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Study on Social Network Mental Disorder Detection Based Markov Model

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ABSTRACT
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. There are many mental disorder encountered noticed of social network mental disorders (SNMDs), the basic parameter at which evaluate the mental level of user such as Cyber-Relationship Addiction, Information Overload, and Net Compulsion, have been recently noted. Symptoms of these mental disorders are usually observed day by day, resulting in delayed clinical intervention. In this work, the mining online social behaviour 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, now propose a machine learning framework, namely, Social Network Mental Disorder Detection (SNMDD), that exploits features extracted from social network data log file to accurately identify potential cases of SNMDs. We also exploit multi-source learning in SNMDD and propose a new SNMDD based Markov Model (SMM) to improve the accuracy. To increase the scalability of SMM, we further improve the efficiency with performance guarantee. Our framework is evaluated via 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.

KEYWORDS*: online social networks, Cyber-Relationship Addiction, Information Overload and Net Compulsion, SNMDs, SMM*

I. INTRODUCTION

In the century we live in, which is called the Digital age, computer and internet have gained an absolutely central importance in human life, and social media had a prominent role in this picture. Besides easy, cheap and fast access to information through computers and the Internet, the expansion of the communication network is one of the factors that lead individuals to use social media. The statistics provided by Tayfun Acarer, who is the Chairman of the Information Technologies and Communication Authority in Turkey, reveal the recent level of social media addiction in Turkey. According to Acarer, monthly Internet usage has increased to 32-33 hours, which is the highest after Britain in Europe, and Turkey is among the countries that use the Internet most in the world, and it also takes the 4th range in social networking site usage hours and 6th range in the user number of social networking sites (www.yesilay.org.tr / Retrieved 18.03.2015). According to statistics, Facebook seems to be the most heavily used social networking site all over the world. Through Facebook, users are able to express themselves freely, establish new friendships and relationships, and follow and engage in dialogues with people or groups they are interested in. Social media has become an indispensable part of the communication age (Aygül, 2010: 95).

The mass appeal of social networks on the Internet could potentially be a cause for concern, particularly when attending to the gradually increasing amounts of time people spend online. On the Internet, people engage in a variety of activities some of which may be potentially to be addictive. Rather than becoming addicted to the medium per se, some users may develop an addiction to specific activities they carry out online. Specifically, Young [7] argues that there are five different types of internet addiction, namely computer addiction (i.e., computer game addiction), information overload (i.e., web surfing addiction), net compulsions (i.e., online gambling or online shopping addiction), cyber sexual addiction (i.e., online pornography or online sex addiction), and cyber-relationship addiction (i.e., an addiction to online relationships). SNS addiction appears to fall in the last category since the purpose and main motivation to use SNSs is to establish and maintain both on- and offline relationships (for a more detailed discussion of this please refer to the section on motivations for SNS usage). From a clinical psychologist's perspective, it may be plausible to speak specifically of 'Facebook Addiction Disorder' (or more generally 'SNS Addiction Disorder') because addiction criteria, such as neglect of personal life, mental preoccupation, escapism, mood modifying experiences, tolerance, and concealing the addictive behavior, appear to be present in some people who use SNSs excessively.

II. LITERATURE SURVEY

SR. NO.	TITLE	AUTHORS	YEAR	METHODOLOGY
1	A Comprehensive Study on Social Network Mental Disorders Detection via Online Social Media Mining	Hong-HanShuai et. alet. al	2017	Social Network Mental Disorder Detection (SNMDD)
2	Mining for Social Media: Usage Patterns of Small Businesses	Shilpa Balan et. al	2017	IBM Watson Analytics
3	Survey on intelligent Data Mining of Social Media for improving health Care	Aradhana S. Ghorpade et. al	2017	Using Data mining in OSNs
4	Social media analytics: a survey of techniques, tools and platforms	Bogdan Batrinca et. al Batrinca et. al	2017	The paper provides a critique of social media tools
5	Survey of Data Mining Techniques for Social Networking Websites	D. Kavitha et. al Bogdan	2016	Novel technique named TRCM
6	A Survey of Data Mining and Social Networking Analysis Based Anamoly Detection Techniques	Ravneet Kaur et. al	*2015*	novel categorization

III. PROBLEM IDENTIFICATION

As per previous work analysis there are following problem identified.

1. The unidentified social users may be classified due to high loss function.
2. Due to high computation time, detection approach becomes complex.
3. Peak memory usage during detection social sites users.
4. Accuracy of detection process becomes low.

IV. METHODOLOGY

The Algorithm of proposed methodology SNMDD-MM (Social Network Mental Disorder Detection with Markov Model) is as follows

for each node $Y_i \in y$ do //bootstrapping

// compute label using only observed nodes in N_i

Computer $\vec{a_i}$ using only $X \cap N_i$

$$y_i \leftarrow f\left(\vec{a_i}\right)$$

End for

Repeat // iterative classification

Generate ordering O over nodes in y

For each node $Y_i \in O$ do

// compute new estimate of y_i

Compute $\vec{a_i}$ using current assignments to N_i

$$y_i \leftarrow f\left(\vec{a_i}\right)$$

End for

Until all class labels have stabilized or a threshold number of iterations have elapsed

The goal of above methodology is classifying nodes in graphs considering its position in the graph. Classic machine learning classification techniques assume that the label of each object is independent from others, however in a graph this assumption is not true and connected nodes will probably be in the same class. In other words, we cannot assume the label of each node as an independent entity from other nodes. For instance in a graph of friendship if a person is infected, her\his friends will have higher probability of infection. Another example can be in scientific paper author graphs, which represent the connection between nodes of the graph when they have at least one common author. In this data set the topic of connected papers are probably the same. In these 2 examples it is obvious that the label of data points is not independent of each other.

This idea is the motivation for us to explore new methods, which consider the dependencies between nodes in a graph. These methods are named "relational classification methods".

Our goal is to solve the collective classification problem when the labels of objects are related to each other.

V. RESULTS AND ANALYSIS

The loss function can be determined on basis given dataset and also different time frame. The time interval is 1 ms and result consider up to 7 ms.

Table 1: Comparison analysis of loss function in between of SNMDD [1] and SNMD-MM (Proposed)

Time (ms)	SNMDD [1]	SNMD-MM(Proposed)
1	0.24	0.18
2	0.23	0.16
3	0.22	0.15
4	0.21	0.14
5	0.19	0.12
6	0.18	0.11
7	0.16	0.1

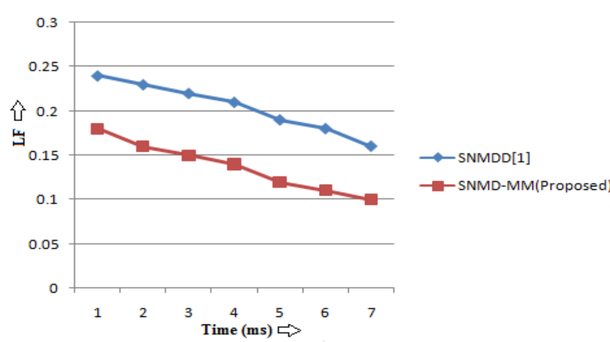

Figure 1: Graphical analysis of loss function in between of SNMDD [1] and SNMD-MM (Proposed)

When time is 1 ms then value of loss function becomes 0.24 for SNMDD [1] and 0.18 for SNMD-MM (Proposed). Similarly when time is 7 ms then value of loss function 0.16 for SNMDD [1] and 0.1 for SNMD-MM (Proposed). Hence loss content in detection process may decrease up to 24%. The computation time can be determined on basis given dataset and also different time frame. The time interval is 1 ms and result consider up to 7 ms.

Table 2: Comparison analysis of computation time in between of SNMDD [1] and SNMD-MM (Proposed)

Time (ms)	SNMDD [1]	SNMD-MM(Proposed)
1	6.14	6.12
2	5.95	5.81
3	5.88	5.82
4	5.8	5.23
5	4.7	4.51
6	4.5	4.25
7	4.1	3.98

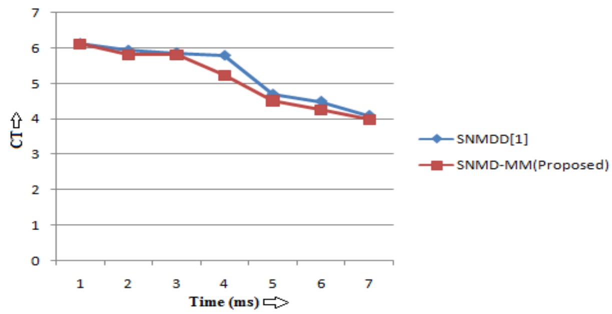

Figure 2: Graphical analysis of computation time in between of SNMDD [1] and SNMD-MM (Proposed)

When time is 1 ms then value of computation time becomes 6.14 for and 6.12 for SNMD-MM (Proposed). Similarly when time is 7 ms then value of computation time 4.1 for SNMDD [1] and 3.98 for SNMD-MM (Proposed). Hence time complexity of detection process may decrease up to 0.34%. The memory utilization can be determined on basis given dataset and also different data size. The time interval is 500 and result consider up to 2500.

Table 3: Comparison analysis of memory utilization in between of SNMDD [1] and SNMD-MM (Proposed)

Data Size	SNMDD [1]	SNMD-MM(Proposed)
500	20	15
1000	50	45
1500	80	75
2000	110	105
2500	140	135

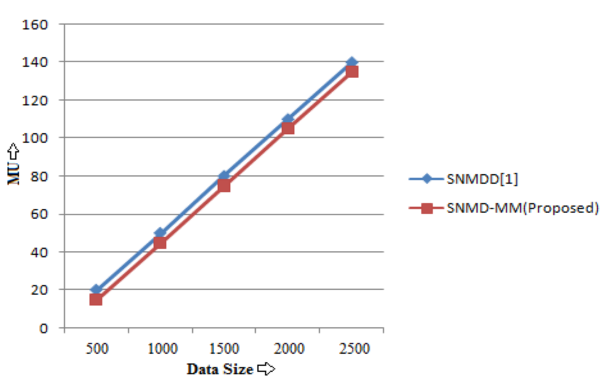

Figure 3: Graphical analysis of memory utilization in between of SNMDD [1] and SNMD-MM (Proposed)

When data size is 500 then value of memory utilization becomes 20 for SNMDD [1] and 15 for SNMD-MM (Proposed). Similarly when data size is 2500 ms then value of memory utilization 140 for SNMDD [1] and 135 for SNMD-MM (Proposed). Hence memory utilization of detection may decrease up to 3.5%. The accuracy can be determined on basis given dataset and also different number of iterations. The time interval is 5 and result consider up to 25.

Table 4: Comparison analysis of accuracy in between of SNMDD [1] and SNMD-MM (Proposed)

Number of Iterations	SNMDD [1]	SNMD-MM(Proposed)
5	87	90
10	91	95
15	90	94
20	89	92
25	88	89

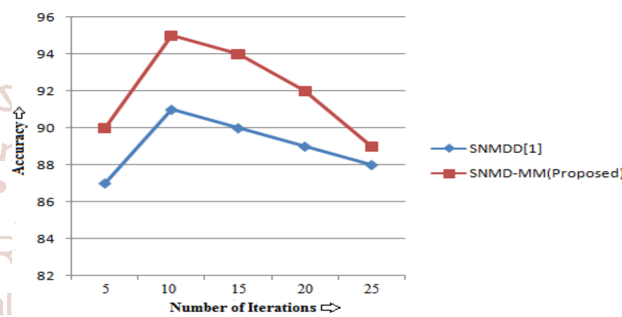

Figure 4: Graphical analysis of accuracy in between of SNMDD [1] and SNMD-MM (Proposed)

When number of iterations is 5 then value of accuracy becomes 87 for SNMDD [1] and 90 for SNMD-MM (Proposed). Similarly when number of iterations is 25 then value of accuracy is 88 for SNMDD [1] and 89 for SNMD-MM (Proposed). Hence accuracy of detection may increase up to 1.13%.

VI. CONCLUSIONS & FUTURE SCOPE

An attempt to automatically identify potential online users with SNMD-MM. Now propose an SNMD-MM framework that explores various features from data logs of OSNs and a new tensor technique for deriving latent features from multiple OSNs for SNMD-MM detection. This work represents a collaborative effort between computer scientists and mental healthcare researchers to address emerging issues in SNMD-MM. On the basis of result and analysis, following observation is find out:

1. Loss content in detection process may decrease up to 24%.
2. Time complexity of detection process may decrease up to 0.34%.
3. Memory utilization of detection may decrease up to 3.5%.
4. Accuracy of detection may increase up to 1.13%.

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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