Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 15, Issue. 1, No.1 : 2024
ISSN : **1906-9685**

RUMOUR DETECTION BASED ON GRAPH CONVOLUTIONAL NEURAL NET

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Abstract:

Rumour detection is an important research topic in social networks, and many methods for detecting rumours have been presented in recent years. Structured information from a discussion can be used to derive effective features for rumour identification. However, many existing rumour detection methods focus on local structural elements, ignoring the global structural features between the initial tweet and its replies. To make maximum advantage of global structural features and content information, we offer Source-Replies relation Graph (SR-graph) for each discussion, where every node denotes a tweet, its node attribute is weighted word vectors, and edges denote the interaction between tweets. For the rumour detection challenge, we present an Ensemble Graph Convolution. Neural Net (EGCN) based on SR-graphs. In tests, we first confirm that the recovered structural characteristics are successful, and then we demonstrate the effects of various word-embedding dimensions on numerous test indices. Furthermore, we demonstrate that our proposed EGCN model is equivalent to, if not better than, current state-of-the-art machine learning models.

Introduction

People are consuming more news via social media than from traditional sources (such as newspapers and television) for the first time in history. Because people trust what they read in the media, they are more susceptible to rumours and false information. This tendency accelerates the spread of rumours. Information that has not been independently verified at the time of publication is referred to as a rumour. Unverified rumours can range in intensity in their ability to incite fear and worry, and it can be challenging for the general public to discern between the two. For this reason, having a reliable automatic rumour detection system is crucial. A rising number of people are interested in researching machine learning techniques for automated rumour identification. believes that rumours will make people on Twitter doubt the accuracy of tweets. While this approach concentrates on substance information, not all rumours result in curious tweets. Scholars suggest a variety of content-based rumour detection algorithms, including Random Forests, TF-IDF based models, and deep learning models, to fully use content information. Syntactic, lexical, and semantic aspects are all included in these content features. While these techniques can extract useful content characteristics, researchers have realised that these rumour detection models are unable to capture the structural information of rumour transmission and that relying solely on content features is insufficient for rumour detection tasks. Researchers add structural elements to their rumour detection models in an effort to improve their performance even more. The structural information is expressed as context features in structure-based rumour detection models, like Multi-features Support Vector Machines (SVMs). Researchers combine context features, like User-based and Network-based features, with content features in their machine learning models. Nevertheless, these contextual data are always local, and various extraction techniques are used to extract local structure features and content features, which complicates training. In order to learn the global structural features and the content features for the rumour detection task end-to-end, our goal is to create a uniform deep learning frame.

The Proposed Model

Global structural information takes into account how each tweet in a conversation interacts with the others. According to our observations, replies to a source tweet that eventually turns out to be a rumour tend to echo the source or the initial comment. We suggest creating a source-replies relation graph (SR-graph) for each conversation in order to extract the structural information from it. A node in an SR-graph represents a tweet, and its accompanying word vectors are the node feature. An Ensemble Graph Convolutional Neural Net with Nodes Proportion Allocation Mechanism (EGCN) is proposed, based on SR-graphs.

Source-Replies Relation Graphs

The original tweet and the responses to it are associated in a discussion; this correlation is global as well as local. As we can see, the overall structure of this conversation is somewhat starlike or linear if a source tweet ultimately turns out to be a rumour. A reply always comes after the source or the previous tweet, and the local structure highlights the relationships and significance of the current message. Consequently, we attempt to model both the global and local structural information in a uniform graph structure. Both the global and the local structure can be considered as significant features for the rumour detection task. Random Walking Kernels and Gaussian Diffusion Kernels are the two most used graph structures. Nevertheless, the neighbouring link is not directly expressed by these two kernels.

An Ensemble Graph Convolutional Neural Net

We perform a binary classification task on the rumour detection task using the weighted word vectors and SR-graphs. Important semantic components and the relationship between the source and its responses are particularly significant for rumour detection as compared to standard classification problems. We create related word vectors and an SR-graph for each tweet and its replies. In order to construct an ensemble deep neural network for various discussions, we suggest using the Nodes Proportion Allocation Mechanism (NPAM). This ensemble deep neural network includes a Text CNN and a GCN.

assuming that the input of an EGCN is a conversation, the corresponding word vectors and the SR-graph of this conversation are built. The SR-graphs and the corresponding word vectors are passed to a Text CNN and a GCN, the feature output of Text CNN is proportional to the rate of N/M . Specifically, assuming that the feature output of the Text CNN is *PT* and the feature output of the GCN is *PG*, the total feature ouput of EGCN is

y=PG×NM+PT(1−NM)

Evaluation Measures

Accuracy is often treated as a suitable evaluation measure for a classifier. In this paper, we also introduce other 3 indices: Precision, Recall, and F1. The evaluating indicators are defined as follows:

Precision=Recall=F1=TPTP+FPTP

TP+FN2×Precison×RecallPrecison+Recall

Evaluation Measures

SVM (Content + Context): Support Vector Machines with the cost coefficient selected via nested cross-validation.

Random Forest (Content): Random forest is a classifier that uses multiple trees to train and predict samples.

Naive Bayes (Content): Naive Bayesian method is a classification method based on Bayesian theorem and independent hypothesis of characteristic conditions.

Experimental Results and Discussion

In experiments, the EGCN contains a Text CNN and a GCN. The Text CNN has 3 layers, and the GCN contains 4 Graph convolution layers, a SortPooling layer, and a 1-dimension convolution layers. The Adam method is used, and the initial learning rate is 1e-5. The structure of source tweets and the replies can be organized as SR-graphs, and different SR-graphs have different numbers of nodes.

Effective GCNs Based on Global Structure Features

To verify that the extracted structural features of our SR-graphs are effective, in our first experiment, we test the F1 scores of the proposed graph structure without embedding word vectors, and the node features are their degrees rather than the weighted word vectors.

Exploring the Structures of Conversations

We replace the degrees in the node features with weighted word vectors and add a node threshold to the model in order to enhance the classification outcomes. A graph with fewer nodes will have a simpler source tweet and reply structure. For the purpose of detecting rumours, a Text CNN would work well. Dataset SR-graphs allow for the calculation of each node's degree.

Exploring the Optimal EGCN

To further explore the effects of different dimensional word-vectors and construct a satisfactory EGCN model, we test 4 different indices on PHEME dataset based on different dimensional word vectors.

Naive Bayes method

R.F denotes the Random Forest algorithm, and N. B is the Naive Bayes method. We use bold black fonts to mark the optimal solutions and bold blue fonts to mark the suboptimal solutions. As Table 8 shows, the proposed EGCN achieves at least one best result in every event and almost all the optimal solutions or suboptimal solutions. Overall, the EGCN obtains the 6 best results and 2 suboptimal solutions in the PHEME dataset and perform better than other models. For comparing, we use a LSTM and a Text CNN, which are commonly used for classification, and the results show that the proposed EGCN performs better than the two commonly used models. The proposed EGCN use both text features and structural features for classification, and the experiments verify that the extracted text features and structural features are effective for the rumor detection task. Moreover, we also add a state-of-the-art Graph Neural Network PGNN, a PGNN is a kind of GCN, and the adjacent relation in a PGNN is transformed into indicator functions in the graph convolution to avoid directly using adjacent matrices. The experiments show that the proposed EGCN uses the structural information and the text information more effectively and performs better than the PGNN on most indexes.

Conclusion

We suggest using a deep neural net to convert the rumour detection challenge into a classification problem. We train word vectors using the Word2Vec model in order to achieve adequate classification results, and we suggest creating an SR-graph for each source tweet along with its replies. We train an EGCN model that outperforms state-of-the-art machine learning models, either by the same margin or even better, based on SR-graph and the accompanying word vectors. We train the word vectors in this research using an existing word-embedding model, since we show through testing that word vectors are critical to the ultimate performance of the proposed EGCN model. On the other hand, we speculate that a word-embedding model tailored for Twitter datasets could perform superior to the current methods. In light of this, our next work will create an unsupervised word-embedding neural net specifically for Twitter.

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