CS 528 Mobile and Ubiquitous Computing

Lecture 8a: Human-Centric Examples: Smartphone Sensing Applications

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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

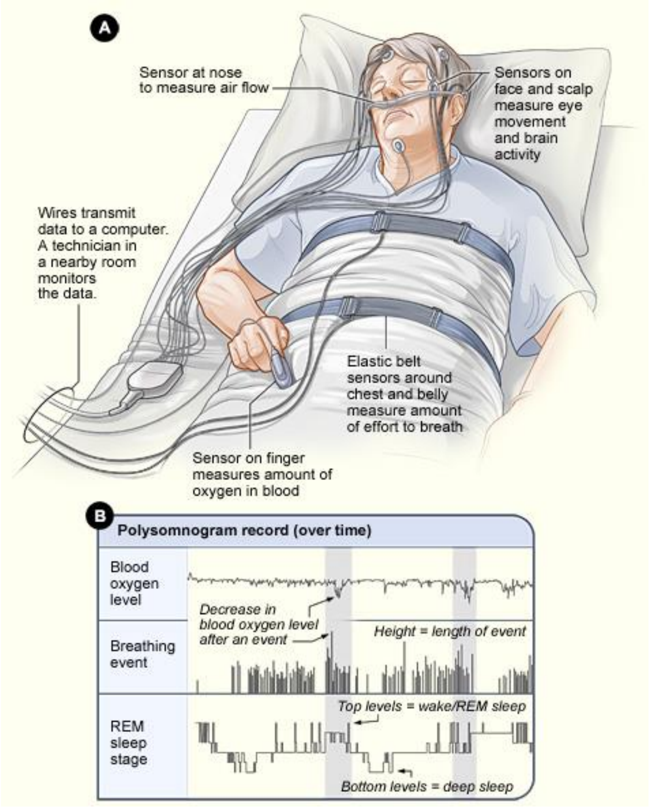
- Many medical treatments require patient records sleep
- Manually recording sleep/wake times is tedious

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, impractical, expensive!



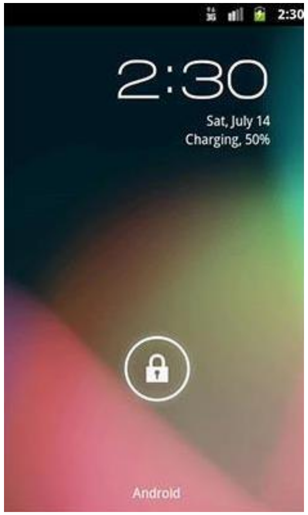
Commercial Wearable Sleep Devices

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

Can we monitor sleep with smartphone?

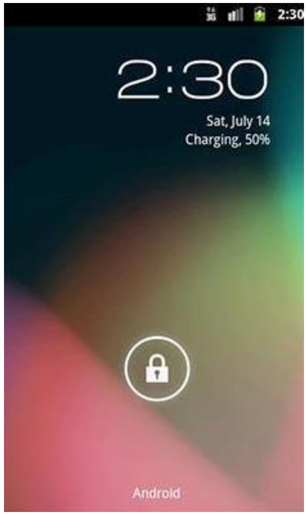
Insights: “Typical” sleep conditions

- 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:
- Phone Usage features.

    --phone-lock (F2)

    --phone-off (F4)

    --phone charging (F3)

  -- Light feature (Fl).

  -- Phone in darkness

  --Phone in a stationary state (F5)

  --Phone in a silent environment (F6)

- Each of these features are weak indicators of sleep
- If they 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 + 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

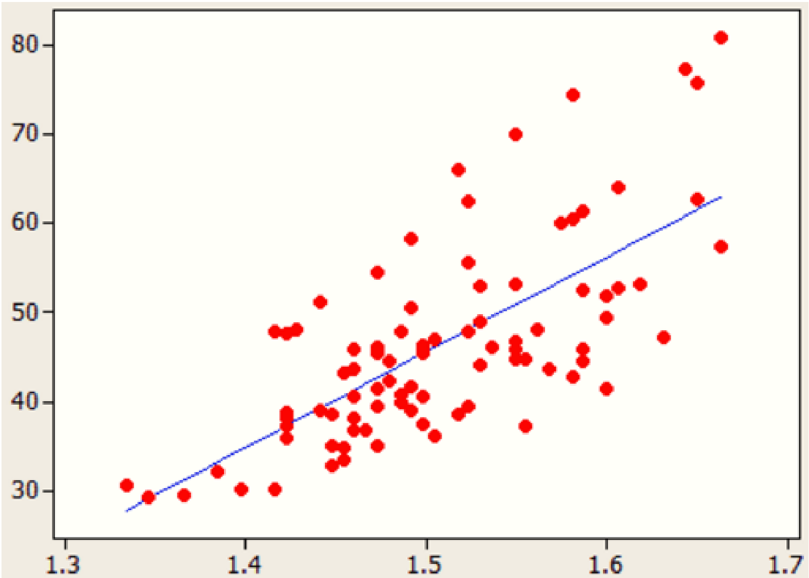
Weight for each feature

Feature (sum)

Regression?

- Gather sleep data (sleep duration, 6 features) from 8 subjects
- Fit data to line
  - **y axis** - sleep duration
  - **x-axes** – Weighted sum of 6 features
- **Weighted sum?** Determine weights for each feature that minimizes error
- Using line of best fit, in future sleep duration can be inferred from feature values

Sleep duration



Weighted sum of features

$$\min_{\alpha_i} \sum_{j=1}^{4} (Sl^j - \sum_{i=1}^{6} \alpha_i \cdot F_i^j)^2$$

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

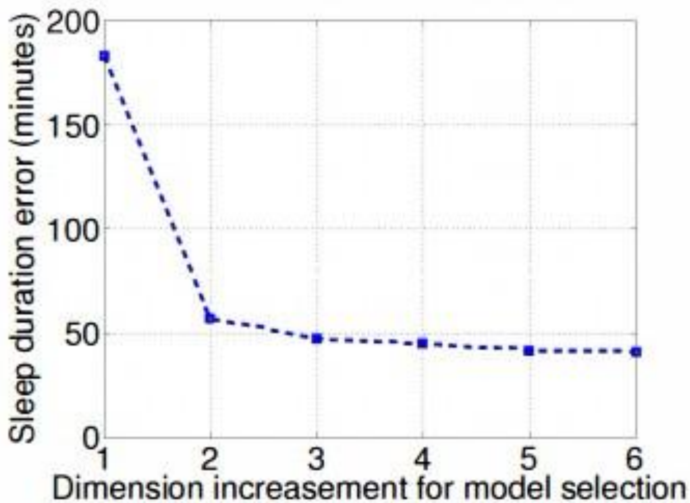


Fig. 2: The reduction in sleep duration error for BES by incrementally adding stationary, silence, phone-lock, phone-charging, light and phone-off features, respectively.

Results

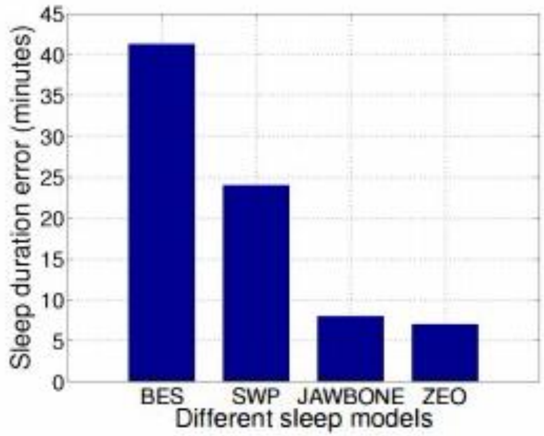


Fig. 3: Overall sleep duration error for BES compared to the three alternative sleep monitoring systems (SWP, Jawbone, Zeo).

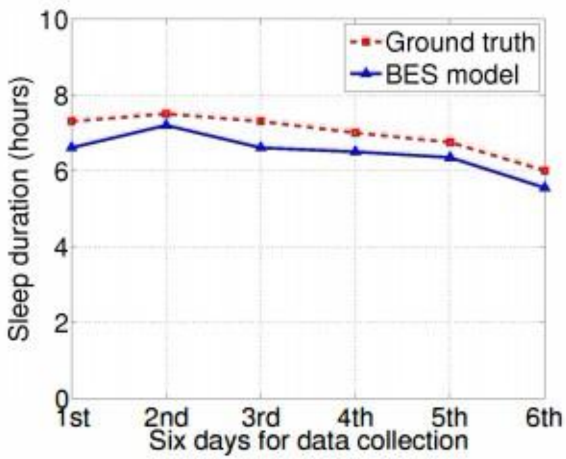


Fig. 5: Comparison of estimated and actual sleep duration under BES for one representative study subject.

My actual Experience

- Worked with undergrad student to implement BES sleep model
- **Results:** About 20 minute error (+ or -) 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

More on Regression

Linear Regression

- Strongest predictors of home prices are:
  1. Number of rooms in the house
  2. Number of low income neighbors in that area
- Linear Regression:
  1. Plot these variables for actual example homes
  2. Fit line of best fit
  3. Can use this line to guess price of any home

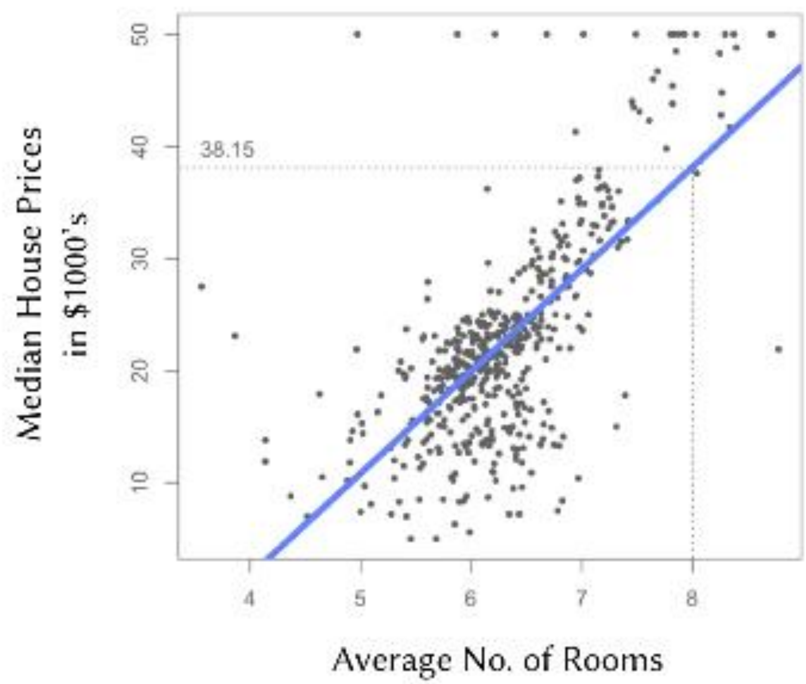


Figure 1. House price against number of rooms.

Linear Regression: Combining Predictors

- Some predictors usually have more weight than others
- Sometimes combine predictors as a weighted sum
- For instance, give larger weights to stronger predictors
- Weights assigned to variables are called **regression coefficients**

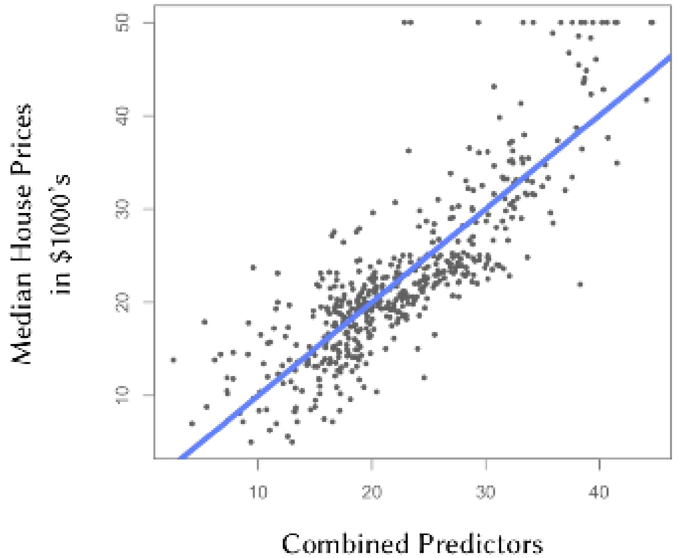
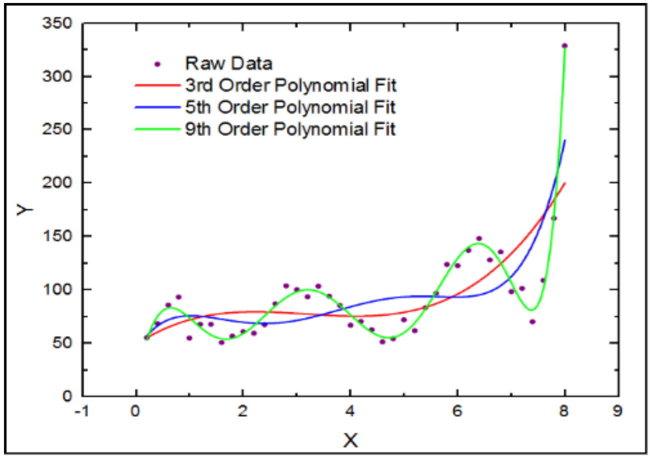


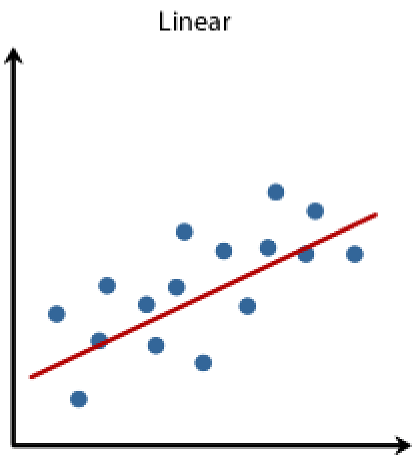
Figure 3. House price against a weighted combination of number of rooms and neighborhood affluence.

Different Types of Regression

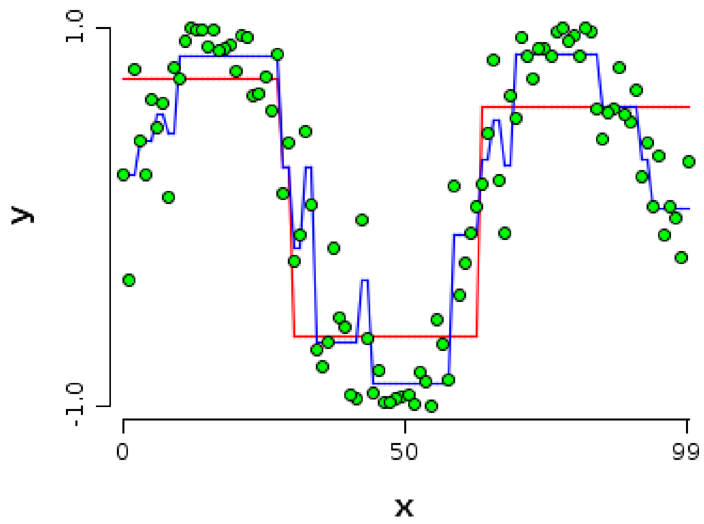
- Different regression functions to fit data to
  - Linear
  - Polynomial
  - Decision tree
  - Etc
- Determine which function has best fit, lowest error (difference)



Polynomial



Linear



Decision Tree

r: Correlation Coefficient

- *r*: A measure of how well points fit line
- **Direction:** positive value means outcome (e.g. housing price) increases with increases in predictor (e.g. number of rooms)
- **Magnitude:** Values closer to 1 or -1 indicate better fit

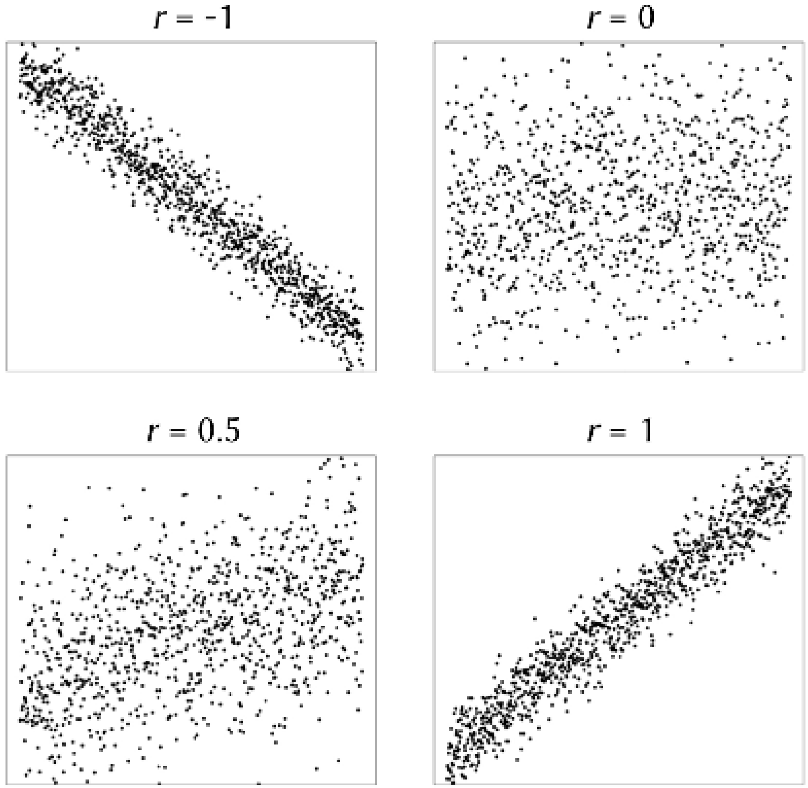
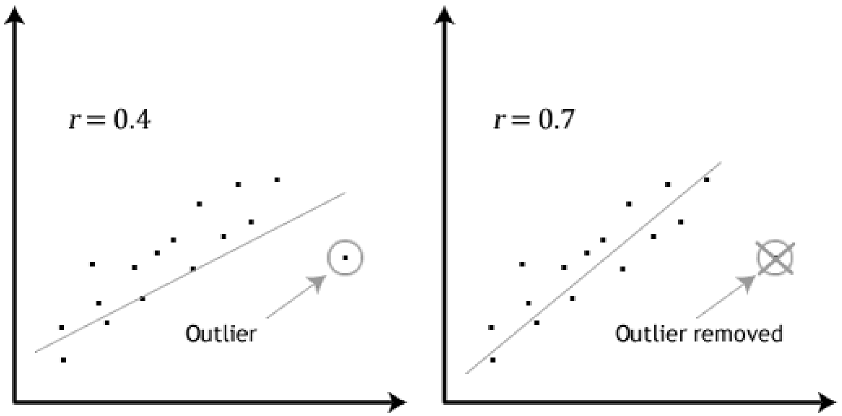


Figure 6. Examples of data spread corresponding to various correlation coefficients.

Regression: Limitations

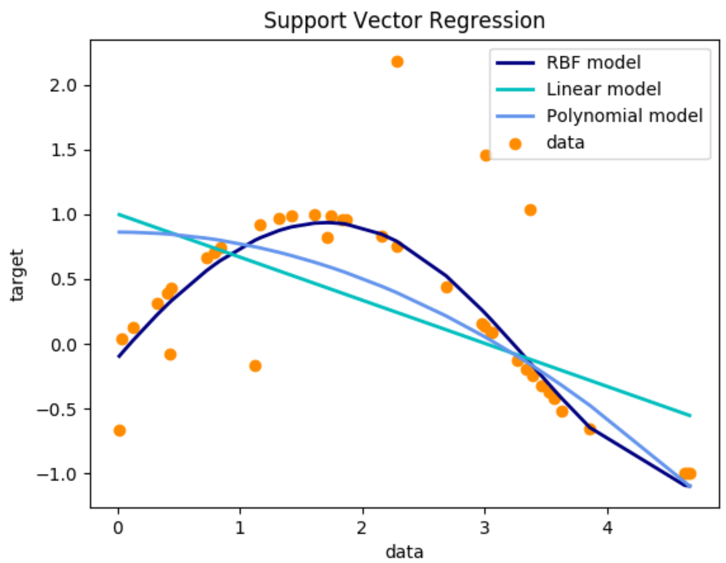
- **Sensitive to outliers:** Since all points are equally weighted, regression line can be affected by outliers
  - Removing outliers can improve regression fit (*r*)



- **Multicollinearity:** Some predictors may be correlated, reducing accuracy of regression line.
  - **Solutions:** Exclude correlated predictors or use advanced techniques (e.g. Lasso or ridge regression)

Regression: Limitations

- **Non-linear or curved trends:** Some trends may not be linear, or may be curved.
  - May use non-linear regression line



- Correlation is not causation:
  - Unrelated things may also seem to be good predictors
  - E.g. dog ownership and house prices

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

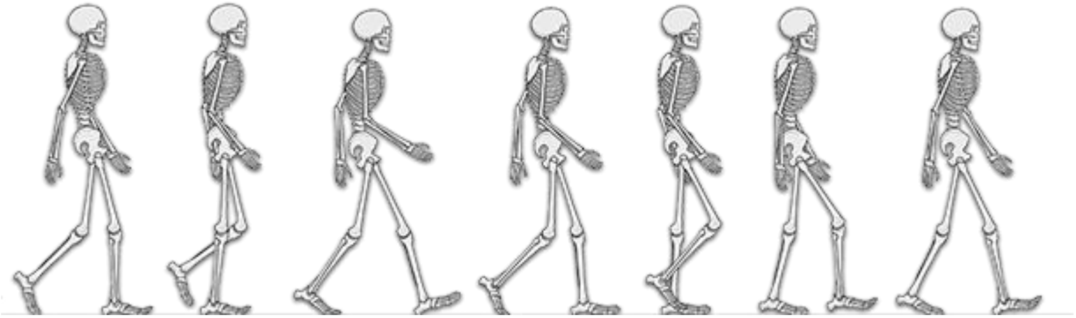
Binge Drinking Consequences

- 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

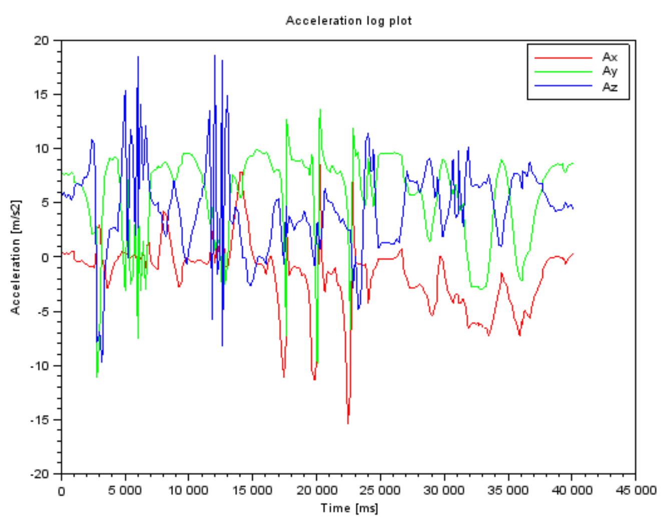
- **Gait:** Way a person walks, impaired by alcohol
- Aside from breathalyzer, gait is most accurate bio- measure of intoxication
- The police also know gait is accurate
  - 68% police DUI tests based on gait e.g. walk and turn test



AlcoGait

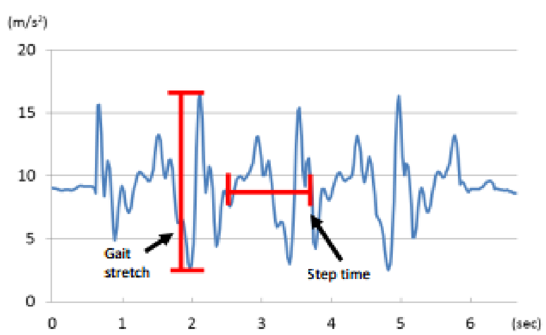
Z Arnold, D LaRose and E Agu, Smartphone Inference of Alcohol Consumption Levels from Gait, in Proc ICHI 2015
Christina Aiello and Emmanuel Agu, Investigating Postural Sway Features, Normalization and Personlization in Detecting Blood Alcohol Levels of Smartphone Users, in Proc Wireless Health Conference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

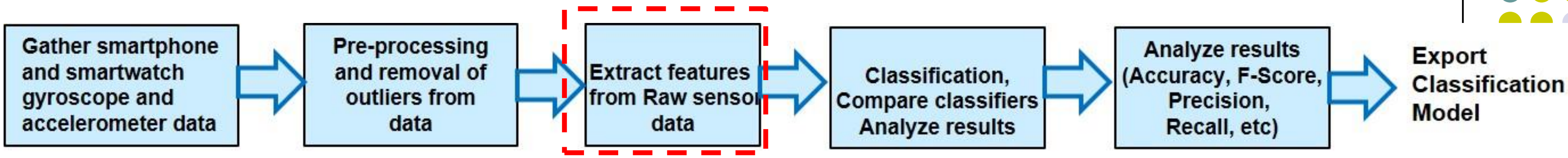
Feature	Feature Description
Steps	Number of steps taken
Cadence	Number of steps taken per minute
Skew	Lack of symmetry in one's walking pattern
Kurtosis	Measure of how outlier-prone a distribution is
Average gait velocity	Average steps per second divided by average step length
Residual step length	Difference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



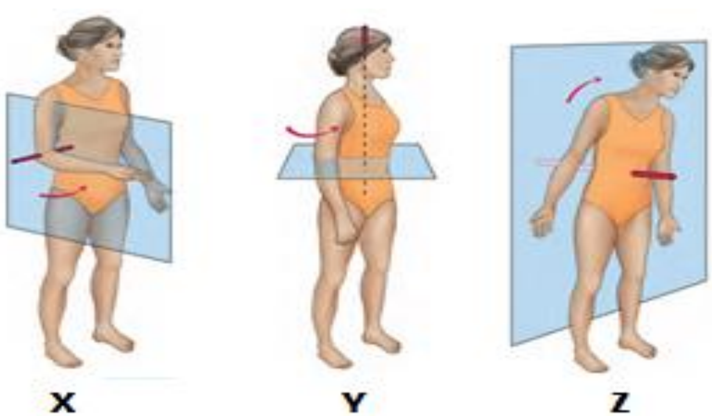
Accelerometer gait features

Posturography Sway Features

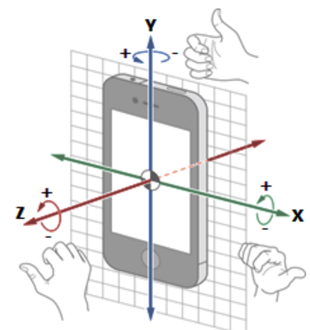
Investigating Postural Sway Features, Normalization and Personlization in Detecting Blood Alcohol Levels of Smartphone Users
Christina Aiello and Emmanuel Agu,*in Proc Wireless Health Conference 2016.*



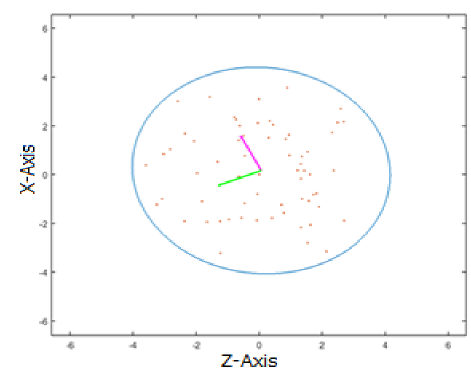
- **Posturography:** clinical approach for assessing balance disorders from gait
- Prior medical studies (Nieschalk *et al*) found that subjects swayed more after they ingested alcohol
- Synthesized sway area features on 3 body planes and sway volume
- Sway area computation: project values of gyroscope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

Different Sways? Swag?

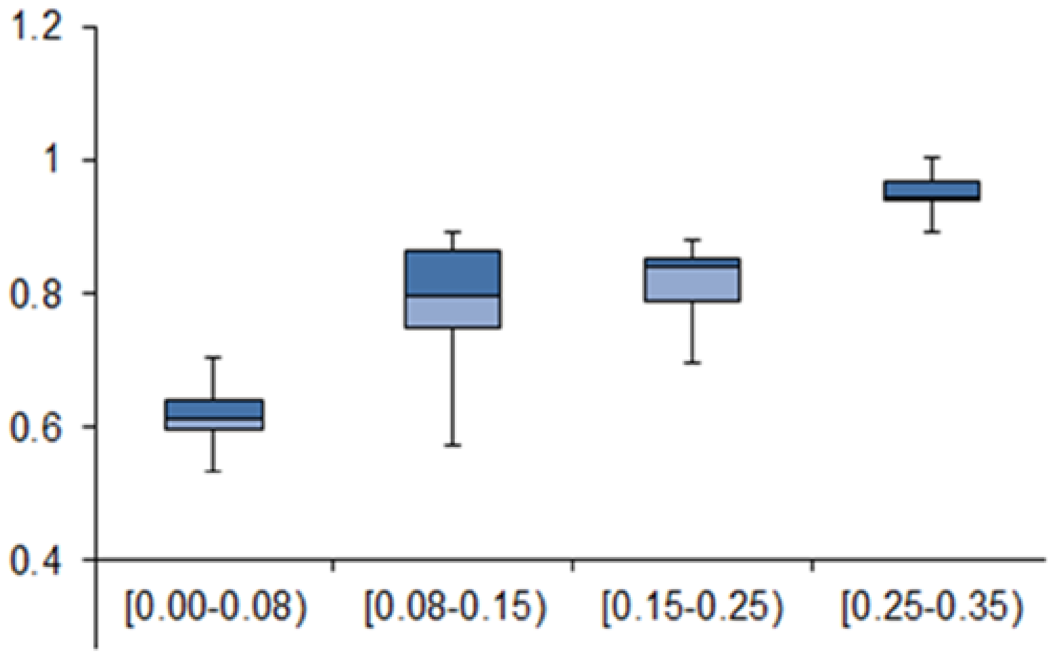
- Different people sway different amounts even when sober
- Some people would be classified drunk even when sober (Swag?)
- Cannot use same absolute sway parameters for everyone
- Normalize!
  - Gather each person's base data when sober
  - Divide possibly drunk gait features by sober features

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

- 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

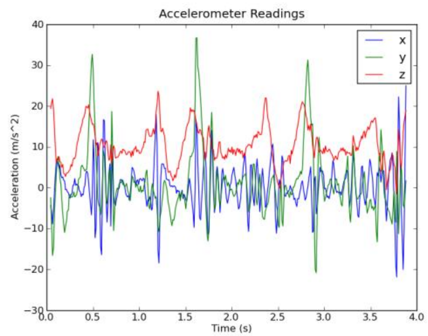
- As subjects got more intoxicated, normalized sway area generally increased



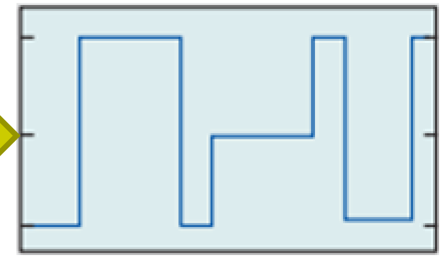
AlcoGait Evolution

- 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

AlcoWatch MQP: Using SmartWatch to Infer Alcohol levels from Gait



Raw accelerometer readings



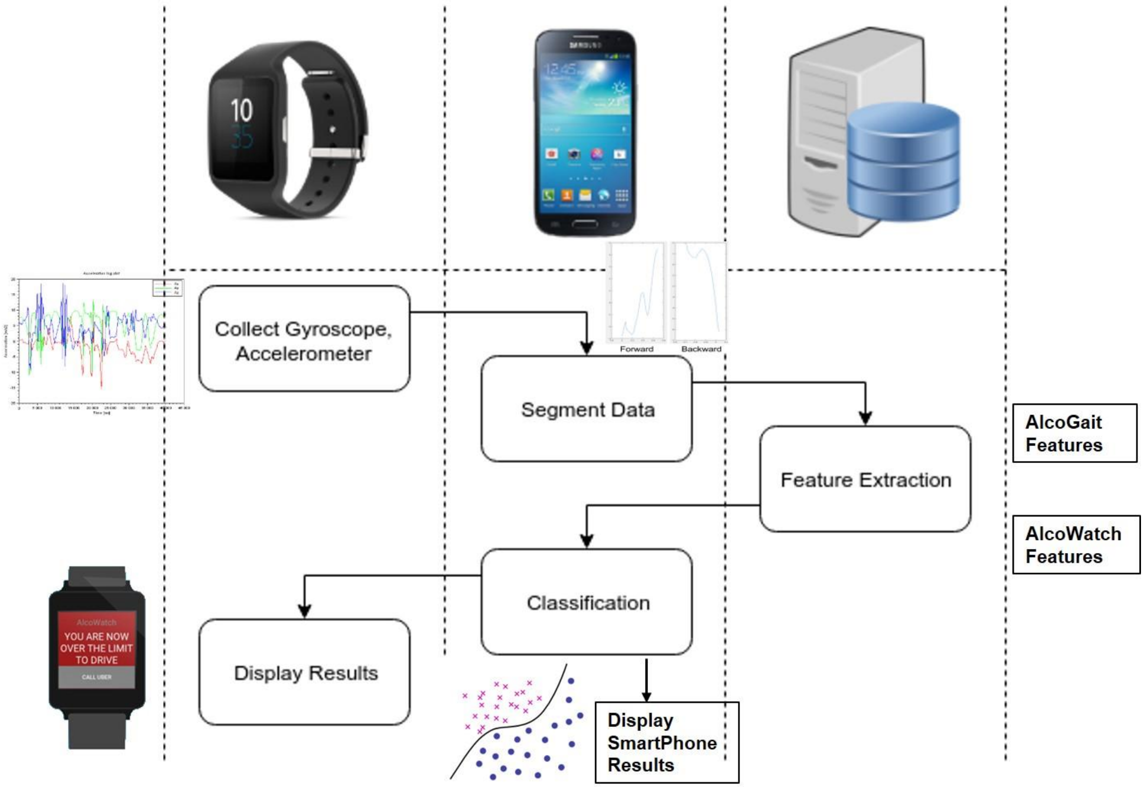
Feature extraction and classification

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

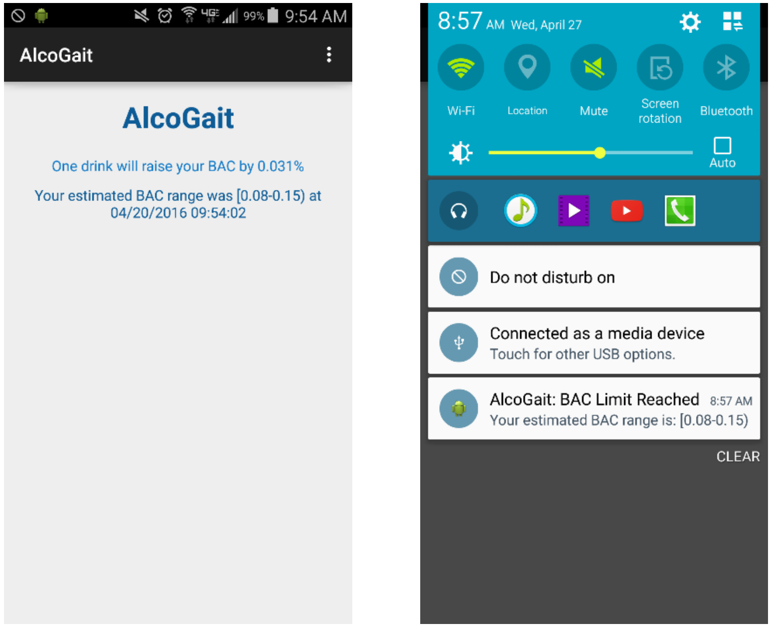
AlcoWear: Overview of How it Works

- 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 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

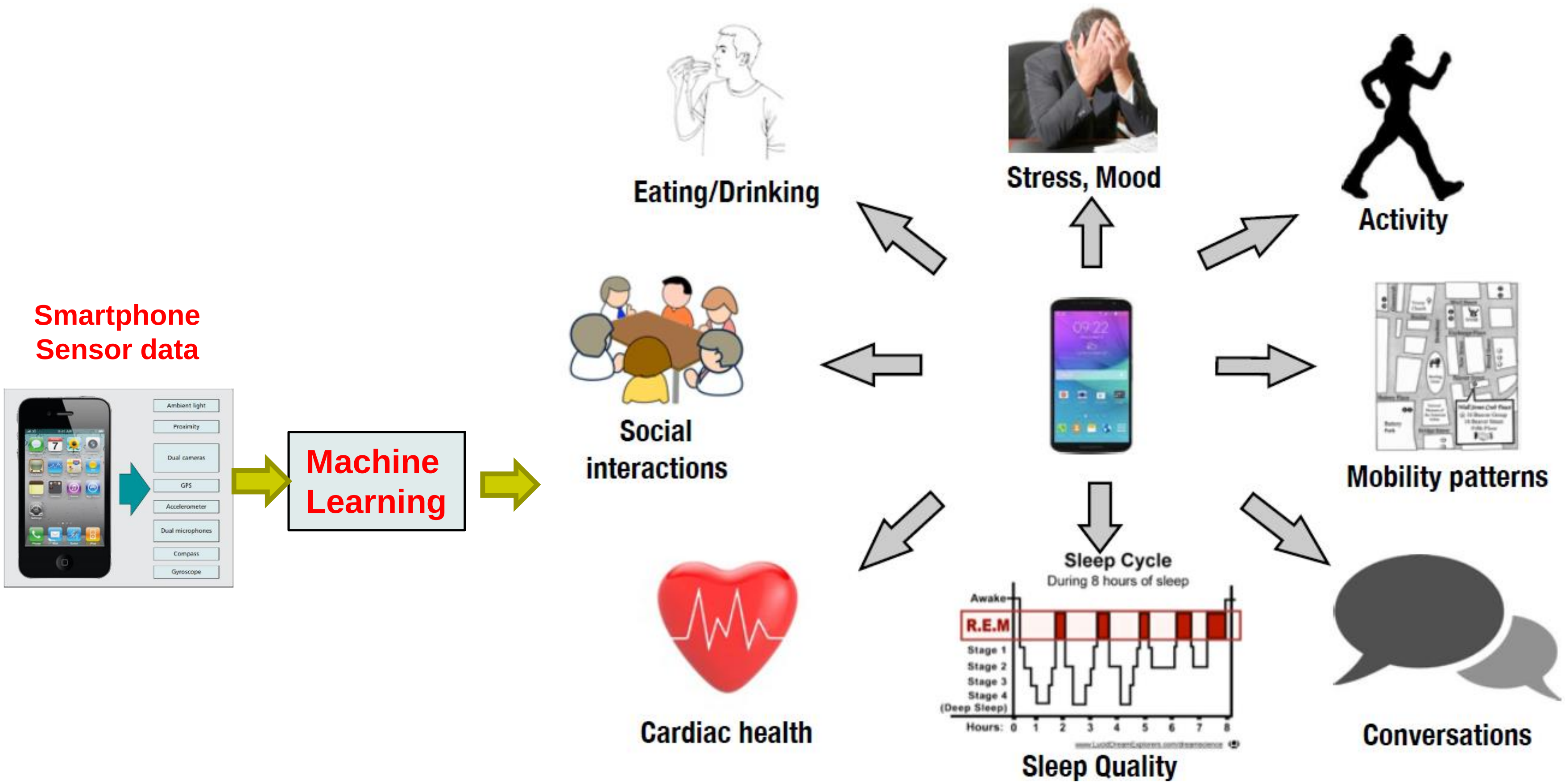
Currently: NIH-Funded Study to Gather Intoxicated Gait Data from 250 Subjects

- 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

WASH Project:
TBI, Infectious Disease Biomarkers

Background: Smartphone Sensing

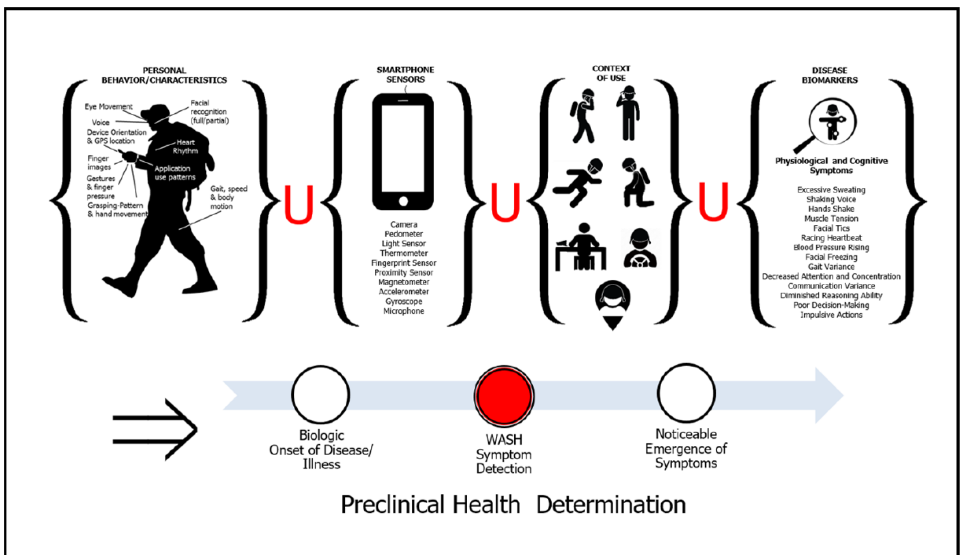
- Smartphones have many (20+) sensors
  - accelerometer, compass, GPS, microphone, camera, proximity
- Can sense physical world, detect user behaviors, sick smartphone user, etc



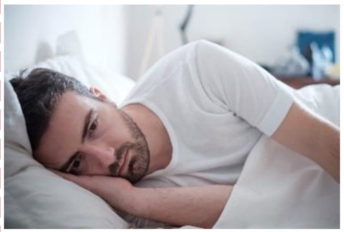
Smartphone BioMarkers to Improve Warfighter Health

PI: Agu, co-PI: Rundensteiner

- US military want early signs of warfighter ailment:
  - Traumatic Brain Injury (bomb blasts, explosions, fall, etc)
  - Infectious diseases (E.g. tuberculosis, pneumonia, measles, meningitis, malaria, Ebola, cholera and influenza)
- **WASH Concept:** Smartphone-sensable biomarkers may manifest first
  - E.g. reduced mobility, sedentary, sleep problems, stay close to home
- WPI received $2.8 from DARPA (military) to research smartphone biomarkers for TBI and infectious diseases



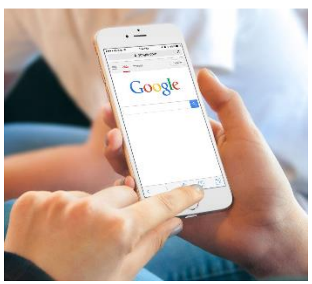
Examples of TBI, Infectious Disease Biomarkers Detectable by Smartphone



Sleep problems

Pupils dilated

Hands shaking



Slow phone interactions

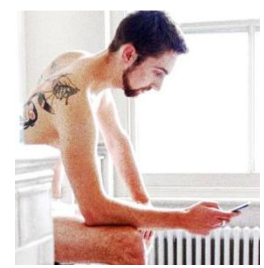
Avoiding light

Slurred speech

Traumatic Brain Injury (TBI) Smartphone Biomarkers

Walking Problems

Coughing



Increased Bathroom usage

Sneezing

Infectious Disease Smartphone Biomarkers

Note: Specific tests (e.g. hands shaking) in specific situations (e.g. user holding phone)

Our Research Approach

- Working with doctors, we now have specific list of 30 contexts in which we will run 14 specific TBI/infectious disease tests
- **Research Question 1:** Can smartphone detect when a smartphone user is in one of our specific contexts?
- Methodology:
  - Run a **scripted** user study
    - Recruit 100 subjects
    - Subjects using smartphone, enter each of 32 contexts
    - Gather smartphone data continuously in background
    - Later: analyze data (machine learning)
  - Run **Unscripted** user study
    - 100 subjects, 2 weeks, periodically prompted, label their context
    - Data is very real, very noisy

Context: Definition & Final List of Contexts

Context = (User Activity, Phone Prioception, App Category, Social)

Sitting
Standing
Walking
Lying down
Sleeping
Awake/not sleeping
Interacting with phone
Coughing
Exercising
Running
Sneezing
Sitting down
Lying down
Standing up
Talking into phone

Phone in Hand
Phone facing down
Phone on table
Trouser pocket
In bag
Briefcase
Jacket pocket

Games
- Video game

Media & Video
- Video Chat
- Video streaming

Communication
- Messaging

Social
- Messaging

Entertainment
- Video streaming

Alone
2 or more speakers
More than 2 speakers
Busy place

30 Contexts Needed for Our Tests

1	<interacting with phone, phone in hand, *, *>
2	<*, phone in hand, *, *>
3	<lying down, *, *, *>
4	<sitting, *, *, *>
5	<standing, *, *, *>
6	<sleeping, *, *, *>
7	<awake, *, *, *>
8	<walking, in pocket, *, *>
9	<walking, in hand, *, *>
10	<walking, in bag, *, *>
11	<*, phone on table, *, *>
12	<*, phone facing down, *, *>
13	<talking into phone, *, *, *>
14	<*, *, *, more than 2 speakers>
15	<Coughing, *, *, *>

16	<Coughing, *, *, in busy place>
17	<Toilet, *, *, *>
18	<Toilet, Phone in pocket, *, *>
19	<sleeping, phone on table, *, 0>
20	<exercising, phone in hand, *, 0>
21	<exercising, phone on table, *, 0>
22	<exercising, *, *, more than 2 speakers>
23	<Sneezing, *, *, 2 or more speakers>
24	In noisy/bust place
25	<lying down, phone on table, *, *>
26	<Sneezing, *, *, alone>
27	<Sitting up, *, *, *>
28	<Standing up, *, *, *>
29	<Sitting down, *, *, *>
30	<Lying down, *, *, *>

WASH Scripted Study

Context Collection Study: Overview

- Scripted, on-campus study to cover the majority of identified contexts
- Each subjects completes a carefully planned circuit, timed
- Each subject given same Essential Android phones to ensu consistent data
- Mobile app automatically gathers sensor data, labels entered manually with timestamps

Context Data Study: Route @ WPI

1. Fuller Labs
   - Briefing
2. Recreation Center
   - Walking, running
   - Bathroom
3. Morgan Hall
   - Phone call
   - Water break
   - Being in a busy place
4. Fuller Labs
   - Lying down
   - Sitting down
   - Standing up

Context Collection Study: Sensors

<u>Standard</u>:

- Gyroscope
- Accelerometer
- Barometer
- Magnetometer
- Location Services
  - Speed
  - Distance traveled over a period of time

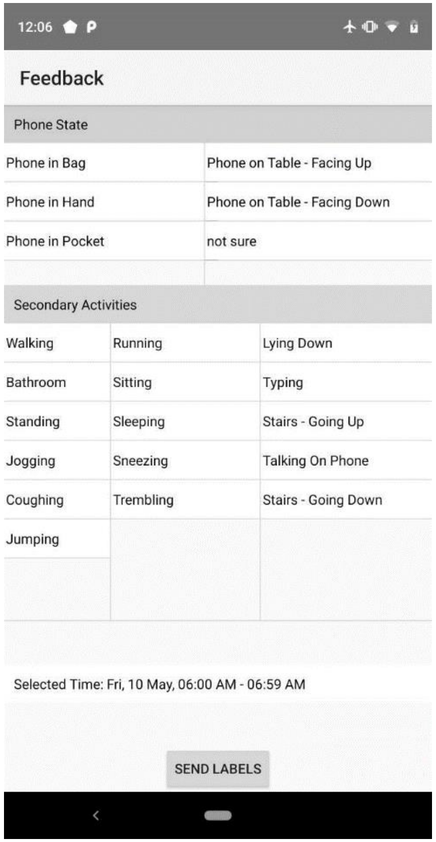
<u>Experimental</u>:

- Audio
  - Feature extraction on phone to mitigate privacy concerns
- Ambient light
- Proximity
- Discrete sensors
  - Is the phone charging?
  - Are they interacting with it?

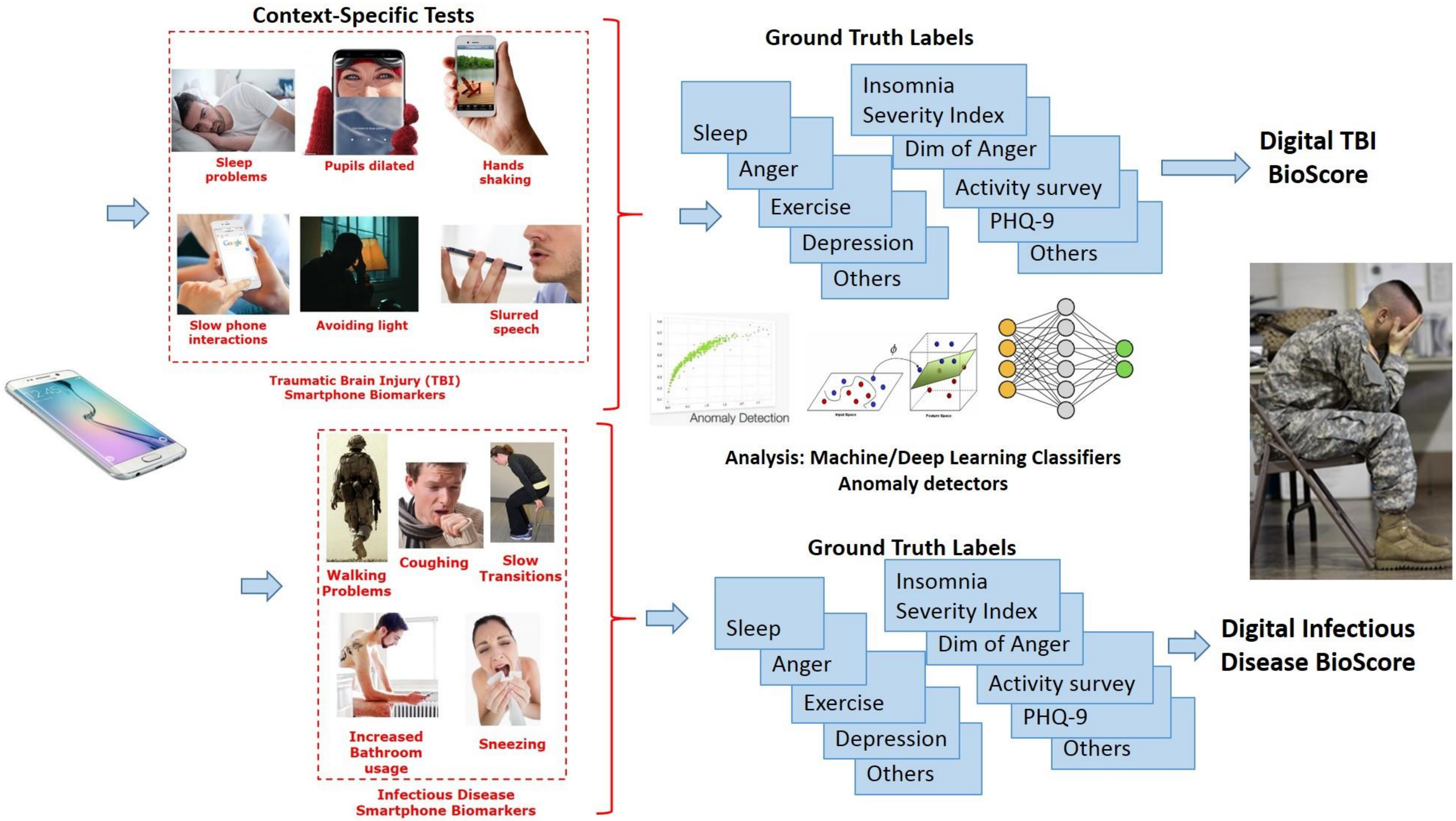
WASH Unscripted Study

WASHSensory App to gather subjects data

- App continuously collected sensor data
- Subjects labeled 25 contexts
    - Laying Down, Phone on Table
    - Excising, Phone in Pocket
    - Toilet, Phone in Pocket
    - Walking, Phone in Bag
    - Walking, Phone in Hand
    - Walking, Phone in Pocket
    - Typing
    - Sleeping
    - Sitting
    - Running
    - Laying Down (state)
    - Jogging
    - Running
    - Standing
    - Talking On Phone
    - Bathroom
    - Phone in Pocket
    - Phone in Hand
    - Phone in Bag
    - Phone on Table, Facing Up
    - Phone on Table, Facing Down
    - Stairs - Going Up
    - Stairs - Going Down
    - Walking

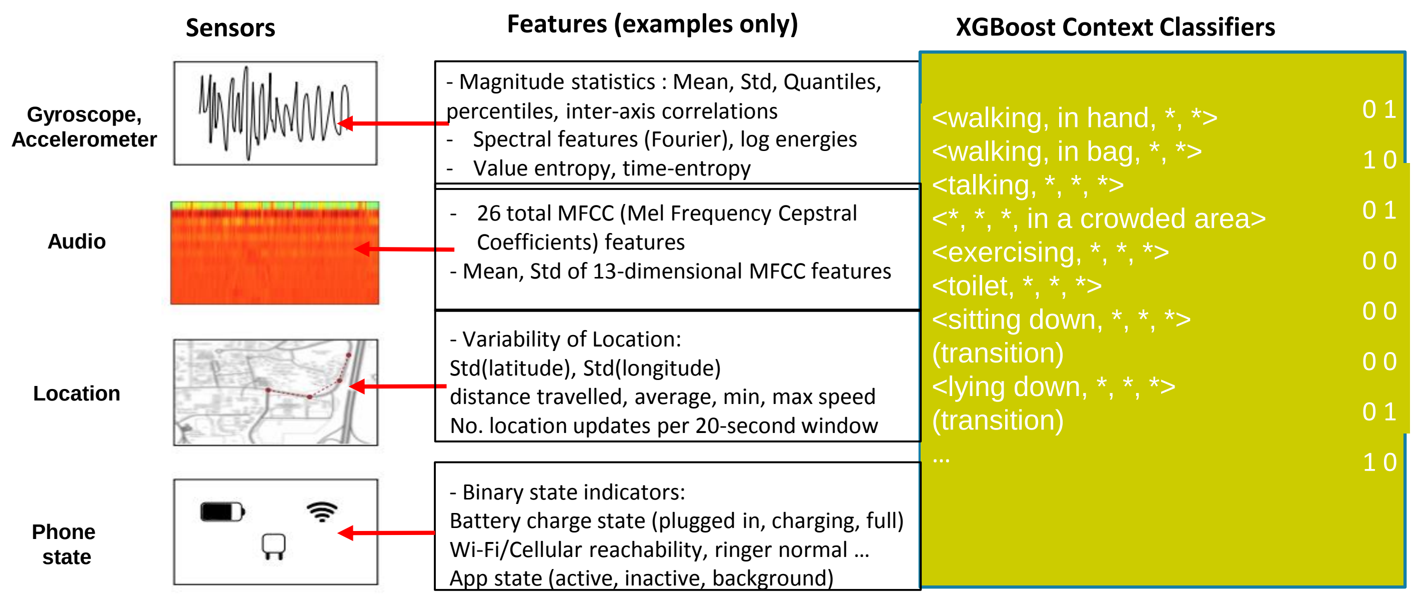


Overview of our Classification Approach



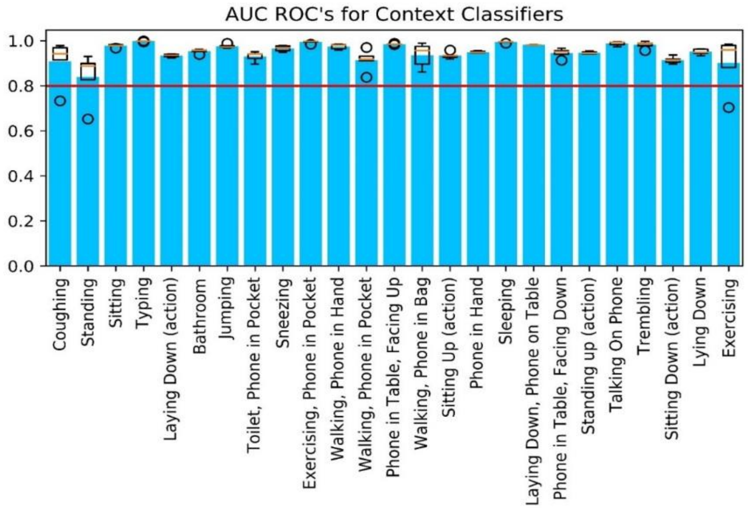
WPI Scripted Study Data Analysis: Extracted **Features** (N=109)

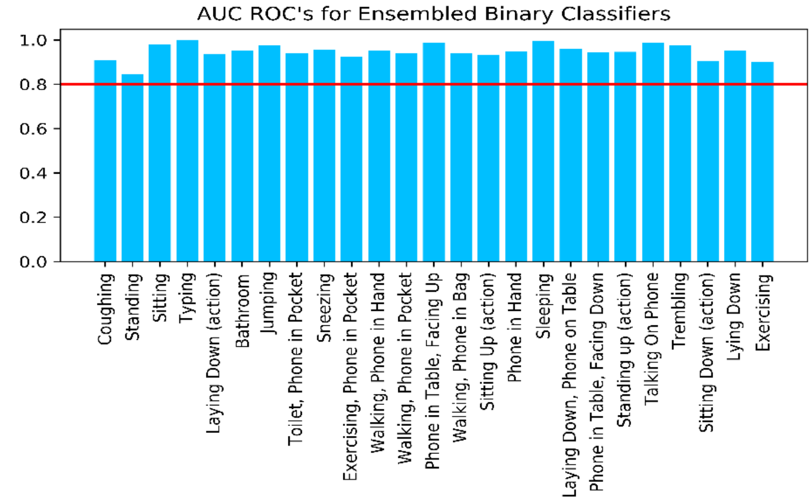
- 175 features extracted from data gathered in our scripted user study
  - Accelerometer, gyroscope, location, audio, phone state feature
  - Also time features (time windows: 3am-9am, 6am-midday, 9am-3pm, etc)
- Classified features using XGBoost



Classified WPI WASH Context Data using XGBoost Classifier

- **Main result:** Over 80% macro AUC-ROC for all 25 contexts, 14 contexts > 90%





- **Approach 1:** Classify individual binary labels, compute macro AUC-ROC
- Macro AUC-ROC is average of individual binary labels in tuple

Approach 2: Classify context tuple as target using XGBoost

Over 80% macro AUC-ROC for all 25 contexts

Over 80% AUC-ROC for 25 ensembled binary contexts

Met program objectives 25/25 contexts detected with > 80% accuracy