Mobile and Ubiquitous Computing on Smartphones
Chapter 8b: Smartphone Sensing

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MIT Epidemiological Change

Introduction

Ref: A. Madan, Social sensing for epidemiological behavior change, *in Proc Ubicomp 2010*

Epidemiology: The study of how infectious disease spreads in a population

- Face-to-face contact is primary means of transmission

- Understanding behavior is key to modeling, prediction, policy

Research Questions

- Can smartphone reliably detect sick owner?
  - Based on sensable behavior changes (movement patterns, etc)

- **Q1:** How do physical and mental health symptoms manifest themselves as behavioral patterns?
  - E.g. worsening cold = reduced movement?

- **Q2:** Given sensed behavioral pattern (e.g. movement), can smartphone user's symptom/ailment be reliably inferred?

Potential Uses of Smartphone Sickness Sensing

- **Early warning system (not diagnosis)**
  - Doesn't have to be so accurate
- Just flag "potentially" ill student, nurse calls to check up
- Insurance companies can reduce untreated illnesses that result in huge expenses

General Approach

- Semester-long Study of 70 MIT Students
  - Continuously gather sensable signs (movement, social interactions, etc)
  - Administer sickness/symptom questionnaires periodically as pop-ups (EMA)

- **Labeling:** what movement pattern, social interaction level = what illness, symptom

Labels (for classifier)

Sickness Questionnaires (EMA)
- Ailment type (cold, flu, etc)
- Symptoms

Autosensed data

Data Gathering app, automatically sense
- Movement
- Social interactions

Methodology

- 70 residents of an MIT dorm
- Windows-Mobile device
- Daily Survey (symptom data)
- Sensor-based Social Interaction Data
- 10 weeks
  - Date: 02/01/2009 - 04/15/2009
  - Peak influenza months in New England

Methodology (Symptom Data)

- Daily pop-up survey
- 6AM every day - respond to symptom questions

Table 1. Symptom Survey Questionnaire. All questions were Yes/No responses

Survey Question (as shown on mobile phone)
Do you have a sore throat or cough?
Do you have a runny nose, congestion or sneezing?
Do you have a fever?
Have you had any vomiting, nausea or diarrhea?
Have you been feeling sad, lonely or depressed lately?
Have you been feeling stressed out lately?

Methodology (Social Interaction Data)

- SMS and Call records (log every 20 minutes)
  - Communication patterns
  - Time of communication (e.g. Late night / early morning)
  - E.g. may talk more on the phone early or late night when in bed with cold

- Tracked number of calls/SMS, and with who (diversity)
  - E.g. sick people may communicate with/seeing same/usual people or new people (e.g. nurse, family?)
  - Intensity of ties, size and dynamics of social network
  - Consistency of behavior

Analyze Syndrome/Symptom/Behavioral Relationships

```
Syndrome [Influenza, Cold/Allergies]
```

⇩

```
Symptoms [
      Sore throat/cough,
      Runny Nose/Conjestion/Sneezing,
      Fever,
      Vomiting/Nausea,
      Sad/Lonely/Depressed
      Stressed]
```

⇩

```
Behavioral [
      Total Communication,
      Late Night Communication,
      Communication Diversity,
      Bluetooth Proximity Entropy
      WLAN Entropy]
```

Data Analysis

- Behavior effects of CDC-defined influenza (Flu)
  - **Flu is somewhat serious, communication, movement generally decreased**

(a) Total Bluetooth interactions and entropy decrease **

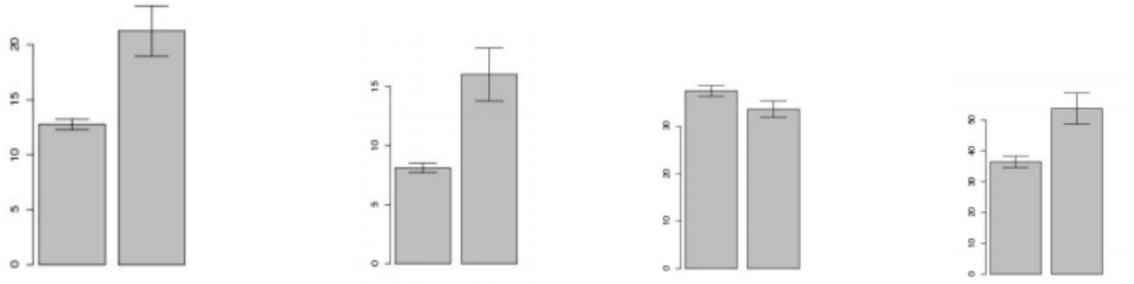
(b) Late night early morning Bluetooth entropy with respect to other participants decreases **

(c) WLAN based entropy with respect to university WLAN APs decreases ***

(d) WLAN Entropy with respect to external WLAN APs decreases ***

Data Analysis

- Behavior effects of runny nose, congestion, sneezing symptom (mild illness)
  - **Cold is somewhat mild, communication, movement generally increased**



(a) Total communication increases ***

(b) Late-night early morning communication increases **

(c) Overall Bluetooth entropy decreases *

(d) Total WLAN APs detected increase **

Results: Conclusion

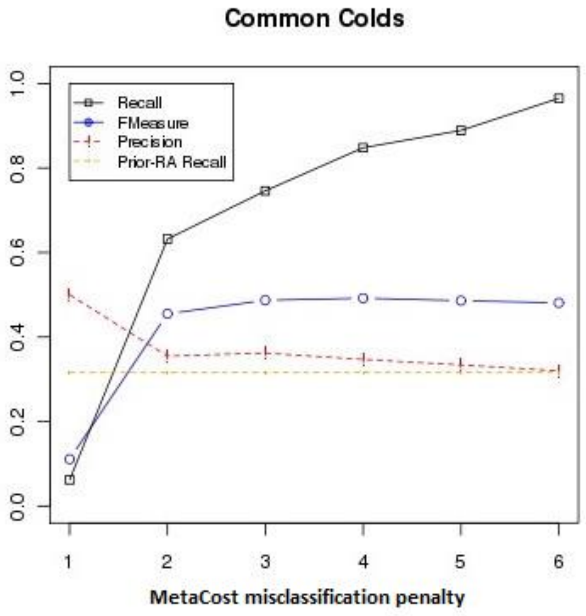
- **Conclusion:** Behavioral changes are identified as having statistically significant association with reported symptoms.

- Can we classify illness, likely symptoms based on observed behaviors?

- Why? Detect variations in behavior -> identify likelihood of symptom and take action

Symptom Classification using Behavioral Features

- Yes!!
- Bayes Classifier w/MetaCost for misclassification penalty
  - **60% to 90% accuracy!!**



Conclusion

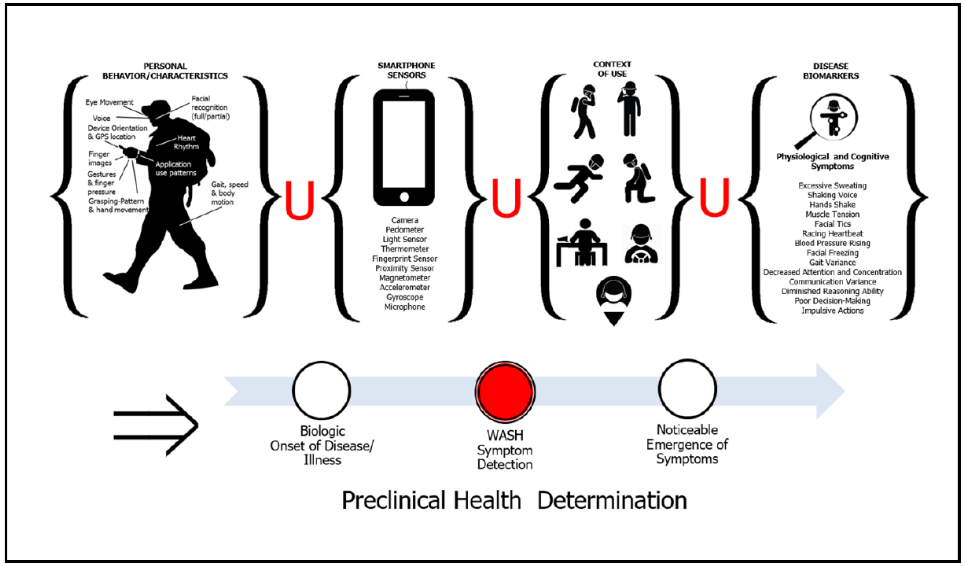
- Mobile phone successfully used to sense behavior changes from cold, influenza, stress, depression
- Demonstrated the ability to predict health status from behavior, without direct health measurements
- Opens avenue for real-time automatic identification and improved modeling
- Led to startup Ginger io (circa 2012)
  - Patients tracked, called by real physician when ill
  - funded > $25 million till date
- Now DARPA is funding us to do similar research for COVID, flu detection

WASH Project:
TBI, Infectious Disease Biomarkers

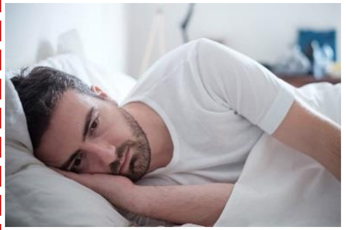
Smartphone BioMarkers to Improve Warfighter Health

PI: Agu, co-PI: Rundensteiner

- US military want early signs of warfighter ailment:
  - Traumatic Brain Injury (bomb blasts, explosions, fall, etc)
  - Infectious diseases (E.g. tuberculosis, pneumonia, measles, meningitis, malaria, Ebola, cholera and influenza)
- **WASH Concept:** Smartphone-sensable biomarkers may manifest first
  - E.g. reduced mobility, sedentary, sleep problems, stay close to home
- WPI received $2.8 from DARPA (military) to research smartphone biomarkers for TBI and infectious diseases

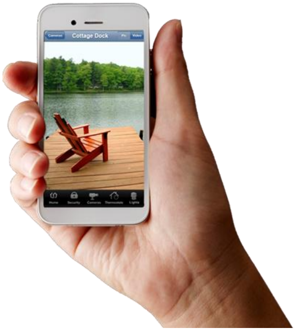


Examples of TBI, Infectious Disease Biomarkers Detectable by Smartphone

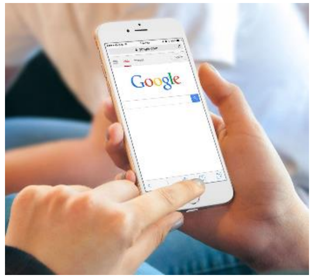


Sleep problems

Pupils dilated



Hands shaking



Slow phone interactions

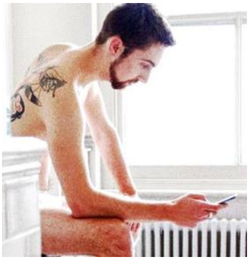
Avoiding light

Slurred speech

Traumatic Brain Injury (TBI) Smartphone Biomarkers

Walking Problems

Coughing



Increased Bathroom usage

Sneezing

Infectious Disease Smartphone Biomarkers

Note: Specific tests (e.g. hands shaking) in specific situations (e.g. user holding phone)

Our Research Approach

- Working with doctors, we now have specific list of 30 contexts in which we will run 14 specific TBI/infectious disease tests
- **Research Question 1:** Can smartphone detect when a smartphone user is in one of our specific contexts?
- Methodology:
  - Run a **scripted** user study
    - Recruit 100 subjects
    - Subjects using smartphone, enter each of 32 contexts
    - Gather smartphone data continuously in background
    - Later: analyze data (machine learning)
  - Run **Unscripted** user study
    - 100 subjects, 2 weeks, periodically prompted, label their context
    - Data is very real, very noisy

Context: Definition & Final List of Contexts

Context = (User Activity, Phone Prioception, App Category, Social)

Sitting
Standing
Walking
Lying down
Sleeping
Awake/not sleeping
Interacting with phone
Coughing
Exercising
Running
Sneezing
Sitting down
Lying down
Standing up
Talking into phone

Phone in Hand
Phone facing down
Phone on table
Trouser pocket
In bag
Briefcase
Jacket pocket

Games
- Video game

Media & Video
- Video Chat
- Video streaming

Communication
- Messaging

Social
- Messaging

Entertainment
- Video streaming

Alone
2 or more speakers
More than 2 speakers
Busy place

30 Contexts Needed for Our Tests

1	<interacting with phone, phone in hand, *, *>
2	<*, phone in hand, *, *>
3	<lying down, *, *, *>
4	<sitting, *, *, *>
5	<standing, *, *, *>
6	<sleeping, *, *, *>
7	<awake, *, *, *>
8	<walking, in pocket, *, *>
9	<walking, in hand, *, *>
10	<walking, in bag, *, *>
11	<*, phone on table, *, *>
12	<*, phone facing down, *, *>
13	<talking into phone, *, *, *>
14	<*, *, *, more than 2 speakers>
15	<Coughing, *, *, *>

16	<Coughing, *, *, in busy place>
17	<Toilet, *, *, *>
18	<Toilet, Phone in pocket, *, *>
19	<sleeping, phone on table, *, 0>
20	<exercising, phone in hand, *, 0>
21	<exercising, phone on table, *, 0>
22	<exercising, *, *, more than 2 speakers>
23	<Sneezing, *, *, 2 or more speakers>
24	In noisy/bust place
25	<lying down, phone on table, *, *>
26	<Sneezing, *, *, alone>
27	<Sitting up, *, *, *>
28	<Standing up, *, *, *>
29	<Sitting down, *, *, *>
30	<Lying down, *, *, *>

WASH Scripted Study

Context Collection Study: Overview

- Scripted, on-campus study to cover the majority of identified contexts
- Each subjects completes a carefully planned circuit, timed
- Each subject given same Essential Android phones to ensure consistent data
- Mobile app automatically gathers sensor data, labels entered manually with timestamps

Context Data Study: Route @ WPI

1. Fuller Labs
   - Briefing
2. Recreation Center
   - Walking, running
   - Bathroom
3. Morgan Hall
   - Phone call
   - Water break
   - Being in a busy place
4. Fuller Labs
   - Lying down
   - Sitting down
   - Standing up

Context Collection Study: Sensors

Standard:

- Gyroscope
- Accelerometer
- Barometer
- Magnetometer
- Location Services
  - Speed
  - Distance traveled over a period of time

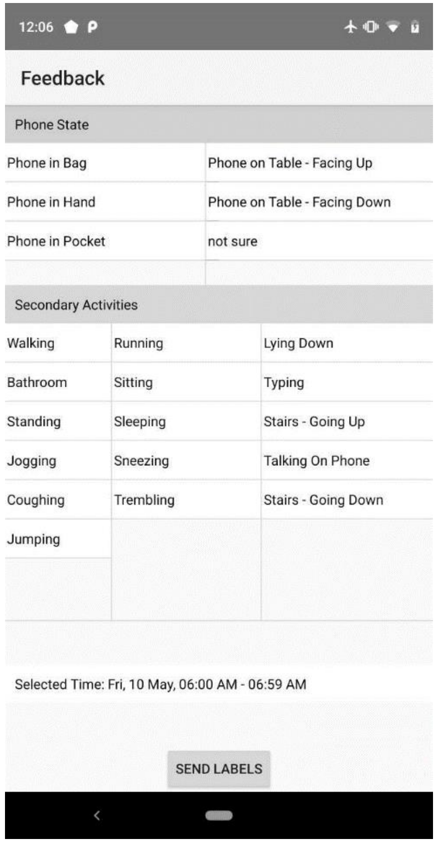
Experimental:

- Audio
  - Feature extraction on phone to mitigate privacy concerns
- Ambient light
- Proximity
- Discrete sensors
  - Is the phone charging?
  - Are they interacting with it?

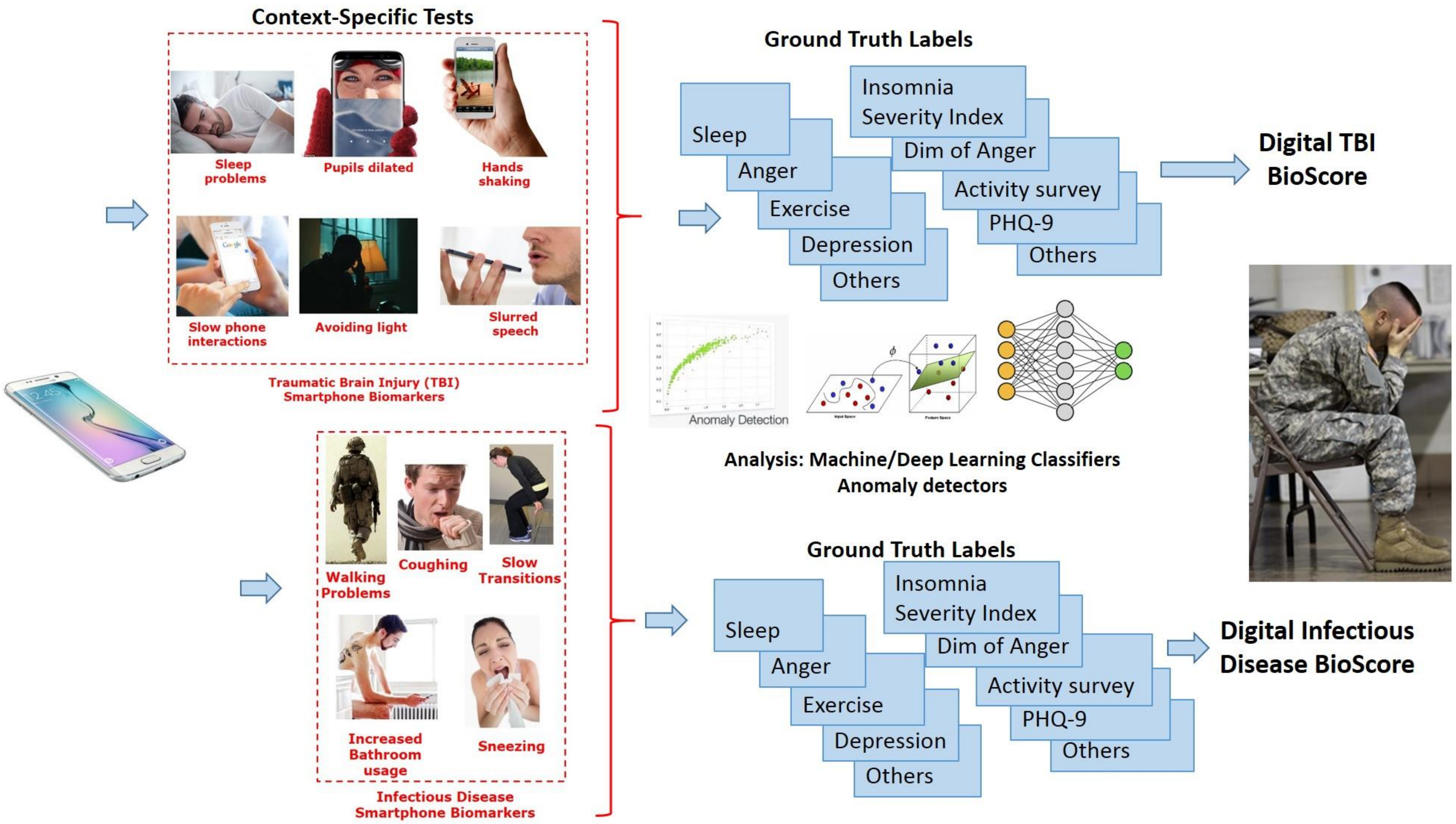
WASH Unscripted Study

WASHSensory App to gather subjects data

- App continuously collected sensor data
- Subjects labeled 25 contexts
    - Laying Down, Phone on Table
    - Excising, Phone in Pocket
    - Toilet, Phone in Pocket
    - Walking, Phone in Bag
    - Walking, Phone in Hand
    - Walking, Phone in Pocket
    - Typing
    - Sleeping
    - Sitting
    - Running
    - Laying Down (state)
    - Jogging
    - Running
    - Standing
    - Talking On Phone
    - Bathroom
    - Phone in Pocket
    - Phone in Hand
    - Phone in Bag
    - Phone on Table, Facing Up
    - Phone on Table, Facing Down
    - Stairs - Going Up
    - Stairs - Going Down
    - Walking

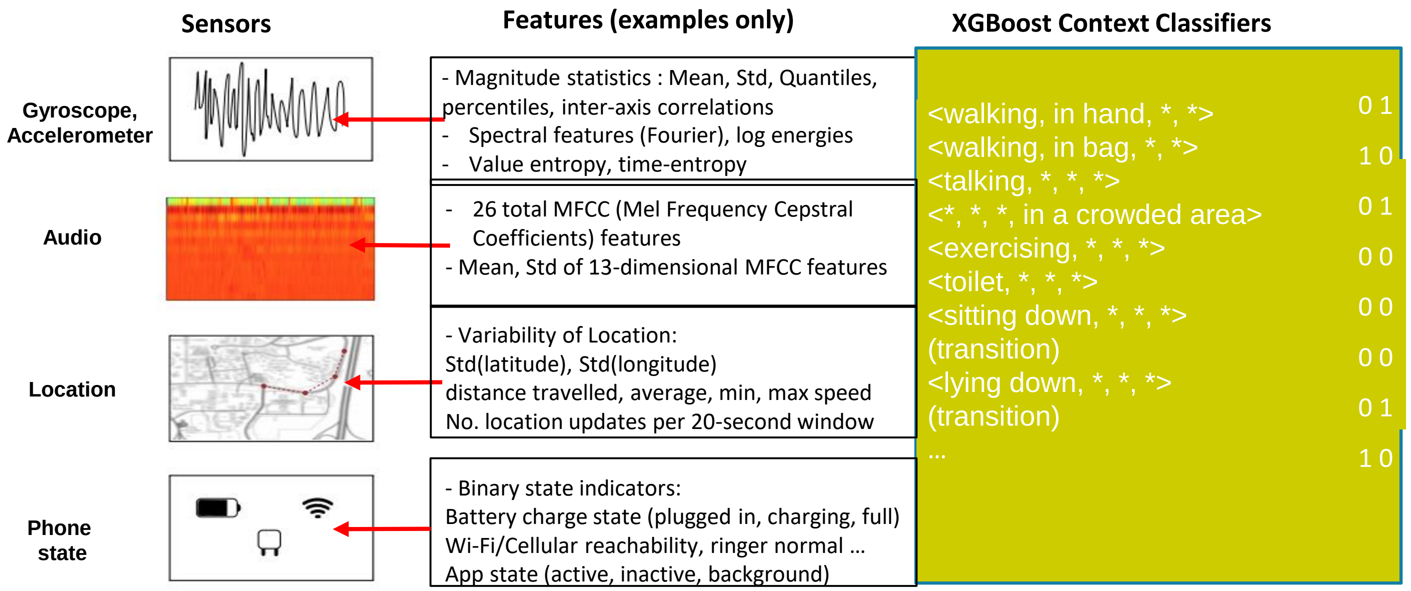


Overview of our Classification Approach



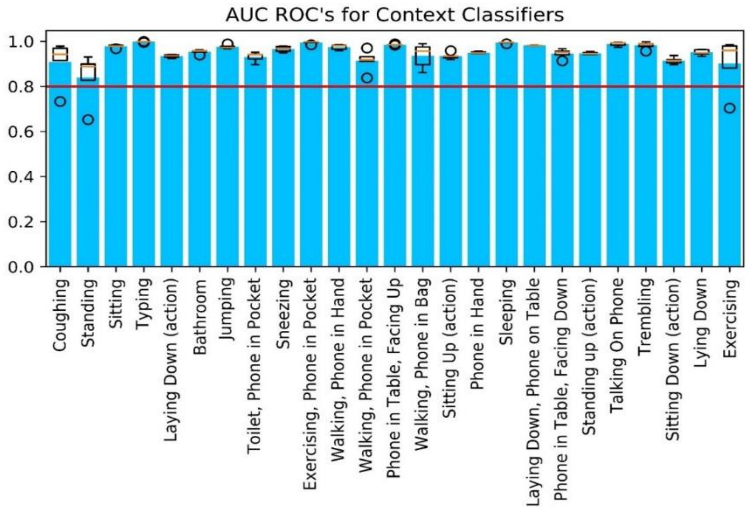
WPI Scripted Study Data Analysis: Extracted Features (N=109)

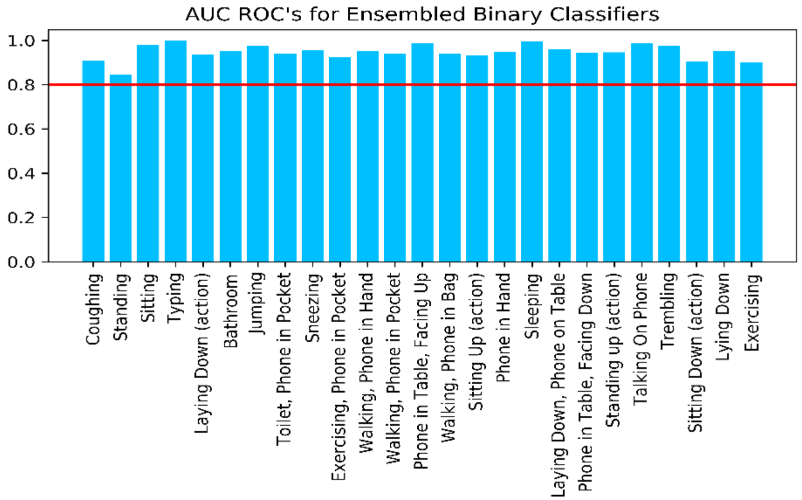
- 175 features extracted from data gathered in our scripted user study
  - Accelerometer, gyroscope, location, audio, phone state feature
  - Also time features (time windows: 3am-9am, 6am-midday, 9am-3pm, etc)
- Classified features using XGBoost machine learning classifier



Classified WPI WASH Context Data using XGBoost Classifier

- **Main result:** Over 80% macro AUC-ROC for all 25 contexts, 14 contexts > 90%





- **Approach 1:** Classify individual binary labels, compute macro AUC-ROC
- Macro AUC-ROC is average of individual binary labels in tuple

Approach 2: Classify context tuple as target using XGBoost

Over 80% macro AUC-ROC for all 25 contexts

Over 80% AUC-ROC for 25 ensembled binary contexts

Met program objectives 25/25 contexts detected with > 80% accuracy

Affect Detection

MoodScope: Detecting Mood from Smartphone Usage Patterns (Likamwa *et al*)

- Define Mood based on Circumplex model in psychology
- Each mood defined on pleasure, activeness axes
  - **Pleasure:** how positive or negative one feels
  - **Activeness:** How likely one is to take action (e.g. active vs passive)

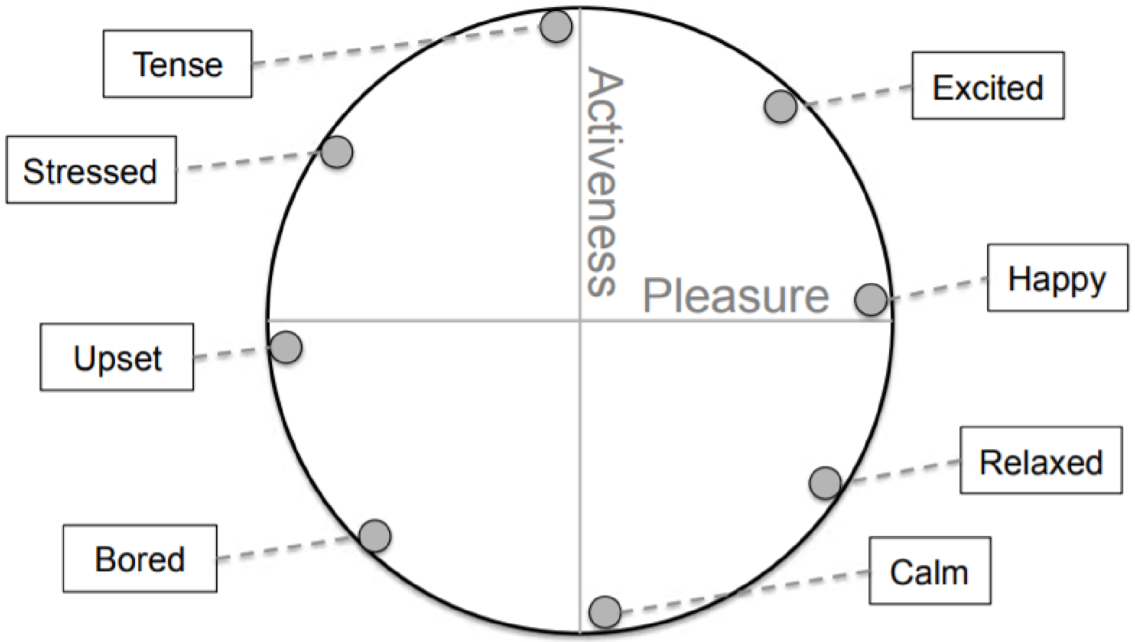


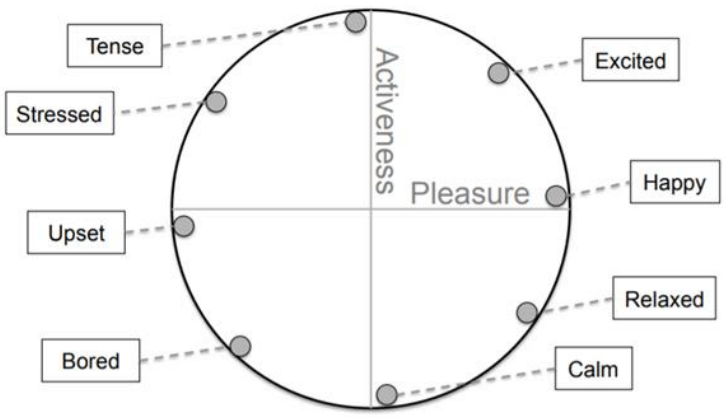
Figure 1: The circumplex mood model

Classification

- **Moodscope:** classifies user mood from smartphone usage patterns

Data type	Features
Email contacts	#messages #characters
SMS contacts	#messages #characters
Phone call contacts	#calls call duration
Website domains	#visits
Location clusters	#visits
Apps	#app launches app duration
Categories of apps	#app launches app duration

Smartphone usage features



Mood

MoodScope Study

- 32 Participants logged their moods periodically over 2 months
- Used mood journaling application
- Subjects: 25 in China, 7 in US, Ages 18-29

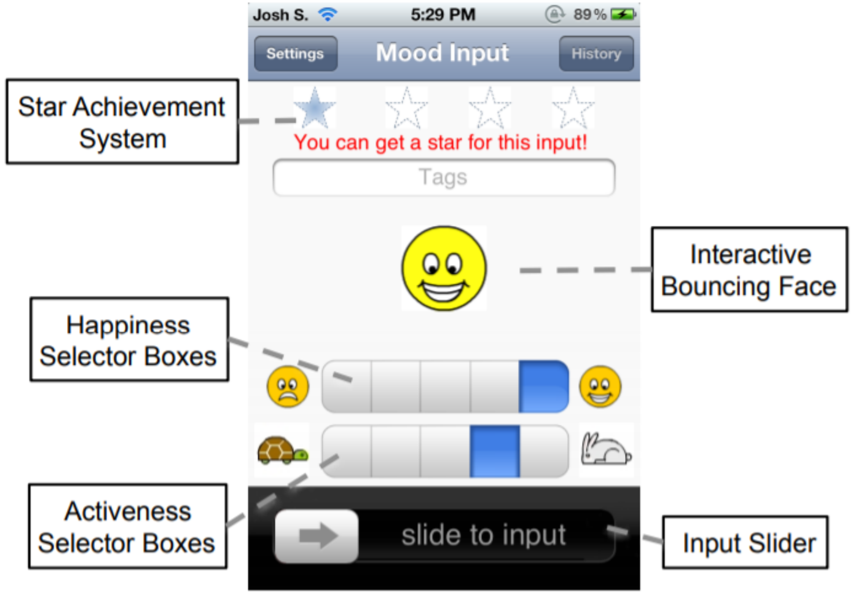


Figure 2: Mood journaling application view

MoodScope: Results

- Multi-linear regression
- 66% accuracy using general model (1 model for everyone)
- 93% accuracy, personalized model after 2 months of training
- Top features?

- Communication
  - SMS
  - Email
  - Phone Calls
- To whom?
  - # messages
  - Length/Duration

Consider "Top 10" Histograms

How many phone calls were made to #1? #2? … #10?

How much time was spent on calls to #1? #2? … #10?

Detecting Boredom from Mobile Phone Usage,
Pielot *et al,* Ubicomp 2015

Introduction

- 43% of time, people seek self-stimulation
  - Watch YouTube videos, web browsing, social media

- **Boredom:** Periods of time when people have abundant time, seeking stimulation

- **Paper Goal:** Develop machine learning model to infer boredom based on features related to:
  - Recency of communication
  - Usage intensity
  - Time of day
  - Demographics

Motivation

If boredom can be detected, opportunity to:

- Recommend content, services, or activities that may help to overcome the boredom
  - E.g. play video, recommend an article
- Suggesting to turn their attention to more useful activities
  - Go over to-do lists, etc

“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
  - Expression recognition (Bixler and D’Mello)
  - Emotional state detection using physiological sensors (Picard *et al*)
  - Rhythm of attention in the workplace (Mark *et al*)

- Inferring Emotions
  - Moodscope: Detect mood from communications and phone usage (LiKamWa *et al*)
  - Infer happiness and stress phone usage, personality traits and weather data (Bogomolov *et al*)

Methodology

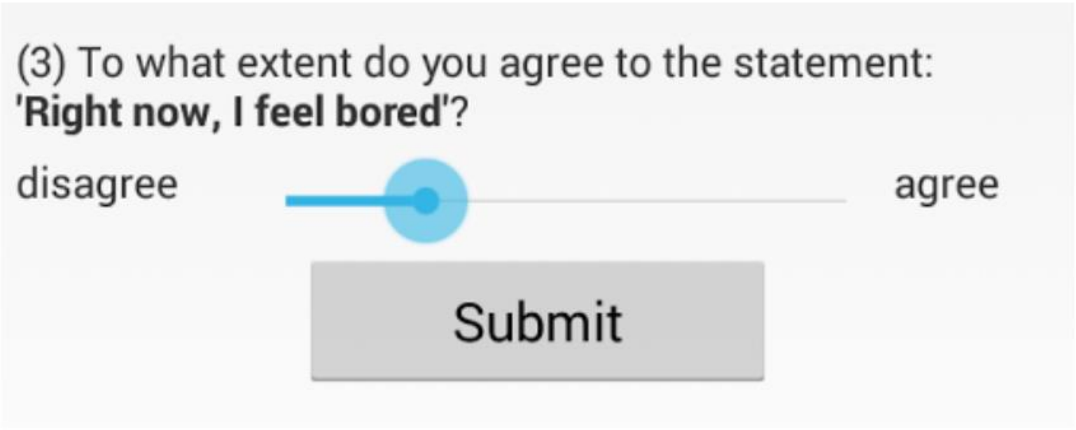
- 2 short Studies

- Study 1
  - Does boredom measurably affect phone use?
  - What aspects of mobile phone usage are 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 participants for at least 14 days
    - Self-reported levels of boredom on a 5-point scale
      - Probes when phone in use + at least 60 mins after last probe
    - App collected sensor data, some sensor data at all times, others just when phone was unlocked



Study 1: Features Extracted

- **Assumption:** Short infrequent activity = less goal oriented
- Extracted 35 features, in 7 categories
  - **Context**
  - **Demograpics**
  - **Time since last activity**
  - Intensity of usage
  - External Triggers
  - Idling

Context	
audio	Indicates whether the phone is connected to a headphone or a bluetooth speaker
charging	Whether the phone is connected to a charger or not
day_of_week	Day of the week (0-6)
hour_of_day	Hour of the day (0-23)
light	Light level in lux measured by the proximity sensor
proximity	Flag whether screen is covered or not
ringer_mode	Ringer mode (silent, vibrate, normal)
semantic_location	Home, work, other, or unknown
Demographics	
age	The participant's age in years
gender	The participant's gender
Last Communication Activity	
time_last_incoming_call	Time since last incoming phone call
time_last_notif	Time since last notification (excluding Borapp probe)
time_last_outgoing_call	Time since the user last made a phone call
time_last_SMS_read	Time since the last SMS was read
time_last_SMS_received	Time since the last SMS was received
time_last_SMS_sent	Time since the last SMS was sent

Table 3. List of features related to context, demographics, and time since last communication activity.

Study 1: Features Extracted (Contd)

- Extracted 35 features, in 7 categories
  - Context
  - Demograpics
  - Time since last activity
  - **Intensity of usage**
  - **External Triggers**
  - **Idling**

Usage (related to usage intensity)	
battery_drain	Average battery drain in time window
battery_level	Battery change during the last session
bytes_received	Number of bytes received during time window
bytes_transmitted	Number of bytes transmitted during time window
time_in_comm_apps	Time spent in communication apps, categorized to none, micro session, and full session
Usage (related to whether it was triggered externally)	
num_notifs	Number of notifications received in time window
last_notif	Name of the app that created the last notification
last_notif_category	Category of the app that created the last notification
Usage (related to the user being idling)	
apps_per_min	Number of apps used in time-window divided by time the screen was on
num_apps	Number of apps launched in time window before probe
num_unlock	Number of phone unlocks in time window prior to probe
time_last_notif_access	Time since the user last opened the notification center
time_last_unlock	Time since the user last unlocked the phone
Usage (related to the type of usage)	
screen_orient_changes	Flag whether there have been screen orientation changes in the time window
app_category_in_focus	Category of the app in focus prior to the probe
app_in_focus	App that was in focus prior to the probe
comm_notifs_in_tw	received in the time window prior to the probe
most_used_app	Name of the app used most in the time window
most_used_app_category	Category of the app used most in the time window
prev_app_in_focus	App in focus prior to *app_in_focus*

Table 4. List of features related to usage intensity, external trigger, idling and type.

Results: Study 1

- Machine-learning to analyze sensor and self-reported data and create a classification model
  - Compared 3 classifier types
    1. Logistic Regression
    2. SVM with radial basis kernel
    3. Random Forests
    - Random Forests performed the best (82% accuracy) and was used
  - Feature Analysis
    - Ranked feature importance
    - Selected top 20 most important features of 35
  - Personalized model: 1 classification model for each person

Results: Study 1, Most Important Features

- **Recency of communication activity:** last SMS, call, notification time
- **Intensity of recent usage:** volume of Internet traffic, number of phonelocks, interaction level in last 5 mins
- **General usage intensity:** battery drain, state of proximity sensor, last time phone in use
- **Context/time of day:** time of day, light sensor
- **Demographics:** participant age, gender

Feature	*Import*	*Correlation*	*The more bored, the ..*
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_cntr_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

- 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 bored people 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, app suggested newest Buzzfeed article
- Buzzfeed has articles on various topics including politics, DIY, recipes, animals and business

Methodology: Study 2 Measures

- **Click-ratio:** how often user opened Buzzfeed article / total number of notifications
- **Engagement-ratio:** How often user opened Buzzfeed article for at least 30 seconds / total number of notifications

Click-Ratio

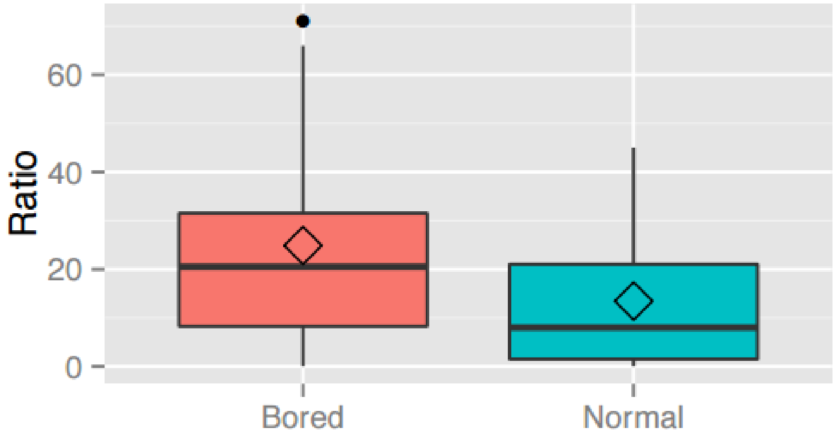


Figure 6. Click-ratio per condition.

Engagement-Ratio

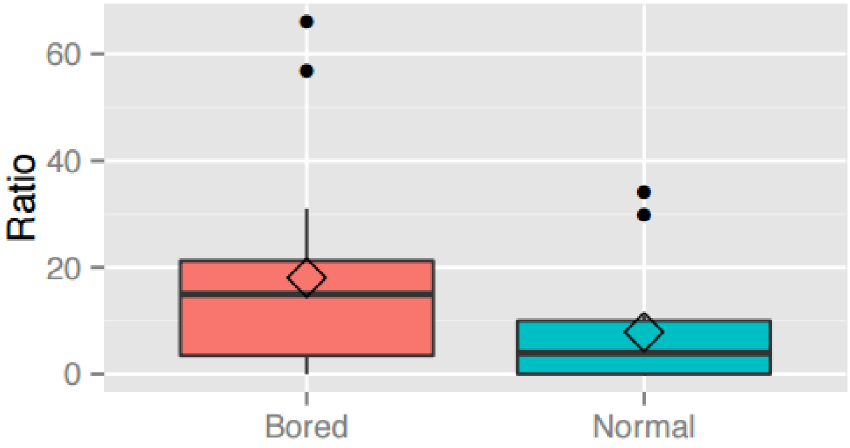


Figure 7. Engagement-ratio per condition.

- Preliminary findings: Bored Users were more likely to click on, and engage with suggested content

References

1. ***A Survey of Mobile Phone Sensing.*** Nicholas D. Lane, Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, Andrew T. Campbell, In IEEE Communications Magazine, September 2010
2. ***Mobile Phone Sensing Systems: A Survey,*** Khan, W.; Xiang, Y.; Aalsalem, M.; Arshad, Q.; , Communications Surveys & Tutorials, IEEE , vol.PP, no.99, pp.1-26