M/EEG source reconstruction: problems & solutions

SPM-M/EEG course

Lyon, April 2012

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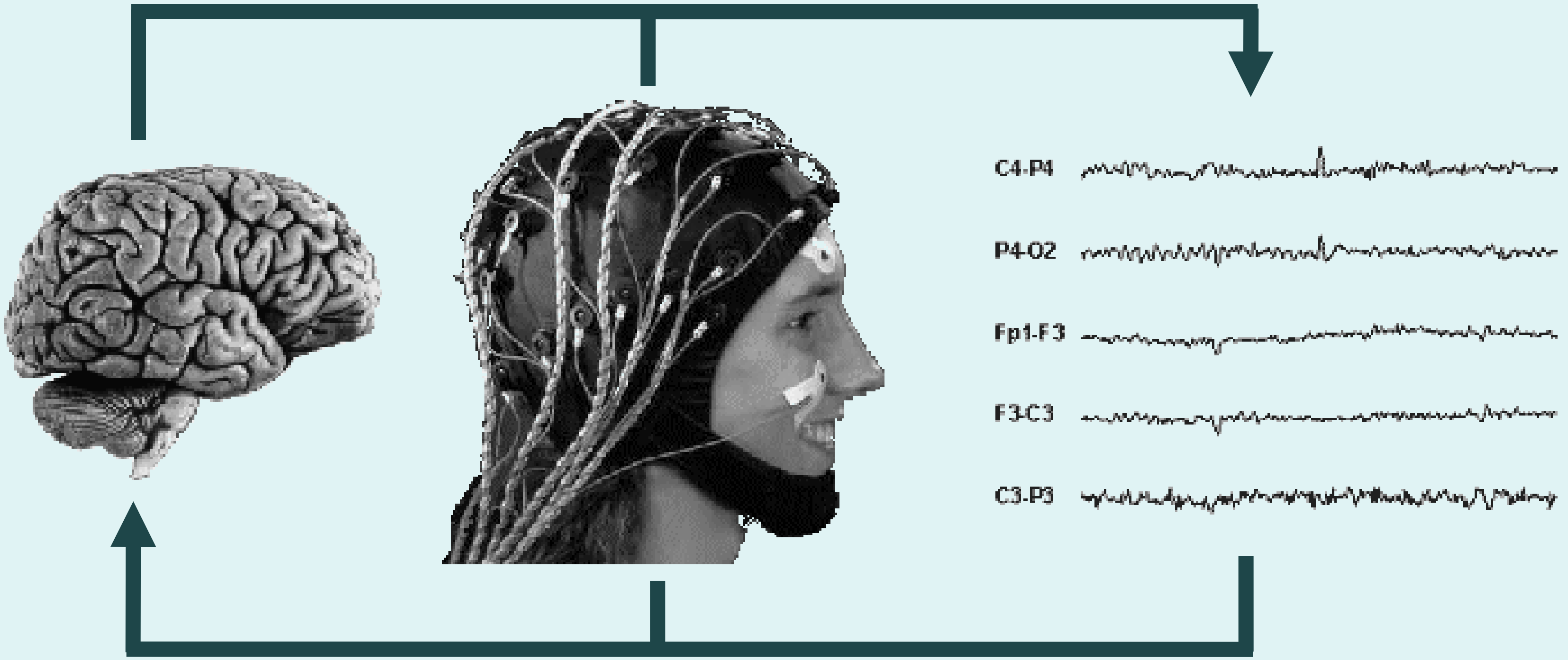
Source localisation in M/EEG

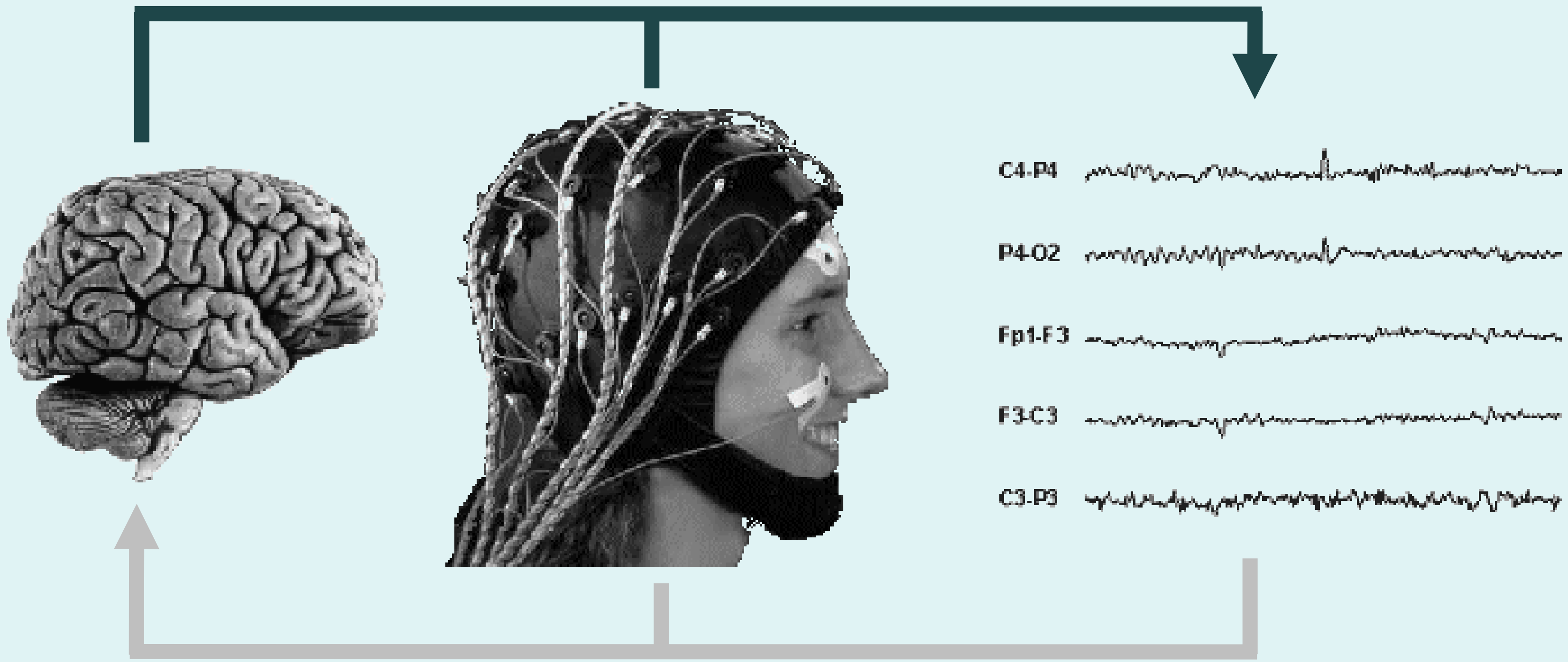
Forward Problem



Inverse Problem

Source localisation in M/EEG

Forward Problem



Inverse Problem

Forward problem

Head anatomy

- Head model : conductivity layout
- Source model : current dipoles

- Solution by Maxwell's equations

Maxwell's equations (1873)

$$\vec{\nabla}\vec{E} = \frac{\rho}{\varepsilon}$$

$$\vec{\nabla}\vec{B} = 0$$

$$\vec{\nabla}\times\vec{E} = -\frac{\partial\vec{B}}{\partial t}$$

$$\vec{\nabla}\times\vec{B} = \mu\vec{j} + \mu\varepsilon\frac{\partial\vec{E}}{\partial t}$$

Ohm's law :

$$\vec{j} = \sigma\vec{E}$$

Continuity equation :

$$\vec{\nabla}\vec{j} = \frac{\partial\rho}{\partial t}$$

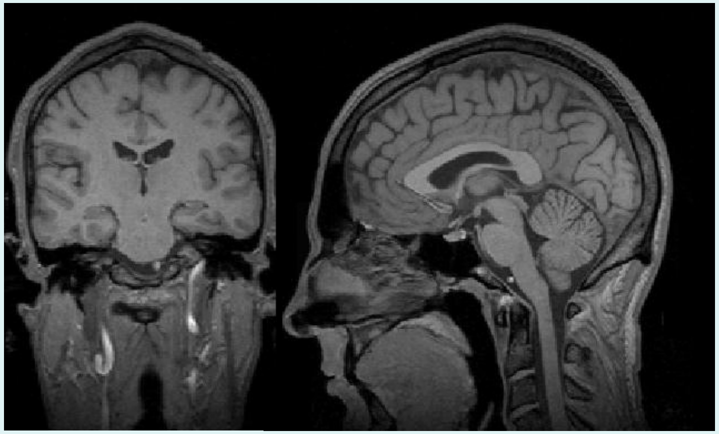
Solving the forward problem

From Maxwell's equations find:

$$M = f(\vec{j}, \vec{r})$$

where M are the measurements and $f(.)$ depends on:

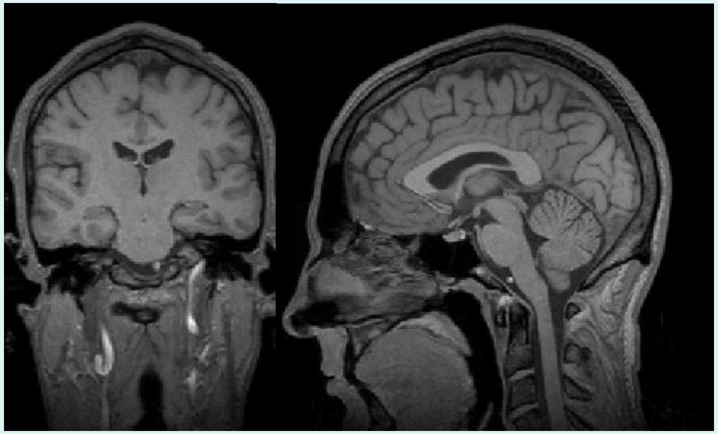
- signal recorded, EEG or MEG
- head model, i.e. conductivity layout adopted
- source location
- source orientation & amplitude



Solving the forward problem

From Maxwell's equations find:

$$M = f(\vec{j}, \vec{r})$$

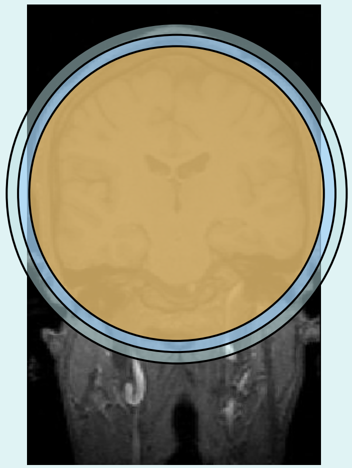
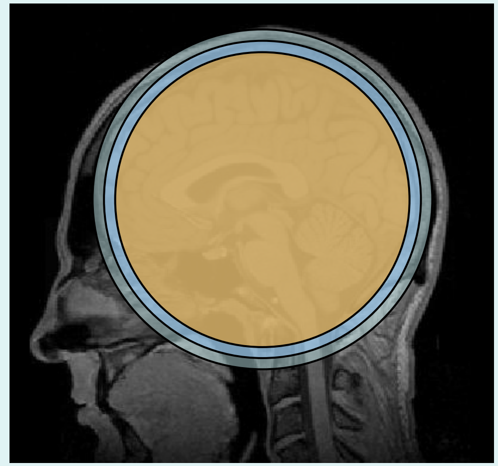


with $f(.)$ as

- an analytical solution
  - highly symmetrical geometry, e.g. spheres, concentric spheres, etc.
  - homogeneous isotropic conductivity
- a numerical solution
  - more general (but still limited!) head model

Analytical solution

Example: 3 concentric spheres

Pro's:

- Simple model
- Exact mathematical solution
- Fast calculation

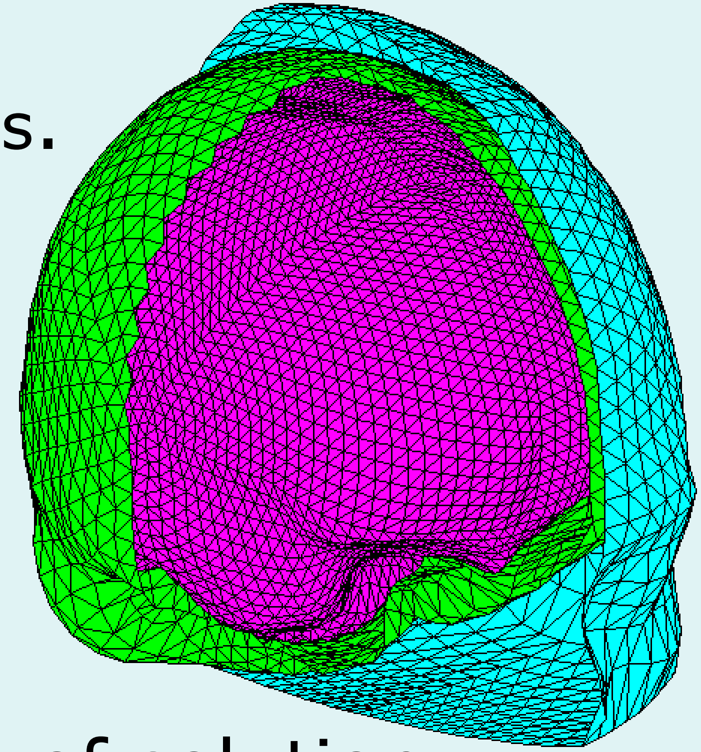
Con's:

- Human head is not spherical
- Conductivity is not homogeneous and isotropic.

Numerical solution

Usually “Boundary Element Method” (BEM) :

- Concentric sub-volumes of homogeneous and isotropic conductivity,
- Estimate values on the interfaces.



Pro’s:

•More correct head shape modelling (not perfect though!)

Con’s:

•Mathematical approximations of solution ➔ numerical errors

•Slow and intensive calculation

Features of forward solution

Find forward solution (any):

$$M = f(\vec{j}, \vec{r})$$

with *f(.)*

- linear in $\vec{j} = \begin{bmatrix} j_x & j_y & j_z \end{bmatrix}^T$
- non-linear in $\vec{r} = \begin{bmatrix} r_x & r_y & r_z \end{bmatrix}^T$

If N sources with *known* & *fixed* location, then

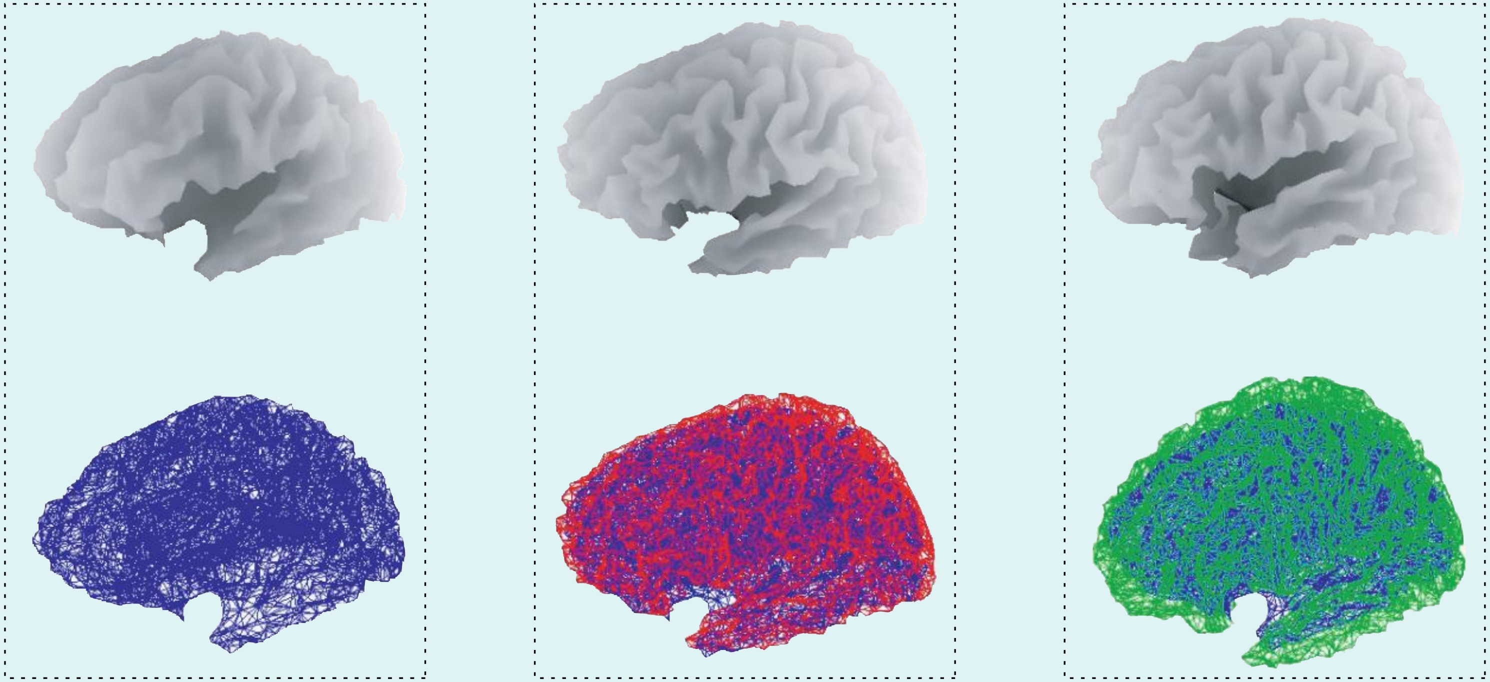
$$M = f\left(\begin{bmatrix} \vec{r}_1 & \vec{r}_2 & \cdots & \vec{r}_N \end{bmatrix}\right) \times J = L \times J$$

SPM solutions

Source space & head model

- Template Cortical Surface (TCS), in MNI space.
- Canonical Cortical Surface (CCS) = TCS warped to subject’s anatomy
- Subject’s Cortical Surface (SCS) = extracted from subject’s own structural image (BrainVisa/FreeSurfer)

SPM solutions



(a) SCS (b) CCS (c) TCS

FIGURE 4: Surface rendering (upper row) and meshes (lower row) encoding the three cortical models: SCS (a), CCS (b), and TCS (c). CCS (red) and TCS (green) meshes are superimposed on the SCS mesh (blue).

Jérémie Mattout, Richard N. Henson, and Karl J. Friston, 2007, Canonical Source Reconstruction for MEG

SPM solutions

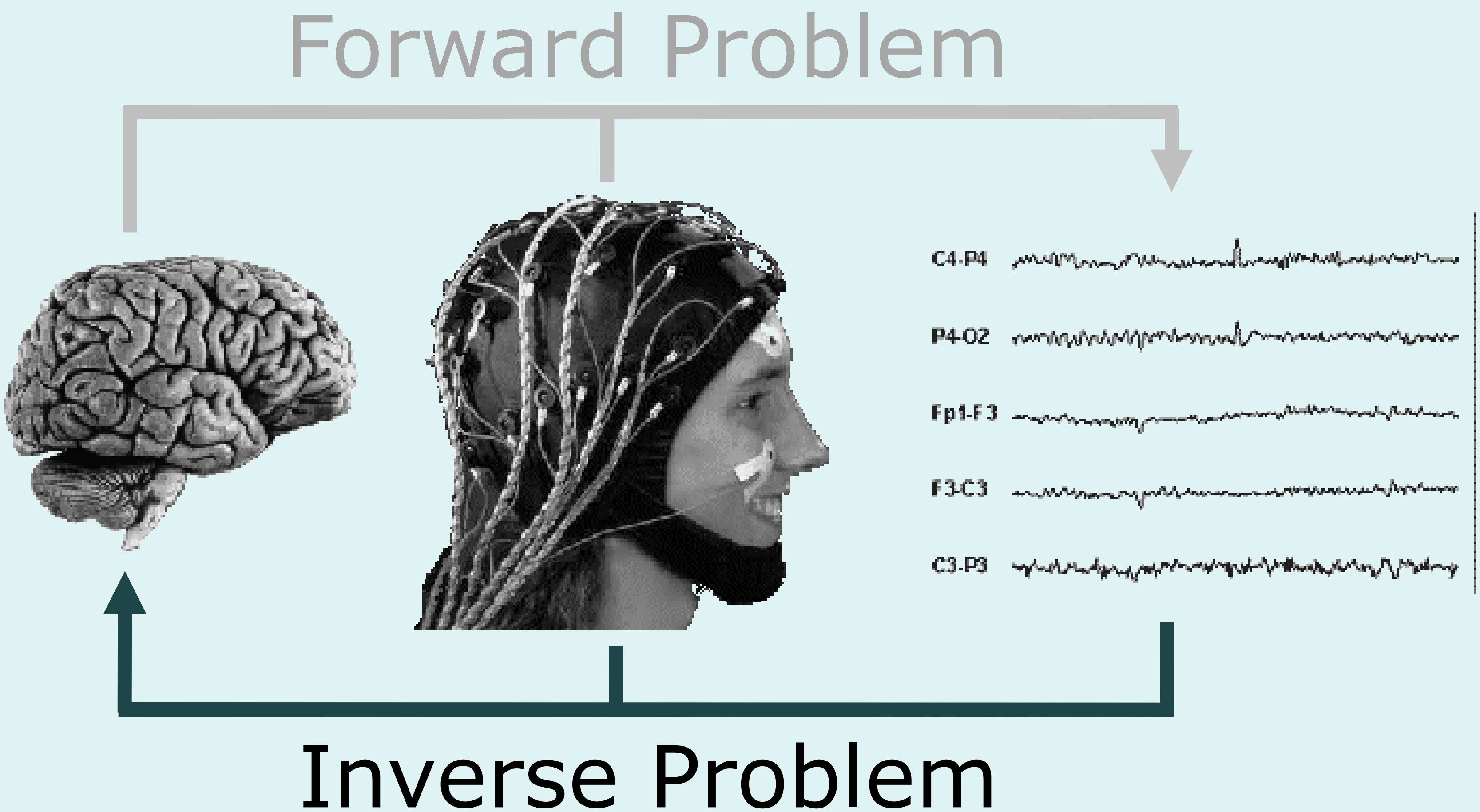
Source space & head model

- Template Cortical Surface (TCS), in MNI space.
- Canonical Cortical Surface (CCS) = TCS warped to subject's anatomy
- Subject's Cortical Surface (SCS) = extracted from subject's own structural image (BrainVisa/FreeSurfer)

Forward solutions:

- Single sphere
- Overlapping spheres
- Concentric spheres
- BEM
- ... (new things get added to SPM & FieldTrip)

Source localisation in M/EEG



Useful priors for cinema audiences

- Things further from the camera appear smaller
- People are about the same size
- Planes are much bigger than people

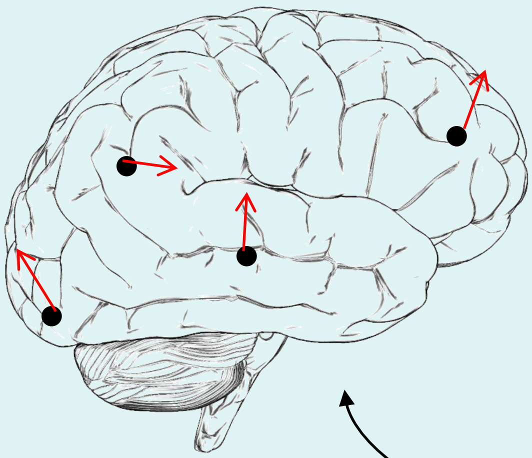
M/EEG inverse problem

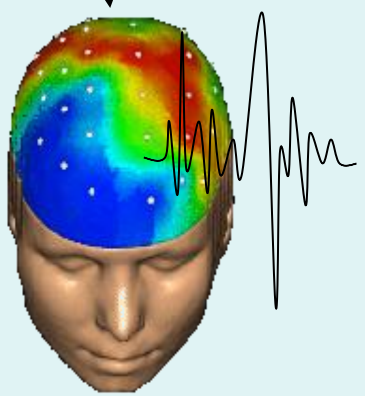
Probabilistic framework

forward computation

Likelihood & Prior

$$p(Y|q,M) \quad p(q|M)$$





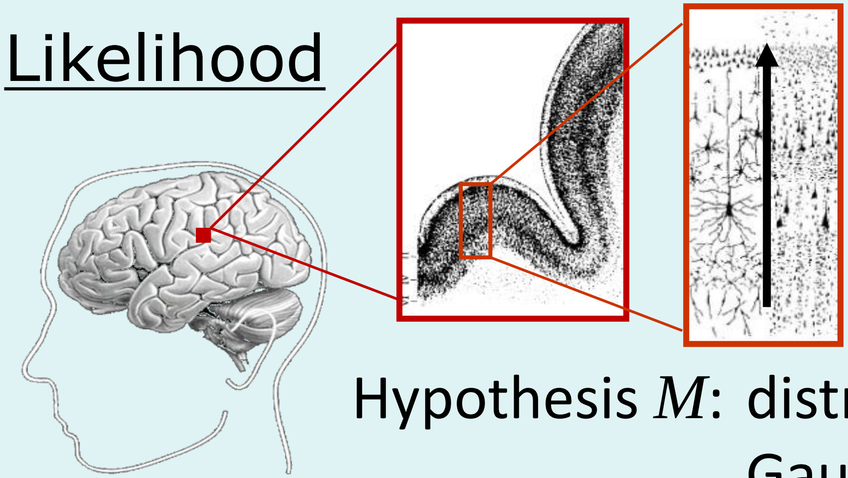
inverse computation

Posterior & Evidence

$$p(q|Y,M) \quad p(Y|M)$$

Distributed or imaging model

Likelihood



$$Y = LJ + \varepsilon \qquad P(Y|\theta, M) = N(LJ, \Sigma)$$

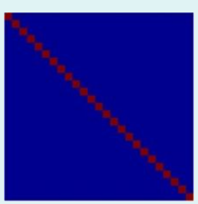
Parameters θ: (J, Σ)

Hypothesis M: distributed (linear) model, gain matrix L, Gaussian distributions

Priors

Sensor level:

$$\Sigma = \sigma^2 I$$



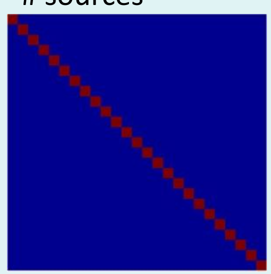
sensors

sensors

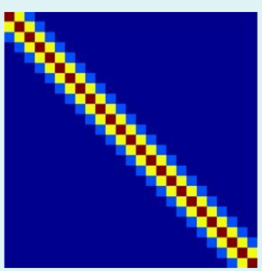
Source level: $P(J) = N(0, \Delta)$

sources

sources

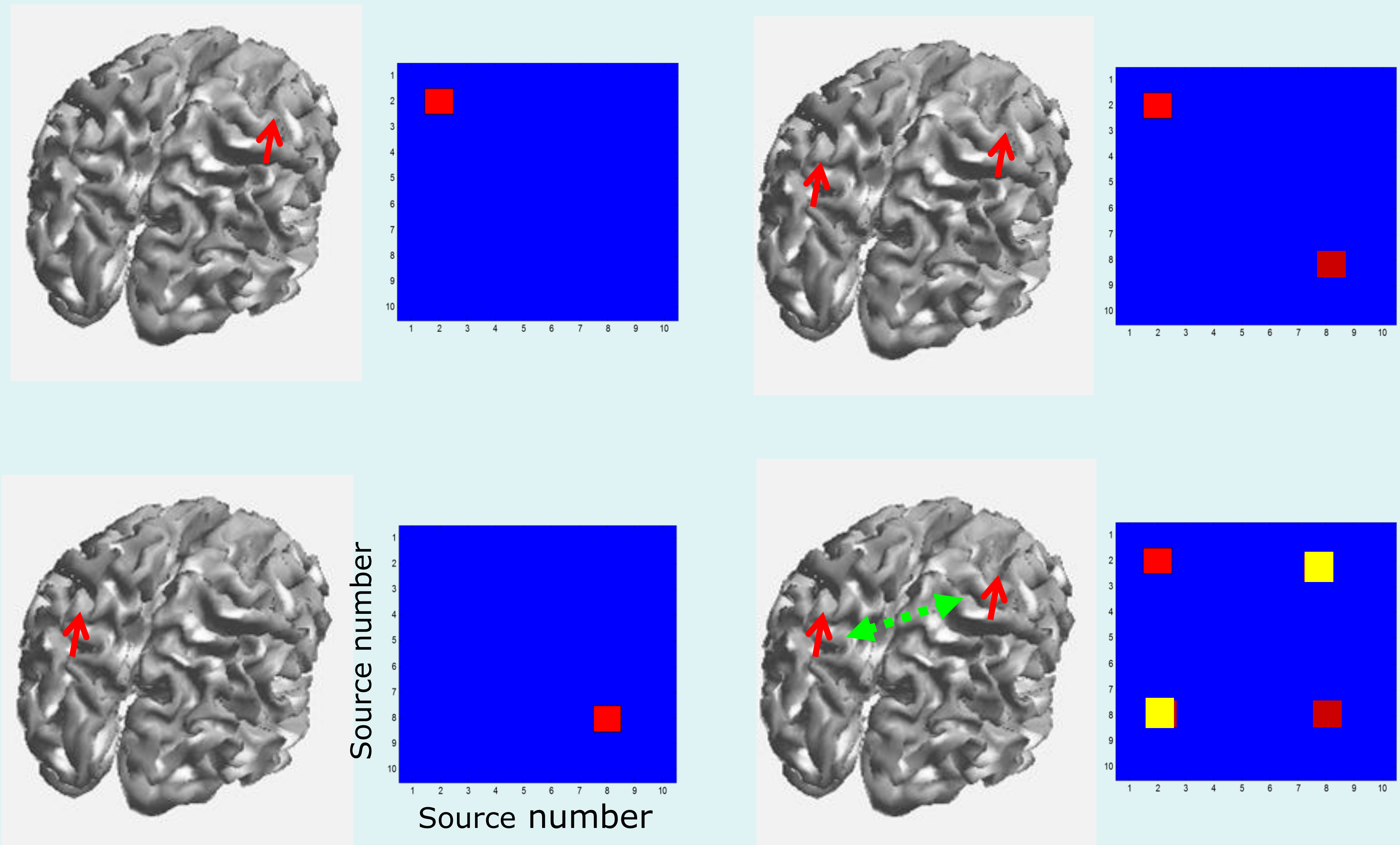


IID
(Minimum Norm)



Maximum Smoothness
(LORETA-like)

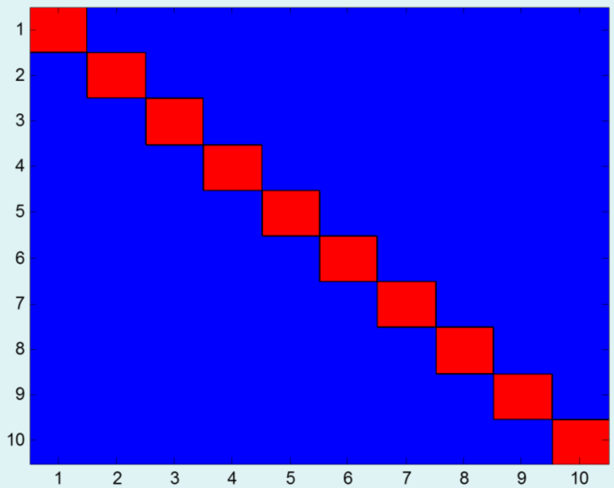
The source covariance matrix



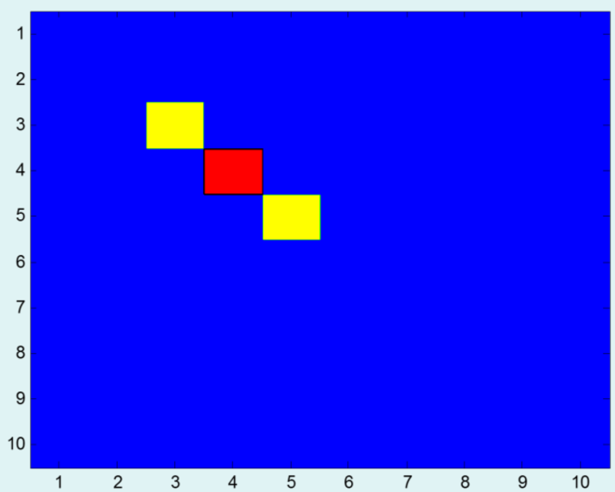
Minimum norm solution

= "allow all sources to be active, but keep energy to a minimum"

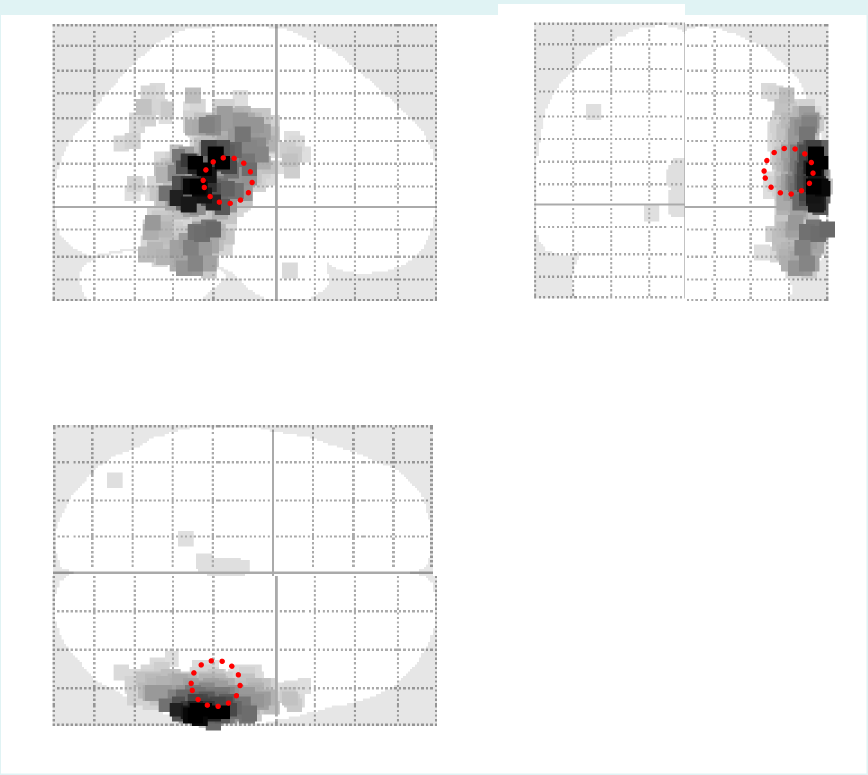
Prior



True
(focal
source)

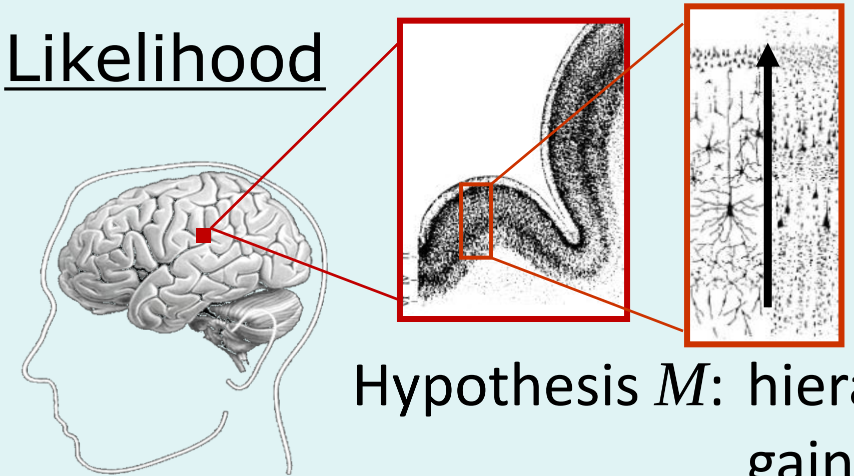


Solution



Incorporating multiple constraint

Likelihood



$$Y = LJ + \varepsilon \qquad P(Y|\theta, M) = N(LJ, \Sigma)$$

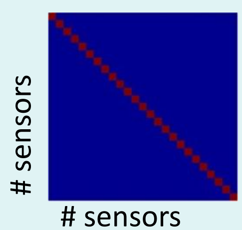
Parameters θ: (J, σ, λ)

Hypothesis M: hierarchical model, Gaussian distributions, gain matrix L, variance components Q^i

Priors

Sensor level:

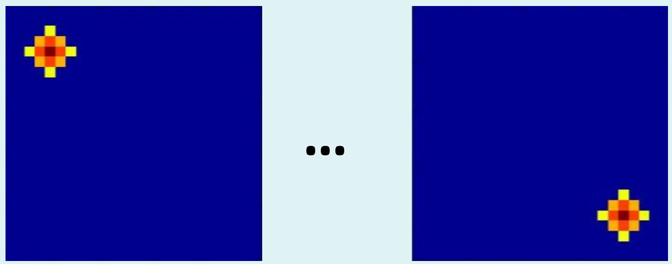
$$\Sigma = \sigma^2 I$$



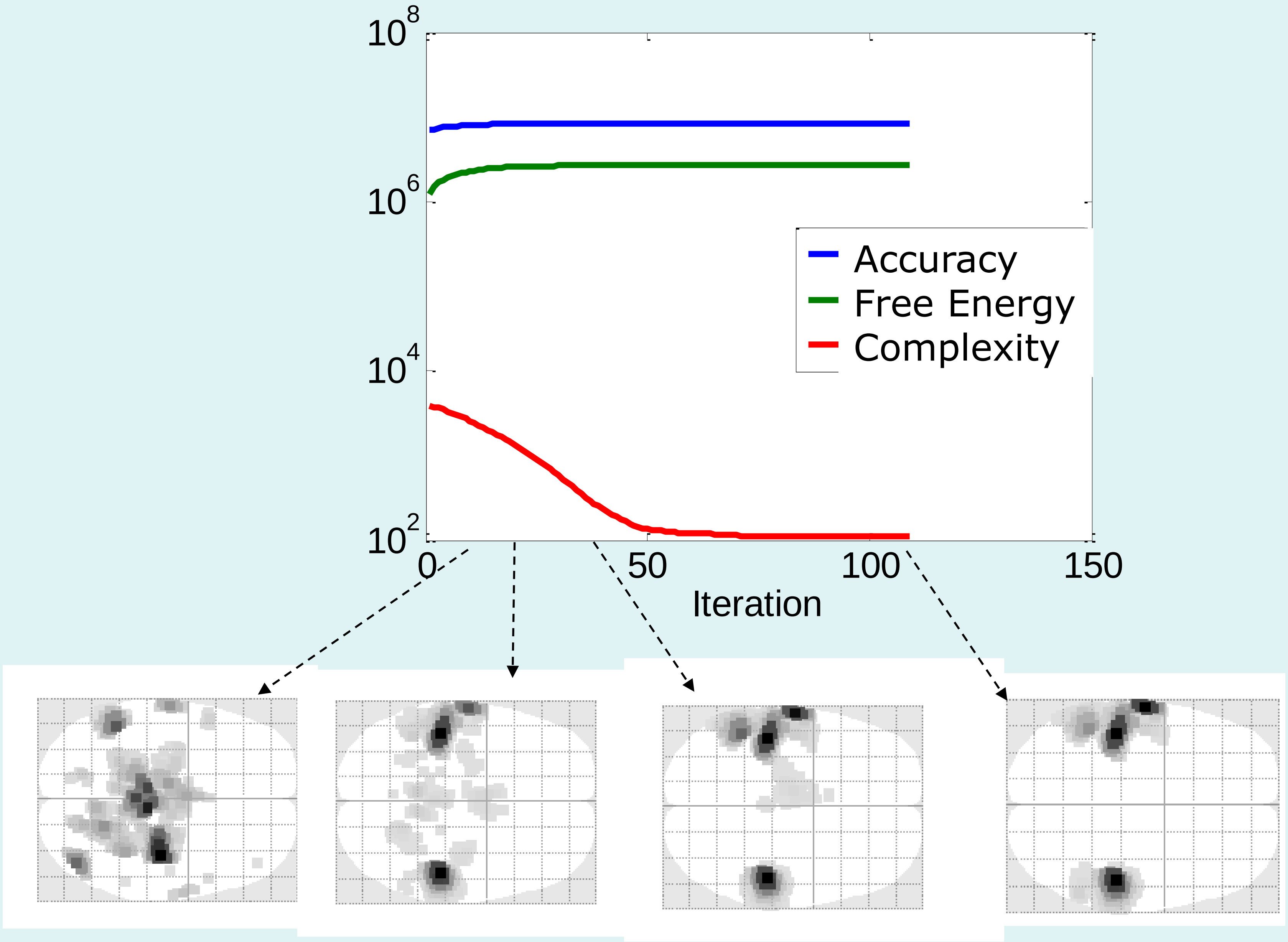
Source level: $P(J) = N(0, \Delta)$

$$\Delta = \lambda_1 Q^1 + \ldots + \lambda_k Q^k$$

$$\log \lambda = N(a, b)$$



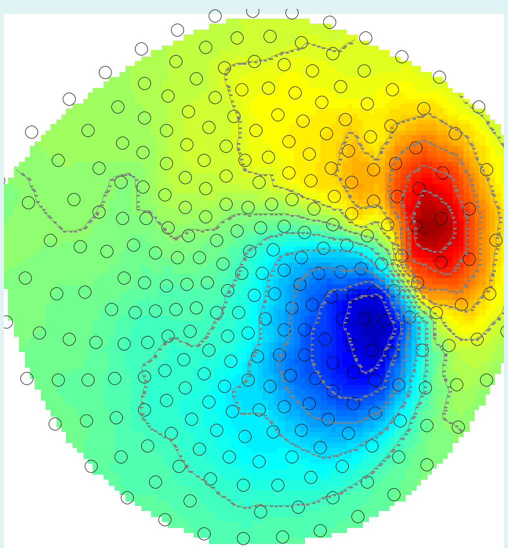
For example: Multiple Sparse Priors (MSP)



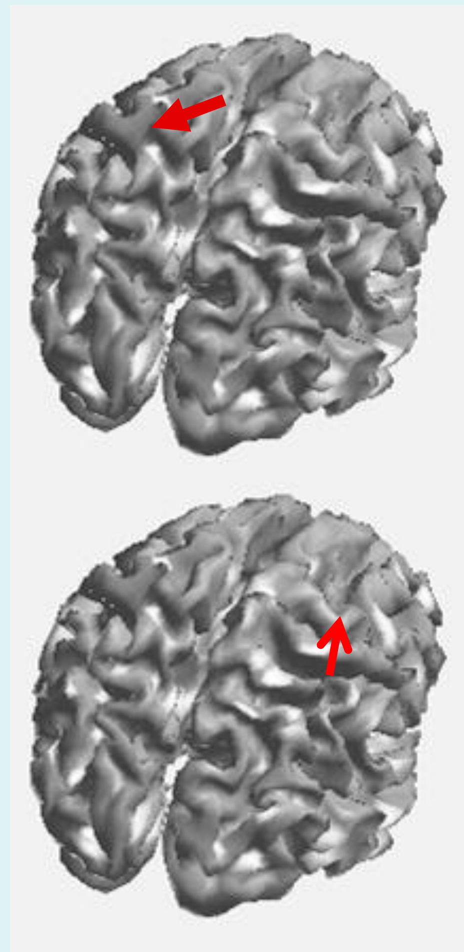
10^8
10^6
10^4
10^2
0
50
100
150
Iteration
Accuracy
Free Energy
Complexity

Dipole fitting

Measured data

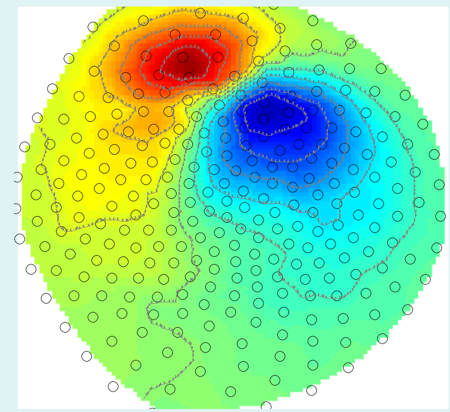


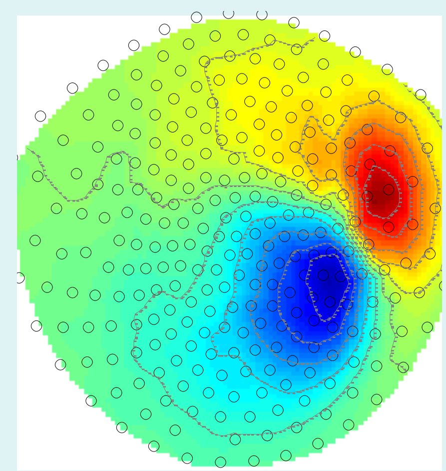
Estimated position



?

Estimated data

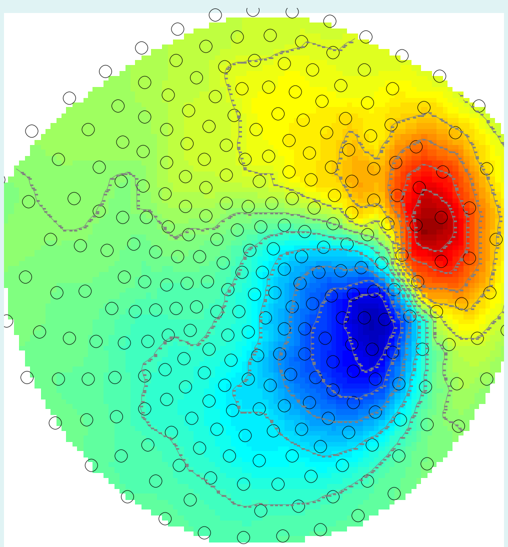




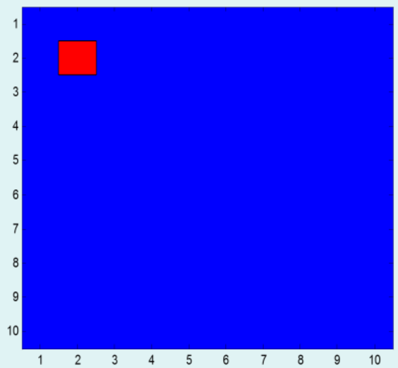
Constraint: *very few dipoles!*

Dipole fitting

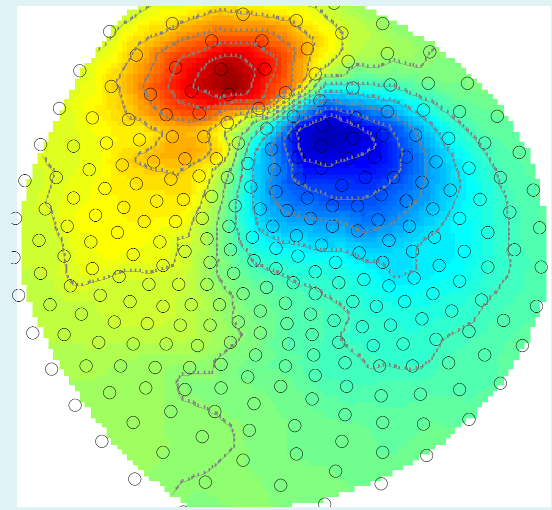
Measured data



Prior source covariance



Estimated data



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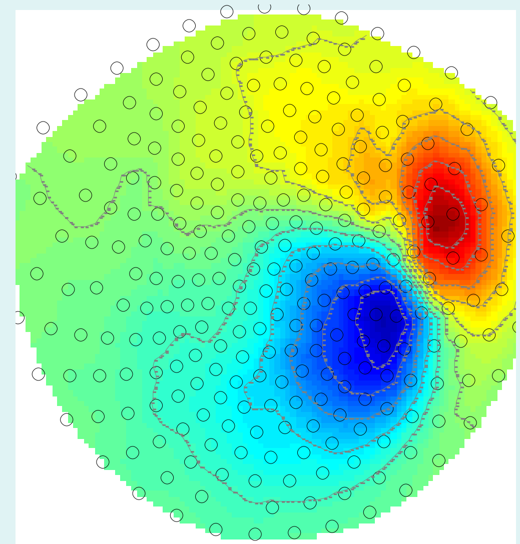
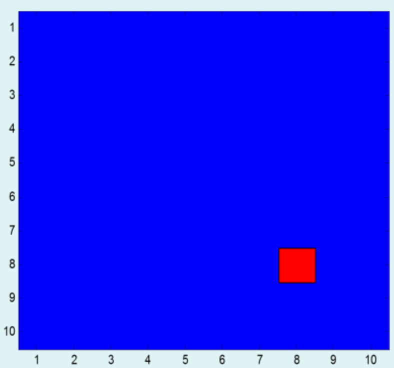
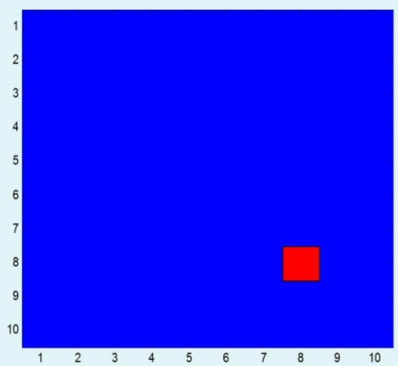


True source covariance





Conclusion

- Solving the Forward Problem is not exciting but necessary…

  …MEG or EEG? individual sMRI available? sensor location available?

- M/EEG inverse problem can be solved…

  …If you provide some *prior* knowledge!

- All prior knowledge encapsulated in a covariance matrices (sensors & sources)
- Can test between models and priors (a.k.a. constraints) in a Bayesian framework.

Thank you for your attention

And many thanks to Gareth and Jérémie for the borrowed slides.