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Analyzing Clinical Depressive Symptoms in Twitter

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Motivation

- 360 million people are suffering from clinical depression worldwide.
- 27 million Americans are diagnosed with clinical depression that is responsible for more than 30,000 suicides each year.
- Our topic is about people who consider suicide have been diagnosed with clinical depression or another imprisoning mental illness.
- According to the World Mental Health Survey conducted in 17 countries, about 5% of people report having an episode of depression.
- Depression remains underdiagnosed, untreated or under-treated phenomenon due to various reasons such as the denial of illness or the social stigma associated with it.
- Early recognition of depression symptoms and their treatment through timely intervention can prevent the onset of major depression.

A common clinical global effort to manage depression involves detecting depression through survey-based methods via phone or online questionnaires. However, these studies suffer from underrepresentation, sampling biases and incomplete information. Additionally, large temporal gaps between data collection and dissemination of findings can delay administration of timely and appropriate remedial measures.

Research Aims

- Study and identify clinical depressive disorders using explicit and implicit expression of depression on social streams.
- Build a reliable platform to automatically detect depressive behaviors in social media that can emulate and extend the functionality of PHQ-9 to monitor user depressive behaviors.
- Evaluate our approach on self-reported profiles on social media.

Approach

- Twitter provides a rich source for studying people’s mood in order to detect depressive behaviors.
- We developed a novel technique to unobtrusively analyze individual posts in social media to detect signs of depression that can be utilized to build a proactive and automatic screening tool for early recognition of depression.
- Leveraging clinical definitions of depression, we build a depressive lexicon that contains common depression symptoms determined by experts such as from the established clinical assessment questionnaires PHQ-9.
- We expanded the terms representing the nine PHQ-9 depression symptoms categories using Urban Dictionary and Big Huge Thesaurus.
- The lexicon contains depression-related symptoms that are likely to appear in the tweets of individuals either having depressive-like symptoms or suffering from depression.
- A subset of high-frequency word terms are selected from this depression lexicon for crawling depression-related tweets. For each lexical term, we calculate its association with all of the variations of the term “depressive” using Pointwise Mutual Information (PMI) and Chi-squared test to quantify their correlation and thereby rank order them.

Architecture

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Conclusion

We demonstrated the potential of social media data for extracting clinical depressive symptoms in individuals that can be leveraged to improve the current questionnaire-driven clinical methods in its ability to detect clinical depression symptoms in a natural setting and in a continuous and ubiquitous manner.

This study leverages effective aspects, linguistic style and topics as features for detecting depressed communities. De Choudhury et al. (10) characterized depression based on factors such as language, emotion, style, ego-network, and user engagement. They utilize these distinguishing characteristics to build a classifier to predict the likelihood of depression in a post or in an individual.

Acknowledgement

We thank our colleagues at Kno.e.sis, Sunil Kumar, Sriram and Anita Iyer, and our collaborators at Weill Cornell Medical College for providing information for creating lexicon of symptoms. This study was supported in part by funding from NIH R01MH105384.

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Data Analysis & Interpretation

- Sentiment associated with topics
- Lost persons: PMI
- How well do tweets express clinical depression symptoms?
- How well can textual content in social media be harnessed to reliably capture clinical depression symptoms of Twitter users over time and build a proactive and automatic depression screening tool?

Information Extraction

- Network information
- Node Location
- User Location
- Social network analysis
- Sentiment associated with topics
- Lost persons: PMI
- How well do tweets express clinical depression symptoms?
- How well can textual content in social media be harnessed to reliably capture clinical depression symptoms of Twitter users over time and build a proactive and automatic depression screening tool?

Sentiment associated with Topics

- Depressed Users Location Analytics
- Data Analysis & Interpretation
- Network information
- Node Location
- User Location
- Social network analysis
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