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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 can predict 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:

Problem Statement Beyond user's tweeting contents, the system analyzes the correlation of users' stress states and their social interactions on the networks, and address the problem from the standpoints of: [1]. Social interaction content, by investigating the content differences between stressed and non- stressed users' social interactions. [2].Social interaction structure, by investigating the structure differences in terms of structural diversity, social influence, and strong/weak tie.

OBJECTIVE:

The objective of the system is in defining a set of attributes for stress detection from tweet-level and user-level aspects respectively:

• Tweet-level attributes from content of user's single tweet.

• 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, re tweeted, or commented) attributes extracted from a single-tweet's text, image, and attention list. The user-level attributes however are composed of:

[1]. posting behavior attributes as summarized from a user's weekly tweet posting.

[2]. social interaction attributes extracted from a user's social interactions with friends.

Implementation:of Learning robust uniform features for cross-media social data by using cross autoencoders As we formulate the problems at two levels, the element level, and the AS level, we address the feature learning problem for social data. In the first problem, we must deal with cross-media social elements. Cross-modality means that social media elements always contain more than one modality; however, the representations are often non- uniform due to heterogeneous modalities and missing modalities. We propose cross autoencoders (CAEs) to learn invariant cross-modality features based on the formulation of autoencoders. In the second problem, we learn uniform features for AS, addressing three challenges: time series, cross- modality, and outliers. To this end, we propose a convolutional cross autoencoder (CCAE) method. In this method, we employ a CNN framework to manage time series data and avoid outliers. Moreover, we propose to use CAEs as filters in CNN for modality-invariant representation. The goal of the CCAE is different from models for low-level independent multimedia data, e.g., denoising autoencoder , the bimodal deep belief network, and CAE. CCAE focuses on learning high- level features for AS.

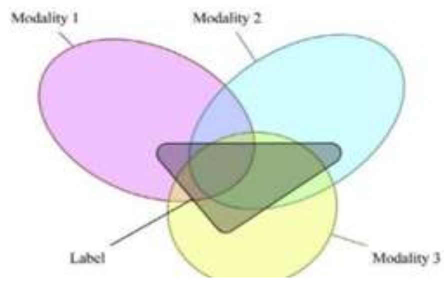

Fig. 1 Data distribution of different modalities and availability of label

	Single modality	Cross-modality
Textual	52.27%	**52.75%**
Social	51.20%	**51.68%**
Visual	78.57%	**79.58%**

Table 1 Comparison of classification accuracy between baseline and proposed AT in Weibo–Stress dataset

To evaluate the quality of the proposed learning algorithm, we conduct experiments with classification tasks using

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real-world datasets from social media websites: Weibo,Sougo, and Flickr. We present experimental results for social elements using CAE and for social AS using CCAE. 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. Results indicate that CAE learns cross-modality correlation from cross-media social data. Further, supervised tasks using features from CAE show significant improvement as compared with baselines, and the experiments for AS show CCAE has superior performance for feature learning.

PROPOSED SYSTEM :

Objectives of Proposed Model Finding stress based on social media is achieved by following objectives:

1. Extract twitter live stream for different users.
2. Use AFINN kind of dictionary words for identifying scores of stress-based words
3. Compare the different user scores using graph.

Algorithms used for Proposed Model

Logistic Regression (LRC):

It trains a logistic regression classification model and then predicts users' labels in the test set. In short, the logistic regression model computes a sum of the input features (in most cases, there is a bias term), and calculates the logistic of the result. Therefore, the outcome must be a categorical or discrete value. It can be either Yes or No, 0 or 1, true or False, etc. but instead of giving the exact value as 0 and 1, it gives the probabilistic values which lie between 0 and 1. The logistic regression algorithm works by estimating the coefficients of the predictor variables in the logistic function. These coefficients are then used to calculate the log odds of the binary response variable, which are then transformed back into probabilities using the logistic function. The logistic regression algorithm is commonly used in various fields, such as healthcare, finance, and marketing, for predicting outcomes such as disease diagnosis, credit risk, and customer behavior. It is also commonly used as a baseline model for more complex classification algorithms

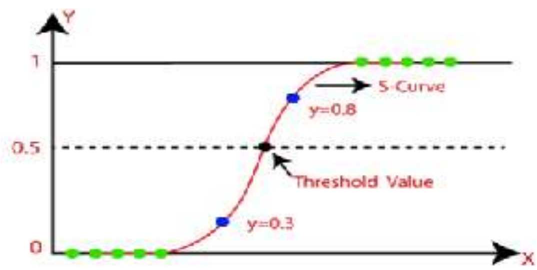

Fig 2 Logistic Regression Graph

Support Vector Machine (SVM):

It is a popular and binary classifier that is proved to be effective on a huge category

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of classification problems. In our problem we use SVM with RBF kernel. The objective of the SVM algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points. The dimension of the hyperplane depends upon the number of features. If the number of input features is two, then the hyperplane is just a line. If the number of input features is three, then the hyperplane becomes a 2-D plane. It becomes difficult to imagine when the number of features exceeds three. Hence, the SVM algorithm helps to find the best line or decision boundary; this best boundary or region is called as a hyperplane. SVM algorithm finds the closest point of the lines from both the classes. These points are called support vectors. The distance between the vectors and the hyperplane is called as margin. And the goal of SVM is to maximize this margin. The hyperplane with maximum margin is called the optimal hyperplane.

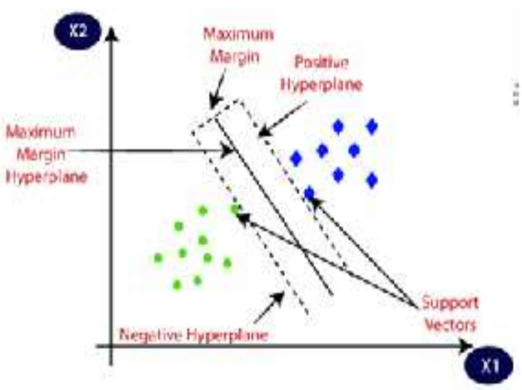

Fig 3 Support Vector Machine

RESULTS:

Comparison of Detection Performance: To evaluate the effectiveness of our model, we first conduct a test using different models based on the Weibo-Stress dataset. . In this experiment, we used all the three attributes described in previous section: user-level social interaction attributes, user-level posting behavior attributes and user-level content attributes generated from the tweet-level attributes by CNN+CAE.

Method	Acc.	Rec.	Prec.	F1	CPU time
LRC	76.18	87.94	78.58	83.00	39.43 s
SVM	72.58	87.39	75.16	80.82	≈10 min
RF	77.73	89.63	79.35	84.18	67.71 s
GBDT	79.75	82.99	85.90	84.43	262.86 s
FGM	91.55	96.56	90.44	93.40	≈20 min

Table 2 Comparison of Efficiency and Effectiveness Using Different Models (%)

Factor Contribution Analysis: The definition of factors is important to the performance of the Factor Graph Model. We have three types of factors in our model, i.e., attribute factor, social factor, and dynamic factor. To analyze the impact of different factors in our model, we compare the detection performance with different combinations of factors.

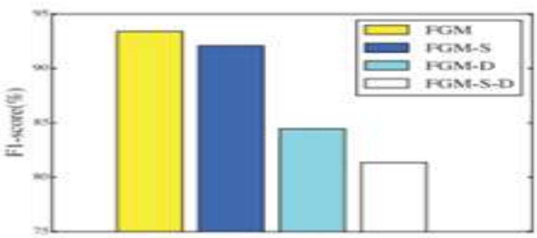

Fig 4 Factor Contribution

CONCLUSION:

In this project, we presented a framework 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, we studied the correlation between user' psychological stress states and their social interaction behaviors. To fully leverage both content and social interaction information of users' tweets, we proposed a hybrid model which combines the factor graph model (FGM) with a convolutional neural network (CNN). In this work, we also discovered several intriguing phenomena of stress. We found that the number of social structures of sparse connection (i.e., with no delta connections) of stressed users is around 14 percent 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. These phenomena could be useful references for future related studies.

FUTURE ENHANCEMENT

The future scope of the project is to develop a system that not only detecting the stress and able to analyze people mind means that it will play as a survey system. So that it may provide a better solution on behalf of people of the society for every debatable concept and also it will indirectly play an important role in political, government and also social media. So we may efficiently analyze stress and also find solution to every social issue by means of polling and analyzing comments.

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