ECE 598HH: Advanced Wireless Networks and Sensing Systems

Lecture 14: Wireless Sensing Part 3

Haitham Hassanieh

ILLINOIS
UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

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)

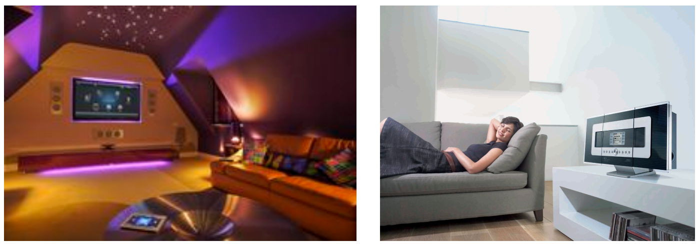
This Lecture

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

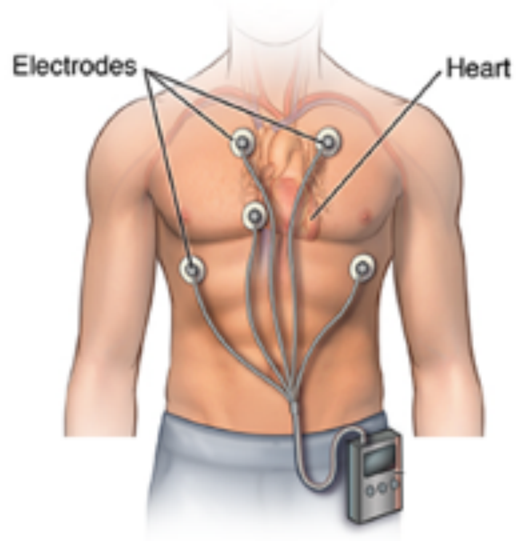
Advisor

Combating Depression

Is the date going well!

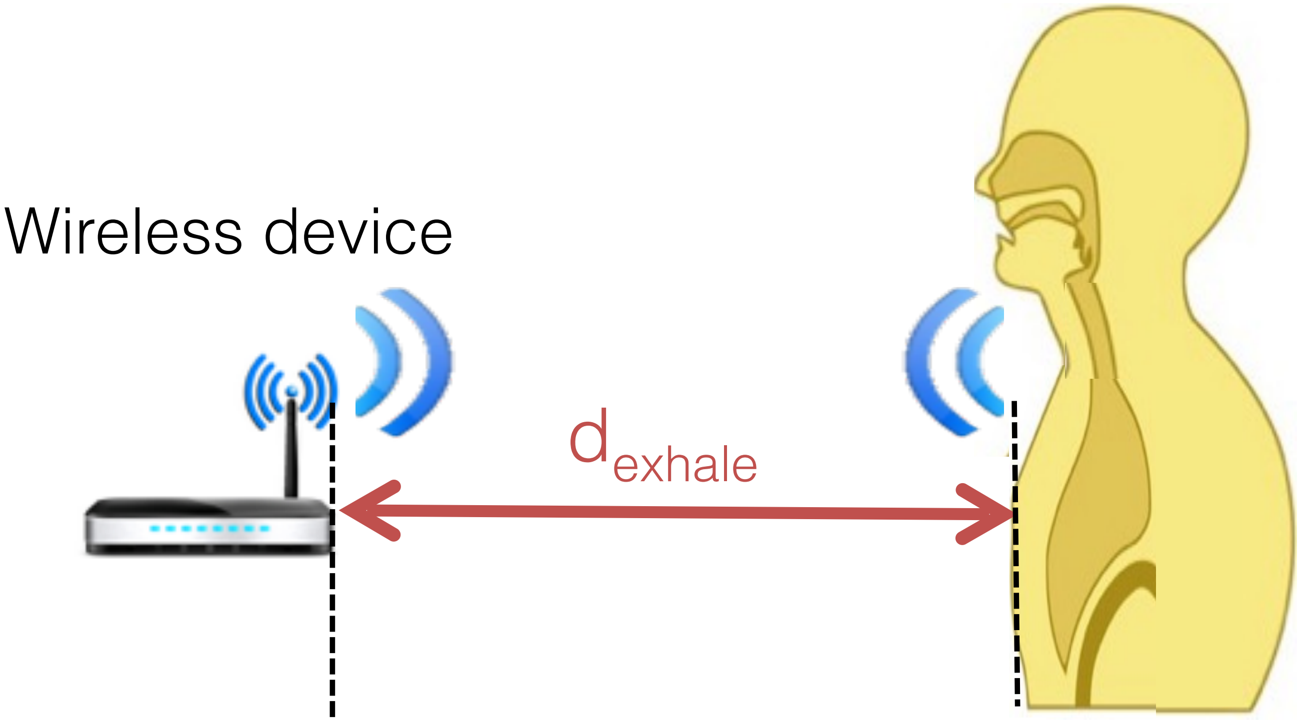
Existing approaches measure vital signs

- Use ECG to get very accurate heartbeats

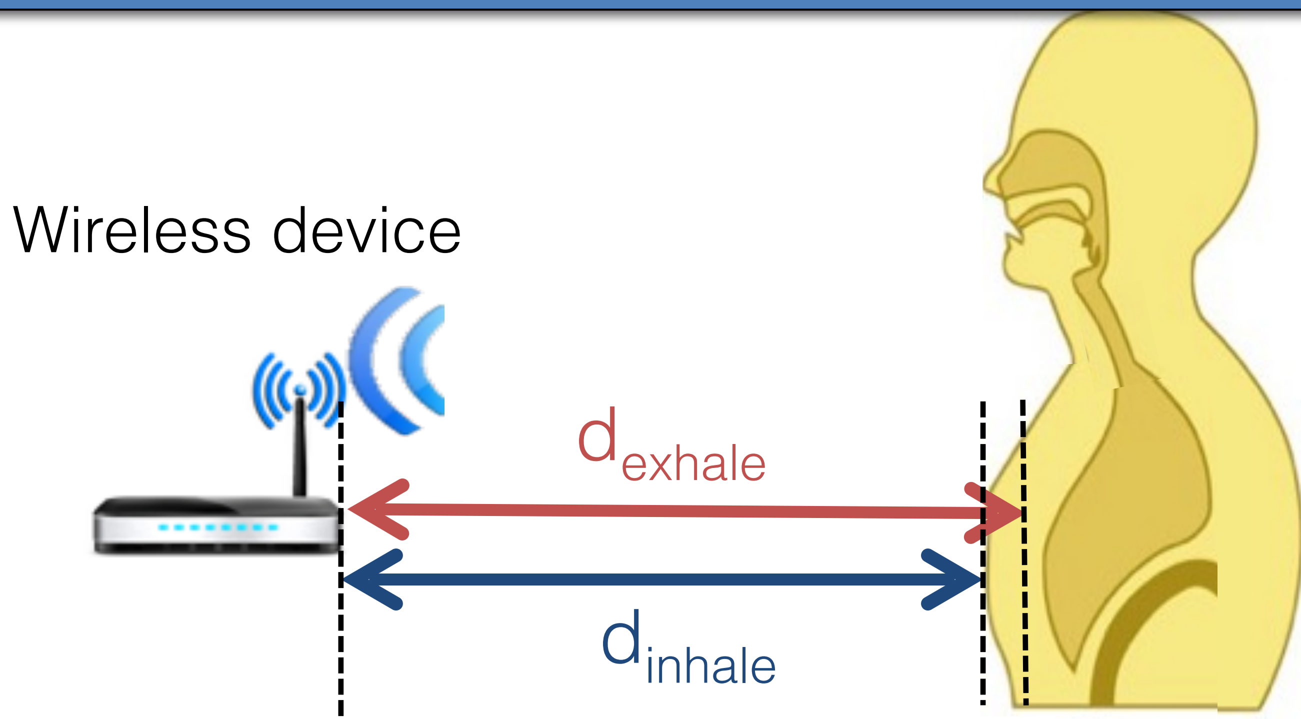


Use wireless reflections off the human body

Use wireless reflections off the human body



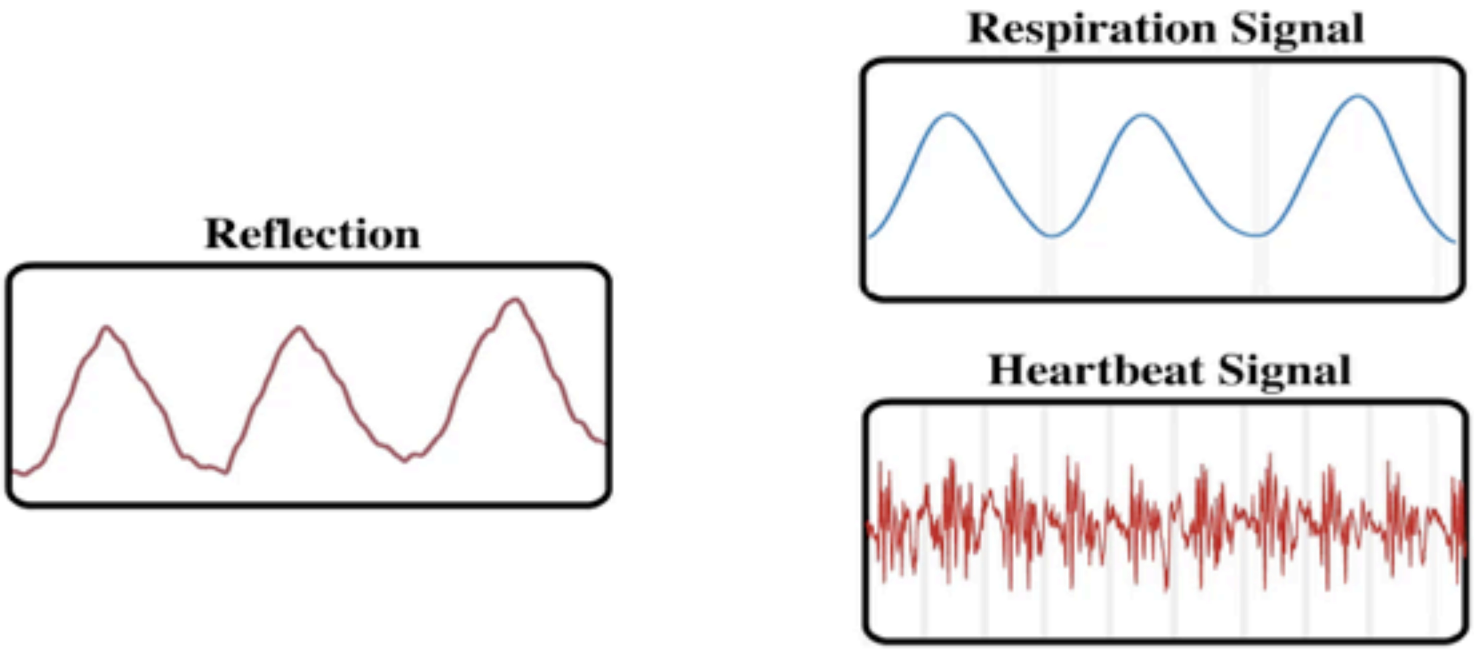
Solution: Use the phase of the wireless reflection



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

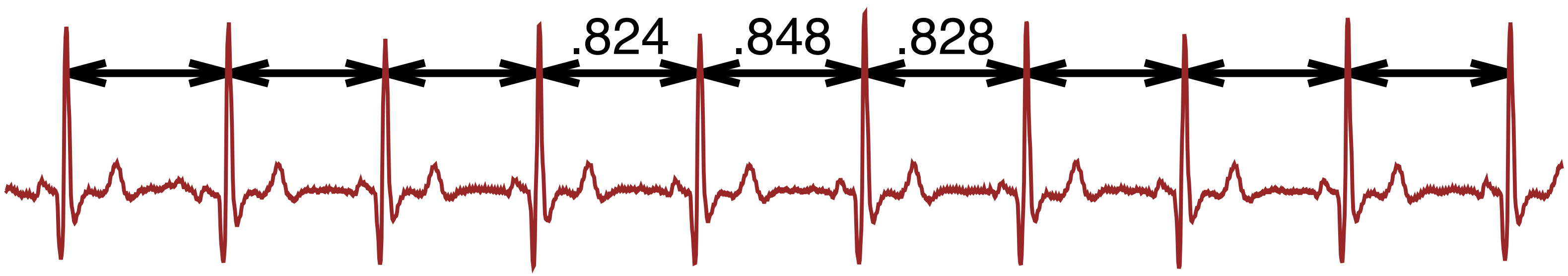
- Chest Motion changes distance
- Heartbeats also change distance

Emotion recognition using wireless signals



Key challenge: Inter-Beat Interval (IBI)

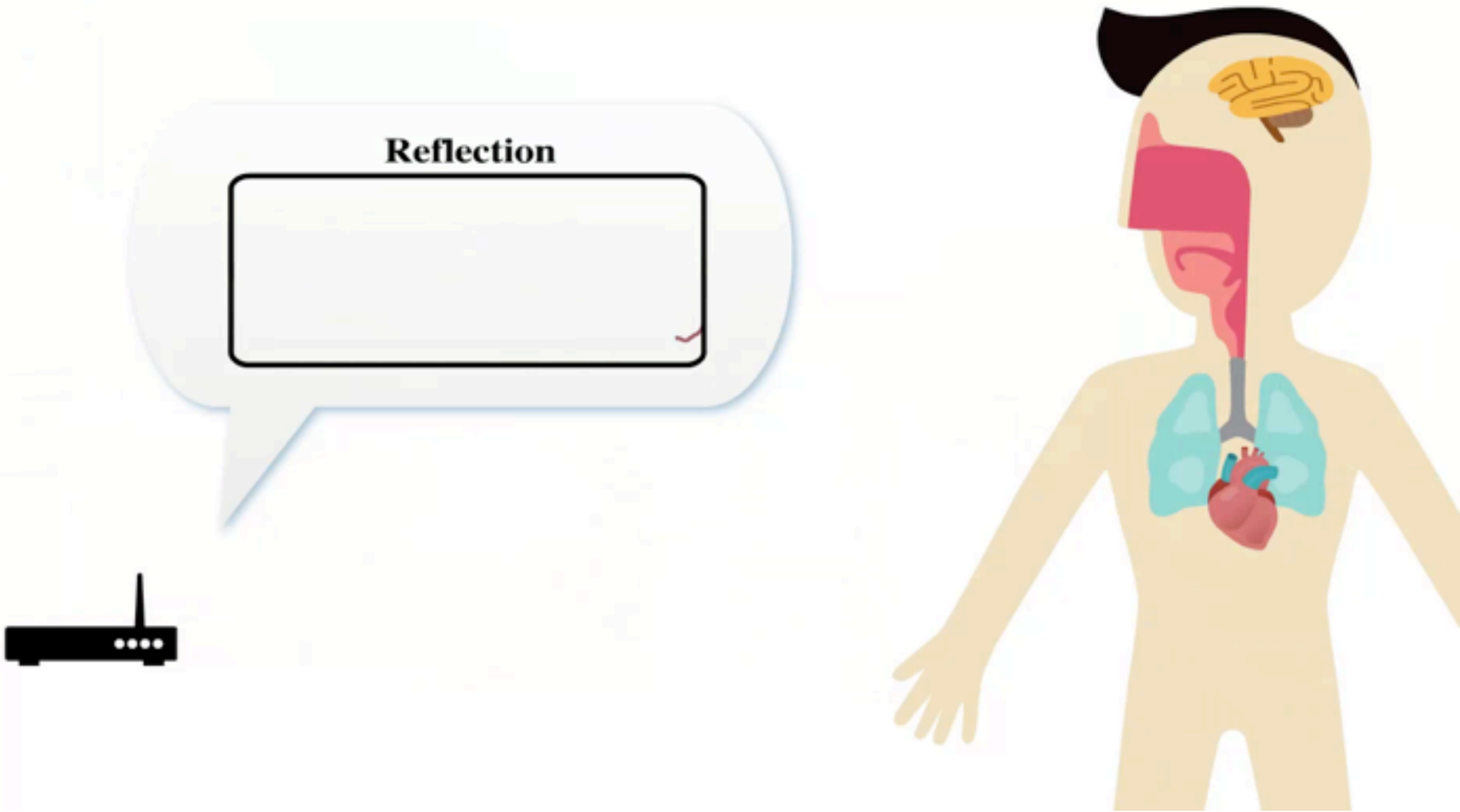
- Emotion recognition needs accurate measurements of the length of every single heartbeat



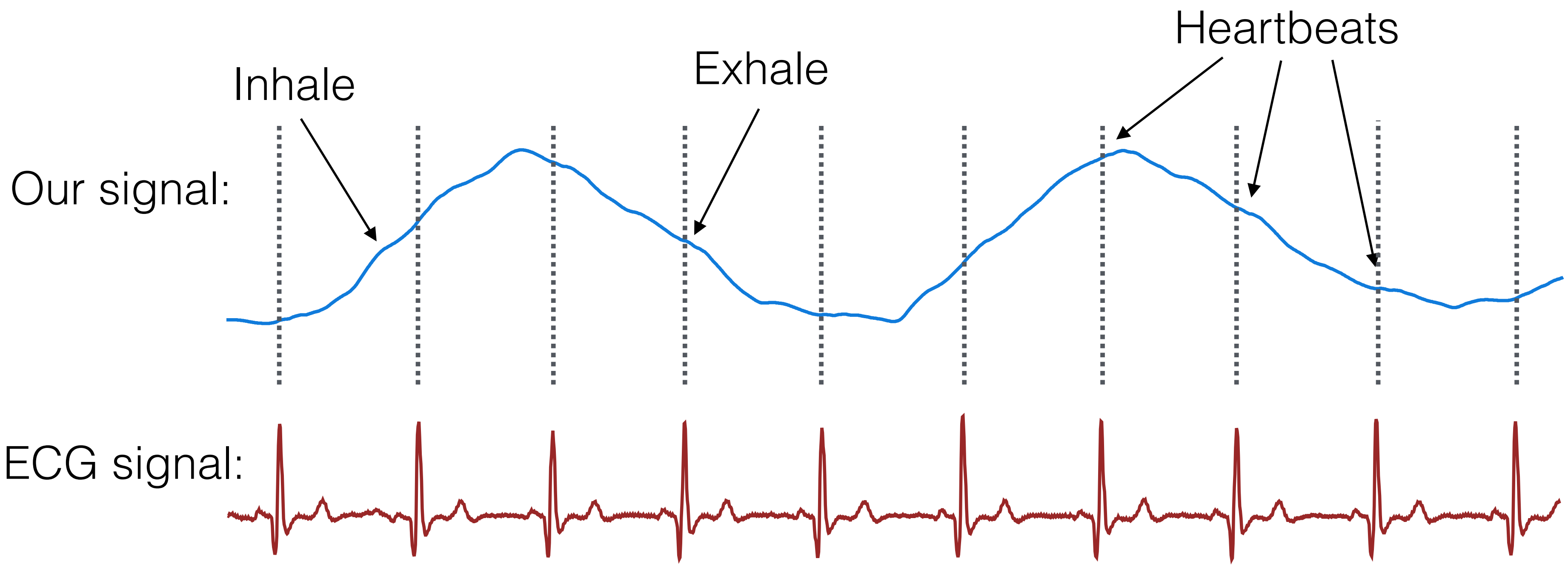
We need to extract IBI with accuracy over 99%

Input signal

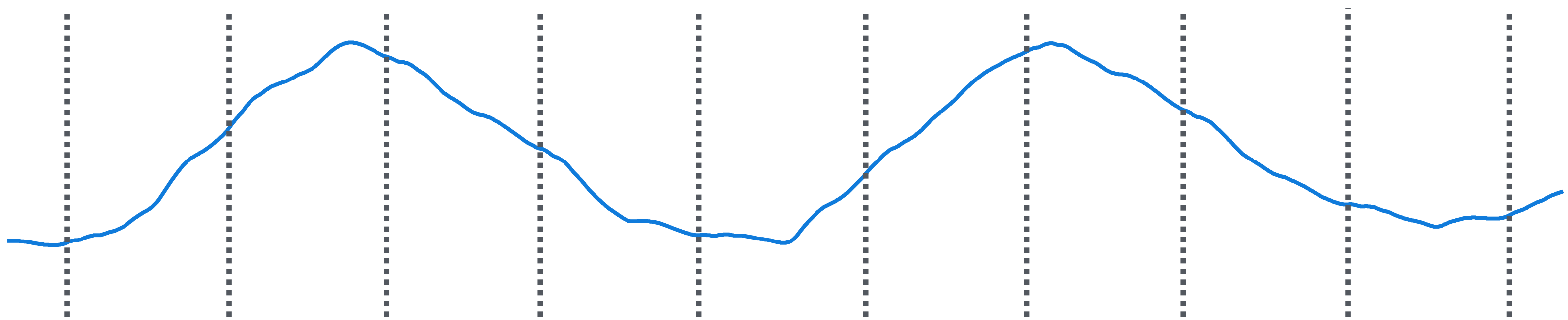
Wireless reflection of the human body



Input signal



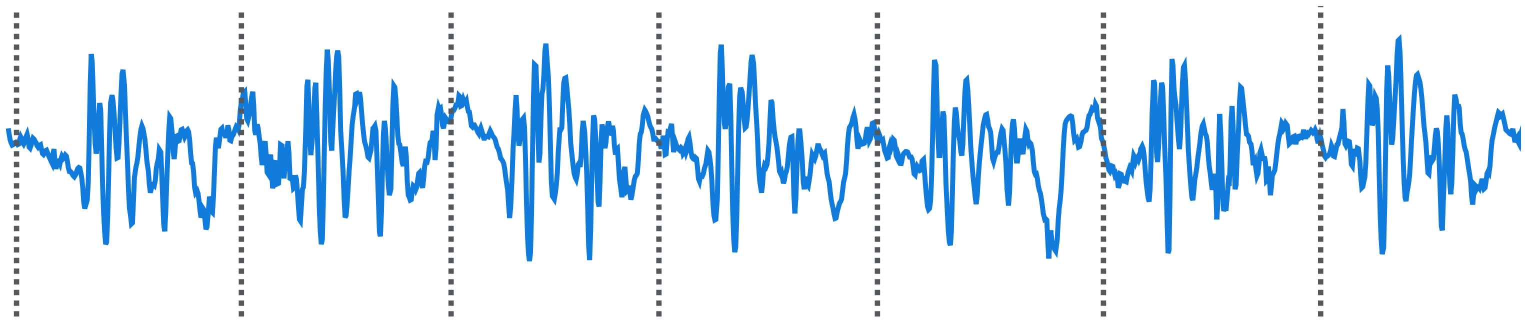
Step 1: Remove breathing signal



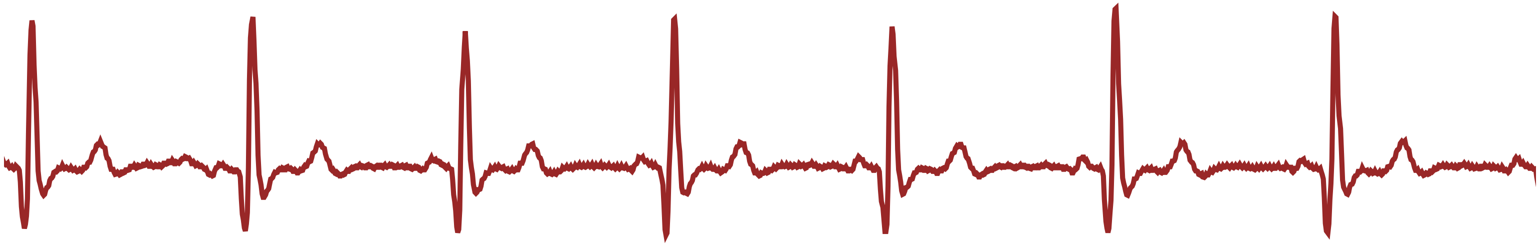
- Breathing masks heartbeats
- We use acceleration filter
    - Heartbeat involves rapid contraction of muscle
    - Breathing is slow and steady

Heartbeat signal

- Output of acceleration filter

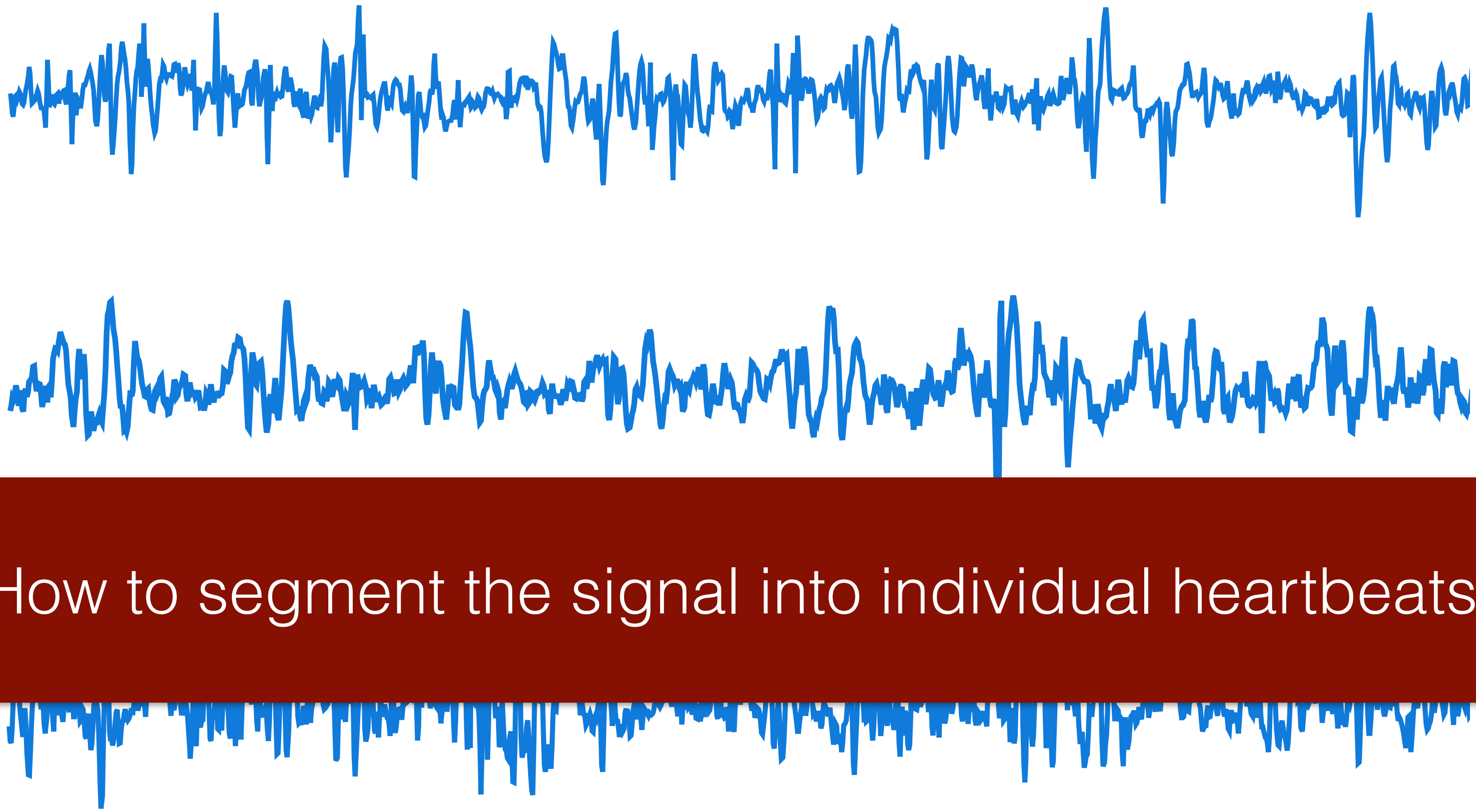


- ECG signal



Heartbeat signal

- Other typical examples:



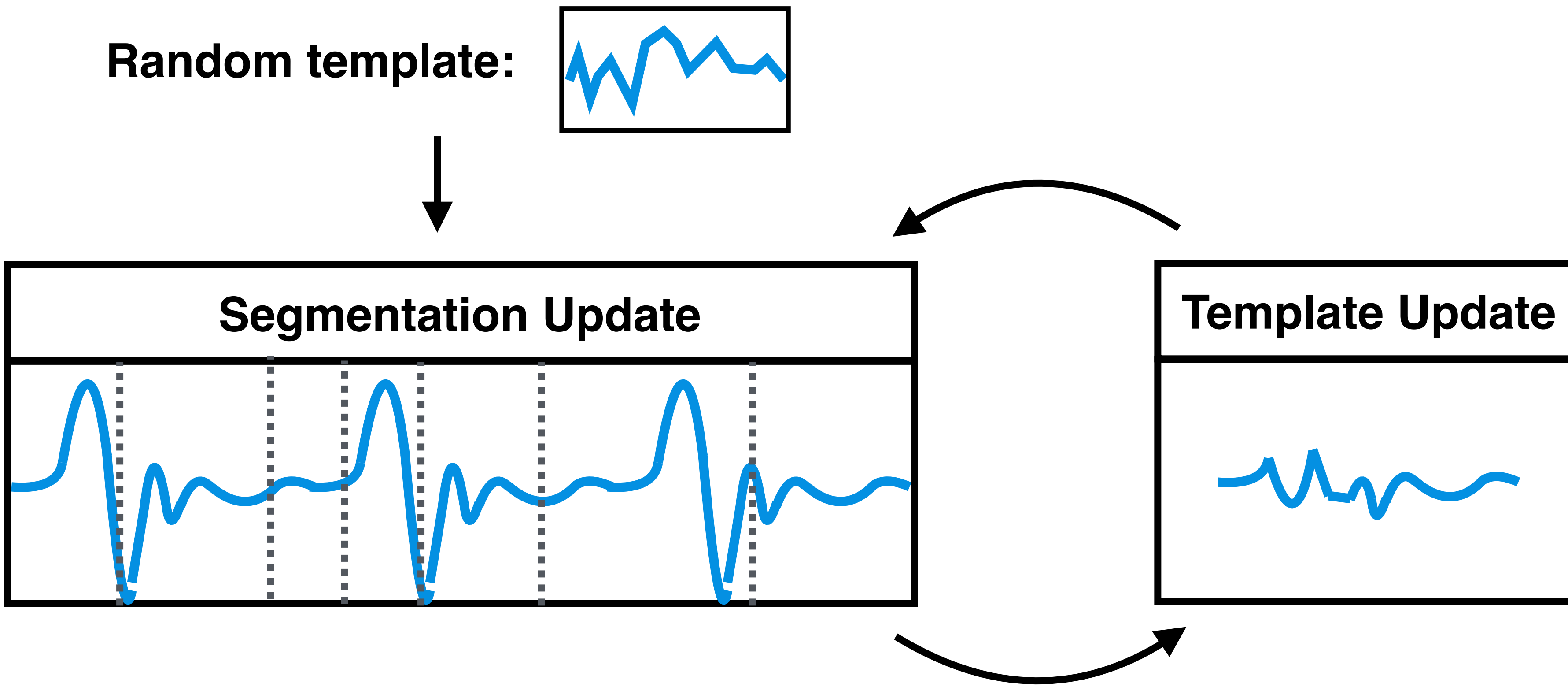
How to segment the signal into individual heartbeats?

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

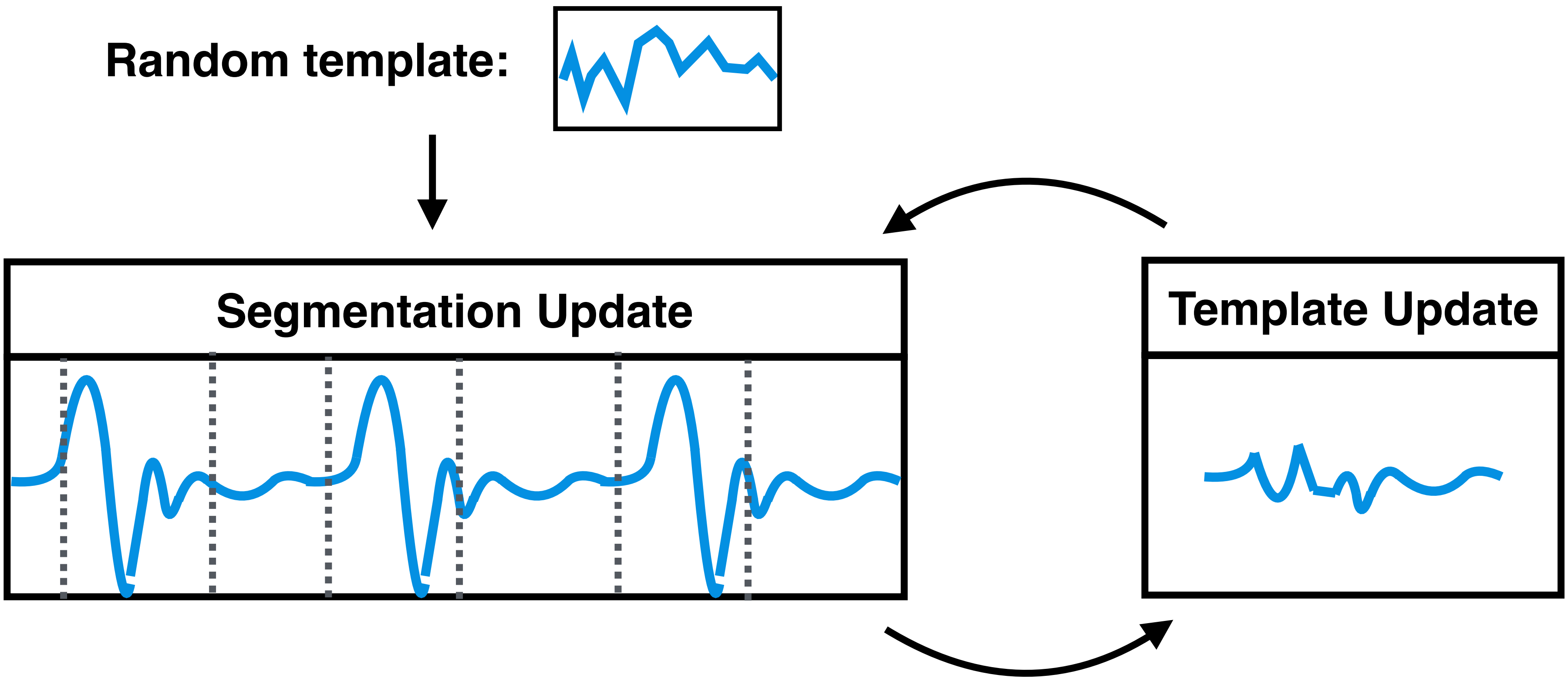
Step 2: Heartbeat segmentation

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



Step 2: Heartbeat segmentation

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



Step 2: Heartbeat segmentation

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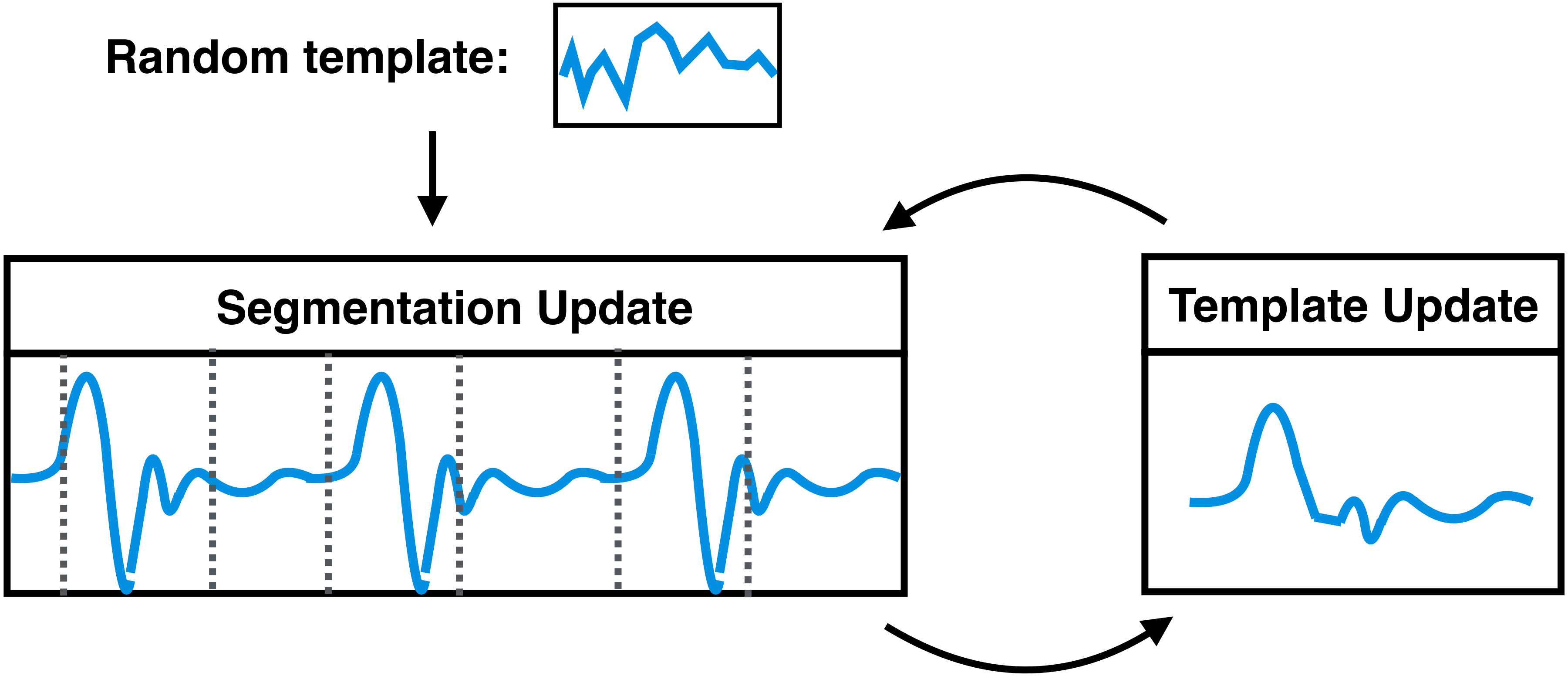

Step 2: Heartbeat segmentation

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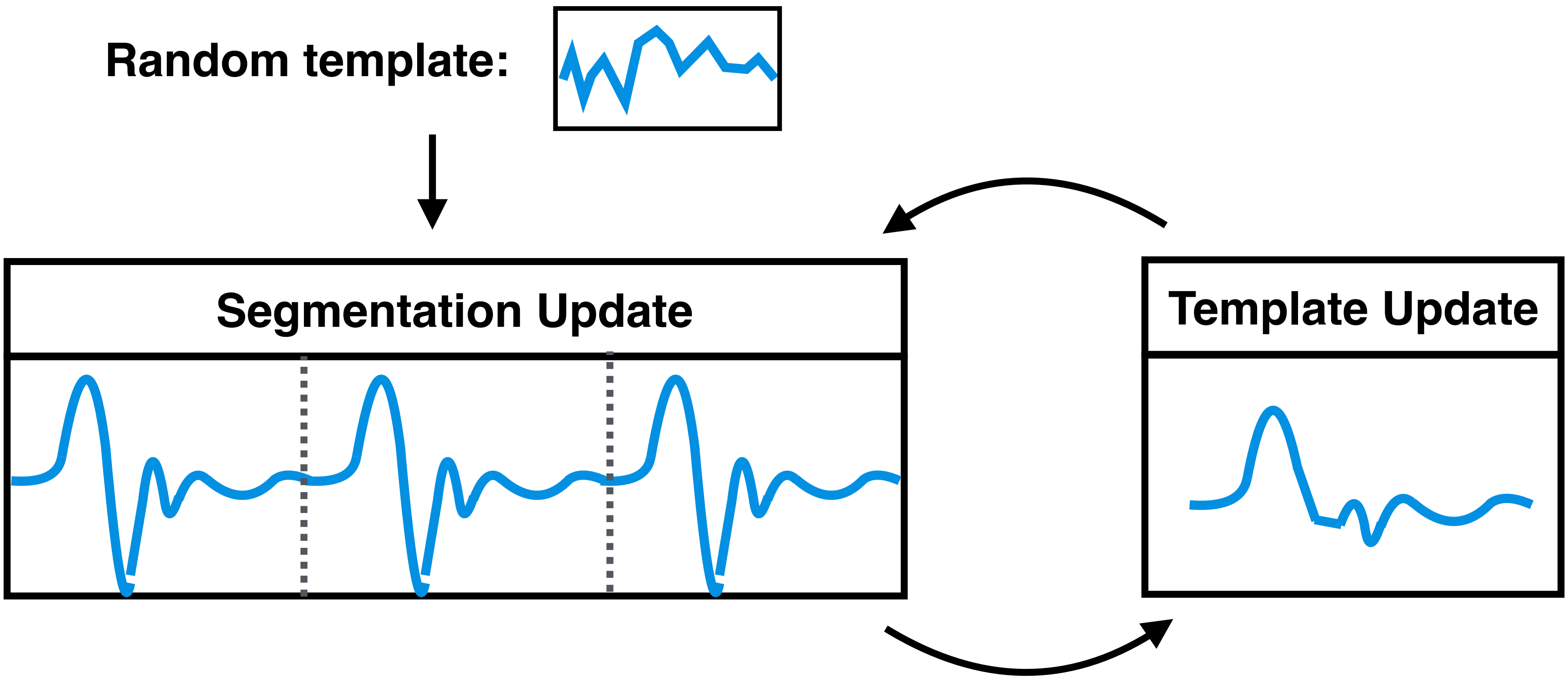

Step 2: Heartbeat segmentation

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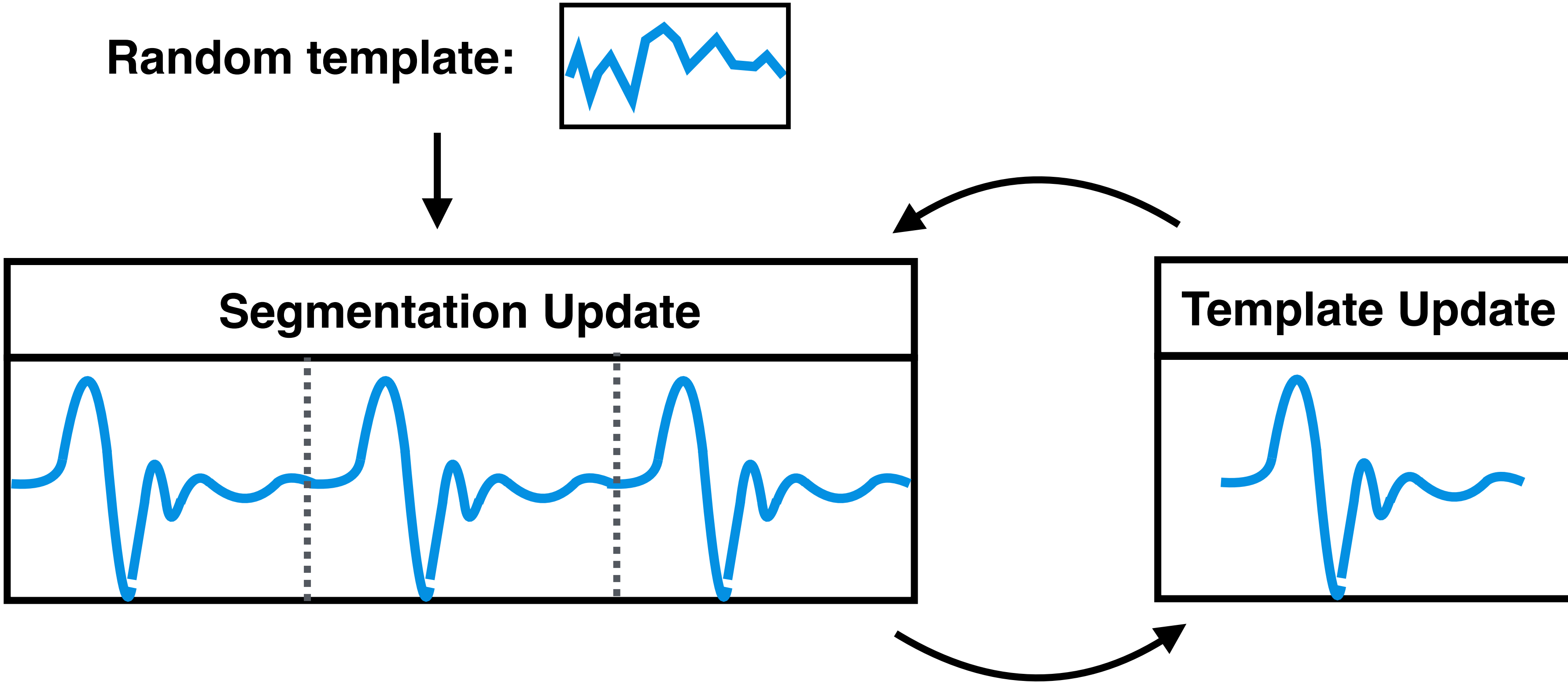
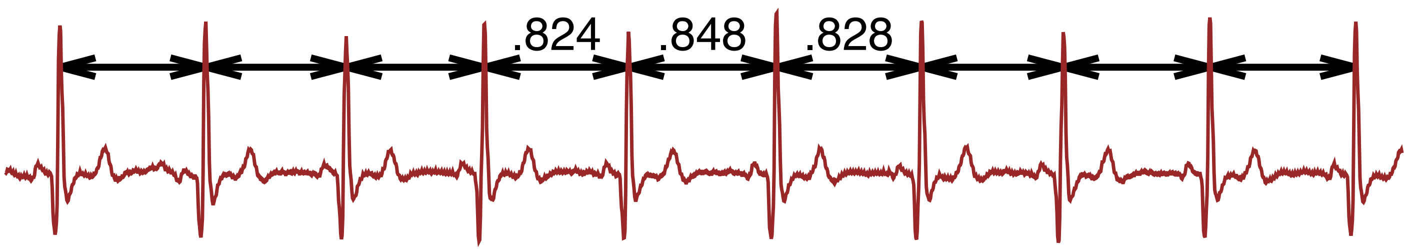


Caveat: Shrinking & Expanding

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

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

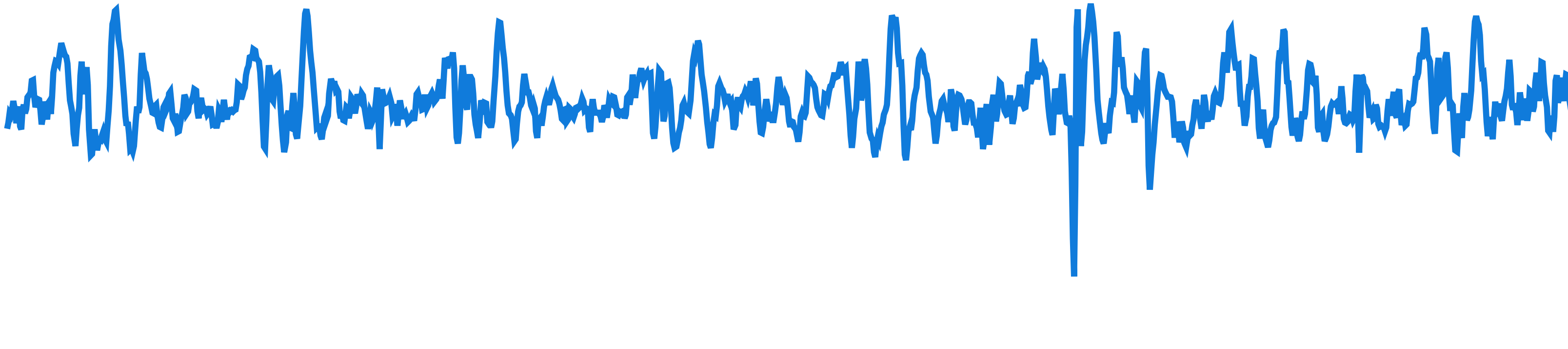
(dynamic programming)

Template Update

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

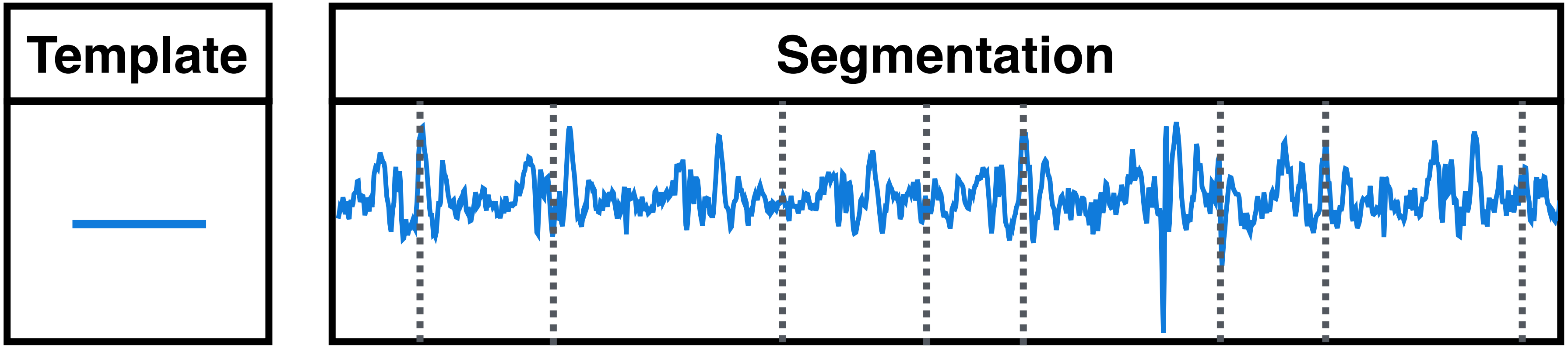
(weighted least squares)

Example run



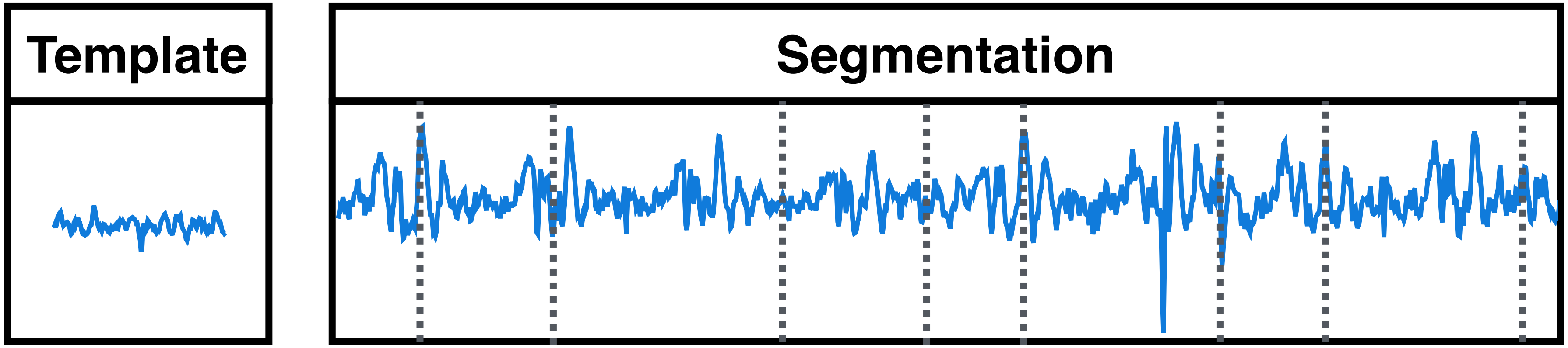
Example run

Iteration 1:



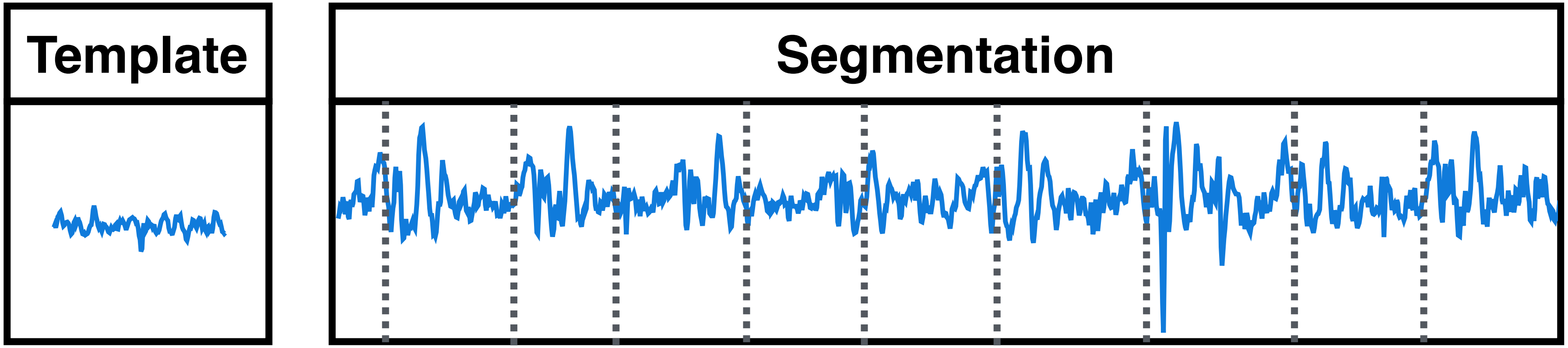
Example run

Iteration 2:



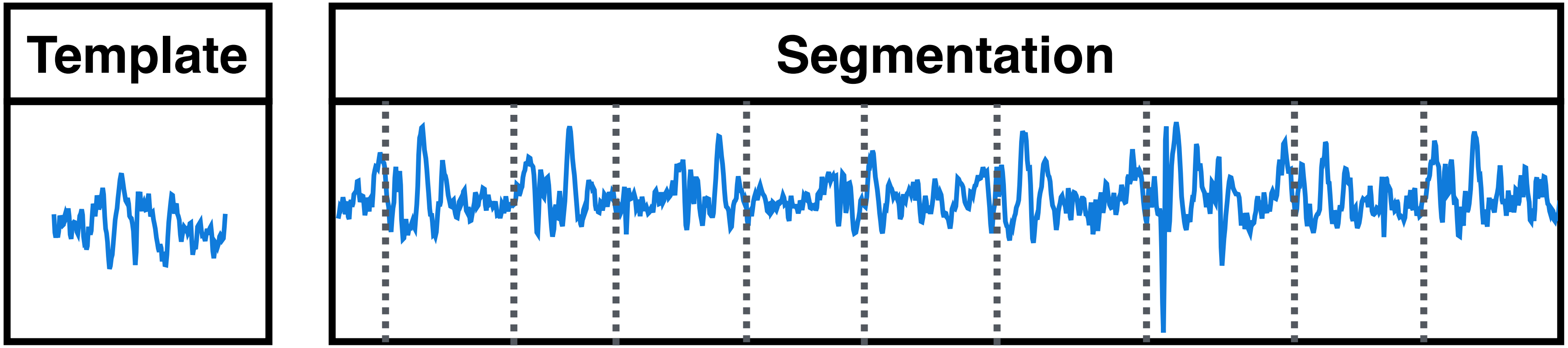
Example run

Iteration 2:



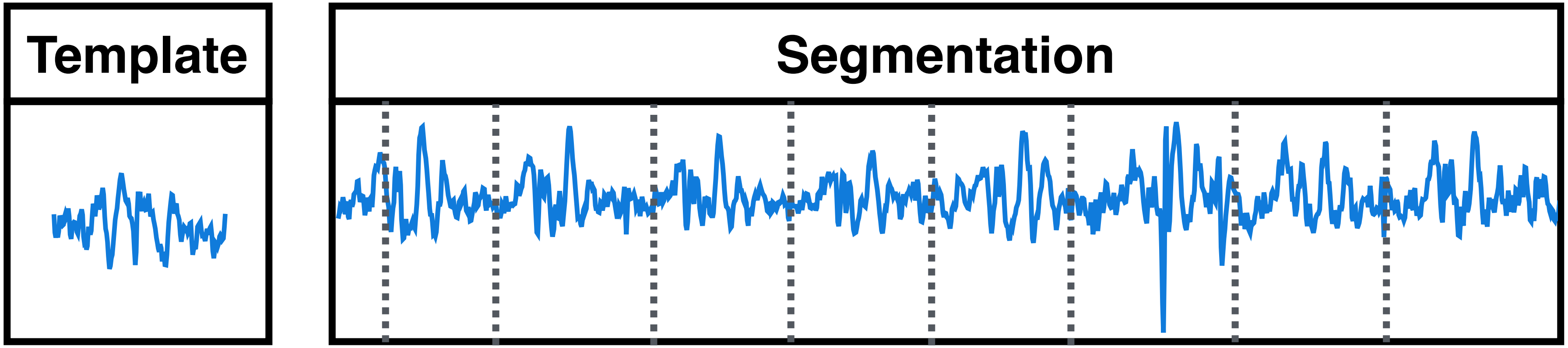
Example run

Iteration 3:



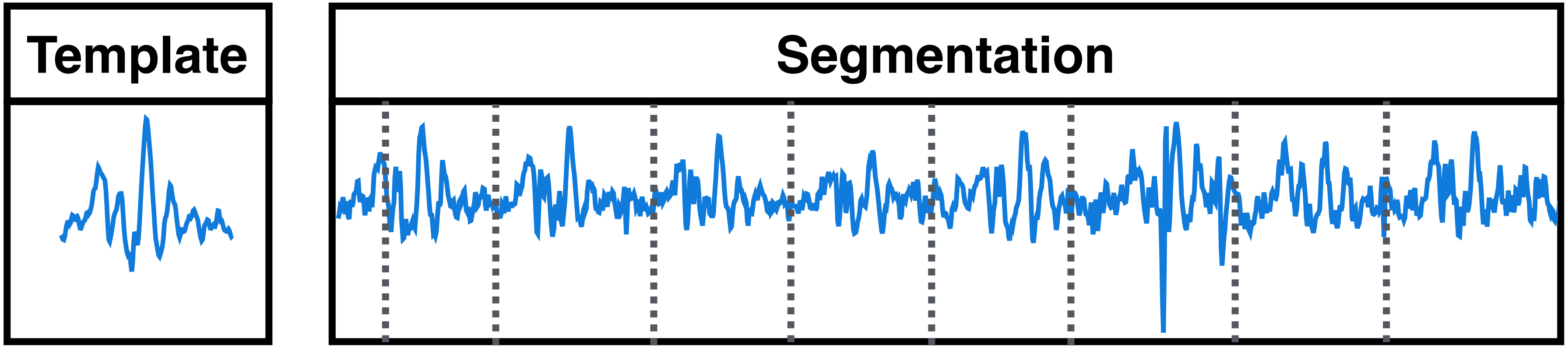
Example run

Iteration 3:



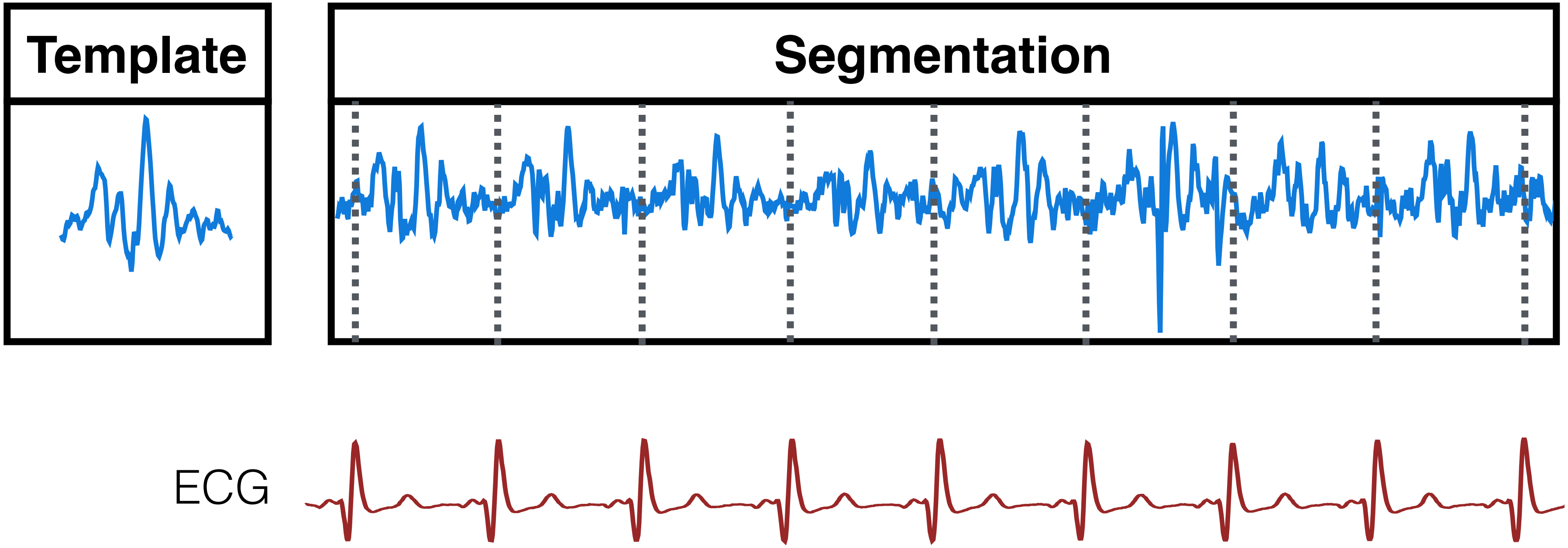
Example run

Iteration 7:



Example run

Iteration 7:



From vital signs to emotions

Physiological Features for Emotion Recognition

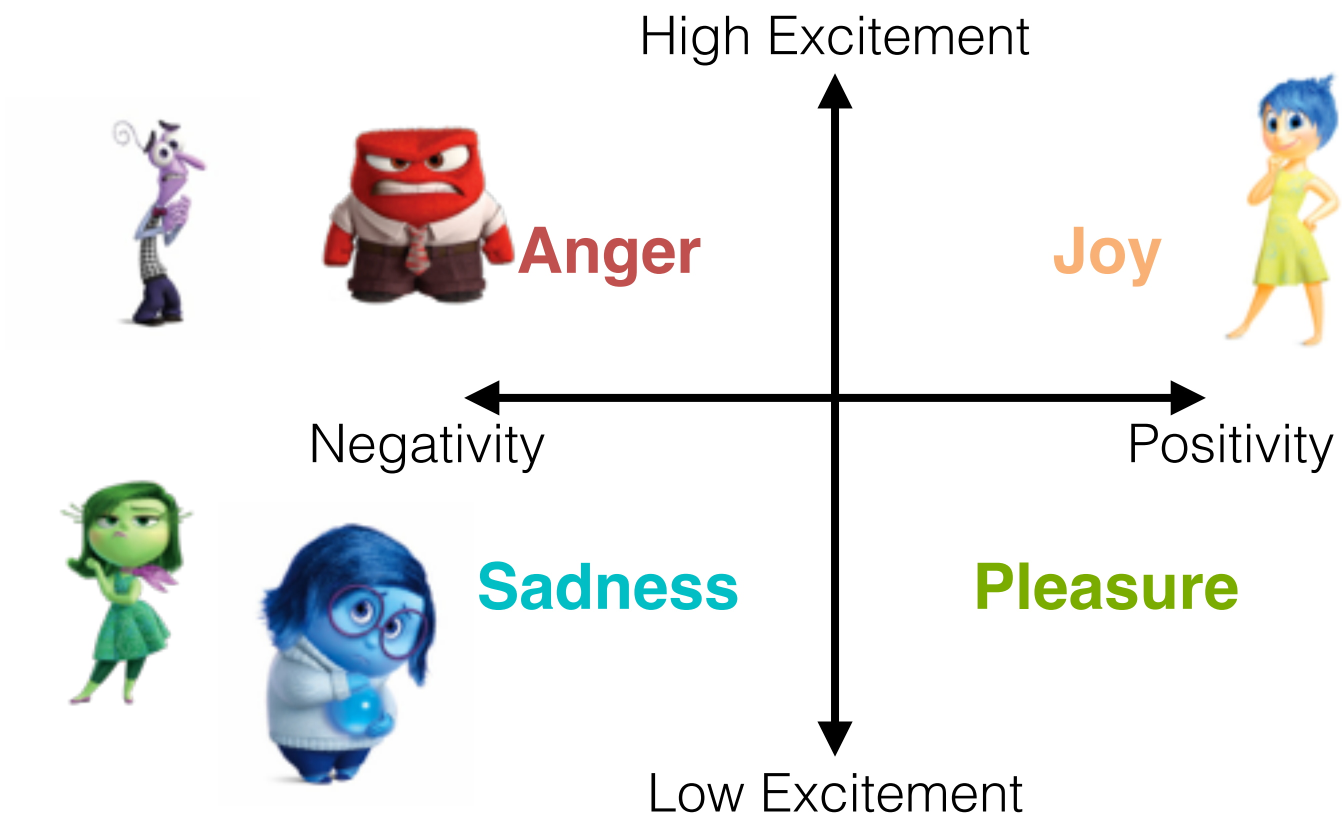
- 37 Features similar to ECG-based methods
    - Variability of IBI
    - Irregularity of breathing

Emotion Classification

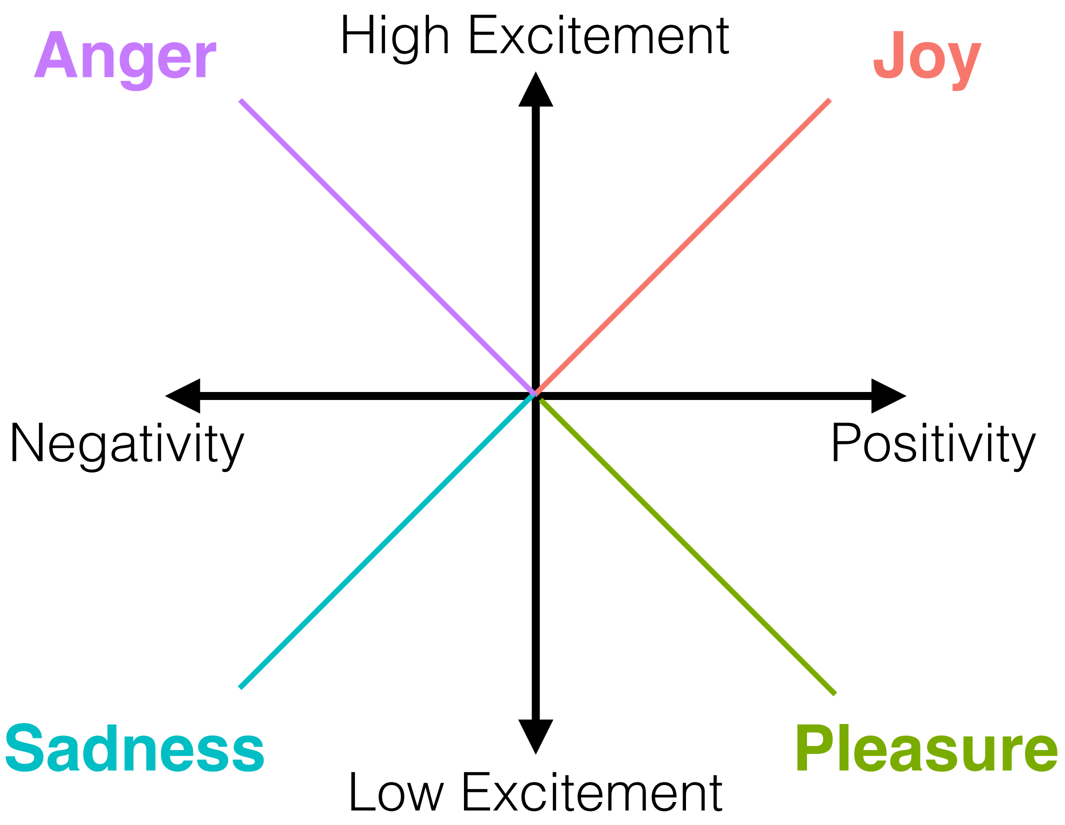
- Recognize emotion using physiological features
- Used L1-SVM classifier
    - select features and train classifier at the same time

Emotion Model

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

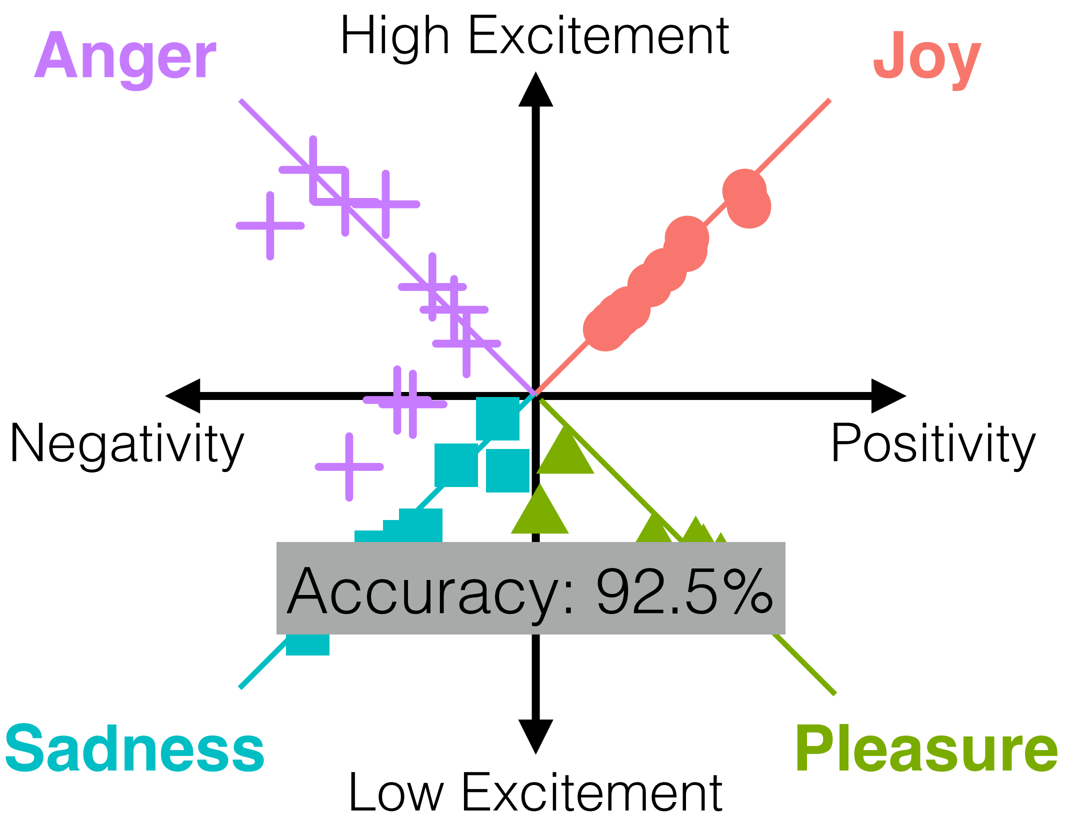


Does it detect emotion accurately?



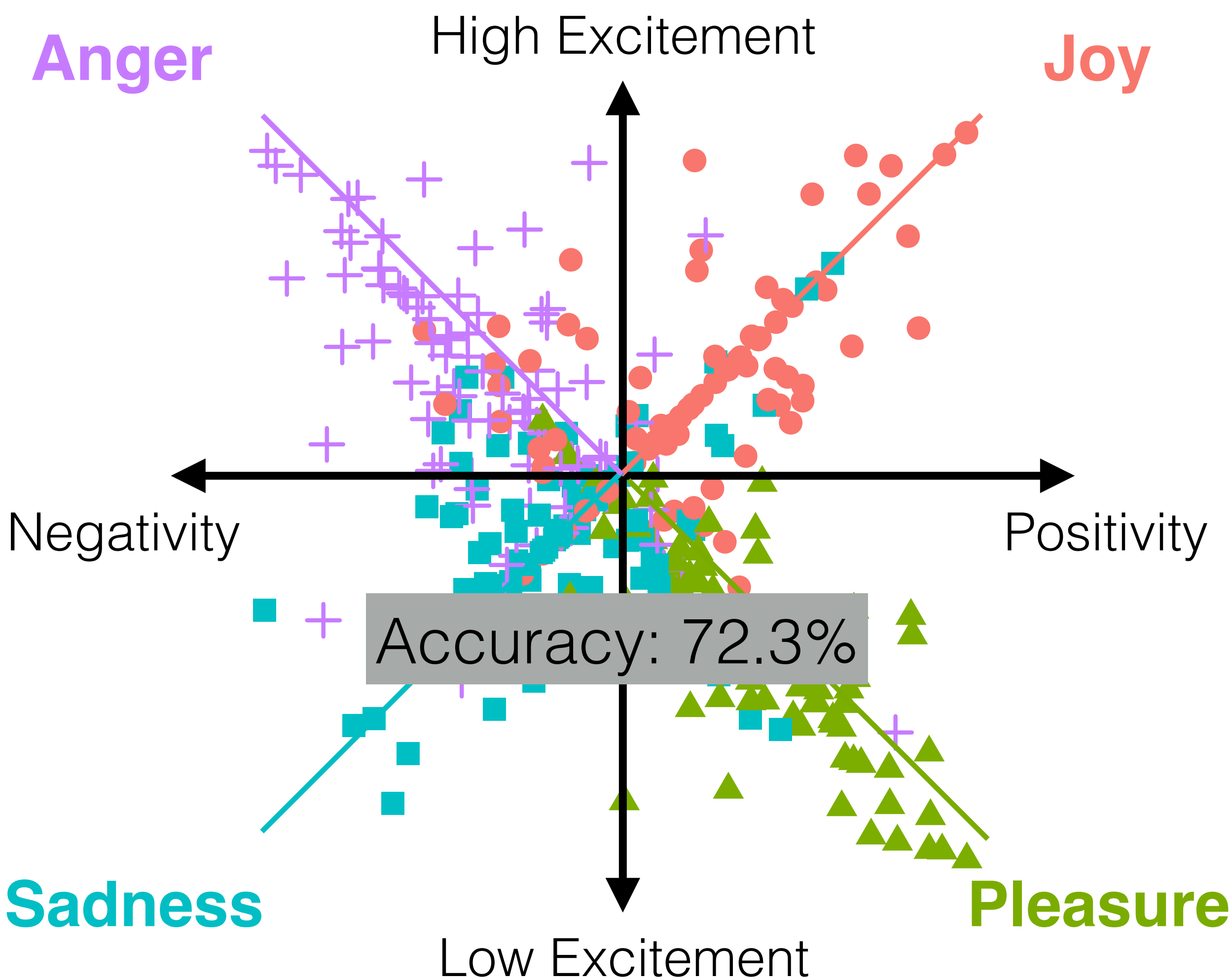
Person-dependent Classification

- Train and test on the same person

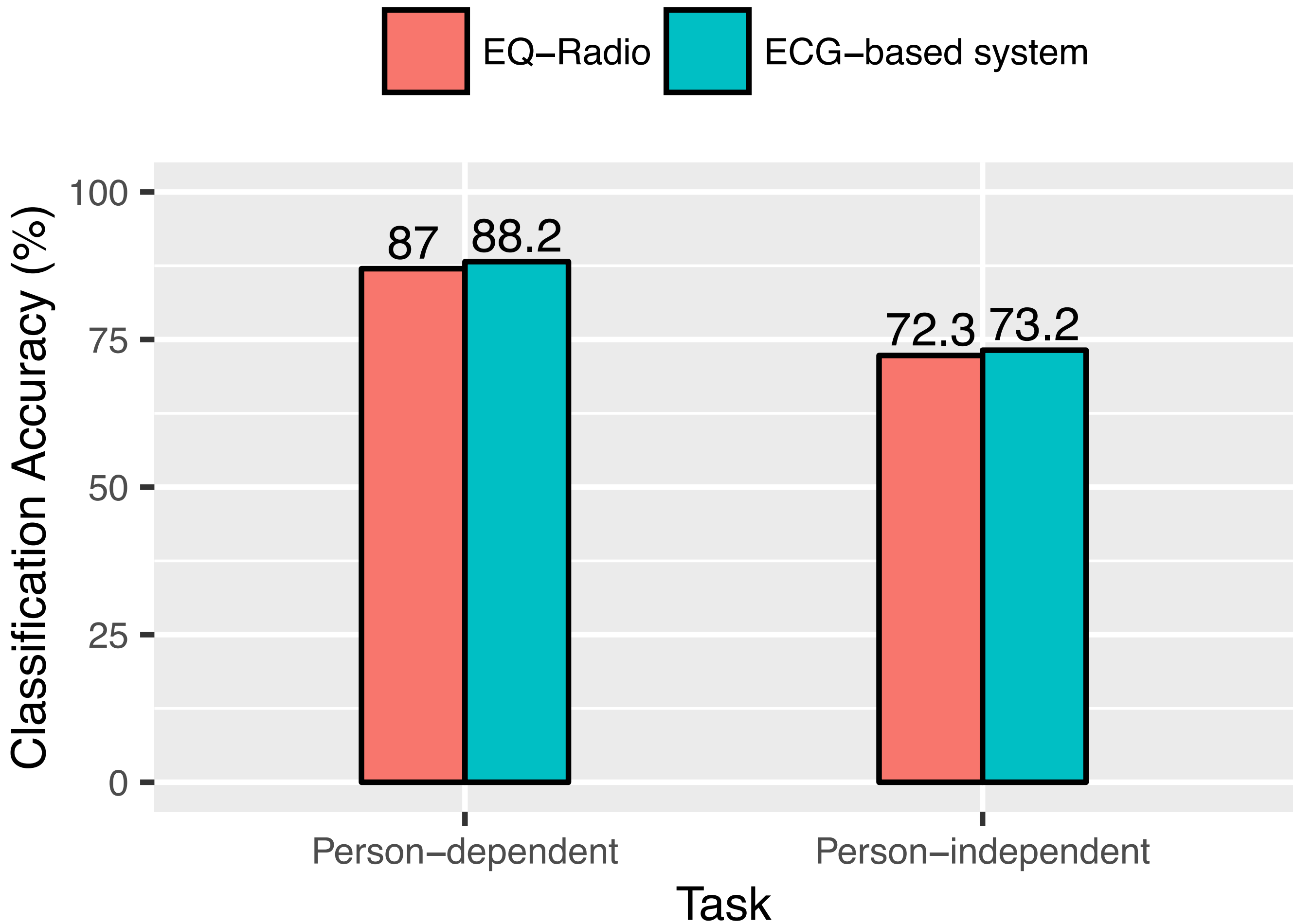


Person-independent Classification

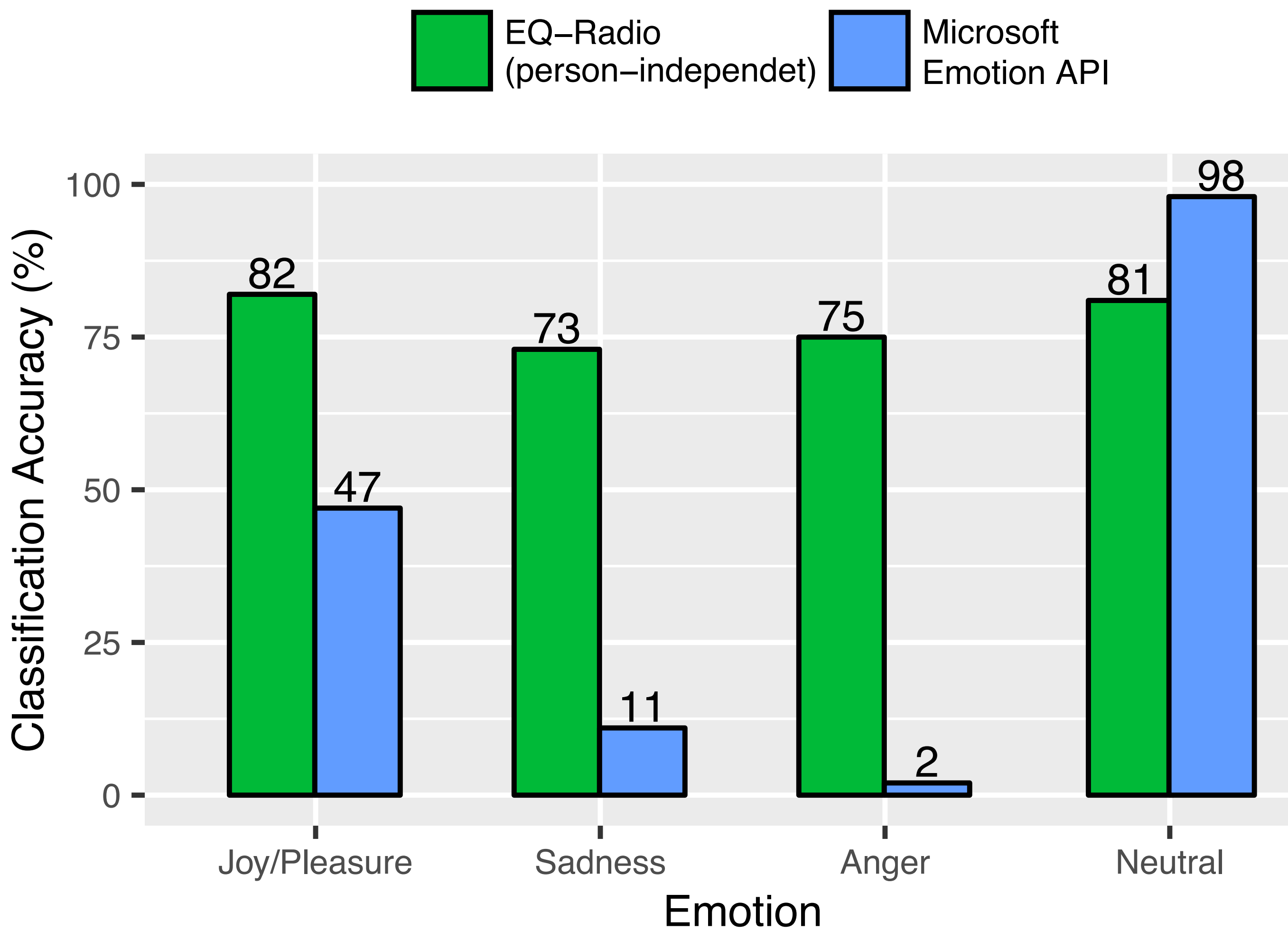
- Train and test on the different person



Comparison with ECG-based system

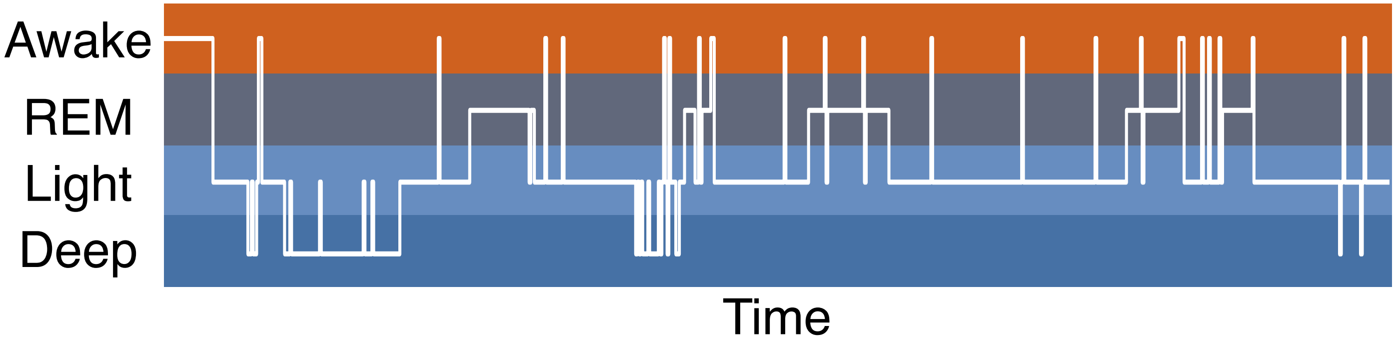


Comparison with Image-based system



Learning Sleep Stages from Radio Signals

Background

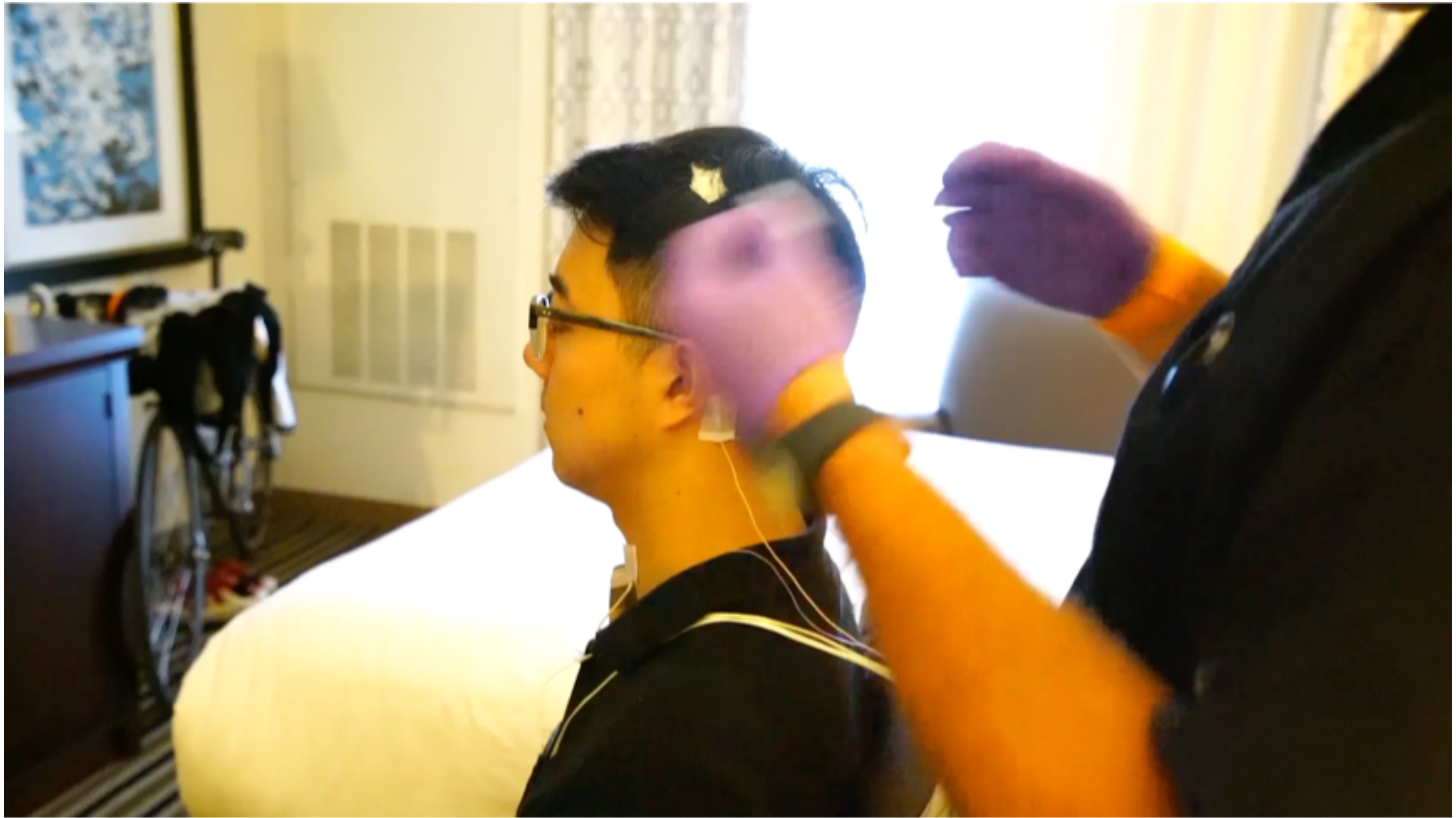

Awake
REM
Light
Deep
Time

Understanding Diseases with Sleep Stages

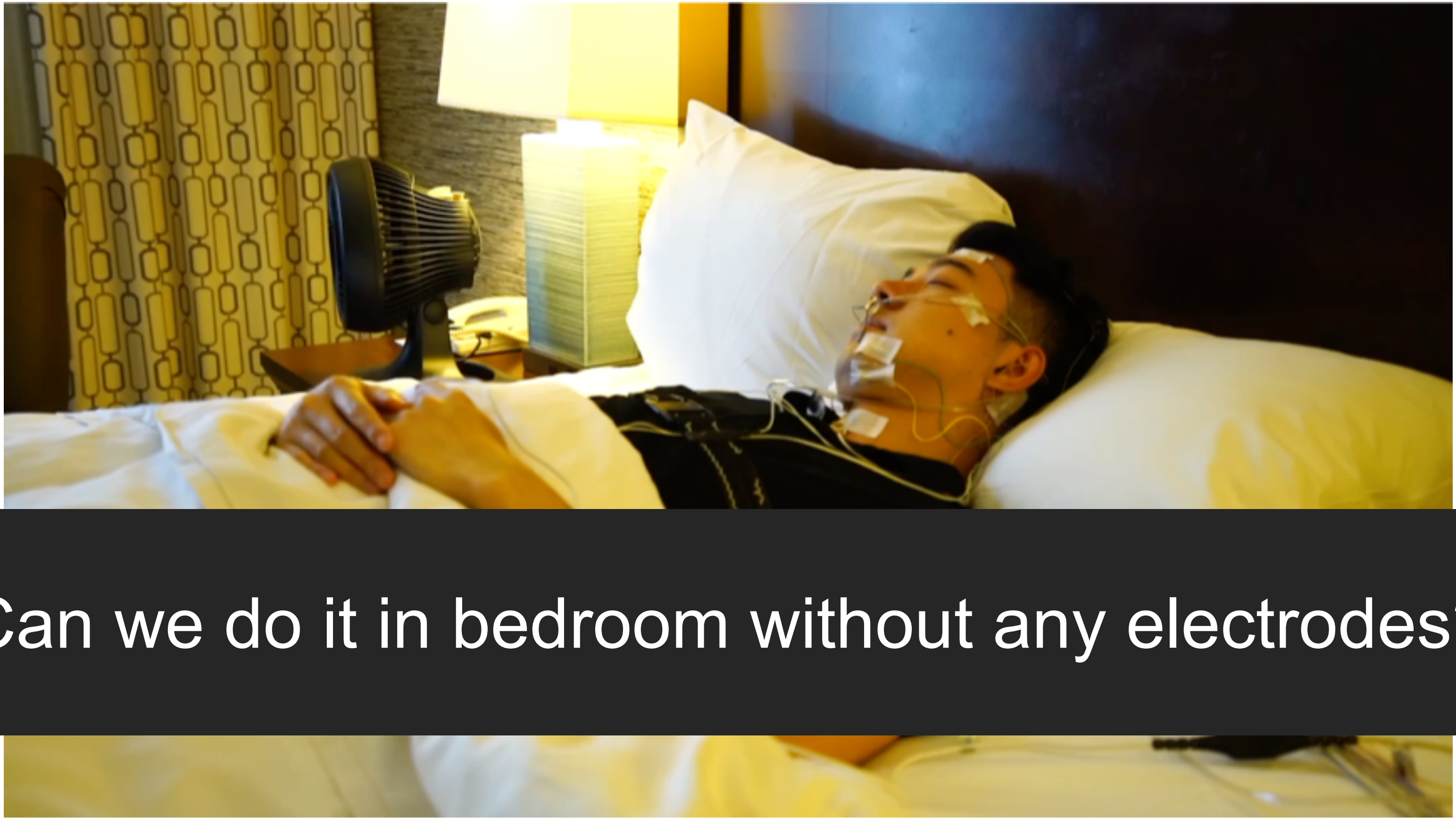
But, monitoring sleep stages is difficult …

done in hospital with many electrodes on the body

Sleep Lab

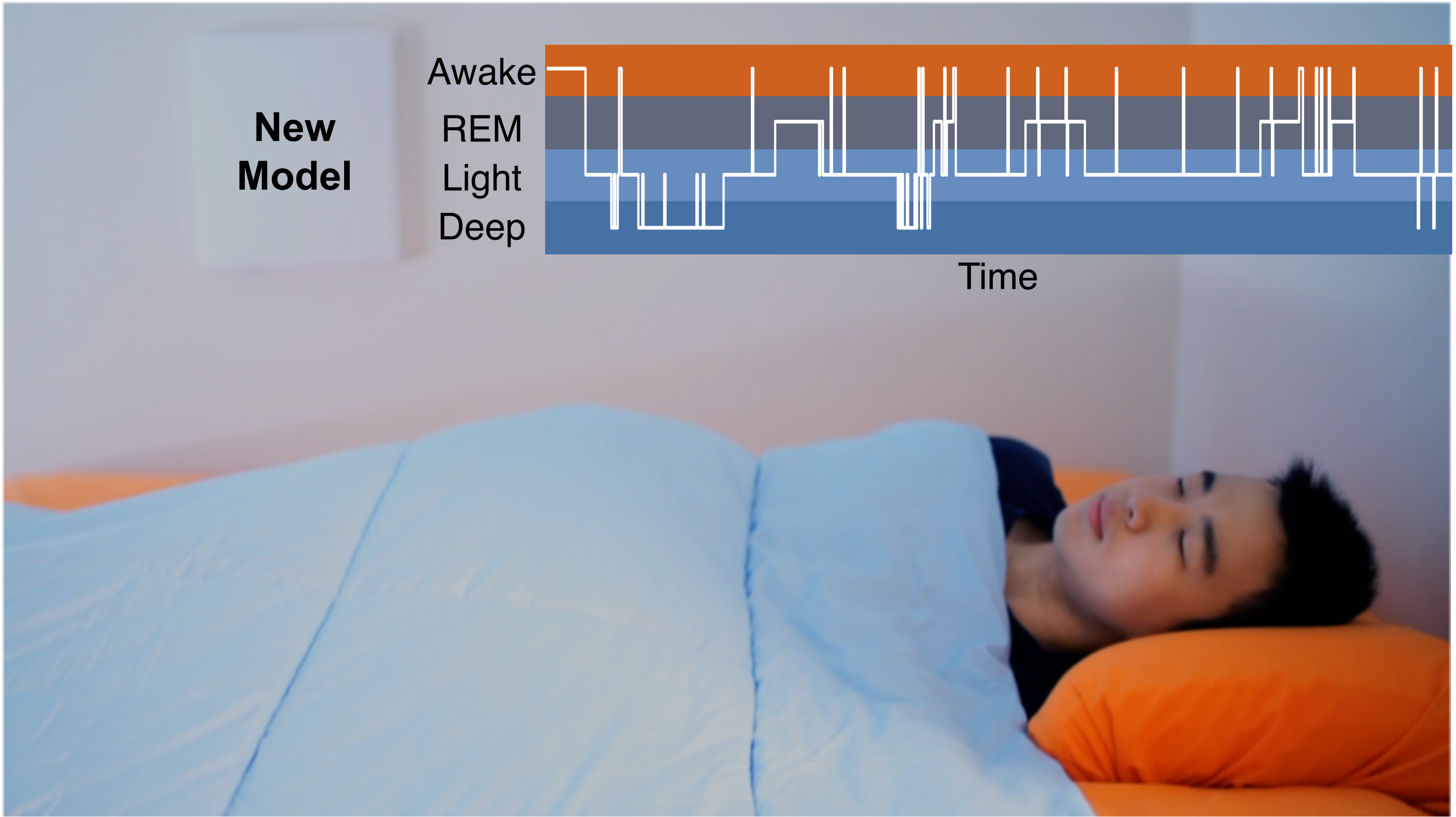


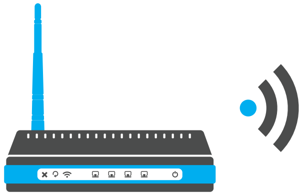
Sleep Lab

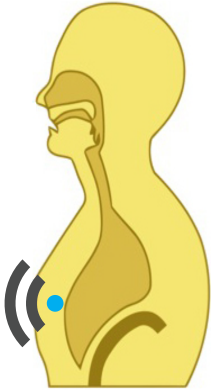


Can we do it in bedroom without any electrodes?

RF-Based Sleep Staging





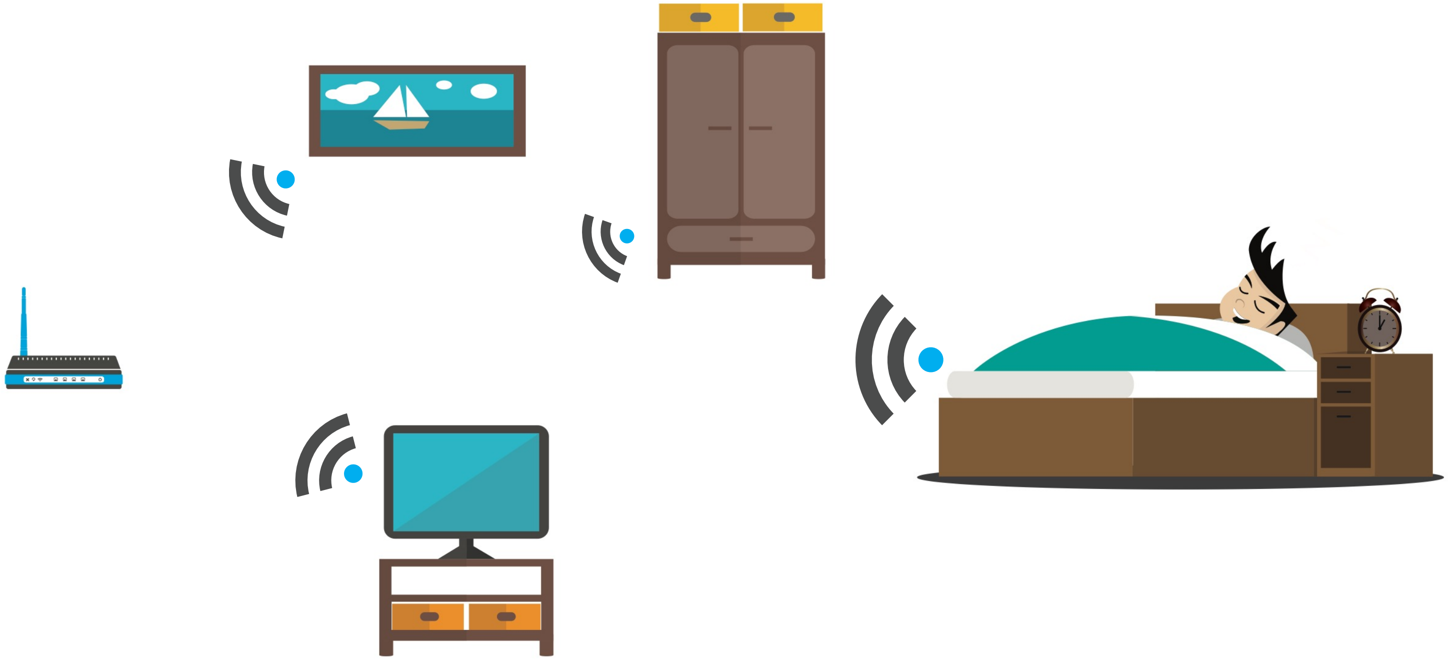


RF signals reflect off body and change with physiological signals

Our objective: 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!

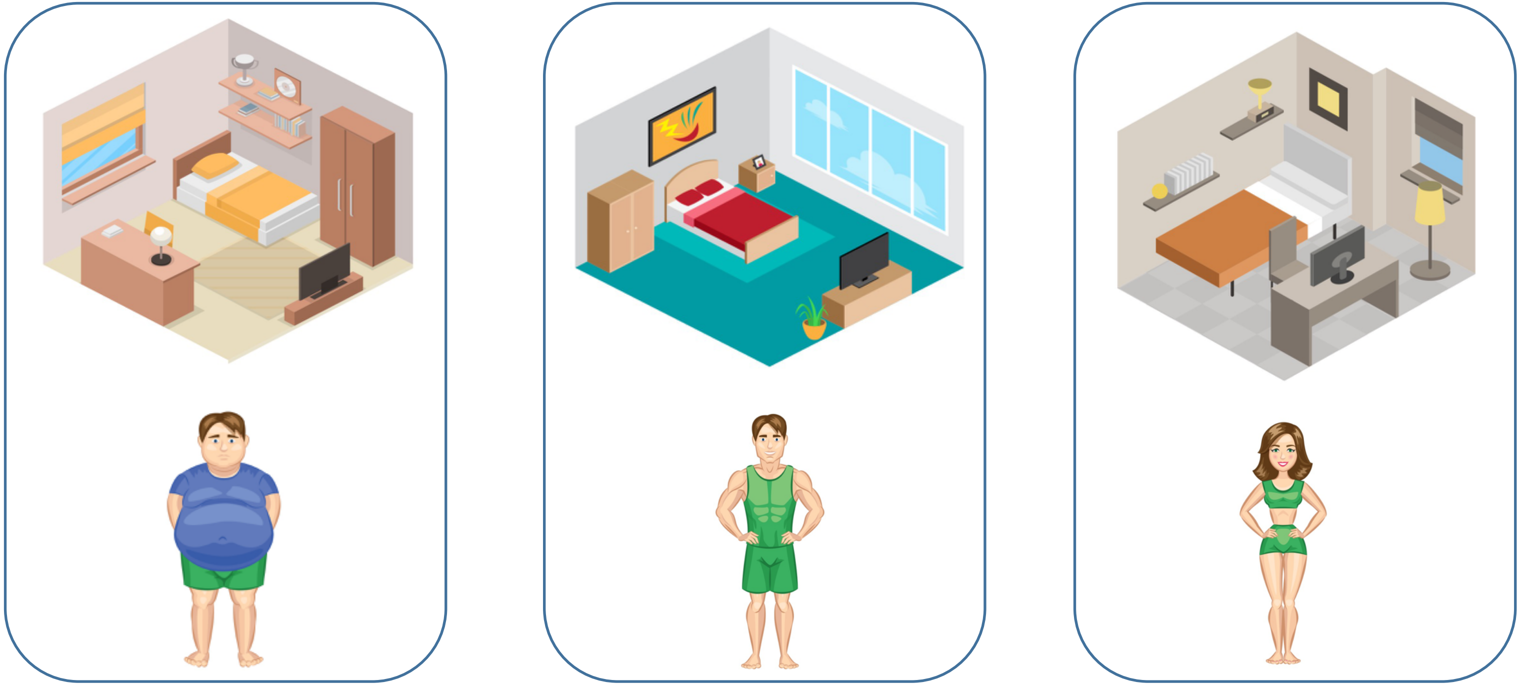





Multi-Source Domain Adaptation

domain = measurement condition + individual

Source domain A | Source domain B | Target domain C



Multi-Source Domain Adaptation

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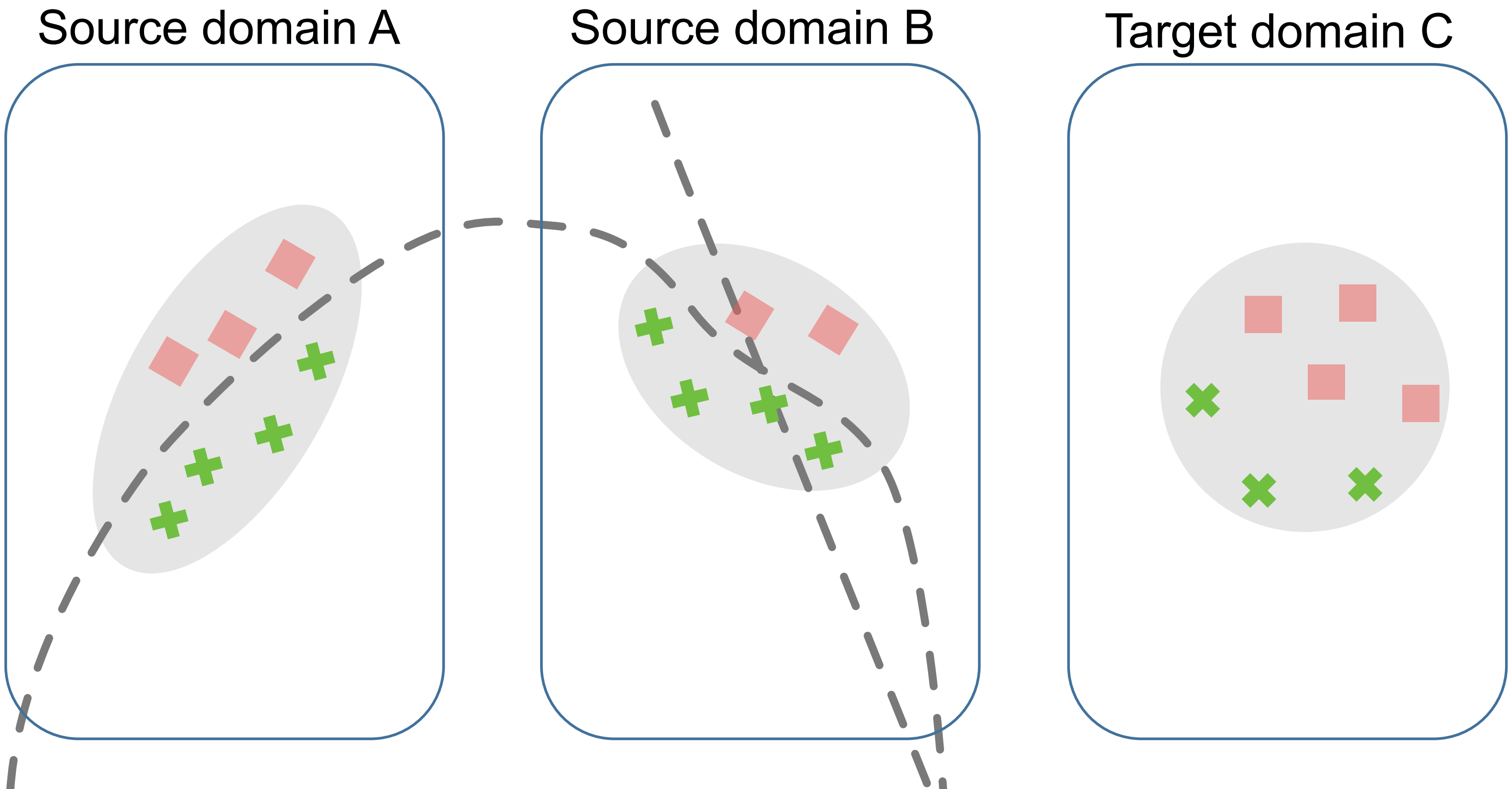
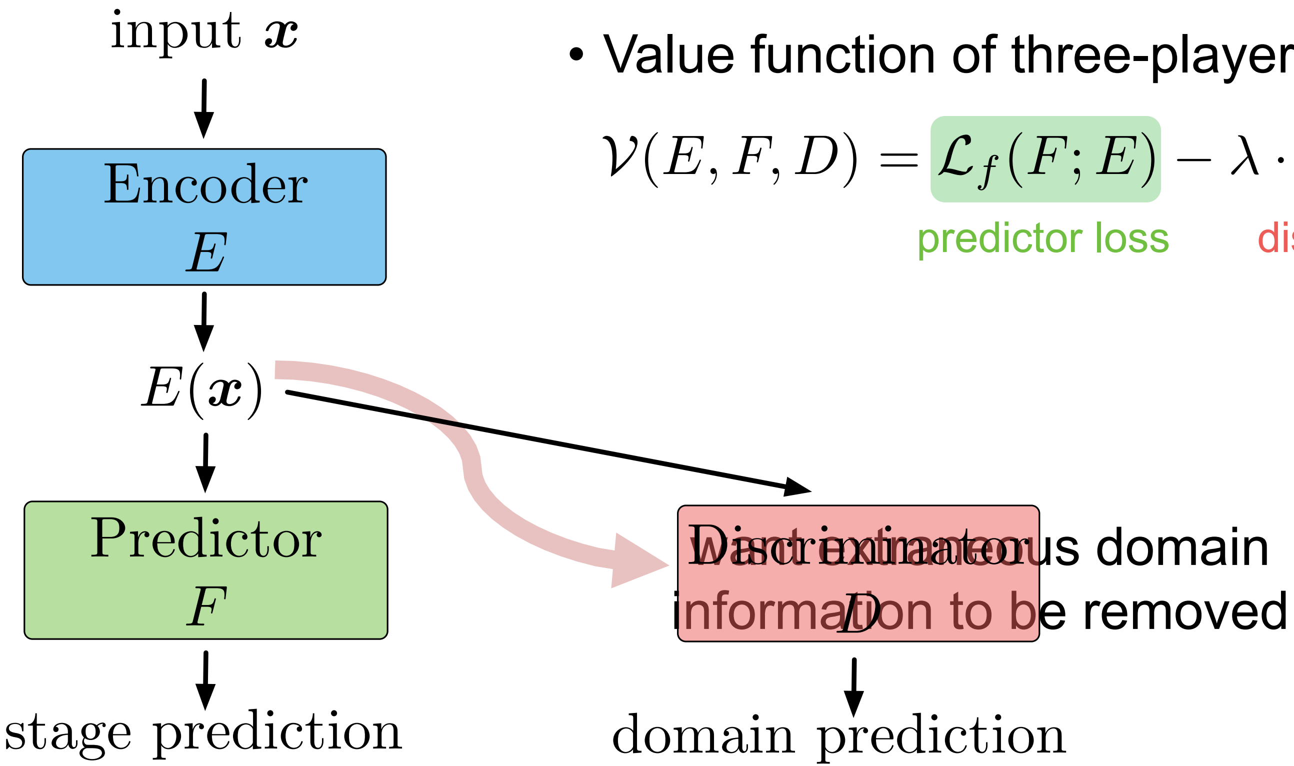


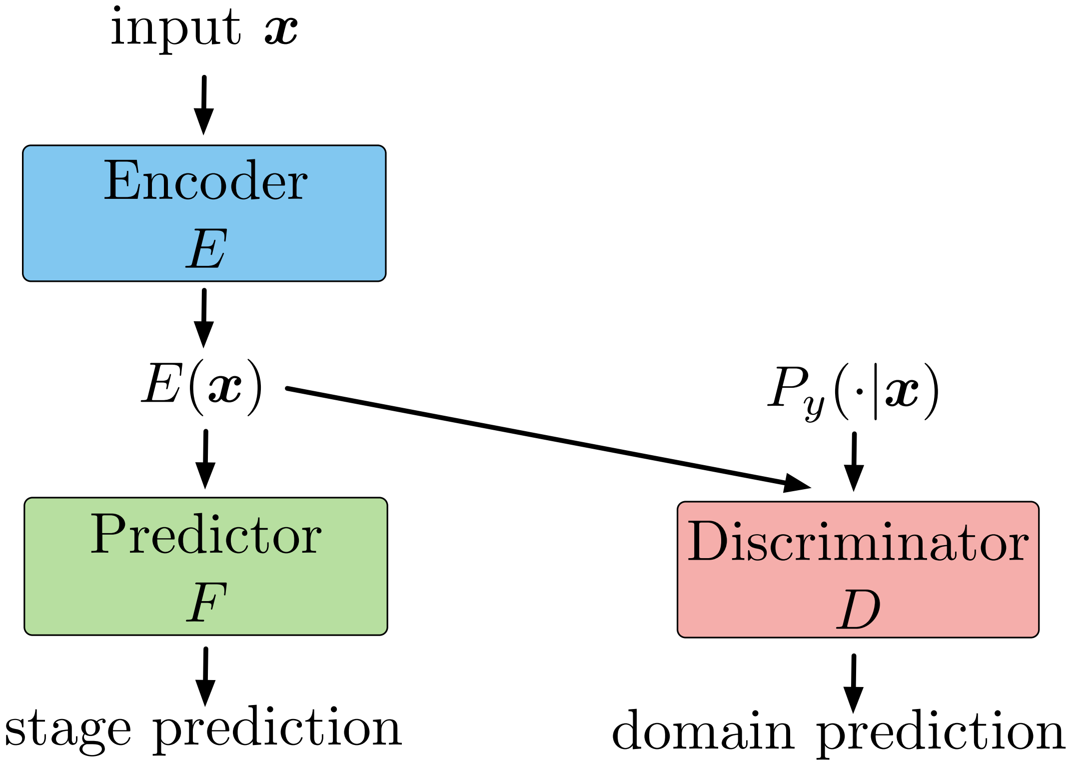
Problem: Discriminator removes both extraneous and useful information

- Value function of three-player game:

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



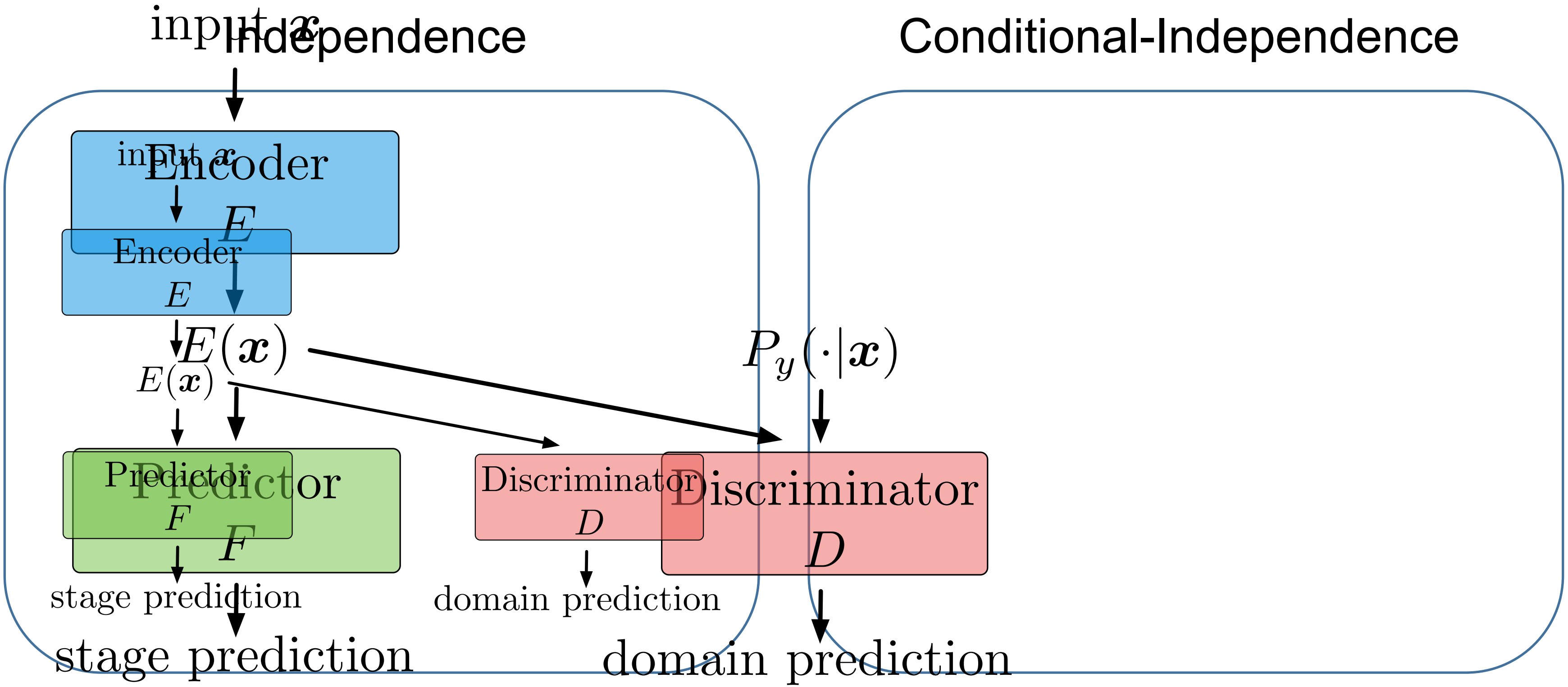
Conditional Adversary



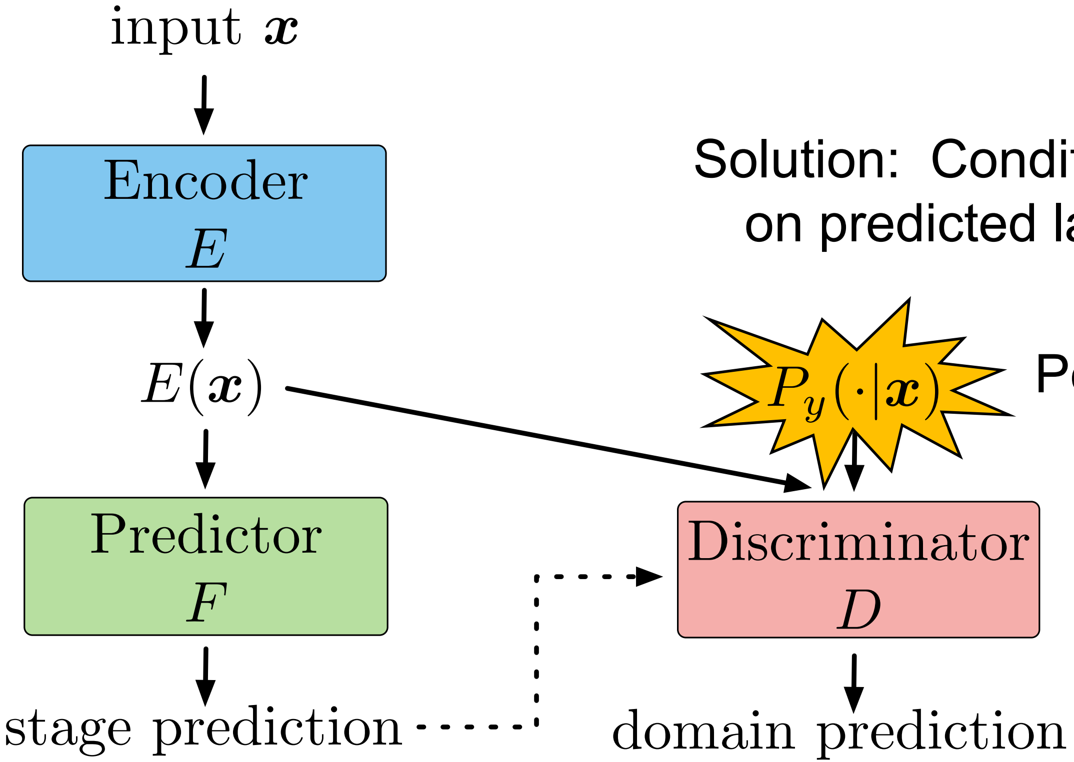
Role of Adversary

Independence

Conditional-Independence



Does it work?



Solution: Condition Discriminator on predicted label distribution

Posterior not available when training!

It Works

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-sencond pairs of RF measurements and corresponding sleep stages

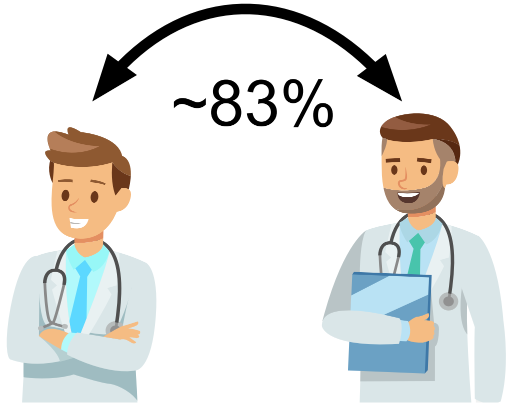
Accuracy

Accuracy of sleep lab
Inter-rater agreement: 83%

Our accuracy 79.8%
(Tested on new subjects not in training, i.e., new domains)

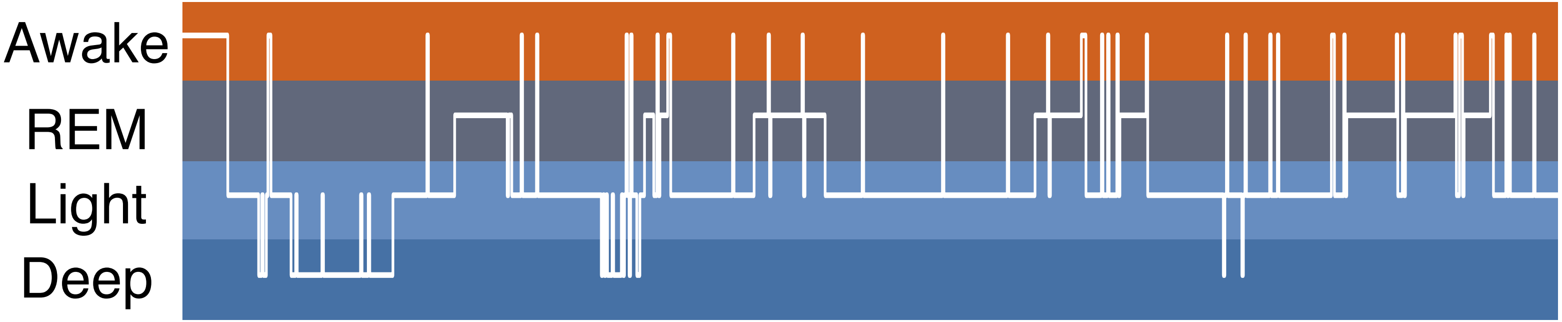
Previous solutions: 64%

Labelling sleep stages is subjective

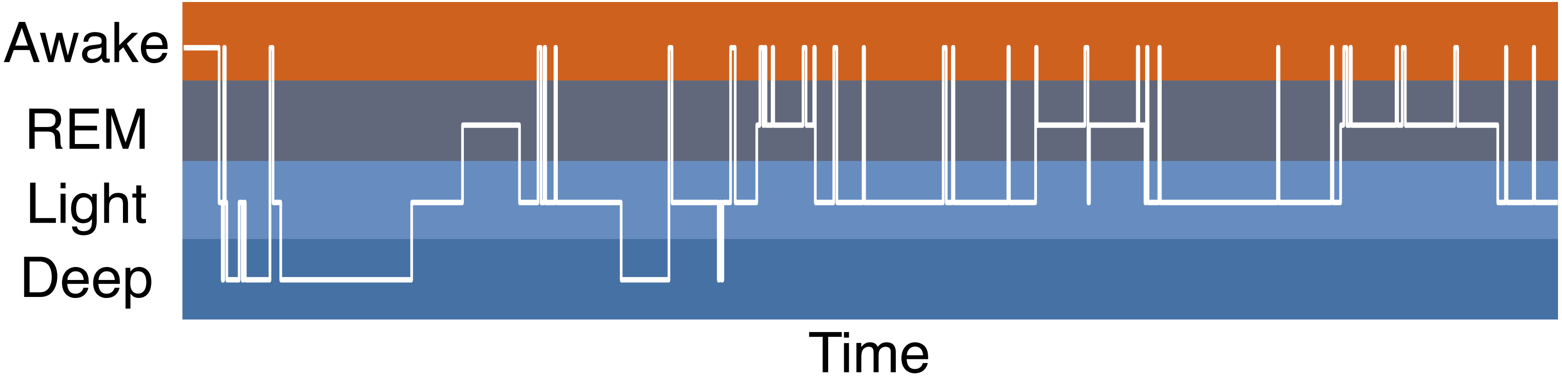


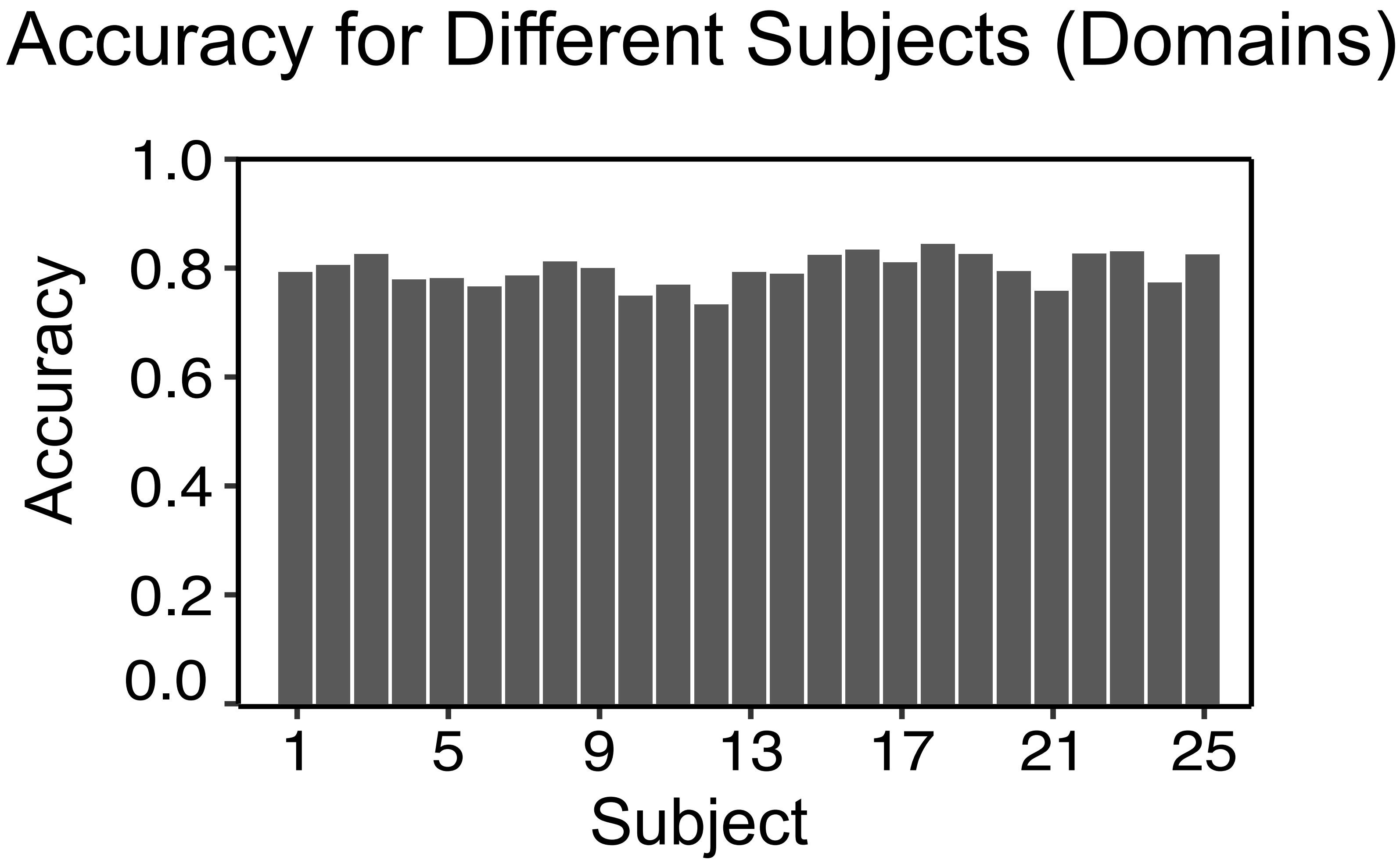
Representative Example Acc = 80%

Ground-truth using EEG



RF-Sleep Prediction




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

Learning sleep stages from wireless signals