M/EEG Connectivity using Dynamic Causal Modelling (DCM)

Pranay Yadav, Rik Henson

CBU Neuroimaging Training, Feb 2023
https://imaging.mrc-cbu.cam.ac.uk/methods/IntroductionNeuroimagingLectures

Overview

- DCM for fMRI (yesterday)
  - Fitting single subject
  - Talk by Rik: https://www.youtube.com/watch?v=1VOKsWWLgjk

- DCM for MEG/EEG (today)
  - Fitting single subject
  - Talk by Pranay: https://www.youtube.com/watch?v=HNaAvKmVCYo

Overview

- MEG/EEG connectivity – lots of methods…
  - Lectures by Olaf (MNE Python)
  - Talk by Rik: https://www.youtube.com/watch?v=6b35VvQpPDU
- …but we will focus on DCM for evoked responses:
  - Talk by Pranay: https://www.youtube.com/watch?v=HNaAvKmVCYo

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REVIEW
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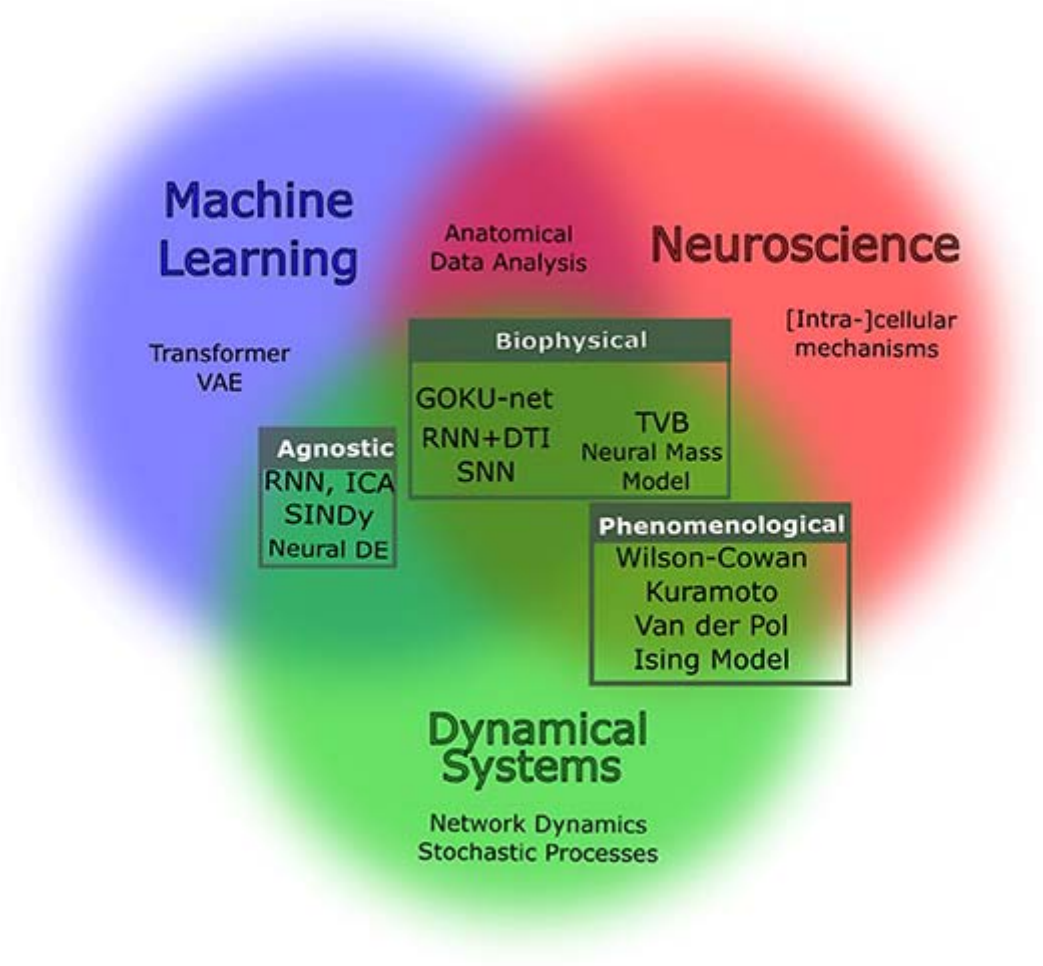

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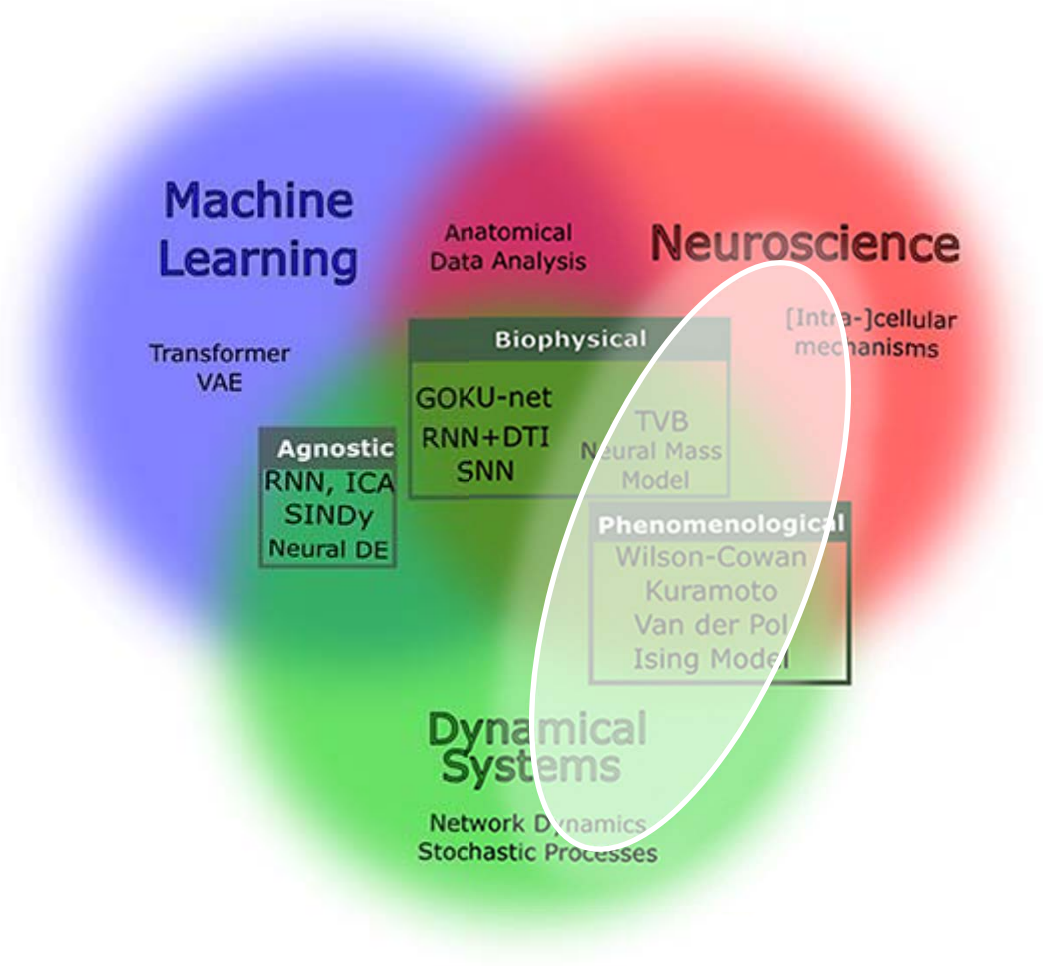

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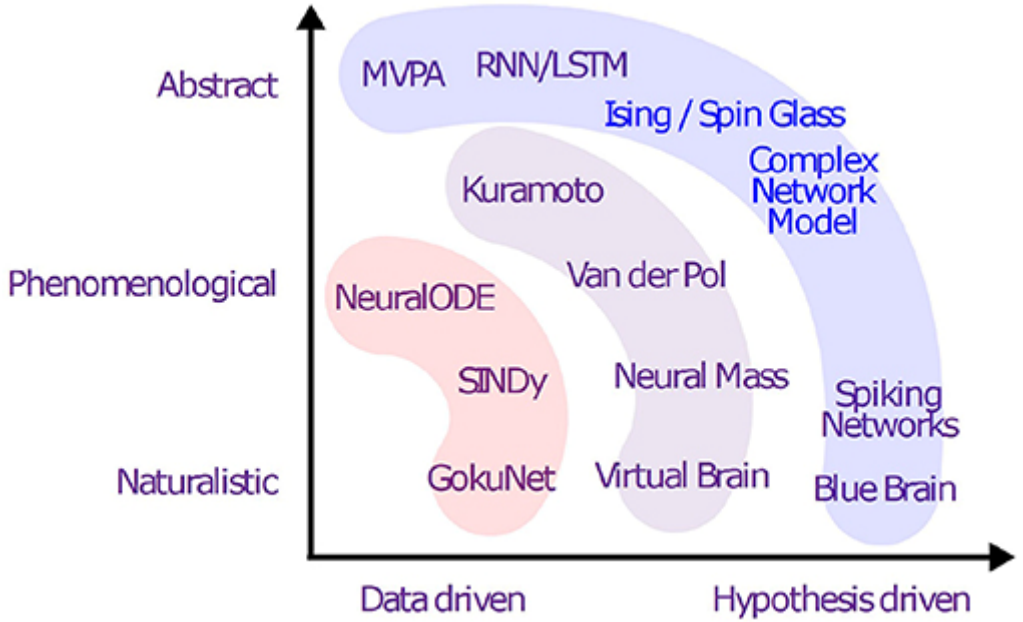

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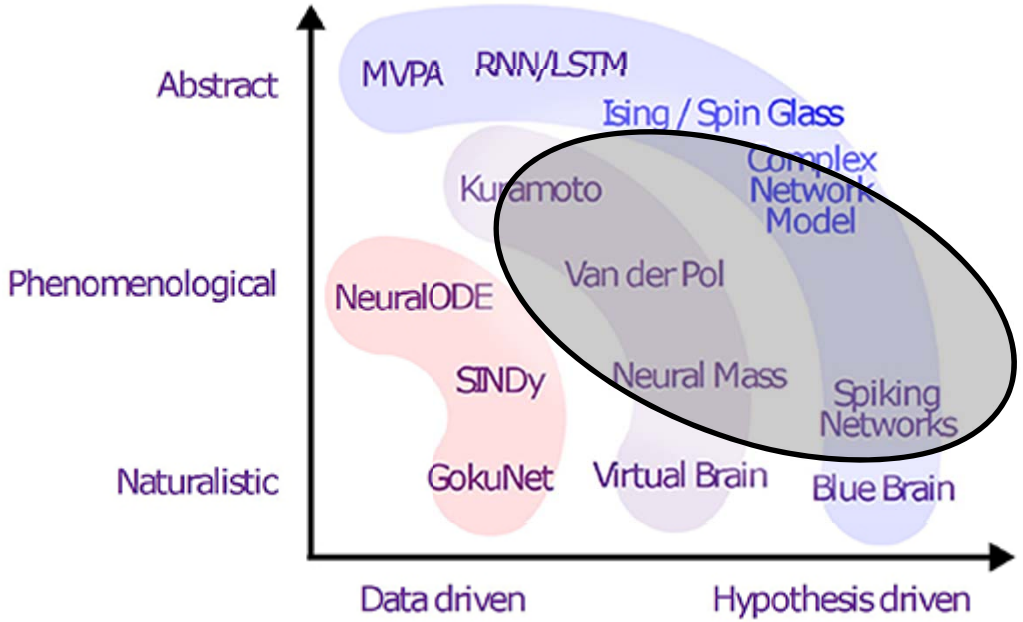

Motivation

Effective Connectivity

2004-2005 onwards

Synaptic Assay

2008-2011 onwards

Motivation

ELSEVIER

NeuroImage

Volume 42, Issue 1, 1 August 2008, Pages 272-284

Bayesian estimation of synaptic physiology from the spectral responses of neural masses

R.J. Moran [a b], K.E. Stephan [b d], S.J. Kiebel [b], N. Rombach [c], W.T. O'Connor [c e], K.J. Murphy [c], R.B. Reilly [a], K.J. Friston [b]

Modelled LFP spectral phenomena
from mPFC of Wistar rats

Motivation

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Modelled spectra in PFC from MEG as a function of AMPA, NMDA and GABA

Current Biology

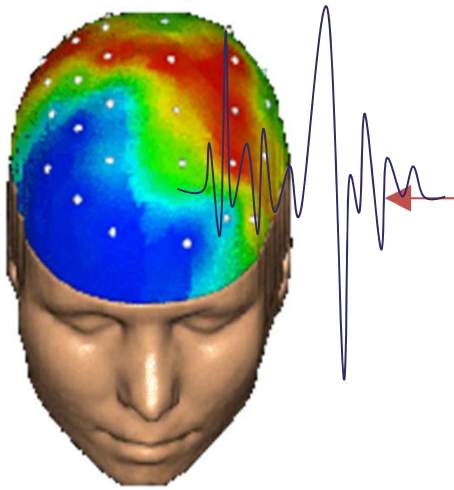
Volume 21, Issue 15, 9 August 2011, Pages 1320-1325

Report

An In Vivo Assay of Synaptic Function Mediating Human Cognition

Rosalyn J. Moran [1], Mkael Symmonds [1], Klaas E. Stephan [1 2], Karl J. Friston [1], Raymond J. Dolan [1]


M/EEG
Neural
Mass
Models



Observed
data features

Neural
Mass
Models

Observed
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Generative
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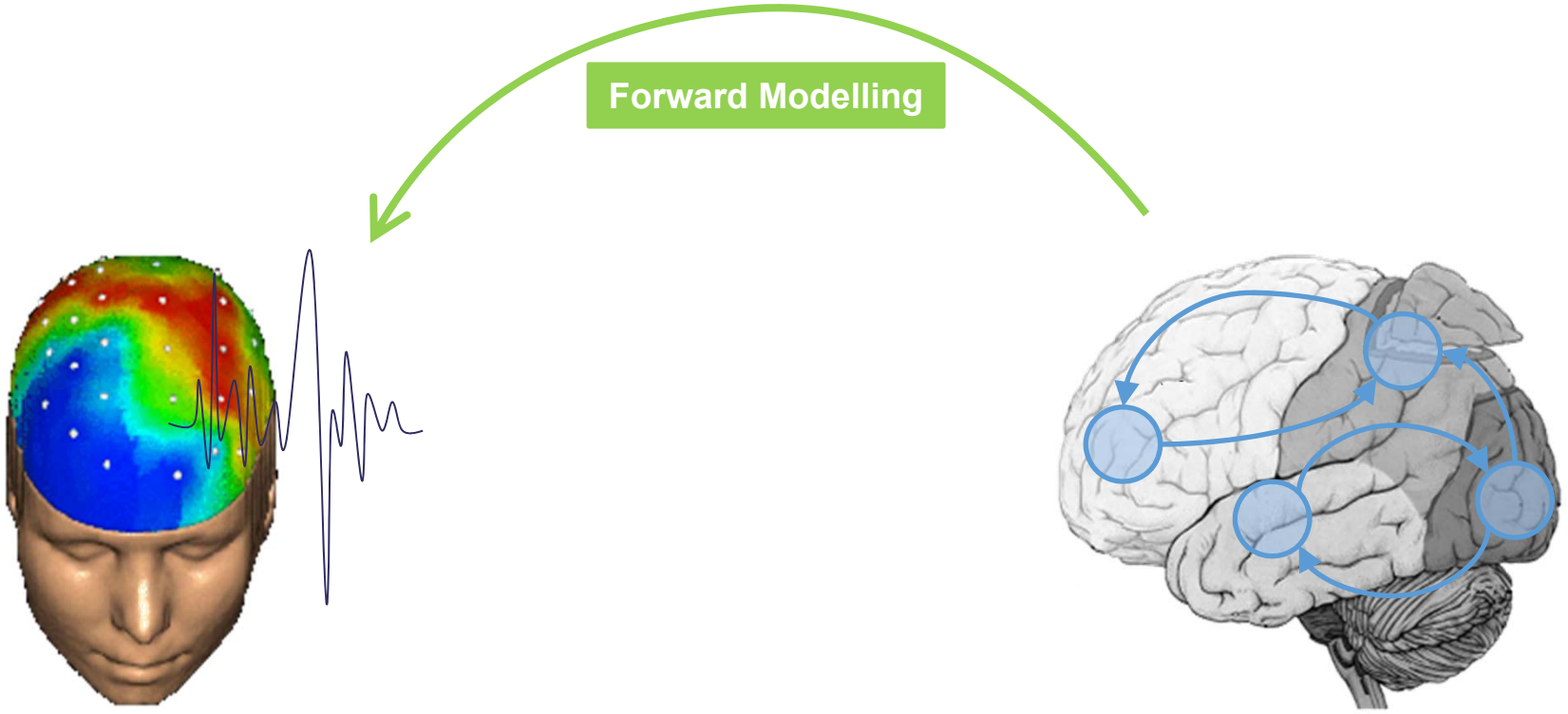

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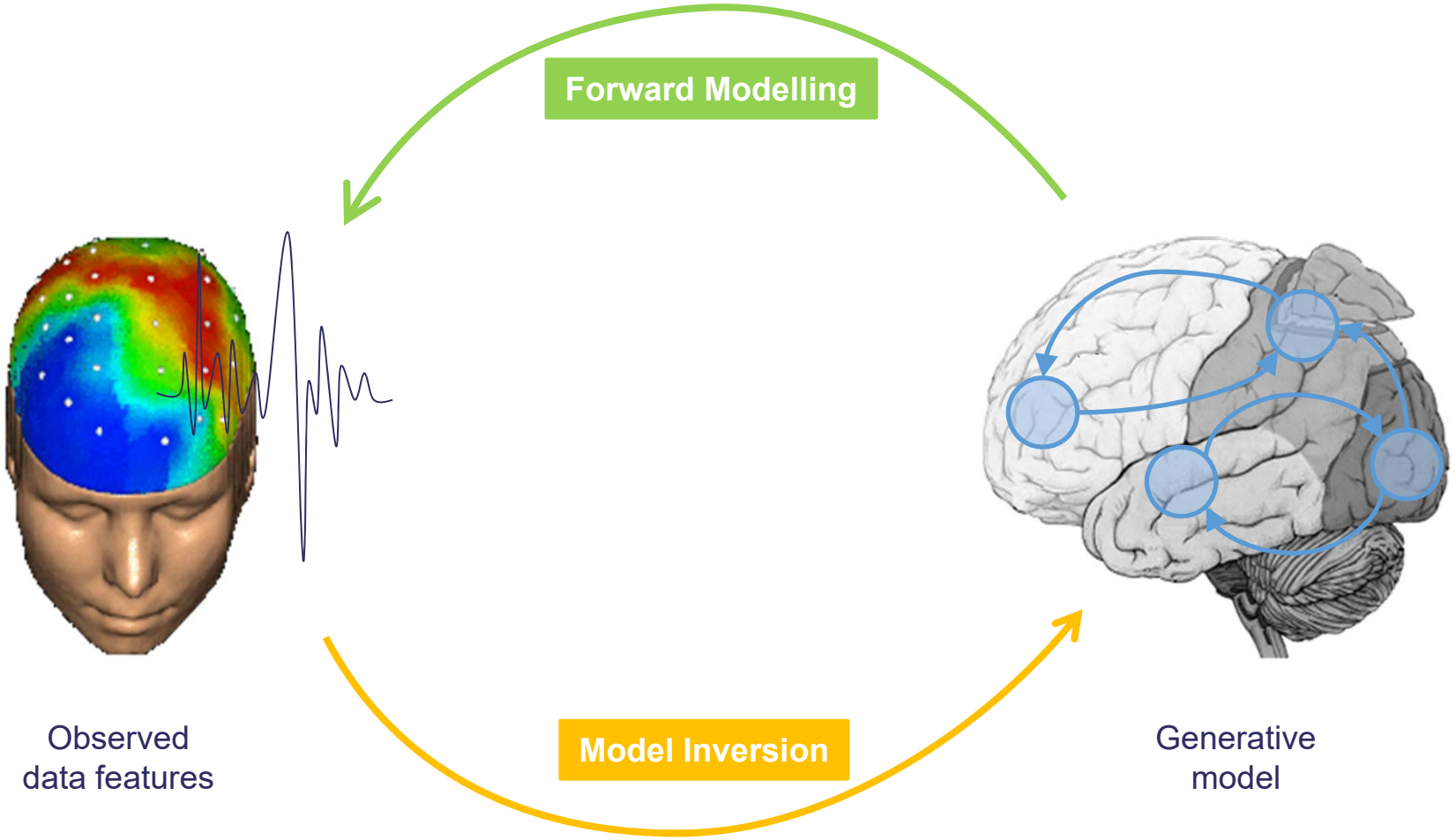
Forward Modelling
Observed
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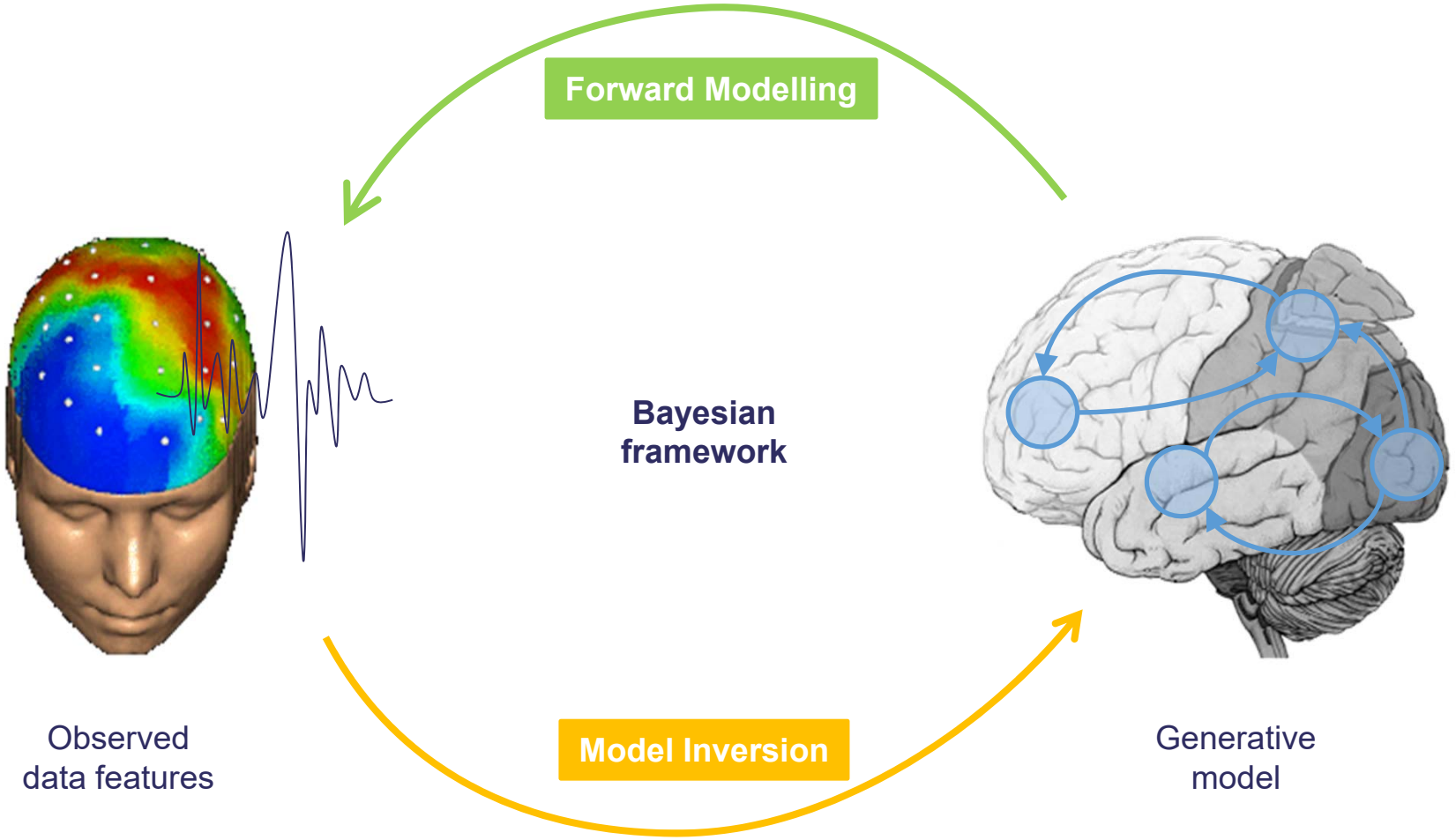
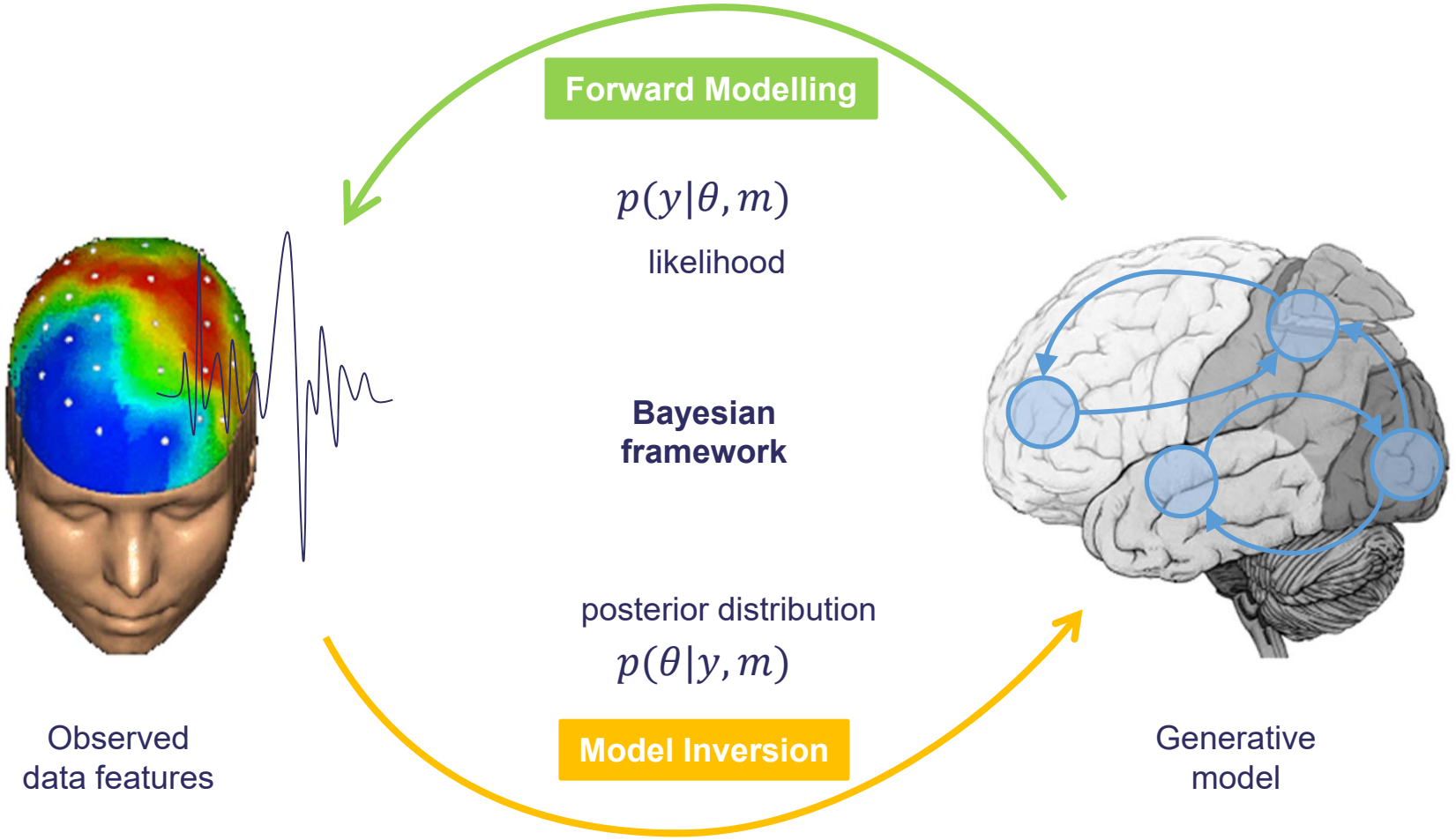
Model Inversion
Generative
model


Forward Modelling
Bayesian framework
Model Inversion
Observed data features
Generative model


Forward Modelling
$p(y|\theta, m)$
likelihood
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posterior distribution
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Background

Generative Modelling in DCM

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Demo

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Generative Modelling in DCM

Neuronal Model

$$\dot{x} = f(x, u, \theta_1)$$

Neural state equations
describe dynamics of brain activity

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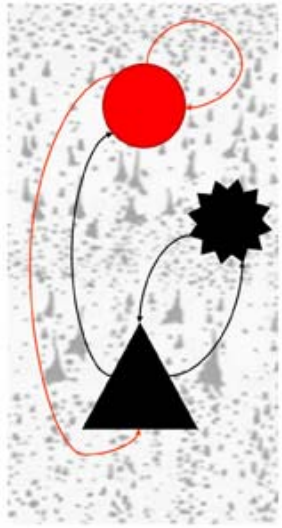

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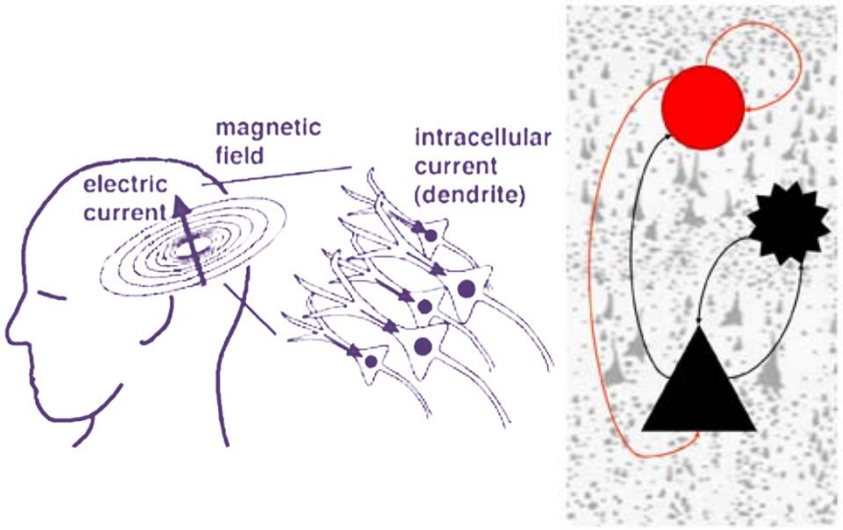

Generative Modelling in DCM

Observation Model

$$y = g(x, \theta_2) + \epsilon$$

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maps brain activity to “observed” data features

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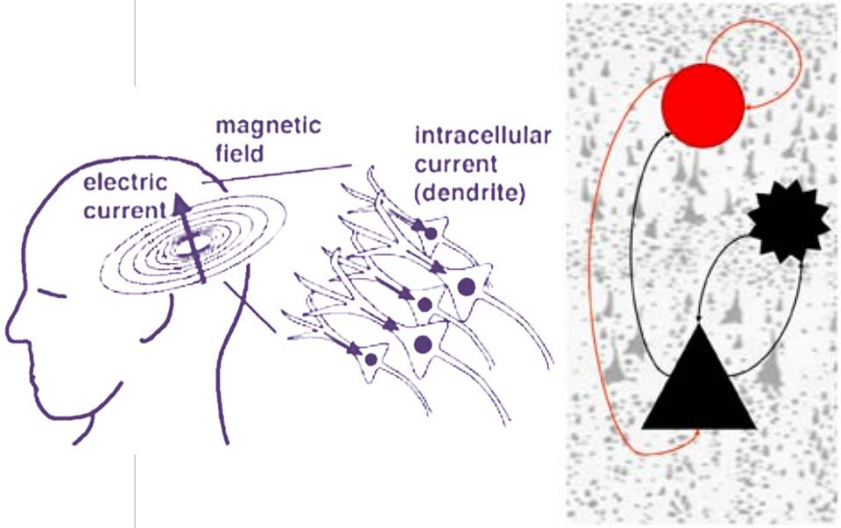

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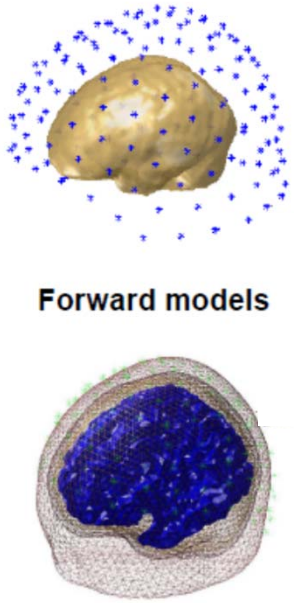
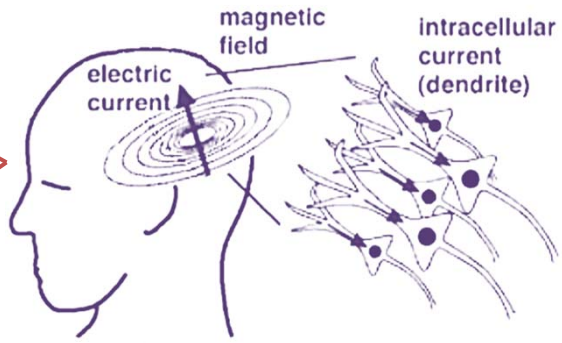
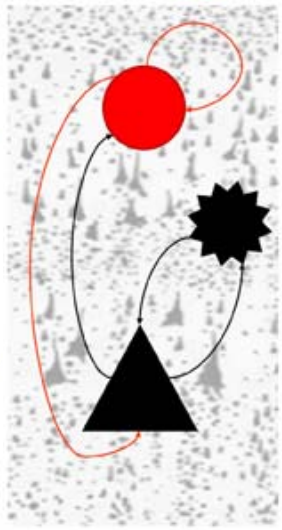


Forward models





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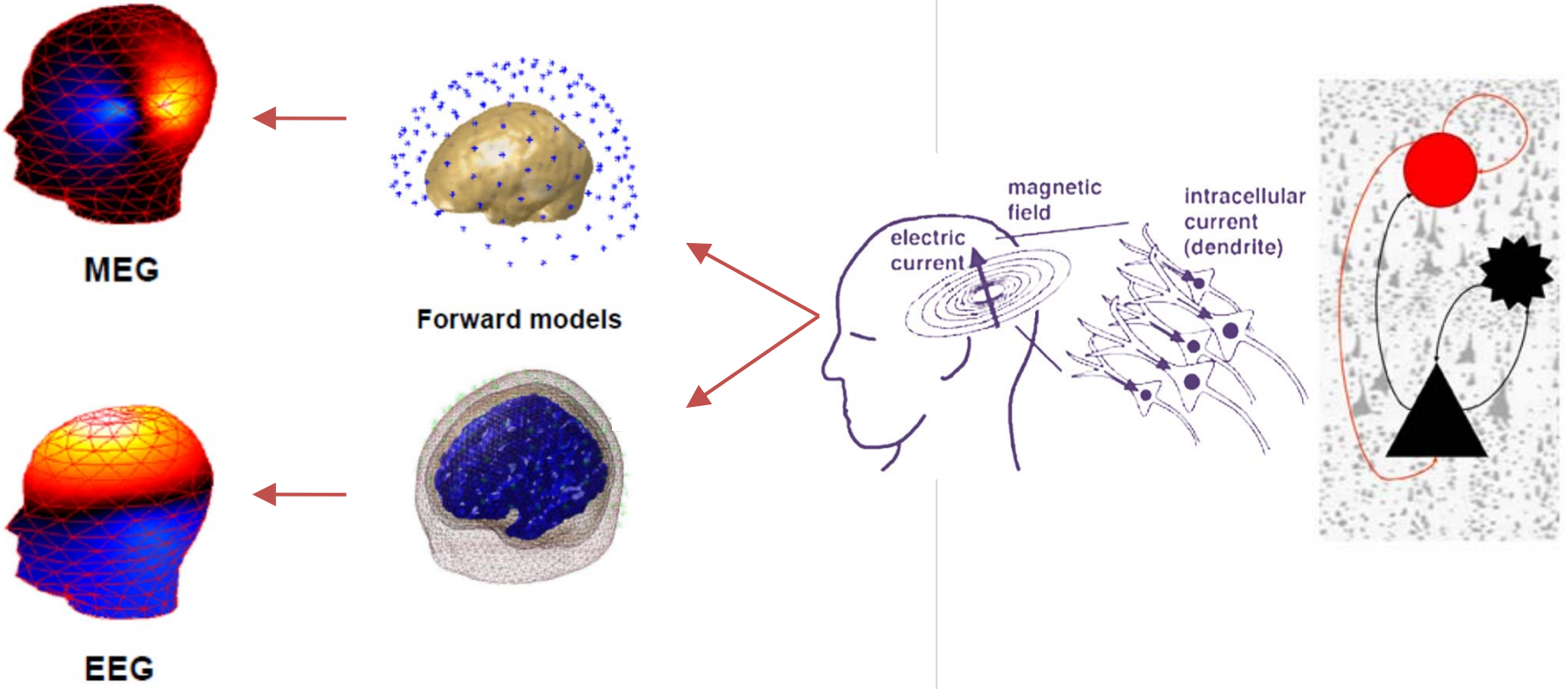

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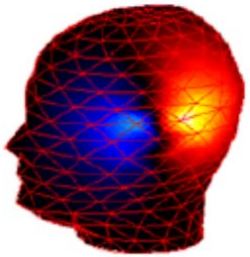
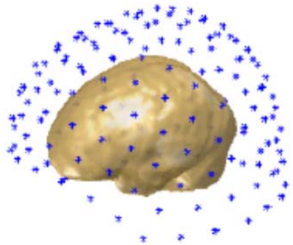
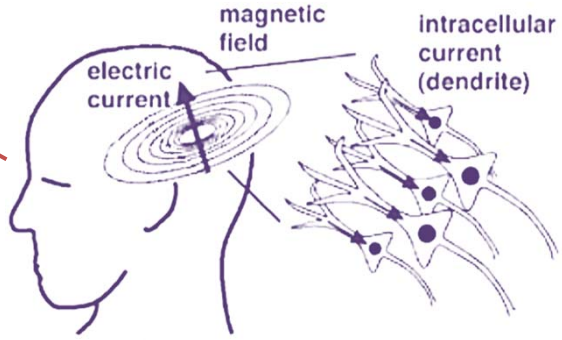
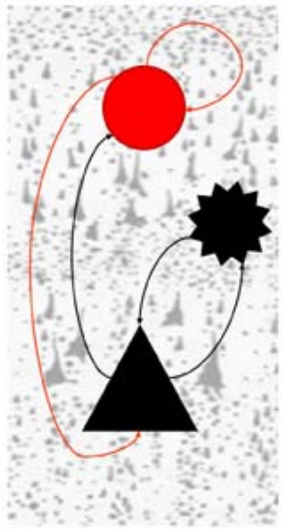


MEG







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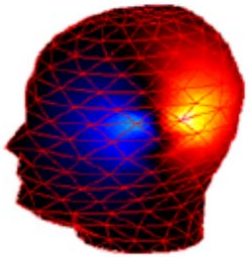

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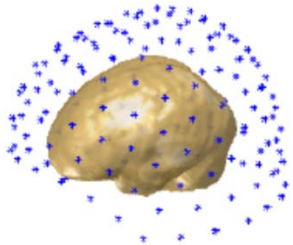
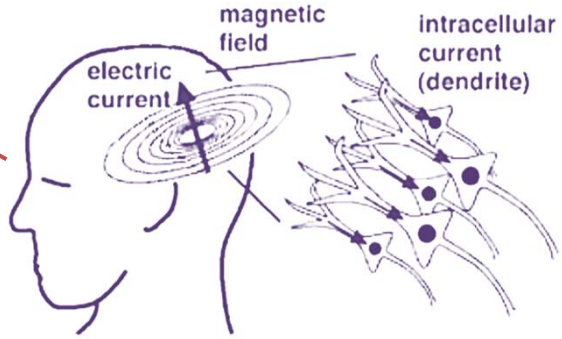
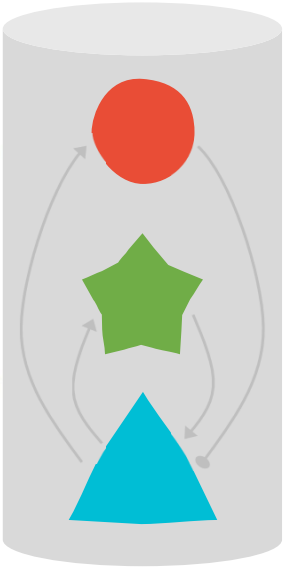
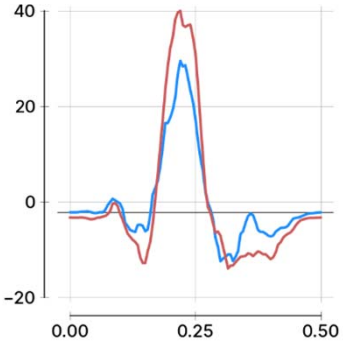






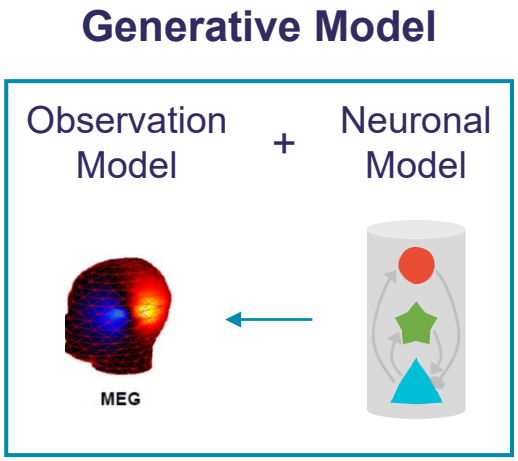


Evoked Responses

Distributed *‘Imaging’* Solution

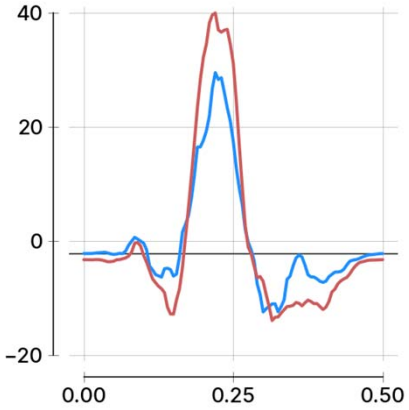
Jansen-Rit Model

DCM for Evoked Responses

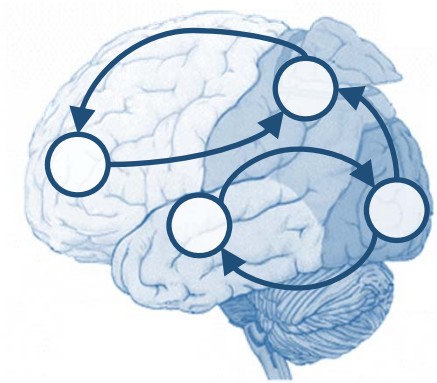


DCM for Evoked Responses

Observed ERP/ERF



Causal Mechanisms

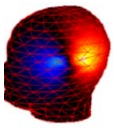


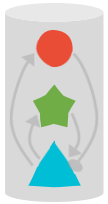
Forward Modelling

What measurements of brain activity does the model predict given some parameters?

Generative Model

Observation Model + Neuronal Model





DCM for Evoked Responses

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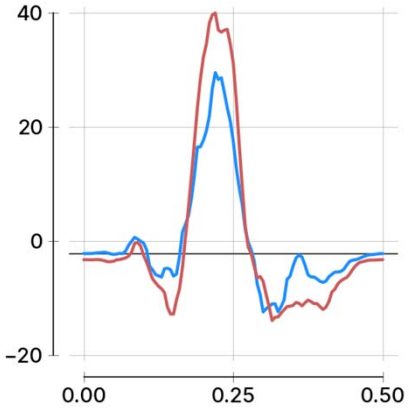

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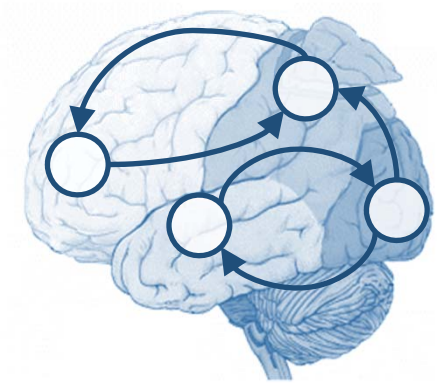


What parameters of the model best explain observed measurements of brain activity?

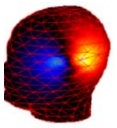
Model Inversion

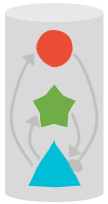
Forward Modelling

What measurements of brain activity does the model predict given some parameters?

Generative Model

Observation Model + Neuronal Model





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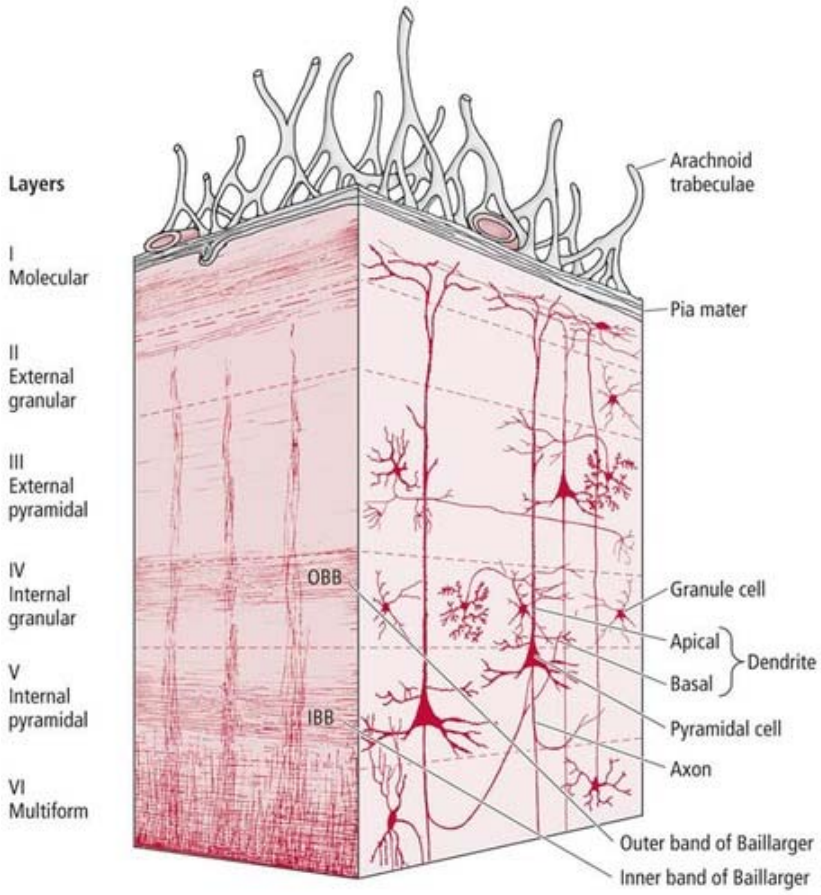

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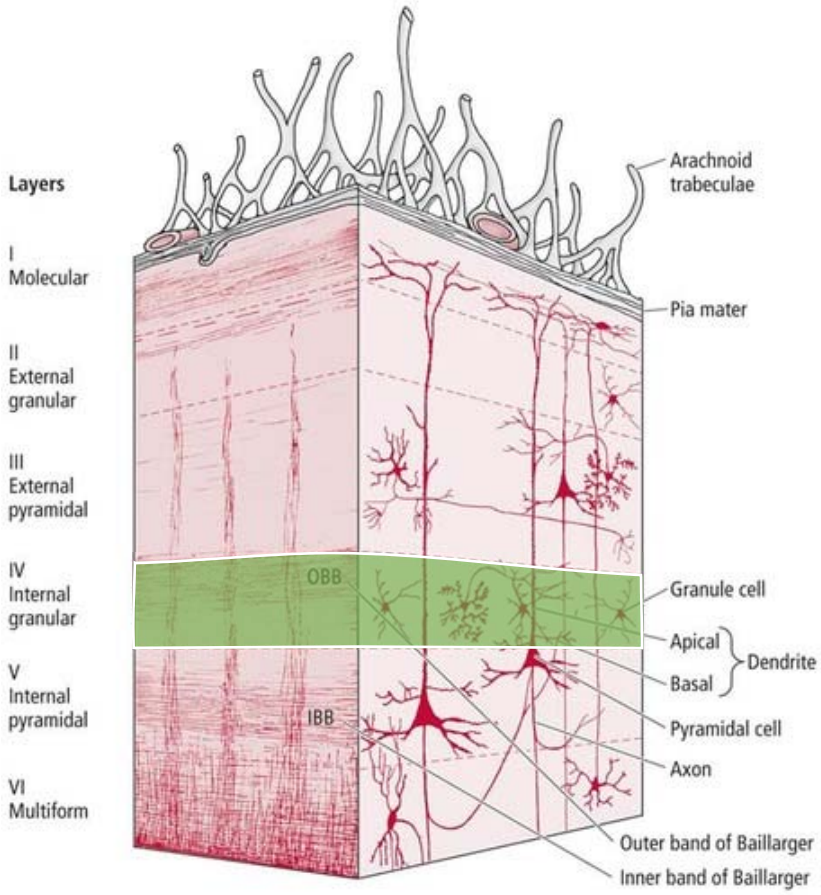

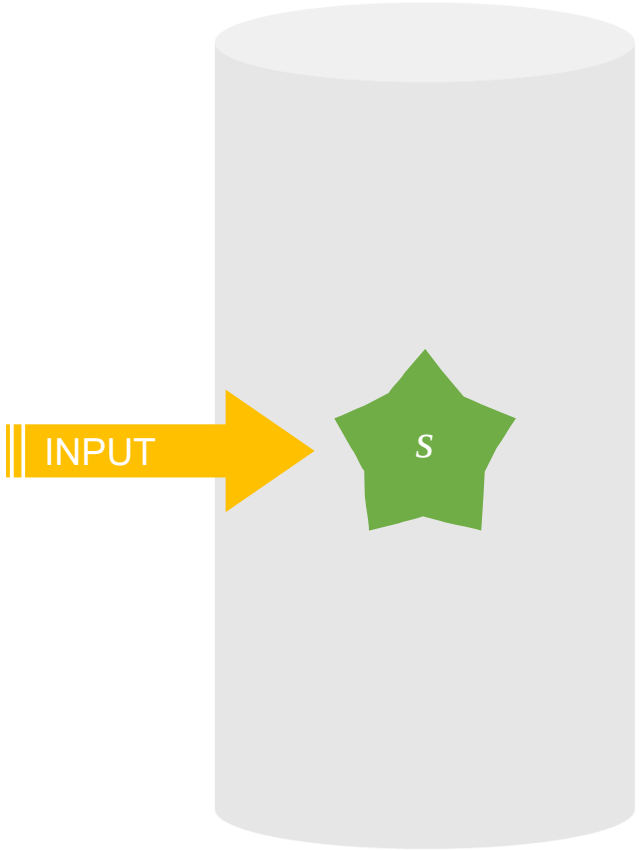

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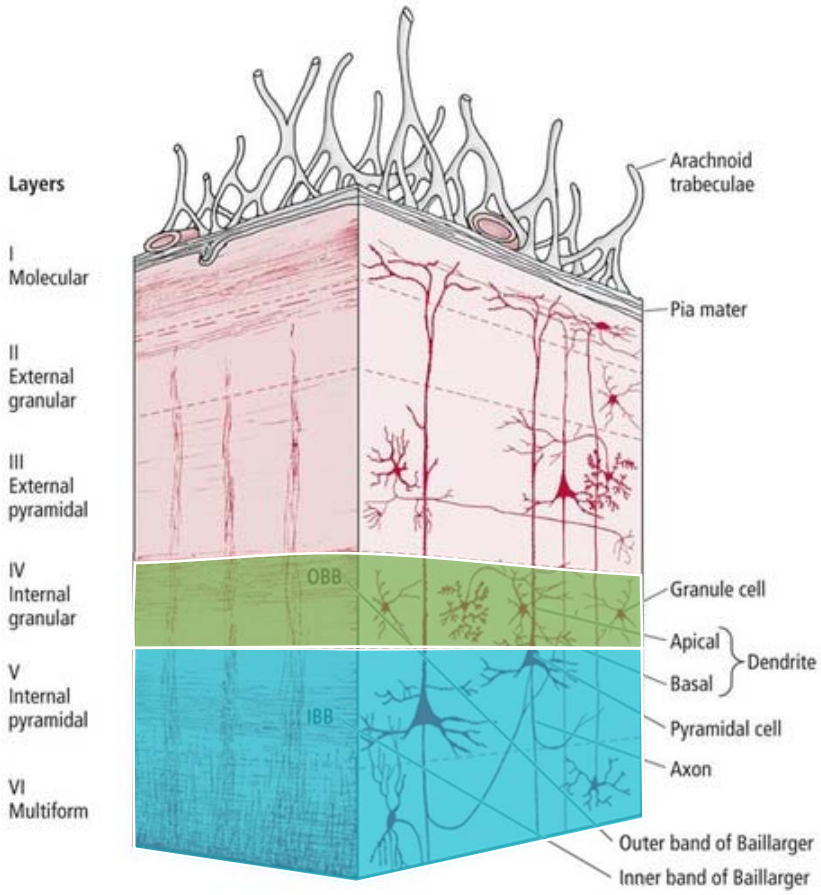

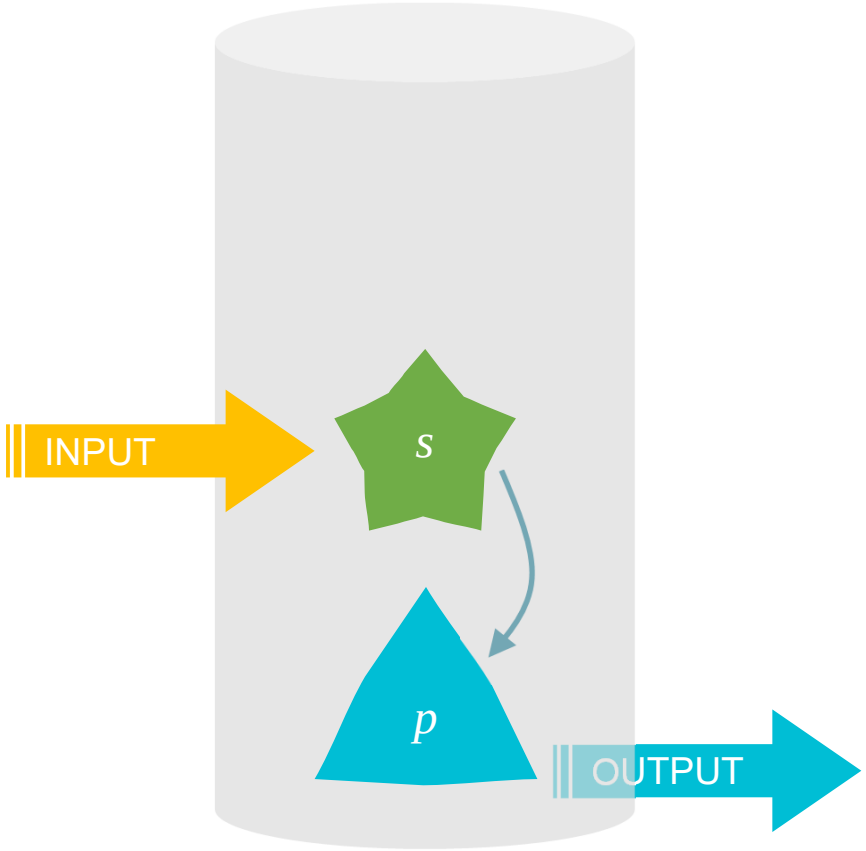

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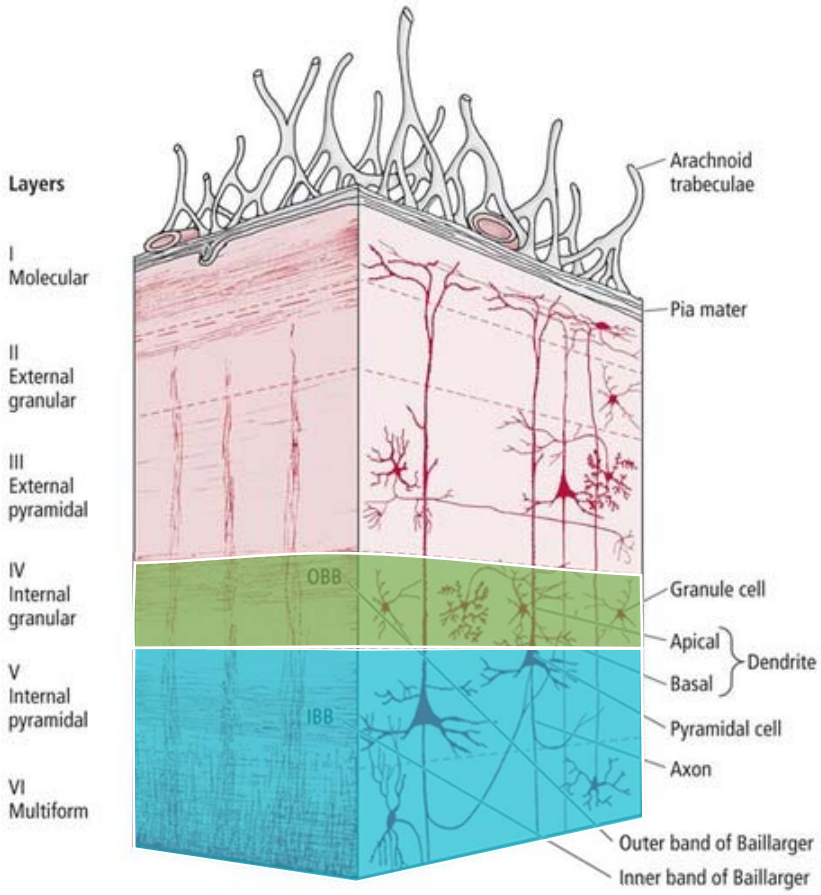

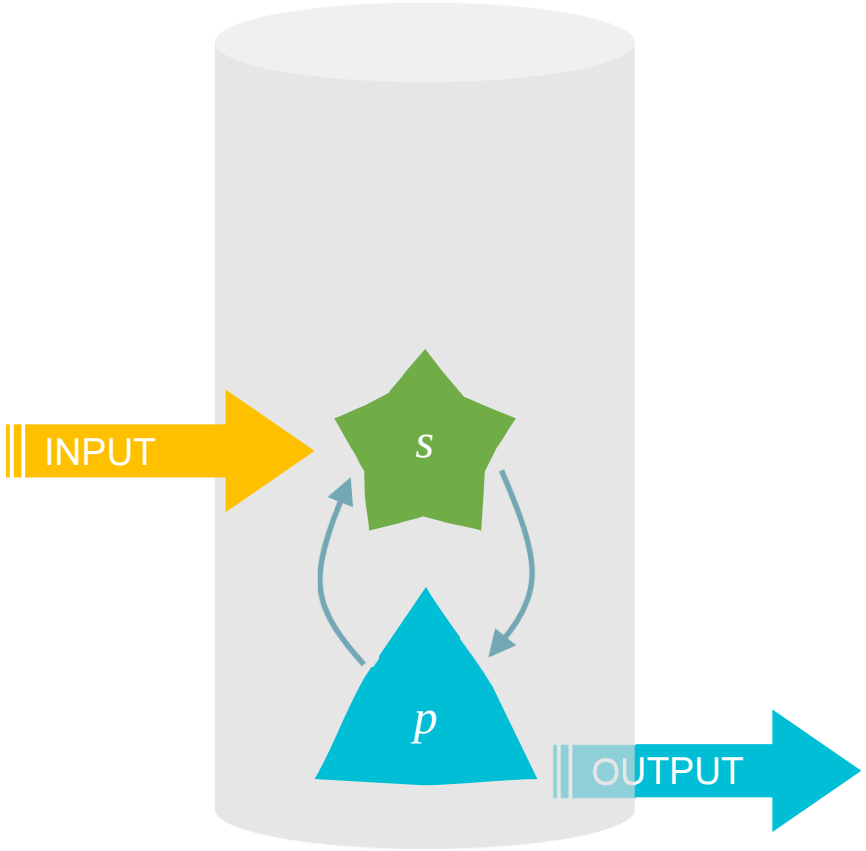

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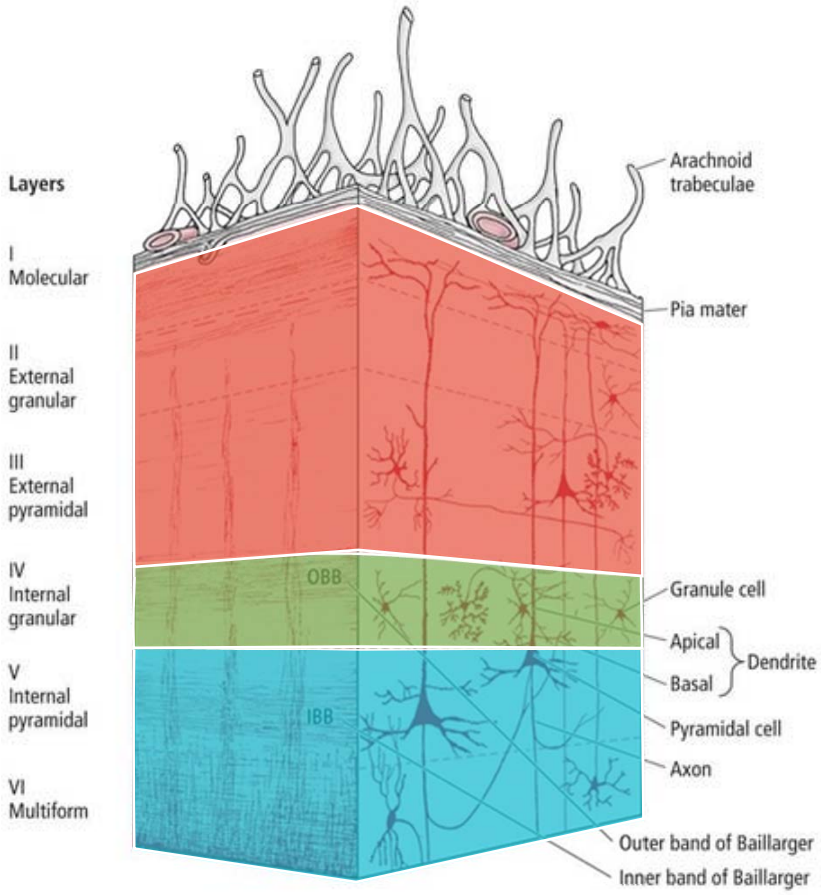

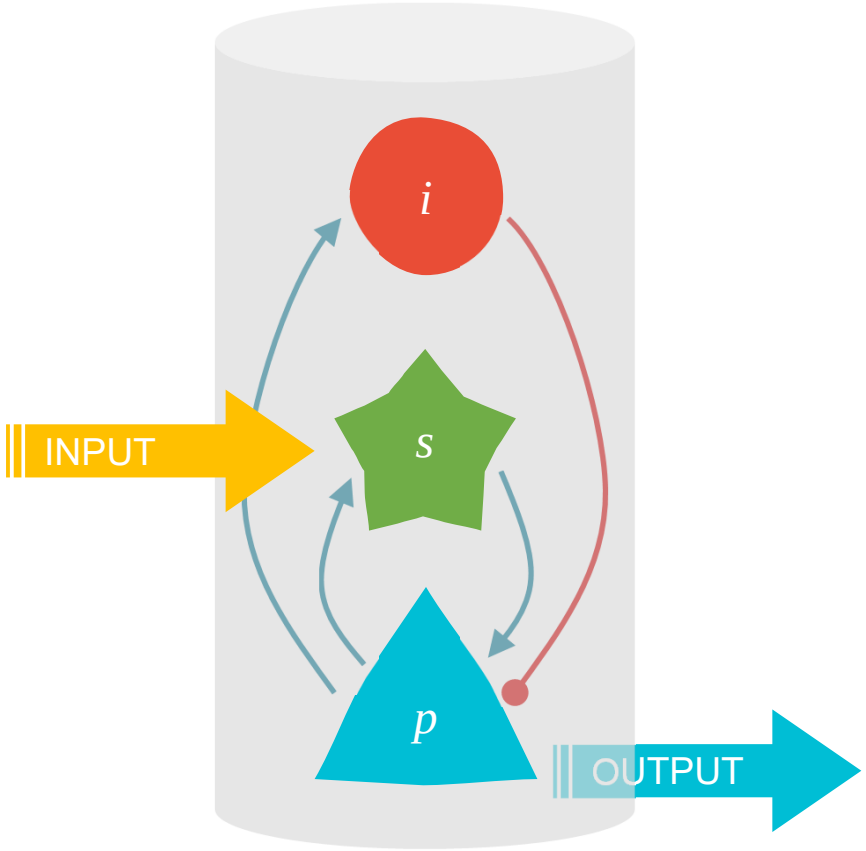

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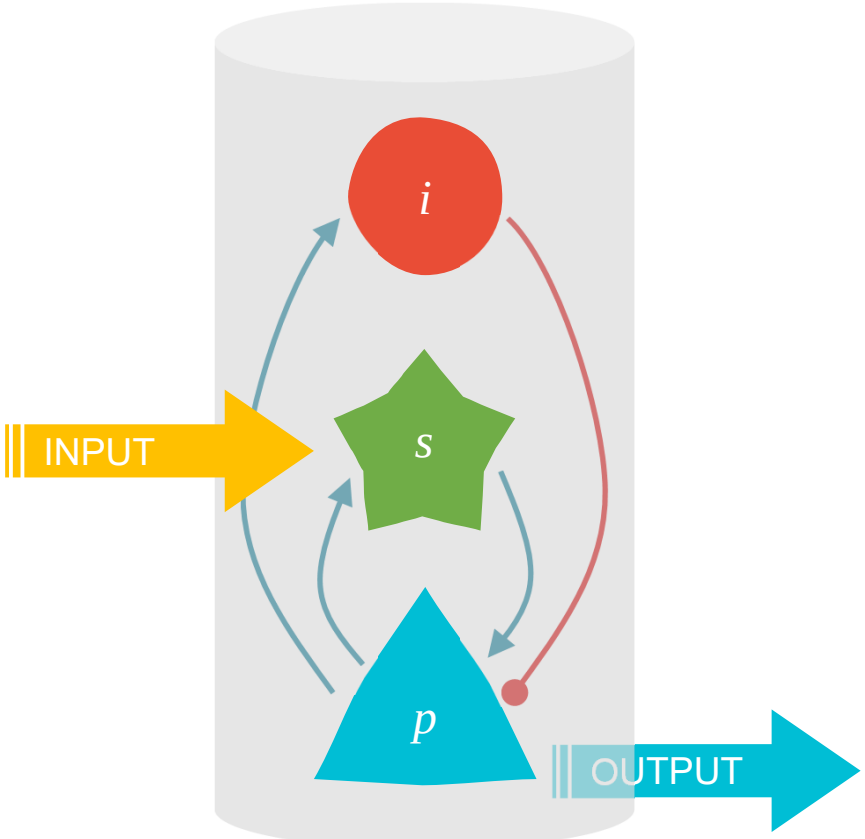


$$\dot{v}_s = c_s$$

$$\dot{c}_s = \frac{H_e}{\tau_e}(S(u) + \gamma_1 S(v_p)) - \frac{2}{\tau_e} c_s - \frac{1}{\tau_e^2} v_s$$

The Jansen-Rit Model

Extrinsic and Pyramidal input as *depolarization* at post-synaptic membrane

PRO
Potential-to-Rate

Sigmoid

Firing Rate

$$\dot{v}_s = c_s$$

$$\dot{c}_s = \frac{H_e}{\tau_e}(S(u) + \gamma_1 S(v_p)) - \frac{2}{\tau_e} c_s - \frac{1}{\tau_e^2} v_s$$

The Jansen-Rit Model

Extrinsic and Pyramidal input as *depolarization* at post-synaptic membrane

PRO
Potential-to-Rate
Sigmoid

Firing Rate

RPO
Rate-to-Potential
Convolution

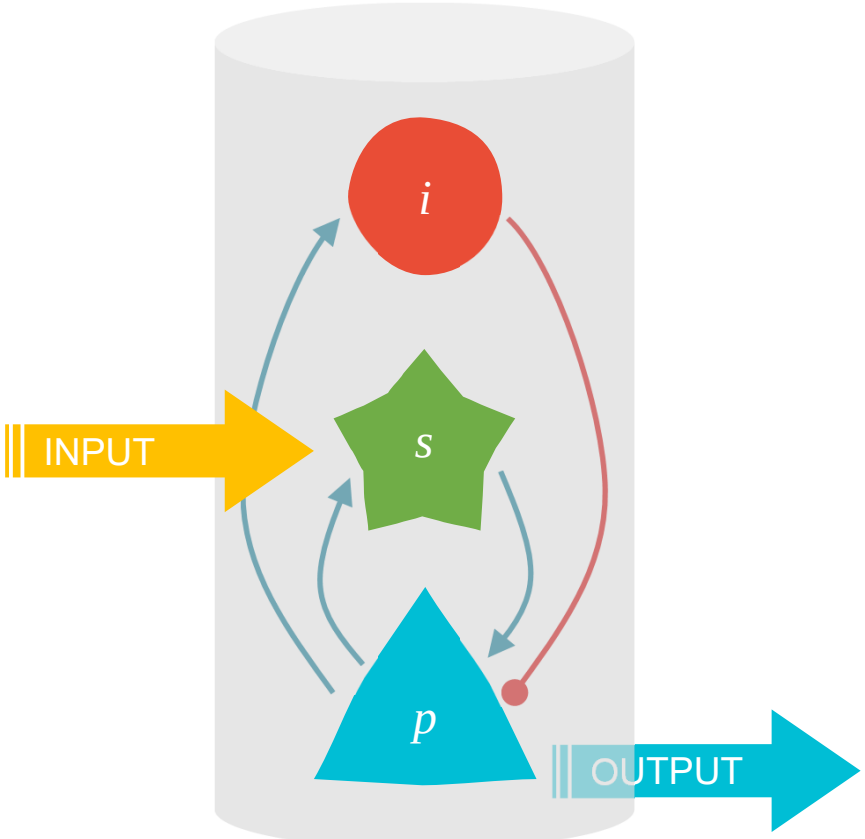
Output as *depolarization* at pre-synaptic membrane

$$\dot{v}_s = c_s$$

$$\dot{c}_s = \frac{H_e}{\tau_e}(S(u) + \gamma_1 S(v_p)) - \frac{2}{\tau_e}c_s - \frac{1}{\tau_e^2}v_s$$

The Jansen-Rit Model

Input ***depolarization*** —PRO (*Sigmoid*)→ **Firing rate** —RPO (*Convolution*)→ **Output** ***depolarization***



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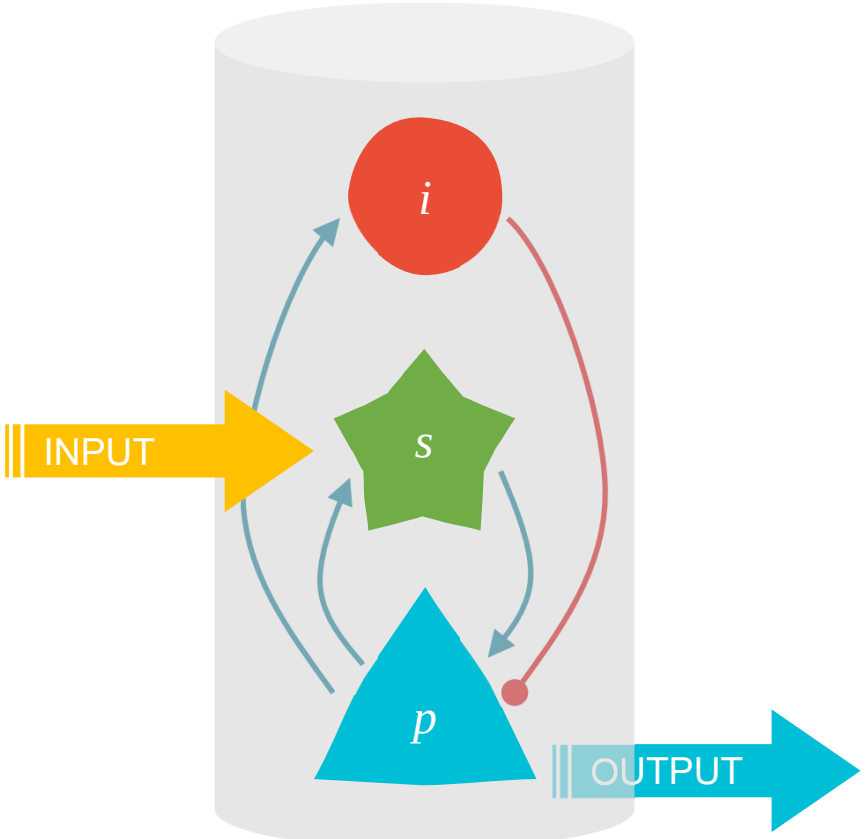
$$\dot{c}_s = \frac{H_e}{\tau_e}(S(u) + \gamma_1 S(v_p)) - \frac{2}{\tau_e}c_s - \frac{1}{\tau_e^2}v_s$$

The Jansen-Rit Model



$$\dot{v}_i = c_i$$
$$\dot{c}_i = \frac{H_e}{\tau_e}\gamma_3 S(v_p) - \frac{2}{\tau_e}c_i - \frac{1}{\tau_e^2}v_i$$

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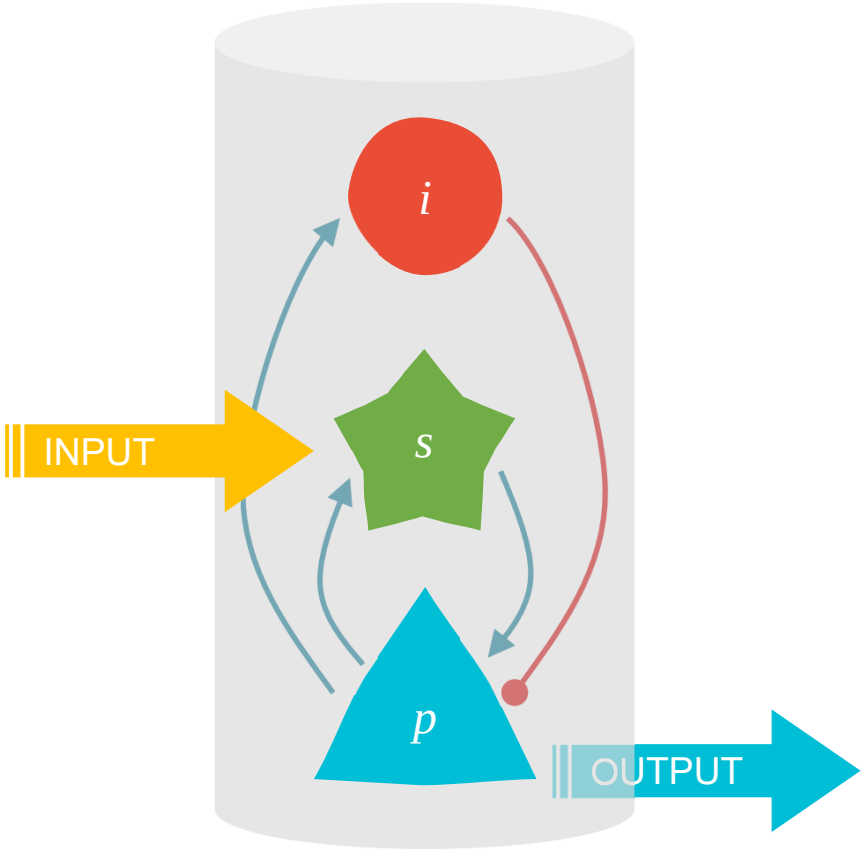
The Jansen-Rit Model



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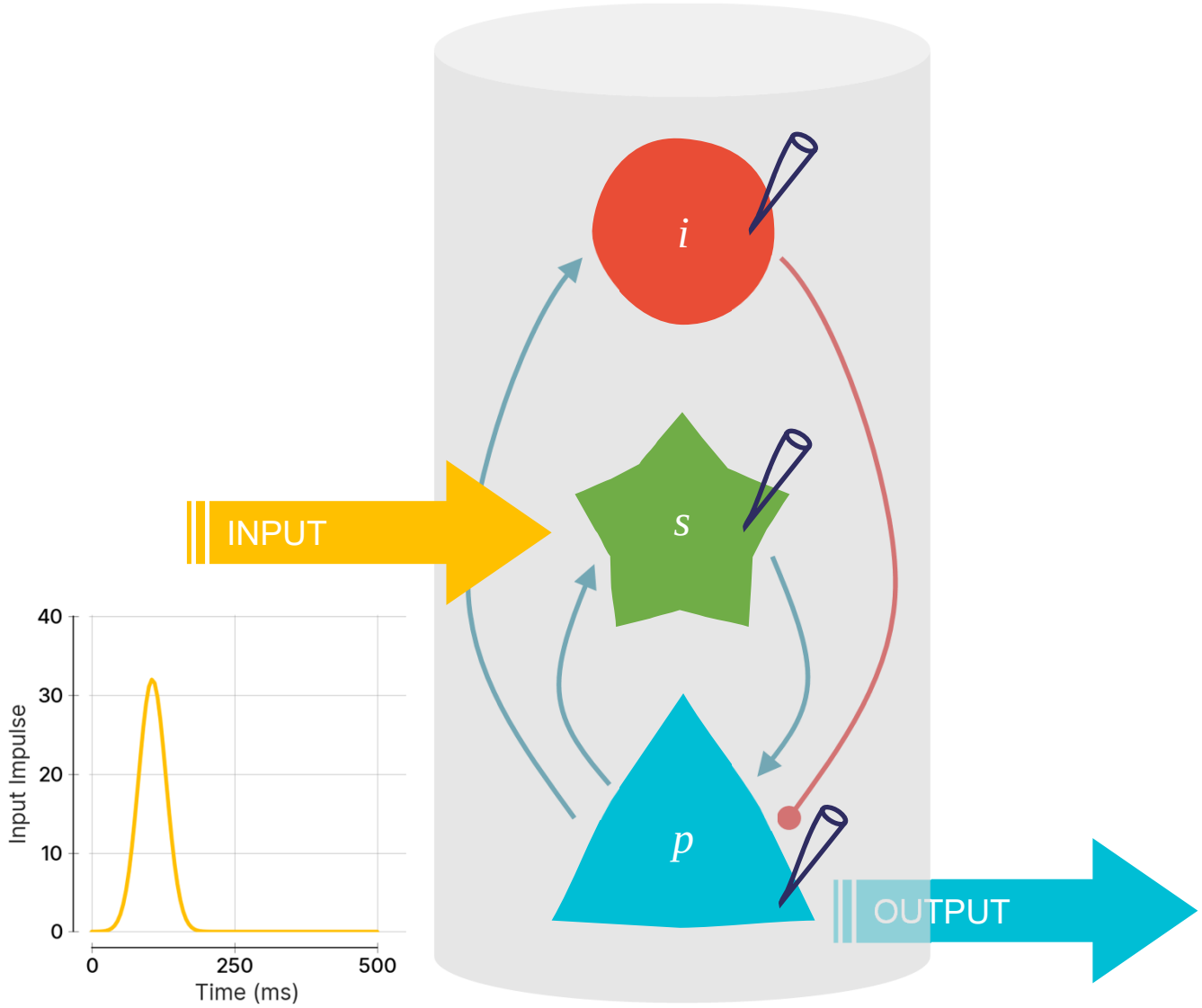
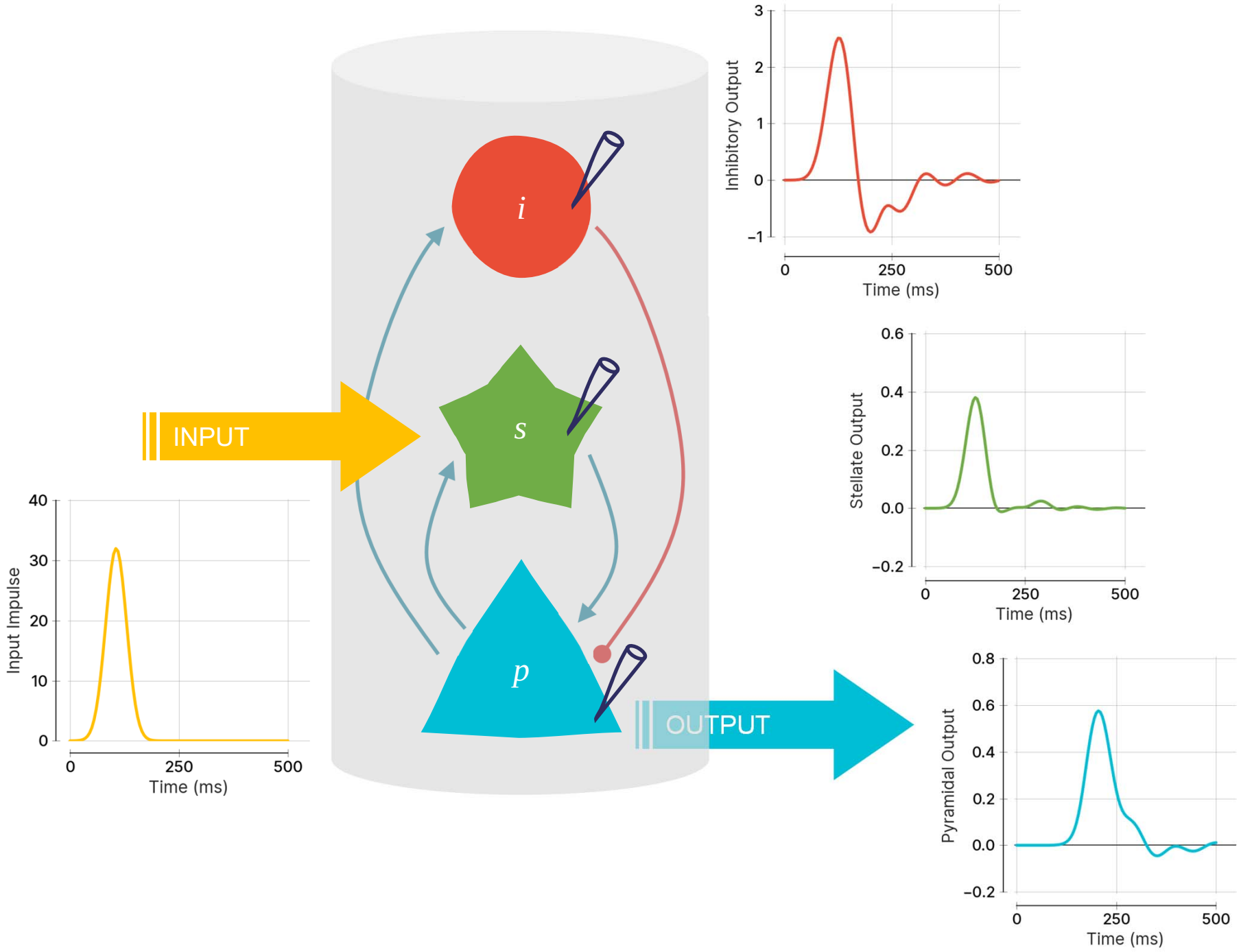
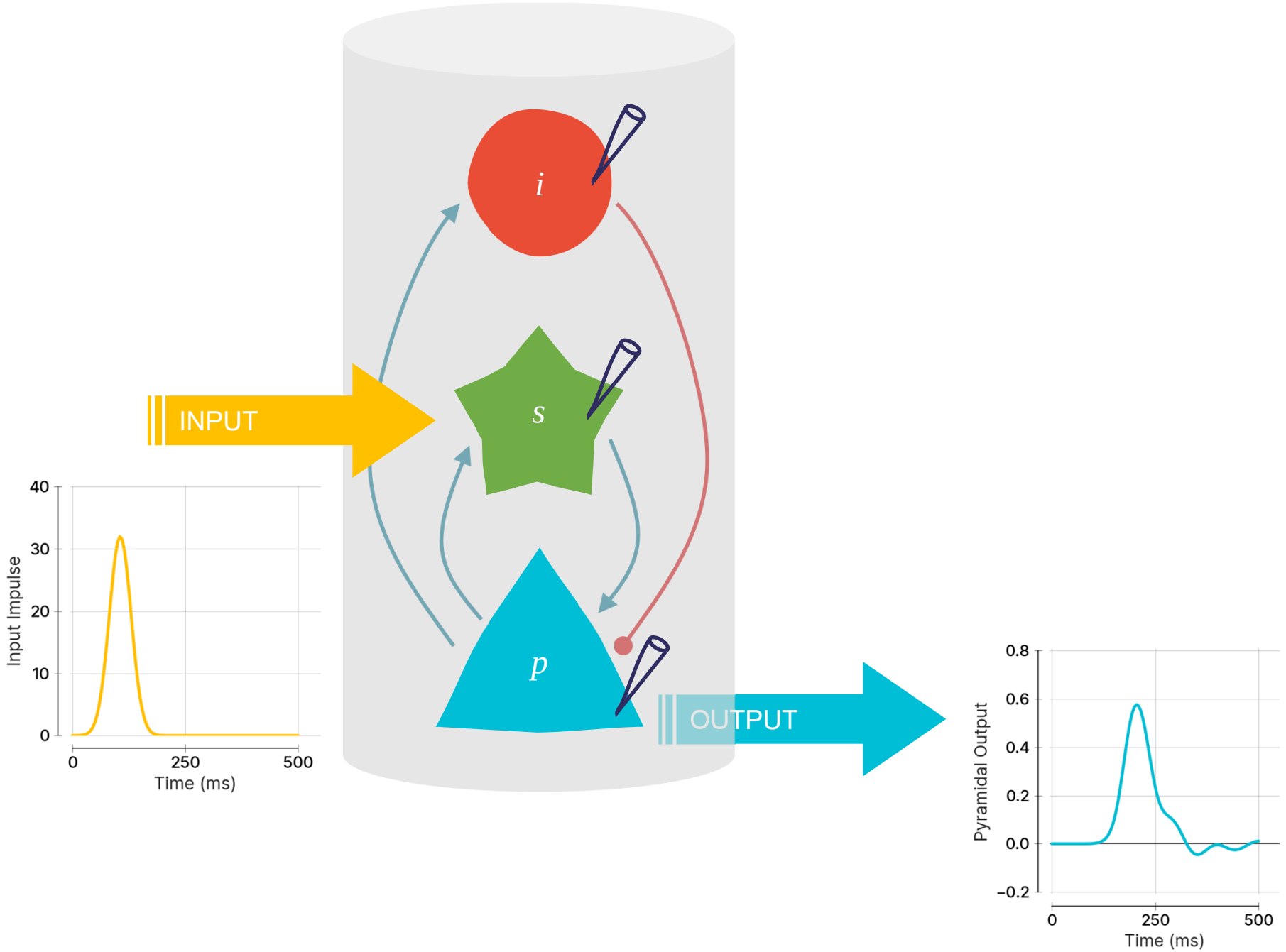
$$\dot{v_{p_i}} = c_{p_i}$$
$$\dot{c_{p_i}} = \frac{H_i}{\tau_i}\gamma_4 S(v_i) - \frac{2}{\tau_i}c_{p_i} - \frac{1}{\tau_i^2}v_{p_i}$$

$$\dot{v}_p = c_{p_e} - c_{p_i}$$


i
s
p
INPUT
OUTPUT
40
30
20
10
0
Input Impulse
0
250
500
Time (ms)


i
s
p
INPUT
OUTPUT
Input Impulse
40
30
20
10
0
0
250
500
Time (ms)
Inhibitory Output
3
2
1
0
−1
0
250
500
Time (ms)
Stellate Output
0.6
0.4
0.2
0.0
−0.2
0
250
500
Time (ms)
Pyramidal Output
0.8
0.6
0.4
0.2
0.0
−0.2
0
250
500
Time (ms)


i
s
p
INPUT
OUTPUT
Input Impulse
40
30
20
10
0
0
250
500
Time (ms)
Pyramidal Output
0.8
0.6
0.4
0.2
0.0
−0.2
0
250
500
Time (ms)

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- Can produce rich dynamics with different configurations of parameters:
  - Dendritic time constants
  - Synaptic gains

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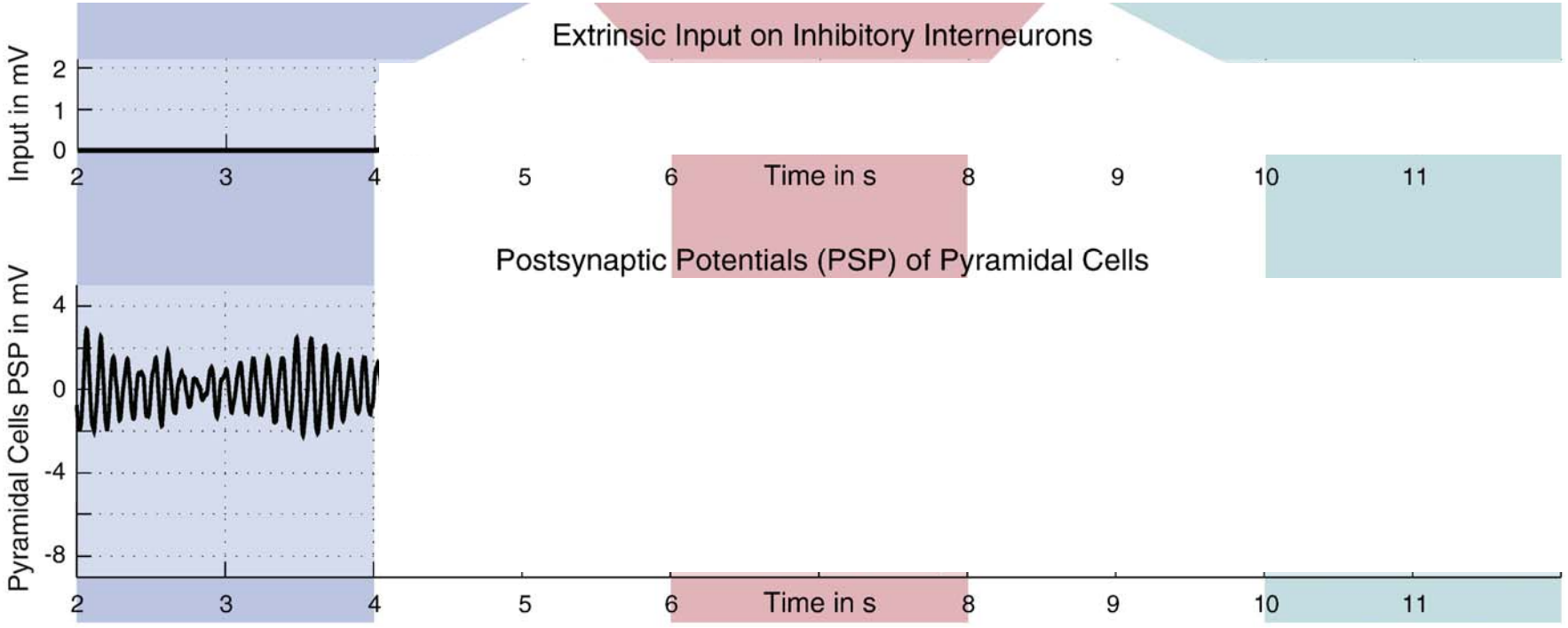

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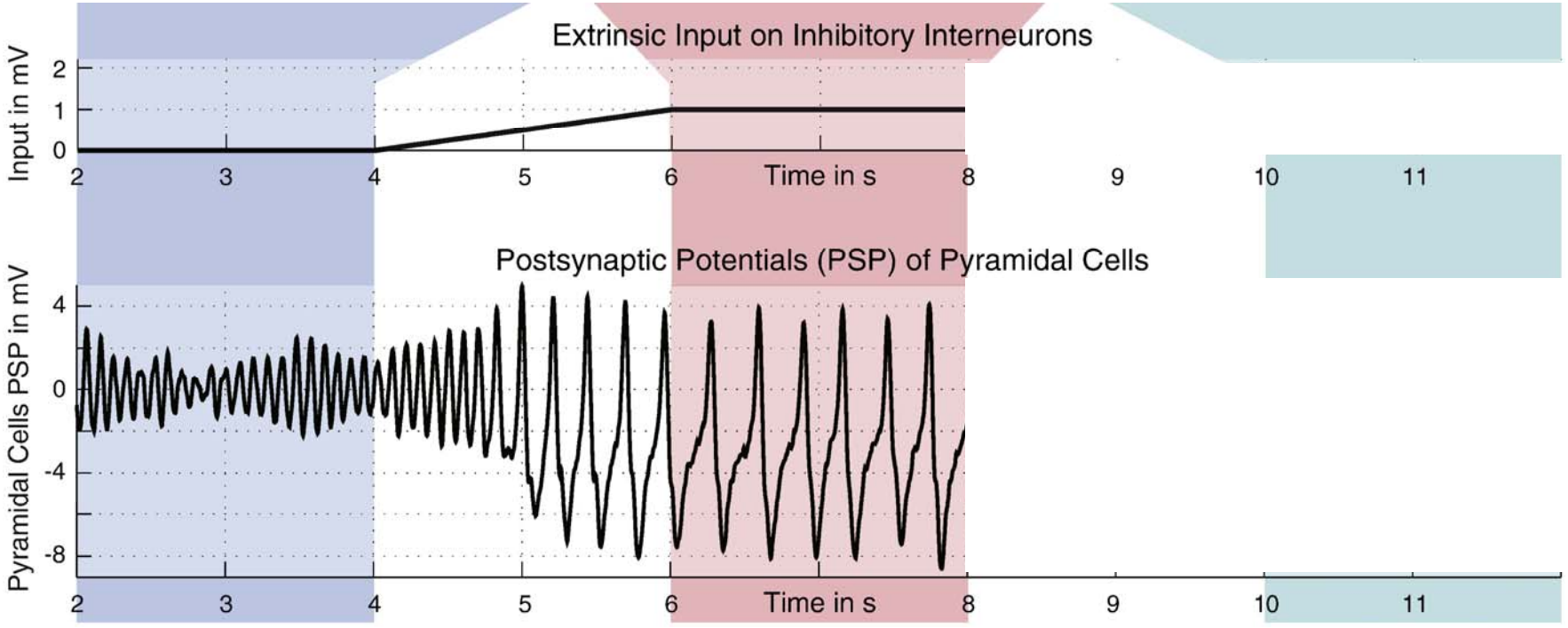

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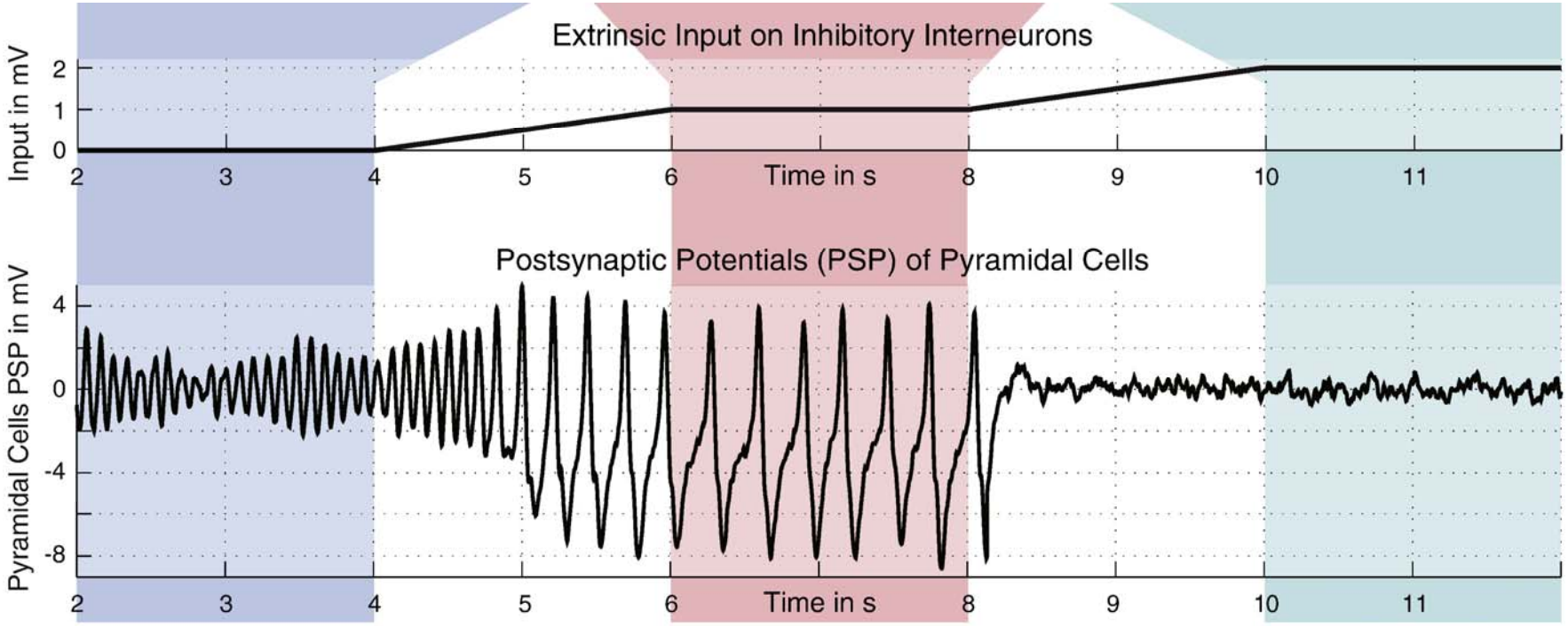


Background

Generative Modelling in DCM

The Jansen-Rit Model

Effective Connectivity

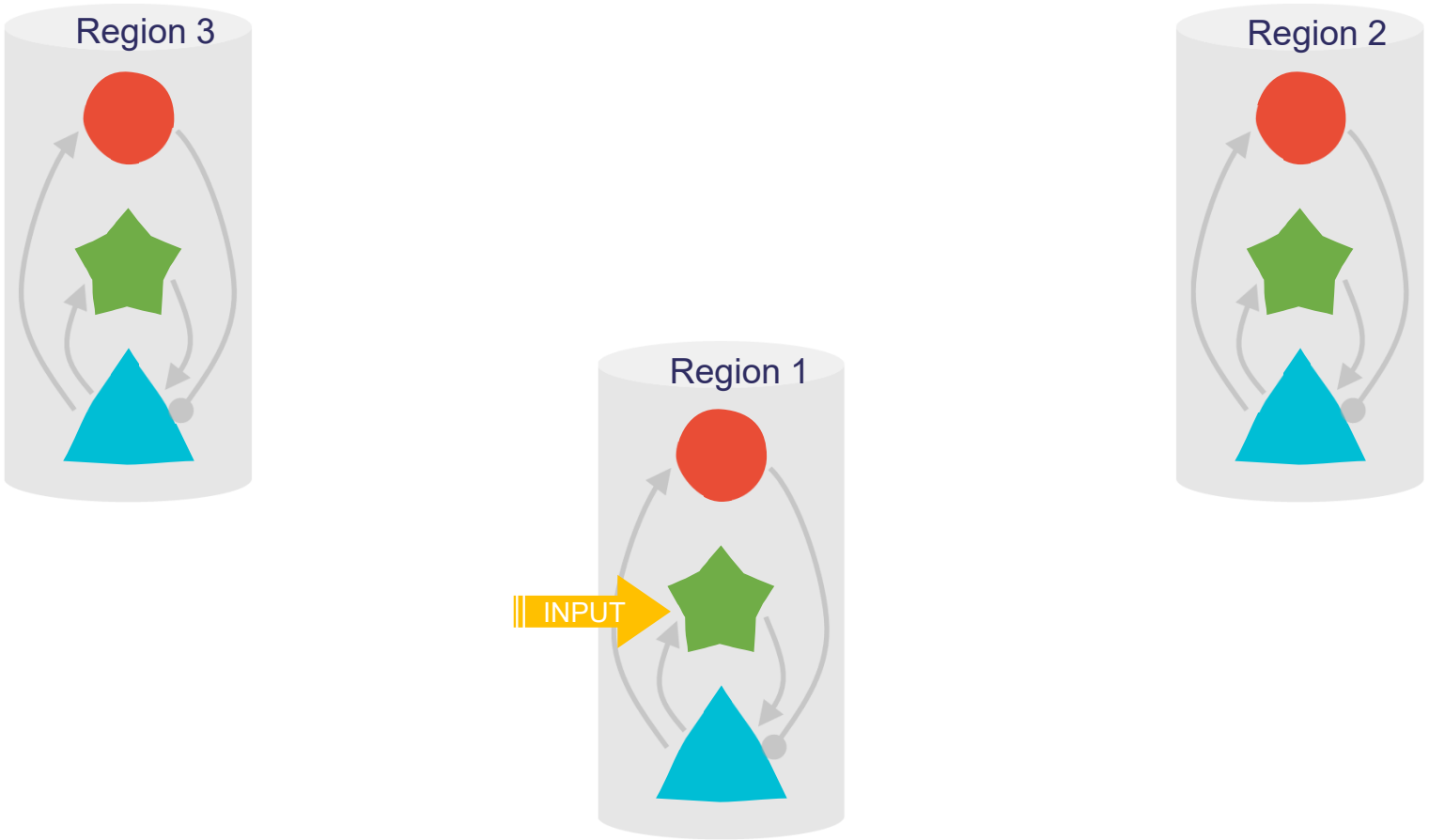
Demo

Data

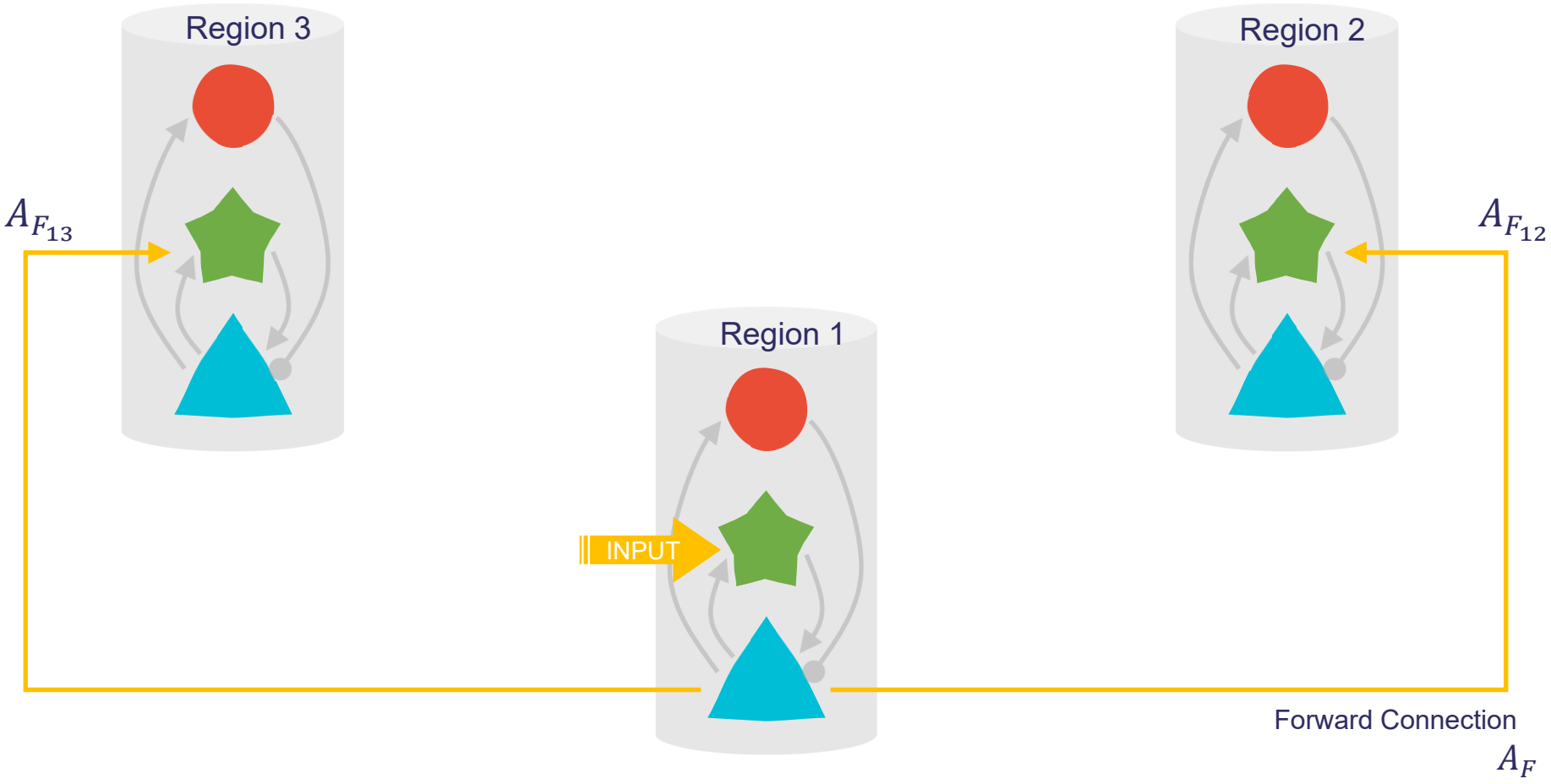
DCM Specification

Review of DCM fit

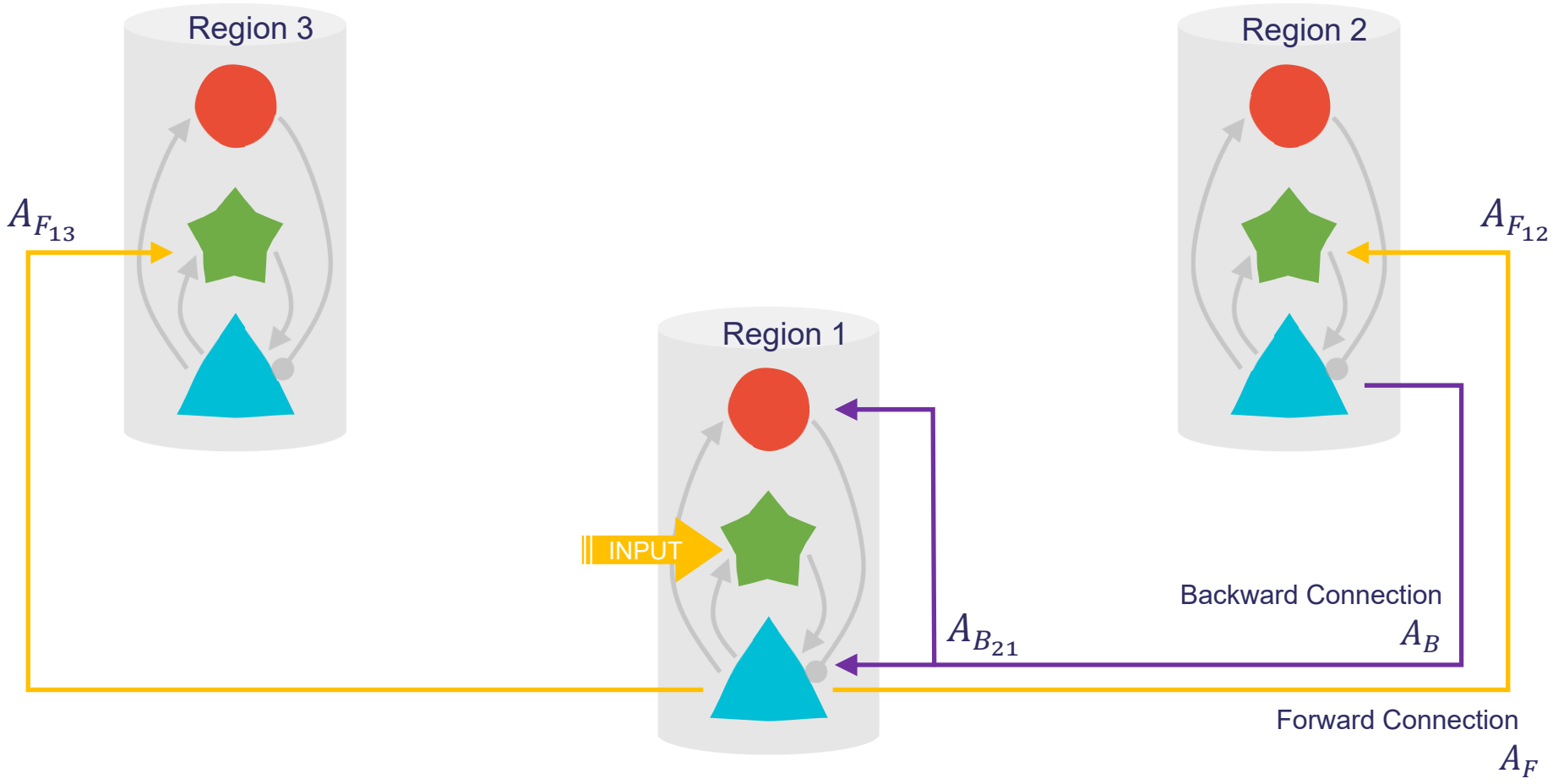
Connecting multiple Jansen-Rit cortical columns



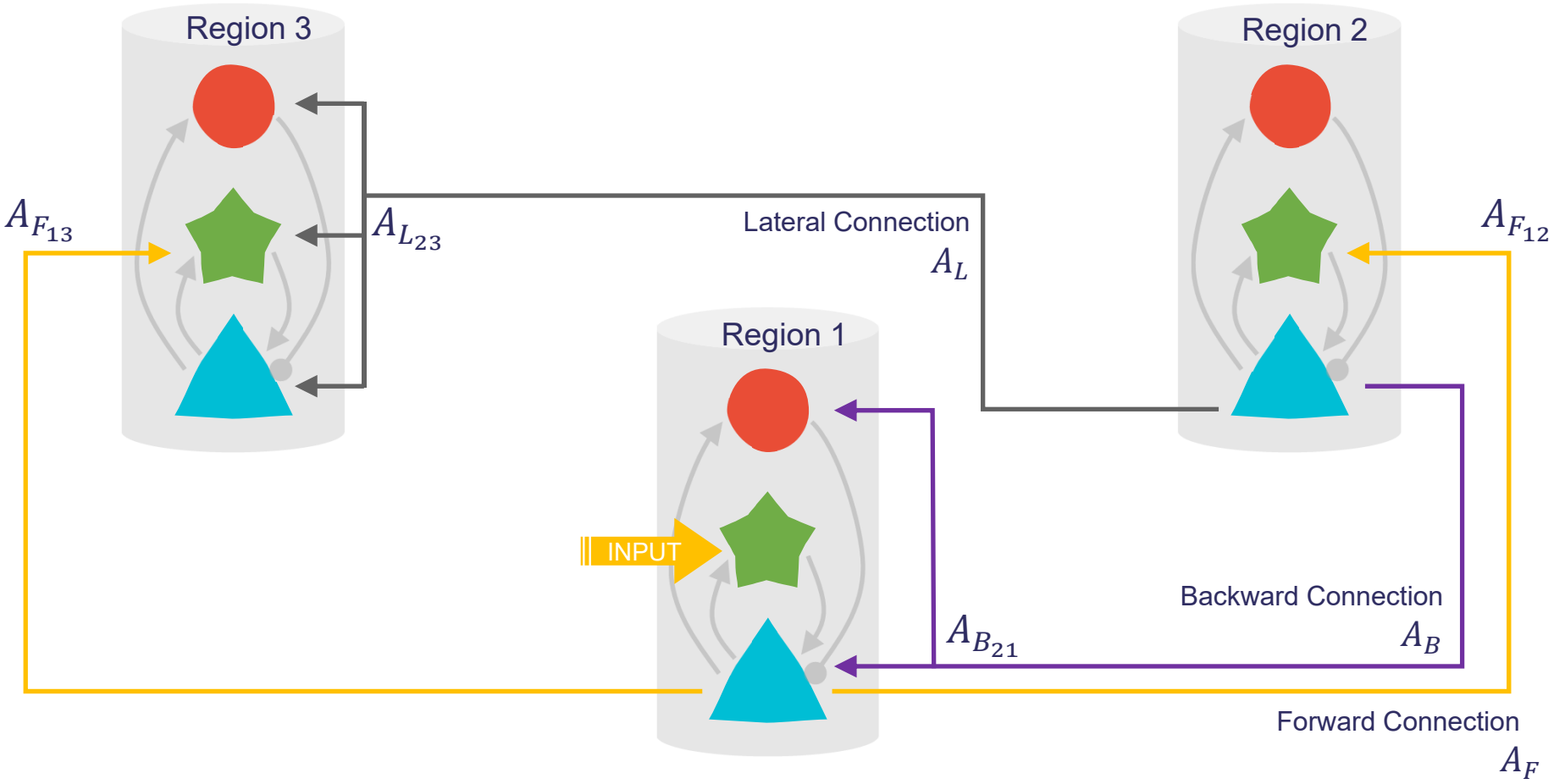
Connecting multiple Jansen-Rit cortical columns



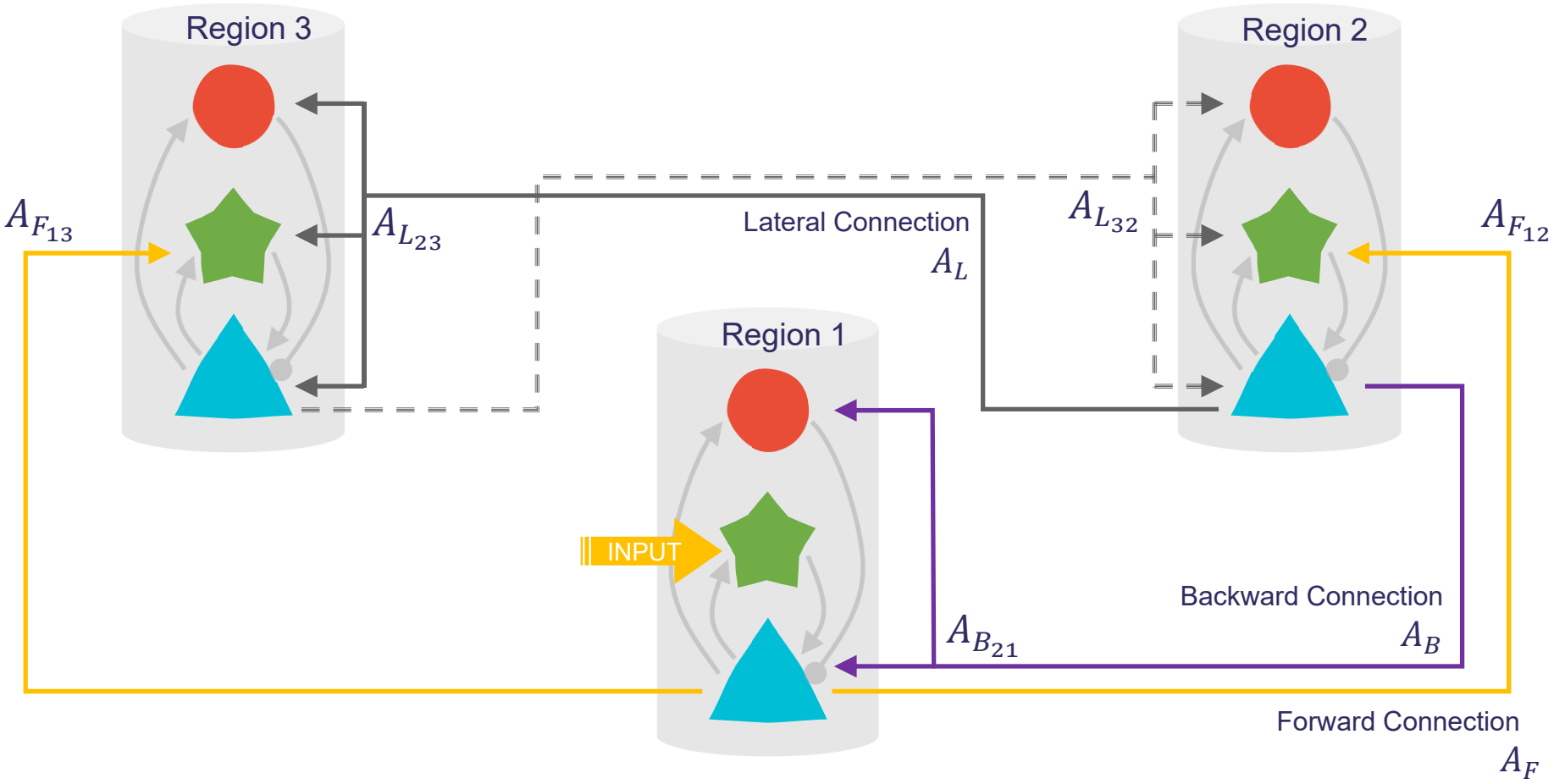
Connecting multiple Jansen-Rit cortical columns



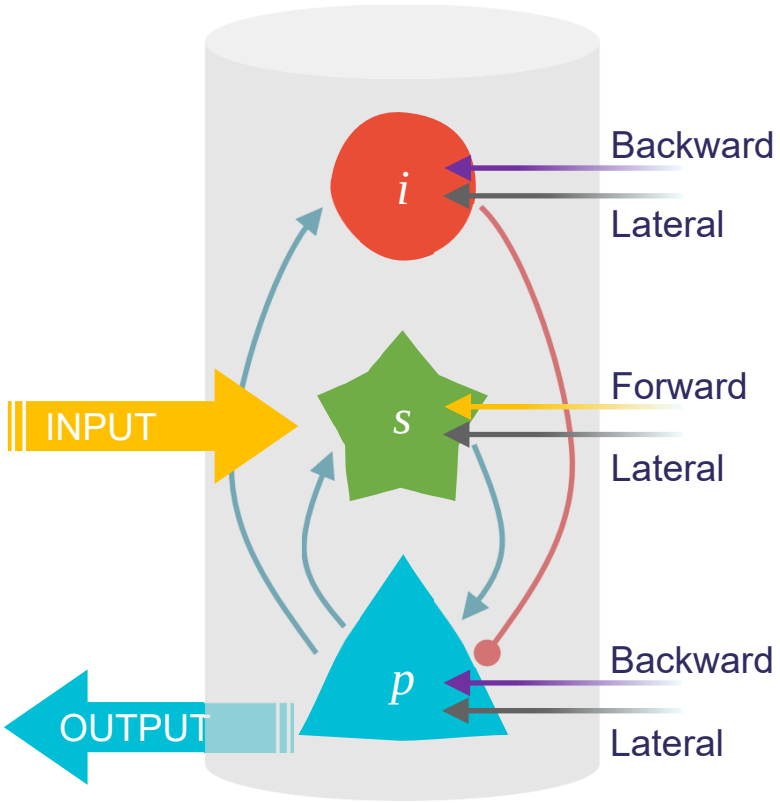
Connecting multiple Jansen-Rit cortical columns



Connecting multiple Jansen-Rit cortical columns



The Jansen-Rit model with extrinsic connections



$$\dot{v}_i = c_i$$

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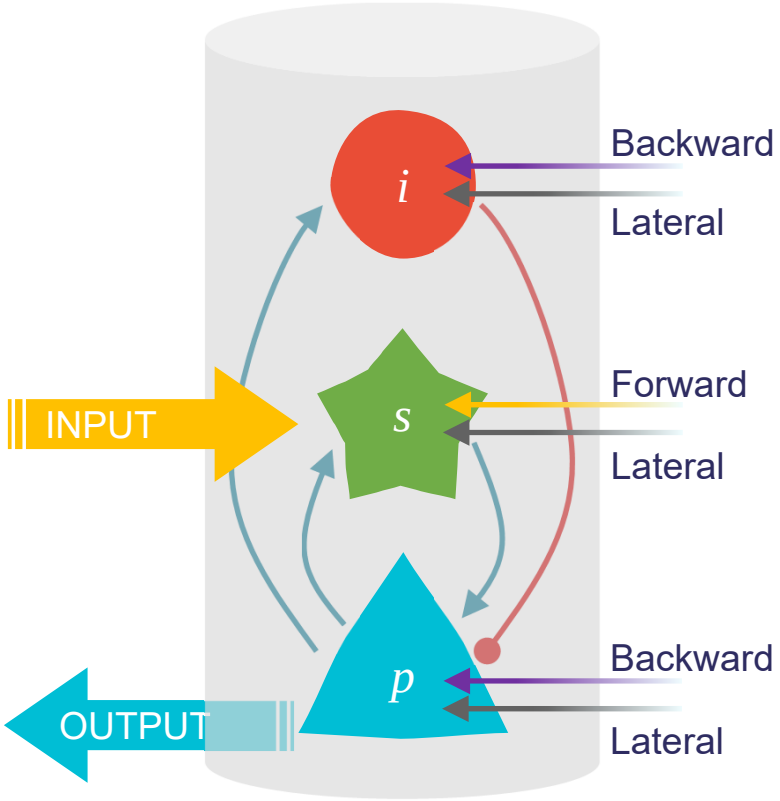
$$\dot{v}_p = c_{p_e} - c_{p_i}$$

The Jansen-Rit model with extrinsic connections

The three ‘A’ Matrices in DCM encode causal interactions between regions as ‘gain’ modulation, which varies as per experimental condition!



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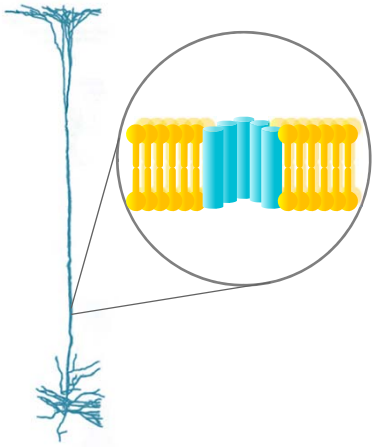
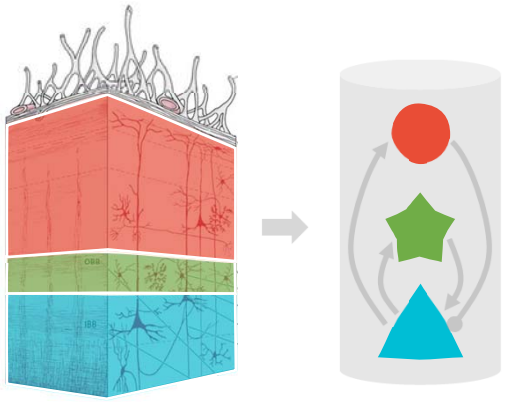
Summary

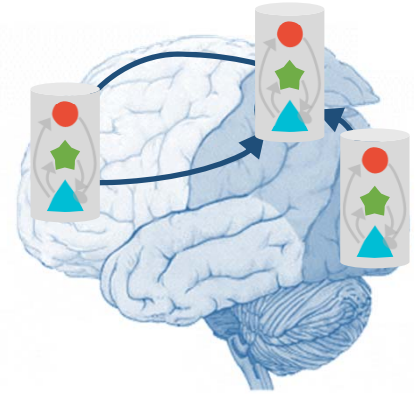
Microscopic



Mesoscopic



Macroscopic



Background

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Context

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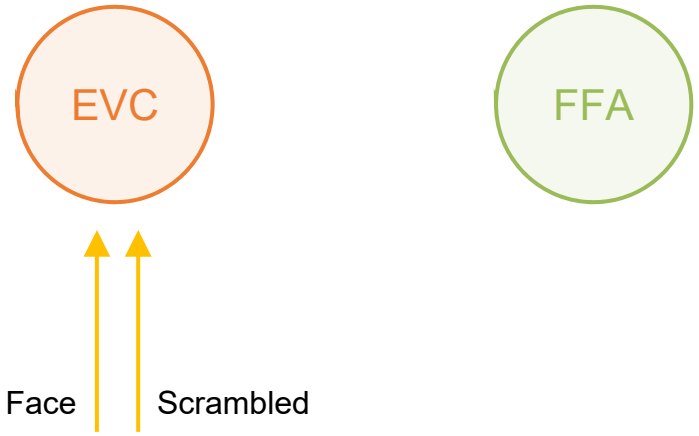
Context

Face Processing

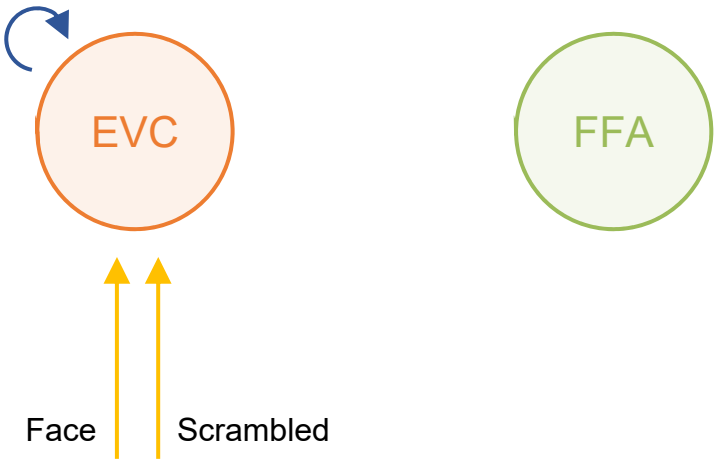
Context

Face Processing



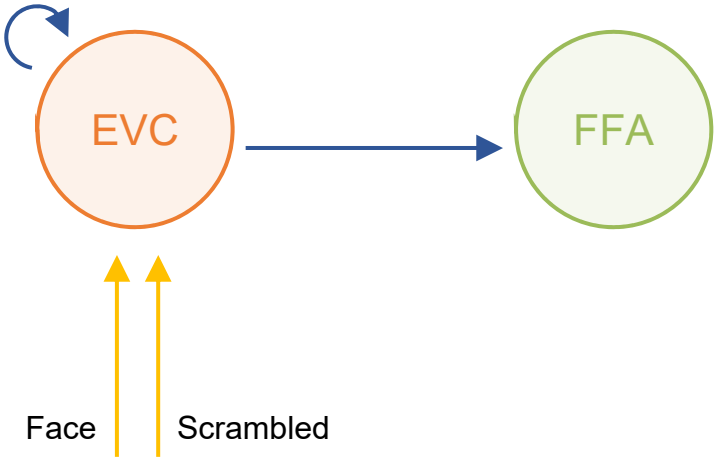
Context

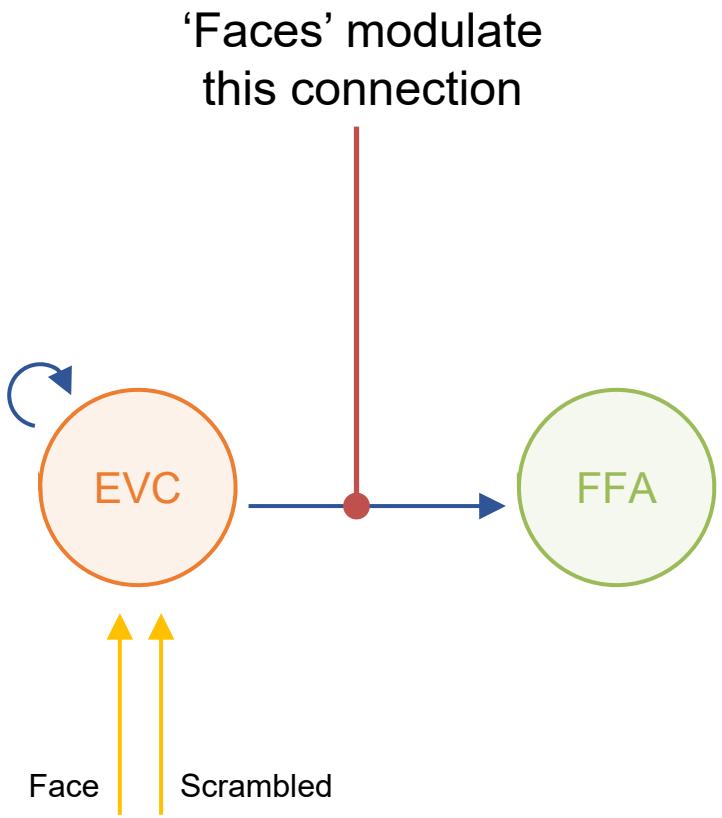
Face Processing

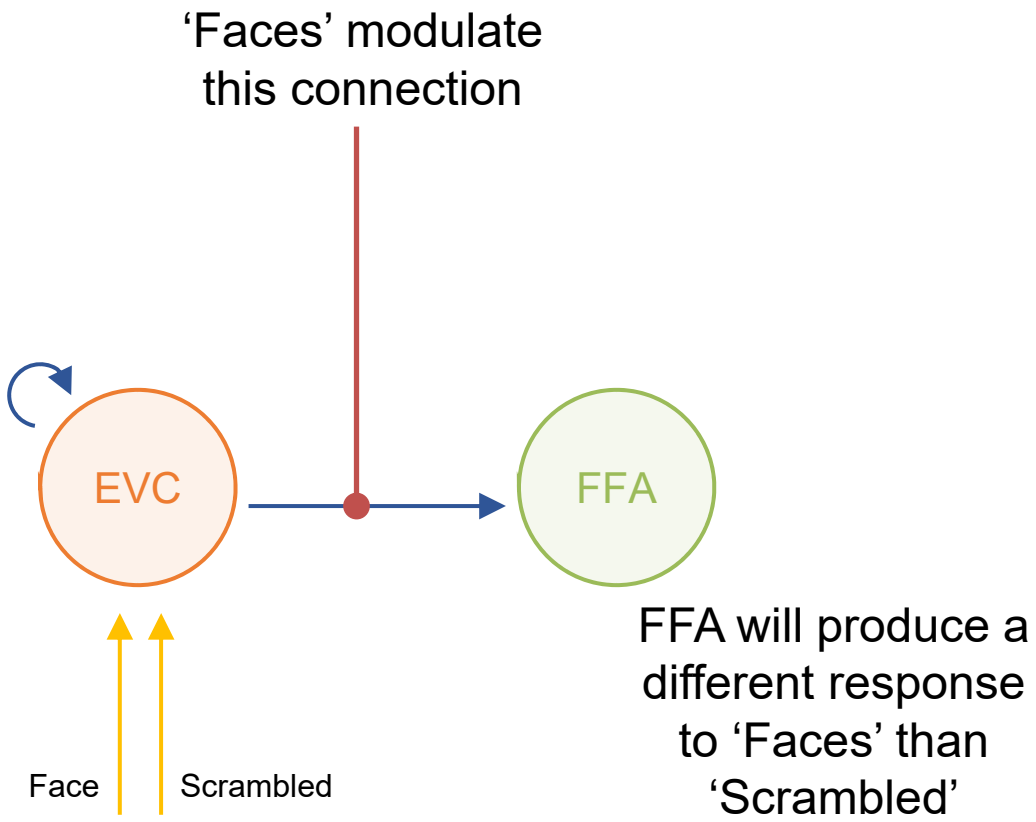


Context

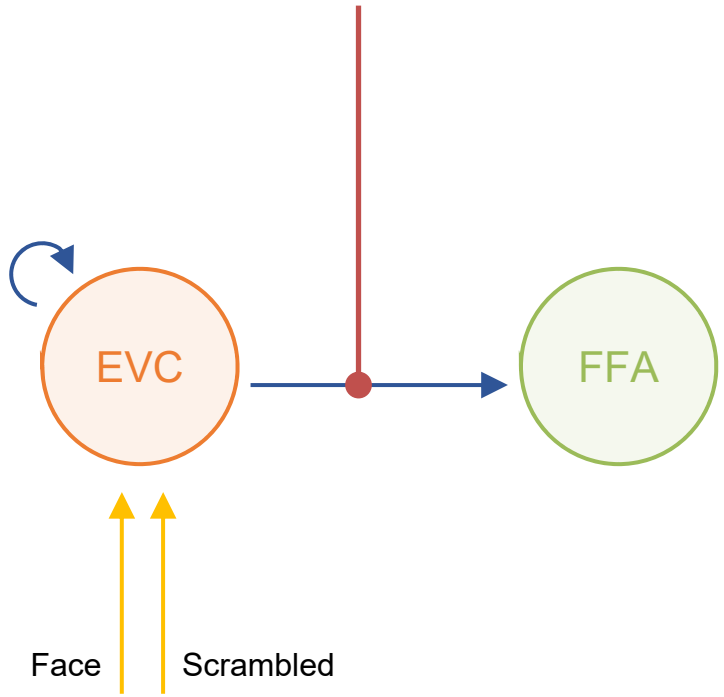
Face Processing

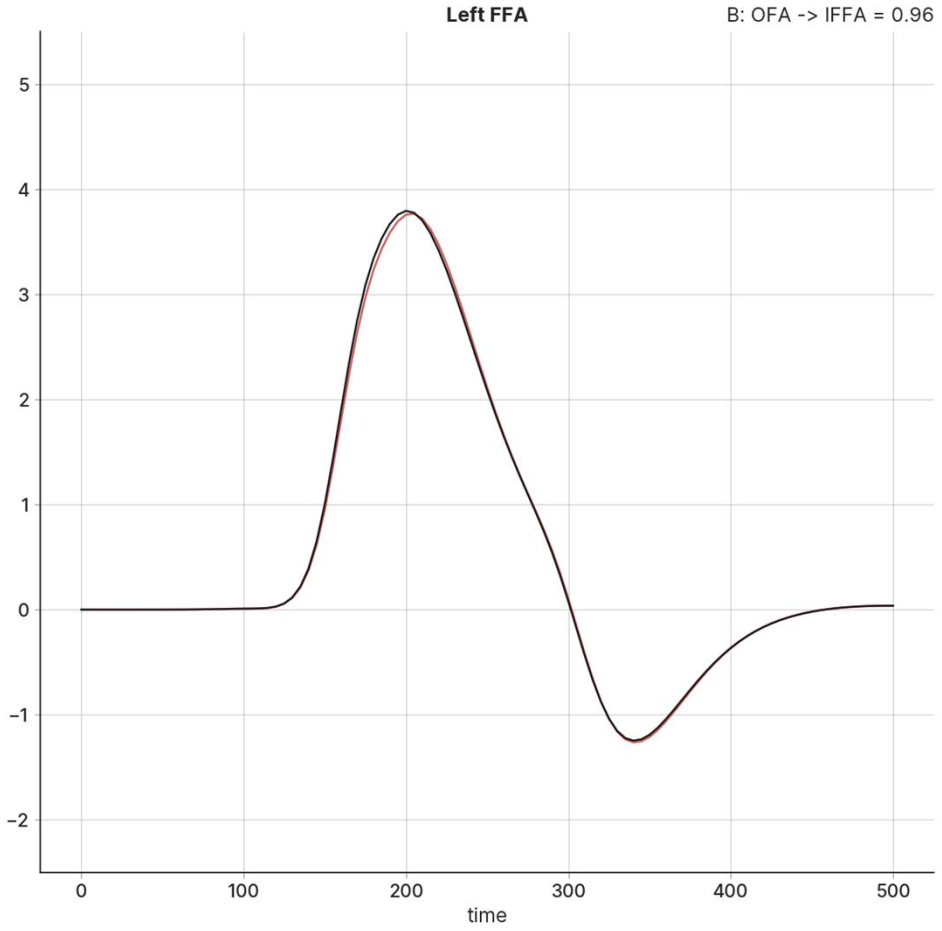



‘Faces’ modulate
this connection
EVC
FFA
Face
Scrambled

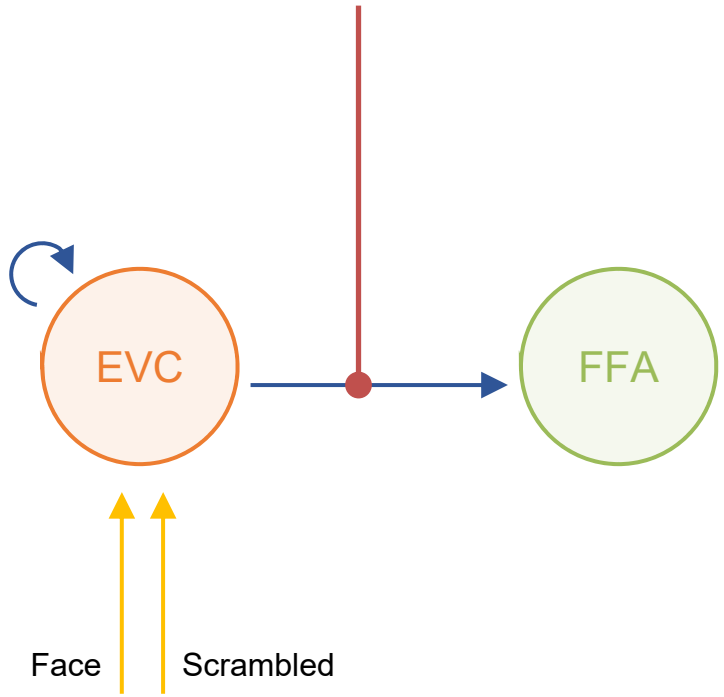

‘Faces’ modulate this connection
EVC
FFA
Face
Scrambled
FFA will produce a different response to ‘Faces’ than ‘Scrambled’

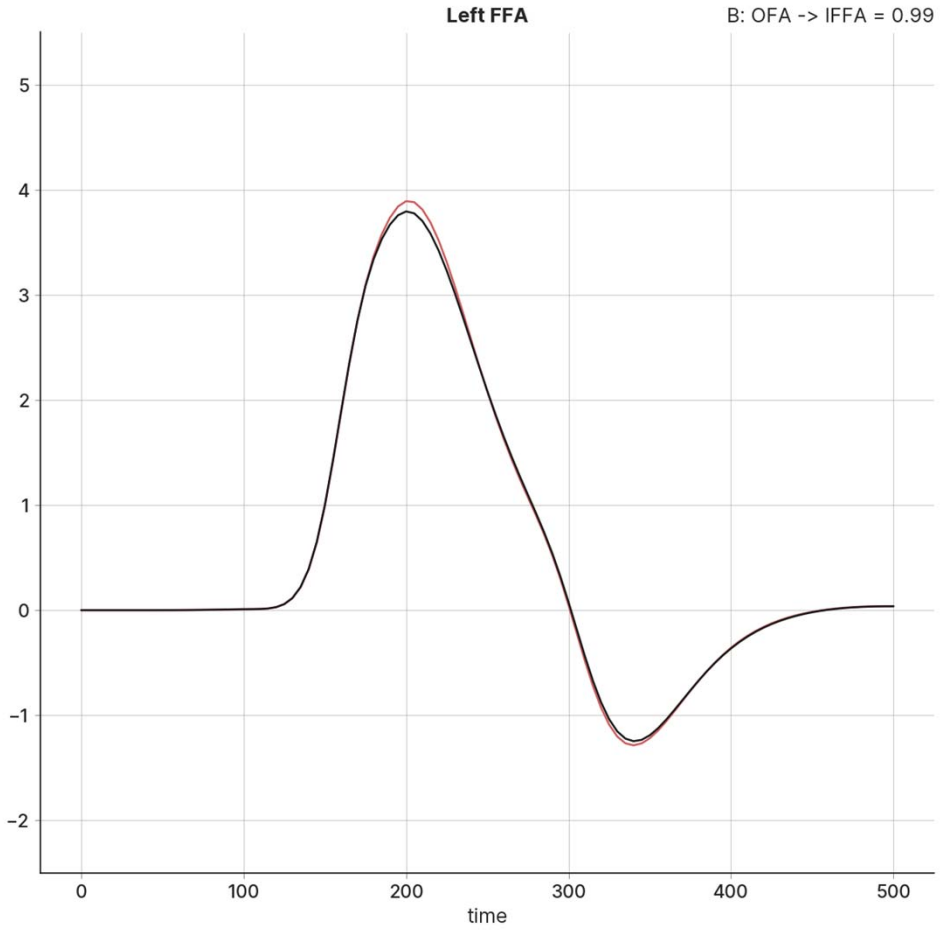
‘Faces’ *don’t* modulate this connection





‘Faces’ *weakly* modulate this connection





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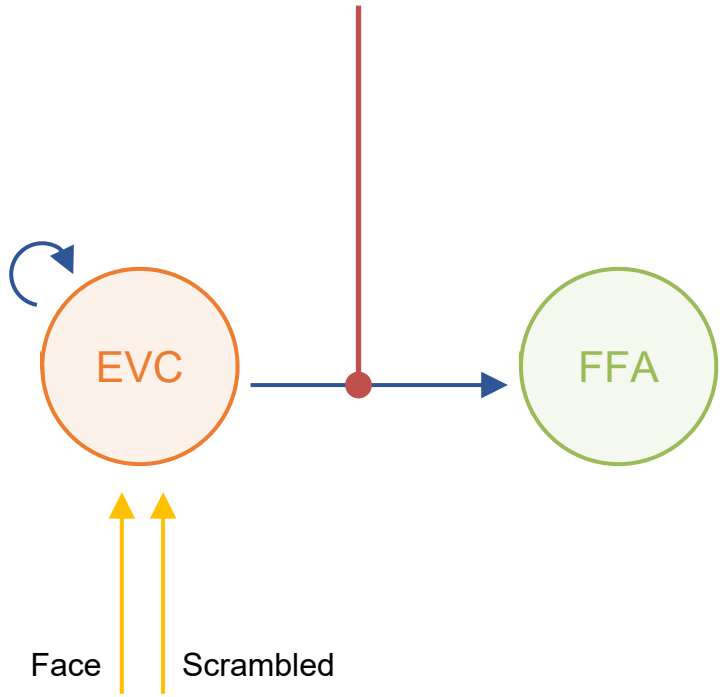
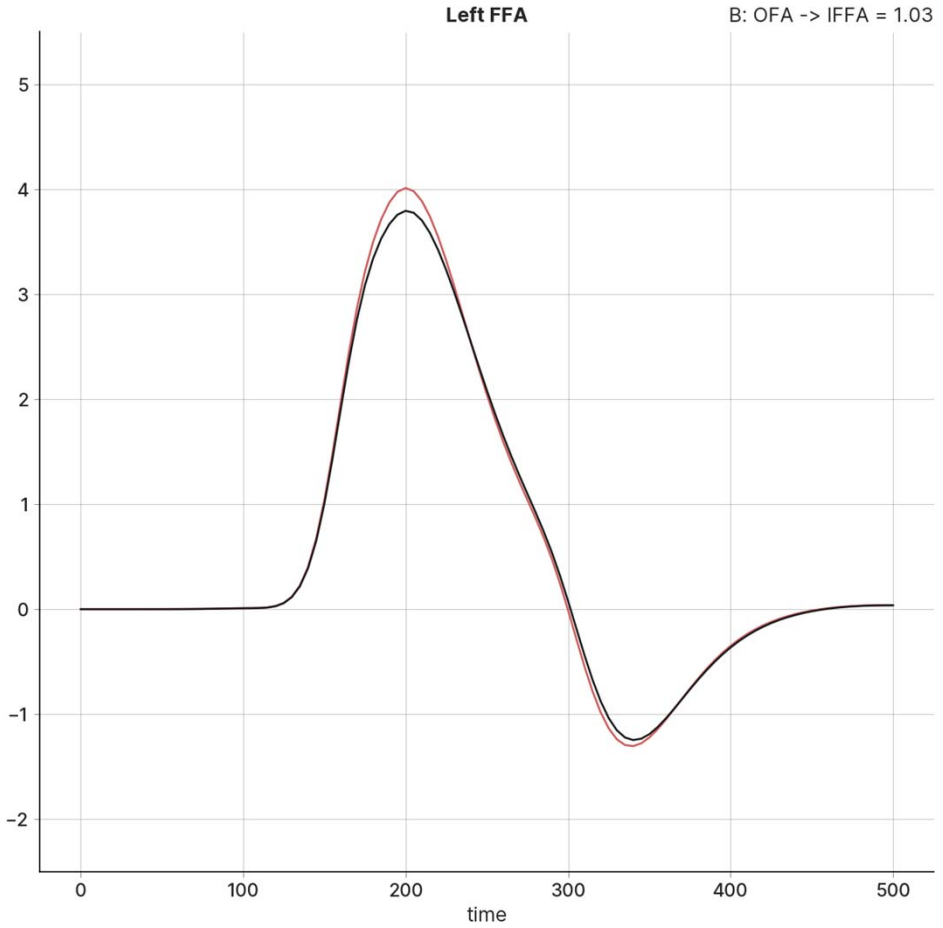
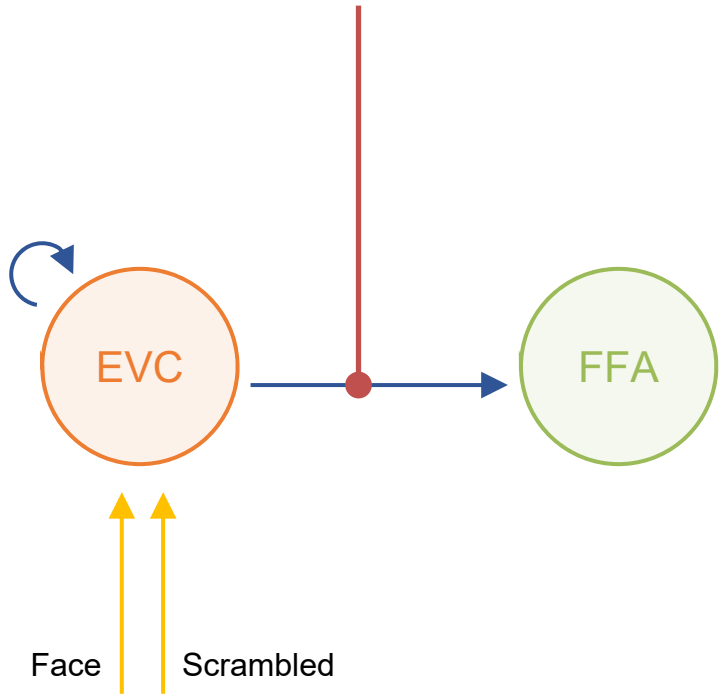
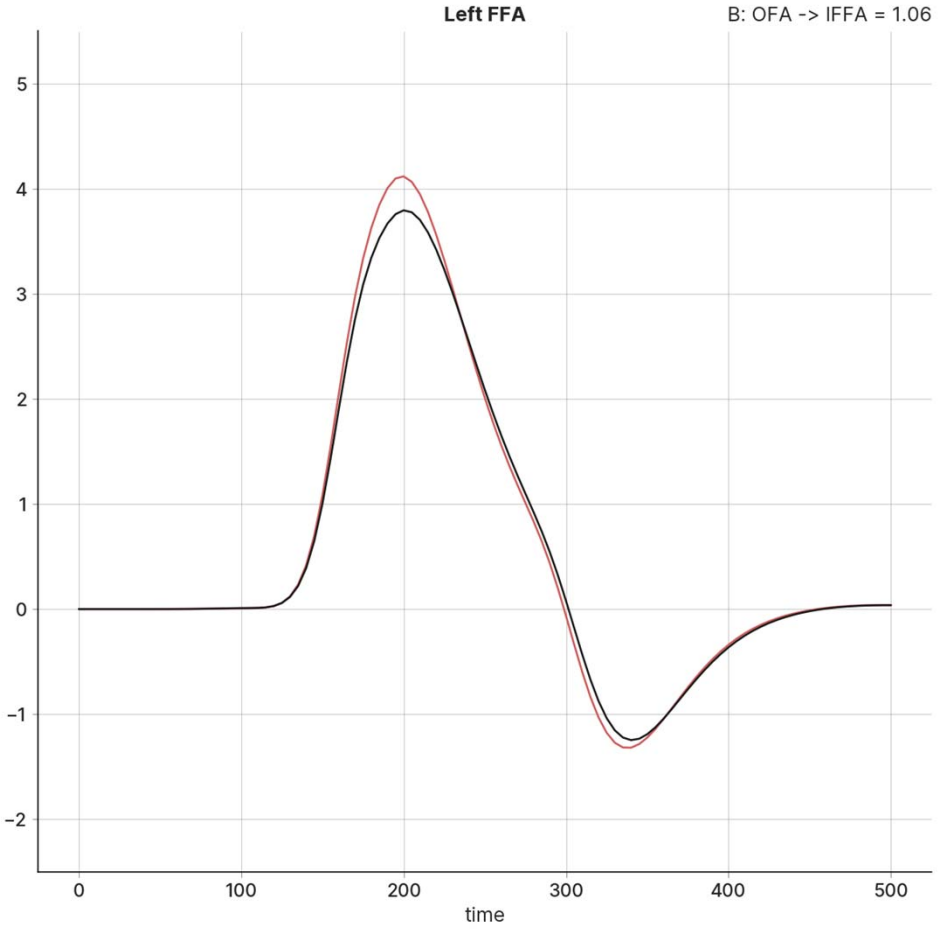


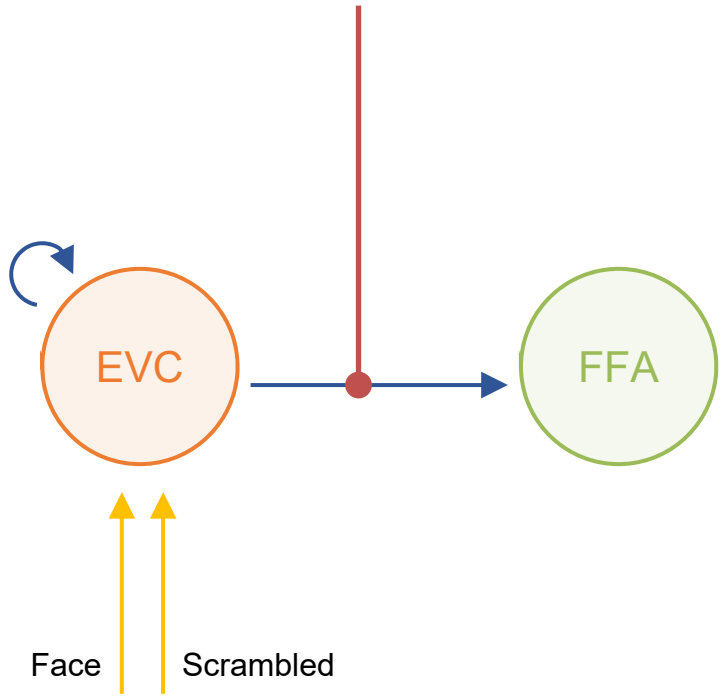


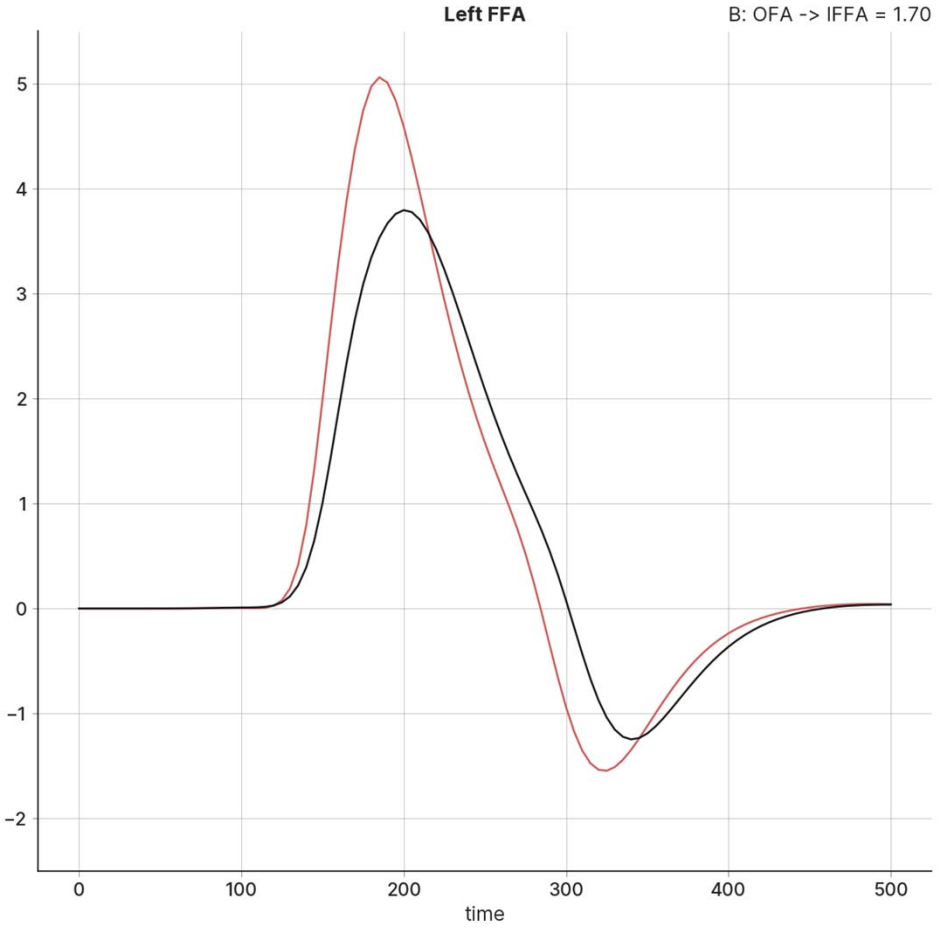
‘Faces’ *weakly* modulate this connection



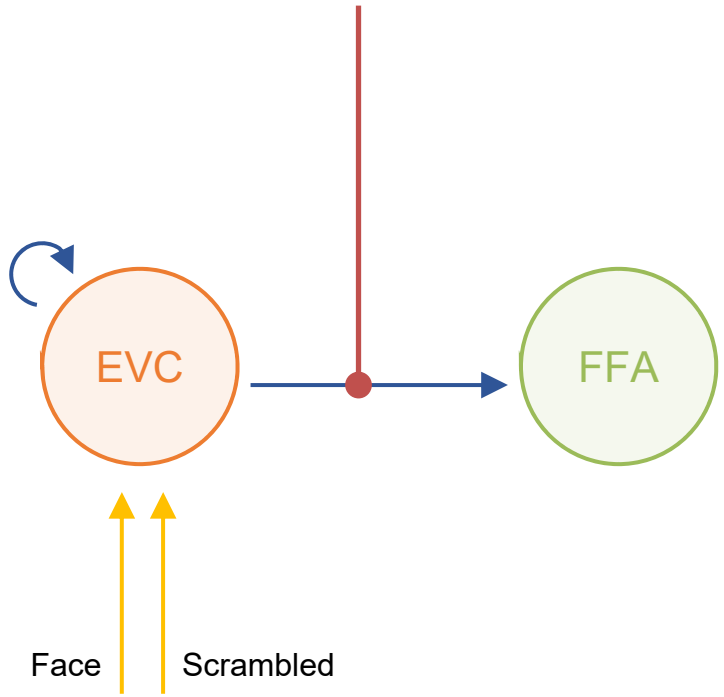


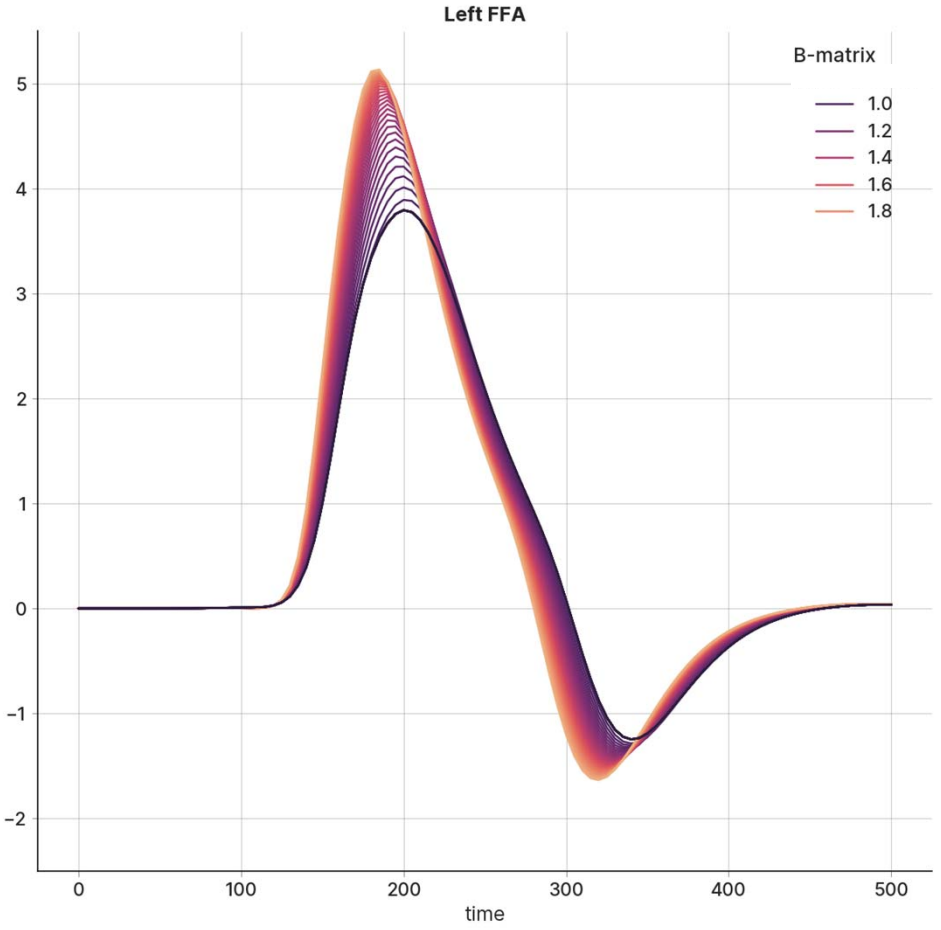
‘Faces’ *strongly* modulate this connection





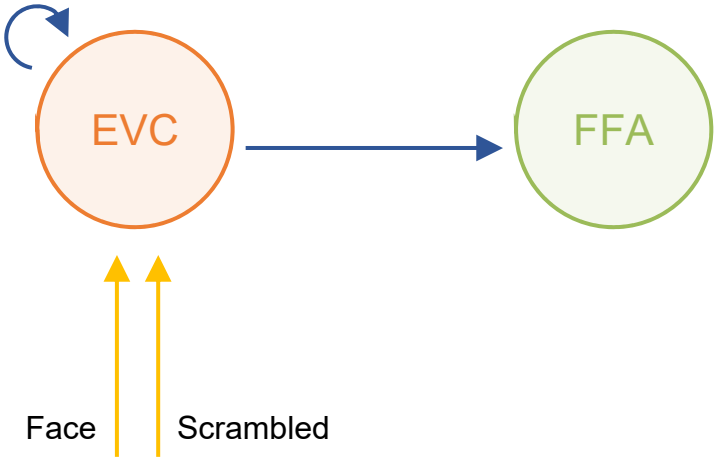
‘Faces’ modulate this connection





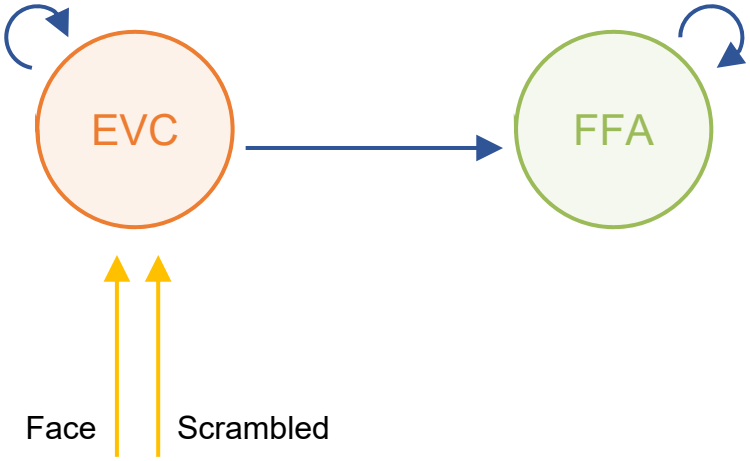
Context

Face Processing



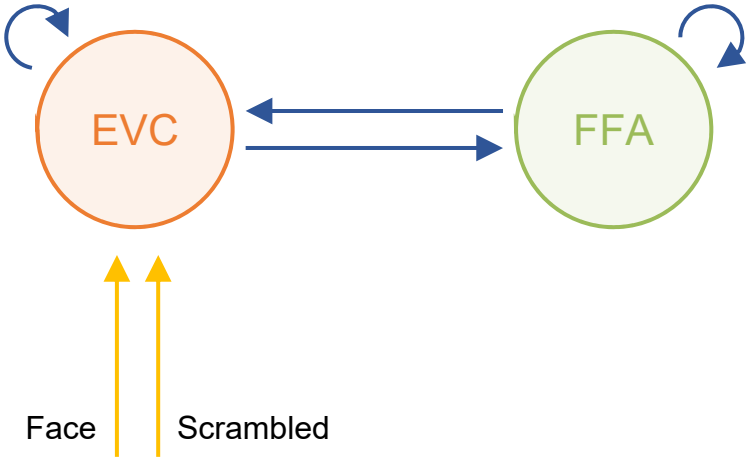
Context

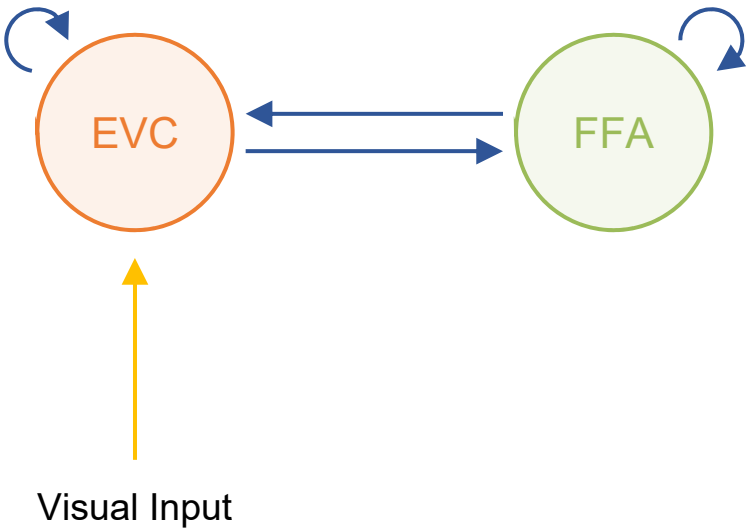
Face Processing



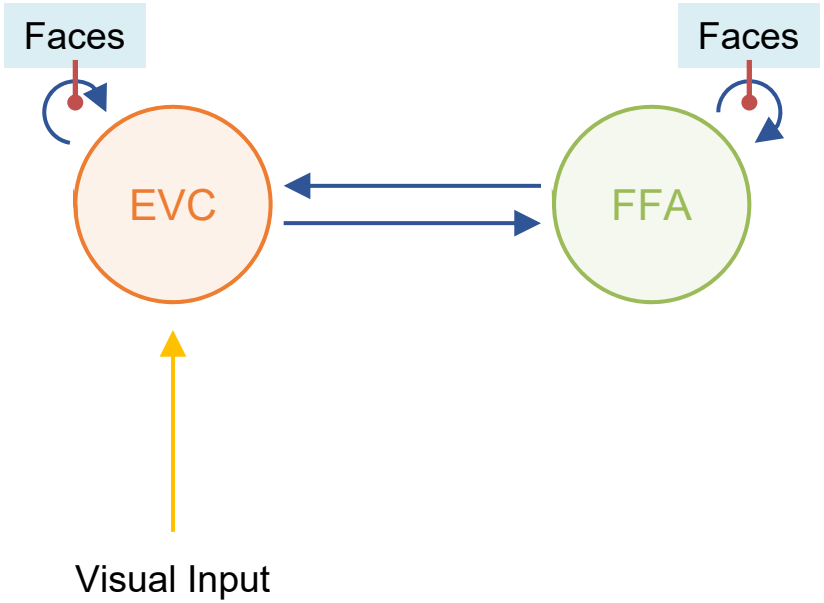
Context

Face Processing

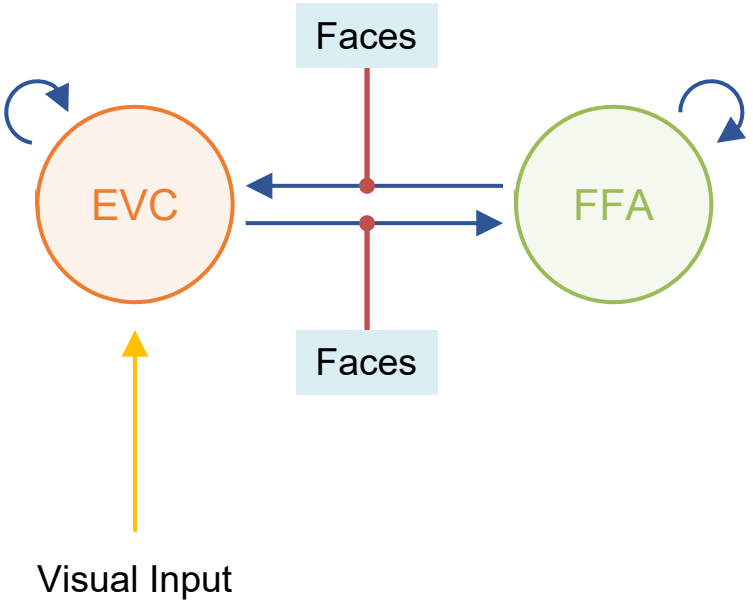



EVC
FFA
Visual Input

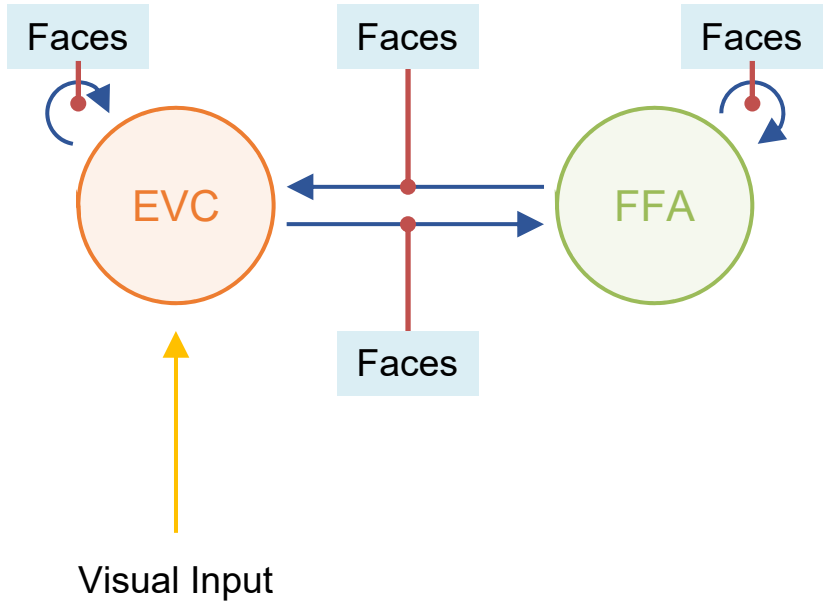
Faces modulate within-EVC & within-FFA connections



Faces modulate bidirectional EVC-FFA connections



Faces modulate both within & bidirectional EVC-FFA connections



Are EVC-FFA connections modulated by Faces?

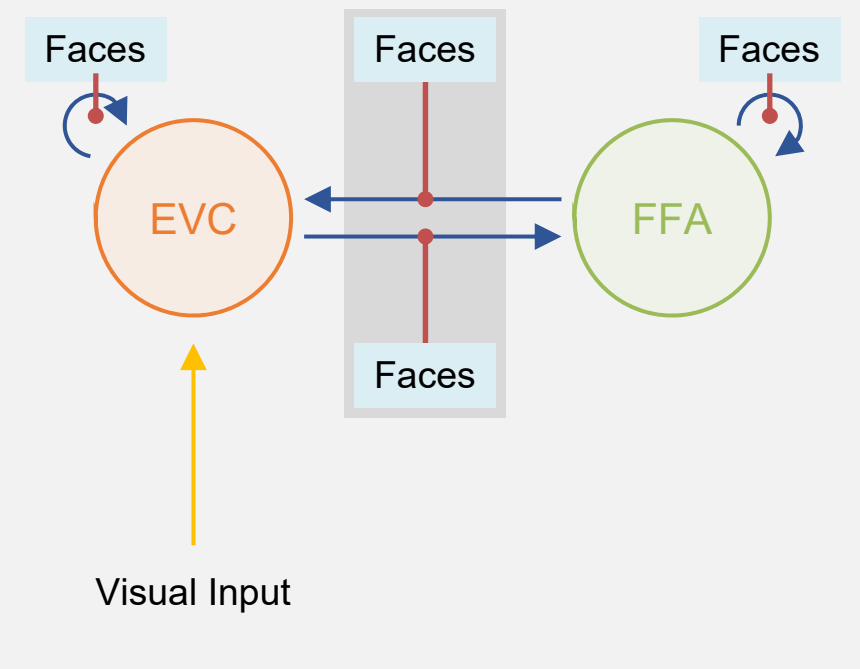
‘Full’ model

Faces modulate bw-region & self-connections

Are EVC-FFA connections modulated by Faces?

‘Full’ model

Faces modulate bw-region & self-connections



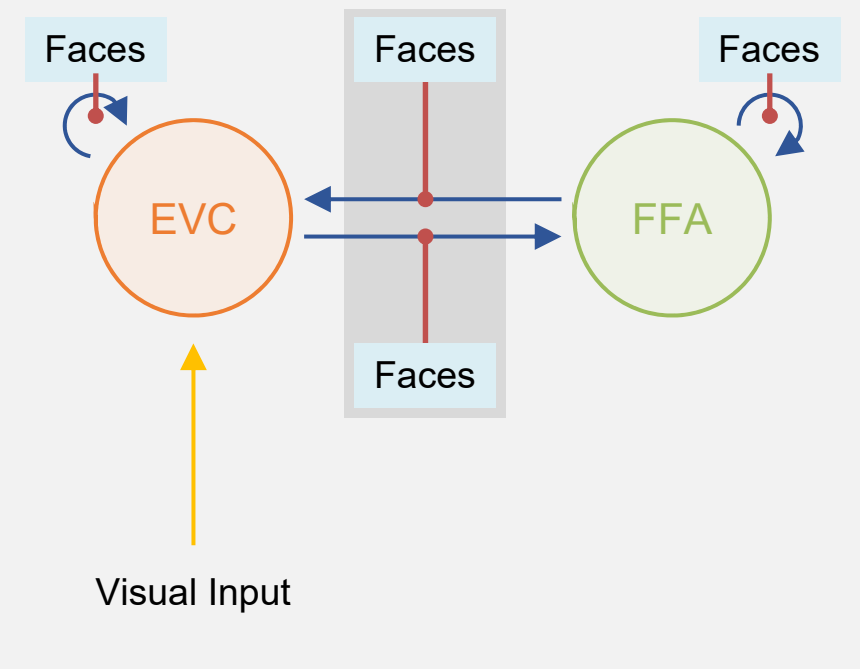
‘Self’ model

Faces modulate only self connections (but not bw)

Are EVC-FFA connections modulated by Faces?

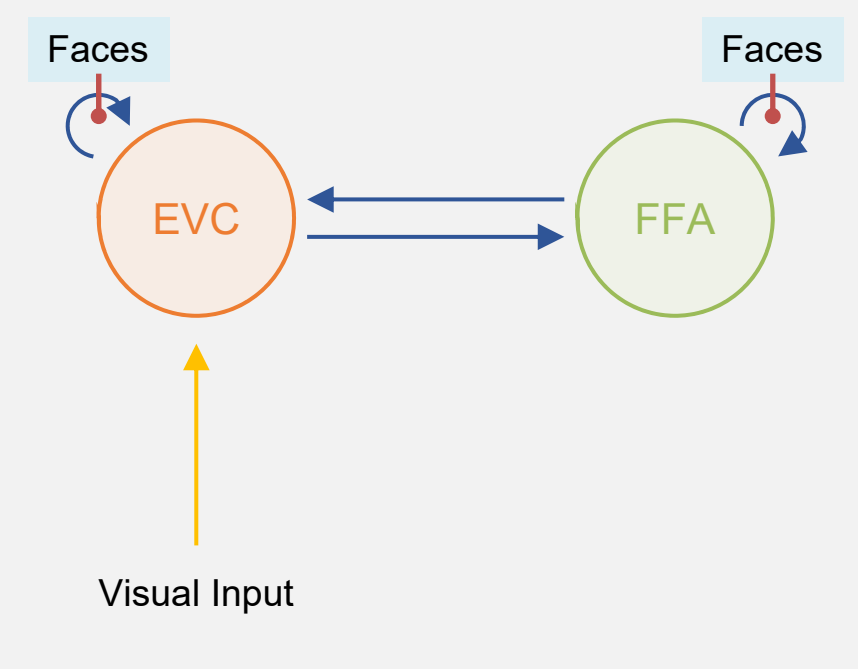
‘Full’ model

Faces modulate bw-region & self-connections



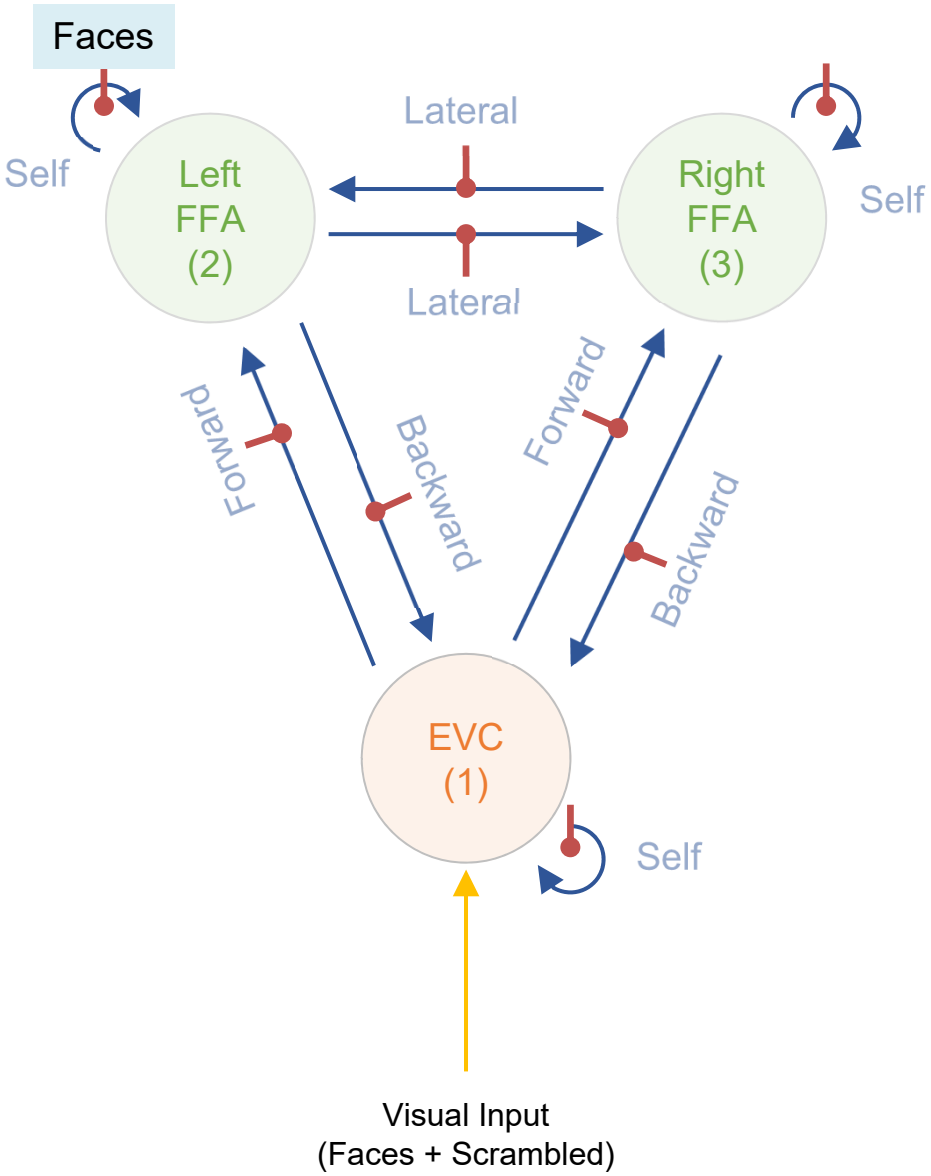
‘Self’ model

Faces modulate only self connections (but not bw)



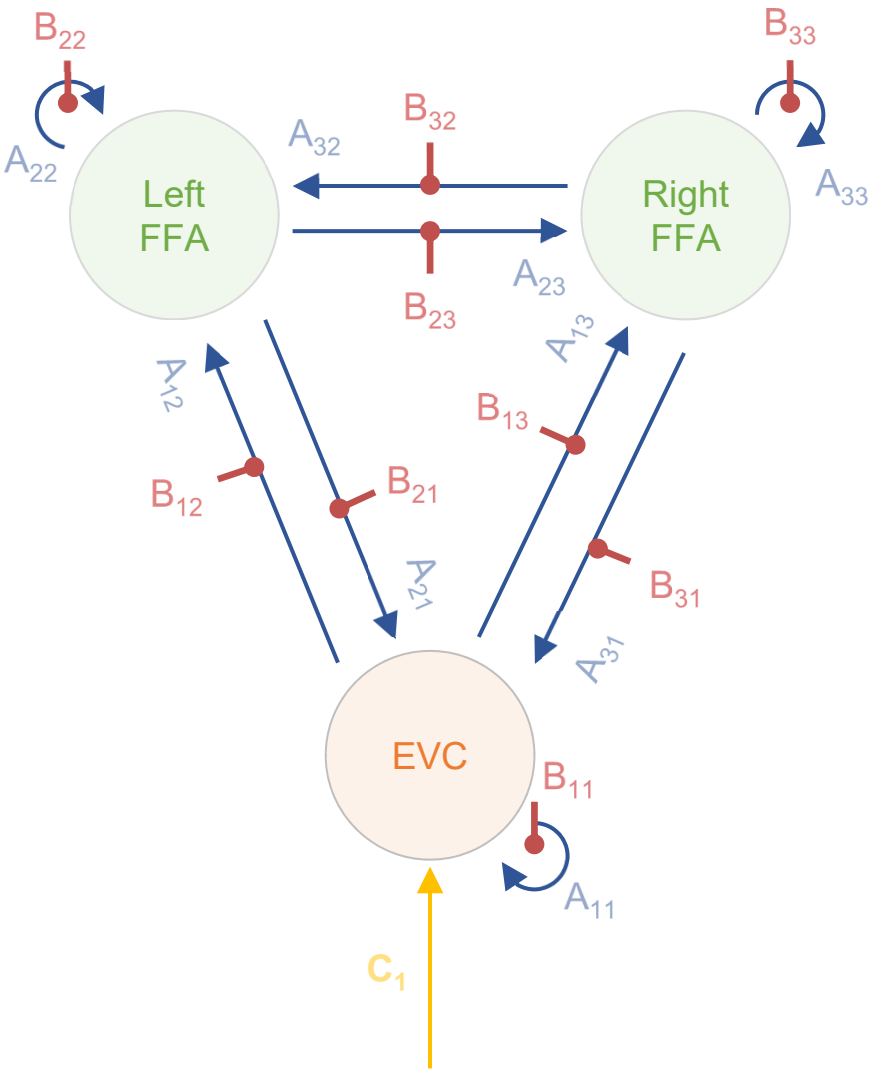
‘Full’ model

Faces modulate both between-region & self connections



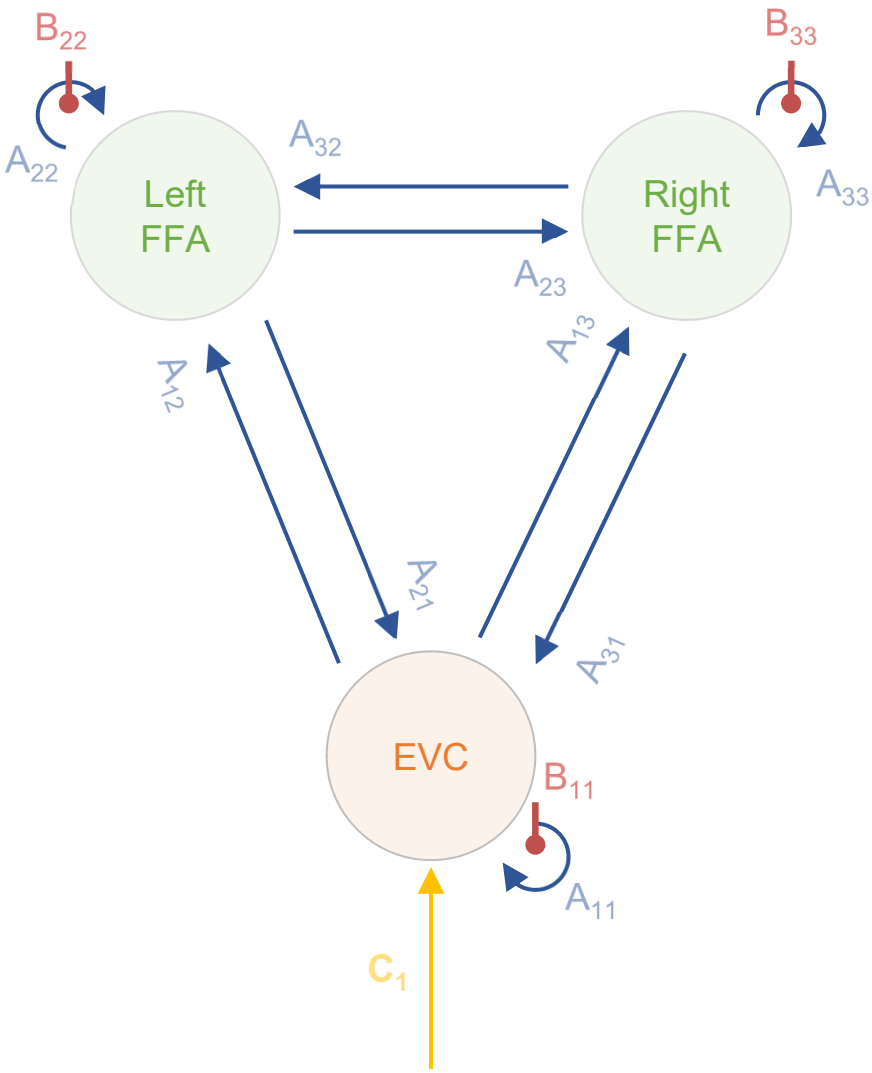
‘Full’ model

Faces modulate both between-region & self connections



‘Self’ model

Faces modulate only self-connections



Background

Generative Modelling in DCM

The Jansen-Rit Model

Effective Connectivity

Demo

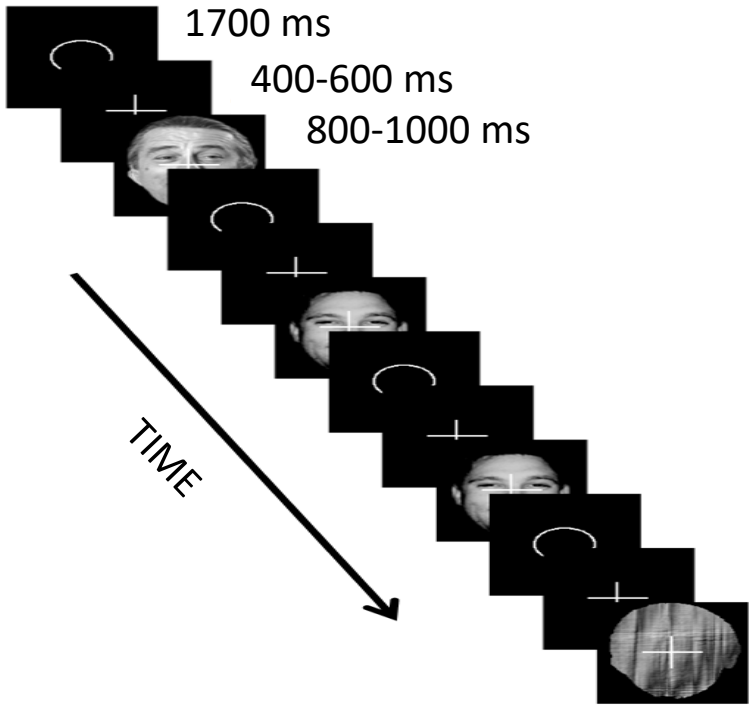
Context

Data

DCM Specification

Review of DCM fit

The Dataset



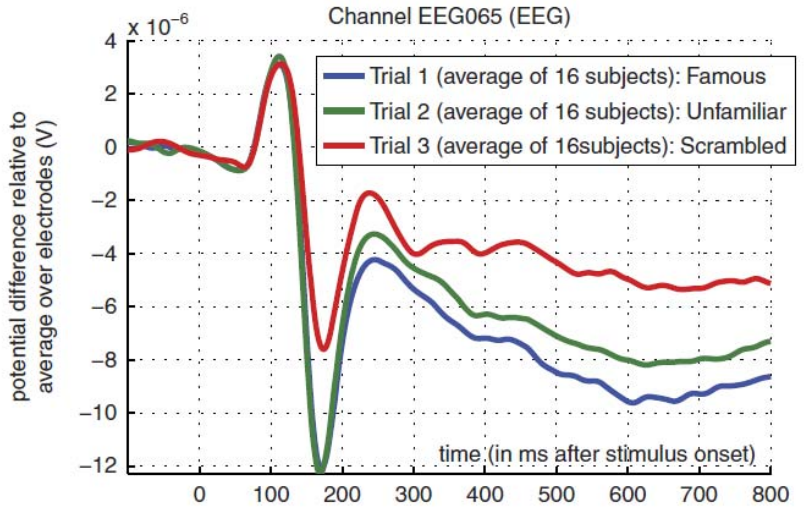
N=16 subjects (BIDS format)

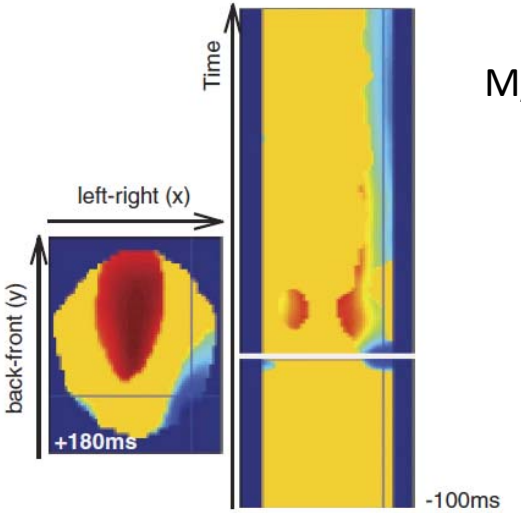
EEG = 70 channels, nose-reference (concurrent with MEG)
MEG = 102 magnetometers + 204 planar gradiometers

fMRI = BOLD EPI 3x3x3mm (3T Siemens Trio)
MRI = T1 MPRAGE 1x1x1mm

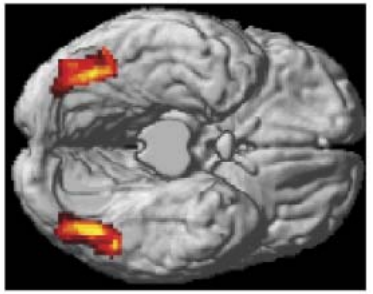
Stimuli: 3 types of greyscale face images:
~300 x Famous
~300 x Nonfamous (previously unseen)
~300 x Phase-scrambled versions of above

Task: Judge left-right symmetry

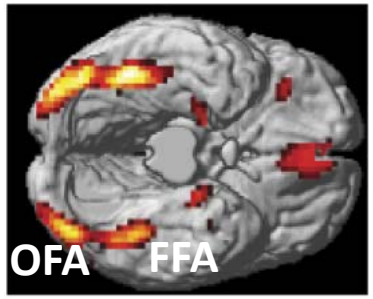




M/EEG



fMRI



Wakeman & Henson (2015), *Scientific Data,* http://www.nature.com/articles/sdata20151

www.nature.com/scientificdata

SCIENTIFIC DATA

OPEN

SUBJECT CATEGORIES

» Electroencephalography -EEG

» Brain imaging

» Functional magnetic resonance imaging

» Cognitive neuroscience

Received: 07 April 2014
Accepted: 05 January 2015
Published: 20 January 2015

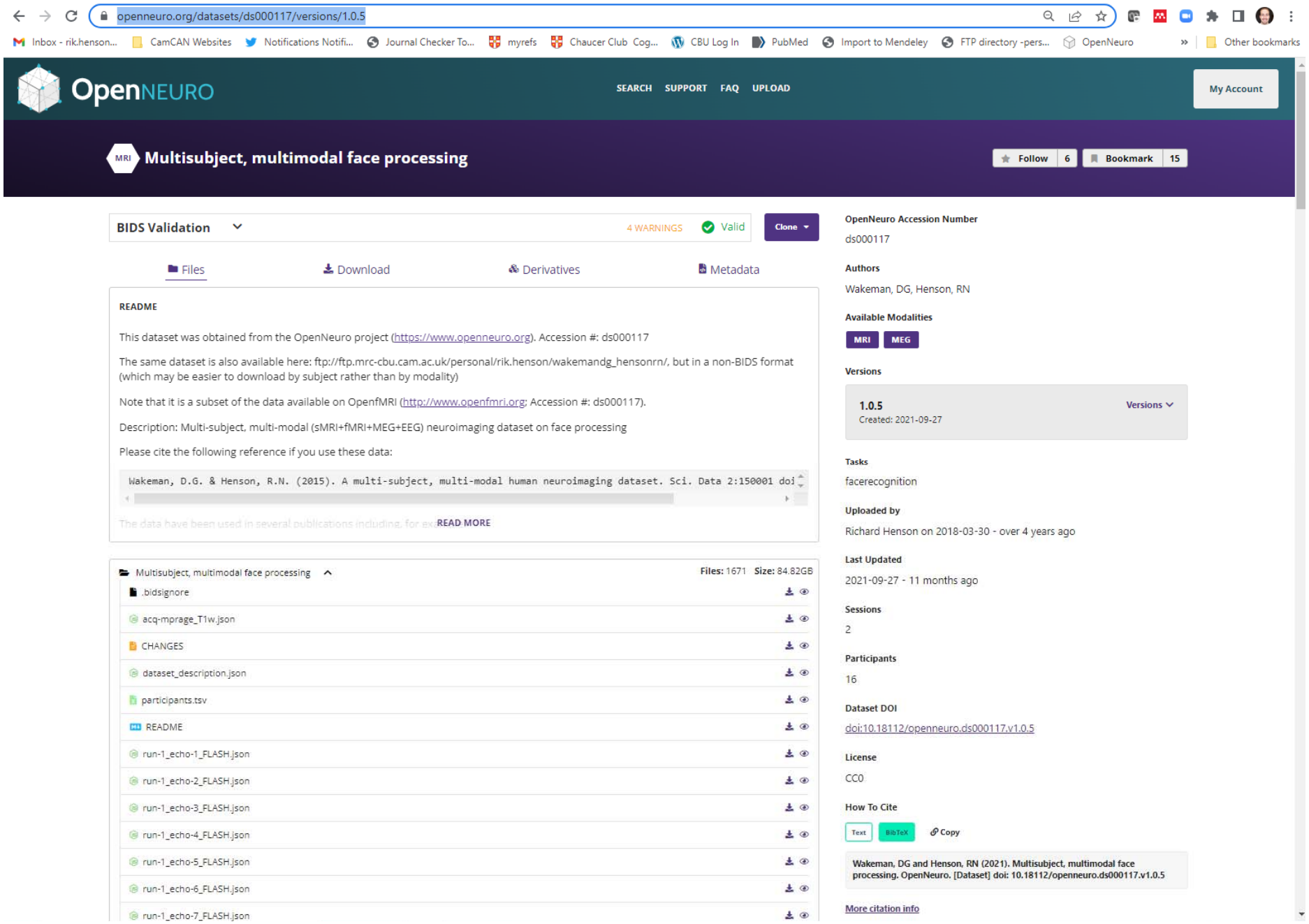
A multi-subject, multi-modal human neuroimaging dataset

Daniel G. Wakeman[1,2] & Richard N. Henson[2]

We describe data acquired with multiple functional and structural neuroimaging modalities on the same nineteen healthy volunteers. The functional data include Electroencephalography (EEG), Magnetoencephalography (MEG) and functional Magnetic Resonance Imaging (fMRI) data, recorded while the volunteers performed multiple runs of hundreds of trials of a simple perceptual task on pictures of familiar, unfamiliar and scrambled faces during two visits to the laboratory. The structural data include T1-weighted MPRAGE, Multi-Echo FLASH and Diffusion-weighted MR sequences. Though only from a small sample of volunteers, these data can be used to develop methods for integrating multiple modalities from multiple runs on multiple participants, with the aim of increasing the spatial and temporal resolution above that of any one modality alone. They can also be used to integrate measures of functional and structural connectivity, and as a benchmark dataset to compare results across the many neuroimaging analysis packages. The data are freely available from https://openfmri.org/.

Wakeman & Henson (2015), *Scientific Data,* http://www.nature.com/articles/sdata20151

https://openneuro.org/datasets/ds000117/versions/1.0.5



SPM Manual for fMRI+M/EEG

SPM12 Manual

The FIL Methods Group
(and honorary members)

John Ashburner
Gareth Barnes
Chun-Chuan Chen
Jean Daunizeau
Guillaume Flandin
Karl Friston
Stefan Kiebel
James Kilner
Vladimir Litvak
Rosalyn Moran
Will Penny
Adeel Razi
Klaas Stephan
Sungho Tak
Peter Zeidman

Darren Gitelman
Rik Henson
Chloe Hutton
Volkmar Glauche
Jérémie Mattout
Christophe Phillips

Chapter 42

Multimodal, Multisubject data fusion

42.1 Overview

This dataset contains EEG, MEG, functional MRI and structural MRI data from 16 subjects who undertook multiple runs of a simple task performed on a large number of Famous, Unfamiliar and Scrambled faces. It will be used to demonstrate:

1. batching and scripting of preprocessing of multiple subjects/runs of combined MEG and EEG data,
2. creation of trial-averaged evoked responses,
3. 3D scalp-time statistical mapping of evoked responses across trials within one subject,
4. 2D time-frequency statistical mapping of time-frequency data across subjects,
5. preprocessing and group analysis of fMRI data from the same subjects and paradigm,
6. source-reconstruction of the "N/M170" face component (using structural MRI for forward modelling),
7. individual and group-based fusion of EEG and MEG during source reconstruction,
8. statistical mapping across subjects of cortical power in a time-frequency window, using the functional MRI results as spatial priors.

Preprocessing

frontiers in Neuroscience

METHODS
published: 24 April 2019
doi: 10.3389/fnins.2019.00300

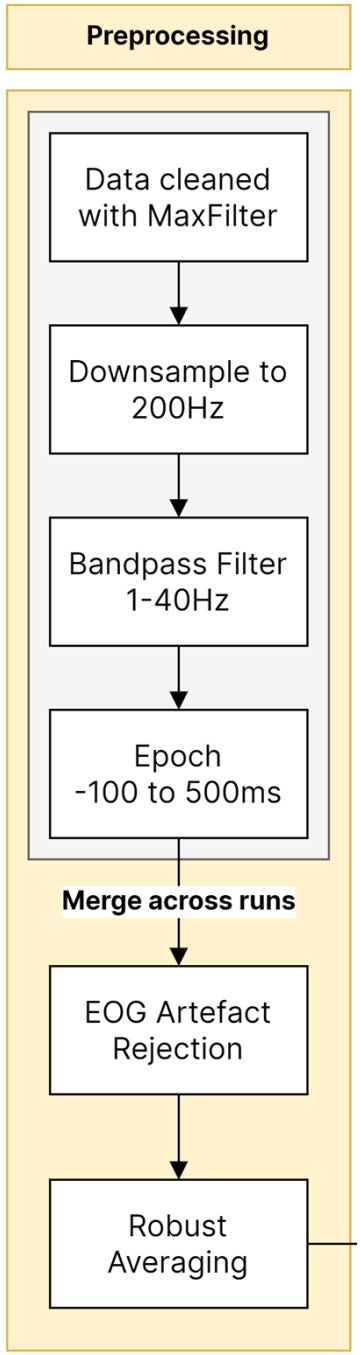
Check for updates

Multimodal Integration of M/EEG and f/MRI Data in SPM12

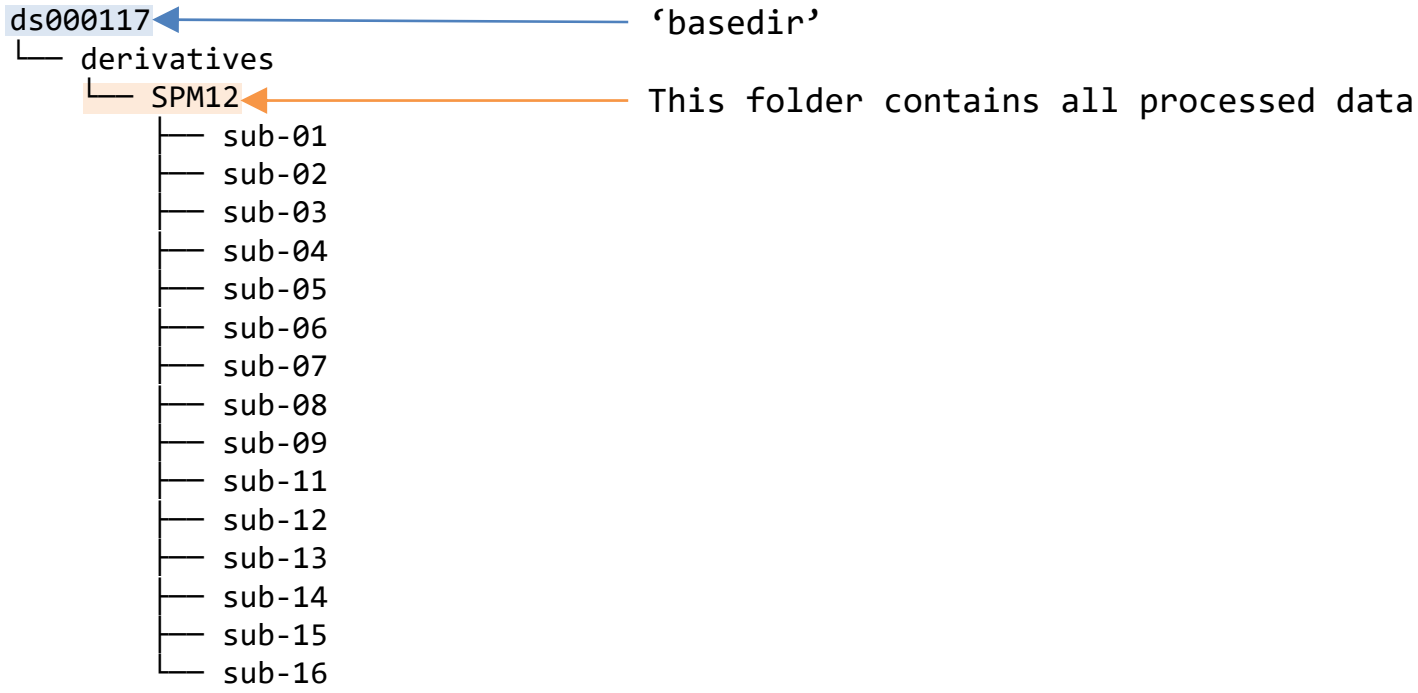
Richard N. Henson[1*], *Hunar Abdulrahman*[1], *Guillaume Flandin*[2] *and Vladimir Litvak*[2]

[1] *MRC Cognition and Brain Sciences Unit, University of Cambridge, Cambridge, United Kingdom,* [2] *Wellcome Centre for Human Neuroimaging, University College London, London, United Kingdom*

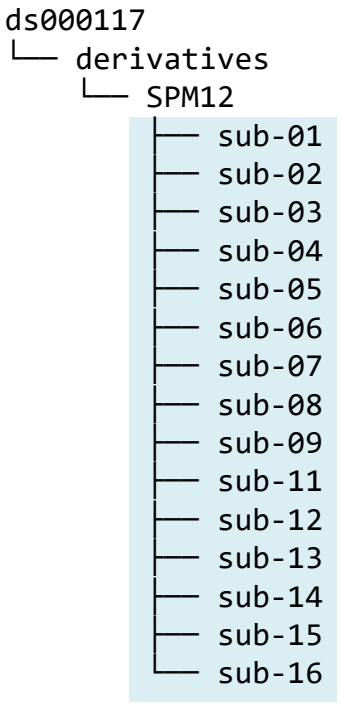
- fMRI preprocessing in Appendix 2 of Supplementary material: https://www.frontiersin.org/articles/10.3389/fnins.2019.00300/full#supplementary-material


Preprocessing
Data cleaned with MaxFilter
Downsample to 200Hz
Bandpass Filter 1-40Hz
Epoch -100 to 500ms
Merge across runs
EOG Artefact Rejection
Robust Averaging

Data organization



Data organization



These should already be present if you began with raw data and processed as per Henson et al 2019.

Else, download from figshare and extract here.

Data organization

```
ds000117
└── derivatives
    └── SPM12
        ├── sub-01
        │   └── meg
        │       ├── wmaMcefspmeeg_sub-01_ses-meg_task-facerecognition_run-01_proc-sss_meg.dat
        │       ├── wmaMcefspmeeg_sub-01_ses-meg_task-facerecognition_run-01_proc-sss_meg.mat
        │       └── SPMgainmatrix_wmaMcefspmeeg_sub-01_ses-meg_task-facerecognition_run-01_proc-sss_meg_1.mat
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        │   └── meg
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        │
         ...
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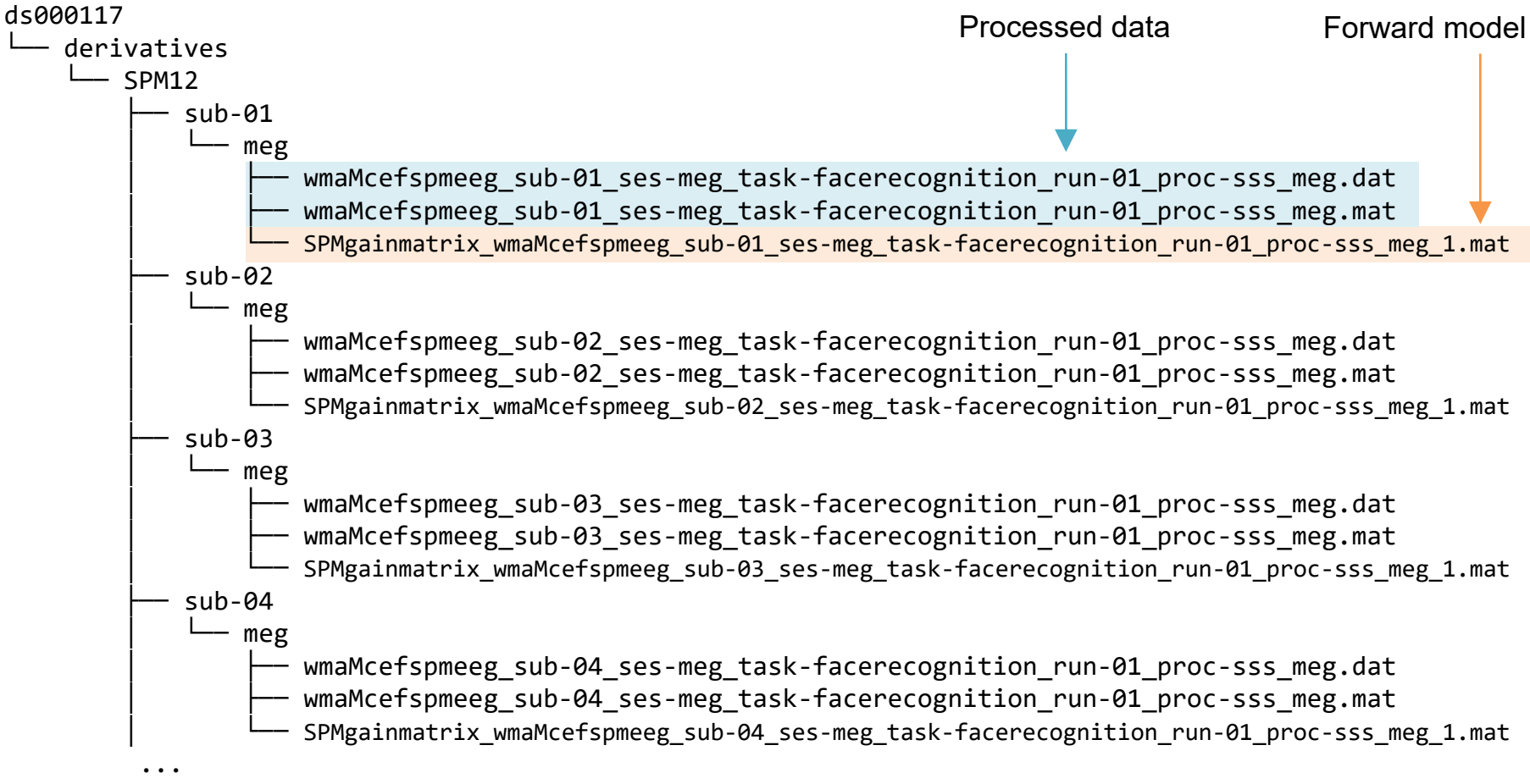
3 files per subject

Data organization



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The Jansen-Rit Model

Effective Connectivity

Demo

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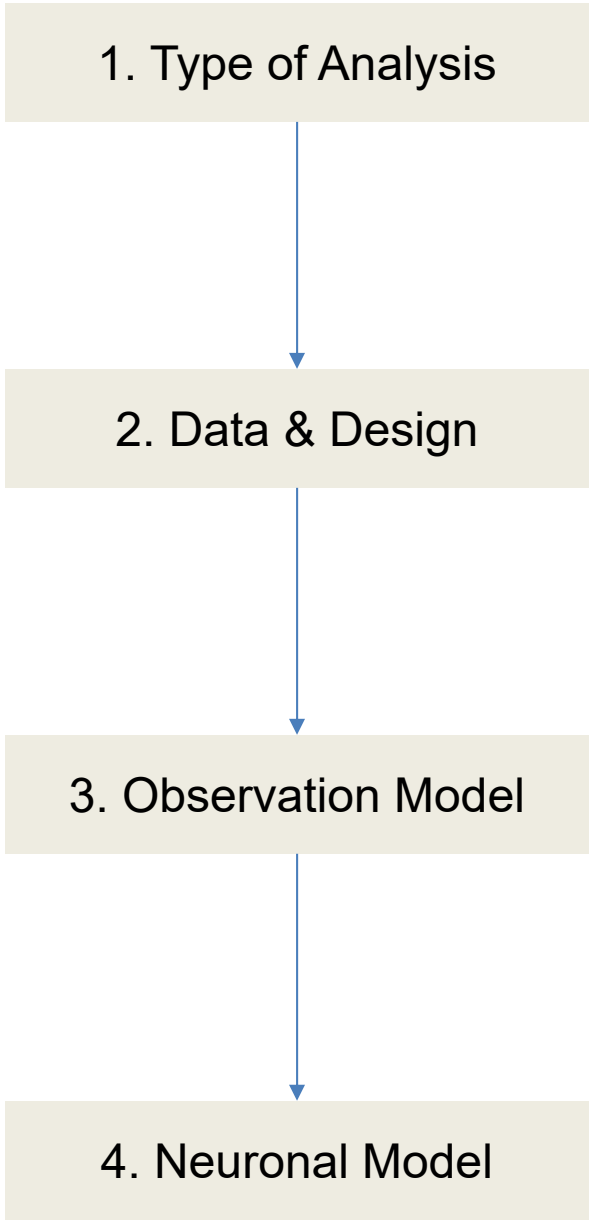
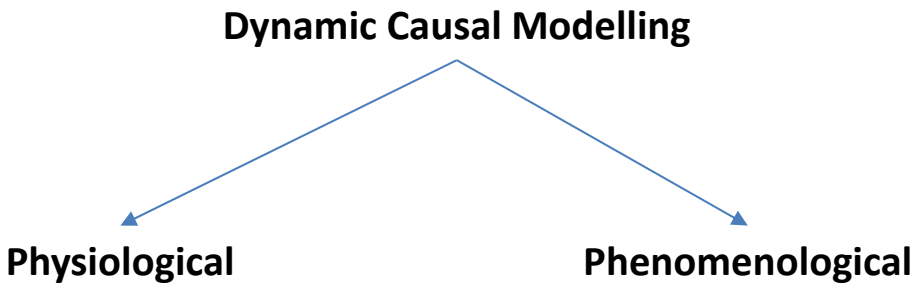
Review of DCM fit

DCM Specification



DCM Specification

1. Type of Analysis



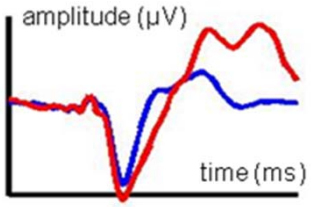
DCM Specification

1. Type of Analysis

Dynamic Causal Modelling

Physiological | **Phenomenological**

Event-Related Potentials (ERP)



David et al 2006
Garrido et al 2007

DCM Specification

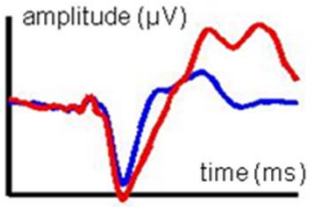
1. Type of Analysis

Dynamic Causal Modelling

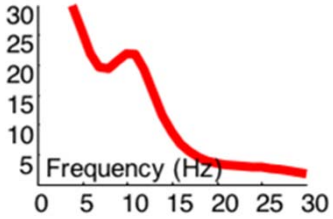
Physiological | **Phenomenological**

Event-Related Potentials (ERP)

Cross-Spectral Densities (CSD)



David et al 2006
Garrido et al 2007



Moran et al 2009, 2011
Friston et al 2012

DCM Specification

1. Type of Analysis

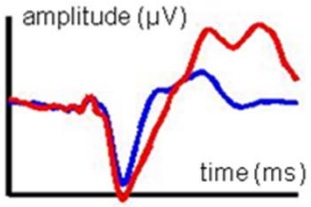
Dynamic Causal Modelling

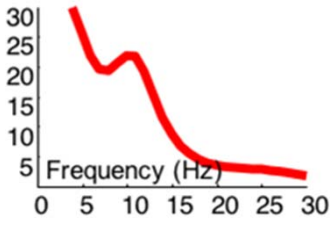
Physiological | **Phenomenological**

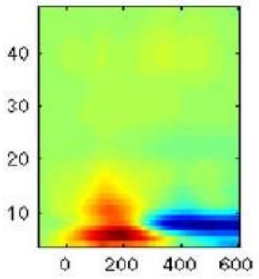
Event-Related Potentials (ERP)

Cross-Spectral Densities (CSD)

Induced Responses (IND)







David et al 2006
Garrido et al 2007

Moran et al 2009, 2011
Friston et al 2012

Chen et al 2008, 2009
Van Wijk et al 2012

DCM Specification

1. Type of Analysis

Dynamic Causal Modelling

Physiological

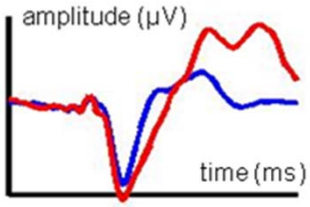
Phenomenological

Event-Related Potentials (ERP)

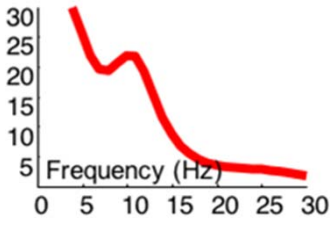
Cross-Spectral Densities (CSD)

Induced Responses (IND)

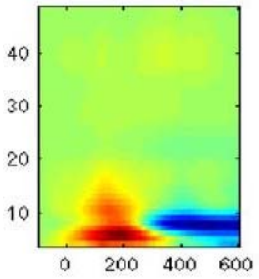
Phase Coupling (PHA)



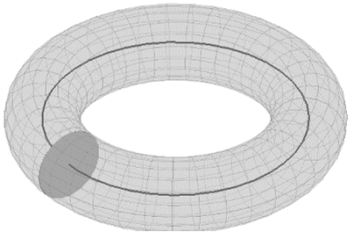
David et al 2006
Garrido et al 2007



Moran et al 2009, 2011
Friston et al 2012



Chen et al 2008, 2009
Van Wijk et al 2012



Penny et al 2009

DCM Specification

1. Type of Analysis

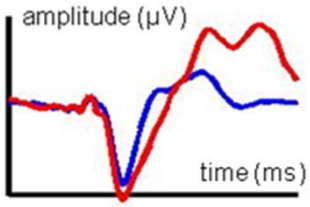
Dynamic Causal Modelling

Physiological

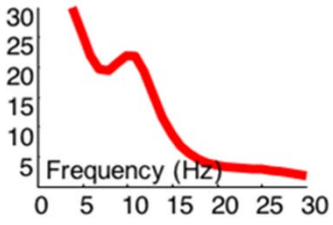
- Event-Related Potentials (ERP)
- Cross-Spectral Densities (CSD)

Phenomenological

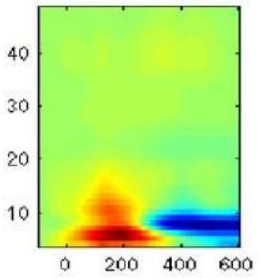
- fMRI
- Induced Responses (IND)
- Phase Coupling (PHA)



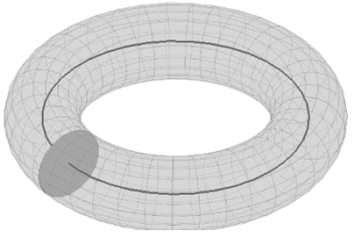
David et al 2006
Garrido et al 2007



Moran et al 2009, 2011
Friston et al 2012



Chen et al 2008, 2009
Van Wijk et al 2012



Penny et al 2009

DCM Specification

1. Type of Analysis

Neuronal Models

How is the cortical column modelled?

eg. how many neuronal populations in each column/source?

DCM Specification

1. Type of Analysis

Neuronal Models

How is the cortical column modelled?

eg. how many neuronal populations in each column/source?

How is the average firing rate derived?

eg. based on mean depolarization (convolution)

or modelled membrane/channel conductance? (conductance)

DCM Specification

1. Type of Analysis

Neuronal Models

How is the cortical column modelled?

eg. how many neuronal populations in each column/source?

How is the average firing rate derived?

eg. based on mean depolarization (convolution)

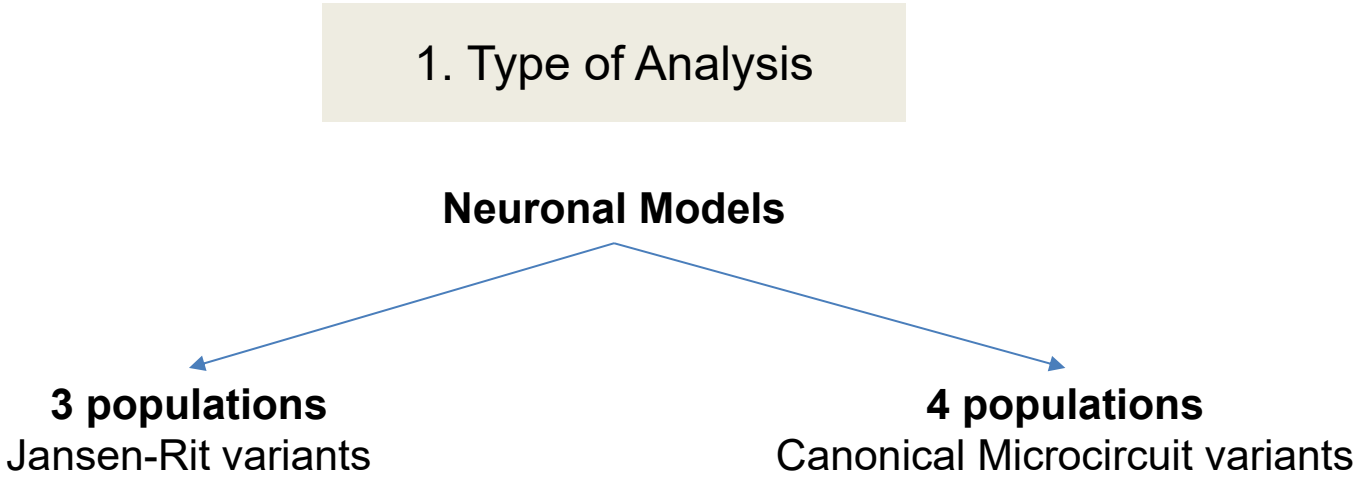
or modelled membrane/channel conductance? (conductance)

How is a neuronal population treated?

eg. are all neurons lumped into a point mass or, (neural masses)

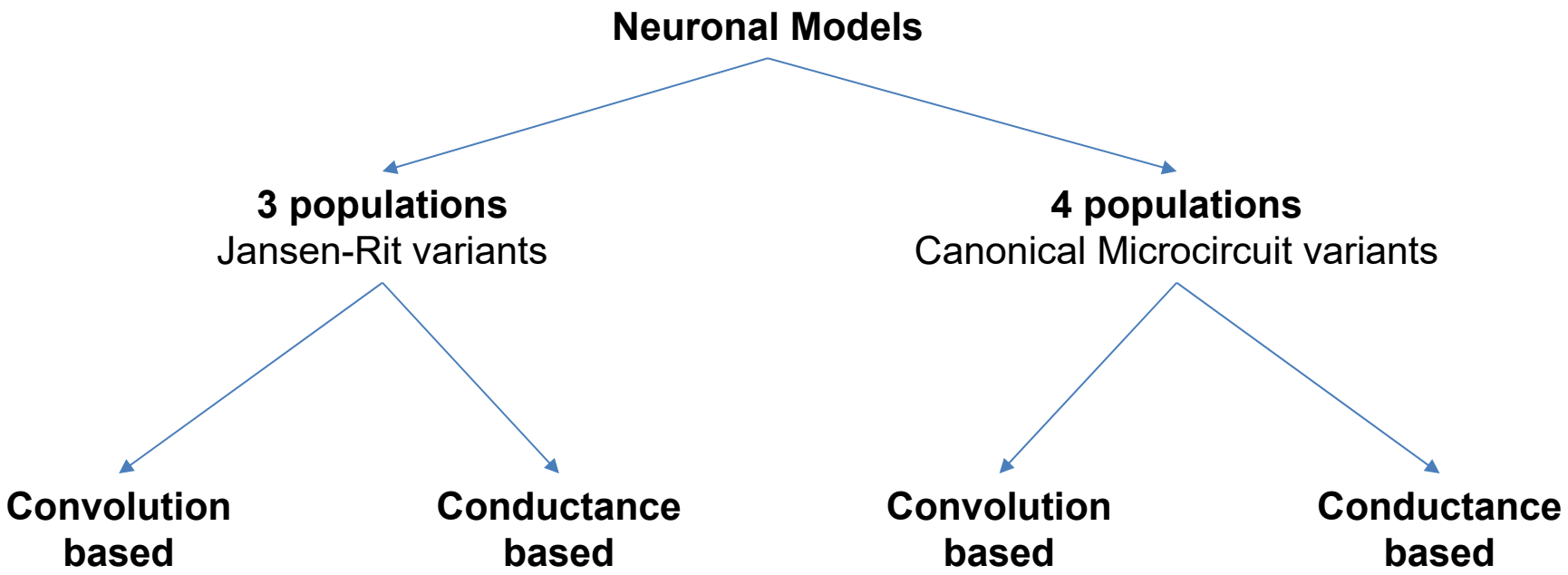
are spatial correlations taken into account? (neural fields)

DCM Specification



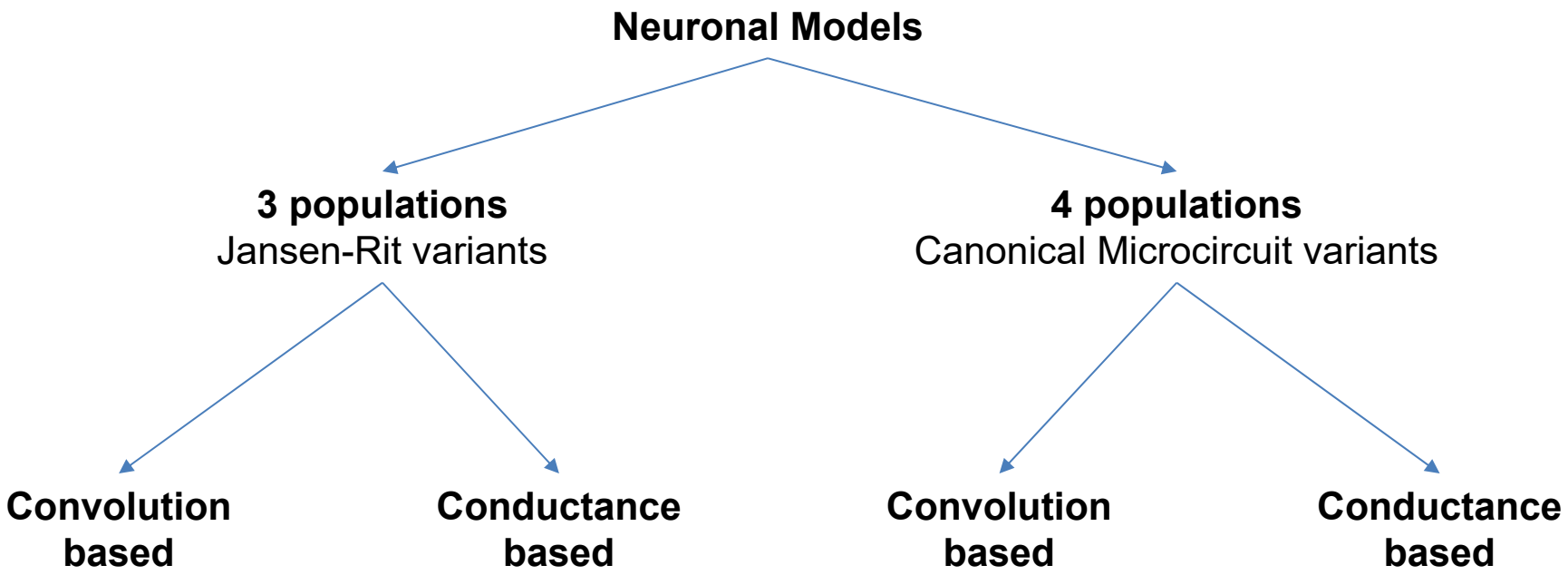
DCM Specification

1. Type of Analysis



DCM Specification

1. Type of Analysis

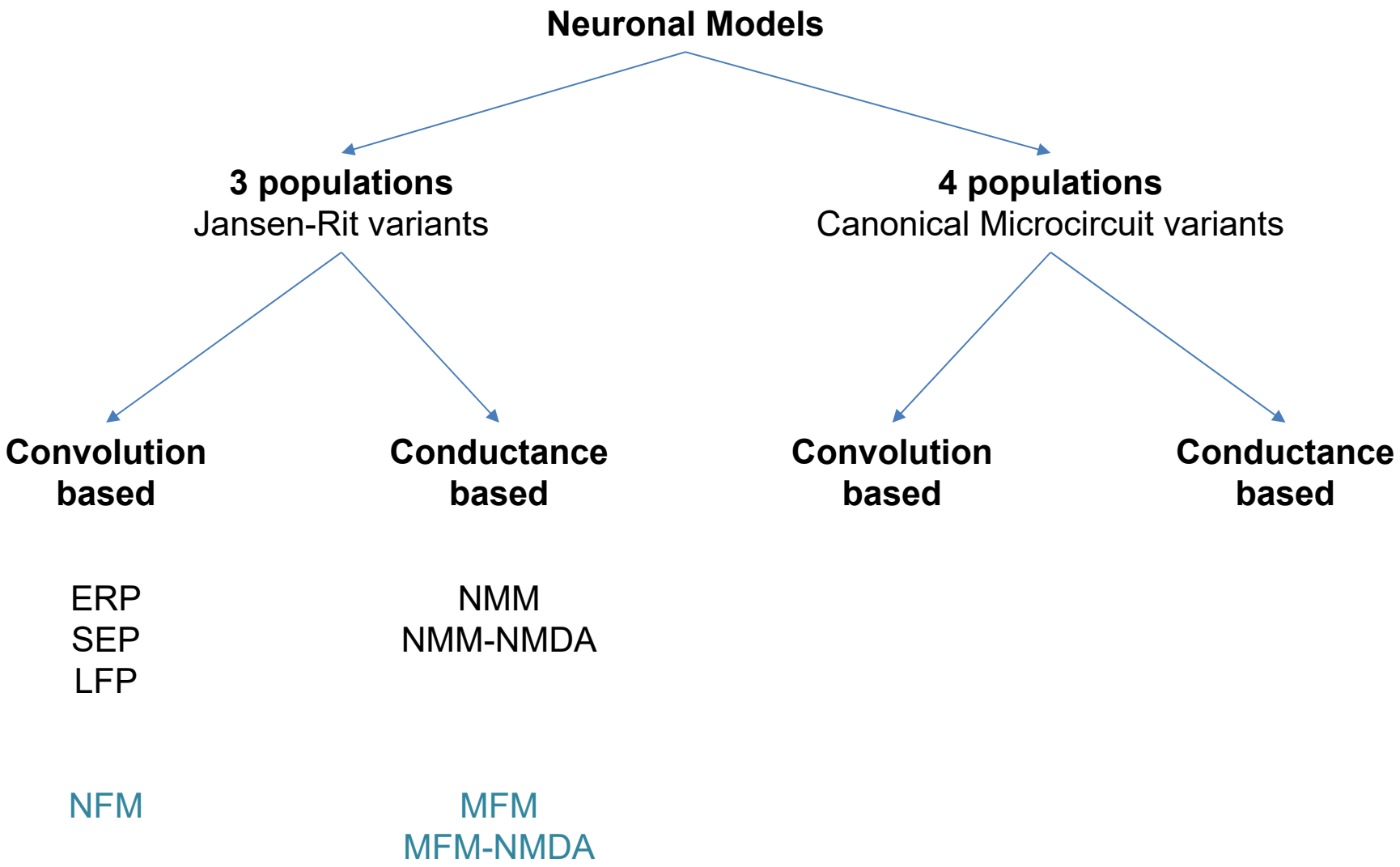


ERP
SEP
LFP

NFM

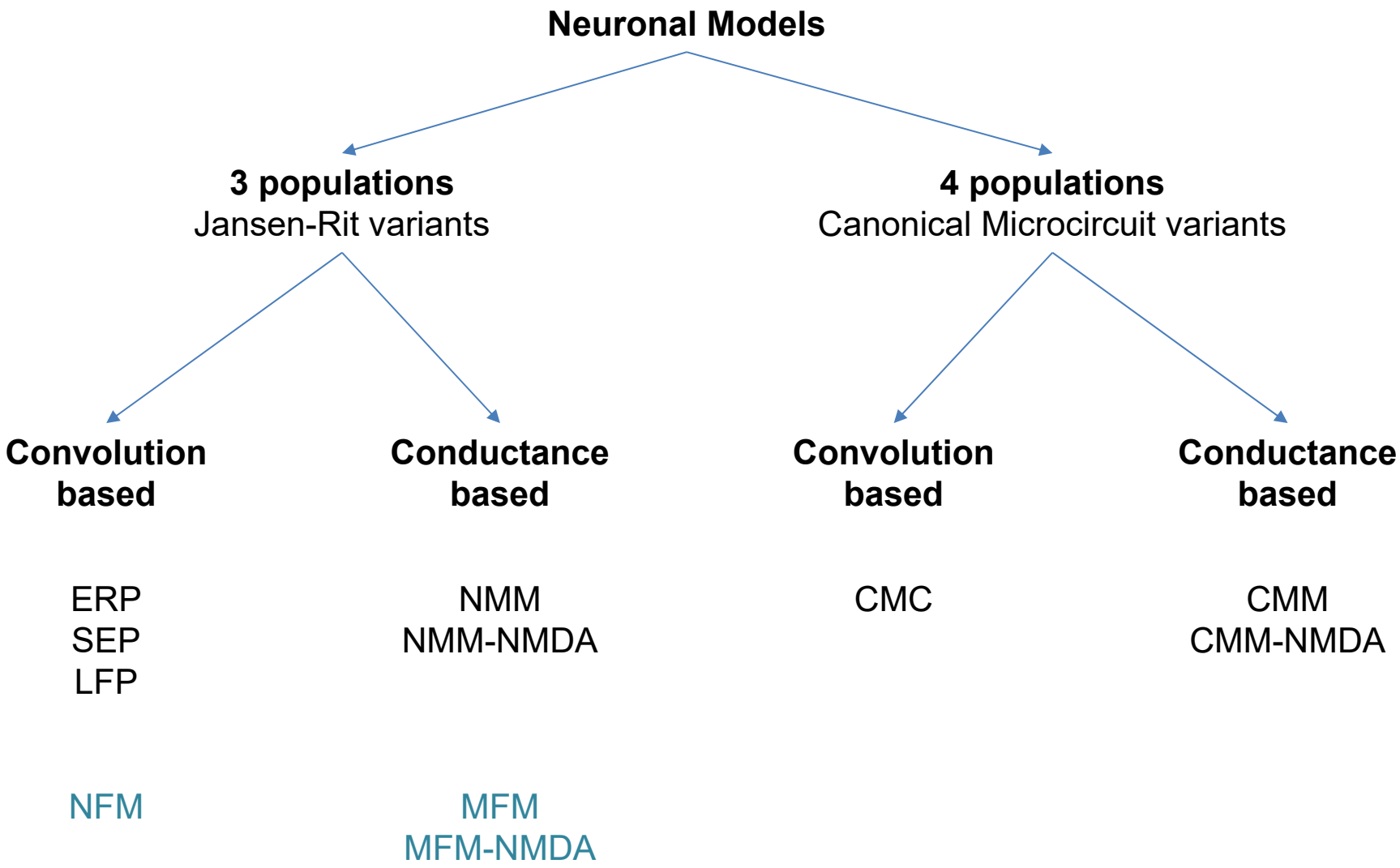
DCM Specification

1. Type of Analysis

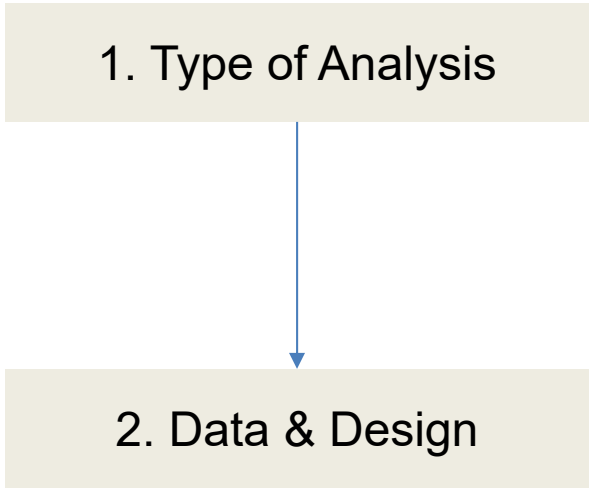


DCM Specification

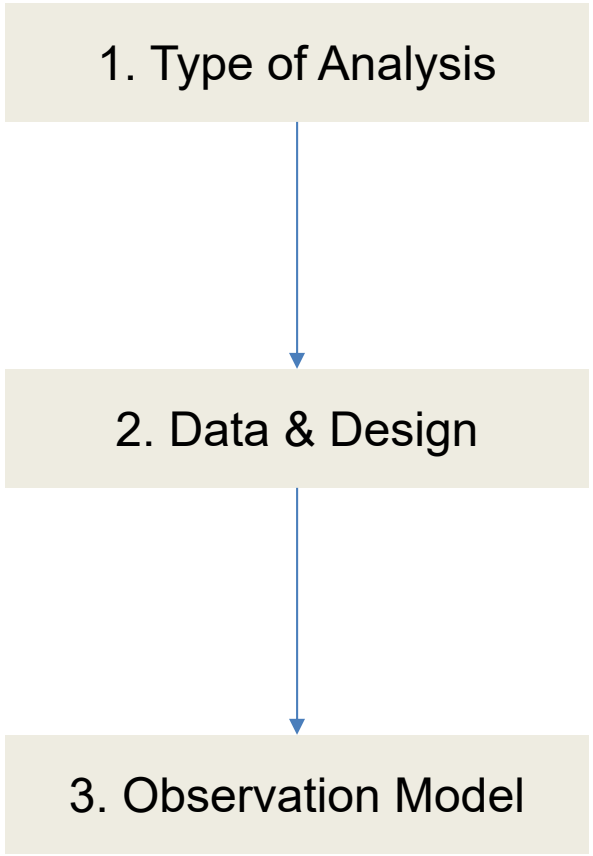
1. Type of Analysis



DCM Specification



DCM Specification



Parametrizing the Leadfield

$$y = g(x, \theta_2) = L(\theta_2)x$$

Simultaneous optimization of **spatial** forward model & **temporal** neuronal model

DCM Specification

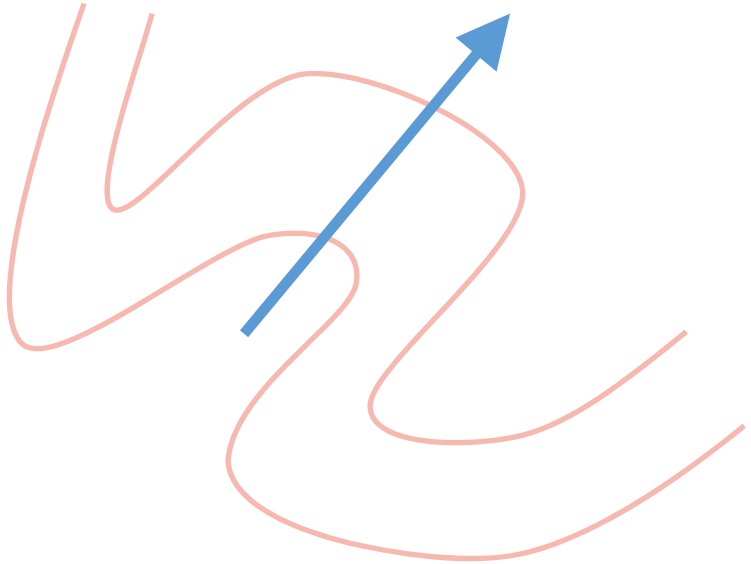
Parametrizing the Leadfield

$$y = g(x, \theta_2) = L(\theta_2)x$$

Simultaneous optimization of **spatial** forward model & **temporal** neuronal model

ECD

Equivalent Current Dipole



Kiebel et al 2006

3 location parameters
3 orientation parameters

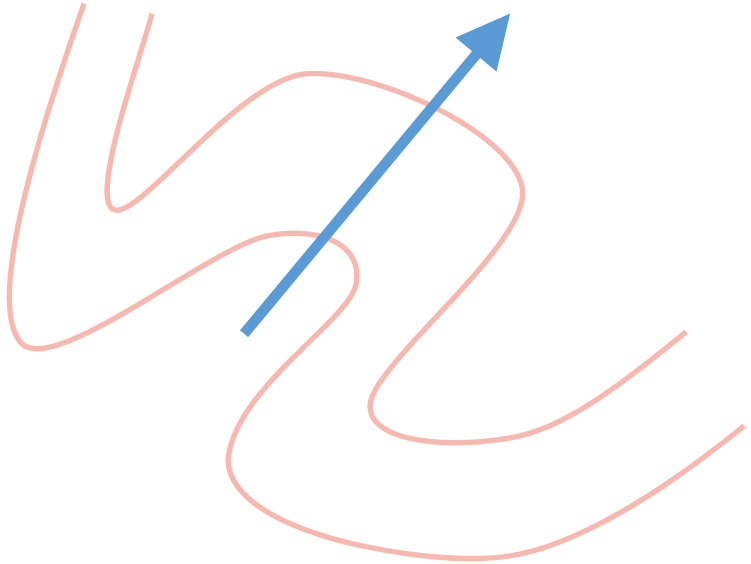
DCM Specification

Observation Model: Parametrizing the Leadfield

$$y = g(x, \theta_2) = L(\theta_2)x$$

Simultaneous optimization of **spatial** forward model & **temporal** neuronal model

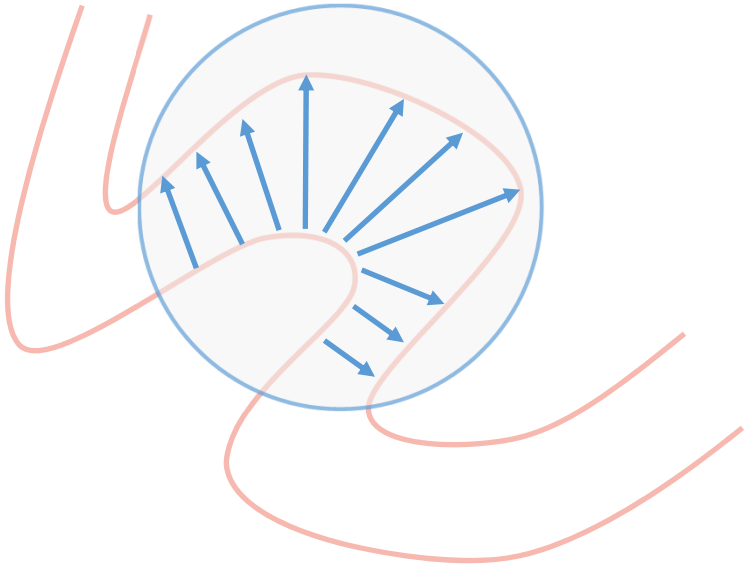
ECD
Equivalent Current Dipole



Kiebel et al 2006

3 location parameters
3 orientation parameters

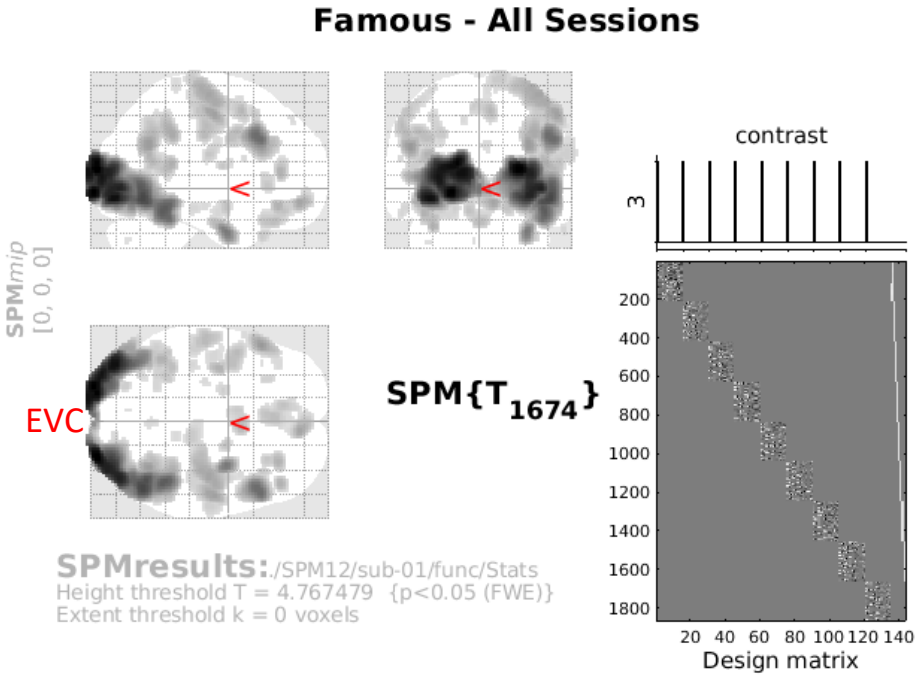
‘Imaging’
Distributed, cortically-constrained patches



Daunizeau et al 2009

radius of sphere
number of modes

Single-subject (fMRI timeseries) GLM (1st-level) SPM



Statistics: ***p-values adjusted for search volume***

set-level		cluster-level				peak-level					mm	mm	mm
p	c	$p_{FWE-corr}$	$q_{FDR-corr}$	k_E	p_{uncorr}	$p_{FWE-corr}$	$q_{FDR-corr}$	T	(Z_E)	p_{uncorr}			
0.000	**37**	**0.000**	**0.000**	**10065**	**0.000**	**0.000**	**0.000**	**22.70**	**Inf**	**0.000**	**26**	**-98**	**12**
						0.000	0.000	22.38	Inf	0.000	-22	-100	-4
						0.000	0.000	21.81	Inf	0.000	-18	-98	16
		0.000	**0.000**	**816**	**0.000**	**0.000**	**0.000**	**13.75**	**Inf**	**0.000**	**48**	**18**	**34**
						0.000	0.000	6.46	6.42	0.000	46	16	50
		0.000	**0.000**	**278**	**0.000**	**0.000**	**0.000**	**12.79**	**Inf**	**0.000**	**32**	**-4**	**-32**
		0.000	**0.000**	**702**	**0.000**	**0.000**	**0.000**	**10.18**	**Inf**	**0.000**	**-52**	**22**	**28**
						0.000	0.000	7.67	7.60	0.000	-46	4	38
						0.000	0.000	7.47	7.41	0.000	-40	0	34
		0.000	**0.000**	**1754**	**0.000**	**0.000**	**0.000**	**9.50**	**Inf**	**0.000**	**54**	**-12**	**50**
						0.000	0.000	9.24	Inf	0.000	42	-16	64
						0.000	0.000	9.02	Inf	0.000	46	-12	58
		0.000	**0.000**	**652**	**0.000**	**0.000**	**0.000**	**9.21**	**Inf**	**0.000**	**8**	**50**	**-12**
						0.000	0.000	7.35	7.29	0.000	0	30	-26
						0.000	0.000	7.07	7.01	0.000	-10	38	-18
		0.000	**0.001**	**83**	**0.000**	**0.000**	**0.000**	**8.42**	**Inf**	**0.000**	**-36**	**-10**	**-28**
		0.000	**0.000**	**139**	**0.000**	**0.000**	**0.000**	**8.40**	**Inf**	**0.000**	**46**	**36**	**10**
		0.000	**0.000**	**104**	**0.000**	**0.000**	**0.000**	**8.39**	**Inf**	**0.000**	**30**	**34**	**-14**
		0.000	**0.000**	**267**	**0.000**	**0.000**	**0.000**	**8.25**	**Inf**	**0.000**	**-38**	**-60**	**22**
						0.000	0.002	6.09	6.05	0.000	-48	-56	14
		0.000	**0.000**	**294**	**0.000**	**0.000**	**0.000**	**8.01**	**Inf**	**0.000**	**6**	**8**	**52**
						0.000	0.000	6.42	6.38	0.000	-6	4	56

table shows 3 local maxima more than 8.0mm apart

Height threshold: T = 4.77, p = 0.000 (0.050)
Extent threshold: k = 0 voxels
Expected voxels per cluster, <k> = 4.518
Expected number of clusters, <c> = 0.05
FWEp: 4.767, FDRp: 5.503, FWEc: 2, FDRc: 23

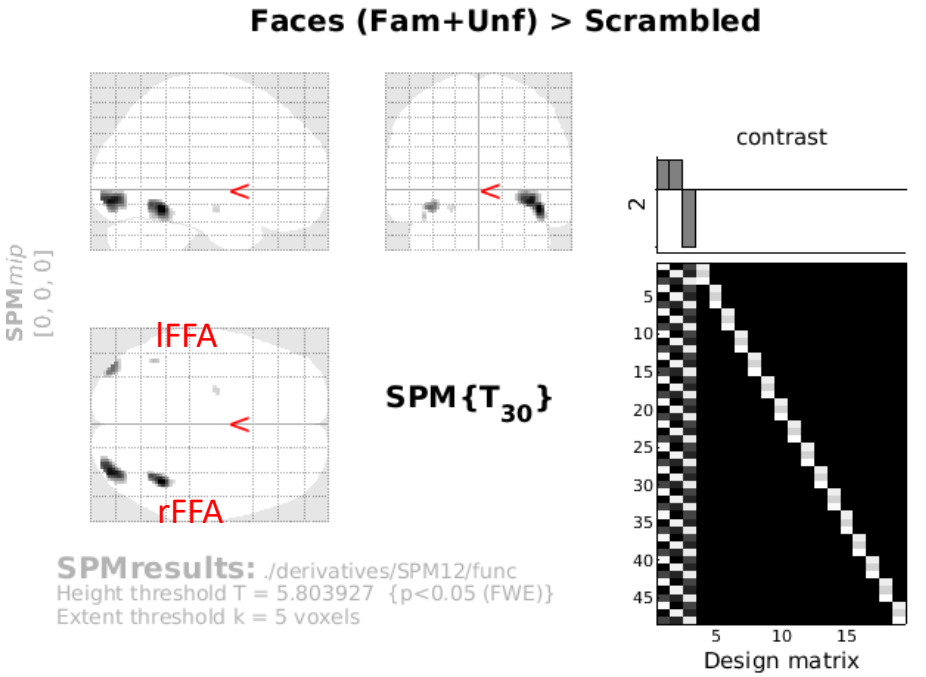
Degrees of freedom = [1.0, 1674.0]
FWHM = 10.6 10.5 10.3 mm mm mm; 5.3 5.3 5.1 {voxe
Volume: 1737816 = 217227 voxels = 1415.5 resels
Voxel size: 2.0 2.0 2.0 mm mm mm; (resel = 142.70 vo

Page 1

1

PY1

Group GLM (2^{nd}-level) SPM (fMRI)



Statistics: ***p-values adjusted for search volume***

set-level		cluster-level				peak-level					mm mm mm
p	c	$p_{FWE-corr}$	$q_{FDR-corr}$	k_E	p_{uncorr}	$p_{FWE-corr}$	$q_{FDR-corr}$	T	(Z_E)	p_{uncorr}	
0.000	5	0.000	0.000	122	0.000	0.000	0.005	9.00	6.22	0.000	42 -52 -14
		0.000	0.000	180	0.000	0.000	0.005	8.68	6.09	0.000	36 -88 -10
		0.000	0.012	39	0.007	0.001	0.042	7.42	5.55	0.000	-38 -86 -14
		0.014	0.284	5	0.284	0.017	0.399	6.27	4.97	0.000	-42 -56 -20
		0.012	0.284	6	0.242	0.031	0.624	6.01	4.83	0.000	-22 -10 -16

table shows 3 local maxima more than 8.0mm apart

Height threshold: T = 5.80, p = 0.000 (0.050)
Extent threshold: k = 5 voxels, p = 0.284 (0.014)
Expected voxels per cluster, <k> = 4.709
Expected number of clusters, <c> = 0.01
FWEp: 5.804, FDRp: 7.424, FWEc: 5, FDRc: 39

Degrees of freedom = [1.0, 30.0]
FWHM = 13.0 12.9 12.6 mm mm mm; 6.5 6.4 6.3 {voxe
Volume: 1515968 = 189496 voxels = 671.9 resels
Voxel size: 2.0 2.0 2.0 mm mm mm; (resel = 261.78 vo

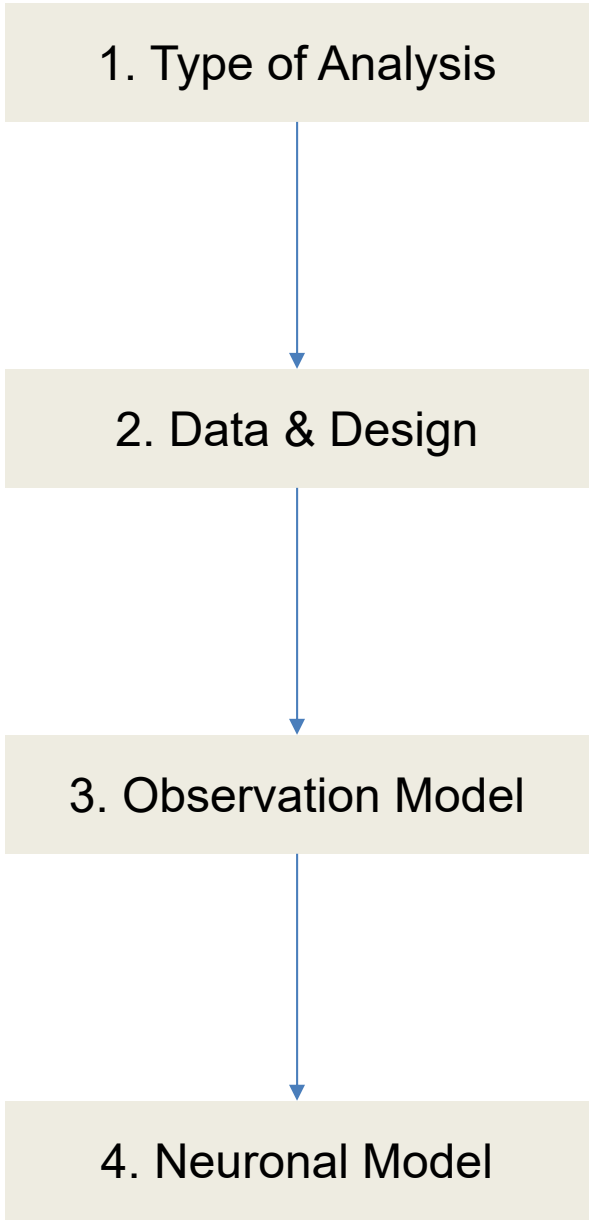
PY1 Update to show EVC

Pranay Yadav, 08/02/2024

Names & Locations of sources

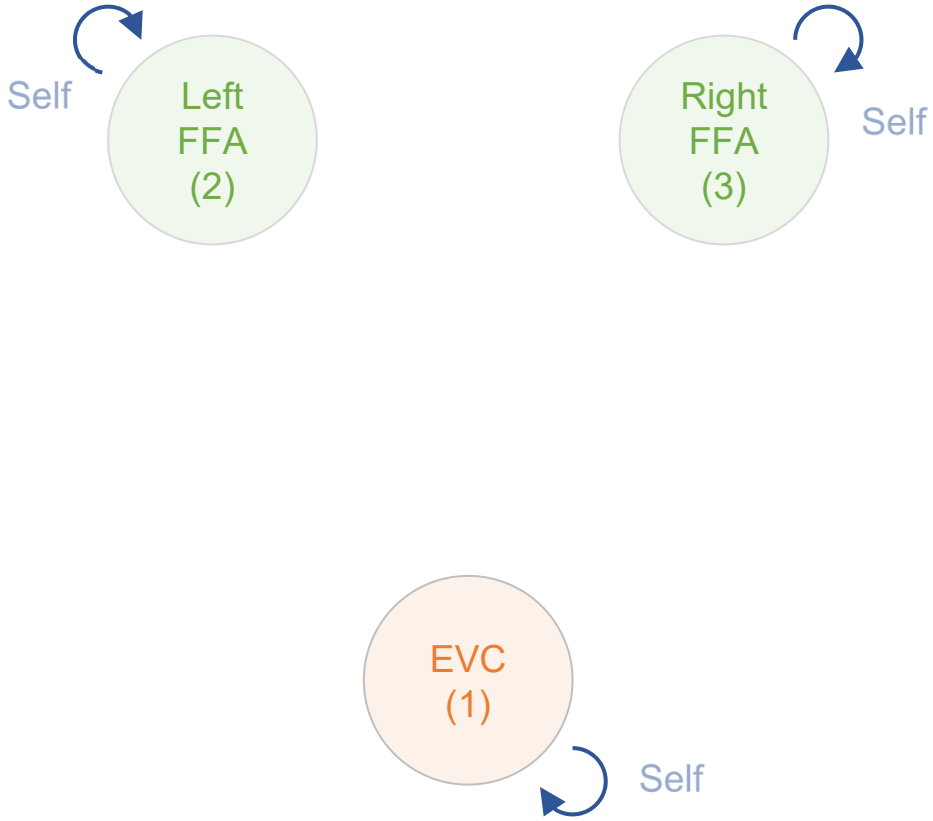
bEVC	0,	-90,	0
lFFA	-42,	-56,	-20
rFFA	+42,	-52,	-14

DCM Specification



DCM Specification

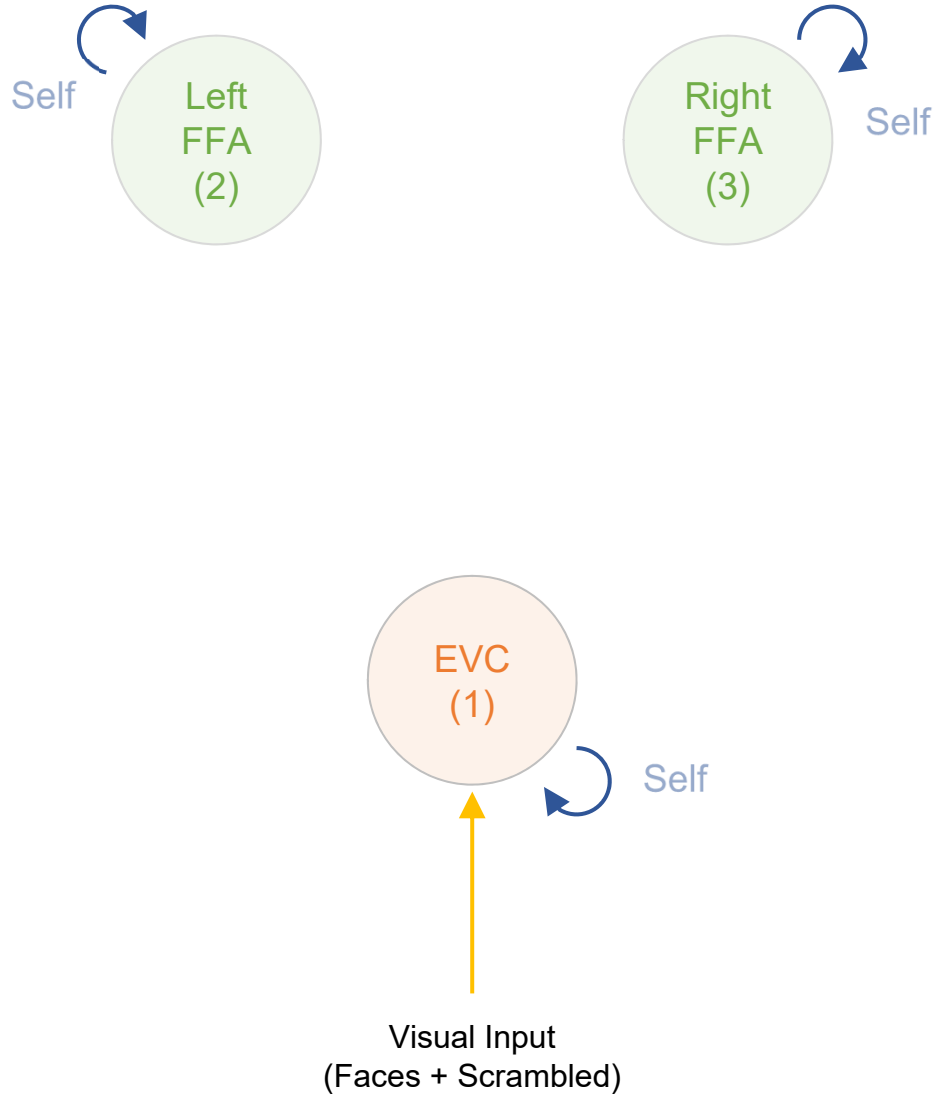
4. Neuronal Model



DCM Specification

4. Neuronal Model

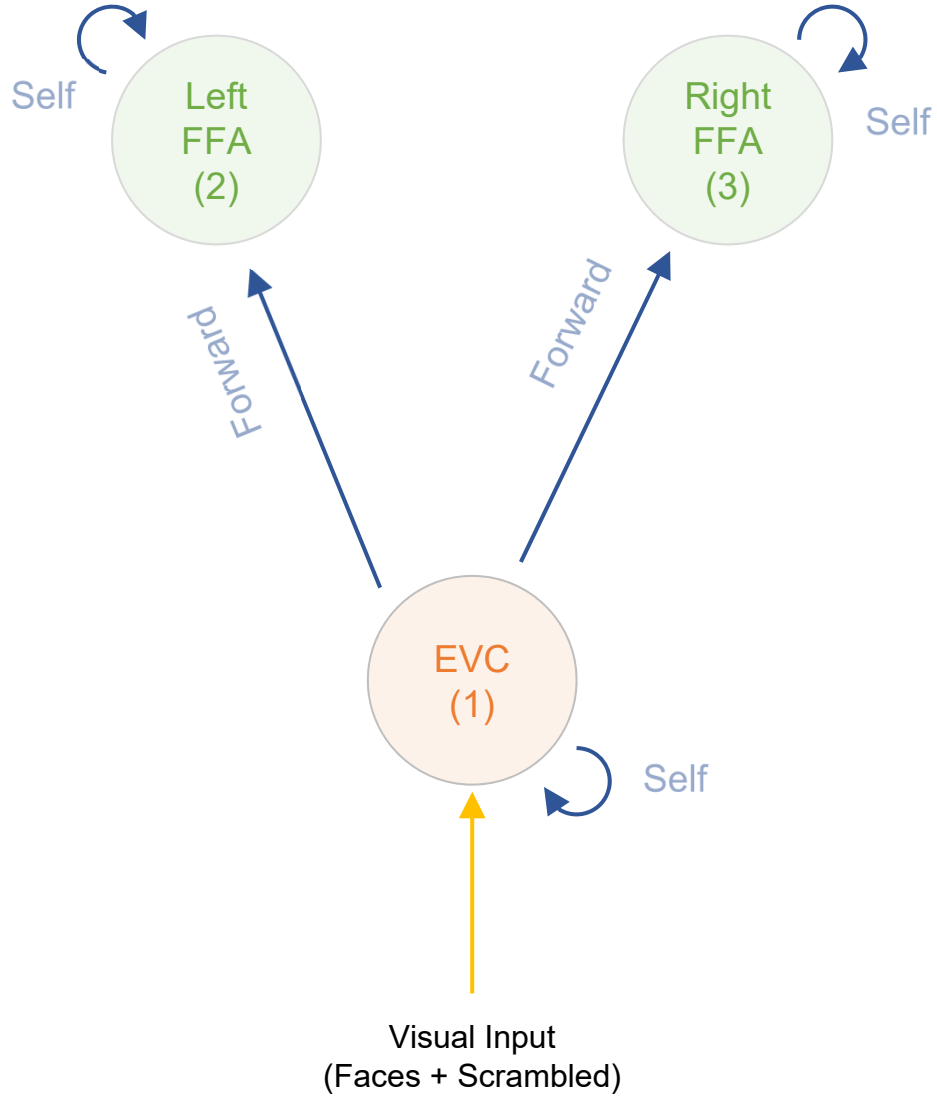
C Matrix



DCM Specification

4. Neuronal Model

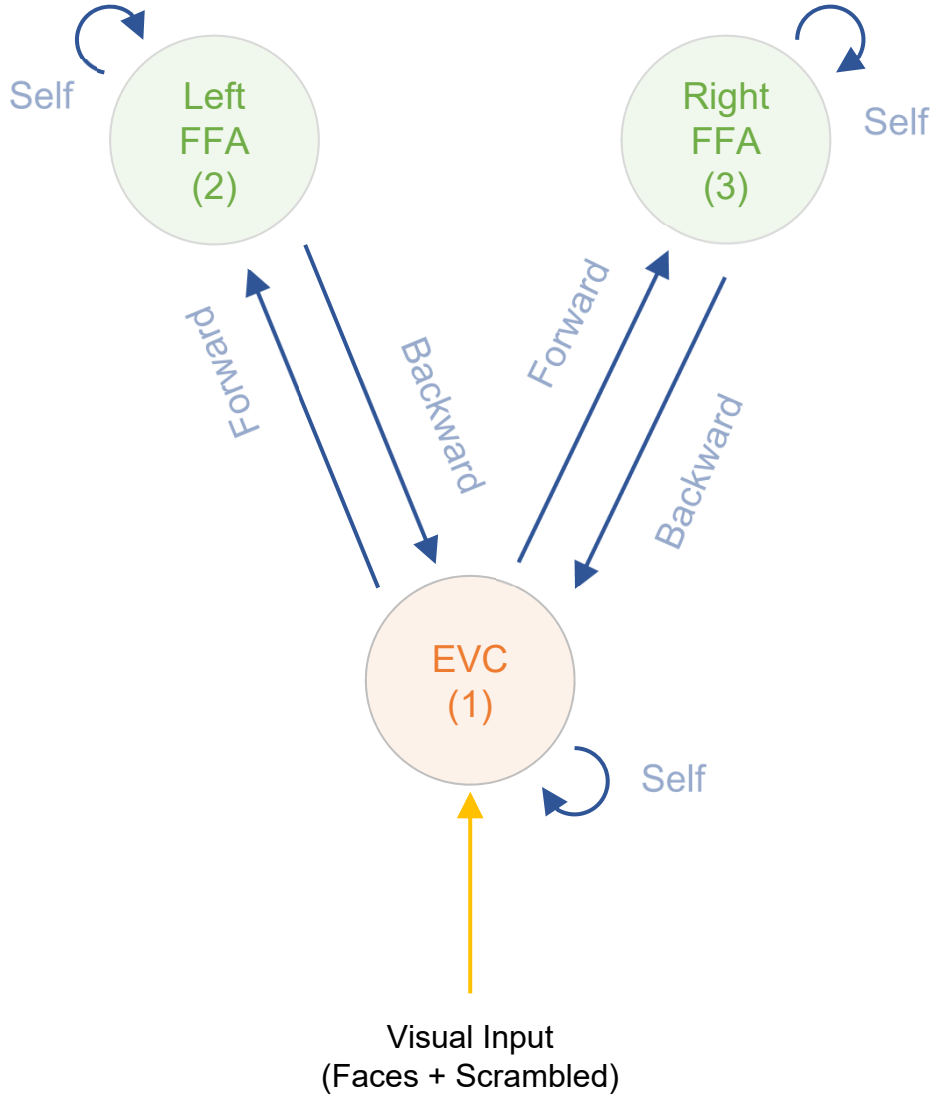
A Matrix
Forward Connections



DCM Specification

4. Neuronal Model

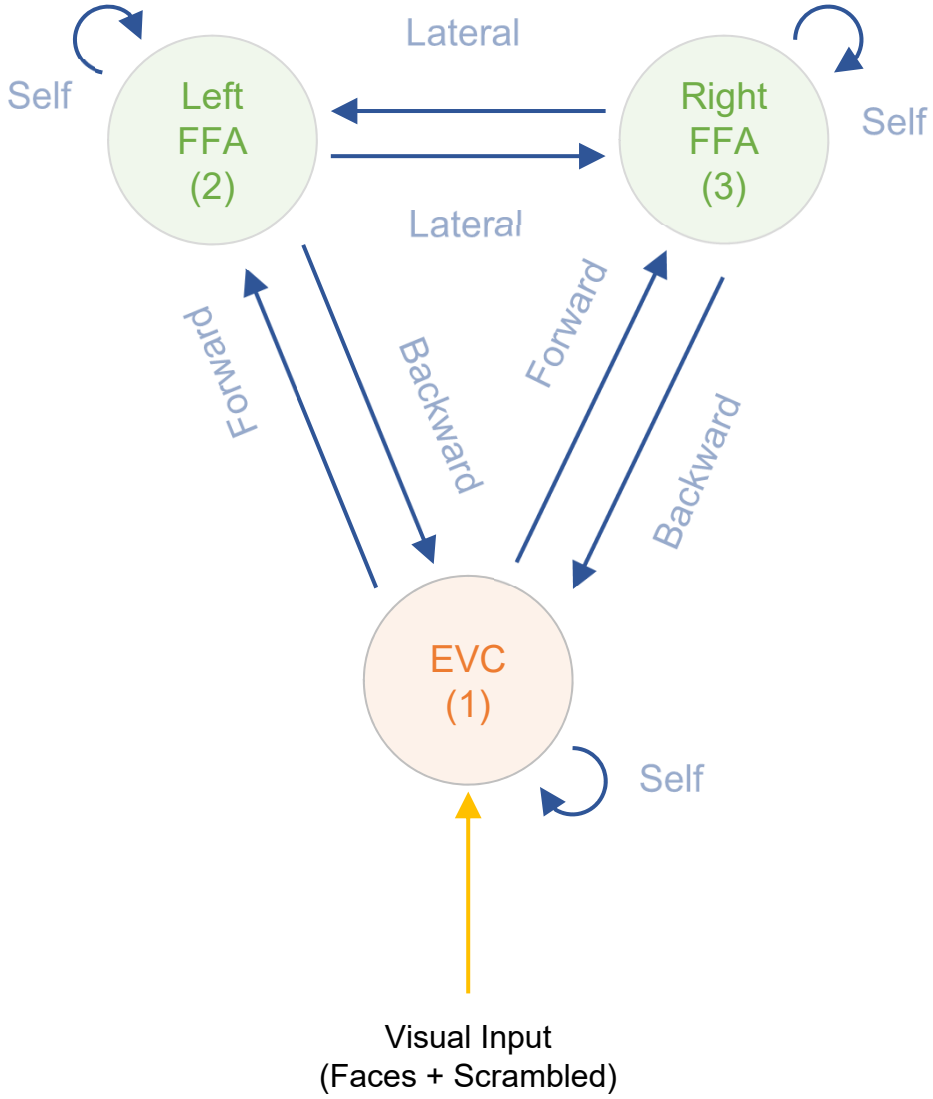
A Matrix
Backward Connections



DCM Specification

4. Neuronal Model

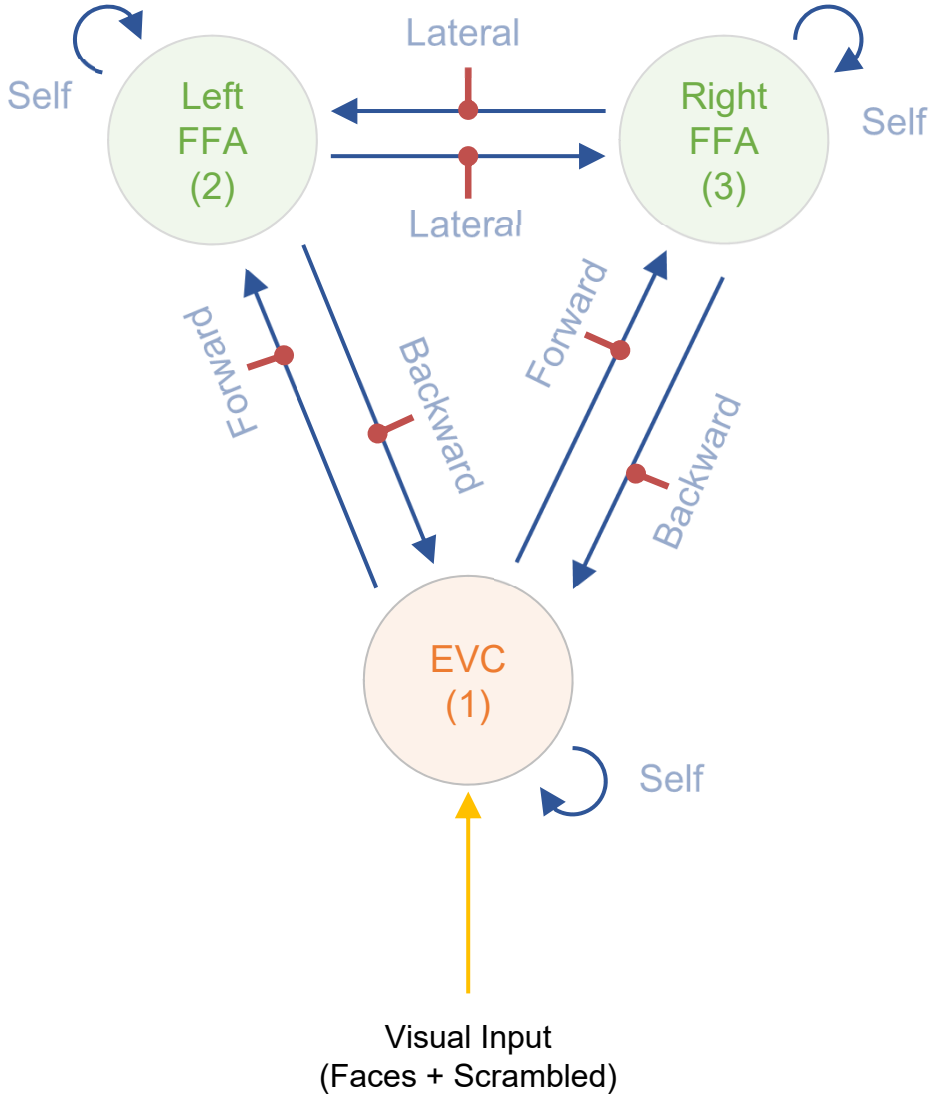
A Matrix
Lateral Connections



DCM Specification

4. Neuronal Model

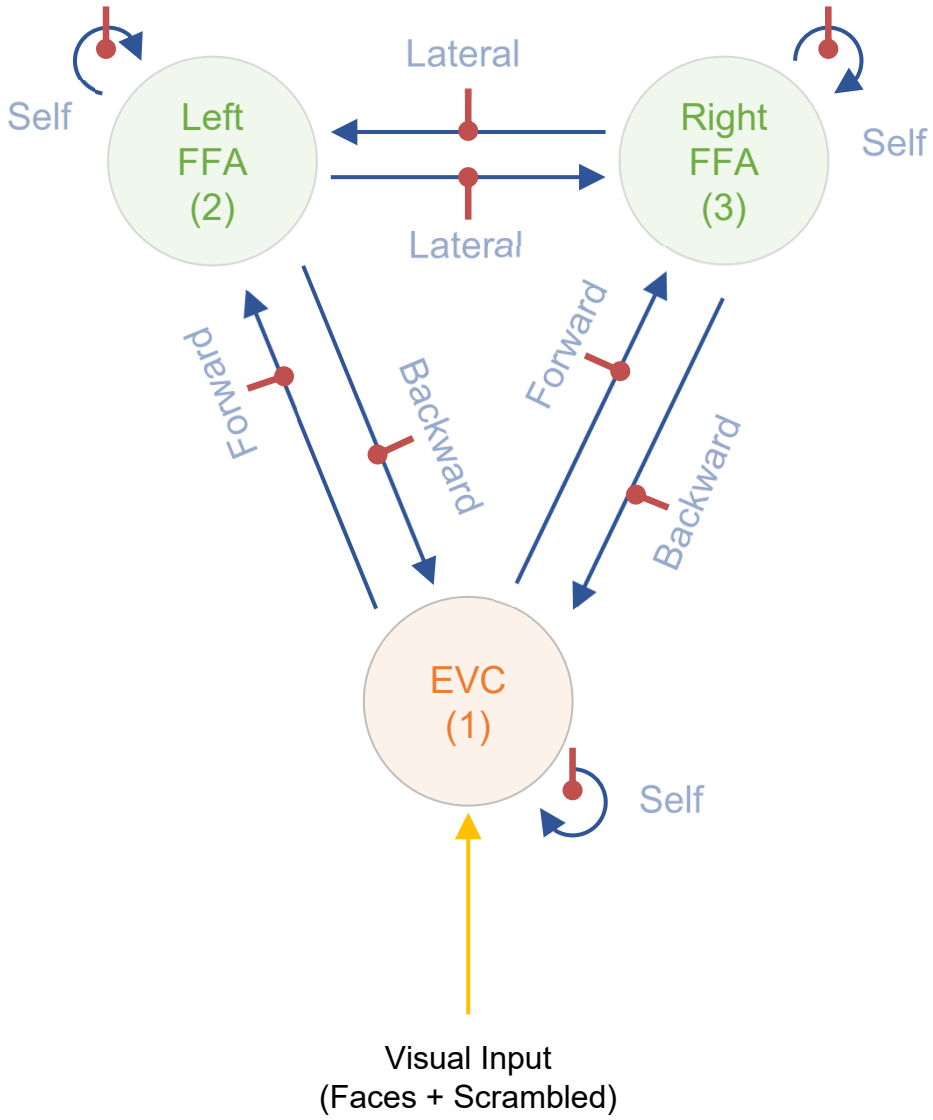
B Matrix
All A-Matrix Connections



DCM Specification

4. Neuronal Model

B Matrix
All A-Matrix + Self Connections

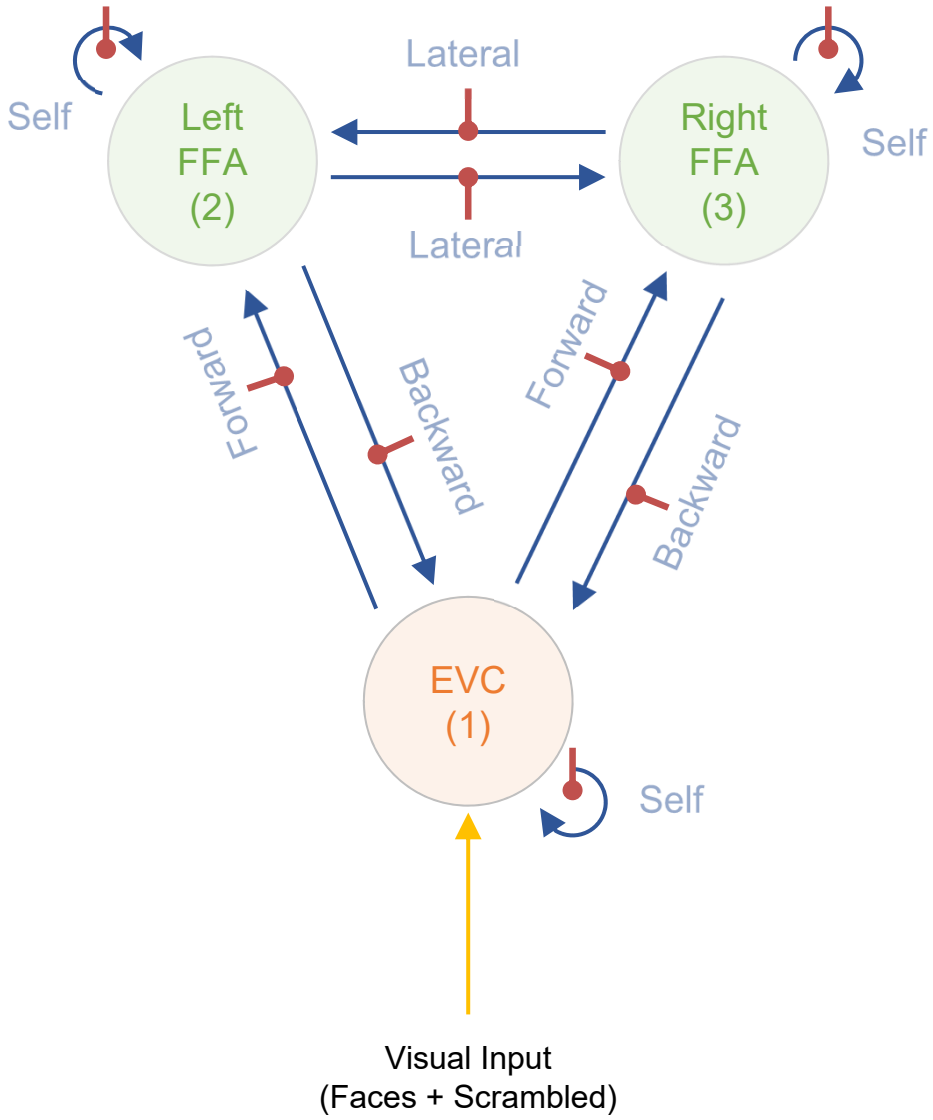


DCM Specification

4. Neuronal Model

Fully specified network:

- Input (C) to EVC
- Fixed connections (A) fully connected between the 3 nodes
- All fixed matrices potentially modulated by Faces (B=A)

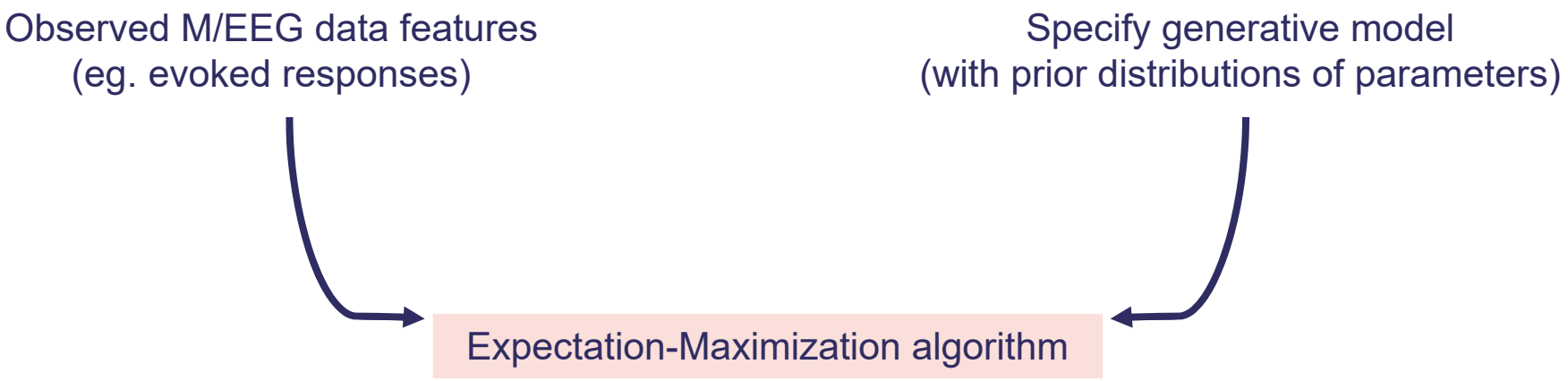


DCM Inversion

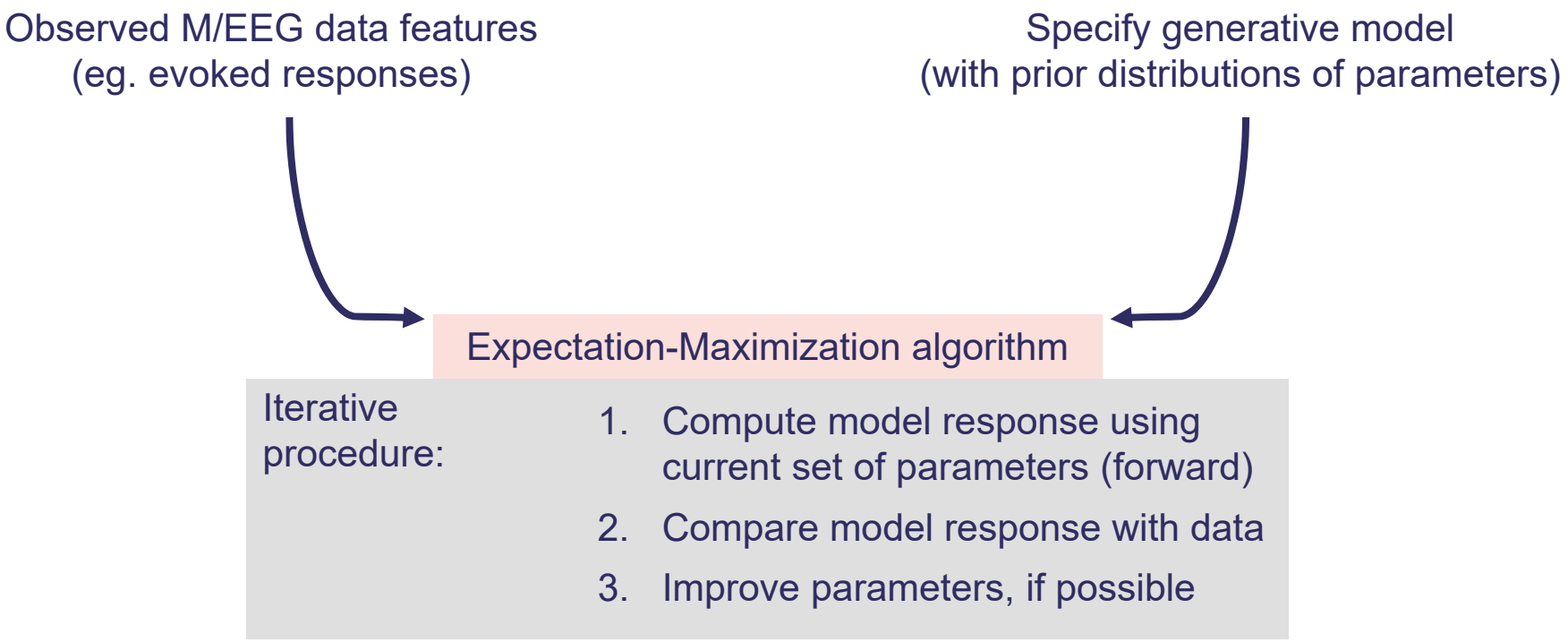
Observed M/EEG data features
(eg. evoked responses)

Specify generative model
(with prior distributions of parameters)

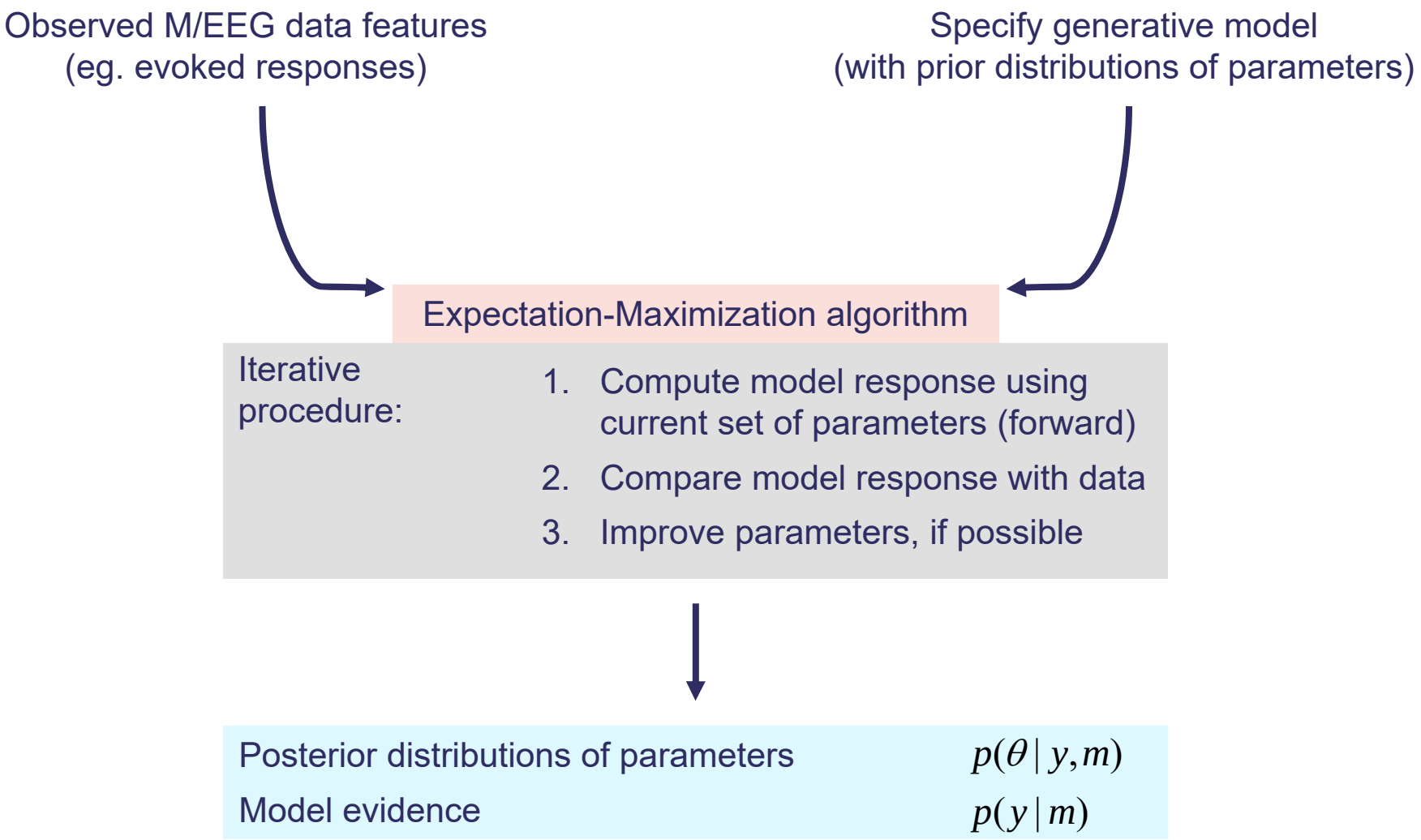
DCM Inversion



DCM Inversion



DCM Inversion



Background

Generative Modelling in DCM

The Jansen-Rit Model

Effective Connectivity

Demo

Context

Data

DCM Specification

Review of DCM fit

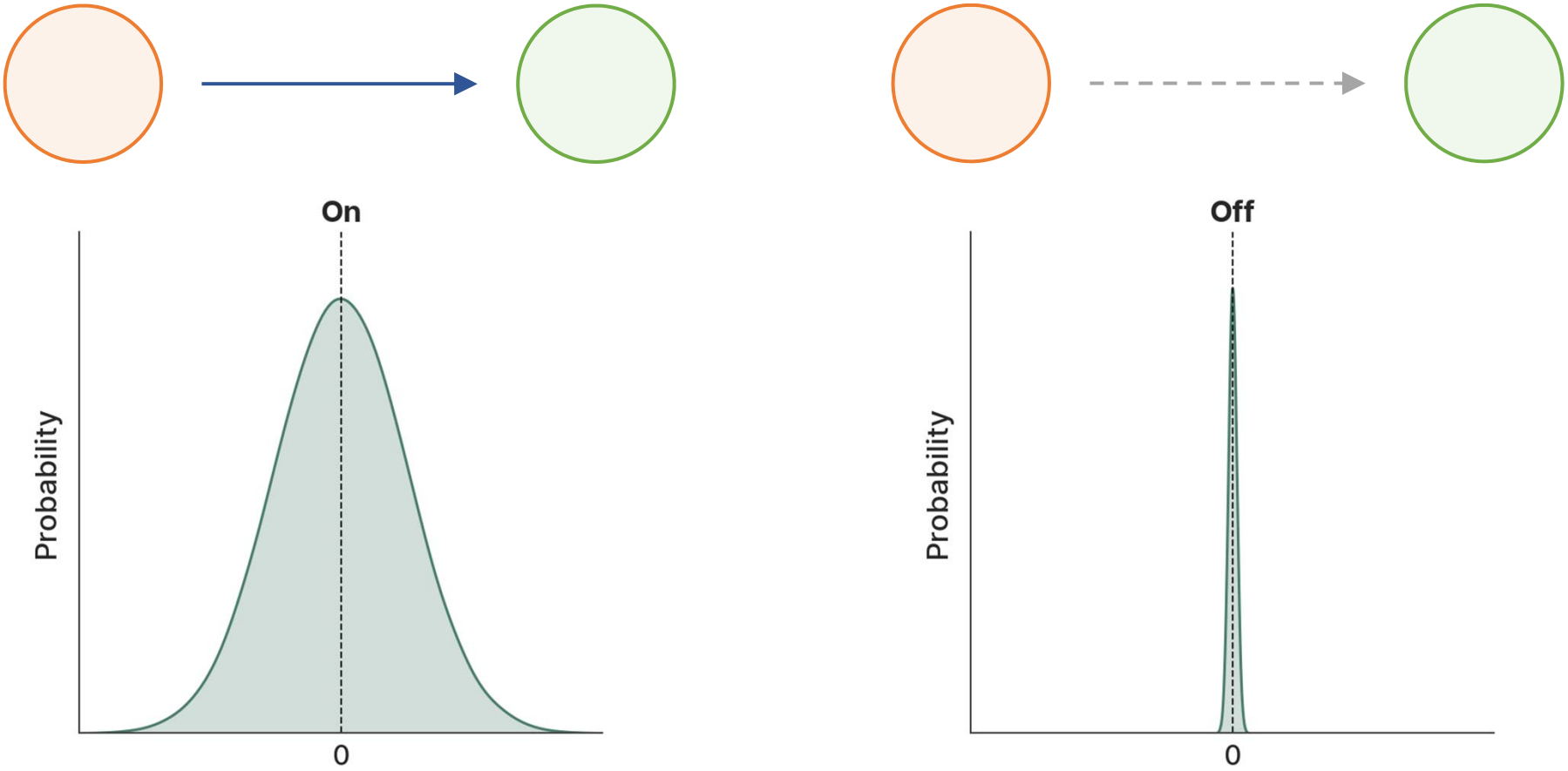
Thank you!

Feedback

https://www.surveymonkey.com/r/K3S6XTH

Extras

Connections = Parameters



Measure	Immume to Field Spread	Directed	Nonlinear	Direct
Cross-Correlation	Y (I>0)	N	N	N
Coherence	Y (imaginary)	N	N	N
PLV/PLI	Y	N	N	N

Measure	Immume to Field Spread	Directed	Nonlinear	Direct
Cross-Correlation	Y (I>0)	N	N	N
Coherence	Y (imaginary)	N	N	N
PLV/PLI	Y	N	N	N
Granger (bivariate)	Y	Y	N	N

Measure	Immume to Field Spread	Directed	Nonlinear	Direct
Cross-Correlation	Y (I>0)	N	N	N
Coherence	Y (imaginary)	N	N	N
PLV/PLI	Y	N	N	N
Granger (bivariate)	Y	Y	N	N
Mutual Information	N	N	Y	N
Generalised Synchrony	N	Y	Y	N
Transfer Entropy	Y	Y	Y	N

Measure	Immume to Field Spread	Directed	Nonlinear	Direct
Cross-Correlation	Y (I>0)	N	N	N
Coherence	Y (imaginary)	N	N	N
PLV/PLI	Y	N	N	N
Granger (bivariate)	Y	Y	N	N
Mutual Information	N	N	Y	N
Generalised Synchrony	N	Y	Y	N
Transfer Entropy	Y	Y	Y	N
MVAR (eg, PDC)	Y	Y	N	Y
Generative (eg, DCM)	Y	Y	Y	Y