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

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

- ResNet CNN
- GRU
- CRF layer

Global Sequence Inference
Neural Conditional Random Field Architecture

- ResNet CNN
- GRU
- CRF layer

5 layered ResNet CNN with ReLU + maxpool + dropout
GRU recurrent layer
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 $t$. 

Flow Signal

$Y_{t-1}$ $e_1$ $Y_t$ $e_2$ $Y_{t+1}$
Neural Conditional Random Field Model

\[ \Psi_n(y_t | H, w_n, b_n) = \exp(w_n^T \phi(y_t, H) + b_n) \]

\[ \Psi_e(y_{t-1}, y_t | H, w_e, b_e) = \exp(w_e^T \phi(y_{t-1}, y_t, H) + b_e) \]

\[ p(y | H, \theta) = \frac{1}{Z(H, \theta)} \prod_{t=1}^{m} \Psi_n(y_t | H, w_n, b_n) \prod_{t=2}^{m} \Psi_e(y_{t-1}, y_t | H, w_e, b_e) \]

\[ \mathcal{L}(\theta) = \log Z - \sum_{t=1}^{m} w_n^T \phi(y_t, H) - b_n - \sum_{t=2}^{m} w_e^T \phi(y_{t-1}, y_t, H) - b_e \]
Cost Sensitive Training and Regularization

\[ \min_{\theta} \mathcal{L}(\theta) + \lambda \|\theta'\|_1 \]

Cost Sensitive Training

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

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

\[
SE = \frac{n_R + n_L + n_D}{n_A + n_R + n_L + n_D}
\]

\[
MAE = \frac{1}{|\mathcal{P}|} \sum_{p \in \mathcal{P}} \frac{|\hat{SE}_p - SE_p|}{SE_p}
\]
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

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy (%)</th>
<th>Kappa</th>
<th>Sleep Efficiency MAE %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditional Random Field</td>
<td>52.4</td>
<td>0.28</td>
<td>29.4</td>
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<tr>
<td>R-CNN</td>
<td>71.5</td>
<td>0.49</td>
<td>12.5</td>
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<tr>
<td>Conditional Adversarial (Zhao et al.)</td>
<td>71.1</td>
<td>0.49</td>
<td>12.6</td>
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<tr>
<td>Attentional R-CNN</td>
<td>70.7</td>
<td>0.48</td>
<td>12.8</td>
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<tr>
<td>Neural CRF</td>
<td>72.3</td>
<td>0.54</td>
<td>10.9</td>
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<tr>
<td>Neural CRF (order 2)</td>
<td>72.5</td>
<td>0.55</td>
<td>10.8</td>
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<tr>
<td>Cost Sensitive Neural CRF</td>
<td>73.9</td>
<td>0.56</td>
<td>10.3</td>
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<tr>
<td>Regularized Cost Sensitive Neural CRF</td>
<td><strong>74.1</strong></td>
<td><strong>0.57</strong></td>
<td><strong>9.9</strong></td>
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</tbody>
</table>
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 sleep has smooth and deep inhale and exhale cycle
(b) REM sleep has irregular pattern inhale and exhale cycle
(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


Backup slides: Saliency Map
### Accuracy vs convenience of different signals

<table>
<thead>
<tr>
<th>Signal</th>
<th>Accuracy</th>
<th>Convenient?</th>
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<tbody>
<tr>
<td>ECG</td>
<td>High</td>
<td>No</td>
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<tr>
<td>Actigraphy (wearables)</td>
<td>Low</td>
<td>Yes</td>
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<tr>
<td>No-contact</td>
<td>Low</td>
<td>Yes</td>
</tr>
<tr>
<td>EKG</td>
<td>Medium</td>
<td>No</td>
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