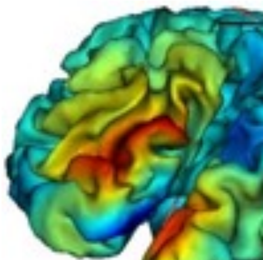
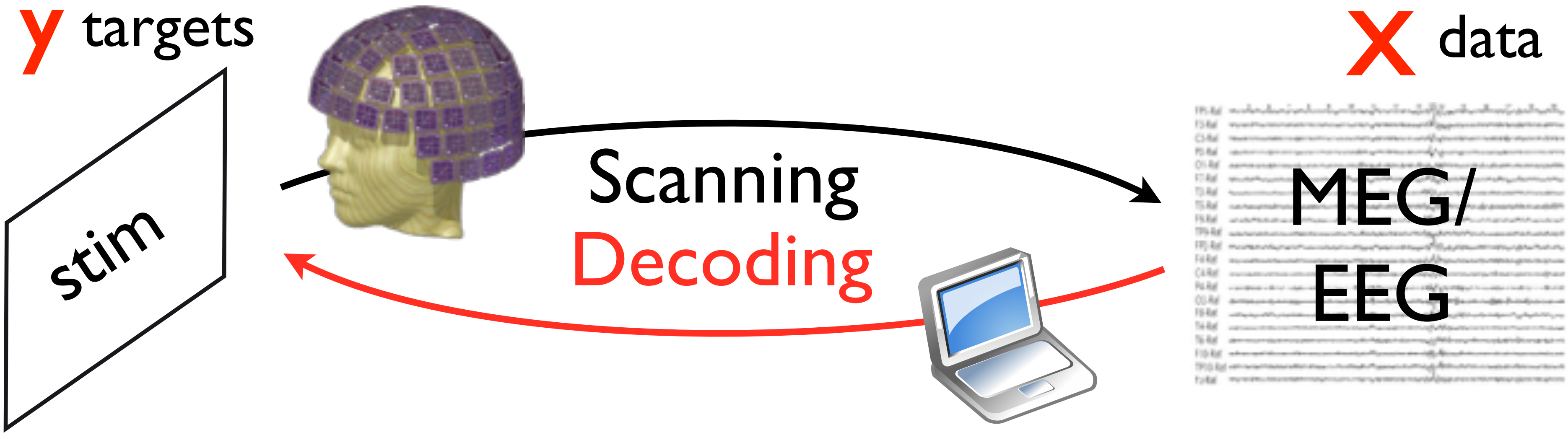
Machine learning with M/EEG a.k.a. "decoding"

Alexandre Gramfort
alexandre.gramfort@telecom-paristech.fr
CNRS, LTCI, Université Paris-Saclay
CEA Neurospin



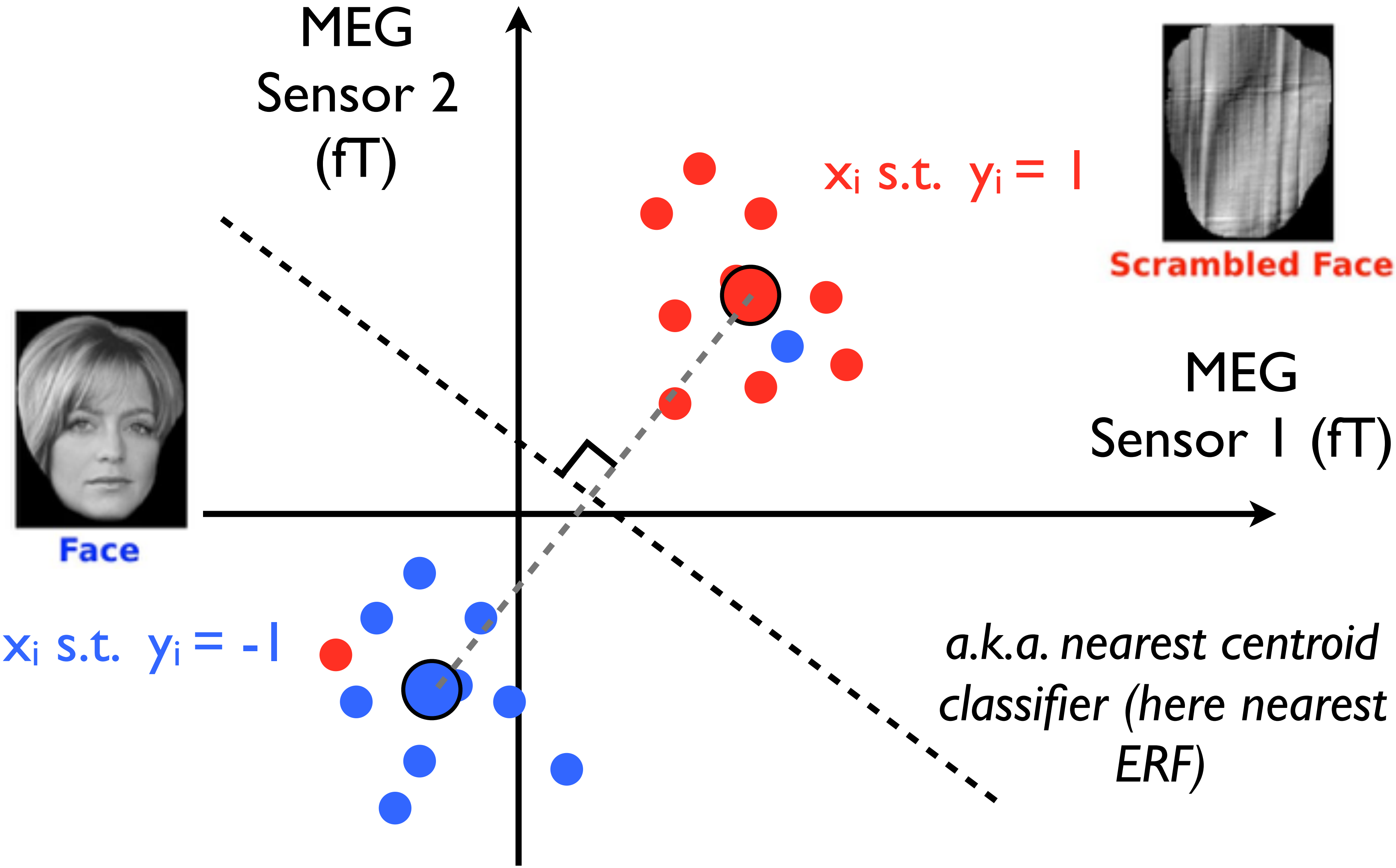
May., 2016

My first “decoder”



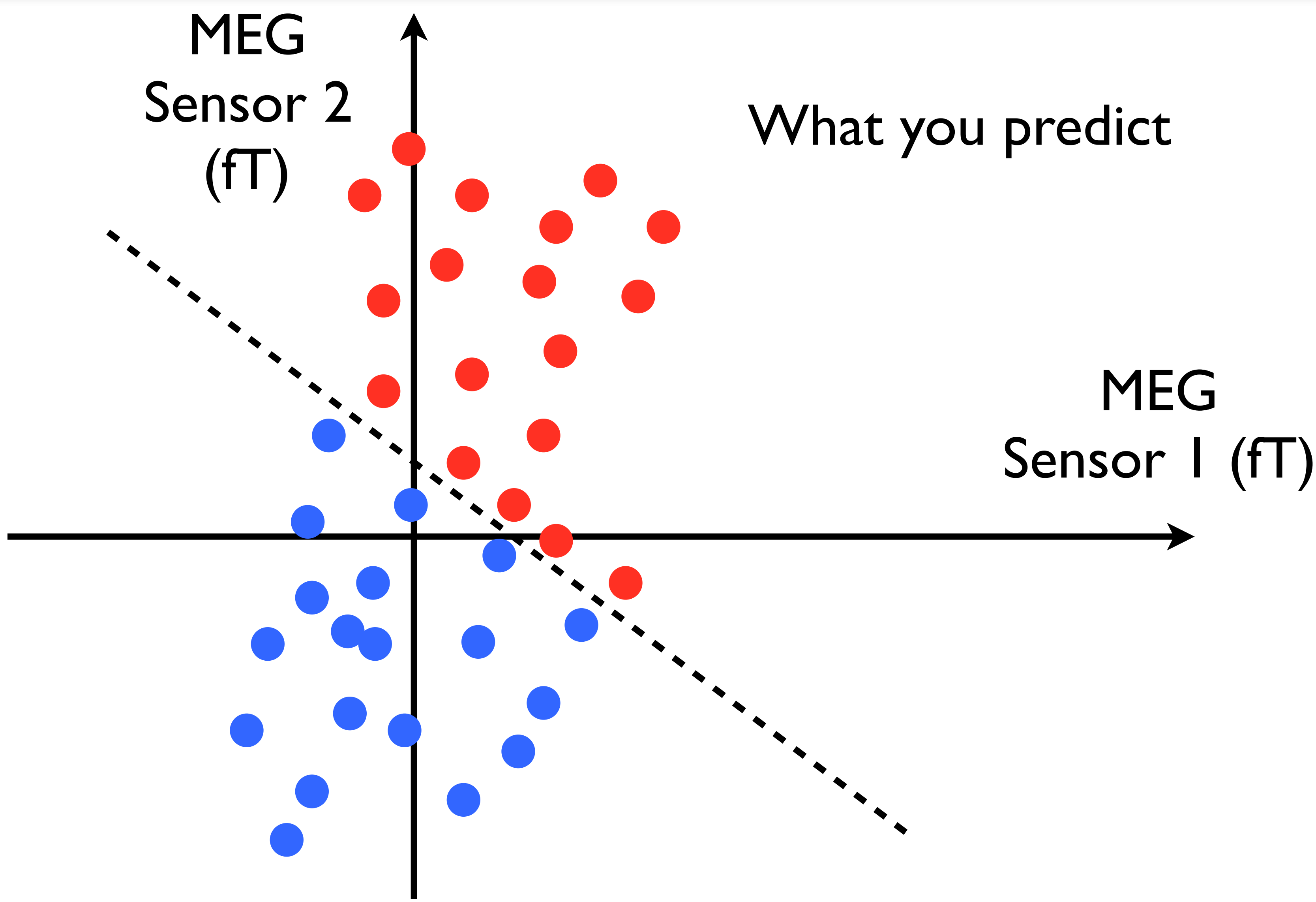
- Visual paradigm with 2 conditions: **faces** or **scrambled faces**
- **Questions:**
  - Can we learn from M/EEG signals to predict on a single trial if the subject saw a face or a scrambled face?
  - When does this happen? How is it encoded in the brain?
  - How do you validate and “open the box”?

A simple decoder with 2 sensors

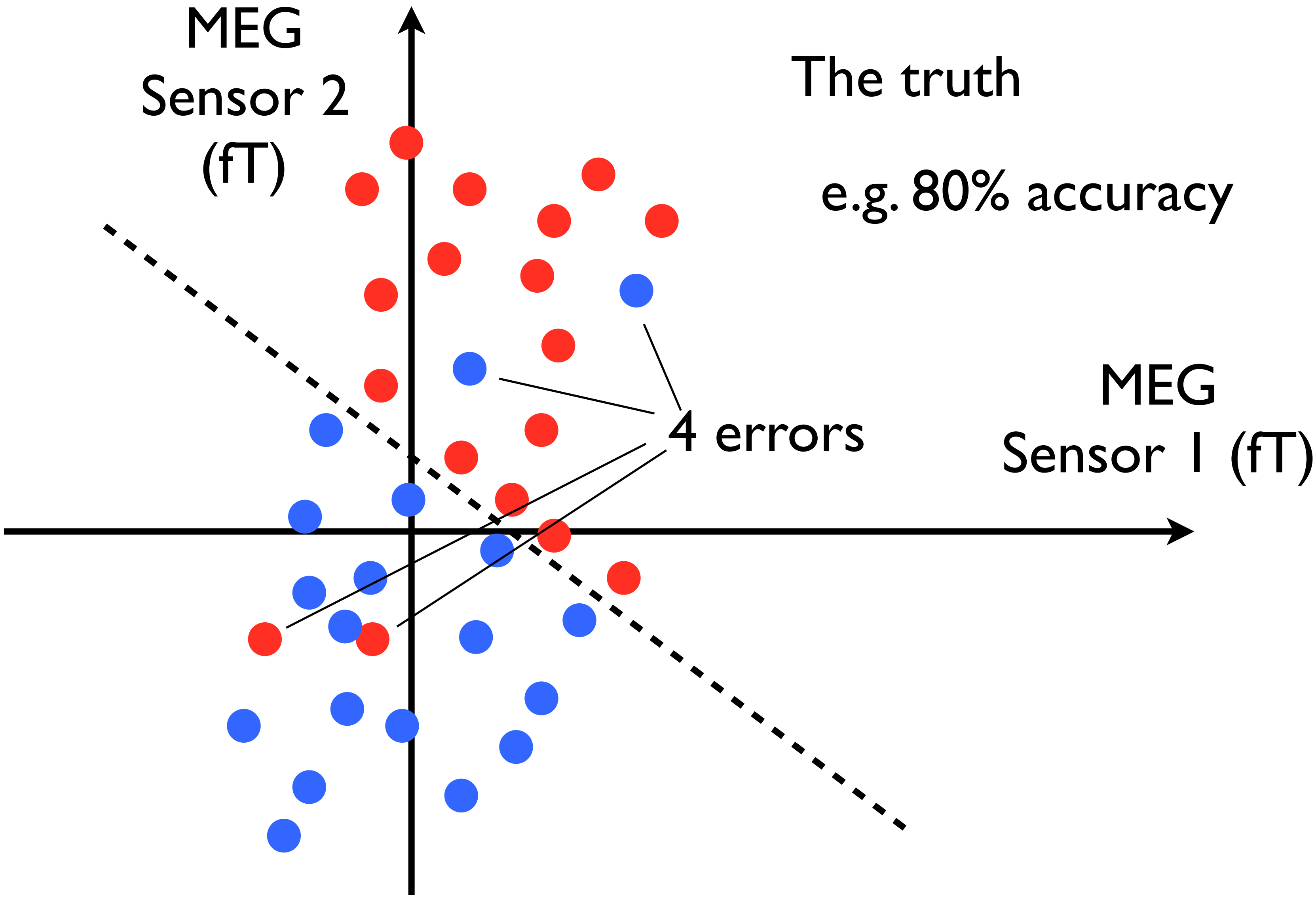


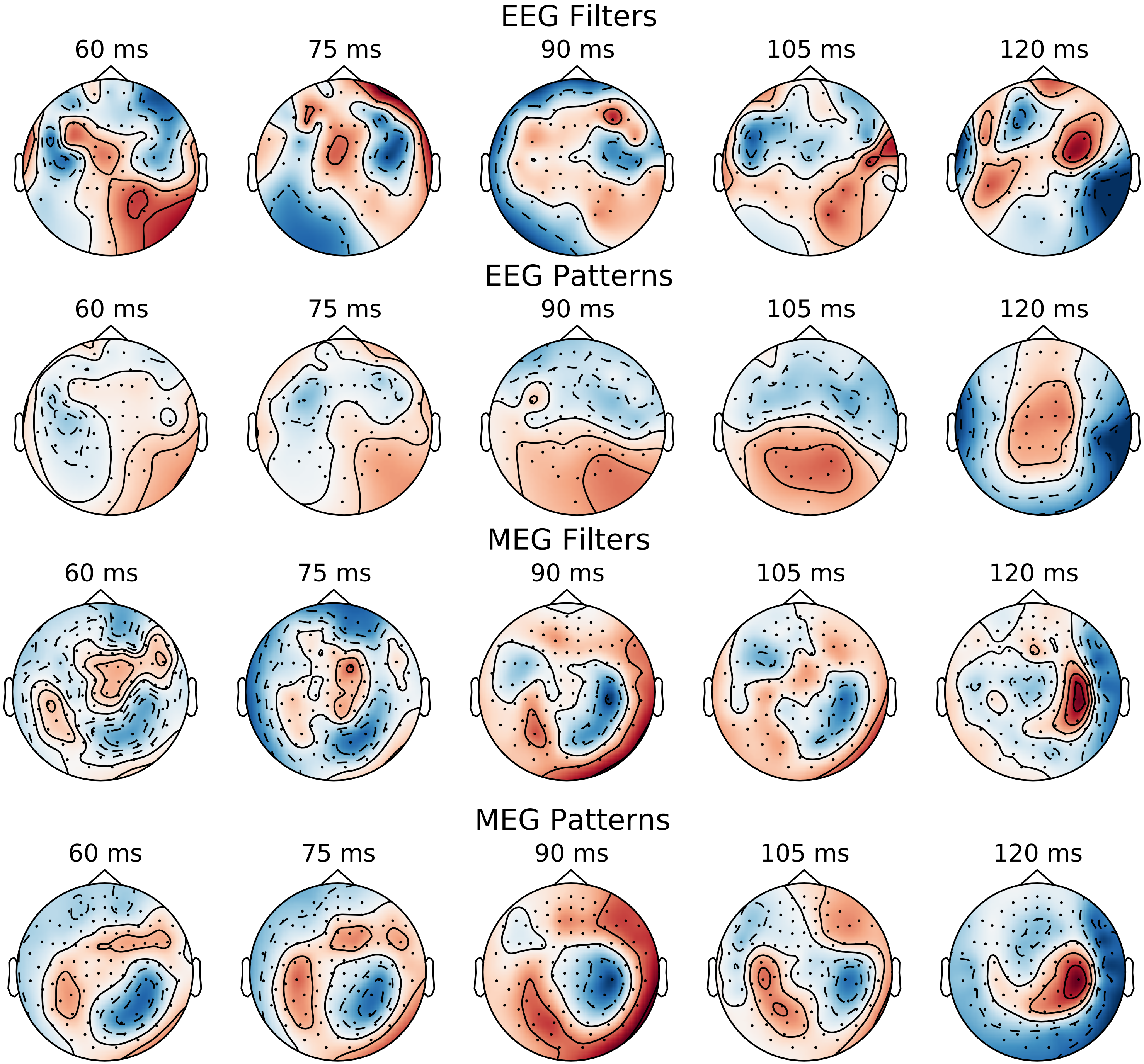
a.k.a. nearest centroid classifier (here nearest ERF)

Testing my first "decoder"



Testing my first "decoder"

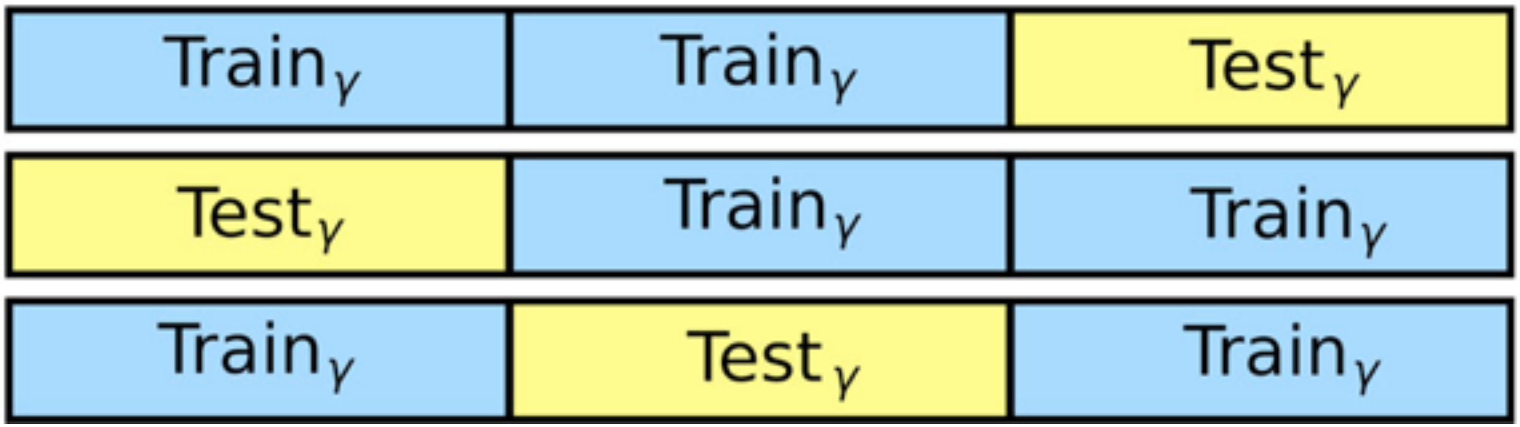




[Haufe et al. Neuroimage 2015]

Cross-validation

Example with 3-Folds



Score 1

Score 2

Score 3

mean(score 1, score 2, score 3) = CV score

std(score 1, score 2, score 3) = CV standard deviation

Example of a 10 folds results: 93% (std. 2)

Recommendation to reduce variance:

- Don't use leave one out (LOO)
- Prefer monte-carlo cross-validation

Classification, (Ordinal) Regression

- **Classification**
  - Predict faces vs. houses i.e. categories (y=-1, 1 or 1, 2, 3, …, K)
- **Regression**
  - Predict the reaction time (y is a scalar)
- **Ordinal regression**
  - Predict disease progression (healthy, MCI, AD): categories but they have a natural order.

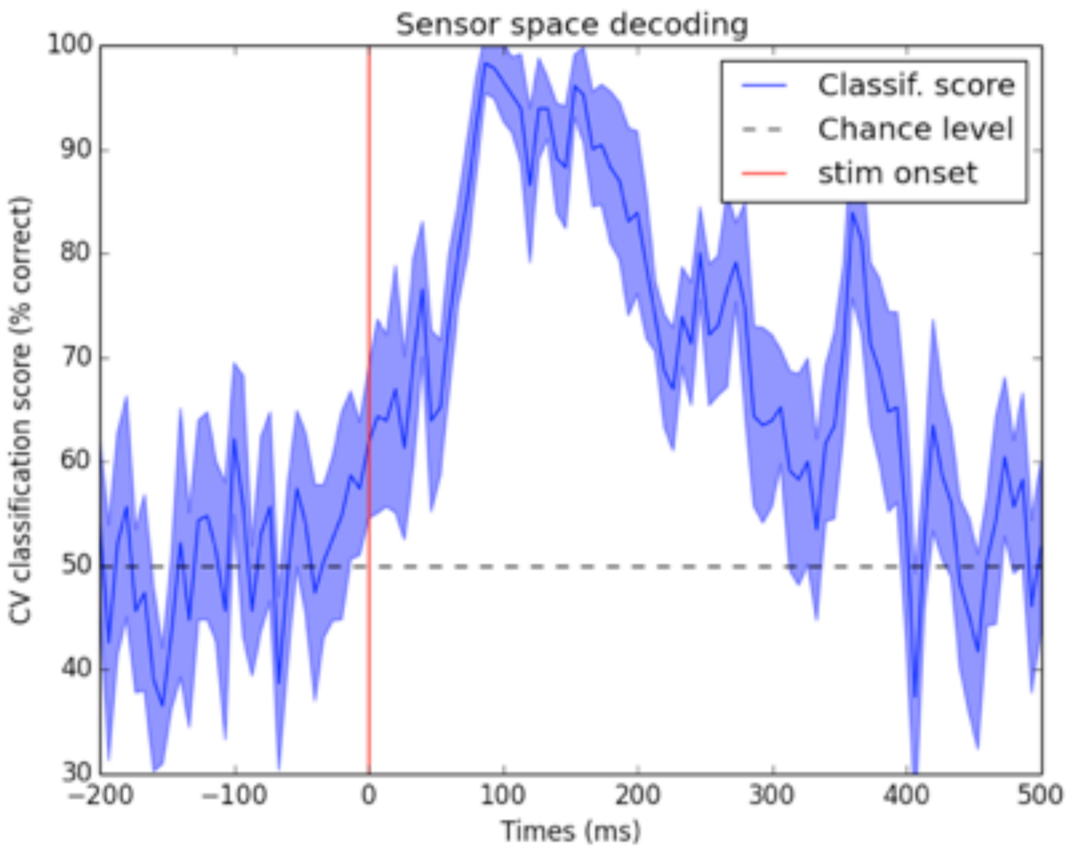
[Pedregosa et al. PRNI 2012]

[Bekhti et al. PRNI 2014]

Decoding the temporal dynamics of MEG/EEG

Decoding over time with MEG/EEG

- **IDEA:** Run a cross-validation loop at each time point



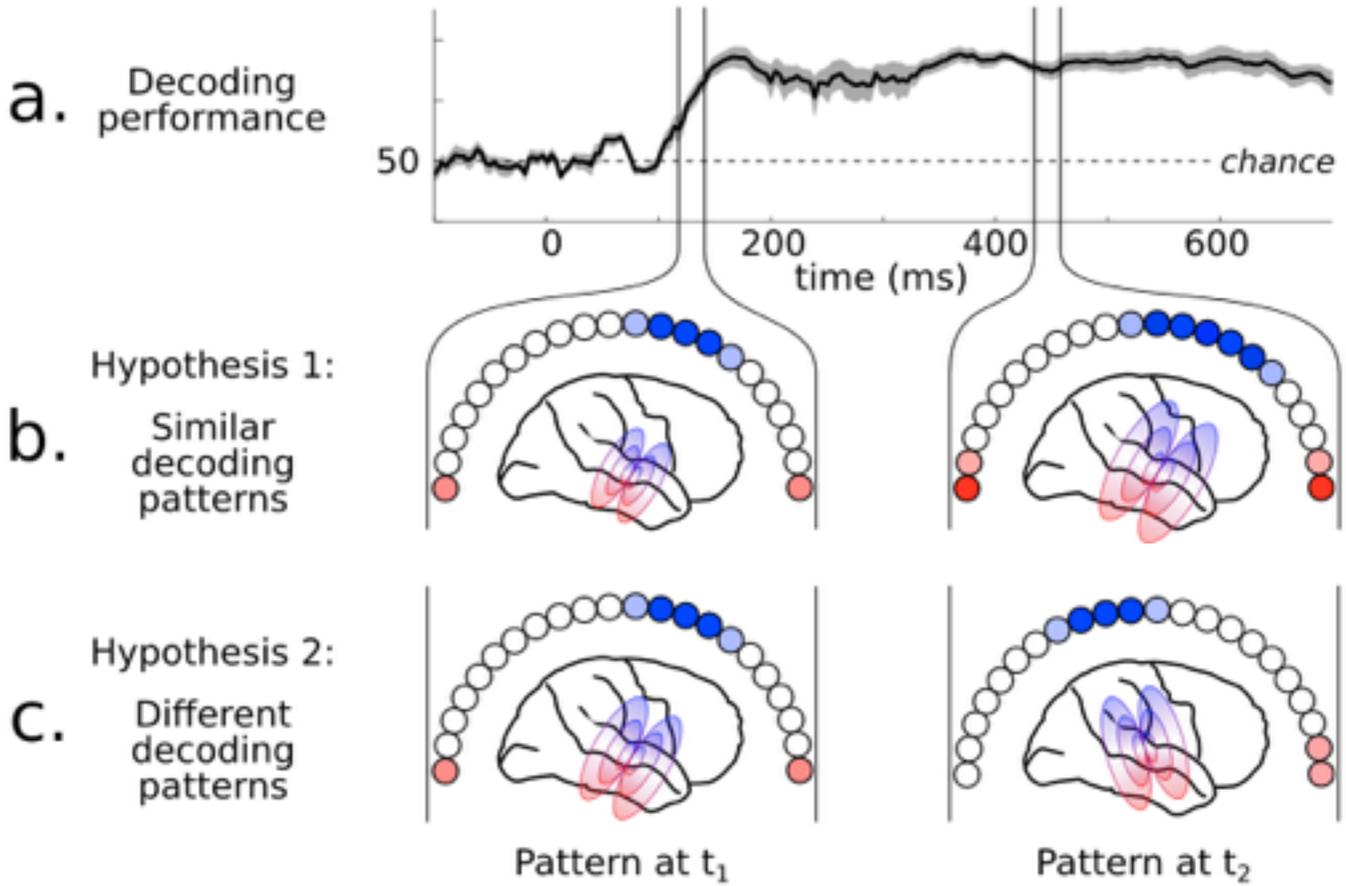
Condition 1(auditory tone in left ear) vs. condition 2 (visual flash in left hemifield)

- 50 epochs per class
- no baseline
- band pass between 2Hz and 40Hz
- Linear SVM (C=1)
- Monte-carlo cross-val.

MNE

http://martinos.org/mne/auto_examples/decoding/plot_decoding_sensors.html

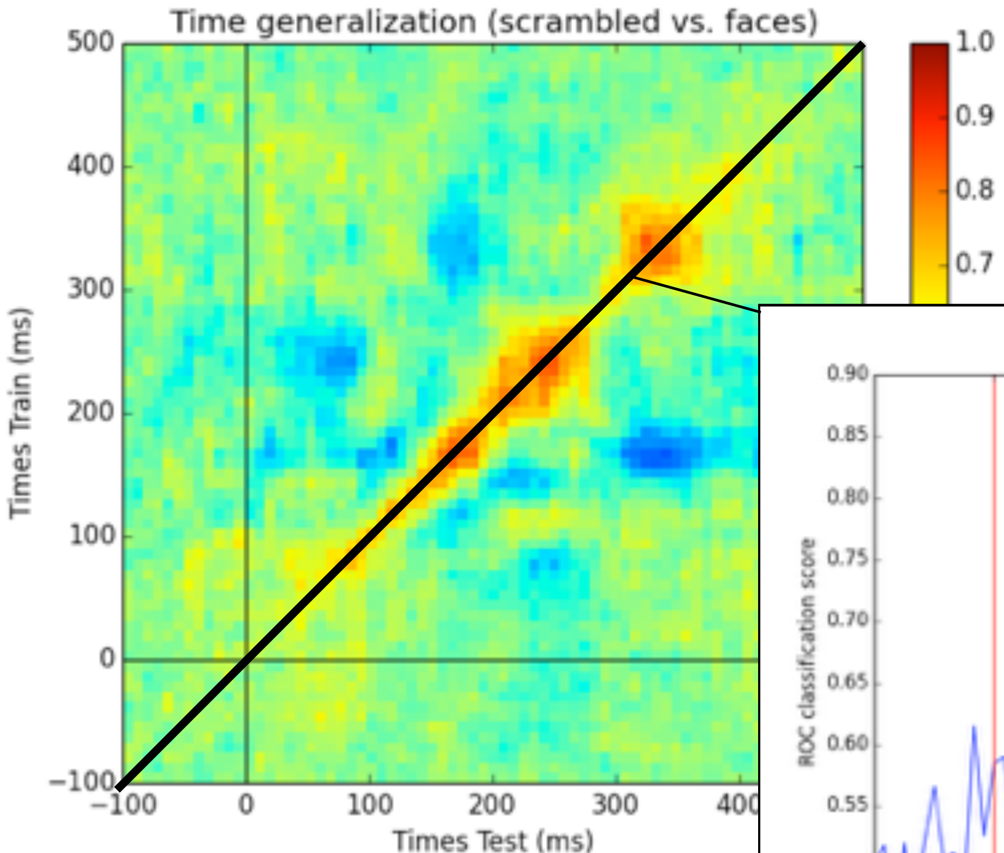
… time generalization



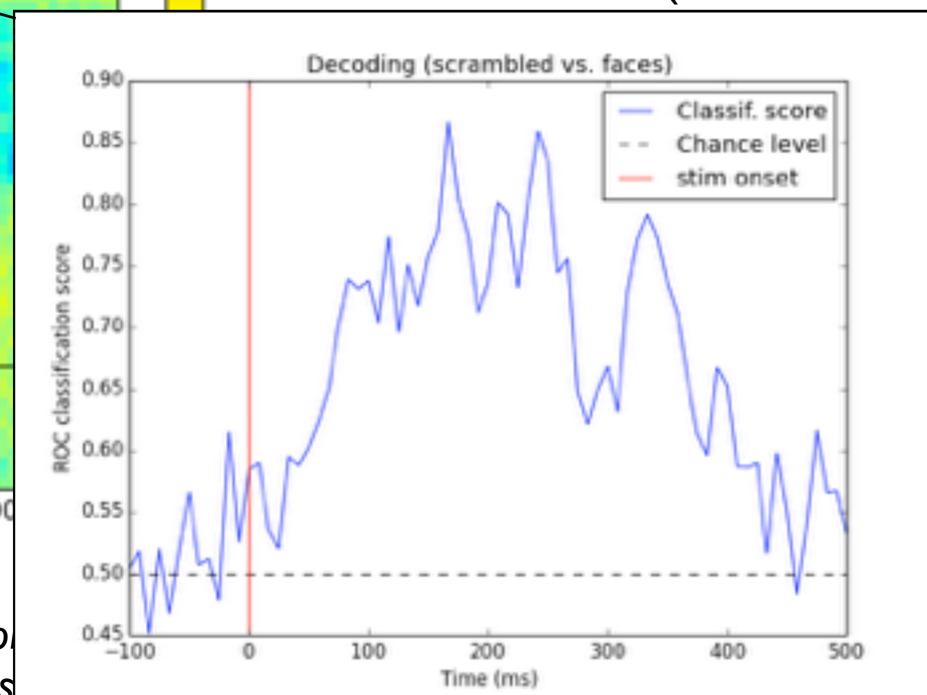
IDEA: If hypothesis 1 is true the decoder should work at t2

courtesy of J.R. King [King & Dehaene Trends in Cognitive Sciences]

… time generalization



SPM MEG dataset
Condition 1 (faces) vs.
Condition 2 (scrambled faces)

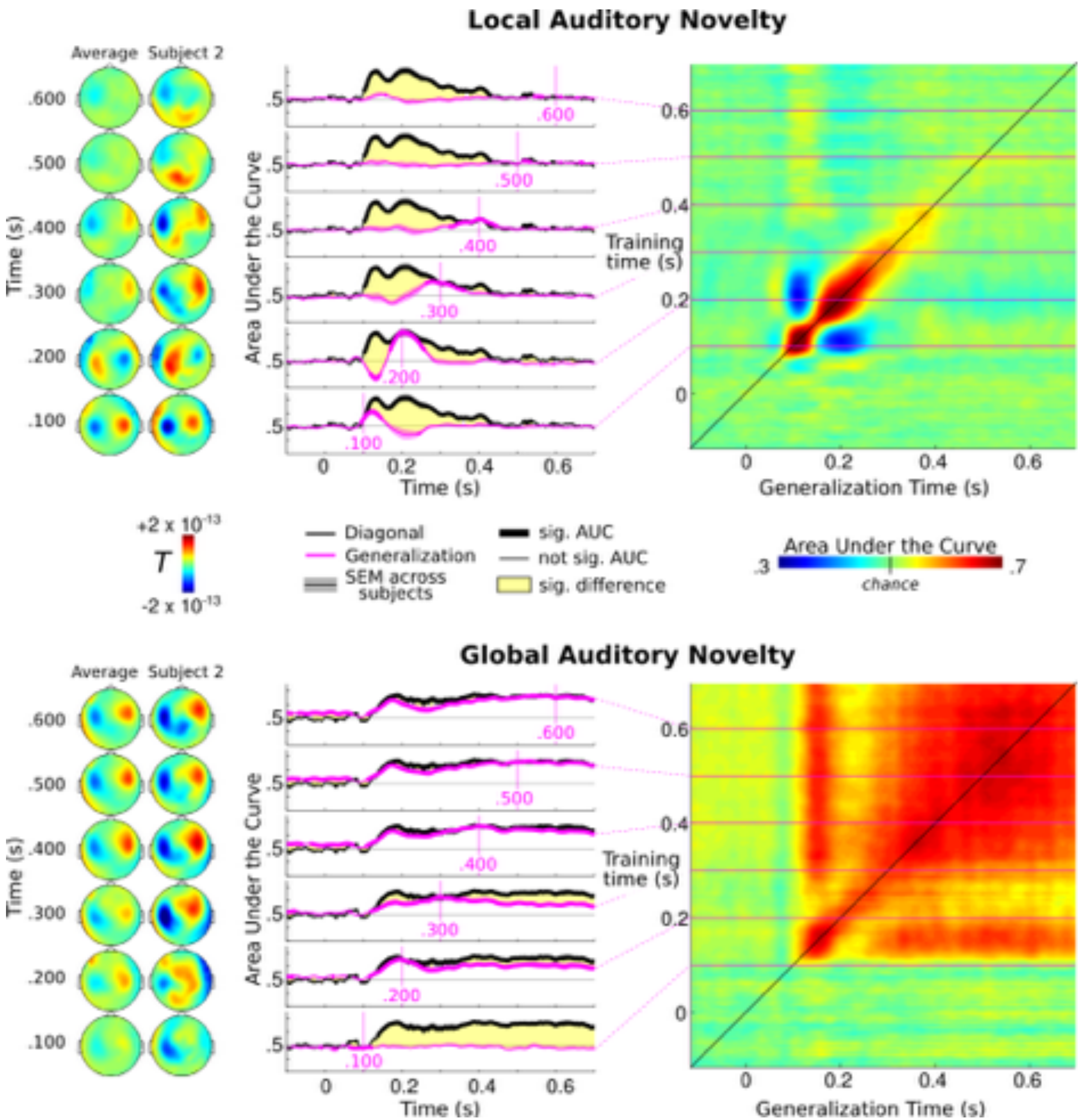


class

z and

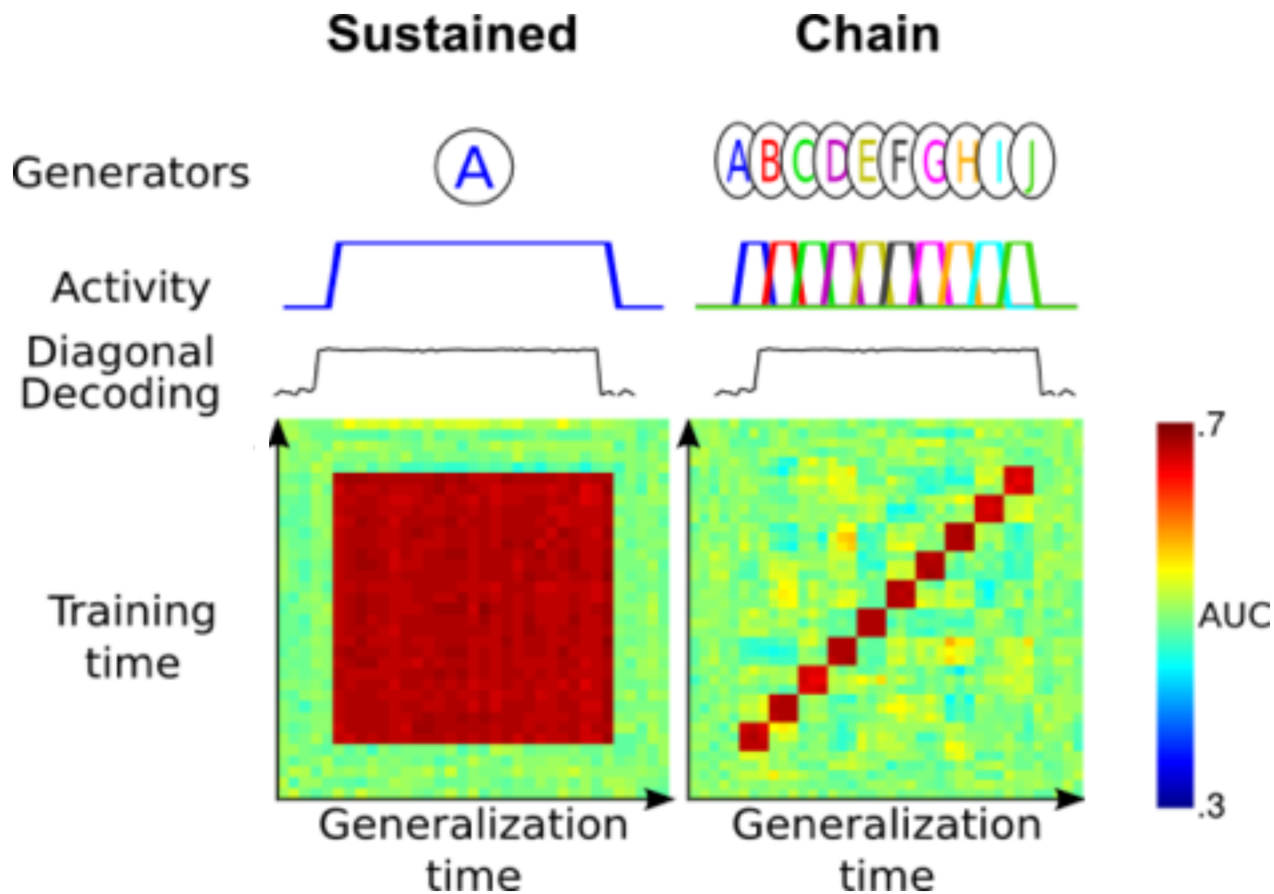
[JR King, A Gramfo … ct dynamic
modes … NE, 2013]

http://martinos.org/mne/dev/auto_examples/decoding/plot_decoding_time_generalization.html



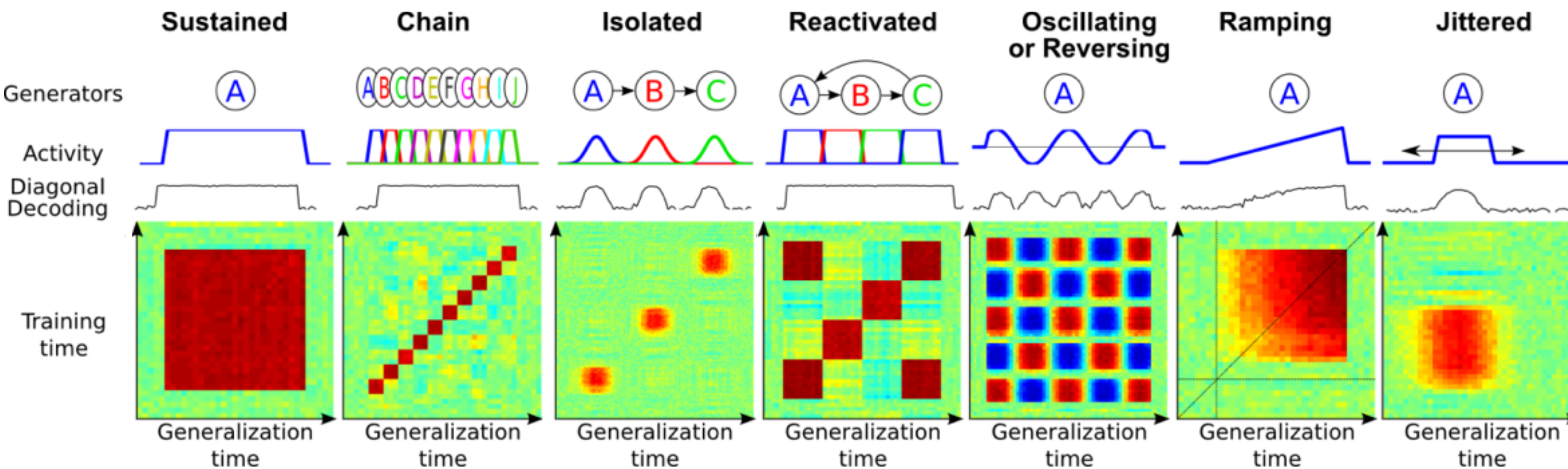
[King, Gramfort, Schurger, Naccache, Dehaene (2014) PLoS One]

… time generalization

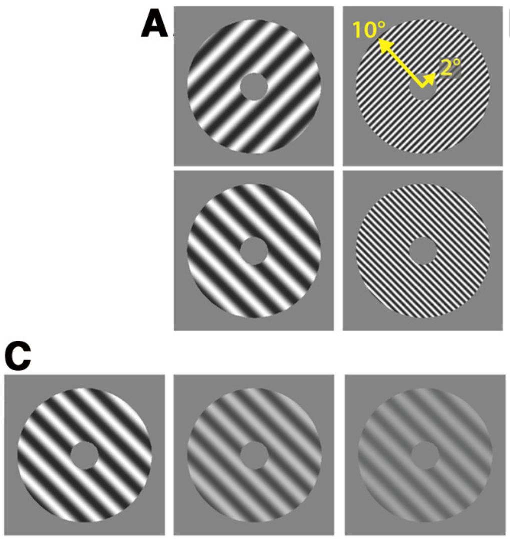


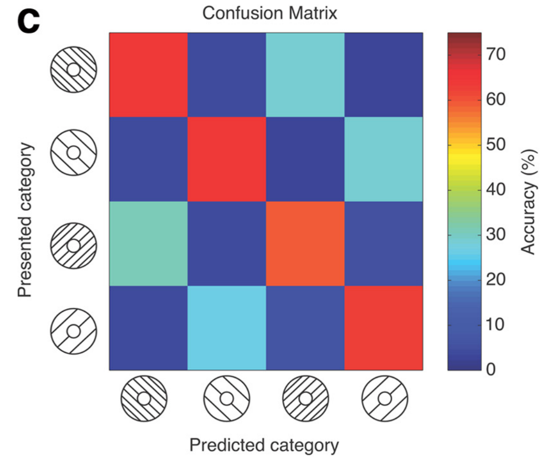
[King & Dehaene Trends in Cognitive Sciences]

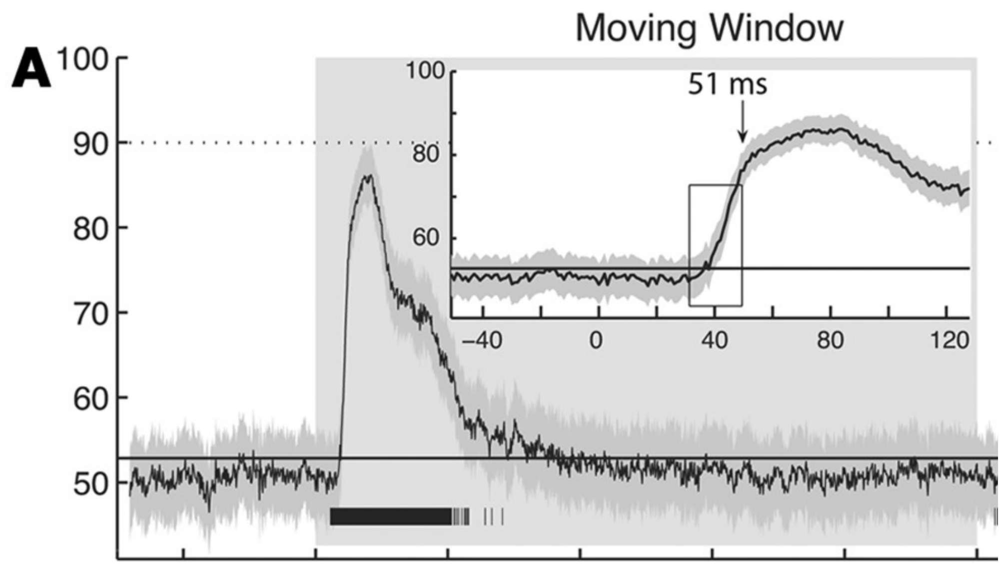
… time generalization



[King & Dehaene Trends in Cognitive Sciences]

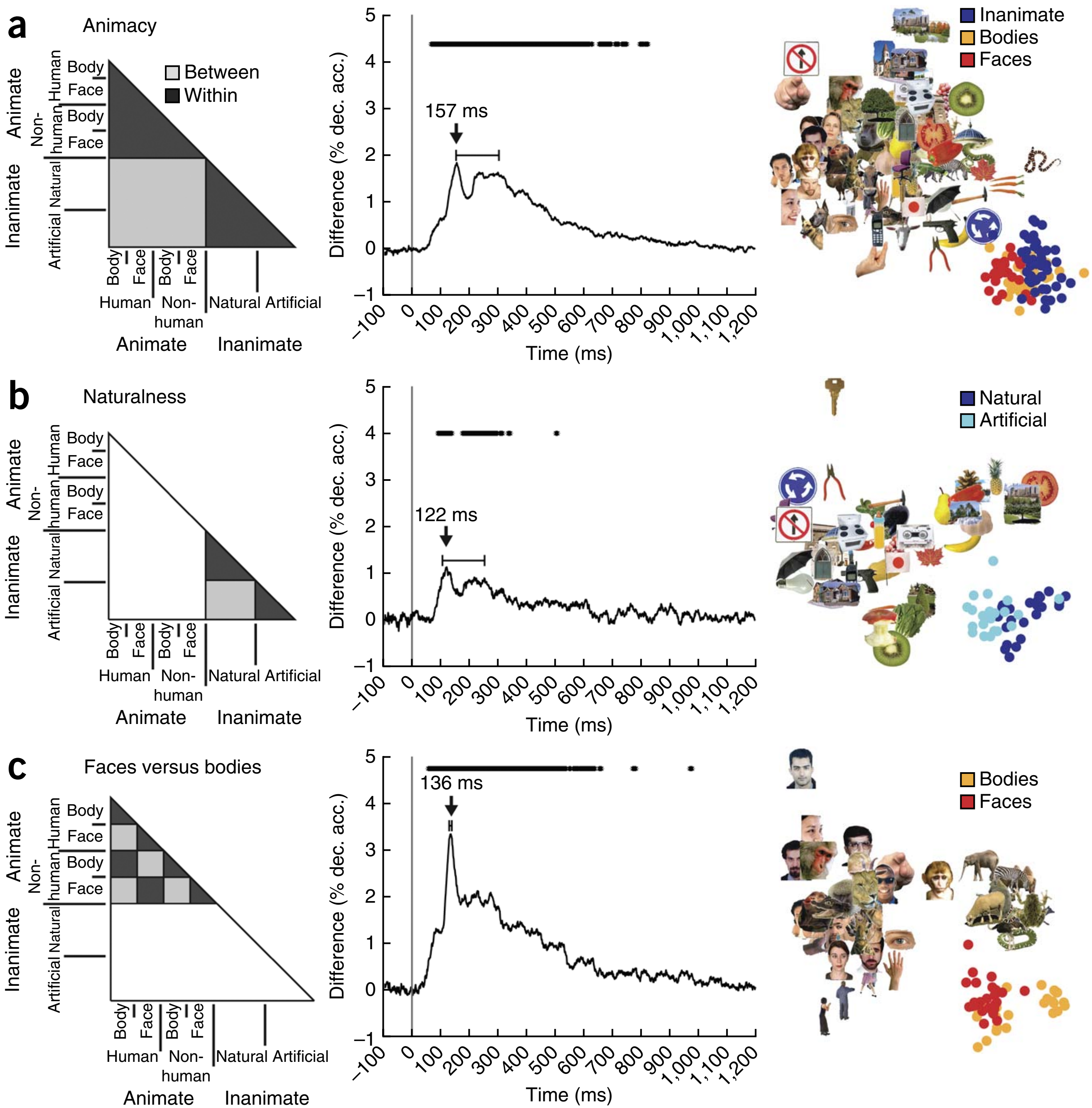




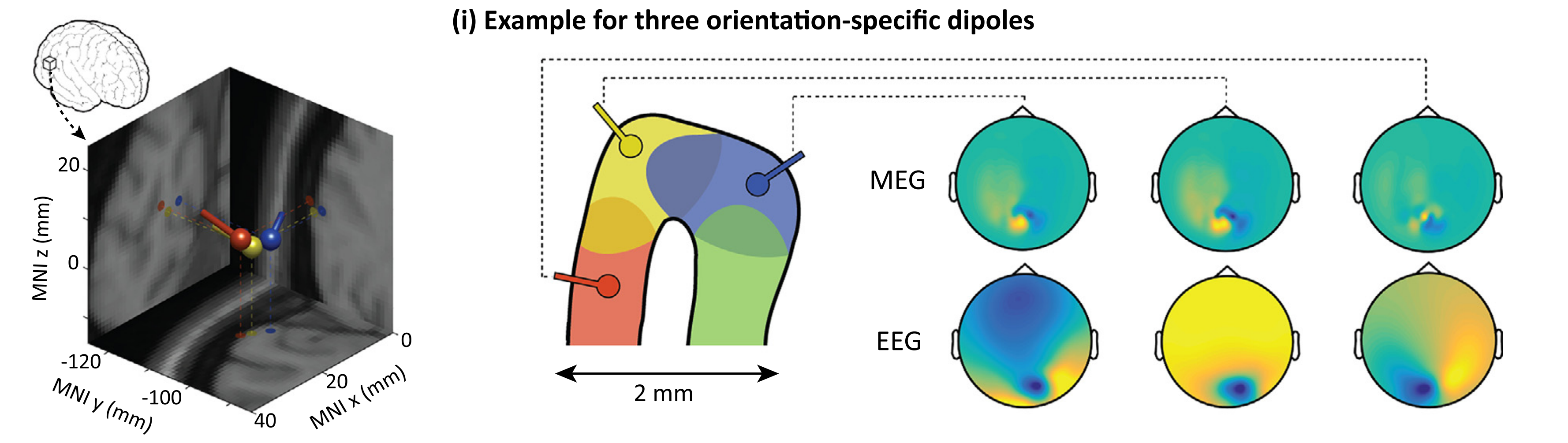


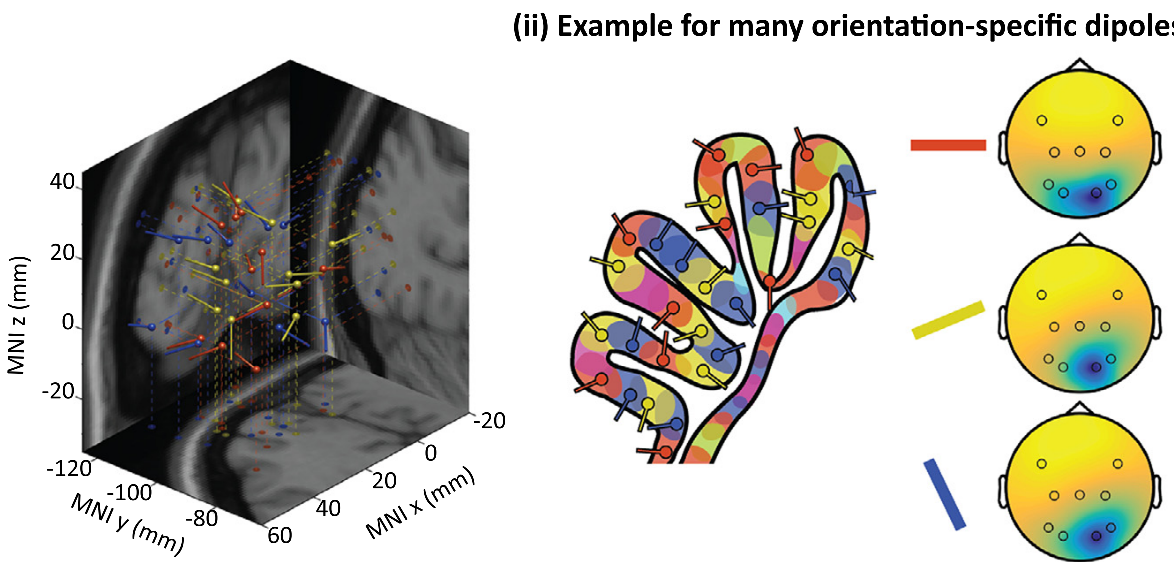
“Time-resolved classifiers using a 20 ms moving window exceeded chance level at 51 ms (the later edge of the window) for spatial frequency, 65 ms for orientation, and 98 ms for rotation direction.”

[Ramkumar, Jas, Pannasch, Hari, Parkkonen, J. Neuroscience (2013)]



[Resolving human object recognition in space and time, Cichy, Pantazis & Oliva, Nat Neuro 2014]





New research suggests that magnetoencephalography (MEG) contains rich spatial information for decoding neural states. Even small differences in the angle of neighbouring dipoles generate subtle, but statistically separable field patterns. This implies MEG (and electroencephalography: EEG) is ideal for decoding neural states with high-temporal resolution in the human brain.

[Decoding Rich Spatial Information with High Temporal Resolution, Stokes, Wolff & Spaak, TICS 2015]

To go beyond

- Common Spatial Patterns (CSP) for ongoing induced signals

  [Zoltan J. Koles. The quantitative extraction and topographic mapping of the abnormal components in the clinical EEG. Electroencephalography and Clinical Neurophysiology, 79(6):440--447, December 1991]

- xDAWN for evoked responses potentially overlapping

  [Rivet, B., Souloumiac, A., Attina, V., & Gibert, G. (2009). xDAWN algorithm to enhance evoked potentials: application to brain-computer interface. Biomedical Engineering, IEEE Transactions on, 56(8), 2035-2043.]

- Riemanian geometry on covariance matrices (affine invariance)

  [Barachant, A., BonneS., Congedo M., & Jutten C., Riemannian geometry applied to BCI classification, IVA-ICA 2010]

MNE Tutorials Gallery Manual API FAQ Cite Site Page Search

MNE

MEG + EEG ANALYSIS & VISUALIZATION

http://www.martinos.org/mne

MNE is a community-driven software package designed for for **processing electroencephalography (EEG) and magnetoencephalography (MEG) data** providing comprehensive tools and workflows for:

1. Preprocessing
2. Source estimation
3. Time-frequency analysis
4. Statistical testing
5. Estimation of functional connectivity
6. Applying machine learning algorithms
7. Visualization of sensor- and source-space data

MNE includes a comprehensive Python package (provided under the simplified BSD license), supplemented by tools compiled from C code for the LINUX and Mac OSX operating systems, as well as a MATLAB toolbox.

Documentation

- Getting Started
- What's new
- Cite MNE
- Related publications
- Tutorials
- Examples Gallery
- Manual
- API Reference
- Frequently Asked Questions
- Advanced installation and setup
- MNE with CPP

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