CS 4518 Mobile and Ubiquitous Computing

Lecture 10: Human-Centric Smartphone Sensing Applications

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BES Sleep Duration Sensing

Unobtrusive Sleep Monitoring

Unobtrusive Sleep Monitoring using Smartphones, Zhenyu Chen, Mu Lin, Fanglin Chen, Nicholas D. Lane, Giuseppe Cardone, Rui Wang, Tianxing Li, Yiqiang Chen, Tanzeem Choudhury, Andrew T. Campbell, in Proc Pervasive Health 2013

- Sleep impacts stress levels, blood pressure, diabetes, functioning

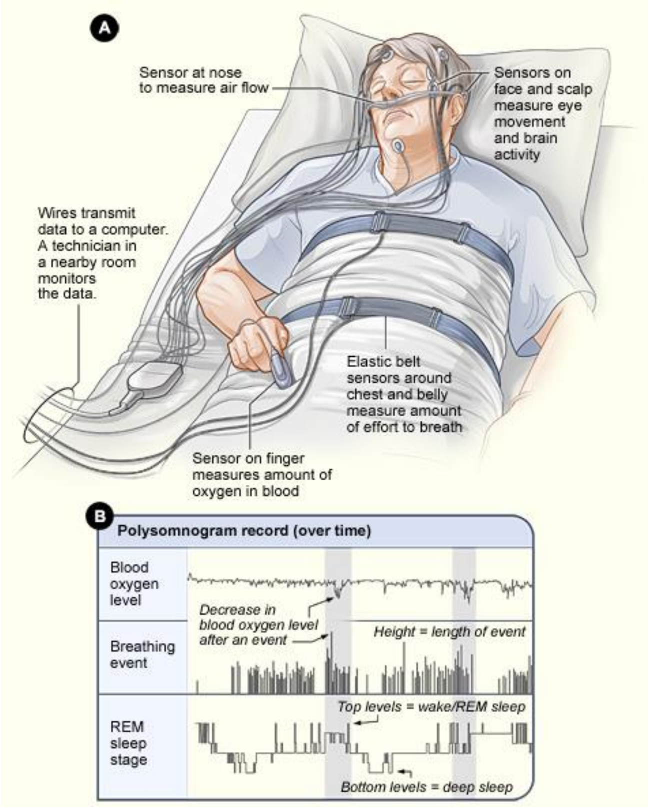
- Many medical treatments require patient records sleep
- Manually recording sleep/wake times is tedious

Unobtrusive Sleep Monitoring

- **Paper goal:** Automatically detect sleep (start, end times, duration) using smartphone, log it
- **Benefit:** No interaction, wear additional equipment,
  - Practical for large scale sleep monitoring
- Even a slightly wrong estimate is still very useful

Sleep Monitoring at Clinics

- Polysomnogram monitors (gold standard)
  - Patient spends night in clinic
- Lots of wires
- Monitors:
  - **Brain waves** using electroencephalography (EEG),
  - **Eye movements** using electrooculography,
  - **Muscle contractions** using electrocardiography,
  - **Blood oxygen levels** using pulse oximetry,
  - **Snoring** using a microphone, and
  - **Restlessness** using a camera
- Complex, impractical, expensive!



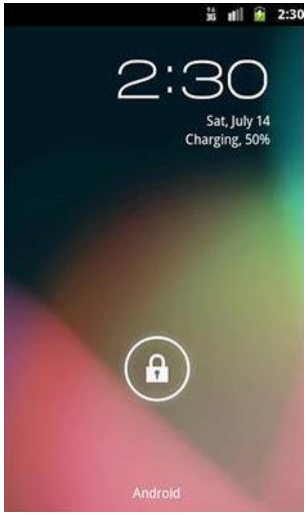
Commercial Wearable Sleep Devices

- Fewer wires
- Still intrusive, cumbersome
- Might forget to wear it

Can we monitor sleep with smartphone?

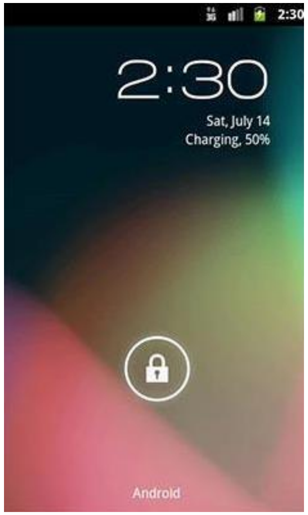
Insights: “Typical” sleep conditions

- Typically when people are sleeping
  - **Room is Dark**
  - **Room is Quiet**
  - **Phone is stationary (e.g. on table)**
  - **Phone Screen is locked**
  - **Phone plugged in charging, off**



Sense typical sleep conditions

- Use Android sensors to sense typical sleep conditions
  - **Dark:** light sensor
  - **Quiet:** microphone
  - **Phone is stationary (e.g. on table):** Accelerometer
  - **Screen locked:** Android system calls
  - **Phone plugged in charging, off:** Android system calls

Best Effort Sleep (BES) Model

- BES model Features:
- Phone Usage features.

    --phone-lock (F2)

    --phone-off (F4)

    --phone charging (F3)

  -- Light feature (Fl).

  -- Phone in darkness

  --Phone in a stationary state (F5)

  --Phone in a silent environment (F6)

- Each of these features are weak indicators of sleep
- Combine these into Best Effort Sleep (BES) Model

BES Sleep Model

- Assume sleep duration is a linear combination of 6 features

$$Sl = \sum_{i=1}^{6} \alpha_i \cdot F_i, \; \alpha_i \geq 0$$

- Gather data (sleep duration + 6 features) from 8 subjects
- Train BES model
- Formalize as a regression problem:

$$\min_{\alpha_i} \sum_{j=1}^{4} (Sl^j - \sum_{i=1}^{6} \alpha_i \cdot F_i^j)^2$$

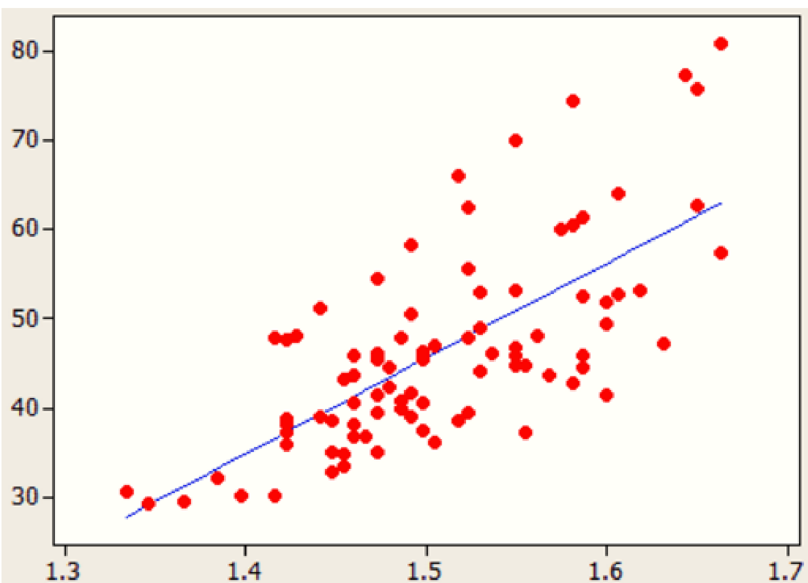
Sleep duration

Weight for each feature

Feature (sum)

Regression?

- Gather sleep data (sleep duration, 6 features) from 8 subjects
- Fit data to line
  - **y axis** - sleep duration
  - **x-axes** – Weighted sum of 6 features
- **Weighted sum?** Determine weights for each feature that minimizes error
- Using line of best fit, in future sleep duration can be inferred from feature values



Sleep duration

Weighted sum of features

$$\min_{\alpha_i} \sum_{j=1}^{4} \left(Sl^j - \sum_{i=1}^{6} \alpha_i \cdot F_i^j\right)^2$$

Sleep duration

Weight for each feature

Feature (sum)

Results

Feature	Coefficient
Light (F_1)	0.0415
Phone-lock (F_2)	0.0512
Phone-off (F_3)	0.0000
Phone-charging (F_4)	0.0469
Stationary (F_5)	0.5445
Silence (F_6)	0.3484

TABLE I: Weight coefficients for each feature in BES

Phone stationary
(e.g. on table) most predictive
.. Then silence, etc

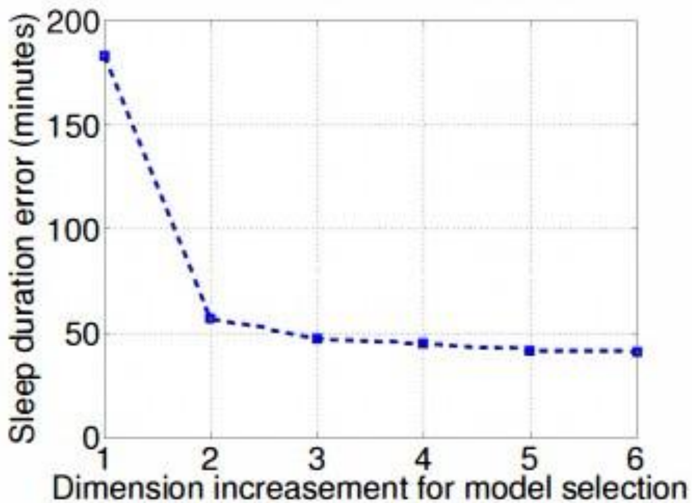


Fig. 2: The reduction in sleep duration error for BES by incrementally adding stationary, silence, phone-lock, phone-charging, light and phone-off features, respectively.

Results

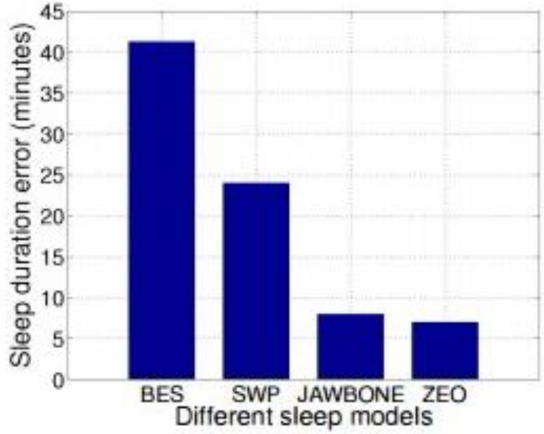


Fig. 3: Overall sleep duration error for BES compared to the three alternative sleep monitoring systems (SWP, Jawbone, Zeo).

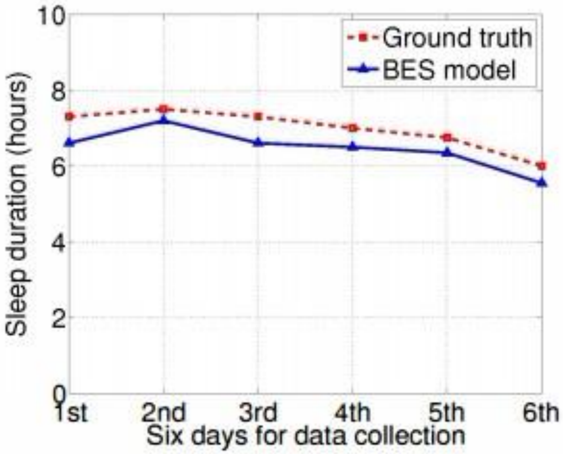


Fig. 5: Comparison of estimated and actual sleep duration under BES for one representative study subject.

My actual Experience

- Worked with undergrad student to implement BES sleep model
- **Results:** About 20 minute error (+ or -) for 8-hour sleep
- Errors/thrown off by:
  - Loud environmental noise. E.g. garbage truck outside
  - Misc ambient light. E.g. Roommates playing video games

AlcoGait

The Problem: Binge Drinking/Drunk Driving

- 40% of college students binge drink at least once a month
  - **Binge drinking defn:** 5 drinks for man, 4 drinks woman
- In 2013, over 28.7 million people admitted driving drunk
- Frequently, drunk driving conviction (DUI) results

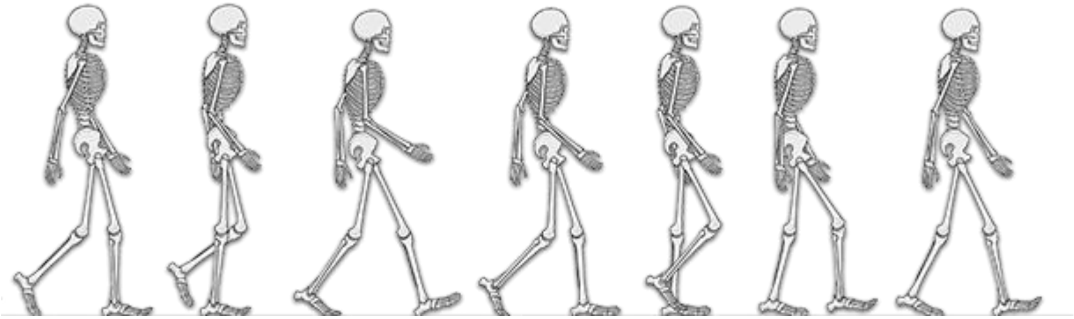
Binge Drinking Consequences

- Every 2 mins, a person is injured in a drunk driving crash
- 47% of pedestrian deaths caused by drunk driving
- In all 50 states, after DUI -> vehicle interlock system
  - Also fines, fees, loss of license, lawyer fees, death
- Can we prevent DUI?

Vehicle Interlock system

Gait for Inferring Intoxication

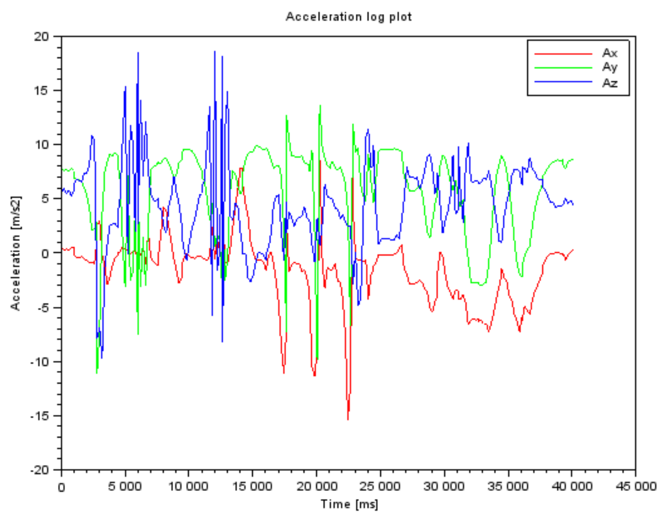
- **Gait:** Way a person walks, impaired by alcohol
- Aside from breathalyzer, gait is most accurate bio- measure of intoxication
- The police also know gait is accurate
  - 68% police DUI tests based on e.g. walk and turn test



AlcoGait

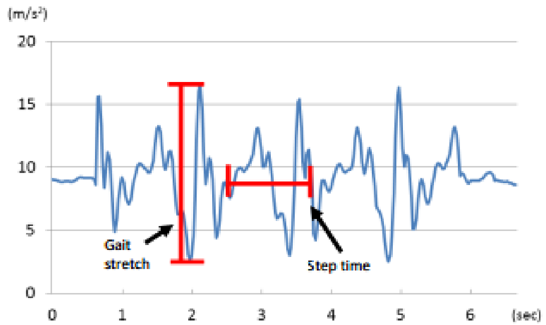
Z Arnold, D LaRose and E Agu, Smartphone Inference of Alcohol Consumption Levels from Gait, in Proc ICHI 2015
Christina Aiello and Emmanuel Agu, Investigating Postural Sway Features, Normalization and Personlization in Detecting Blood Alcohol Levels of Smartphone Users, in Proc Wireless Health Conference 2016

- Can we test drinker's before DUI? Prevent it?
  - At party while socializing, during walk to car
- How? Alcogait smartphone app:
  - Samples accelerometer, gyroscope
  - Extracts accelerometer and gyroscope features
  - Classify features using Machine Learning
  - Notifies user if they are too drunk to drive



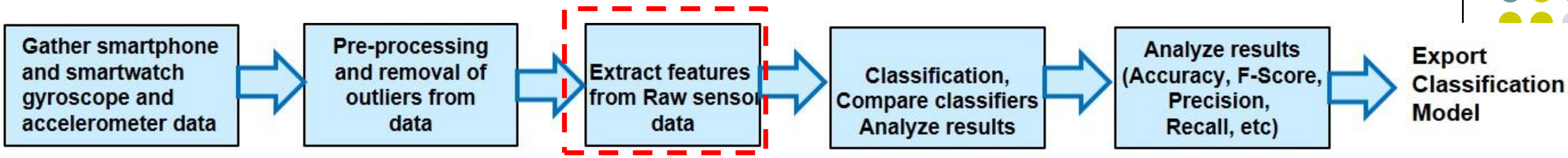
Accelerometer Features Extracted

Feature	Feature Description
Steps	Number of steps taken
Cadence	Number of steps taken per minute
Skew	Lack of symmetry in one's walking pattern
Kurtosis	Measure of how outlier-prone a distribution is
Average gait velocity	Average steps per second divided by average step length
Residual step length	Difference from the average in the length of each step
Ratio	Ratio of high and low frequencies
Residual step time	Difference in the time of each step
Bandpower	Average power in the input signal
Signal to noise ratio	Estimated level of noise within the data
Total harmonic distortion	"Determined from the fundamental frequency and the first five harmonics using a modified periodogram of the same length as the input signal" [22]

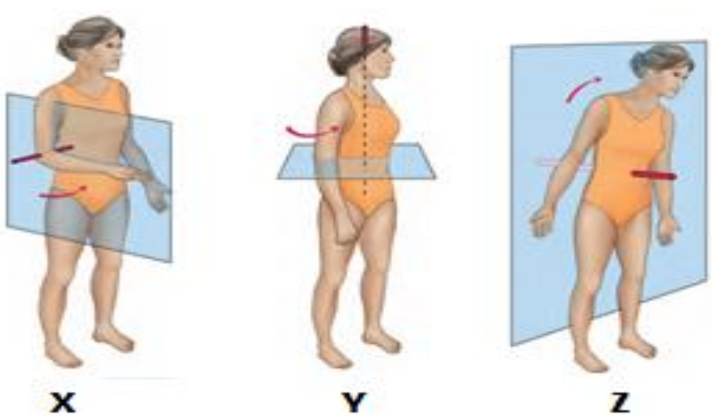


Accelerometer gait features

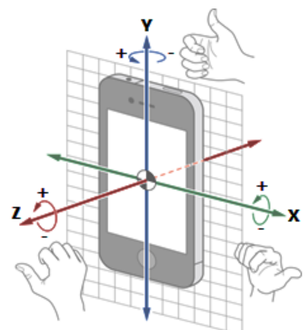
Posturography Sway Features



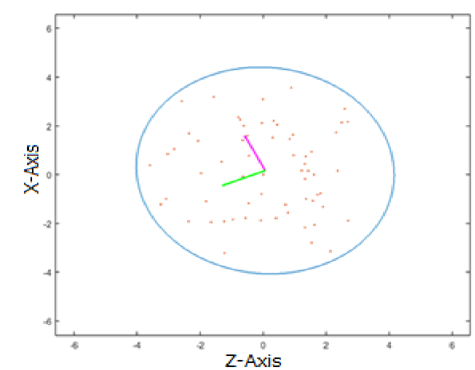
- **Posturography:** clinical approach for assessing balance disorders from gait
- Prior medical studies (Nieschalk *et al*) found that subjects swayed more after they ingested alcohol
- Synthesized sway area features on 3 body planes and sway volume
- Sway area computation: project values of gyroscope unto plane
- E.g. XZ sway area:
  - Project all observed gyroscope X and Z values in a segment an X-Z plane
  - Area of smallest ellipse that contains all X and Z points in a segment is its **XZ sway area**



3 planes of body



Gyroscope axes



XZ Sway Area

Gyroscope Features Extracted

Table 1: Features Generated from Gyroscope Data			
Feature Name	Feature Description	Formula	
XZ Sway Area	Area of projected gyroscope readings from Z (yaw) and X (pitch) axes	$XZ\ Sway\ Area = \pi r^2$	
YZ Sway Area	Area of projected gyroscope readings from Z (yaw) and Y (roll) axes	$YZ\ Sway\ Area = \pi r^2$	
XY Sway Area	Area of projected gyroscope readings from X (pitch) and Y (roll) axes	$XY\ Sway\ Area = \pi r^2$	
Sway Volume	Volume of projected gyroscope readings from all three axes (pitch, roll, yaw)	$Sway\ Volume = \frac{4}{3}\pi r^3$	

Steps for Training AlcoGait Classifier

- Similar to Activity recognition steps we covered previously

1. Gather data samples + label them
    - 30+ users data at different intoxication levels
2. Import accelerometer and gyroscope samples into classification library (e.g. Weka, MATLAB)
3. Pre-processing (segmentation, smoothing, etc)
    - Also removed outliers (user may trip)
4. Extract features (gyroscope sway and accelerometer features)
5. Train classifier
6. Export classification model as JAR file
7. Import into Android app

Specific Issues: Gathering Data

- **Gathering alcohol data at WPI very very restricted**
  1. Must have EMS on standby
  2. Alcohol must be served by licensed bar tender
  3. IRB were concerned about law suits
- We improvised: used drunk buster Goggles
- "Drunk Busters" goggles distort vision to simulate effects of various intoxication (BAC) levels on gait
- Effects on goggle wearers:
  - Reduced alertness, delayed reaction time, confusion, visual distortion, alteration of depth and distance perception, reduced peripheral vision, double vision, and lack of muscle coordination.
- Previously used to educate individuals on effects of alcohol on one's motor skills.

Different Sways? Swag?

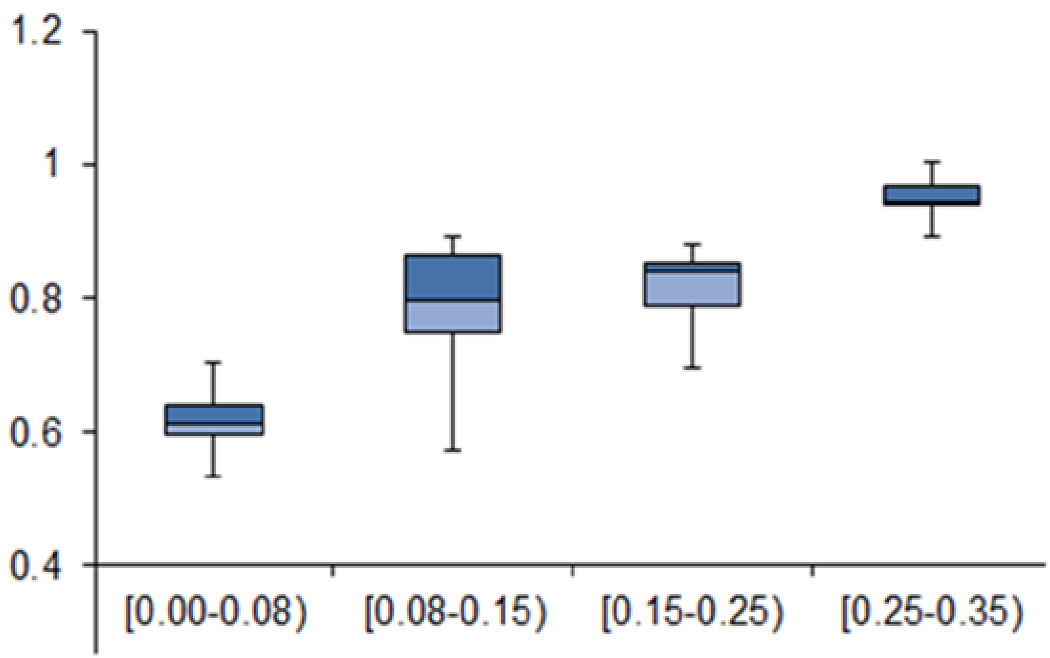
- Different people sway different amounts even when sober
- Some people would be classified drunk even when sober (Swag?)
- Cannot use same absolute sway parameters for everyone
- Normalize!
  - Gather each person's base data when sober
  - Divide possibly drunk gait features by sober features

$$\frac{drunk\_feature}{sober\_feature}$$

- Similar to how dragon dictate makes each reader read a passage initially
  - Learns unique inflexions, pronounciation, etc
- Classify absolute + normalized values of features

Box Plot of XZ Sway Area

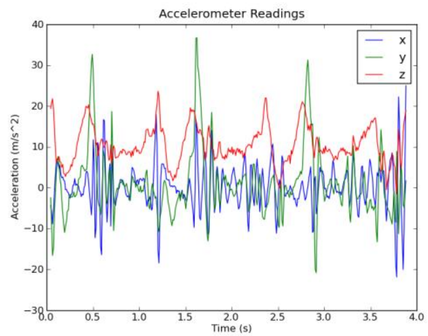
- As subjects got more intoxicated, normalized sway area generally increased



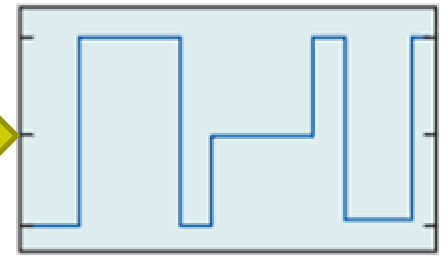
AlcoGait Evolution

- Zach Arnold, Danielle LaRose
  - Initial AlcoGait prototype, accelerometer features (time, freq domain)
  - Real intoxicated gait data from 9 subjects, 57% accuracy
  - **Best CS MQP 2015**
- Christina Aiello
  - Data from 50 subjects wearing drunk busters goggles
  - Gyroscope features: sway area, 89% accurate
  - **Best Masters grad poster 2016**
- Muxi Qi (ECE)
  - Signal processing, compared 27 accelerometer features

AlcoWatch MQP: Using SmartWatch to Infer Alcohol levels from Gait



Raw accelerometer readings



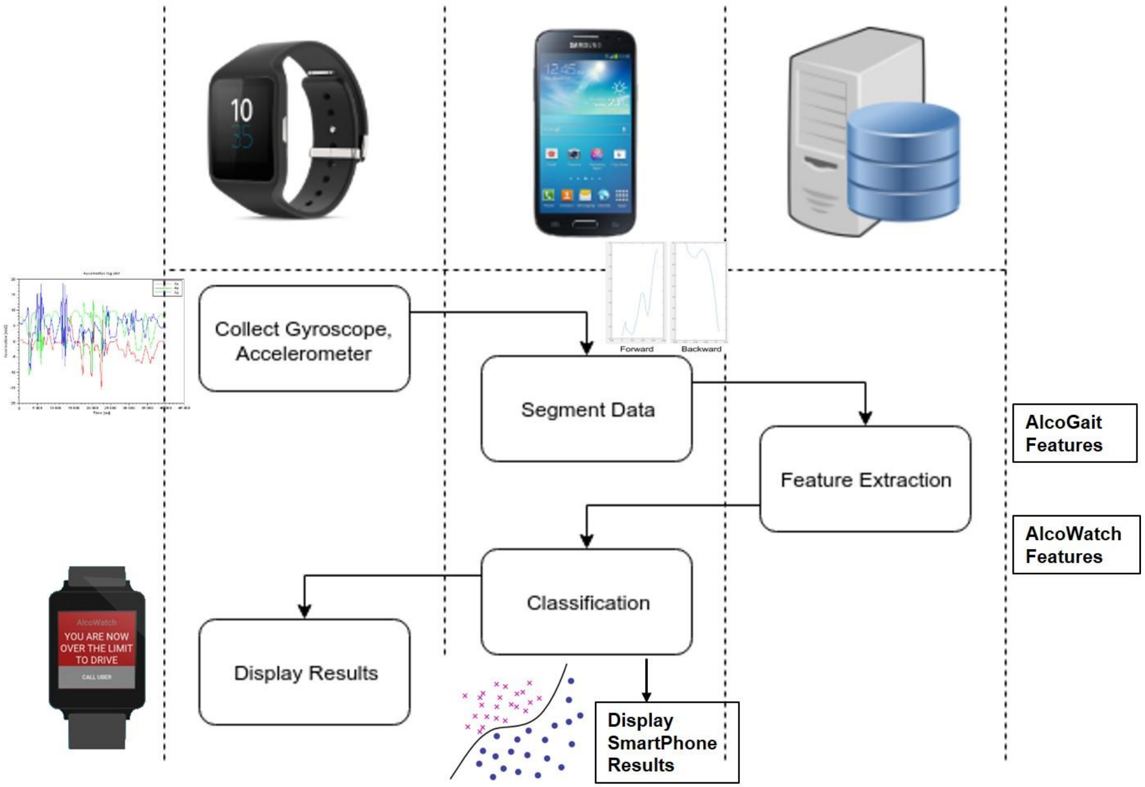
Feature extraction and classification

BAC/How much alcohol consumed?

- AlcoGait limitations:
  - Users leave phones in drawers, bags, on table 50% of the time
  - Many women don’t have pockets, or carry their phones on their body
- **Alcowatch MQP: Detect alcohol consumption using smartwatch**
  - Classify accelerometer, gyroscope data
- **Students:** Ben Bianchi, Andrew McAfee, Jacob Watson

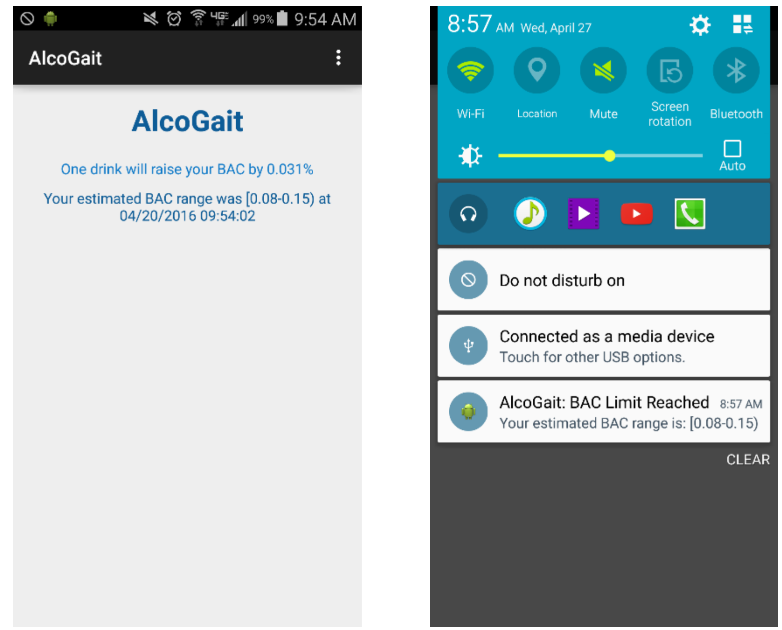
AlcoWear: Overview of How it Works

- Whenever user is walking, accelerometer + gyroscope data gathered simultaneously from smartphone + smartwatch
- Data sent to server for feature extraction classification
- Inferred BAC sent back to smartwatch, smartphone for display



AlcoWatch and AlcoGait Screens

AlcoWatch
(Smartwatch)



AlcoGait
(Smartphone)

AlcoWatch Features

- AlcoGait Smartphone features
  - Sway features (captures trunk sway)
  - Frequency-, Time-, Wavelet- and information-theoretic domain features

- AlcoWatch Features
  - Sway features
  - Arm velocity, rotation (pitch, yaw, roll) along X,Y.Z

Currently: NIH-Funded Study to Gather Intoxicated Gait Data from 250 Subjects

- Alcohol studies extremely tough at WPI (many rules)
  - **Rules:** Need EMS, bar tender, etc for controlled study
- Collaboration with physician, researchers at Brown university
- Gather intoxicated gait data from 250 subjects
- Controlled study:
  - Drink 1… walk
  - Drink 2… walk..
  - Etc
- Gather data, classify

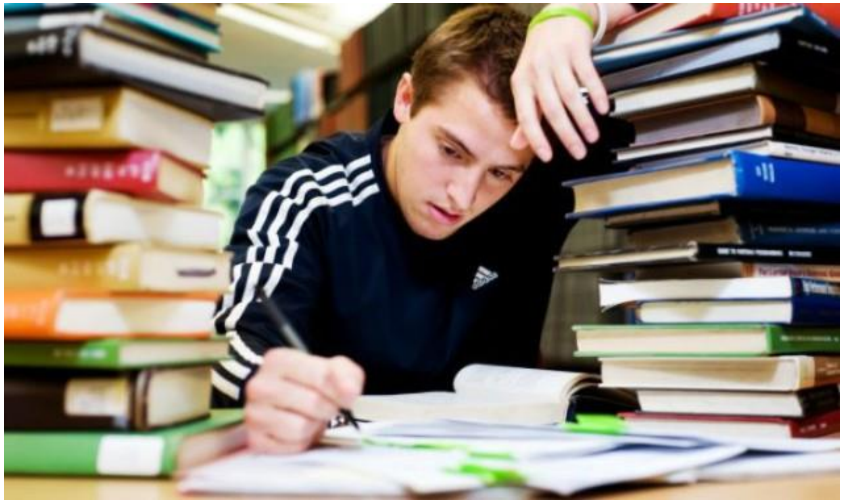
StudentLife

College is hard…

Rui Wang, Fanglin Chen, Zhenyu Chen, Tianxing Li, Gabriella Harari, Stefanie Tignor, Xia Zhou, Dror Ben-Zeev, and Andrew T. Campbell. 2014. StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (UbiComp '14)

- **Lots of Stressors in College**
  - Lack of sleep
  - Exams/quizzes
  - High workload
  - Deadlines
  - 7-week term
  - Loneliness (e.g. freshmen, international students)

- **Consequences**
  - Burnout
  - Decline in psychological well-being
  - Academic Performance (GPA)



Students who Need Help Not Noticed

- Many stressed/overwhelmed students not noticed
  - Even worse in large classes (e.g. intro classes with 150-200 students)
  - Many do not seek help
  - E.g. < 10% of clinically depressed students seek counseling

StudentLife: Continuous Mobile Sensing

- **Research questions:** Are sensable patterns (sleep, activity, social interactions, etc) reliable indicator of suffering student (e.g. low GPA, depressed, etc)?

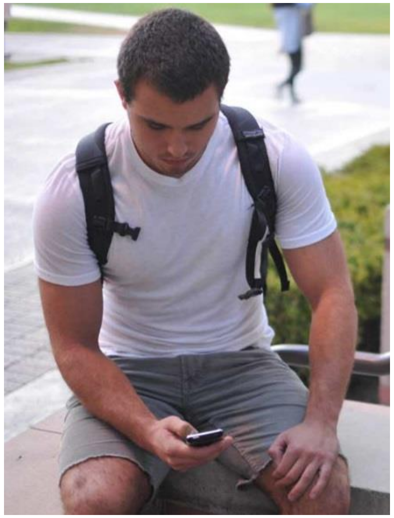
Stressors
- Deadlines
- Exams
- Quiz
- Break-ups
- Social pressure

Consequences
- Anxiety
- Depression
- Poor exam scores
- Low GPA
- ??

Sensable symptoms
- Sleep
- Social interactions
- Conversations
- Activity Level
- ??

StudentLife Continuous Sensing App

- **Goal:** Use smartphone sensing to assess/monitor student:
  - Psychological well-being (depression, anxiety, etc)
  - Academic performance
  - Behavioral trends, stress patterns as term progresses
- Demonstrate strong correlation between sensed data and clinical measures of mental health (depression, loneliness, etc)
- **Show smartphone sensing COULD be used to give clinically valid diagnoses?**
  - Get clinical quality diagnosis without going to clinic
- Pinpoint factors (e.g. classes, profs, frats) that increase depression/stress



Potential Uses of StudentLife

- Student planning and stress management
- Improve Professors’ understanding of student stress
- Improve Administration’s understanding of students’ workload

StudentLife Approach

- Semester-long Study of 49 Dartmouth College Students
  - Continuously gather sensible signs (sleep, activity level, etc)
  - Administer mental health questionnaires periodically as pop-ups (called EMA)
  - Also retrieve GPA, academic performance from registrar
- **Labeling:** what activity, sleep, converstation level = high depression

Labels
(for classifier)

GPA
(from registrar)

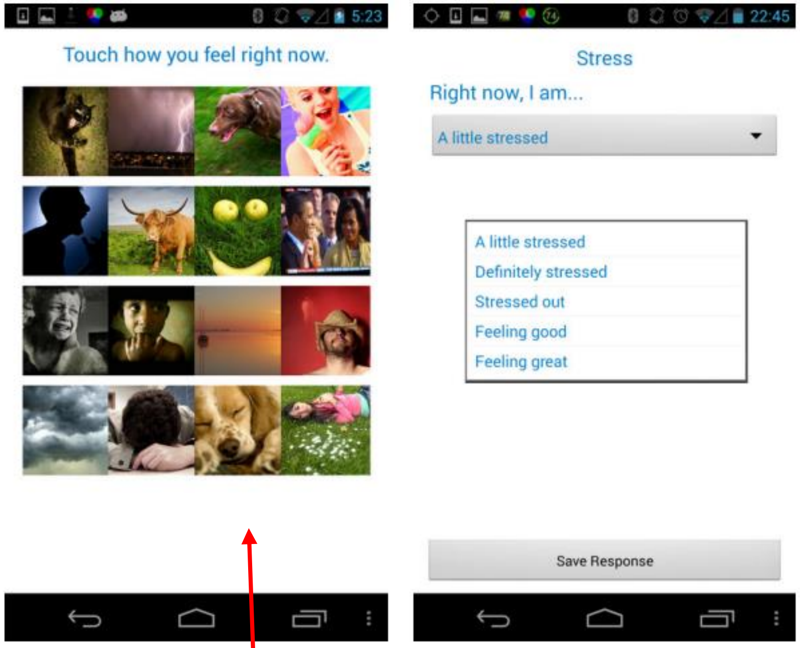
Mental Health Questionnaires (EMA)
- Anxiety
- Depression
- Loneliness
- Flourishing

Autosensed
data

Data Gathering app, automatically sense
- Sleep
- Social interactions
- Conversations
- Activity Level, etc

Specifics: Data Gathering Study

- **Entry and exit surveys at Semester (2 times) start/end**
  - on Survey Monkey
  - E.g. PHQ-9 depression scale
- **8 MobileEMA and PAM quizzes per day**
  - Stress
  - Mood (PAM), etc
- **Automatic smartphone sensed data**
  - **Activity Detection:** activity type, WiFi's APs
  - **Conversation Detection:**
  - **Sleep Detection:** duration



(a) PAM EMA (b) Stress EMA

PAM: Pick picture depicting your current mood

StudentLife Data Gathering Study Overview

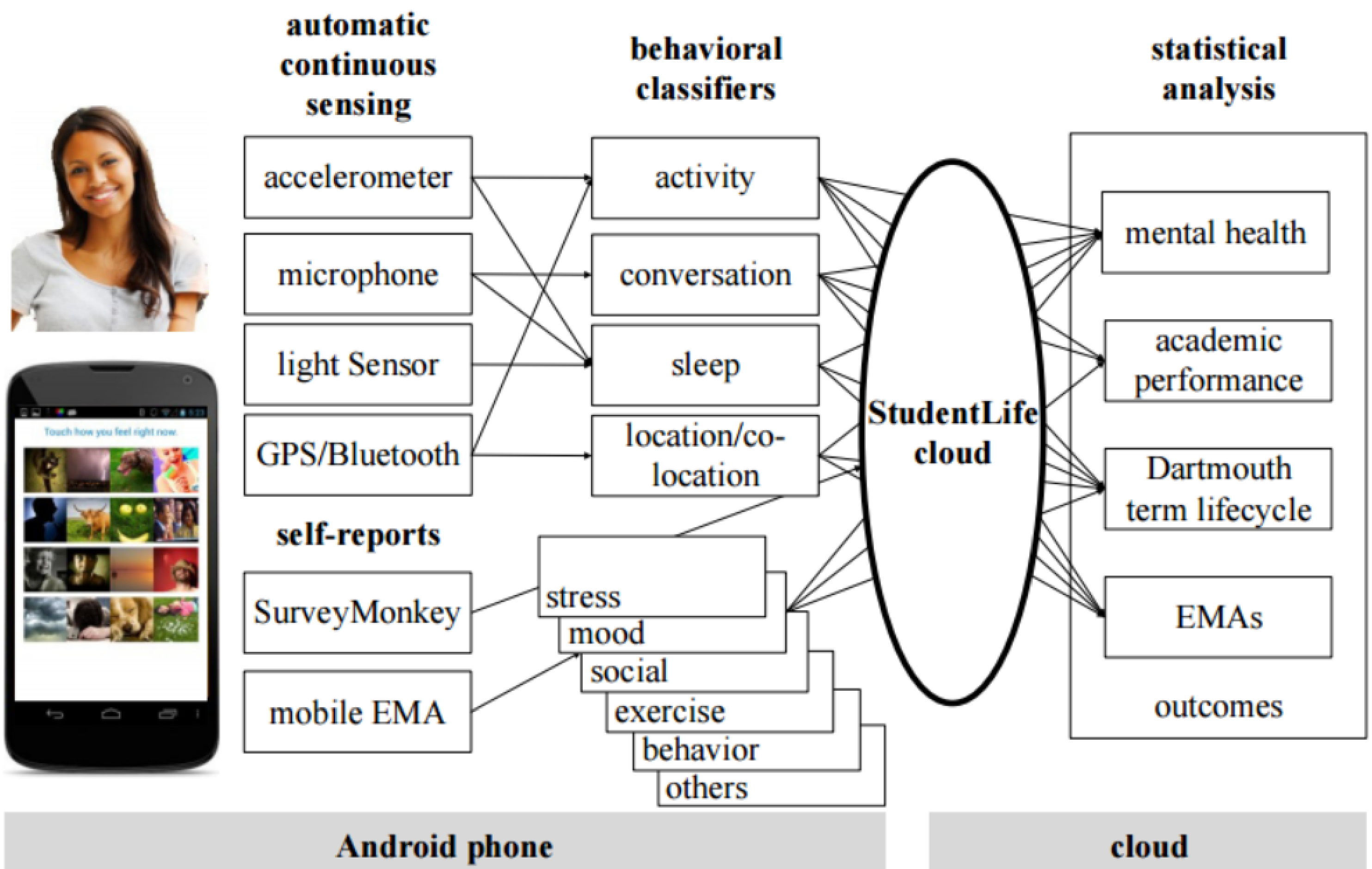
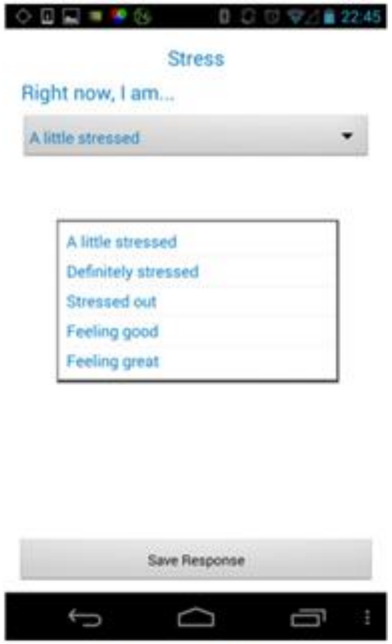


Figure 2. StudentLife app, sensing and analytics system architecture.

Clinical Mental Health Questionnaires

- MobileEMA popped up mental health questionnaires (widely used by psychologists, therapists, etc), provides labelled data
  - **Patient Health Questionnaire (PHQ-9)**
    - Measures depression level
  - **Perceived Stress Scale**
    - Measures Stress level
  - **Flourishing Scale**
    - Measures self-perceived success in relationships, self-esteem, etc
  - **UCLA loneliness survey**
    - Measures loneliness (common in freshmen, int'l students)



(b) Stress EMA

Study Details

- 60 Students started study
  - All enrolled in CS65 Smartphone Programming class
  - 12 students dropped class during study
  - 30 undergrad/18 graduate level
  - 38 male/10 female
- Incentives:
  - StudentLife T-shirt (all students)
  - **Week 3 & 6:** 5 Jawbone UPs (like fitbit) raffled off
  - **End of study:** 10 Google Nexus phones in raffle
- 10 weeks of data collection

Correlation Analysis

- Compute correlation between smartphone-sensed features and various questionnaire scores, GPA, etc
- E.g. correlation between sensor data and PHQ-9 depression score, GPA

Table 3. Correlations between automatic sensor data and PHQ-9 depression scale.

automatic sensing data	r	p-value
sleep duration (pre)	-0.360	0.025
sleep duration (post)	-0.382	0.020
conversation frequency during day (pre)	-0.403	0.010
conversation frequency during day (post)	-0.387	0.016
conversation frequency during evening (post)	-0.345	0.034
conversation duration during day (post)	-0.328	0.044
number of co-locations (post)	-0.362	0.025

Some Findings

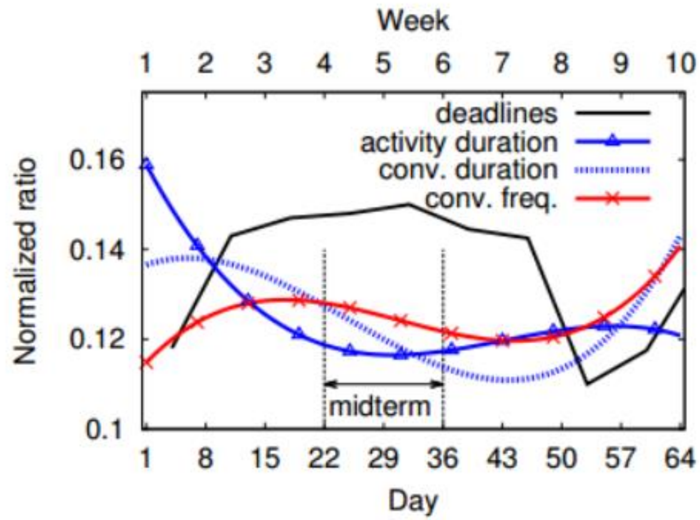
- Fewer conversations or co-locations correlate with
  - Higher chance of depression
- Higher stressed correlated with
  - Higher chance of depression
- More social interactions correlated with
  - Higher flourishing, GPA scores
  - Lower stress
- More sleep correlates with
  - Lower stress

Findings (cont'd)

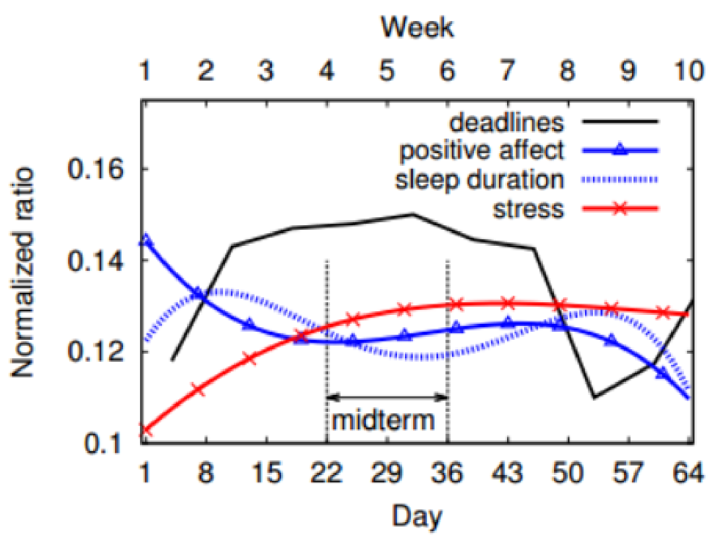
- Less sleep?
  - Higher chance of depression
- Less activity?
  - More likely to be lonely, lower GPAs
- No correlation between class attendance and academic performance (Hmm…)
- As term progressed:
  - Positive affect and activity duration plummeted

Findings (cont'd)

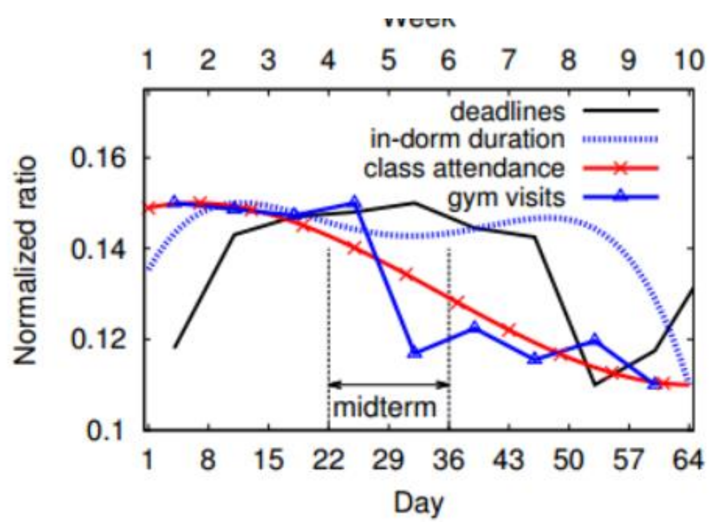
- Plotted total values of sensed data, EMA etc for all subjects through the term



(b) Automatic sensing data



(a) EMA and sleep data



(c) Location-based data

Study Limitations/Trade Offs

- Sample Selection
  - Voluntary - CS65 Smartphone Programming class (similar to CS 4518)
- User participation
  - **Burden:** Surveys, carrying phone
  - Disinterest (Longitudinal study, EMA annoyance)
- Lost participants
- Sleep measurement inaccuracy
  - Naps

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**

(a) Total Bluetooth interactions and entropy decrease **

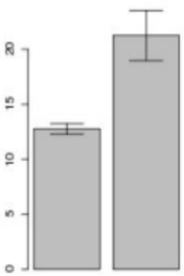
(b) Late night early morning Bluetooth entropy with respect to other participants decreases **

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

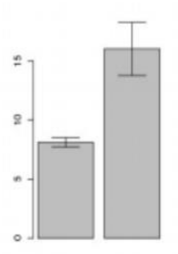
(d) WLAN Entropy with respect to external WLAN APs decreases ***

Data Analysis

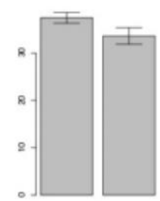
- Behavior effects of runny nose, congestion, sneezing symptom (mild illness)
  - **Cold is somewhat mild, communication, movement generally increased**



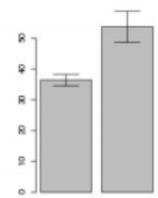
(a) Total communication increases ***



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



(c) Overall Bluetooth entropy decreases *



(d) Total WLAN APs detected increase **

Results: Conclusion

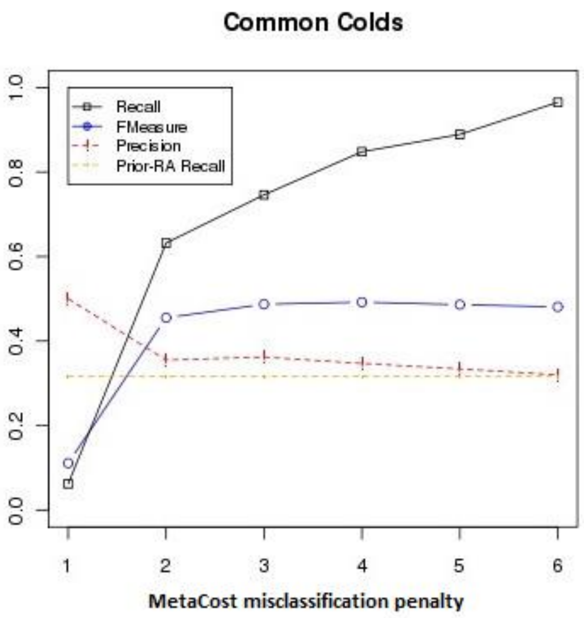
- **Conclusion:** Behavioral changes are identified as having statistically significant association with reported symptoms.

- 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

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)

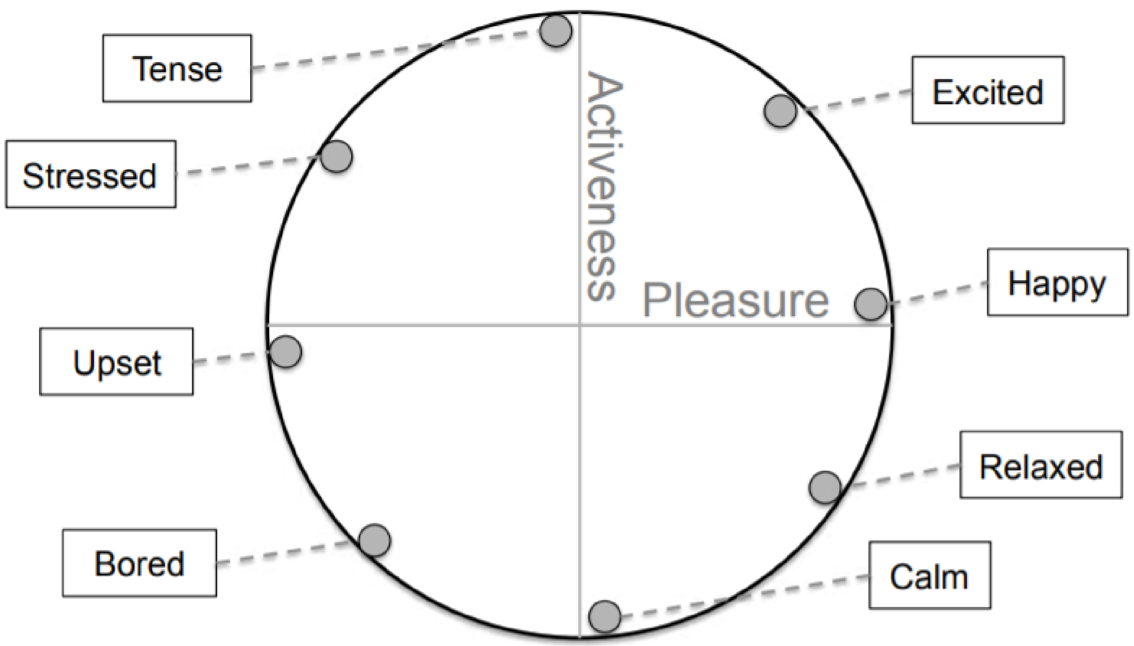


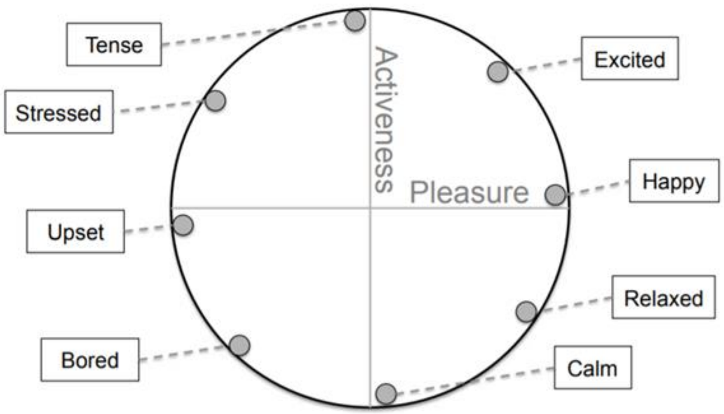
Figure 1: The circumplex mood model

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

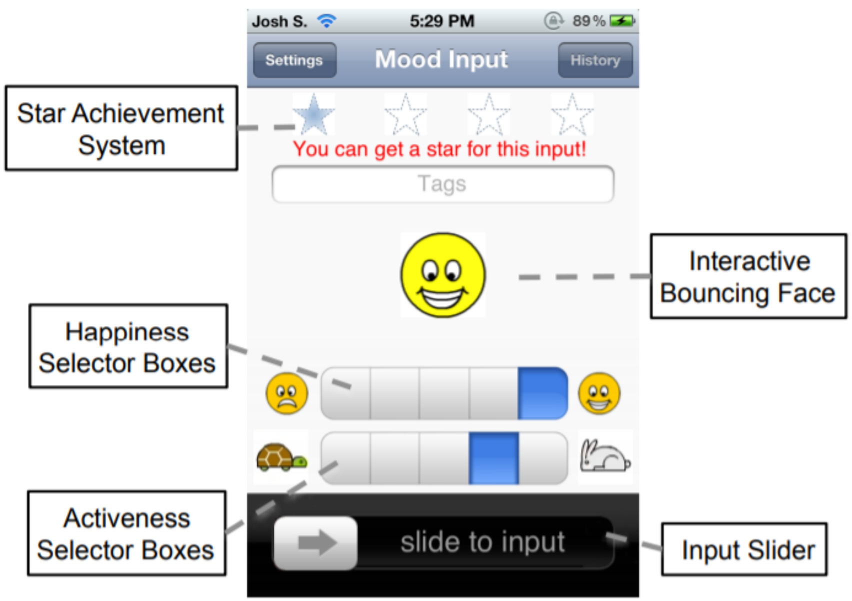


Figure 2: Mood journaling application view

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?

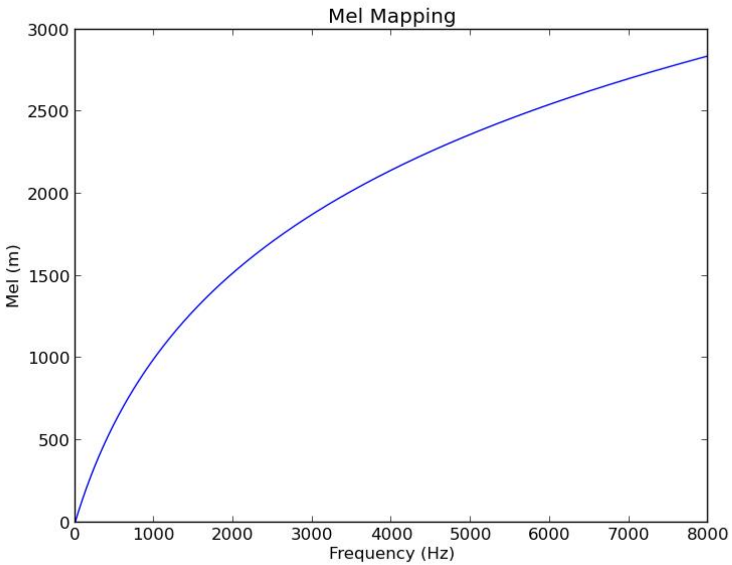
Voice-Based/Speech Analytics

Voice Based Analytics

- Voice can be analyzed, lots of useful information extracted
  - Who is talking? (Speaker identification)
  - How many social interactions a person has a day
  - Emotion of person while speaking
  - Anxiety, depression, intoxication, of person, etc.
- For speech recognition, voice analytics used to:
  - Extract information useful for identifying linguistic content
  - Discard useless information (background noise, etc)

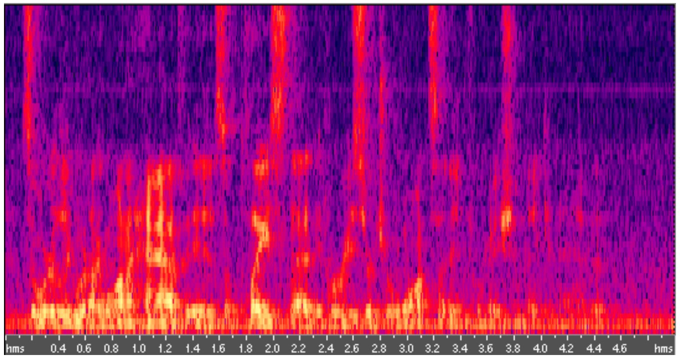
Mel Frequency Cepstral Coefficients (MFCCs)

- MFCCs widely used in speech and speaker recognition for representing power at various frequencies of voice
- Transforms speech attributes (frequency, tone, pitch) on non-linear scale based on human perception of voice
  - Non-linear amplification, MFCC features that mirror human perception
  - E.g. humans good at perceiving small change at low frequency than at high frequency



Audio Features for Emotion Detection

- **Intensity:** Energy of speech, intensity. E.g.
  - Angry speech: sharp rise in energy
  - Sad speech: low intensity



- **Temporal features:**
  - Speech rate, voice activity (e.g. pauses)
  - E.g. Sad speech: slower, more pauses

- **Other emotion features:** Voice quality, spectrogram, statistical measures

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
- **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:

1. Recommend content, services, or activities that may help to overcome the boredom
    - E.g. play video, recommend an article
2. 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

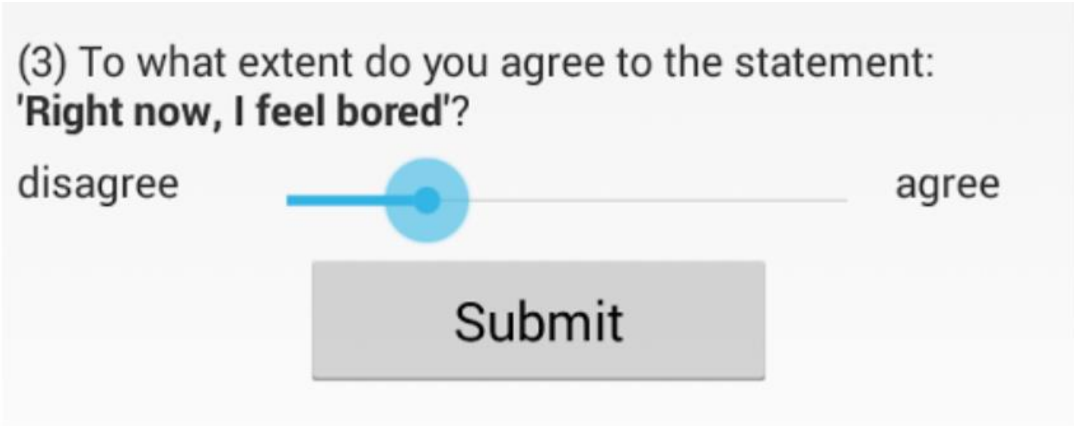
Methodology: 2 Studies

- Study 1
  - Can boredom be sensed using smartphone?
  - What aspects of mobile phone usage are most indicative of boredom?

- Study 2
  - Are bored people 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

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 and was used
  - Feature Analysis
    - Ranked feature importance
  - 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
- **Could predict boredom ~82% of time!**

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

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

Results: Study 2

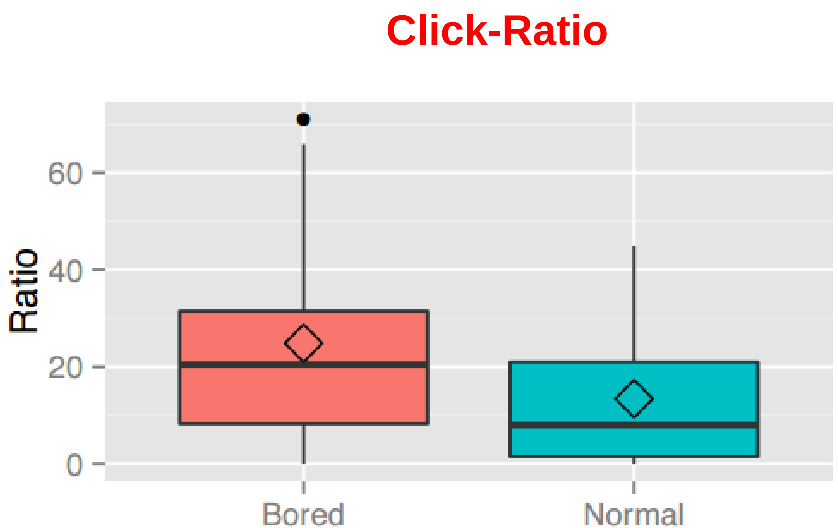


Figure 6. Click-ratio per condition.

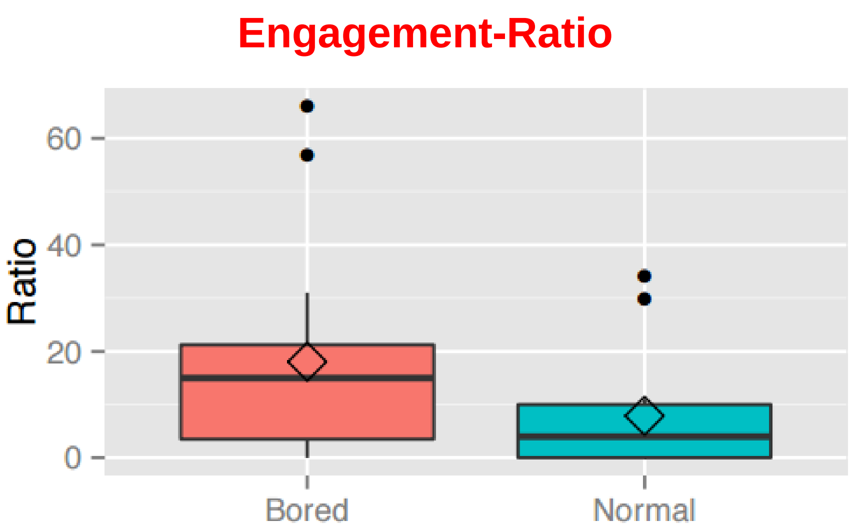


Figure 7. Engagement-ratio per condition.

- Bored Users **more likely to click on, engage more** with suggested content

Secure Mobile Software Development Modules

Introduction

- Many Android smartphones compromised because users download malicious software disguised as legitimate apps
- Malware vulnerabilities can lead to:
  - Stolen credit card numbers, financial loss
  - Stealing user’s contacts, confidential information
- Frequently, unsafe programming practices by software developers expose vulnerabilities and back doors that hackers/malware can exploit
- Examples:
  - Attacker can send invalid input to your app, causing confidential information leakage

Secure Mobile Software Development (SMSD)

- **Goal:** Teach mobile (Android) developers about backdoors, reduce vulnerabilities in shipped code
- Hackers generally attack Android devices more than iOS
- SMSD: Android Plug-In:
  - Alerts Android coder about vulnerabilities in their code
  - Hands-on, engaging labs to instill concepts, principles

SMSD: 8 Modules

- **M0: Getting started**
- **M1: Data sanitization for input validation**
- **M2: Data sanitization for output encoding**
- M3: SQL injections
- **M4: Data protection**
- M5: Secure inter-process communication (IPC)
- M6: Secure mobile databases
- M7: Unintended data leakage
- M8: Access control

- **Lab:** Go through M0, M1, M2 and M4 + fill out a survey
- **My thought process:** SMSD modules more useful for you, easier than research papers

M1: Data Sanitization for Input Validation

- Malicious inputs can:
  - Leak confidential information to the attacker
  - Lead to system crashes
  - Cause malicious database manipulation, corrupt database
- Countermeasure strategies:
  - **White list valid inputs:**
    1. Use regular expression to check whether an input is of the authorized type, rejects everything else
       - E.g. if a date is expected, Regular expression determines if input is valid date
    2. If input is from a fixed set of limited options, use a drop-down menu or radio button
  - **Black list invalid inputs:**
    1. Build blacklist of known common attack characters and patterns (‘, <script>)
    2. Compare input to blacklist entries

Important: This Lab REPLACES Quiz 5

- No quiz 5 on Thursday
- Just do this lab online, due 11.59, Friday, March 2, 2018