Dynamic Causal Modeling

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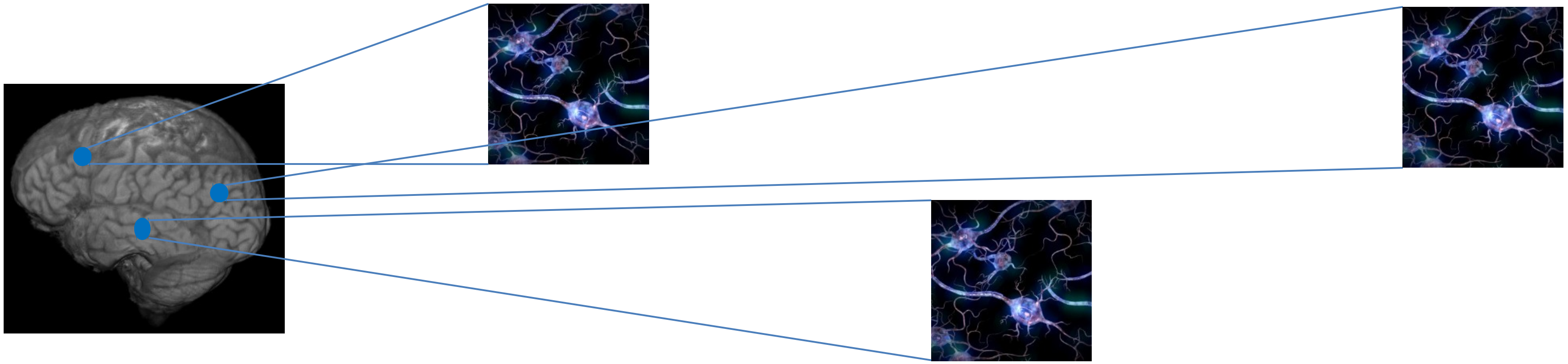
Model of brain mechanisms

Neural model

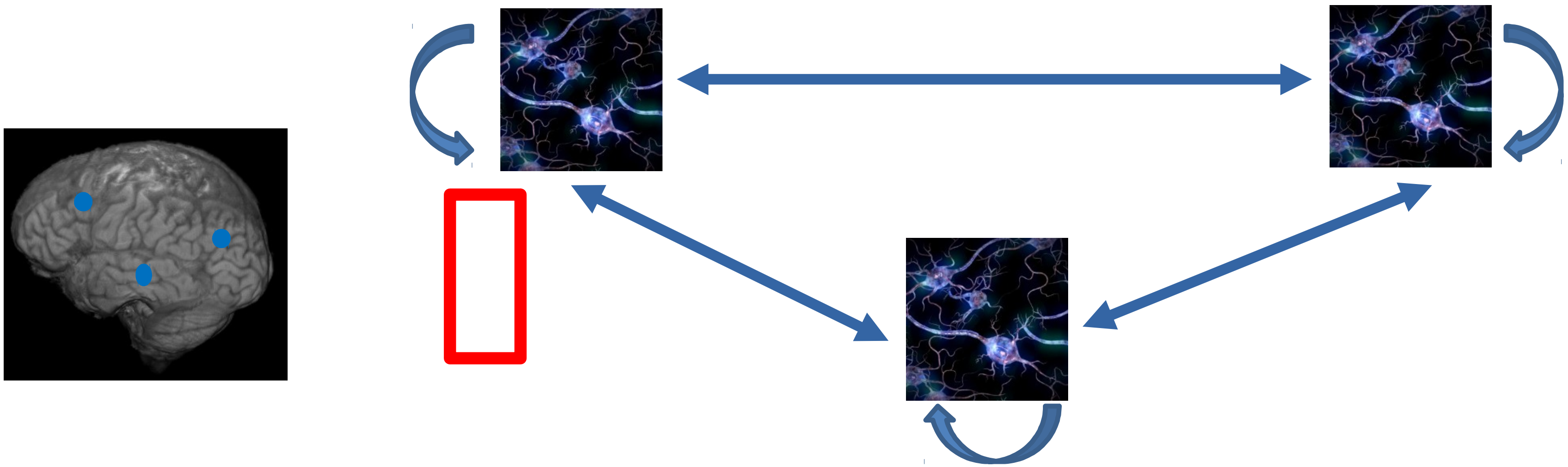
Neural
populations



Neural model

Interactions
between and within
neural populations

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



Neural model

Interactions
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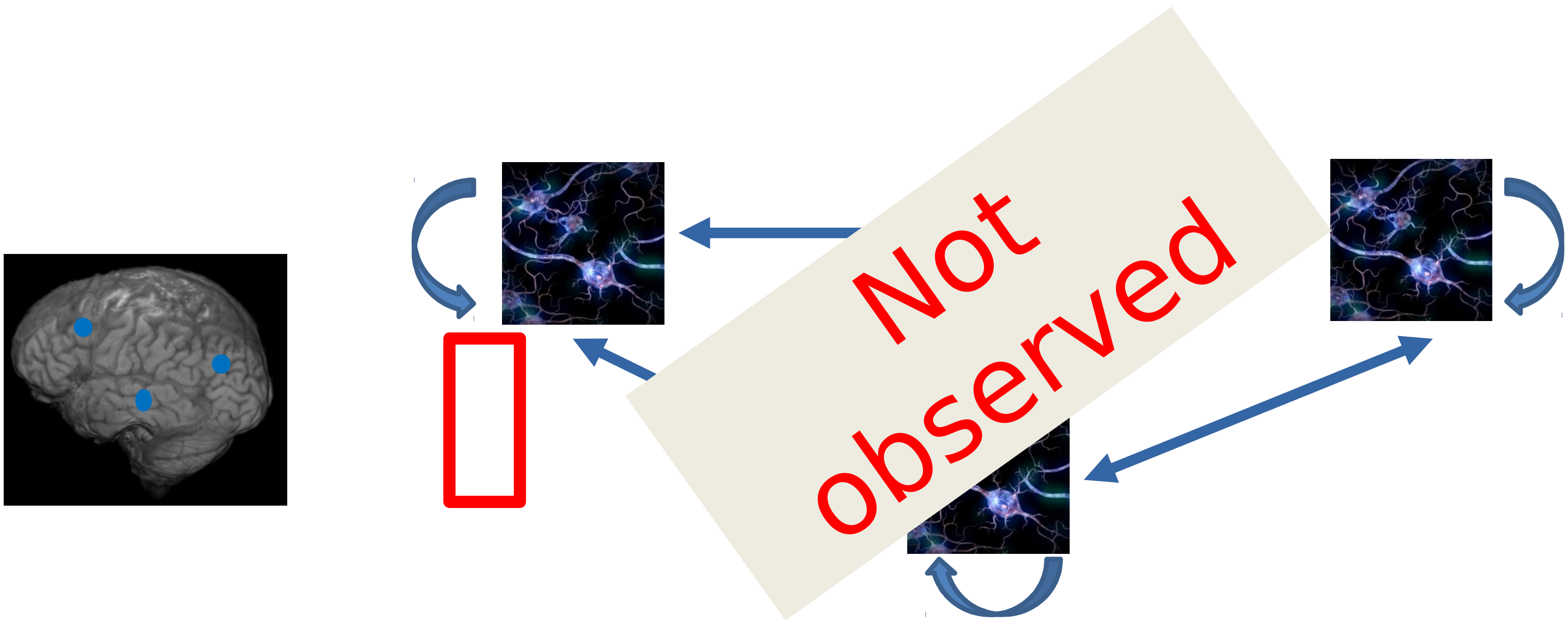
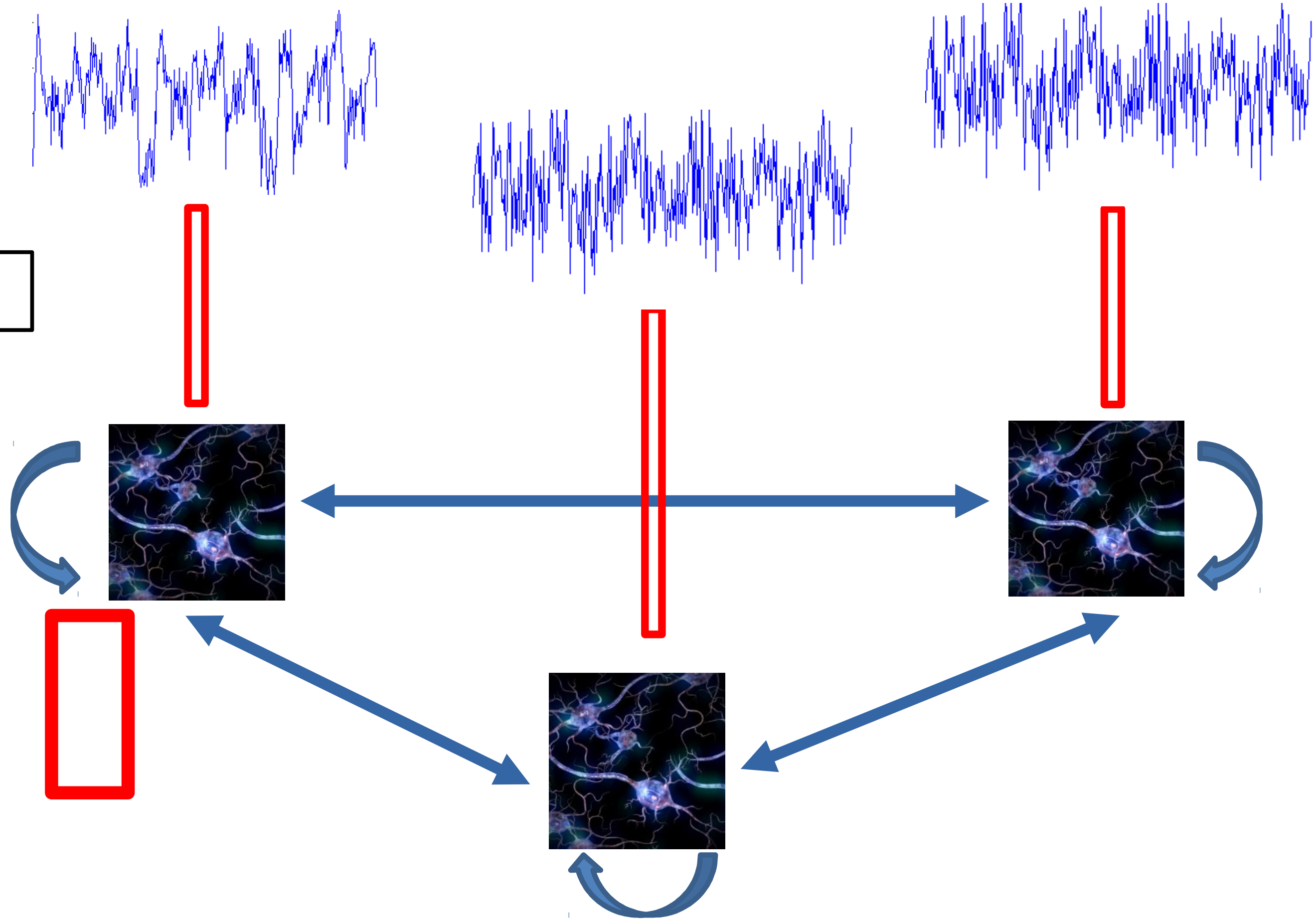


Forward model

OBSERVED signals
(e.g., BOLD)

$$y = g(x, \theta) + \varepsilon$$

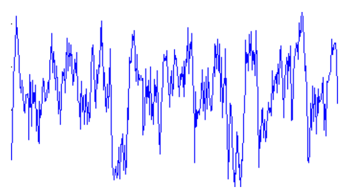
UNOBSERVED
neural states &
interactions



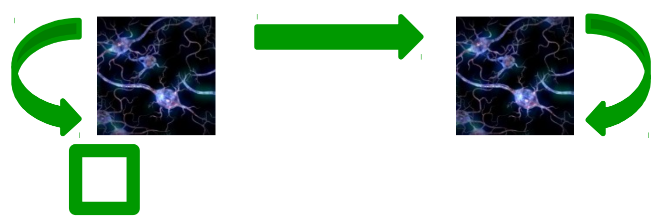
Bayesian model inversion

$$P(\theta \mid y, m) = \frac{P(y \mid \theta, m) * P(\theta \mid m)}{P(y \mid m)}$$

y = data



m = model



θ = parameter

θ^c = neural parameters

θ^h = (hemodynamic) parameters

Bayesian model inversion

What **parameter estimates** (θ) have highest probability given the **data** (y) and the **model** (m)?

Likelihood

Prior

$$P(\theta \mid y, m) = \frac{P(y \mid \theta, m) * P(\theta \mid m)}{P(y \mid m)}$$

Posterior

Model evidence

Bayesian model inversion

- **Prior:** Specifies what connections are included in the model

- **Likelihood:** Incorporates the generative model and prediction errors

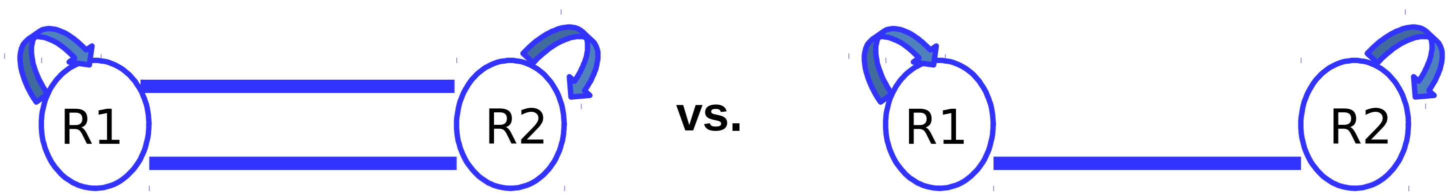
- **Model evidence:** Quantifies the ‘goodness’ of a model (i.e., accuracy minus complexity). Used to draw inference on model structure.

- **Posterior:** Probability density function of the parameters given the data and model. Used to draw inference on model parameters.

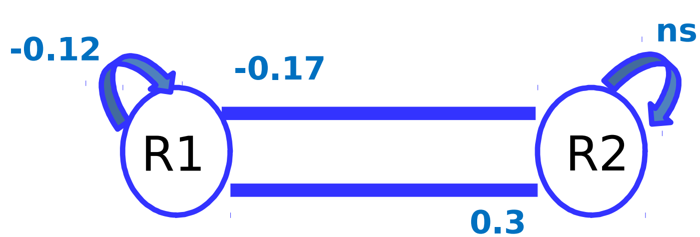
$$P(\theta \mid y, m) = \frac{P(y \mid \theta, m) * P(\theta \mid m)}{P(y \mid m)}$$

Inference

- On the level of **model structure**: Which model (or family of models) has highest evidence?



- On the level of **model parameters**: What parameters are statistically significant, and what is their size/sign?



Inference on model structure

- Inference on **model structure** is a necessary step in DCM studies

→ Unless strong prior knowledge about model structure

- **Bayesian model comparison (BMS)** compares the (log) model evidence of different models (i.e., probability of the data given model)

→ log model evidence is approximated by free energy

$$\boxed{\ln p(y|m) = F(y,q) + D_{KL}[q(\Theta)||p(\Theta|y,m)]}$$

Inference on model parameters

- Inference on **model parameters** is often a second step in DCM studies

- If a clear **'winning' model**:

  → Inference on parameters of this optimal model

Inference on model structure

- If no clear 'winning' model (or if optimal model structure differs between groups) then **Bayesian model averaging (BMA)** is an option

→ Final parameters are weighted average of individual model parameters and posterior probabilities

Group-level inference

- Different DCM’s are fitted to the data for every subject.

- <u>Group inference on the models:</u> themselves or groups of models (in DCM terminology families of models e.g. all models with input to DLPFC vs. input to FFA vs. both → three families): **Bayesian model selection**

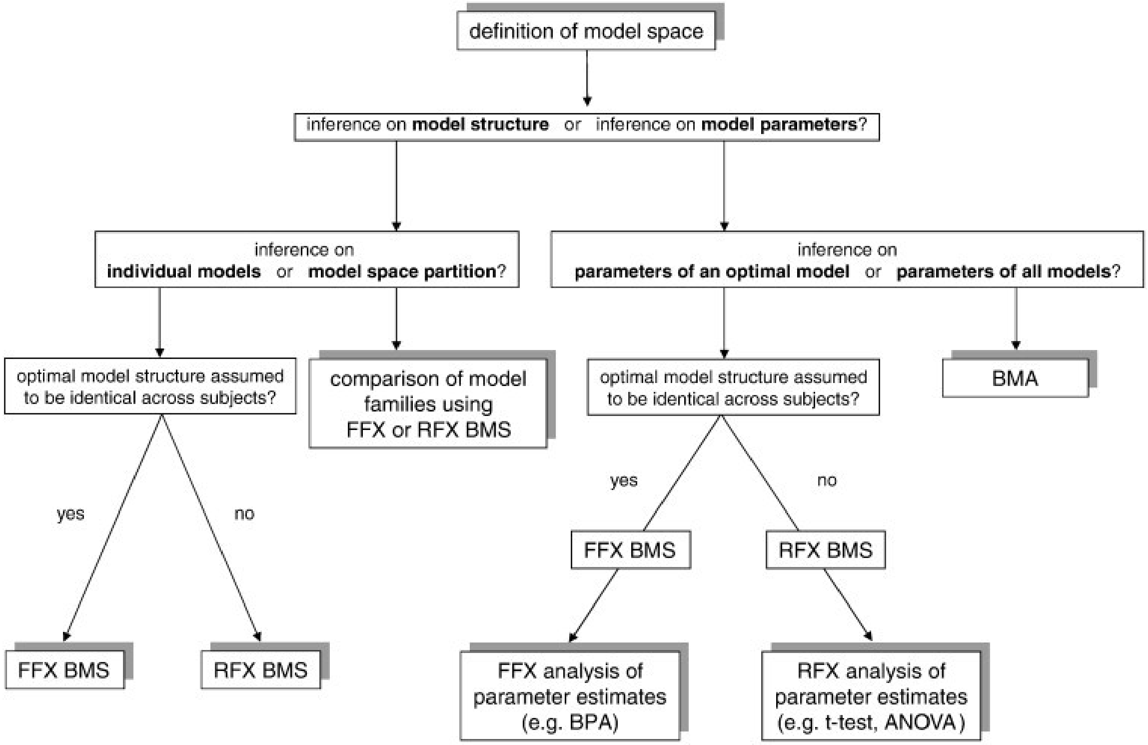
- Winning model/family is the one with highest exceedance probability

Group-level inference

- <u>Group inference on model parameter:</u> Either on the winning model or Bayesian model averaging (BMA) across models (within a winning family or all models when BMS reveal no clear winner)

- (BMA) Parameter(s) of interest are harvested for every subject and subjected to frequentist inference (e.g. t-test)

Inference: summary



Stephan et al., 2010

Different variants of DCM

Different variants of DCM

- DCM has been developed for specific contexts (e.g., fMRI and EEG data, time and frequency domain, task-induced and resting state paradigms,...)

- The following types of DCM are often used:

  - DCM for task-fMRI (Friston et al., 2003)*

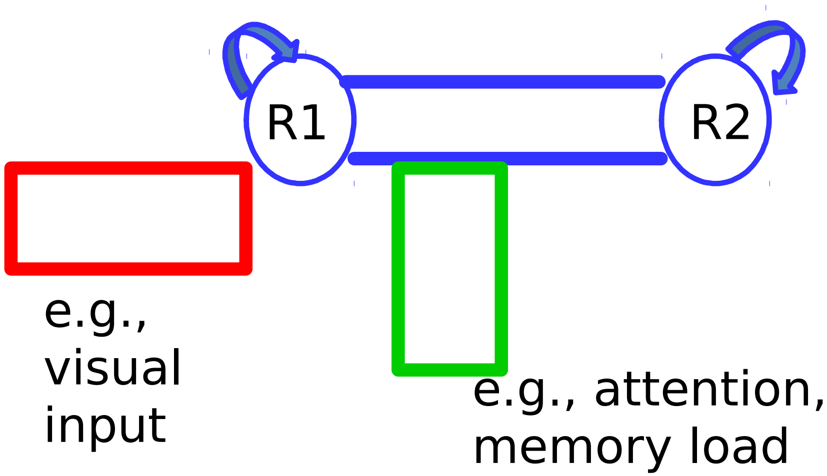
  - DCM for resting state fMRI (Friston et al., 2014)*

  - DCM for ERP/ERF (David et al., 2006)

*stochastic DCM (Friston et al., 2010, Li et al., 2011) is also applicable to both task- and resting state fMRI

DCM for task-fMRI

Neural model



- Structure (effective connections)

- Modulation of connections

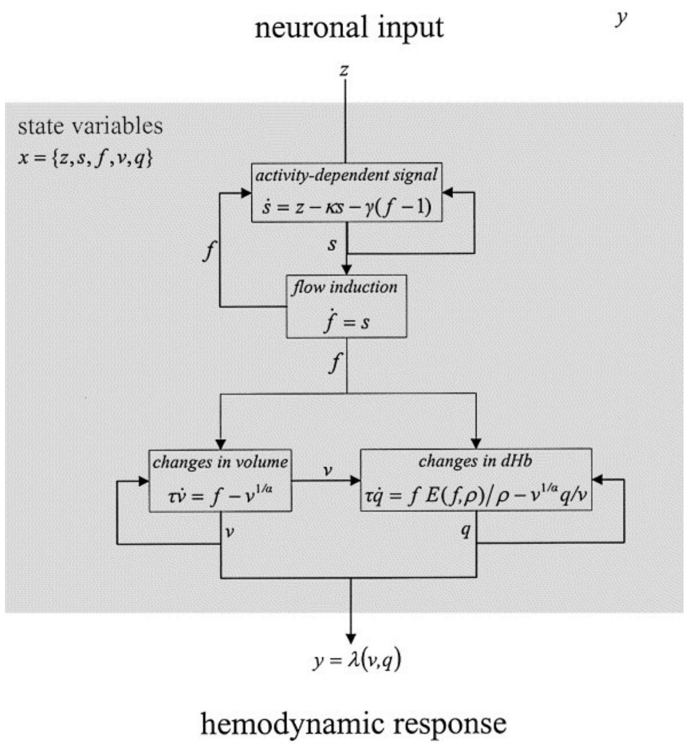
- Driving inputs

$$\dot{x} = (\,A + \Sigma_j\, u_j\, B^j\,)\; x + Cu$$

DCM for task-fMRI

Forward model:

→ Embeds Balloon-Windkessel model



Friston et al., 2003

DCM for task-fMRI

Bayesian Model Inversion

→ Variational Expectation Maximization

Assumes (approximate) posterior is **Gaussian**

Maximizes free energy by updating (hyper)parameters

DCM for resting state fMRI

Neural model

$$\dot{x} = Ax + v$$

- A → Structure (effective connections)
- v → neuronal fluctuations (drive the system)

DCM for resting state fMRI

Parametrization of spectral densities

$g_v(\omega,\theta) = \alpha_v \omega^{-\beta v}$ → neuronal fluctuations

$g_e(\omega,\theta) = \alpha_e \omega^{-\beta e}$ → observation noise

DCM for resting state fMRI

Forward model:

Modeled with Volterra kernels [κ(t)]

Is a function of effective connectivity

DCM for resting state fMRI

Generative model (in frequency domain)

- $g_y(\omega,\theta) = |K(\omega)|^2\, g_v(\omega,\theta) + g_e(\omega,\theta)$

Predicted cross spectra

Fourier transform
Volterra kernels

DCM for resting state fMRI

Bayesian Model Inversion

→ Variational Expectation Maximization

Quality check

- After estimating DCMs, diagnostics should be consulted

- Code for fMRI: spm_dcm_fmri_check(DCM):

  - Proportion explained variance should be sufficient (at least 10% for task-fMRI)

  - Largest extrinsic connection’s strength should be > 0.125Hz

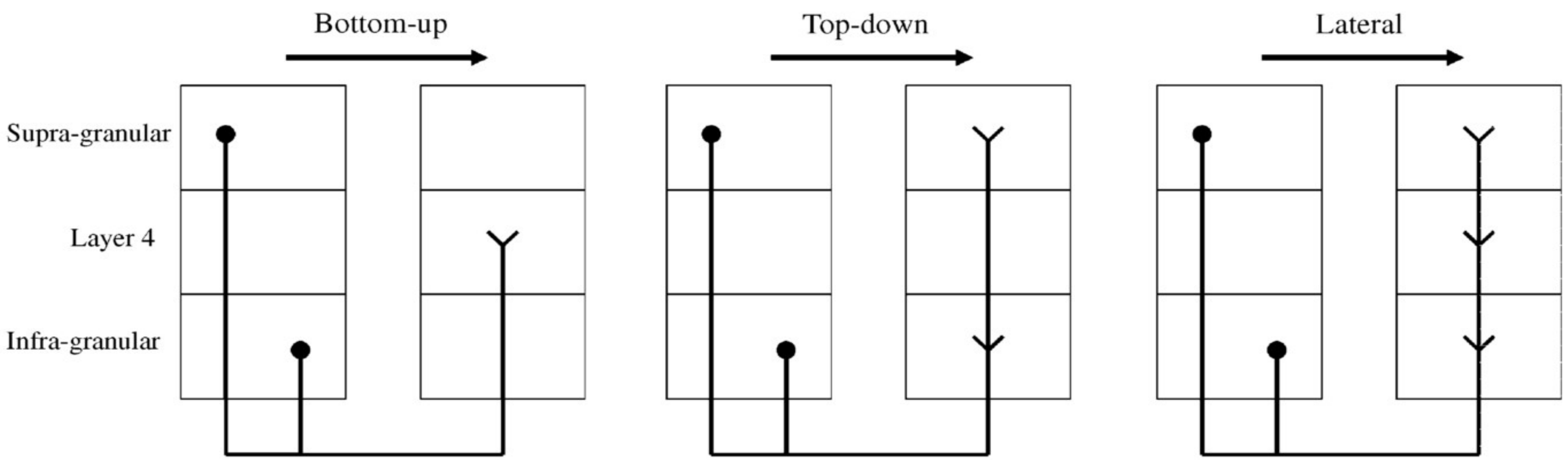
  - Estimable parameters should be greater than 1

→ If one of the above is not satisfied, respective subtitle will be shown in red

DCM for ERP/ERF

- Neural model: much more complex compared to DCM for fMRI
- Each region (‘node’) is modelled with neural mass (or field) models
- 3 layer per node: supra, infra-granular layer and layer IV
- Nodes are connected by either forward, backward or lateral connection (the extrinsic connections)

DCM for ERP/ERF



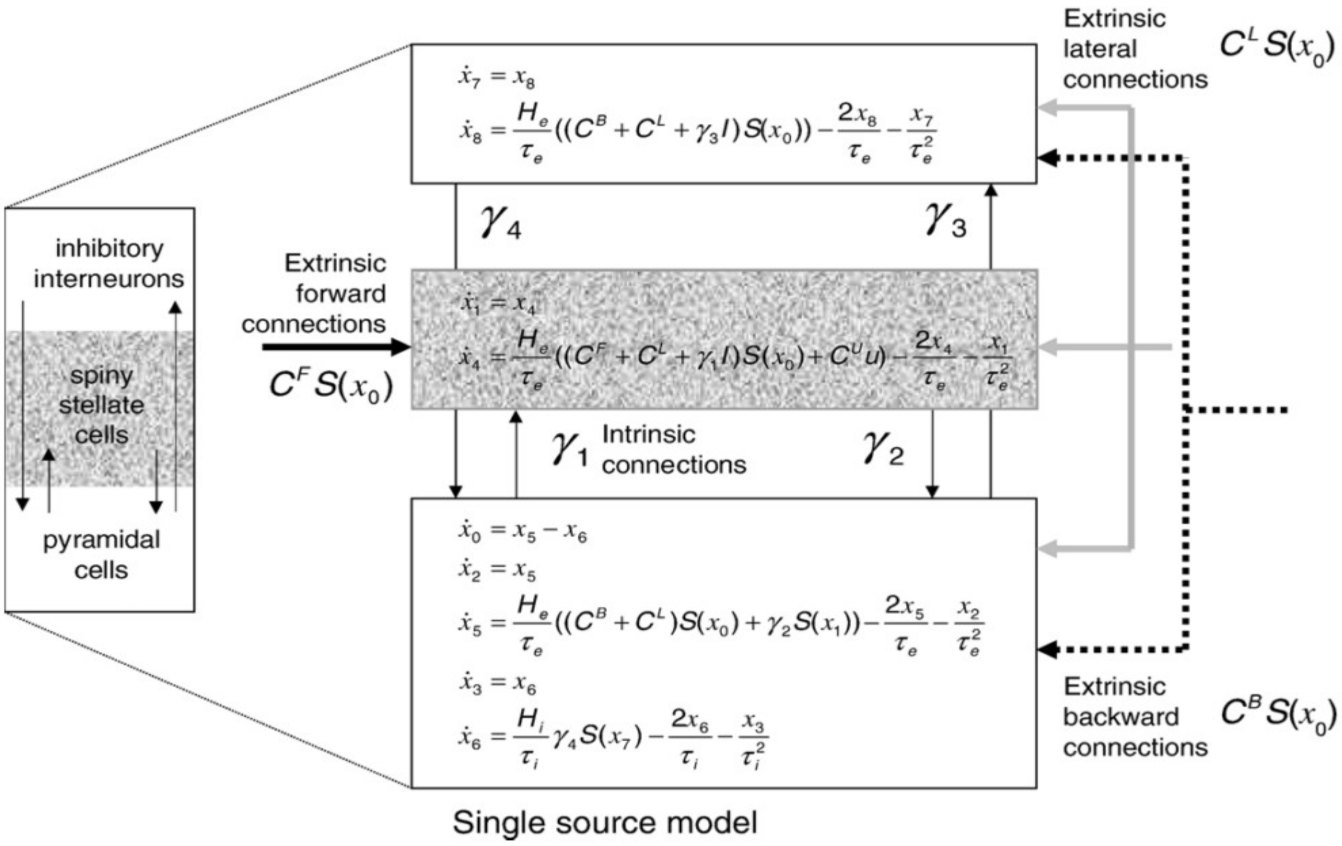
- Bottom-up: connection from low to high hierarchical areas (Felleman 1991)
- top-up: connection from high to low hierarchical areas (Felleman 1991)
- Lateral: same level in hierarchical organization (e.g. interhemispheric connection)
- Prior on connection: forward>backward>lateral

DCM for ERP/ERF

- Layers within regions interact via intrinsic connection

- What is measured with the EEG/MEG sensor are the potentials generated by pyramidal cells

DCM for ERP/ERF



DCM for ERP/ERF

- The forward model in EEG/MEG is much simpler compared to fMRI:
- $Y(t) = LX_0(t) + \varepsilon(t)$
- Y(t) are the channel time series, L is the leadfield (conduction of electromagnetic fields), X_0 are the pyramidal potentials of all sources and ε is measurement noise.
- In words: each channel is a weighted sum of source activities where the weights depend on position and orientation of the sources and channels

DCM for ERP/ERF

- ROIs need to be specified based on prior knowledge/assumptions regarding the location of the sources or based on data itself via source reconstruction

- Models with different ROIs can be compared (not the case with fMRI)

- Search in literature for determining type of connection between ROIs (e.g. forward connection from low to higher cortical areas)

Recommended articles

DCM for task-fMRI:

→ Friston et al., 2003: Dynamic causal modeling (NI)

DCM for resting state fMRI:

→ Friston et al., 2014: A DCM for resting state fMRI (NI)
→ Razi et al., 2015: Construct validation of a DCM for resting state fMRI (NI)

DCM for ERP/ERF:

→ David et al., 2006: Dynamical causal modelling of evoked reponses in EEG and MEG (NI)

Practical recommendations:

→ Stephan et al., 2010: Ten simple rules for dynamic causal modeling (NI)
→ Penny et al., 2004: Comparing Dynamic causal models (NI)