Mobile and Ubiquitous Computing on Smartphones
Lecture 8a: Smartphone Sensing

Emmanuel Agu

Smartphone Sensing

Recall: Smartphone Sensors

- Typical smartphone sensors today
  - accelerometer, compass, GPS, microphone, camera, proximity
- Use machine learning to classify sensor data

Future sensors?

- Heart rate monitor,
- Activity sensor,
- Pollution sensor,
- etc

Recall: Growth of Smartphone Sensors

- Every generation of smartphone has more and more sensors!!

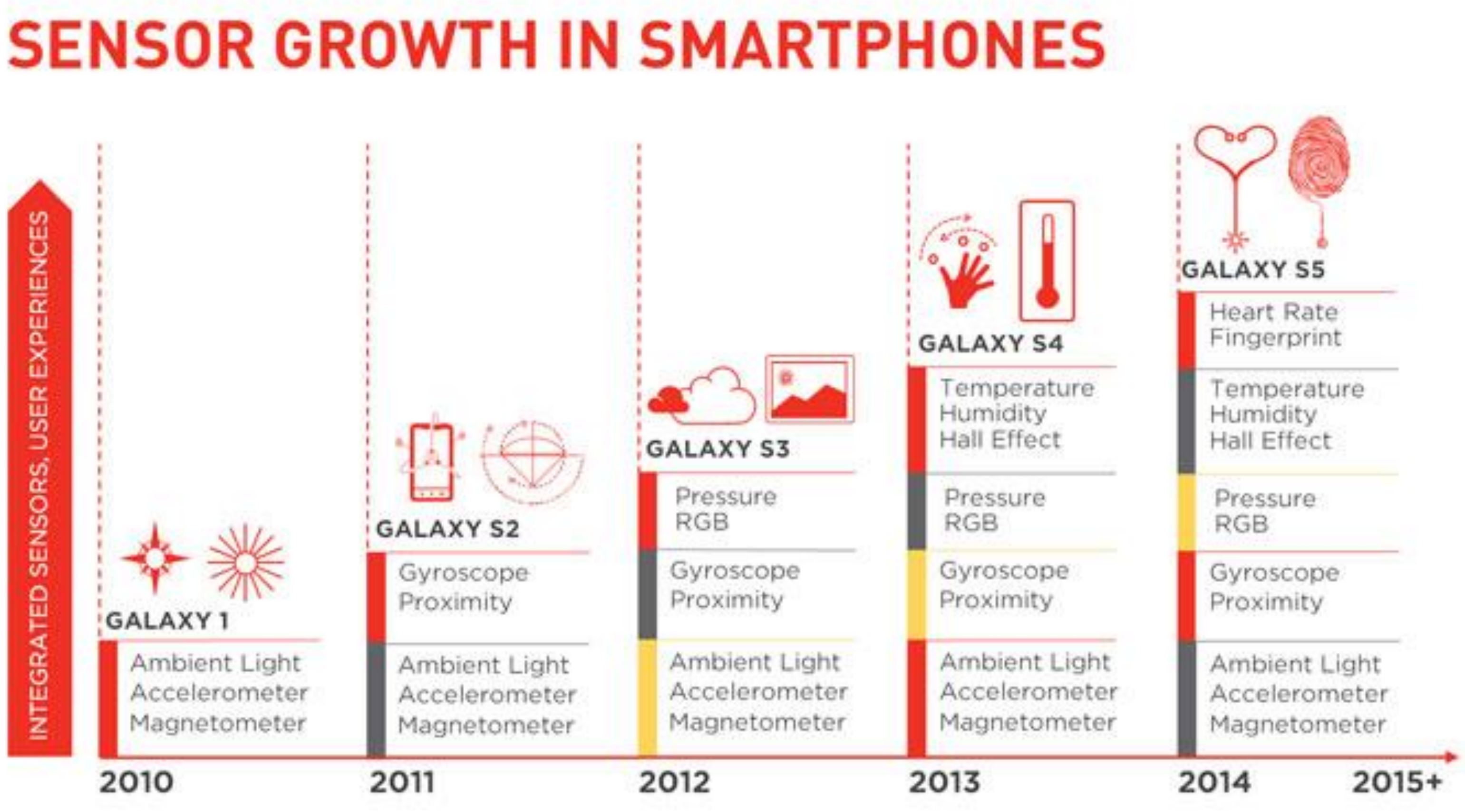


Image Credit: Qualcomm

Recall: What Can We Detect/Infer using Smartphone Sensors

24/7 detection, in natural settings

Smartphone Sensor data

Machine Learning

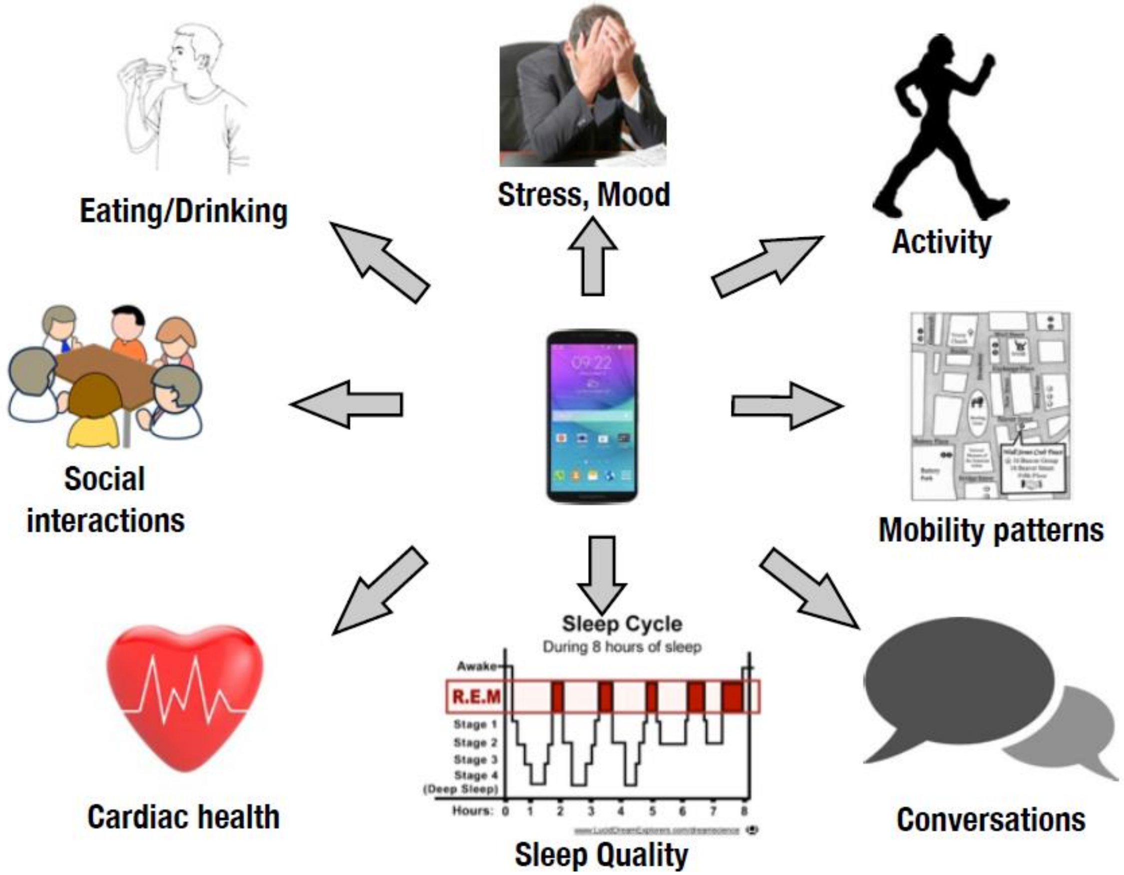
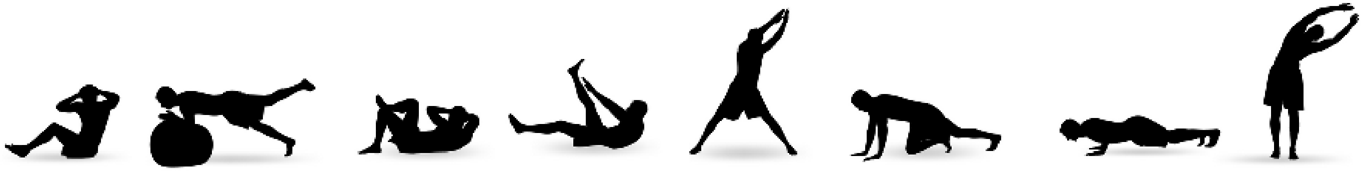


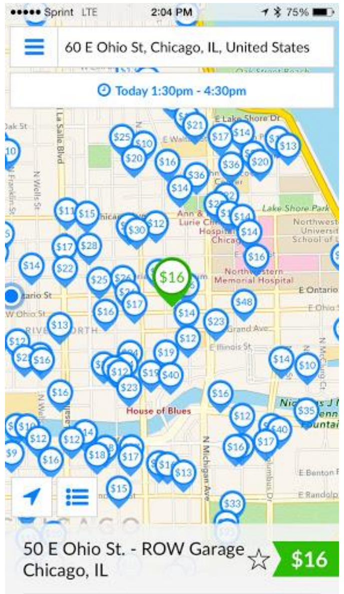
Image Credit: Deepak Ganesan, UMass

Sense What?

- **Environmental:** pollution, water levels in a creek
- **Transportation:** traffic conditions, road conditions, available parking
- **City infrastructure:** malfunctioning hydrants and traffic signs
- **Social:** photoblogging, share bike route quality, petrol price watch
- **Health and well-being:**
  - Share exercise data (amount, frequency, schedule),
  - share eating habits and pictures of food



myFitnessPal

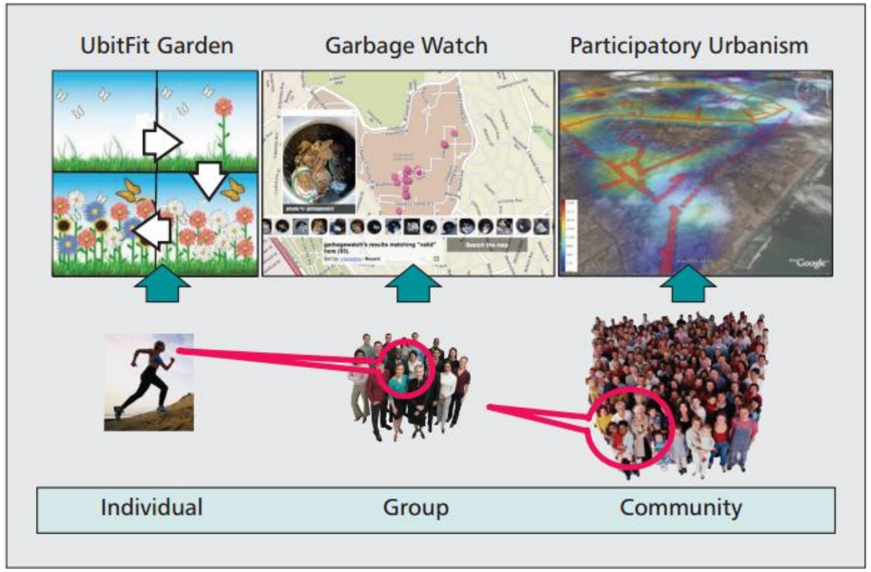


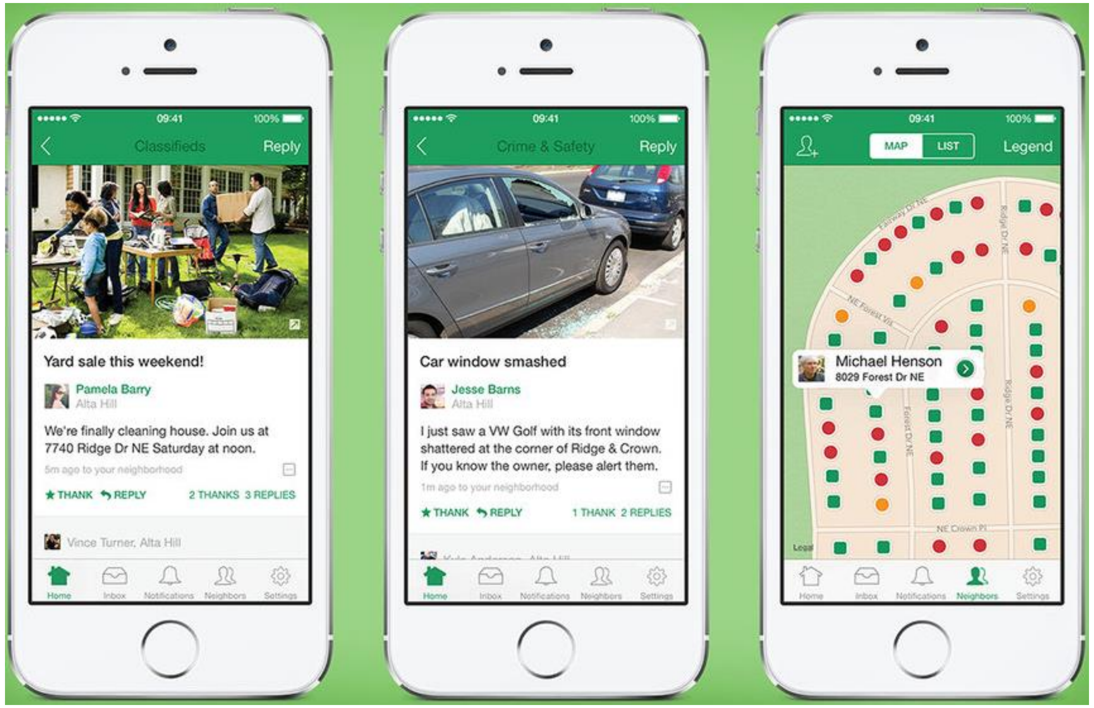
SpotHero Parking

AQI India

Mobile CrowdSensing

- **Mobile CrowdSensing:** Sense collectively
- **Personal sensing:** phenomena for an individual
  - E.g: activity detection for health monitoring
- **Group:** friends, co-workers, neighborhood
  - E.g. GarbageWatch, recycling reports, neighborhood surveillance

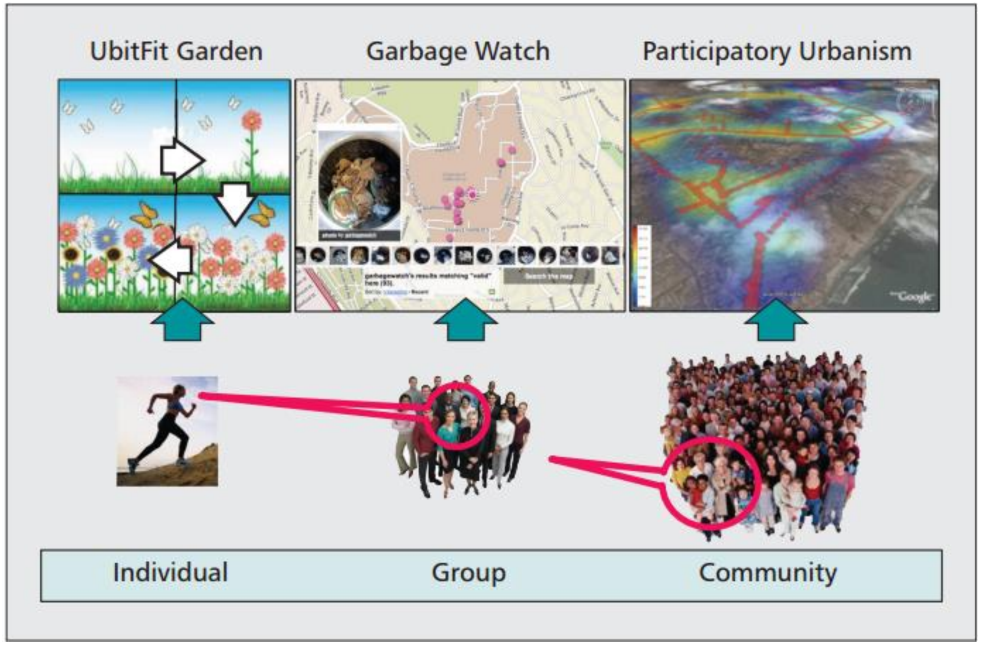


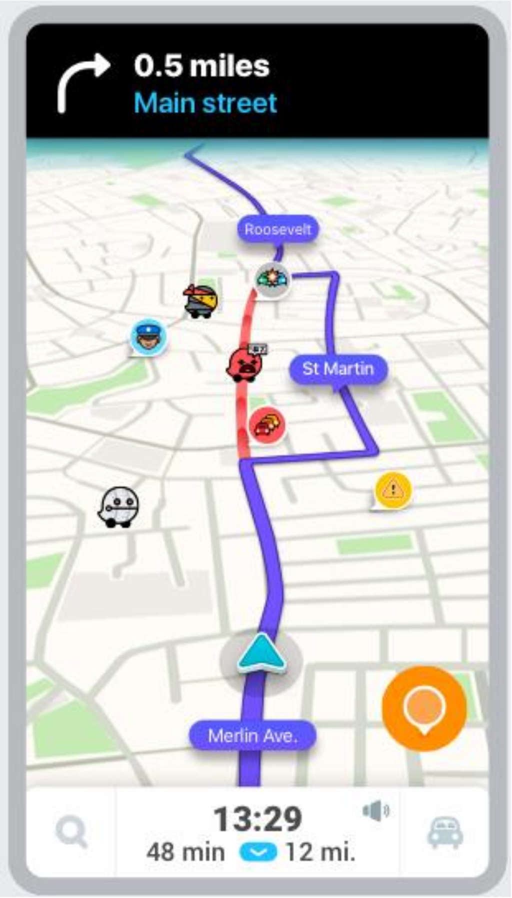


NextDoor Neighbourhood Surveillance App

Mobile CrowdSensing

- **Community sensing (mobile crowdsensing):**
  - Large-scale phenomena monitoring
  - Many people contribute their individual readings
  - **Examples:** Traffic congestion, air pollution, spread of disease, migration pattern of birds, city noise maps

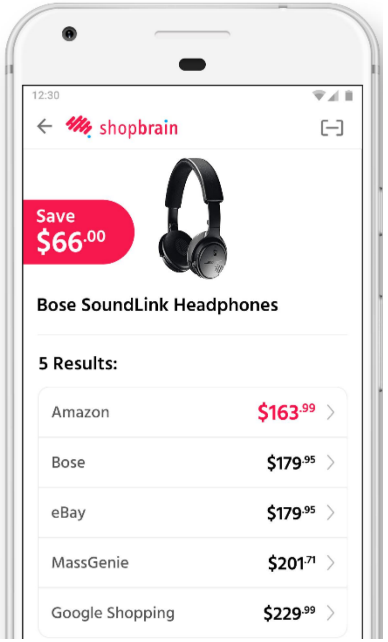




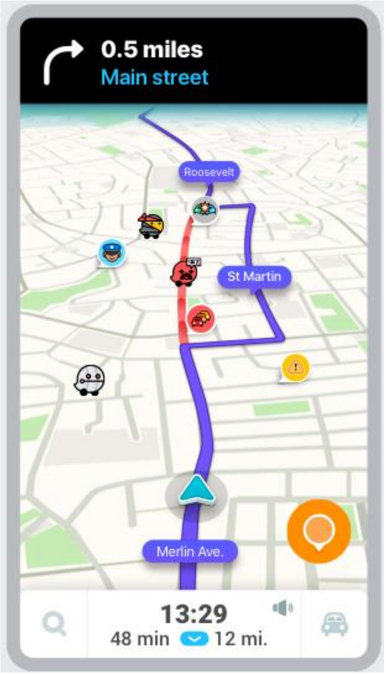
Waze Traffic app

Mobile Crowd Sensing Types

- Many people cooperate, share sensed values
- 2 types:
  1. ***Participatory Sensing:*** User manually enters values (**active** involvement)
     - E.g. Comparative shopping: Compare price of toothpaste at CVS vs Walmart
  2. ***Opportunistic Sensing:*** Mobile device automatically senses values (**passive** involvement)
     - E.g. Waze crowdsourced traffic



ShopBrain Comparative Shopping

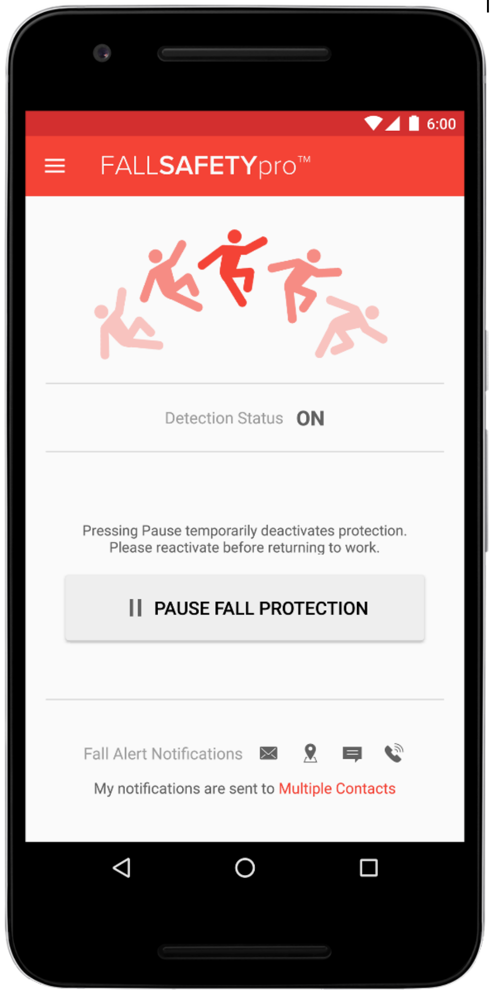


Waze Traffic app

More examples:
Smartphone Sensing

Personal Opportunistic Sensing

- FallSafetyPro
  - Detects if user falls using sensor
  - Target users:
    - Extreme work environments by detecting falls and inactivity, and automatically (e.g. construction)
    - Seniors living alone
  - Sends alerts for workers in distress.

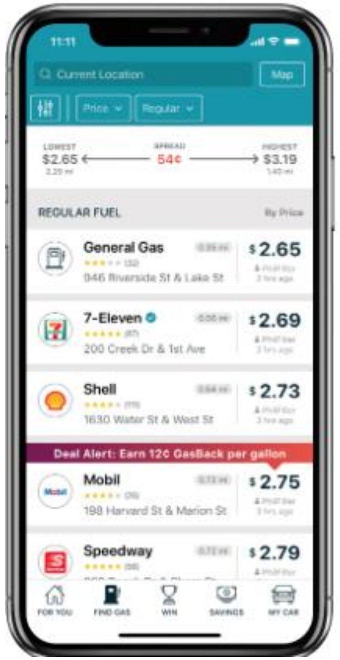


Public Opportunistic Sensing

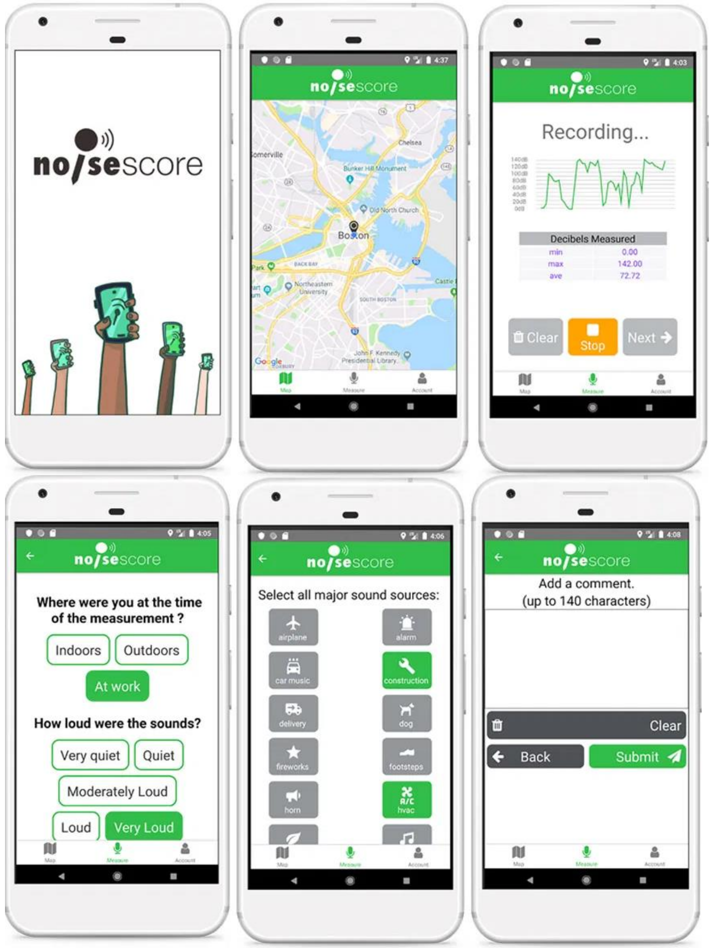
- Crowd Counting: Crowd size, density estimation
  - E.g. Concerts, large malls
  - Manage crowds, risk of blockage, crushing
  - Analyze passively gathered audio

Public Participatory Sensing Examples

- NoiseScore: Cooperate to monitor city noise levels
- GasBuddy: Cooperate to find cheap gas
  - Compare gas prices
  - Uses GPS to know when gas station is near



GasBuddy



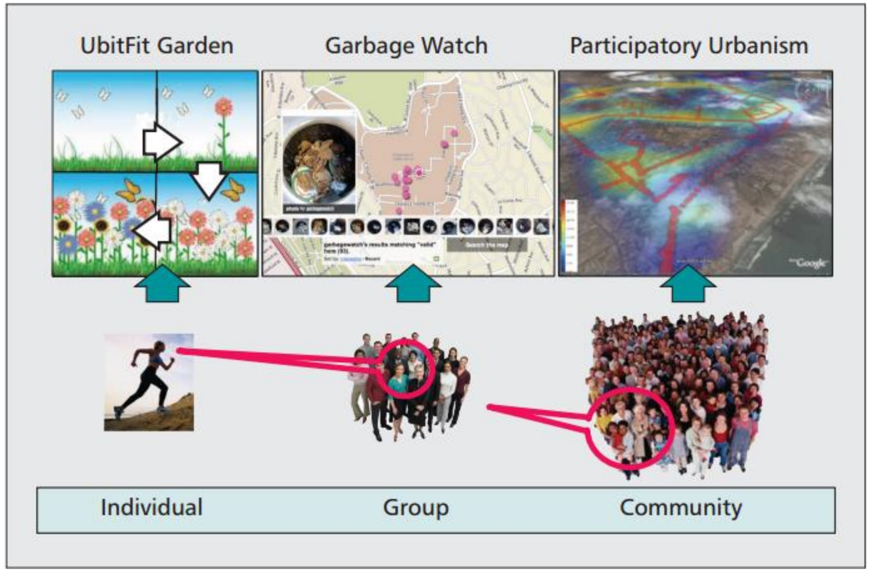
NoiseScore

Public Participatory Sensing

- **Pothole Monitor**
  - Combines GPS and accelerometer
- **Party Thermometer**
  - Asks you questions about parties
  - Detects parties through GPS and microphone
- **BOS:311 app**
  - Report potholes, missed trash collection, Corona: people not wearing masks

Mobile CrowdSensing

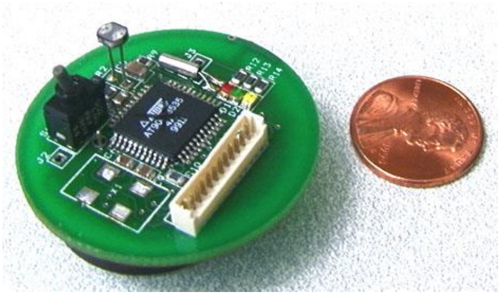
- **Mobile CrowdSensing:** Sense collectively
- **Personal sensing:** phenomena for an individual
  - E.g: activity detection and logging for health monitoring
- **Group:** friends, co-workers, neighborhood
  - E.g. GarbageWatch recycling reports, neighborhood surveillance



Other Mobile Crowdensing apps?

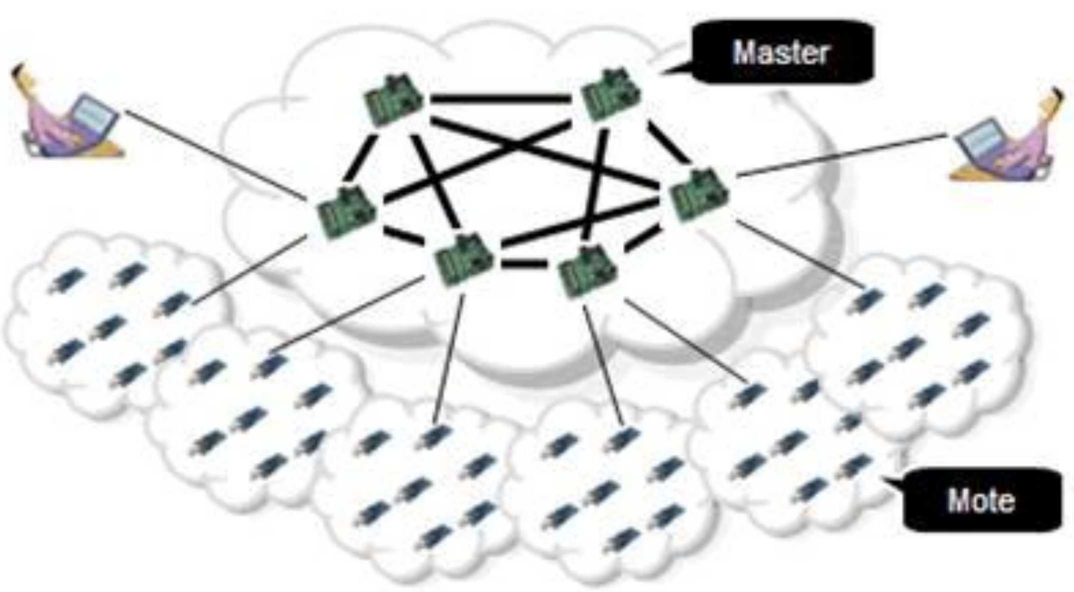
Smartphone Sensing vs Dedicated Sensors

VS

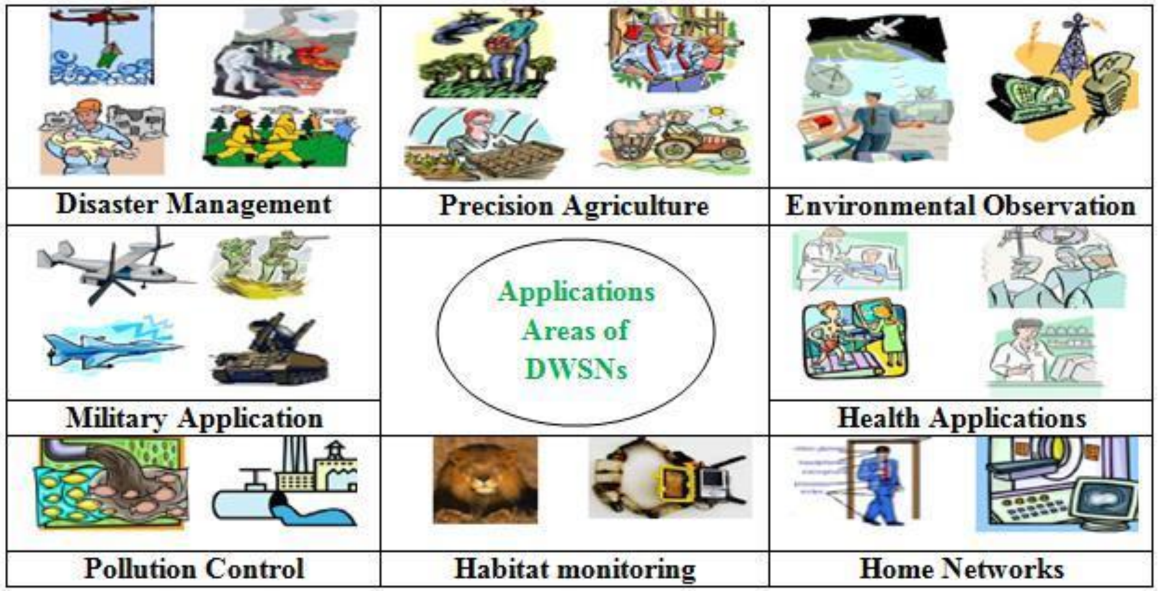


Background: Wireless Sensors for Environment Monitoring

- Embedded in room/environment
- Many sensors cooperate/communicate to perform task
- Monitors conditions (temperature, humidity, etc)
- User can query sensor (What is temp at sensor location?)



WSN Architecture



WSN Applications

Sensing with Smartphones vs Dedicated Sensors

Smartphone pros:

- **More resources:** Smartphones have much more processing and communication power

- **Easy deployment:** Millions of smartphones already owned by people
  - Instead of installing sensors in road, we detect traffic congestion using smartphones carried by drivers
  - Makes maintance easier. E.g. owner will charge their phone promptly

Smartphone cons:

- **Time-varying data:** population of mobile devices, type of sensor data, accuracy changes often due to user mobility and differences between smartphones

Sensing with Smartphones vs Dedicated Sensors

Additional considerations

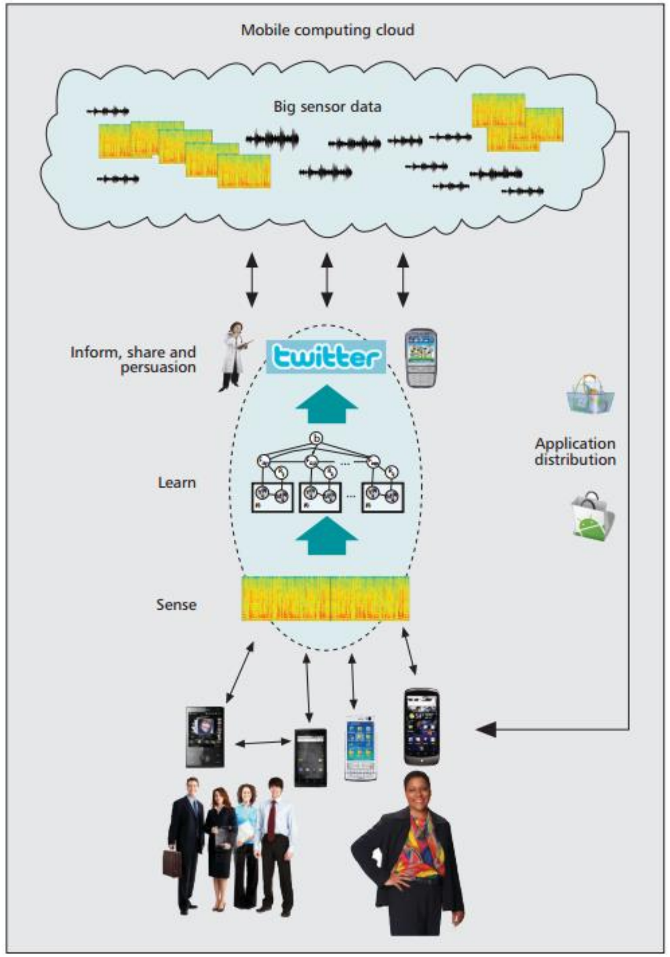
- **Reuse of few general-purpose sensors:** While sensor networks use dedicated sensors, smartphones reuse relatively few sensors for wide-range of applications
  - E.g. Accelerometers used in transportation mode identification, pothole detection, human activity pattern recognition, etc

- **Human involvement:** humans who carry smartphones can be involved in data collection (e.g. taking pictures)
  - Human in the loop can collect complex data
  - Incentives must be given to humans

Smartphone Sensing Architecture

Smartphone Sensing Architecture

- Paradigm proposed by Lane *et al*
- **Sense:** Phones collect sensor data
- **Learn:** Information is extracted from sensor data by applying **machine learning and data mining** techniques
- **Inform, share and persuasion:** inform user of results, share with group/community or persuade them to change their behavior
  - **Inform:** Notify users of accidents (Waze)
  - **Share:** Notify friends of fitness goals (MyFitnessPal)
  - **Persuasion:** avoid speed traps (Waze)



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

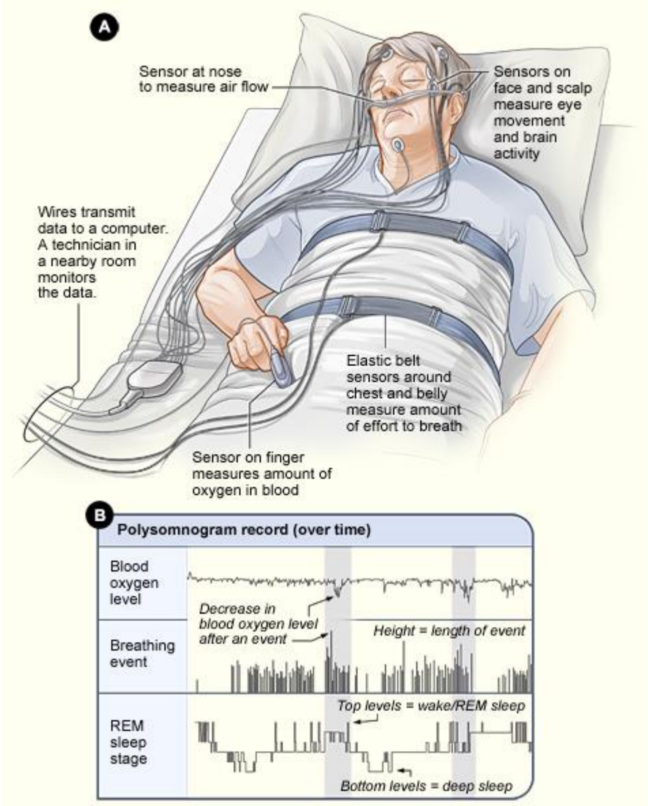
- Many medical treatments require patient records sleep
- Manually recording sleep/wake times is tedious

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, often impractical, expensive!



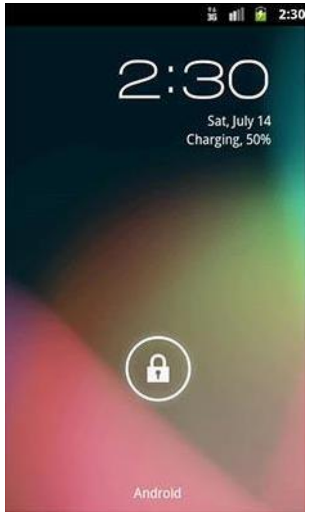
Commercial Wearable Sleep Devices

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

Can we monitor sleep with smartphone?

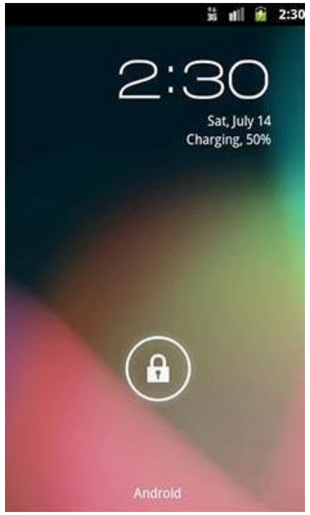
Observations: "Typical" sleep conditions

- 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 used in paper:
- Phone Usage features.

    --phone-lock (F2)

    --phone-off (F4)

    --phone charging (F3)

  -- Light feature (FI).

  -- Phone in darkness

  --Phone in a stationary state (F5)

  --Phone in a silent environment (F6)

- Used alone, each of these features are weak indicators of sleep
- If they co-occur (together), stronger indicator
- 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 + data, extract 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)

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

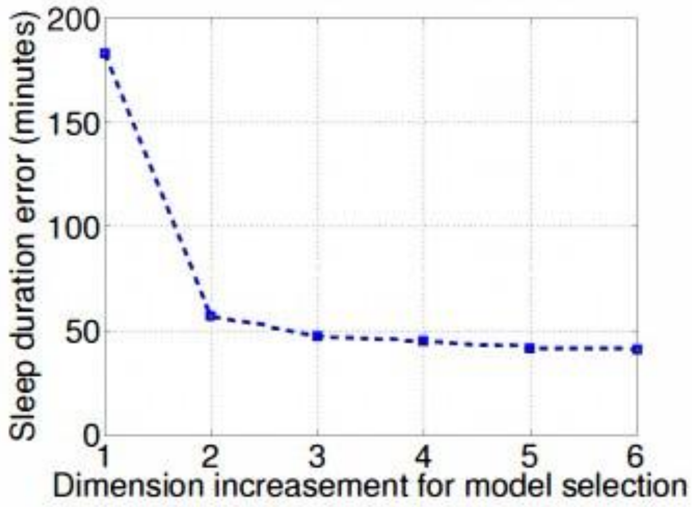


Fig. 2: The reduction in sleep duration error for BES by incrementally adding stationary, silence, phone-lock, phone-charging, light and phone-off features, respectively.

Results

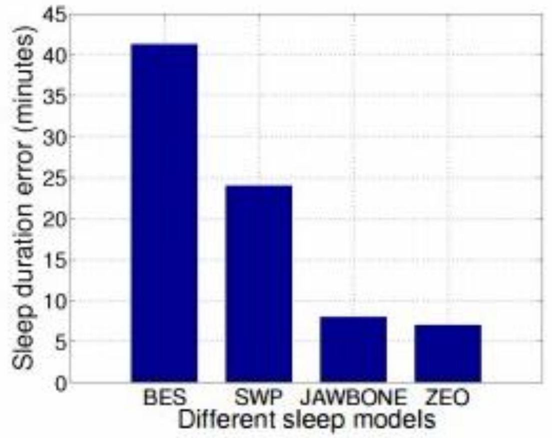


Fig. 3: Overall sleep duration error for BES compared to the three alternative sleep monitoring systems (SWP, Jawbone, Zeo).

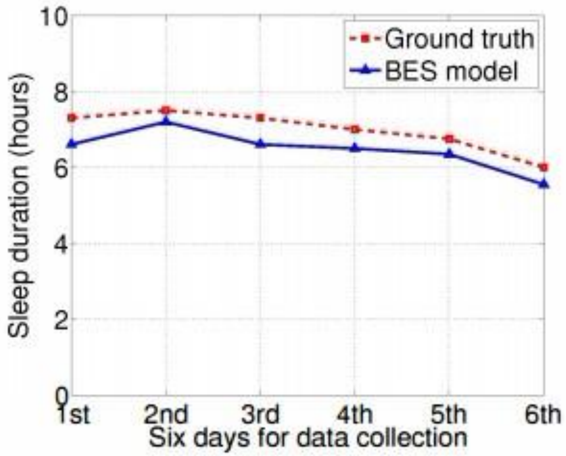


Fig. 5: Comparison of estimated and actual sleep duration under BES for one representative study subject.

My actual Experience

- Worked with undergrad student to implement BES sleep model
- **Results:** About ± 20 minute error 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

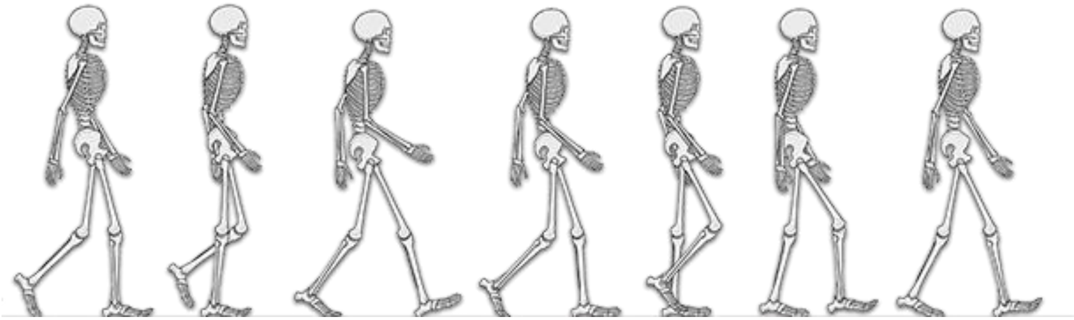
Binge Drinking Consequences

- 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 detect drunk person, prevent DUI?

Vehicle Interlock system

Gait for Inferring Intoxication

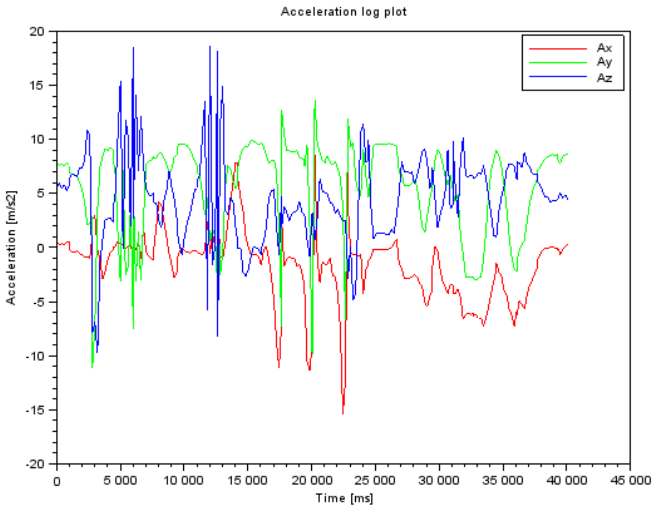
- **Gait:** Way a person walks, impaired by alcohol
- Aside from breathalyzer, gait is most accurate bio- measure of intoxication
- The police also know gait is accurate
  - 68% police DUI tests based on gait e.g. walk and turn test



AlcoGait

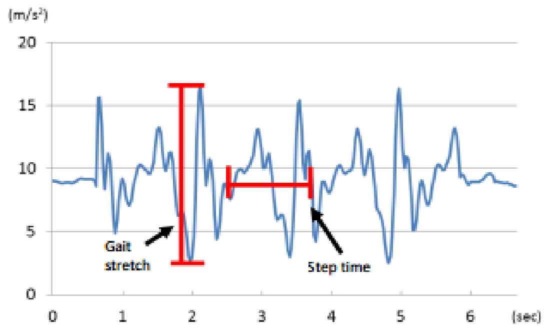
Z Arnold, D LaRose and E Agu, Smartphone Inference of Alcohol Consumption Levels from Gait, in Proc ICHI 2015
Christina Aiello and Emmanuel Agu, Investigating Postural Sway Features, Normalization and Personlization in Detecting Blood Alcohol Levels of Smartphone Users, in Proc Wireless Health Conference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

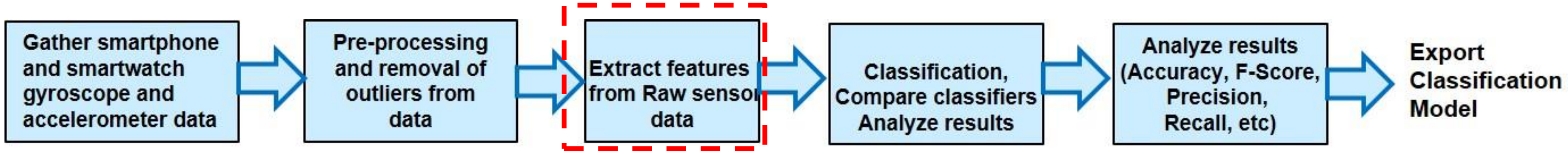
Feature	Feature Description
Steps	Number of steps taken
Cadence	Number of steps taken per minute
Skew	Lack of symmetry in one's walking pattern
Kurtosis	Measure of how outlier-prone a distribution is
Average gait velocity	Average steps per second divided by average step length
Residual step length	Difference 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]



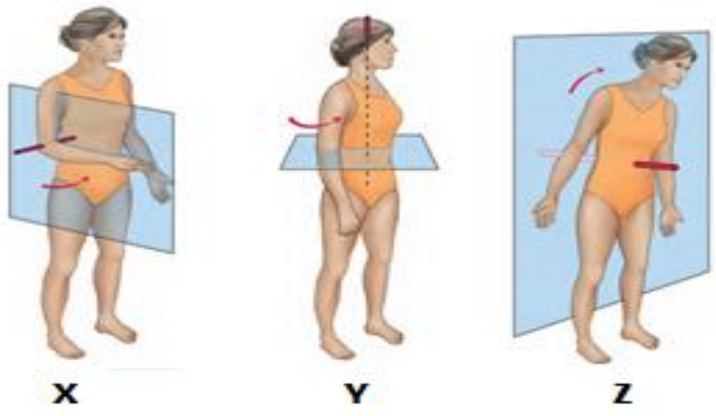
Accelerometer gait features

Posturography Sway Features

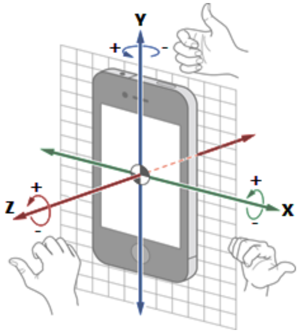
Investigating Postural Sway Features, Normalization and Personlization in Detecting Blood Alcohol Levels of Smartphone Users
Christina Aiello and Emmanuel Agu,*in Proc Wireless Health Conference 2016.*



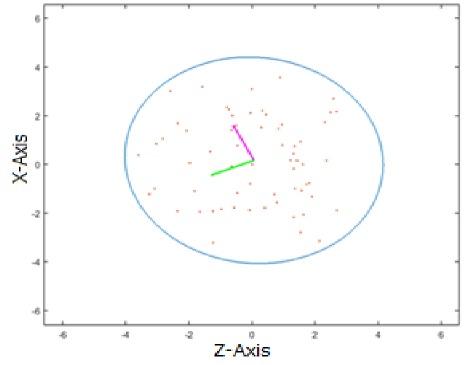
- **Posturography:** clinical approach for assessing balance disorders from gait
- Prior medical studies (Nieschalk *et al*) found that subjects swayed more after they ingested alcohol
- Synthesized sway area features on 3 body planes and sway volume
- Sway area computation: project values of gyroscope 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 alcoho on one's motor skills.

Different Sways? Swag?

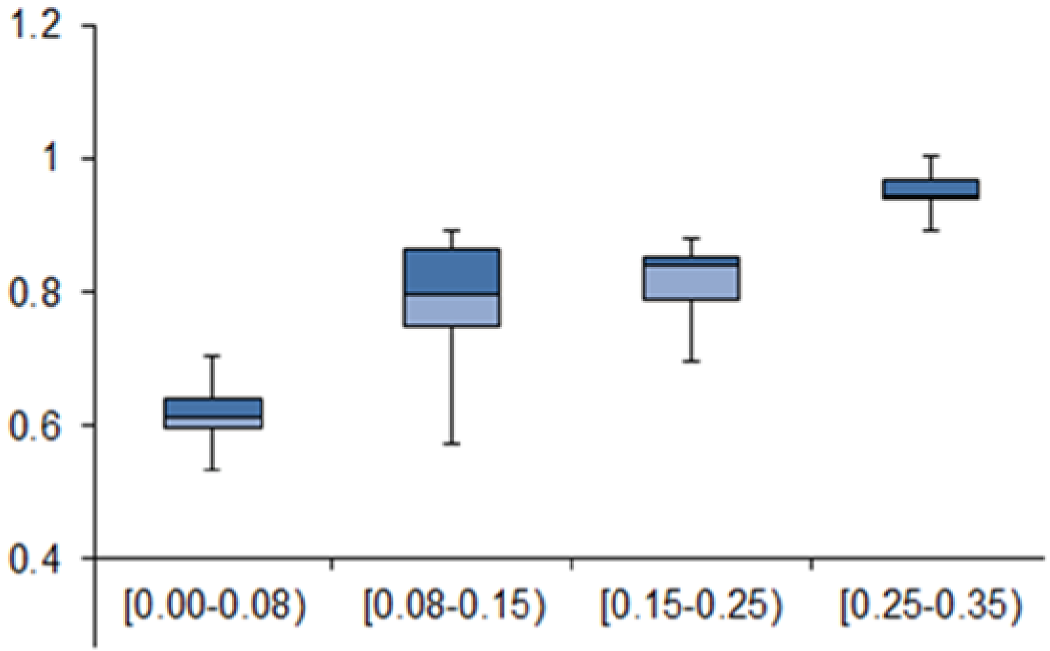
- Different people sway different amounts even when sober
- Some people would be classified drunk even when sober (Swag?)
- Cannot use same absolute sway parameters for everyone
- Normalize!
  - Gather each person's base data when sober
  - Divide possibly drunk gait features by sober features

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

- 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

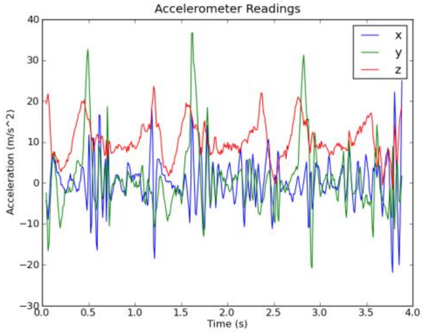
- As subjects got more intoxicated, normalized sway area generally increased



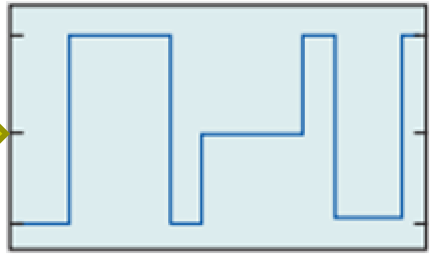
AlcoGait Evolution

- 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
- MQP team: Ben Bianchi, Andrew McAfee, Jacob Watson
  - Combine Smartphone + SmartWatch
- MQP team: JS Bremner, NG Cheung, QH Lam, S Huang
  - Intoxigait: Smartphone + smartwatch + deep learning
- Ruojun Li, Ganesh Balakrishnan, Jiaming Nie, Yu Li
  - Grad students now exploring cutting edge deep learning

AlcoWatch MQP: Using SmartWatch to Infer Alcohol levels from Gait



Raw accelerometer readings



Feature extraction and classification

BAC/How much alcohol consumed?

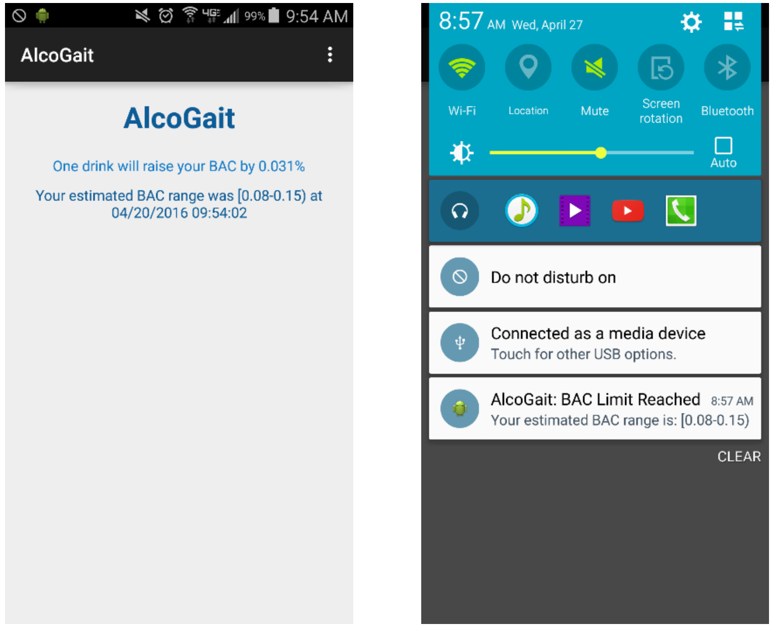
- AlcoGait limitations:
  - Users leave phones in drawers, bags, on table 50% of the time
  - Many women don't have pockets, or carry their phones on their body
- **Alcowatch MQP: Detect alcohol consumption using smartwatch**
  - Classify accelerometer, gyroscope data
- **Students:** Ben Bianchi, Andrew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

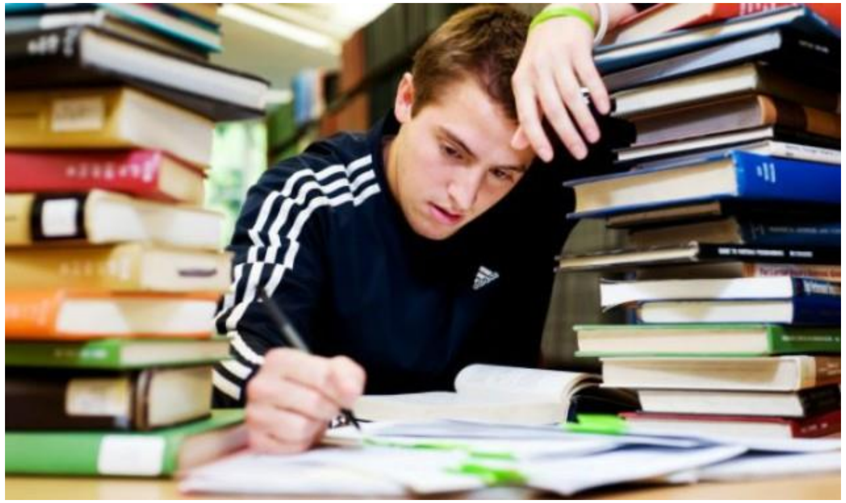
- Alcohol studies extremely tough at WPI (many rules)
  - **Rules:** Need EMS, bar tender, etc for controlled study
- Collaboration with physician, researchers at Brown university
- Gather intoxicated gait data from 250 subjects
- Controlled study:
  - Drink 1… walk
  - Drink 2… walk..
  - Etc
- Gather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

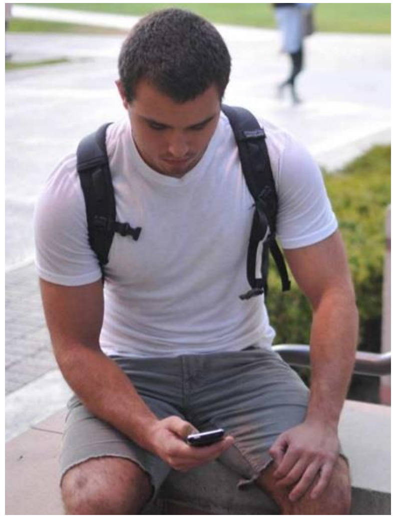
Stressors
- Deadlines
- Exams
- Quiz
- Break-ups
- Social pressure

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, conversation level = high depression

Labels (for classifier)

GPA
(from registrar)

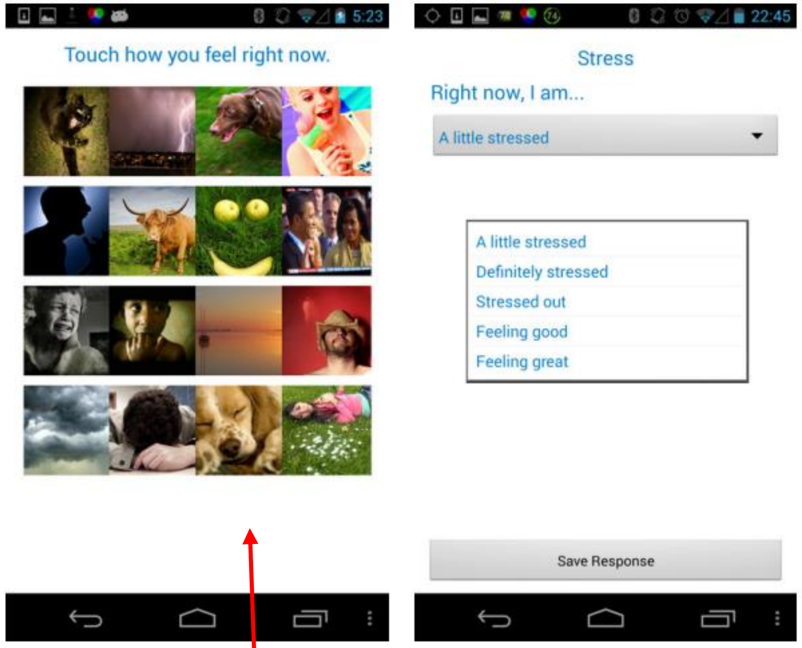
Mental Health Questionnaires (EMA)
- Anxiety
- Depression
- Loneliness
- Flourishing

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

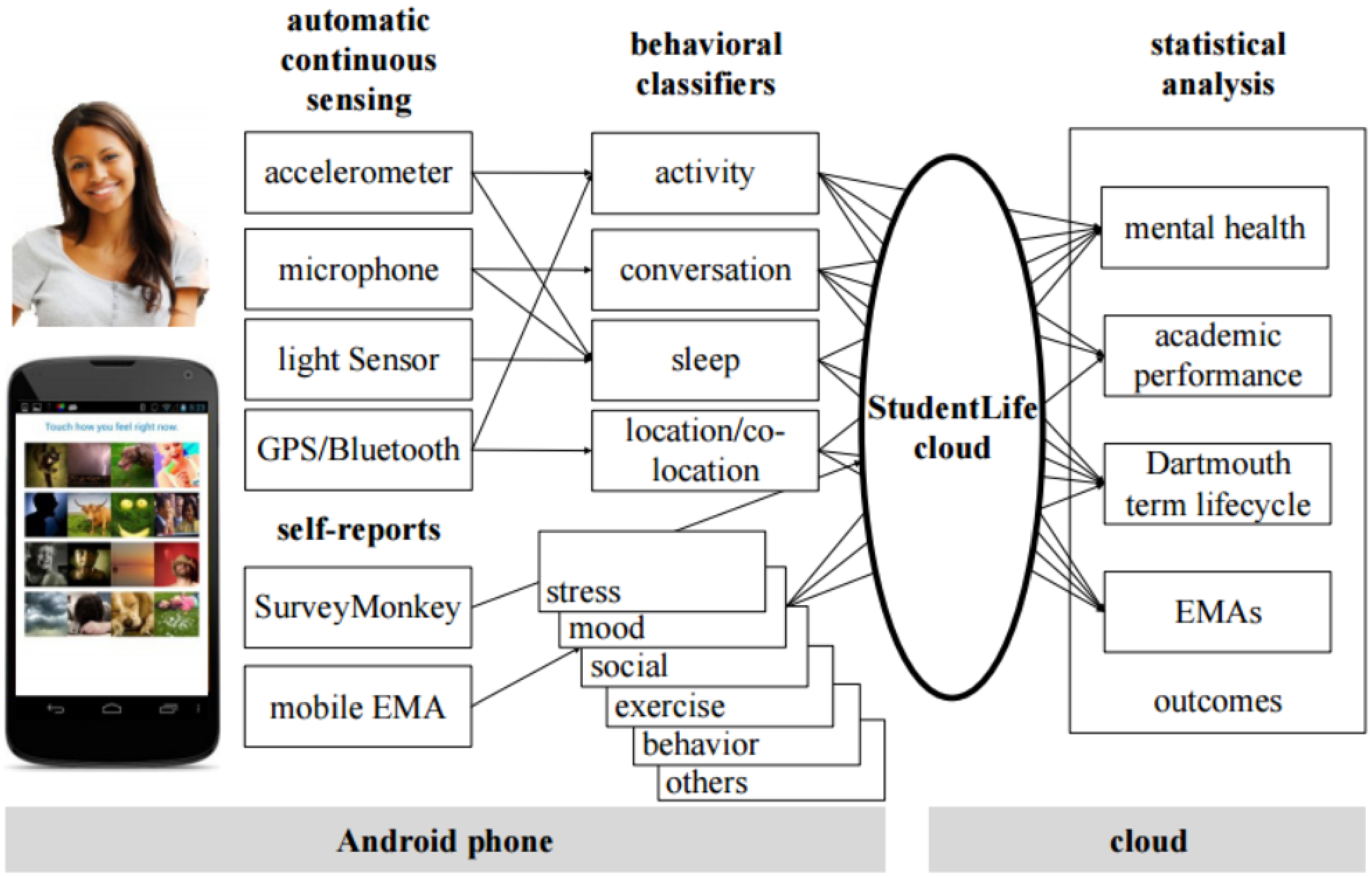


Figure 2. StudentLife app, sensing and analytics system architecture.

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

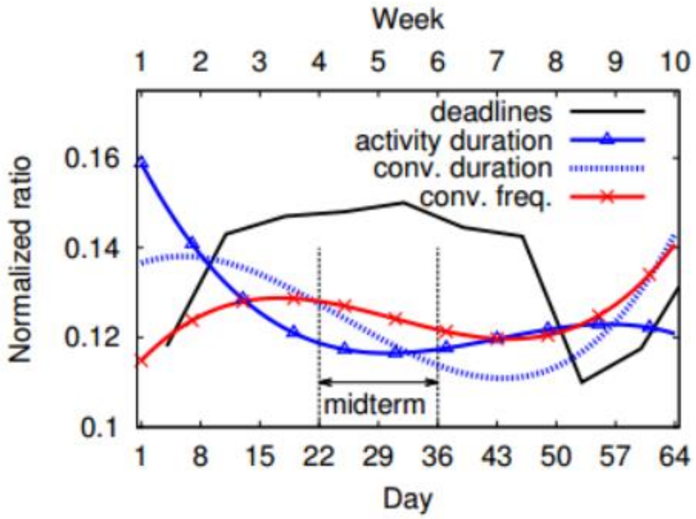
- Fewer conversations or co-locations correlate with
  - Higher chance of depression
- Higher stress correlated with
  - Higher chance of depression
- More social interactions correlated with
  - Higher flourishing, GPA scores
  - Lower stress
- More sleep correlates with
  - Lower stress

Findings (cont'd)

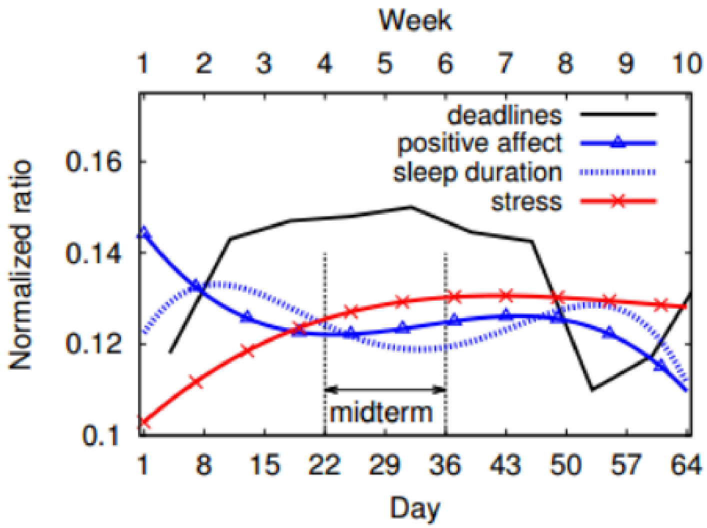
- Less sleep?
  - Higher chance of depression
- Less activity?
  - More likely to be lonely, lower GPAs
- No correlation between class attendance and academic performance (Hmm…)
- As term progressed:
  - Positive affect and activity duration plummeted

Findings (cont'd)

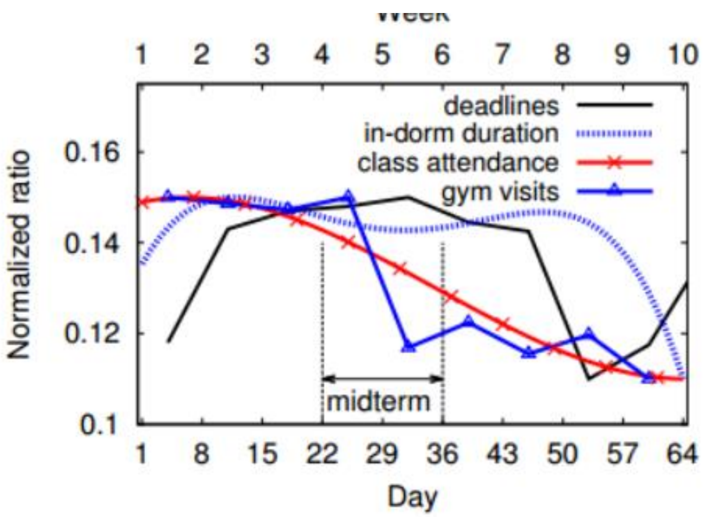
- Plotted total values of sensed data, EMA etc for all subjects through the term



(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

References

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