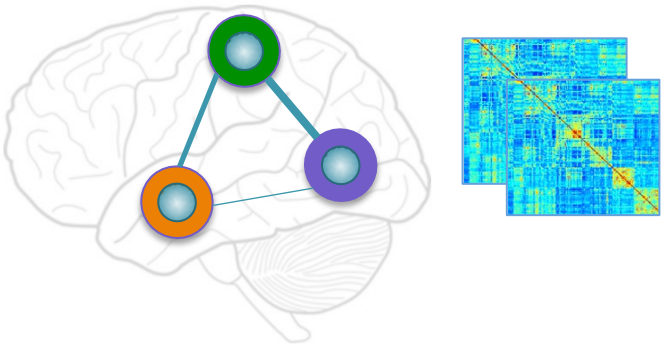
Dynamic Causal Modelling for EEG Practical

Pamela K Douglas
UCLA
NITP 2016

Brief Recap: DCM infers Effective Connectivity

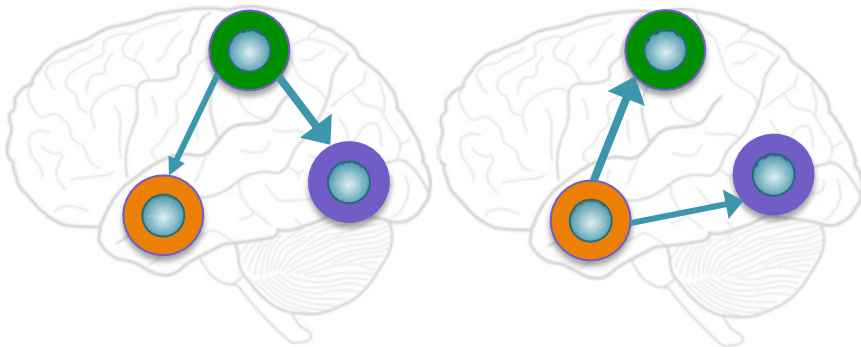
- Functional Connectivity -

statistical dependency among measurements (typically time series correlations)

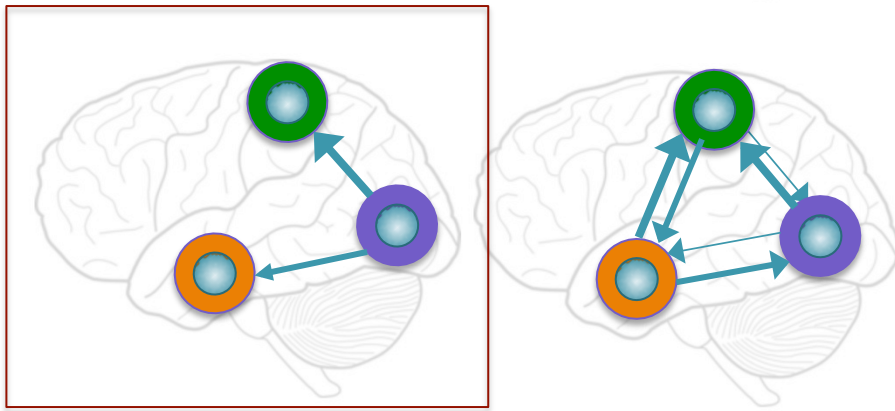


- Effective Connectivity –

influence of one neural system on another, or simplest possible circuit diagram that would explain dynamic couplings between measurements (Friston 2011)

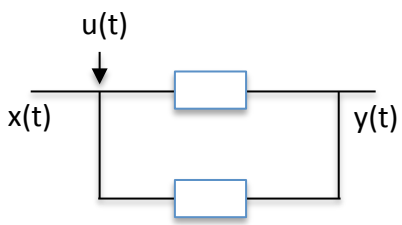


Bayesian Model Selection



DCM – Similar to State Space Methods

- This analogy may be useful for some people..
- Although the notation is slightly different, many of the key concepts are similar to that of DCM
- Key elements of state space - equation of states (x(t), an output equation y(t), and an observation equation z(t)



$$\dot{x}(t,p) = A(p)x(t,p) + B(p)u(t)$$
$$y(t,p) = C(p)x(t,p)$$
$$z(t,p) = y(t,p) + e(t)$$

Classic State Space Equations

DCM can be formulated in a similar way

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

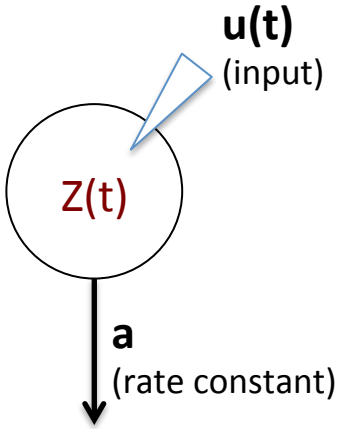
Equation of (Hidden) Neuronal States

$$y = g(x, u, \theta) + v$$

Observed Responses

Single Compartment Example

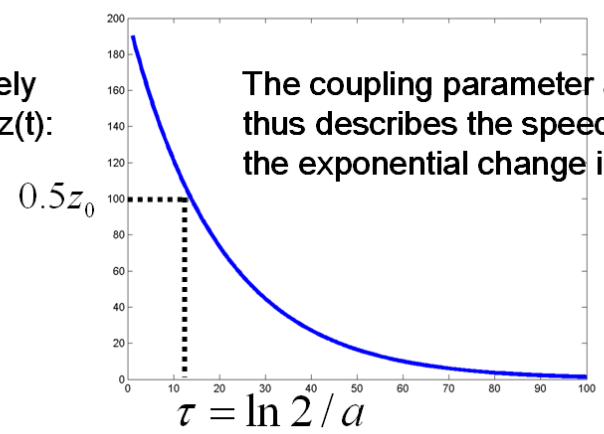
- Suppose we have a single region or "compartment" with a single input and a "leak". This amounts to integrating a first-order linear differential equation.



$$\frac{dz}{dt} = az \quad \Rightarrow \quad z(t) = z_0 \exp(at)$$

Coupling parameter a is inversely proportional to the half life τ of z(t):

$$z(\tau) = 0.5 z_0$$
$$= z_0 \exp(a\tau)$$
$$\Rightarrow \boxed{a = \ln 2 / \tau}$$



The coupling parameter a thus describes the speed of the exponential change in z(t)

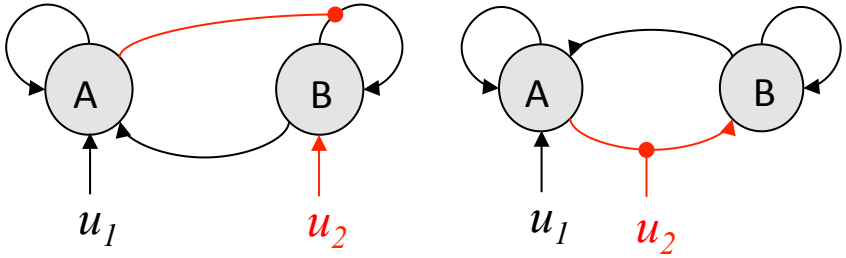
- In a very simple example, if one were measuring mass, then the measurement model (y(t)) might simply equal to z itself.
- For example, modeling Mn2+ transport throughout brain (PK Douglas et. al. 2011)

Other Notes:

- Not all hypotheses are suitable for DCM testing.
- Model comparisons are only valid if the data, y, are identical in all models
- In DCM for fMRI, direct comparison can only be made between models that contain the same # of areas (dimensions of the A matrix are typically equal)
- In DCM for EEG, however, the data measured at the sensor level are independent of how many neuronal sources are assumed in a given model.
  - Model selection can therefore be used to determine which sources should be included in the model

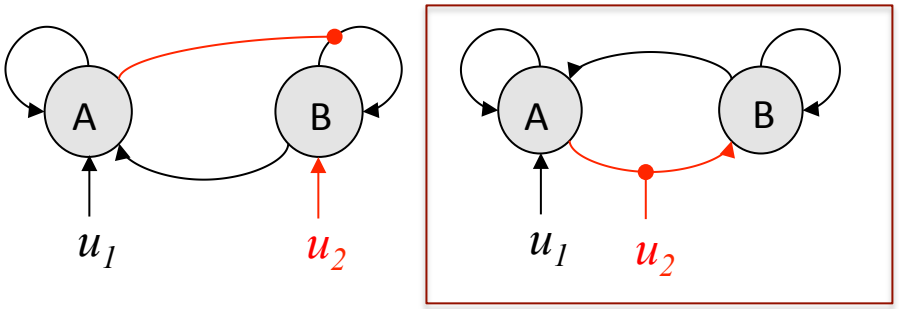
General Framework

- Create series of candidate model hypotheses



- Perform Model Inversion
  - Variational bayes

- Select Model with Highest Evidence
  - Bayesian Model Selection



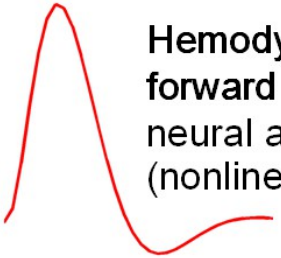
DCM for EEG

- Overall Concept is the same… but

….. the Measurement or Observation Model Must be different

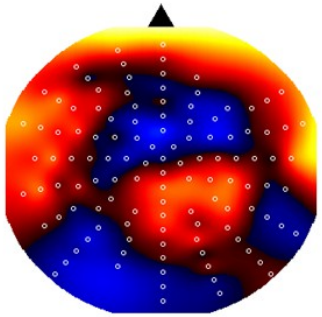
Dynamic Causal Modelling

DCM: generative model for fMRI and ERPs



Hemodynamic forward model:
neural activity→BOLD
(nonlinear)

Electric/magnetic forward model:
neural activity→EEG
MEG
LFP
(linear)



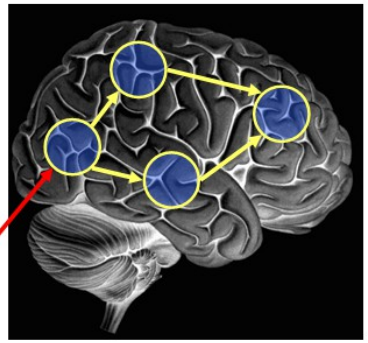
Neural state equation:

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

fMRI

ERPs

Neural model:
1 state variable per region
bilinear state equation
no propagation delays

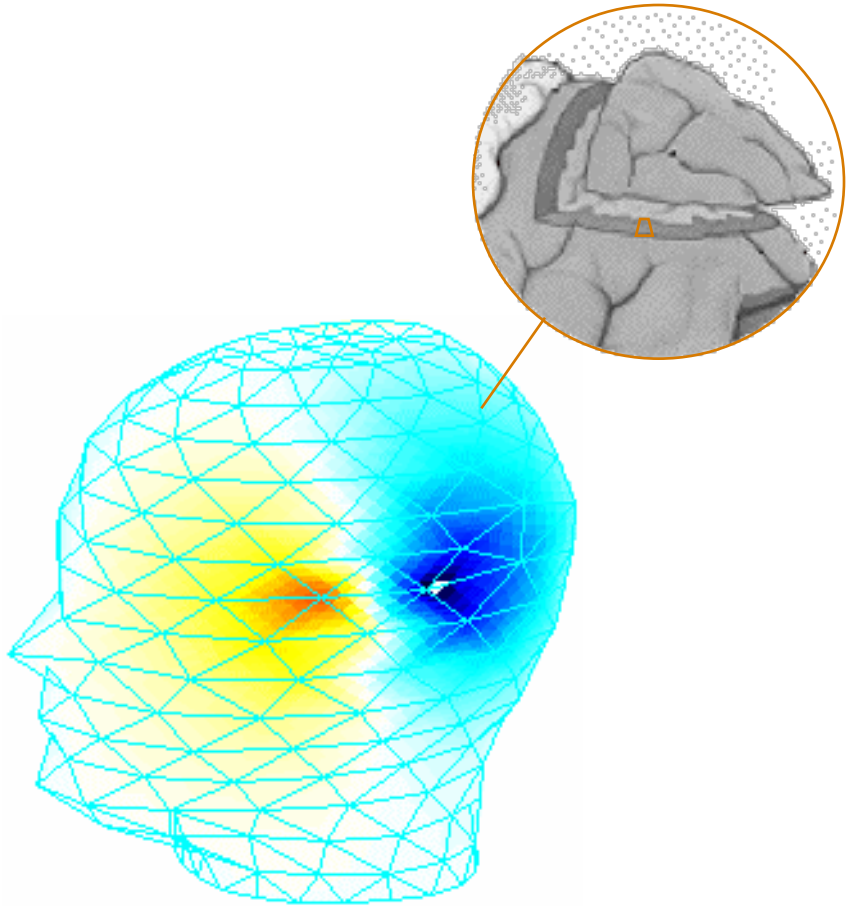


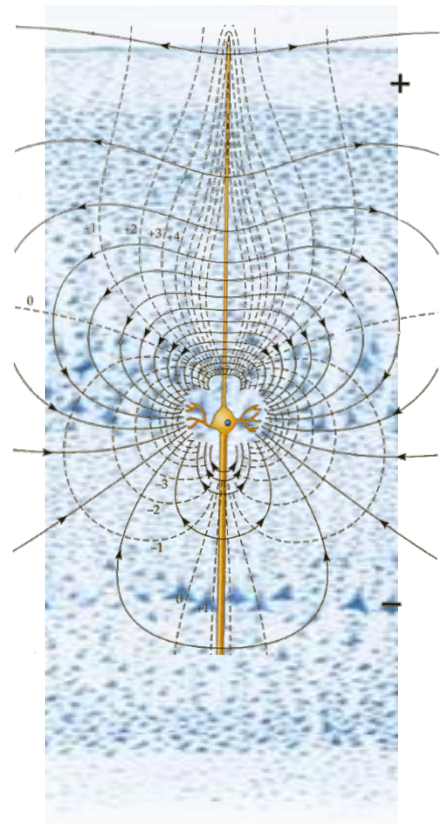
Neural model:
8 state variables per region
nonlinear state equation
propagation delays

Observation mappings

the electromagnetic forward model

$$\mathbf{y}(t) = \sum_i \mathbf{L}^{(i)} \mathbf{w}_0^{(i)} \sum_j \beta_j \mu^{(ij)}(t) + \varepsilon(t) \qquad \varepsilon(t): \; N(0, Q_y)$$





Considerations in DCM for EEG

Initial Considerations:

Will I be modelling evoked or steady state potentials?

Time domain or frequency domain (cross spectral densities) ?

Which neural mass model should I choose?

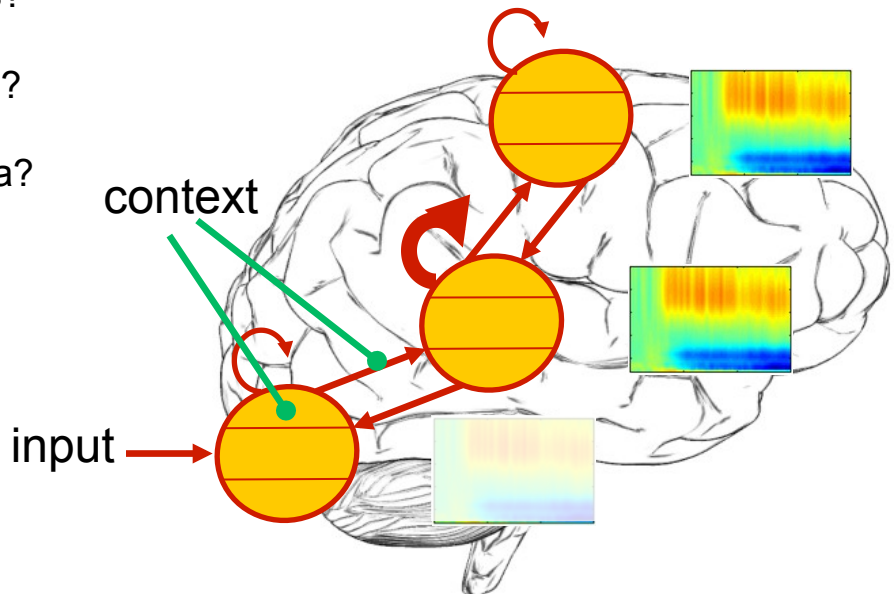
Model Hypothesis Considerations:

Is my effect driven by extrinsic or intrinsic connections?

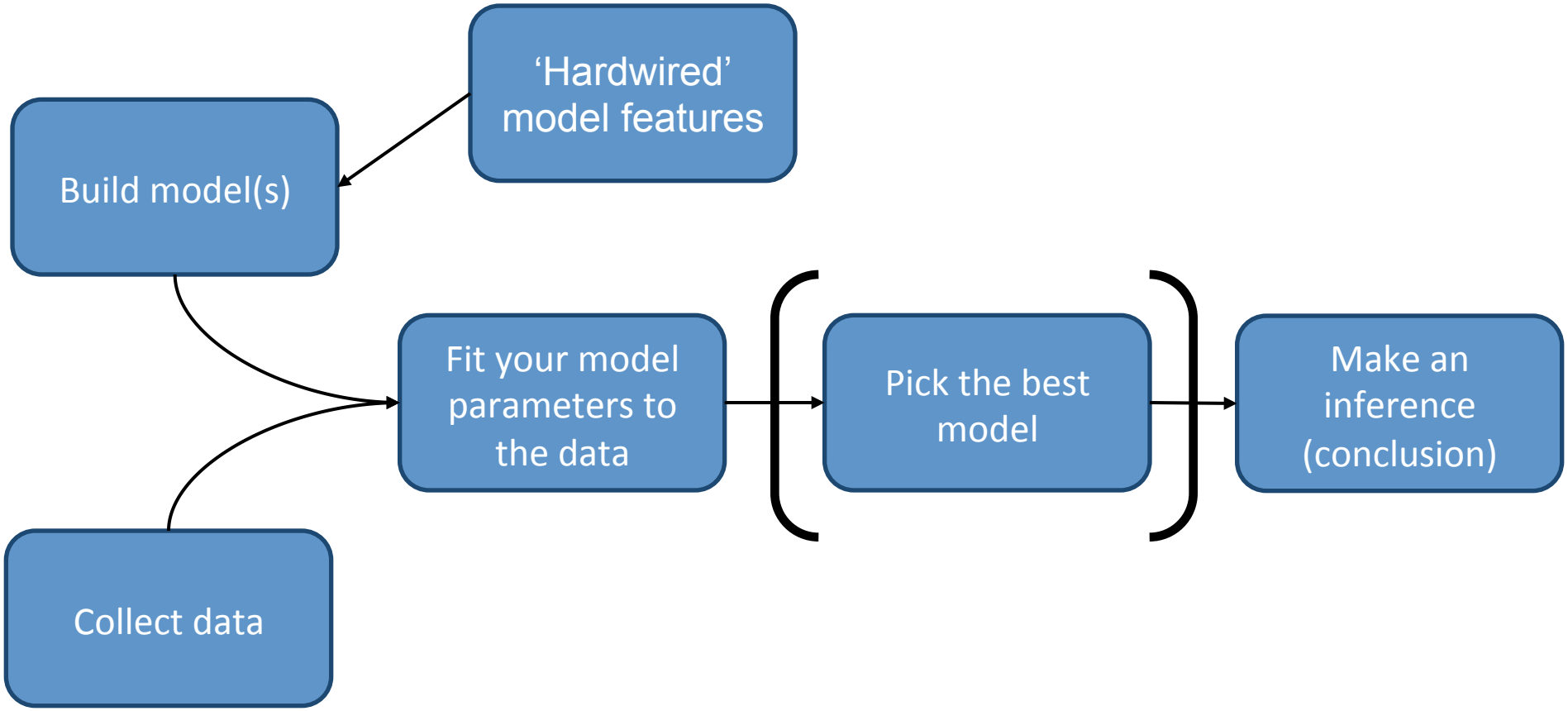
Which neural populations are affected by contextual factors?

Which connections determine observed frequency coupling?

How changing a connection/parameter would influence data?

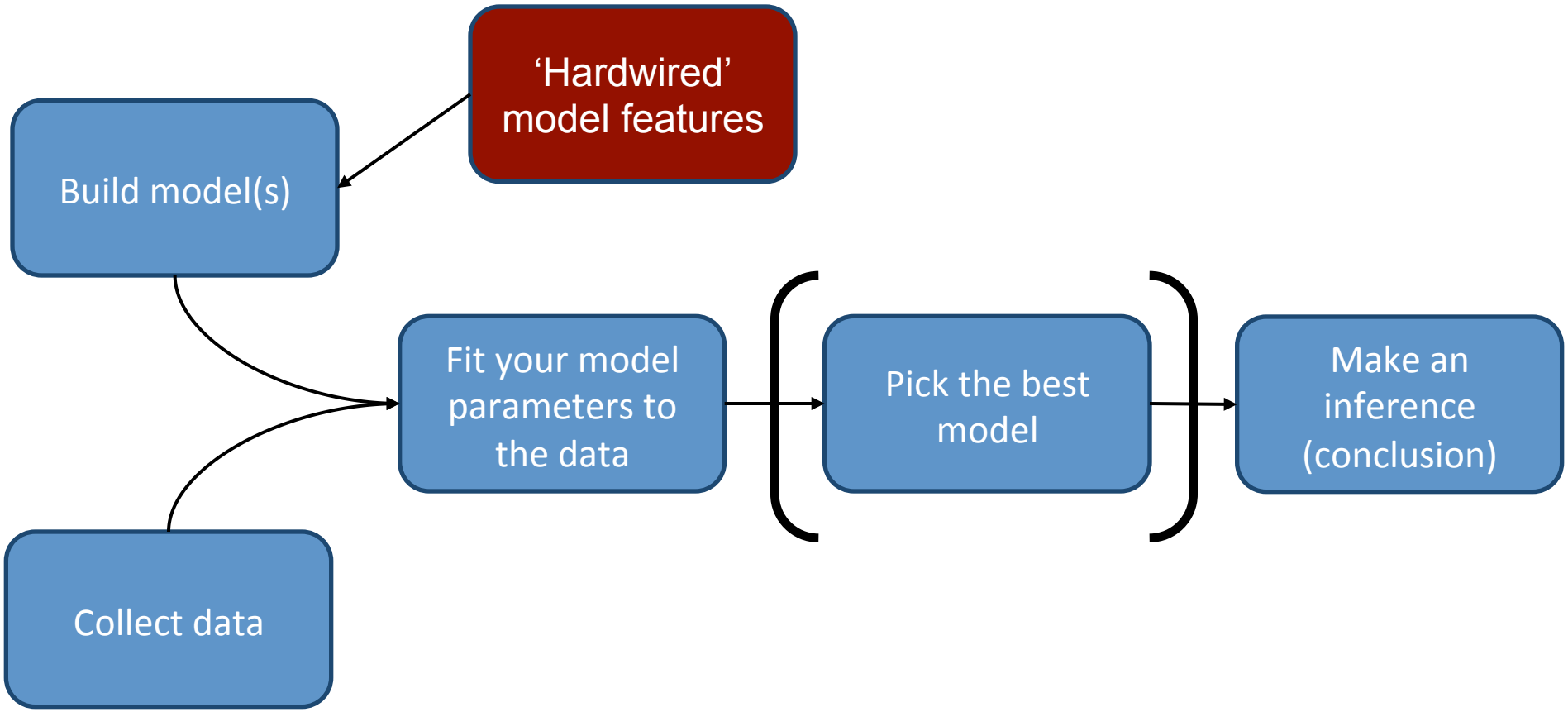


The DCM analysis pathway



Slide from Ryszard Auksztulewicz & SPM Course 2016

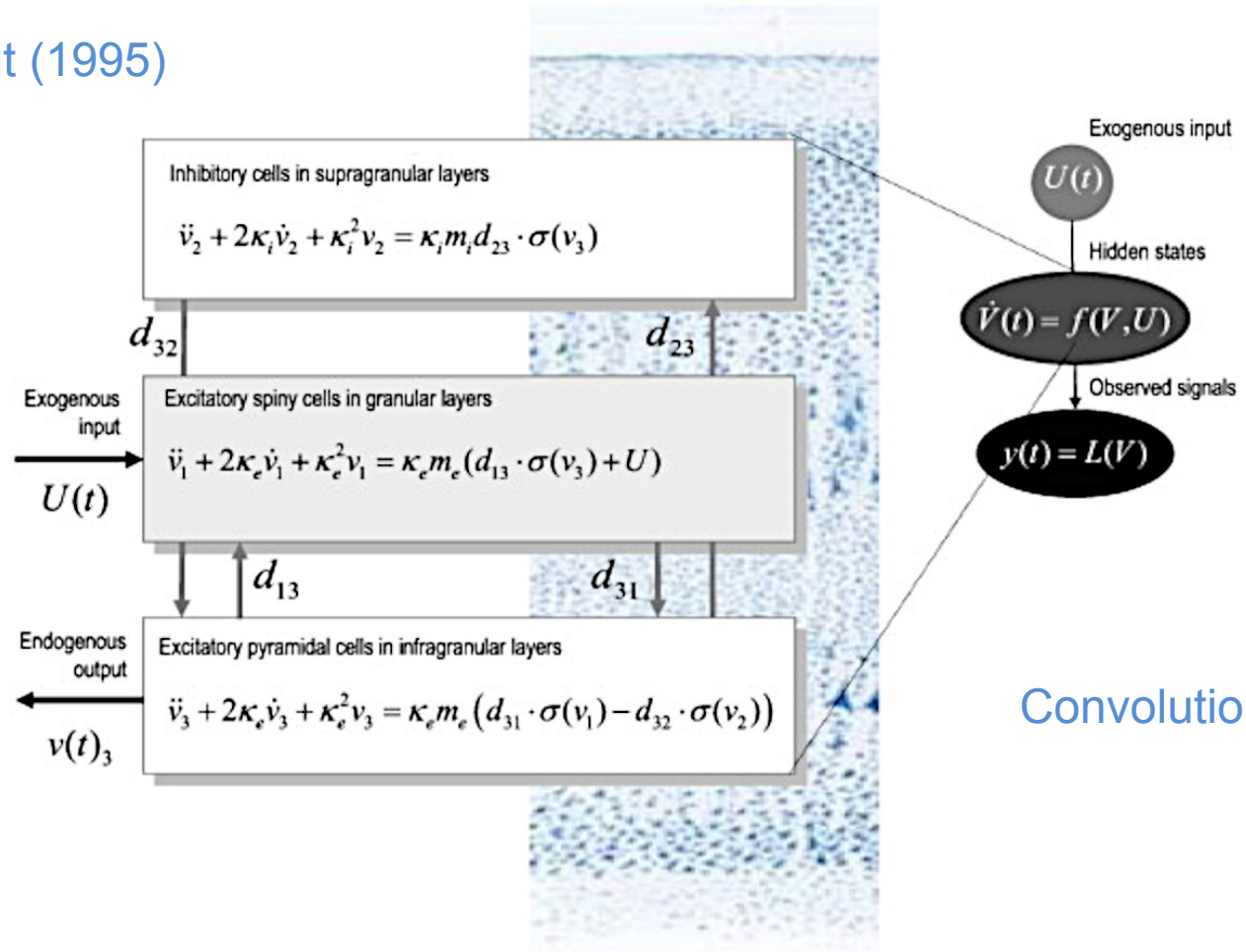
The DCM analysis pathway



Slide from Ryszard Auksztulewicz & SPM Course 2016

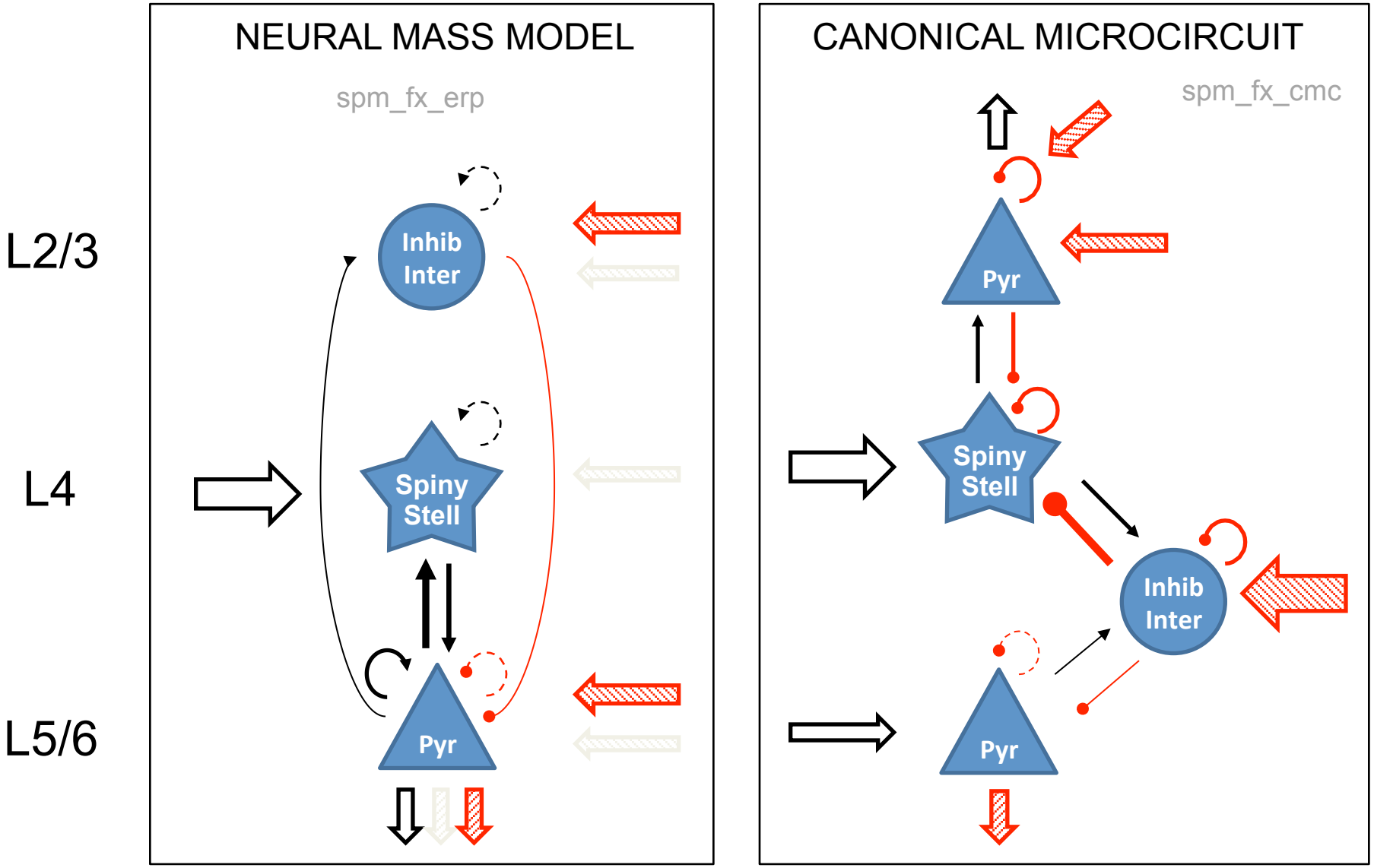
Neural Mass Models

Jansen and Rit (1995)



Convolution based

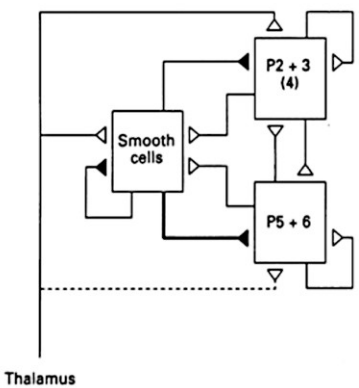
DCMs for MEG/EEG can use neural mass models (David and Friston, 2003) to explain source activity in terms of the ensemble dynamics of interacting inhibitory and excitatory subpopulations of neurons, based on Jansen and Rit (1995).



- The underlying generative model can be a neural mass or a neural field model.
- Here, each cortical source is modeled as a point source comprising coupled subpopulations assigned to a specific cortical layers

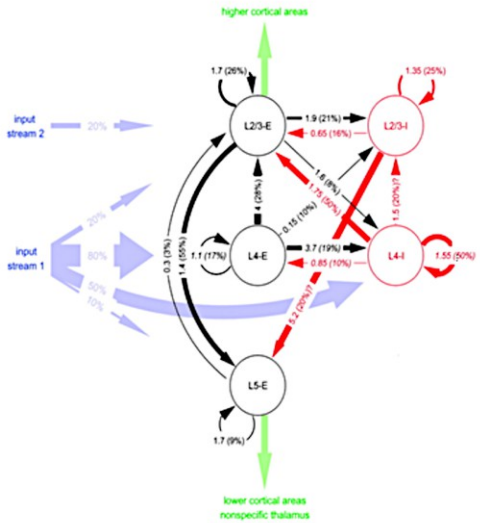
Canonical Microcircuit Model ('CMC')

Original proposal for canonical microcircuit



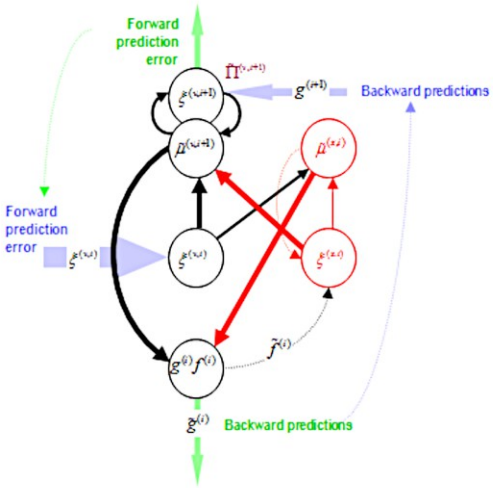
Douglas & Martin (1991)

Updated microcircuit



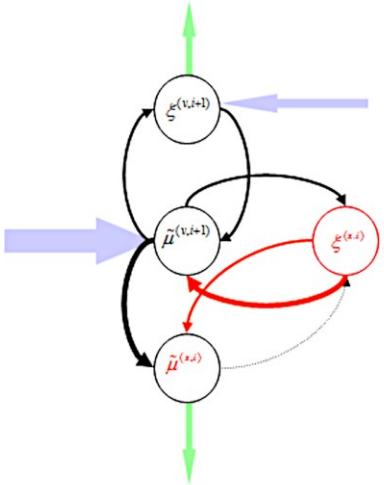
Adapted from Haeusler & Maass (2006)

Canonical microcircuit for predictive coding (full model)



Bastos et al. (2012)

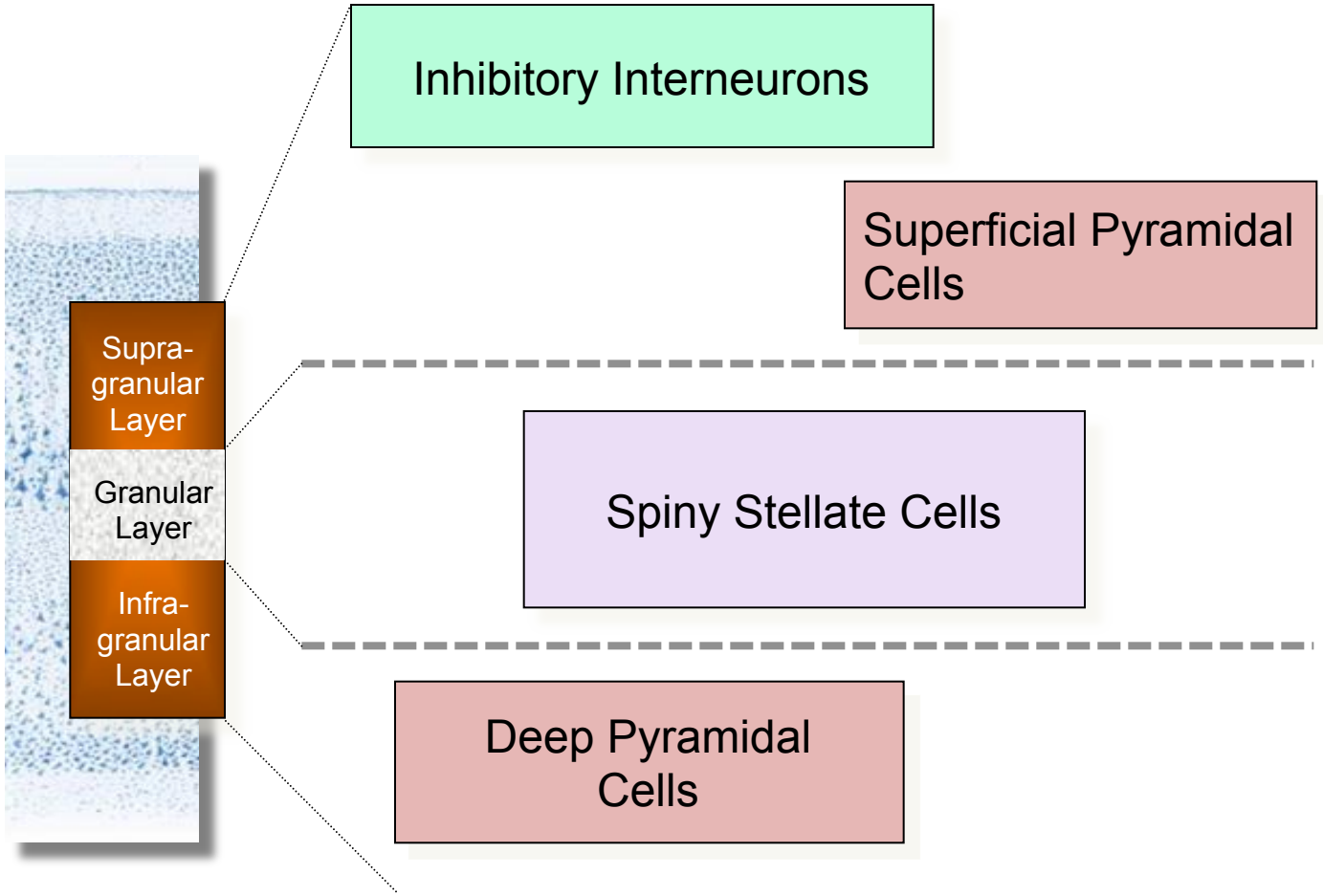
Reduced model (used in DCM)



Pinotsis et al. (2012)

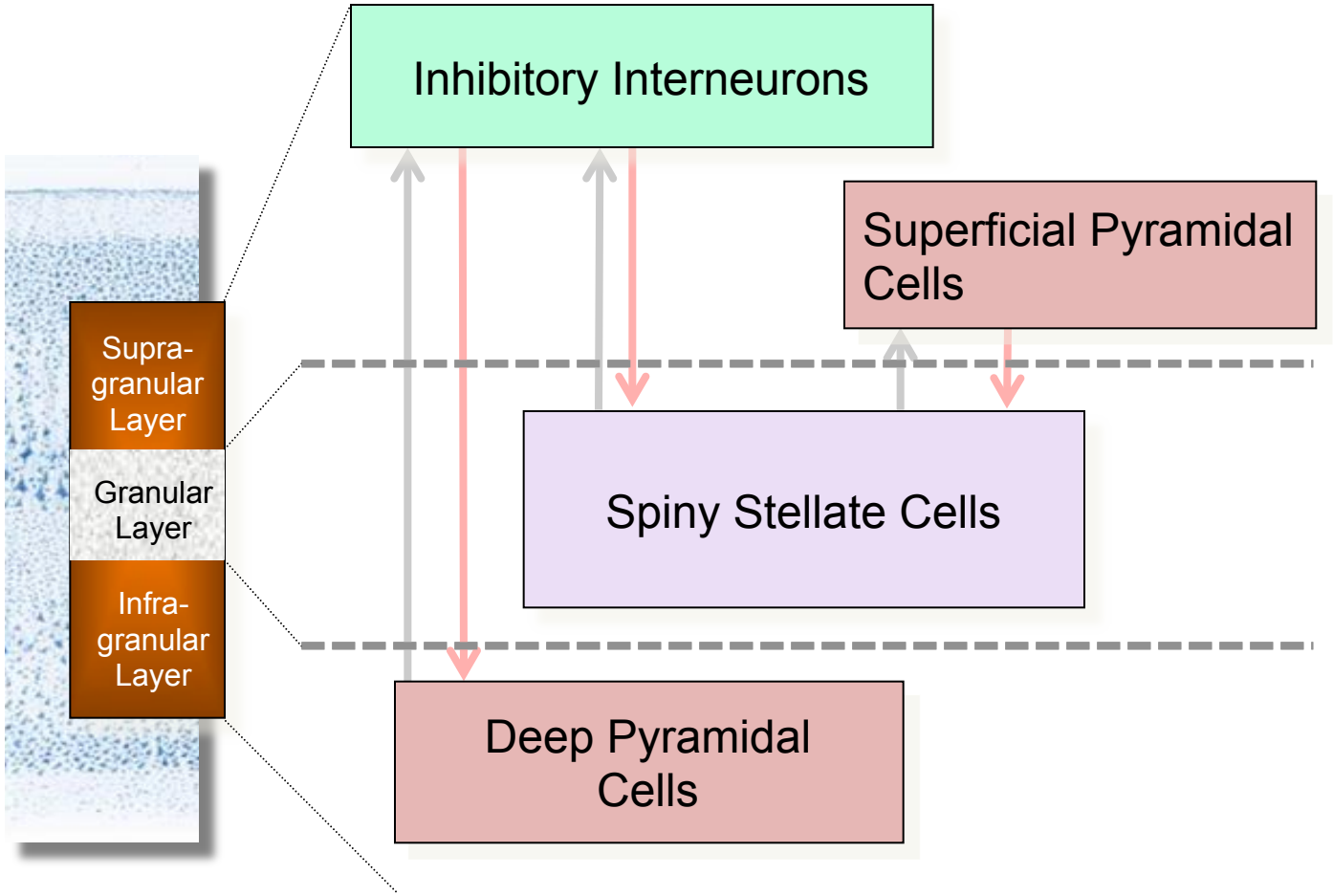
Canonical Microcircuit Model ('CMC')

Canonical Microcircuit Model ('CMC')



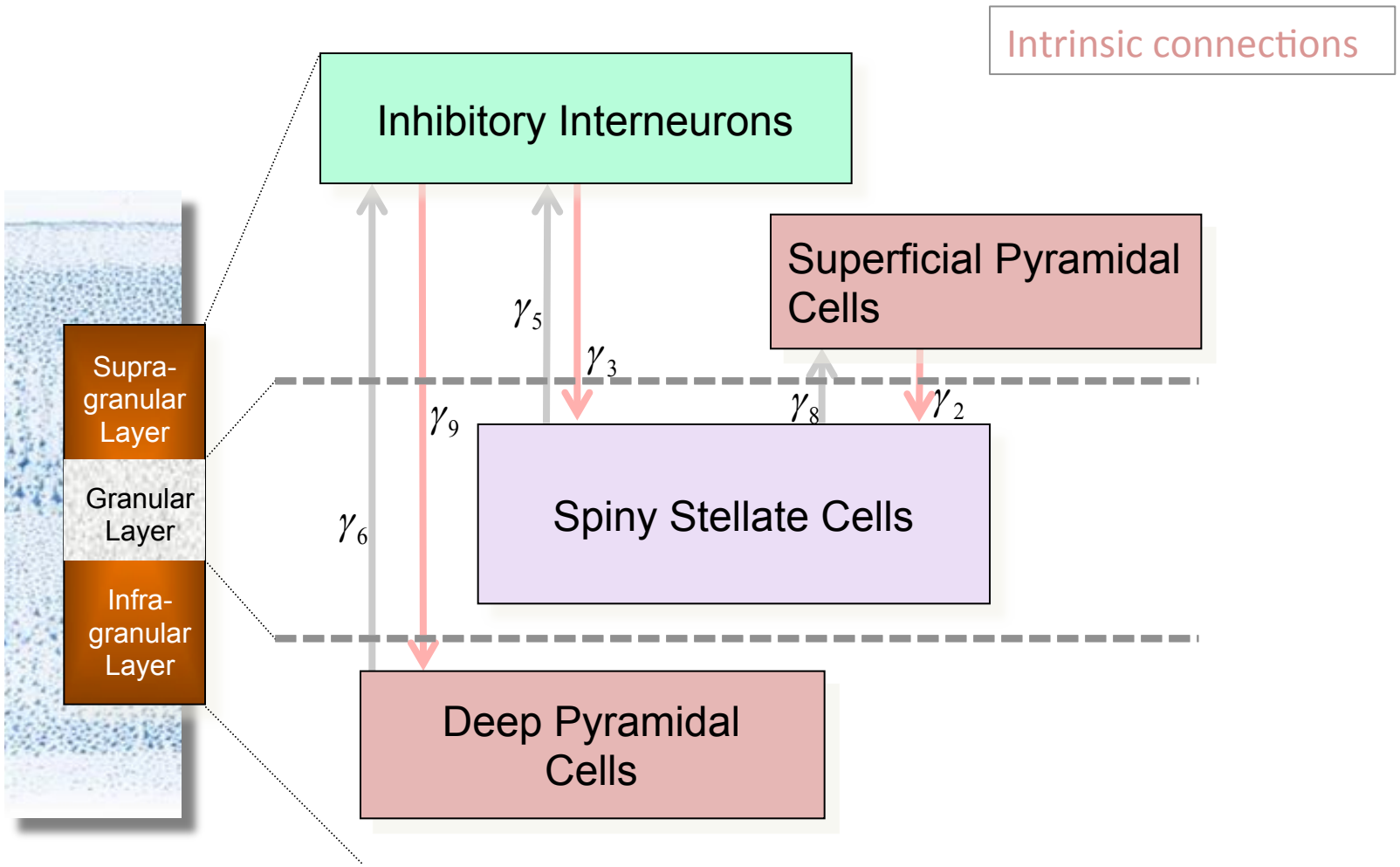
Pinotsis et al., 2012

Canonical Microcircuit Model ('CMC')



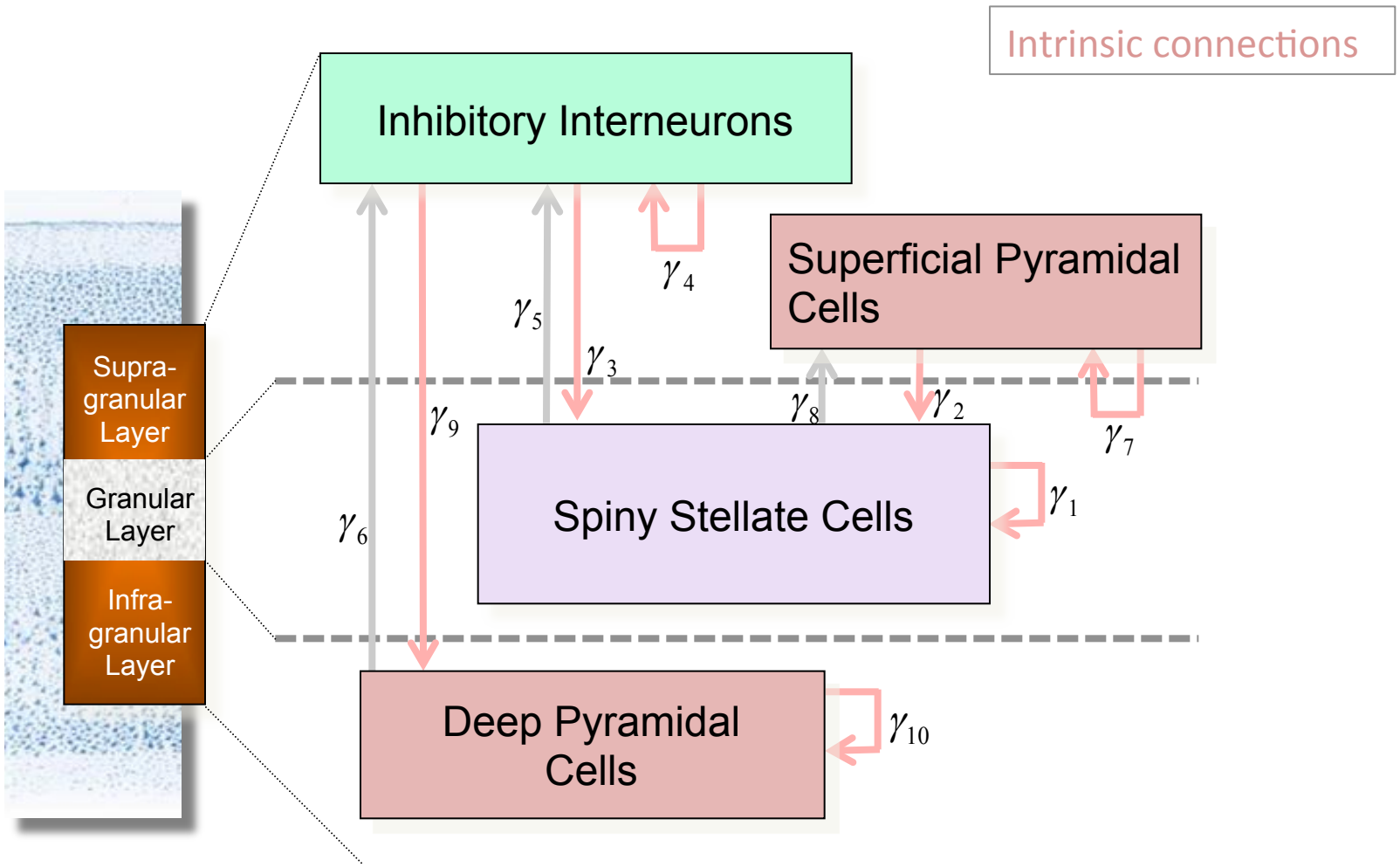
Pinotsis et al., 2012

Canonical Microcircuit Model ('CMC')



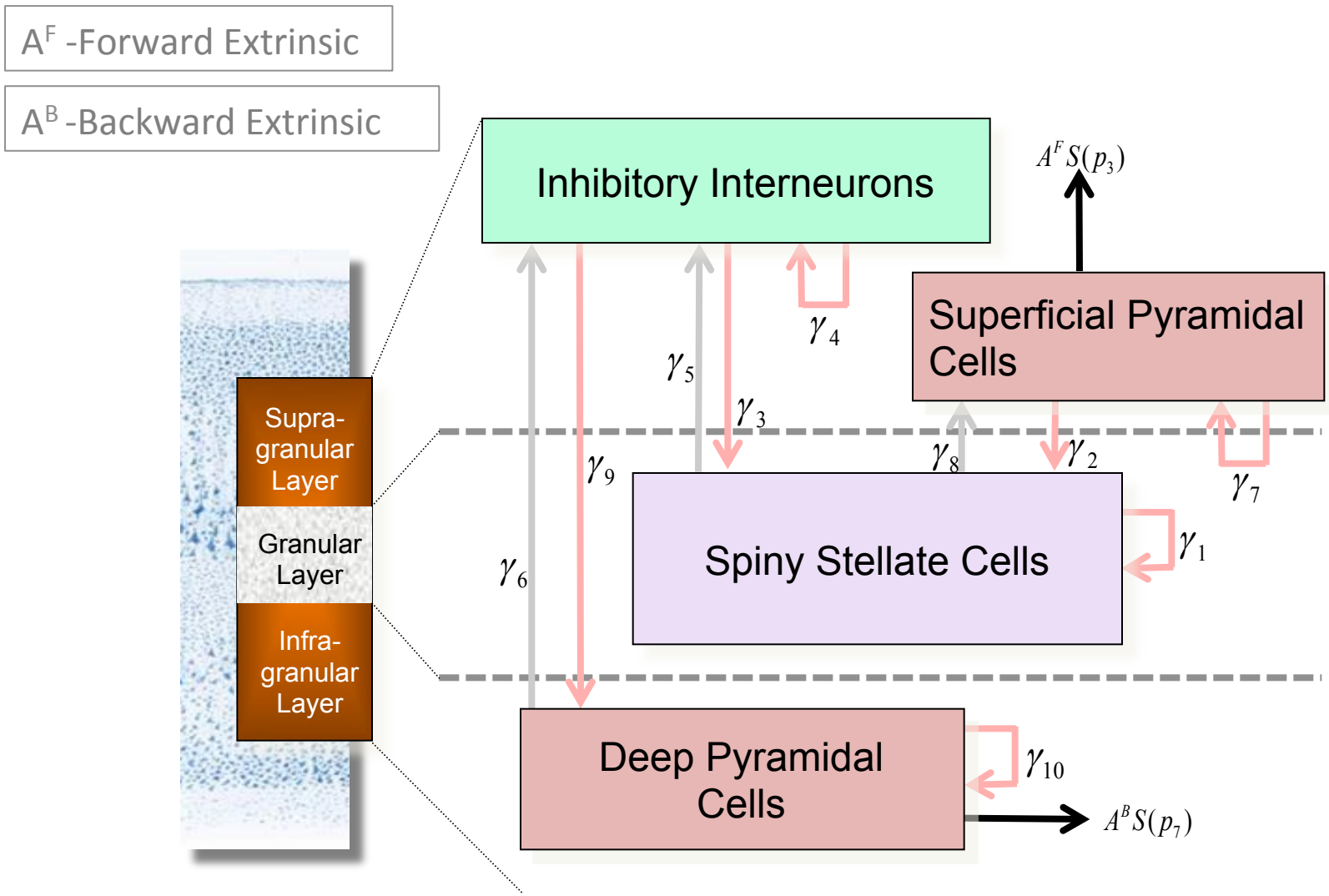
Pinotsis et al., 2012

Canonical Microcircuit Model ('CMC')



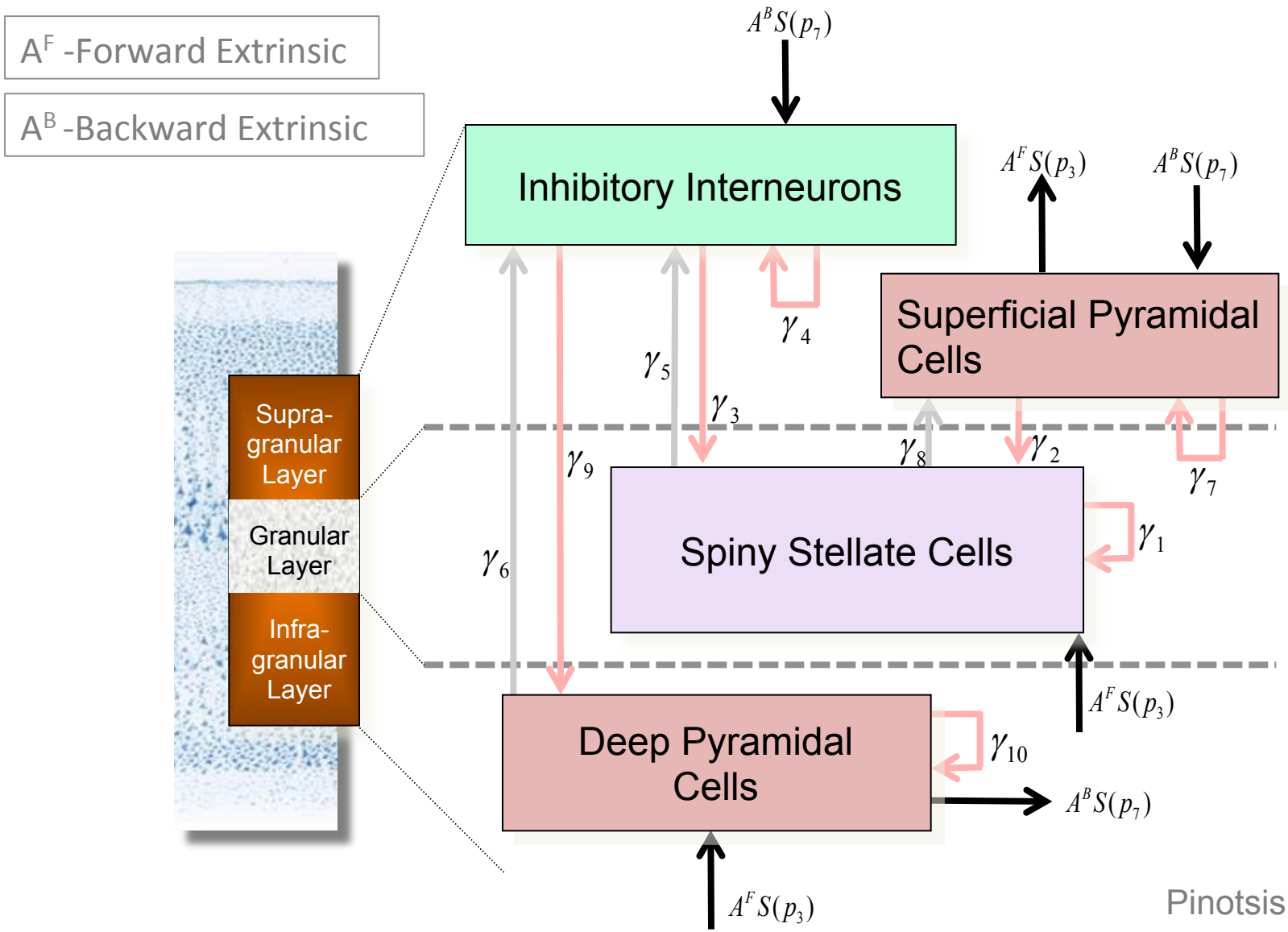
Pinotsis et al., 2012

Canonical Microcircuit Model ('CMC')



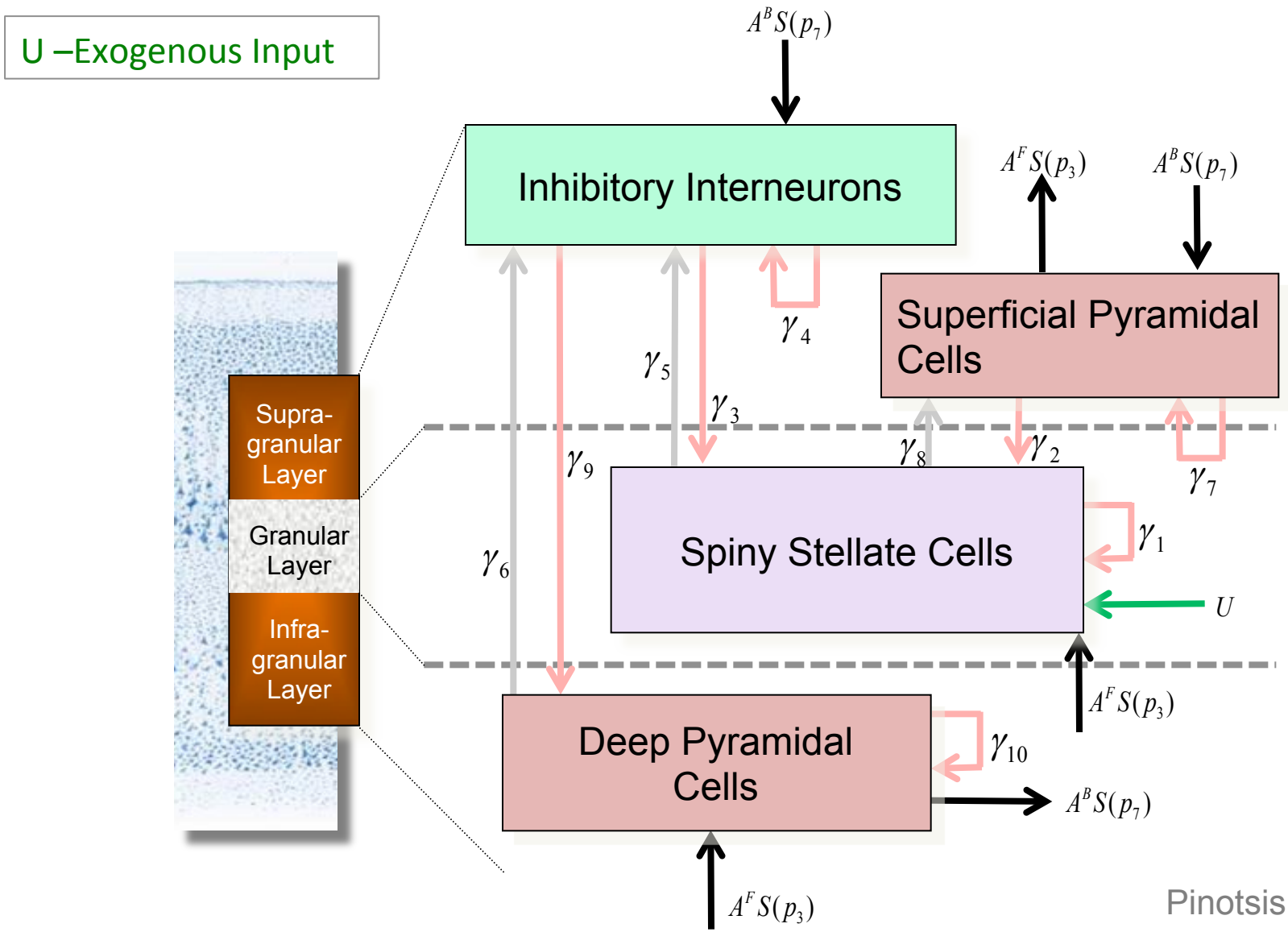
Pinotsis et al., 2012

Canonical Microcircuit Model ('CMC')



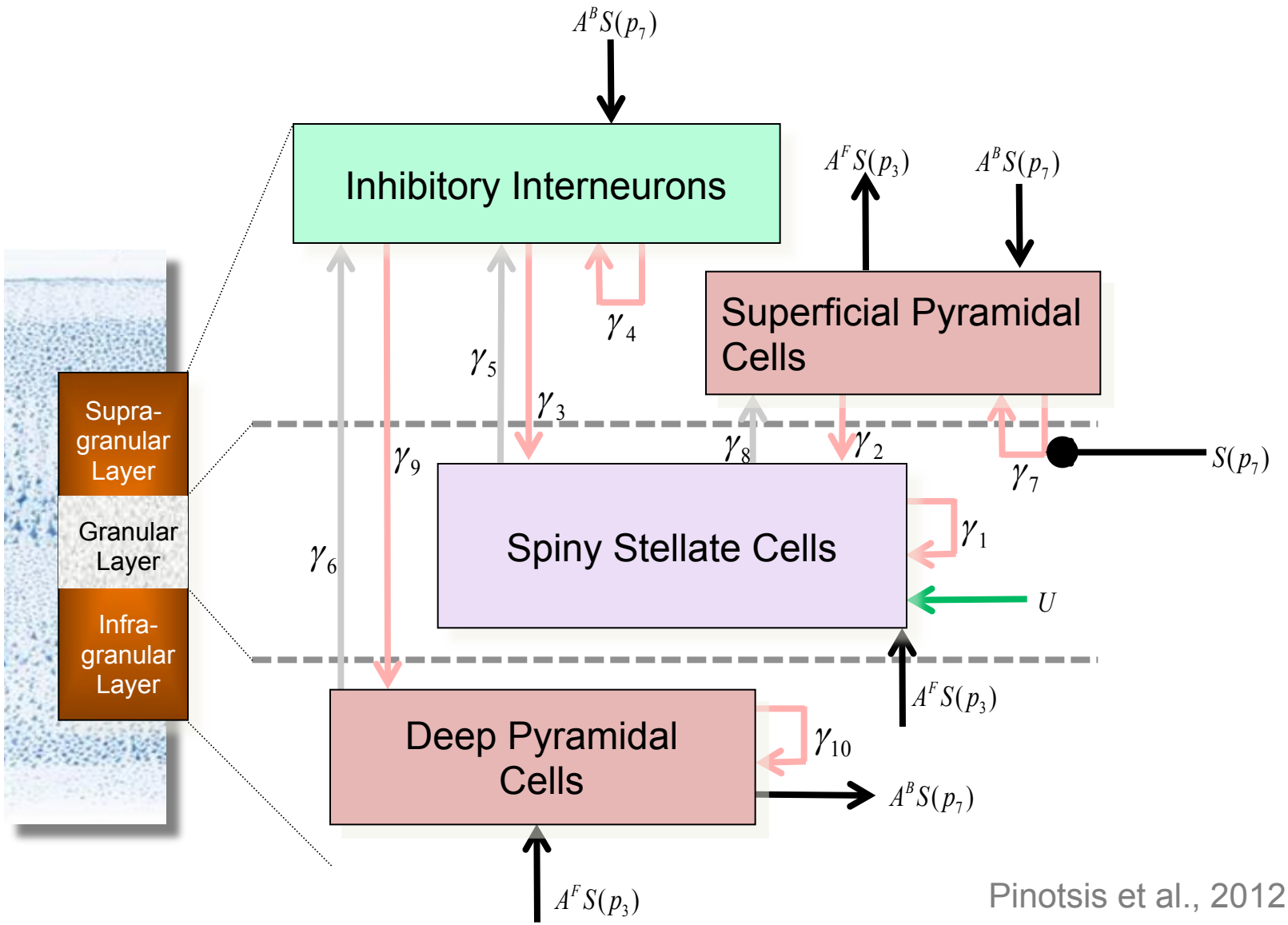
Pinotsis et al., 2012

Canonical Microcircuit Model ('CMC')



Pinotsis et al., 2012

Canonical Microcircuit Model ('CMC')

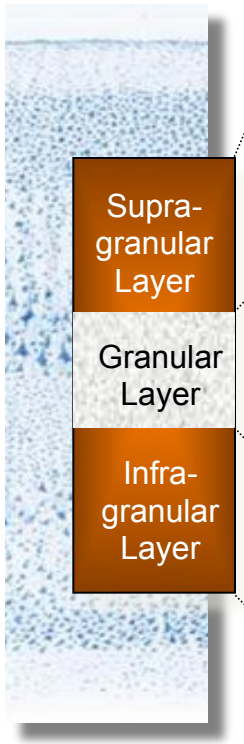


Pinotsis et al., 2012

Canonical Microcircuit Model ('CMC')

S –Sigmoid operator

$$y = Lp_3$$



$$\dot{p}_5 = p_6$$
$$\dot{p}_6 = \frac{H_3}{\tau_3}(-A^B S(p_7) - \gamma_5 S(p_1) + \gamma_6 S(p_7) - \gamma_4 S(p_5)) - \frac{2p_6}{\tau_3} - \frac{p_5}{\tau_3^2}$$

$$\dot{p}_3 = p_4$$
$$\dot{p}_4 = \frac{H_2}{\tau_2}((-A^B S(p_7) + \gamma_8 S(p_1) - \gamma_7 S(p_3)) - \frac{2p_4}{\tau_2} - \frac{p_3}{\tau_2^2}$$

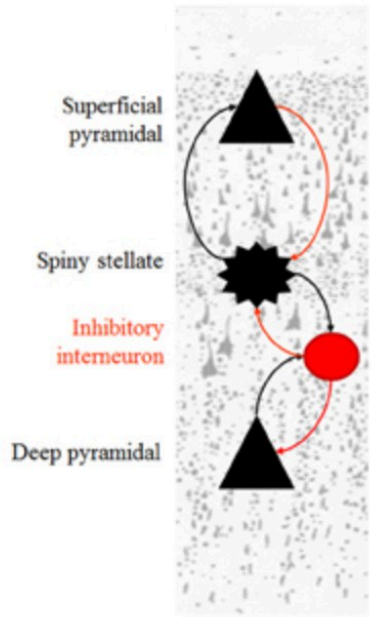
$$\dot{p}_1 = p_2$$
$$\dot{p}_2 = \frac{H_1}{\tau_1}((A^F S(p_3) - \gamma_1 S(p_1) - \gamma_3 S(p_5) - \gamma_2 S(p_3) Cu) - \frac{2p_2}{\tau_1} - \frac{p_1}{\tau_1^2}$$

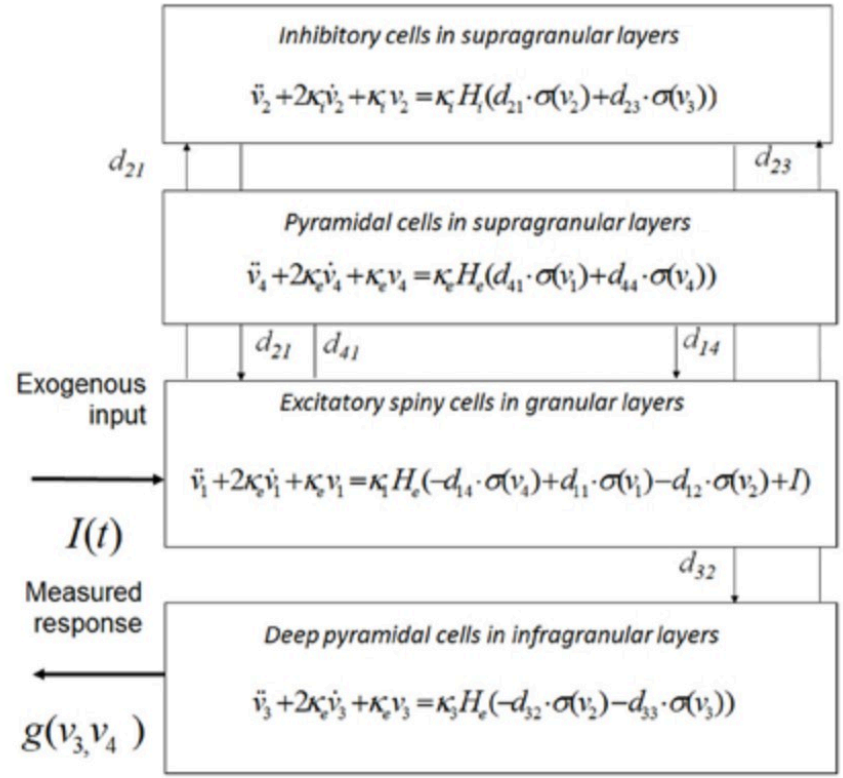
$$\dot{p}_7 = p_8$$
$$\dot{p}_8 = \frac{H_4}{\tau_4}(A^F S(p_2) - \gamma_{10} S(p_7) - \gamma_9 S(p_5)) - \frac{2p_8}{\tau_4} - \frac{p_7}{\tau_4^2}$$

$A^B S(p_7)$ $A^F S(p_3)$ $A^B S(p_7)$ γ_4 γ_5 γ_3 γ_9 γ_8 γ_2 γ_7 $S(p_7)$ γ_1 γ_6 U $A^F S(p_3)$ γ_{10} $A^B S(p_7)$ $A^F S(p_3)$

Pinotsis et al., 2012

Canonical Microcircuit (with Neural Field Properties)





Maximum PSP

Connectivity Parameter

$$\ddot{v} + 2\kappa_{e/i}\dot{v} + \kappa_{e/i} v = \kappa_{e/i} H_{e/i} d \cdot \sigma(v)$$

Neural Mass

$$\ddot{v} + 2\kappa_{e/i}\dot{v} + \kappa_{e/i} v = \kappa_{e/i} H_{e/i} \iint d \cdot \sigma(v) dx a$$

Neural Field

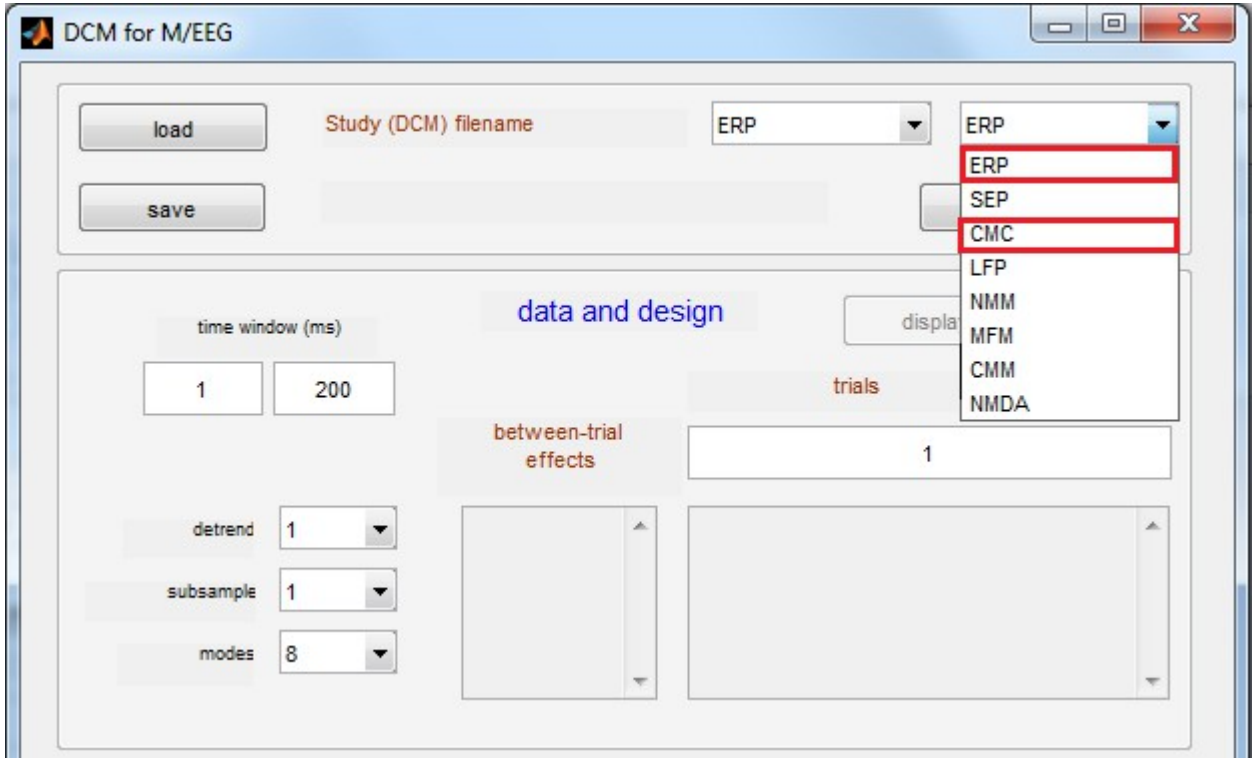
Inverse Time Constant

Connectivity Matrix

Parameterised Sigmoid

Moran et al. (2013)

Specifying CMC Models in SPM



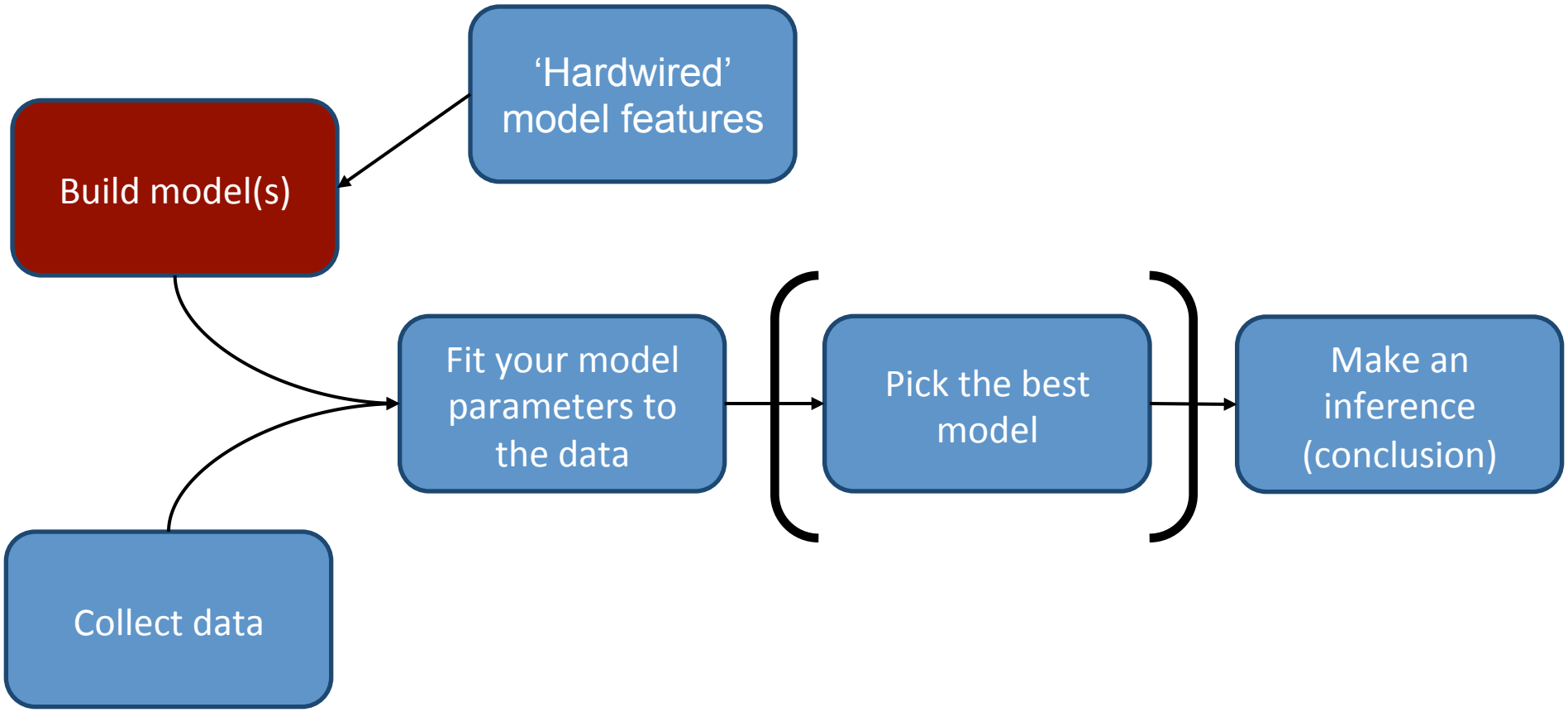
frontiers in
COMPUTATIONAL NEUROSCIENCE

REVIEW ARTICLE
published: 28 May 2013
doi: 10.3389/fncom.2013.00057

Neural masses and fields in dynamic causal modeling

Rosalyn Moran[1,2,3*†], *Dimitris A. Pinotsis*[1†] *and Karl Friston*[1]

The DCM analysis pathway

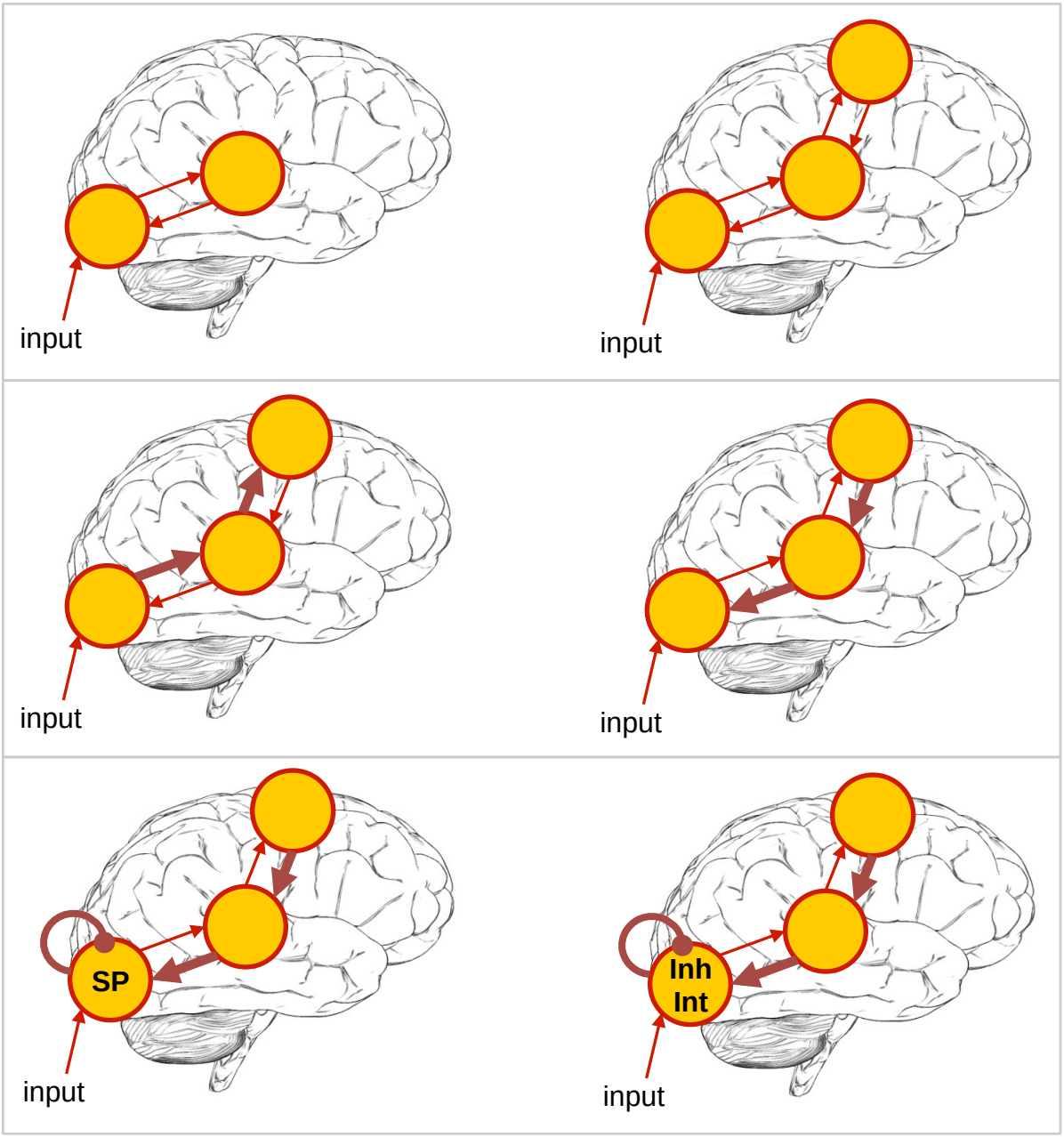


Slide from Ryszard Auksztulewicz & SPM Course 2016

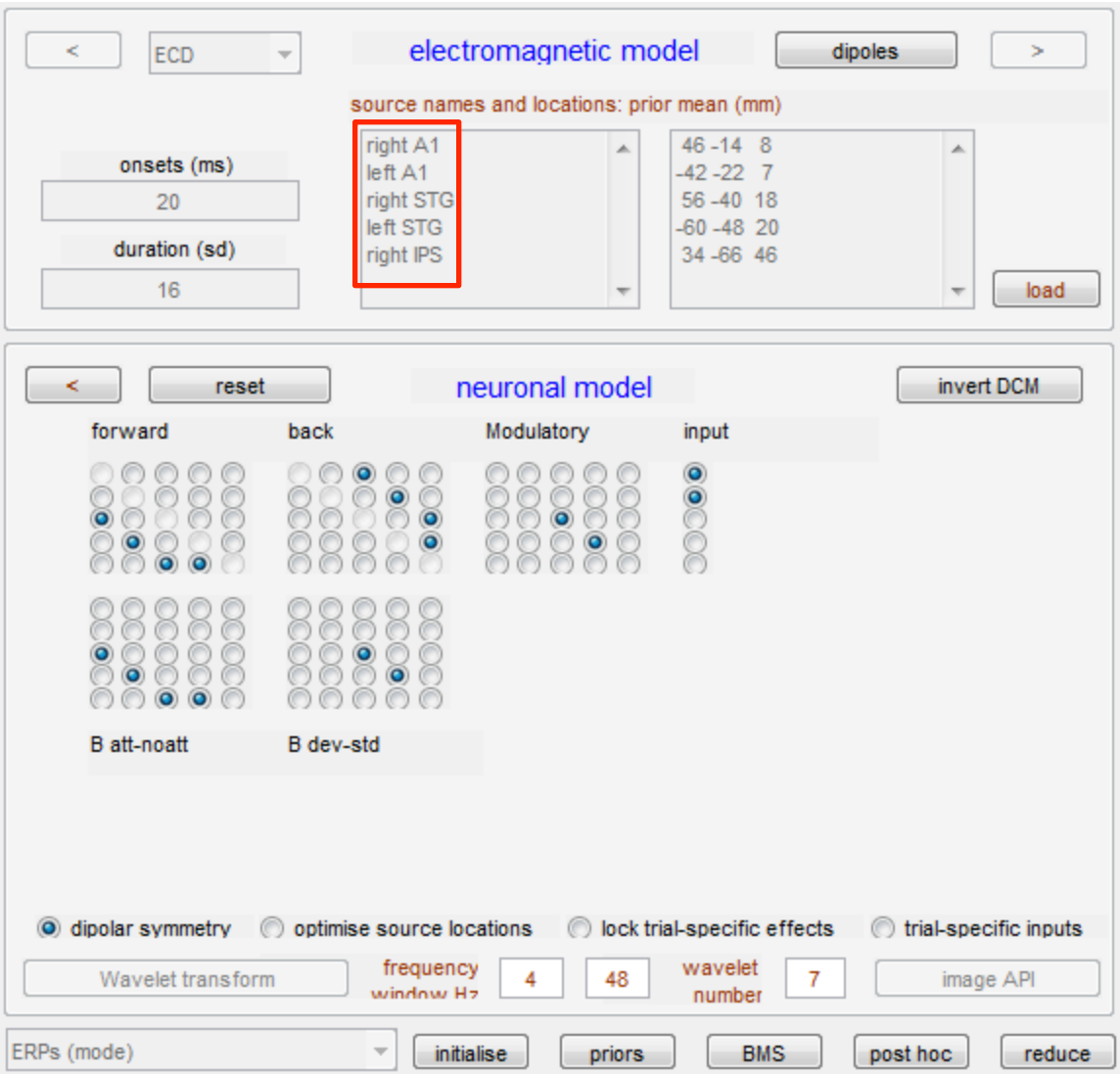
Connectivity structure

Extrinsic modulation

Intrinsic modulation



Specify Model in SPM



5

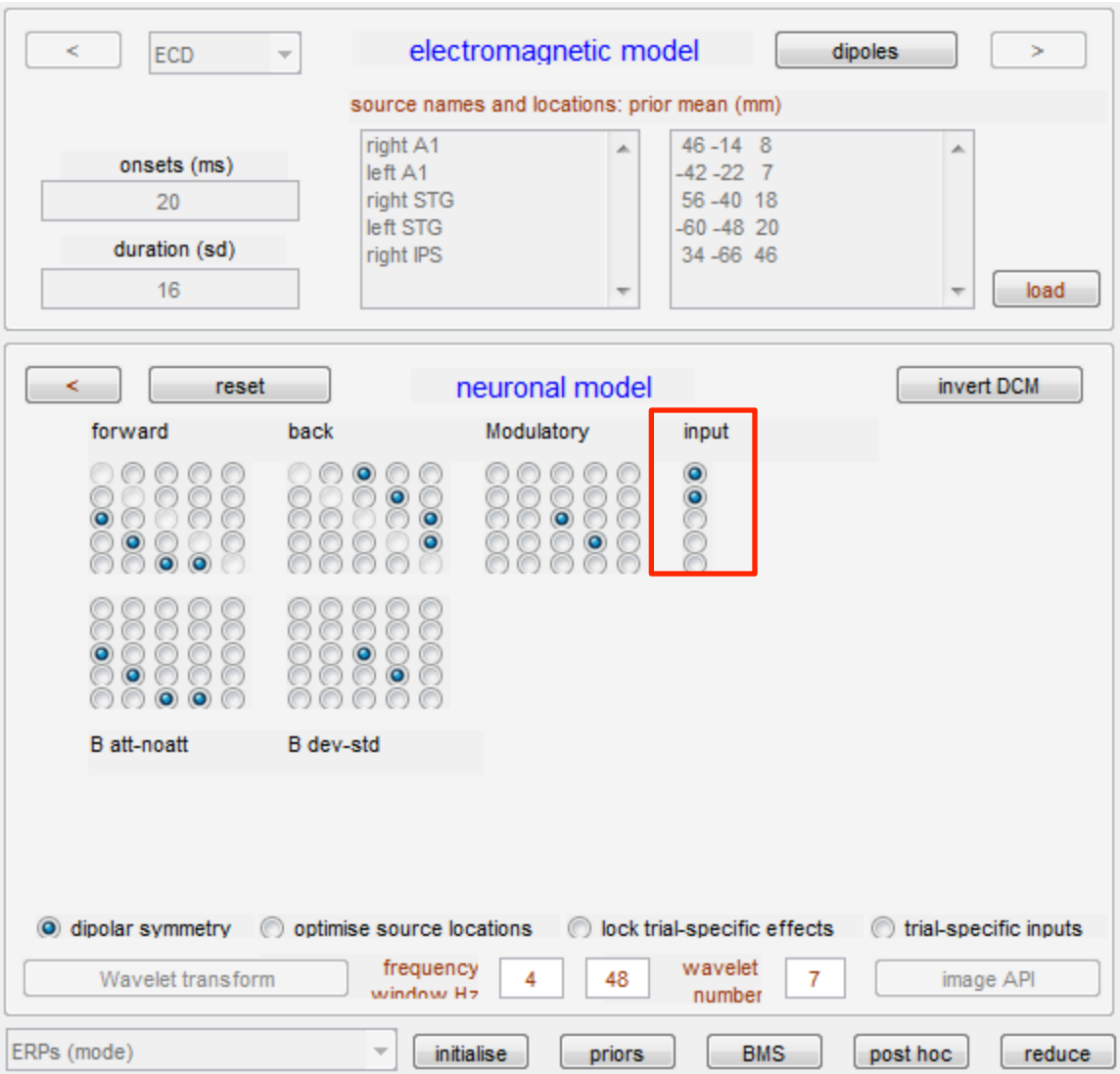
4

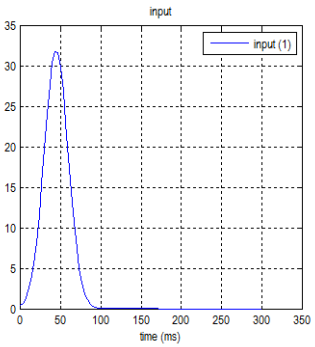
3

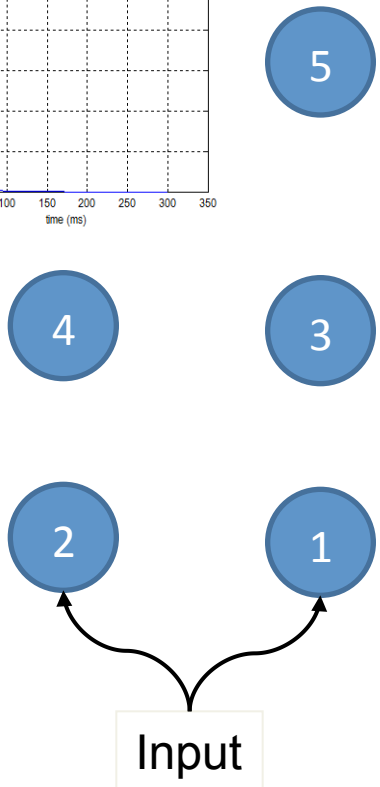
2

1

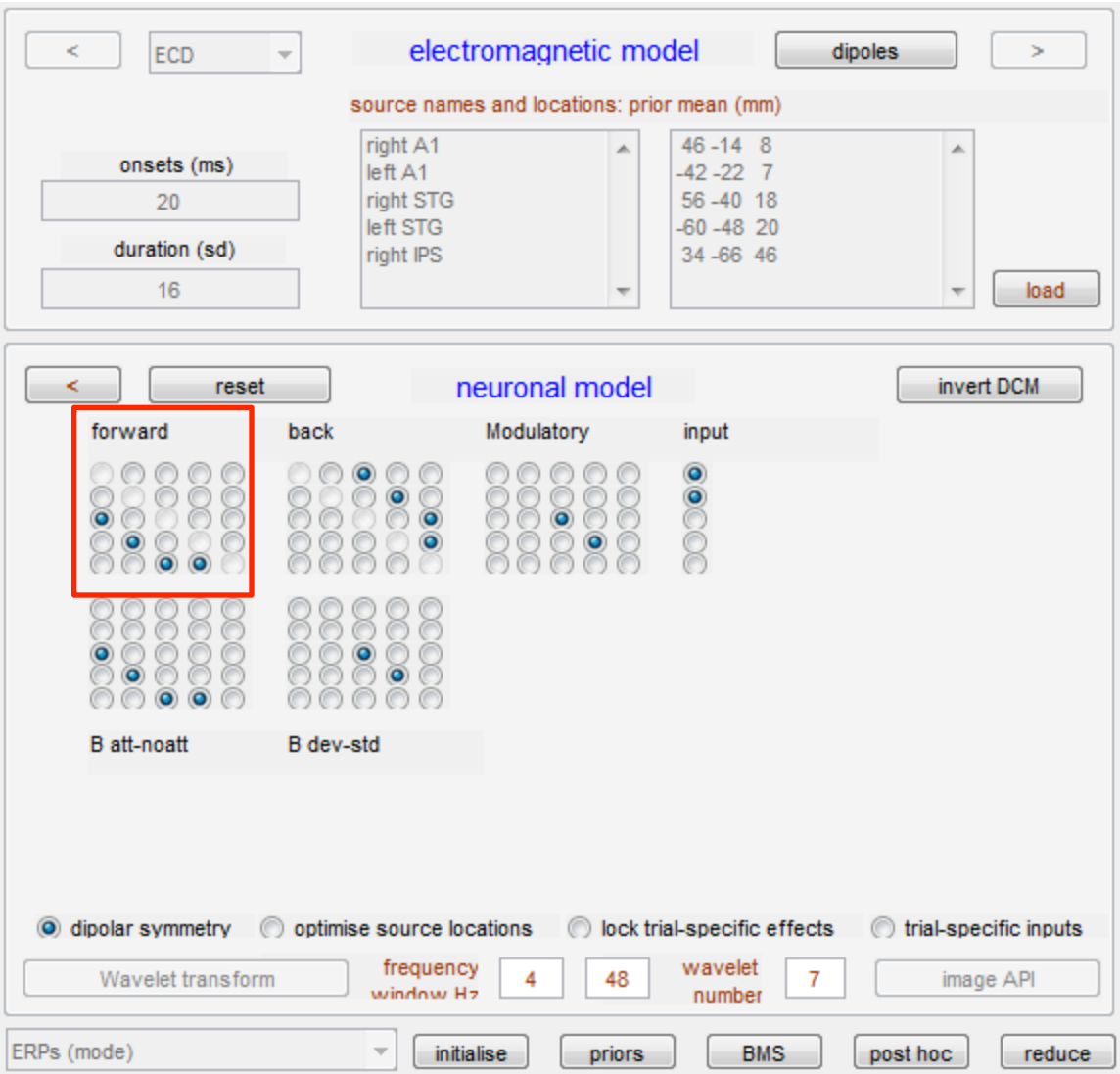
Specify Model in SPM

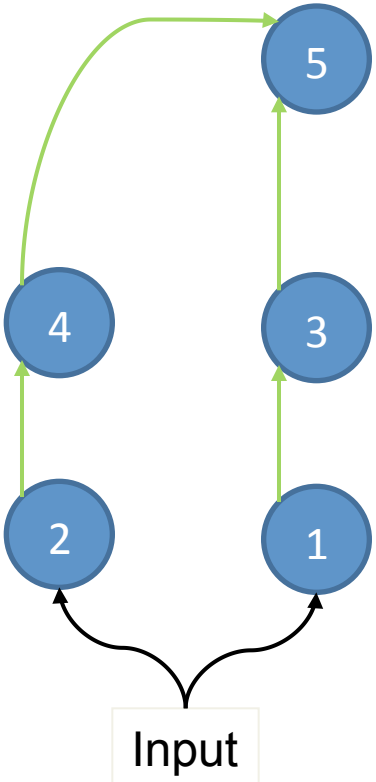




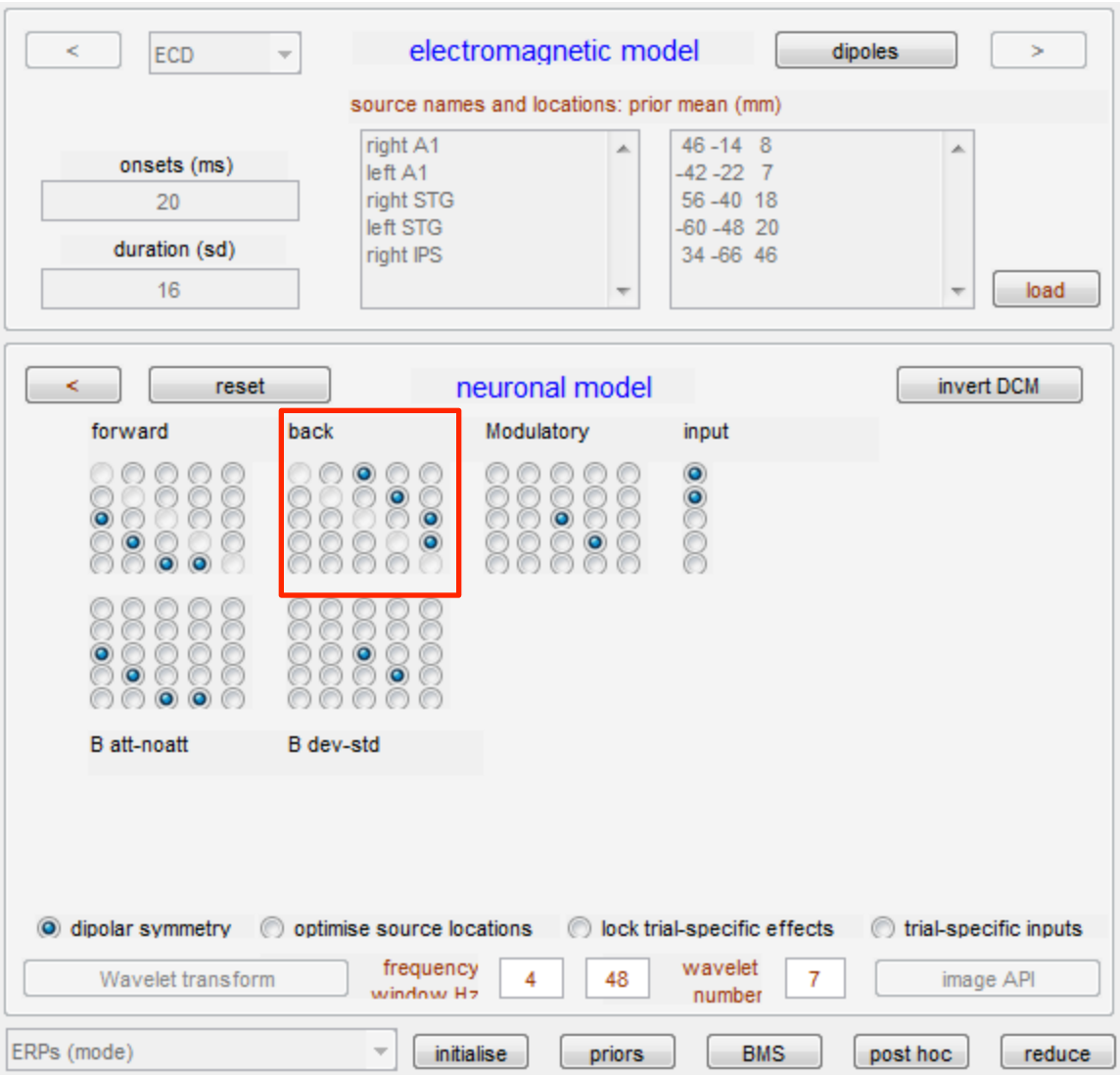


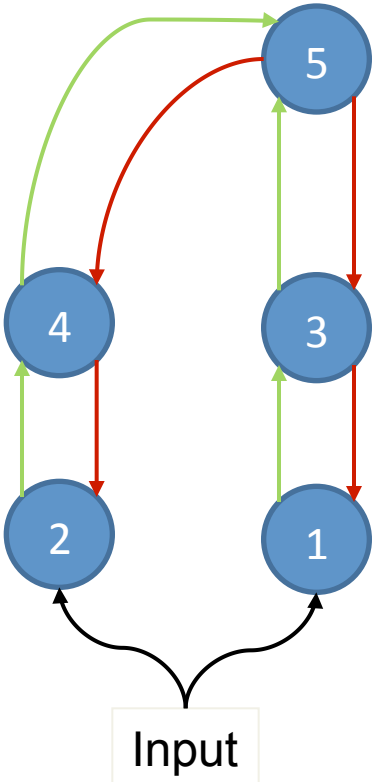
Specify Model in SPM



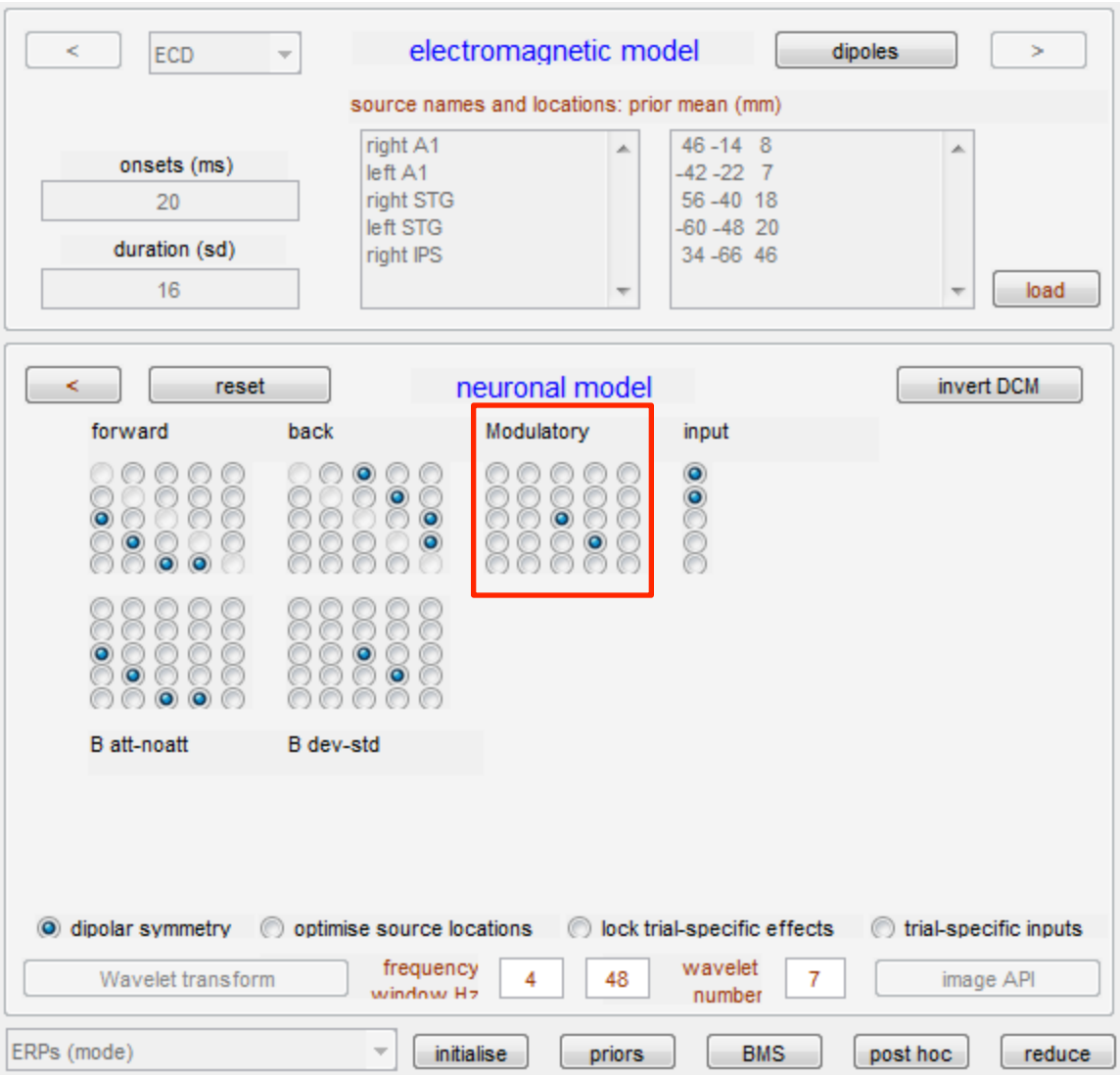


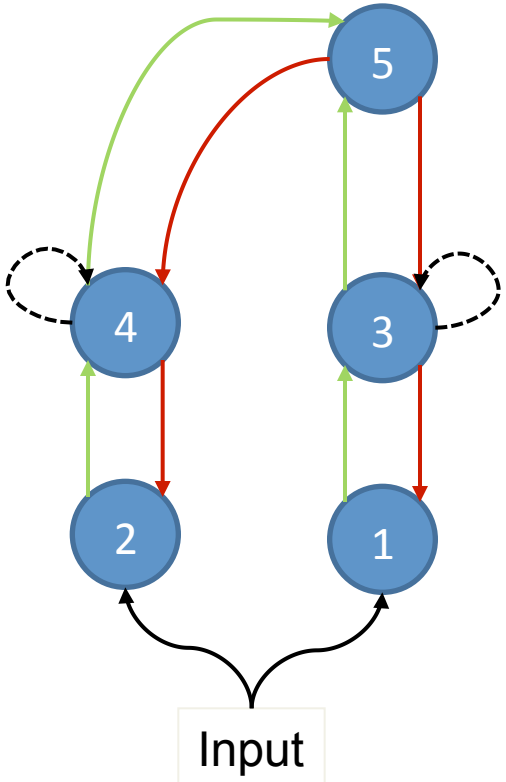
Specify Model in SPM



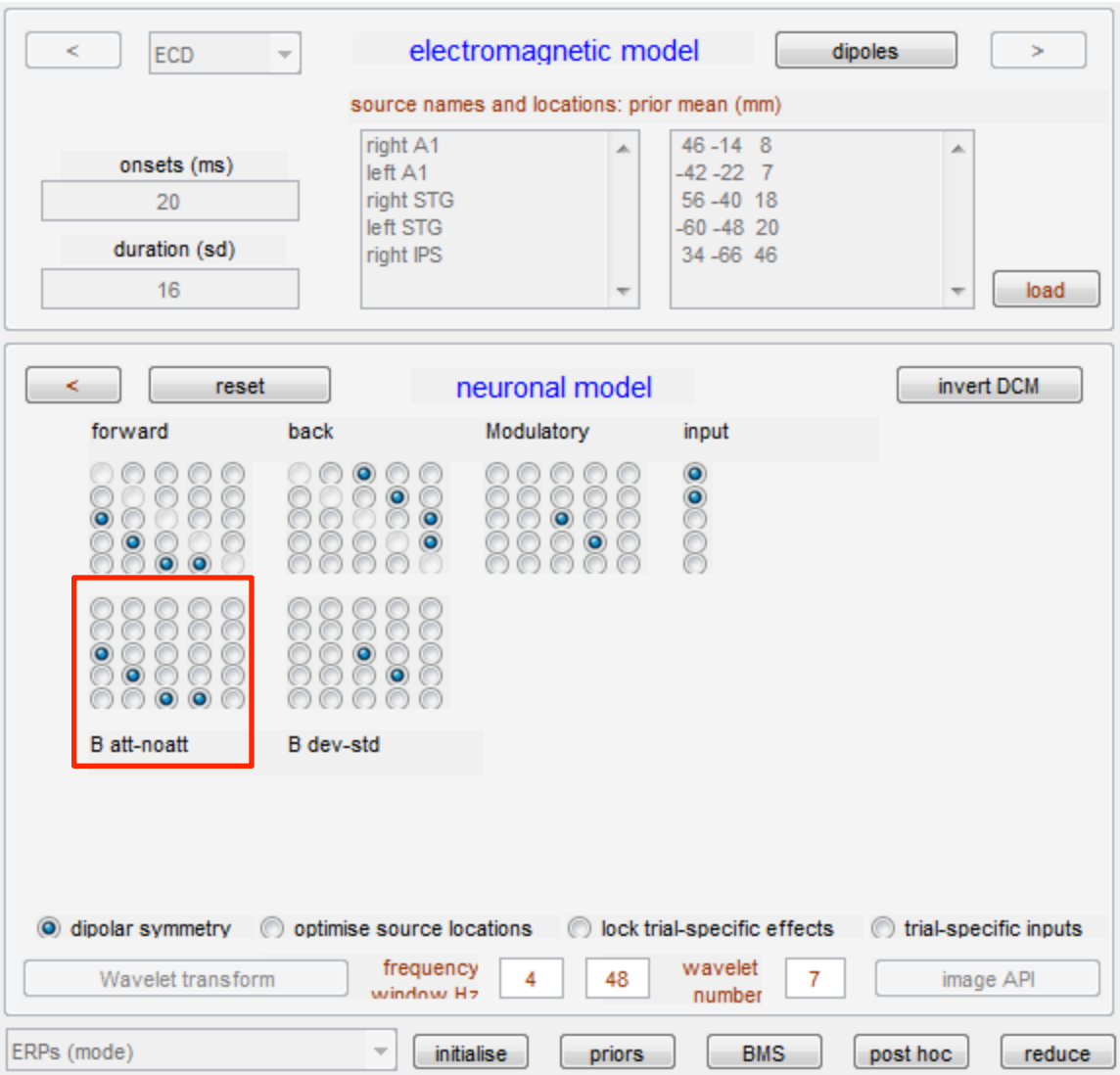


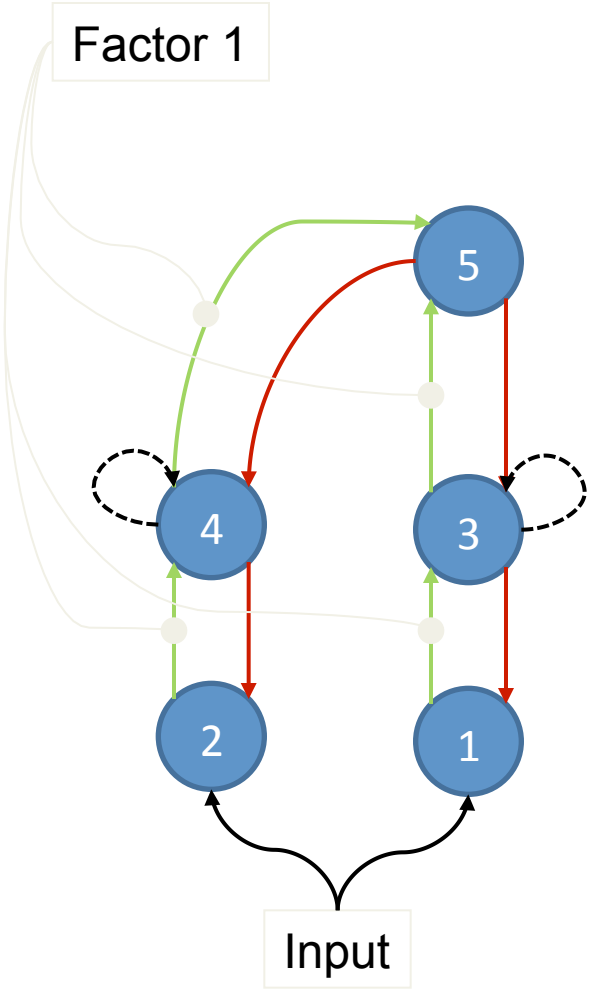
Specify Model in SPM



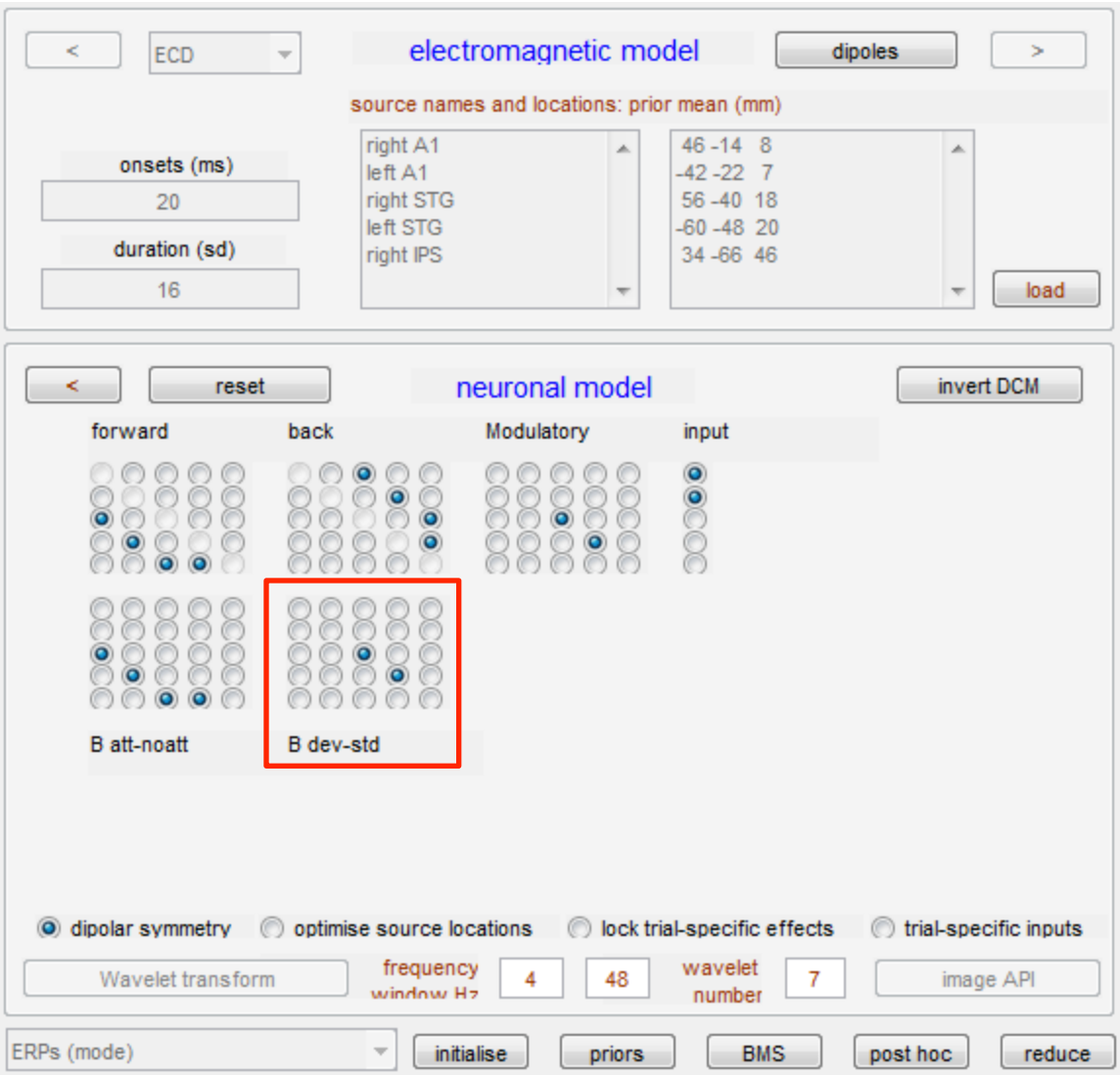


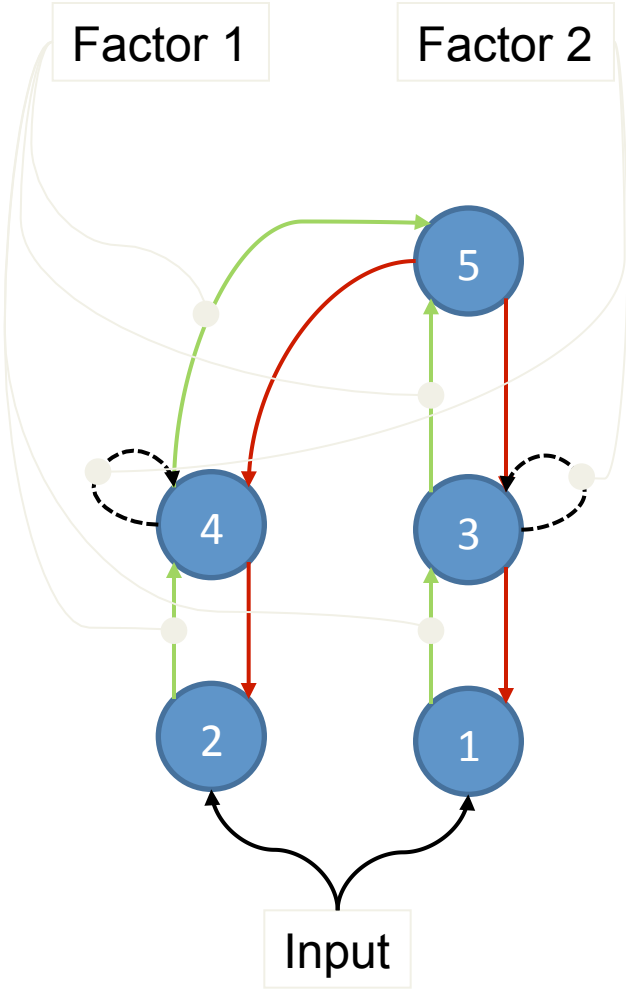
Specify Model in SPM



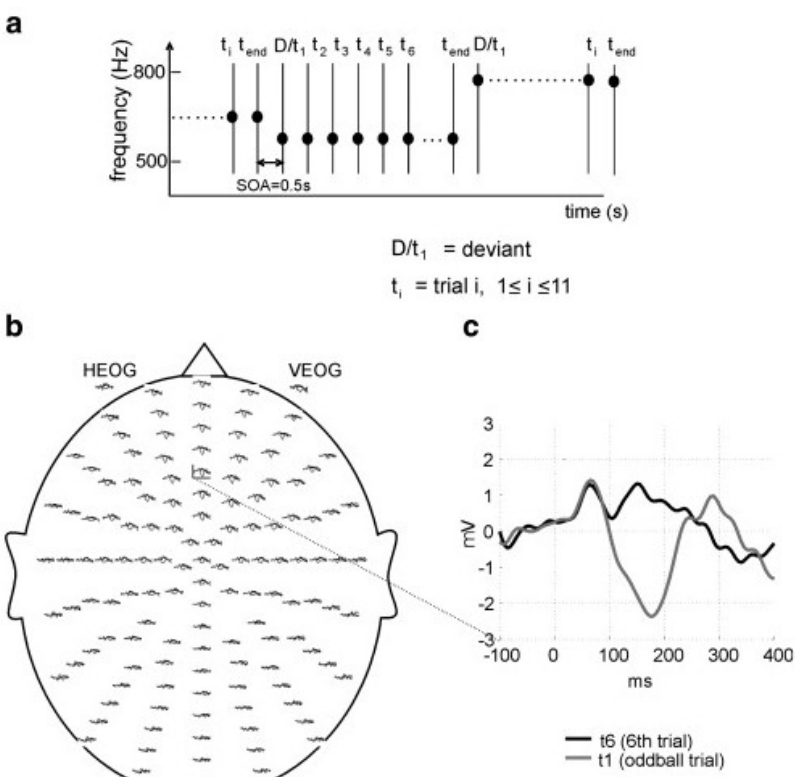


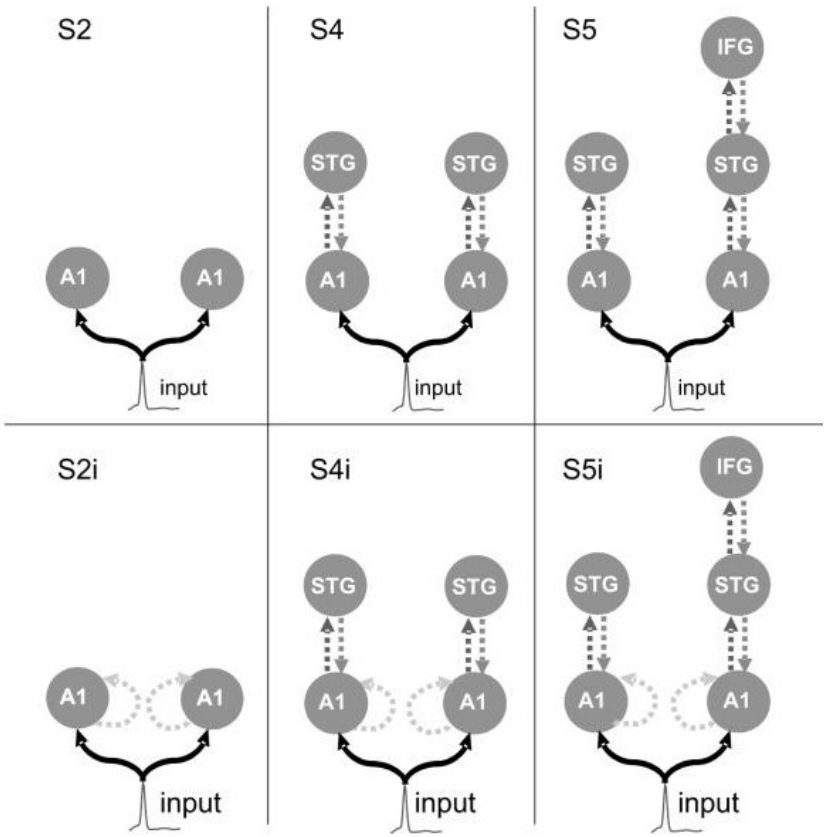
Specify Model in SPM





Example Architecture: Mismatched Negativity

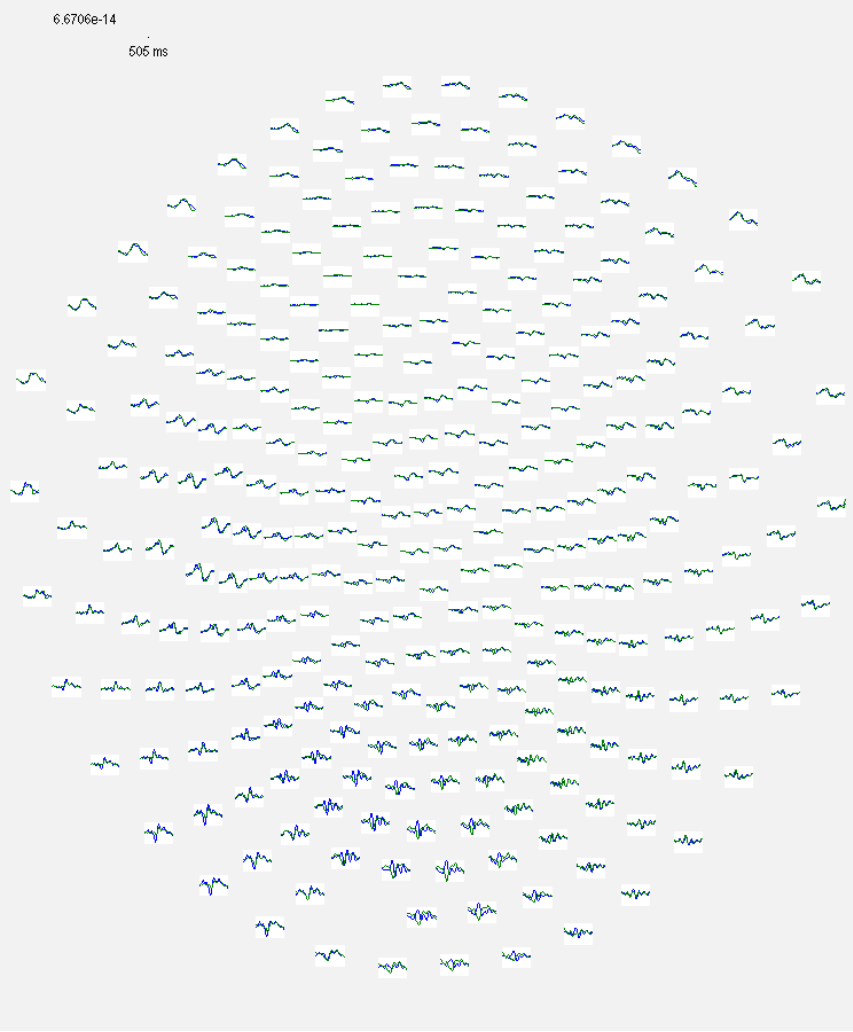




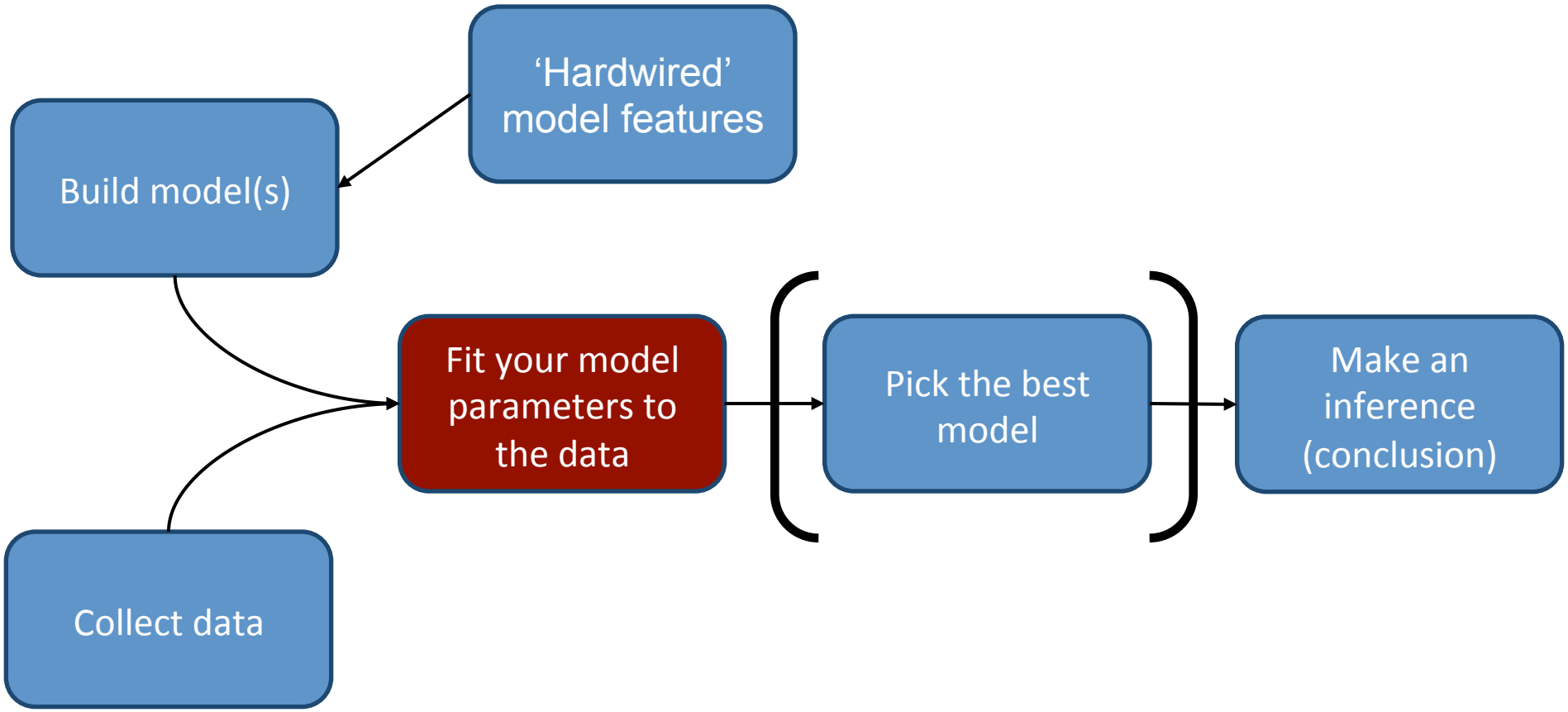
Garrido et al., 2008

Data for DCM for ERPs / ERFs

1. Downsample
2. Filter (e.g. 1-40Hz)
3. Epoch
4. Remove artefacts
5. Average
   - Per subject
   - Grand average
6. Plausible sources
   - Literature / a priori
   - Dipole fitting / 3D source reconstruction

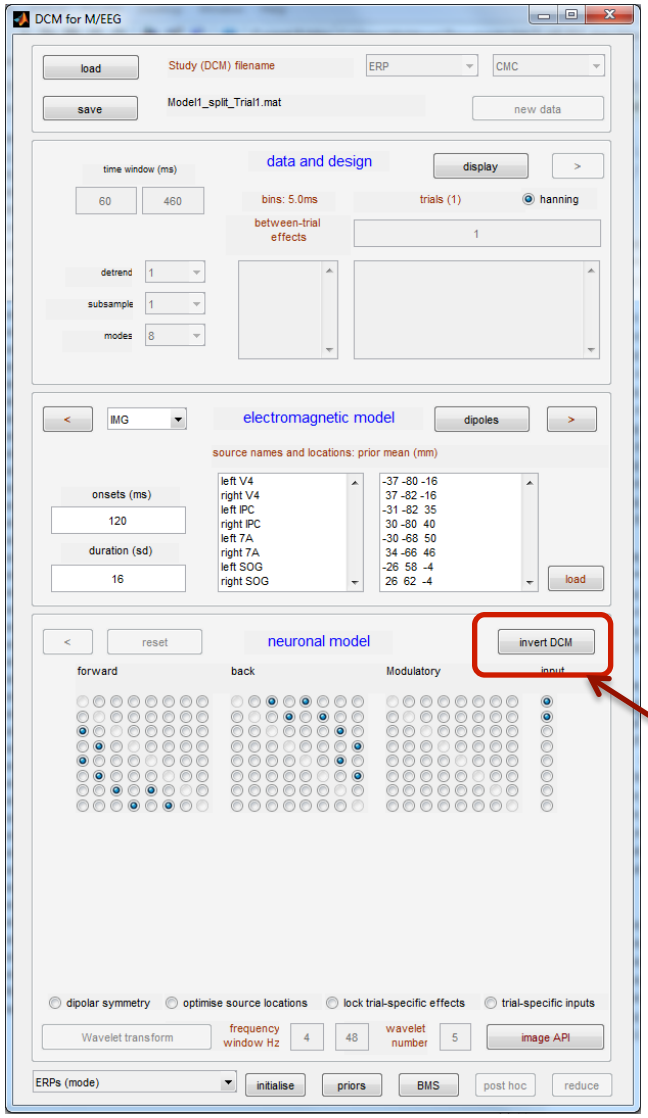


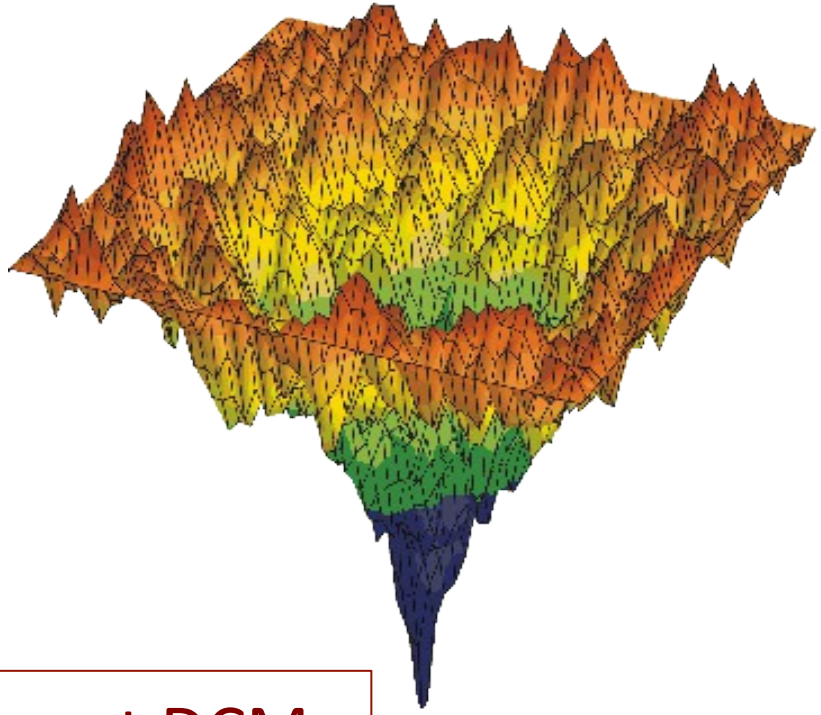
The DCM analysis pathway



Slide from Ryszard Auksztulewicz & SPM Course 2016

Fitting DCMs to data

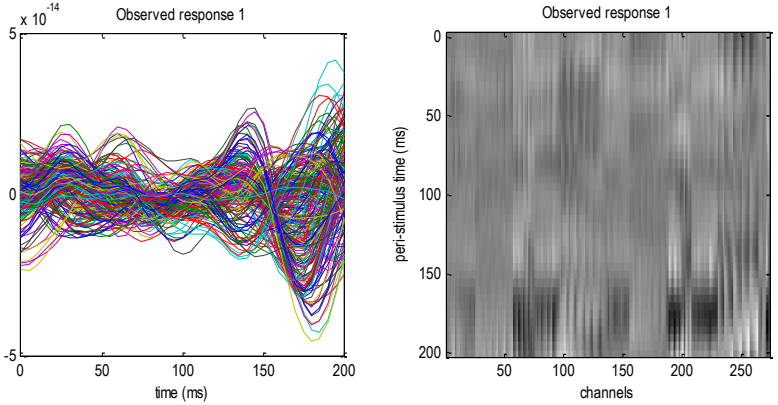


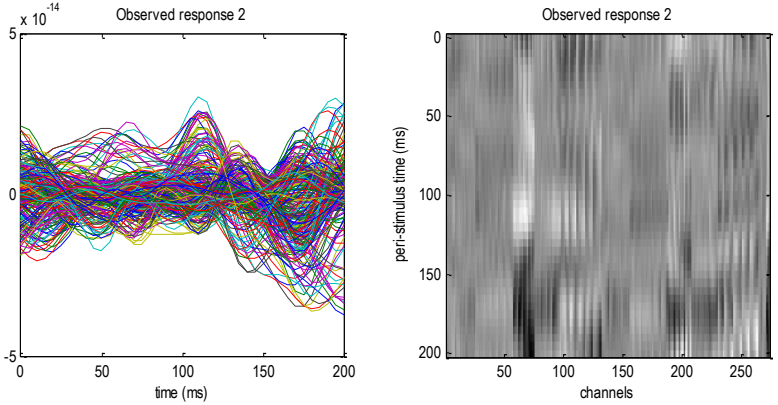


Invert DCM

Fitting DCMs to data

1. Check your data

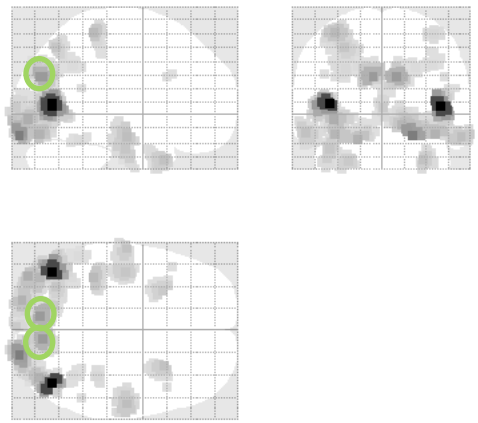




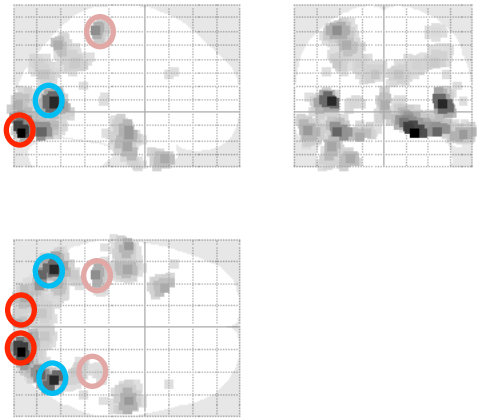
H. Brown

Fitting DCMs to data

1. Check your data



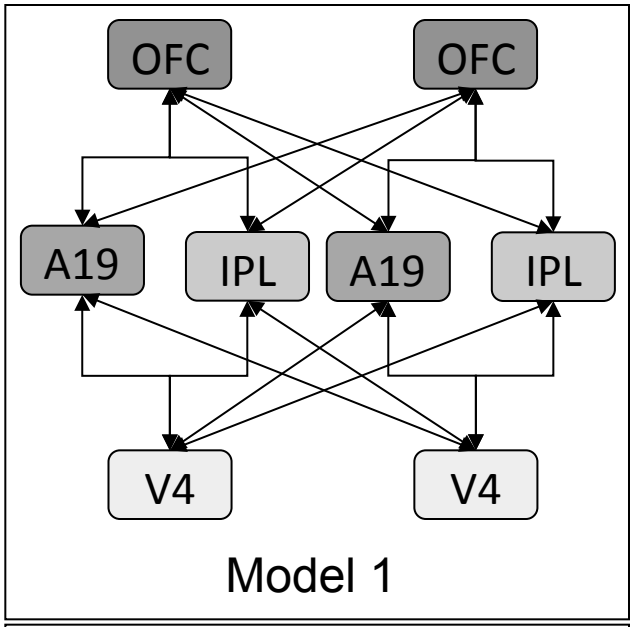
2. Check your sources

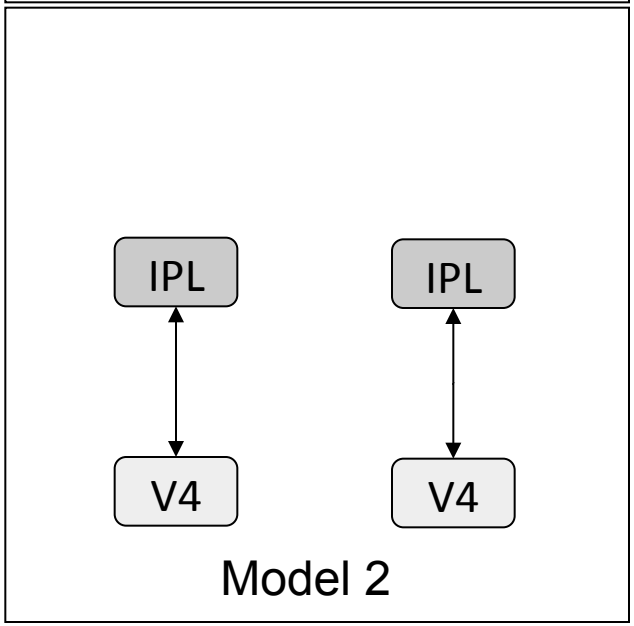


H. Brown

Fitting DCMs to data

1. Check your data
2. Check your sources
3. Check your model

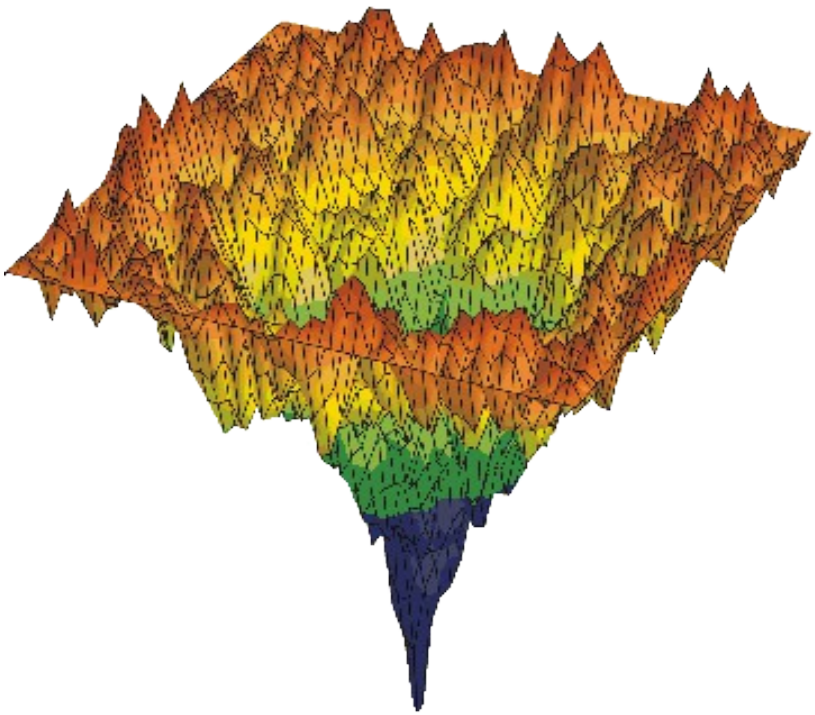




H. Brown

Fitting DCMs to data

1. Check your data
2. Check your sources
3. Check your model
4. Re-run model fitting (if necessary)



H. Brown

Model Inversion in the Spectral Domain

State Equations:

$$\dot{x} = f(x,u) \quad y = g(x,u)$$

$$\dot{x} = Ax(t) + bu(t)$$

$$y = Cx(t) + \xi$$

Take Laplace Transform

$$sX(s) = AX(s) + bU(s)$$

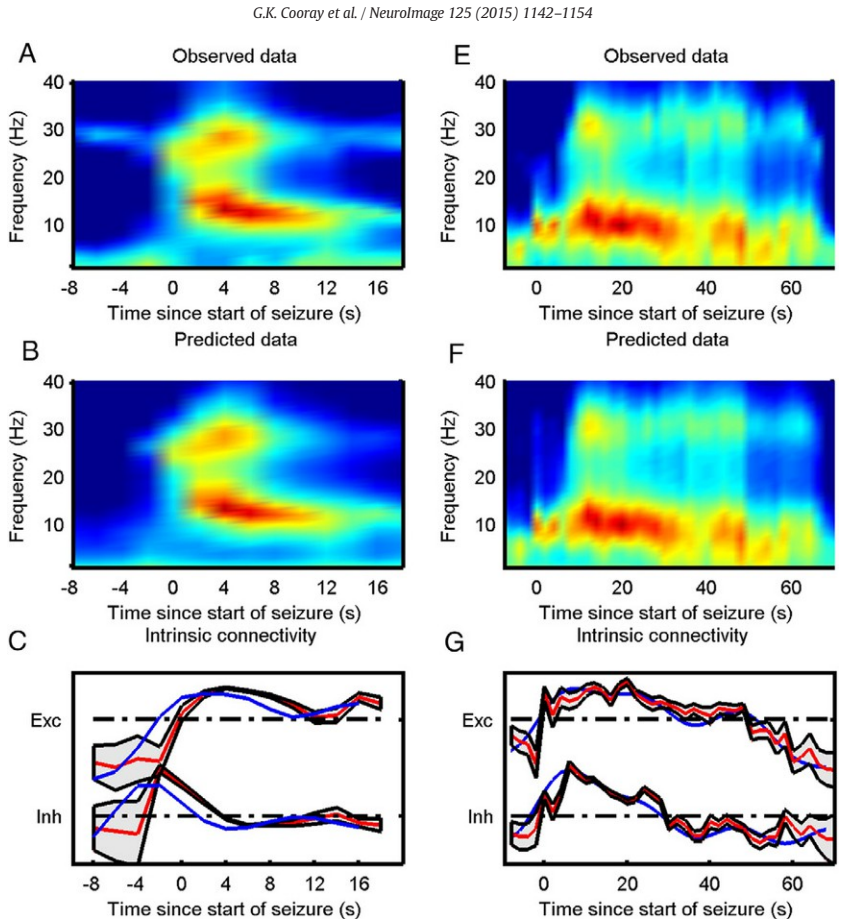
$$(sI - A)X(s) = bU(s)$$

$$X(s) = (sI - A)^{-1} bU(s)$$

$$Y(s) = c^T (sI - A)^{-1} bU(s) + \xi$$

Model inversion tries to optimize parameters that yield the best estimates of cross spectral densities

Bayesian Belief Updating



Cooray et al. 2015

Numerically burdensome to estimate parameters over entire time window. Therefore use posteriors from previous window as priors in next time step window.

Bayesian Model Selection

- Candidate generative models of the data, where **each model corresponds to a specific hypothesis about the functional brain architecture**
- Bayes rule:

$$p(\theta|y,m) = \frac{p(y|\theta,m)p(\theta|m)}{p(y|m)}$$

- DCM uses the Laplace approximation, and automatically penalizes for model complexity.

$$lnp(y|m) \quad = \quad accuracy(m) - complexity(m)$$

- Model inversion approximates the model evidence with a quantity called free energy: See (Friston, Mattout et al. 2007).

$$BF_{ij} = \frac{p(y|m_i)}{p(y|m_j)}$$

Bayes Factor

B_{ij}	$p(m=i\|y)(\%)$	Evidence in favour of model i
1 to 3	50-75	Weak
3 to 20	75-95	Positive
20 to 150	95-99	Strong
≥ 150	≥ 99	Very Strong