CS 6474/CS 4803 Social Computing: Health and Well-Being

Munmun De Choudhury
munmund@gatech.edu
Week 10 | March 15, 2023
Assignment II available (Due: Apr 12)
Social Media Derived Behavioral and Affective Markers Predict Postpartum Changes

(De Choudhury, Counts, Horvitz, CSCW 2013; CHI 2013)
Social Media Derived Behavioral and Affective Markers Predict Postpartum Changes

376 users (new mothers); 40,426 posts between March 2011 and July 2012
Measuring Levels of Acute Stress in College Campuses with Social Media

(Saha and De Choudhury, PACM/CSCW 2018)
Temporal and Linguistic Patterns of Stress
Social media depression index

Socio-demographic, spatio-temporal patterns of prevalence of depression
Multi-Task Learning for Mental Health using Social Media Text

Adrian Benton
Johns Hopkins University
adrianb@jhu.edu

Abstract

We introduce initial groundwork for estimating suicide risk and mental health in a deep learning framework. By modeling multiple conditions, the system learns to make predictions about suicide risk and normal health at a fine-grained positive rate. Conditions are modeled as tasks in a multi-task learning (MTL) framework, with good predictions as an additional auxiliary task. We demonstrate the effectiveness of multi-task learning by comparison to well-tuned single-task baseline with the same number of parameters. Our best MTL model predicts positive and negative risk with a limited training data set.

Facebook Language Predictiveness in Social Media Records

Johannes C. Eichstaedt1,2, John T. Crawford1,2, Melissa B. M嘣, Jessica R. Murphy3,4, Paul Resnick3,4, and Jure Leskovec3,4

Introduction

Facebook users are self-reporting their mental health status through a series of questionnaire responses. In this work, we predict depression status from Facebook data. Our method is based on regression models that use a combination of text, demographic, and social features as input. The models are trained on anonymized Facebook data and tested on a held-out validation set. The results show that our method is able to accurately predict depression status.

Detecting Depression and Mental Illness on Social Media: an Integrative Review

Sharanth Chandrakanth, David B. Yaden, Margaret L. Kern, Lyle H. Ung, and Johannes C. Eichstaedt

Abstract

Asymptomatic mental illness is a major public health concern in the United States. This study reviews and synthesizes the existing literature on the use of social media to detect depression and mental illness. A systematic search of electronic databases and the grey literature was conducted. The results show that social media can be a valuable tool for detecting depression and mental illness, but more research is needed to improve the accuracy and reliability of these methods.

Identifying Social Media Markers of Machine Learning and Clinical

M. Reza Mirzaei, J. Maslow, and J. D. Coss

Abstract

This study proposes a novel approach for detecting suicidal ideation using natural language processing (NLP) techniques. The approach combines machine learning and NLP methods to identify suicidal ideation in social media text. The results show that the proposed approach is effective in detecting suicidal ideation, and can be used to improve the accuracy and reliability of suicide detection models.

Facebook Language Predictiveness in Social Media Records

Johannes C. Eichstaedt1,2, Robert J. Smith,3,4, Rachel M. M嘣,5,6, Patrick R. Gratch,7, and Jure Leskovec3,4

Introduction

Facebook is the largest social media platform and has a vast amount of user-generated information. In this work, we predict depression status from Facebook data. Our method is based on regression models that use a combination of text, demographic, and social features as input. The models are trained on anonymized Facebook data and tested on a held-out validation set. The results show that our method is able to accurately predict depression status.

Natural Language Processing of Social Media as a Screening Tool for Suicide Risk

Olen Deppen, Phyllis Leser, Patrick Gratch, and Alex Fire

Introduction

The use of social media by suicide-at-risk individuals provides a unique opportunity to detect suicidal ideation. In this work, we present a novel approach for detecting suicidal ideation in social media text using natural language processing techniques. The results show that the proposed approach is effective in detecting suicidal ideation, and can be used to improve the accuracy and reliability of suicide detection models.

Facebook Language Predictiveness in Social Media Records

Johannes C. Eichstaedt1,2, Robert J. Smith,3,4, Rachel M. M嘣,5,6, Patrick R. Gratch,7, and Jure Leskovec3,4

Introduction

Facebook is the largest social media platform and has a vast amount of user-generated information. In this work, we predict depression status from Facebook data. Our method is based on regression models that use a combination of text, demographic, and social features as input. The models are trained on anonymized Facebook data and tested on a held-out validation set. The results show that our method is able to accurately predict depression status.
Predicting Depression via Social Media
Summary

- Can social media activities and connectedness predict risk to major depressive disorder?
- Recruitment of a sample of Twitter users through a survey methodology over Amazon’s Mechanical Turk
  - ~40% provided access to Twitter data
Summary

- Social engagement
- “Insomnia index” – mean z-score of an individual’s volume of Twitter activity per hour
- Ego-centric social graph – nodal properties (inlinks, outlinks); dyadic properties (reciprocity, interpersonal exchange); neighborhood properties (density, clustering coefficient, two-hop neighborhood, embeddedness, number of ego components)
- Language
  - Depression lexicon – top uni- and bigrams compiled from Yahoo! Answers category on mental health
  - Linguistic style
Summary

The graphs show the relationship between posts per hour and time. The equations given are:

1. \( f(x) = 0.00070393x^2 - 0.015183x + 0.0045778x + 0.16 \)
2. \( f(x) = -6.9926e-05x^2 + 0.0045778x + 0.16 \)

These equations represent the functions for the non-depression class.

The graphs also show the volume and replies over time, with equations:

1. \( f(x) = -0.0010968x + 1.5931 \)
2. \( g(x) = 0.0013533x + 1.9698 \)
3. \( f(x) = -0.00015787x + 0.24883 \)
4. \( g(x) = 0.00014436x + 0.09113 \)

The graphs illustrate the increase in volume and replies over time for both classes.
Summary

<table>
<thead>
<tr>
<th>Egonetwork measures</th>
<th>Depres. class</th>
<th>Non-depres. class</th>
</tr>
</thead>
<tbody>
<tr>
<td>#followers/inlinks</td>
<td>26.9 (σ=78.3)</td>
<td>45.32 (σ=90.74)</td>
</tr>
<tr>
<td>#followees/outlinks</td>
<td>19.2 (σ=52.4)</td>
<td>40.06 (σ=63.25)</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.77 (σ=0.09)</td>
<td>1.364 (σ=0.186)</td>
</tr>
<tr>
<td>Prestige ratio</td>
<td>0.98 (σ=0.13)</td>
<td>0.613 (σ=0.277)</td>
</tr>
<tr>
<td>Graph density</td>
<td>0.01 (σ=0.03)</td>
<td>0.019 (σ=0.051)</td>
</tr>
<tr>
<td>Clustering coefficient</td>
<td>0.02 (σ=0.05)</td>
<td>0.011 (σ=0.072)</td>
</tr>
<tr>
<td>2-hop neighborhood</td>
<td>104 (σ=82.42)</td>
<td>198.4 (σ=110.3)</td>
</tr>
<tr>
<td>Embeddedness</td>
<td>0.38 (σ=0.14)</td>
<td>0.226 (σ=0.192)</td>
</tr>
<tr>
<td>#ego components</td>
<td>15.3 (σ=3.25)</td>
<td>7.851 (σ=6.294)</td>
</tr>
</tbody>
</table>
In this paper, the ground truth was obtained from Amazon mechanical turk workers. Anything unique about this population that may have affected the findings? What would be alternative ways of recruiting people or gathering high quality ground truth?
Depression is not an online condition, but one that spans both the online and the offline life. The paper does not take offline attributes into their models.

Is there a way to that into account? What would be the most significant offline attributes to consider?
Combining Search, Social Media, and Traditional Data Sources to Improve Influenza Surveillance

Mauricio Santillana¹,²,³*, André T. Nguyen¹, Mark Dredze⁴, Michael J. Paul⁵, Elaine O. Nsoesie⁶,⁷, John S. Brownstein²,³

¹ Harvard School of Engineering and Applied Sciences, Cambridge, Massachusetts, United States of America, ² Boston Children’s Hospital Informatics Program, Boston, Massachusetts, United States of America, ³ Harvard Medical School, Boston, Massachusetts, United States of America, ⁴ Department of Computer Science, Johns Hopkins University, Baltimore, Maryland, United States of America, ⁵ Department of Information Science, University of Colorado, Boulder, Colorado, United States of America, ⁶ Department of Global Health, University of Washington, Seattle, Washington, United States of America, ⁷ Institute for Health Metrics and Evaluation, Seattle, Washington, United States of America

* msantill@fas.harvard.edu

Abstract

We present a machine learning-based methodology capable of providing real-time (“now-cast”) and forecast estimates of influenza activity in the US by leveraging data from multiple data sources including: Google searches, Twitter microblogs, nearly real-time hospital visit records, and data from a participatory surveillance system. Our main contribution consists of combining multiple influenza-like illnesses (ILI) activity estimates, generated indepen-
Development of a Machine Learning Model Using Multiple, Heterogeneous Data Sources to Estimate Weekly US Suicide Fatalities

Daejin Choi, PhD; Steven A. Sumner, MD; Kristin M. Holland, PhD; John Draper, PhD; Sean Murphy, PhD; Daniel A. Bowen, MPH; Marissa Zwald, PhD; Jing Wang, MD; Royal Law, PhD; Jordan Taylor, BS; Chaitanya Konjeti, BS; Munmun De Choudhury, PhD

Key Points

Question Can real-time streams of secondary information related to suicide be used to accurately estimate suicide fatalities in the US in real time?
Discussion Point III

But are models trained on aggregated group-level differences useful at the individual level?
Correlation and causation
I used to think correlation implied causation.

Then I took a statistics class. Now I don't.

Sounds like the class helped. Well, maybe.
What comes next?
What comes next?

Social Media + Machine Learning for clinical interventions

Efficacy

Validity
SOCIAL MEDIA + MACHINE LEARNING

Ground truth label:
Readily available

Proxy ground truth labels

Ground truth label:
Clinical assessment
Construct Validity: Do the proxy diagnostic signals objectively and accurately measure what they claim to measure (clinical mental illness diagnosis)
Theoretical/Clinical grounding: Is what is being measured by the proxy diagnostic signals valid in itself?
Proxy data sets: diagnostic signals for schizophrenia on Twitter

- Affiliation Data: N = 861
- Self-reports Data: N = 412
- Appraised Data: N = 153
- Matched Control Data: N = 640
Patient’s social media data

Schizophrenia Patient Data
N = 88

Healthy Control Data
N = 55

Northwell Health
Methodology: Triangulation

Binary classification task:
Distinguishing those with schizophrenia from control populations
## Efficacy

High internal validity  
Very low external validity

<table>
<thead>
<tr>
<th>Model</th>
<th>Cross Validation</th>
<th>Testing on patient data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Affiliation Model</td>
<td>0.89</td>
<td>0.21</td>
</tr>
<tr>
<td>Self-report Model</td>
<td>0.72</td>
<td>0.48</td>
</tr>
<tr>
<td>Appraised Model</td>
<td>0.80</td>
<td>0.55</td>
</tr>
<tr>
<td>Patient Model</td>
<td>0.72</td>
<td>0.76</td>
</tr>
</tbody>
</table>
## Issues with Construct Validity

<table>
<thead>
<tr>
<th>Affiliation</th>
<th>β</th>
<th>Appraised β</th>
<th>Patient</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>i’m</td>
<td>-0.825</td>
<td>NegAffect</td>
<td>cog mech</td>
<td>-0.003</td>
</tr>
<tr>
<td>stigma</td>
<td>0.665</td>
<td>negation</td>
<td>present</td>
<td>-0.002</td>
</tr>
<tr>
<td>mhchat</td>
<td>0.696</td>
<td>present</td>
<td>body</td>
<td>-0.002</td>
</tr>
<tr>
<td>body</td>
<td>0.729</td>
<td>help</td>
<td>verbs</td>
<td>-0.002</td>
</tr>
<tr>
<td>bipolar</td>
<td>0.774</td>
<td>thought</td>
<td>social</td>
<td>-0.002</td>
</tr>
<tr>
<td>work</td>
<td>0.919</td>
<td>i’m</td>
<td>aux verbs</td>
<td>-0.002</td>
</tr>
<tr>
<td>self</td>
<td>0.961</td>
<td>die</td>
<td>help</td>
<td>0.0002</td>
</tr>
<tr>
<td>social</td>
<td>1.109</td>
<td>alone</td>
<td>feeling</td>
<td>0.001</td>
</tr>
<tr>
<td>care</td>
<td>1.111</td>
<td>hard</td>
<td>i’m</td>
<td>0.002</td>
</tr>
<tr>
<td>depression</td>
<td>1.116</td>
<td>cry</td>
<td>gonna</td>
<td>0.002</td>
</tr>
<tr>
<td>suicide</td>
<td>1.133</td>
<td>body</td>
<td>angel</td>
<td>0.002</td>
</tr>
<tr>
<td>thanks</td>
<td>1.445</td>
<td>feeling</td>
<td>burning</td>
<td>0.002</td>
</tr>
<tr>
<td>illness</td>
<td>1.447</td>
<td>verbs</td>
<td>pray</td>
<td>0.003</td>
</tr>
<tr>
<td>help</td>
<td>1.632</td>
<td>sorry</td>
<td>lifetime</td>
<td>0.005</td>
</tr>
<tr>
<td>mental health</td>
<td>1.866</td>
<td>gonna</td>
<td>attack</td>
<td>0.006</td>
</tr>
</tbody>
</table>
Main Takeaway

If the broader research agenda is to use social media data to inform clinical decision-making, such as early diagnosis, treatment or patient-provider interventions, (social media) data collection and machine learning model development should happen in context.
Class Exercise

Describe a design idea where we can use social media based depression (or other mental health condition like schizophrenia) predictors to help people. How would it negotiate privacy and ethical issues?
Improving “Blanket” Interventions

Everything okay?

If you or someone you know is struggling with thoughts of suicide, the Lifeline is here to help: call 1–800–273–8255.

If you are experiencing any other type of crisis, consider chatting confidentially with a volunteer trained in crisis intervention at www.imalive.org, or anonymously with a trained active listener from 7 Cups of Tea.

And, if you could use some inspiration and comfort in your dashboard, you should consider following the Lifeline on Tumblr.

Go back

View search results
Need help? United States:

1 (800) 273-8255
National Suicide Prevention Lifeline

Hours: 24 hours, 7 days a week
Languages: English, Spanish
Website: www.suicidepreventionlifeline.org

Hi Gerald, a friend thinks you might be going through something difficult and asked us to look at your recent post.

Only you can see this. Anything you do there will be kept private.
A Taxonomy of Ethical Tensions in Inferring Mental Health States from Social Media

Stevie Chancellor  
Georgia Tech  
Atlanta, GA, US  
schancellor3@gatech.edu

Michael L Birnbaum  
Northwell Health  
Glen Oaks, NY, US  
mbirnbaum@northwell.edu

Eric D. Caine  
University of Rochester  
Rochester, NY, US  
Eric_Caine@urmc.rochester.edu

Vincent M. B. Silenzio  
University of Rochester  
Rochester, NY, US  
vincen.t.silenzio@rochester.edu

Munmun De Choudhury  
Georgia Tech  
Atlanta, GA, US  
munmumde@gatech.edu

ABSTRACT
Powered by machine learning techniques, social media provides an unobtrusive lens into individual behaviors, emotions, and psychological states. Recent research has successfully employed social media data to predict mental health states of individuals, ranging from the presence and severity of mental disorders like depression to the risk of suicide. These algorithmic inferences hold great potential in supporting early detection and treatment of mental disorders and in the design of interventions. At the same time, the outcomes of this research can pose great risks to individuals, such as issues of incorrect, opaque algorithmic predictions, involvement of bad or unaccountable actors, and potential biases from intentional or inadvertent misuse of insights. Amplifying these tensions, there are also divergent and sometimes inconsistent methodological gaps and under-explored ethics and privacy dimensions. This paper presents a taxonomy of these concerns and ethical challenges, drawing from existing literature, and poses questions to be resolved as this research gains traction. We identify three areas of tension: ethics committees and the gap of social media research; questions of validity, data, and machine learning; and implications of this research for key stakeholders. We conclude with calls to action to begin resolving these interdisciplinary dilemmas.

CCS CONCEPTS
- Human-centered computing → Collaborative and social computing; Social media;  
- Applied computing → Psychology;

1 INTRODUCTION
Last year, Facebook unveiled automated tools to identify individuals contemplating suicide or self-injury [75, 62]. The company claims that they “use pattern recognition technology to help identify posts and live streams as likely to be expressing thoughts of suicide,” which then can deploy resources to assist the person in crisis [75]. Reactions to Facebook’s suicide prevention artificial intelligence (AI) are mixed, with some concerned about the use of AI to detect suicidal ideation as well as potential privacy violations [86]. Other suicide prevention AIs, however, have been met with stronger public backlash. Samaritan’s Radar, an app that scanned a person’s friends for concerning Twitter posts, was pulled from production, citing concerns for data collection without user permission [54], as well as enabling harassers to intervene when someone was vulnerable [4].

Since 2013, a new area of research has incorporated techniques from machine learning, natural language processing, and clinical psychology to categorize individuals’ moods and expressed well-being from social media data. These algorithms are powerful enough to infer with high accuracy whether an individual might be suffering from disorders such as major depression [28, 19, 84, 73, 78], postpartum depression [26, 27], post-traumatic stress [21], schizophrenia [60, 6], and suicidality [15, 22]. These algorithms can also reveal symptomatology linked to psychiatric challenges,