DCM for evoked responses

Ryszard Auksztulewicz

SPM for M/EEG course, 2019
Does network XYZ explain my data better than network XY?

Which XYZ connectivity structure best explains my data?

Are X & Y linked in a bottom-up, top-down or recurrent fashion?

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

1. Collect data
2. Build model(s)
3. Fit your model parameters to the data
4. Pick the best model
5. Make an inference (conclusion)
The DCM analysis pathway

1. Collect data
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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
   - Source reconstruction
The DCM analysis pathway

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The DCM analysis pathway

1. Collect data
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3. Fit your model parameters to the data
4. ‘Hardwired’ model features
5. Pick the best model
6. Make an inference (conclusion)
Neural masses and fields in dynamic causal modeling

Rosalyn Moran⁴, Dimitris A. Pinotsis⁵ and Karl Friston¹
Neuronal (source) model

\[
\begin{align*}
\dot{x}_7 &= x_8 \\
\dot{x}_8 &= \frac{H_e}{\tau_e}((A^B + A^L + \gamma_3 I)S(x_7)) - \frac{2x_8}{\tau_e} - \frac{x_7}{\tau_e^2} \\
\dot{x}_1 &= x_1 \\
\dot{x}_4 &= \frac{H_e}{\tau_e}((A^B + A^L + \gamma_1 I)S(x_0) + Cu) - \frac{2x_4}{\tau_e} - \frac{x_1}{\tau_e^2} \\
\dot{x}_0 &= x_5 - x_6 \\
\dot{x}_2 &= x_5 \\
\dot{x}_5 &= \frac{H_e}{\tau_e}((A^B + A^L)S(x_0) + \gamma_2 S(x_1)) - \frac{2x_5}{\tau_e} - \frac{x_2}{\tau_e^2} \\
\dot{x}_3 &= x_6 \\
\dot{x}_6 &= \frac{H_i}{\tau_i} \gamma_4 S(x_7) - \frac{2x_6}{\tau_i} - \frac{x_3}{\tau_i^2}
\end{align*}
\]

State equations

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

Kiebel et al., 2008
NEURAL MASS MODEL

L2/3

Inhib Inter

L4

Spiny Stell

L5/6

Pyr

spm_fx_erp
Canonical Microcircuit Model (‘CMC’)

**Original microcircuit**

**Updated microcircuit**

**Canonical microcircuit (predictive coding)**

**Reduced model (DCM)**

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Douglas & Martin (1991)  
Adapted from Haeusler & Maass (2006)  
Bastos et al. (2012)  
Pinotsis et al. (2012)
Canonical Microcircuit Model (‘CMC’)
Canonical Microcircuit Model (‘CMC’)

- Supra-granular Layer
- Granular Layer
- Infra-granular Layer

**Cells**

- Inhibitory Interneurons
- Superficial Pyramidal Cells
- Spiny Stellate Cells
- Deep Pyramidal Cells

Pinotsis et al., 2012
Granular Layer

Supra-granular Layer

Granular Layer

Infra-granular Layer

Inhibitory Interneurons

Superficial Pyramidal Cells

Spiny Stellate Cells

Deep Pyramidal Cells

Pinotsis et al., 2012
Canonical Microcircuit Model (‘CMC’)
Canonical Microcircuit Model (‘CMC’)

- **Supra-granular Layer**
- **Granular Layer**
- **Infra-granular Layer**

- **Inhibitory Interneurons**
- **Superficial Pyramidal Cells**
- **Spiny Stellate Cells**
- **Deep Pyramidal Cells**

Pinotsis et al., 2012
Canonical Microcircuit Model (‘CMC’)

**Layering:**
- Supragranular Layer
- Granular Layer
- Infragranular Layer

**Cell Types:**
- Inhibitory Interneurons
- Superficial Pyramidal Cells
- Spiny Stellate Cells
- Deep Pyramidal Cells

Connections indicated with arrows and parameters labeled as $\gamma_i$.

**References:**
Pinotsis et al., 2012
Canonical Microcircuit Model (‘CMC’)
Canonical Microcircuit Model (‘CMC’)

Inhibitory Interneurons

Superficial Pyramidal Cells

Spiny Stellate Cells

Deep Pyramidal Cells

\[ A^B S(p_7) \]

\[ A^F S(p_3) \]

\[ A^B S(p_7) \]

\[ A^F S(p_3) \]

\[ A^B S(p_7) \]

\[ A^F S(p_3) \]

\[ A^B S(p_7) \]

\[ A^F S(p_3) \]

Pinotsis et al., 2012
Canonical Microcircuit Model (‘CMC’)
Canonical Microcircuit Model (‘CMC’)

\[ \dot{p}_7 = p_8 \]

\[ \dot{p}_8 = \frac{H^4}{\tau_4} \left( A^F S(p_2) - \gamma_{10} S(p_7) - \gamma_9 S(p_5) \right) - \frac{2 p_8}{\tau_4} - \frac{p_7}{\tau_4^2} \]

**Voltage** change rate: f(current)

**Current** change rate: f(voltage, current)

Pinotsis et al., 2012
**Canonical Microcircuit Model (‘CMC’)**

\[
\dot{p}_7 = p_8
\]

**Voltage** change rate: \( f(\text{current}) \)

**Current** change rate: \( f(\text{voltage}, \text{current}) \)

\[
\dot{p}_8 = \frac{H^4}{\tau_4} \left( A^F S(p_2) - \gamma_{10} S(p_7) - \gamma_9 S(p_5) \right) - \frac{2 p_8}{\tau_4} - \frac{p_7}{\tau_4^2}
\]

**\( H, \tau \)** Kernels: pre-synaptic inputs \( \rightarrow \) post-synaptic membrane potentials

[ **\( H \):** max PSP; **\( \tau \):** rate constant ]

**\( S \)** Sigmoid operator: PSP \( \rightarrow \) firing rate

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David et al., 2006; Pinotsis et al., 2012
Canonical Microcircuit Model (‘CMC’)

\[ y = Lp_3 \]

\[ \dot{p}_3 = p_5 \]

\[ \dot{p}_5 = \frac{H_5}{\tau_3} (-A^S(p_7) - \gamma_5 S(p_1) + \gamma_1 S(p_1) - \gamma_6 S(p_1)) - \frac{2p_5}{\tau_3} \frac{p_3}{\tau_3} \]

\[ \dot{p}_4 = \frac{H_4}{\tau_2} ((-A^S(p_7) + \gamma_3 S(p_1) - \gamma_7 S(p_1)) \frac{2p_4}{\tau_2} \frac{p_1}{\tau_2} \]

\[ \dot{p}_6 = \frac{H_3}{\tau_3} (-A^S(p_7) - \gamma_5 S(p_1) + \gamma_1 S(p_1) - \gamma_6 S(p_1)) - \frac{2p_6}{\tau_3} \frac{p_3}{\tau_3} \]

\[ \dot{p}_1 = p_2 \]

\[ \dot{p}_2 = \frac{H_1}{\tau_1} ((A^F S(p_3) - \gamma_5 S(p_2) - \gamma_7 S(p_2) - \gamma_5 S(p_2)) \sum \frac{2p_2}{\tau_1} \frac{p_1}{\tau_1} \]

\[ \dot{p}_7 = p_8 \]

\[ \dot{p}_8 = \frac{H_4}{\tau_4} (A^F S(p_3) - \gamma_4 S(p_7) - \gamma_6 S(p_7) - \gamma_4 S(p_7)) \frac{2p_8}{\tau_4} \frac{p_7}{\tau_4} \]

\[ S(p_7) \]

\[ U \]

Pinotsis et al., 2012
The DCM analysis pathway

Collect data

Build model(s)

‘Hardwired’ model features

Fit your model parameters to the data

Pick the best model

Make an inference (conclusion)
Input

Factor 1

neuronal model

<table>
<thead>
<tr>
<th>forward</th>
<th>back</th>
<th>Modulatory</th>
<th>input</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

electromagnetic model

source names and locations: prior mean (mm)

- right A1: 46 - 14, 8
- left A1: -42 - 22, 7
- right STG: 56 - 46, 18
- left STG: -60 - 48, 20
- right IPS: 34 - 86, 46

onsets (ms)
- 20

duration (sd)
- 16
The DCM analysis pathway

1. Collect data
2. Build model(s)
3. Fit your model parameters to the data
4. Fixed parameters
5. Pick the best model
6. Make an inference (conclusion)
Fitting DCMs to data
Fitting DCMs to data
Fitting DCMs to data
Fitting DCMs to data

1. Check your data

H. Brown
Fitting DCMs to data

1. Check your data

2. Check your sources
Fitting DCMs to data

1. Check your data
2. Check your sources
3. Check your model
Fitting DCMs to data

1. Check your data
2. Check your sources
3. Check your model
4. Re-run model fitting
The DCM analysis pathway

1. Collect data
2. Build model(s)
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4. Pick the best model
5. Make an inference (conclusion)
The DCM analysis pathway

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Does network XYZ explain my data better than network XY?

Which XYZ connectivity structure best explains my data?

Are X & Y linked in a bottom-up, top-down or recurrent fashion?

Is my effect driven by extrinsic or intrinsic connections?

Which connections/populations are affected by contextual factors?
Example #1: Architecture of MMN

(a) Schematic representation of the experimental design. 

(b) Topographical distribution of the MMN. 

(c) Grand average waveforms for the oddball paradigm (open circles) and the control paradigm (open squares).
Example #2: Role of feedback connections

Garrido et al., 2007
Example #3: Group differences

A. DCM models

B. Family inference - number of regions

C. Family inference - type of connections

D. Population-level best model

Fronto-temporal backward connectivity

Controls | MCS | VS

* ns
Example #4: Factorial design & CMC

FORWARD PREDICTION ERROR

BACKWARD PREDICTIONS

Bastos et al., *Neuron* 2012

Attention

cf. Feldman & Friston, 2010

Auksztulewicz & Friston, 2015
2x2 design: 
**Attended vs unattended**
**Standard vs deviant**
(Only trials with 2 tones)

N=20
Flexible factorial design
Thresholded at p<.005 peak-level
Corrected at a cluster-level pFWE<.05

Auksztulewicz & Friston, 2015
Flexible factorial design

Thresholded at \( p < 0.005 \) peak-level
Corrected at a cluster-level \( p_{FWE} < 0.05 \)

Contrast estimate

A1E1  A1E0  A0E1  A0E0

Auksztulewicz & Friston, 2015
Connectivity structure

Extrinsic modulation

Intrinsic modulation
Example #5: Same paradigm, different data

Phillips et al., 2016
Example #5: Same paradigm, different data

Phillips et al., 2016
Example #6: Hierarchical modelling

Evoked response potentials at Fz

Rosch et al., 2017
Example #6: Hierarchical modelling

A First level model space: Effects of repetition

B Second level model space: Effects of ketamine

Rosch et al., 2017
Motivate your assumptions!

- Useless data → Perfect model → Useless results
- Perfect data → Useless model → Useless results
Thank you!

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