DCM workshop

Part 1

Timerseries extraction
First-level DCM model

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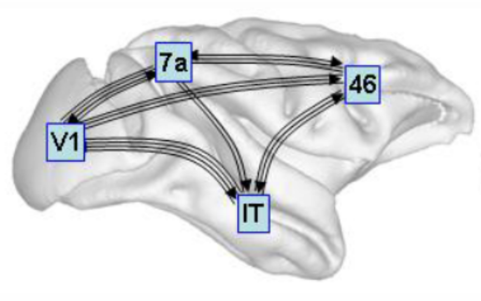
Workshop

Today (Nov 10)

- Some backgound on effective connectivity analysis
- How to identify functional networks
- How to extract time series information
- How to build a first-level DCM
- Review model fit

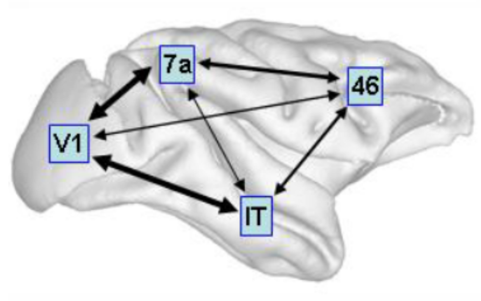
Background

structural connectivity



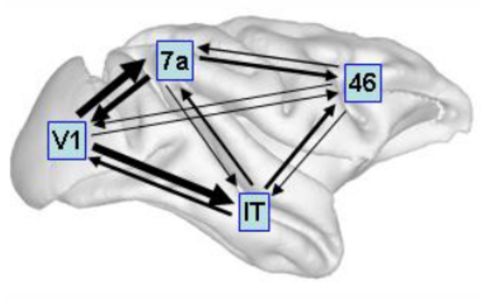
- presence of physical connections
- Diffusion weighted imaging (DWI), tractography, tracer studies

functional connectivity



- statistical dependencies between regional time series
- correlations, Independent Component Analysis (ICA)

effective connectivity



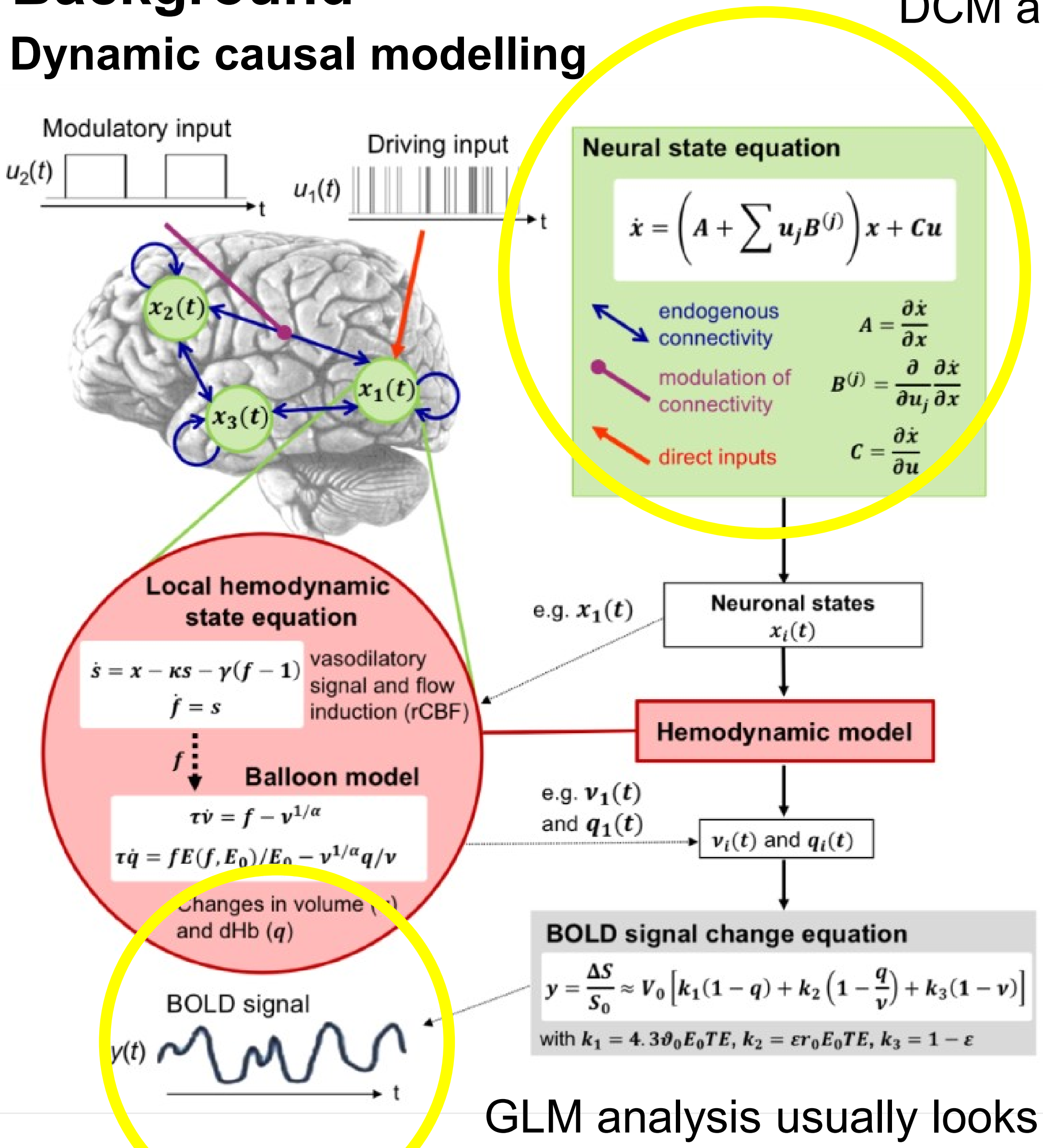
- causal (directed) influences between neuronal populations
- Dynamic causal modeling (DCM)

Sporns, 2007, *Scholarpedia*

Background

Dynamic causal modelling

DCM analysis looks at this



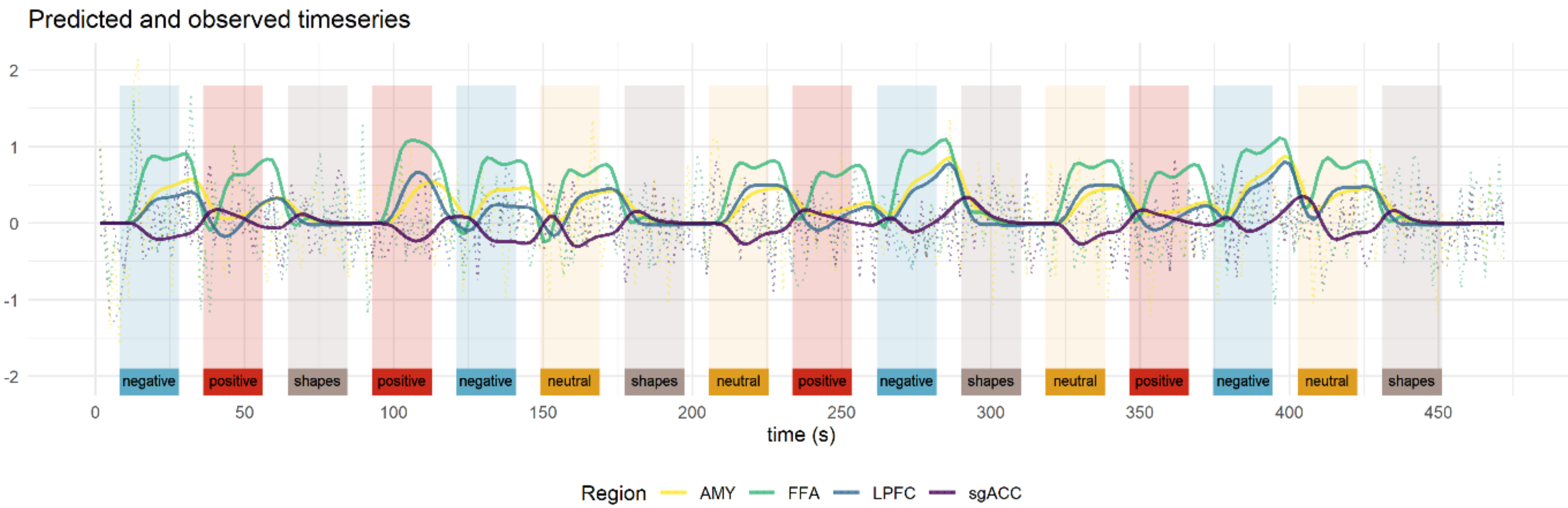
„How does change of activity in region A affect region B?“

Parameter matrices A, B and C

GLM analysis usually looks at this

Background
Dynamic causal modelling

Example (face matching):



Background

Dynamic causal modelling

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

A … „intrinsic / average connectivtiy“
→ Represents the average connectivity during the task („intercept“)

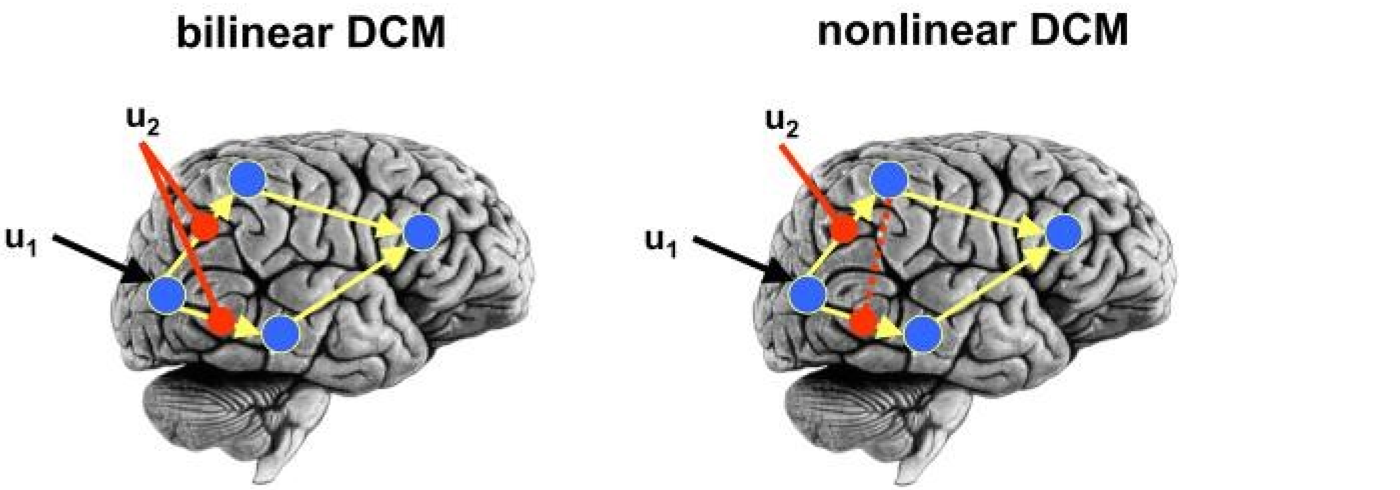
B … „modulatory parameters“
→ B matrix can model additive connectivity changes for a **condition**

C … driving input
→ Generally, we will use an „all events“ regressor as input

D … non-linear connectivity changes of one region between others
→ extension of B-matrix to explicitly model „source region“

This is typically supplied via an SPM.mat (GLM model)

Background
Dynamic causal modelling



Bilinear state equation

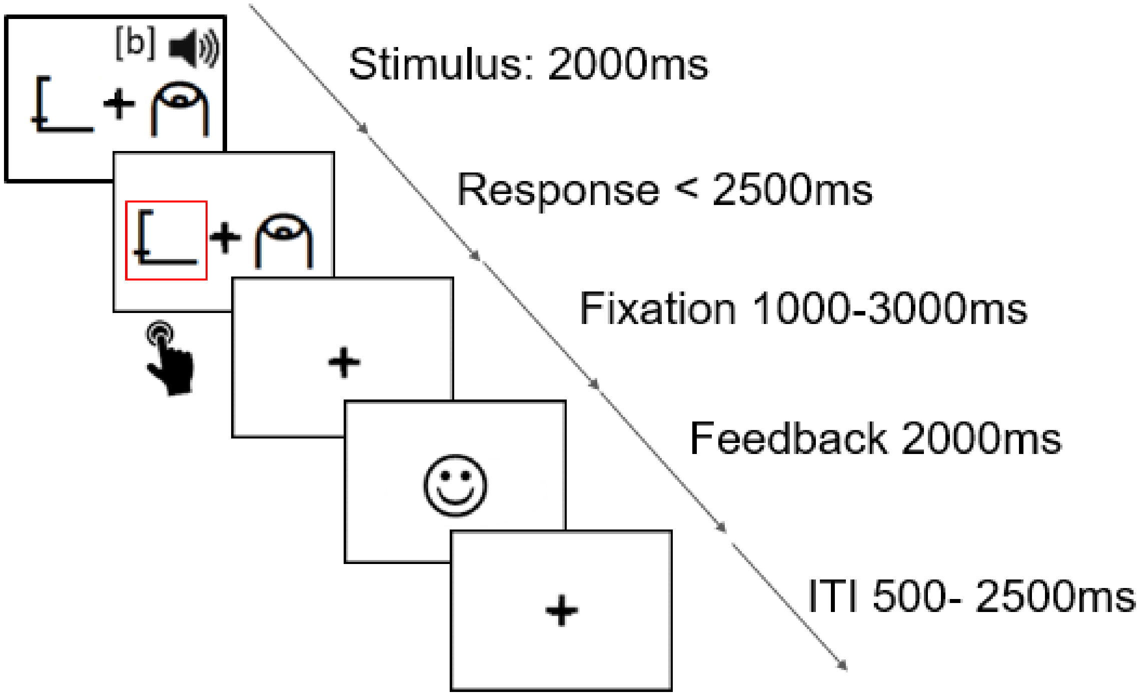
$$\frac{dx}{dt} = \left(A + \sum_{i=1}^{m} u_i B^{(i)} \right) x + Cu$$

Nonlinear state equation

$$\frac{dx}{dt} = \left(A + \sum_{i=1}^{m} u_i B^{(i)} + \sum_{j=1}^{n} x_j D^{(j)} \right) x + Cu$$

Stephan et al., 2008

DCM Example: Task



AllRead

- Associative learning task
- Analysis contains two runs
- Reinforcement learning model captures learned association strength (values 0-1)

Sample

from the 99 kids:

- Movement 4 no good block, 10 only 1 good block => -14, To good performers (0 error): -5

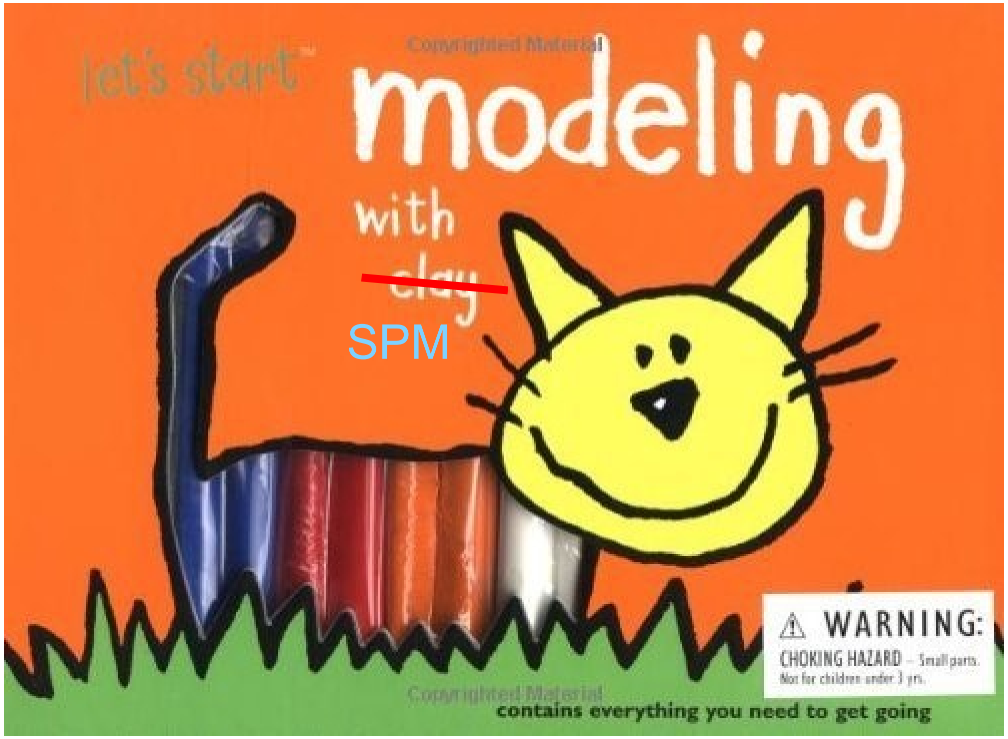
➔ 80

Groups

- 27 poor (<16 SLRT)
- 42 typical (>25 SLRT)
- 11 gap (in between)

Demographics

- aged 8.9 ± 0.74 years (group difference)
- 44 male, 36 female
- SLRT whole group: mean 40.35 ± 42.12
- 27 poor SLRT mean: 5.01 ± 4.25, 42 typical SLRT mean: 58.57 ± 21.53
- 8 left handed
- nonverbal IQ: 105.1 ± 7.01 (no significant groups difference)


let's start
Copyrighted Material
modeling
with ~~clay~~
SPM
WARNING:
CHOKING HAZARD – Small parts.
Not for children under 3 yrs.
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contains everything you need to get going

Prerequisites 1: Identify your hypothesis

- DCM is not good in exploratory analysis
- We need to formulate hypotheses and networks we are interested in a priori
- Typically:
  - How is connectivity modulated by condition A vs B
  - How do groups differ in connectivity
  - How does connectivity vary with a covariate

Prerequisites 2: Identify your network

- **Goal**: reveal the brain regions that are **related to the task**, such that we can extract the timecourse

- If a GLM analysis does not show activity in a region for any contrast, there is **no motivation** to include it in a DCM analysis → nothing to explain by our model

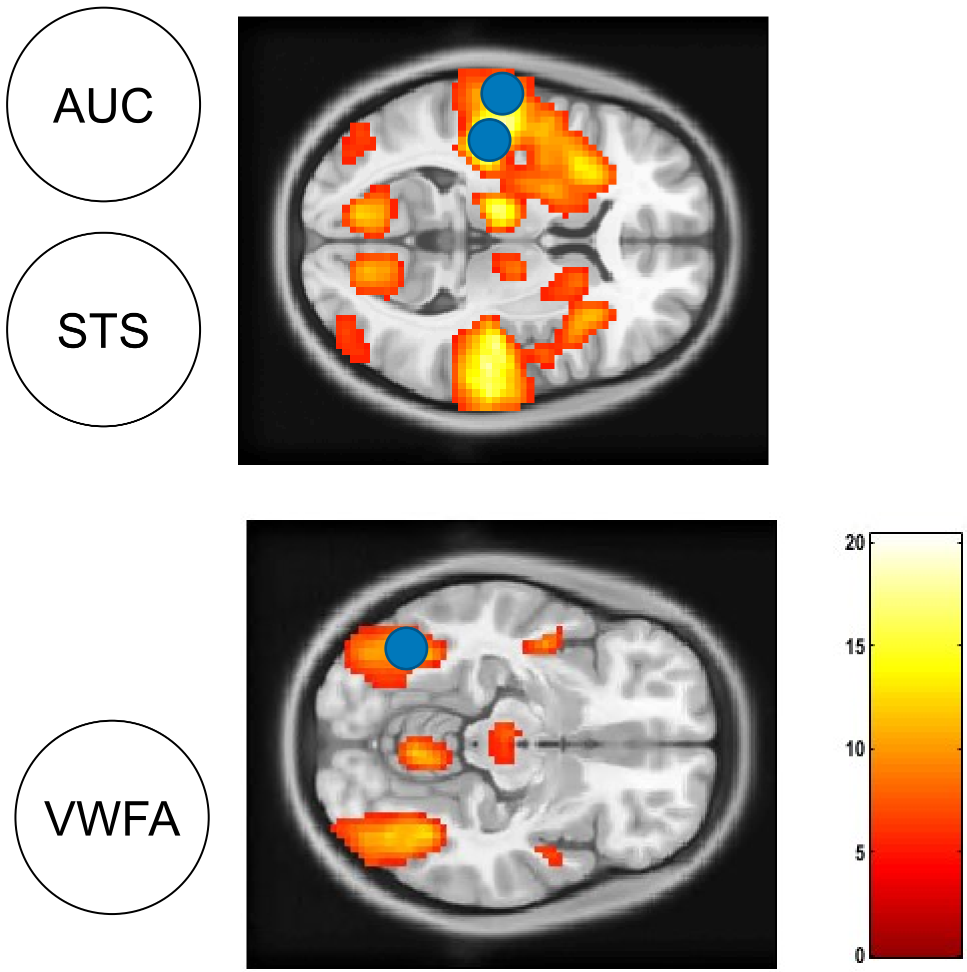
- Our example:

  - Is connectivity between regions supporting audiovisual integration affected by learning?

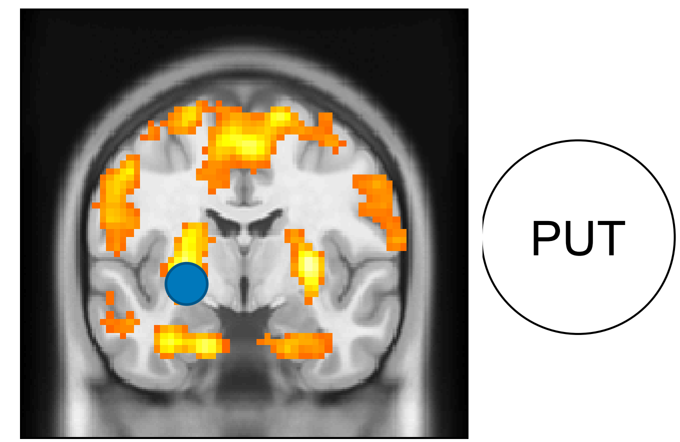
  - Do poor readers and typical readers differ?

DCM Example: Identify your network

Main effect of audiovisual stimulus



Effect of associative strength (AS)



den Ouden et al. (2010); Li et al. (2017, 2019)

Step 1: Timeseries extraction

- **Goal**: Extract the timeseries from all regions for all subjects
- This **multivariate timeseries** will be data to be modeled!
- Important:
  - Contains only signal from voxels with *at least some degree* of experimental effect (puncorr. < 0.05)
  - Can be constrained functionally and/or anatomically
  - Size of regions depends on structures investigated and smoothing kernel! Rule of thumb (radius ~ smoothing kernel ~ 6-8mm)
- After extraction **check for subjects** that do not show activity in single regions → will have to be excluded

Step 2: Create GLM for DCM

- **Goal**: Create a model for DCM analysis (separate SPM.mat)
- Includes all regressors that enter the DCM
- Usually simpler than GLMs of activity analysis
- If we have multiple sessions, we need to **concatenate them**

Step 3: Create DCMs

- **Goal**: Create a model for DCM analysis based on previously created SPM.mat (results in a **DCM.mat**)

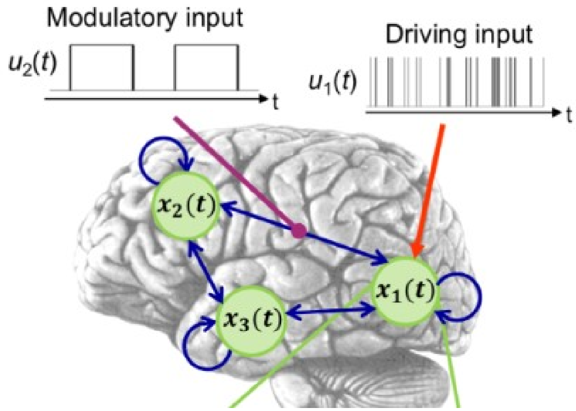
- Stores information about model inputs, priors of connectivity and haemondynamic parameters, timing, onsets, …

- Connectivity priors → do I have prior knowledge of connections?

- Task modulations

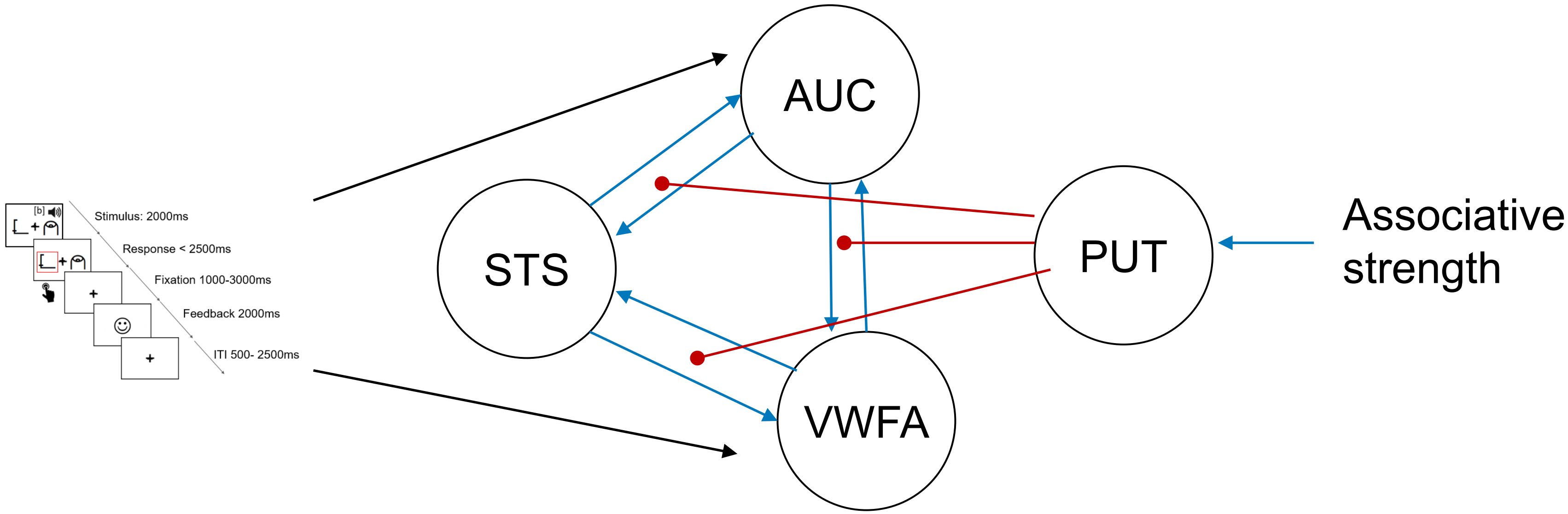
- **Model input** = where does TASK enter? ("ping the network")

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



DCM example: start with a fully connected graph

– Unless you have a very good reason to assume no connections between two regions



DCM example: Assessment of first-level results

– spm_dcm_fmri_check

DCM example: Assessment of first-level results

– spm_dcm_review