Dynamic Causal Modeling

Hannes Almgren, Frederik van de Steen, Daniele Marinazzo

daniele.marinazzo@ugent.be
@daniele.marinazzo
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 between and within neural populations

Not observed
**Forward model**

**OBSERVED** signals (e.g., BOLD)

\[ y = g(x, \theta) + \epsilon \]

**UNOBSERVED** neural states & interactions
Bayesian model inversion

\[ P(\theta \mid y, m) = \frac{P(y \mid \theta, m) \cdot P(\theta \mid m)}{P(y \mid m)} \]

\( y = \text{data} \)

\( m = \text{model} \)

\( \theta = \text{parameter} \)

\( \theta^c = \text{neural parameters} \)

\( \theta^h = \text{(hemodynamic) parameters} \)
Bayesian model inversion

What parameter estimates ($\theta$) have highest probability given the data ($y$) and the model ($m$)?

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

- **Likelihood**
- **Prior**
- **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.

\[
P(\theta|y, m) = \frac{P(y|\theta, m) \times P(\theta|m)}{P(y|m)}
\]
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

\[
\ln p(y|m) = F(y,q) + D_{KL}[q(\Theta)||p(\Theta|y,m)]
\]
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
Different DCM’s are fitted to the data for every subject.

Group inference on the models: 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

- **Group inference on model parameter**: 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

\[ \dot{x} = (A + \sum_j u_j B_j)x + Cu \]
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

\[ g_v(\omega, \theta) = a_v \omega^{-\beta_v} \rightarrow \text{neuronal fluctuations} \]

\[ g_e(\omega, \theta) = a_e \omega^{-\beta_e} \rightarrow \text{observation noise} \]
DCM for resting state fMRI

Forward model:

Modeled with Volterra kernels $[\kappa(t)]$

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 greater than 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

\[ \begin{align*}
    \dot{x}_7 &= x_4 \\
    \dot{x}_8 &= \frac{H_e}{\tau_e} \left( (C^e + C^i + \gamma_3 I) S(x_8) \right) - \frac{2x_8}{\tau_e} \frac{x_7}{\tau_e^2}
\end{align*} \]

Extrinsic forward connections

\[ C^F S(x_0) \]

Extrinsic lateral connections

\[ C^L S(x_0) \]

Inhibitory interneurons

Spiny stellate cells

Pyramidal cells

Intrinsic connections

Extrinsic backward connections

Single source model

\[ \begin{align*}
    \dot{x}_1 &= x_1 \\
    \dot{x}_2 &= \frac{H_e}{\tau_e} \left( (C^e + C^i + \gamma_4 I) S(x_1) \right) - \frac{2x_2}{\tau_e} \frac{x_1}{\tau_e^2}
\end{align*} \]
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 \( \varepsilon \) 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
• 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 responses 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)