DETECTING STRESS BASED ON SOCIAL INTERACTIONS IN SOCIAL NETWORKS

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ABSTRACT

Psychological stress is threatening people's health. It is non-trivial to detect stress timely for proactive care. With the popularity of social media, people are used to sharing their daily activities and interacting with friends on social media platforms, making it feasible to leverage online social network data for stress detection. In this paper, we find that users stress state is closely related to that of his/her friends in social media, and we employ a large-scale dataset from real-world social platforms to systematically study the correlation of users' stress states and social interactions. We first define a set of stress-related textual, visual, and social attributes from various aspects, and then propose a novel hybrid model-a factor graph model combined with Convolutional Neural Network to leverage tweet content and social interaction information for stress detection. Experimental results show that the proposed model can improve the detection performance by 6-9% in F1-score. By further analyzing the social interaction data, we also discover several intriguing phenomena, i.e. the number of social structures of sparse connections (i.e. with no delta connections) of stressed users is around 14% higher than that of non-stressed users, indicating that the social structure of stressed users' friends tend to be less connected and less complicated than that of non-stressed users.

INTRODUCTION

Data mining, or knowledge discovery, is the computer-assisted process of digging through and analyzing enormous sets of data and then extracting the meaning of the data. Data mining tools predict behaviors and future trends, allowing businesses to make proactive, knowledge-driven decisions. Data mining tools can answer business questions that traditionally were too time consuming to resolve. They scour databases for hidden patterns, finding predictive information that experts may miss because it lies outside their expectations. Generally, data mining (sometimes called data or knowledge discovery) is the process of analyzing data from different perspectives and summarizing it into useful information - information that can be used to increase revenue, cuts costs, or both. Data mining software is one of a number of analytical tools for analyzing data. It allows users to analyze data from many different dimensions or angles, categorize it, and summarize the relationships identified. Technically, data mining is the process of finding correlations or patterns among dozens of fields in large relational databases. Although data mining is a relatively new term, the technology is not. Companies have used powerful computers to sift through volumes of supermarket scanner data and analyze market research reports for years. However, continuous innovations in computer processing power, disk storage, and statistical software are dramatically increasing the accuracy of analysis while driving down the cost.

Although data mining is still in its infancy, companies in a wide range of industries - including retail, finance, health care, manufacturing transportation, and aerospace - are already using data mining tools and techniques to take advantage of historical data. By using pattern recognition technologies and statistical and mathematical techniques to sift through warehoused information, data mining helps analysts recognize significant facts, relationships, trends, patterns, exceptions and anomalies that might otherwise go unnoticed.

For businesses, data mining is used to discover patterns and relationships in the data in order to help make better business decisions. Data mining can help spot sales trends, develop smarter marketing campaigns, and accurately predict customer loyalty. Specific uses of data mining include:

RELATED WORK

Psychological stress detection is related to the topics of sentiment analysis and emotion detection. Research on tweet-level emotion detection in social networks. Computer-aided detection, analysis, and application of emotion, especially in social networks, have drawn much attention in recent years. Relationships between psychological stress and personality traits can be an interesting issue to consider providing evidence that daily stress can be reliably recognized based on behavioral metrics from users mobile phone activity. Many studies on social media based emotion analysis are at the tweet level, using text-based linguistic features and classic classification approaches. proposed a system called Mood Lens to perform emotion analysis on the Chinese micro-blog platform Weibo, classifying the emotion categories into four types, angry, disgusting, joyful, and sad. studied the emotion propagation problem in social networks, and found that anger has a stronger correlation among different users than joy, indicating that negative emotions could spread more quickly and broadly in the network. As stress is mostly considered as a negative emotion, this conclusion can help us in combining the social influence of users for stress detection. However, these work mainly leverage the textual contents in social networks. In reality, data in social networks is usually composed of sequential and inter-connected items from diverse sources and modalities, making it be actually cross-media data. Research on user-level emotion detection in social networks.

While tweet-level emotion detection reflects the instant emotion expressed in a single tweet, people's emotion or psychological stress states are usually more enduring, changing over different time periods. In recent years, extensive research starts to focus on user-level emotion detection in social networks. Our recent work proposed to detect users psychological stress states from social media by learning user-level presentation via a deep convolution network on sequential tweet series in a certain time period. Motivated by the principle of homophily,]incorporated social relationships to improve user-level sentiment analysis in Twitter. Though some user level emotion detection studies have been done, the role that social relationships plays in one's psychological stress states, and how we can incorporate such information into stress detection have not been examined yet.

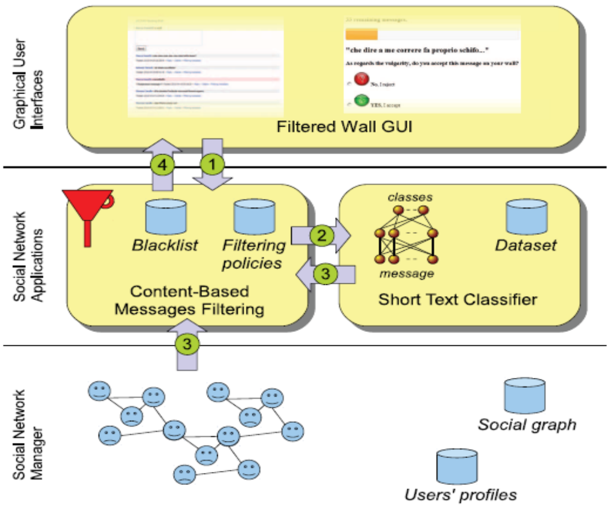
PROPOSED SYSTEM:

We extend the proposed algorithm which analysis the student's learning experiences by giving solutions to their problems. The suggested solution is forwarded to the student's individual email-ids to attain the privacy of student and for improving security a novel secure algorithm called BIRCH is proposed. Finally we get the feedback from the students about solution provided and comparison graph is generated

ADVANTAGES

- It is local in that each clustering decision is made without scanning all data points and currently existing clusters.
- It exploits the observation that data space is not usually uniformly occupied and not every data point is equally important.
- It makes full use of available memory to derive the finest possible sub-clusters while minimizing I/O costs.
- It is also an incremental method that does not require the whole data set in advance.

SYSTEM MODEL



Filtered wall GUI

CONCLUSION

Our study is beneficial to researchers in learning analytics, educational data mining, and learning technologies. It provides a workflow for analyzing social media data for educational purposes that overcomes the major limitations of both manual qualitative analysis and large scale computational analysis of user-generated textual content. Our study can inform educational administrators, practitioners and other relevant decision makers to gain further understanding of engineering students' college experiences.

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