An extensive analysis and review on Identification of Mental Disorders related to Social Network via Social Media Mining based on Tensor decomposition model

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***Abstract*—**The strongest weapon to conquer the knowledge in today's world - "Internet" , has unfortunately turned out to be one of our greatest obsessions in killing time and is affecting our daily activities and responsibilities with a massive desire to get rid of everything to be able to 'Netflix and relax' all the time. Though the 'Internet Addiction' is gaining attention in the mental health field and had been recently added to the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) as a disorder, it needs a lot of research and standardized diagnosis. Their detection at an early stage is extremely important because the clinical interventions only during the last stage will make things worse and critical. In this paper, we argue that the potential Social Network Mental Disorder (SNMD) users can be automatically identified and classified into various categories like Virtual Relationship Addiction, Obsessive Online Gambling and Information Glut using SNMD based tensor model, with the data sets collected from data logs of various Online Social Networks (OSNs). The proposed model stands out in the list as the users are not involved in revealing their habits to understand and diagnose the symptoms manually. We also exploit multi-source learning in IMDSN (Identification of Mental Disorders related to Social Network) and propose a new SNMD based Tensor Model (STM) to improve the accuracy. The results show that IMDSN is reliable for identifying online social network users with potential SNMDs.

Keywords*—Online social network, Social network mental disorder identification, feature extraction, data logs, tensor decomposition.*

I. INTRODUCTION

Internet Addiction has undoubtedly become the growing epidemic as the number of cases getting registered for the treatment of these mental disorders due to excessive Internet Usage every year is drastically increasing. As per the latest report, this addiction has got so much to do with depression, anxiety disorders, insomnia, isolation, mood swings, procrastination and many more. 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. Conceptually, it's diagnosis is a compulsive-impulsive spectrum disorder that involves online and/or offline computer usage and consists of at least three subtypes: excessive gaming, sexual preoccupations, and e-mail/text messaging. All of the variants share the following four components: 1) excessive use, often associated with a loss of sense of time or a neglect of basic drives, 2) withdrawal, including feelings of anger, tension, and/or depression when the computer is inaccessible, 3) tolerance, including the need for better computer equipment, more software, or more hours of use, and 4)negative repercussions, including arguments, lying, poor achievement, social isolation, and fatigue.

These symptoms form important diagnostic criteria for SNMDs like Cyber-Relationship Addiction, Information Overload, Net Compulsion, Cyber-Sexual and Computer Addiction. The symptoms of these disorders were till now observed passively and hence the clinical intervention got delayed. Research shows that the early diagnosis of such mental disorders can greatly reduce the risk. Hence the practice of SNMD identification, that relies on self-revealing of those mental factors via questionnaires in Psychology is not adopted in our proposed model as the users might try to over smart the diagnosis by answering questions dishonestly. We propose a new innovative machine learning framework called Identification of Mental Disorders related to Social Network (IMDSN) that detects potential SNMD users by designing and analysing many important features for identifying SNMDs from OSNs, such as disinhibition, parasociality, self-disclosure, etc.

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 IMDSN is expected to improve by effectively integrating information from multiple sources for model training. A naive 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 IMDSN .

We study the multi-source learning problem for SNMD identification and significantly improve the efficiency and achieve the solution uniqueness by CANDECOMP/PARAFAC (CP) decomposition. Specifically, we formulate the task as a semi-supervised classification problem to detect three types of SNMDs and the new framework can be deployed to provide an early alert for potential patients.

The remnant of the paper is organized as follows. Section II describes the Background or the related work of our scheme.Section III describes proposal of the new framework. Section IV describes the Expected outcomes of the SNMD Framework and the Section V describes the Conclusions and Future enhancement.

II. BACKGROUND

A. Purpose

The purpose of developing this new IMDSN framework is to identify the potential SNMD users at an early stage and to reduce the severity of the disorder at later stages. The strange fact is that many people will not even be aware of the fact that they are affected by a mental disorder like SNMD. The importance of identifying this kind of mental disorders is extremely important as it is a significant medical condition that can affect many areas of life. It impacts mood and behavior as well as various physical functions, such as appetite and sleep quality. People with SNMD often lose interest in offline activities and value online relationships and activities more to such an extent that they reach a point where they strongly believe that they cannot live without online social media and games. This sort of mental health disorders can since damage the victim's life significantly , the proposed work discusses about its detection and stresses about having a digital detox for the SNMD patients.

B. Existing solutions

There are many research studies in Psychology and Psychiatry stating the important factors, co-relations and effects of Internet Addiction Disorder. Beginning from the mental health practitioners' reporting increased caseloads of clients whose primary complaint involved Internet and hence surveyed therapists who treated clients suffering from cyber related problems to specifically, discovering that young people with narcissistic tendencies are particularly vulnerable to addiction with OSNs, all the research happened offline and forcibly questioning online users to reveal their mental status. In addition to which, the following drawbacks exist:

- Although several crucial mental factors related to SNMDs are identified, 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.
- The developed schemes are not designed to handle the sparse data from multiple OSNs.
- The SNMD data from different OSNs may be incomplete due to the heterogeneity.

III. PROPOSED SOLUTIONS

We suggest 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 Identification of Mental Disorders related to Social Network(IMDSN). We propose an SNMD-based Tensor Model (STM) to deal with this multi-source learning problem in IMDSN .

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 for which we develop a machine learning framework to detect SNMDs, called Identification of Mental Disorders related to Social Network (IMDSN). 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 with the following merits:

- The novel STM incorporates the SNMD characteristics into the tensor model according to Tucker decomposition.
- The tensor factorization captures the structure, latent factors, and correlation of features to derive a full portrait of user behavior.
- Different features pertaining to Social Interaction and several personal features of a profile are identified and categorized under 3 different types of mental disorders.
- This semi-supervised task is highly alerting and useful to the mental health care researchers to understand the mental status of the potential SNMD users.

A. Social network mental disorder Identification

In this paper, we aim to explore data mining techniques to detect three types of SNMDs [2]:

- Virtual Relationship Addiction(VR), which includes the addiction to social networking, checking and messaging to an extent where virtual and online friends become more important than real-life relationships with family and friends.

- Obsessive Online Gambling(OG), which includes compulsive online social gaming or gambling, often leading to financial and job-related problems; and

- Information Glut(IG), addresses how the information technology revolution would shape the world, and how the large amount of data available on the Internet would make it more difficult to sift through and separate fact from fiction.

Accordingly, we formulate the detection of SNMD cases as a classification problem. We detect each type of SNMDs with a binary SVM. In this study, we propose a two-phase framework, called Identification of Mental Disorders related to Social Network (IMDSN). 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) [3]. Two major challenges in the design of IMDSN are:

- We are not able to directly extract mental factors like those extracted via questionnaires in Psychology and hence need new features to learn the classification models;

- We aim to exploit user data logs from multiple OSNs and thus need new techniques to integrate multi-source data based on SNMD characteristics.

1) Feature Extraction: We first focus on extracting discerning and factual features for design of IMDSN . This task is nontrivial for the following three causes.

a)Deficit of mental features: Psychological studies have shown that many mental factors are related to SNMDs, e.g., low self-esteem [4], loneliness [5]. Thus, questionnaires are designed to reveal those factors for SNMD detection. Some parts of Psychology questionnaire for SNMDs are based on the subjective comparison of mental states in online and offline status, which cannot be observed from OSN logs. As it is difficult to directly observe all the factors from data collected from OSNs, psychiatrists are not able to directly assess the mental states of OSN users under the context of online SNMD detection.

*b) Heavy users vs. addictive users:*To detect SNMDs, an intuitive idea is to simply extract the usage (time) of a user as a feature for training IMDSN . But, this feature is not sufficient because

- The status of a user may be shown as “online” if she does not log out or close the social network applications on mobile phones, and
- Heavy users and addictive users all stay online for a long period, but heavy users do not show symptoms of anxiety or depression when they are not using social apps. To distinguish them by extracting discriminative features is critical.

c) *Multi-source learning with the SNMD characteristics:*As we intend to exploit user data from different OSNs in IMDSN , extracting complementary features to draw a full portrait of users while considering the SNMD characteristics into the tensor model is a challenging problem.

To address the these complexities, we consider a number of factors to understand the mental states of users, e.g., self-esteem and loneliness. The goal is to distinguish users with SNMDs from normal users. Two types of features are extracted to capture the social interaction behavior and personal profile of a user. It is worth noting that each individual feature cannot precisely classify all cases, as research shows that exceptions may occur. Therefore, it is necessary to exploit multiple features to effectively remove exceptions.

B. Effective features as proxies to capture the mental states of users

A fundamental problem in text data mining is to extract meaningful structure from document streams that arrive continuously over time. Newsfeeds, messages exchanged, posts shared on an individual’s wall are all the natural examples of such streams, each characterized by topics that appear, grow in intensity for a period of time, and then fade away. The published literature in a particular research field can also be seen to exhibit similar phenomena over a much longer time scale. Underlying much of the text mining work in this area is the following intuitive premise that the appearance of a topic in a document stream is signaled by a “burst of activity," with certain features rising sharply in frequency as the topic emerges. The human appetitive system is in charge of the addictive behavior. A recent study has shown that social searching (actively reading news feeds from friends’ walls) creates more pleasure than social browsing (passively reading personal news feeds) [6].This finding indicates that goal-directed activities of social searching are more likely to activate the appetitive system of a person as drug rewards do, and it is more related to SNMDs because the appetitive system is responsible for finding things in the environment that promote species survival(i.e., food, sexual mates) and thus is inclined to form addictive behavior after several rewards. While users with SNMDs perform social searching more frequently than non-SNMDs, it is not easy to distinguish these two behavior on social media. This example is just one such kind of a feature that could be used to analyse a user’s social interaction and personal features. The new system will have many more similar features that are exploited to understand the mental status and habits of a SNMD user that considers online/offline interaction ratios, the temporal behavior, his self-obsessive characteristics hinting the possibility of SNMD.

C. Identification of Mental Disorders related to Social Network (IMDSN) Schema

We devise the identification of SNMD cases as a classification problem and detect each type of SNMDs with a binary SVM. Here, we propose a two-phase framework, called Identification of Mental Disorders related to Social Network (IMDSN), as shown in *Fig. 1*. The first phase extracts several 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).

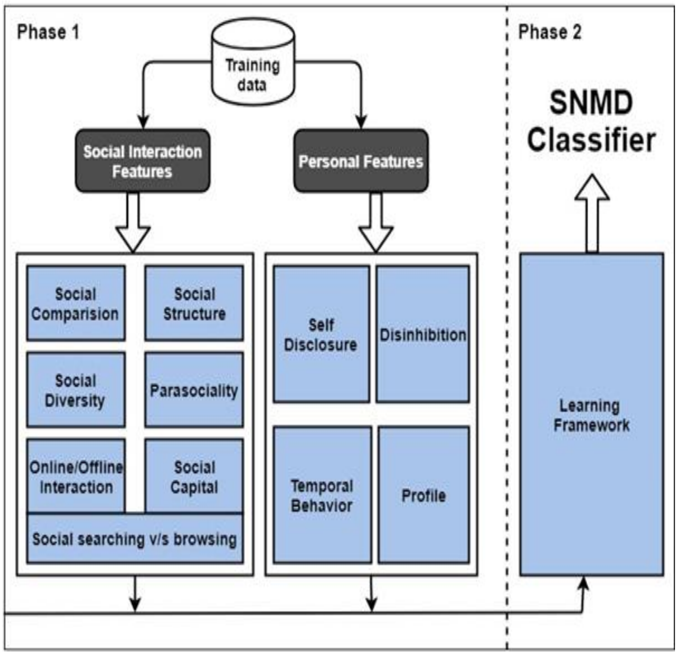

Fig. 1 Identification of Mental Disorders related to Social Network (IMDSN) Schema

1. *Social Interaction Features*

a) *Social comparison based features:*

Nevertheless, there is great variability in our tendency to make social comparisons. As individuals we constantly compare ourselves to others. Though social comparisons may seem to serve several positive functions, including self-enhancement, frequent social comparisons, however, have a dark side. The situation becomes increasingly critical as status exchanges among friends are now very convenient via various online social networks and due to frequent social comparisons people are more likely to experience envy, guilt, regret, and defensiveness, and to lie, blame others, and to have unmet cravings. The experience of benign envy leads to a moving-up motivation aiming at improving one's own position, whereas the experience of malicious envy produces a pulling-down motivation and depression. Malicious envy is incurred from the comparison among close friends with similar backgrounds and states, and it usually leads to SNMDs, such as information overload or net compulsion, because a person in this case usually feels pressure and tends to frequently check the updated status of the corresponding friends and in contrast, benign envy is usually generated from distant friends with different backgrounds and rarely leads to SNMDs. Therefore, we first exploit the existing techniques of emotional signal processing [7] to identify positive news feeds and then calculate the profile similarity and relation familiarity between friends.

b) Social structure based features : In Sociology, each person in a social network belongs to one of the following three types of social roles: structural holes are the users who have high indegree but not necessarily influential in terms of spawning retweets or mentions, influential users who can hold significant influence over a variety of topics, and normal users whose influence is not gained spontaneously or accidentally, but through concerted effort. According to the above observations, we exploit the state-of-the-art approach [8] to quantify users' tendencies of being structural holes . We also extract the network topology based features, i.e., closeness centrality, betweenness centrality, eigenvector centrality, information centrality, flow betweenness, the rush index, as social structure based features for detecting SNMDs. For example, flow betweenness indicates how much information has been propagated through the node, which relates to information overload. Moreover, eigenvector centrality is a measure of the influence of a node in a network, and the score is similar to the page rank, i.e., connections to high-scoring neighbours are inclined to increase the score of a node. Therefore, the scores of unpopular users are usually small and correlated to Virtual-Relationship Addiction.

c) Social diversity based features: The impact of social network diversity is increasingly important and inspires us to incorporate them for effective SNMD detection. Specifically, the diversities of nationality, racial, ethical, religious, and education can be extracted as social diversity based features with Shannon index H as the diversity index which increases when there is a more significant evenness. For example, a person with a more diverse background and many friends is less inclined to suffer from SNMDs because she is often supported by friends and thereby rarely feels lonely and isolated . In other words, the diversity index is maximized when all type of attributes are of the equal quantities.

d)Parasocial relationship: Parasocial relationships are one-sided relationships, where one person extends emotional energy, interest and time, and the other party, the persona, is completely unaware of the other's existence are viewed as pathological and a symptom of loneliness, isolation and social anxieties. The feature of parasocial relationship is represented as $|a_{out}|/|a_{on}|$, where $|a_{out}|$ and $|a_{on}|$ denote the number of actions a user takes to friends and the number of actions friends take to the user, respectively. As the ratio increases, the extent of parasocial relationship also grows.

e) Online and Offline interaction ratio: The amount of online interactions is recently inclined to significantly exceed their interactions offline. We extract the number of check-in logs with friends and the number of "going" events as an indicator of the number of offline activities to estimate the online ($|a_{on}|$)/offline ($|a_{out}|$) interaction ratio. Although the number of offline events observed from online is smaller than the actual number, the ratio is relative and is a good indicator, because the frequent check-in records of a user imply that the user is active in offline activities, which is an indicator of non-SNMD.

f) Social Capital: Two types of friendship ties are usually involved in the theory of social capital

- Bond intensification (strong-tie), which represents the use of OSNs to strengthen the relationships creating more interactions in order to increase the social tightness and is related to Virtual-Relationship Addiction; and
- Information probing(weak-tie), corresponds to the use of social media to find valuable information concentrates more on finding and reading the information and is thus related to Information Glut. Therefore, the ratio between the number of strong (n_{strong}) and weak ties (n_{weak}) could be used for differentiating the VR and IG types. We also exploit the ratio between the number of friends the user interacts online (likes, comments, and posts) and the total number of the user's friends as proxy features.

g) Social searching vs. browsing: While users with SNMDs perform social searching more frequently than non-SNMDs, it is not easy to differentiate these two on social media. Let x_i denote the total number of the ith action for posts among friends. For example, if a user is the second one among his friends who click "likes" on a post, the x_2 increases 1 for the user. As most social media provide friends' comments and "likes" in the form of news feeds to users, we consider the number of likes/comments on news feeds from friends as social browsing take an initiative to search for someone's profile and like/comment on it, we consider this as a social searching (i.e., the number of likes/comments on others' news feeds that are not liked/commented by his friend before (x_1)) [9]. The social searching features are related to CR because CR users tend to find social supports, whereas social browsing is more related to IO. Compared with social capital, this feature focuses on different behavior in reading news feeds, rather than the different types of friend ties.

2. *Personal features*

a) *Self-disclosure based features :* Despite the frequency with which humans disclose the contents of their own thoughts, humans willingly self-disclose because doing so represents an event with intrinsic value, in the same way as with primary rewards such as food and sex. However, to conduct a sentiment analysis on the contents associated with a user is very complicated and computationally expensive. Inspired by emotional signal detection, which shows that when the users use emoticons, they are effectively expressing an emotional state , we retrieve and exploit the numbers of emoticons, stickers, and selfies in each post as the features for self-disclosure [10].

b) Disinhibition based features : The mental factor of disinhibition is also one of the primary reasons the users excessively access online social media. When surfing online, some people tend to act out more frequently or intensely than they act offline due to the dissociative anonymity, asynchronicity, solipsistic introjection, which is called the online disinhibition effect [11]. When user identities can be anonymous or the conversation is not face-to-face (e.g., Instagram, Snapchat), offline-shy users are more inclined to addict to Virtual relationships due to disinhibition. The disinhibition effect is more related to VR and OG because they both show stronger intensity of usage under the anonymity.

c) Temporal behavior features : Relapse is the state that a person is inclined to quickly revert back to the excessive usage of social media after an abstinence period, while tolerance is the state that the time spent by a person with SNMDs tends to increase due to the mood modification effect. It is worth noting that the above two mental states have been exploited to evaluate clinical addictions [5]. We aim to use them to distinguish heavy users and addictive users because heavy users do not suffer from relapse and tolerance in use of OSNs. An issue arising here is how to assess relapse and tolerance quantitatively. It is observed that the use of social media by an SNMD patient is usually in the form of intermittent bursts . Therefore, given a stream of a user's activities on an OSN, e.g., "likes", "comments", "posts", we exploit Kleinberg's burst detection algorithm [12], which is based on an infinite Markov model, to detect periods of the user's activities as bursty and non-bursty periods. The bursty period refers to a period during which the activities significantly increase.

d) Usage time: The time duration that a user spends on social media a day is estimated by consecutive activity logs and the number of online states during a day is also important. It was widely believed that a person spending a lot of time on OSNs usually belongs to VR or IG. However, a recent study points out that the usage time is only moderately correlated to VR and IG. Indeed, both heavy users and the users with SNMDs tend to stay online for lengthy time periods, but heavy users do not feel anxious and depressed when they are not using social apps. With the bursts detected earlier, we aim to use the relapse and tolerance to distinguish users with SNMDs from heavy users. For example, given a heavy user spends the same amount of time online as a user with SNMDs does, the standard deviation of burst length for the heavy user is expected to be smaller than that of the user with SNMDs since the heavy user explores OSNs more regularly and does not suffer from the tolerance of increasing usage.

e) Profile features: We also extract some demographic features commonly adopted in questionnaires from user profiles, such as age and gender which shows that the age when a user logs in Facebook the first time is correlated to the intensity of SNMDs. For children growing up with the Internet, this is a key position in their lives. Studies tell that gender difference results in varying degrees of SNMDs because the goals of using OSNs are different for different genders, e.g., females are more inclined to use online communication whereas males are inclined to follow news and play online games. Also, the number of game posts is extracted.

It's important to note that integrating important social and personal features provides good results because effective personal features, e.g., the temporal behavior features, can be used to differentiate the users suffering from withdrawal or relapse symptoms and heavy users, while social features capture the interactions among users to differentiate different SNMDs.

D. Multi-Source semi supervised learning

Many users are inclined to use different OSNs, and it is expected that data logs of these OSNs could provide enriched and complementary information about the user behavior. Thus, we aim to explore multiple data sources (i.e., OSNs) in IMDSN , in order to derive a more complete portrait of users' behavior and effectively deal with the data sparsity problem. To exploit multi-source learning in IMDSN , one simple way is to directly concatenate the features of each person derived from different OSNs as a huge vector. However, the above approach tends to miss the correlation of a feature in different OSNs and introduce interference. Thus, we explore tensor techniques which have been used increasingly to model multiple data sources because a tensor can naturally represent multi-source data. We aim to employ tensor decomposition to extract common latent factors from different sources and objects [9].

Given SNMD features of users extracted from OSN sources, we construct a three-mode tensor and then conduct Tucker decomposition, a renowned tensor decomposition technique, on the tensor to extract a latent feature matrix , which presents the latent features of each person summarized from all OSNs. The matrix effectively estimates a deficit feature (e.g., a missing feature value unavailable due to privacy setting) of an OSN from the corresponding feature of other OSNs, together with the features of other users with similar behavior. Based on Tucker decomposition on the tensor , we present a new SNMD-based Tensor Model (STM), which enables latent feature matrix to incorporate important characteristics of SNMDs, such as the correlation of the same SNMD sharing among close friends. Finally, equipped with the new tensor model which is different from conventional tensor models, we conduct semi-supervised learning to classify each user by exploiting Transductive Support Vector Machines (TSVM).

IV. EXPECTED OUTCOMES

A two-phase framework called Identification of Mental Disorders related to Social Network (IMDSN), is developed which is a flexible and reliable SNMD based tensor model to automatically identify the potential online users with SNMDs such as Virtual Relationship Addiction(VR), Obsessive Online Gambling(OG) and Information Glut(IG).

With this work, the mental health care researchers in a way will be equipped to diagnose the users severely affected by various mental disorders pertaining to Online Social Network and can synergistically work with technology experts to address emerging issues in SNMDs.

V. CONCLUSION

In this paper, we attempt to automatically identify potential online users with SNMD. We propose a new tensor method for deriving potential features from multiple OSNs for SNMD detection and IMDSN framework to search various characteristics from OSN data logs. As a next step, we are planning to investigate new issues from the perspective of social network service providers such as Facebook and Instagram such as exploring the possibilities of automatically blocking the account usage after a threshold time of user engagement for SNMD users, various other digital detox plugins instilled to monitor and control the usage for improving the well-being of OSN users without compromising user commitment.

ACKNOWLEDGMENT

The authors would like to thank all the faculties of Dept. of studies in Computer Science and Engineering, VTU Regional office, Mysuru, their parents, family members, friends and anonymous reviewers' encouragement and constructive piece of advice that prompted for a new round of rethinking of research, additional experiments and clearer presentation of technical content.

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