

# Ubiquitous and Mobile Computing

## CS 528: *Detecting Boredom from Mobile Phone Usage*

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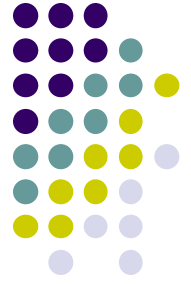
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# Outline



- Introduction
- Motivation
- Related Work
- Study 1
  - Methodology
  - Results
- Study 2
  - Motivation
  - Methodology
  - Results
- Conclusion
- Future work
- References



# 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

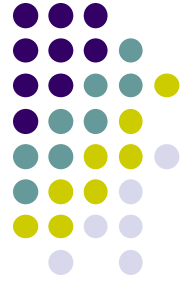
- Bored Detection
  - Bixler and D'Mello
    - Expression recognition
  - Picard *et al*
    - Emotional state detection using physiological sensors
    - Significantly more invasive
  - Mark *et al*
    - Rhythm of attention in the workplace
- Inferring Emotions
  - LiKamWa *et al*
    - Determining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

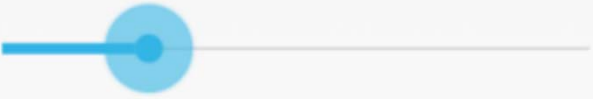
- Study 1
  - Does boredom measurably affect phone use?
  - What aspects of mobile phone usage are the most indicative of boredom?
- Study 2
  - Are people who are bored more likely to consume suggested content on their phones?



# 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

(3) To what extent do you agree to the statement:  
**'Right now, I feel bored'?**

disagree  agree

Submit



# 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





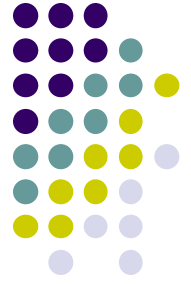
# Results: Study 1, Features

<i>Feature</i>	<i>Import</i>	<i>Correlation</i>	<i>The more bored, the ..</i>
time_last_outgoing_call	0.0607	-0.143	less time passed
time_last_incoming_call	0.0580	0.088	more time passed
time_last_notif	0.0564	0.091	more time passed
time_last_SMS_received	0.0483	0.053	more time passed
time_last_SMS_sent	0.0405	-0.090	less time passed
time_last_SMS_read	0.0388	-0.013	less time passed
light	0.0537	-0.010	darker
hour_of_day	0.0411	0.038	later
proximity	0.0153	-0.186	less covered
gender (0=f, 1=m)	0.0128	0.099	more male (1)
age	0.0093	n.a.	+20s/40s, -30s
num_notifs	0.0123	0.061	more notifications
time_last_notif_ctr_acc	0.0486	-0.015	less time passed
time_last_unlock	0.0400	-0.007	less time passed
apps_per_min	0.0199	0.024	more apps per minute
num_apps	0.0124	0.049	more apps
bytes_received	0.0546	-0.012	less bytes received
bytes_transmitted	0.0500	0.039	more bytes sent
battery_level	0.0268	0.012	the higher
battery_drain	0.0249	-0.014	the lower

# 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

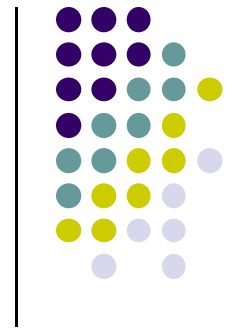
- Created app *Borapp2*
- 16 new participants took part in a quasi-experiment
  - When participant was bored, the app would suggest the newest BuzzFeed article
  - When the participant was not bored, there was a 1/9 chance the app would suggest the newest BuzzFeed article
    - 48% of the time an article 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



Click-Ratio: Bored v Normal

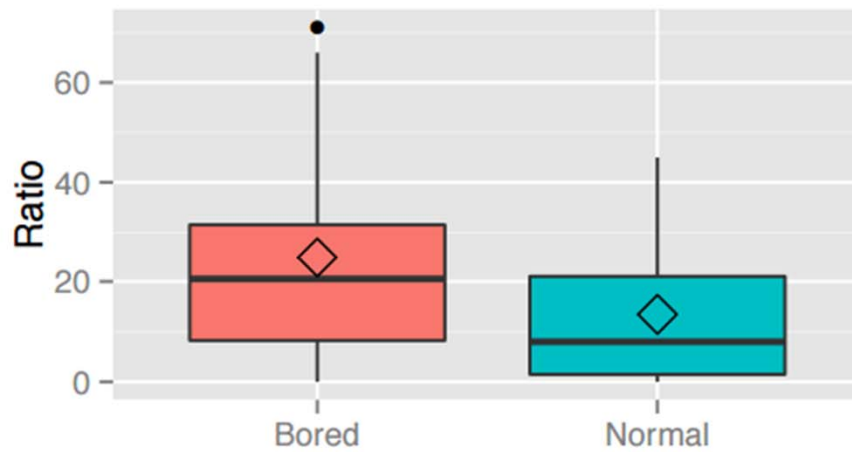


Figure 6. Click-ratio per condition.

Engagement-Ratio: Bored v Normal

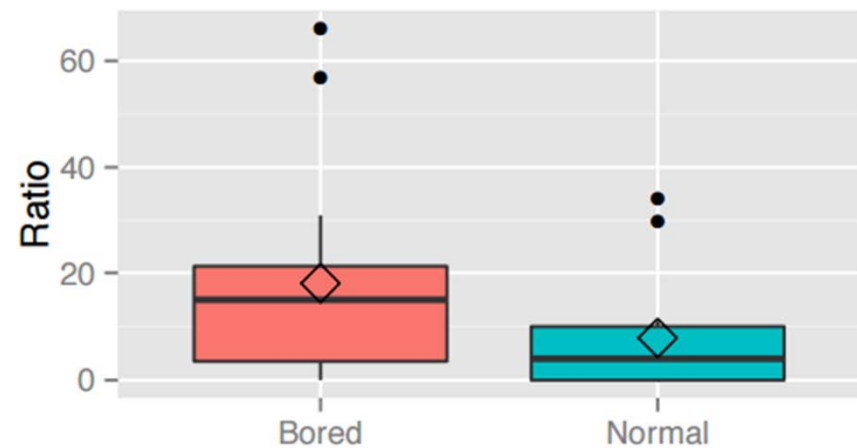
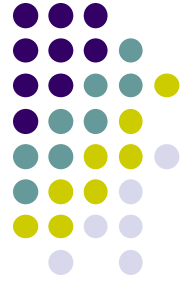


Figure 7. Engagement-ratio per condition.

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



## 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

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