

**Assistant Professor:** *thehabitslab.com*

**email :** [nabil@northwestern.edu](mailto:nabil@northwestern.edu)

*Computer Science St.*

*Behavior Medicine Rd.*

mobile health, HCI, &  
passive sensing analytics

*Preventive Medicine Way*

**Preventive Medicine**  
**Computer Science (courtesy)**  
**Electrical Computer Engineering (courtesy)**

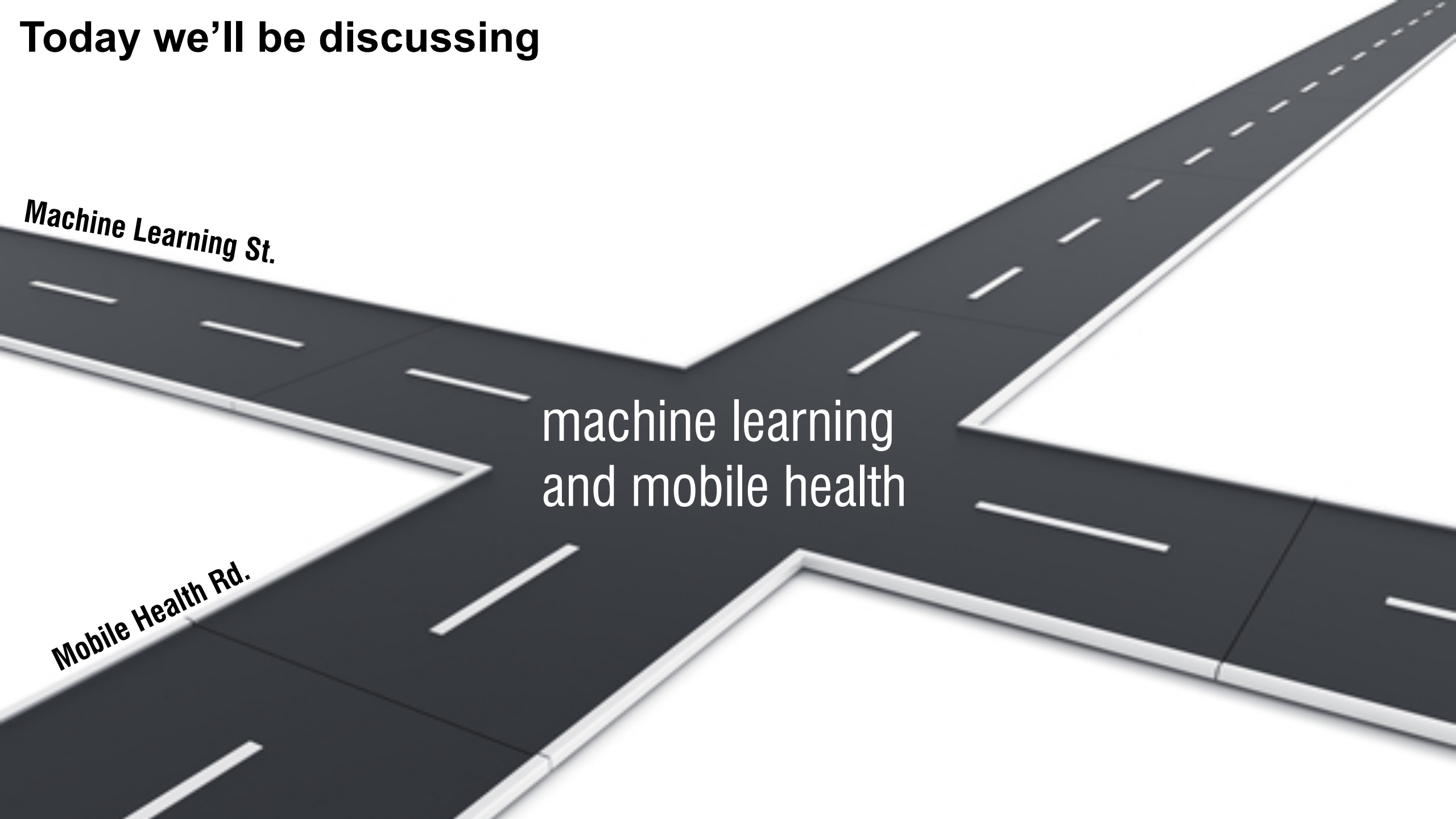
**HAB**  
its

**Today we'll be discussing**

***Machine Learning St.***

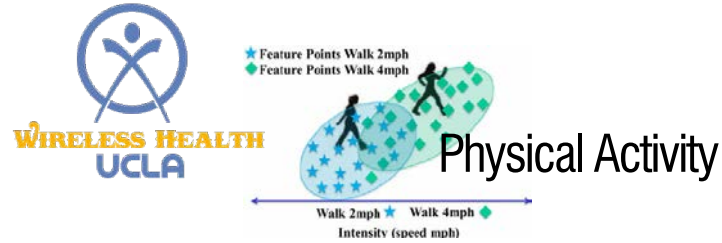
***Mobile Health Rd.***

**machine learning  
and mobile health**

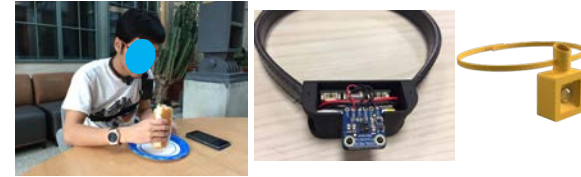


# my story...

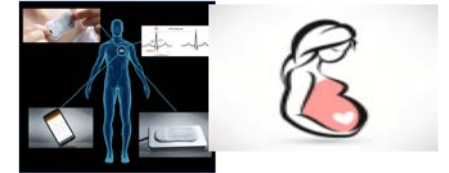
HABits Lab  
Health Aware Bits Lab



Eating

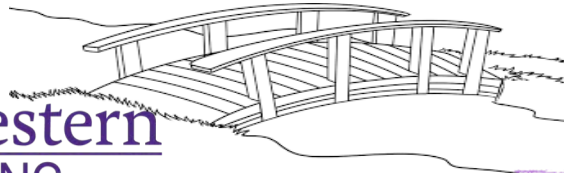


Stress



HABits Lab  
Faculty at Northwestern

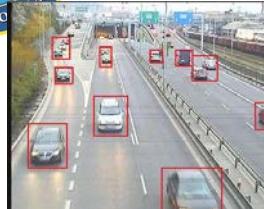
Northwestern  
ENGINEERING



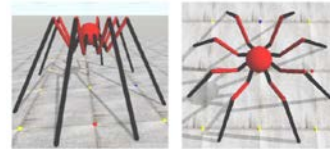
Ucla



PhD in Computer Science  
(Wireless and mHealth)



Defense contractor  
for 8 years



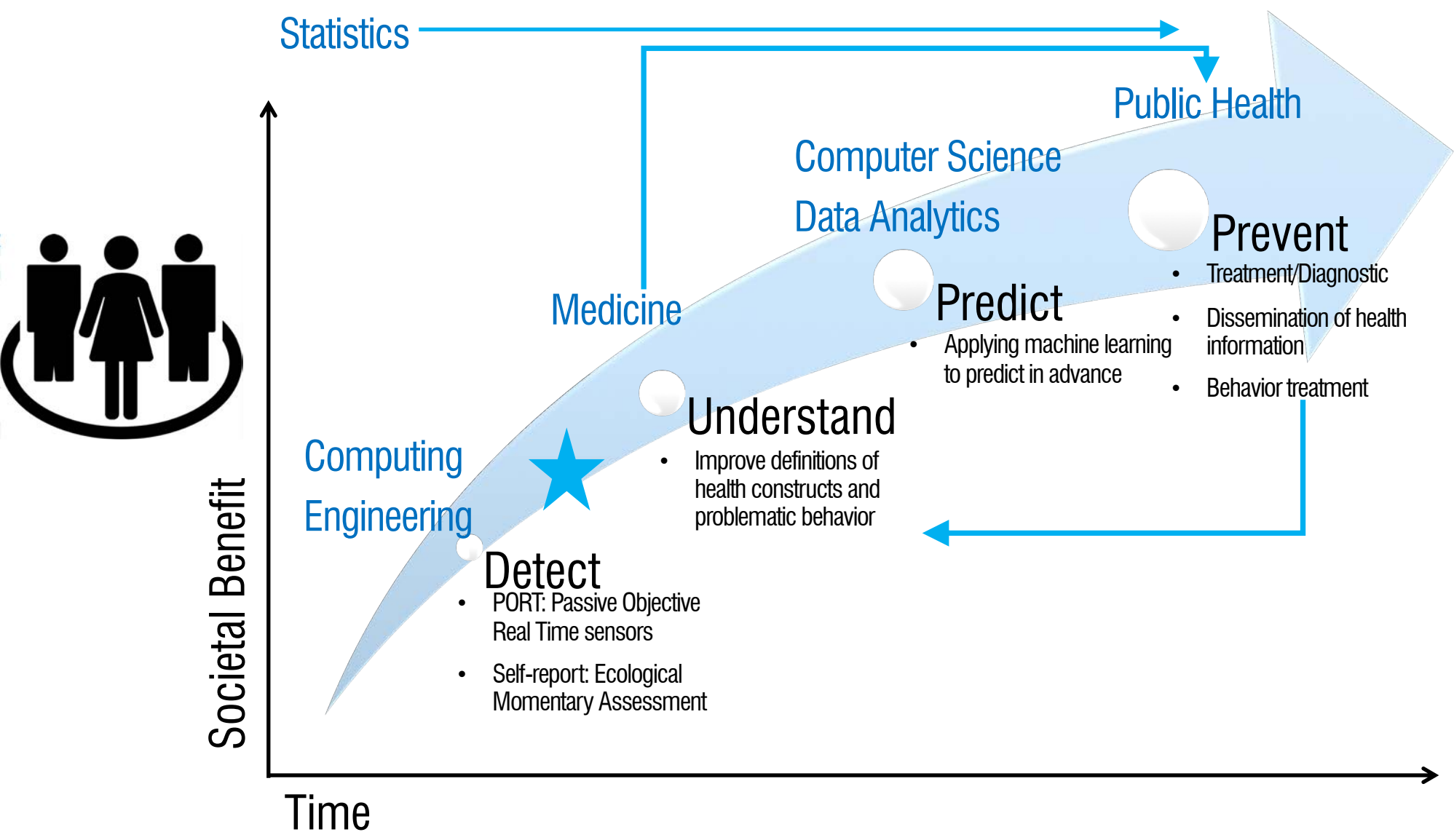
Masters in  
AI/Robotics

Ucla

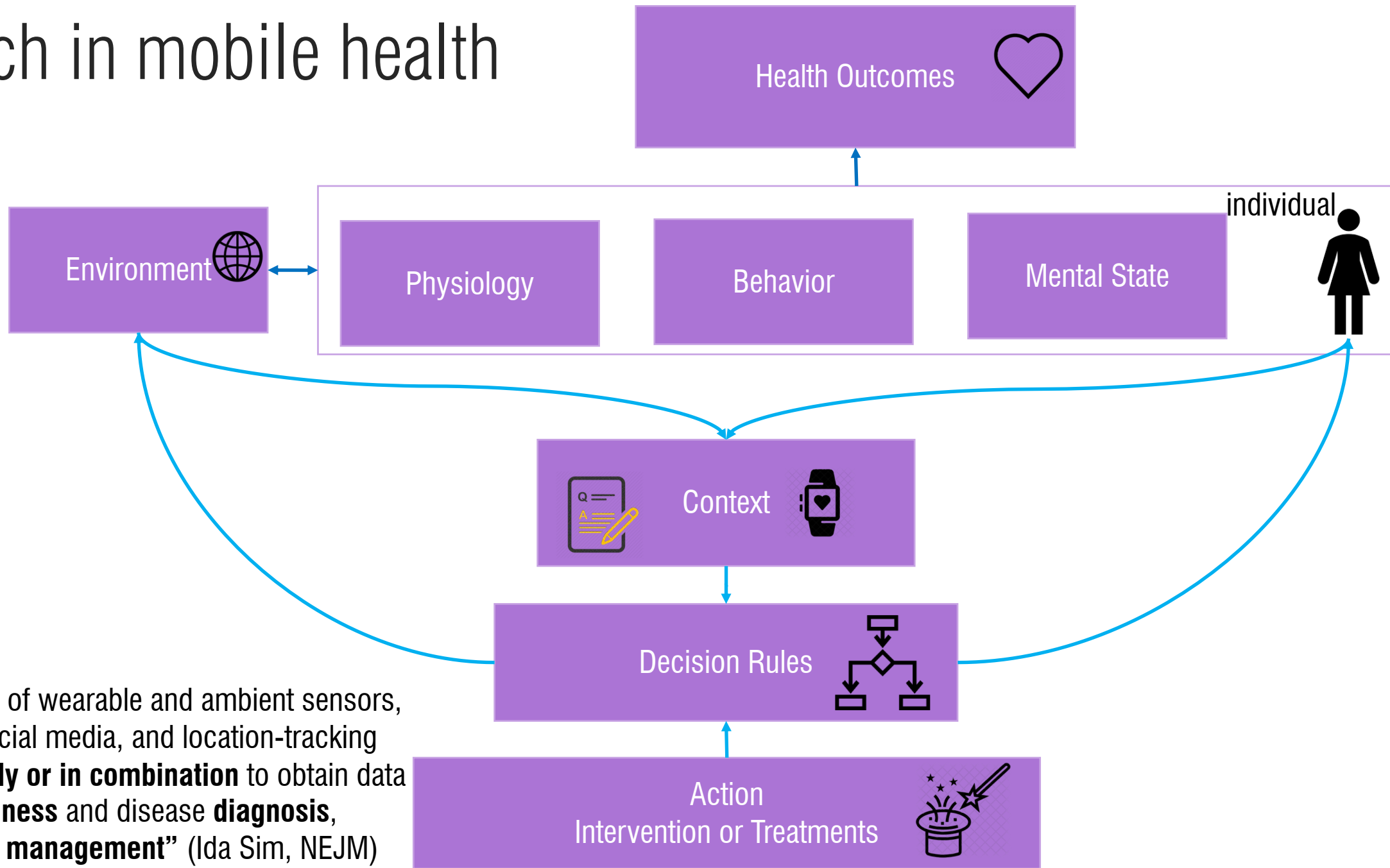
BS in CS and Minor  
in Sociology



# stages of research in mobile health and prevention



# research in mobile health



“The application of wearable and ambient sensors, mobile apps, social media, and location-tracking technology **singly or in combination** to obtain data pertinent to **wellness** and disease **diagnosis, prevention, and management**” (Ida Sim, NEJM)

# questions in mobile health

1. Measures: How do we assess or measure *outcome* or *context*?

- Direct
- Indirect (proxy)

2. Gold Standard Measure

3. Time Points: When and how often do we run observations and decision rules?

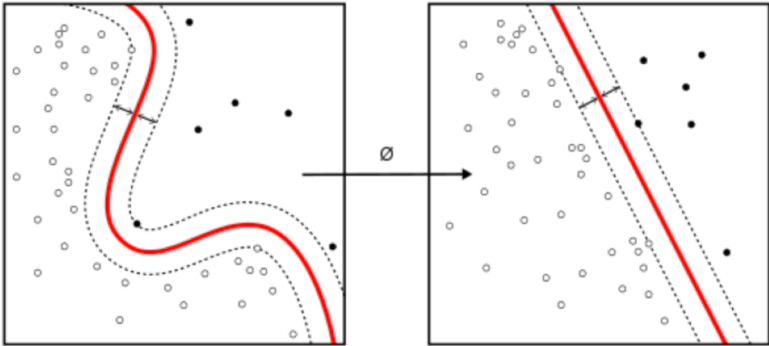
- Continuous or not
- Frequency/sample rate
- Real-time or end of day

4. Decision Rule: How do I construct a data analytic pipeline?

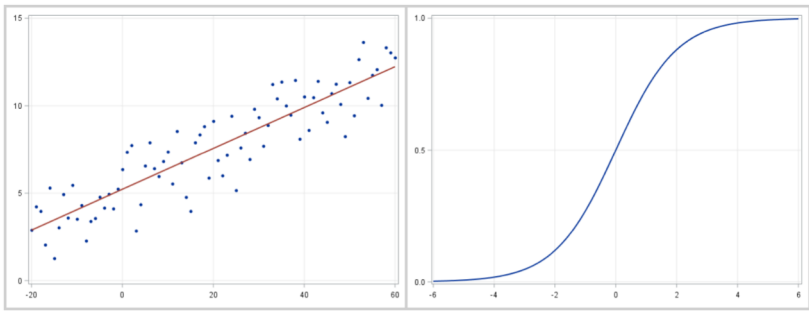
5. Treatments: What should the set of treatment options or intervention component's be?

# Supervised ...to detect and predict

## Classification

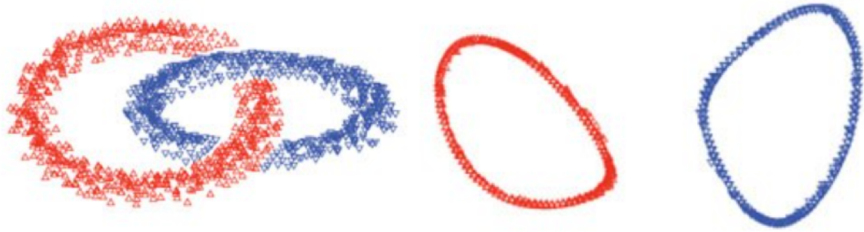


## Regression

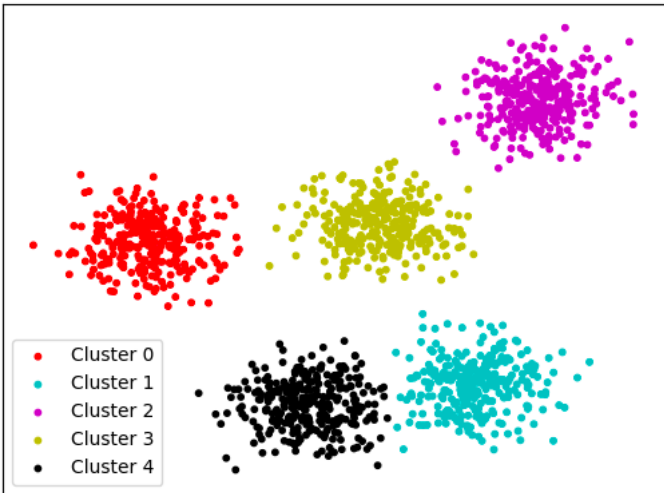


# Unsupervised ...to represent and organize

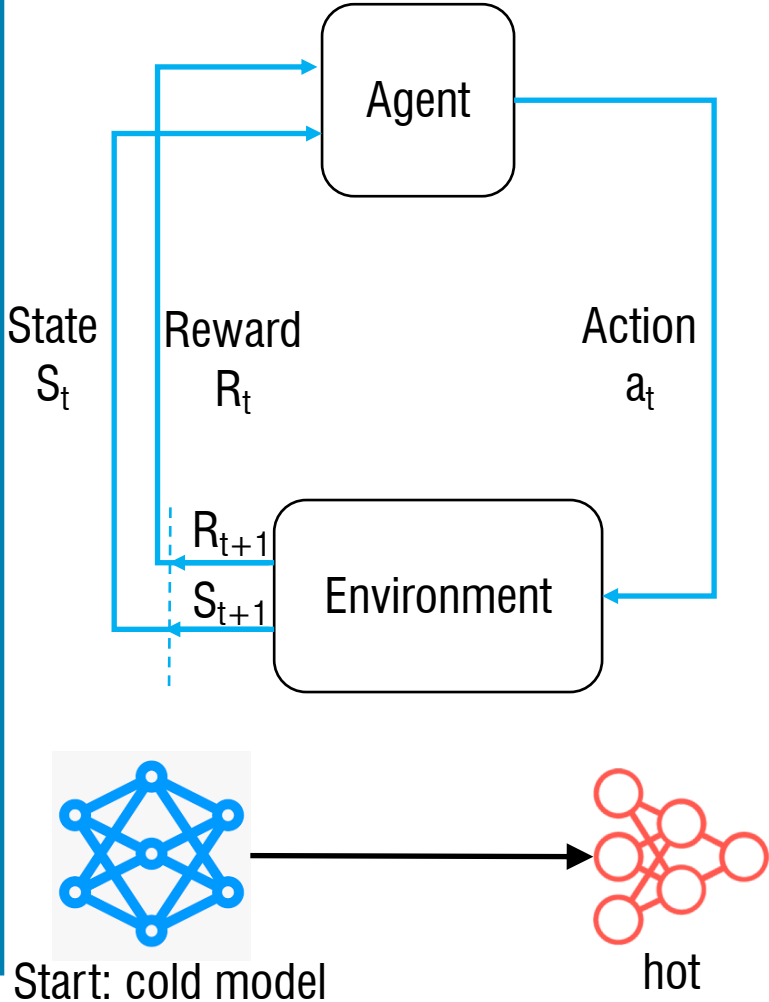
## Dimensionality Reduction



## Clustering



# Reinforcement Learning ...to act optimally



*Construct*



Eating



Stress



UV exposure

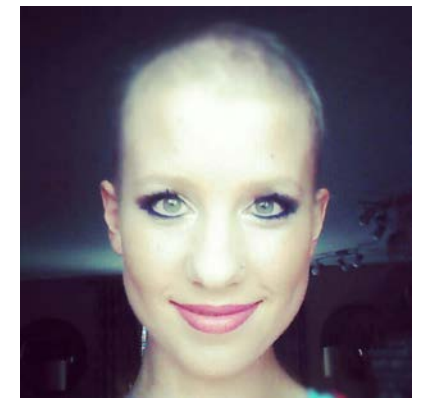
*Population*



Obesity



Pregnant women



Melanoma Survivors

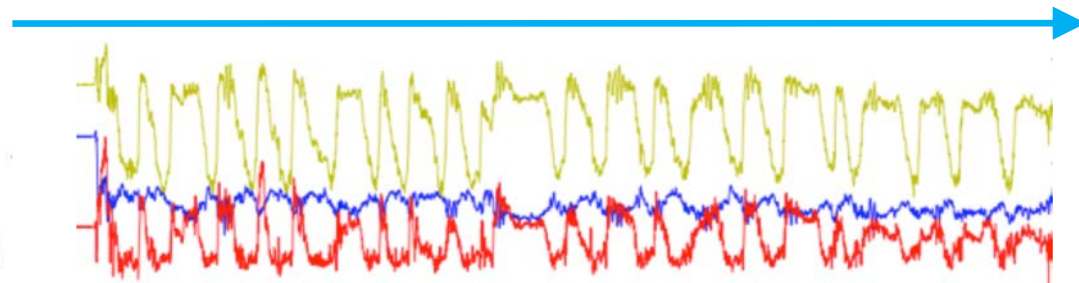
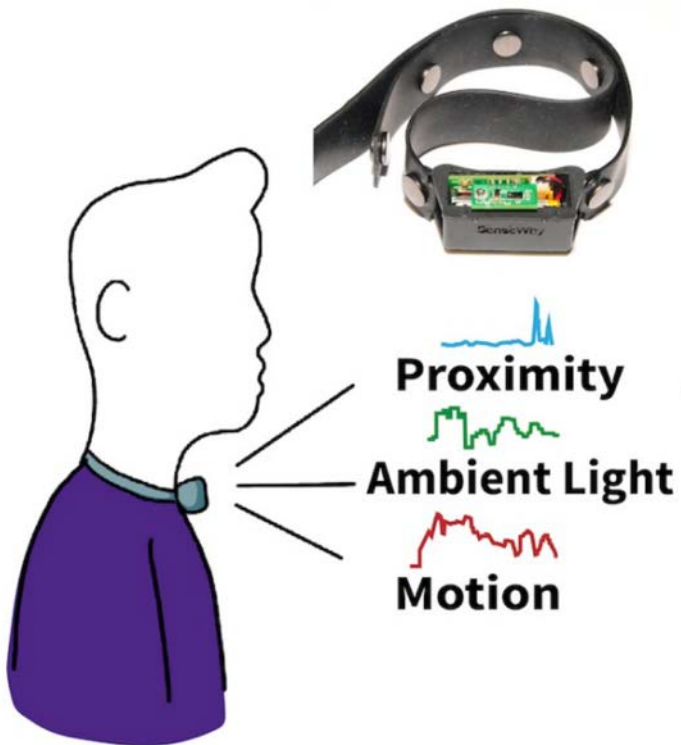


## event detection problem

Def: Suppose we have a dynamical system in which an event of interest is either occurring or not occurring at each time instant  $t$ . Given a numerical representation  $x_t$  of the state of the system at time  $t$ , infer whether the event occurred at time  $t$  or not.

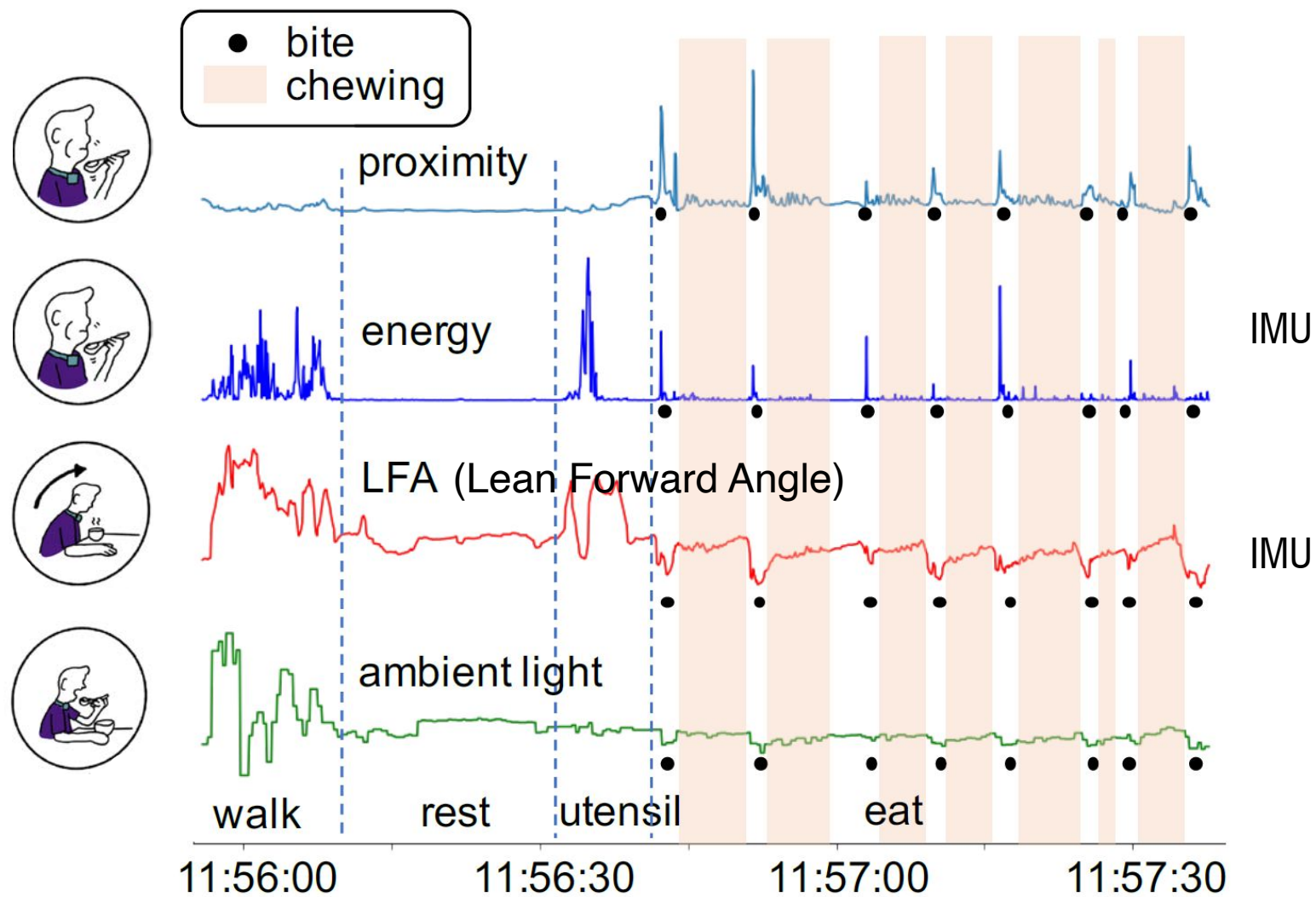
# example

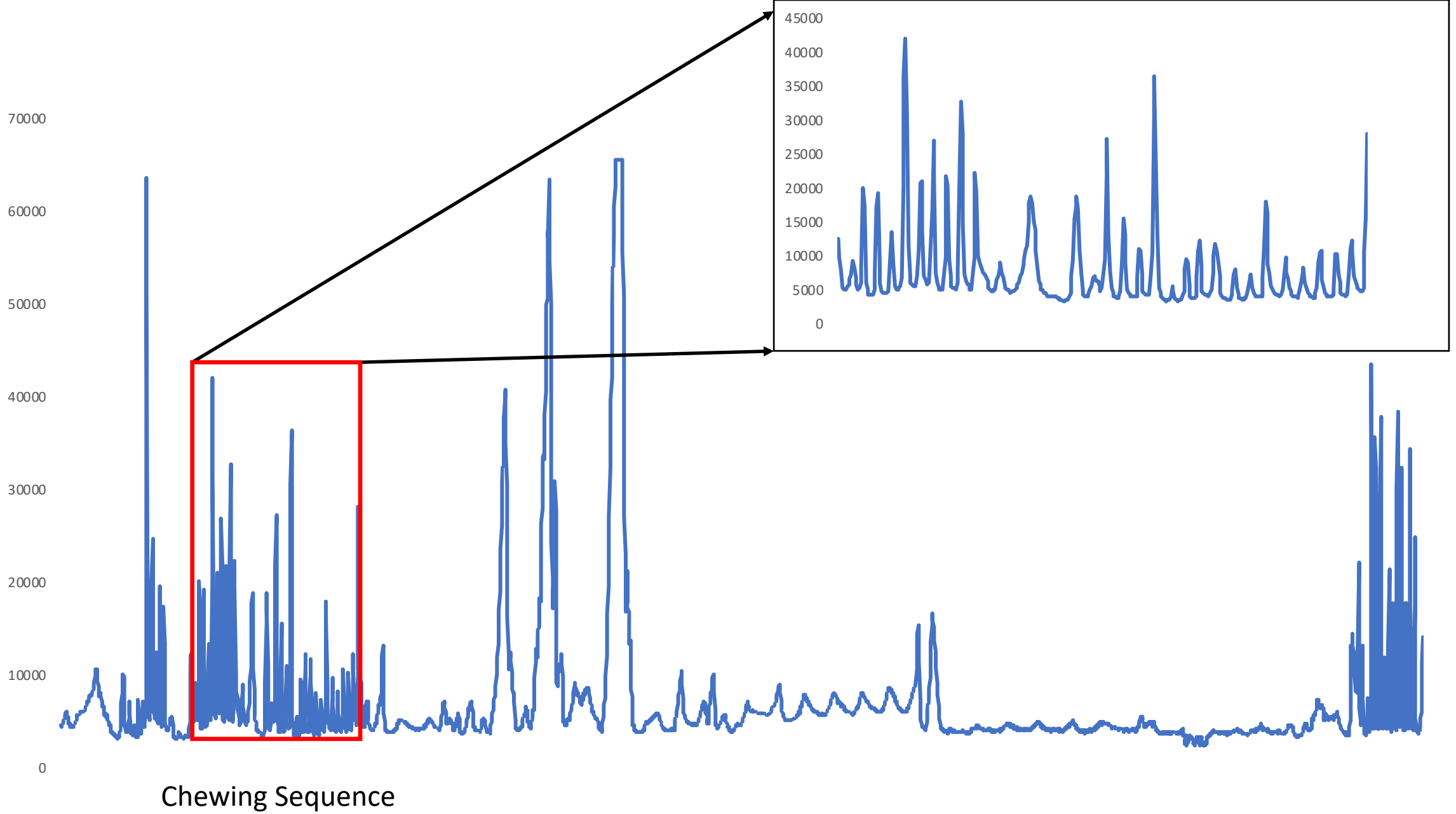
Suppose we have data from a wearable neckworn sensor. Based on the data from the proximity, ambient light, and motion sensor, within a given time segment  $\Delta t$ , determine whether that time segment involves chewing or not.

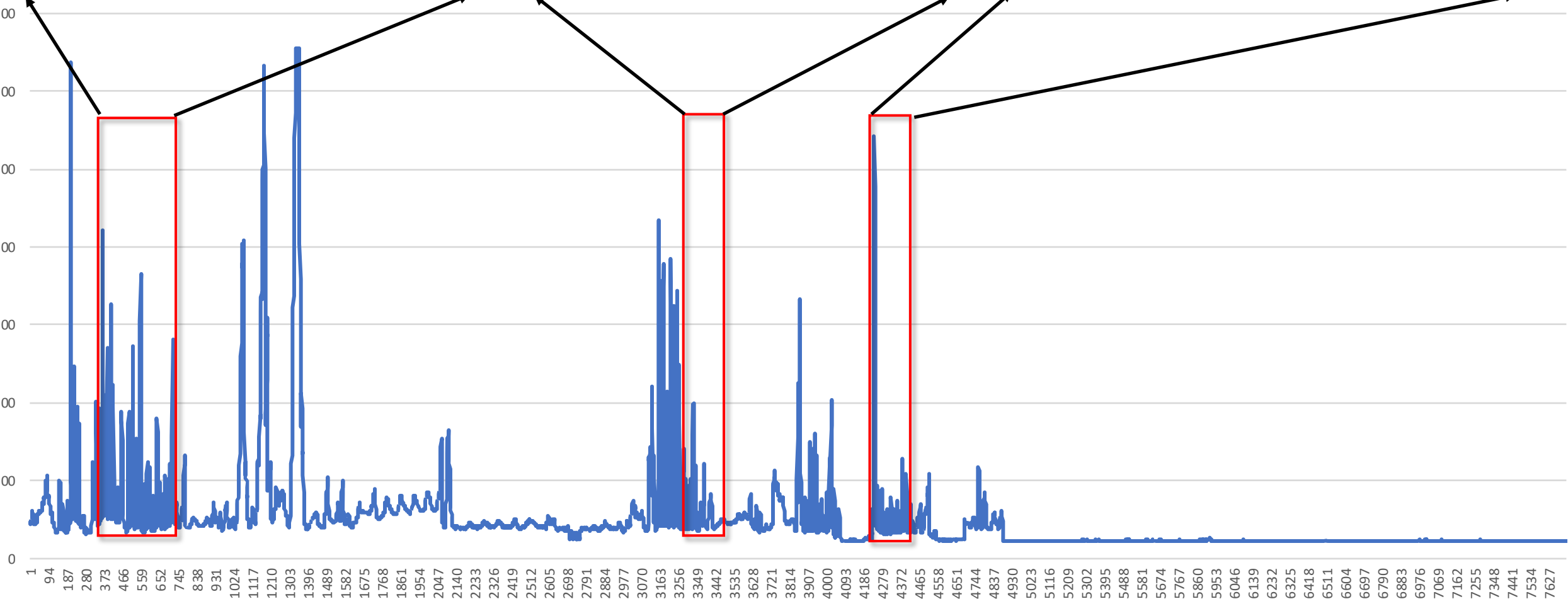
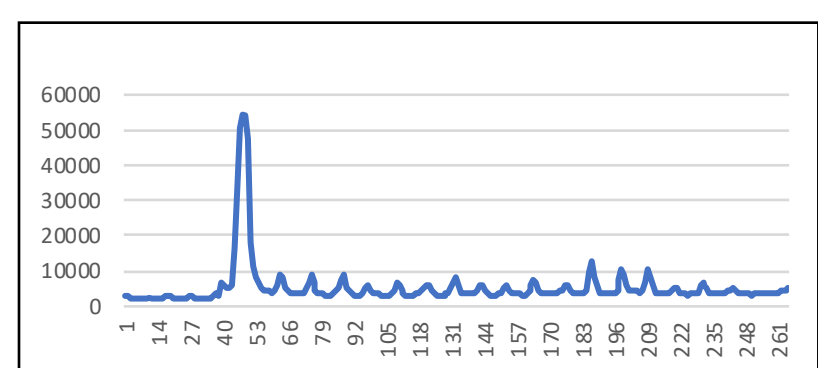
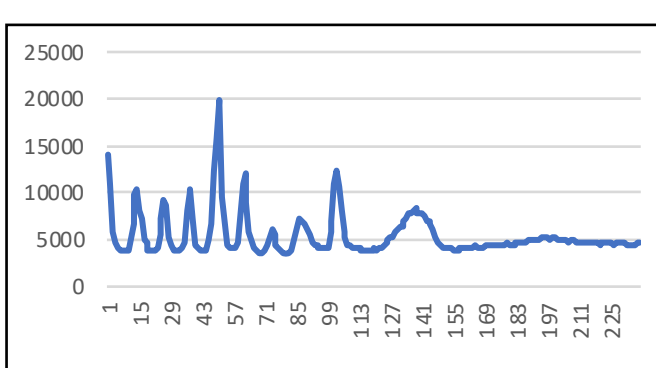
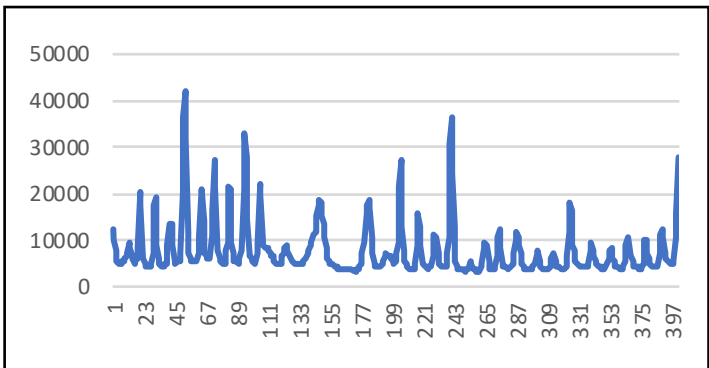


Chewing?

# processing **four** signals from NeckSense



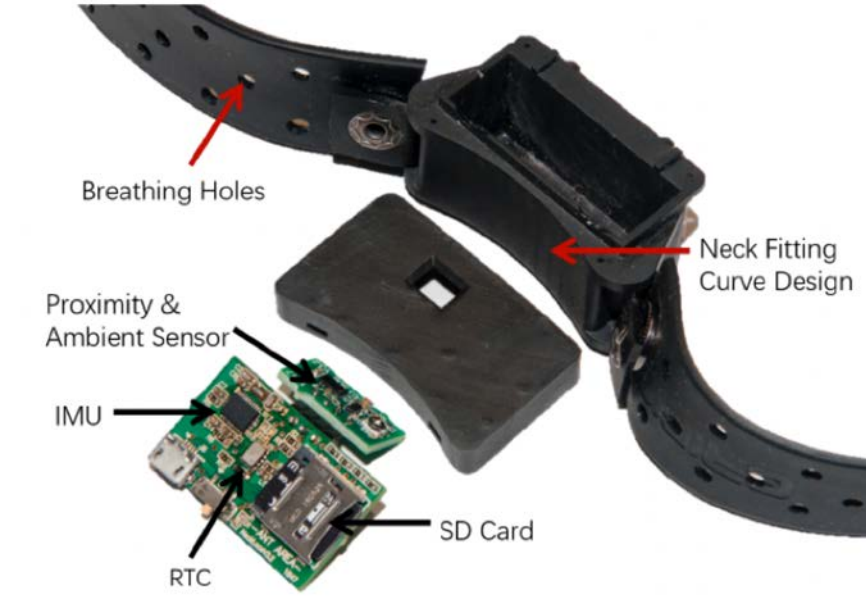




Chewing Sequence

Chewing Sequence

Chewing Sequence



# NeckSense

multi-sensor necklace for detecting eating activities  
activities in free-living conditions

read our paper & learn about NeckSense: [necksense.info](http://necksense.info)

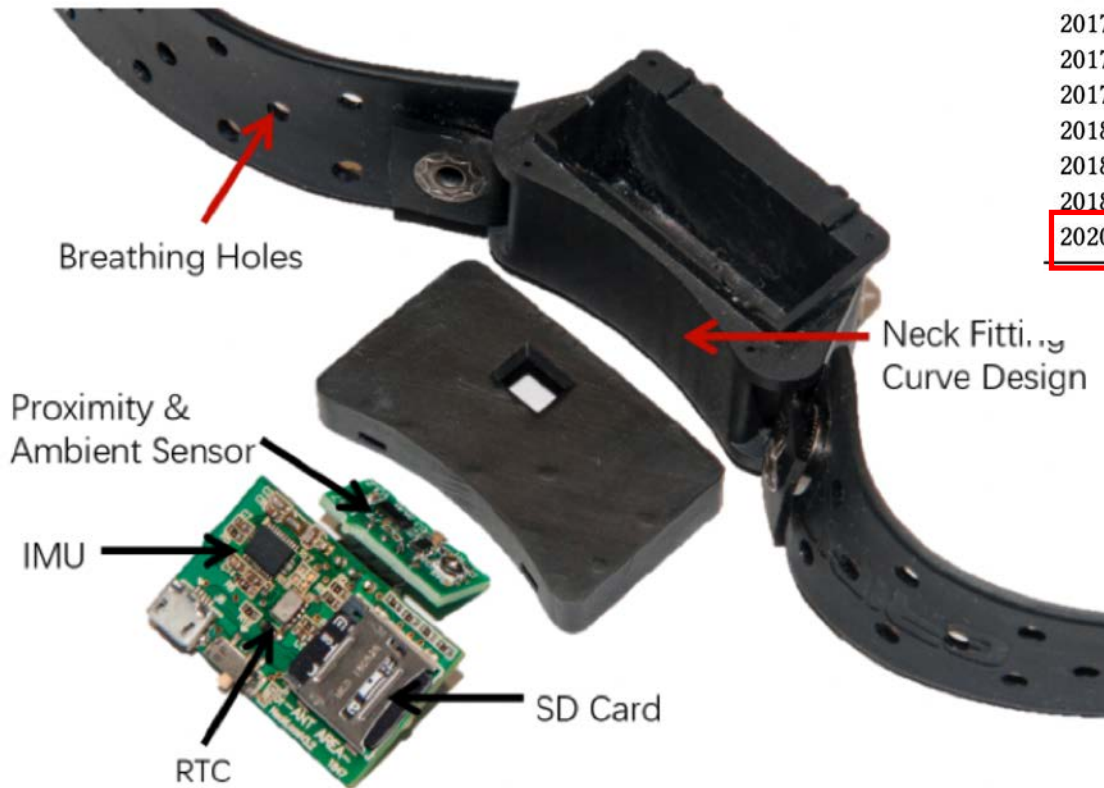
Shibo Zhang, Yuqi Zhao, Dzung Nguyen, Runsheng Xu, Sougata Sen, Josiah Hester, Nabil Alshurafa

ACM UbiComp 2020



Won Best Presentation (Runner Up) at UbiComp 2020

novel **neck-worn** device with multiple embedded sensors  
 ...**infer eating behavior** from **contactless** sensors  
 ...**tested** on people with **obesity**  
 ...tested in **real-world settings**

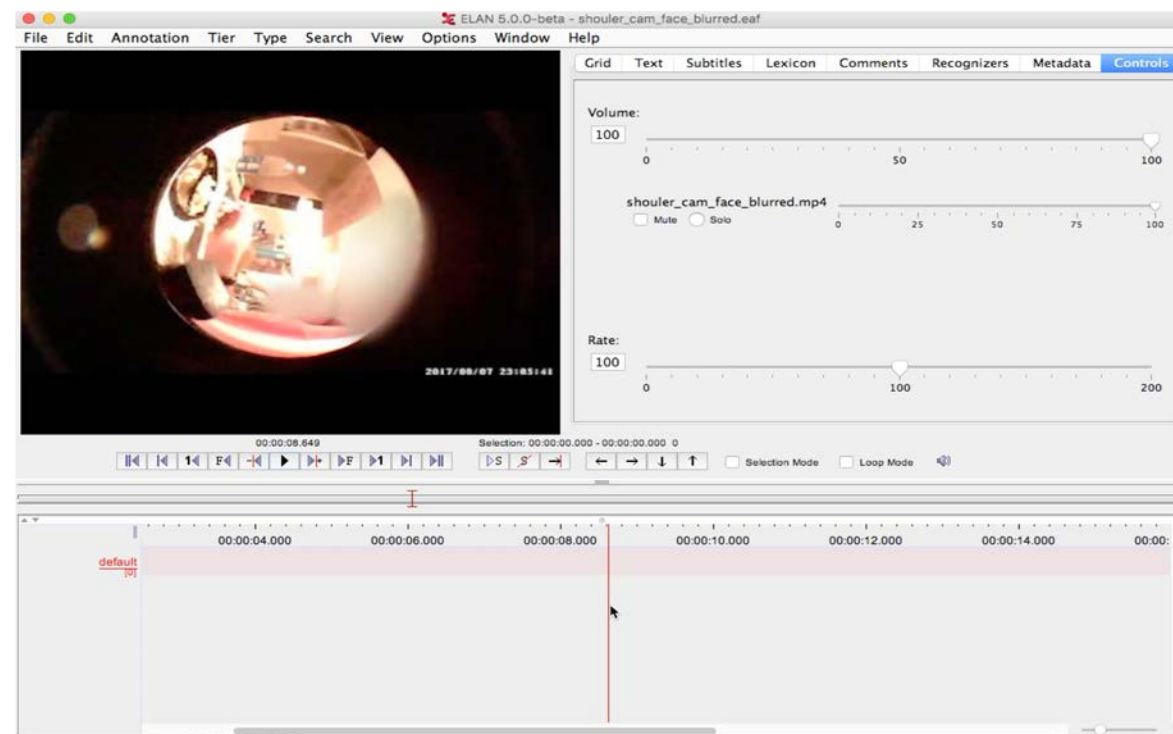
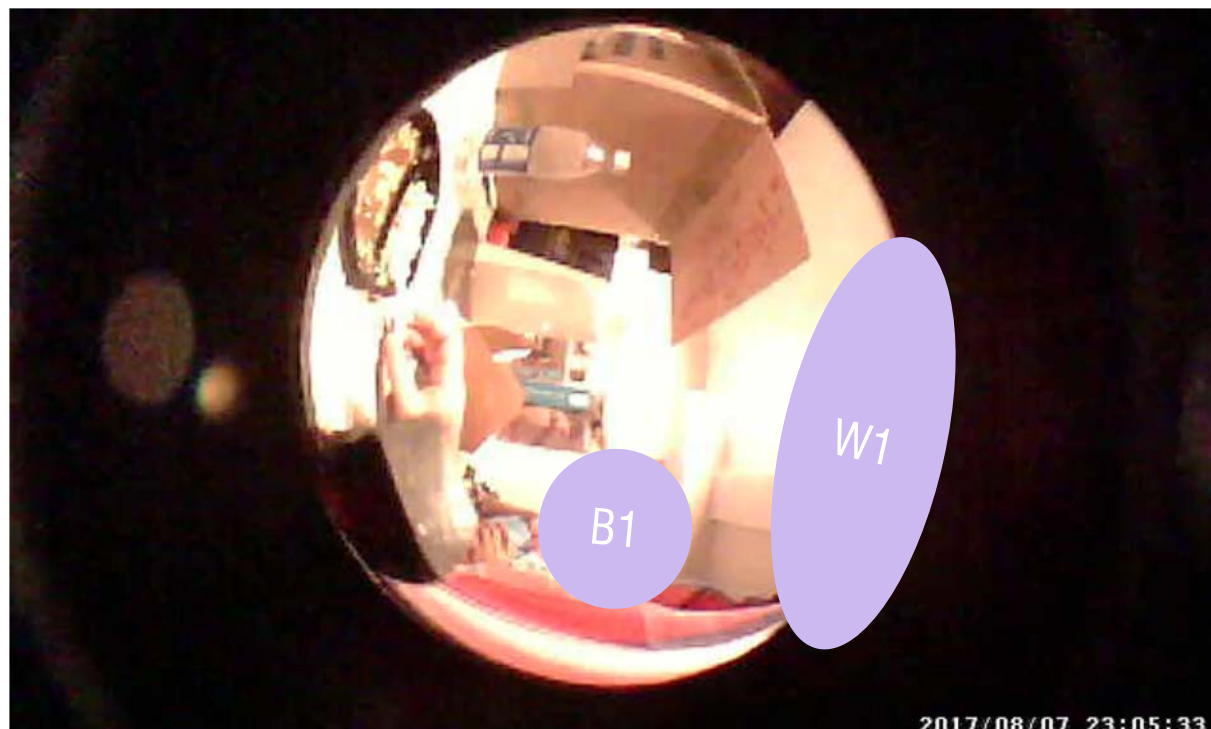


Year	Study	Sensors	On-body position	No. of participants	Avg hours per day	Validation video	Non-student	Obese
2014	Fontana et al. [22]	S1, S4, S6	Ear, wrist, chest	12	24.0	X	✓	✓
2015	Thomaz et al. [55]	S1	Wrist	7+1	5.7/13.6	X	X	X
2015	Bedri et al. [10]	S2, S5	Ear, head	6	6.0	X	✓	X
2016	Farooq et al. [21]	S4	Temple	8	3.0	X	✓	X
2017	Bedri et al. [9]	S1-S3, S5, S7	Neck, ear	10	4.5	✓	✓	X
2017	Zhang et al. [60]	S8	Ear	10	6.1	X	X	X
2017	Mirtchouk et al. [35]	S1-S3, S7	Ear, wrist, head	11	11.7	X	✓	X
2018	Sen et al. [49]	S1, S2, S10	Wrist	9	5.8	X	✓	X
2018	Chun et al. [15]	S5	Neck	17	4.6	X	X	X
2018	Bi et al. [13]	S7	Ear	14	2.3	✓	X	X
2020	This work	S1-S3, S5, S9	Neck	10+10	4.9/9.5	✓	✓	✓

S1 - accelerometer, S2 - gyroscope, S3 - magnetometer, S4 - piezo, S5 - proximity, S6 - radio frequency, S7 - microphone, S8 - electromyography, S9 - light, S10 - camera



**validated** using a wearable video camera for **270 hours in-the-wild**  
...provide **data** and **code** to the community

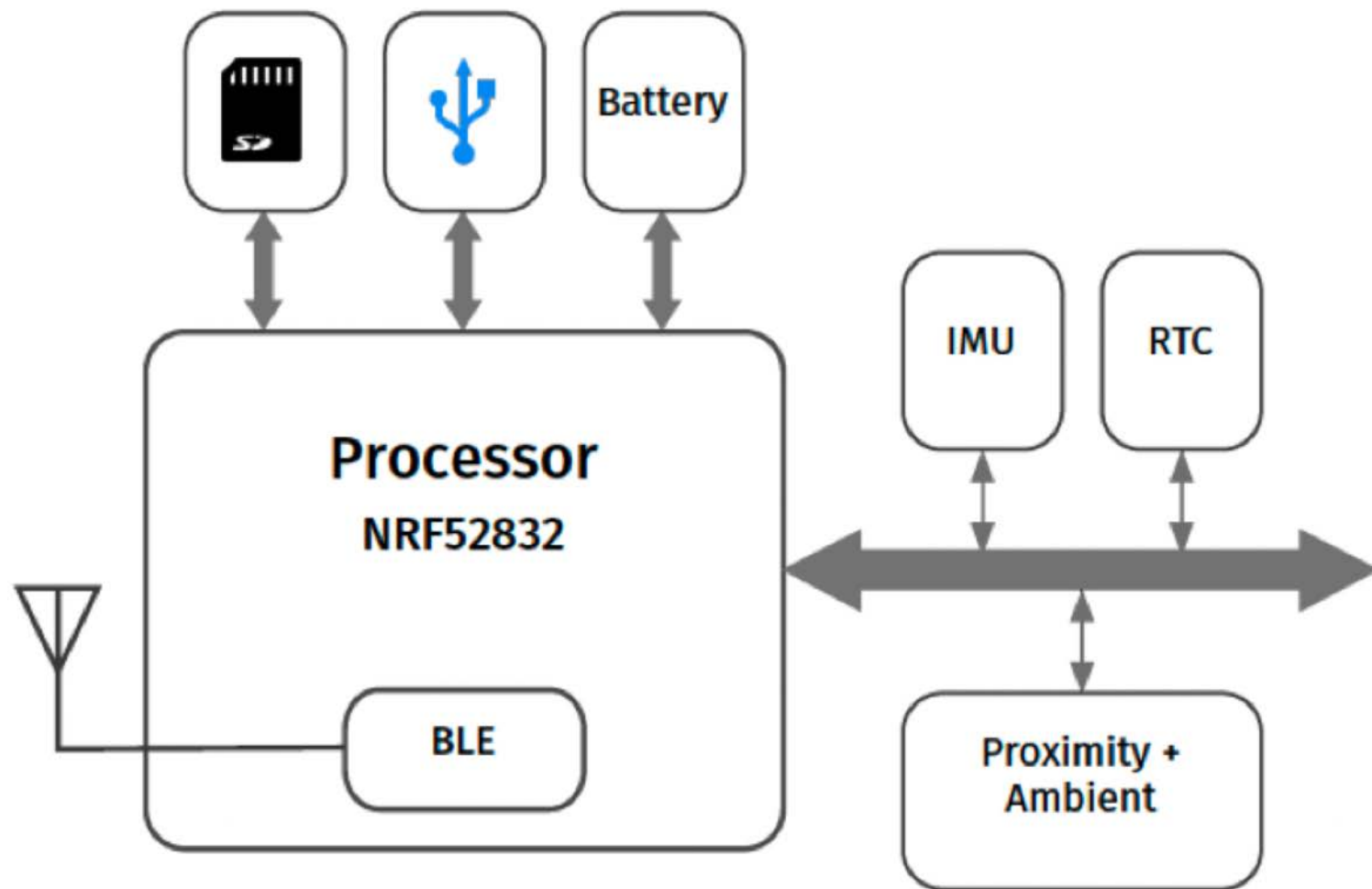




## benefits to NeckSense

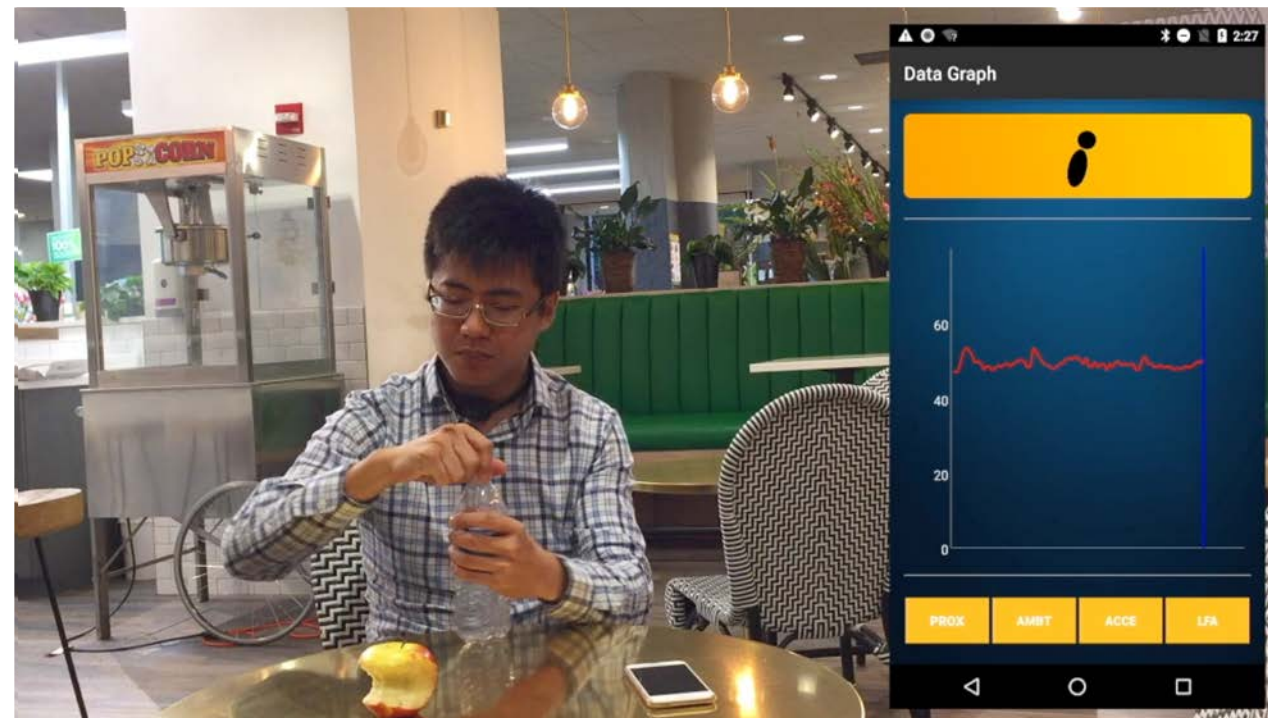
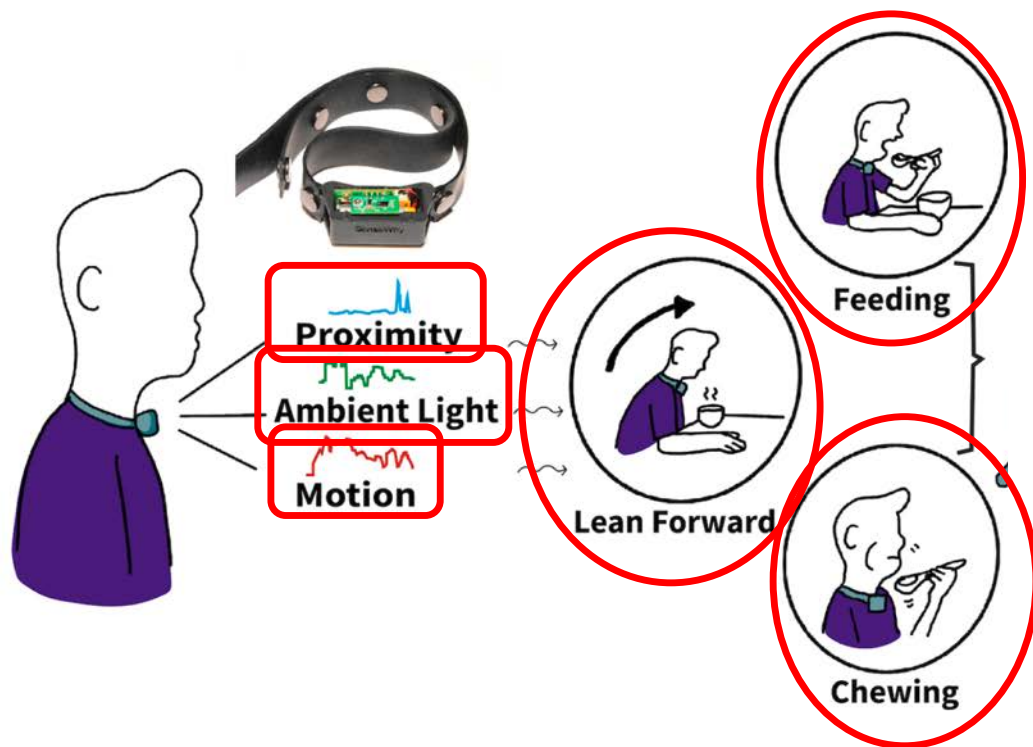
- ... understand characteristics of an eating episode
- ... **detect eating** in real-time
- ... **trigger timely interventions** for diet recall and behavior change



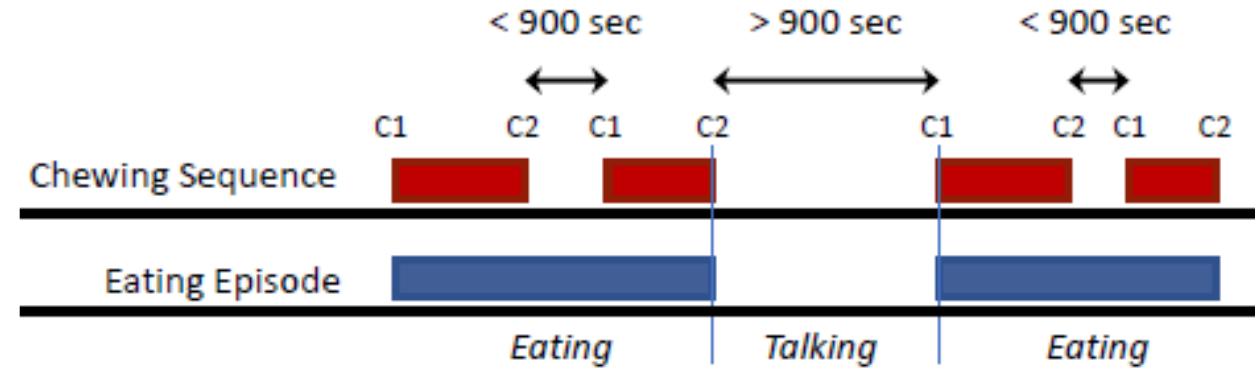
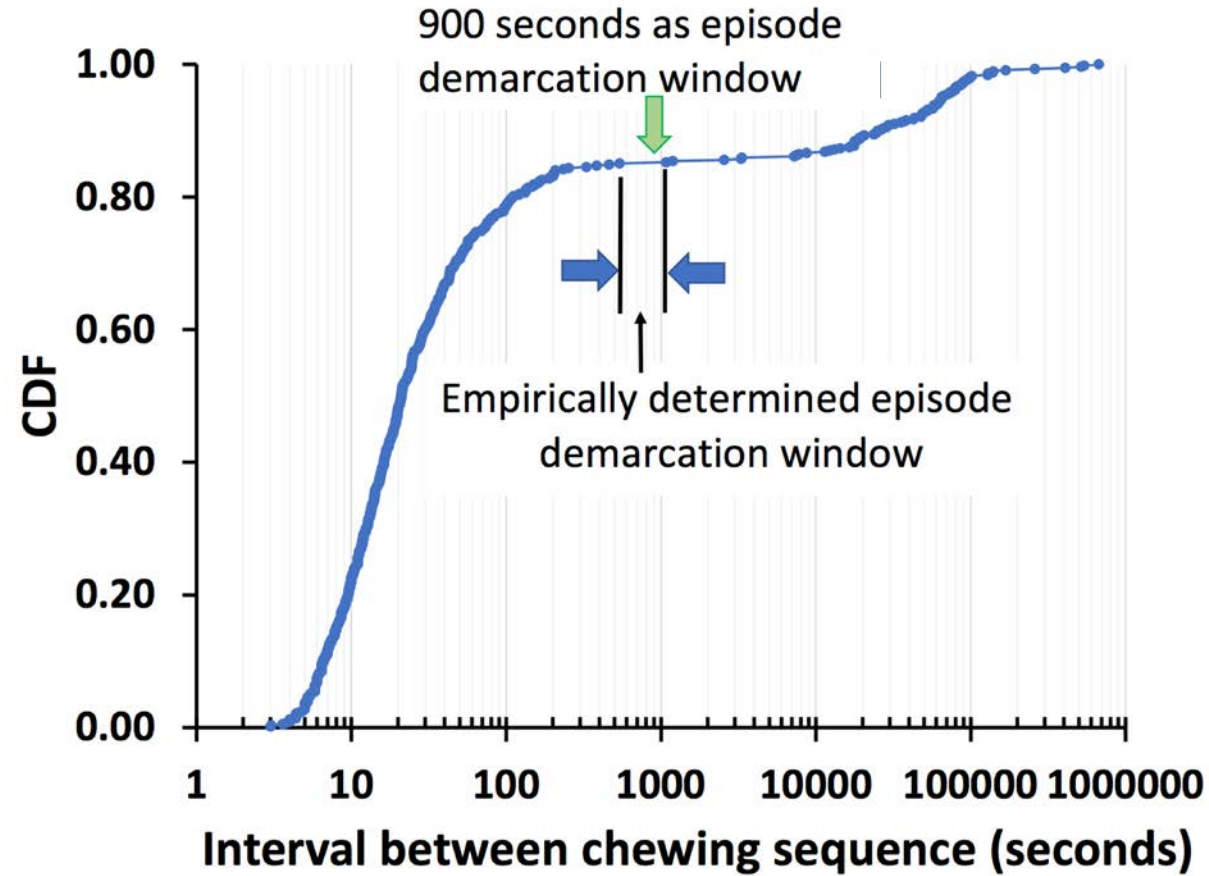


# Multiple sensors capture eating

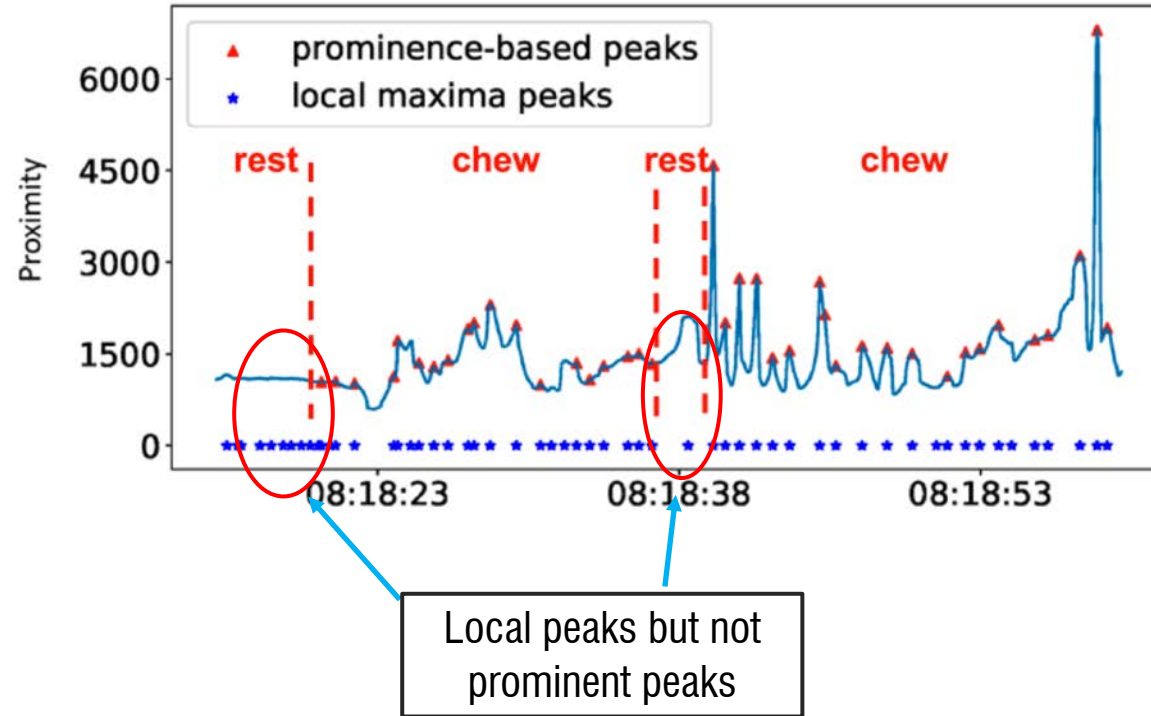
- ... **proximity signal** captures periodicity of chew
- ... **ambient light** as a proxy to feeding gestures
- ... **IMU** calculates leaning forward and backward angle to infer bite



# defining an eating episode



# segmentation using proximity sensing signal



# segmentation using proximity sensing signal

**DEFINITION 1.  $\epsilon$ -periodic:** Given a sequence of increasing timestamps  $t_i$ , where  $i \in \{1 \dots N\}$ , the difference between consecutive numbers is  $p_i = t_{i+1} - t_i, \forall i = \{1 \dots (N - 1)\}$ , if  $p_{min}$  and  $p_{max}$  are the smallest and largest values of these differences, respectively, then the sequence is defined to be  $\epsilon$ -periodic if:

$$\frac{p_{max}}{p_{min}} < 1 + \epsilon$$

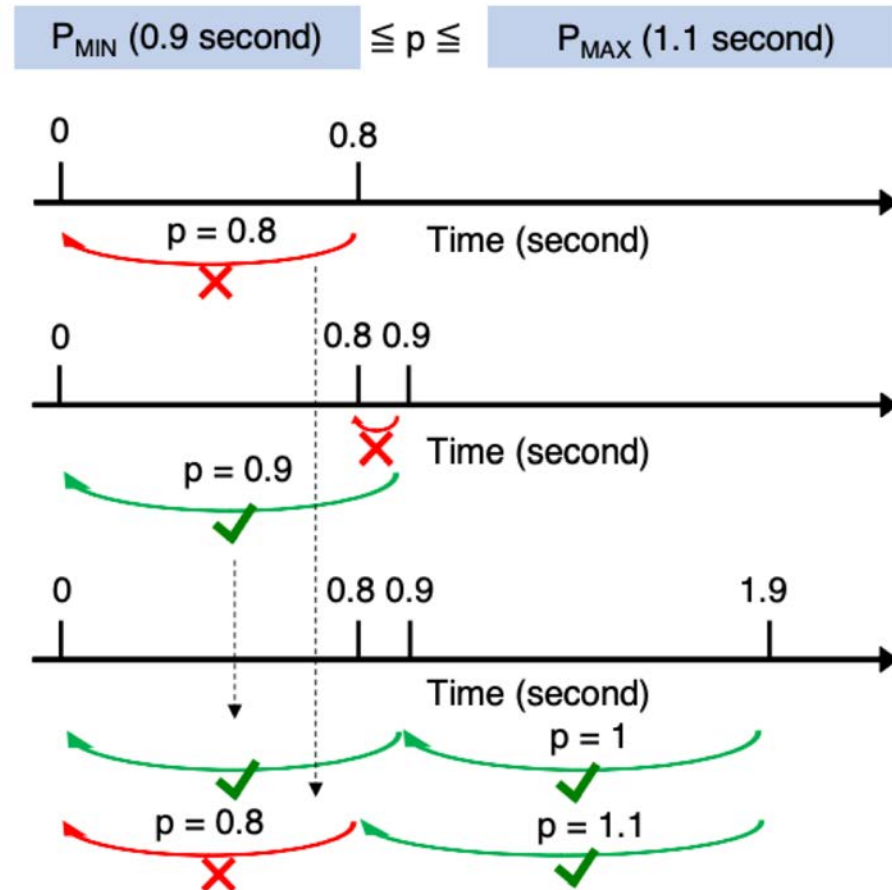
**PROBLEM 1. Relative error periodic subsequence:** Given a sequence of increasing numbers  $t_i$ , find all longest subsequences that are  $\epsilon$ -periodic.

**PROBLEM 2. Absolute error periodic subsequence:** Given a sequence of increasing numbers  $t_i$ , find all longest subsequences such that consecutive differences are bounded by  $p_{min}$  and  $p_{max}$ .

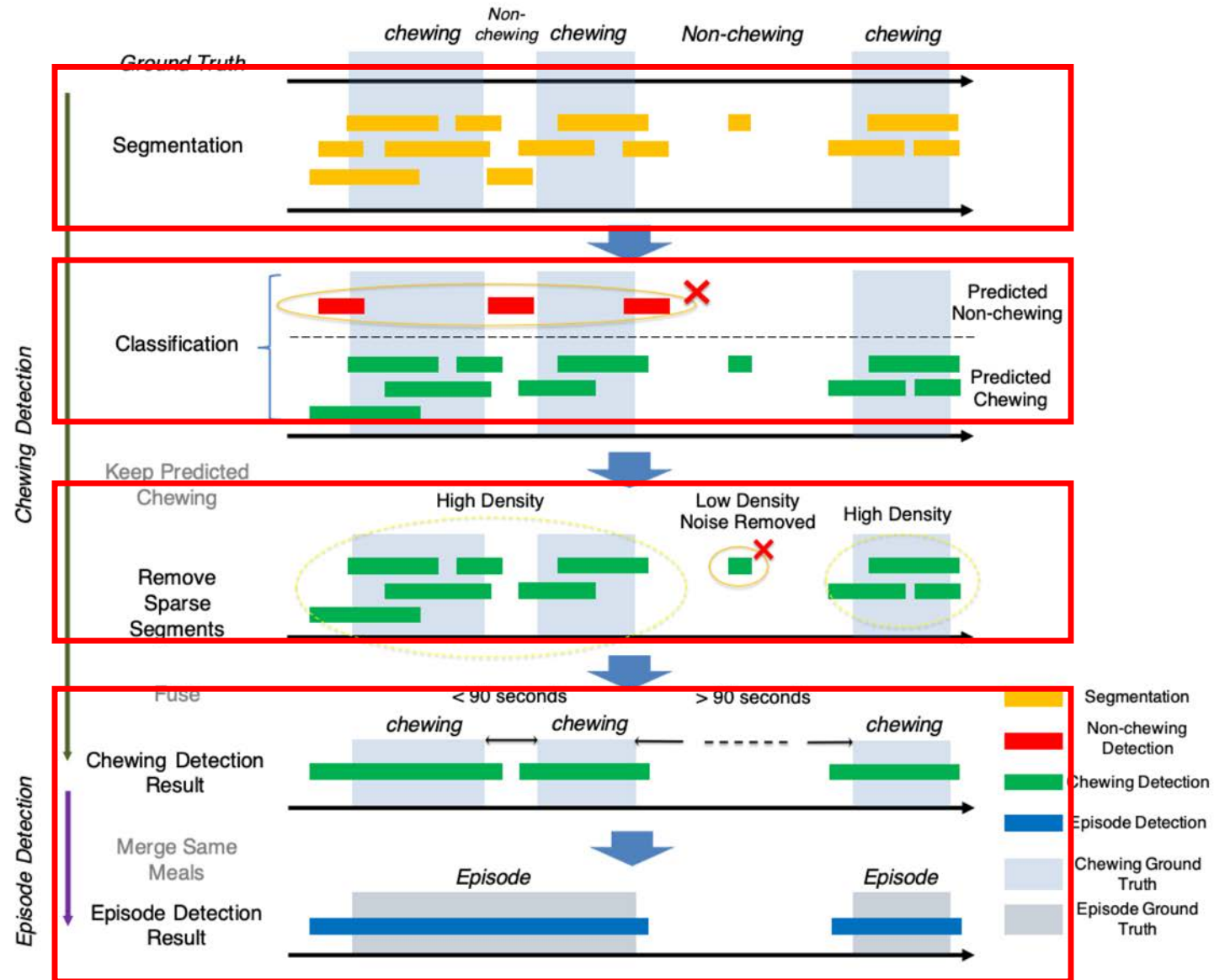
- Beat Gfeller. 2011. Finding longest approximate periodic patterns. In Workshop on Algorithms and Data Structures (WADS). Springer, 463–474. [https://doi.org/10.1007/978-3-642-22300-6\\_39](https://doi.org/10.1007/978-3-642-22300-6_39)
- Shibo Zhang, Yuqi Zhao, Dzung Tri Nguyen, Runsheng Xu, Sougata Sen, Josiah Hester, and Nabil Alshurafa. 2020. NeckSense: A Multi-Sensor Necklace for Detecting Eating Activities in Free-Living Conditions. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 4, 2, Article 72 (June 2020), 26 pages. <https://doi.org/10.1145/3397313>

# segmentation using proximity sensing signal

$$\epsilon\text{-periodic: } \frac{\rho_{max}}{\rho_{min}} < 1 + \epsilon$$

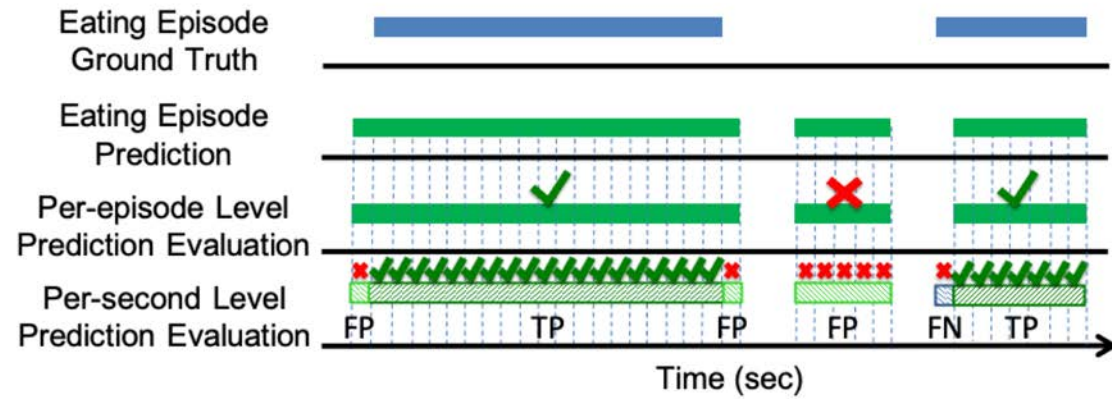


# pipeline





# Evaluation criteria (fine-grained and coarse grained)



# feature extraction

Category	Features
Statistics	Max, min, mean, median, standard deviation, RMS, correlation, skewness, kurtosis, 1st and 3rd quartile, interquartile range
Frequency	Frequency amplitude of 0.25 Hz, 0.5 Hz, 0.75 Hz, 1 Hz, 1.25 Hz, 1.5 Hz, 1.75 Hz, 2 Hz, 2.25 Hz, 2.5 Hz
Statistics of Frequency	Skewness and kurtosis of spectrum from frequency features
Time-series	Count below/above mean First location of min/max Longest strike below/above mean Number of peaks
Periodic subsequence	$p_{min}$ , $p_{max}$ , $\epsilon$ , length
Time	Hour of datetime

Chewing Sequence?

XGBoost Classifier

Eating episode?

Fusion

Yes? No?

# Machine Learning Algorithms Cheat Sheet

## Unsupervised Learning: Clustering



START

## Unsupervised Learning: Dimension Reduction



## Supervised Learning: Classification



## Supervised Learning: Regression



# XGBoost (eXtreme Gradient Boosted trees)

wins Kaggle competitions (easy to use, fast)

ensemble method

...each tree introduces a weak learner or boosts attributes that led to misclassifications of the previous tree

regularized boosting (prevents overfitting)

parallel processing

cross validation at each iteration

...evaluate performance at each step of training (early stopping)

...incremental training (stop training, save, and re-run later)

can plug own optimization objective

Dmatrix

...structure used to hold features and labels---easy to create from a numpy array

# XGBoost (eXtreme Gradient Boosted trees) hyperparameters

booster

...gbtree (classification) or gblinear (regression)

objective

...multi:softmax or multi:softprob

eta (learning rate –adjusts weights on each step)

max\_depth (depth of the tree)

min\_child\_weight

...can control overfitting

GridSearchCV

AWS SageMaker: hyperparameter tuning

we performed the following **exploratory** study...

Total Hours: 134 hours

in-the-wild

- Camera wear
- Data transfer and delete
- 24-hour diet recall



- Taught to use technology
  - Told to **wear during eating episodes**
- Pre-study questionnaire

- Returned technology
- Post-study questionnaire
- Trained Labelers Annotate using ELAN

we performed the following **free-living** study...

Total Hours: 137 hours

in-the-wild

- Camera wear
- Data transfer and delete
- 24-hour diet recall



- Taught to use technology
  - Told to **wear all day**
- Pre-study questionnaire

- Returned technology
- Post-study questionnaire
- Trained Labelers Annotate using ELAN

in the exploratory study... **81.6% Average F-score**  
in the free-living study... **77.1% Average F-score**

When **trained** on people **without** obesity,  
show **poor test** performance on people **with** obesity

		Test	
		Obese	Non-obese
Train	Obese	71.21%	75.33%
	Non-obese	66.75%	79.88%

Per-episode LOPO evaluation



# results

Sensor(s) used	Exploratory Study	Free-Living Study
Proximity only (ref)	73.4%	66.4%
Proximity + IMU*	81.5%	78.7%
Proximity + ambient light	72.7%	70.3%
<b>All Sensors*</b>	<b>81.6%</b>	<b>77.1%</b>

\*Post hoc analyses with Bonferroni correction show statistically significant improvement of Proximity+IMU and All Sensors over Proximity only at the  $P < .05$  level.

# NeckSense is ...

- designed to **detect eating episodes** in the real-world for **long-term wear**
- validated using longest periodic subsequence algorithm
- validated on people with and without **obesity** and solely in **free-living** settings

Data set available and device available upon request ([www.necksense.info](http://www.necksense.info))

Let's make sure we validate our wearables  
on people we are designing it for !



[nabil@northwestern.edu](mailto:nabil@northwestern.edu)

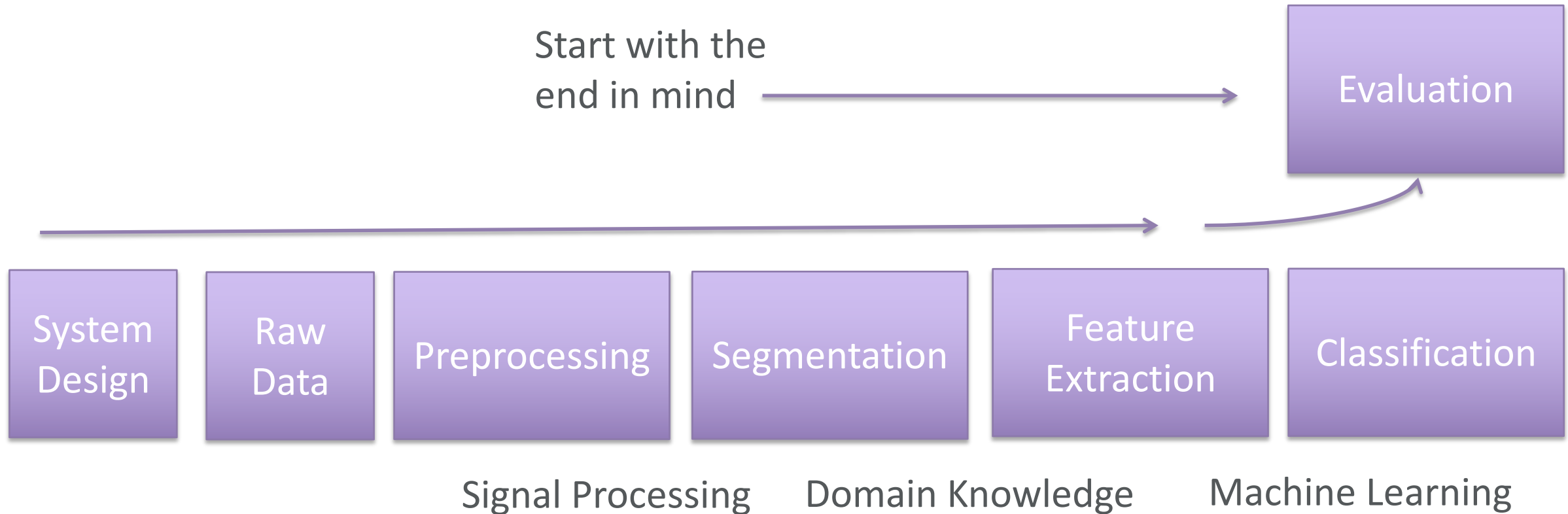


@HABitsLab

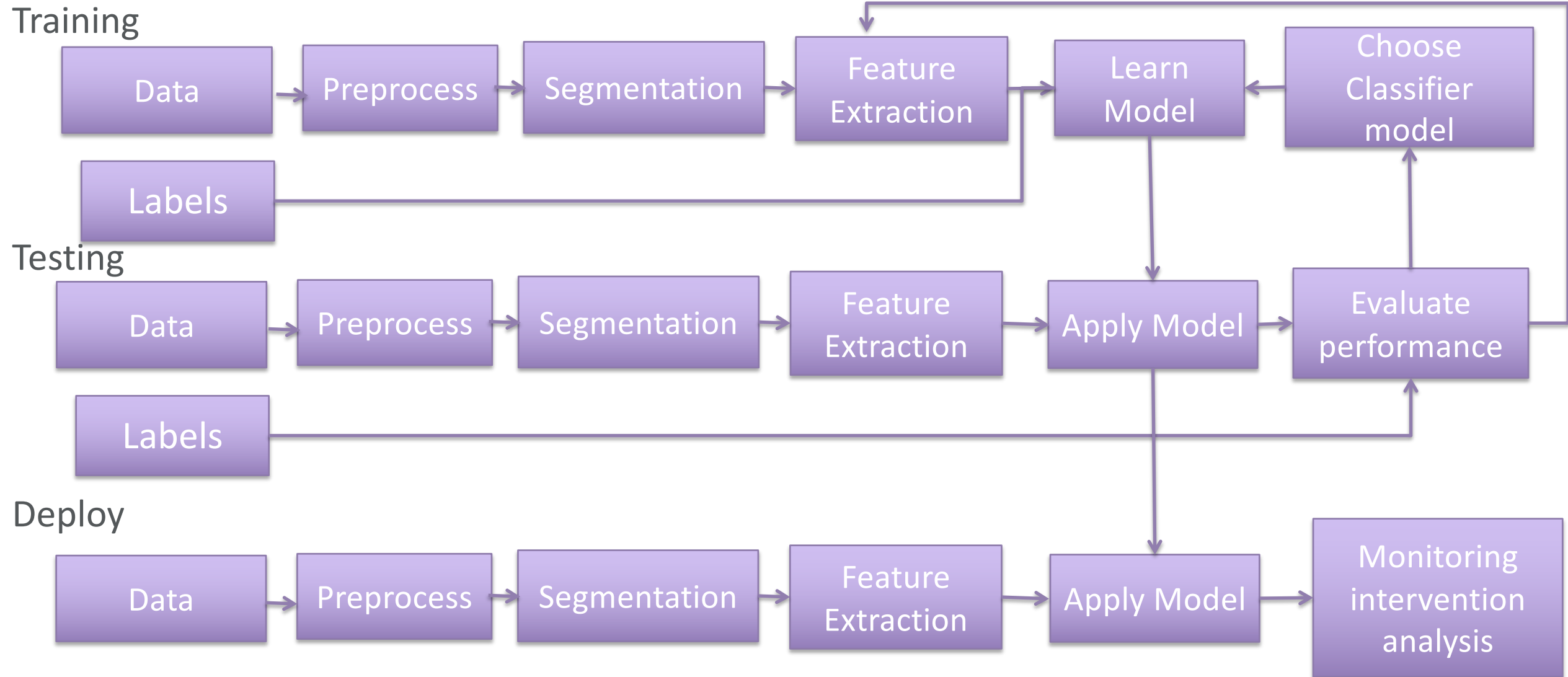


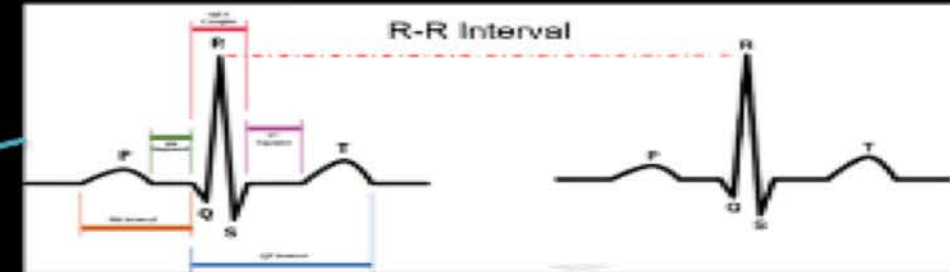
# Passive Sensing Data Analytic Chain (PASDAC)

High Level



# Full model learning process for detection



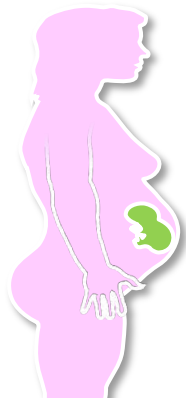


# microStress-EMA

Passive Sensing Framework for Detecting in-the-wild  
Stress in Pregnant Mothers



# Promoting Healthy Brain Project



Randomized  
Clinical Trial (RCT):  
Prenatal Stress  
Reduction

Improve  
Neurodevelopmental  
Health

?

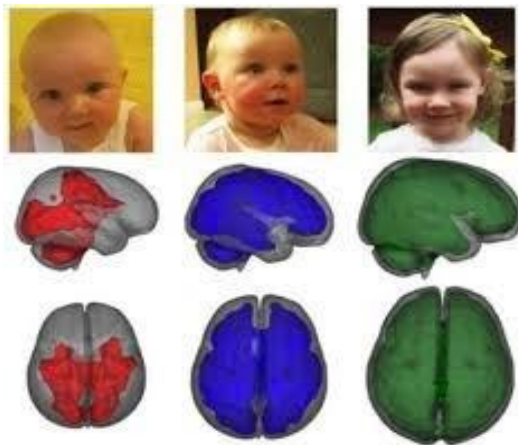
Measure Stress



Tailored Messaging

Customization

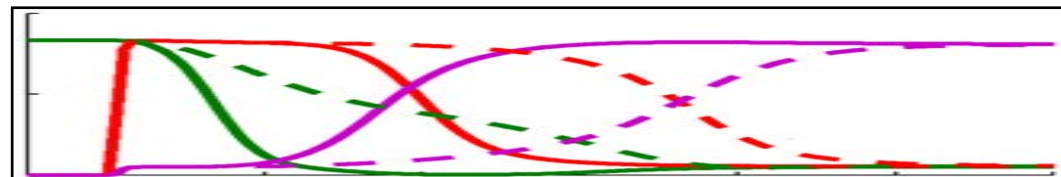
Neurodevelopmental Brain:Behavior Trajectories:  
Birth, 6 mos. & 12 MOS.



Infant  
Natural Sleep MRI &  
EEG



Task-Based  
Executive  
Function



# Biostamp Research Connect



BioStamp Research Connect™

Reshaping Research™

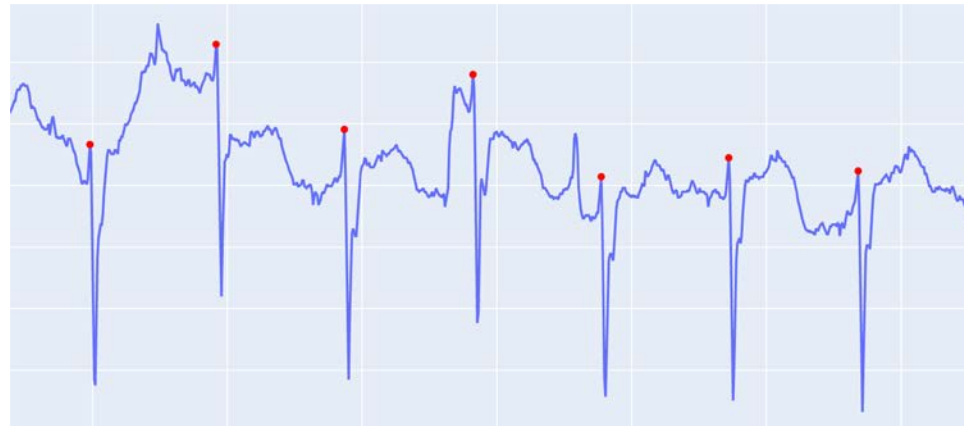
## event detection problem

*Def: Suppose we have a dynamical system in which an event of interest is either occurring or not occurring at each time instant  $t$ . Given a numerical representation  $x_t$  of the state of the system at time  $t$ , infer whether the event occurred at time  $t$  or not.*



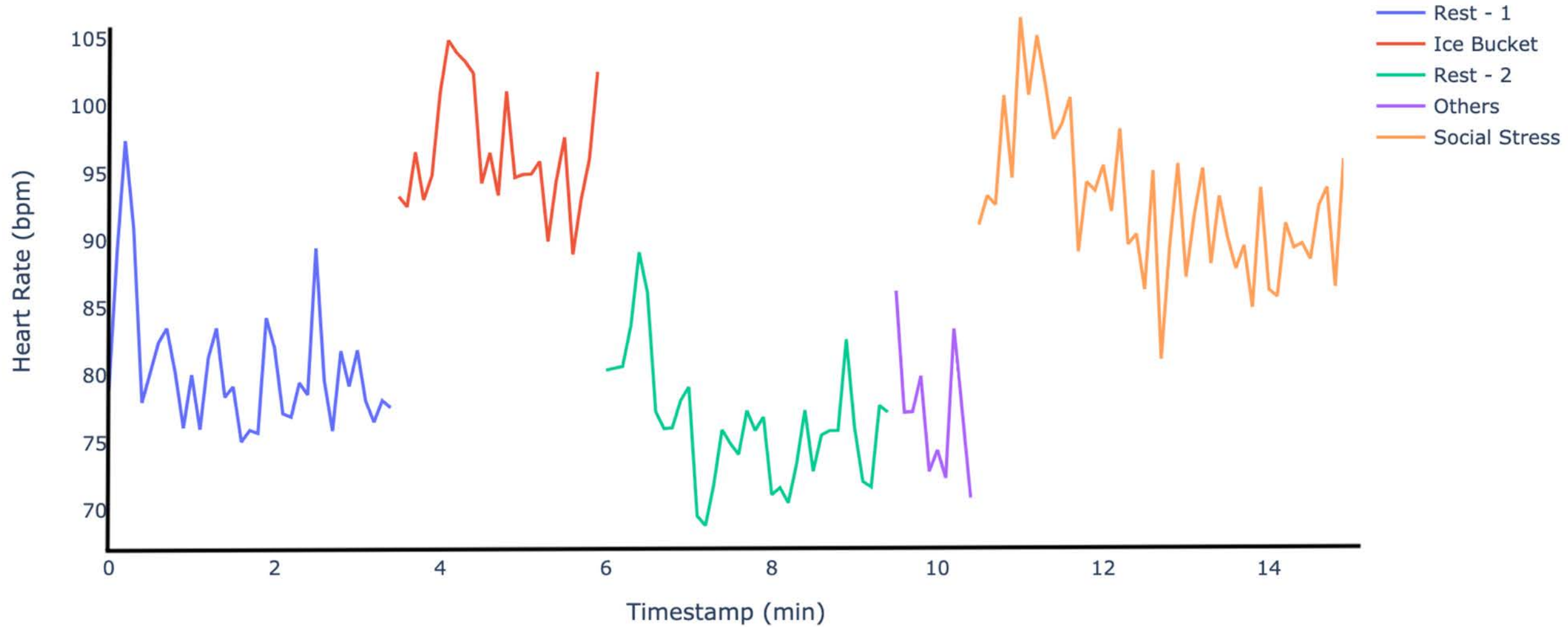
# example

Suppose we have data from a wearable ECG sensor. Based on the data from the ECG sensor, within a given time segment  $\Delta t$ , determine whether the wearer is exhibiting stress or not.

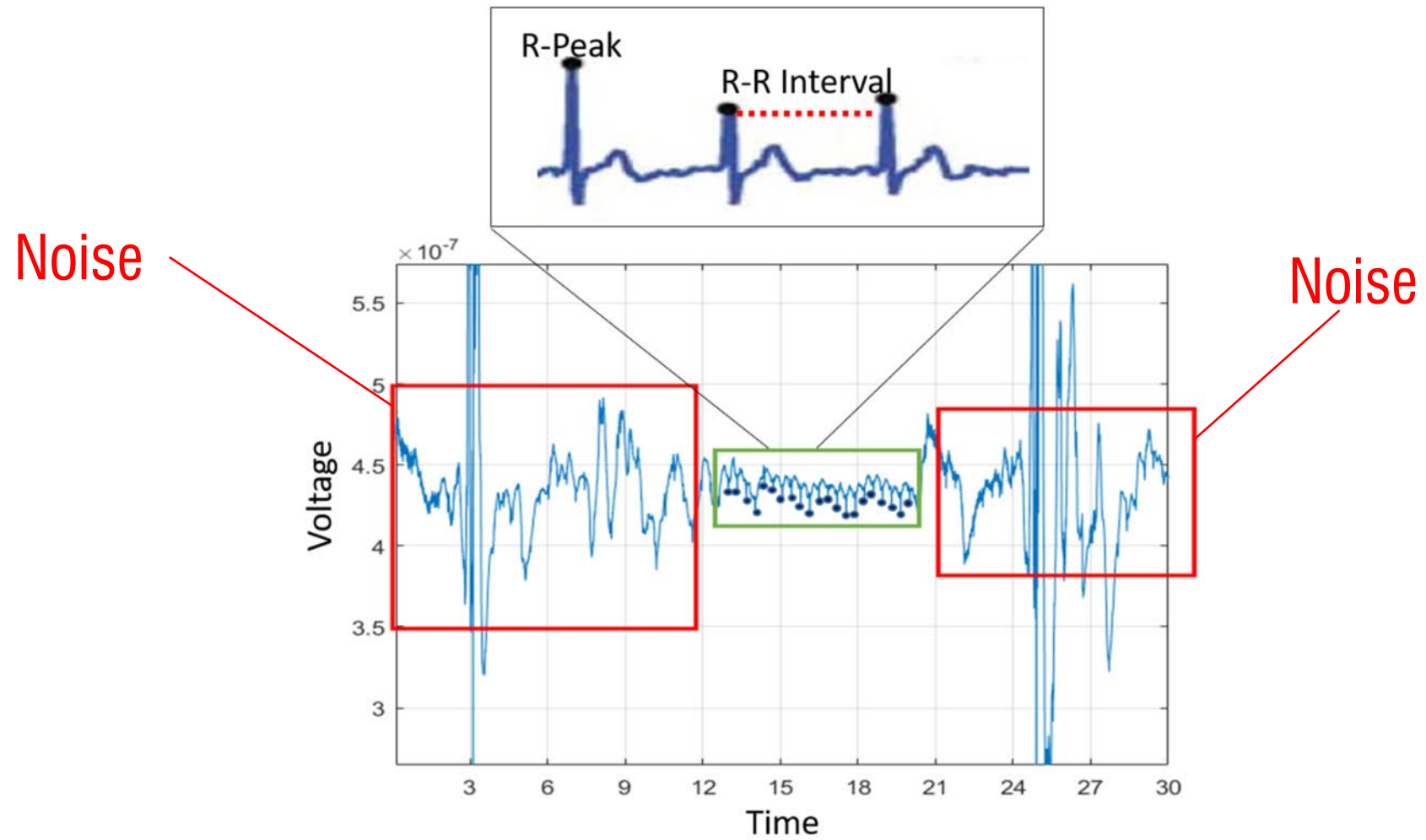


Stress?

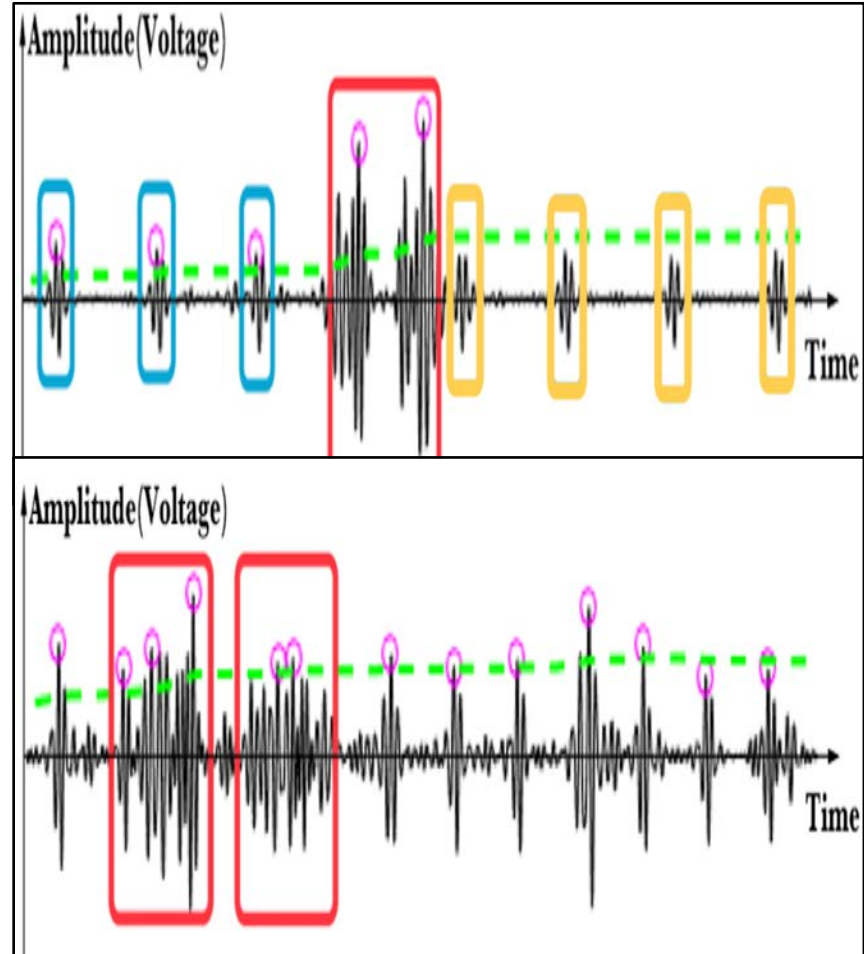
# heart rate estimates from Biostamp data



43  
Noise in ECG data



# noise effects Pan Tompkins



noise effects the detection of R-peaks by the Pan-Tompkins algorithm

# new study to build a pre-processing module that detects noise

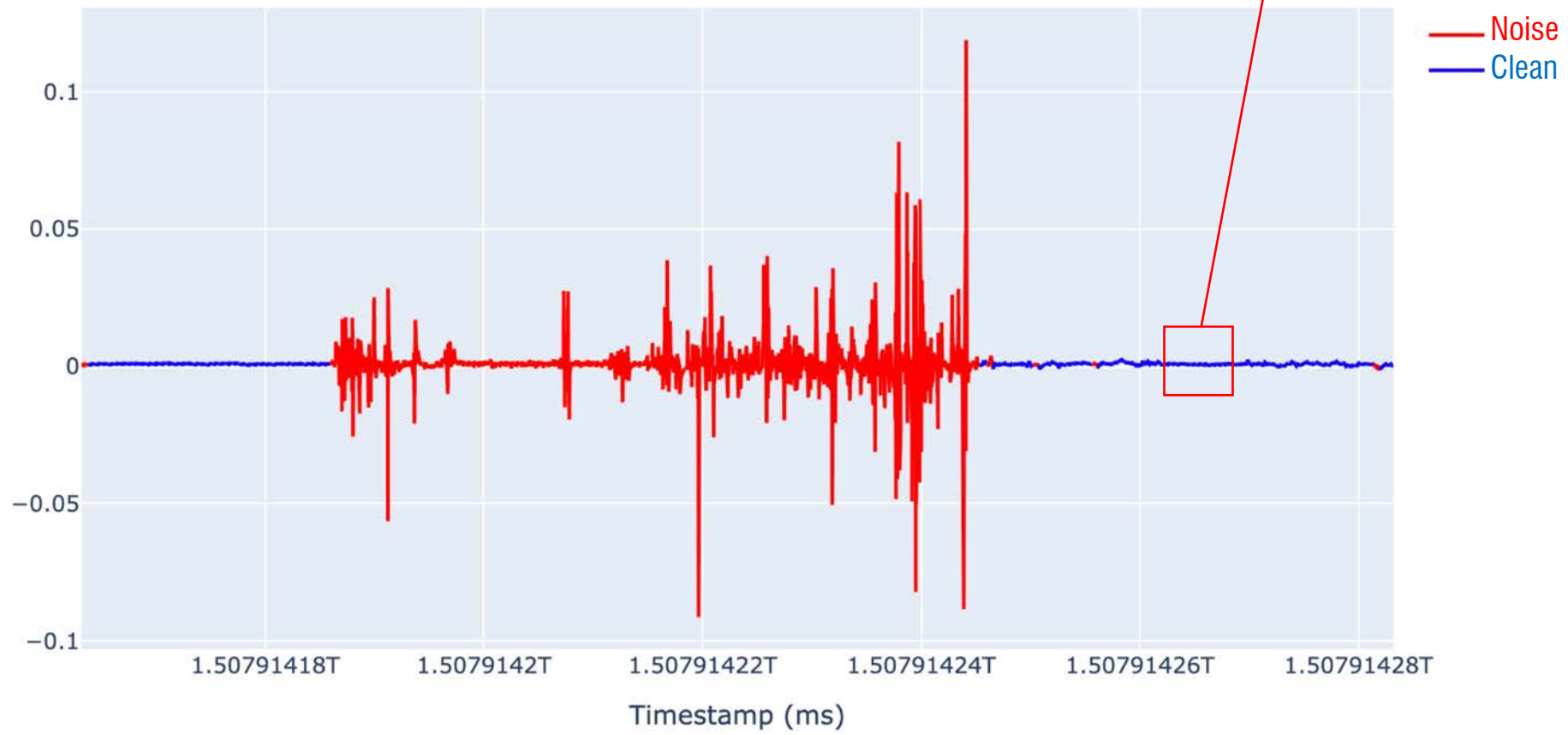
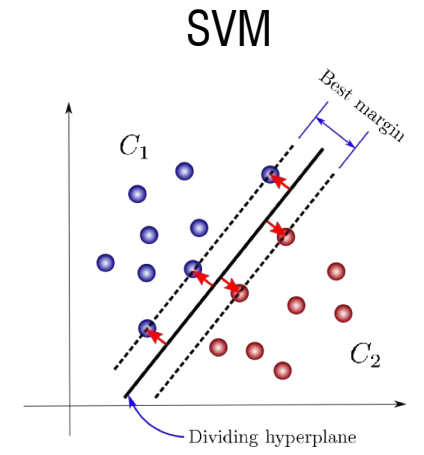
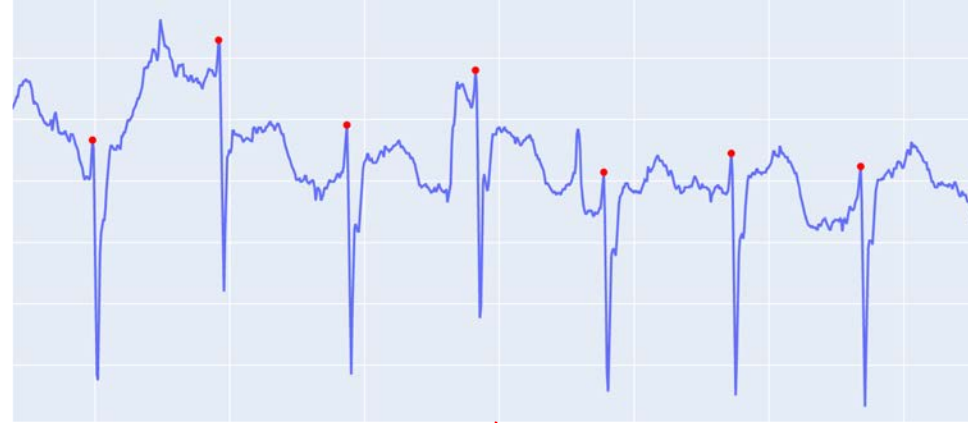
## 16 activities that involved stretching

Task	Description	Label
Dressing & Grooming	Dress yourself	stretching
Rest	Have a talk.	non-stretching
Arising	Stand up from a chair. Get in and out of bed.	stretching
Rest	Check social media/email/text.	non-stretching
Walking	Carry a backpack, walk and climb.	non-stretching
Rest	Rest on the chair	non-stretching
Hygiene	Wash hands. Use toilet. Brush teeth.	stretching
Rest	Work on laptop	non-stretching
Reaching	Get down stuffs from above head. Dust the bookshelf. Pick up clothing from the floor.	stretching
Rest	Read a book	non-stretching
Gripping	Open house door and jars. Turn faucets on and off.	stretching
Rest	lie down on couch	non-stretching
Teaching	Write on a blackboard and clean it.	stretching
Rest	Take notes on a paper.	non-stretching
Cleaning	Vacuum the living room. Wipe down the dining table.	stretching
Stretching	Stretch your body.	non-stretching

+ 1 pitcher

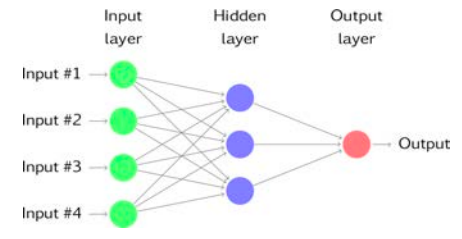


# consensus noise model



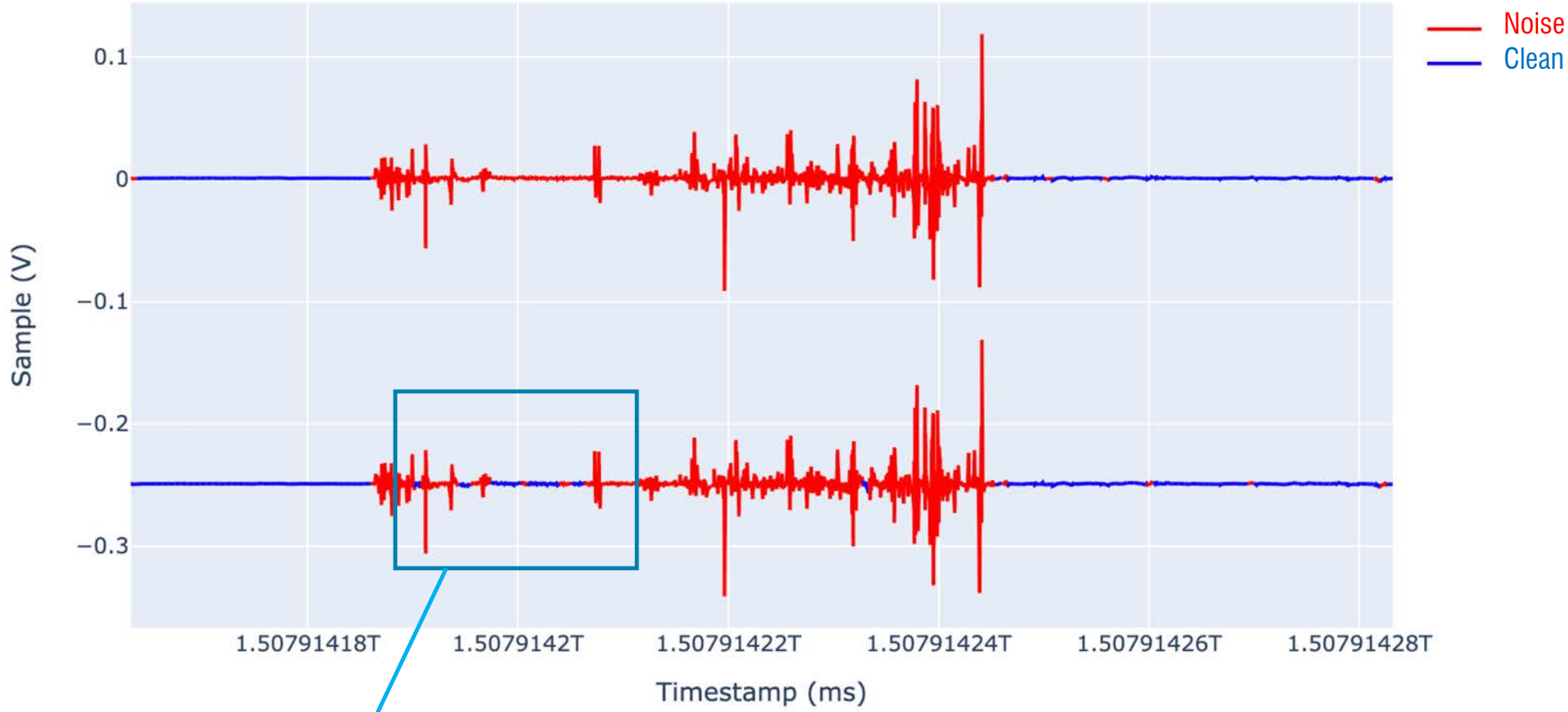
— Noise  
— Clean

+  
NN



**93.2%**  
improvement in  
heart-rate  
estimation

# noise model corrects labeler

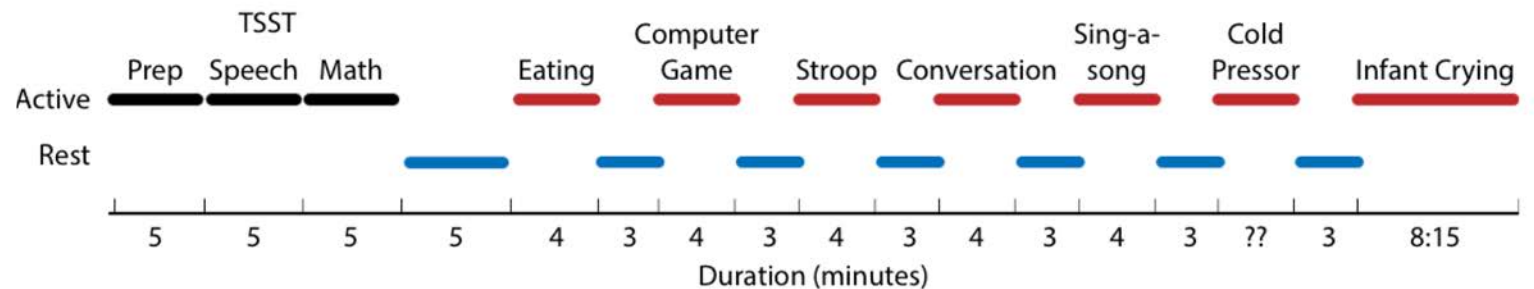


Noise model corrects

# stress induction to detect physiological stress

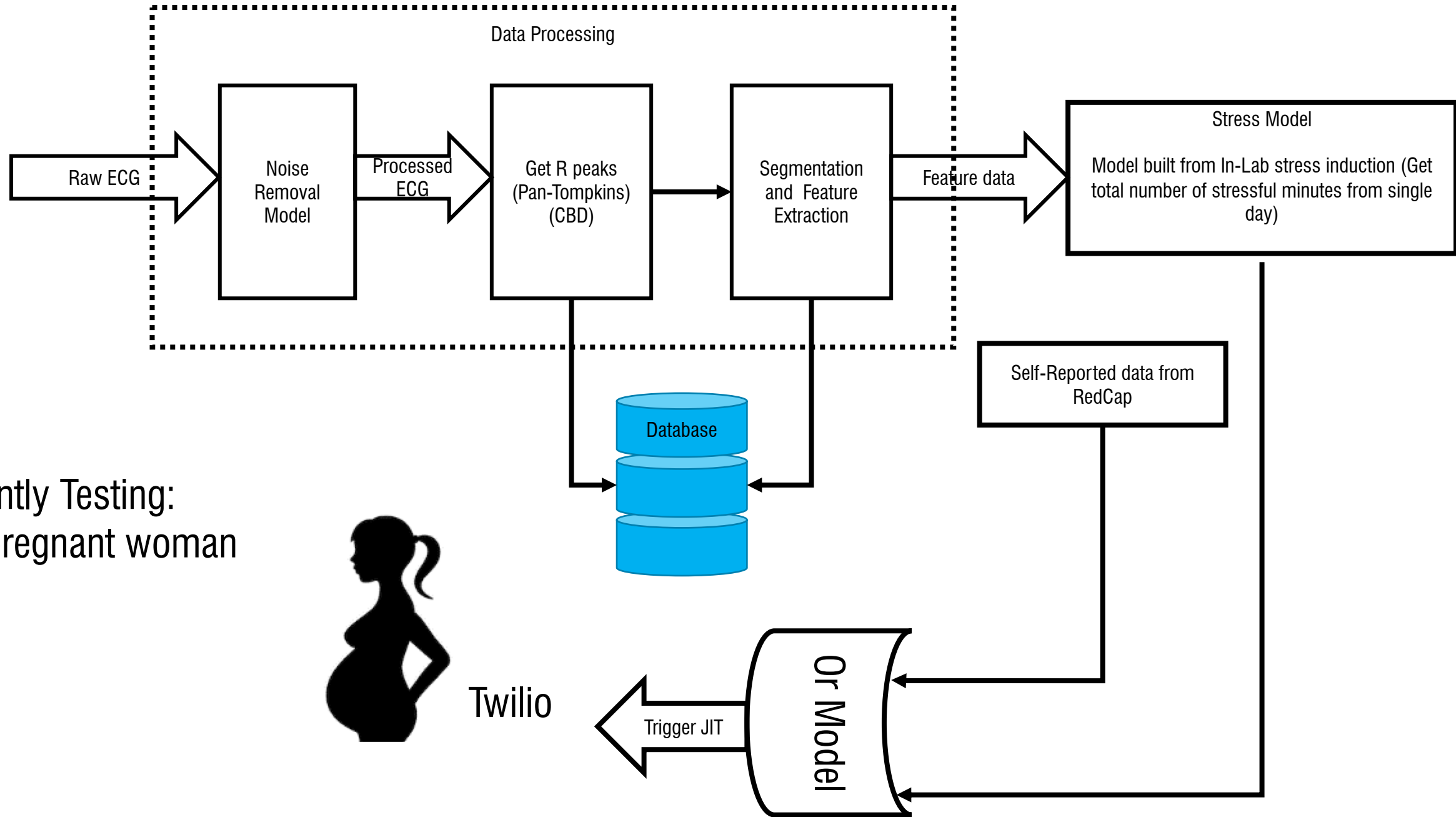
## Before and After every activity

Definition	Question
Intended (-)	Based on whether the activity was intended to cause stress
LikertStress (-)	How Stressed were you?(0-6)
BinaryStress (-)	Were you Stressed?(yes/no)
PSS-Control (-)	Did you feel you could not control important things?(0-4)
PSS-Overcome (-)	Did you feel difficulties piling up so you cannot overcome them?(0-4)
WorriedStress (-)	How Worried were you?(0-100)
SadStress (-)	How Sad were you?(0-100)
IrritableStress (-)	How Irritable/Angry were you?(0-100)
PSS-Confident (+)	Did you feel confident in your ability to handle problems?(0-4)
PSS-Your Way (+)	Did you feel things are going your way?(0-4)
ContentStress (+)	How Content were you?(0-100)
HappyStress (+)	How Happy were you?(0-100)
ExcitedStress (+)	How Excited were you?(0-100)





# model flow pipeline



Currently Testing:  
100 pregnant woman



Twilio

Trigger JIT

Or Model

Database

Self-Reported data from  
RedCap

Stress Model

Model built from In-Lab stress induction (Get  
total number of stressful minutes from single  
day)

Feature data

Segmentation  
and Feature  
Extraction

Get R peaks  
(Pan-Tompkins)  
(CBD)

Processed  
ECG

Noise  
Removal  
Model

Raw ECG

Data Processing

# combining self-report and sensor data

- Self-reported stress model from EMA (PSS-Q4)
- Physiological stress model built using signal processing, machine learning, & domain knowledge

## Self-Report



In the past hour, how stressed were you feeling?  
\* must provide value

In the past hour, did you feel you could not control important things?  
\* must provide value

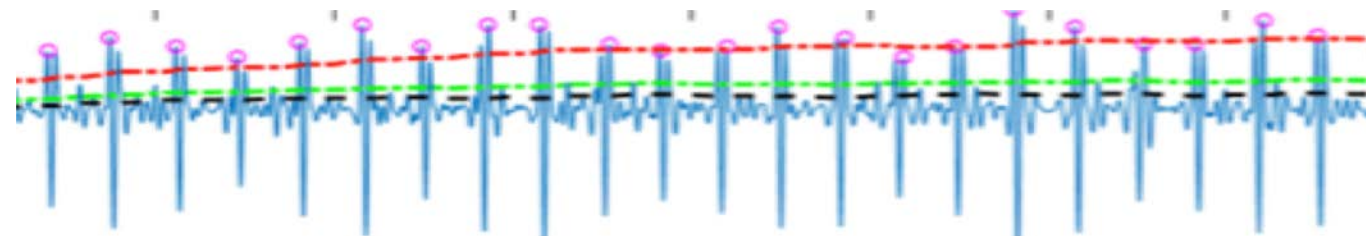
In the past hour, did you feel confident in your ability to handle problems?  
\* must provide value

In the past hour, did you feel things are going your way?  
\* must provide value

$P_{self-report}(Stress)$

## Stress Probability

$P_{physiology}(Stress)$



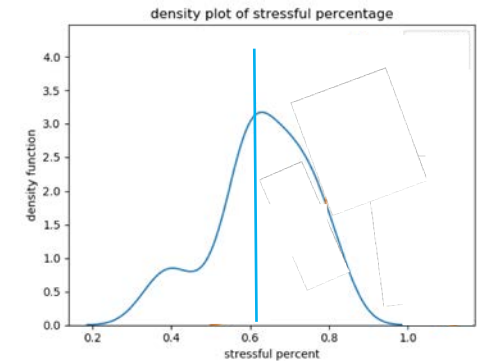
Non-Stress

Stress

$P_{self-report}(Stress) > \text{National PSSQ-4 Threshold}$

OR

$P_{physiology}(Stress) > \text{Mean Threshold (Minutes a day)}$

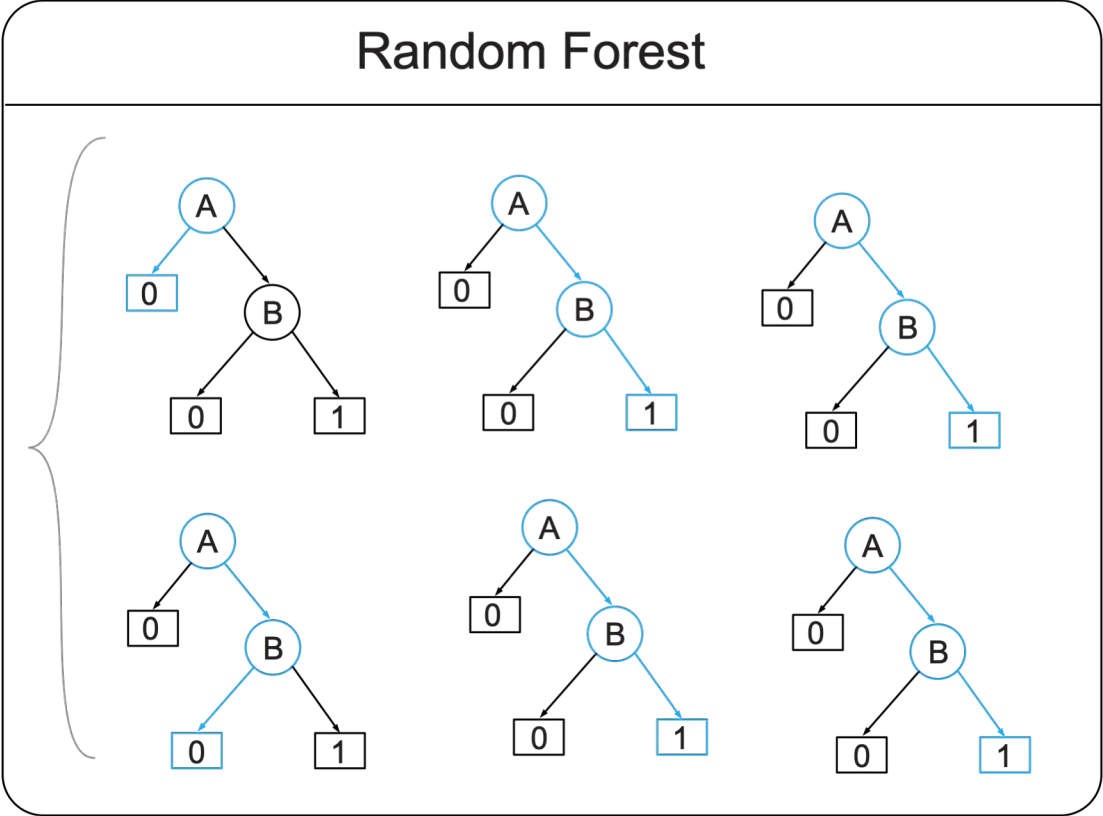
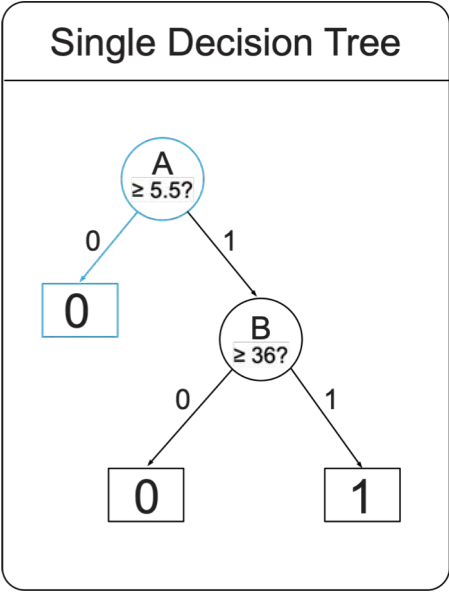


# challenges and opportunities

1. Explainability AI: How do I take a black box ML-based algorithm and make it interpretable?
2. Interactive ML: E.g., Active Learning
3. Sample Size: How do I know when I have enough data?
4. Speed/Real-time: Fast Machine Learning for Science
5. Optimization: Trade-off between Accuracy and {Battery Lifetime, Privacy, Engagement/Adherence}
6. Symbolic Reasoning VS. or WITH Deep Learning
7. Have we reached a dead-end with certain sensing modalities?

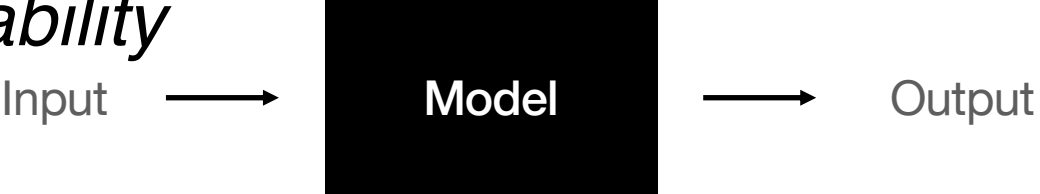
# Explainable AI

## *What? Why? Interpretability vs Explainability*

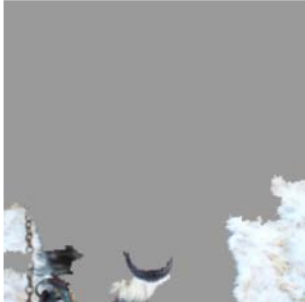
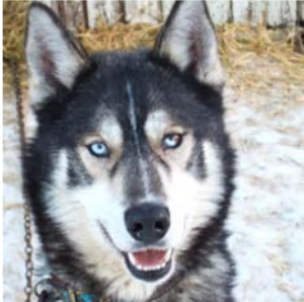
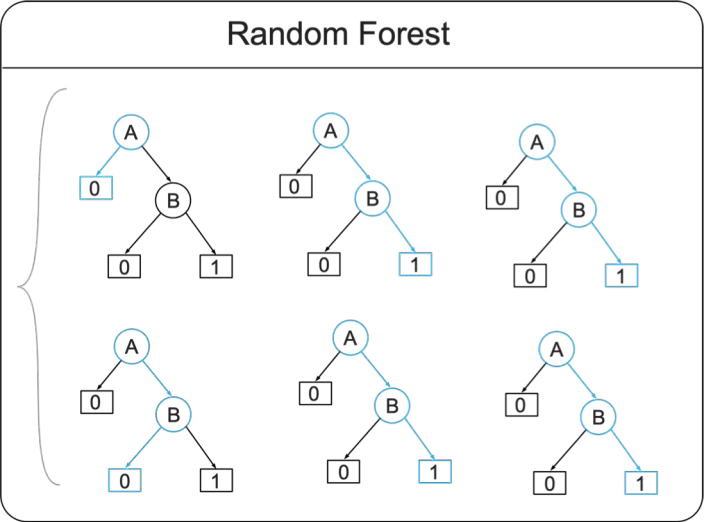
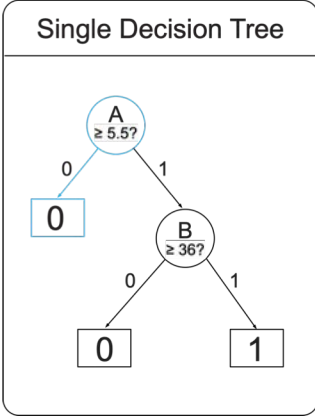


# Explainable AI

## *What? Why? Interpretability vs Explainability*



- Developing Methods and Techniques => Results of AI solution can be understood by humans
- Biases and Risks

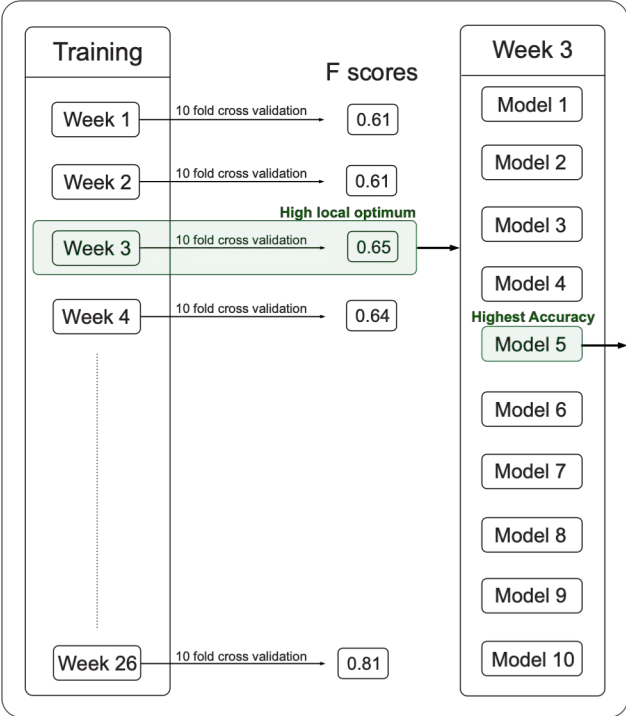


# Explainable AI

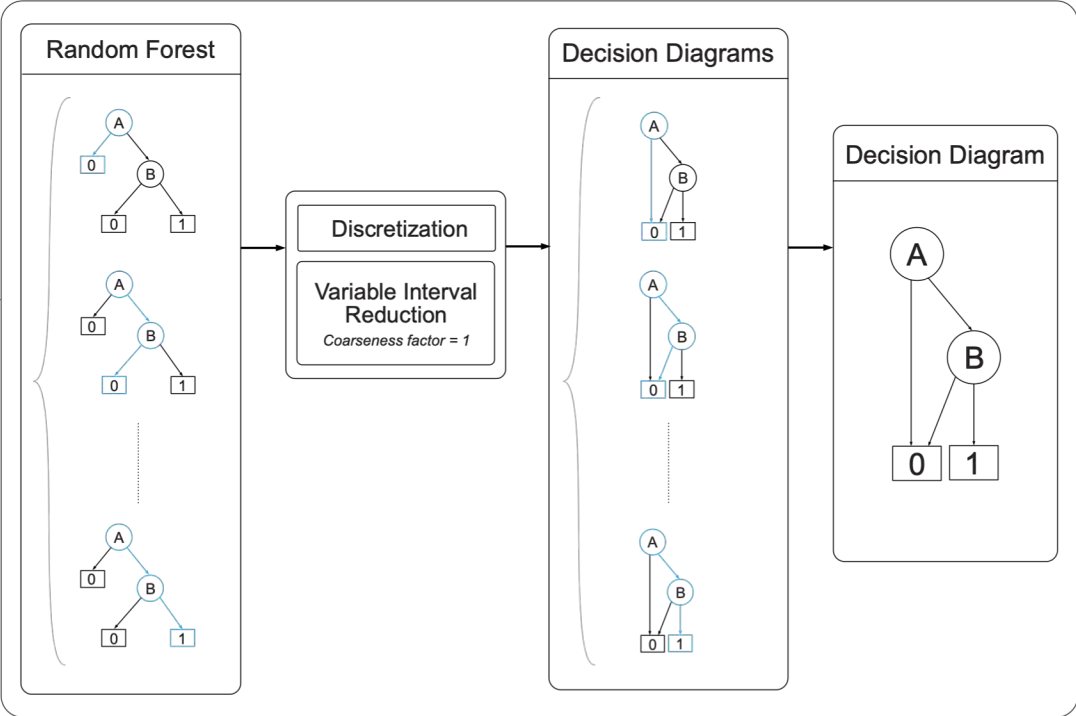
## Overview of work



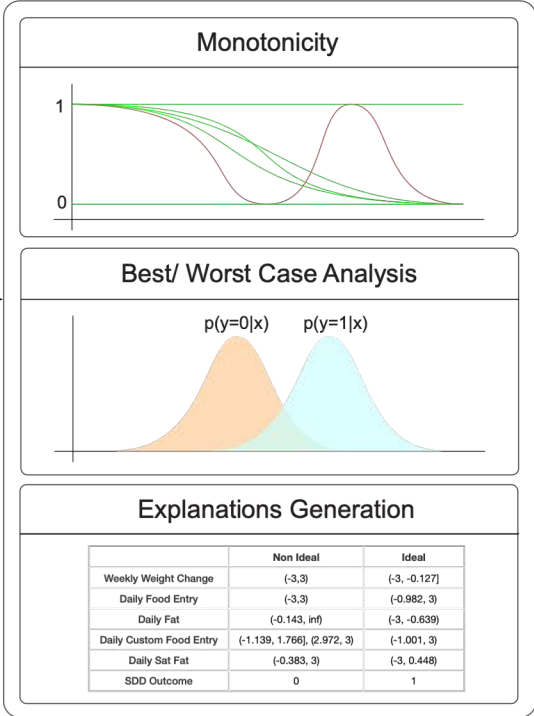
Optimal Early Prediction Time-point



Generating Tractable Representation of Machine Learning Model

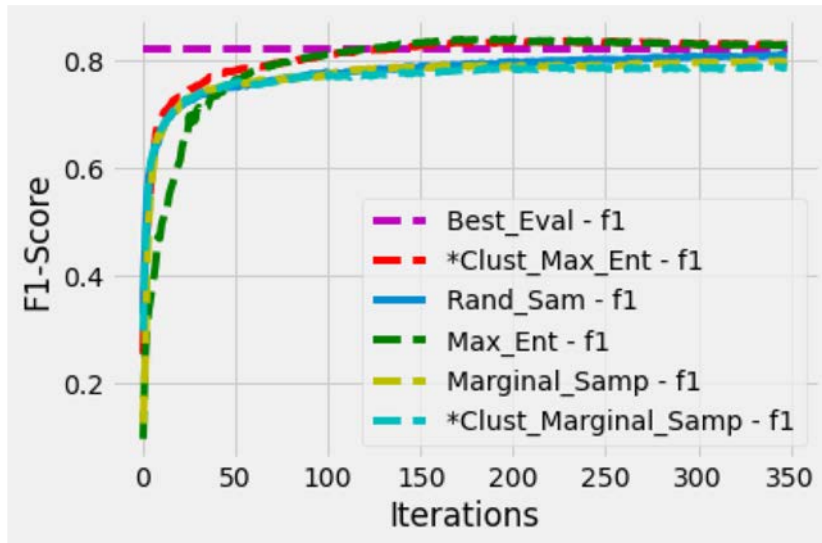


Creation of Explainability Metrics

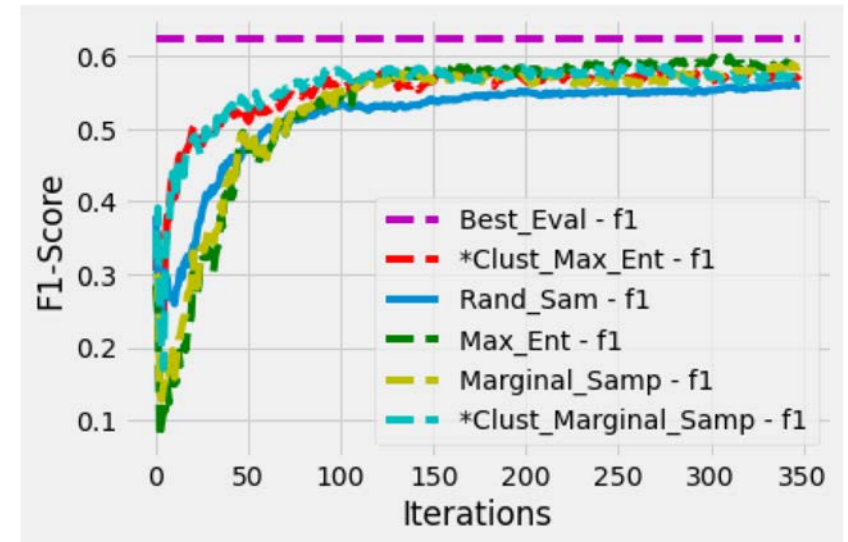


# Active Learning and Sample Size

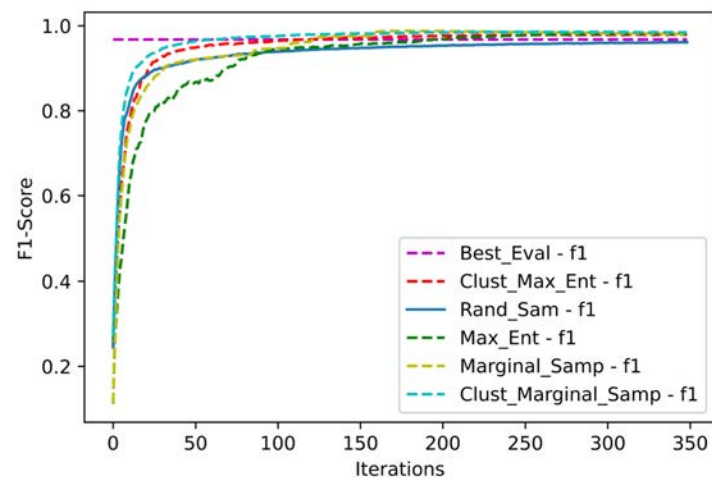
WISDM Dataset



FIC Dataset



UCI HAR Dataset



# To Mask or Not to Mask?: Balancing Privacy with Visual Confirmation Utility in Activity-Oriented Wearable Cameras



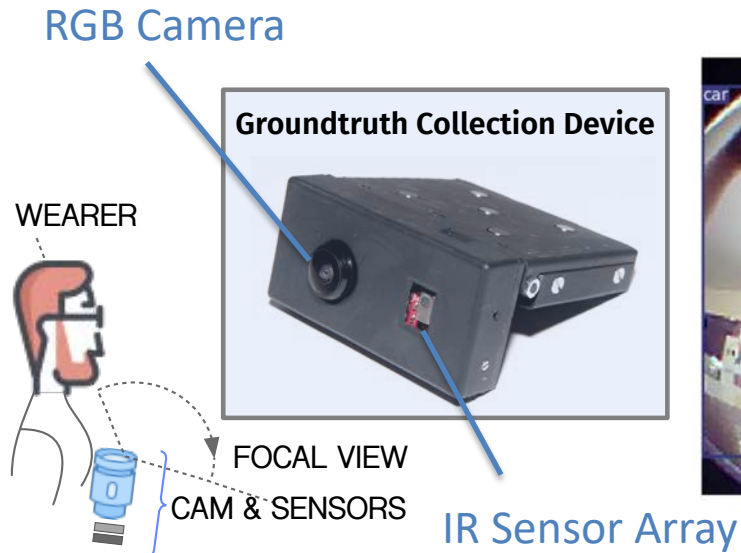
**Authors:** Rawan Alharbi, Mariam Tolba, Lucia C. Petito, Josiah Hester, Nabil Alshurafa

[Authors Info & Affiliations](#)

**Publication:** Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies • September 2019  
• Article No.: 72 • <https://doi.org/10.1145/3351230>

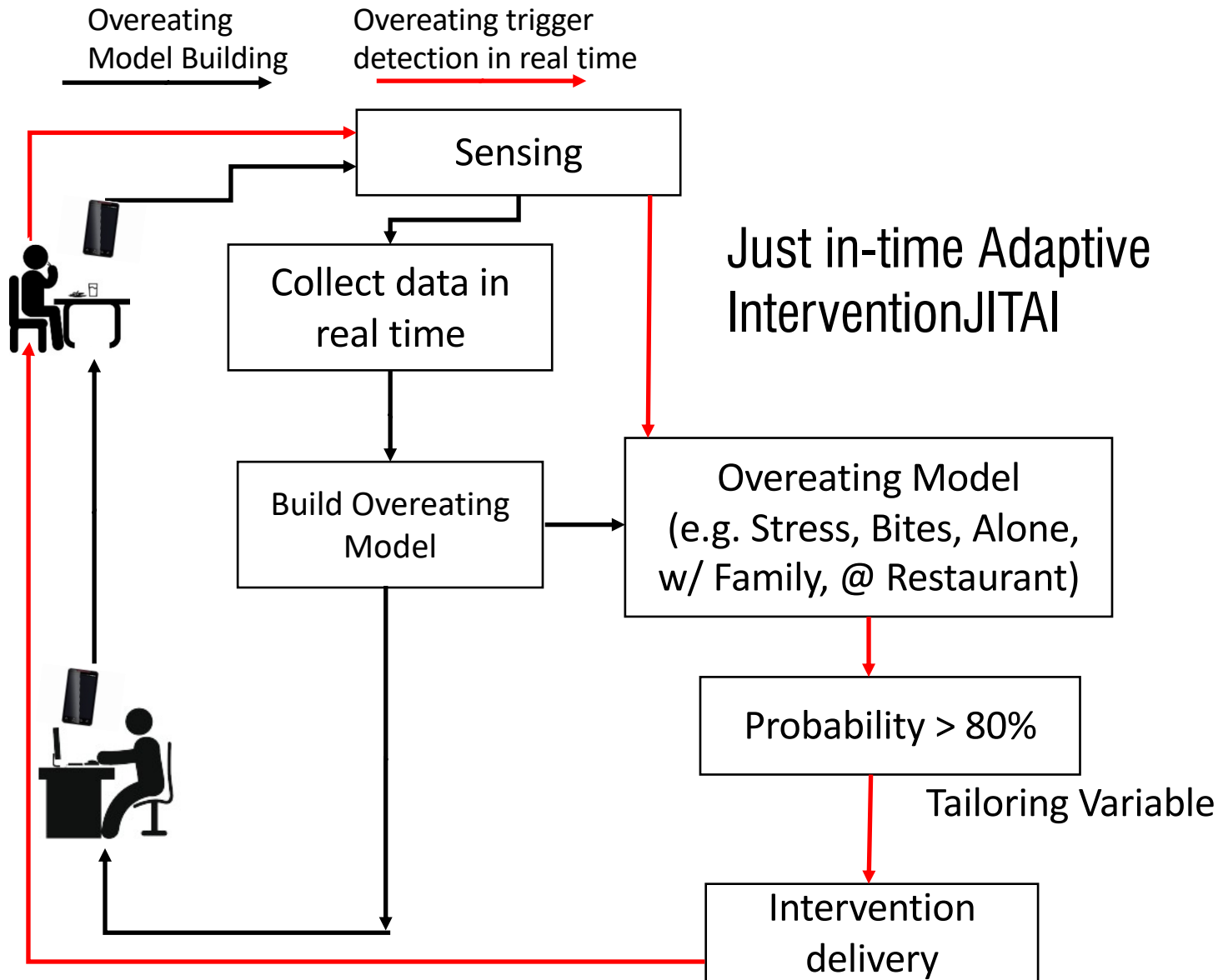


National Institute of Biomedical Imaging and Bioengineering





# SenseWhy: Overeating in Obesity Through the Lens of Passive Sensing, K25



- Entirely passive sensing of factors that relate to overeating
- Computer Science
  - Optimization of machine-learned models
- Behavior Science
  - Understanding human behavior through passive sensing



Personalized Medicine



from the lab to the wild



# Summary

“The best solution could be an algorithmic model, or maybe a data model, or maybe a combination.....

But the trick to being a scientist is to be open to using a wide variety of tools.”

L. Breiman

# Acknowledgements

## HABits Lab Students (PhD, Masters, Undergrads)

- Rawan Alharbi
- Shibo Zhang
- Jayalakshmi Jain
- Dzung Nguyen
- Zachary King
- Yuqi Zhao
- Samanvitha Sundar
- Mariam Tolba
- Chunlin Feng
- Wilson Wang, Amro Ashmeik
- Glenn Fernandes
- Boyang Wei
- Farzad Shahabi
- Soroush Shahi

Health Aware Bits Lab

HABits Lab



## Funding

- K25 NIDDK, NIH (K25DK1132424)
- CNS, NSF (1915847)
- Lurie Children's Hospital
- NCI
- Northwestern Data Science Initiative



National Institute of  
Diabetes and Digestive  
and Kidney Diseases



Ann & Robert H. Lurie  
Children's Hospital of Chicago



Northwestern  
University

## Mentors

- Bonnie Spring, Northwestern University
- Santosh Kumar, University of Memphis
- Donald Hedeker, University of Chicago
- Robert Kushner, Northwestern University
- Linda Van Horn, Northwestern University
- Evan Forman, Drexel University
- Peter Dinda, Northwestern University



## Collaborators

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- June Robinson, Northwestern University
- Angela Pfammatter, Northwestern University
- Tammy Stump, Northwestern University

Northwestern  
ENGINEERING

# HABits Lab

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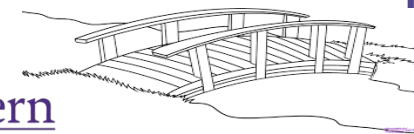


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