

Source reconstruction using beamformer techniques



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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

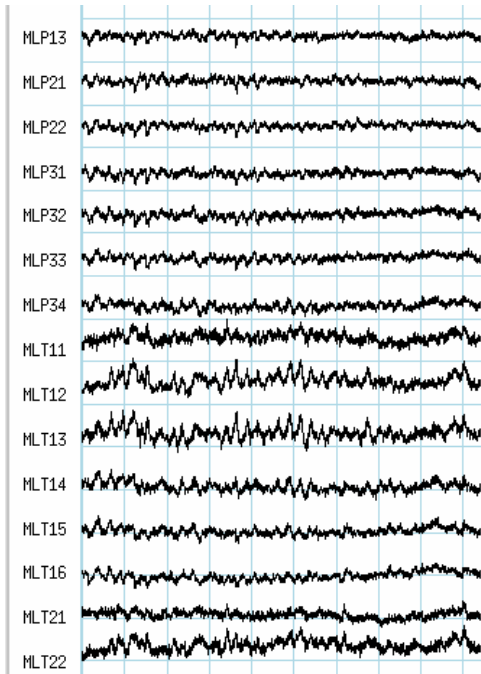
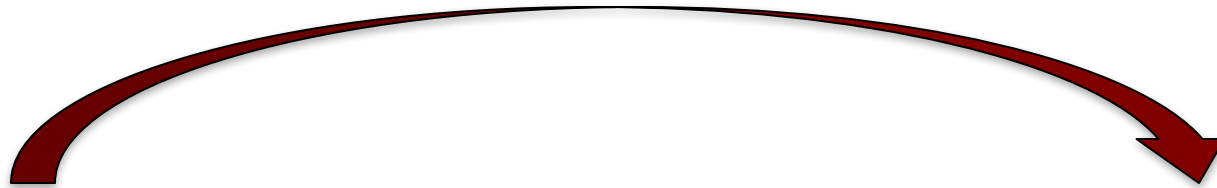
Spectral decomposition

Use the spatial aspects of the data

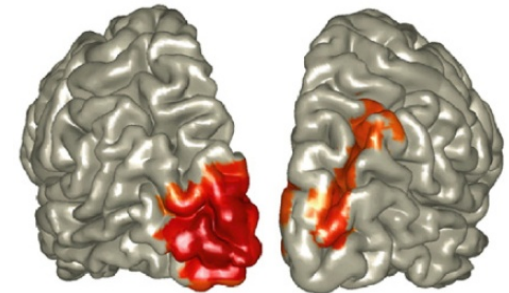
Volume conduction model of head

Estimate source model parameters

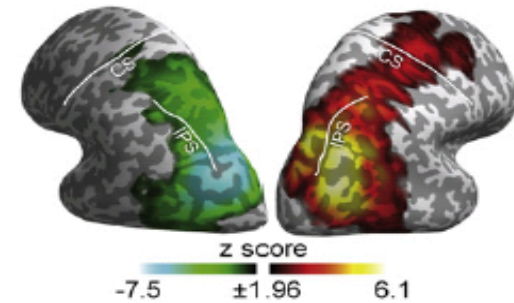
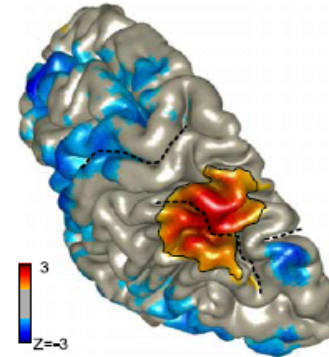
How did the brain get these red and blue blobs?



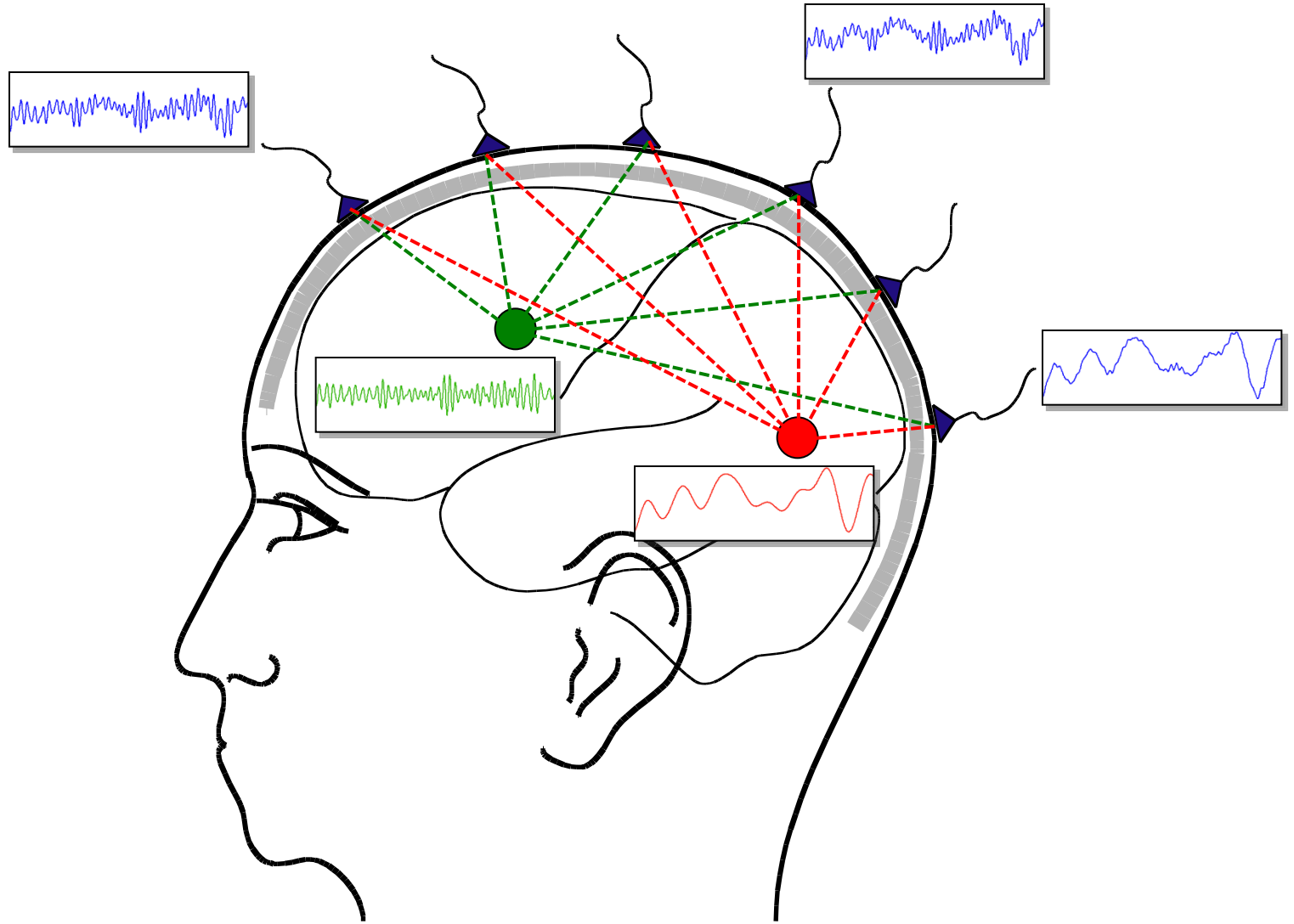
to



Dorsal view



Superposition of source activity



Superposition of source activity

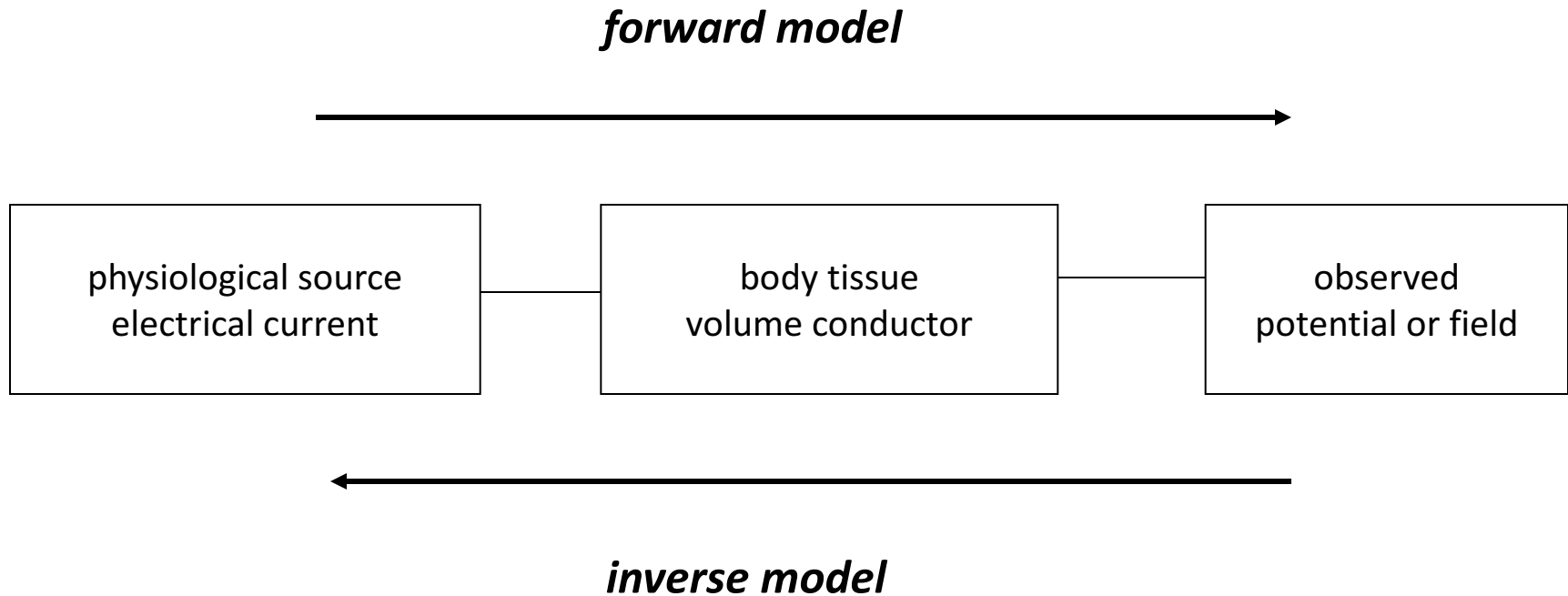
Varying “visibility” of each source to each channel

Timecourse of each source contributes to each channel

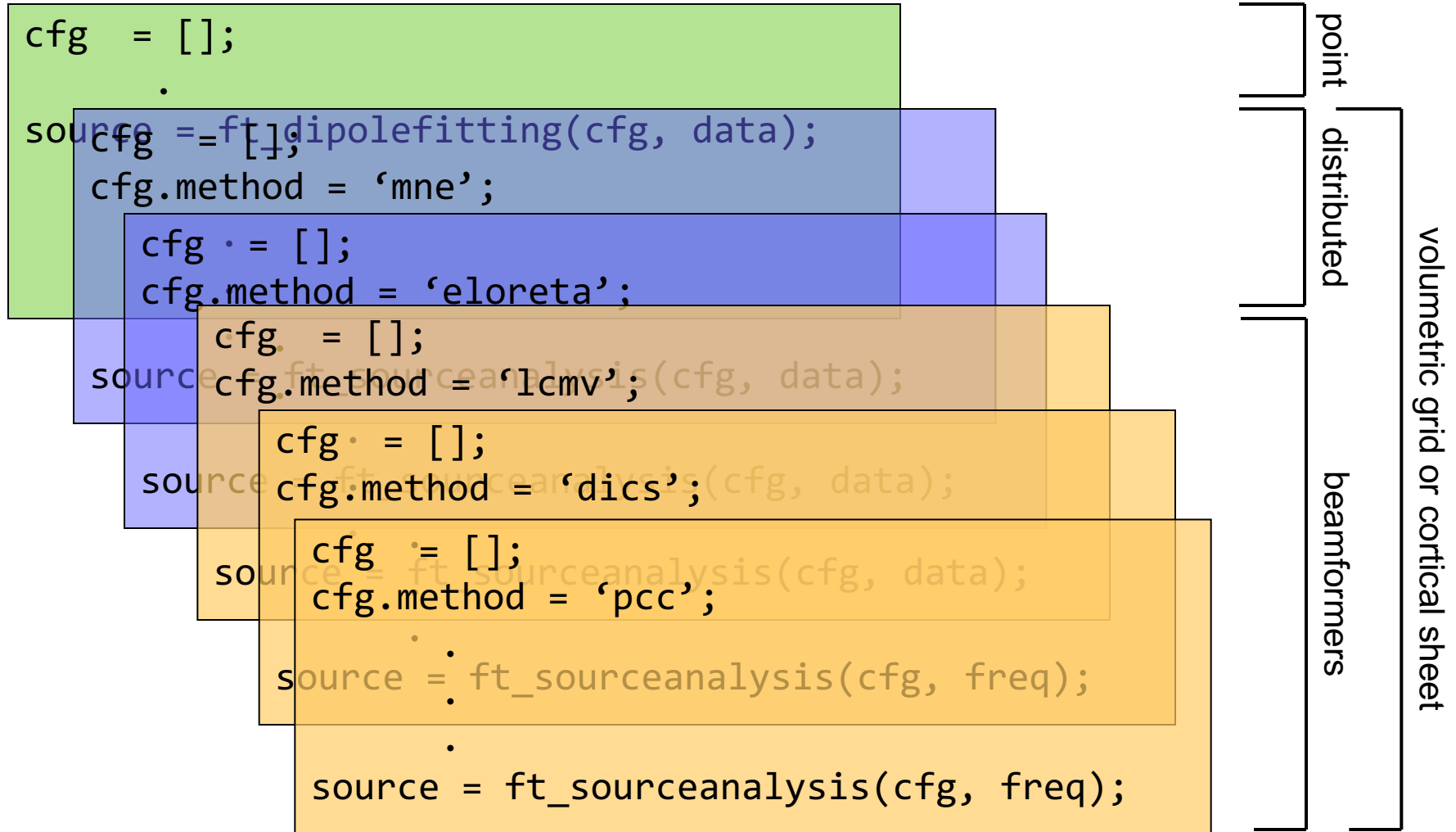
The contribution of each source depends on its “visibility”

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

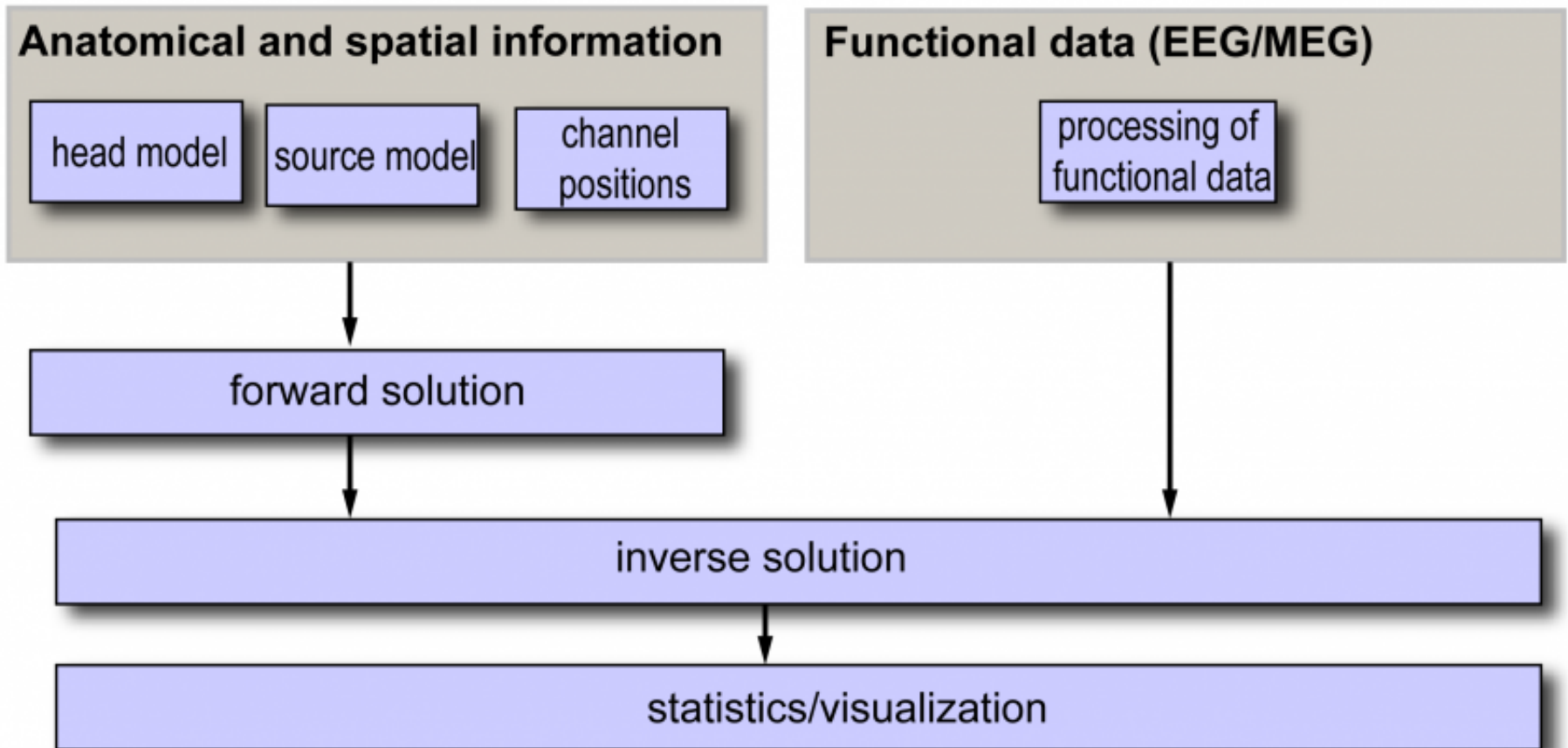
What is the distribution of activity over the brain?

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



Stage 1: Design experiment

Baseline recommendable

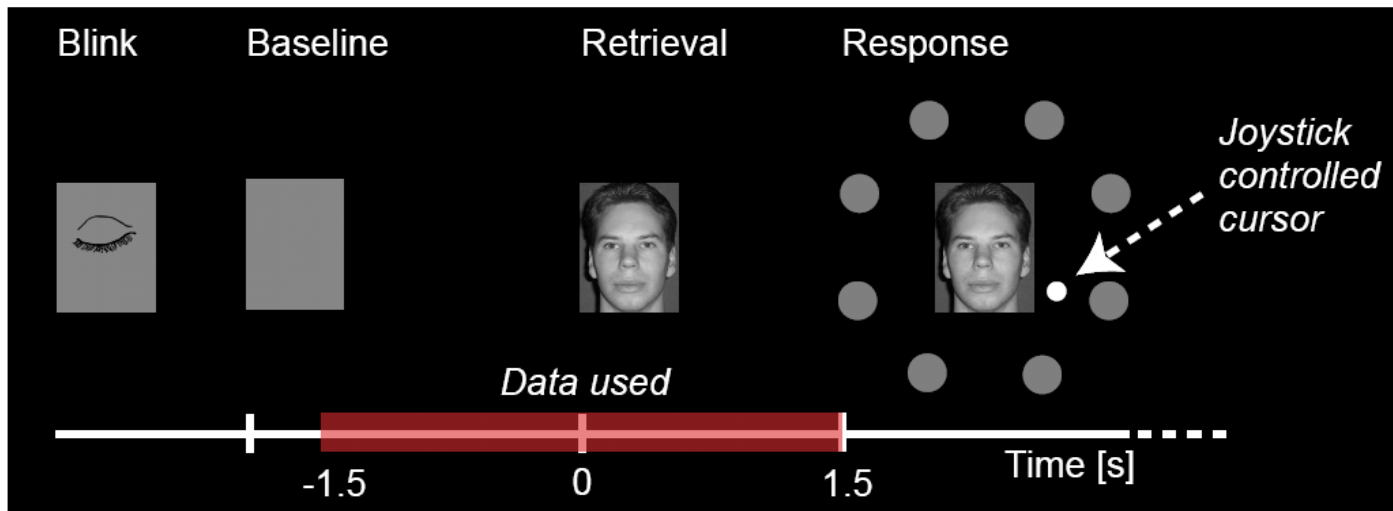
Sufficient length of stationary signal

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)

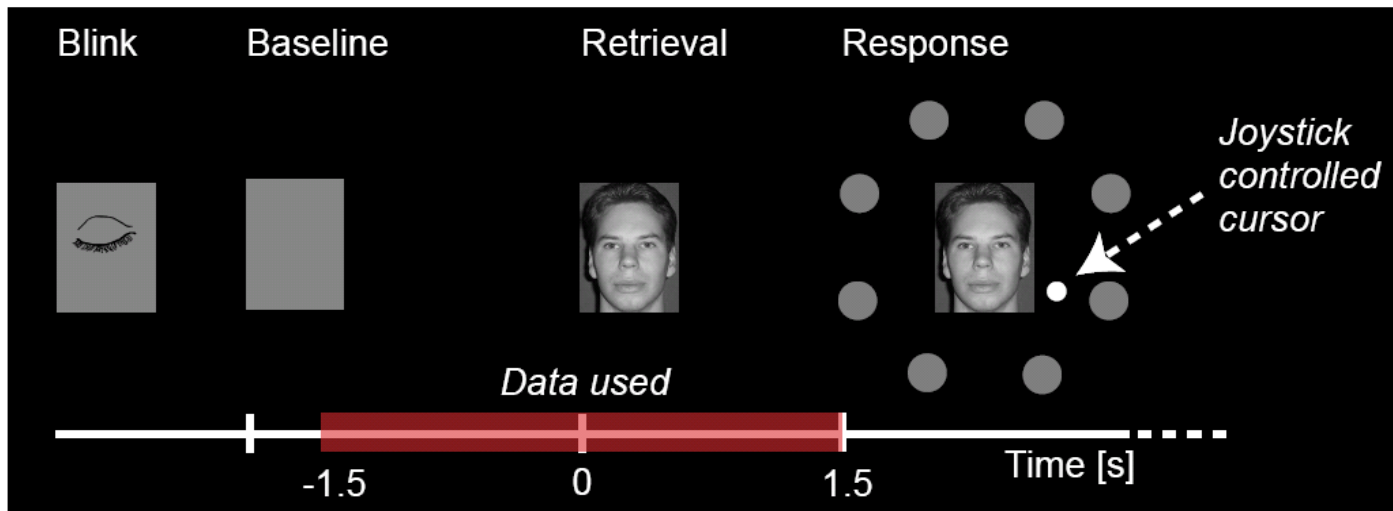
Make anatomical MRI scan for realistic head model
and for spatial normalization over subjects

Perform (if applicable and possible) a localizer task

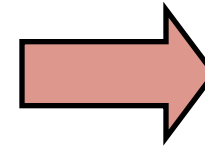
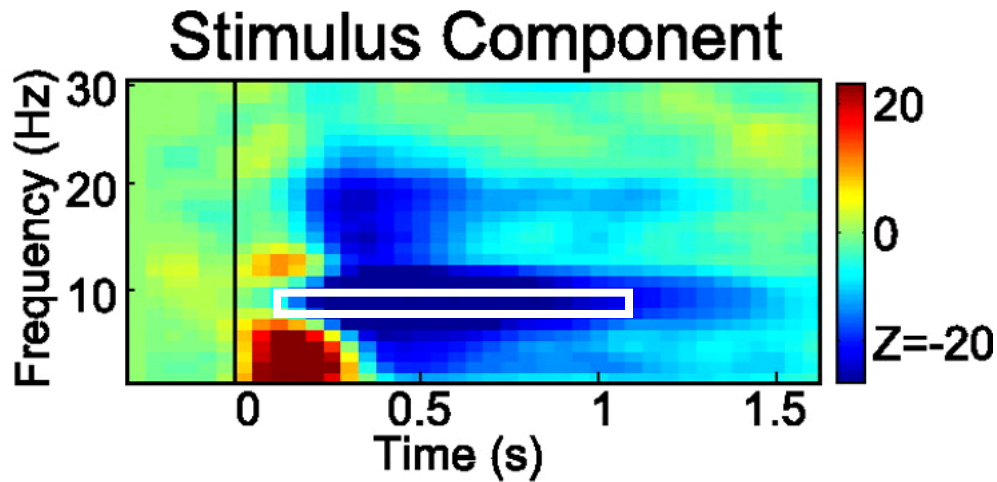
Stage 3: Data analysis: Preprocessing

Data segmentation

Artifact removal



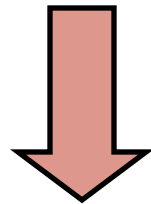
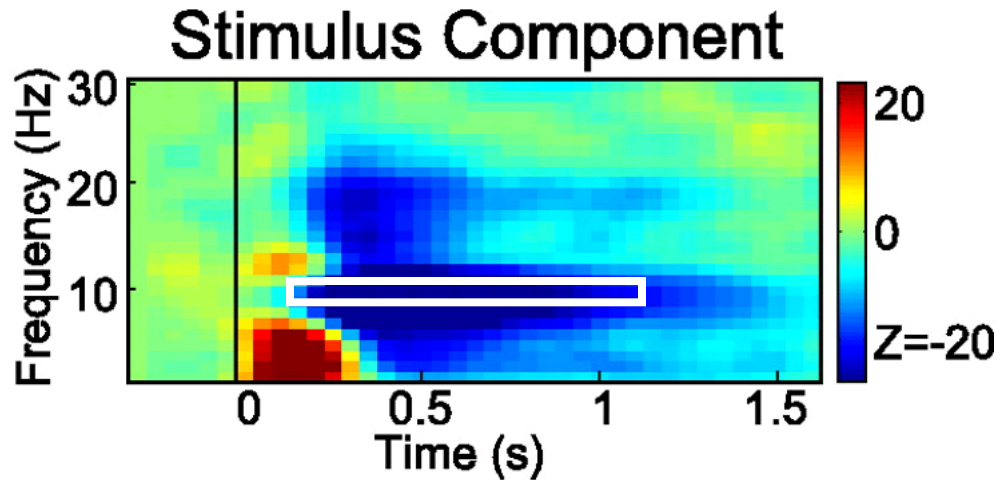
Stage 3: Data analysis: Time frequency analysis



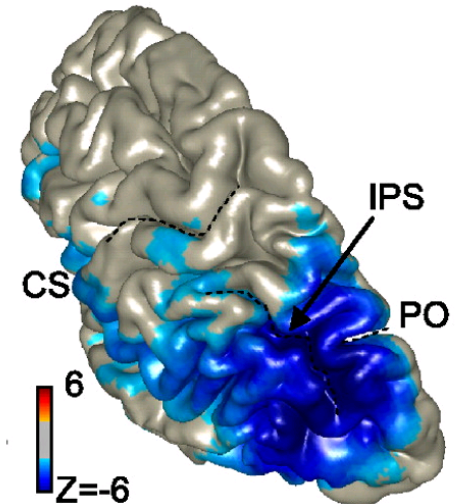
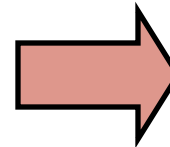
**“Beam” this
time-frequency
tile**

**0.1 to 1.1 s
~10 Hz**

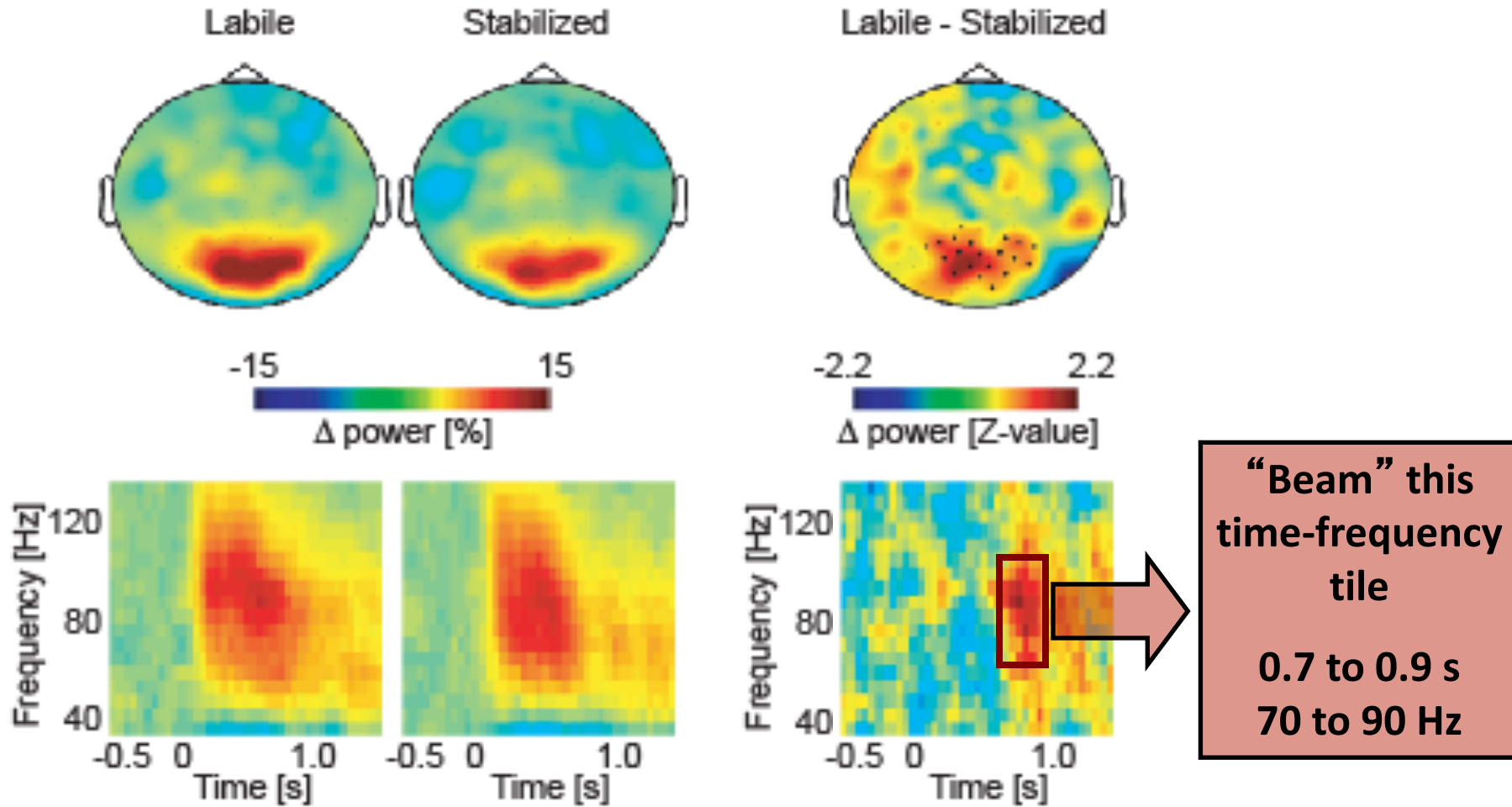
Stage 3: Data analysis: Time frequency analysis



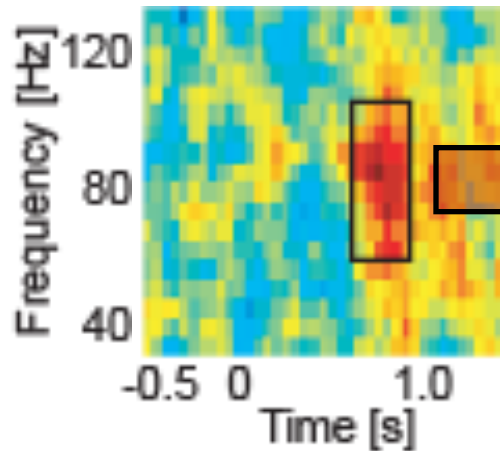
Time window of 1 second:
Frequency resolution 1 Hz
Bandwidth: 9.5 – 10.5 Hz



Stage 3: Data analysis: Time frequency analysis

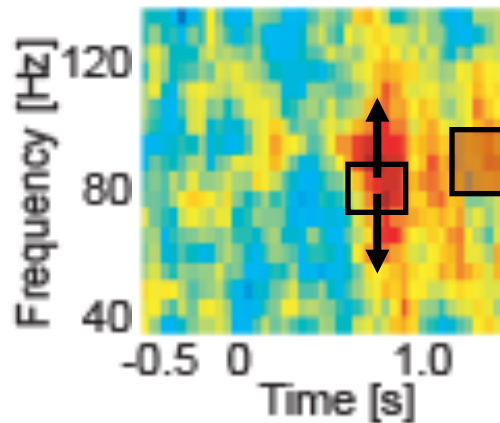


Stage 3: Data analysis: Time frequency analysis



I want to “beam”
this
time-frequency tile

0.7 to 0.9 s
70 to 90 Hz



I get:

0.2 s

↓

5 Hz resolution

↓

77.5 - 82.5 Hz

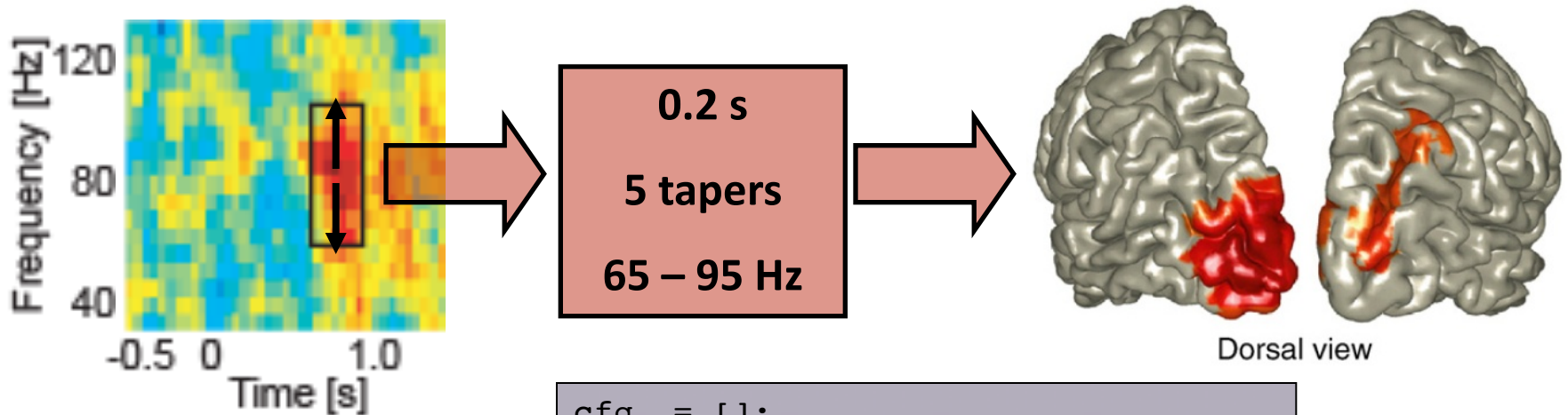
Increase
frequency
smoothing
without
changing length
time window

MULTITAPERS

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.

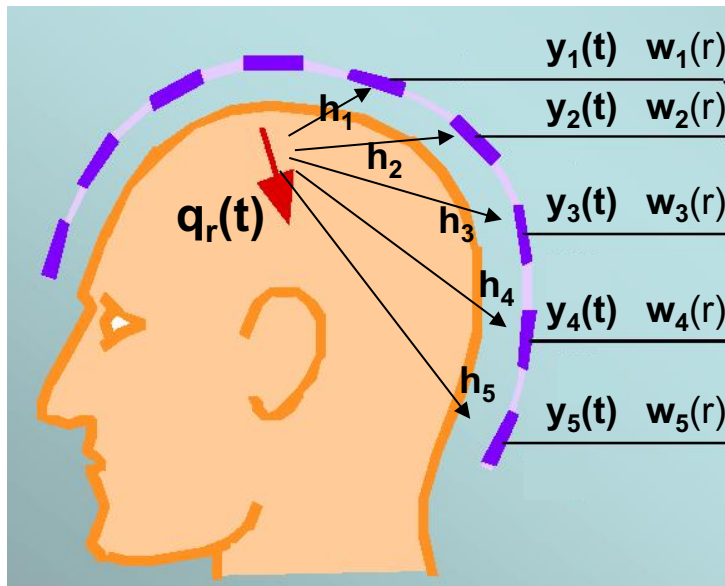


```
cfg = [];  
cfg.method = 'mtmconvol';  
cfg.output = 'powandcsd';  
cfg.toi = 0.8;  
cfg.foi = 80;  
cfg.t_ftimwin = 0.2;  
cfg.tapsmofrq = 15;  
freq = ft_freqanalysis(cfg, data);
```


Beamformer: the question

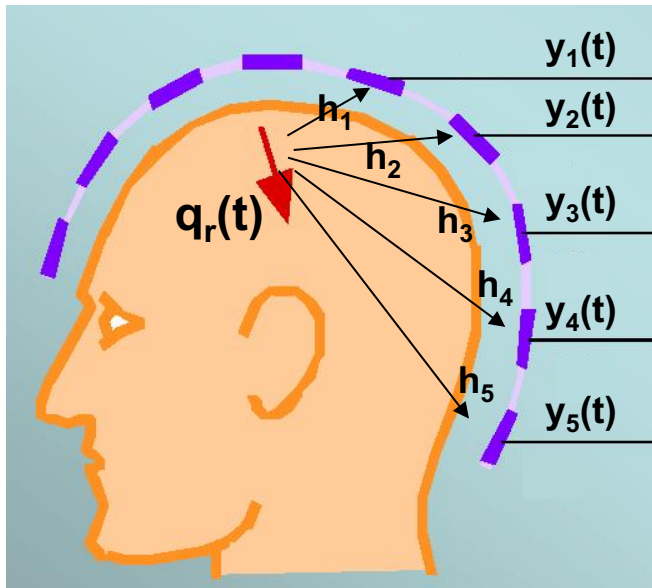
What is the activity of a source \mathbf{q} , at a location \mathbf{r} , given the data \mathbf{y} ?

We estimate \mathbf{q} with a spatial filter \mathbf{w}



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

Beamformer ingredients: forward model



forward model

$$Y(t) = G * q(t)$$

The diagram shows a large red square labeled $Y(t)$ on the left, followed by an equals sign, a vertical red bar labeled G , an asterisk, and a horizontal red bar labeled $q(t)$ on the right. An arrow points from the text "forward model" to the G bar.

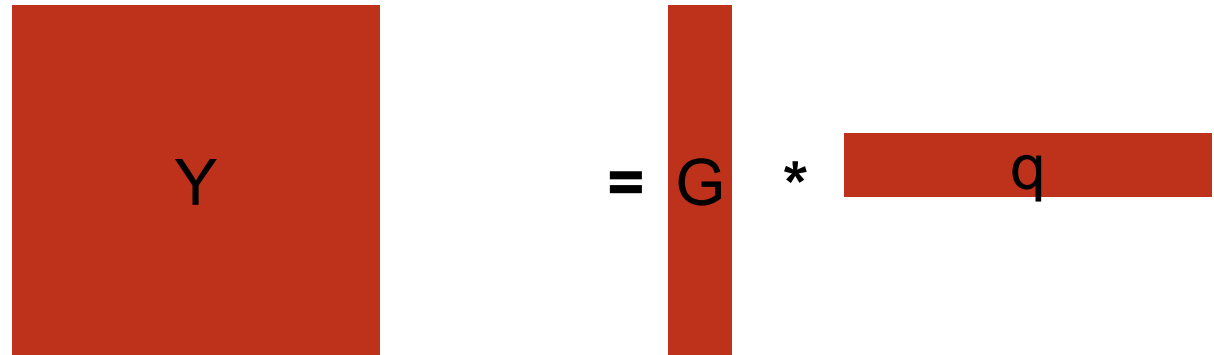
Beamformer: the question revisited

What is the activity of a source \mathbf{q} , at a location \mathbf{r} , given the data \mathbf{Y} ?

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

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

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



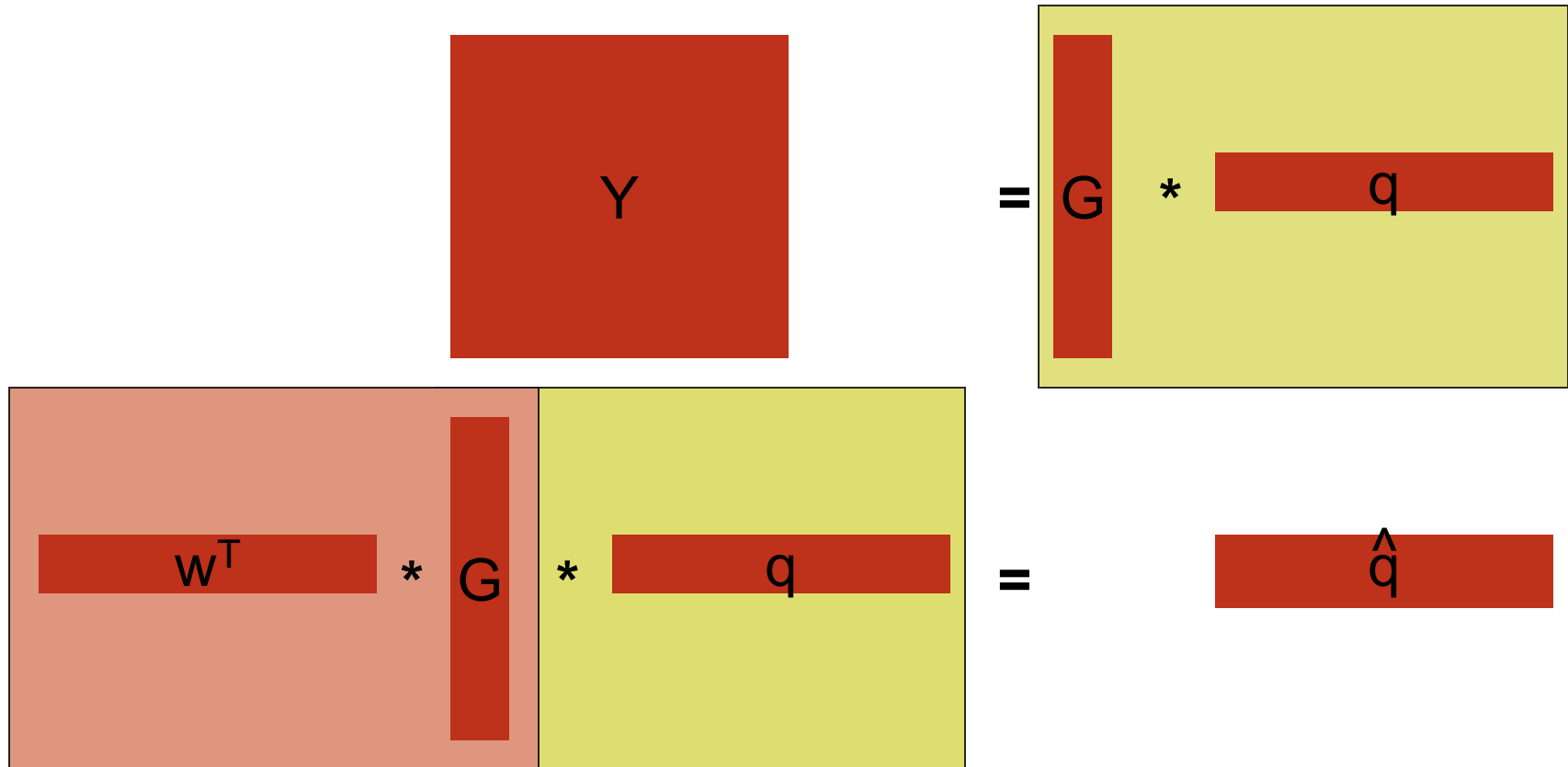
Beamformer: the question revisited

What is the activity of a source \mathbf{q} , at a location \mathbf{r} , given the data \mathbf{Y} ?

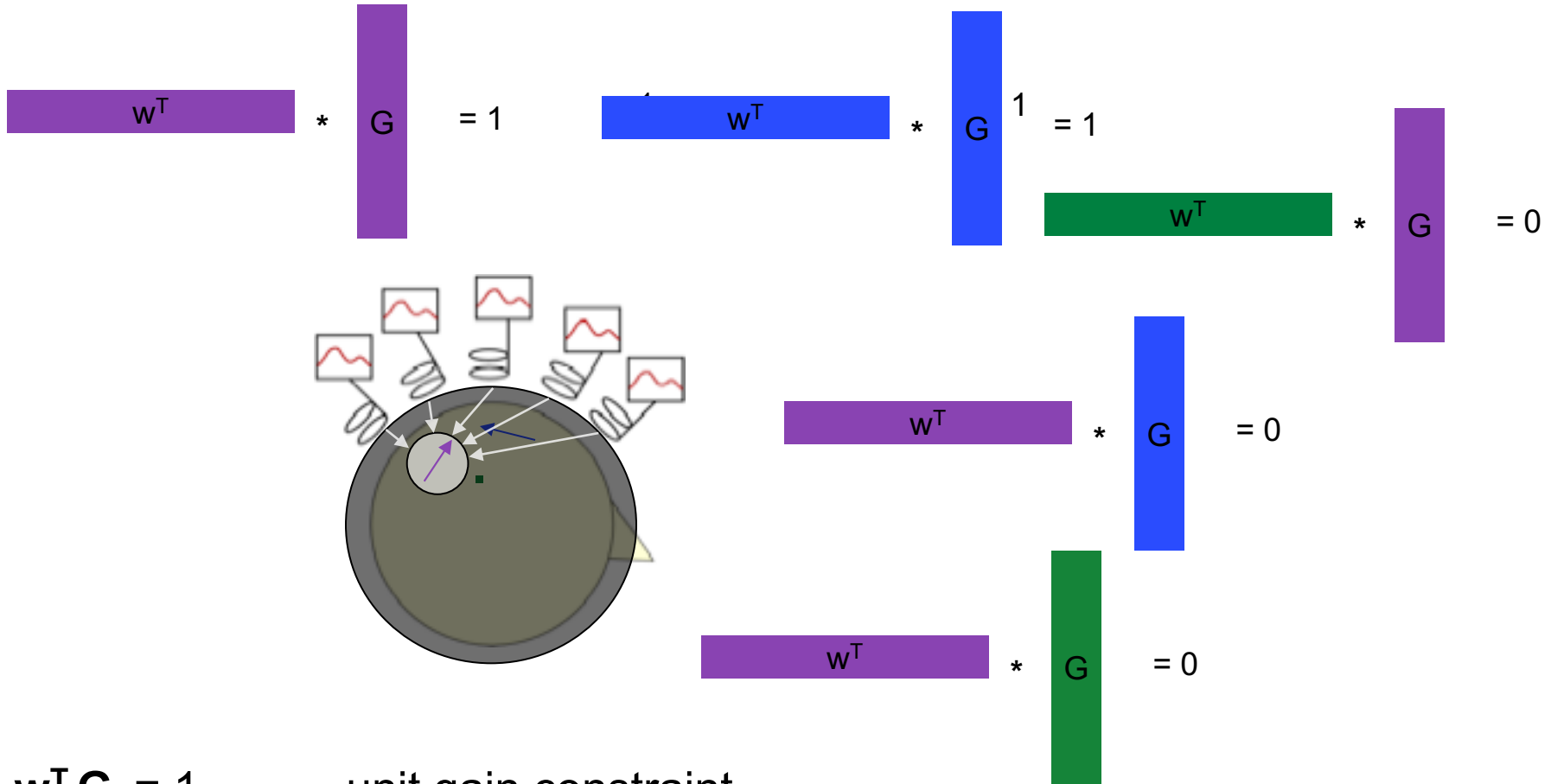
*We know how to get from source to data: $\mathbf{Y} = \mathbf{G} * \mathbf{q}$*

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

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



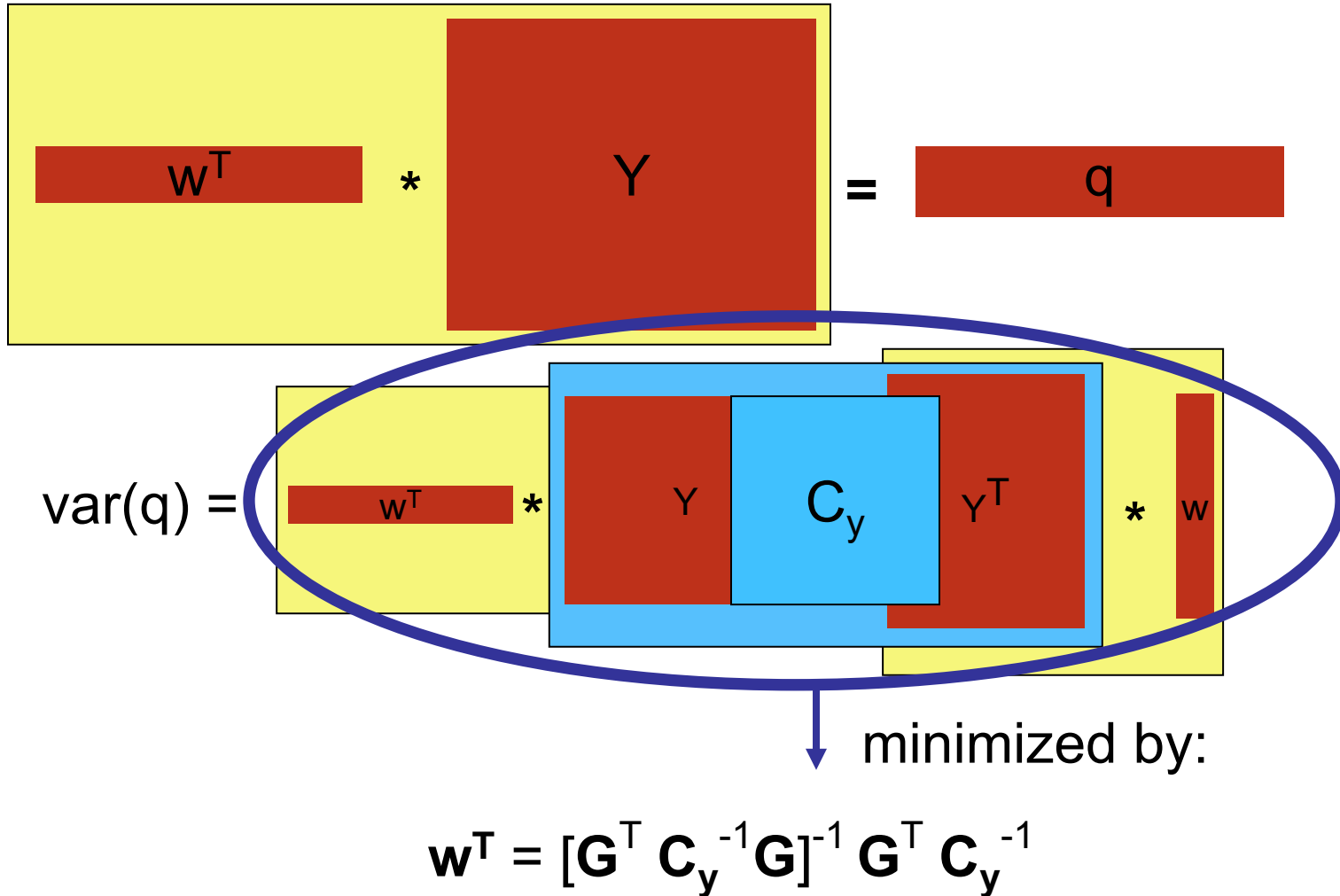
What would we like a spatial filter to do?



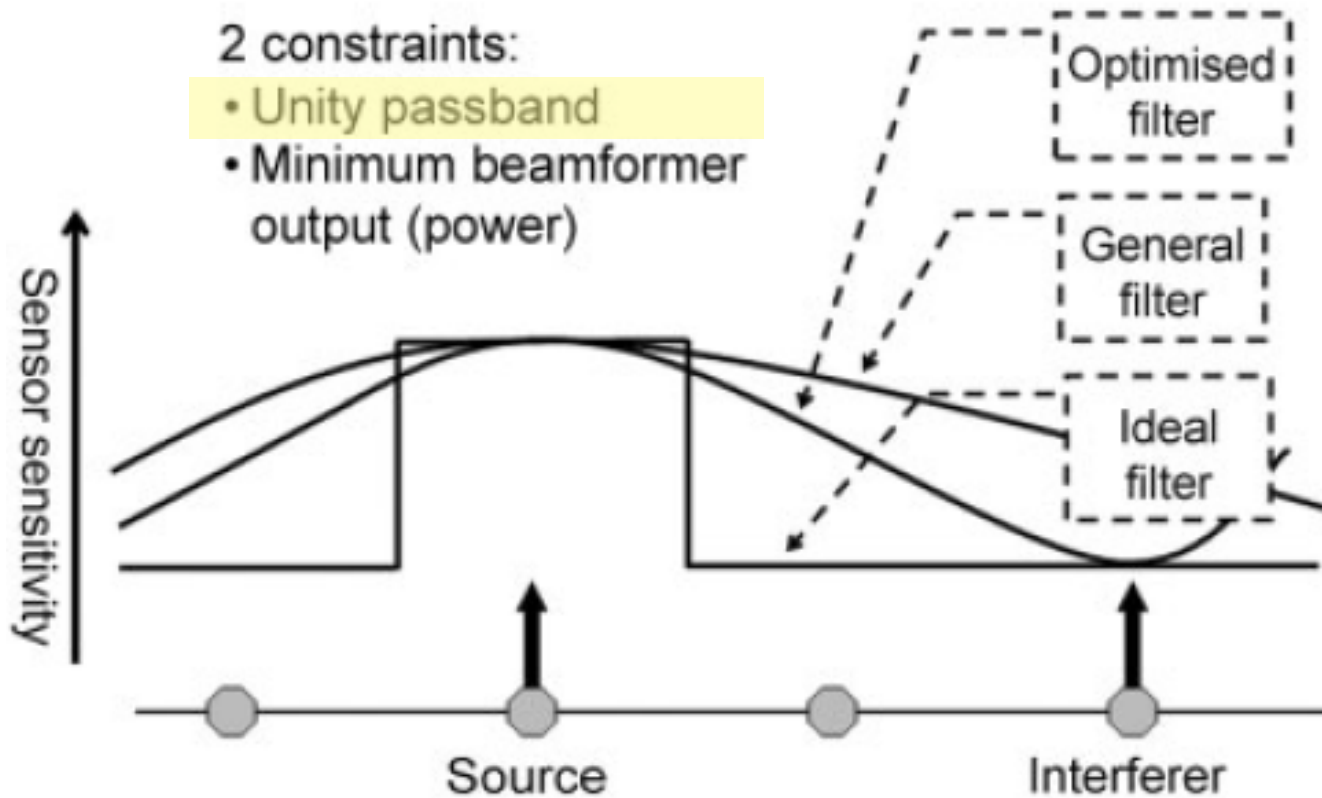
$$w_i^T G_i = 1$$
$$w_i^T G_k = 0$$

unit gain constraint
cannot generally be fulfilled, hence we
minimize the *variance* of the filter output

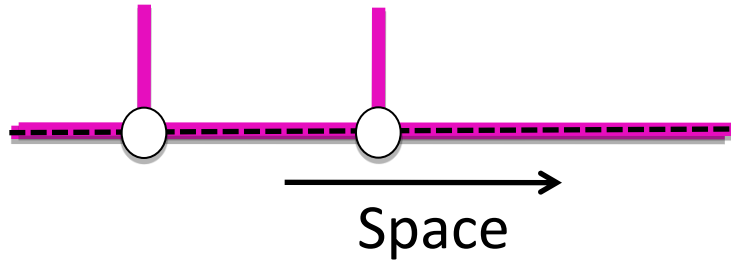
Adaptive spatial filter: minimum variance constraint



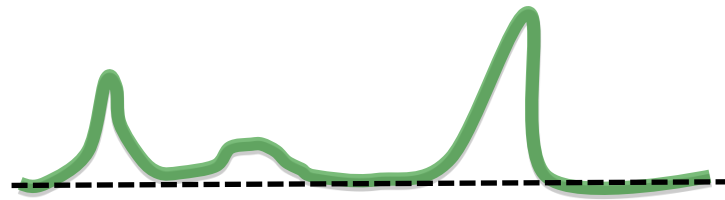
Spatial sensitivity and leakage of a filter



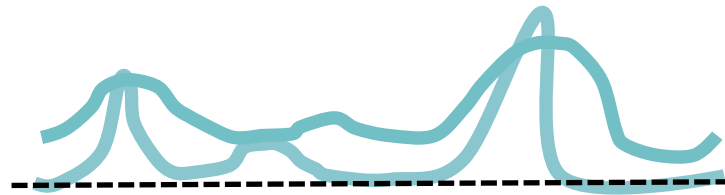
Spatial sensitivity and leakage of a filter



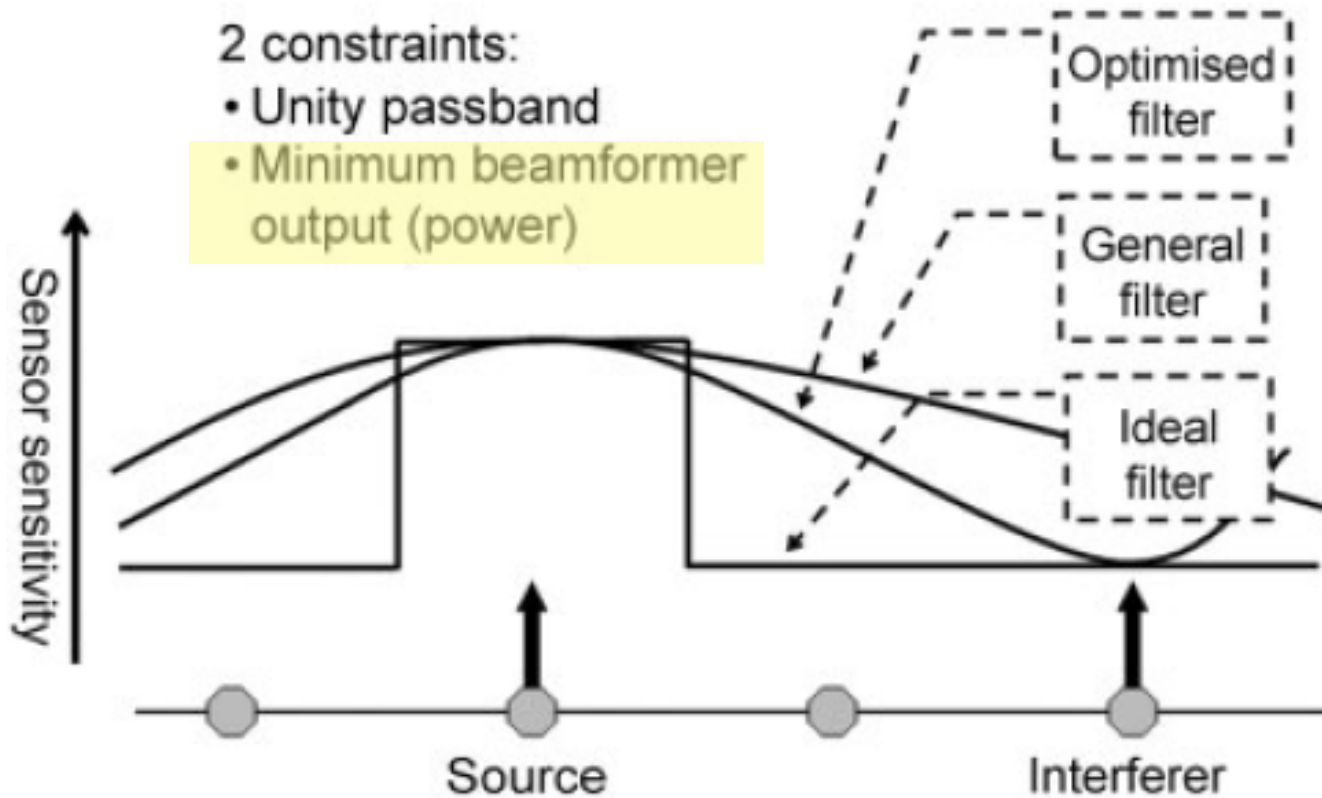
True source activity



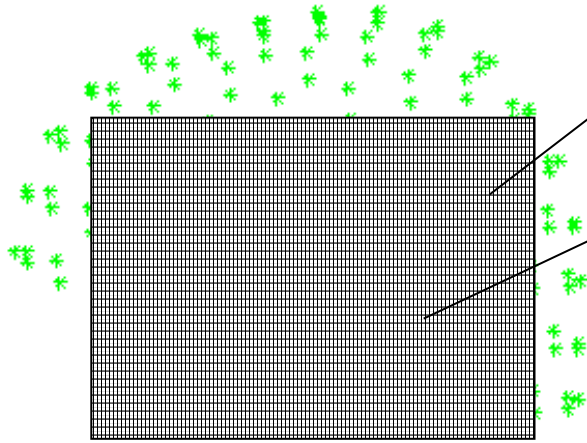
Estimated source activity



Spatial sensitivity and leakage of a filter

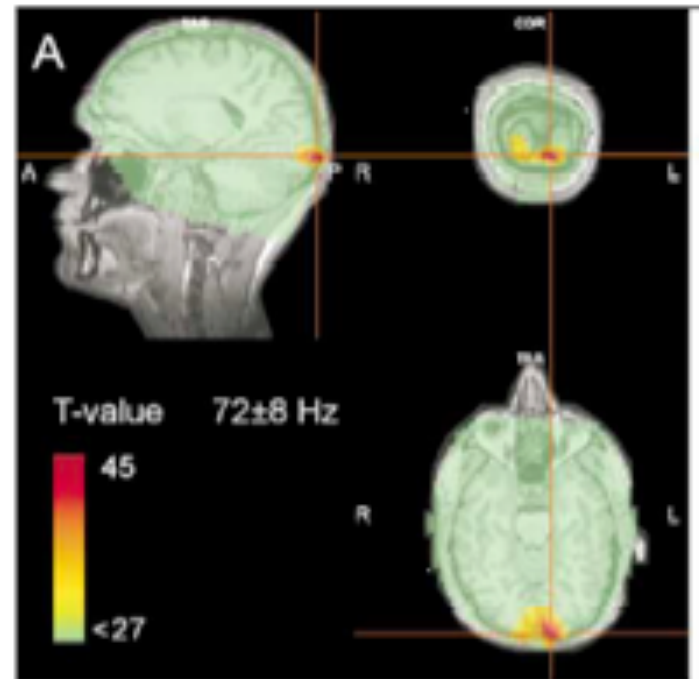
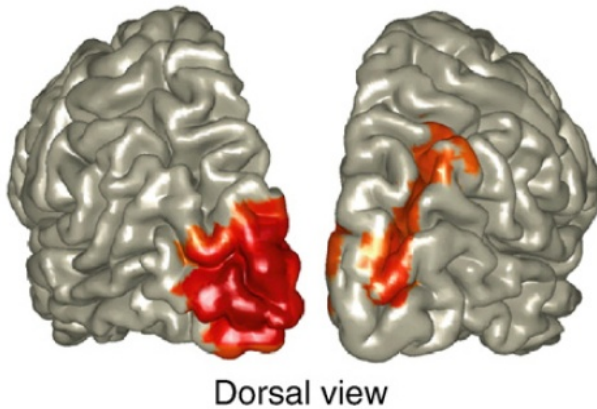


Beamforming: in practice



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

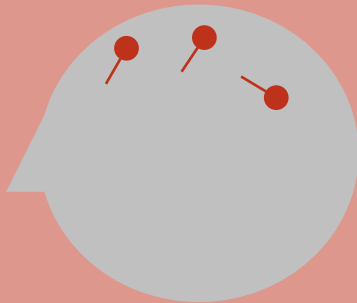
$$\mathbf{w}^T = [\mathbf{G}^T \mathbf{C}_y^{-1} \mathbf{G}]^{-1} \mathbf{G}^T \mathbf{C}_y^{-1}$$



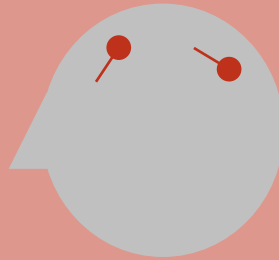
Strengths of beamforming

Easier to average over subjects
(compared to dipole methods)

Subject 1



Subject 2



Suitable for SPM-like
statistics

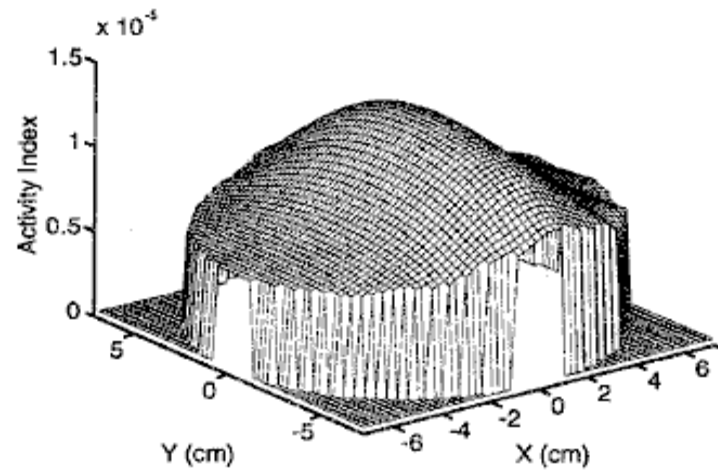
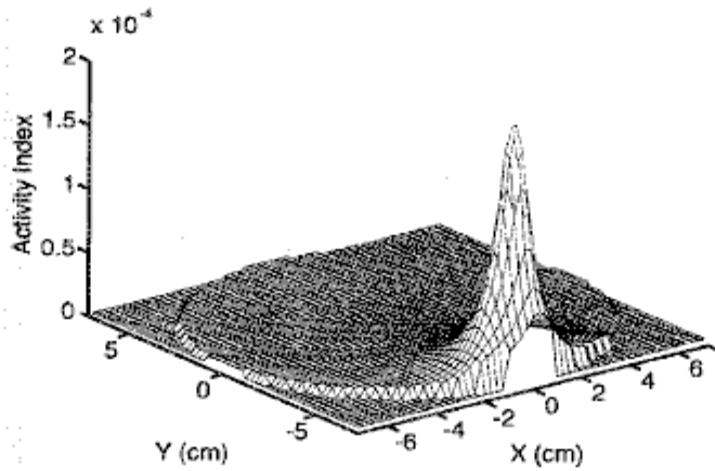
Because source
estimation at each point
independent of other
points

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

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

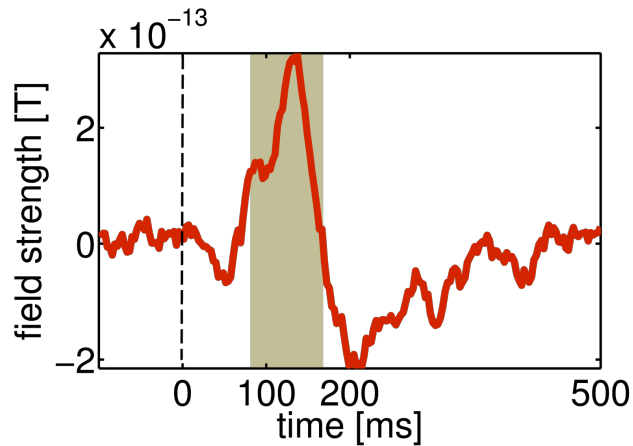
Limitation of beamforming

Sources should not be too correlated



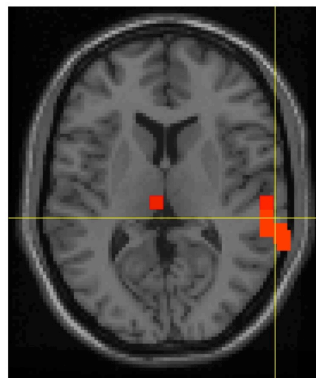
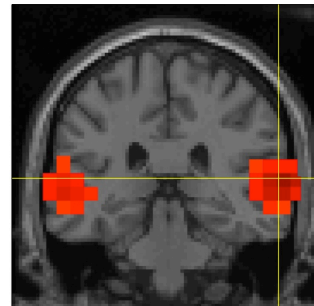
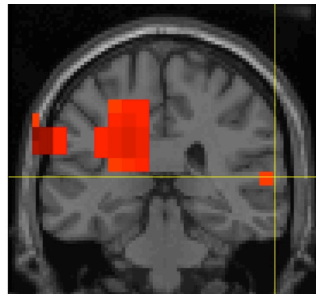
uncorrelated sources (1997)
mildly correlated sources
perfectly correlated sources

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

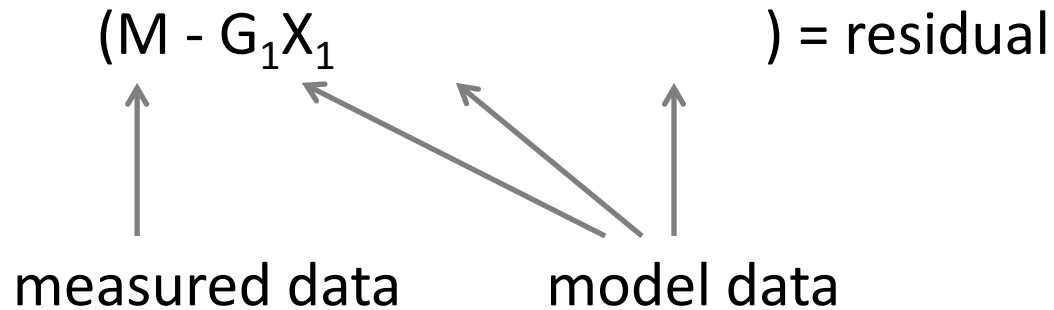
$$M = G_1 X_1 + G_2 X_2 + \dots + G_n X_n + \text{noise}$$

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

Data model for sequential dipole fitting

$$M = G_1 X_1 + G_2 X_2 + \dots + G_n X_n + \text{noise}$$

n is typically small



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

Data model for distributed source estimates

$$M = G_1 X_1 + G_2 X_2 + \dots + G_n X_n + \text{noise}$$

n is typically large (> # channels)

$$M = (G_1 X_1 + G_2 X_2 + \dots + G_n X_n) + \text{noise}$$

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

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

Data model for spatial filtering

$$M = G_1 X_1 + G_2 X_2 + \dots + G_n X_n + \text{noise}$$

any number of n

$$M = (G_1 X_1 + G_2 X_2 + \dots) + G_n X_n + (\text{noise})$$

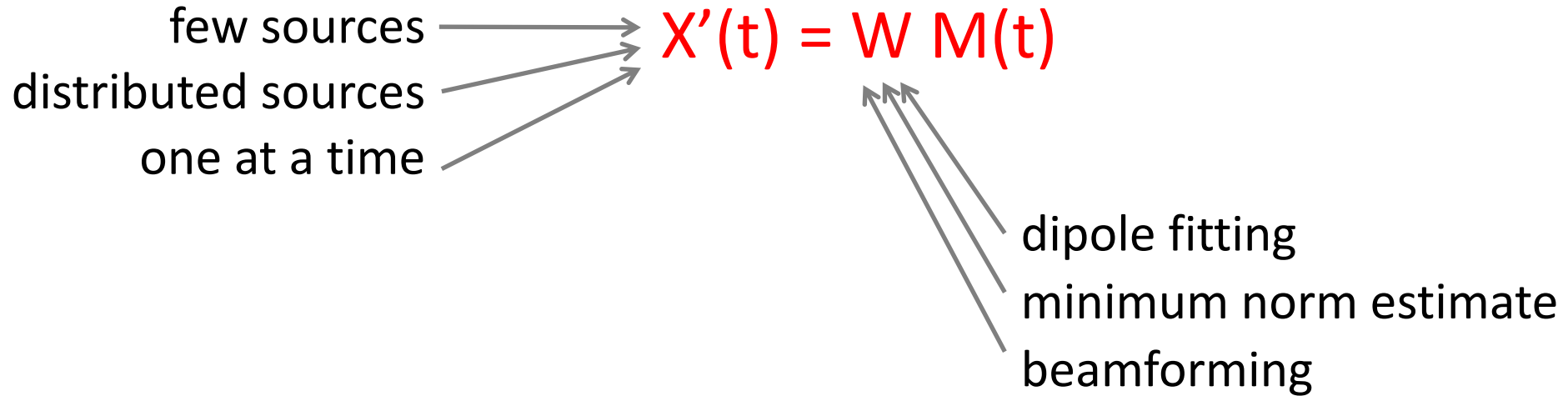
$$X'_n = W_n M, \quad \text{where } W^T = [G_n^T C_M^{-1} G_n]^{-1} G_n^T C_M^{-1}$$

Data model

$$X = h_1s_1 + h_2s_2 + \dots + h_ns_n + \text{noise}$$

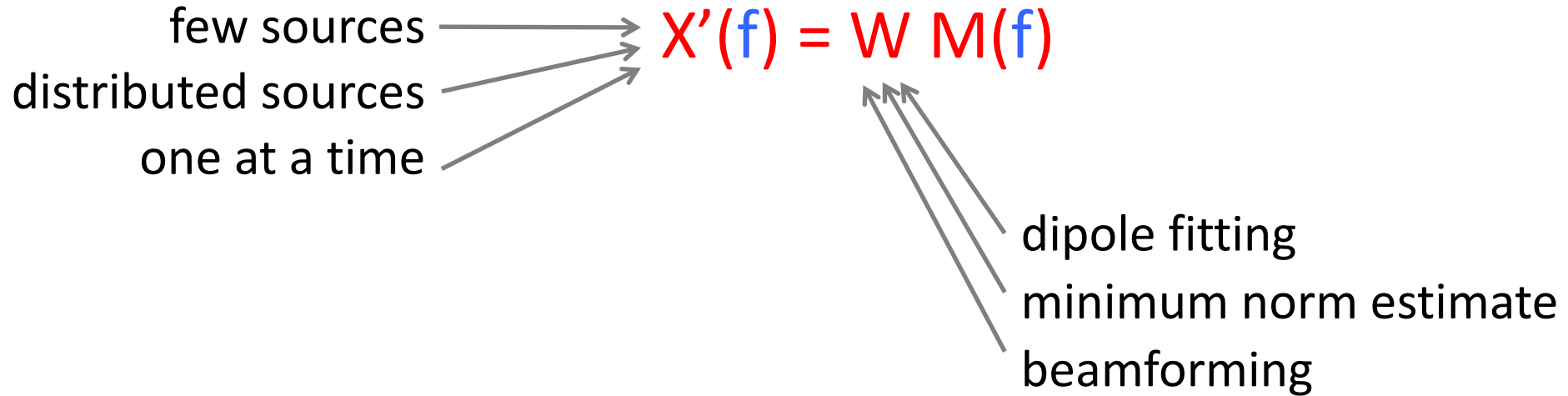
Data model to estimate source timeseries

$$M = G_1 X_1 + G_2 X_2 + \dots + G_n X_n + \text{noise}$$

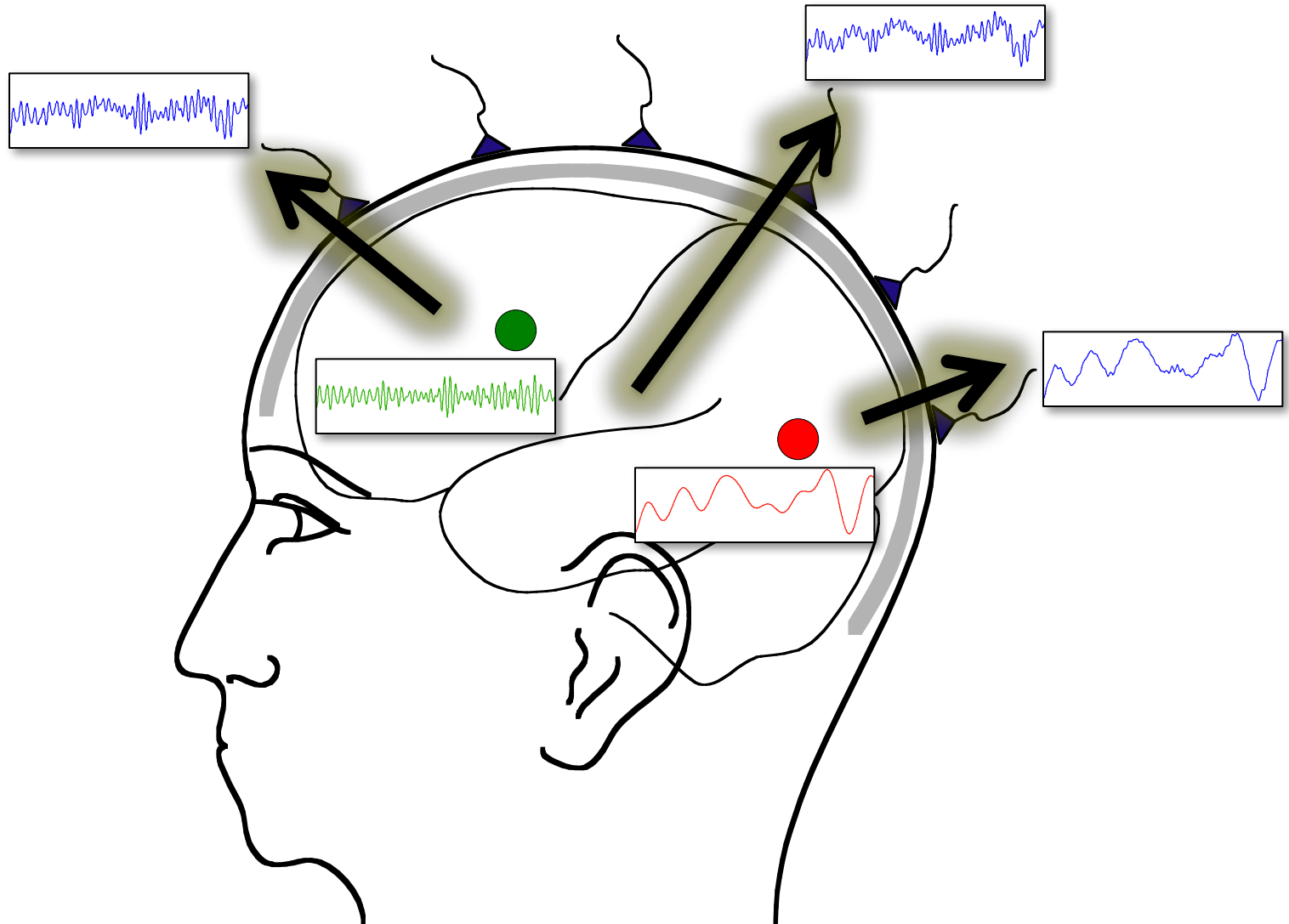


Data model to estimate **spectral** representations

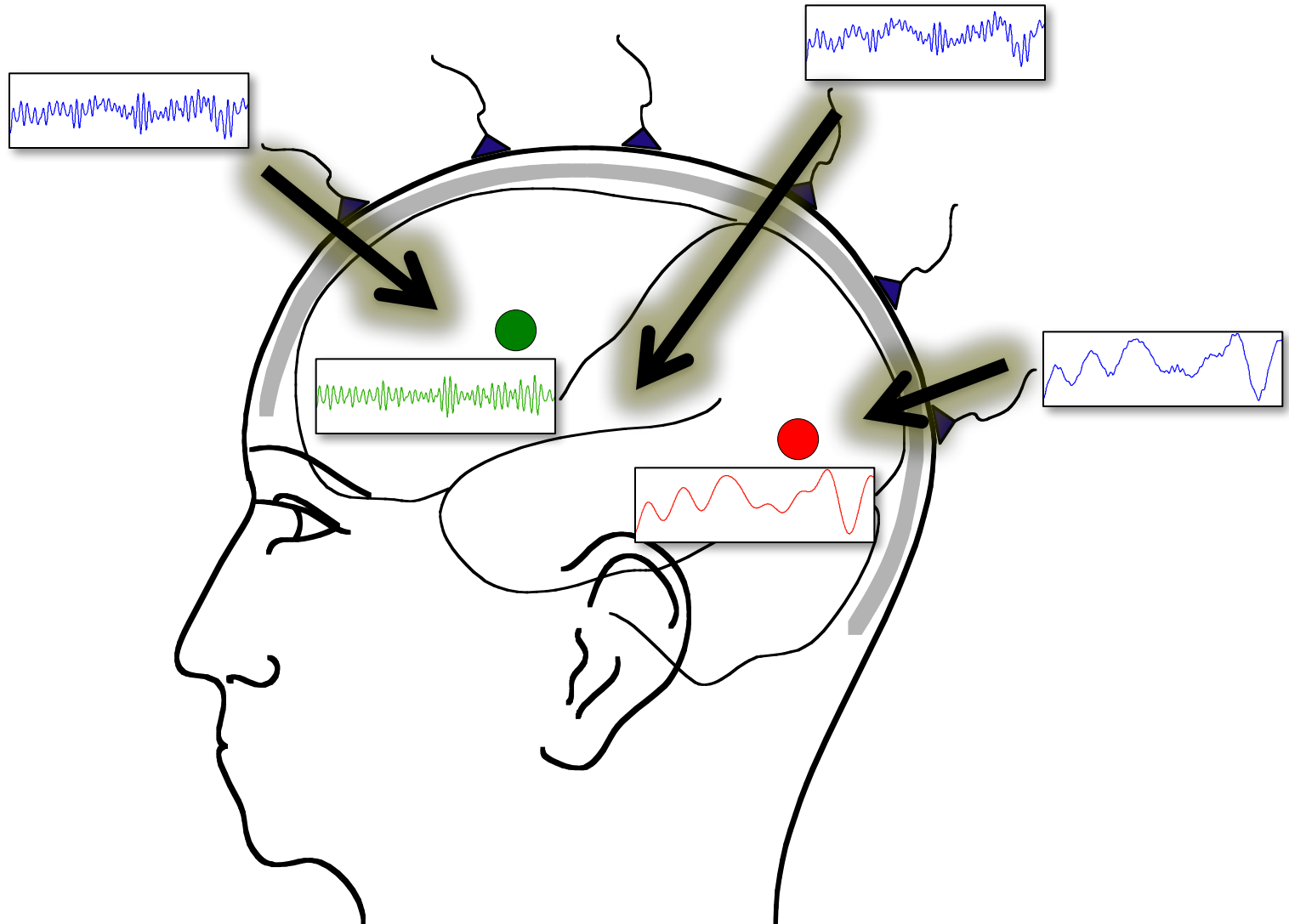
$$M = G_1 X_1 + G_2 X_2 + \dots + G_n X_n + \text{noise}$$



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)