Multi-modal integration of MEG, EEG & fMRI

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Cambridge, UK

Multi-modal Integration

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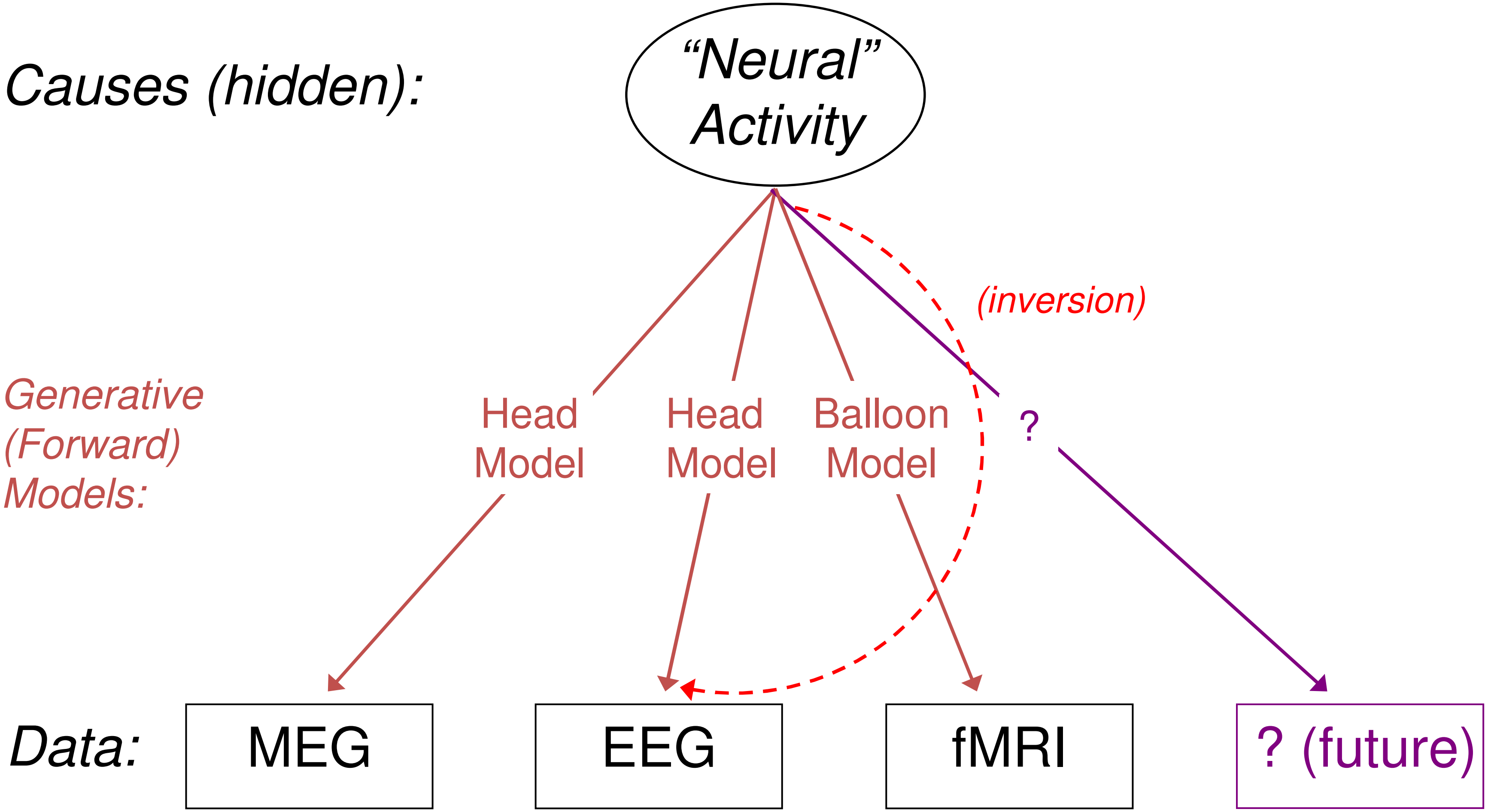
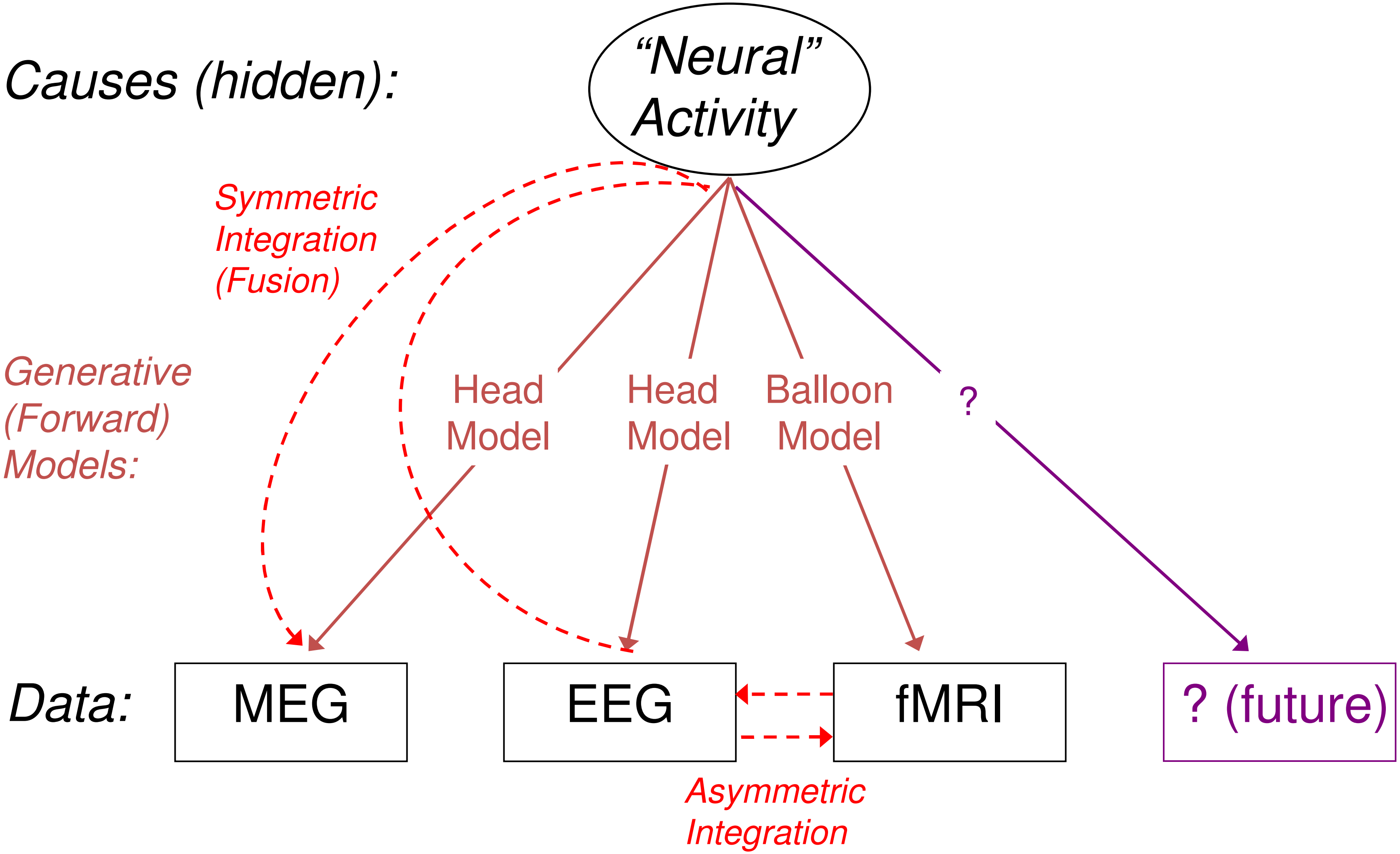


Multi-modal Integration



Daunizeau et al (2007), Neuroimage

Talk Overview

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1. MEG + EEG symmetric integration (fusion)

2. M/EEG + fMRI asymmetric integration

Symmetric Integration of MEG+EEG
Background

- MEG generally has superior spatial resolution vs. EEG (less blurred by skull/scalp)

- MEG cannot detect radial component of current sources; EEG can!

Symmetric Integration of MEG+EEG Background

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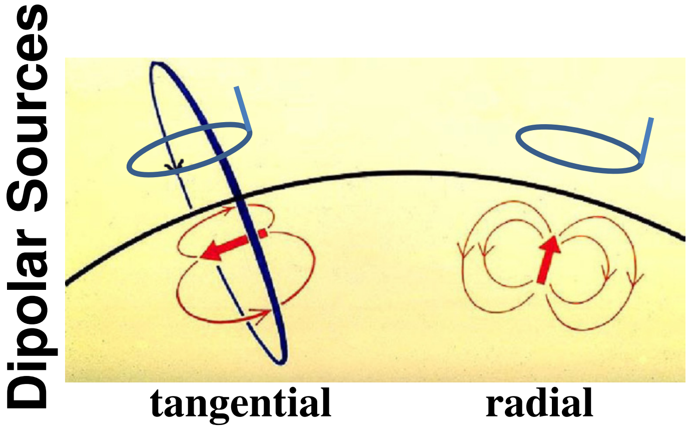
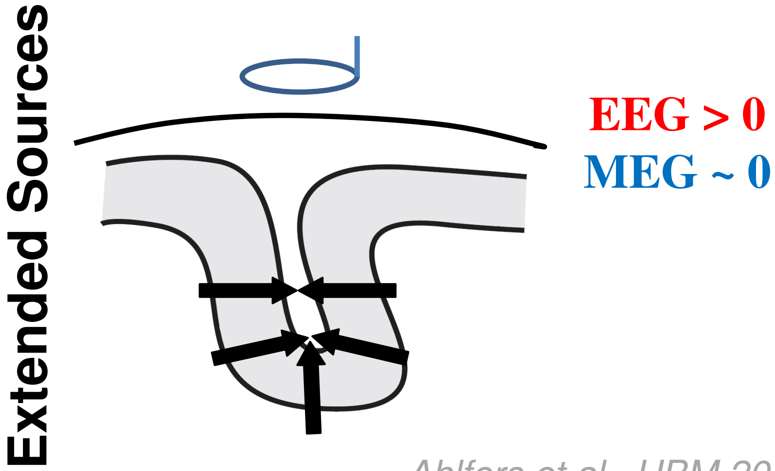
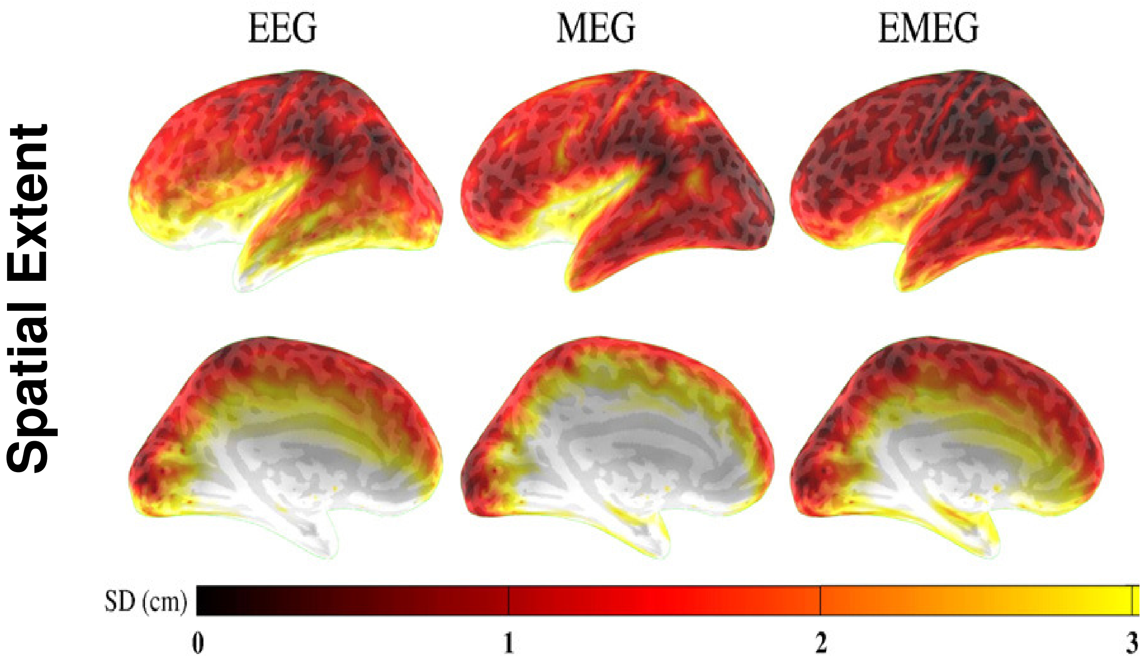
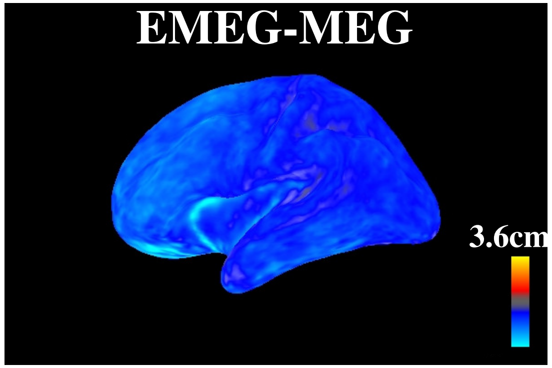




Ahlfors et al., HBM 2010





Stenroos & Hauk, in prep

Molins et al., Neuroimage 2008

Symmetric Integration of MEG+EEG Background

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- MEG generally has superior spatial resolution vs. EEG (less blurred by skull/scalp)
- MEG cannot detect radial component of current sources; EEG can!
- And few practical problems acquiring concurrent EEG (apart from extra time attaching electrodes)
- …but EEG data is more sensitive to head geometry and conductivity (potentially biasing any joint-localisation)…
- …and has different noise characteristics…

MEG Linear Forward Model

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Given *n* sensors and *p* sources fixed in location and orientation (e.g, on a cortical mesh), then linear Forward Model (for single timepoint):

$$\begin{bmatrix} d_1 \\ \vdots \\ d_n \end{bmatrix} = \begin{bmatrix} L_{11} & L_{12} & \cdots L_{1p} \\ \vdots & \ddots & \vdots \\ L_{n1} & \cdots & \cdots L_{np} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_p \end{bmatrix} + \begin{bmatrix} e_1 \\ \vdots \\ e_n \end{bmatrix}$$

d = Data	*n* sensors
s = Sources	*p*>>*n* sources
L = Leadfields	*n* sensors *x p* sources
e = Error (noise)	*n* sensors…

Equivalent matrix format:

$$\mathbf{d} = \mathbf{L}\mathbf{s} + \mathbf{e}$$

Assume sensor noise is zero-mean Gaussian with error covariance $\mathbf{C}^{(e)}$:

$$e \sim N(0, \mathbf{C}^{(e)})$$

Assume sources similarly Gaussian with source covariance $\mathbf{C}^{(s)}$:

$$s \sim N(0, \mathbf{C}^{(s)})$$

MEG Linear Forward Model Assumptions to Solve

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$$\mathbf{d} = \mathbf{L}\mathbf{s} + \mathbf{e}$$

$$\mathbf{e} \sim N(0, \mathbf{C}^{(e)})$$

$$\mathbf{s} \sim N(0, \mathbf{C}^{(s)})$$

d = Data
s = Sources
L = Leadfields
e = Error (noise)

n sensors
p>>*n* sources
n sensors *x* *p* sources
n sensors…

General solution is:

Hauk (2004), Neuroimage

$$\hat{\mathbf{s}} = \mathbf{C}^{(s)}\mathbf{L}^T(\mathbf{L}\mathbf{C}^{(s)}\mathbf{L}^T + \lambda\mathbf{C}^{(e)})^{-1}\mathbf{d}$$

λ = Regularisation (hyperparameter)

But how calculate $\mathbf{C}^{(e)}$ and $\mathbf{C}^{(s)}$?

MEG Linear Forward Model
Assumptions to Solve

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One approach is to model sources and noise by variance components:

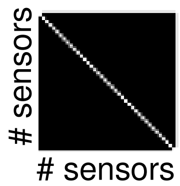
$$\mathbf{C} = \sum_i \lambda_i \mathbf{Q}_i$$

C = Sensor/Source covariance
Q = Covariance components
λ = Hyper-parameters

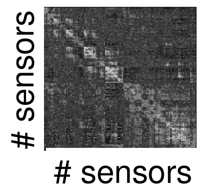
Friston et al (2008) Neuroimage

1. Sensor components, $\mathbf{Q}_i^{(e)}$ (error):

"IID" (white noise):

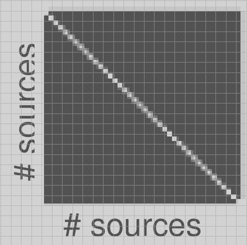


Empty-room:

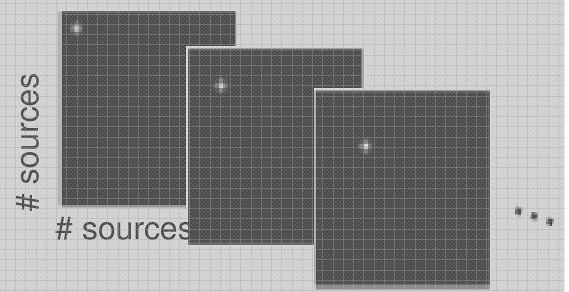


2. Source components, $\mathbf{Q}_i^{(s)}$ (priors/regularisation):

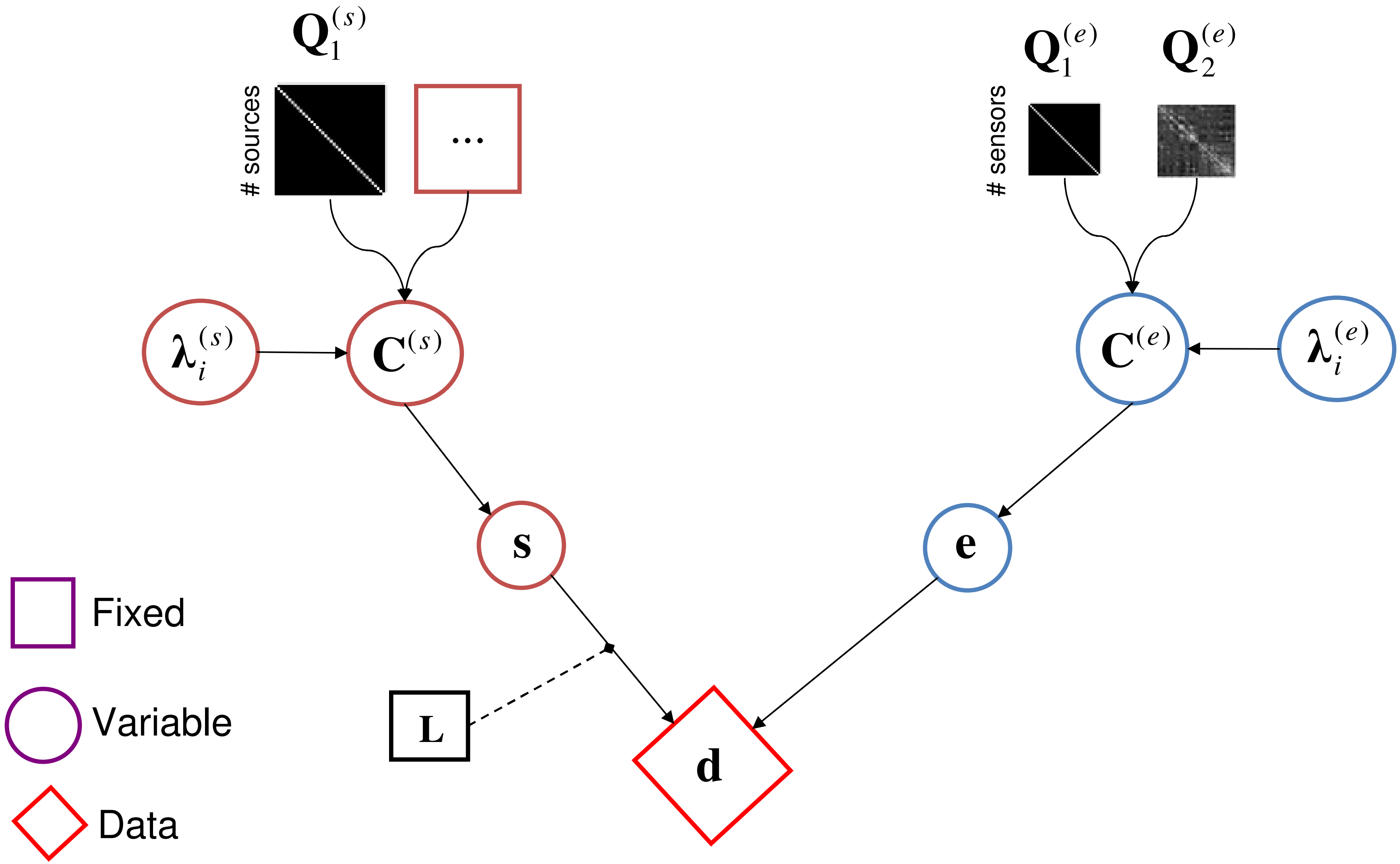
"IID" (min norm):



Multiple Sparse Priors (MSP):



MEG Generative Model



Henson et al (2009) Neuroimage

Symmetric Integration of MEG+EEG Generative Model

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For fusing MEG and EEG, we can simply concatenate the MEG+EEG data:

$$\begin{bmatrix} \mathbf{d}_{(MEG)} \\ \mathbf{d}_{(EEG)} \end{bmatrix} = \begin{bmatrix} \mathbf{L}_{(MEG)} \\ \mathbf{L}_{(EEG)} \end{bmatrix} \mathbf{s} + \begin{bmatrix} \mathbf{e}_{(MEG)} \\ \mathbf{e}_{(EEG)} \end{bmatrix}$$

$$\mathbf{e} \sim N(0, \mathbf{C}^{(e)})$$

$$\mathbf{s} \sim N(0, \mathbf{C}^{(s)})$$

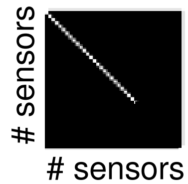
Note same sources, eg, for Minimum (L2) Norm solution:

$$\mathbf{C}^{(s)} = \mathbf{I} \qquad \hat{\mathbf{s}} = \mathbf{L}^T (\mathbf{L}\mathbf{L}^T + \hat{\mathbf{C}}^{(e)})^{-1} \mathbf{d}$$

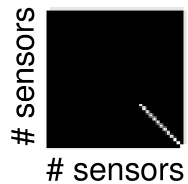
Noise expressed by MEG and EEG terms (e.g, white noise):

$$\hat{\mathbf{C}}^{(e)} = \lambda_1^{(e)} \mathbf{Q}_{(MEG)}^{(e)} + \lambda_2^{(e)} \mathbf{Q}_{(EEG)}^{(e)}$$

$$\mathbf{Q}_{(MEG)}^{(e)} =$$



$$\mathbf{Q}_{(EEG)}^{(e)} =$$



The separate hyperparameters allow for different noise levels (SNR)

The multiple hyperparameters are estimated by maximising **model evidence** (using a variational Bayesian approach, eg EM algorithm)

Symmetric Integration of MEG+EEG Generative Model

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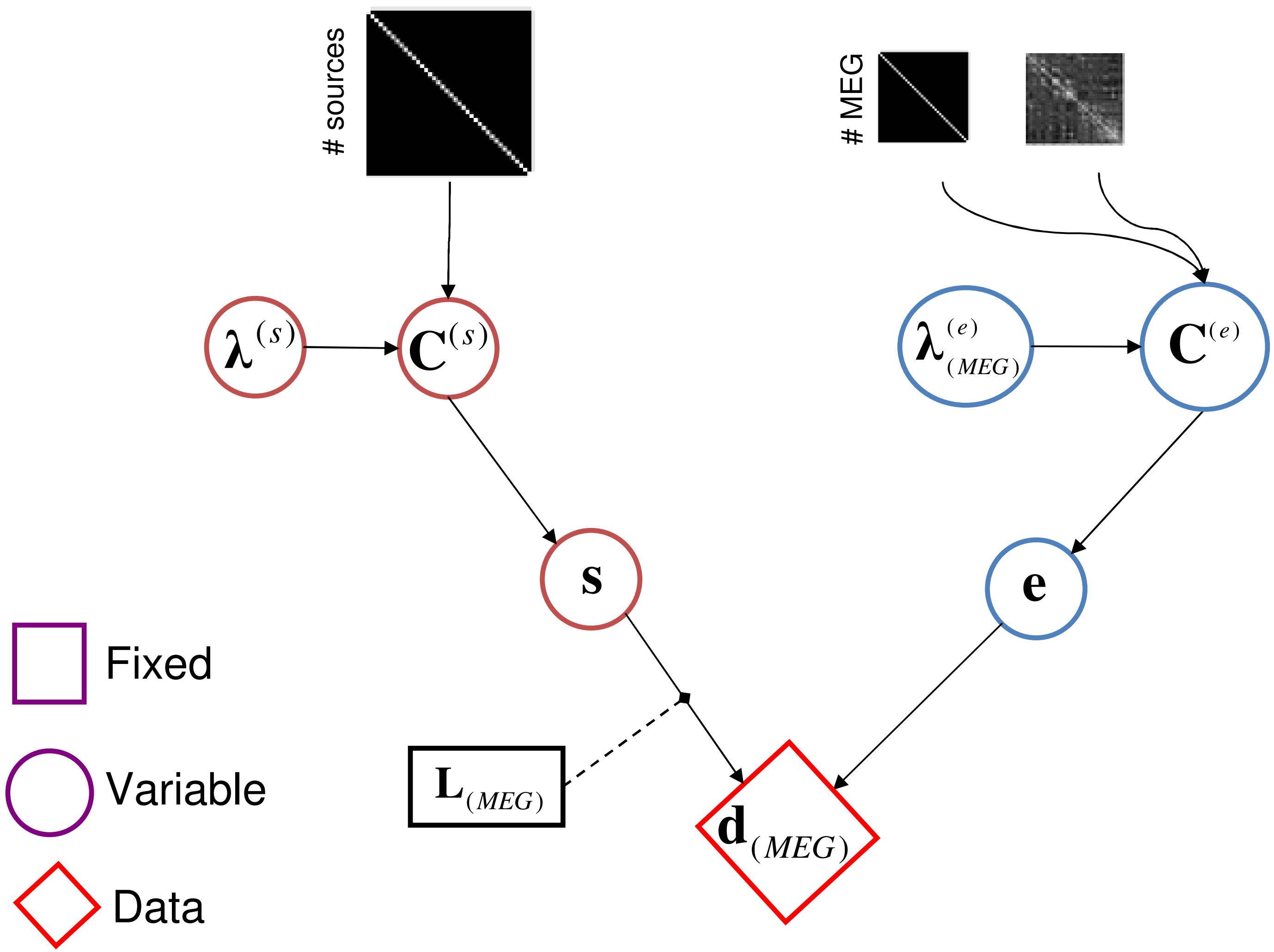

Henson et al (2009) Neuroimage

Symmetric Integration of MEG+EEG Generative Model

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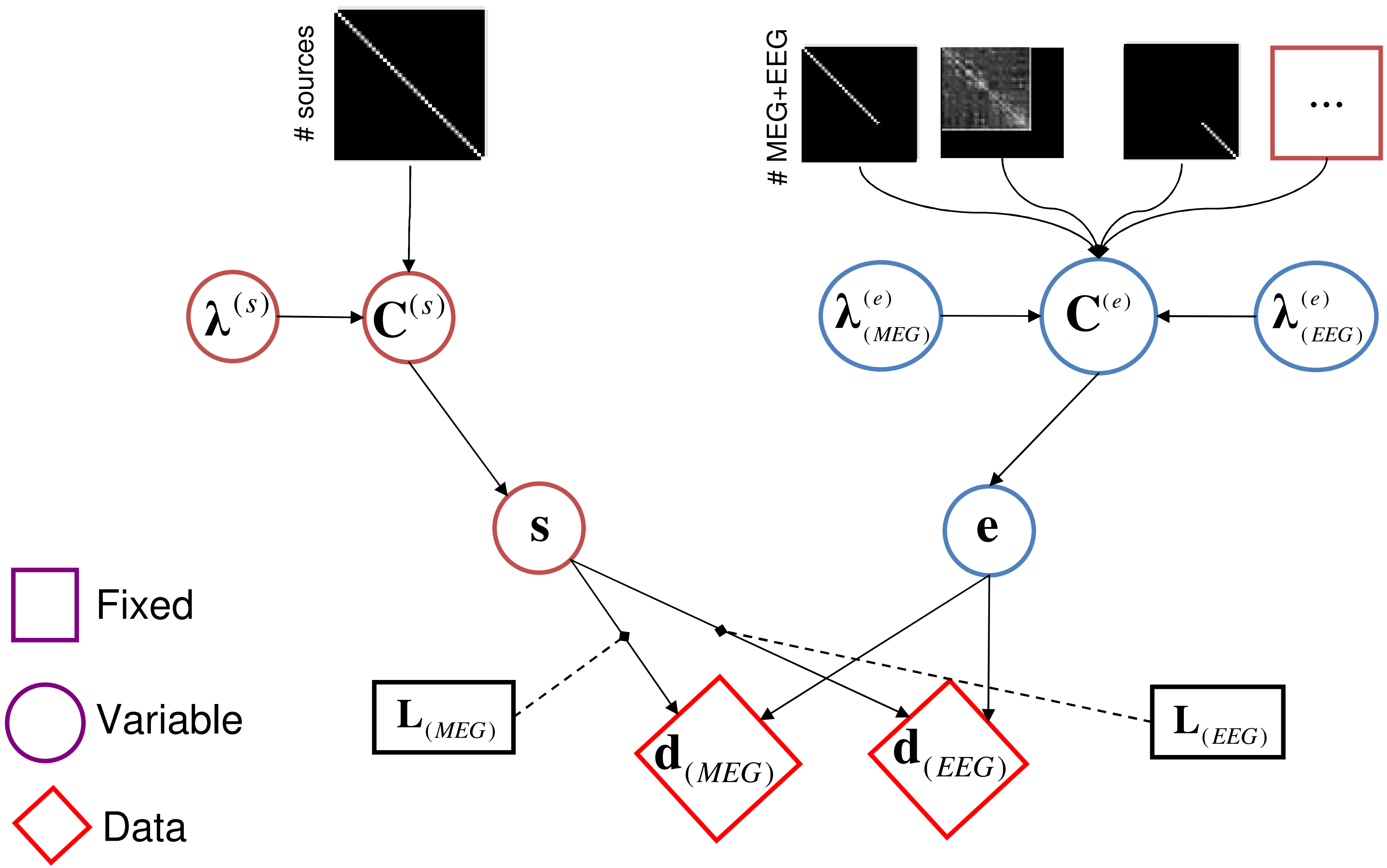

Henson et al (2009) Neuroimage

One final problem…

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- Though this allows for different additive noise levels in MEG and EEG…
- …we are assuming mapping from common electrical sources to sensor values (in terms of Telsa and Volts) is known precisely…
- …whereas in reality, this depends on several unknowns (e.g, precise conductivity of skull/scalp)
- One solution is to scale data/leadfields to have same variance:

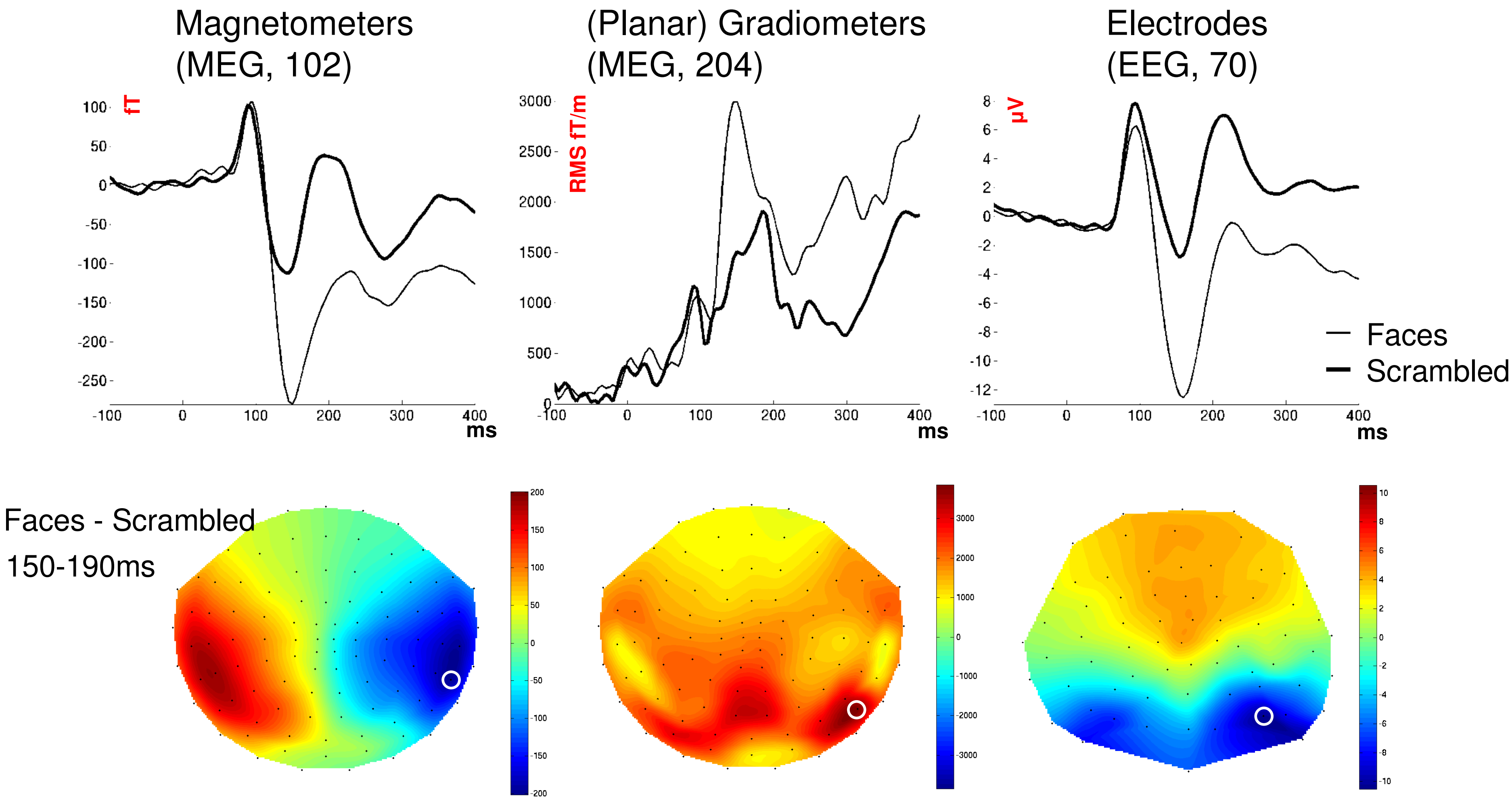
$$\tilde{Y}_i = \frac{Y_i}{\sqrt{\frac{1}{n_i} tr(Y_i Y_i^T)}} \qquad \tilde{L}_i = \frac{L_i}{\sqrt{\frac{1}{n_i} tr(L_i L_i^T)}}$$

i = ith modality, ie MEG or EEG
n_i = Number of sensors for modality *i*

Henson et al (2009) Neuroimage

Symmetric Integration of MEG+EEG Example

ERs from 12 subjects for 3 simultaneously-acquired Neuromag sensor-types:



Henson et al (2009) Neuroimage

Symmetric Integration of MEG+EEG

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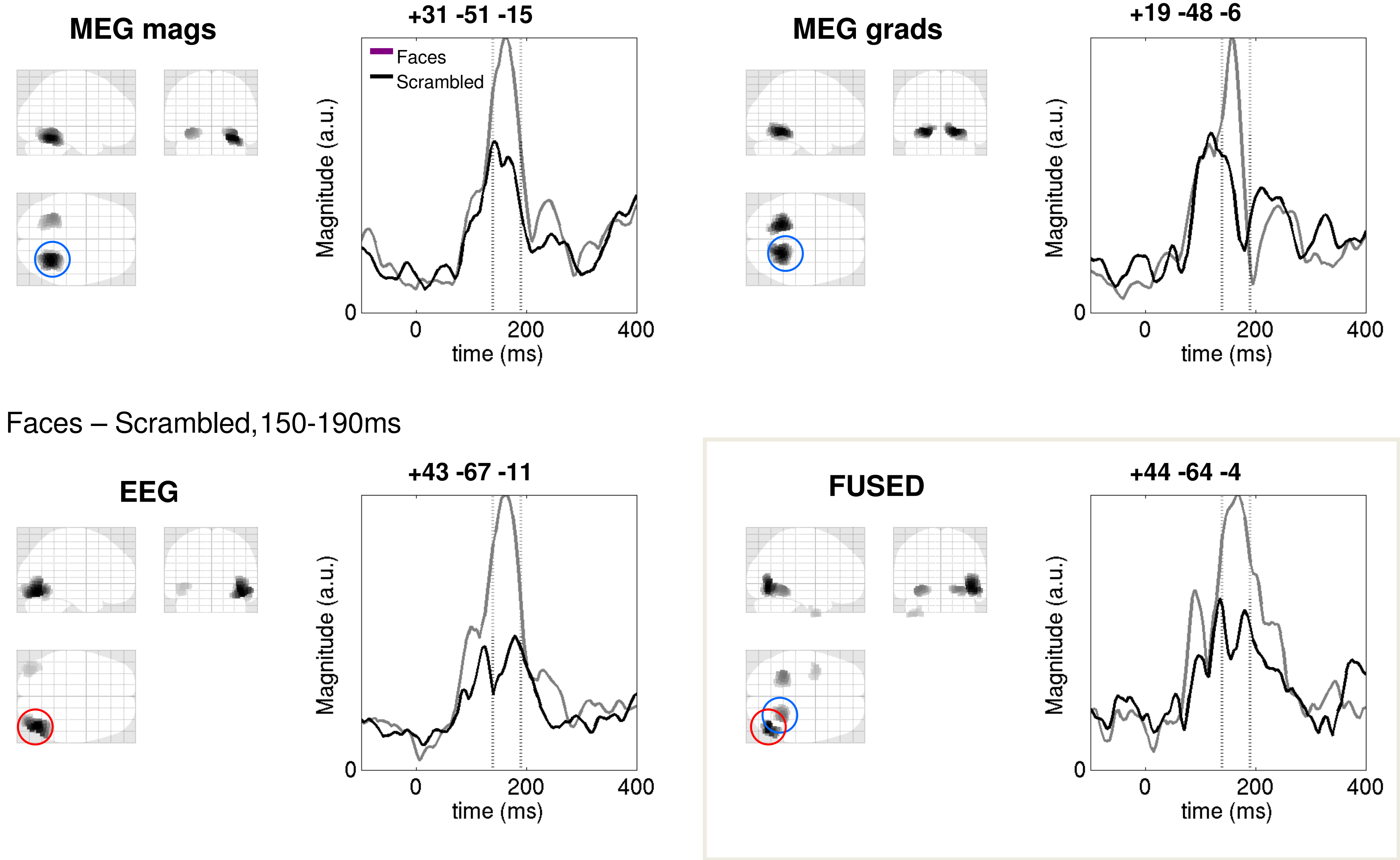

IID noise for each modality; common MSP for sources

Henson et al (2009) Neuroimage

Other Approaches to M/EEG fusion

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- Estimate noise covariance from pre-stimulus baseline (**b**):

$$\mathbf{C}^{(e)} = \begin{bmatrix} cov(\mathbf{b}_{(MEG)}) & \mathbf{0} \\ \mathbf{0} & cov(\mathbf{b}_{(EEG)}) \end{bmatrix}$$

Molins et al (2008), Neuroimage

(which can also be used to pre-whiten data and leadfields, scaling to noise units)…

…but downside is that **baseline contains source activity**, so not estimate of true sensor noise

- Maximise mutual information between MEG and EEG

Baillet et al (1999), IEEE

- Re-parameterise leadfields in terms of radial/tangential components

Huang et al (2007), Neuroimage

Talk Overview

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1. MEG + EEG symmetric integration (fusion)

2. M/EEG + fMRI asymmetric integration

Asymmetric Integration of MEG+fMRI Background

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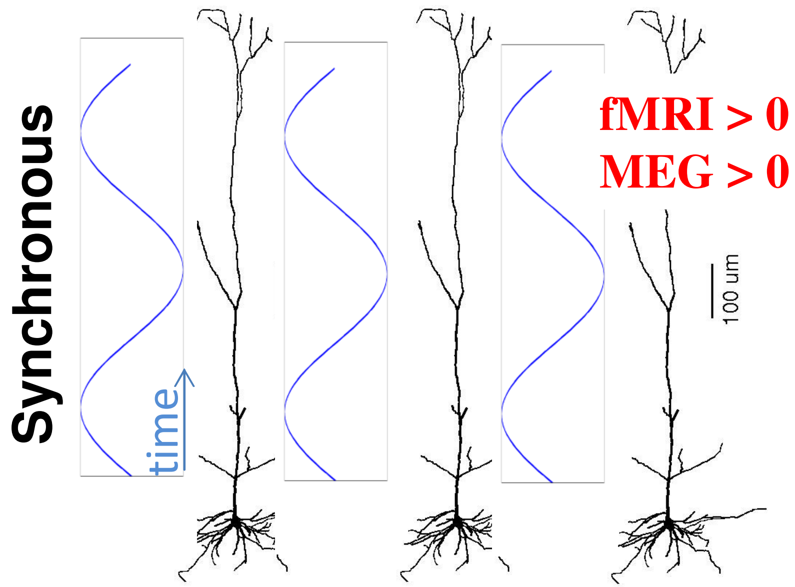
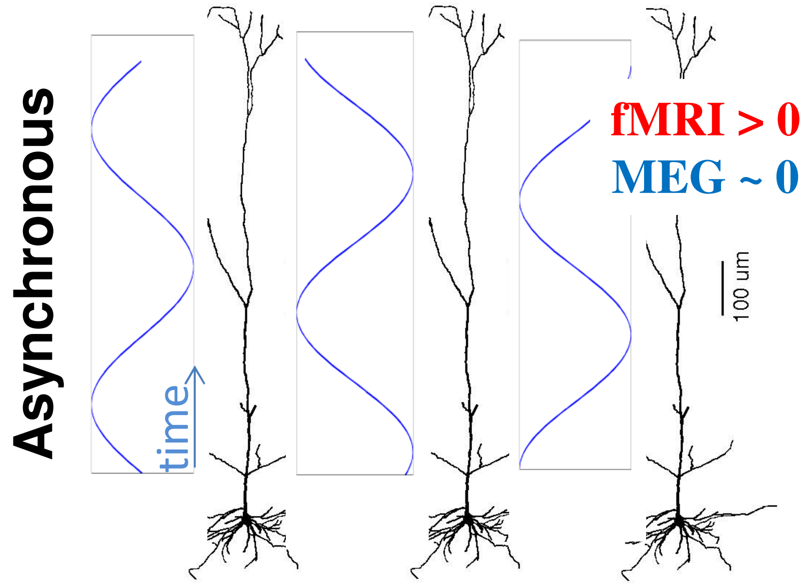
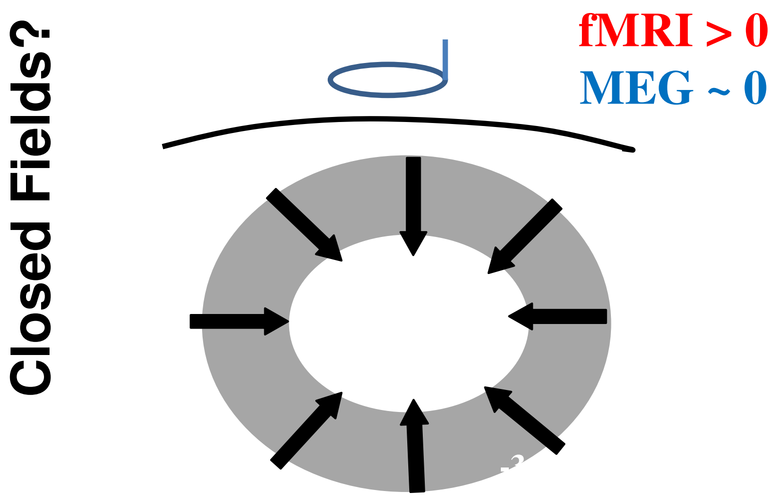
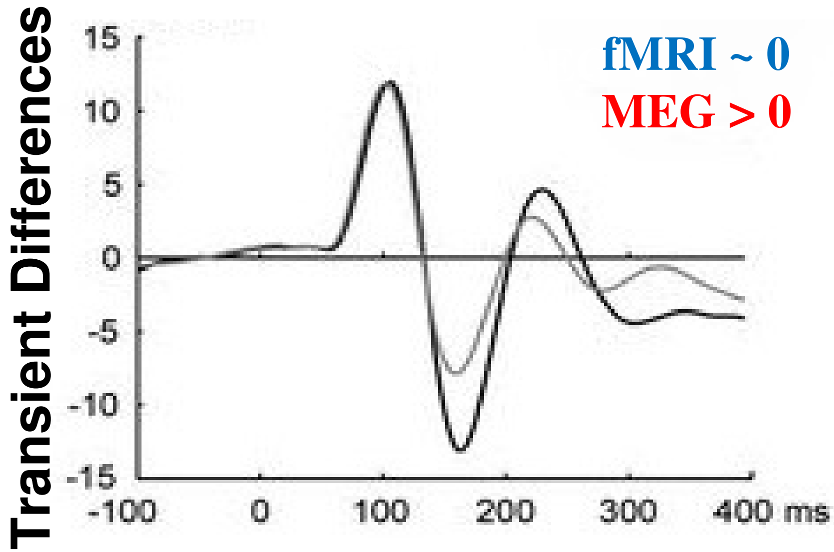
- fMRI has superior spatial resolution (~mm) vs. M/EEG, but inferior temporal resolution (integrating over seconds)
- fMRI and M/EEG measure similar, but not identical, neural activity
- Eg, some source configurations give detectable fMRI signal, but no detectable M/EEG signal…
- …and vice versa

Asymmetric Integration of MEG+fMRI
Background









Asymmetric Integration of MEG+fMRI Background

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- fMRI has superior spatial resolution (~mm) vs. M/EEG, but inferior temporal resolution (integrating over seconds)
- fMRI and M/EEG measure similar, but not identical, neural activity
- Eg, some source configurations give detectable fMRI signal, but no detectable M/EEG signal…
- …and vice versa
- Use fMRI as a soft, rather than hard, constraint on localisation of sources of M/EEG data…

Asymmetric Integration of MEG+fMRI

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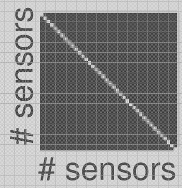
Specifying (co)variance components (priors/regularisation):

$$\mathbf{C} = \sum_i \lambda_i \mathbf{Q}_i$$

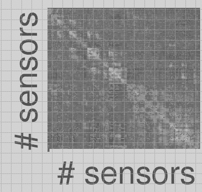
C = Sensor/Source covariance
Q = Covariance components
λ = Hyper-parameters

1. Sensor components, $Q_i^{(e)}$ (error):

"IID" (white noise):

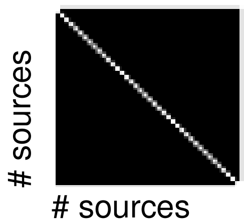


Empty-room:

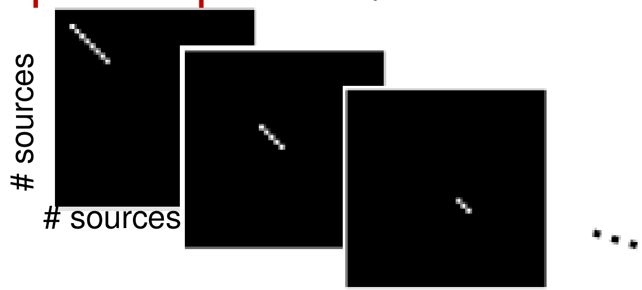


2. Each suprathreshold fMRI cluster becomes a separate prior $\mathbf{Q}_i^{(s)}$

"IID" (min norm):



fMRI Priors:



Henson et al (2010) Hum. Brain Map.

Asymmetric Integration of MEG+fMRI

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General solution again:

$$\hat{\mathbf{s}} = \mathbf{C}^{(s)}\mathbf{L}^T(\mathbf{L}\mathbf{C}^{(s)}\mathbf{L}^T + \lambda\mathbf{C}^{(e)})^{-1}\mathbf{d}$$

$$\mathbf{e} \sim N(0, \mathbf{C}^{(e)})$$
$$\mathbf{s} \sim N(0, \mathbf{C}^{(s)})$$

Now source covariance expressed as number of fMRI clusters:

$$\mathbf{C}^{(s)} = \lambda_1^{(s)}\mathbf{Q}^{(s)}_{(fMRI1)} + \lambda_2^{(s)}\mathbf{Q}^{(s)}_{(fMRI2)} + \ldots$$

When $\mathbf{Q}_i^{(s)}$ does not help maximise model evidence, $\lambda_i^{(s)} \rightarrow 0$,
i.e, constraints ignored…

…catering for situations where fMRI signal does not reflect same activity as in M/EEG signal (e.g, occurring later than time-window than M/EEG data)

Symmetric Integration of MEG+EEG Generative Model

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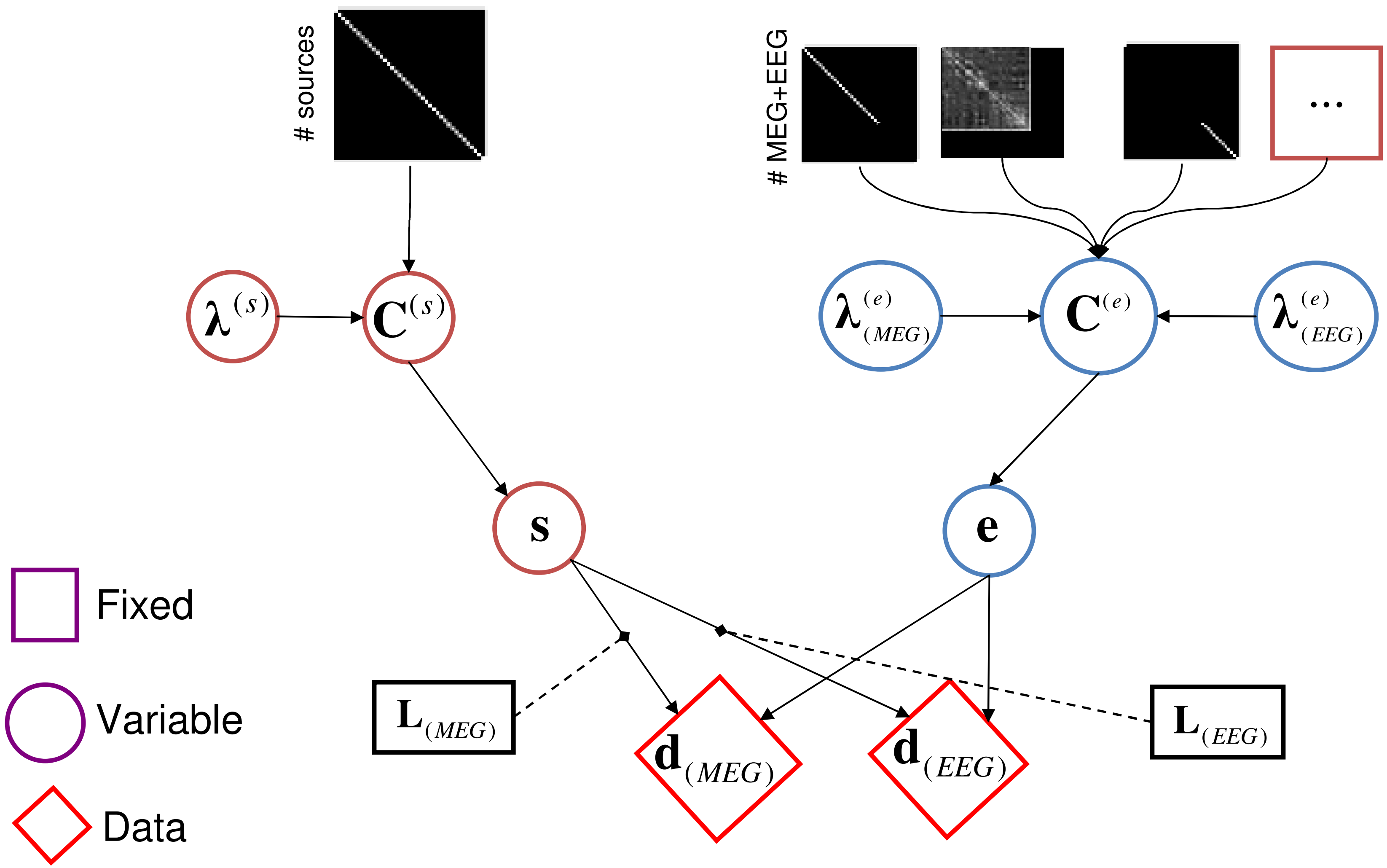
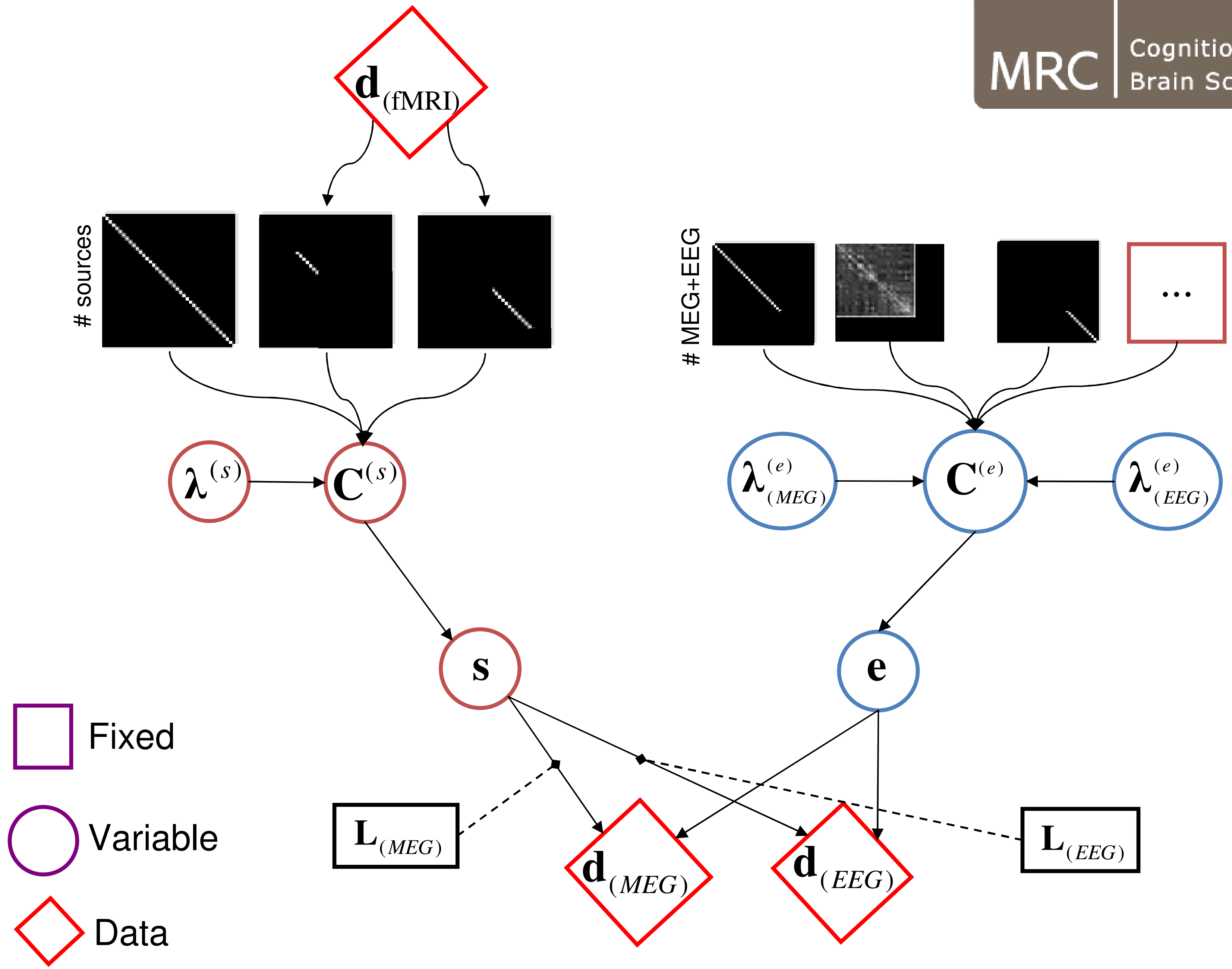


Henson et al (2009) Neuroimage



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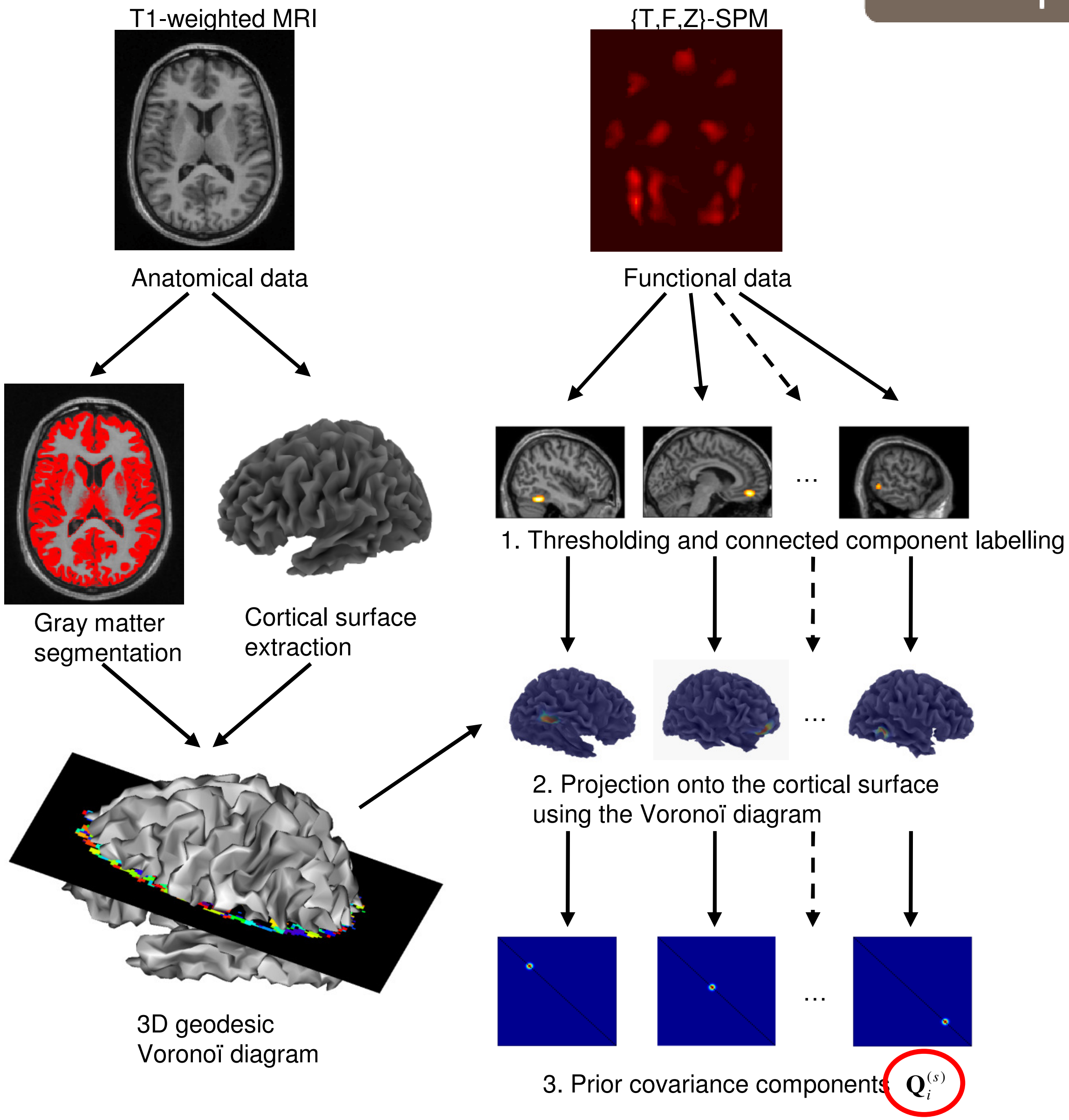

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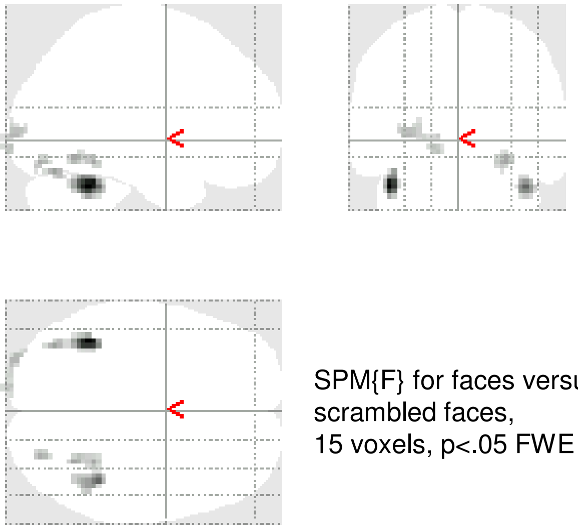
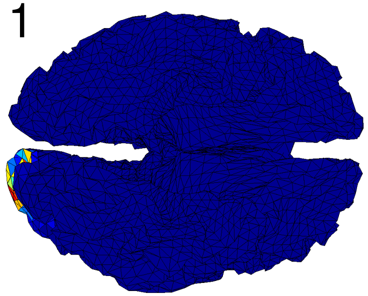


SPM{F} for faces versus
scrambled faces,
15 voxels, p<.05 FWE

1


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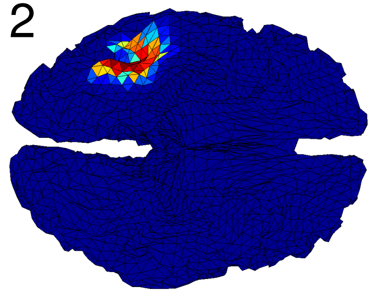

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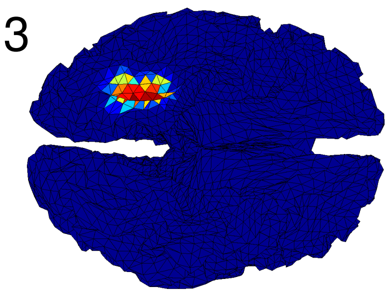

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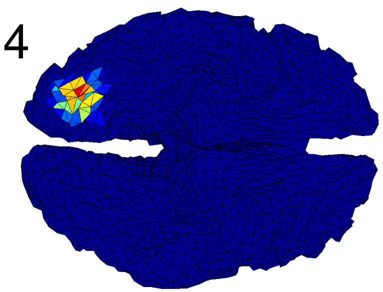
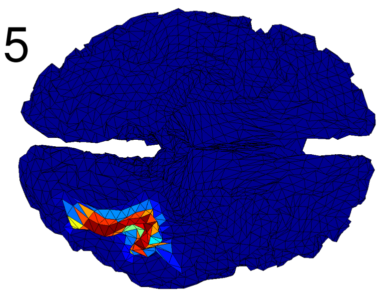


5


5 clusters from SPM of fMRI data from separate group of (18) subjects in MNI space

Henson et al (2010) Hum. Brain Map.

Asymmetric Integration of M/EEG+fMRI

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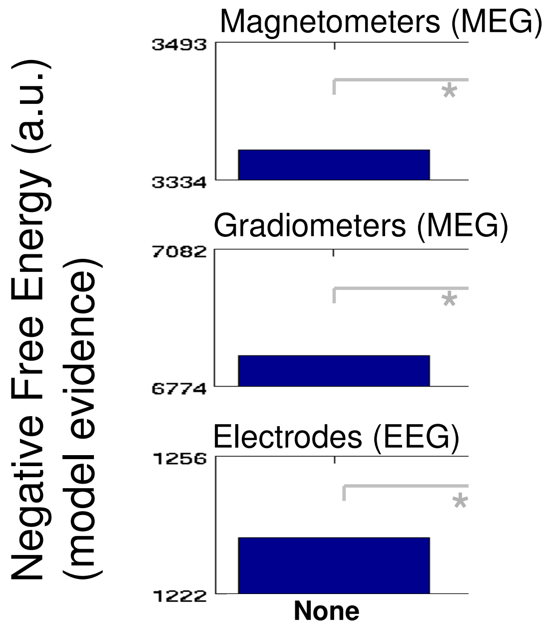

Henson et al (2010) Hum. Brain Map.

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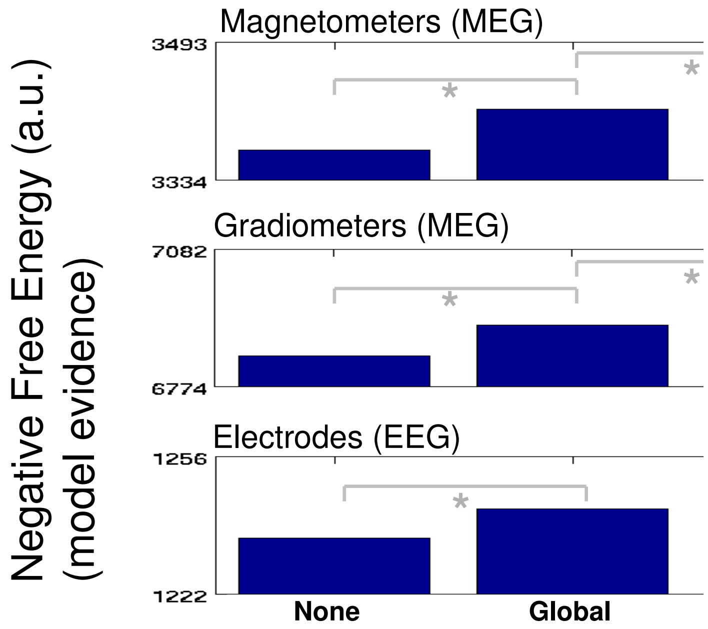

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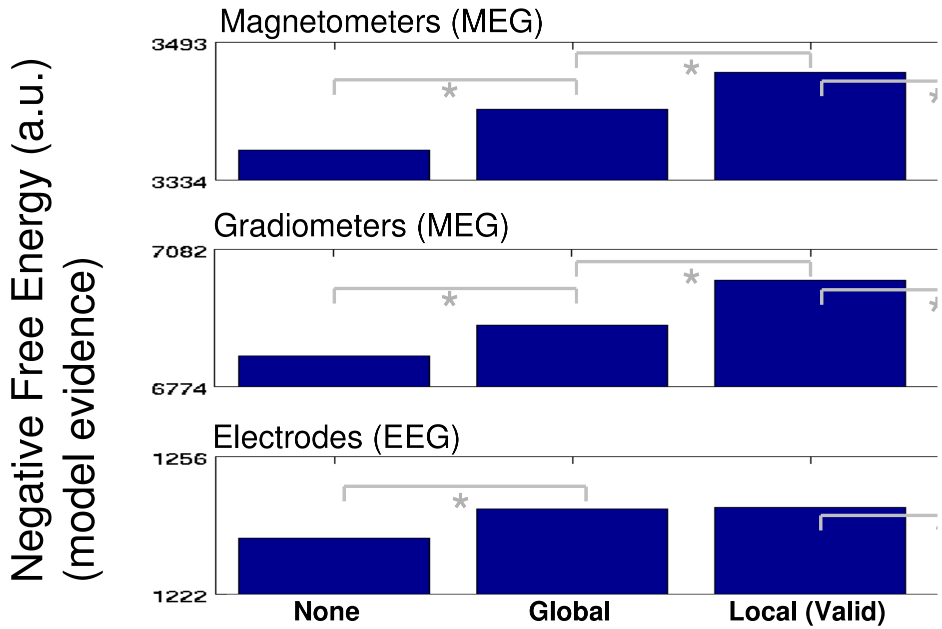

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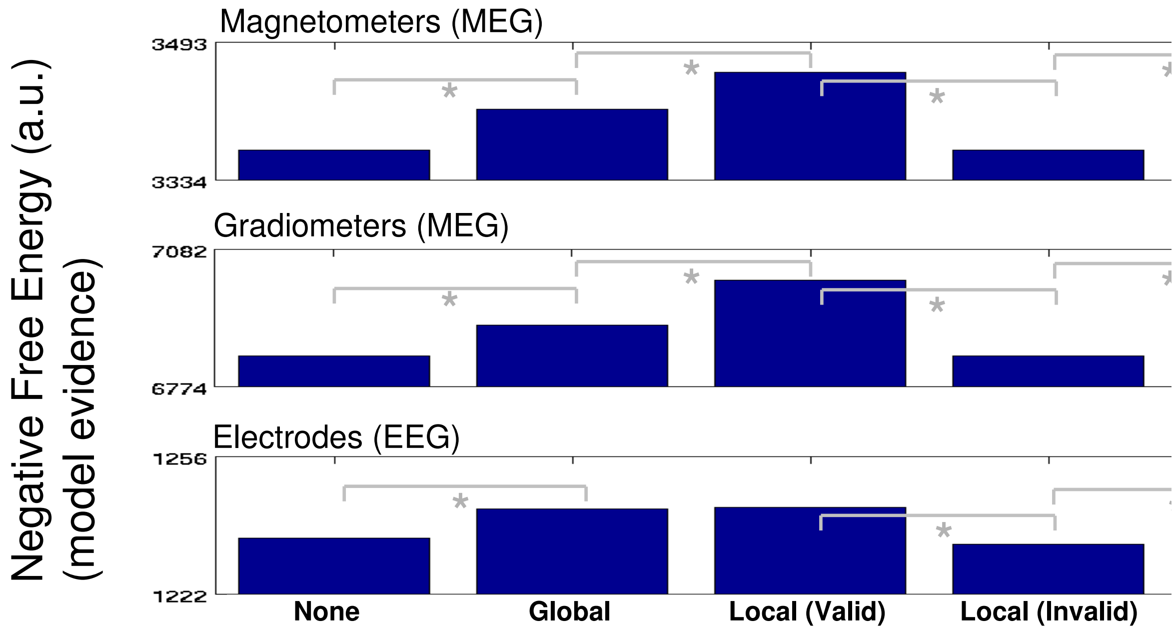

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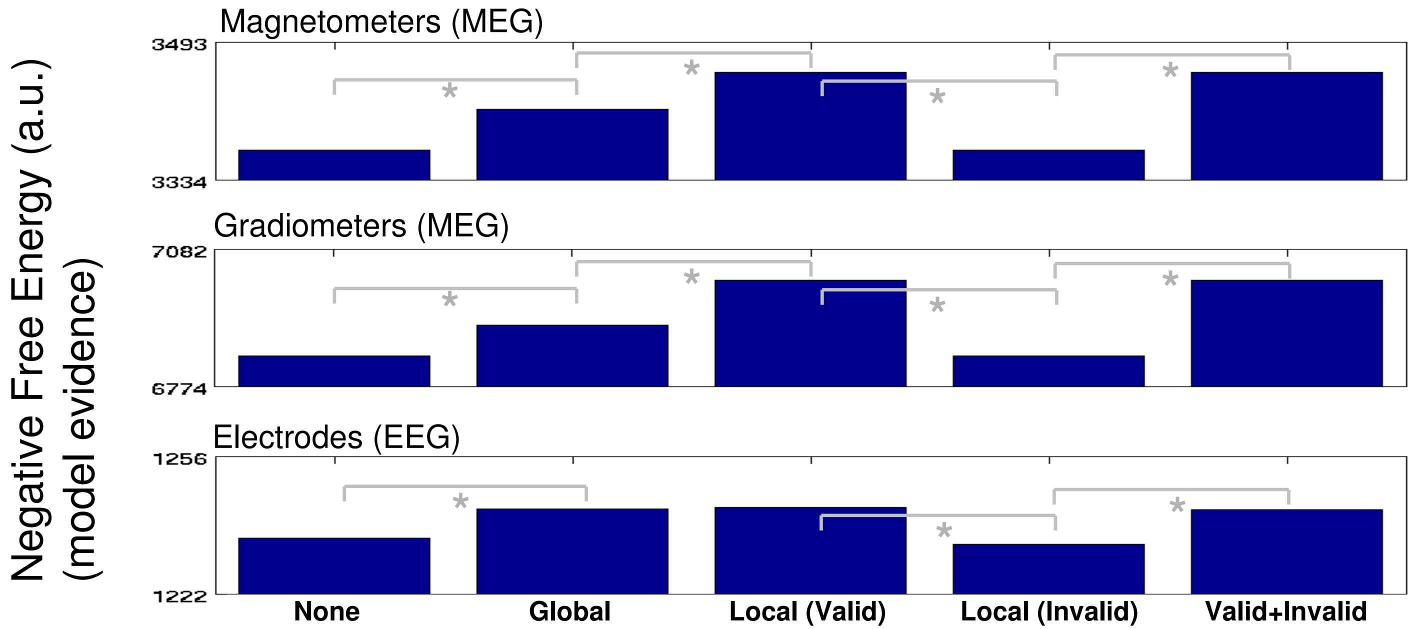
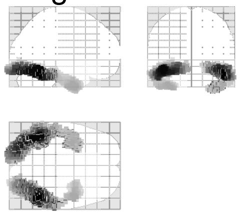


Henson et al (2010) Hum. Brain Map.

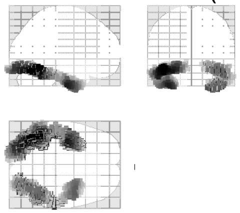
Asymmetric Integration of M/EEG+fMRI

IID sources and IID noise (L2 MNM)

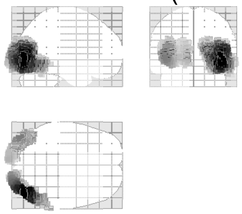
Magnetometers (MEG)



Gradiometers (MEG)



Electrodes (EEG)



None

Henson et al (2010) Hum. Brain Map.

Asymmetric Integration of M/EEG+fMRI

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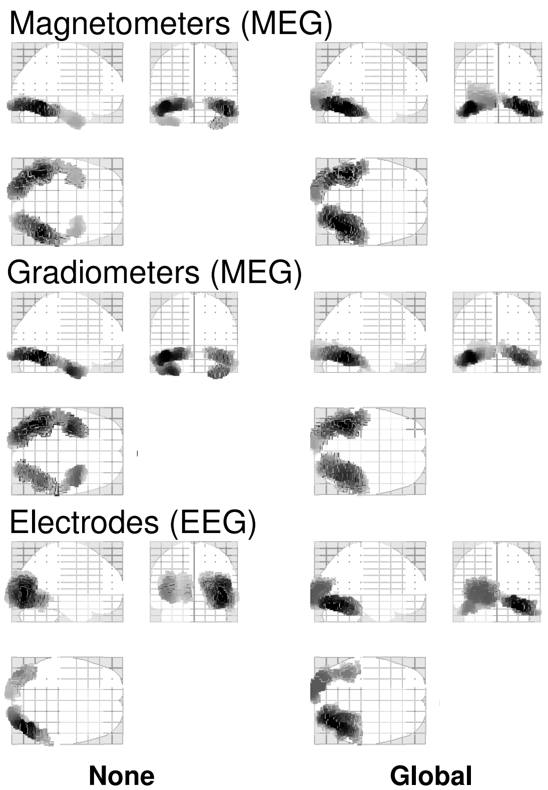
IID sources and IID noise (L2 MNM)



Henson et al (2010) Hum. Brain Map.

Asymmetric Integration of M/EEG+fMRI

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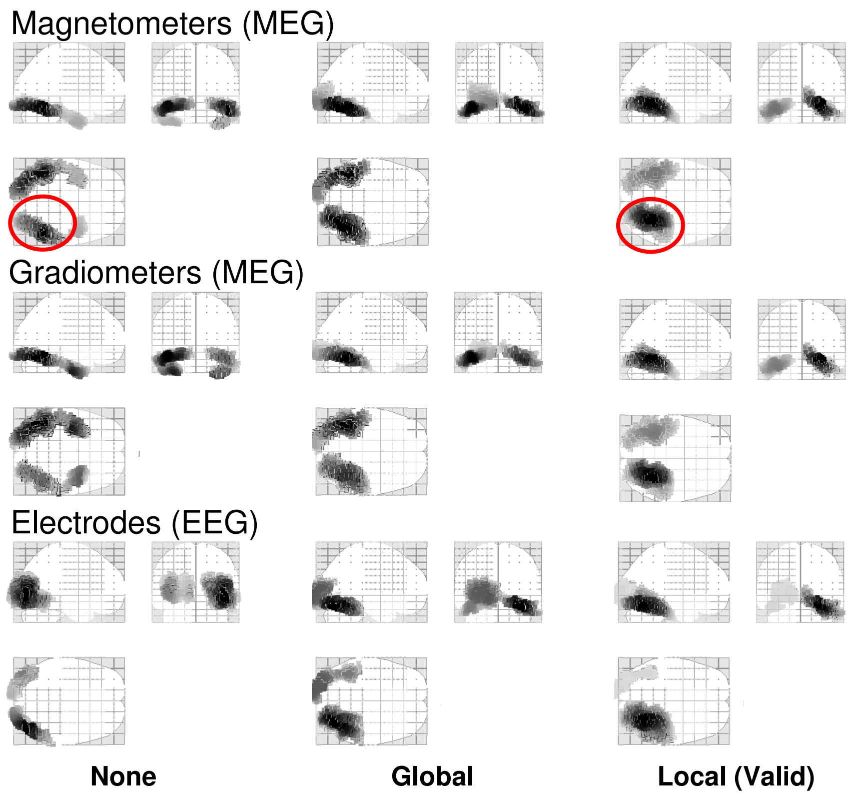

fMRI priors counteract superficial bias of Min Norm

Henson et al (2010) Hum. Brain Map.

Asymmetric Integration of M/EEG+fMRI

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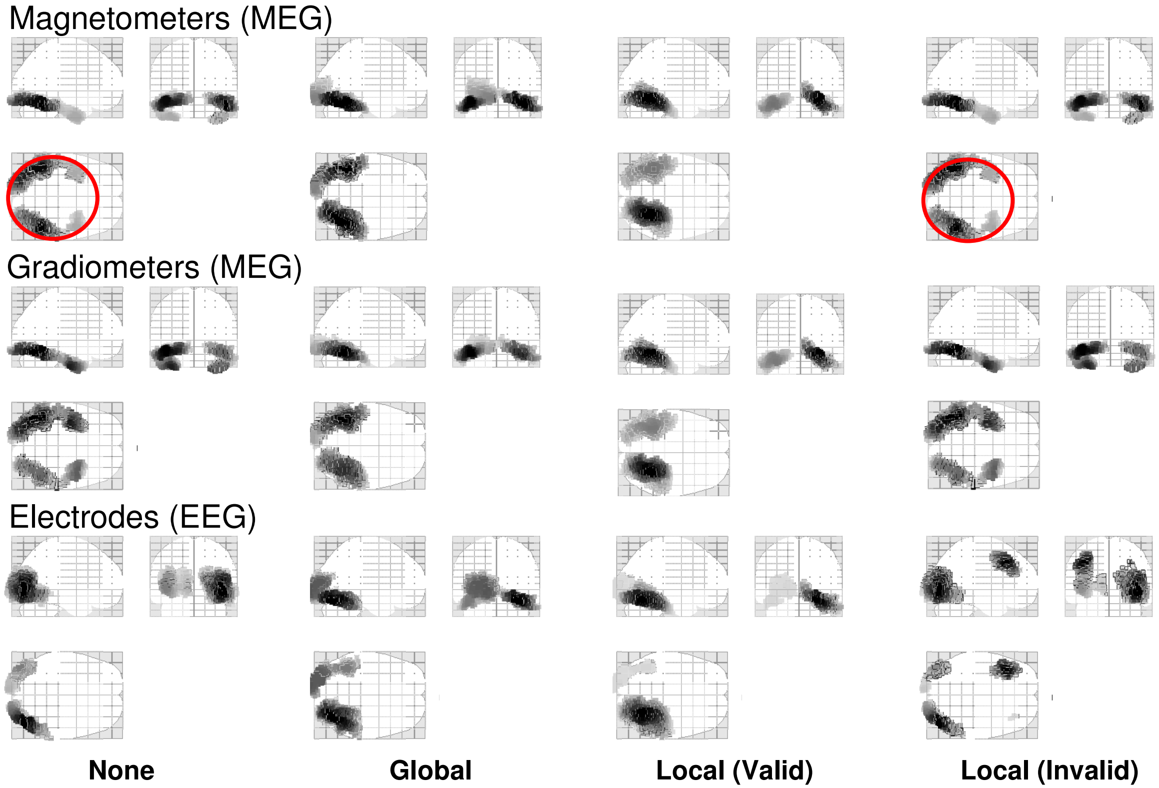
IID sources and IID noise (L2 MNM)



Invalid priors generally discounted (at least for MEG)

Henson et al (2010) Hum. Brain Map.

Asymmetric Integration of M/EEG+fMRI

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- Adding a single, global fMRI prior increases model evidence
- Adding multiple valid priors increases model evidence further
- Adding invalid priors does not necessarily increase model evidence, particularly in conjunction with valid priors
  Helpful if some fMRI regions produce no MEG/EEG signal (or arise from neural activity at different times)
- Can counteract superficial bias of, e.g, minimum-norm
- Makes some allowance for different sensitivities of fMRI and M/EEG to certain types of neural activity

Henson et al (2010) Hum. Brain Map.

Other Approaches to fMRI/MEG/EEG

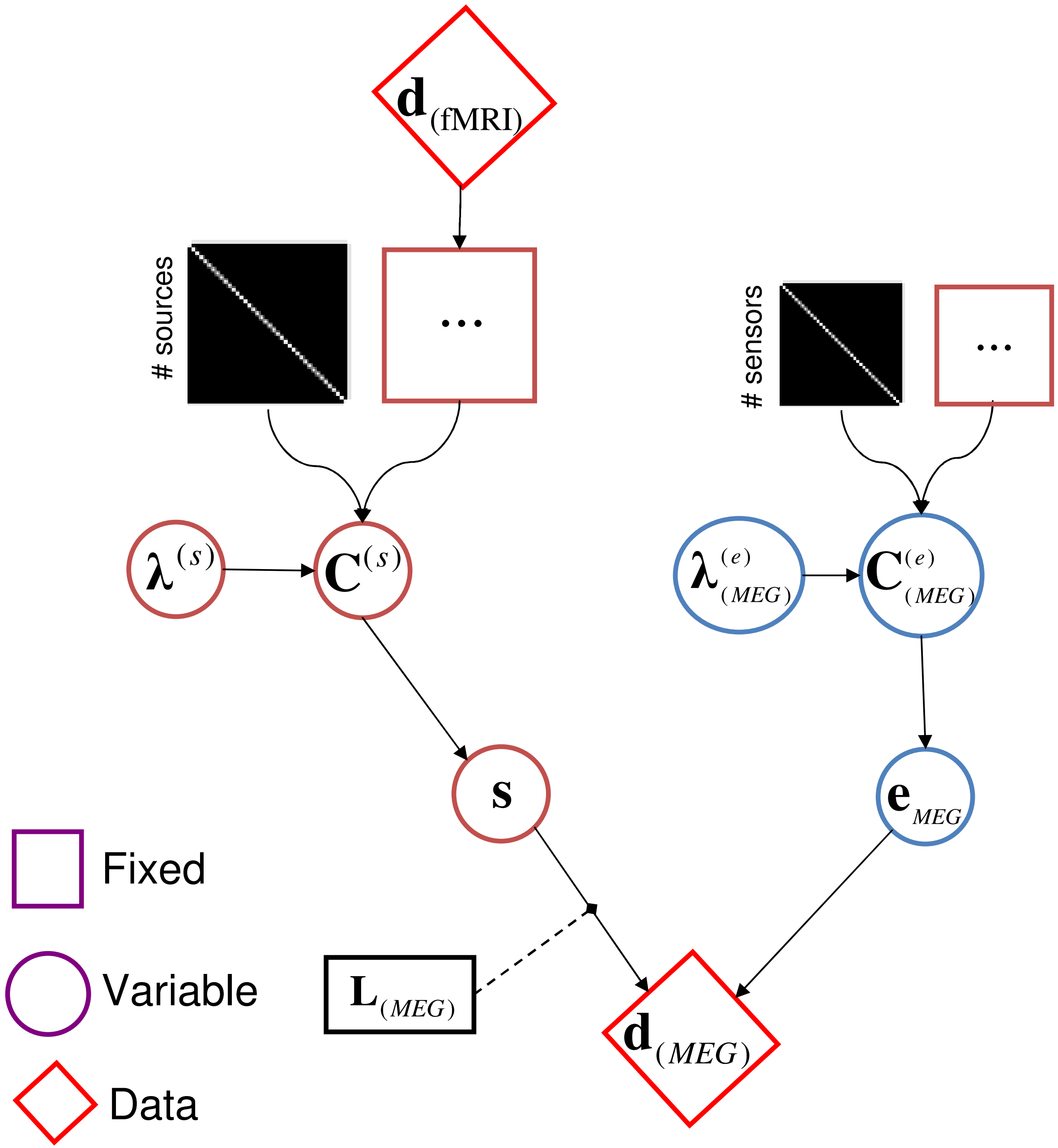
Symmetric Integration (fusion) of fMRI and M/EEG

- e.g based on ROIs:

Ou et al (2010), Neuroimage

- e.g, full biophysical model

Sotero & Trujillo-Barreto (2008), Neuroimage



Henson et al (2011) Frontiers

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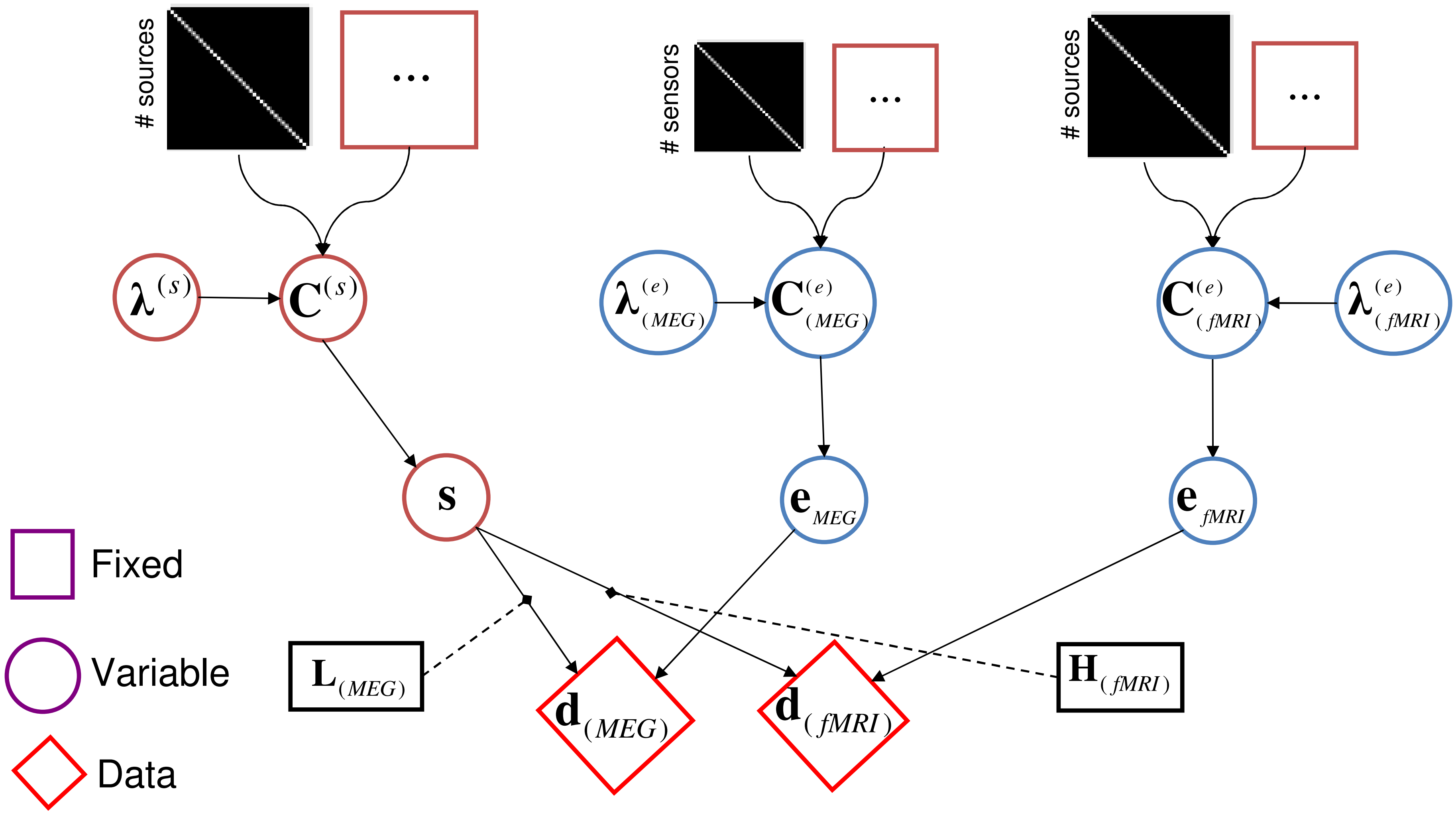

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The End