CS 528 Mobile and Ubiquitous Computing

Lecture 7b: Human-Centric Smartphone Sensing Applications

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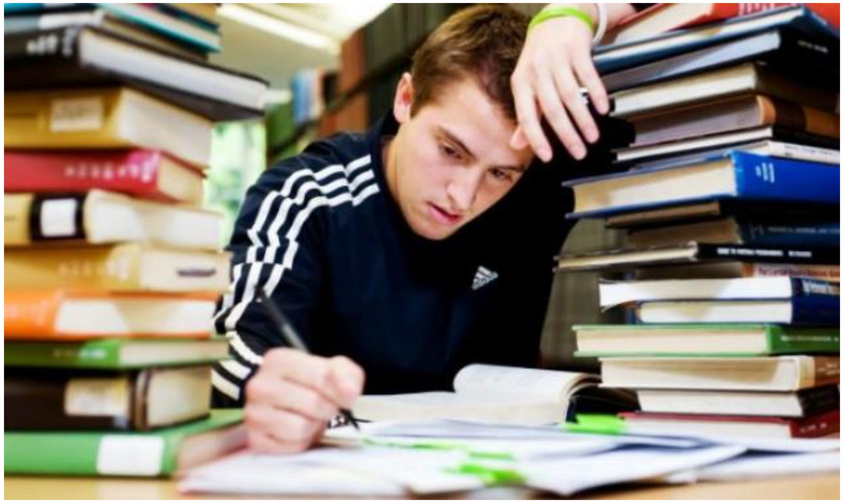
StudentLife

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)?

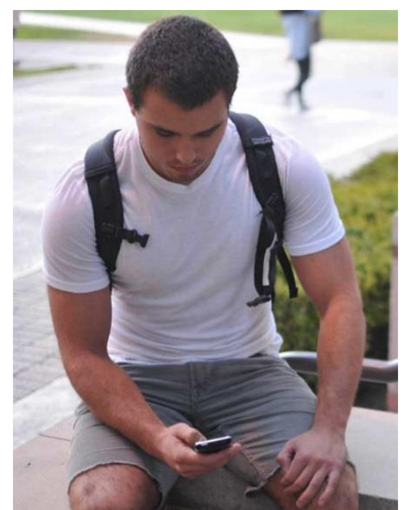
Stressors
- Deadlines
- Exams
- Quiz
- Break-ups
- Social pressure

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)

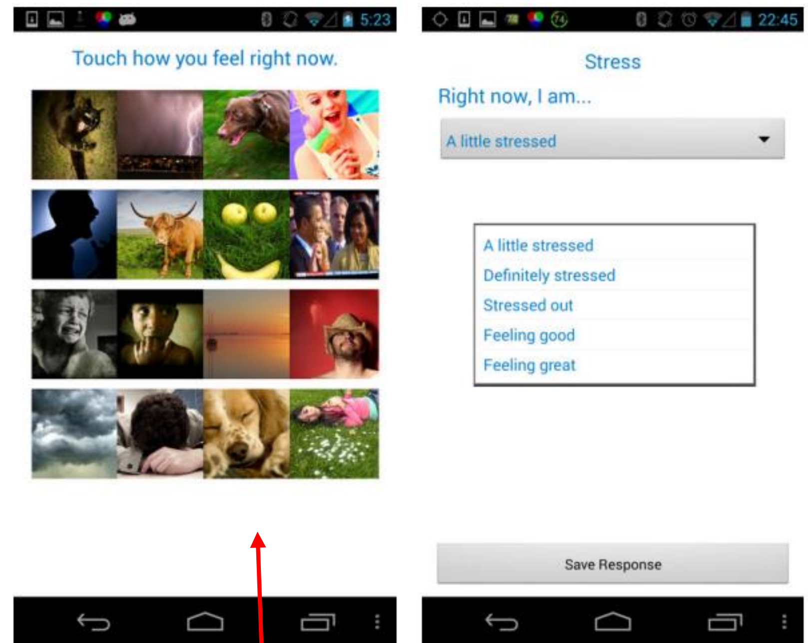
Mental Health Questionnaires (EMA)
- Anxiety
- Depression
- Loneliness
- Flourishing

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

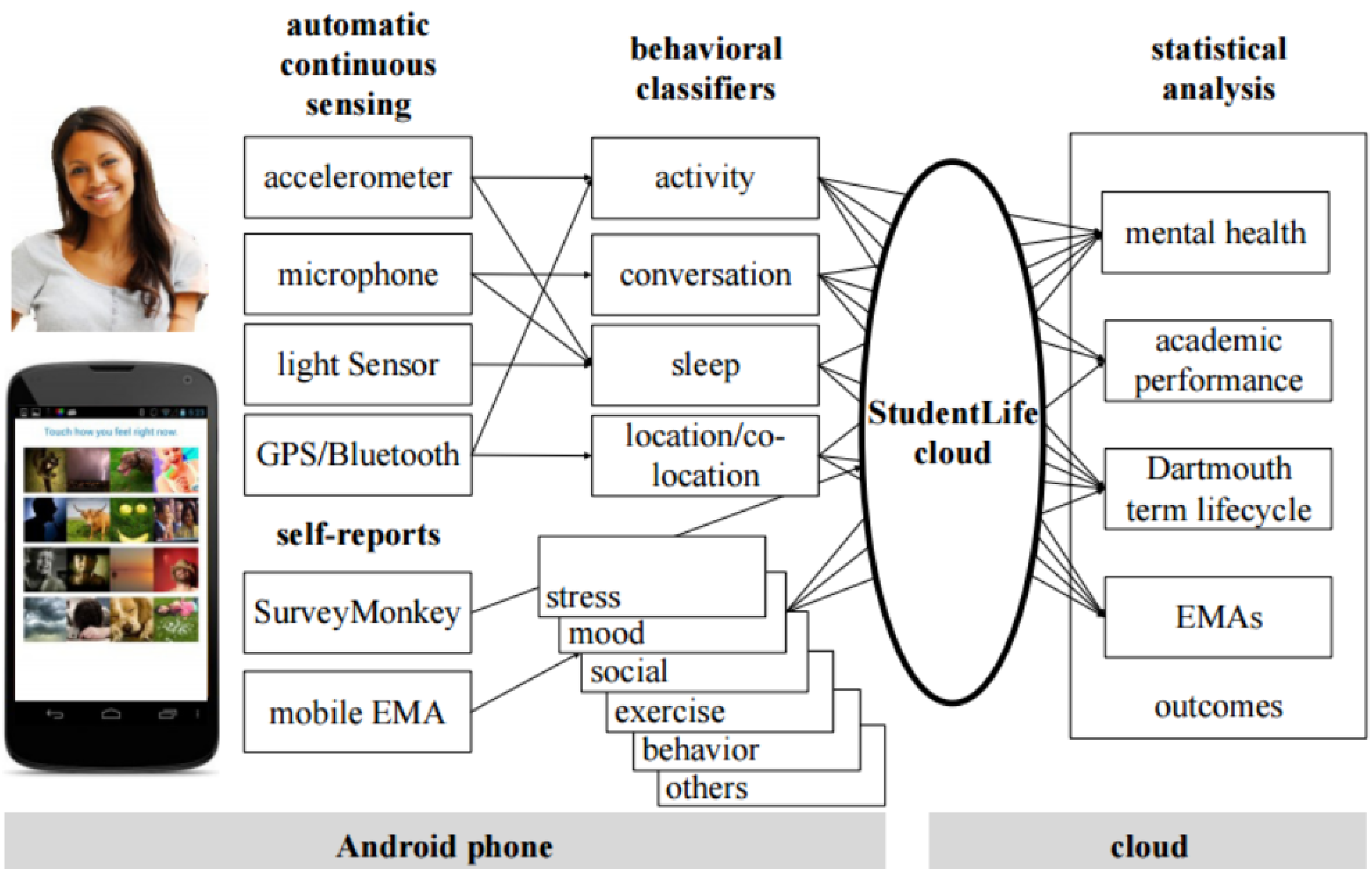
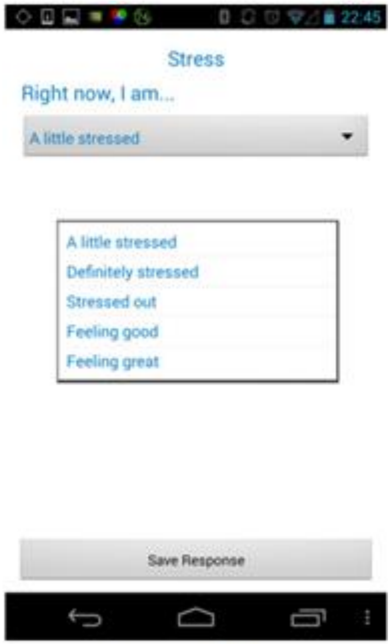


Figure 2. StudentLife app, sensing and analytics system architecture.

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

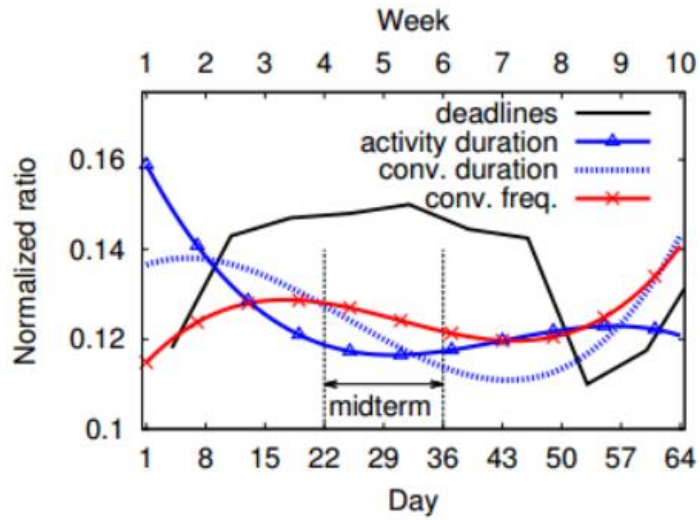
- Fewer conversations or co-locations correlate with
  - Higher chance of depression
- Higher stressed correlated with
  - Higher chance of depression
- More social interactions correlated with
  - Higher flourishing, GPA scores
  - Lower stress
- More sleep correlates with
  - Lower stress

Findings (cont'd)

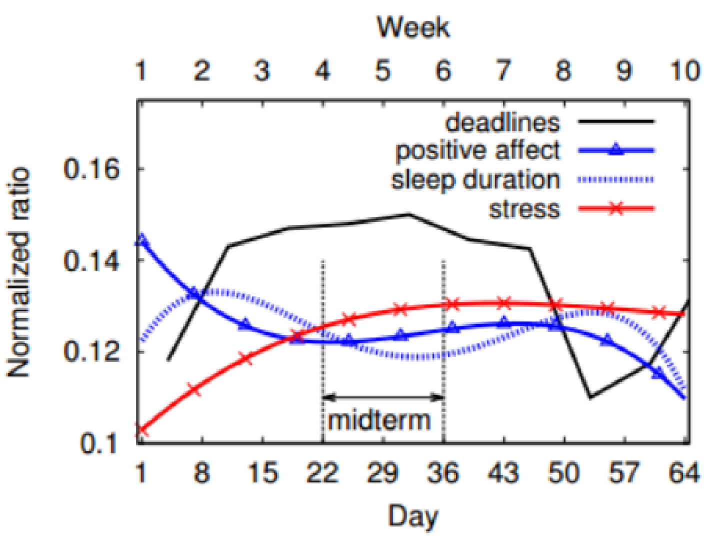
- Less sleep?
  - Higher chance of depression
- Less activity?
  - More likely to be lonely, lower GPAs
- No correlation between class attendance and academic performance (Hmm…)
- As term progressed:
  - Positive affect and activity duration plummeted

Findings (cont'd)

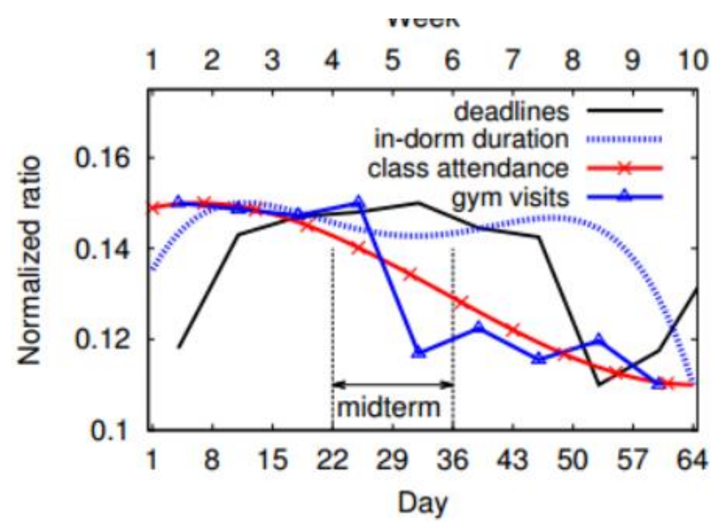
- Plotted total values of sensed data, EMA etc for all subjects through the term



(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

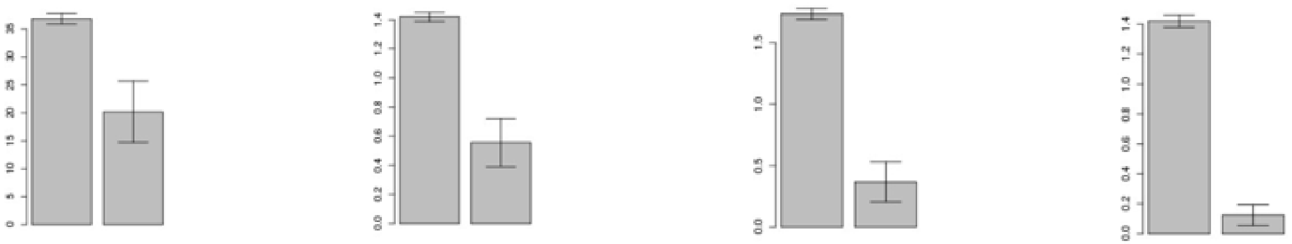
```
Syndrome [Influenza, Cold/Allergies]

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 **

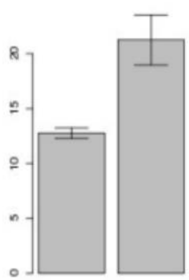
(b) Late night early morning Bluetooth entropy with respect to other participants decreases **

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

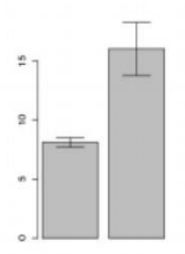
(d) WLAN Entropy with respect to external WLAN APs decreases ***

Data Analysis

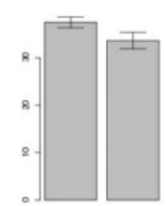
- Behavior effects of runny nose, congestion, sneezing symptom (mild illness)
  - **Cold is somewhat mild, communication, movement generally increased**



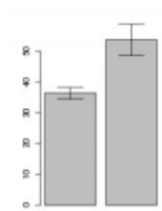
(a) Total communication increases ***



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



(c) Overall Bluetooth entropy decreases *



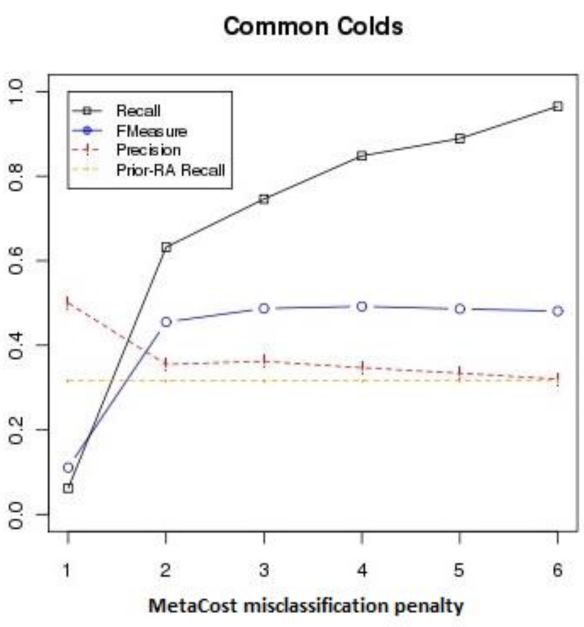
(d) Total WLAN APs detected increase **

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)

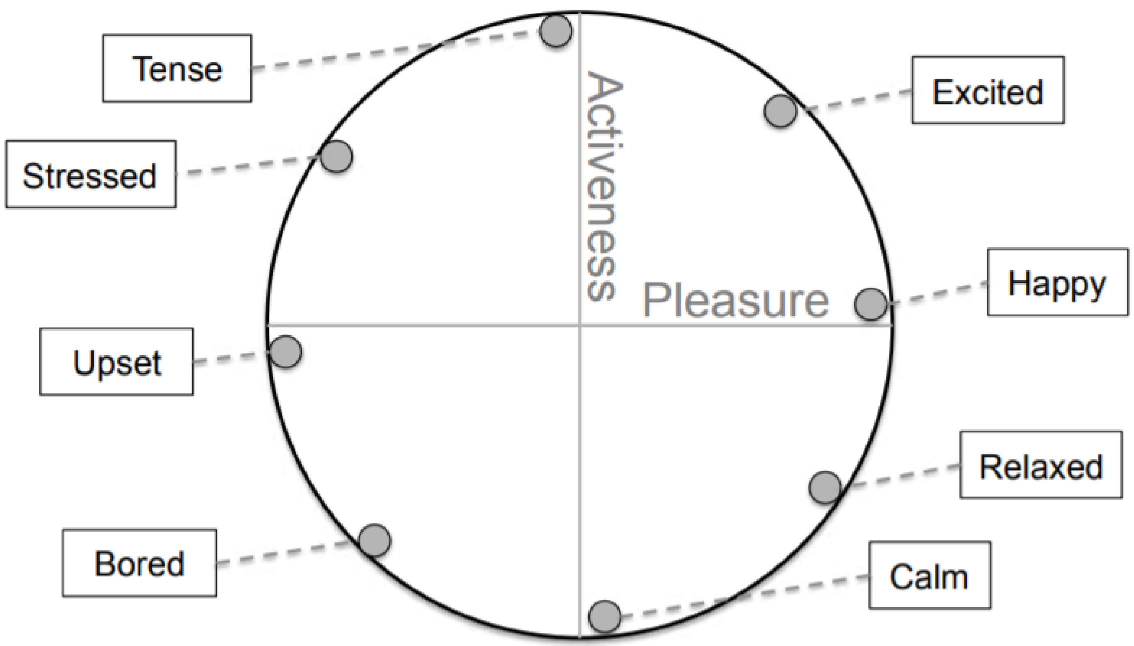


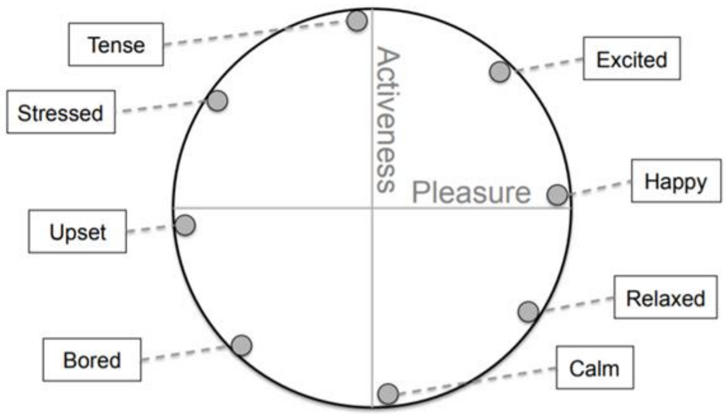
Figure 1: The circumplex mood model

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

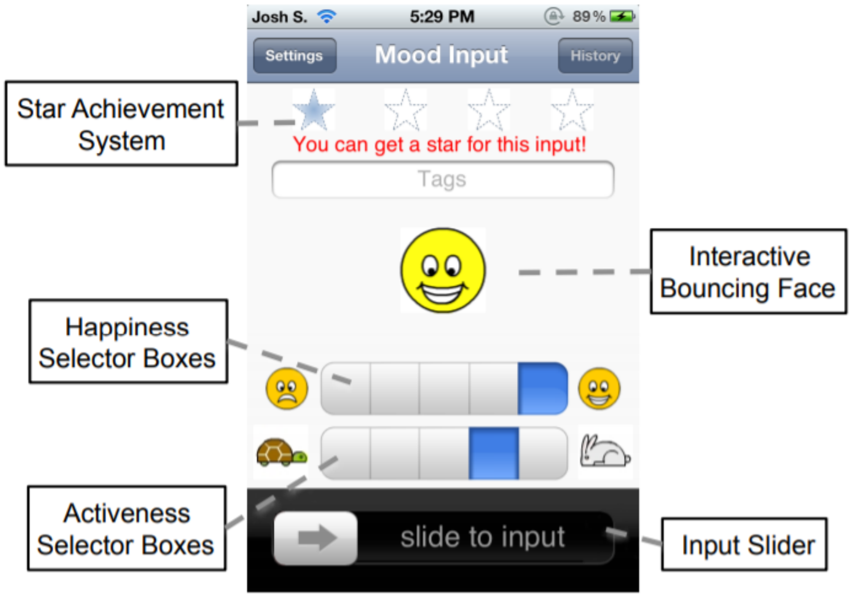


Figure 2: Mood journaling application view

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?

Next Week: Project Proposal

Final Project Proposal

http://web.cs.wpi.edu/~emmanuel/courses/cs528/F18/projects/final_project/

- 15-min Proposal Pitch (8/30 of project grade)
  a) what problem your app/machine learning classification/regression will tackle
  b) Why that problem is important and
  c) Review of other similar work/apps
  d) Summary of how your app will work/solve this problem.
  e) Implementation plan
     - **App:** Android Modules used, software architecture, screen mockups or sketches and timeline with who will do what.)
     - **Machine learning project:** what dataset(s) you will utilize or how you will run a study to gather data.

Final Project Proposal

http://web.cs.wpi.edu/~emmanuel/courses/cs528/F18/projects/final_project/

- Use Powerpoint template for your presentation
- Mail me your presentation slides after your talk (due 11.59PM) next week
- See proposal website for more details (rubric, etc)
- Ask me if you are confused about any aspect