CS 4518 Mobile and Ubiquitous Computing

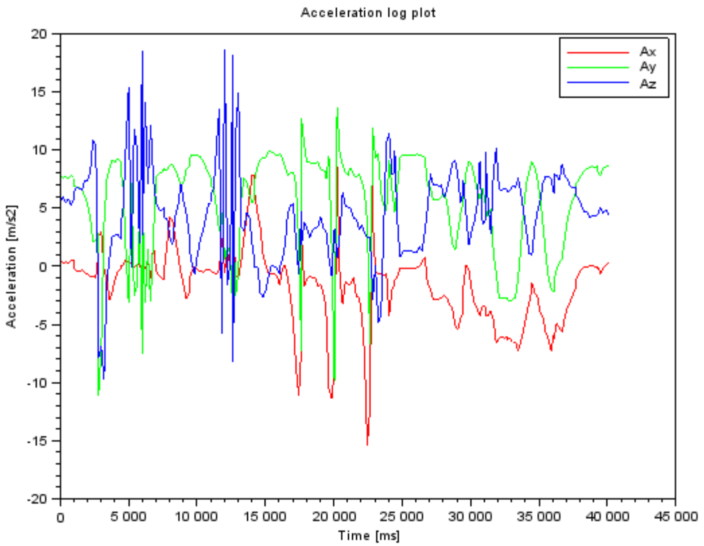
Lecture 16: Smartphone Sensing Apps

Emmanuel Agu

Applications of Activity Recognition

Recall: Activity Recognition

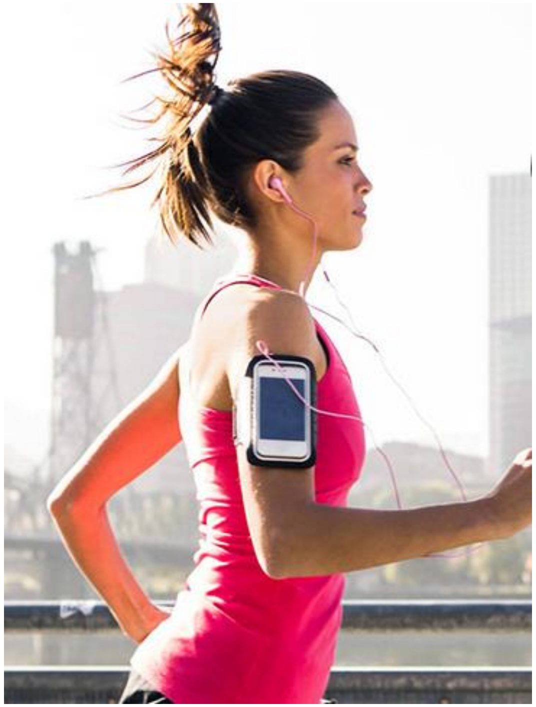
- **Goal:** Want our app to detect what activity the user is doing?
- **Classification task:** which of these 6 activities is user doing?
  - Walking,
  - Jogging,
  - Ascending stairs,
  - Descending stairs,
  - Sitting,
  - Standing



- Typically, use machine learning classifers to classify user's accelerometer signals

Applications of Activity Recognition (AR)

- **Fitness Tracking:**
  - **Initially:**
    - Physical activity type,
    - Distance travelled,
    - Calories burned
  - **Newer features:**
    - Stairs climbed,
    - Physical activity
      (duration + intensity)
    - Activity type logging + context
      e.g. Ran 0.54 miles/hr faster
      during morning runs
    - Sleep tracking
    - Activity history



Note: AR refers to algorithm
But could run on a range of devices
(smartphones, wearables, e.g. fitbit)

Applications of Activity Recognition

- **Health monitoring:** How **well** is patient performing activity?
- Make clinical monitoring pervasive, continuous, real world!!
  - Gather context information (e.g. what makes condition worse/better?)
  - E.g. timed up and go test
- Show patient contexts that worsen condition => Change behavior
  - E.g. walking in narror hallways worsens gait freeze

Parkinsons disease
Gait freezing

Question: What data would you need to build PD gait classifier? From what types of subjects?

COPD, Walk tests in the wild

Applications of Activity Recognition

- **Fall:** Leading cause of death for seniors
- **Fall detection:** Smartphone/watch, wearable detects senior who has fallen, alert family
  - Text message, email, call relative

Fall detection + prediction

Applications of Activity Recognition (AR)

- **Context-Aware Behavior:**
  - In-meeting? => Phone switches to silent mode
  - Exercising? => Play song from playlist, use larger font sizes for text
  - Arrived at work? => download email

- Study found that messages delivered when transitioning between activities better received

- **Smart home:**
  - Determine what activities people in the home are doing,
    - **Why?** infer illness, wellness, patterns, intrusion (security), etc
    - E.g. TV automatically turns on at about when you usually lie on the couch

Applications of AR

- **Adaptive Systems to Improve User Experience:**
  - Walking, running, riding bike? => Turn off Bluetooth and WiFi (save power)
  - Can increase battery life up to 5x

Applications of AR: 3rd Party Apps

- **Targeted Advertising:**
  - AR helps deliver more relevant ads
  - E.g user runs a lot => Get exercise clothing ads
  - Goes to pizza places often + sits there => Get pizza ads

Applications of AR: 3rd Party Apps

- **Research Platforms for Data Collection:**
  - E.g. public health officials want to know how much time various people (e.g. students) spend sleeping, walking, exercising, etc
  - Mobile AR: inexpensive, automated data collection

- **Track, manage staff on-demand:**
  - E.g. at hospital, determine “availability of nurses”, assign them to new jobs/patients

Applications of AR: Social Networking

- **Automatic Status updates:**
  - E.g. Bob is sleeping
  - Tracy is jogging along Broadway with track team
  - Privacy/security concerns => Different Levels of details for different friends
- **Activity-Based Social Networking:**
  - Automatically connect users who do same activities + live close together
- **Activity-Based Place Tagging:**
  - Automatically "popular" places where users perform same activity
  - E.g. Park street is popular for runners (activity-based maps)

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

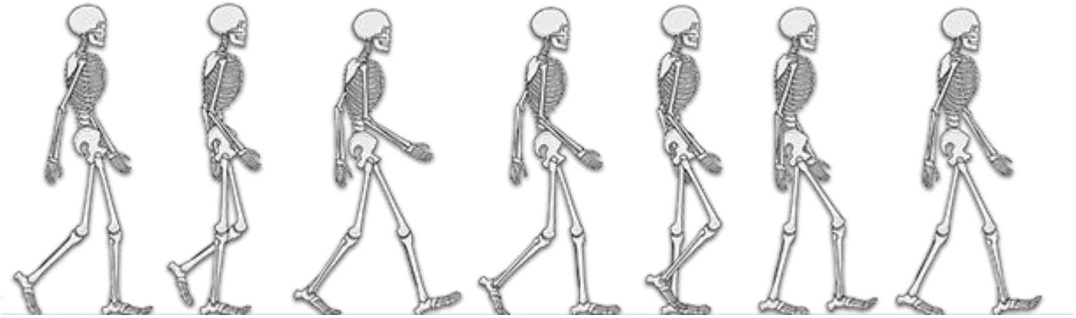
Binge Drinking Consequences

- 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 prevent DUI?

Vehicle Interlock system

Gait for Inferring Intoxication

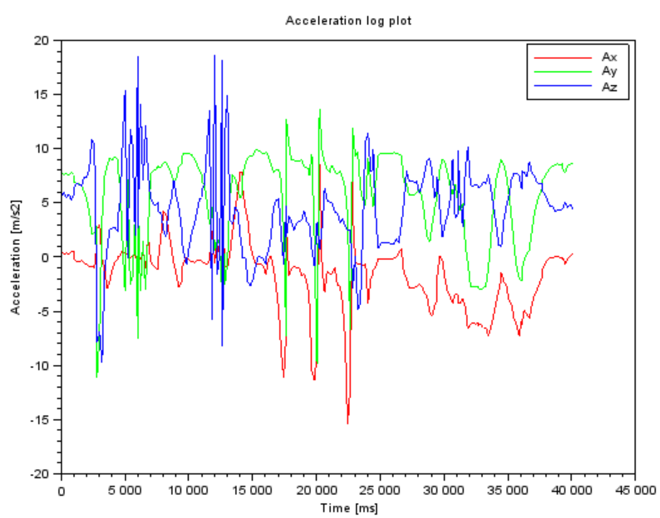
- **Gait:** Way a person walks, impaired by alcohol
- Aside from breathalyzer, gait is most accurate bio- measure of intoxication
- The police also know gait is accurate
  - 68% police DUI tests based on e.g. walk and turn test



AlcoGait

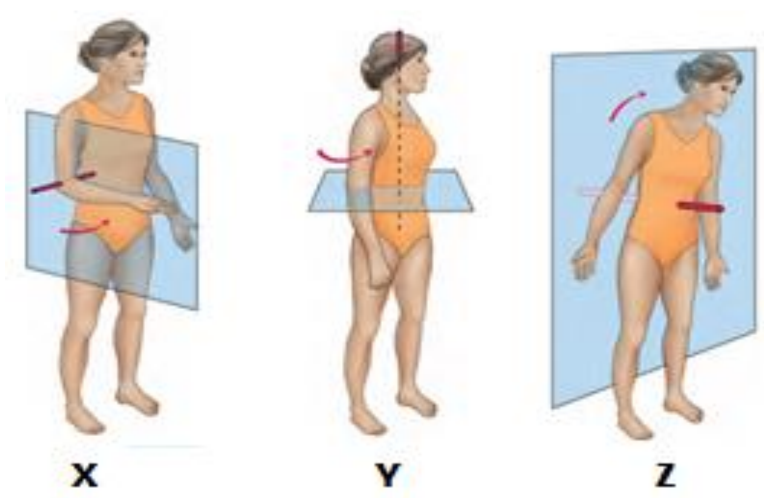
Z Arnold, D LaRose and E Agu, Smartphone Inference of Alcohol Consumption Levels from Gait, in Proc ICHI 2015
Christina Aiello and Emmanuel Agu, Investigating Postural Sway Features, Normalization and Personlization in Detecting Blood Alcohol Levels of Smartphone Users, in Proc Wireless Health Conference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

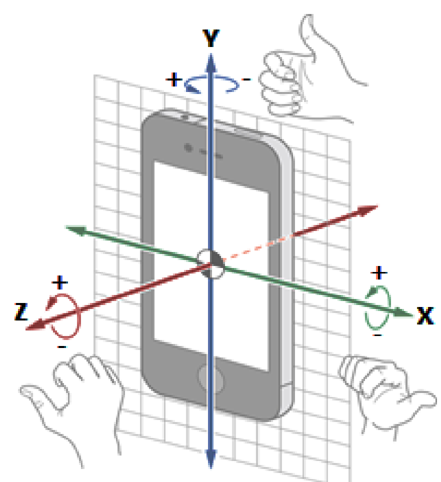


AlcoGait Features

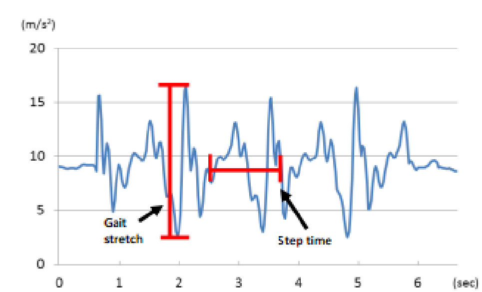
- Prior medical studies (Ando *et al*) found that subjects swayed more after they ingested alcohol
- Smartphone on user's trunk (hip pocket, etc) can measure increased sway
- Alcogait uses gyroscope features that measure user's sway along 3 body axes (x, y and z below)
  - Sway area on x,y and z axes (sway on XY, YZ, and XZ planes)
- Also accelerometer features (gait velocity of walking speed), etc



Sway along Body axes



Gyrosope axes



Accelerometer gait features

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**
  - Must have EMS on standby
  - Alcohol must be served by licensed bar tender
  - IRB were uneasy 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

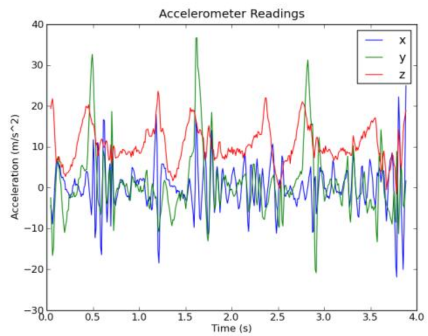
$$\frac{drunk\_feature}{sober\_feature}$$

- Similar to how dragon dictate makes each reader read a passage initially
  - Learns unique inflexions, pronounciation, etc

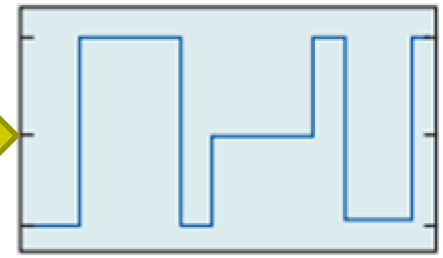
AlcoGait Evolution

- Zach Arnold, Danielle LaRose
  - Initial AlcoGait prototype, accelerometer features (time, freq domain)
  - 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
- **IQP:** Public acceptance to alcohol technology

AlcoWatch MQP: Using SmartWatch to Infer Alcohol levels from Gait



Raw accelerometer readings



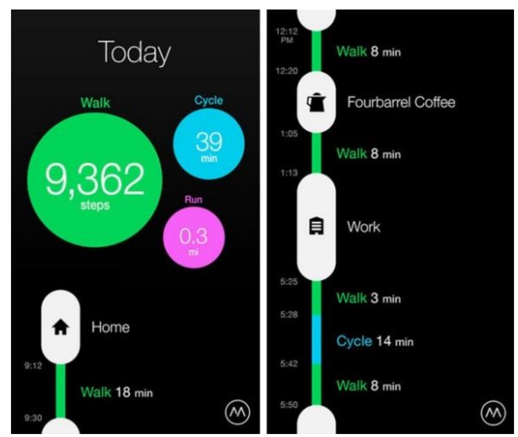
Feature extraction and classification

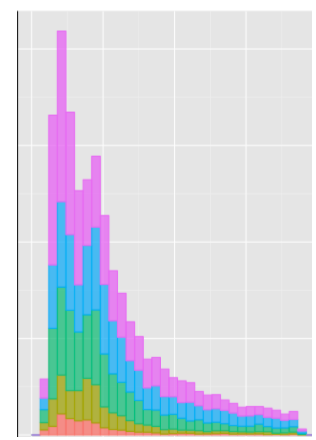
BAC/How much alcohol consumed?

- 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

Alco-Contextualizer MQP

- Drinking contexts repeat but drinker may not know
- **Alco-Contextualizer:** Phone tracks drinking contexts, track, display/visualize
  - Places types of places
  - People with: John, Sally
  - Times (after dinner? Late night? Weekends)
- **Students:** Rupak Lamsal, Matt Nguyen, Jules Voltaire





The Future: Gather more Drunk Gait Data in NIH Funded Study

- 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

BES Sleep App

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

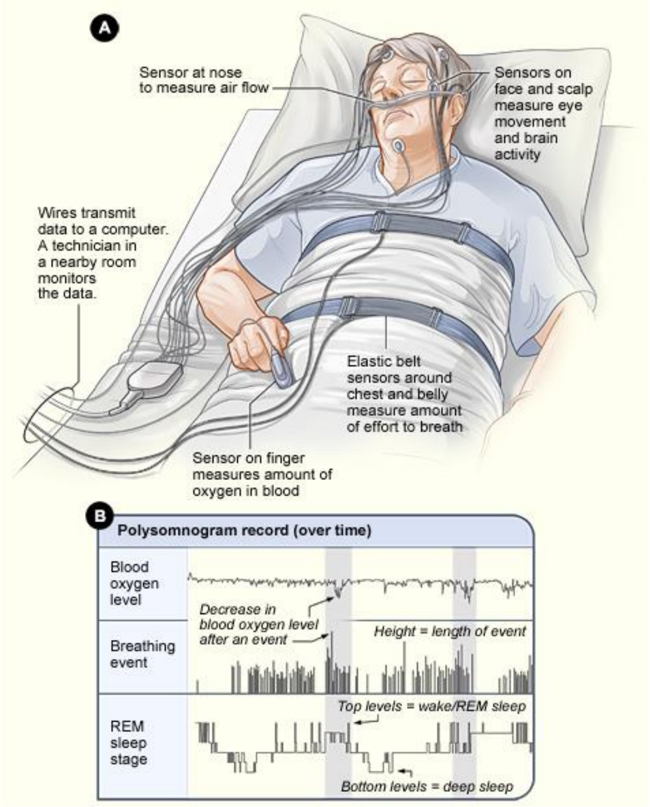
- Many medical treatments require patient records sleep
- Manually recording sleep/wake times is tedious

Unobtrusive Sleep Monitoring

- **Paper goal:** Automatically detect sleep duration (start, end times) 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!



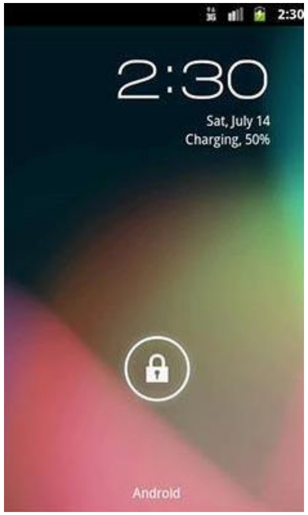
Commercial Wearable Sleep Devices

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

Can we monitor sleep with smartphone?

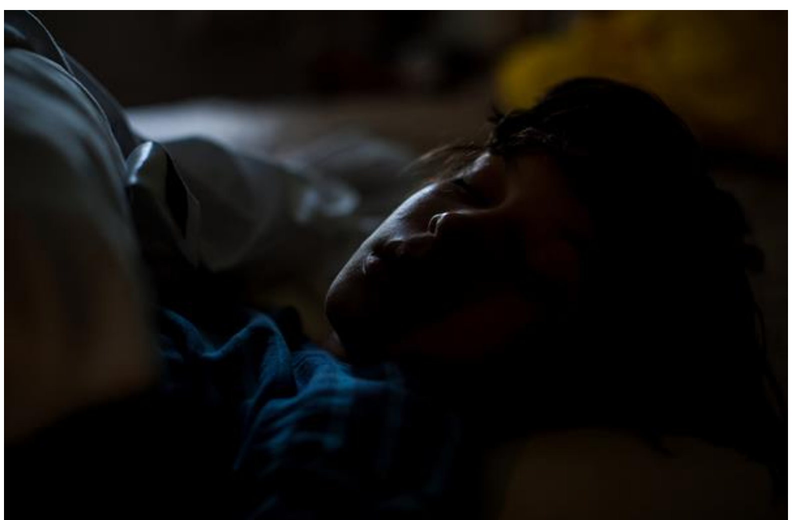
Insights: “Typical” sleep conditions

- 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
- 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:

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

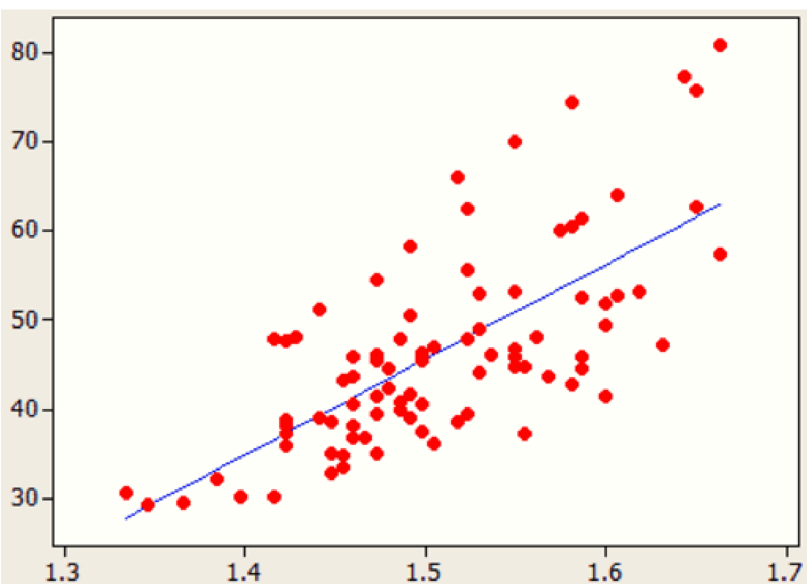
Sleep duration

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



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

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

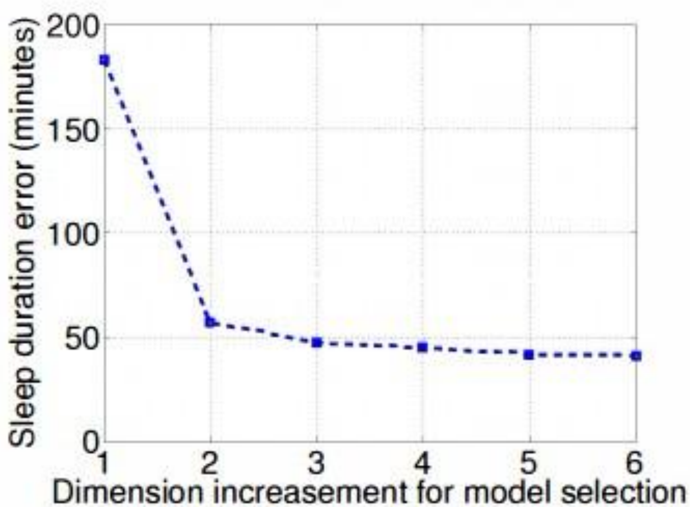


Fig. 2: The reduction in sleep duration error for BES by incrementally adding stationary, silence, phone-lock, phone-charging, light and phone-off features, respectively.

Results

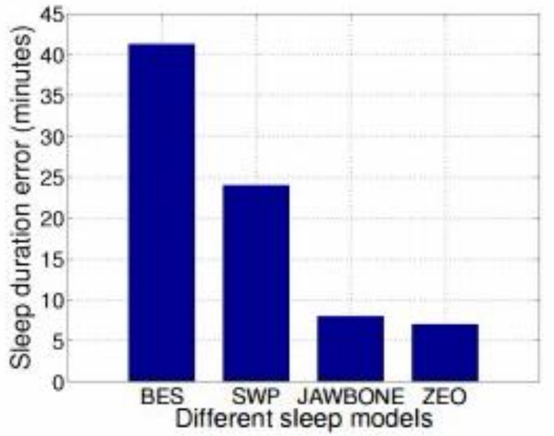


Fig. 3: Overall sleep duration error for BES compared to the three alternative sleep monitoring systems (SWP, Jawbone, Zeo).

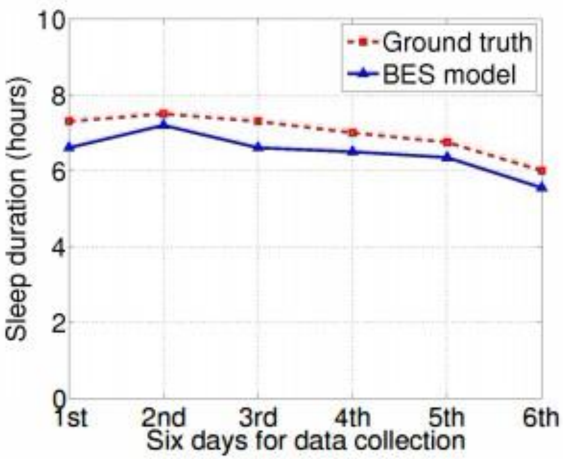


Fig. 5: Comparison of estimated and actual sleep duration under BES for one representative study subject.

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