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DETECTING STRESS BASED ON SOCIAL INTERACTION IN SOCIAL NETWORK

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Abstract: In today's world, it is undeniable that social media plays an important role in impacting our culture, our economy and our overall view of the world. Social media is a new forum that brings people to exchange idea, connect with, relate to, and mobilize for a cause, seek advice, and offer guidance. Most research on social network mining focuses on discovering the knowledge behind the data for improving peoples 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. Some social network mental disorders (SNMDs), Journal of Psychiatry have reported that excessive use, depression, social withdrawal, and a range of other negative repercussions. 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. We can find out the stressed users on social media platforms.

I INTRODUCTION

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) Net Compulsion, which shows compulsive behavior for online social gaming or gambling; and iii) Information 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) parasocial 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. With the explosive growth in popularity of social networking and messaging apps, online social networks

(OSNs) have become a part of many peoples daily lives. Most research on social network mining focuses on discovering the knowledge behind the data for improving peoples 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 this system, we aim 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, 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 Social Network Mental Disorder Detection (SNMDD), as shown in Figure 1. 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) [13]. 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; 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. We develop a machine learning 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. We study the 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 non divergence. 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.

II LITERATURE SURVEY

1. Rony Germon, Karina Sokolova "Analyzing User Generated Content on Instagram: the Case of Travel Agencies" This paper has described our first exploratory study on the indicators of Instagram communication success and on the role of user-generated content on community engagement. We analysed Instagram images with different engagement levels produced by online travel agencies. We observed that UGC has a higher success for the online travel agencies community than for specially created images, and that is especially the case with AirBnB. The most engaging photographs depicted landscapes and contained calls for action in the description: calls such as like, retweet or comment. The most successful content came from Instagram users or, more often, from non Instagram bloggers sharing their experiences. Although our current dataset is limited, it

already shows the importance of user-generated content in community management on Instagram

2. Liang Zhao, "Hierarchical Incomplete Multi-source Feature Learning for Spatiotemporal Event Forecasting"

In this paper, Significant societal events are prevalent in multiple aspects of society, e.g., economics, politics, and culture. To accommodate all the intricacies involved in the underlying domain, event forecasting should be based on multiple data sources but existing models still suffer from several challenges. This paper has proposed a novel group-Lasso-based feature learning model that characterizes the feature dependence, feature sparsity, and interactions among missing values. An efficient algorithm for parameter optimization is proposed to ensure global optima. Extensive experiments on 10 real-world datasets with multiple data sources demonstrated that the proposed model outperforms other comparison methods in different ratios of missing values.

3. Animashree Anandkumar, "Learning Overcomplete Latent Variable Models through Tensor Methods" In this paper, We provide guarantees for learning latent variable models emphasizing on the overcomplete regime, where the dimensionality of the latent space exceeds the observed dimensionality. In particular, we consider multiview mixtures, ICA, and sparse coding models. Our main tool is a new algorithm for tensor decomposition that works in the overcomplete regime. In the semi-supervised setting, we exploit label information to get a rough estimate of the model parameters, and then refine it using the tensor method on unlabeled samples. We establish learning guarantees when the number of components scales as $k = o(d^{p/2})$, where d is the observed dimension, and p is the order of the observed moment employed in the tensor method (usually $p = 3, 4$).

4. Katarzyna Wegrzyn-Wolska, "EXPLORE THE EFFECTS OF EMOTICONS ON TWITTER SENTIMENT ANALYSIS" In this paper, With the significance of sentiment analysis being recognized and the popularity rate of emoticon in social network getting higher and higher, the role of emoticon cannot be ignored on polarity classification. Our key contribution in this paper lies in validating the important role emoticon plays in conveying overall sentiment of a text in TSA through a series of experiments. We compare 3 emoticon pre-processing methods and emoticon-weight lexicon method on the base of Twitter aware tokenizer and NB Model. We propose a combination strategy using factor alpha to integrate the Emoticon-Weight Lexicon with classifier. The result shows that the usage of emoticon-weight lexicon model improves the performance of NB model on TSA task. We can get the conclusion that some emoticons dominate the sentiment of a tweet and conquer the emotion of verbal cues.

III SYSTEM ARCHITECTURE

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 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. We study the 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 non divergence. 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. we propose STM to better extract the latent factors from different sources to improve the accuracy.

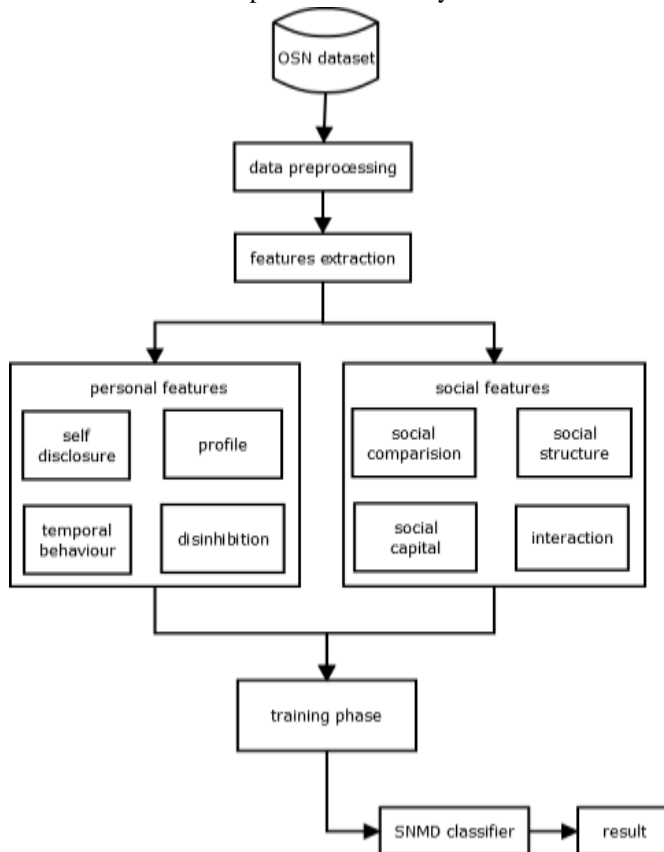


Figure 1: System Architecture

The screenshot shows a web interface titled 'Social Network Mental Disorders Detection'. It features a 'Load Data Set' button at the top. Below it is a table with columns for user IDs and various numerical values. A 'Remove Missing Attribute Record' button is located at the bottom of the table.

3804	59	0	5	2	7	NC
11328	801	3	187	36	226	CR
3412	459	2	69	26	97	CR
3068	437	2	82	24	108	CR
3996	58	0	12	2	14	NC
3094	440	2	56	25	83	CR
2842	393	1	44	21	66	CR
4876	660	21	277	80	378	CR
2820	432	1	74	28	103	CR
3300	431	1	79	30	110	CR
3302	437	1	105	46	152	CR
10720	220	0	128	9	137	NC
5348	699	17	185	55	257	CR
3230	422	10	125	41	176	CR
2876	392	5	53	26	84	CR
2104	301	0	33	22	75	CR
2388	363	4	93	18	115	CR
2452	370	7	91	38	136	CR
2200	316	0	91	28	119	CR

Figure 2: Remove Missing Attribute Record

The screenshot shows a web interface titled 'SNMDD Detection - Data'. It displays a table with columns for user IDs and various numerical values. A 'Preprocess' button is located at the bottom of the table.

788	487	7	84	36	127	CR
124	722	56	360	99	513	CR
804	59	0	5	2	7	NC
1328	801	3	187	36	226	CR
412	453	2	69	26	97	CR
1068	437	2	82	24	108	CR
996	58	0	12	2	14	NC
094	440	2	56	25	83	CR
842	393	1	44	21	66	CR
876	660	21	277	80	378	CR
820	432	1	74	28	103	CR
300	431	1	79	30	110	CR
502	437	1	105	46	152	CR
0720	220	0	128	9	137	NC
348	699	17	185	55	257	CR
230	422	10	125	41	176	CR
876	392	5	53	26	84	CR
104	301	0	33	22	75	CR
388	363	4	93	18	115	CR
452	370	7	91	38	136	CR

Figure 3: Preprocess

The screenshot shows a web interface titled 'SNMDD Detection Accuracy'. It contains a table comparing the accuracy of different machine learning algorithms.

Algorithm	Accuracy
Decision Tree	87.68
SMD	86.87
Tucker	87.07
STM	90.82

Figure 4: SNMDD Detection Accuracy

IV CONCLUSION

In this system 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. we propose STM to better extract the latent factors from different sources to improve the accuracy.

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