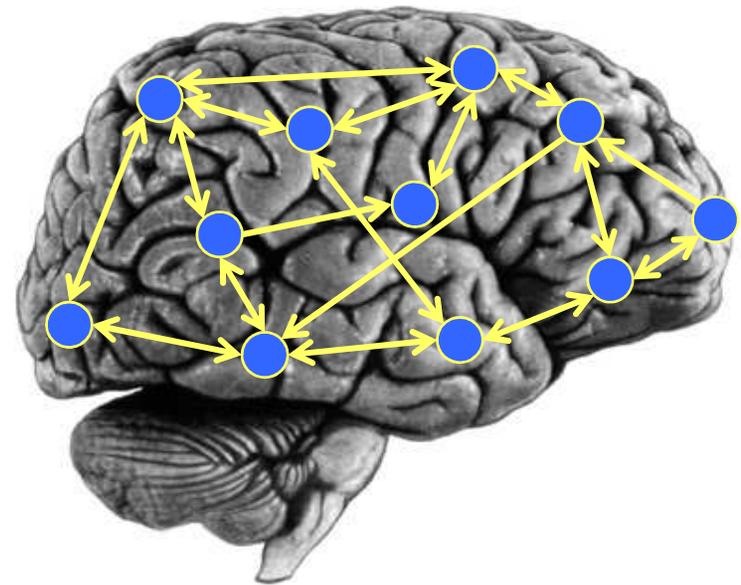


# Models of Effective Connectivity & Dynamic Causal Modelling

*Hanneke den Ouden*

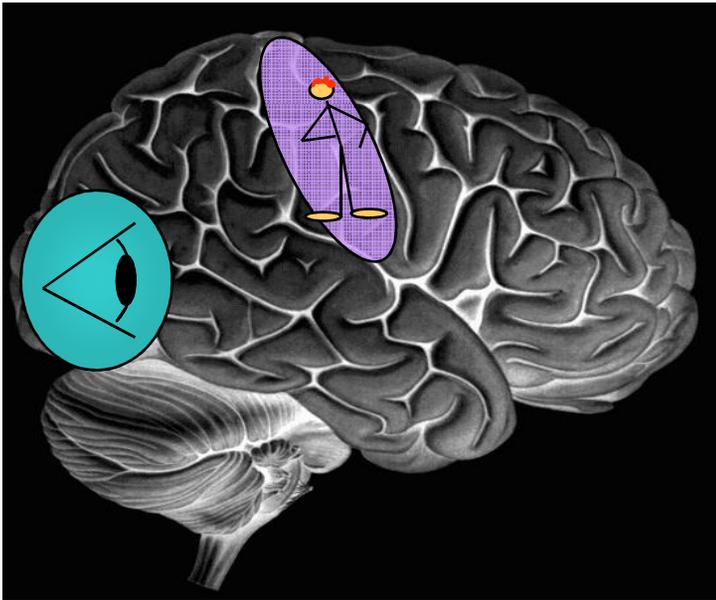
Donders Institute for Brain, Cognition  
and Behaviour, Nijmegen, the  
Netherlands



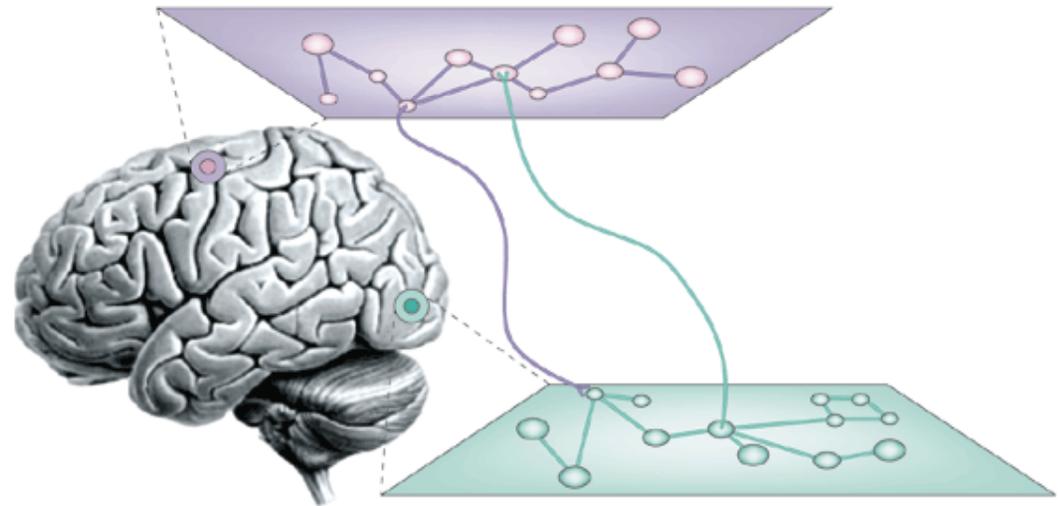
SPM Course, London  
13-15 May 2010

# Principles of Organisation

Functional specialization



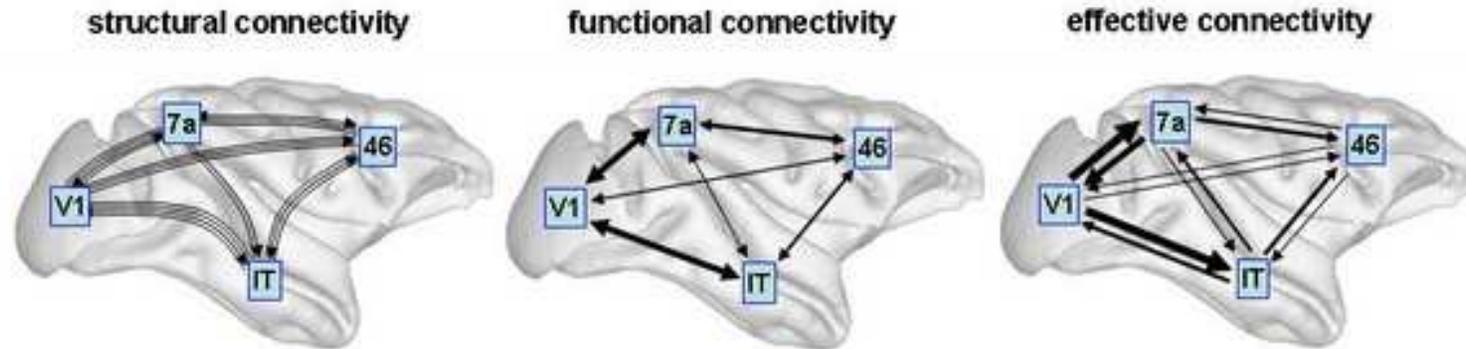
Functional integration



# Overview

- Brain connectivity: types & definitions
  - anatomical connectivity
  - functional connectivity
  - effective connectivity
- Functional connectivity
- Psycho-physiological interactions (PPI)
- Dynamic causal models (DCMs)
- Applications of DCM to fMRI data

# Structural, functional & effective connectivity



Sporns 2007, *Scholarpedia*

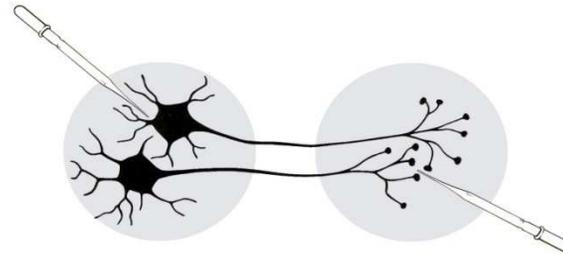
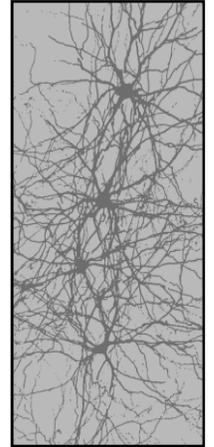
- **anatomical/structural connectivity**  
= presence of axonal connections
- **functional connectivity**  
= statistical dependencies between regional time series
- **effective connectivity**  
= causal (directed) influences between neurons or neuronal populations

# Anatomical connectivity

## *Definition:*

*presence of axonal connections*

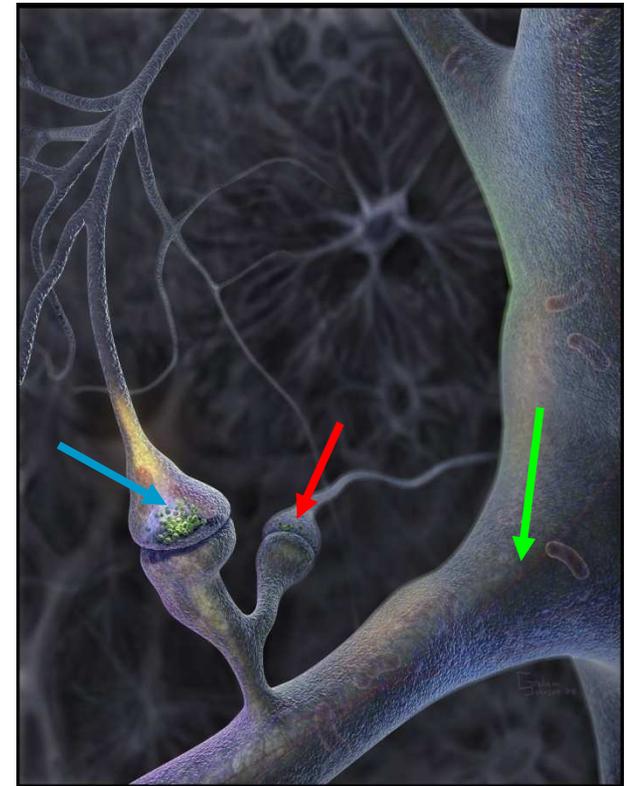
- neuronal communication via synaptic contacts
- Measured with
  - tracing techniques
  - diffusion tensor imaging (DTI)



# Knowing anatomical connectivity is not enough...

- Context-dependent recruiting of connections :
  - Local functions depend on network activity
- Connections show synaptic plasticity
  - change in the structure and transmission properties of a synapse
  - even at short timescales

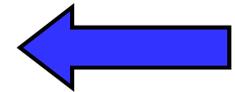
→ Look at functional and effective connectivity



# Functional connectivity

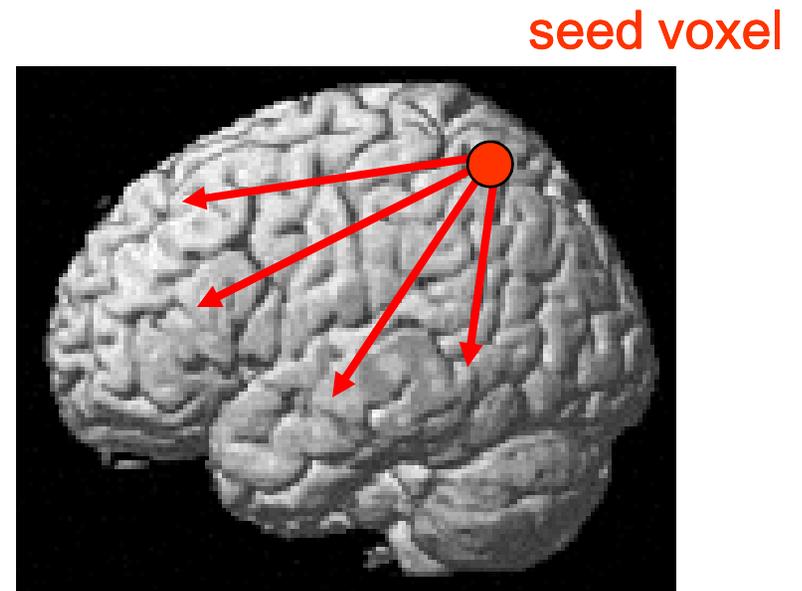
*Definition: statistical dependencies between regional time series*

- Seed voxel correlation analysis
- Coherence analysis
- Eigen-decomposition (PCA, SVD)
- Independent component analysis (ICA)
- any technique describing statistical dependencies amongst regional time series



# Seed-voxel correlation analyses

- hypothesis-driven choice of a seed voxel
- extract reference time series
- voxel-wise correlation with time series from all other voxels in the brain

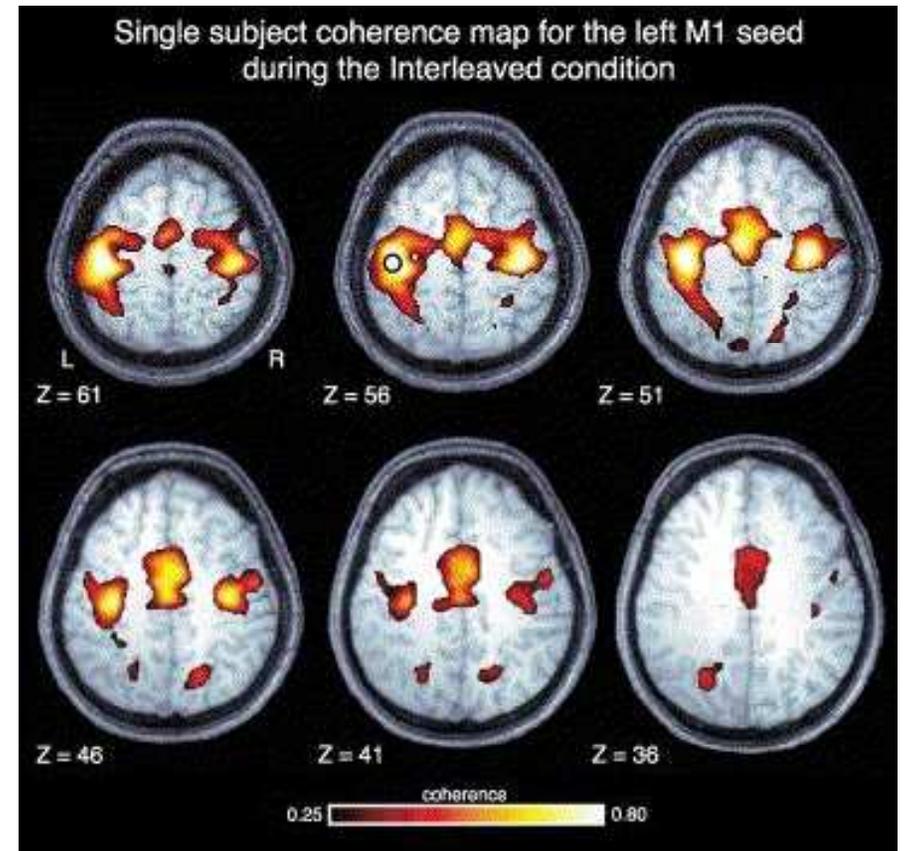


# SVCA example: Task-induced changes in functional connectivity

2 bimanual finger-tapping tasks:

During task that required more bimanual coordination, SMA, PPC, M1 and PM showed increased functional connectivity ( $p < 0.001$ ) with left M1

→ No difference in SPMs!



# Does functional connectivity not simply correspond to co-activation in SPMs?

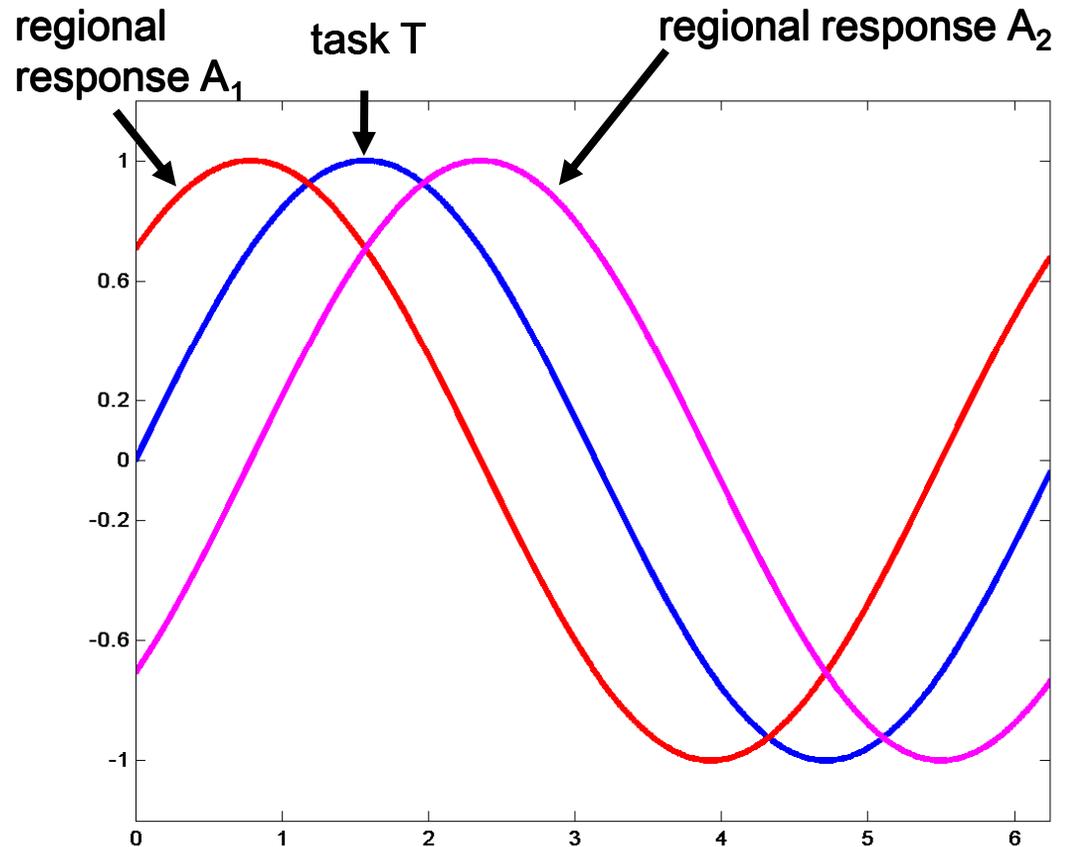
No

Here both areas  $A_1$  and  $A_2$  are correlated identically to task  $T$ , yet they have zero correlation among themselves:

$$r(A_1, T) = r(A_2, T) = 0.71$$

but

$$r(A_1, A_2) = 0 !$$



# Pros & Cons of functional connectivity analysis

- Pros:
  - useful when we have no experimental control over the system of interest and no model of what caused the data (e.g. sleep, hallucinations, etc.)
- Cons:
  - interpretation of resulting patterns is difficult / arbitrary
  - no mechanistic insight
  - usually suboptimal for situations where we have a priori knowledge / experimental control

→ Effective connectivity



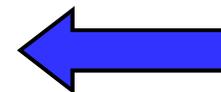
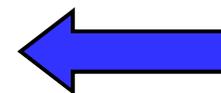
# Effective connectivity

*Definition: causal (directed) influences between neurons or neuronal populations*

- *In vivo* and *in vitro* stimulation and recording
- 
- 
- 
- Models of **causal interactions** among neuronal populations
  - explain **regional effects** in terms of **interregional connectivity**

# Some models for computing effective connectivity from fMRI data

- Structural Equation Modelling (SEM)  
McIntosh et al. 1991, 1994; Büchel & Friston 1997; Bullmore et al. 2000
- regression models  
(e.g. psycho-physiological interactions, PPIs)  
Friston et al. 1997
- Volterra kernels  
Friston & Büchel 2000
- Time series models (e.g. MAR, Granger causality)  
Harrison et al. 2003, Goebel et al. 2003
- Dynamic Causal Modelling (DCM)  
*bilinear*: Friston et al. 2003; *nonlinear*: Stephan et al. 2008



# Psychophysiological interaction (PPI)

- bilinear model of how the psychological context **A** changes the influence of area **B** on area **C** :

$$B \times A \rightarrow C$$

- A PPI corresponds to differences in regression slopes for different contexts.

# Psycho-physiological interaction (PPI)

		Task factor	
		Task A	Task B
Stimulus factor	Stim 1	A1	B1
	Stim 2	A2	B2

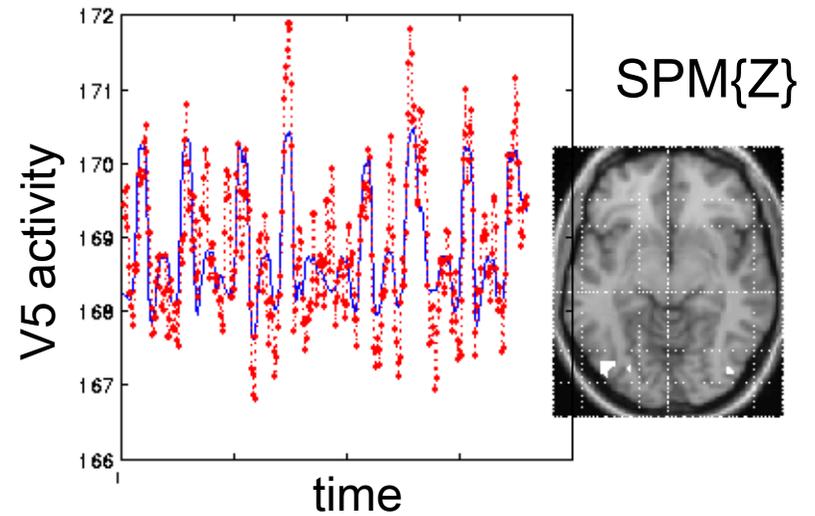
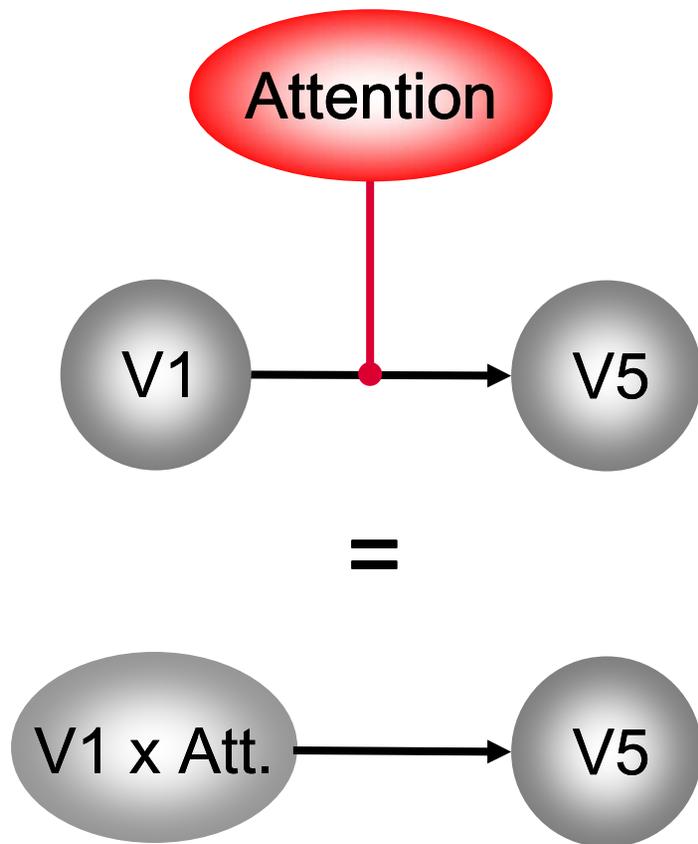
GLM of a 2x2 factorial design:

$$\begin{aligned}
 y = & (T_A - T_B) \beta_1 && \leftarrow \text{main effect of task} \\
 & + (S_1 - S_2) \beta_2 && \leftarrow \text{main effect of stim. type} \\
 & + (T_A - T_B) (S_1 - S_2) \beta_3 && \text{interaction} \\
 & + e
 \end{aligned}$$

We can replace one main effect in the GLM by the time series of an area that shows this main effect.

$$\begin{aligned}
 y = & (T_A - T_B) \beta_1 && \leftarrow \text{main effect of task} \\
 & + V1 \beta_2 && \leftarrow \text{V1 time series} \\
 & + (T_A - T_B) V1 \beta_3 && \leftarrow \text{psycho-physiological interaction} \\
 & + e
 \end{aligned}$$

# Example PPI: Attentional modulation of V1→V5



# Pros & Cons of PPIs

- Pros:
  - given a single source region, we can test for its context-dependent connectivity across the entire brain
  - easy to implement
- Cons:
  - only allows to model contributions from a single area
  - operates at the level of BOLD time series
  - ignores time-series properties of the data

 Dynamic Causal Models

# Overview

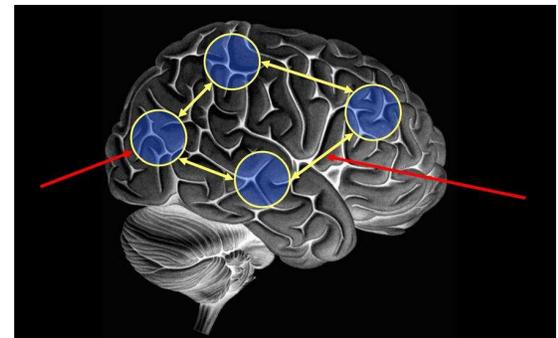
- Brain connectivity: types & definitions
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- Dynamic causal models (DCMs)
  - Basic idea
  - Neural level
  - Hemodynamic level
  - Parameter estimation, priors & inference
- Applications of DCM to fMRI data

# Basics of Dynamic Causal Modelling

**DCM allows us to look at how areas within a network interact:**

Investigate functional integration & modulation of specific cortical pathways

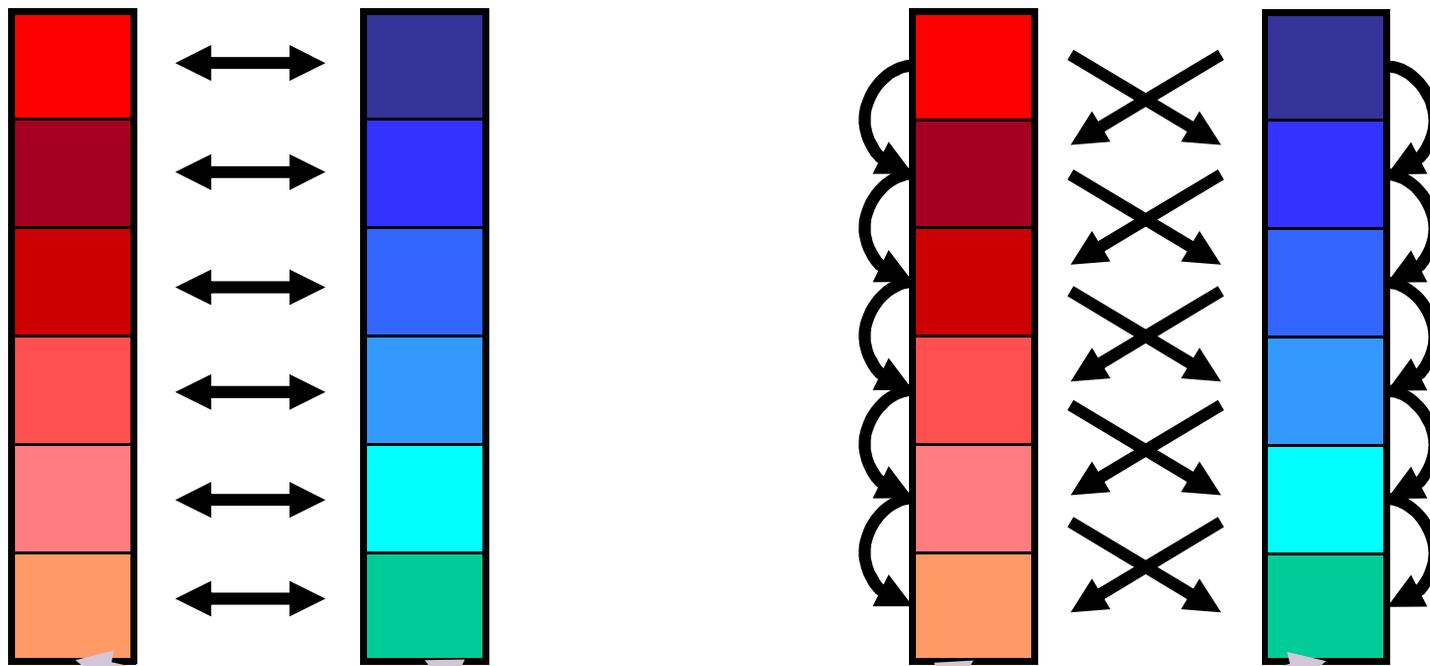
- Temporal dependency of activity within and between areas (causality)



# Temporal dependence and causal relations

Seed voxel approach, PPI etc.

Dynamic *Causal* Models



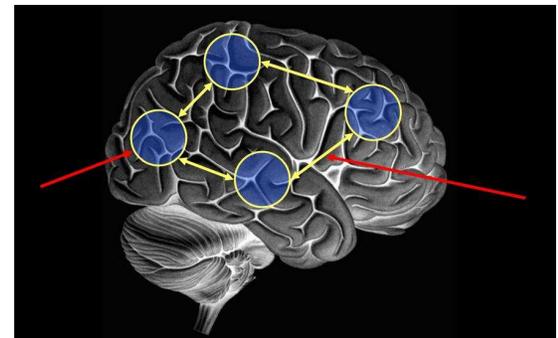
timeseries (neuronal activity)

# Basics of Dynamic Causal Modelling

**DCM allows us to look at how areas within a network interact:**

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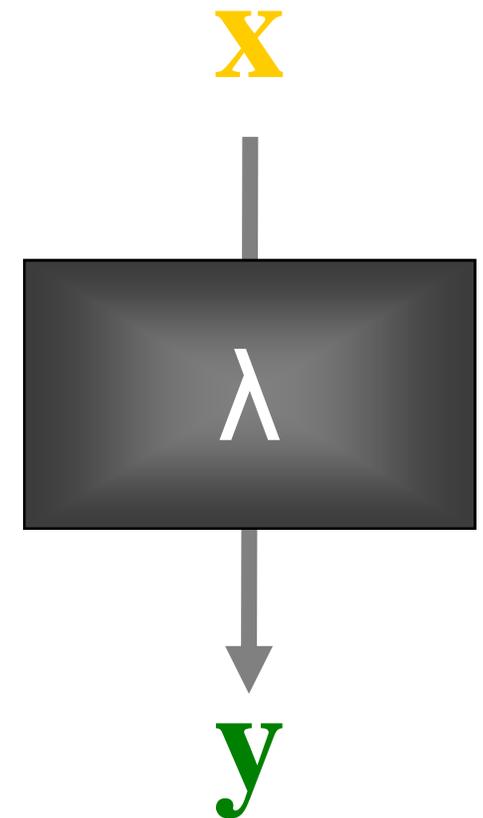
- Temporal dependency of activity within and between areas (causality)
- Separate neuronal activity from observed BOLD responses



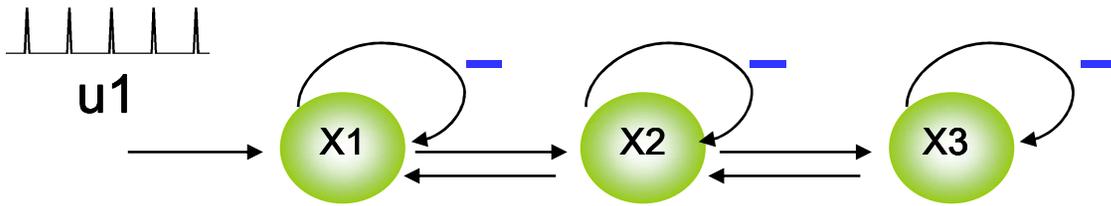
# Basics of DCM: Neuronal and BOLD level

- Cognitive system is modelled at its underlying neuronal level (not directly accessible for fMRI).
- The modelled neuronal dynamics ( $\mathbf{x}$ ) are transformed into area-specific BOLD signals ( $\mathbf{y}$ ) by a hemodynamic model ( $\lambda$ ).

The aim of DCM is to estimate parameters at the neuronal level such that the modelled and measured BOLD signals are maximally\* similar.



# DCM: Linear Model



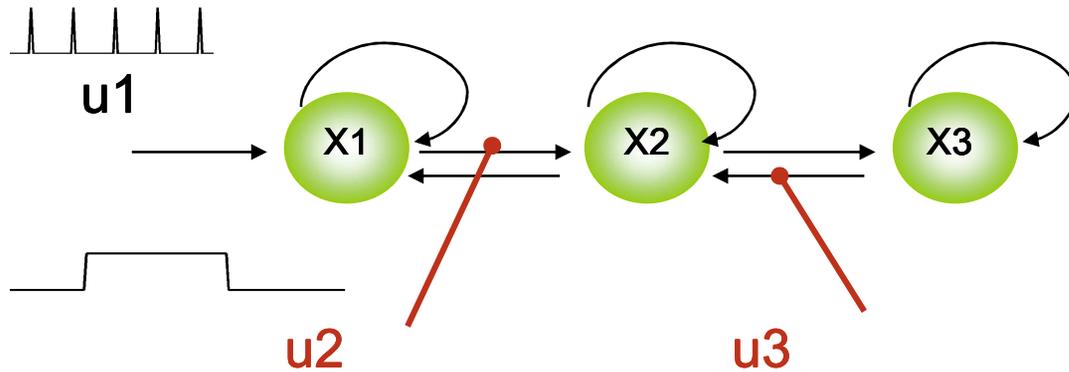
$$\dot{x} = Ax + Cu$$

$$\theta = \{A, C\}$$

$$\dot{x}_2 = a_{21}x_1 + a_{22}x_2 + a_{23}x_3$$

state changes	effective connectivity	system state	input parameters	external inputs
↓	↓	↓	↓	↓
$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix}$	$= \begin{bmatrix} a_{11} & a_{12} & 0 \\ a_{21} & a_{22} & a_{23} \\ 0 & a_{32} & a_{33} \end{bmatrix}$	$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$	$+ \begin{bmatrix} c_{11} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}$

# DCM: Bilinear Model



## Neural State Equation

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

$$\theta = \{A, B, C\}$$

$$\dot{x}_1 = a_{11}x_1 + a_{12}x_2 + c_1u_1$$

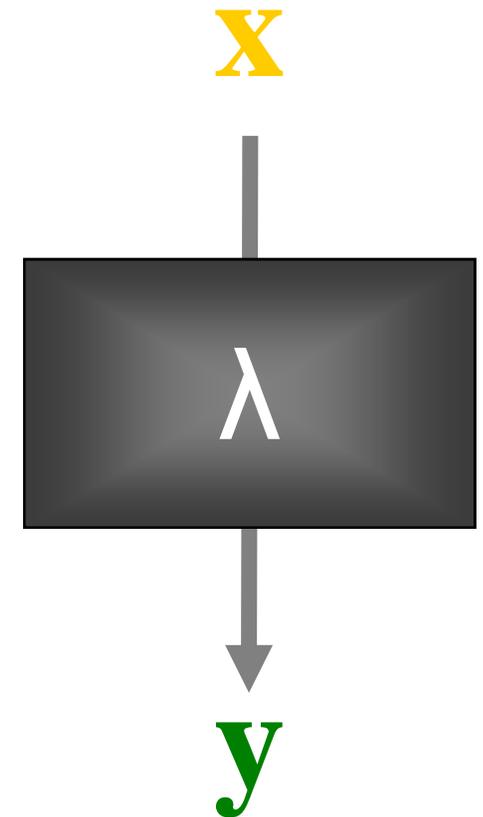
$$\dot{x}_2 = (a_{21} + u_2b_{21}^{(2)})x_1 + a_{22}x_2 + (a_{23} + u_3b_{23}^{(3)})x_3$$

$$\dot{x}_3 = a_{32}x_2 + a_{33}x_3$$

<b>state changes</b>	<b>fixed effective connectivity</b>	<b>modulatory effective connectivity</b>	<b>system state</b>	<b>input parameters</b>	<b>external inputs</b>
↓	↓	↓	↓	↓	↓
$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix}$	$= \begin{bmatrix} a_{11} & a_{12} & 0 \\ a_{21} & a_{22} & a_{23} \\ 0 & a_{32} & a_{33} \end{bmatrix}$	$+ u_2 \begin{bmatrix} 0 & 0 & 0 \\ b_{21}^{(2)} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	$+ u_3 \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & b_{23}^{(3)} \\ 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$	$+ \begin{bmatrix} c_{11} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}$

# Basics of DCM: Neuronal and BOLD level

- Cognitive system is modelled at its underlying neuronal level (not directly accessible for fMRI).
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# The hemodynamic model

- 6 hemodynamic parameters:

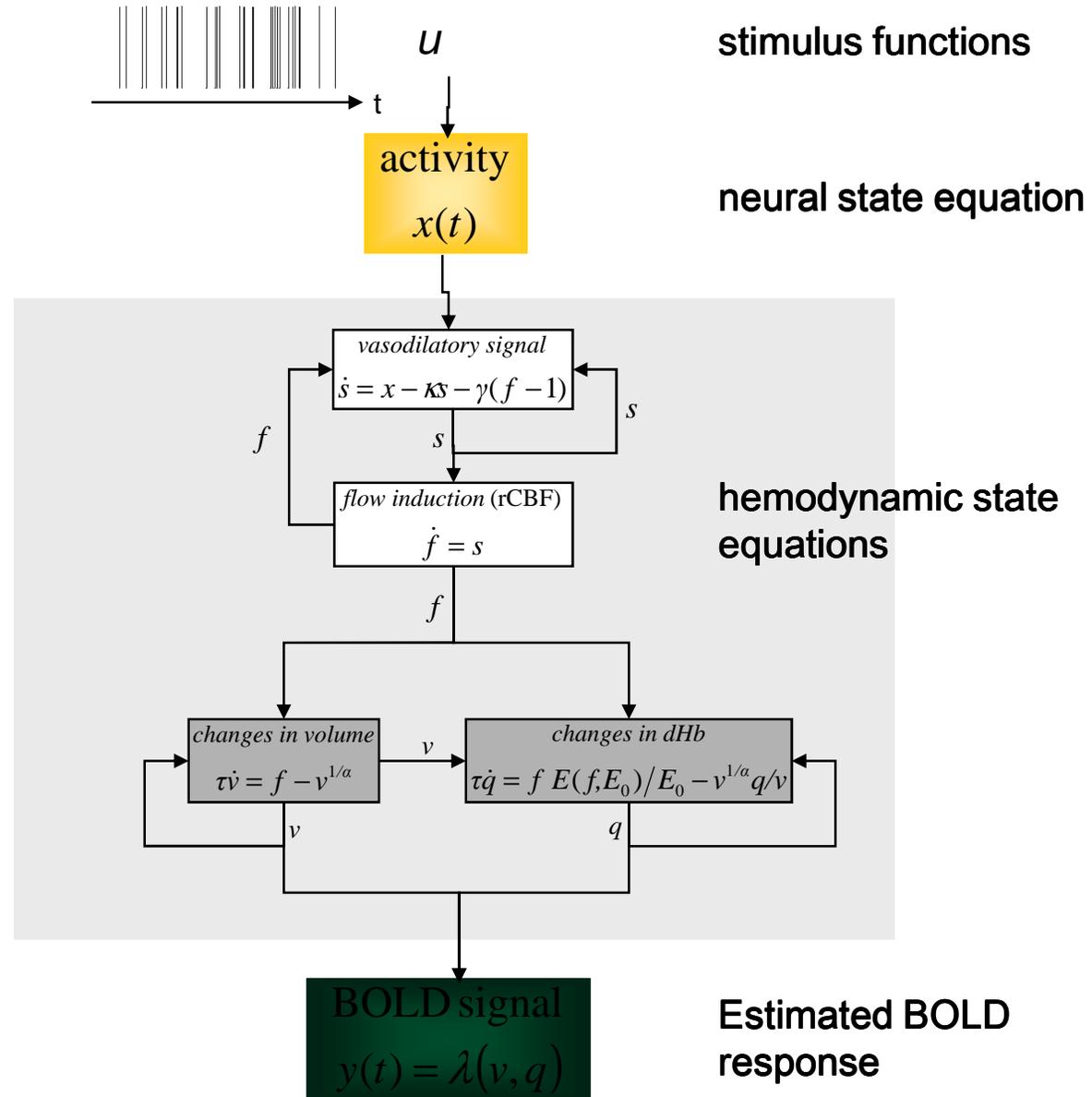
$$\theta^h = \{\kappa, \gamma, \tau, \alpha, \rho, \varepsilon\}$$



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

- Computed separately for each area → region-specific HRFs!

Friston et al. 2000, *NeuroImage*  
Stephan et al. 2007, *NeuroImage*



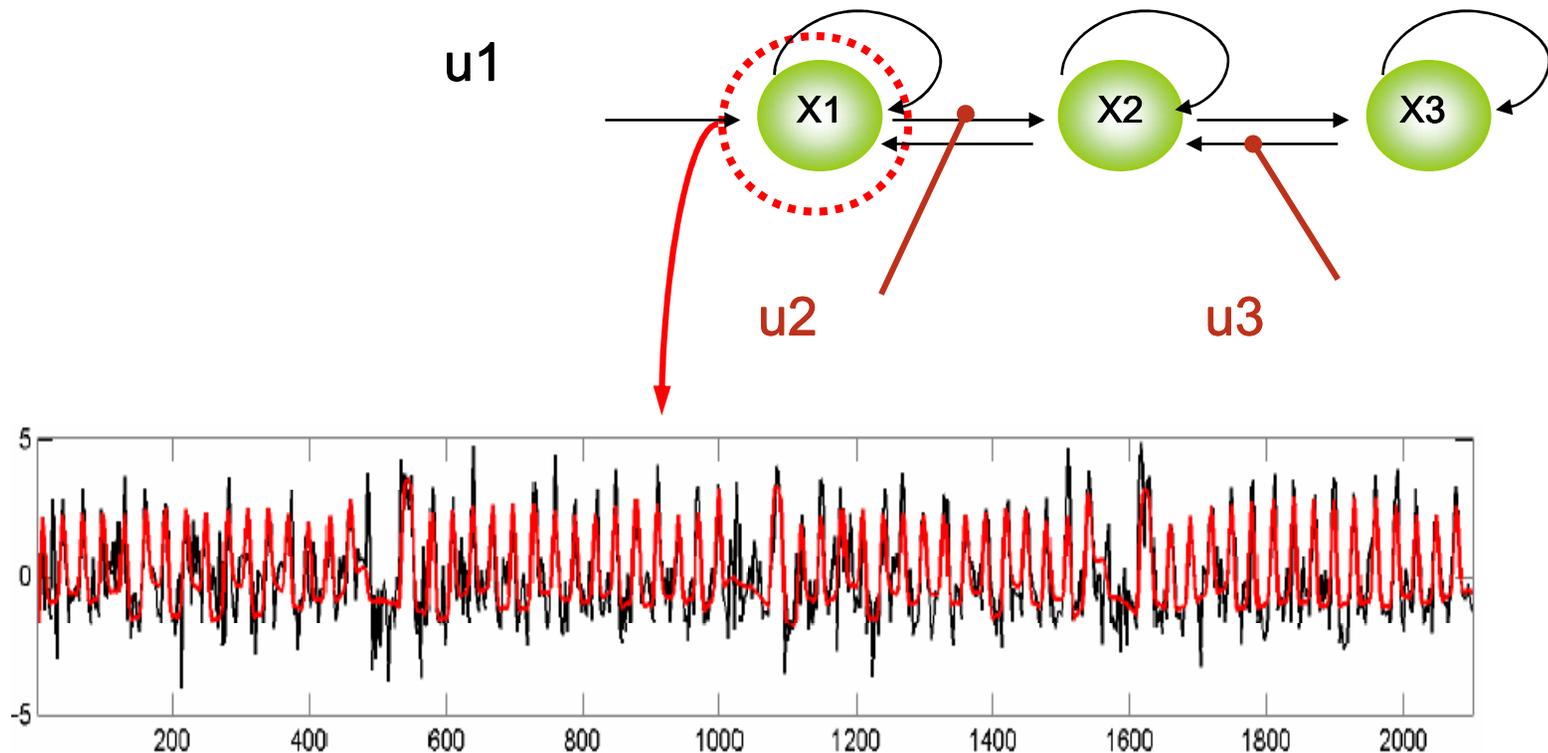
# Measured vs Modelled BOLD signal

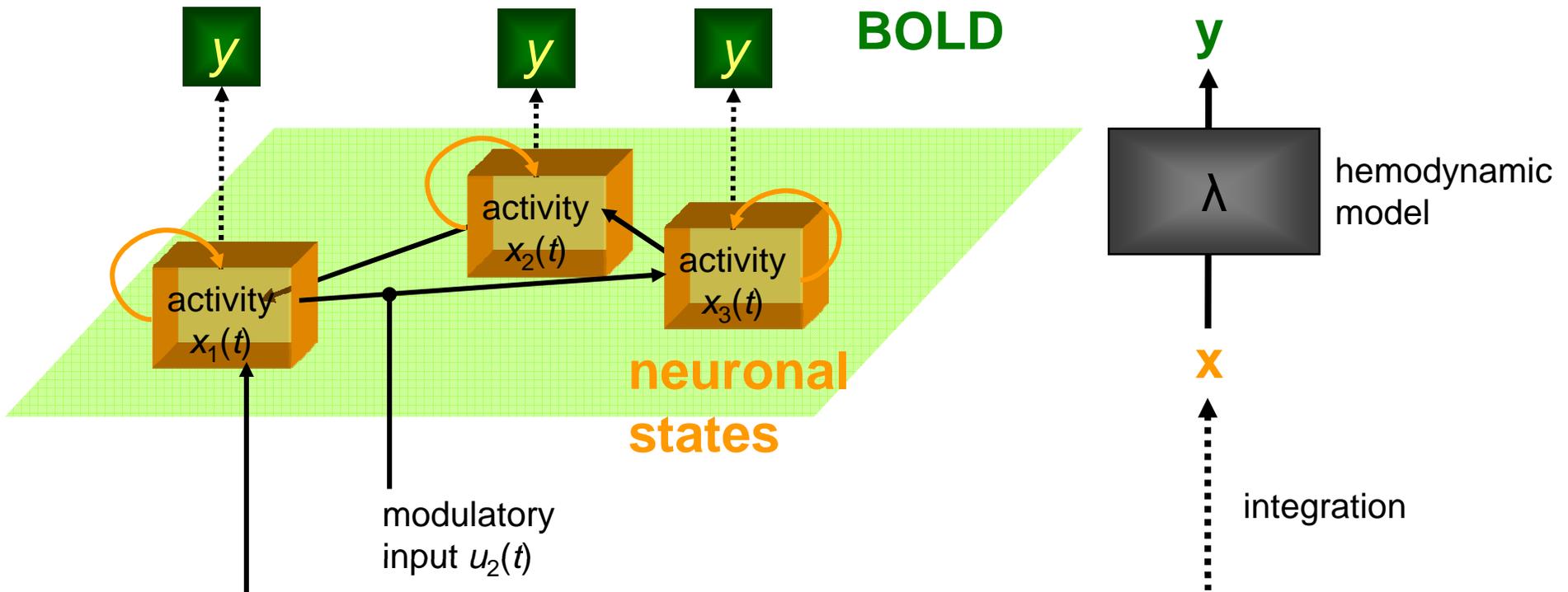
## Recap

The aim of DCM is to estimate

- neural parameters  $\{A, B, C\}$
- hemodynamic parameters

such that the **modelled** and measured BOLD signals are maximally similar.





**Neural state equation**  $\dot{x} = (A + \sum u_j B^{(j)})x + Cu$

endogenous connectivity  $\longrightarrow A = \frac{\partial \dot{x}}{\partial x}$

modulation of connectivity  $\longrightarrow B^{(j)} = \frac{\partial}{\partial u_j} \frac{\partial \dot{x}}{\partial x}$

direct inputs  $\longrightarrow C = \frac{\partial \dot{x}}{\partial u}$

# Overview

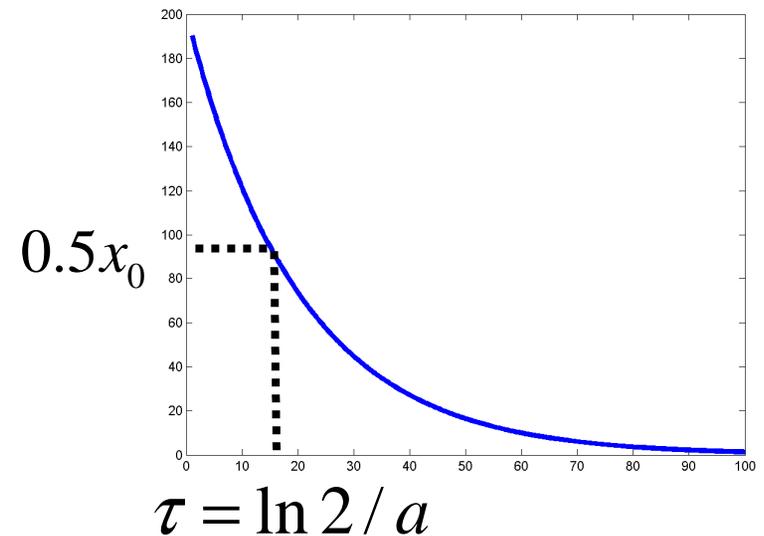
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  - Neural level
  - Hemodynamic level
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- Applications of DCM to fMRI data

# DCM parameters = rate constants

Integration of a first-order linear differential equation gives an exponential function:

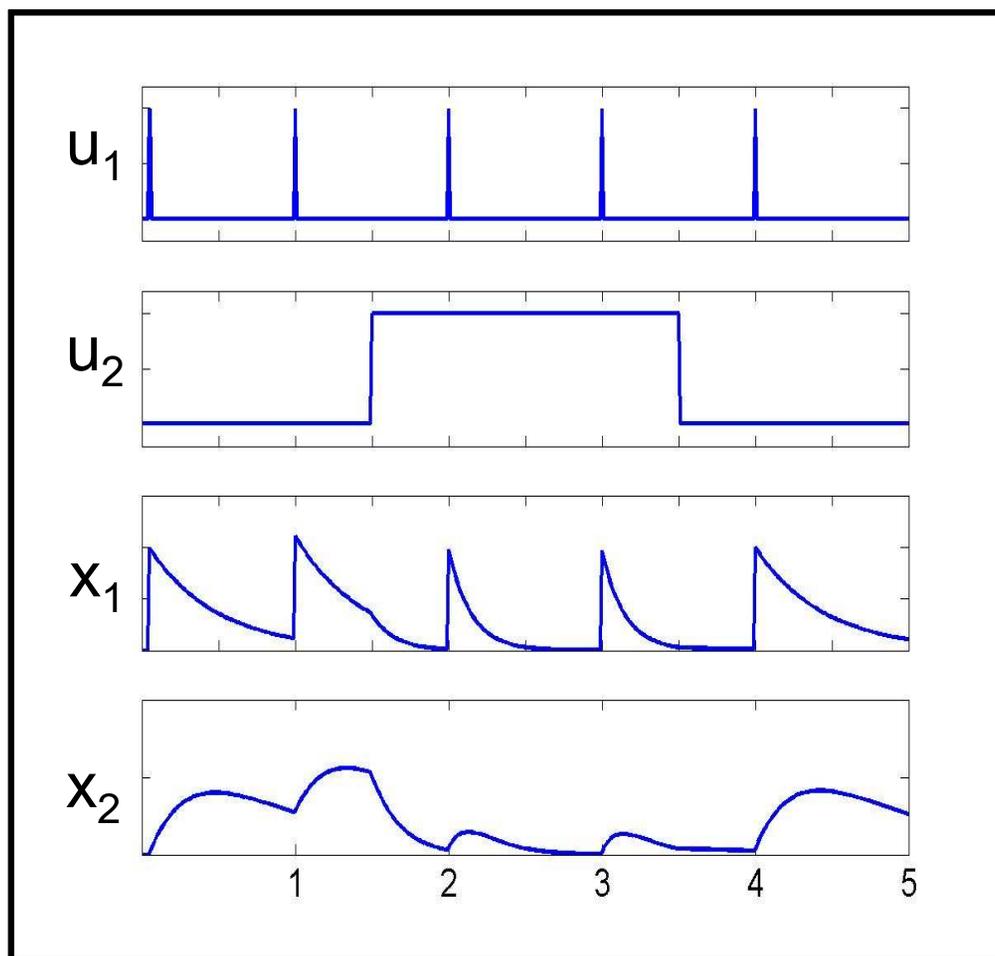
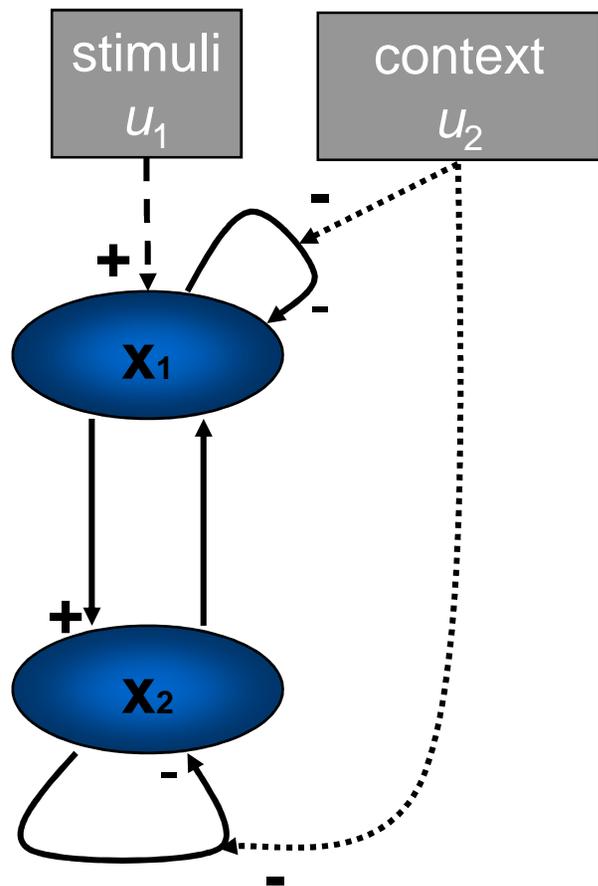
$$\frac{dx}{dt} = ax \longrightarrow x(t) = x_0 \exp(at)$$

The coupling parameter  $a$  determines the half life of  $x(t)$ , and thus describes the speed of the exponential change



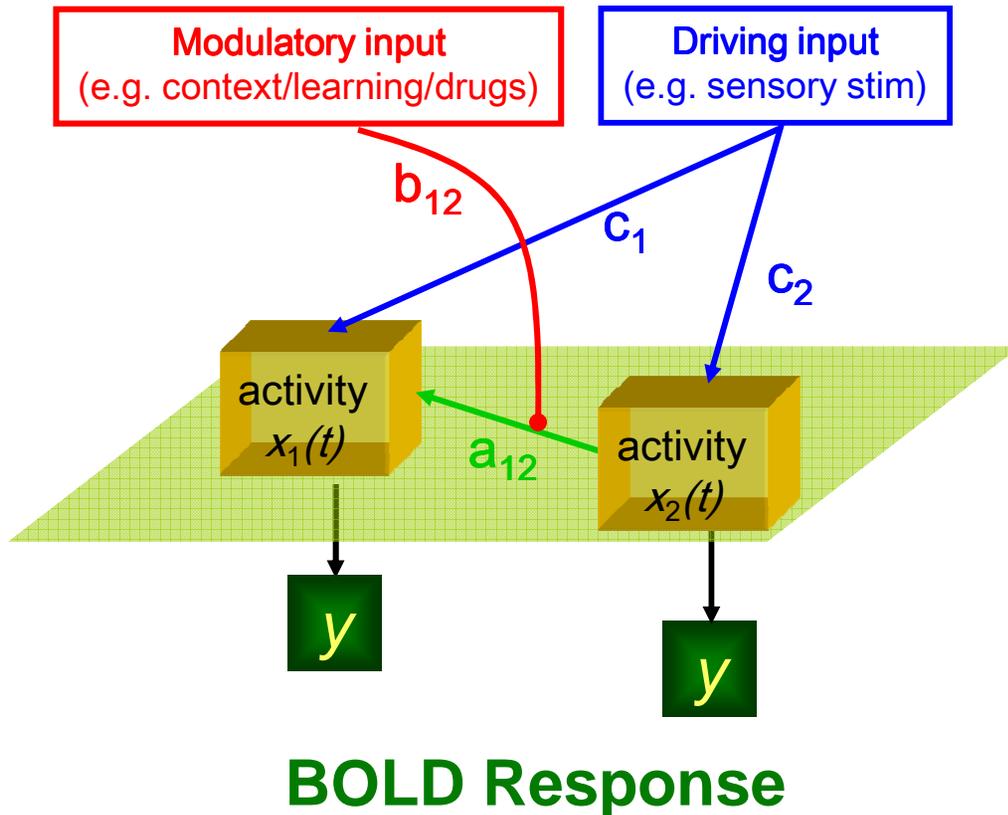
If  $A \rightarrow B$  is  $0.10 \text{ s}^{-1}$  this means that, per unit time, the increase in activity in B corresponds to 10% of the activity in A

# Example: context-dependent decay



# Conceptual overview

## Neuronal states



**Parameters are optimised so that the predicted matches the measured BOLD response**

**→ How confident are we about these parameters?**

# Bayesian statistics

Express our prior knowledge or “belief” about parameters of the model

new data

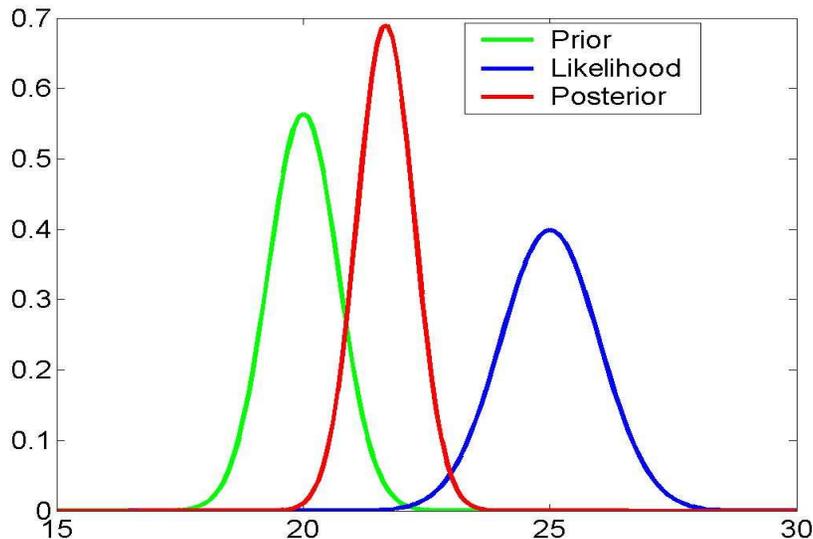
prior knowledge

$$p(y | \theta)$$

$$p(\theta)$$

$$p(\theta | y) \propto p(y | \theta) p(\theta)$$

posterior  $\propto$  likelihood  $\cdot$  prior



Parameters governing

- Hemodynamics in a single region
- Neuronal interactions

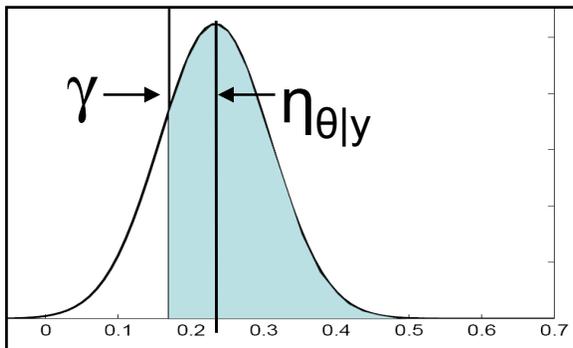
Constraints (priors) on

- Hemodynamic parameters
  - empirical
- Self connections
  - principled
- Other connections
  - shrinkage

# Inference about DCM parameters

## Bayesian single subject analysis

- The model parameters are distributions that have a mean  $\eta_{\theta|y}$  and covariance  $C_{\theta|y}$ 
  - Use of the cumulative normal distribution to test the probability that a certain parameter is above a chosen threshold  $\gamma$ :



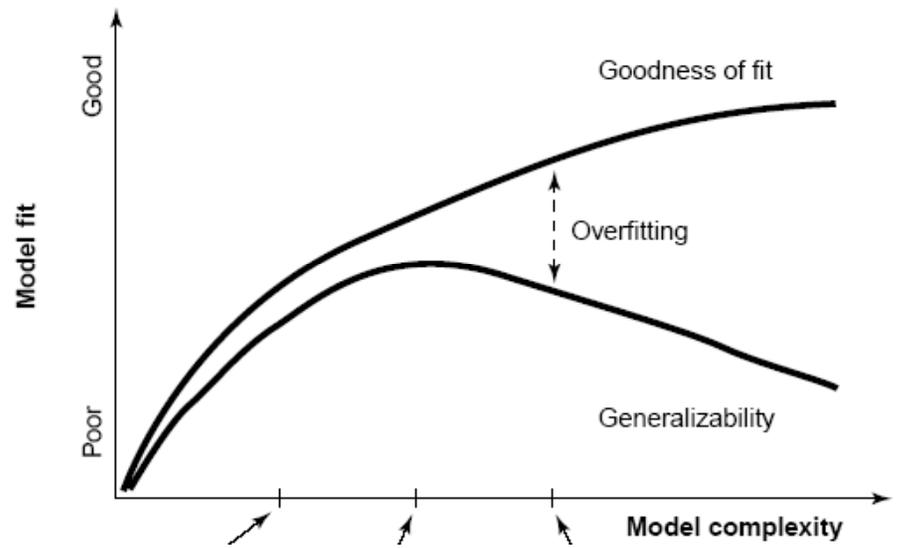
## Classical frequentist test across Ss

- Test summary statistic: mean  $\eta_{\theta|y}$ 
  - One-sample t-test: Parameter  $> 0$ ?
  - Paired t-test: parameter 1  $>$  parameter 2?
  - rmANOVA: e.g. in case of multiple sessions per subject

## Bayesian model averaging

# Inference about model space

Model evidence: The optimal balance of fit and complexity

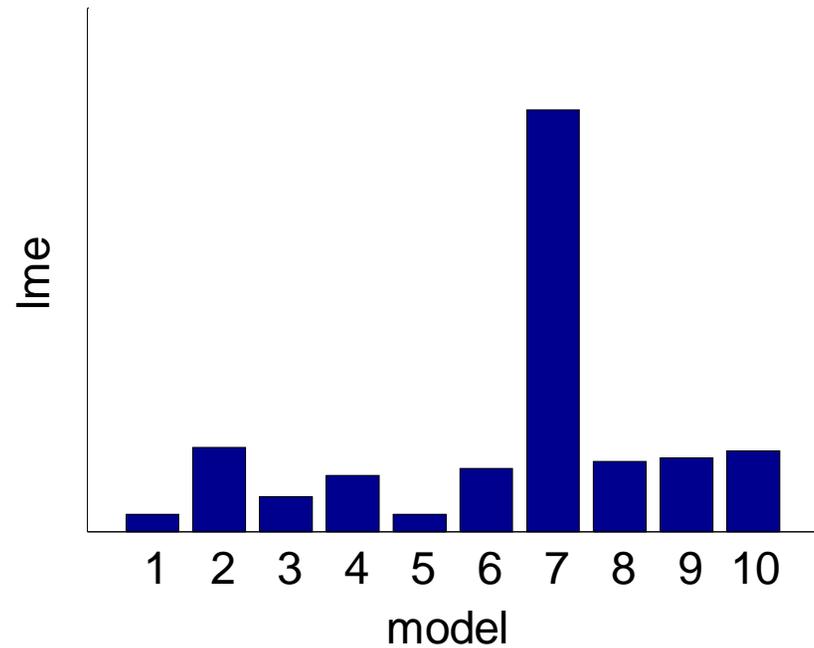
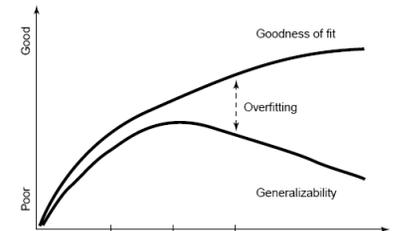


# Inference about model space

Model evidence: The optimal balance of fit and complexity

Comparing models

- Which is the best model?



# Inference about model space

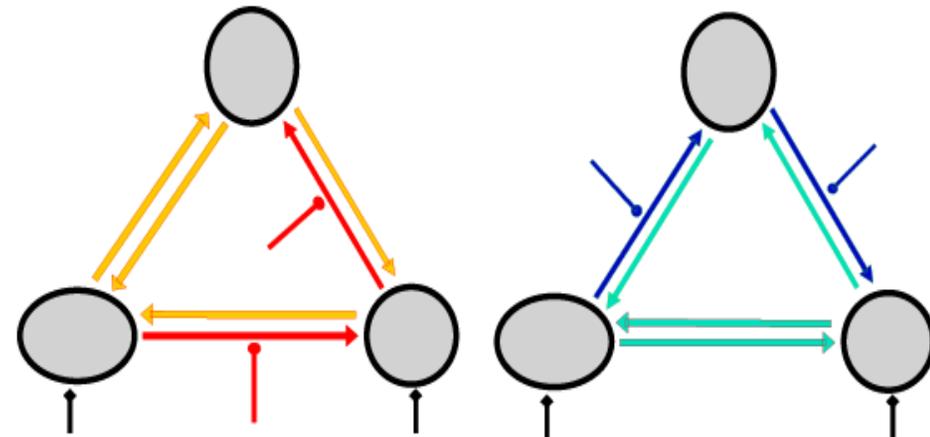
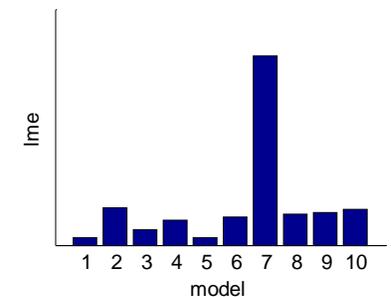
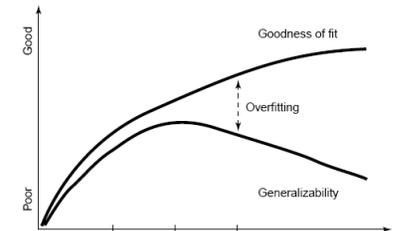
Model evidence: The optimal balance of fit and complexity

Comparing models

- Which is the best model?

Comparing families of models

- What type of model is best?
  - Feedforward vs feedback
  - Parallel vs sequential processing
  - With or without modulation



# Inference about model space

Model evidence: The optimal balance of fit and complexity

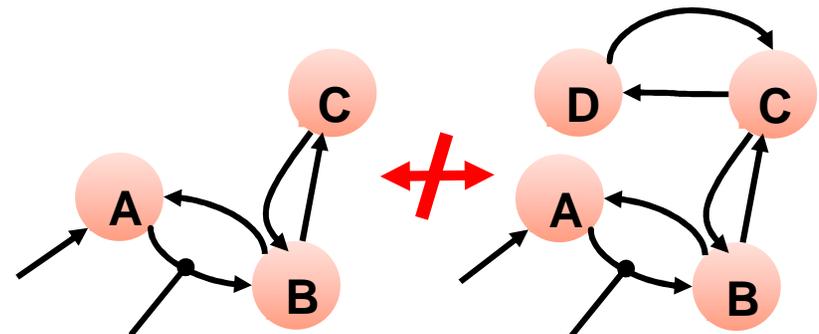
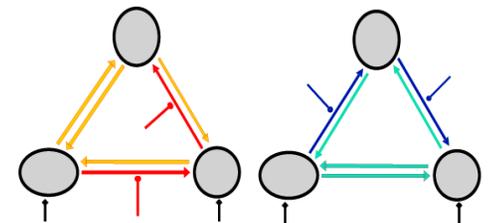
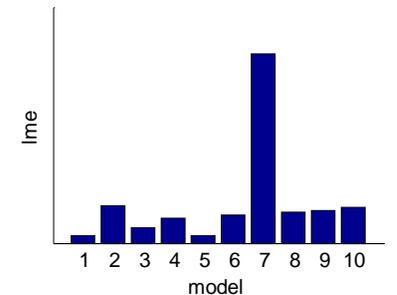
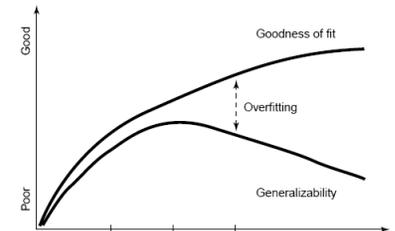
## Comparing models

- Which is the best model?

## Comparing families of models

- What type of model is best?
  - Feedforward vs feedback
  - Parallel vs sequential processing
  - With or without modulation

Only compare models with the same data



# Overview

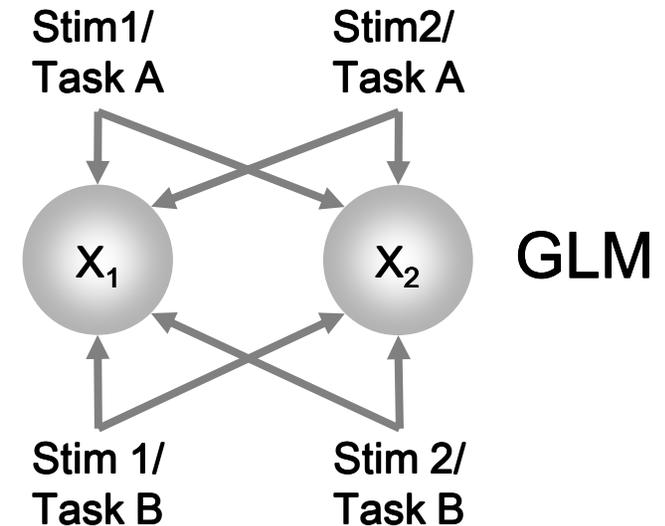
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- Dynamic causal models (DCMs)
- Applications of DCM to fMRI data
  - Design of experiments and models
  - Generating data

# Planning a DCM-compatible study

- Suitable experimental design:
  - any design that is suitable for a GLM
  - preferably multi-factorial (e.g. 2 x 2)
    - e.g. one factor that varies the driving (sensory) input
    - and one factor that varies the contextual input
- Hypothesis and model:
  - Define specific *a priori* hypothesis
  - Which parameters are relevant to test this hypothesis?
  - If you want to verify that intended model is suitable to test this hypothesis, then use simulations
  - Define criteria for inference
  - What are the alternative models to test?

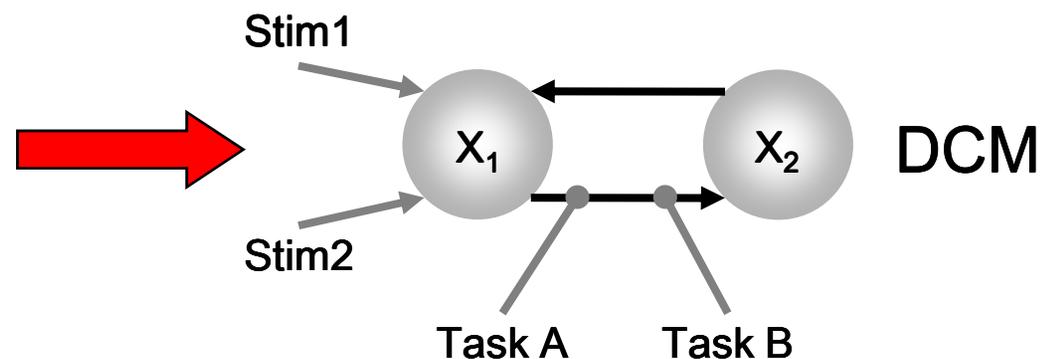
# Multifactorial design: explaining interactions with DCM

		Task factor	
		Task A	Task B
Stimulus factor	Stim 1	A1	B1
	Stim 2	A2	B2

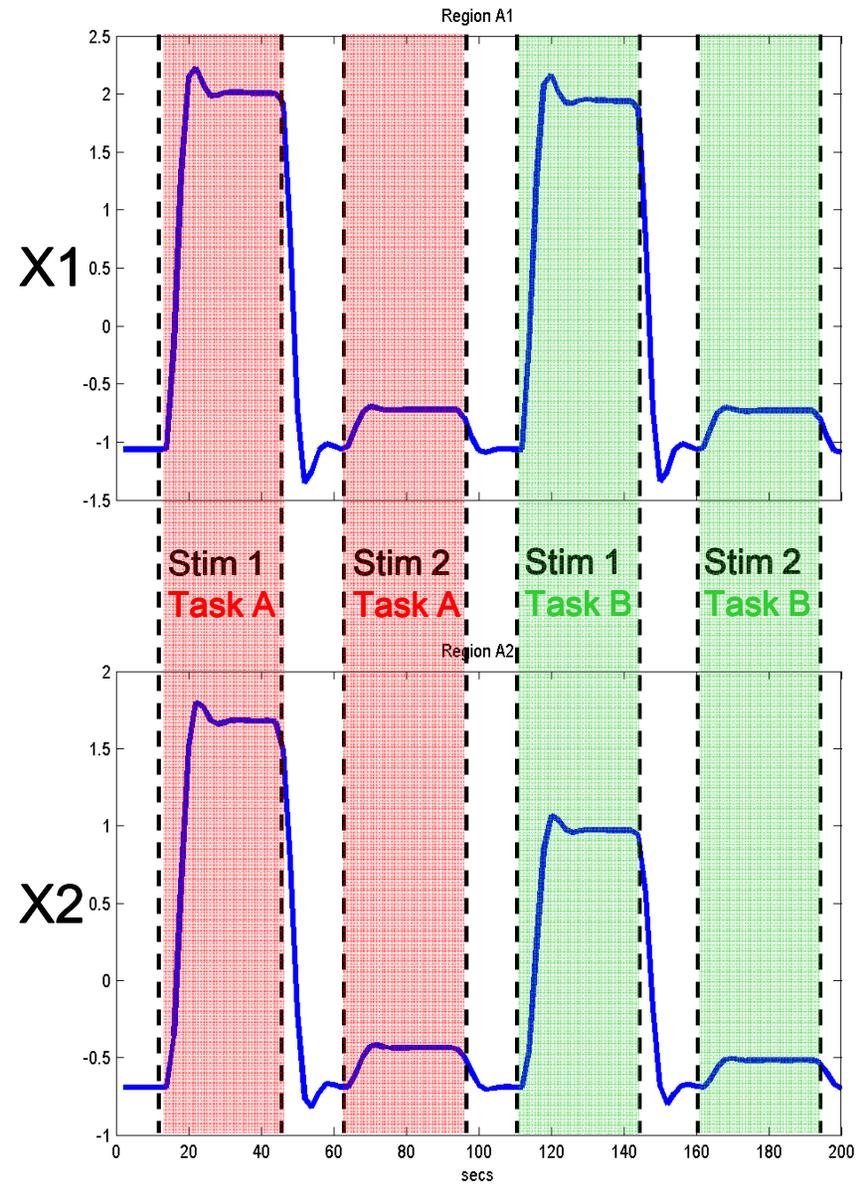
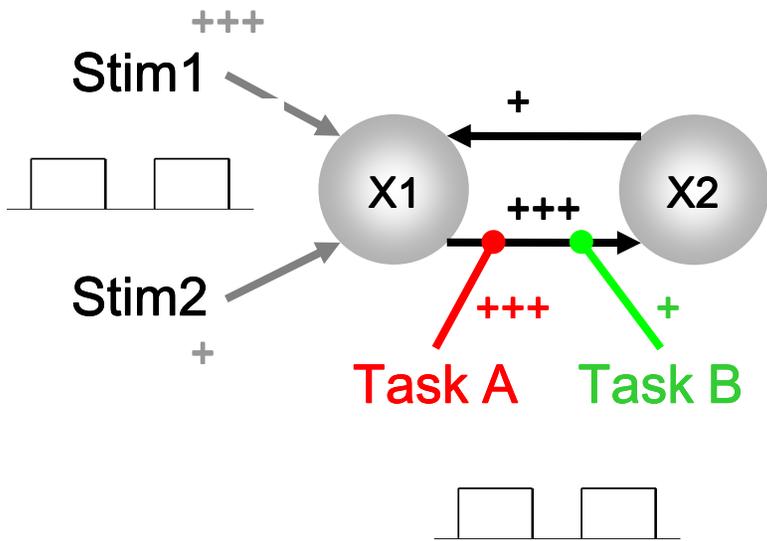


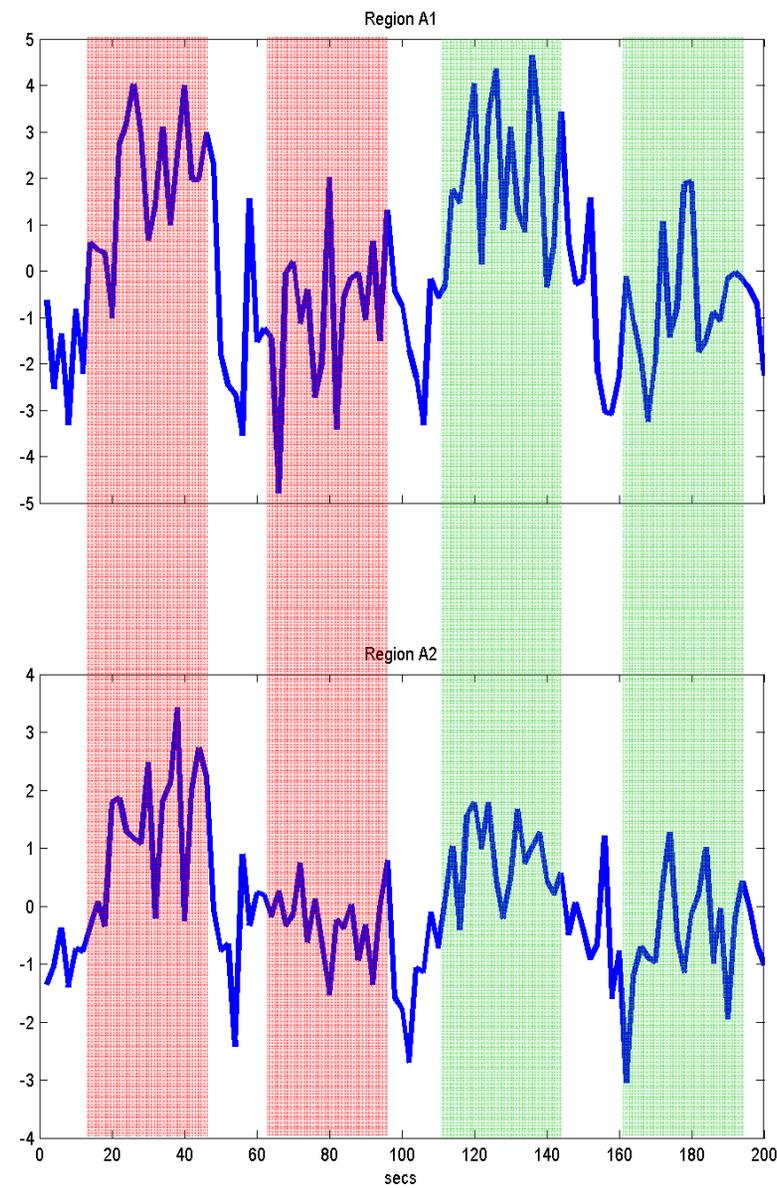
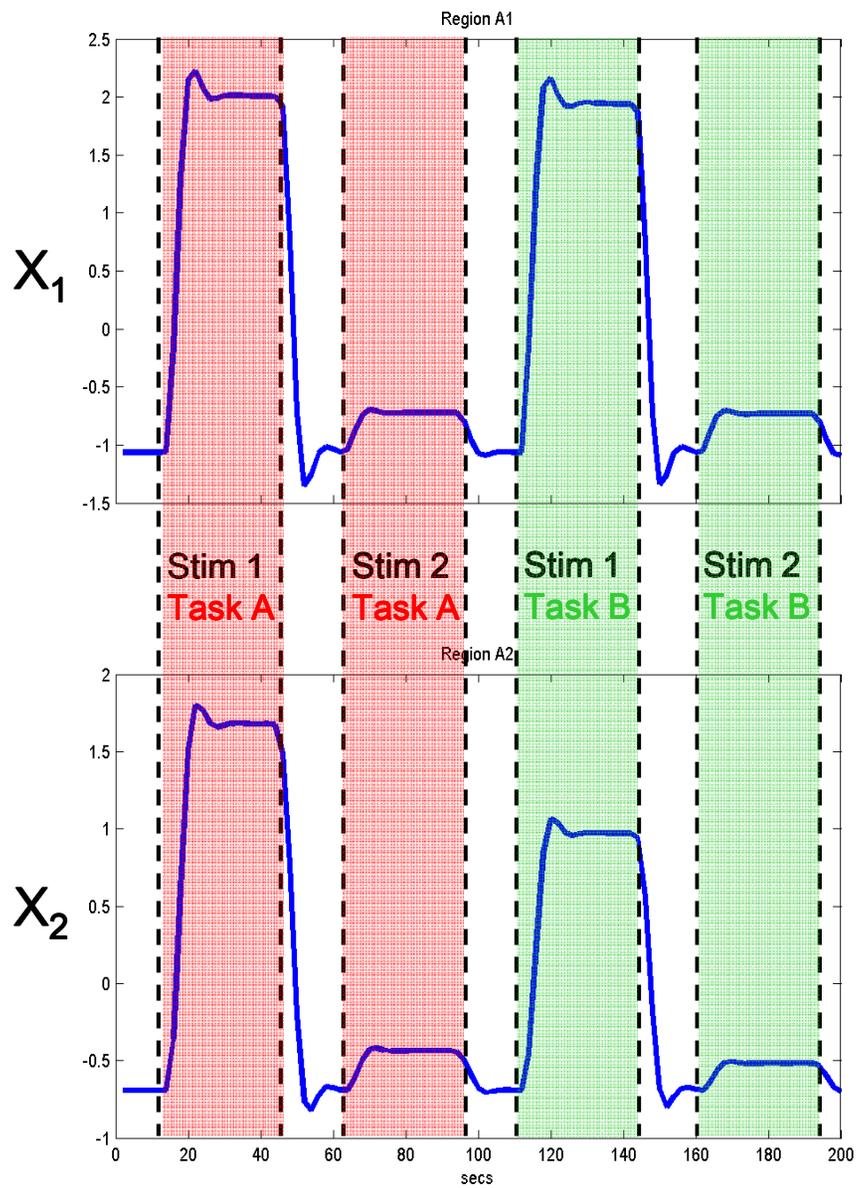
Let's assume that an SPM analysis shows a main effect of stimulus in  $X_1$  and a stimulus  $\times$  task interaction in  $X_2$ .

How do we model this using DCM?



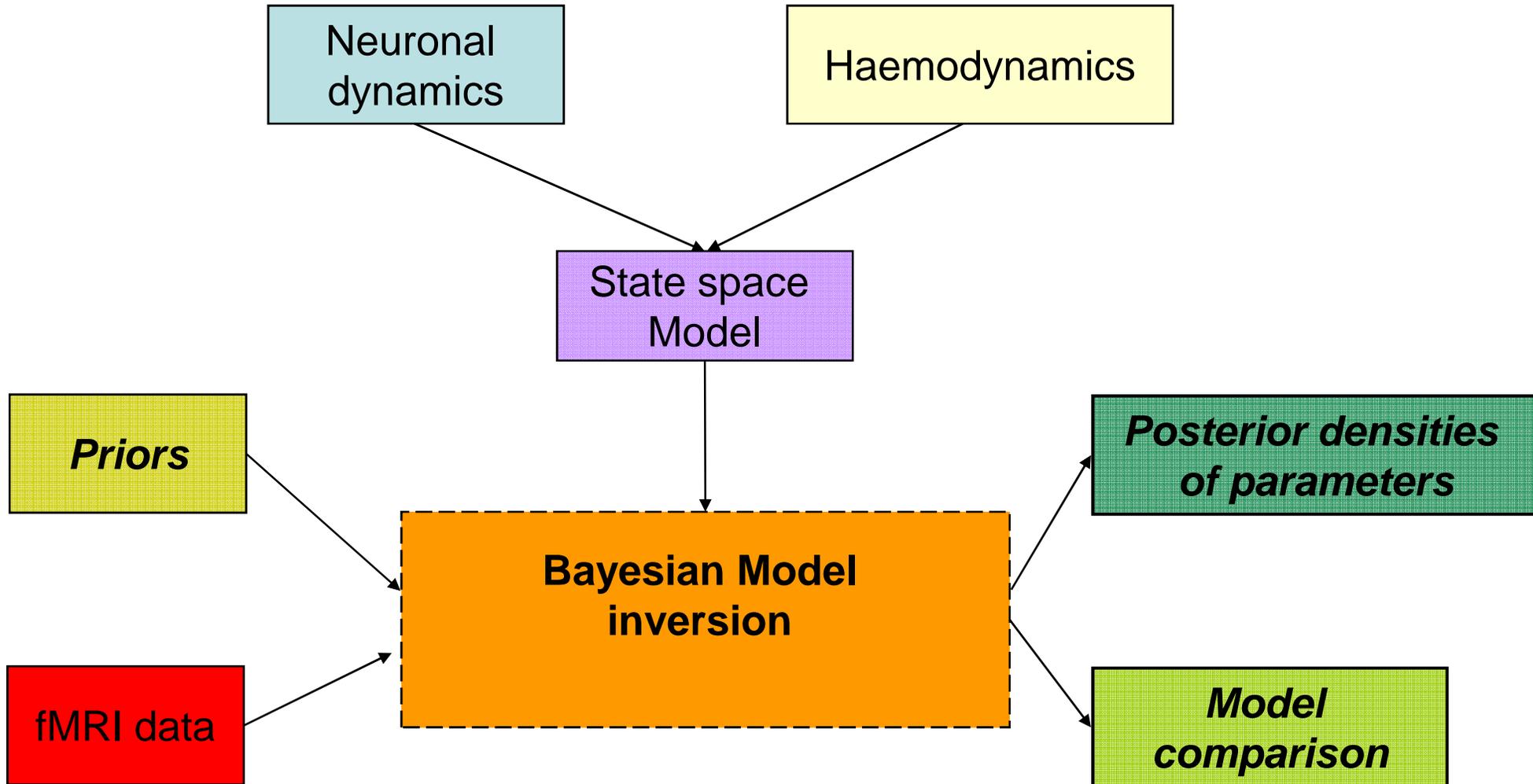
# Simulated data





plus added noise (SNR=1)

# DCM roadmap



# So, DCM....

- enables one to **infer hidden neuronal processes** from fMRI data
- tries to model the same phenomena as a GLM
  - **explaining experimentally controlled variance** in local responses
  - based on connectivity and its modulation
- allows one to **test mechanistic hypotheses** about observed effects
- is informed by anatomical and physiological principles.
- uses a **Bayesian framework** to estimate model parameters
- is a generic approach to modeling experimentally perturbed dynamic systems.
  - provides an observation model for neuroimaging data, e.g. fMRI, M/EEG
  - DCM is **not model or modality specific** (Models will change and the method extended to other modalities e.g. ERPs)

# Some useful references

- **The first DCM paper:** Dynamic Causal Modelling (2003). Friston et al. *NeuroImage* 19:1273-1302.
- **Physiological validation of DCM for fMRI:** Identifying neural drivers with functional MRI: an electrophysiological validation (2008). David et al. *PLoS Biol.* 6 2683–2697
- **Hemodynamic model:** Comparing hemodynamic models with DCM (2007). Stephan et al. *NeuroImage* 38:387-401
- **Nonlinear DCMs:** Nonlinear Dynamic Causal Models for FMRI (2008). Stephan et al. *NeuroImage* 42:649-662
- **Two-state model:** Dynamic causal modelling for fMRI: A two-state model (2008). Marreiros et al. *NeuroImage* 39:269-278
- **Group Bayesian model comparison:** Bayesian model selection for group studies (2009). Stephan et al. *NeuroImage* 46:1004-10174
- **10 Simple Rules for DCM (2010).** Stephan et al. *NeuroImage* 52.

Thank you



**Time to do a DCM!**

# Dynamic Causal Modelling

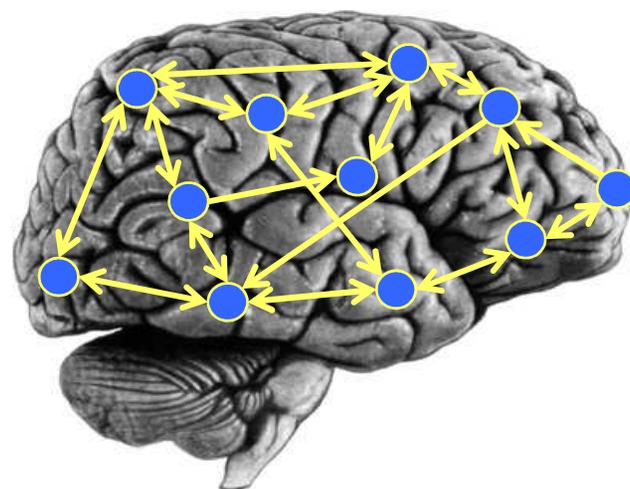
## PRACTICAL

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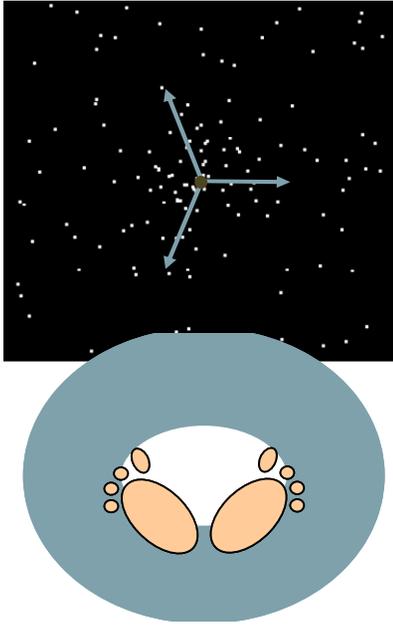
Donders Centre for Cognitive Neuroimaging  
Radboud University Nijmegen



SPM Course, London  
13-15 May 2010

# Attention to Motion in the visual system

## Paradigm



**Stimuli** 250 radially moving dots at 4.7 degrees/s

## Pre-Scanning

5 x 30s trials with 5 speed changes (reducing to 1%)  
Task - detect change in radial velocity

## Scanning (no speed changes)

F A F N F A F N S ....

F - fixation

S - observe static dots

N - observe moving dots

A - attend moving dots

+ photic

+ motion

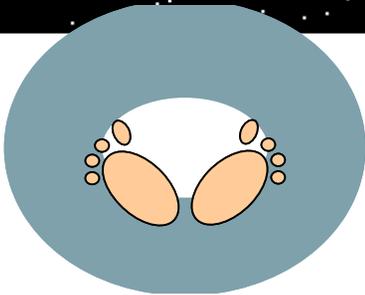
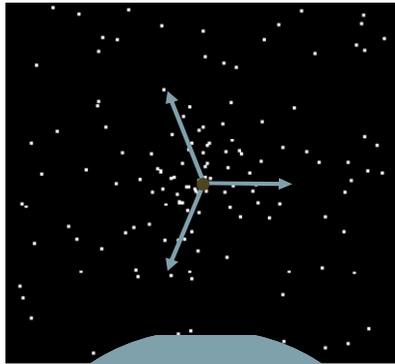
+ attention

## Parameters

- blocks of 10 scans
- 360 scans total
- TR = 3.22 seconds

# Attention to Motion in the visual system

## Paradigm

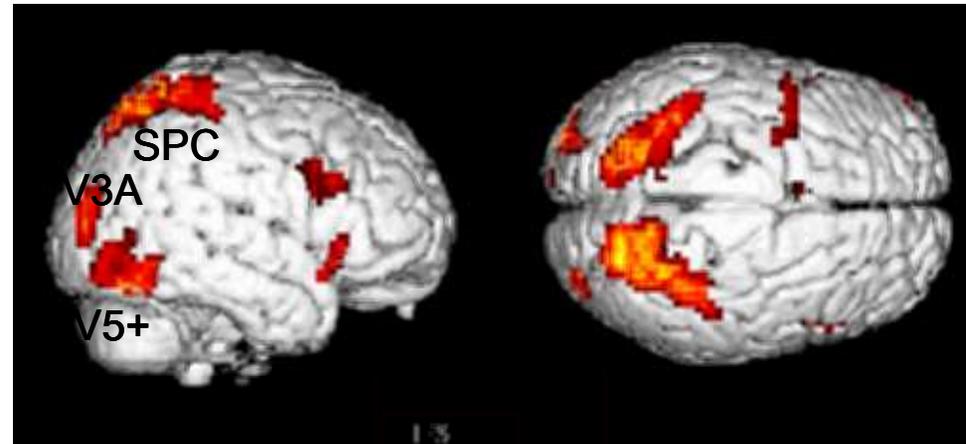


- fixation only
- observe static dots
- observe moving dots
- task on moving dots

- + photic
- + motion
- + attention

- V1
- V5
- V5 + parietal cortex

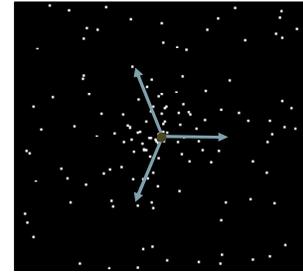
## Results



Attention – No attention

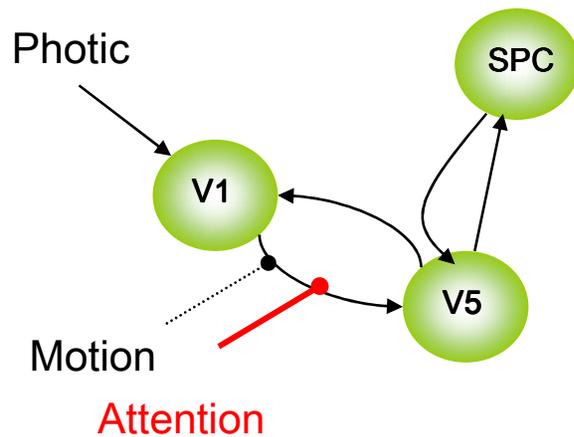
Büchel & Friston 1997, Cereb. Cortex  
Büchel et al. 1998, Brain

# DCM: comparison of 2 models



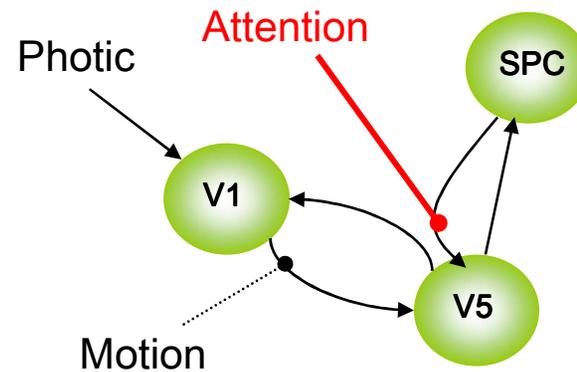
## Model 1

attentional modulation  
of V1→V5: forward



## Model 2

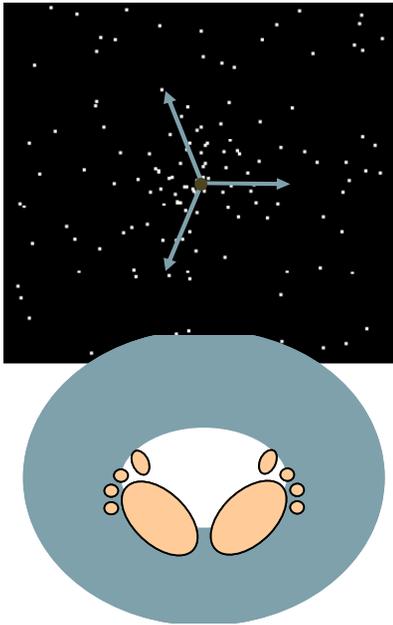
attentional modulation  
of SPC→V5: backward



Bayesian model selection: Which model is optimal?

# Attention to Motion in the visual system

## Paradigm



## Ingredients for a DCM

Specific hypothesis/question

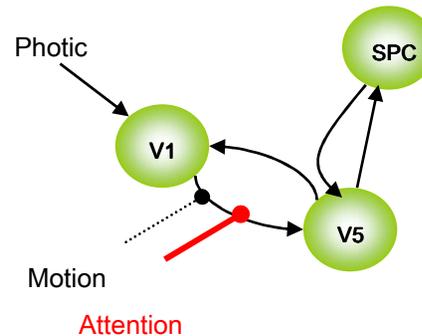
Model: based on hypothesis

Timeseries: from the SPM

Inputs: from design matrix

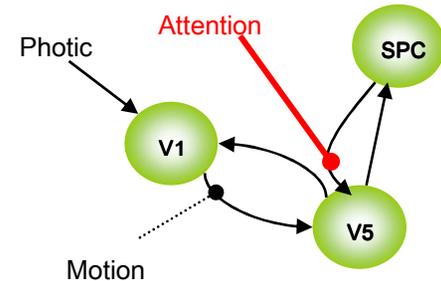
### Model 1

attentional modulation  
of V1→V5: forward



### Model 2

attentional modulation  
of SPC→V5: backward



# Attention to Motion in the visual system

## DCM – GUI basic steps

- 1 – Extract the time series (from all regions of interest)
- 2 – Specify the model
- 3 – Estimate the model
- 4 – Review the estimated model
- 5 – Repeat steps 2 and 3 for all models in model space
- 6 – Compare models