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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 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.*

1. Introduction

Psychological stress is becoming a threat to people's health nowadays. With the rapid pace of life, more and more people are feeling stressed. According to a worldwide survey reported by New business, over half of the population has experienced an appreciable rise in stress over the last two years. 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. According to existing research works, long-term stress has been found to be related to many diseases, e.g., clinical depressions, insomnia etc.. Moreover, according to Chinese Center for Disease Control and Prevention, suicide has become the top cause of death among Chinese youth, and excessive stress is considered to be a major factor of suicide. All these reveal that the rapid increase of stress has become a great challenge to human health and life quality.

Thus, there is significant importance to detect stress before it turns into severe problems. Traditional psychological stress detection is mainly based on face-to face interviews, self-report questionnaires or wearable sensors. However, traditional methods are actually reactive, which are usually labor-consuming, time-costing and hysteretic. Are there any timely and proactive methods for stress detection? more and more people are willing to share their daily events and moods, and interact with friends through the social networks. As these social media data timely reflect users' real-life states and emotions in a timely manner, it offers new opportunities for representing, measuring, modeling, and mining users behavior patterns through the large-scale social networks, and such social information can find its theoretical basis in psychology research. For example, found that stressed users are more likely to be socially less active, and more recently, there have been research efforts on harnessing social media data for developing mental and physical healthcare tools. For example, proposed to leverage Twitter data for real-time disease surveillance; while tried to bridge the vocabulary gaps between health seekers and providers using the community generated health data. There are also some research works using user tweeting contents on social media platforms to detect users' psychological stress. Existing works demonstrated that leverage social media for healthcare, and in particular stress detection, is feasible.

Limitations exist in tweeting content based stress detection. Firstly, tweets are limited to a maximum of 140 characters on social platforms like Twitter and Sina Weibo, and users do not always express their stressful states directly in tweets. Secondly, users with high psychological stress may exhibit low activeness on social networks, as reported by a recent study in Pew Research Center3. These phenomena incur the inherent data sparsity and ambiguity problem, which may hurt the performance of tweeting content based stress detection performance. The tweet contains only 13 characters, saying that the user wished to go home for the Spring Festival holiday. Although no stress is revealed from the tweet itself, from the follow-up interactive comments made by the user and her friends, we can find that the user is actually stressed from work. Thus, simply relying on a user's tweeting content for stress detection is insufficient.

2. Literature Survey:

Daily stress recognition from mobile phone data, weather conditions and individual traits

In our paper, we propose an alternative approach providing evidence that daily stress can be reliably recognized based on behavioral metrics, derived from the user's mobile phone activity and from additional indicators, such as the weather conditions (data pertaining to transitory properties of the environment) and the personality traits (data concerning permanent dispositions of individuals). Our 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 (32d). Moreover, we identify and discuss the indicators which have strong predictive Power.

Semantic concept discovery for large-scale zero-shot event detection

We focus on detecting complex events in unconstrained Internet videos. While most existing works rely on the abundance of labeled training data, we consider a more difficult zero-shot setting where no training data is supplied. We first pre-train a number of concept classifiers using data from other sources. Then we evaluate the semantic correlation of each concept w.r.t. the event of interest. After further refinement to take prediction inaccuracy and discriminative power into account, we apply the discovered concept classifiers on all test videos and obtain multiple score vectors. These distinct score vectors are converted into pairwise comparison matrices and the nuclear norm rank aggregation framework is adopted to seek consensus. To address the challenging optimization formulation, we propose an efficient, highly scalable algorithm that is an order of magnitude faster than existing alternatives. Experiments on recent TRECVID datasets verify the superiority of the proposed approach.

Computational Personality Recognition in Social Media.

In this paper, we perform a comparative analysis of state-of-the-art computational personality recognition methods on a varied set of social media ground truth data from Face book, Twitter and YouTube. We answer three questions: (1) should personality prediction be treated as a multi-label prediction task (i.e., all personality traits of a given user are predicted at once), or should each trait be identified separately? (2) Which predictive features work well across different on-line environments? And (3) what is the decay in accuracy when porting models trained in one social media environment to another?

Social interaction via new social media: (how) can interactions on twitter affect effectual thinking and behavior?

Social interaction plays a central role in effectuation processes, yet we know little about the implications for effectuation when an entrepreneur interacts via particular channels such as social media. To address this gap, our paper uses an inductive, theory-building methodology to develop propositions regarding how effectuation processes are impacted when entrepreneurs adopt Twitter. Twitter is a micro blogging platform that can facilitate a marked increase in interaction. We posit that Twitter-based interaction can trigger effectual cognitions, but that high levels of interaction via this medium can lead to effectual churn. We also posit that there is one factor, perceived time affordability that predicts the level of social interaction in which an entrepreneur engages via Twitter. Further, we propose two factors that moderate the consequences of social interaction through Twitter. These factors are community orientation and community norm adherence. Implications for our understanding of effectuation, of social interaction, and of the impact of social media on entrepreneurial firms are discussed.

Real-time disease surveillance using twitter data: demonstration on flu and cancer.

In this paper, we describe a novel real-time flu and cancer surveillance system that uses spatial, temporal and text mining on Twitter data. The real-time analysis results are reported visually in terms of US disease surveillance maps, distribution and timelines of disease types, symptoms, and treatments, in addition to overall disease activity timelines on our project website. Our surveillance system can be very useful not only for early prediction of seasonal disease outbreaks such as flu, but also for monitoring distribution of cancer patients with different cancer types and symptoms in each state and the popularity of treatments used. The resulting insights are expected to help facilitate faster response to and preparation for epidemics and also be very useful for both patients and doctors to make more informed decisions.

User-level psychological stress detection from social media using deep neural network

We propose a deep neural network (DNN) model to incorporate the two types of user scope attributes to detect users' psychological stress. We test the trained model on four different datasets from major micro-blog platforms including Sina Weibo, Ten cent Weibo and Twitter. Experimental results show that the proposed model is effective and efficient on detecting psychological stress from micro-blog data. We believe our model would be useful in developing stress detection tools for mental health agencies and individuals.

3. System Analysis:

3.1 Existing System

- Rapid increase of stress has become a great challenge to human health and life quality. Thus, there is significant importance to detect stress before it turns into severe problems. Traditional psychological
- Stress detection is mainly based on face-to face interviews, self-report questionnaires

- There are also some research works, using user tweeting contents on social media platforms to detect users’ psychological stress. Existing works, demonstrated that leverage social media for healthcare, and in particular stress detection, is feasible.

- Users' social interactions on social networks contain useful cues for stress detection.

3.1.1 Disadvantages

- There are no timely and proactive methods for stress detection.

- Firstly, tweets are limited to a maximum of 140 characters on social platforms like Twitter and SinaWeibo, and users do not always express their stressful states directly in tweets.

- Users with high psychological stress may exhibit low activeness on social networks, as reported by a recent study.

- These phenomena incur the inherent data sparsity and ambiguity problem, which may hurt the performance of tweeting content based stress detection performance.

3.2 Proposed System

- Inspired by psychological theories, we first 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.

- Here, we define user-level attributes from two aspects to measure the differences between stressed and non-stressed states based on users' weekly tweet postings: 1) *user-level posting behavior attributes* from the user's weekly tweet postings; and 2) *user-level social interaction attributes* from the user's social interactions beneath his/her weekly tweet postings.

3.2.1 ADVANTAGES

- 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.

- We proposed a hybrid model which combines the factor graph model (FGM) with a convolutional neural network (CNN).

Modules:

1. OSN System Construction Module.
2. Design CN Module:
3. User level tweet calculation:

4. User level social Interaction calculation:
5. User level statistics Attributes calculation:
6. Risk calculation Module:

MODULES DESCSRIPTION:

ADMIN:

The attributes of tweets, which come from a user's weekly tweets in timeline, form a time series. To model a user as a subject of series of tweets, we apply CNN which has large learning capacity, but has much fewer connections and parameters to learn than similar-size standard network layers.

USER LEVEL CONTENT CALCULATION:

- User-level content attributes from a series of individual tweets in a time series to describe a user's stress state over a week.

USER LEVEL SOCIAL INTERACTION CALCULATION:

- We use social factor to represent the correlation between user stress states according to *c* at time *t*:

USER LEVEL STATISTICS (POSTING) ATTRIBUTES CALCULATION:

- Posting behavior attributes as summarized from a user's weekly tweet postings.

RISK CALCULATION:

- To examine structure properties (i.e., social influence and strong/weak tie) of (non) stressed users, we use risk ratio (RR) to measure the correlation between users' stress states and different structural attributes. Risk ratio is an effective measurement widely used in the statistical analysis and relevant fields. The risk ratio of a stressed state, associated with a structural attribute *a*, is calculated as follows:

  - *RR*(*a*) =*P*(*stressed user has attribute a*)
    - *P*(*stressed user does not have attribute a*)

  - A larger risk ratio implies that users with attribute *a*are more likely to be stressed.

USER:

OSN System Construction Module

- In the first module, we develop the Online Social Networking (OSN) system module. We build up the system with the feature of Online Social Networking. Where, this module is used for new user registrations and after registrations the users can login with their authentication.
- Where after the existing users can send messages to privately and publicly, options are built. Users can also share post with others. The user can able to

search the other user profiles and public posts. In this module users can also accept and send friend requests.

- With all the basic feature of Online Social Networking System modules is build up in the initial module, to prove and evaluate our system features.

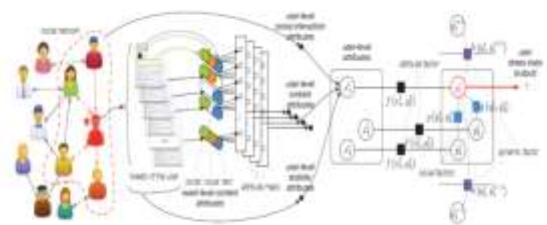
DESIGN CNN:

- There are three types of information that we can use as the initial inputs, i.e., tweet-level attributes, user-level posting behavior attributes, and user-level social interaction attributes.

- We design a CNN with cross auto encoders (CAE) to generate user-level interaction content attributes from tweet-level attributes. The CNN has been found to be effective in learning stationary local attributes for series posts.
- The user-level content attributes, user level posting behavior attributes, and user-level social interaction attributes together form the user-level attributes.

- The user-level attributes of a user at time t are denoted by x_{ti} ($i=1,2,\cdots$) in Figure 3. The route of the other users' attributes in Figure 3 is similar, which finally form their user-level attributes. We focus on the attribute flow of the user with red star and omit the detailed route of other users' attributes in the figure. The stress state of each user at time t is denoted by $y_t\ i$ ($i=1,2,\cdots$), respectively. The user-level attributes and the stress states are connected by an attribute factor, while stress states of different users are connected by social factors.

4. System Design:



4.1 System Architecture

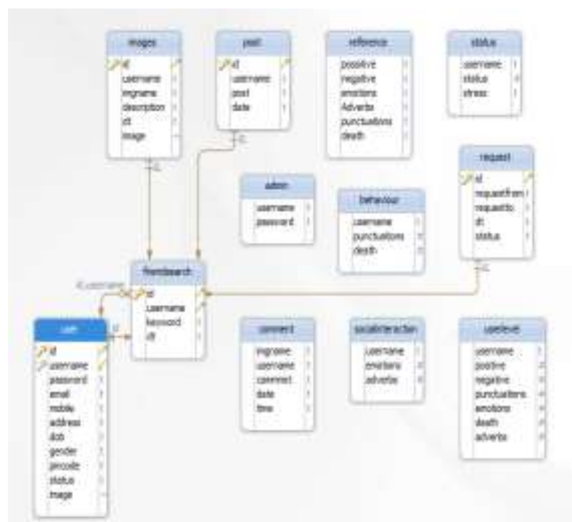


Image 4.2 ER Diagram

5. Output Results:

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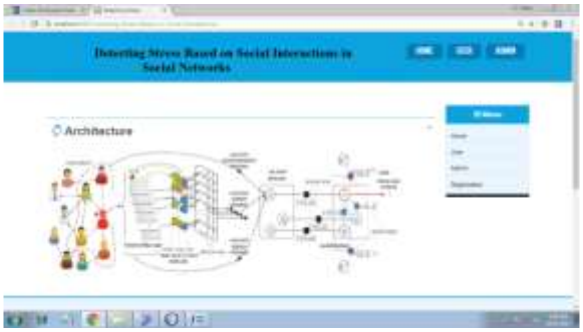

Fig 5.1: Home Page

Fig 5.2: Admin Login

Fig 5.3: Admin Home

Fig 5.5: Select User

Fig 5.6: Content Level

Fig 5.7: Posting Behaviour

Fig 5.8: Social Interactions

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Fig 5.9: Stress status

Fig 5.10: User Home Page

Fig 5.11: Search Friend

Fig 5.12: What's on your Mind?

6. Conclusion

In this paper, 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 convolution 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% 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.

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