Multivariate Time Series Visualization for Sleep Electroencephalograms

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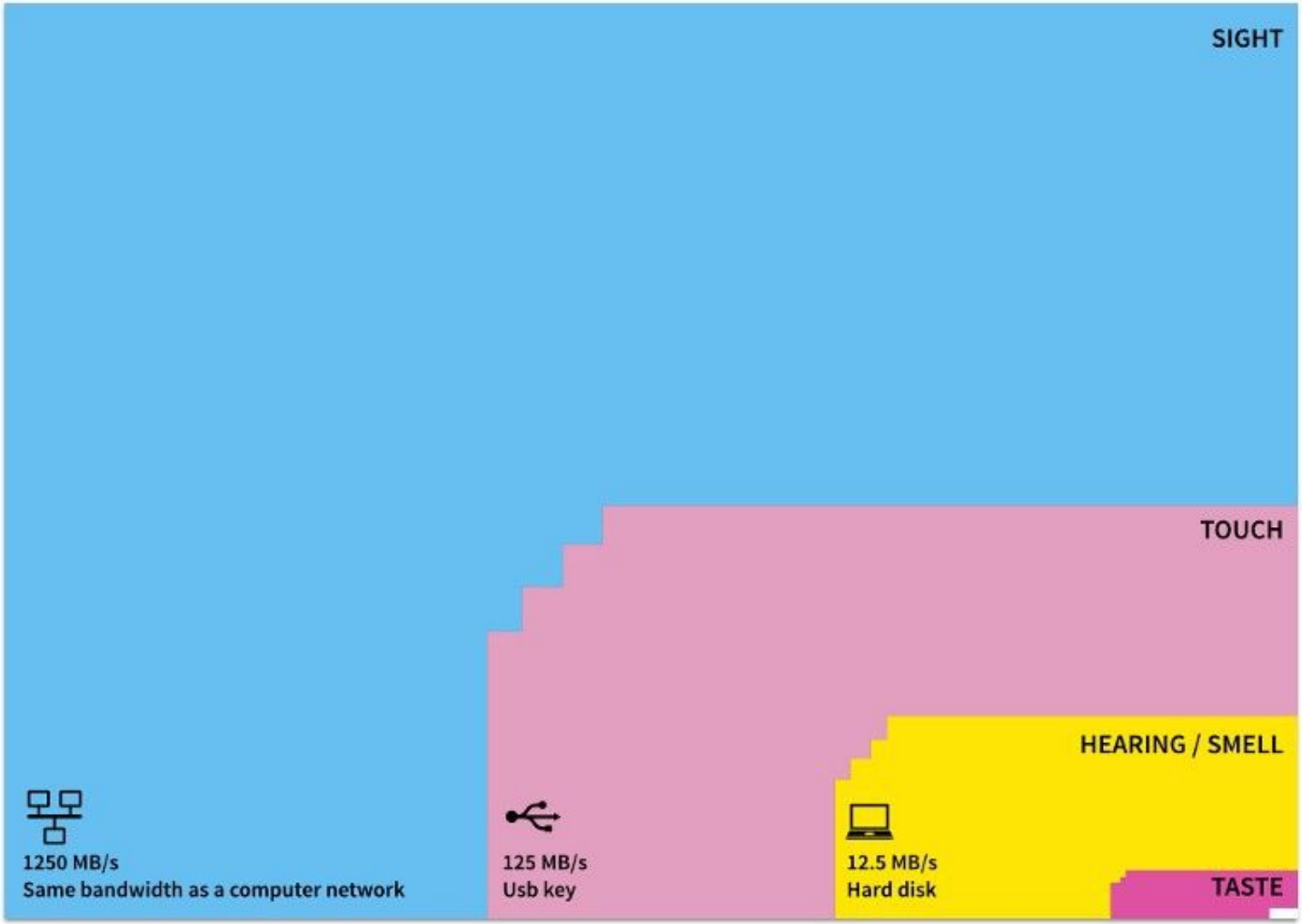
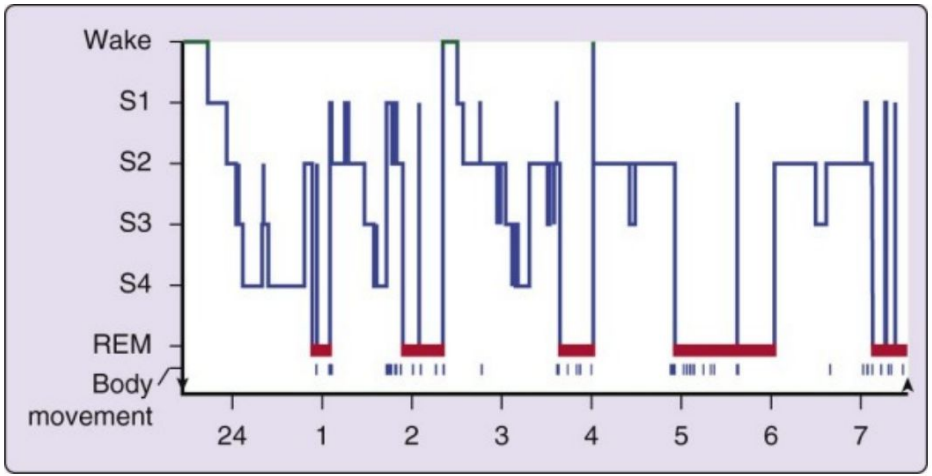
Outline

1. Introduction
2. Related Work
3. Methodology
4. Experiments and Results
5. Conclusions and Future Work

Bandwidth of our Senses by Tor Nørretranders





Carskadon, M. A., & Dement, W. C. (2011). Chapter 2-normal human sleep: an overview. *Principles and practice of sleep medicine*, *4*, 13-23.

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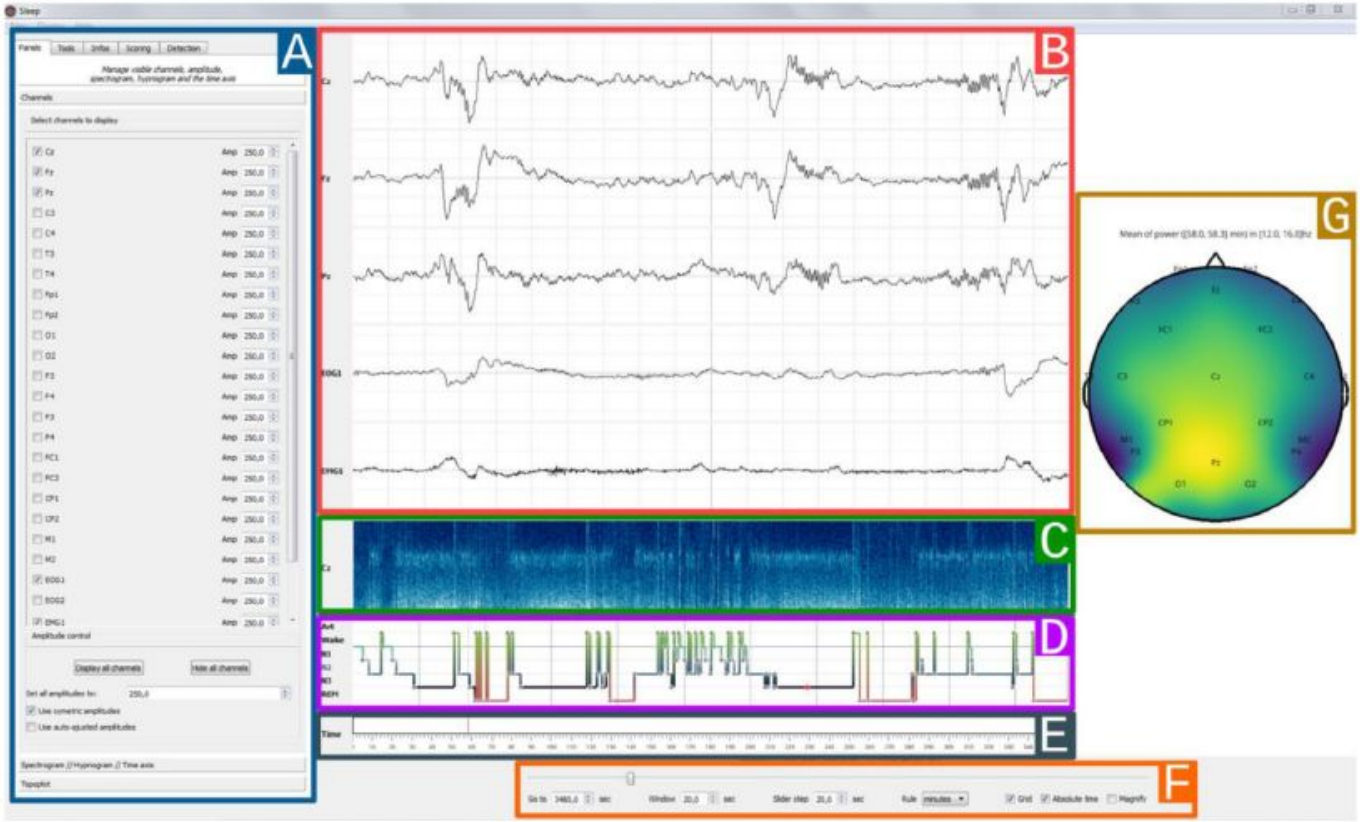
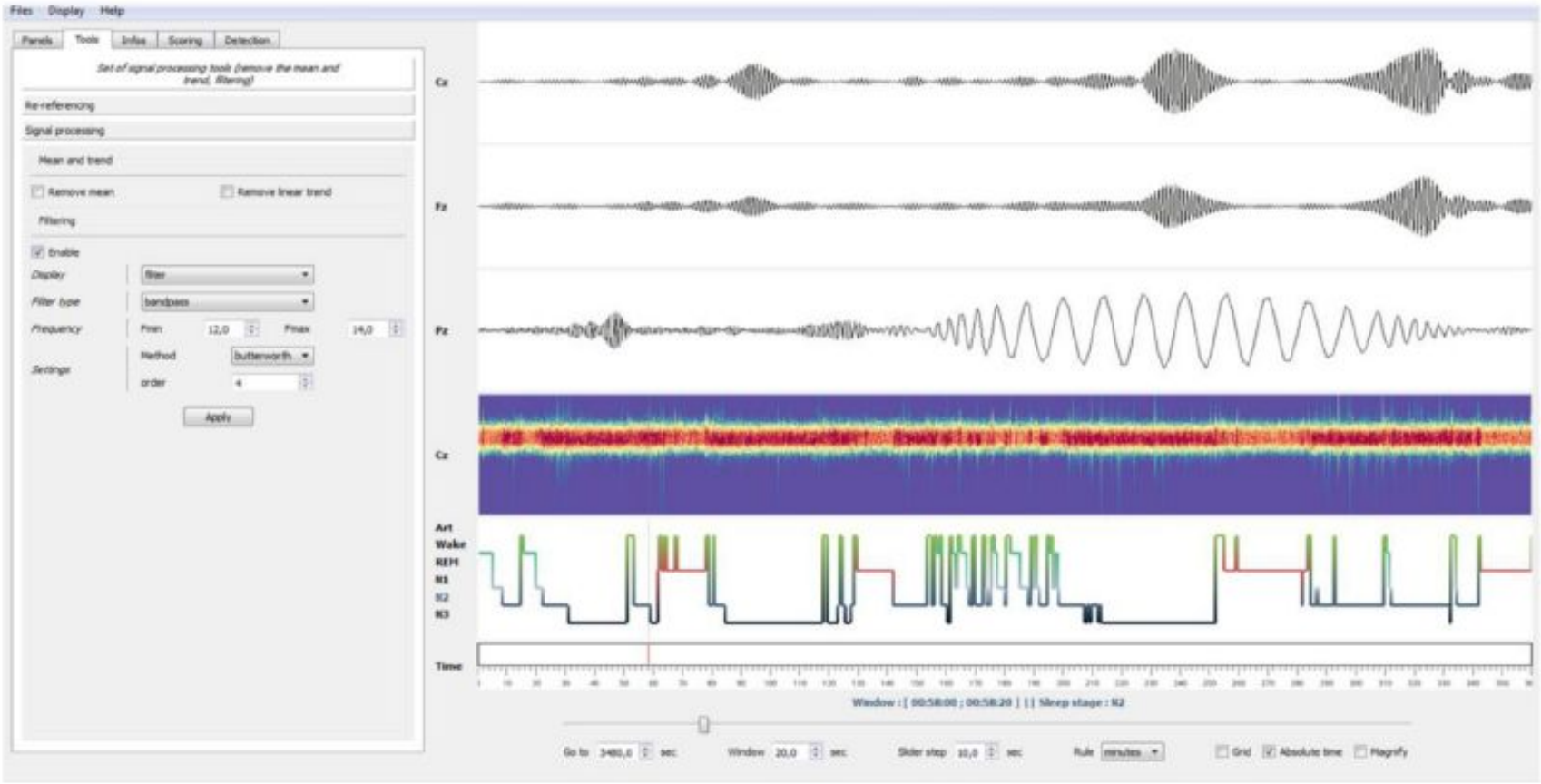
Sleep: An Open-Source Python Software for Visualization, Analysis, and Staging of Sleep Data



Etienne Combrisson, Raphael Vallat, Jean-Baptiste Eichenlaub, Christian O'Reilly, Tarek Lajnef,Aymeric Guillot, Perrine M Ruby, and Karim Jerbi. Sleep: An open-source python software forvisualization, analysis, and staging of sleep data.Frontiers in Neuroinformatics, 11:60, 2017



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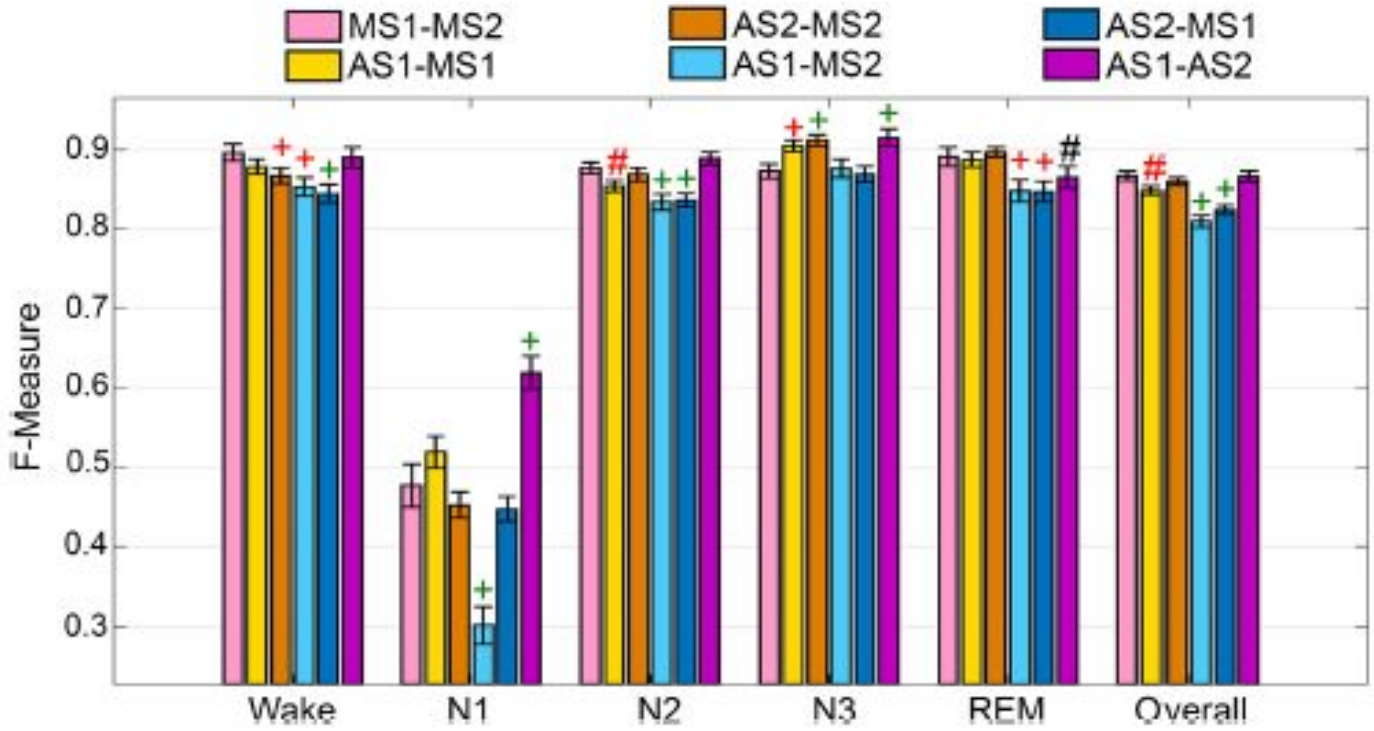
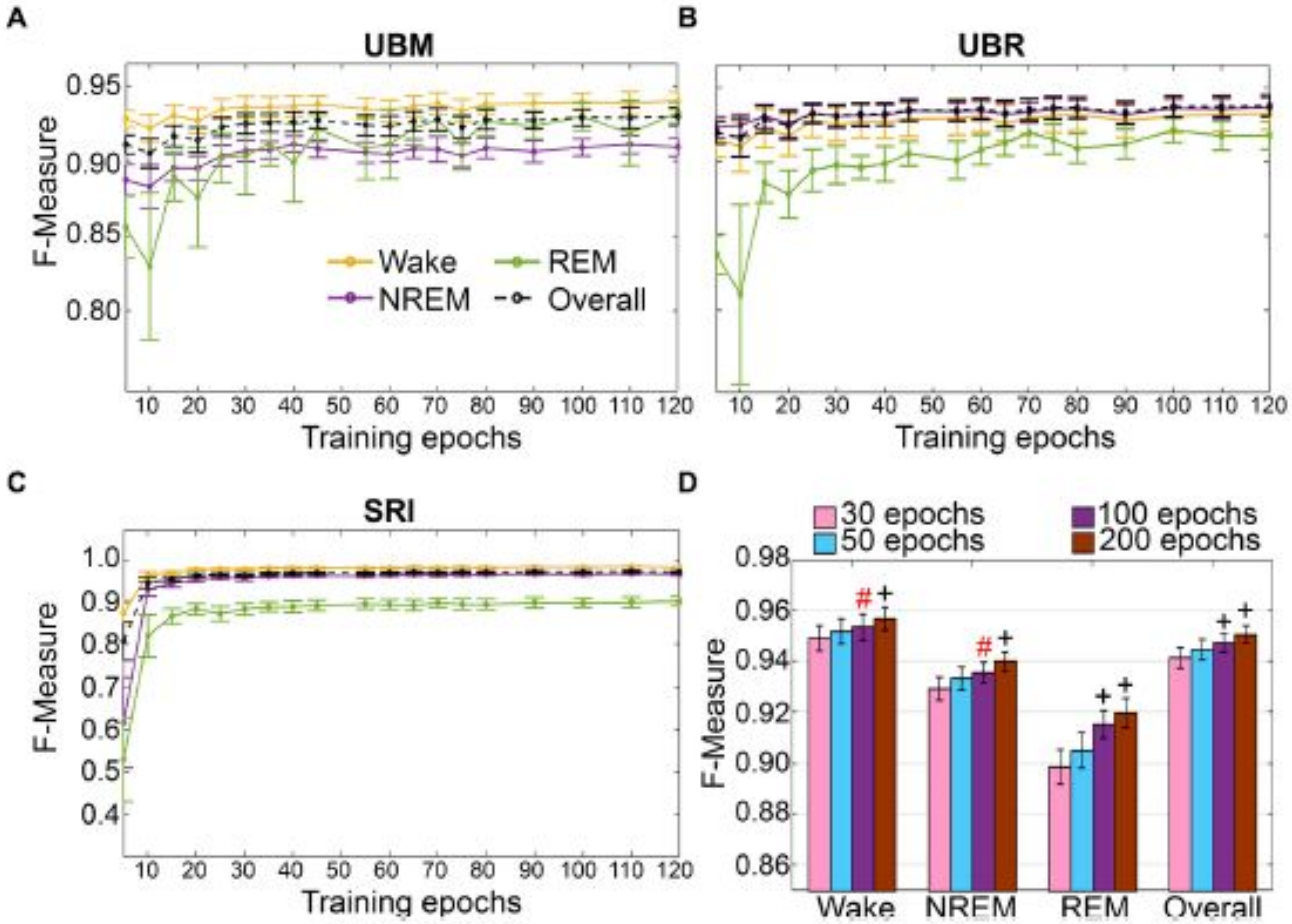
Validation of ‘Somnivore’, a Machine Learning Algorithm for Automated Scoring and Analysis of Polysomnography Data



Giancarlo Allocca, Sherie Ma, Davide Martelli, Matteo Cerri, Flavia Del Vecchio, Stefano Bastian-ini, Giovanna Zoccoli, Roberto Amici, Stephen R Morairty, Anne E Aulsebrook, et al. Validationof'somnivore', a machine learning algorithm for automated scoring and analysis of polysomnographydata.Frontiers in Neuroscience, 13:207, 2019.



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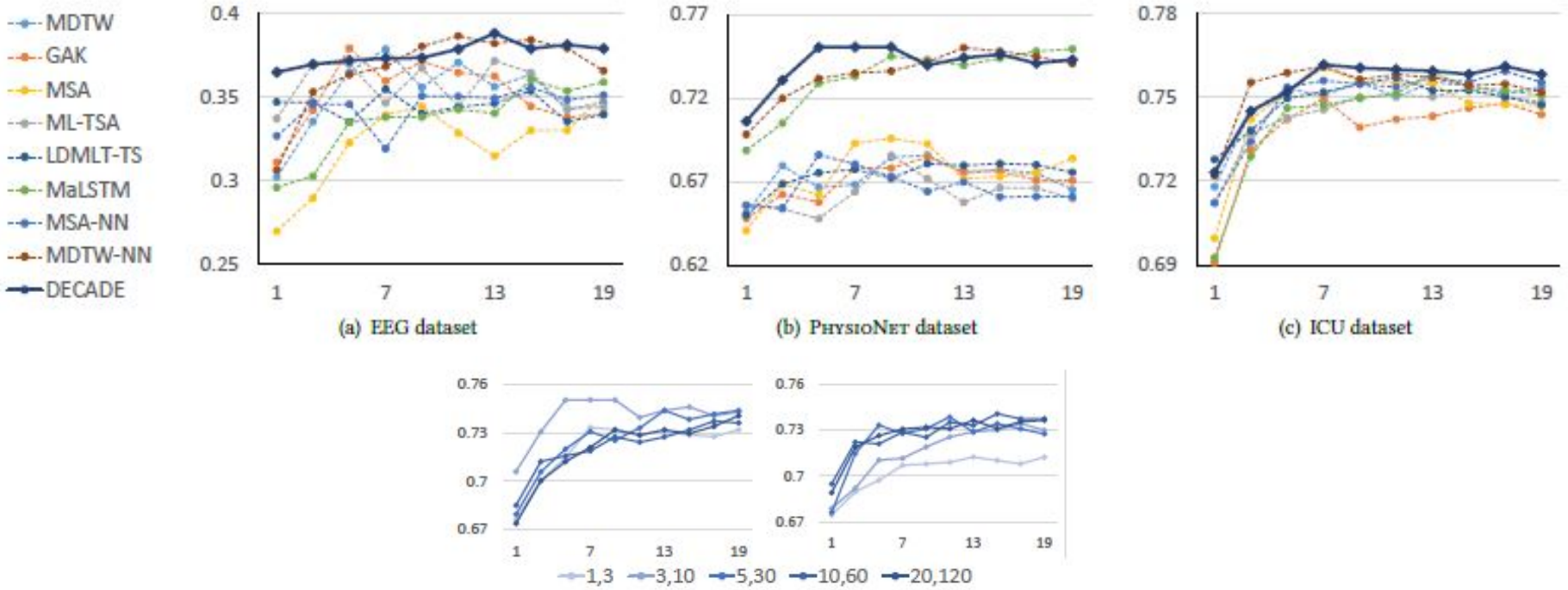
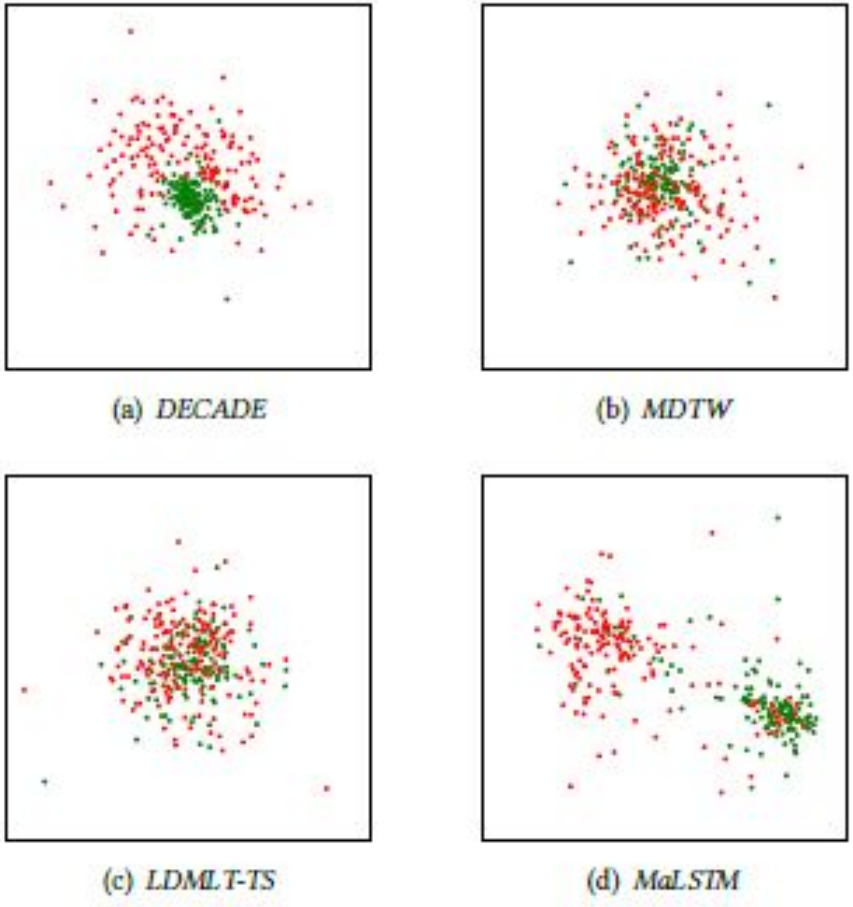
DECADE: A Deep Metric Learning Model for Multivariate Time Series



Zhengping Che, Xinran He, Ke Xu, and Yan Liu. Decade: a deep metric learning model for multivariatetime series. InKDD workshop on mining and learning from time series, 2017.



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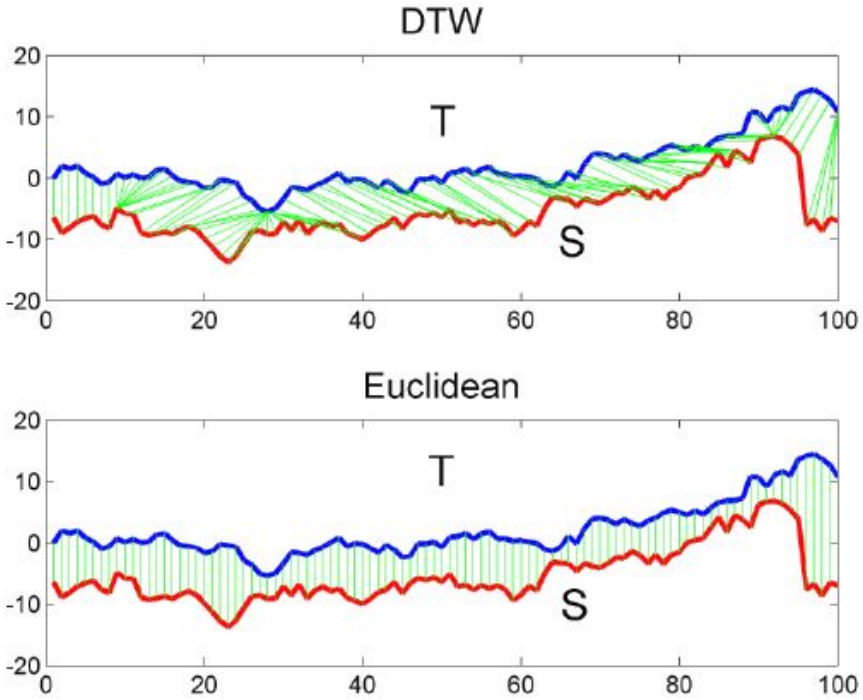
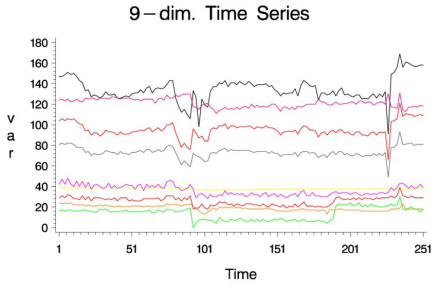
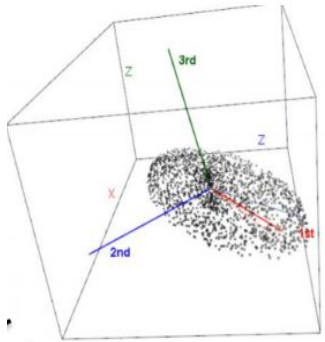
Similarity measures



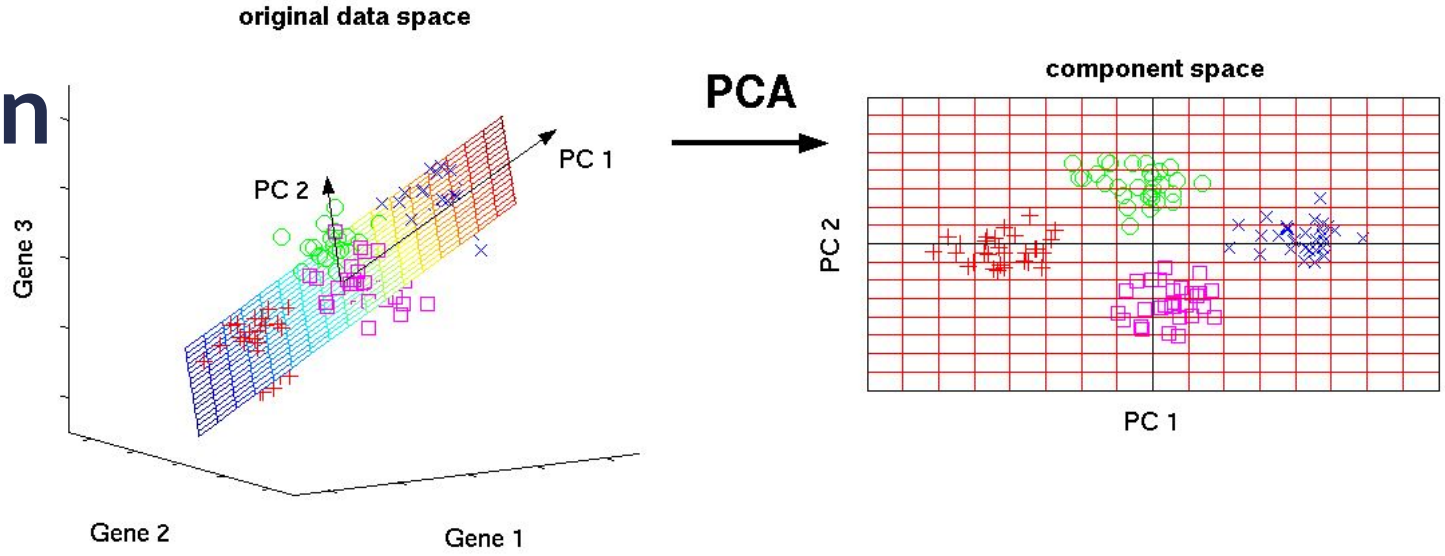
EROS

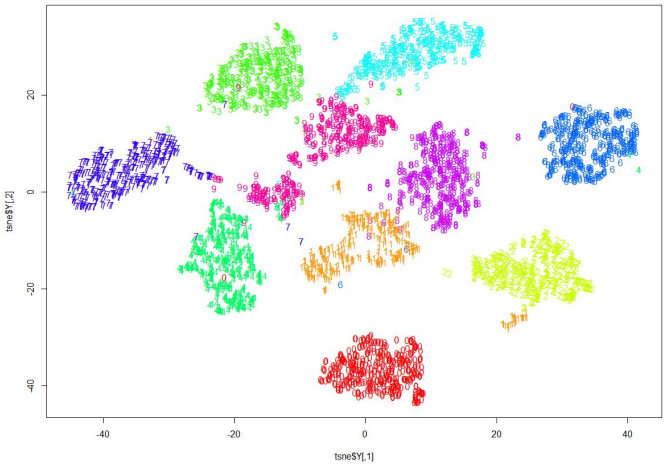


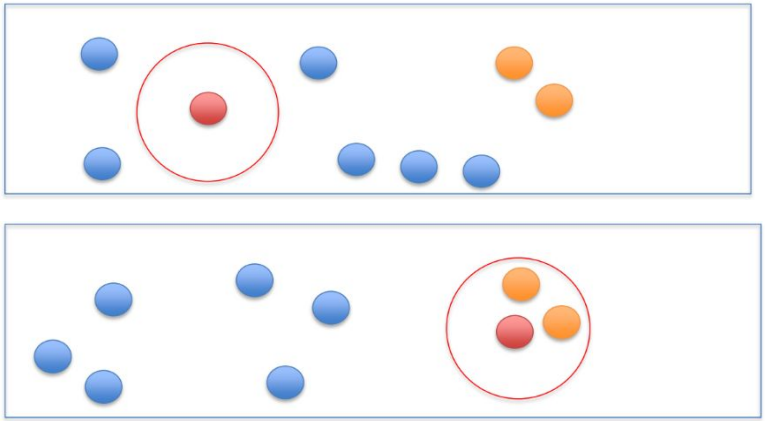


Extended Frobenius Norm
[Yang&Shahabi]

Projection



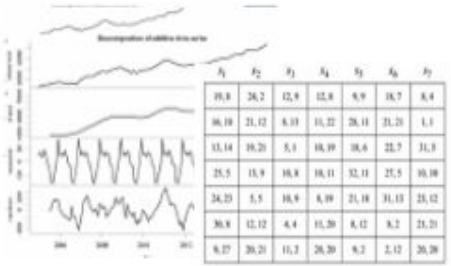




TSNE

Pipeline

Sleep dataset
Feature Extraction

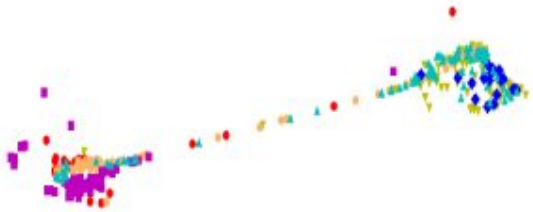


Similarity
measure

	Item1	Item2	Item3	Item4	Item5
Item1	,178	,111	-,022	,089	,044
Item2	,111	,278	,000	,111	,111
Item3	-,022	,000	,267	-,067	,022
Item4	,089	,111	-,067	,267	,133
Item5	,044	,111	,022	,133	,178

DTW EROS

Low-dimensional
projection



mTSNE

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Dataset

Sleep Recordings and Hypnograms in European Data Format (EDF) of Physionet.

70 healthy patients

23 patients with sleep problems

Age range is between 20 to 66 years old.

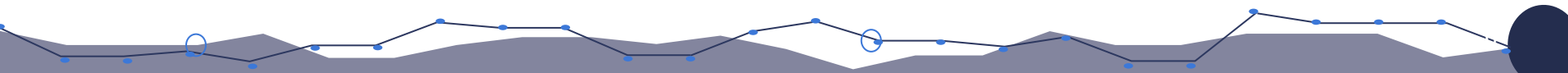
From the 7 EEG signals provided, 4 to 100 Hz were used.

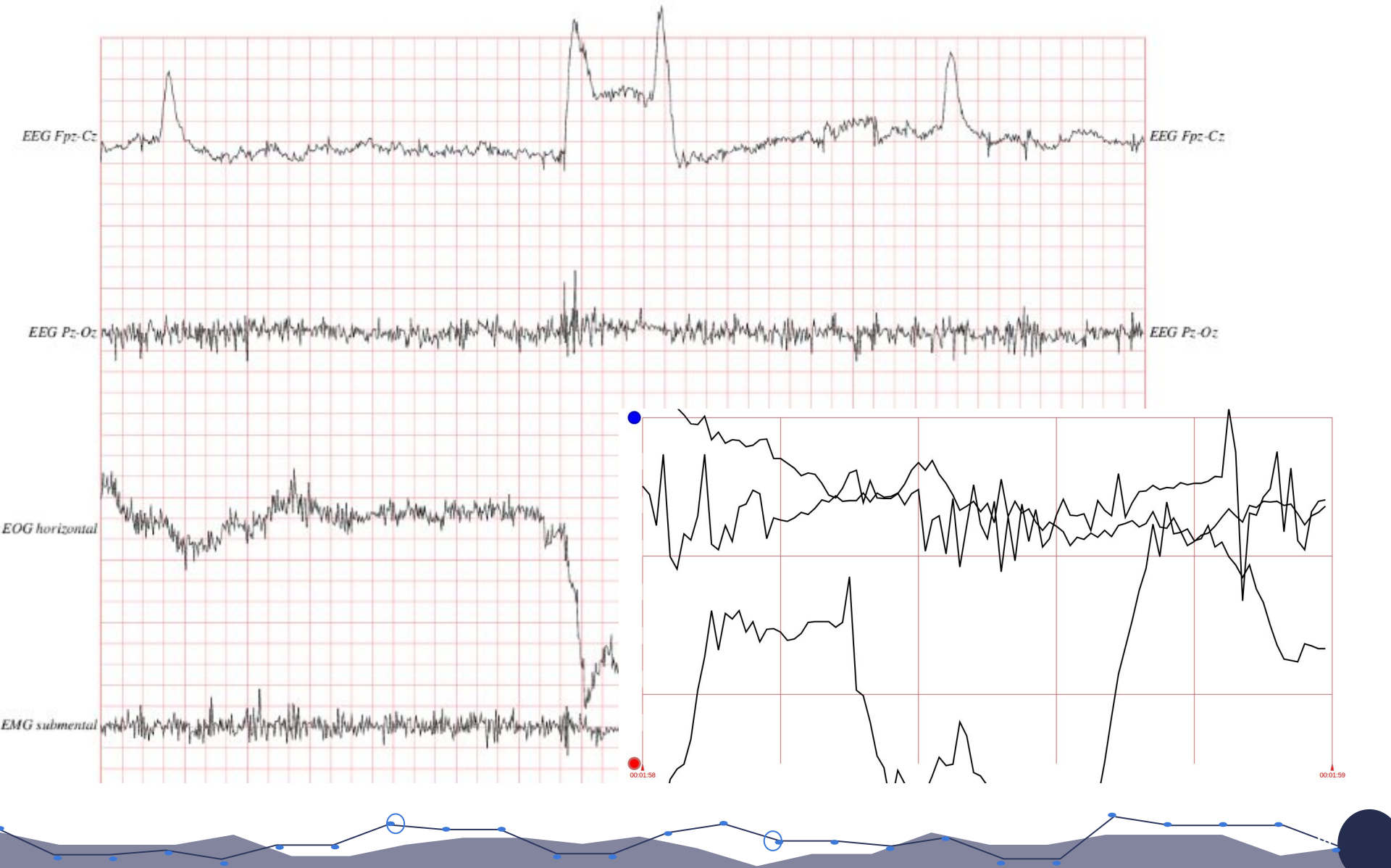
Results

Processing time in a Core i7 2.40 GHz:

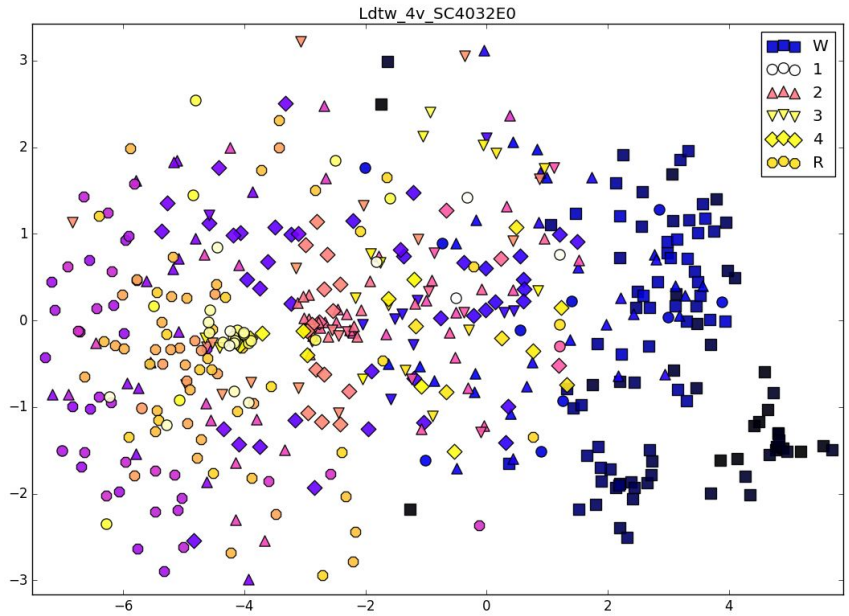
DTW: 13 hr 15 min

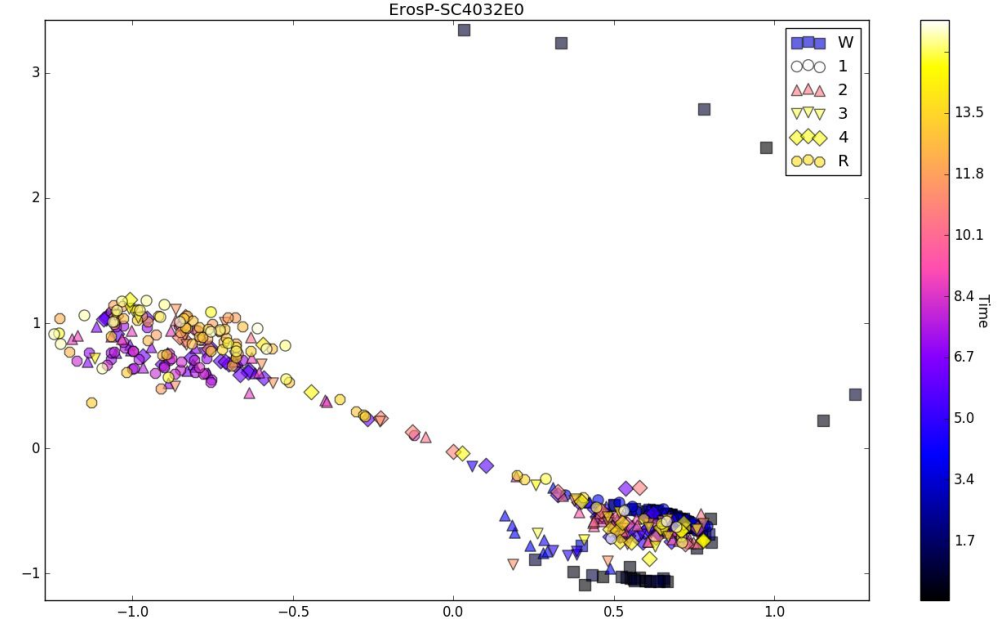
EROS : 58 sec.



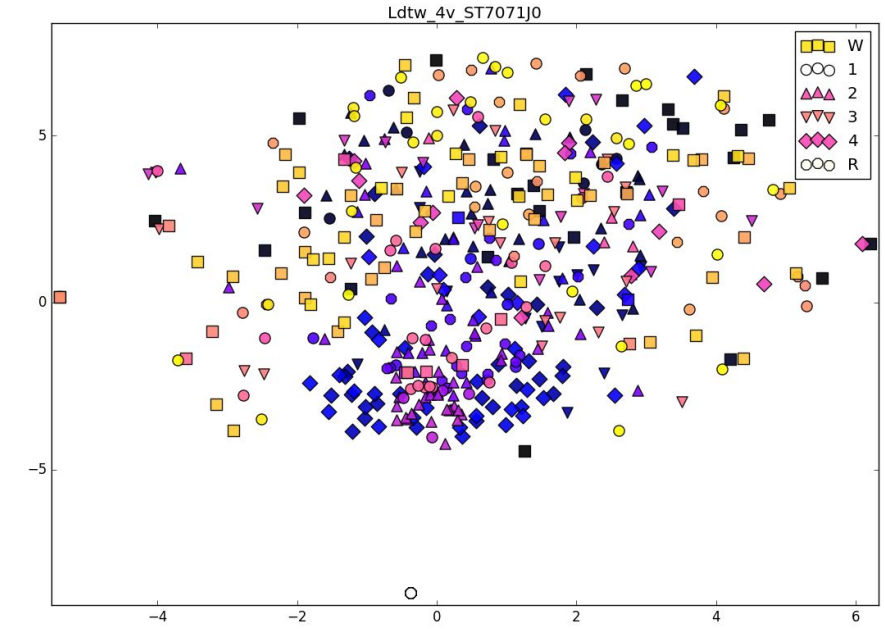

EEG Fpz-Cz
EEG Fpz-Cz
EEG Pz-Oz
EEG Pz-Oz
EOG horizontal
EMG submental
00:01:58
00:01:59

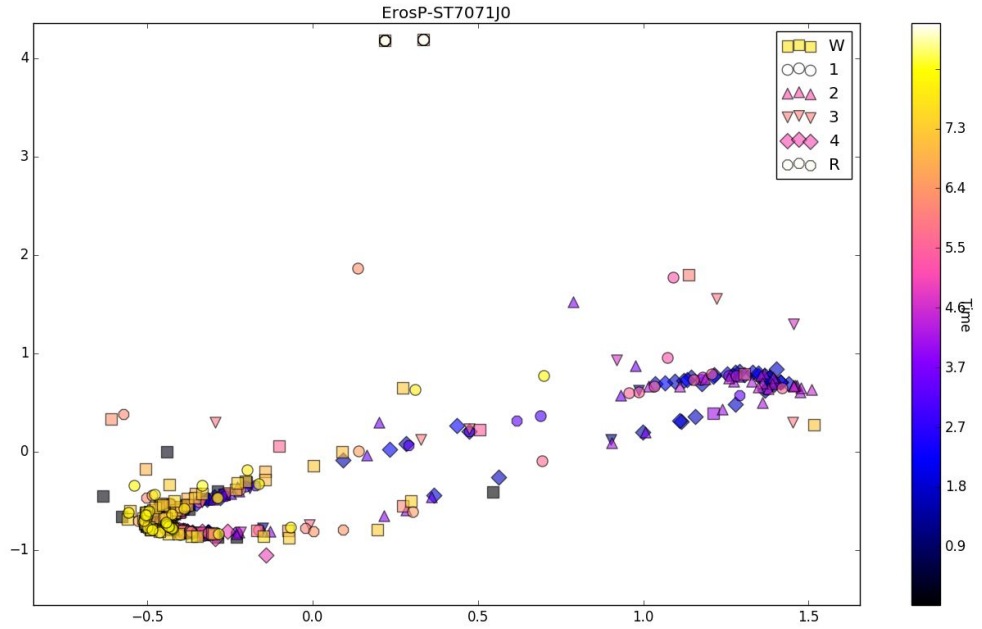
Healthy Patients

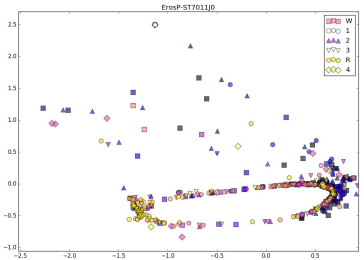




Patients with Sleep Problems



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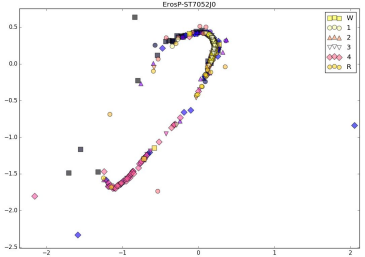
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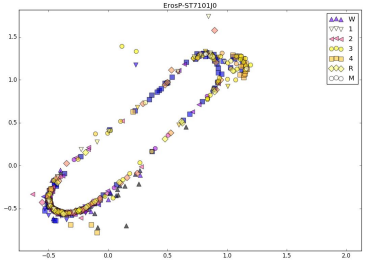
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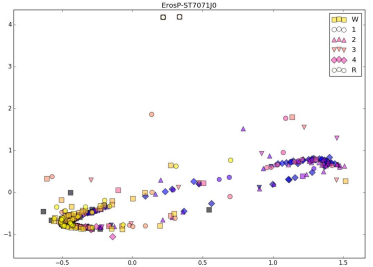
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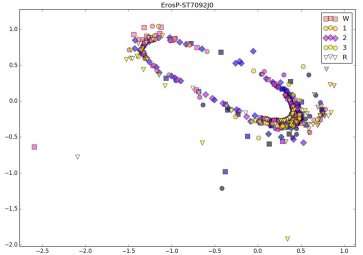
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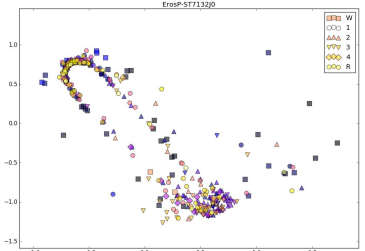
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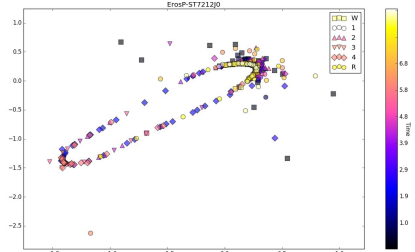
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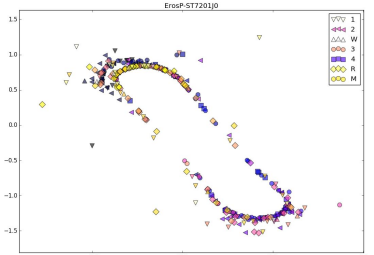
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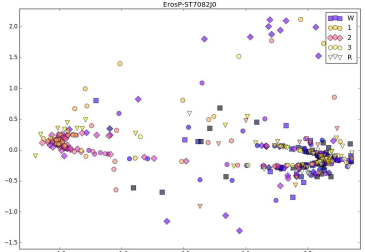
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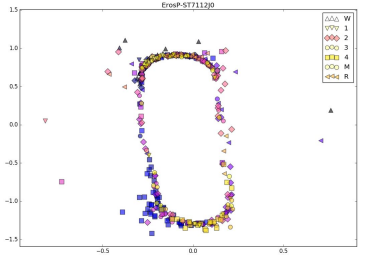
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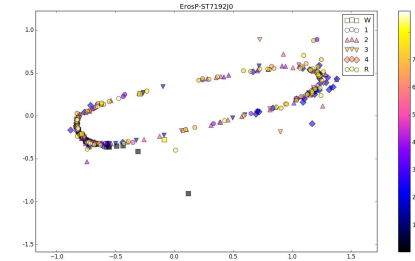
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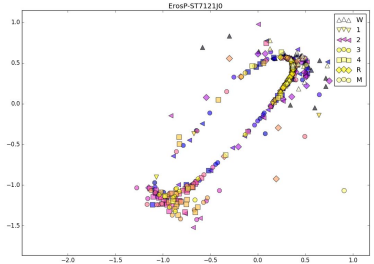
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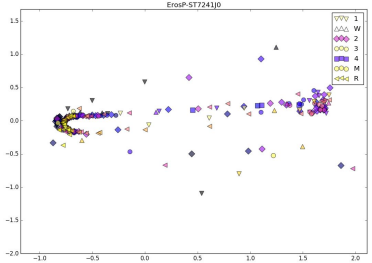
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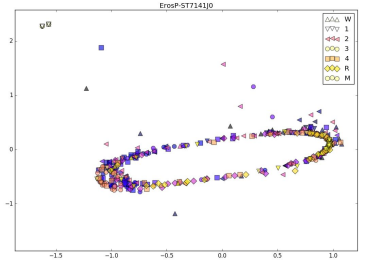
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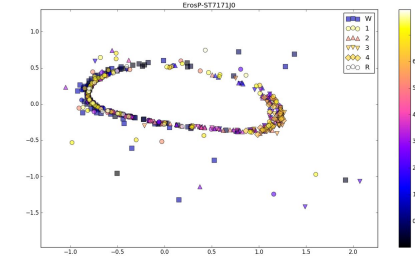
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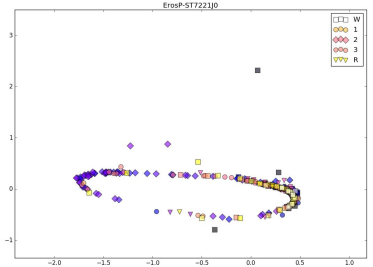
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Conclusions

The visualization obtained showed that the approach used provides interpretable information, while other visualization methods are more difficult to interpret.

The used approach shows an improvement in run-time in 75x speedup over classic methods.

We discovered an interesting pattern in visualization for patients with sleep problems.

Future works

Interactive visualization will be carried out where one of the segments can be selected, observing their temporal location, with their respective sleep stages, using a linear correlation diagram.

Find similarities between set of series and thus be able to visualize patterns and anomalies among the patients.

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