INFERRING MOOD INSTABILITY ON SOCIAL MEDIA BY LEVERAGING ECOLOGICAL MOMENTARY ASSESSMENTS

Koustuv Saha, Larry Chan, Kaya de Barbaro, Gregory D. Abowd, Munmun De Choudhury

Background

Quantifying attributes of mental well-being

Survey Instruments
- Self-Report Questionnaires

Active Sensing
- Ecological Momentary Assessments (EMAs)

Passive Sensing
- Smartphones and Wearables
- Social Media

SOCIAL MEDIA AS PASSIVE SENSOR!

Challenge

Ground-truth Data
Mood Instability
Goals & Contributions

Broad tasks

- Combination of Active and Passive Sensing
- A machine learning framework identifying mood instability for a larger population
- Psycholinguistic cues and Mood Instability Lexicon
Objective: Inferring Mood Instability

Participants (Dataset 1)

- Actively Sensed
  - EMAs
  - Social Media

- Passively Sensed
  - Social Media

Public (Dataset 2)

- Large-scale
- Unlabeled

• Small-scale
• Actively sensed data as Ground-truth
Study and Data

CampusLife, Georgia Tech
Recruitment

- 51 participants
- Mean age: 22 Years
- Incentives: $40-$120
- 5 weeks (Spring 2016)

Data

- Survey Questionnaire (Entry and Exit)
- Active Sensing: EMAs (Daily)
- Smartphone sensors (Barometer, Call, Accelerometer, App usage..)
- Social Media (Facebook, Twitter)
Privacy & Ethics

- IRB approval
- Data sharing consent
- Secure servers
- De-identification
EMA Data

Photographic Affect Meter (PAM)
(Pollak et al., 2011)


1,606 EMA Responses
(Mean responses/participant: 32)
Social Media Data

CampusLife Population

- 23 Participants
  - 13k+ status updates

- 10 Participants
  - 1.5k tweets

One-time collection
### Social Media Data-II

Unlabeled Twitter data with self-disclosure

(Coppersmith et al., 2014)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bipolar</strong></td>
<td>- Self-Disclosure of Bipolar Disorder</td>
</tr>
<tr>
<td></td>
<td>- Eg: <em>I have been diagnosed with Bipolar Disorder</em></td>
</tr>
<tr>
<td><strong>Borderline</strong></td>
<td>- Self-Disclosure of Borderline Personality Disorder</td>
</tr>
<tr>
<td></td>
<td>- Eg: <em>I suffer from bpd</em></td>
</tr>
<tr>
<td><strong>Control</strong></td>
<td>- Random Twitter Stream</td>
</tr>
<tr>
<td></td>
<td>- Excludes <em>Bipolar</em> and <em>Borderline</em></td>
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37m+ tweets, 19k+ unique users

**Linguistic Equivalence**

Cross-platform & Cross-population

(Baldwin et al., 2013)

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<table>
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<tr>
<th>Pair-wise comparison of word-vectors (cosine similarities)</th>
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<td>Cross-platform Linguistic Equivalence (Facebook and Twitter)</td>
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<tr>
<td>Cross-population Linguistic Equivalence (College and General population)</td>
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Data: Recap

- Actively Sensed
  - EMA Data
  - Facebook Data
- Passively Sensed
  - Twitter Data

**CampusLife (Dataset 1)**
- Small-scale
- Actively sensed data as Ground-truth

**Public (Dataset 2)**
- Large-scale
- Unlabeled
Methods and Results
Methods: Overview

- Actively Sensed
  - EMA Data
  - Mood Instability
  - Psycholinguistic Features
  - Seed Classifier

- Passively Sensed
  - Facebook Data
  - Psycholinguistic Features
  - Final Classifier

- Twitter Data
  - Psycholinguistic Features
  - Final Classifier

Campus (Dataset 1) → Public (Dataset 2) → Lexicon
Quantifying Mood Instability

Adjusted Successive Differences (ASDs)

(Jahng et al., 2008)


Non-uniform time differences in EMA responses

\[ ASD_{i+1} = \frac{x_{i+1} - x_i}{(t_{i+1} - t_i)/\text{Mdn}(t_{i+1} - t_i)} \]

![Graph showing ASD values over time with labels for Valence and Arousal](image)
Labeling Mood Instability

- ASD: Adjusted Successive Differences
- MAD: Mean Absolute Deviation
- MI: Mood Instability
Machine Learning Classifier

Seed Classifier

Linguistic Inquiry and Word Count (Pennebaker et al., 2003)

- Psycholinguistic Lexicon: Linguistic Inquiry and Word Count (LIWC)
- Supervised machine learning classifier
  - 23 CampusLife participants
  - k-fold cross-validation (k=5) for parameter tuning
  - Naïve Bayes, Logistic Regression, Random Forest, Support Vector Machine

# Seed Classifier: Accuracy Metrics

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<th>Metric</th>
<th>mean</th>
<th>stddev.</th>
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<td>0.58</td>
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<td>0.68</td>
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**Challenge**

Unstable Classification?
Semi-Supervised Classifier

Self-Training

(Dara et al., 2002)

- $K$-Means clustering ($K=2$)
- Classification of centroids using seed classifier

## Semi-supervised Classifier: Stability

| Data      | k-fold CV accuracies of SS Classifier (%High MI) | | | | | | | stdev. |
|-----------|--------------------------------------------------|---|---|---|---|---|---|---|<br>0.39|<br>0.68|<br>0.32 |
| Folds     | 1 | 2 | 3 | 4 | 5 | mean |<br>Bipolar |<br>Borderline |<br>Control |
| Bipolar   | 62.87 | 63.64 | 62.66 | 63.18 | 63.38 | 63.15 |<br>0.39 |<br>0.68 |<br>0.32 |
| Borderline| 61.06 | 61.81 | 62.44 | 62.84 | 62.31 | 62.09 |<br>0.39 |<br>0.68 |<br>0.32 |
| Control   | 36.70 | 36.54 | 36.56 | 36.47 | 37.26 | 36.71 |<br>0.39 |<br>0.68 |<br>0.32 |
Results

Machine Learning Classification

- High Accuracy

- Higher Occurrence of High MI in *Bipolar* and *Borderline* datasets as compared to *Control*
Analyzing the Language

Psycholinguistic Features

Mood Instability Lexicon

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<th>Psycholinguistic Group</th>
<th>H. MI vs. L. MI</th>
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<tr>
<td>Affective Attributes</td>
<td>83%</td>
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<td>Cognitive Attributes</td>
<td>521%</td>
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<td>Interpersonal Focus</td>
<td>124%</td>
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<td>Lexical Density and Awareness</td>
<td>195%</td>
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<tr>
<td>Social/Personal Concerns</td>
<td>90%</td>
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High MI

Low MI
Discussion
Implications

- Social media as a passive sensor
- Ability to detect Mood Instability
- Tackle the challenges of lack of labeled data
- Application in other health sensing problems
- Integrate multiple sensors
Limitations & Future Work

- Clinical Relevance
- Causal Claims
- Self-Reported and Social Media Data
- Multimodal Data
Acknowledgements

- CampusLife Consortium
- StudentLife Project
- Human-Facing Privacy Thrust of the IISP Institute at Georgia Tech


Thank You

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## Data

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<td><strong>Bipolar</strong></td>
<td>66.81  69.86  64.64  43.76  62.82  51.38</td>
<td><strong>10.30</strong></td>
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<tr>
<td><strong>Borderline</strong></td>
<td>61.37  63.81  54.41  34.04  56.13  45.06</td>
<td><strong>11.76</strong></td>
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<tr>
<td><strong>Control</strong></td>
<td>42.04  46.05  37.35  24.79  37.94  31.40</td>
<td><strong>7.99</strong></td>
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