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IDENTIFYING MENTAL DISORDERS OF USERS IN ONLINE SOCIAL NETWORKS

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Abstract:
The explosive growth in popularity of social networking leads to the problematic usage. An increasing number of social network mental disorders (SNMDs), such as Cyber-Relationship Addiction, Information Overload, and Net Compulsion, have been recently noted. Symptoms of these mental disorders are usually observed passively today, resulting in delayed clinical intervention. In this paper, we argue that mining online social behavior provides an opportunity to actively identify SNMDs at an early stage. It is challenging to detect SNMDs because the mental status cannot be directly observed from online social activity logs. Our approach, new and innovative to the practice of SNMD detection, does not rely on self-revealing of those mental factors via questionnaires in Psychology. Instead, we propose a machine learning framework, namely, Social Network Mental Disorder Detection (SNMDD), that exploits features extracted from social network data to accurately identify potential cases of SNMDs. We also exploit multi-source learning in SNMDD and propose a new SNMD-based Tensor Model (STM) to improve the accuracy. To increase the scalability of STM, we further improve the efficiency with performance guarantee. Our framework is evaluated via a user study with 3126 online social network users. We conduct a feature analysis, and also apply SNMDD on large-scale datasets and analyze the characteristics of the three SNMD types. The results manifest that SNMDD is promising for identifying online social network users with potential SNMDs.

Introduction:
With the explosive growth in popularity of social networking and messaging apps, online social networks (OSNs) have become a part of many people's daily lives. Most research on social network mining focuses on discovering the knowledge behind the data for improving people's life. While OSNs seemingly expand their users' capability in increasing social contacts, they may actually decrease the face-to-face interpersonal interactions in the real world. Due to the epidemic scale of these phenomena, new terms such as Phubbing (Phone Snubbing) and Nomophobia (No Mobile Phone Phobia) have been created to describe those who cannot stop using mobile social networking apps.In fact, some social network mental disorders (SNMDs), such as Information Overload and Net Compulsion[1],have been recently noted.1

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For example, studies point out that 1 in 8 Americans suffer from problematic Internet use2. Moreover, leading journals in mental health, such as the American Journal of Psychiatry [2], have reported that the SNMDs may incur excessive use, depression, social withdrawal, and a range of other negative repercussions. Indeed, these symptoms are important components of diagnostic criteria for SNMDs [3] e.g., excessive use of social networking apps – usually associated with a loss of the sense of time or a neglect of basic drives, and withdrawal – including feelings of anger, tension, and/or depression when the computer/apps are inaccessible. SNMDs are social-oriented and tend to happen to users who usually interact with others via online social media. Those with SNMDs usually lack of interactions, and as a result seek cyber-relationships to compensate. Today, identification of potential mental disorders often falls on the shoulders of supervisors (such as teachers or parents) passively. However, since there are very few notable physical risk factors, the patients usually do not actively seek medical or psychological services. Therefore, patients would only seek clinical interventions when their conditions become very severe. However, a recent study shows a strong correlation between suicid al attempt and SNMDs[4],which in dicates that adolescents suffering from social network addictions have a much higher risk of suicidal inclination than non-addictiv eusers. The research also reveals that social network addiction may negatively impact emotional status,causing higher hostility, depressive mood, and compulsive behavior. Even more alarming is that the delay of early intervention may seriously damage individuals' social functioning. In short, it is desirable to have the ability to actively detect potential SNMD users on OSNs at an early stage. Although previous work in Psychology has identified several crucial mental factors related to SNMDs, they are mostly examined as standard diagnostic criteria in survey questionnaires. To automatically detect potential SNMD cases of OSN users, extracting these factors to assess users' online mental states is very challenging. For example, the extent of loneliness and the effect of disinhibition of OSN users are not easily observable.3 Therefore, there is a need to develop new approaches for detecting SNMD cases of OSN users. We argue that mining the social network data of individuals as a complementary alternative to the conventional psychological approaches provides an excellent opportunity to actively identify those cases at an early stage. In this paper, we develop a machine learning framework for detecting SNMDs, which we call Social Network Mental Disorder Detection (SNMDD). Specifically, we formulate the task as a semi-supervised classification problem to detect three types of SNMDs [1]: i) Cyber-Relationship Addiction, which shows addictive behavior for building online relationships;ii)NetCompulsion, which shows compulsive behavior for online social gaming or gambling; and iii) Information

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Overload, which is related to uncontrollable surfing. By exploiting machine learning techniques with the ground truth obtained via the current diagnostic practice in Psychology[1],we extract and analyze the following crucial categories of features from OSNs: 1) social comparison, 2) social structure, 3) social diversity, 4) para social relationships, 5) online and offline interaction ratio, 6) social capital, 7) disinhibition, 8) self-disclosure, and 9) bursting temporal behavior. These features capture important factors or serve as proxies for SNMD detection. For example,studies manifest that users exposed to positive posts from others on Facebook with similar background are inclined to feel malicious envy and depressed due to the social comparison [36]. The depression leads users to disorder behaviors, such as information overload or net compulsion. Therefore, we first identify positive newsfeeds and then calculate the profile similarity and relation familiarity between friends. As another example, a para social relationship is an asymmetric inter personal relationship,i.e., one party cares more about the other, but the other does not. This asymmetric relationship is related to loneliness, one of the primary mental factors pushing users with SNMDs to excessively access online social media [5]. Therefore, we extract the ratioof the number of actions to and from friends of auserasa feature.In this paper,the extrated features are carefully examined through a user study. Furthermore, users may behave differently on different OSNs, resulting in inaccurate SNMD detection. When the data from different OSNs of a user are available, the accuracy of the SNMDD is expected to improve by effectively integrating information from multiple sources for model training. A na¨ıve solution that concatenates the features from different networks may suffer from the curse of dimensionality. Accordingly, we propose an SNMD-based Tensor Model(STM)to deal with this multi-source learning problem in SNMDD. Advantages of our approach are: i) the novel STM incorporates the SNMD characteristics into the tensor model according toTucker decomposition; and ii) the tensor factorization captures the structure, latent factors, and correlation of features to derive a full portrait of user behavior. We further exploit CANDECOMP/PARAFAC (CP) decomposition based STM and design as to chastic gradient descent algorithm, i.e., STM-CP-SGD, to address the efficiency and solution uniqueness issues in traditional Tucker decomposition. The convergence rate is significantly improved by the proposed second-order stochastic gradient descent algorithm, namely, STM-CP-2SGD. To further reduce the computation time, we design an approximation scheme of the second-order derivative, i.e., Hessian matrix, and provide a theoretical analysis. The contributions of this paper are summarized below.• Today online SNMDs are usually treated at a late stage. To actively identify potential SNMD cases, we propose an innovative approach, new to the current practice of SNMD detection, by mining data logs of OSN users as an early detection system. • We develop a machine learning

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framework to detect SNMDs, called Social Network Mental Disorder Detection(SNMDD).We also design and analyze many important features for identifying SNMDs from OSNs, such as disinhibition, parasociality, self-disclosure, etc. The proposed framework can be deployed to provide an early alert for potential patients. • Westudythe multi-source learning problem for SNMD detection. We significantly improve the efficiency and achieve the solution uniqueness by CP decomposition, and we provide theoretical results on nondivergence. By incorporating SNMD characteristics into the tensor model, we propose STM to better extract the latent factors from different sources to improve the accuracy. • We conduct a user study with 3126 users to evaluate the effectiveness of the proposed SNMDD framework. To the best of our knowledge, this is the first dataset crawled online for SNMD detection. Also, we apply SNMDD on large-scale real datasets, and the results reveal interesting insights on network structures in SNMD types, which can be of interest to social scientists and psychologists.The rest of this paper is organized as follows. Section 2 surveys the related work. Section 3 presents SNMDD,focusingonfeatureextraction.Sectio n4presentstheproposed STM for multi-source learning and the acceleration of tensor decomposition with the theoretical results

Existing system:

- King et al. [40] investigate the problem of simulated gambling via digital and social media to analyze the correlation of different factors, e.g., grade, ethnicity. Baumer et al. [10] report the Internet user behavior to investigate the reason of addiction. Li et al. [41] examine the risk factors related to Internet addiction.
- Kim et al. [42] investigate the association of sleep quality and suicide attempt of Internet addicts. On the other hand, recent research in Psychology and Sociology reports a number of mental factors related to social network mental disorders. Research indicates that young people with narcissistic tendencies and shyness are particularly vulnerable to addiction with OSNs. However, the above research explores various negative impacts and discusses potential reasons for Internet addiction. By contrast, this paper proposes to automatically identify SNMD patients at the early stage according to their OSN data with a novel tensor model that efficiently integrate heterogeneous data from different OSNs.
- Chang et. al [43] employ an NLP-based approach to collect and extract linguistic and content-based features from online social media to identify Borderline Personality Disorder and Bipolar

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Disorder patients. Saha et al. [44] extract the topical and linguistic features from online social media for depression patients to analyze their patterns.

- ❖ Choudhury et al. [45] analyze emotion and linguistic styles of social media data for Major Depressive Disorder (MDD). However, most previous research focuses on individual behaviors and their generated textual contents but do not carefully examine the structure of social networks and potential Psychological features.

Proposed system:

- ❖ In the proposed system, the system aims to explore data mining techniques to detect three types of SNMDs [1]: 1) Cyber-Relationship (CR) Addiction, which includes the addiction to social networking, checking and messaging to the point where social relationships to virtual and online friends become more important than real-life ones with friends and families; 2) Net Compulsion (NC), which includes compulsive online social gaming or gambling, often resulting in financial and job-related problems; and 3) Information Overload (IO), which includes addictive surfing of user status and news feeds, leading to lower work productivity and fewer social interactions with families and friends offline.
- ❖ Accordingly, the system formulates the detection of SNMD cases as a classification problem. We detect each type of SNMDs with a binary SVM. In this study, the system proposes a two-phase framework, called Social Network Mental Disorder Detection (SNMDD). The first phase extracts various discriminative features of users, while the second phase presents a new SNMD-based tensor model to derive latent factors for training and use of classifiers built upon Transductive SVM (TSVM).
- ❖ Two key challenges exist in design of SNMDD: i) we are not able to directly extract mental factors like what have been done via questionnaires in Psychology and thus need new features for learning the classification models;4 ii) we aim to exploit user data logs from multiple OSNs and thus need new techniques for integrating multi-source data based on SNMD characteristics.

Modules:

- **Admin**

  In this module, the Admin has to login by using valid user name and password. After login successful he can perform some operations such as View Users and Authorize(Give link on user to view Profile),View all Uses Friend Request and Response,Add Filter category ,Add filter name by selecting filter category,View all Users Post and with comments and score(Give link on user to view Profile),View all users post like Mentally Disorders Detection and Normal users based on cluster ,View all Mentally Disorders Detection and Normal users based on cluster based on Other users Comments,View all Social Similar users based on Post ,View all Social Diversity users based on Post Comment,View User Search Transactions,View Seach score by keyword in Chart,View Post score in chart,View number of Mentally disorder users and Normal Users in Chart,View all Social Similar users based on Post in Chart,View all Social Social Diversity users based on Post Comment in Chart

Friend Request & Response

In this module, the admin can view all the friend requests and responses. Here all the requests and responses will be displayed with their tags such as Id, requested user photo, requested user name, user name request to, status and time & date. If the user accepts the request then the status will be changed to accepted or else the status will remains as waiting.

- **User**

In this module, there are n numbers of users are present. User should register before performing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user can perform some operations like View Your Profile, Search Friends, View Friend Request and Response, View My Friends, Create post ,Search post and give comment(increase score while viewing),View all your posts with comments and scores, View all your Friends posts with comments and scores by Mentally Disorders and Normal Post

Searching Users to make friends

In this module, the user searches for users in Same Network and in the Networks and sends friend requests to them. The user can search for users in other Networks to make friends only if they have permission.

Conclusion:

In this paper, we make an attempt to automatically identify potentialonline users with SNMDs.We propose an SNMDD framework that explores various features from data logs of OSNs and a new tensor technique for deriving latent features from multiple OSNs for SNMD detection. This work represents a collaborative effort between computer scientists and mental healthcare researchers to address emerging issues in SNMDs. As for the next step, we plan to study the features extracted from multimedia contents by techniques on NLP and computer vision. We also plan to further explore new issues from the perspective of a social network service provider, e.g.,Facebook or Instagram, to improve the well-beings of OSN users without compromising the user engagement.

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