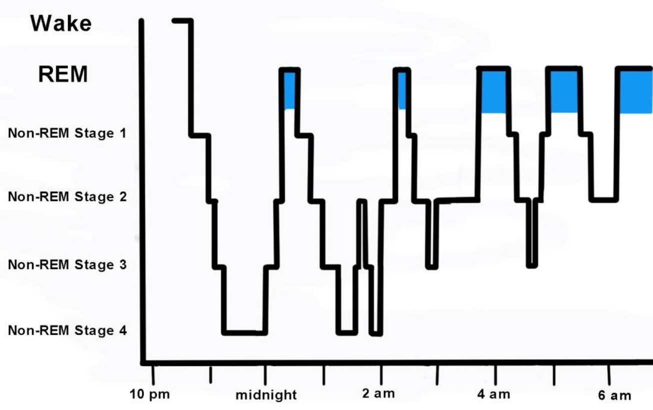
Learning Sleep Stages from Radio Signals

A Conditional Adversarial Architecture

Mingmin Zhao, Shichao Yue, Dina Katabi,
Tommi S. Jaakkola, Matt T. Bianchi

Presenters: Dennis Ai, Michael Chen,
Hansohl Kim, Sam Kim, Jimmy Wu

Stages of Sleep



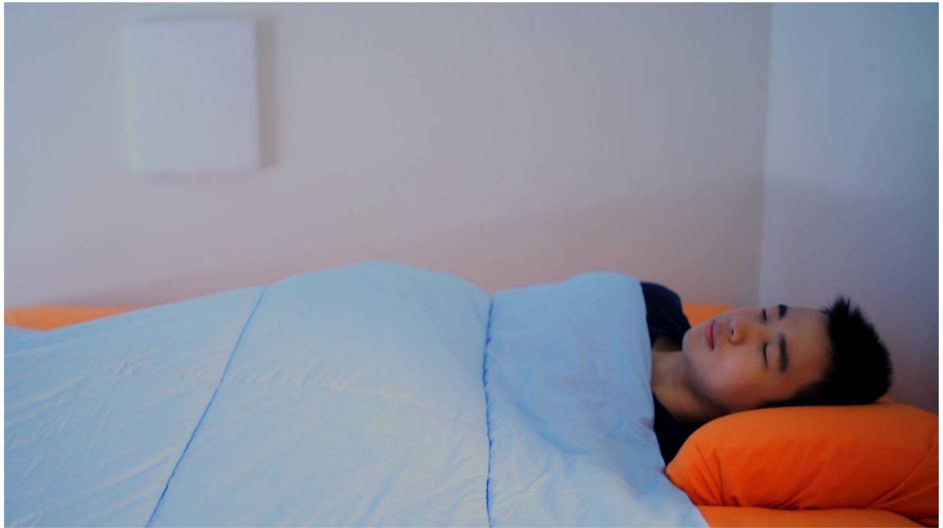
NREM Stage 1	NREM Stage 2	NREM Stage 3	REM
Lightly asleep	**Slowing heart rate, decreasing body temperature**	**Larger, slower brain waves**	**Deep and powerful dreams**
Easy to wake up, sometimes sensations of falling	Harder to wake up, larger brain waves	Large, slow brain waves Can sleep through most disturbances	Eyes move rapidly, sleepwalking, increase in heart rate

Sleep Lab

Requires sensors on scalp, chest, nose

Sleep at Home

Box with RF sensor



Current State-of-the-art Methods

Polysomnography (PSG)

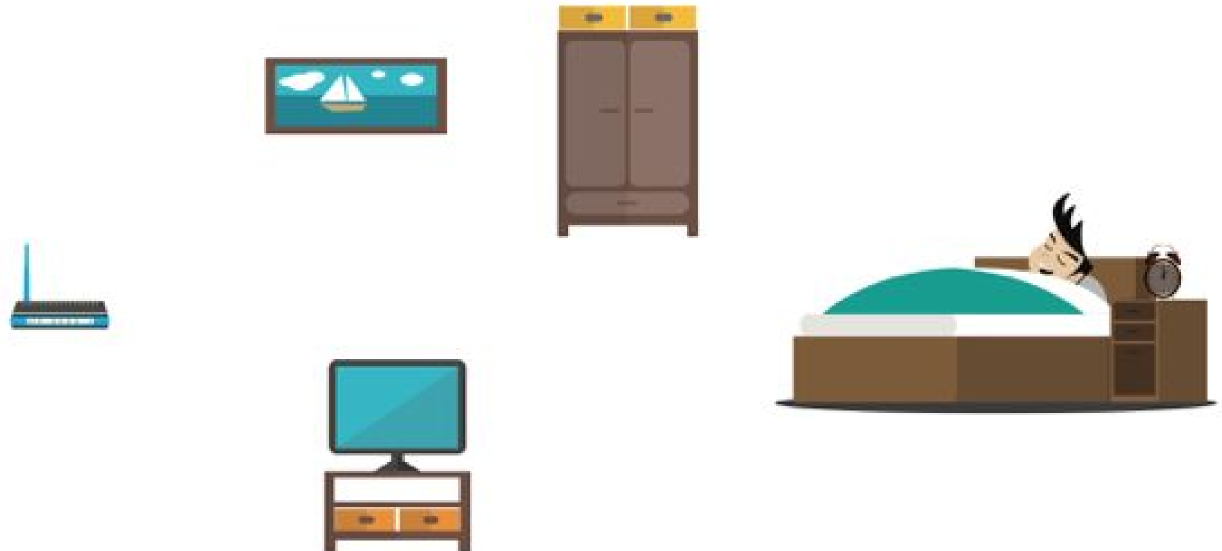
- intrusive i.e. requires patient to wear sensors, electrodes, monitors, probes, etc
- expensive
- uncomfortable

Radio Technology

- capture physiological signals without body contact
- transmit low power radio signal
- less intrusive

Key Challenge

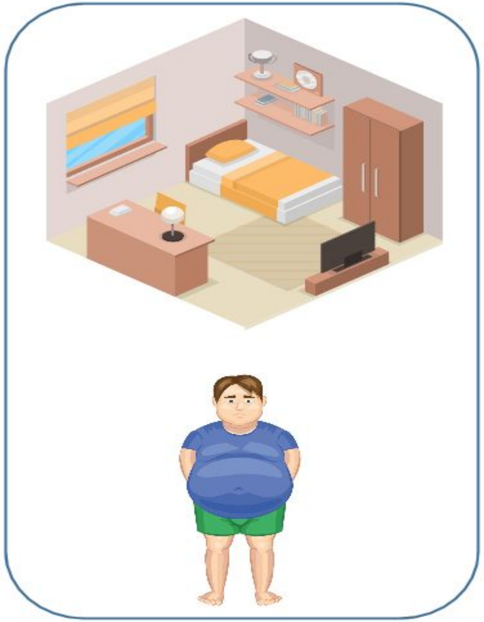
Radio frequency reflections are highly dependent on the **measurement conditions** and the **individual**



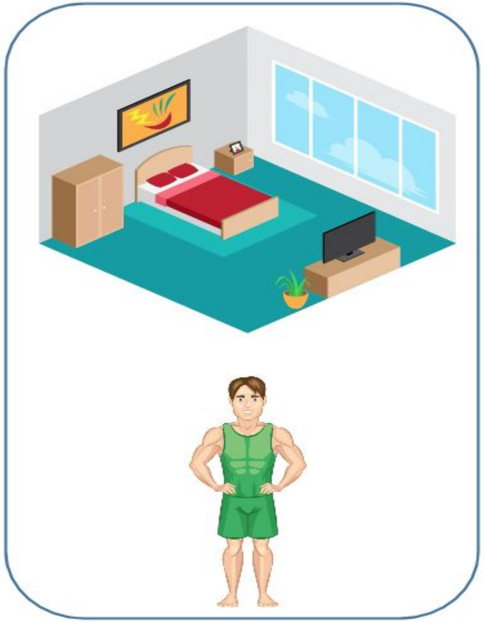
Multi-Source Domain Adaptation

domain = measurement condition + individual

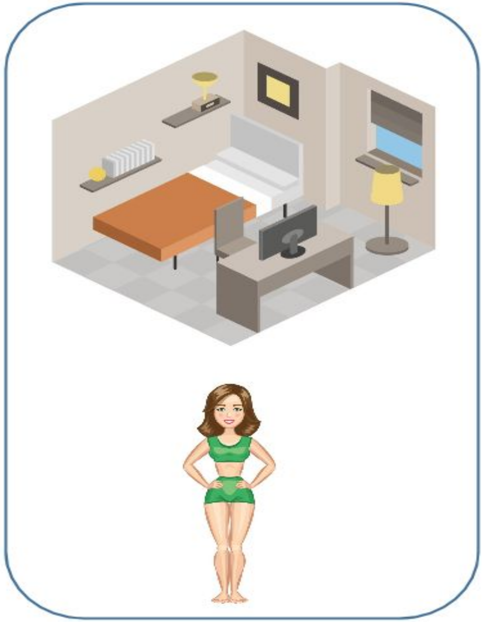
Source Domain A



Source Domain B

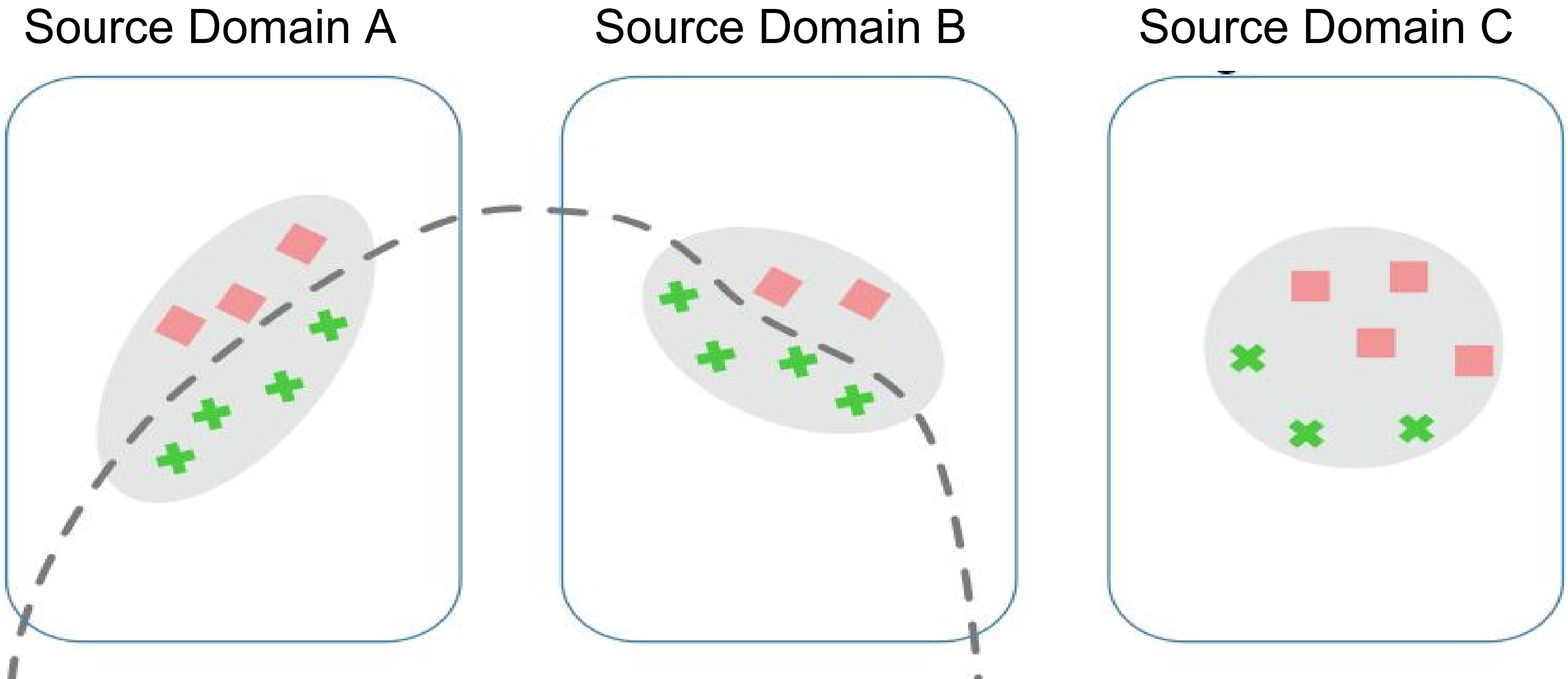


Source Domain C

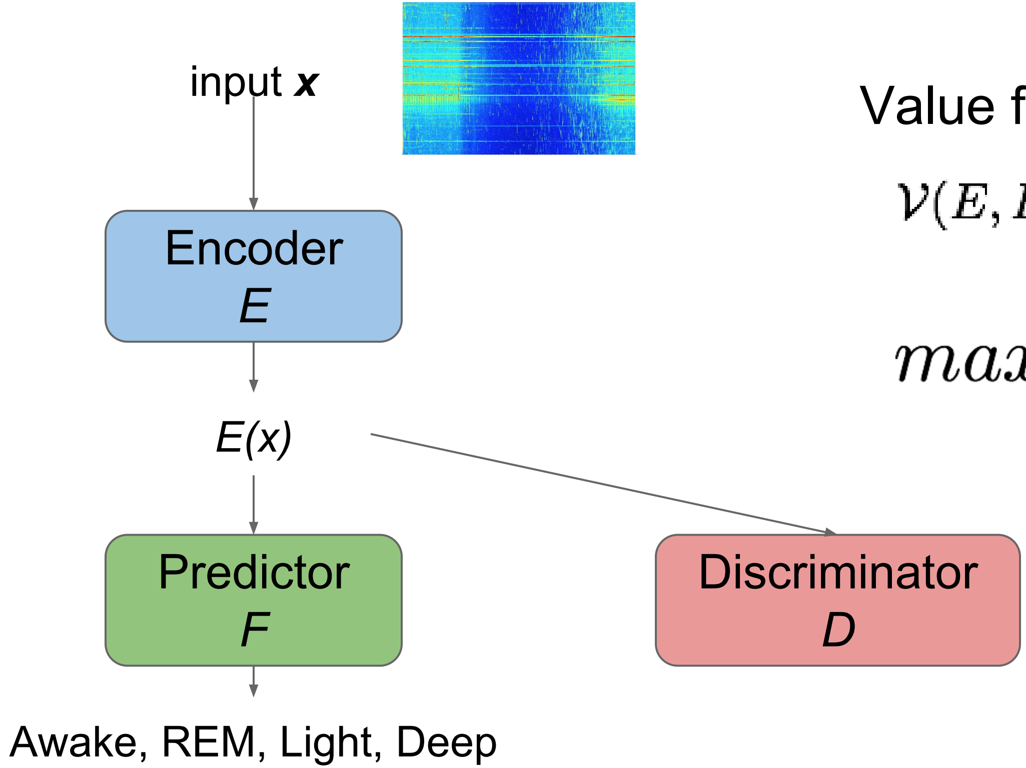


Multi-Source Domain Adaptation

domain = measurement condition + individual



Conditional Adversary Architecture



Value function of three-player game:

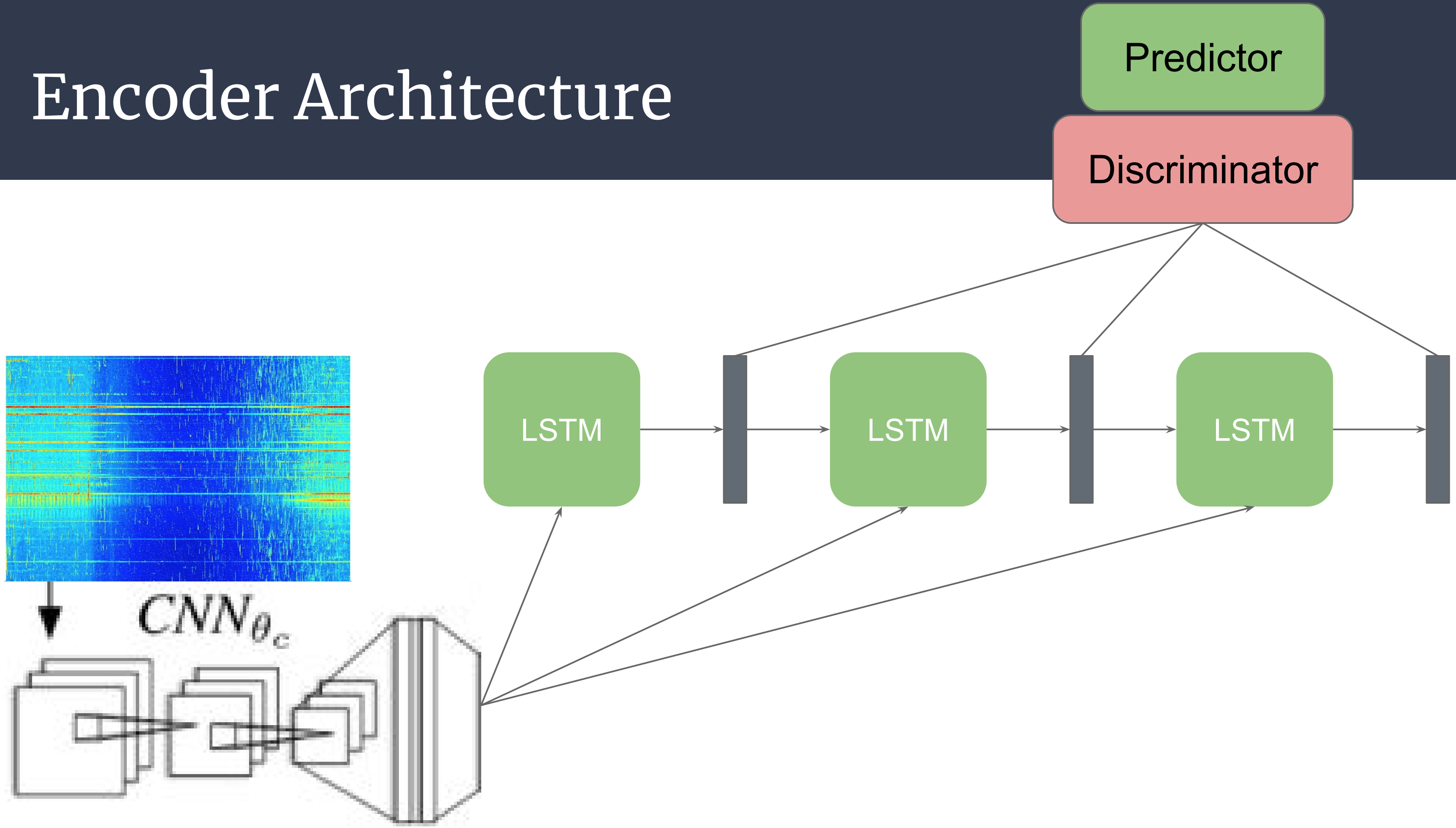
$$\mathcal{V}(E,F,D) = \mathcal{L}_f(F;E) - \lambda \cdot \mathcal{L}_d(D;E)$$

predictor loss discriminator loss

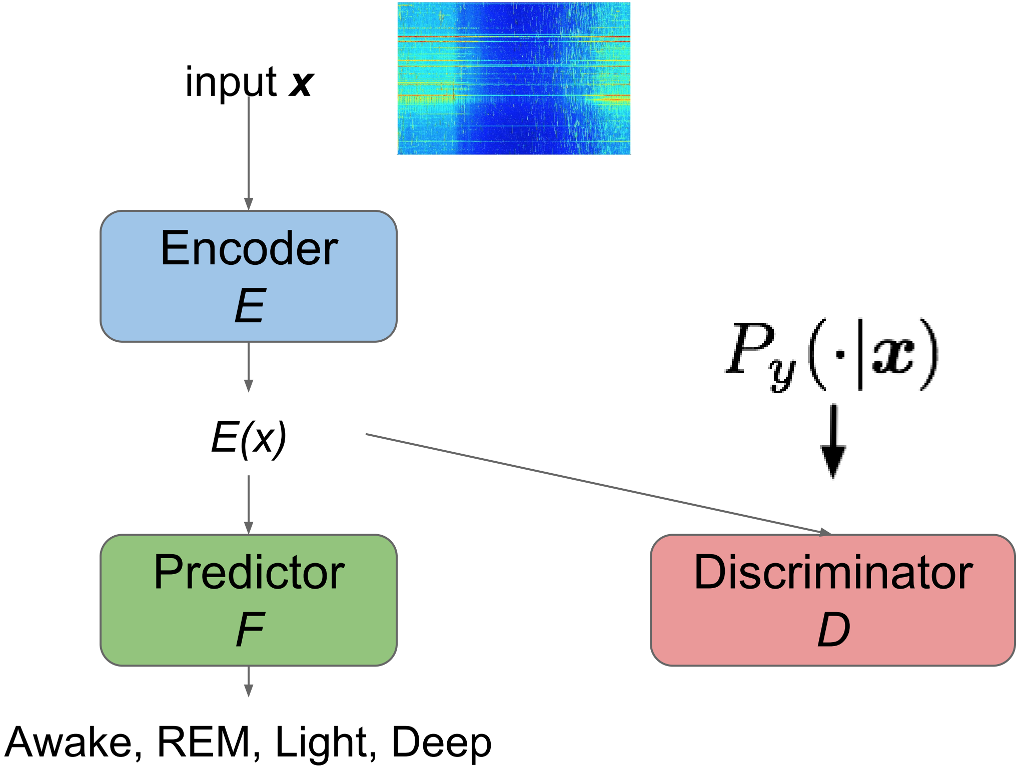
$$max_D min_{E,F} V(E,F,D)$$

we want extraneous domain information to be removed

Encoder Architecture

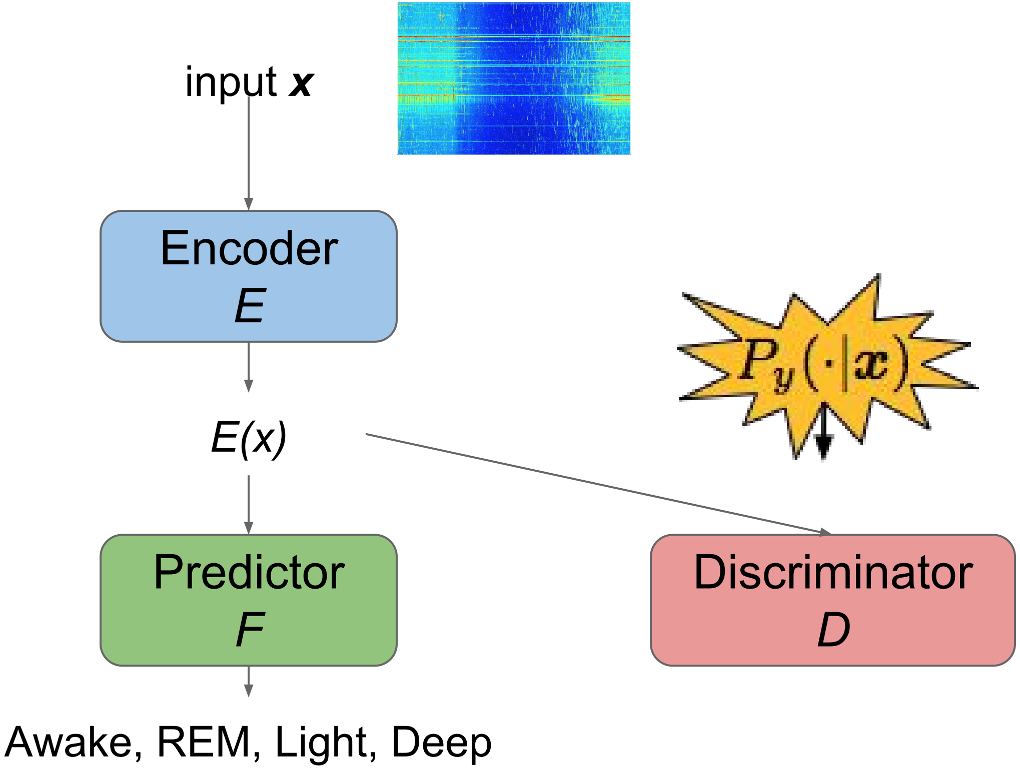


Conditional Adversary



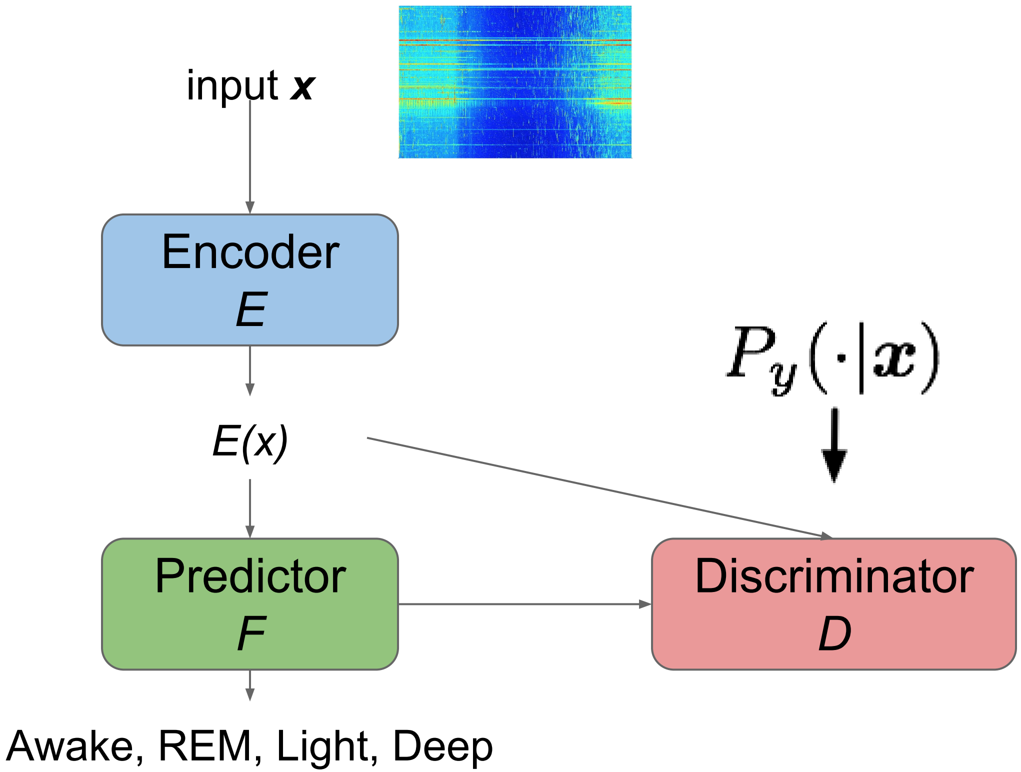
Add a posterior of the label distribution (don't want this information removed)

Conditional Adversary



Usually, posterior is not available during training!

Conditional Adversary



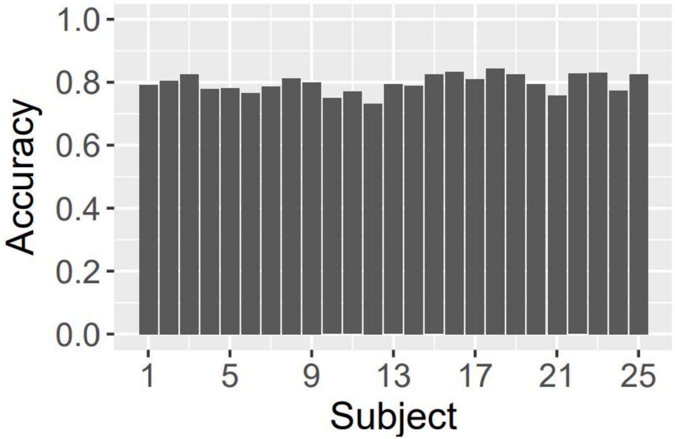
Solution: Condition the discriminator on predicted label distribution

Dataset

- 25 different bedrooms, 100 nights
- ~90K 30-second pairs of RF spectrograms and corresponding sleep stages
- Ground-truth labels: FDA-approved EEG-based sleep profiler of sleep stages

Testing

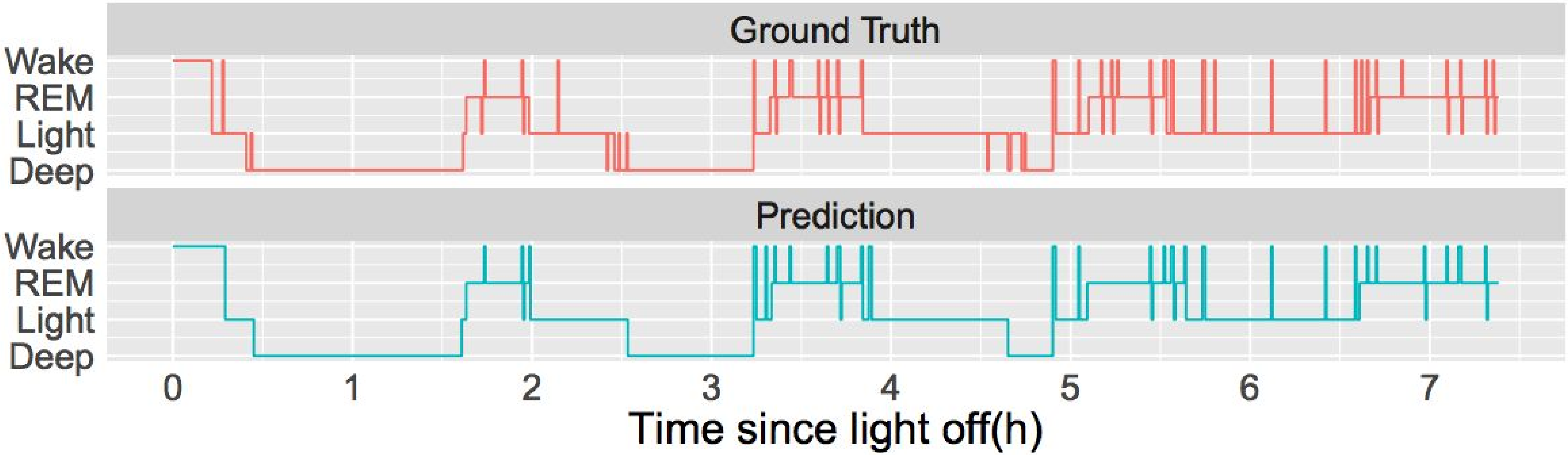
- Encoder: ResNet CNN + LSTM
- Predictor and Discriminator: 2-layer FC
- Each subject evaluated after training on all others
- Metrics: Accuracy + Cohen's Kappa
- Consistently high across subjects
- Standard Deviation: 2.9%



Results

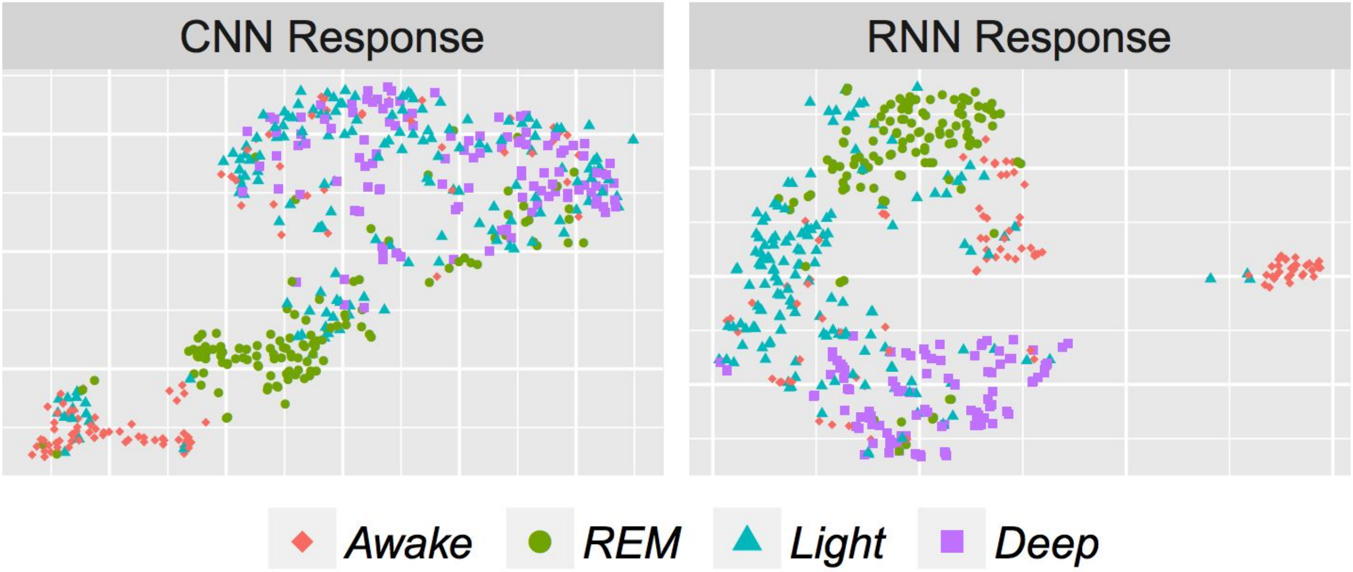
Signal Source		Accuracy (%)	Cohen's Kappa (*k*)	Comfort
EEG		83	.76	Low
Cardiorespiratory		71	0.56	Medium
Actigraphy		Low	-	High
RF	State-of-the-art	64	0.49	High
	Conditional Adversary	79.8	0.70	High

Ground Truth vs. Predicted Sleep Staging

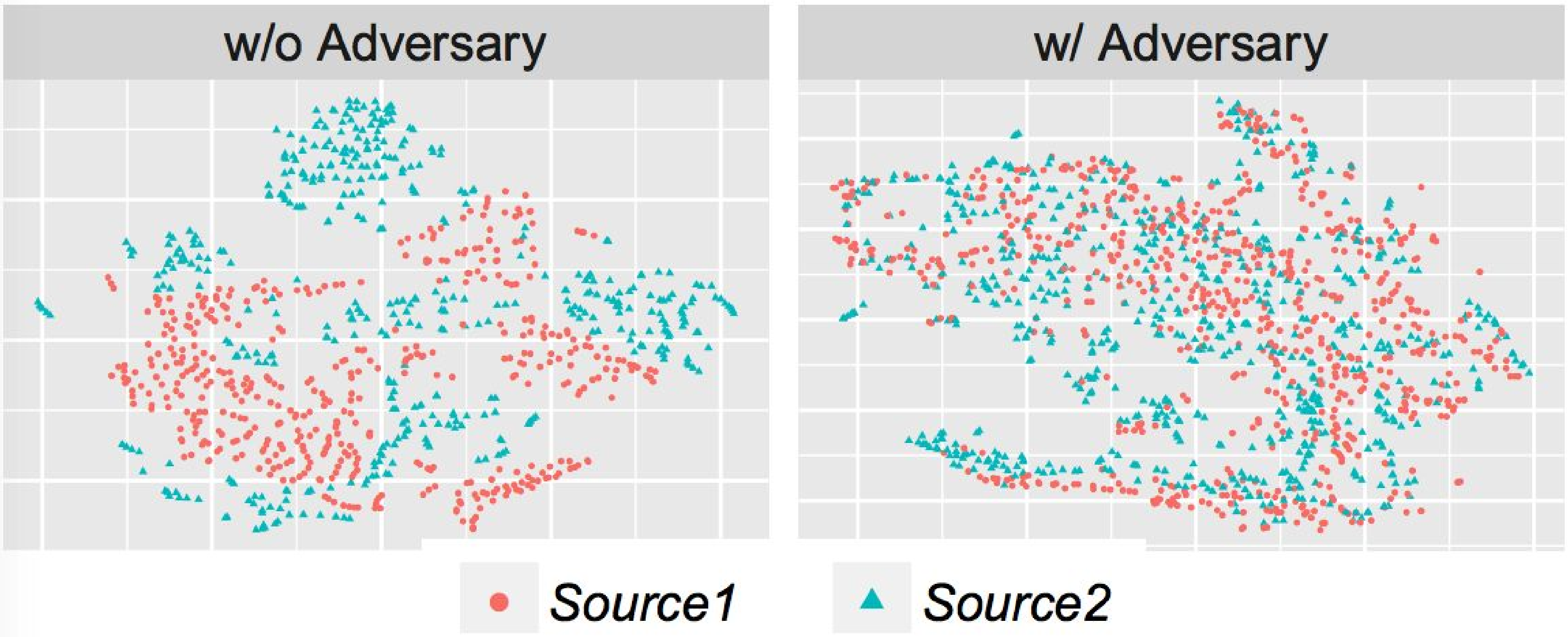


t-SNE Visualizations

CNN Response - successful at separating Wake, REM from Light and Deep Sleep
RNN Response - successful at separating Light and Deep Sleep



Role of Adversarial Discriminator



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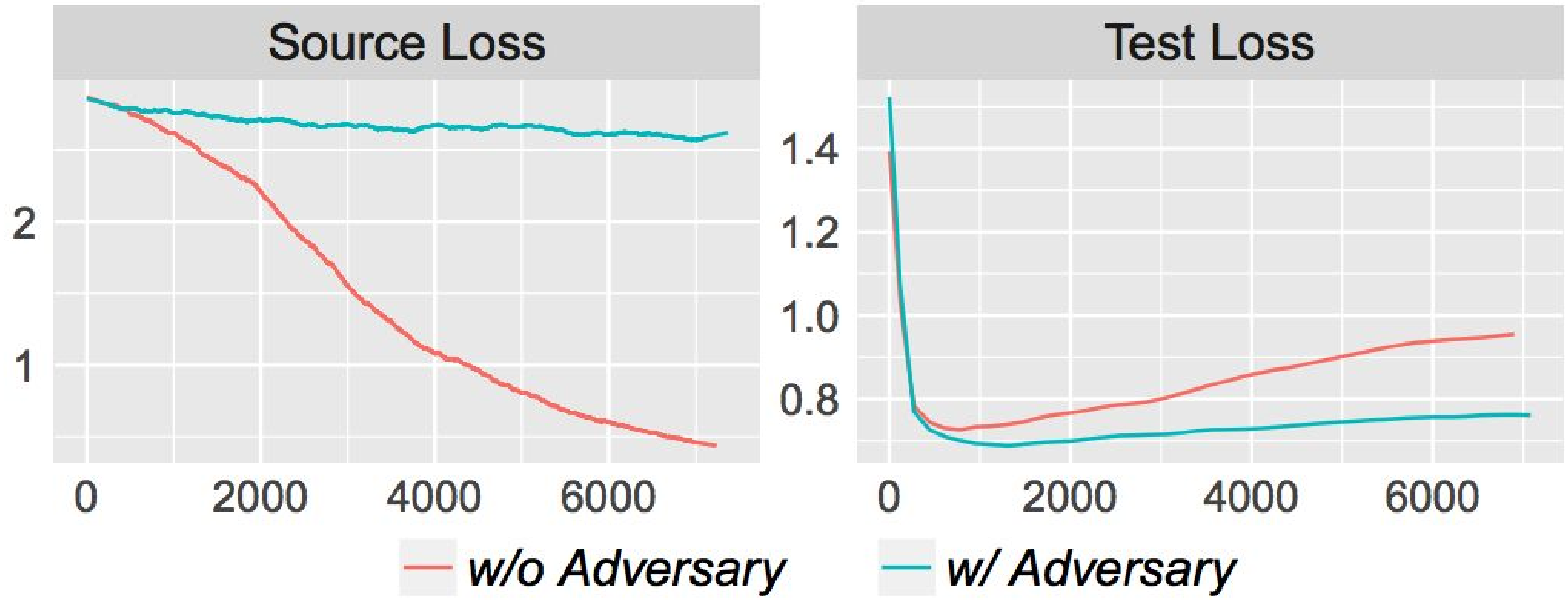
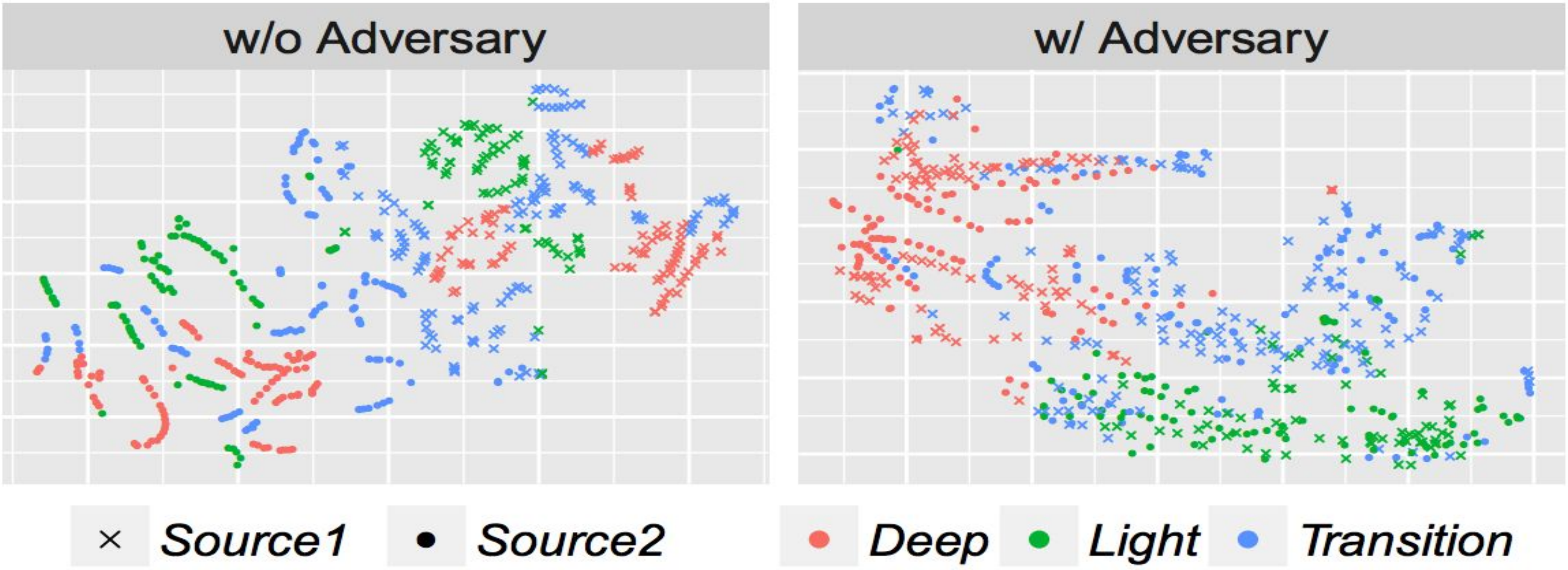


Conditioning on the Posterior Distribution



Criticisms

RF signals are inherently noisy, which a network could learn to remove with lots of data, which the authors didn’t have. Could have leveraged more signal processing techniques.

Encoder could just learn to output the posterior distribution.

Could include more information about analyzing encoding versus labels/environment.

The paper does not specify the details and hyperparameters of their architecture and thus does not allow its results to easily be replicated.

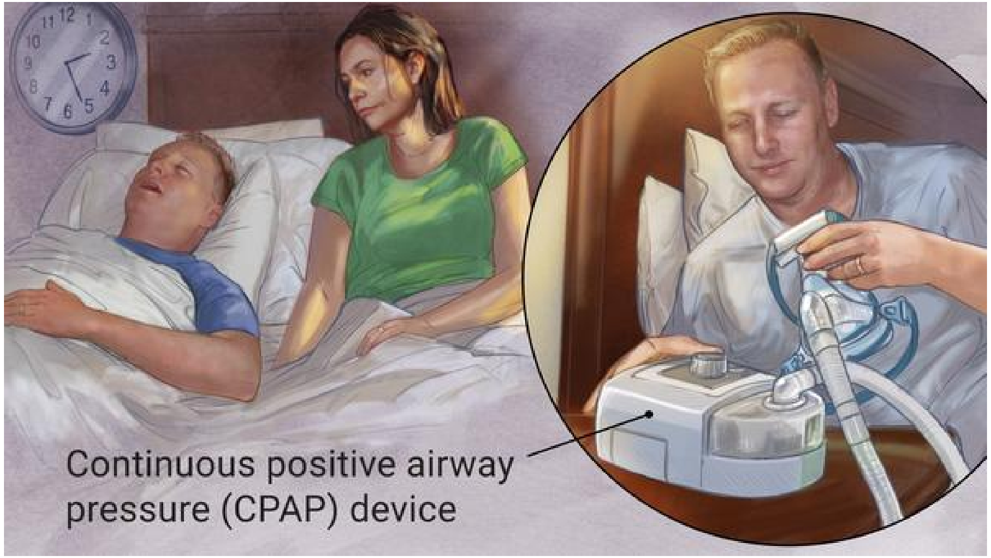
Future Work

In the confusion matrix, the true positive rate for the awake state is much lower than for other sleep stages (63% vs ~80%). Why is this the case?

What changes could be made to the encoder architecture to improve performance, better model transitions between sleep stages, or provide more fine-grained categorization of sleep stages?

Can this model truly be extended to non-healthy individuals, or individuals across a large variety of demographics (e.g. age)?

Can this solution be applied to diagnosis sleep apnea or other sleep disorders, which affects over 50 million people in the United States? This would mean measuring nasal or oral airflow, respiratory effort, and oximetry.



Questions