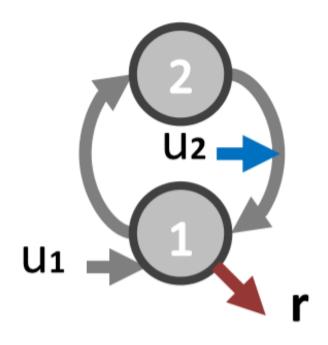
Behavioural DCM in practice

Lionel Rigoux

Outline

- Preparing the data
 - Extracting ROI time series
 - · Behavioural responses and resampling
 - Defining the inputs
- Specifying the model
 - DCM connectivity
 - Behavioural mapping
 - Behavioural response transformation
- Model simulation & inversion
 - Sources and hyperpriors
 - Wrapping up
- Model Simulation and analysis
 - Artificial lesions
 - Susceptibility analysis



Preparing the data

Extracting timeseries

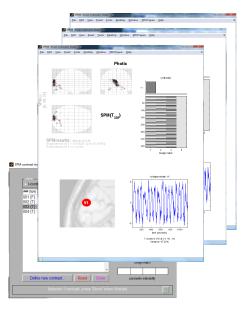
From a DCM specified in SPM:

• DCM.y'

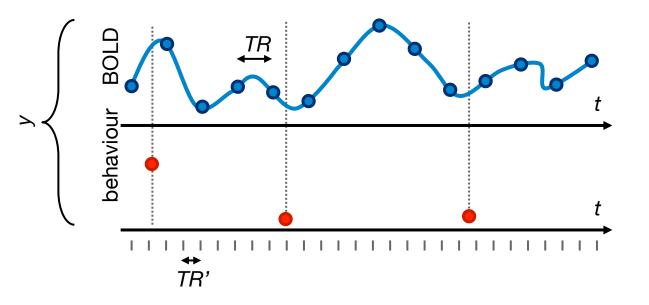
Using SPM:

- Define your ROI
- Extract 1st eigenvariate
- Adjust for effect of interest
- Save





Preparing the data



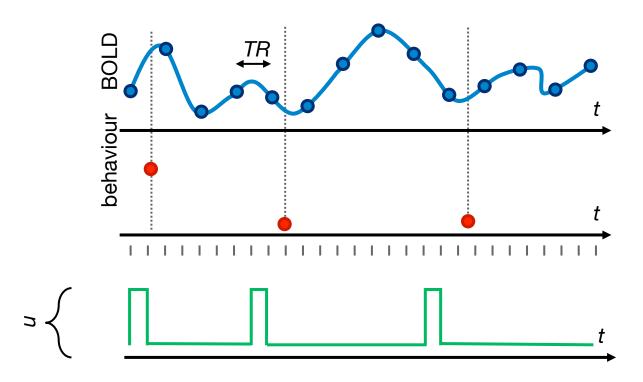
In practice

- Resample BOLD and behaviour at the same frequency (eg. TR/4 or TR/20)
- Fill in missing value with NaNs
- Store in one matrix $y = [y_bold ; y_resp]$

Tips

- Increasing the frequency will slow down the inversion
- Response predictor is smoothed by a kernel: round to the next timestep

Preparing the data



In practice

- · You can use DCM.U.u'
- Resample the inputs:
 - at the same frequency as y
 - at the microtime resolution DCM.U.dt

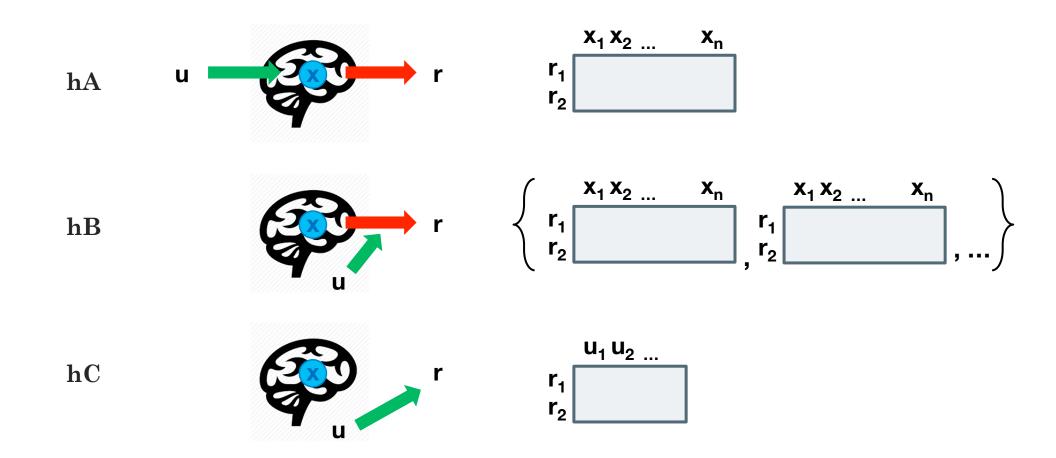
Define the brain connectivity model

```
A = DCM.a intrinsic connectivity
```

B = DCM.b modulatory influences

C = DCM.c inputs

D = DCM.d quadratic effects



Define the brain connectivity model

A = DCM.a intrinsic connectivity

B = DCM.b modulatory influences

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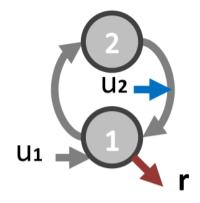
D = DCM.d quadratic effects

Define the behavioural mapping

hA neuro-behavioural mapping

hB neural modulation of inputs

hC direct input



$$A = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}$$
$$B_2 = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix}$$
$$C = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$hA = (10)$$

Define the behavioural transformation

• Dynamics of the bDCM is computed by the evolution function *f_DCMwHRFext*

$$[\blacksquare x @r] = f([\blacksquare x @r], u, \theta)$$

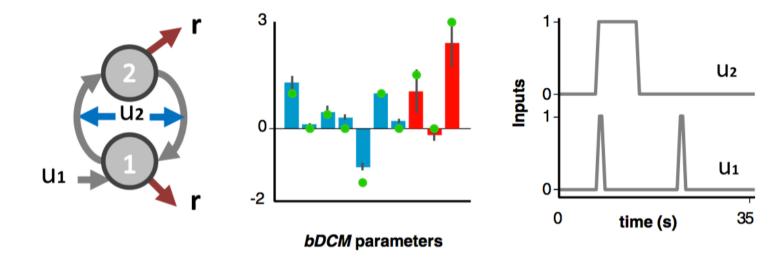
- Need to map the response predictor(s) r onto the response
 - sigmoid for binomial response
 - exponential for RT
 - softmax for multinomial
 - etc.
- The HRF and the response transformation must be combined into one observation function, eg. *g_DCMwHRFext*

 $[\blacksquare y \downarrow mri @y \downarrow beh] = g([\blacksquare x @r], u, \phi)$

Model simulation

Model simulation

- Set the parameters of the connectivity and the mapping
- $y = simulateNLSS(n_t, f_fname, g_fname, theta, phi, u, alpha, sigma, options);$



Model inversion

Source specification

- Need to use the different data types differently
 - Different distributions
 - Different noise variances
 - > options.sources to split the observations y into separate distributions

Hyperpriors

- All sources are influencing the inversion according to their respective precision
- Hyperpriors define the (prior) precision of Gaussian sources
 - > getHyperpriors() to set priors as a function of expected explained variance

Model inversion

You need

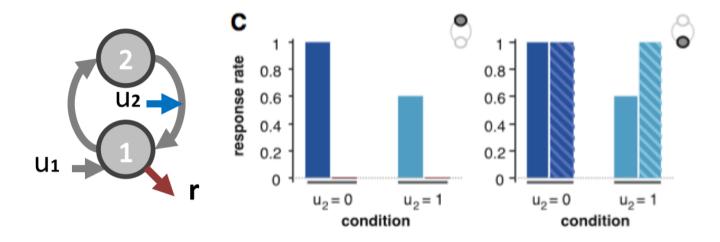
- Combined observations y and inputs u
- options structure containing the model definition: prepare_fullDCM
- Combined observation function
- Add priors to the options: getPriors
- Specify how to split the data: *options.sources*

Then run

 $[posterior, out] = VBA_NLStateSpaceModel(y, u, f_fname, g_fname, dim, options);$

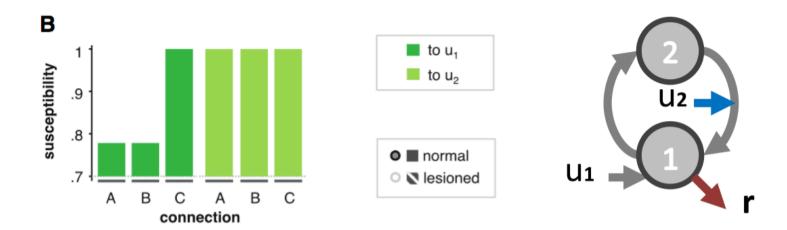
Virtual lesions

- Switch off all the afferences to a ROI and simulate the reduced model
- res = VBA_bDCM_lesion (posterior,out);



Susceptibility analysis

- res = VBA_susceptibility(posterior,out);
- res



Thank you