ECE 598HH: Advanced Wireless Networks and Sensing Systems

Lecture 13: Machine Learning For Wireless Sensing
Part 1

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CSL: COORDINATED SCIENCE LAB

*Slides Courtesy of Mingmin Zhao

Previous Lectures

WiVi: Sensing humans through walls with WiFi

WiTrack: Accurately Localizing humans through walls

RF-Capture: Capturing human figure through walls

Vital Ratio: Extracting vital signs (Breathing rate and heart rate)

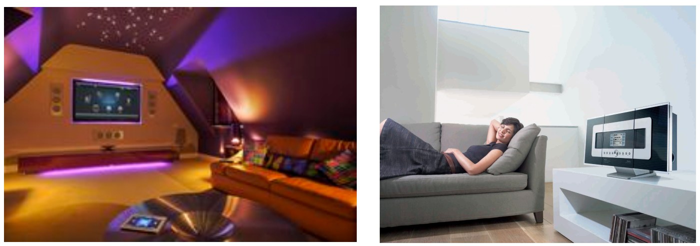
This Lecture

EQ-Radio: Detecting emotions from wireless signals

RF-Sleep: Detecting sleep stages from wireless signals

Can you tell people's emotions even if they don't show up on their faces?

Smart Homes that adapt to our mood



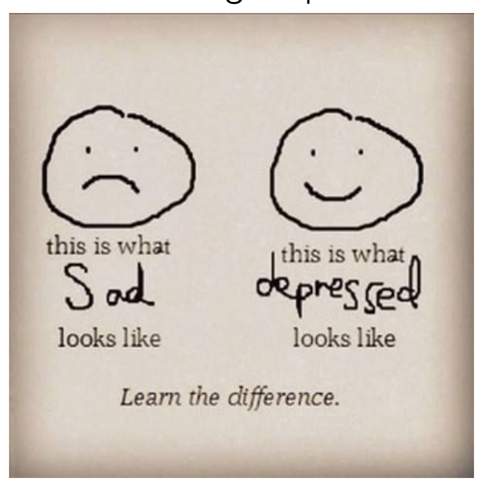
Did I get the Job? …. No

Does my advisor like my work?

Graduate student

Advisor

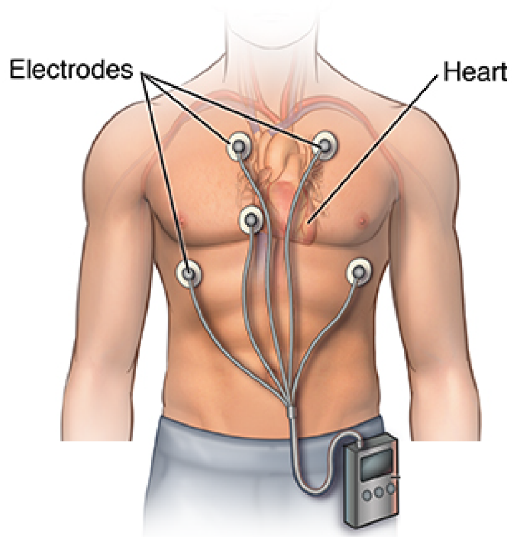
Combating Depression



Is the date going well!

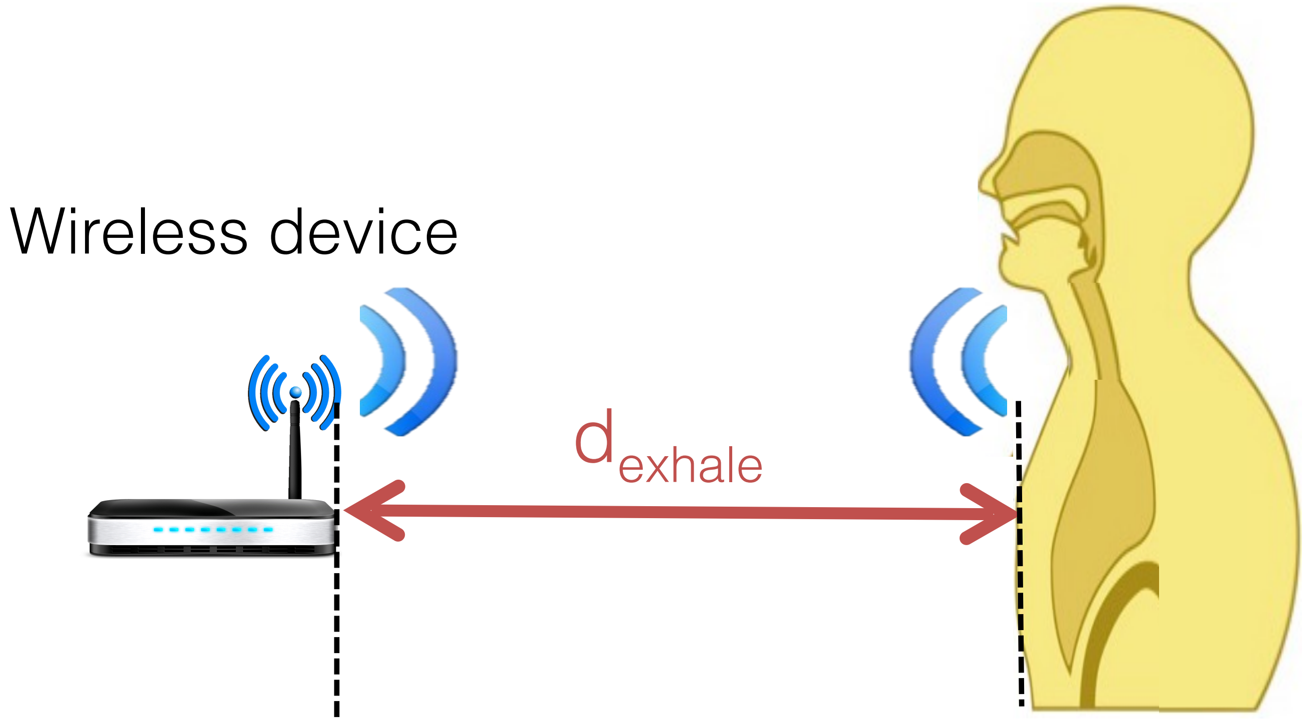
Existing approaches measure vital signs

- Use ECG to get very accurate heartbeats

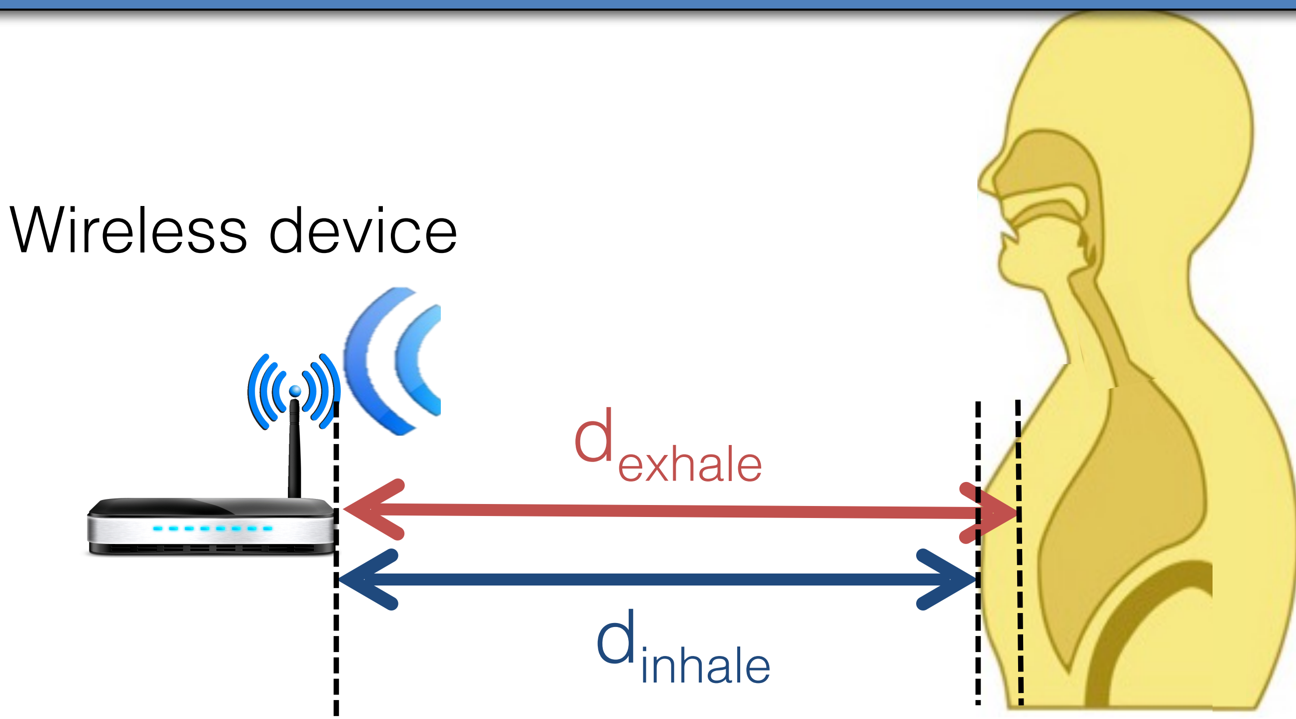


Use wireless reflections off the human body

Use wireless reflections off the human body



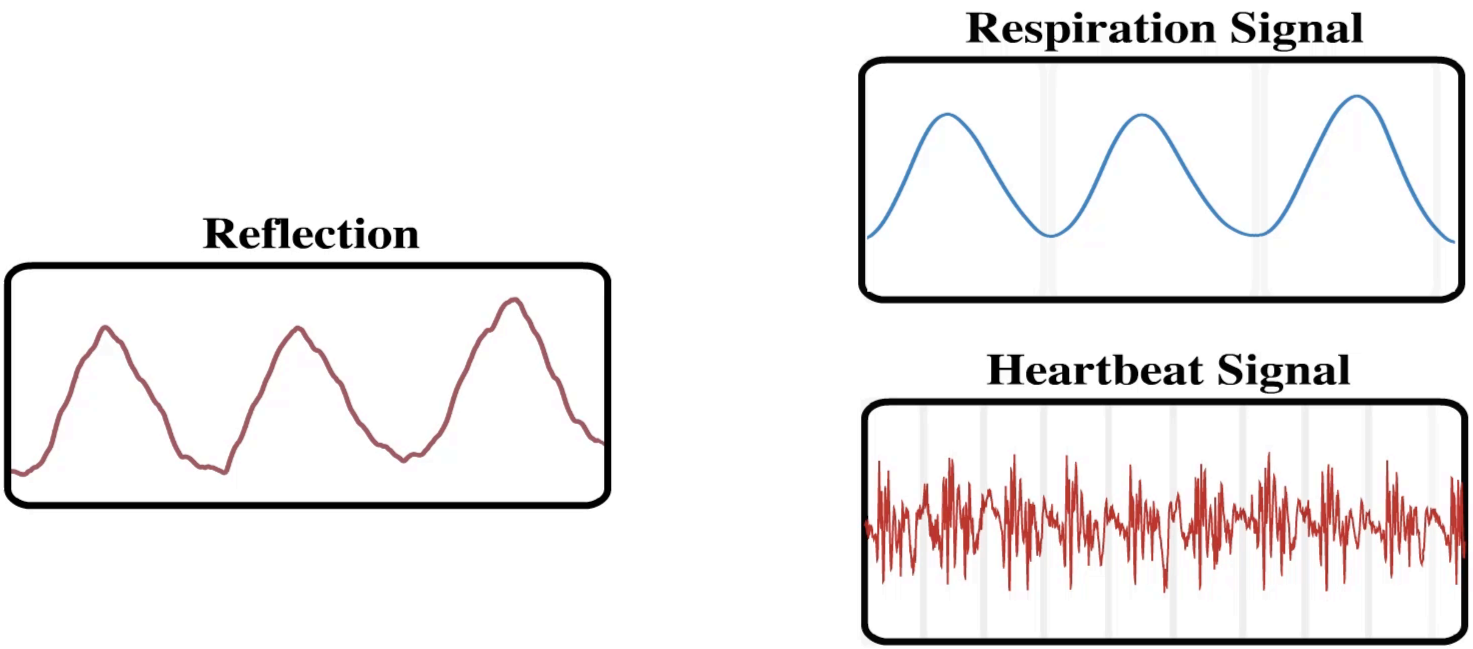
<u>Solution:</u> Use the phase of the wireless reflection



Wireless wave has a phase: $\boxed{\phi} = 2\pi \frac{\boxed{\text{distance}}}{\text{wavelength}}$

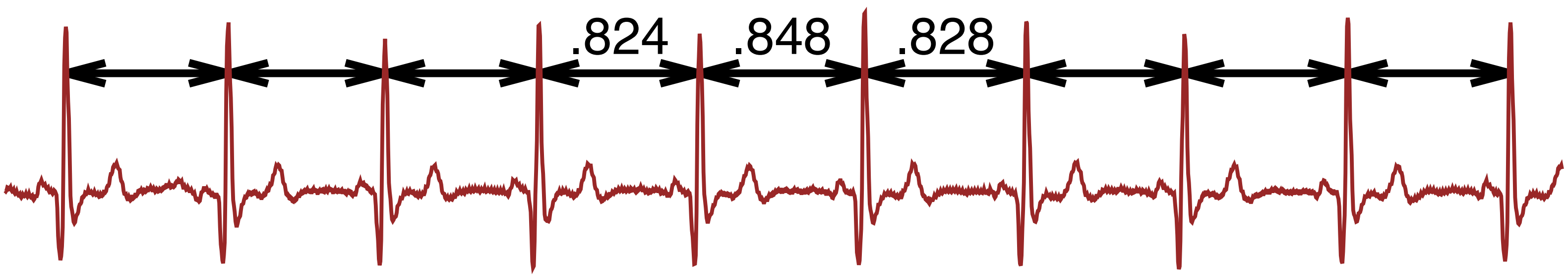
- Chest Motion changes distance
- Heartbeats also change distance

Emotion recognition using wireless signals



Key challenge: Inter-Beat Interval (IBI)

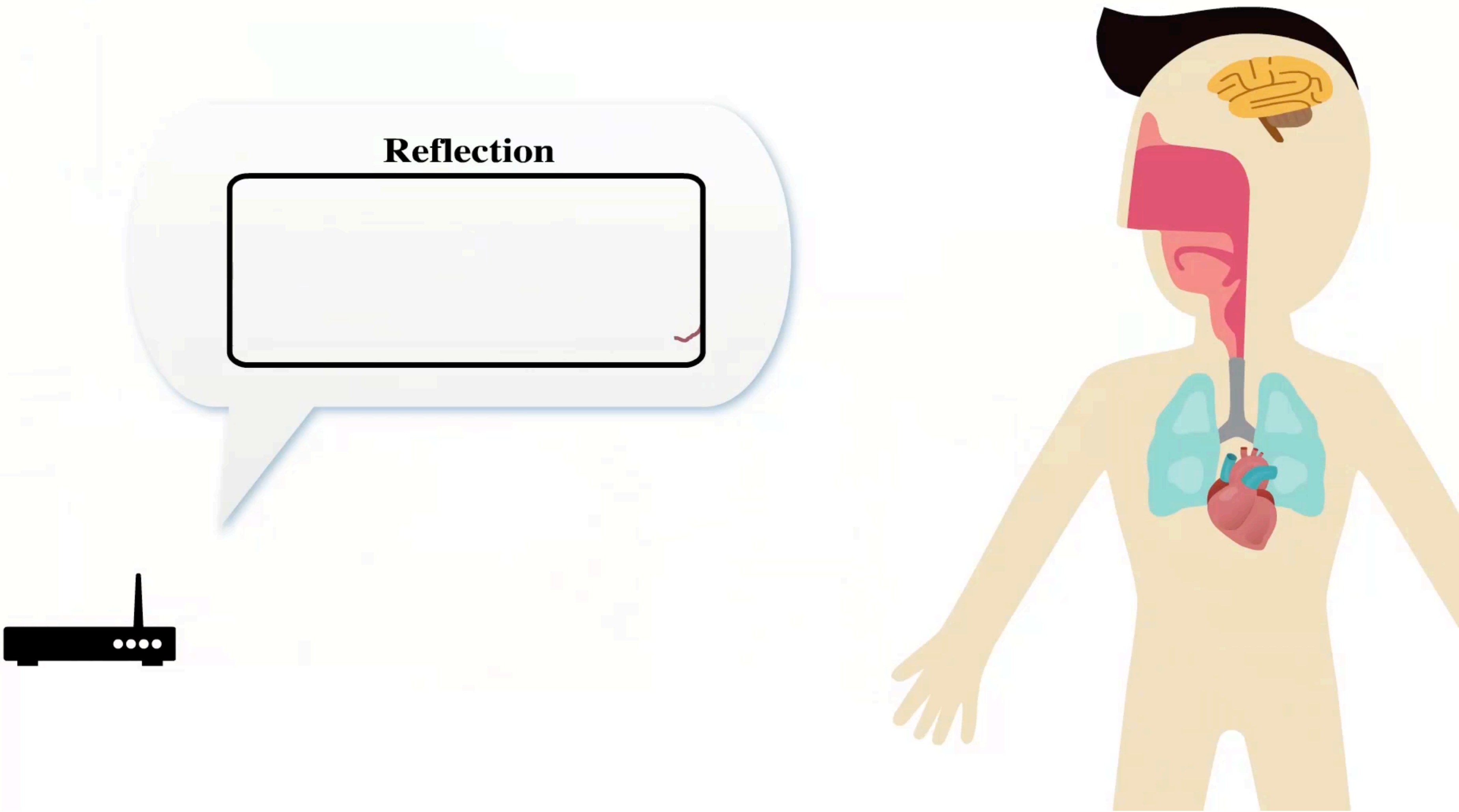
- Emotion recognition needs accurate measurements of the length of every single heartbeat



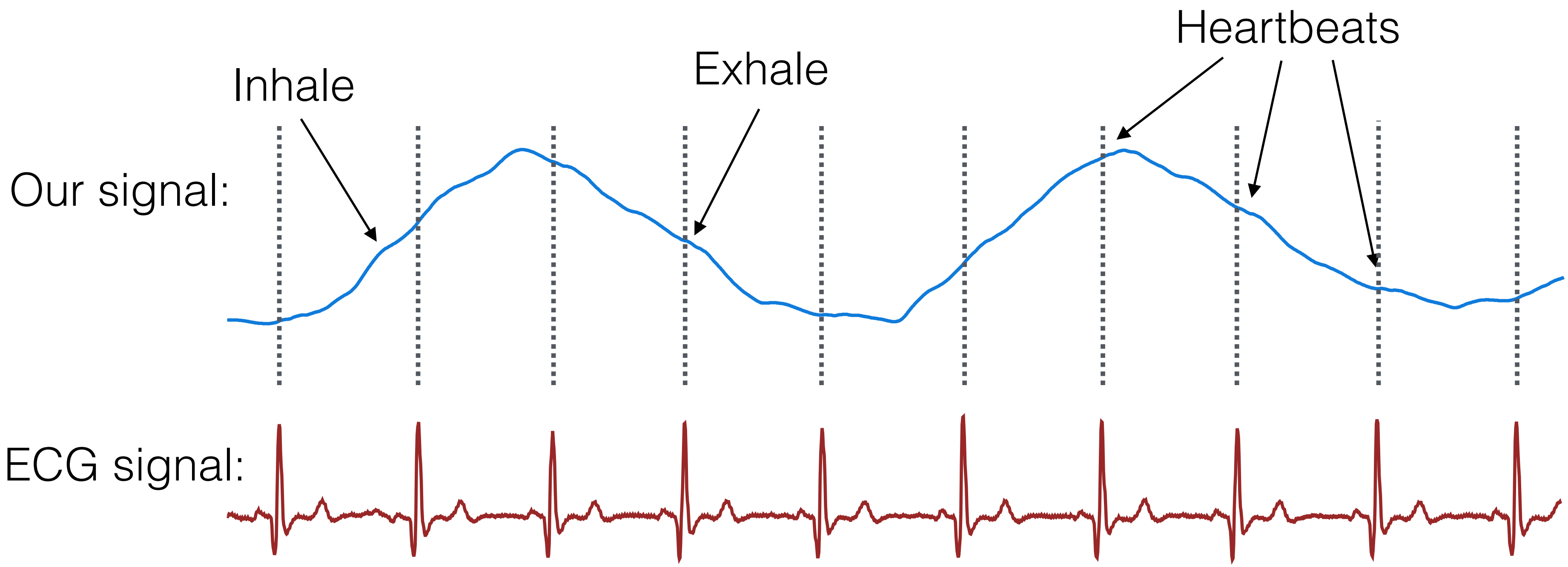
We need to extract IBI with accuracy over 99%

Input signal

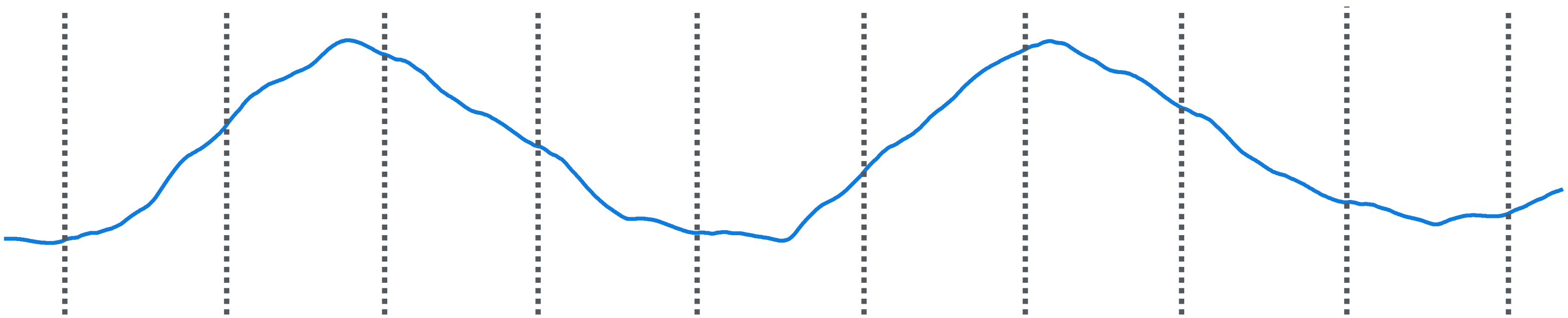
Wireless reflection of the human body



Input signal



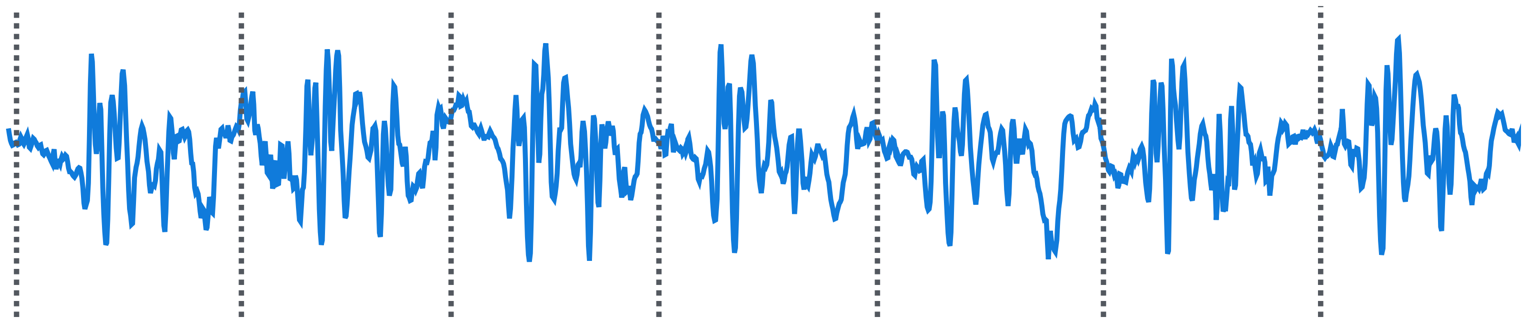
Step 1: Remove breathing signal



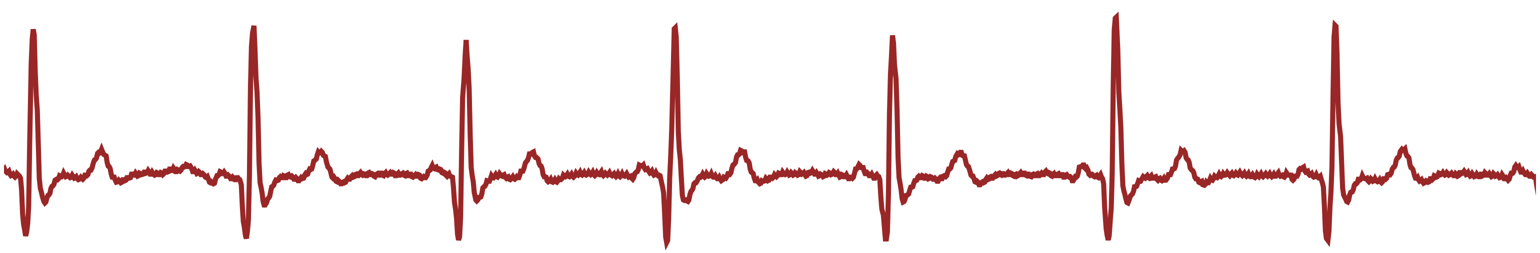
- Breathing masks heartbeats
- We use acceleration filter
  - Heartbeat involves rapid contraction of muscle
  - Breathing is slow and steady

Heartbeat signal

- Output of acceleration filter

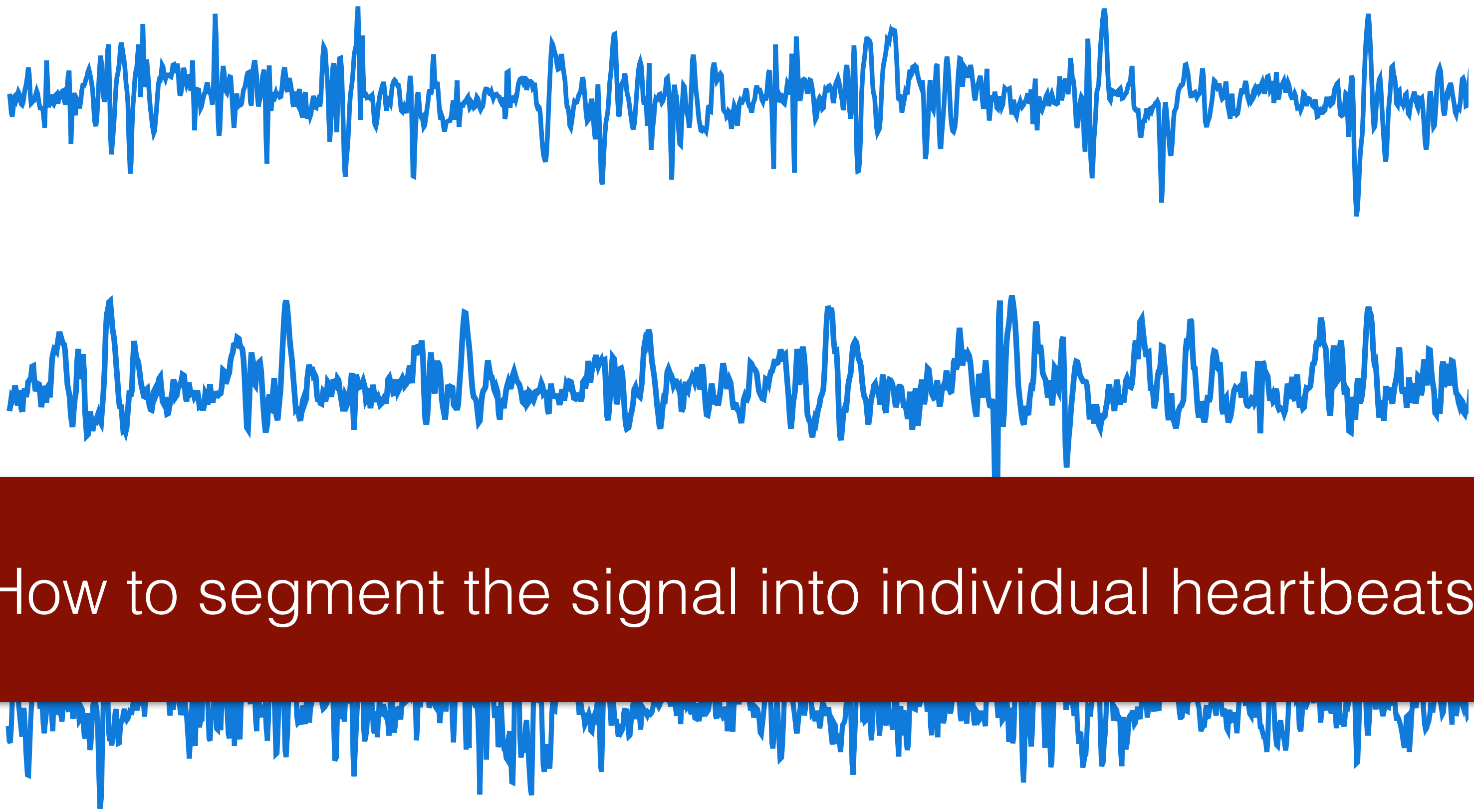


- ECG signal



Heartbeat signal

- Other typical examples:

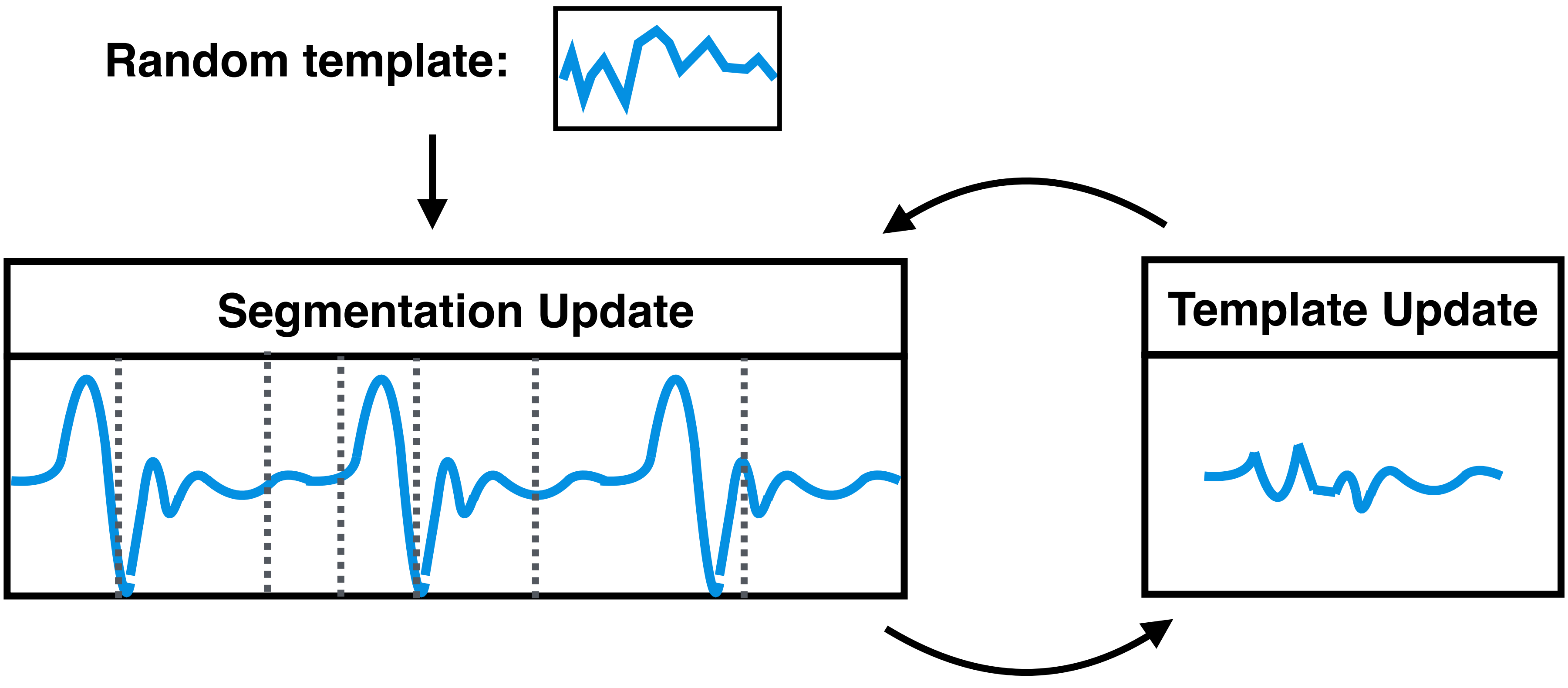


Step 2: Heartbeat segmentation

- **Intuition**: heartbeat repeats with certain shape (template)
- If we can somehow discover the template, then we can segment into individual heartbeats

Step 2: Heartbeat segmentation

- **Intuition**: heartbeat repeats with certain shape (template)



Step 2: Heartbeat segmentation

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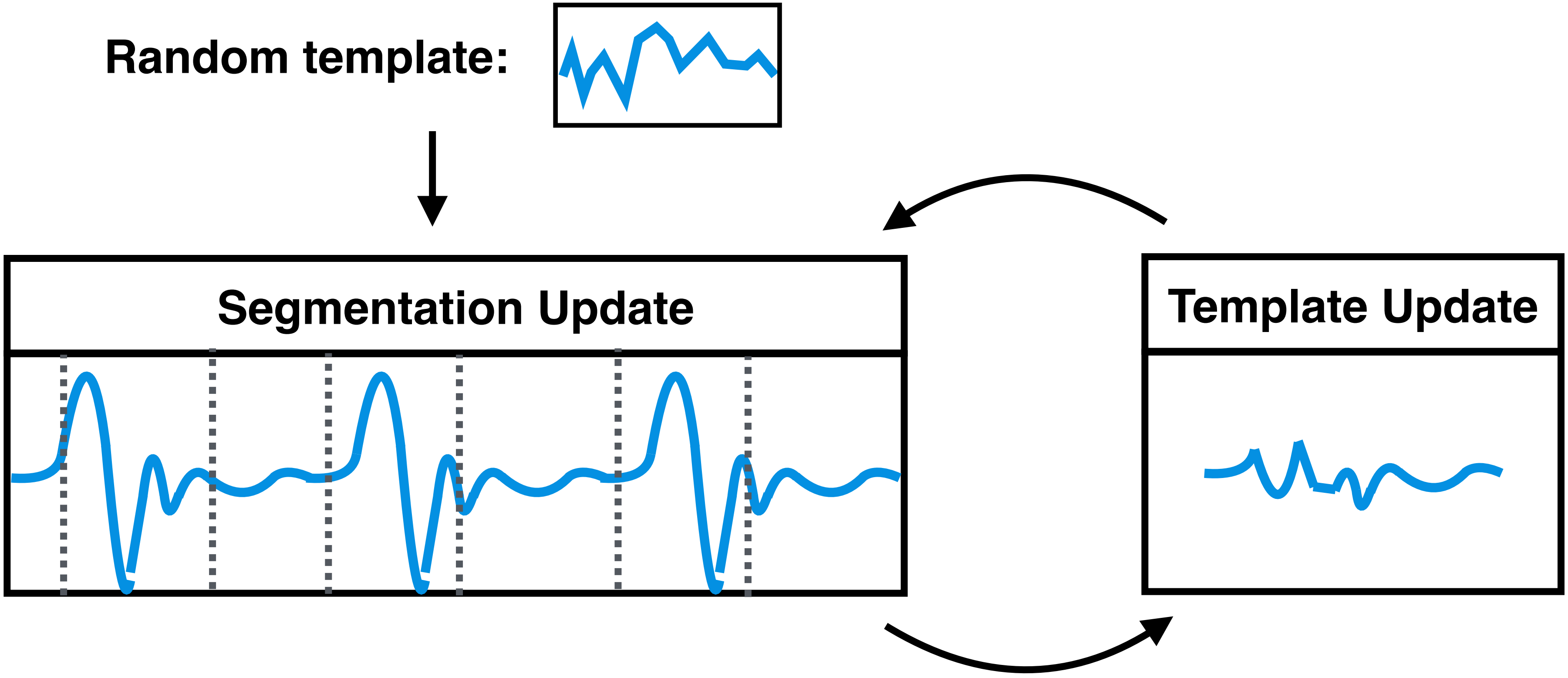

Step 2: Heartbeat segmentation

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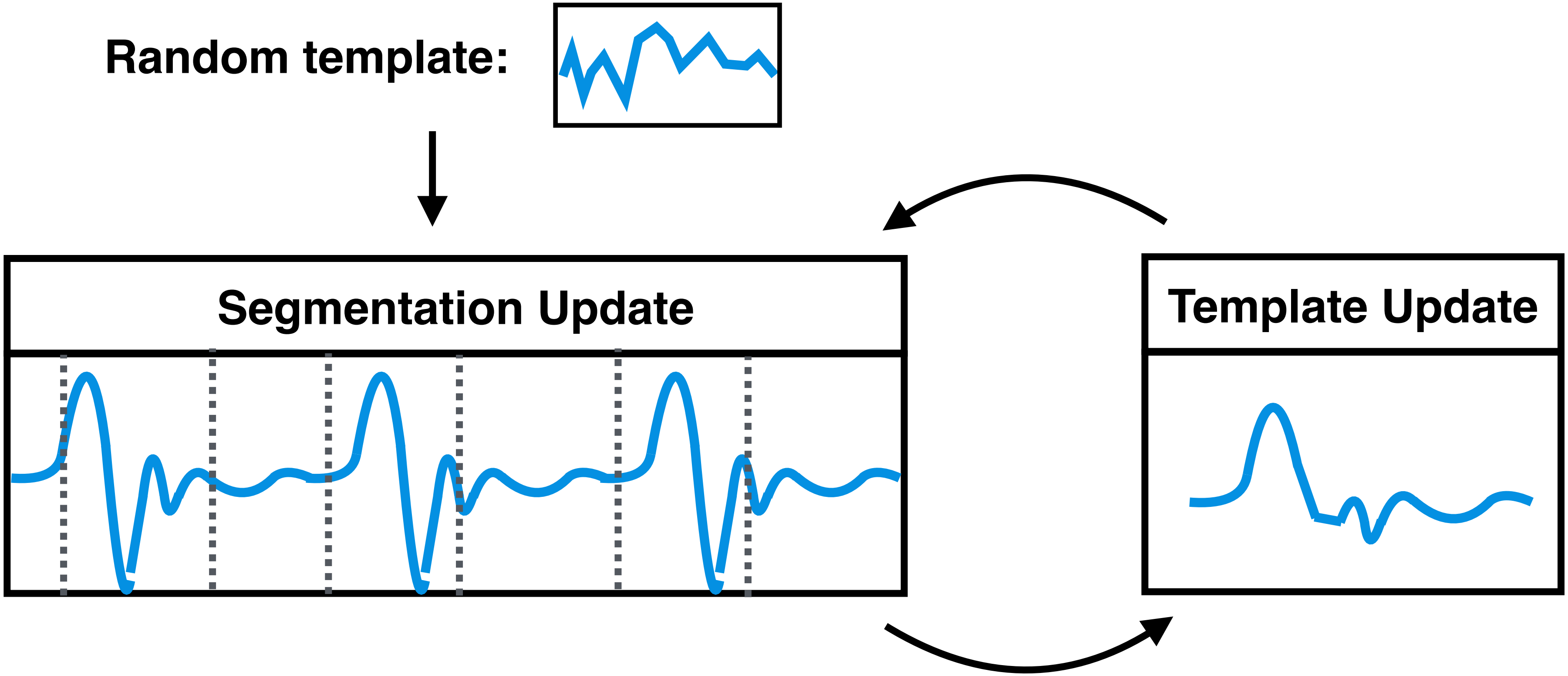

Step 2: Heartbeat segmentation

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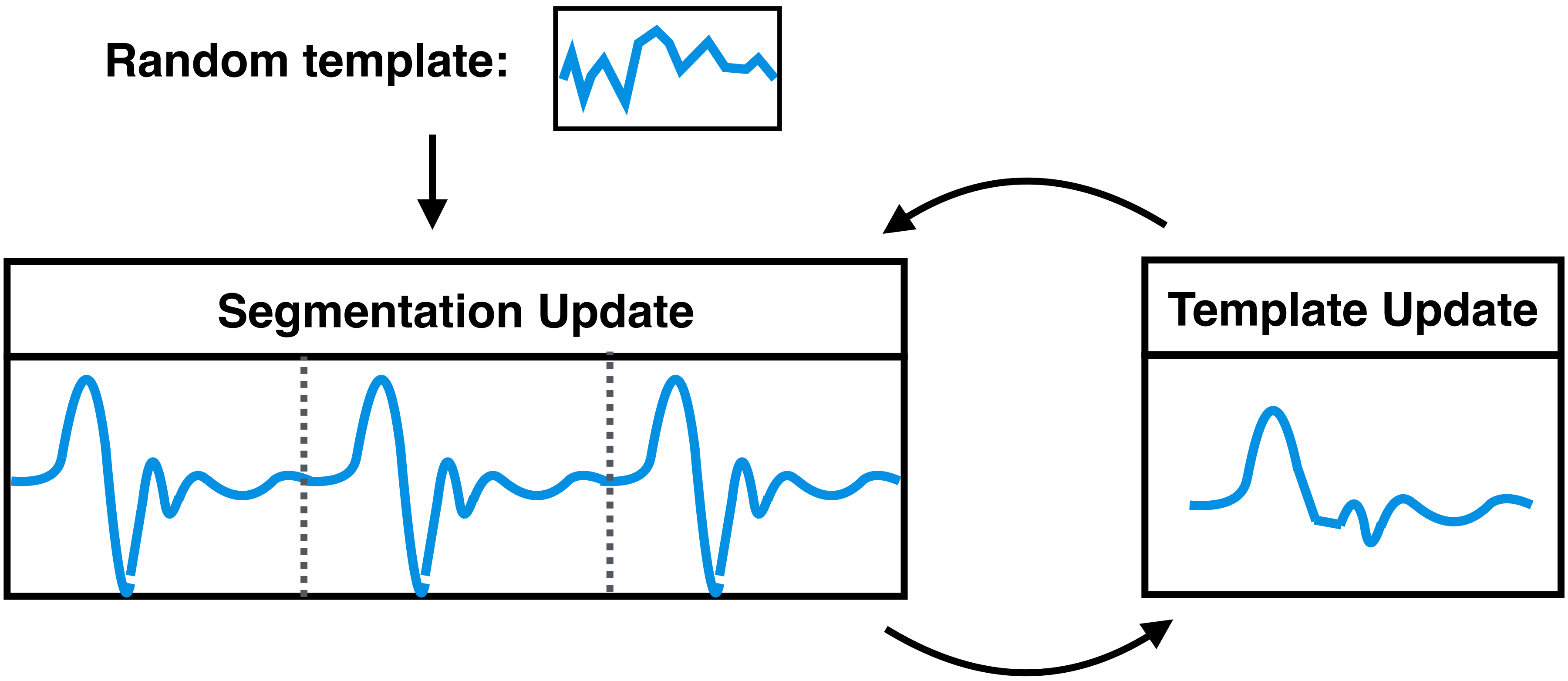

Step 2: Heartbeat segmentation

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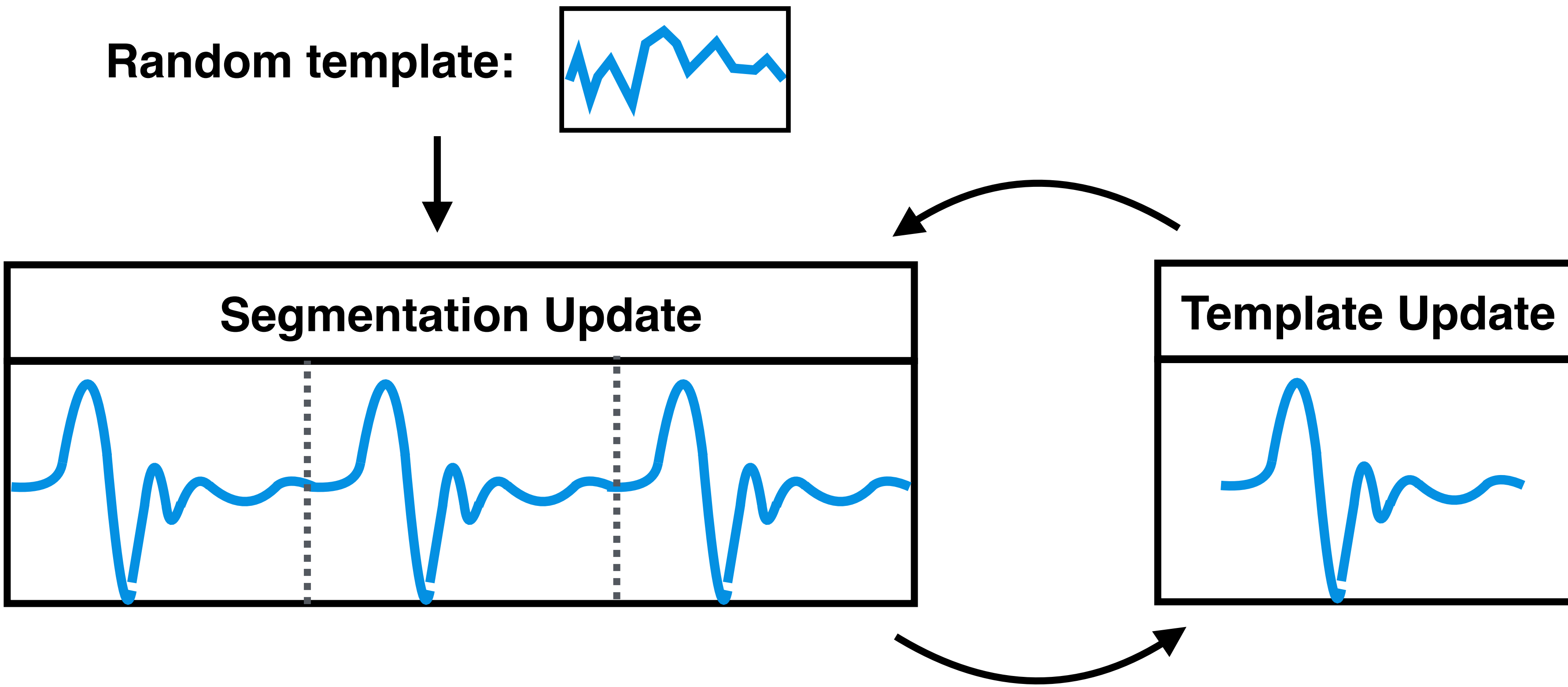
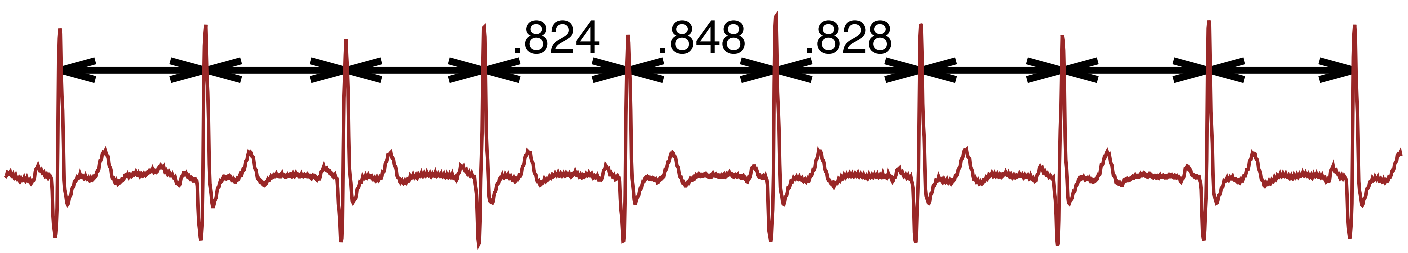


Caveat: Shrinking & Expanding

- IBI are not always the same



- Template subject to shrink and expanding
    - Linear warping

Algorithm

Need to recover both segmentation and template

- Joint optimization: $$\underset{\mathcal{S},\boldsymbol{\mu}}{\text{minimize}} \sum_{s_i \in \mathcal{S}} \| s_i - \omega(\boldsymbol{\mu}, |s_i|) \|^2$$

segmentation template warping

Segmentation Update
$$\mathcal{S}^{l+1} = \arg\min_{\mathcal{S}} \sum_{s_i \in \mathcal{S}} \| s_i - \omega(\boldsymbol{\mu}^l, |s_i|) \|^2$$ (dynamic programming)

Template Update
$$\boldsymbol{\mu}^{l+1} = \arg\min_{\boldsymbol{\mu}} \sum_{s_i \in \mathcal{S}^{l+1}} \| s_i - \omega(\boldsymbol{\mu}, |s_i|) \|^2$$ (weighted least squares)

Algorithm

Need to recover both segmentation and template

- Joint optimization: $$\underset{\mathcal{S},\boldsymbol{\mu}}{\text{minimize}} \sum_{s_i \in \mathcal{S}} \|s_i - \omega(\boldsymbol{\mu}, |s_i|)\|^2$$

segmentation template warping

Segmentation Update

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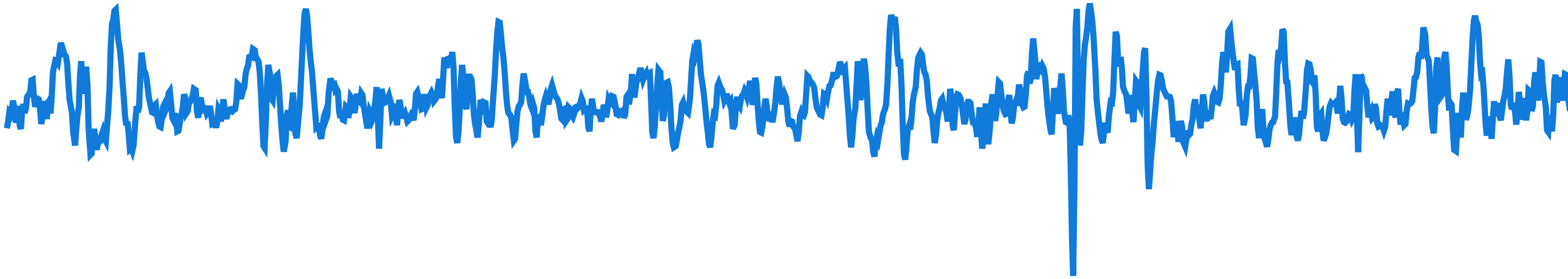
(dynamic programming)

Template Update

$$\boldsymbol{\mu}^{l+1} = \arg\min_{\boldsymbol{\mu}} \sum_{s_i \in \mathcal{S}^{l+1}} \|s_i - \omega(\boldsymbol{\mu}, |s_i|)\|^2$$

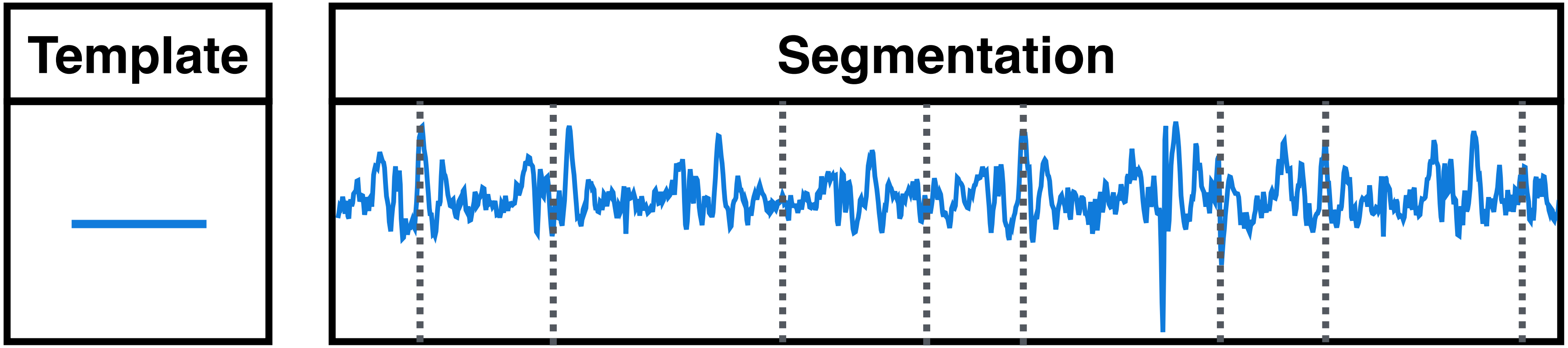
(weighted least squares)

Example run



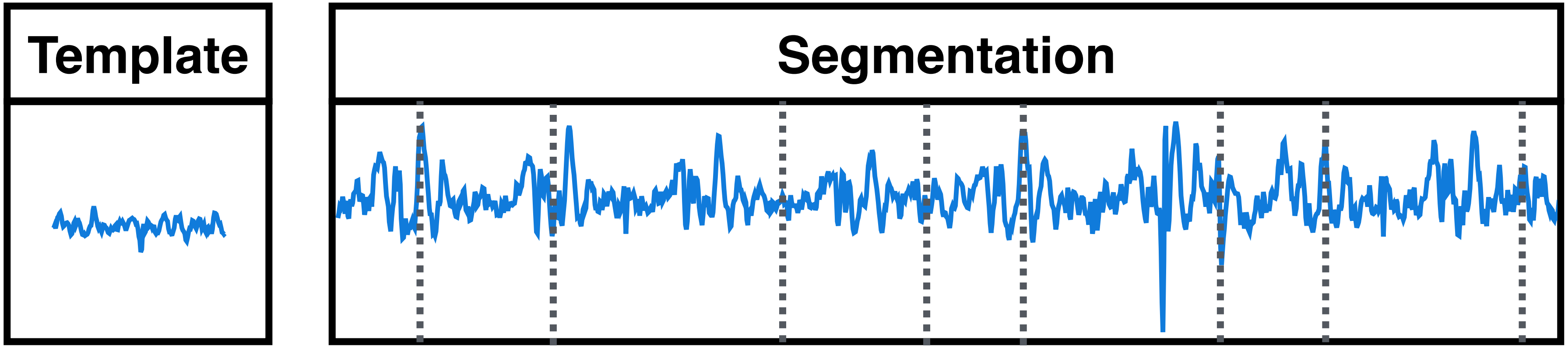
Example run

Iteration 1:



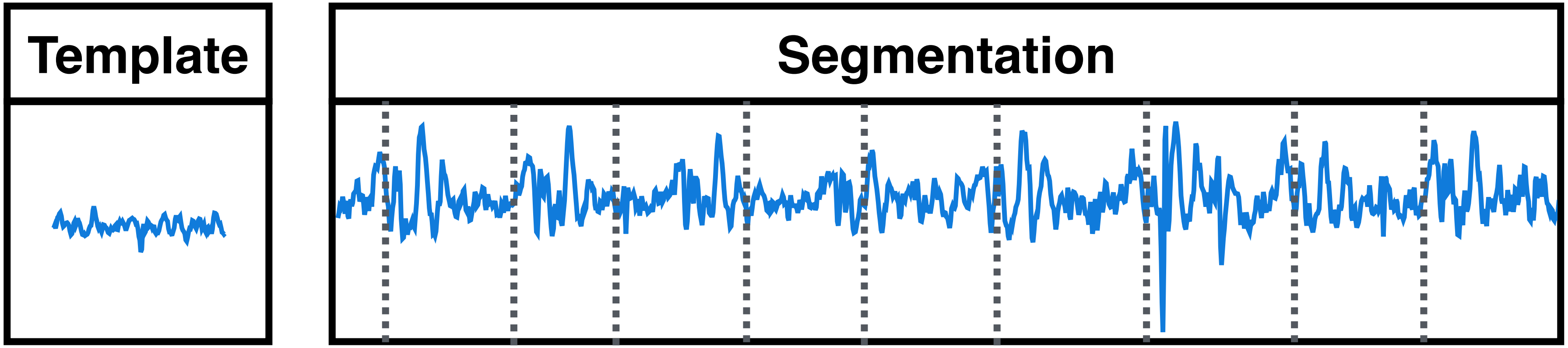
Example run

Iteration 2:



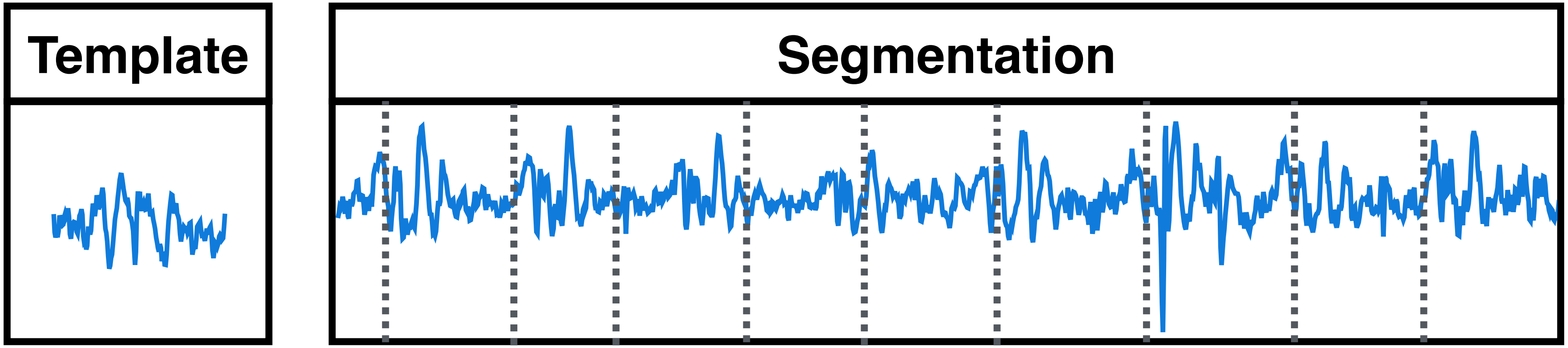
Example run

Iteration 2:



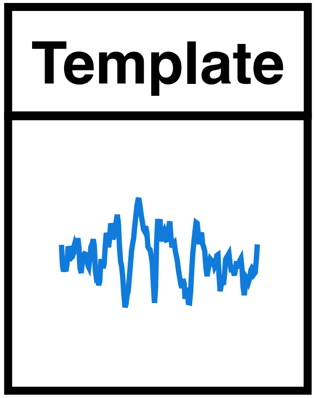
Example run

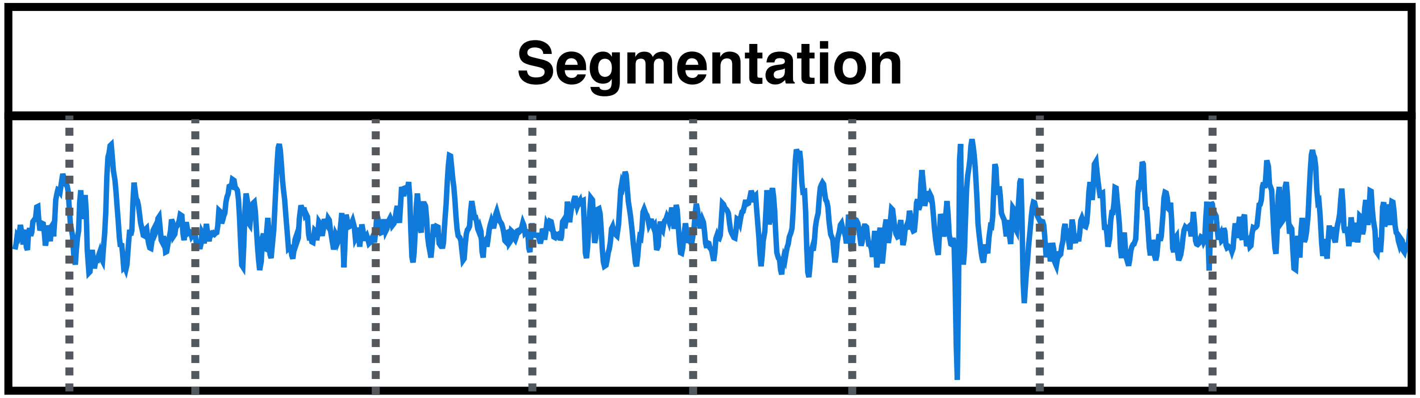
Iteration 3:



Example run

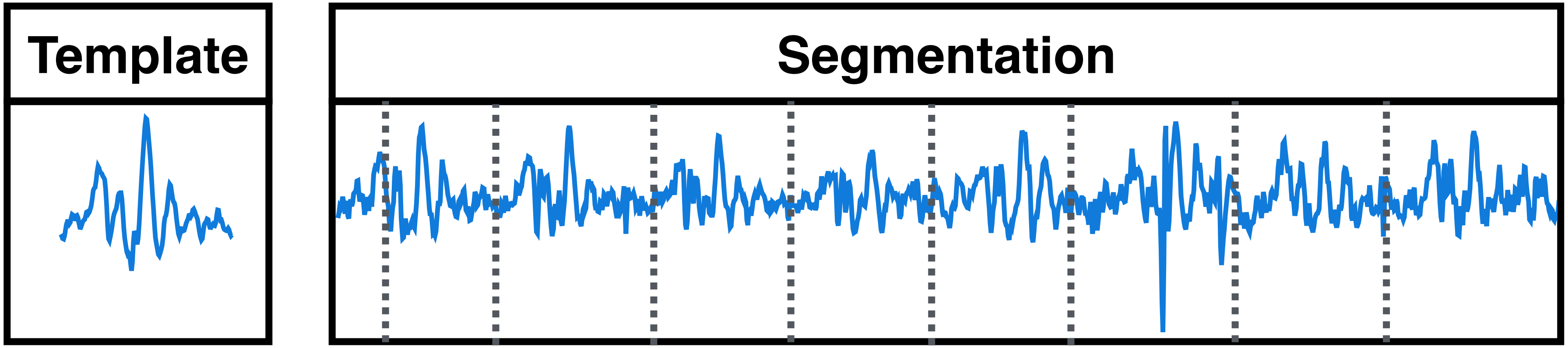
Iteration 3:





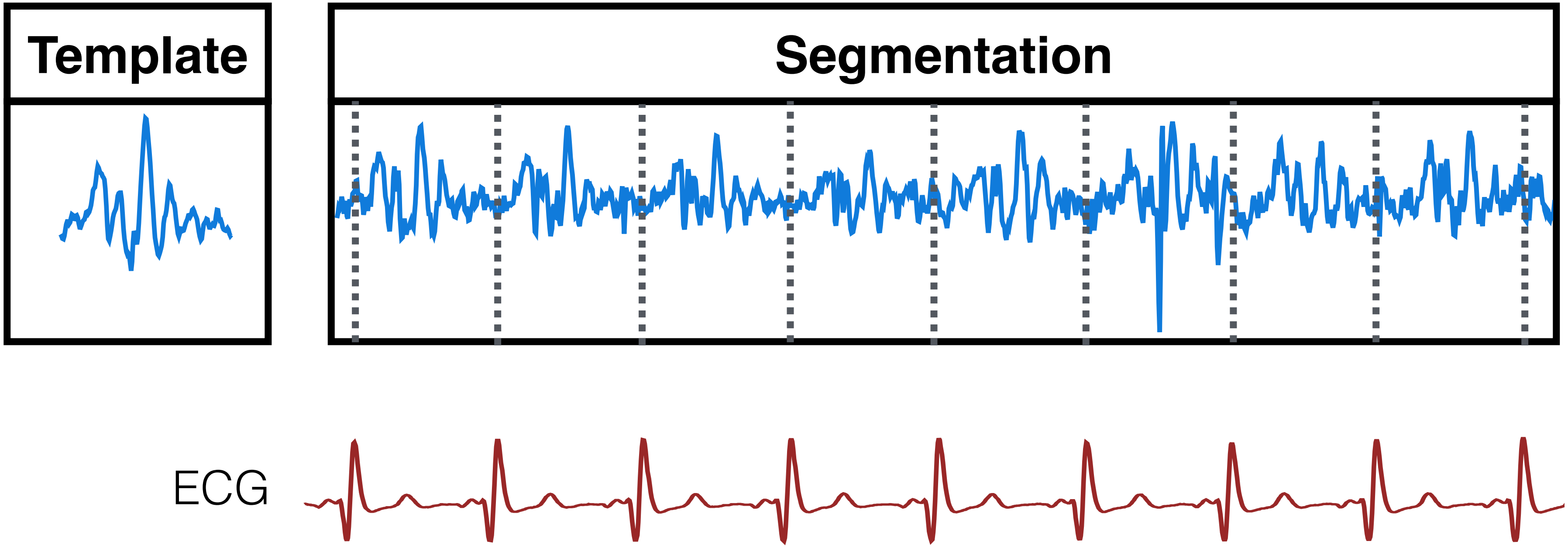
Example run

Iteration 7:



Example run

Iteration 7:



From vital signs to emotions

Physiological Features for Emotion Recognition

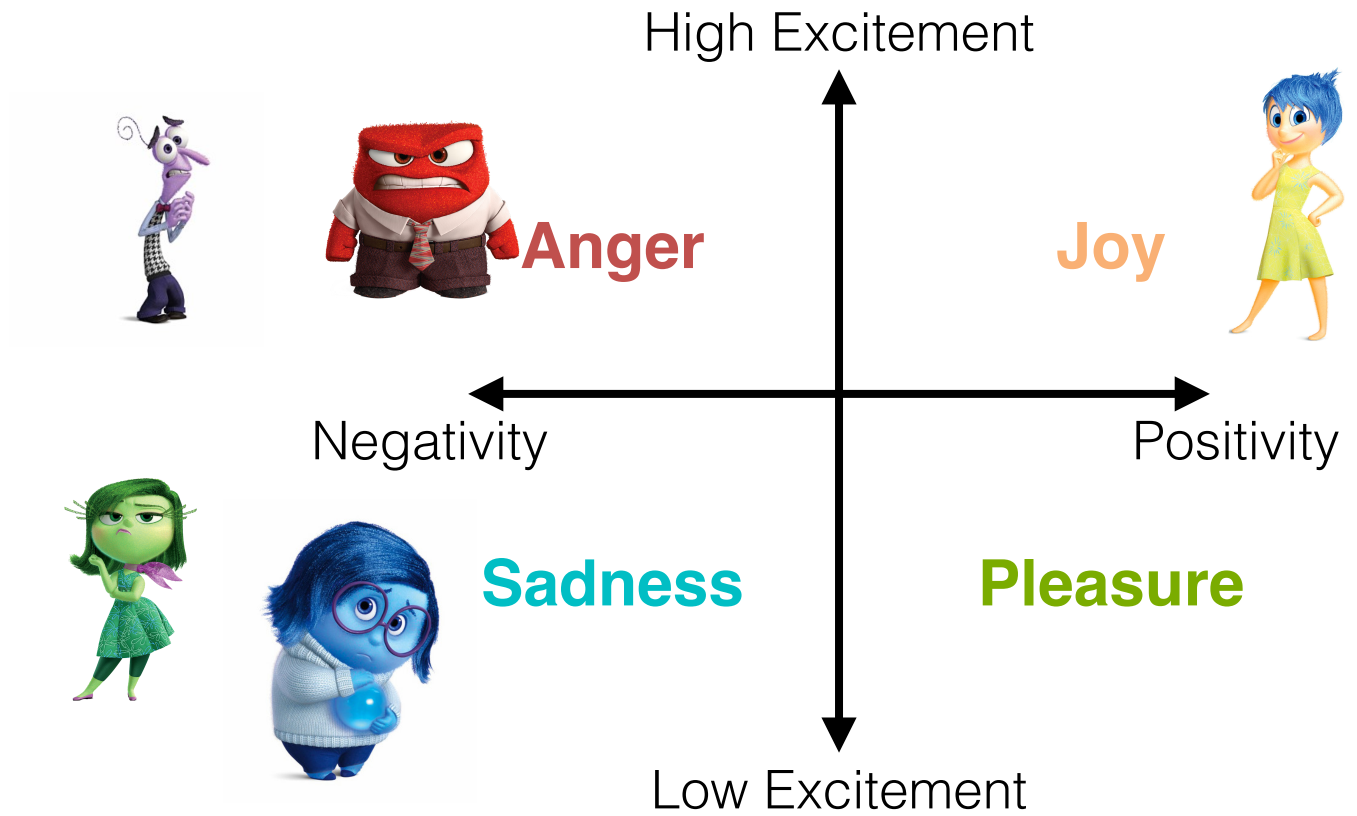
- 37 Features similar to ECG-based methods
  - Variability of IBI
  - Irregularity of breathing

Emotion Classification

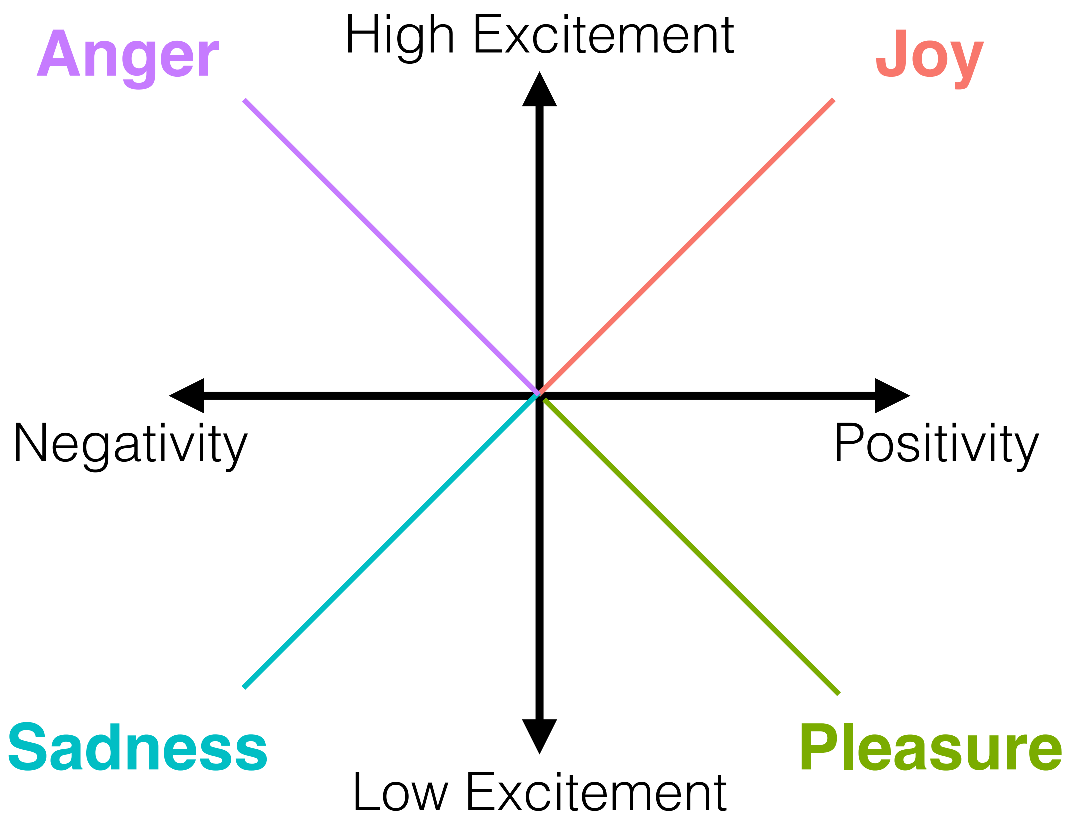
- Recognize emotion using physiological features
- Used L1-SVM classifier
  - select features and train classifier at the same time

Emotion Model

- Standard 2D emotion model
- Classify into **anger**, **sadness**, **pleasure** and **joy**

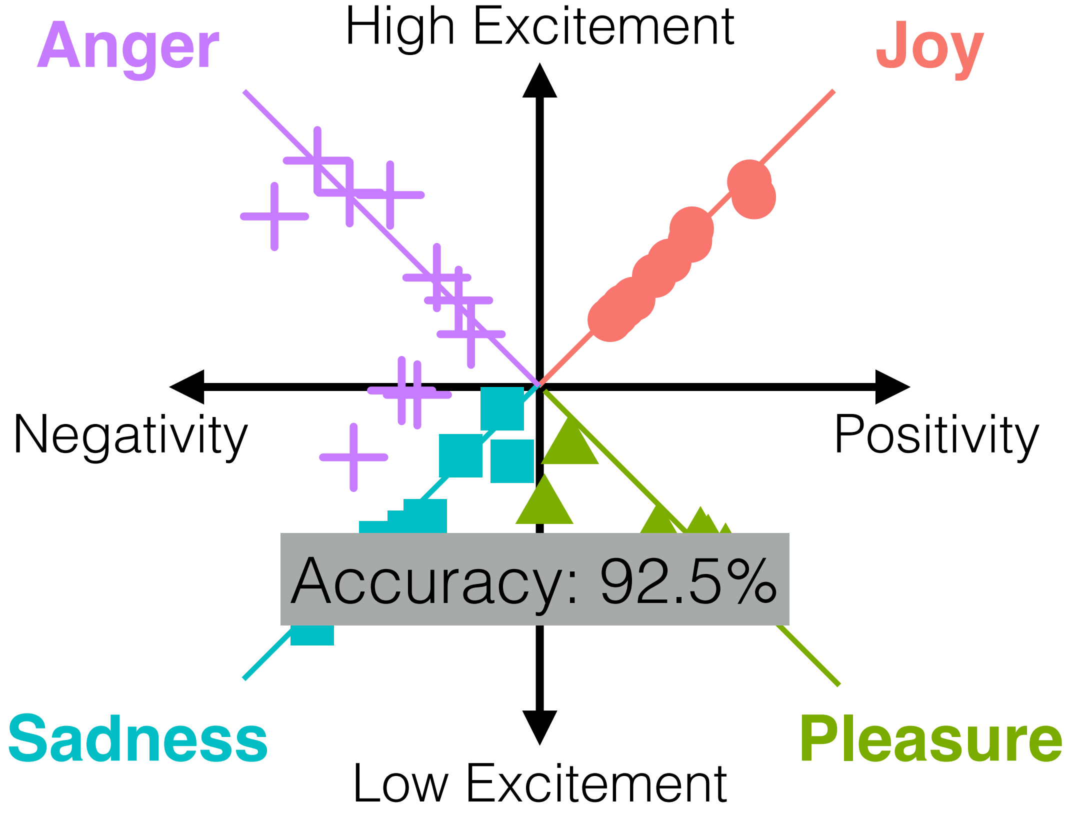


Does it detect emotion accurately?



Person-dependent Classification

- Train and test on the same person



Person-independent Classification

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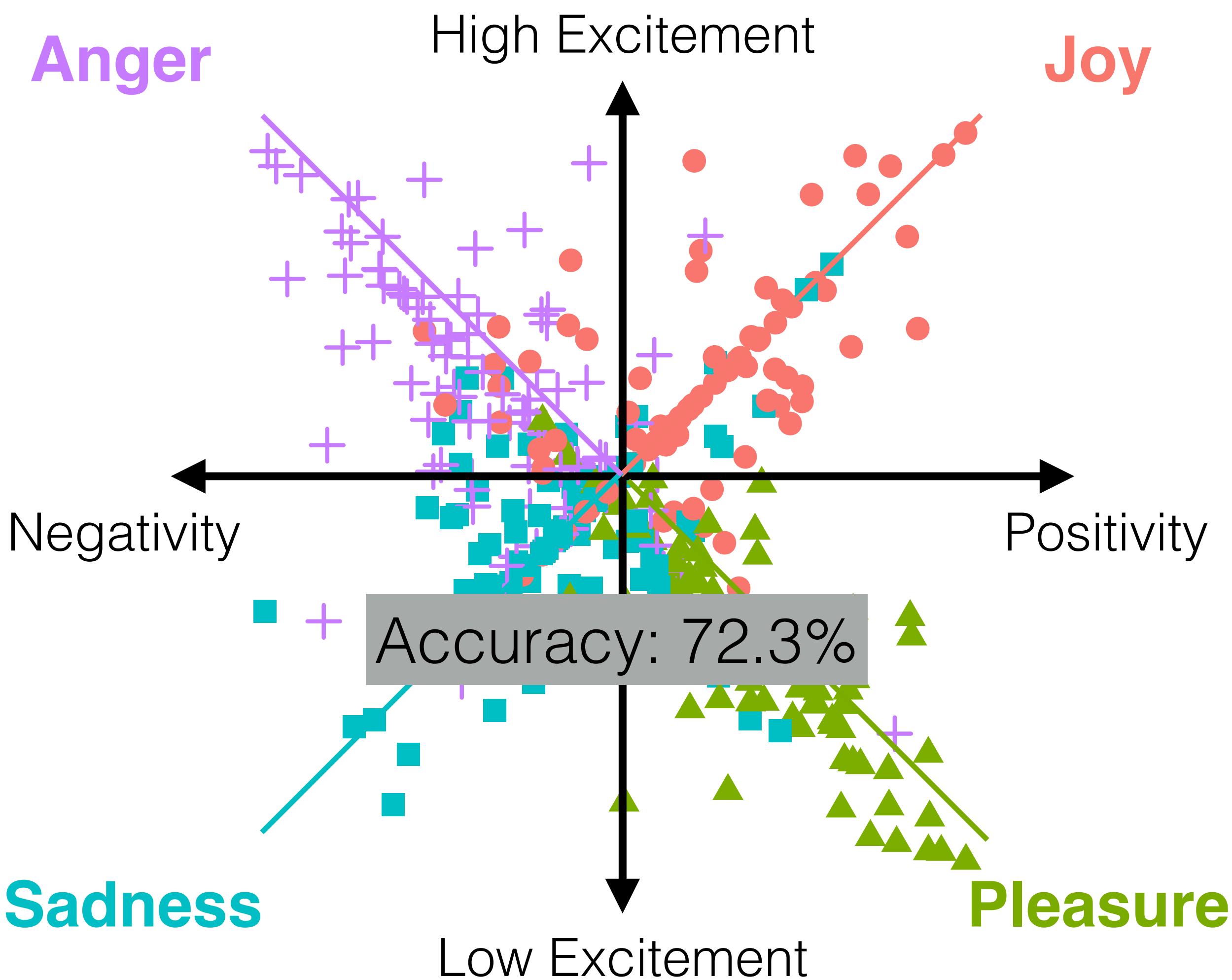
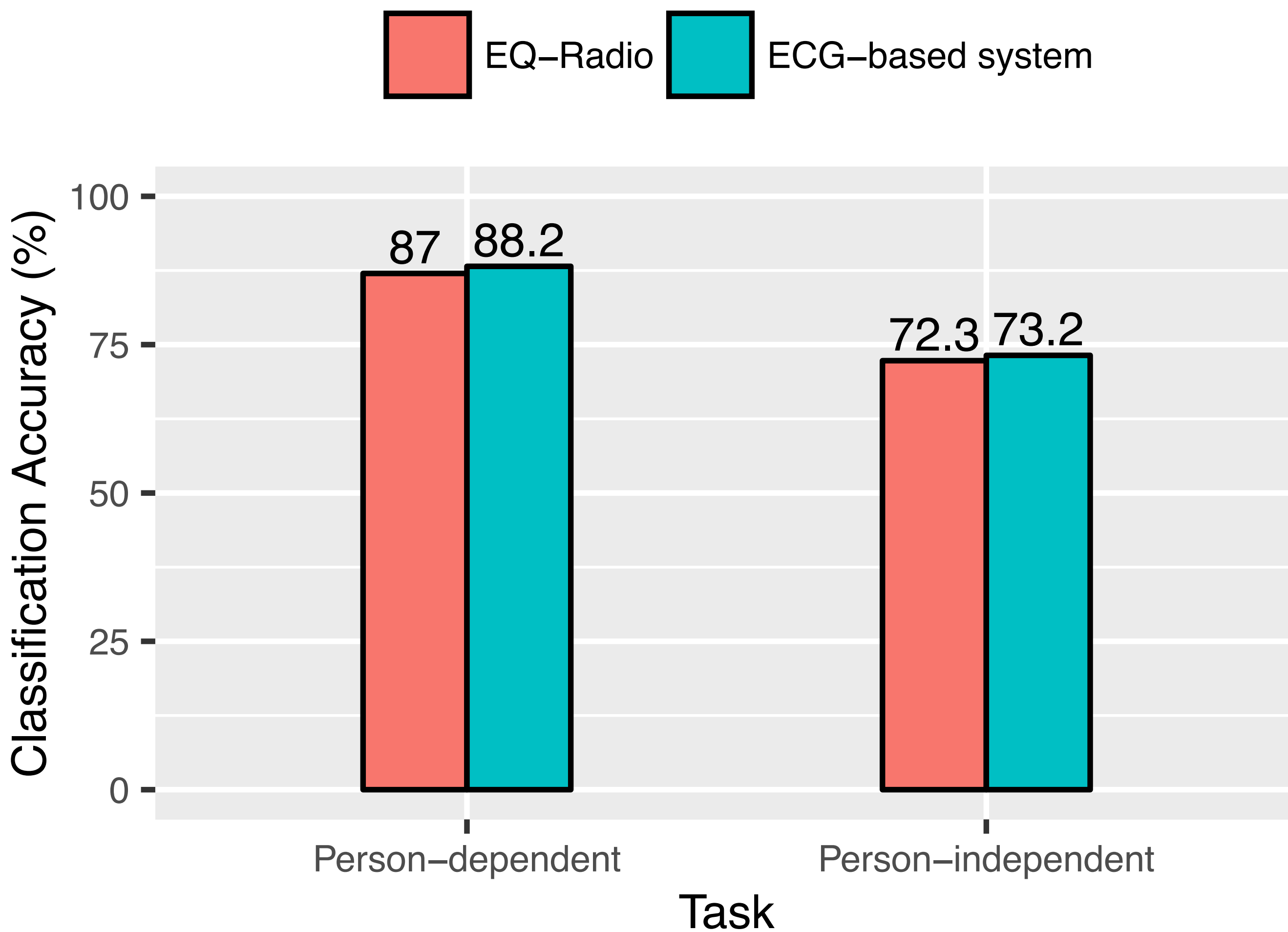
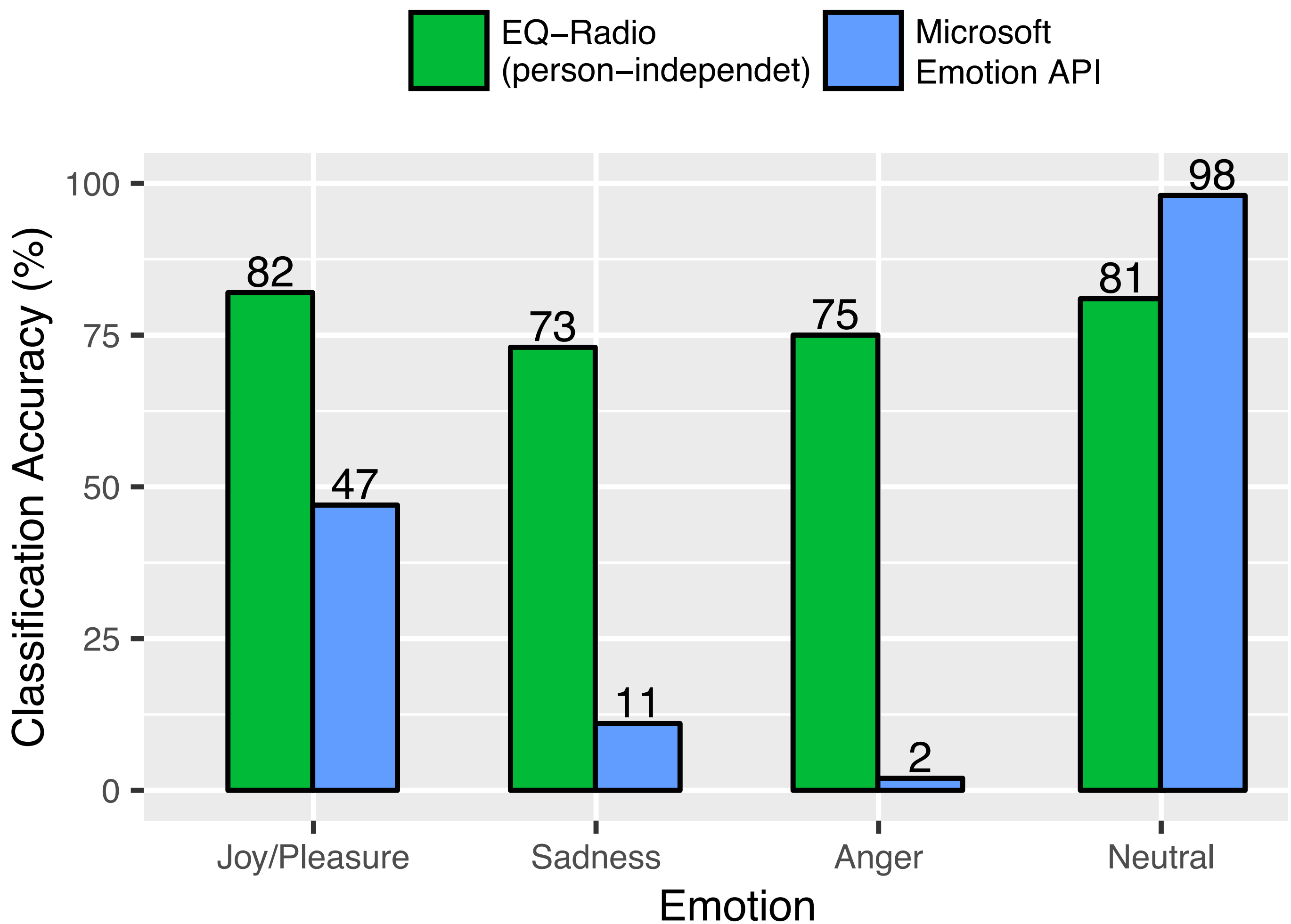


Comparison with ECG-based system

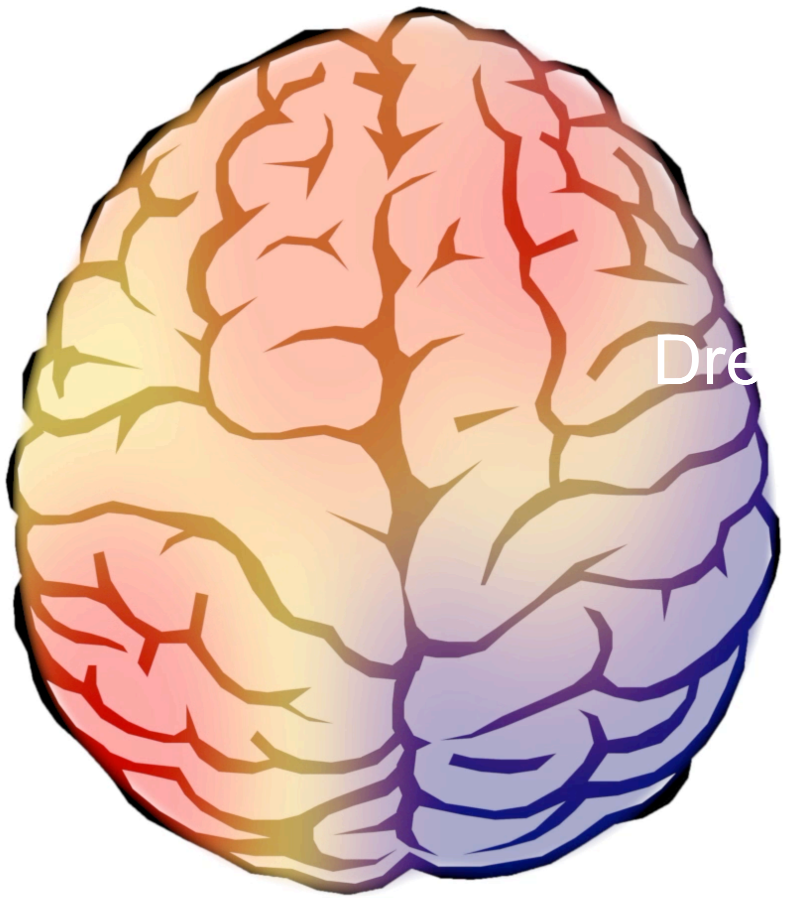


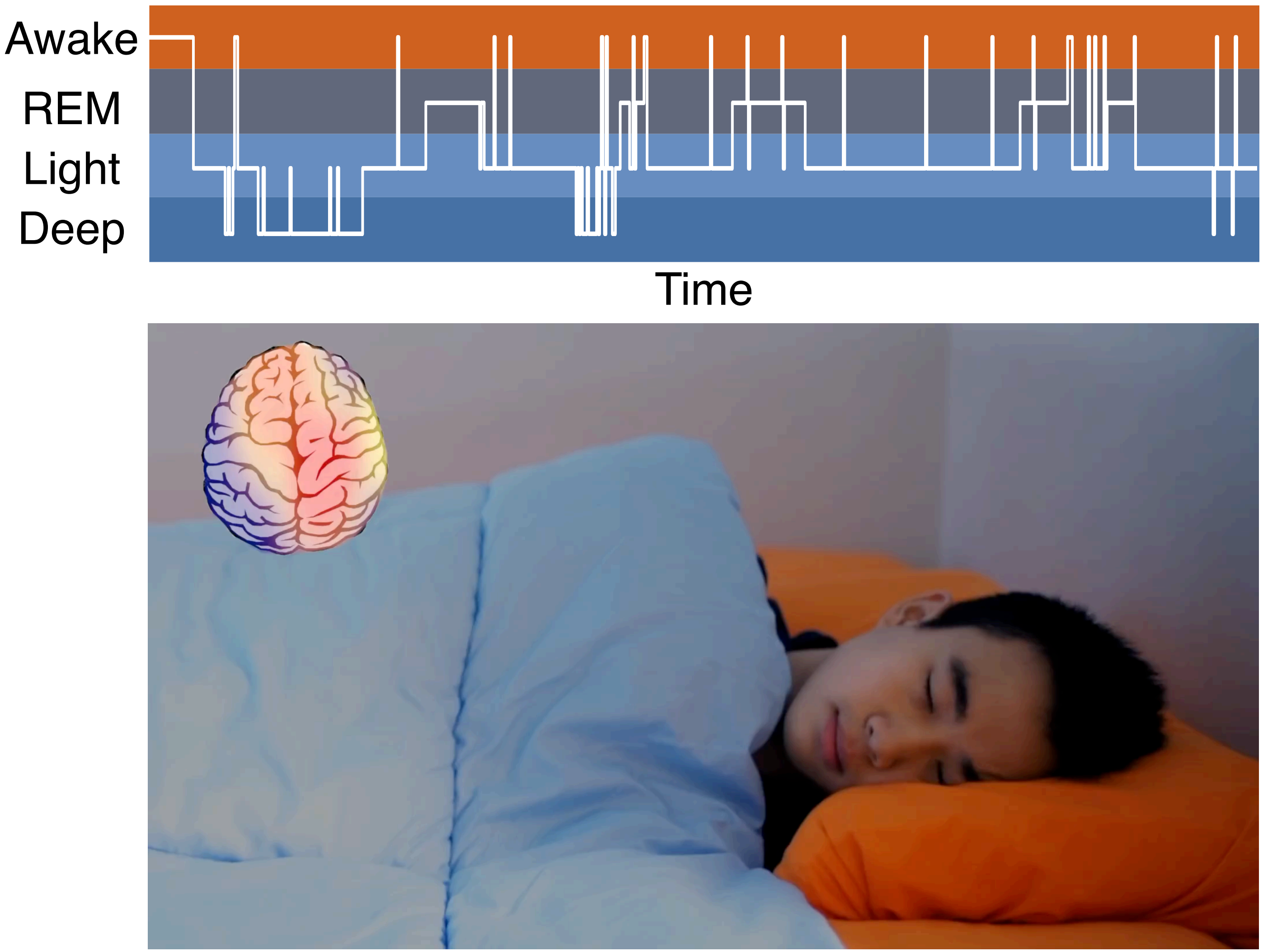
Comparison with Image-based system



Learning Sleep Stages from Radio Signals: A Conditional Adversarial Architecture

Background



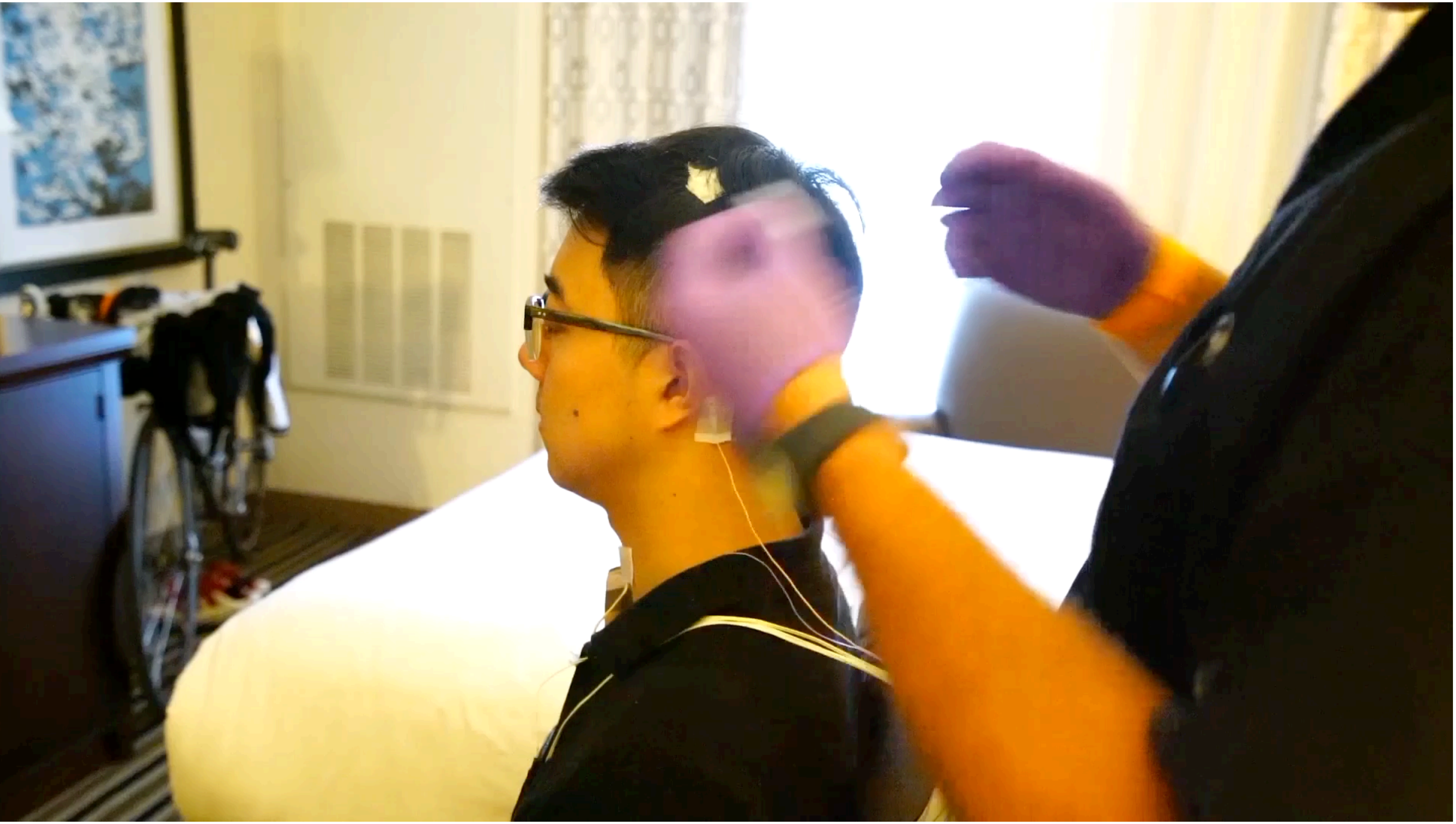

Awake
REM
Light
Deep
Time

Understanding Diseases with Sleep Stages

But, monitoring sleep stages is difficult …

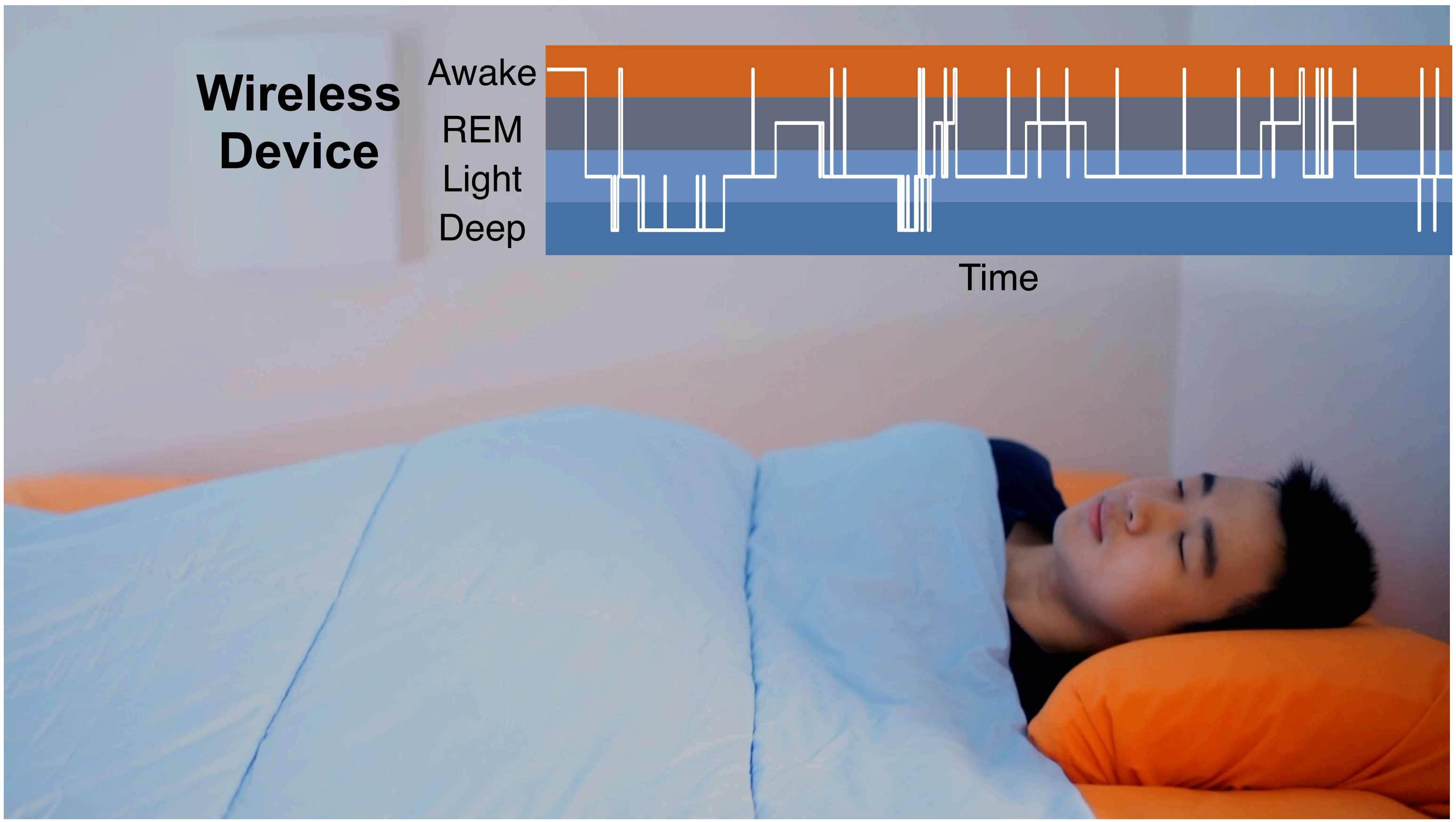
done in hospital with many electrodes on the body

Experience in Sleep Lab



Experience in Sleep Lab

Wireless Sensing Sleep Stages



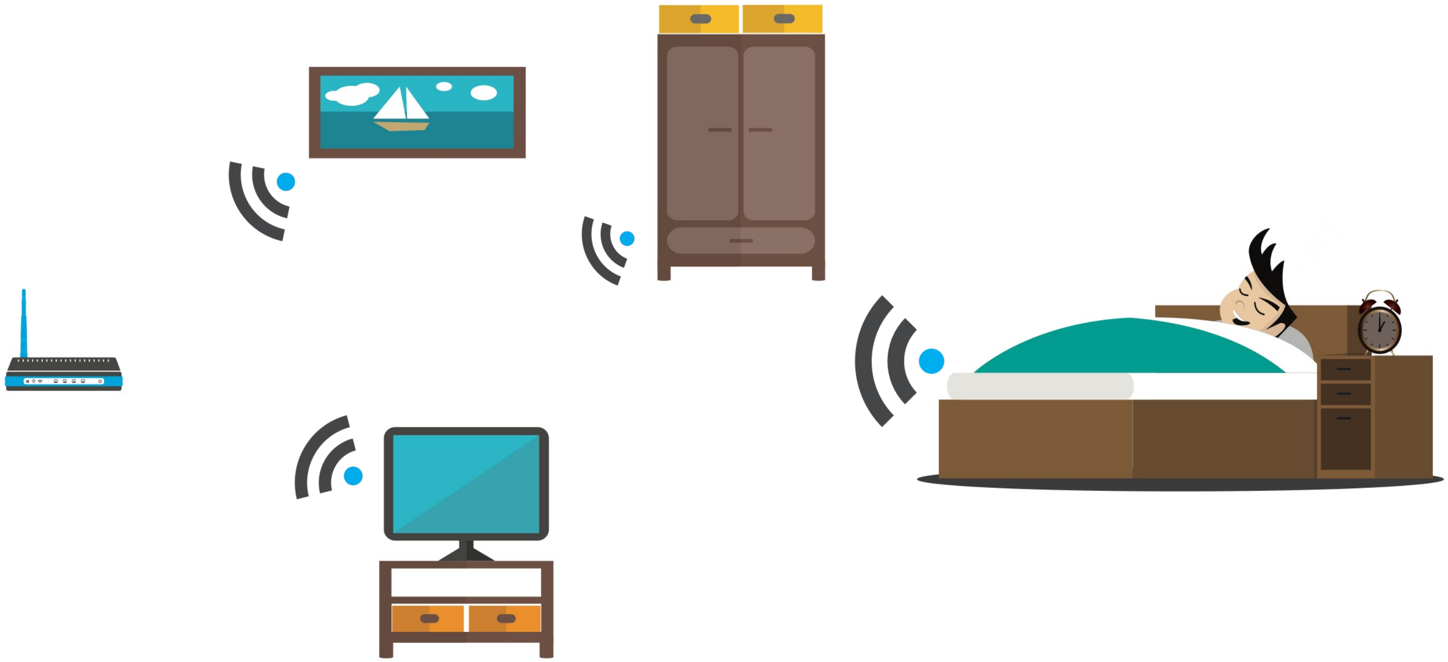
RF signals reflect off the body and change with physiological signals

Breathing Rate, Heart Rate, Inter Beat Interval

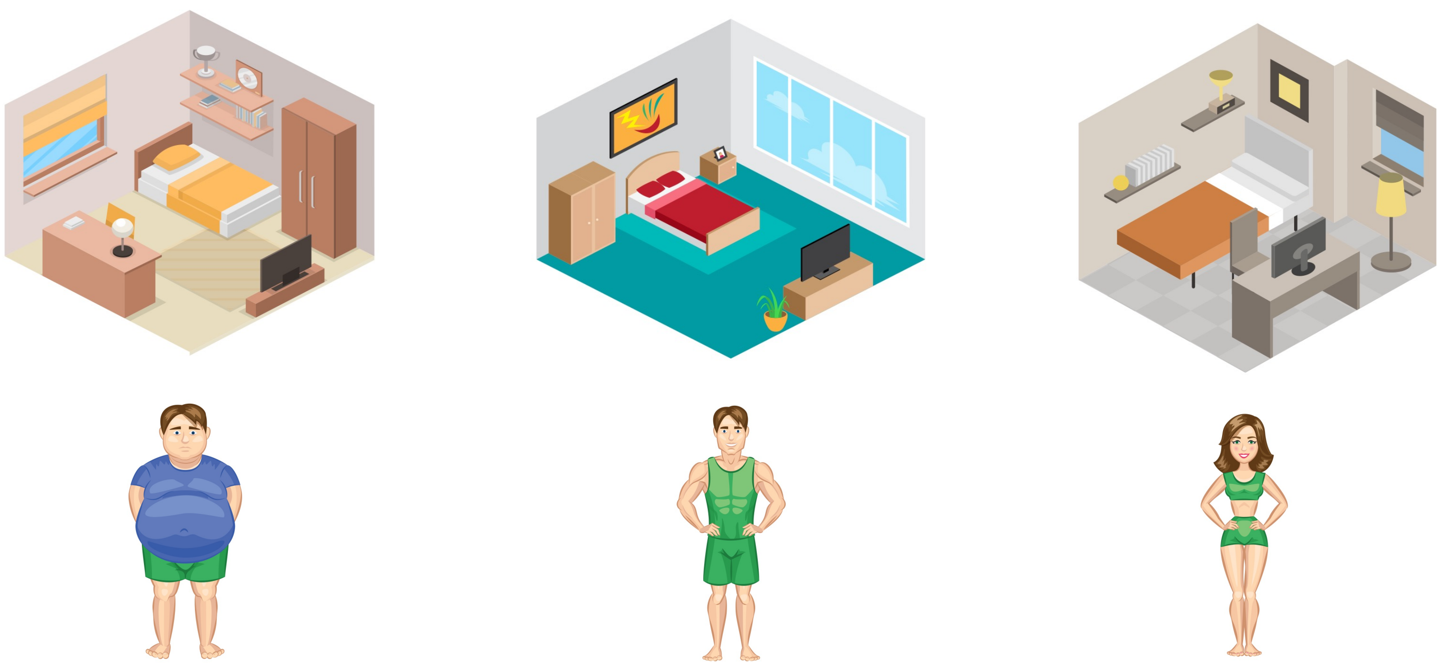
<u>Objective</u>: High accuracy on par with sleep lab, but in one's bedroom and without electrodes on the body

Key Challenge

RF reflections are highly dependent on the **measurement conditions** and the **individuals**.



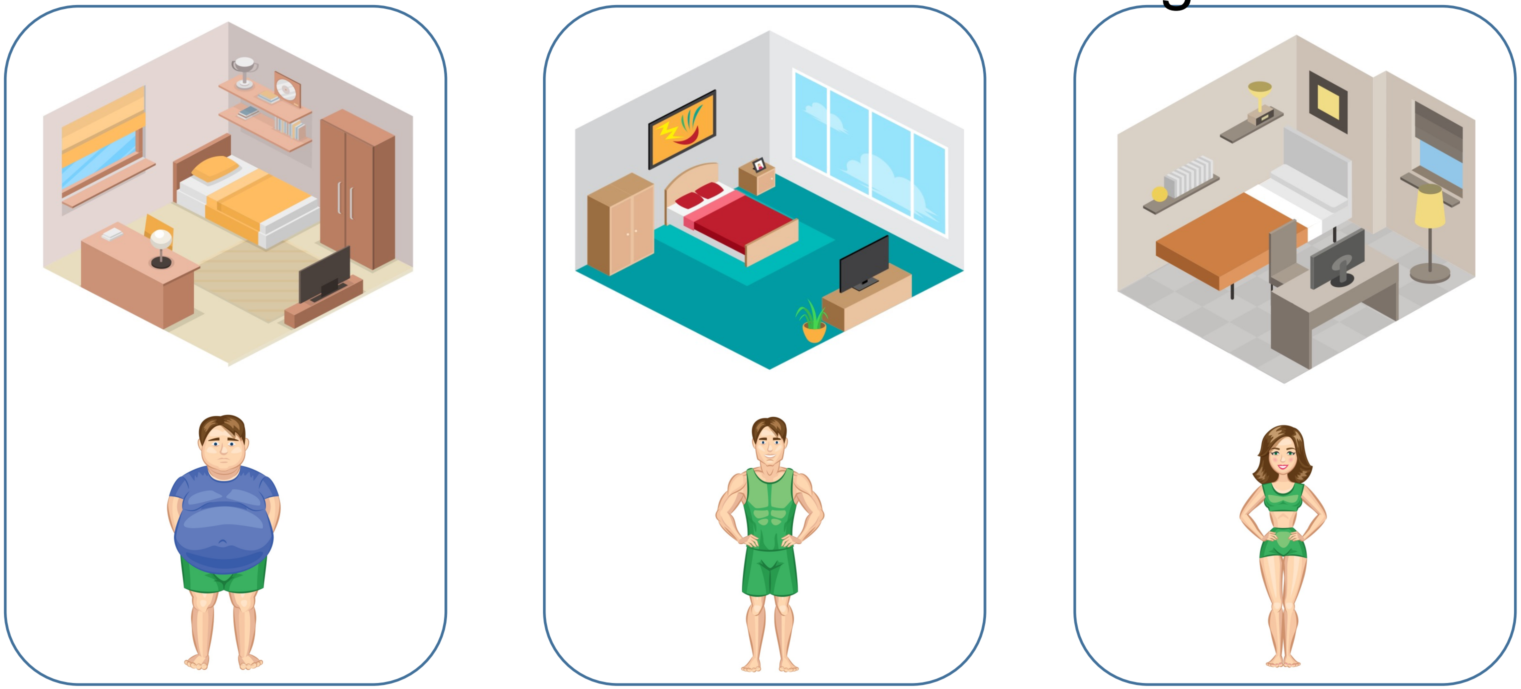
Need to remove such extraneous information!



Multi-Source Domain Adaptation

domain = measurement condition + individual

Source domain A Source domain B Target domain C



Multi-Source Domain Adaptation

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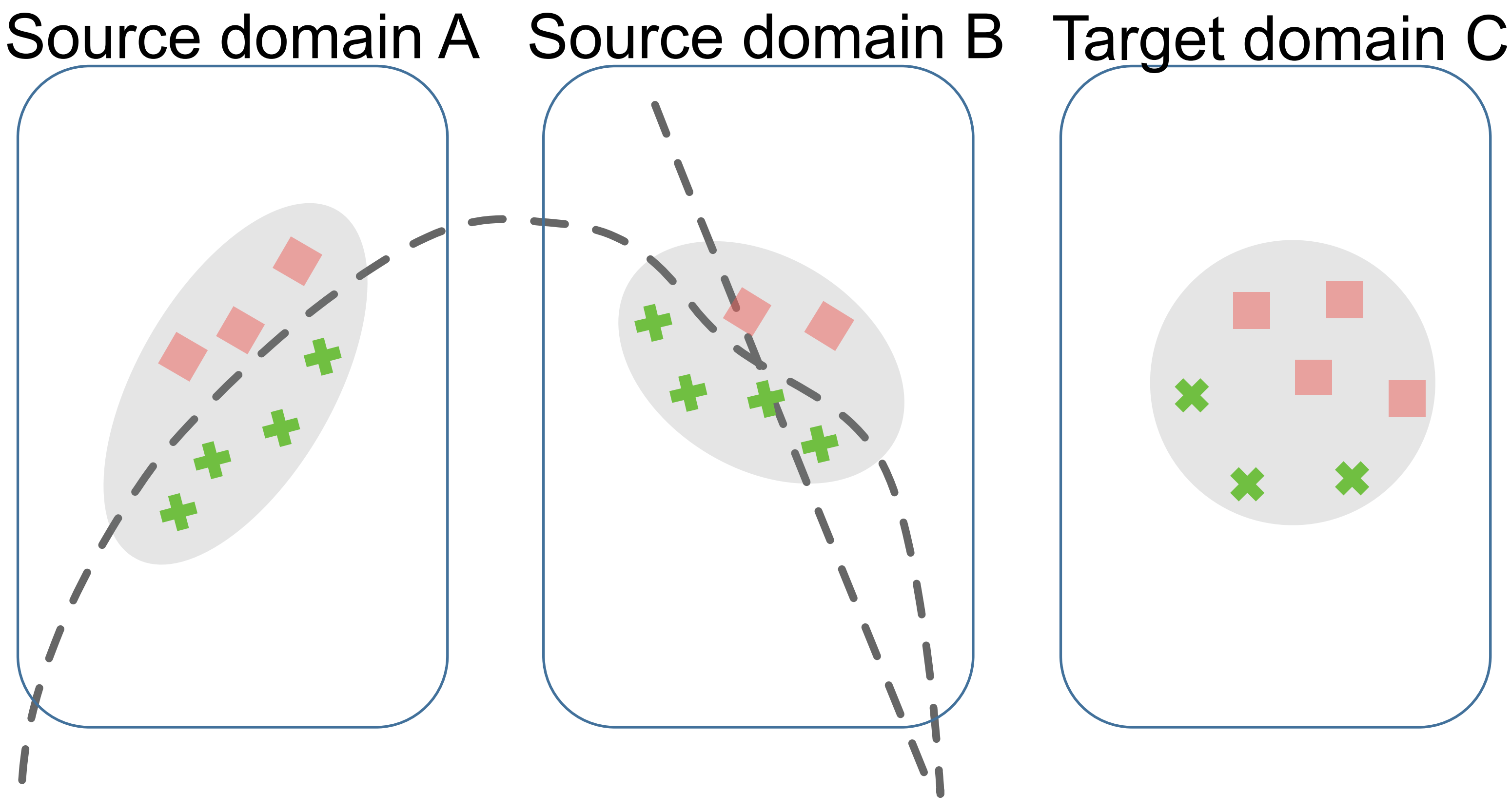
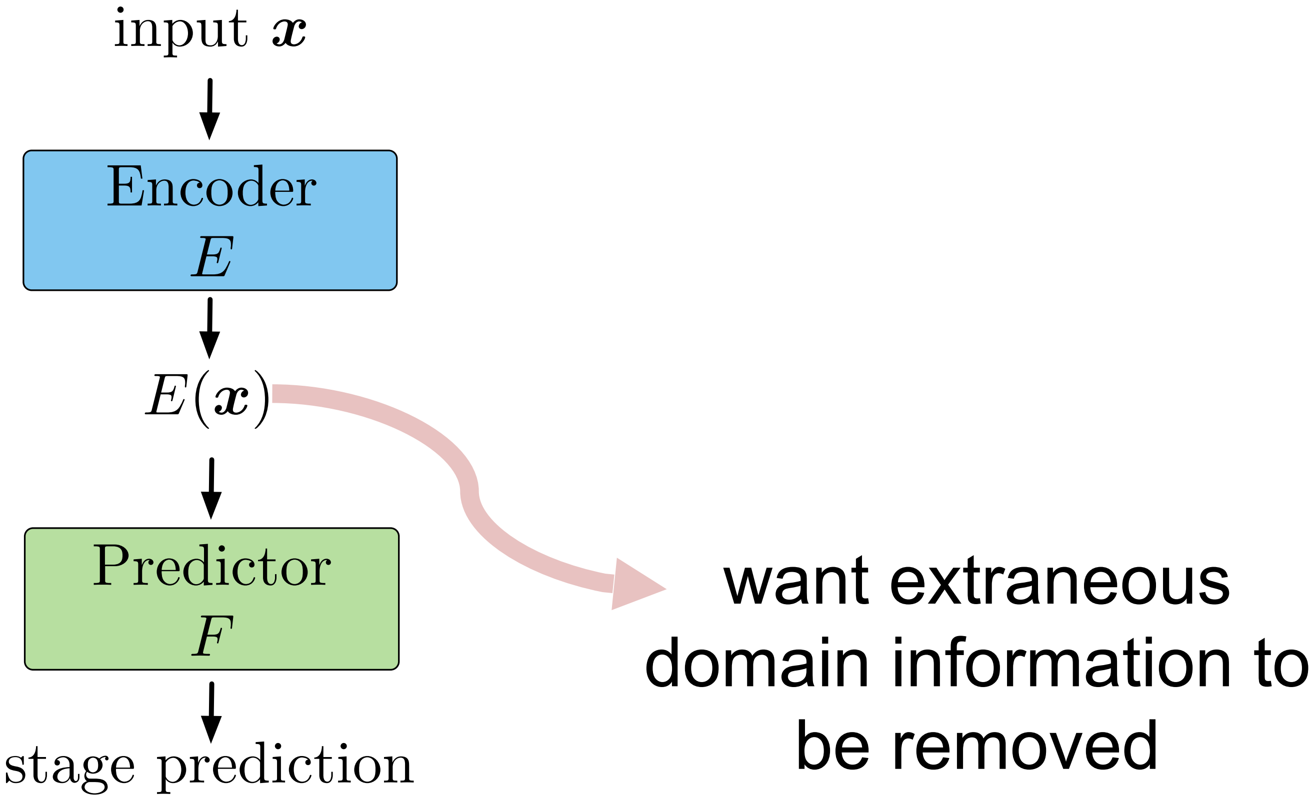
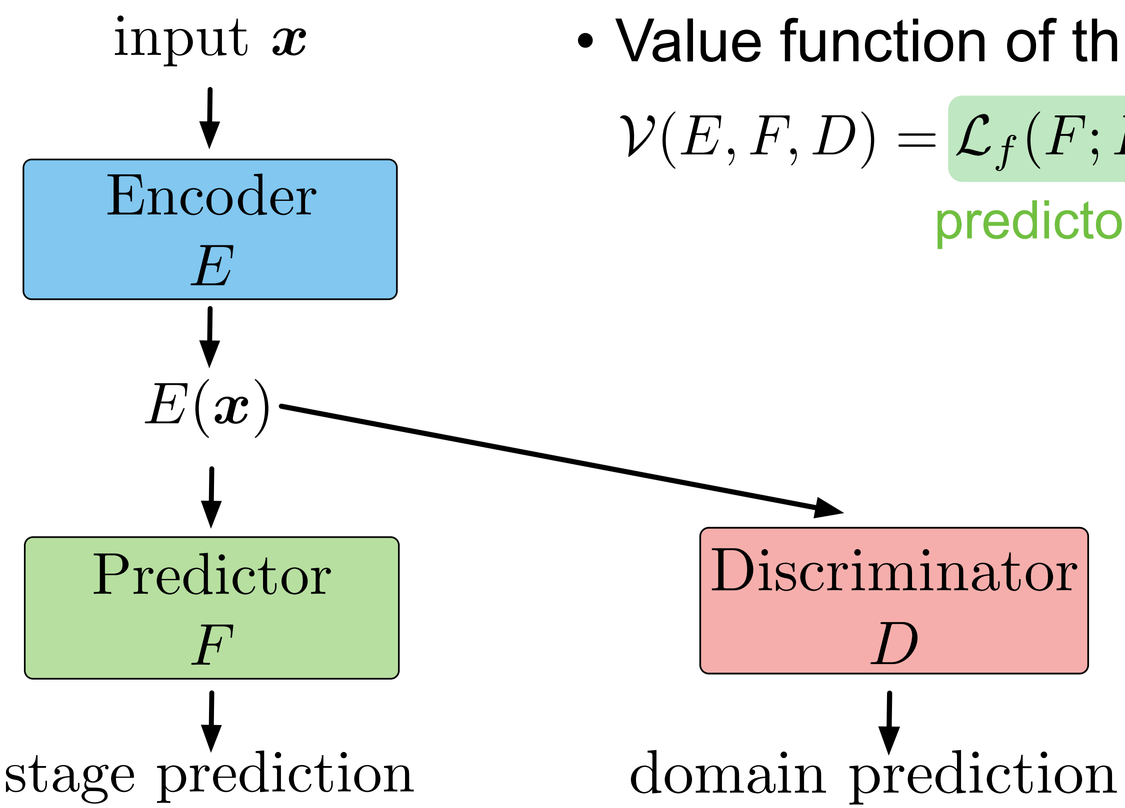


Initial Solution: Adversarial Domain Adaptation



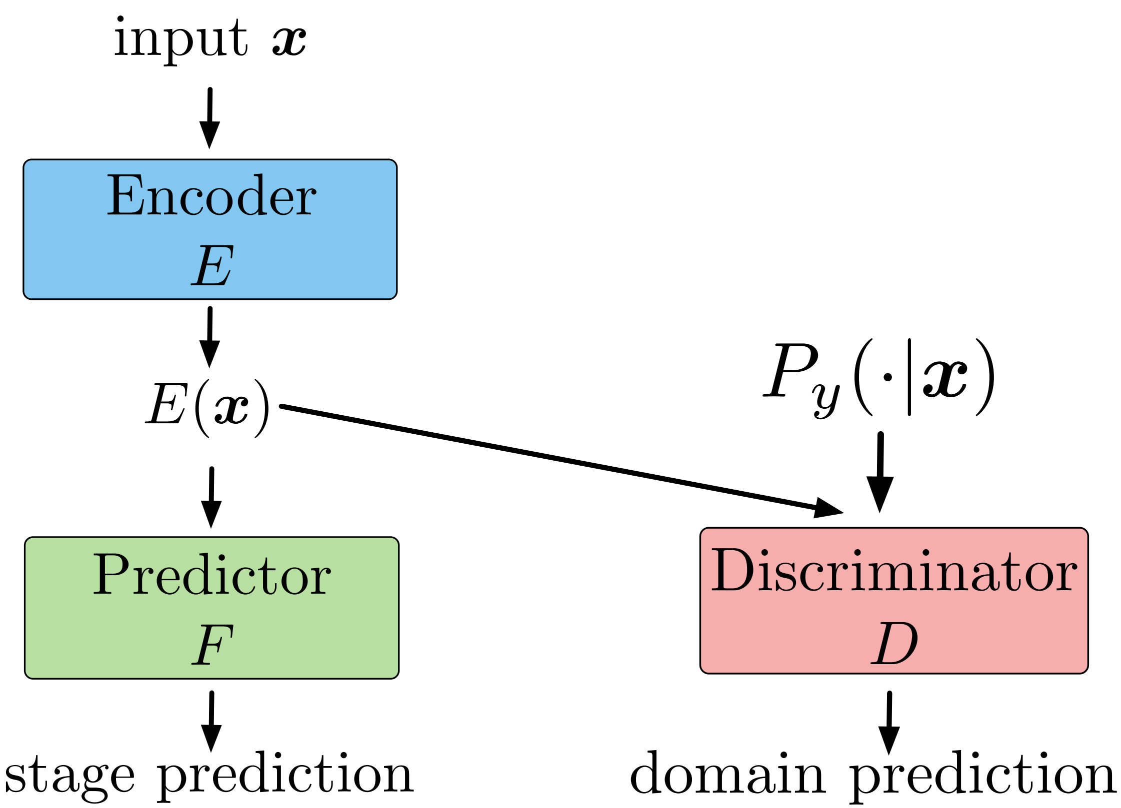
Problem: Discriminator removes both extraneous and useful information



- Value function of three-player game:

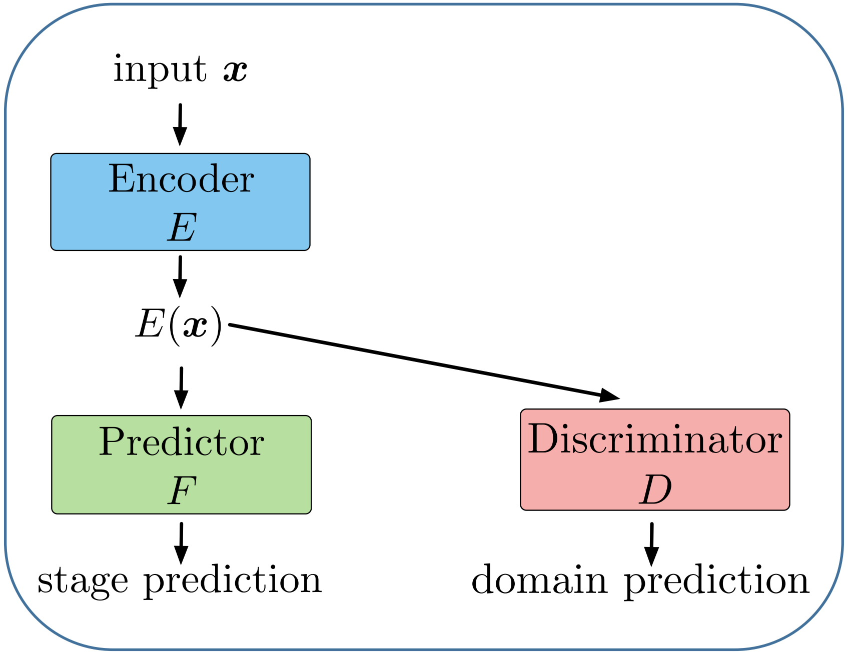
$$\mathcal{V}(E, F, D) = \underbrace{\mathcal{L}_f(F; E)}_{\text{predictor loss}} - \lambda \cdot \underbrace{\mathcal{L}_d(D; E)}_{\text{discriminator loss}}$$

Conditional Adversary

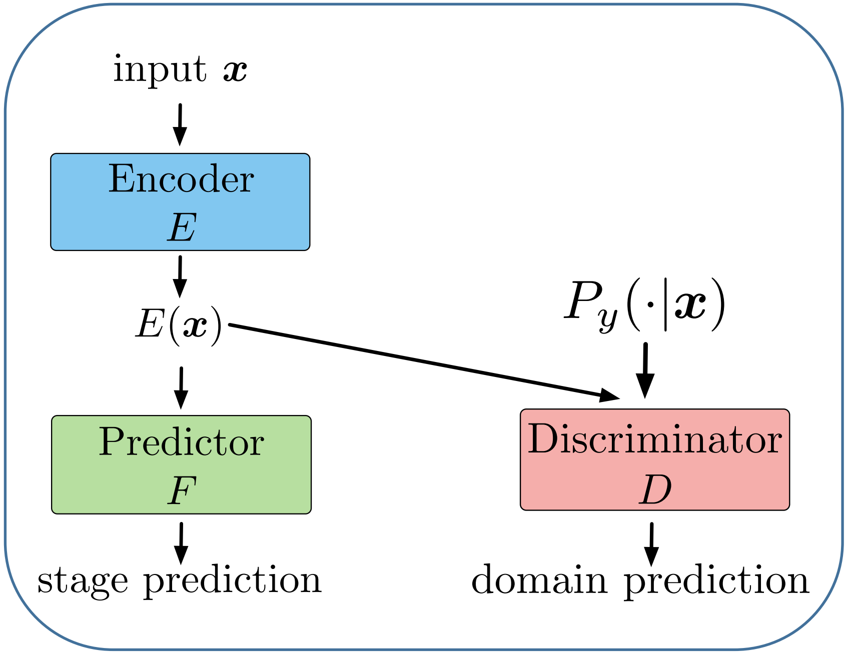


Role of Adversary

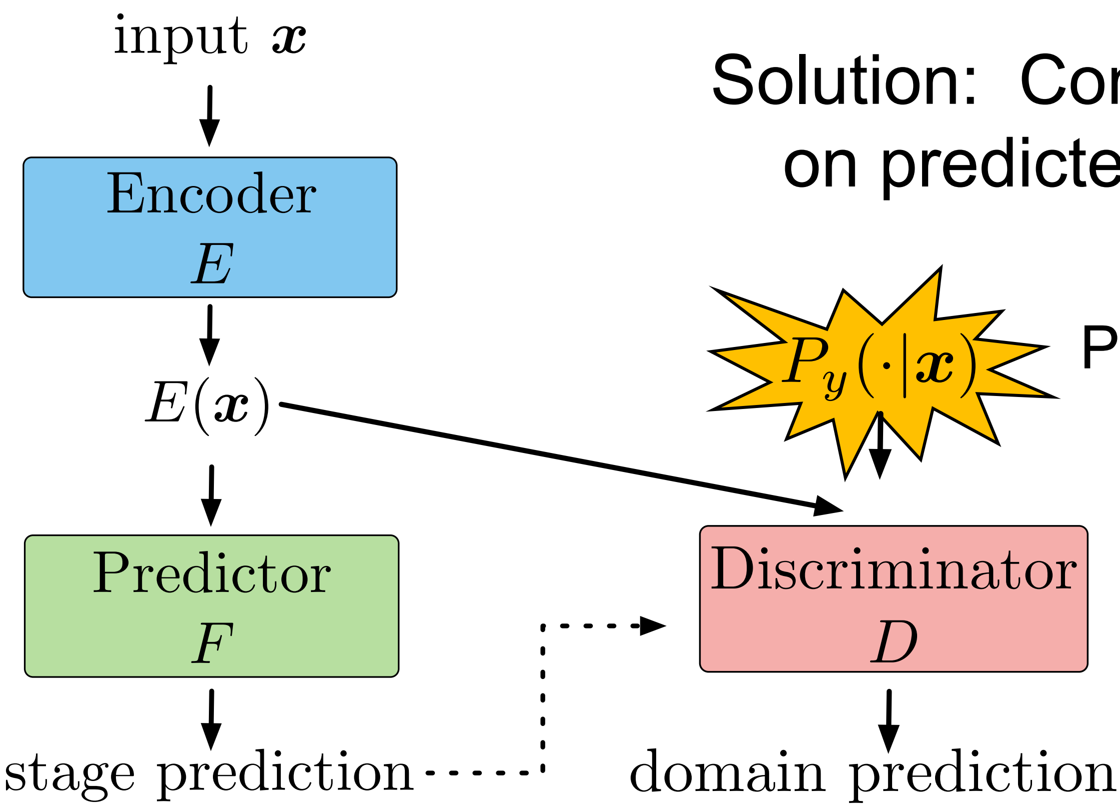
Independence



Conditional-Independence



Does it work?



Solution: Condition Discriminator on predicted label distribution

Posterior not available when training!

Theorem (informal): Given enough capacity, the encoder at equilibrium discards all extraneous information specific to domains, while retaining the relevant information for the predictive task.

Evaluation

- 25 different bedrooms and 100 nights
- Ground-truth: FDA-approved EEG-based sleep profiler provides sleep stage labels
- ~90k 30-second pairs of RF measurements and corresponding sleep stages

Accuracy

Accuracy of sleep lab

Inter-rater agreement: 83%

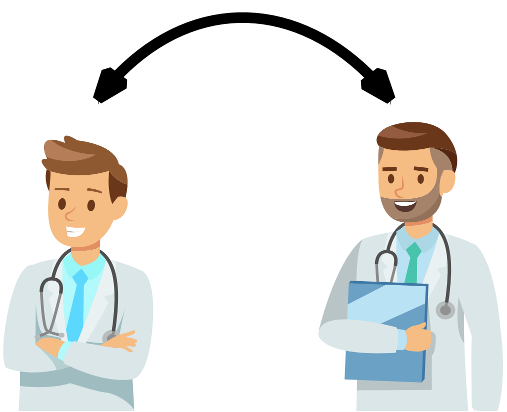
RFSleep accuracy 79.8%

(Tested on new subjects not in training, i.e., new domains)

Previous solutions: 64%

Labelling sleep stages is subjective

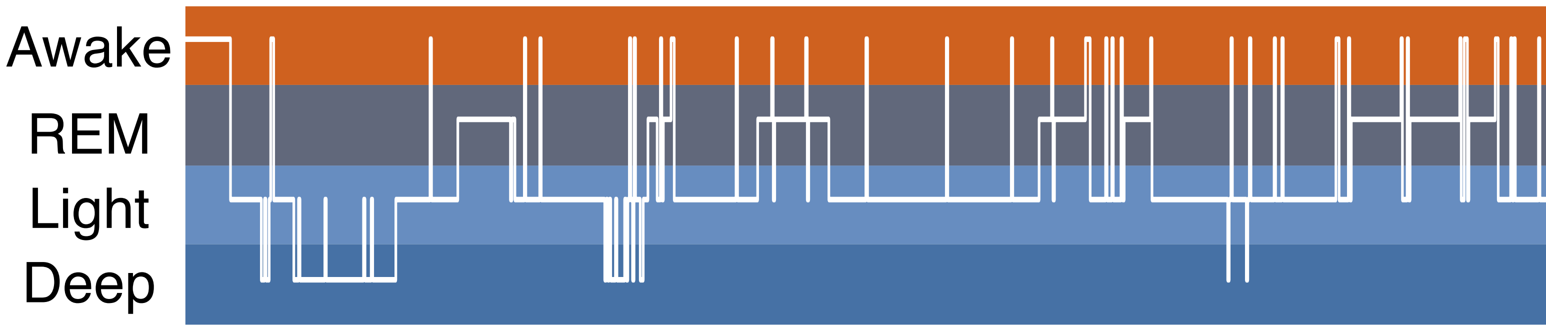
~83%



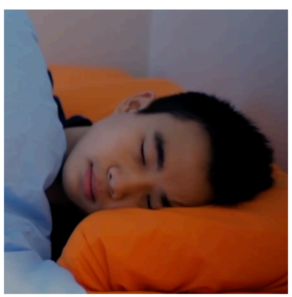
Representative Example

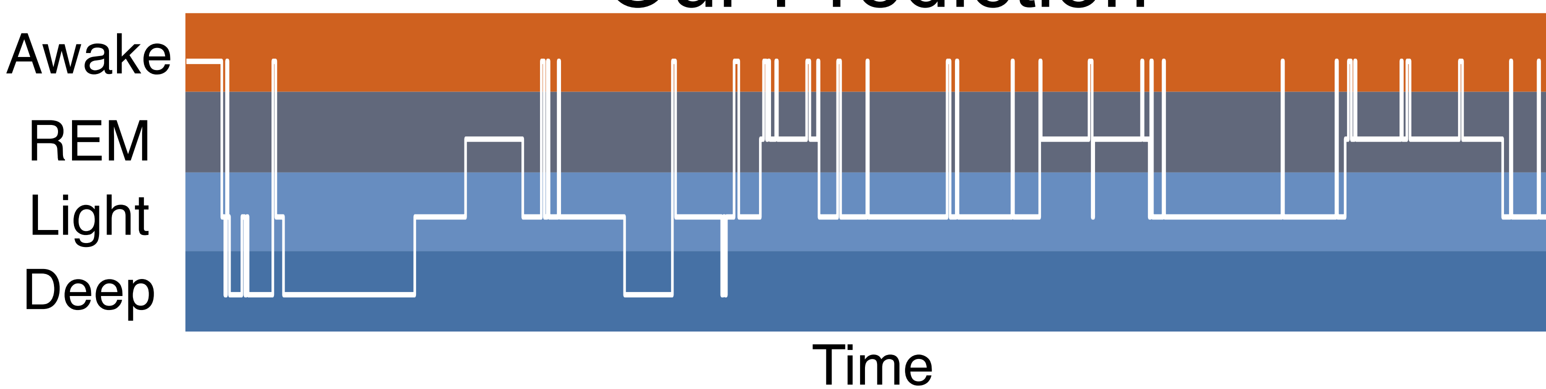
Accuracy = 80%

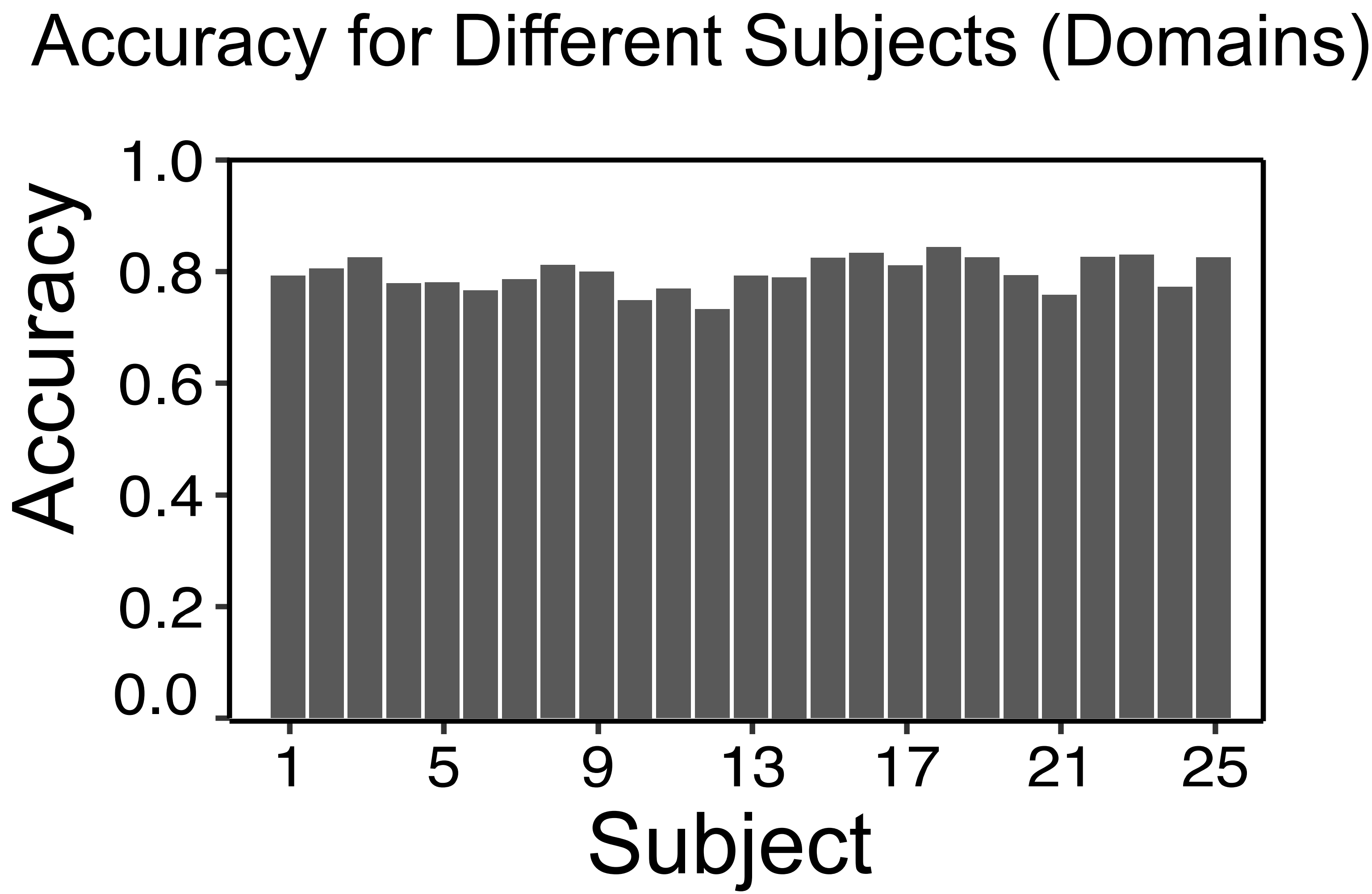
Ground-truth using EEG



Our Prediction






Accuracy for Different Subjects (Domains)
Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
1
5
9
13
17
21
25
Subject

Previous Lectures

WiVi: Sensing humans through walls with WiFi

WiTrack: Accurately Localizing humans through walls

Vital Ratio: Extracting vital signs (Breathing rate and heart rate)

RF-Capture: Capturing human figure through walls

This Lecture

EQ-Radio: Detecting emotions from wireless signals

RF-Sleep: Detecting sleep stages from wireless signals

Next Lecture

RF-Pose (3D): Reconstructing human pose and skeleton

RF-Action: Action and behavior recognition