StudentLife
College is hard...


- **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 sensible 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
- ??

**Sensible 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, conversation level = high depression

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

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

**Labels**

GPA
(from registrar)

Autosensed data
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

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)
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>
<thead>
<tr>
<th>automatic sensing data</th>
<th>r</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>sleep duration (pre)</td>
<td>-0.360</td>
<td>0.025</td>
</tr>
<tr>
<td>sleep duration (post)</td>
<td>-0.382</td>
<td>0.020</td>
</tr>
<tr>
<td>conversation frequency during day (pre)</td>
<td>-0.403</td>
<td>0.010</td>
</tr>
<tr>
<td>conversation frequency during day (post)</td>
<td>-0.387</td>
<td>0.016</td>
</tr>
<tr>
<td>conversation frequency during evening (post)</td>
<td>-0.345</td>
<td>0.034</td>
</tr>
<tr>
<td>conversation duration during day (post)</td>
<td>-0.328</td>
<td>0.044</td>
</tr>
<tr>
<td>number of co-locations (post)</td>
<td>-0.362</td>
<td>0.025</td>
</tr>
</tbody>
</table>
Some Findings

- Fewer conversations or co-locations correlate with
  - Higher chance of depression

- Higher stress 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
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 sensible 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 sensible signs (movement, social interactions, etc)
  - Administer sickness/symptom questionnaires periodically as pop-ups (EMA)

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

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

**Data Gathering app, automatically sense**
- Movement
- Social interactions

Labels (for classifier)

Autosensed data
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>
<thead>
<tr>
<th>Survey Question (as shown on mobile phone)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do you have a sore throat or cough?</td>
</tr>
<tr>
<td>Do you have a runny nose, congestion or sneezing?</td>
</tr>
<tr>
<td>Do you have a fever?</td>
</tr>
<tr>
<td>Have you had any vomiting, nausea or diarrhea?</td>
</tr>
<tr>
<td>Have you been feeling sad, lonely or depressed lately?</td>
</tr>
<tr>
<td>Have you been feeling stressed out lately?</td>
</tr>
</tbody>
</table>
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
Data Analysis

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

![Graphs showing data analysis results]

- (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)

![Circumplex Mood Model](image-url)

*Figure 1: The circumplex mood model*
**Classification**

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

<table>
<thead>
<tr>
<th>Data type</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Email contacts</td>
<td>#messages #characters</td>
</tr>
<tr>
<td>SMS contacts</td>
<td>#messages #characters</td>
</tr>
<tr>
<td>Phone call contacts</td>
<td>#calls call duration</td>
</tr>
<tr>
<td>Website domains</td>
<td>#visits</td>
</tr>
<tr>
<td>Location clusters</td>
<td>#visits</td>
</tr>
<tr>
<td>Apps</td>
<td>#app launches app duration</td>
</tr>
<tr>
<td>Categories of apps</td>
<td>#app launches app duration</td>
</tr>
</tbody>
</table>

**Smartphone usage features**

![Mood diagram](image)
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/F19/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/F19/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