EEG/MEG Source Estimation
Workshop 4 March 2015

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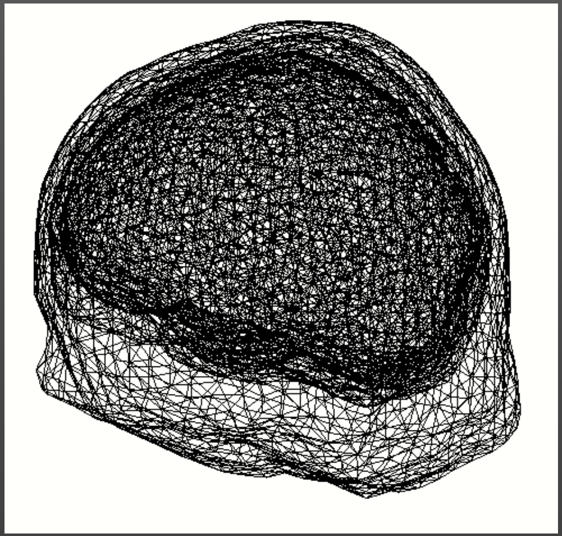
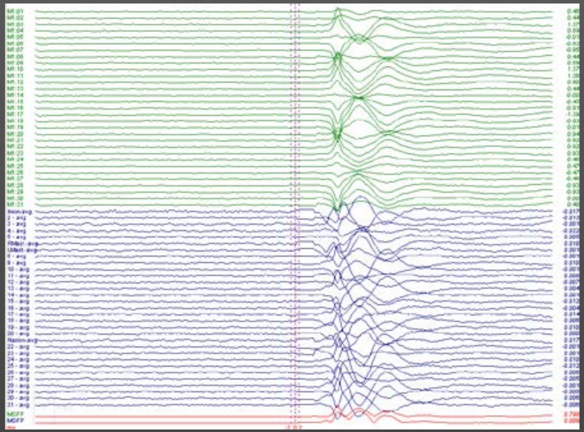
Ingredients for Source Estimation

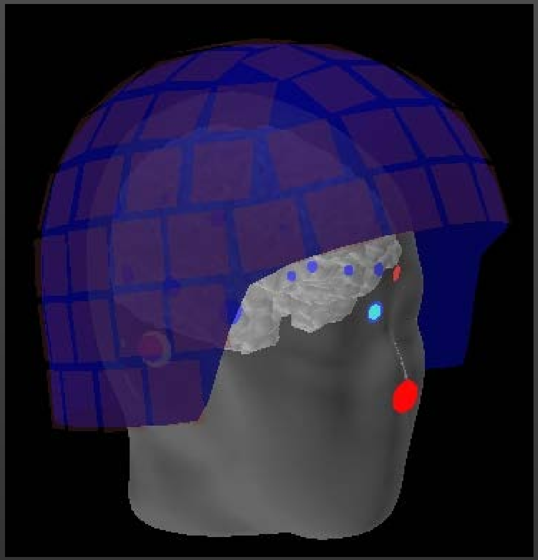
Volume Conductor/
Head Model



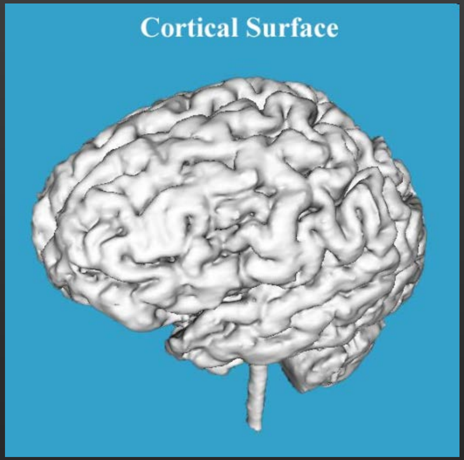
MEG data



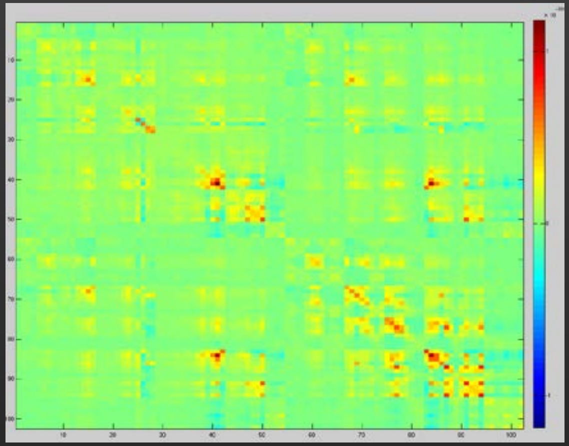
Coordinate
Transformation



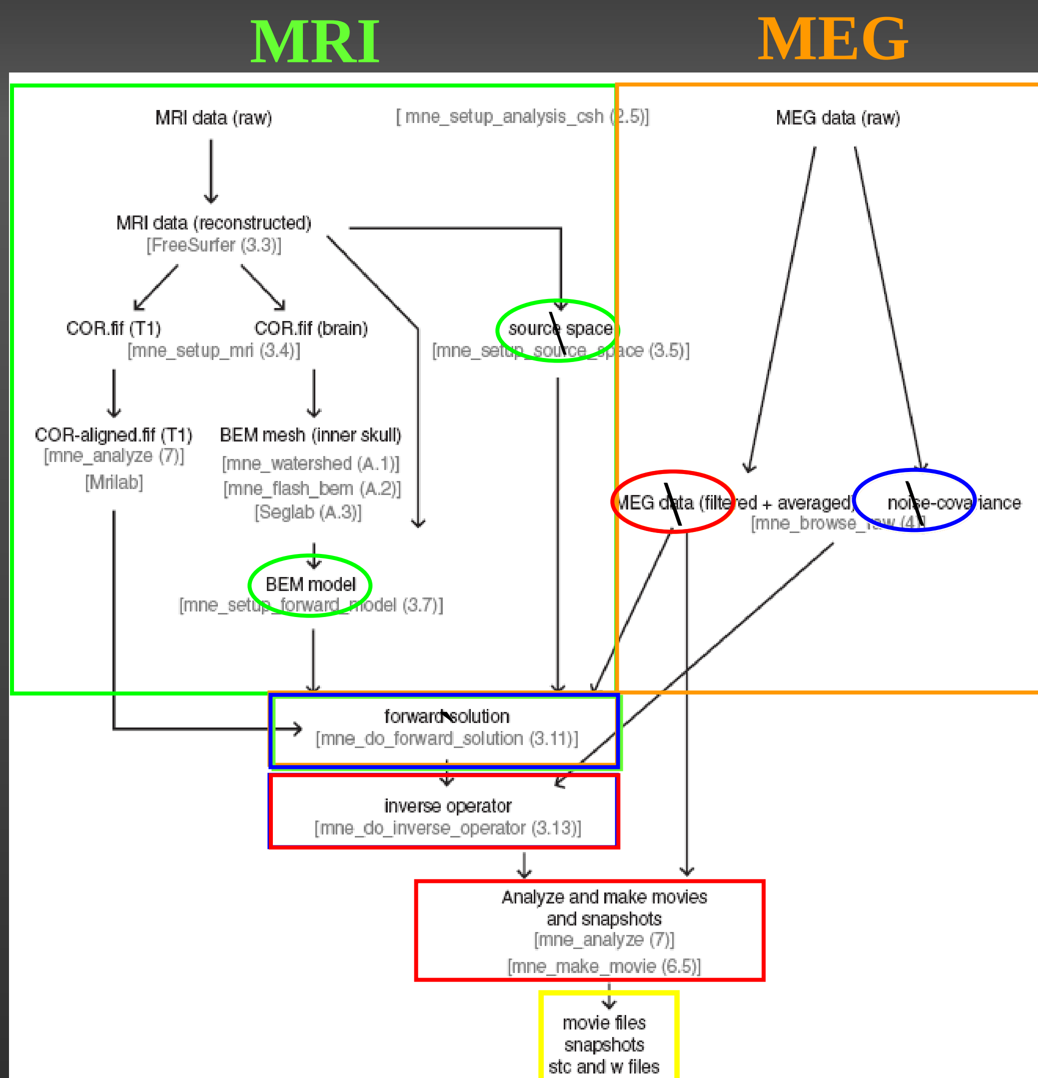
Source Space



Noise/Covariance Matrix



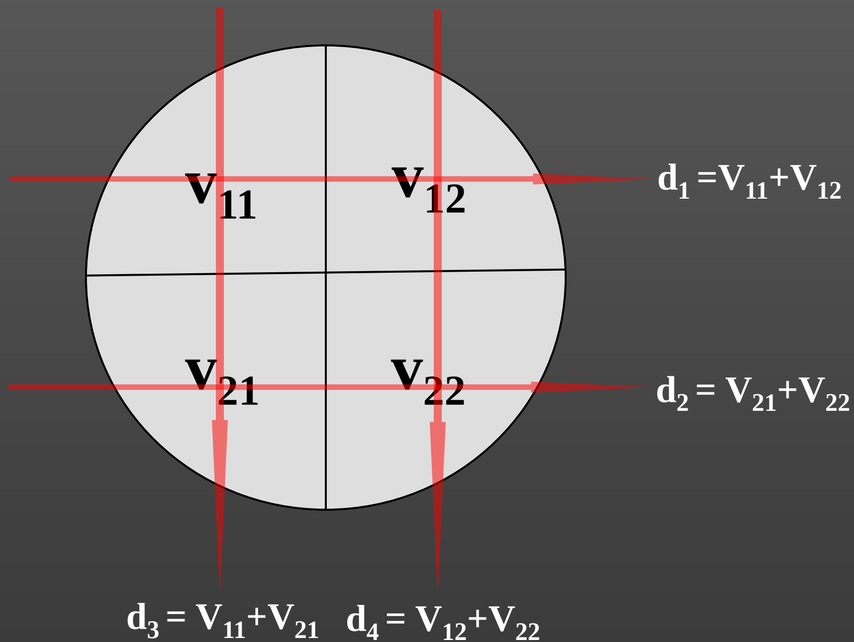
The Path to the Source



MNE software: http://www.martinos.org/mne/
See also: http://www.mrc-cbu.cam.ac.uk/methods-and-resources/imaginganalysis/

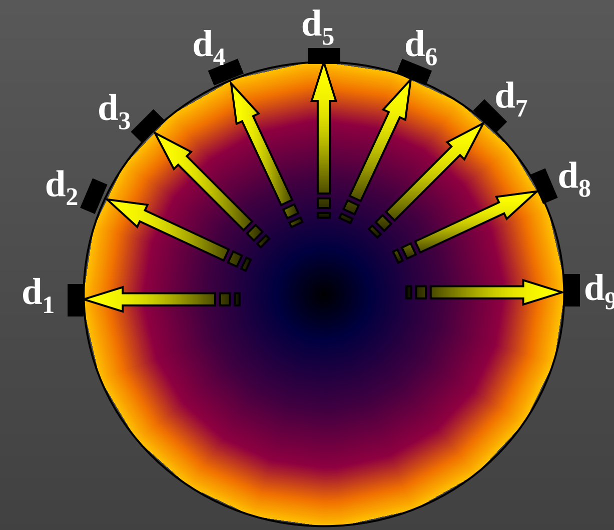
Why Inverse "Problem"?

Tomography (CT, fMRI…)



$$d_1 = V_{11}+V_{12}$$
$$d_2 = V_{21}+V_{22}$$
$$d_3 = V_{11}+V_{21}$$
$$d_4 = V_{12}+V_{22}$$

EEG/MEG



$$d_1 = V_{11}+V_{12}+V_{13}+V_{14} \ldots$$

$$d_2 = V_{21}+V_{22}+V_{23}+V_{24} \ldots$$

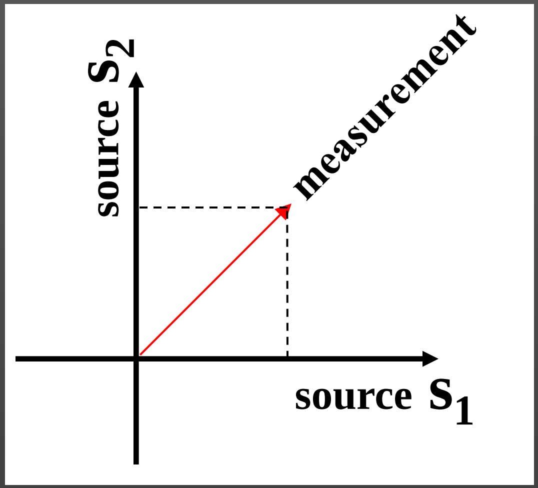
Information is lost during measurement

Cannot be retrieved by mathematics

Inherently limits spatial resolution

Why Inverse "Problem"?

Reconstructing information from an incomplete projection:



We only see a faint shadow of the real distribution of brain activity.

If you are not shocked by the EEG/MEG inverse problem…

… then you haven't understood it yet.

(freely adapted from Niels Bohr)

Non-Uniquely Solvable Problem

What is the solution to

$$\mathbf{x_1 + x_2 = 1}$$

Maybe

$x_1 = 0 \; ; \; x_2 = 1$?

$x_1 = 1 \; ; \; x_2 = 0$?

$x_1 = 1000 \; ; \; x_2 = -999$?

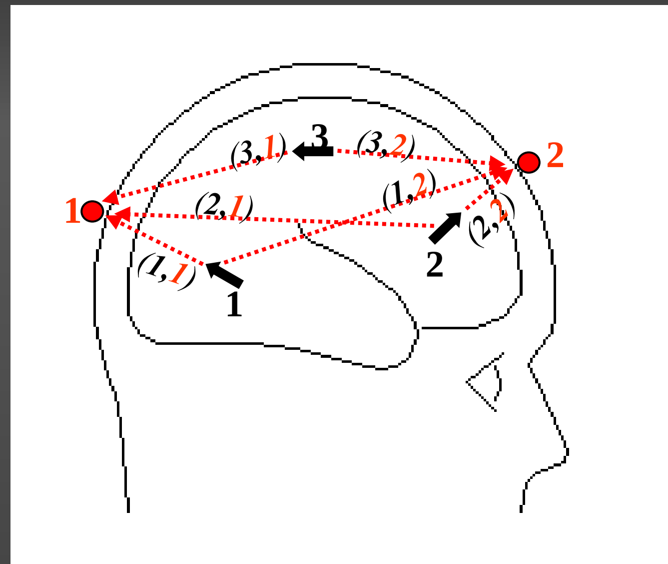
$x_1 = \pi \; ; \; x_2 = (1-\pi)$?

The minimum norm solution is:

$$\mathbf{x_1 = 0.5 \; ; \; x_2 = 0.5}$$

with $(0.5^2 + 0.5^2)=0.5$ the minimum norm among all possible solutions

Non-Uniquely Solvable Problem



"Minimum Norm Solution"

data "leadfield" dipoles

$$\begin{pmatrix} d_1 \\ d_2 \end{pmatrix} = \begin{pmatrix} 0.5 & 0 & 0.3 \\ 0 & 1 & -0.3 \end{pmatrix} \begin{pmatrix} j_1 \\ j_2 \\ j_3 \end{pmatrix}$$

?

inversion

dipoles inverse data

$$\begin{pmatrix} j_1 \\ j_2 \\ j_3 \end{pmatrix} = \begin{pmatrix} 1.5034 & 0.1241 \\ 0.2483 & 0.9379 \\ 0.8276 & -0.2069 \end{pmatrix} * \begin{pmatrix} d_1 \\ d_2 \end{pmatrix}$$

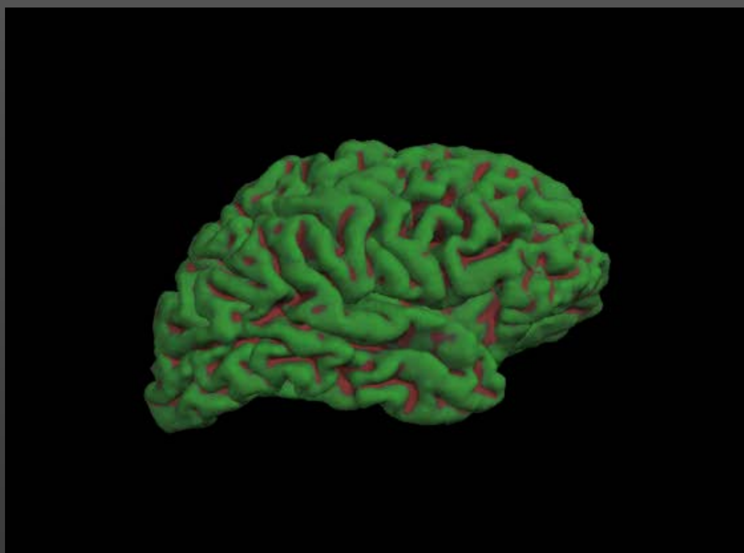
MNE produces solution with minimal power or "norm":

$$\left(j_1^2 + j_2^2 + j_3^2\right)$$

MRI Preprocessing: Source Space and Head Model

Source Space,

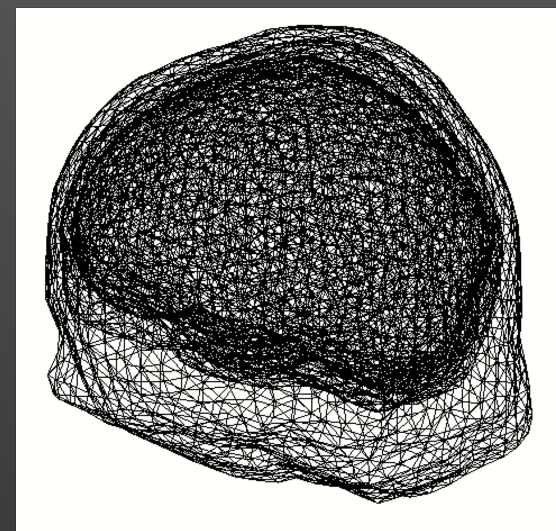
e.g. grey matter, 3D volume



http://www.cogsci.ucsd.edu/~sereno/movies.html

Volume Conductor/Head Model

e.g. sphere, 1- or 3-compartments from MRI

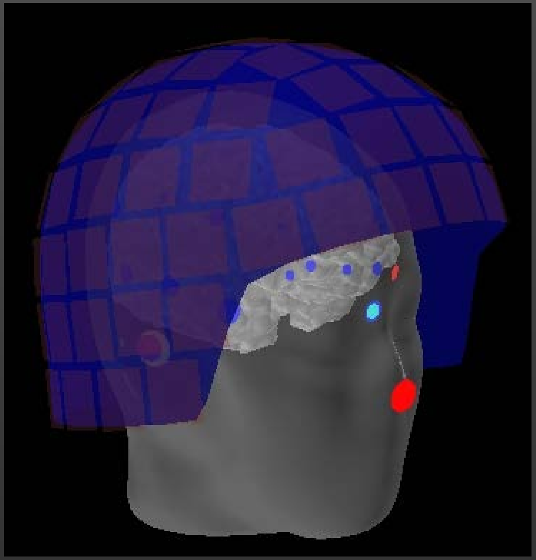


Sometimes “standard head models” are used, when no individual MRIs available.

SPM uses the same “canonical mesh” as source space for every subjects, but adjusts it individually.

Coregistration of EEG/MEG and MRI Spaces

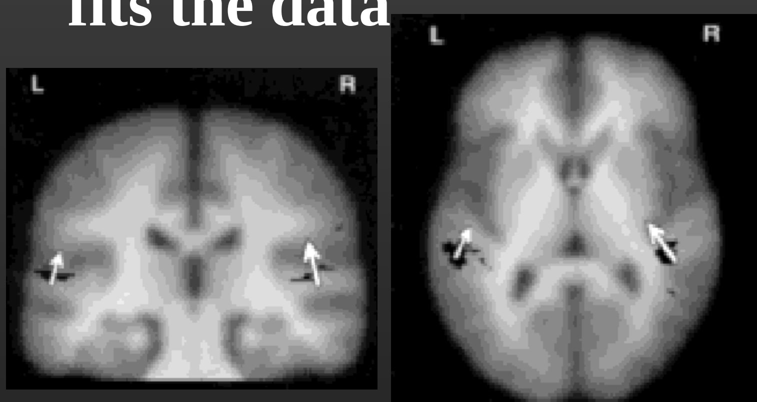
Coordinate
Transformation



Source Estimation Approaches

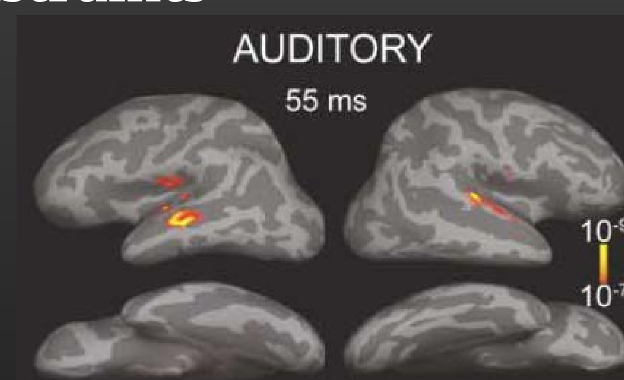
"Dipole Fitting"

1. Assume there are only a few distinct sources
2. Iteratively adjust the location, orientation and strength of a few dipoles…
3. …until the result best fits the data



"Distributed Sources"

1. Assume sources are everywhere (e.g. distributed across the whole cortex)
2. Find the distribution of source strengths that explains the data…
3. …AND fulfils other constraints



Minimum Norm Estimation: Minimal Modelling Assumptions

"No frills" solution (Minimum Norm)

$$(\hat{\mathbf{s}}-\hat{\mathbf{s}}_0)^T \mathbf{C}_s (\hat{\mathbf{s}}-\hat{\mathbf{s}}_0) = \min$$
$$(\mathbf{L}\hat{\mathbf{s}}-\mathbf{d})^T \mathbf{C}_d (\mathbf{L}\hat{\mathbf{s}}-\mathbf{d}) = \varepsilon > 0$$

$$\Rightarrow \quad \hat{\mathbf{s}} = \hat{\mathbf{s}}_0 + \mathbf{C}_s^{-1}\mathbf{L}^T\left(\mathbf{L}\mathbf{C}_s^{-1}\mathbf{L}^T + \lambda\,\mathbf{C}_d^{-1}\right)^{-1}(\mathbf{d}-\mathbf{L}\hat{\mathbf{s}}_0) \quad \Rightarrow \quad \hat{\mathbf{s}} = \mathbf{L}^T\left(\mathbf{L}\mathbf{L}^T + \lambda\,\mathbf{I}\right)^{-1}\mathbf{d}$$

"Most likely" solution (Maximum Likelihood)

$$\mathbf{P}\ (\mathbf{s}) \sim \exp\{-(\hat{\mathbf{s}}-[\mathbf{s}])^T \mathbf{C}_s (\hat{\mathbf{s}}-[\mathbf{s}])\}$$
$$\mathbf{P}\ (\mathbf{d},\hat{\mathbf{s}}) \sim \exp\{-(\mathbf{d}-\mathbf{L}\hat{\mathbf{s}})^T \mathbf{C}_d^{'} (\mathbf{d}-\mathbf{L}\hat{\mathbf{s}})\}$$

$$\Rightarrow \quad \hat{\mathbf{s}} = [\mathbf{s}] + \mathbf{C}_s^{-1}\mathbf{L}^T(\mathbf{L}\mathbf{C}_s^{-1}\mathbf{L}^T + \lambda\mathbf{C}_d^{-1})^{-}(\mathbf{d}-\mathbf{L}[\mathbf{s}]) \quad \Rightarrow \quad \hat{\mathbf{s}} = \mathbf{L}^T\left(\mathbf{L}\mathbf{L}^T + \lambda\,\mathbf{I}\right)^{-1}\mathbf{d}$$

"Best focussing" solution (Beamformer)

$$Min\,(\mathbf{W}(\mathbf{r}_i - \mathbf{t}_i))^2$$
$$Min([\mathbf{G}_{i.}\mathbf{n}]^2) \Rightarrow Min(\mathbf{G}_{i.}\mathbf{C}_n\mathbf{G}_{i.}^T)$$

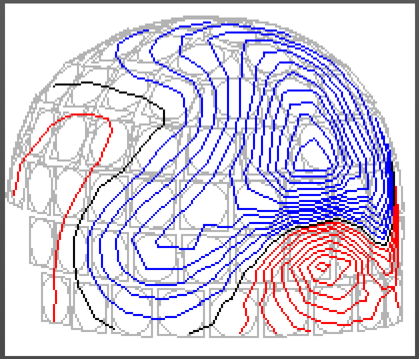
$$\Rightarrow \quad \mathbf{G}_{i.} = (\mathbf{S} + \lambda\mathbf{C}_n)^{-1}\mathbf{u} \qquad \mathbf{S} = \mathbf{L}\mathbf{L}^T \quad \mathbf{u} = \mathbf{L}_{.i} \qquad \mathbf{G}_{i.} = (\mathbf{L}\mathbf{L}^T + \lambda\mathbf{I})^{-1}\mathbf{L}_{.i} \quad \Rightarrow \quad \hat{\mathbf{s}} = \mathbf{L}^T\left(\mathbf{L}\mathbf{L}^T + \lambda\,\mathbf{I}\right)^{-1}\mathbf{d}$$

"Minimum Least-Squares Solution"

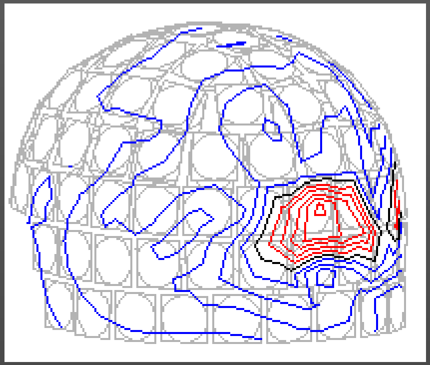
All approaches converge to the same solution if no a priori information is available

There are many possible assumptions, and therefore many different methods – but unfortunately no gold standard to properly compare them

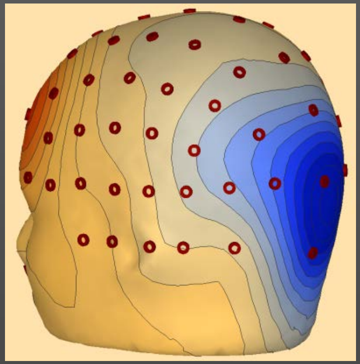
Visually Evoked Activity ~100 ms



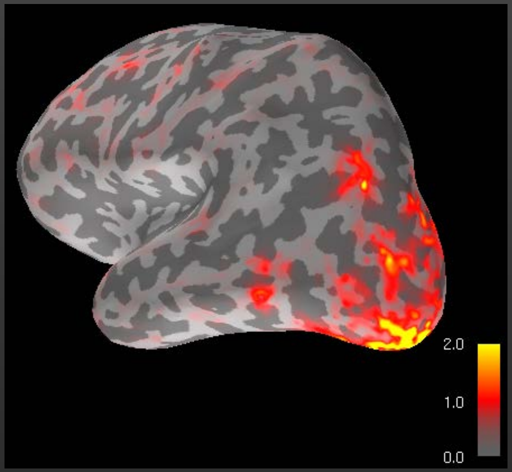
Magnetometers



Gradiometers

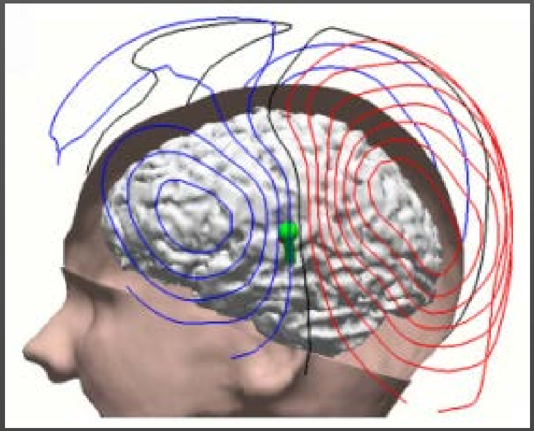


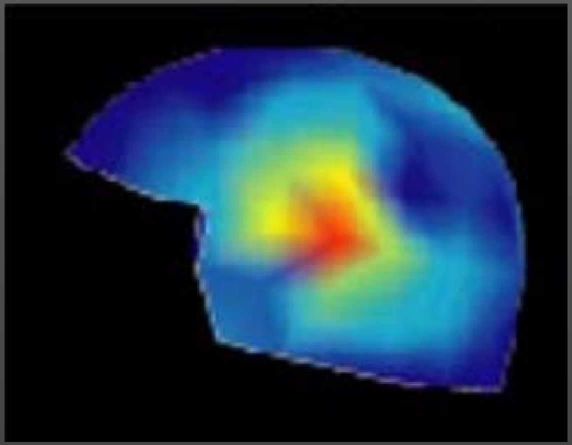
EEG

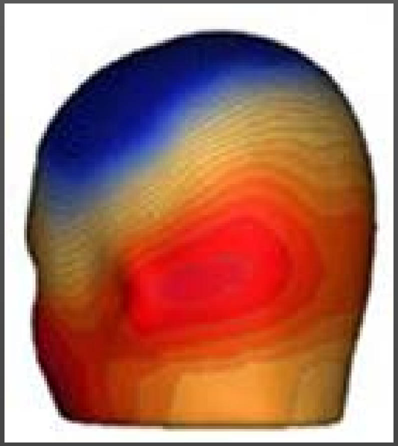


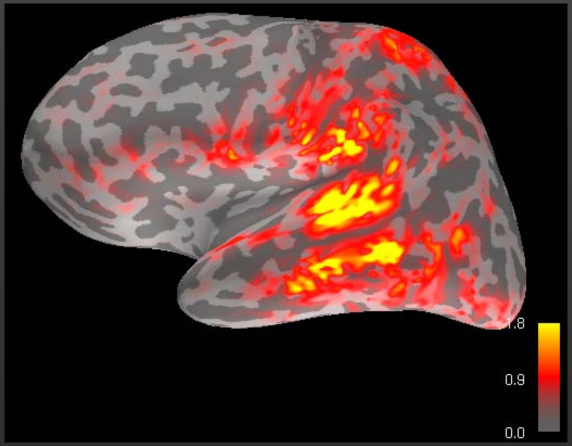
Minimum Norm Estimate

Auditorily Evoked Activity



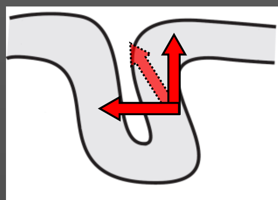


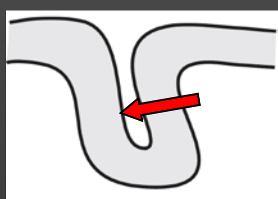


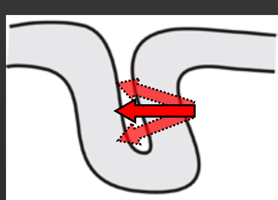


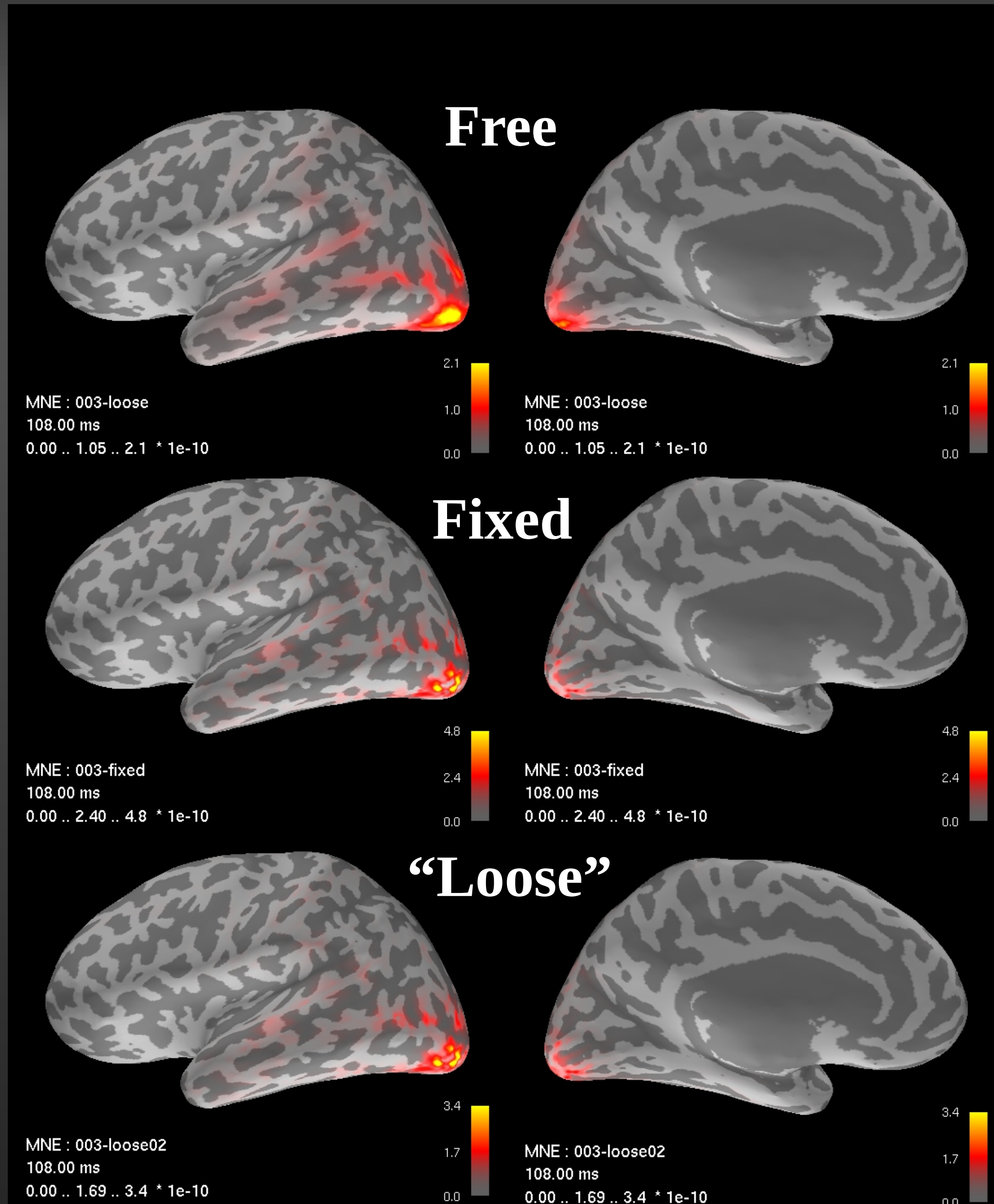
Minimum Norm Estimate

Source Orientation Constraints



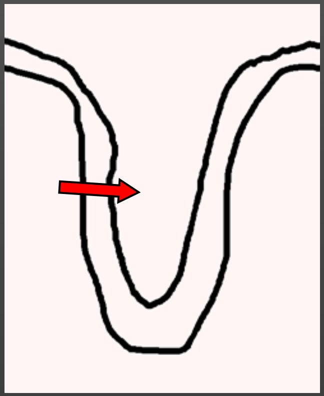




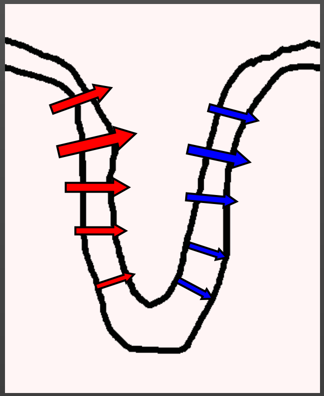


Direction of Current Flow

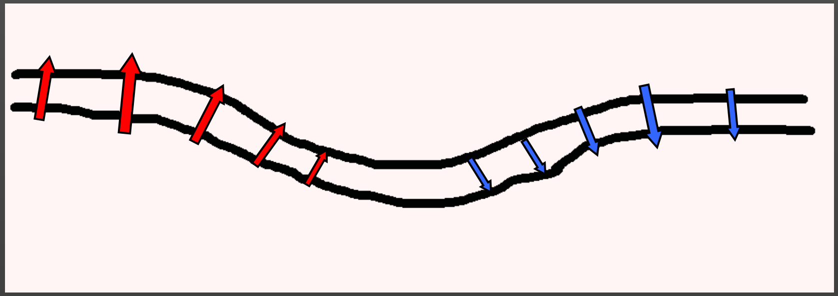
Dipole Source



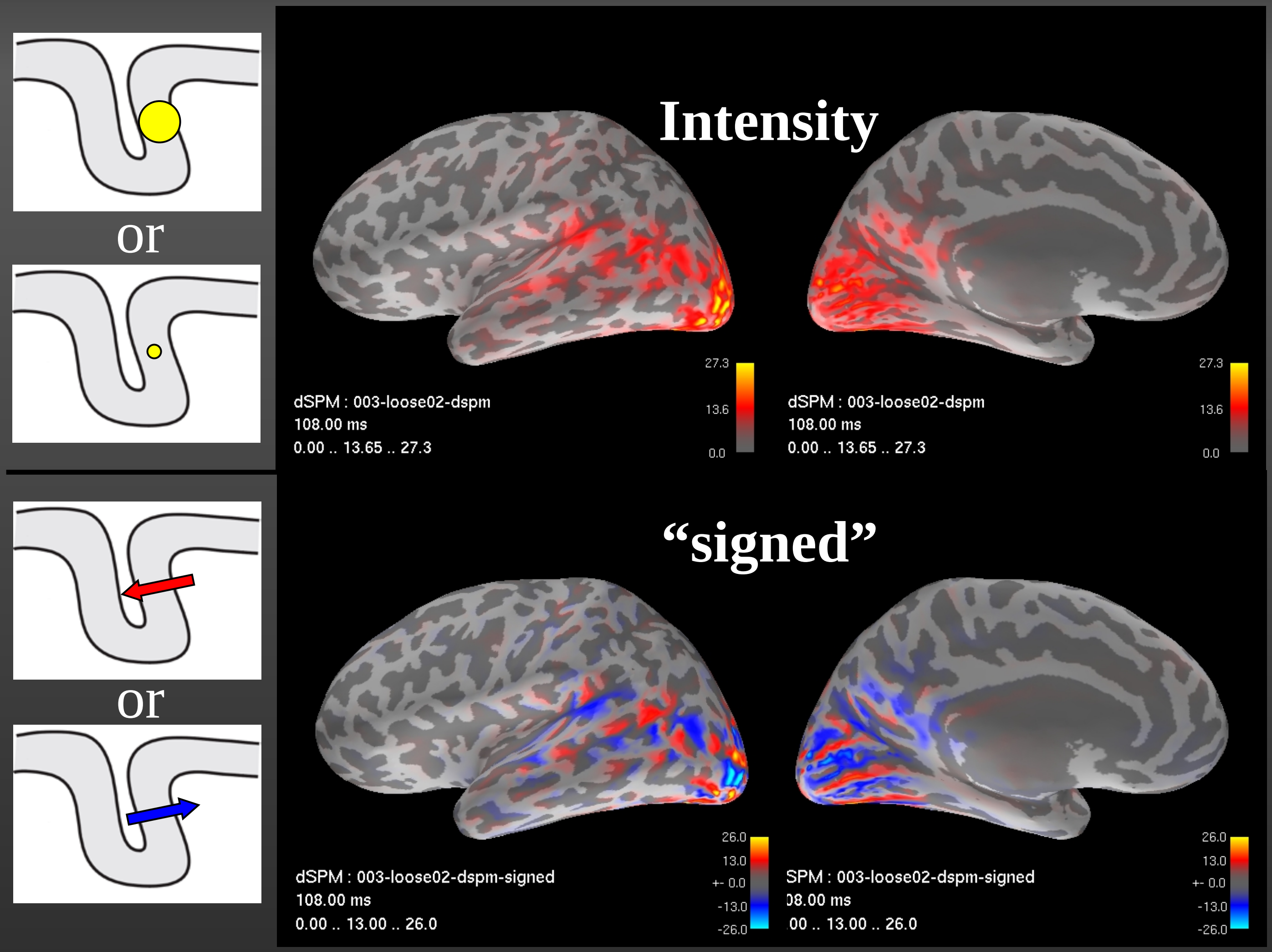
Distributed Source



Distributed Source, Inflated Surface

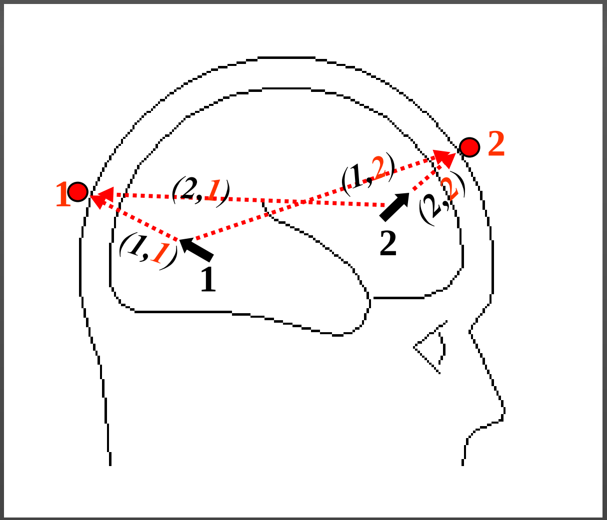


Direction of Current Flow

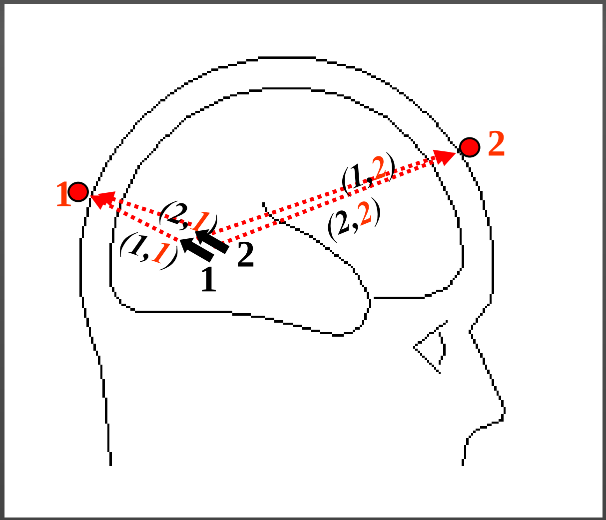


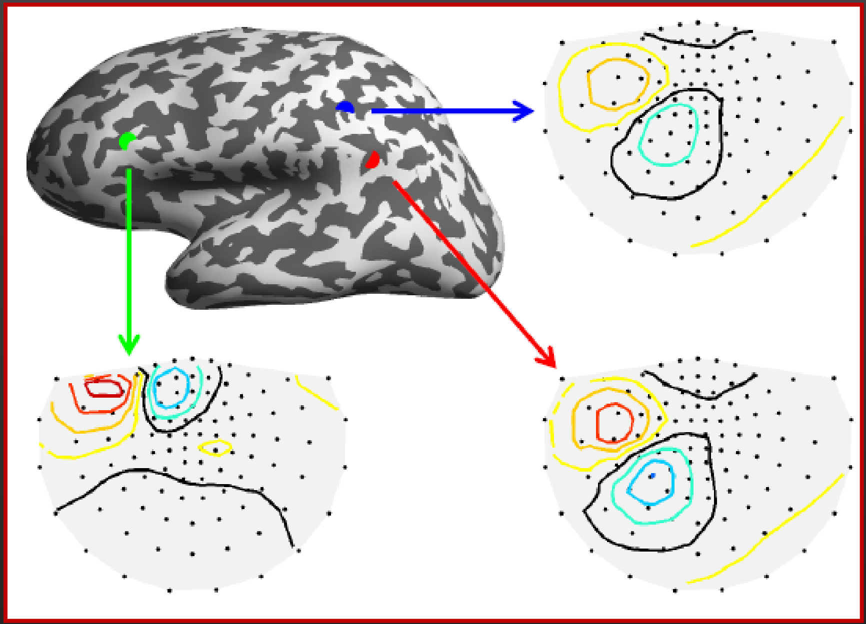
(In)Stability – Sensitivity to Noise

Stable



Instable





Similar topographies are difficult to distinguish, especially in the presence of noise.

Noise covariance

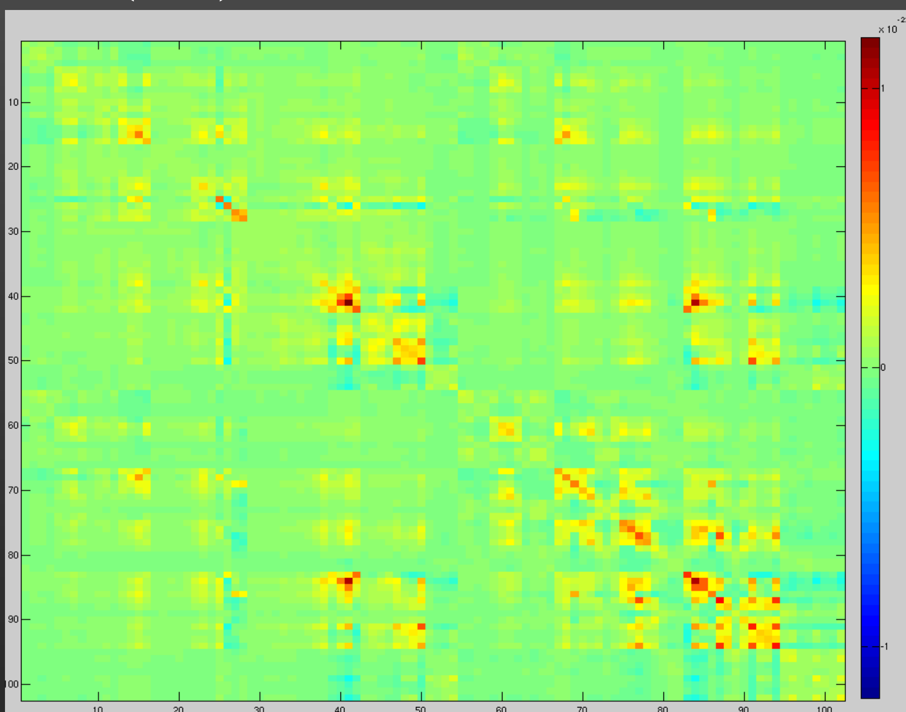
Some channels are noisier than others

⇒They should get different weights in your analysis

Sensors are not independent

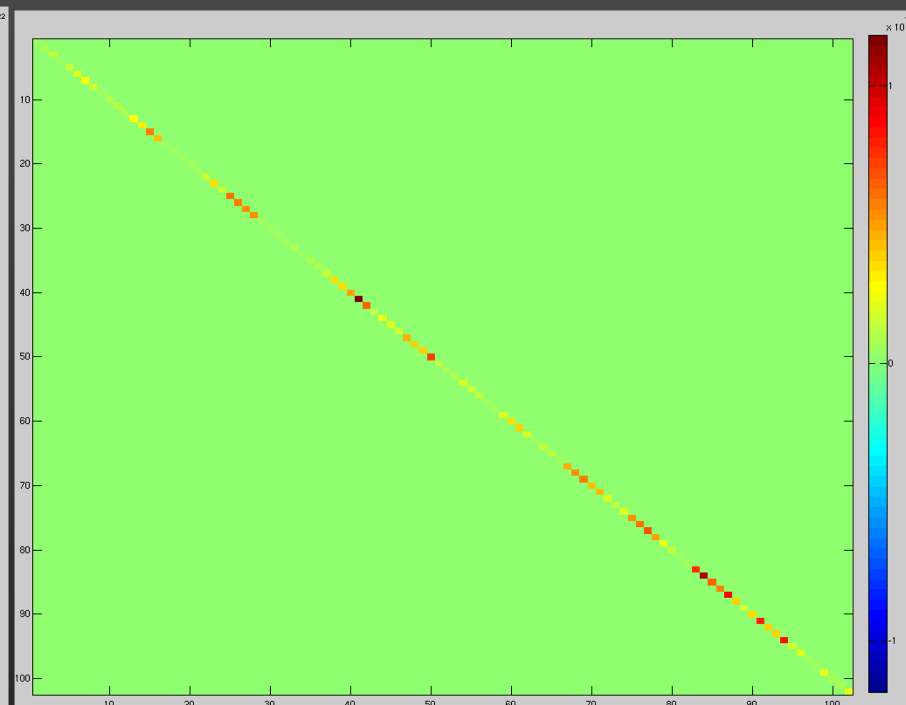
=> Sensors that carry the same information should be downweighted relative to more independent sensors

(Full) Noise Covariance Matrix



(Diagonal) Noise Covariance Matrix

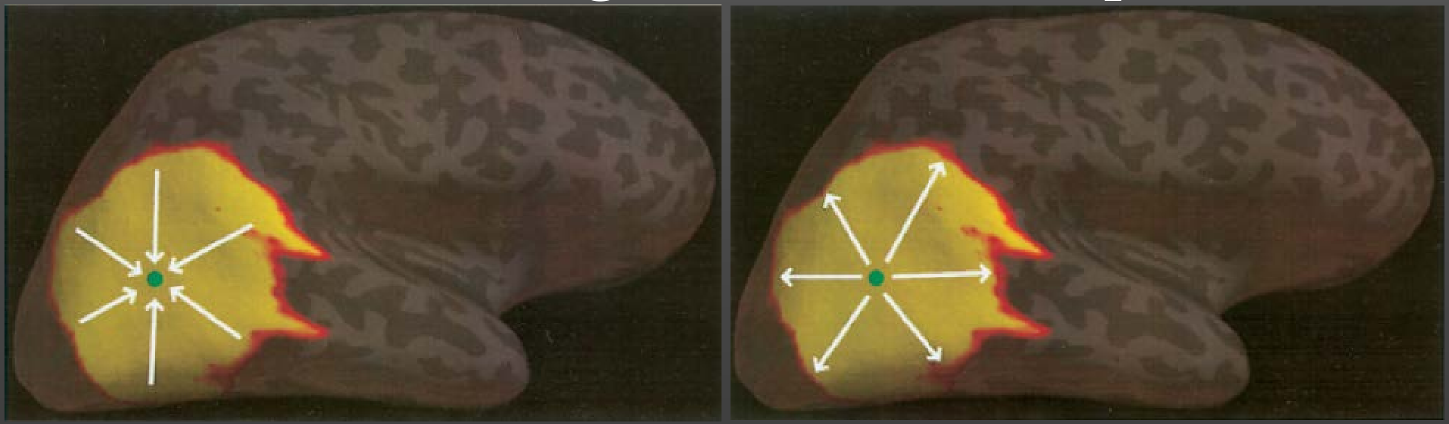
(contains only variance for sensors)



Spatial Resolution:

Point-Spread and "Cross-Talk"/"Leakage"

Cross-Talk/Leakage | **Point-Spread**



Liu et al., HBM 2002

"How other sources may affect the spatial filter for this source"

"How this source affects other spatial filters"

Spatial Resolution of Source Estimation

Spatial resolution depends on:

modeling assumptions

number of sensors (EEG/MEG or both)

source location

source orientation

signal-to-noise ratio

head modeling

=> difficult to make general statement

Spatial Resolution – A Naïve Estimate

With ***n*** sensors:
-> ***n*** independent measurements
-> ***n*** independent parameters estimable
-> at best separate activity from ***n*** brain regions
Sensors are not independent -> ~ 50 degrees of freedom

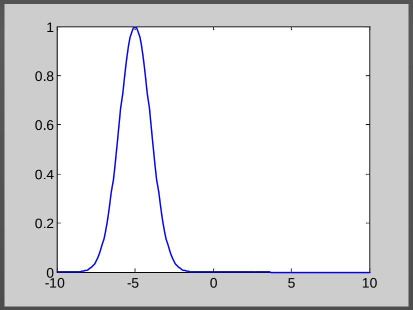
Volume of source space:
Sphere 8cm minus sphere 4 cm: volume ~5600 cm^3

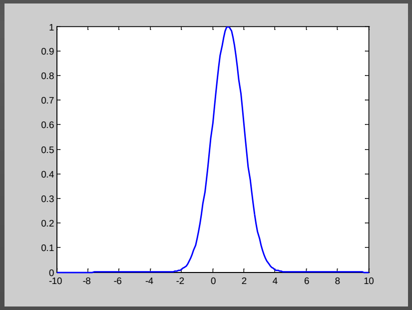
"Resel": 113 cm^3 -> **<u>4.8</u>**^3 cm^3

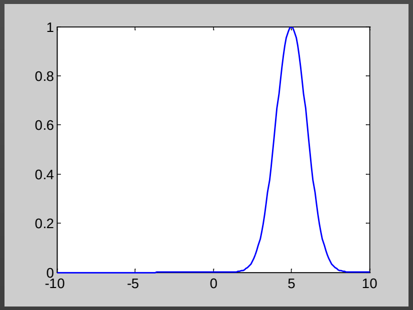
The spatial resolution of the **measurement** is inherently limited!

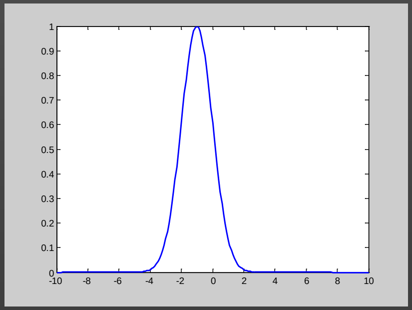
Linear Methods are Convenient Because Of…

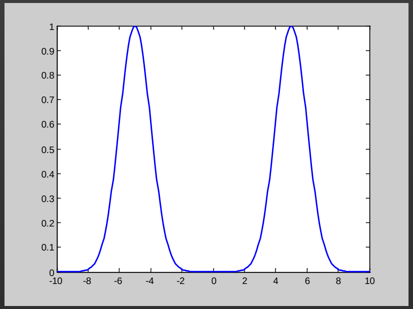
…the Superposition Principle

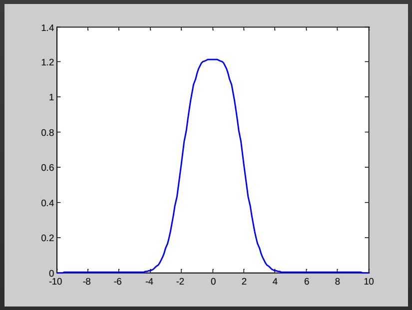










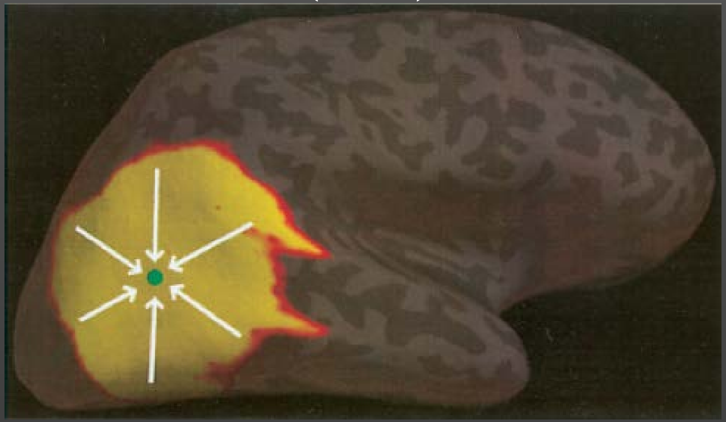


If you know the behaviour for point sources, you can predict the behaviour for complex sources

Spatial Resolution:

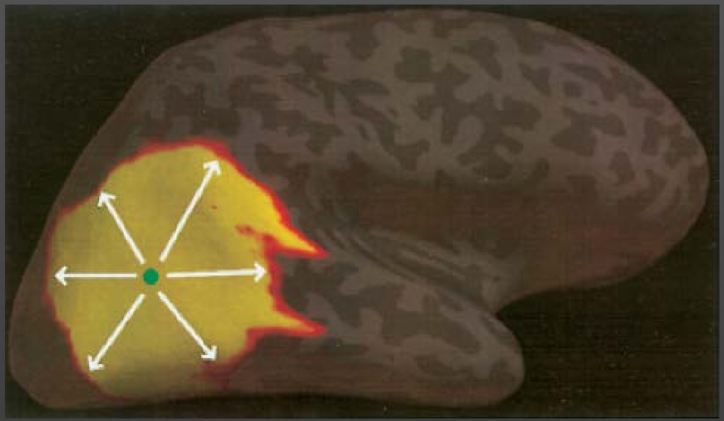
Point-Spread and Cross-Talk/Leakage

Cross-Talk Function (CTF)



How other sources may affect the estimate for this source

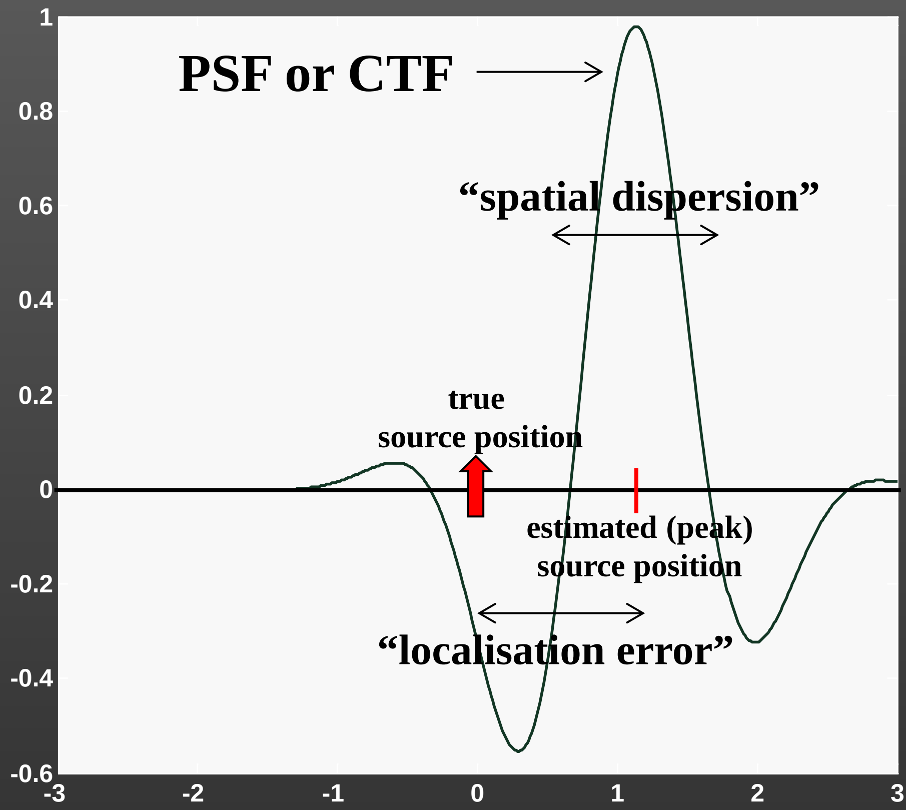
Point-Spread Function (PSF)



Liu et al., HBM 2002

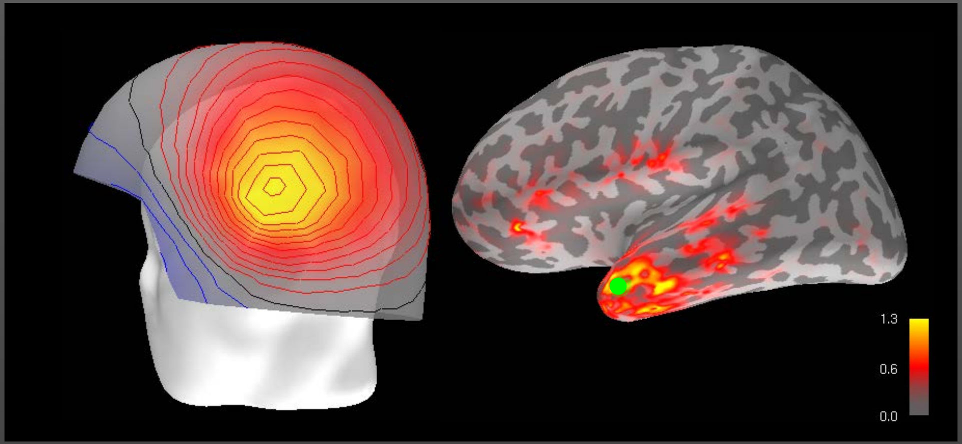
How this source affects estimates for other sources

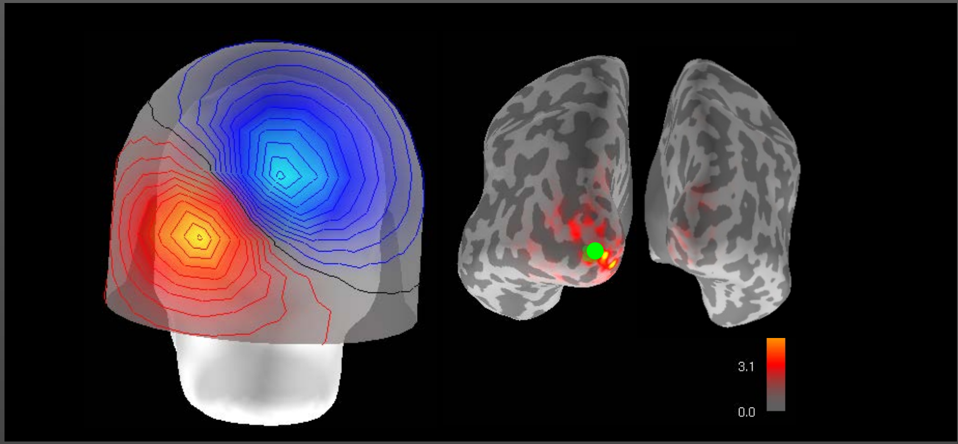
Quantifying "Resolution"



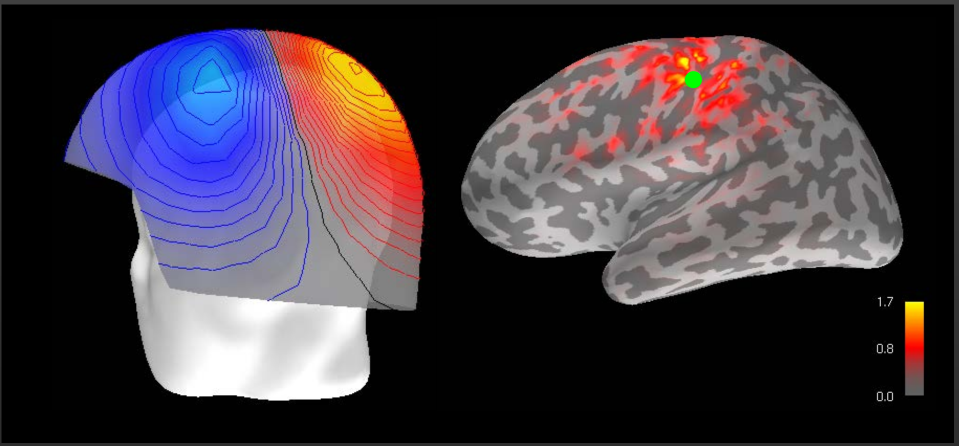
PSFs and CTFs for Some ROIs

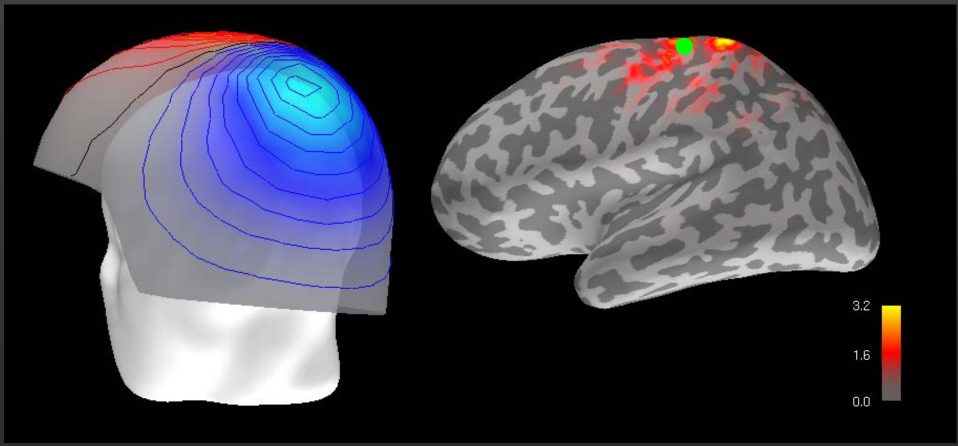
For MNE, PSFs and CTFs turn out to be the same



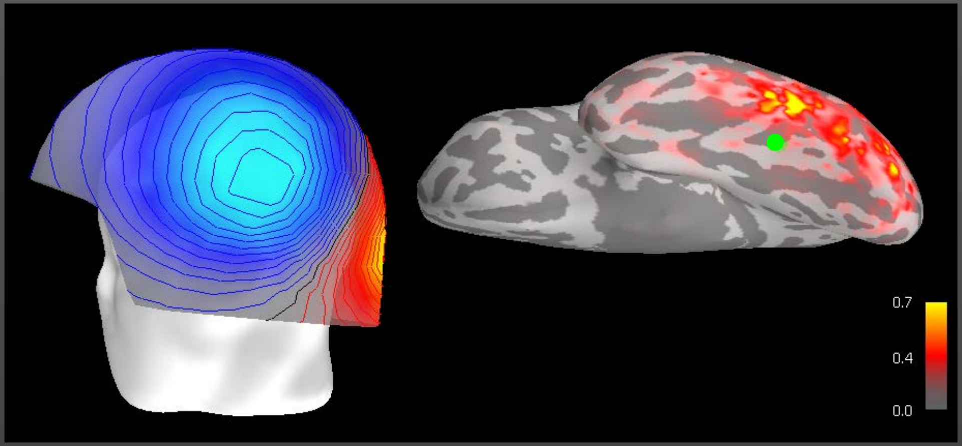


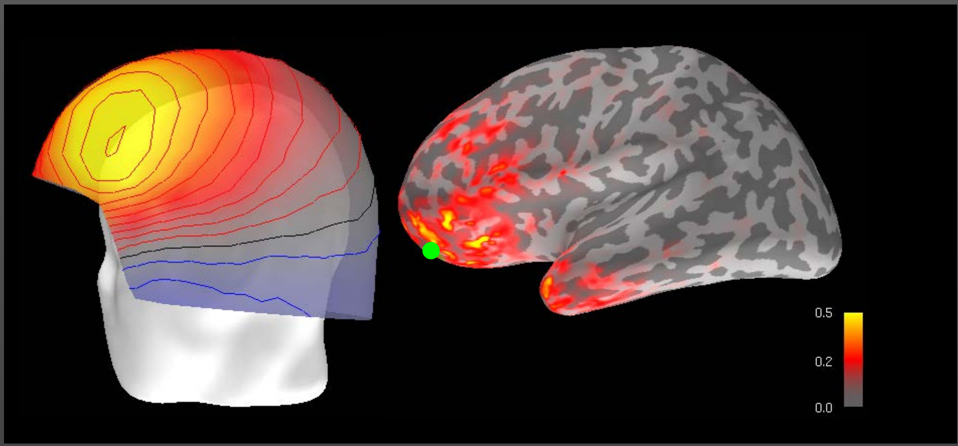
Good



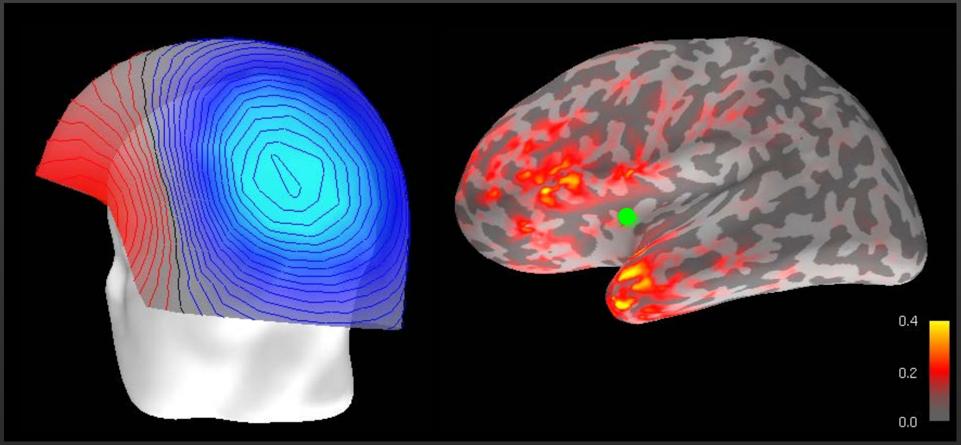


Localisation for Some ROIs





Less good



Comparing Methods

Different methods make different compromises.

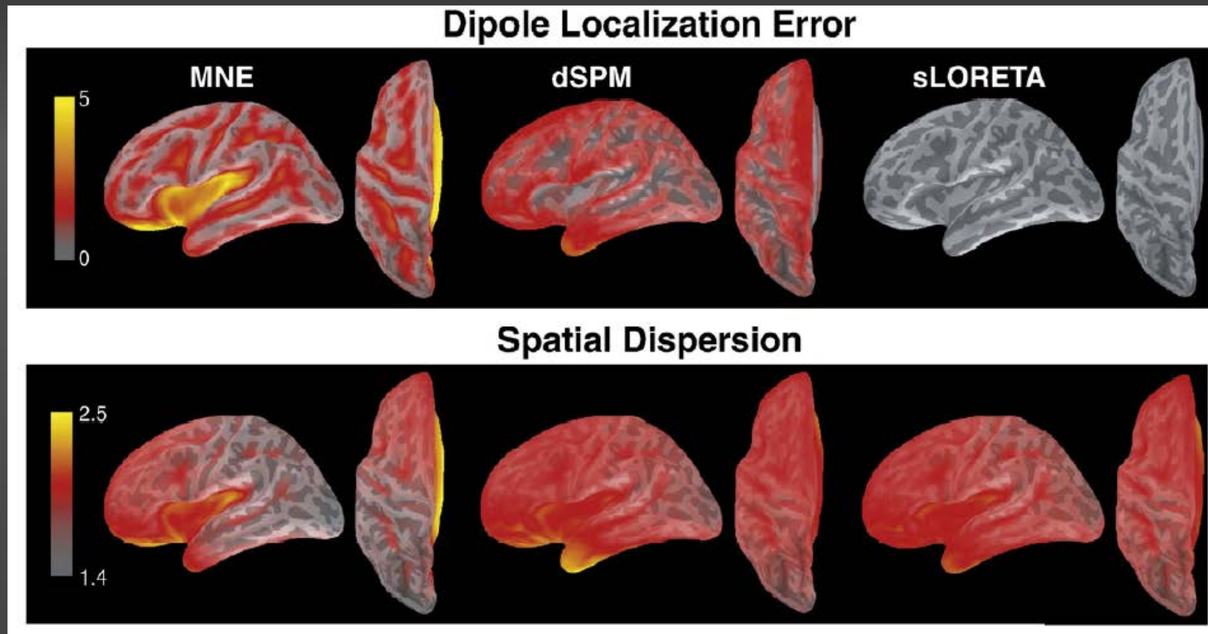
There is no “best” method – best for what?

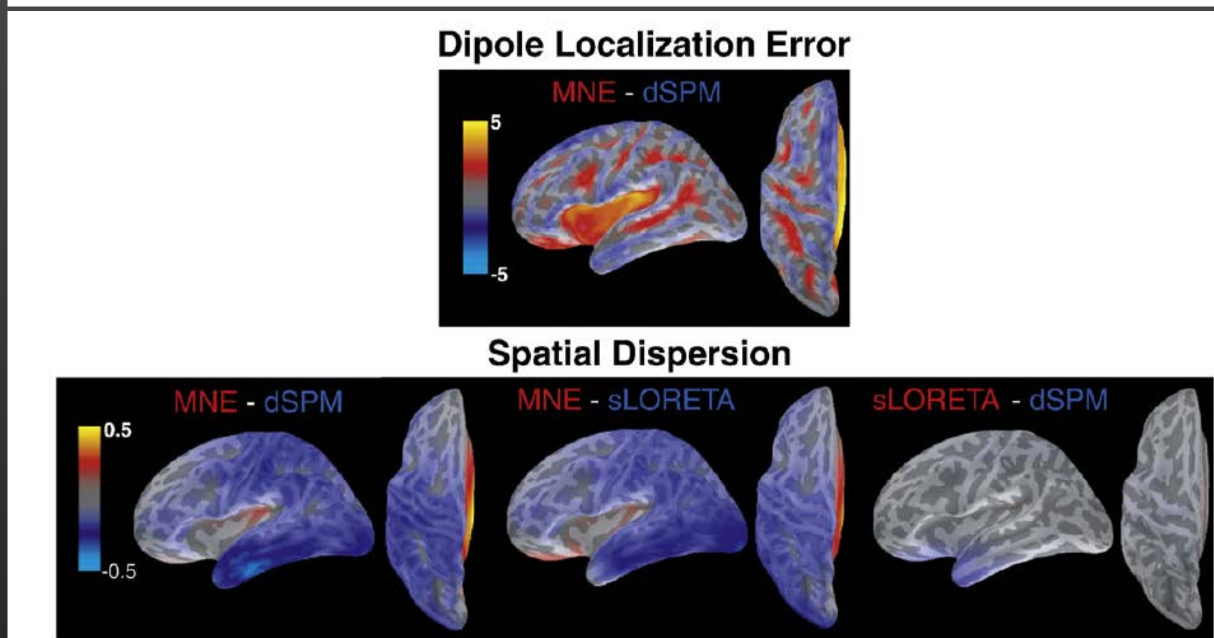
One should compare methods for the same purpose and under the same assumptions.

Difficult to generalize results from one example or data set

=> Important to understand the principles

Method Comparison

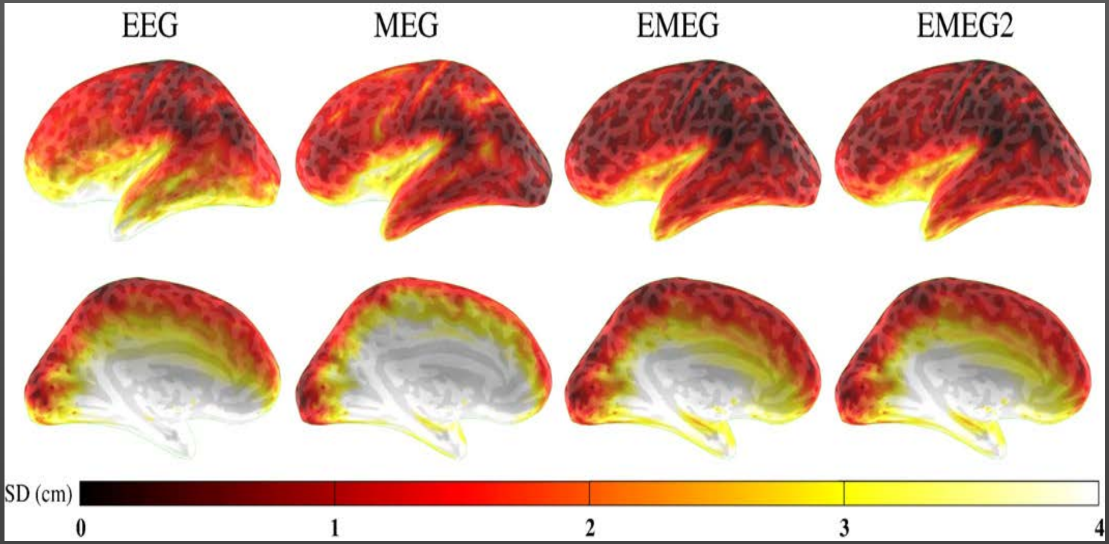




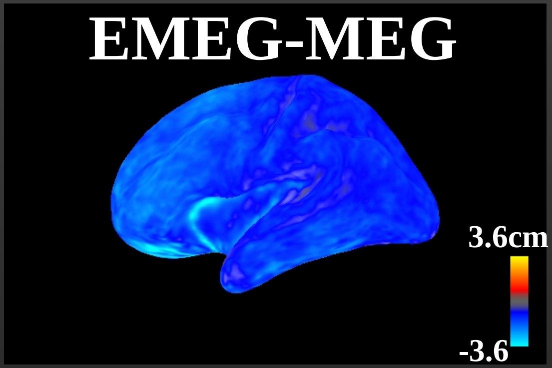
Hauk/Wakeman/Henson, Neuroimage 2011

Combining EEG and MEG Increases Resolution

Spatial Extent



Molins et al., Neuroimage 2008



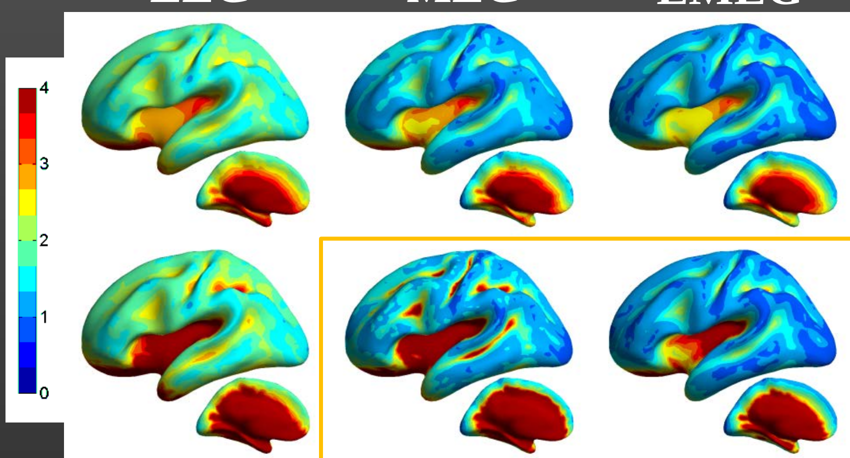
Stenroos&Hauk, in prep

Combining EEG and MEG Improves Resolution

…especially in the presence of (correlated) noise

Spatial Deviation (cm)

EEG MEG EMEG

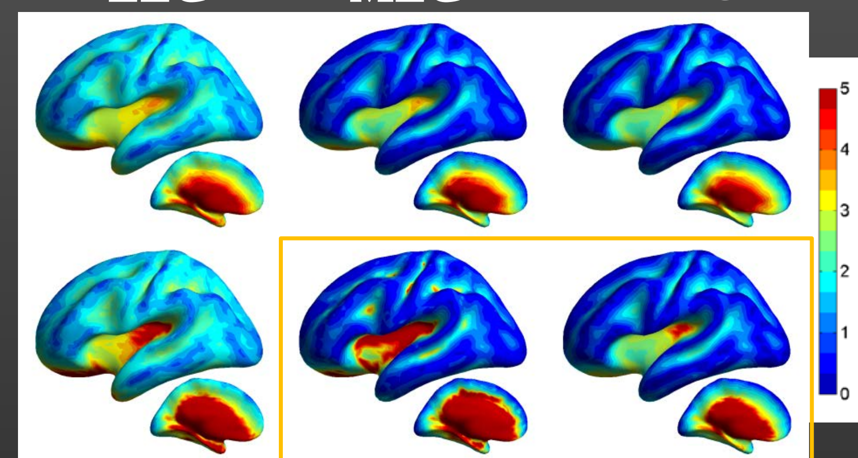


No noise

With noise

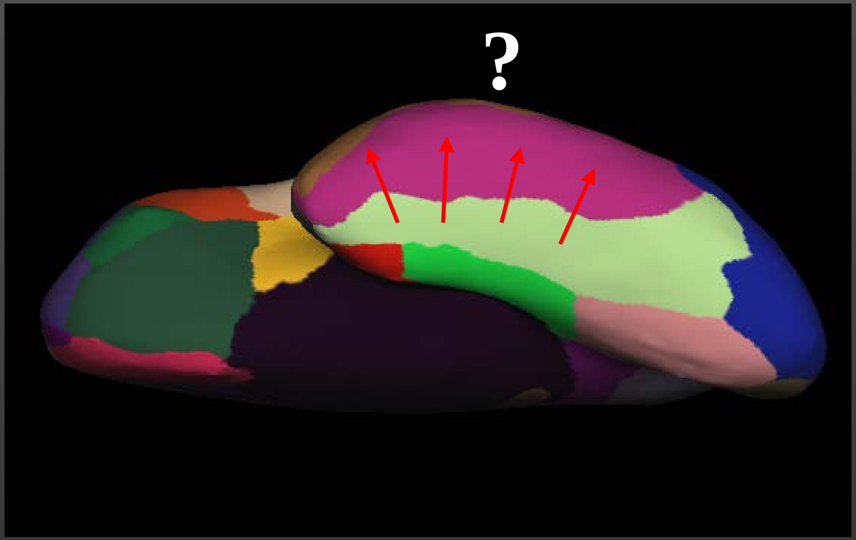
Localisation Error (cm)

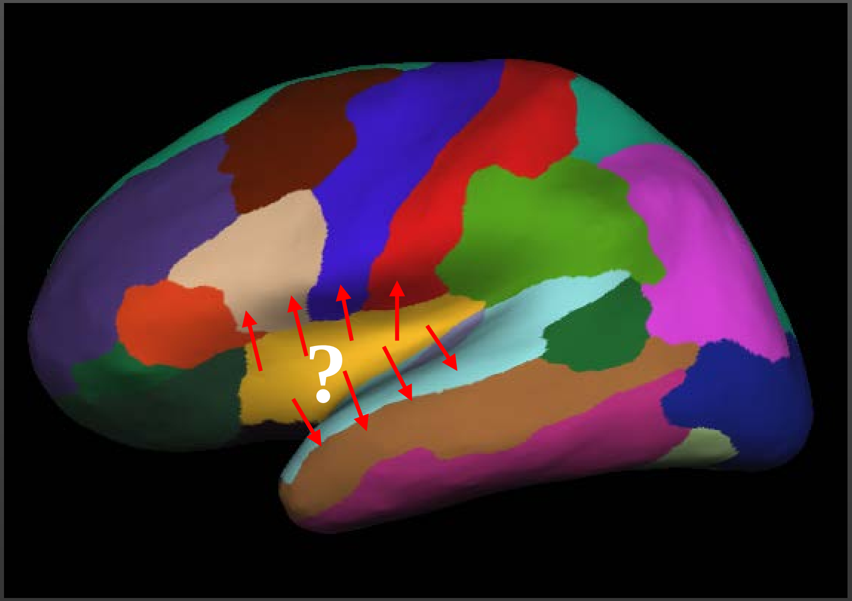
EEG MEG EMEG



Stenroos&Hauk, in prep

Localisation Bias Has Consequences for ROI analysis





Desikan-Killiany Atlas parcellation