Introduction to Dynamic Causal Modelling (DCM)

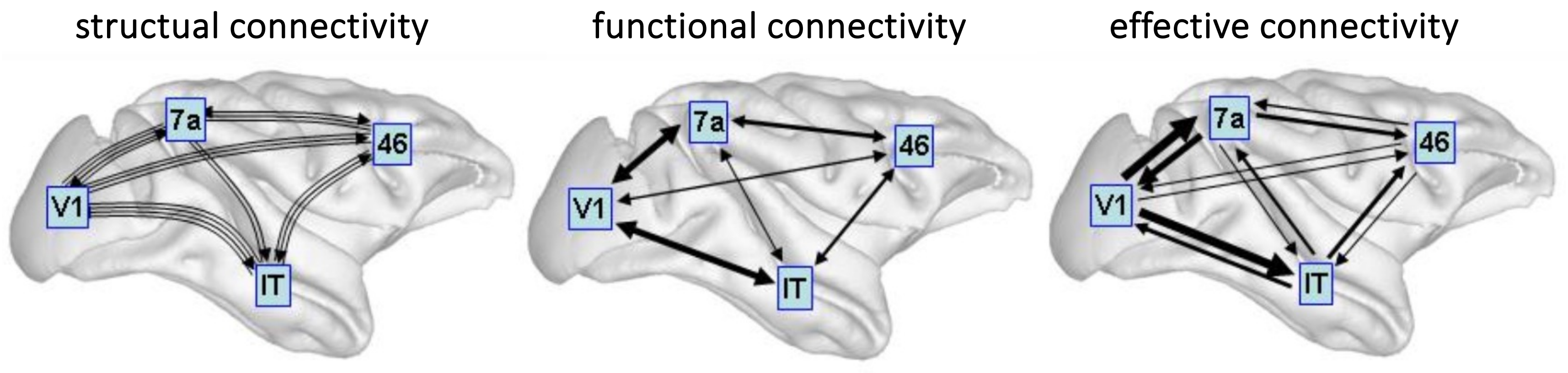
Dr. Edda Bilek

Central Institute for Mental Health
Heidelberg University
Germany

Learning objectives

- What is dynamic causal modelling (DCM)?
- How do we model task related fMRI data (forward model)?
- How are parameters estimated and model evidence inferred
- How is a subject DCM specified in SPM? *Demo & practical sessions!*

Structural, functional & effective connectivity



Sporns, 2007, Scholarpedia

Structural connectivity

- Presence of axonal connections / white matter tracks (e.g., DWI)

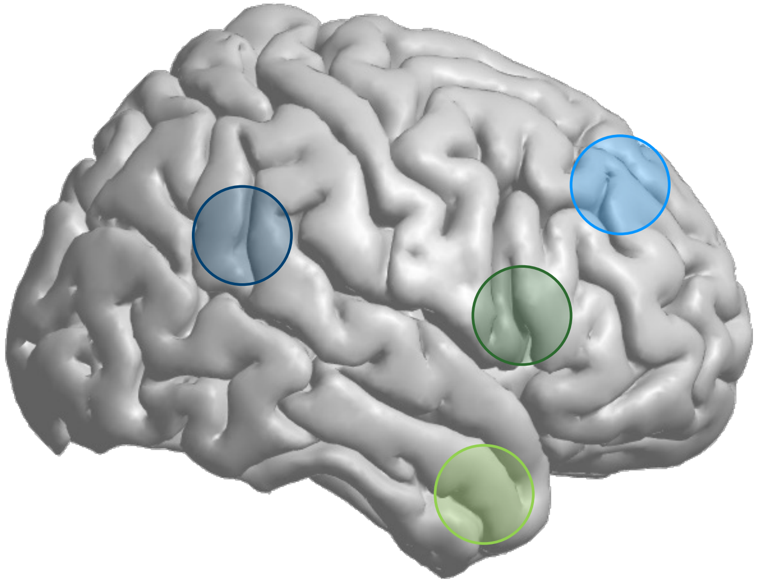
Functional connectivity

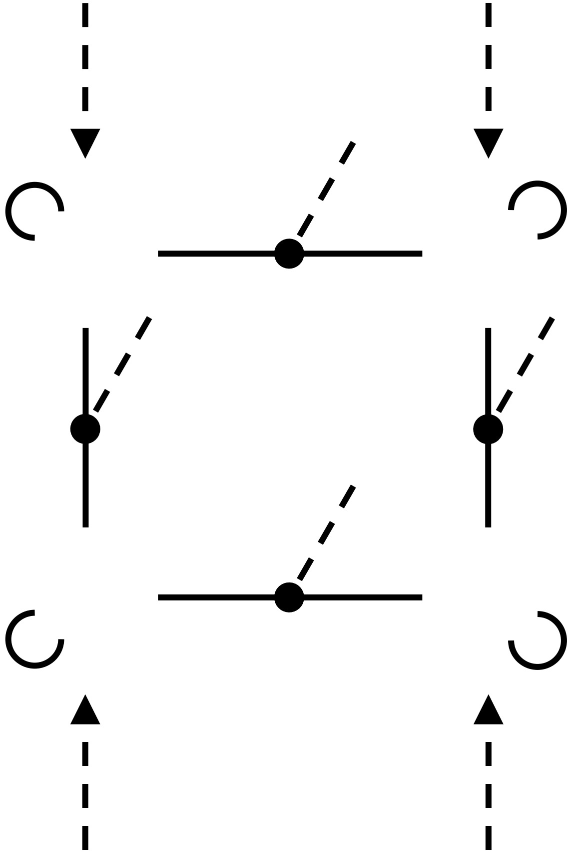
- Statistical dependencies between regional time series (e.g., ICA)

Effective connectivity

- Causal (directed) influences between neuronal populations (e.g., DCM; based on explicit network models)

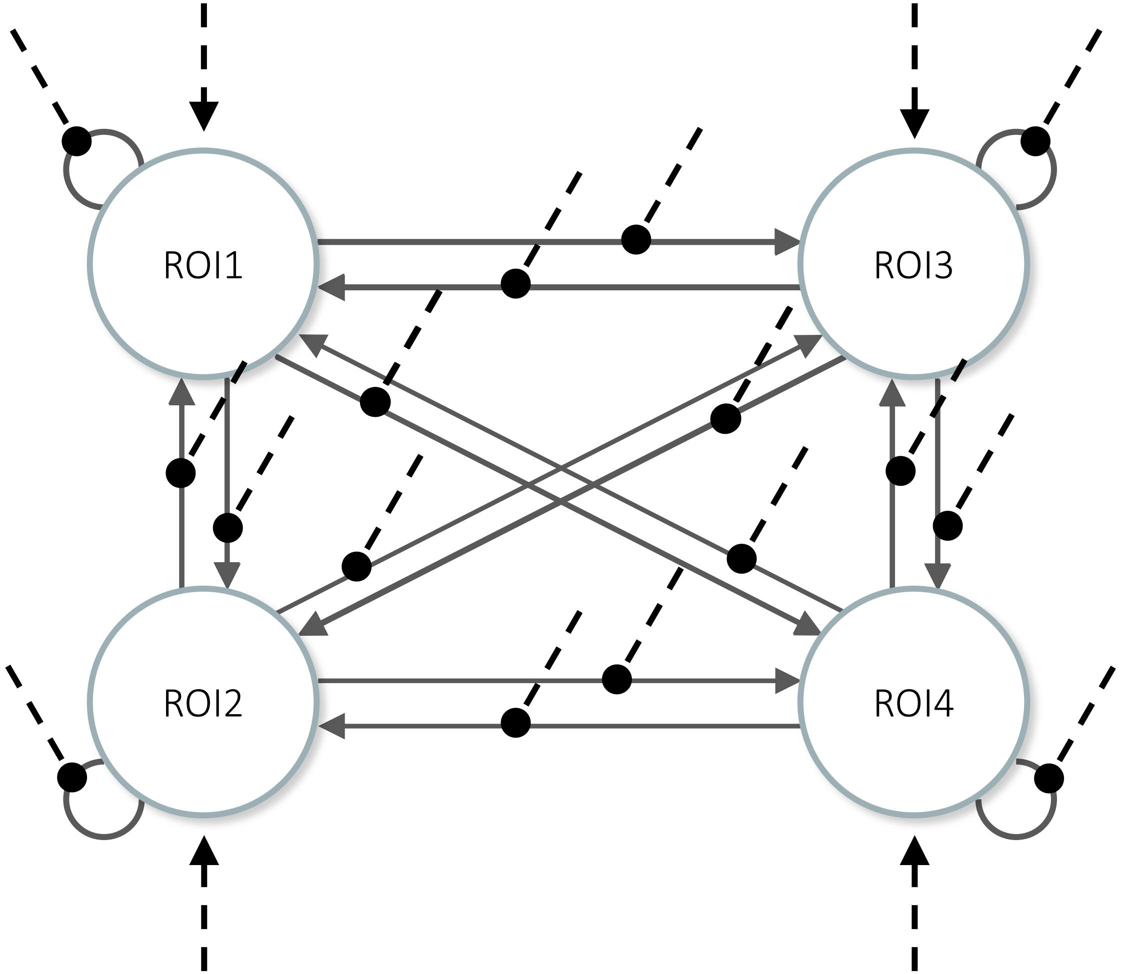
Neural model basics



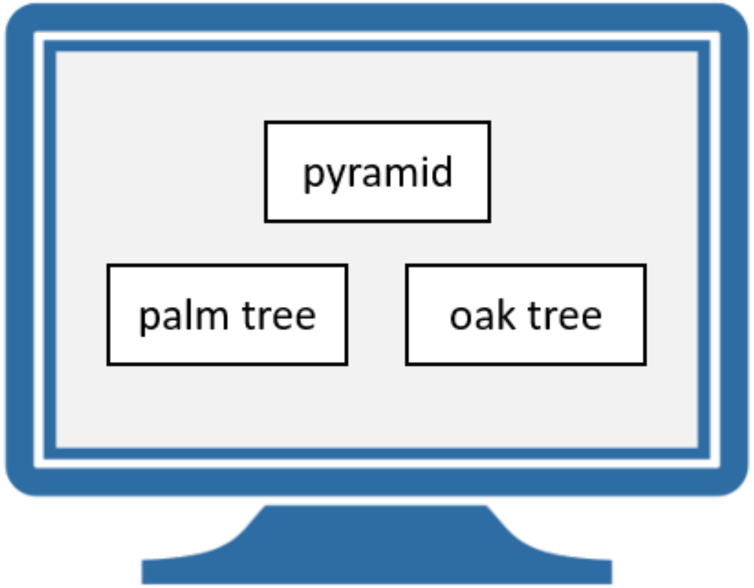


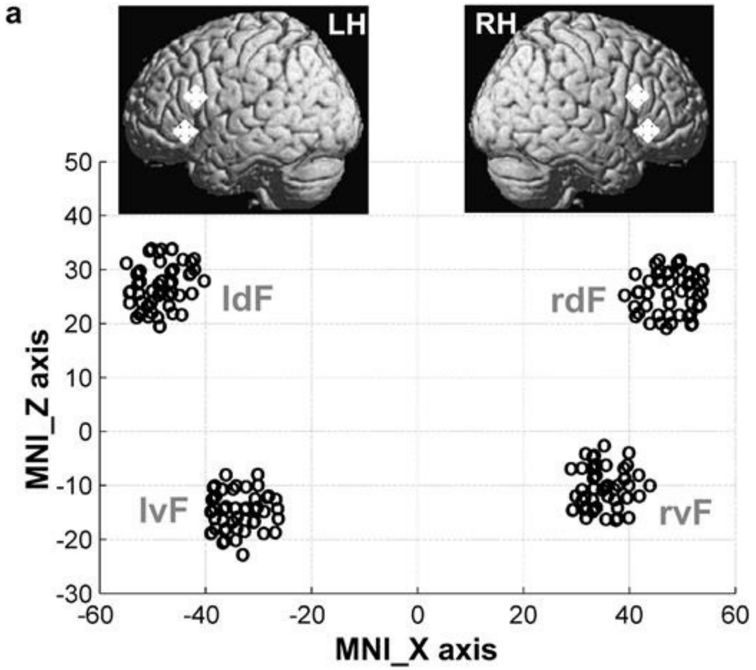
Neural model basics

- Which regions?
  - Z
- Which connections in network?
  - A
- U = all input (driving, modulating)
- Where does driving input enter the network?
  - C
- Which connections are modulated e.g. by conditions
  - B



Task (for demo and practicals)





Subject-level GLM (analysis of brain *activity*)

- Factor 1: Semantic (match meaning of the stimulus) vs. perceptual (match similar looking stimulus)
- Factor 2: simulus pictures vs. words

Task (for demo and practicals)

Subject-level factors

- Factor 1: Semantic (match meaning of the stimulus) vs. perceptual (match similar looking stimulus)
- Factor 2: simulus pictures vs. words

Group-level hypothesis

- Hypothesis: In semantic, some people use left/right hemisphere more. What is the underlying connectivity that causes lateralization?

Group-level factor

- Laterlization index (one value for each subject)

https://www.fil.ion.ucl.ac.uk/spm/docs/tutorials/dcm/dcm_fmri_first_level/
Seghier et al. (2011)

Task (for demo and practicals)

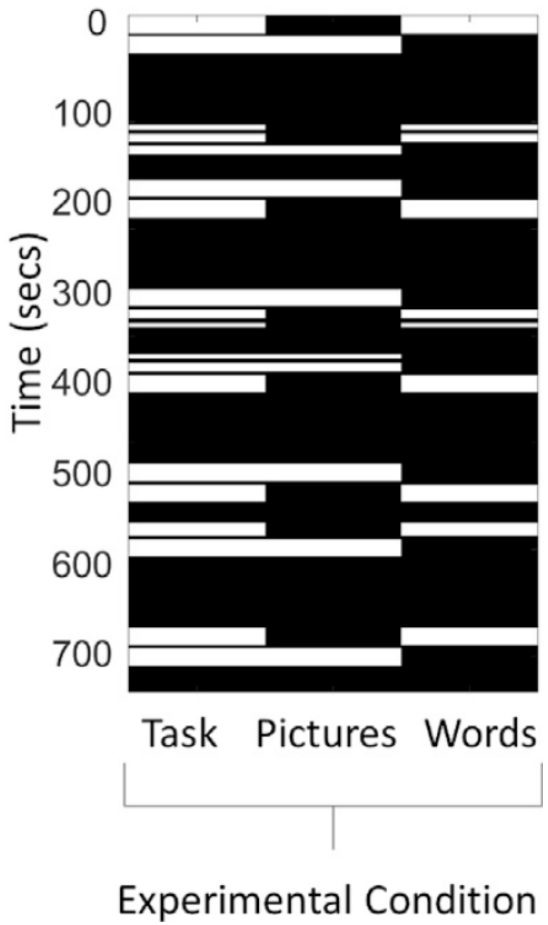
Driving (external) input

- Semantic: pictures and words („task“)

Modulators

- Task condition „pictures“
- Task condition „words“

- Group-level (lateralization index) -> Group-level analysis (PEB)



https://www.fil.ion.ucl.ac.uk/spm/docs/tutorials/dcm/dcm_fmri_first_level/
Seghier et al. (2011)

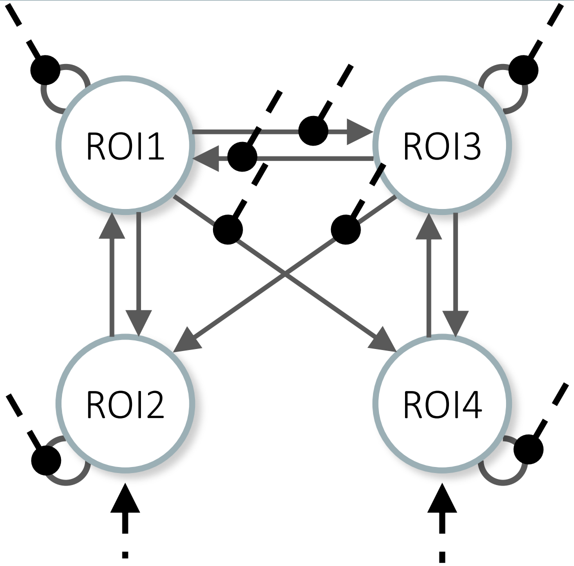
Neural model specification

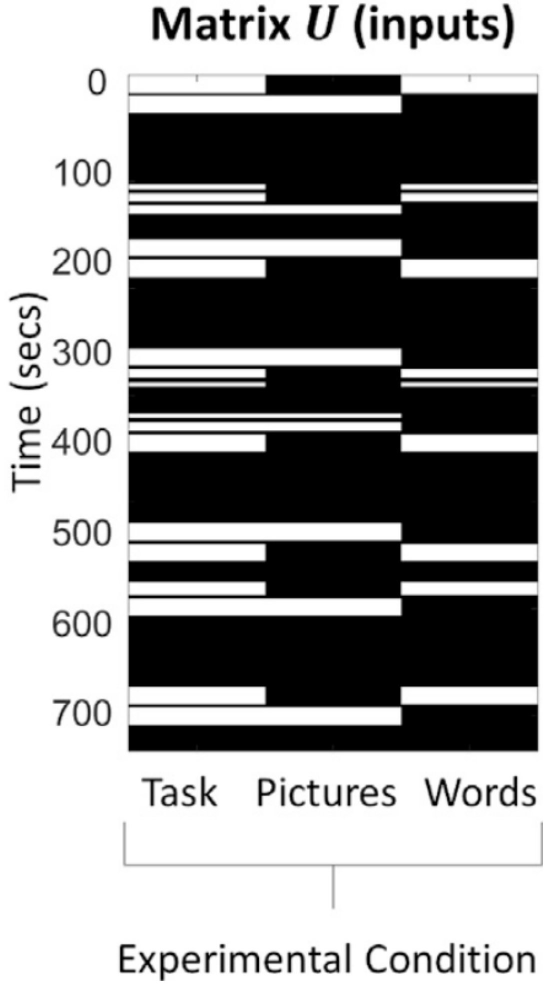
- U = task, conditions, covariates (subject level)
- Z = ROI1, ROI2, ROI3, ROI4

- $A = \text{to} \begin{array}{c} \\ R1 \\ R2 \\ R3 \\ R4 \end{array} \begin{array}{c} \text{from} \\ \begin{array}{cccc} R1 & R2 & R3 & R4 \end{array} \\ \begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 1 \end{bmatrix} \end{array}$

- $B_1 = \begin{array}{c|cccc} & R1 & R2 & R3 & R4 \\ \hline R1 & 0 & 0 & 0 & 0 \\ R2 & 0 & 0 & 0 & 0 \\ R3 & 0 & 0 & 0 & 0 \\ R4 & 0 & 0 & 0 & 0 \end{array} \quad B_2 = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \quad B_3 = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix}$

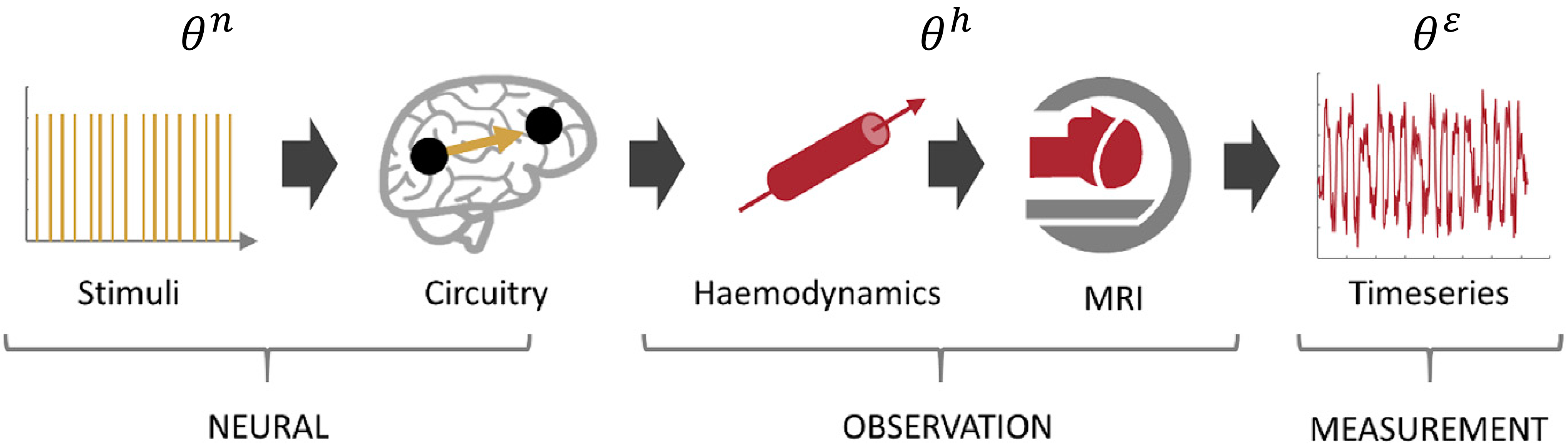
- $C = \begin{array}{c|ccc} & \text{task} & \text{pic} & \text{words} \\ \hline R1 & 0 & 0 & 0 \\ R2 & 1 & 0 & 0 \\ R3 & 0 & 0 & 0 \\ R4 & 1 & 0 & 0 \end{array}$





Zeidman et al., 2019a, Neuroimage

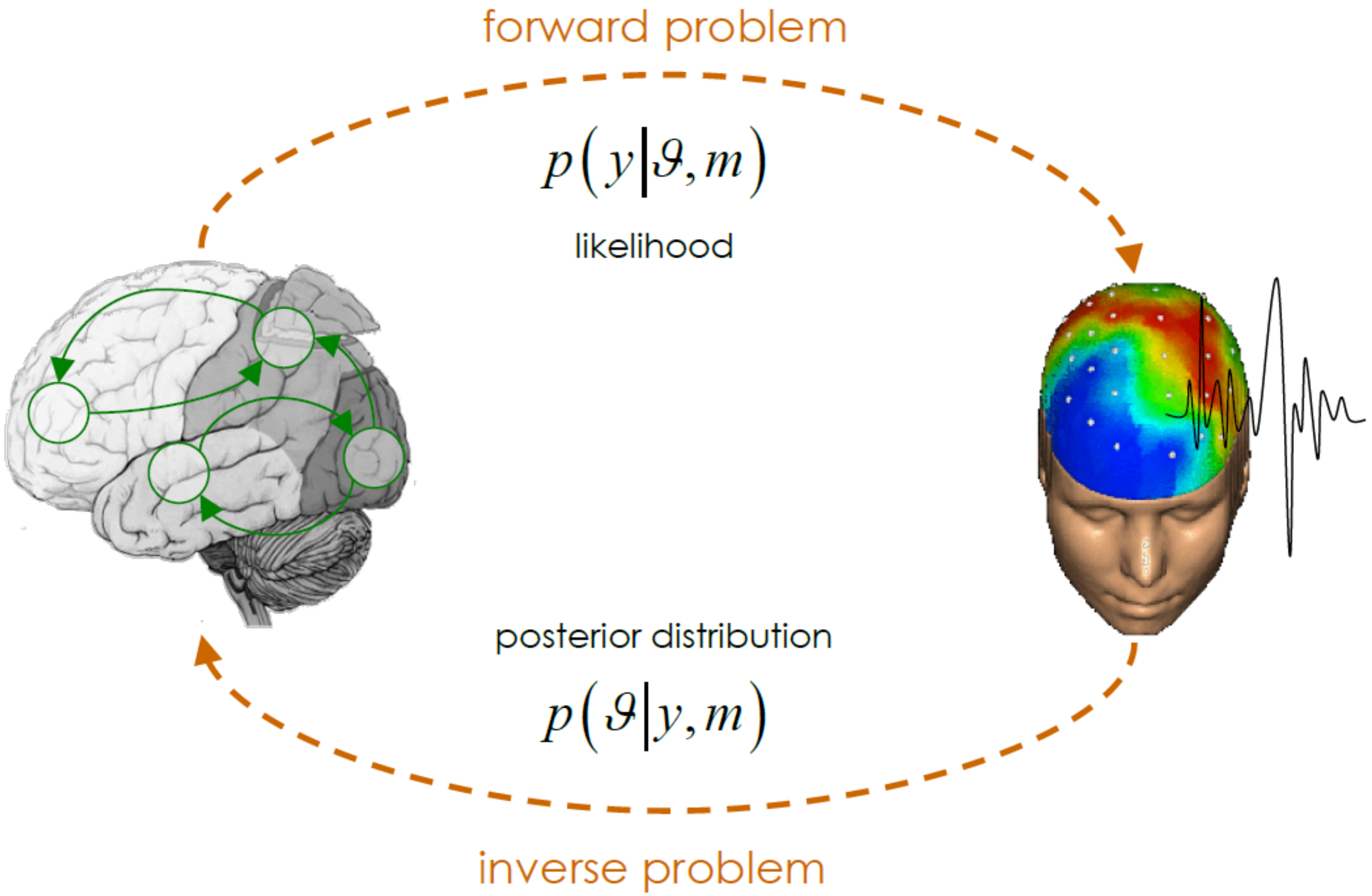
Forward model



- Different forward models depending on the data
- Enables data simulation
- Bayesian model inversion, Bayesian model comparison

Zeidman et al., 2019a, Neuroimage

Bayesian inference: forward and inverse model



Bilinear state equation

Neural and non-neural sources

- $\dot{z} = f(z, U, \theta^{(n)})$
- $y = g\left(z, \theta^{(h)}\right) + X_0\beta_0 + \varepsilon$

Neuronal state equation

- $\dot{z} = \left(A + \sum_{j=1}^{m} u_j\, B^{j}\right)z + Cu$

Bilinear state equation

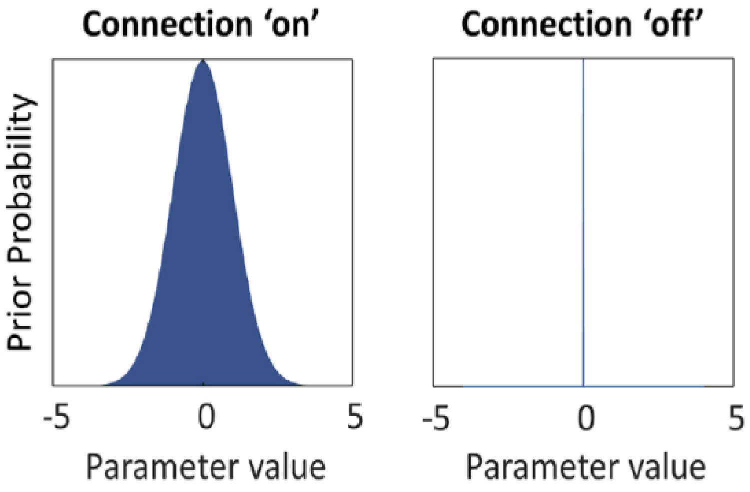
$$\overset{\text{state changes}}{\begin{bmatrix} \dot{z}_1 \\ \vdots \\ \dot{z}_n \end{bmatrix}} = \left\{ \overset{\text{connectivity}}{\begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}} + \sum_{j=1}^{m} u_j \overset{\text{modulation of connectivity}}{\begin{bmatrix} b_{11}^{j} & \cdots & b_{1n}^{j} \\ \vdots & \ddots & \vdots \\ b_{n1}^{j} & \cdots & b_{nn}^{j} \end{bmatrix}} \right\} \overset{\text{system state}}{\begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix}} + \overset{\text{direct inputs}}{\begin{bmatrix} c_{11} & \cdots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nm} \end{bmatrix}} \overset{m\text{ external inputs}}{\begin{bmatrix} u_1 \\ \vdots \\ u_m \end{bmatrix}}$$

Parameter estimation

- Which model (parameters) best explains y?
- Bayesian inference to quantify uncertainty

Priors

- Connection on: expected = 0, variance ≠ 0
- Connection off: expected = 0, variance = 0



Model inversion

- Maximize log evidence $\ln p(y|m)$
- Approximation by negative variational free energy

$$\ln p\ (y|m) \cong F = accuracy\ (y|m) - complexity(m)$$

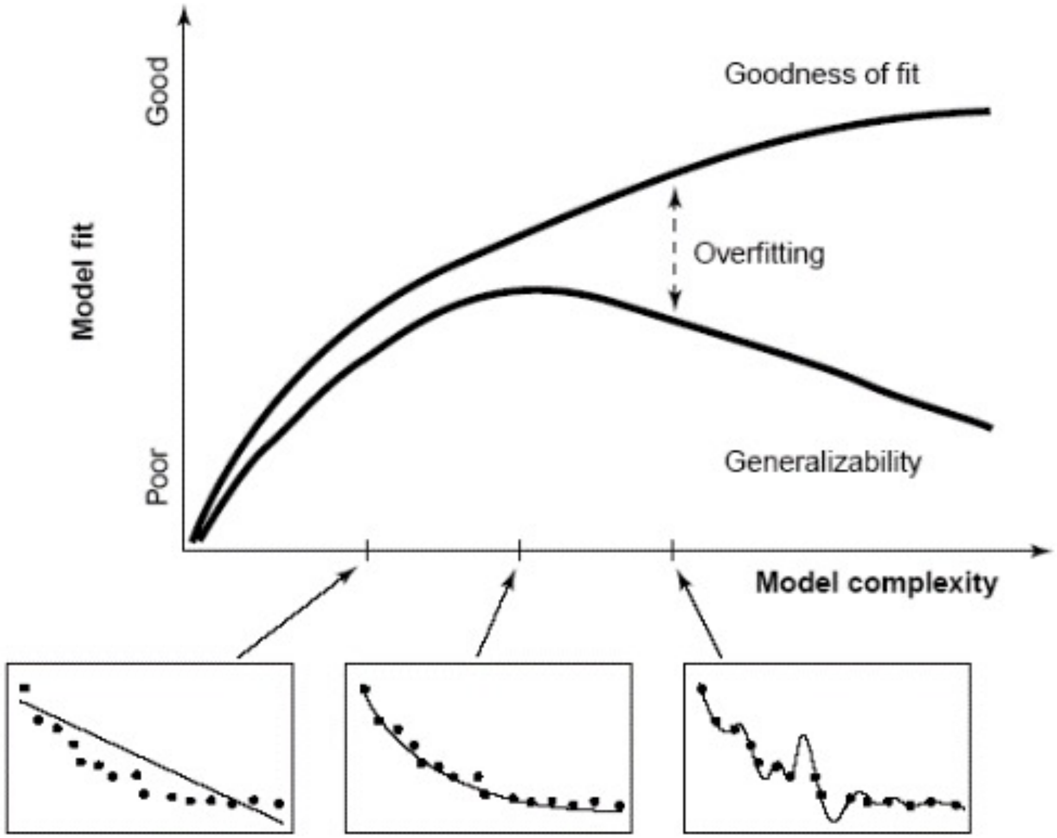
- Probability density over possible parameter values

Bayesian model comparison

Overfitting

- construct complex models with excellent or perfect fit, which are mechanistically meaningless and do not generalize

► Bayesian model selection mandatory



Bayes factor

$$\log\, p(y|m) = accuracy(m) - complexity(m)$$

$$B_{ij} = \frac{p(y|m_i)}{p(y|m_j)}$$ Bayes Factor

Pitt & Miyung (2002), TICS

Reading

Introduction and tutorials

- K.J. Friston, L. Harrison, and W.D. Penny. Dynamic Causal Modelling. NeuroImage, 19(4):1273–1302, 2003.
- Tutorial papers (Zeidman et al., 2019ab, Neuroimage)
  - DCM: doi:10.1016/j.neuroimage.2019.06.031
  - PEB: doi:10.1016/j.neuroimage.2019.06.032
- Resources: papers, step-by-step guide, data: https://github.com/pzeidman/dcm-peb-example

Other

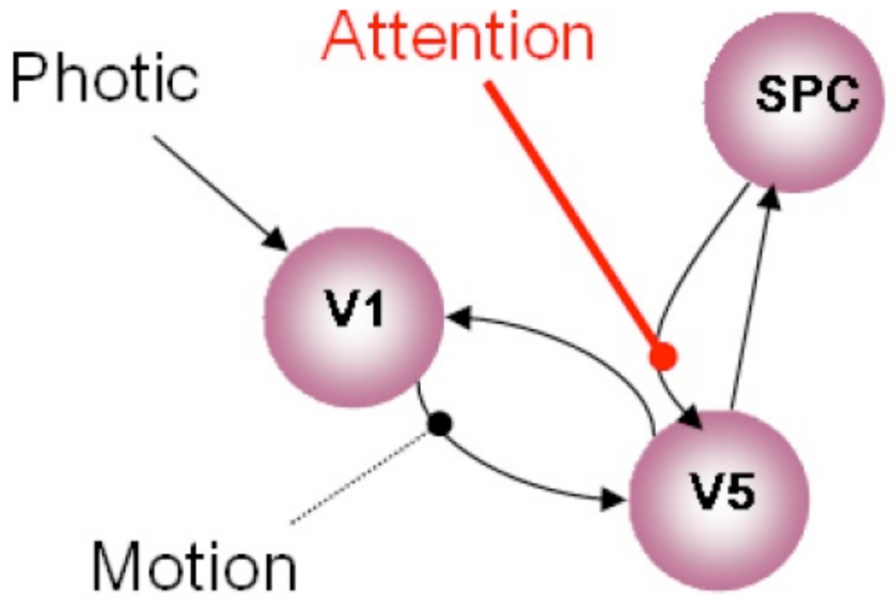
- https://en.wikibooks.org/wiki/SPM/Parametric_Empirical_Bayes_(PEB)

Thank you

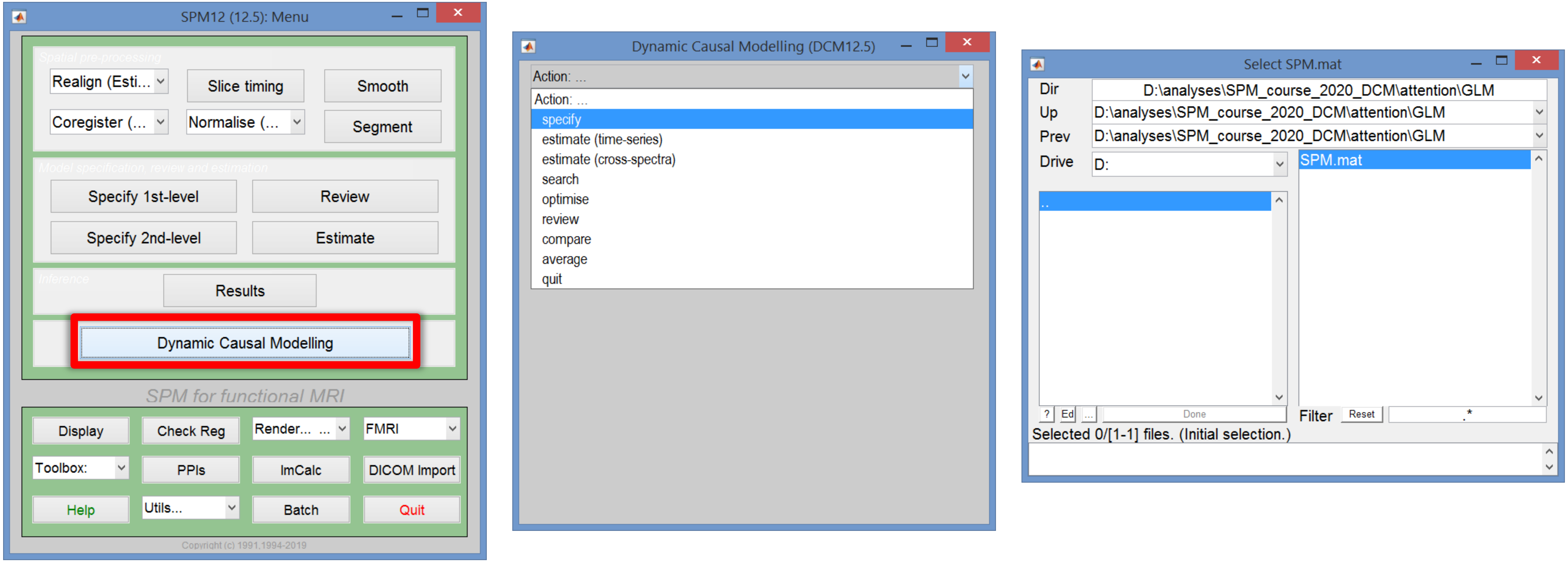
DCM functions in SPM: Practical example

DCM in SPM

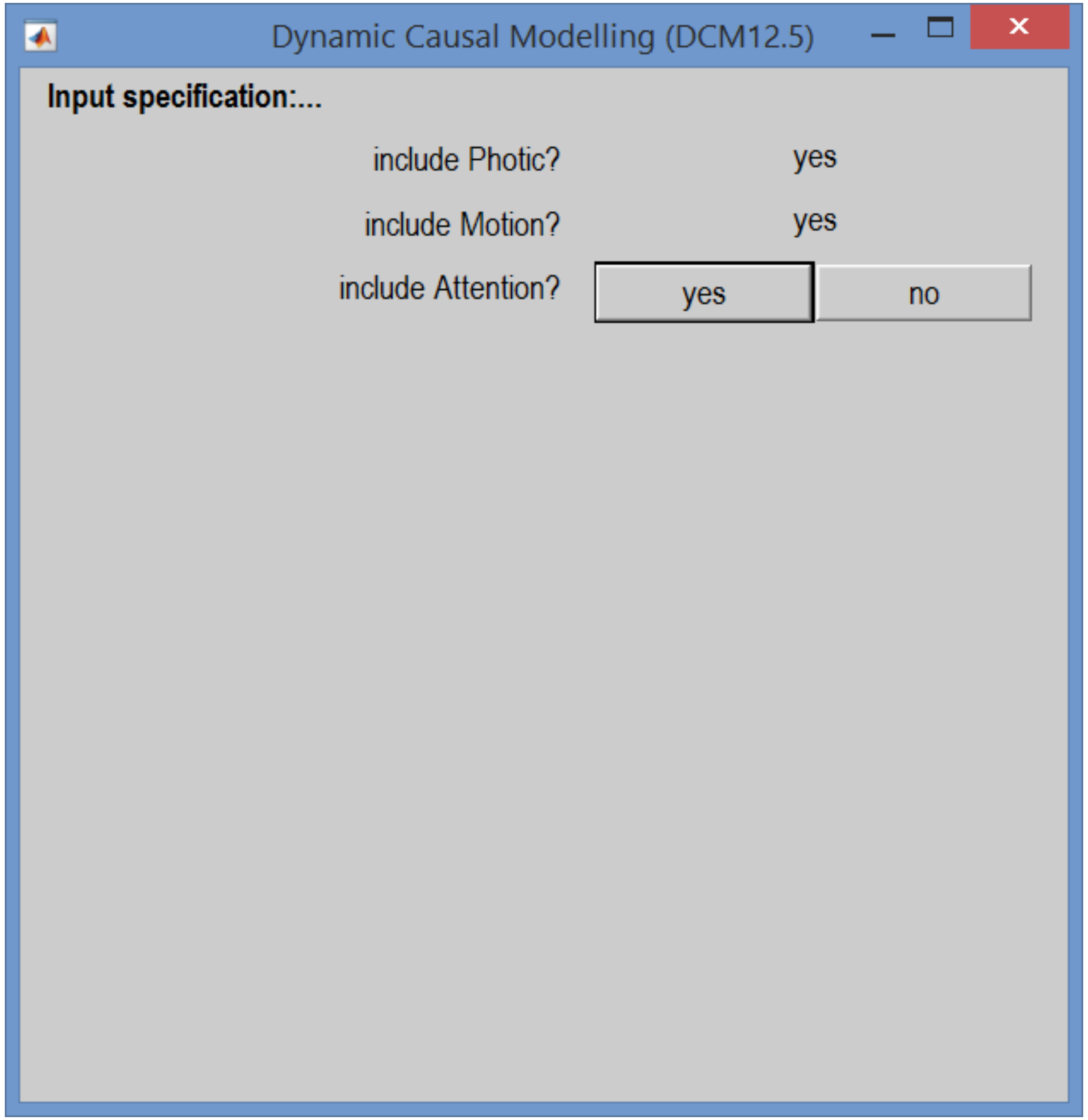
- Visually presented dots (static, moving; with/out attention)
- 3 conditions:
  - photic: all conditions with visual input
  - motion: all conditions with moving dots
  - attention: attention-to-motion condition only
- 3 ROIs:
  - V1: visual stimulation
  - V5: motion (e.g. V5)
  - V5 and superior parietal cortex (SPC)

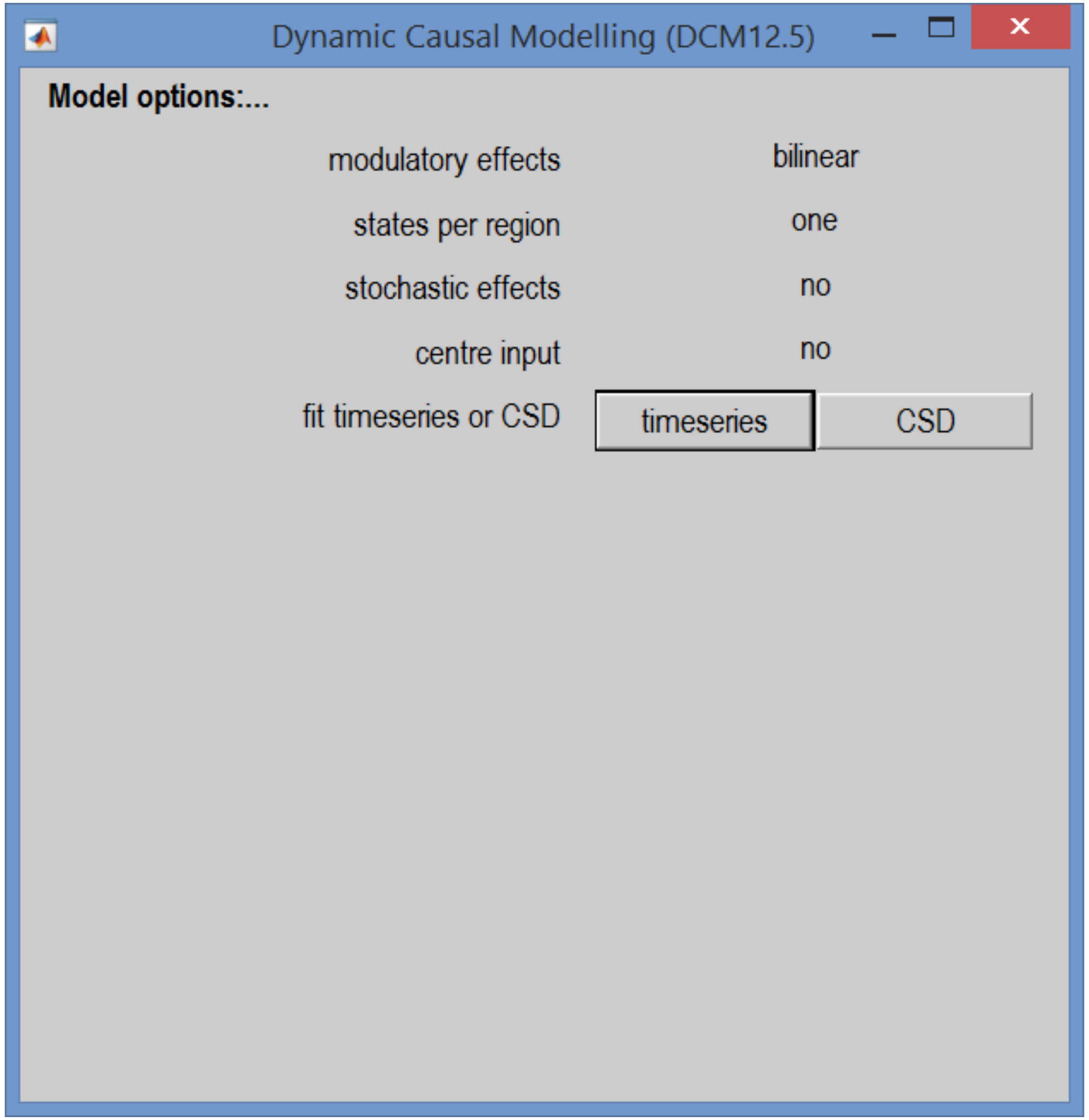


SPM: Choose SPM.mat

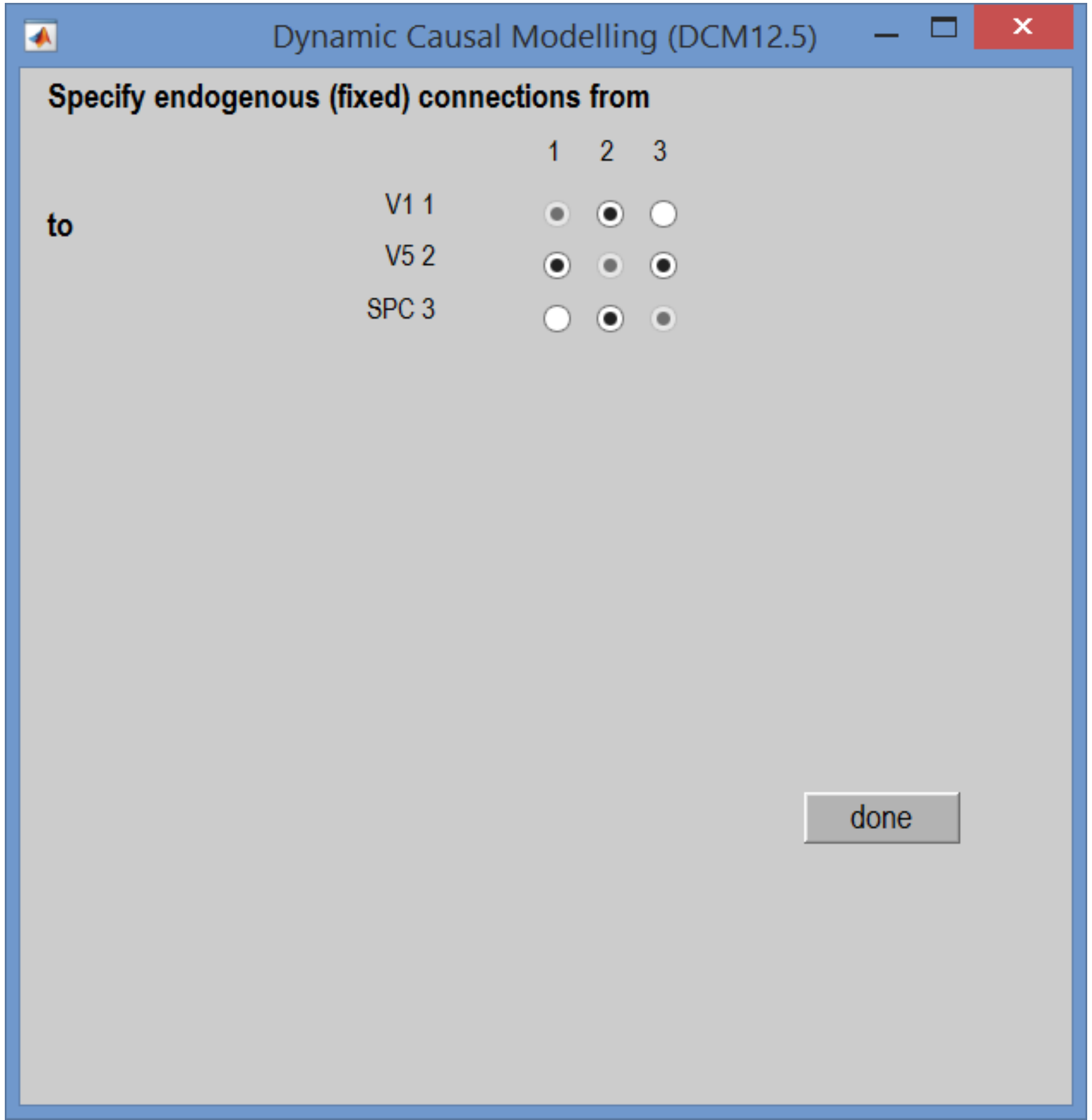


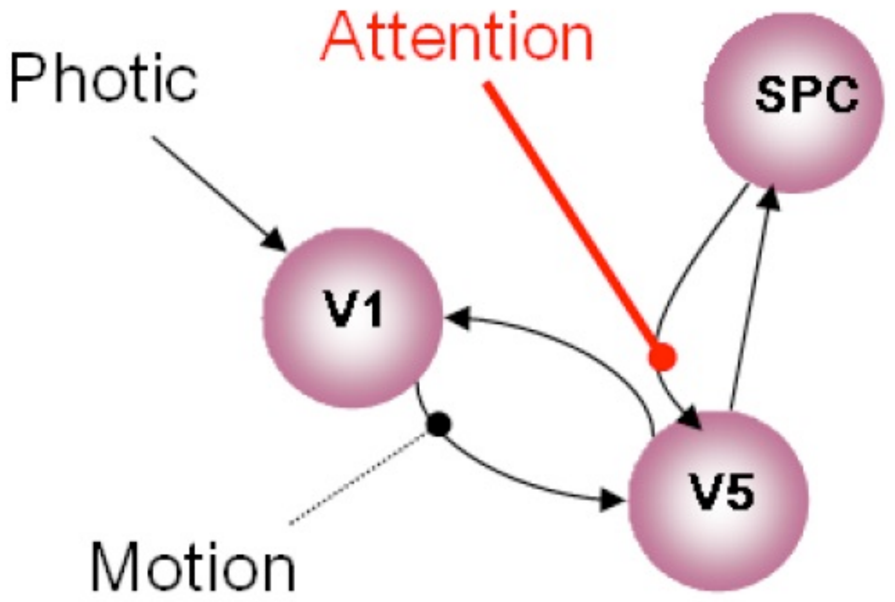
SPM: Select input from SPM.mat & options



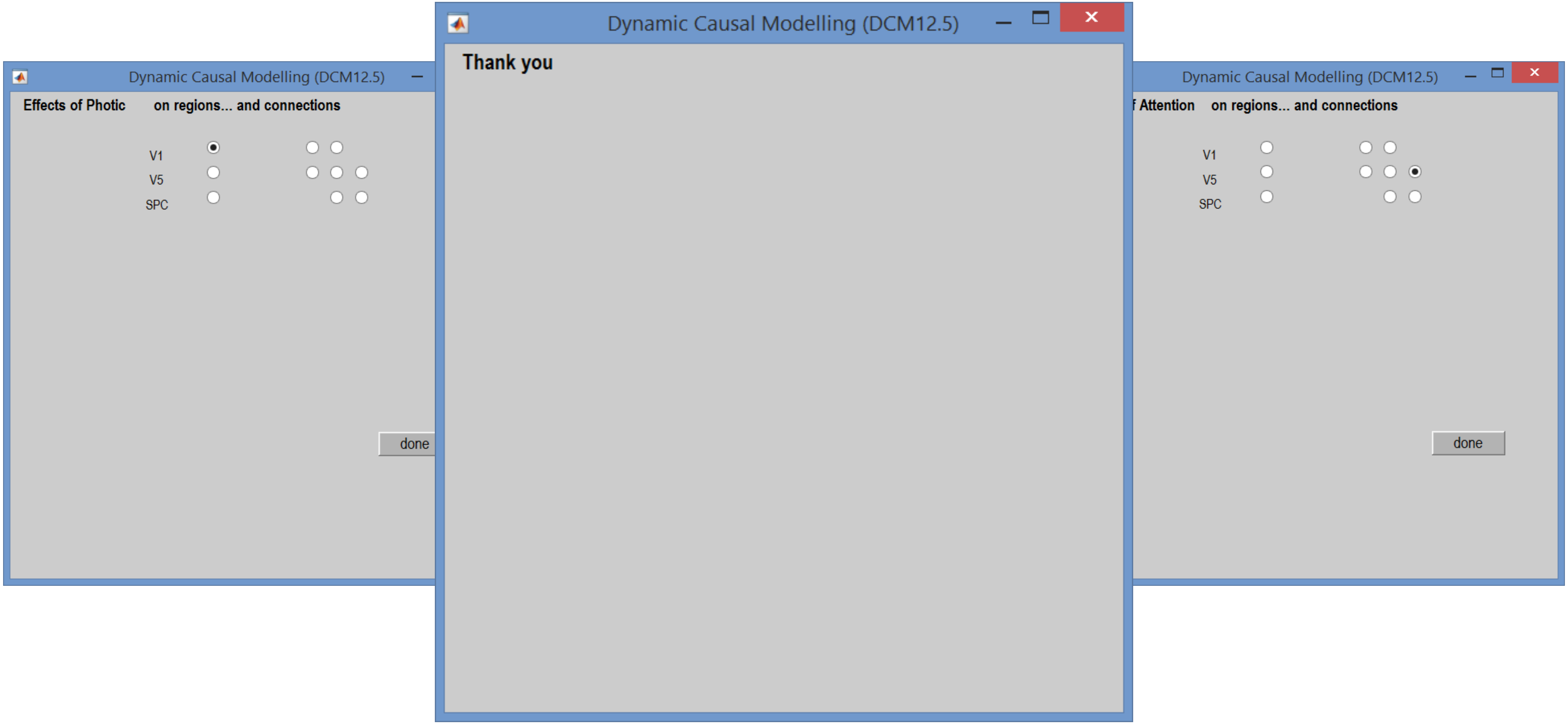


SPM: fixed connections (A-matrix)





SPM: driving input and modulators (B- and C-matrices)



SPM: DCM model

DCM

1x1 struct with 12 fields

Field	Value
xY	*1x3 struct*
n	3
v	360
Y	*1x1 struct*
U	*1x1 struct*
delays	[1.6100;1.6100;1.6100]
TE	0.0400
options	*1x1 struct*
a	[1,1,0;1,1,1;0,1,1]
b	*3x3x3 double*
c	[1,0,0;0,0,0;0,0,0]
d	*[ ]*

```
>> DCM.a

ans =

     1     1     0
     1     1     1
     0     1     1
```

```
>> DCM.b

ans(:,:,1) =

     0     0     0
     0     0     0
     0     0     0


ans(:,:,2) =

     0     0     0
     1     0     0
     0     0     0


ans(:,:,3) =

     0     0     0
     0     0     1
     0     0     0
```

```
>> DCM.c

ans =

     1     0     0
     0     0     0
     0     0     0
```

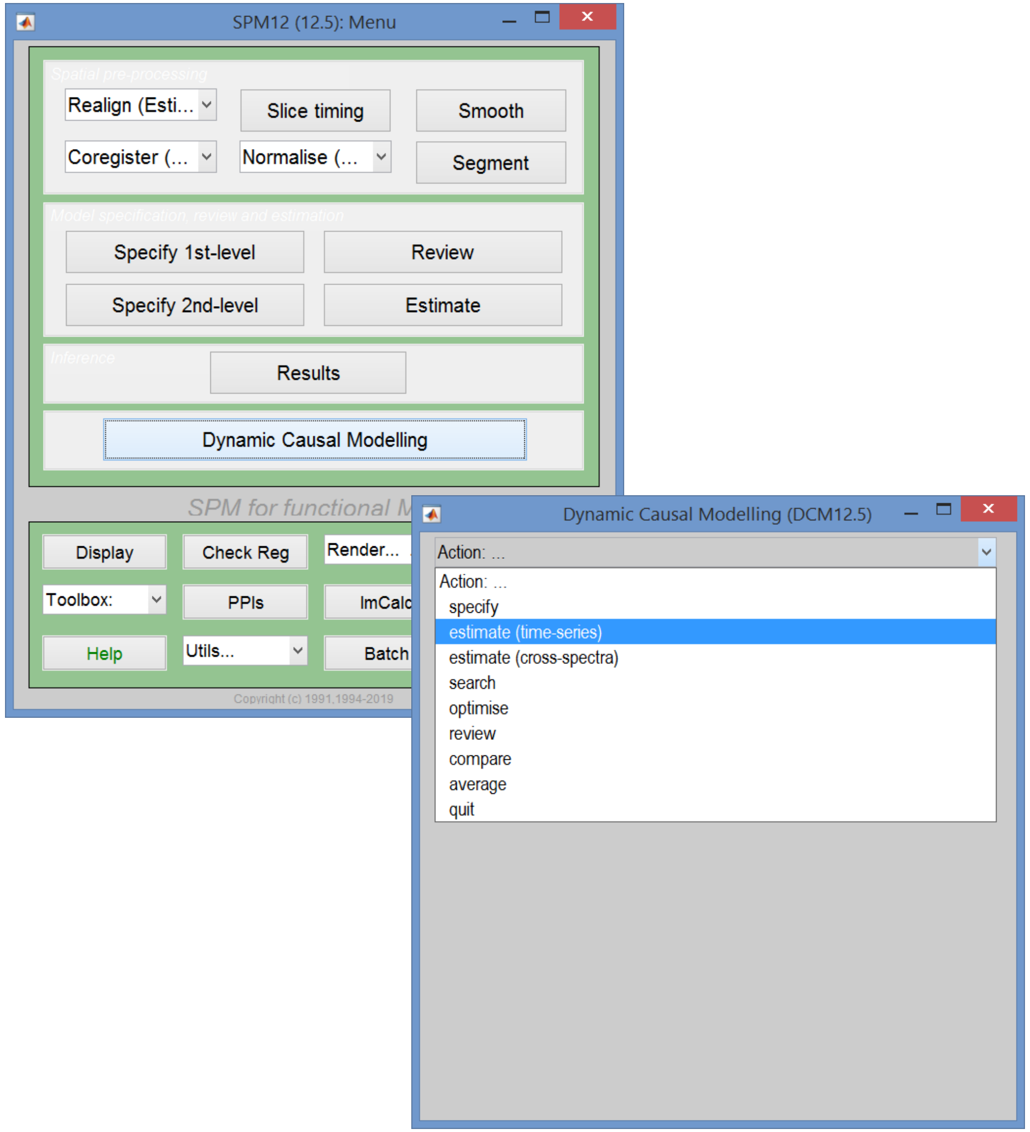
```
>> DCM.U

ans =

  struct with fields:

      dt: 0.2013
    name: {'Photic'  'Motion'  'Attention'}
       u: [5760×3 double]
```

SPM: DCM estimate



DCM

1x1 struct with 28 fields

Field	Value
xY	1x3 struct
n	3
v	360
Y	1x1 struct
U	1x1 struct
delays	[1.6100;1.6100;1.6100]
TE	0.0400
options	1x1 struct
a	[1,1,0;1,1,1;0,1,1]
b	3x3x3 double
c	[1,0,0;0,0,0;0,0,0]
d	[ ]
M	1x1 struct
Ce	[0.0845;0.0979;0.0274]
Ep	1x1 struct
Cp	50x50 sparse double
Pp	1x1 struct
Vp	1x1 struct
H1	64x3x3 double
K1	64x3x3 double
R	360x3 double
y	360x3 double
T	0
F	-3.2608e+03
ID	625.9589
AIC	385.7901
BIC	356.6443
version	1x1 struct