Unsupervised clustering of sleep data

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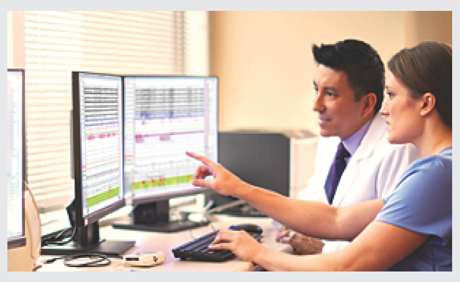
Background

- Current sleep scoring manual (AASM) is designed for the human eye.
- Limited information is extracted from polysomnographic data.
- Interscorer agreements are poor for patients with sleep disorders.



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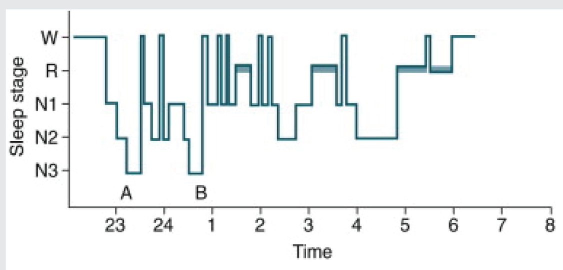

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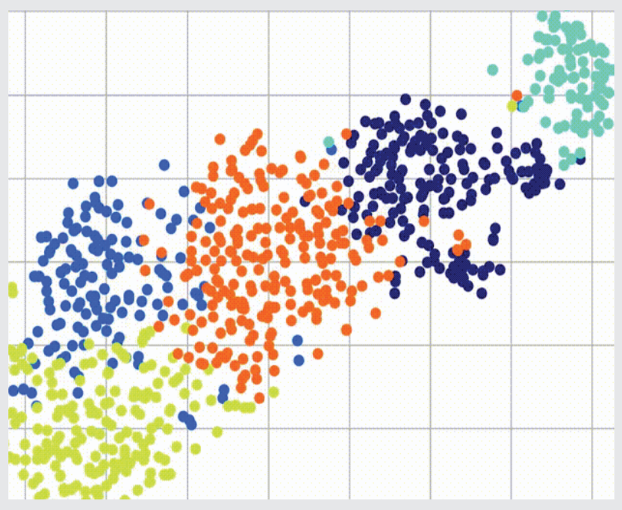
Aim

- Novel approach to cluster sleep data using unsupervised classification
- Moving towards a data-driven sleep classification system
- Application to non-standard cases (e.g. lucid dreaming)



Methods

Pre-processing → Feature extraction & selection (*hctsa*) [3] → ***k*-means clustering** → Cluster mapping → Cross-validation ◄◄◄◄ Psychophysics Experiment

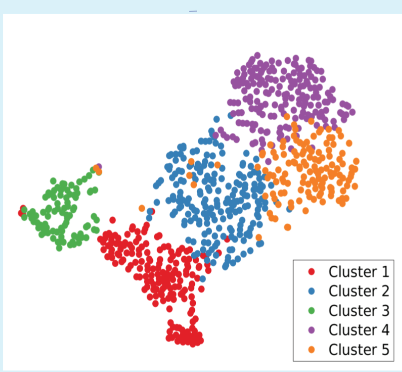
k-means clustering → REM-like cluster identification (manual inspection) → Lucid dreaming detection (2nd *k*-means clustering)

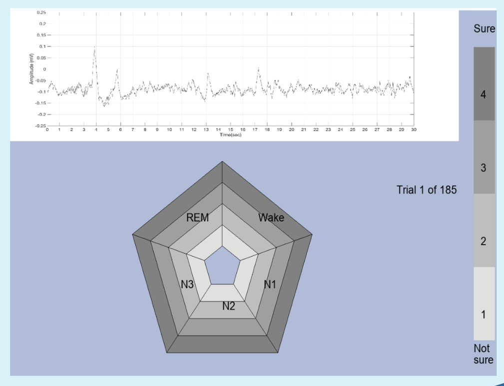
sleep.org CCSHS dataset [1] (5 females, 5 males) random

Lucid dreaming dataset [2] (3 participants, 6 nights)

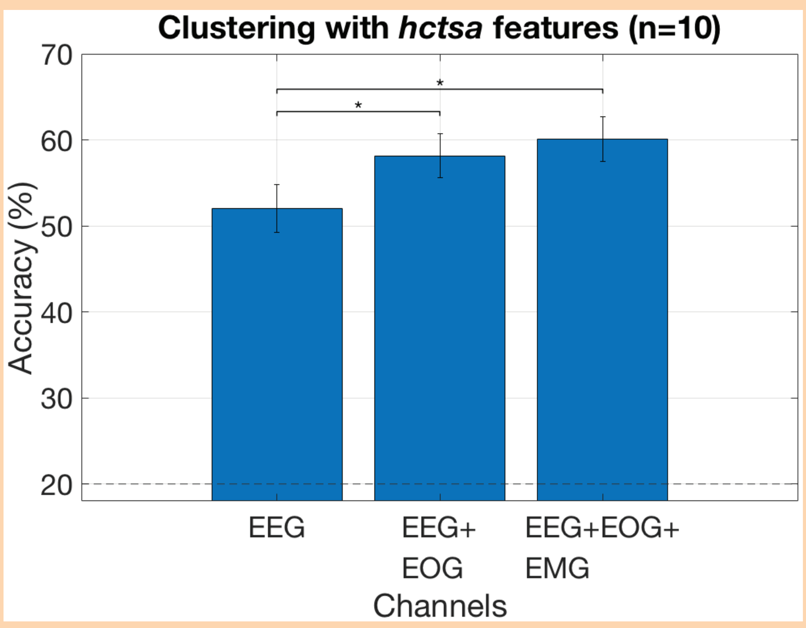
Generalised time-series feature extration tool

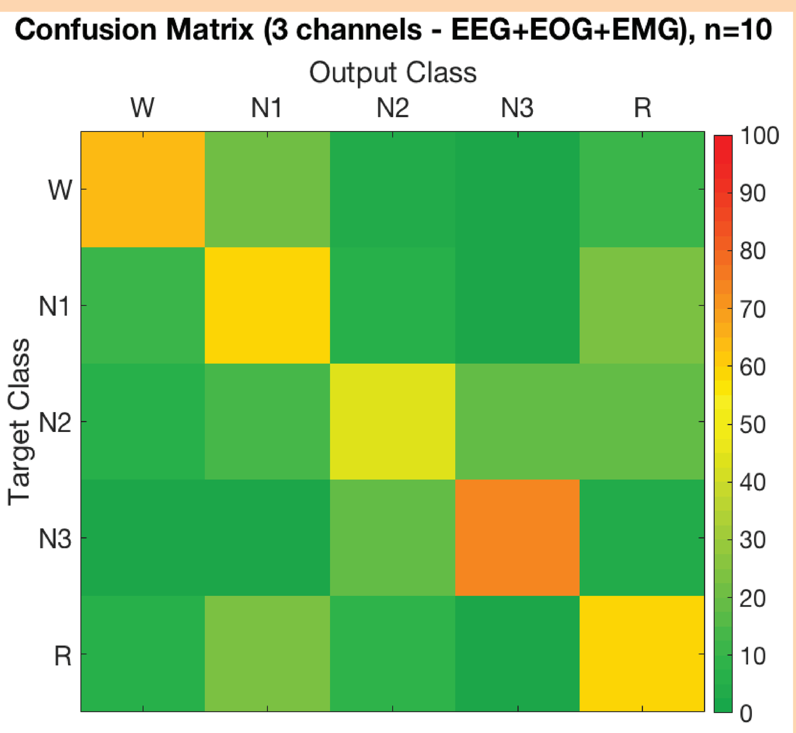
Basic statistics	Correlation	Fourier & Wavelet Transform
Entropy	Nonlinear analysis & fractal scaling	Fitting & Forecasting



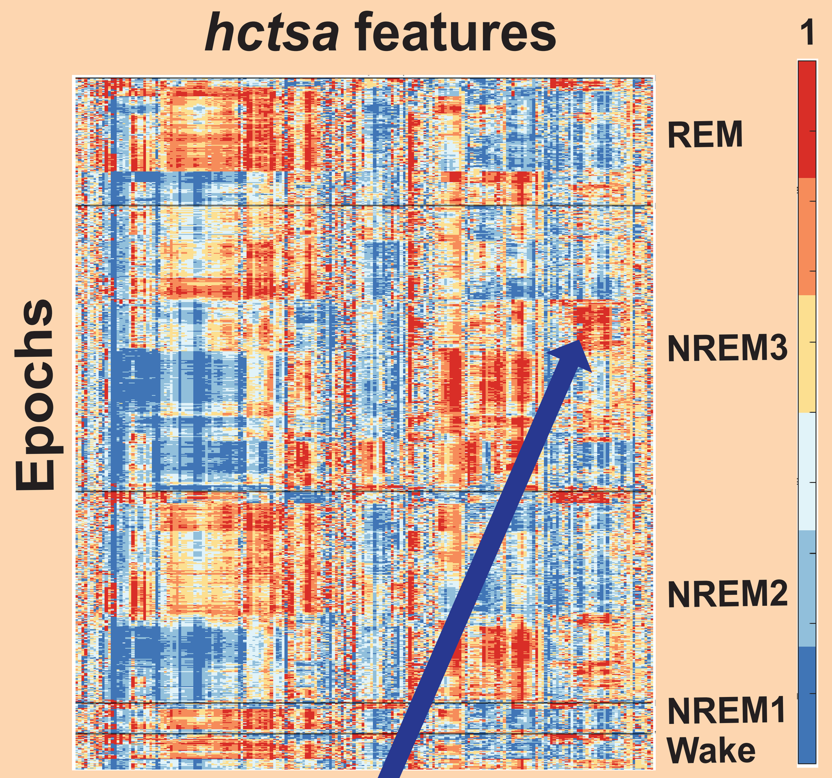


Result - Clustering

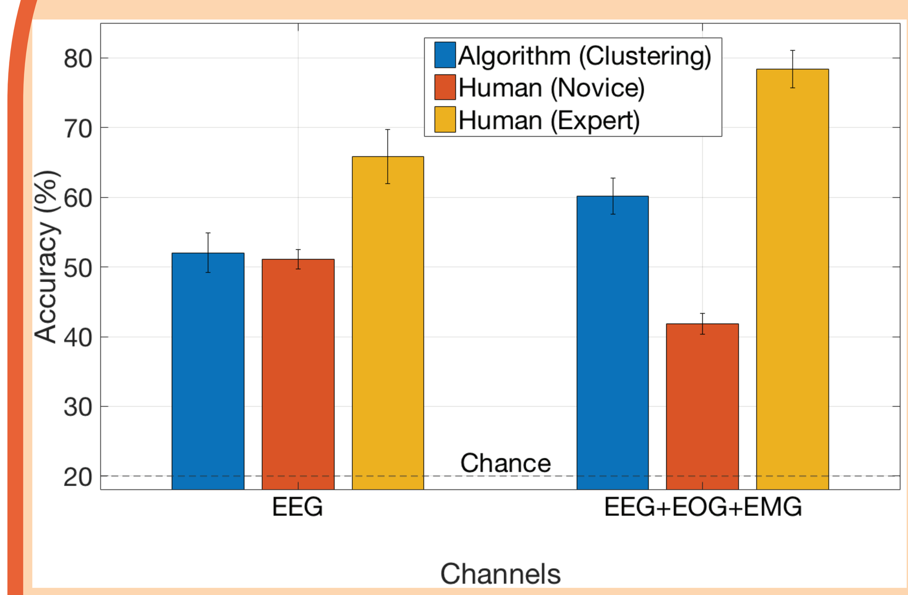




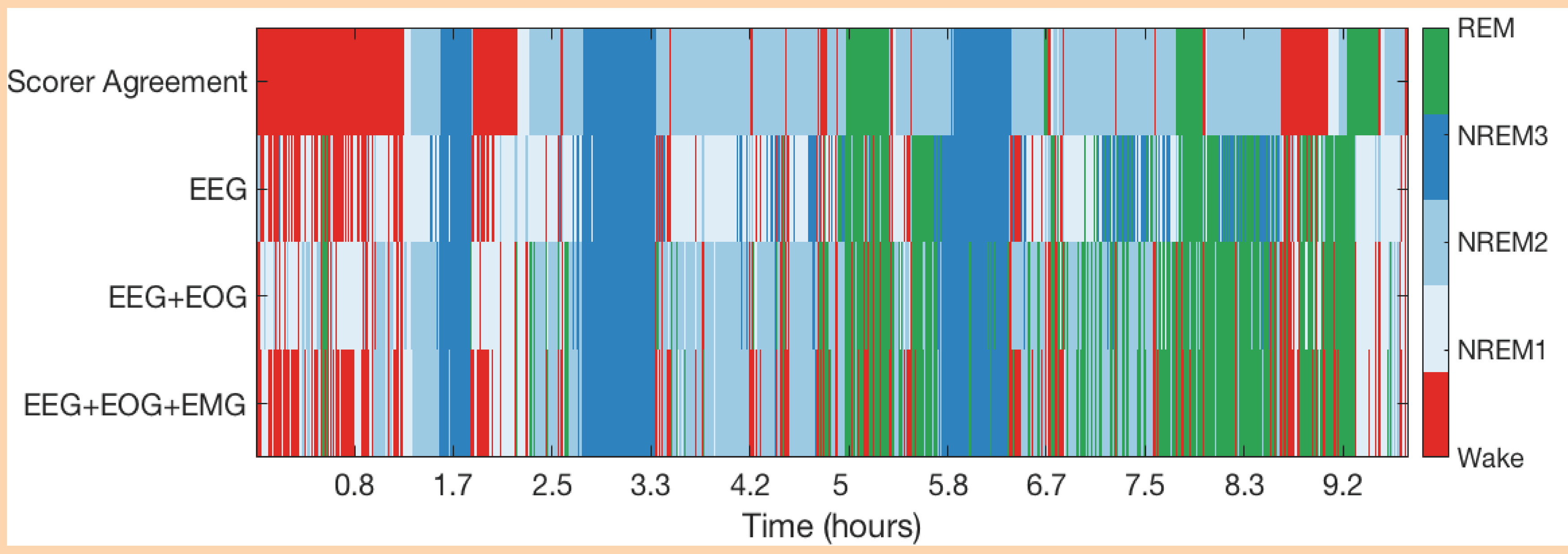
- Clustering performance is **better** with EEG+EOG+EMG (600 features) than EEG alone (200 features)
- More features do not necessarily improve performance (Accuracies between EEG+EOG and EEG+EOG+EMG are not significantly different)



Result - Algorithm vs Human

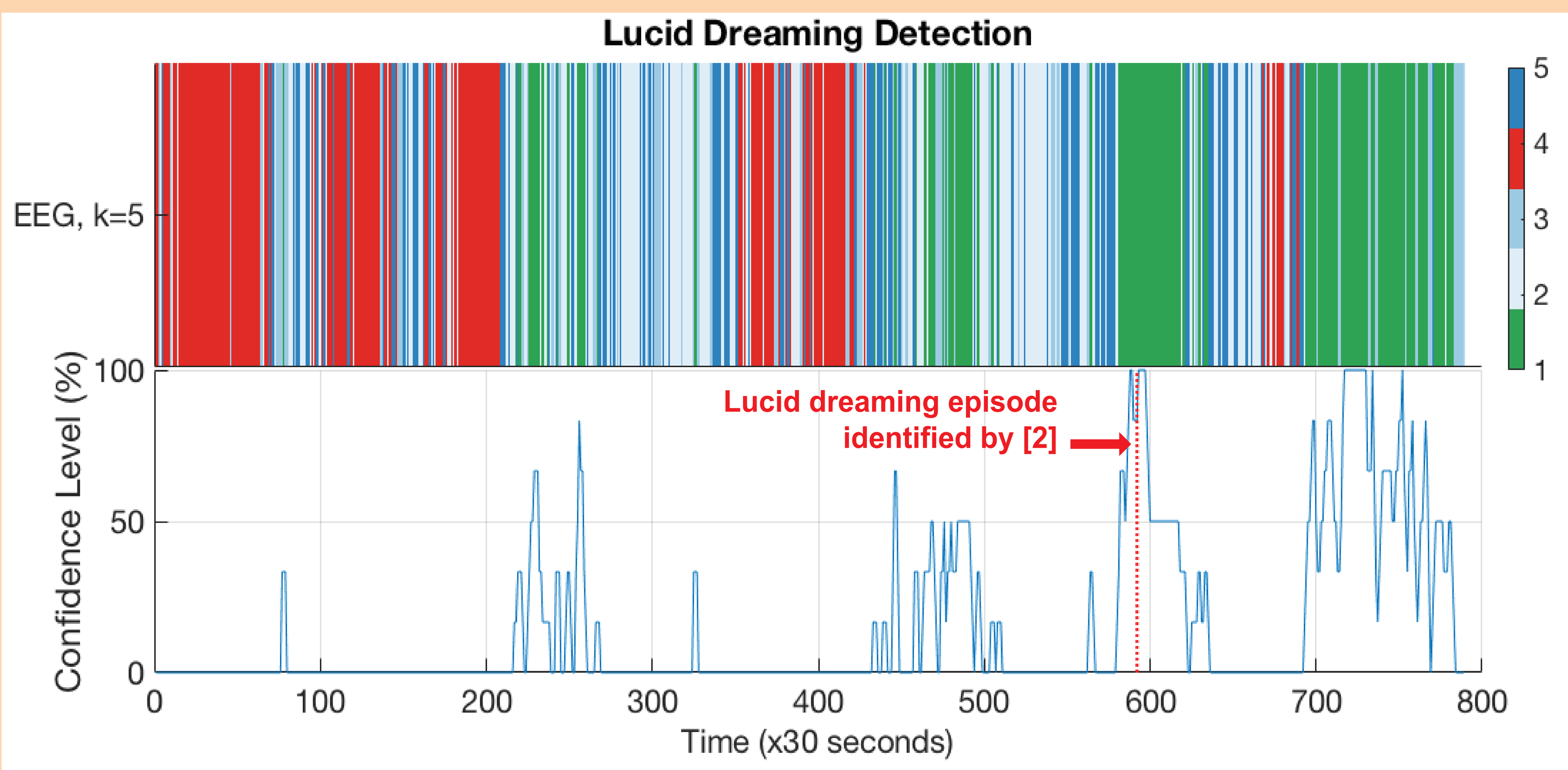


- Algorithm and humans scored 30-second epochs with no prior knowledge.
- Algorithm **outperformed** novice human scorers in 3 channels.
- Human experts had the **best** performance in scoring 1 channel and 3 channels.



- Algorithm scores align well with human scorers, especially in the sleep stage NREM3.
- Without prior knowledge, algorithm scored the Wake stage (determined by human scorers) with a combination of Wake, NREM1 and REM stages.

Result - Lucid dreaming



- Algorithm prediction of the approximate occurrence of lucid dreaming.

Discussion

- Our **unsupervised** approach has reasonable agreement with human experts and has strong potential in detecting lucid dreaming episodes.
- This novel approach could analyse more complex features and richness of sleep data, compared to current sleep scoring practice.
- Automating our approach could improve consistencies in sleep scoring, potentially including sleep disorders data.

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