Mental Health Analysis via Social Media Data

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***Abstract*—With ubiquity of social media platforms, millions of people are routinely sharing their moods, feelings and even their daily struggles with mental health issues by expressing it verbally or indirectly through images they post. In this study, we aim to examine exploitation of big multi-modal social media data for studying depressive behavior and its population trend across the U.S. to better understand a regions influence on the prevailing environment and available care. In particular, employing statistical techniques along with the fusion of heterogeneous features gleaned from different modalities (shared images and textual content), we build models to detect depressed individuals and their demographics.**

***Keywords*-Multi-modal Analysis, Machine Learning, Natural Language Processing, Statistical analysis, Social Media, Mental Health, Regression**

I. Introduction

Depression is a highly prevalent public health challenge and a major cause of disability worldwide. According to the World Mental Health Survey conducted in 17 countries, on average, about 5% of people reported having an episode of depression in 2011[1]. It also affects 6.7% of Americans (that is, more than 16 million) each year [1]. Untreated or under-treated clinical depression can be serious enough to lead to suicide and other risky behaviors such as drug or alcohol addiction[2]. More than 90% of people who commit suicide have been diagnosed with depression [2].

A global effort to curb clinical depression involves identifying it through survey-based methods via phone or online questionnaires. These approaches mainly suffer from under-representation as well as sampling biases (a small group of respondents). Besides, survey data also exhibit problems due to temporal gaps between the data collection and dissemination of findings, reflecting participant's responses over a short period of time. In contrast, with an unprecedented growth of social media, large number of people voluntarily share large amounts of data by expressing their moods, feelings, emotions, and daily struggles with mental health problems on social media platforms like Twitter. This offers opportunities for new understanding of these communities. For instance, the news headlines such as "Twitter Fail:Teen Sent 144 Tweets Before Committing Suicide & No One Helped" highlights the need for better tools for gleaning useful insights from user generated content on social media.

Recent years have witnessed rapid growth in the analysis of social media for studying a wide range of health problems, from detecting influenza epidemic [3], [4] and cardiac arrest [5] to study mood and mental health conditions [6], [7]. Previous research efforts suggested that language style, sentiment, ego-network, and user engagement are discriminating features to predict the likelihood of depression in a post [8] or in an individual [9], [10]. These studies often represent psychological status of online users via their language via psycholinguistic analysis, supervised and unsupervised language modeling, or studying individuals topic of interest. However, except few attempts [cite, cite, cite] investigations in the fields are seldom concerned with visual attributes of mental health reflects on various social media platforms. Interestingly, according to eMarketer, photos accounted for 75% of content posted by Facebook pages worldwide and they are the most engaging type of content on Facebook (87%). It has been argued that sharing them is the best way get more attention from the followers. Indeed, an old saying of "a picture is worth a thousand words" recently changed to "photos are worth a million likes". Similar to Facebook, photos are more engaging for Twitter users. The tweets attached with image links get two times more engagement rate of those without 4. We recall that getting social support from peers has been highlighted as a primary motivation for sharing depressive indicative content in social media [6].

[1]http://bit.ly/2okBKNy

[2]http://www.webmd.com/depression/guide/untreated-depression-effects#1

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DOI 10.1109/ICHI.2018.00102

The easiness of expressing emotion through images where they often gaining more attention compared to the verbal form, is plausible motivation for sharing depressive images. Besides, as the psychologist Carl Rogers highlights, we often pursue attitudes which bring us closer to our Ideal-Self. In this regard, the choice of profile image can either represent our online persona or persona we choose to paint for others to see. We believe this can have roots in the mental health status of a person, and the visual attributes of it can provide emotional expression that can yield insights into mental illness. Inspired by that, we study the profile pictures of likely depressed individuals in order to discover relevant signals from colors, aesthetic and facial attributes, to better understand the psychology and the intent behind choosing the personal profile image.

Furthermore, the recent advancements in deep-convolutional neural networks, specifically for the image analysis task, has lead to a significant improvement in age and gender classification. Inspired by that, we develop a big data approach to automatically detect likely depressed individuals by exploiting heterogeneous set of features gleaned from different modality from studying the content of posted images (colorfulness, hue variance, sharpness, brightness, blurriness, naturalness), the choice of profile picture (gender, age, and emotion estimation), the choice of screen name, language features from both generated textual content and profiles description (n-gram, emotion, sentiment [11], [12], [13])(see Figure 1). In particular, we address the following research questions: 1) How well do the content of posted images (colors, aesthetic and facial presentation) can reflect depressive behavior? Does the choice of profile picture show any psychological trait of online depressed persona? Are they reliable enough to represent the demographics such as age and gender? 2)Are there any underlying common themes among depressed individuals generated visual and textual content?

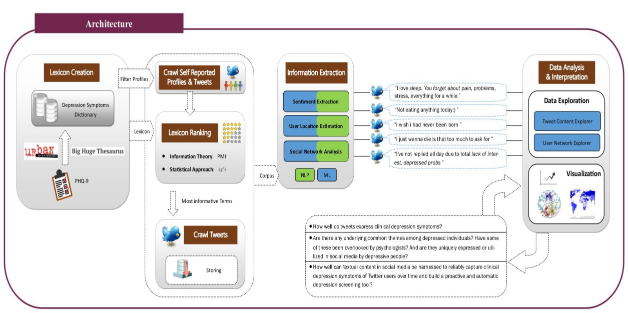

Figure 1. System architecture and the overall process

Acknowledgment

Research reported in this publication was supported in part by NIMH of the National Institutes of Health (NIH) under award number R01MH105384-01A1.

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