CIS 3990

Mobile and IoT Computing

https://penn-waves-lab.github.io/cis3990-24spring

Lecture 8: ML-based Sensing & Sleep Staging

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Objectives of This Module

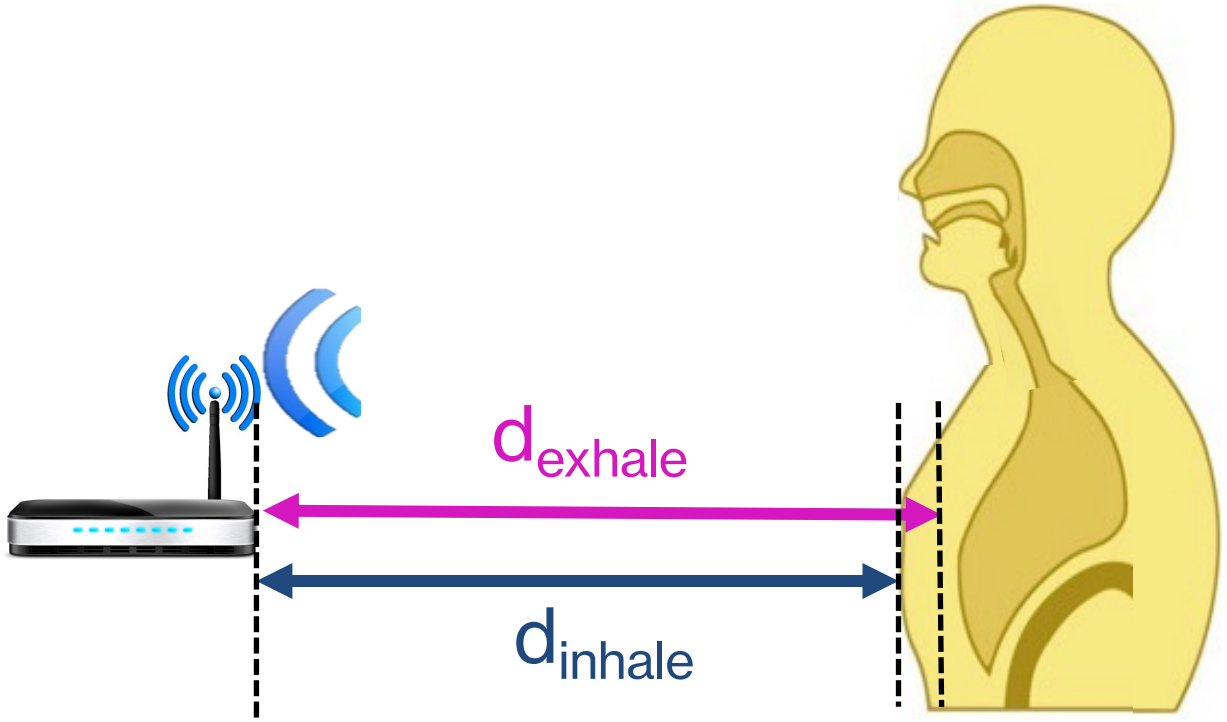
Learn how foundational sensing technologies can be used to extract diverse and meaningful insights

1. What are important application areas of Mobile and IoT sensing?
2. What are the foundational sensing mechanisms and how are they related to localization?
3. What processing algorithms can be used to transform raw sensor data?
4. Example sensing systems/solutions with real-world case studies.

Focus of this lecture:

ML algorithms to extract insights from raw sensor data

Previous lecture: Contactless Vitals Monitoring



$$h = \frac{1}{d} e^{j2\pi \frac{d}{\lambda}} \qquad \phi = 2\pi \frac{d}{\lambda}$$

FMCW

- FMCW Transmitted Signal:

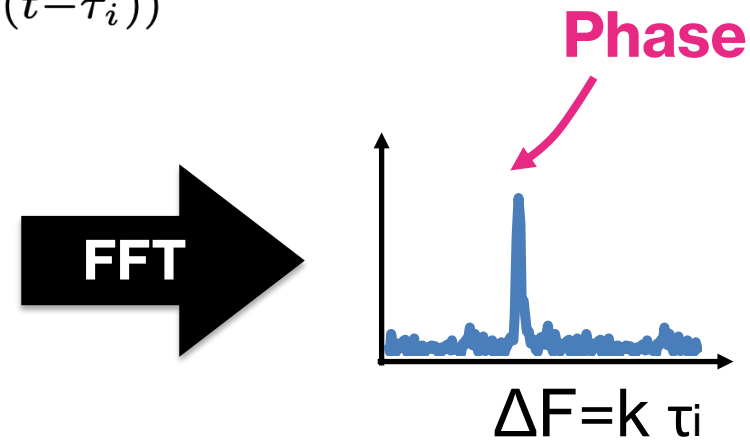
$$x(t) = e^{j2\pi(\frac{k}{2}\ t^2 + f_0 t)}$$

- FMCW Received Signal:

$$y(t) = \sum_i A_i e^{j2\pi(\frac{k}{2}\ (t-\tau_i)^2 + f_0(t-\tau_i))}$$

- FMCW after down-conversion:

$$y_b(t) = \sum_i A_i e^{j2\pi(k\tau_i t + f_0\tau_i)}$$



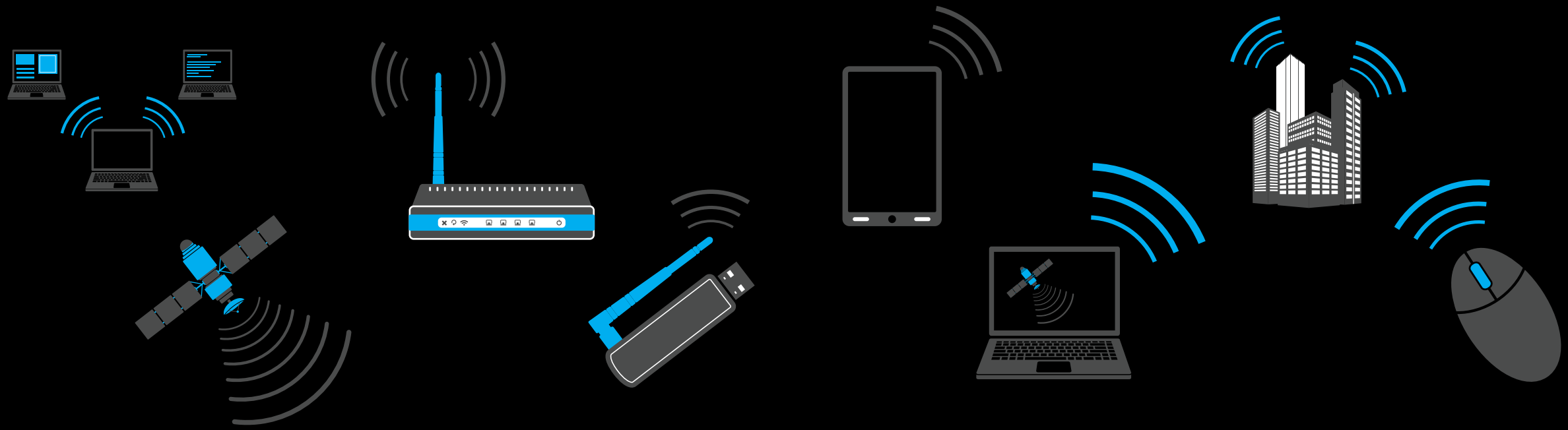
Phase of peak = $f_0\tau_i$

- Phase wraps around 2π
- Use peak position $\Delta F = k\,\tau_i$ for course estimate of τ_i
- Use peak phase $f_0\tau_i$ for fine estimate of τ_i

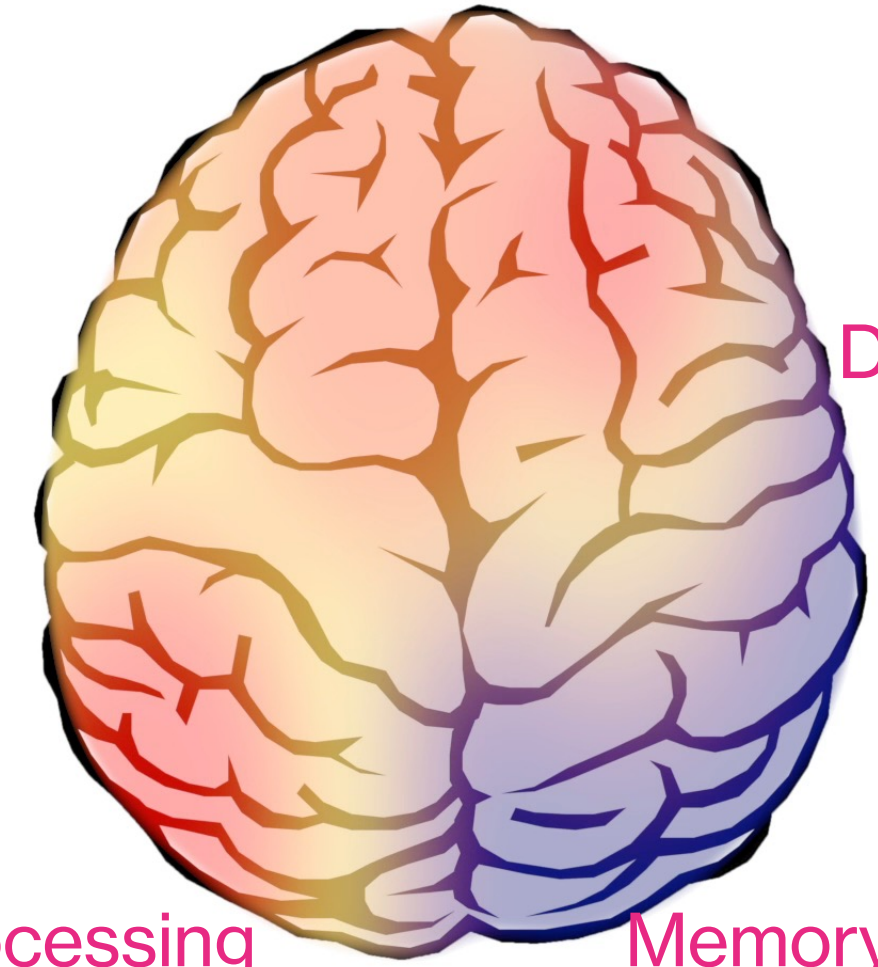
Wireless Signals for Sleep Monitoring

What if wireless signals can be used to understand:

+ when you are dreaming
+ when your brain is consolidating memory
+ sleep stages



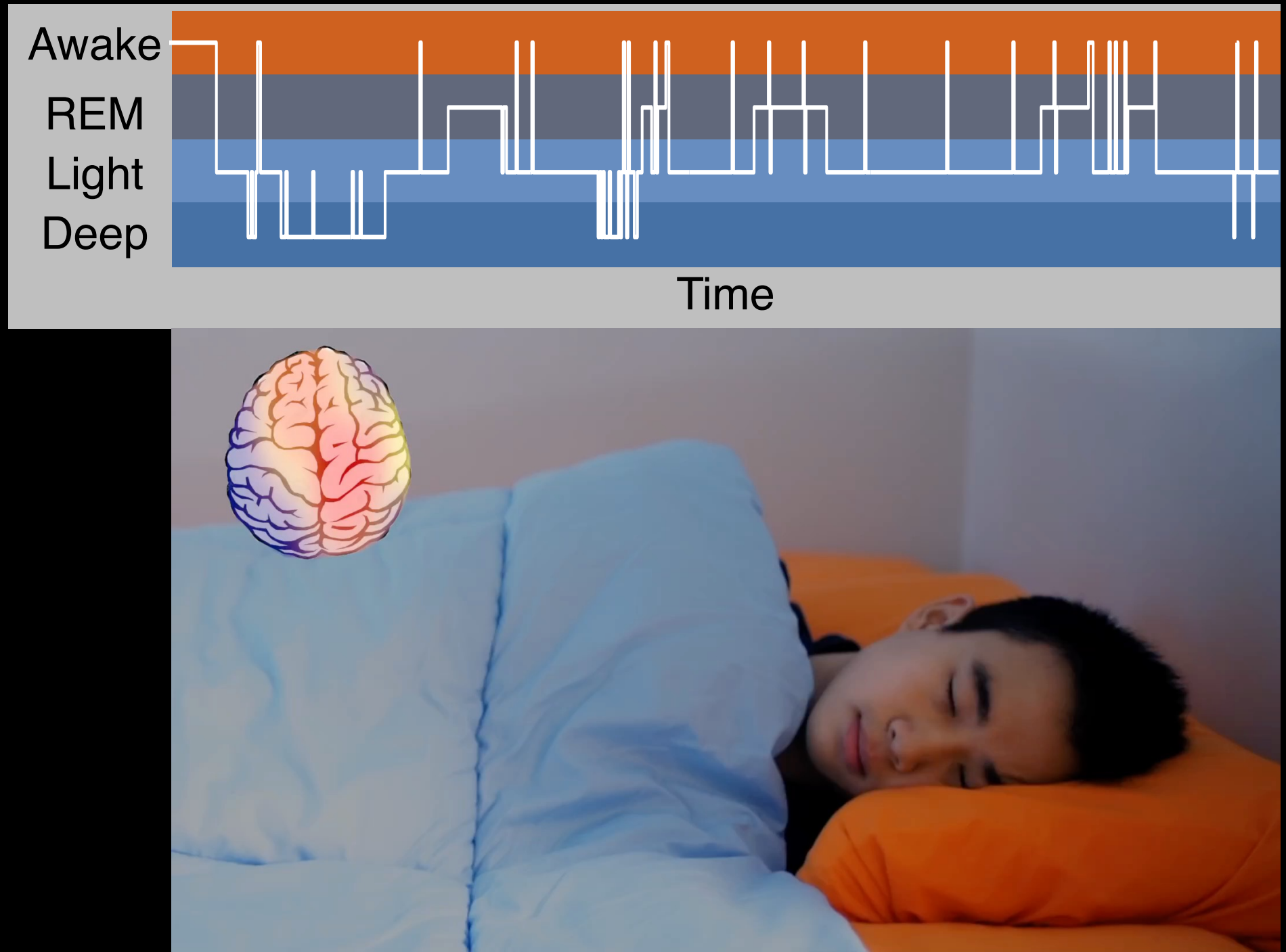
Background



Dreaming

Cognitive Processing

Memory Consolidation


Awake
REM
Light
Deep
Time

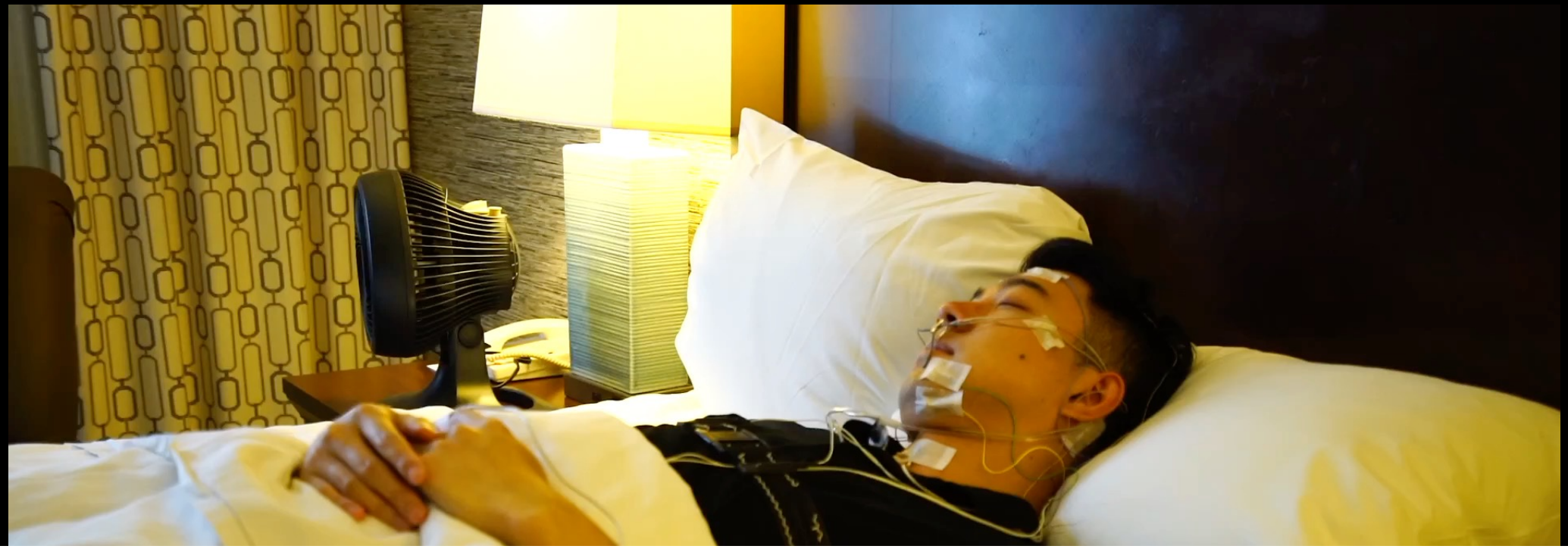
Understanding Diseases with Sleep Stages

But, monitoring sleep stages is difficult ...

done in hospital with many electrodes on the body

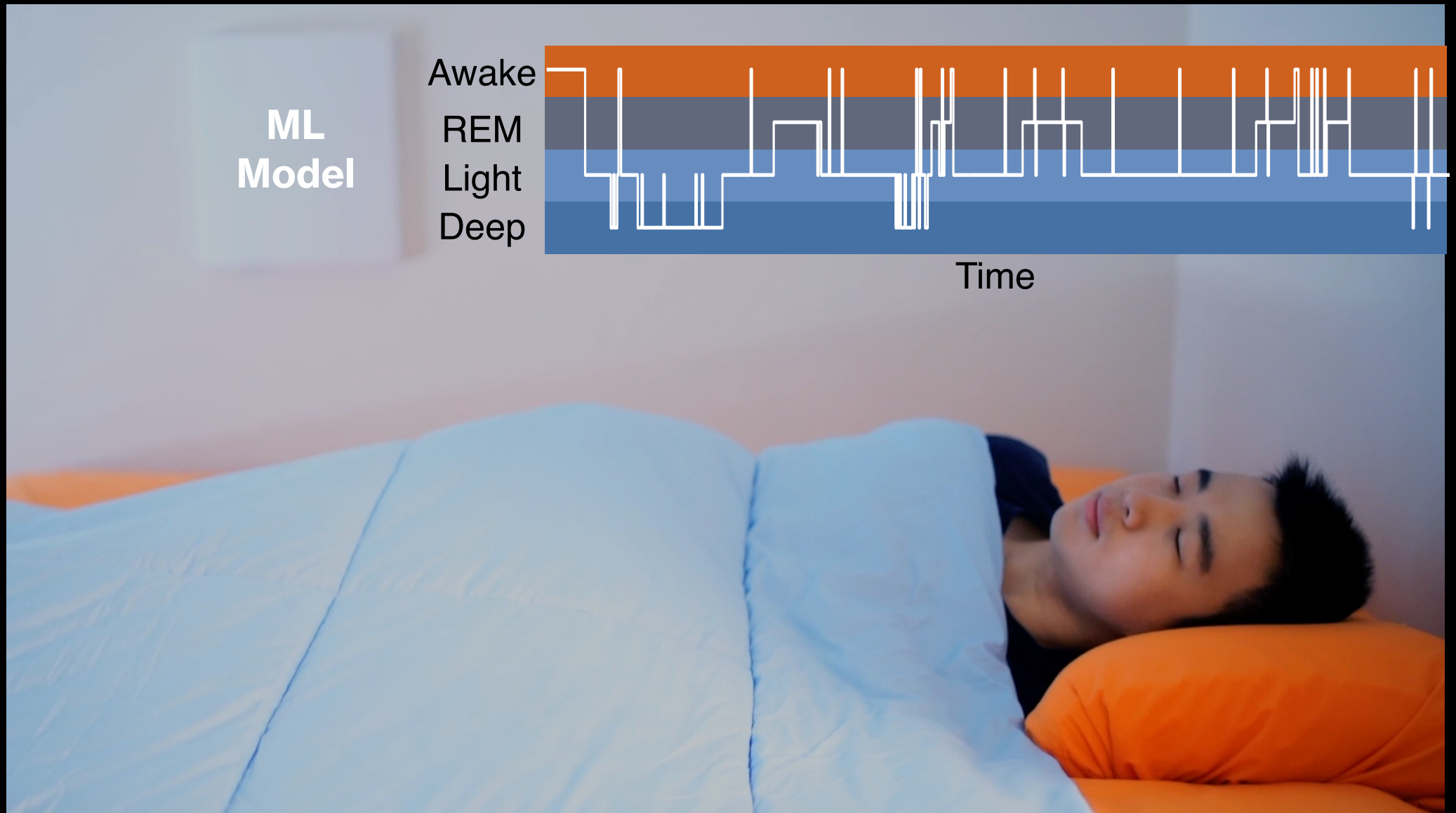
My Experience in Sleep Lab

My Experience in Sleep Lab



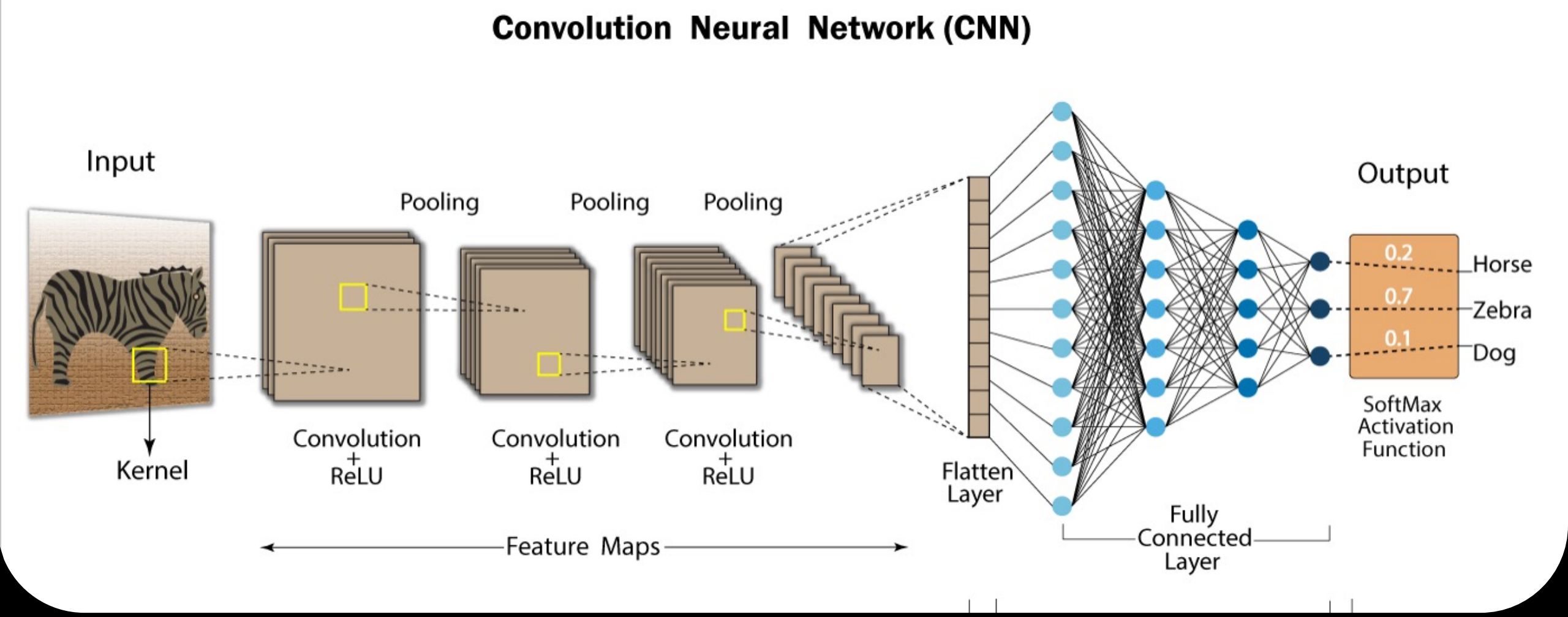
Can we do it in bedroom without any electrodes?

RF-Sleep

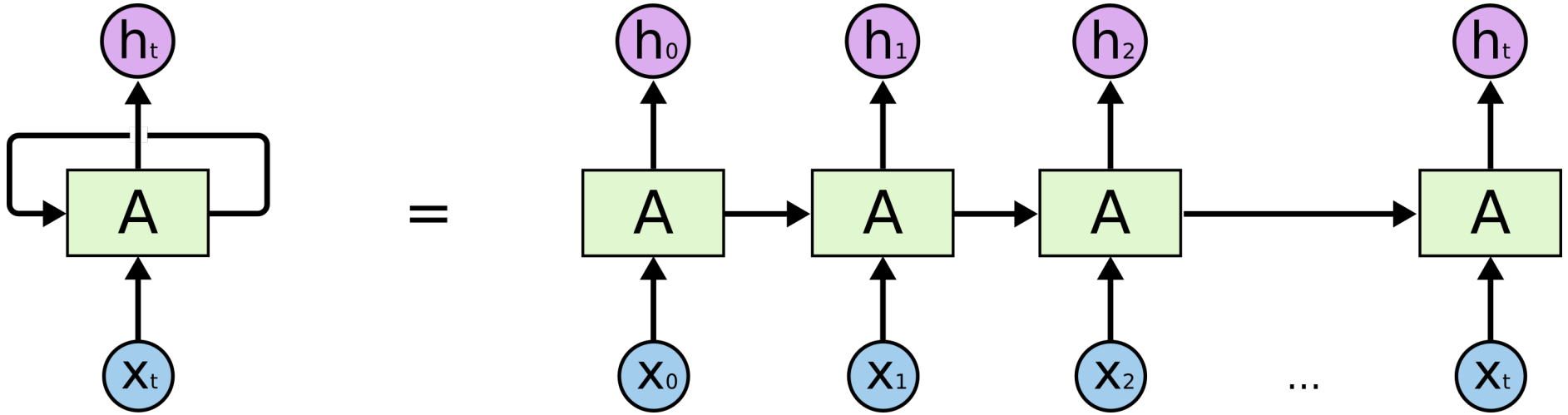


Background: What is ML/AI?

- Classification with Logistic regression
- Loss function and parameter optimization
- Training and testing performance, generalization, regularization

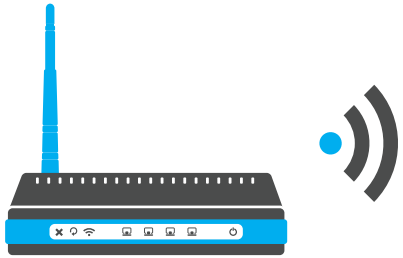


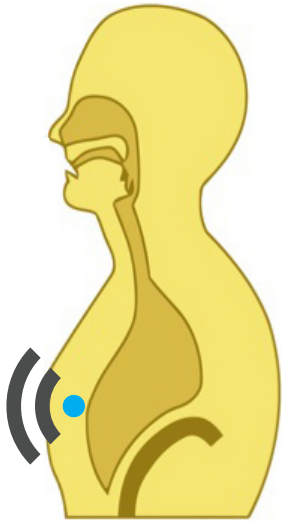
Background: Convolutional Neural Network (CNN)



Background: Recurrent Neural Network (RNN)

Objective

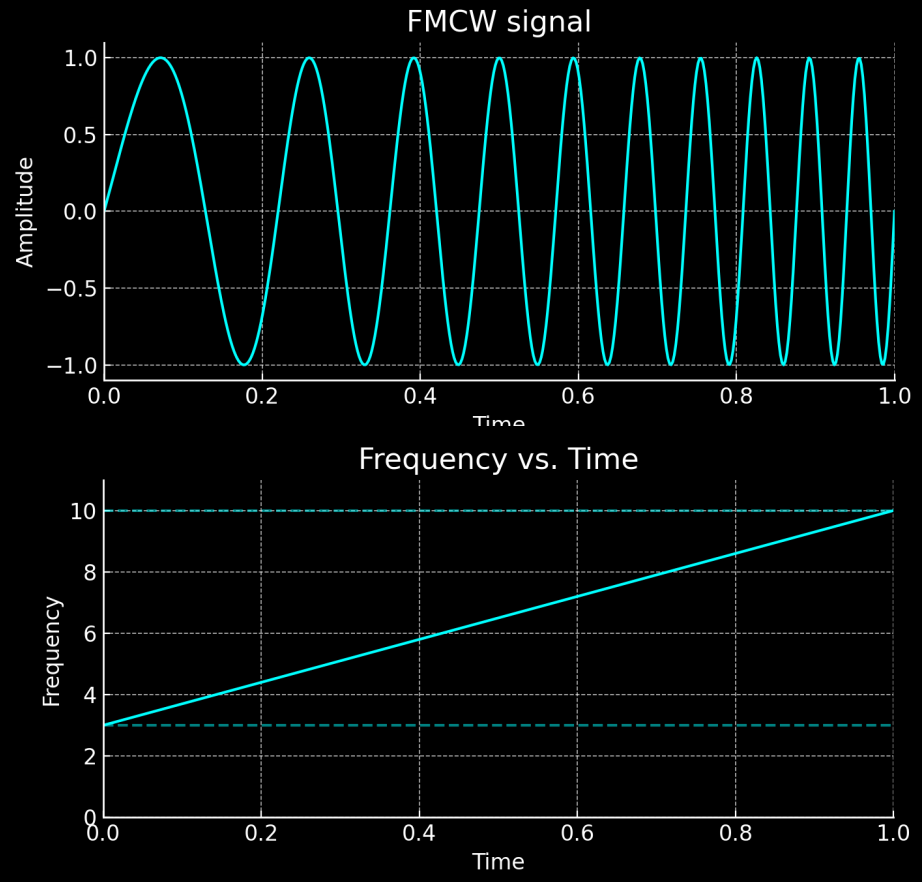




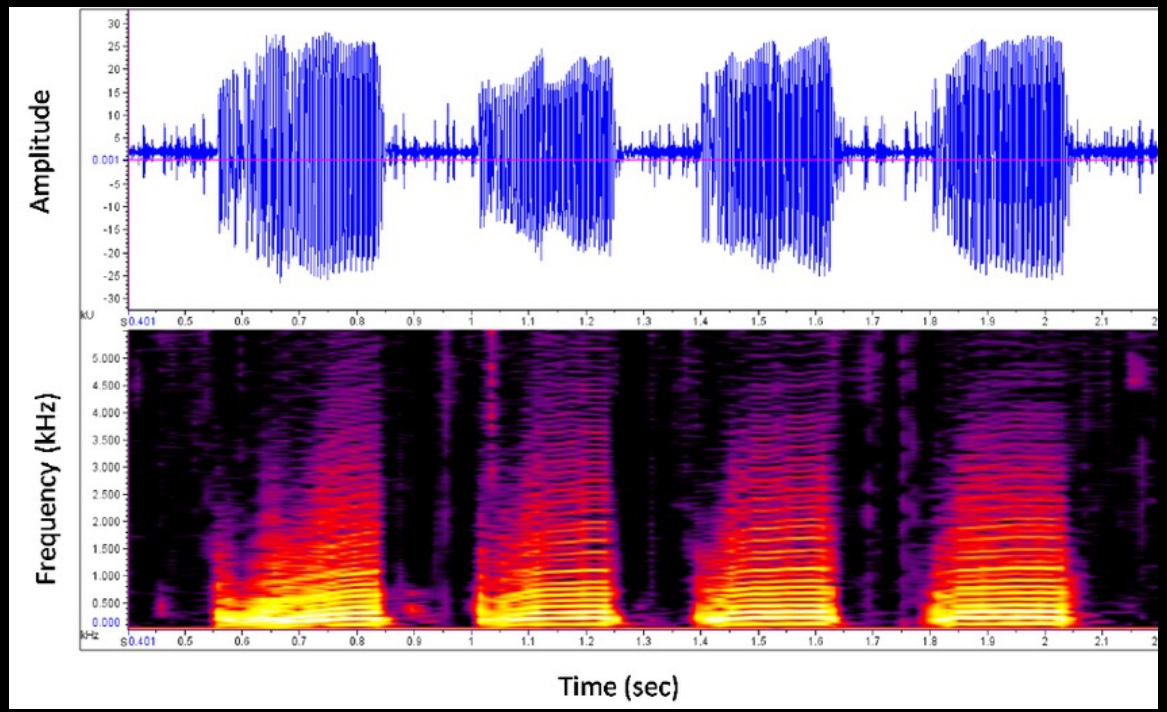
RF signals reflect off body and change with physiological signals

Our objective: High accuracy on par with sleep lab, but in one's bedroom and without electrodes on the body

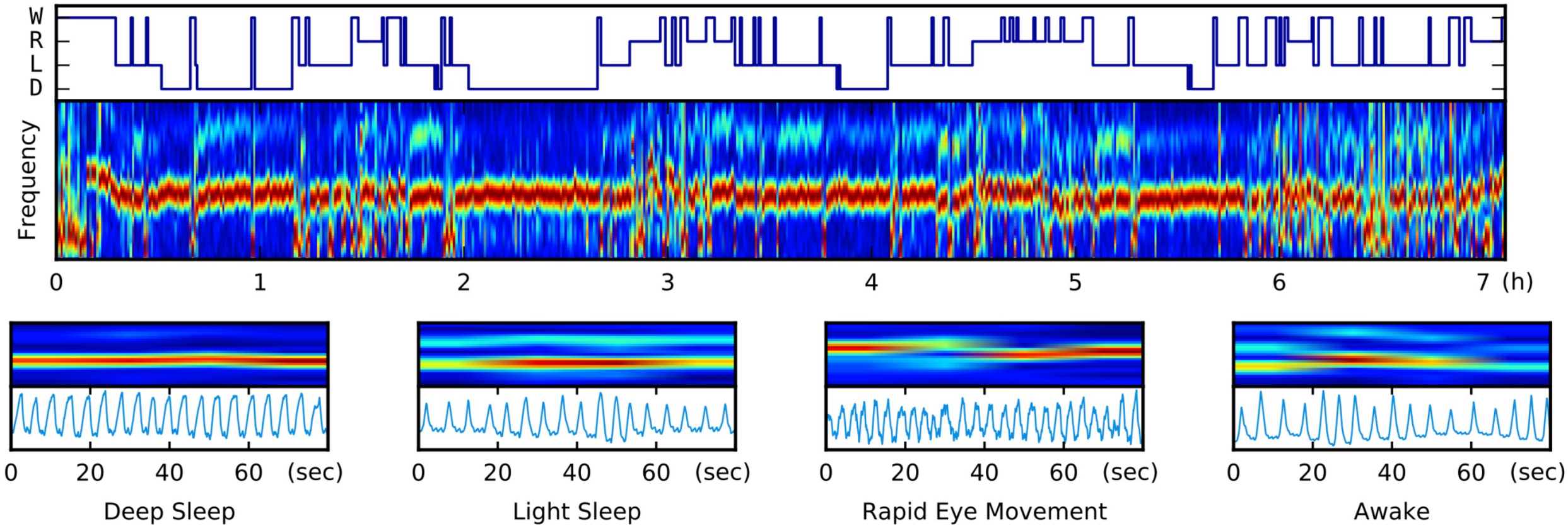
Time Signals and Spectrogram



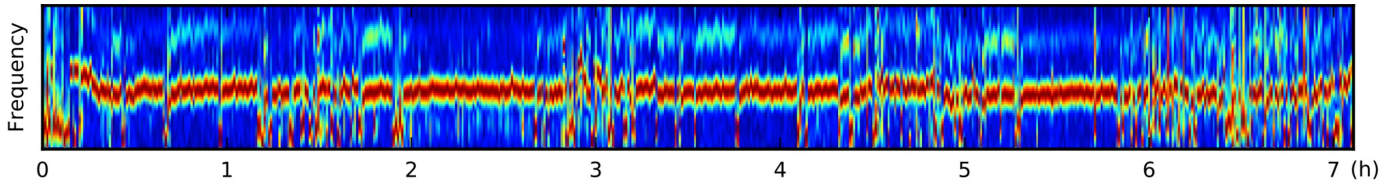
Spectrogram: A representation of the spectrum of frequencies of a signal as it varies with time.

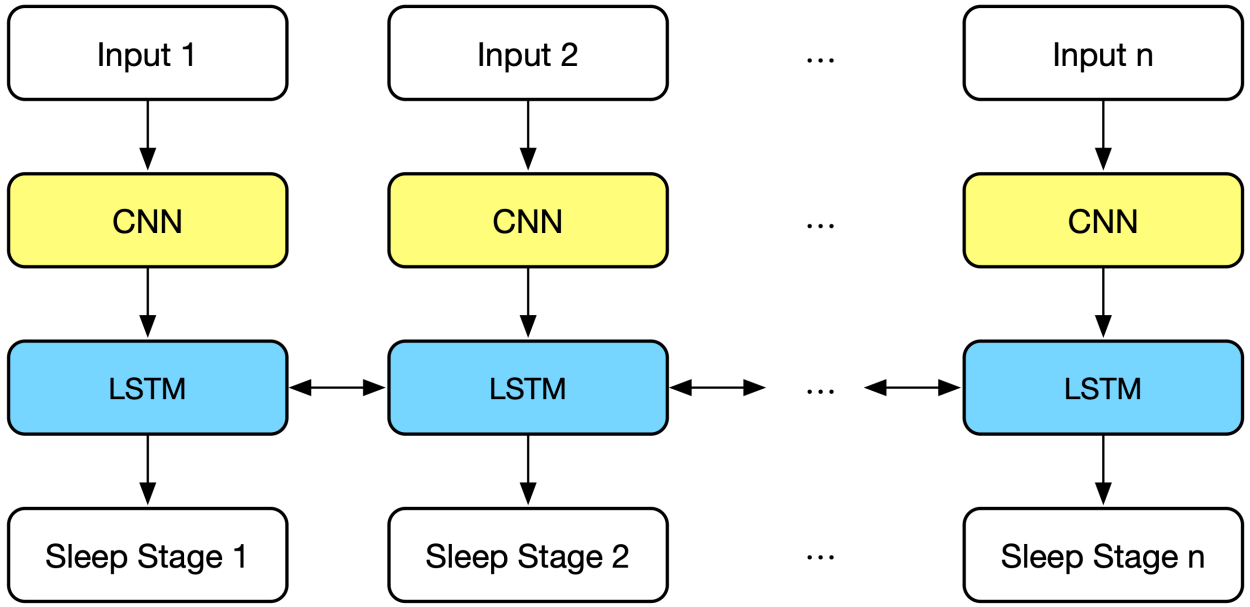


Time Signals and Spectrogram



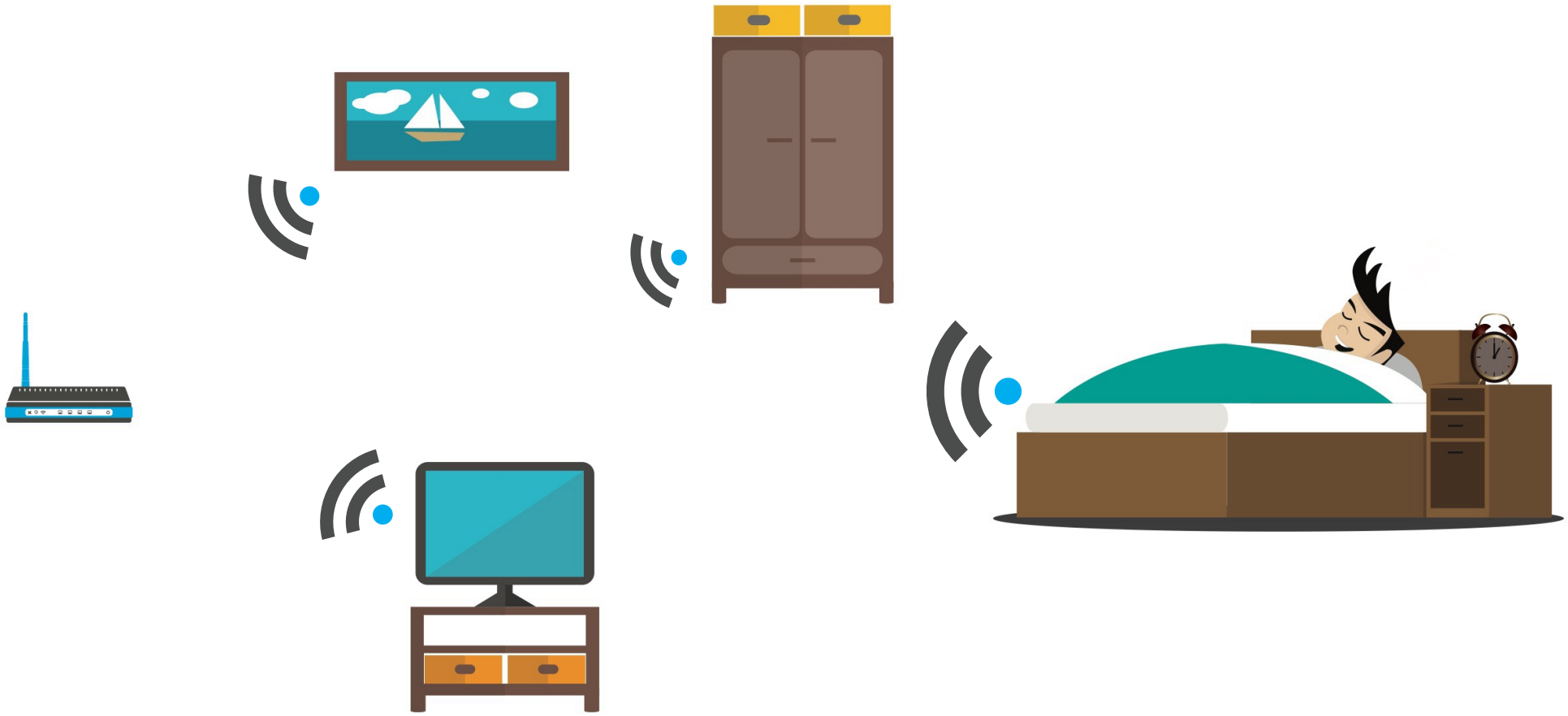
A Basic Model Architecture





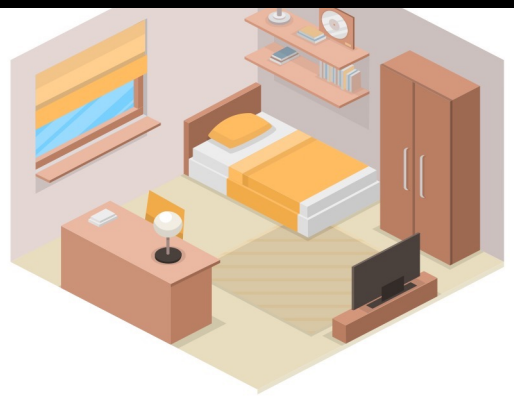
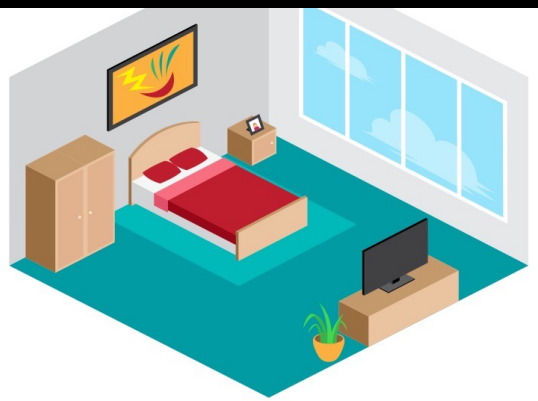
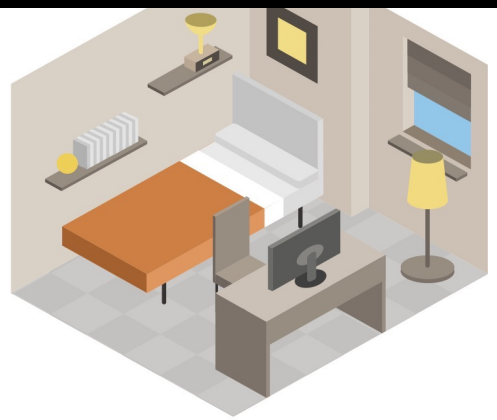
Key Challenge

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



Key Challenge

Need to remove such extraneous information!


Multi-Source Domain Adaptation

domain = measurement condition + individual

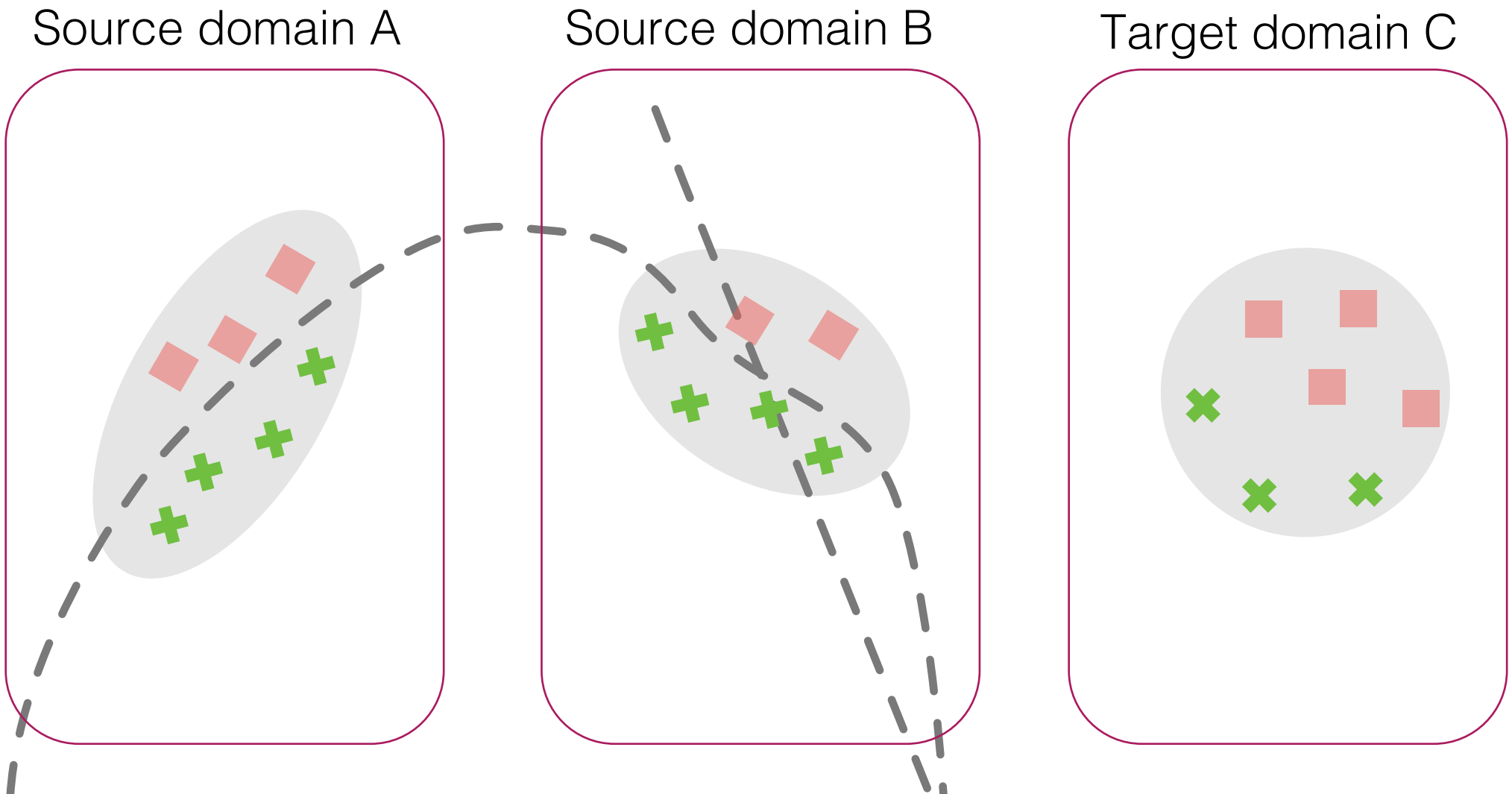
Source domain A

Source domain B

Target domain C

Multi-Source Domain Adaptation

domain = measurement condition + individual



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

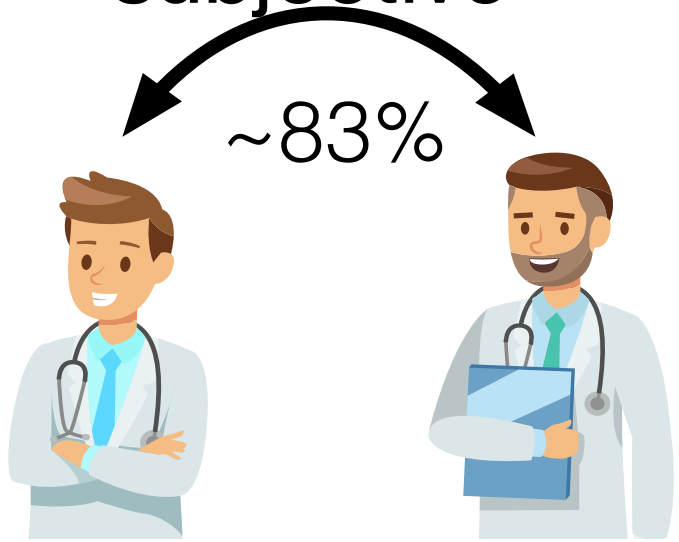
Accuracy

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



Comparison with Past Work

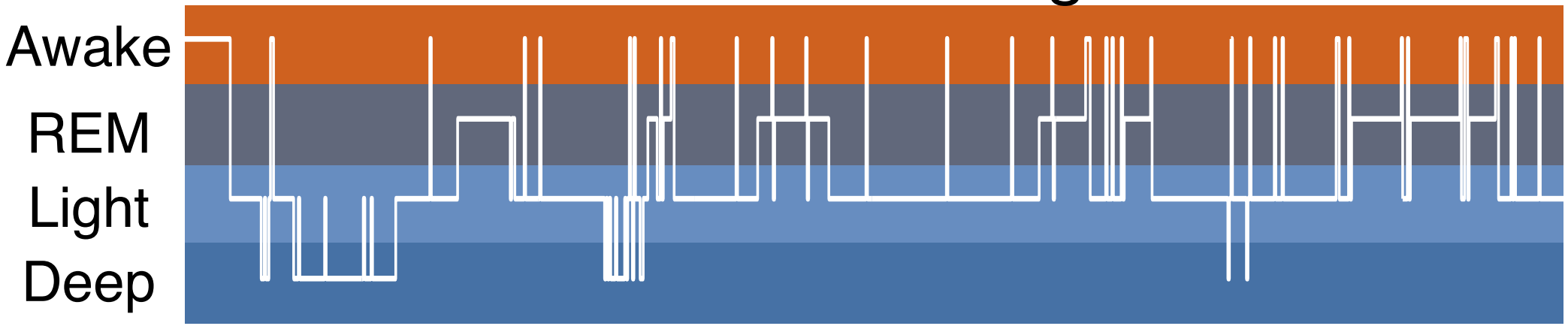
Metrics: Accuracy and Cohen's Kappa

Approach	*Accuracy*	κ
Tataraidze et al. (2016b)	0.635	0.49
Zaffaroni et al. (2014)	0.641	0.45
Ours	**0.798**	**0.70**

Representative Example

Accuracy: 80%

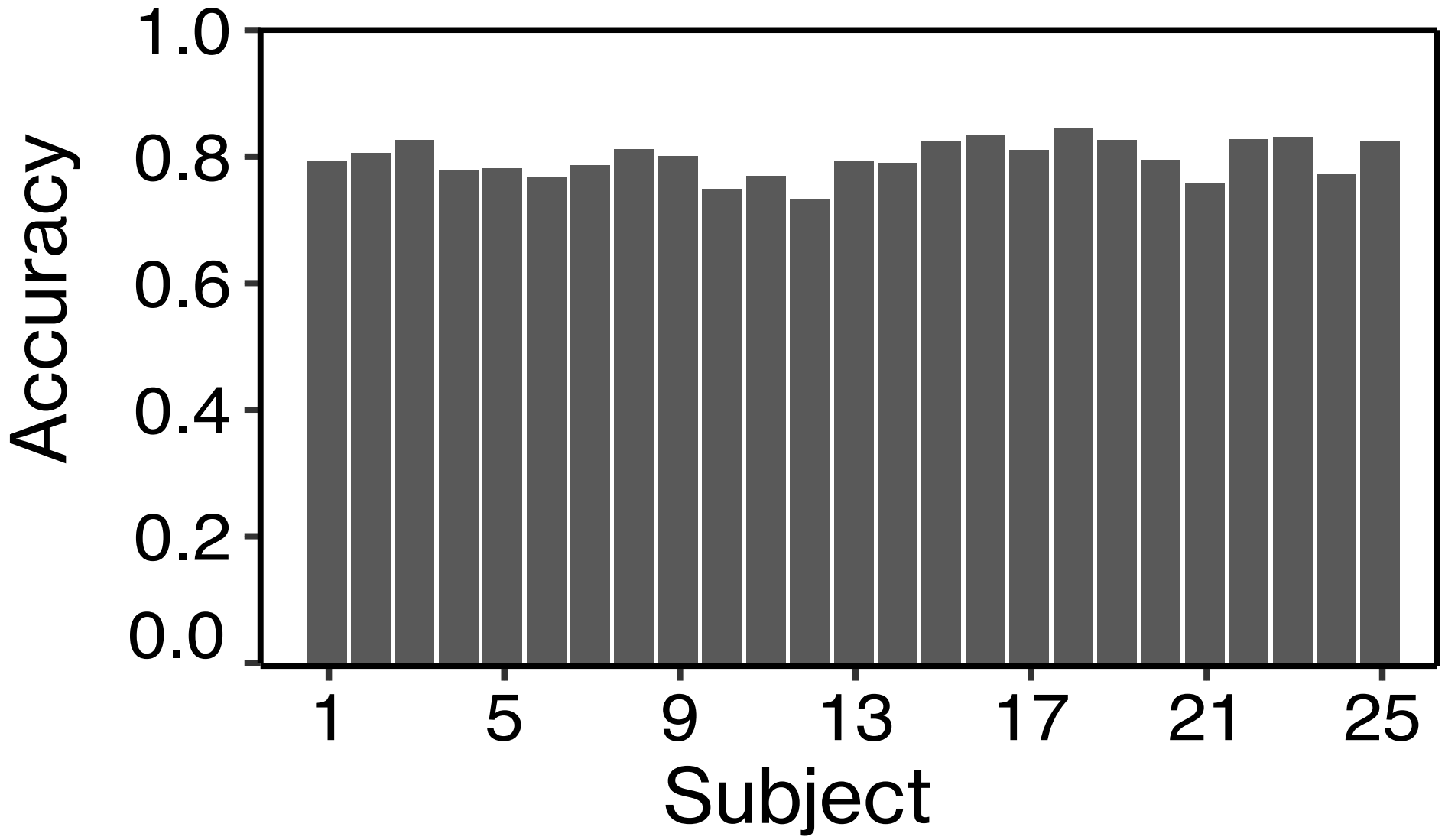
Ground-truth using EEG



Our Prediction

Time

Accuracy for Different Subjects (Domains)



iOS Lab 1 is out

- Topic: Develop a location app and explore the power drain vs accuracy trade-off
- Due: Mon Feb 19th, 11:59 pm

Next Lecture

- Time: Mon Feb 19th
- Topic: Applied ML for Mobile and IoT Sensing – Through-wall vision
- Readings: RF-Pose (details on the course website)