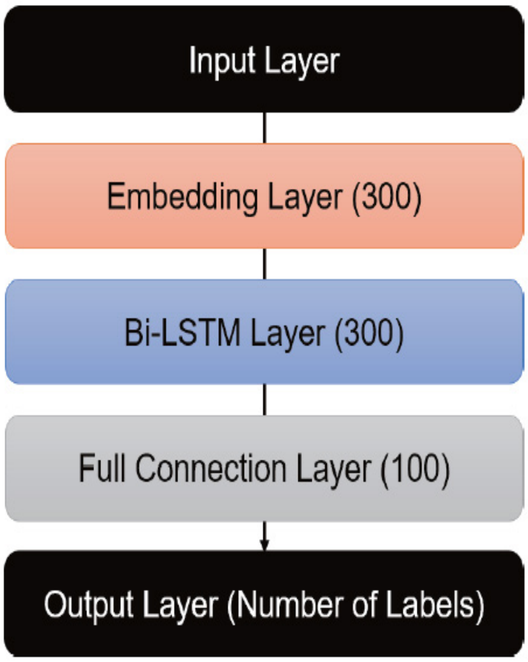

Figure 5: Structure of Bi-LSTM using GloVe model or emotion GloVe model.

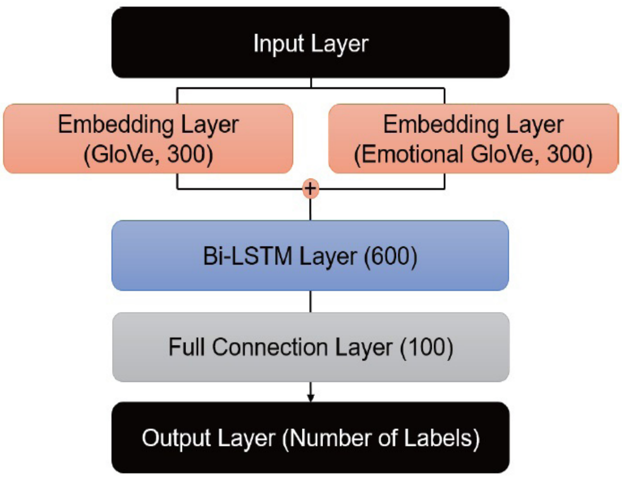

Figure 6: Structure of Bi-LSTM using a concatenation model.

Quantity of epoch	10
Learning rate of the *n* th epoch	$1.0 \times 10^{-2} \times 0.10^{[\frac{1}{2}n]}$
Dropout rate for each pooling layer output after consolidation	0.20

Table 10: Parameters of Bi-LSTM.

Verification Method

In this study, the correct response rate of the test data (hereinafter referred to as CR) was used to evaluate the accuracy of each detection model. We conducted 10 tests, and the average value of the 10 CRs was used to evaluate the model.

Experimental Results

The average values of the 10 CRs for each neural network structure and each label are shown in Table 11.

Classification model		binary [%]	6 valued [%]	false 4 valued [%]
Logistic regression model	GloVe	60.5	24.7	36.2
	Emotional GloVe	60.7	25.6	36.3
	Coupled	60.7	26.0	36.4
CNN	GloVe	58.1	23.8	35.2
	Emotional GloVe	59.6	24.5	36.0
	Coupled	59.9	24.6	36.2
Bi-LSTM	GloVe	60.5	24.2	35.1
	Emotional GloVe	61.6	25.1	36.3
	Coupled	61.8	25.8	37.4

Table 11: CR.

From Table 11, when binary classification, 6 valued classification, and false 4 valued classification were performed for all neural network structures, the accuracy of the emotional GloVe model was higher than that of the GloVe model when the CR of the emotional GloVe model and the GloVe model were compared. Similarly, when the CR of the concatenation model and the GloVe model were compared, the concatenation model exhibited a higher accuracy. From Table 11, for each neural network structure, the average of the difference between the CR of each of the emotional GloVe and concatenation models and the CR of the GloVe model is shown in Table 12.

	Emotional GloVe model [%]	Concatenation model [%]
Logistic regression model	+0.40	+0.57
CNN	+0.97	+1.17
Bi-LSTM	+1.06	+1.73

Table 12: Average of the difference between the Globe model and the CR.

From Table 12, when the emotional GloVe and concatenation models were used, the neural network structure that improved the CR the most was Bi-LSTM.

Evaluation and Discussion

Usefulness of emotion vectors

Table 11 confirms the usefulness of using emotion vectors to detect fake news, because the CR is improved in all neural network structures and classification problems using emotion vectors.

Difference of CR by neural network structure

Table 12 shows that in Bi-LSTM, the CR was improved the most when the emotion GloVe and the concatenation model were used, because Bi-LSTM treated sentences as time-series information unlike the logistic regression model and CNN, which captured the emotion vectors more complexly.

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On the contrary, in the logistic regression model, the improvement in the CR was the lowest when the emotional GloVe and concatenation model was used. This is because the use of the EmbeddingBag layer in the logistic regression model resulted in the loss of information about each word and word order.

Label bias

From Table 11, we can observe that when binary classification was performed in the logistic regression model, the emotional GloVe model and concatenation model showed similar CR because of the loss of information about each word, word order, and label bias due to the use of the EmbeddingBag layer.

Figure 7 and Figure 8 show the confusion matrix of the logistic regression model when binary classification is performed using the emotional GloVe and linkage models, respectively.

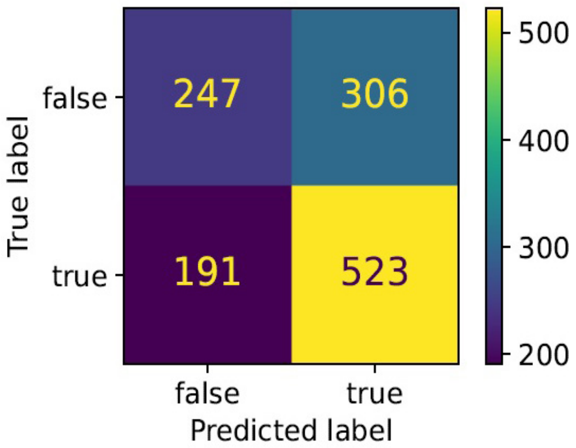

Figure 7: Confusion matrix (binary classification) of the logistic regression model with the emotional GloVe model.

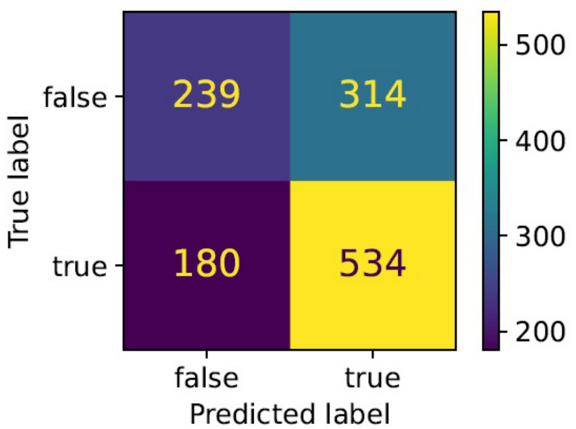

Figure 8: Confusion matrix (binary classification) for the logistic regression model with the linkage model.

In general, the confusion matrix is considered to be good when the value of the square overlapping the predicted label, which is the prediction output by the detection model, and the true label, which is the original correct answer in the dataset, is large.

Label	Quantity
True	7134
False	5657
Total amount	12791

Table 13: Quantity of labels for binary classification.

From Table 13, true was more common than false in the labels of binary classification. From Figure 7 and Figure 8, a similar bias occurred in the output of the emotion GloVe and concatenation model respectively. This bias in the output of the detection model was because of the bias of the dataset. When binary classification was performed in the logistic regression model, the concatenated model fitted the bias of the dataset better than the emotion learning GloVe model.

Future Work

Dataset

In this experiment, a small amount of data (Table 2) was used because a large fake news dataset was not publicly available. The types of fake news include complete falsehoods, distortions of the original information, correct information used in the wrong context, and parodies. As such, fake news datasets are underdeveloped. Once such an environment is established, it will be possible to build a system with higher accuracy.

Emotions dedicated to fake news

"Says Barack Obama is a socialist."

In general, detecting fake news requires prior knowledge of the news. In the aforementioned example[4], the following prior knowledge is required.

The capitalist camp, with the United States as its ally, and the socialist camp, with the Soviet Union in the East as its ally, were at odds with each other.

Barack Obama is the 44th President of the United States.

If the goal is to focus on emotions and detect them, focus should be given to the word ”socialist”. The word ”socialist” produces negative emotions such as disgust in people from capitalist countries, but positive emotions in people from socialist countries. These emotions are formed due to prior knowledge such as common sense acquired. Further improvement in accuracy can be expected by learning prior knowledge and obtaining emotions specific to fake news.

We also expect that the completion of a highly accurate fake news detection system will provide a means to analyze human emotions and the nature of fake news using techniques such as Explainable AI (XAI)

Conclusion

In this paper, we proposed, implemented, and evaluated a method for detecting fake news using emotions in sentences. Experimental results showed the usefulness of emotion vectors in detecting fake news. The study of fake news will become more and more important in the future, as fakenews has been the cause of many large-scale incidents in recent years.

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Competing Interests

The author declare that he has no competing interests.

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