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Information Cocoons and Rumor Propagation Detection Using Graph Neural Networks

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ABSTRACT

This research focuses on the problem of rumor detection in social media platforms. With the rapid spread of information on the network, rumors can spread rapidly through the interaction between users, which leads to the spread of misinformation and has a negative impact on society. Therefore, how to effectively identify rumors has become an important research topic.This paper proposes a modeling method based on graph structure to describe the information dissemination process. Specifically, social media data is represented as a graph structure, in which nodes represent users or posts, while forwarding, commenting and other interactive relationships. On this basis, the Graph Convolutional Network (GCN) is used to learn the representation of nodes. By aggregating the information of neighboring nodes, the model can use text features and disseminate structural information at the same time. The evaluation of the proposed method through experiments shows that compared with the method that relies only on text information, the introduction of communication structure can effectively improve the performance of rumor detection. Overall, this study provides a structured method for rumor communication modeling and reflects the application value of graph-based models in social media analysis.

KEYWORDS

Component; Rumor detection; GCN; Social media; Information propagation

1 Introduction

With the rapid development of social media, information dissemination has become more efficient and extensive, but it has also exacerbated the spread of rumors. Rumors will not only mislead the public's perception, but also may cause social panic and have a negative impact on social stability. Therefore, how to effectively identify and control the spread of rumors has become an important research topic in the field of data science and information security.

In the study of rumor detection, traditional methods mainly rely on text characteristics such as support vector machines (SVM) (Cortes & Vapnik, 1995).This kind of method is simple to implement, but it is more dependent on feature engineering, and it is difficult to capture complex semantic information. With the development of deep learning, convolutional neural networks (CNN) and circular neural networks (RNN) are widely used in text classification tasks (Ma et al., 2016), which has improved model performance to a certain extent. However, these methods usually only focus on text content and ignore the dissemination structure of information in social networks.

In recent years, Graph Neural Networks (GNN) has gradually been applied to rumor detection tasks. By expressing users and information as graphical structures, the information dissemination path can be effectively portrayed, and the graph convolutional network (GCN) can be used for modeling, so as to use text characteristics and structural information at the same time to improve the classification effect. Based on the above background, this paper proposes a rumor dissemination detection method based on graph neural network, which improves the accuracy and robustness of rumor detection by constructing a social network diagram structure and modeling it in combination with text features.

2 Related Work

In recent years, with the rapid development of social media, rumor detection has gradually become an important research direction in the field of data science and information security.

Early research is mainly based on traditional machine learning methods, such as support vector machine (SVM) and Naive Bayes, which are classified by manually extracting text features. This kind of method is simple to implement, but it is more dependent on feature engineering, and it is difficult to capture complex semantic information.

With the development of deep learning, convolutional neural networks (CNN) and circular neural networks (RNN) are widely used in text classification tasks. This kind of method can automatically extract features, which improves the performance of the model to a certain extent. However, these methods mainly focus on text content and ignore the dissemination structure of information in social networks. In recent years, Graph Neural Networks (GNN) has gradually been applied to rumor detection tasks. By constructing a graph structure to represent the information dissemination relationship, and using the graph convolutional network (GCN) for modeling, text information and communication structure can be used at the same time to improve the classification effect of the model. Fake news detection has also been widely studied from a data mining perspective (Shu et al., 2017; Zhou & Zafarani, 2020).

Although some progress has been made in research, there are still some problems, such as insufficient modeling of complex transmission paths and insufficient portrayal of the dynamic transmission process. Therefore, it is necessary to further study more effective methods to improve the accuracy and robustness of rumor detection.

3 Methodology

3.1 Data Preprocessing

The data used by this research institute mainly comes from social media platforms, including text information published by users and interactive behaviors between users, such as forwarding, commenting and replying. This kind of data usually has the characteristics of high noise and complex structure, so systematic preprocessing is required before modeling. First, clean the original text data, including removing irrelevant symbols, special characters and duplicate content, while unifying the text encoding format to ensure the consistency of the data. In addition, process missing values or abnormal data, such as deleting severely missing samples or filling them reasonably, so as to improve data quality. After completing the basic cleaning, the data will be screened and only the content related to the dissemination of rumors will be retained. The purpose of this step is to reduce the interference of irrelevant information on model training and make the model more focused on the target task. At the same time, the data is divided into training sets and test sets to ensure the objectivity and reliability of model evaluation. In order to input text data into the model, the text also needs to be converted into numerical representation. This study adopts the word vector representation method to convert the text into a low-dimensional dense vector, so as to retain the semantic information. Compared with the traditional word frequency representation method, this method can better capture the contextual relationship of the text and provide effective input for subsequent model learning.

3.2 Graph Construction

In order to portray the structural characteristics of information dissemination in social networks, this paper converts the original data into a graph structure for modeling. Specifically, build an undirectional graph:G=(V,E), Among them, the node collection V indicates the user or post, while collecting E represents the interaction between nodes.

In this study, nodes can be represented as users or specific posts in social media, while edges are built according to the interaction behavior between users, such as forwarding, commenting or replying. When there is an interaction between two nodes, establish an edge in the diagram to represent their connection.

The graph structure constructed in the above way can effectively reflect the transmission path of information in the network and provide important structural information for subsequent model learning.

3.3 GCN Model

After constructing the graph structure, this study uses the Graph Convolutional Network (GCN) to learn the representation of nodes and use it for rumor classification tasks. GCN is a data modeling method based on graph structure (Kipf & Welling, 2017). Its core idea is to update the representation of the current node by aggregating the information of neighboring nodes. In each layer of graph convolution, the representation of the node not only depends on its own characteristics, but also depends on the characteristics of its neighboring nodes to be updated. Through this information transmission mechanism, the model can gradually integrate local structural information, so as to learn richer node representation. With the increase of the number of layers, nodes can receive more distant information, thus improving the model's ability to model complex propagation structures. In this study, the GCN model is composed of a multi-layered convolutional layer, and each layer is connected to a nonlinear activation function (such as ReLU) to enhance the expression ability of the model. At the same time, in the process of model training, by constantly adjusting the parameters, the model can better distinguish between rumors and non-rumor information. Compared with the traditional text-based method, GCN can use text characteristics and disseminate structural information at the same time. For example, in the process of spreading rumors, if most of the neighboring nodes of a node belong to the category of rumors, then the node is more likely to be judged as a rumor. This structural information is important for classification.

3.4 Training and Optimization

After the model construction is completed, it needs to be trained and optimized to obtain better performance. During the training process, the training data is first input into the model, the predicted results are obtained through forward propagation, and then the loss function is calculated according to the difference between the predicted results and the real label. This study adopts cross-entropy loss as the optimization target (Goodfellow et al., 2016), which performs well in classification tasks. By minimizing the loss function, the model's prediction results can gradually approach the real label.

In terms of parameter optimization, this study adopts the Adam optimization algorithm. (Kingma & Ba, 2014) Compared with the traditional stochastic gradient descent method, the Adam optimizer can adaptively adjust the learning rate, thus accelerating the convergence speed of the model and improving the stability of training.

In order to prevent the model from over-fitting, the dropout mechanism is introduced during the training process to enhance the generalization ability of the model by randomly discarding some neurons. In addition, the model performance can be further optimized by adjusting the learning rate, hidden layer dimension and other hyperparameters.

After the model training is completed, use the test set to evaluate the model. By calculating indicators such as Accuracy, Precision, Recall and F1-score, the classification performance of the model can be comprehensively evaluated and a basis for subsequent improvements can be provided.

4 Experiments

4.1 Experimental Setup

This study implements the model based on the PyTorch framework, and conducts experimental verification on the constructed data set. In order to ensure the fairness of the experiment, the data set is divided into training set and test set, of which the training set is used for model training and the test set is used to evaluate the performance of the model.

During the training process, set appropriate hyperparameters, including learning rate, training number (epochs) and hidden layer dimension, etc. The optimizer adopts the Adam optimization algorithm to improve the convergence speed and stability of the model. At the same time, the model is iterated in multiple rounds during the training process to obtain better parameter configuration.

4.2 Evaluation Metrics

In order to comprehensively evaluate the performance of the model in the rumor detection task, this paper adopts a variety of evaluation indicators, including accuracy and F1-score. The accuracy rate is used to measure the correct sample ratio predicted by the model, and the F1-score comprehensively considers the accuracy rate and the recall rate, which can more comprehensively reflect the performance of the model in the case of unbalanced data.

4.3 Results

The experimental results show that the GCN-based model has achieved certain performance in rumor detection tasks. Specifically, the accuracy rate of the model on the test set reached 68.32%, and the F1-score was 0.6806.

Judging from the overall results, the model can identify rumors and non-rumor information to a certain extent, which shows that it is effective to introduce the graph structure to model the communication relationship.

In addition, it can be seen from the classification results that there are differences in the performance of models in different categories. Among them, the identification effect of most categories (non-rumors) is better, while the identification ability of minority categories (rumors) is relatively weak, which affects the overall performance to a certain extent. The experimental results show that the GCN-based model has achieved certain performance in rumor detection tasks. Specifically, the accuracy rate of the model on the test set reached 68.32%, and the F1-score was 0.6806.

As shown in Figure 1, the training loss gradually decreases with the increase of epochs, indicating that the model converges effectively during the training process.

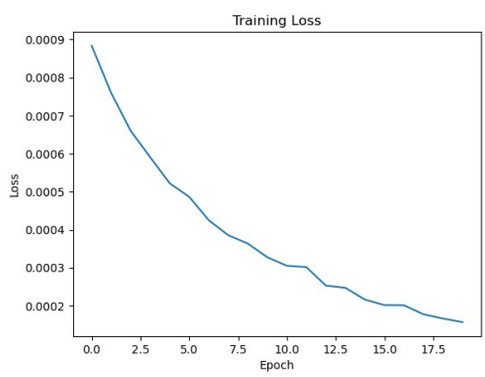


Figure 1 Training loss curve

As shown in Figure 2, the training accuracy quickly reaches 100%, while the test accuracy remains around 66%–68%. This gap suggests that the model may suffer from overfitting.

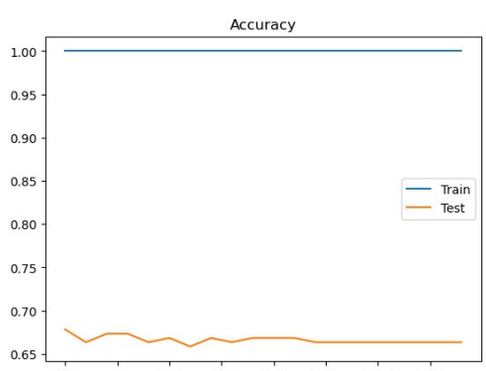


Figure 2 Training and test accuracy

Judging from the overall results, the model can identify rumors and non-rumor information to a certain extent, which shows that it is effective to introduce the graph structure to model the communication relationship.

4.4 Analysis

It can be seen from the experimental results that graph structure information plays an important role in rumor detection. Compared with the method based only on text content, GCN can capture the propagation path through the connection between nodes, thus improving the discrimination ability of the model.

However, some shortcomings were also found in the experiment. For example, when the data distribution is uneven, there is still room for improvement in the performance of the model in a few categories. In addition, GCN has certain limitations in handling dynamic propagation processes and long-distance dependencies, which affects the performance of the model to a certain extent.

5 Discussion

It can be seen from the experimental results that the GCN-based model can achieve certain results in the rumor detection task, which shows that the introduction of graph structure information helps to improve the model's modeling ability of the information dissemination process. By building a network between users and posts, the model can capture the interaction information between nodes, thus improving the ability to identify the rumor dissemination pattern.

However, the experimental results also reflect that the model has certain limitations. First of all, judging from the classification results, the performance of the model in the majority class (non-rumor) is obviously better than that in the minority category (rumor), indicating that the uneven distribution of data has had a great impact on the performance of the model. This imbalance will cause the model to be biased towards predicting the majority of classes during training, thus reducing the ability to identify rumors.

Secondly, the GCN model mainly relies on local neighborhood information when modeling the propagation structure, and the capture ability of long-distance dependencies is limited. In actual social networks, rumors often have the characteristics of cross-level and multi-jump transmission, and relying only on local aggregation may not be able to fully portray its complex transmission path. In addition, the current model does not explicitly consider the time factor, and the spread of rumors has obvious dynamic characteristics, which also limits the performance of the model to a certain extent.

In response to the above problems, future research can be improved from many directions. On the one hand, the category imbalance problem can be alleviated by resampling data or introducing a weighted loss function, thus improving the performance of the model in a few categories. On the other hand, more advanced model structures, such as Transformer-based models, can be explored to enhance the modeling ability of global dependencies. At the same time, the introduction of time information to build a timing chart model is expected to more accurately portray the dynamic process of rumor dissemination.

6 Conclusion

This article focuses on the problem of information cocoon and rumor spread in social media, and puts forward a modeling method based on graph neural networks. By preprocessing the original data and building the graph structure between the user and the post, and using the graph convolution network to learn the node, the detection and classification of rumors can be realized.

The experimental results show that the proposed method can improve the effect of rumor detection to a certain extent and verify the effectiveness of graph structure modeling in the task. However, the model still has some shortcomings in dealing with category imbalance and capturing complex transmission patterns.

Future work will further explore more advanced model methods, such as the structure based on Transformer, and model the communication process in combination with time information to improve the performance of the model in a complex social network environment.

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