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Prediction of Rumor Diffusion in Social Network Using Game Model

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ABSTRACT

The spread of a rumor's information happens more quickly than ever before because to the bridge that billions of mobile phones provide between mobile sensor networks and social networks. Because of this, rumor dispersion becomes a significant problem in those two networks, and understanding how to predict it is crucial when dealing rumors that initially have only a minor influence. Modern diffusion models, however, neglect the microcosmic individual impact in favor of the macroscopic group impact. Since there is only one rumor spreader at the start of rumor diffusion, they are not appropriate to perform rumor diffusion prediction. We suggest a unique game theory-based model dubbed the Equal Responsibility Rumor spreading Game Model (ERRDGM) to simulate the rumor spreading process in order to address that issue and predicate it. In this model, we first show the diffusion process as a game between people and their neighbours who decide whether to retweet or not based on their game revenues; second, the players will split the responsibility of spreading a rumor in calculating their game revenues; and finally, when the game reaches the Nash equilibrium state, we build the rumor diffusion prediction graph which shows the diffusion scale and network structure of rumor diffusion in a system.

Keywords: Social Networks, Rumor Diffusion, Game Theory Model, Nash Equilibrium State.

1. INTRODUCTION

Millions of mobile phones were utilised to spread information more quickly in the present information culture. Mobile phones, one type of sensor in a sensor network, provide a sizable sensor network that transmits information as well as a virtual social network. A social network is described as a social structure in Wikipedia that consists of a group of social players (such as people or organisations), groups of dyadic links, and other social interactions amongst the actors. Rumors were disseminated one by one across the social links in a social network based on the complex social network structure. According to Peterson and Gist, a rumor is a wild story with unsubstantiated details about an event that is spread from person to person and is of interest to the general public. All rumors in our investigation were marked by humans, indicating that they had all been verified by authorities. To make rumor analysis more straightforward, we assume that all rumors are appropriately tagged and that authorities can be trusted, even though they occasionally err and incorrectly label a message as a rumor [1]-[3]. Although the sensor network and the social network have different network structures and functions from the perspective of rumor diffusion, they work closely together in this area (the sensor network handles rumor content transmission and the social network handles the impact of rumor semantic diffusion). Therefore, rumors spread more quickly than ever thanks to mobile phones in both sensor networks and social networks, making it one of the major issues with social media. According to Vosoughiet al. [3], misleading information on Twitter spread more quickly, deeply, widely, and quickly than any other information that was true. 3 million participants in their experiment shared roughly 126,000 stories between 2006 and 2017.

In spite of the fact that the experiment's authors were unable to demonstrate whether rumors spread more quickly than breaking news, they did discover that false information was more novel than accurate information and that people were more eager to share novel information. According to the SoroushVosoughi's conclusion, rumors will challenge the outdated rumor analysis techniques and have a significant impact on both actual society and virtual social networks. Weibo, the largest Micro blog in China, was found to be the source of 59% of rumors in 2015, according to the New Media Blue Book [4] published by the Chinese Academy of Social Science (Figure 1). Weibo in China turns as a hub for rumors due to its unrestricted access and massive user base.

Since there is only one rumor spreader at the start of rumor diffusion, they are not appropriate to perform rumor diffusion prediction. Dissemination of rumors differs from that of shocking news. When a rumor is identified, users concentrate on whether it is true or false. Users will pay attention to the subject and their feelings in the case of shocking news, in contrast. In this method, the majority of people will spread frightening news multiple times in various sentiments and subtopics rather than a rumor. Because the majority of users would share some postings that can increase their influence in a social network, the diffusion process of users' focus is comparable to a game process. Determining the diffusion lattice, diffusion scale, and diffusion network topology, we attempt to represent the rumor diffusion process as an individual game process in this research. To make the game model more straightforward, we make the assumption that there is no topic excursion problem, meaning that we ignore the diffusion content and its changes. Instead, we model social individual behaviour based on his or her revenue and risk, which are calculated using the Equal Responsibility assumption in rumor diffusion.

2. LITERATURE SURVEY

In this section we will discuss about several other articles which are discussed by different authors about rumor diffusion model.

1. Developing Simplified Chinese Psychological Linguistic Analysis Dictionary for Micro blog

The words that people use could reveal their emotional states, intentions, thinking styles, individual differences, etc. LIWC (Linguistic Inquiry and Word Count) has been widely used for psychological text analysis, and its dictionary is the core. The Traditional Chinese version of LIWC dictionary has been released, which is a translation of LIWC English dictionary. However, Simplified Chinese which is the world's most widely used language has subtle differences with Traditional Chinese. Furthermore, both English LIWC dictionary and Traditional Chinese version dictionary were both developed for relatively formal text. Micro blog has become more and more popular in China nowadays. Original LIWC dictionaries take less consideration on micro blog popular words, which makes it less applicable for text analysis on micro blog. In this study, a Simplified Chinese LIWC dictionary is established according to LIWC categories. After translating Traditional Chinese dictionary into Simplified Chinese, five thousand words most frequently used in micro blog are added into the dictionary. Four graduate students of psychology rated whether each word be-longed in a category. The reliability and validity of Simplified Chinese LIWC dictionary were tested by these four judges. This new dictionary could contribute to all the text analysis on micro blog in future.

Disadvantages

1. Can analyze only Single behavior tweets
2. There is no option to tweet based on user emotions

2. Learning robust uniform features for cross-media social data by using cross autoencoders

Cross-media analysis exploits social data with different modalities from multiple sources simultaneously and synergistically to discover knowledge and better understand the world. There are two levels of cross- media social data. One is the element , which is made up of text, images, voice, or any combinations of modalities. Elements from the same data source can have different modalities. The other level of cross- media social data is the new notion of aggregative subject (AS)—a collection of time-series social elements sharing the same semantics (i.e. , a collection of tweets, photos, blogs, and news of emergency events). While traditional feature learning methods focus on dealing with single modality data or data fused across multiple modalities, in this study, we systematically analyze the problem of feature learning for cross-media social data at the previously mentioned two levels. The general purpose is to obtain a robust and uniform representation from the social data in time-series and across different modalities. We propose a novel unsupervised method for cross-modality element-level feature learning called cross auto encoder (CAE). CAE can capture the cross-modality correlations in element samples. Furthermore, we extend it to the AS using the convolutional neural network (CNN), namely convolutional cross au- to encoder (CCAE). We use CAEs as filters in the CCAE to handle cross-modality elements and the CNN framework to handle the time sequence and reduce the impact of outliers in AS. We finally apply the proposed method to classification tasks to evaluate the quality of the generated representations against several real-world social media datasets. In terms of accuracy, CAE gets 7.33% and 14.31% overall incremental rates on two element-level datasets. CCAE gets 11.2% and 60.5% overall incremental rates on two AS-level datasets. Experimental results show that the proposed CAE and CCAE work well with all tested classifiers and perform better than several other baseline feature learning methods.

Disadvantages

1. There is only Feature engineering technique which fails to detect the different type of stress.
2. There is no Support vector classification technique to categorize the different type of user emotions.

3. PSYCHOLOGICAL STRESS DETECTION FROM CROSS-MEDIA MICROBLOG DATA USING DEEP SPARSE NEURAL NETWORK

Long-term stress may lead to many severe physical and mental problems. Traditional psychological stress detection usually relies on the active individual participation, which makes the detection labor-consuming, time-costing and hysteretic. With the rapid development of social networks, people become more and more willing to share moods via micro blog platforms. In this paper, we propose an automatic stress detection method from cross-media micro blog data. We construct a three-level framework to formulate the problem. We first obtain a set of low-level features from the tweets. Then we define and extract middle-level representations based on psychological and art theories: linguistic attributes from tweets' texts, visual attributes from tweets' images, and social attributes from tweets' comments, retweets and favorites. Finally, a Deep Sparse Neural Network is designed to learn the stress categories' incorporating the cross-media attributes. Experiment results show that the proposed method is effective and efficient on detecting psychological stress from micro blog data.

Disadvantages

1. There is only Low level Semantics in detecting Stress.
2. There is no Option to analyze the stress based on Stress Category.

3. EXISTING SYSTEM

As they attempt to determine the rumor based on the conversation that is posted by others, all social media platforms, including Twitter, are currently unable to distinguish between rumor-related tweets and regular tweets separately. Additionally, they are unable to automatically determine which tweets are rumors and which are regular from the many tweets that are posted by OSN users.

Limitations of Existing System

The following are the limitation of existing system. They is as follows:

1. There isn't a single technique that can distinguish between tweets about rumors and tweets that aren't about rumors.

2. There is no system in place to precisely classify and separate the tweets.

3. Every system now in use tries to categorise tweets using a human process.

4. There isn't a technique like NLP, which is utilised in Twitter, to separate out rumors from messages that are just linked.

4. PROPOSED SYSTEM

The proposed system created a model that describes the diffusion lattice, diffusion scale, and diffusion network structure and treats the spread of rumors as an individual game process. To make the game model more straightforward, we make the assumption that there is no topic excursion problem, meaning that we ignore the diffusion content and its changes. Instead, we model social individual behaviour based on his or her revenue and risk, which are calculated using the Equal Responsibility assumption in rumor diffusion.

Advantages of the Proposed System

The suggested system has the advantages listed below. These are what they are:

1. It may analyse a large amount of twitter data at once.

2. A user can tweet rumors and those rumors can be quickly discovered.

3. It can distinguish between tweets that are related to rumors and tweets that aren't related to rumors with accuracy and ease.

5. SOFTWARE PROJECT MODULES

The front end of the application takes JSP,HTML and Java Beans and as a Back-End Data base we took My-SQL Server. The application is divided mainly into following 2 modules. They are as follows:

1. Admin Module

2. User Module

Now let us discuss about each and every module in detail as follows:

1) ADMIN MODULE

The administrator must log in to this module using a valid user name and password. Once logged in successfully, he can perform certain tasks, including View all authorized End Users, View every friend request and comment Add a category for tweets like "Stressed," "Negative," etc.Choose the category for your tweets, choose a filter, and then list them all below. List all micro blog posts from users on Twitter, View Tweets With Positive (+) Emotions, Tweets With Negative (-) Emotions, View Twitter's Stress & Emotions, View all tweets and count the positive, negative, and stressed-out tweets. List of past searches, Find the number of positive, negative, or stressed tweets in the graph.

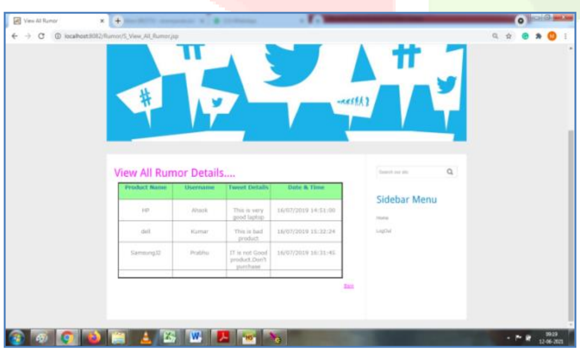
2) USER MODULE

There are n numbers of users present in this module. Before doing any operations, the user should register. Once a user registers, the database will record their information. After successfully registering, he must log in with an authorized user name and password. The user can perform some actions after successful login, such as seeing their profile, searching for friends, and requesting friends. Observe all of Your Friends Create a tweet using the following fields: name, description, image, and time. View all of your published Tweets to identify positive, negative Add emotional content to your Tweets, View all of your friends' tweets and retweet them by adding a comment or your feelings.

6. EXPERIMENTAL REPORTS

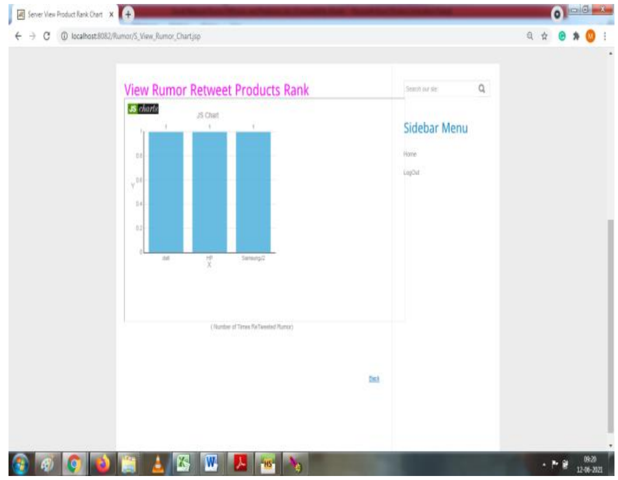
Here we try to implement the current application using JSP,HTML and CSS as front end technologies and as a back end we use My-SQL server as database.As our application contains two modules admin and user, we wish to show the implementation of the two modules under Social Network platform and then clearly explain the implementation of rumor diffusion based on user tweets.

Admin View the Rumor Details:



From the above window we can clearly see admin views the list of rumor details which are posted on User wall.

Admin can see Rumor Tweets Rank Chart



From the above window we can clearly see admin views the list of rumor details in chart manner.

7. CONCLUSION

Because of the intricate social network structures and unique diffusion motives, rumor prediction is a difficult task. We use game theory to model the diffusion revenue and present an ERRDGM model, which is based on the presumption that the spreaders will share the duty of dispersing a rumor, in order to mimic the rumor diffusion process at the first stage of rumor diffusion. The findings of the experiment demonstrate that our model is capable of simulating the spread of rumors through social networks, and the simulated outcomes are consistent with actual diffusion networks. However, the attribute of the individual is not taken into account in our approach. As a result, in our future work, we'll employ user posts to create user profiles that will enable us to carefully evaluate the reasons why a person might dispel a rumor. In the future, we aim to be able to automatically identify rumors based on the messages that users choose to send and attempt to remove those social rumor users from the pool of all OSN users.

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