Dynamic Causal Modelling for EEG and MEG

Stefan Kiebel

Max Planck Institute for
Human Cognitive and Brain Sciences
Leipzig, Germany

Overview

1 M/EEG analysis

2 Dynamic Causal Modelling – Motivation

3 Dynamic Causal Modelling – Generative model

4 Bayesian inference

5 Applications

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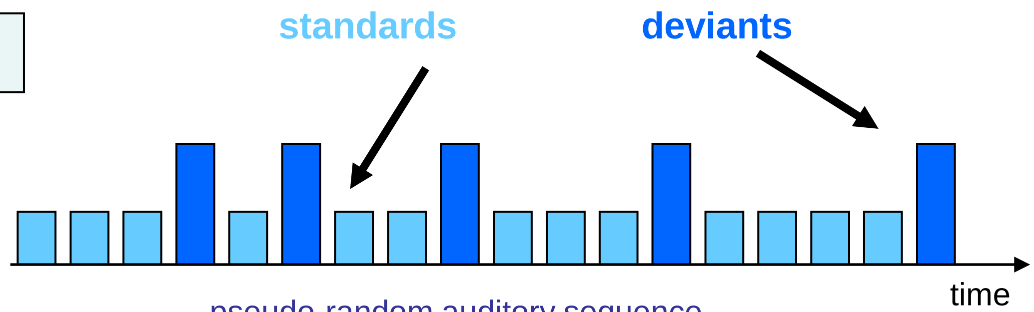
Mismatch negativity (MMN)

Paradigm

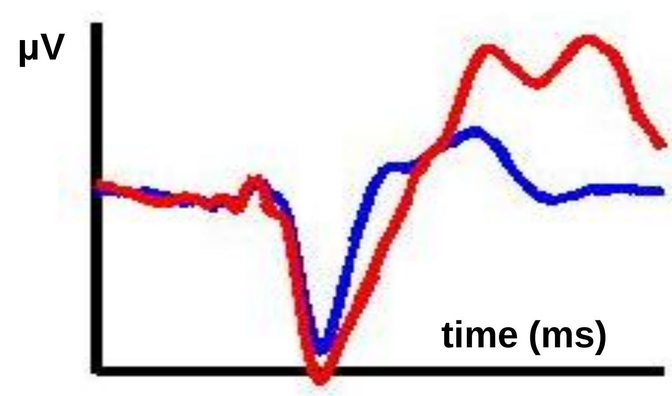


pseudo-random auditory sequence

80% standard tones – 500 Hz

20% deviant tones – 550 Hz

Raw data (e.g., 128 sensors) → Preprocessing (SPM8) → Evoked responses (here: single sensor)



Garrido et al., NeuroImage, 2007

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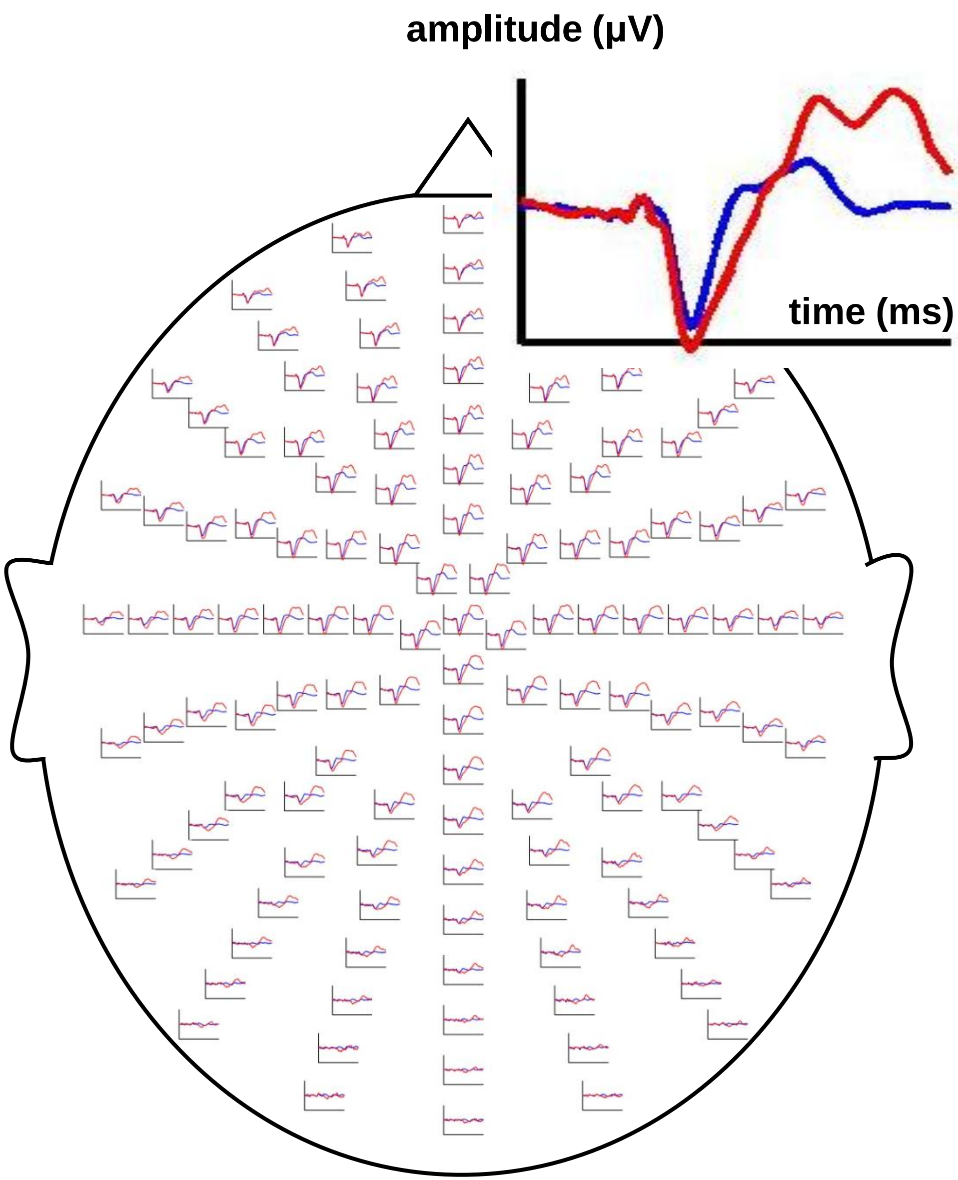
Electroencephalography (EEG)



<u>Modelling aim</u>:
Explain **all** data with few parameters

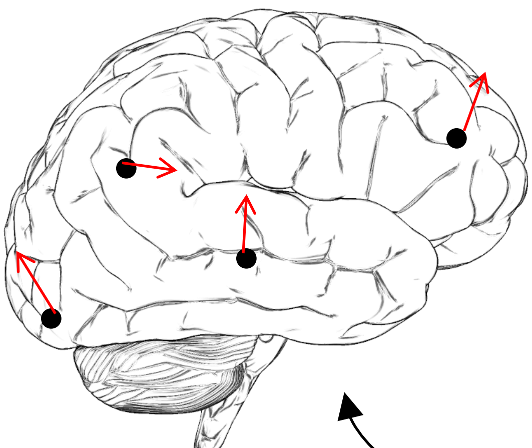
<u>How to:</u>
Assume data are caused by few interacting brain sources

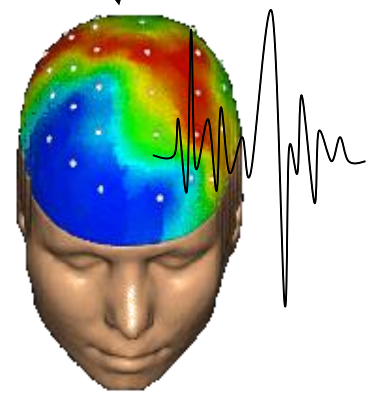
Probabilistic inference

Forward problem

$$p(y \mid \theta, m)$$

Likelihood





Posterior distribution

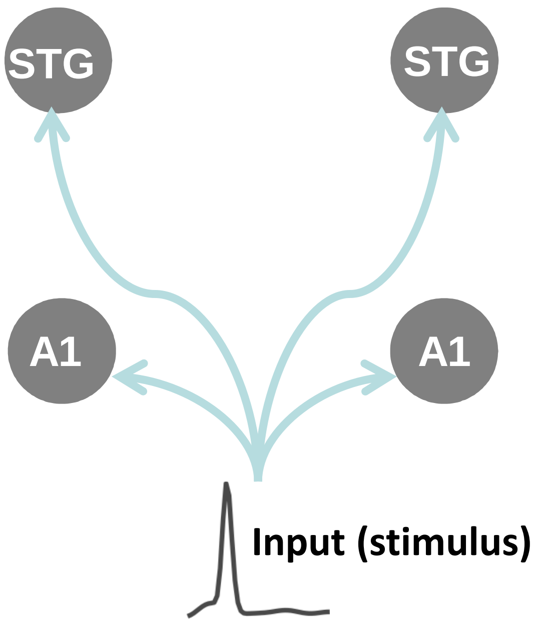
$$p(\theta \mid y, m)$$

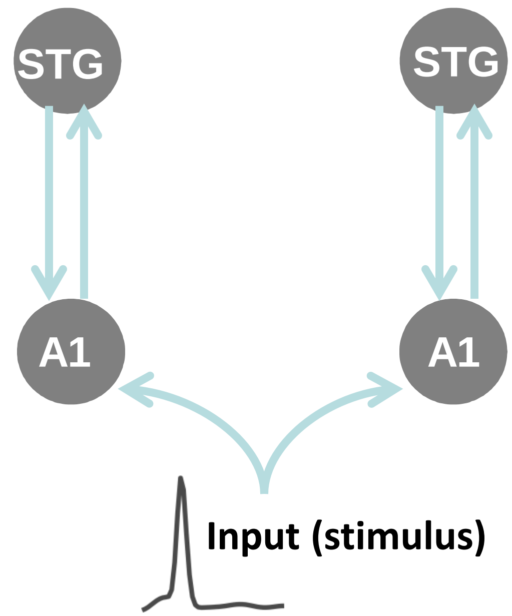
Inverse problem

Connectivity models

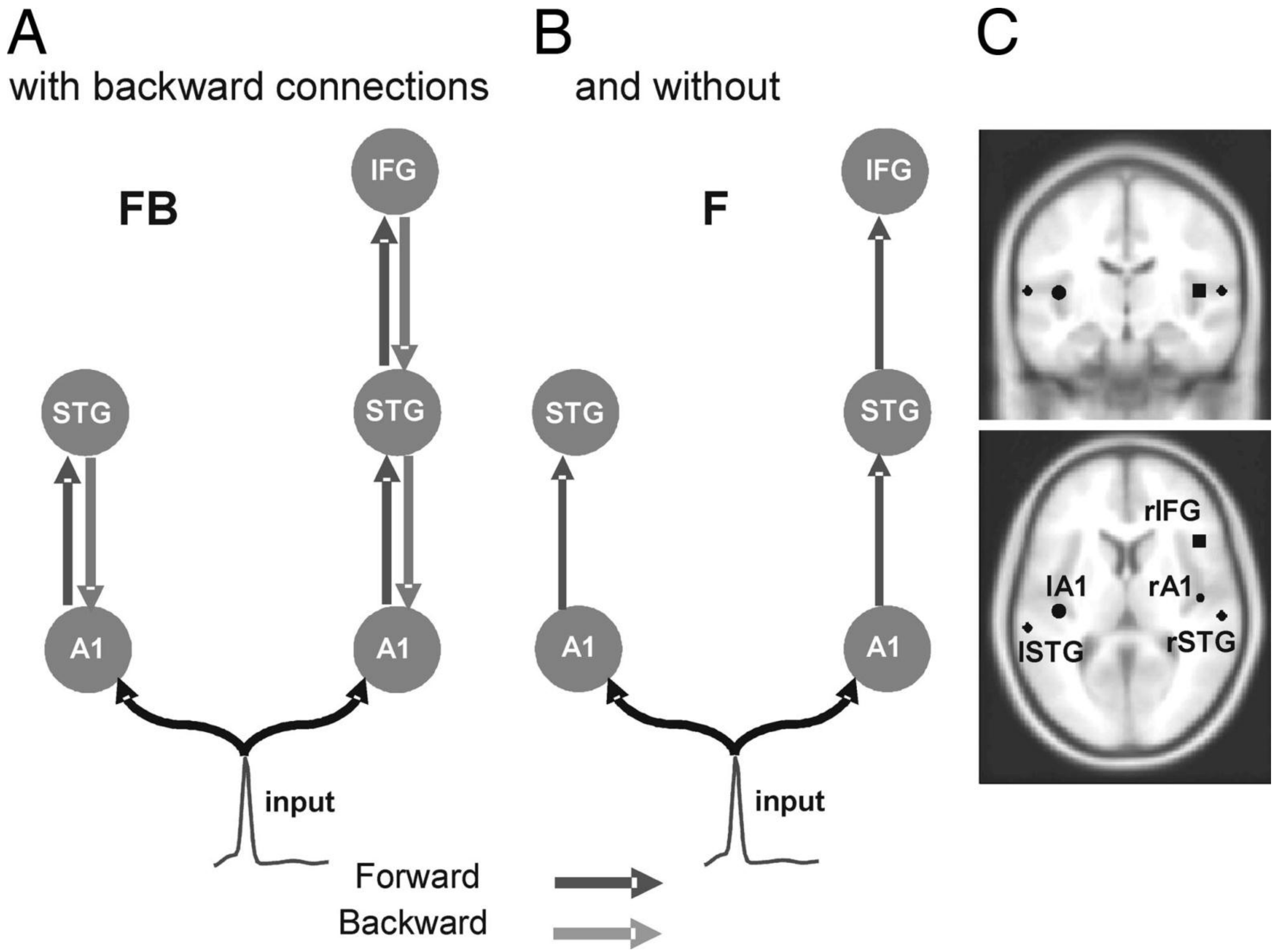
Conventional analysis:
Which regions are involved in task?

DCM analysis:
How do regions communicate?





Model for auditory evoked response



Garrido et al., PNAS, 2007

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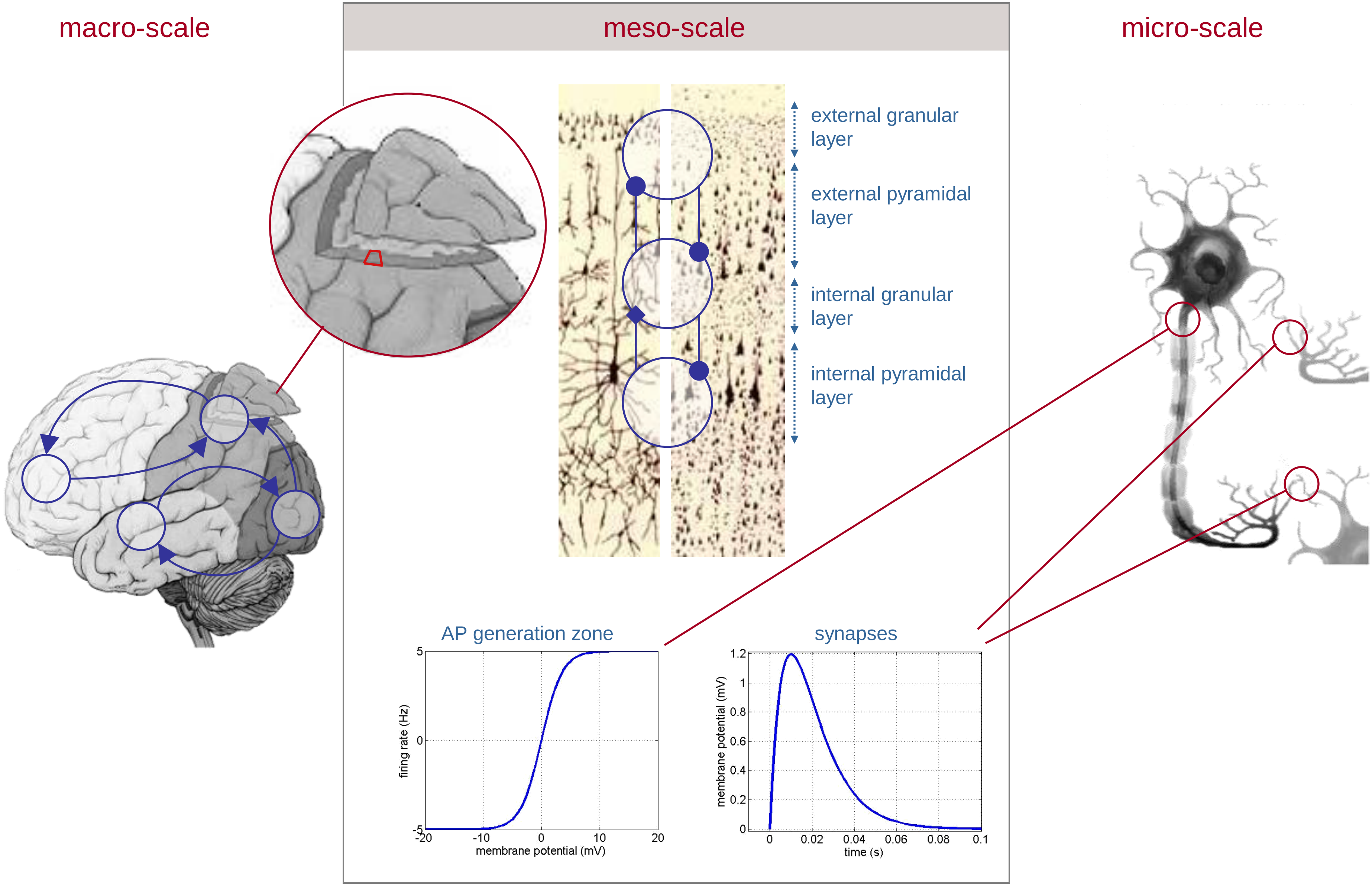
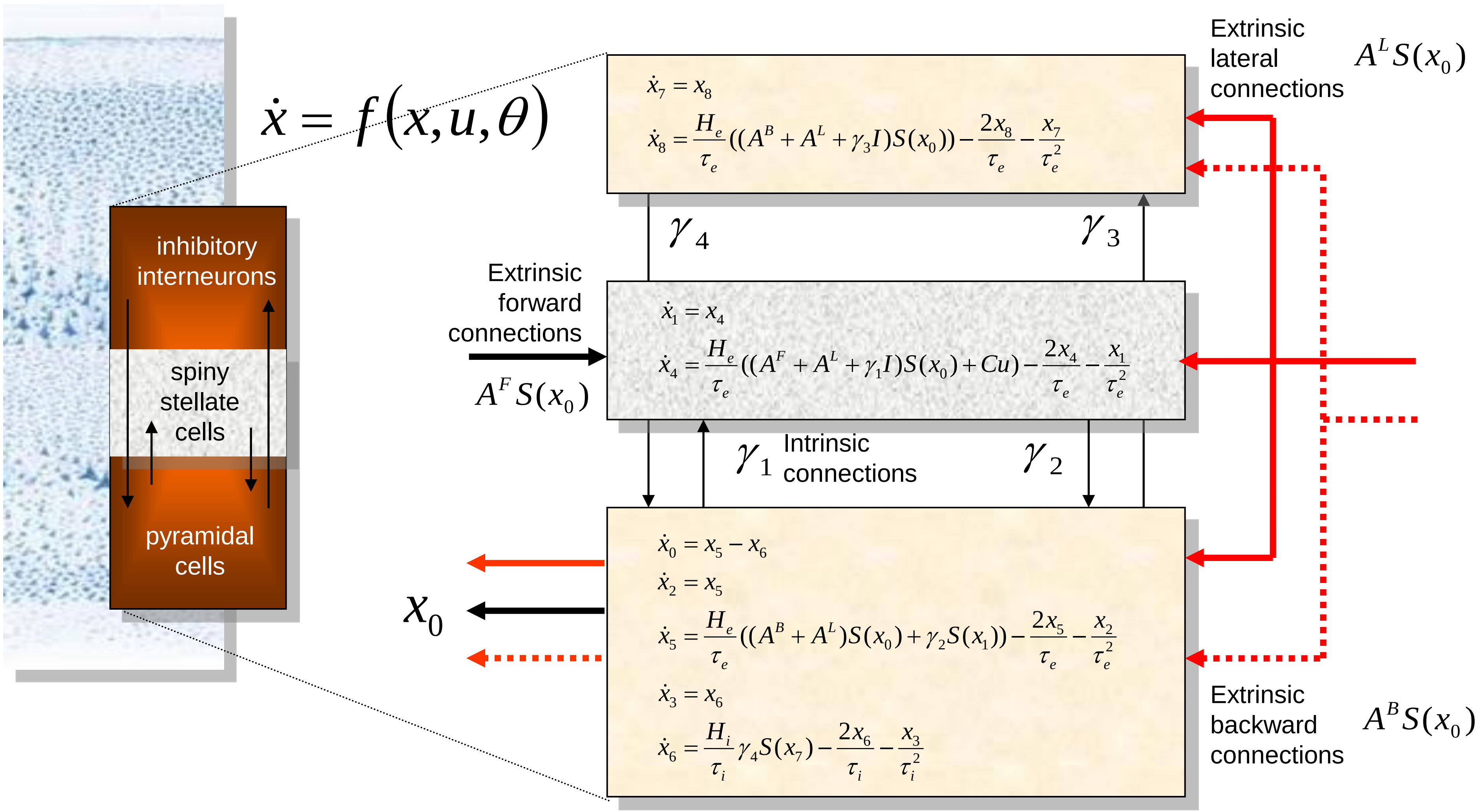
Inference at meso-scale

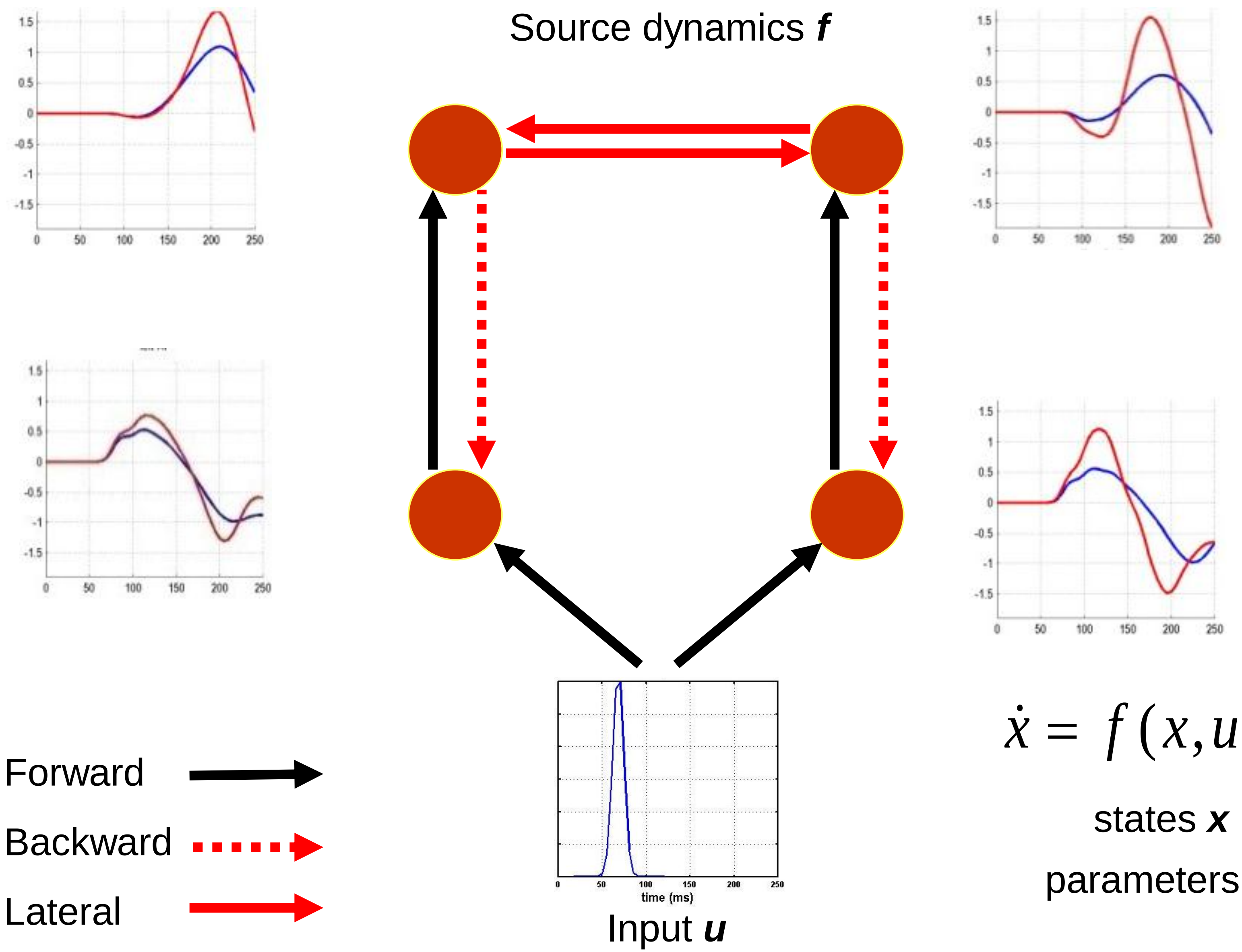


Neural mass equations and connectivity



Jansen et Rit, Biol Cybern,1995
David et al., NeuroImage, 2006

Source activity over time

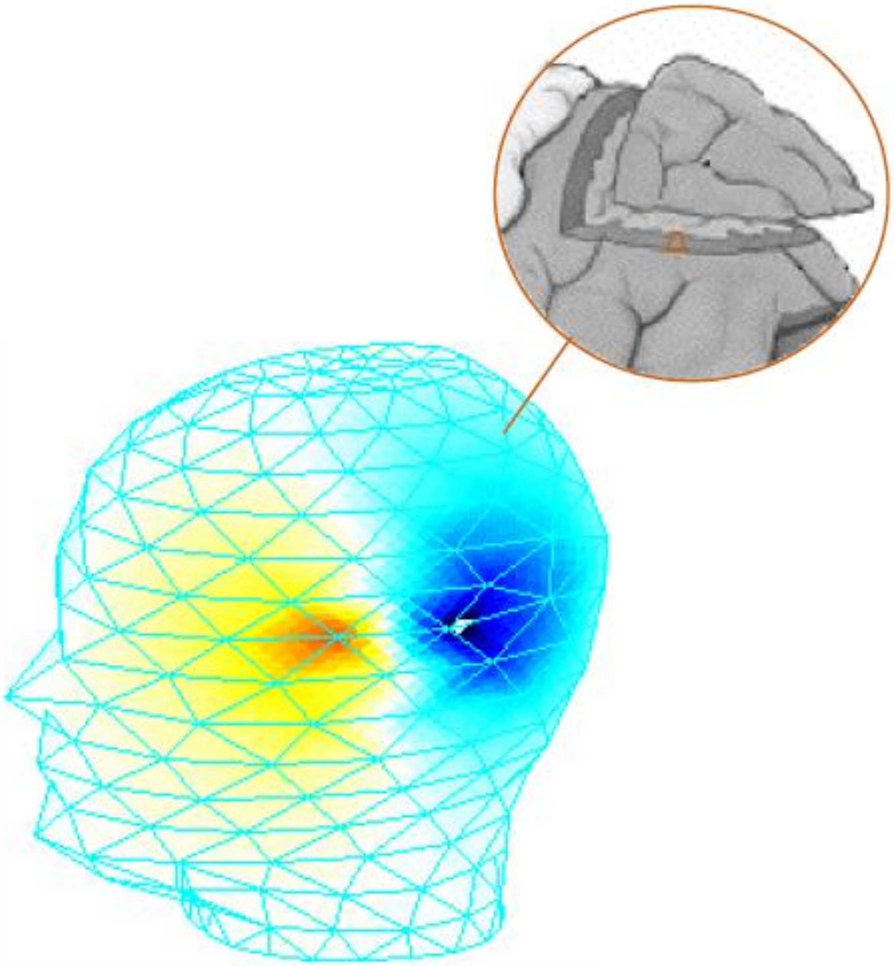


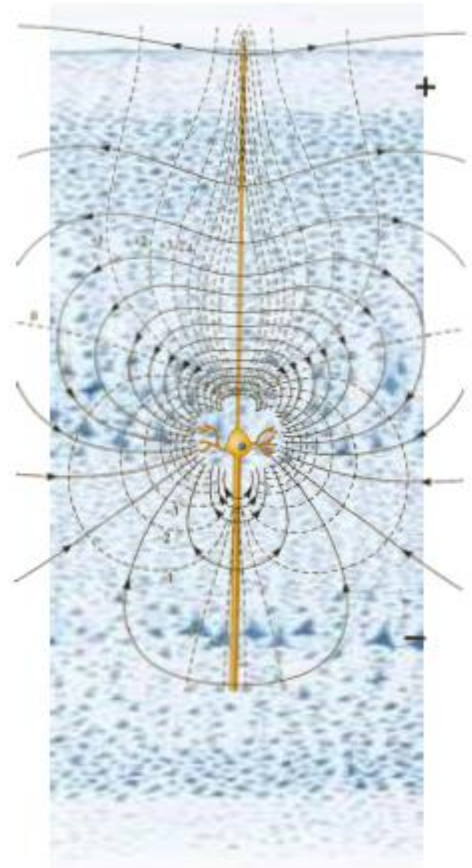
$$\dot{x} = f(x, u, \theta)$$

states ***x***

parameters ***θ***

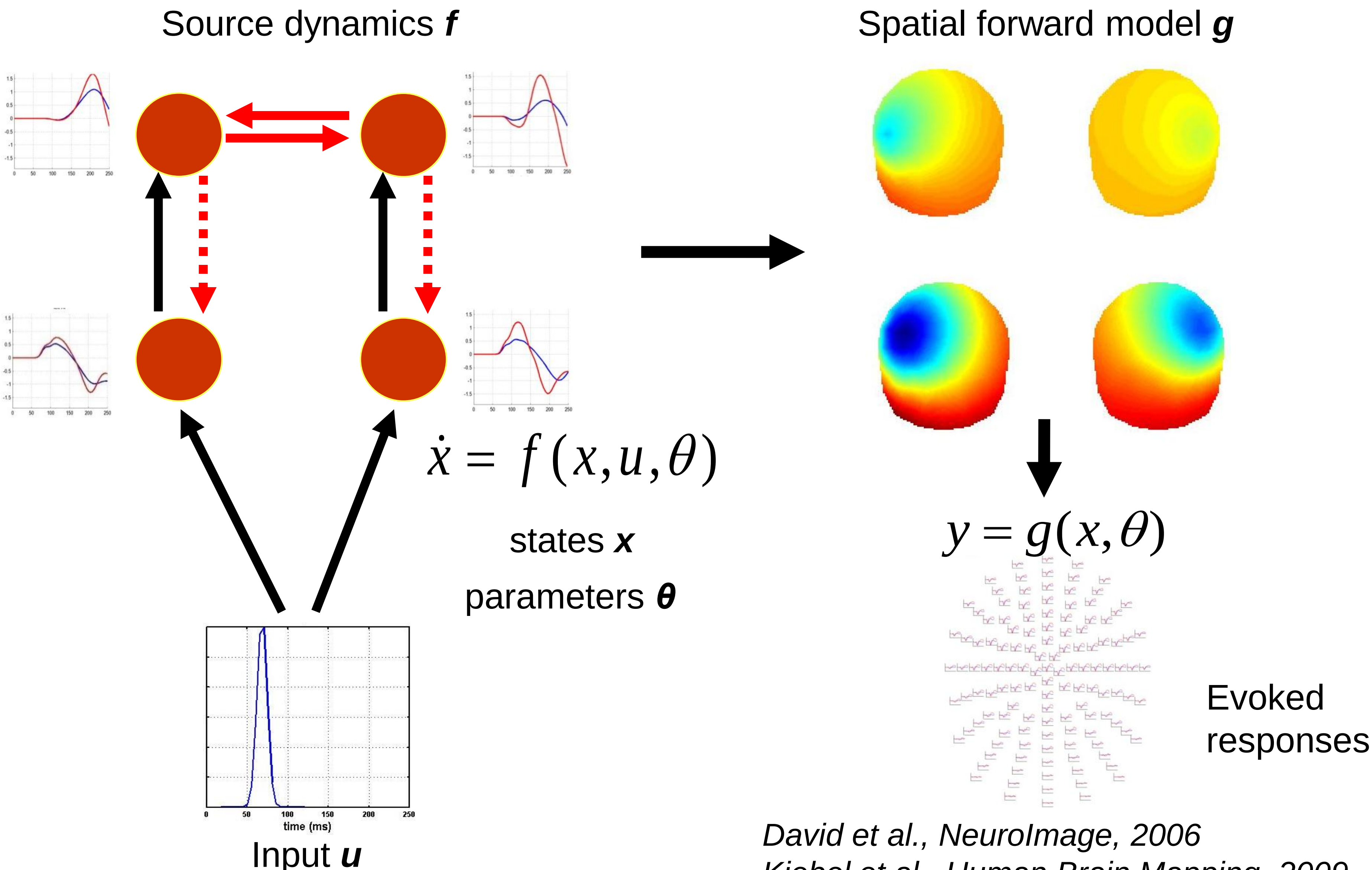
Spatial forward model





Kiebel et al., NeuroImage, 2006
Daunizeau et al., NeuroImage, 2009

The generative model



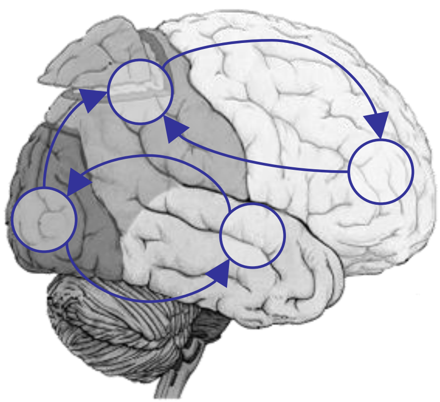
David et al., NeuroImage, 2006
Kiebel et al., Human Brain Mapping, 2009

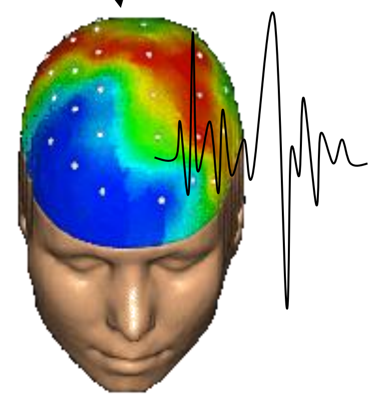
Probabilistic inference

Forward problem

$$p(y \mid \theta, m)$$

Likelihood





Posterior distribution

$$p(\theta \mid y, m)$$

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Bayesian inference

Evoked responses

Specify generative forward model
(with prior distributions of parameters)

Variational (Bayesian) algorithm

<u>Iterative procedure:</u>

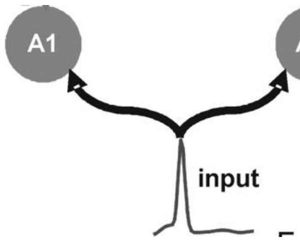
1. Compute model response using current set of parameters
2. Compare model response with data
3. Improve parameters, if possible

1. Posterior distributions of parameters $p(\theta \mid y, m)$

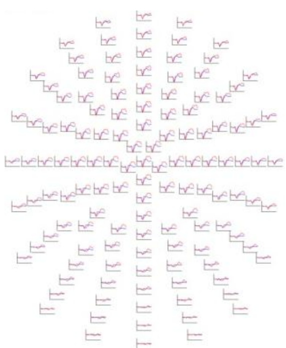
2. Model evidence $p(y \mid m)$

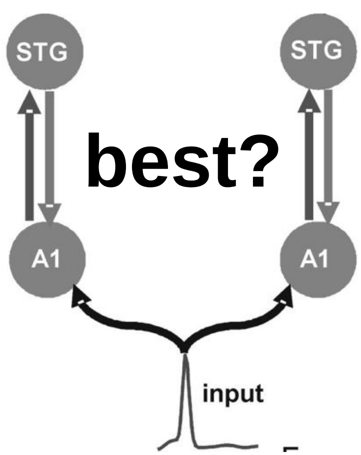
Model selection:
Which model is the best?

best?



data y





Model *1* → $p(y \mid m_1)$, $p(\theta \mid y, m_1)$

Model *2* → $p(y \mid m_2)$, $p(\theta \mid y, m_2)$

⋮

Model *n* → $p(y \mid m_n)$, $p(\theta \mid y, m_n)$

Model selection: Select model with highest model evidence

$$p(y \mid m_i)$$

Stephan et al., NeuroImage, 2009
Penny et al., PLoS Comp Biol, 2010

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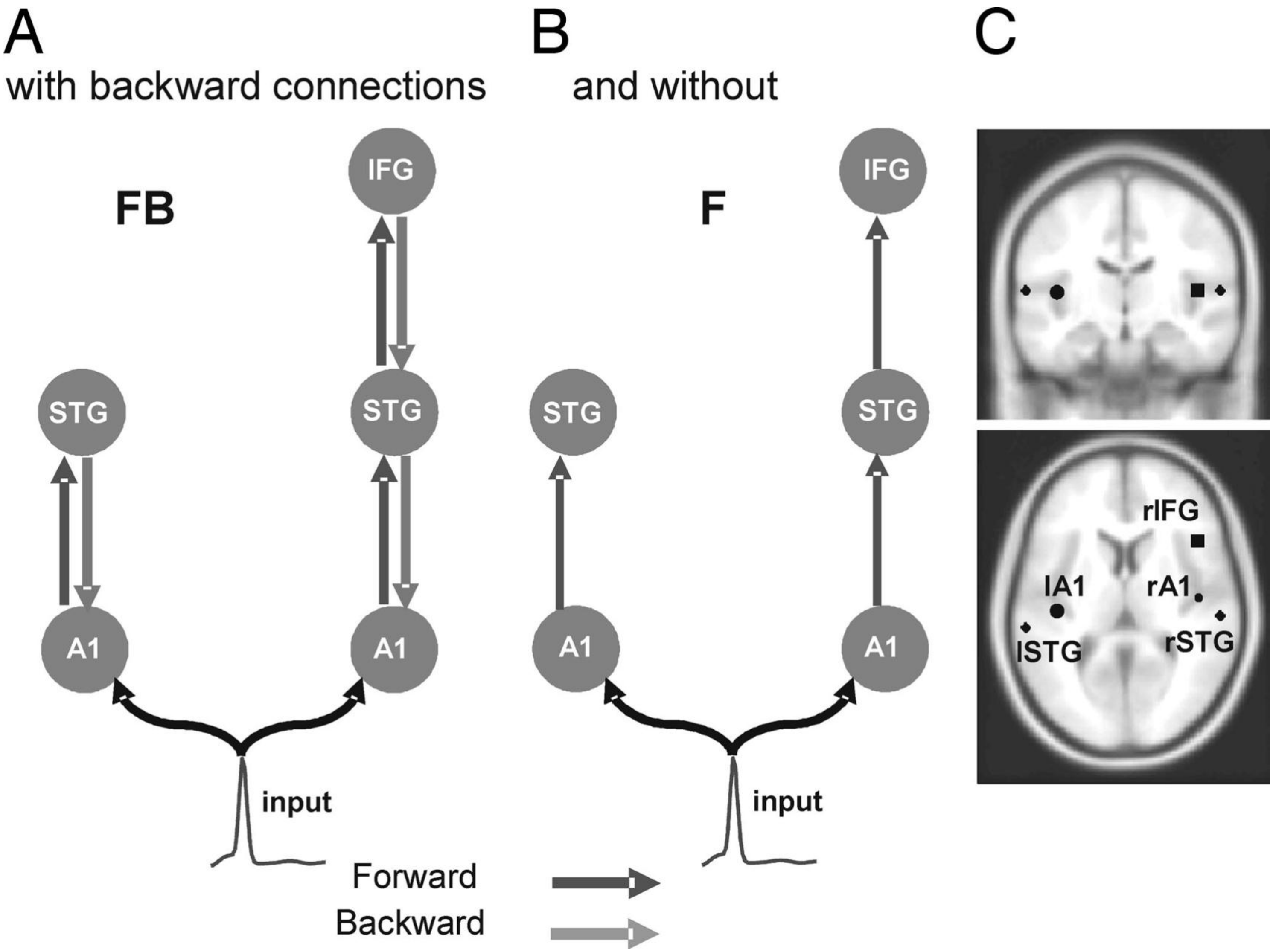
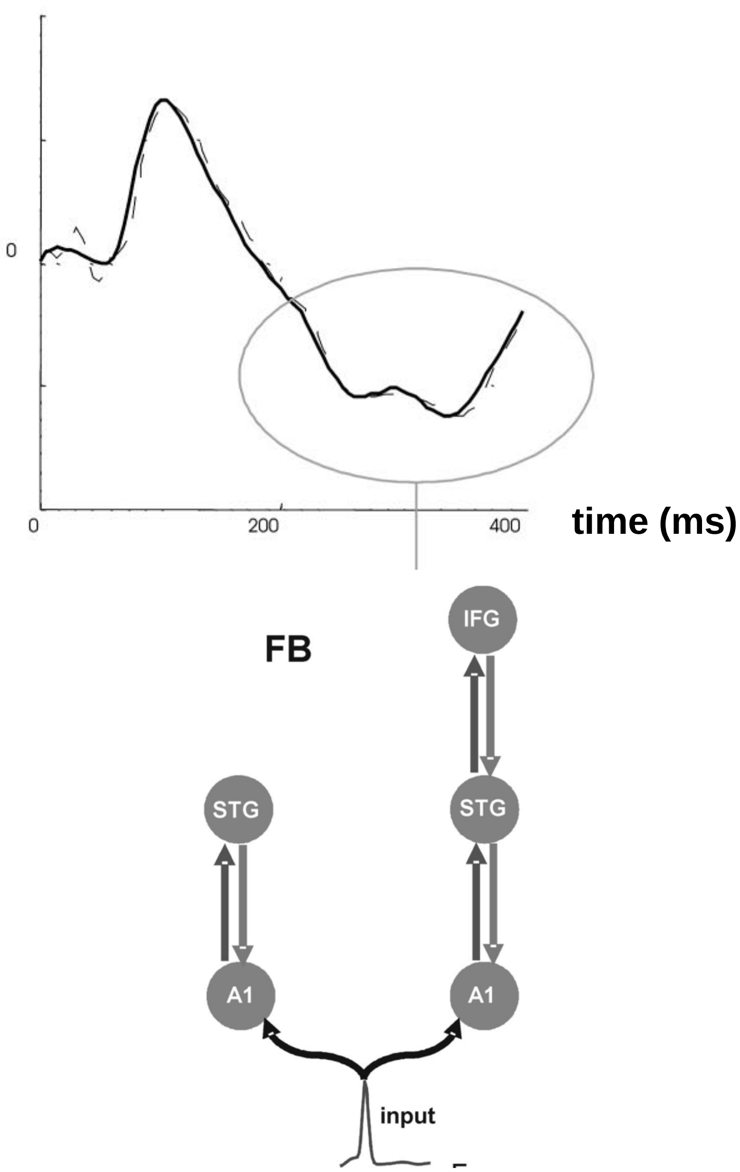
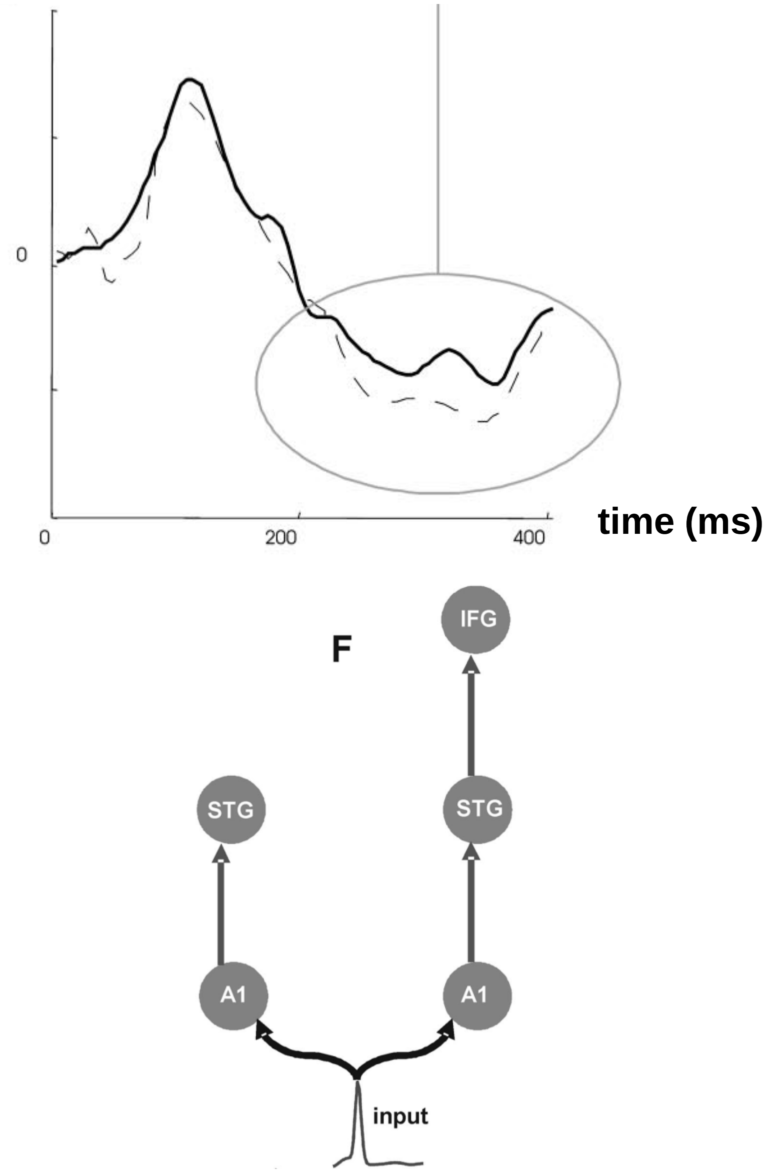
Auditory evoked potential



Garrido et al., PNAS, 2007

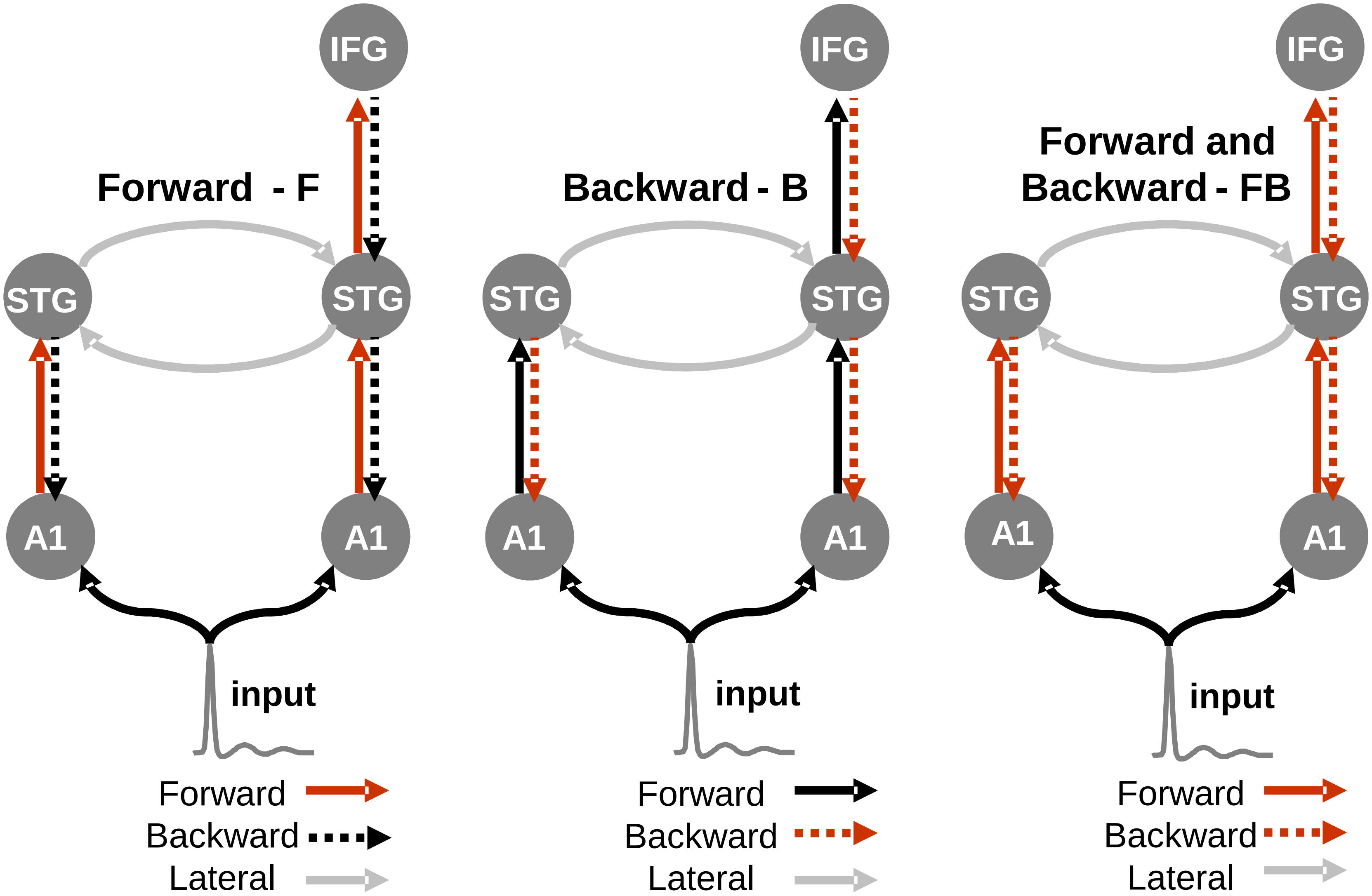
Auditory evoked potential





Garrido et al., PNAS, 2007

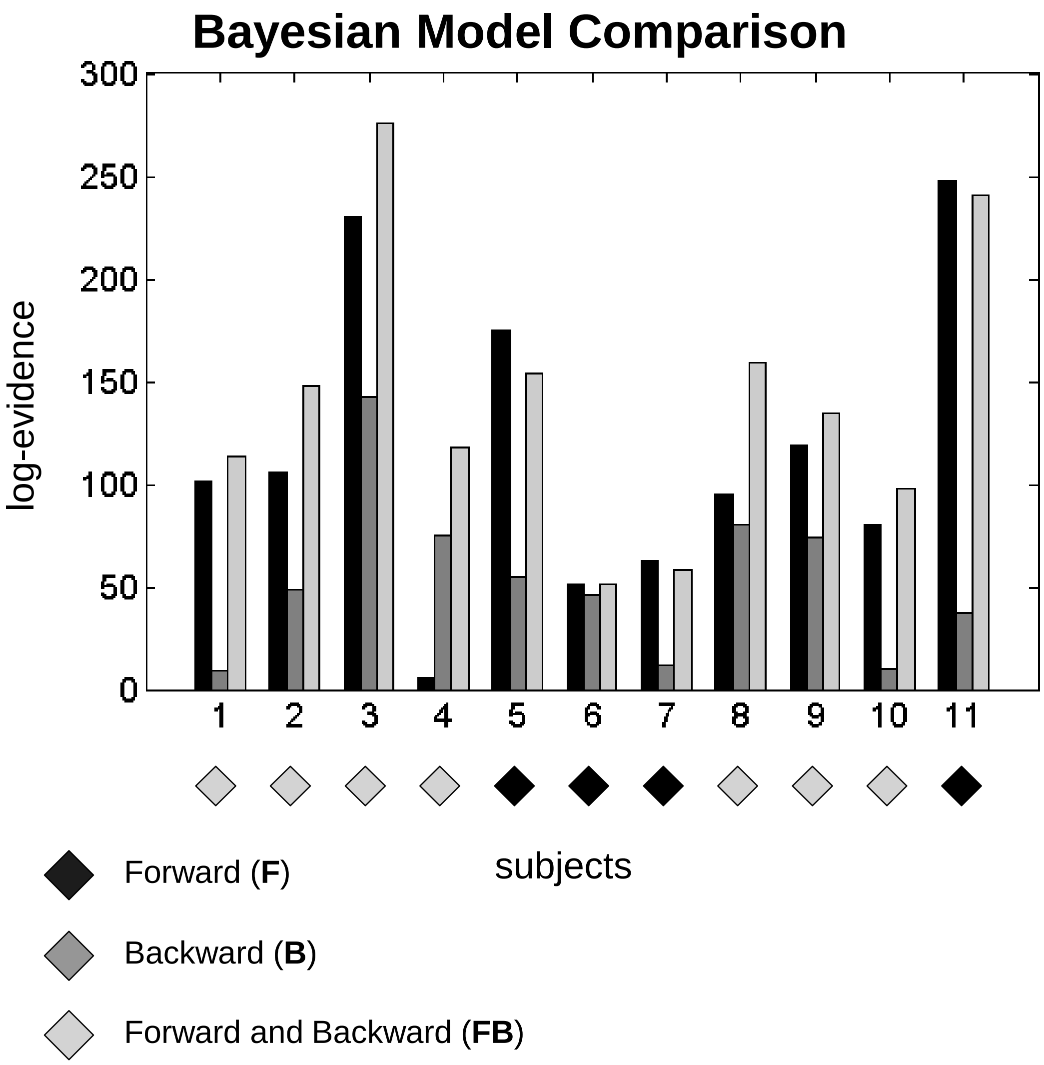
Mismatch negativity: EEG

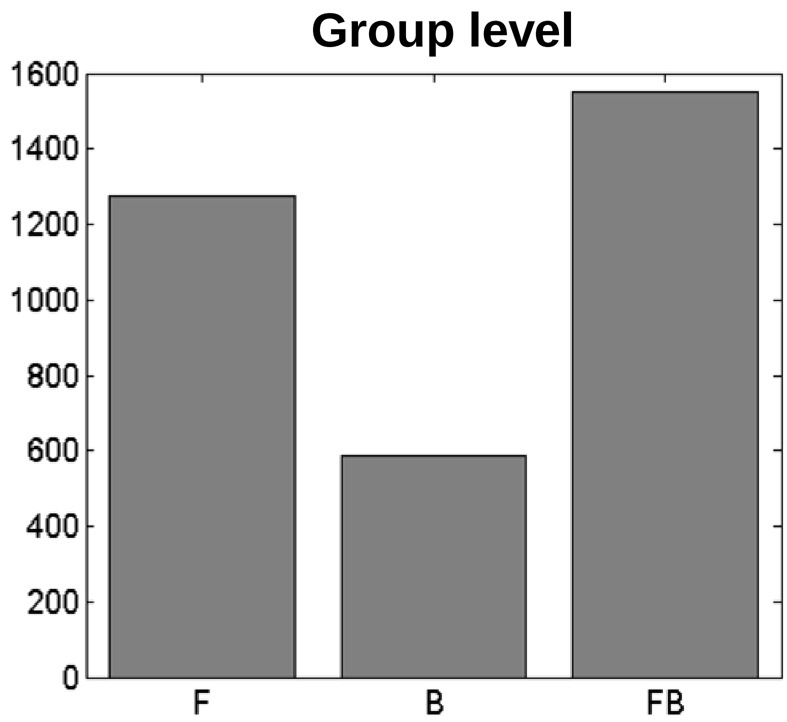


modulation of effective connectivity

Garrido et al., NeuroImage, 2007

MMN: Group model comparison

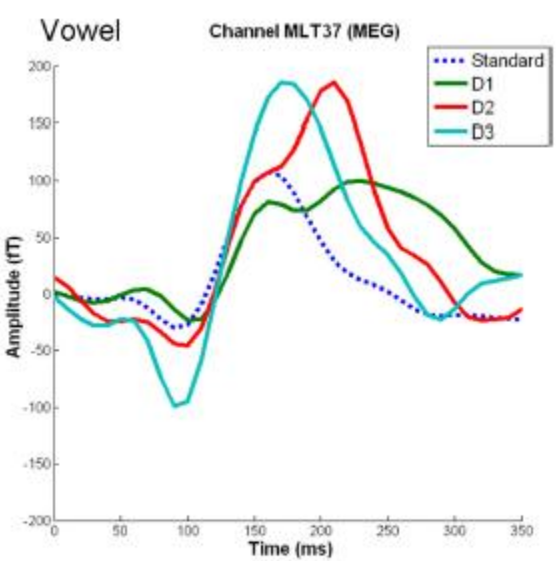


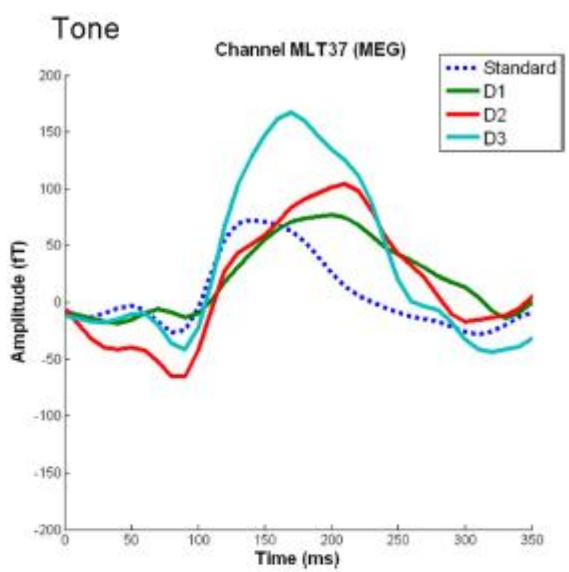


Garrido et al., NeuroImage, 2007

Mismatch negativity: MEG

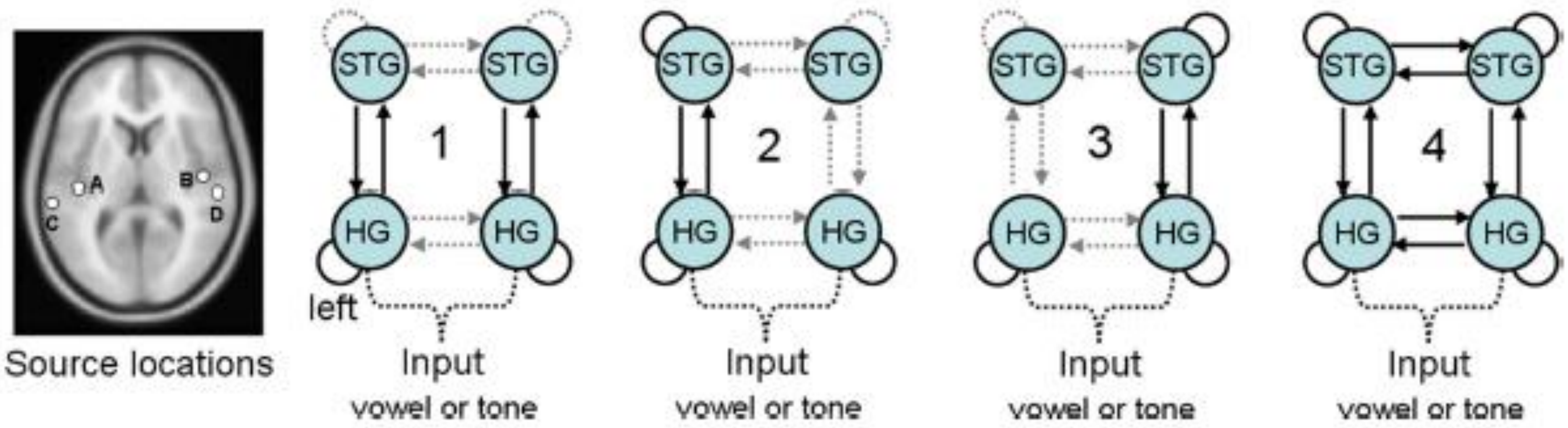
	CVC	Tone
Standard	Bart	Matched to formants of vowel
D1	Bart	
D2	Burt	
D3	beat	

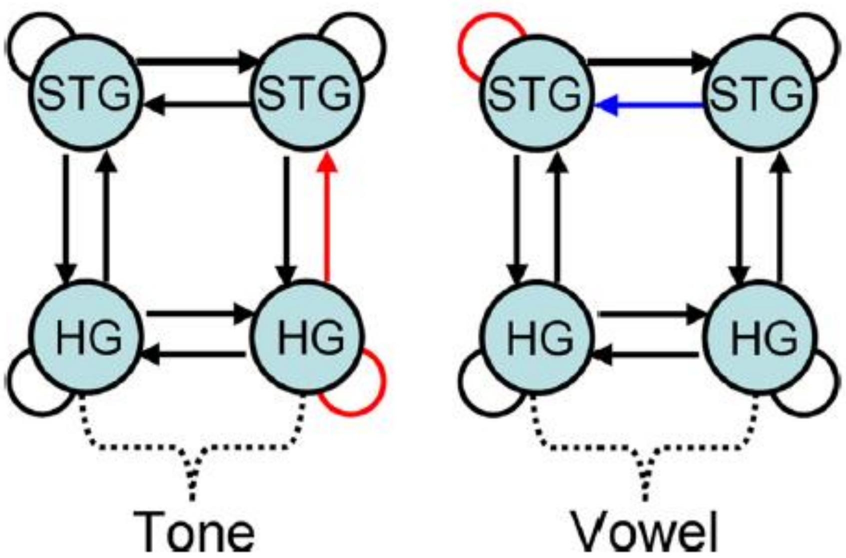




Schofield et al., PNAS, 2009

Mismatch negativity: MEG





Schofield et al., PNAS, 2009

Summary

• DCM enables testing of hypotheses about how brain sources communicate.

• Differences between conditions or groups are modelled as modulation of connectivity.

• Bayesian inference is used to take into account the variability over models and parameters.

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Thank you!