M/EEG toolkit, Nijmegen, April 5, 2017

Source reconstruction using beamformer techinques

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M/EEG signal characteristics considered during analysis

timecourse of activity
-> ERP

spectral characteristics
-> power spectrum

temporal changes in power
-> time-frequency response (TFR)

spatial distribution of activity over the head
-> source reconstruction

Separating activity of different sources (and noise)

Use the temporal aspects of the data
at the channel level

- ERF latencies
- ERF difference waves
- Filtering the time-series
- Spectral decomposition

Use the spatial aspects of the data

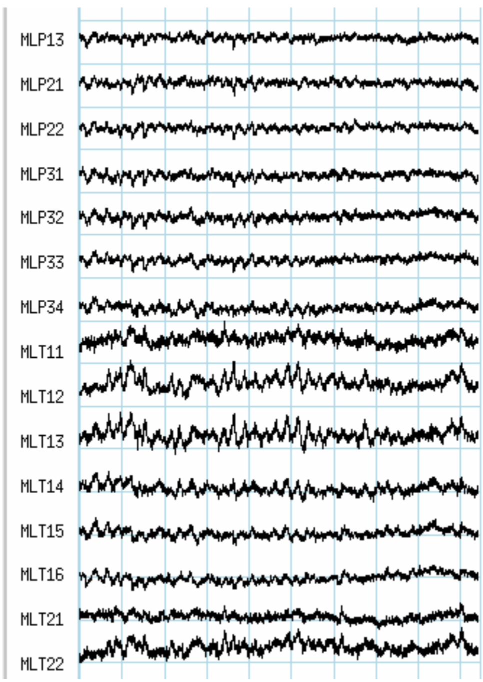
- Volume conduction model of head
- Estimate source model parameters

Separating activity of different sources (and noise)

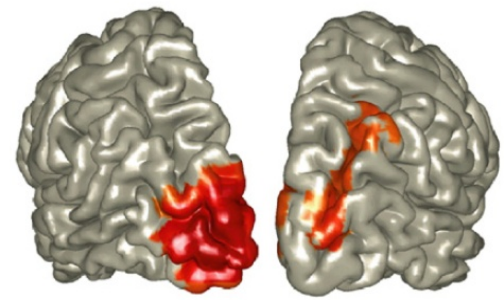
Use the temporal aspects of the data
  at the channel level
  - ERF latencies
  - ERF difference waves
  - Filtering the time-series
  - Spectral decomposition

Use the spatial aspects of the data
  - Volume conduction model of head
  - **Estimate source model parameters**

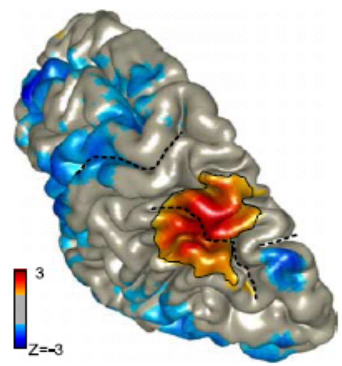
How did the brain get these red and blue blobs?

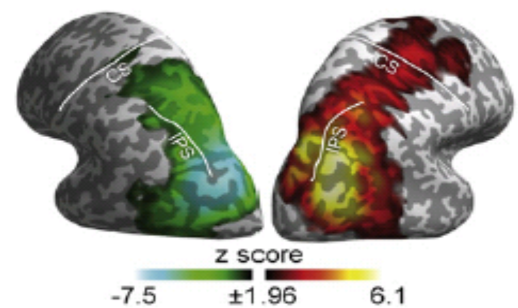


to

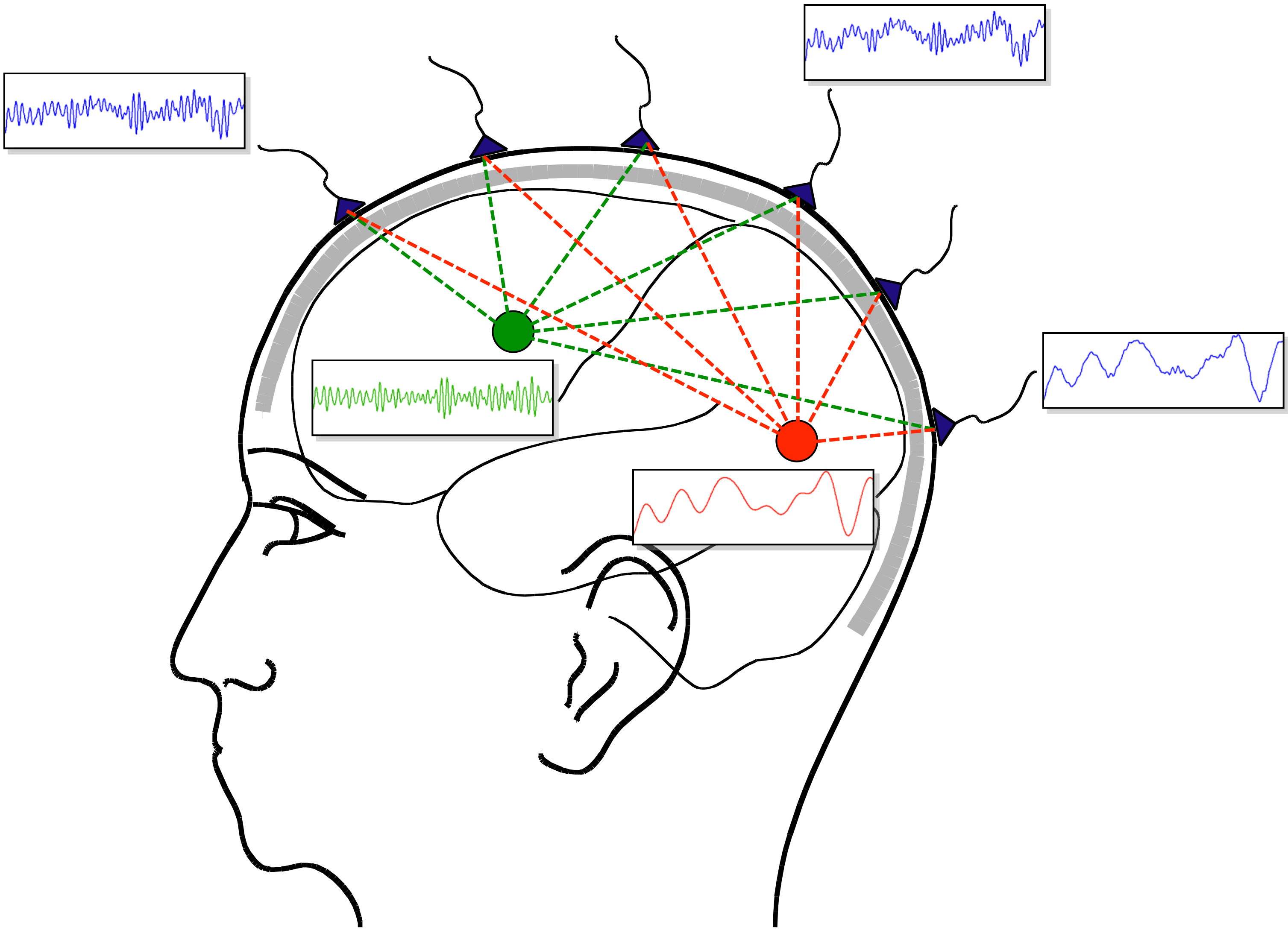


Dorsal view





Superposition of source activity



Superposition of source activity

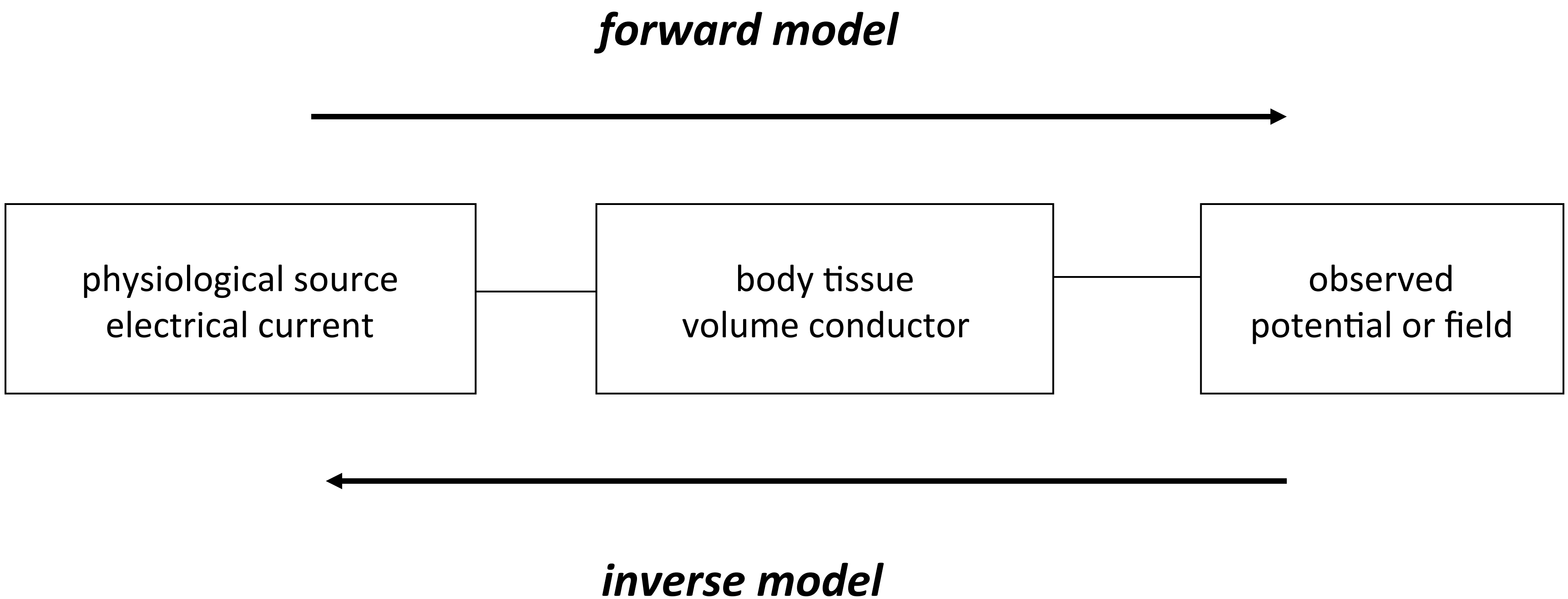
Varying "visibility" of each source to each channel

Timecourse of each source contributes to each channel

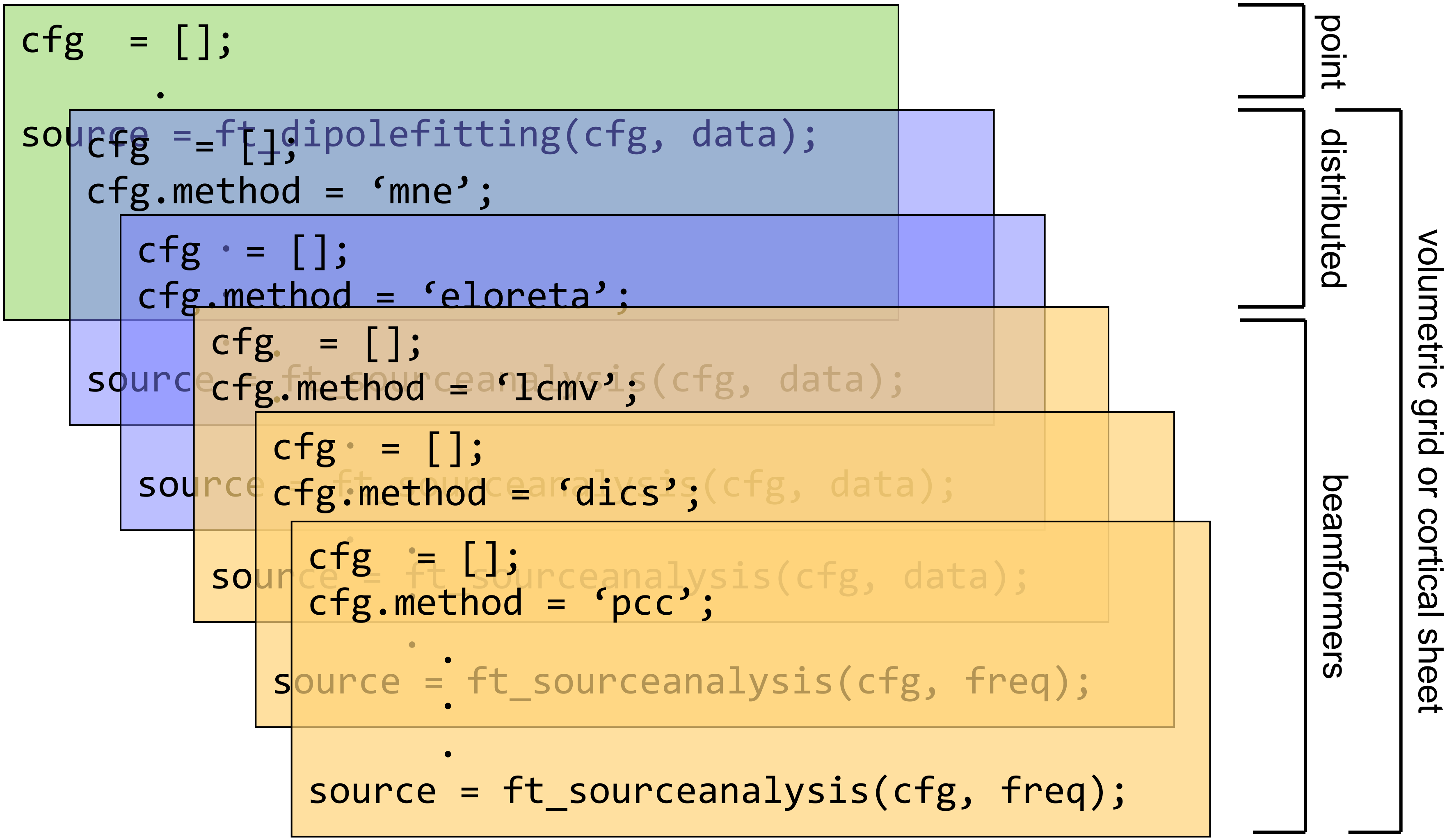
The contribution of each source depends on its "visibility"

The activity on each channel is a superposition of
all source activity

Source modelling: overview



Source reconstruction in FieldTrip



Source reconstruction methods

Single and multiple (point-like) dipole models

Assume a small number of sources

Where (& how many) are the strongest sources?

Distributed dipole models

Assume activity everywhere

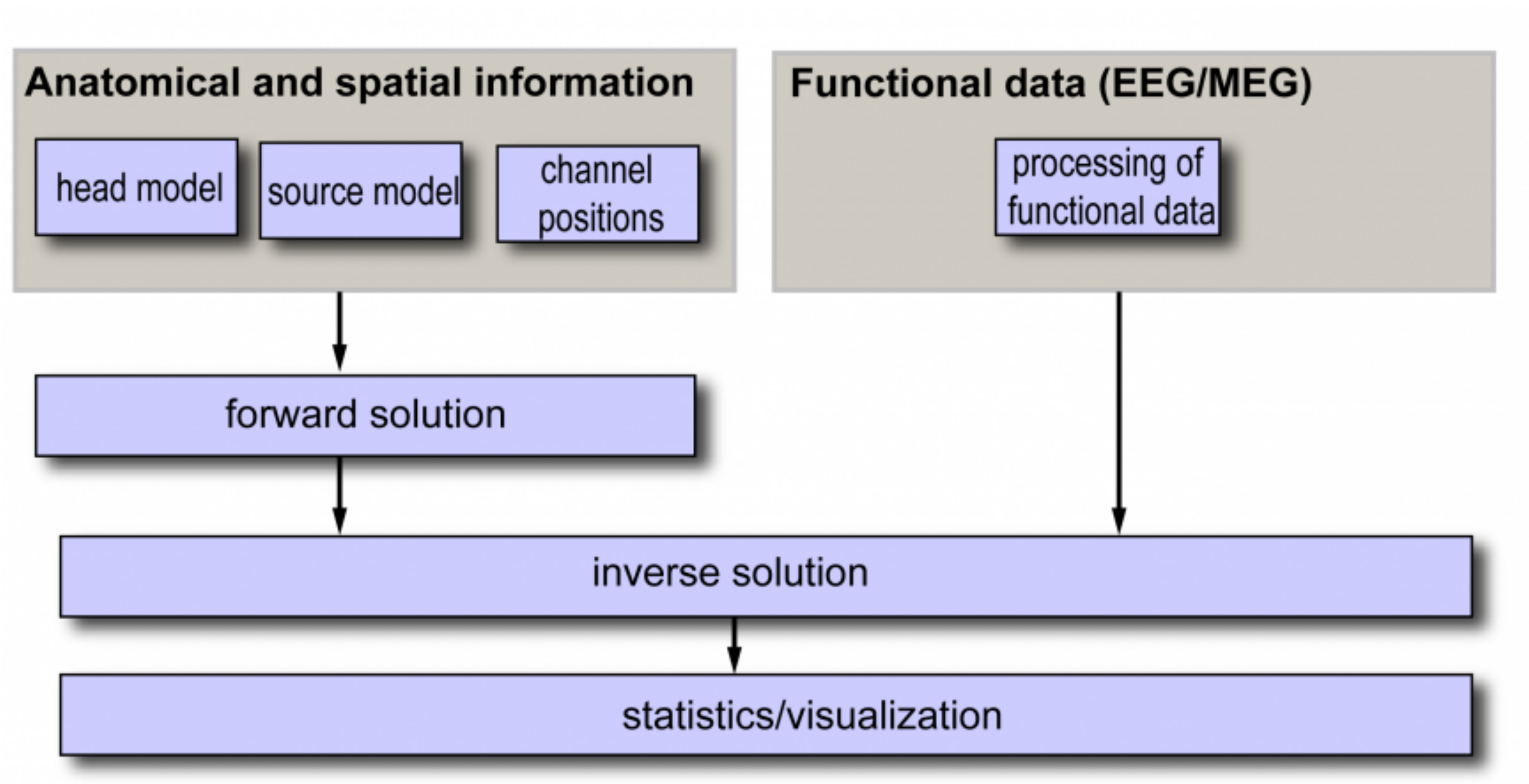
What is the distribution of activity over the brain?

Spatial filtering

Assume that the time-courses of different sources are uncorrelated

What is the amount of activity at a given brain location?

Procedure for reconstructing oscillatory activity



http://www.fieldtriptoolbox.org

Stage 1: Design experiment

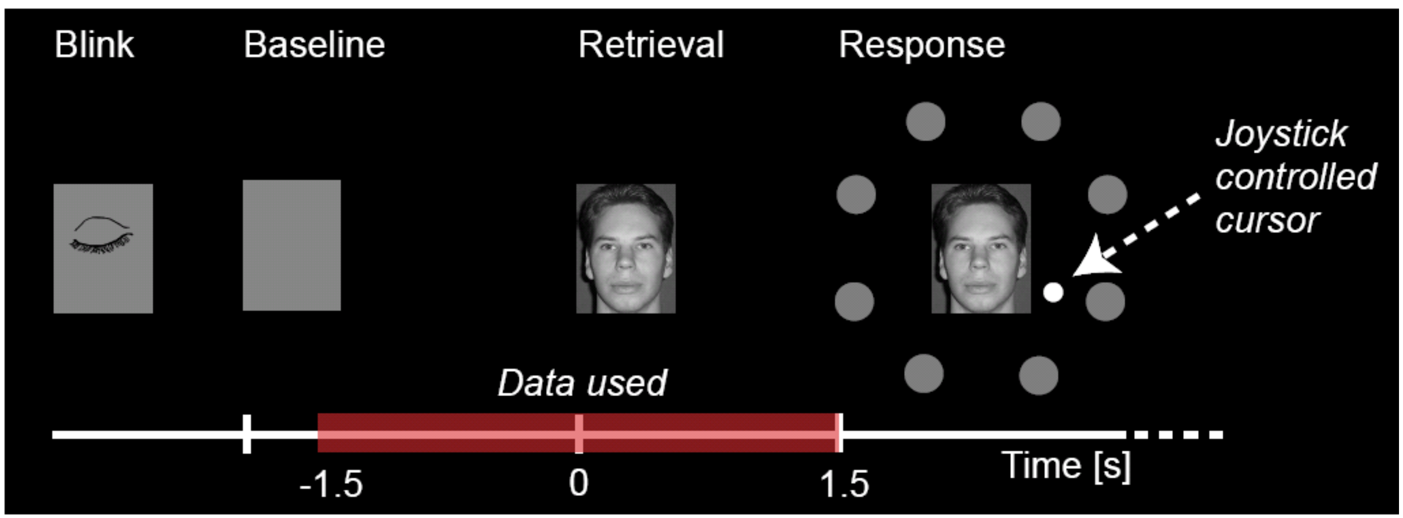
Baseline recommendable

Sufficient length of stationary signal

- Delayed response

Avoid artifacts

- Eyeblink stimulus
- Experiment not too long, or introduce breaks (muscle artifacts)



Stage 2: Measuring brain activity

Record EOG and ECG to remove artifacts

Measure positions sensors/electrodes in relation to head

Reduce head movement (MEG)

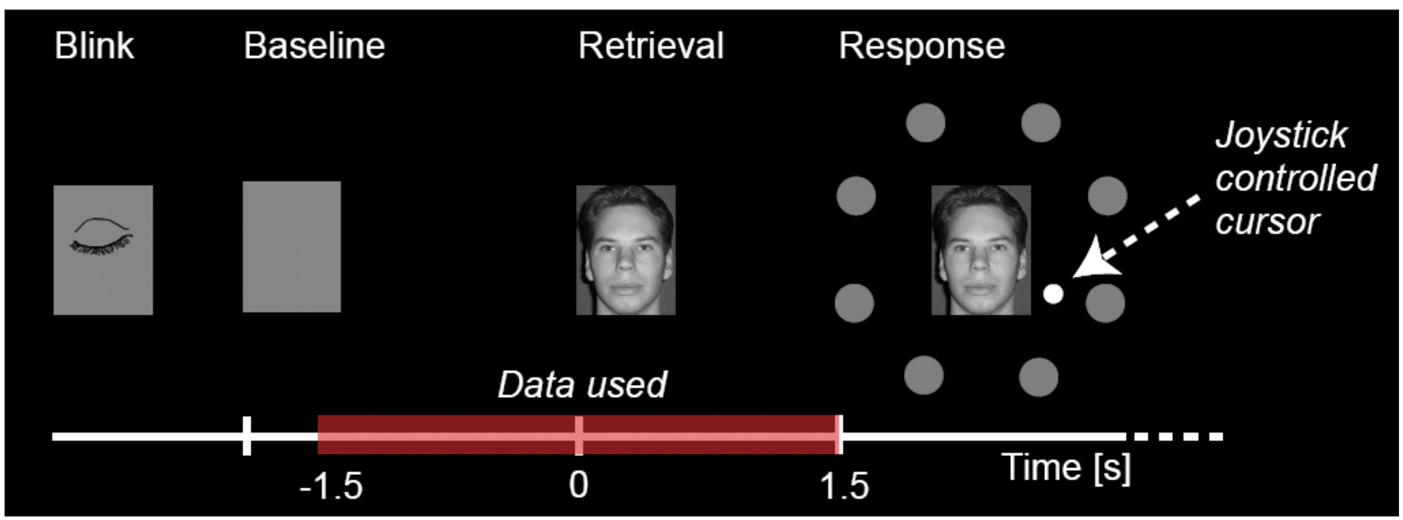
Make anatomical MRI scan for realistic head model
and for spatial normalization over subjects

Perform (if applicable and possible) a localizer task

Stage 3: Data analysis: Preprocessing

Data segmentation

Artifact removal



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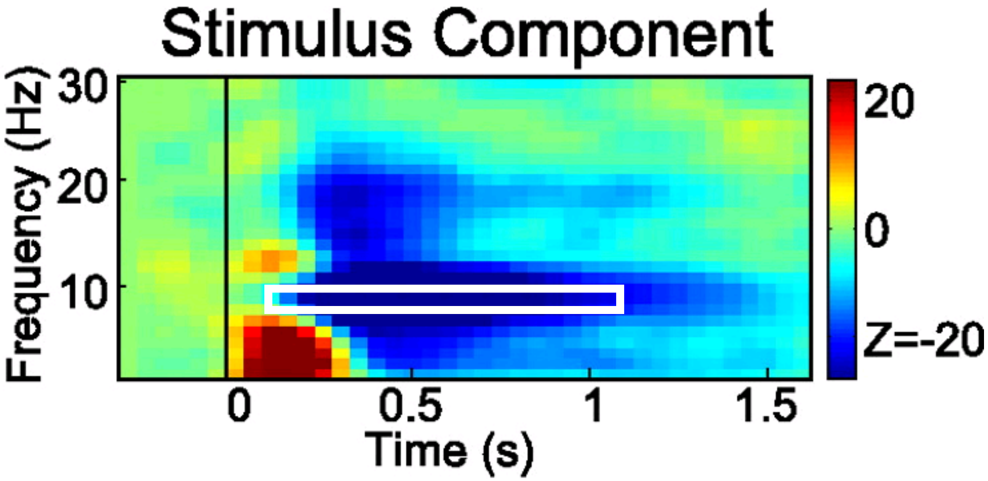
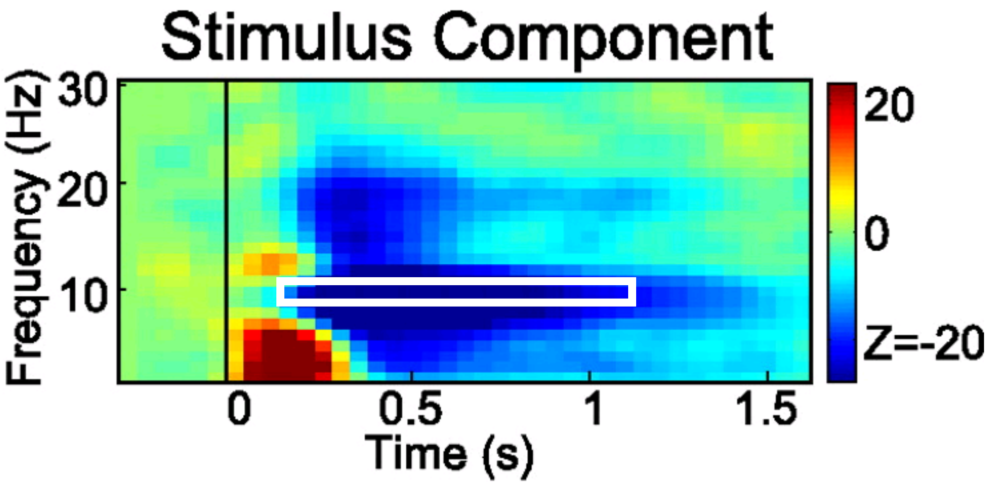
Stage 3: Data analysis: Time frequency analysis



“Beam” this time-frequency tile

0.1 to 1.1 s
~10 Hz

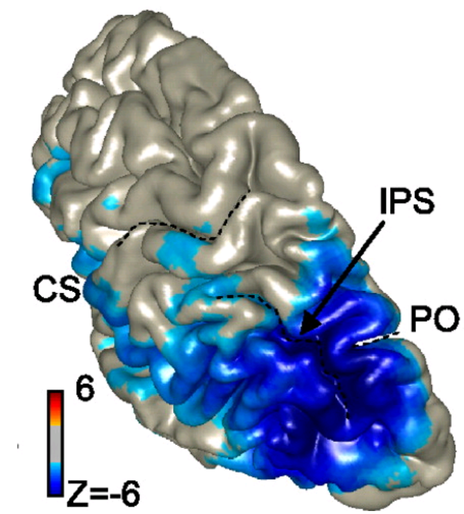
Stage 3: Data analysis: Time frequency analysis



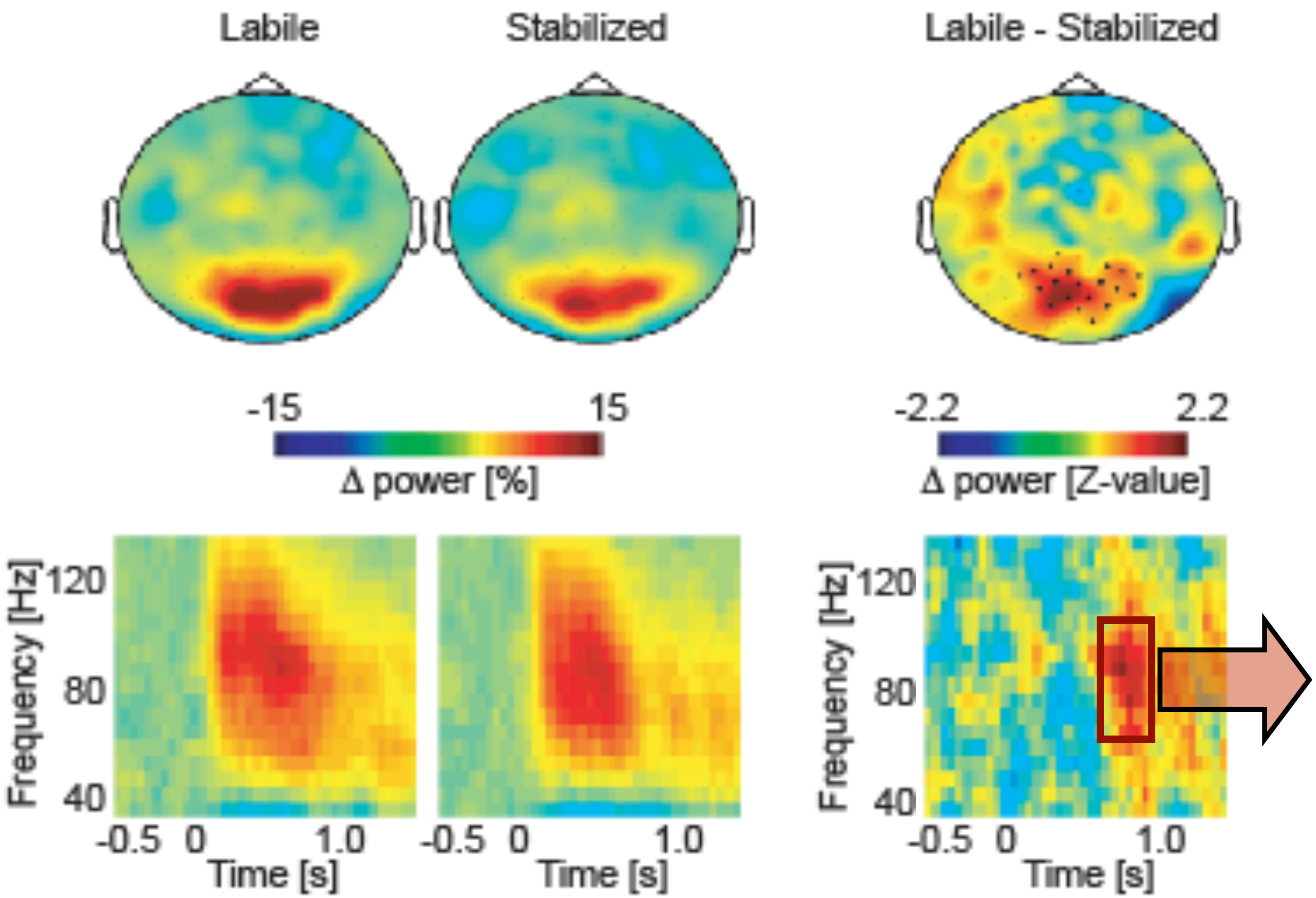
Time window of 1 second:

Frequency resolution 1 Hz

Bandwidth: 9.5 – 10.5 Hz



Stage 3: Data analysis: Time frequency analysis

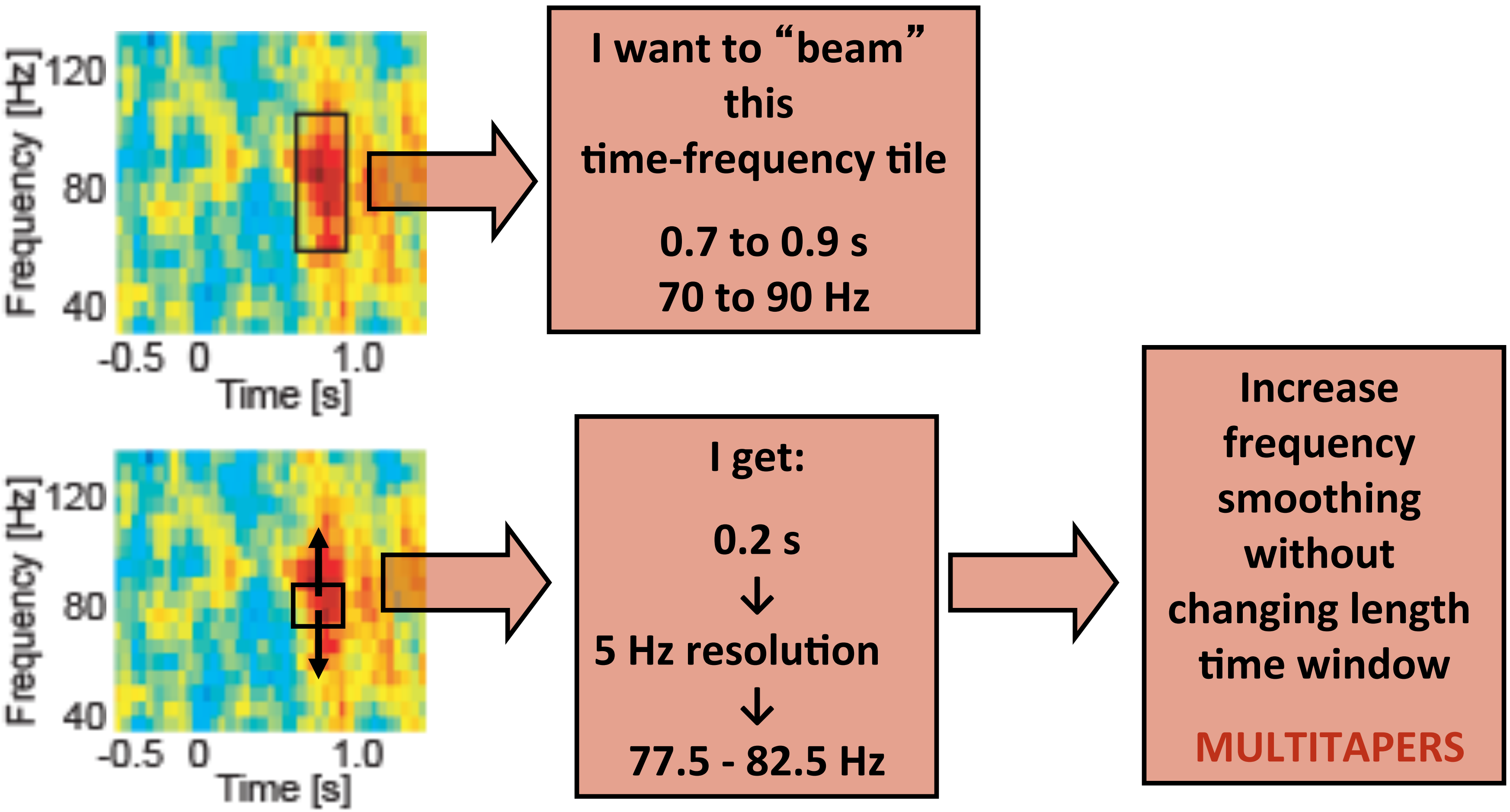


"Beam" this time-frequency tile

0.7 to 0.9 s
70 to 90 Hz

http://www.fieldtriptoolbox.org

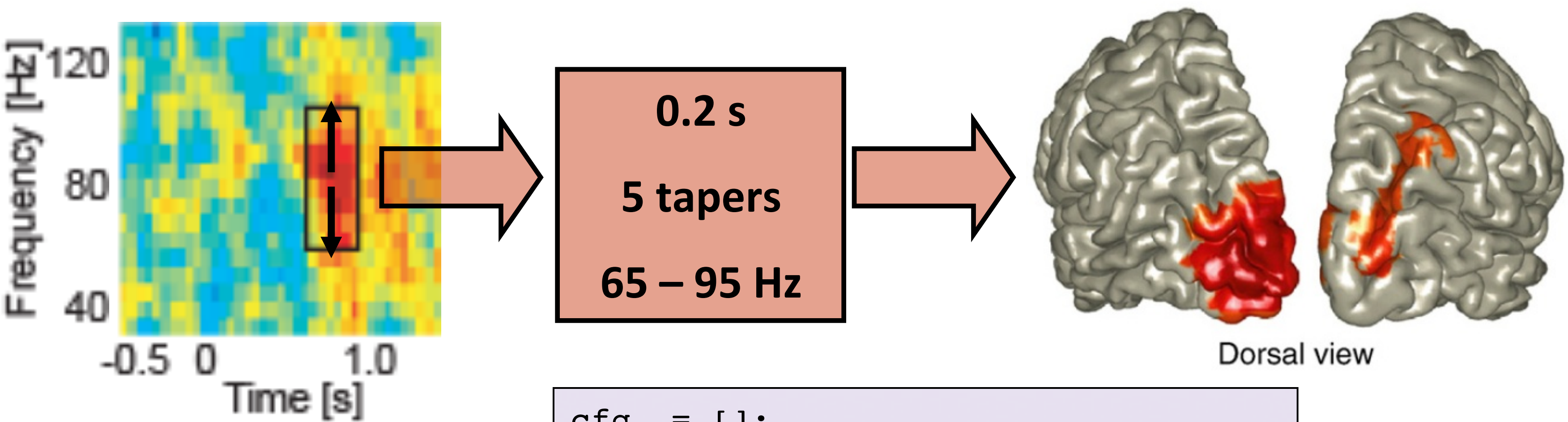
Stage 3: Data analysis: Time frequency analysis



Recap: multitapers

More tapers for a given time window will result in more spectral smoothing

Several orthogonal tapers are used for the time window, subsequently the Fourier transform is calculated for each tapered data segment and then combined.

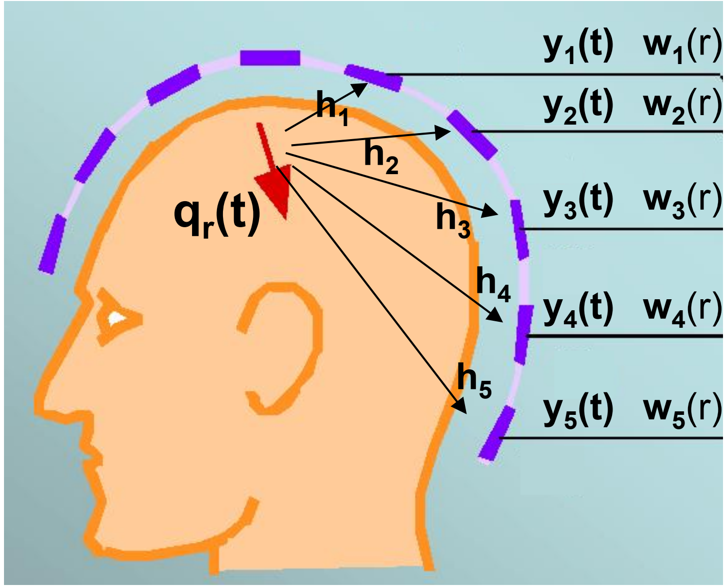



```
cfg  = [];
cfg.method = 'mtmconvol';
cfg.output = 'powandcsd';
cfg.toi    = 0.8;
cfg.foi    = 80;
cfg.t_ftimwin = 0.2;
cfg.tapsmofrq = 15;
freq = ft_freqanalysis(cfg, data);
```

Beamformer: the question

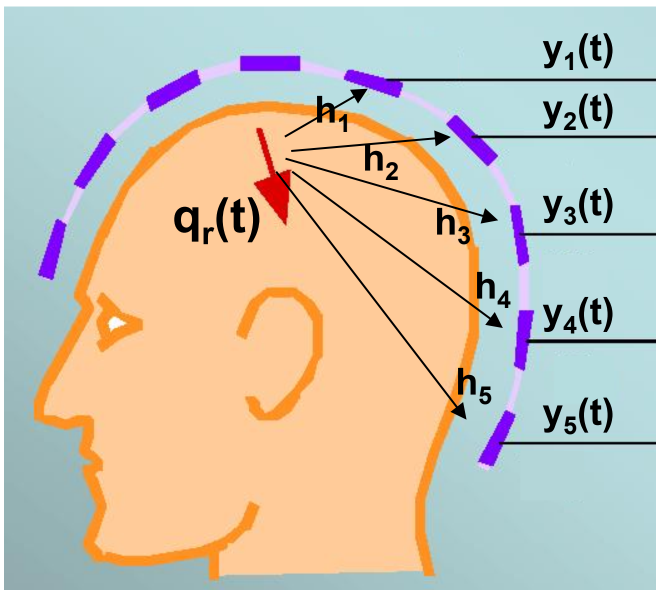
What is the activity of a source **q**, at a location **r**, given the data **y**?

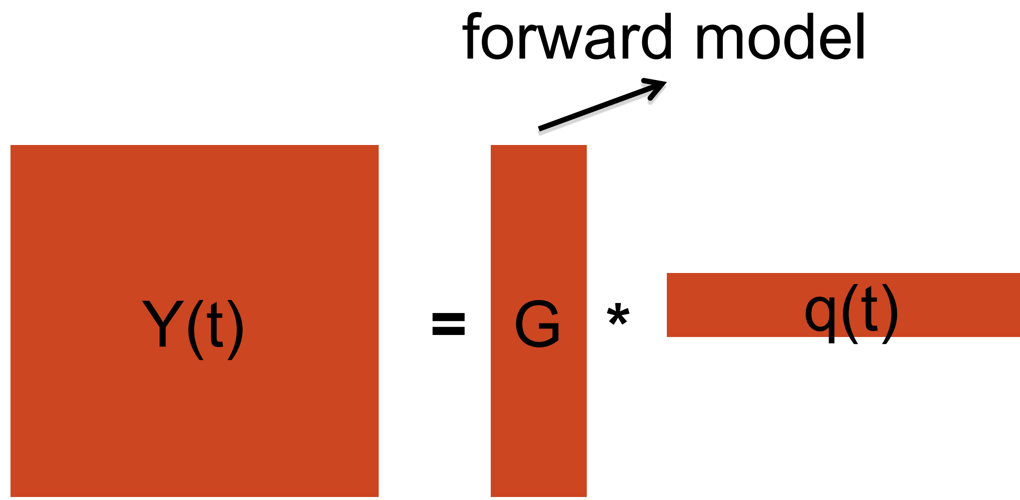
We estimate **q** with a spatial filter **w**



$$\hat{q}_r(t) = \mathbf{w}(r)^T \mathbf{y}(t)$$

Beamformer ingredients: forward model





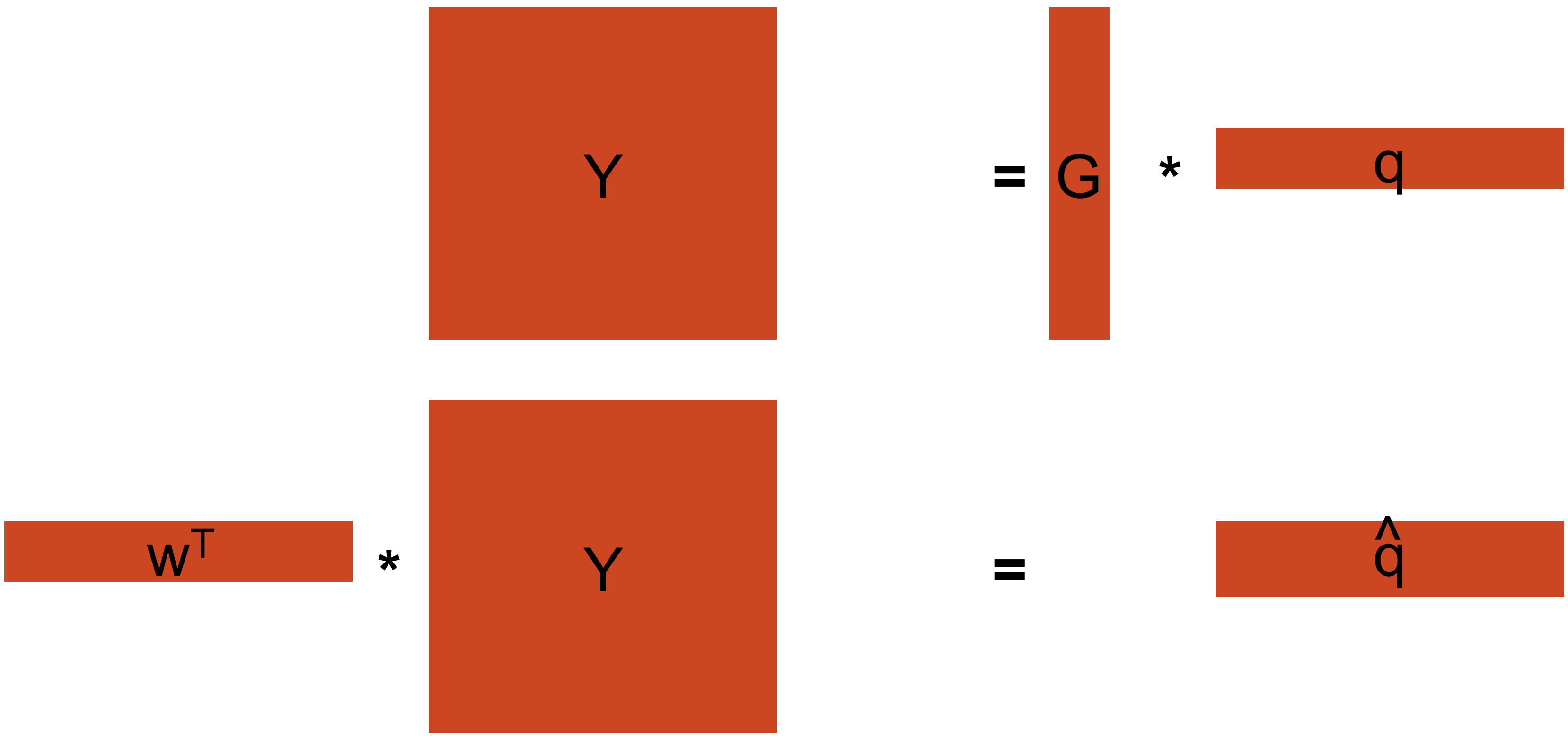
Beamformer: the question revisited

What is the activity of a source **q**, at a location **r**, given the data **Y**?

We know how to get from source to data: $\boldsymbol{Y} = \boldsymbol{G} * \boldsymbol{q}$

We want to go from data to source: $\boldsymbol{w}^{T} * \boldsymbol{Y} = \hat{\boldsymbol{q}}$

$\mathbf{w}^{\mathbf{T}}$ is called a spatial filter



Beamformer: the question revisited

What is the activity of a source **q**, at a location **r**, given the data **Y**?
We know how to get from source to data: $\boldsymbol{Y} = \boldsymbol{G} * \boldsymbol{q}$
We want to go from data to source: $\boldsymbol{w}^T * \boldsymbol{Y} = \hat{\boldsymbol{q}}$
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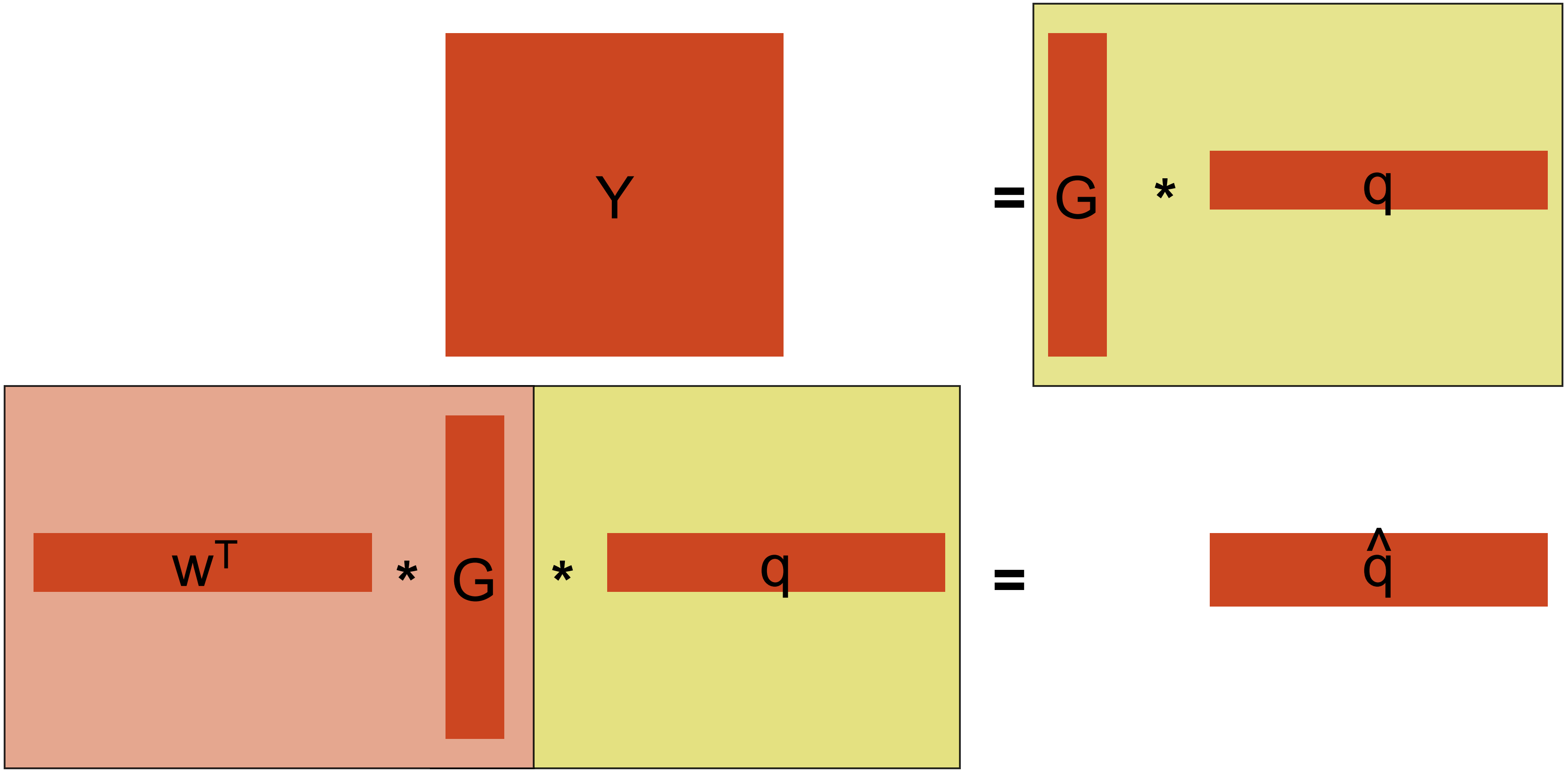
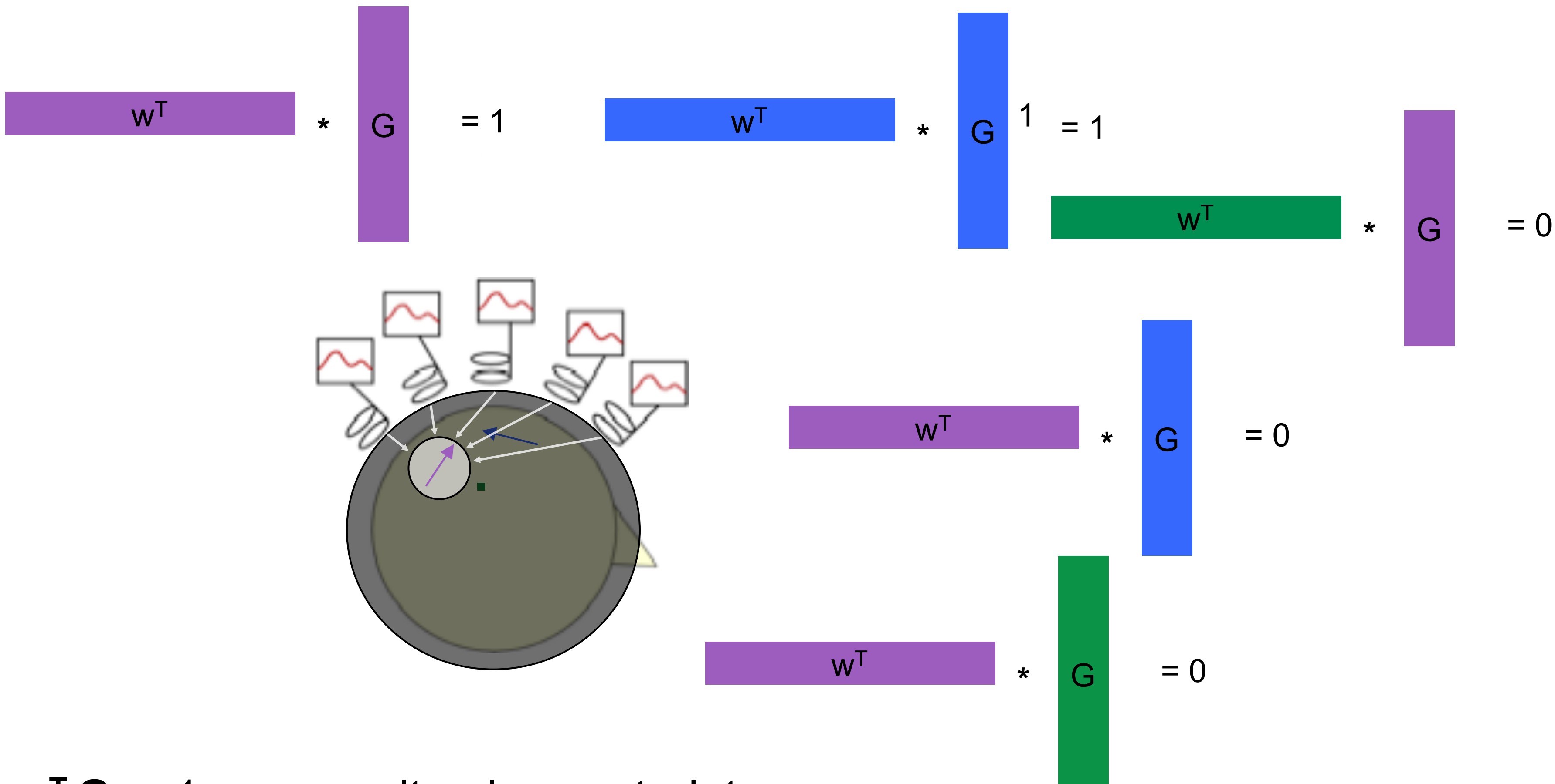


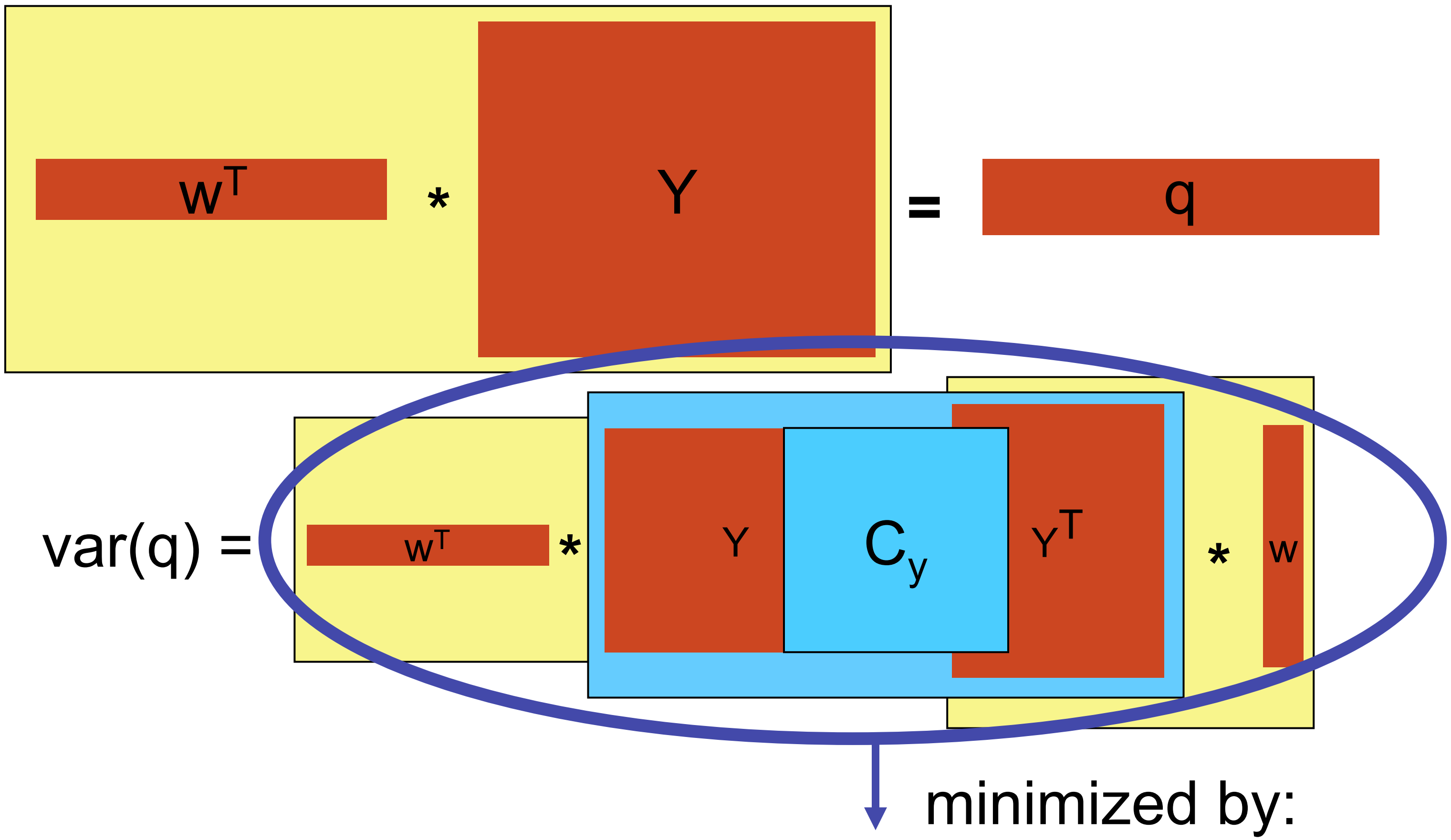
What would we like a spatial filter to do?



$\mathbf{w^T{}_i G_i}$ = 1 unit gain constraint

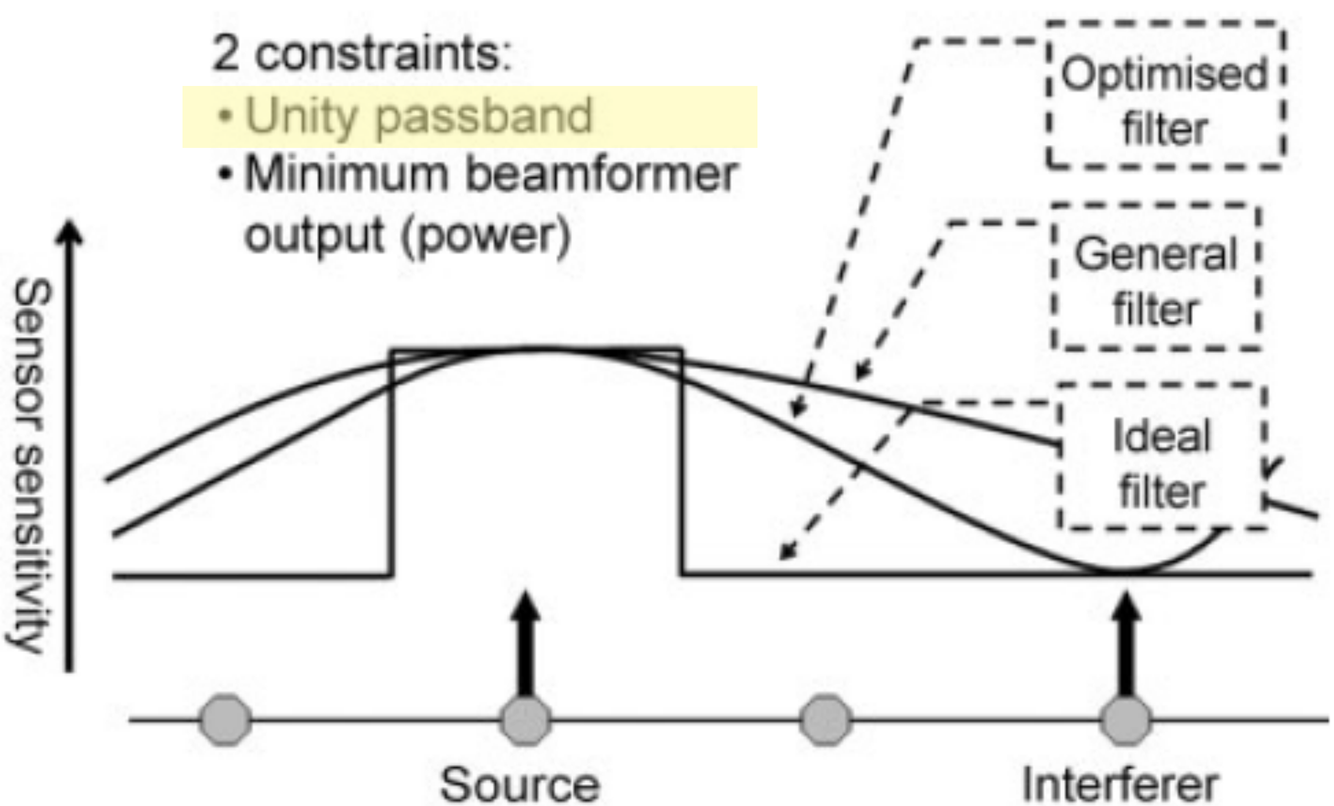
$\mathbf{w^T{}_i G_k}$ = 0 cannot generally be fulfilled, hence we minimize the *variance* of the filter output

Adaptive spatial filter: minimum variance constraint

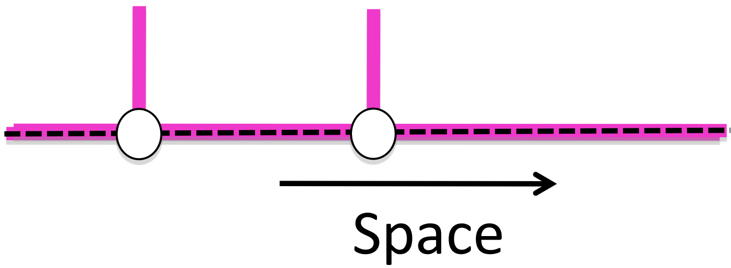


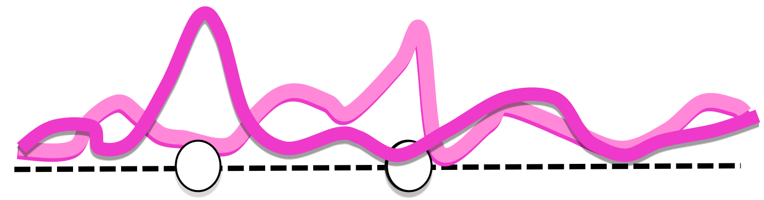
$$\mathbf{w^T = [G^T C_y^{-1} G]^{-1} G^T C_y^{-1}}$$

Spatial sensitivity and leakage of a filter

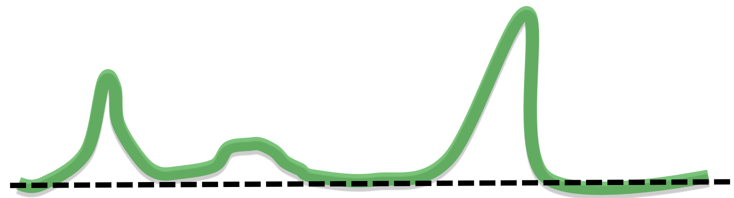


Spatial sensitivity and leakage of a filter

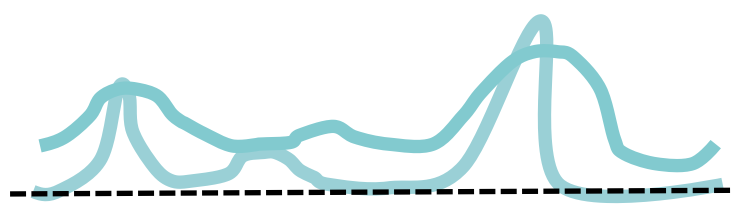




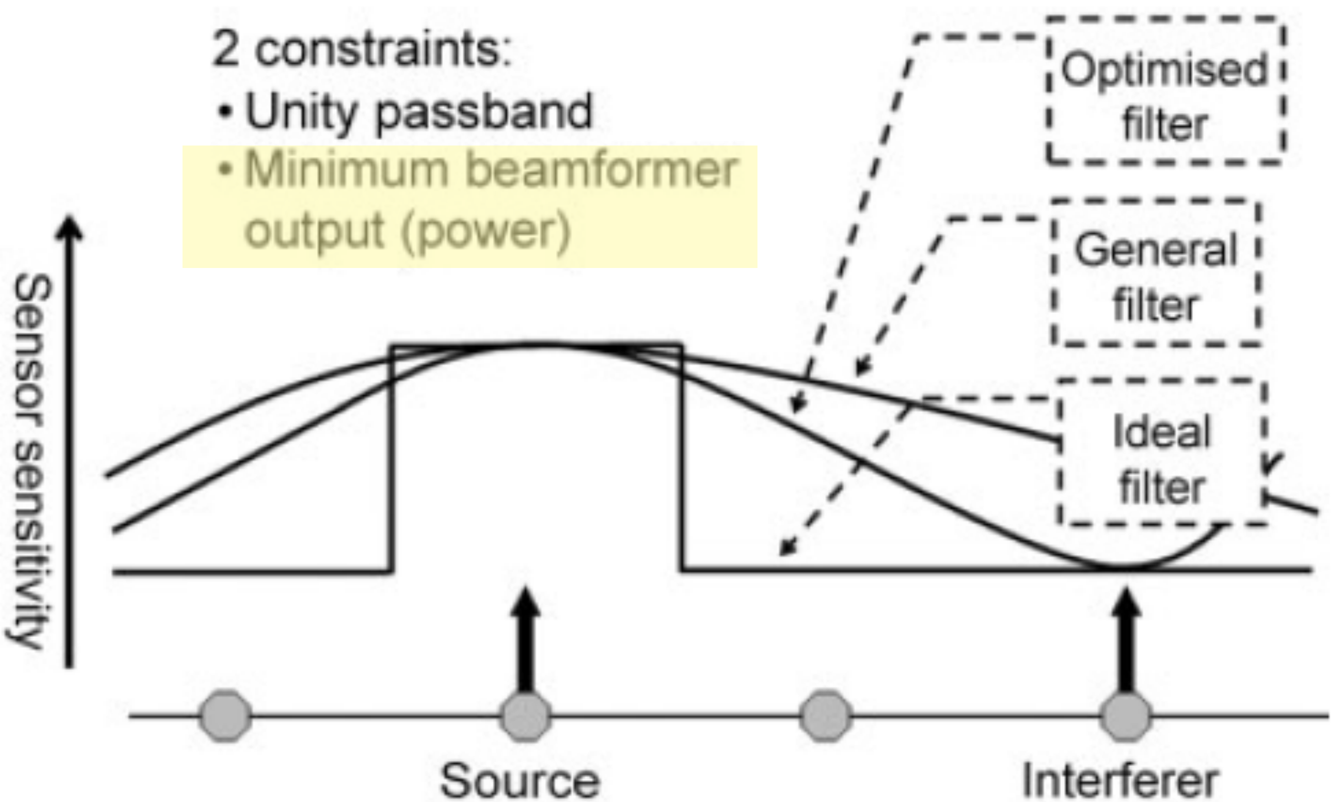
True source activity



Estimated source activity



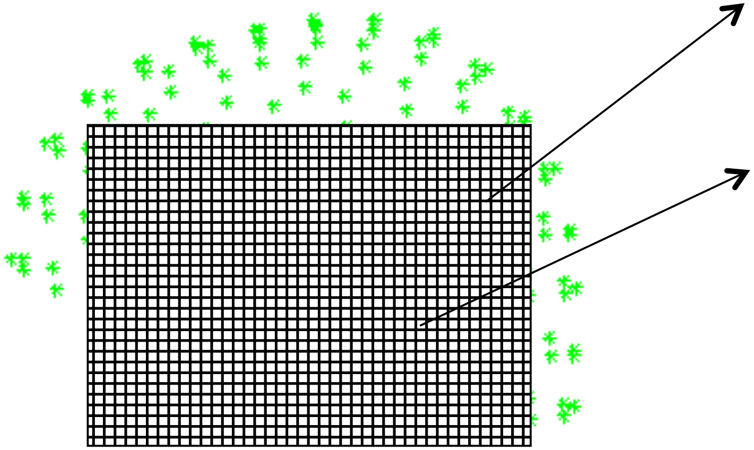
Spatial sensitivity and leakage of a filter

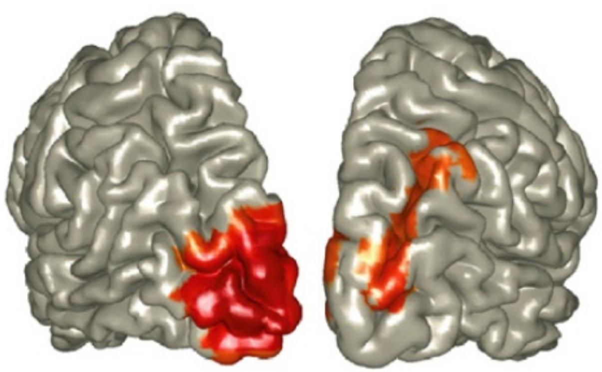


Beamforming: in practice

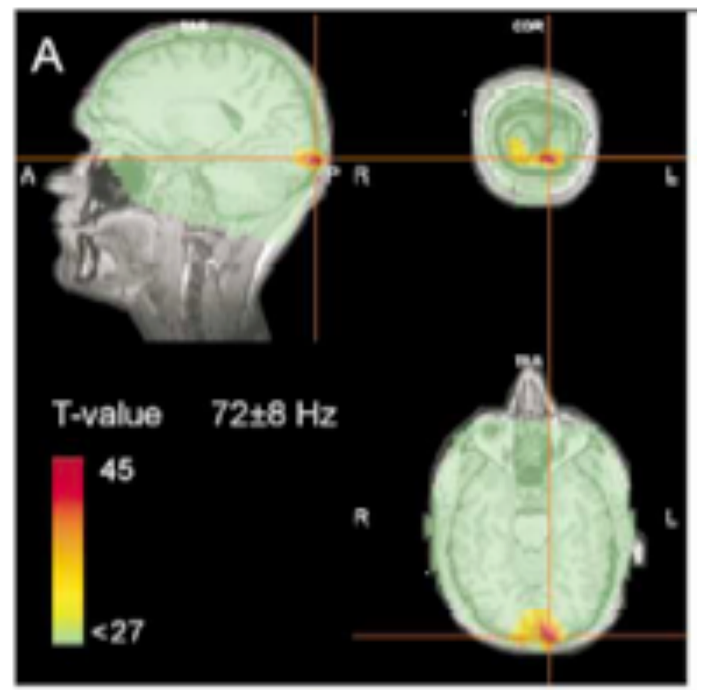
$$w^T = [G^T C_y^{-1} G]^{-1} G^T C_y^{-1}$$

$$w^T = [G^T C_y^{-1} G]^{-1} G^T C_y^{-1}$$



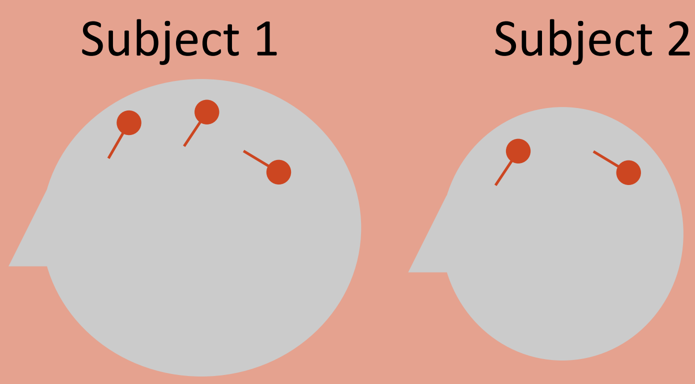


Dorsal view



Strengths of beamforming

Easier to average over subjects (compared to dipole methods)



Suitable for SPM-like statistics

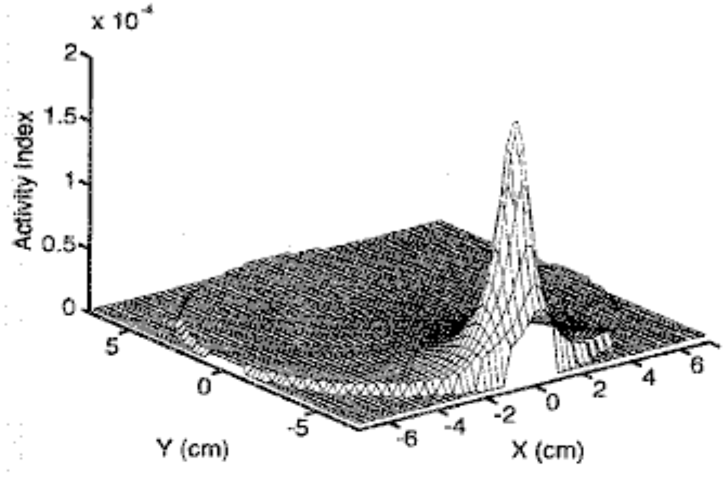
Because source estimation at each point independent of other points

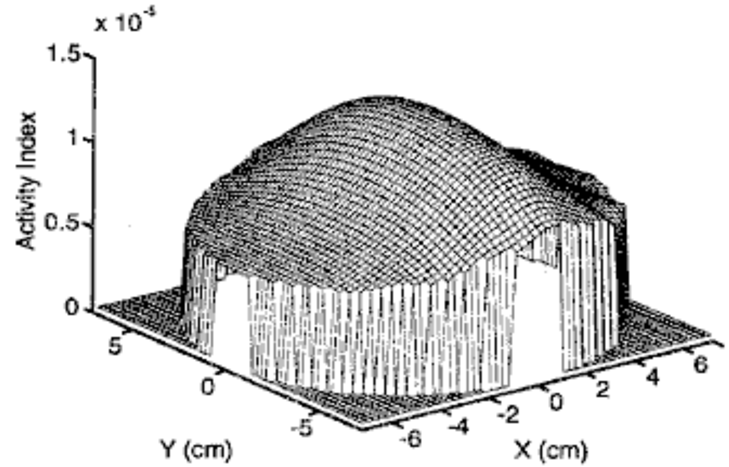
(Most often) beamforming more spatially focal than distributed source (min norm) methods

No a priori assumptions about amount of sources or locations of sources

Limitation of beamforming

Sources should not be too correlated



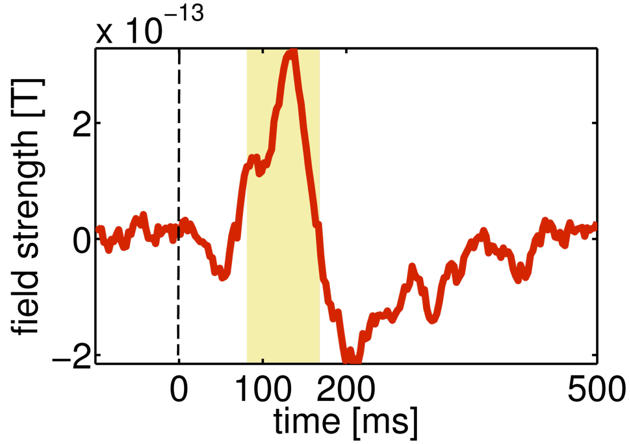


uncorrelated sources, van Veen et al. (1997)

mildly correlated sources

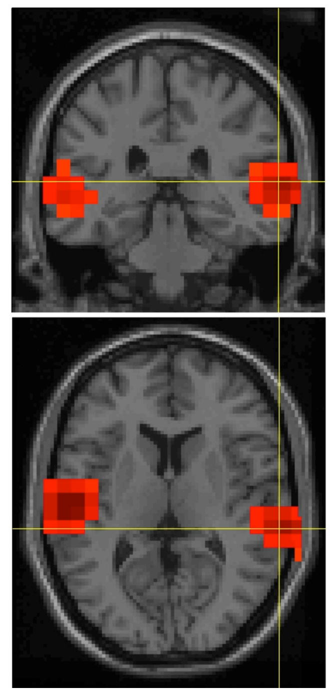
perfectly correlated sources

Limitation of beamforming




```
cfg = [];
cfg.covariance='yes';
cfg.covariancewindow = [-.2 .2];
avg = ft_timelockanalysis(cfg,tlk);
```

```
cfg  = [];
cfg.method = 'lcmv';
      .
      .
source=ft_sourceanalysis(cfg, avg);
```



Summary of beamforming

- Scanning method, each point is estimated independently
- Inverse modeling by spatial filter
  - Unifies two constraints:
  - (1) pass all activity at location of interest while
  - (2) suppressing as much activity (i.e. noise, other sources) as possible
  - Makes use of covariance of data, and forward model
- Both possible in time and frequency domain
- No a priori assumptions about source configurations
- Applicable in very many scenarios
  - Except when you have good reason to expect strongly correlated sources

Comparing beamforming to other methods

Data model

$$M = G_1X_1 + G_2X_2 + ... + G_nX_n + noise$$

$$M = G\ X\ + noise$$

Data model
for sequential dipole fitting

$$M = G_1X_1 + G_2X_2 + ... + G_nX_n + \text{noise}$$

n is typically small

$$(M - G_1X_1 \qquad\qquad) = \text{residual}$$

measured data　　model data

$X' = W M$, where $W = G^T (G G^T)^{-1}$

Data model
for distributed source estimates

$$M = G_1X_1 + G_2X_2 + \ldots + G_nX_n + \text{noise}$$

n is typically large (> # channels)

$$M = (G_1X_1 + G_2X_2 + \ldots + G_nX_n) + \text{noise}$$

$$M = G\,X + \text{noise}$$

X' = W M,   where W ensures $\min_X \{\| M - G \cdot X \|^2 + \lambda \cdot \| X \|^2\}$

Data model
for spatial filtering

$$M = G_1X_1 + G_2X_2 + ... + G_nX_n + noise$$

any number of n

$$M = (G_1X_1 + G_2X_2 + ...) + G_nX_n + (noise)$$

$X'_n = W_n M$, where $W^T = [G_n^T C_M^{-1} G_n]^{-1} G_n^T C_M^{-1}$

Data model

$$X = h_1 s_1 + h_2 s_2 + \ldots + h_n s_n + \text{noise}$$

Data model
to estimate source timeseries

$$M = G_1X_1 + G_2X_2 + \ldots + G_nX_n + \text{noise}$$

few sources
distributed sources
one at a time

$$X'(t) = W\,M(t)$$

dipole fitting
minimum norm estimate
beamforming

Data model
to estimate spectral representations

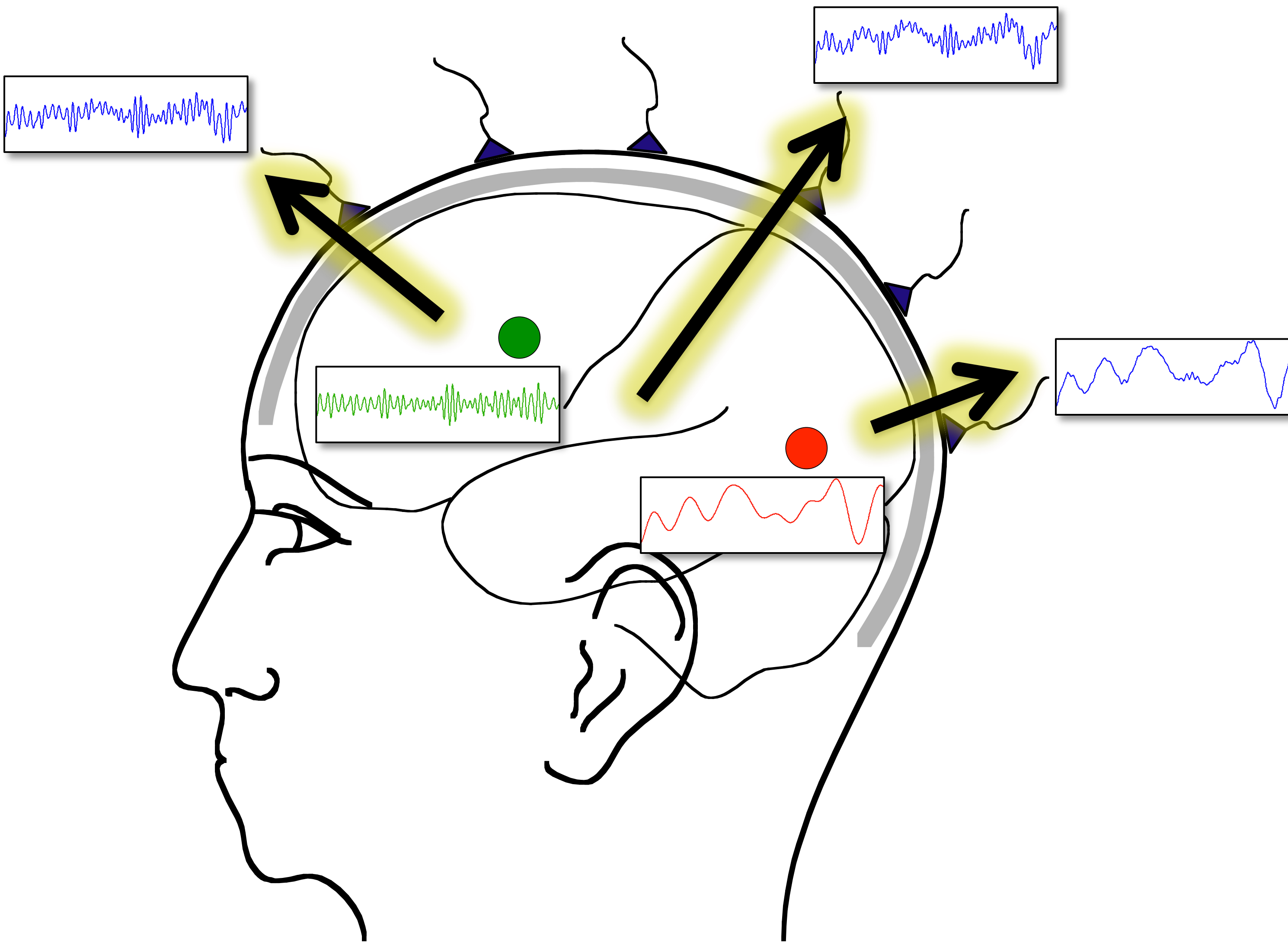
$$M = G_1X_1 + G_2X_2 + \ldots + G_nX_n + \text{noise}$$

$$X'(f) = W\, M(f)$$

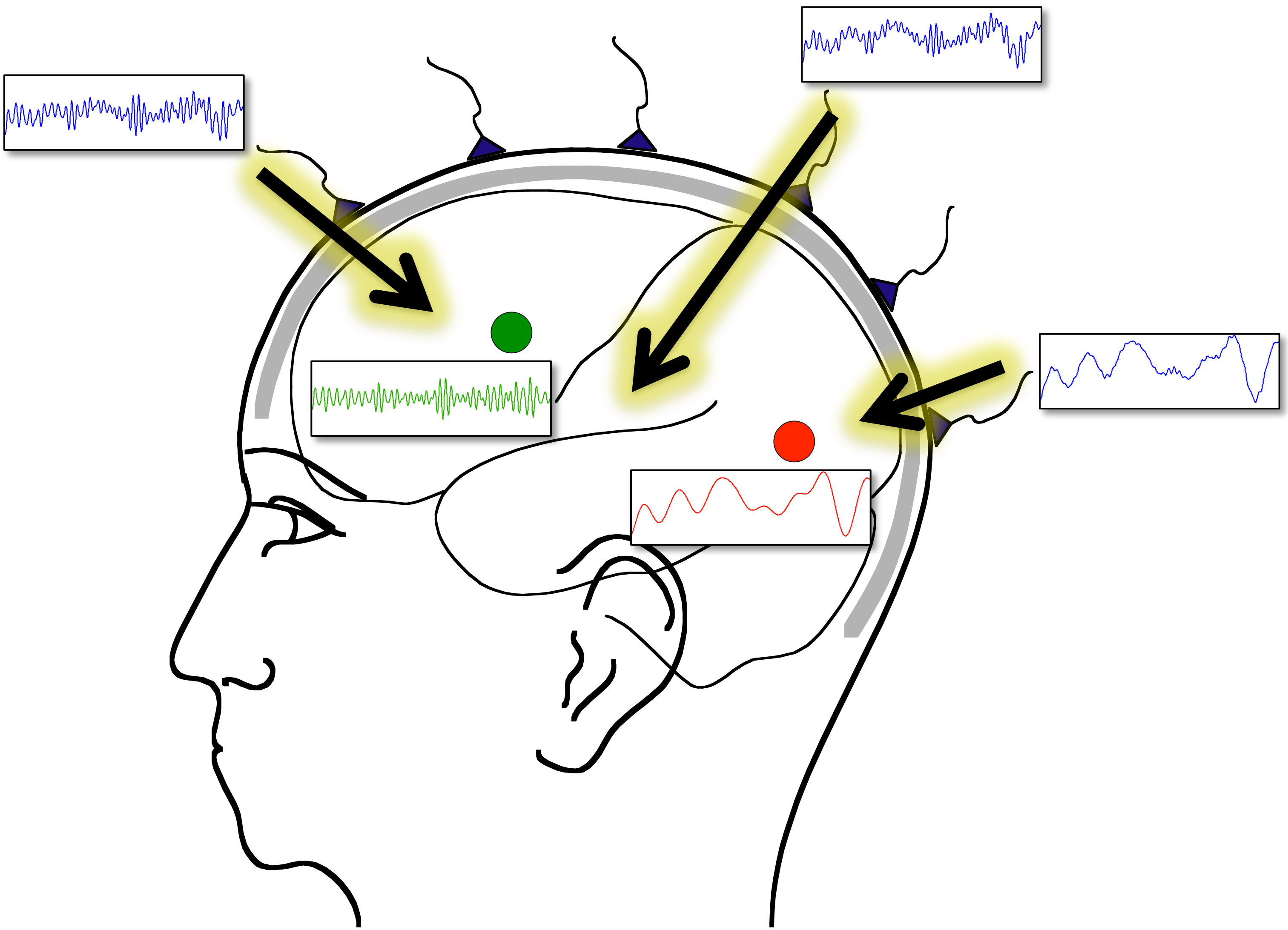
few sources
distributed sources
one at a time

dipole fitting
minimum norm estimate
beamforming

Linear mixing and unmixing



Linear mixing and unmixing



Summary of source reconstruction

Forward modelling

- Required for the interpretation of scalp topographies
- Different methods with varying accuracy

Inverse modelling

- Estimate source location and timecourse from data

Assumptions on source locations

- Single or multiple point-like source
- Distributed source

Assumptions on source timecourse

- Uncorrelated (and dipolar)