Role of Social Media in Tackling Challenges in Mental Health

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ABSTRACT

Mental illness is a serious and widespread health challenge in our society today. Tens of millions of people each year suffer from depression and only a fraction receives adequate treatment. This position paper highlights some recent attempts examining the potential for leveraging social media postings as a new type of lens in understanding mental illness in individuals and populations. Information gleaned from social media bears potential to complement traditional survey techniques in its ability to provide finer grained measurements of behavior over time while radically expanding population sample sizes. We conclude highlighting how this research direction may be useful in developing tools for identifying the onset of depressive disorders in individuals, for use by healthcare agencies; or on behalf of individuals, enabling those suffering from mental illness to be more proactive about their mental health.

Categories and Subject Descriptors

H.5.m [Information Systems]: Information Systems Applications – Miscellaneous.

Keywords

behavior, depression, emotion, health, language, multimedia, social media, mental health, public health, Twitter, wellness

1. INTRODUCTION

Over the last few years, the rapid proliferation of social platforms online has enabled a growing body of research that has investigated several nuanced aspects of human behavior—diffusion of information [13], evolution of communities [28], crisis mitigation [29], and even sociopolitical phenomena [3]. Beyond these, platforms like Twitter and Facebook are increasingly becoming a rich source of "sensors" that record and reflect individual-centric thoughts, feeling or opinions about small and big happenings in one's life. As many of these platforms increasingly gain traction among individuals, they are building up large user bases, including many people who have been using the service for years.

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What could analyses of individual-centric behavior, thus manifested over long periods of time, explain? Potentially, the longitudinal records of behavior can help detect behavioral changes around a variety of life events: childbirth, marriage, loss of a job, divorce, or a severe car accident. Detecting these changes could be useful not only from a self-refection perspective, some of these changes could also indicate and reveal otherwise not apparent mental or behavioral health concerns.

Today, mental illness is a major cause of disability in the United States [19]. Besides being directly debilitating to sufferers, mental illness can adversely affect chronic health conditions, such as cardiovascular disease, cancer, diabetes, and obesity. It is also known to have negative influences on individuals' family and personal relationships, work or school life, and sleeping and eating habits. The World Health Organization (WHO) now ranks major depression, a common form of mental illness, as one of the most burdensome diseases in the world [5,19]. Although a number of primary care programs have been devised for its detection and treatment, the majority of the millions of Americans who meet depression criteria are untreated or undertreated [16]. Furthermore, ethnic minority groups such as Mexican Americans and African Americans are significantly less likely to receive depression therapies than are other ethnic groups [14].

As part of a national-scale effort to curb depression, every few years the Centers for Disease Control and Prevention (CDC) administers the Behavioral Risk Factor Surveillance System (BRFSS) survey via telephone to estimate the rate of depression among adults in the US [5]. However the large temporal gaps across which these measurements are made, as well as the limited number of participant responses (on the order of thousands) makes it difficult for agencies to track and identify risk factors that may be associated with mental illness, or to develop effective intervention programs.

This position paper examines recent research pursuing the potential of social media as a new tool for mental health measurement and surveillance. The emotion and language used in social media postings may indicate feelings of worthlessness, guilt, helplessness, and self-hatred that characterize depression as manifested in everyday life. Additionally, depression sufferers often show withdrawal from social situations and activities—i.e., the etiology of depression typically includes social environmental factors [20]. Characterization of social media activity and changing social ties within social media can provide measurement of such withdrawal and capture the depression sufferers' social context in a manner that might help detect depression in populations.

Relying on social media as a behavioral health assessment tool has other advantages as well. For instance, in contrast to the selfreport methodology in behavioral surveys, where responses are prompted by the experimenter and typically comprise recollection of (sometimes subjective) health facts, social media measurement of behavior captures social activity and language expression in a naturalistic setting. Such activity is real-time, and happens in the course of a person's day-to-day life. Hence it is less vulnerable to memory bias or experimenter demand effects, and can help track concerns at a fine-grained temporal scale.

Finally, based on a recent Pew Internet study[1], social networking sites (SNSes) have become an increasingly common aspect of daily life. As of August 2012, 69% of online American adults used SNSes; Facebook was the most popular, used by 66%, followed by LinkedIn (a professionally-focused network) at 20% penetration, and then Twitter at 16%. This gives us additional evidence that such social platforms may be utilized to make sense of people's behavioral over time and over heterogeneous samples.

In fact, of late popular media[2] has also been covering news around how social media tools may be a way for individuals suffering from mental health concerns to seek out for treat and diagnosis information, as well as for social and emotional support. Together, these provide evidence of how these platforms might be emergent tools to understand and learn about people's mental and behavioral health, so as to provide them with appropriate options of coping with this stigmatic condition, as well as interventions to manage this psychological challenge.

2. BACKGROUND

Rich bodies of work in psychiatry, psychology, medicine, and sociolinguistics describe efforts to identify and understand correlates of behavioral disorders in individuals. Cloninger et al. [7] examined the role of personality traits in the vulnerability of individuals to a future episode of depression, through a longitudinal study. On the other hand, Rude et al. [25] found support for the claim that negative processing biases, particularly (cognitive) biases in resolving ambiguous verbal information can predict subsequent depression. Robinson and Alloy [24] similarly observed that negative cognitive styles and stress-reactive rumination were predictive of the onset, number and duration of depressive episodes. Finally, Brown et al. [4] found that lack of social support and lowered self-esteem are important factors linked to higher incidences of depression. Among a variety of somatic factors, reduced energy, disturbed sleep, eating disorders, and stress and tension have also been found to be correlates of depressive disorders [1].

In the field of sociolinguistics, Oxman et al. [21] showed that linguistic analysis of speech could classify patients into groups suffering from depression and paranoia. Computerized analysis of written text through the LIWC program has also been found to reveal predictive cues about neurotic tendencies and psychiatric disorders [26].

Offline social networks and attributes relating to the psychological environment of individuals have also been consistently used to study behavioral health concerns. Billings and Moos [2] studied the roles of stress, social resources, and coping among individuals entering treatment for depression. On similar lines, in [15], Kawachi et al. explored the role of social ties and social capital in the maintenance of psychological wellbeing and treatment of behavioral health concerns. This prior research provides strong evidence that individuals' social environments contain vital information useful for understanding and intervening on mental health. Neils Rosenquist, Fowler, and Christakis [20] found that levels of depression showed diffusion upto three degrees of separation in a large social network, suggesting a network influence component to depression.

Although studies to date have improved our understanding of factors that are linked to mental disorders, a notable limitation of this research is that it relies heavily on small, often homogeneous samples of individuals, who may not necessarily be representative of the larger population. Further, these studies typically are based on surveys, relying on retrospective self-reports about mood and observations about health: a method that limits temporal granularity. That is, such assessments are designed to collect high-level summaries about experiences over long periods of time. Collecting finer-grained longitudinal data has been difficult, given the resources and invasiveness required to observe individuals' behavior over months and years.

With the increasing uptake of social sites, the hope is that continuing streams of evidence from social media on posting activity may often reflects people's psyches and social milieus. Seeking to use this data about people's social and psychological behavior to predict their vulnerabilities to depression in an unobtrusive and fine-grained manner therefore shows promise. We will discuss some research in this light in the following paragraphs.

Leveraging internet data for modeling and analyzing health behaviors has been a ripe area of research in the recent past. Google Flu Trends[3] provides nuanced predictions of flu infections based on online search queries. Paul and Dredze [23] developed a disease-specific topic model based on Twitter's posts in order to model behavior around a variety of diseases of importance in public health. Through language modeling of Twitter posts, Collier et al. [8] found evidence of high correlation between social media signals and diagnostic influenza case data. Sadelik et al. [27] developed statistical models that predicted infectious disease (e.g. flu) spread in individuals based on geotagged postings made on Twitter (also see [18]).

Although still in infancy in the context of the behavioral health domain, Park et al. [22] found initial evidence that people do post about their depression and even their treatment for depression on Twitter. Kotikalapudi et al. in [17] analyzed patterns of web activity of college students that could signal emotional concerns. In other related work, De Choudhury et al. examined linguistic and emotional correlates for postnatal course of new mothers [9], and thereafter built a model to predict extreme behavioral changes in new mothers [10]. They found that behavioral concerns such as post-partum depression may be reflected in mothers' social media use: including lowered positive affect and raised negativity, and use of greater first person pronouns indicating higher self-attentional focus. In fact, the behavioral changes of mothers could be predicted by leveraging their activity from simply the *prenatal* period. This early work thus points to the potential of social media as a signal to leverage in the study of depression.

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[1] http://www.pewinternet.org/

[2] http://www.abc.net.au/news/2013-08-20/rural-twitter-mental/4899000

[3] http://www.google.org/flutrends/

3. OPPORTUNITIES WITH SOCIALLY SHARED MULTIMEDIA

The social interactions people engage in today online are not just limited to text-based interactions, but multimedia is central to social sharing—be it images on Pinterest, or videos on Tumblr. Twitter and Facebook clients in fact provide built in mechanisms to share instantaneously captured multimedia objects. In essence, such shared media objects that occur in the course of people's day to day lives gives richer signals to capture their behavior than text alone. Potentially, such shared multimedia can be used in conjunction with text to characterize the challenges in the lives of people suffering from mental illness such as depression.

We illustrate some intuitions behind this. Greater sharing of pictures with other individuals may signal a person's more active social life—which is usually anti-correlated with depression. In general greater number of photos on a person's profile may indicate the person's desire to be open to different experiences, which is again likely to be anti-correlated to mental disorders.

The content of photos and videos that are socially shared may also signal a variety of behavioral traits—e.g., a person's mood—note that prior research in psychology has indicated that facial expressions are one of the most stable indicators of types of moods, and that they are fairly consistent across demographics like race, gender, and culture [12]. Mood expressions are known to be a strong indicator of a person's depressive state [11]. Beyond that, there is much to be explored in terms of the content of an image or a video in terms of the context a person is embedded in—what are the surroundings like? Are they disorderly, gloomy, or morose? Are the individuals with people who are their strong ties (indicative of social bond)?

Text-based paradigms have found that references to pronoun types are a known attribute indicative of mental illness—depressed individuals use greater number of first person singular pronouns, and to a lesser extent, second and third person pronouns [6]. This is explained by the fact that depression suffering individuals show greater self-attention focus than others—hence the greater use of first person singular pronouns, and they discuss less about other individuals around them or otherwise—hence the lowered usage of 2nd and 3rd person pronouns. Beyond text, multimedia objects shared socially can provide a lot of opportunities to study such self-attention focus—are the media uploaded by the person always focused on themselves? Are other individuals involved? What does it say about the degree or extent of self-attention focus, e.g., is it a media about themselves doing something, or an object to illustrate or show an artifact or process? There are several research challenges along this path, which might potentially be very helpful in pursing the direction on using social multimedia in detecting and characterizing mental disorders in people, and ways to generate early awareness among them, or simply to connect them with appropriate resources when things go awry.

4. DESIGN AND ETHICAL CHALLENGES

The ability to illustrate and model individual behavior using their social media data, that can predict their mental health state, shows promise in the design and deployment of next-generation wellness facilitating technologies. We envision privacy-preserving software applications and services that can serve as early warning systems providing personalized alerts and information to individuals. These tools perhaps can enable adjuvant diagnosis of depression and other mental illness, complementary to survey approaches (e.g., CES-D, BDI).

Beyond monitoring behavioral trends in real-time, social media-based measures, such as degrees of activity, emotional expression etc. can serve as a diary-type narrative resource logging "behavioral fingerprints" over extended periods of time. The application might even assign a "depression risk score" to individuals based on predictions made about forthcoming extreme changes in their behavior and mood. In operation, if inferred likelihoods of forthcoming extreme changes surpass a threshold, they could be warned or engaged, and information might be provided about professional assistance and/or the value of social and emotional support from friends and family. In short, we hope analytic approaches based on social media data can play a role in helping depression-suffering individuals find timely and appropriate support from health care professionals and others.

Concerns regarding individual privacy, including certain ethical considerations, may arise with this form of analyses of social media as they ultimately leverage information that may be considered sensitive, given their focus on behavioral and emotional health. We envision the systems described above to be designed as privacy preserving applications that are deployed by and for individuals, thereby honoring the sensitive aspect of revealing mental health related information to them. Closely intertwined with this privacy issue is the challenge of interventions. Can we design effective interventions for people, whom we have inferred to be vulnerable to a certain mental illness, in a way that is private, while raising awareness of this vulnerability to themselves and trusted others (doctors, family, friends)? In extreme situations, when an individual's inferred vulnerability to a mental illness is alarmingly high (e.g., if the individual is suicide-prone), what should be our responsibility as a research community? For instance, should there be other kinds of special interventions where appropriate counseling communities or organizations are engaged?

In short, finding the *right* types of interventions that can actually make a positive impact on people's behavioral state as well as abide by adequate privacy and ethical norms is a research question on its own. We hope this work triggers conversations and involvement with the ethics and clinician community to investigate opportunities and caution in this regard.

Beyond interventions, there is need for work on educating users about the privacy risks of sharing sensitive information online that can potentially be linked to their behavioral health. Participants' social multimedia use suggests that they might not be aware of the implications of some of these sharing practices, indicating that they may be unaware of how some advertising companies may be collecting and distributing their information. Even though a lot of the behavioral health inferences that encompasses prior research are derived from implicit patterns in activity and language, the ability to derive any information about a person's mental state from a public venue like Twitter may have serious repercussions (e.g., higher insurance rates, denial of employment, etc.). Developing interfaces that remind users of these risks (perhaps by throwing up an "are you sure?" dialogue when detecting sensitive information being entered into post) is an important area for further work.

To summarize, we believe that it is important to bring the possibilities to the fore, so as to leverage the benefits of these methods and ideas to enhance the quality of life for people, as well as to stimulate discussion and awareness of the potential role that policies could play in supporting the identities and practices that individuals suffering mental illness develop in the face of social disadvantage.

Finally, it should also be noted here that social media data has its own limitations, especially from a statistical sampling perspective. Although the analysis of social media postings makes it possible to track mental illness levels in ways there are not feasible offline, there are inherent population biases. According to Pew Research Center, among the 74% of American adults who use the internet, only about 8% report using Twitter. Additionally, unlike surveys, we have little knowledge about people's idiosyncratic behavior "behind the scenes", their social, cultural and psychological environment, or socio-economic status. Potentially, the limitations of Twitter may be tackled in one way by adding complementary sources of behavioral data, such as about social ties from Facebook, web browsing behavior, or search query logs, in conjunction with health records, such as antidepressant purchases, or healthcare claims data. These opportunities remain ripe areas of future research.

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