CS 6474/4803 Social Computing: Analyzing Language II

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Language is the most common and reliable way for people to translate their internal thoughts and emotions into a form that others can understand. Words and language, then, are the very stuff of psychology and communication -- Tausczczik & Pennebaker
Diurnal and Seasonal Mood Vary with Work, Sleep, and Day length Across Diverse Cultures
Summary

• One of the early works examining relationship between social media mood and behavior and psychological theories.
• The potential of online social media to study individual behavior.
• Identify daily and seasonal mood variations and relate it to work, sleep and daylight.
• Validate circadian rhythms in humans.
  • PA spike in the morning, NA increases as the day progresses
• Measure positive affect and negative affect based on the lexicon LIWC.
• PA and NA are not mirror images of each other.
Twitter is used by millions and both the papers extensively leverage this source of data in measuring mood and affect.

How does use of Twitter for this purpose address limitations in existing mood or affect measurement methods?
Twitter is used by millions and both the papers extensively leverage this source of data in measuring mood and affect.

But could Twitter also have bias?
How do you expect the results relating to mood to be different if the paper used: 1) Facebook 2) Instagram?
Could platform affordances impact specific moods and their manifestations on social media? How?
Class Exercise
Why is measuring mood useful? Some examples follow...
Modeling Public Mood and Emotion: Twitter Sentiment and Socioeconomic Phenomena – (Bollen, Pepe, Mao, 2010)

- Examine how Twitter moods reflect social, political, and economic events
- Use POMS (profile of mood states) for detecting mood-indicative twitter posts.
  - POMS dimensions: tension, depression, anger, vigor, fatigue and confusion
- Investigate how a six vector representation of moods deviates during different big scope events.
- High stress/tension during elections; excitement/vigor during thanksgiving.
deviations from the mean as shown in Fig. 9. Discussed peaks and troughs are nearly or above 2 standard deviations from the mean. A scale is not provided for each of the POMS mood dimensions, z-score normalized.

The y-axis corresponds to mood z-scores, expressed in standard deviations from the mean. This is used to assess changing mood levels over time in relation to long-term changes in socio-economic indicators. Notably, Obama’s victory was recorded on November 4, 2008, with public sentiment fluctuating significantly in this tumult. Throughout this period, the emotional response of the Twitter community was highly diverse, with notable examples: the failure of several large, international banks, the DJIA dropping in value from above 11,000 points to less than 9,000. Significant changes in the price of gasoline and the Dow Jones underwent significant changes in value. We examine the effects of particular short-term events; for example, the 2008 Presidential elections of November 4, 2008, and calls for action on election day which lead to a move of nearly one day. Vertical lines originate in the timeline’s events, namely the U.S. Presidential election of November 4, 2008, and after Thanksgiving on November 27, 2008.

To assess the effects of socio-economic indicators, we focus on the period two days before and after election day. This period spans 15 days before and after election day. The period two days before and after election day is shown as a gray area for the period under study.

4. RESULTS

4.1 Case studies

For the period under study: The x-axis expresses time in days; it rounds the presidential election reflect a move of nearly one day. Vertical lines originate in the timeline’s events, namely the U.S. Presidential election of November 4, 2008, and after Thanksgiving on November 27, 2008. Figure 5: Sparklines for public mood before, during and after election day. This could indicate a surge in tweets that mark a sharp drop in Fatigue that started two days before election day. This could indicate a surge in tweets that mark a sharp drop in Fatigue that started two days before election day. Tension. Thanksgiving corresponds to the most significant of 1 standard deviation. This is used to assess changing

Tension. Thanksgiving corresponds to the most significant changes in the DJIA and WTI on October 20, 2008 to December 20, 2008. DJIA-I: August 1 to 24, DJIA-II: August 25 to 31, DJIA-III: September 1 to 17, DJIA-IV: September 18 to 24. Figure 7 shows the sparklines for the six mood dimensions before, during and after the 2008 Presidential elections. Figure 8 shows the sparklines for the six mood dimensions before, during and after Thanksgiving.

The mood curves shown in Fig. 5 provide a fine-grained picture of the changes in public mood. They are based on the analysis of Twitter data over a period of two days before and two days after the election. The curves show that there was a significant drop in Fatigue on November 3, followed by a spike in Depression and Confusion on November 4, which peaked on November 5. The spike in Vigour and Tension is also noticeable. The curves are consistent with the findings of previous studies that have shown a decrease in Fatigue and an increase in Depression and Confusion during election periods.

Our investigation of the produced public mood time series production outlined above are summarized in the main text. Second, we examine the long-term effects of particular short-term events; for example, the failures of several large, international banks, the DJIA dropping in value from above 11,000 points to less than 9,000. Significant changes in the price of gasoline and the Dow Jones underwent significant changes in value. We examine the effects of particular short-term events; for example, the failure of several large, international banks, the DJIA dropping in value from above 11,000 points to less than 9,000. Significant changes in the price of gasoline and the Dow Jones underwent significant changes in value. We examine the effects of particular short-term events; for example, the failure of several large, international banks, the DJIA dropping in value from above 11,000 points to less than 9,000. Significant changes in the price of gasoline and the Dow Jones underwent significant changes in value.
Temporal Patterns of Happiness and Information in a Global Social Network: Hedonometrics and Twitter

Peter Sheridan Dodds, Kameron Decker Harris, Isabel M. Kloumann, Catherine A. Bliss, Christopher M. Danforth

Bailout of the U.S. financial system: $T_{\text{ref}}$: 7 days before and after ($h_{\text{avg}}=6.00$) $T_{\text{comp}}$: Monday, 2008/09/29 ($h_{\text{avg}}=5.95$)

Royal Wedding of Prince William & Catherine Middleton: $T_{\text{ref}}$: 7 days before and after ($h_{\text{avg}}=5.98$) $T_{\text{comp}}$: Friday, 2011/04/29 ($h_{\text{avg}}=6.04$)

Death of Osama Bin Laden: $T_{\text{ref}}$: 7 days before and after ($h_{\text{avg}}=5.98$) $T_{\text{comp}}$: Monday, 2011/05/02 ($h_{\text{avg}}=5.89$)
Not All Moods Are Created Equal! Exploring Human Emotional States in Social Media, by De Choudhury, Counts, and Gamon 2012
• **Emotion** – brief conscious experience characterized by intense mental activity and a high degree of pleasure or displeasure

• **Affect** – an instinctual reaction to stimulation occurring before the typical cognitive processes considered necessary for the formation of a more complex emotion

• **Mood** – emotional state. Moods differ from emotions or affects in that they are less specific, less intense, and less likely to be triggered by a particular stimulus or event

• **Sentiment** – attitude or opinion with respect to a specific topic, event or situation
Personality, Gender, and Age in the Language of Social Media: The Open-Vocabulary Approach
Summary

- Facebook data of 75K individuals
- Users took personality tests
  - Participants volunteered to share their status updates as part of the My Personality application, where they also took a variety of questionnaires
- Authors found striking variations in language with personality, gender, and age
  - Use of an open vocabulary approach
- Results confirmed previously known social science findings, suggested new hypotheses, and showed sustained face validity
Summary

Volunteer Data

- Social media messages
- Gender, personality, location, age, health, ...

1) Linguistic feature extraction
   a) words and phrases
   b) topics

2) Correlation analysis

3) Visualization

EXTRACTION

- Words and phrases
- Topics

CORRELATION

- Analysis with visualizations

VISUALIZATION

- Tag cloud with positive words
- Graphical representations
Summary

- **Open Vocabulary: Differential Language Analysis**
- **Key characteristics:**
  - Open-vocabulary – it is not limited to predefined word lists. Rather, linguistic features including words, phrases, and topics (sets of semantically related words) are automatically determined from the texts. (i.e., it is “data-driven”.) This means DLA is classified as a type of open-vocabulary approach.
  - Discriminating – it finds key linguistic features that distinguish psychological and demographic attributes, using stringent significance tests.
  - Simple – it uses simple, fast, and readily accepted statistical techniques.
Summary
<table>
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<tr>
<th>features</th>
<th>Gender</th>
<th>Age</th>
<th>Extraversion</th>
<th>Agreeableness</th>
<th>Conscientious.</th>
<th>Neuroticism</th>
<th>Openness</th>
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<tbody>
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<td></td>
<td>accuracy</td>
<td>R</td>
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<tr>
<td>LIWC</td>
<td>78.4%</td>
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<td>.21</td>
<td>.29</td>
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<tr>
<td>Topics</td>
<td>87.5%</td>
<td>.80</td>
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<td>.38</td>
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<tr>
<td>WordPhrases</td>
<td>91.4%</td>
<td>.83</td>
<td>.37</td>
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</tr>
<tr>
<td>WordPhrases + Topics</td>
<td>91.9%</td>
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*accuracy:* percent predicted correctly (for discrete binary outcomes). *R:* Square-root of the coefficient of determination (for sequential/continuous outcomes). *LIWC:* All *a priori* word-categories from Linguistic Inquiry and Word Count. *Topics:* Automatically created LDA topic clusters. *WordPhrases:* words and phrases (n-grams of size 1 to 3, passing a collocation filter). Bold indicates significant (*p*<.01) improvement over the baseline set of features (use of *LIWC* alone).

doi:10.1371/journal.pone.0073791.t002
Why is gender and personality inference useful for social computing researchers and professionals?
How is an open vocabulary approach more suitable for social media language data over closed vocabulary ones?
People use social media for all kinds of reasons and purposes. On Facebook in particular, people are heavily concerned about impression management.

Why do you think the assessments of personality are still accurate?
Facebook Tinkers With Users’ Emotions in News Feed Experiment, Stirring Outcry

By VINDU GOEL  JUNE 29, 2014

To Facebook, we are all lab rats.

Facebook routinely adjusts its users’ news feeds — testing out the number of ads they see or the size of photos that appear — often without their knowledge. It is all for the purpose, the company says, of creating a more alluring and useful product.

But last week, Facebook revealed that it had manipulated the news feeds of over half a million randomly selected users to change the number of positive and negative posts they saw. It was part of a psychological study to examine how emotions can be spread on social media.

The company says users consent to this kind of manipulation when they agree to its terms of service. But in the quick judgment of the Internet, that argument was not universally accepted.

“I wonder if Facebook KILLED anyone with their emotion manipulation stunt. At their scale and with depressed people out there, it’s possible,” the privacy activist Lauren Weinstein wrote in a Twitter post.

On Sunday afternoon, the Facebook researcher who led the study, Adam D. I. Kramer, posted a public apology on his Facebook page.