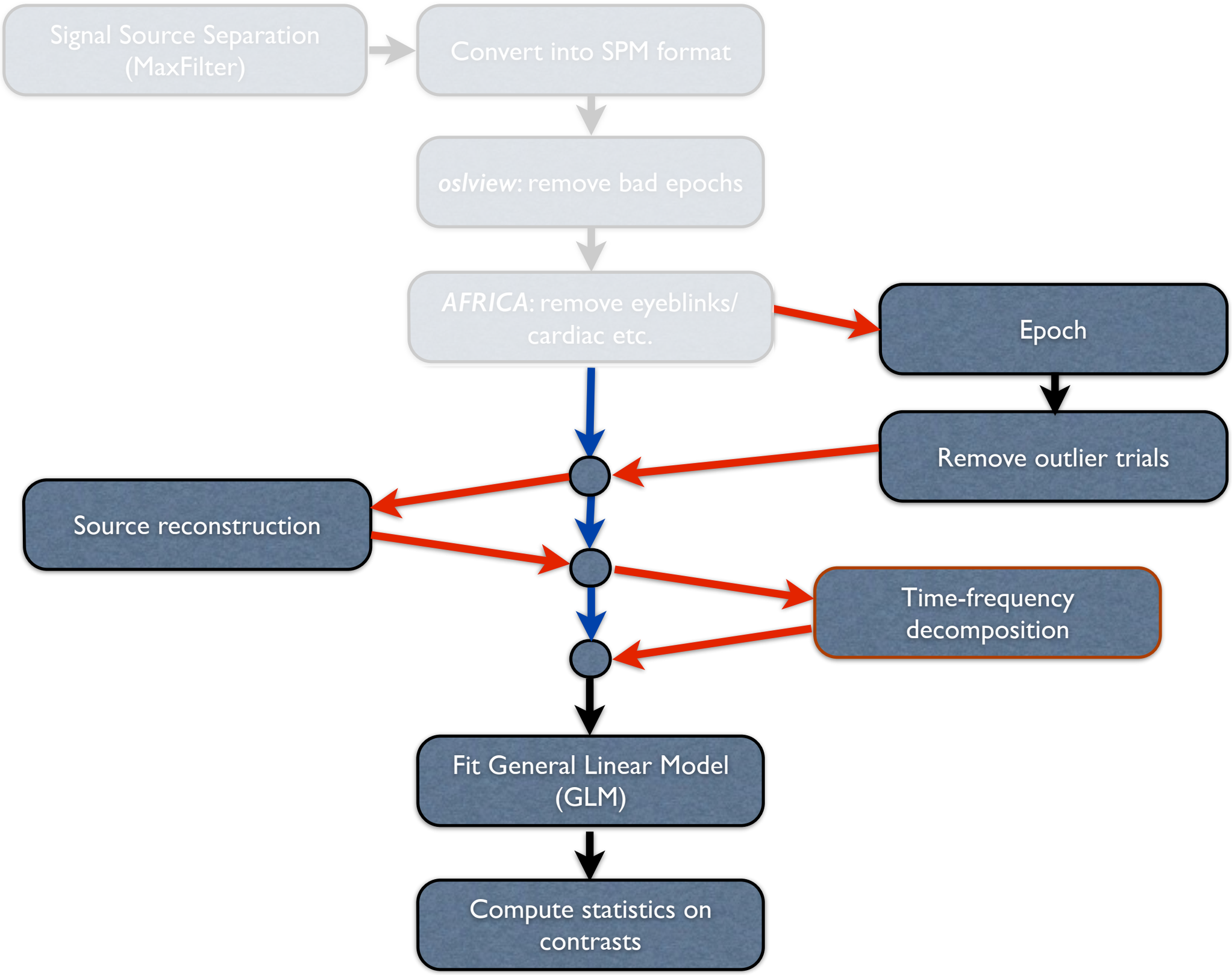
Source Reconstruction in OSL

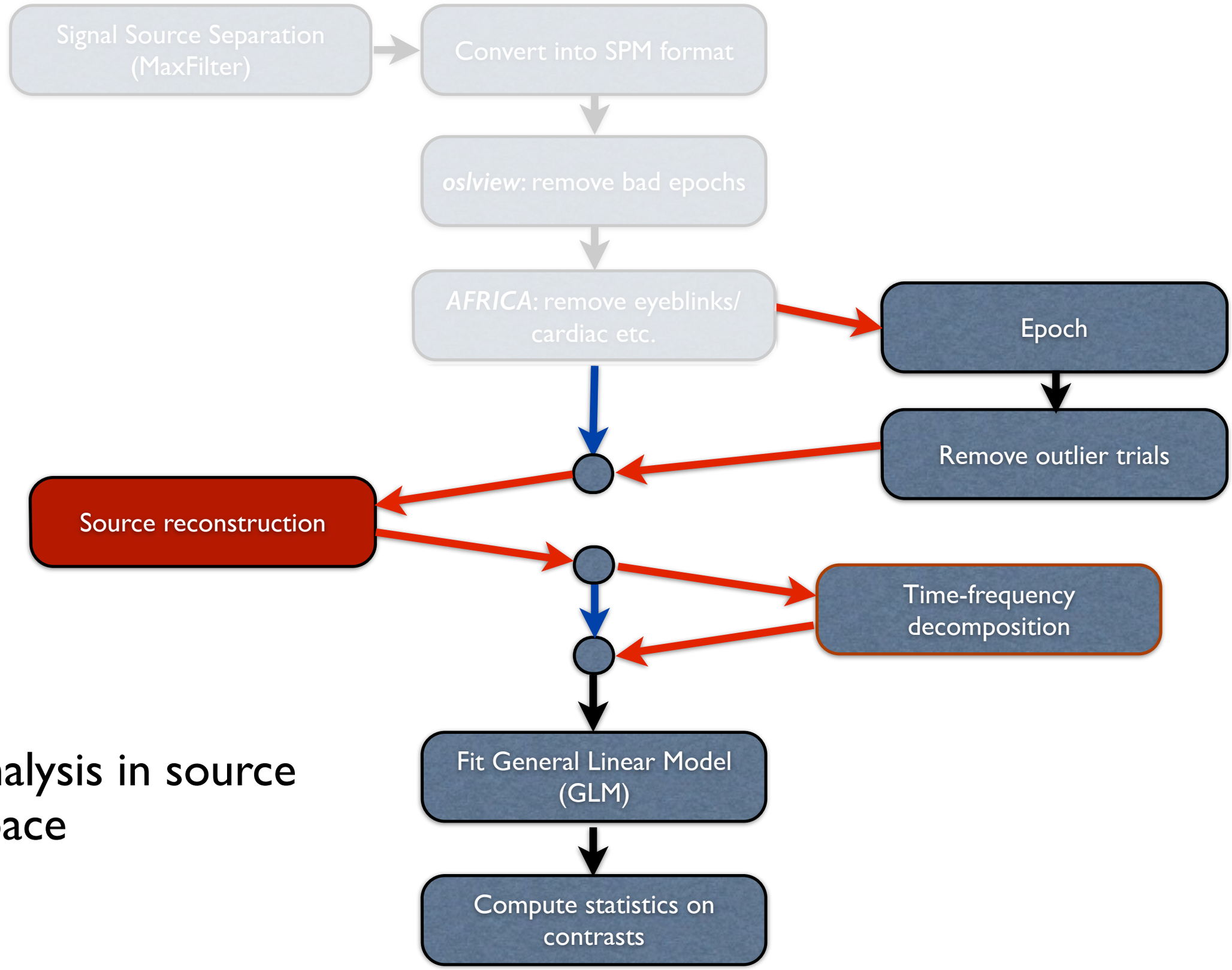
OHBA Analysis Workshop

Talk Outline

- Source reconstruction background
    - Co-registration and forward modelling
    - Inverse problem:
        - Dipole fitting
        - Minimum norm
        - Beamforming

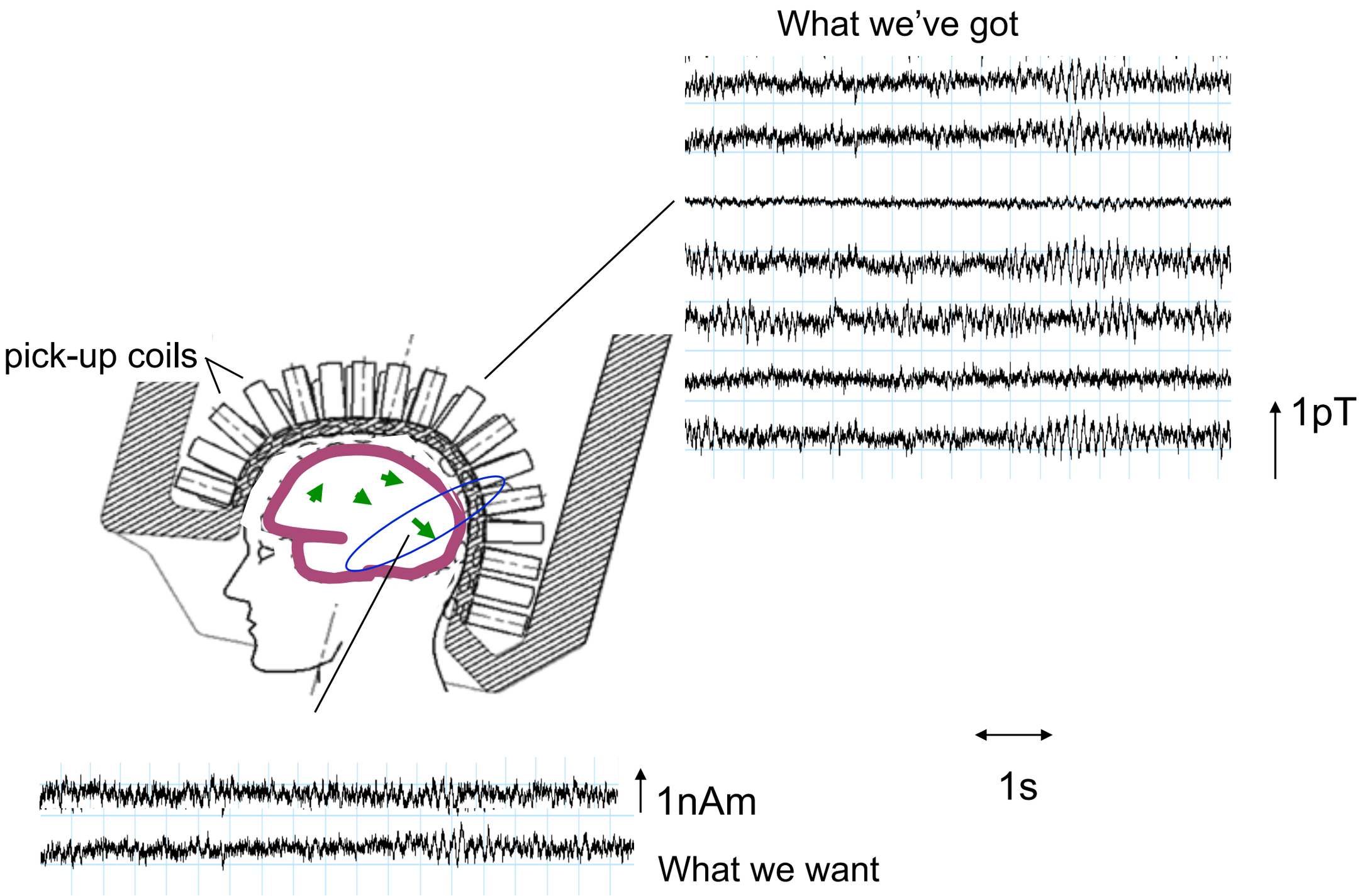
- OSL (OHBA's Software Library):
    - OAT (OHBA's easy Analysis Tool)


Signal Source Separation (MaxFilter)
Convert into SPM format
oslview: remove bad epochs
AFRICA: remove eyeblinks/ cardiac etc.
Epoch
Remove outlier trials
Source reconstruction
Time-frequency decomposition
Fit General Linear Model (GLM)
Compute statistics on contrasts

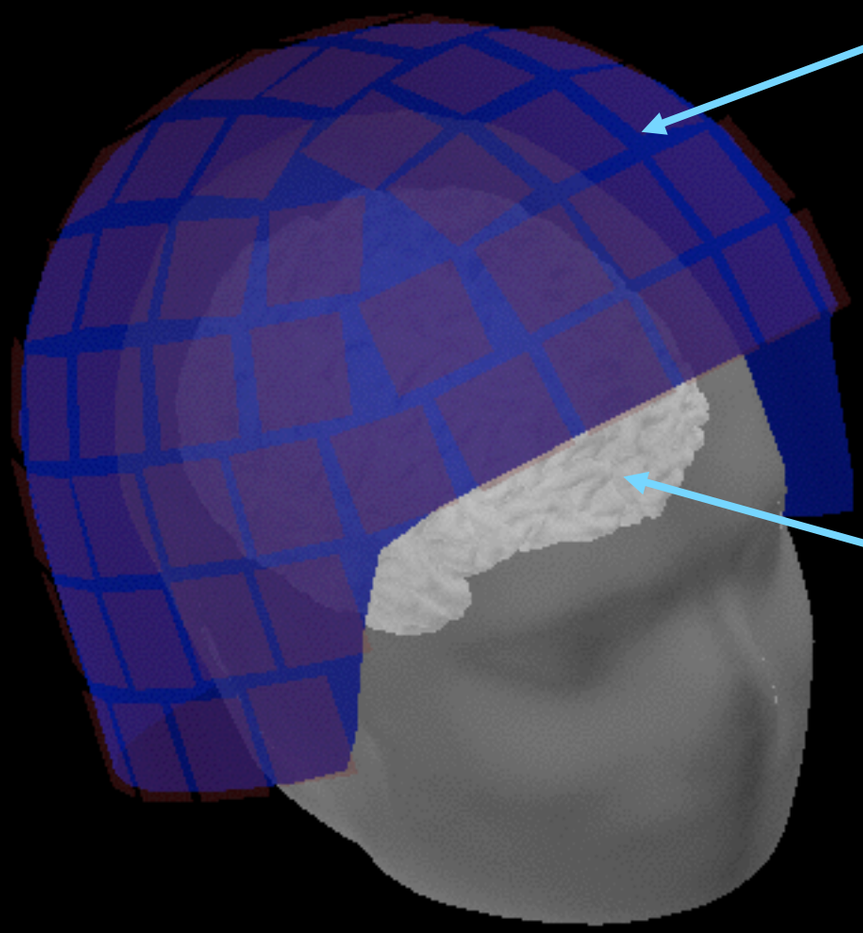


- analysis in source space

The Problem - MEG Source Reconstruction



Forward Model



306 x T

"Sensor space" y

306 MEG sensors

Simulate Maxwell equations

1 x T

"Source space" $m(r_i)$

Brain activity at this location

$$y = \sum_{i=1}^{L} H(r_i) m(r_i) + e$$

306 x T — 306 x L — 306 x 1 — 1 x T

Lead field matrix

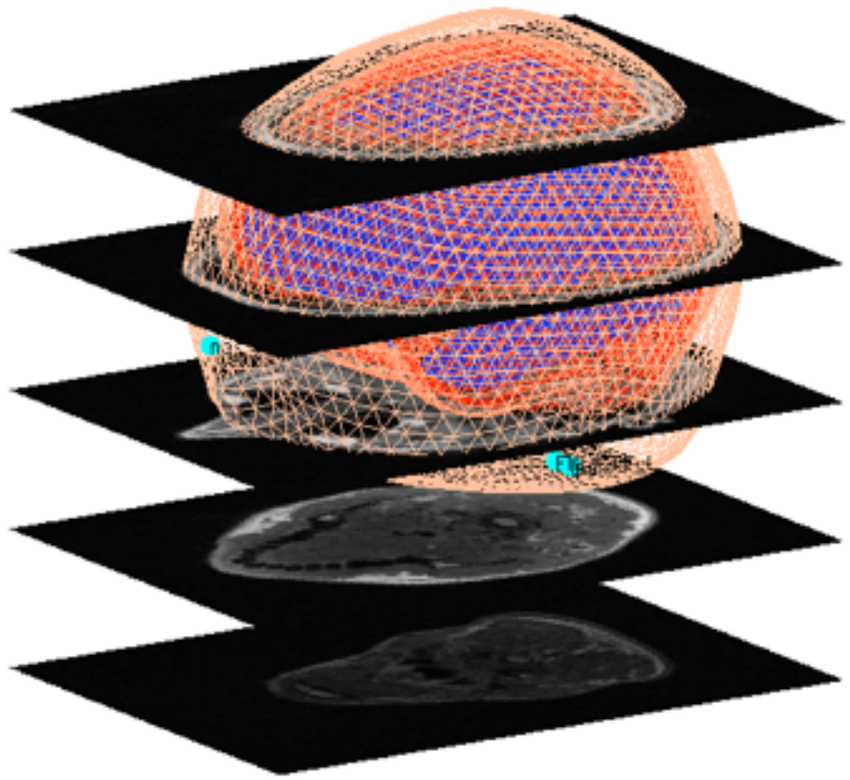
Gaussian noise

Setting up the head meshes

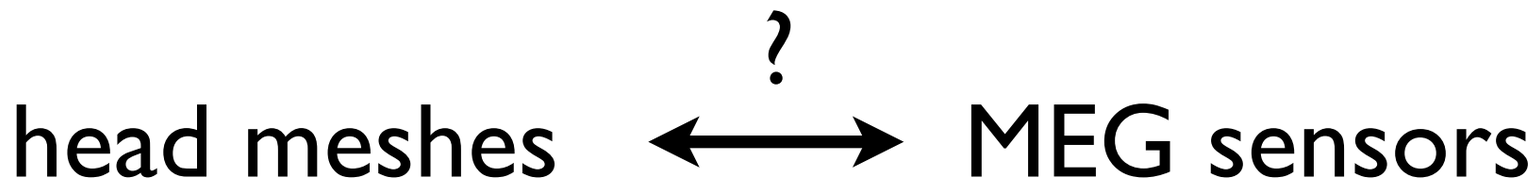
- Can use an individual's MRI or the MNI "template"
- Creates cortex (blue), inner skull (red) and scalp (orange)

➡ created by:

- nonlinear registration of the subject's MRI to a "canonical" template (with known mesh surfaces)
- Canonical meshes can then be transformed into subject's head coordinates



Co-registration



The coordinate systems and what we can locate in them:

- **MNI coordinates** are defined using a standard template brain.
  - 3 fiducials (via anatomical features)
  - Scalp (and cortex, inner skull) head mesh

- **Head coordinates** are defined based on the 3 fiducials: nasion, left/right preauricula.
  - 3 fiducials (via Polhemus)
  - Head Position Indicator (HPI) coil (via Polhemus)
  - Headshape points (via Polhemus)

- **Device coordinates** are defined relative to some point external to the subject and fixed with respect to the measuring device.
  - Head Position Indicator (HPI) coils (via detection by MEG sensors)
  - Sensors

Co-registration

head meshes ? MEG sensors

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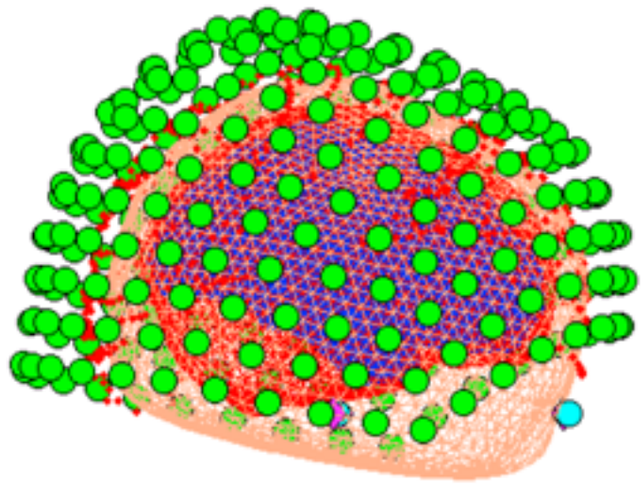
Landmarked based co-reg



Co-registration

head meshes ?⟷ MEG sensors

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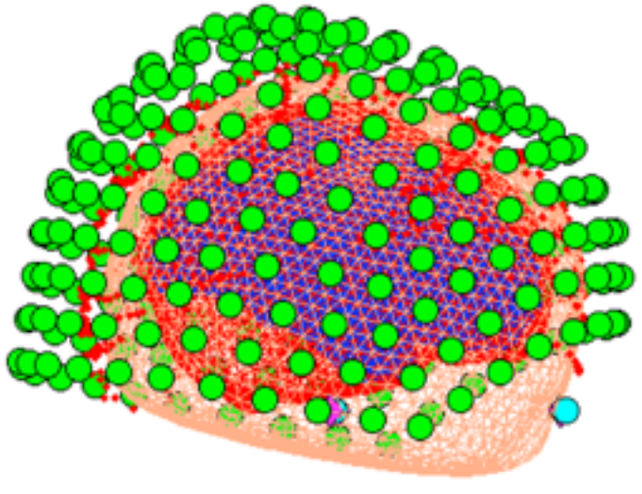
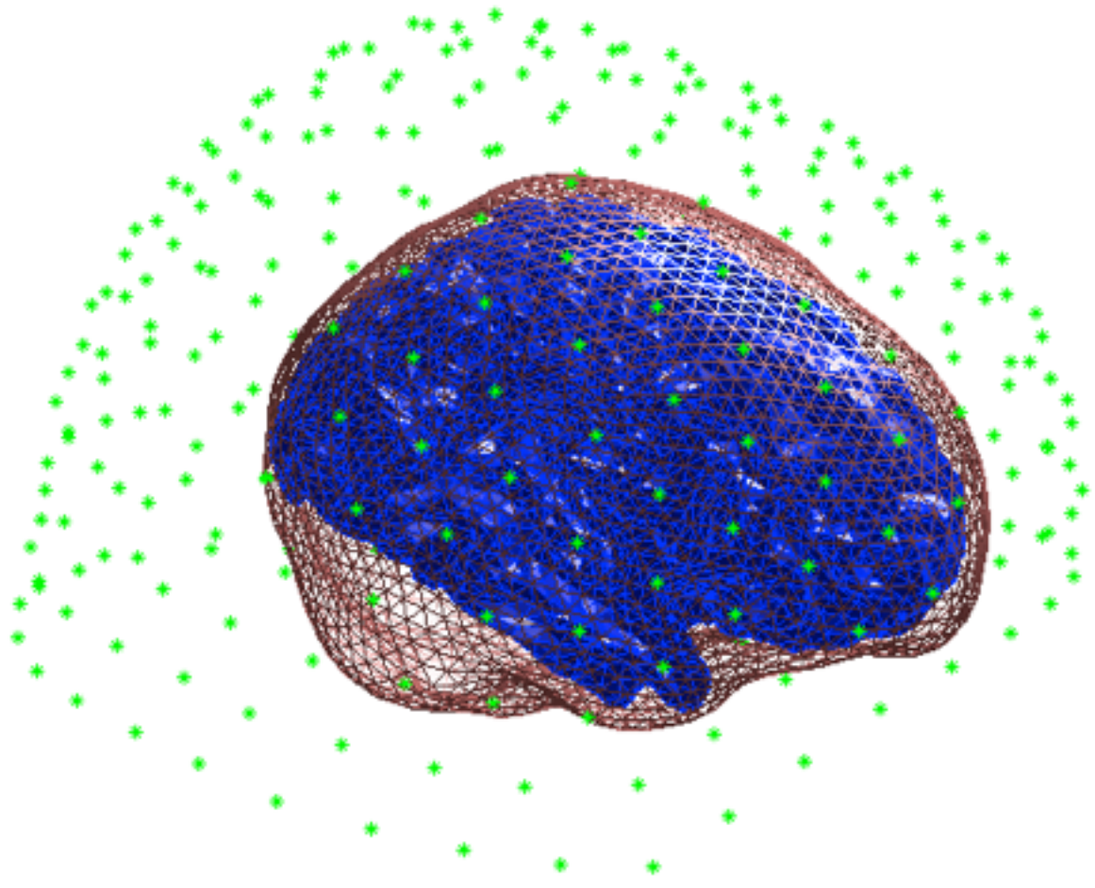
Surface matching co-reg



Forward Model

- Computes the lead fields, $H(r_i)$
- Model just the inner skull surface, using:
  - ➡ Single sphere
  - ➡ MEG local spheres
    - ➡ a sphere fitted separately to the local curvature below each sensor
  - ➡ Single shell



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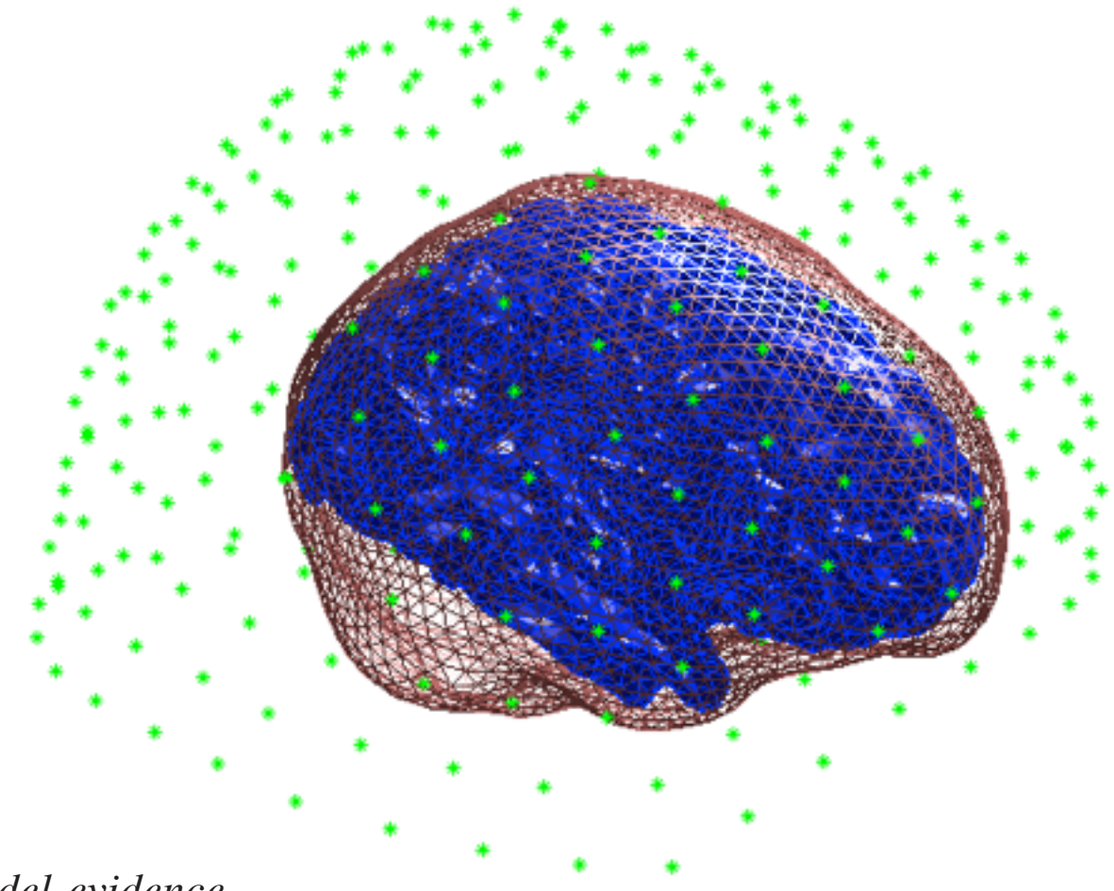


Selecting forward models for MEG source-reconstruction using model-evidence R.N. Henson et al, Neuroimage 2009.

OSL forward modelling
(and co-registration)

- Use call to *osl_forward_model* (Note: OAT will automatically do this):

S2=[];

S2.D = spm_file_name;

S2.sMRI = structural_file_name; % set S2.sMRI=''; if there is no structural available

S2.useheadshape=1;

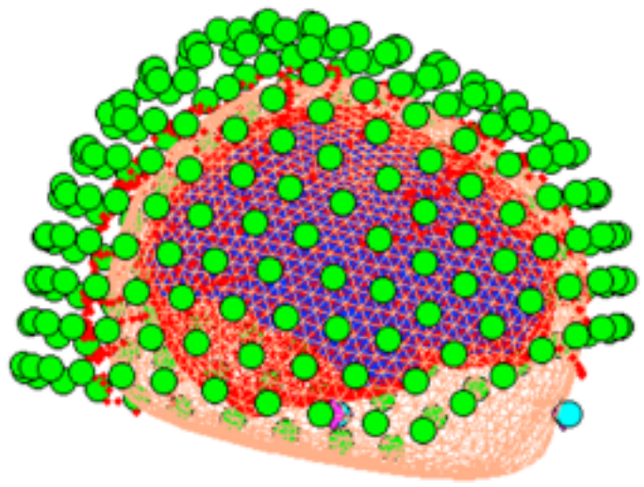
S2.forward_model='Single Shell';

D=osl_forward_model(S2);

Check the Result

- Call spm_eeg_inv_checkdatareg(D).

  ➡ shows everything co-registered



- Things to look out for are:

  ➡ Are the headshape points (small red dots) well matched to the scalp surface?

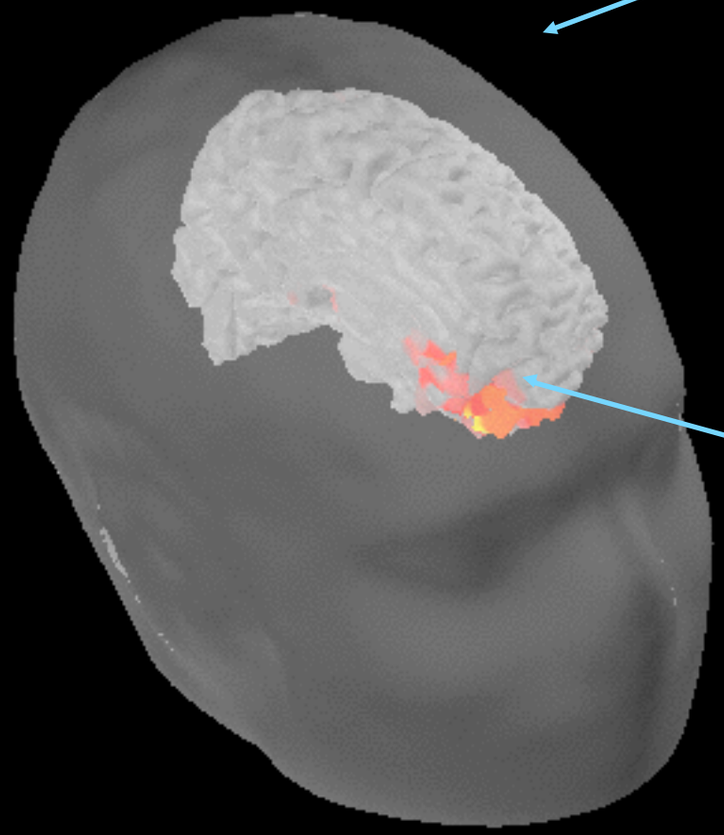
  ➡ Is the head sensibly inside the sensor array (green circles)?

  ➡ Are the MRI fiducials (pink diamonds) located sensible close to the Polhemus fiducials (light blue circles), and are they sensibly located with respect to the head?

Source Reconstruction

“Sensor space” $\boldsymbol{y}$

306 MEG sensors



under-constrained

forward problem

inverse problem

“Source space” $\boldsymbol{m}(r_i)$

L=~10,000 vertices

Activity estimates

$$\boldsymbol{y} = \sum_{i=1}^{L} \boldsymbol{H}(r_i)\boldsymbol{m}(r_i) + \boldsymbol{e}$$

Inverse problem: reconstruction of the underlying neuronal current distribution given the data at the sensors.

We need to apply constraints/priors

- Only a small number of dipoles are active, i.e. sparseness (Dipole Fitting)
- Distributed solutions
  - Allow all dipoles across a whole brain grid to be active
  - E.g.:
    - All dipoles are active but their power is minimized (Minimum Norm)
    - All dipoles are active but their spatial pattern is smooth (LORETTA)
    - All dipoles are active but their spatial pattern is smooth and sparse (SPM MSP (Multiple Sparse Priors))

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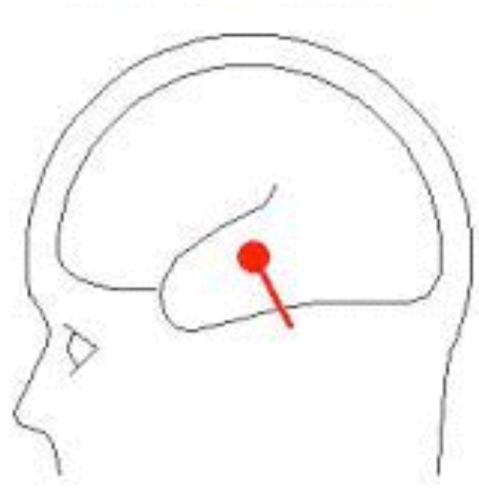
Dipole Fitting

$$\boldsymbol{y} = \sum_{i=1}^{L} \boldsymbol{H}(r_i)\boldsymbol{m}(r_i) + \boldsymbol{e}$$

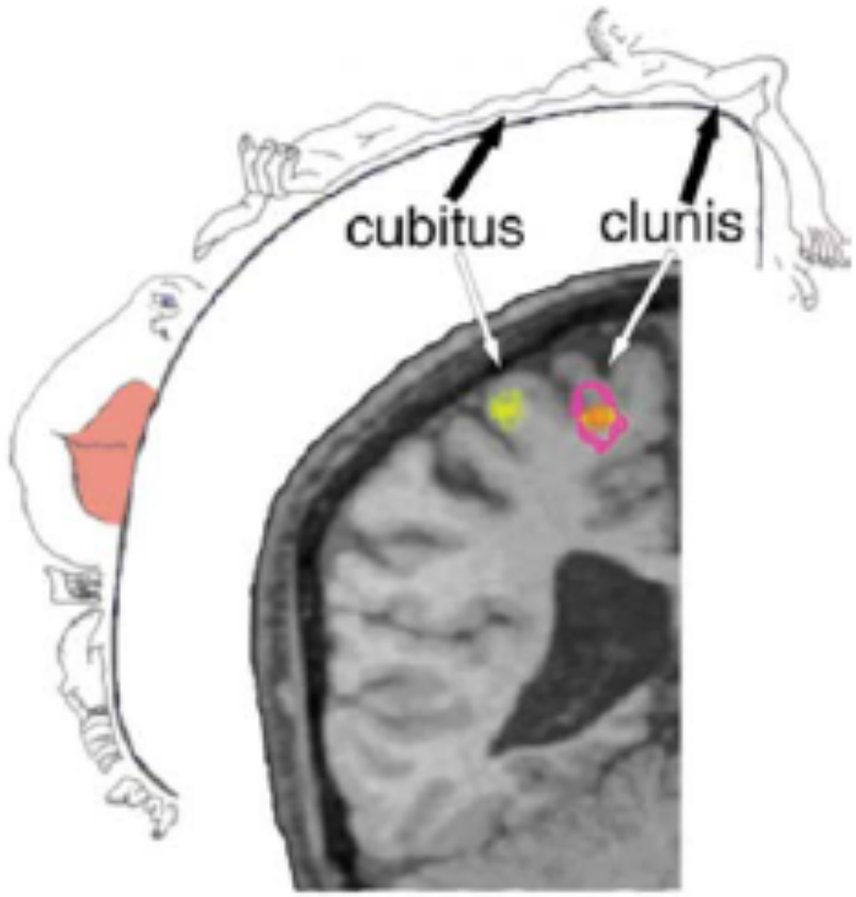
Assumes a small number of dipoles (e.g. $L = 1$)

and finds the largest ***goodness of fit*** (smallest least-squares error between the data and the model) achievable by adjusting the dipole:

- orientation
- location
- amplitude



Dipole Fitting



Magnetoencephalography identified sites of brain activity in the left hemisphere, including 95% confidence ellipsoids, for stimulation of right cubitus (yellow) and clunis (purple). Note the close correspondence with Penfield's homunculus[1]

Can you tell your clunis from your cubitus? A benchmark for functional imaging

Fisher et al. 2004

- Effective at modelling short (<200ms) latency **evoked** responses

- BUT, what about more distributed brain activity? Non-linear minimization becomes unstable for more sources.

We need to apply constraints/priors

- Only a small number of dipoles are active, i.e. sparseness (Dipole Fitting)
- **Distributed solutions**
  - **Allow all dipoles across a whole brain grid to be active**
  - **E.g.:**
    - **All dipoles are active but their power is minimized (Minimum Norm)**
    - All dipoles are active but their spatial pattern is smooth (LORETTA)
    - All dipoles are active but their spatial pattern is smooth and sparse (SPM MSP (Multiple Sparse Priors))

Minimum Norm

- Cost function combines goodness of fit:

$$\boldsymbol{y} = \sum_{i=1}^{L} \boldsymbol{H}(r_i)\boldsymbol{m}(r_i) + \boldsymbol{e}$$

with the requirement that all dipoles are active but their power is minimised, i.e.:

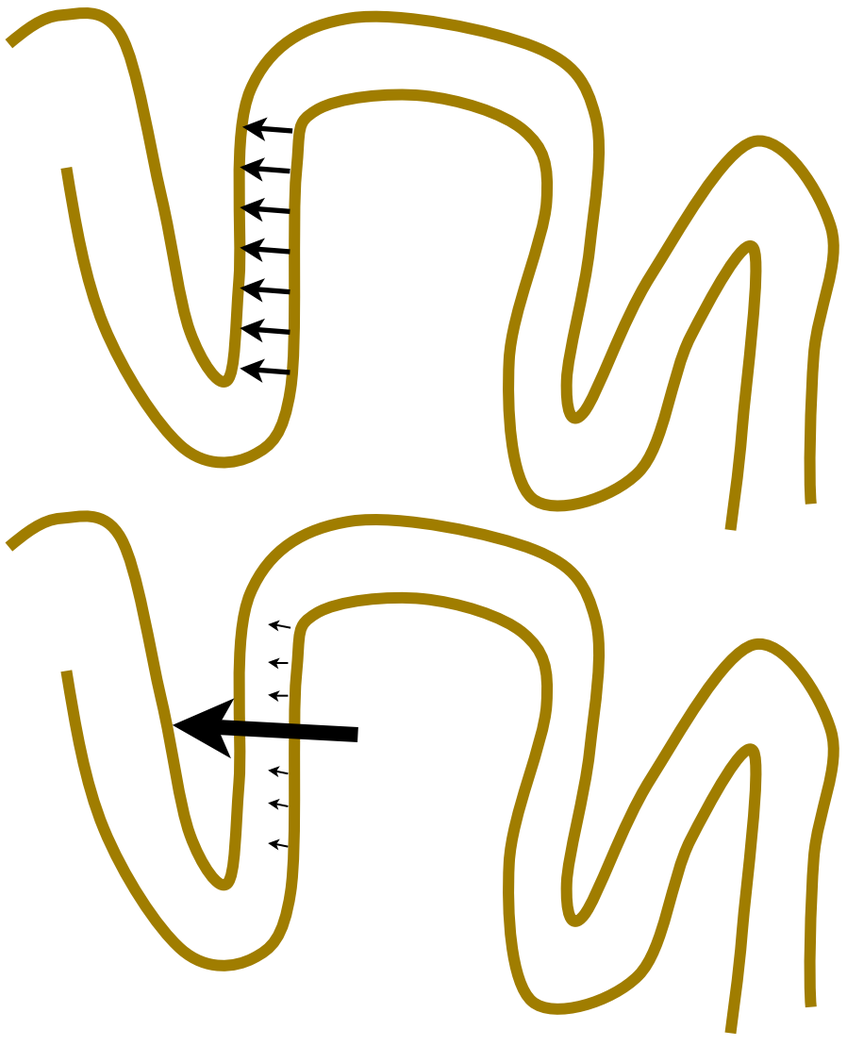
$$\text{minimise}(-\text{Goodness of fit} + k \times \text{Penalty for large power in } \boldsymbol{m}(\text{r}))$$

(Note that this is the "IID" option in SPM)

Minimum Norm

- All dipoles are active but their power is minimized

prefers this



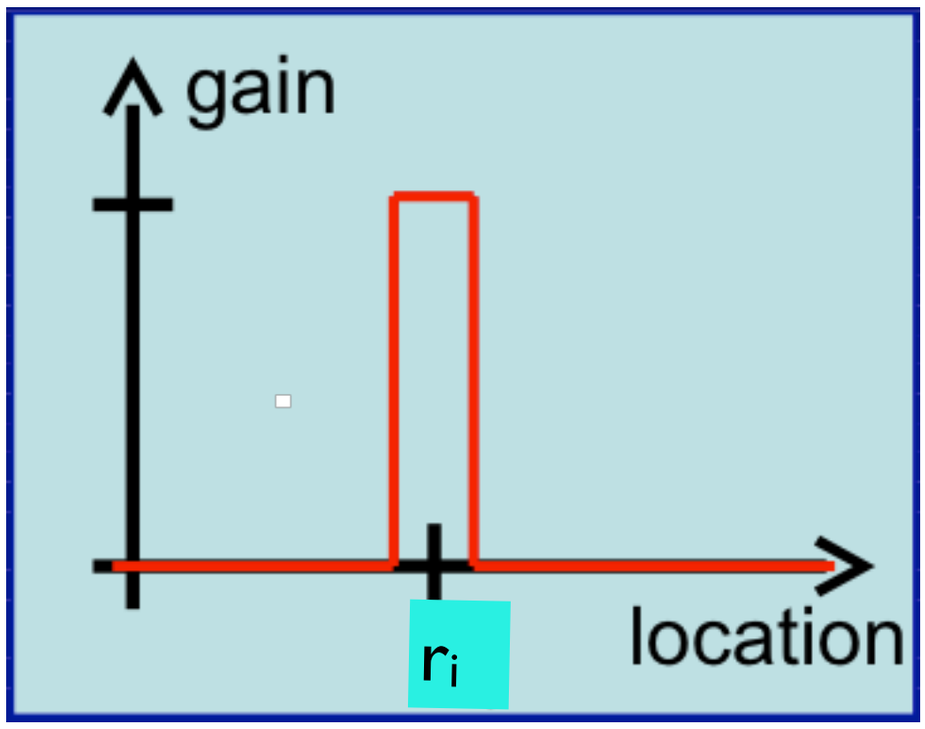
to this

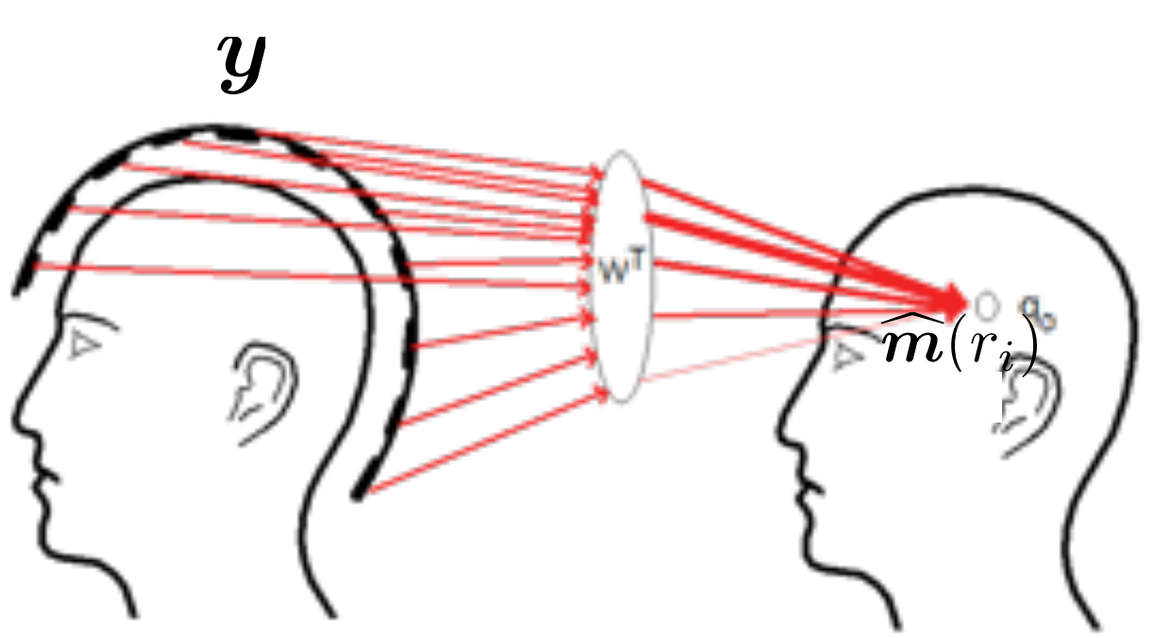
Indirectly gives solutions that are diffuse/smooth

Beamforming

Beamformer methods:

- do not try to explain the complete measured field
- construct a spatial filter that blocks the contributions of all sources not at the location in question



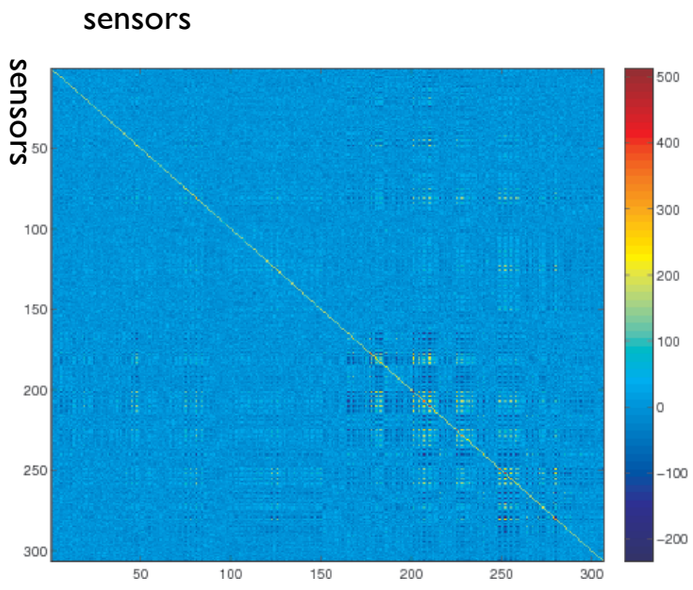


$$\widehat{\boldsymbol{m}}(r_i) = \boldsymbol{W^T}(r_i)\boldsymbol{y}$$

Beamforming

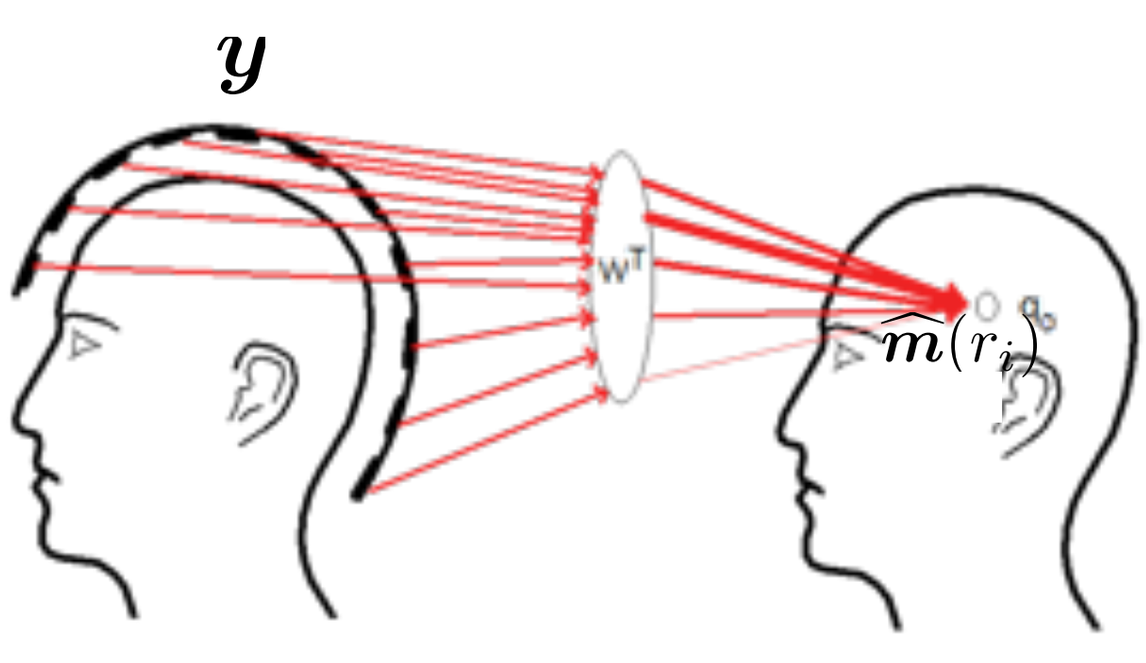
Beamformer weights, $W(r_i)$, just depend on:

1) The lead field matrix at location r_i , $H(r_i)$.
2) The data covariance.



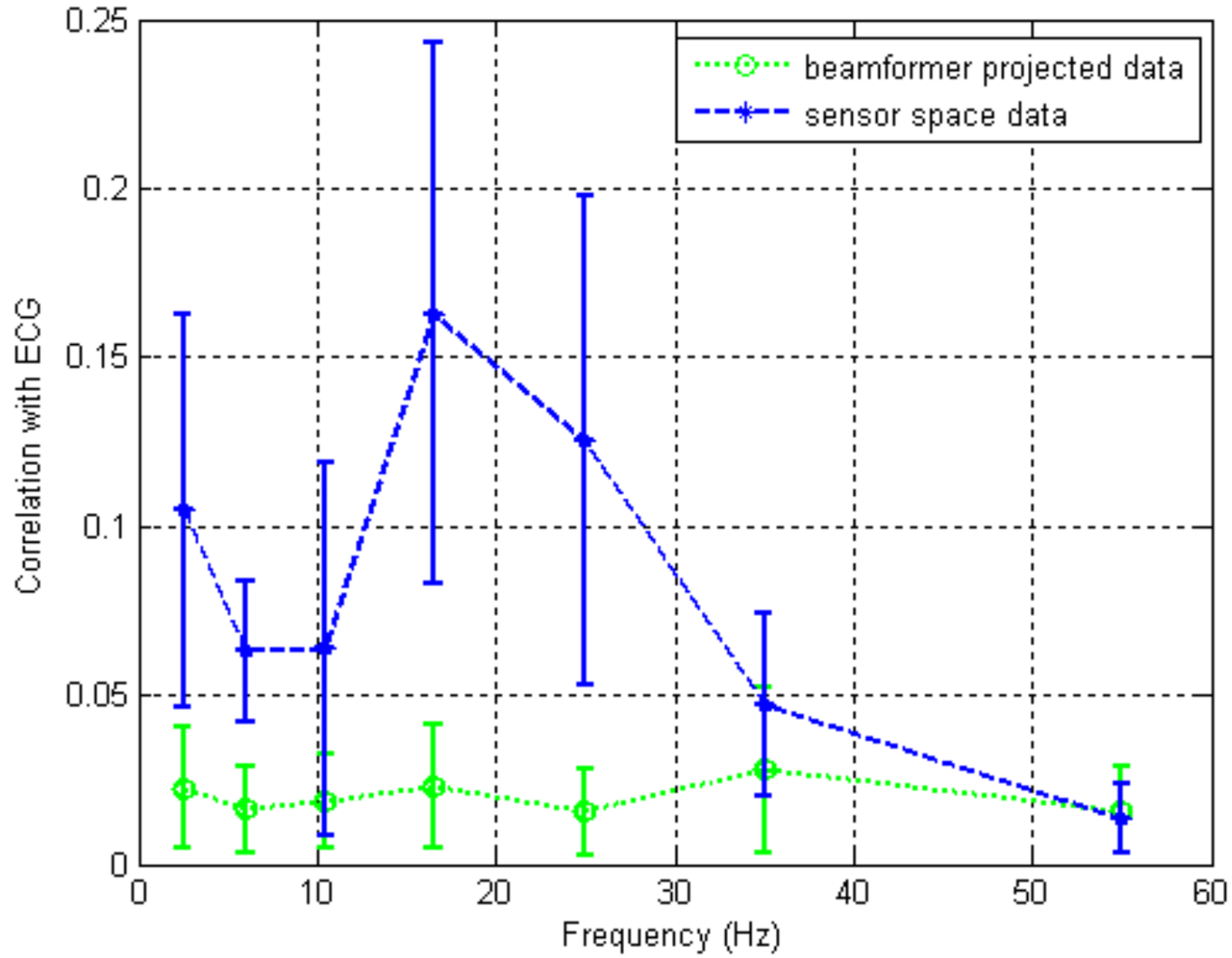
data covariance matrix, cov(y)

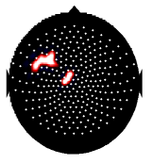
(represents the activity across the whole brain AND from elsewhere)



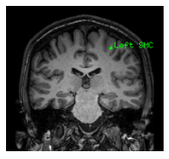
$$\widehat{\boldsymbol{m}}(r_i) = \boldsymbol{W^T}(r_i)\boldsymbol{y}$$

Beamformers block out interference





Correlation between ECG and MEG channels over the left motor cortex



Correlation between ECG and beamformer projected time course in left motor cortex

Data courtesy of Matthew Brookes (Nottingham University)

OSL Beamformer

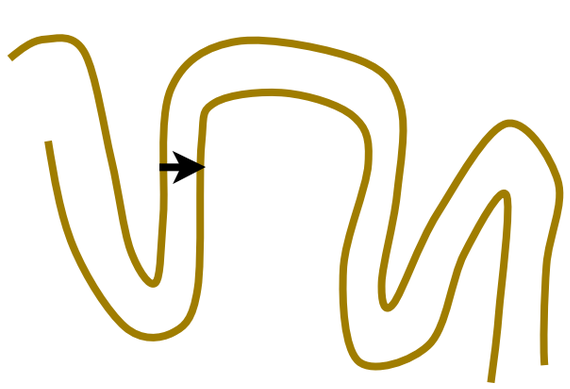
- Bandpass temporal filtering is done on the continuous, before any epoching
- Normalises the different sensor types using the noise variance to allow fusion
- **Works in a PCA subspace combined over both sensor types**
  - ➡ dimensionality can be specified
  - ➡ e.g. restricted to a dimensionality of <64 for Maxfiltered Elekta data)

ERF rectification

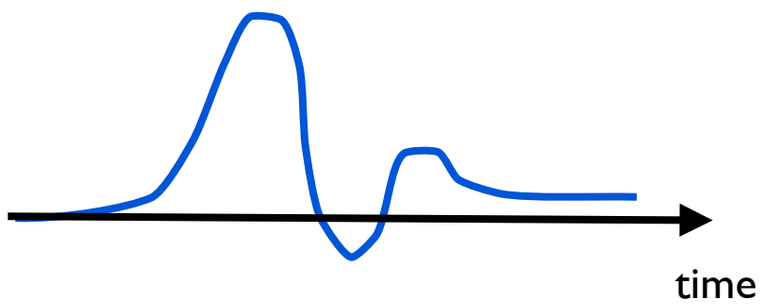
- Problem:

  ➡ there is an ***ambiguity*** between the reconstructed dipole direction and the sign of the reconstructed time series

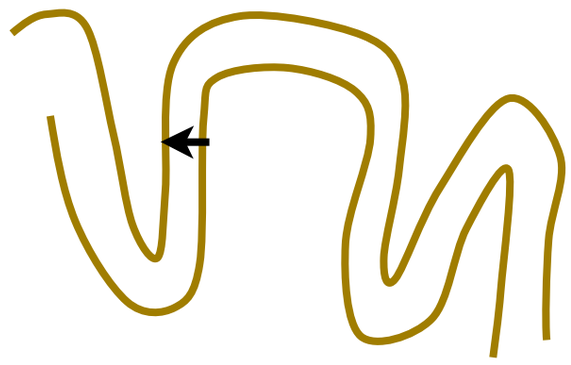
  ➡ not trivial to resolve this, e.g.



raw COPE estimate:



LOOKS THE SAME AS



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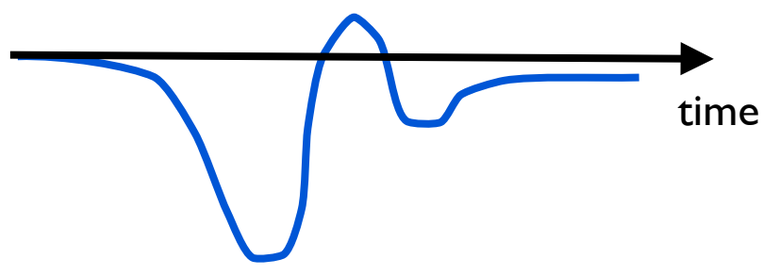


ERF rectification

- We need to find a way to do tests/comparisons that is insensitive to this ambiguity so that the COPEs are:

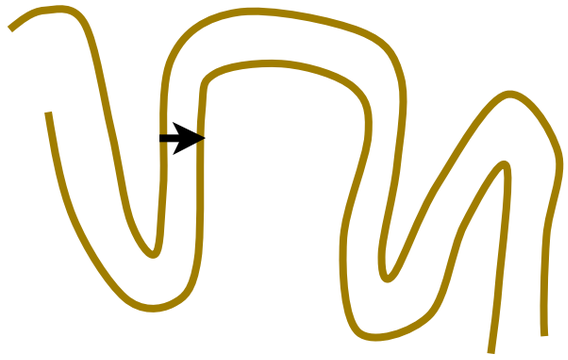
  ➡ comparable over space (e.g. so we can do spatial smoothing)

  ➡ comparable over subjects (e.g. so we can do group averaging)

- Solution: use abs(COPE)

ERF rectification

- Solution rectification: use abs(COPE)



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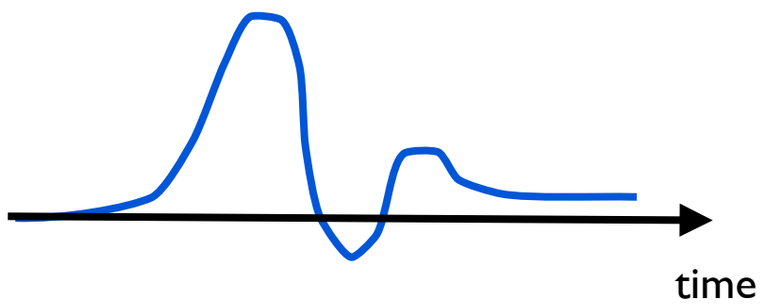

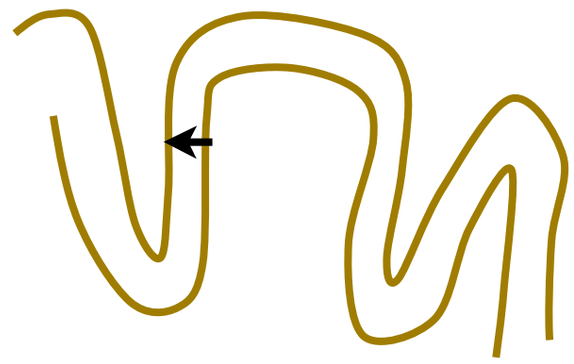

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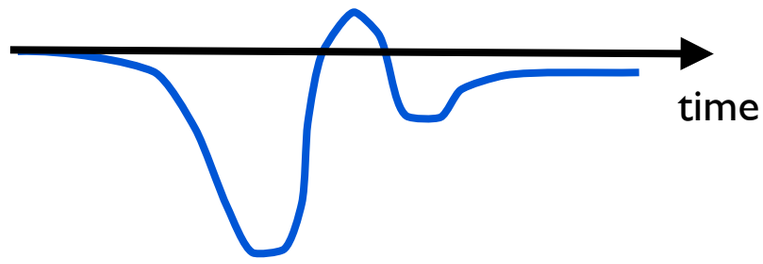
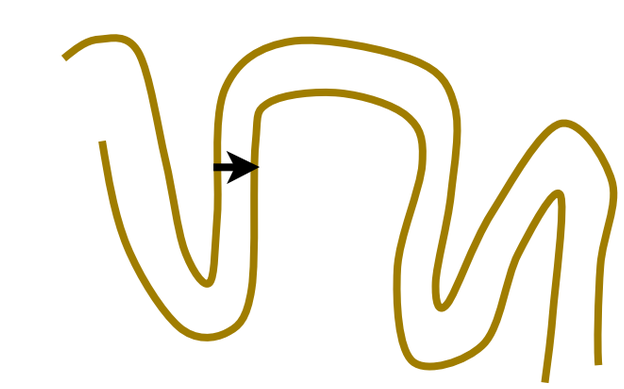
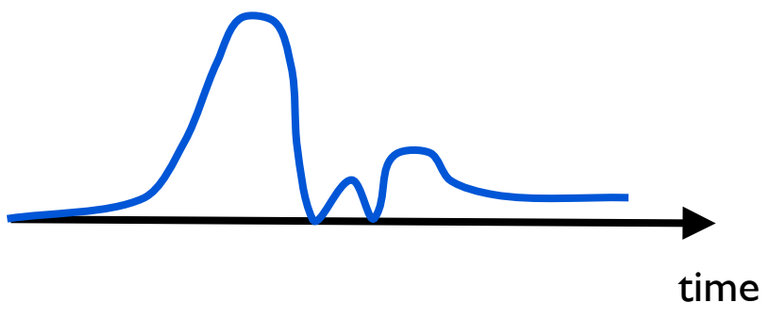


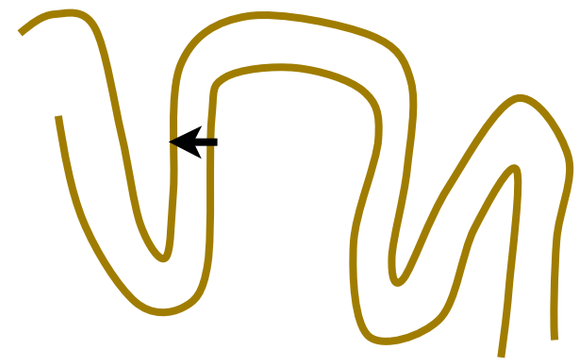
ERF rectification

- Solution rectification: use abs(COPE)



abs(COPE) estimate:





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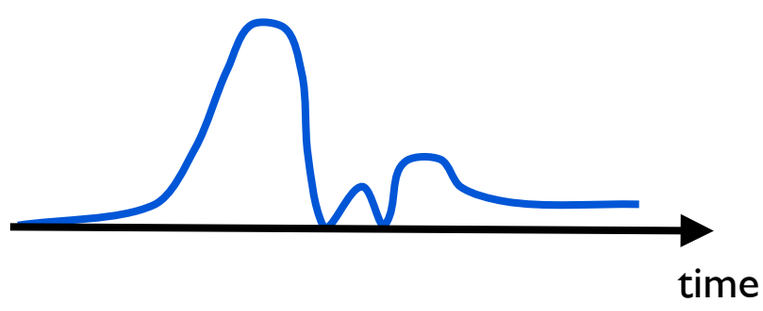

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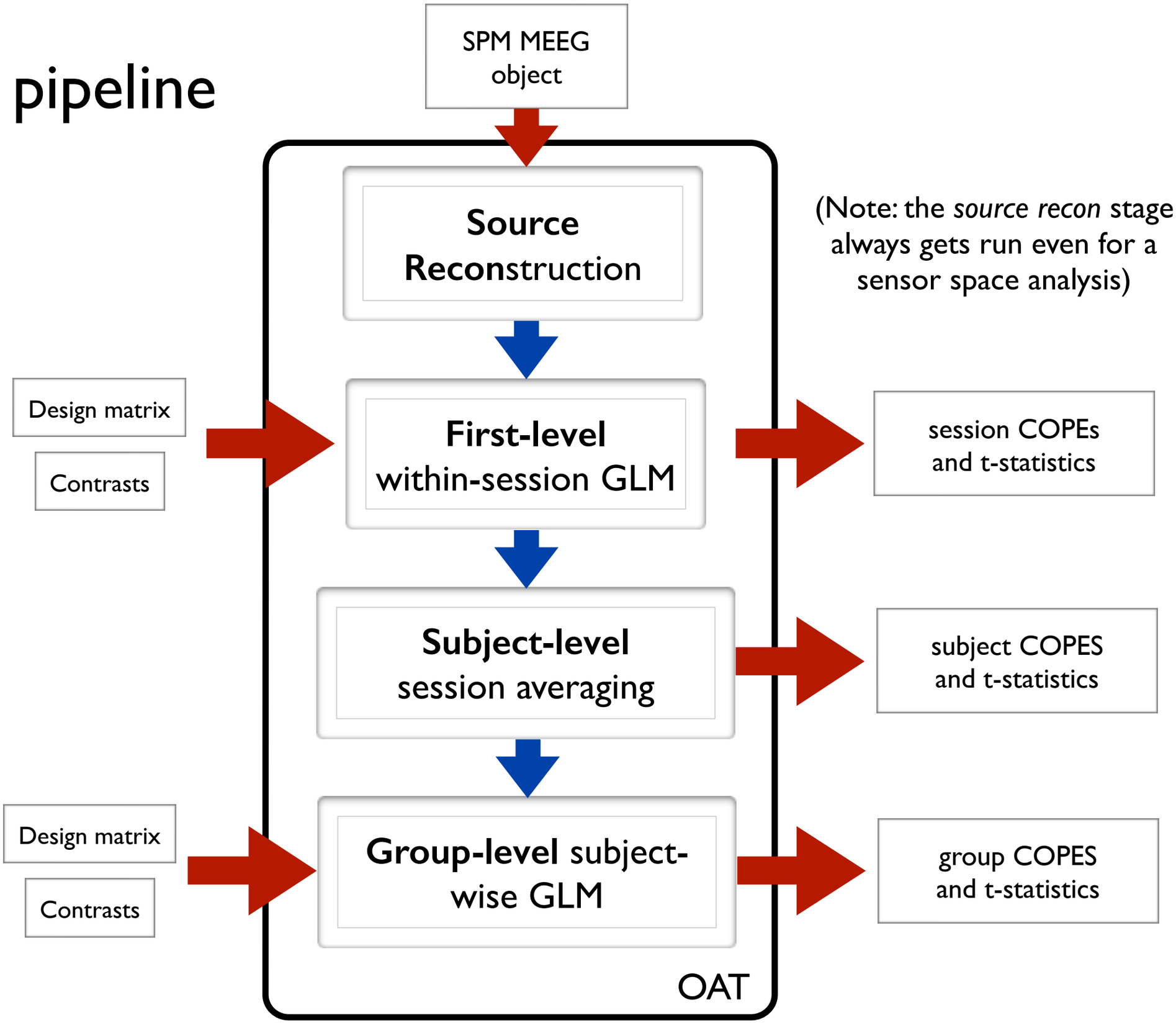
- **Solution: use abs(COPE). This means:**

  ➡ for main effects we need to do baseline correction (e.g. *oat.first_level.bc=1*)

  ➡ do ***not*** do spatial smoothing or averaging (e.g. over an ROI) until after ERF rectification (i.e. after the first-level stats have been computed)

OAT Pipeline Stages

- 4 distinct pipeline stages:



(Note: the *source recon* stage always gets run even for a sensor space analysis)

OAT

- To beamform, use the setting:
    - *oat.source_recon.method='beamform';*
- Analysis in:
    - ➡ time domain (e.g. ERF-style), or
    - ➡ in time-frequency domain (e.g. induced responses)
- **Analysis over:**
    - ➡ whole brain, or
    - ➡ ROIs (All in MNI coordinates)
- **First-level (within-subject) analysis, using:**
    - ➡ trial-wise GLM on epoched data
    - ➡ time-wise GLM on continuous data
- **Group-level (between-subject) subject-wise GLM analysis**

Practical

1) Source space trial-wise GLM using OAT on **epoched** data:

a) Time-domain (ERF) analysis

b) Time-frequency (induced response) analysis

c) Whole brain / ROIs

2) Source space time-wise GLM using OAT on **continuous** data.