Detecting Stress Based on Social Interaction in Social Network

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Abstract

Psychological stress is becoming a threat to people's health now a day. Psychological stress refers to the emotional and physiological reactions experienced when an individual confronts a situation in which, the demands go beyond their coping resources (e.g. financial crisis). According to a worldwide survey reported by new business in 2010, over half of the population has experienced an appreciable rise in stress over the last years. In this paper a framework is designed for detecting users 'psychological stress states from users' weekly social media data, leveraging tweets' content as well as users' social interactions. In this system firstly a set of stress-related textual, visual, and social attributes from various aspects is defined, and then a novel hybrid model is proposed - a factor graph model combined with Convolution Neural Network to leverage tweet content and social interaction information for stress detection. The proposed system is efficient to detect user psychological stress.

Keywords: Psychological Stress, Social media, Tweets.

1. Introduction

Now a days the number of mobile phone users are increased rapidly, which effects the human life and causes Psychological stress. It is non-trivial to detect stress timely for proactive care. With the rapid pace of life, more and more people are suffering from stress. Though stress itself is non-clinical and common in our life, excessive and chronic stress can be rather harmful to people's physical and mental health. In recent past, we can use social media data to study mental health, where the data can provide a fair and equal collection of a person's language and behavior, which is helpful to diagnose the condition. Whereas social media provides huge data to find the types of Public health conditions, mental health studies still face serious challenges. To overcome these problem our objective is to 1) detect stress on social networks. 2) detect which user are stressed state based on tweets. 3) develop a mechanism for experimental results that shows the effectiveness of a proposed system.

The process of analyzing data from different perspectives and summarizing it into useful information, which can be used to increase revenue, cuts costs or both is called as data mining. It is used 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.

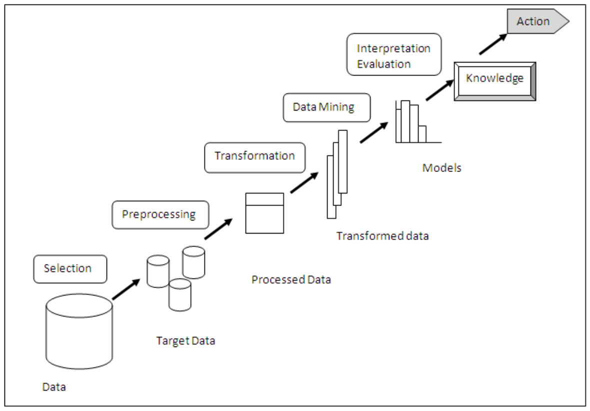

Figure 1. Structure of Data Mining

Data Mining: Data mining consists of five major elements 1) Extract, transform, and load transaction data onto the data warehouse system. 2) Store and manage the data in a multidimensional database system. 3) Provide data access to analysts. 4) Analyze the data by application software. 5) Present the data in a useful format, such as a graph or table

Characteristics of Data Mining:

- *Large quantities of data*: The volume of data so great it has to be analyzed by automated techniques e.g. satellite information, credit card transactions etc.
- *Noisy, incomplete data*: Imprecise data is the characteristic of all data collection.
- *Complex data structure*: conventional statistical analysis not possible
- *Heterogeneous data stored in legacy systems*

Existing System:

As when we see the existing system many studies on social media based emotion analysis are at the tweet level, using text-based linguistic features and classic classification approaches. A system called Mood Lens to perform emotion analysis on the Chinese micro-blog platform Weibo, classifying the emotion categories into four types, i.e., angry, disgusting, joyful, and sad. An existing system studies 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.

Disadvantages of Existing System:

Traditional psychological stress detection is mainly based on face to face interviews, self report questionnaire or wearable sensors. However, traditional methods are actually reactive, which are usually labor consuming, time costing and hysteretic.

2. Related Work

Andrey Bogomolov, Bruno Lepri [1] has proven that stress affects the quality of life and it may cause many diseases. Due to this reason, various researchers introduced stress detection systems based on physiological parameters. However, for such systems it requires sensors which needed to be carried out by the user. Further the system describes an alternative approach with daily stress recognition from mobile phone data, weather conditions and individual traits. It can be reliably recognized based on behavioral metrics, derived from the user's activities on mobiles and social media, such as the weather conditions (data pertaining to transitory properties of the environment) and the characteristics of person (data concerning permanent dispositions of individuals). The system describes Multifactorial statistical model, which is person-independent, obtains the accuracy score of 72.28% for a 2-class daily stress recognition problem. The model is efficient to implement for most of multimedia applications due to highly reduced low-dimensional feature space. Moreover, the system identifies and discusses the indicators which have strong predictive power.

Glen Coppersmith, Craig Harman, and Mark Dredze [2] presented a novel method to obtain a PTSD classifier for social media using simple searches of available Twitter data, a significant reduction in training data cost compared to previous work. This method demonstrate its utility by examining differences in language use between PTSD and random individuals, building classifiers to separate these two groups and by detecting elevated rates of PTSD at and around U.S. military bases using our classifiers.

Fan, Jichang Zhao, Yan Chen, and KeXu [3] have described that, Weibo a Twitter-like service, has attracted more than 500 million users in less than five years in China. With the help of online social sites the different users might share similar affective states. The correlation of anger among users is significantly higher than that of joy can be identified easily. While the correlation of sadness is surprisingly low. Moreover, there is a stronger sentiment correlation between a pair of users if they share more interactions. And users with larger number of friends possess more significant sentiment correlation with their neighborhoods. The findings could provide insights for modeling sentiment influence and propagation in online social networks.

Golnoosh Farnadi, Geetha Sitaraman, [4] have proposed a comparative analysis of state-of-the-art computational personality recognition methods on a different set of social media data from Facebook, Twitter and YouTube. The differences between univariate and multivariate models were not significant though. Overall the best performing models for this task are the multi-target stacking corrected (MTSC) model and the ensemble of regressor chains corrected (ERCC) model by using a decision tree as a 0base learner utilized different content-based features (e.g., linguistic features such as LIWC) and context-based features (e.g., audio and video features extracted from vlog videos) in each dataset, and collected the common correlated features with traits among three datasets. From 166 common features for five characteristics, only 15 common correlations were found. These results suggested that it may not be possible to generalize the correlation between features and the personality traits, as it may vary depending on the underlying data. And conducted six cross-media learning experiments in which Expanding a model with training examples from another source has not improved the performance of the learner.

3. Methodology

This paper describes psychological theories firstly define a set of attributes for stress detection from tweet-level and user-level aspects respectively: 1) tweet-level attributes from content of user's single tweet, and 2) user-level attributes from user's weekly tweets. The tweet-level attributes are mainly composed of linguistic, visual, and social attention (i.e., being liked, retweeted, or commented) attributes extracted from a single-tweet's text, image, and attention list. The user-level attributes however are composed of: (a) posting behavior attributes as summarized from a user's weekly tweet postings; and (b) social interaction attributes extracted from a user's social interactions with friends. In particular, the social interaction attributes can further be broken into: (i) social interaction content attributes extracted from the content of users' social interactions with friends; and (ii) social interaction structure attributes extracted from the structures of users' social interactions with friends.

Further this paper presents a module concerned with detecting stress using social media data which is developed using water fall model. This is the legacy model for software development projects. In this model, development lifecycle has fixed phases and linear timelines. The whole process of software development is divided into separate phases. In this Waterfall model, typically, the outcome of one phase acts as the input for the next phase sequentially.

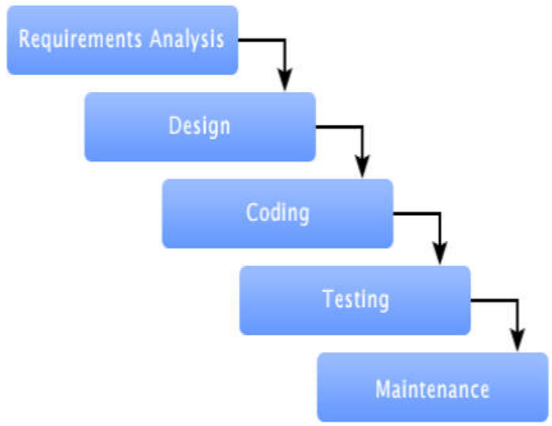

Figure 2. Waterfall Model

The sequential phases in Waterfall model are:
Requirement Gathering and analysis − All possible requirements are captured in this phase using social media like tweet messages and documented in a requirement specification document.

System Design − the requirement specifications from first phase are studied in this phase and the system design is prepared. This system design helps in specifying hardware and system requirements and helps in defining the overall system architecture.

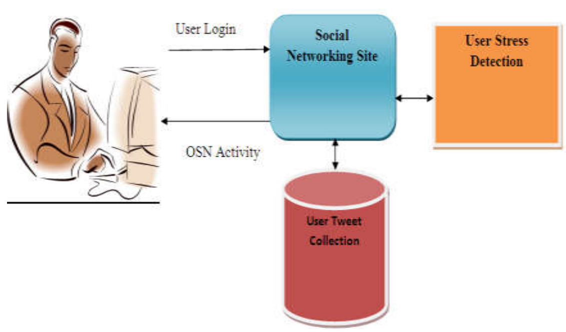

Figure 3. System Architecture

Modules Description

- System Framework
- Social Interactions
- Attributes categorization
- Tweet-level Attributes
- User-Level Attributes

System Framework: In this framework we propose a novel hybrid model - a factor graph model combined with Convolution Neural Network to leverage tweet content and social interaction information for stress detection.
Social Interactions: We analyze the correlation of users' stress states and their social interactions on the networks, and address the problem.
Attributes categorization: We first define two sets of attributes to measure the differences of the stressed and non-stressed users on social media platforms: 1) tweet-level attributes from a user's single tweet; 2) user level attributes summarized from a user's weekly tweets.
Tweet-level Attributes: Tweet-level attributes describe the linguistic and visual content, as well as social attention factors (being liked, commented, and retweeted) of a single tweet. We can classify words into different categories, e.g. positive/negative emotion words, degree adverbs. Twitter adopts Unicode as the representation for all emojis, which can be extracted directly.
User-Level Attributes: Compared to tweet-level attributes extracted from a single tweet, user-level attributes are extracted from a list of user's tweets in a specific sampling period. We use one week as the sampling period in this paper.

4. Results and Discussion

A. User need to create account with details for logging in to the system using registration page. Once user logged in to the site user can get tweet home page.
B. After logged in user can create new tweet and can upload a photos into the tweet site.
C. Admin can view the user details using administrative privileges.
D. Admin can view the stress level of users. Also can get the percentagewise graphical view of user stress status.
E. The admin can view the overall stress levels of all users with level of percentage.

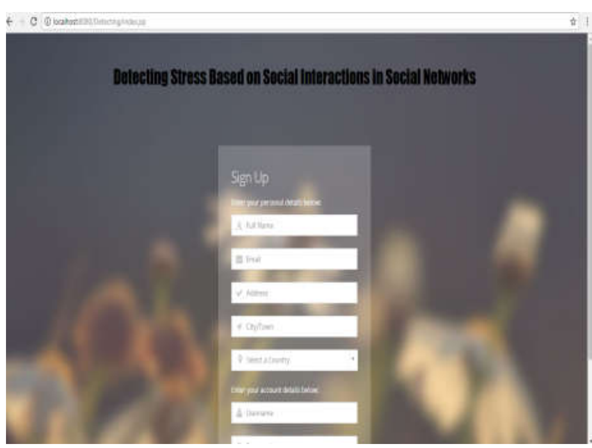

Figure 4. User Registration

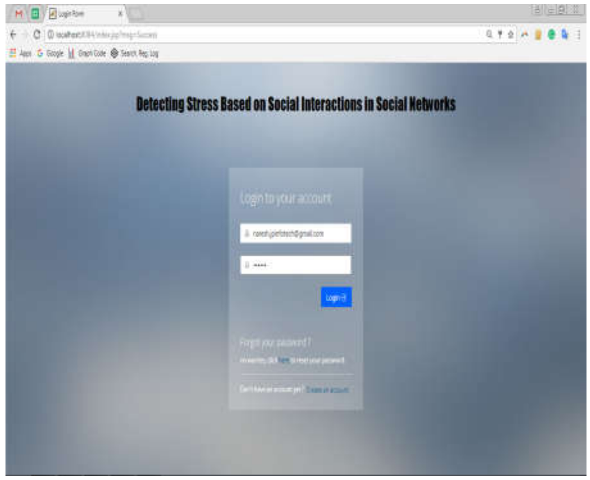

Figure 5. User Login

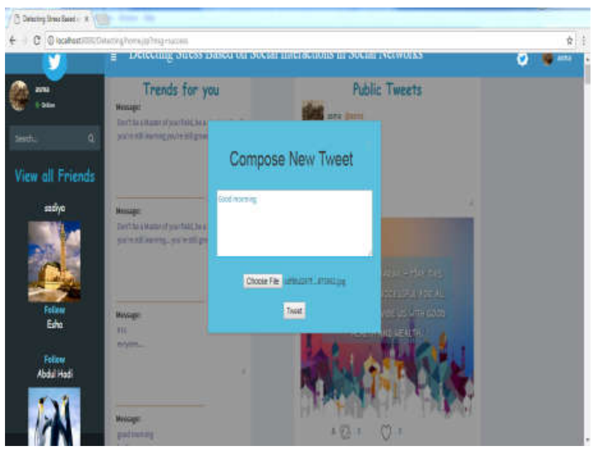

Figure 6. Compose new tweet

Figure 7. User Details

Figure 8. User Stress state

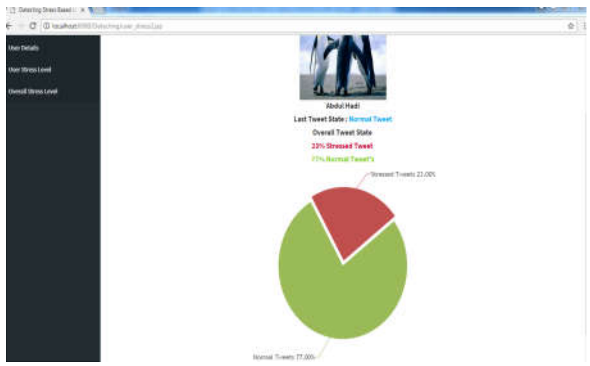

Figure 9. Particular User Stress State

Figure 10.Overall Stress Level of all User

5. Conclusion

In this paper a framework is presented for detecting users 'psychological stress states from users' weekly social media data, leveraging tweets' content as well as users' social interactions. Employing real-world social media data as the basis, and the correlation between user' psychological stress states and their social interaction behaviors is studied. To fully leverage both content and social interaction information of users' tweets, a hybrid model is proposed which combines the factor graph model (FGM) with a convolution neural network (CNN). In this work, we also discovered several intriguing phenomena of stress and the number of social structures of sparse connection (i.e. with no delta connections)of stressed users is around 14% higher than that of non-stressed users is found , indicating that the social structure of stressed users' friends tend to be less connected and less complicated than that of non-stressed users. These phenomena could be useful references for future related studies.

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