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

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Week 10 | March 16, 2022
Assignment II available (Due: Apr 13)
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

actual (BRFSS data)  
predicted (SMDI)

Socio-demographic, spatio-temporal patterns of prevalence of depression
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 normal mental health at a high positive rate. Conditions are modeled as tasks in a multi-task learning (MTL) framework, with each task as an 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 33% of the time, as well as the mental health, with AUC additional findings to multi-task learning on 7 with limited training data.

1 Introduction

Suicide is one of the leading causes of death worldwide, and over 90% of those who experience a suicide attempt die as a result. However, the risk of suicide does not begin and end with a single event. Effective mental health interventions are needed to help individuals who might be at risk of suicide.

Multi-task learning (MTL) has been applied to various domains, including healthcare, to address this challenge. However, applying MTL to suicide prevention presents unique challenges. In this paper, we introduce an initial framework for estimating suicide risk and normal mental health using a deep learning approach. Our model is trained on a dataset of social media posts, where we use multi-task learning to simultaneously predict both suicide risk and mental health.

2 Related Work

Previous research has shown that social media can be a valuable source of information for mental health interventions. For example, previous studies have used natural language processing (NLP) techniques to identify suicidal ideation in social media posts. However, these studies have focused on identifying specific signs of suicide, such as phrases or keywords, rather than using MTL to simultaneously predict both suicide risk and mental health.

3 Methodology

Our model is trained on a dataset of social media posts, where we use multi-task learning to simultaneously predict both suicide risk and mental health. We use a deep learning framework to process the social media posts and predict both suicide risk and mental health.

4 Experiments

We evaluate our model on a dataset of social media posts, where we use multi-task learning to simultaneously predict both suicide risk and mental health. Our model achieves an AUC of 0.73 for suicide risk and 0.78 for mental health.

5 Conclusion

In conclusion, we introduced an initial framework for estimating suicide risk and normal mental health using a deep learning approach. Our model is trained on a dataset of social media posts, where we use multi-task learning to simultaneously predict both suicide risk and mental health. Future work will focus on improving the accuracy of our model and expanding its application to other domains.
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 illustrate the relationship between different variables and their time-dependent changes. The equations provided indicate the mathematical models used to describe these relationships.

- The first graph shows a quadratic function $f(x) = 0.00070393x^2 - 0.015183x + 0.1$, and a linear function $f(x) = -6.9926e-05x^2 + 0.0045778x + 0.5$.

- The second graph displays volume and replies over time, with corresponding linear models.

- The third graph demonstrates an exponential growth model for posts per hour, with terms related to depression.

- The fourth graph presents another linear model for depression terms with time.
## 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

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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\textsuperscript{1}; Steven A. Sumner, MD\textsuperscript{2}; Kristin M. Holland, PhD\textsuperscript{3}; John Draper, PhD\textsuperscript{4}; Sean Murphy, PhD\textsuperscript{4}; Daniel A. Bowen, MPH\textsuperscript{3}; Marissa Zwald, PhD\textsuperscript{3}; Jing Wang, MD\textsuperscript{3}; Royal Law, PhD\textsuperscript{5}; Jordan Taylor, BS\textsuperscript{6}; Chaitanya Konjeti, BS\textsuperscript{6}; Munmun De Choudhury, PhD\textsuperscript{6}

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

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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;  