

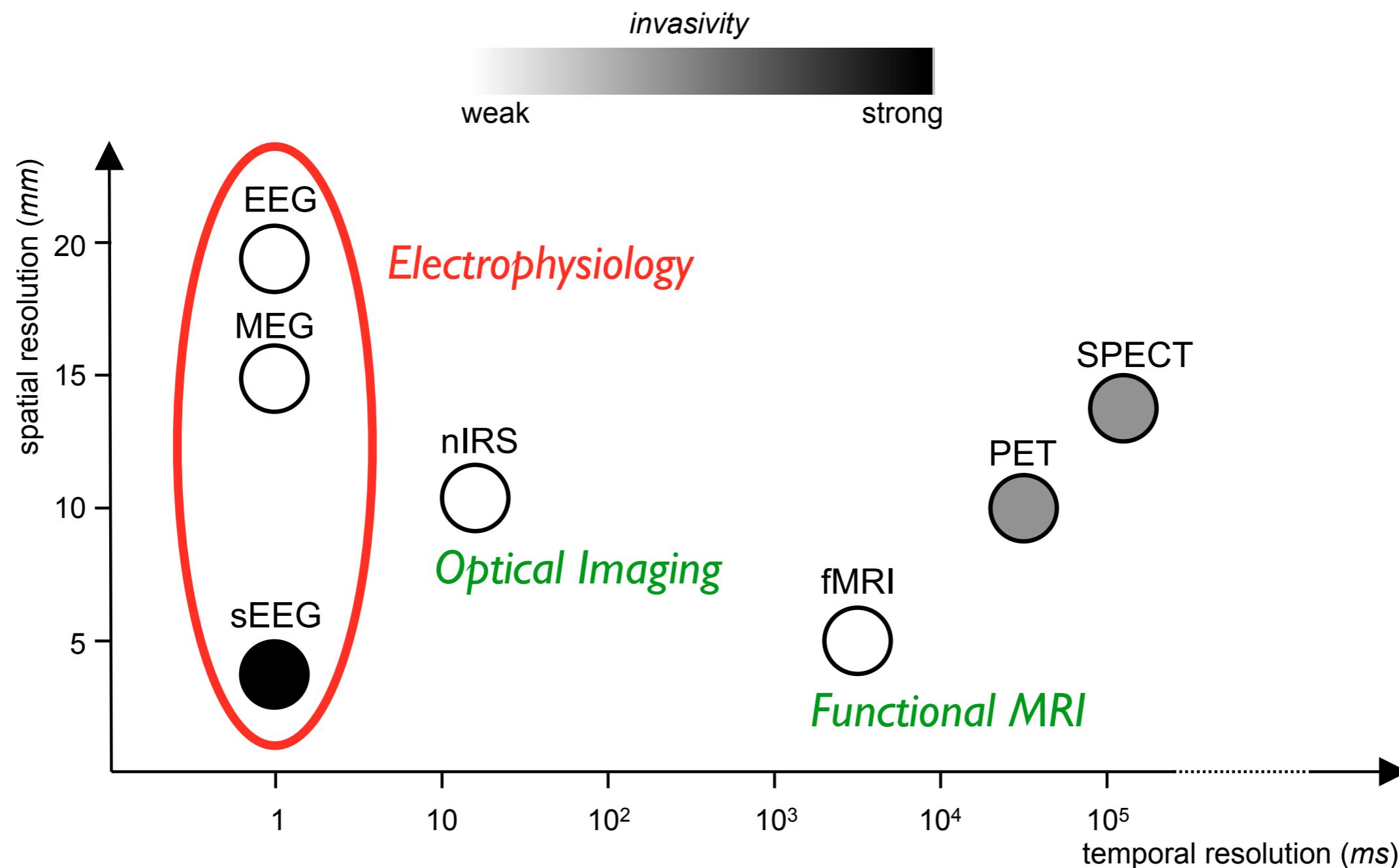
# Functional Brain Imaging with MEG (Magnetoencephalography) and EEG (Electroencephalography)

Alexandre Gramfort

[alexandre.gramfort@telecom-paristech.fr](mailto:alexandre.gramfort@telecom-paristech.fr)



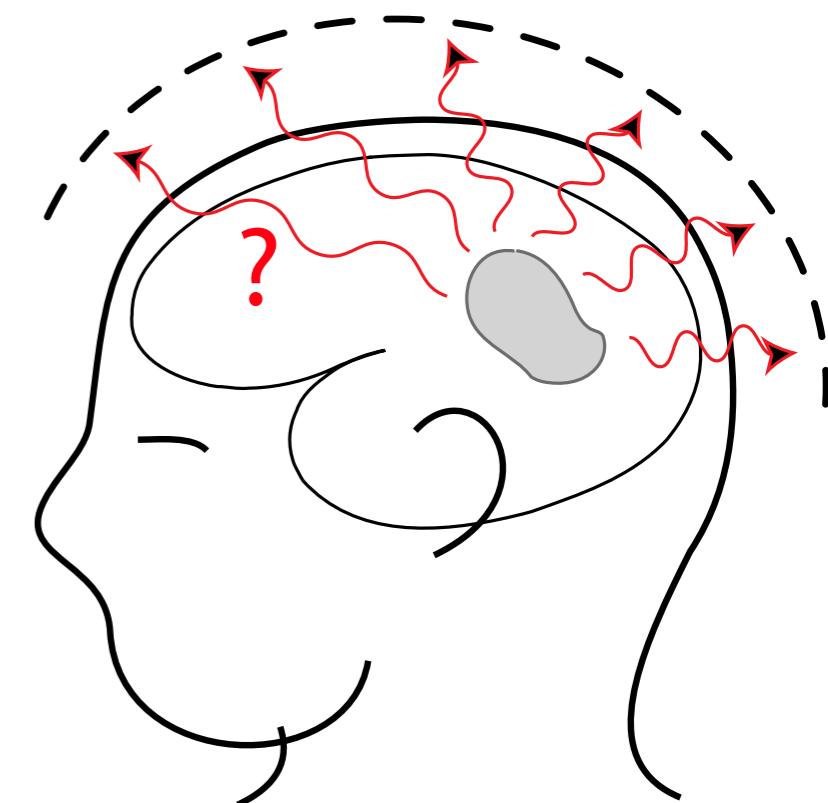
# Functional neuroimaging landscape



# Source localisation with M/EEG: The forward and inverse problems

# Forward problem: Objective

**Predict what is the Electric Potential or the Magnetic Field produced by a current generator outside of the head**



**How to do it?**

- Find from **Maxwell equations** the equations adapted to the problem.
- Define a **model for the current generators** (e.g., sources modeled by equivalent current dipoles).
- **Solve numerically the differential equations** obtained for a real anatomy obtained by MRI.

# Maxwell

## Maxwell Equations with quasi-static approximation

$$\left\{ \begin{array}{l} \nabla \times \vec{E} = 0 \\ \nabla \cdot \vec{B} = 0 \\ \nabla \times \vec{B} = \mu_0 \vec{J} \\ \nabla \cdot \vec{E} = \frac{\rho}{\epsilon_0} \end{array} \right.$$

Total currents:  $\vec{J} = \vec{J}_p + \vec{J}_c$

The diagram shows a horizontal vector sum  $\vec{J} = \vec{J}_p + \vec{J}_c$ . A red arrow points from the label "Primary currents" to the vector  $\vec{J}_p$ . A green arrow points from the label "Conduction currents" to the vector  $\vec{J}_c$ .

Ohm's law:  $\vec{J}_c = -\sigma \nabla V$

$V$  Electric potential

$\sigma$  Tissue conductivity

Remark: *quasi-static implies no temporal derivatives and no propagation delay*

# Maxwell

**Potential equation** (relation between the potential and the sources):

$$\nabla \cdot \nabla \times \vec{B} = 0 \Rightarrow \nabla \cdot (\vec{J}_p + \vec{J}_c) = 0$$
$$\Rightarrow \nabla \cdot \vec{J}_p = \nabla \cdot (\sigma \nabla V)$$

*Poisson Equation*

**Magnetic field equation:**

*Remark: Relation with Kirchoff's law*

$$\vec{B} = \frac{\mu_0}{4\pi} \int \vec{J}(r') \times \frac{r - r'}{\|r - r'\|^3} dr' \quad \textit{Biot and Savart's law}$$

$$\Rightarrow \vec{B} = \vec{B}_0 - \frac{\mu_0}{4\pi} \int \sigma \nabla V \times \frac{r - r'}{\|r - r'\|^3} dr'$$

where  $\vec{B}_0 = \frac{\mu_0}{4\pi} \int \vec{J}_p \times \frac{r - r'}{\|r - r'\|^3} dr'$

**Observations:**

- $B$  is obtained after  $V$
- $B$  decreases in  $1/R^2$
- $B$  is due both to primary currents and volume currents

# Head models

Requires to model the properties of the different tissues: skin, skull, brain etc.

**Hypothesis:** The conductivities are piecewise constant

## Sphere models

Analytical solutions fast to compute but very coarse head model (esp. for EEG)

EEG : [Berg et al. 94, De Munck 93, Zhang 95]  
MEG : [Sarvas 87]

## Realistic models

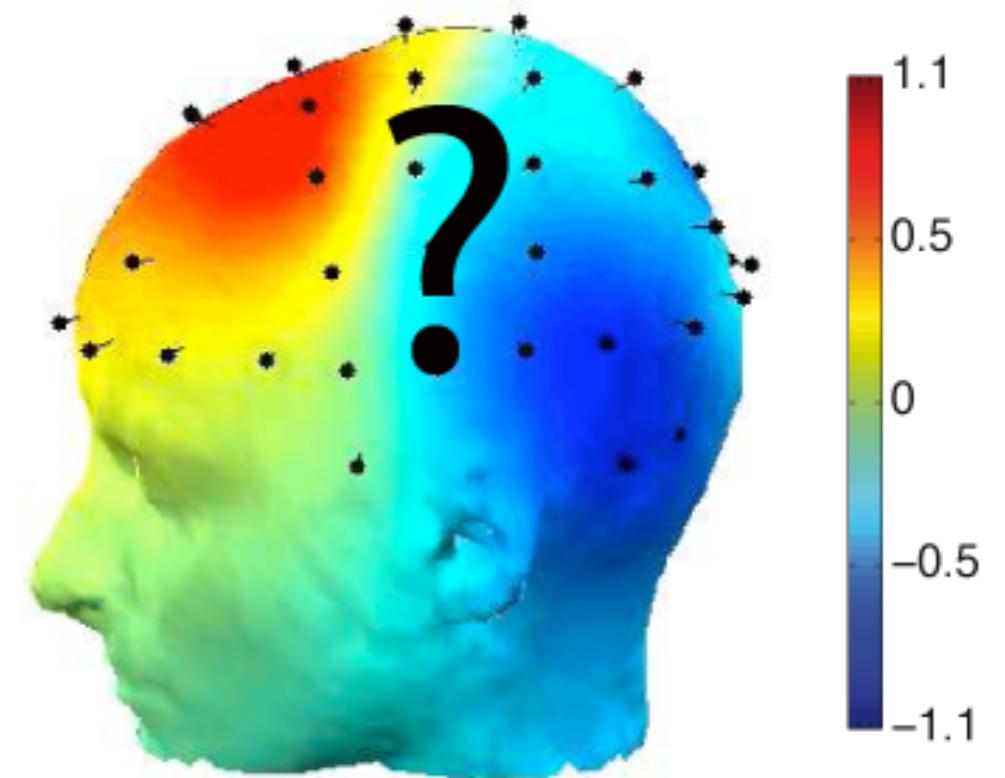
Boundary element method (BEM), i.e., numerical solver with approximate solution.

[Geselowitz 67, De Munck 92, Kybic et al. 2005]

# The M/EEG inverse problem

# Inverse problem: Objective

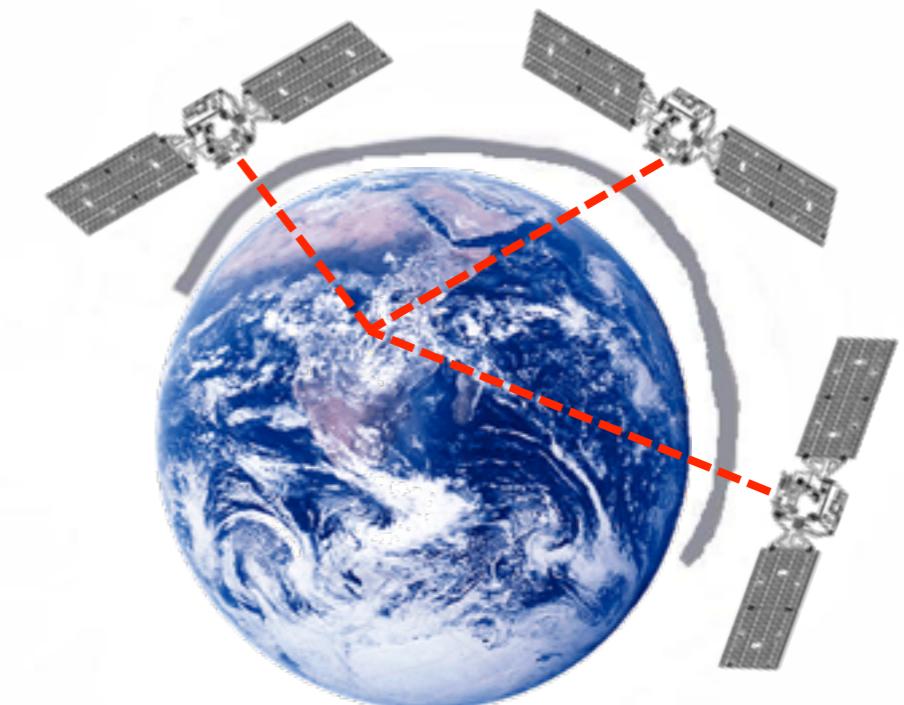
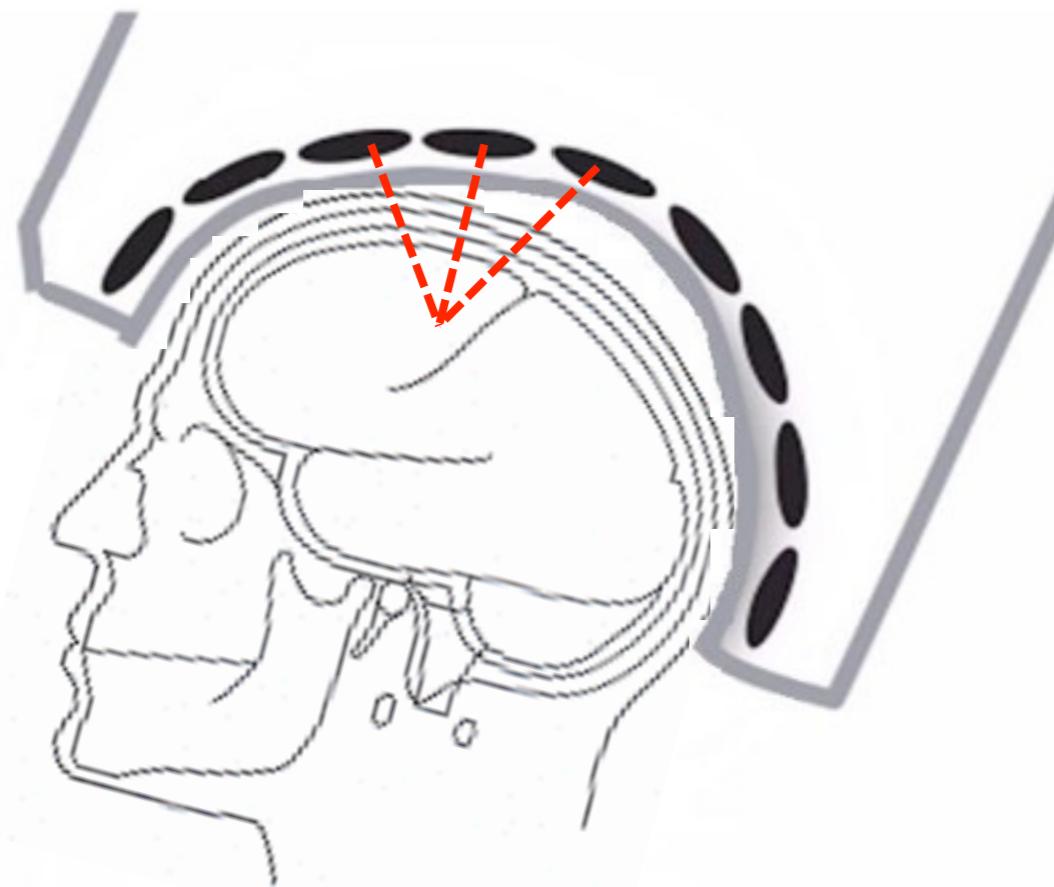
**Find the current  
generators that  
produced the M/EEG  
measurements**



# Inverse problem approaches

- Dipole fitting
- Scanning methods
- Distributed models

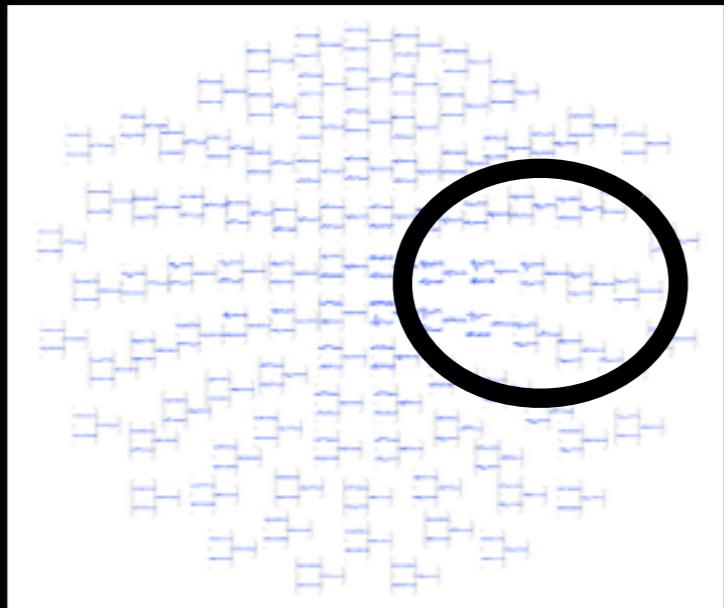
# Dipole fitting



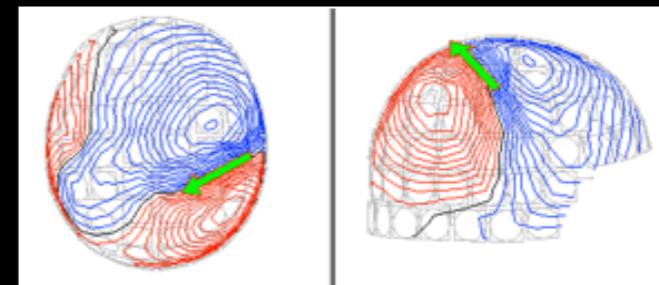
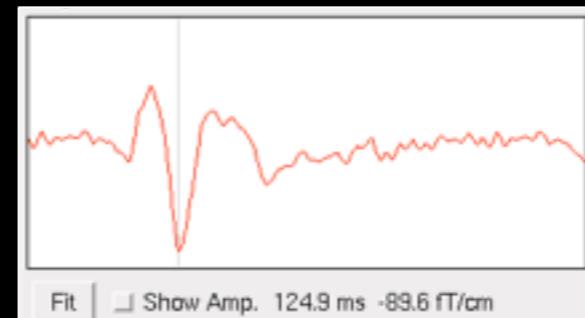
The equivalent of triangulation

# Dipole fitting: procedure

1) Pick subset of sensors w/ peak



2) Pick Time Point; Observe Mag Field



Equivalent  
Current Dipole  
Technique

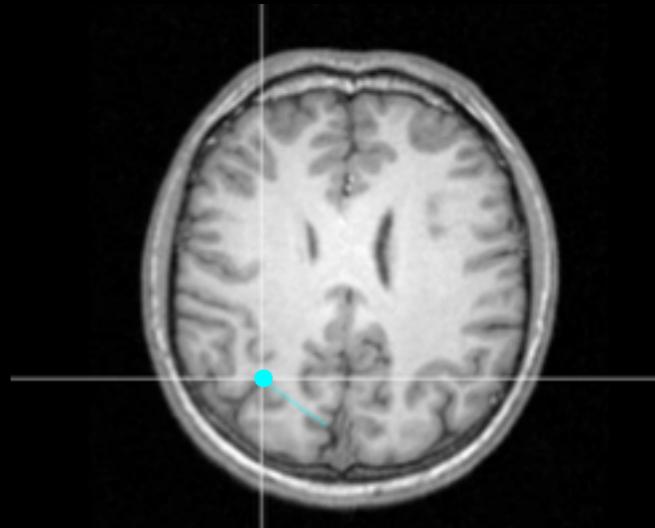
## Goodness of Fit

% of activity explained by forward solution based on single dipole

## Confidence Volume

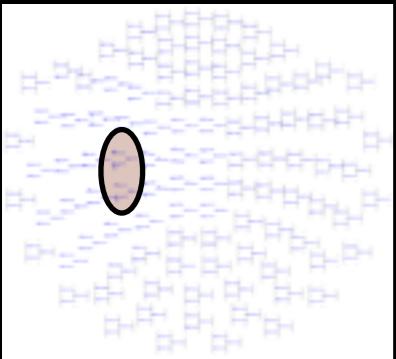
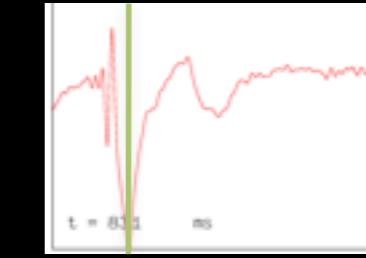
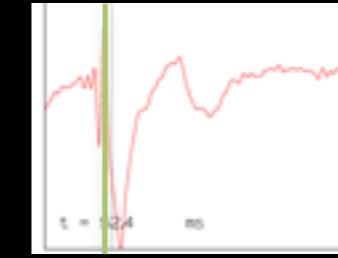
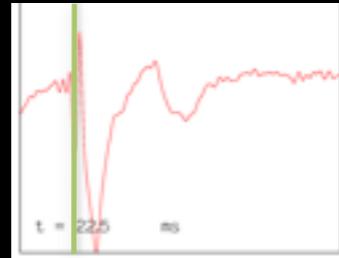
volume within which you can be 95% confident that the dipole exists

3) Measures of Quality

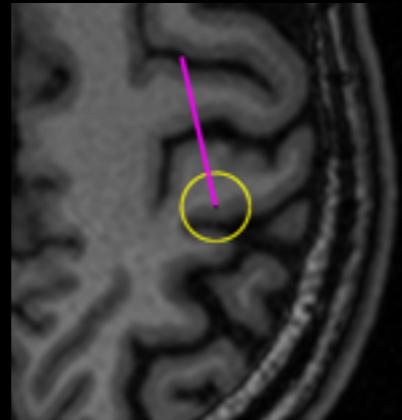


4) Map to MRI

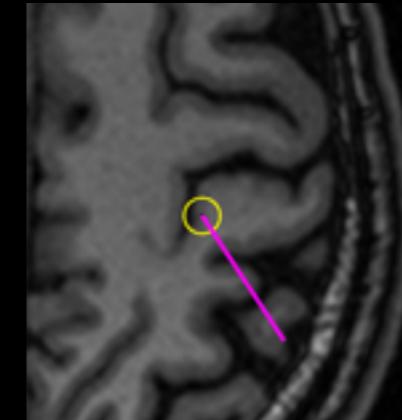
# Median Nerve Dipole Fitting Results



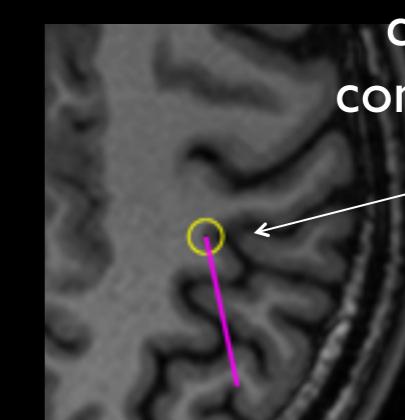
7 sensors



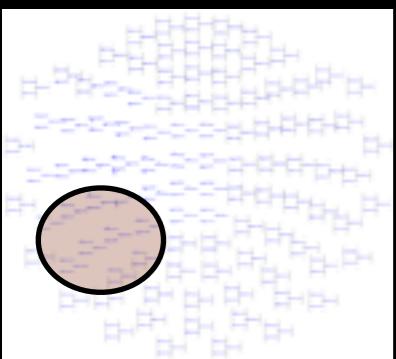
99.7%



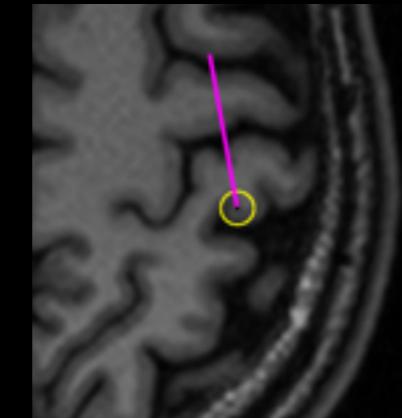
99.2%



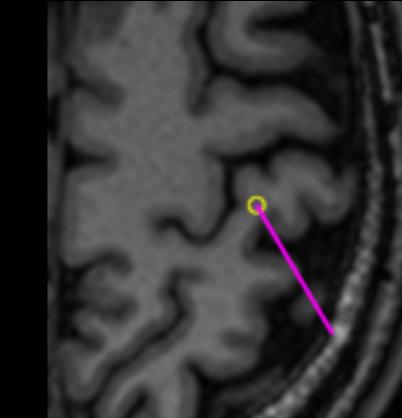
98.2%



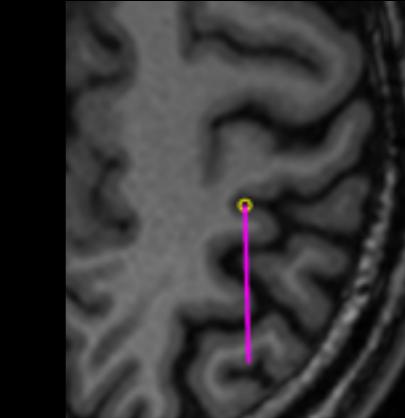
42 sensors



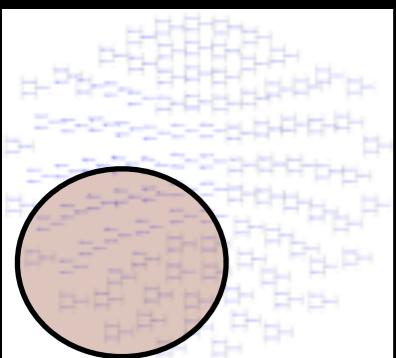
84.6%



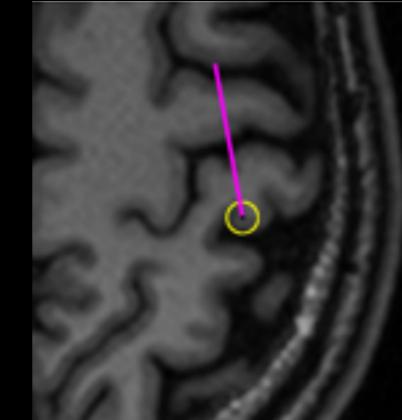
97.6%



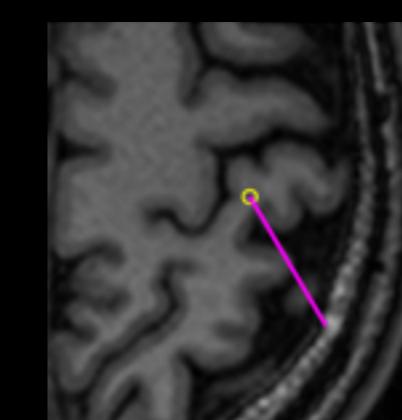
85.8%



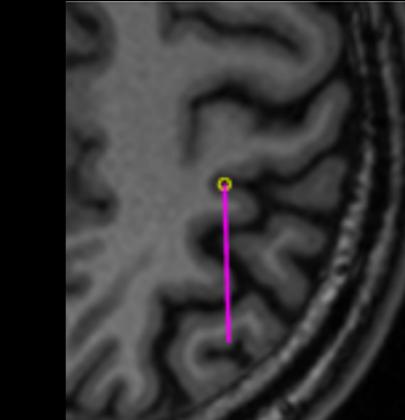
92 sensors



84.6%



97.6%



85.8%



# Time course of SEF



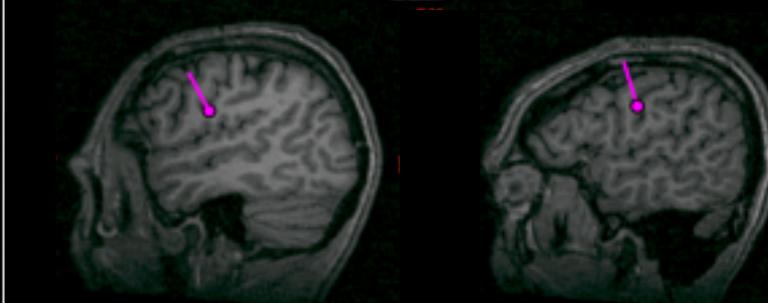
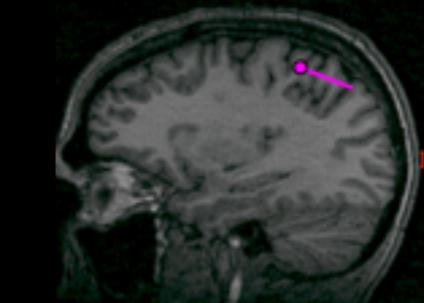
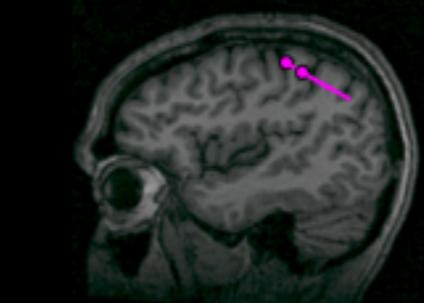
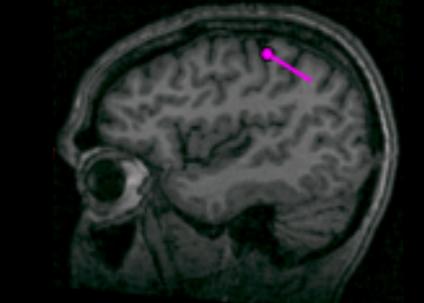
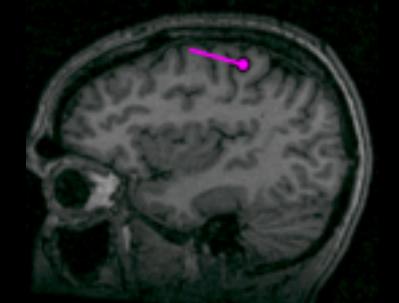
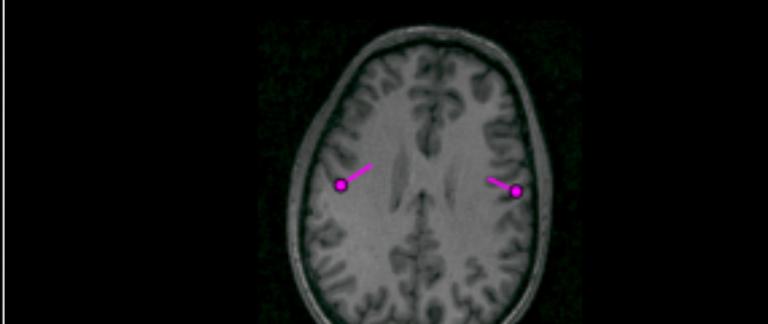
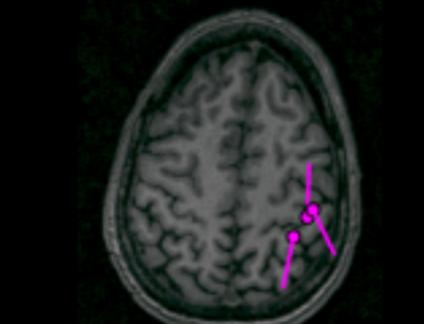
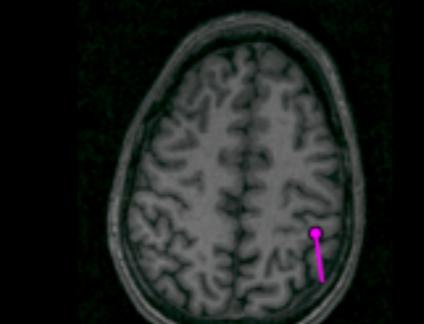
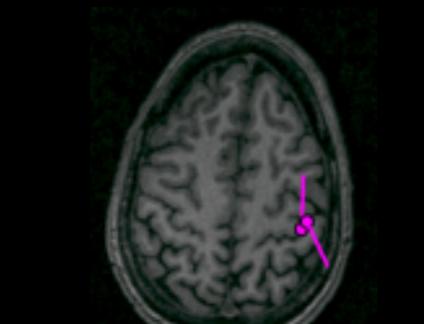
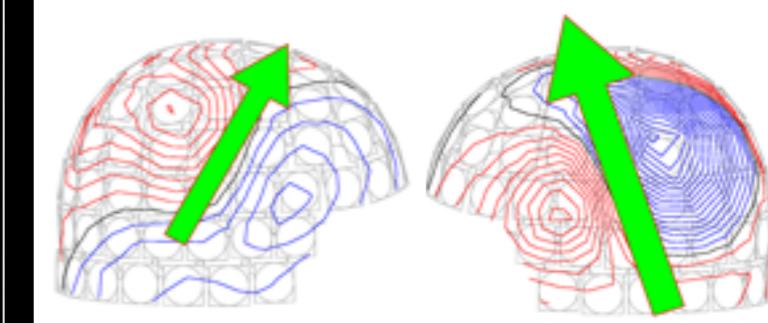
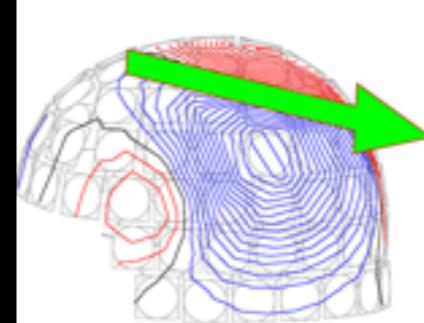
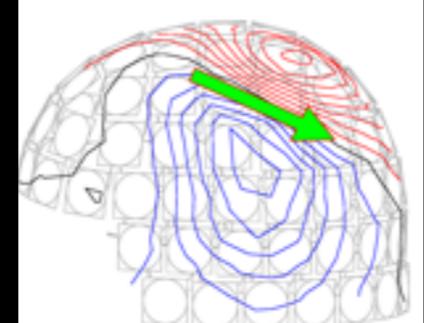
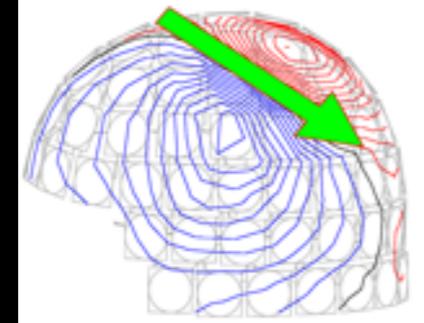
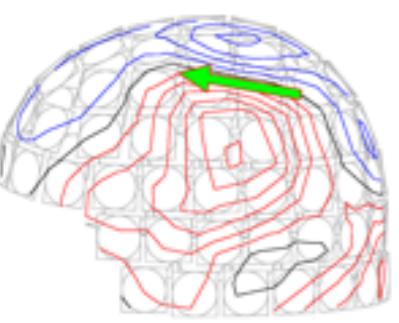
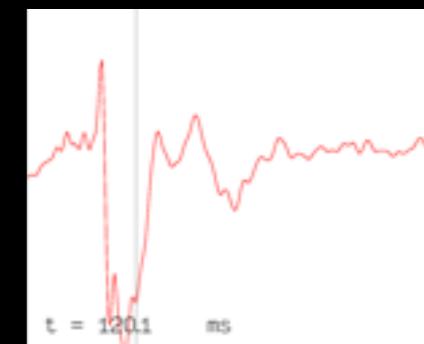
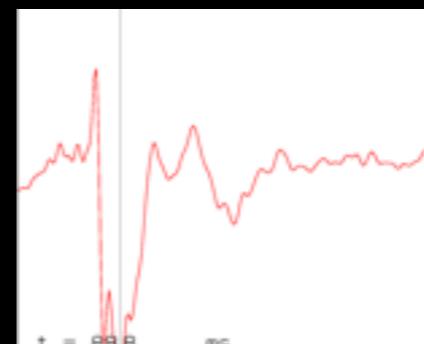
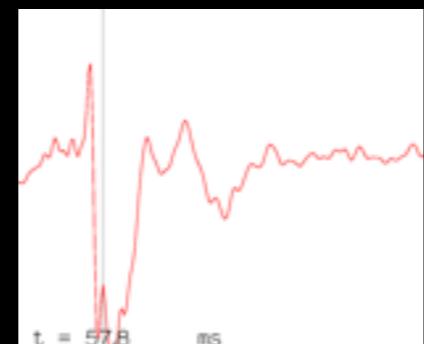
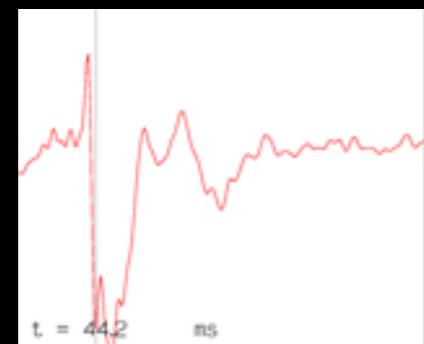
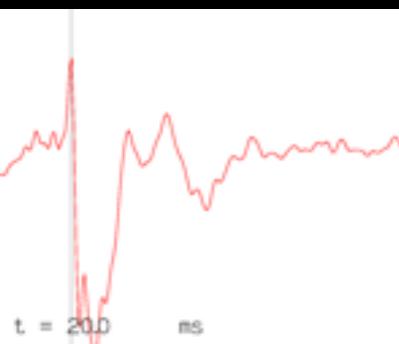
20 ms

44 ms

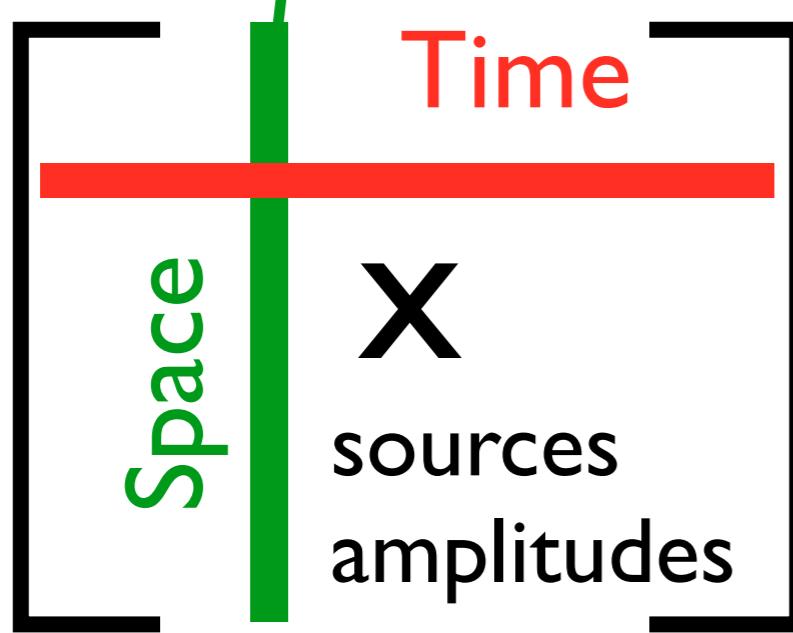
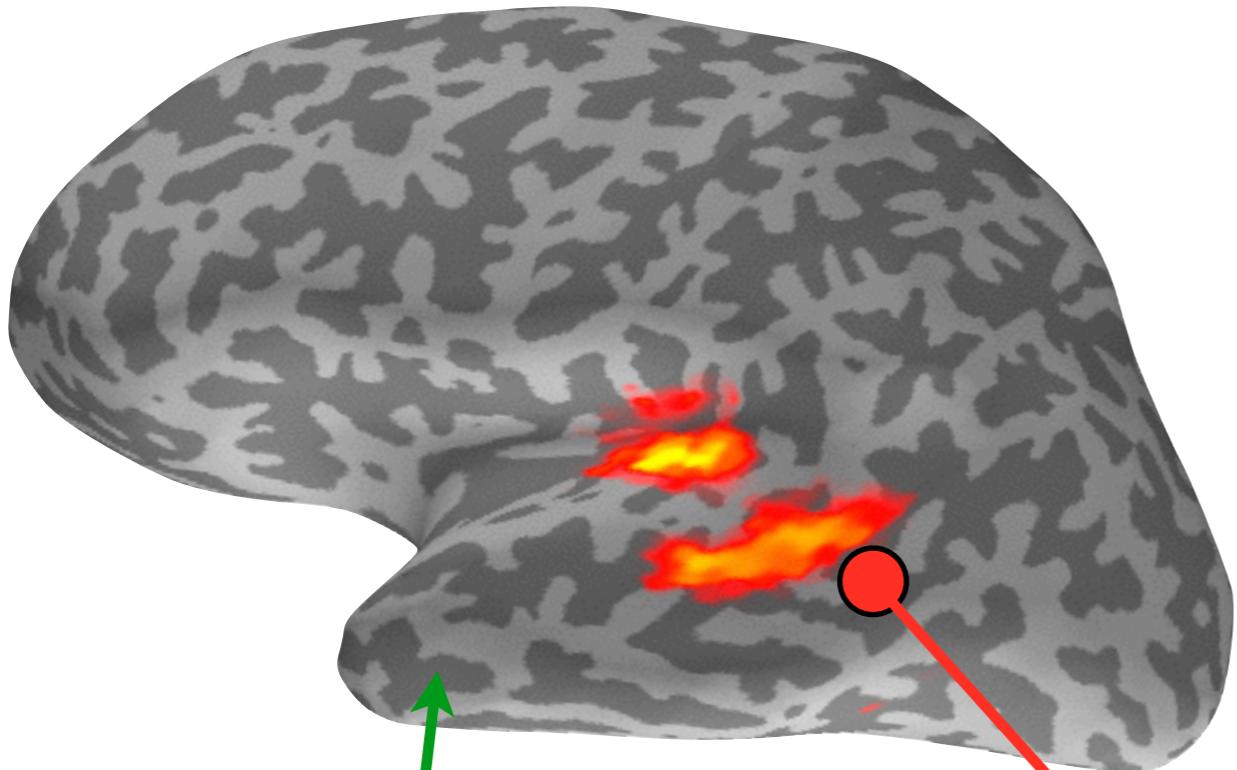
57 ms

88 ms

120 ms

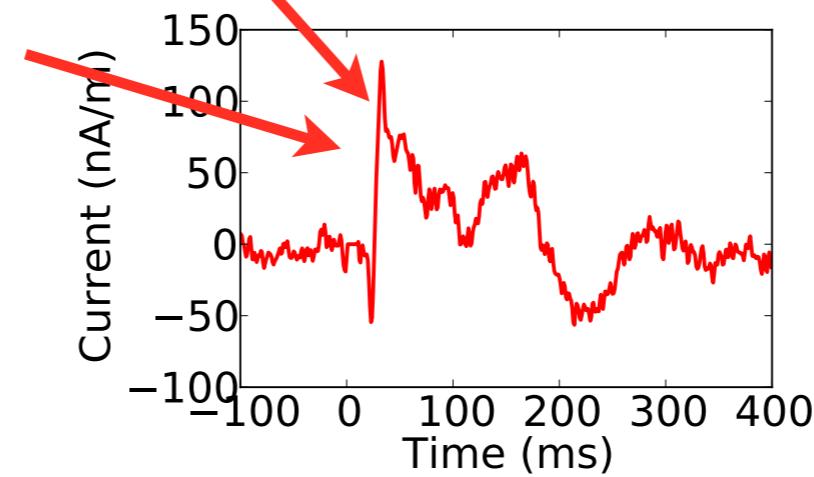


# Distributed model



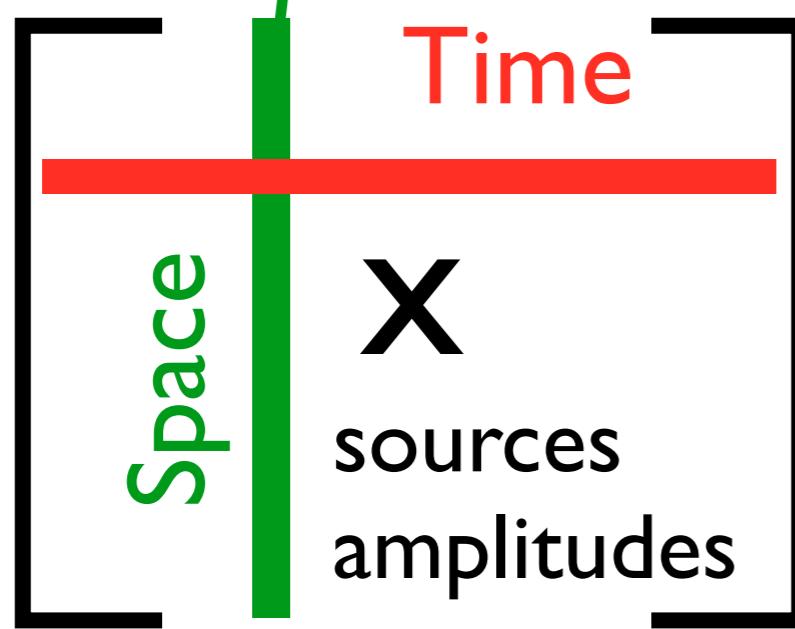
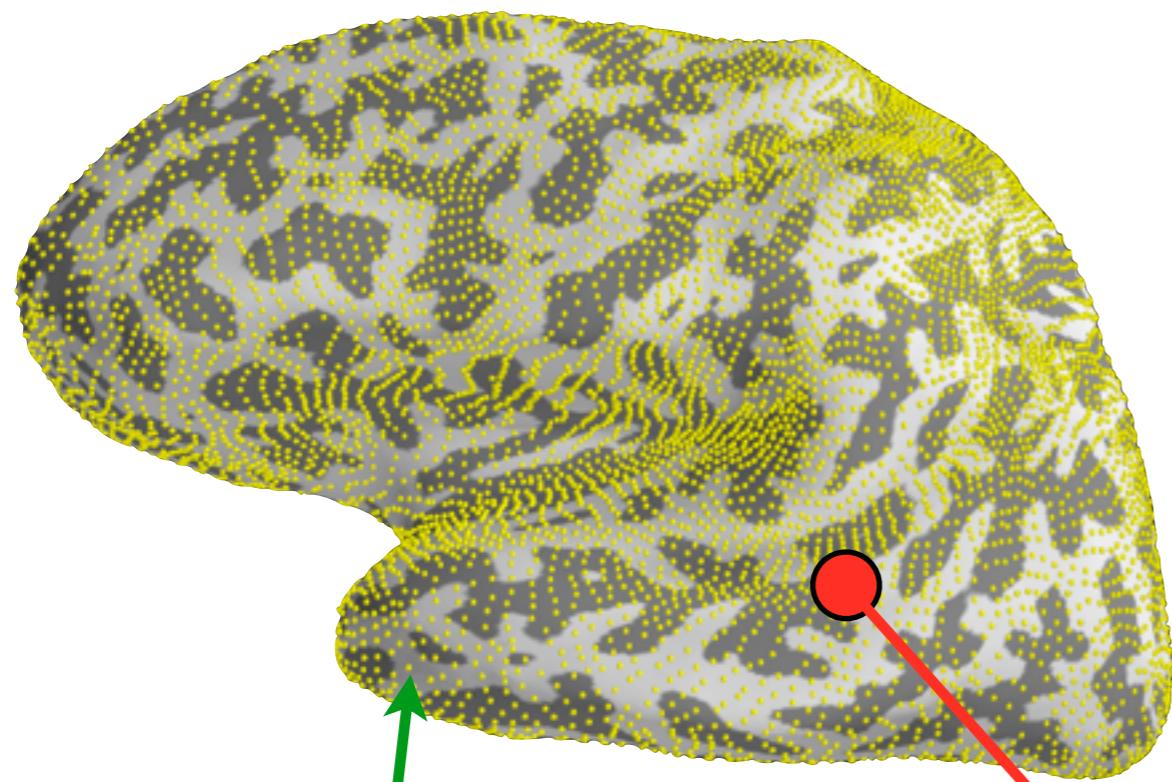
*Scalar field defined over time*

Position 5000 candidate sources over each hemisphere  
(e.g. every 5mm)



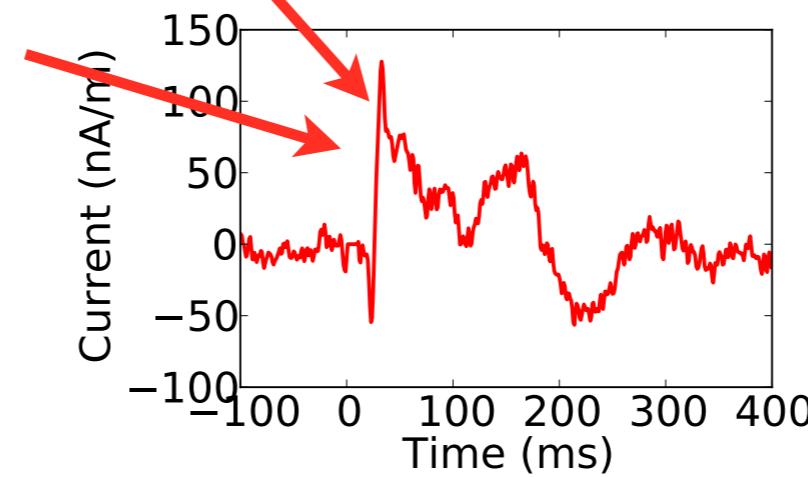
[Dale and Sereno 93]

# Distributed model



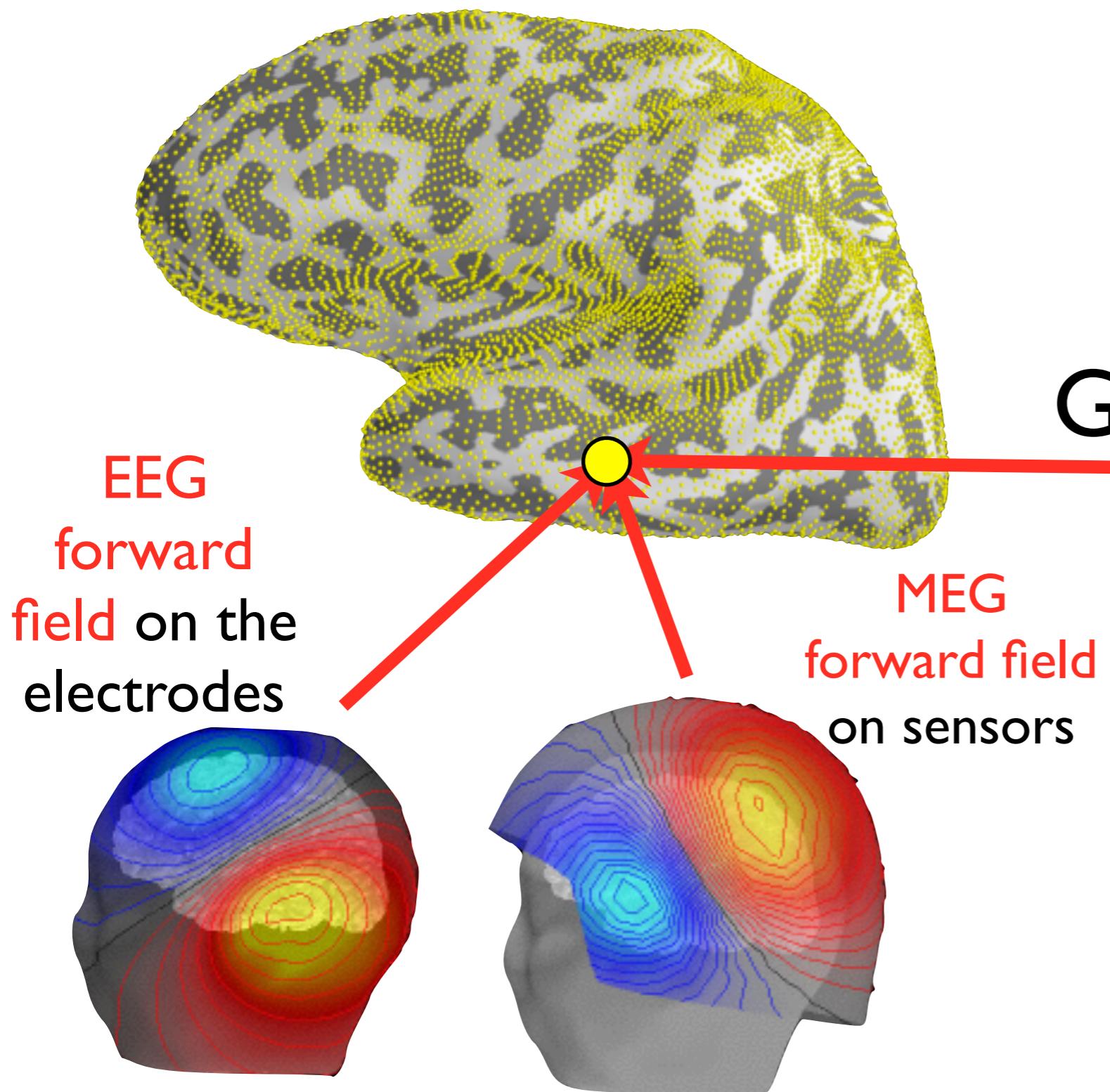
Scalar field defined over time

Position 5000 candidate sources over each hemisphere  
(e.g. every 5mm)



[Dale and Sereno 93]

# Distributed model

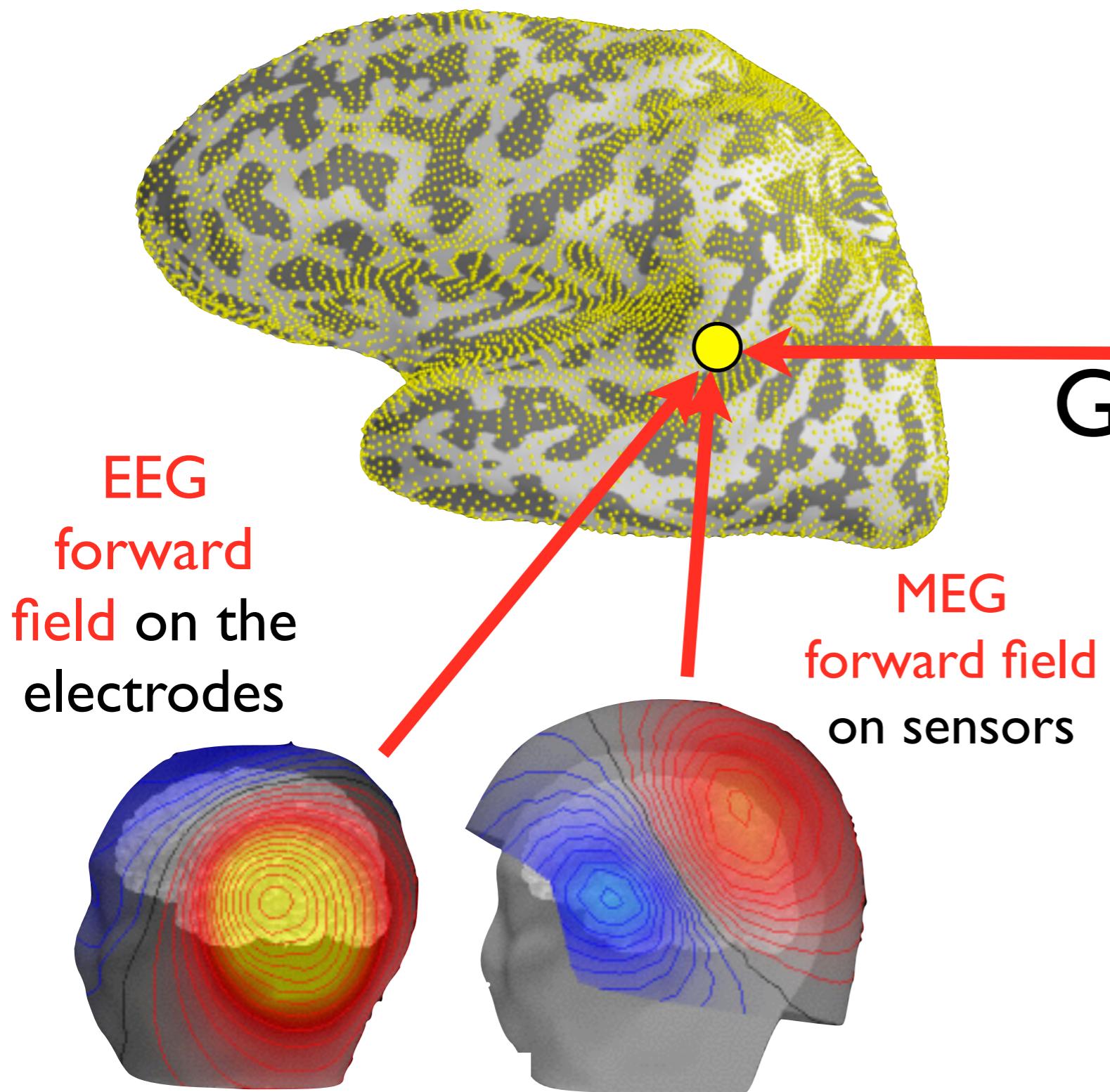


one column = Forward  
field of one dipole

$$G = \begin{bmatrix} \text{---} & | & \text{---} \\ G_{\text{EEG}} & | & G_{\text{MEG}} \\ \text{---} & | & \text{---} \end{bmatrix}$$

G is the gain matrix  
obtained by concatenation  
of the forward fields

# Distributed model

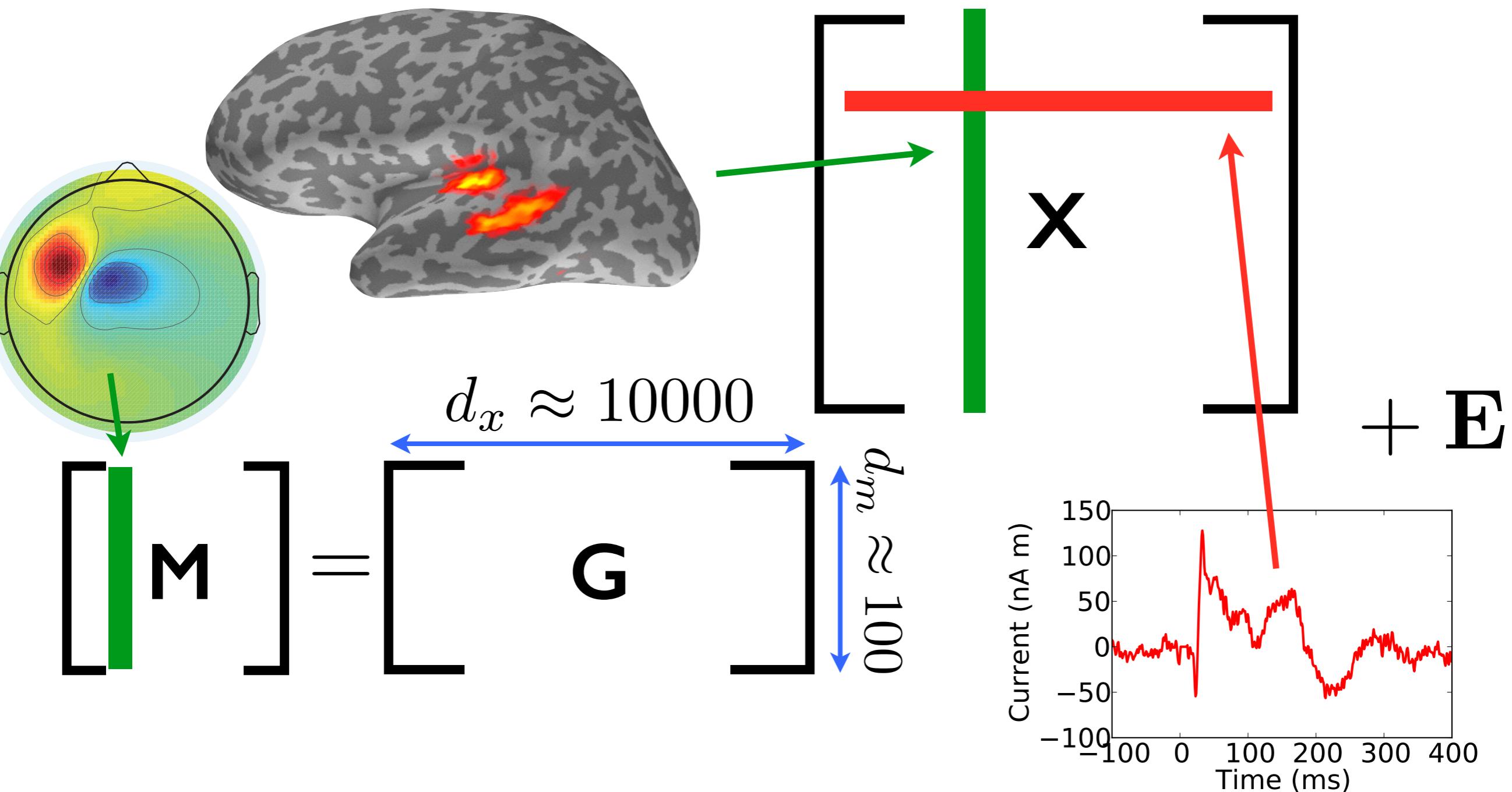


one column = Forward  
field of one dipole

$$G = \begin{bmatrix} G_{EEG} \\ G_{MEG} \end{bmatrix}$$

G is the gain matrix  
obtained by concatenation  
of the forward fields

# $M = GX + E$ : An ill-posed problem



Linear problem with more unknowns than the number of equations: it's ill-posed => Regularize

# Inverse problem framework

An optimization problem:

$$\mathbf{X}^* = \arg \min_{\mathbf{X}} \|\mathbf{M} - \mathbf{G}\mathbf{X}\|_F^2 + \lambda \phi(\mathbf{X}), \lambda > 0$$

**Data fit**      **Regularization**

$\lambda$  : Trade-off between the **data fit** and the **regularization**

where  $\|\mathbf{A}\|_F = \text{tr}(\mathbf{A}^T \mathbf{A})$

$\phi(\mathbf{X})$  Measures the *complexity* of  $\mathbf{X}$ , it's **the prior**.

Examples for  $\phi(\mathbf{X})$  :  $\ell_1$ ,  $\ell_2$ ,  $\ell_p$  with  $p \geq 1$ , entropy . . .

Remark: If  $\phi(\mathbf{X})$  is strictly convex we have a unique minimizer  
(sufficient but not a necessary condition)

# Inverse problem framework

Penalized (variational) formulation (with whitened data):

$$\mathbf{X}^* = \arg \min_{\mathbf{X}} \|\mathbf{M} - \mathbf{G}\mathbf{X}\|_F^2 + \lambda \phi(\mathbf{X}), \lambda > 0$$

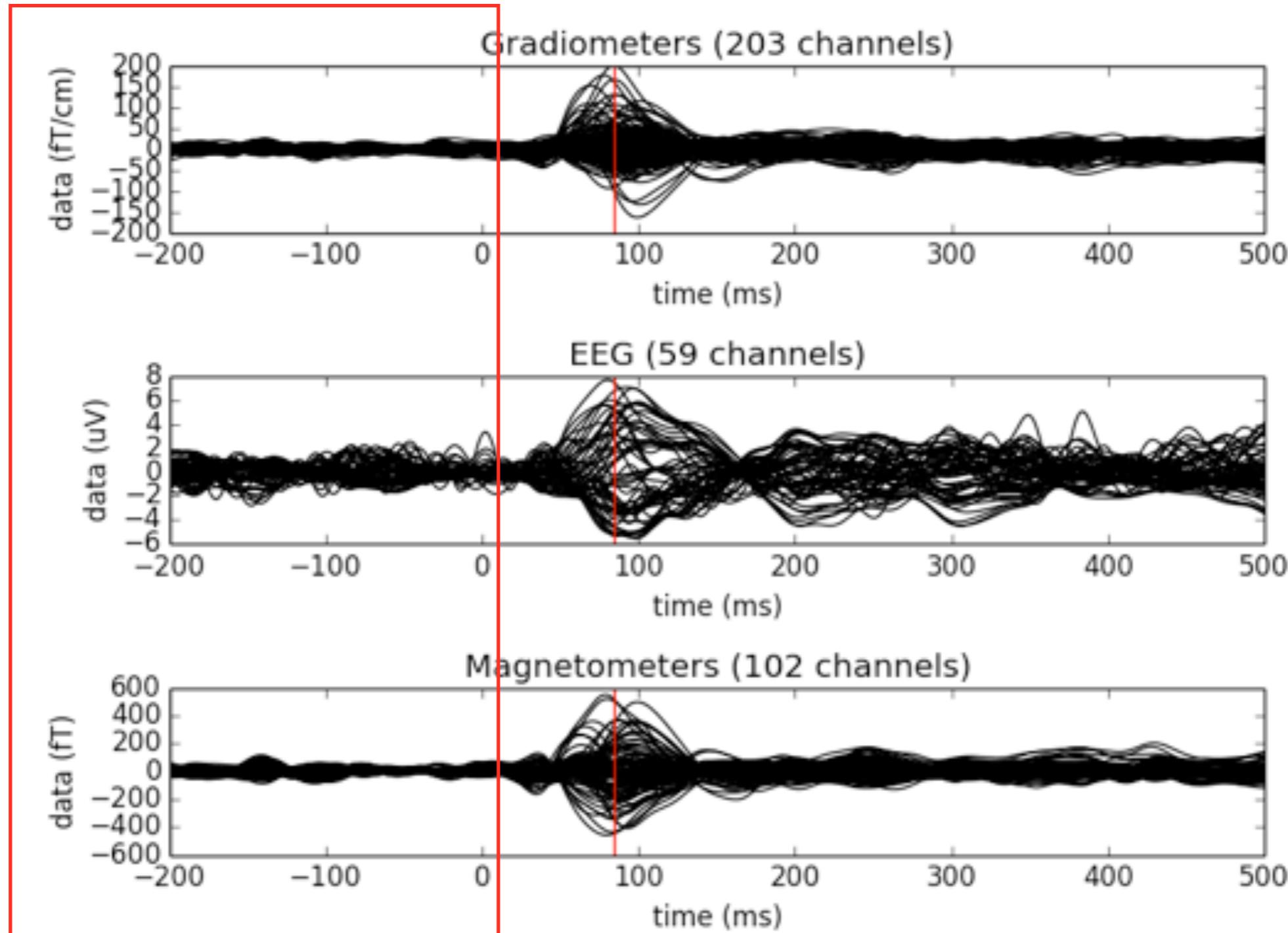
Data fit      Regularization

$\lambda$  : Trade-off between the **data fit** and the **regularization**

where  $\|\mathbf{A}\|_F^2 = \text{tr}(\mathbf{A}^T \mathbf{A})$

How do you whiten data?

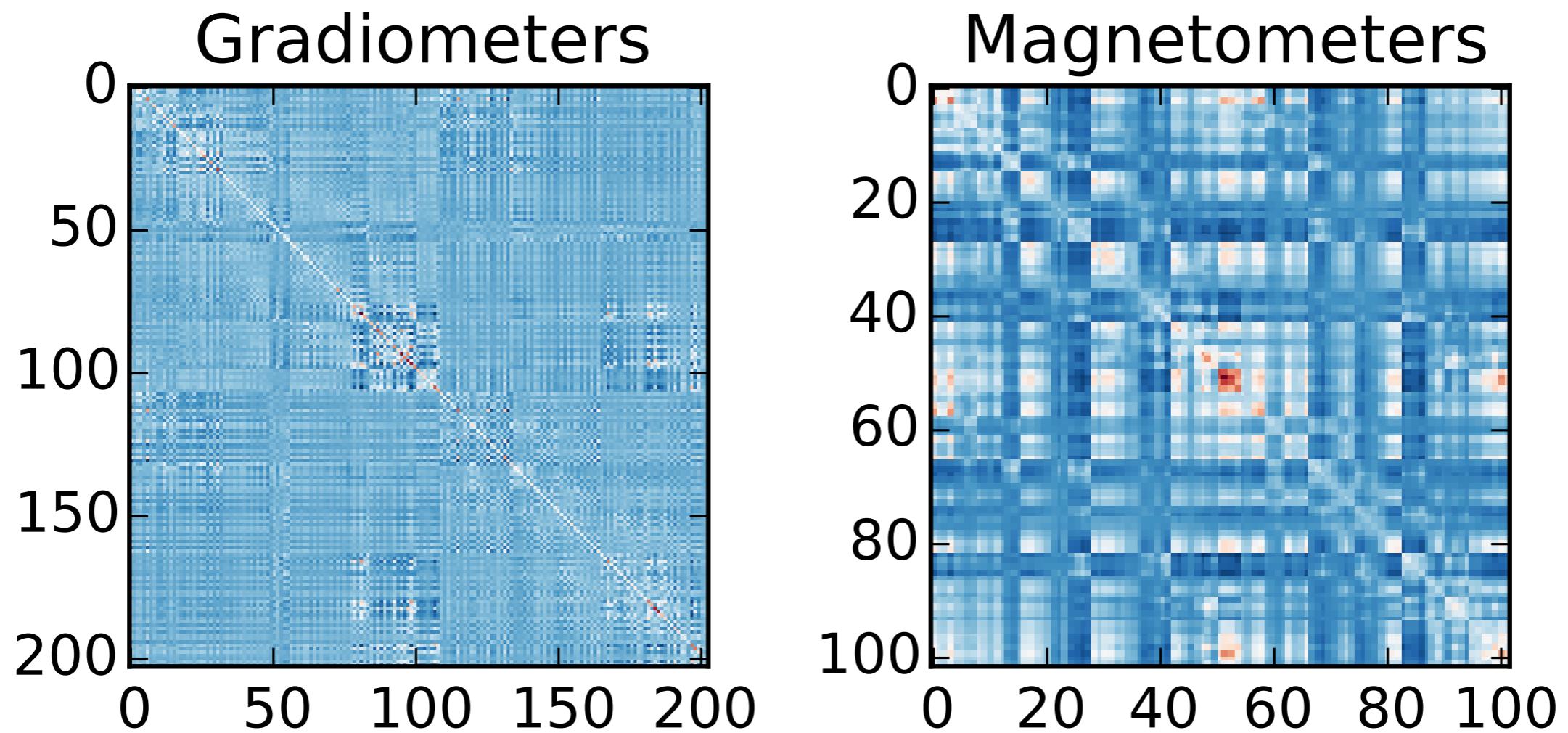
# To know what is signal look at the noise



Baseline

Data from different sensors have  
to be put on the same scale.

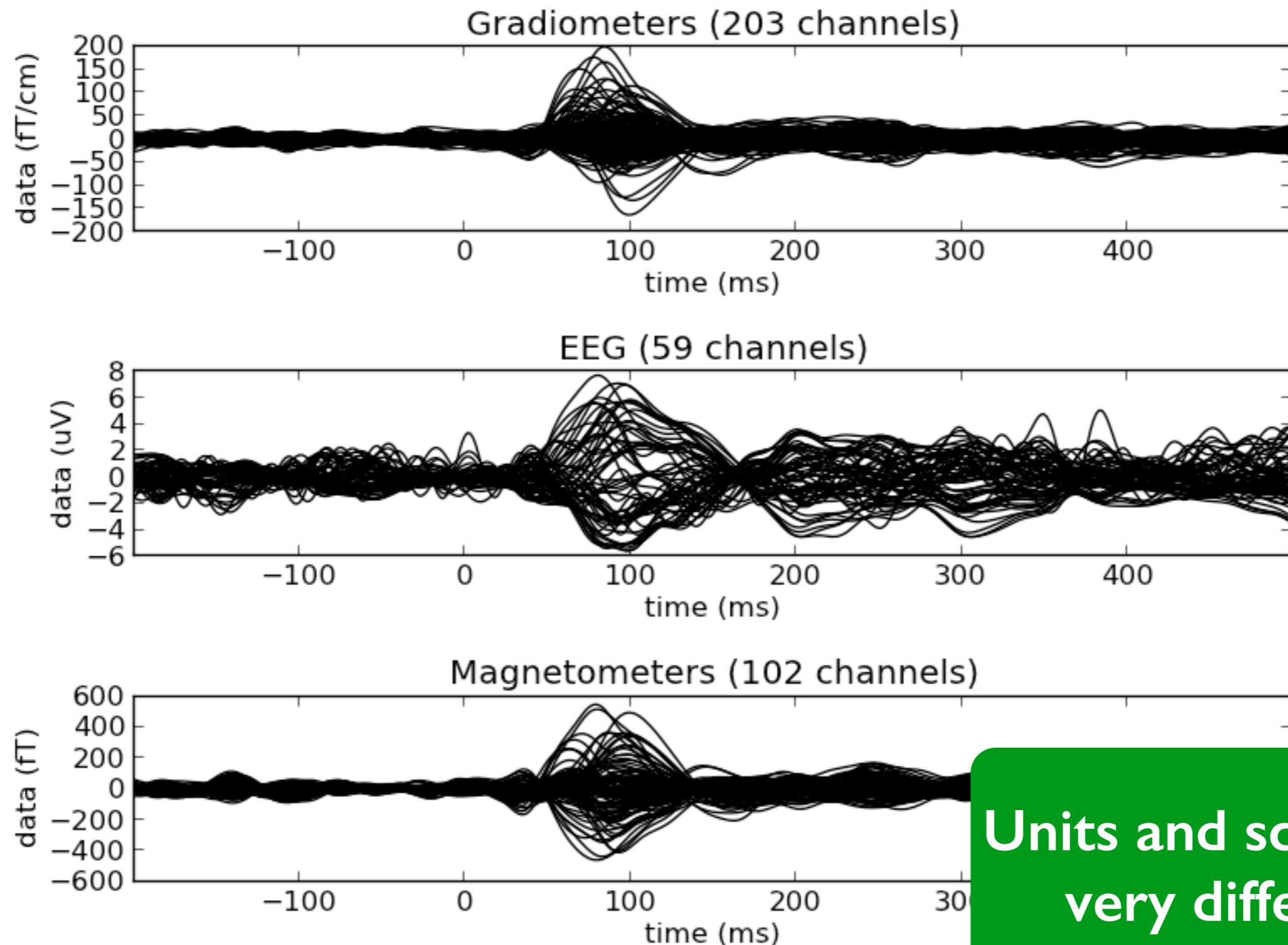
# To know what is signal look at the noise



$$C = \frac{MM^T}{d_t}$$

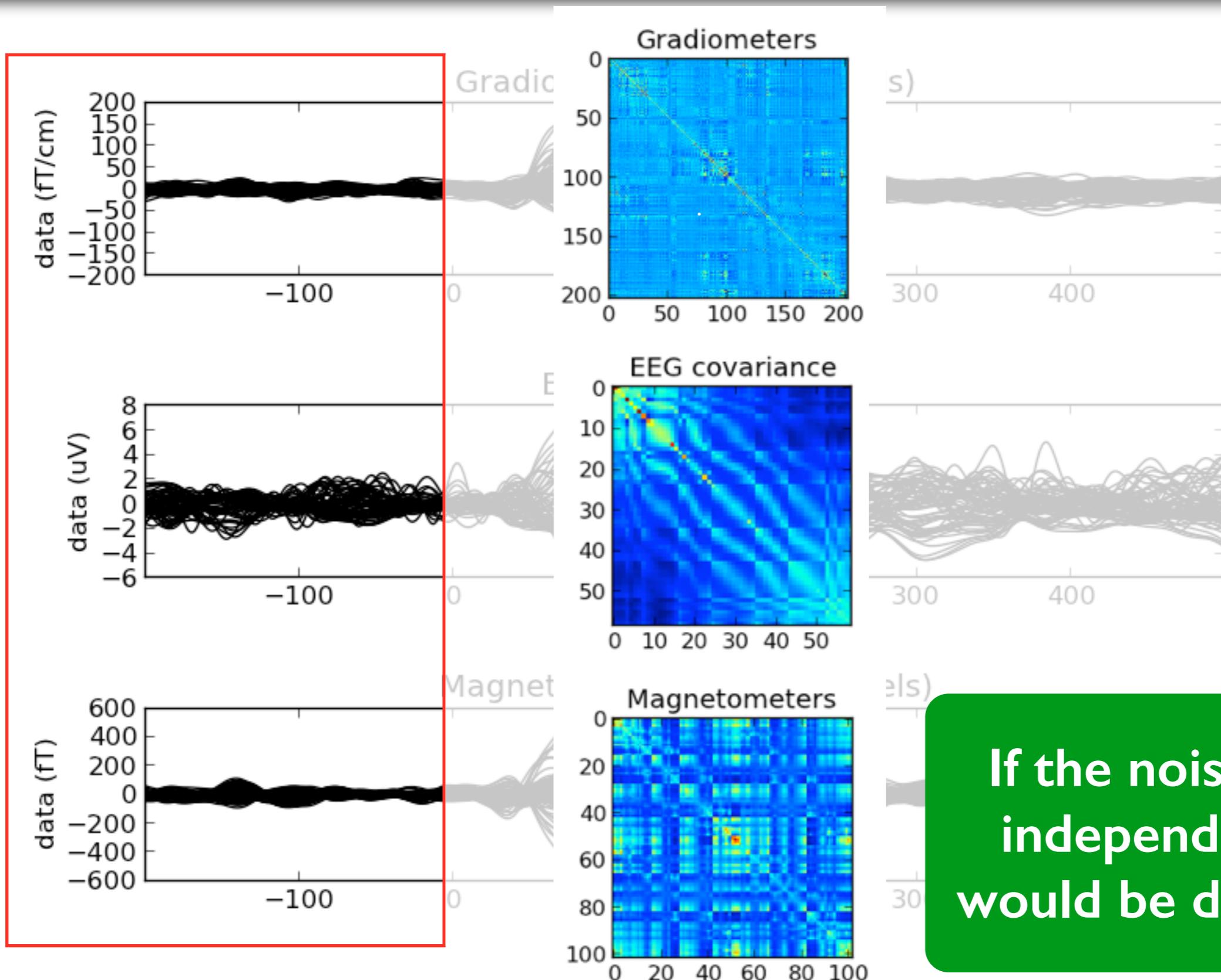
With whitened data the covariance would be diagonal

# Spatial whitening



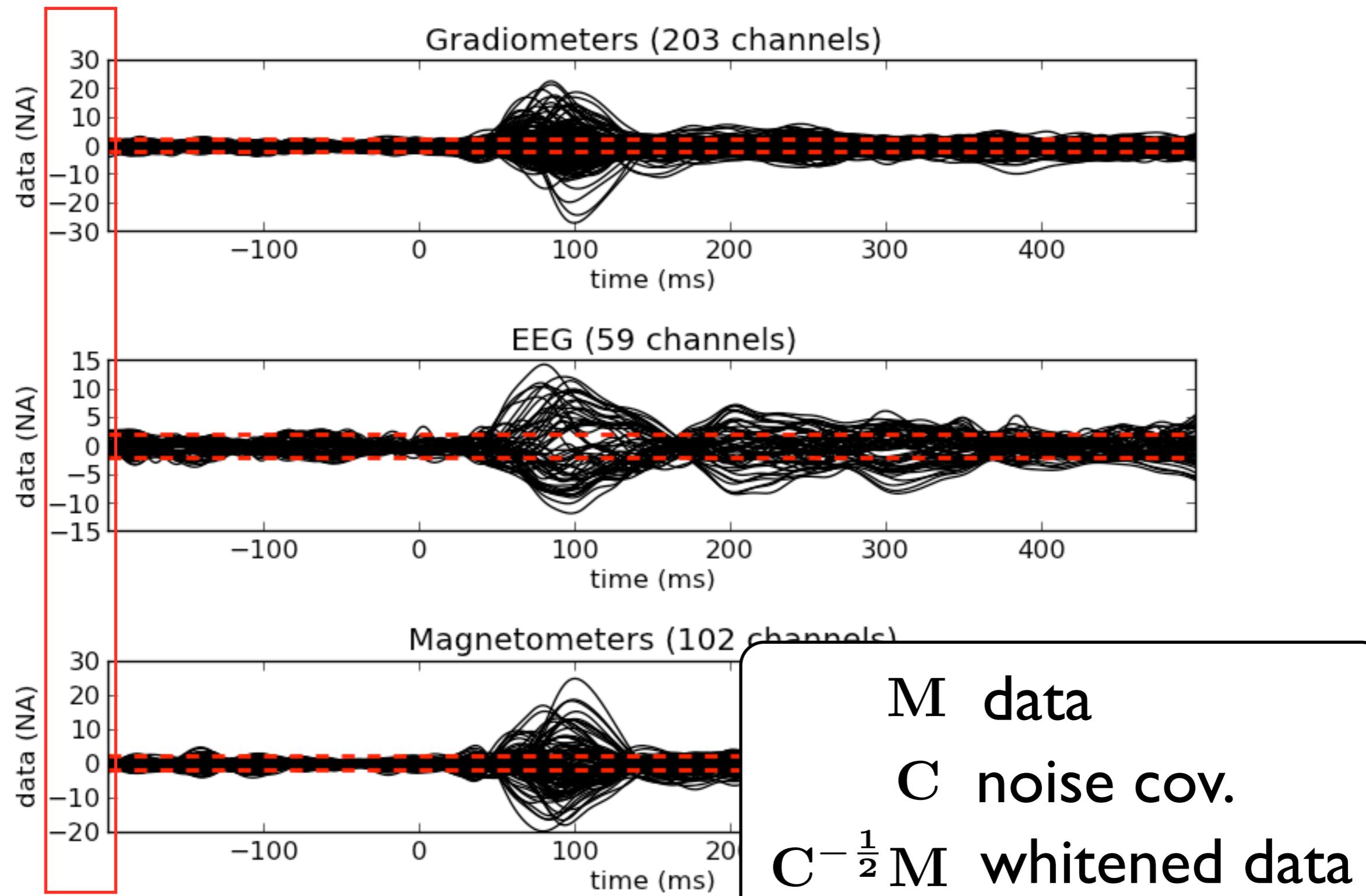
Units and scales are  
very different

# Spatial whitening

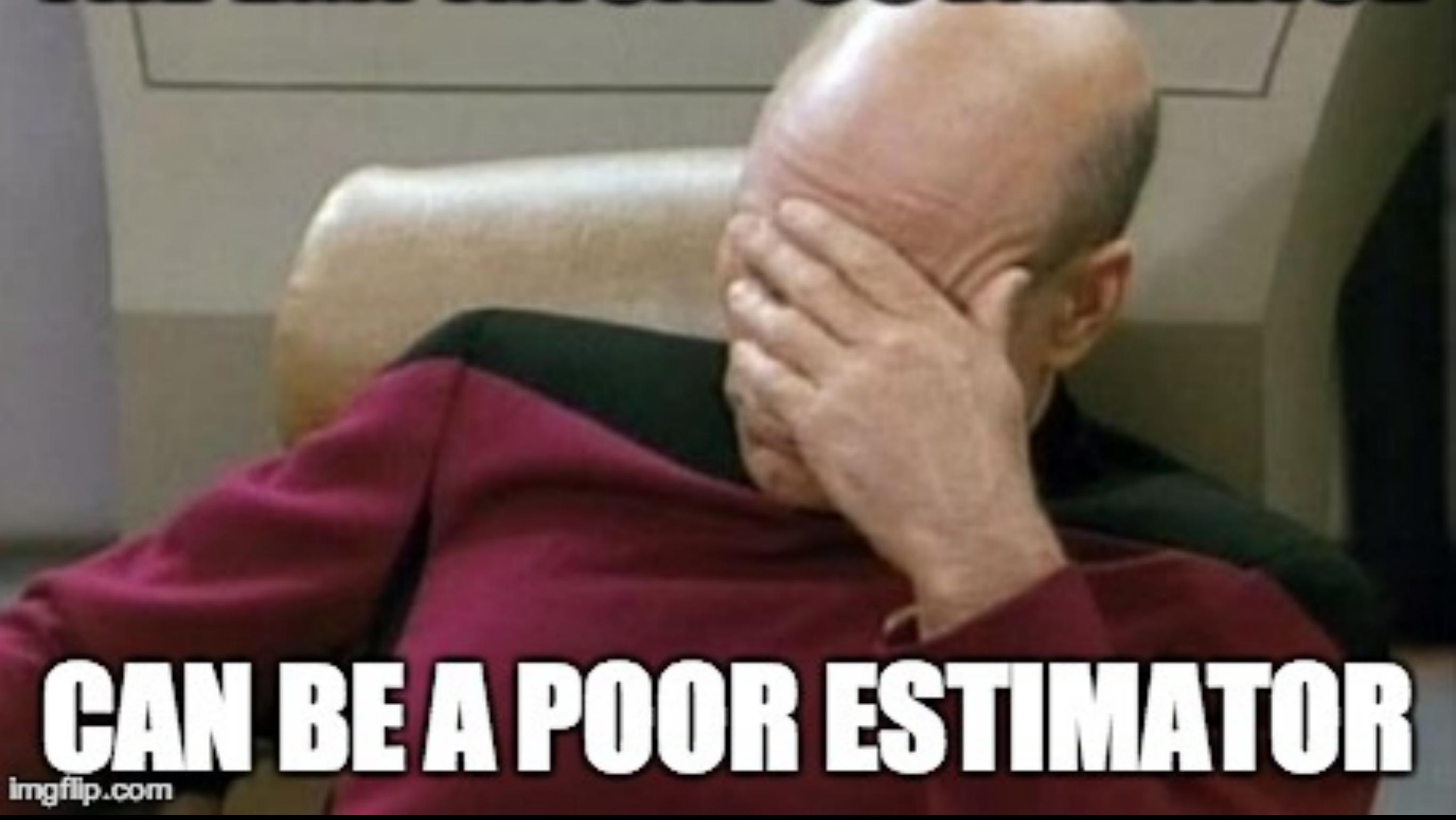


If the noise was independent it would be diagonal

# Spatial whitening



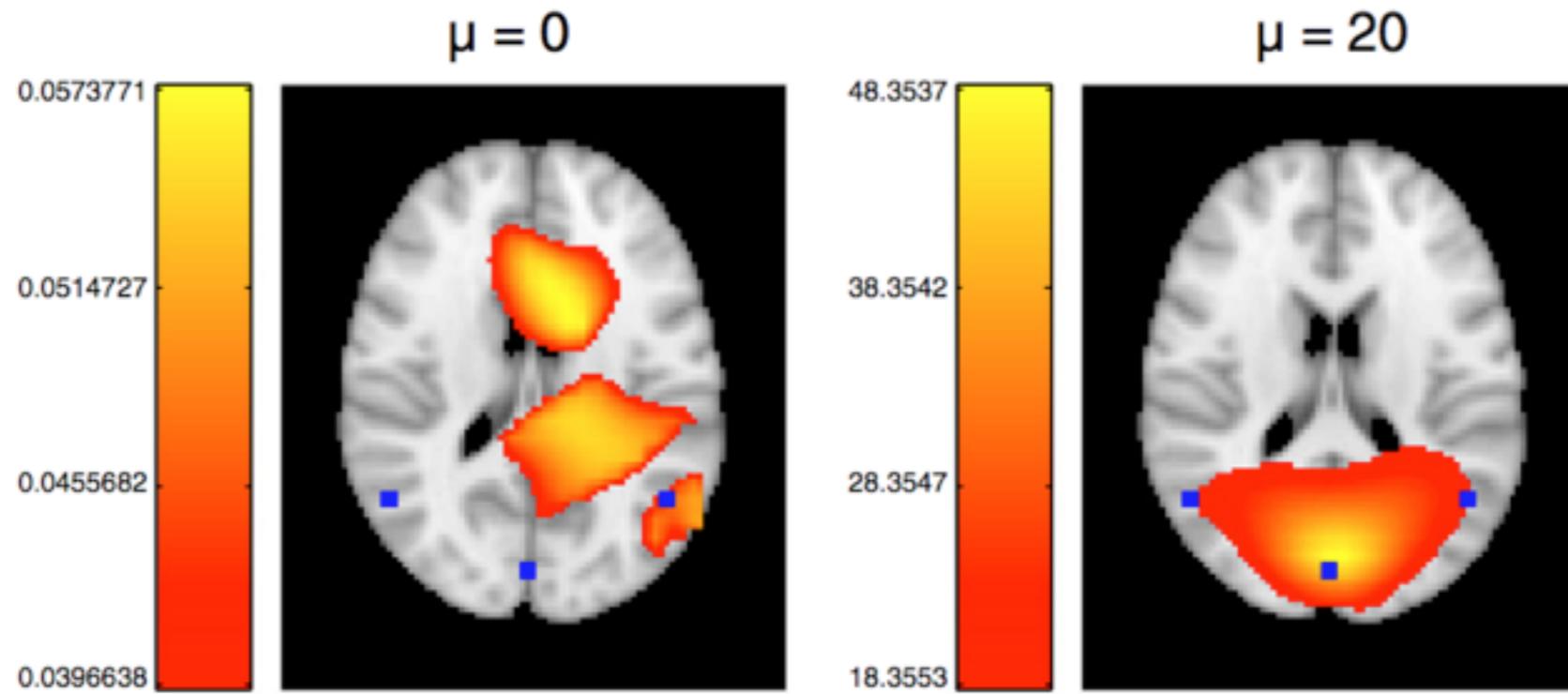
# THE EMPIRICAL COVARIANCE



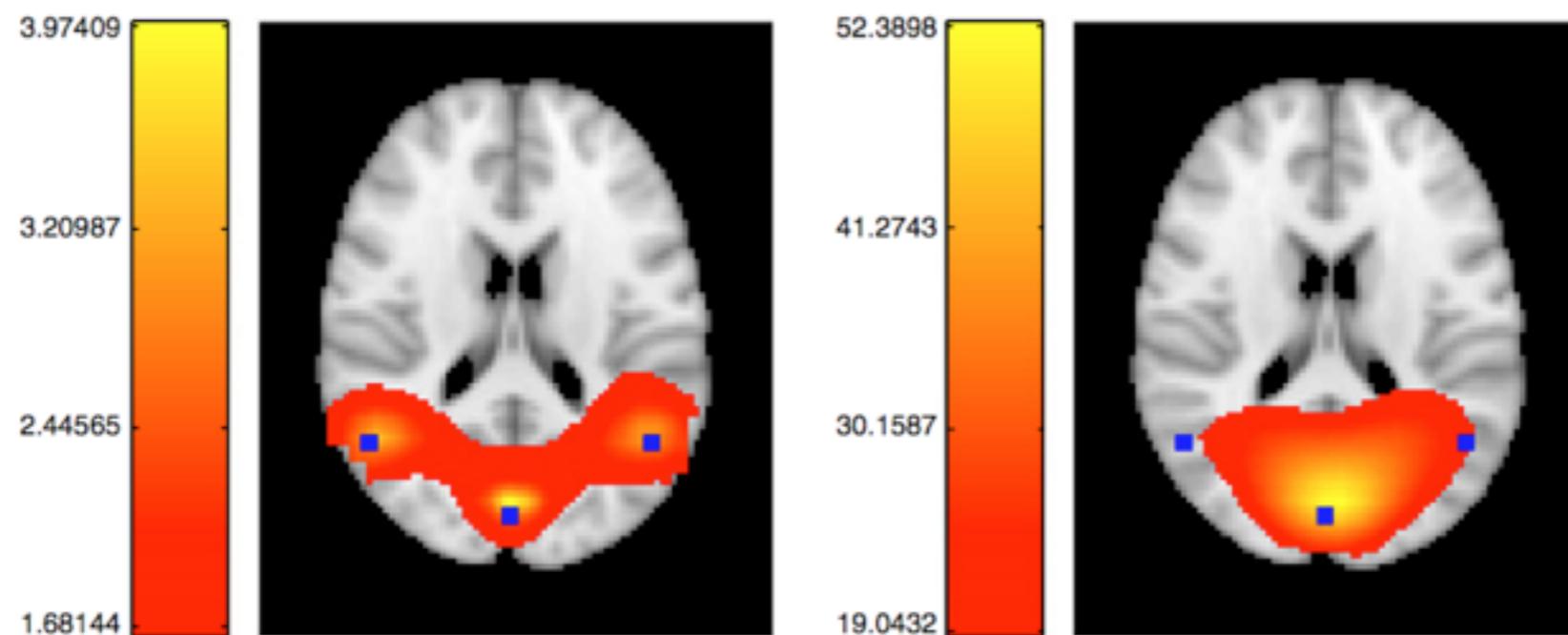
## CAN BE A POOR ESTIMATOR

# True sources VS LCMV Beamformer given C

10s



80s



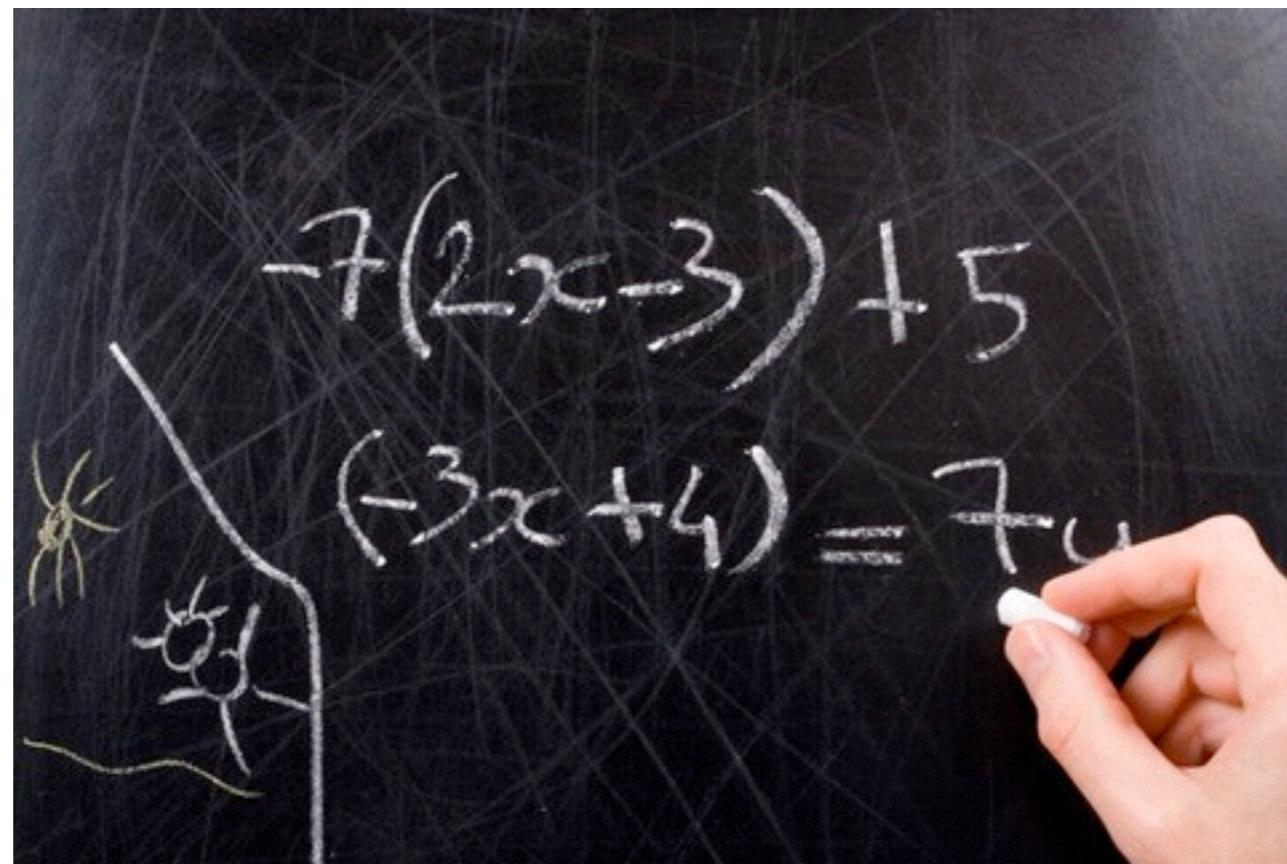
$$C_\mu = \mu\sigma_e^2 I + \frac{1}{T} M M^t$$

[Woolrich, 2011, Neuroimage]

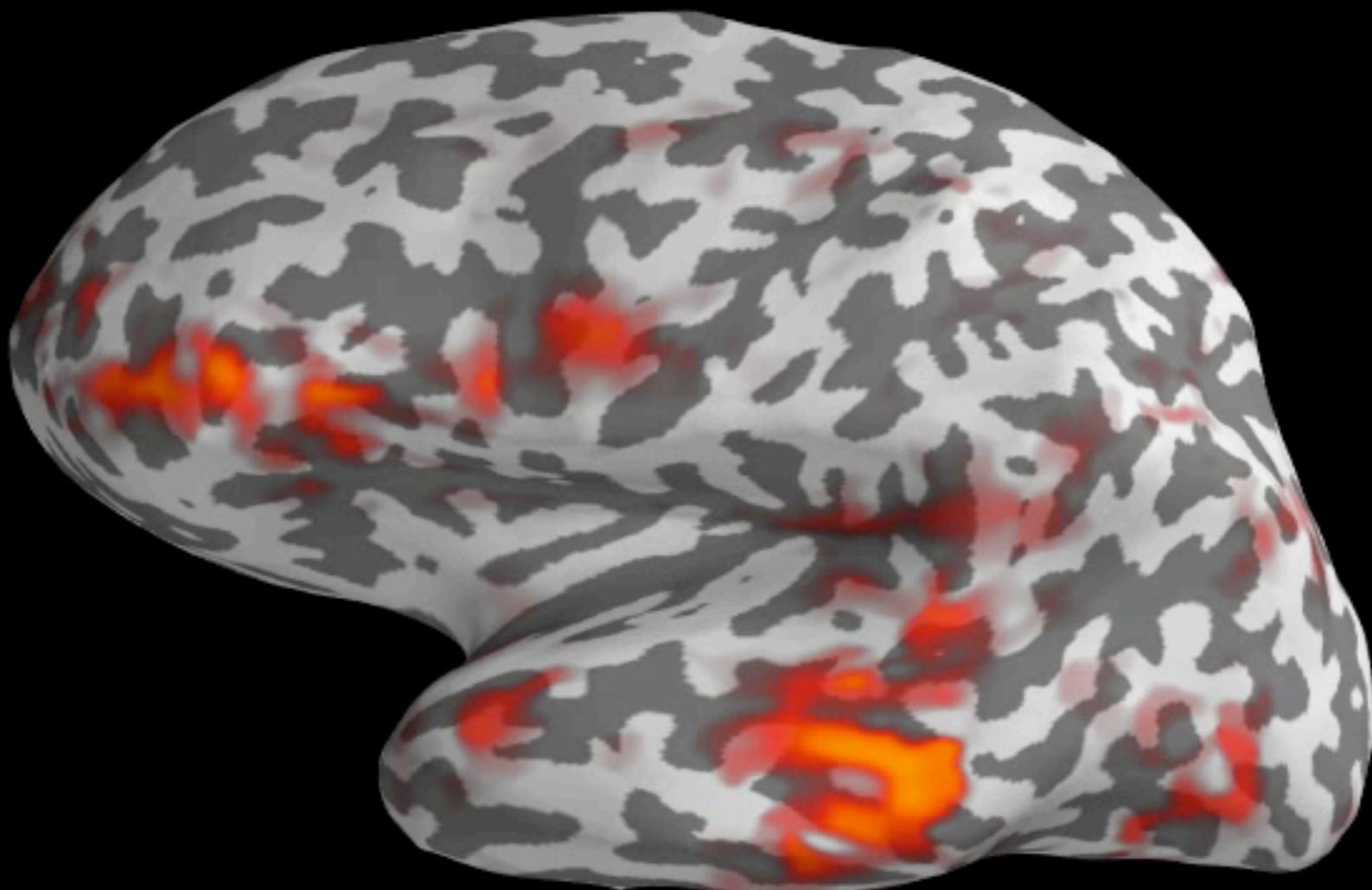
# $\phi(\mathbf{X})$ with M/EEG data: L2

Simple L2 (Tikhonov):

$$\mathbf{X}^* = \arg \min_{\mathbf{X}} \mathbf{E}(\mathbf{X}) = \arg \min_{\mathbf{X}} \|\mathbf{M} - \mathbf{G}\mathbf{X}\|_F^2 + \lambda \|\mathbf{X}\|_F^2, \lambda > 0$$



<http://youtu.be/Uxr5Pz7JPrs>



time=0.00 ms

# FreeSurfer recon

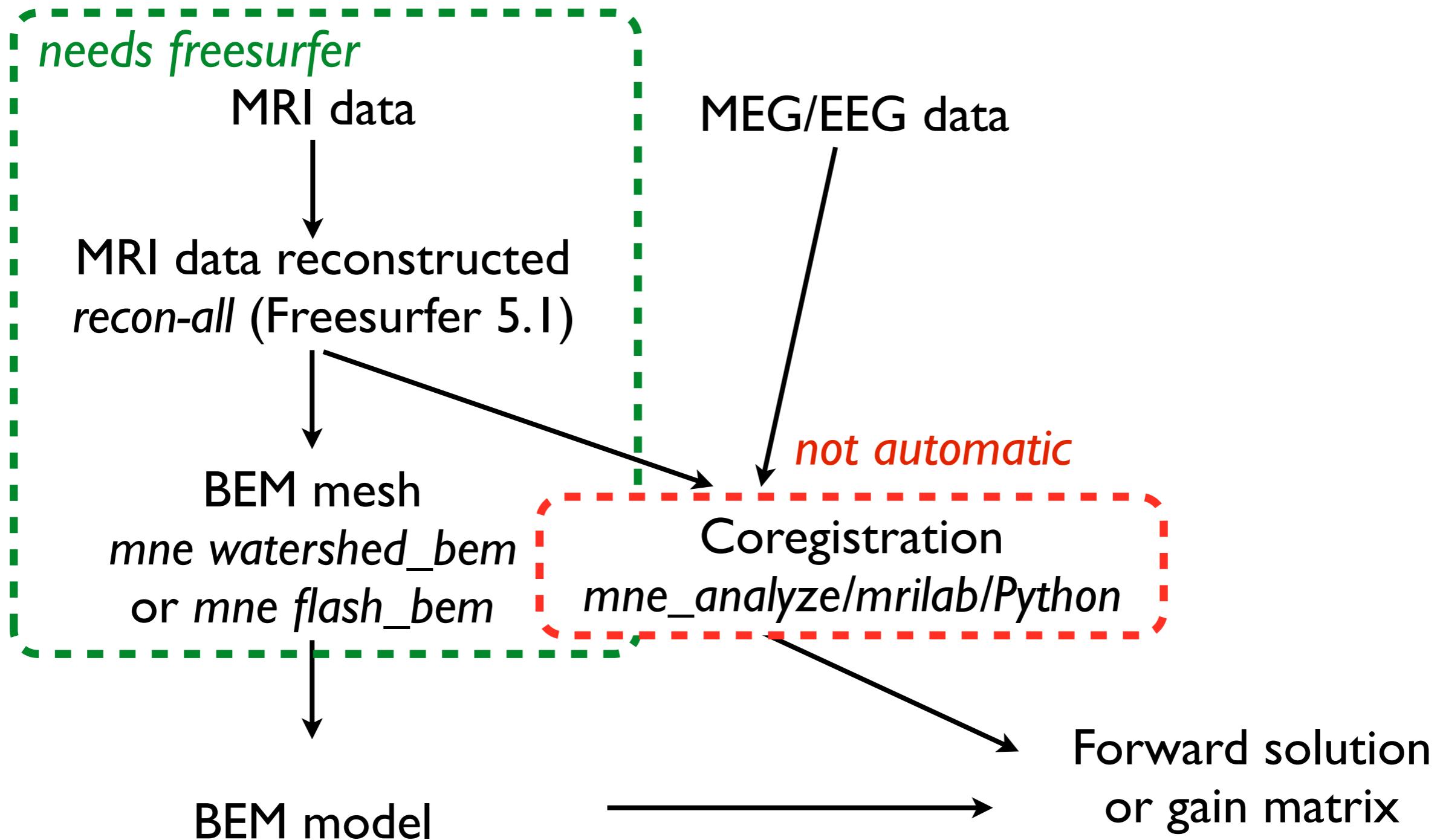
```
$ recon-all -s ${SUBJECT} -i xy000000.nii -all
```

*and just wait...*



*or better go to bed and  
come back tomorrow...*

# Anatomy workflow



# Demo