

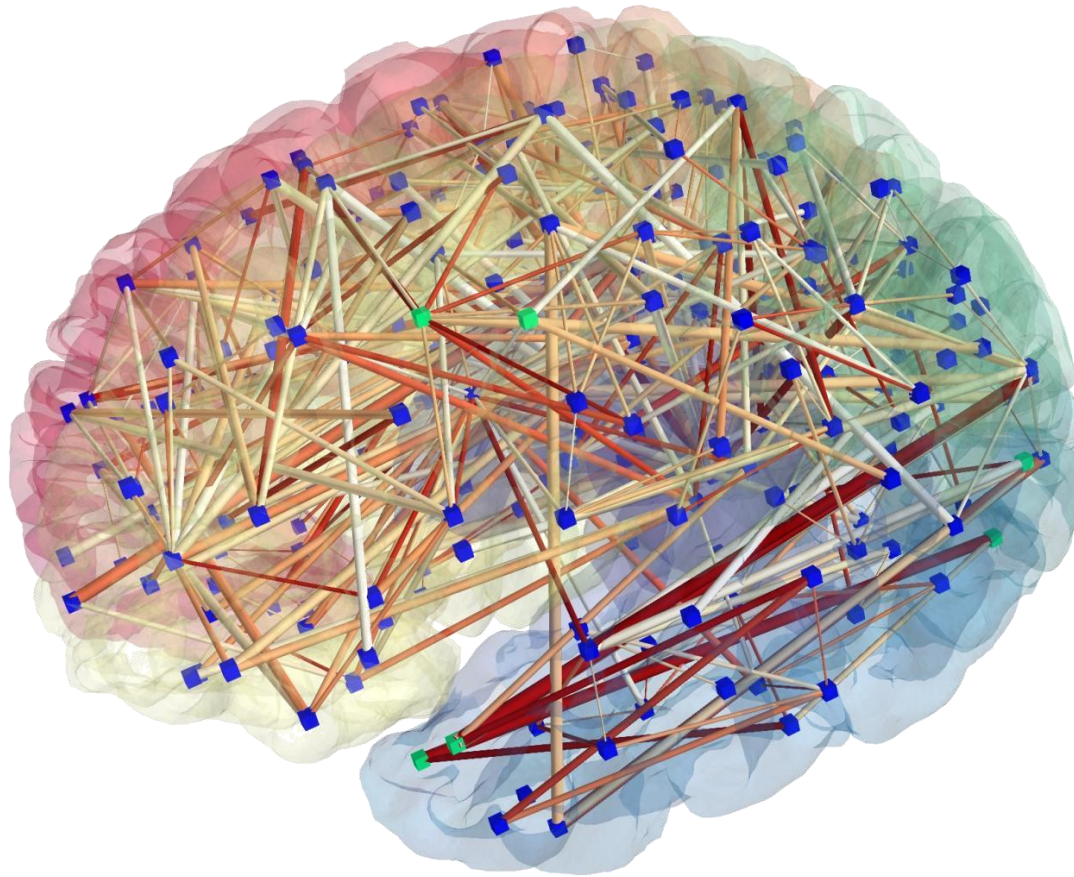
Time series analysis

Lecture 10. Causality in time series

Dr. Khamidov Obidjon

- Theory
 - **Why DCM?**
 - **What DCM does**
 - **The State Equation**
- Application
 - Planning DCM studies
 - Hypotheses
 - How to complete in SPM

Brains as Systems



Background to DCM

“DCM is used to test the specific hypothesis that motivated the experimental design. It is not an exploratory technique [...]; the results are specific to the tasks and stimuli employed during the experiment.”

[Friston et al. 2003 *Neuroimage*]

Connectivity analyses

	Whole time series	Condition specific	
Not causal	FUNCTIONAL CONNECTIVITY	PSYCHOPHYSICAL INTERACTIONS	← Classical inferential
Causal	STRUCTURAL EQUATION MODELLING	DYNAMIC CAUSAL MODELLING	← P(Data) Bayesian P(Model)

Model evidence = Model fit – model complexity

Key features of DCM

DCM is a generative model

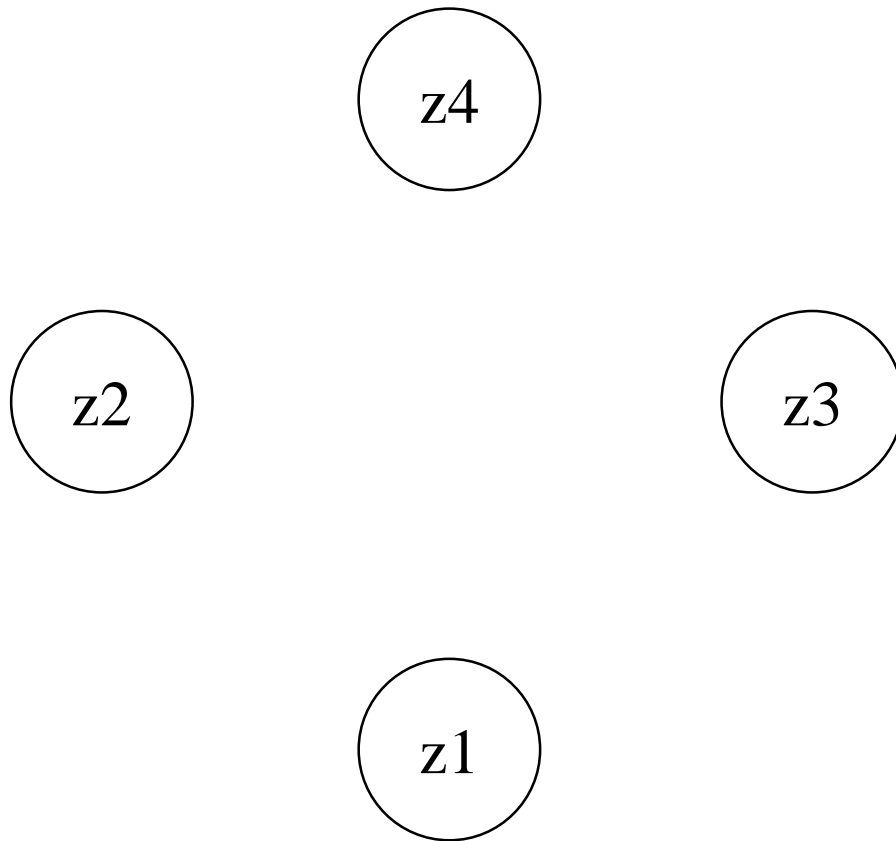
= a quantitative / mechanistic description of how observed data are generated.

- **1- Dynamic**
- **2- Causal**
- **3- Neuro-physiologically motivated**
- **4- Operate at hidden neuronal interactions**
- **5- Bayesian in all aspects**
- **6- Hypothesis-driven**
- **7- Inference at multiple levels.**

How do we do DCM?

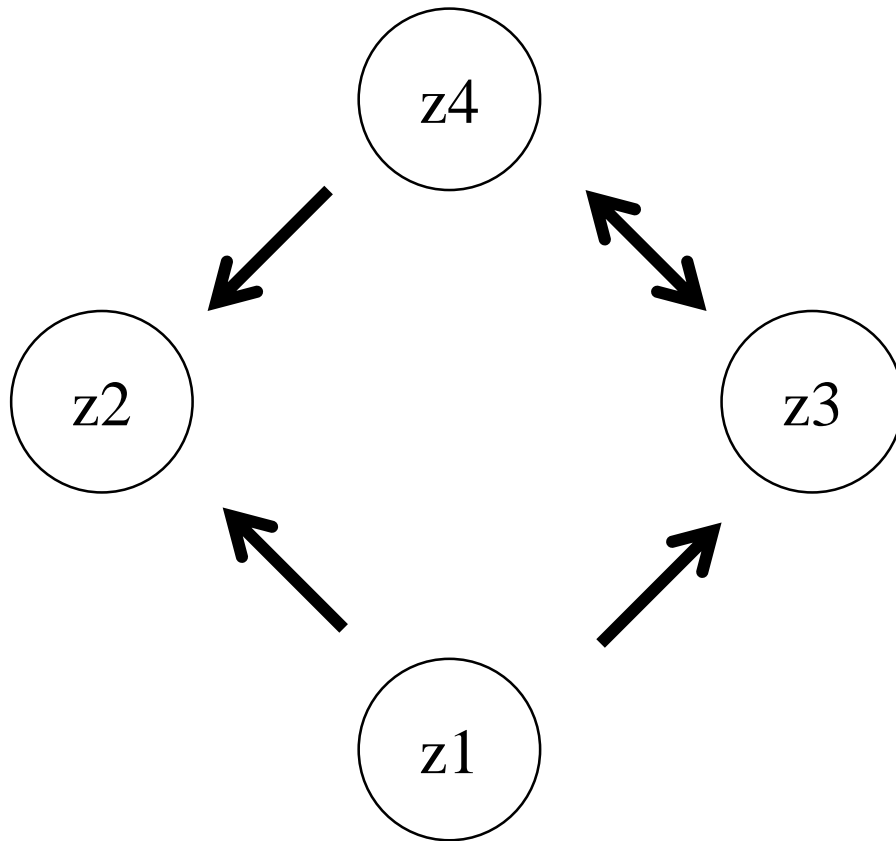
1. Create a neural model to represent our hypothesis
2. Convolve it with a haemodynamic model to predict real signal from the scanner
3. Compare models in terms of model fit and complexity

The Neural Model for the state equation



Recipe
Z - Regions

The Neural Model

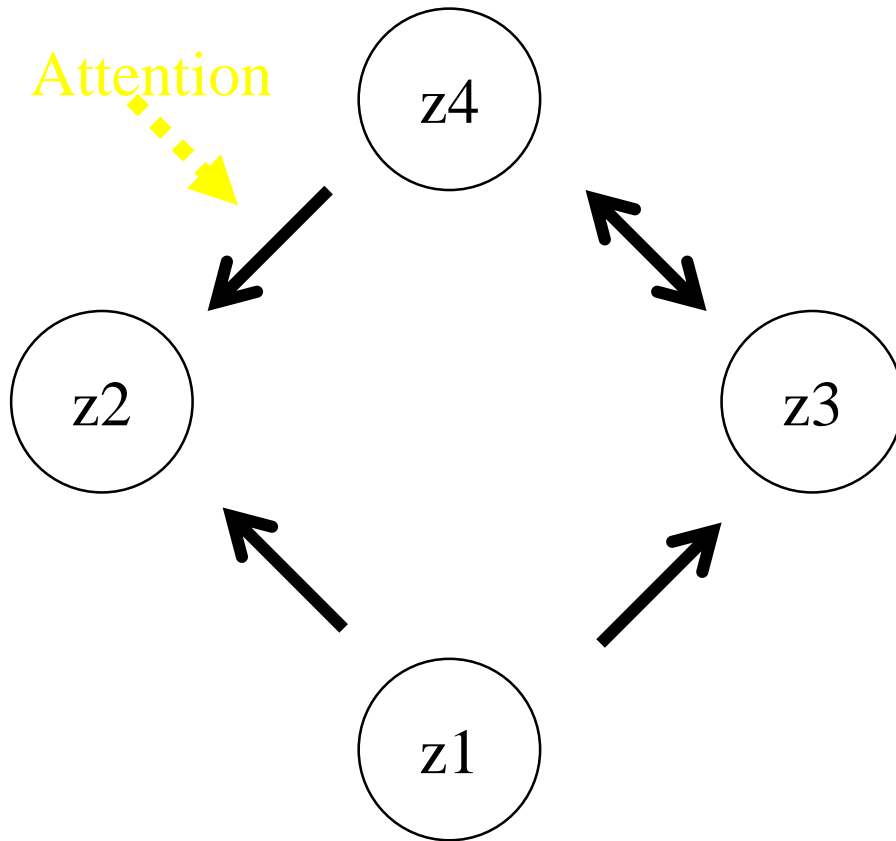


Recipe

Z - Regions

A - Average
connections

The Neural Model



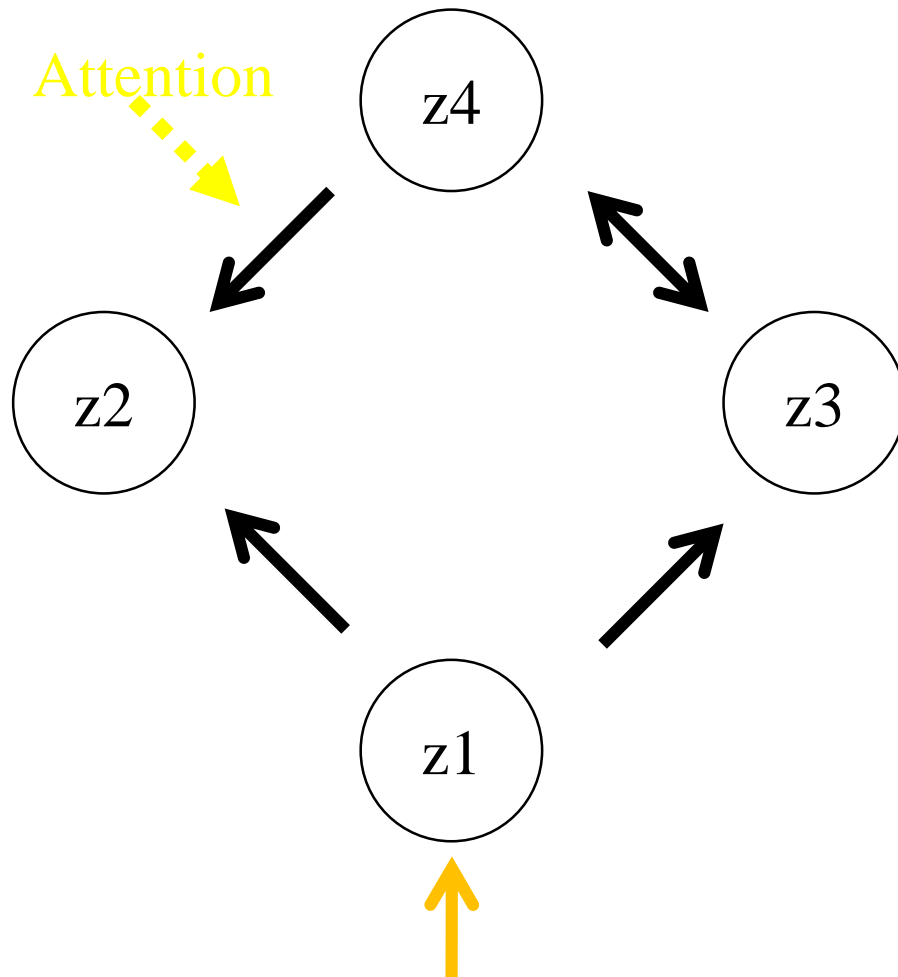
Recipe

Z - Regions

A - Average
connections

B - Modulatory
Inputs

The Neural Model



Recipe

Z - Regions

A - Average
Connections

B - Modulatory
Inputs

C - External
Inputs

$$\dot{z} = \left(\underbrace{A}_{\text{green}} + \sum_{j=1}^m u_j \underbrace{B^j}_{\text{red}} \right) z + \underbrace{Cu}_{\text{blue}}$$

“C”, the direct or driving effects:

- extrinsic influences of inputs on neuronal activity.

“A”, the endogenous coupling or the latent connectivity:

- fixed or intrinsic effective connectivity;
- first order connectivity among the regions in the absence of input;
- average/baseline connectivity in the system (DCM10/DCM8).

“B”, the bilinear term, modulatory effects, or the induced connectivity:

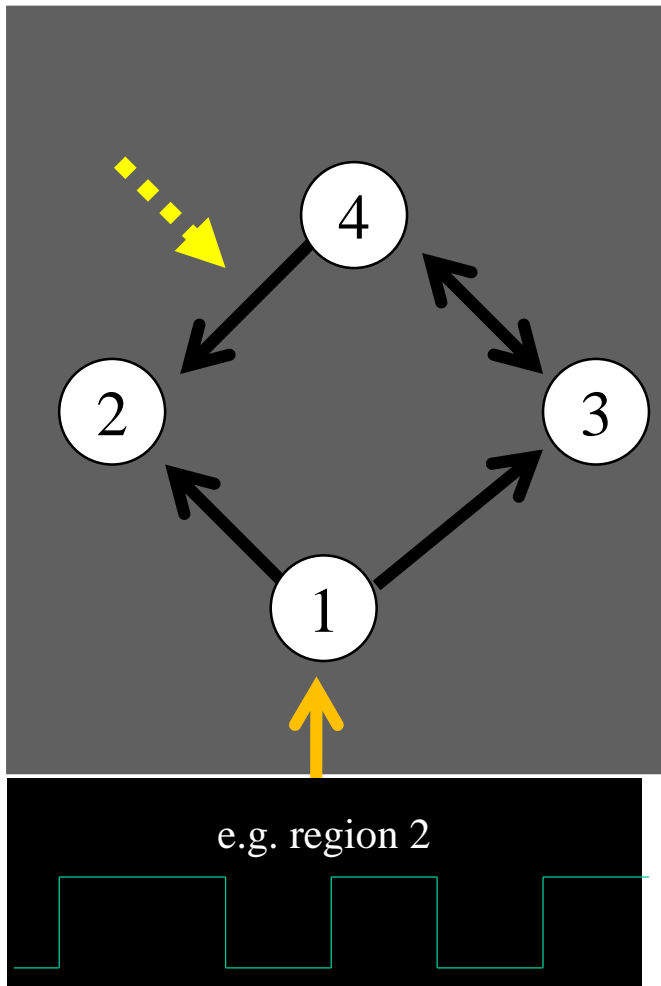
- context-dependent change in connectivity;
- eq. a second-order interaction between the input and activity in a source region when causing a response in a target region.

[Units]: rates, [Hz];

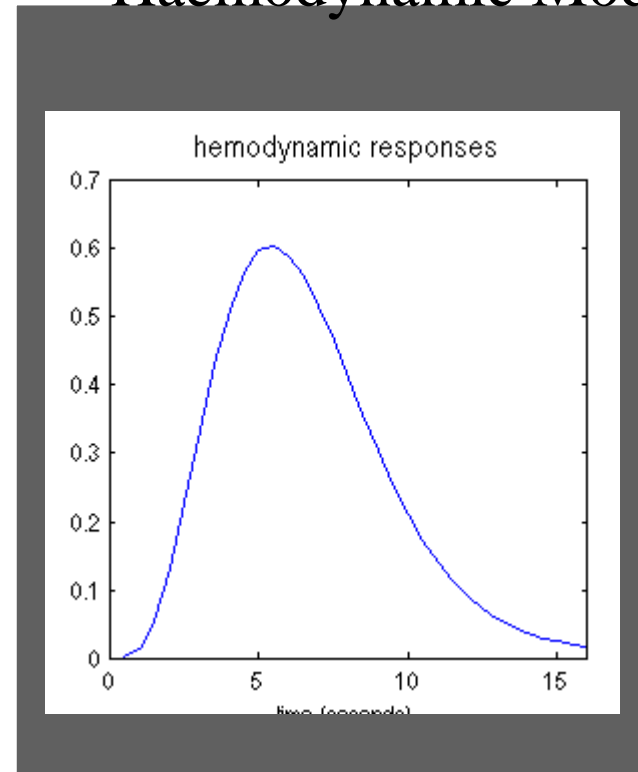
Strong connection = an effect that is influenced quickly or with a small time constant.

DCM Overview

Neural Model



Haemodynamic Model

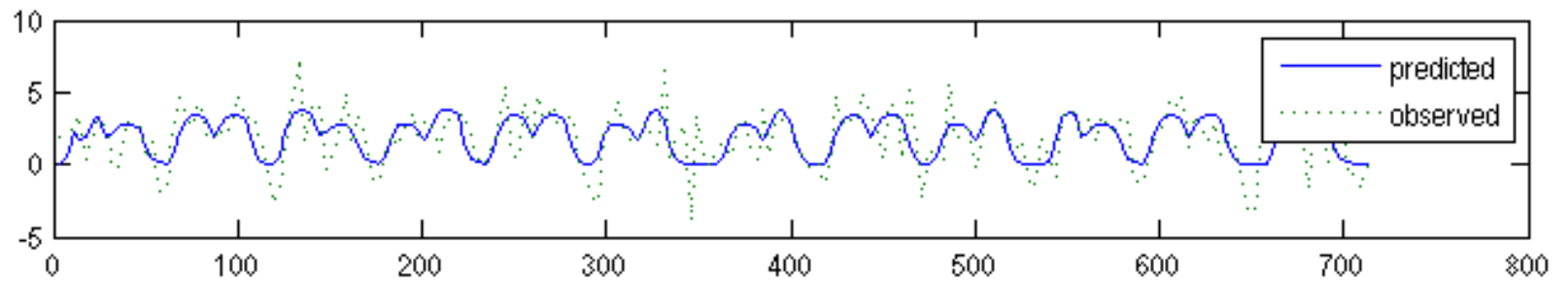


x

=

DCM Overview

=



Region 2 Timeseries

The hemodynamic model

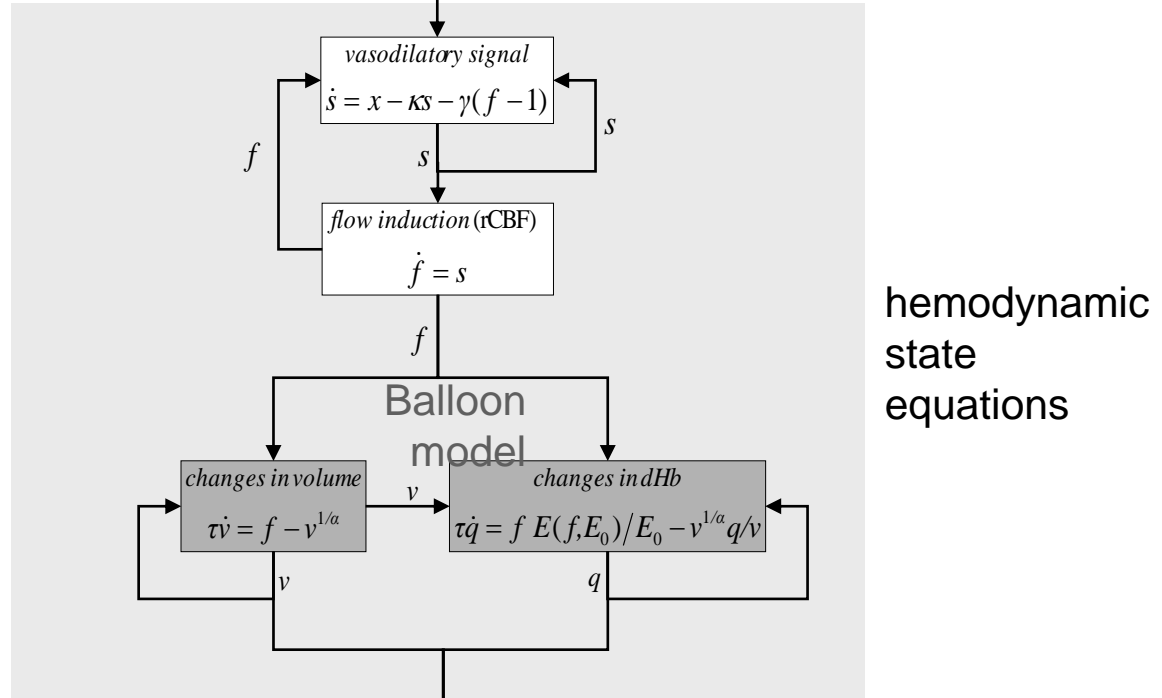
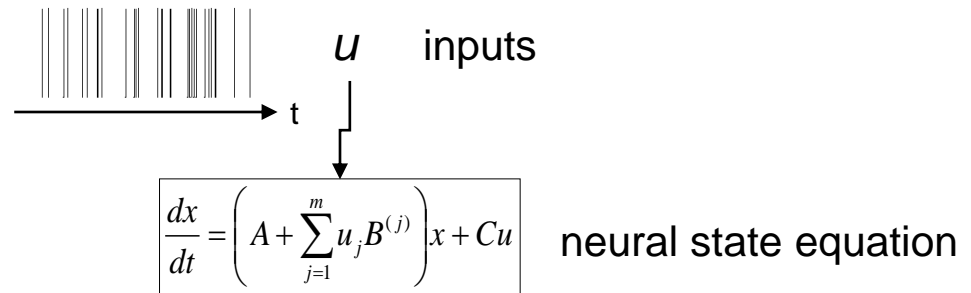
- 6 hemodynamic parameters:

$$\theta^h = \{\kappa, \gamma, \tau, \alpha, \rho, \varepsilon\}$$

important for model fitting, but of no interest for statistical inference

- Empirically determined *a priori* distributions.
- Area-specific estimates (like neural parameters) → **region-specific HRFs!**

[Friston et al. 2003, *NeuroImage*]
 [Stephan et al. 2007, *NeuroImage*]



$$\lambda(q, v) = \frac{\Delta S}{S_0} \approx V_0 \left[k_1(1-q) + k_2 \left(1 - \frac{q}{v}\right) + k_3(1-v) \right]$$

$$k_1 = 4.39_0 E_0 TE$$

$$k_2 = \varepsilon_0 E_0 TE$$

$$k_3 = 1 - \varepsilon$$

BOLD signal change equation

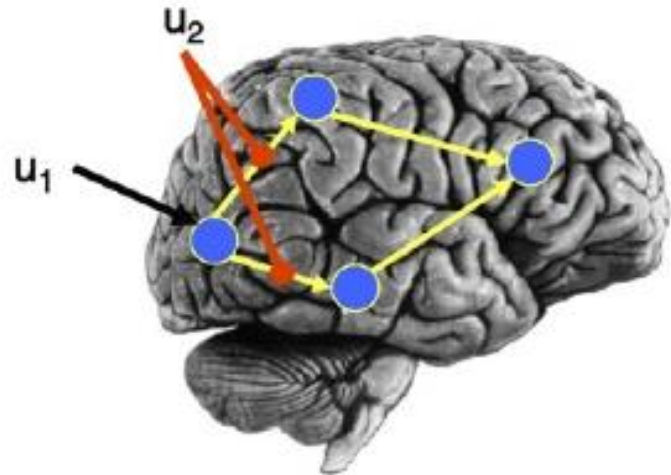


DCM: Methods and Practice

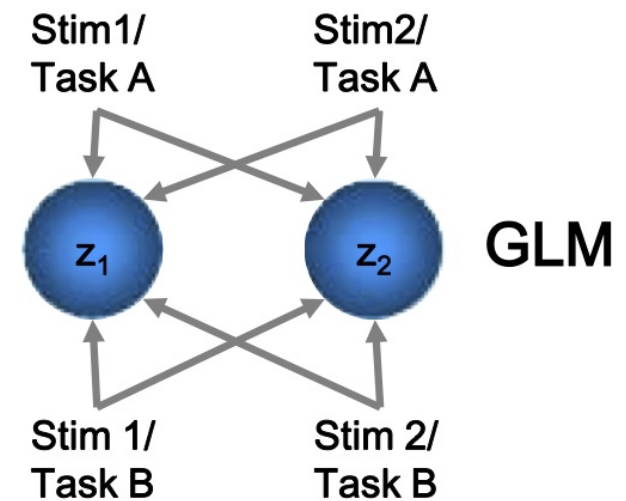
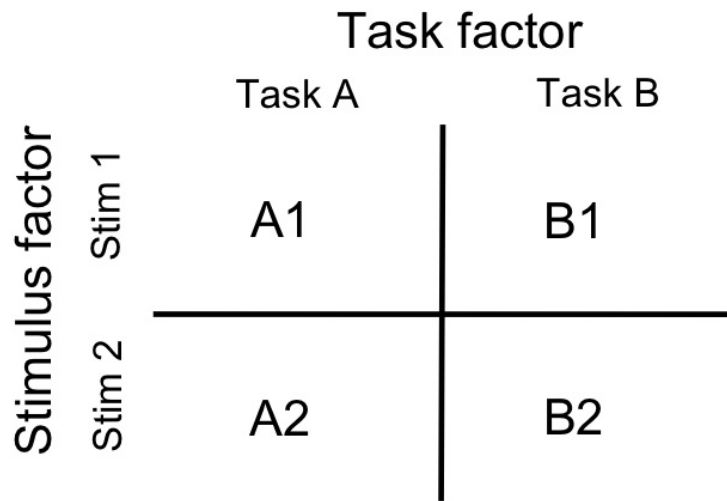
- Experimental Design and Motivation
 - Simulated data
- How to conduct DCM in SPM
 - A practical example and guide
 - Basic steps
 - Interpreting results
- Bayesian Model Selection
- Parameter estimates and group level statistics

Experimental Design and Motivation

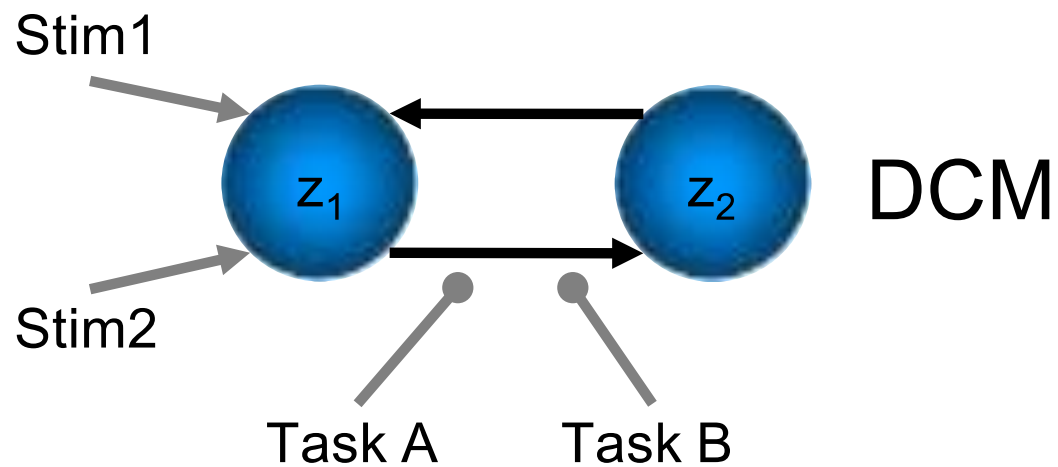
- Can apply DCM to any design used in a GLM analysis
- If the GLM does not detect activation in a given region, there is no motivation to include this region in a (deterministic) DCM
- Deterministic DCM tests generative models of how the GLM data arose



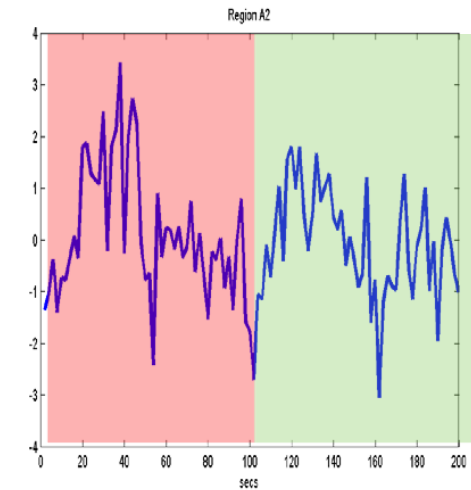
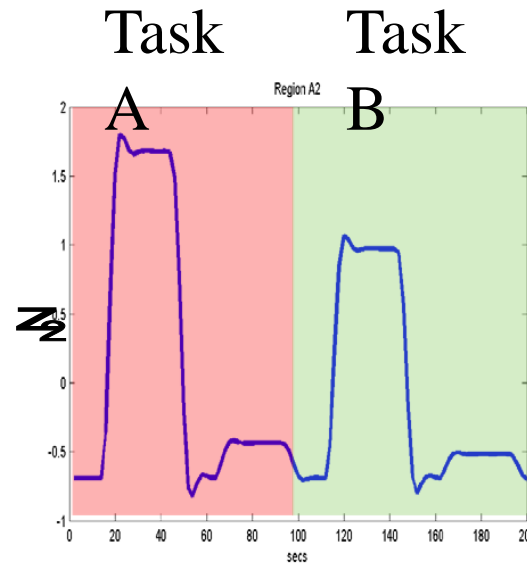
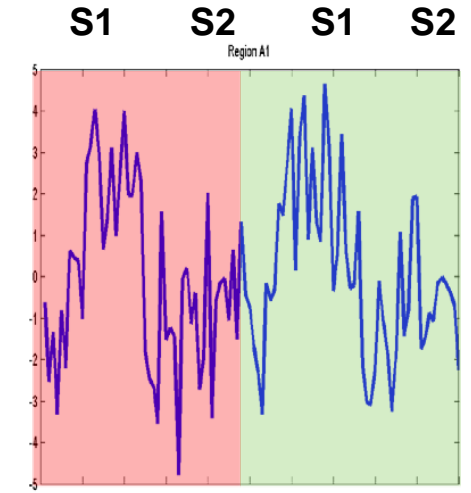
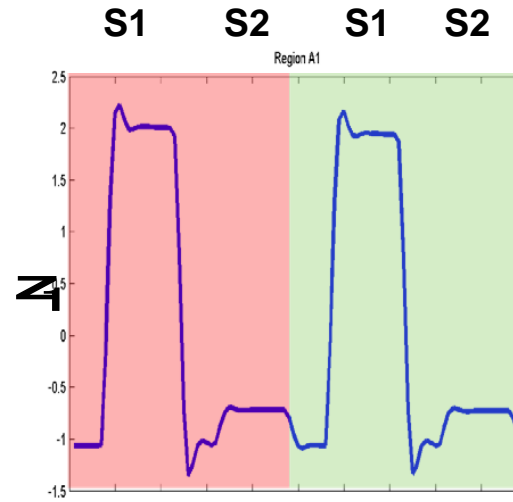
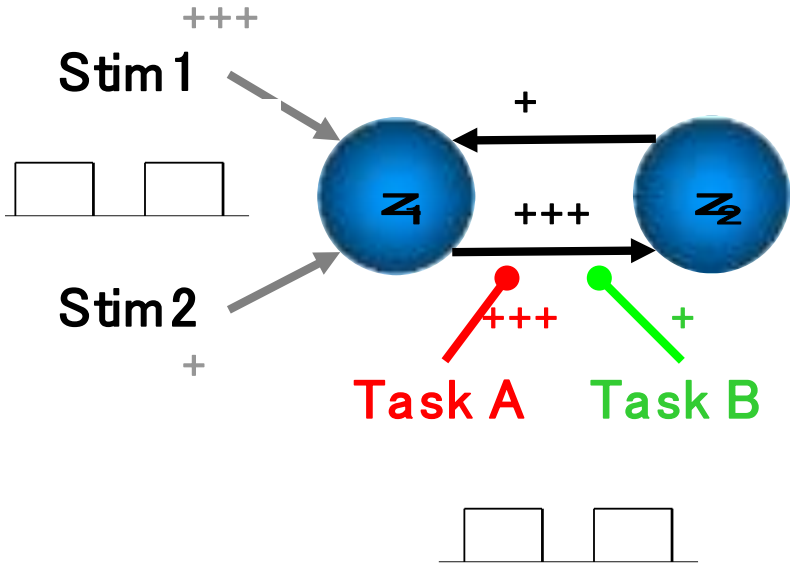
Multifactorial Design



Modeling interactions



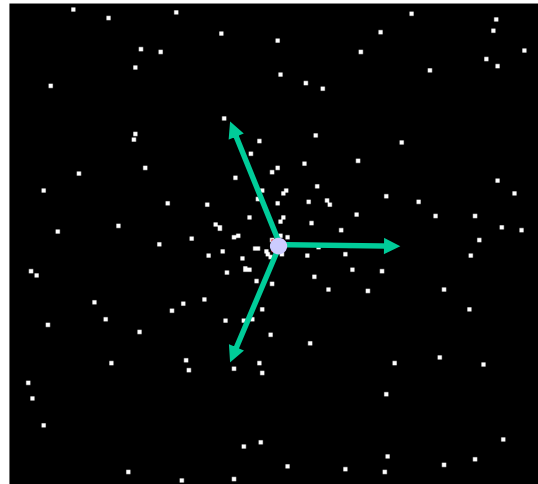
Simulated data



Attention to motion in the visual system

Stimuli

4 Conditions



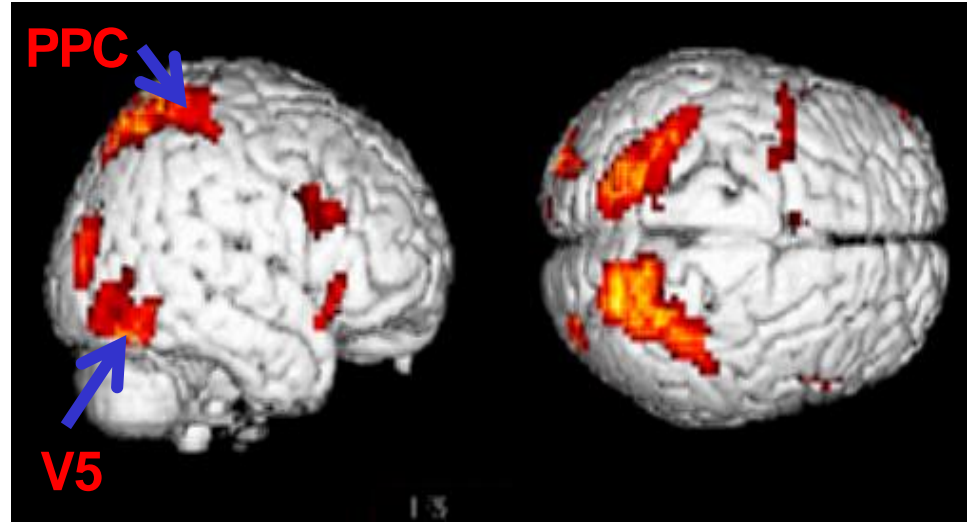
Parameters:

Sensory input

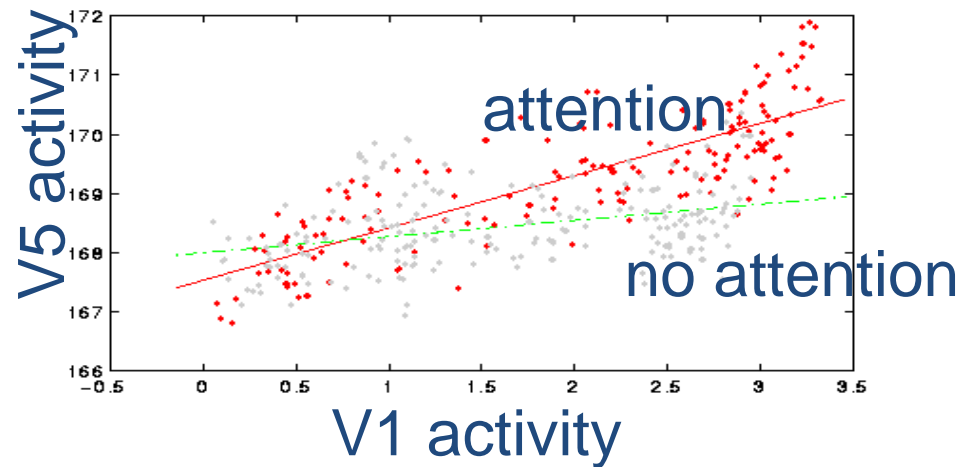
	static	motion
<u>Contextual factor</u> No atten	No motion/ attention	Motion / no attention
t Atten		Motion / attention
t.		

GLM Results

- fixation only – baseline
- observe static dots → V1
- observe moving dots → V5
- attention to moving dots
→ V5 + SPC



- GLM analysis showed that motion activated V5, but that attention enhanced this activity.



Modeling inputs in DCM analysis

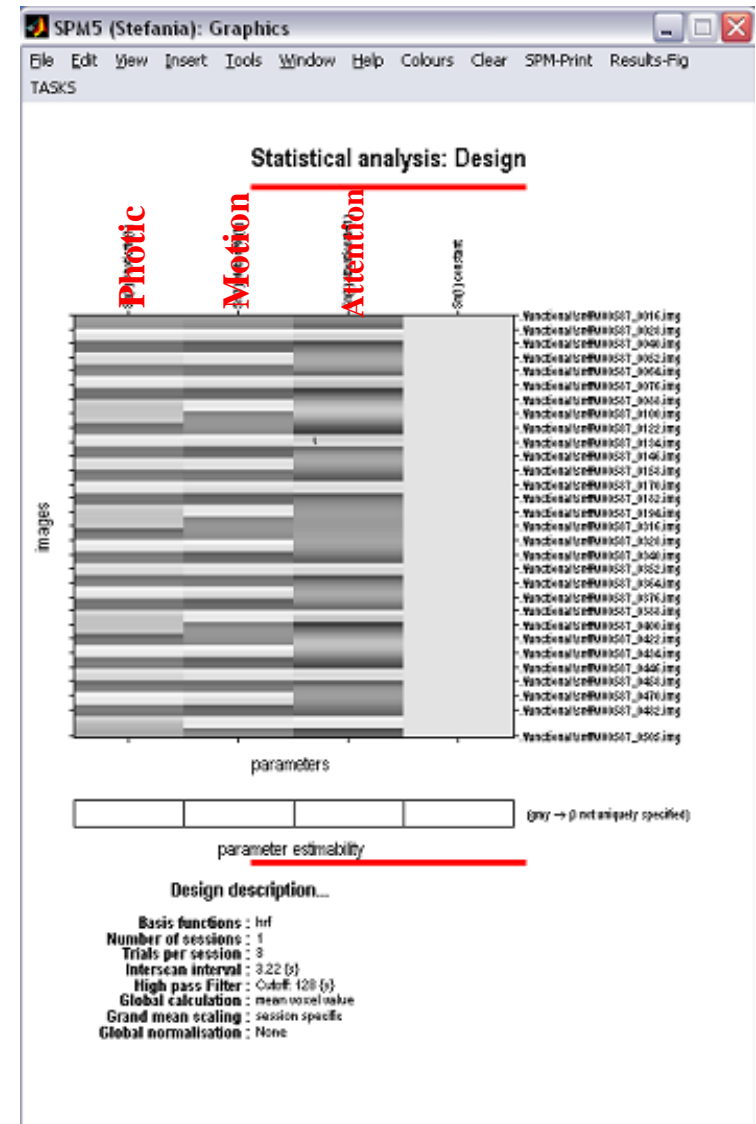
Specify regressors for DCM as driving inputs and modulators:

Driving input

- Photic: all visual input – static+ motion+ attention to motion

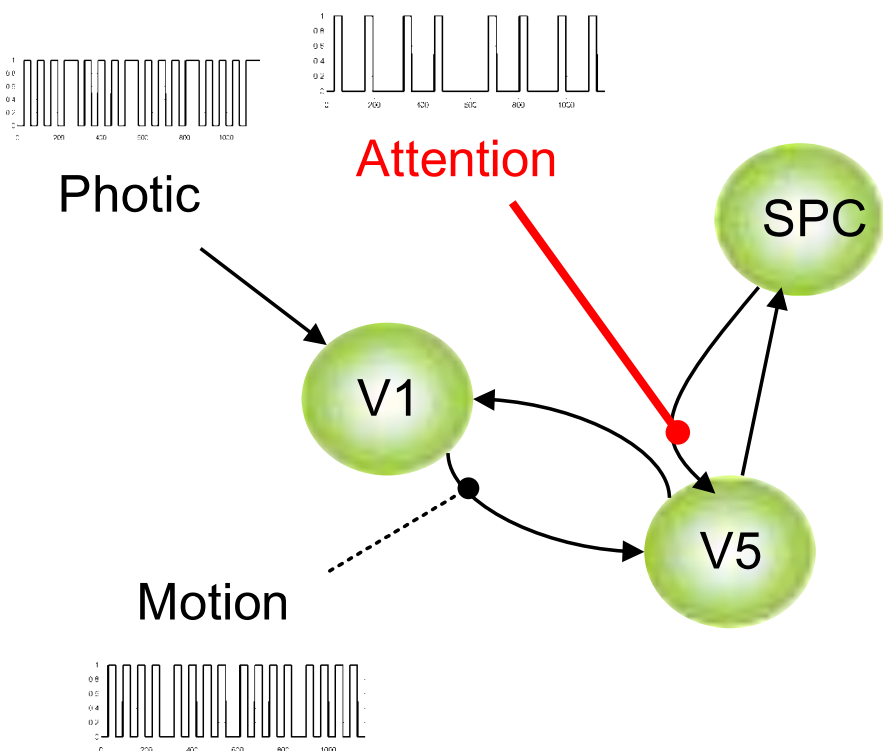
Modulatory input

- Motion
- Attention

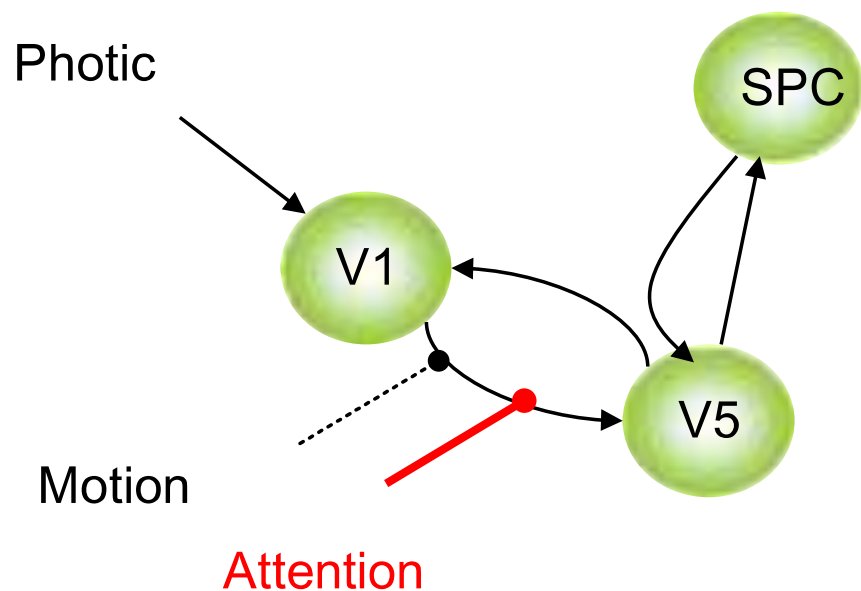


Alternate Dynamic Causal Models

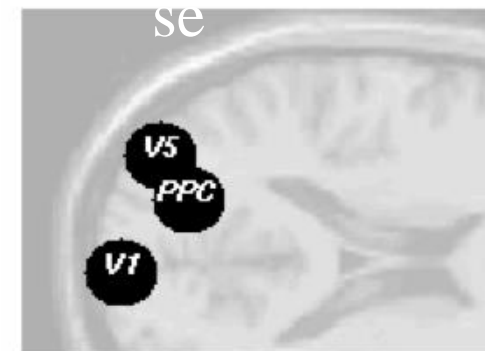
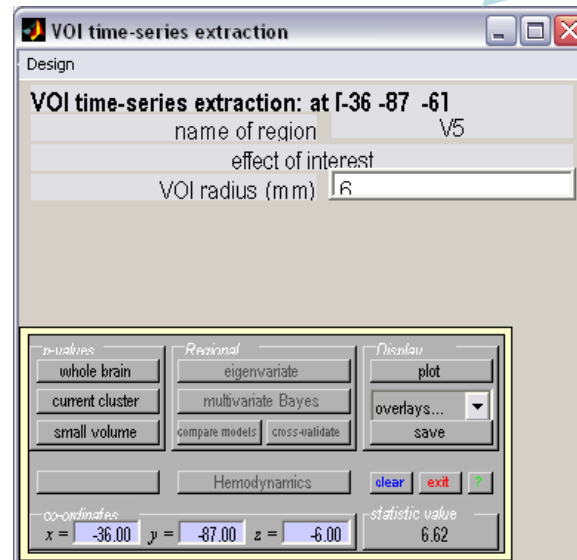
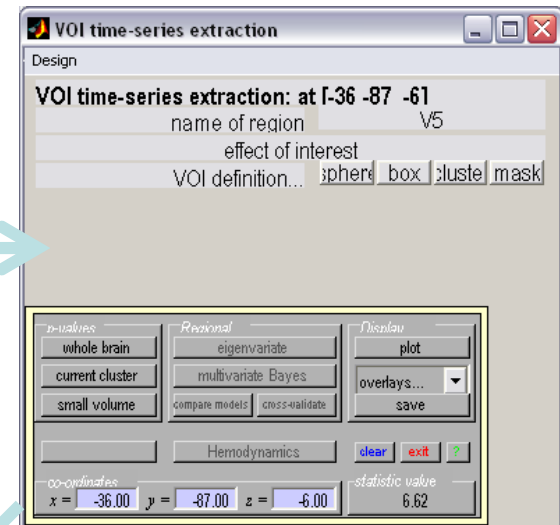
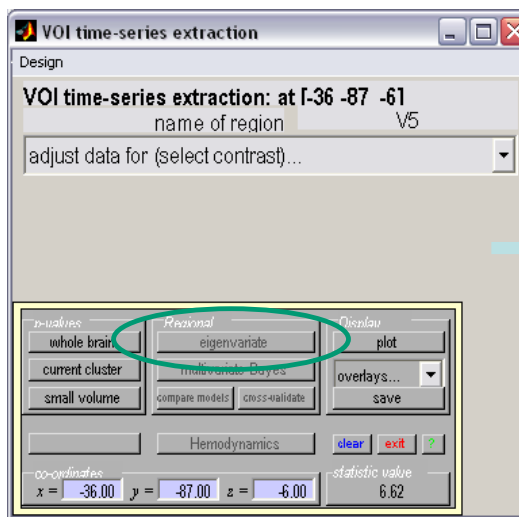
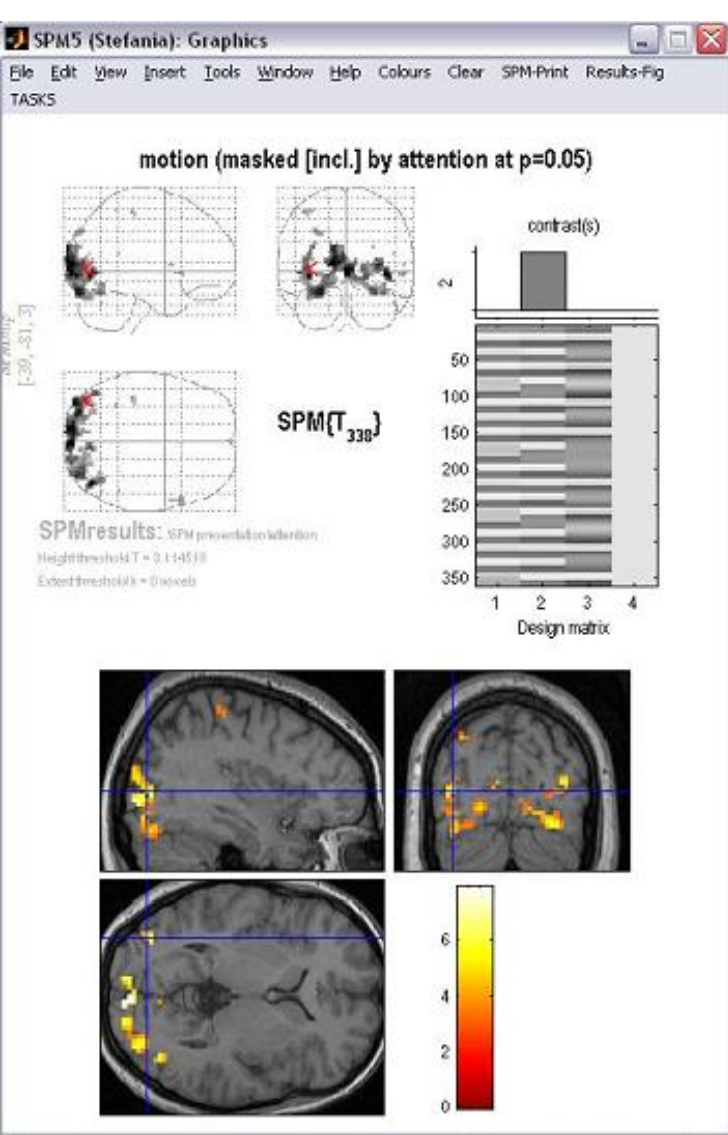
Model 1 (backward):



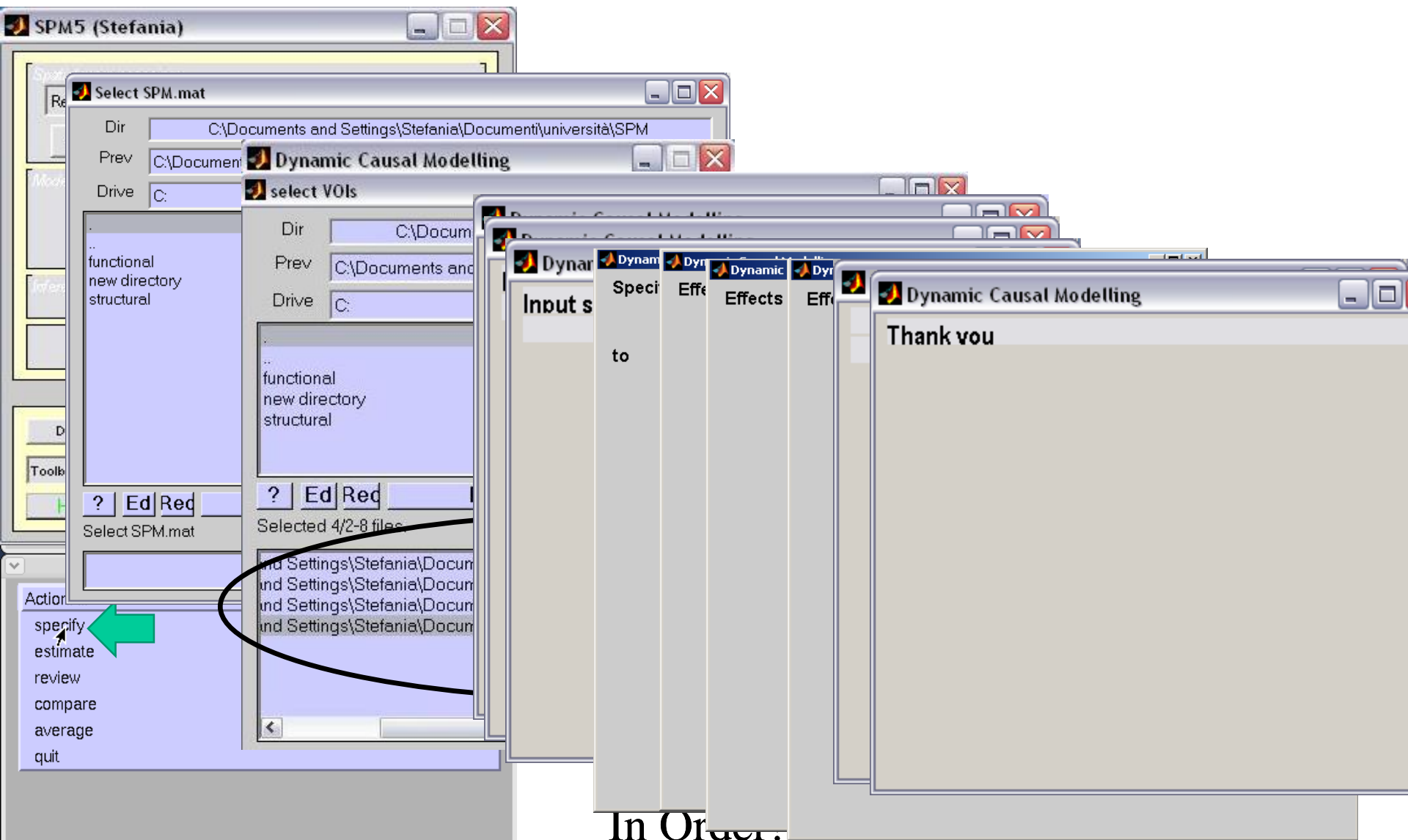
Model 2 (forward):



Defining VOIs: time series extraction

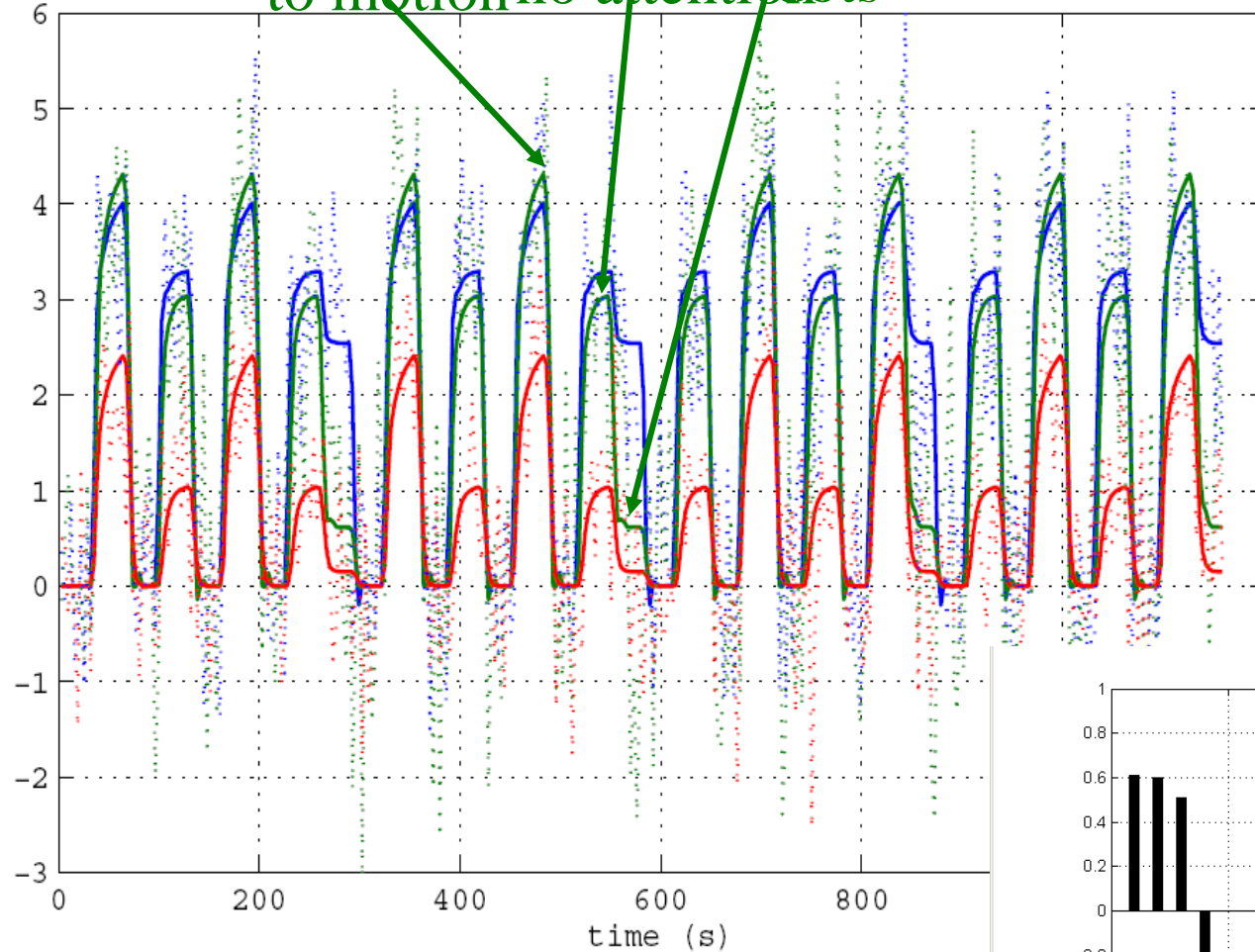


Specifying the model



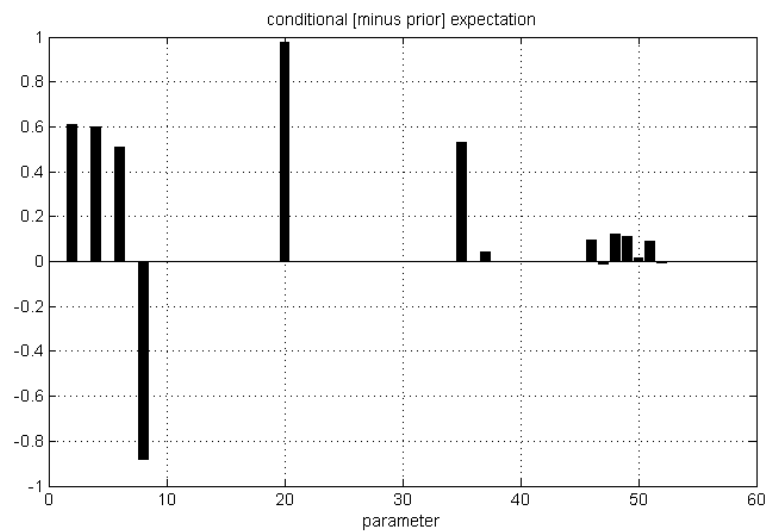
In Order.

Attention Motion & static
to motion no attention



— V1
— V5
— PPC

···· observed
— fitted



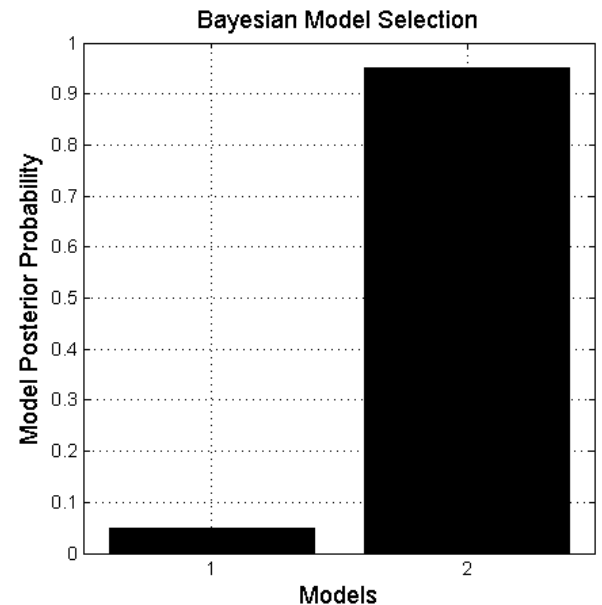
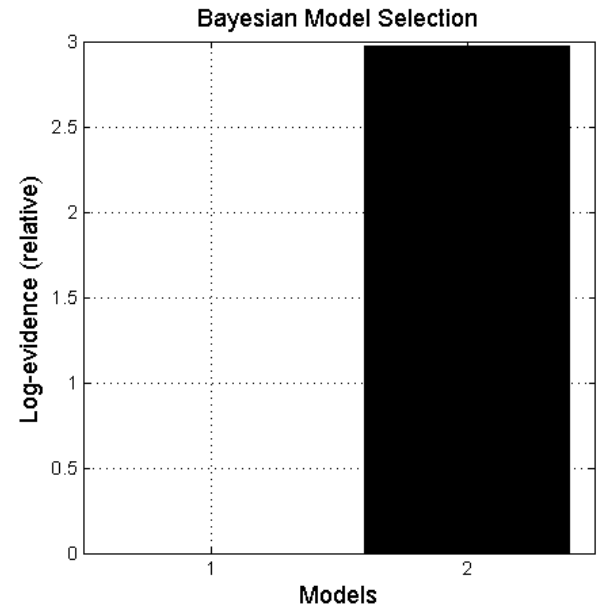
Bayesian Model Comparison

$$p(y|m) = \int p(y|\theta, m) \cdot p(\theta|m) d\theta$$

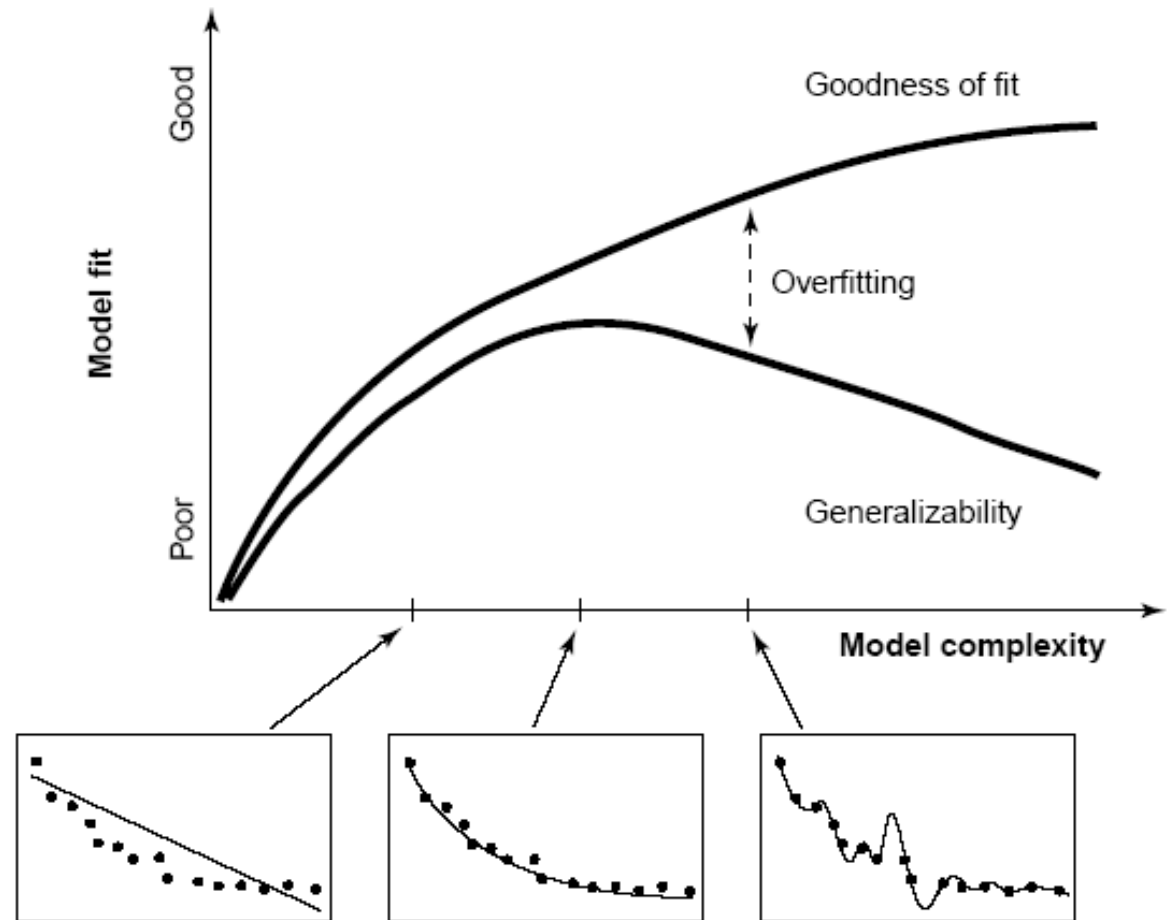
$$\log p(y|m) = \text{accuracy}(m) - \text{complexity}(m)$$

$$B_{ij} = \frac{p(y|m=i)}{p(y|m=j)}$$

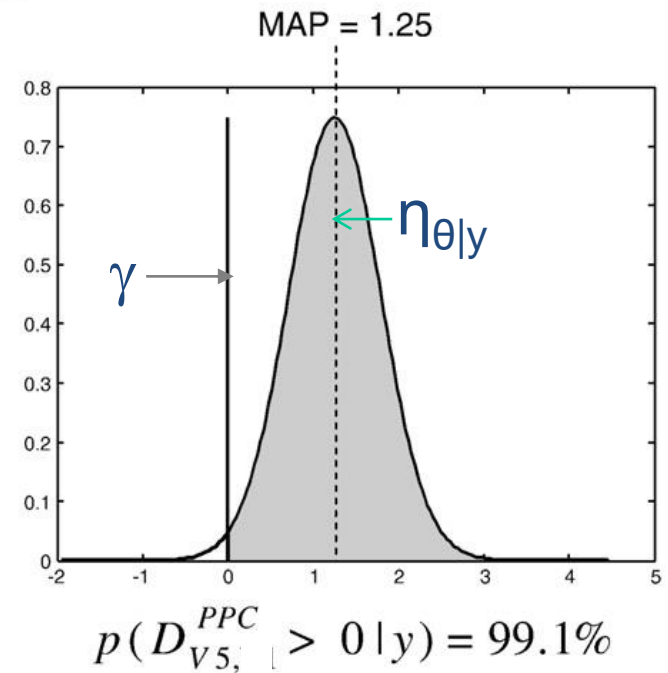
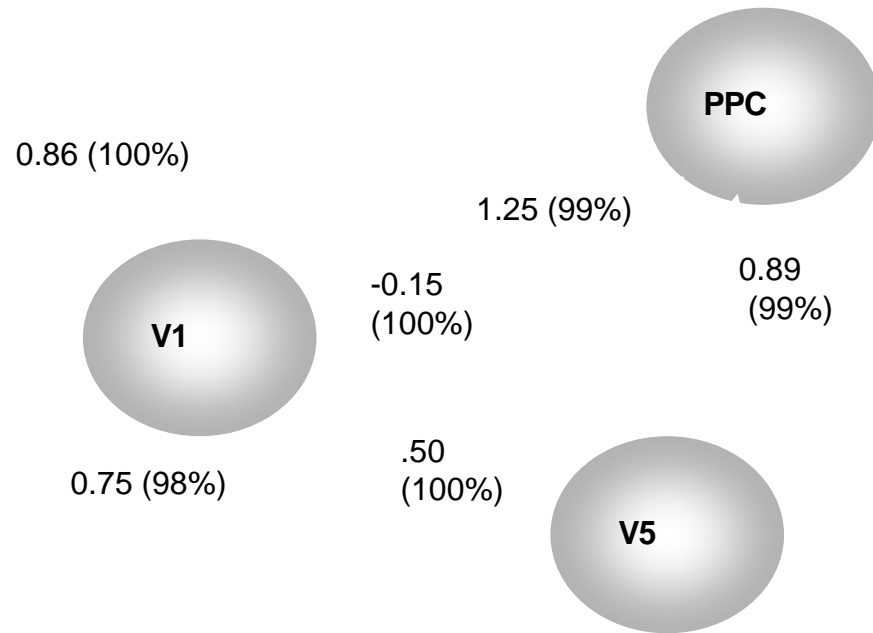
B_{12}	$p(m_1 y)$	Evidence
1 to 3	50-75%	weak
3 to 20	75-95%	positive
20 to 150	95-99%	strong
≥ 150	$\geq 99\%$	Very strong



Model evidence and selection



Review Winning Model and Parameters



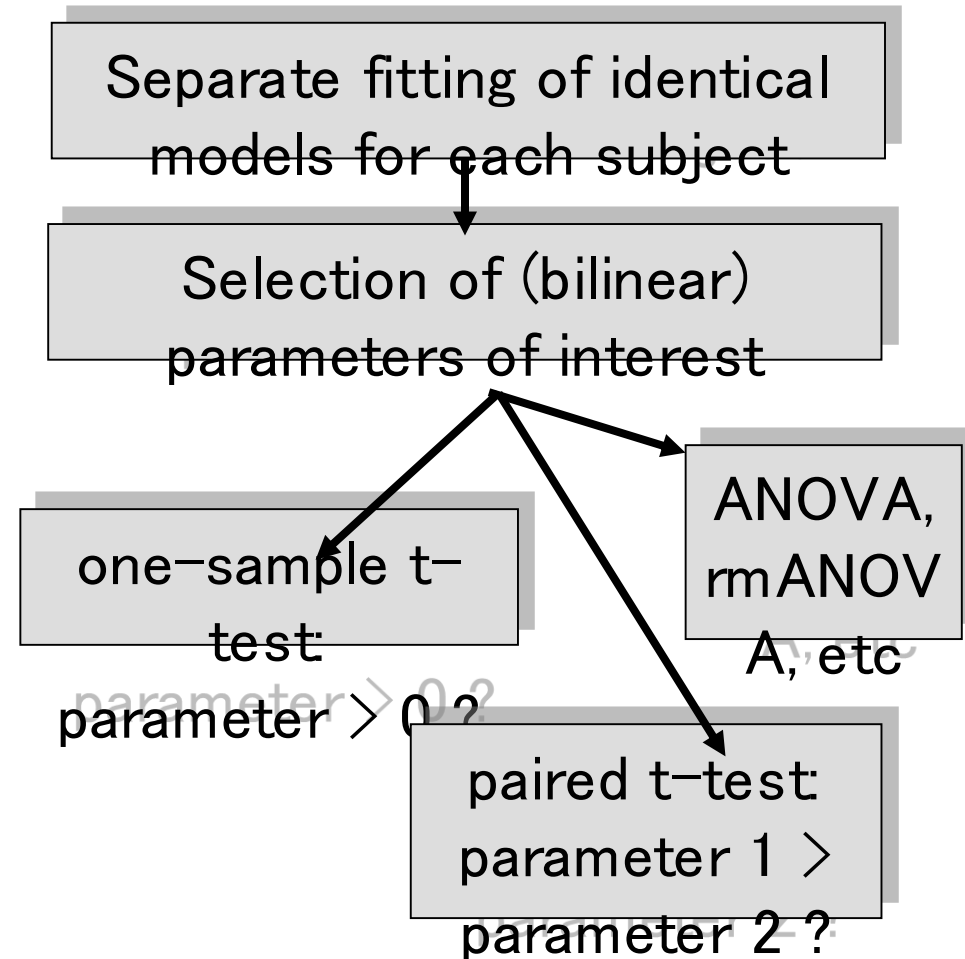
Inference about DCM parameters: Group level

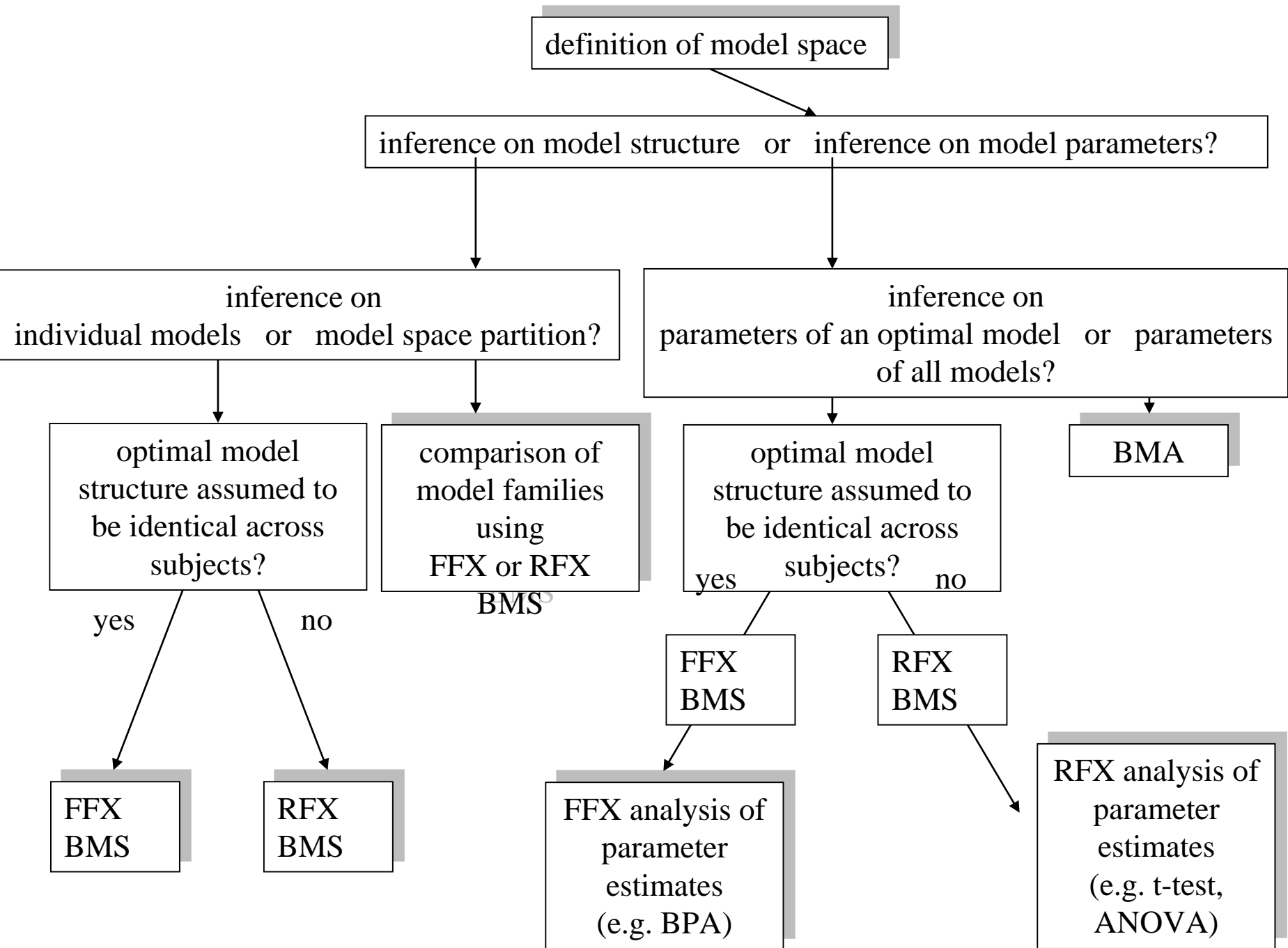
RFX group analysis

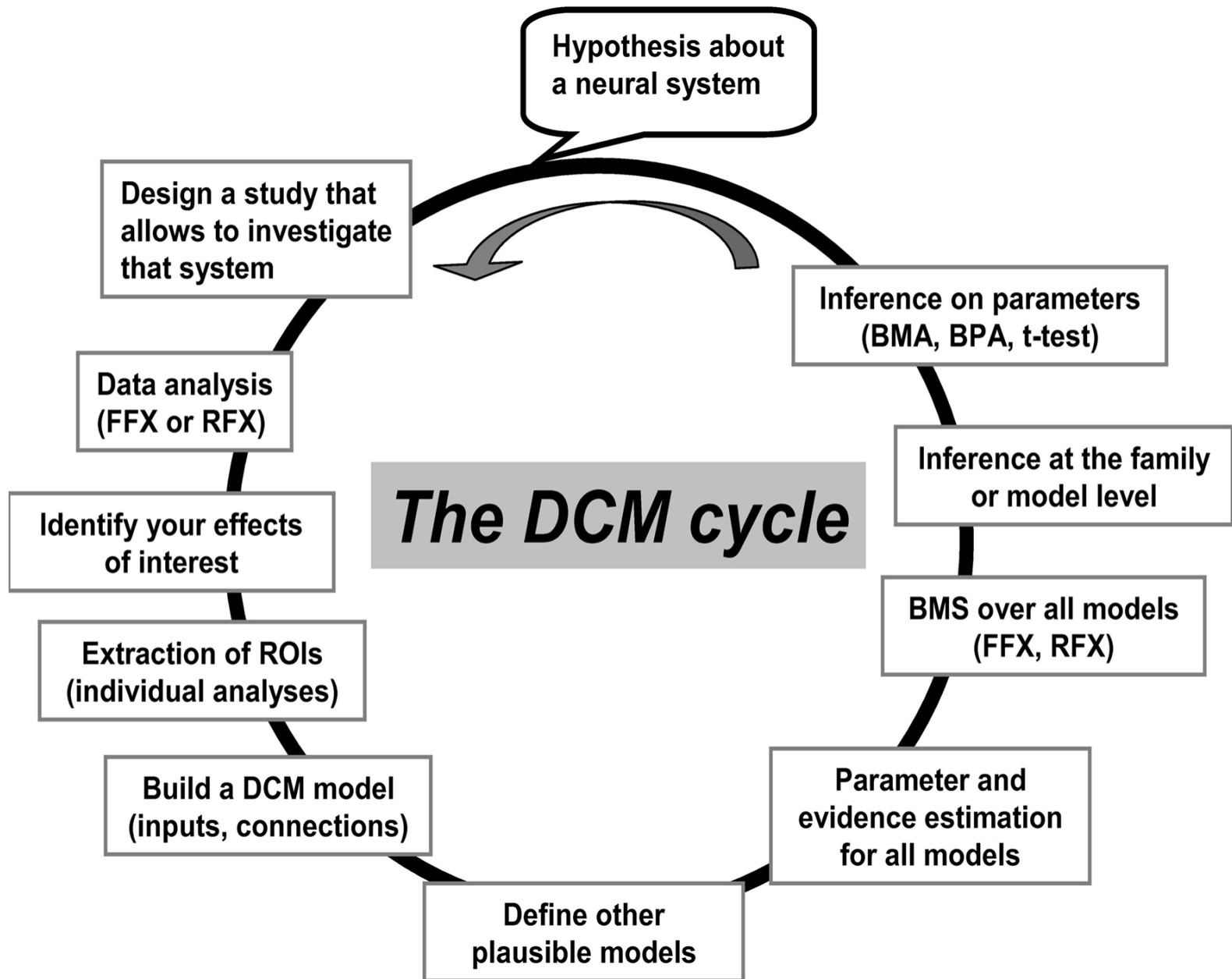
FFX group analysis

- Likelihood distributions from different subjects are independent
- Subject assumed to use identical systems
- One can use the posterior from one subject as the prior for the next

- Optimal models vary across subjects







DCM Summary

test mechanistic hypotheses

- Operates at the neuronal level

Bayesian framework

Thank you to our expert,
Mohamed Seghier!

References

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