Ubiquitous and Mobile Computing
CS 528: Detecting Boredom from Mobile Phone Usage

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Outline

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Introduction

- People have periods of time where attention is sparse, and time when attention is abundant and people are looking for stimulus.
- The goal was to show that “a user-independent machine-learning model of boredom-leveraging features related to recency of communication, usage intensity, time of day, and demographics—can infer boredom with accuracy”
Motivation

Boredom is an opportunity:

- Recommending content, services, or activates that may help to overcome the boredom
- Suggesting to turn their attention to more useful activities

“Feeling bored often goes along with an urge to escape such a state. This urge can be so severe that in one study … people preferred to self-administer electric shock rather than being left alone with their thoughts for a few minutes”

- Pielot et al, citing Wilson et al
Related Work

- **Bored Detection**
  - Bixler and D’Mello
    - Expression recognition
  - Picard *et al*
    - Emotional state detection using physiological sensors
    - Significantly more invasive
  - Mark *et al*
    - Rhythm of attention in the workplace

- **Inferring Emotions**
  - LiKamWa *et al*
    - Determining mood based on communications and routine activities
  - Bogomolov *et al*
    - Daily happiness and stress can be inferred from mobile phone usage, personality traits and weather data
Methodology

Points of inquiry

● Study 1
  ● Does boredom measurably affect phone use?
  ● What aspects of mobile phone usage are the most indicative of boredom?

● Study 2
  ● Are people who are bored more likely to consume suggested content on their phones?
Methodology: Study 1

- Created data collection app *Borapp*
  - 54 valid participants for at least 14 days
    - Self-reported levels of boredom on a 5 point scale at semi-regular intervals
    - App collected sensor data, some sensor data at all times, others just when phone was unlocked
Results: Study 1

- Use machine-learning to analyze sensor and self-reported data and create a model
  - Classifier Selection
    - Nested-cross validation of three widely used classifiers
    - Random Forests performed the best and was used
  - Feature Analysis
    - Ranked feature importance using Mean Impurity Decrease
    - Selected top 20 most important features of 35
Results: Study 1, Features

<table>
<thead>
<tr>
<th>Feature</th>
<th>Import</th>
<th>Correlation</th>
<th>The more bored, the..</th>
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<tbody>
<tr>
<td>time_last_outgoing_call</td>
<td>0.0607</td>
<td>-0.143</td>
<td>less time passed</td>
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<td>0.088</td>
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<td>0.091</td>
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<td>0.053</td>
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<td>0.0405</td>
<td>-0.090</td>
<td>less time passed</td>
</tr>
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<td>0.0388</td>
<td>-0.013</td>
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<td>light</td>
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<td>-0.010</td>
<td>darker</td>
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<tr>
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<td>0.0411</td>
<td>0.038</td>
<td>later</td>
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<tr>
<td>proximity</td>
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<td>-0.186</td>
<td>less covered</td>
</tr>
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<td>0.099</td>
<td>more male (1)</td>
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<tr>
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<td>n.a.</td>
<td>+20s/40s, -30s</td>
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<tr>
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<td>more apps per minute</td>
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<tr>
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<tr>
<td>battery_drain</td>
<td>0.0249</td>
<td>-0.014</td>
<td>the lower</td>
</tr>
</tbody>
</table>
Results: Study 1

- End Result:
  - A model that could predict boredom ~82% of the time
  - Found correlation between boredom and phone use
  - Found features that indicate boredom
Motivation: Study 2

Now that we can predict when people are bored.

- Are people who are bored more likely to consume suggested content?
Methodology: Study 2

- Created app *Borapp2*
- 16 new participants took part in a quasi-experiment
  - When participant was bored, the app would suggest the newest BuzzFeed article
  - When the participant was not bored, there was a $1/9$ chance the app would suggest the newest BuzzFeed article
  - 48% of the time an article was suggested the algorithm predicts the user was bored, 52% of the time the user was not bored
Methodology: Study 2

- Measured Click-ratio: how often the user opened the Buzzfeed article divided by the total number of notifications
- Engagement-ratio: How often the user opened the Buzzfeed article for at least 30 seconds divided by the total number of notifications
Results: Study 2

- Preliminary findings: Users were more likely to open and engage with suggested content.

Figure 6. Click-ratio per condition.

Figure 7. Engagement-ratio per condition.
Future Work

- More studies to provide stronger statistical proof
  - This study was small and biased (Self-selection)
  - High error rate in boredom model makes the second study impure
- Expanded studies into boredom
- Personalize suggested content to user tastes during periods of boredom
References

- Pielot, M., Dingler, T., Pedro, J. S., and N. Oliver When Attention is not Scarce - Detecting Boredom from Mobile Phone Usage