Large scale sleep pattern recognition

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What is this talk about?

Machine learning for sleep monitoring and understanding

- Automation of sleep scoring for high-throughput studies
- Computational modeling of sleep for acquiring new biological insights

Case studies – our present and future work

Outline

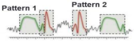
- Introduction
- Automated sleep scoring from EEG/EMG
- Computational modeling of sleep mechanics

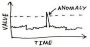
Introduction

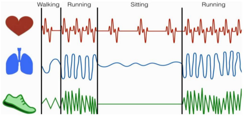
Our research interests

- Dynamical systems
  - Mathematical modeling of time-varying phenomena
  - Statistical inference of parametrized models
  - Structured and interpretable prediction
- Learning of graph structures and dependencies
- Sensor fusion – learning from multimodal data
- Learning for control applications
- etc.

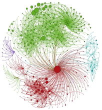
Our research interests

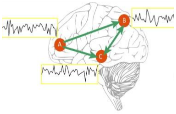






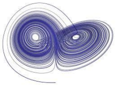
Time series pattern recognition





Discovering causal dependencies and communities in graphs

Learning to control complex dynamical systems

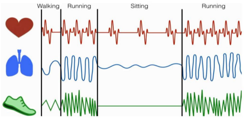


Modeling and statistical inference in dynamical systems

Our research interests

ETH Eidgenössische Technische Hochschule Zürich Swiss Federal Institute of Technology Zurich

MAX PLANCK INSTITUTE FOR INTELLIGENT SYSTEMS



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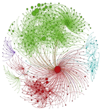

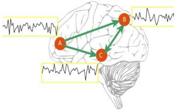

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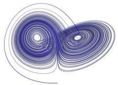
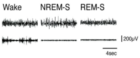
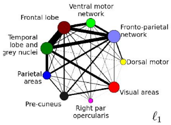


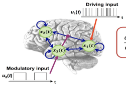
Modeling and statistical inference in dynamical systems



Vigilance state classification



Sleeping Brain state clustering



$$\frac{dx}{dt} = \left(A + \sum_{i=1}^{m} u_i B^{(i)} + \sum_{j=1}^{n} x_j D^{(j)}\right) x + Cu$$

Modeling of brain dynamics and neural populations during sleep

Audio-control of sleep

Applications to sleep analytics

Current collaborations

Universität Zürich[UZH]

INSELSPITAL
UNIVERSITÄTSSPITAL BERN
HOPITAL UNIVERSITAIRE DE BERNE
BERN UNIVERSITY HOSPITAL

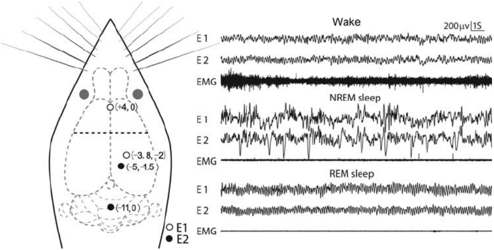
UniversitätsSpital Zürich

UKBB

UNIVERSITÄTS KLINIKUM TÜBINGEN

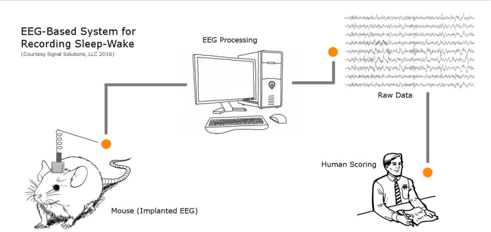
Automated sleep scoring from EEG/EMG

Sleep scoring in animals



- Sleep monitoring in animals is commonly done through vigilance state classification of EEG/EMG recordings
- EEG/EMG signals are partitioned into short epochs of equal size
- Each epoch is then individually scored accordingly, w.r.t. corresponding vigilance state

Sleep scoring in animals



Typical experimental pipeline:

1. Perform "intervention" on an animal subset
2. Record EEG/EMG signals over some period of time
3. Manually score EEG/EMG
4. Perform statistical posthoc analysis on scored data

Manual sleep scoring is a bottleneck

- Slow!
- Laborious
- Prone to human errors
- Non-standardized
- Decoupled from posthoc analysis

Automating sleep scoring

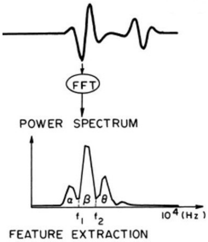
Some research efforts aim to replace visual inspection

- Automation of sleep scoring for both animals* and humans
- Current state-of-the-art solution offer promising prediction performance
- Some generalization issues of current solutions still remain

*Sunagawa, G. A., Sei, H., Shimba, S., Urade, Y., & Ueda, H. R. (2013). FASTER: an unsupervised fully automated sleep staging method for mice. Genes to Cells, 18(6), 502-518.

Current solutions take 2-step approach

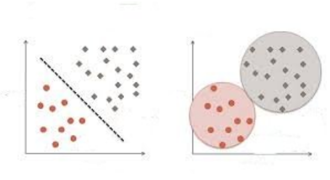
1. Feature extraction



- Features = frequency band energies

2. Classification

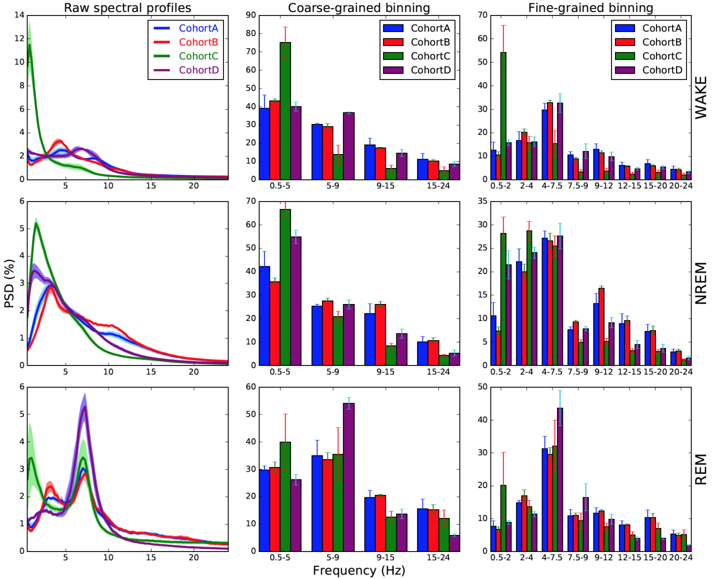
- Supervised classification (e.g. using SVMs or RFs)
- Clustering techniques for unsupervised learning



Problems with 2-step approach

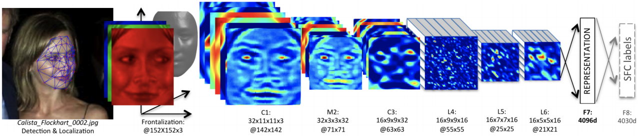
- Feature inconsistency
- Different distribution for different cohorts

Problem: feature inconsistency across animal cohorts



Idea

- "End-to-end" deep learning framework to combine the two steps
- Convolutional neural networks achieve translational invariance



DeepFace architecture for facial recognition *

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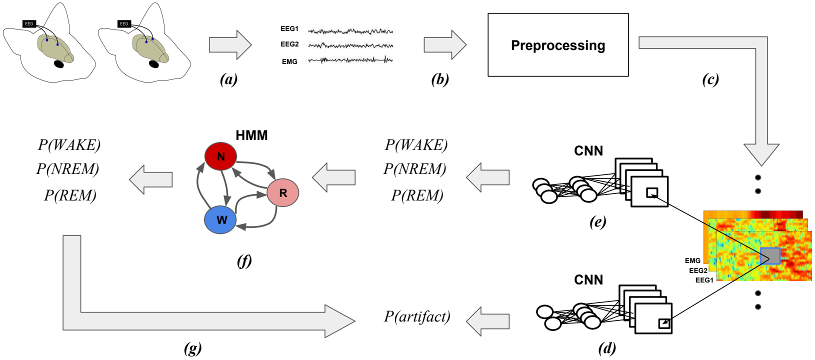
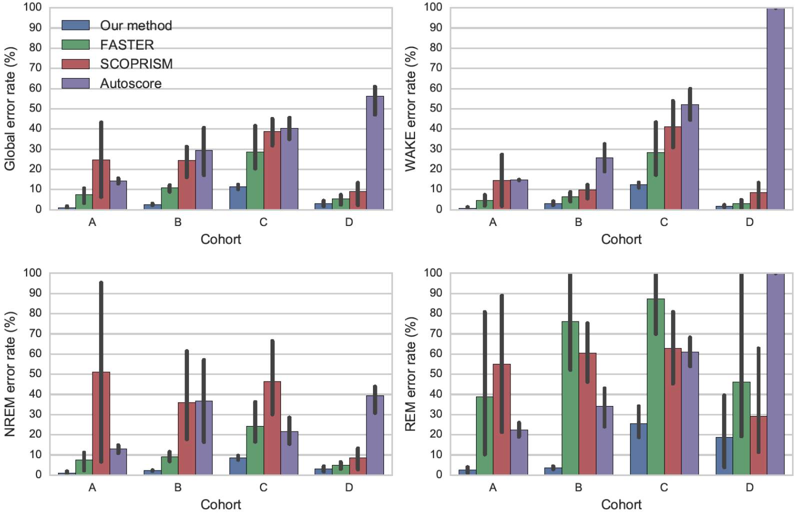
*TAIGMAN, Yaniv, et al. Deepface: Closing the gap to human-level performance in face verification. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2014. S. 1701-1708.

Our proposal pipeline (paper under review)

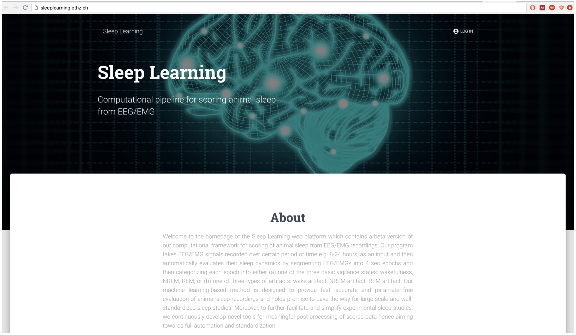


Performance comparison with other solutions



Publicly available web service

http://sleeplearning.ethz.ch/



- "Plug and play" framework
- Seamless integration with downstream analysis
- Simple and efficient interaction with sleep practitioners
- Possibility to include meta information

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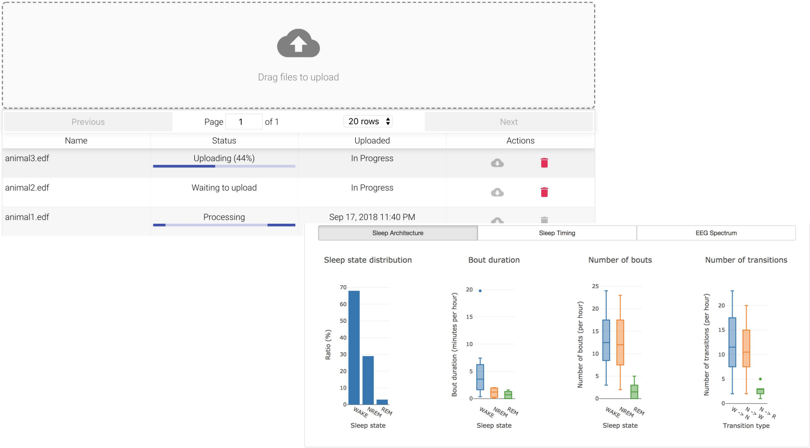
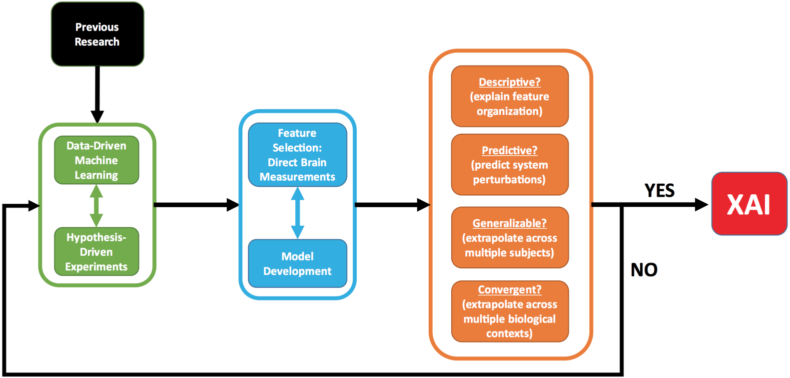


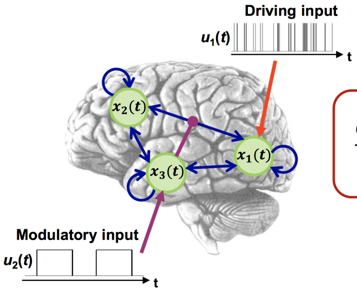
Computational modeling of sleep mechanics

Machine learning and neuroscience: shared vision



Vu et al. "A shared vision for machine learning in neuroscience." Journal of Neuroscience, 2018

Mechanism behind Neurodegenerative Diseases *



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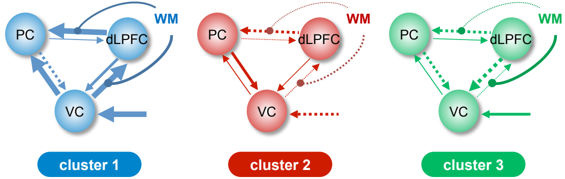
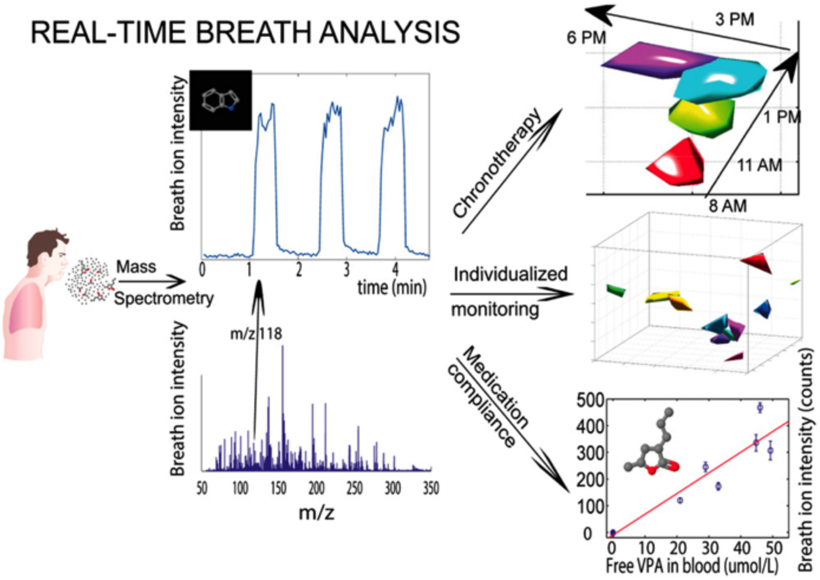


WM:	working memory
dLPFC:	dorsolateral prefrontal cortex
PC:	parietal cortex
VC:	visual cortex

Kay Brodersen (2012)

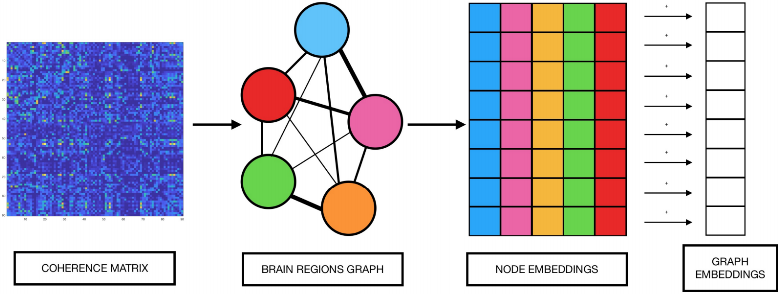
*Ongoing work with Klaas Enno Stephan, Nico Gorbach, Frances Hubis, Joachim M. Buhmann

Zurich Exhalomics*



*Ongoing work with Pablo Sinues, Steven Brown

Sleeping Brain State Clustering



Joint work with Emily Coffey, Steffen Gais, Jan Born.

Sleeploop Zurich

Joint work with Reto Huber, Walter Karlen, Christian Baumann.

Further Interests

Modeling of whole Brain Dynamics

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Interventional Studies based on Sleep Scoring

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Computational Modeling of Sleep
e.g. Costa et al. "A thalamocortical neural mass model of the EEG during NREM Sleep and its response to auditory stimulation." *PLoS computational biology*, 2016

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Meta-Data for Server

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Usage of the Sleep Server

Questions?