A Structured Learning Approach with Neural Conditional Random Fields for Sleep Staging

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Background

- Brain undergoes different activities during the sleep representing neurological functions
- These activities have been identified as different stages of sleep
- Four major types of sleep stages: wake, light, deep, and REM

Background: Sleep Stages

Wake

Lying in the bed

Light

Transition state, Heart rate and breathing slow

Deep

Restorative sleep, physical recovery processes

REM

"Dreaming" state, memory consolidation, emotion regulation

Background: Obstructive Sleep Apnea

- Airway collapse leads to a reduced oxygen supply during the sleep
- Highly underdiagnosed disease
- Estimated to affect nearly 10% of the US population
- Restless Sleep, snoring, fatigue and potentially fatal for heart

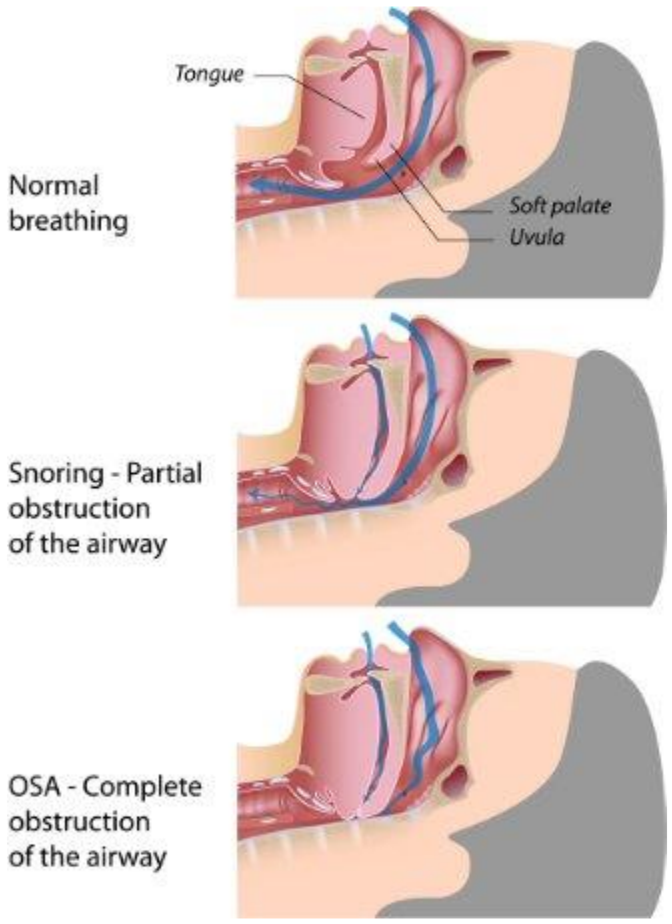


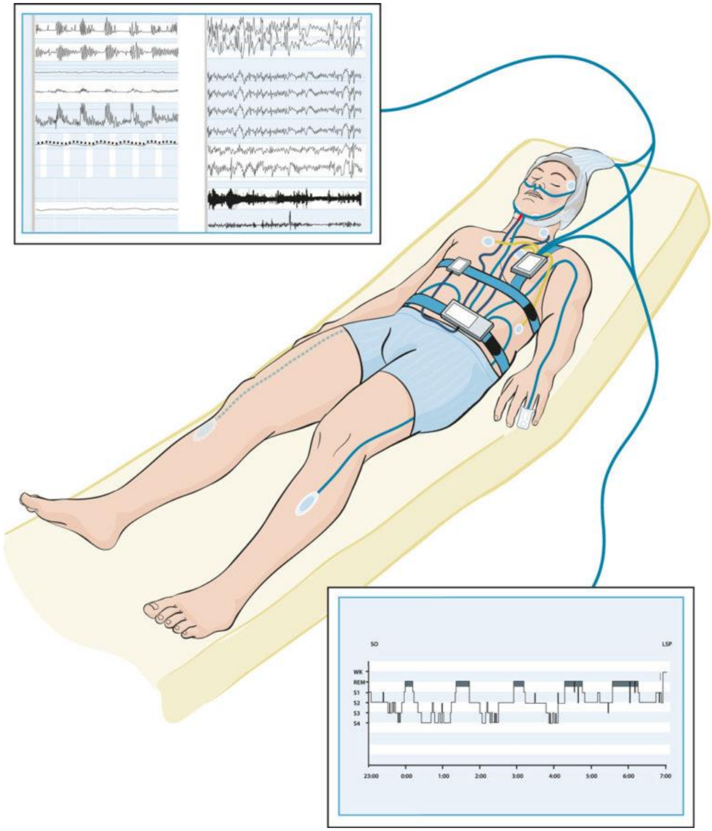
Image credits: https://www.alaskasleep.com/blog/types-of-sleep-apnea-explained-obstructive-central-mixed

Background: CPAP Therapy

- Continuous Positive Airway Pressure (CPAP) therapy is the most common therapy sleep apnea patients are administered
- User wears a mask, connected to a flow generating device, which delivers an adaptive pressure to prevent the airway collapse

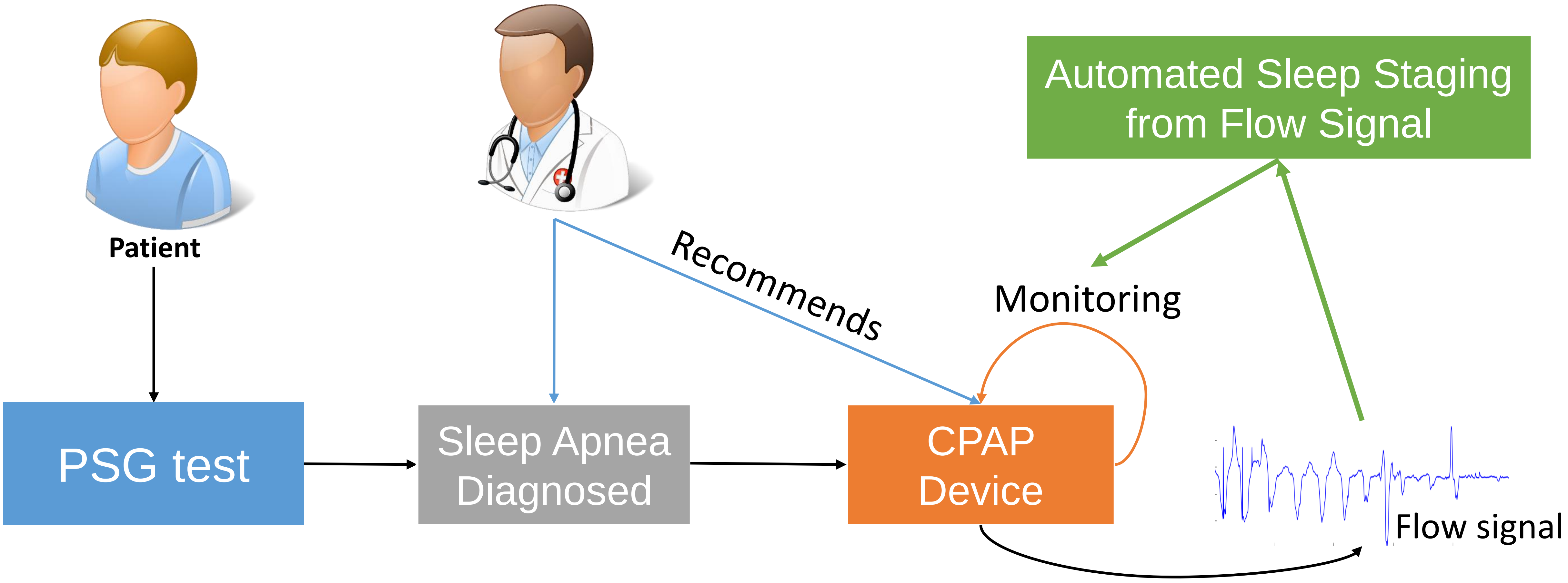
Background: Polysomnography

- Currently patients undergo an overnight lab stay for polysomnography (PSG) test
- Extremely difficult to do longitudinal tracking, patient has to visit the lab at regular intervals
- By determining the sleep stages from the PSG, doctors can monitor their progress



Picture taken from https://aystesis.com/polysomnography/

Motivation


Patient
PSG test
Sleep Apnea Diagnosed
Recommends
CPAP Device
Monitoring
Automated Sleep Staging from Flow Signal
Flow signal

Related Works

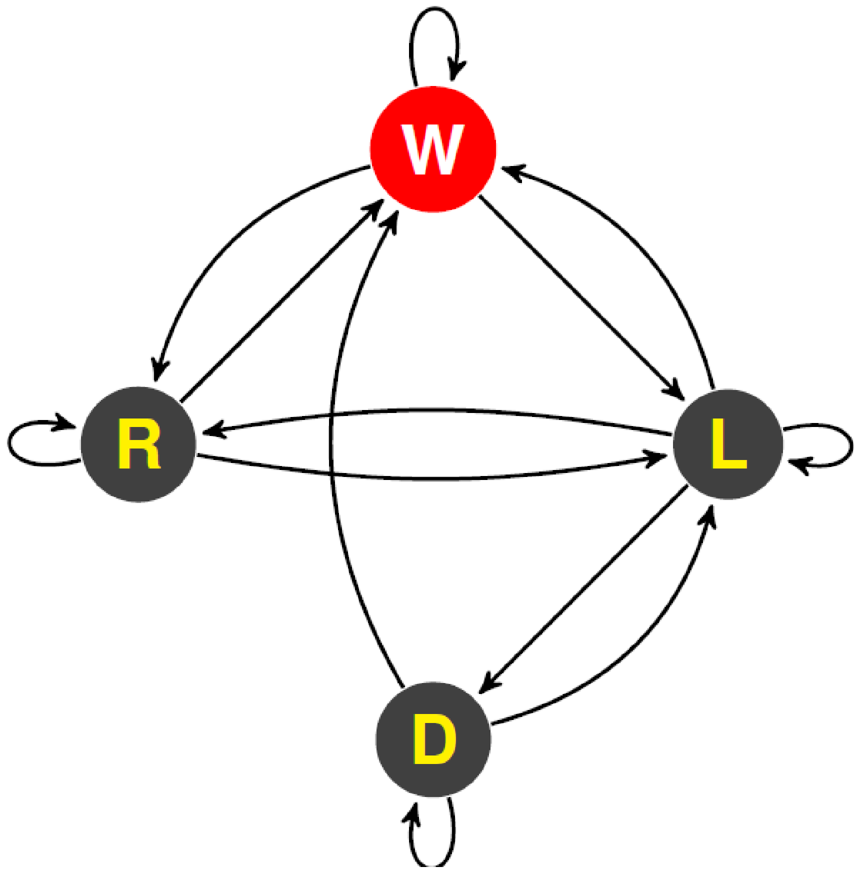
The literature focuses on reducing the number of sensors from PSG or evaluating new medical devices

Machine Learning Models for Sleep Staging: Recent deep networks have shown state-of-the-art results:

- Supratak et al. and Biswal et al. showed human level annotation on EEG signals using a **Recurrent-Convolution Network**
- Zhao et al. showed state-of-the-art results on radio-frequency signals using a **conditional adversarial architecture**

However, these methods either don't have existing use cases owing to infancy of device adoption (Zhao et al.) or impracticality (EEG based methods)

Sleep State Transition Diagram

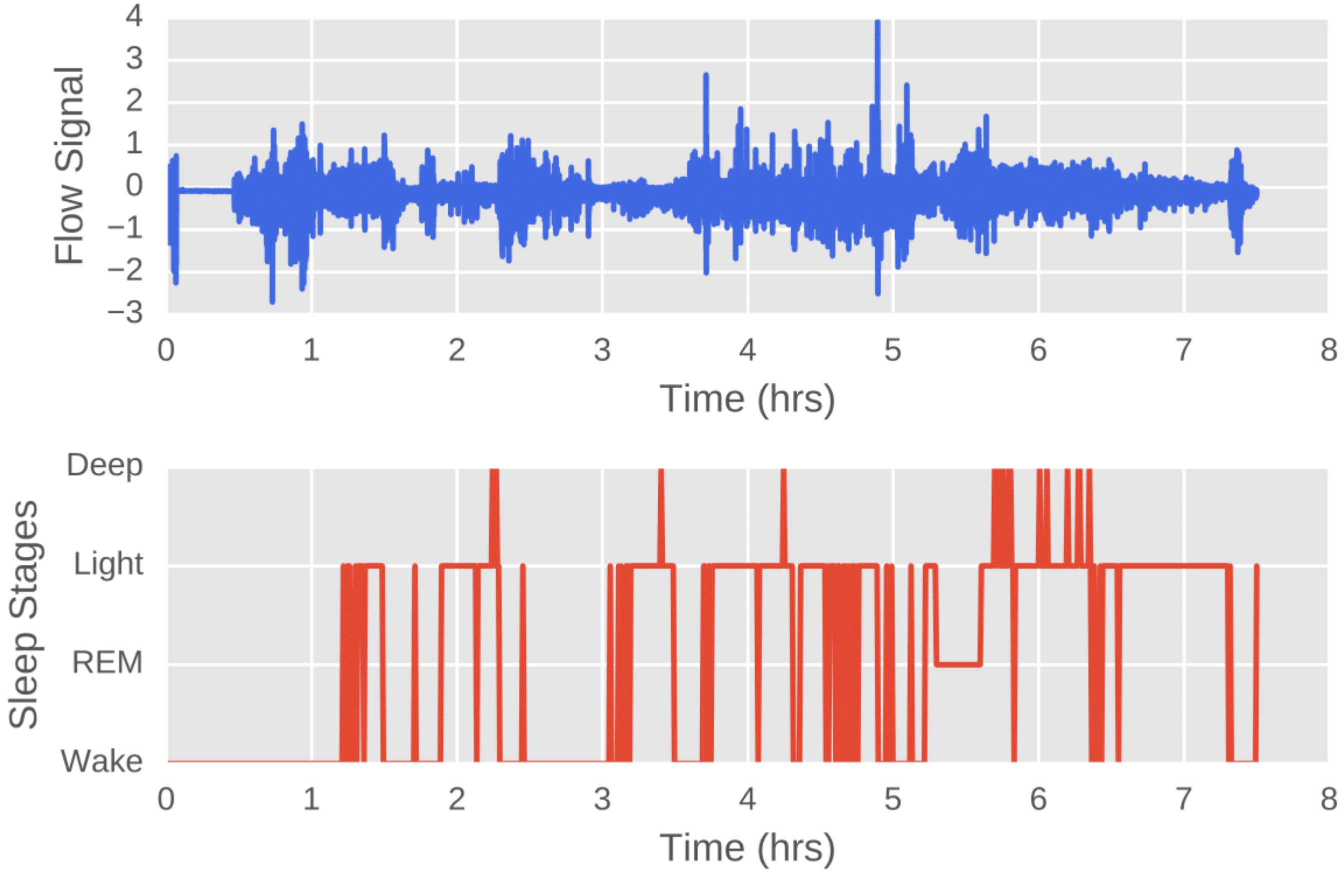


Four sleep states shown are: (**W**)ake, (**R**)EM, (**L**)ight and (**D**)eep.

Contributions

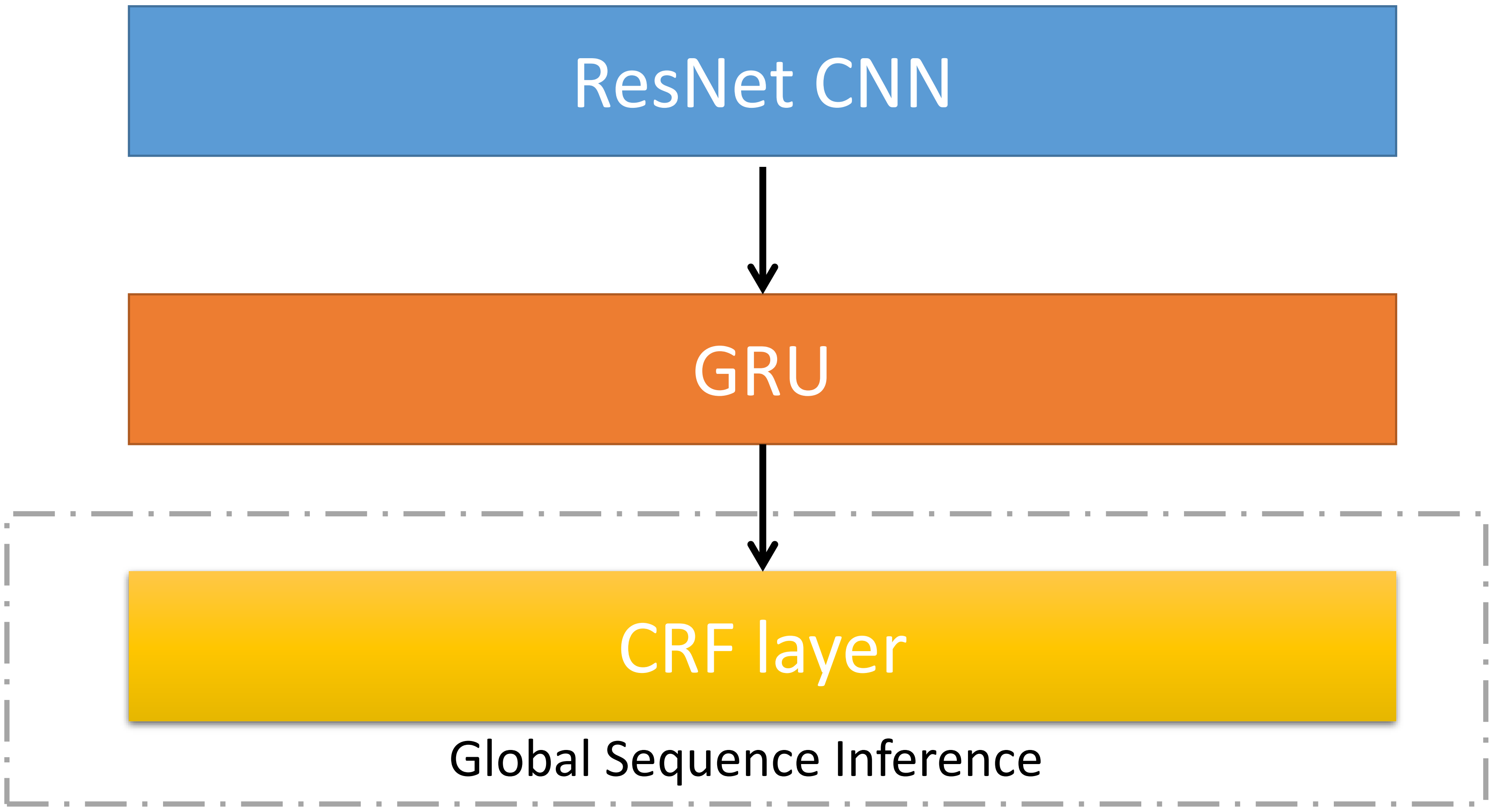
- **Application**: First Study on using sleep staging using flow signal that can be used to track the Obstructive Sleep Apnea patients on the CPAP therapy
- **Technical**: Current state-of-the-art on sleep staging focuses entirely on extracting best possible features from the input signal for sleep staging ignoring the sleep staging transition dynamics. We use structural learning with CRFs for better accuracy

Sample Sleep Stage Annotation

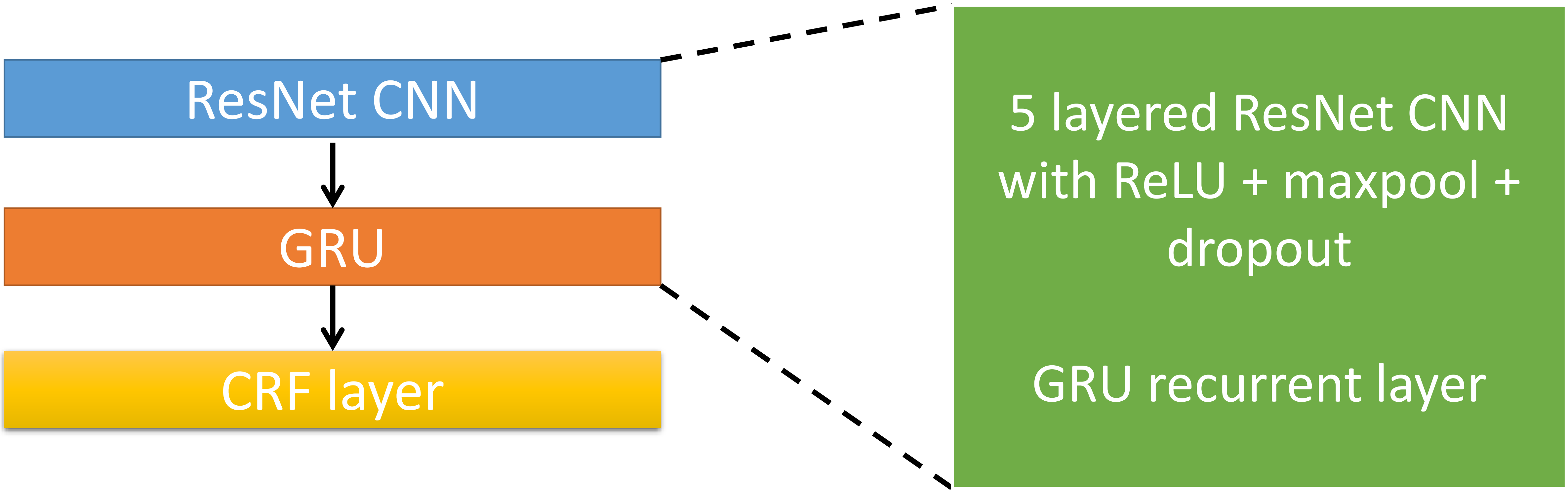


An example of sleep stage evolution

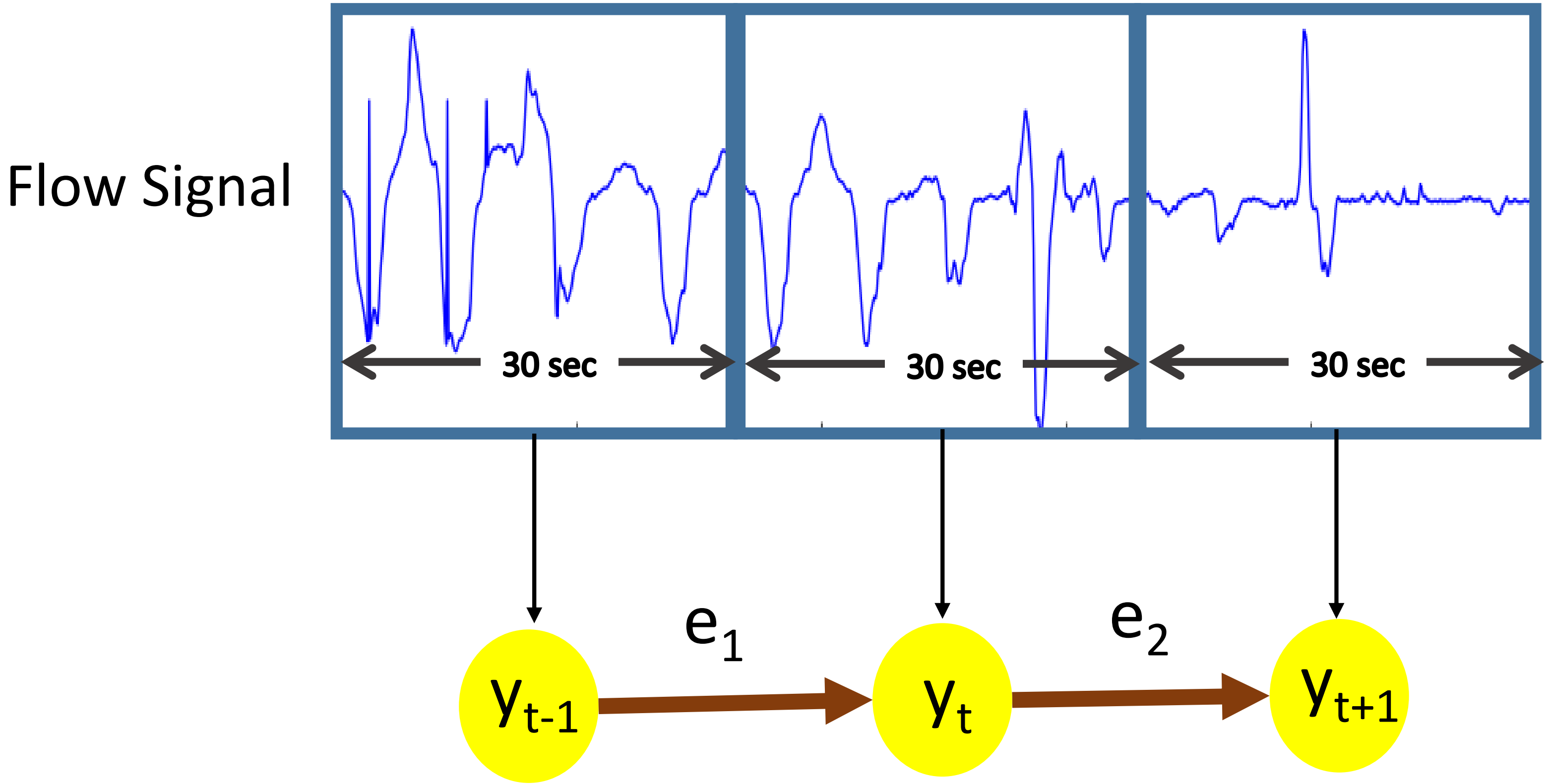
Neural Conditional Random Field Architecture



Neural Conditional Random Field Architecture



Neural Conditional Random Field Model



Conditional Random Field models the edge transitions in addition to the probability of a sleep stage class at each step t

Neural Conditional Random Field Model

Node Potential

$$\boldsymbol{\Psi}_n(y_t|H,\mathbf{w}_n,b_n) = \exp(\mathbf{w}_n^T\phi(y_t,H)+b_n)$$

Edge Potential

$$\boldsymbol{\Psi}_e(y_{t-1},y_t|H,\mathbf{w}_e,b_e) = \exp(\mathbf{w}_e^T\phi(y_{t-1},y_t,H)+b_e)$$

Likelihood

$$p(\mathbf{y}|H,\theta) = \frac{1}{Z(H,\theta)}\prod_{t=1}^{m}\boldsymbol{\Psi}_n(y_t|H,\mathbf{w}_n,b_n)\prod_{t=2}^{m}\boldsymbol{\Psi}_e(y_{t-1},y_t|H,\mathbf{w}_e,b_e)$$

Negative Log Likelihood

$$\mathcal{L}(\theta) = \log Z - \sum_{t=1}^{m}\mathbf{w}_n^T\phi(y_t,H) - b_n - \sum_{t=2}^{m}\mathbf{w}_e^T\phi(y_{t-1},y_t,H) - b_e$$

RNN Output

Cost Sensitive Training and Regularization

l1 Regularization of Edge Weights

$$\min_{\theta} \mathcal{L}(\theta) + \lambda \left\| \theta' \right\|_1$$

Cost Sensitive Training

$$\min_{\theta} \; -\sum_{k=1}^{K} \sum_{t=1}^{m} \mathcal{I}(y_t = k)\alpha_k \log \; p(y_t = k|\theta) + \lambda \left\| \theta' \right\|_1$$

Inverse of class k's samples

Dataset

From MESA (Multi-Ethnic Study of Atherosclerosis) dataset

- 400 Sleep Apnea patients
- 7.5 hours of sleep data per person
- Flow signal is sampled at 32 Hz -> 960 samples for every 30 second epoch.
- Has inter-rater agreement of 85% on the annotated sleep stages

Evaluation Metrics Used

- Accuracy: % of states accurately classified
- Cohen's Kappa: Degree of concordance between prediction and ground truth
- Sleep Efficiency Mean Absolute Error (in %):

Sleep efficiency is a metric used for measuring the quality of sleep

$$\mathrm{SE} = \frac{n_R + n_L + n_D}{n_A + n_R + n_L + n_D}$$

$$\mathrm{MAE} = \frac{1}{|\mathcal{P}|} \sum_{p \in \mathcal{P}} \frac{|\widehat{SE_p} - SE_p|}{SE_p}$$

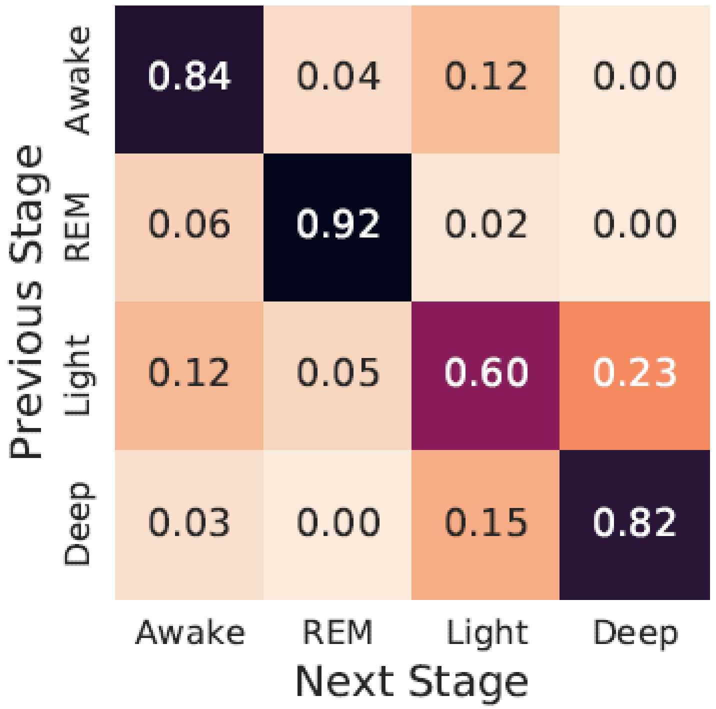
Baselines

- Conditional Random Field: With signal power density features as input
- R-CNN (ResNet-RNN)
- Conditional Adversarial R-CNN (Zhao et al.)
- Attention R-CNN

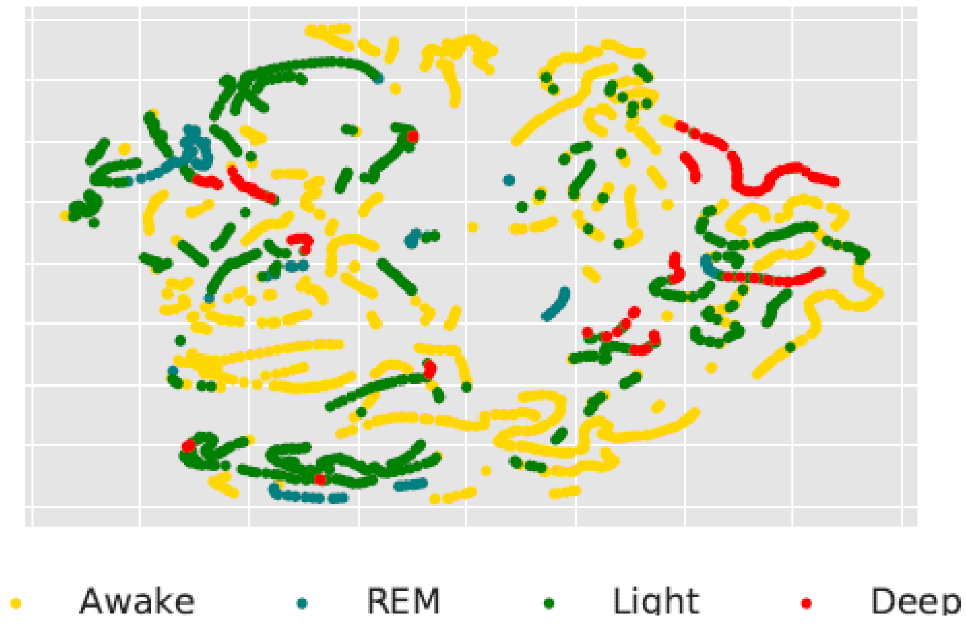
Results

Method	Accuracy (%)	Kappa	Sleep Efficiency MAE %
Conditional Random Field	52.4	0.28	29.4
R-CNN	71.5	0.49	12.5
Conditional Adversarial (Zhao et al.)	71.1	0.49	12.6
Attentional R-CNN	70.7	0.48	12.8
Neural CRF	72.3	0.54	10.9
Neural CRF (order 2)	72.5	0.55	10.8
Cost Sensitive Neural CRF	73.9	0.56	10.3
Regularized Cost Sensitive Neural CRF	**74.1**	**0.57**	**9.9**

Results

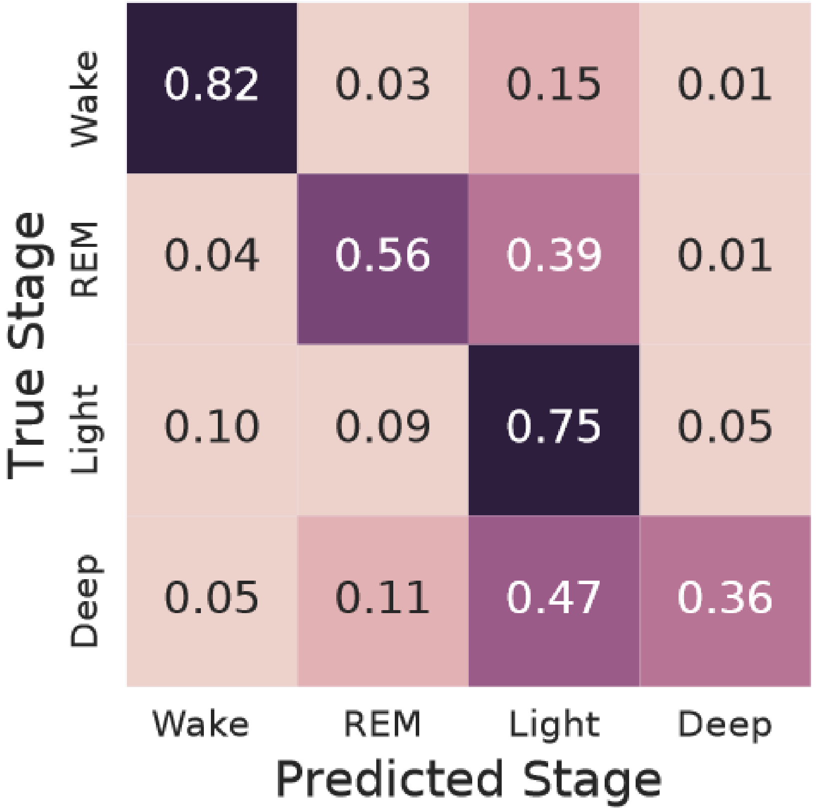


Sleep stage transition matrix
from CRF layer

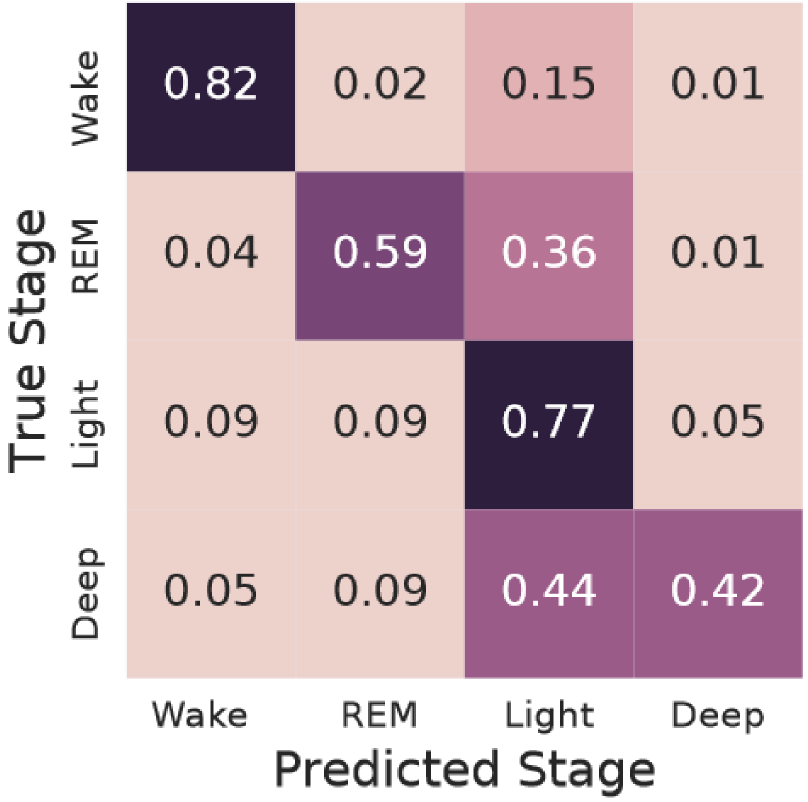


t-SNE clusters for embeddings
from the GRU layer

Results



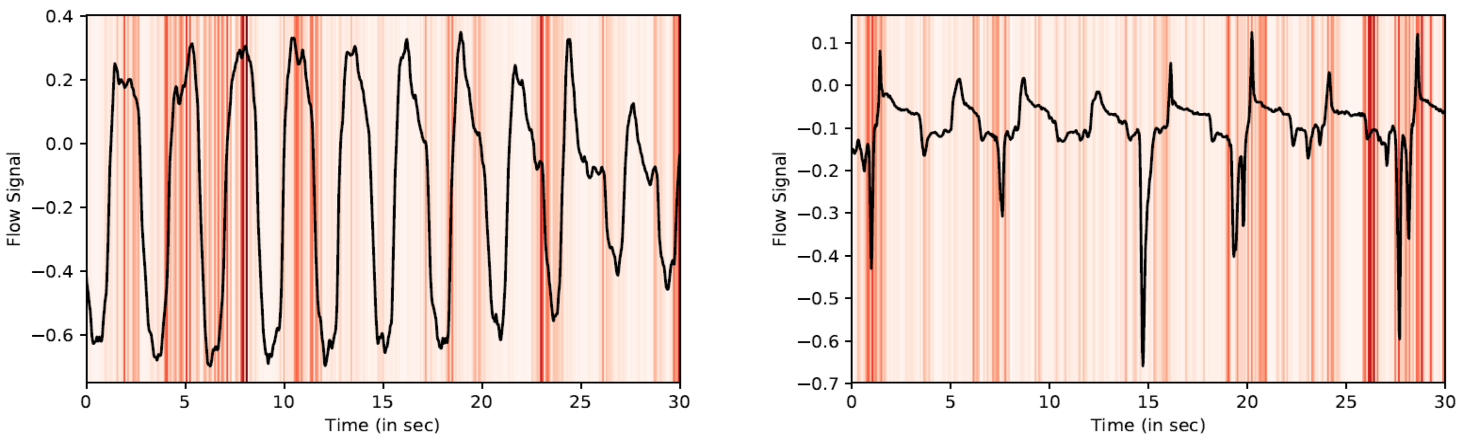
Neural CRF model



Cost-Sensitive Neural CRF model

Sample Saliency Map

View decision made by the deep network using saliency map technique from Simonyan et al. [2]

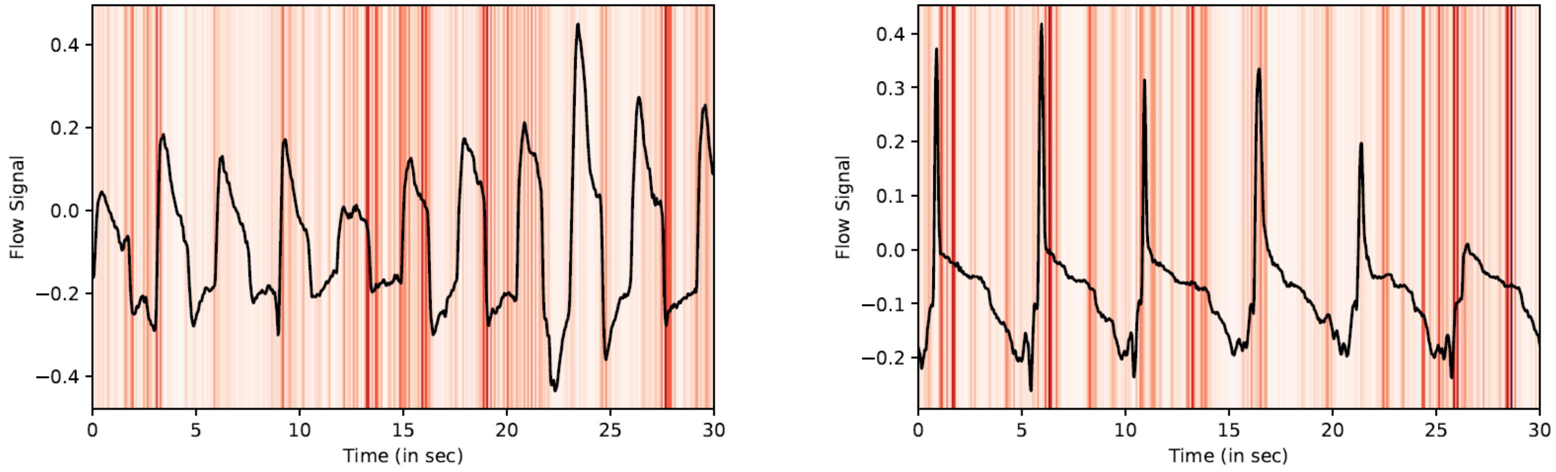


(a) Awake (b) REM

(a) Awake sleep has smooth and deep inhale and exhale cycle

(b) REM sleep has irregular pattern inhale and exhale cycle

Sample Saliency Map



(c) Light (d) Deep

(c) Light sleep has comparatively shallow respiratory cycle

(d) Deep sleep has sharp inhale but slow exhale patterns

Conclusions

- Our first study on using flow signal for automated sleep staging shows that we can find the wake and light sleep with a high accuracy
- Using a structured learning approach by taking into account the transition structure helps in more accurate sleep staging
- This method can be used to track the sleep efficiency of the patients under CPAP therapy with a high accuracy, providing an existing use-case unlike the most of other methods

Thank you!

References

[1] M. Zhao, S. Yue, D. Katabi, T. S. Jaakkola, and M. T. Bianchi, “Learning sleep stages from radio signals: A conditional adversarial architecture,” in International Conference on Machine Learning, 2017, pp. 4100–4109.

[2] K. Simonyan, A. Vedaldi, and A. Zisserman, “Deep inside convolutional networks: Visualising image classification models and saliency maps,” arXiv preprint arXiv:1312.6034, 2013.

[3] T. Lajnef, S. Chaibi, P. Ruby, P.-E. Aguera, J.-B. Eichenlaub, M. Samet, A. Kachouri, and K. Jerbi, “Learning machines and sleeping brains: automatic sleep stage classification using decision-tree multi-class support vector machines,” Journal of neuroscience methods, vol. 250, pp. 94–105, 2015.

[4] A. Supratak, H. Dong, C. Wu, and Y. Guo, “Deepsleepnet: A model for automatic sleep stage scoring based on raw single-channel EEG,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 25, no. 11, pp. 1998–2008, 2017.

[5] S. Biswal, J. Kulas, H. Sun, B. Goparaju, M. B. Westover, M. T. Bianchi, and J. Sun, “Sleepnet: Automated sleep staging system via deep learning,” arXiv preprint arXiv:1707.08262, 2017.

Backup slides: Saliency Map

Accuracy vs convinience of different signals

Signal	Accuracy	Convenient?
ECG	High	No
Actigraphy (wearables)	Low	Yes
No-contact	Low	Yes
EKG	Medium	No