Predicting intoxication with smart phone accelerometer data.

Machine learning spring 2020

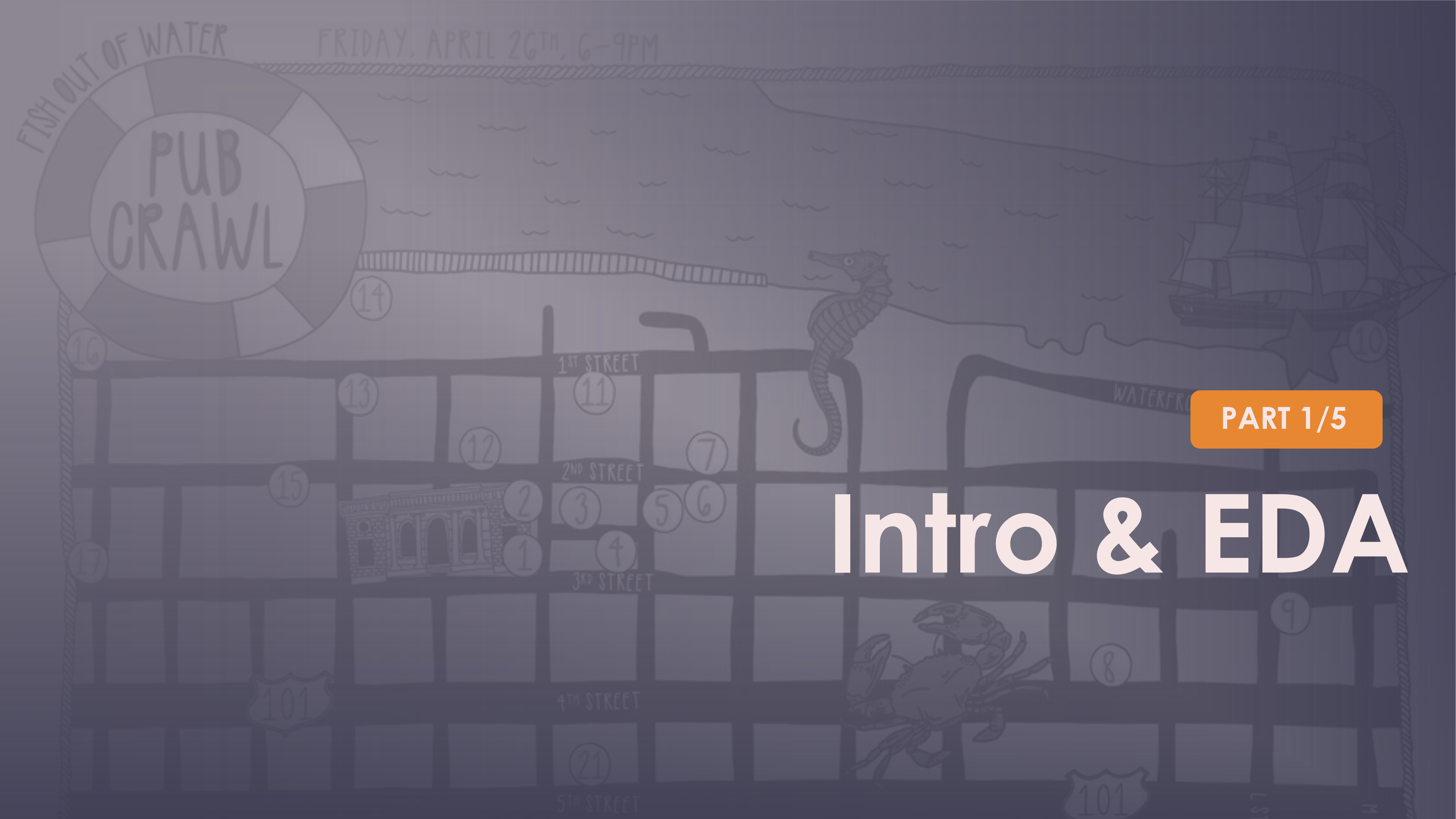
Peter Eusebio | Lola Johnston | Yannik Kumar

AGENDA

Intro ....
EDA ....
Features...........
Modeling ....
Evaluation ....
Takeaways ......

PART 1/5

Intro & EDA



Objective

PROBLEM TO SOLVE

Is it possible to predict intoxication (blood alcohol content of > 0.08%) using smartphone accelerometer data

GOALS

Explore different engineered features

Explore different modeling approaches

MEASURE OF SUCCESS

Achieve higher performance on task

Learning to Detect Heavy Drinking Episodes Using Smartphone Accelerometer Data

Jackson A Killian[1], Kevin M Passino[2], Arnab Nandi[2], Danielle R Madden[1], John Clapp[1]

[1]University of Southern California, Los Angeles CA 90089, USA

[2]The Ohio State University, Columbus OH 43210, USA

{jakillia,dmadden,johnclap}@usc.edu,{passino.1,nandi.9}@osu.edu

Abstract

Excessive alcohol consumption is a significant cause of death worldwide and an especially severe risk on college campuses. Recent work aimed at promoting healthier drinking habits has shown promise for the effectiveness of just-in-time adaptive interventions (JITAIs) delivered on mobile platforms *just before* the onset of heavy drinking episodes. However, delivering well-timed JITAIs is difficult for alcohol-related interventions because accurately detecting the onset of such episodes is challenging. Recent work has explored how smartphone data can be used to classify user drinking behavior, but current methods lack generalizability or make liberal use of private user information. We address these shortcomings to develop a reliable mobile classifier that uses only non-sensitive accelerometer data to detect periods of heavy drinking. Additionally, we examine multiple models and discern a new feature set that increases prediction power by as much as 14%. To build our data set, we collected and analyzed smartphone accelerometer readings and transdermal alcohol content (TAC) for 13 subjects participating in an alcohol consumption field study. The TAC readings served as the ground-truth when training the system to make classifications, unlike previous literature which used potentially biased self-reports. Our best classifier detected heavy drinking events with 77.5% accuracy.

1 Introduction

Excessive alcohol consumption is an avoidable health risk, yet in 2016 it accounted for 5.3% of deaths worldwide [WHO, 2018]. On college campuses, alcohol-related risk is especially

drinking. However, a recent study which delivered *hourly* mobile interventions to participants during drinking events showed no significant reduction in the amount of alcohol consumed [Wright *et al.*, 2018], suggesting that overly frequent messaging can reduce the effectiveness of interventions. This highlights the need for accurate, *targeted* messages to participants during drinking episodes. In fact, such just-in-time adaptive interventions (JITAIs) are an active and promising area of research for health domains such as physical inactivity [Consolvo *et al.*, 2008], smoking [Riley *et al.*, 2008], obesity [Patrick *et al.*, 2009], and alcoholism [Nahum-Shani *et al.*, 2017]. One study of recovering alcoholics showed that JITAIs delivered while approaching a bar significantly reduced risky drinking behavior [Gustafson *et al.*, 2014], showcasing how well-timed messages delivered *just before* risky episodes could promote healthier behavior. While promising, work is needed to design JITAIs that apply to college students in general, since their drinking episodes can begin in a variety of complex scenarios from bars, to house parties, to private settings.

The most reliable method for detecting a drinking event is by directly measuring blood alcohol content (BAC) or a proxy such as transdermal alcohol content (TAC). To deliver alcohol-related JITAIs, researchers must passively measure BAC or TAC in real time, but this can be challenging. Some smartphone applications allow users to enter their height, weight, and number of drinks consumed over a period of time to calculate their estimated BAC, but these require active user input that could lead to selection bias and hinder large-scale adoption [Myrecek, 2019]. Some smartwatches can measure TAC but these devices are expensive [BACtrack, 2019] among other roadblocks [Adapa *et al.*, 2018]. *In this work we develop a smartphone-based system to passively track a user's level of intoxication via accelerometer signals to support the delivery of mobile just-in-time adaptive interventions during heavy drinking events.* Smartphone-based solutions are

Our data comes from electronic devices carried by each participant.

13 participants

RAW DATA
14 MILLION
ROWS

18 hour
bar crawl

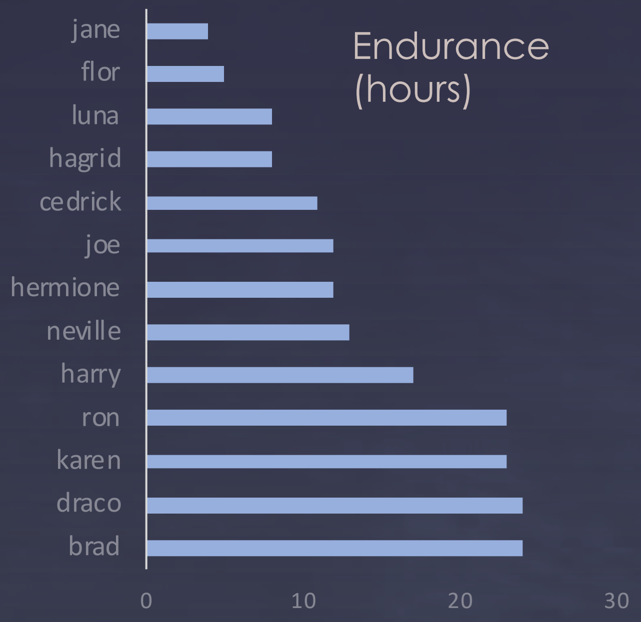
Smart Phone
Accelerometer
(50 hz)

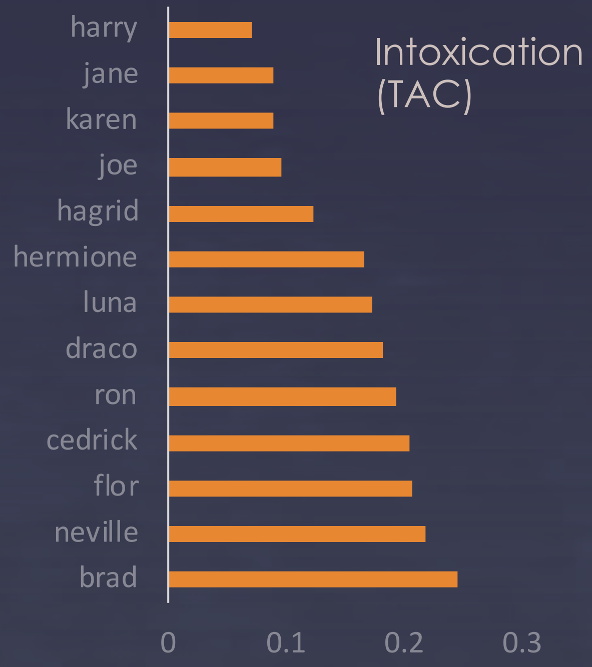
TAC Readings

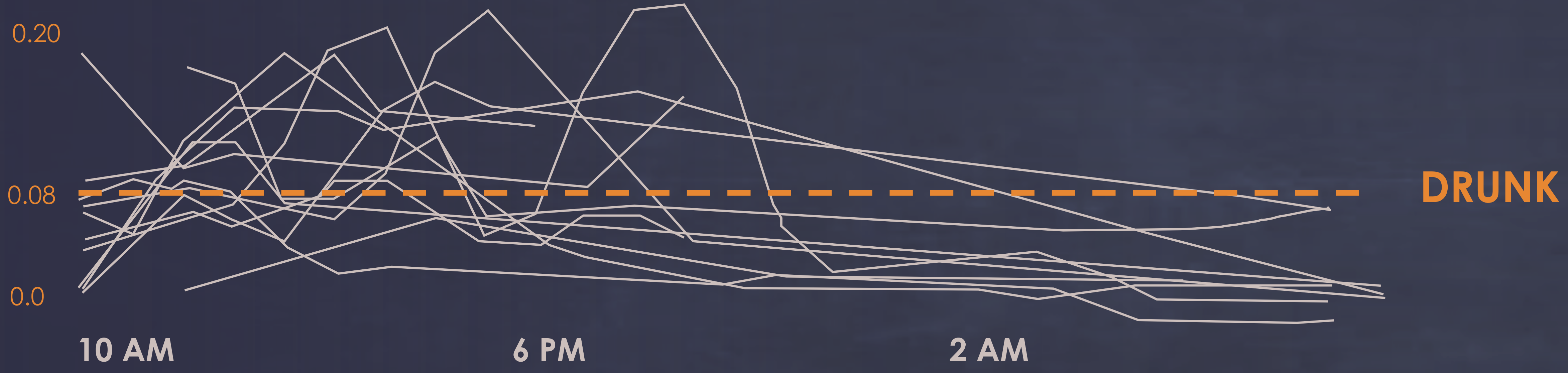
Our participants were very active.

Longest endurance: **Brad**

Highest Intoxication: **Brad**

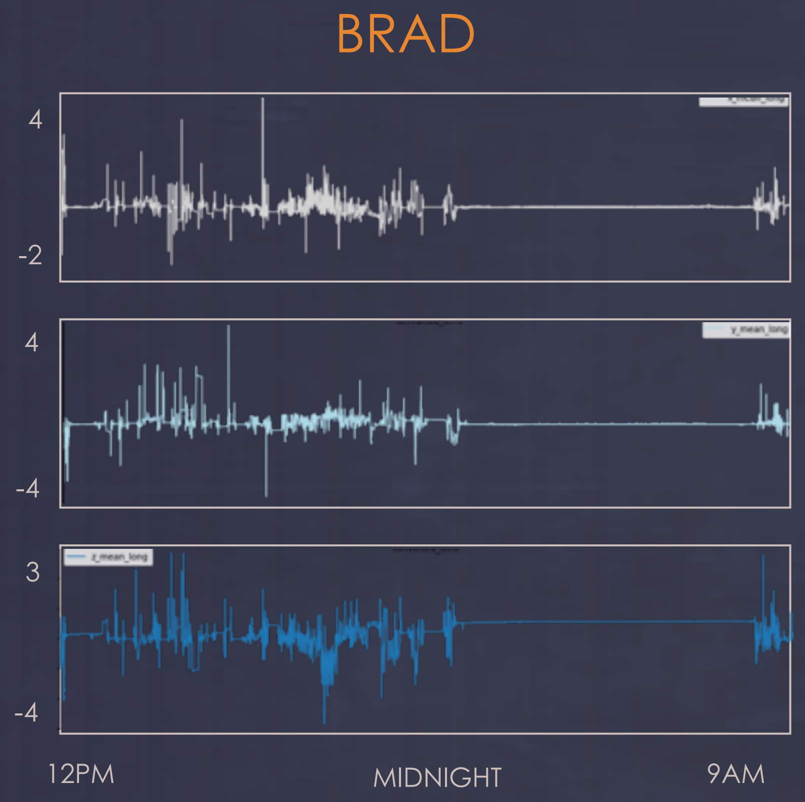


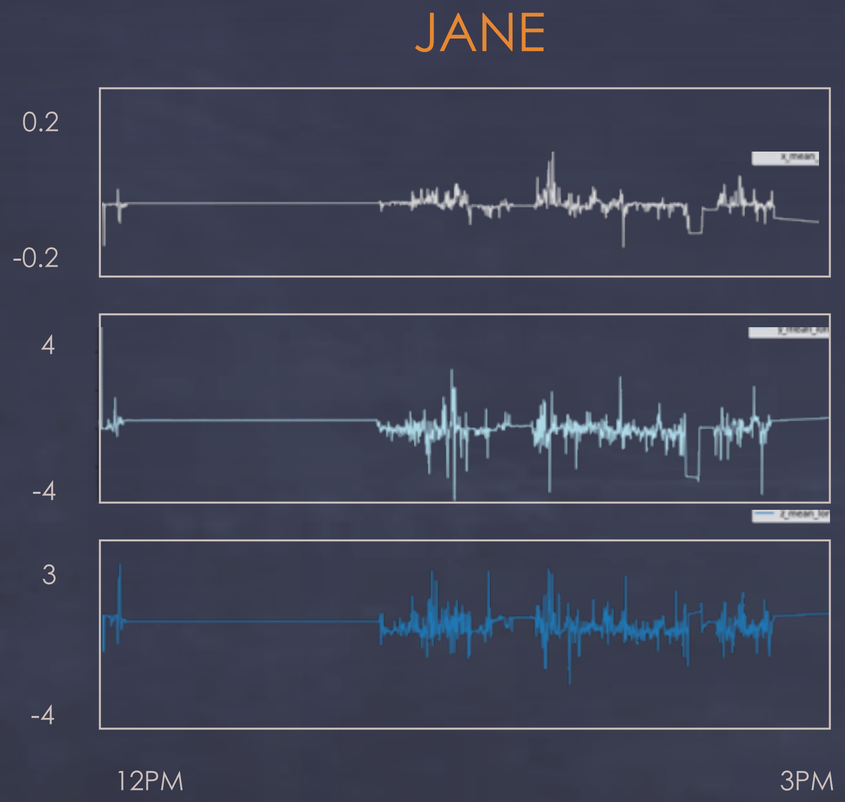




Our data comes from electronic devices carried by each participant.

Smart Phone Accelerometer





PART 2/5

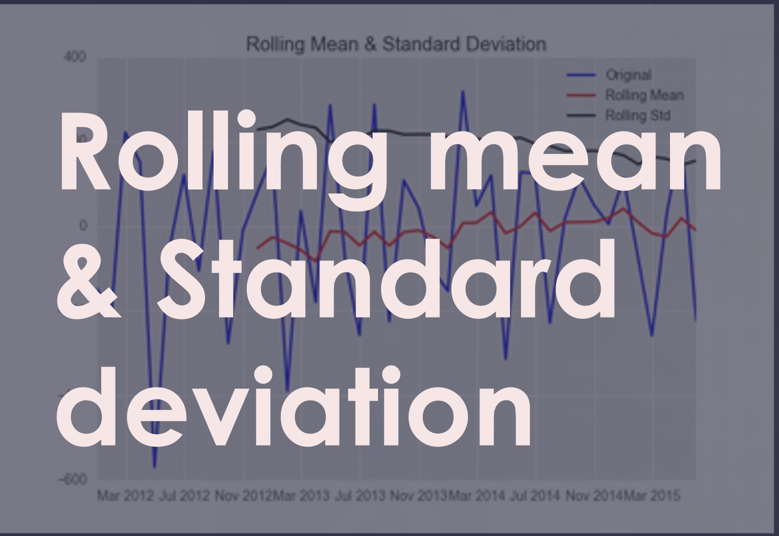
Feature selection

We made some assumptions and avoided others.

1) Assume some periodicity in acceleration
2) Uncertain reference frame
3) Cannot assume that participant drinking times are uncorrelated

We analyzed the behavior of acceleration over time.

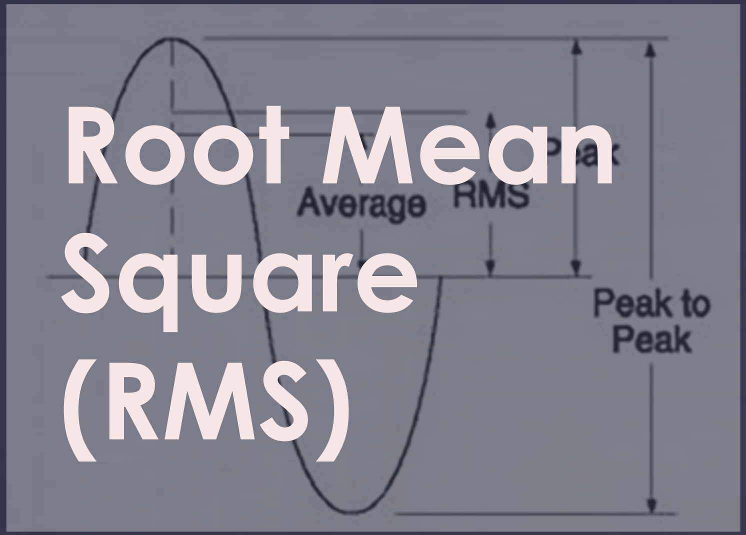
Rolling mean & Standard deviation



Analyze behavior of accelerometer data on each axis

Windows (sec): 0.25, 2.00, 10.00

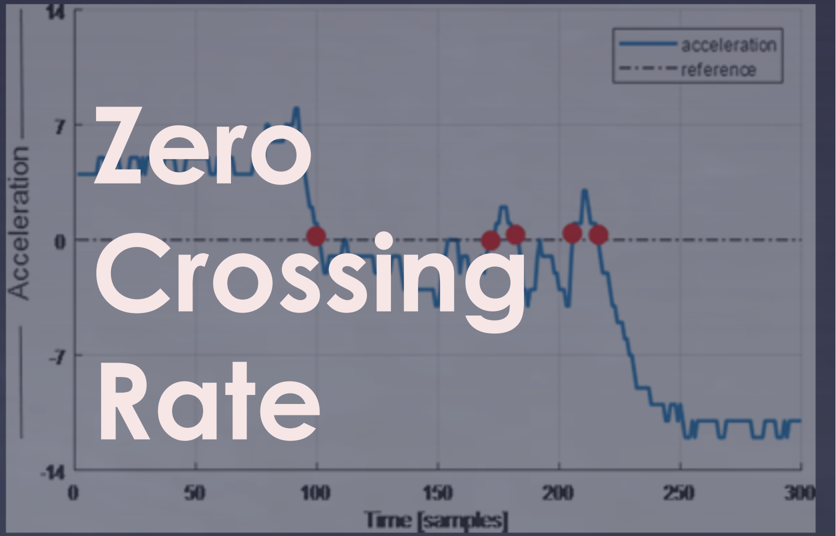
Root Mean Square (RMS)



Gauge activity levels of 2 sec RMS for raw acceleration on each axis

Difference in RMS over 1 and 5 sec

Zero Crossing Rate



Shows how motion changes over time

Zero crossing rate in a 500 second window

#of sign changes / # of samples

https://www.linearmotiontips.com/what-does-rms-mean-and-how-does-it-apply-to-linear-systems/
https://link.springer.com/article/10.1007/s11042-019-08463-7/figures/5
https://www.researchgate.net/figure/Rolling-Mean-and-Rolling-STD-Seasonal-First-Difference-Results-of-Dickey-Fuller-Test_fig8_310245845

We looked for frequency information in acceleration.

Inconsistent periodicity

MFCCs used instead of Direct FFT

Existing literature treated acceleration like audio signal

Extracted mel-frequency cepstral coefficients as representation of short-term power spectrum

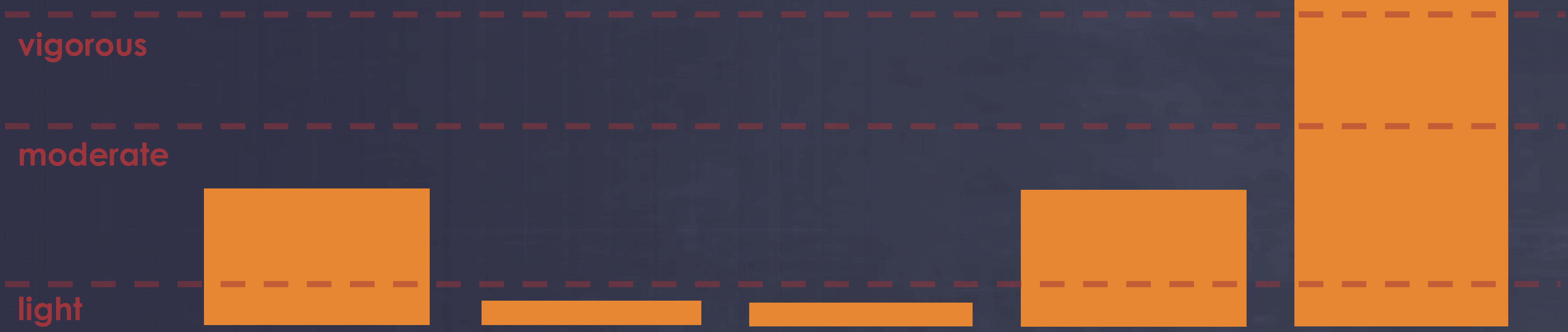
~10 sec windows

Power Spectrum

We assessed activity levels of our participants.

Gait Analysis sensormotion

1) Smooth *a* for x, y, z with 0.25 sec avg
2) Apply low-pass filter with 10 hz cutoff
3) Identify peaks as min 0.6 g, min 10 samples apart (~5 hz)
4) Extract step count and cadence for 500 second window

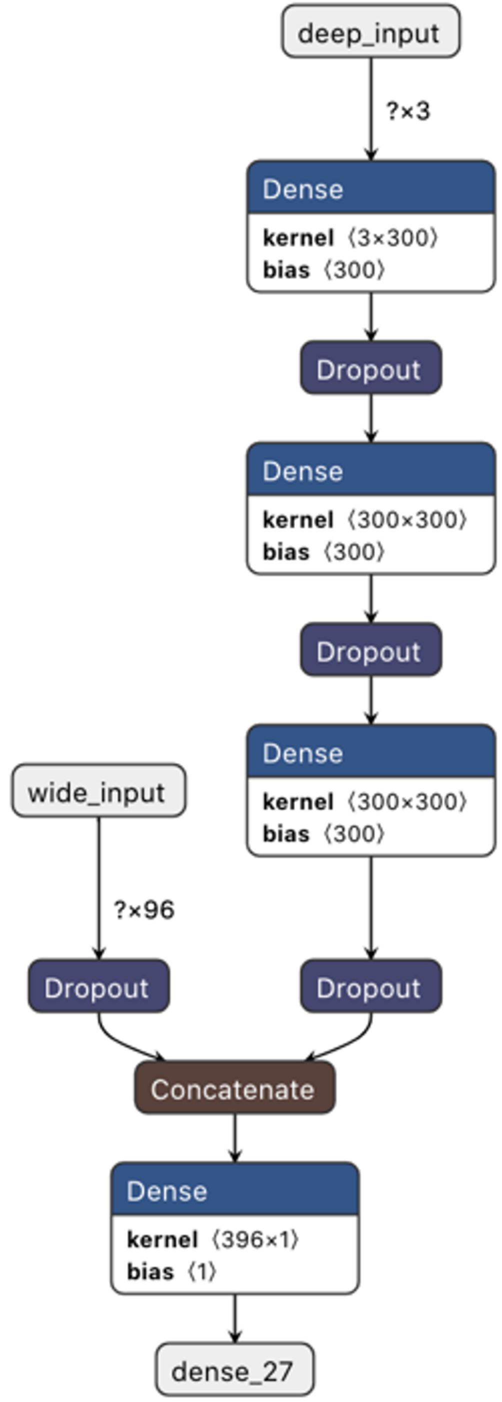


https://github.com/sho-87/sensormotion


PART 3/5
modeling

We fit many classes of models.

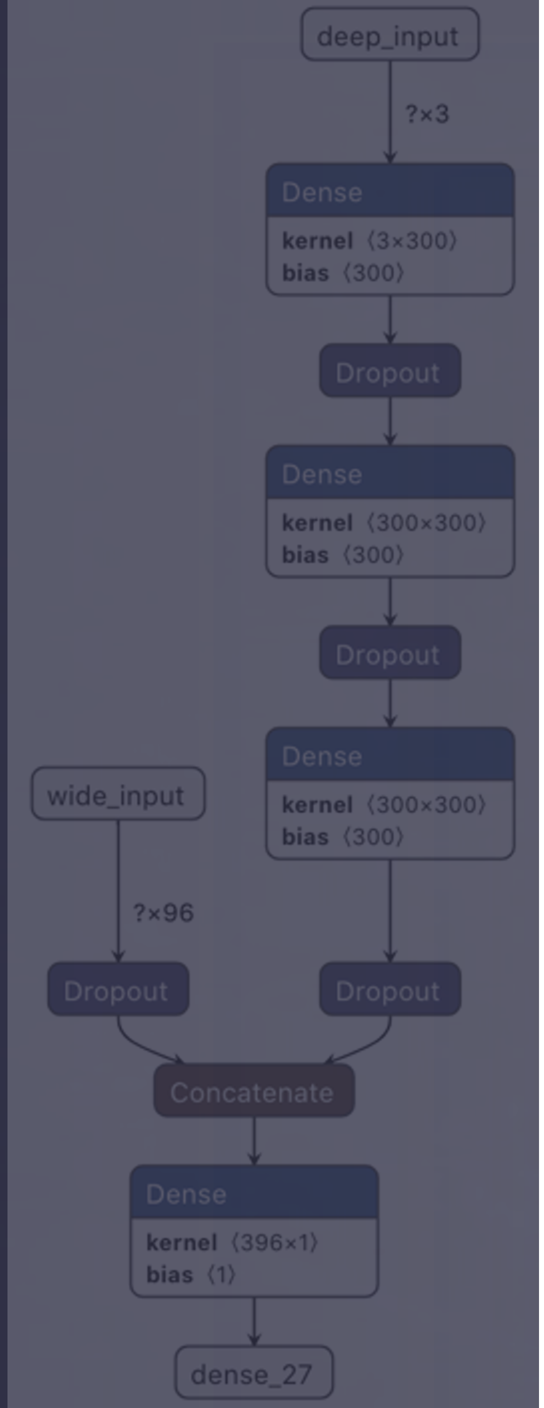
LOGISTIC REGRESSION
NAÏVE BAYES
ADABOOST
GRADIENT BOOST
RANDOM FOREST CLASSIFIER
SUPPORT VECTOR MACHINES
K NEAREST NEIGHBORS

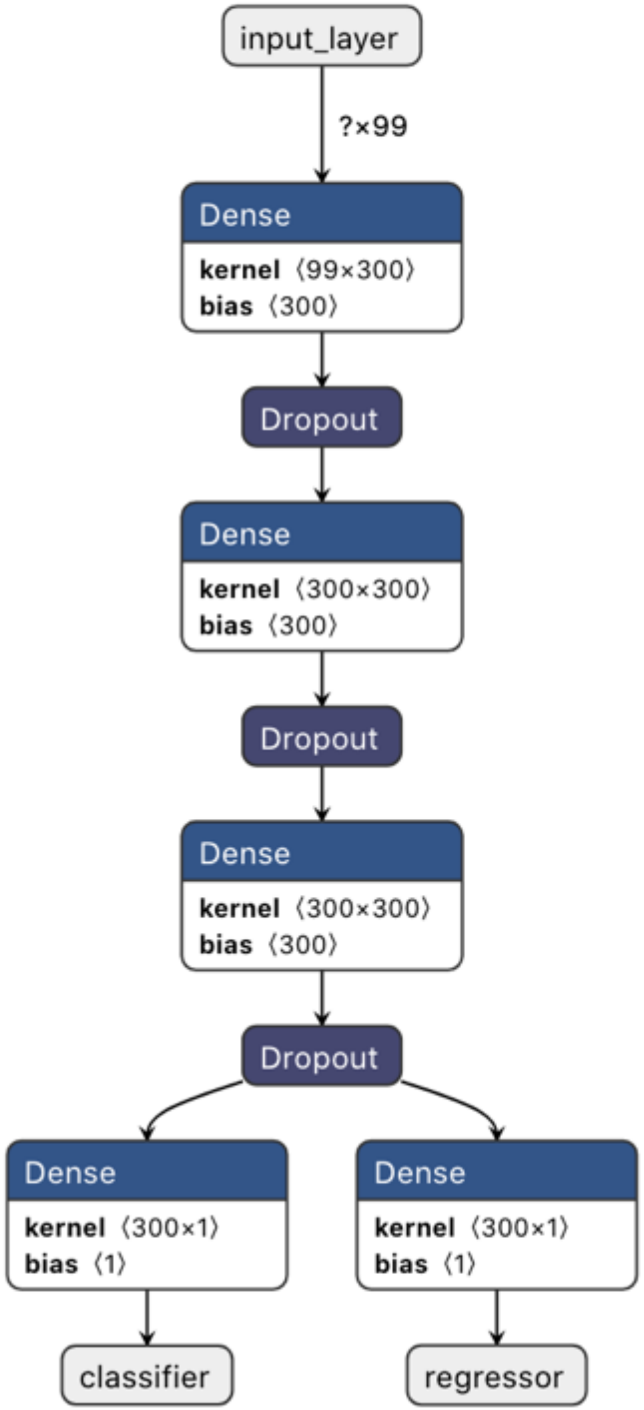


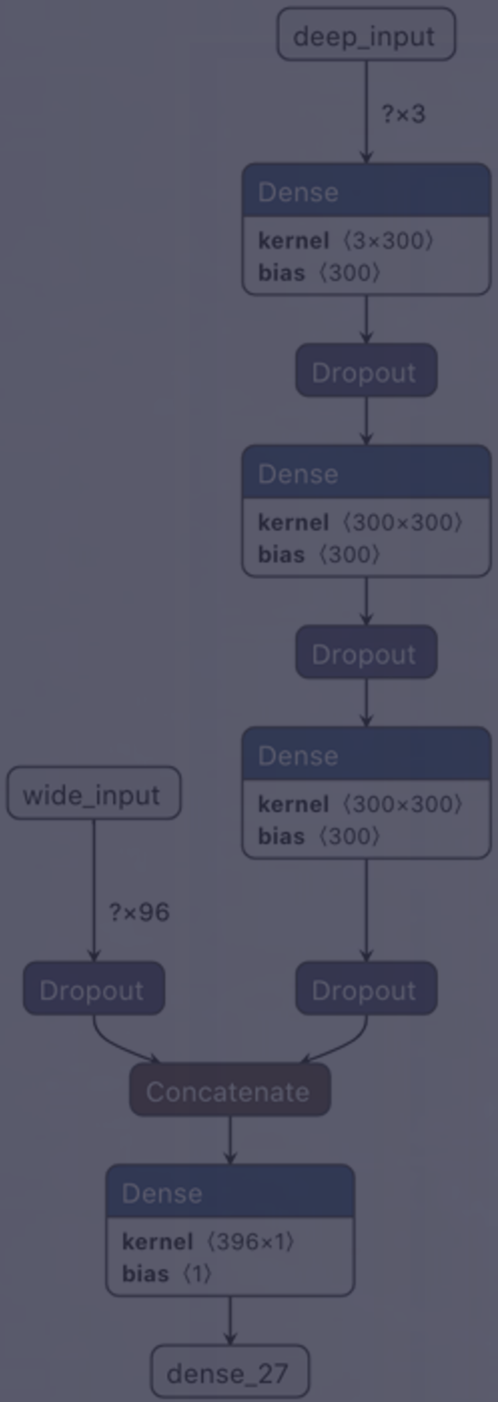
Wide and deep

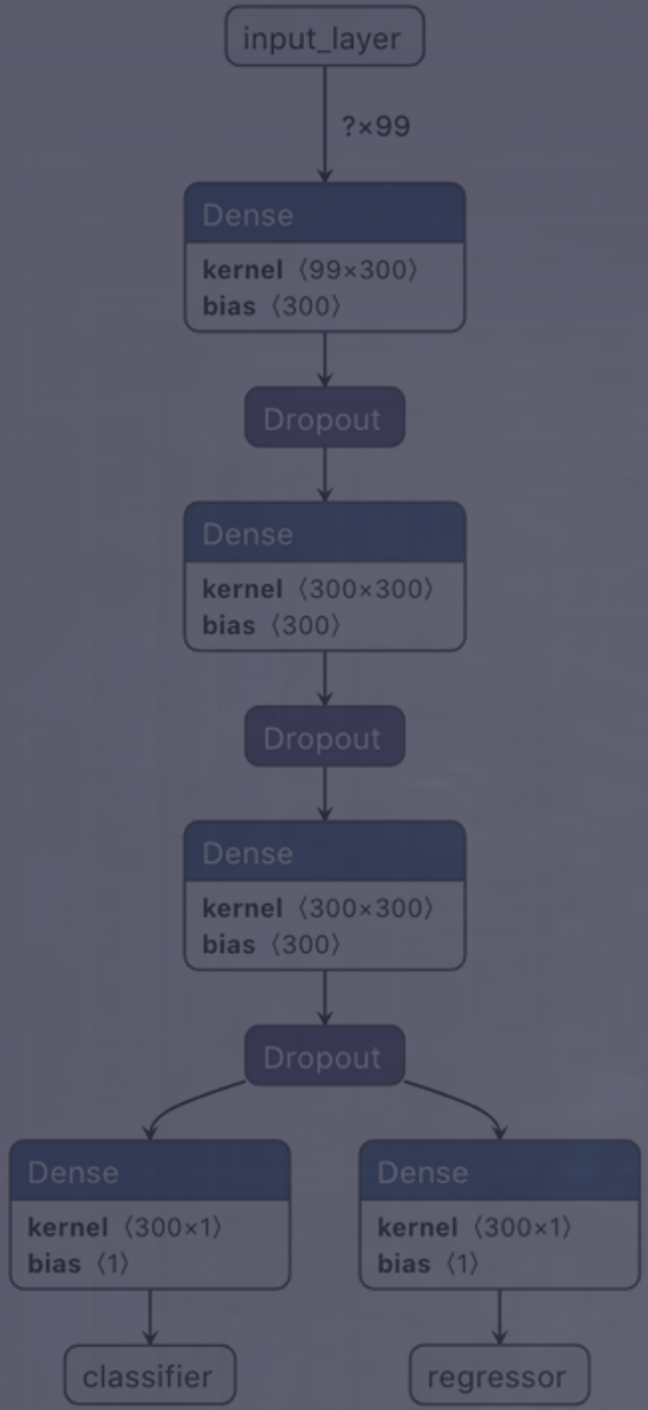
Wide and deep

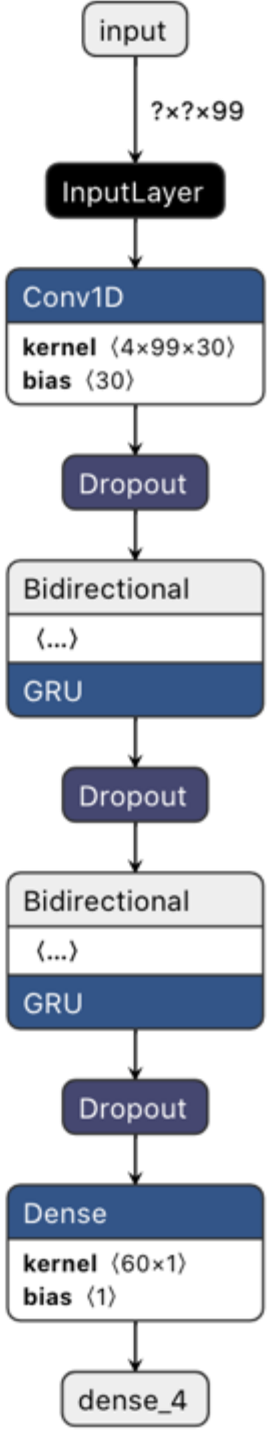
Multi-task







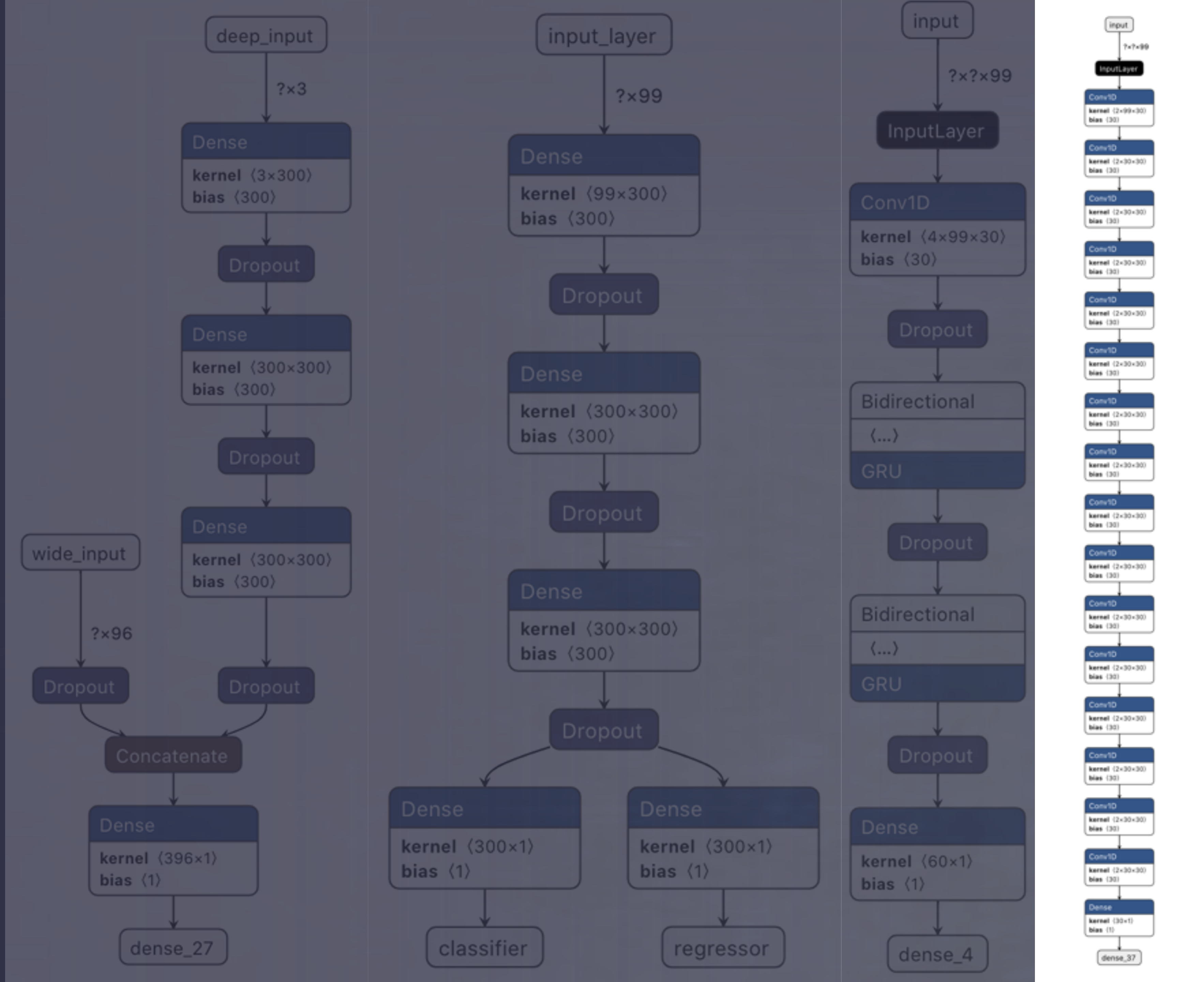




Wide and deep

Multi-task

Convolutional + bidirectional recurrent



Wide and deep

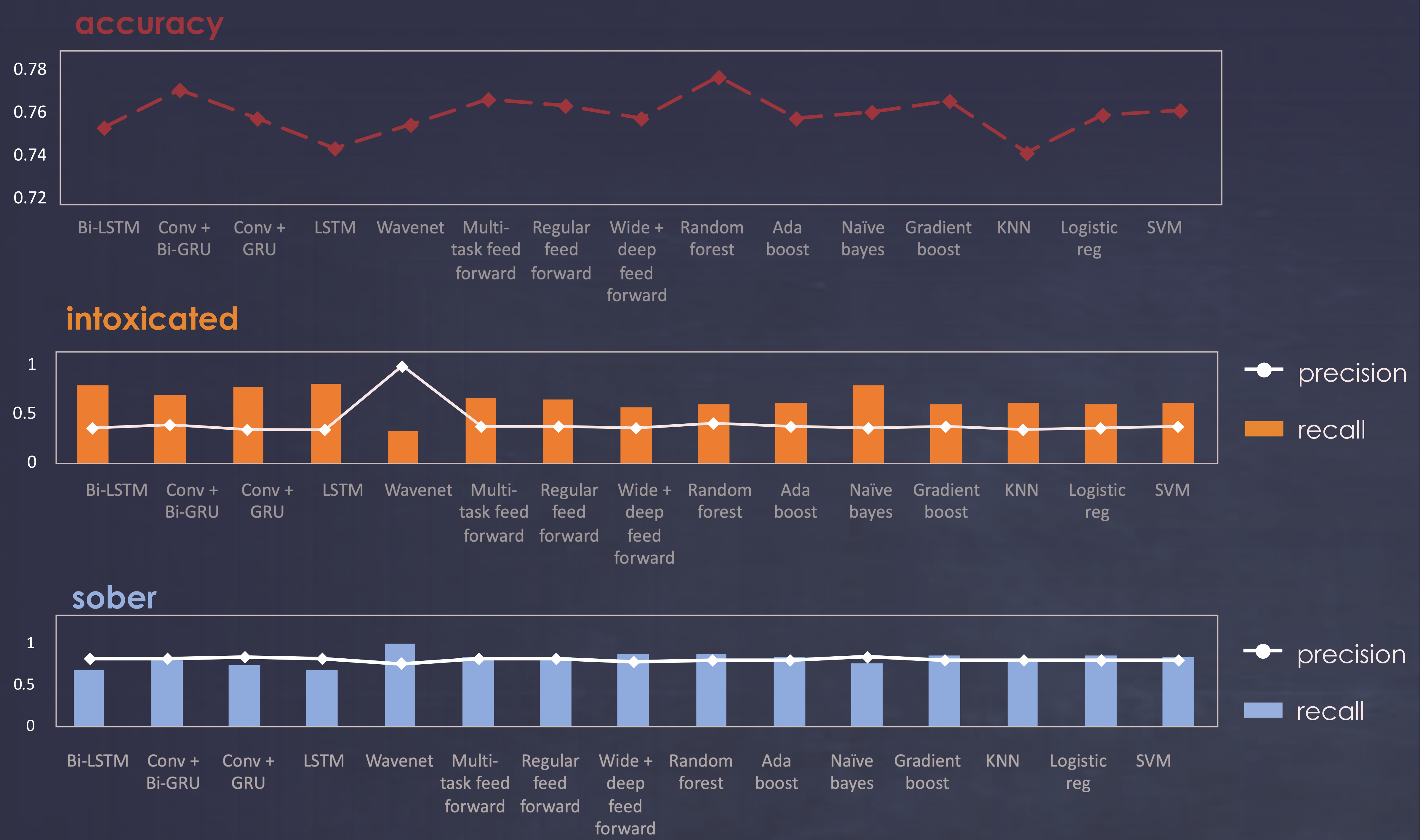
Multi-task

Convolutional + bidirectional recurrent

Wavenet

PART 4/5

evaluation


accuracy
0.78
0.76
0.74
0.72
Bi-LSTM
Conv + Bi-GRU
Conv + GRU
LSTM
Wavenet
Multi-task feed forward
Regular feed forward
Wide + deep feed forward
Random forest
Ada boost
Naïve bayes
Gradient boost
KNN
Logistic reg
SVM
intoxicated
1
0.5
0
precision
recall
Bi-LSTM
Conv + Bi-GRU
Conv + GRU
LSTM
Wavenet
Multi-task feed forward
Regular feed forward
Wide + deep feed forward
Random forest
Ada boost
Naïve bayes
Gradient boost
KNN
Logistic reg
SVM
sober
1
0.5
0
precision
recall
Bi-LSTM
Conv + Bi-GRU
Conv + GRU
LSTM
Wavenet
Multi-task feed forward
Regular feed forward
Wide + deep feed forward
Random forest
Ada boost
Naïve bayes
Gradient boost
KNN
Logistic reg
SVM

takeaways

PART 5/5

Some considerations for the future.

1) Shift focus to better data not more complex models

2) Features that capture angular motion GYROSCOPE

3) Increase participant size

individual contribution

Lola – eda, modeling sklearn
Yannik – modeling deep learning
Peter – feature extraction


Thank you.