SLAB: Signal and Learning Applied to Brain data

Alexandre Gramfort

CNRS - Télécom ParisTech

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Oct. 2009 — *Nov. 2010* — *Sep. 2012*

PhD → Postdoc → Postdoc → PI

***Contributions**: Signal processing, optimization, statistical machine learning, numerical methods for brain imaging data*

6 PhD co-supervisions
ANR-NSF Grant
400 k€ managed as PI

> 45 publications, 2840 citations - H-Index 18

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scikit learn

Scikit-Learn JMLR 2011
> 1700 citations

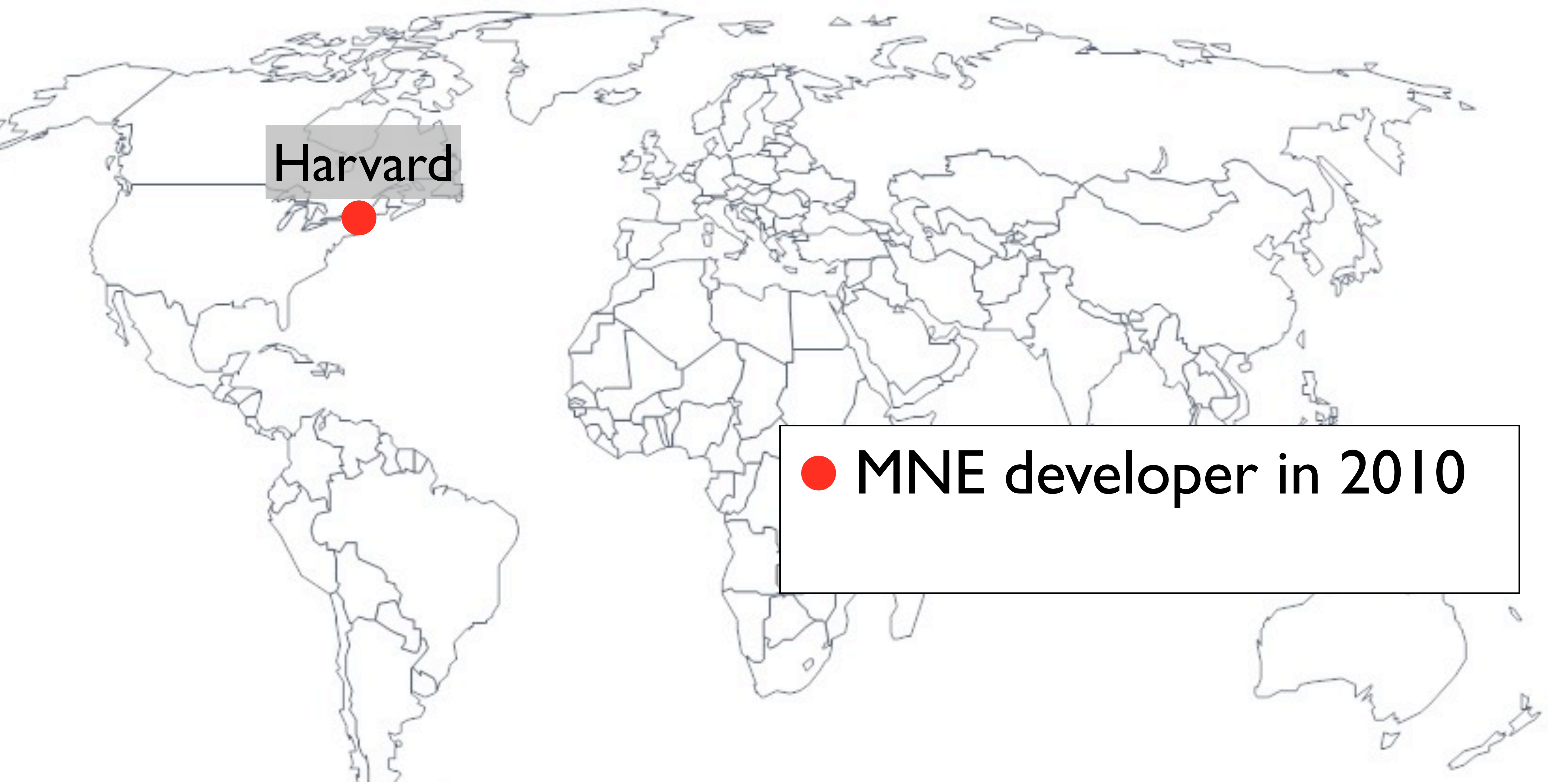
OpenMEEG

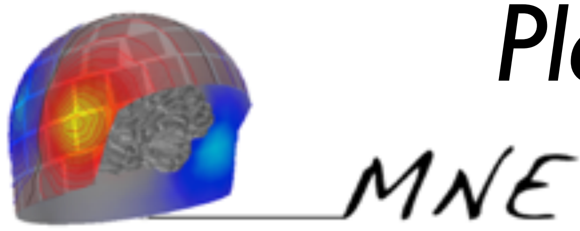
State-of-the-art solver for EEG in leading academic packages

MNE

Neuroimage 2014
> 66 citations in 18 months

Impact of MNE software on neuroscience





Platform for collaborations, easy data sharing & results dissemination

[Gramfort et al. Neuroimage 2014]

http://martinos.org/mne/

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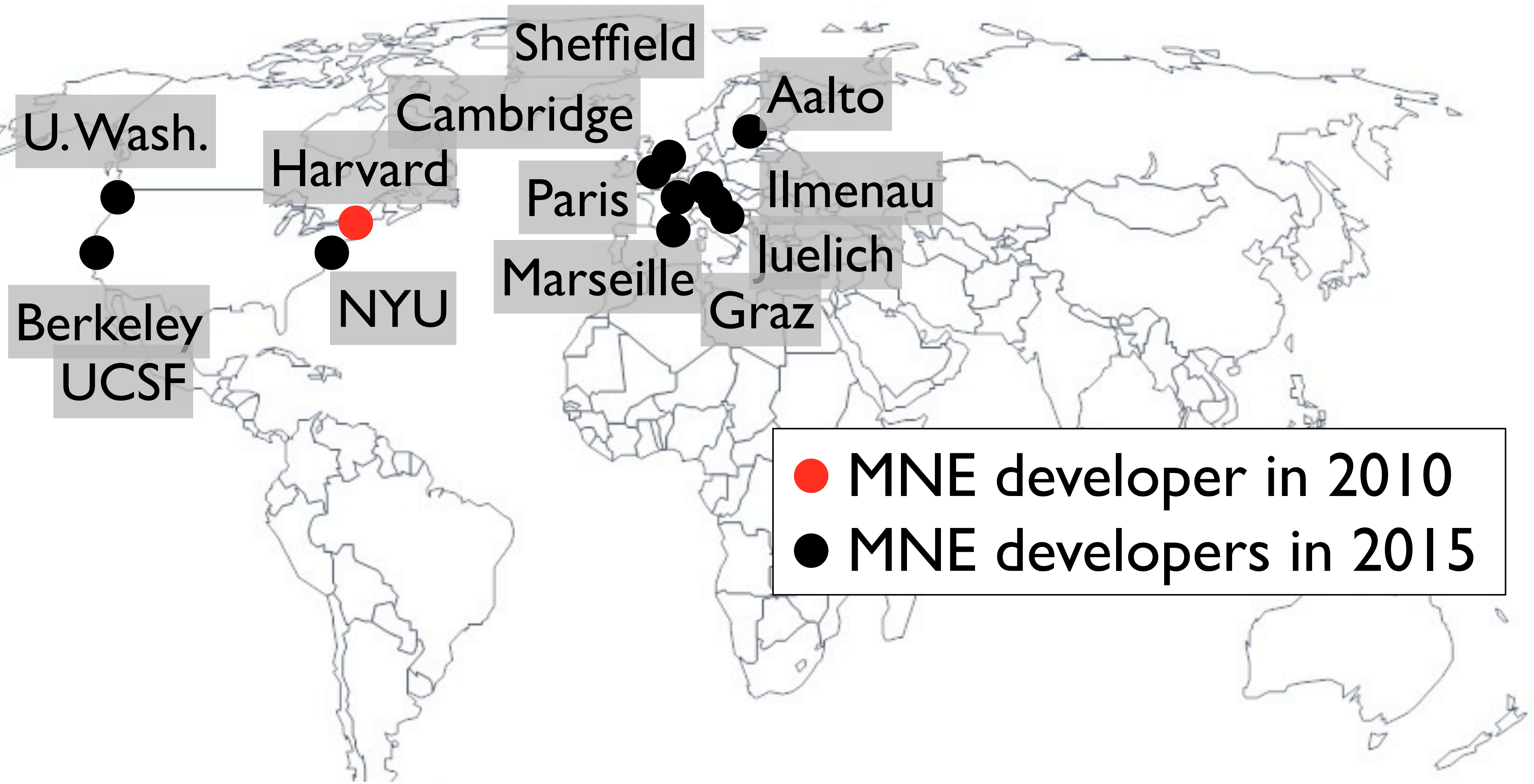

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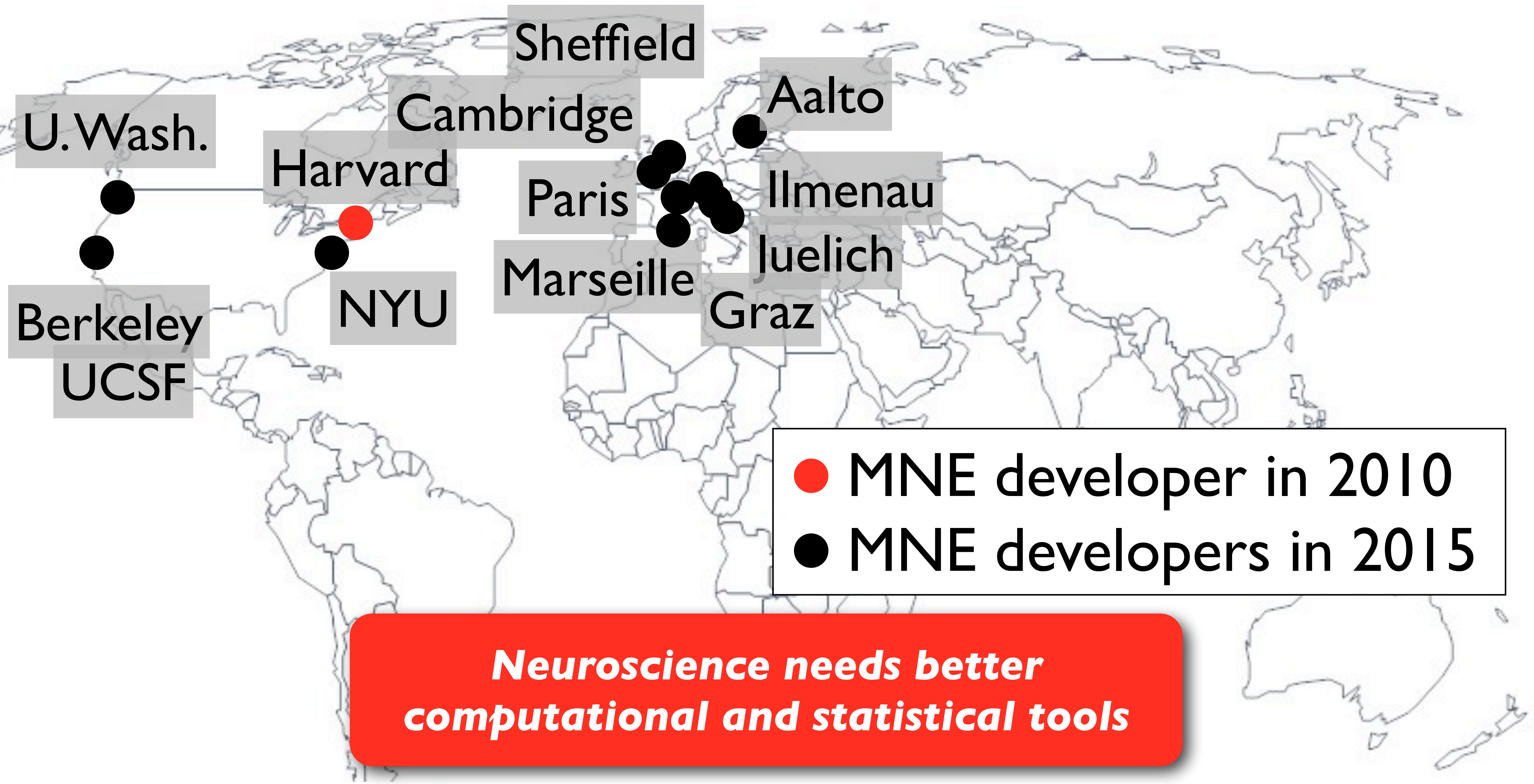

Neuroscience needs better computational and statistical tools

MNE

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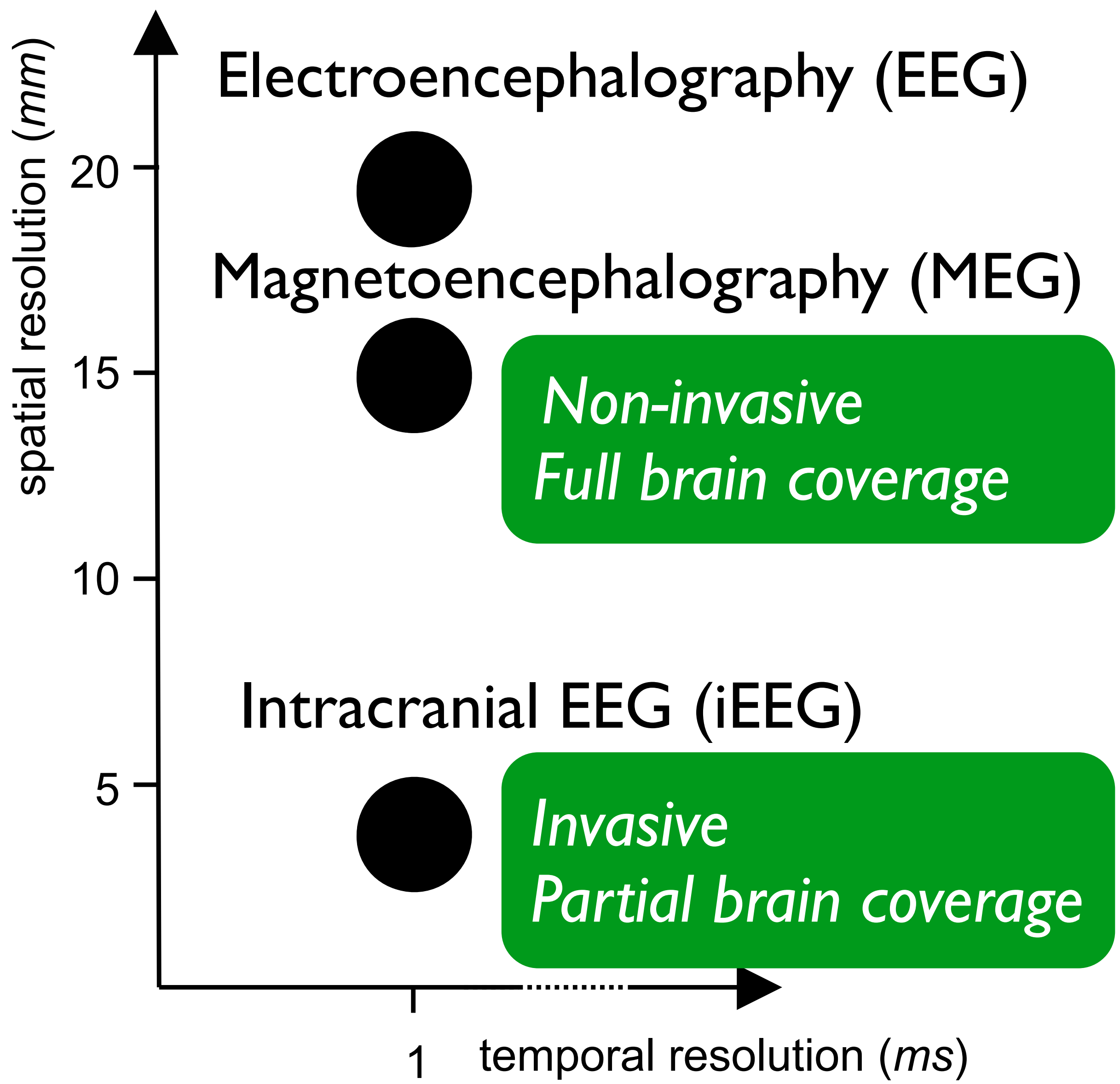
Context: Functional Brain Signals



Clinical (sleep, epilepsy, stroke, autism) & Cognitive Neurosience, Neuroengineering (BCI)

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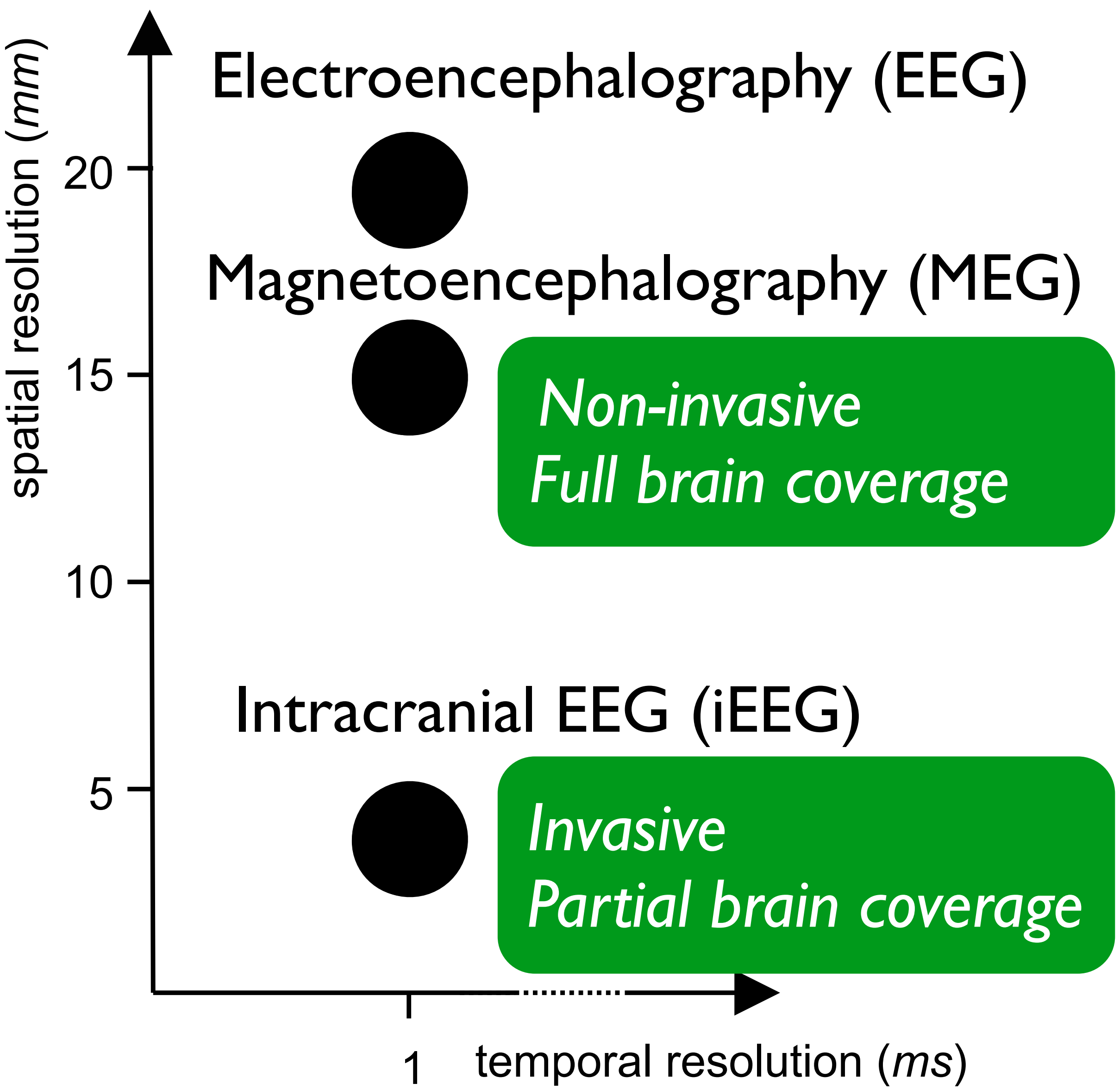
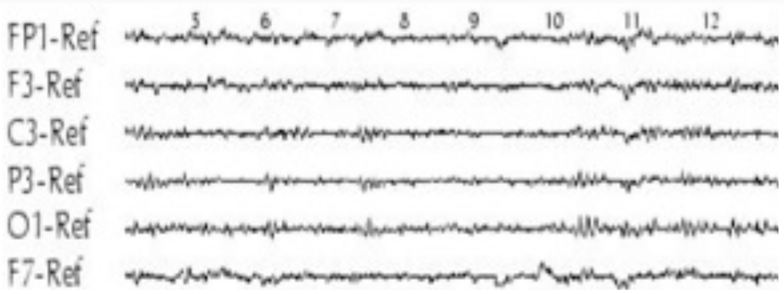


Non-invasive
Full brain coverage

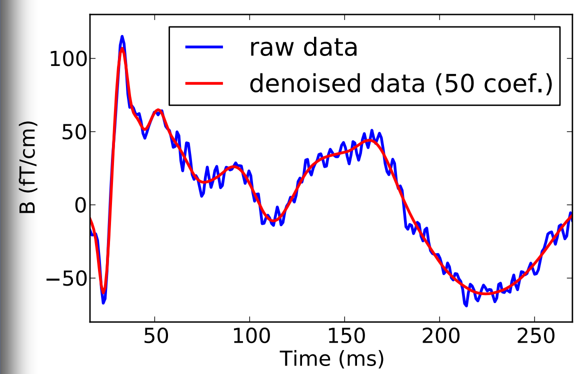
Invasive
Partial brain coverage

Clinical (sleep, epilepsy, stroke, autism) & Cognitive Neurosience, Neuroengineering (BCI)

Multivariate Time-Series



Signal: *non-linear, non-stationary, with oscillations continuously varying in frequency and amplitude & sharp local transient*



Noise (biological & external): *non-white and sensor dependent*

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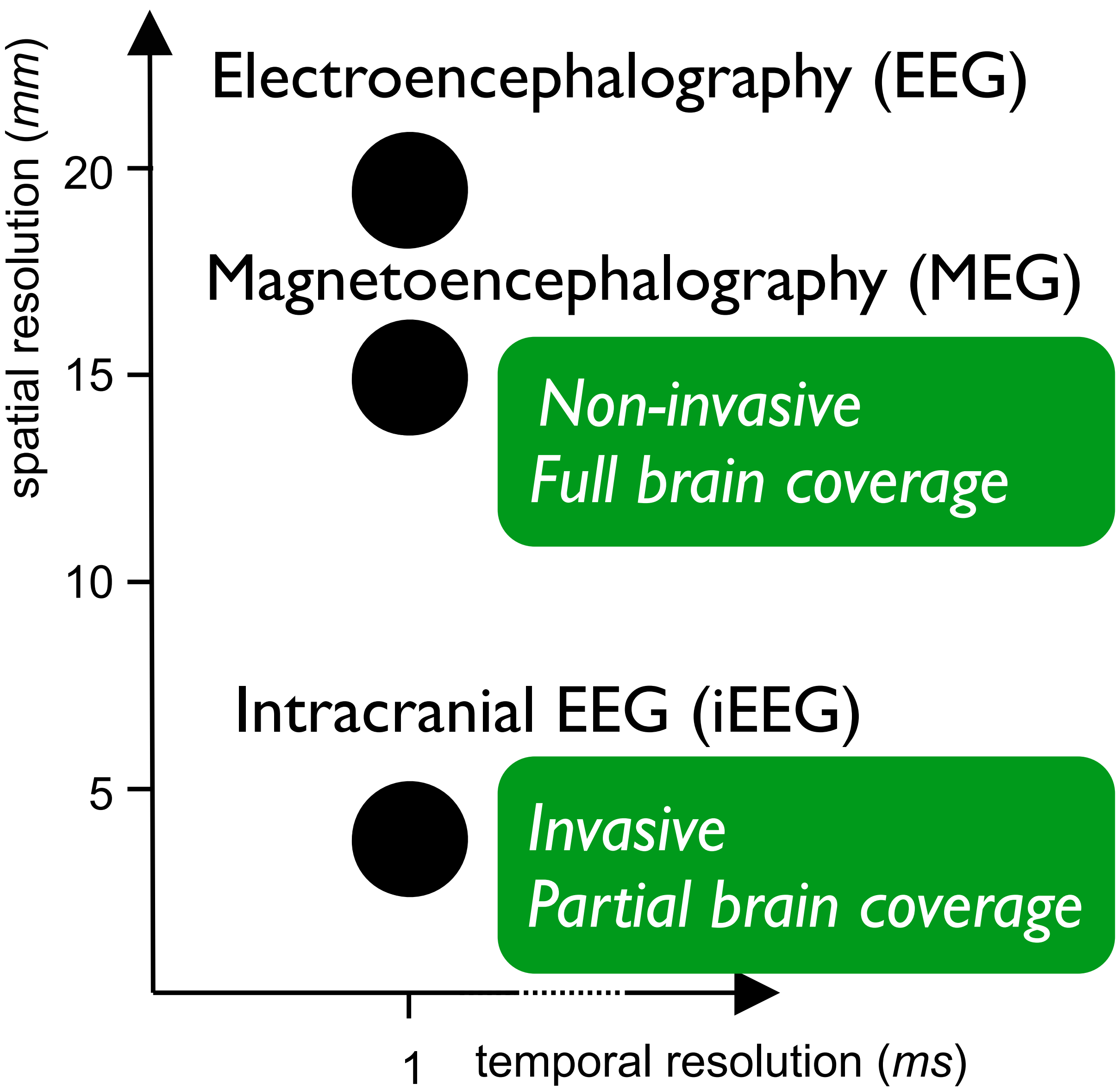

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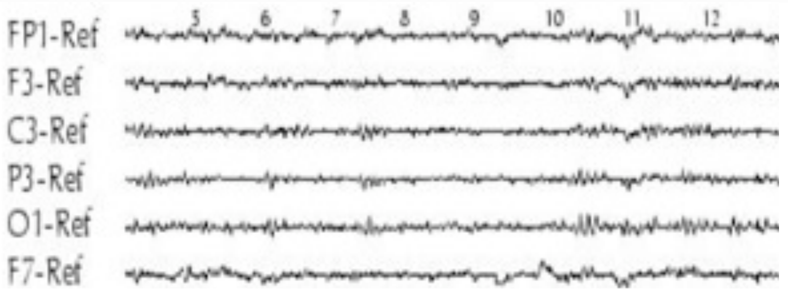

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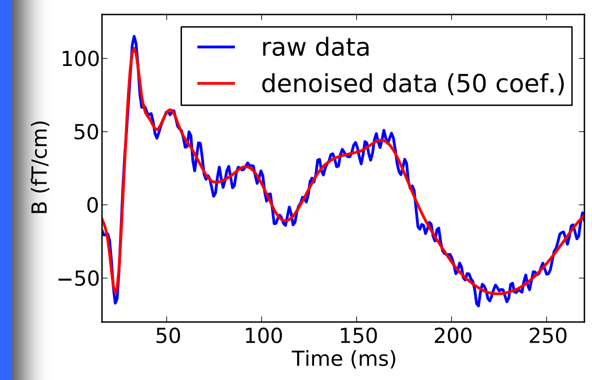


Noise (biological & external): *non-white and sensor dependent*

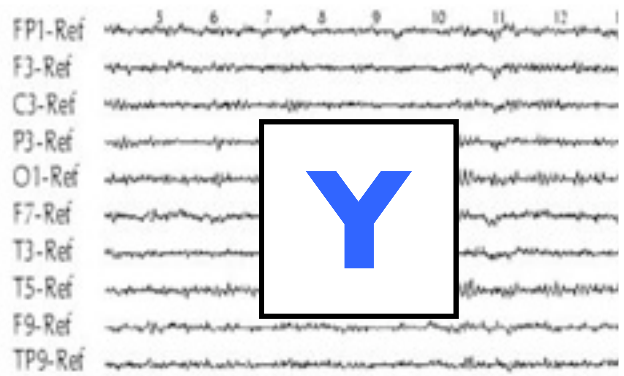
Clinical (sleep, epilepsy, stroke, autism) & Cognitive Neurosience, Neuroengineering (BCI)

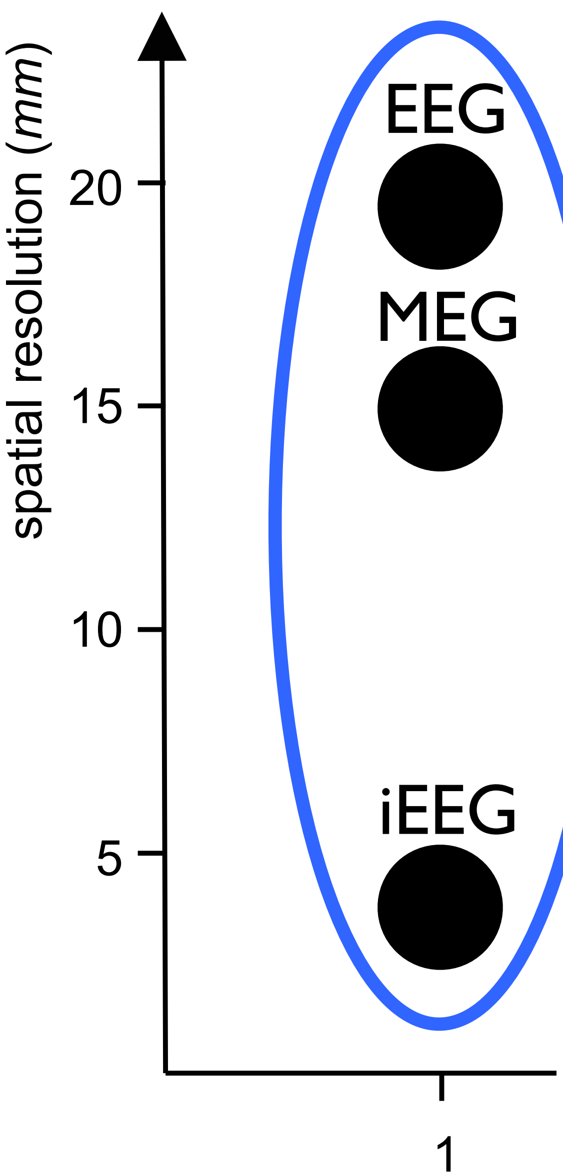
Among the most difficult time series you can ever try to model

SLAB WP 1

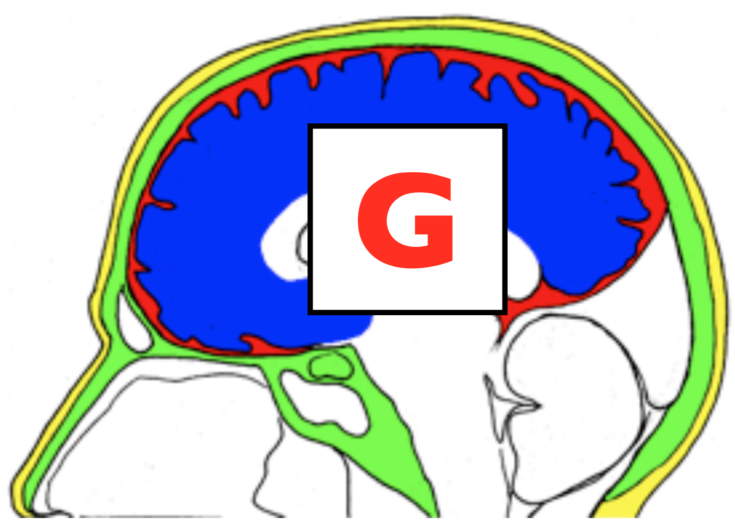
Objective: high resolution imaging of the entire brain at 1 ms time scale

Data





Forward Model

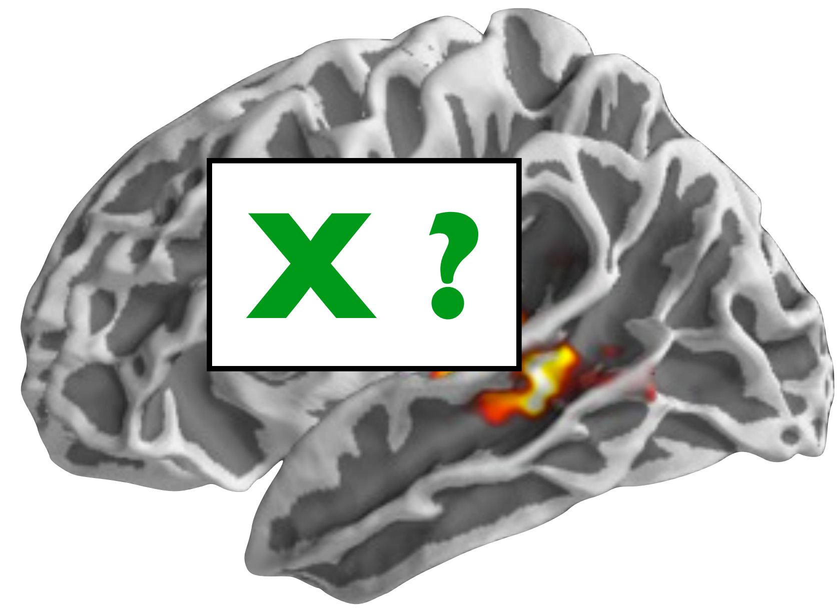


$$\nabla \times \vec{B} = \mu_0 \vec{J}$$

OpenMEEG

[Gramfort et al. 2011]

Source localization



Linear Physical System:

$$\mathbf{Y} = \mathbf{G}\mathbf{X} + \mathbf{E}$$

Regression / Inverse problem: high dimensional, ill-posed, spatio-temporal

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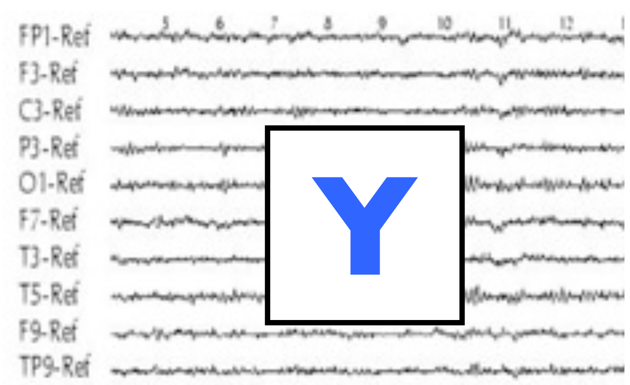

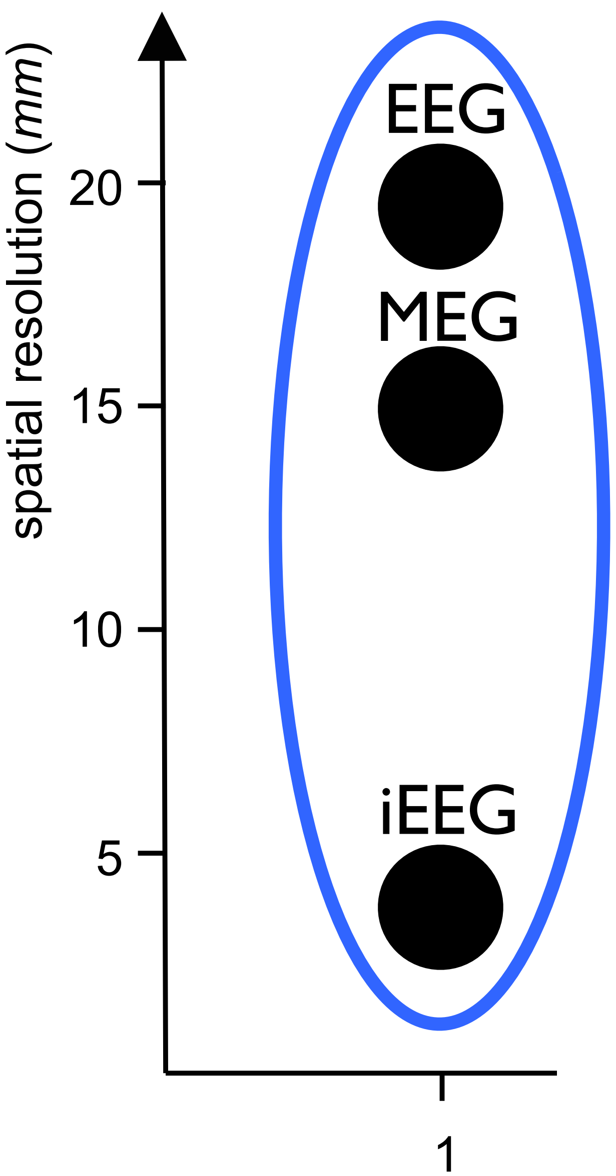

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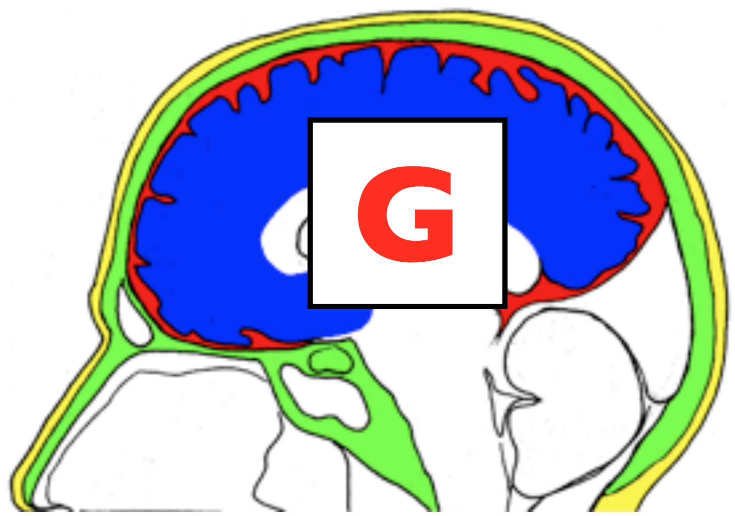

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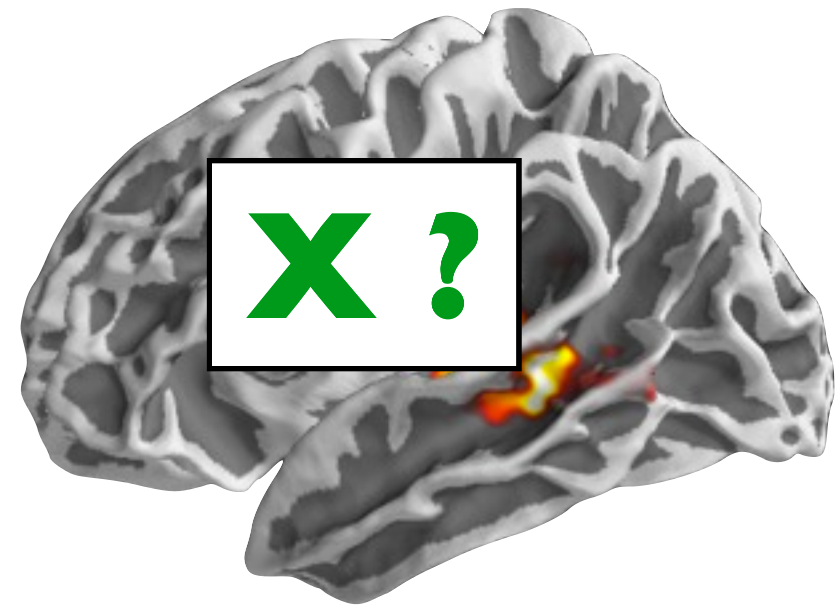

Linear Physical System:

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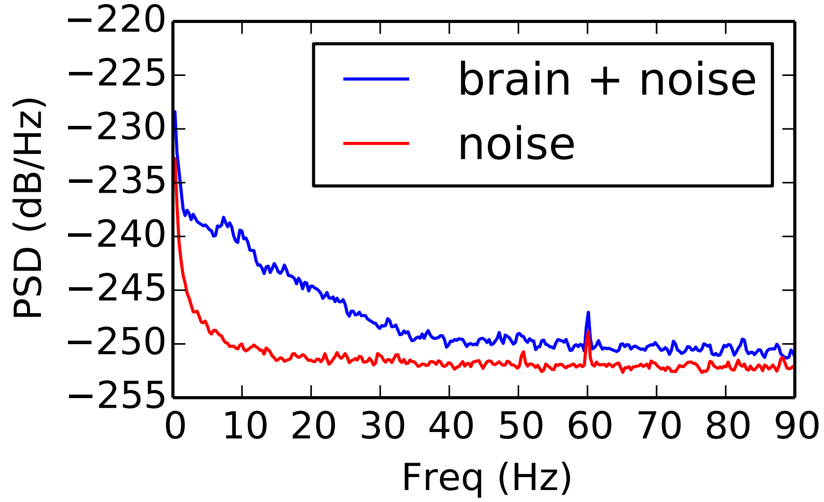
Regression / Inverse problem: high dimensional, ill-posed, spatio-temporal

Current method in brain imaging labs:

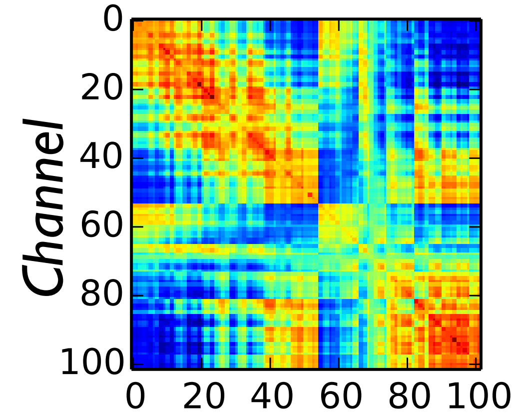
$$\hat{\mathbf{X}} = \underset{\mathbf{X} \in \mathbb{R}^{10^4 \times 500}}{\operatorname{argmin}} \|\mathbf{Y} - \mathbf{G}\mathbf{X}\|_F^2 + \lambda \|\mathbf{X}\|_F^2$$

Limits of the current approach:

- neglects the temporal dynamics of the signal: *oscillations and transients*
- ignores the complex noise structure: *colored and heteroscedastic*



Spectrum



Channel

Spatial correlation

[Engemann & Gramfort, Neuroimage 2015]

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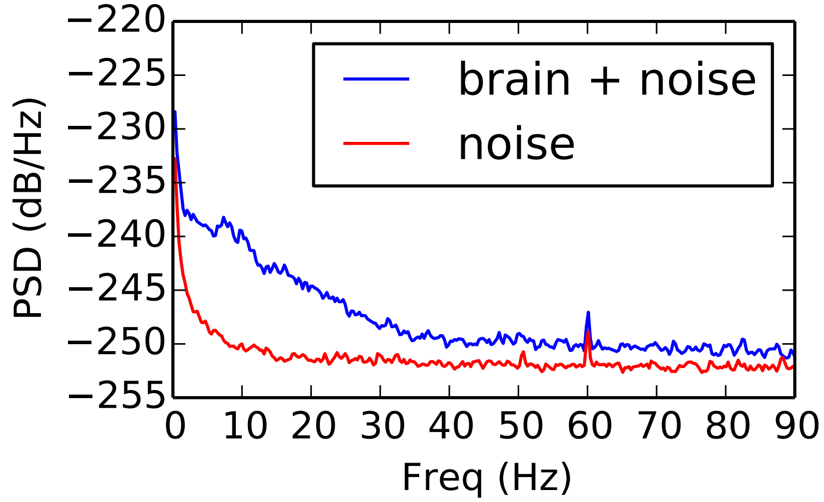

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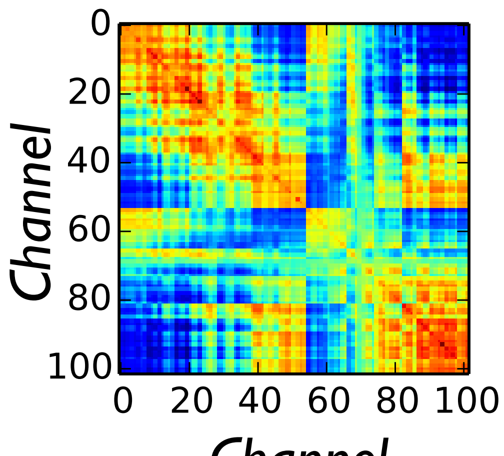


Spatial correlation

[Engemann & Gramfort, Neuroimage 2015]

New model:

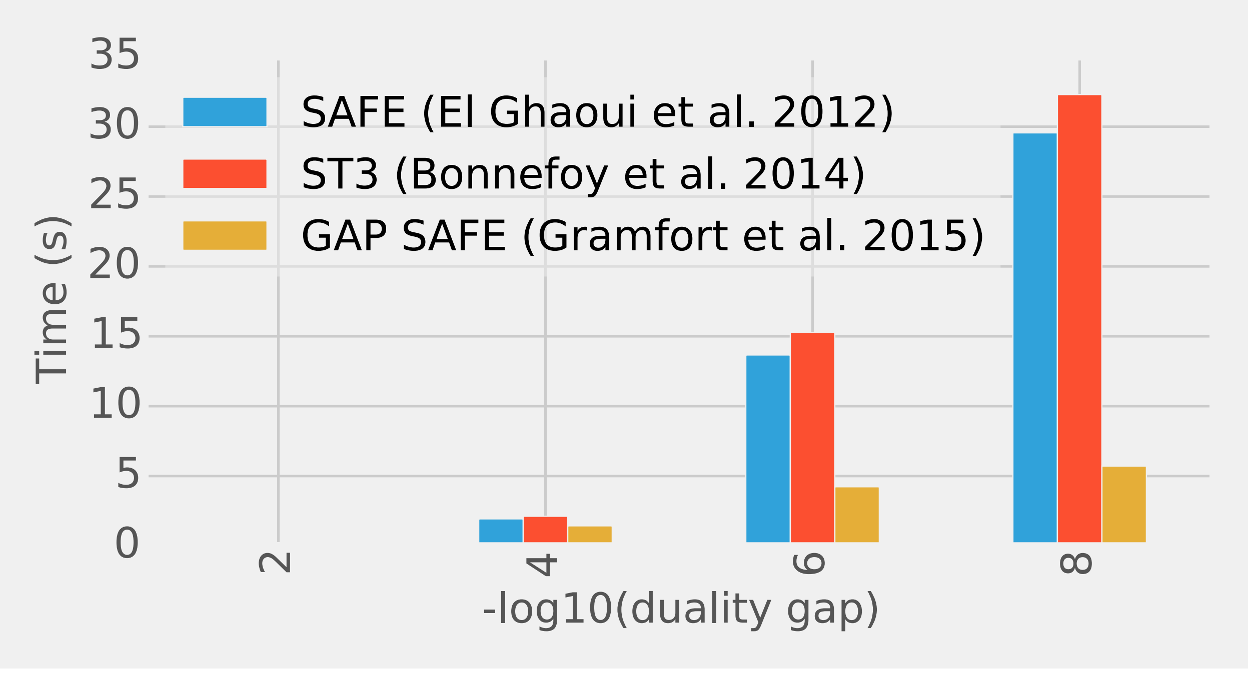
Time-Frequency domain | sparse (non-)convex regularization | Beyond $\|\cdot\|_F$ loss

$$\hat{\mathbf{Z}} = \underset{\mathbf{Z} \in \mathbb{C}^{10^4 \times 2000}}{\operatorname{argmin}} \|\mathbf{Y} - \mathbf{G}\mathbf{Z}\mathbf{\Phi}\|^2_{\Sigma(f)} + \lambda \phi(\mathbf{Z})$$

New solvers:

Coord. Descent for dense G & implicit TF operators, active set & (safe) screening rules

Preliminary result: Lasso Screening [ICML 2015] + [NIPS 2015]



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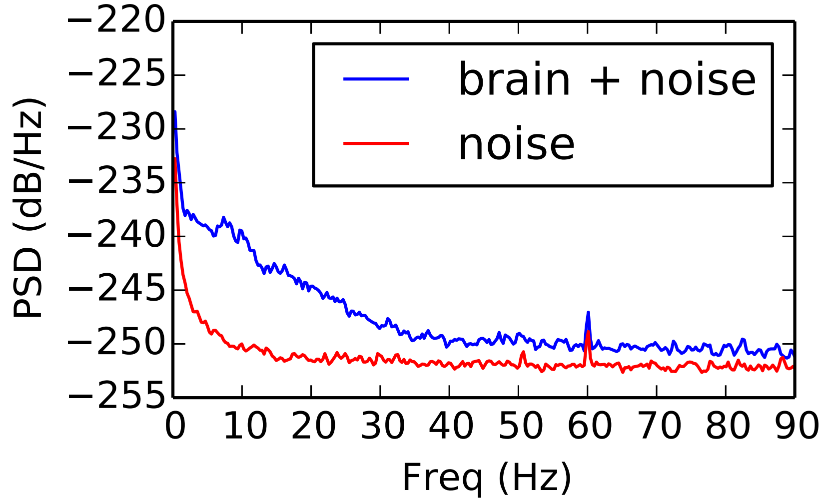

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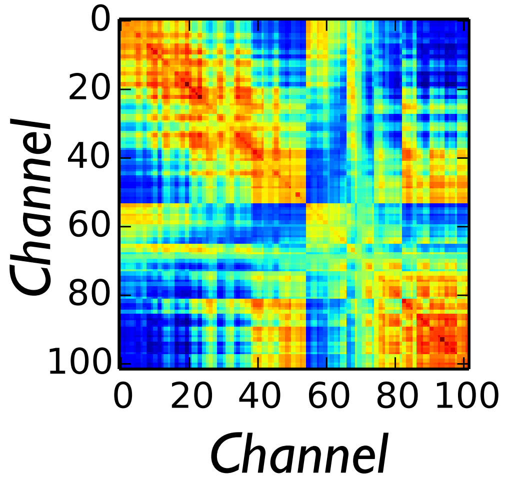

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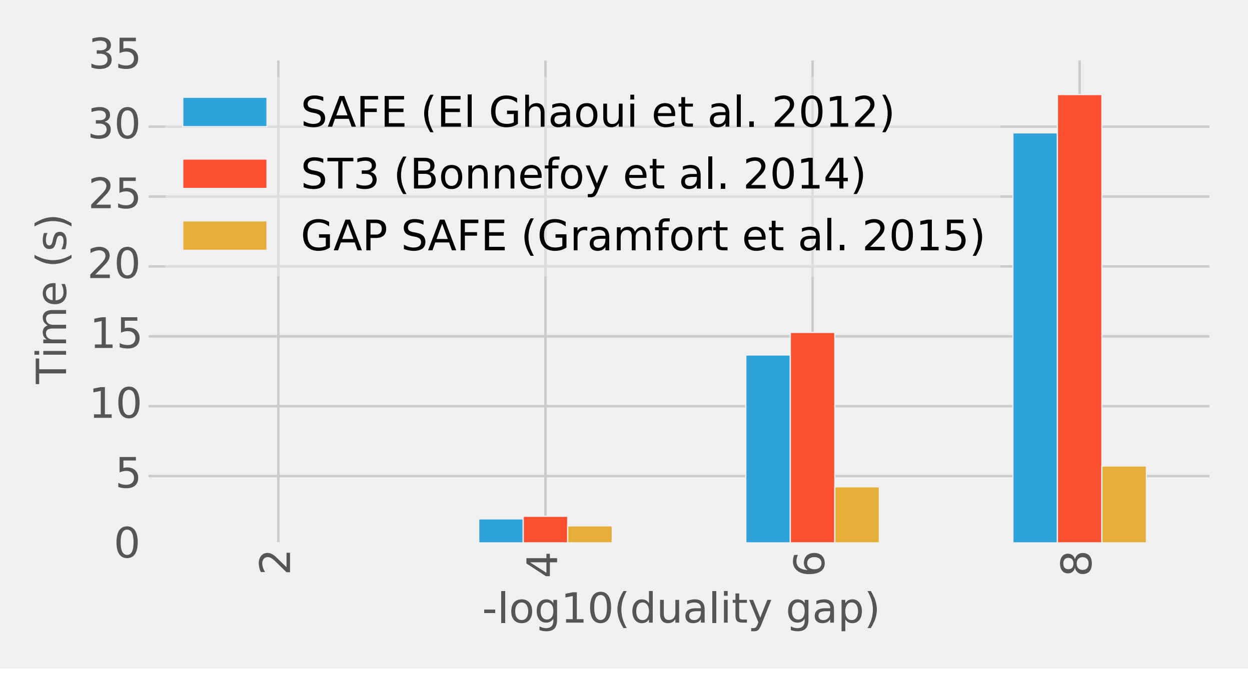
up to x10 speed up



SLAB WP 2

Objective: boost statistical power by learning temporal representations

Problem: No equivalent of Maxwell's equations for temporal dynamics

Current situation: models too simple (splines, damped oscillator) or too complex (require unobserved quantities)

Idea: Directly <u>learn</u> models from empirical data !

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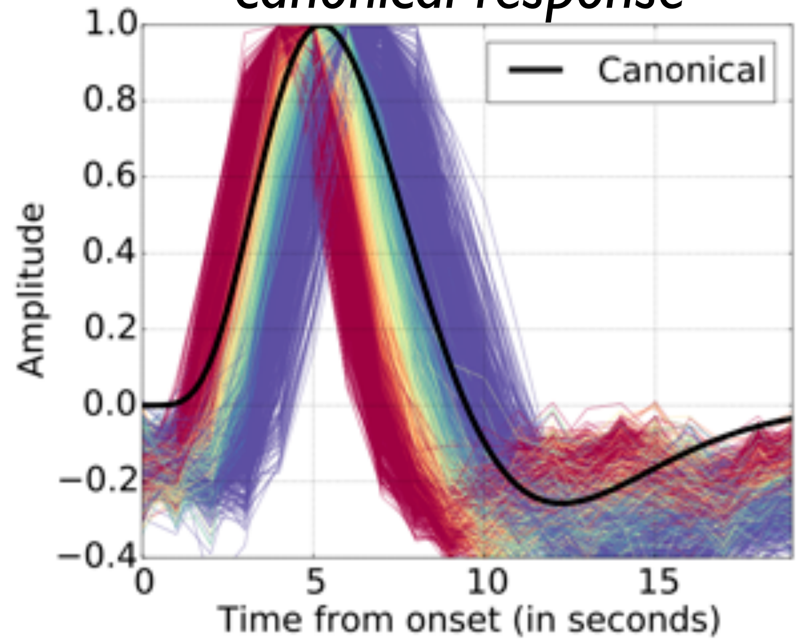
Example: *Learning the temporal response of 10^5 fMRI voxels using low rank regression model*

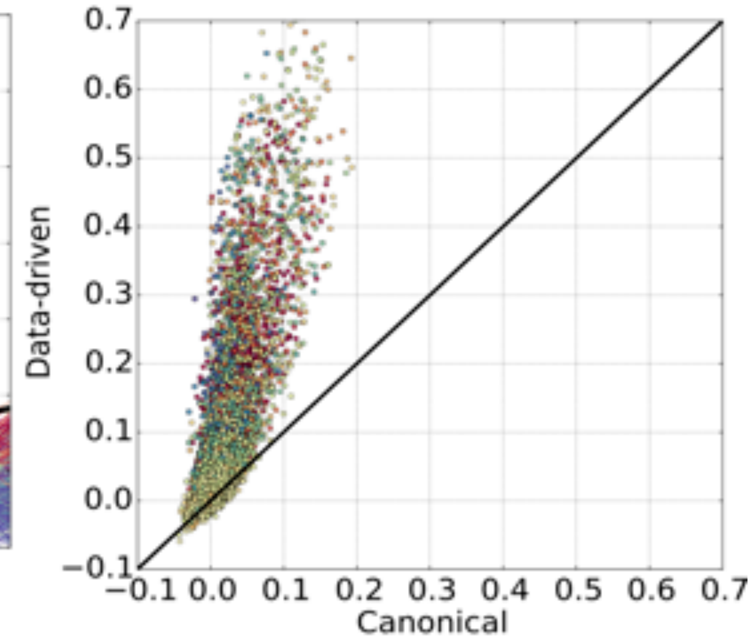
[Pedregosa, …, Gramfort, Neuroimage 2015]

Data from [Kay et al. Nature 2008]

Data-driven responses vs. canonical response



Explained variance: data-driven > canonical



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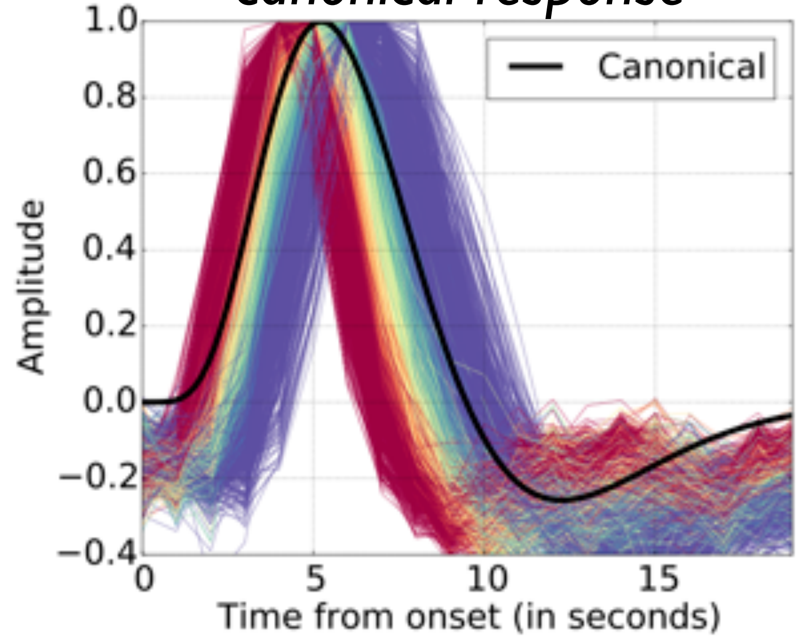

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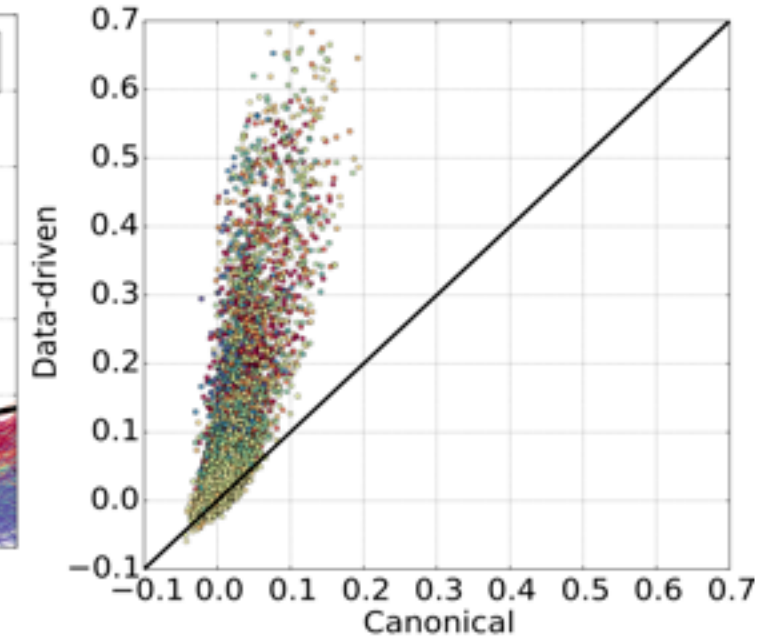

New approach:

Convolutional sparse coding (multivariate data, complex noise, known physics)

Massive data pooling via MNE & large scale non-smooth optimization

SLAB WP 3

Objective: signal models to capture non-stationary spectral interactions

Problem: The signature of active neurons is in the spectrum of the signals

SOTA: Parametric MVAR: *stationary* & non-parametric (Fourier): *slow inference*

Idea: Model the spectrum of a brain region as a function of a driving signal

How: Non-linear auto-regressive (AR) models

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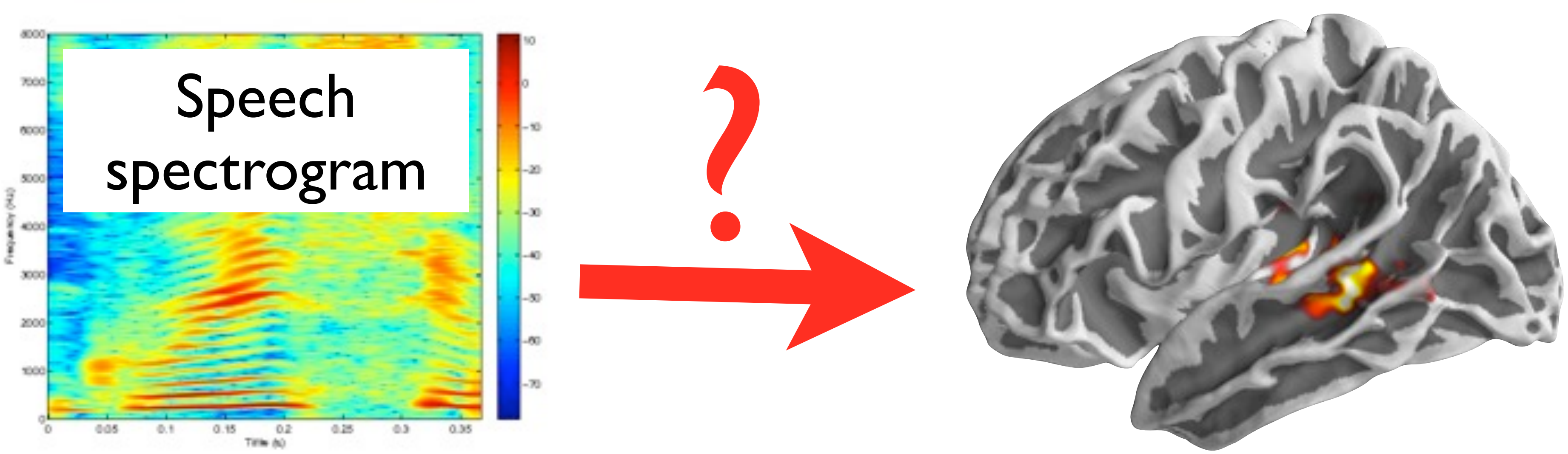
Scenario 1: Speech driven linear prediction of neural activations



Objective: Learn how speech is encoded in the spectra of M/EEG neural sources

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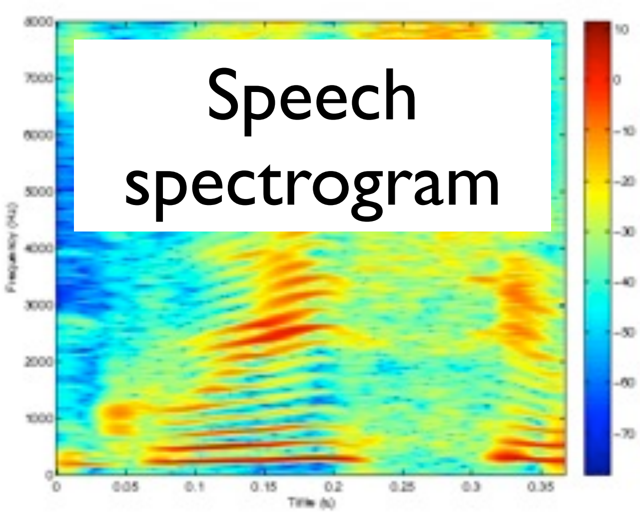

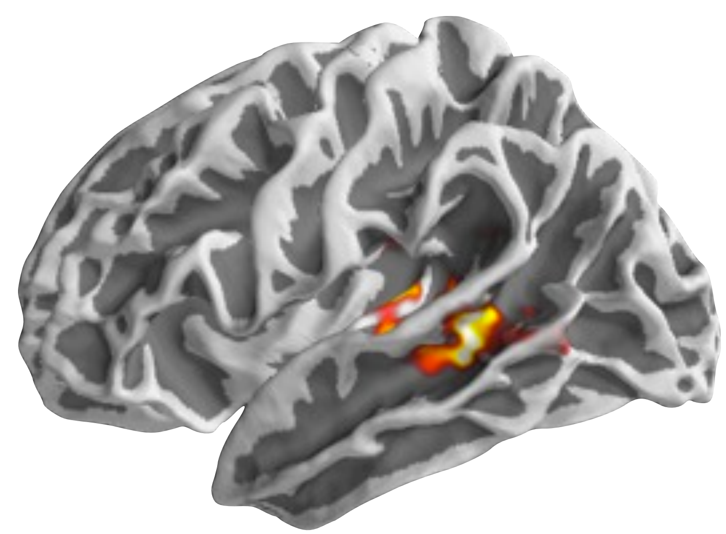

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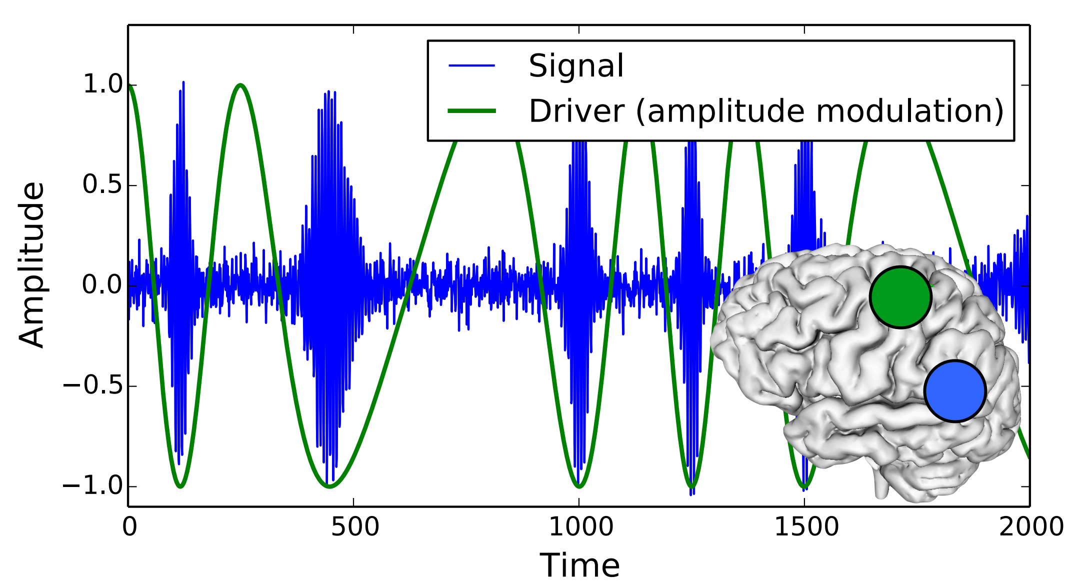
Scenario 2:

region 1 drives the spectrum of region 2



Objective: extract automatically such interactions & learn the driving signal

Why now?

Computational Reasons : Volume

- Standard MEG Study (25 subjects, 10 GB per subject)
- Human Connectome Project (18GB x1000 subjects), USA with first MEG data released in March 2015 (100 subjects)
- Human Brain Project, EU

Users and clinicians lack time & need interactive analysis

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Statistical Reasons : Data variability

- 7000 fMRI pipelines lead to different neuroscience findings [Carp 2012]

Neuroscience needs automatic parameter tuning

SLAB:

Develop the next technology to extract knowledge from brain signals

New methods, theory and algorithms

- Statistical machine learning for spatiotemporal data
- High dimensional inference with complex noise and non-stationarities
- Fast algorithms for large scale non-smooth problems

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New insights for clinical and cognitive neuroscience

- Functional brain imaging data with unprecedented spatiotemporal resolution and statistical power
- Investigate new hypotheses about the brain in healthy and pathological conditions
- Community driven software for reproducible research

Collab: Hôpital La Timone Marseille & Salpétrière Paris & CEA Saclay Neurospin