Mobile and Ubiquitous Computing on Smartphones
Lecture 9a: Smartphone Sensing

Emmanuel Agu

Announcements

- Quiz next Thursday:
  - Covers: Lecture 8 (from October 26) and 9 (today's class)
  - Same as previous ones. In-class, multiple choice
- Student paper presentations:
  - November 16 and 30
  - Paper assignments already posted on Canvas

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
- Frequently leads to drunk driving conviction (DUI)
- 47% of pedestrian deaths caused by drunk driving
- In all 50 states, after DUI -> fees, loss of license, death, vehicle interlock system
- Can we detect drunk person in advance, prevent DUI?

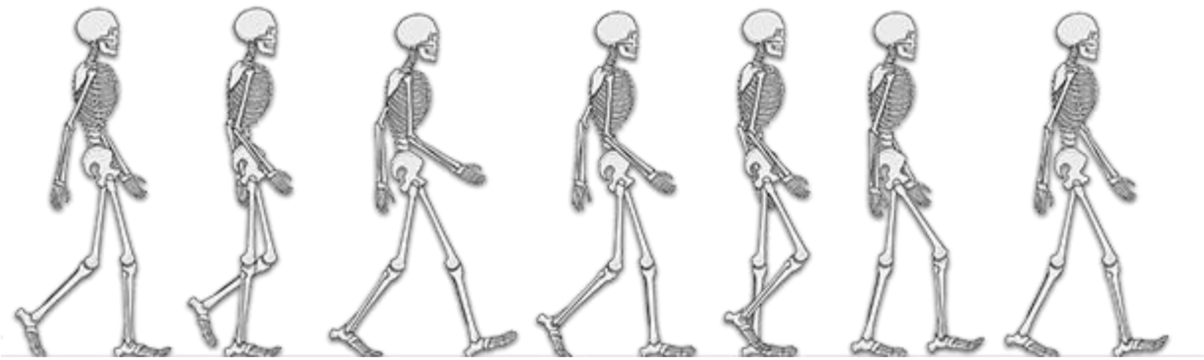
Binge drinking

Driving Under the Influence (DUI)

Vehicle Interlock system

Detecting Intoxication from Gait

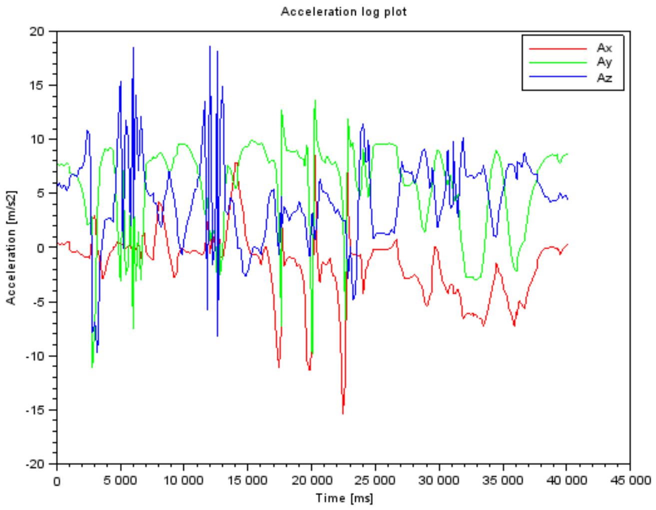
- **Gait:** a persons way of walking, impaired by alcohol
- Second most accurate bio-measure of intoxication
  - Breathalyzer is most accurate
- The police also know gait is accurate
  - 68% police DUI tests based on gait test at roadside e.g. walk and turn test



AlcoGait

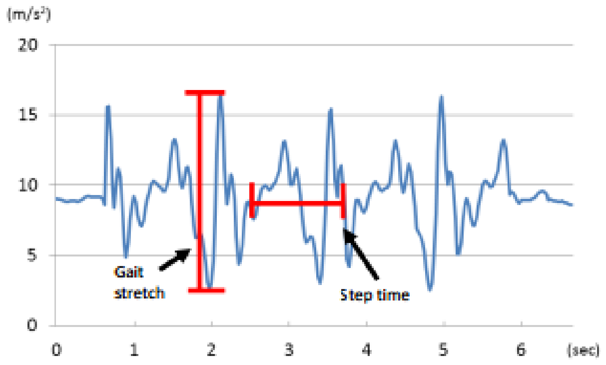
Z Arnold, D LaRose and E Agu, Smartphone Inference of Alcohol Consumption Levels from Gait, in Proc ICHI 2015
Christina Aiello and Emmanuel Agu, Investigating Postural Sway Features, Normalization and Personlization in Detecting Blood Alcohol Levels of Smartphone Users, in Proc Wireless Health Conference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

- Can we test drinker’s gait before DUI? Prevent DUI?
  - At party, bar while socializing, during walk to car
- Proposed: Alcogait smartphone app:
  - Smartphone accelerometer, gyroscope data
  - Extracts accelerometer and gyroscope features
  - Classify features using Machine Learning
  - Notifies user if too drunk to drive safely



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"

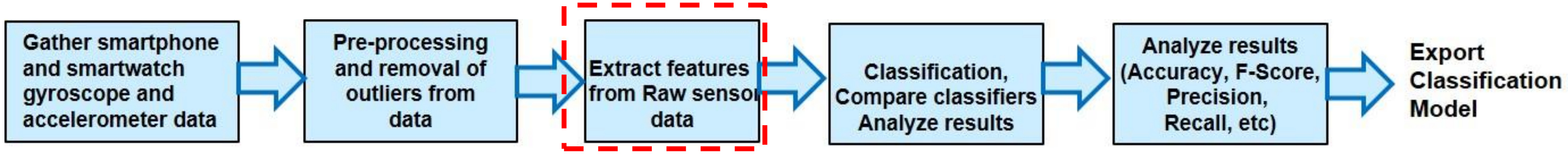


Accelerometer gait features

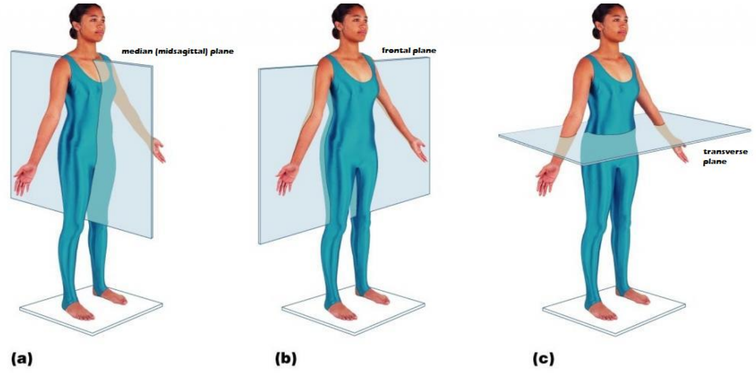
Posturography Sway Features

Investigating Postural Sway Features, Normalization and Personlization in Detecting Blood Alcohol Levels of Smartphone Users

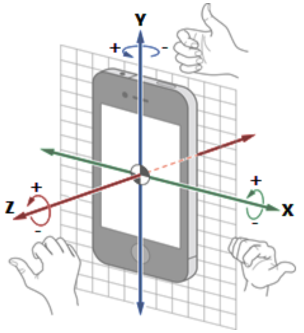
Christina Aiello and Emmanuel Agu, *in Proc Wireless Health Conference 2016.*



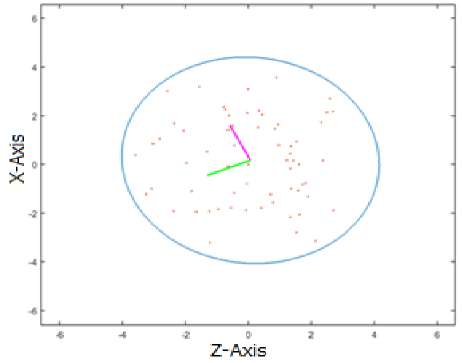
- **Posturography:** clinical approach for assessing balance disorders from gait
- Prior medical studies (Nieschalk *et al*) found that subjects swayed more after they ingested alcohol
- **Added posturography features:** sway area features on 3 body/phone planes and sway volume
- Sway area computation: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



3 planes of body



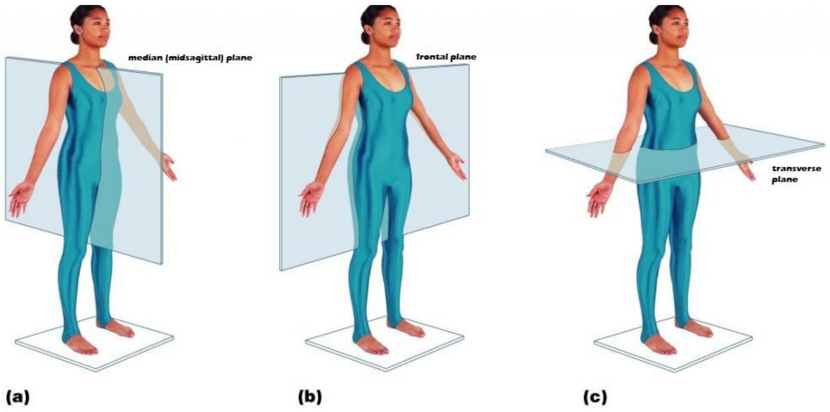
Gyroscope axes



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)	$Sway\ Volume = \frac{4}{3}\pi r^3$	



3 planes of body

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. WPI IRB worried about law suits
- We improvised: used drunk buster Goggles
- "Drunk Busters" goggles distort vision to simulate effects of various intoxication (BAC) levels on gait
- Previously used to educate individuals on effects of alcohol on one's motor skills.
- 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.

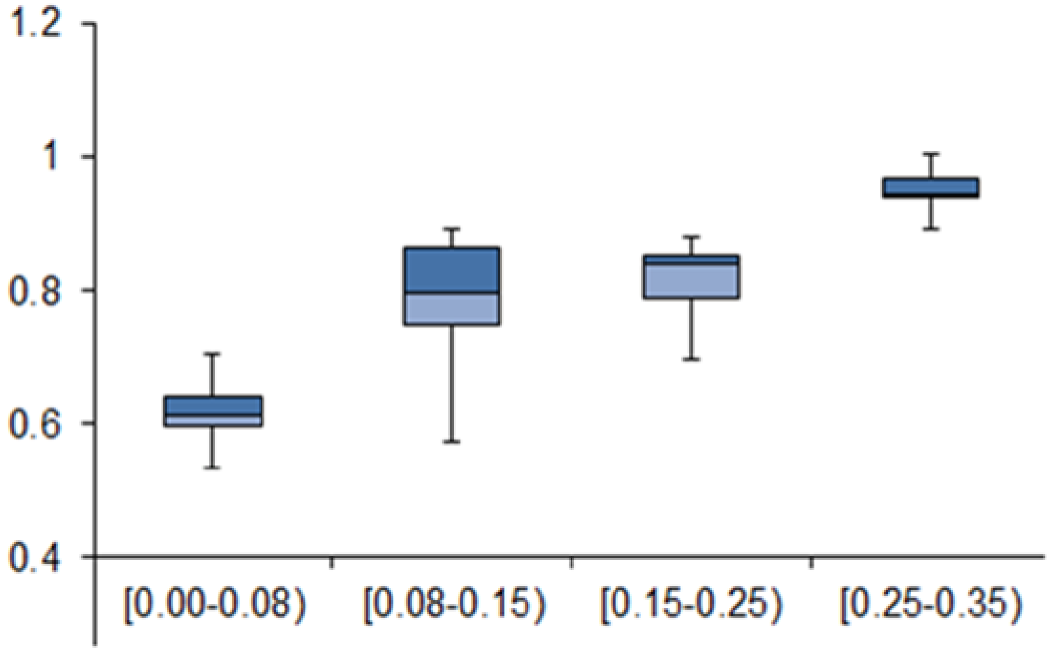
Steps for Training AlcoGait Classifier

- Similar to Activity recognition steps we covered previously

1. Gather data samples + label them
   - 100+ users data at different intoxication levels (we used different strengths of drunk buster goggles)
2. Import accelerometer and gyroscope samples into classification library (e.g. Scikit-Learn, 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. … etc

Box Plot of XZ Sway Area

- **Our findings:** As subjects got more intoxicated, normalized sway area generally increased



AlcoGait Evolution: Several students

- 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 Intoxication from Gait

- AlcoGait limitations:
  - Users leave phones in drawers, bags, on table 50% of the time
  - Many women don’t have pockets, or carry phones on their body

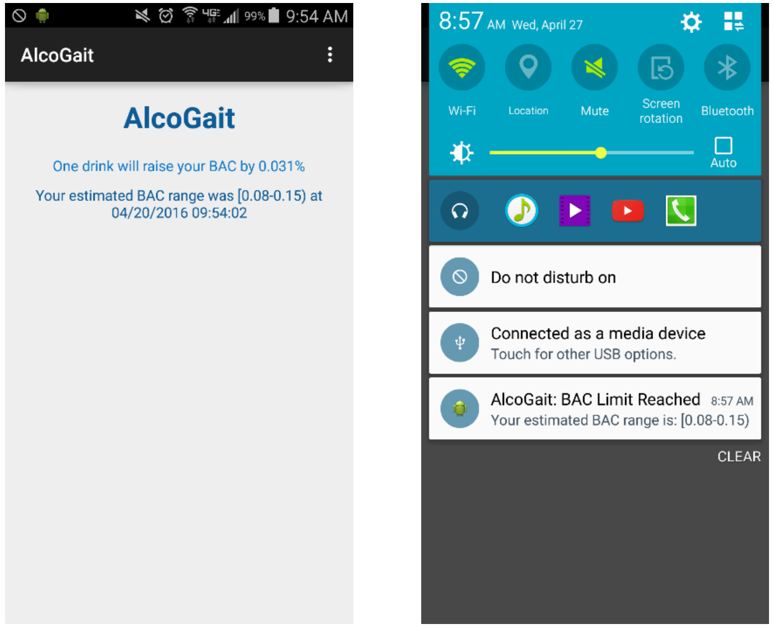
- **Alcowatch MQP:** Detect intoxication using **smartwatch** accelerometer and gyroscope data
  - **Students:** Ben Bianchi, Andrew McAfee, Jacob Watson
  - Data sent to server for feature extraction classification
  - Intoxication classification results sent back to smartwatch, smartphone for display

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

AlcoWatch and AlcoGait Screens



AlcoWatch (Smartwatch)

AlcoGait (Smartphone)

NIH-Funded Study to Gather Intoxicated Gait Data

- Drunk buster goggles results good.
- But needed real data to confirm/validate
- Collaborated with medical researchers at Brown university/Butler hospital
- Controlled data gathering study
- Gait data from 250 subjects
  - Drink 1, breathalyze..... walk
  - Drink 2, breathalyze… walk..
  - Etc
- Gather data, classify

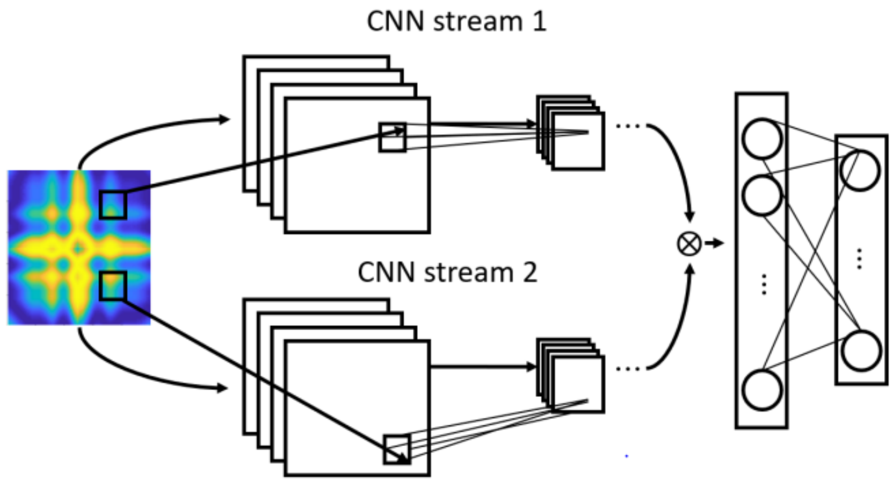
State of the Art Intoxication Detection

Paper: Li, R., Agu, E., Sarwar, A., Grimone, K., Herman, D., Abrantes, A.M. and Stein, M.D., 2023. Fine-Grained Intoxicated Gait Classification using a Bi-linear CNN. *IEEE Sensors Journal*.

- Intoxication classification uses deep learning:
  1. Normalize smartphone accelerometer/gyroscope data by subject's BMI
  2. Convert smartphone accelerometer, gyroscope data to Gramian Angular Field (GAF) **image representation**
  3. Use CNN (deep learning) to classify GAF image: over limit vs. under limit
  4. Results: 80.25% accurate

- Weedgait: detect marijuana impairment from gait
  - > 90% accurate

- Distinguish intoxication substance (alcohol vs. marijuana)
  - Different legal implications, punishment

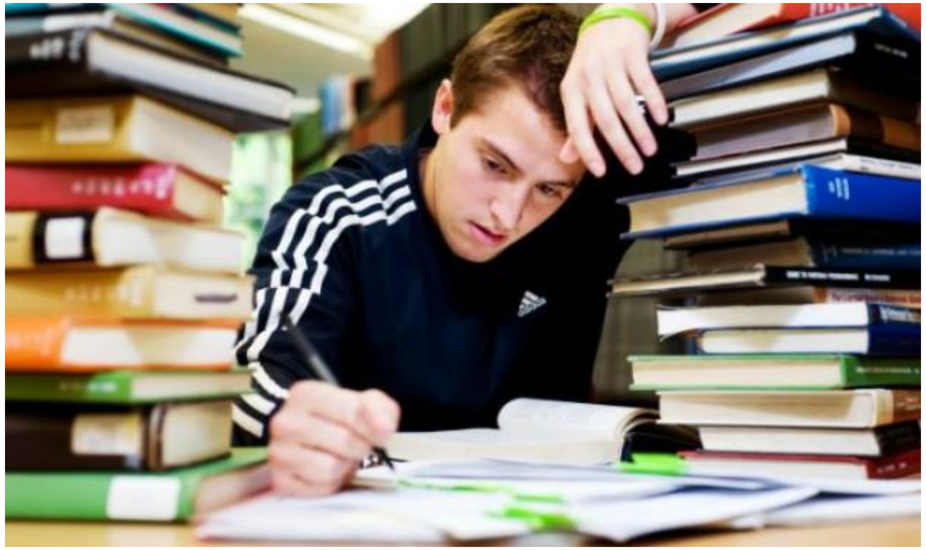


StudentLife

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
  - 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 smartphone-sensable patterns (sleep, activity, social interactions, etc) reliable indicators of suffering student (e.g. low GPA, depressed, etc)?

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

→

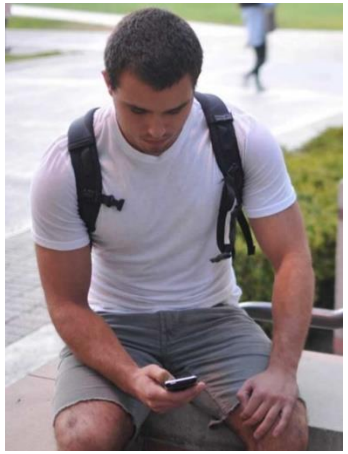
Consequences
- Anxiety
- Depression
- Poor exam scores
- Low GPA
- ??

→

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

StudentLife Continuous Sensing App

- **Goal:** Use smartphone sensing to assess/monitor student:
  - Psychological health (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, inform solutions
  - E.g. particular profs who stress many students



StudentLife Approach

- Semester-long Study of 60 Dartmouth College Students
  - Smartphone continuously gather sensable signs (sleep, activity level, etc)
  - Administer mental health questionnaires every few hours as pop-ups (called EMA)
  - Also retrieve student GPA, academic performance from registrar
- **Machine Learning:** what activity, sleep, conversation patterns = high depression

Ground truth Labels (for classifier)

GPA
(from registrar)

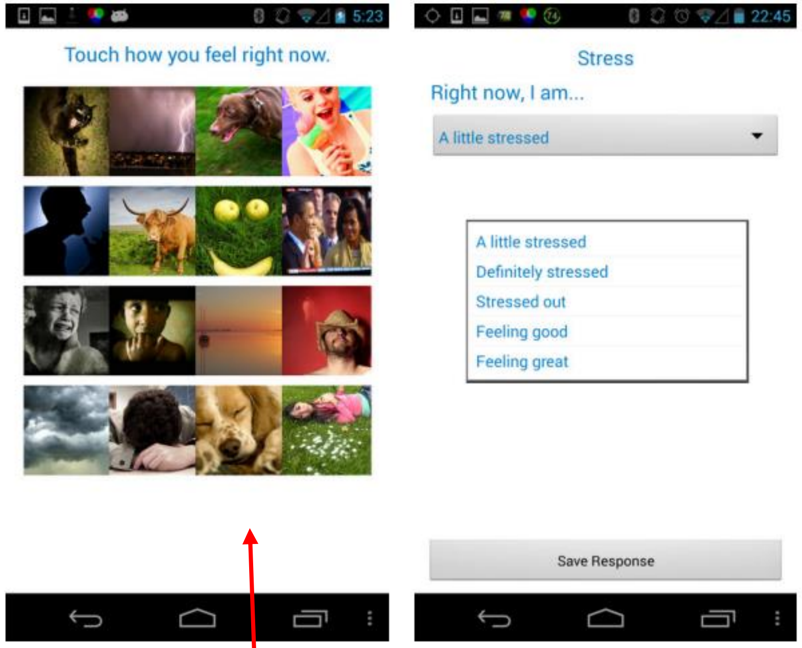
Mental Health Questionnaires (EMA)
- Anxiety
- Depression
- Loneliness
- Flourishing

Autosensed data

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

Specifics: Data Gathering Study

- **Beginning and end of semester/study: surveys**
  - 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 types**
  - **Conversations of users**
  - **Sleep duration**
  - **WiFi's APs**

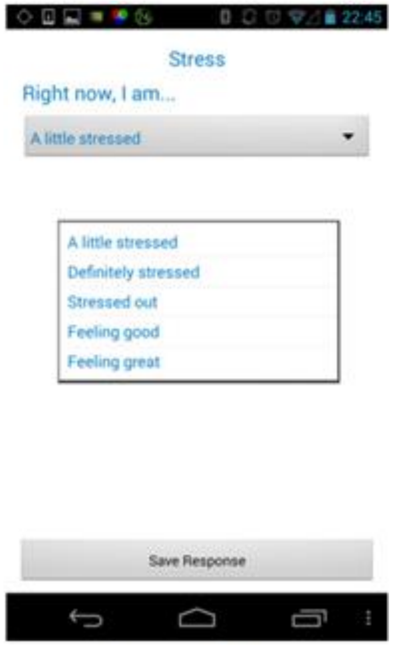


(a) PAM EMA (b) Stress EMA

PAM: Pick picture depicting your current mood

Clinical Mental Health Questionnaires

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



(b) Stress EMA

StudentLife Data Gathering Study Overview

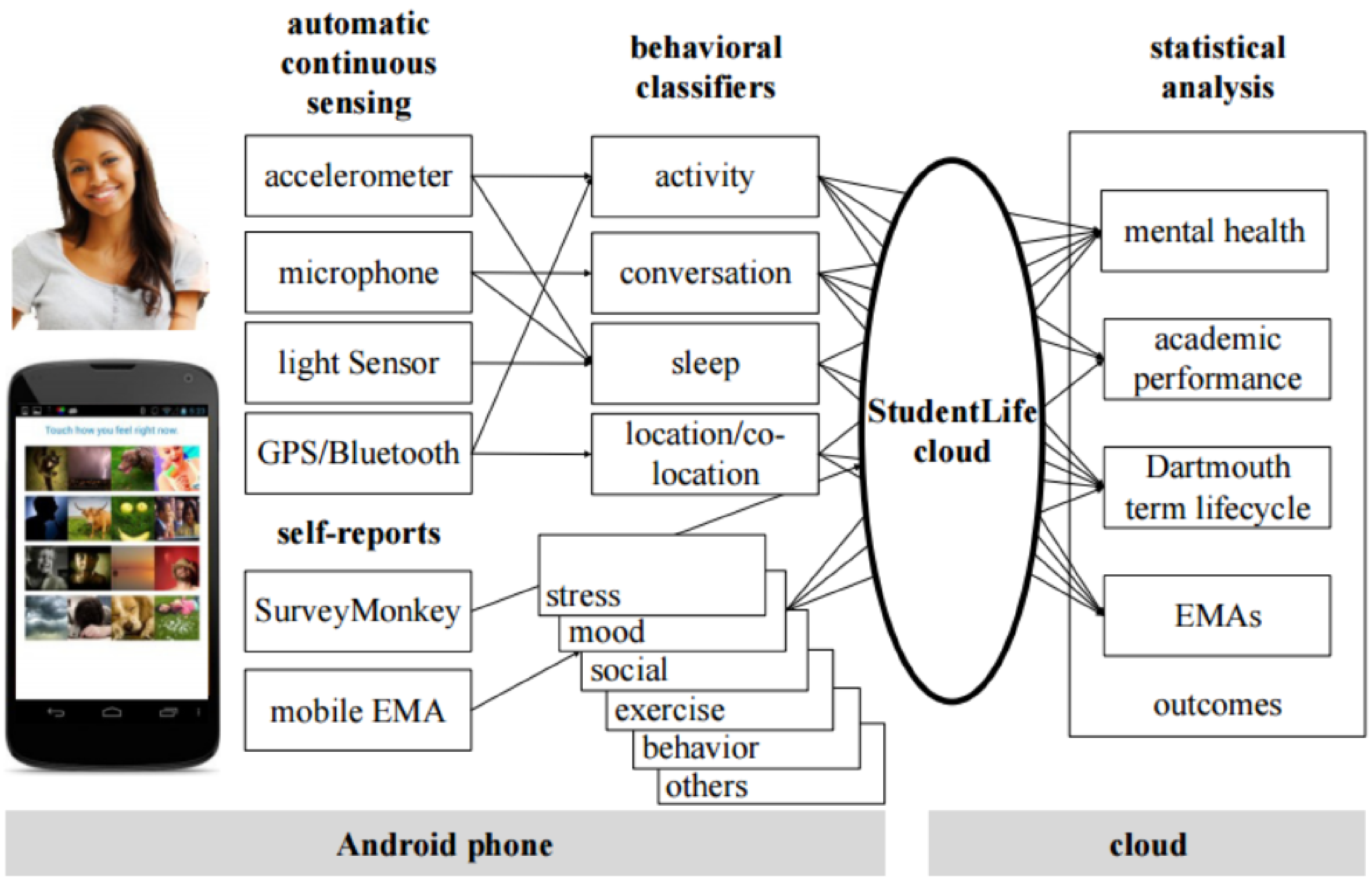


Figure 2. StudentLife app, sensing and analytics system architecture.

Study Details

- 60 Students started study, 10 weeks of data collection
  - All enrolled in CS65 Smartphone Programming class
  - 48 students at the end, 12 dropped class
  - 30 undergrad/18 graduate level
  - 38 male/10 female

- Incentives for participants:
  - StudentLife T-shirt (all students)
  - **Week 3 & 6:** 5 Jawbone UPs (like fitbit) raffled off
  - **End of study:** 10 Google Nexus phones in raffle

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

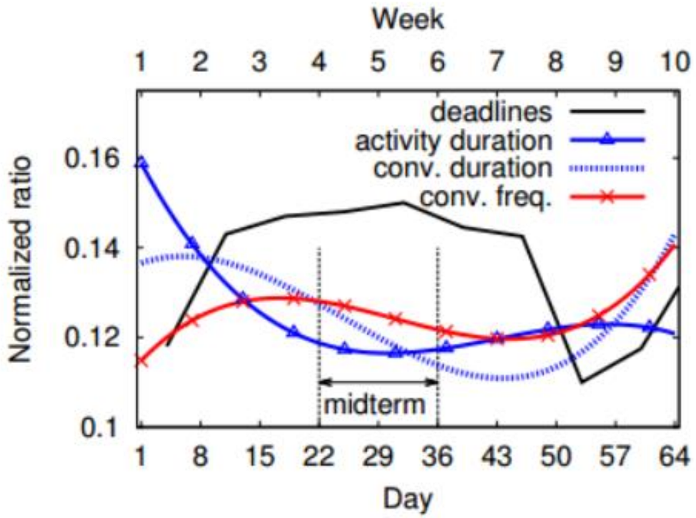
Some Findings

- Fewer conversations or co-locations (walking around) correlate with
  - Higher chance of depression
- More social interactions correlated with
  - Higher flourishing, GPA scores
  - Lower stress
- More sleep correlates with
  - Lower stress
- Less sleep?
  - Higher chance of depression
- No correlation between class attendance and academic performance (Hmm…)

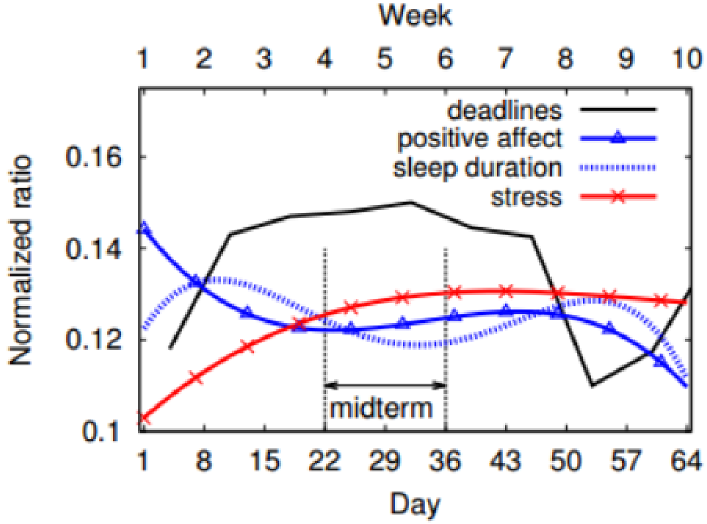
Findings (cont'd)

- Plotted total values of sensed data, EMA etc. for all subjects through the term
- As term progressed:
  - Activity duration, conversations plummeted

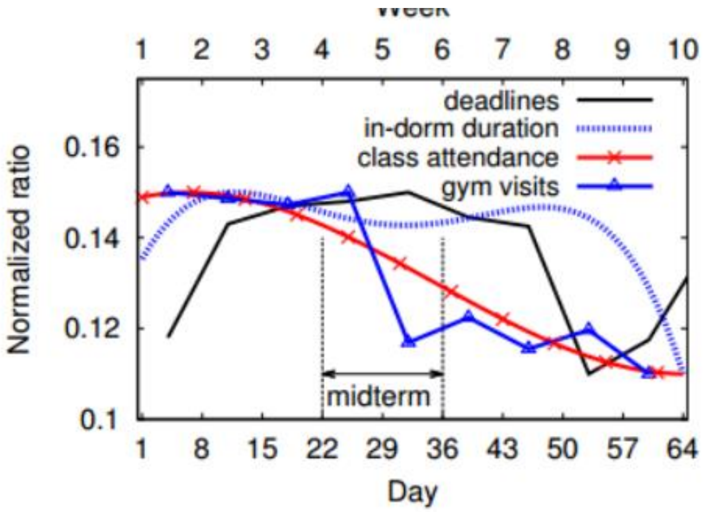
Week of 10-week term



(b) Automatic sensing data



(a) EMA and sleep data



(c) Location-based data

Study Limitations/Trade Offs

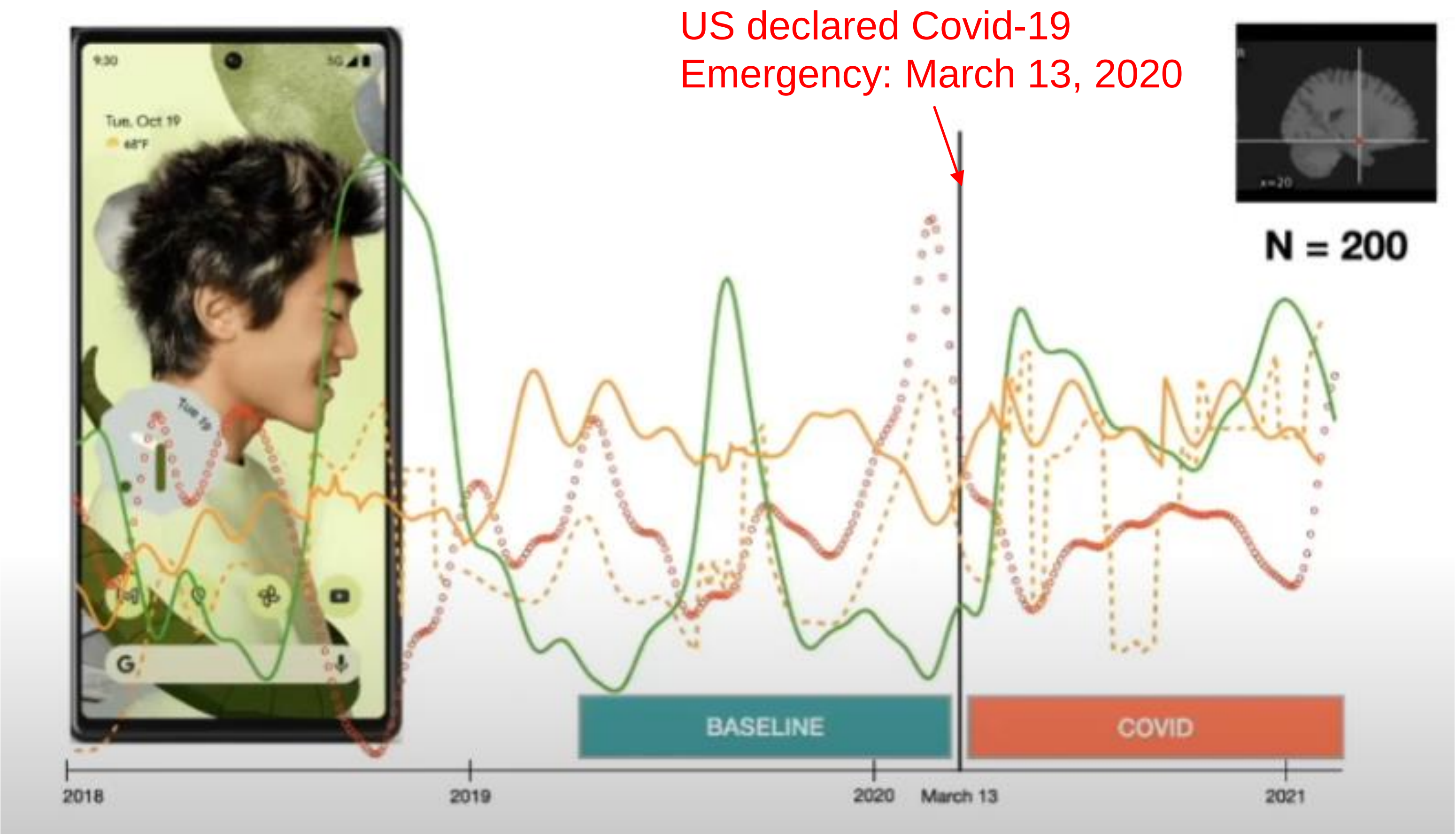
- Limited sample:
  - Students in CS65 Smartphone Programming class (similar to CS 528)
- User participation
  - **Burden:** Surveys, carrying phone
  - Disinterest (Longitudinal study, EMA annoyance)
- Lost participants
- Sleep measurement inaccuracy
  - Naps

Covid-19 Smartphone Sensing Study

Covid-19 Smartphone Sensing Study: Dartmouth College

- Team has been running studies since 2012(?), 10 years
  - Has also predited student student academic performance/GPA, mental health GPA from Smartphone sensor data
- Already had NIH-funded mental health study running
- Then Covid-19 happened
  - Lockdowns, stay home
  - Take classes via zoom
- Question: Can smartphone detect behavior changes before/after Covid-19?
- Just added Covid-19 questions to their ongoing mental health study

Covid-19 Smartphone Sensing Study: Dartmouth College



Nepal, S., Wang, W., Vojdanovski, V., Huckins, J.F., Dasilva, A., Meyer, M. and Campbell, A., 2022, April. COVID student study: A year in the life of college students during the COVID-19 pandemic through the lens of mobile phone sensing. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1-19).

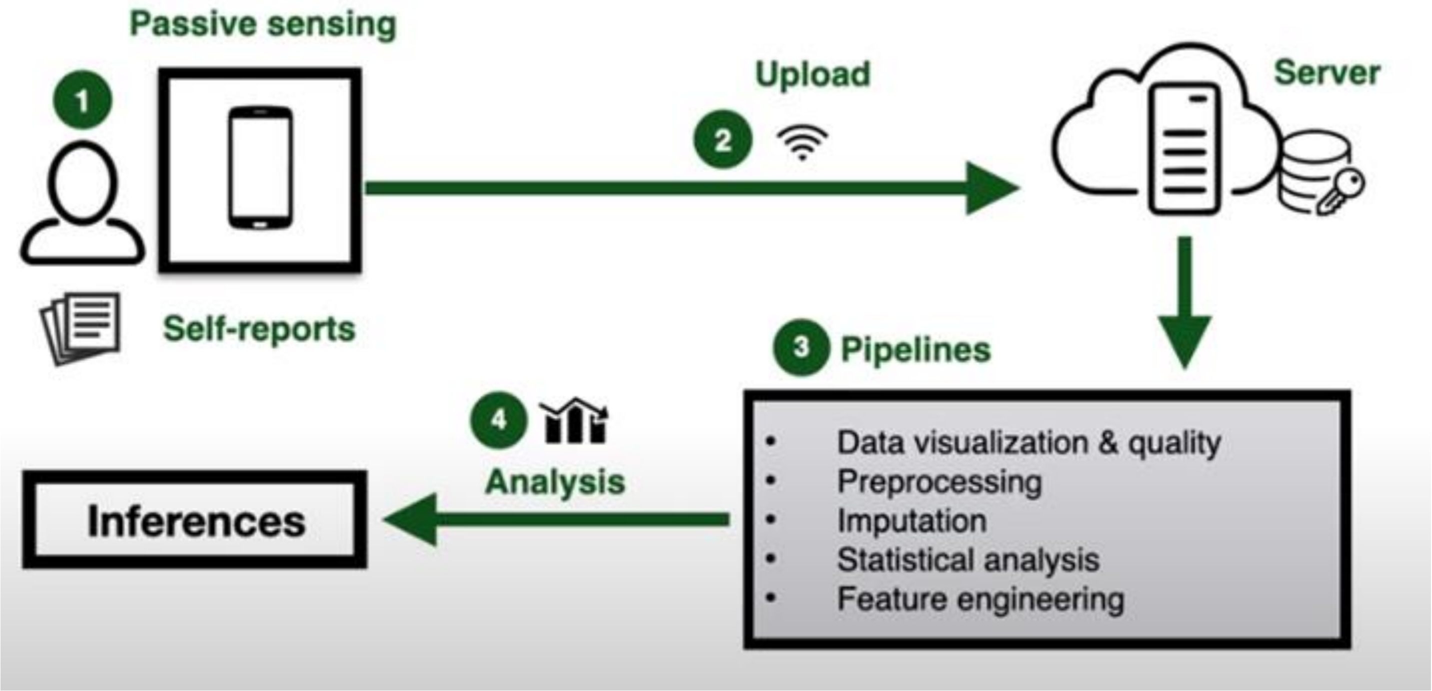
Covid-19 Smartphone Sensing Study: Dartmouth College

- ~200 students ran Studentlife app continuously for 4 years
- Collected:
  - Smartphone sensors continuously
  - Answered questions periodically on on app: anxiety, depression, stress levels, etc

Study demographics

Category	Count	Percentage
Sex		
Female	124	68.9%
Male	56	31.1%
Race		
White	110	61.1%
Asian	42	23.4%
Black or African American	6	3.3%
American Indian/Alaska Native	5	2.8%
More than one race	11	6.1%
Not reported	6	3.3%

Covid-19 Smartphone Sensing Study: Dartmouth College



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Features Extracted from Raw Sensor Data

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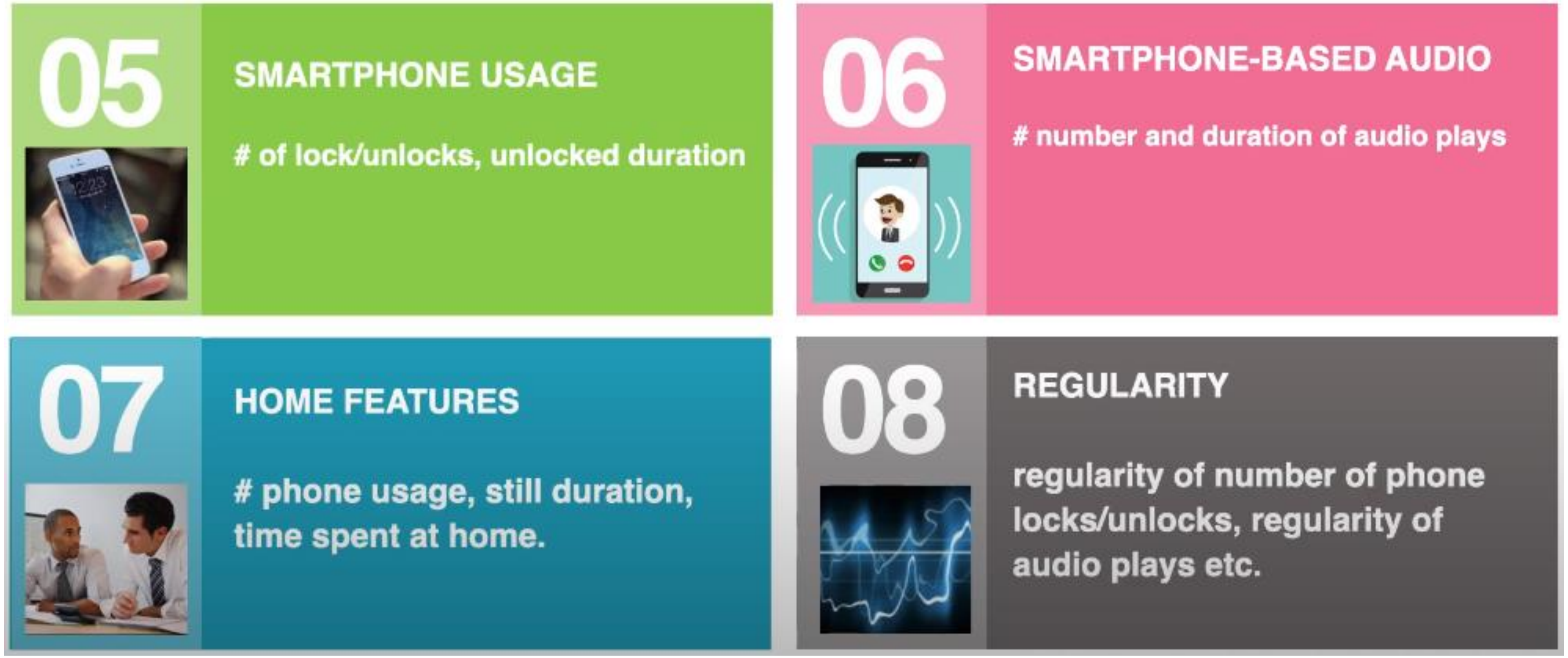

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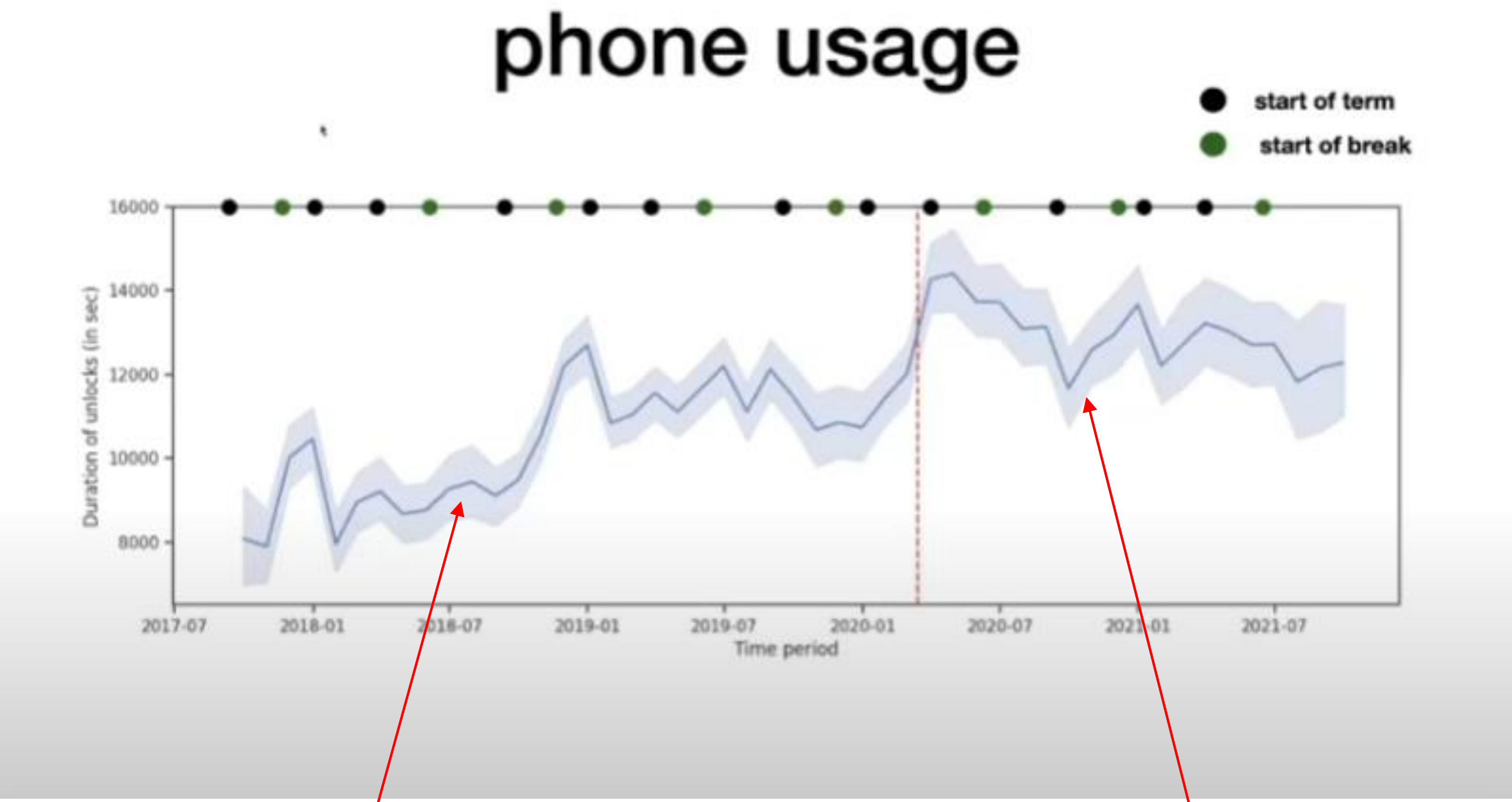
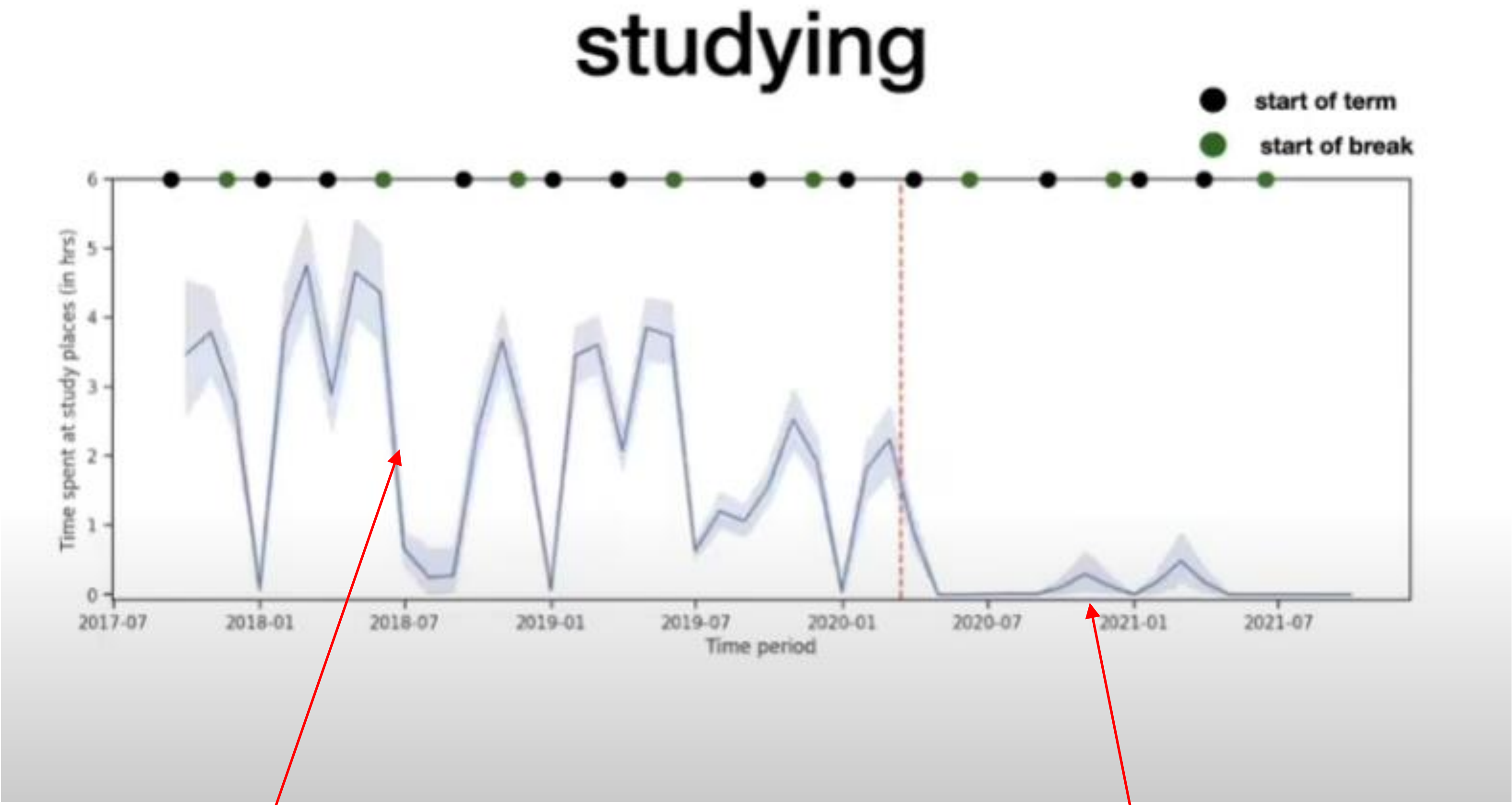


Before Covid:
Cyclic usage of phone (followed terms)

During Covid:
Significant rise in usage of phones

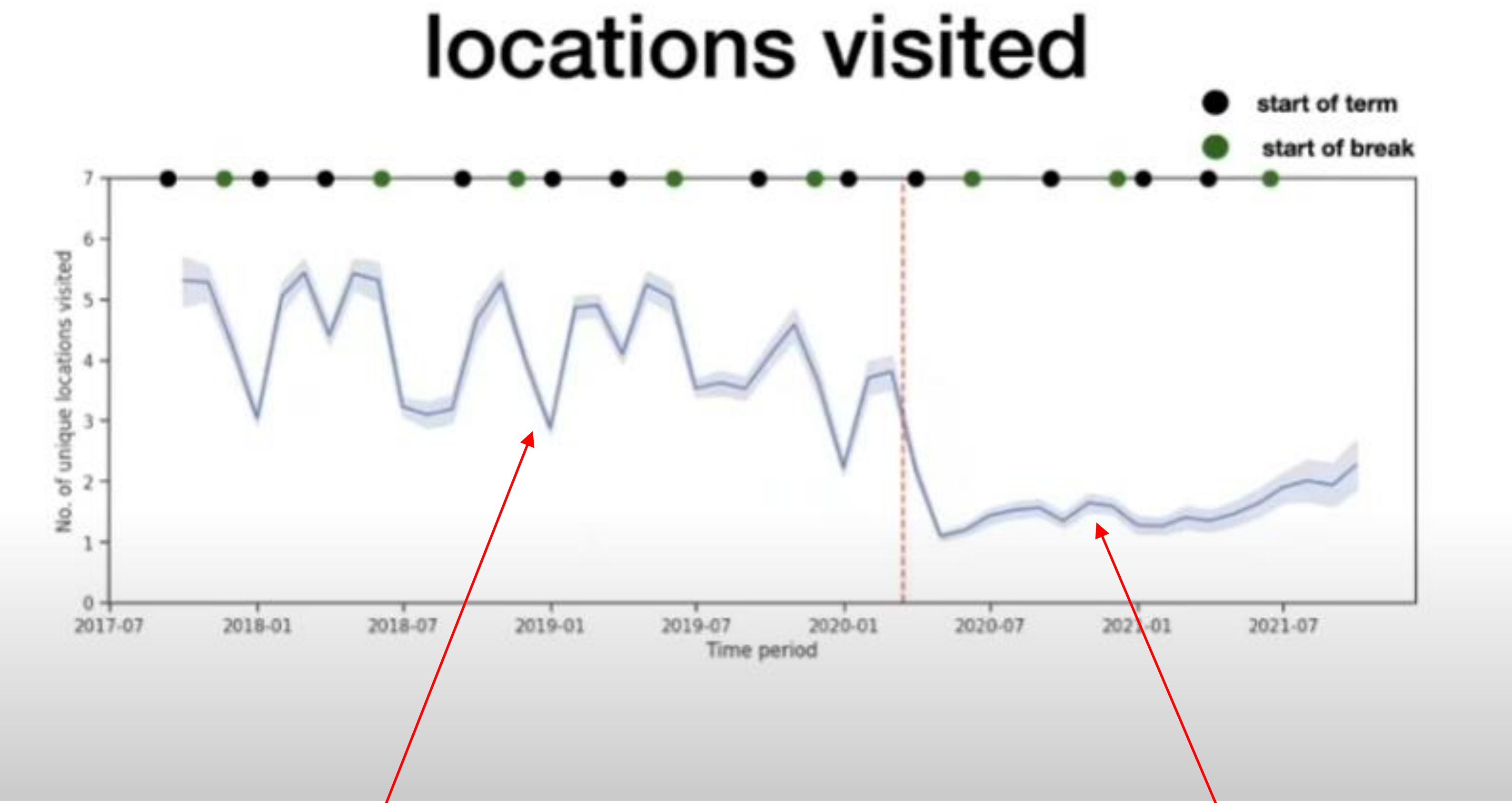
Nepal, S., Wang, W., Vojdanovski, V., Huckins, J.F., Dasilva, A., Meyer, M. and Campbell, A., 2022, April. COVID student study: A year in the life of college students during the COVID-19 pandemic through the lens of mobile phone sensing. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1-19).



Before Covid:
Cycles of visiting studying locations
followed term

During Covid:
Drop in visits to study locations

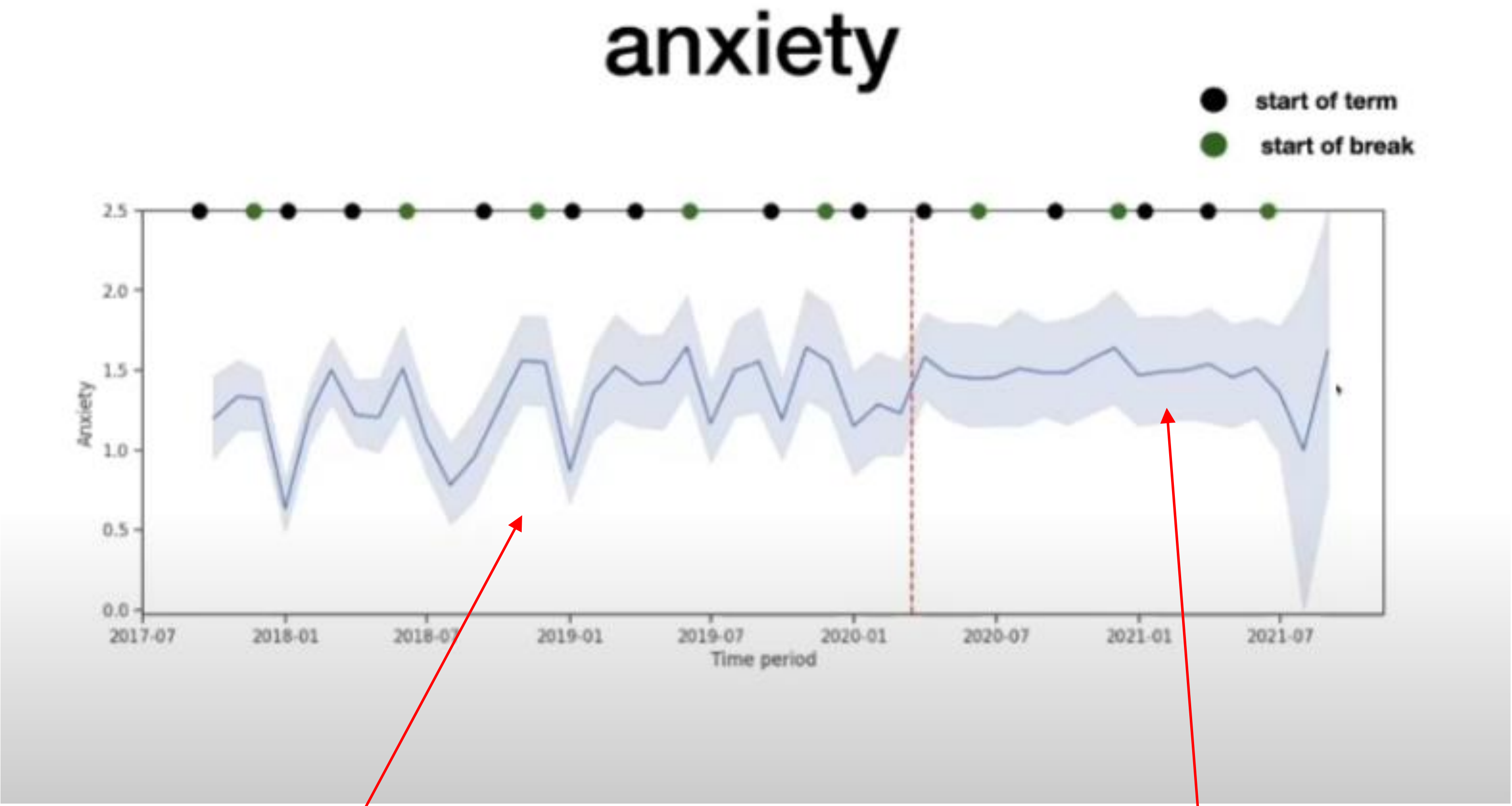
Nepal, S., Wang, W., Vojdanovski, V., Huckins, J.F., Dasilva, A., Meyer, M. and Campbell, A., 2022, April. COVID student study: A year in the life of college students during the COVID-19 pandemic through the lens of mobile phone sensing. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1-19).



Before Covid:
Visited lots of different locations
Cycles followed term

During Covid:
Large drop in no. of places visited

Nepal, S., Wang, W., Vojdanovski, V., Huckins, J.F., Dasilva, A., Meyer, M. and Campbell, A., 2022, April. COVID student study: A year in the life of college students during the COVID-19 pandemic through the lens of mobile phone sensing. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1-19).

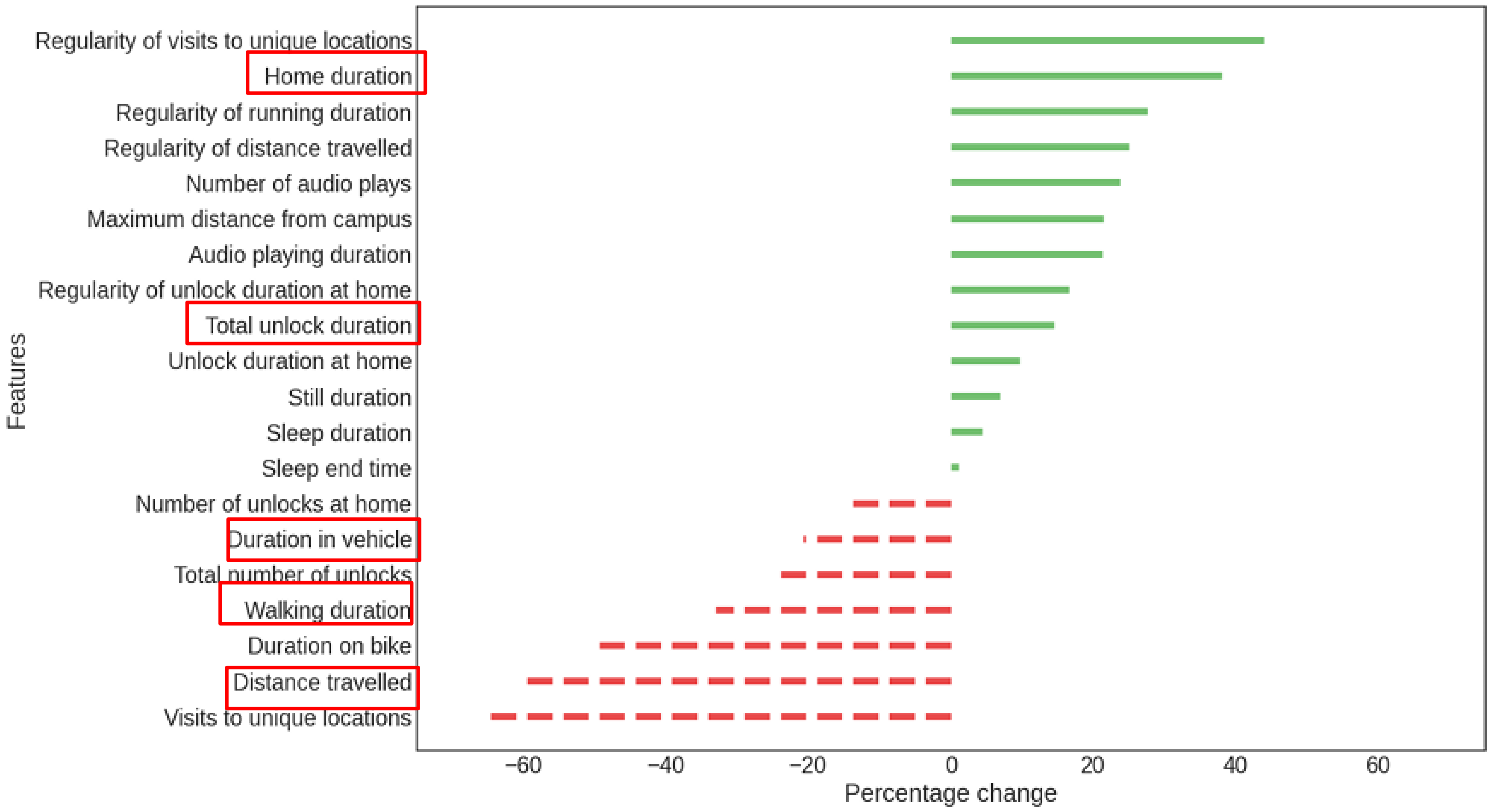


Before Covid:
Anxiety cycles followed term

During Covid:
Anxiety high continuously

Nepal, S., Wang, W., Vojdanovski, V., Huckins, J.F., Dasilva, A., Meyer, M. and Campbell, A., 2022, April. COVID student study: A year in the life of college students during the COVID-19 pandemic through the lens of mobile phone sensing. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1-19).

Features that Changed Across Participants



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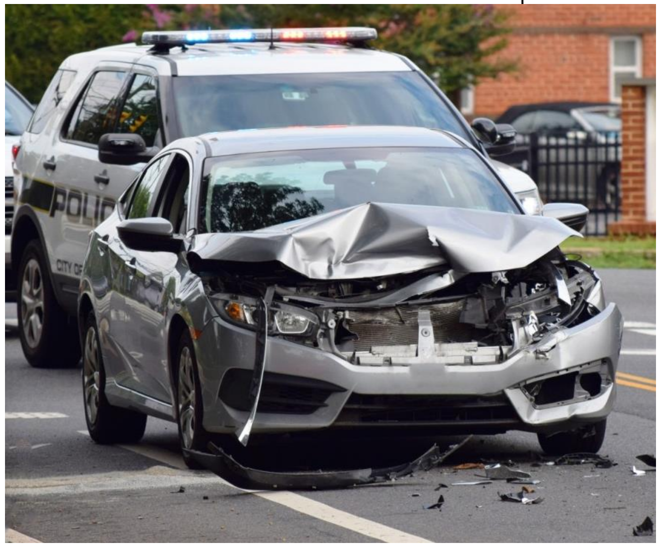
Bad Driving Detection

Driving Behavior Profiling

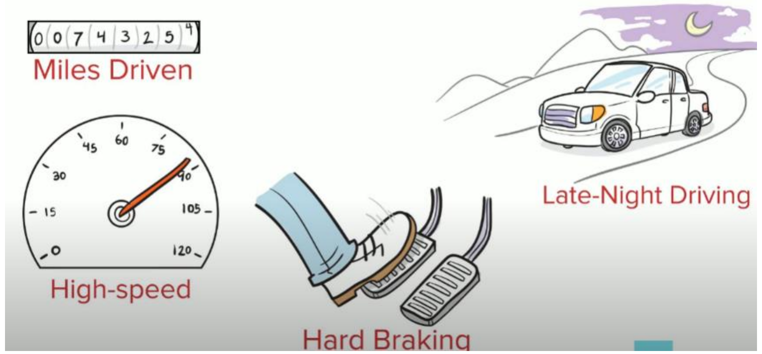
- Bad driving can cause:
  - Accidents
  - Increased use of gas/petrol, which harms the environment
- In the US in 2010, accidents caused
  - 24 million damaged vehicles
  - 33,000 fatal accidents
  - 4 million non-fatal injuries
  - 242 billion costs
- Driver behavior profiling automatically:
  - Collects drivers data (E.g. from driver’s smartphone)
  - Generates safety score for each driver



Ferreira, J., Carvalho, E., Ferreira, B.V., de Souza, C., Suhara, Y., Pentland, A. and Pessin, G., 2017. Driver behavior profiling: An investigation with different smartphone sensors and machine learning. *PLoS one*, *12*(4), p.e0174959.

Driver Behavior Profiling

- **Old way:** Insurance premium based on broad groups. E.g. high premium for males 18-25
- **New way:** Driver profiling can charge premium based on driving behavior
  - Usage-based insurance (UBI)
  - Pay-How-You-Drive (PHYD)
- Real-time feedback to rough drivers (e.g. swerving) can prevent accidents
- Driving data collected include:
  - High Speed
  - Acceleration
  - Hard braking
  - Swerving
  - Late night driving



- 19 major US insurance companies offer UBI. E.g. Allstate Drive wise, Geico DriveEasy
  - Collects data from either smartphone or telematics device plugged into car
- [UBI clip]

Ferreira, J., Carvalho, E., Ferreira, B.V., de Souza, C., Suhara, Y., Pentland, A. and Pessin, G., 2017. Driver behavior profiling: An investigation with different smartphone sensors and machine learning. *PLoS one*, *12*(4), p.e0174959.

https://wallethub.com/edu/ci/usage-based-insurance/14118

Driver Behavior Profiling

- Driving data collection could be from:
  - Smartphones
  - Monitoring cameras
  - Telematics boxes
  - On-board diagnostics adapters
- Smartphone
  - Pro: already owned
  - Con: not attached, can shift

Smartphone on (E.g. on car seat)

Monitoring cameras

Car telematics boxes (fixed unto car)

On-board diagnostics adapters

Ferreira, J., Carvalho, E., Ferreira, B.V., de Souza, C., Suhara, Y., Pentland, A. and Pessin, G., 2017. Driver behavior profiling: An investigation with different smartphone sensors and machine learning. *PLoS one*, *12*(4), p.e0174959.

Smartphone Driving Data + Machine Learning Analysis

Ferreira, J., Carvalho, E., Ferreira, B.V., de Souza, C., Suhara, Y., Pentland, A. and Pessin, G., 2017. Driver behavior profiling: An investigation with different smartphone sensors and machine learning. *PLoS one*, *12*(4), p.e0174959.

- Driving data analyses: machine learning on smartphone sensor data. E.g Ferreira *et al*
- Data collection collected 2 drivers executed driving events in a 2011 Honda Civic
  - Smartphone: Motorola running Android 5.1 (old?)
  - 4 car trips, each about 13 minutes long
- Smartphone sensor data
  - Accelerometer
  - Linear acceleration
  - Magnetometer
  - Gyroscope

Driving Event Type
Aggressive breaking
Aggressive acceleration
Aggressive left turn
Aggressive right turn
Aggressive left lane change
Aggressive right lane change
Non-aggressive event
Total

Smartphone Driving Data + Machine Learning Analysis

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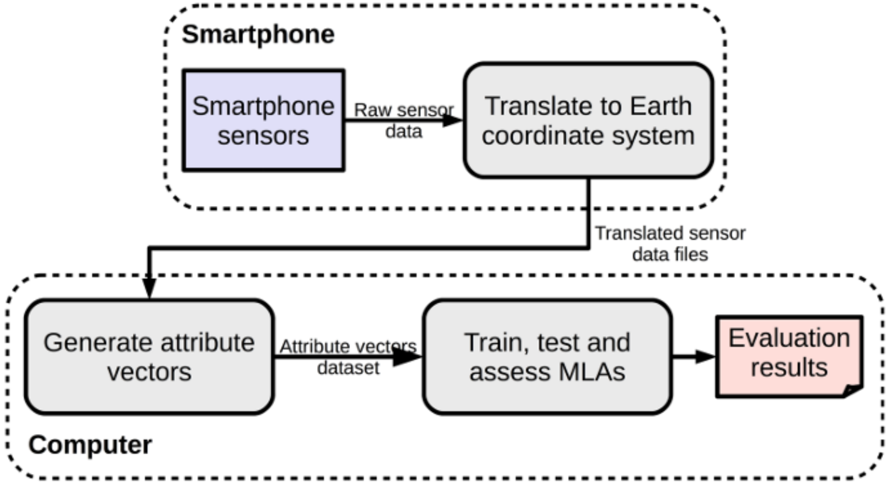
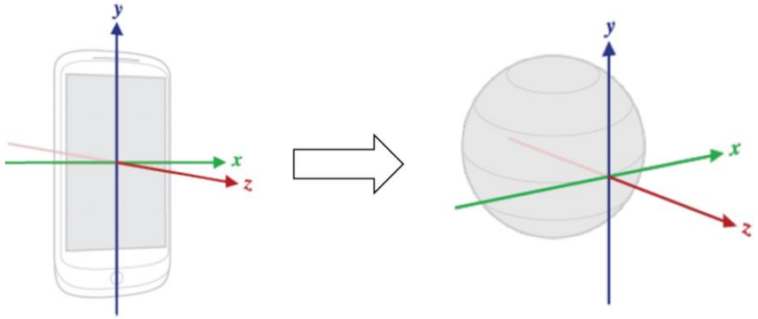
- Approach overview



- Translate from phone coordinates to world coordinate for device independent data



Smartphone Driving Data + Machine Learning Analysis

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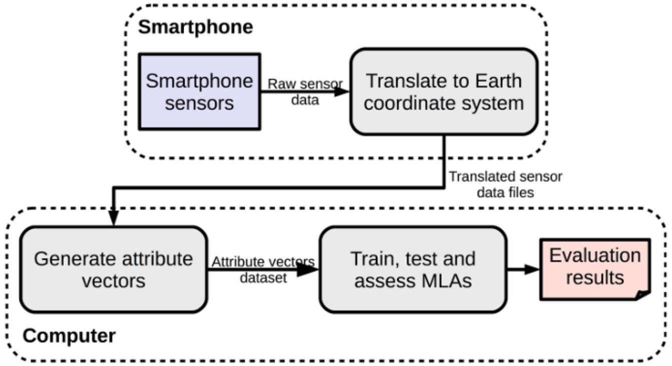
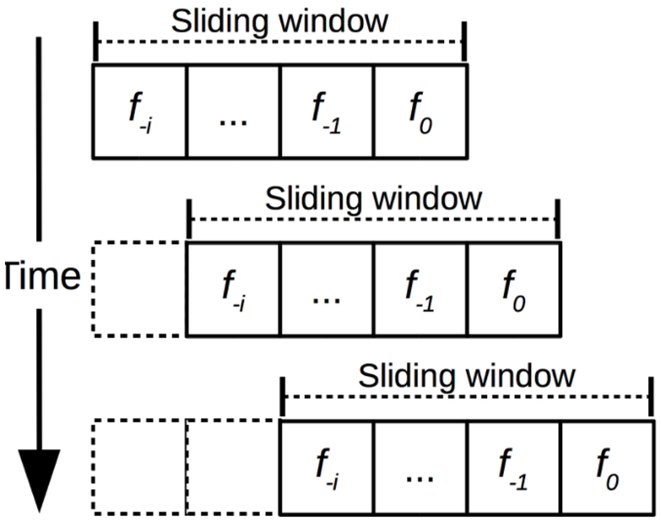
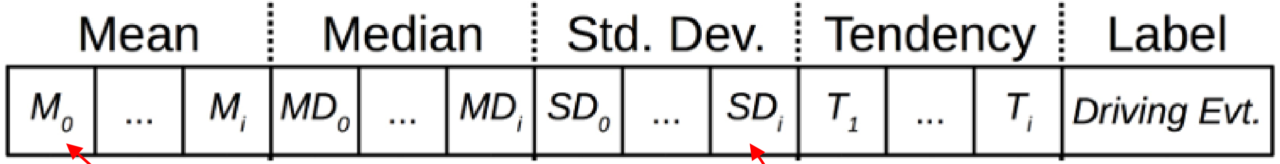
- Approach overview



- Divide data from 4 sensors into



Extract (Calculate) features in each window of data to Create attribute vector



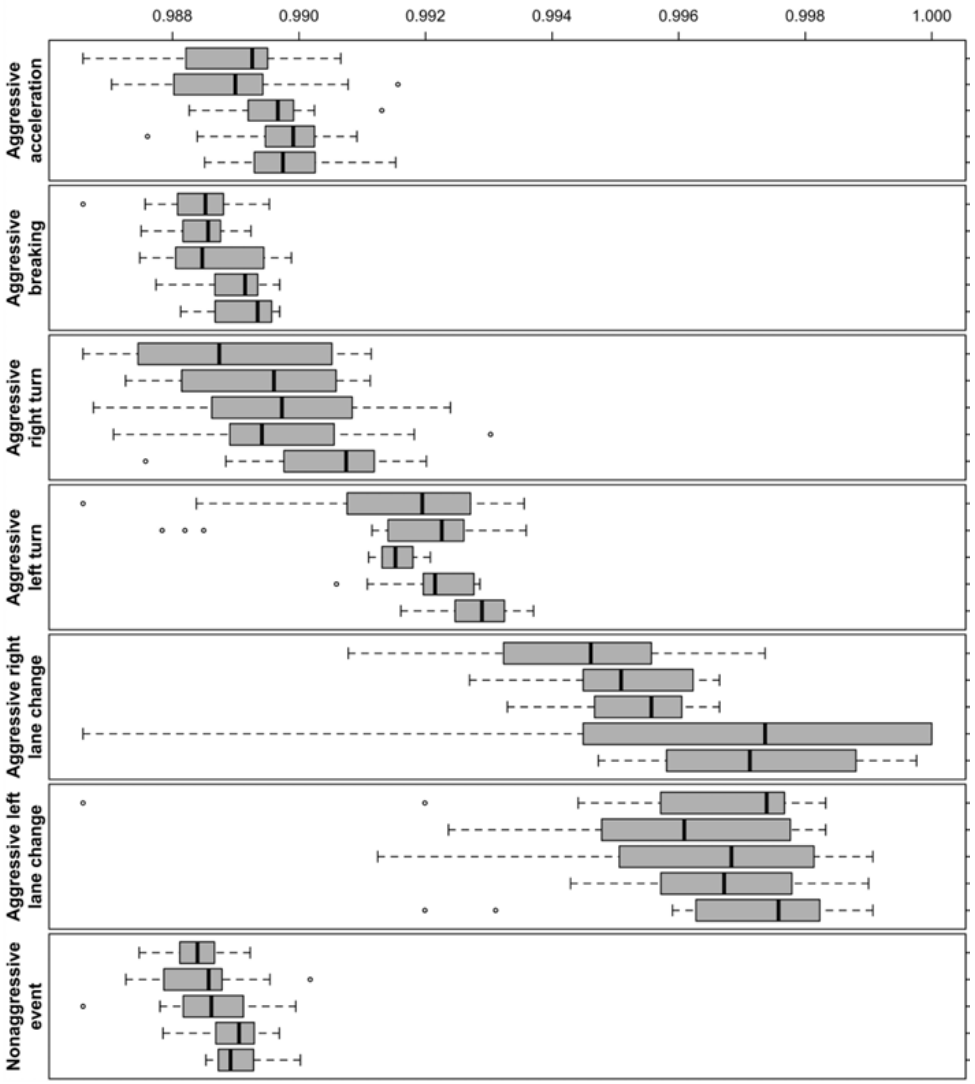
Std. dev. of window 1, 2, .. etc

Mean of window 1, 2, .. etc

Smartphone Driving Data: Results and Findings

Ferreira, J., Carvalho, E., Ferreira, B.V., de Souza, C., Suhara, Y., Pentland, A. and Pessin, G., 2017. Driver behavior profiling: An investigation with different smartphone sensors and machine learning. *PLoS one*, *12*(4), p.e0174959.

- Compared ML classification algorithms
  - Artificial Neural Networks, Support Vector Machines (SVM), Random Forest, Bayesian Networks
- Some findings
  - Accelerometer and gyroscope most suitable sensors
  - Random Forest machine learning algorithm performed best
- Hardest event to detect (lowest AUC): Aggressive acceleration
- Easiest event to detect (highest AUC): Aggressive right lane change



Driving Behavior: What Else?

Arumugam, S. and Bhargavi, R., 2019. A survey on driving behavior analysis in usage based insurance using big data. *Journal of Big Data*, *6*, pp.1-21.

- Beyond driving behavior profiling, some work on detecting driver states that increase likelihood of accidents
  - **Driver fatigue:** affects response time, decision making and causes 20% of accidents
  - **Drowsiness detection:** causes 328,000 accidents annually
  - **Driver distraction:** e.g. talking, texting, eating, fiddling with stereo, causes 8% of fatal accidents

Driver fatigue

Drowsy driving

Distracted driving