

Research on Rumor Detection Based on a Graph Attention Network With Temporal Features

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ABSTRACT

The higher-order and temporal characteristics of tweet sequences are often ignored in the field of rumor detection. In this paper, a new rumor detection method (T-BiGAT) is proposed to capture the temporal features between tweets by combining a graph attention network (GAT) and gated recurrent neural network (GRU). First, timestamps are calculated for each tweet within the same event. On the premise of the same timestamp, two different propagation subgraphs are constructed according to the response relationship between tweets. Then, GRU is used to capture intralayer dependencies between sibling nodes in the subtree; global features of each subtree are extracted using an improved GAT. Furthermore, GRU is reused to capture the temporal dependencies of individual subgraphs at different timestamps. Finally, weights are assigned to the global feature vectors of different timestamp subtrees for aggregation, and a mapping function is used to classify the aggregated vectors.

KEYWORDS

Gated Recurrent Neural Network, Graph Attention Network, Rumor Detection, Temporal Features, Timestamp

INTRODUCTION

From the 20th century to the present, the world industrial pattern has gradually tilted toward Internet-related fields. Many IT companies, such as Microsoft, Google, and Alibaba, began to rise rapidly. They do not hesitate to invest huge sums of money and recruit a large number of researchers to seize new fields. At present, the information dissemination carrier represented by Twitter has become the main tool for people to communicate. Users can communicate through social software without leaving home and learn about major events in the world. However, people with ulterior motives have begun to spread rumors with the help of social networks, making it difficult for users to distinguish between true and rumor without their knowledge. Since rumors cover a very wide range and users

DOI: 10.4018/IJDWM.319342

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who publish rumors are very concealed, it is very difficult to supervise them. At present, Baidu, Tencent, Weibo, and other well-known Internet companies have established rumor-refuting platforms. Various Internet platforms organize researchers to explore efficient rumor detection methods that can adapt to the big data environment. Text features (Azri et al., 2021; GuangJun et al., 2020; Li et al., 2022; Ma et al., 2022; Shelke & Attar, 2022; Xu et al., 2021), image features (Azri et al., 2021; Li et al., 2022), user features (Shelke & Attar, 2022), and spread features (Ma et al., 2022) have become mainstream research directions.

To adapt to the environmental requirements of big data, the related methods of rumor detection are gradually transferred from manual-based related methods to machine learning-based related methods. Since the related methods based on machine learning cannot model the social relations of users, this method cannot effectively extract the high-level and abstract features of rumors. In 2016, Kipf & Welling (2016) proposed graph convolutional neural networks. The related methods of graph neural networks gradually entered the field of view of many scholars and achieved good performance. Since the graph convolutional neural networks (GCN) needs to introduce an adjacency matrix, out-degree nodes and in-degree nodes need to participate in the node aggregation process at the same time, which limits the aggregation direction. At this stage, the related methods of rumor detection mainly consist of related methods based on machine learning and related methods based on graph neural networks.

Related technologies based on machine learning have been very mature. Most scholars use classifiers or classification functions to determine whether tweets are rumors by extracting relevant features and inputting them into trained models. Ma et al. (2016) captured the time-varying contextual features through a recurrent neural network and proposed a rumor detection model that fuses temporal feature information; Shi et al. (2018) not only improved the detection efficiency but also solved the problem of data sparseness by fusing the recurrent neural network with the topic features of emergencies; Min et al. (2016) combined a momentum model and temporal analysis-based method to filter fake microblogs. These methods demonstrate the importance of temporal features in rumor detection by extracting temporal relationships between tweets or keywords. Gao et al. (2020) used task-specific features based on bidirectional language models to learn contextual embedded textual information and event sequence information; Liu et al. (2020) used deep learning to extract the text features of tweets, image features and text information in images. However, these kinds of methods only stay at the most basic surface features and cannot extract high-level, abstract global features of rumors.

The related techniques of machine learning have achieved great success in dealing with the problem of Euclidean space, but the results of processing in non-Euclidean space are unsatisfactory. Related graph neural network methods have been developed, which can solve these problems very well. Graph neural networks usually model information as a graph structure and then extract relevant features. This idea can effectively extract the dependencies that exist between different individuals. Xue et al. (2021) extracted user features, propagation features, and text features by combining GAT and multimodal gating unit and proposed a multifeature rumor detection model; Lotfi et al. (2021) constructed a user graph and a tweet graph, captured user line features and tweet response relationship features through a graph convolutional neural network, and concatenated the two feature vectors and used a classifier to discriminate. Related methods based on graph neural networks extract high-order and abstract features by converting tweets or words into individual nodes and through node aggregation. Different from traditional deep learning methods, they lack the temporal expression between tweets.

Among the existing research methods of rumors, most people have begun to study temporal features. As the graph neural network has only ushered in a development climax in recent years, the research methods of centralized temporal features are mainly distributed in the traditional deep learning method, and there are few studies on the temporal features of sibling nodes. Typically, within the same hierarchy, tweets posted first have some influence on tweets posted later. There is no perfect solution for fully expressing the relationship between sibling nodes and effectively extracting the temporal features of the event life cycle.

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