Machine Learning on EEG: From sleep to brain age

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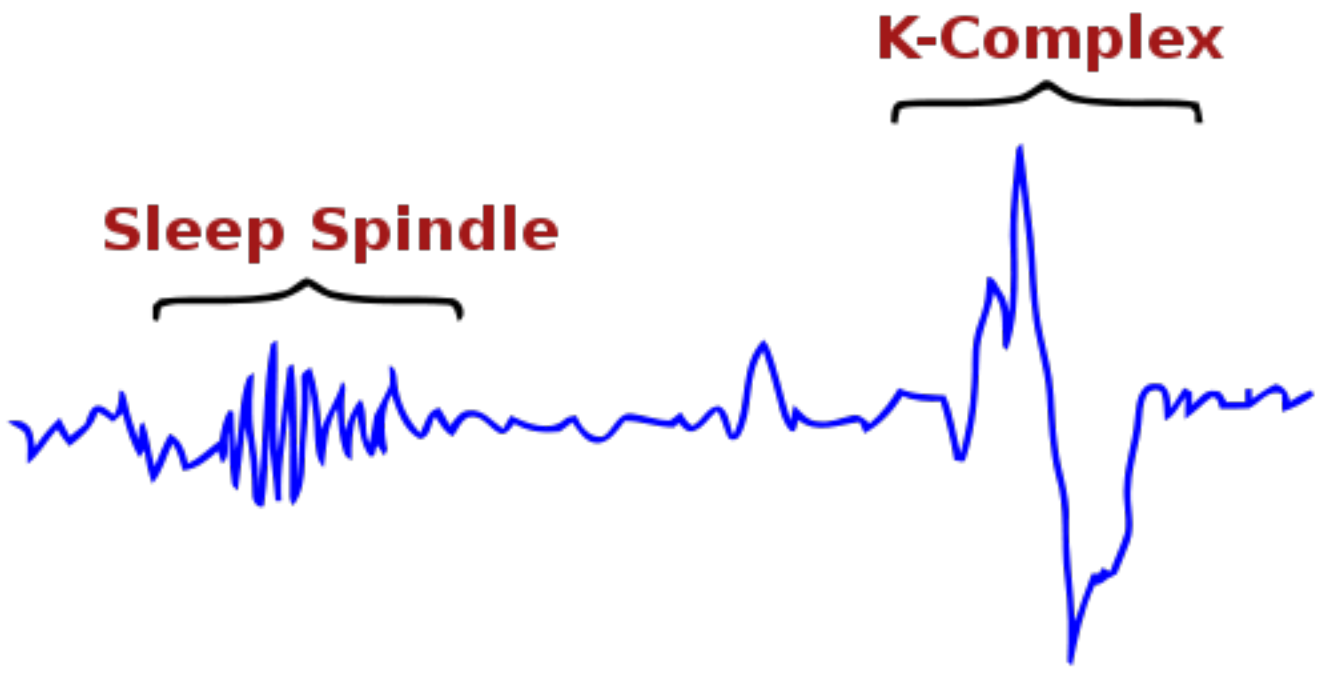
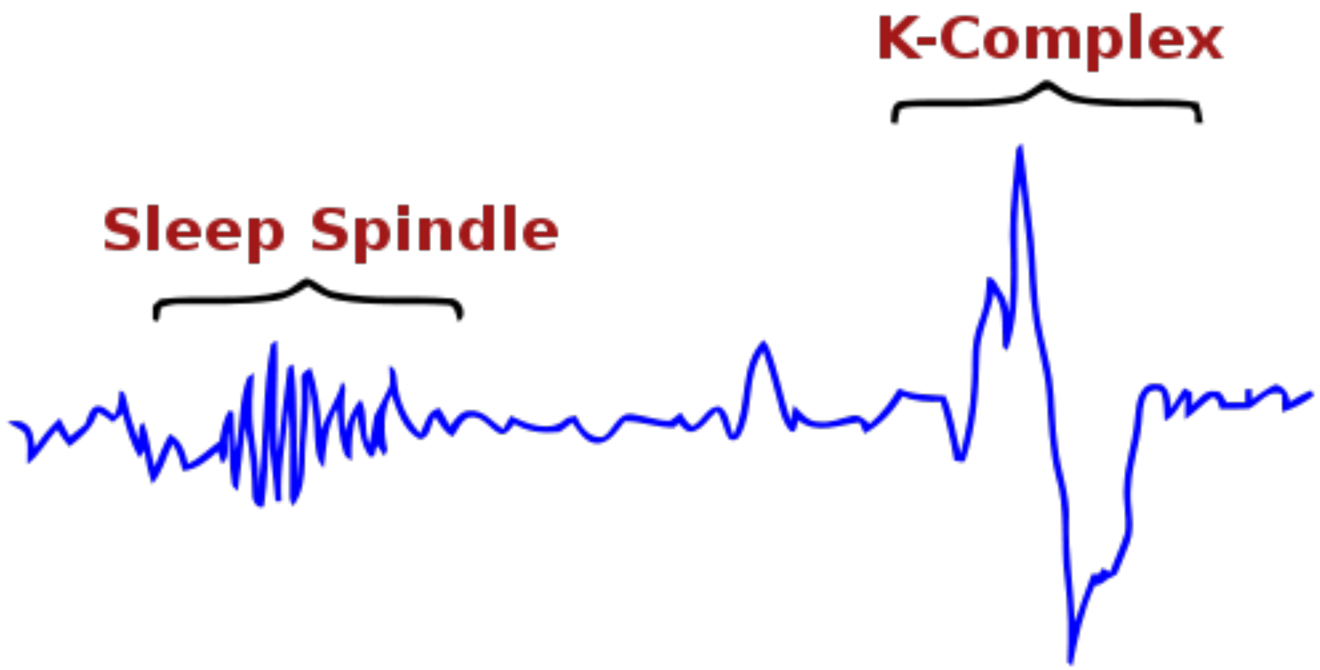
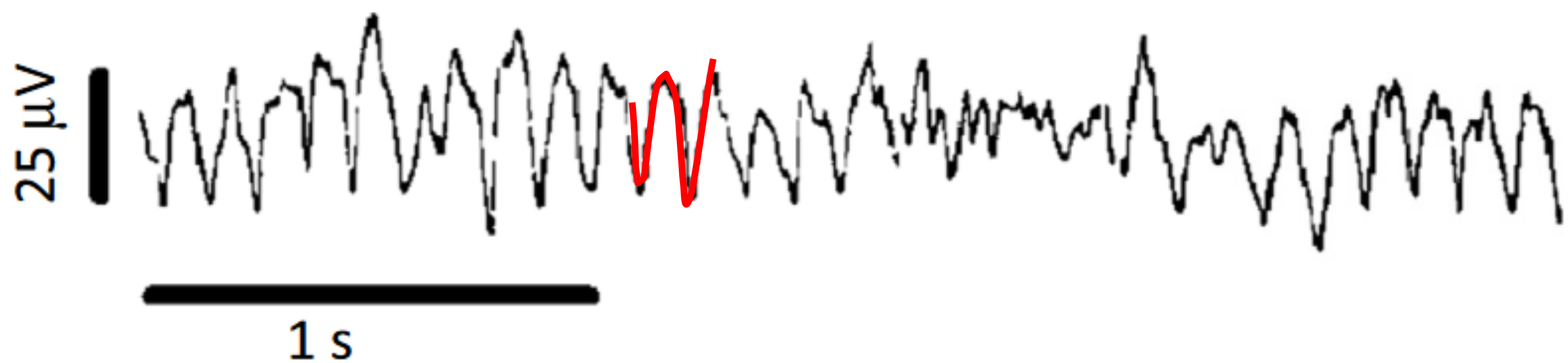
NeoBrain - 2021

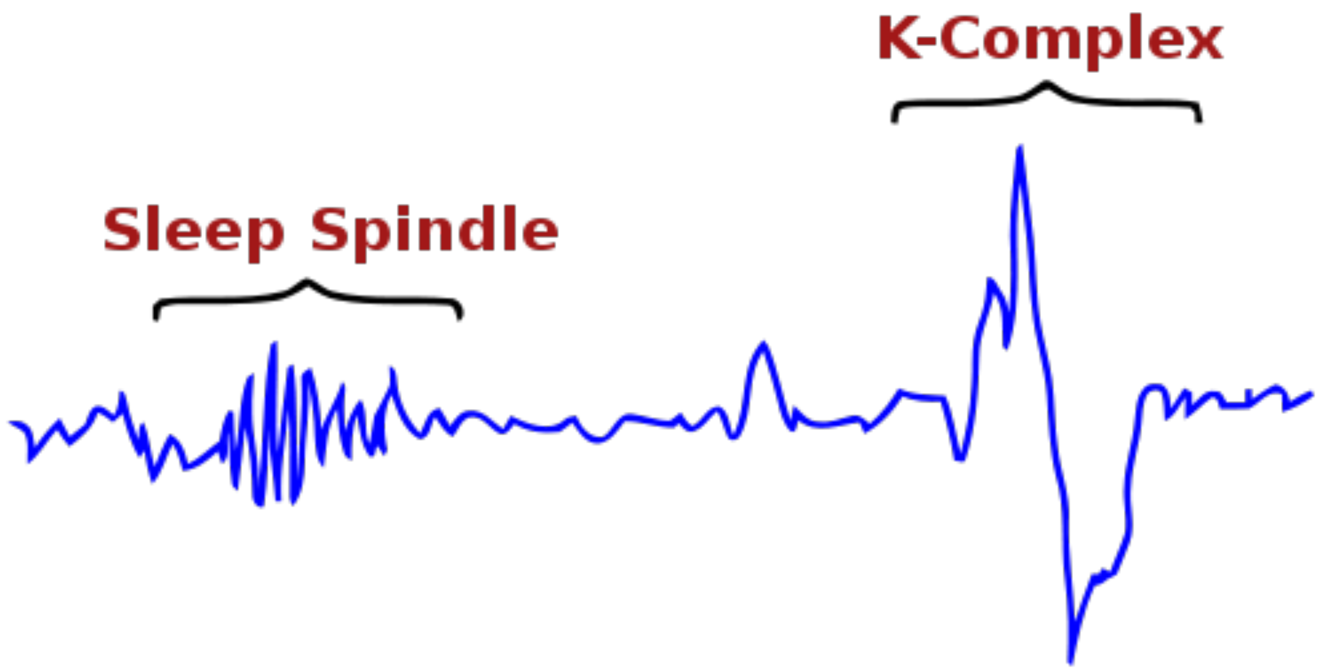


K-Complex
Sleep Spindle



μ rhythm





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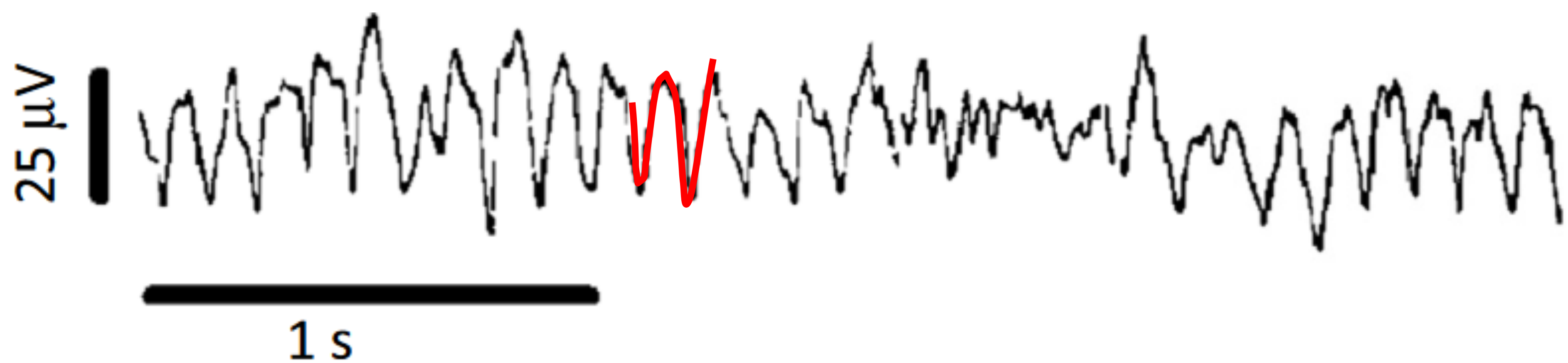
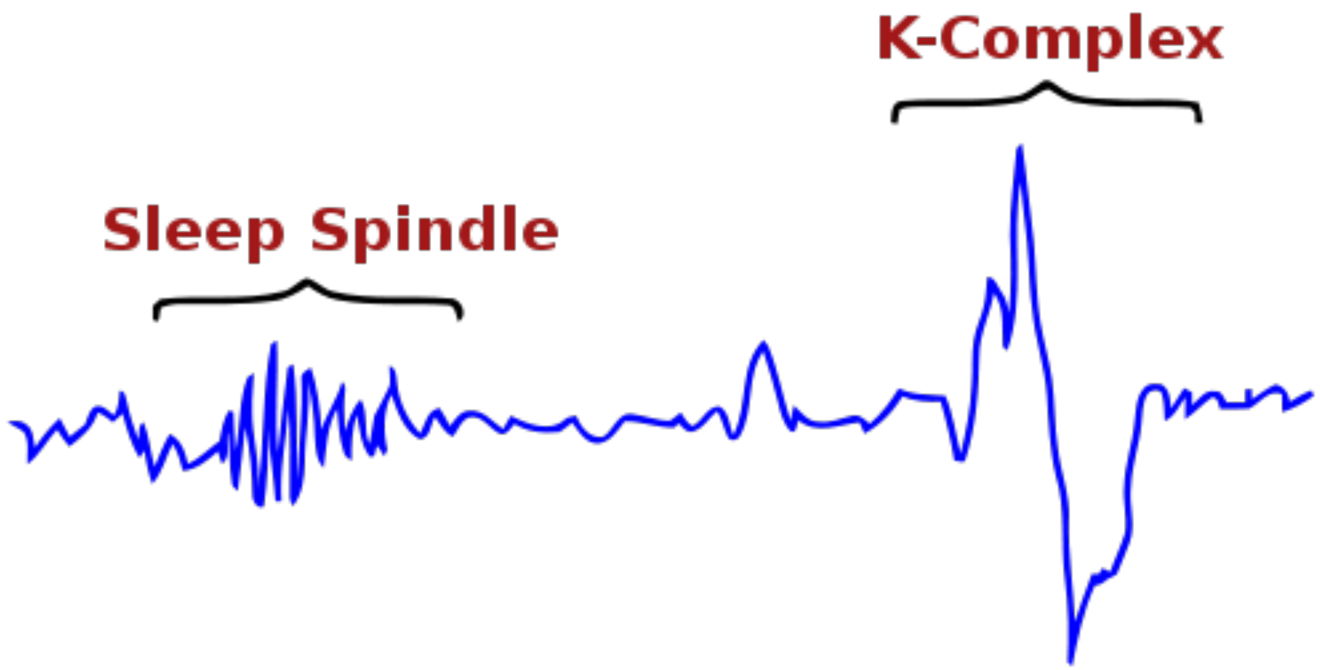
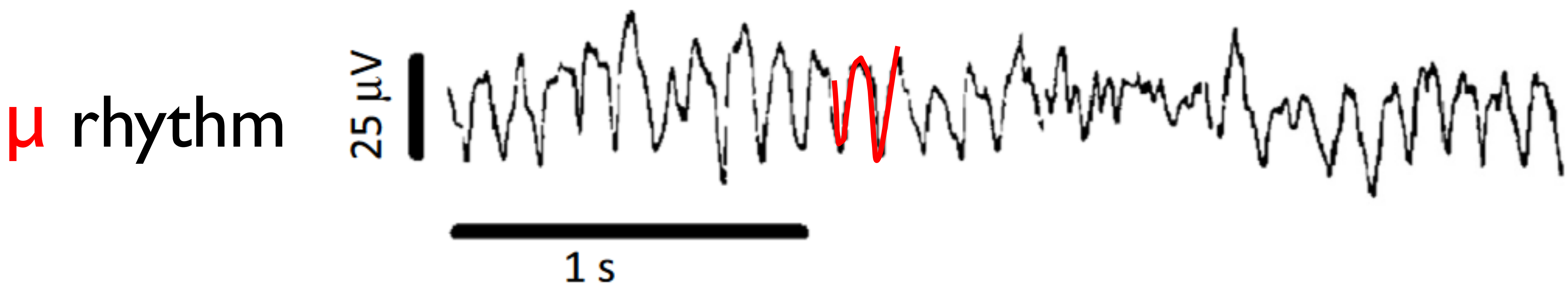


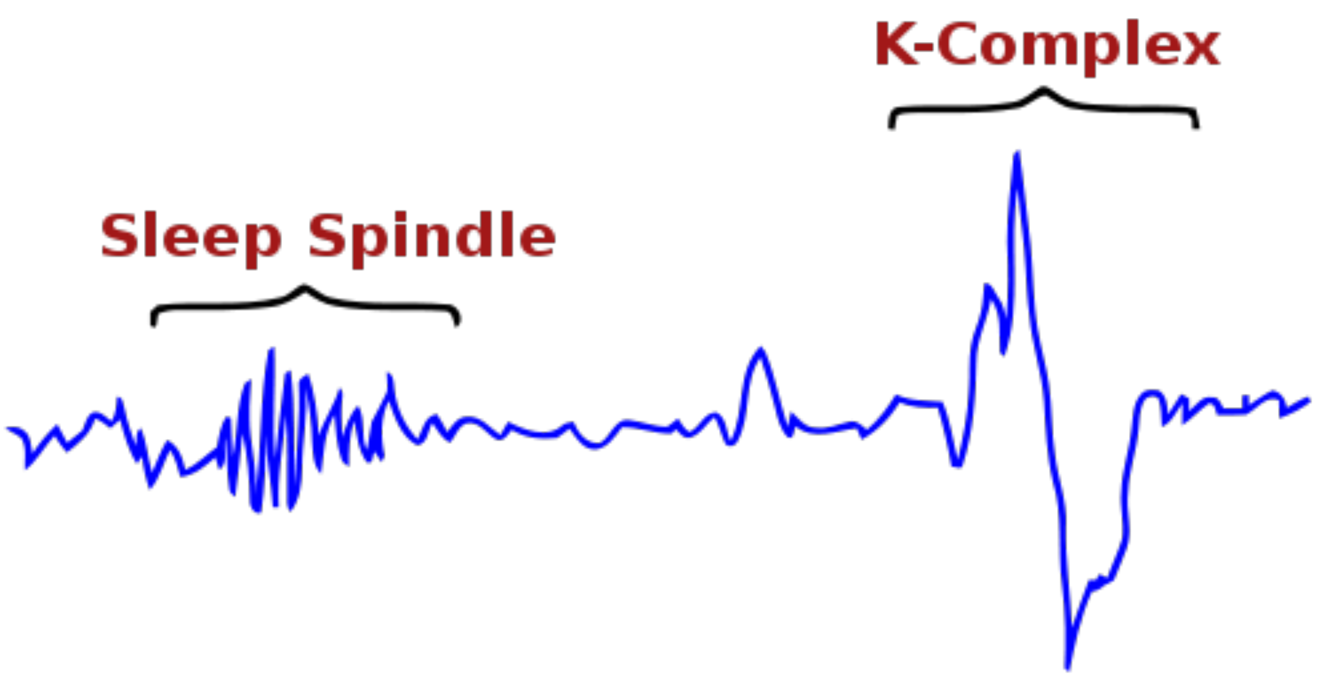
[T. Dupré la Tour, L. Tallot, L. Grabot, V. Doyère, V. van Wassenhove, Y. Grenier, A. Gramfort, (2017) PLOS Computational biology]



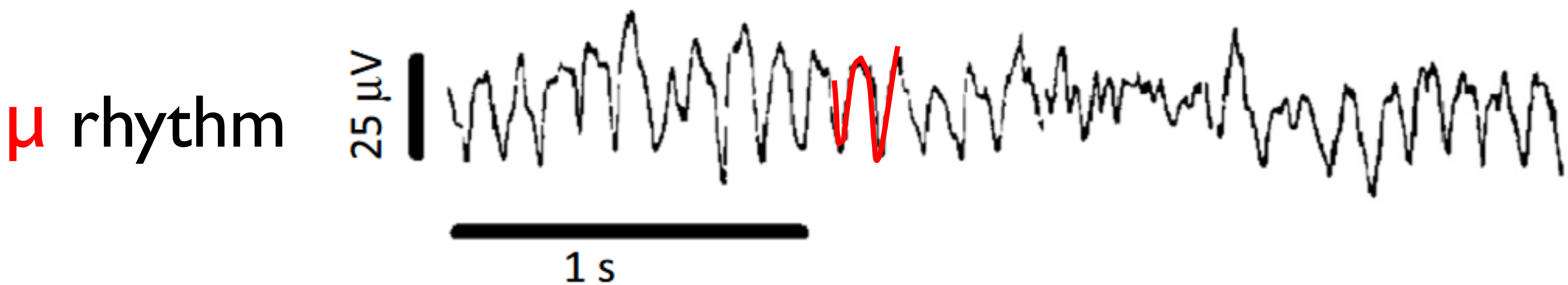


CFC: High frequency bursts coupled with slow waves

[T. Dupré la Tour, L. Tallot, L. Grabot, V. Doyère, V. van Wassenhove, Y. Grenier, A. Gramfort, (2017) PLOS Computational biology]



Neural signals exhibit diverse and complex morphologies



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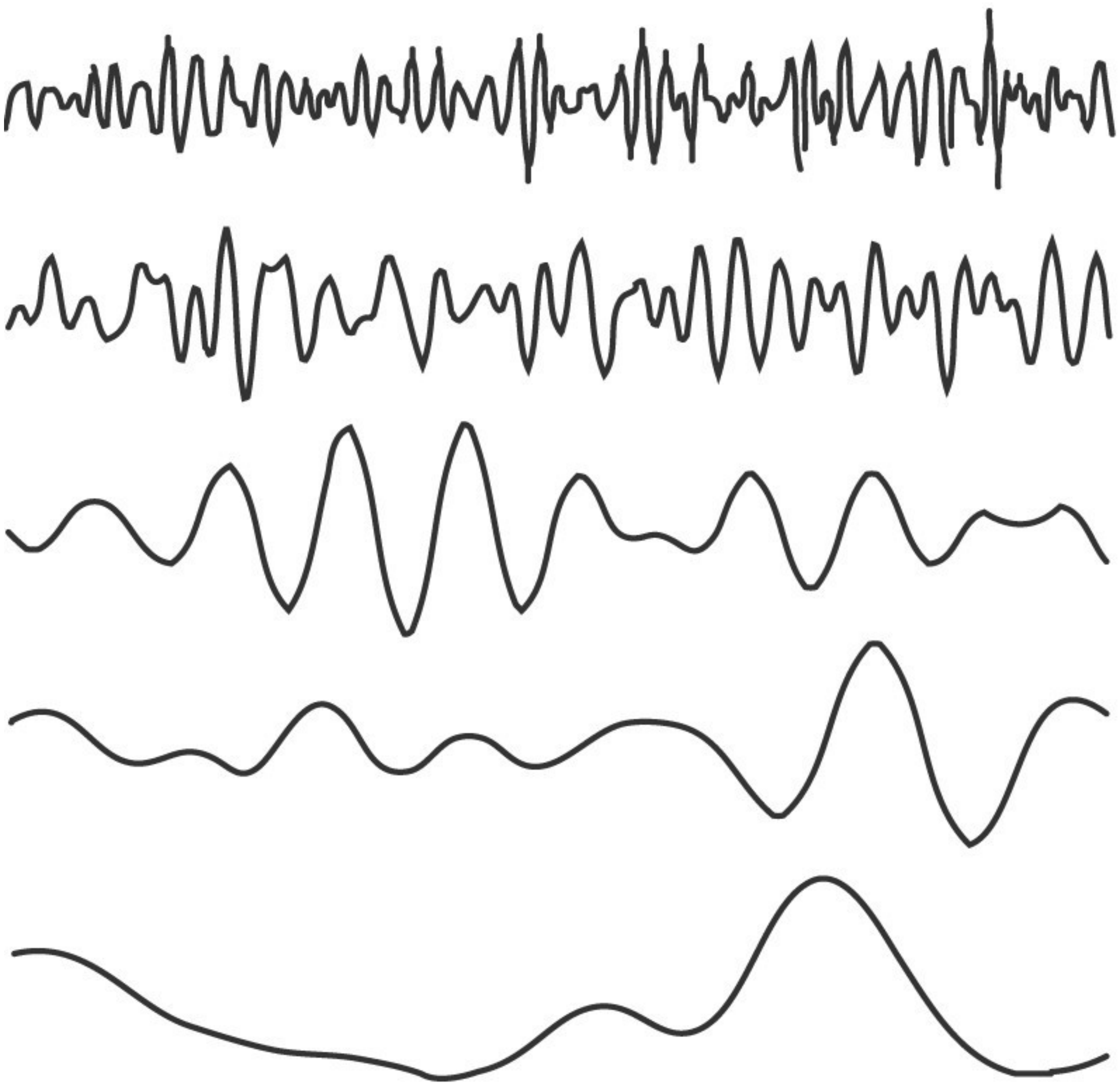
“Bandology”



Gamma
(> 25 Hz)

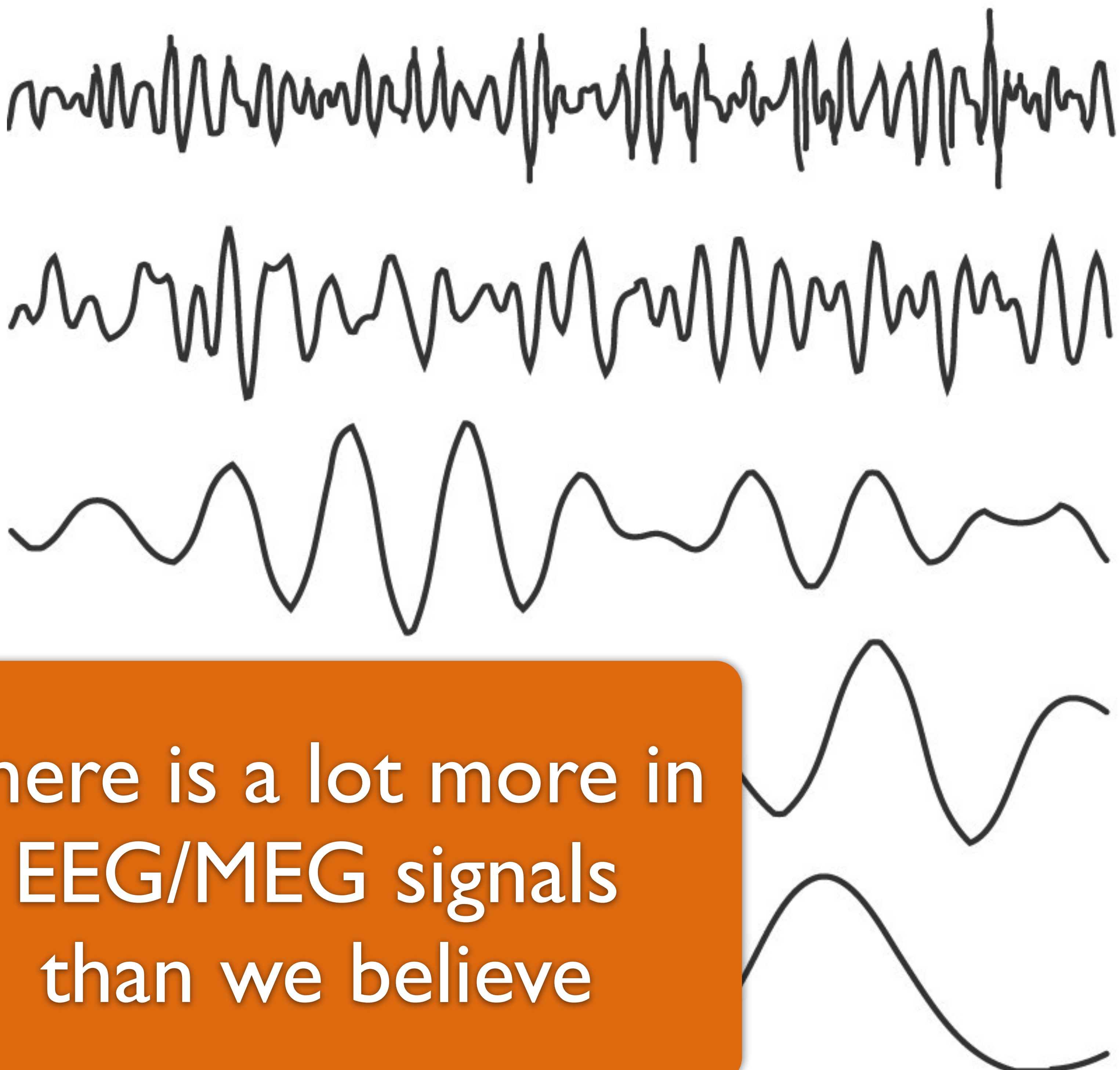
Beta
(12-25 Hz)

Alpha
(8-12 Hz)

Theta
(4-8 Hz)

Delta
(1-4 Hz)

“Bandology”



Gamma
(> 25 Hz)

Beta
(12-25 Hz)

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(8-12 Hz)

Theta
(4-8 Hz)

Delta
(1-4 Hz)

There is a lot more in EEG/MEG signals than we believe

1

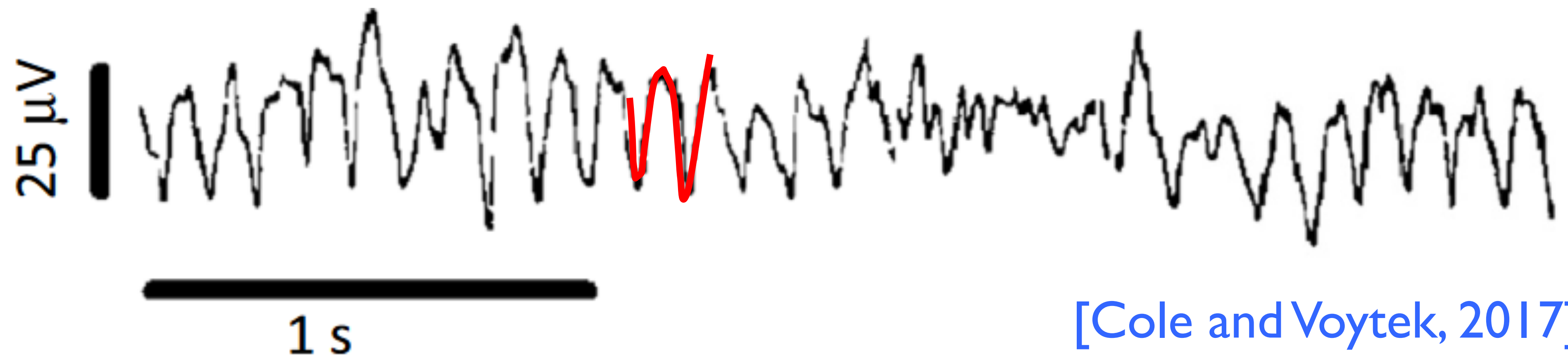
Convolutional Sparse Coding (CSC) for learning the morphology of neural signals

Multivariate Convolutional Sparse Coding for Electromagnetic Brain Signals, (2018), T. Dupré la Tour, T. Moreau, M. Jas, A. Gramfort, Proc. NIPS Conf.
Learning the Morphology of Brain Signals Using Alpha-Stable Convolutional Sparse Coding, (2017), M. Jas, T. Dupré la Tour, U. Simsekli, A. Gramfort, Proc. NIPS Conf.

Code: https://alphacsc.github.io

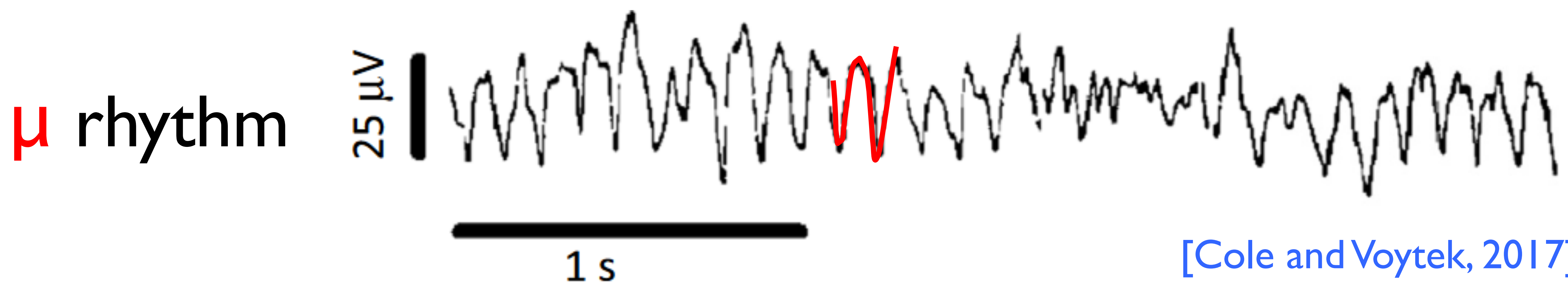
Shape of brain rhythms matter

μ rhythm



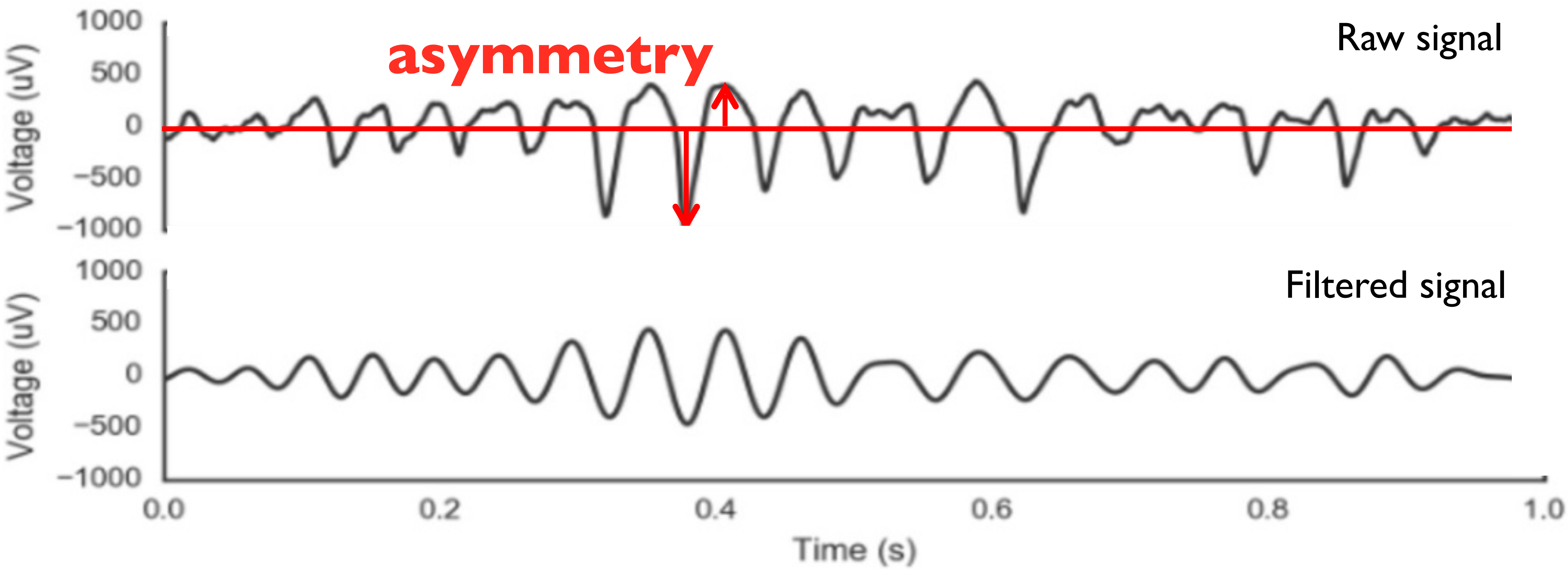
[Cole and Voytek, 2017]

Shape of brain rhythms matter



[Cole and Voytek, 2017]

Problem of linear filtering:



Shape of brain rhythms matter

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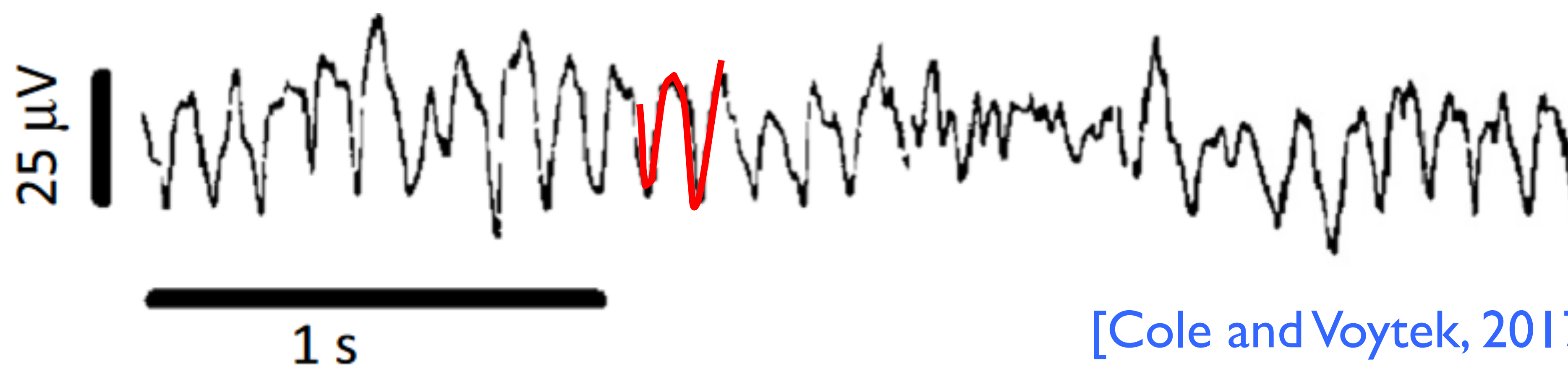
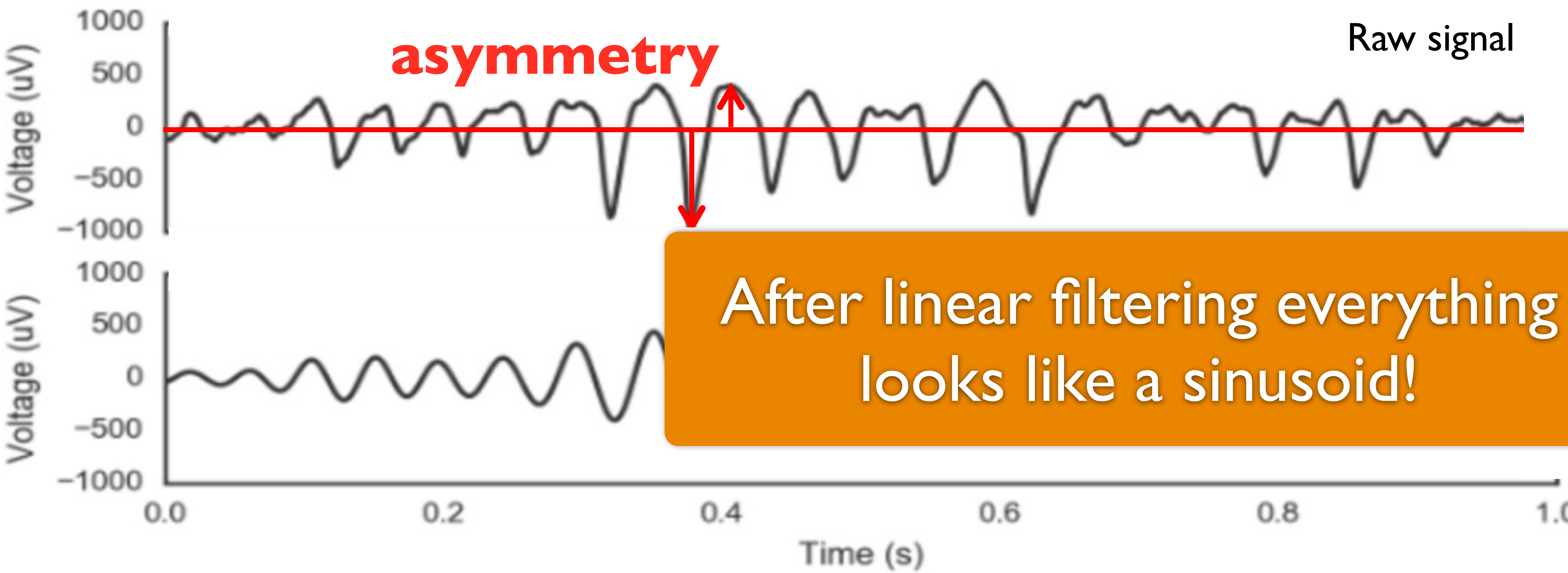


[Cole and Voytek, 2017]

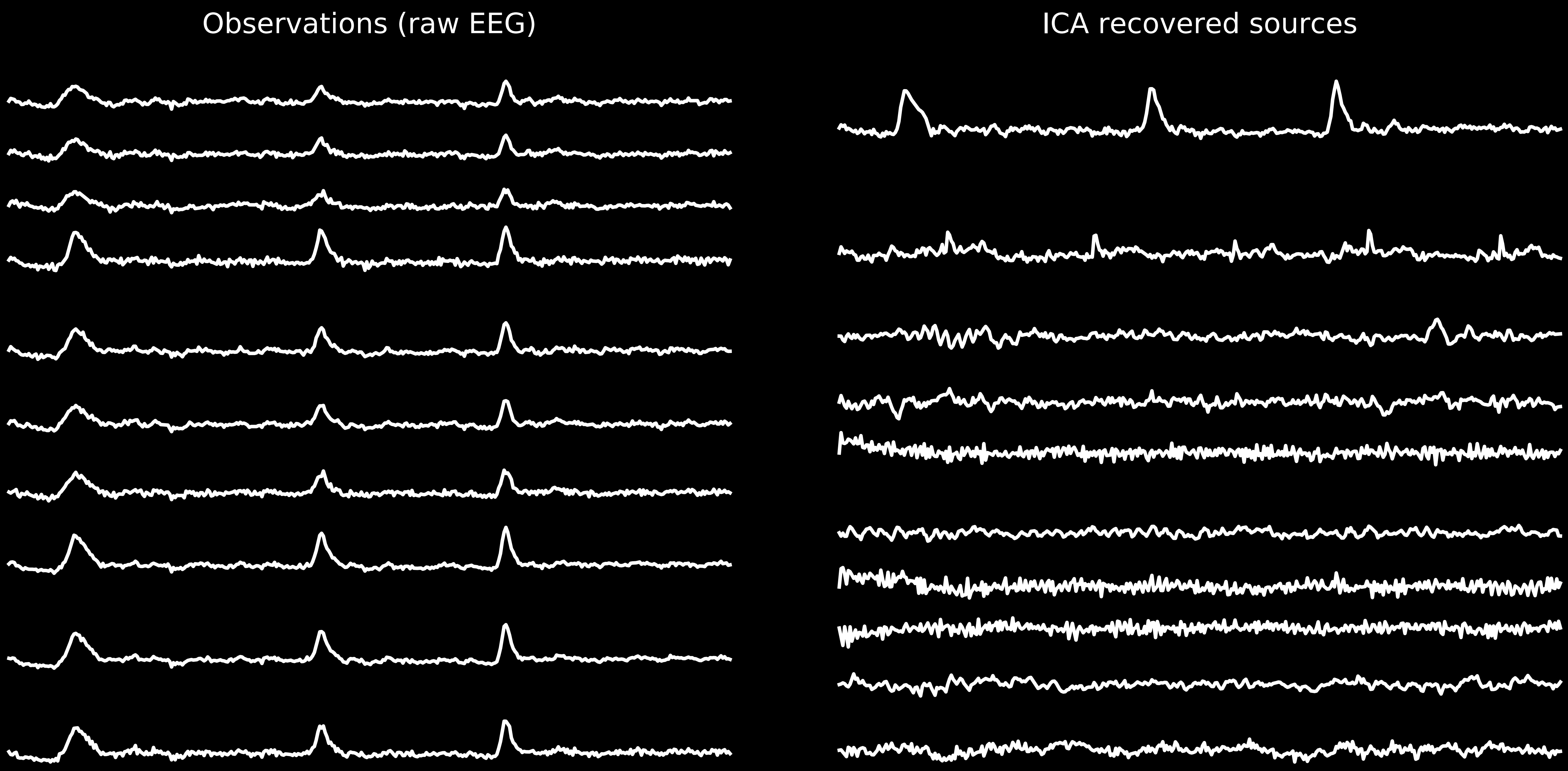
Problem of linear filtering:



After linear filtering everything looks like a sinusoid!

From ICA to CSC

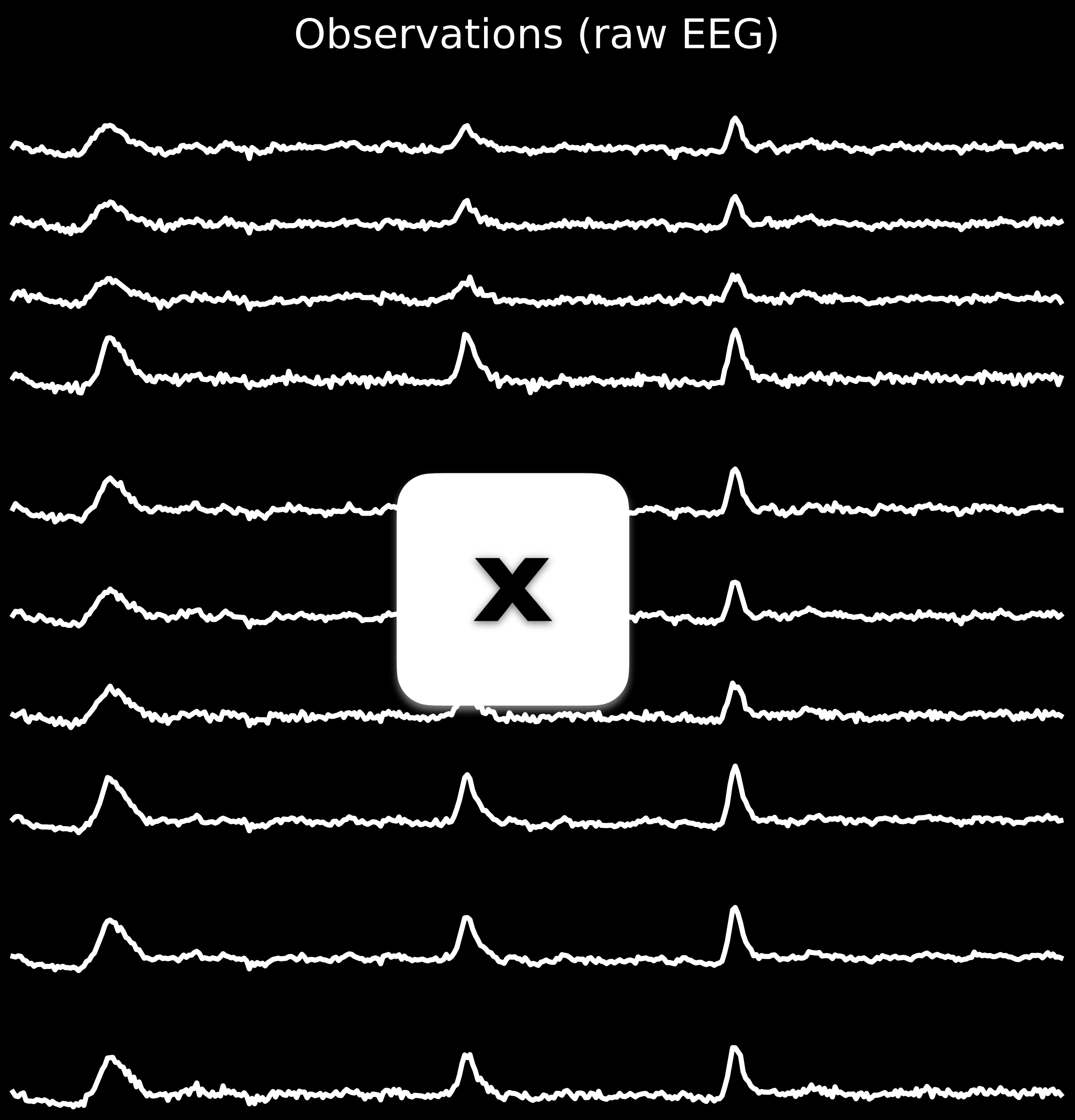
Independent Component Analysis (ICA)

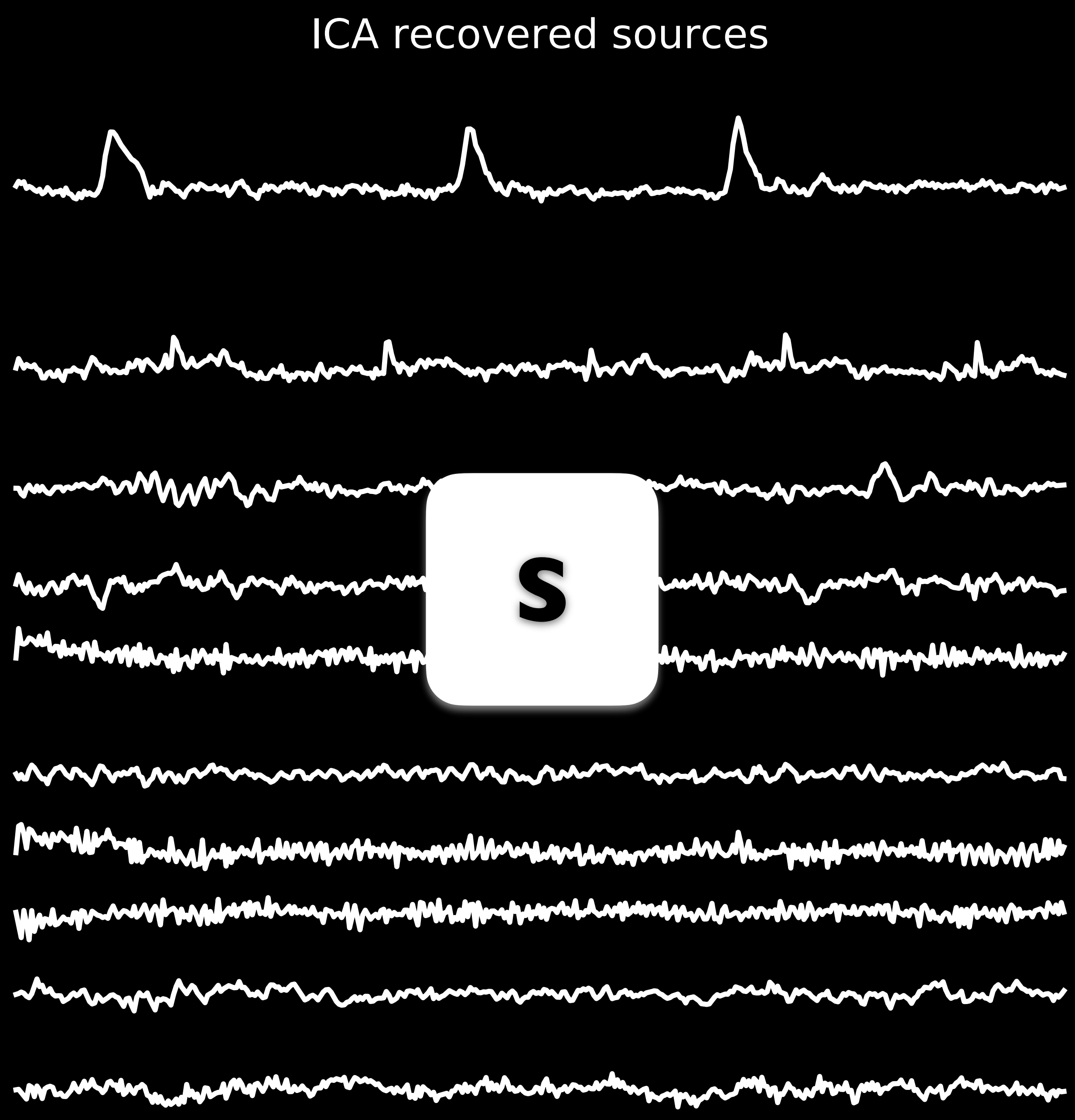


https://pypi.python.org/pypi/python-picard/0.1

From ICA to CSC

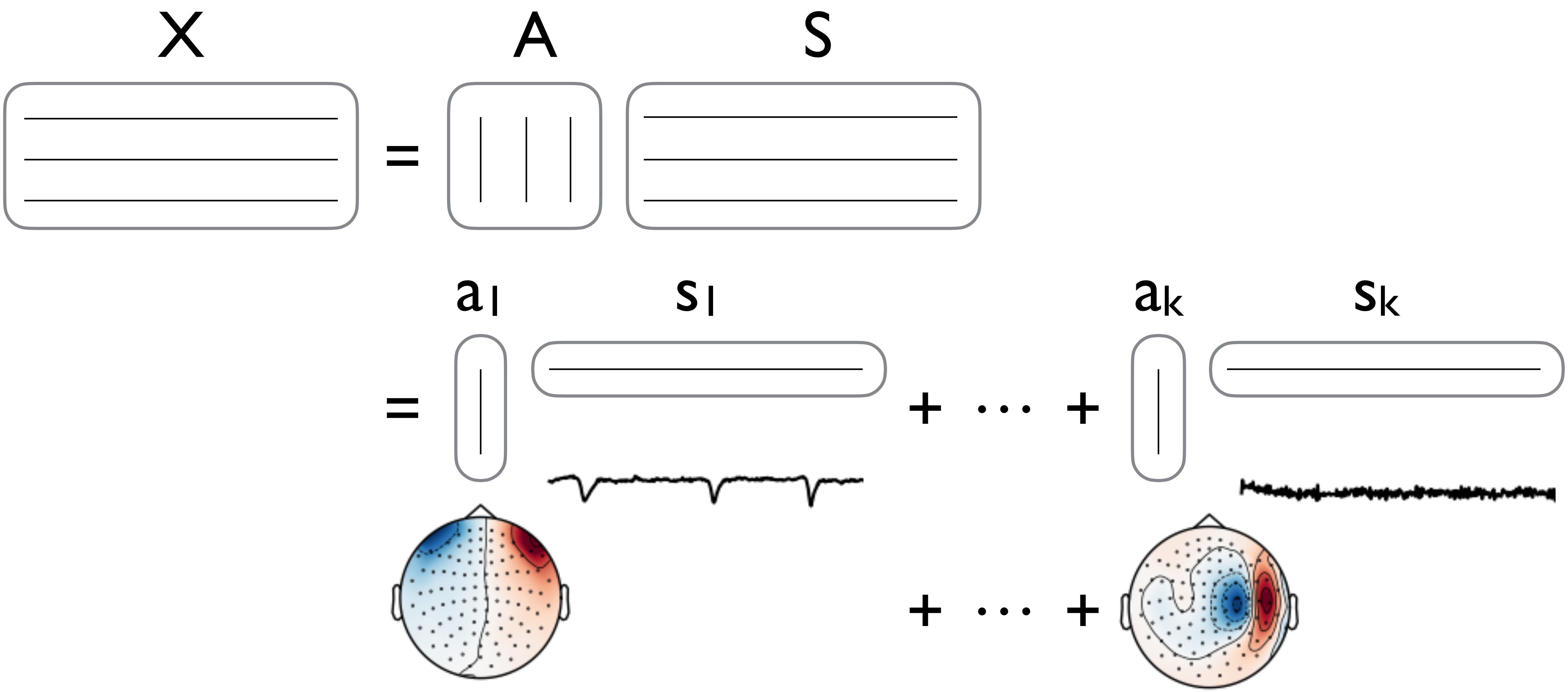
Independent Component Analysis (ICA)





https://pypi.python.org/pypi/python-picard/0.1

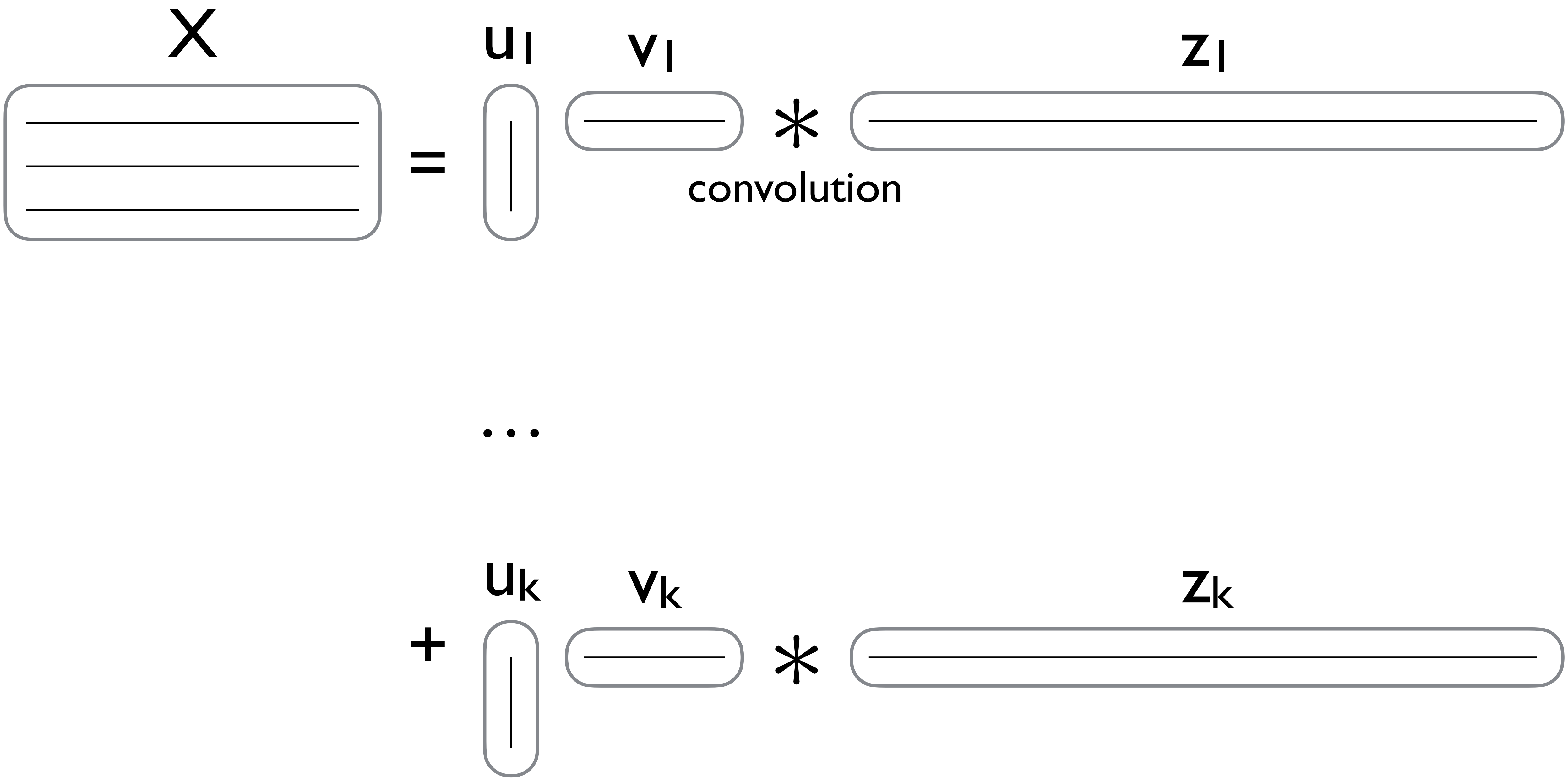
From ICA...



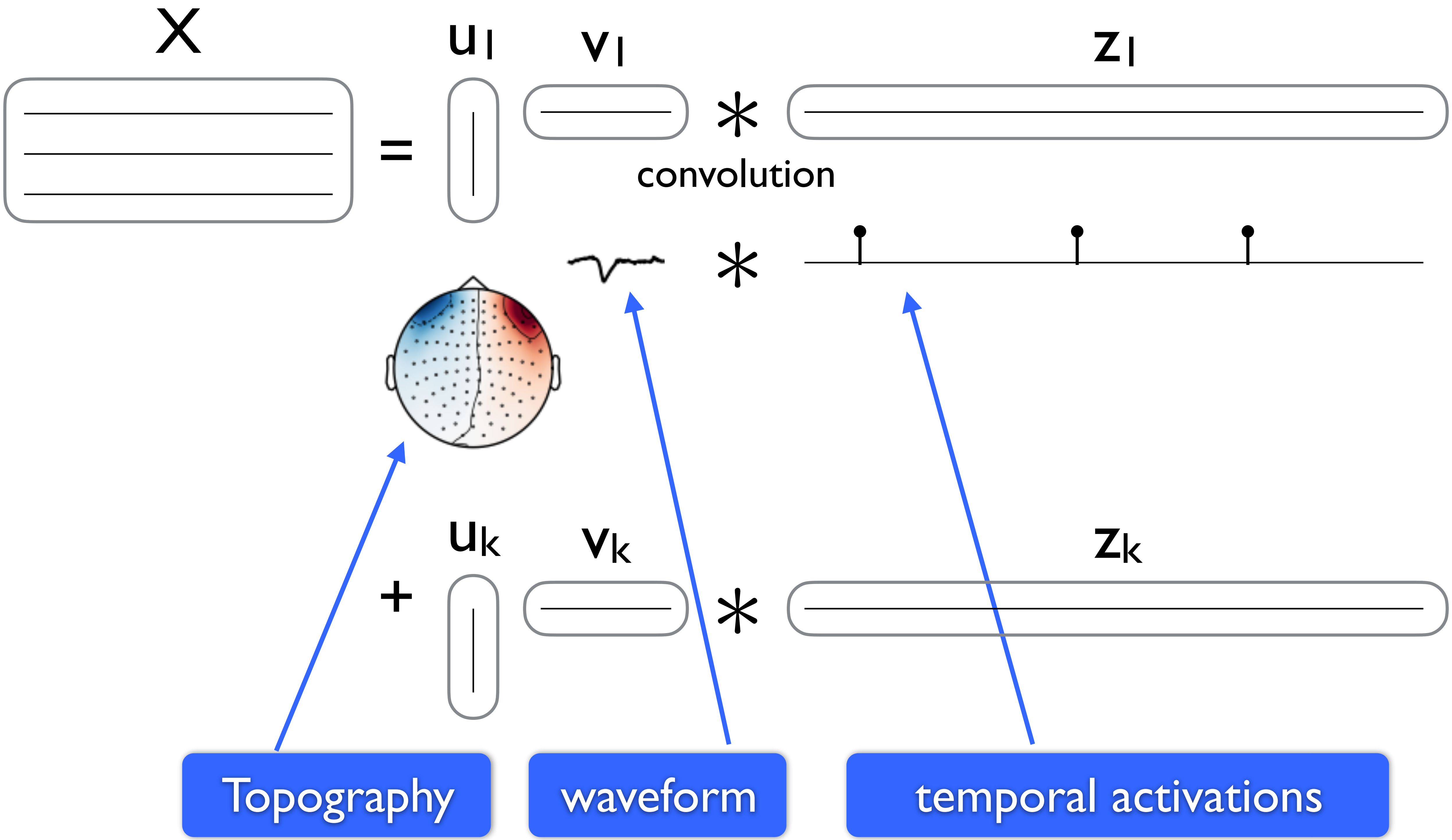
https://mne.tools/stable/auto_tutorials/preprocessing/plot_40_artifact_correction_ica.html

https://pierreablin.github.io/picard/auto_examples/plot_ica_eeg.html

… to CSC

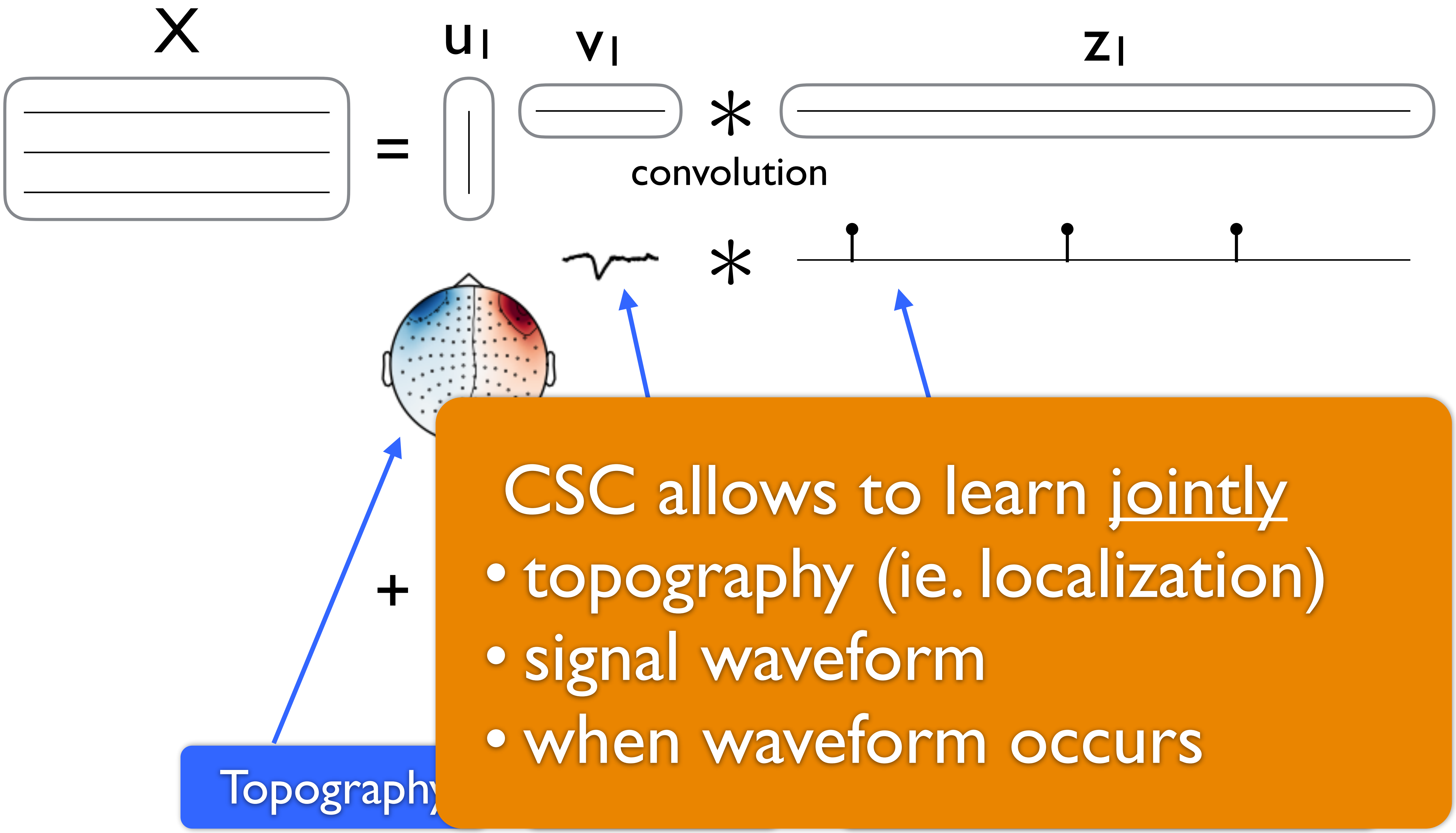


... to CSC



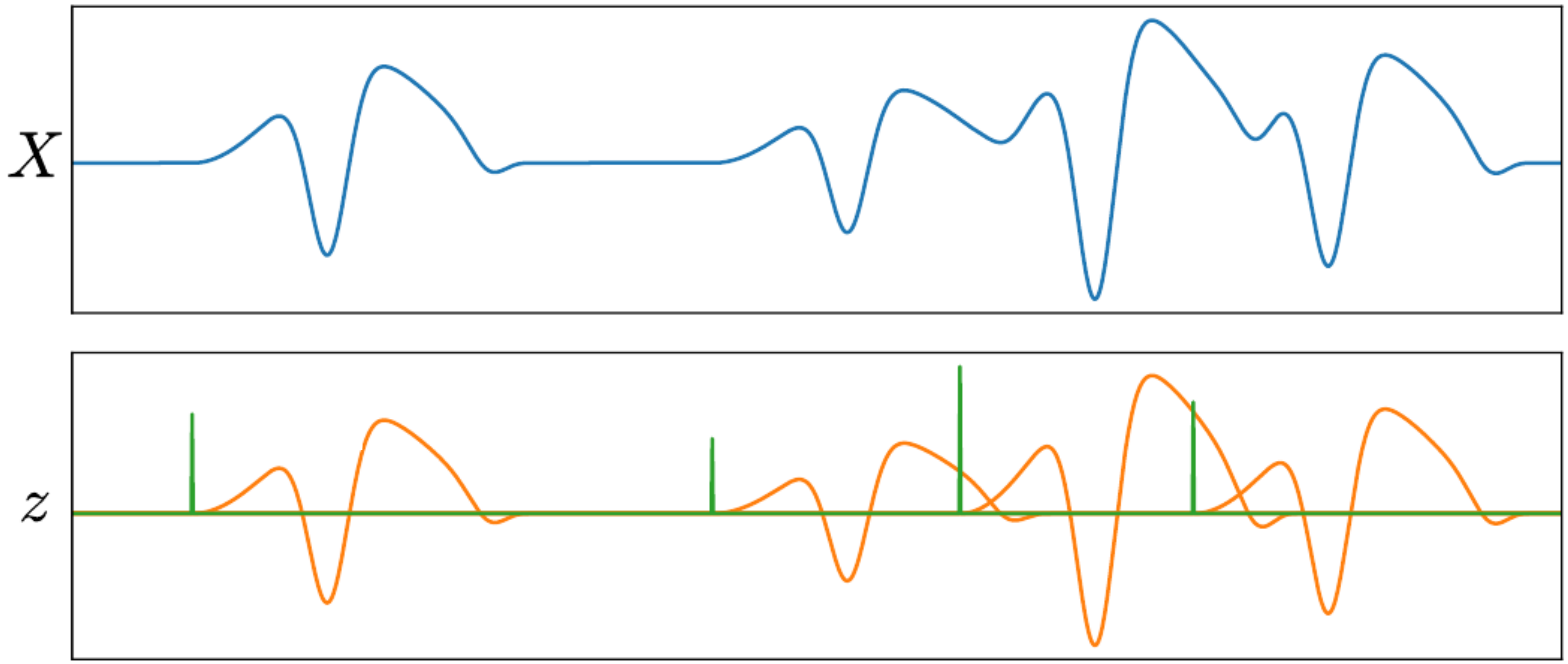
X
=
u_1
v_1
z_1
convolution
+
u_k
v_k
z_k
Topography
waveform
temporal activations

. . . to CSC



CSC allows to learn <u>jointly</u>
- topography (ie. localization)
- signal waveform
- when waveform occurs

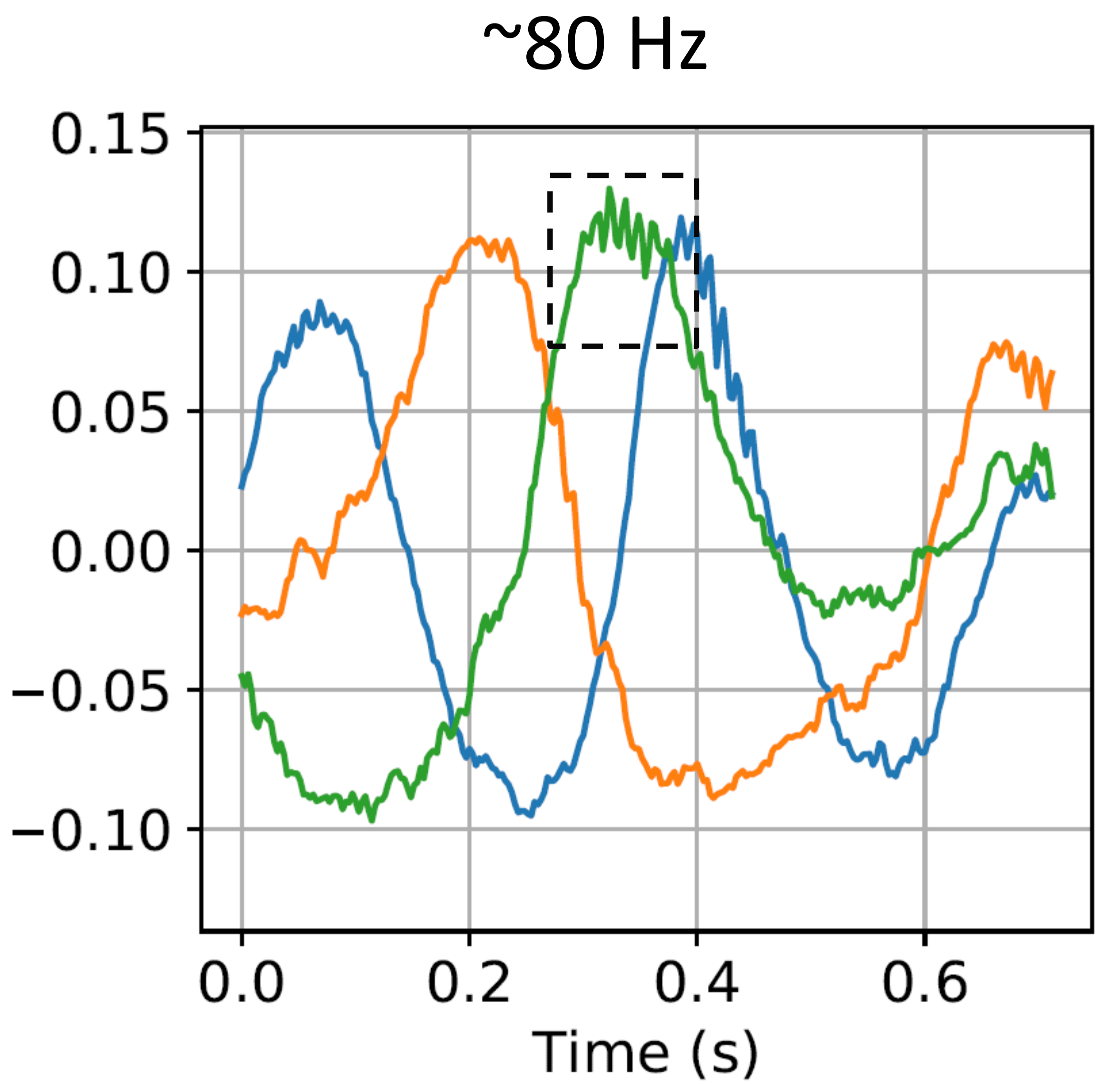
Multivariate CSC

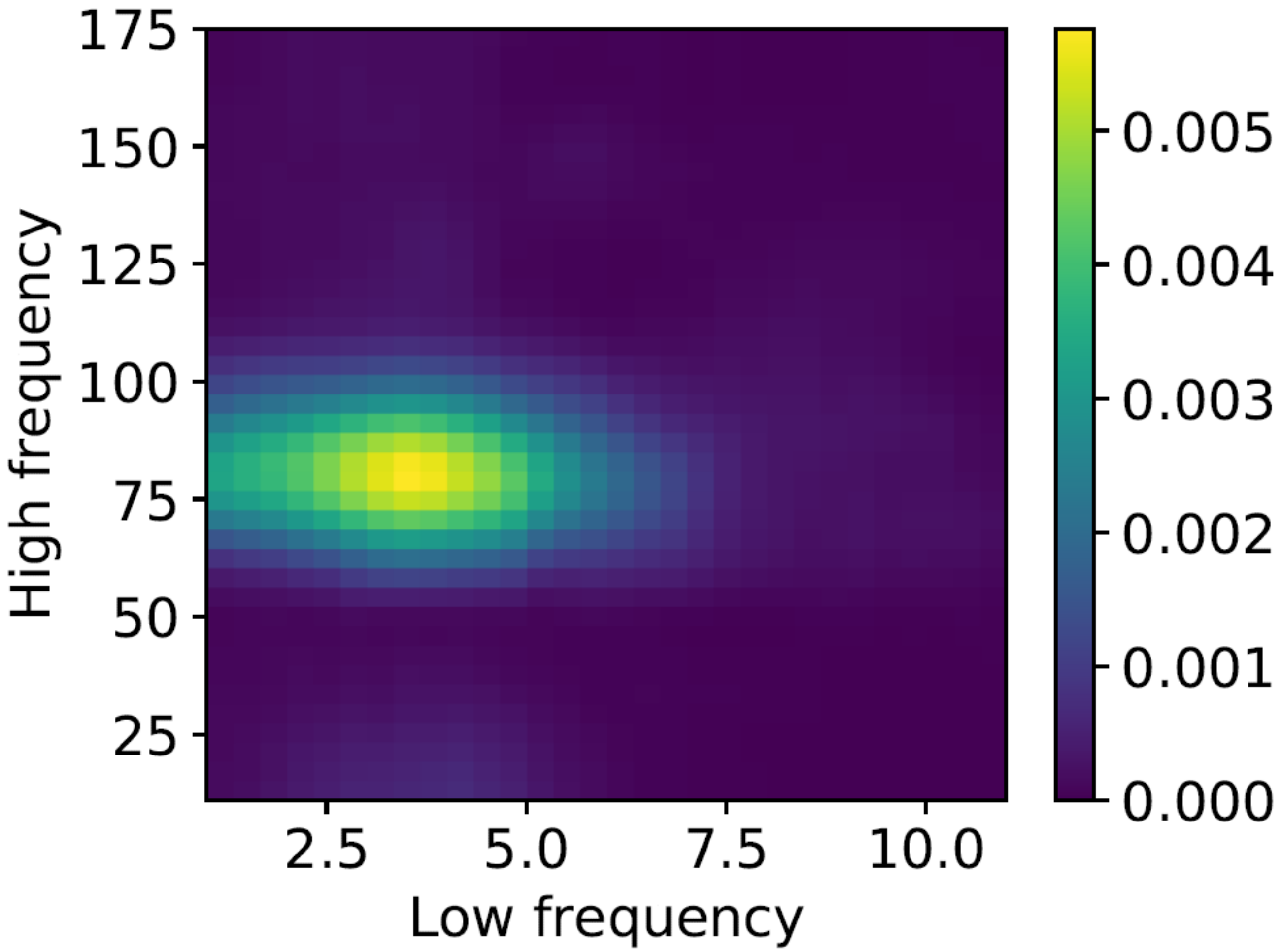


$$\min_{u,v,z} \sum_{n=1}^{N} \frac{1}{2} \left\| \boxed{X^n} - \sum_{k=1}^{K} \boxed{z_k^n} * \boxed{(u_k v_k^\top)} \right\|_2^2 + \lambda \sum_{k=1}^{K} \|z_k^n\|_1 \,,$$
$$\text{s.t.} \quad \|u_k\|_2^2 \leq 1 \;,\; \|v_k\|_2^2 \leq 1 \text{ and } z_k^n \geq 0.$$

[Multivariate Convolutional Sparse Coding for Electromagnetic Brain Signals, (2018), T. Dupré la Tour, T. Moreau, M. Jas, A. Gramfort, Proc. NeurIPS Conf.]

CSC on LFP





Signal from the striatum of a rodent

[Learning the Morphology of Brain Signals Using Alpha-Stable Convolutional Sparse Coding, (2017), M. Jas, T. Dupré la Tour, U. Simsekli, A. Gramfort, Proc. NIPS Conf.]

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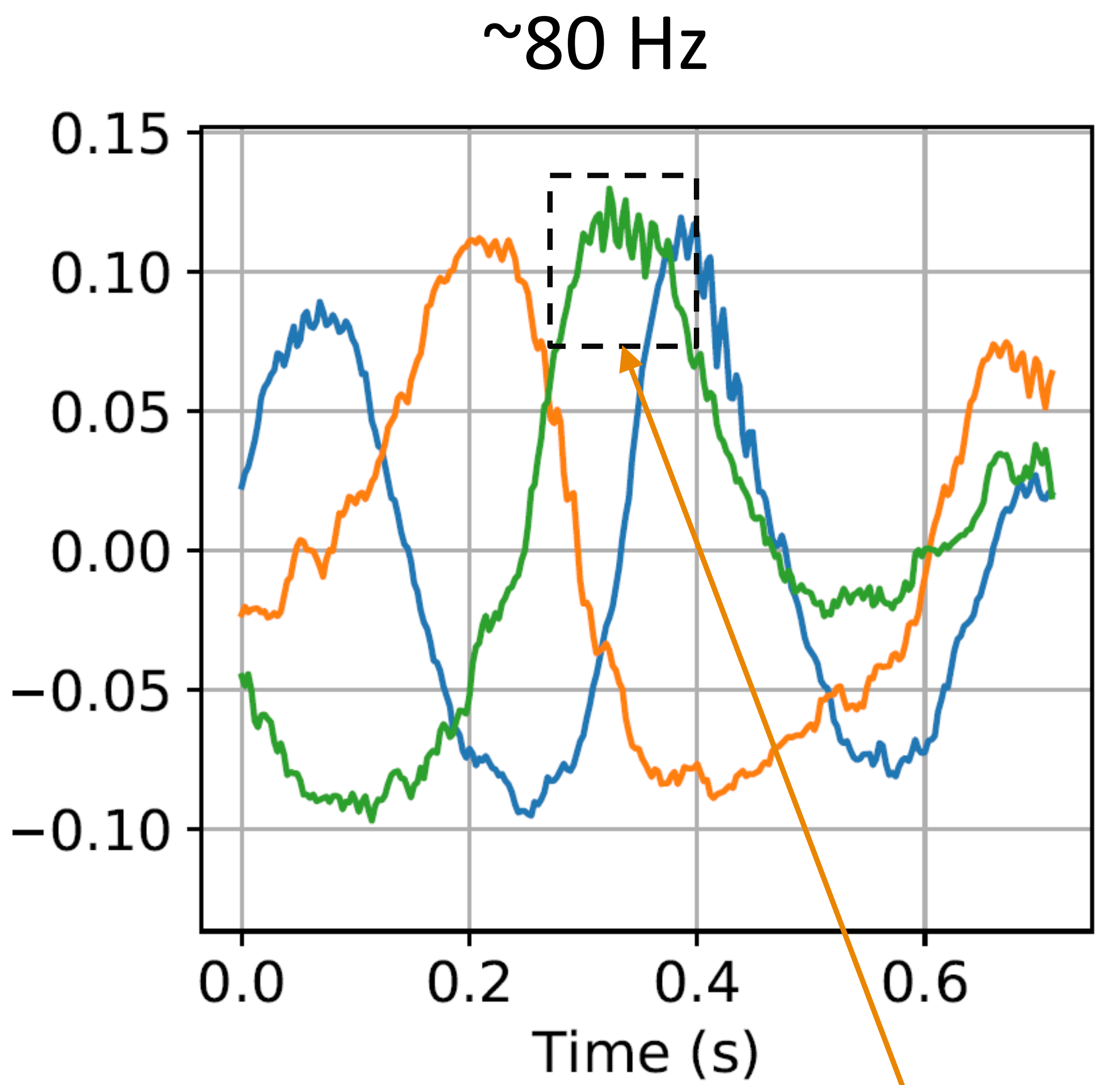

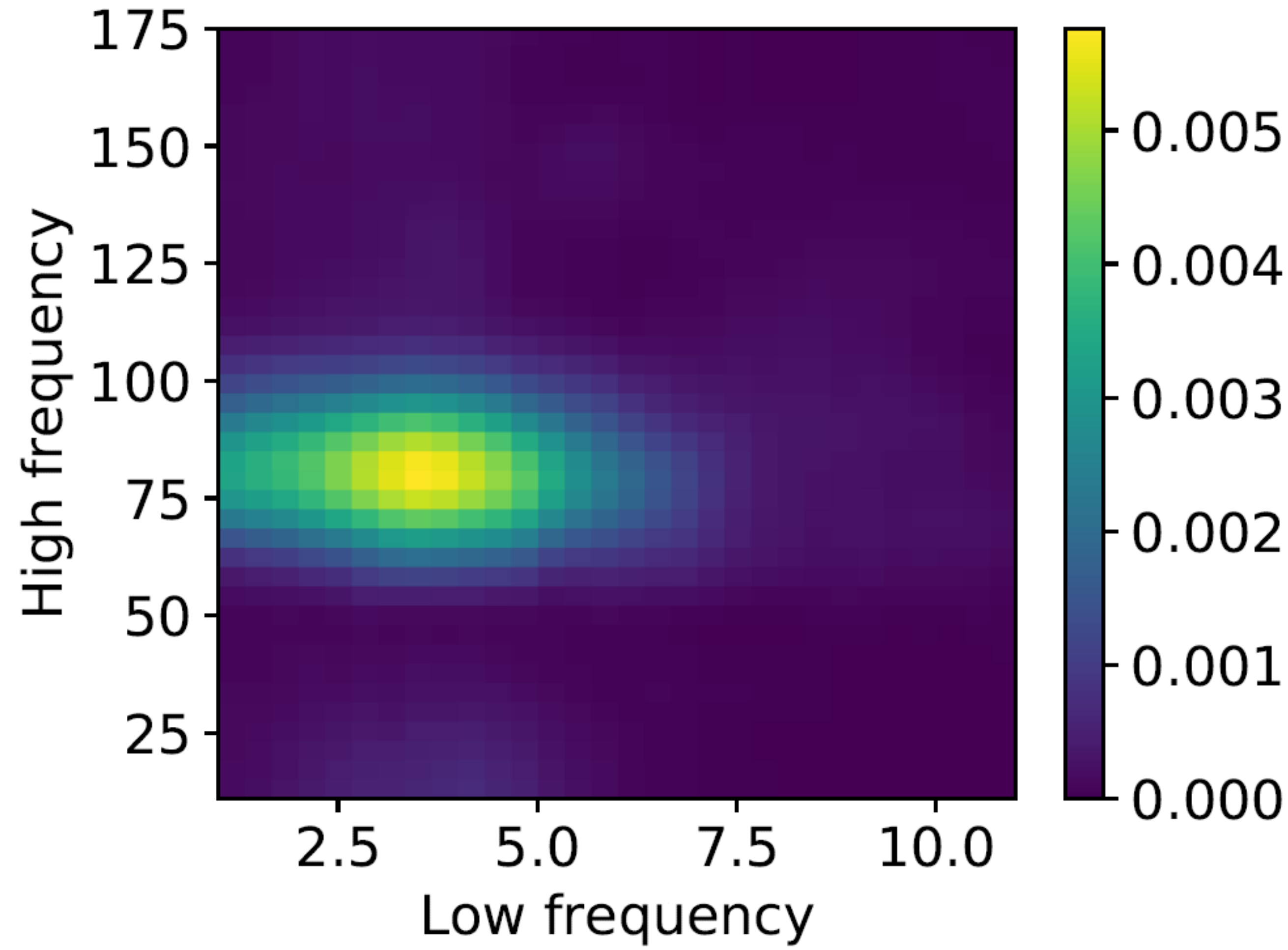

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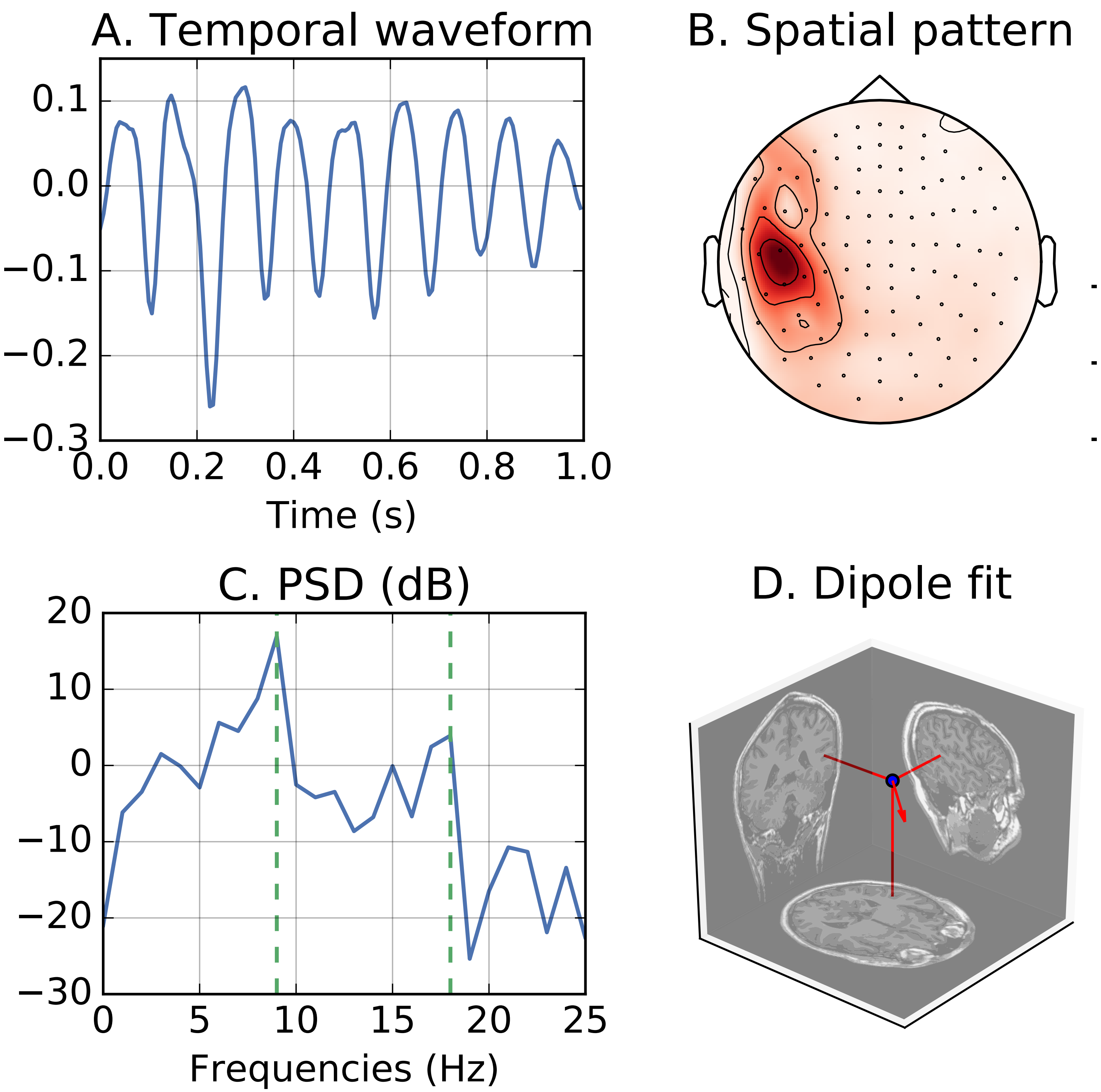
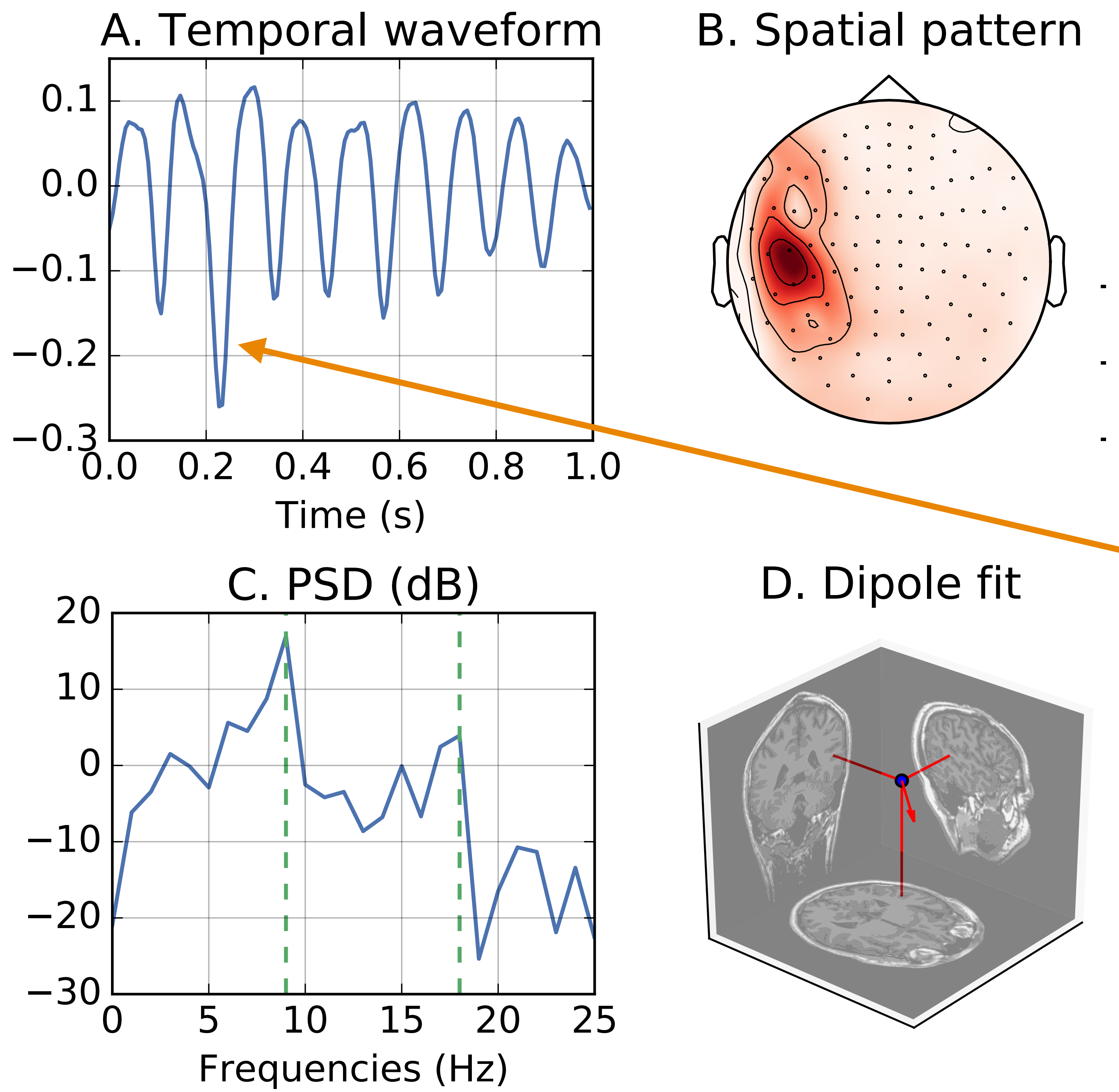
CSC on MEG



- MEG vectorview
- Median nerve stim.

[Multivariate Convolutional Sparse Coding for Electromagnetic Brain Signals, (2018), T. Dupré la Tour, T. Moreau, M. Jas, A. Gramfort, Proc. NIPS Conf.]

CSC on MEG



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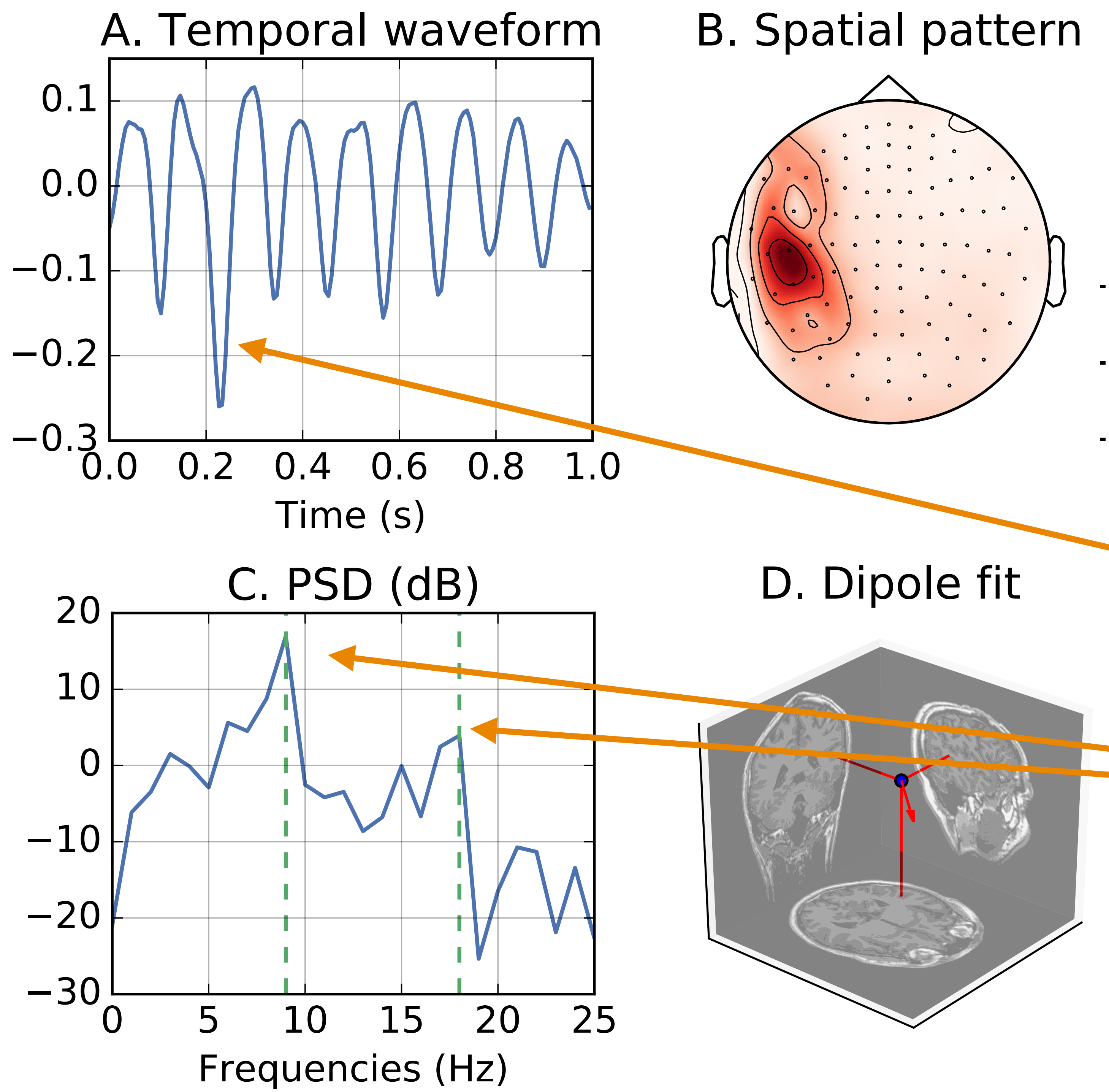
- Median nerve stim.

CSC reveals mu-shaped waveforms

[Multivariate Convolutional Sparse Coding for Electromagnetic Brain Signals, (2018), T. Dupré la Tour, T. Moreau, M. Jas, A. Gramfort, Proc. NIPS Conf.]

CSC on MEG



- MEG vectorview
- Median nerve stim.

CSC reveals mu-shaped waveforms

See the frequency harmonics

[Multivariate Convolutional Sparse Coding for Electromagnetic Brain Signals, (2018), T. Dupré la Tour, T. Moreau, M. Jas, A. Gramfort, Proc. NIPS Conf.]

alphacsc 0.2dev Models Examples API GitHub Site ▾ Search

alphaCSC: Convolution sparse coding for time-series

build passing codecov 81%

This is a library to perform shift-invariant sparse dictionary learning, also known as convolutional sparse coding (CSC), on time-series data. It includes a number of different models:

1. univariate CSC
2. multivariate CSC
3. multivariate CSC with a rank-1 constraint [1]
4. univariate CSC with an alpha-stable distribution [2]

A mathematical descriptions of these models is available in the documentation.

Installation

To install this package, the easiest way is using `pip`. It will install this package and its dependencies. The `setup.py` depends on `numpy` and `cython` for the installation so it is advised to install them beforehand. To install this package, please run

```
pip install numpy cython
pip install git+https://github.com/alphacsc/alphacsc.git#egg=alphacsc
```

If you do not have admin privileges on the computer, use the `--user` flag with `pip`. To upgrade, use the `--upgrade` flag provided by `pip`.

To check if everything worked fine, you can run:

```
python -c 'import alphacsc'
```

and it should not give any error messages.

https://alphacsc.github.io

Quickstart

Here is an example to present briefly the API:

```
import numpy as np
```

Extracting artifact and evoked response atoms from the sample dataset

This example illustrates how to learn rank1 atoms on the sample dataset from `mne`. We display a selection of atoms, featuring heartbeat and eyeblink artifacts, three atoms of evoked responses, and a non-sinusoidal oscillation.

```
# Authors: Thomas Moreau <thomas.moreau@inria.fr>
#          Mainak Jas <mainak.jas@telecom-paristech.fr>
#          Tom Dupre La Tour <tom.duprelatour@telecom-paristech.fr>
#          Alexandre Gramfort <alexandre.gramfort@telecom-paristech.fr>
#
# License: BSD (3-clause)
```

Let us first define the parameters of our model.

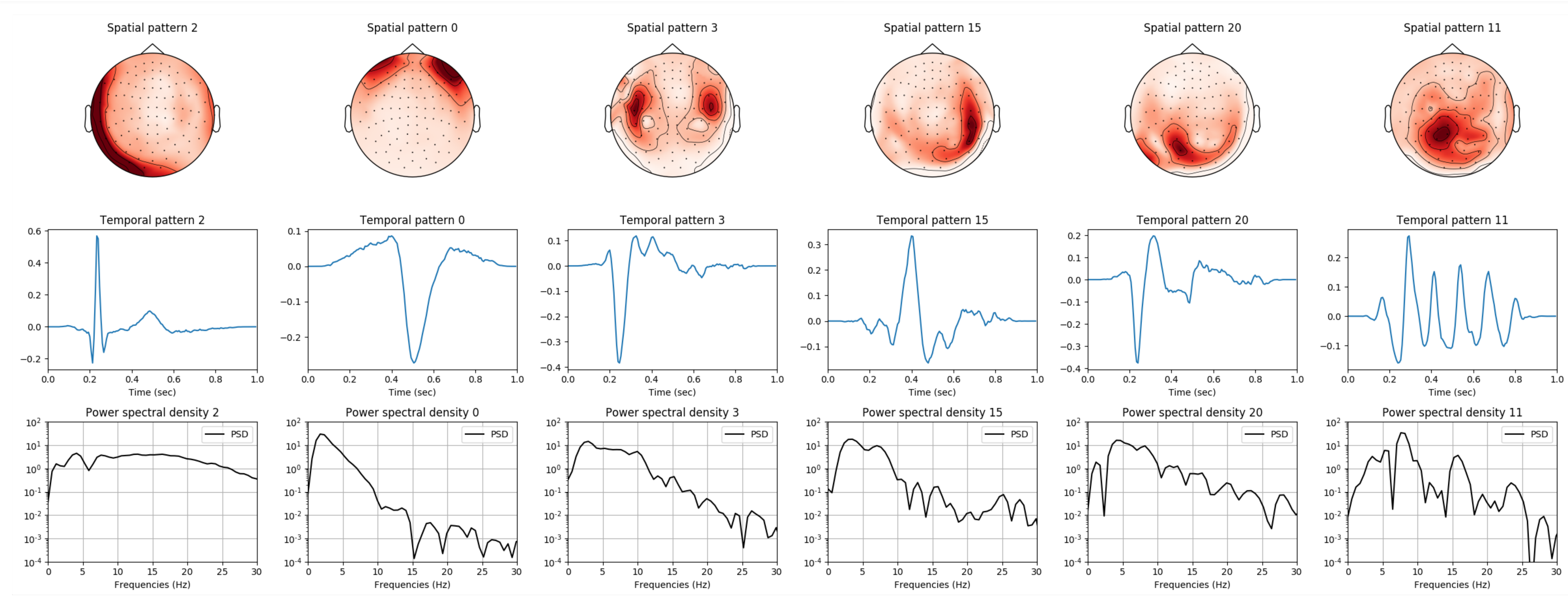
```
# sample frequency
sfreq = 150.

# Define the shape of the dictionary
n_atoms = 40
n_times_atom = int(round(sfreq * 1.0))  # 1000. ms

# Regularization parameter which control sparsity
reg = 0.1

# number of processors for parallel computing
n_jobs = 5
```

Next, we define the parameters for multivariate CSC

https://alphacsc.github.io/auto_examples/multicsc/plot_sample_evoked_response.html

Extracting artifact and evoked response atoms from the sample dataset

Th
ey

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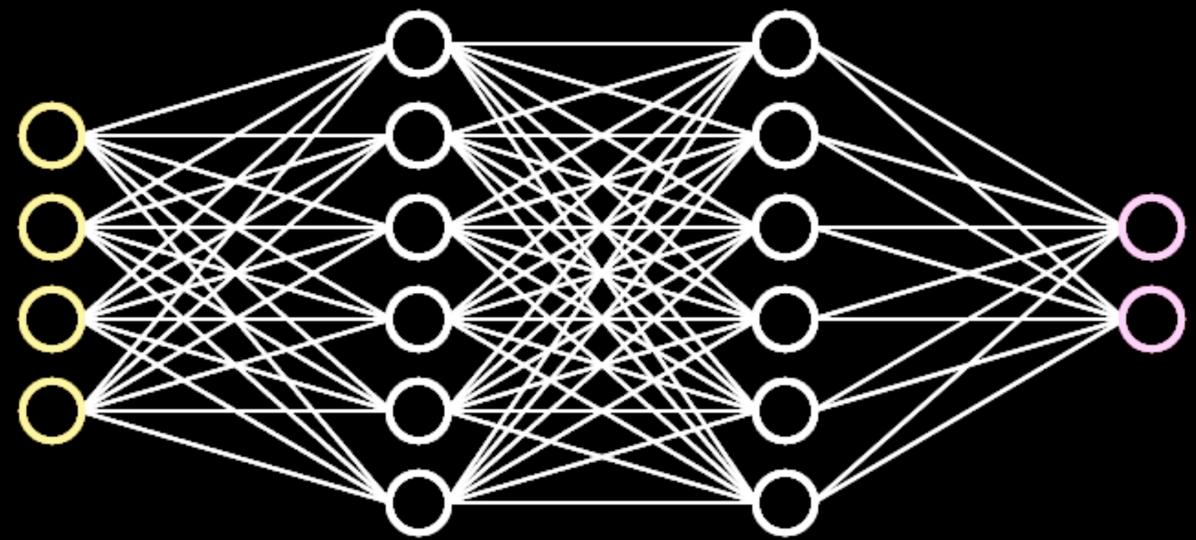
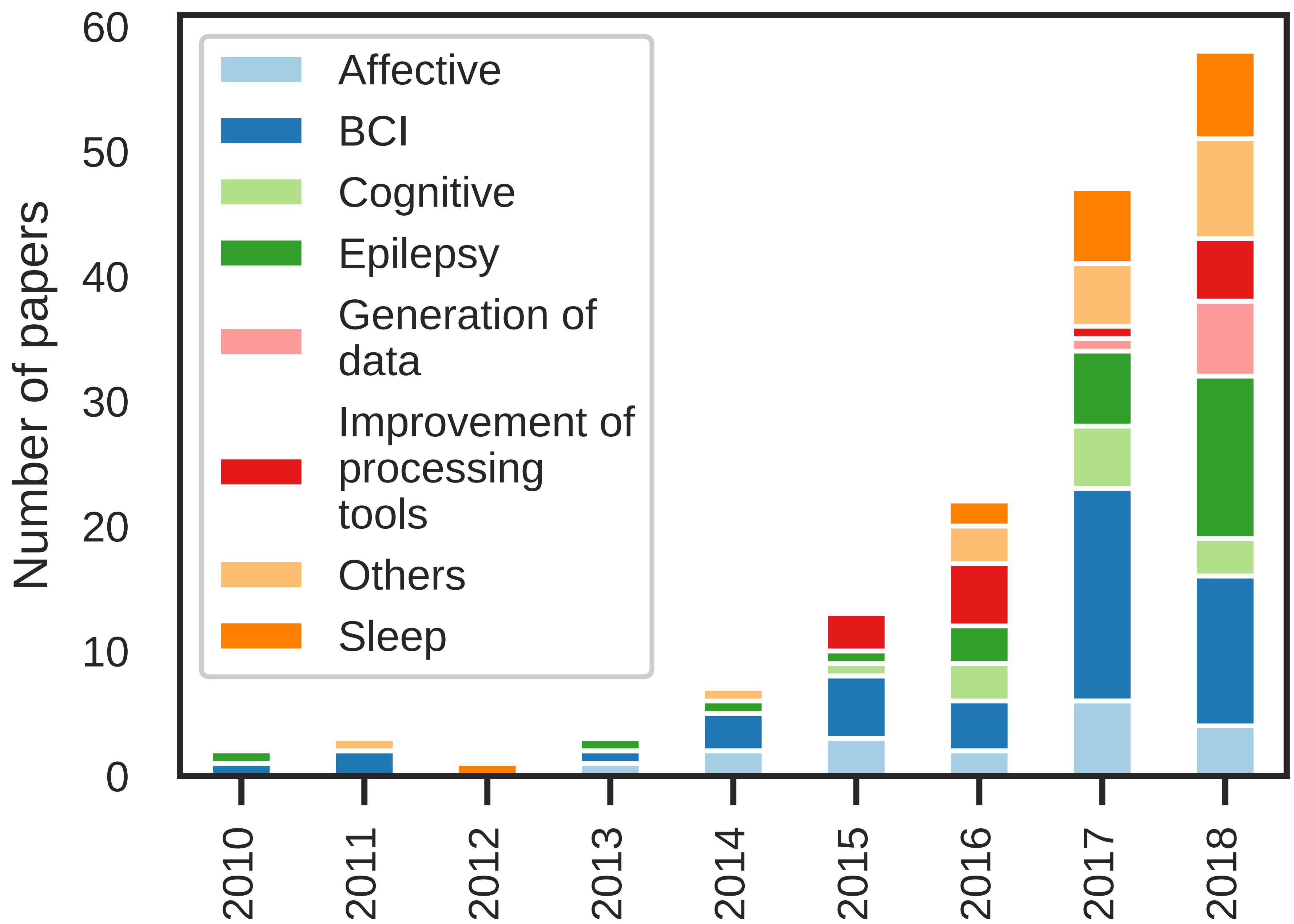
2

Self-supervised learning on EEG



Uncovering the structure of clinical EEG signals with self-supervised learning
Banville, H., Chehab, O., Hyvärinen, A., Engemann, D. and Gramfort, A. (2020)
ArXiv abs/2007.16104
Self-supervised representation learning from electroencephalography signals
Banville, H., Albuquerque, I., Moffat, G., Engemann, D. and Gramfort, A. (2019)
Proc. Machine Learning for Signal Processing (MLSP) .

Deep Learning papers on EEG



[Deep learning-based electroencephalography analysis: a systematic review
Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T. and Faubert, J. (2019)
Journal of Neural Engineering 16: (051001).]

Challenges of ML on EEG

- Low signal-to-noise ratio (SNR)
- Strong variability (intra/inter-subjects)
- Expensive/Time-consuming to collect & annotate

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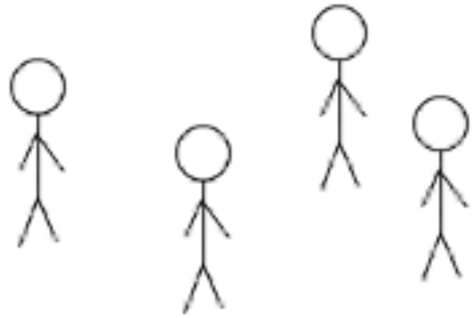
Example: Sleep recording (polysomnography)

Requires controlled environment (e.g., clinic)

Need experts (e.g., sleep technologists) to annote the data manually

Variability between subjects and for the same subject from day-to-day



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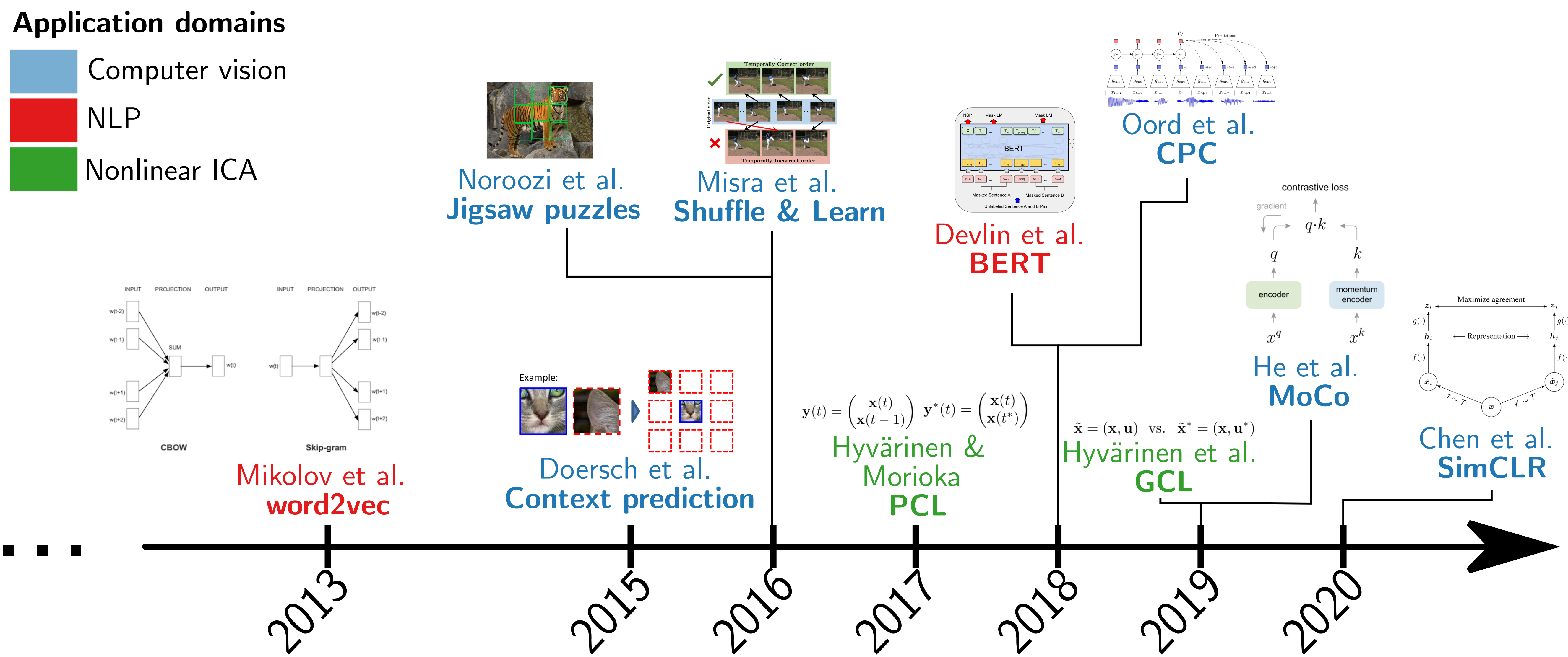
Question: Can we reduce our dependence on labels?

Self-supervision

[Noroozi & Favaro 2016] use a deep neural network to solve the Jigsaw puzzle

Use the **structure** of the data to pretrain a **feature extractor** with a supervised *pretext task* – then use the features on a *downstream task*.

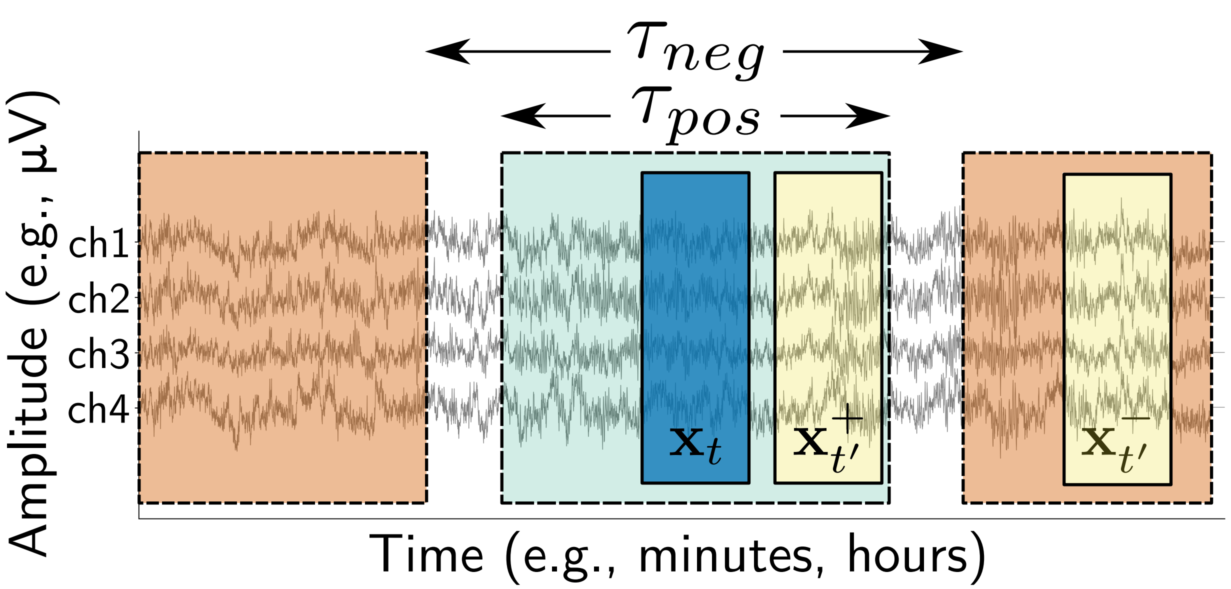
(Partial) History of SSL beyond EEG



Pretext Task

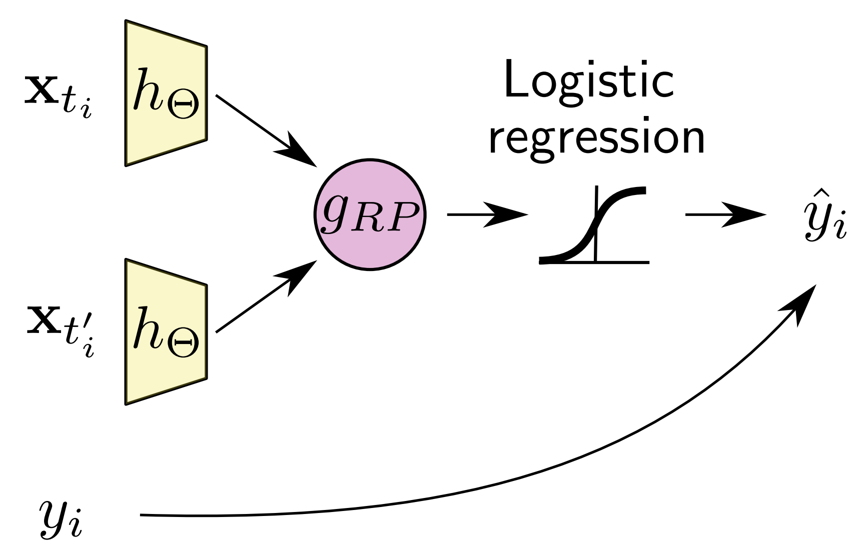
Relative positioning (RP)

1 Sampling



$$y_i = \begin{cases} 1, & \text{if } |t_i - t_i'| \leq \tau_{pos} \\ \text{-}1, & \text{if } |t_i - t_i'| > \tau_{neg} \end{cases}$$

2 Training



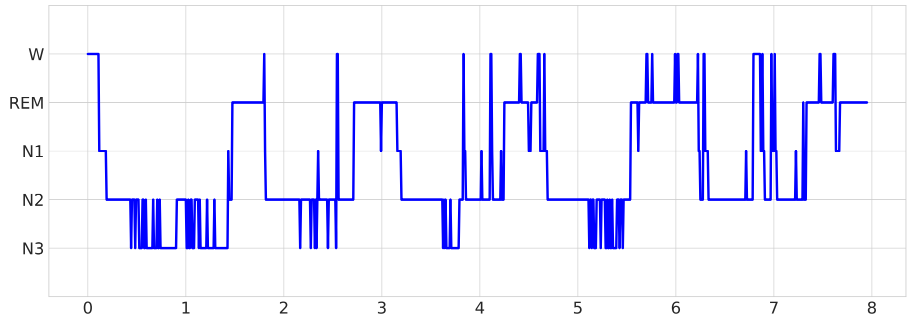
Predict if 2 windows of data are close in time

Other approaches: CPC [Oord et al. 2018], PCL [Hyvärinen et al. 2017] etc.

Downstream tasks on clinical EEG

Sleep staging:

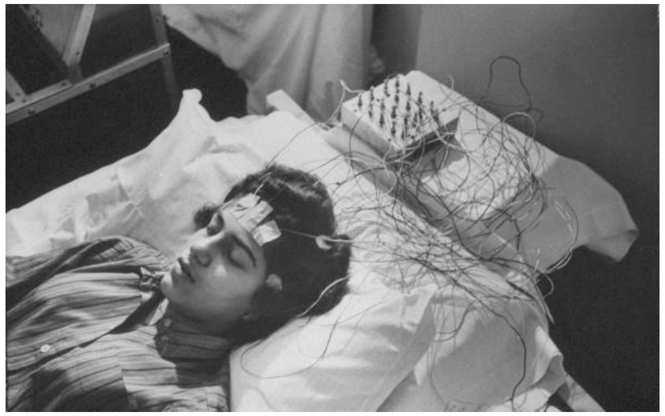
Predict sleep stage from EEG
(5-class: W, N1, N2, N3, R)



Hypnogram

Pathology detection:

Is someone's EEG pathological?
(2-class: normal, abnormal)



Datasets

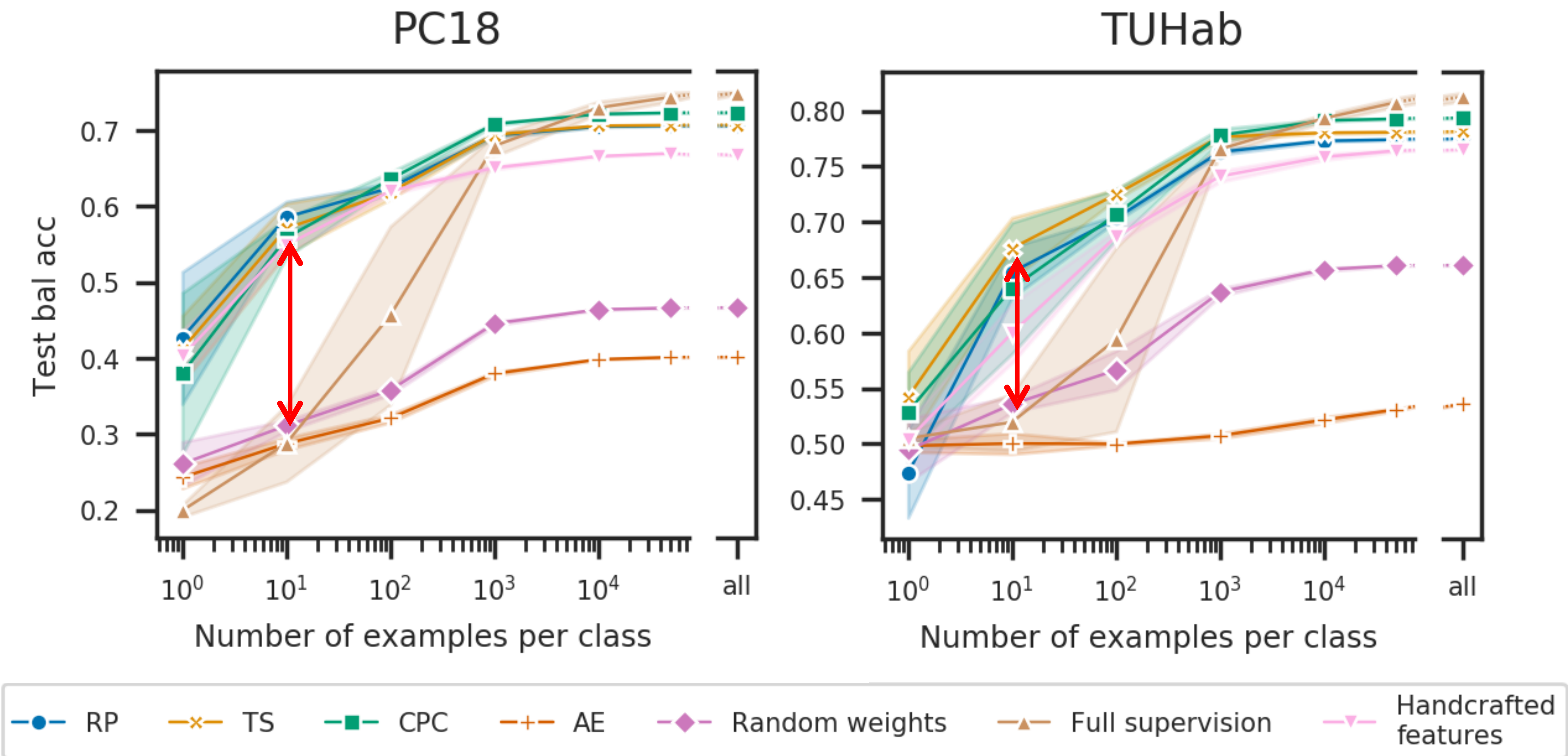
Two public datasets with hundreds of recordings:

- **Sleep staging**: Physionet Challenge 2018 (PC18) [Ghassemi et al. 2018]
- **Pathology detection**: TUH Abnormal EEG (TUHab) [López 2017]

	PC18 (train)
	# windows
W	158,020
N1	136,858
N2	377,426
N3	102,492
R	116,872
Total	891,668
# unique subjects	994
# recordings	994
Sampling frequency	200 Hz
# EEG channels	6
Reference	M1 or M2

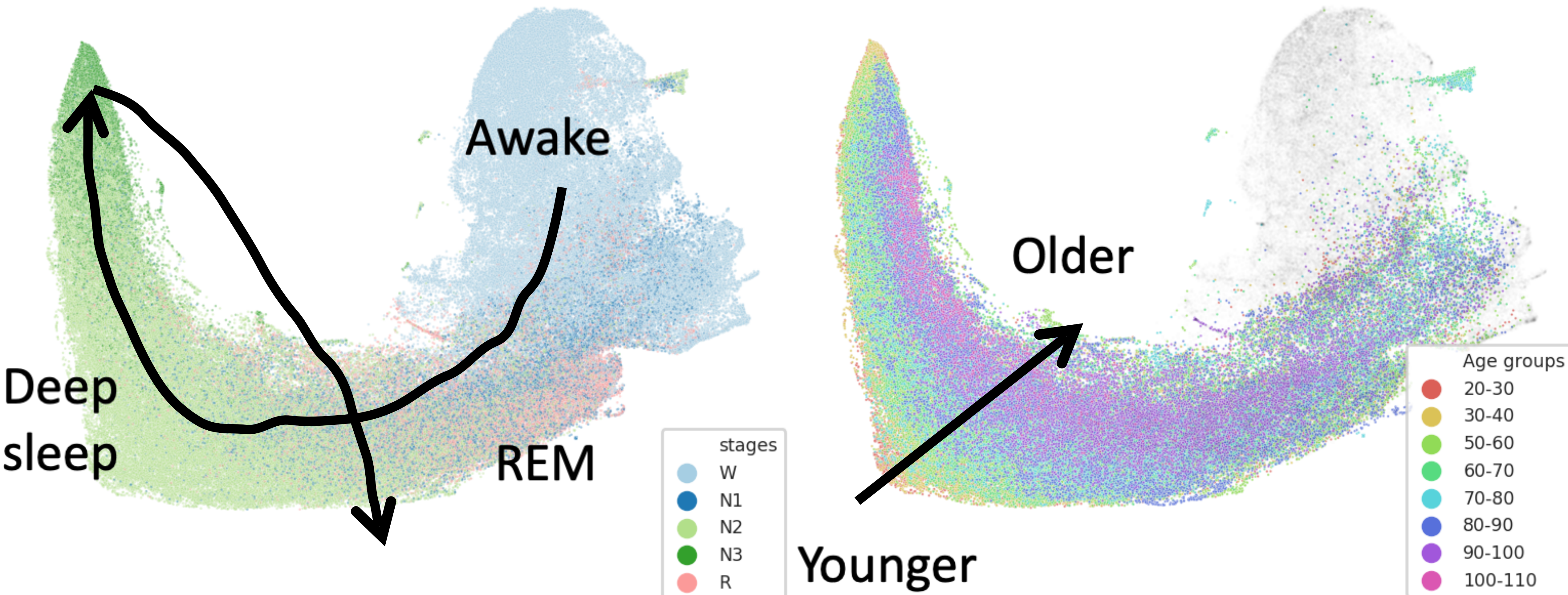
	TUHab (train)	TUHab (eval)
	# recordings	# recordings
Normal	1371	150
Abnormal	1346	126
Total	2717	276
# unique subjects	2329	
# recordings	2993	
Sampling frequency	250, 256, 512 Hz	
# EEG channels	27 to 36	
Reference	Common average	

Results: Prediction accuracy



SSL is **better than full supervision** when limited data is available, and **competitive** when all data is available.

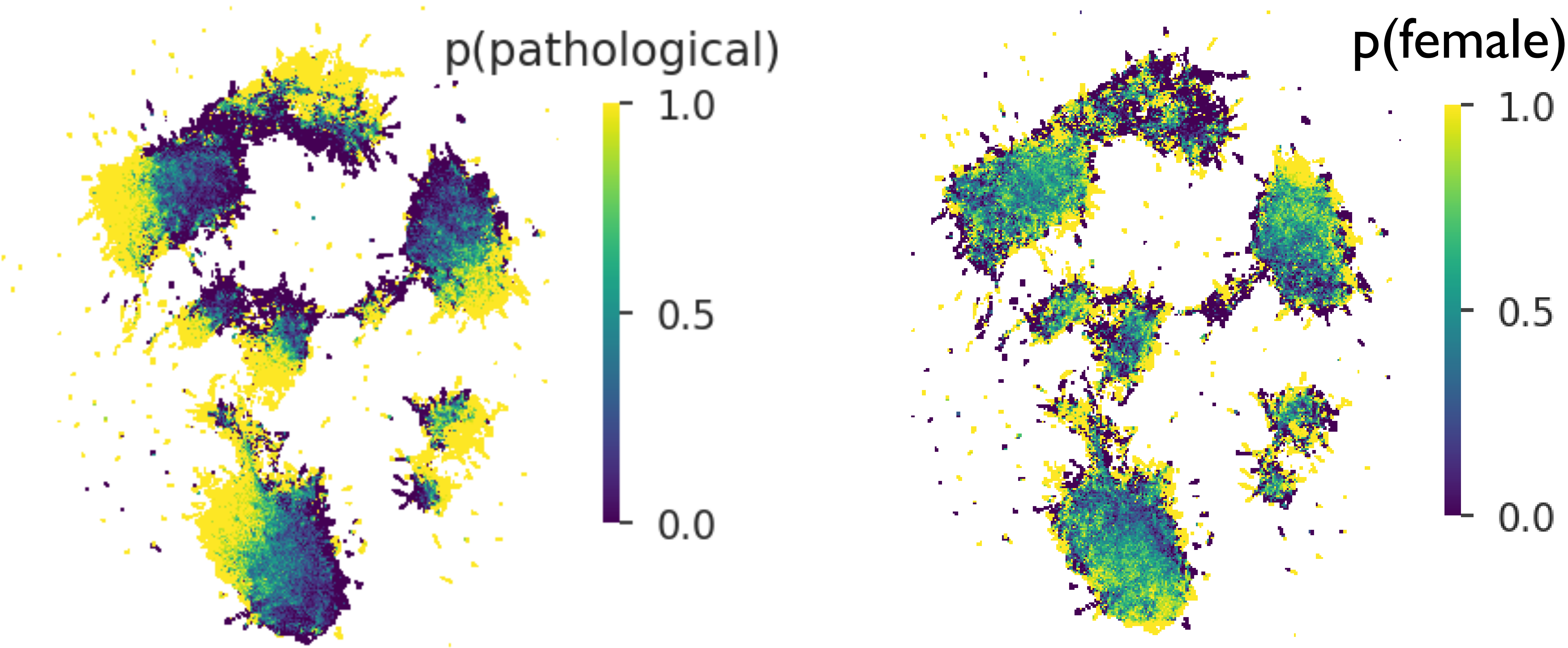
Results on sleep EEG



SSL can **uncover structure** without human supervision

[Banville et al. MLSP 2019]

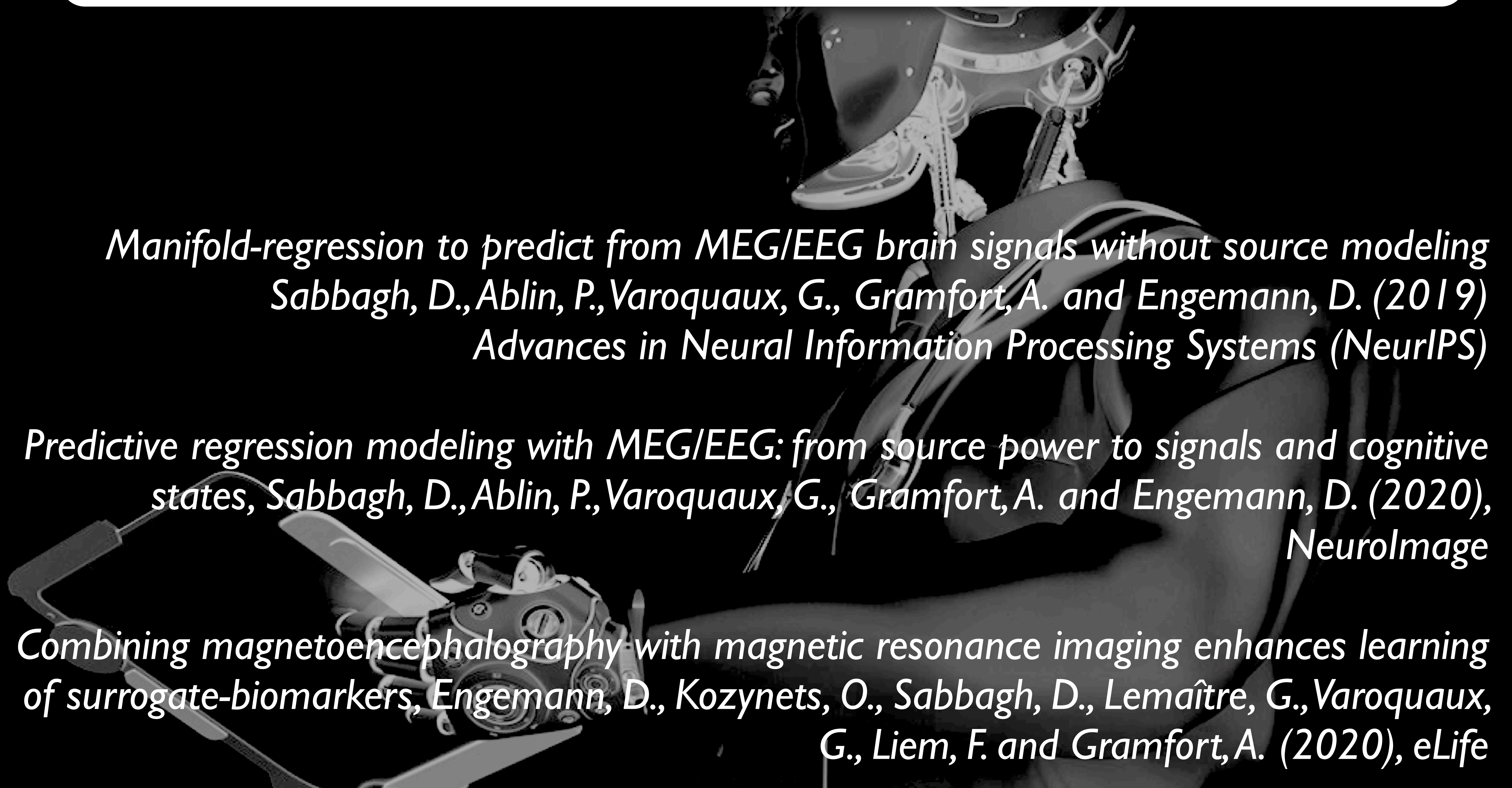
Results on TUH data



SSL can **uncover clinically-relevant structure**
without human supervision

3

MEG and EEG for precision medicine and biomarkers



Manifold-regression to predict from MEG/EEG brain signals without source modeling Sabbagh, D., Ablin, P., Varoquaux, G., Gramfort, A. and Engemann, D. (2019) Advances in Neural Information Processing Systems (NeurIPS)

Predictive regression modeling with MEG/EEG: from source power to signals and cognitive states, Sabbagh, D., Ablin, P., Varoquaux, G., Gramfort, A. and Engemann, D. (2020), NeuroImage

Combining magnetoencephalography with magnetic resonance imaging enhances learning of surrogate-biomarkers, Engemann, D., Kozynets, O., Sabbagh, D., Lemaître, G., Varoquaux, G., Liem, F. and Gramfort, A. (2020), eLife

Precision medicine / Biomarkers

IMPAC

IMaging-PsychiAtry Challenge: predicting autism

A data challenge on Autism Spectrum Disorder detection

Deadline: July 1, 2018 - 8 pm (UTC)

https://paris-saclay-cds.github.io/autism_challenge/

Days	Hours	Minutes	Seconds

Paris-Saclay Center for Data Science

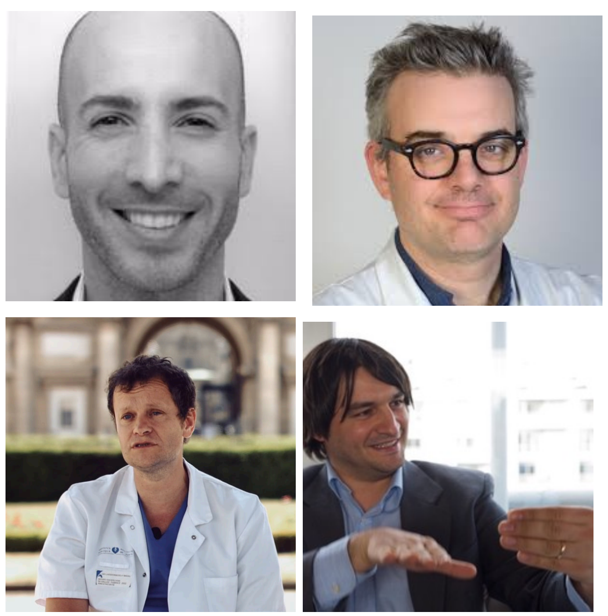
Hôpital universitaire Robert-Debré

ASSISTANCE PUBLIQUE HÔPITAUX DE PARIS

Institut Pasteur

Predict of brain “fragility” for optimal drug dosage across age

Joint work with:



informatiques Inria mathématiques

Inserm
Institut national
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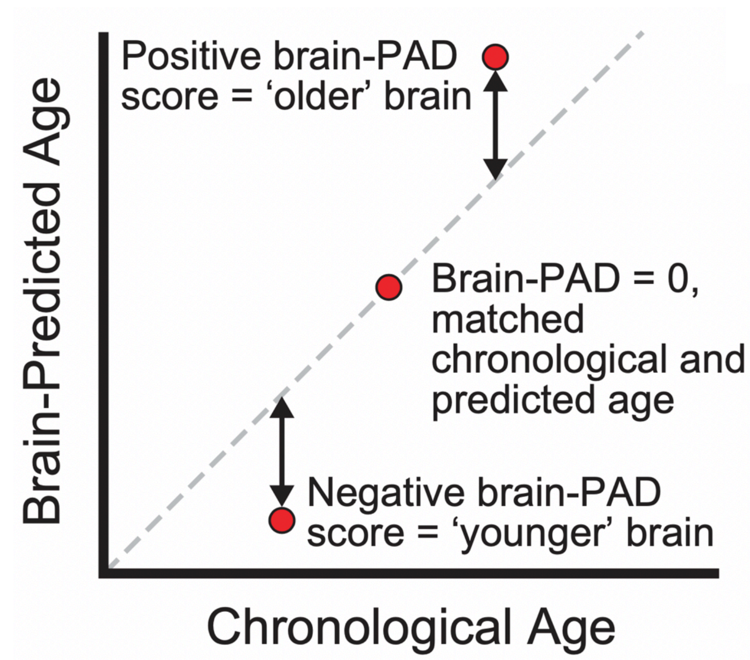
GH LARIBOISIÈRE

Solution: Surrogate Biomarker *e.g.* Brain Age

- **Problem:** few / expensive data on outcome *e.g.* cognitive decline

- **Idea:** Predict widely available outcome; exploit correlation with the outcome of interest, *e.g.* age

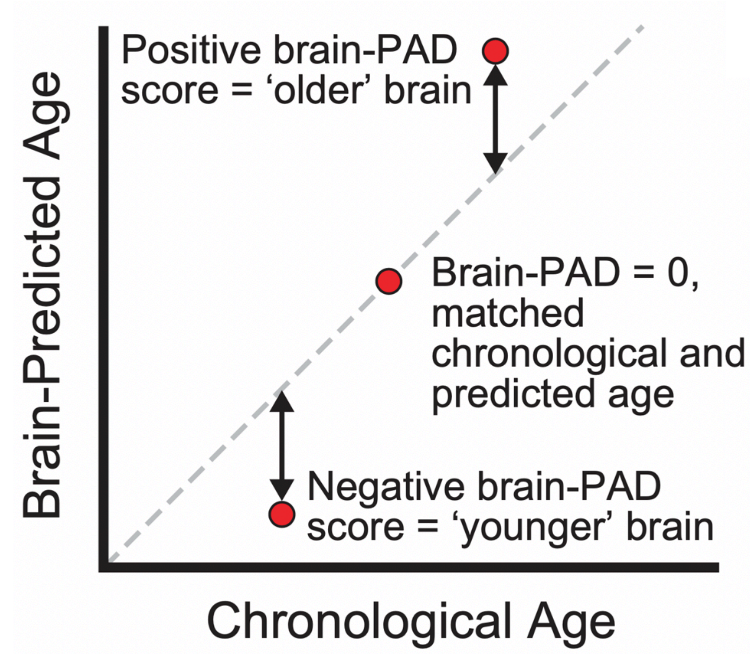
- Brain Age Delta = predicted age (PAD) - passport age

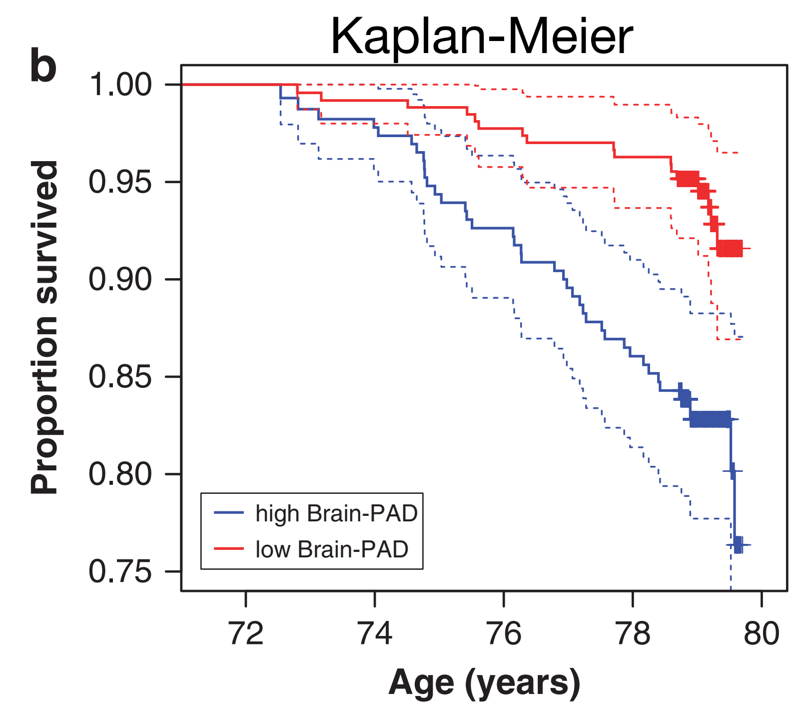


Cole et al. Mol. Psych. 2018

Solution: Surrogate Biomarker *e.g.* Brain Age

- **Problem:** few / expensive data on outcome *e.g.* cognitive decline
- **Idea:** Predict widely available outcome; exploit correlation with the outcome of interest, *e.g.* age
- Brain Age Delta = predicted age (PAD) - passport age
- High PAD is not good …
- **Typically estimated with MRI!**





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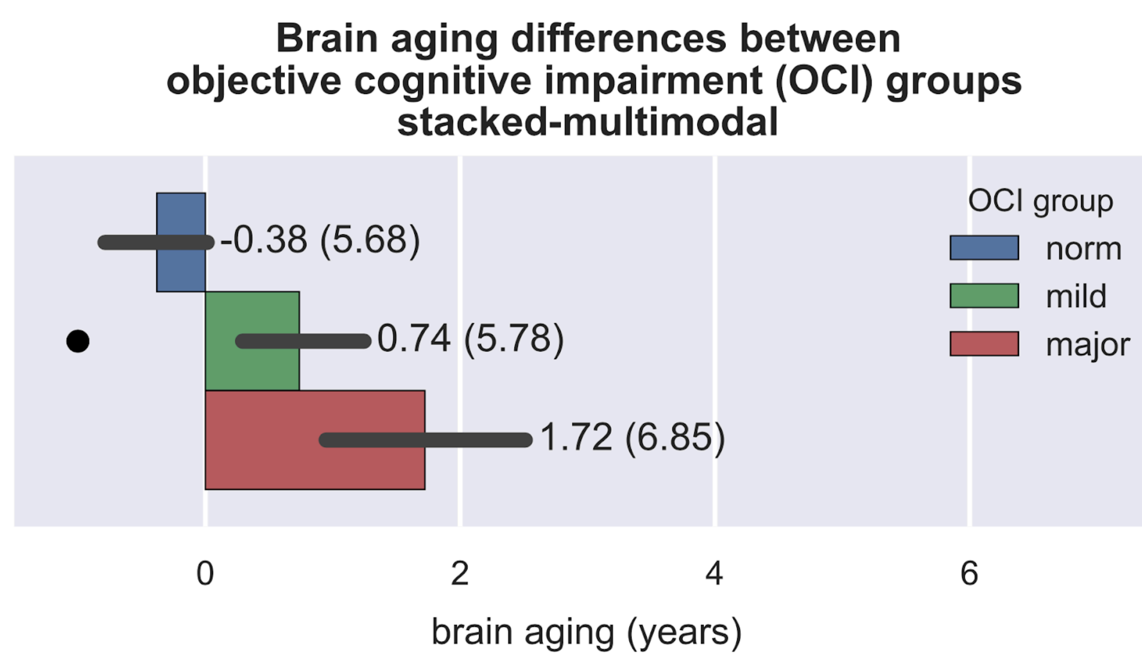
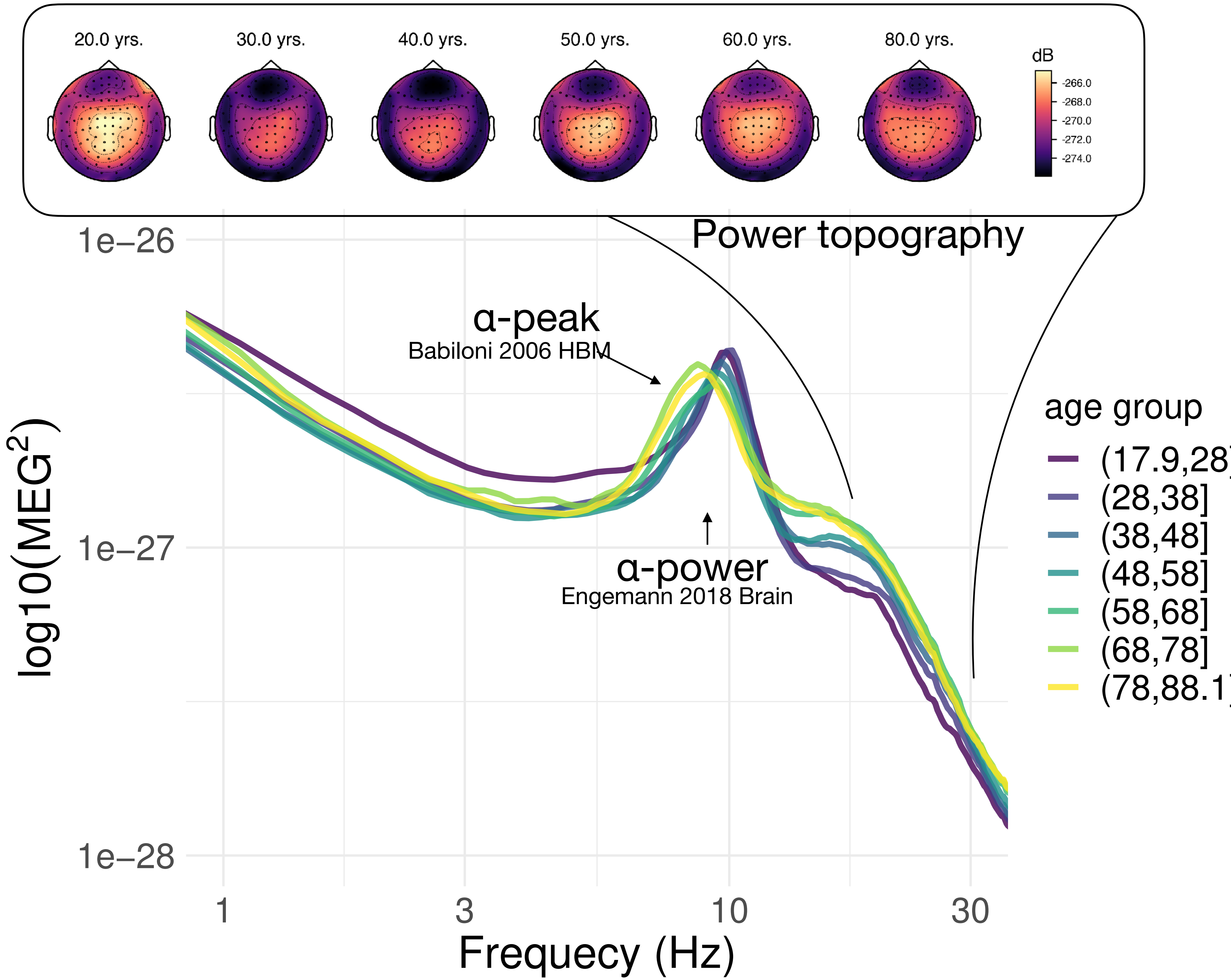


Liem et al 2017 NIMG

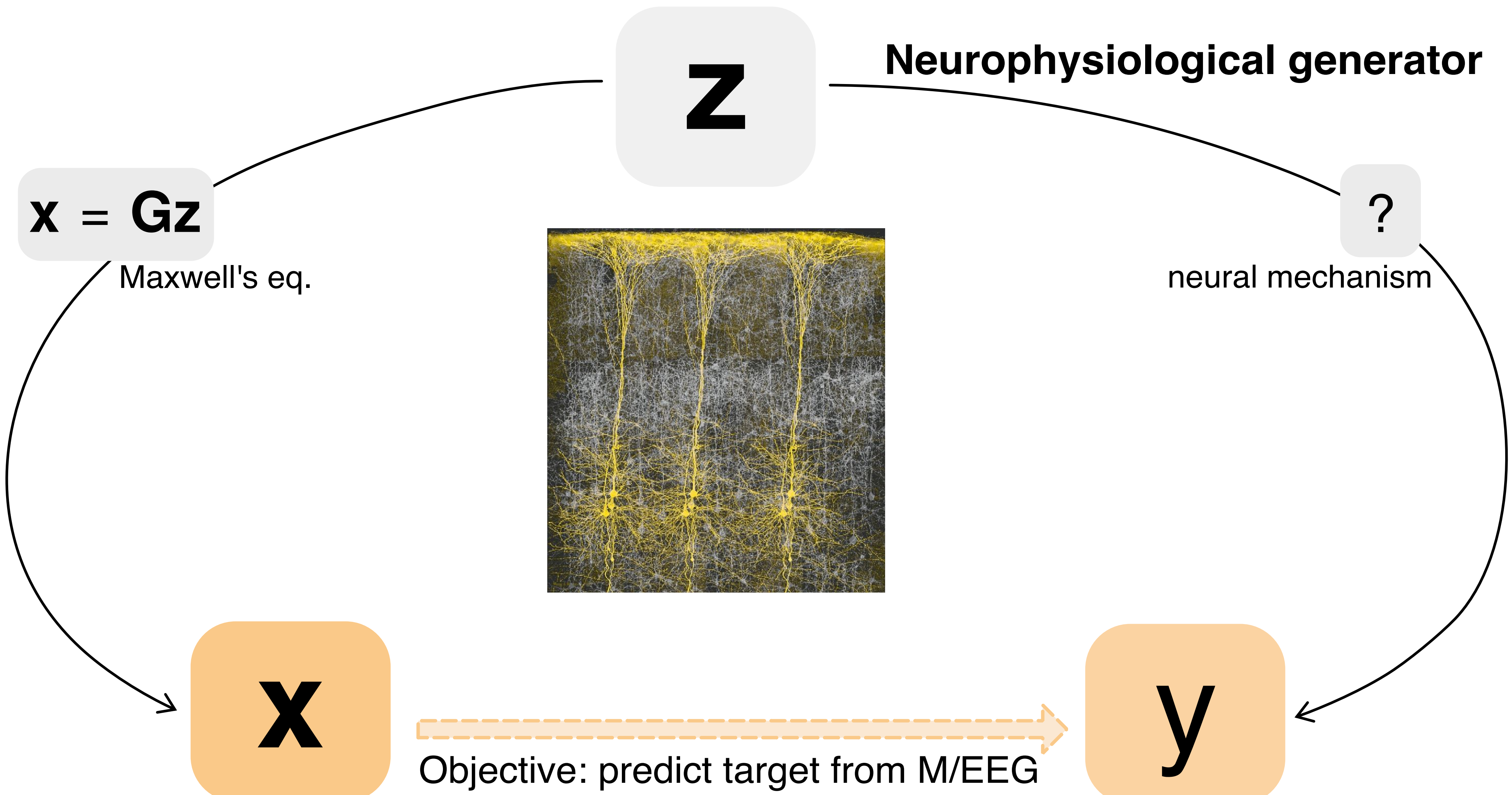
Using MRI

Age prediction: Which M/EEG features?



Based on Cam-CAN data [Taylor et al. 2017] https://www.cam-can.org/

How to build MEG-based regression models?



Sabbagh et al. 2019 (NeurIPS) 2020 (NIMG)

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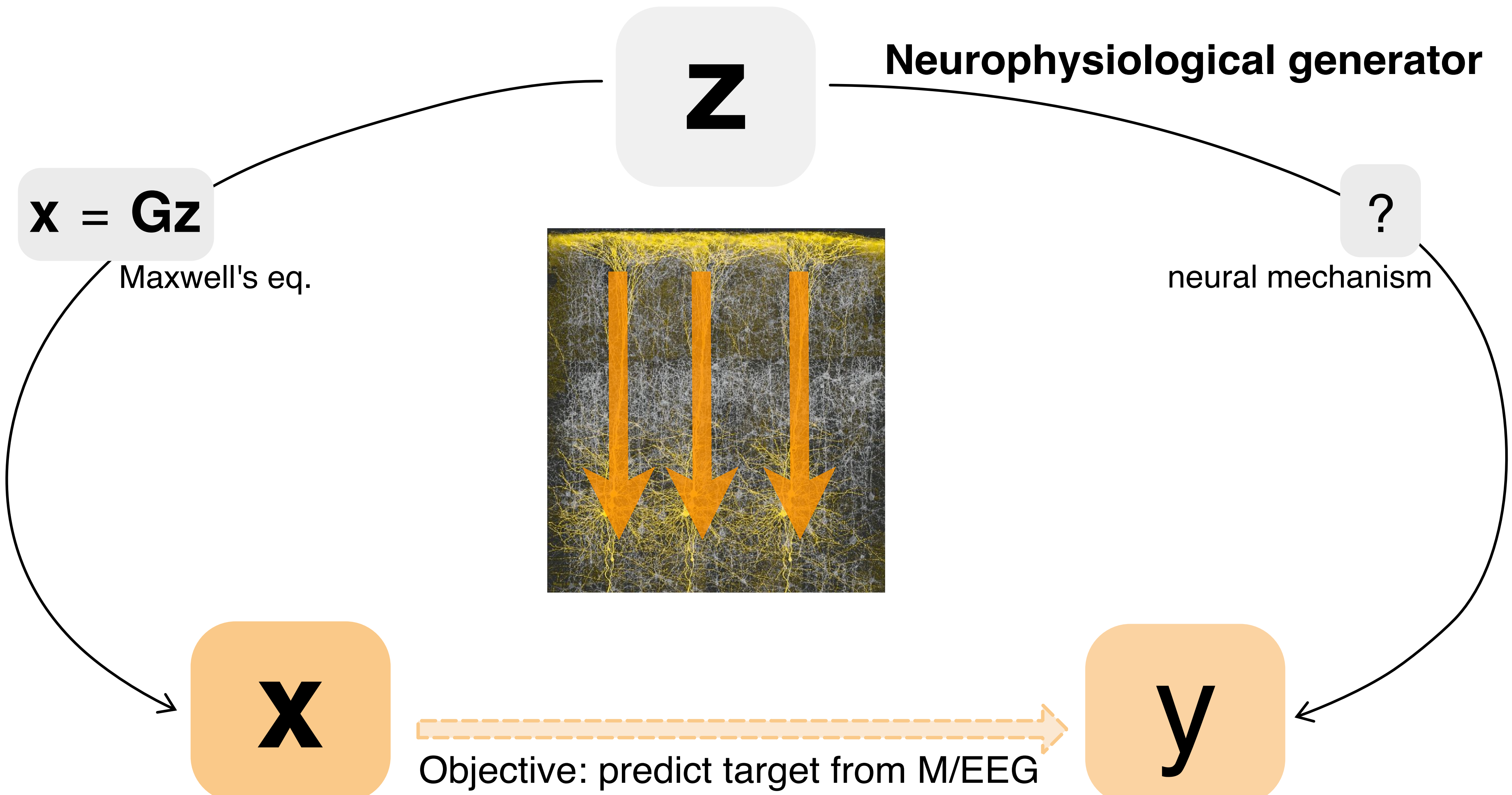

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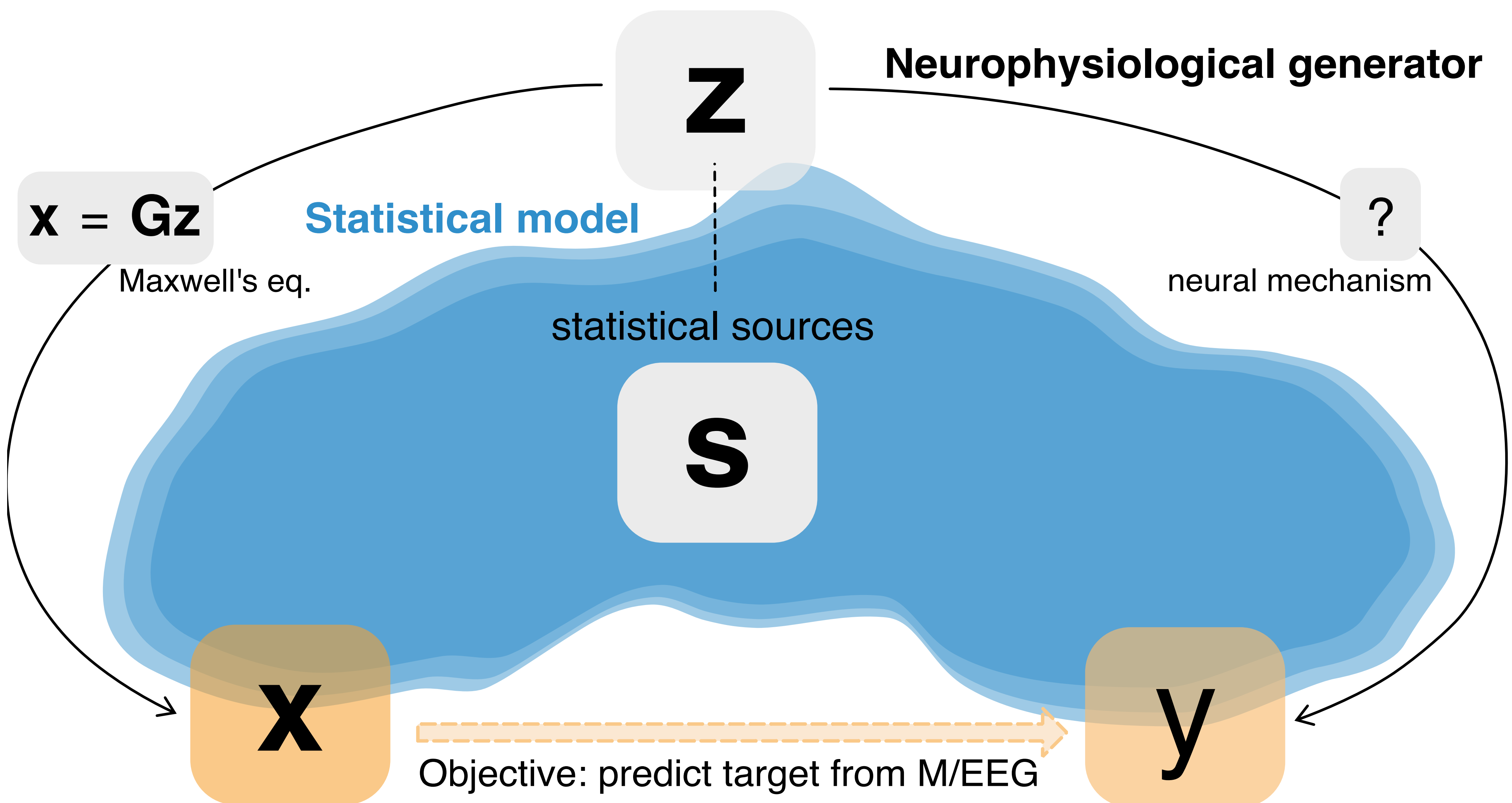

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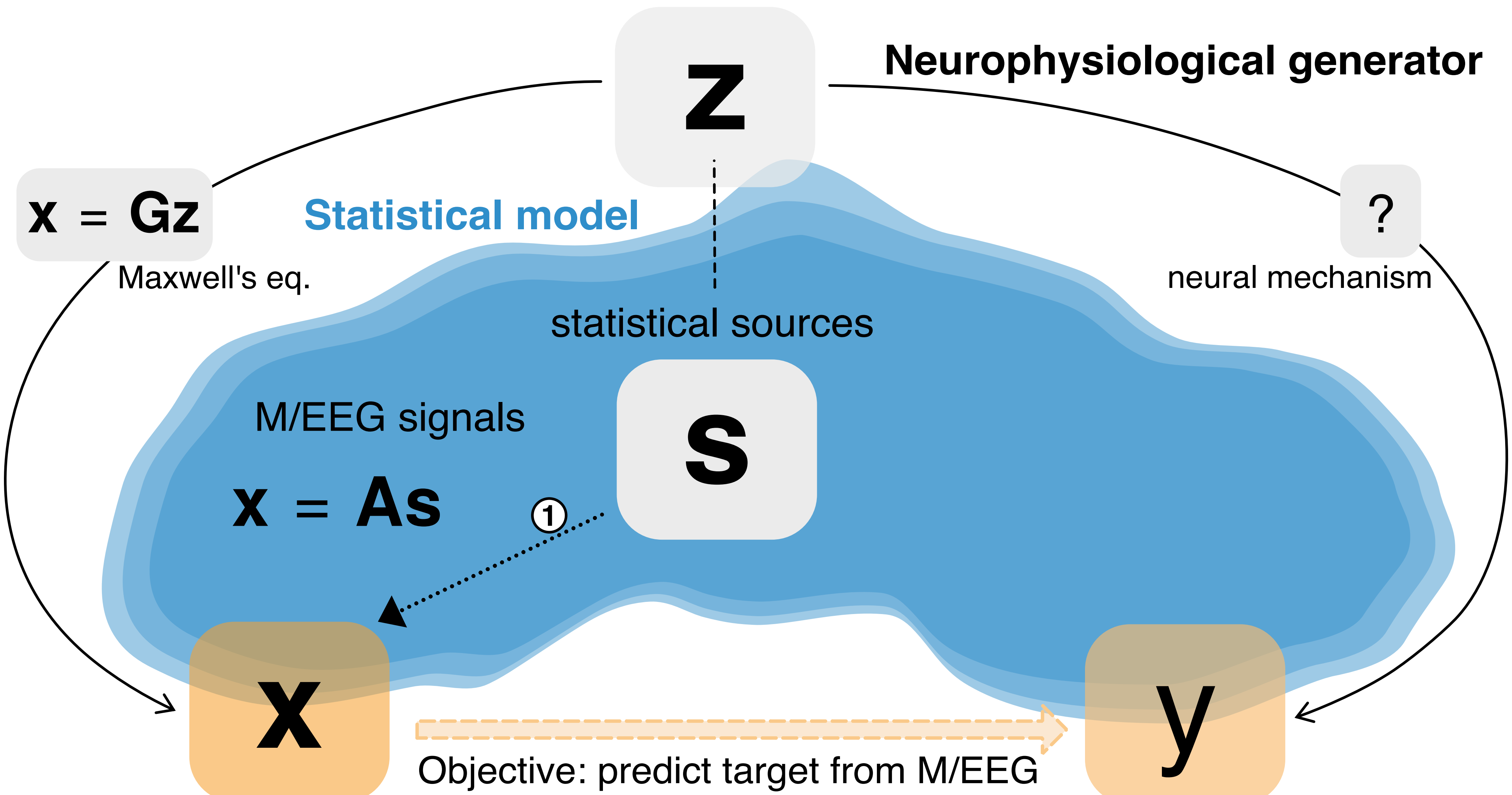

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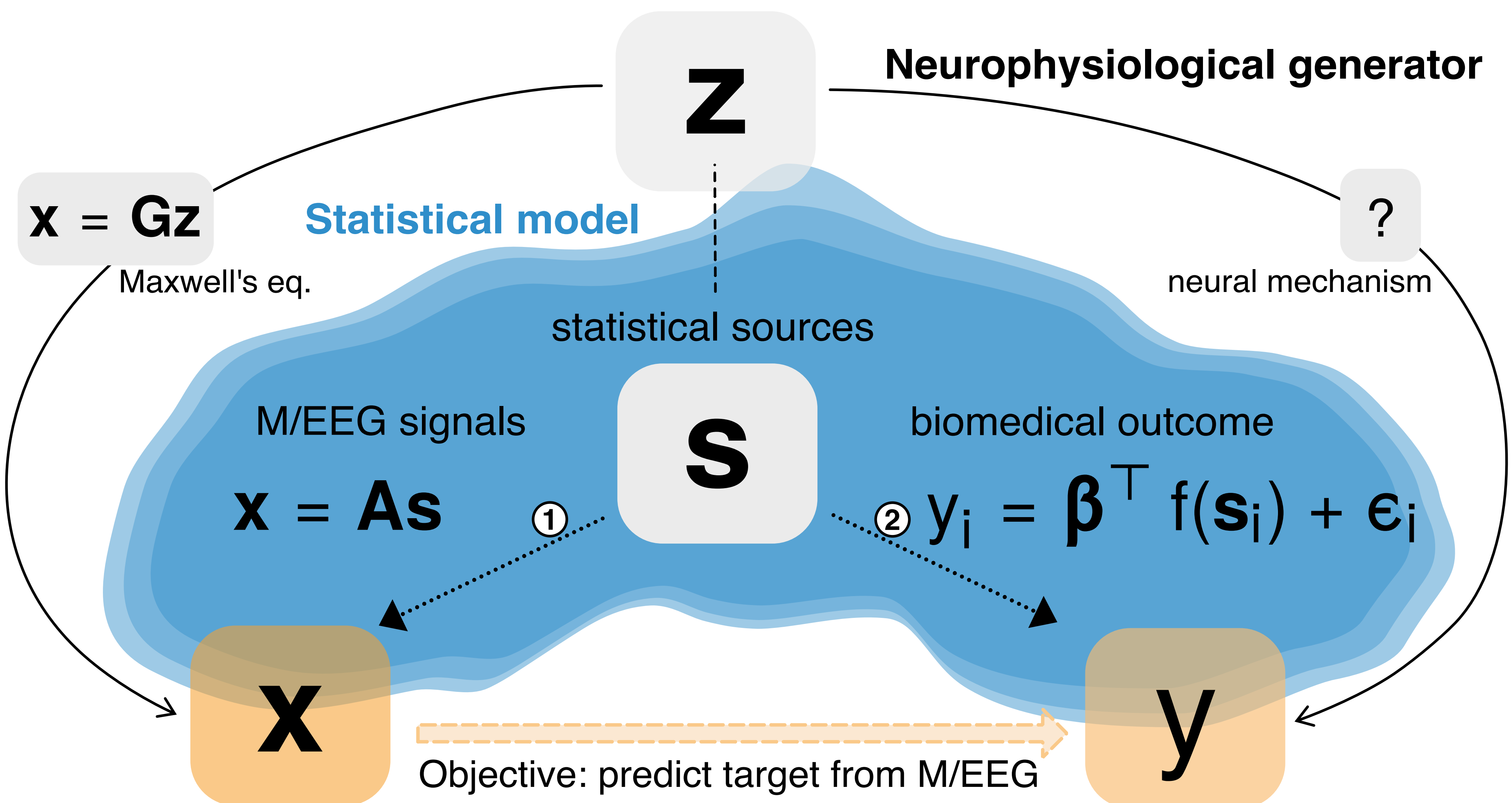

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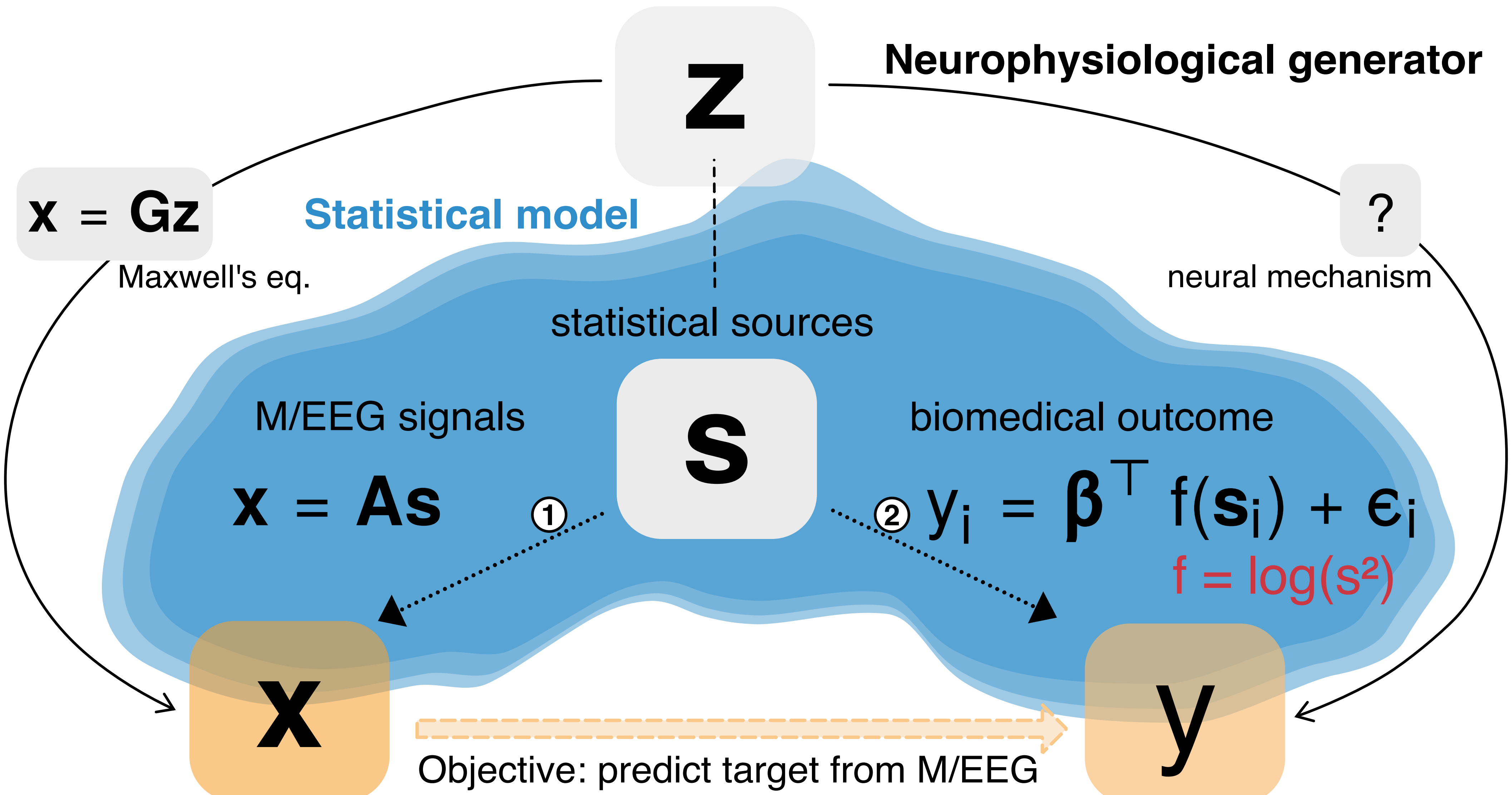


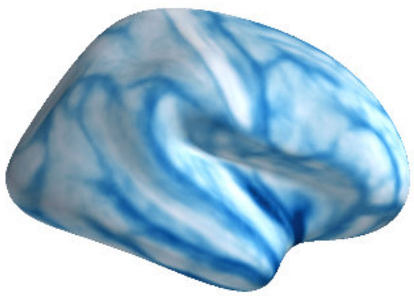
Sabbagh et al. 2019 (NeurIPS) 2020 (NIMG)

How shall we combine MEG with MRI?

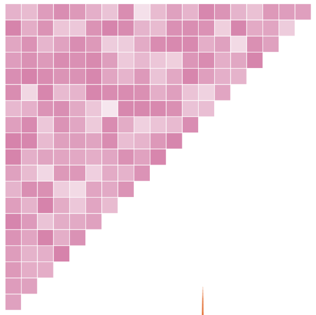
And is it worth the effort?

Multimodal input data

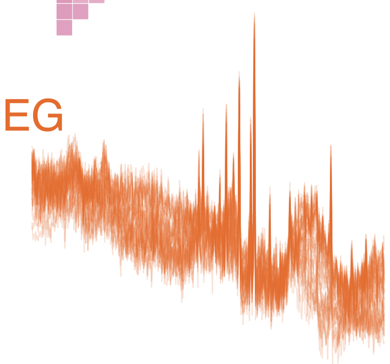
anatomical MRI



functional MRI



MEG



Stacking method: Wolpert 1992, Liem et al. 2017, NIMG; Karrer et al. 2019, HBM, …

Engemann et al. (2020) **eLife**

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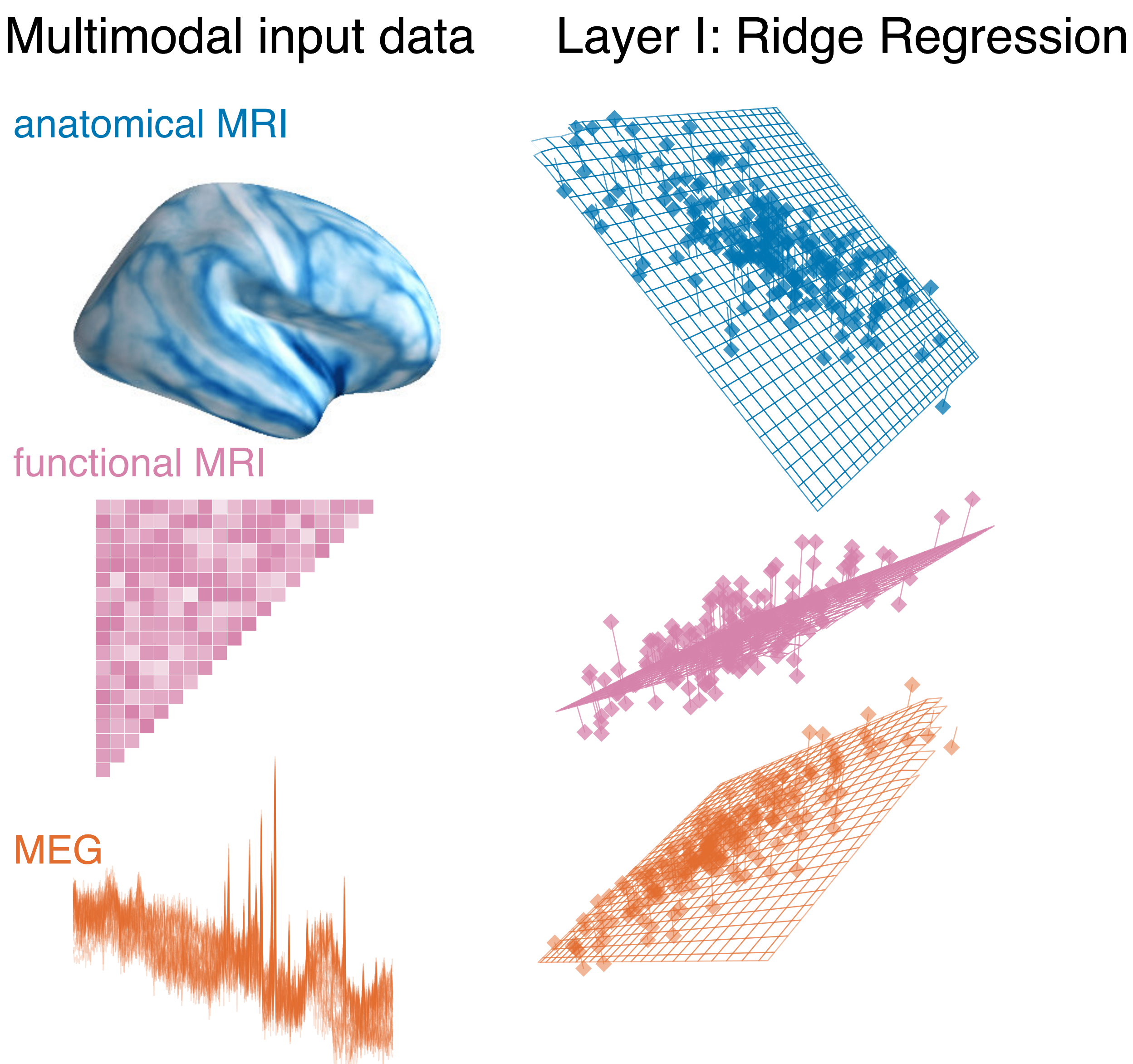

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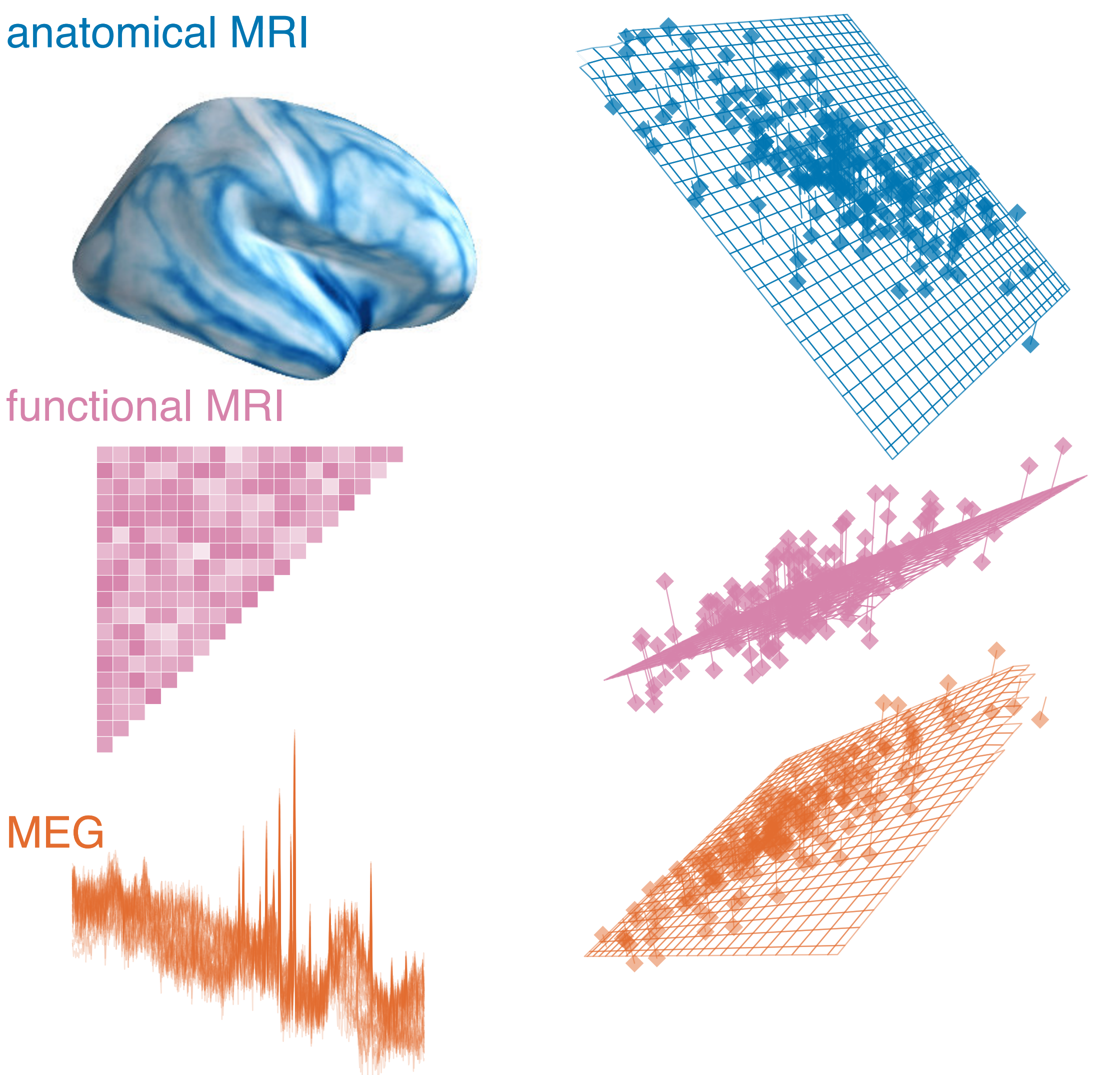
Multimodal input data

Layer I: Ridge Regression



Age predictions

				true age
20	19	24		23
34	30	29		33
NA	23	21		21
56	51	NA		48
71	NA	NA		70
69	77	81		79

Missing value coding

							true age
20	19	24	20	19	24		23
34	30	29	34	30	29		33
-1e3	23	21	1e3	23	21		21
56	51	-1e3	56	51	1e3		48
71	-1e3	-1e3	71	1e3	1e3		70
69	77	81	69	77	81		79

Stacking method: Wolpert 1992, Liem et al. 2017, NIMG; Karrer et al. 2019, HBM, …

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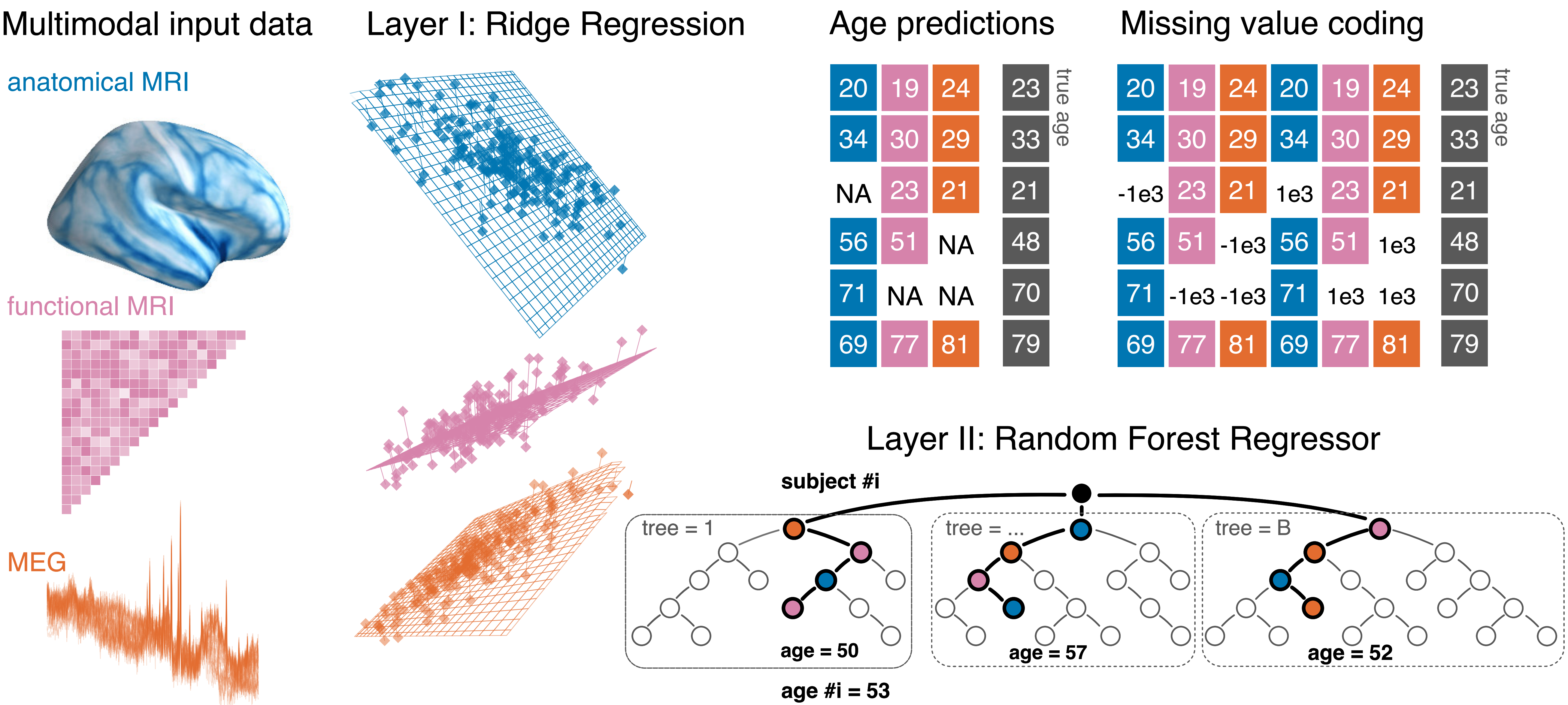

Stacking method: Wolpert 1992, Liem et al. 2017, NIMG; Karrer et al. 2019, HBM, …

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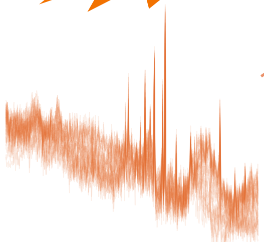
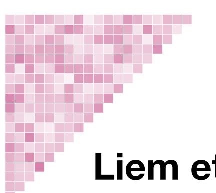
Overview on all features

Table 1. Frequency band definitions.

Name	Low	δ	θ	α	β_1	β_2	γ_1	γ_2	γ_3
range (Hz)	0.1 - 1.5	1.5 - 4	4 - 8	8 - 15	15 - 26	26 - 35	35 - 50	50 - 74	76 - 100





Liem et al 2017 NIMG

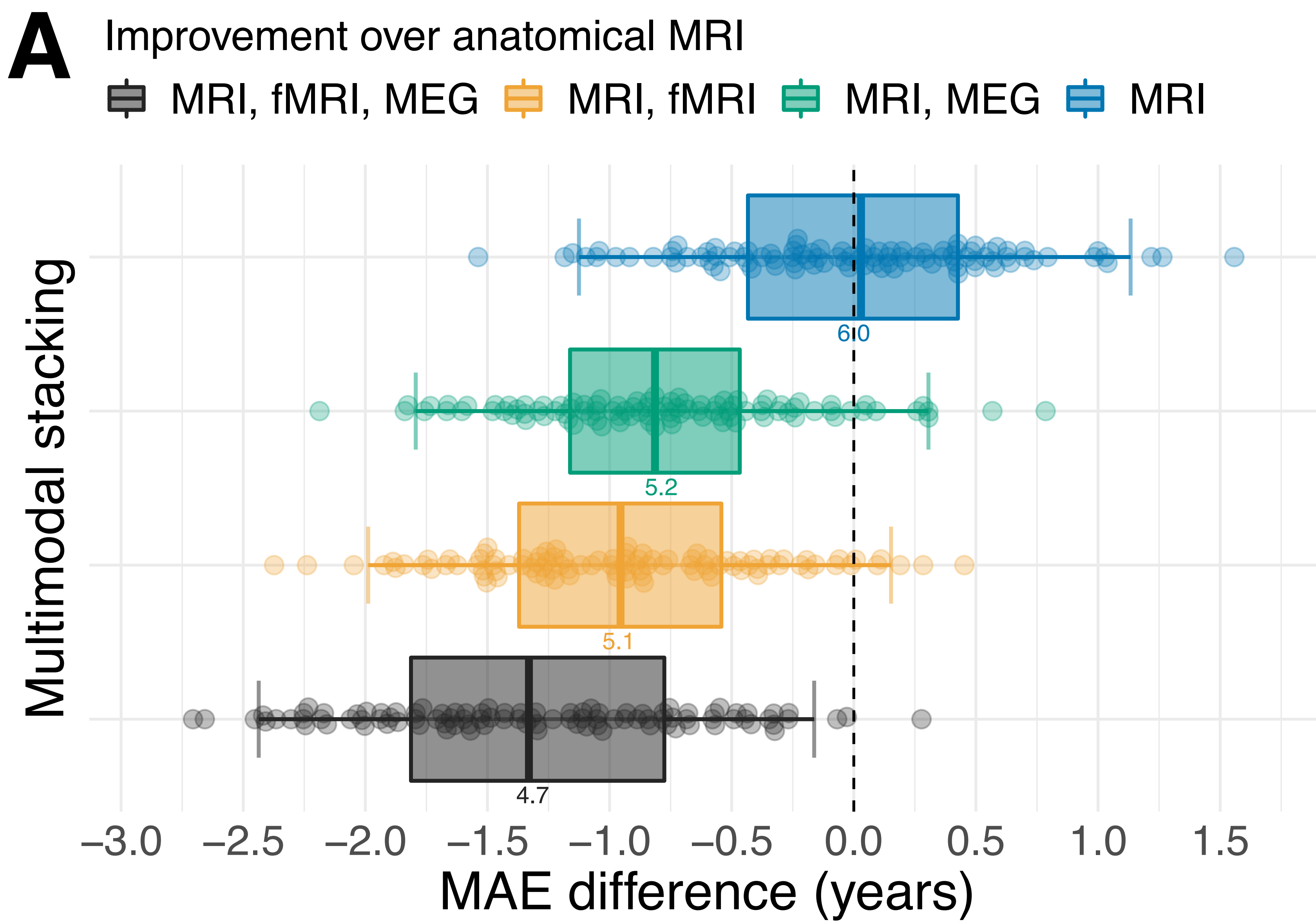
Table 2. Summary of extracted features.

#	Modality	Family	Input	Feature	Variants	Spatial selection
1	MEG	sensor mixed	ERF	latency	aud, vis, audvis	max channel
2	...	...	PSDα	peak		max channel
3	...	...	PSD	1/f slope	low, γ	max channel in ROI
4	...	source activity	signal	power	low,δ,θ,α,$\beta_{1,2}$, $\gamma_{1,2,3}$	MNE, 448 ROIs
5	...	...	envelope	...	...	...
6	...	source connectivity	signal	covariance	...	...
7	...	...	envelope	...	...	...
8	...	...	env.	corr.	...	...
9	...	...	env.	corr. ortho.	...	...
10	fMRI	connectivity	time-series	correlation	...	256 ROIs
11	MRI	anatomy	volume	cortical thickness		5124 vertices
12	...	...	surface	cortical surface area		5124 vertices
13	...	...	volume	subcortical volumes		66 ROIs

Note. ERF = event related field, PSD = power spectral density, MNE = Minimum Norm-Estimates, ROI = region of interest, corr. = correlation, ortho. = orthogonalized.

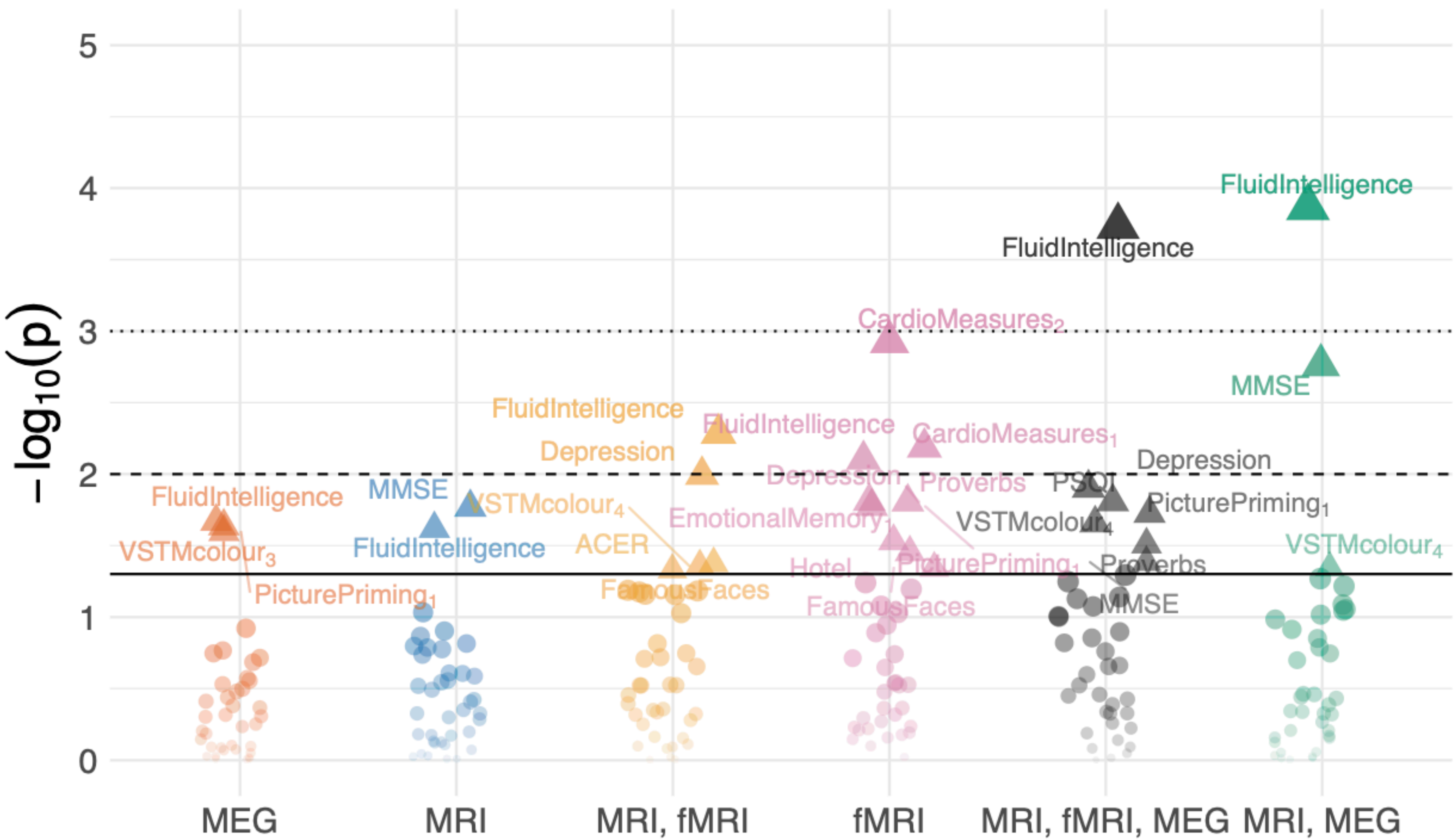
Engemann et al. (2020) **eLife**

Predicting brain age from MRI & MEG enhances predictive performance



Engemann et al. (2020) **eLife** - *Cam-CAN dataset*

Predicting brain age from MRI & MEG enhances predictive performance & cognitive phenotyping



Engemann et al. (2020) **eLife** - *Cam-CAN dataset*

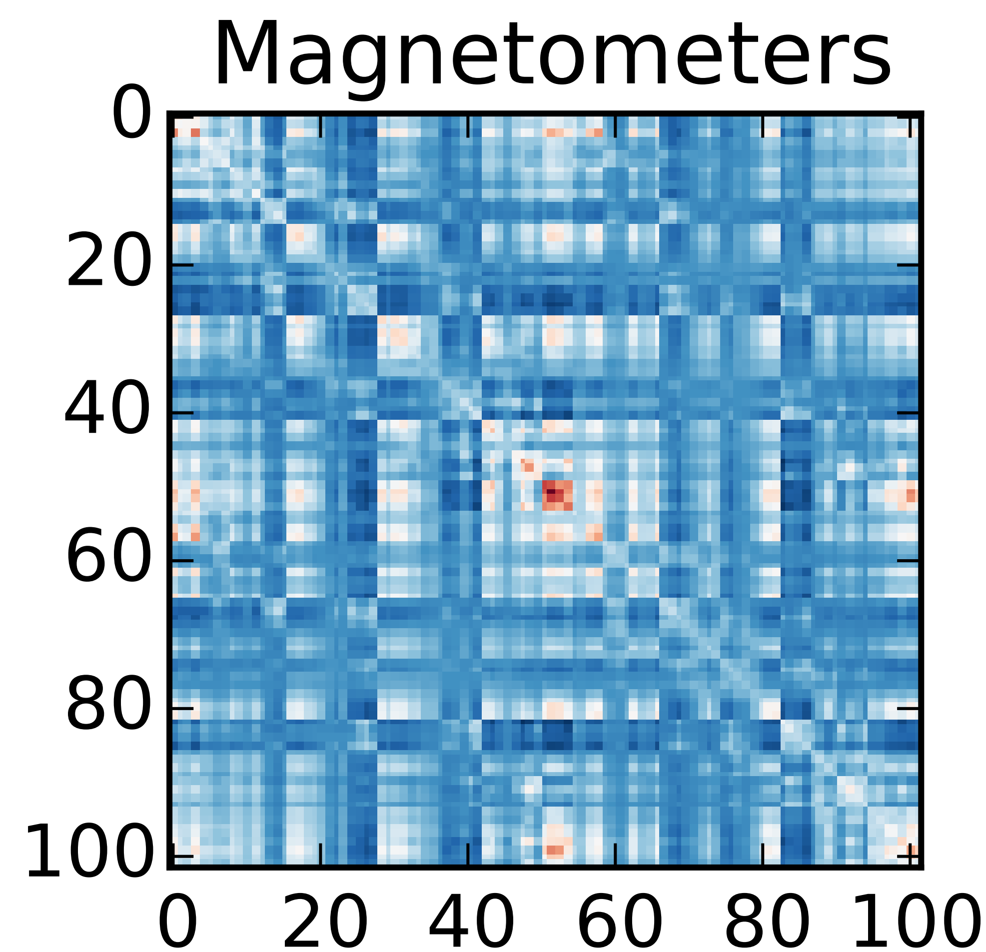

What if I don't have MRI and only electrophysiology?

Covariance

$X_i \in \mathbb{R}^{C \times T}$: MEG/EEG signals

C : number of channels

T : number of time samples



Definition [Covariance]:

$$\Sigma_i = \frac{X_i X_i^\top}{T} \in \mathbb{S}_+^C \subset \mathbb{R}^{C \times C}$$

Set of non-negative symmetric matrices

Remark: Estimation of cov. requires care

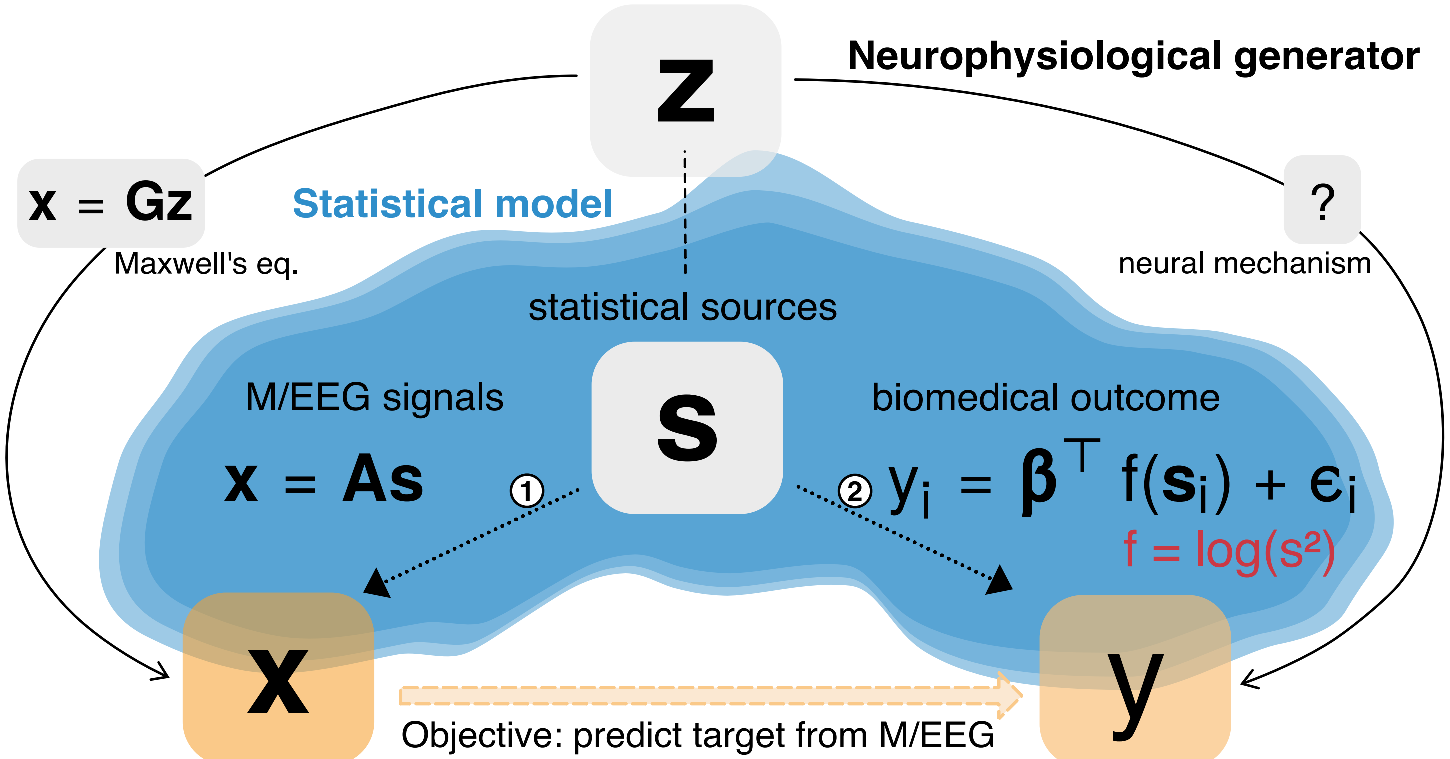
[Engemann & Gramfort, Neuroimage 2017]

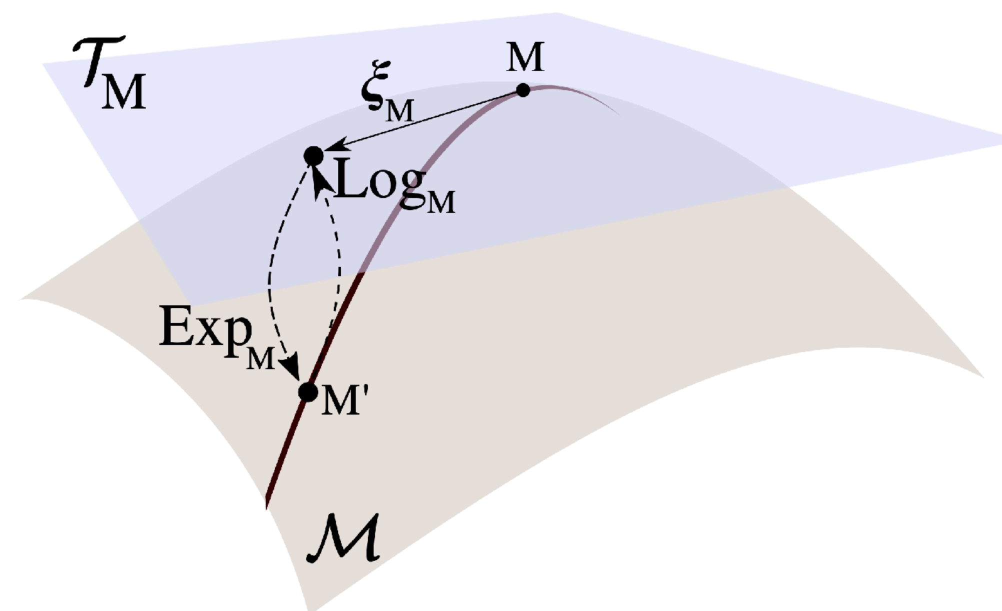
Predicting from M/EEG source power

Without biophysical source localization (estimation of z)

Problem: A is unknown

Idea: use affine invariant distances between covariances





Take out volume conduction using Riemannian distance

Use cov. as representation

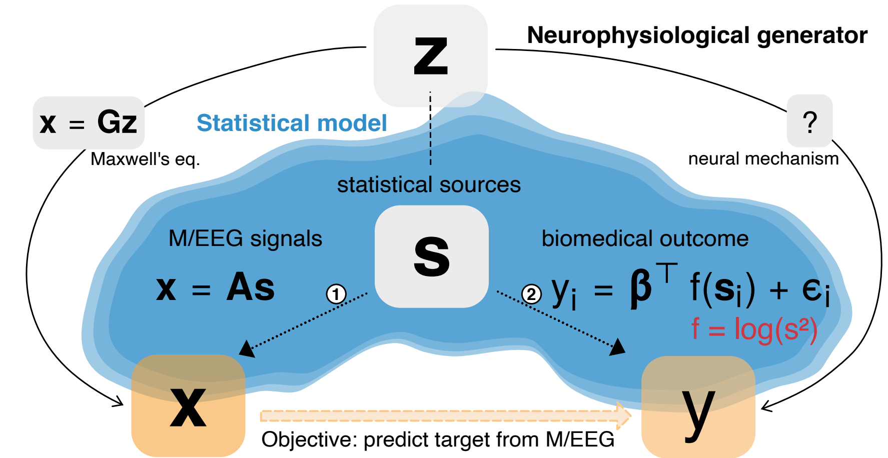
$$\Sigma_i = \frac{S_i S_i^\top}{T} \in \mathbb{S}_{+}^{C} \subset \mathbb{R}^{C \times C}$$

$$d_G(\Sigma_1, \Sigma_2) = \| \log(\Sigma_1^{-\frac{1}{2}} \Sigma_2 \Sigma_1^{-\frac{1}{2}}) \|_F$$

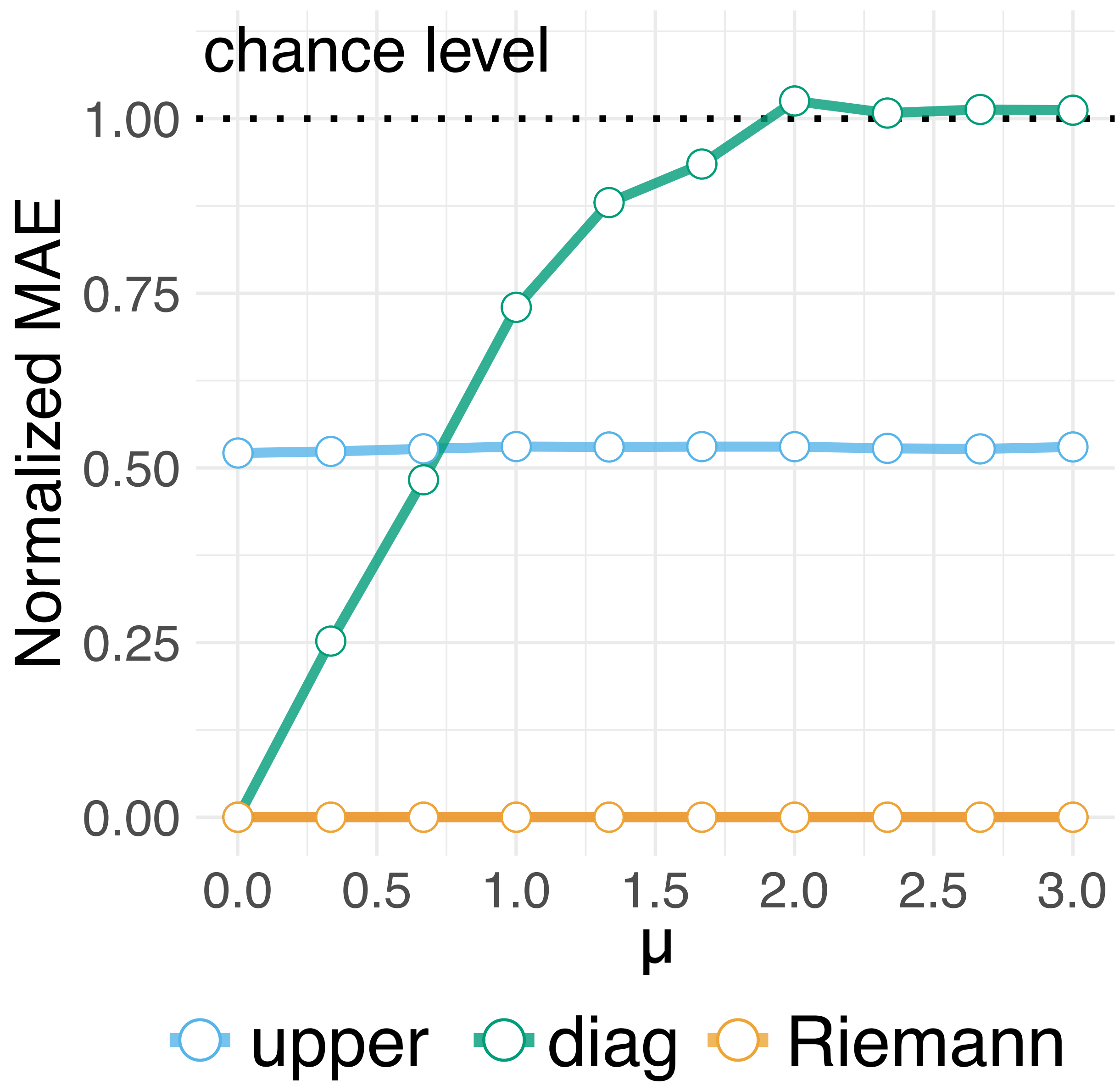
Sabbagh et al. 2019 (NeurIPS) 2020 (NIMG)

Simulations

Are shortcuts — in principle — possible?



$A = \exp(\mu B)$ with B random.

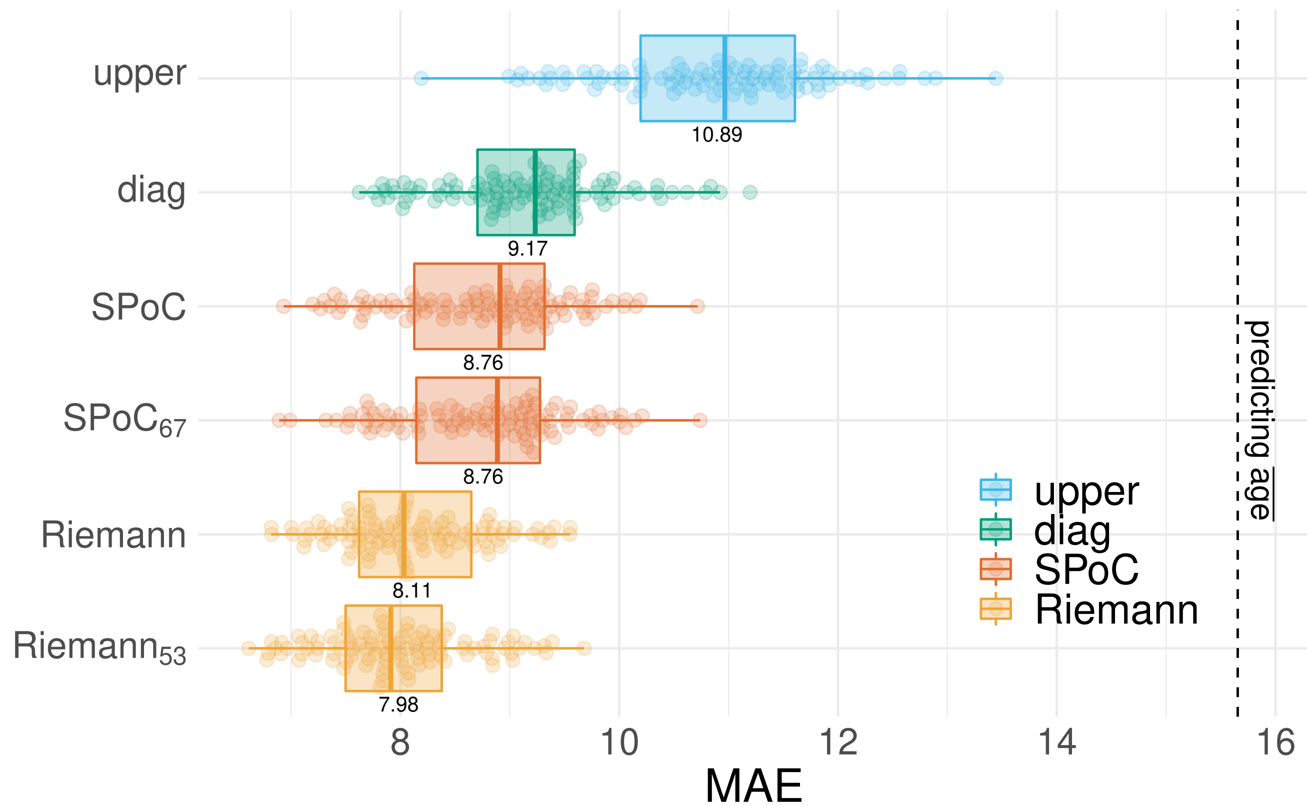


We have empirical and mathematical *proven statistical consistency*

Sabbagh et al. 2019 (NeurIPS) 2020 (NIMG)

Empirical benchmarks

MEG (Cam-CAN, n=650)



Sabbagh et al. 2020 (NIMG)

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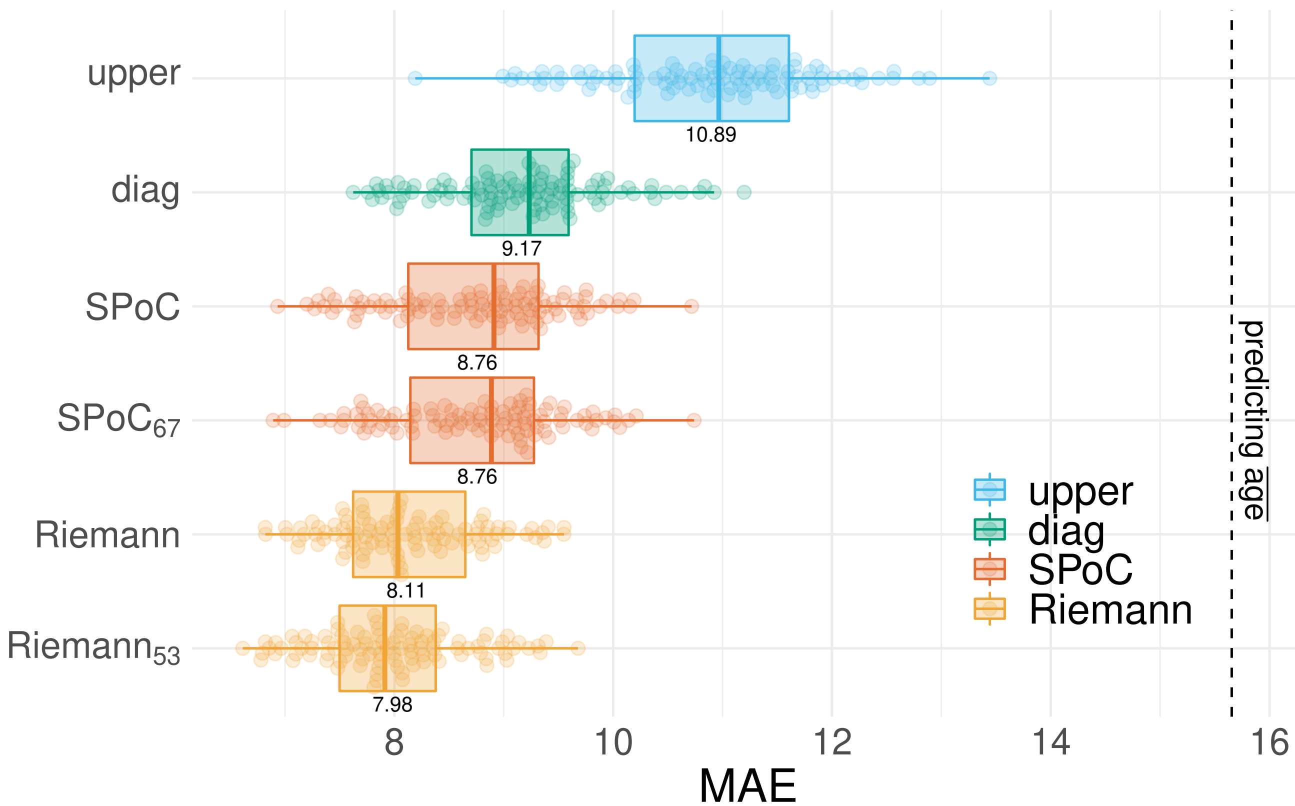
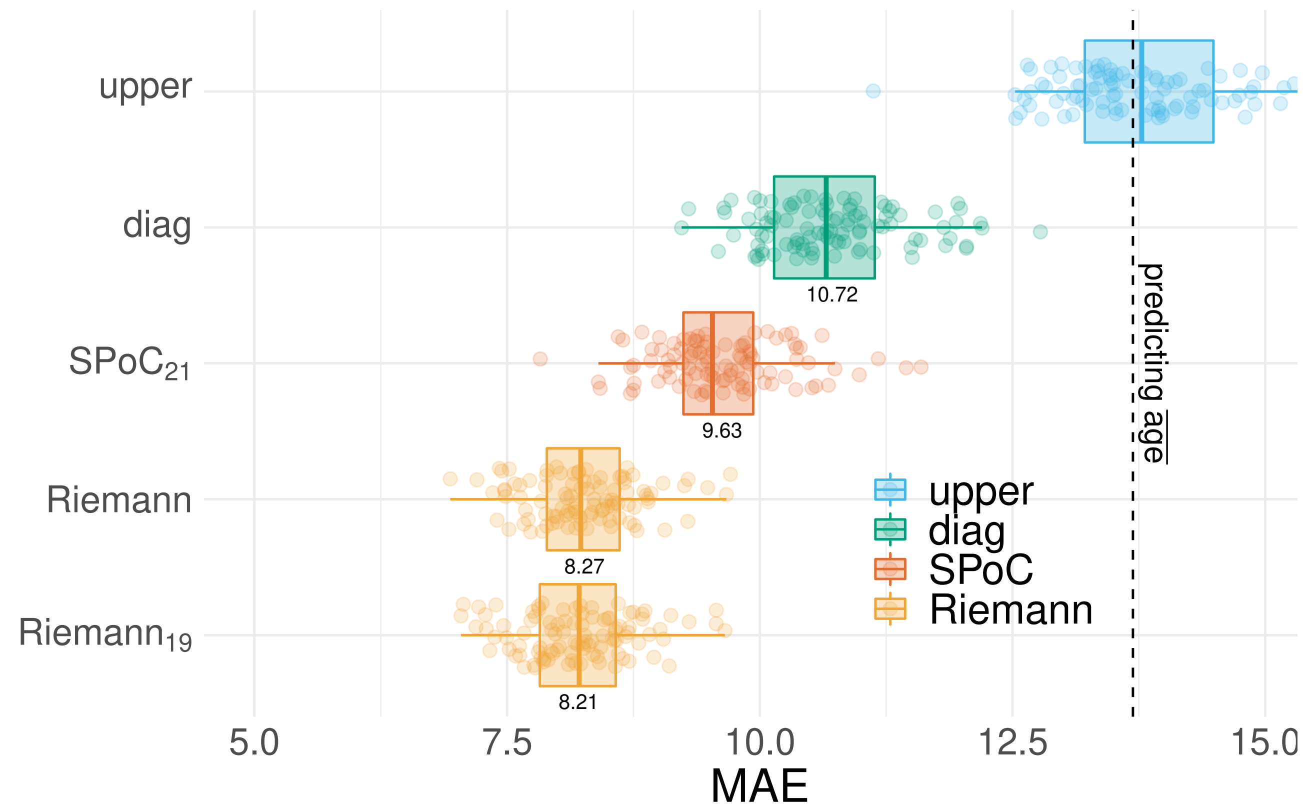


EEG (TUH data, n=1385)



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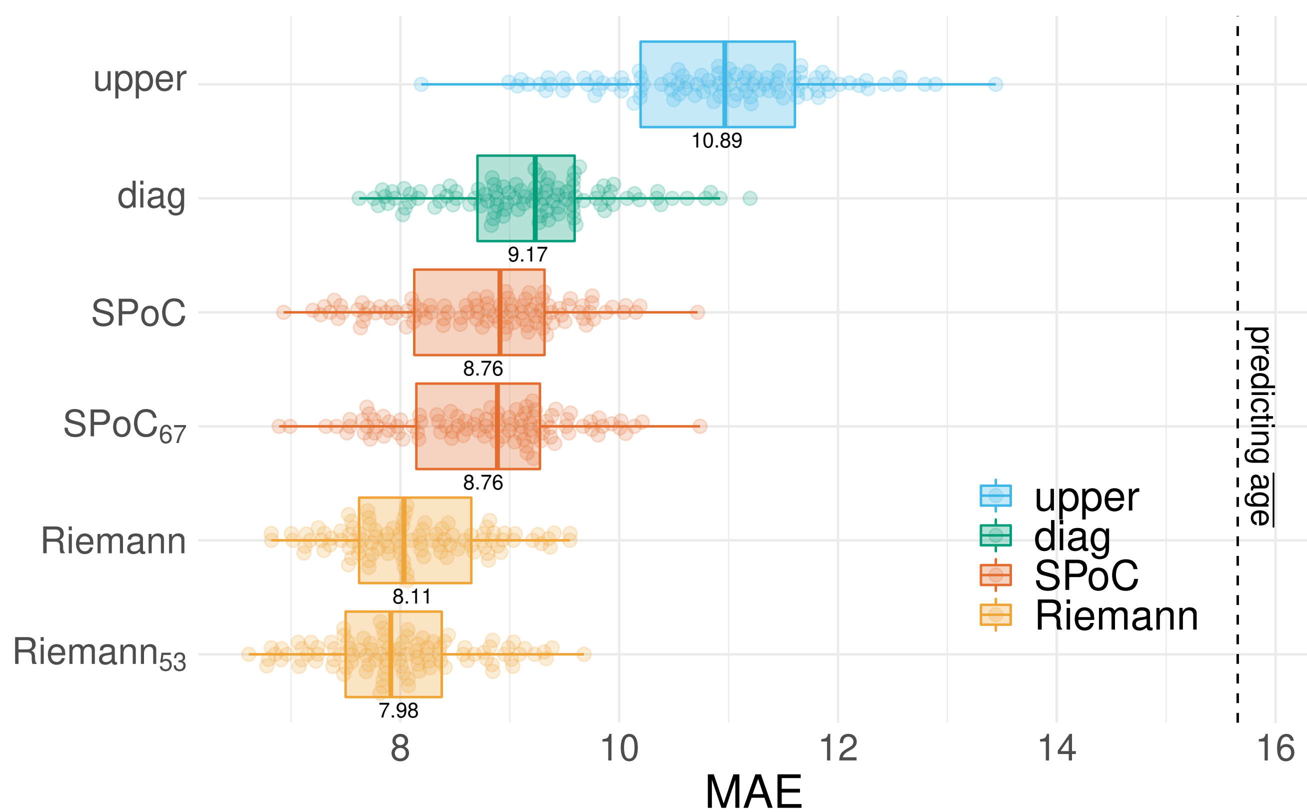

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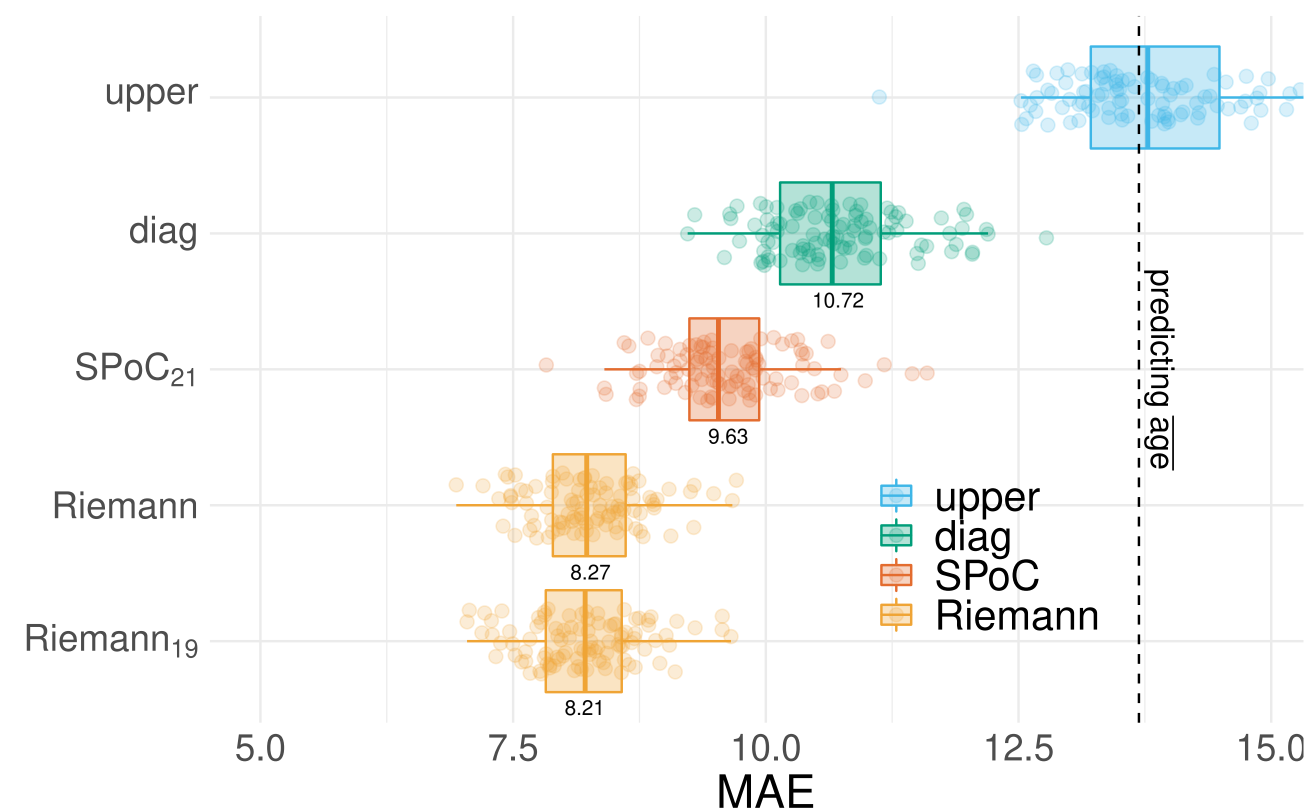


EEG can in principle be substituted for MEG

Sabbagh et al. 2020 (NIMG)

Conclusion

- Neuroscience signals are under exploited
- Need for better models and tools
- Need more interdisciplinary work (CS, ML, stats, neuro, physics…)
- If you want the maths look at papers…

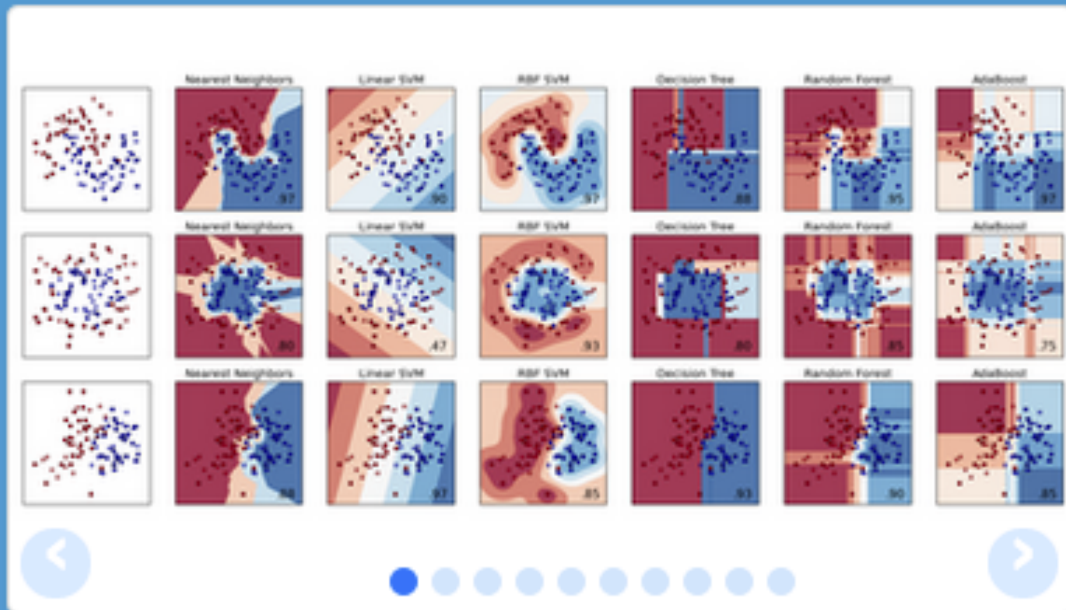
"All models are wrong but some come with good open source implementation and good documentation so use those."

scikit learn

Home Installation Documentation Examples

Google™ Custom Search

Fork me on GitHub



scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: *SVM*, *nearest neighbors*, *random forest*, ... — *Examples*

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: *SVR*, *ridge regression*, *Lasso*, ... — *Examples*

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: *k-Means*, *spectral clustering*, *mean-shift*, ... — *Examples*

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: *PCA*, *feature selection*, *non-*

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: *grid search*, *cross validation*

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.
Modules: *preprocessing*, *feature extraction*.

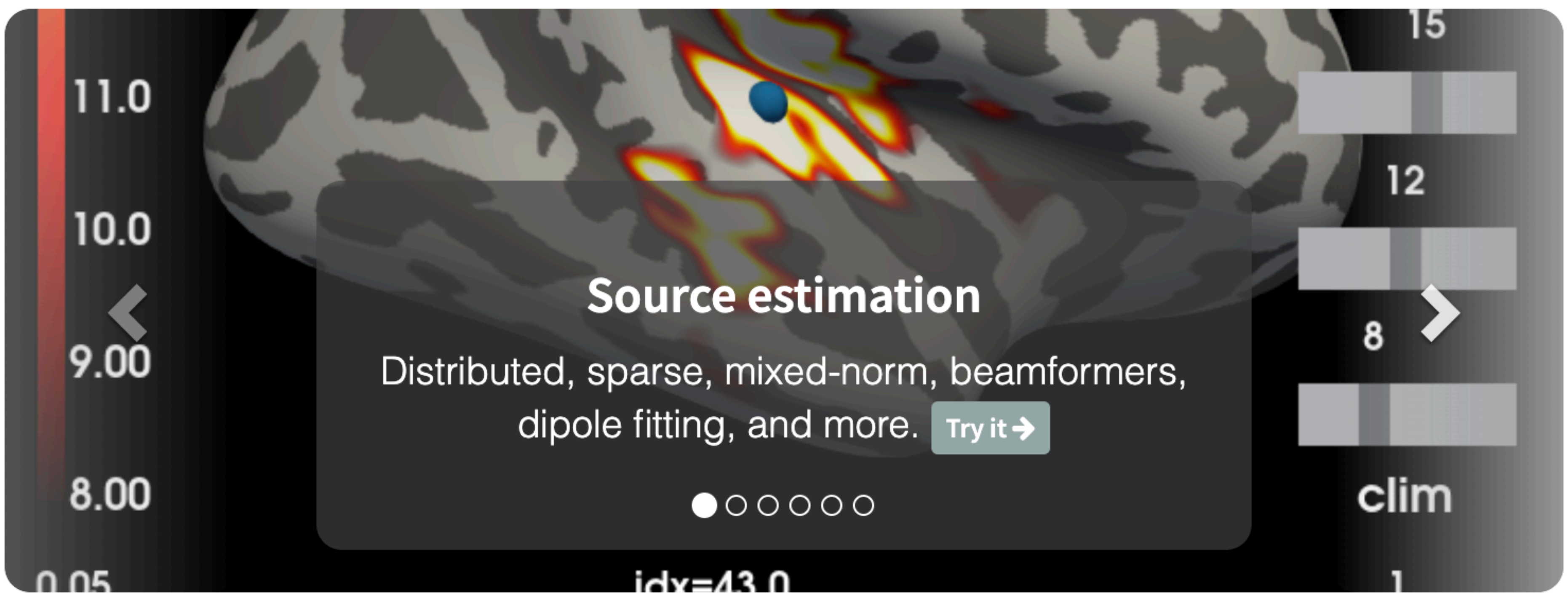
http://scikit-learn.org

MNE Install Overview Tutorials Examples Glossary API More v0.21.dev0 Search

MNE

MEG + EEG ANALYSIS & VISUALIZATION

Open… huma… https://mne.tools/ …nalyzing …RS, and



Version 0.21.dev0

- What's new
- Installation
- Documentation
- Cite

Direct financial support

National Institutes of Health: R01-EB009048, EB009048, EB006385, HD40712, NS44319, NS37462, NS104585, **P41**-EB015896, RR14075-06

US National Science Foundation: 0958669, 1042134

European Research Council: YStG-263584, 676943

US Department of Energy: DE-FG02-99ER62764 (MIND)

Agence Nationale de la Recherche: 14-NEUC-0002-01
IDEX Paris-Saclay, 11-IDEX-0003-02

Paris-Saclay Center for Data Science: PARIS-SACLAY

Google: Summer of code (×6)

Amazon: AWS Research Grants

Chan Zuckerberg Initiative: Essential Open Source Software for Science

MNE software for processing MEG and EEG data, A. Gramfort, M. Luessi, E. Larson, D. Engemann, D. Strohmeier, C. Brodbeck, L. Parkkonen, M. Hämäläinen, Neuroimage 2013

Thanks !


D. Sabbagh


D. Engemann

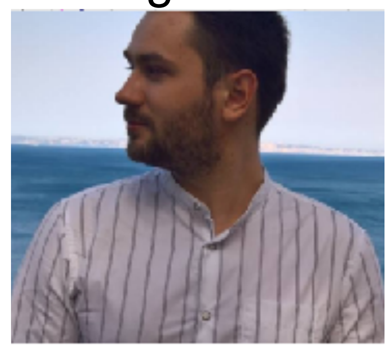

G. Varoquaux


B. Thirion


T. Dupré La Tour

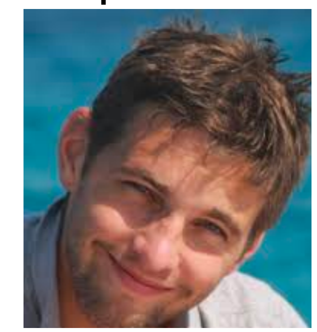

M. Jas


F. Liem


O. Kozynets


G. Lemaitre


P. Ablin


T. Moreau


H. Banville

as well as A. Hyvärinen, U. Simsekli, O. Chehab

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MEG + EEG ANALYSIS & VISUALIZATION

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Support

ANR-NSF Grant Thalameeg
European Research Council (ERC SLAB-YStG-676943)

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Inserm
Institut national
de la santé et de la recherche médicale

Main references

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