

# DCM for Evoked Responses

Daniel Hauke

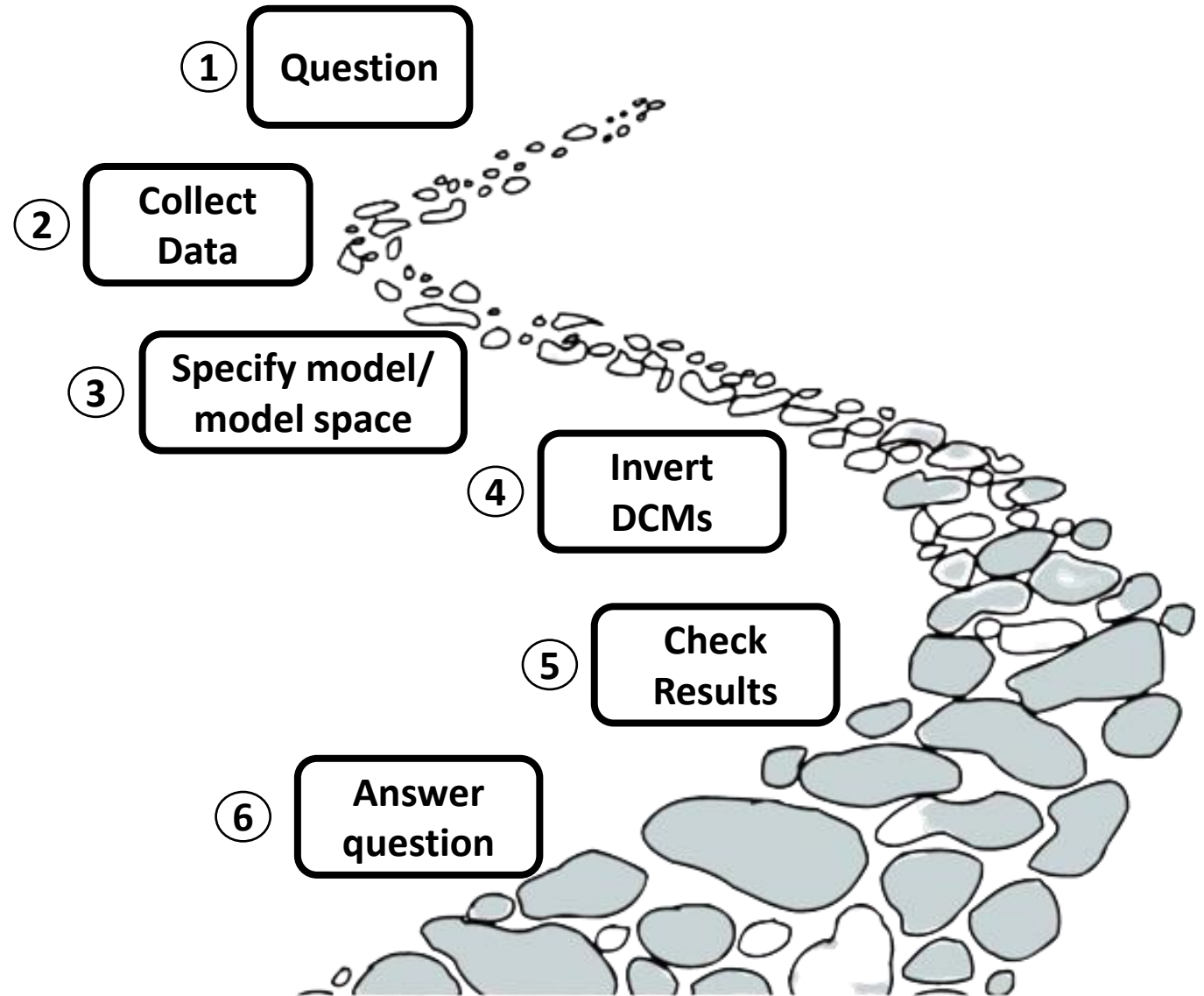
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Centre for Medical Image Computing  
Department of Computer Science  
University College London

# SPM for MEG/EEG Course

Course Agenda – Thursday 1 <sup>st</sup> June		
9.30-10.00	Day 3: Welcome and Registration	Registration (Conservatory) Refreshments (Boardroom)
	Chair: Benjy Barnett	
10.00 - 11.30	The principles of dynamic causal modelling Multimodal DCM	Amirhossein <a href="#">Jafarian</a>
11.30 - 12.35	DCM for evoked responses	Daniel <a href="#">Hauke</a>
12.35 -13.35	DCM for Cross-Spectral Densities	Dimitris <a href="#">Pinotsis</a>
13.35-14.35	Lunch	Boardroom
	Chair: Mansoureh Fahimi	
14.35 – 15.20	DCM demo	Julia Rodriguez-Sanchez
15.20 -16.35	Bayesian model selection and averaging	Peter <a href="#">Zeidman</a>
16.35-17.35	Q&A clinic	Karl <a href="#">Friston</a>

# Outlook - The DCM analysis path

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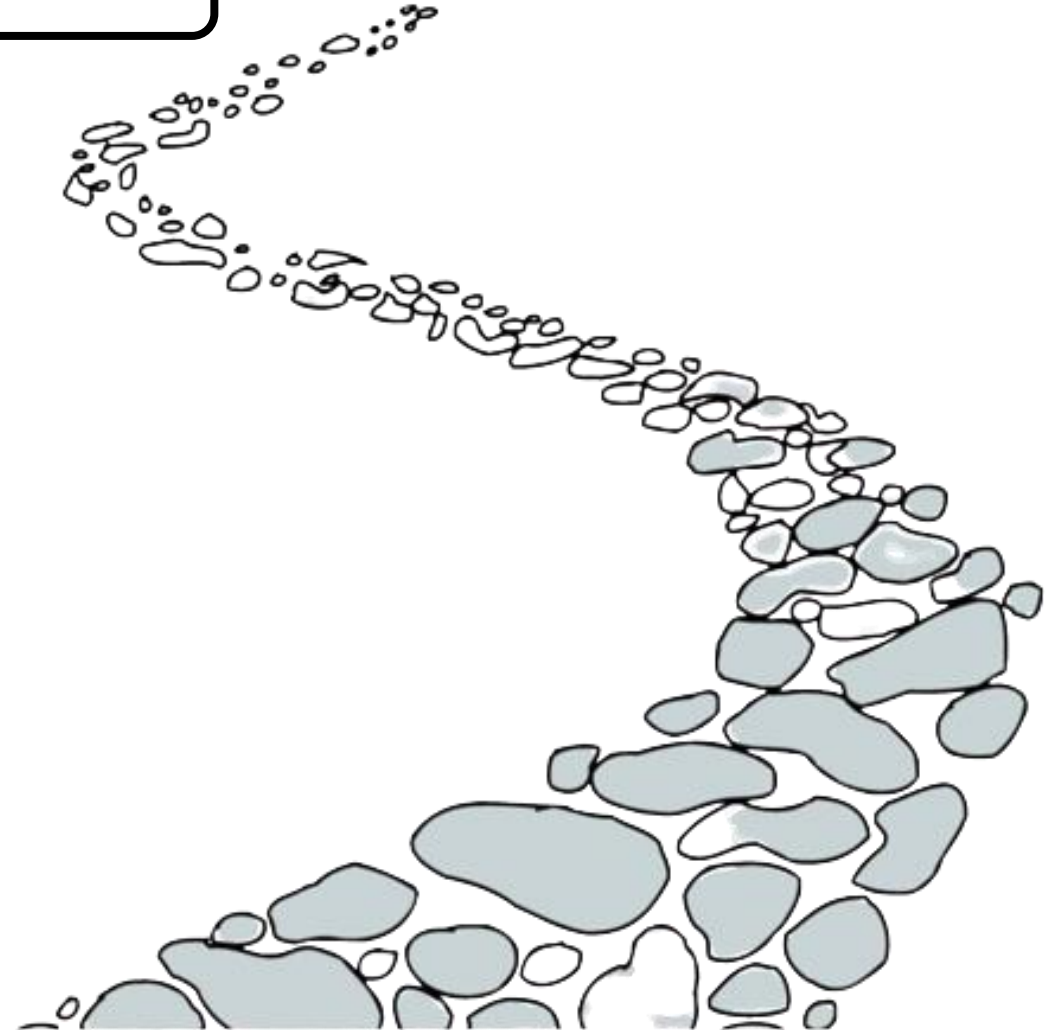
# Which questions can DCM for evoked responses answer?

## Good questions

- Does the network with regions A, B and C explain my data better than the network with regions A and B?
- Are regions A and B linked in a bottom-up, top-down or recurrent manner?
- How does my experimental manipulation change the effective connectivity between regions?  
• Or within a region?
- What EEG signal would I expect if I increase the connectivity even further?

①

Question



# Which questions can DCM for evoked responses answer?

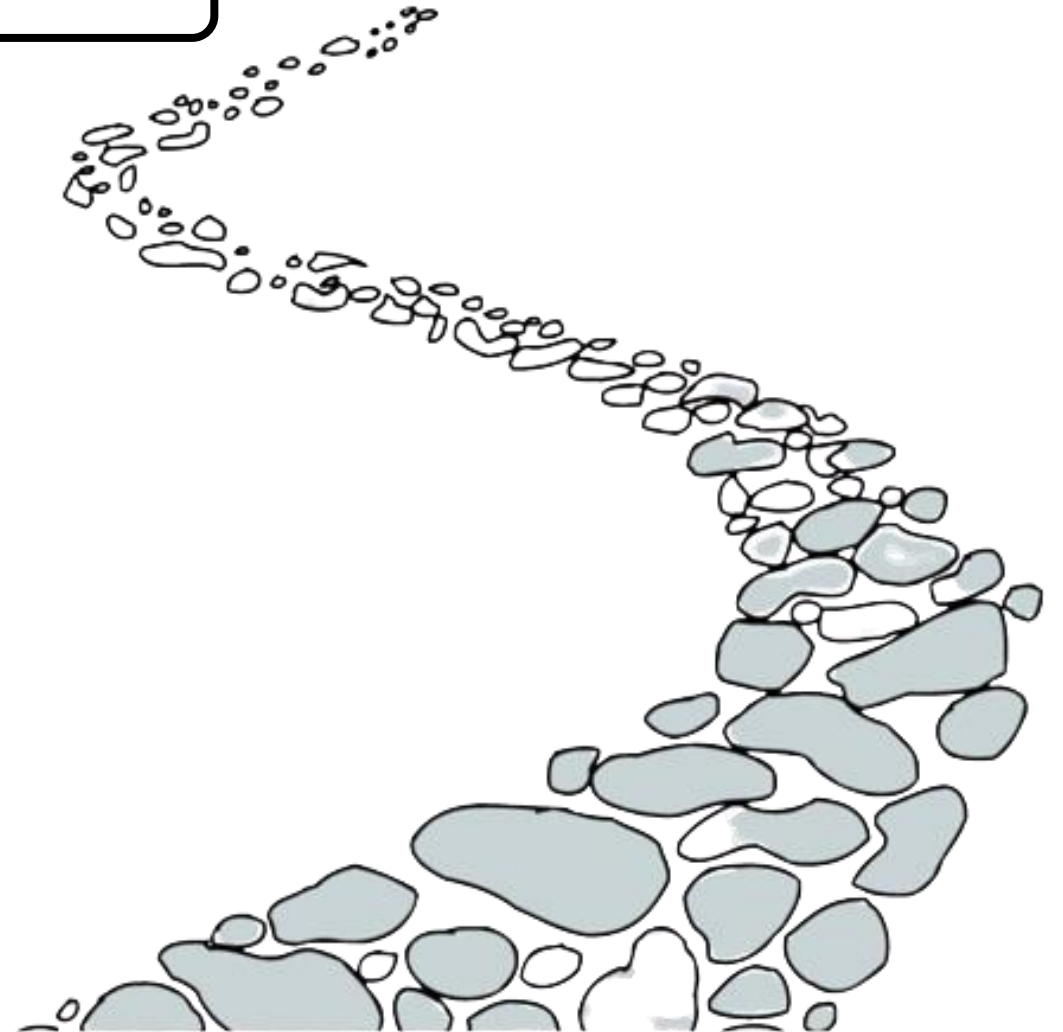
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## Not-so-good questions

- We did not find an effect in our ERP analysis - Can you model the data with DCM to find some effects to publish a cool paper?
- How does the connectivity change within our 200-region network?
- How does the connectivity change within our 20-region network?

①

Question

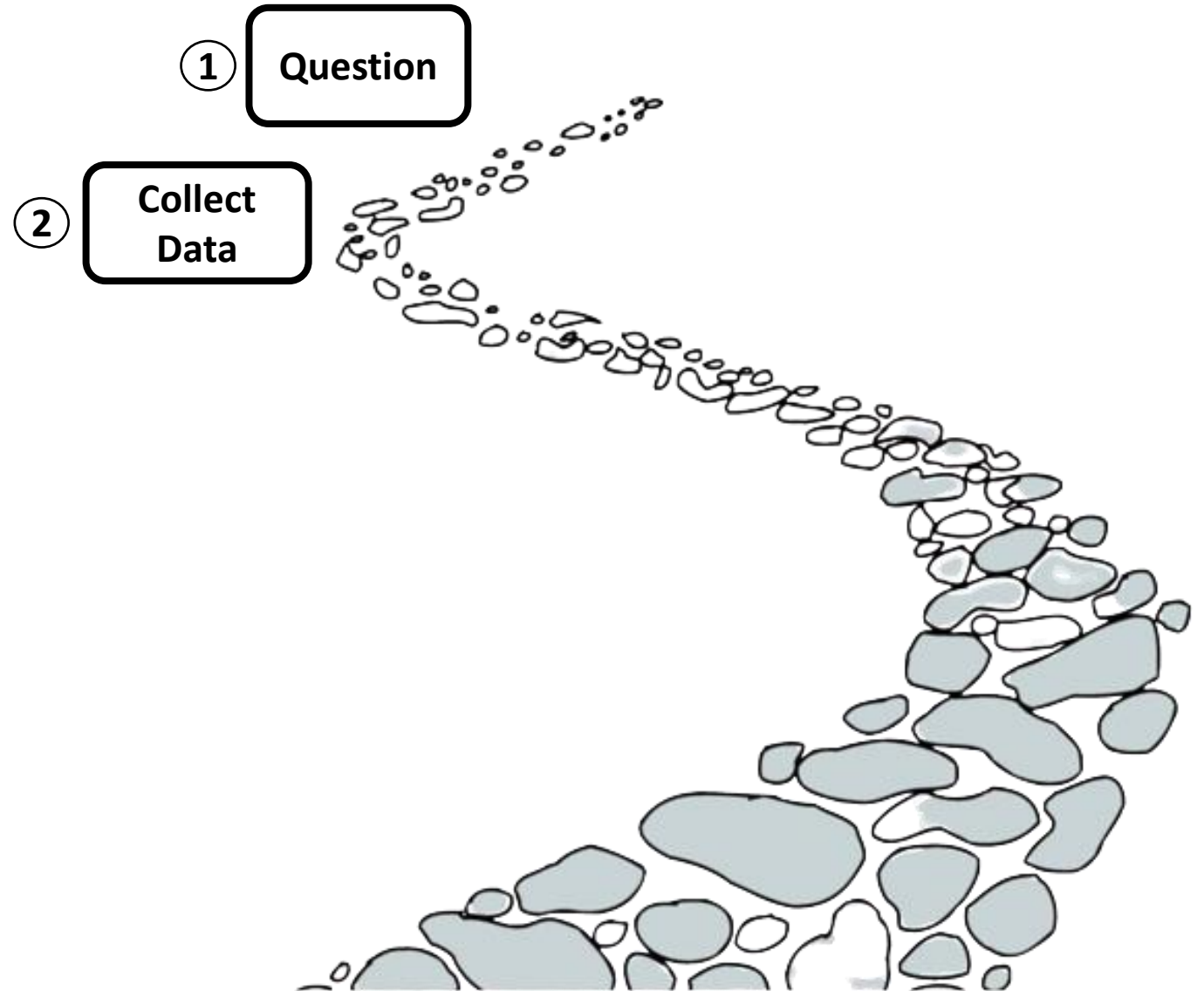


# Data collection

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## Preprocessing

- Downsample (e.g., 100 Hz)
- Filter (e.g., 1-40 Hz)
- Epoch
- Remove artefacts
- Average
  - Per subject
  - Grand average

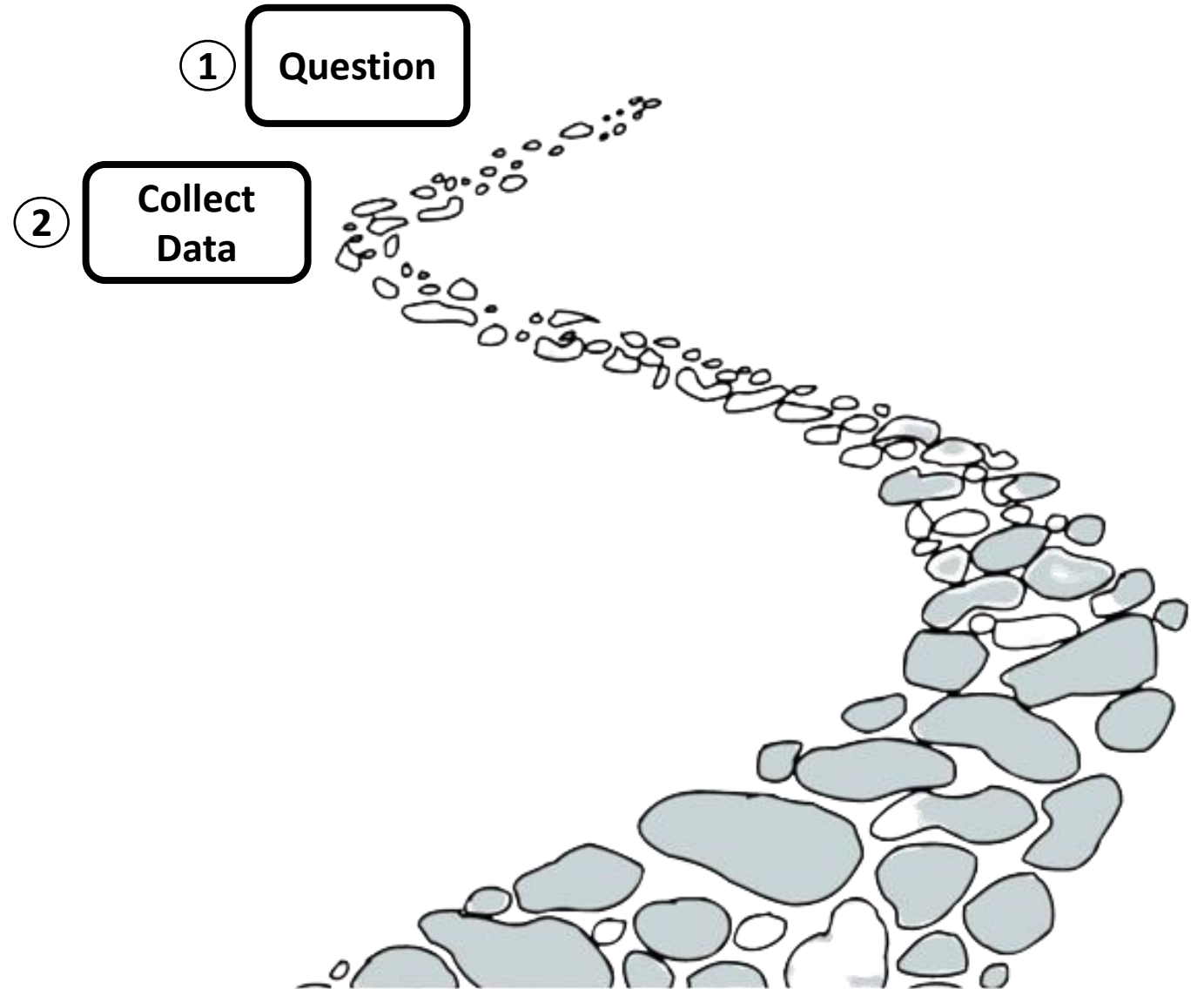


# Data collection

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## Classical analysis

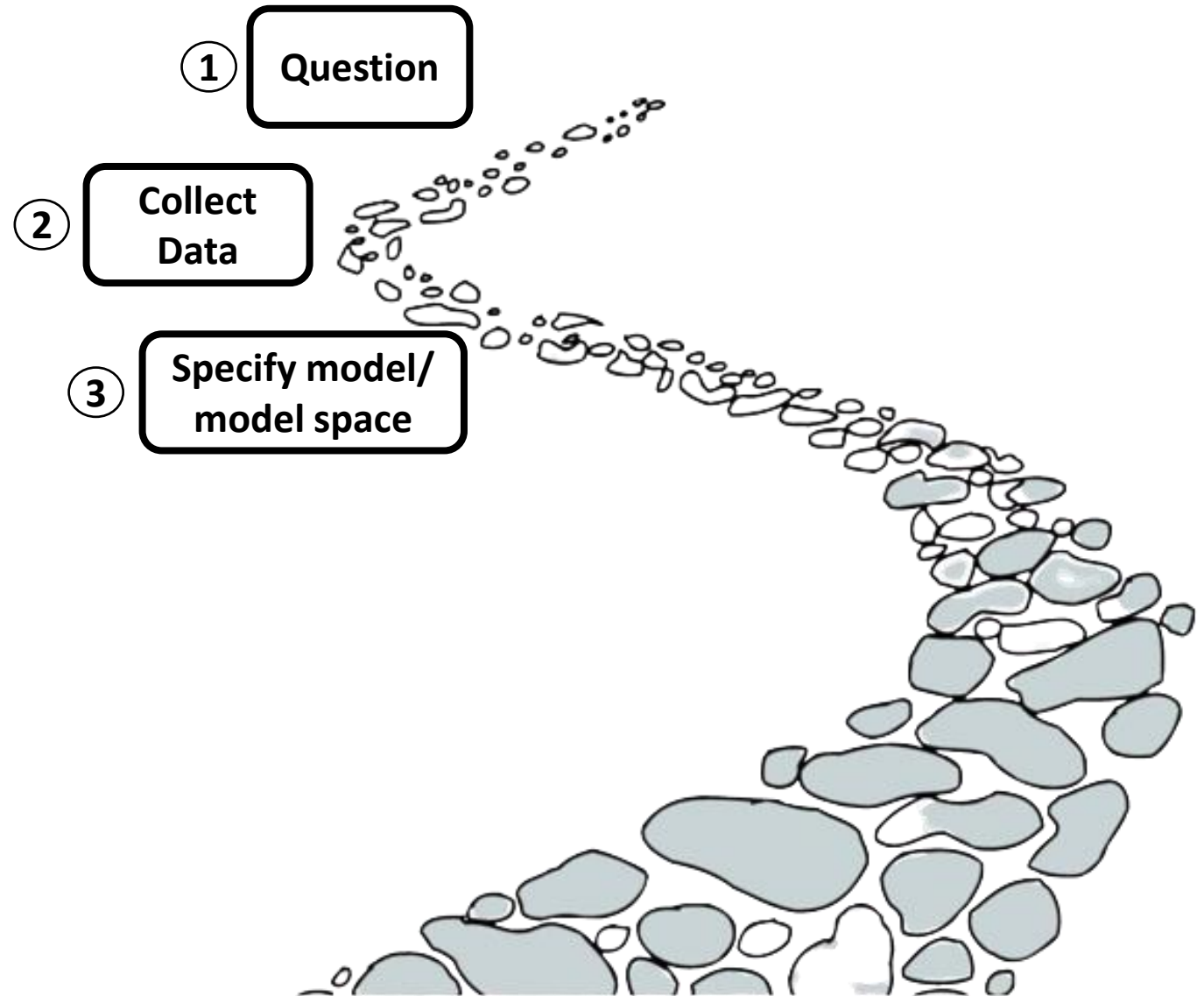
- Make sure there are effects!
- DCM is used to **explain** these effects



# Specify model/model space

## Steps

- Translate your question into a model comparison or a parameter inference problem
- Select regions
- Select a variant of DCM
- Example: The “ERP” model
- Specify connectivity architecture

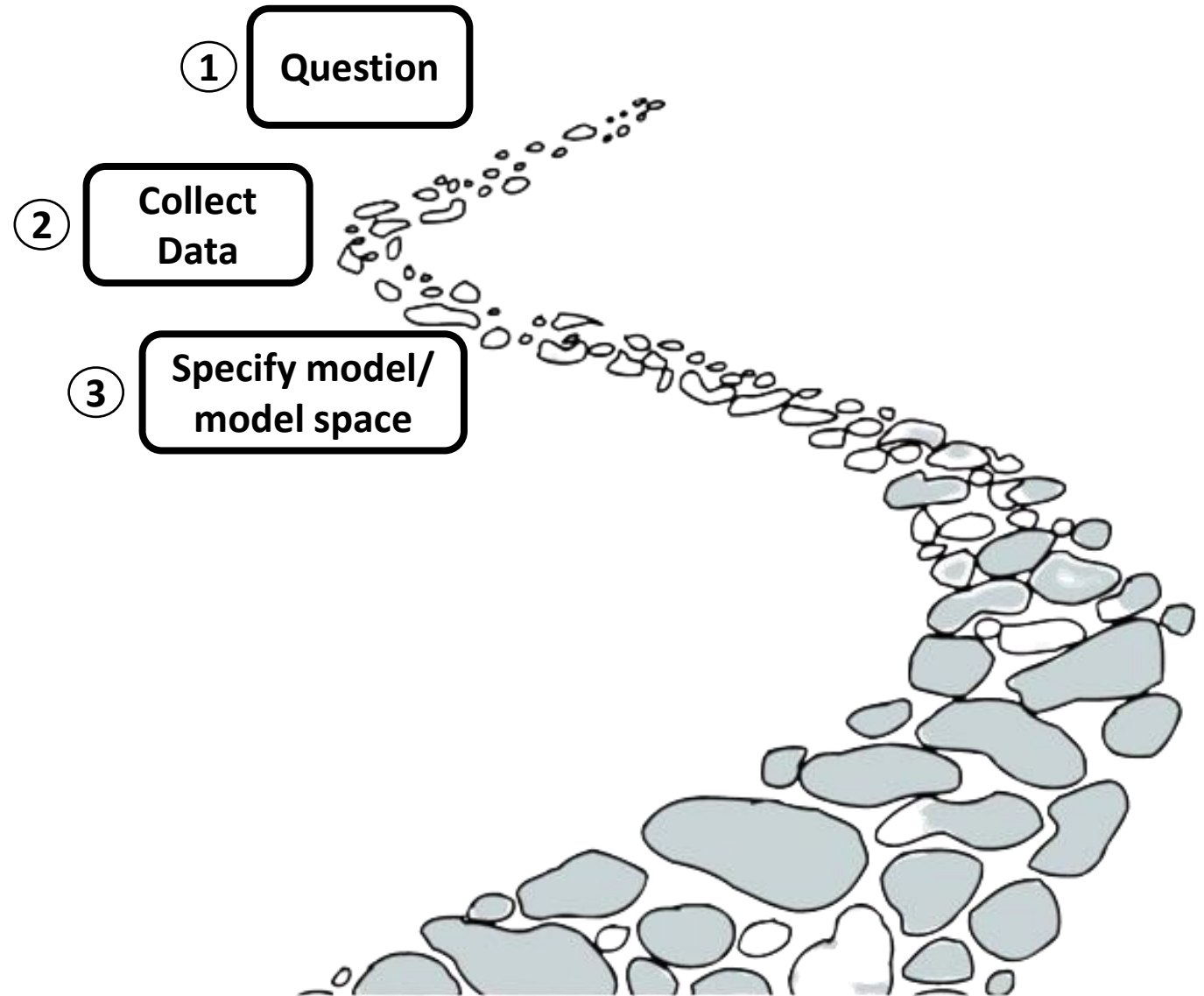




# Specify model/model space

## Steps

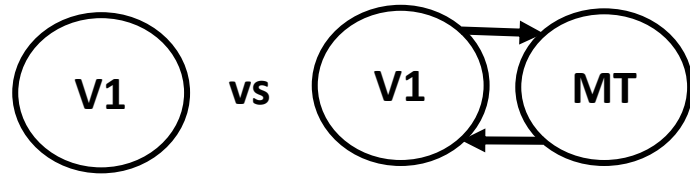
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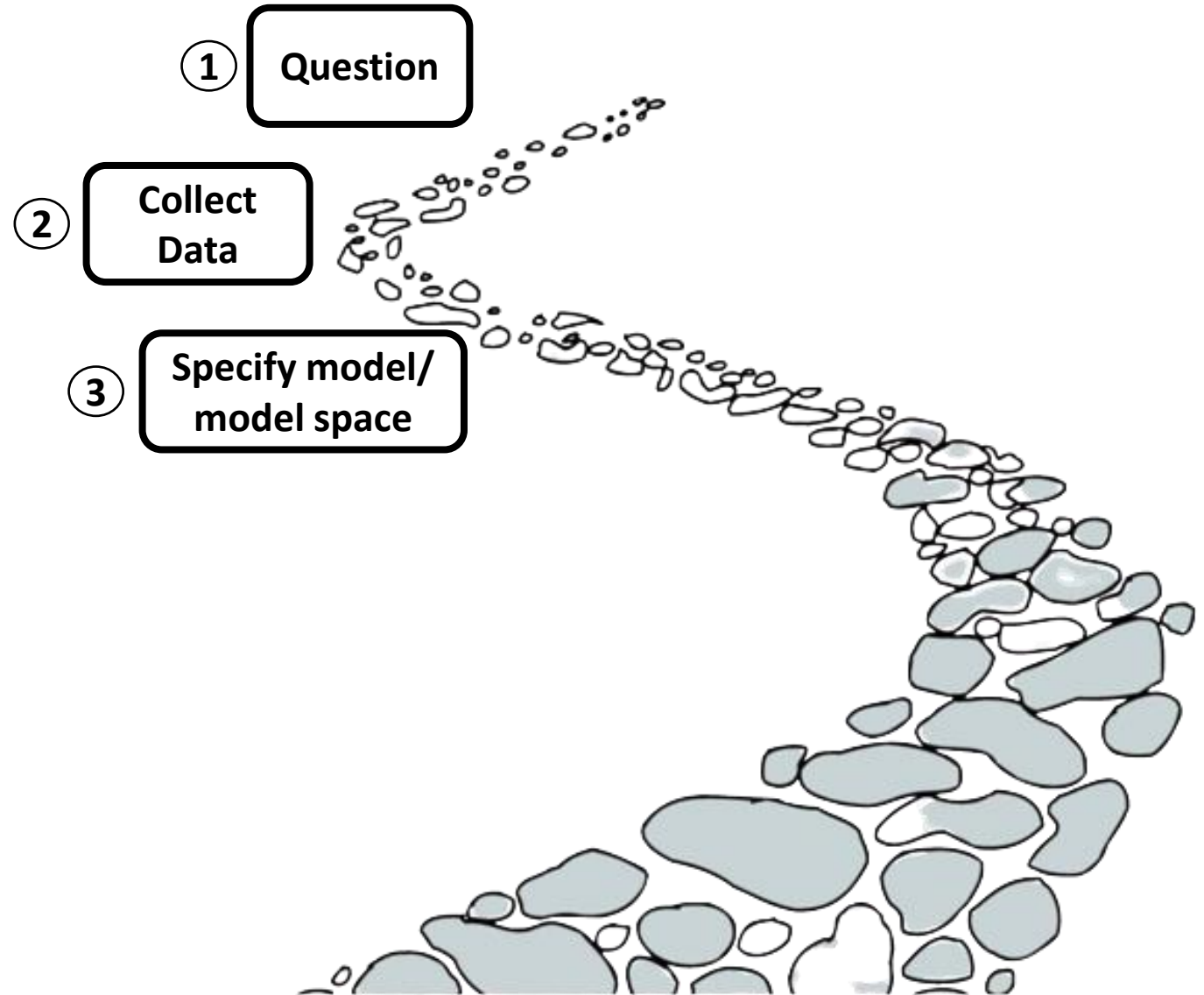
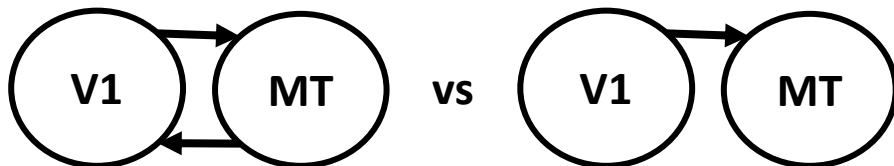
# Translate your question

## Model comparison example

- Is my task activating MT and V1 or only V1?



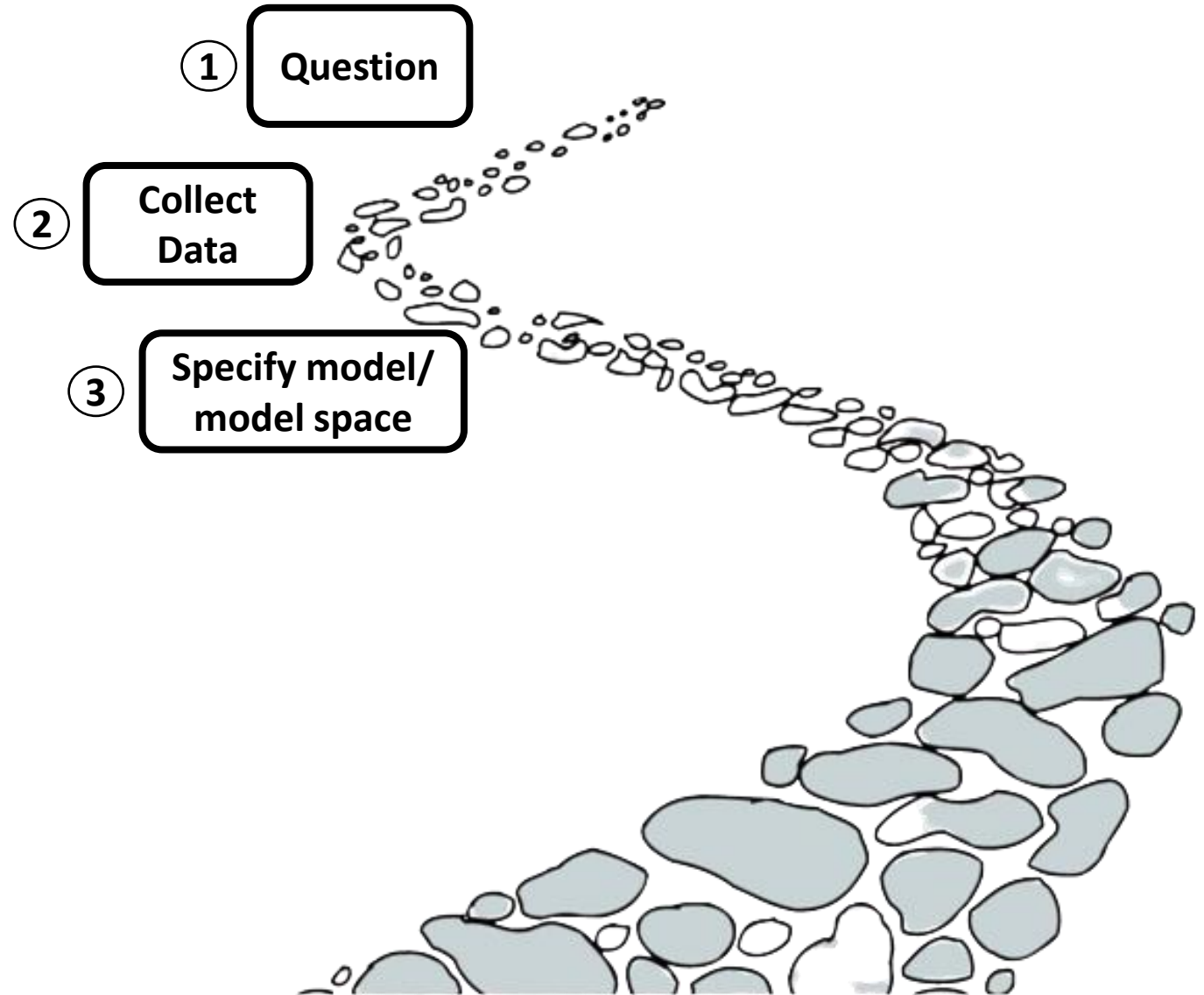
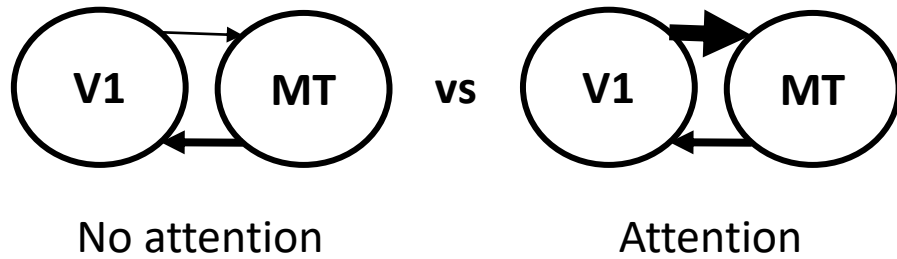
- Are backward connections switched off when individuals are sleeping?



# Translate your question

## Parameter inference example

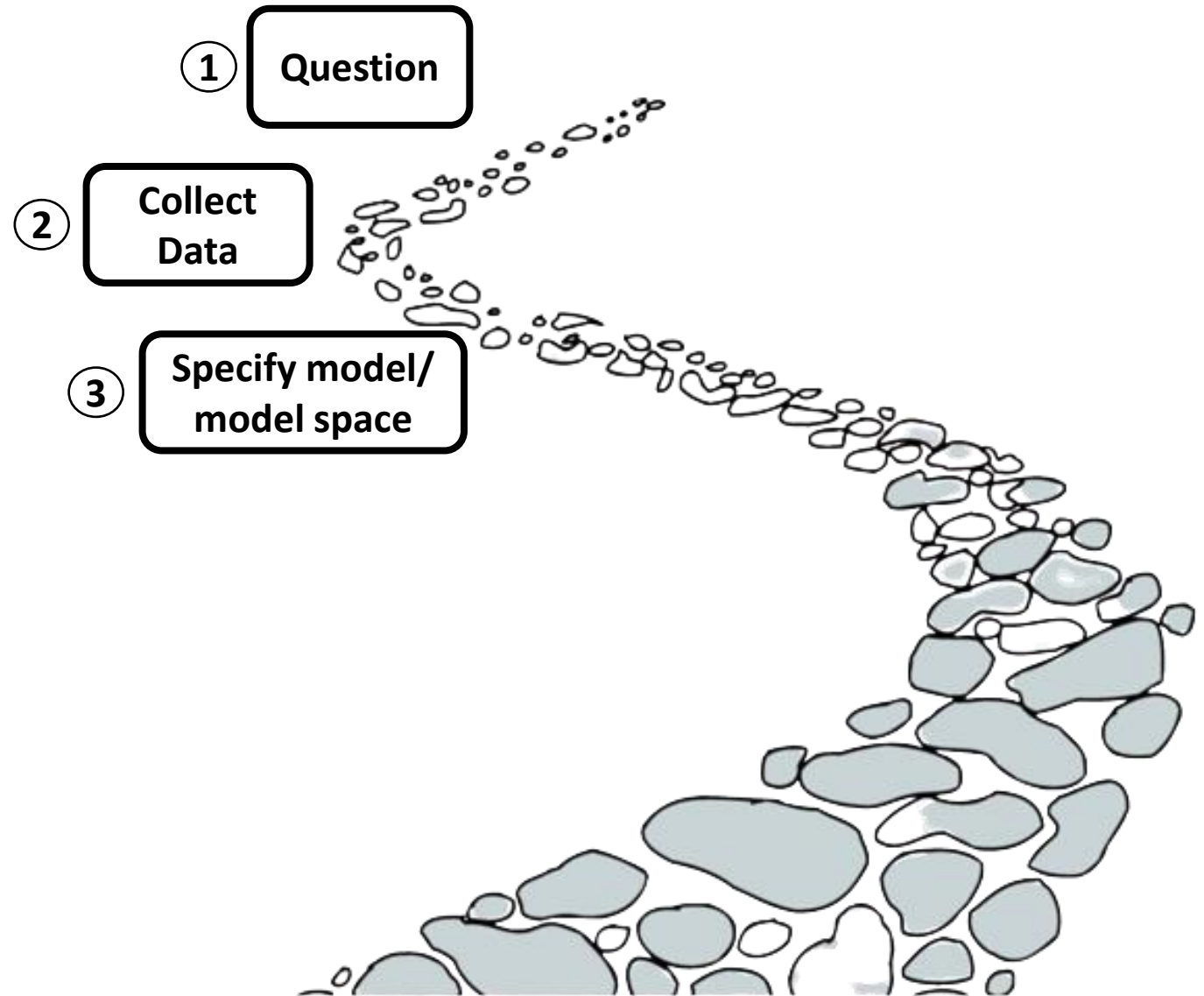
- Is attention increasing forward connectivity?



# Specify model/model space

## Steps

- Translate your question into a model comparison or a parameter inference problem
- **Select regions**
- Select a variant of DCM
- Example: The “ERP” model
- Specify connectivity architecture

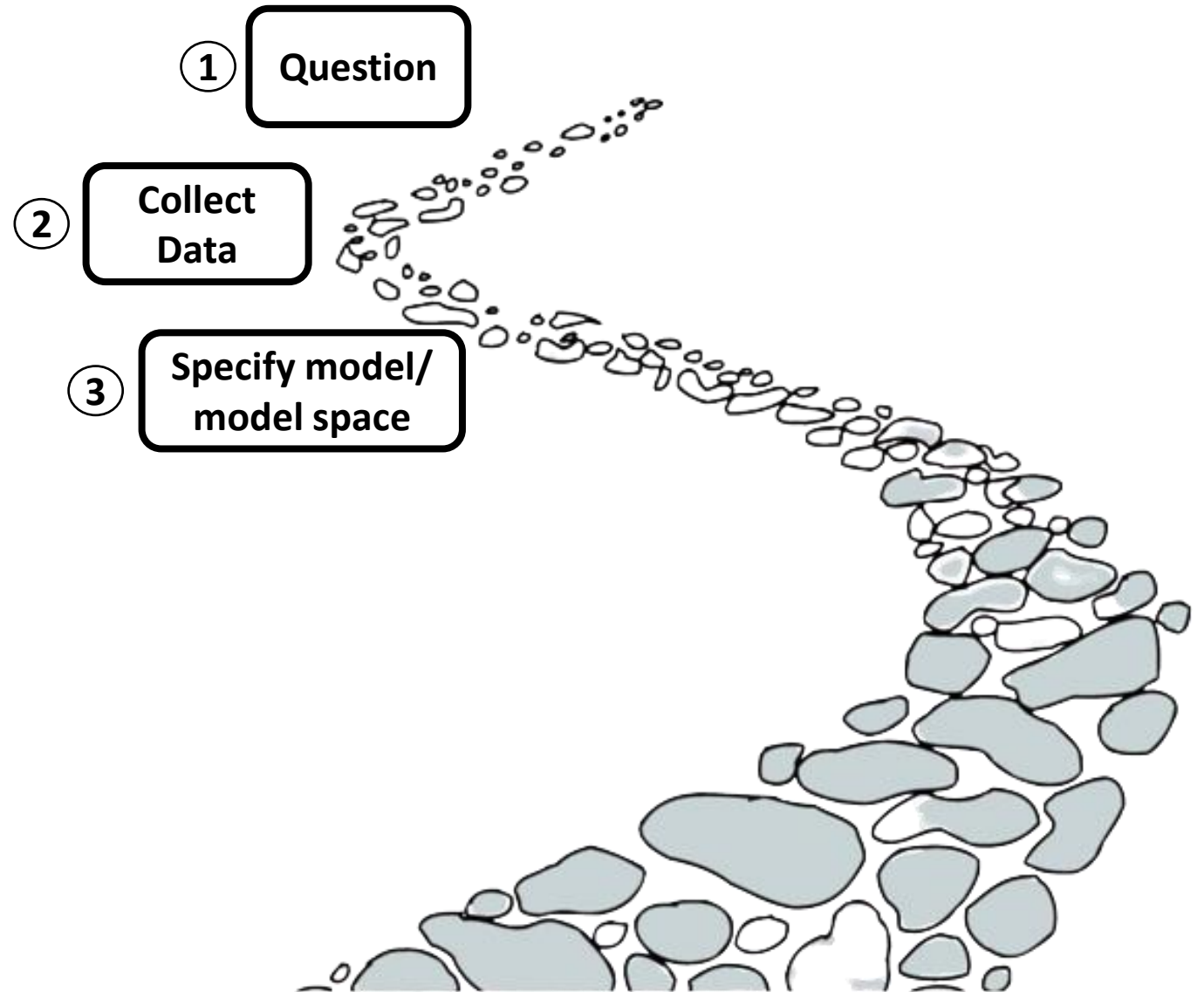


# Select regions

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## Ways to select regions

- Literature
- MRI
- Source reconstruction
- Dipole fitting

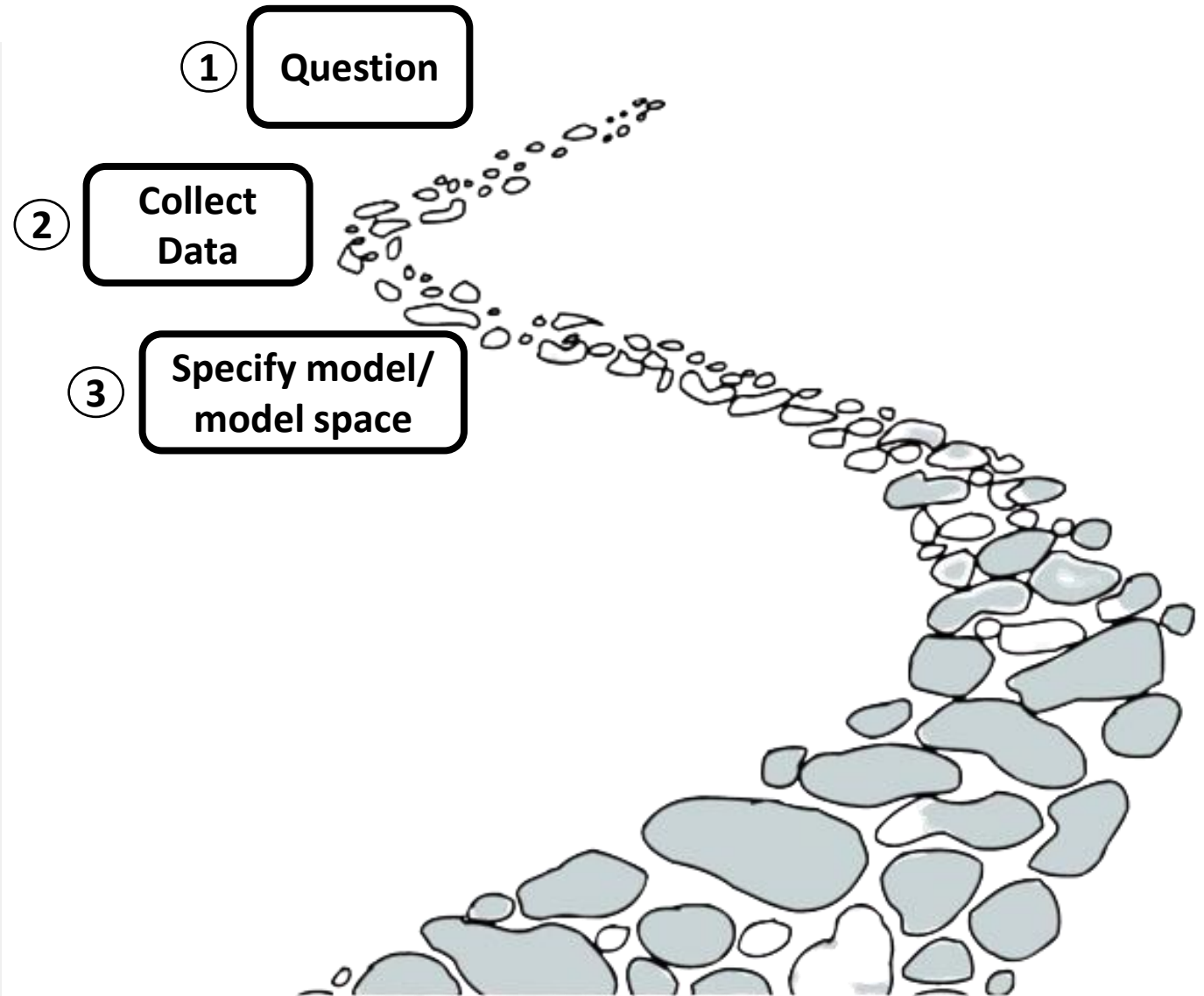


# The DCM analysis path

The screenshot shows the DCM software interface. The 'data and design' section includes fields for 'time window (ms)' (1, 200), 'bins: 5.0ms', 'between-trial effects', 'rare', 'trials' (1, 2), 'hanning', 'detrend' (1), 'subsample' (1), and 'modes' (8). A red arrow points from the 'rare' dropdown to the 'electromagnetic model' section. The 'electromagnetic model' section includes 'ECD', 'dipoles', 'onsets (ms)' (60), 'duration (sd)' (16), and a table of dipole locations. A red box highlights the table:

left A1	-42 -22 7
right A1	46 -14 8
left STG	-61 -32 8
right STG	59 -25 8
right IFG	46 20 8

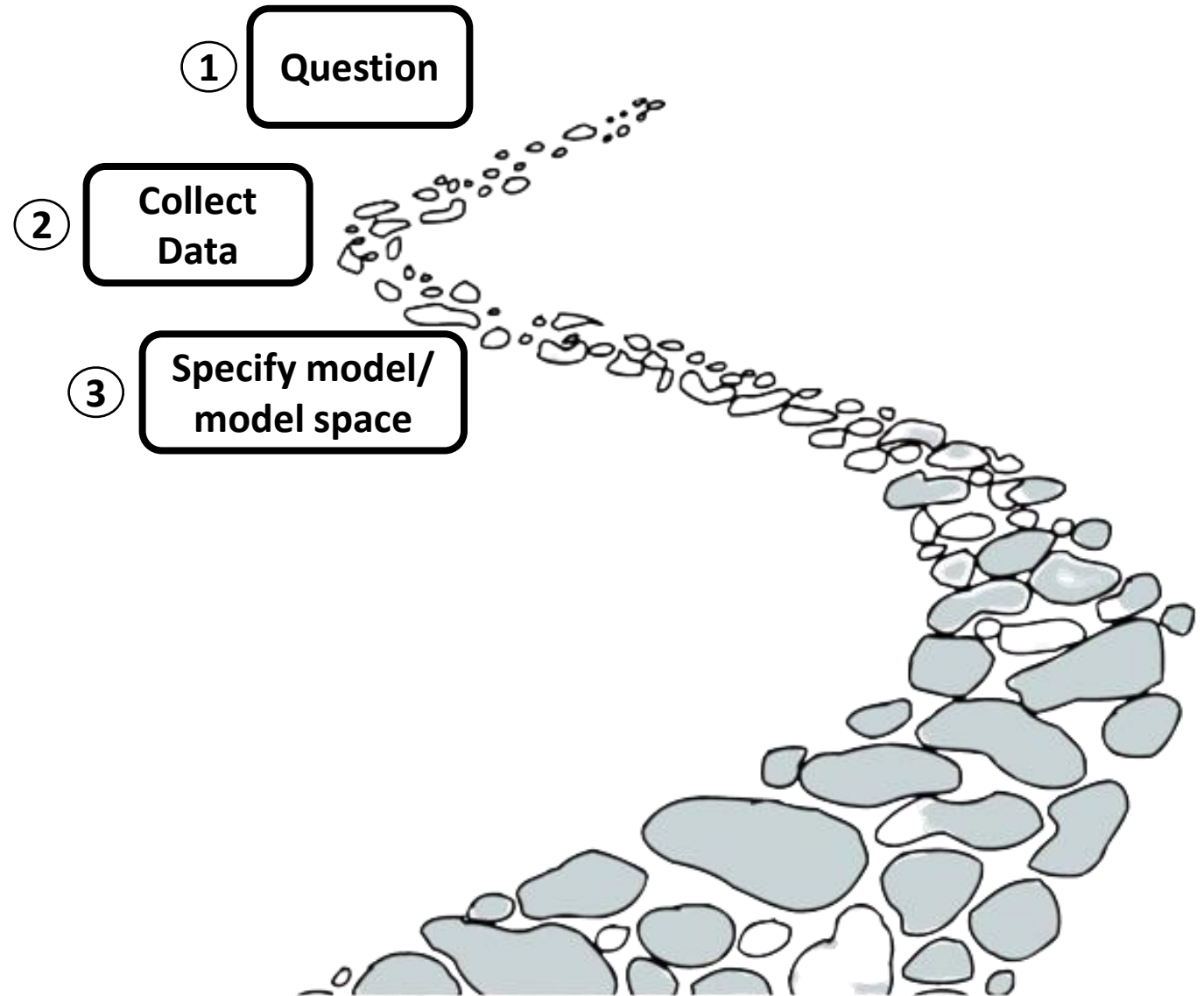
The 'neuronal model' section includes 'forward', 'back', 'lateral', and 'input' connectivity matrices.



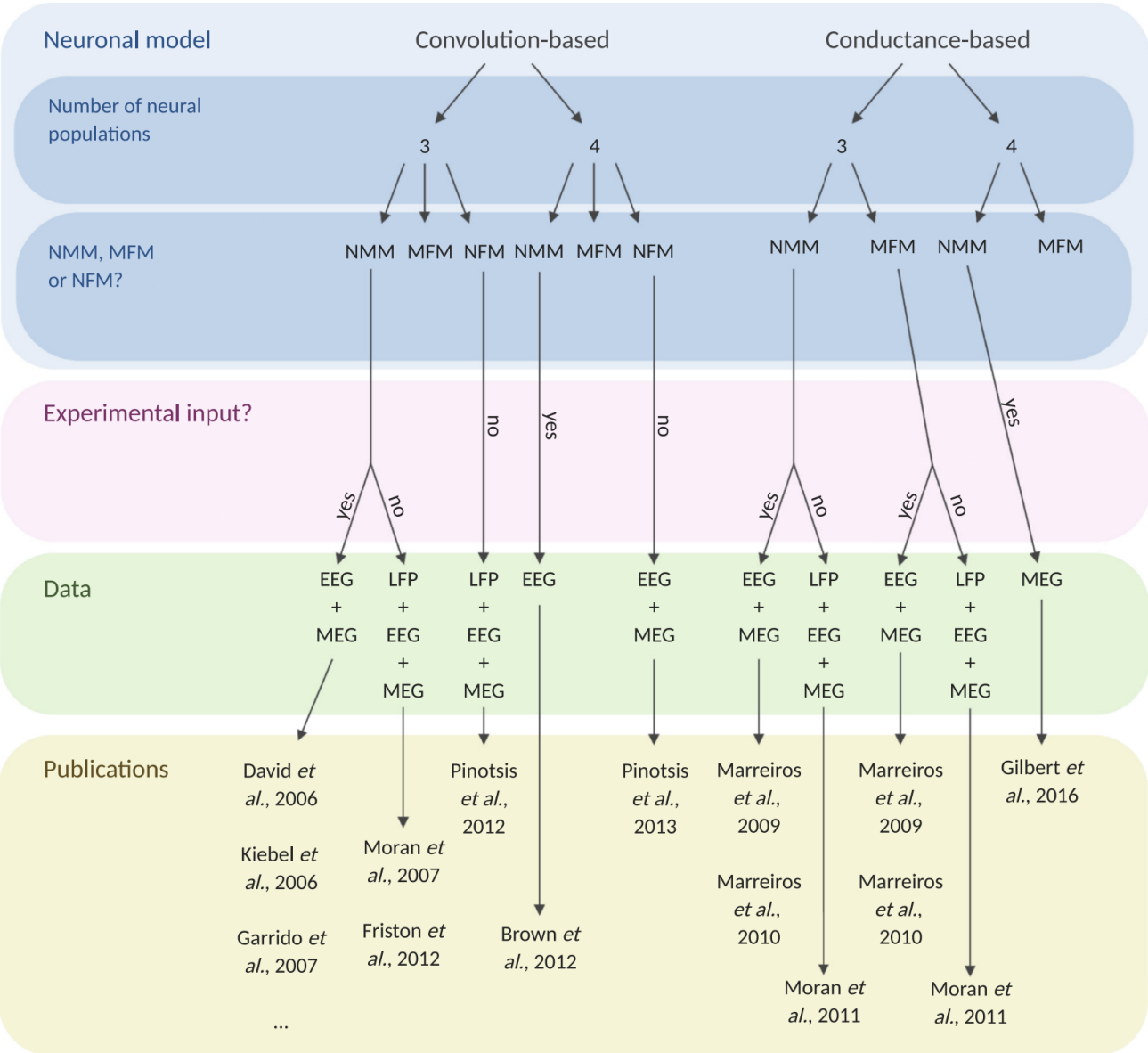
# Specify model/model space

## Steps

- Translate your question into a model comparison or a parameter inference problem
- Select regions
- **Select a variant of DCM**
- Example: The “ERP” model
- Specify connectivity architecture



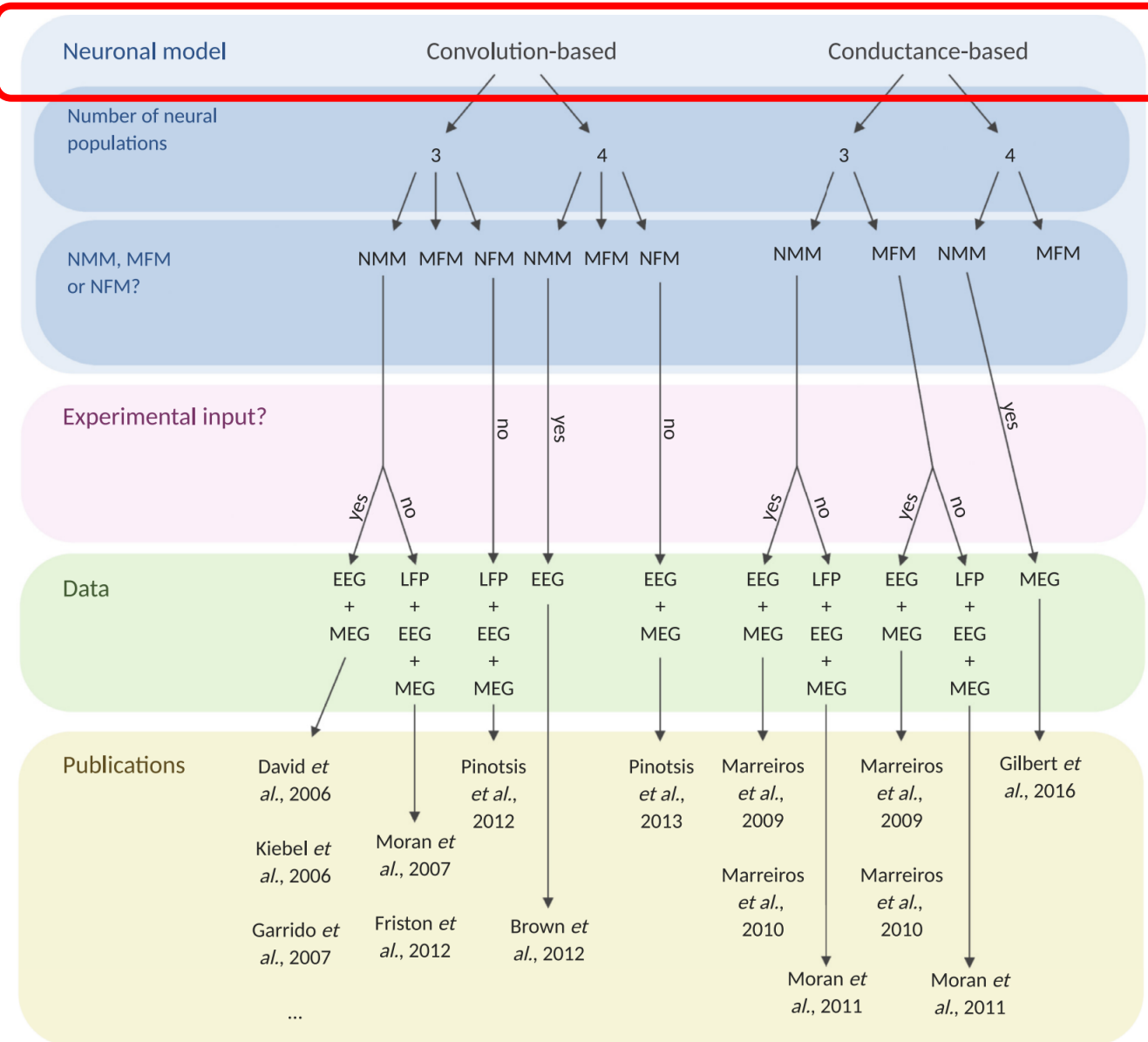
# Select a variant of DCM for evoked responses



Pereira et al (2021), *NeuroImage*



# Select a variant of DCM for evoked responses



Pereira et al (2021), *NeuroImage*

## Convolution-based

SPM: ERP, SEP, LFP, CMC, NFM

- Wilson & Cowan (1973), Jansen & Ritt (1995)

## Conductance-based

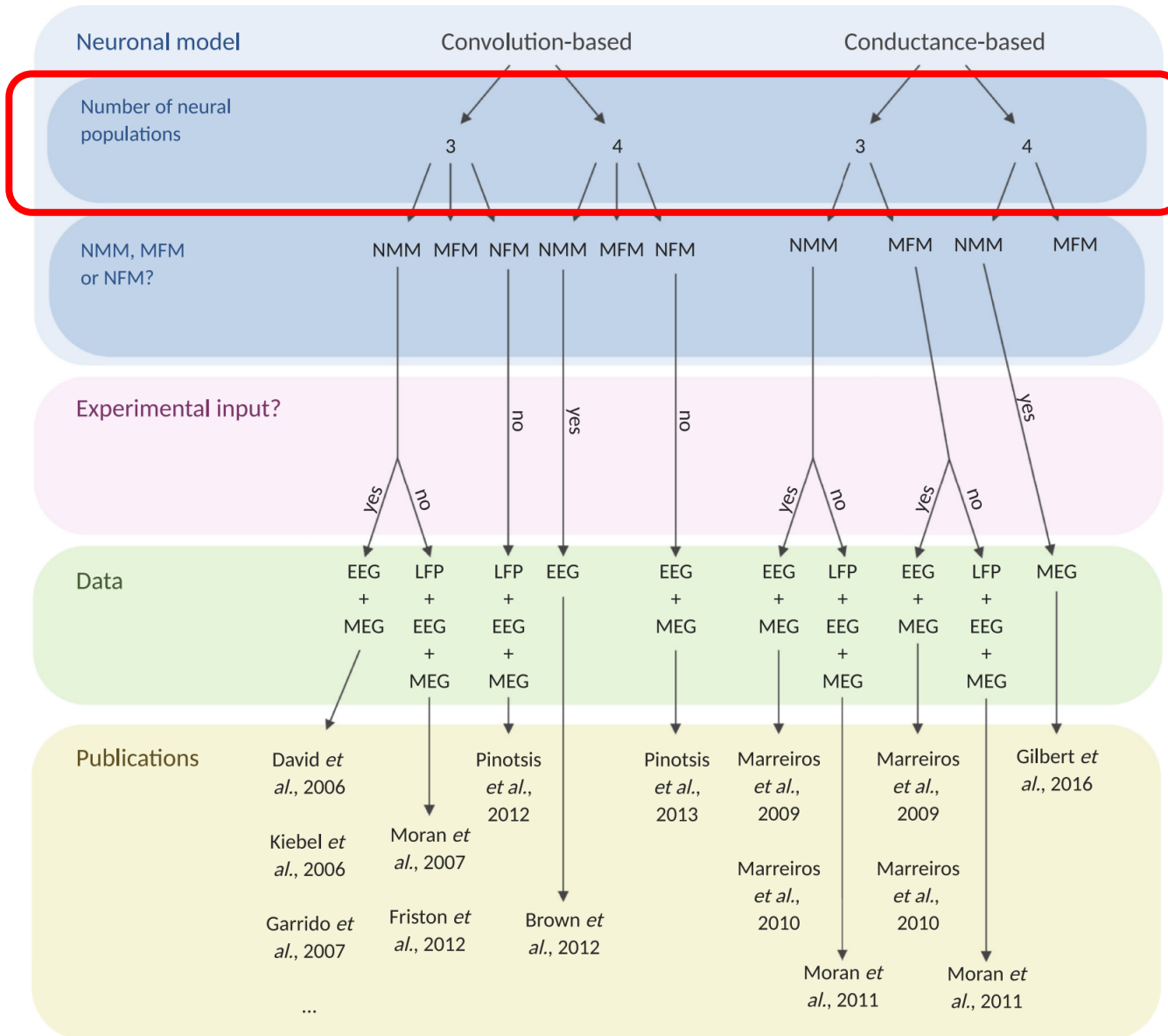
SPM: NMM, NFM, CMM, NMDA, CMM\_NMDA

- Hodgkin & Huxley (1952), Morris & Lecar (1981)

## How to choose?

- Are you interested in ion channels: conductance-based
- Otherwise: Convolution

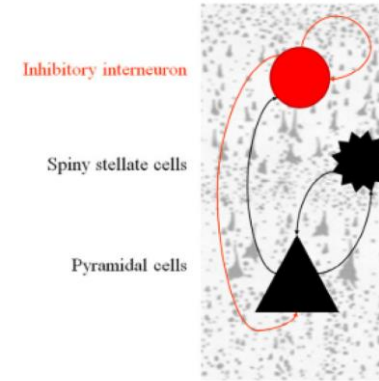
# Select a variant of DCM for evoked responses



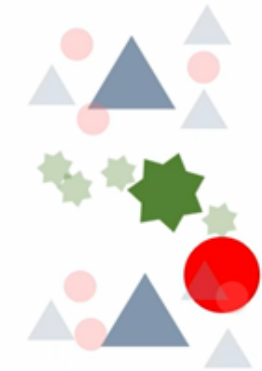
Pereira et al (2021), *NeuroImage*

**3 populations**  
(ERP, SEP, LFP, NFM)

**4 populations**  
(CMM, CMC, CMM\_NMDA)



Moran et al. (2013), *Front .Comput. Neurosci.*



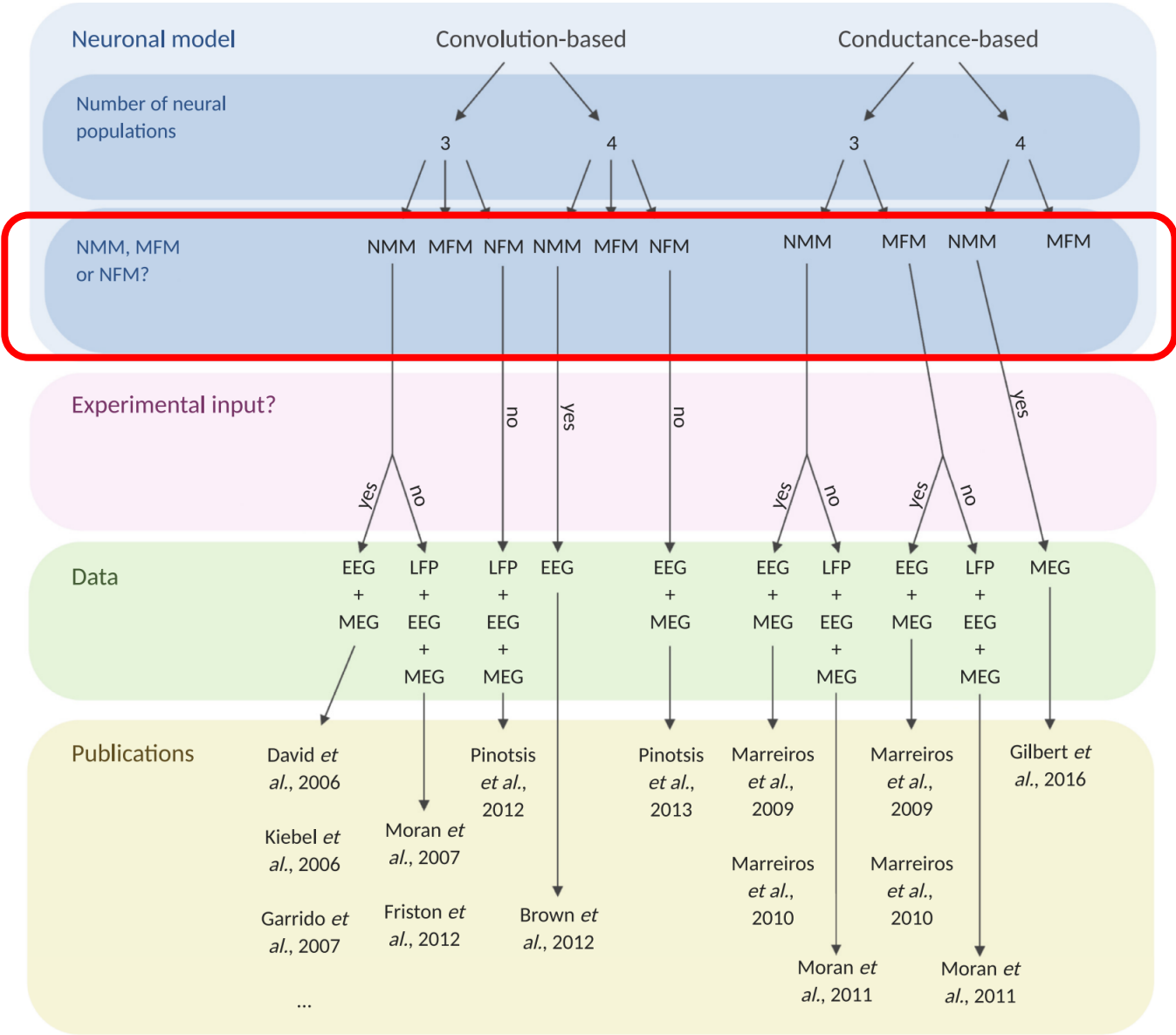
Schöbi (2019), CPC Lecture

## How to choose?

- Do you want to test predictive coding?
- Do you expect specific effects in either deep or superficial pyramidal cells?

=> Canonical microcircuit

# Select a variant of DCM for evoked responses



Pereira et al (2021), *NeuroImage*

## MFM: Mean-field model

- Considers mean and covariance

## NMM: Neural mass model

- Describes populations by their mean activity (special case of MFM)

## NFM: Neural field model

- Considers spatial dimension

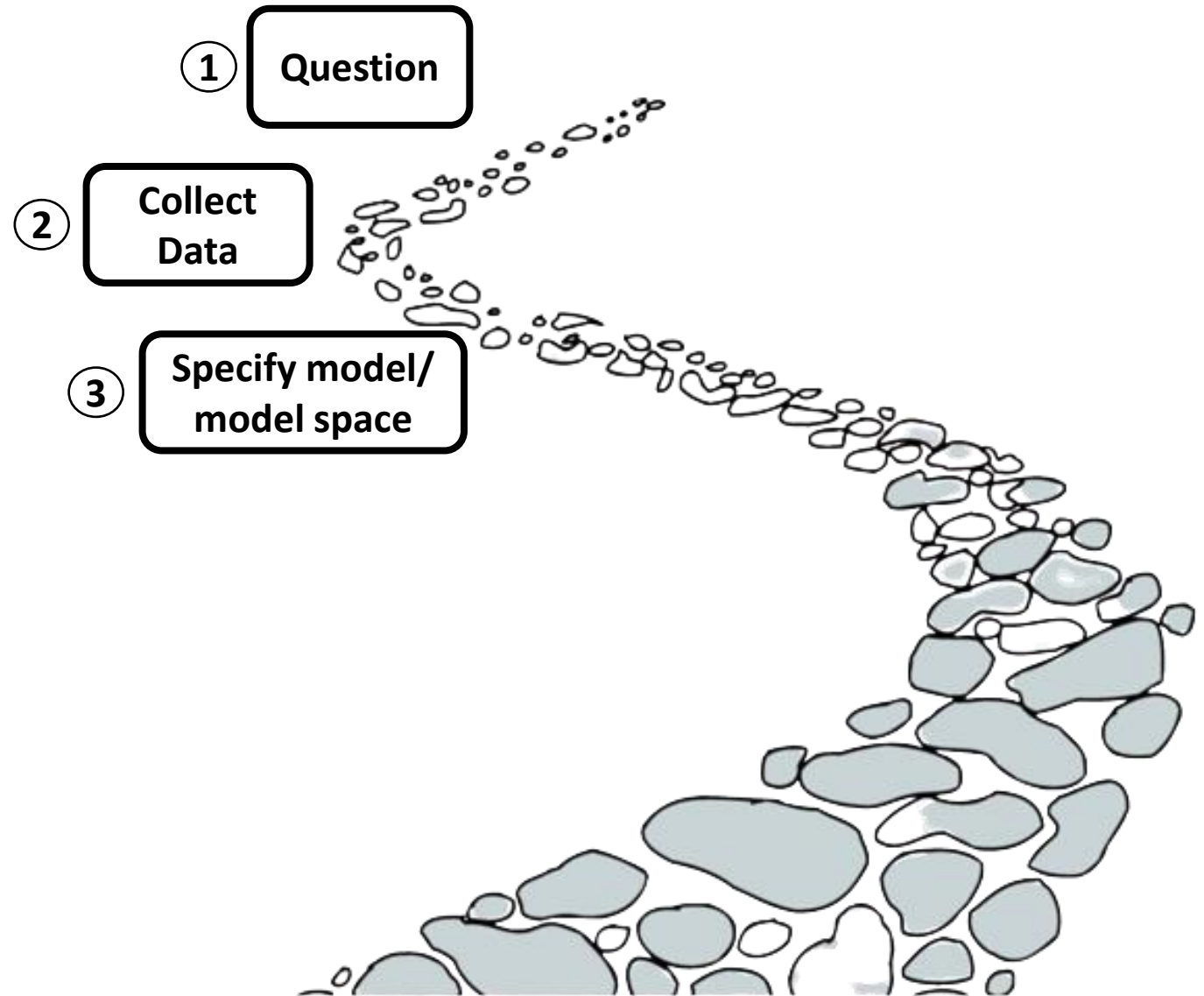
## How to choose?

- MFM and NFM can express more complex dynamics (Marreiros et al., 2009)
- Go there if this is needed, otherwise stick to the simpler model

# Specify model/model space

## Steps

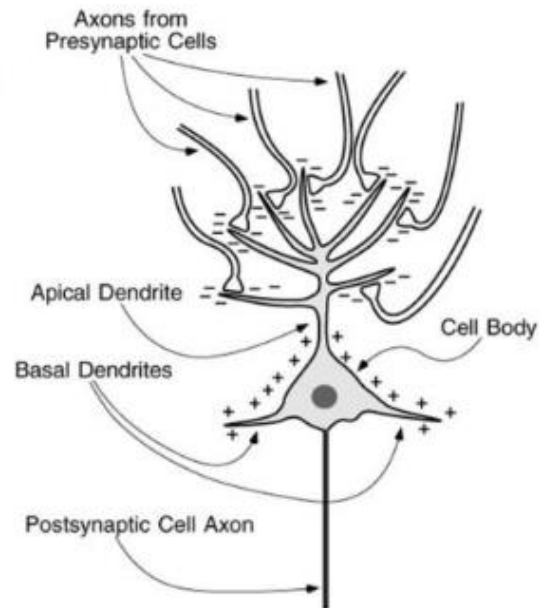
- Translate your question into a model comparison or a parameter inference problem
- Select regions
- Select a variant of DCM
- **Example: The “ERP” model**
- Specify connectivity architecture



# What do we measure with EEG?

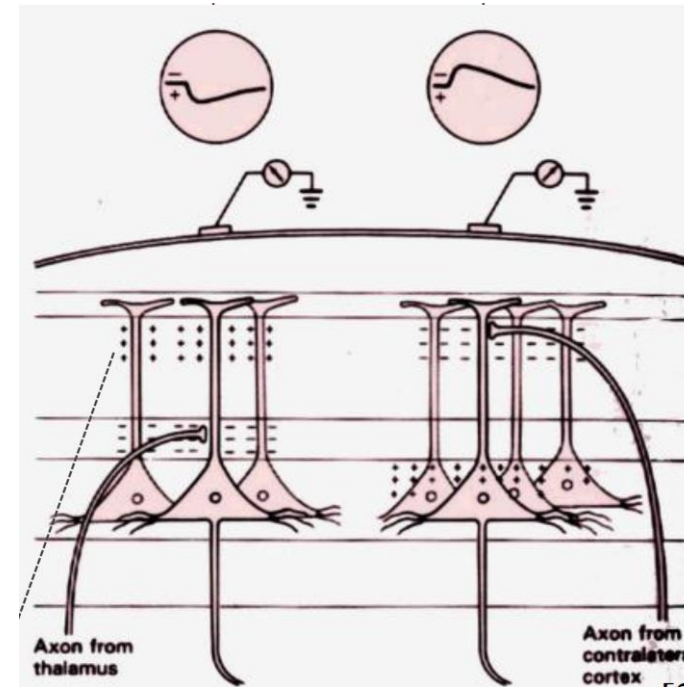
## Background

- Underlying mechanisms generating EEG



[www.neurofeedbackalliance.org/eeg-electrophysiology/](http://www.neurofeedbackalliance.org/eeg-electrophysiology/)

## Measurable dipoles

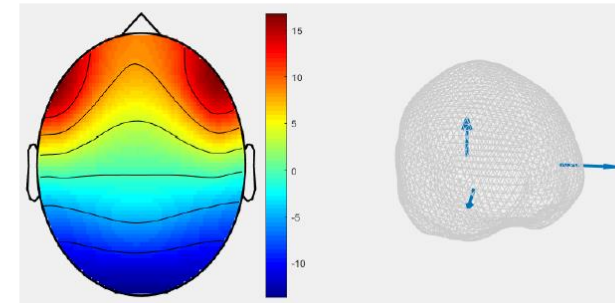
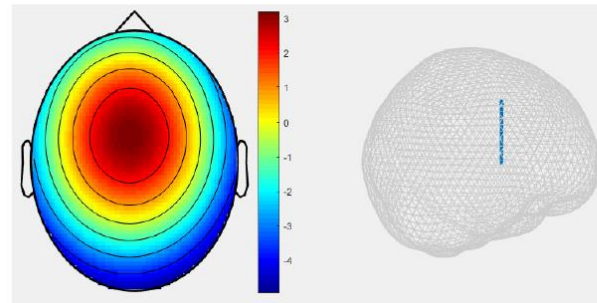
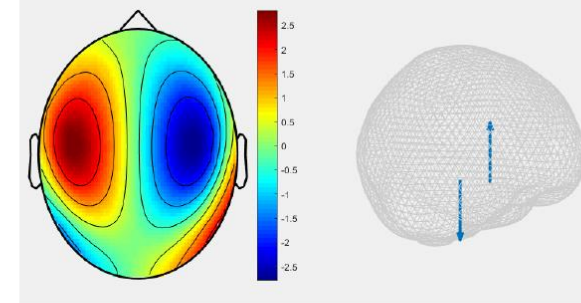
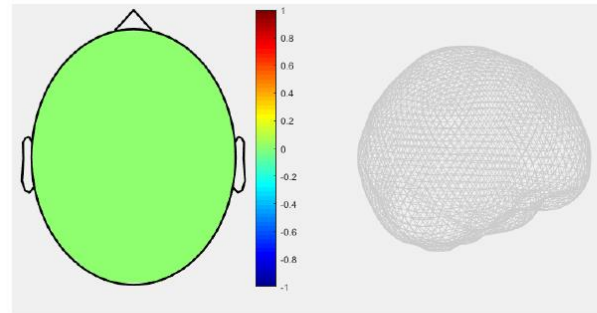
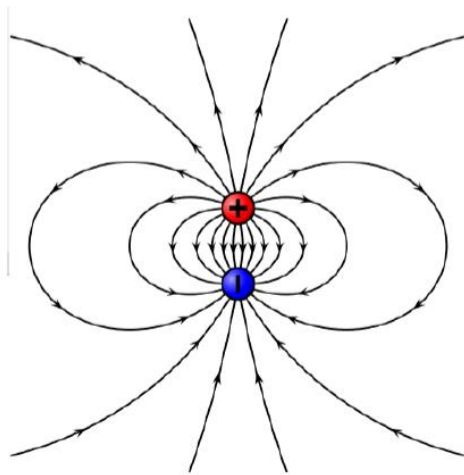


Buzsáki et al (2012), Nature Reviews

# What do we measure with EEG?

## Background

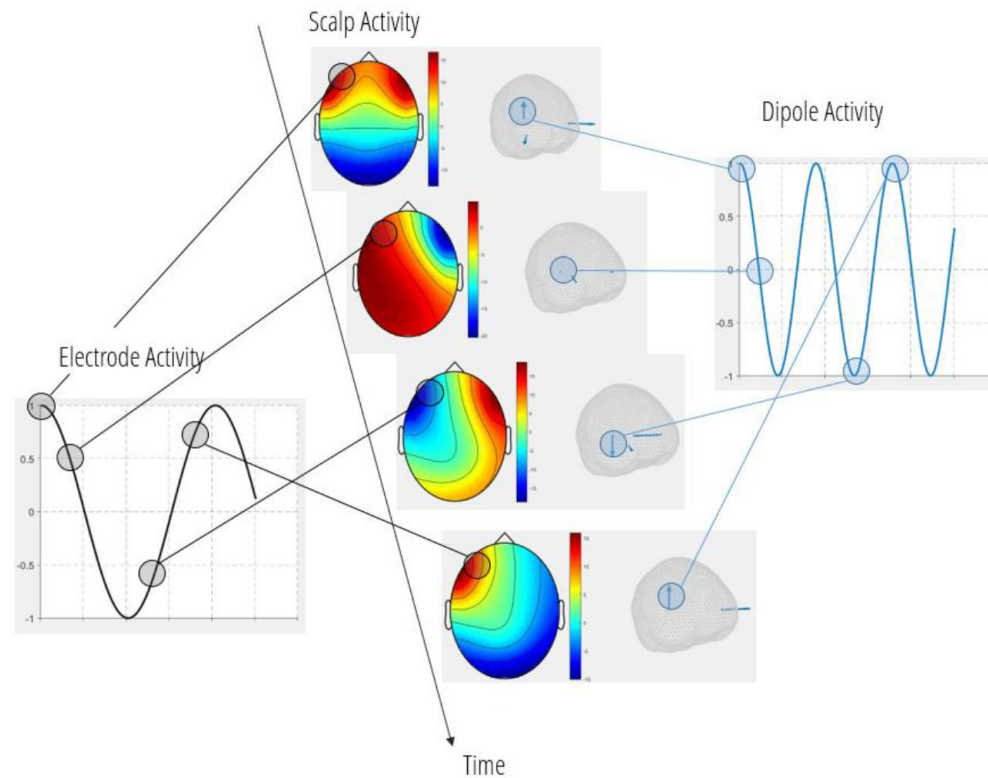
- Dipole generates to measurable electrical fields in EEG sensors



# What do we measure with EEG?

## Background

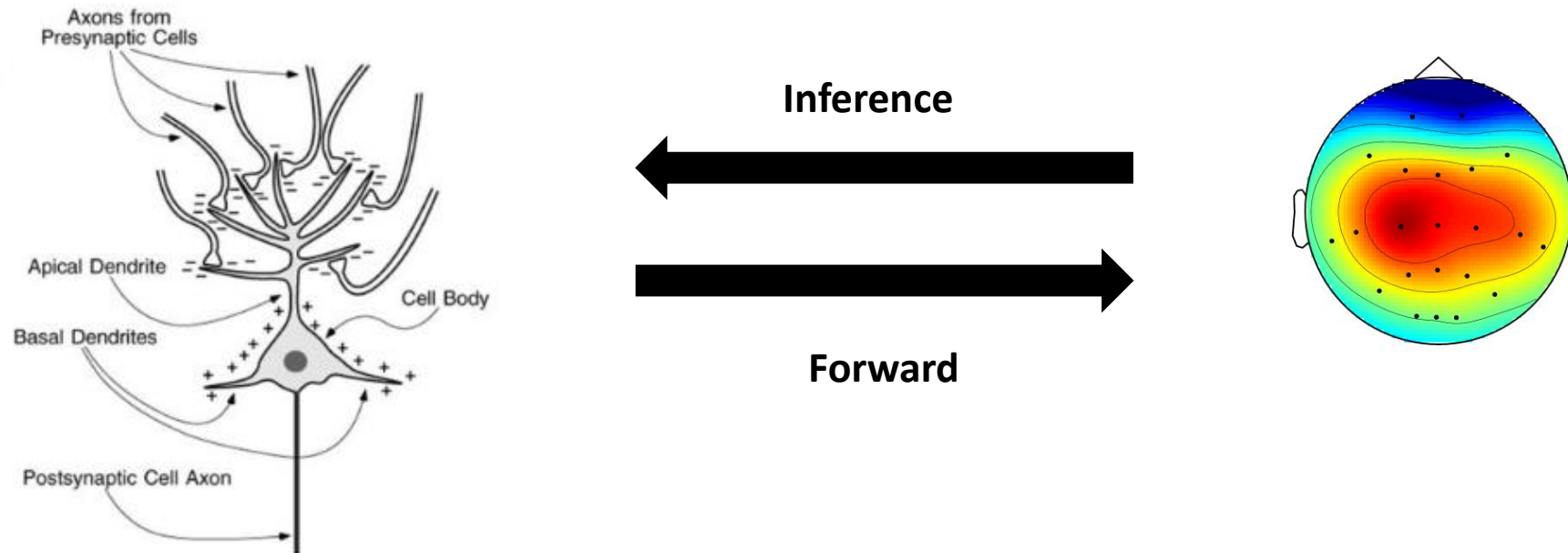
- Dipole moments change over time and lead to changes in measured scalp potentials



# What do we measure with EEG?

## Question

- Can we make inferences about properties of the neuronal sources that generate these signals?





# Scales of analysis

Microscale

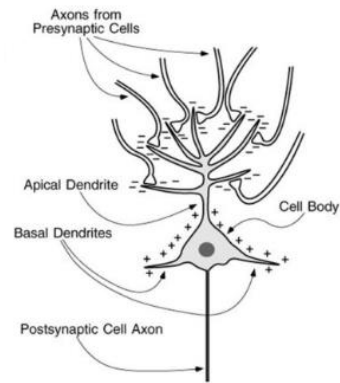
Mesoscale

Macroscale

Increasing spatial scale

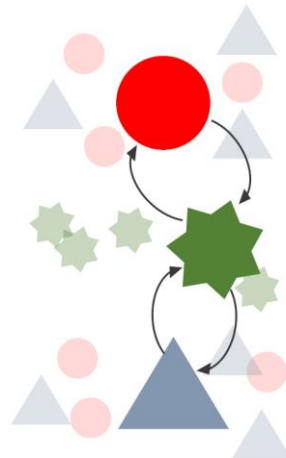
Single cell

1-10  $\mu\text{m}^2$



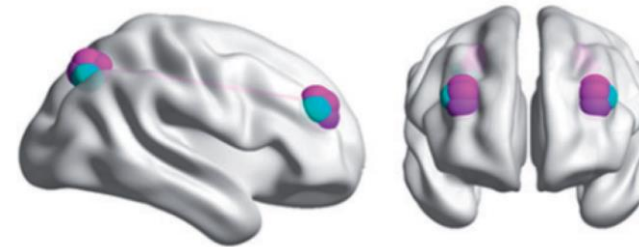
Cortical Column

1-10  $\text{mm}^2$  to 1-5  $\text{cm}^2$



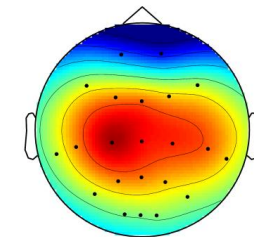
Brain Networks

5-20  $\text{cm}^2$



Scalp potentials

30-38  $\text{cm}^2$



# Scales of analysis

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**Microscale**

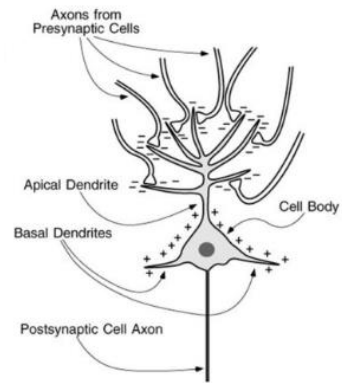
**Mesoscale**

**Macroscale**

Increasing spatial scale

**Single cell**

1-10  $\mu\text{m}^2$



# Source modelling at the microscale



Microscale

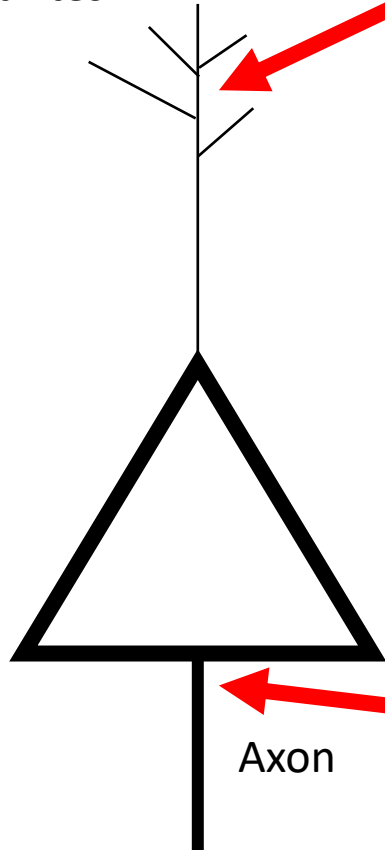
Mesoscale

Macroscale



Dendrites

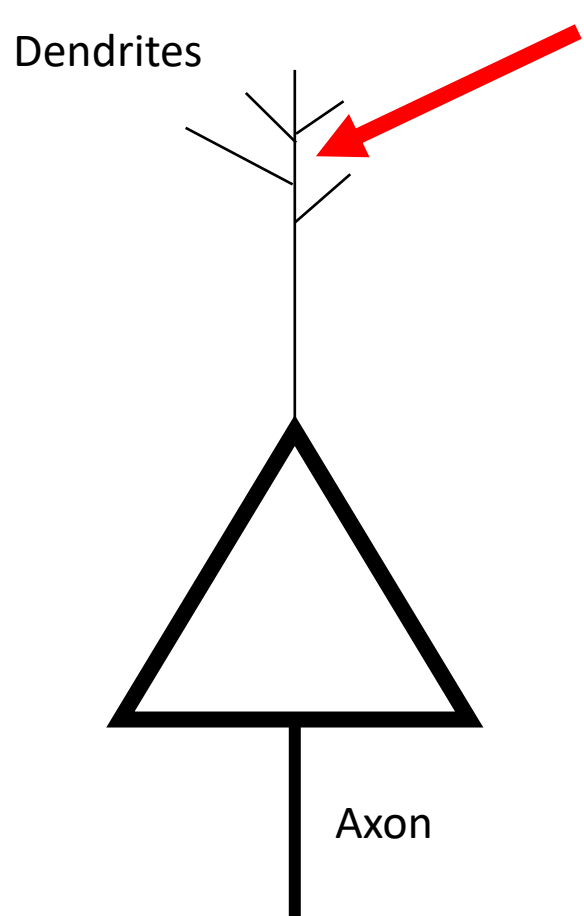
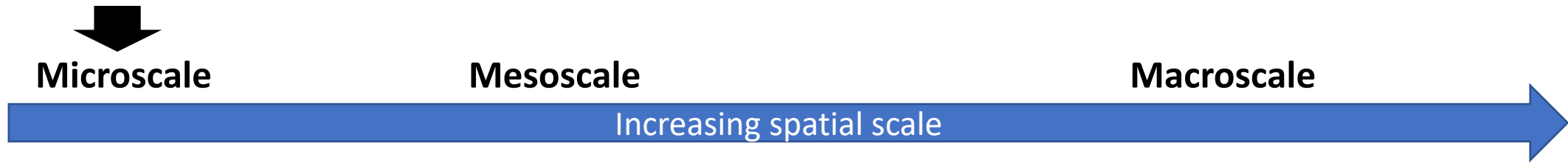
**Input:** Spikes of a presynaptic cell are converted into postsynaptic potentials (PSPs)



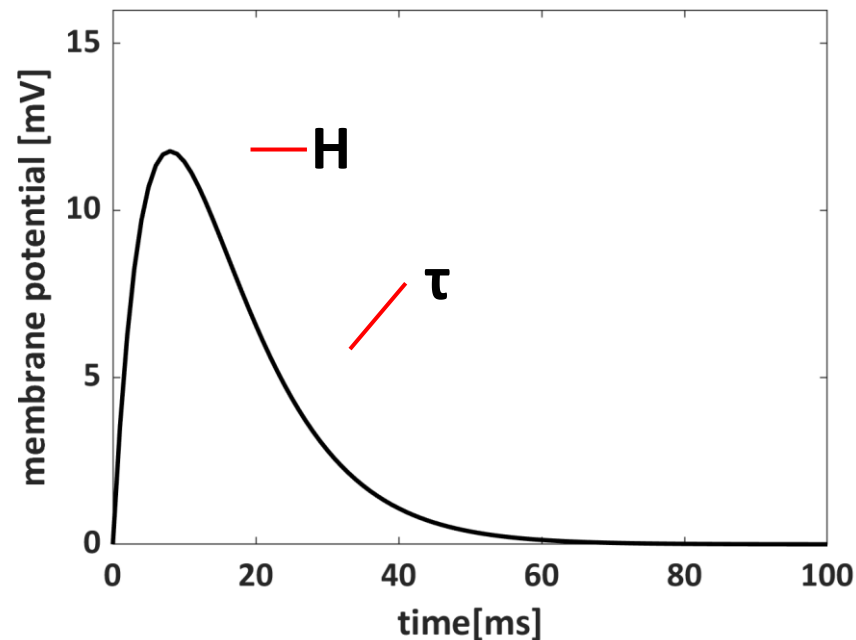
Axon

**Output:** Postsynaptic potentials are converted into a spike

# Source modelling at the microscale



**Input:** Spikes of a presynaptic cell are converted into postsynaptic potentials (PSPs)

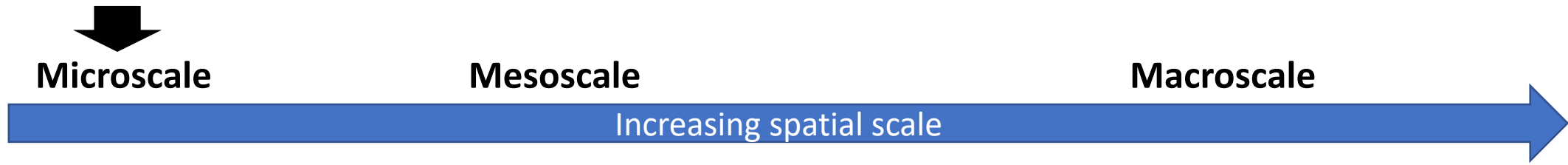


David et al (2005), NeuroImage

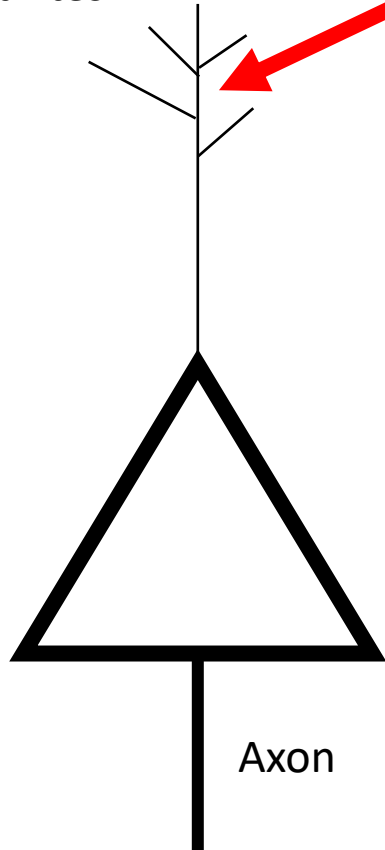
$$h(t) = \begin{cases} \frac{Ht \exp(-t/\tau)}{\tau} & t \geq 0 \\ 0 & t < 0 \end{cases}$$

**Convolution** of incoming neural activity with synaptic kernel

# Source modelling at the microscale

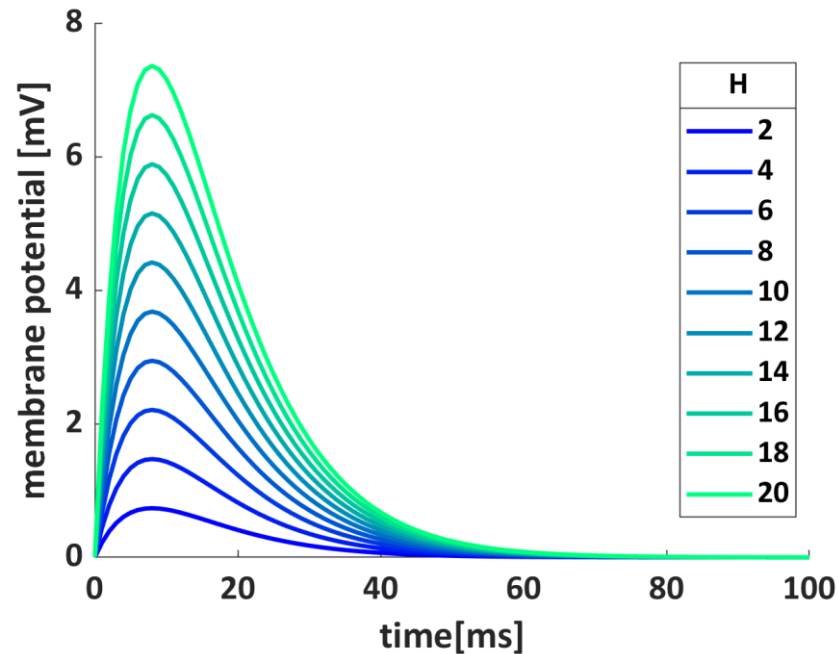


Dendrites



Axon

**Input:** Spikes of a presynaptic cell are converted into postsynaptic potentials (PSPs)



**H:** Maximum postsynaptic potential

# Source modelling at the microscale



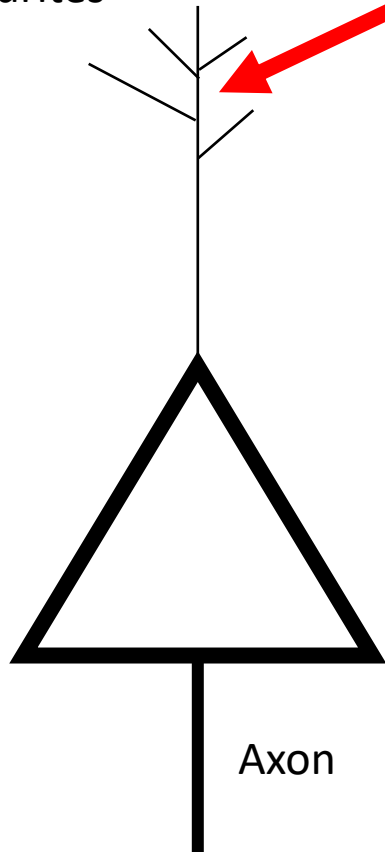
Microscale

Mesoscale

Macroscale

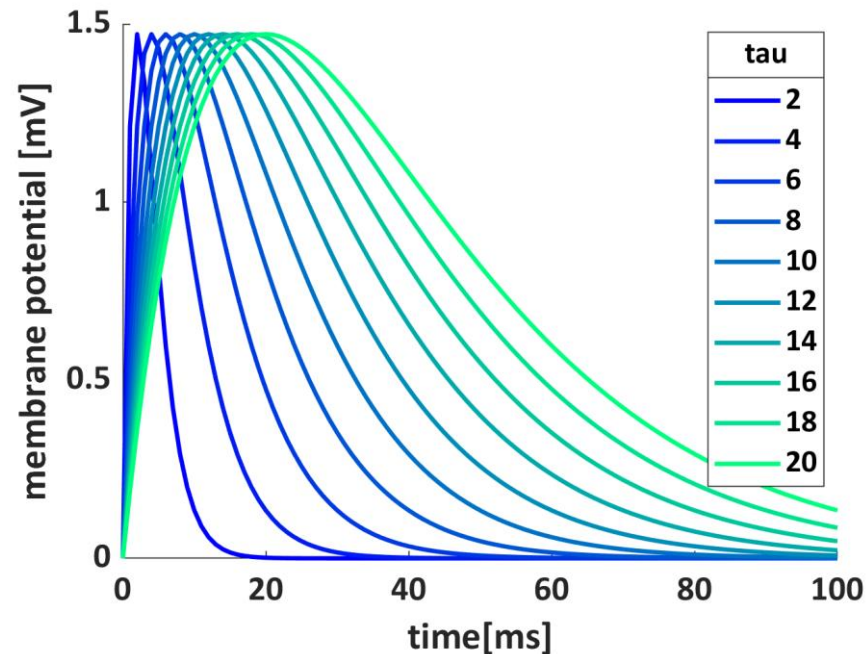


Dendrites



Axon

**Input:** Spikes of a presynaptic cell are converted into postsynaptic potentials (PSPs)



$\tau$ : Inverse time constant

# Source modelling at the microscale



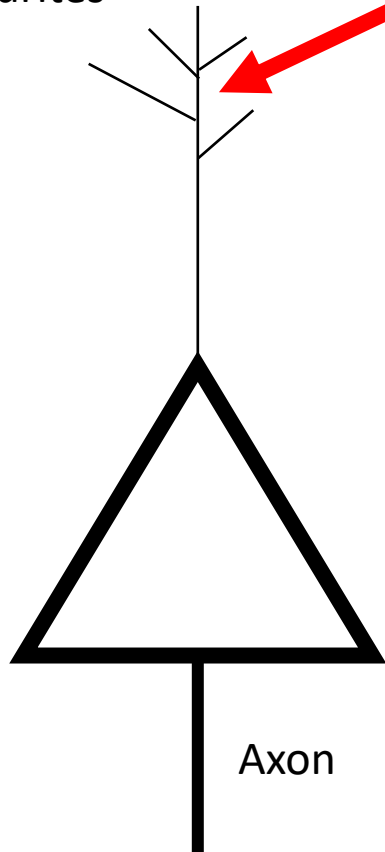
Microscale

Mesoscale

Macroscale

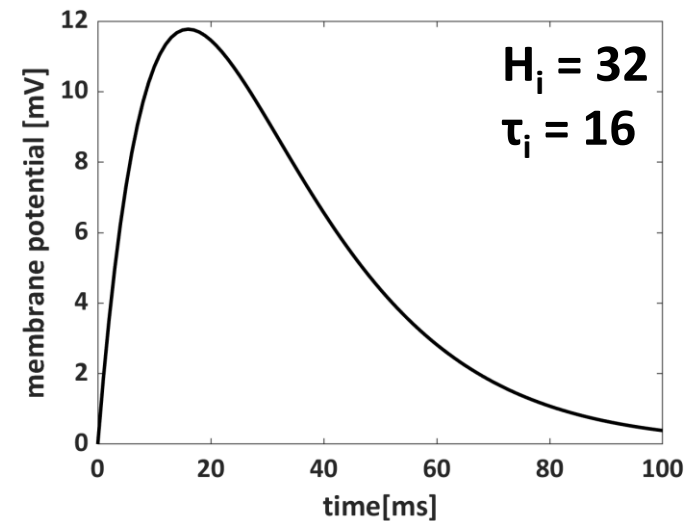
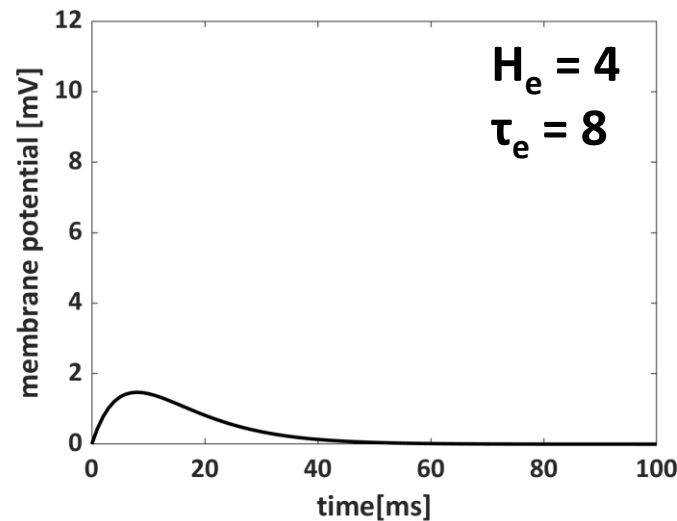


Dendrites



Axon

**Input:** Spikes of a presynaptic cell are converted into postsynaptic potentials (PSPs)



spm\_fx\_erp.m

$H_i > H_e$ , because inhibitory synapse is closer to the soma

Jansen & Ritt (1995), Biol. Cyb.

# Source modelling at the microscale



Microscale

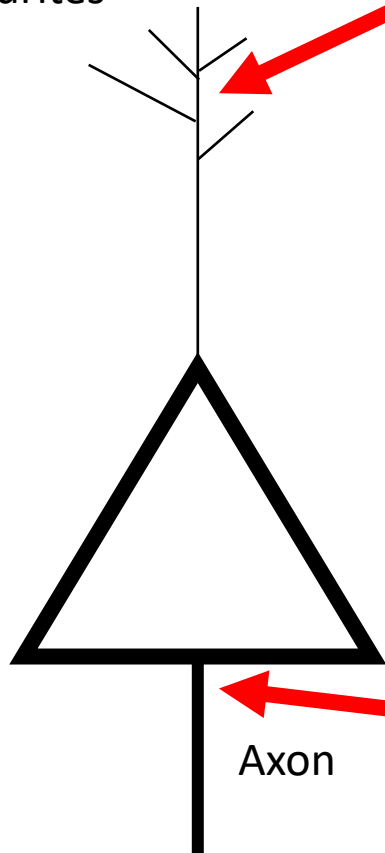
Mesoscale

Macroscale



Dendrites

**Input:** Spikes of a presynaptic cell are converted into postsynaptic potentials (PSPs)



Axon

**Output:** Postsynaptic potentials are converted into a spike



# Source modelling at the microscale



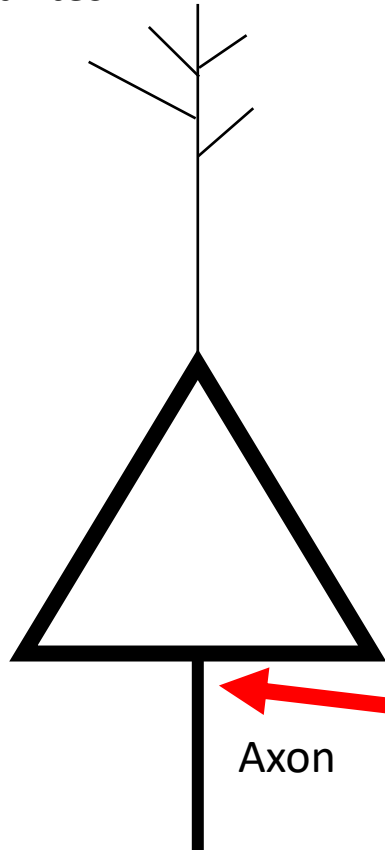
Microscale

Mesoscale

Macroscale

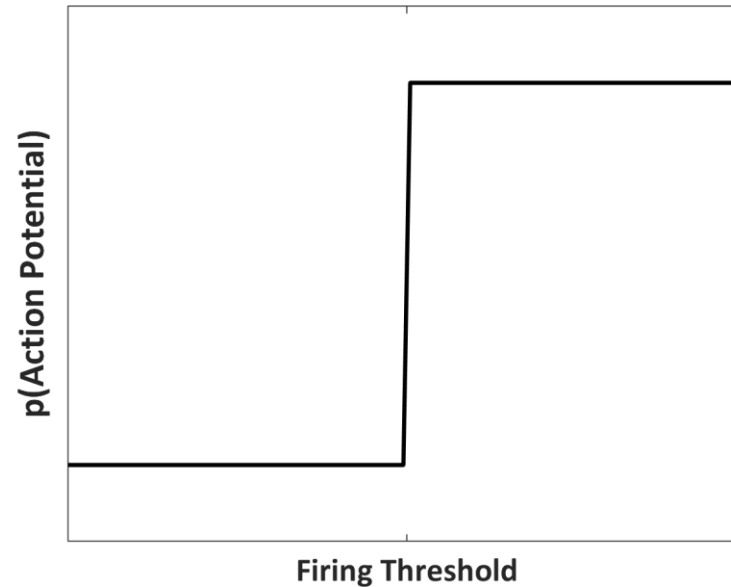


Dendrites



Axon

**Output:** Postsynaptic potentials are converted into a spike



# Source modelling at the microscale



Microscale

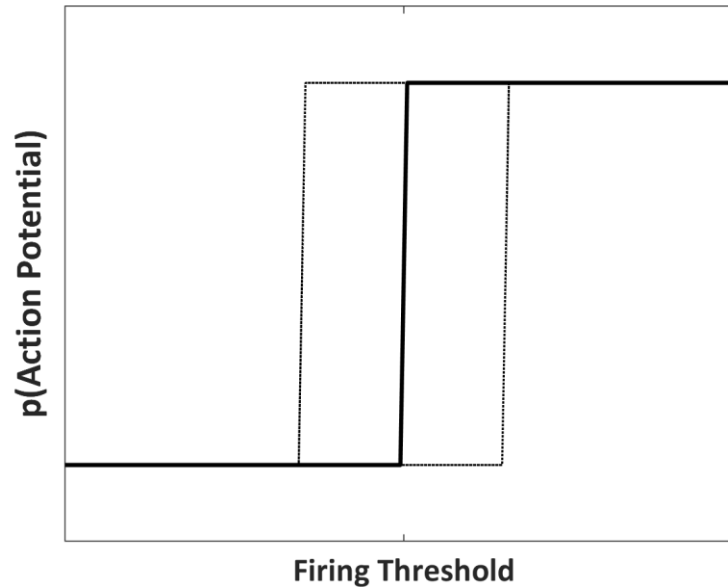
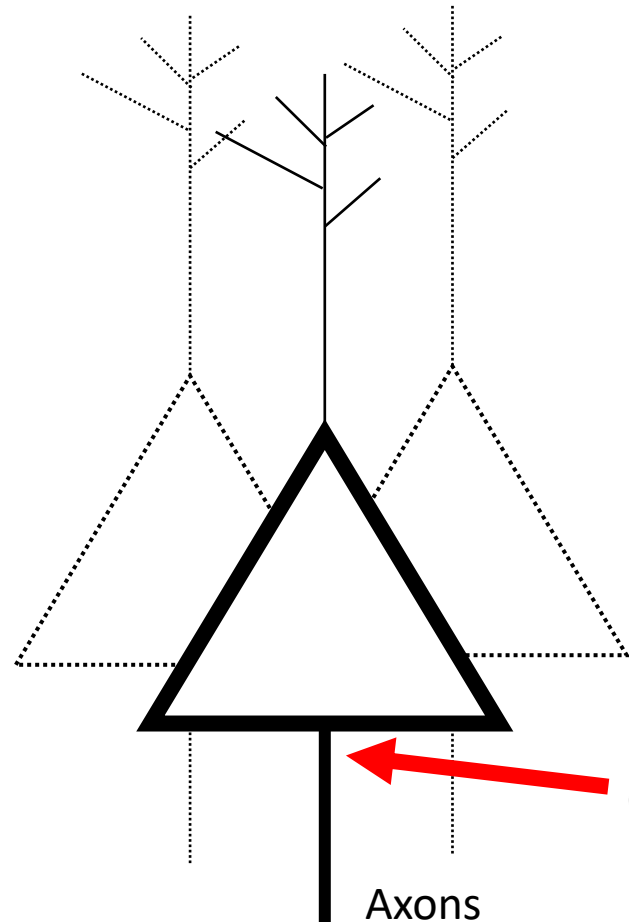
Mesoscale

Macroscale

Increasing spatial scale



Dendrites



**Output:** Postsynaptic potentials are converted into a spike

# Source modelling at the microscale



Microscale

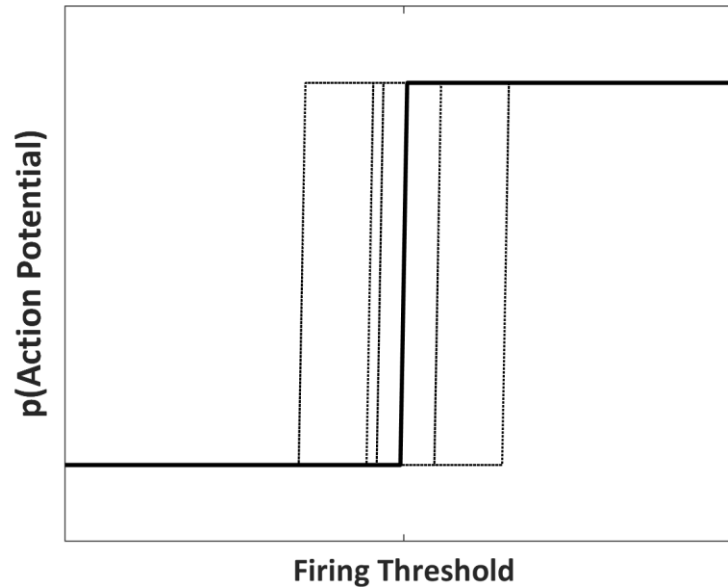
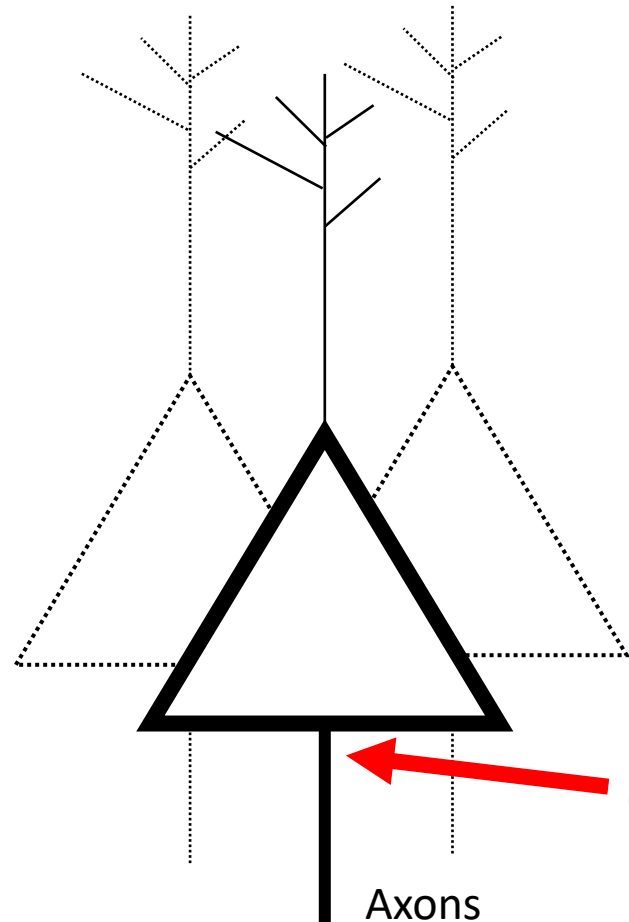
Mesoscale

Macroscale

Increasing spatial scale



Dendrites



**Output:** Postsynaptic potentials are converted into a spike

# Source modelling at the microscale



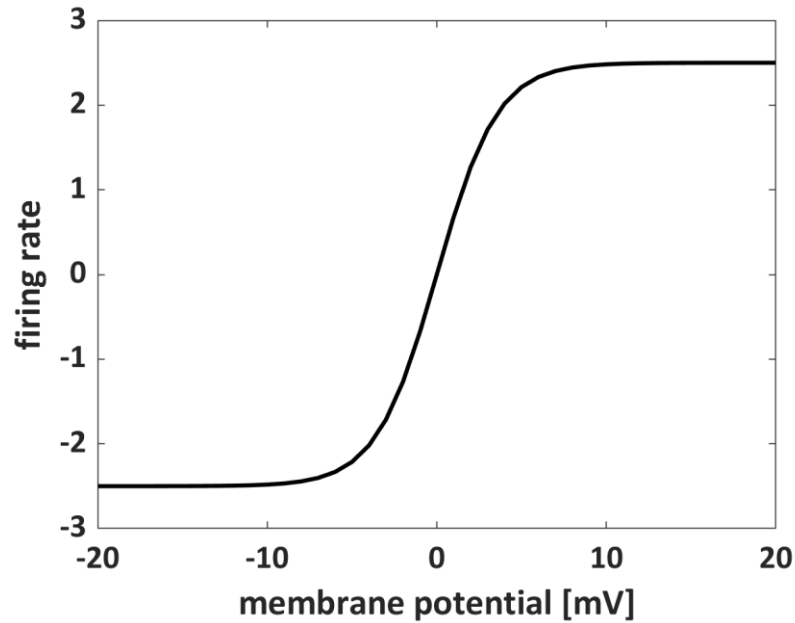
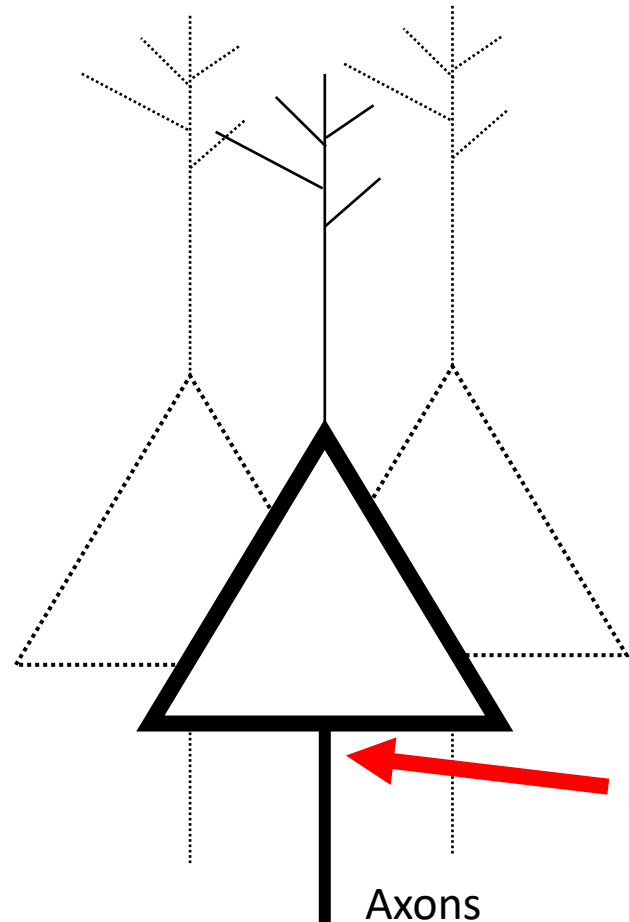
Microscale

Mesoscale

Macroscale



Dendrites



Mean-field approximation

**Output:** Postsynaptic potentials are converted into an average spike rate

# Source modelling at the microscale



Microscale

Mesoscale

Macroscale

Increasing spatial scale

Mean-field  
approximation



# Source modelling at the microscale



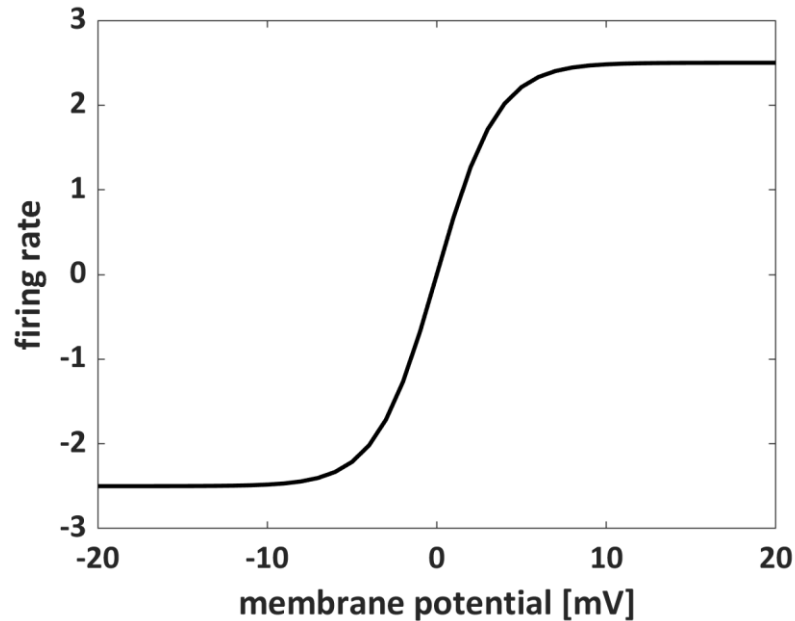
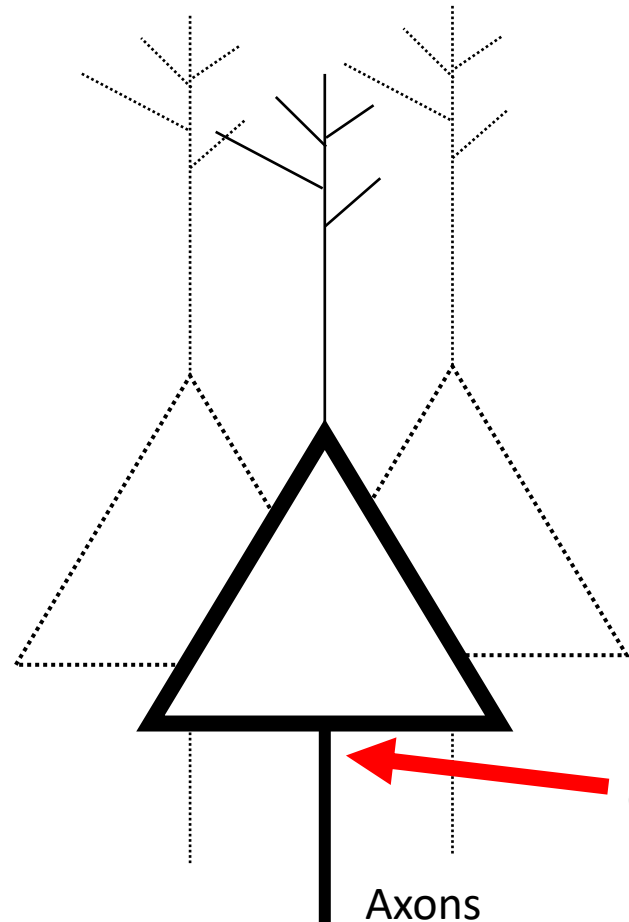
Microscale

Mesoscale

Macroscale

Increasing spatial scale

Dendrites



$$S(v) = \frac{2e_0}{1 + \exp(-rv)} - e_0$$

$$e_0 = 2.5$$
$$r = 0.56$$

**Output:** Postsynaptic potentials are converted into an average spike rate

David et al (2005), NeuroImage

# Source modelling at the microscale



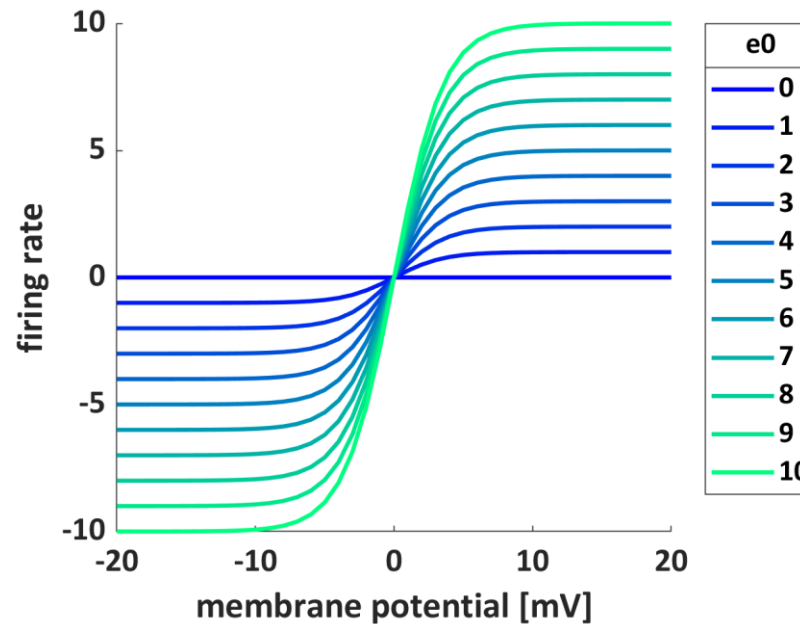
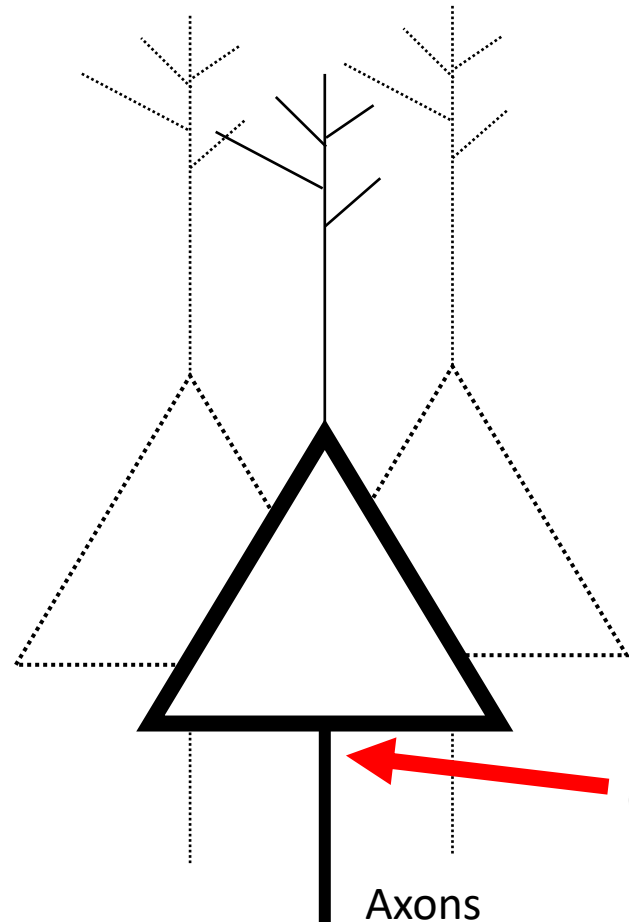
Microscale

Mesoscale

Macroscale

Increasing spatial scale

Dendrites



$$S(v) = \frac{2e_0}{1 + \exp(-rv)} - e_0$$

$e_0$ : Maximal firing rate

David et al (2005), NeuroImage

# Source modelling at the microscale



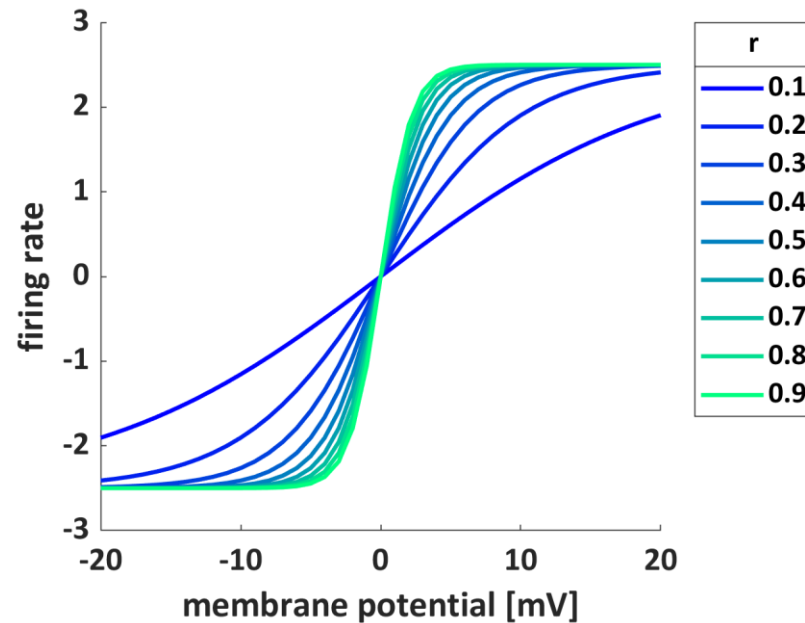
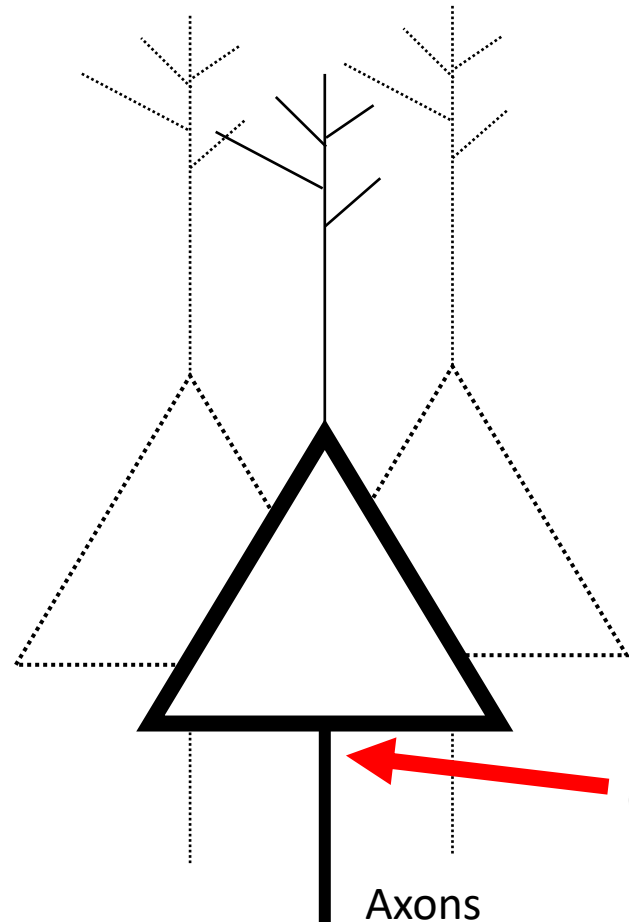
Microscale

Mesoscale

Macroscale

Increasing spatial scale

Dendrites



$$S(v) = \frac{2e_0}{1 + \exp(-rv)} - e_0$$

**r**: Stochasticity

David et al (2005), NeuroImage



# Source modelling at the microscale



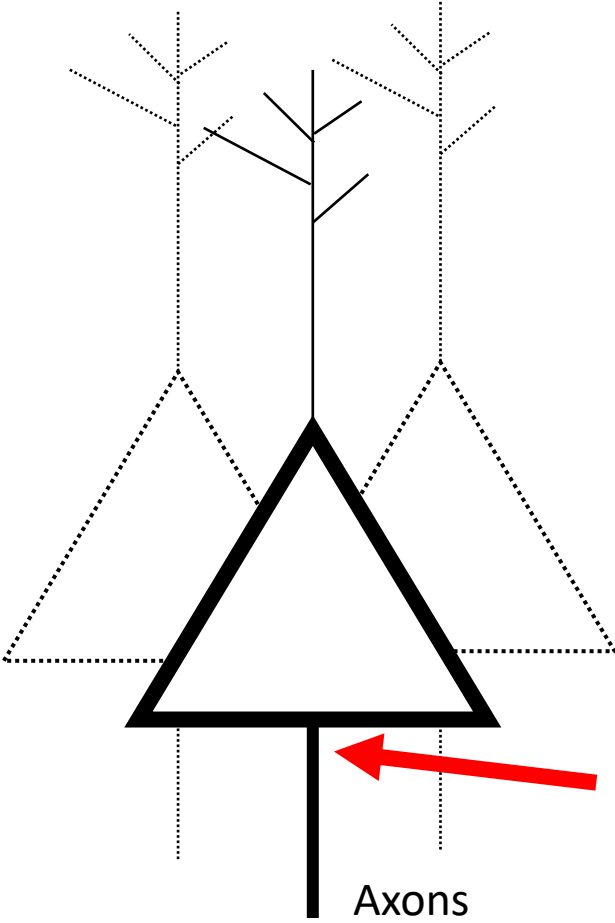
Microscale

Mesoscale

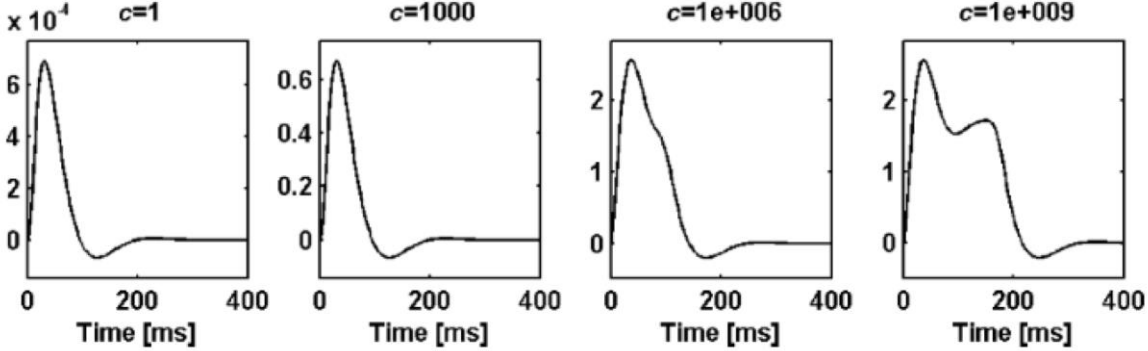
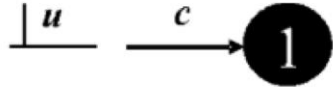
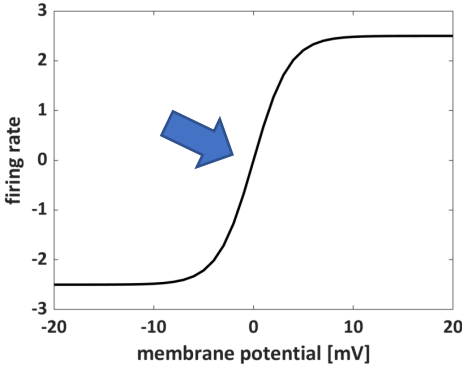
Macroscale



Dendrites



**Output:** Postsynaptic potentials are converted into an average spike rate



David et al (2005), NeuroImage

# Source modelling at the microscale



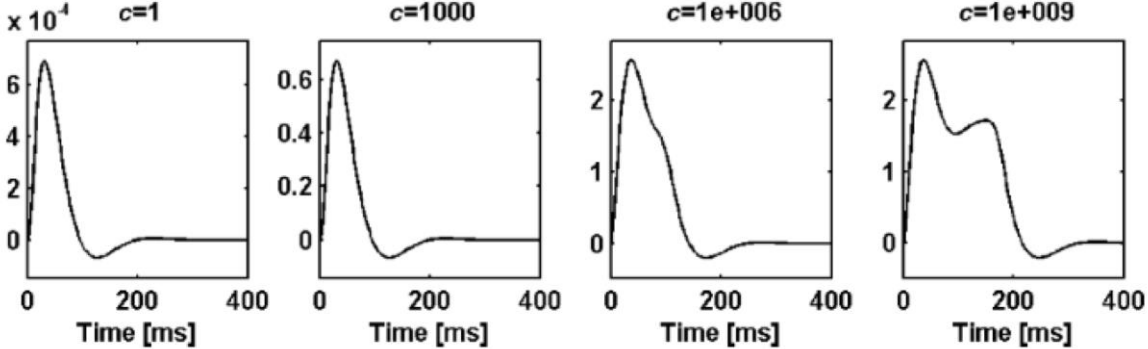
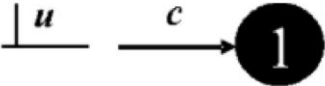
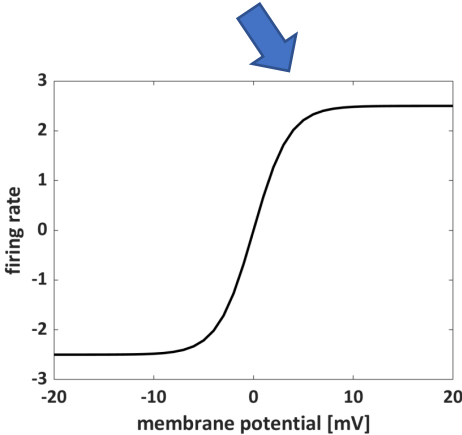
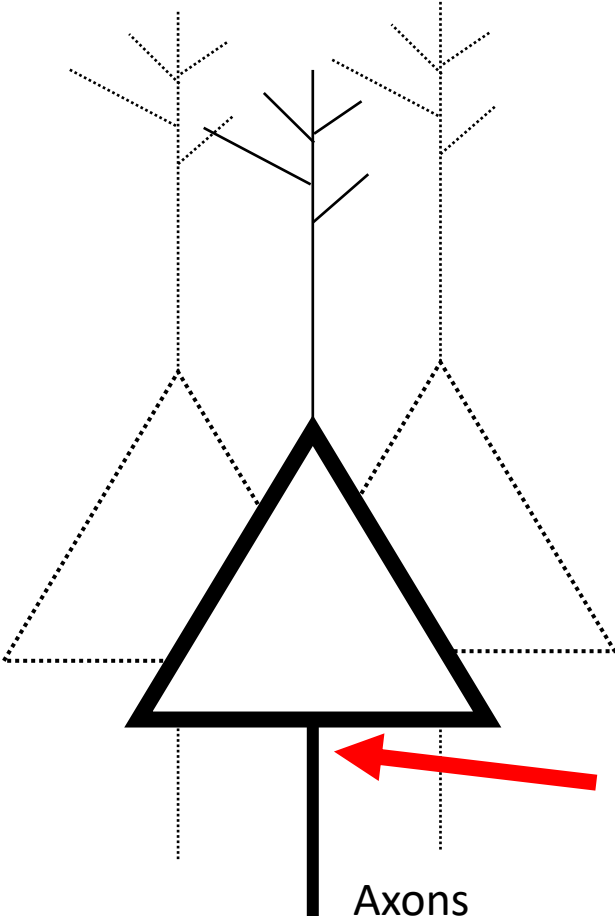
Microscale

Mesoscale

Macroscale



Dendrites



**Output:** Postsynaptic potentials are converted into an average spike rate

David et al (2005), NeuroImage

# Source modelling at the microscale



Microscale

Mesoscale

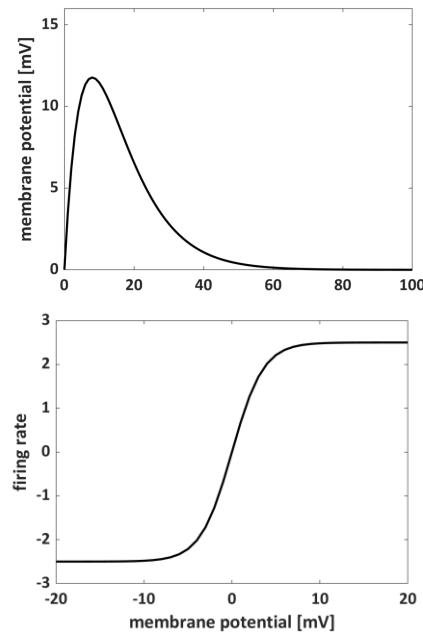
Macroscale

Increasing spatial scale



Dendrites

**Input:** Spike rates of a presynaptic cells are converted into postsynaptic potentials (PSPs)

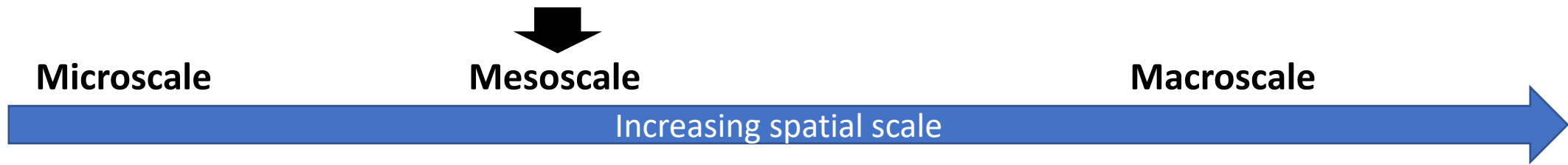


**Output:** Postsynaptic potentials are converted into an average spike rate

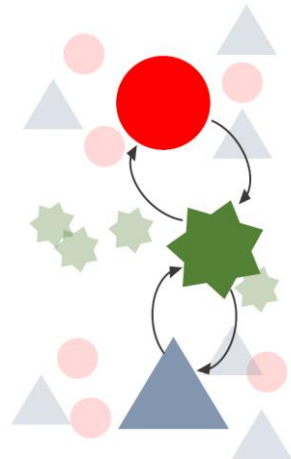
Axons

# Scales of analysis

---



**Cortical Column**  
1-10 mm<sup>2</sup> to 1-5 cm<sup>2</sup>



Schöbi (2019), CPC Lecture

# Source modelling at the mesoscale

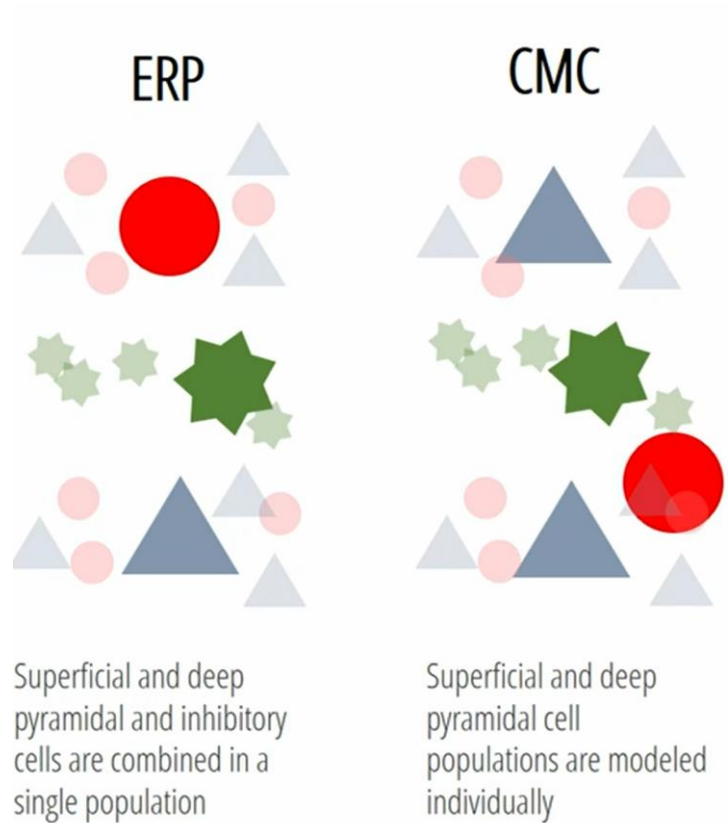


Microscale

Mesoscale

Macroscale

Increasing spatial scale



Schöbi (2019), CPC Lecture

# Source modelling at the mesoscale

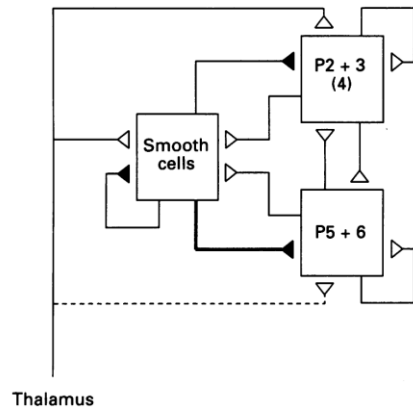
Microscale

Mesoscale

Macroscale

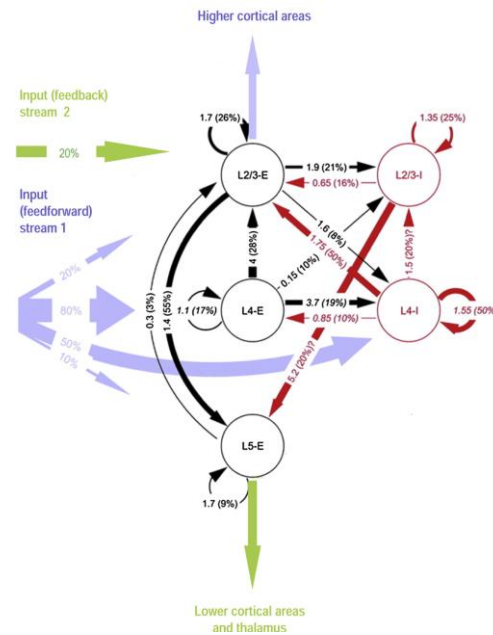
Increasing spatial scale

Original microcircuit



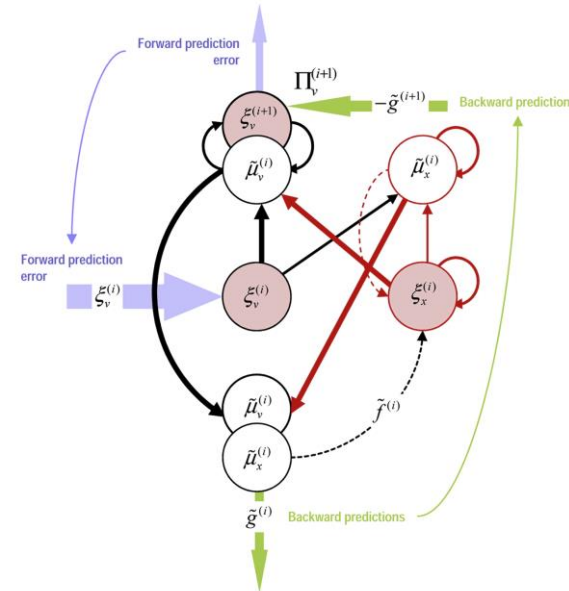
Douglas & Martin (1991),  
J. Physiol.

Updated microcircuit



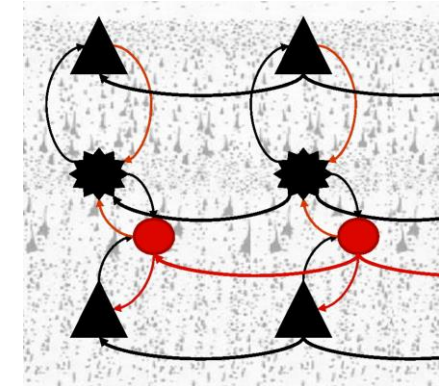
Haeusler & Maass (2006),  
Cerebral Cortex

Canonical microcircuit



Bastos et al. (2012),  
Neuron

Reduced microcircuit (DCM)



Pinotsis et al. (2012),  
NeuronImage

# Source modelling at the mesoscale

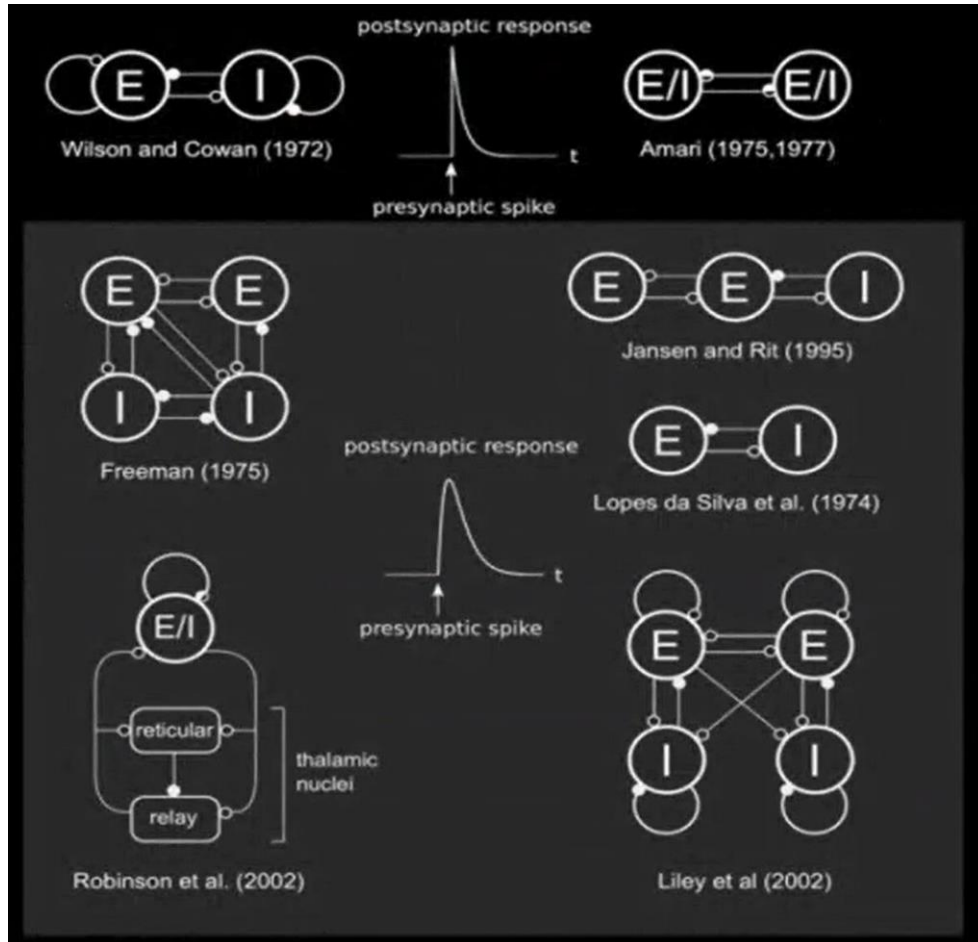


Microscale

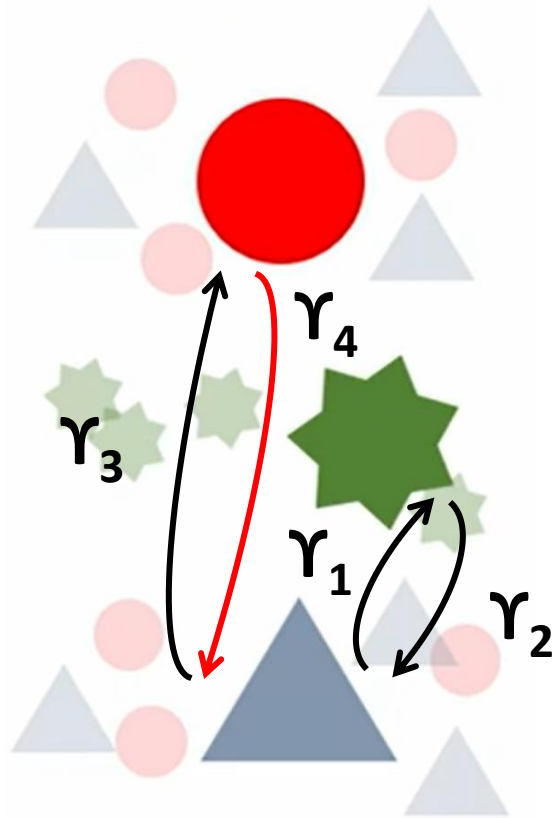
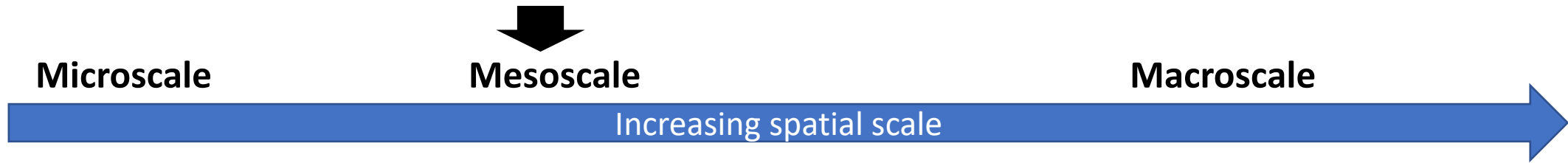
Mesoscale

Macroscale

Increasing spatial scale



# Source modelling at the mesoscale



Schöbi (2019), CPC Lecture

But what value should  $\gamma$  have?

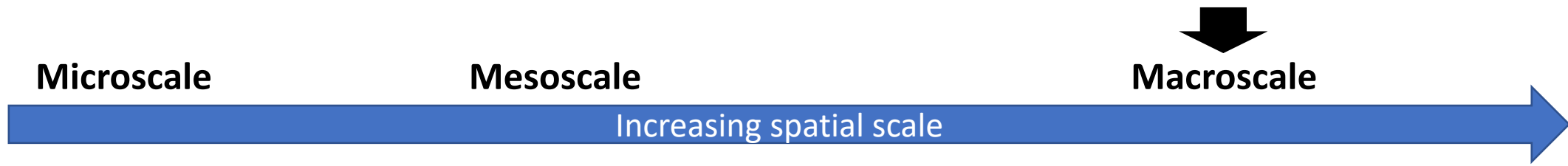
$$\gamma_2 = 0.8\gamma_1, \quad \gamma_3 = \gamma_4 = 0.25\gamma_1$$

- Based on counts of synapses
- Animal studies (mouse, cat)
- Visual cortex

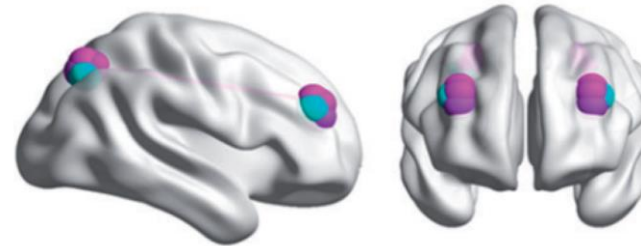
Jansen & Ritt (1995), Biol. Cyb.



# Source modelling at the macroscale

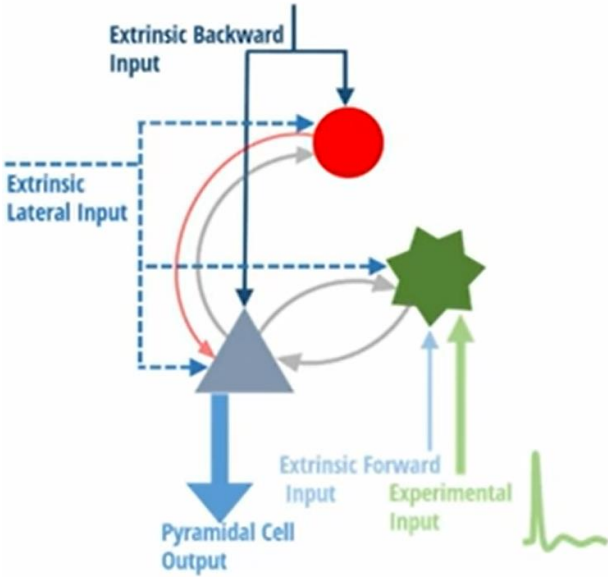
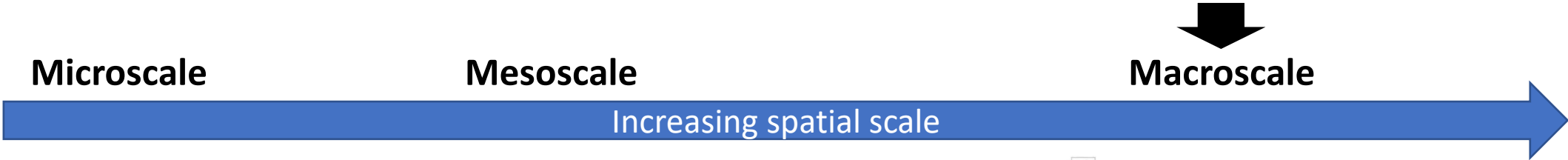


**Brain Networks**  
5-20 cm<sup>2</sup>

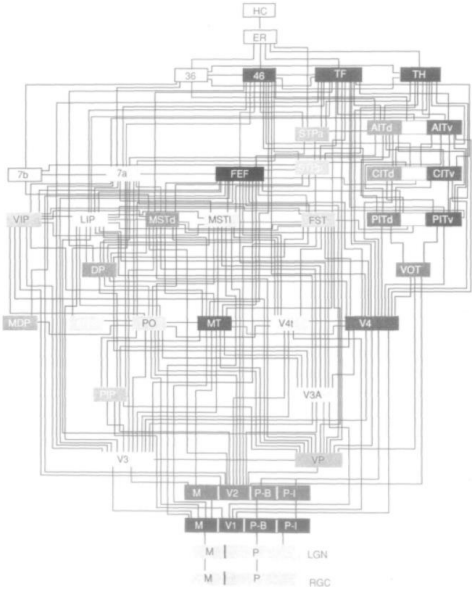


Symmonds et al. (2018), Brain

# Source modelling at the macroscale



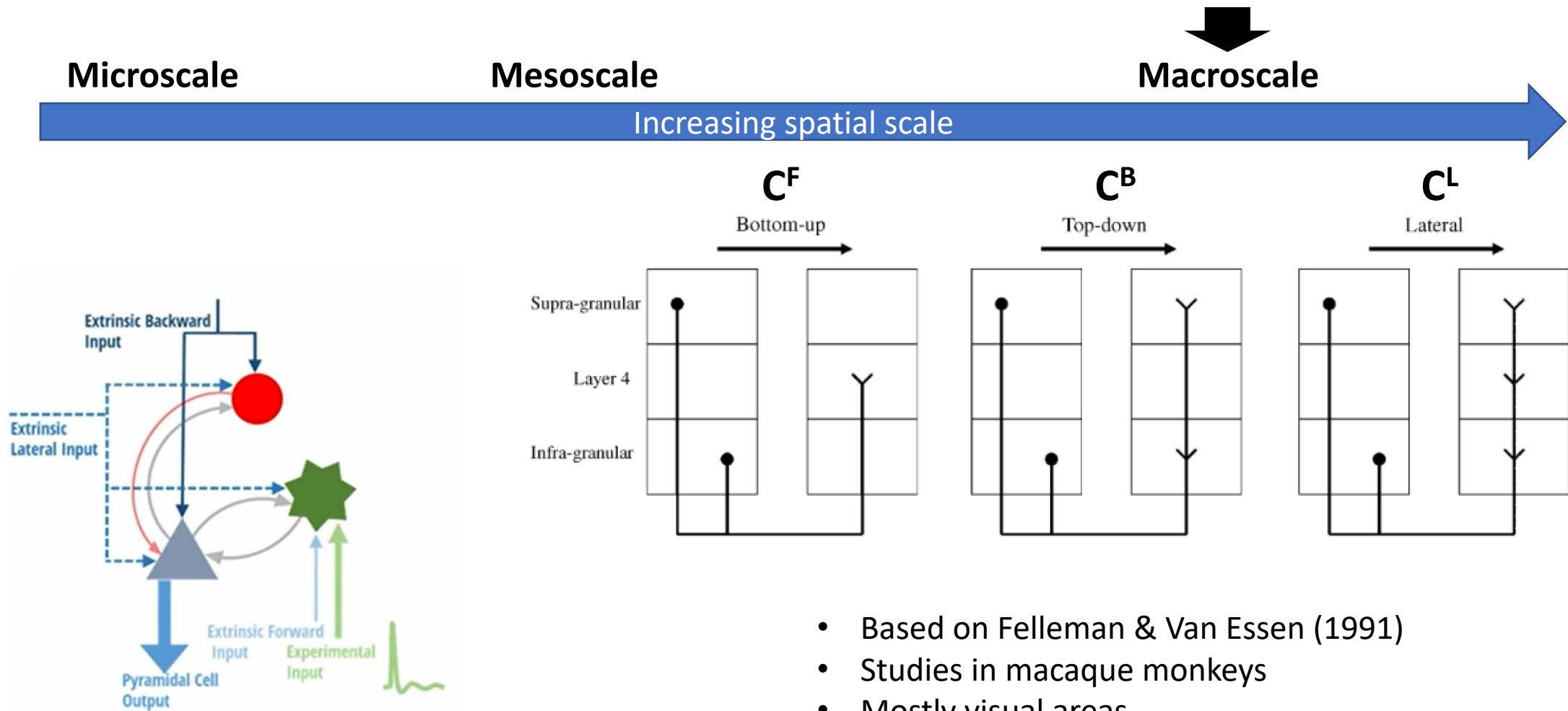
Schöbi (2019), CPC Lecture



- Based on Felleman & Van Essen (1991)
- Studies in macaque monkeys
- Mostly visual areas
- But see Markov et al (2013)

David et al (2005), NeuroImage

# Source modelling at the macroscale

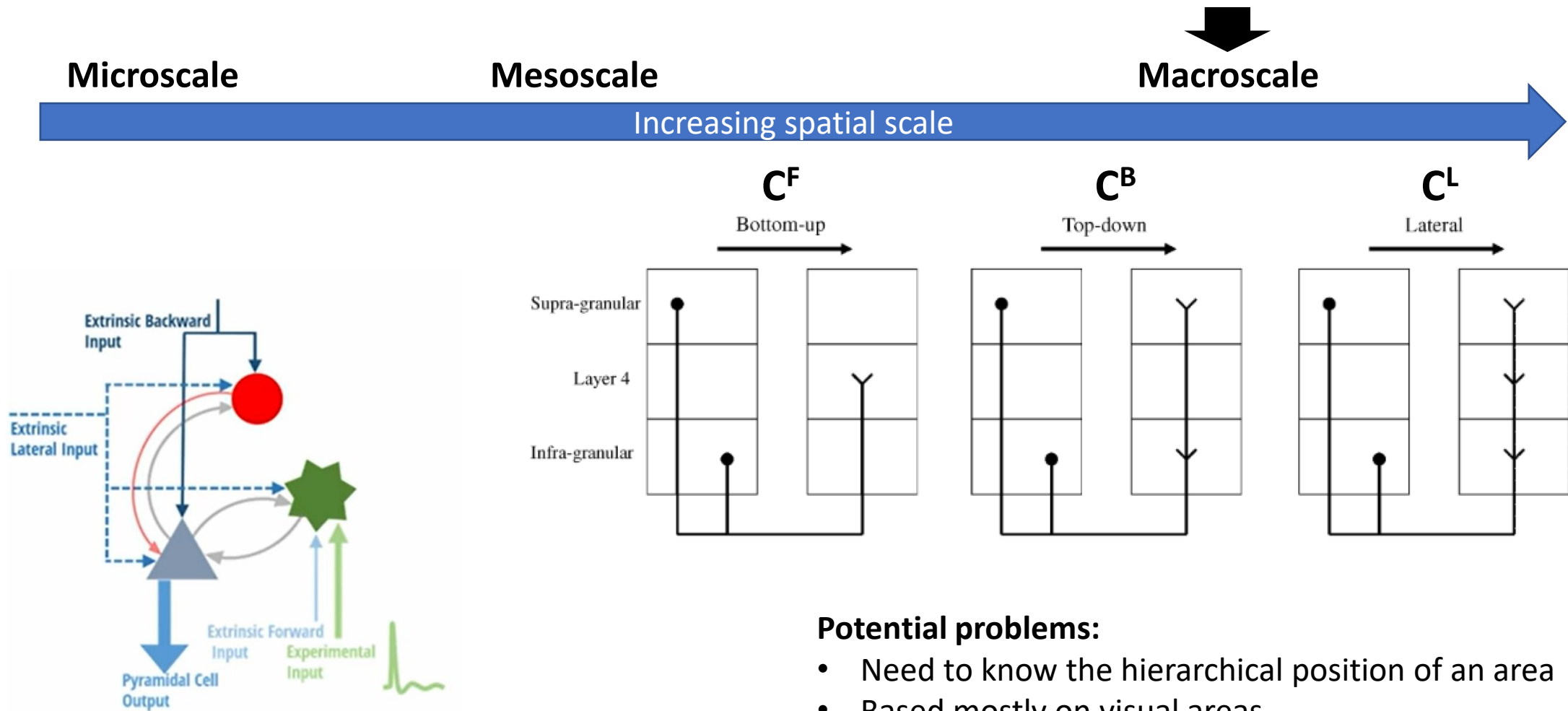


- Based on Felleman & Van Essen (1991)
- Studies in macaque monkeys
- Mostly visual areas
- But see Markov et al (2013)

Schöbi (2019), CPC Lecture

David et al (2005), NeuroImage

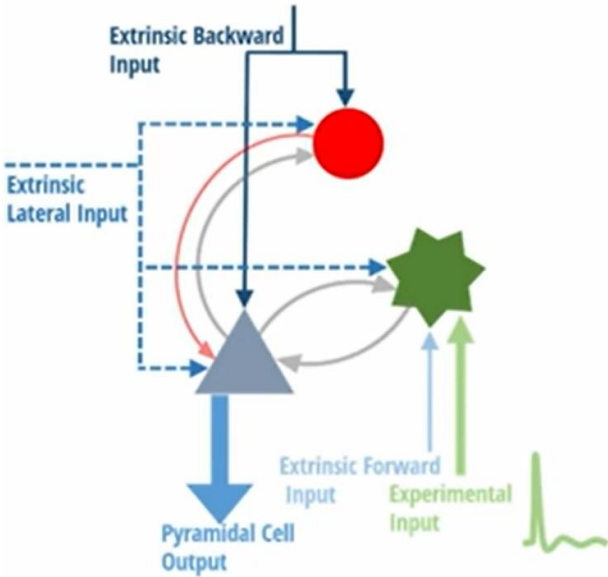
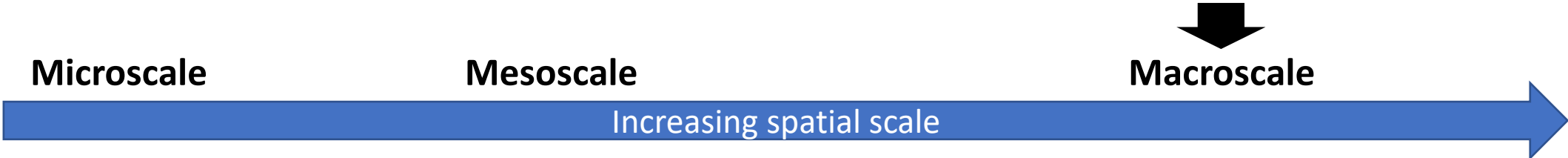
# Source modelling at the macroscale



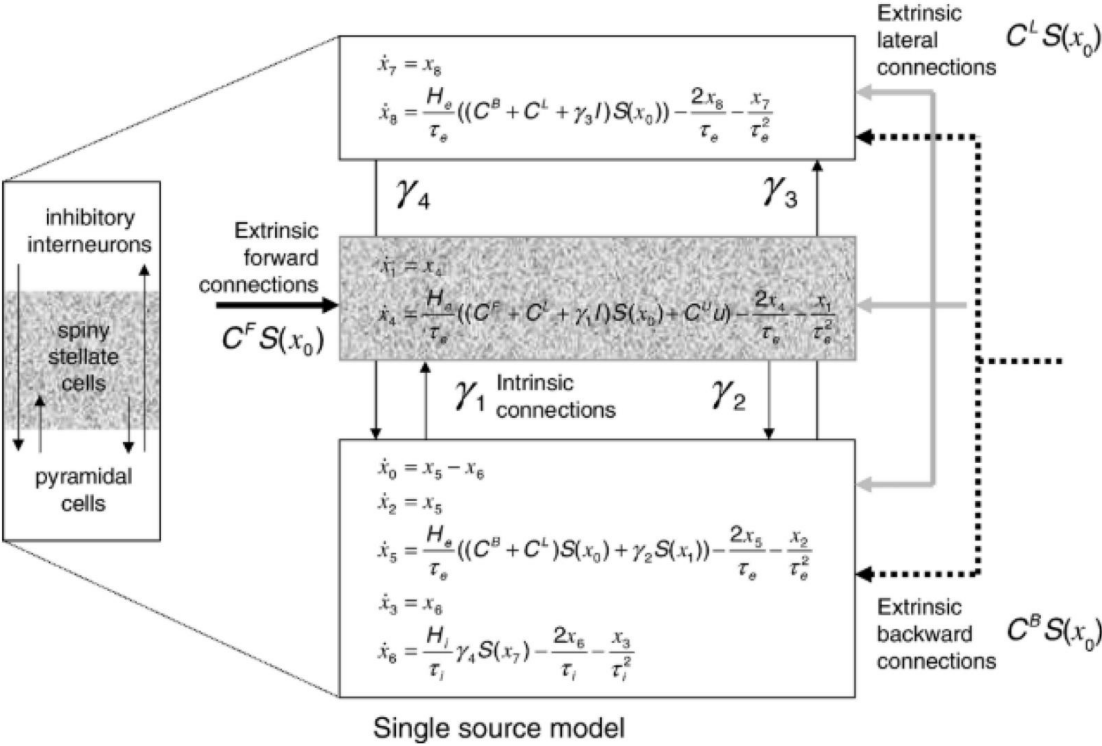
## Potential problems:

- Need to know the hierarchical position of an area
- Based mostly on visual areas
- Based on areas with a 6-layer structure

# Source modelling at the macroscale

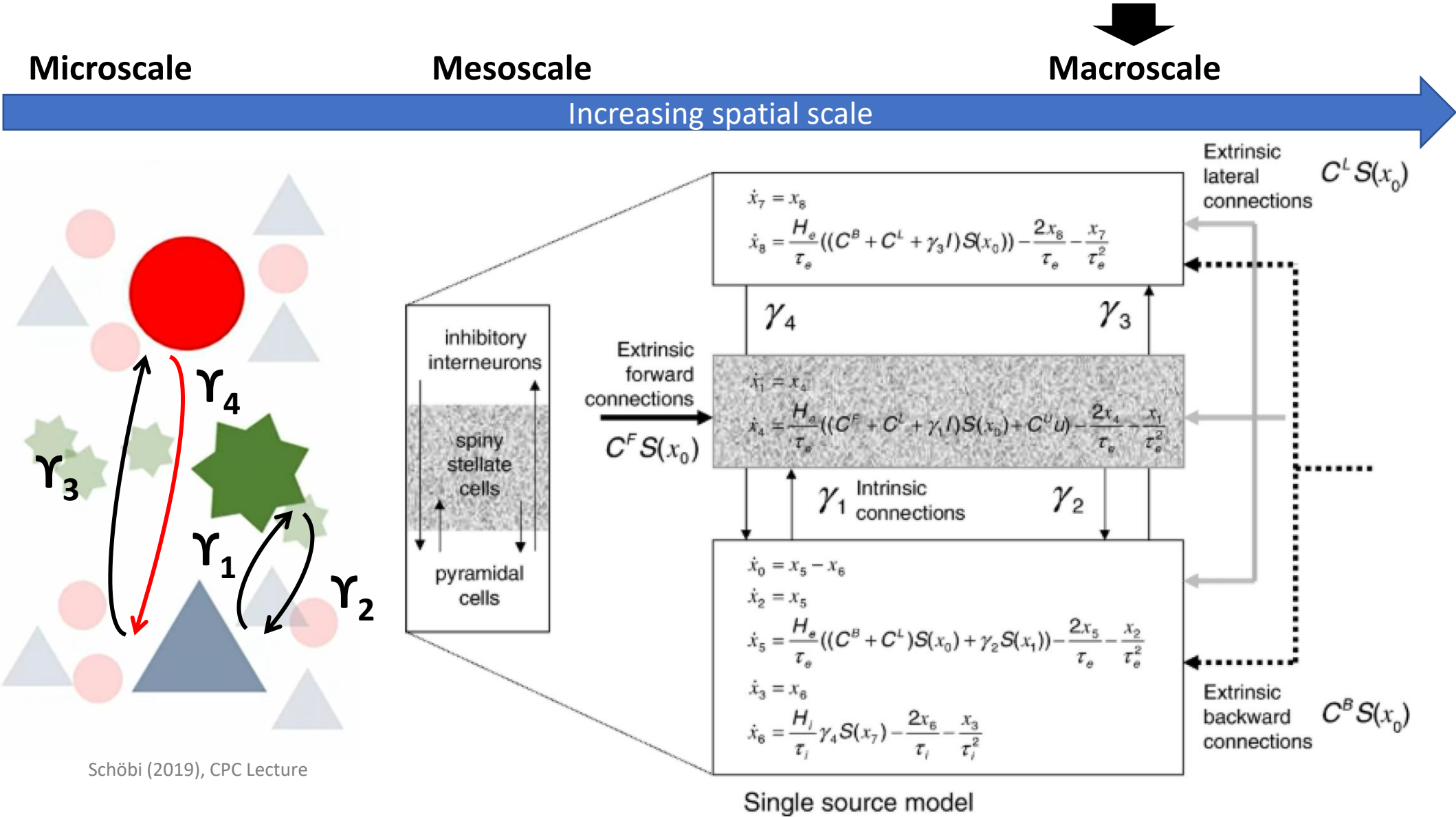


Schöbi (2019), CPC Lecture



David et al (2006), Neuroimage

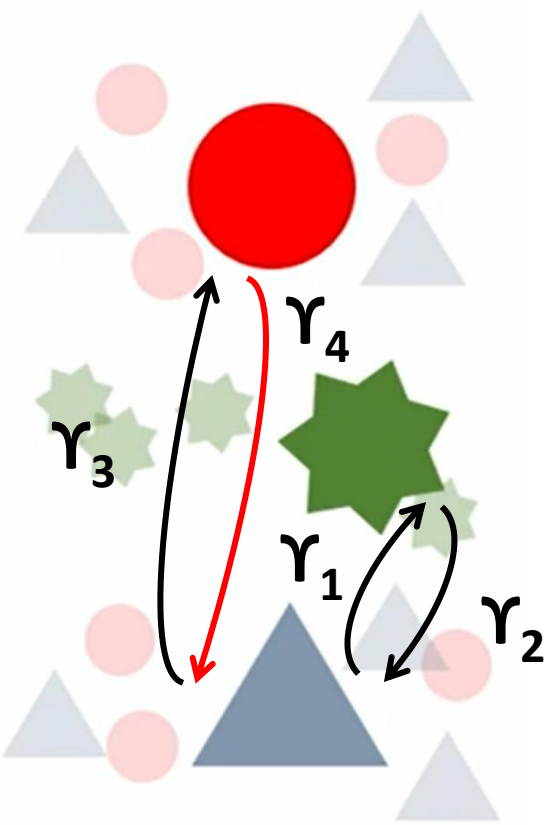
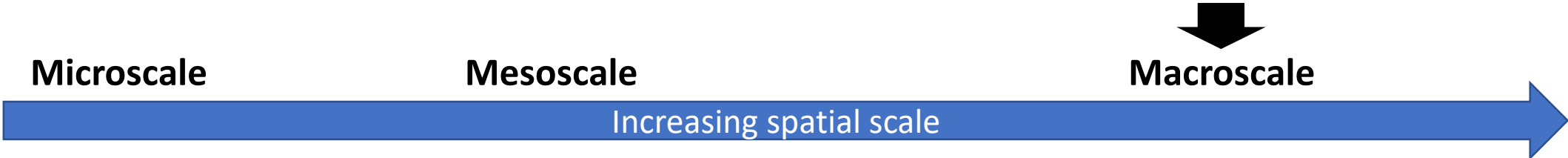
# Source modelling at the macroscale



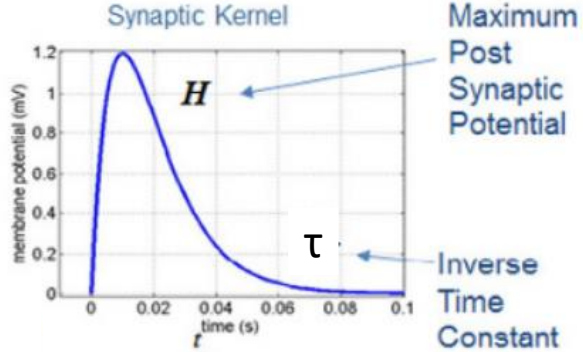
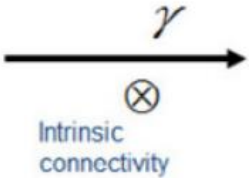
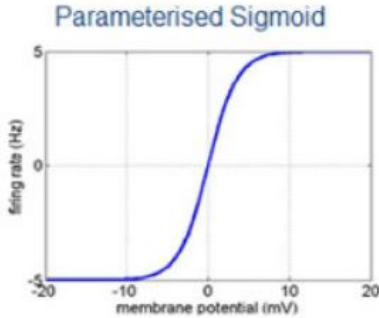
Schöbi (2019), CPC Lecture

David et al (2006), NeuroImage

# Source modelling at the macroscale

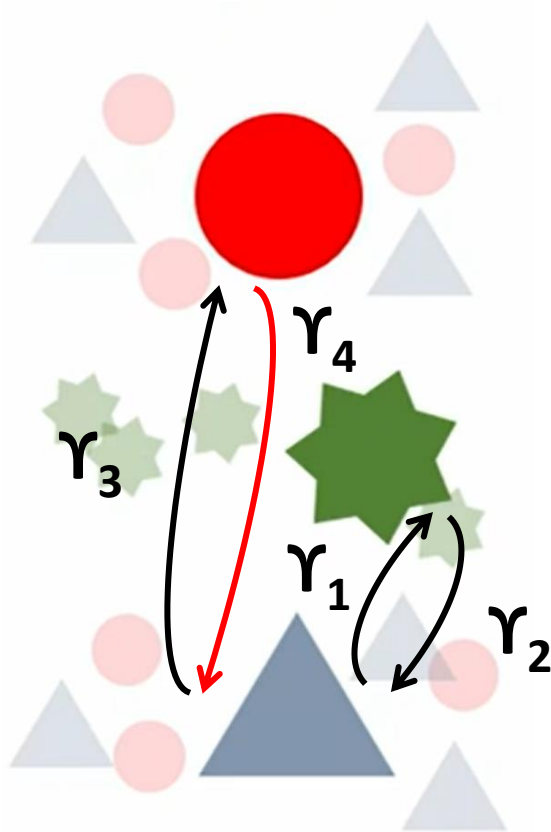
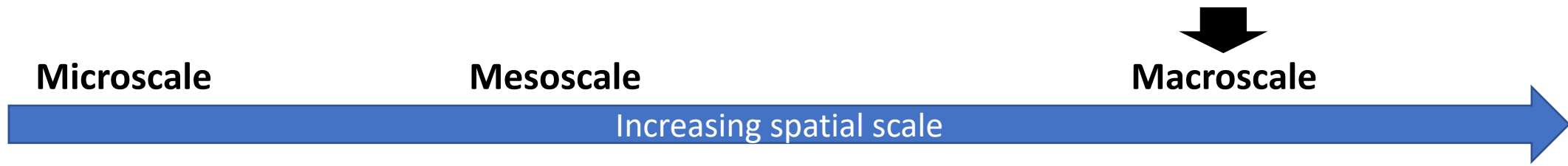


Schöbi (2019), CPC Lecture



$$v = h \otimes p \quad h(t) = \begin{cases} \frac{Ht \exp(-t/\tau)}{\tau} & t \geq 0 \\ 0 & t < 0 \end{cases} \quad v = \int_{-\infty}^t h(t - \delta)\sigma dt$$

# Source modelling at the macroscale



Schöbi (2019), CPC Lecture

$$v = h \otimes p \quad h(t) = \begin{cases} \frac{Ht \exp(-t/\tau)}{\tau} & t \geq 0 \\ 0 & t < 0 \end{cases} \quad v = \int_{-\infty}^t h(t - \delta) \sigma dt$$

**System of Ordinary Differential Equations (ODEs)**

$$\dot{v} = i$$

$$i = \underbrace{\frac{H}{\tau} \gamma \sigma(v_{aff})}_{f(\text{Input})} - \frac{2}{\tau} \dot{v} - \frac{1}{\tau^2} v$$



# Source modelling at the macroscale

Microscale

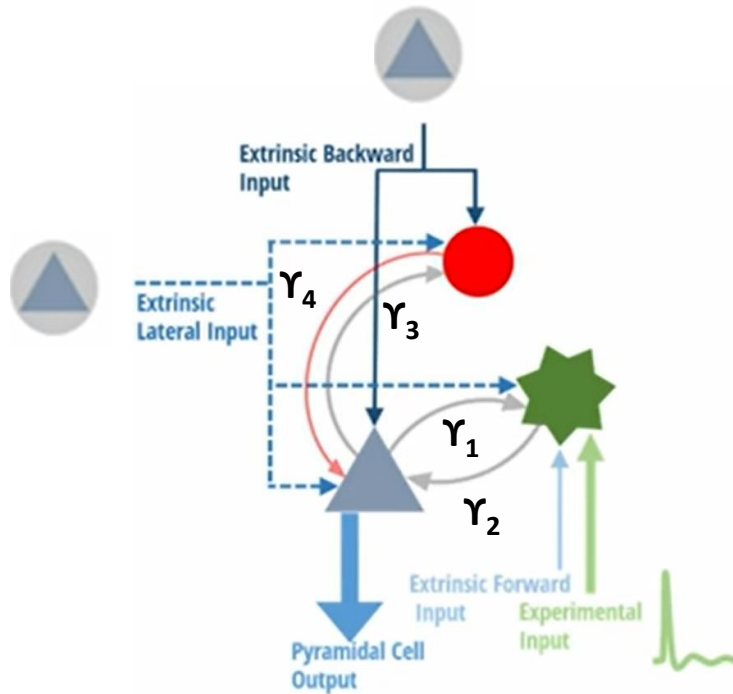
Mesoscale

Macroscale

Increasing spatial scale

$$\dot{v} = i$$

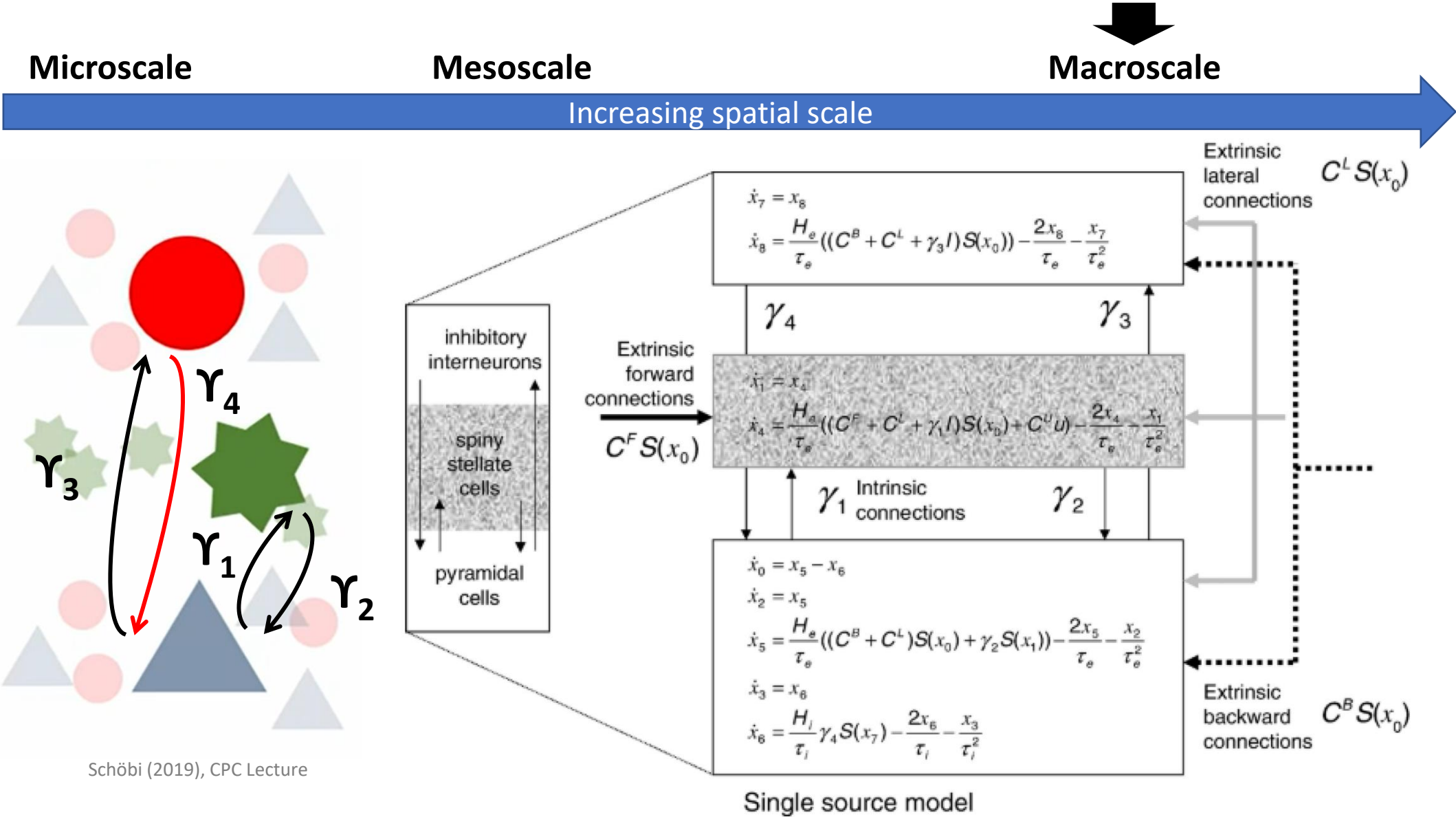
$$i = f(\text{Input}) - \frac{2}{\tau} \dot{v} - \frac{1}{\tau^2} v$$



	:	$\frac{H_e}{\tau_e} C^B$		+	$\frac{H_e}{\tau_e} C^L$		+	$\frac{H_e}{\tau_e} \gamma_3$				
	:	$\frac{H_e}{\tau_e} C^F$		+	$\frac{H_e}{\tau_e} C^L$		+	$\frac{H_e}{\tau_e} \gamma_1$		+	$C^U$	
	:	$\frac{H_e}{\tau_e} C^B$		+	$\frac{H_e}{\tau_e} C^L$		+	$\frac{H_e}{\tau_e} \gamma_2$				
	:	$\frac{H_i}{\tau_i} \gamma_3$										

Schöbi (2018, 2019), CPC Lectures

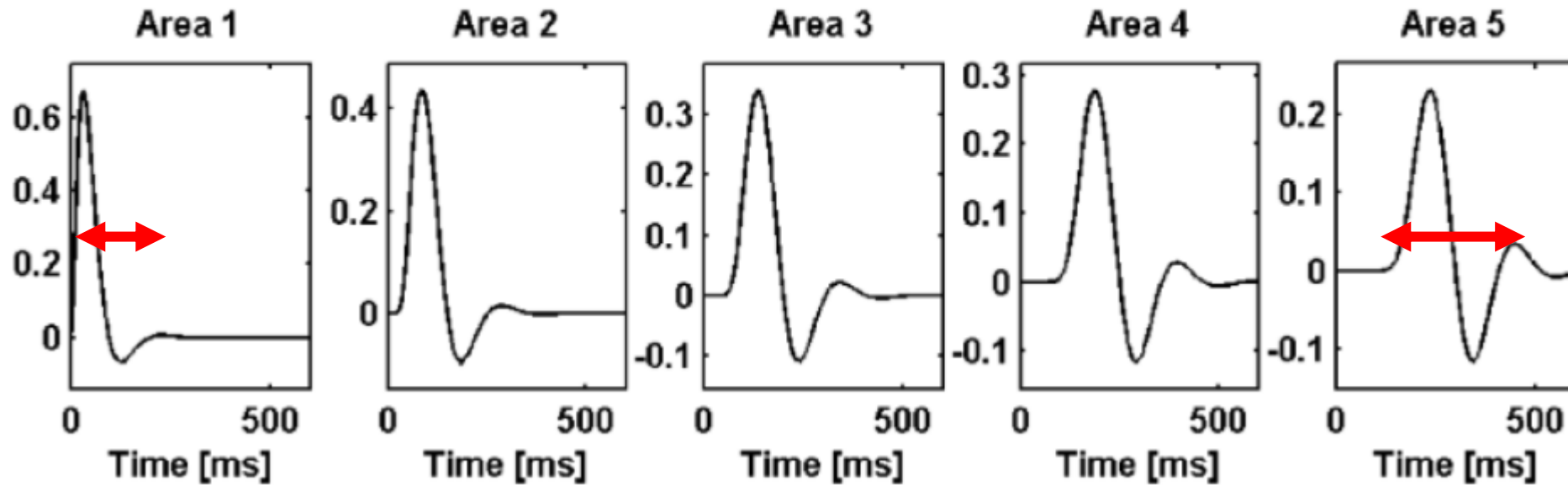
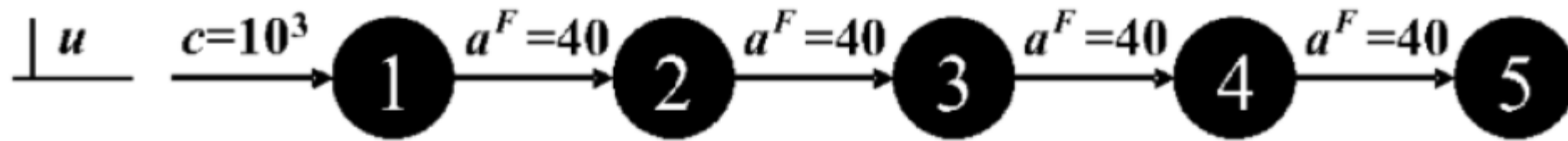
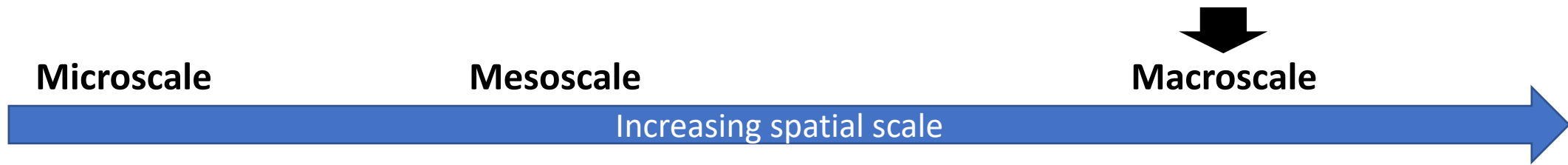
# Source modelling at the macroscale



Schöbi (2019), CPC Lecture

David et al (2006), NeuroImage

# Source modelling at the macroscale



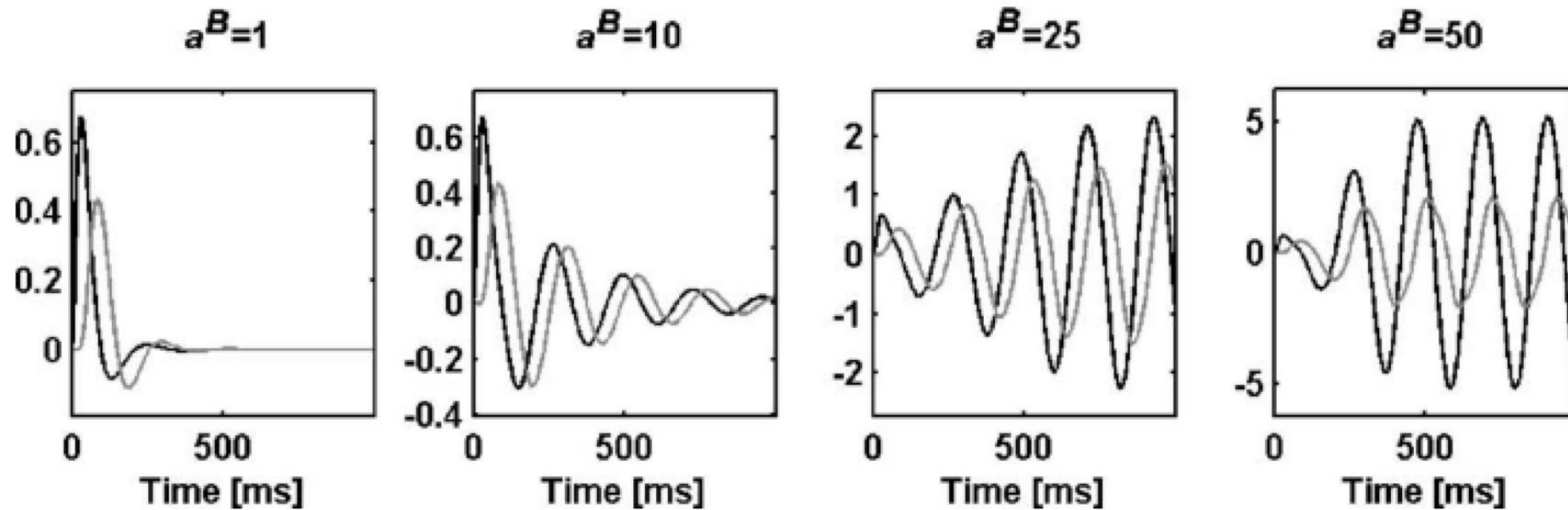
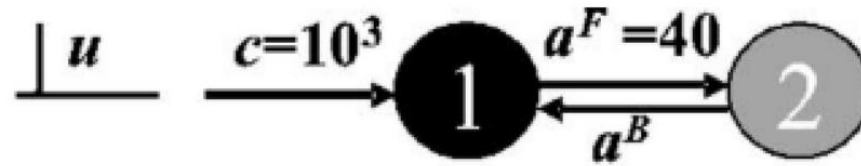
# Source modelling at the macroscale

Microscale

Mesoscale

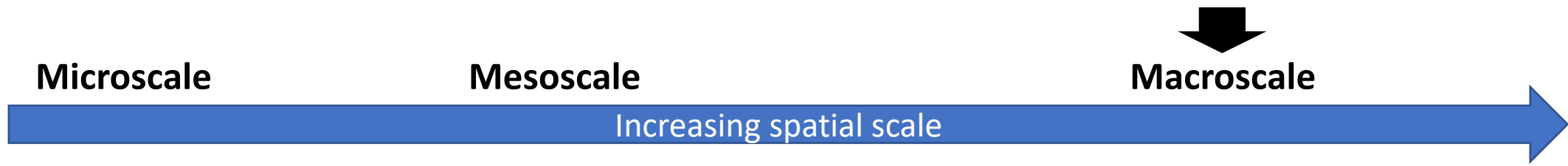
↓  
Macroscale

Increasing spatial scale →

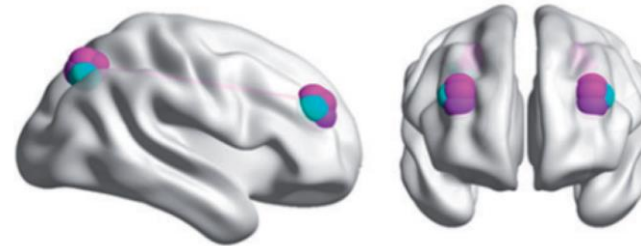


# Scales of analysis

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**Brain Networks**  
5-20 cm<sup>2</sup>

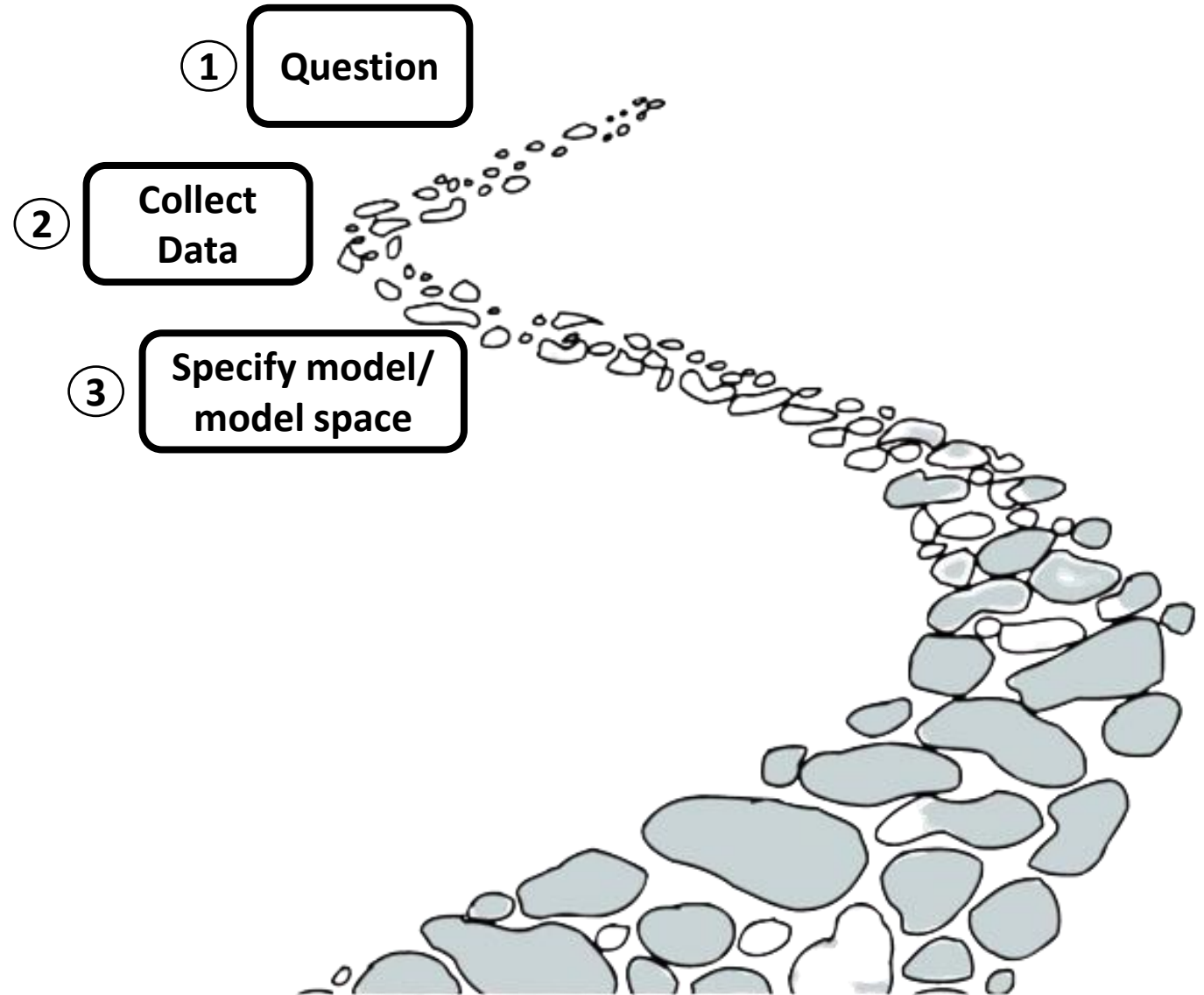


Symmonds et al. (2018), Brain

# Specify model/model space

## Steps

- Translate your question into a model comparison or a parameter inference problem
- Select regions
- Select a variant of DCM
- Example: The “ERP” model
- **Specify connectivity architecture**



# The DCM analysis path

load Study (DCM) filename ERP ERP

save DCM\_subject1.mat new data

time window (ms) 1 200 display >

bins: 5.0ms between-trial effects trials 1 2 hanning

detrend 1 rare 0.00 1.00

subsample 1

modes 8

< ECD electromagnetic model dipoles >

source names and locations: prior mean (mm)

left A1	-42 -22 7
right A1	46 -14 8
left STG	-61 -32 8
right STG	59 -25 8
right	46 20 8

onsets (ms) 60

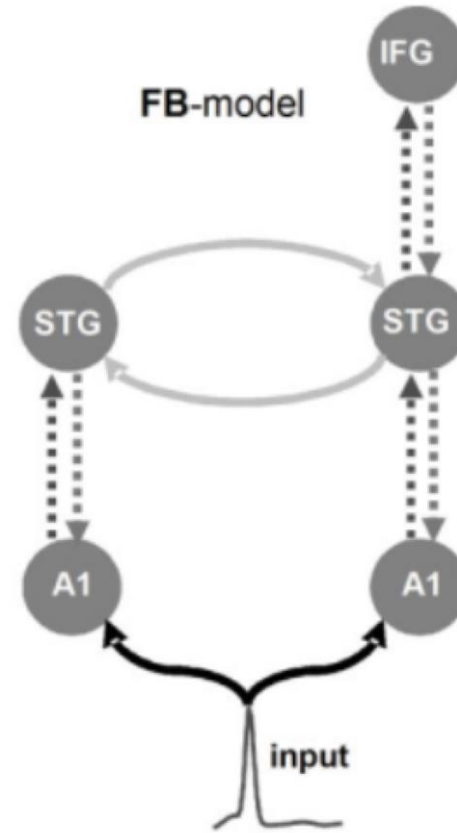
duration (sd) 16

load

invert DCM

neural model

forward back lateral input



Garrido et al. (2009), *HBM*

# The DCM analysis path

load Study (DCM) filename ERP ERP

save DCM\_subject1.mat new data

time window (ms) 1 200 display >

bins: 5.0ms trials 1 2

between-trial effects 0.00 1.00

detrend 1 rare

subsample 1

modes 8

< ECD electromagnetic model dipoles >

source names and locations: prior mean (mm)

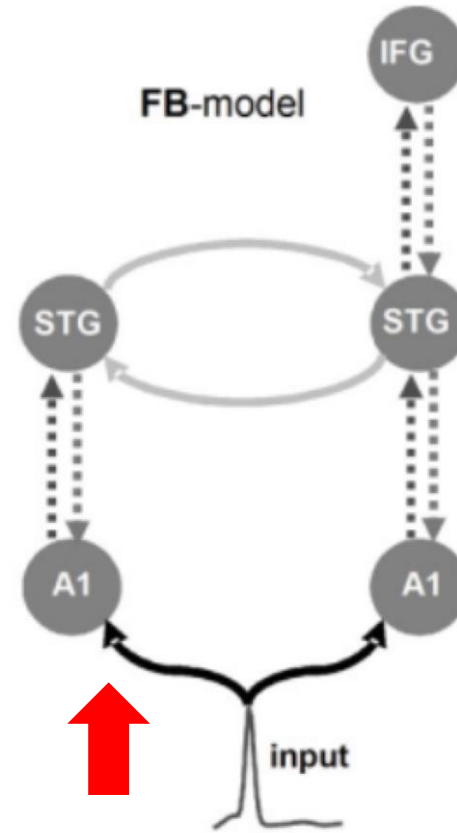
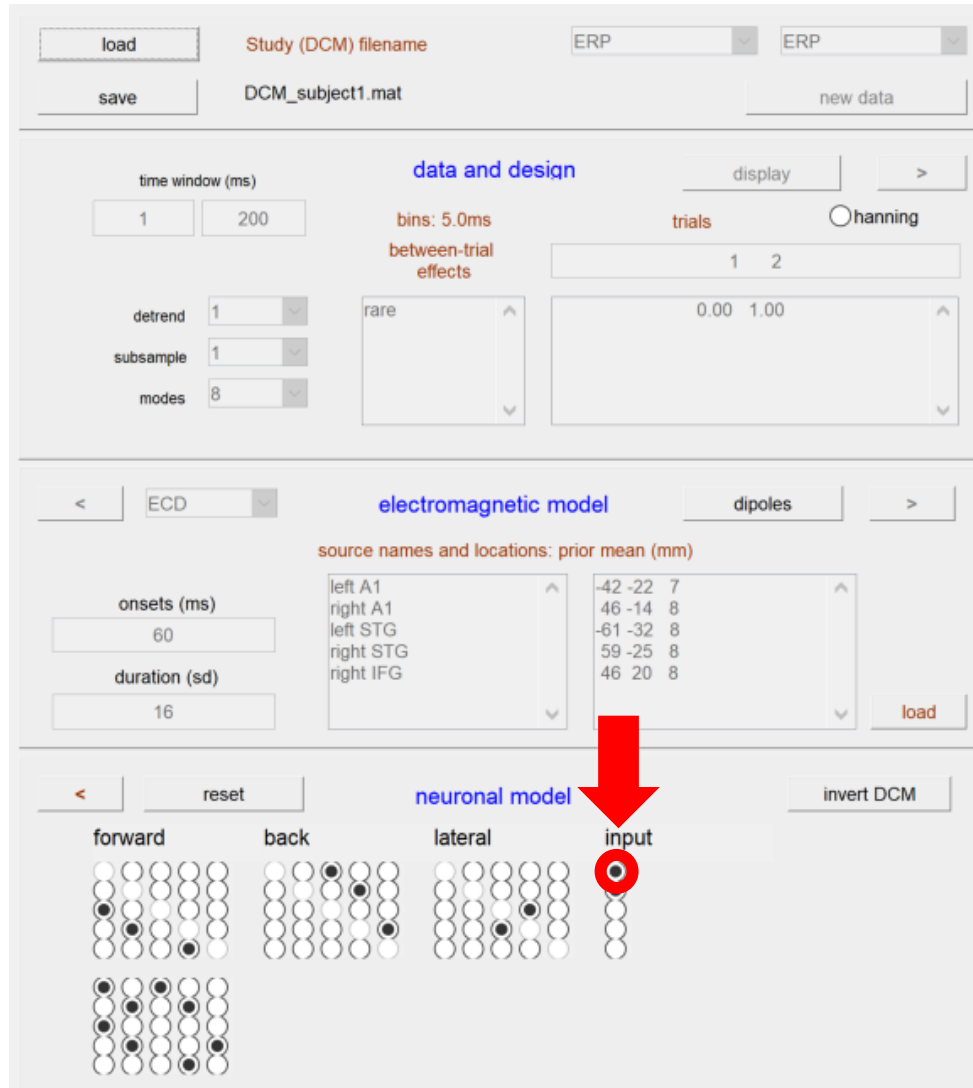
left A1	-42 -22 7
right A1	46 -14 8
left STG	-61 -32 8
right STG	59 -25 8
right IFG	46 20 8

onsets (ms) 60

duration (sd) 16

< reset neuronal model invert DCM

forward back lateral input



Garrido et al. (2009), *HBM*



# The DCM analysis path

load Study (DCM) filename ERP ERP

save DCM\_subject1.mat new data

time window (ms) 1 200 display >

bins: 5.0ms trials 1 2 hanning

between-trial effects 0.00 1.00

detrend 1

subsample 1

modes 8

< ECD electromagnetic model dipoles >

source names and locations: prior mean (mm)

1.	left A1	-42 -22 7
2.	right A1	46 -14 8
3.	left STG	-61 -32 8
⋮	right STG	59 -25 8
⋮	right IFG	46 20 8

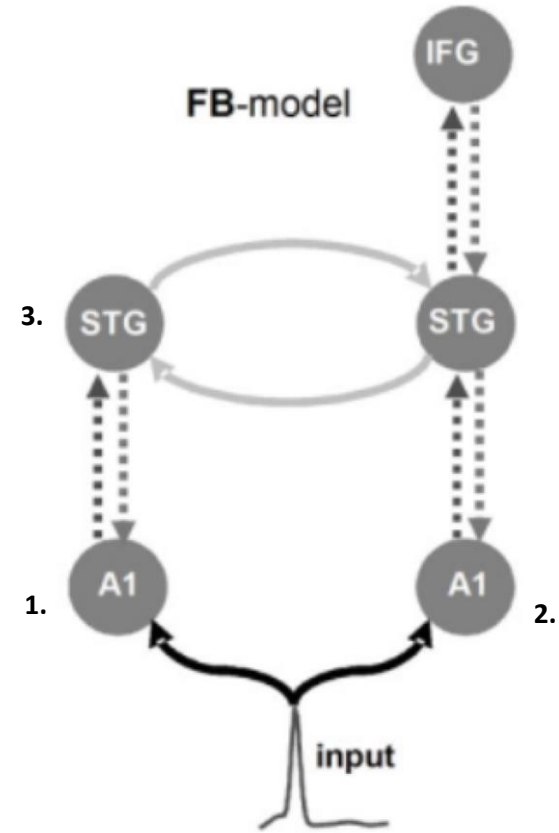
onsets (ms) 60

duration (sd) 16

< From reset neuronal model invert DCM

forward back lateral input

To



Garrido et al. (2009), *HBM*

# The DCM analysis path

load Study (DCM) filename ERP ERP

save DCM\_subject1.mat new data

time window (ms) 1 200 display >

bins: 5.0ms trials 1 2

between-trial effects 0.00 1.00

detrend 1 rare

subsample 1

modes 8

< ECD electromagnetic model dipoles >

source names and locations: prior mean (mm)

left A1	-42 -22 7
right A1	46 -14 8
left STG	-61 -32 8
right STG	59 -25 8
right IFG	46 20 8

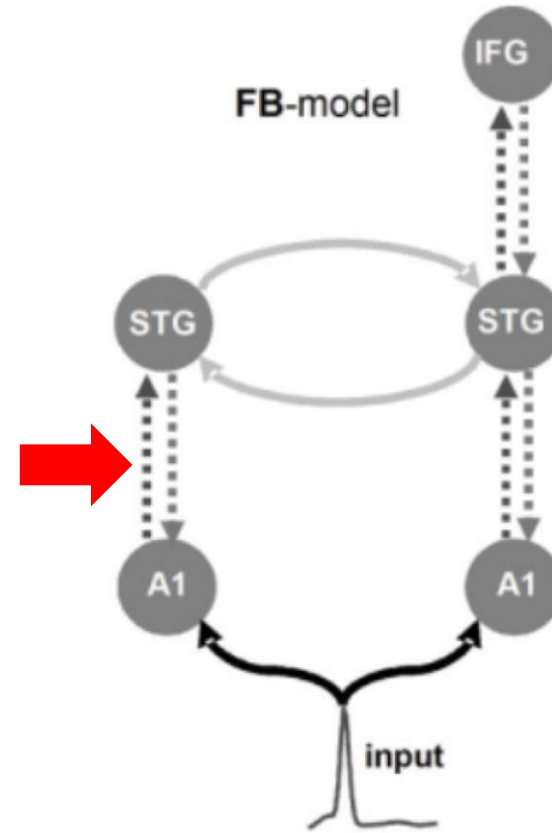
onsets (ms) 60

duration (sd) 16

load

reset neuronal model invert DCM

forward back lateral input



Garrido et al. (2009), *HBM*

# The DCM analysis path

load Study (DCM) filename ERP ERP

save DCM\_subject1.mat new data

time window (ms) 1 200 display >

bins: 5.0ms trials 1 2 hanning

between-trial effects 0.00 1.00

detrend 1

subsample 1

modes 8

< ECD electromagnetic model dipoles >

source names and locations: prior mean (mm)

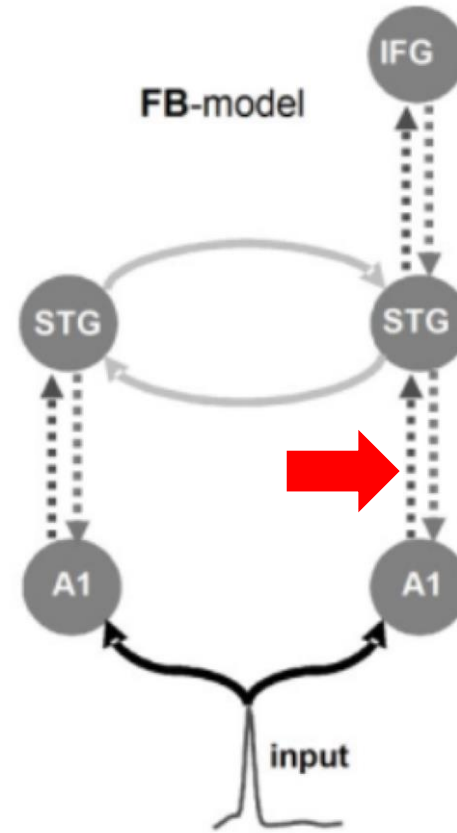
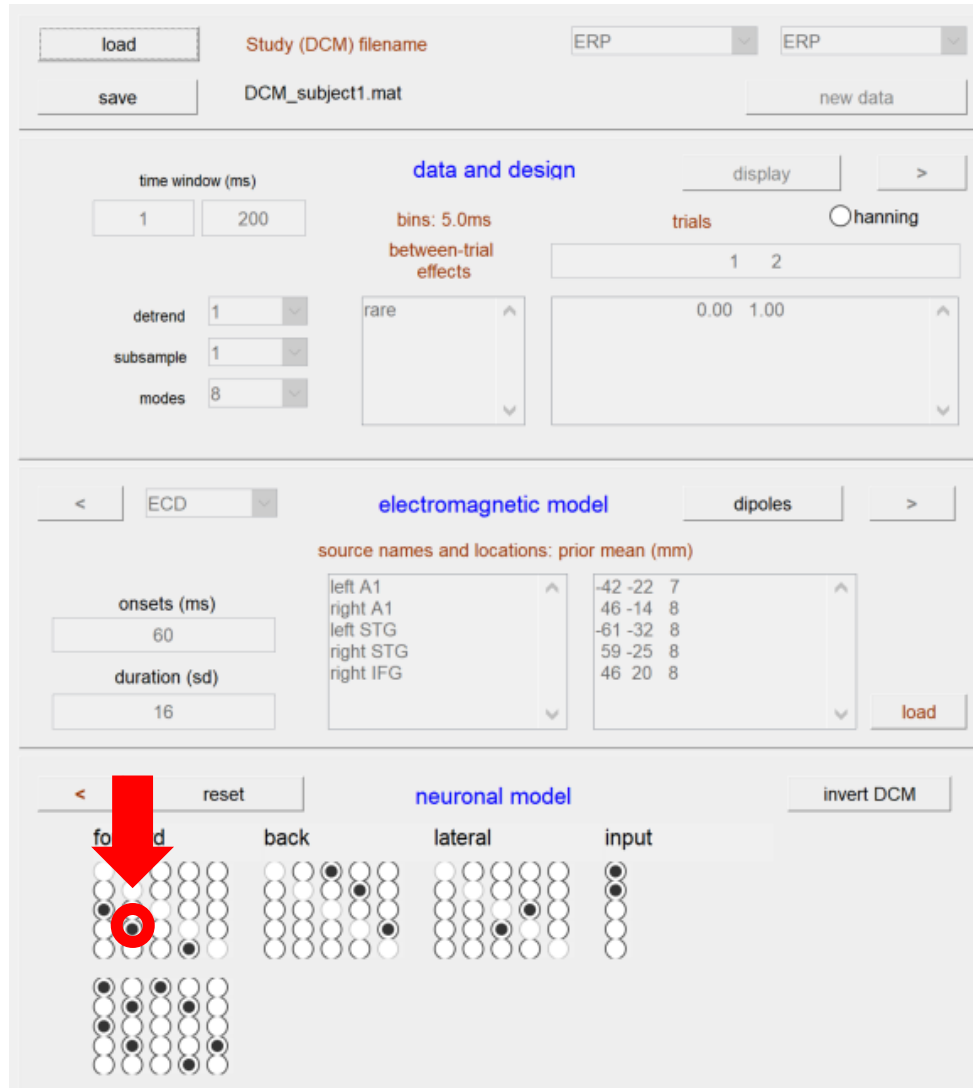
left A1	-42 -22 7
right A1	46 -14 8
left STG	-61 -32 8
right STG	59 -25 8
right IFG	46 20 8

onsets (ms) 60

duration (sd) 16

< reset neuronal model invert DCM

forward back lateral input



Garrido et al. (2009), *HBM*

# The DCM analysis path

load Study (DCM) filename ERP ERP

save DCM\_subject1.mat new data

time window (ms) 1 200 display >

bins: 5.0ms trials 1 2 hanning

between-trial effects 0.00 1.00

detrend 1 rare

subsample 1

modes 8

< ECD electromagnetic model dipoles >

source names and locations: prior mean (mm)

left A1	-42 -22 7
right A1	46 -14 8
left STG	-61 -32 8
right STG	59 -25 8
right IFG	46 20 8

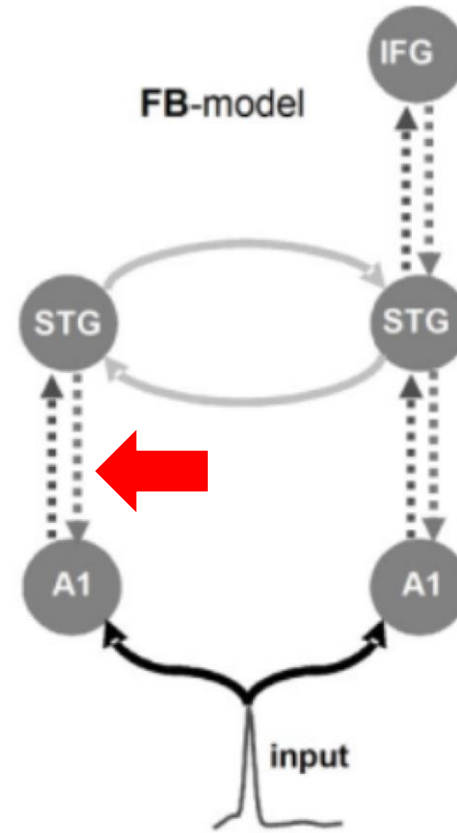

onsets (ms) 60

duration (sd) 16

load

< reset neuronal model invert DCM

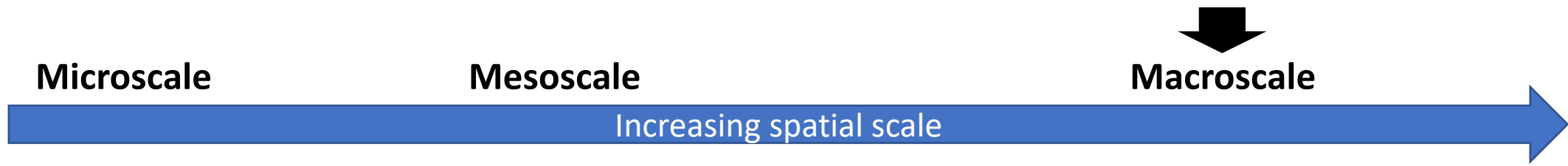
forward back lateral input



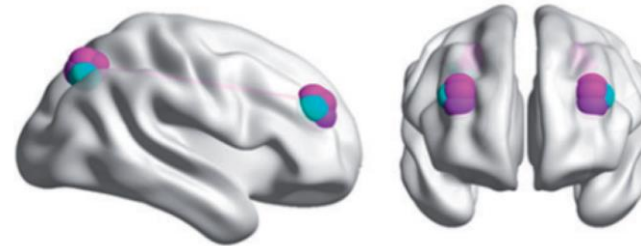
Garrido et al. (2009), *HBM*

# Scales of analysis

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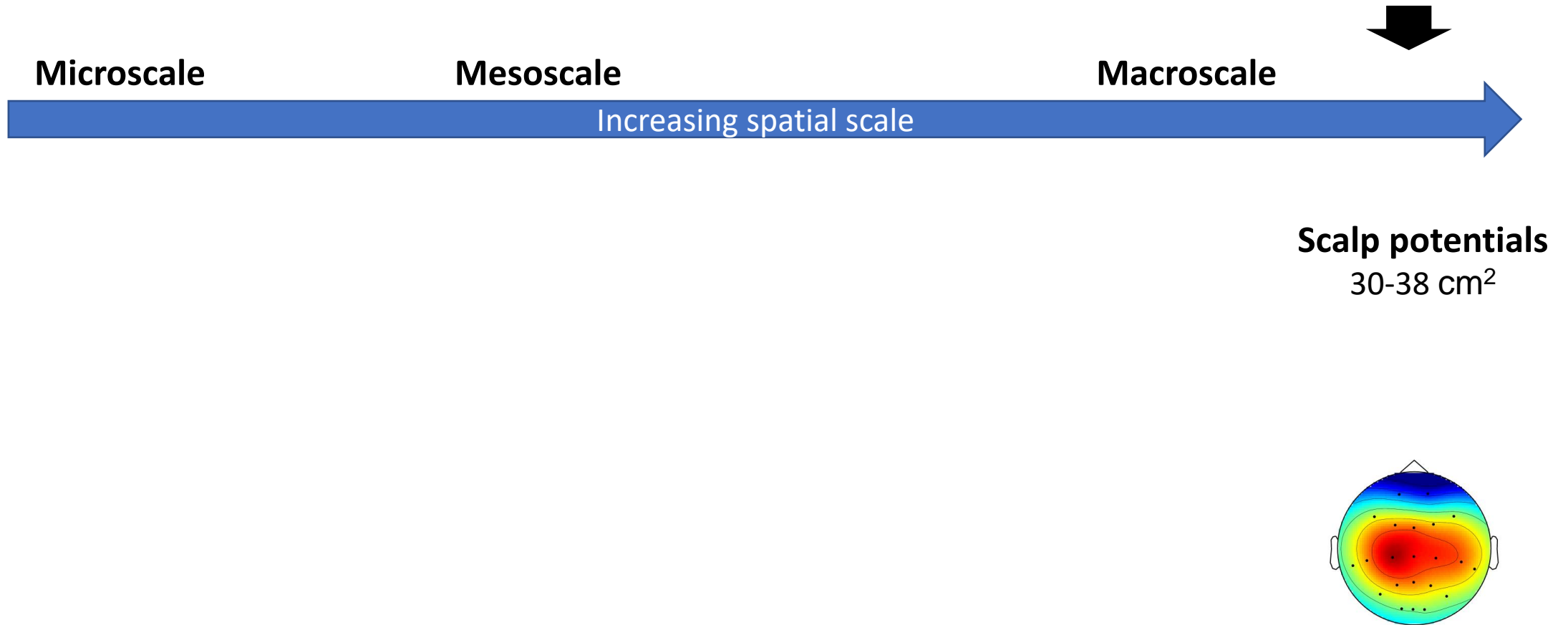
**Brain Networks**  
5-20 cm<sup>2</sup>



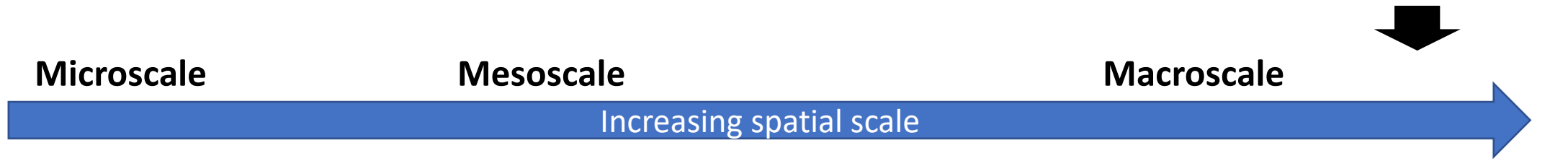
Symmonds et al. (2018), Brain

# Scales of analysis

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# Scales of analysis



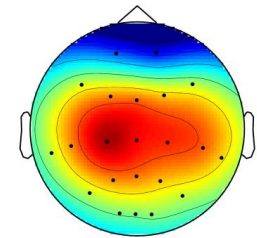
Scalp potentials  
30-38 cm<sup>2</sup>

Scalp responses

Leadfield

$$y = Lx + \epsilon$$

Neuronal source activity



# Scales of analysis

Microscale

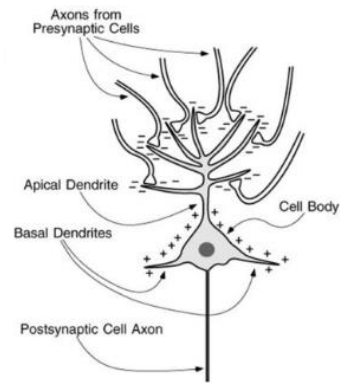
Mesoscale

Macroscale

Increasing spatial scale

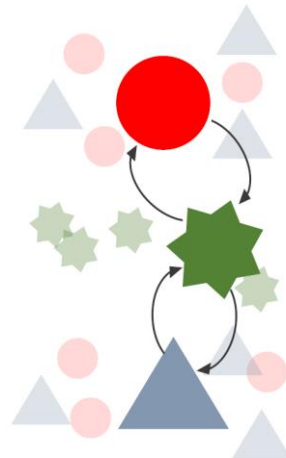
Single cell

1-10  $\mu\text{m}^2$



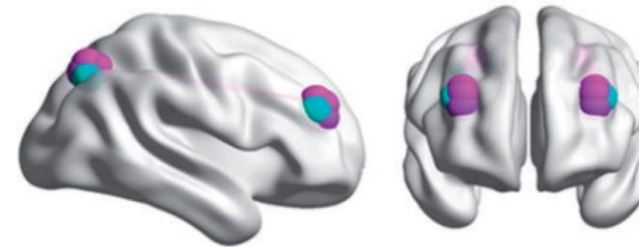
Cortical Column

1-10  $\text{mm}^2$  to 1-5  $\text{cm}^2$



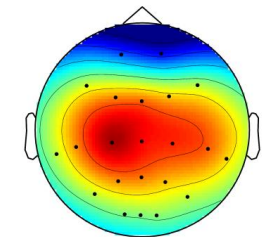
Brain Networks

5-20  $\text{cm}^2$



Scalp potentials

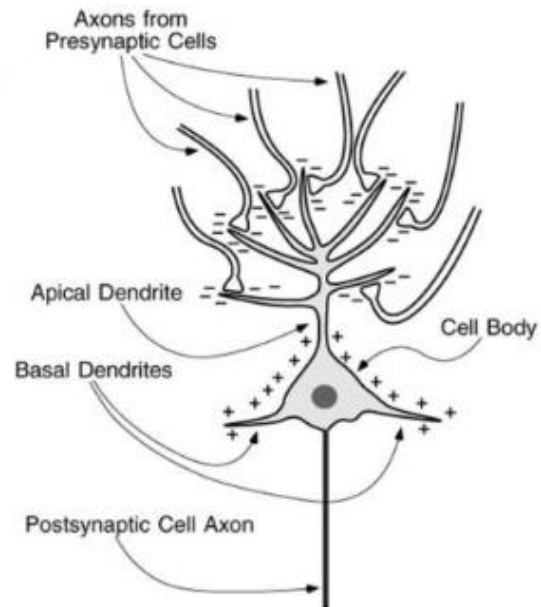
30-38  $\text{cm}^2$



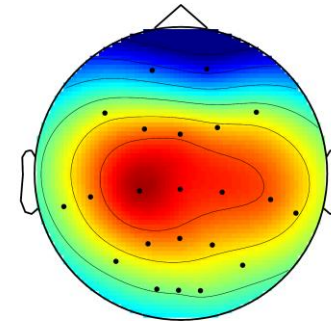


# What do we measure with EEG?

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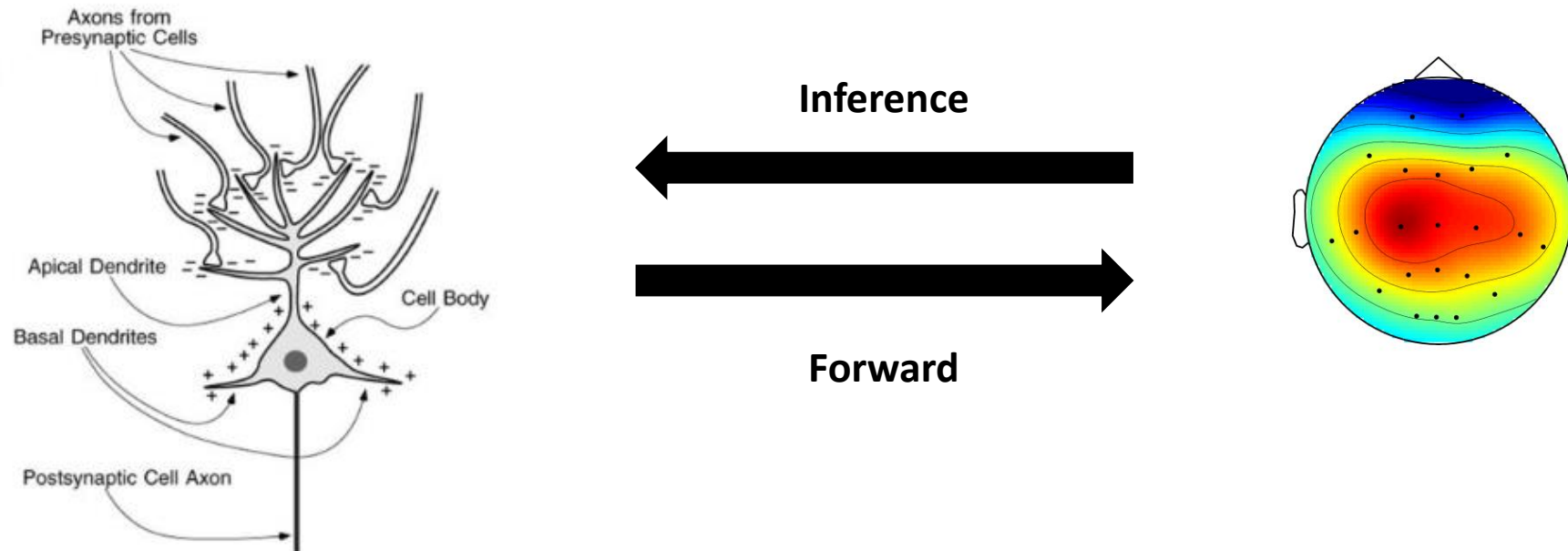
**Forward**



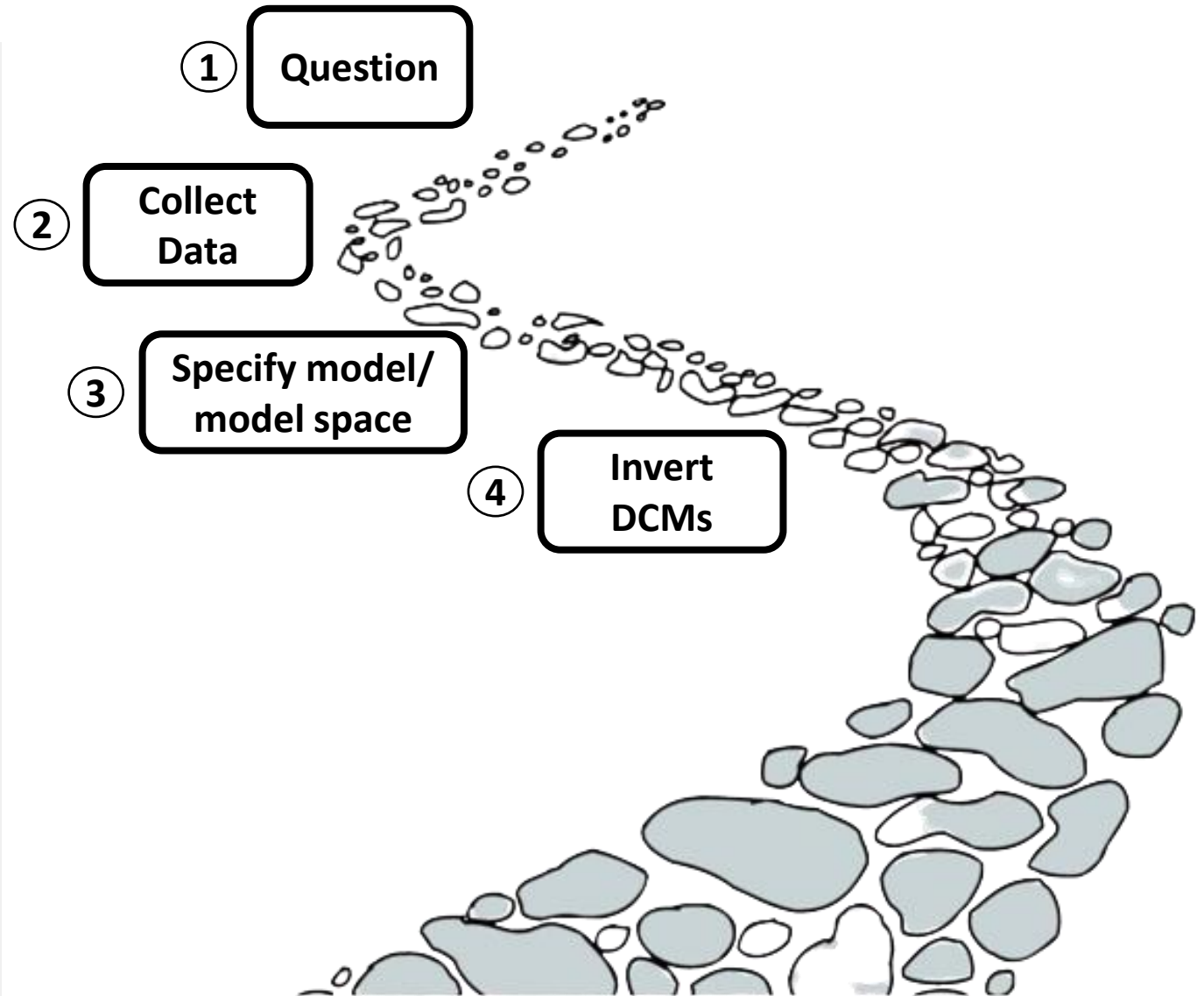
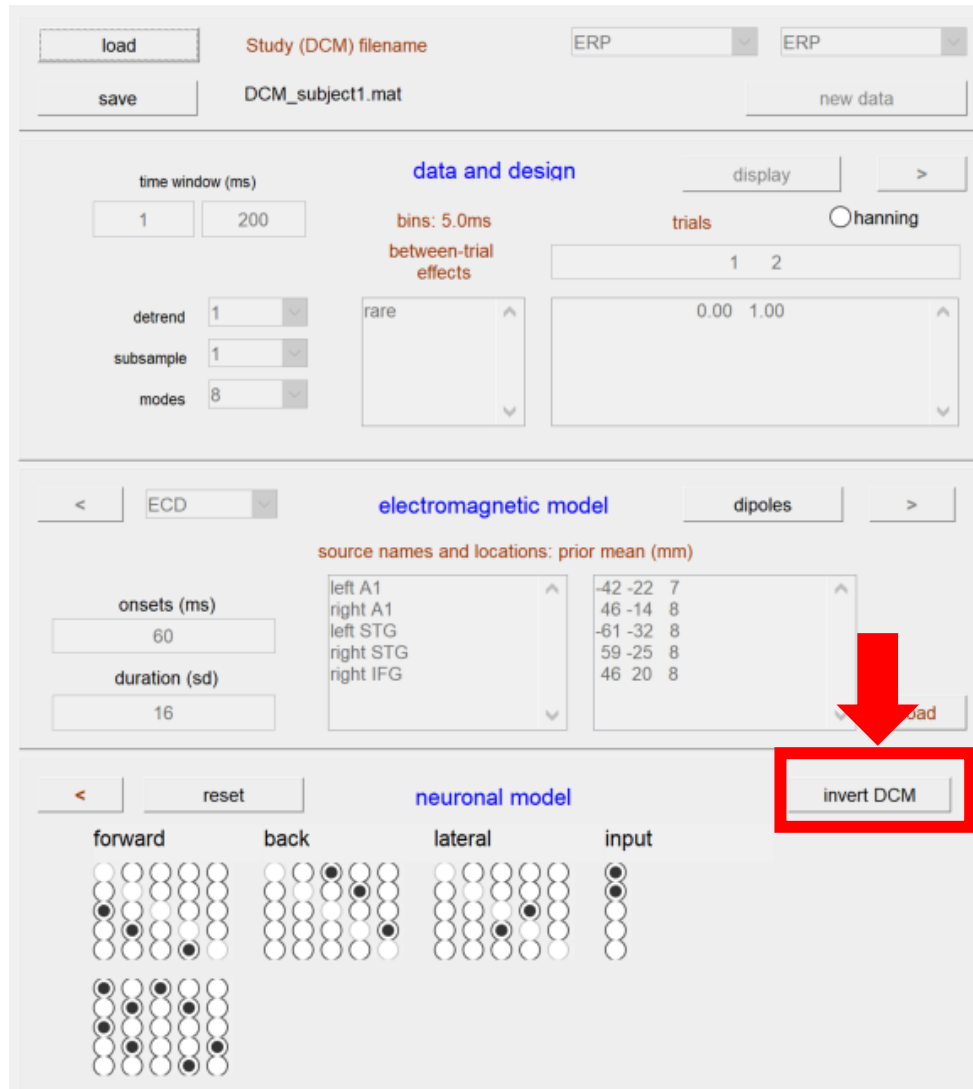
# What do we measure with EEG?

## Question

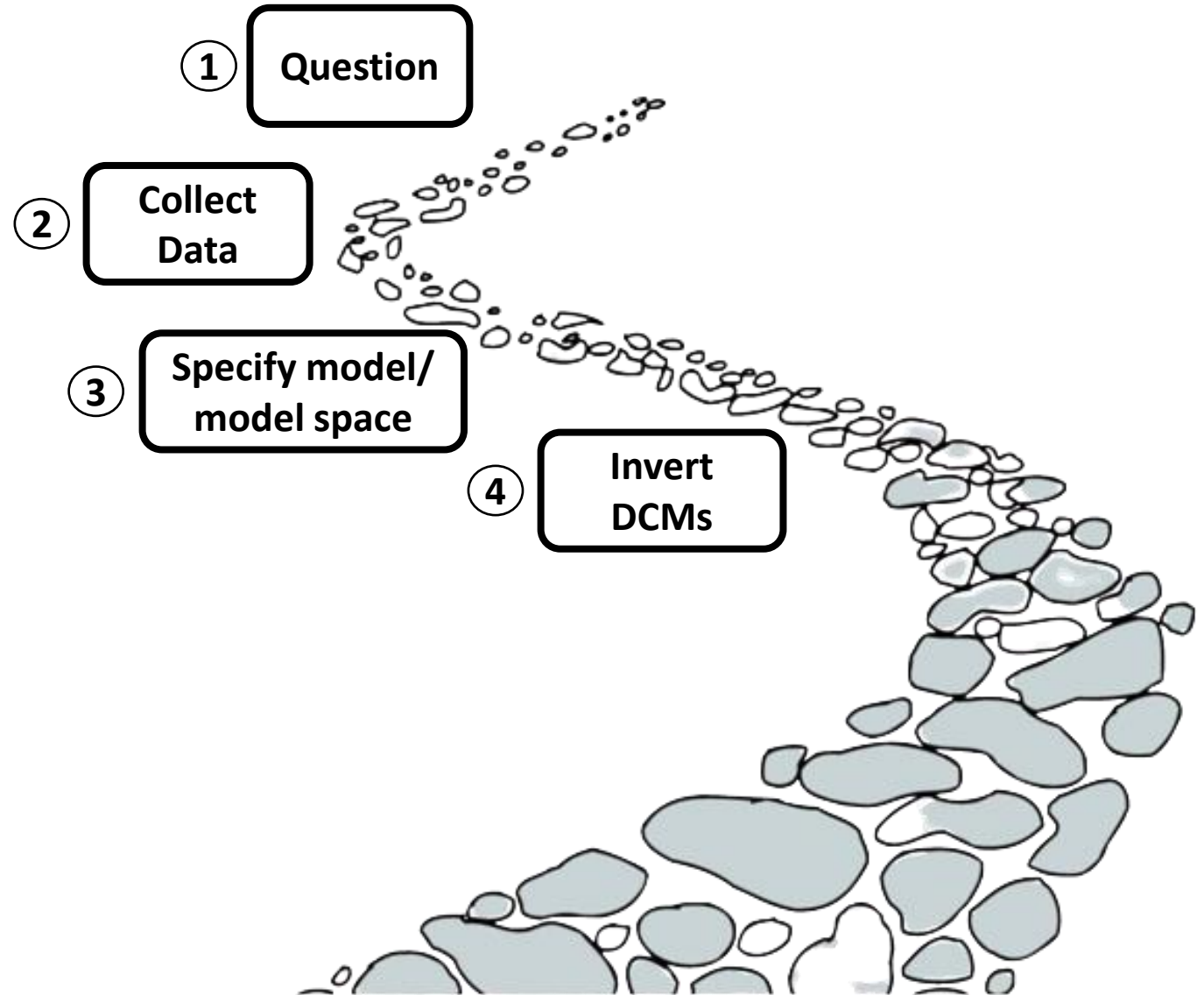
- Can we make inferences about properties of the neuronal sources that generate these signals?



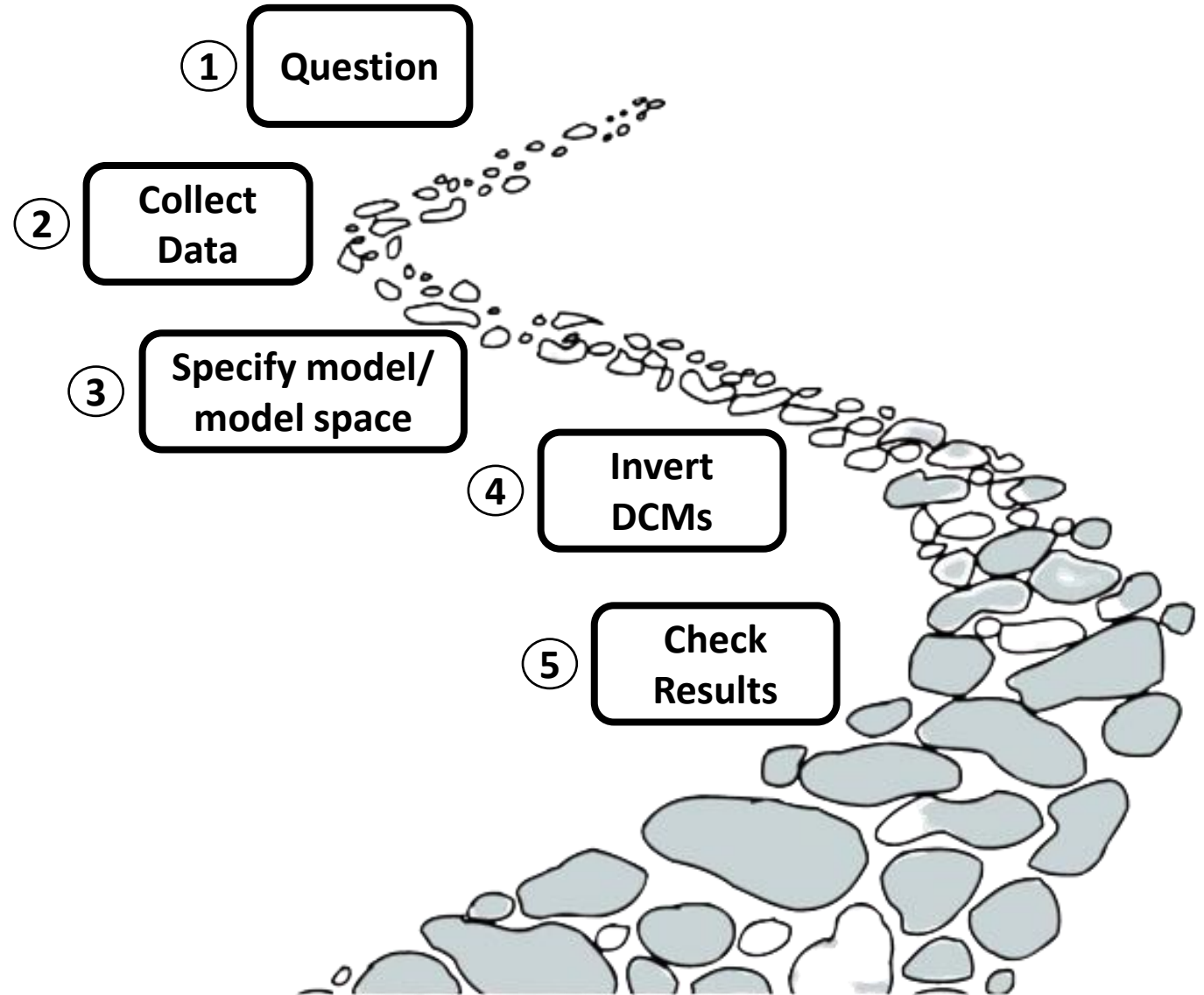
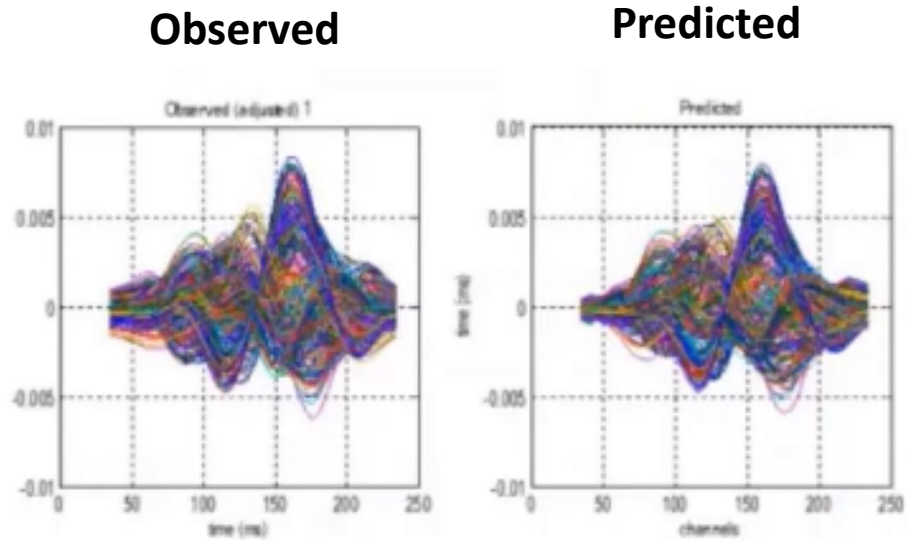
# The DCM analysis path



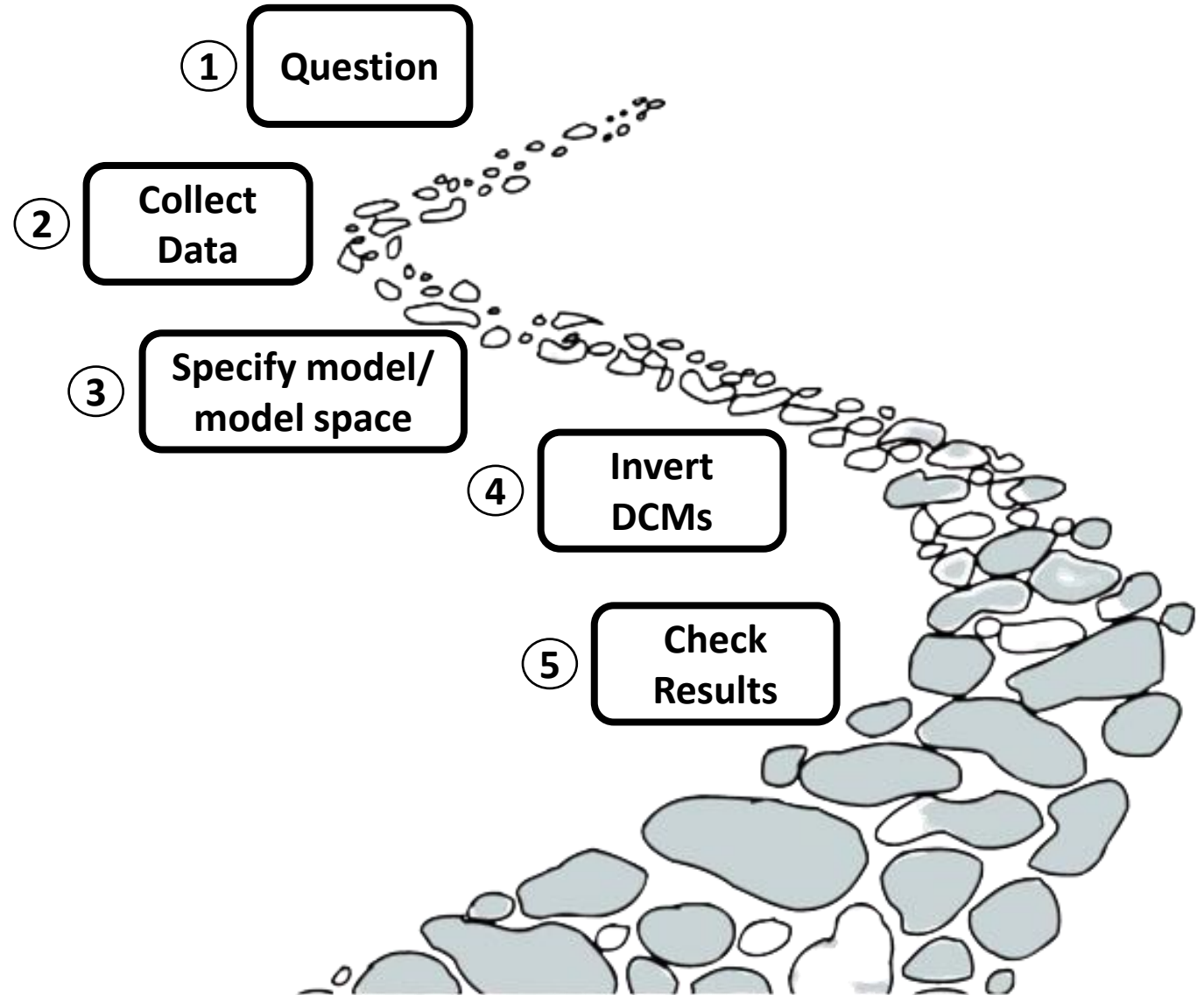
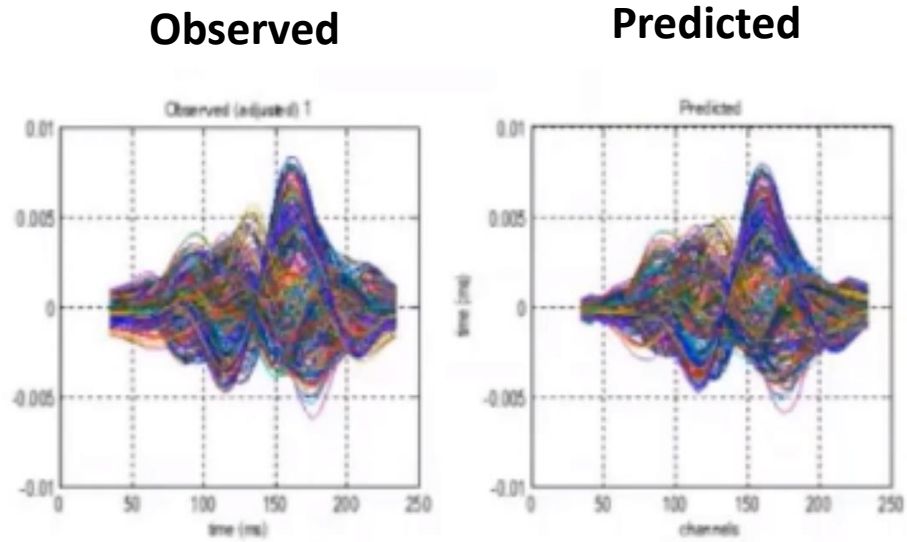
# The DCM analysis path



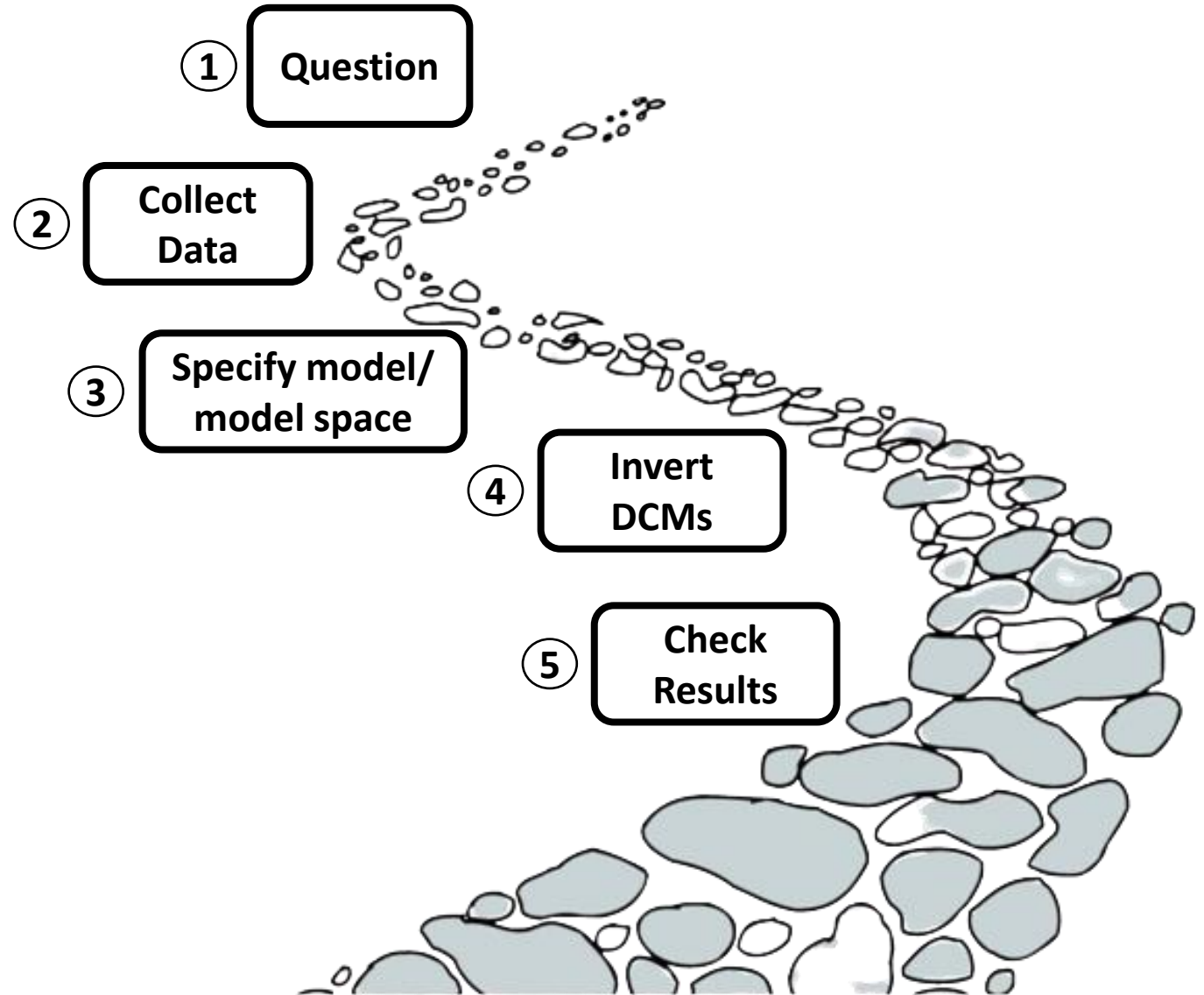
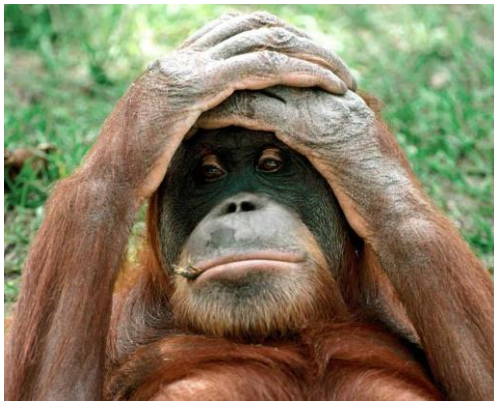
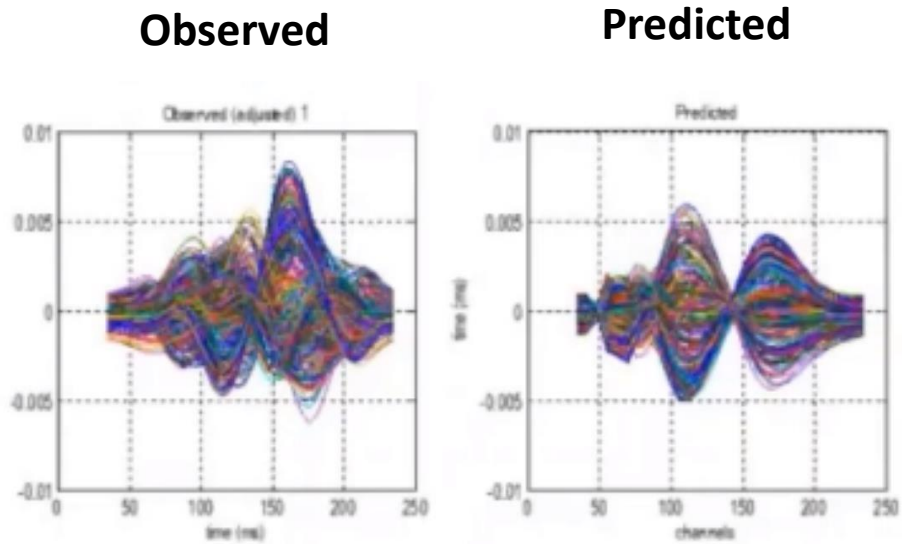
# The DCM analysis path



# The DCM analysis path



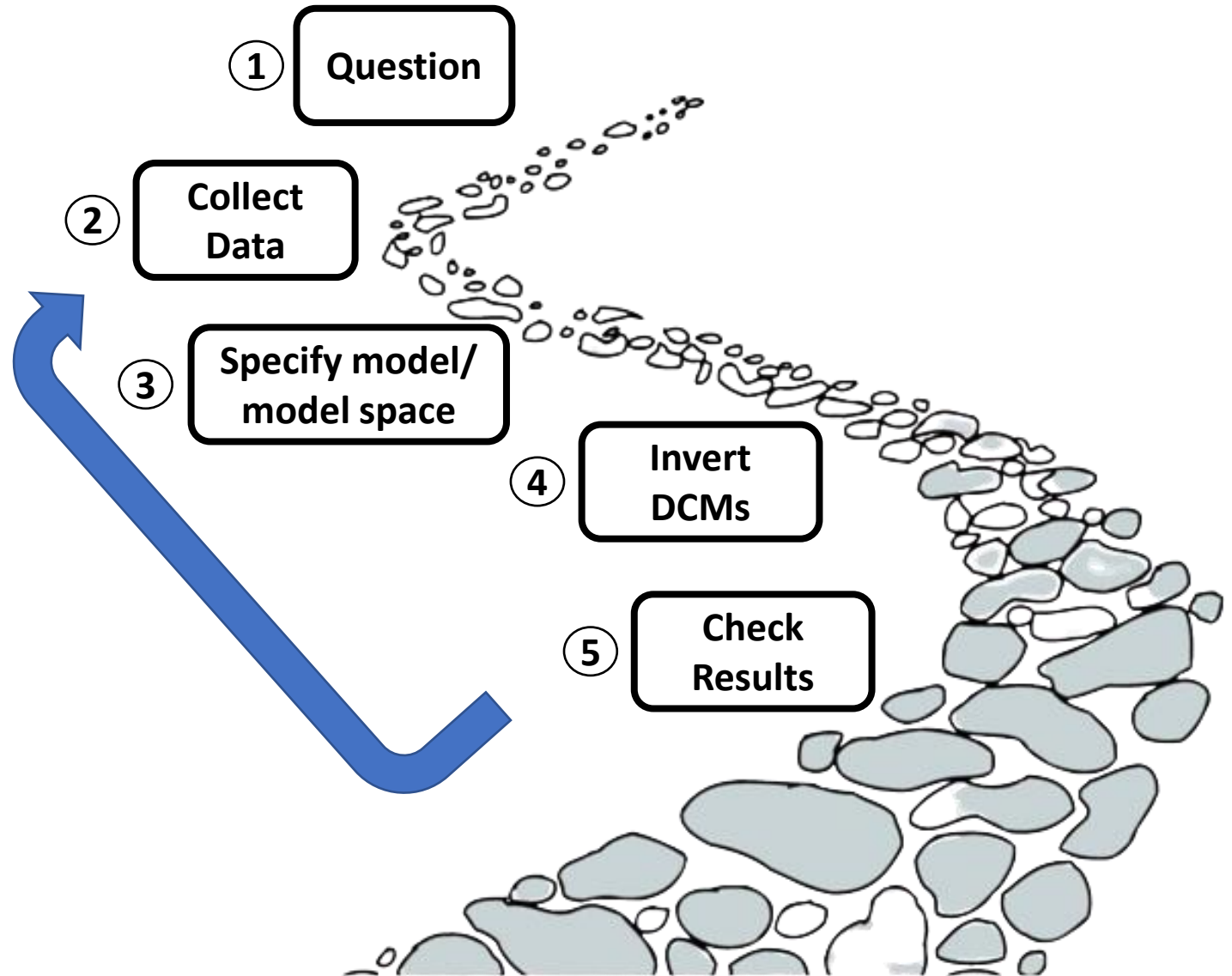
# The DCM analysis path



# The DCM analysis path

## Check your data

- Did something go wrong with preprocessing?
- Are there artefact?
- Is there high-frequency noise?
- ...

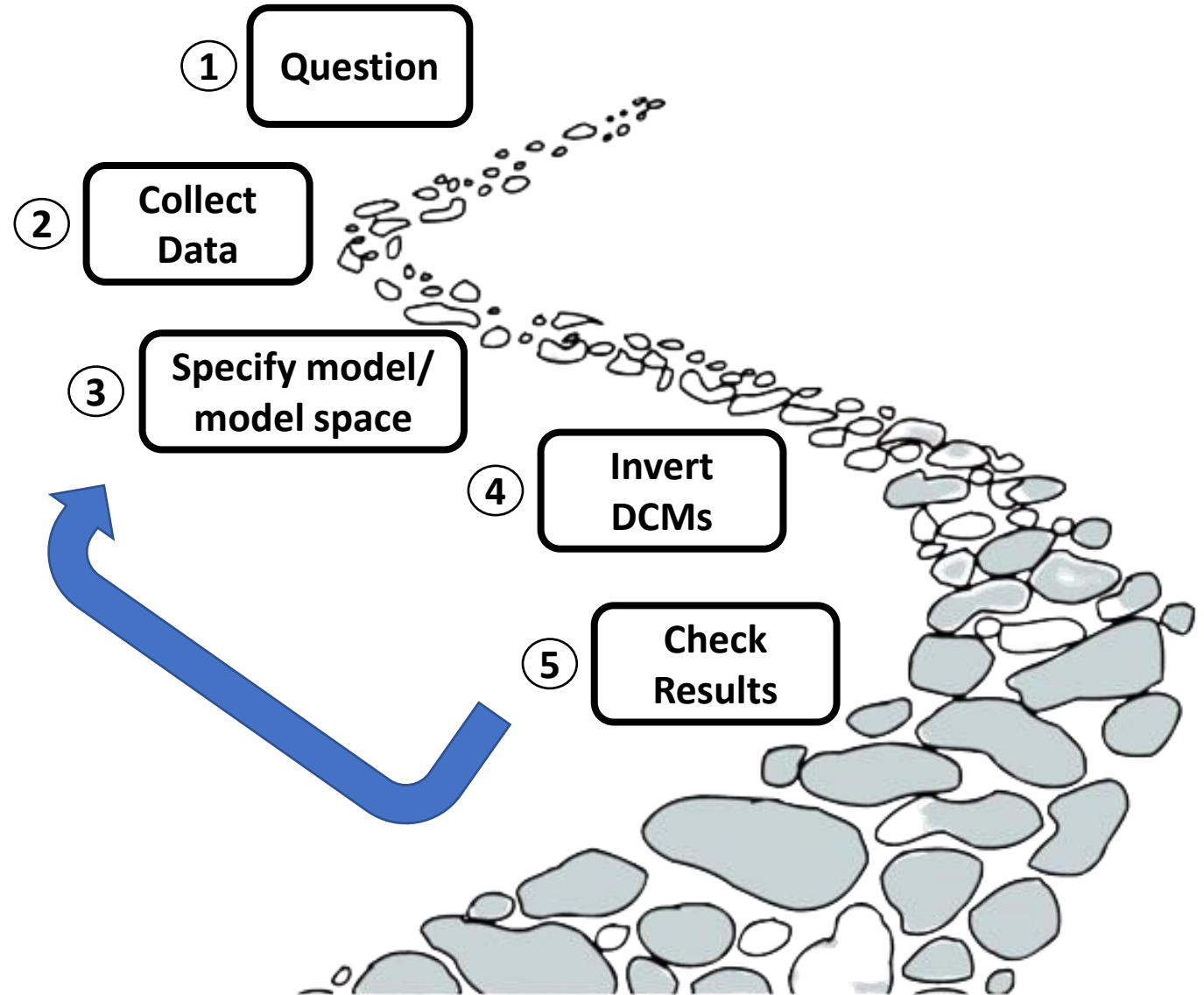




# The DCM analysis path

## Check your sources

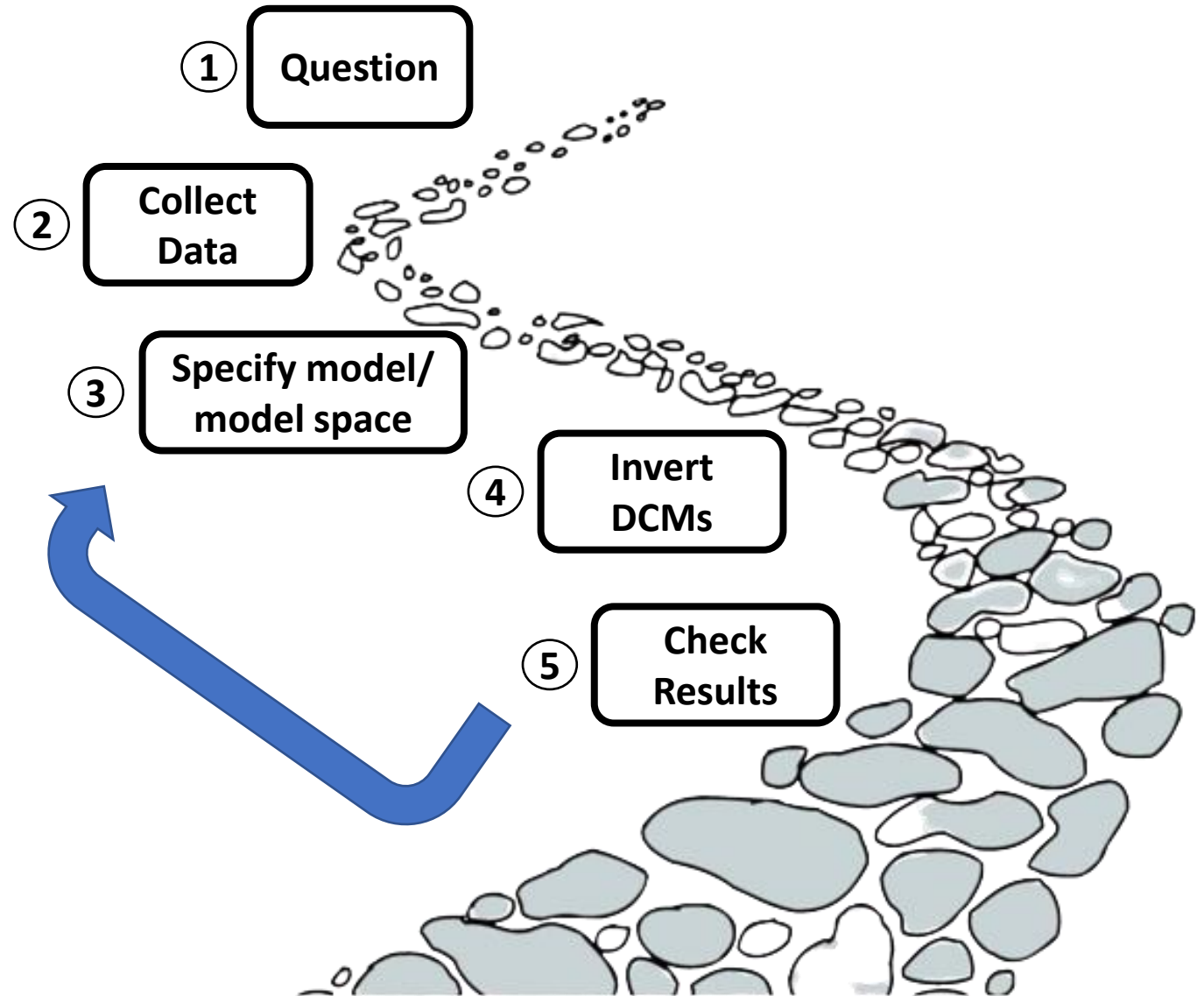
- Is there a relevant source that you have not considered in your network?



# The DCM analysis path

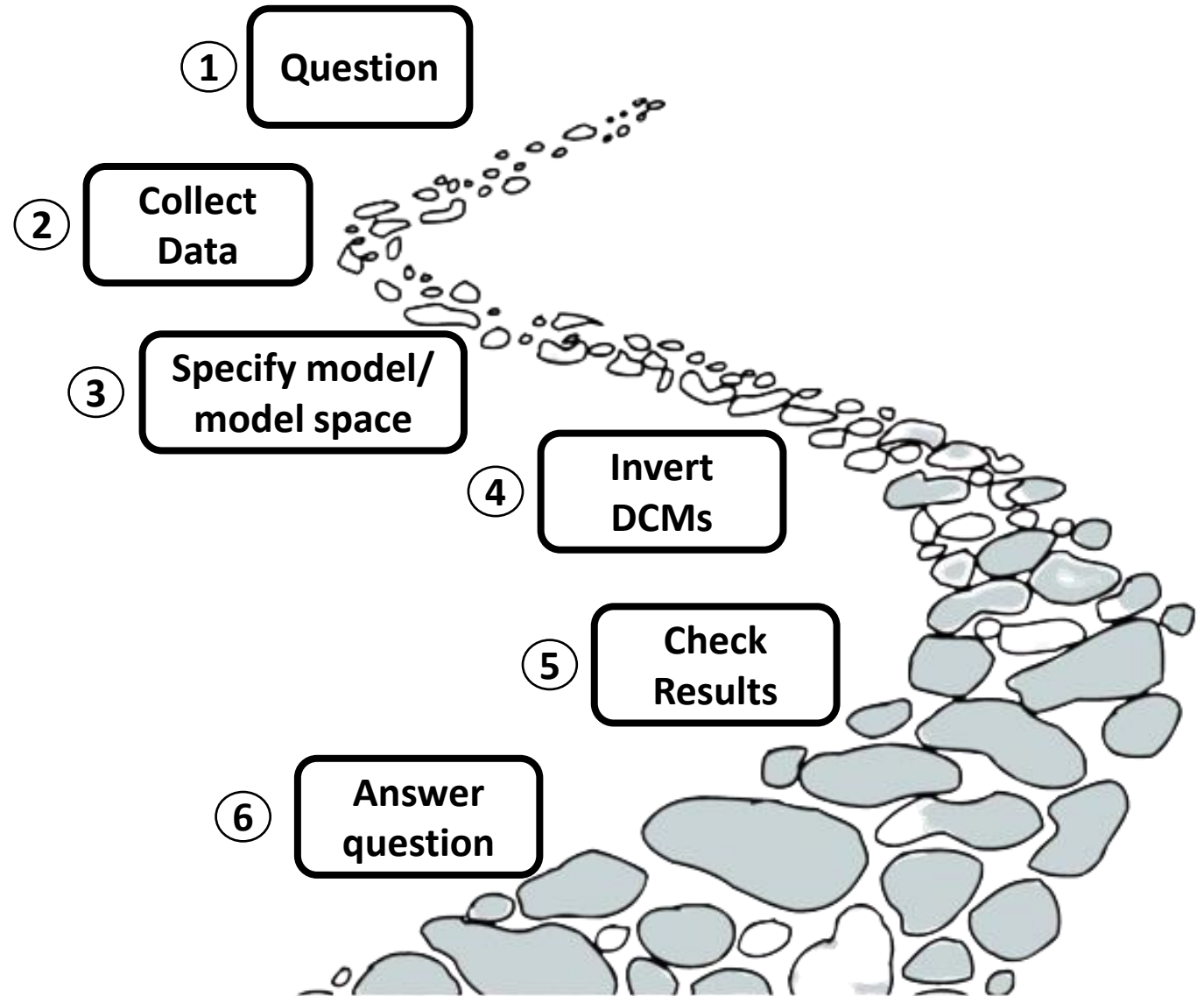
## Check your model

- If you simulate from your model can you produce the effects in simulations?
- Do you need to estimate additional parameters?
- Pick a more complex model?



# The DCM analysis path

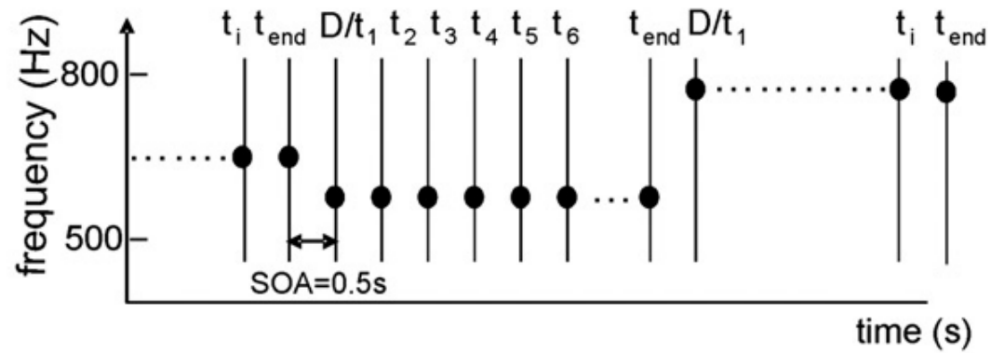
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# Example 1

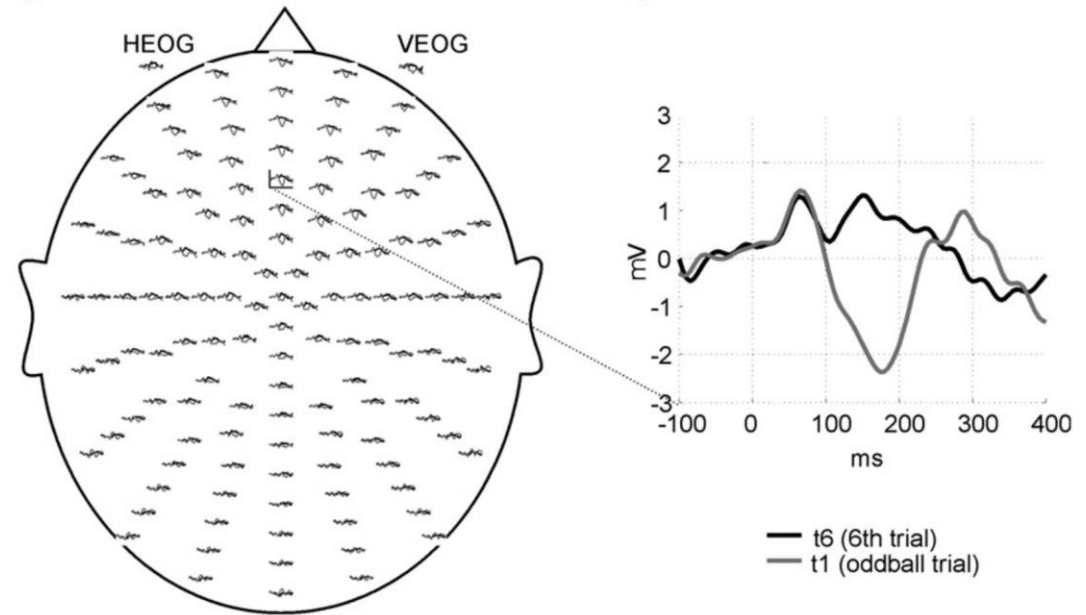
What network explains the mismatch negativity best?

- Roving paradigm to elicit MMN



$D/t_1$  = deviant

$t_i$  = trial  $i$ ,  $1 \leq i \leq 11$

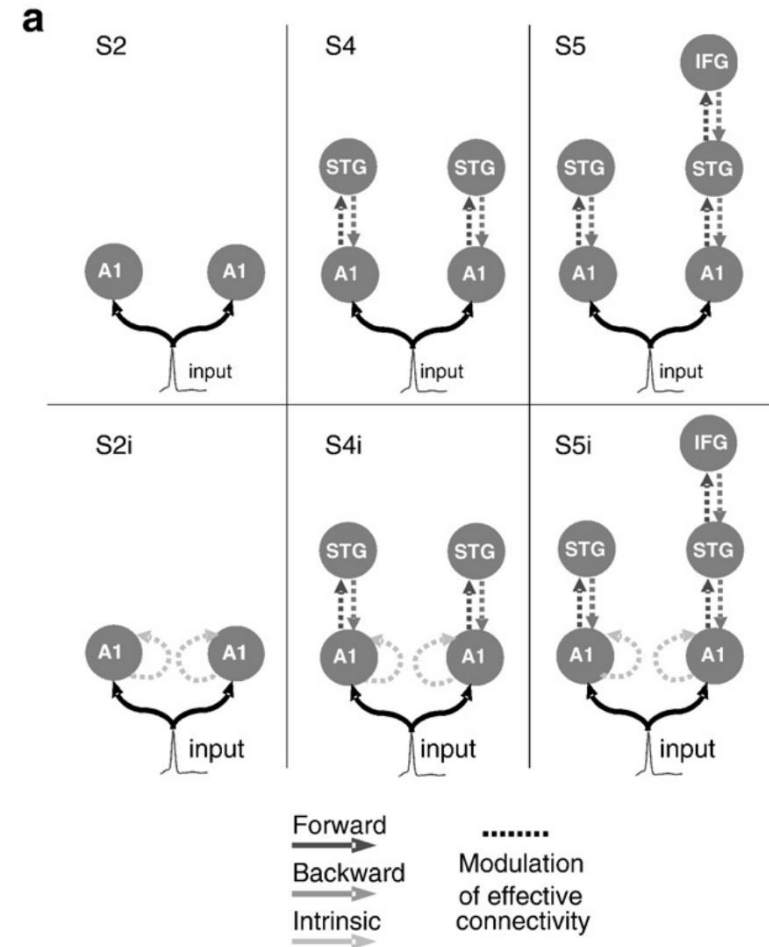
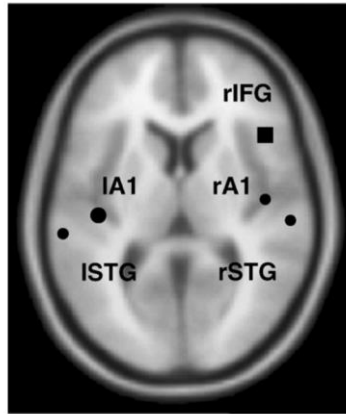


Garrido et al. (2006), NeuroImage

# Example 1

What network explains the mismatch negativity best?

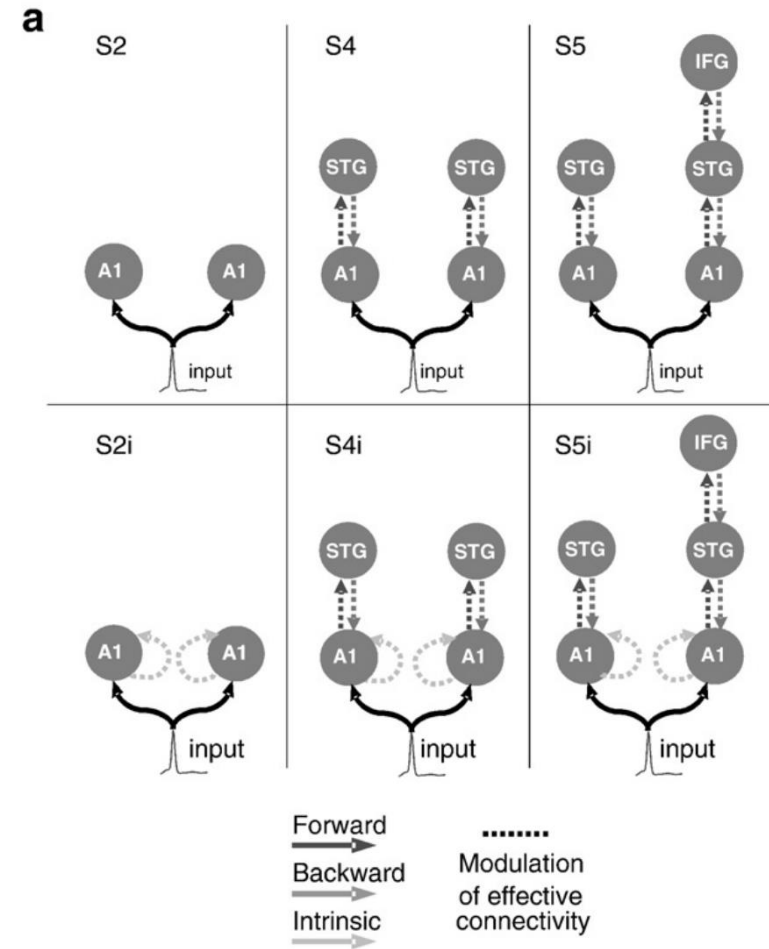
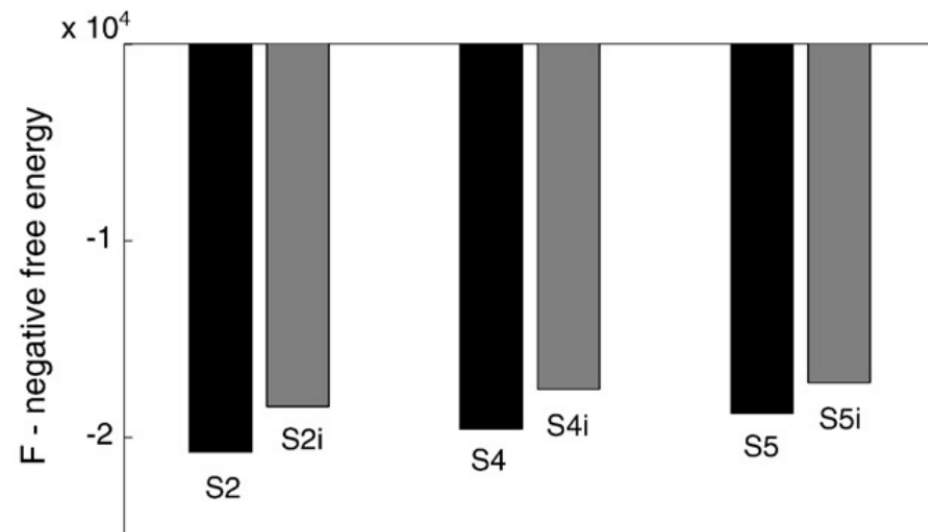
- Model space: Networks with different regions



# Example 1

What network explains the mismatch negativity best?

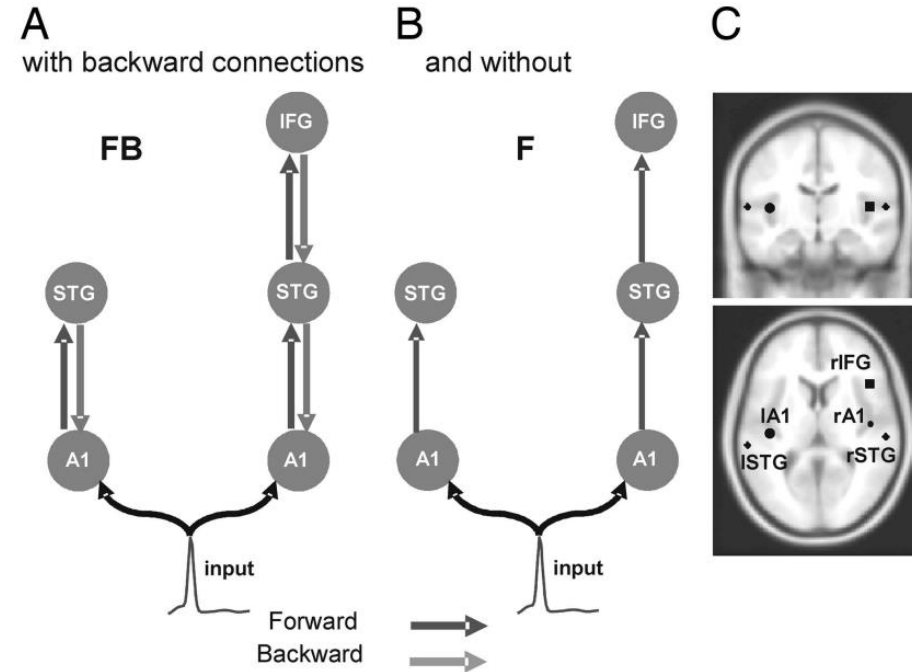
- Model space: Networks with different regions



# Example 2

Are backward connections required to explain the mismatch negativity?

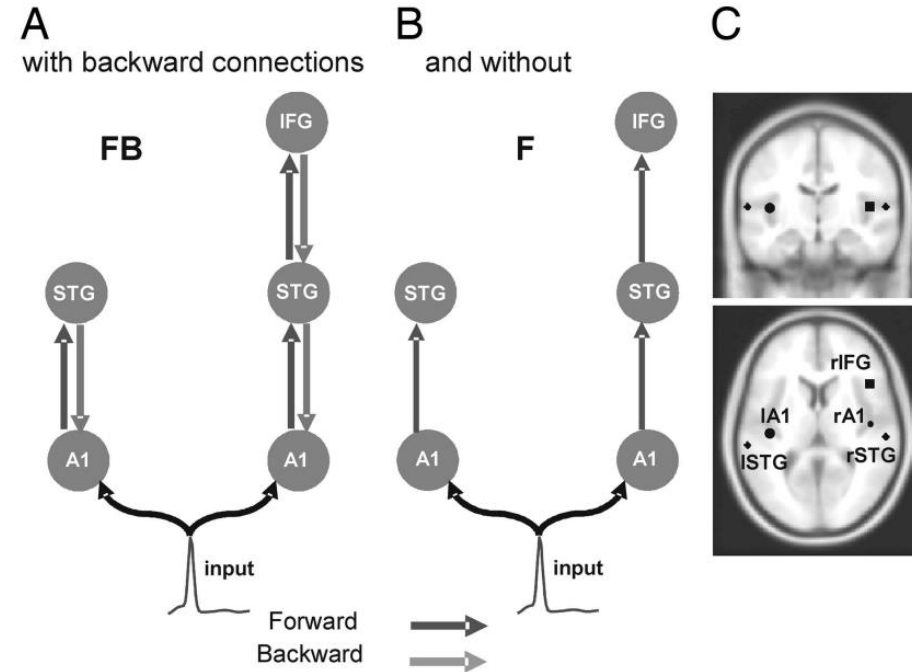
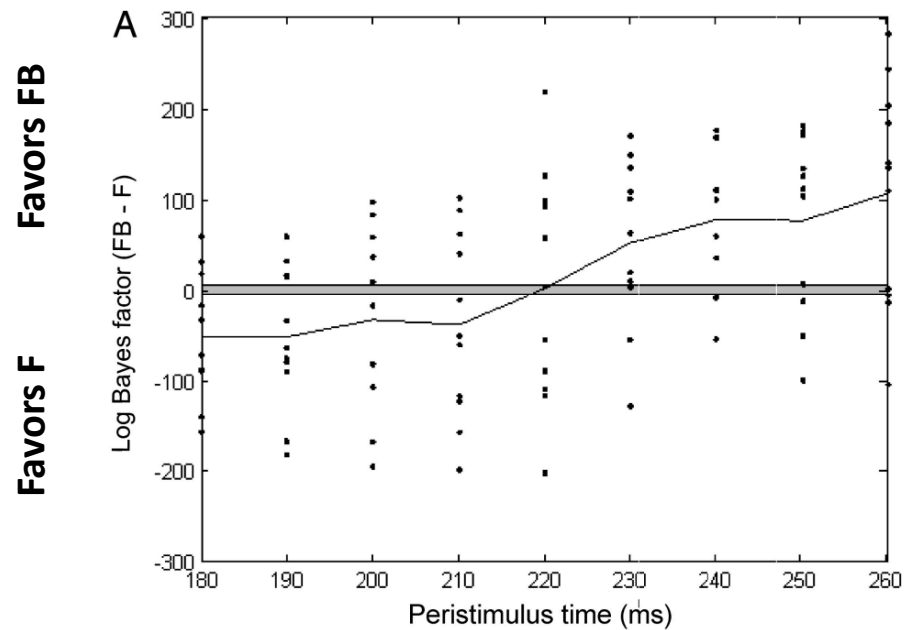
- Model space: Models with and without backward connections



# Example 2

Are backward connections required to explain the mismatch negativity?

- Model space: Models with and without backward connections

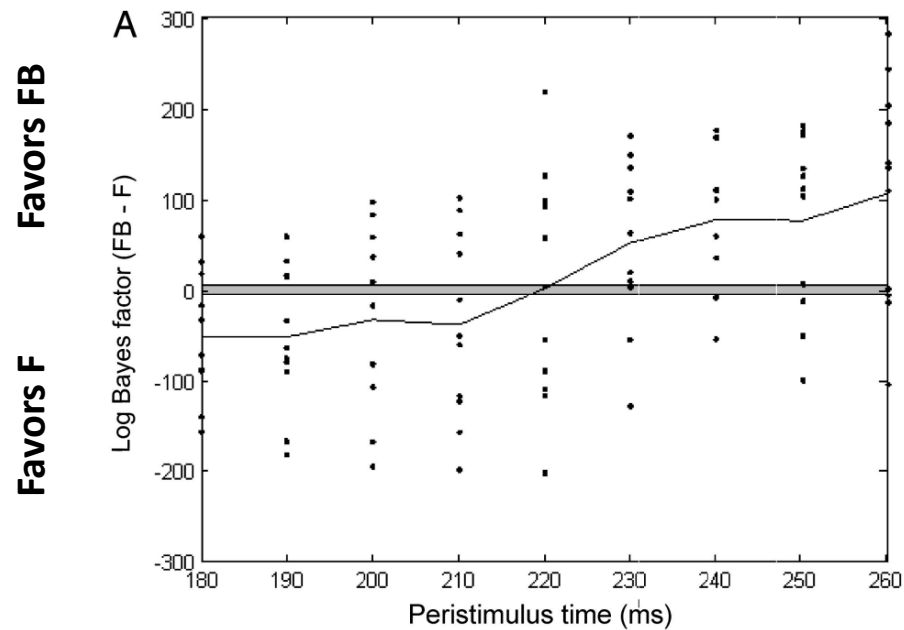




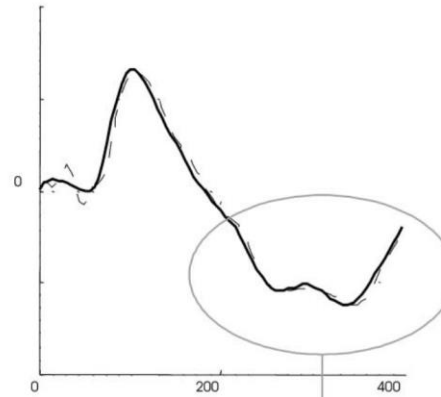
# Example 2

## Are backward connections required to explain the mismatch negativity?

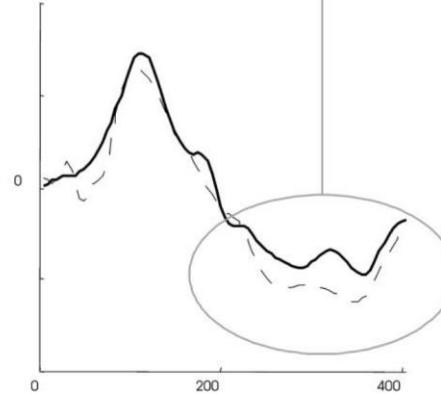
- Model space: Models with and without backward connections



**A** Predicted and observed response with backward connections

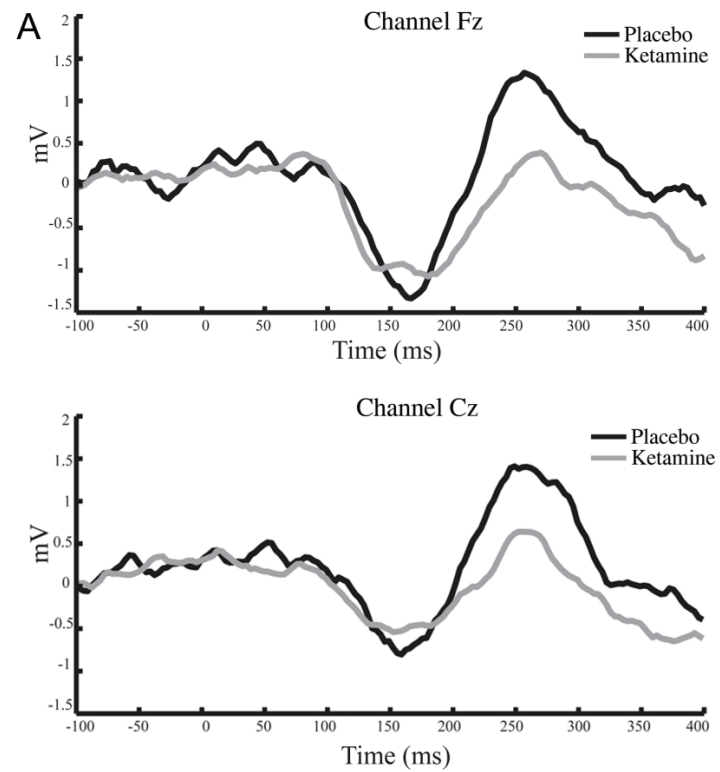


**B** and without backward connections



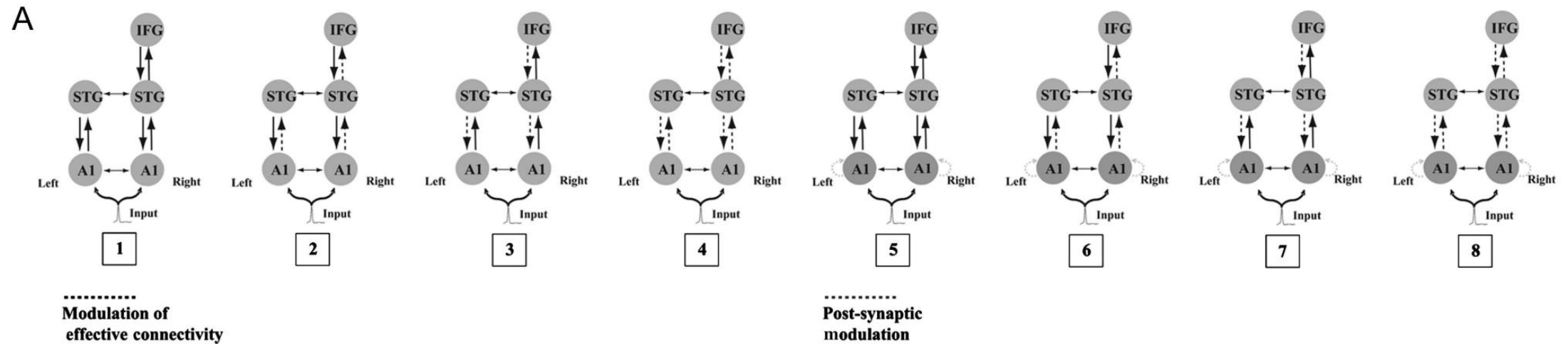
# Example 3

How does ketamine affect connectivity during the mismatch negativity?



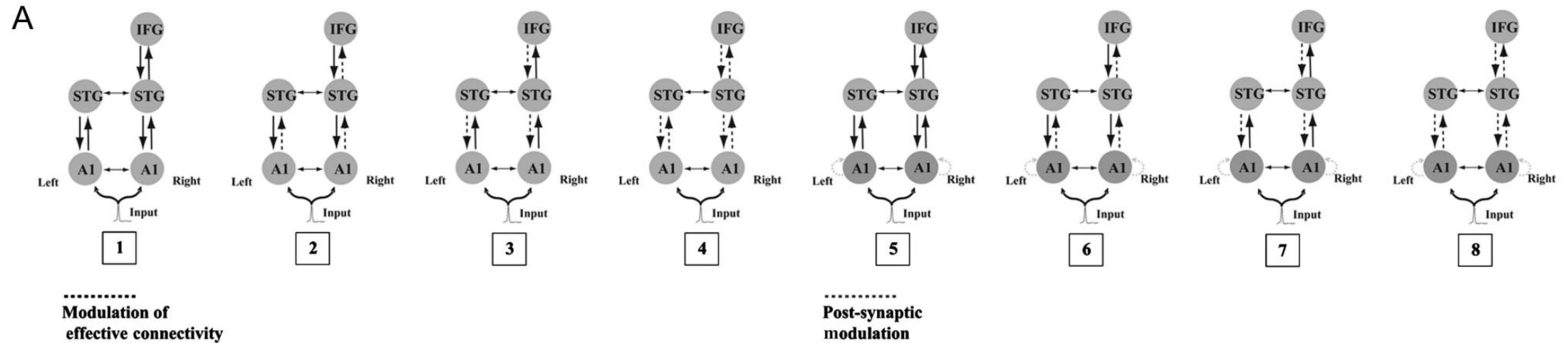
# Example 3

How does ketamine affect connectivity during the mismatch negativity?

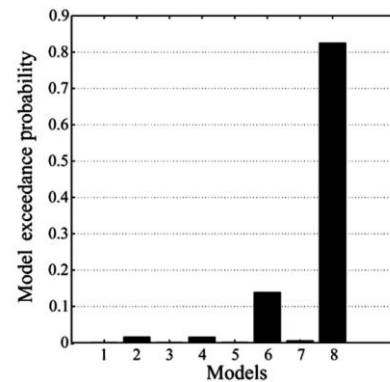


# Example 3

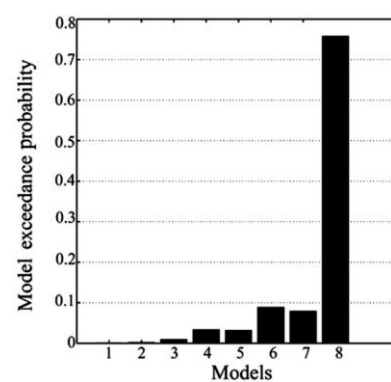
How does ketamine affect connectivity during the mismatch negativity?



B Placebo: population-level best model

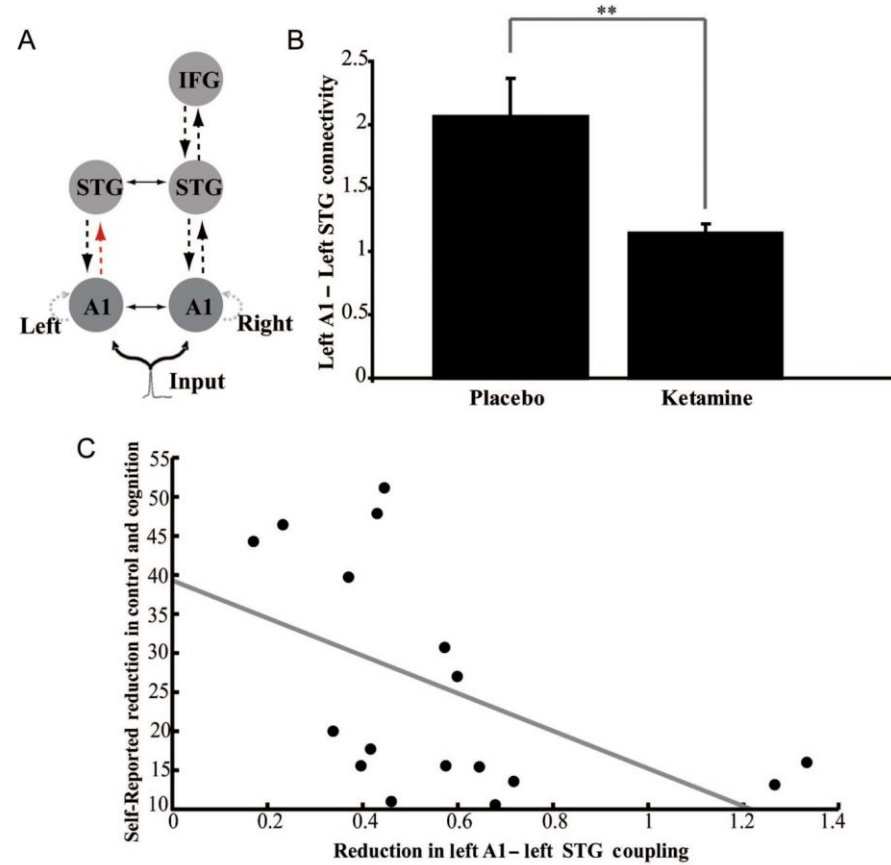


C Ketamine: population-level best model



# Example 3

How does ketamine affect connectivity during the mismatch negativity?



# Example 4

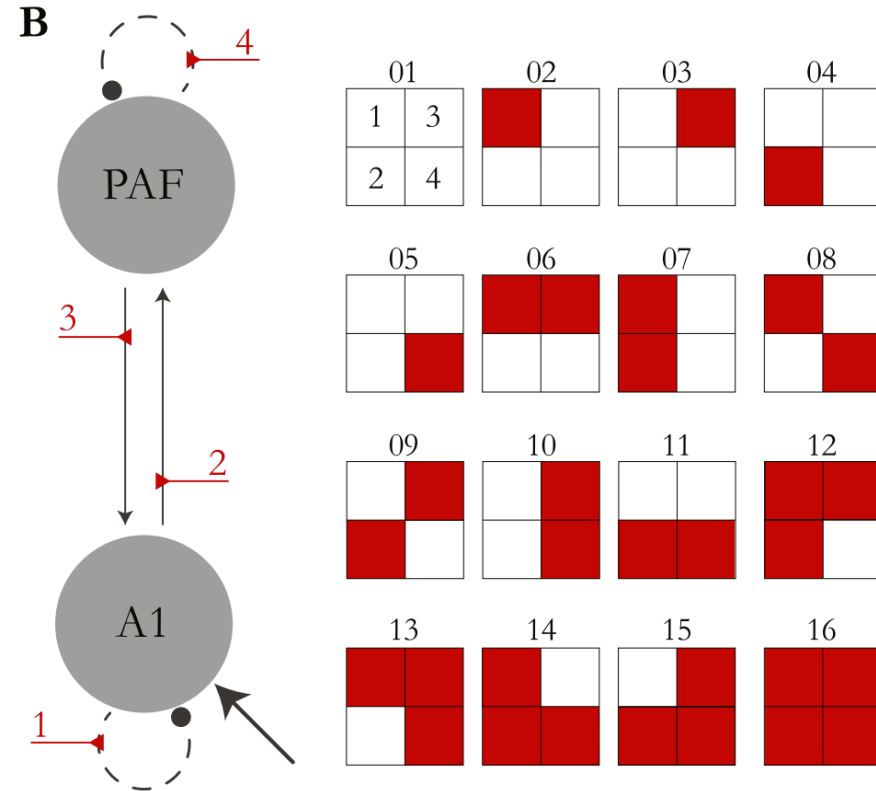
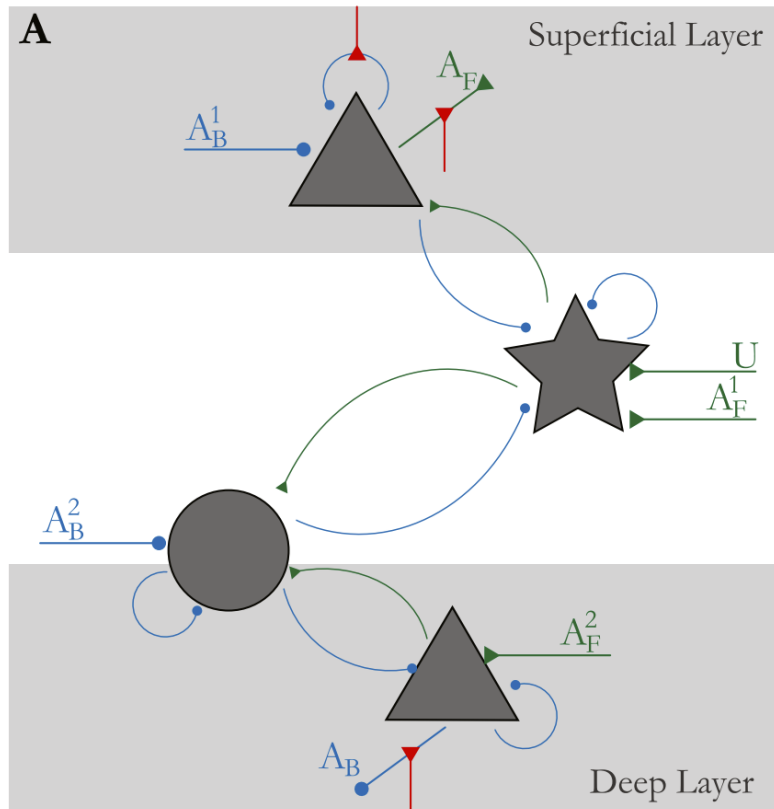
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## **What is the role of muscarinic receptor function for MMN generation?**

- Oddball task in rats
- Pharmacological intervention: muscarinic receptor agonist scopolamine and antagonist pilocarpine
- Intracranial recordings
- DCM: Canonical microcircuit/LFP

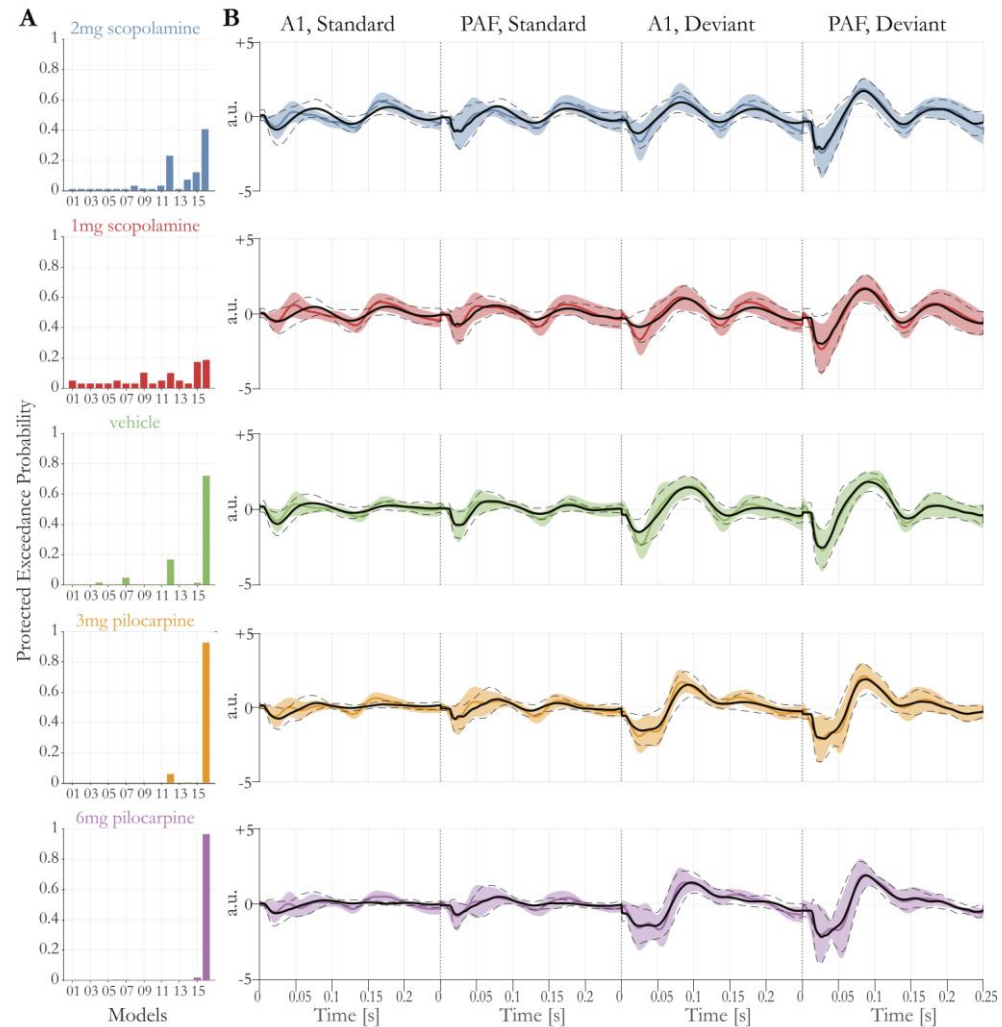
# Example 4

What is the role of muscarinic receptor function for MMN generation?



# Example 4

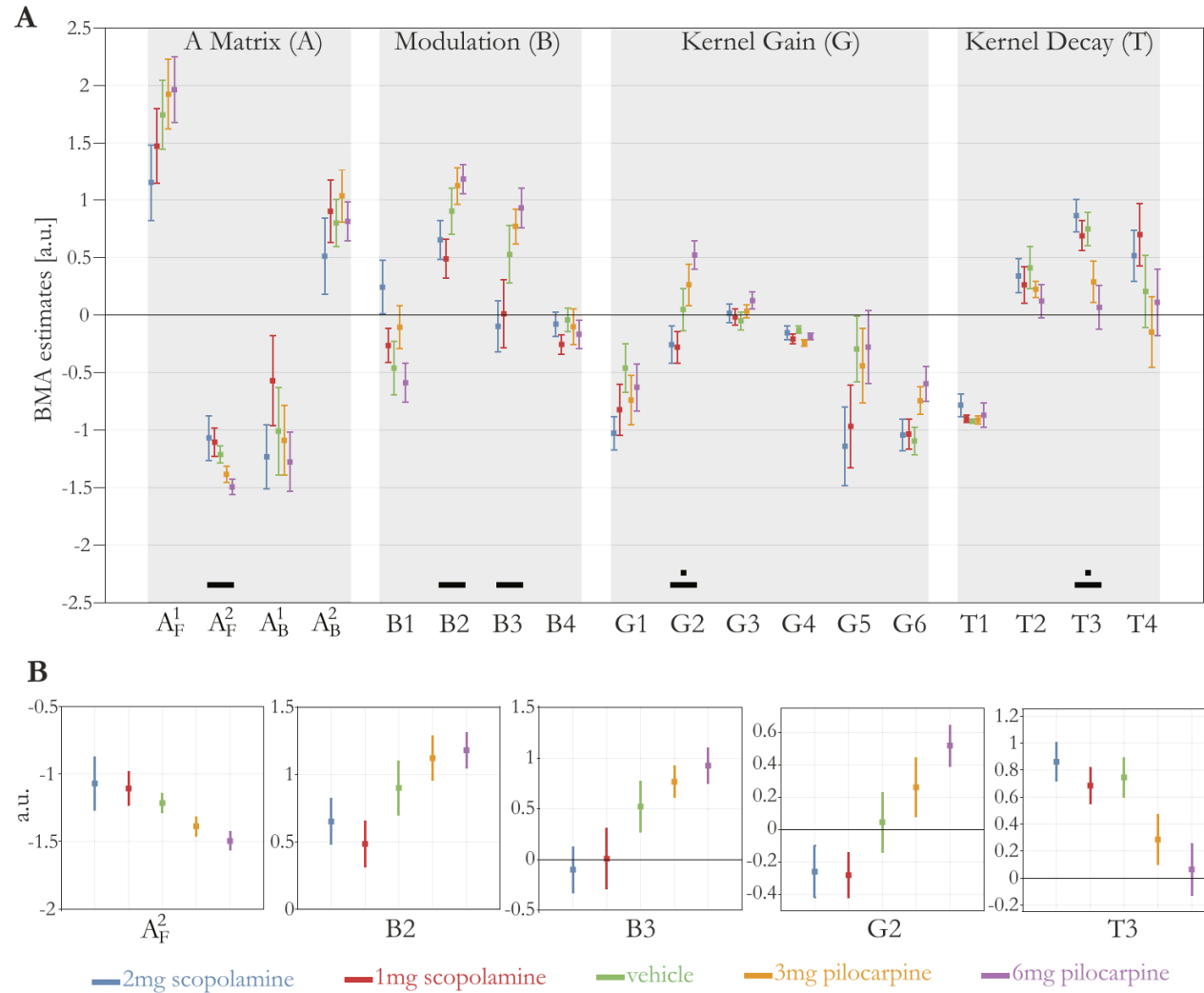
What is the role of muscarinic receptor function for MMN generation?





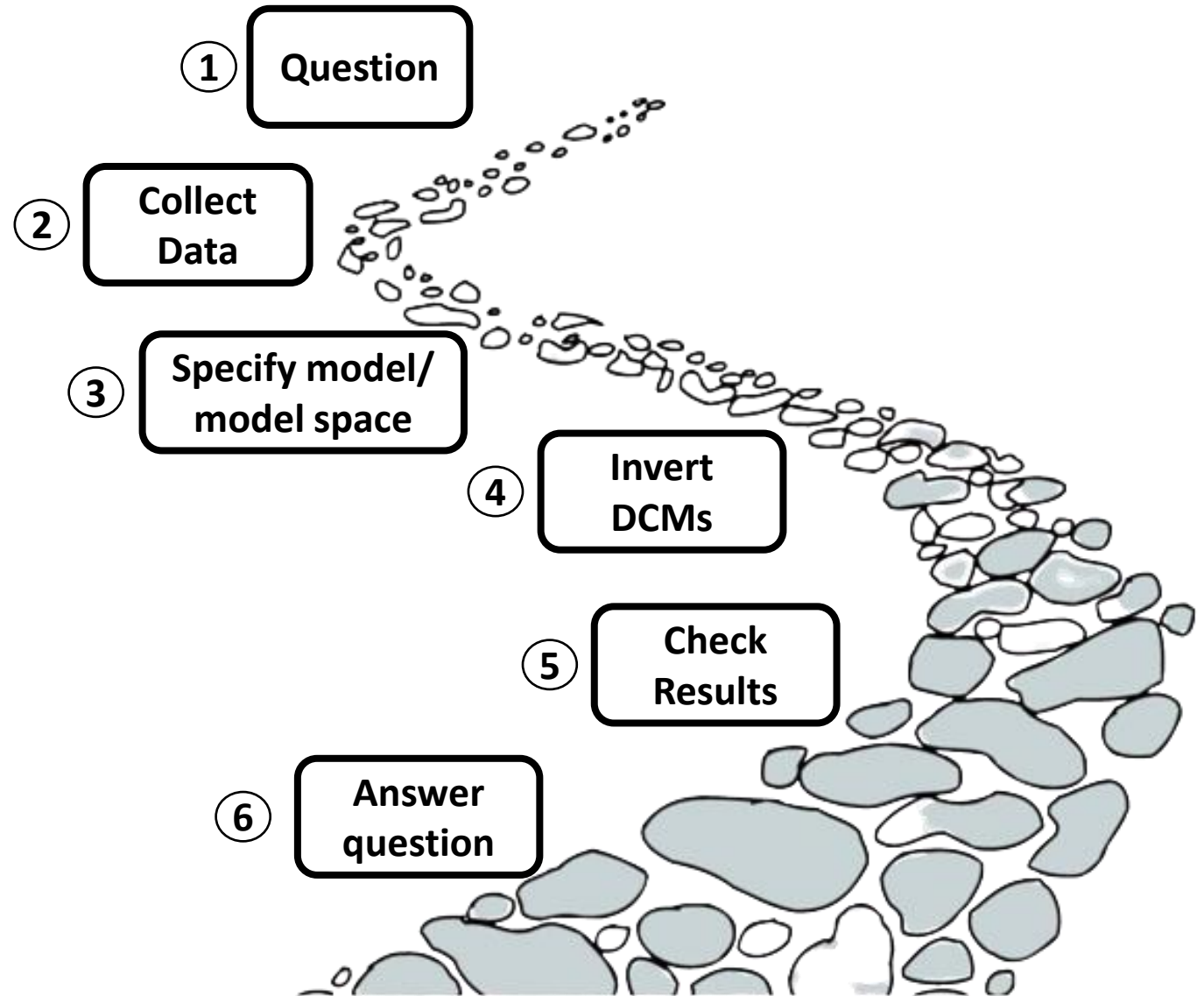
# Example 4

## What is the role of muscarinic receptor function for MMN generation?

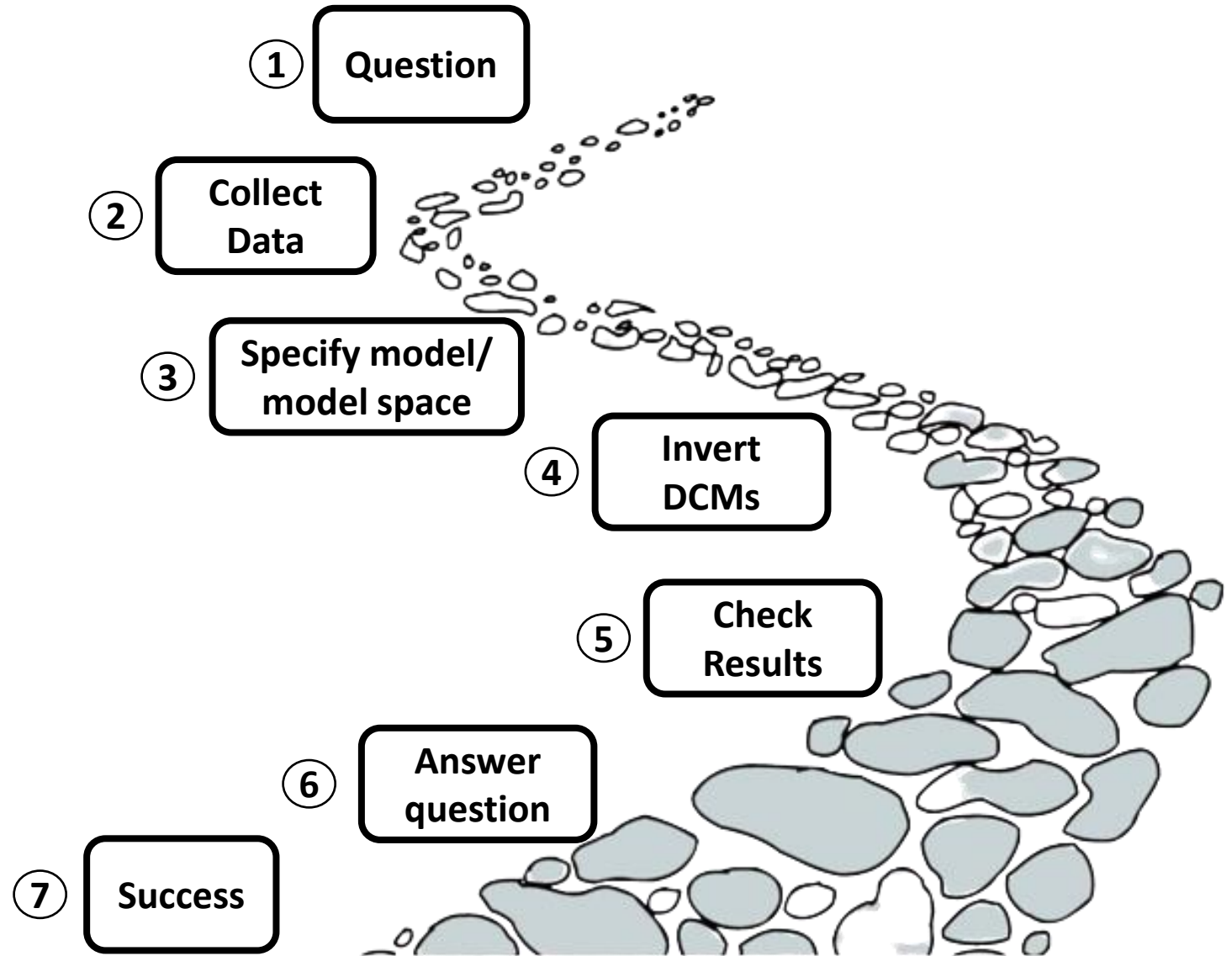


# The DCM analysis path

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# The DCM analysis path



# Resources

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## Overview Papers

- Moran, Pinotsis, & Friston (2013), Neural masses and fields in dynamic causal modeling, *Front. Comput. Neurosci.*
- Pereira et al. (2021), Conductance-based dynamic causal modeling: A mathematical review of its application to cross-power spectral densities, *NeuroImage*

## Books

- SPM manual: <https://www.fil.ion.ucl.ac.uk/spm/doc/manual.pdf>

## Videos

- Previous SPM courses: <https://www.fil.ion.ucl.ac.uk/spm/course/>
- Zurich CPC courses: <https://www.tnu.ethz.ch/de/teaching/cpcourse>
- KCNI Summer School: <https://www.crowdcast.io/e/kcni-summer-school-2021>

## In-depth reading

- Garrido, M.I., Kilner, J.M., Kiebel, S.J. and Friston, K.J., 2007. Evoked brain responses are generated by feedback loops. *Proceedings of the National Academy of Sciences*, 104(52), pp.20961-20966.
- David, O., Harrison, L. and Friston, K.J., 2005. Modelling event-related responses in the brain. *NeuroImage*, 25(3), pp.756-770.
- Hodgkin, A.L. and Huxley, A.F., 1952. A quantitative description of membrane current and its application to conduction and excitation in nerve. *The Journal of physiology*
- Jansen BH, Rit VG (1995) Electroencephalogram and visual evoked potential generation in a mathematical model of coupled cortical columns. *Biol Cybern*
- Marreiros, A.C., Kiebel, S.J., Daunizeau, J., Harrison, L.M. and Friston, K.J., 2009. Population dynamics under the Laplace assumption. *Neuroimage*
- Litvak, V., Jafarian, A., Zeidman, P., Tibon, R., Henson, R.N. and Friston, K., 2019, October. There's no such thing as a 'true' model: the challenge of assessing face validity. In 2019 IEEE
- Zeidman P, Friston K, Parr T (2022) A primer on Variational Laplace
- Pinotsis, D.A., Leite, M. and Friston, K.J., 2013. On conductance-based neural field models. *Frontiers in computational neuroscience*
- Pinotsis, D.A. and Friston, K.J., 2014. Neural fields, masses and Bayesian modelling. In *Neural fields* (pp. 433-455). Springer, Berlin, Heidelberg.
- Marreiros, A.C., Pinotsis, D.A., Brown, P. and Friston, K.J., 2015. DCM, conductance based models and clinical applications. *Validating Neuro-Computational Models of Neurological and Psychiatric Disorders*, pp.43-70. [https://www.researchgate.net/publication/274078765\\_DCM\\_Conductance\\_Based\\_Models\\_and\\_Clinical\\_Applications](https://www.researchgate.net/publication/274078765_DCM_Conductance_Based_Models_and_Clinical_Applications)

# Acknowledgments

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- Rick Adams
- Julia Rodriguez-Sanchez
- Hope Oloye
- Ingrid Martin
- Victorita Neacsu
- Lioba Berndt
- Vladimir Litvak
- Dimitris Pinotsis

# Thank you for your attention!

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# Questions & Discussion

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