CS 6474/CS 4803 Social Computing: Health and Well-Being
Assignment II available (Due: Apr 8)
Social MediaDerived 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)

Oct 31, 2012
Man shoots 4 at Halloween Party.

University of Southern California

Mar 18, 2013
A student shoots himself after threatening his roommate.

University of Central Florida

Jan 21, 2014
A student shoots and kills another in classroom.

Purdue University

Nov 20, 2014
Gunman open fires in or near Library.

Florida State University

Feb 10, 2015
Perpetrator kills 3 members of a Muslim family.

University of North Carolina, Chapel Hill

Jun 01, 2016
Murder-suicide between a professor and his ex-student.

University of California, Los Angeles

February 12, 2013
A murder-suicide, where a grad student sets several small fires and then shoots two roommates.

Massachusetts Institute of Technology

April 18, 2013
Campus Police officer shot and murdered.

University of California, Santa Barbara

May 23, 2014
Isla Vista tragedy : 22 year old person kills 6 and injures 14.

University of Southern California

Feb 05, 2015
Professor and ex-wife involved in murder-suicide.

North Arizona University

Oct 09, 2015
Shooting near a dormitory.

Ohio State University

Nov 28, 2016
Allegedly Muslim radicalism based attack – 14 casualties.
Temporal and Linguistic Patterns of Stress
Social media depression index

actual (BRFSS data)  
predicted (SMDI)

Socio-demographic, spatio-temporal patterns of prevalence of depression

(De Choudhury, Counts, Horvitz, ICWSM 2013; WebSci 2013)
Multi-Task Learning for Mental Health 
using Social Media Text

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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 mental health at a high positive rate. Conditions are modeled as tasks in a multi-task learning (MTL) framework, with each task representing another form of another type of condition. 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 mental health outcomes, as well as the mental health conditions with much less tuned finite training data.

1 Introduction

Suicide is one of the leading causes of death worldwide, and over 90% of suicide deaths are preceded by mental illness. It is generally agreed that suicide is a psychiatric condition, and that people with mental illness are more likely to take their own lives than those without. However, the rate of suicide among the general population and in those with mental illness is still unknown, and therefore, the extent to which mental illness can be used is also unknown. Consequently, conditions are non-adequate.

2 Methods

A number of previous studies have shown that depression, anxiety, and bipolar disorder are associated with suicide risk. In this study, we investigate the relationship between mental health conditions and suicide risk using a multi-task learning framework.

3 Results

Our model was trained on a dataset of approximately 100,000 patient records, each containing information about mental health and suicide risk. The model achieved high accuracy in predicting suicide risk and mental health conditions. The results suggest that mental illness is a significant factor in predicting suicide risk.

4 Conclusion

Our findings indicate that mental illness is a significant factor in predicting suicide risk. This highlights the importance of mental health conditions in suicide risk prediction.

Facebook language processing predicts depression in medical records

Johannes C. Eichhorn1,2, Robert J. Johnson2, Israel M.ostil2, Rabe M. Mergler3, Jia-Peng Shih4, Patrick Grubich5,6,7,8, and Andrew Schuhmacher9

Abstract

Depression is a major health concern worldwide, and affects millions of people. In this paper, we investigate the relationship between language processing and depression risk. We performed a retrospective analysis of medical records containing information about depression and suicide risk. The results show that language processing is a significant factor in predicting depression risk.

Introduction

Depression is a major health concern worldwide, and affects millions of people. In this paper, we investigate the relationship between language processing and depression risk. We performed a retrospective analysis of medical records containing information about depression and suicide risk. The results show that language processing is a significant factor in predicting depression risk.

Natural Language Processing of Social Media as Cues for Suicide Risk

Owen O'Donoghue, John S. Lee, Patrick Grubich, and Alex Fire

Abstract

Cues for suicide risk in social media are becoming increasingly common. In this paper, we investigate the relationship between natural language processing and suicide risk. We performed a retrospective analysis of social media posts containing information about suicide risk. The results show that natural language processing is a significant factor in predicting suicide risk.

Introduction

Cues for suicide risk in social media are becoming increasingly common. In this paper, we investigate the relationship between natural language processing and suicide risk. We performed a retrospective analysis of social media posts containing information about suicide risk. The results show that natural language processing is a significant factor in predicting suicide risk.
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

Graphs showing the distribution of posts/hour over hours with quadratic functions for non-depression and depression classes. Additional graphs illustrate the relationship between time (in days) and volume, replies, and depression terms, with corresponding linear functions.
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=0.072)</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?
Representativeness of Twitter data – not everyone is on Twitter or another social media. Can findings from a study that uses social media data to infer mental health states be generalized? Why or why not?
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 Santillana\textsuperscript{1,2,3*}, André T. Nguyen\textsuperscript{1}, Mark Dredze\textsuperscript{4}, Michael J. Paul\textsuperscript{5}, Elaine O. Nsoesie\textsuperscript{6,7}, John S. Brownstein\textsuperscript{2,3}

\textsuperscript{1} Harvard School of Engineering and Applied Sciences, Cambridge, Massachusetts, United States of America, \textsuperscript{2} Boston Children’s Hospital Informatics Program, Boston, Massachusetts, United States of America, \textsuperscript{3} Harvard Medical School, Boston, Massachusetts, United States of America, \textsuperscript{4} Department of Computer Science, Johns Hopkins University, Baltimore, Maryland, United States of America, \textsuperscript{5} Department of Information Science, University of Colorado, Boulder, Colorado, United States of America, \textsuperscript{6} Department of Global Health, University of Washington, Seattle, Washington, United States of America, \textsuperscript{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 (“nowcast”) 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, PhD¹; Steven A. Sumner, MD²; Kristin M. Holland, PhD³; John Draper, PhD⁴; Sean Murphy, PhD⁴; Daniel A. Bowen, MPH³; Marissa Zwald, PhD³; Jing Wang, MD³; Royal Law, PhD⁵; Jordan Taylor, BS⁶; Chaitanya Konjeti, BS⁶; Munmun De Choudhury, PhD⁶


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?
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

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
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>( \beta )</th>
<th>Appraised ( \beta )</th>
<th>Patient</th>
<th>( \beta )</th>
</tr>
</thead>
<tbody>
<tr>
<td>i’m</td>
<td>-0.825</td>
<td>NegAffect</td>
<td>0.063</td>
<td></td>
</tr>
<tr>
<td>stigma</td>
<td>0.665</td>
<td>negation</td>
<td>0.074</td>
<td></td>
</tr>
<tr>
<td>mhchat</td>
<td>0.696</td>
<td>present</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>body</td>
<td>0.729</td>
<td>help</td>
<td>0.401</td>
<td></td>
</tr>
<tr>
<td>bipolar</td>
<td>0.774</td>
<td>thought</td>
<td>0.41</td>
<td></td>
</tr>
<tr>
<td>work</td>
<td>0.919</td>
<td>i’m</td>
<td>0.44</td>
<td></td>
</tr>
<tr>
<td>self</td>
<td>0.961</td>
<td>die</td>
<td>0.45</td>
<td></td>
</tr>
<tr>
<td>social</td>
<td>1.109</td>
<td>alone</td>
<td>0.45</td>
<td></td>
</tr>
<tr>
<td>care</td>
<td>1.111</td>
<td>hard</td>
<td>0.457</td>
<td></td>
</tr>
<tr>
<td>depression</td>
<td>1.116</td>
<td>cry</td>
<td>0.50</td>
<td></td>
</tr>
<tr>
<td>suicide</td>
<td>1.133</td>
<td>body</td>
<td>0.52</td>
<td></td>
</tr>
<tr>
<td>thanks</td>
<td>1.445</td>
<td>feeling</td>
<td>0.523</td>
<td></td>
</tr>
<tr>
<td>illness</td>
<td>1.447</td>
<td>verbs</td>
<td>0.58</td>
<td></td>
</tr>
<tr>
<td>help</td>
<td>1.632</td>
<td>sorry</td>
<td>0.662</td>
<td></td>
</tr>
<tr>
<td>mental health</td>
<td>1.866</td>
<td>gonna</td>
<td>0.63</td>
<td></td>
</tr>
</tbody>
</table>

\( \beta \) values range from -1 to 1, indicating the strength and direction of the relationship between variables.
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.
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
Need help? United States:
1 (800) 273-8255
National Suicide Prevention Lifeline
Hours: 24 hours, 7 days a week
Languages: English, Spanish
Website: www.suicidprevlactionlifeline.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.

See Post  Continue
A Taxonomy of Ethical Tensions in Inferring Mental Health States from Social Media

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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,