CS 4518 Mobile and Ubiquitous Computing

Lecture 18: Smartphone Sensing Apps: Epidemiological Change & Urbanopoly

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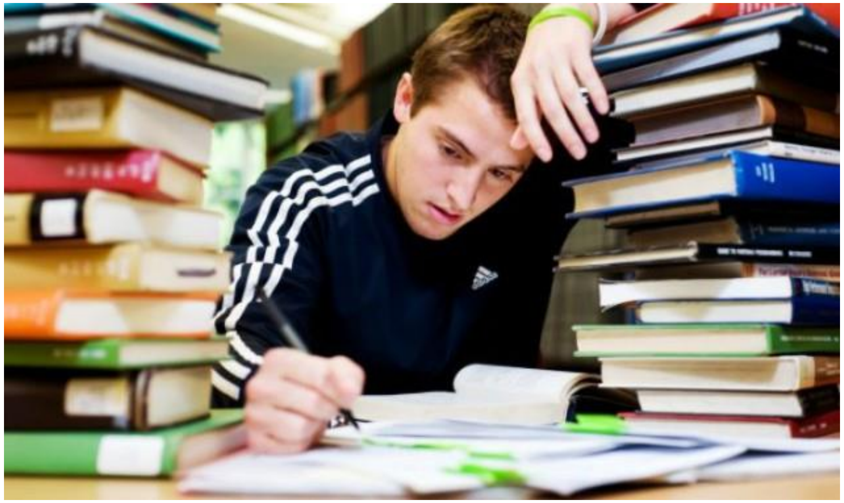
StudentLife

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

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)?

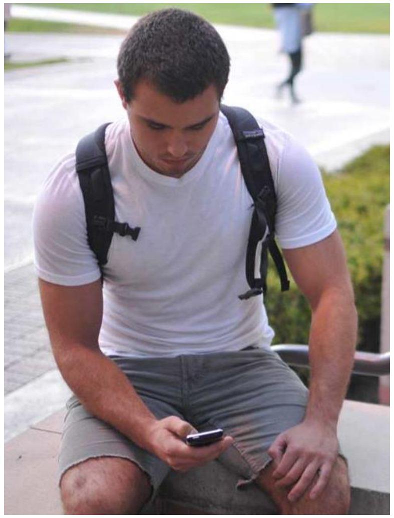
Stressors
- Deadlines
- Exams
- Quiz
- Break-ups
- Social pressure

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

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

StudentLife Continuous Sensing App

- Use smartphone sensing to assess/monitor student:
  - Psychological well-being (depression, anxiety, etc)
  - Academic performance
  - Behavioral trends, stress patterns as term progresses
- Demonstrates strong correlation between sensed data and clinical measures of mental health (depression, loneliness, etc)
- **Shows 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

General 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)

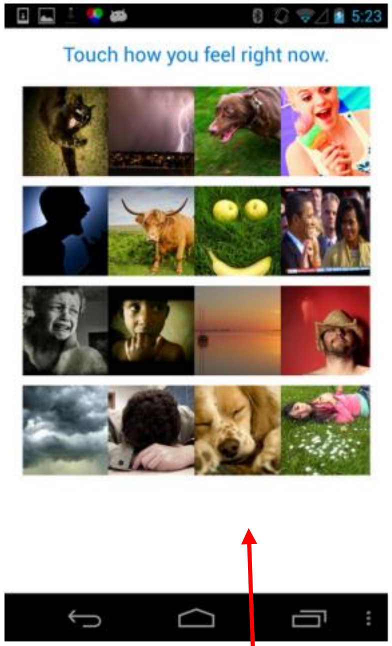
Mental Health Questionnaires (EMA)
- Anxiety
- Depression
- Loneliness
- Flourishing

Autosensed data

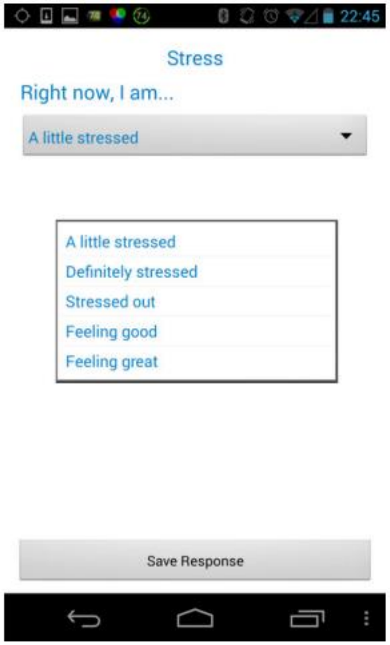
Data Gathering app, automatically sense
- Sleep
- Social interactions
- Conversations
- Activity Level, etc

Specifics: Data Gathering Study

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



(a) PAM EMA



(b) Stress EMA

PAM: Pick picture depicting
your current mood

StudentLife Data Gathering Study Overview

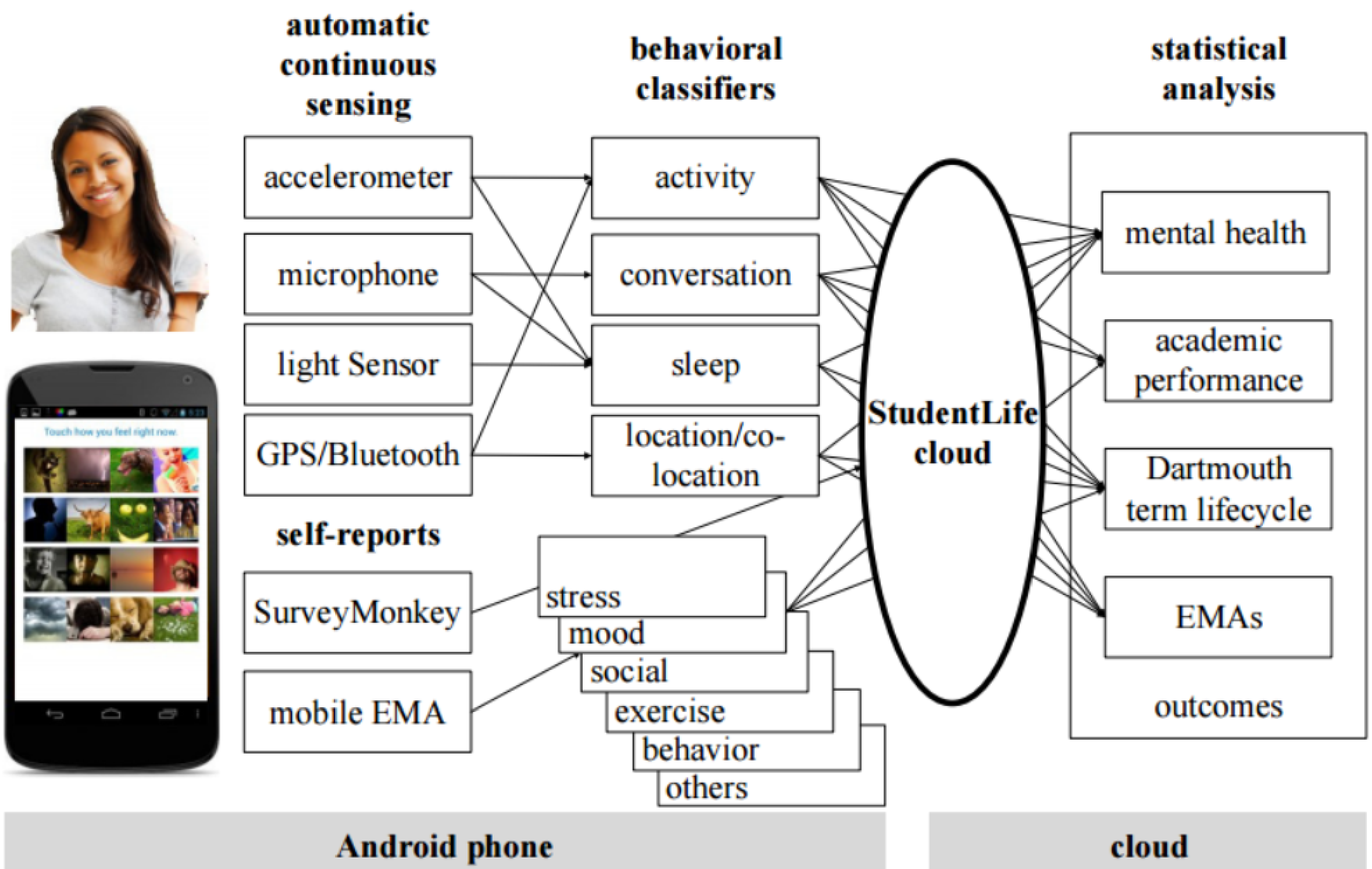
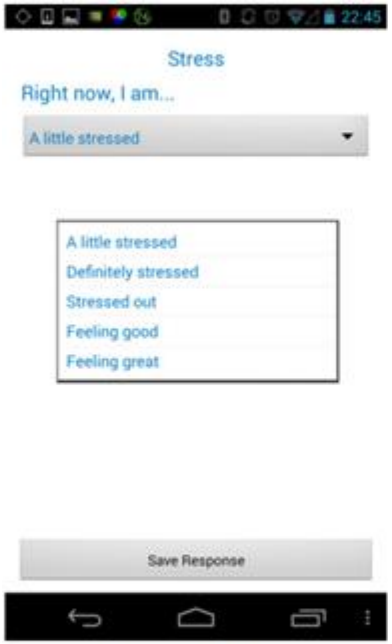


Figure 2. StudentLife app, sensing and analytics system architecture.

Clinical Mental Health Questionnaires

- MobileEMA popped up mental health questionnaires (widely used by psychologists, therapists, etc)
  - **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 lost during study (NR’d class?)
  - 30 undergrad/18 graduate level
  - 38 male/10 female
- Incentives given to study participants
  - StudentLife T-shirt (all students)
  - **Week 3 & 6:** 5 Jawbone UPs (like fitbit) to 5 in raffle
  - **End of study:** 10 Google Nexus phones in raffle
- 10 weeks of data collection

Some Findings

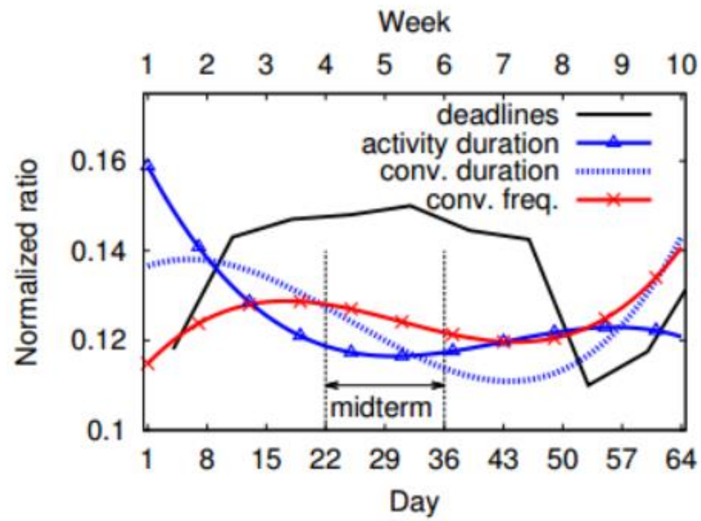
- Fewer conversations or co-locations correlate with
  - Higher chance of depression
- Higher stressed correlated with
  - Higher chance of depression
- More social interactions correlated with
  - Higher flourishing, GPA scores
  - Lower stress
- More sleep correlates with
  - Lower stress

Findings (cont'd)

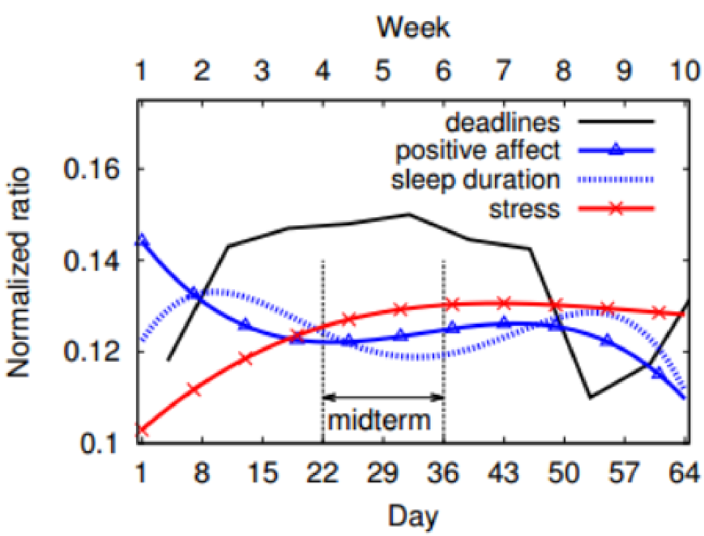
- Less sleep?
  - Higher chance of depression
- Less activity?
  - More likely to be lonely, lower GPAs
- No correlation between class attendance and academic performance (Hmm…)
- As term progressed:
  - Positive affect and activity duration plummeted

Findings (cont'd)

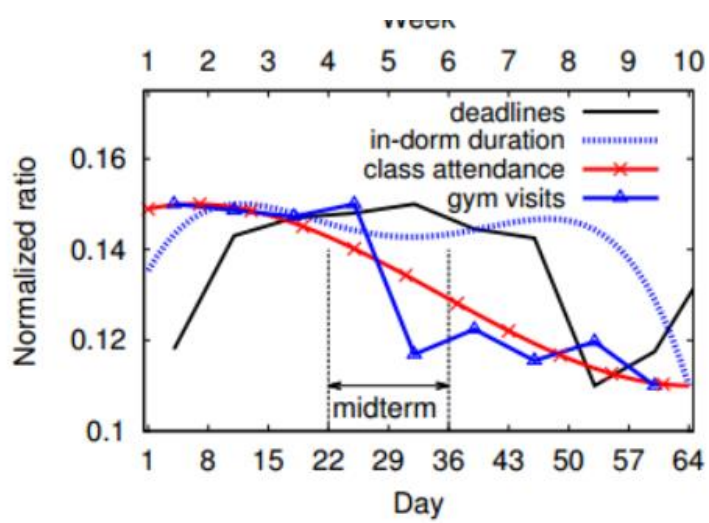
- Plotted total values of sensed data, EMA etc for all subjects through the term



(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

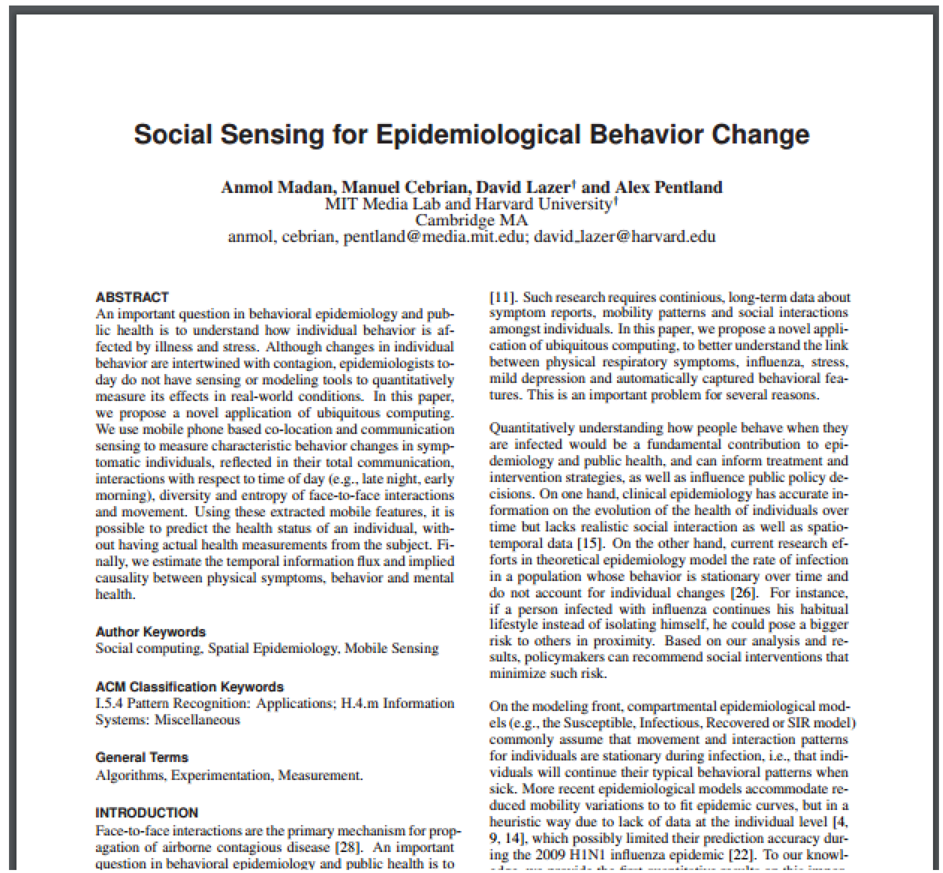
Discussion

- Expand to other colleges
  - Semester vs 10 week vs 7 week term
  - Similar results?
- Privacy concerns

MIT Epidemiological Change

Outline

- Introduction
- Related Work
- Methodology
- Evaluation/Results
- References



Social Sensing for Epidemiological Behavior Change

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ABSTRACT
An important question in behavioral epidemiology and public health is to understand how individual behavior is affected by illness and stress. Although changes in individual behavior are intertwined with contagion, epidemiologists today do not have sensing or modeling tools to quantitatively measure its effects in real-world conditions. In this paper, we propose a novel application of ubiquitous computing. We use mobile phone based co-location and communication sensing to measure characteristic behavior changes in symptomatic individuals, reflected in their total communication, interactions with respect to time of day (e.g., late night, early morning), diversity and entropy of face-to-face interactions and movement. Using these extracted mobile features, it is possible to predict the health status of an individual, without having actual health measurements from the subject. Finally, we estimate the temporal information flux and implied causality between physical symptoms, behavior and mental health.

Author Keywords
Social computing, Spatial Epidemiology, Mobile Sensing

ACM Classification Keywords
I.5.4 Pattern Recognition: Applications; H.4.m Information Systems: Miscellaneous

General Terms
Algorithms, Experimentation, Measurement.

INTRODUCTION
Face-to-face interactions are the primary mechanism for propagation of airborne contagious disease [28]. An important question in behavioral epidemiology and public health is to [11]. Such research requires continious, long-term data about symptom reports, mobility patterns and social interactions amongst individuals. In this paper, we propose a novel application of ubiquitous computing, to better understand the link between physical respiratory symptoms, influenza, stress, mild depression and automatically captured behavioral features. This is an important problem for several reasons.

Quantitatively understanding how people behave when they are infected would be a fundamental contribution to epidemiology and public health, and can inform treatment and intervention strategies, as well as influence public policy decisions. On one hand, clinical epidemiology has accurate information on the evolution of the health of individuals over time but lacks realistic social interaction as well as spatio-temporal data [15]. On the other hand, current research efforts in theoretical epidemiology model the rate of infection in a population whose behavior is stationary over time and do not account for individual changes [26]. For instance, if a person infected with influenza continues his habitual lifestyle instead of isolating himself, he could pose a bigger risk to others in proximity. Based on our analysis and results, policymakers can recommend social interventions that minimize such risk.

On the modeling front, compartmental epidemiological models (e.g., the Susceptible, Infectious, Recovered or SIR model) commonly assume that movement and interaction patterns for individuals are stationary during infection, i.e., that individuals will continue their typical behavioral patterns when sick. More recent epidemiological models accommodate reduced mobility variations to to fit epidemic curves, but in a heuristic way due to lack of data at the individual level [4, 9, 14], which possibly limited their prediction accuracy during the 2009 H1N1 influenza epidemic [22]. To our knowl-

Introduction

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

The Problem

- Disease spread models exist, but lack **real data on behavior changes** due to infection:
  - large numbers of people, many interactions
  - Accurate, timely symptom reports
  - behavior, mobility patterns, social interactions
- Clinical symptoms/effects are understood, but...
  - Identification requires in-person physician or self-diagnosis
  - Real-time automatic data collection challenging

Research Questions

- Can smartphone reliably detect sick owner?
  - Based on sensible behavior changes (movement patterns, etc)
- How do physical and mental health symptoms manifest themselves as behavioral patterns?
  - E.g. worsening cold = reduced movement?
- 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 (called 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 survey launcher
- 6AM - 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)

- Bluetooth (scan every 6 minutes)
  - Proximity to other phones

- WLAN: (scan every 6 minutes)
  - Approximate location (Access Points)
  - On campus / off campus

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

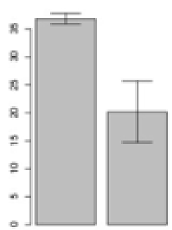
- Tracked absolute counts, diversity (with who?)
  - E.g. communicating with/seeing same/usual people or new people (e.g. nurse, family?)
  - Intensity of ties, size and dynamics of social network
  - Consistency of behavior

Analyze Syndrome/Symptom/Behavioral Relationships

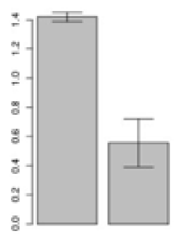
```
Syndrome [Influenza, Cold/Allergies]

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

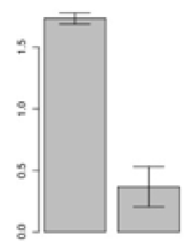
- Behavior effects of CDC-defined influenza (Flu)
  - Communication, movement generally reduced



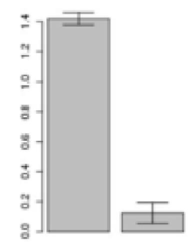
(a) Total Bluetooth interactions and entropy decrease **



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



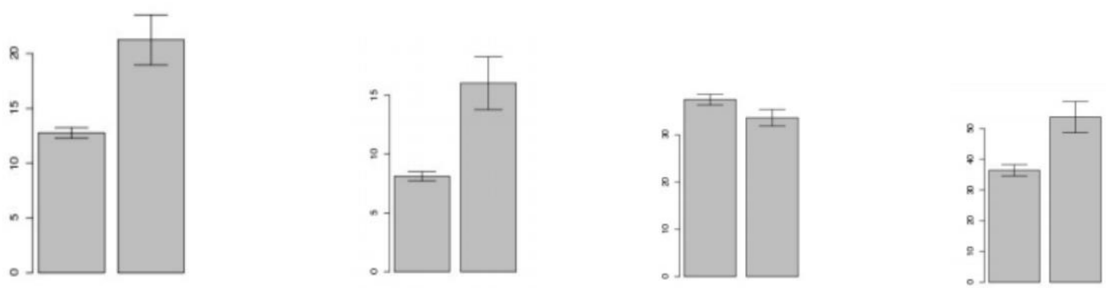
(c) WLAN based entropy with respect to university WLAN APs decreases ***



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

Data Analysis

- Behavior effects of runny nose, congestion, sneezing symptom (mild illness)
  - Communication, movement increased



(a) Total communication increases ***

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

(c) Overall Bluetooth entropy decreases *

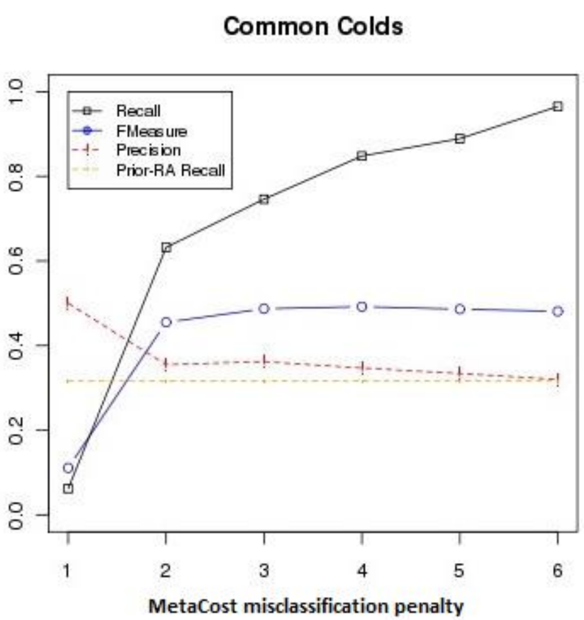
(d) Total WLAN APs detected increase **

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 4 symptom classes!!**



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

Urbanopoly

The Problem: Curated Datasets

- Location-based recommendations excellent
  - E.g. Best pizza spot near me, ratings pictures

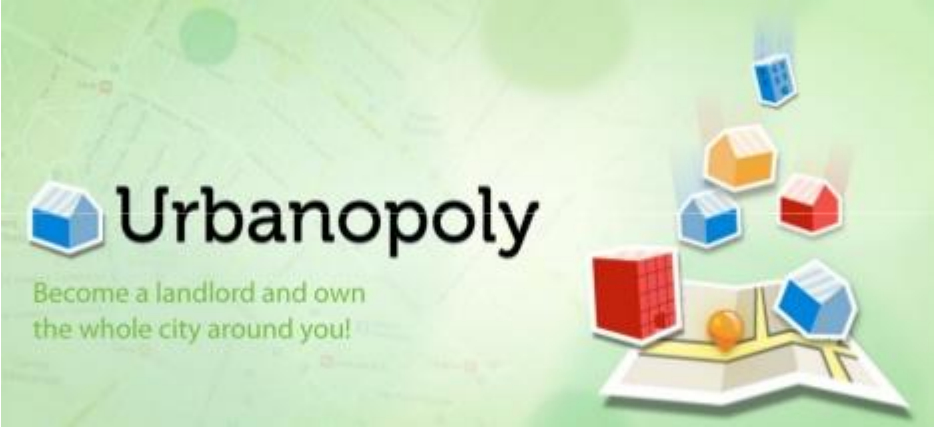
- Gathering such curated data takes lots of time/money
- Users frequently unmotivated to help
- Very few people (< 10%) rate their experiences

- Can we crowdsource curation? Gamify it?

What is Urbanopoly?

Celino *et al*, Urbanopoly – a Social and Location-based Game with a Purpose to Crowdsource your Urban Data

- A Game with a Purpose (GWP) or “serious games” designed to conduct quality assurance on urban data (e.g. restaurant information) using the user's current location and social graph
- Monopoly-like



What is Urbanopoly?

- **Urbanopoly:** crowdsource data using an interactive, social monopoly-like mobile game (Urbanopoly)
  - Players given multiple types of tasks
  - Involve their social network (e.g. Facebook), post update messages

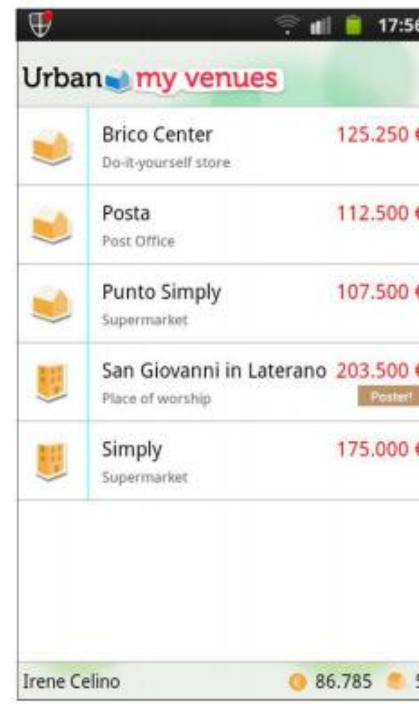
- Try to increase:
  - Number of contributions/player
  - Time each contributor/player spends

Methodology

- OpenStreetMap for map data
  - Free geographic info
- Facebook API for social sharing
- **Urbanopoly goal:** crowdsource, pics, reviews, data from users to augment OpenStreetMap data
  - Mini-games to incentivize users
- Achieves QA using:
  - Data collection
  - Data validation
  - Data ranking

Urbanopoly GamePlay

- User is a landlord, whose aim is to create a "rich portfolio of venues“ (like monopoly)
  - Venues
    - Real places surrounding the user (e.g. shops, restaurants, etc)
    - Venues retrieved from OpenStreetMap
    - Orange ones belong to the user, blue ones do not
    - have monetary values
  - Player Budget
    - User uses money to buy venues



Venues

- Location
  - Type
  - Hours
  - Rating
  - Extra info (food served, smoking rules)

Urbanopoly GamePlay

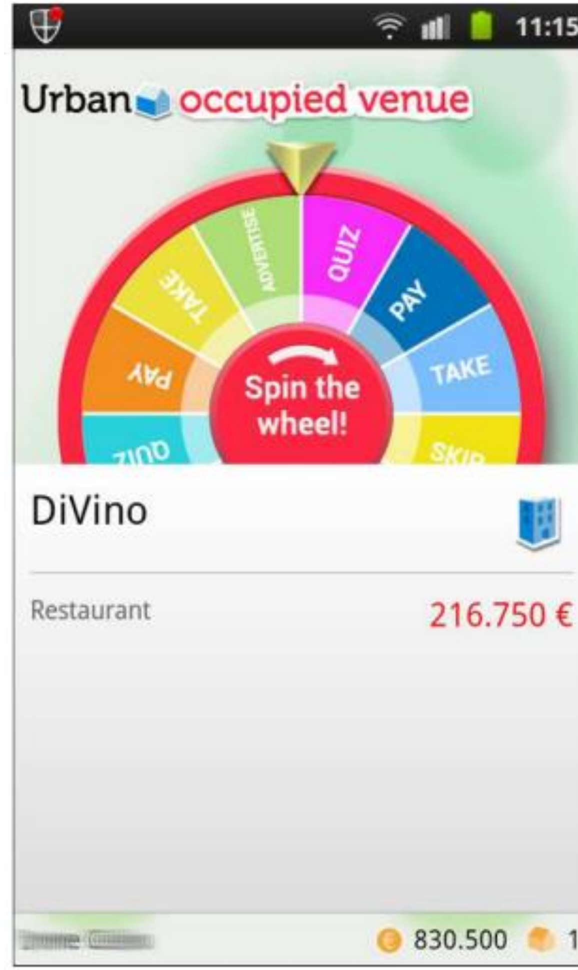
- User can buy venues they visit if not currently owned, they can afford it
- If venue owned, spin a “wheel of fortune”
- Result of wheel spin
  - Solve a puzzle that can give him/her more “money”
  - Direct enjoyment (given money, steal a venue)
- Players get daily bonus for participation
- Game maintains leaderboard

Urbanopoly: Other Gaming Features

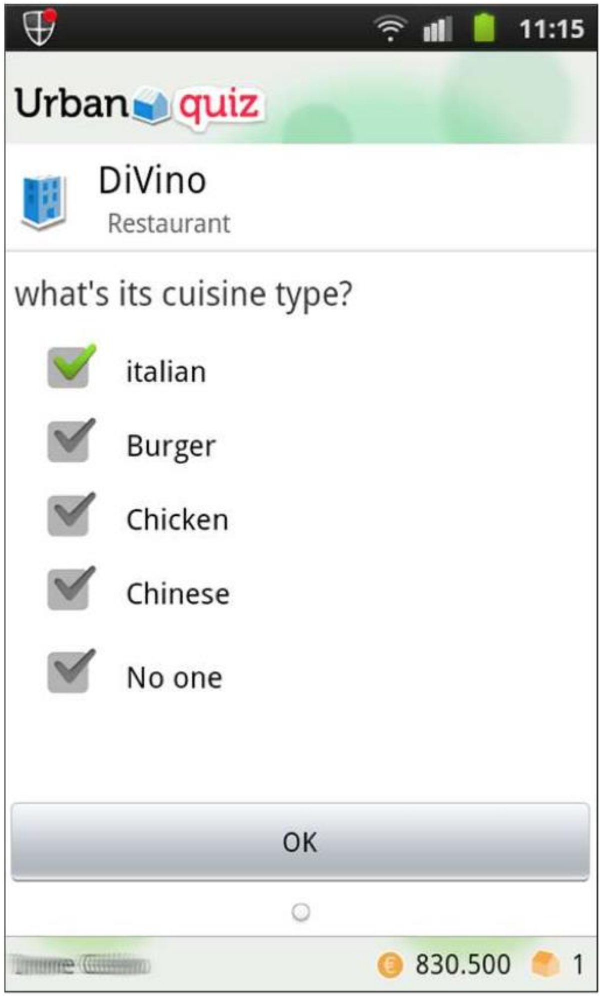
- Venue trading
- Mortgaging option: Get immediate cash from bank

Gameplay

- Data Collection
  - Venue purchase
    - Users required to name venue and specify its type, edit info
  - Venue advertisement
    - If venue already owned, user answers questions about venue (ad)
    - Store owners can rank ads
  - Quizzes
    - Results from spinning wheel
    - Player asked questions about venue



Example Quizzes



Similar Work

- While not specifically mentioned, similar apps exist:
  - Foursquare
  - Yelp
  - Google Maps

- Urbanopoly differs by gathering data through gamification
  - Other apps usually use surveys
  - Gathers more data types

Pros Vs Cons

- Pros
  - Social aspect makes it more appealing
  - Gaming aspect makes it very engaging for users; more "fun" than just surveys (e.g. Google Rewards)
  - Leaderboard to compete against friends
- Cons
  - Only available in certain locations in Italy
  - Possibly slow to start (classic crowdsourcing issue)

Quiz 5

Quiz 5

- Quiz in class next Monday (2/27)
- Short answer questions
- Try to focus on understanding, not memorization
- Covers:
  - Lecture slides for lectures 15-18
  - 1 paper
    - StudentLife paper