INFERRING INFORMATION FLOW IN THE WHITE MATTER OF THE BRAIN

NEW INFORMATION PROVIDED BY THE FUSION OF DMRI AND M/EEG

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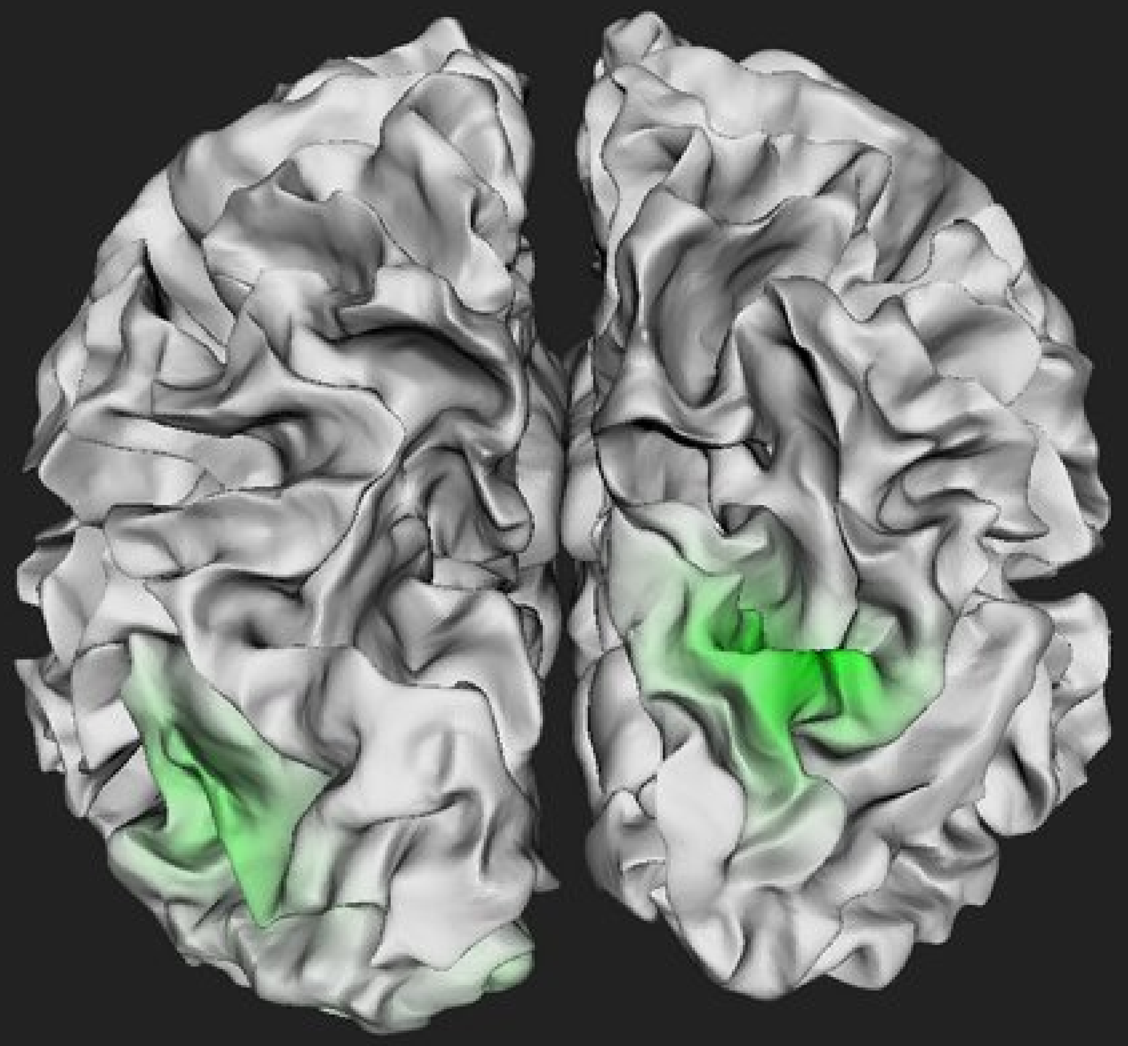
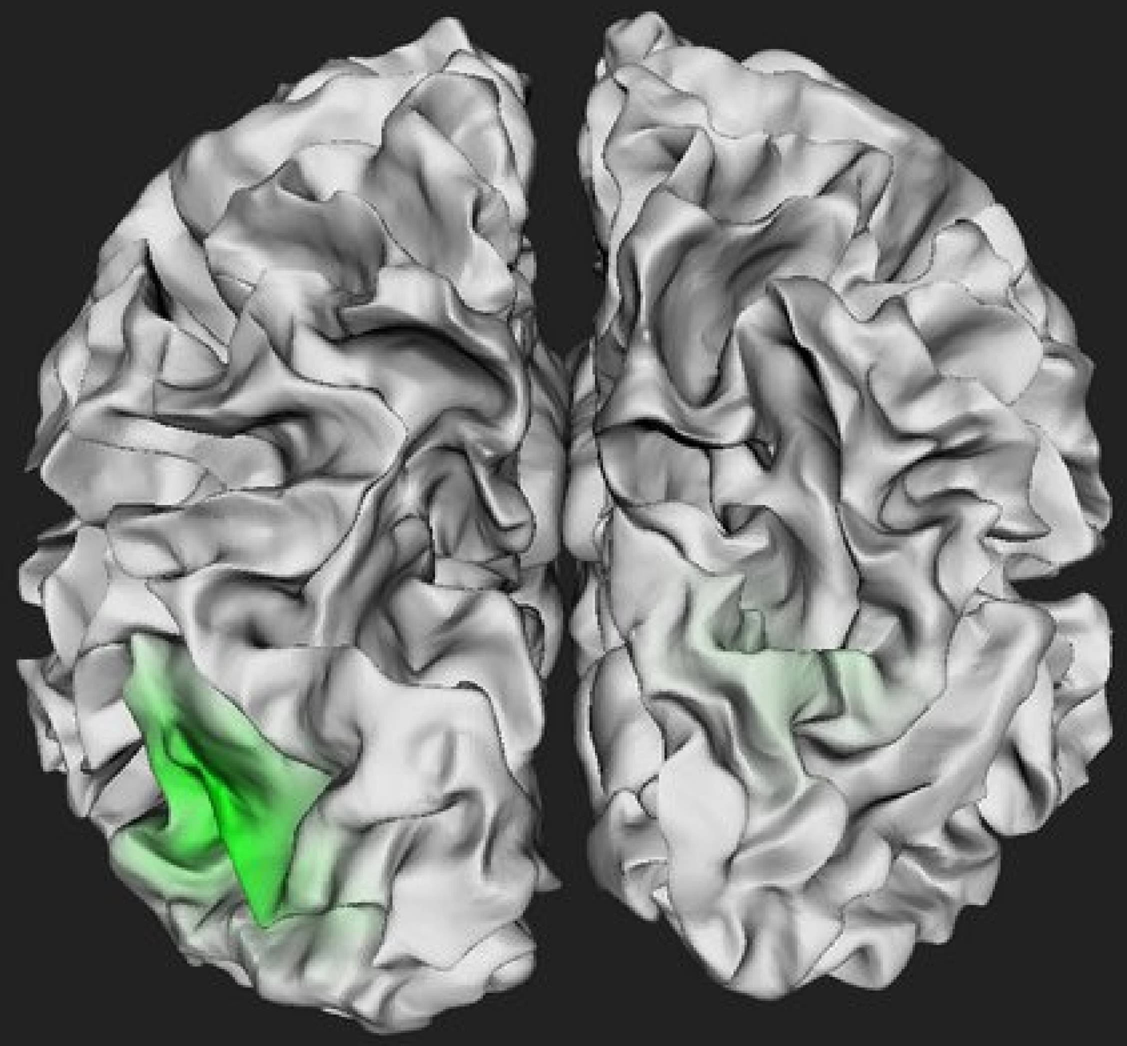
INFORMATION FLOW?

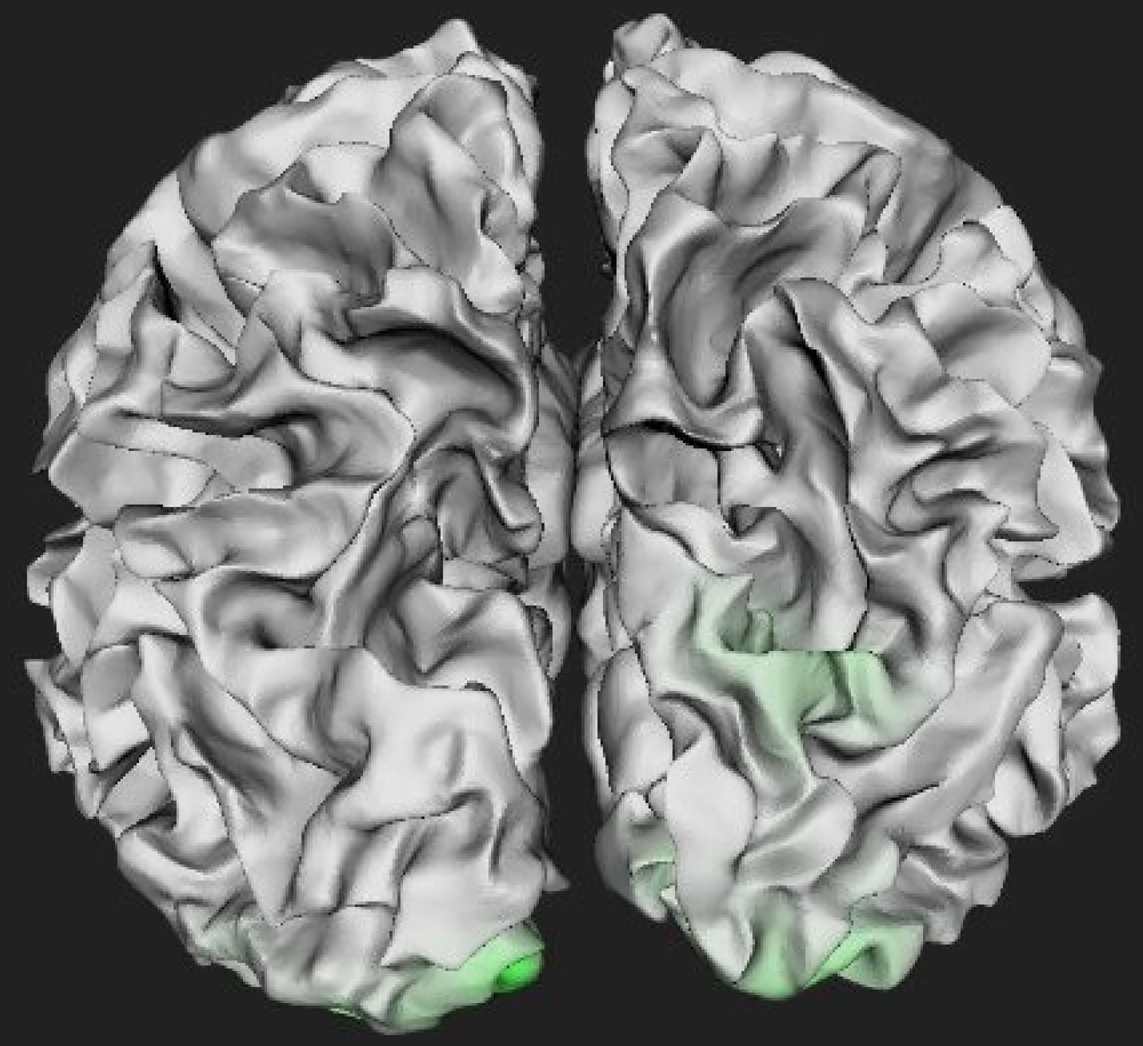




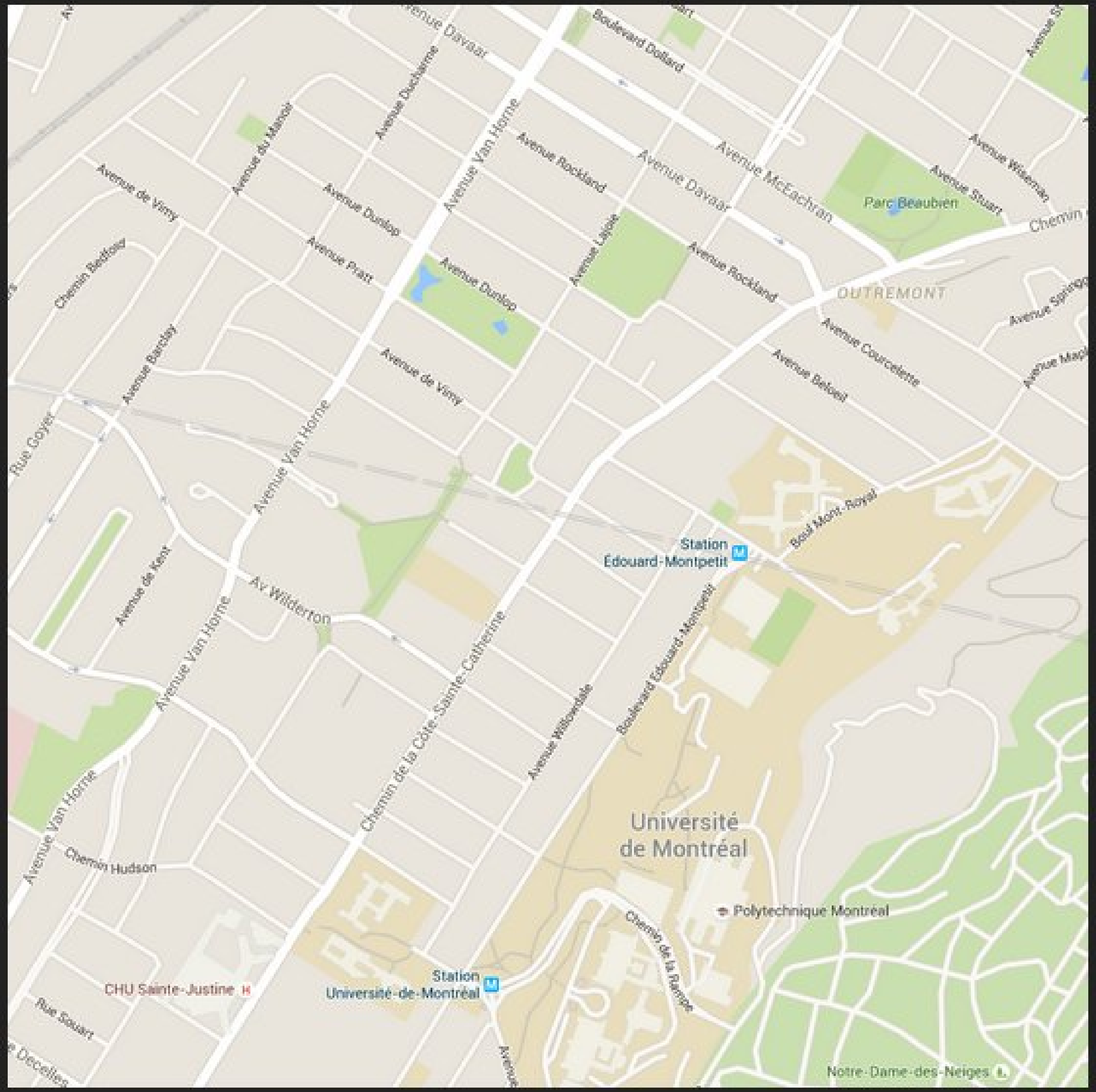
Interraction between *brain* regions on a very large scale

Related to but not equivalent to action potentials

What is the link?



Tractography : Road network



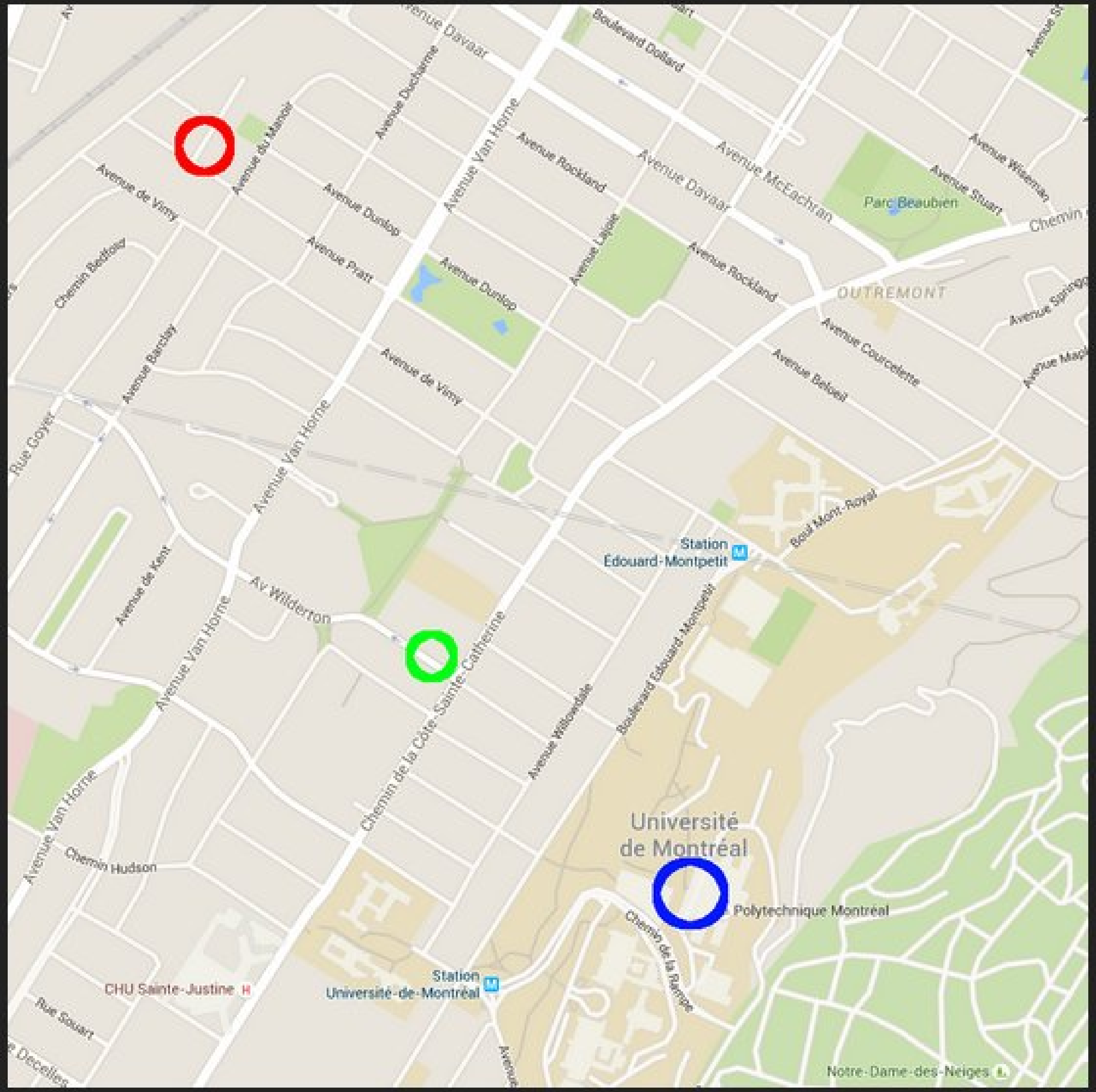
What is the shortest path from A to B?

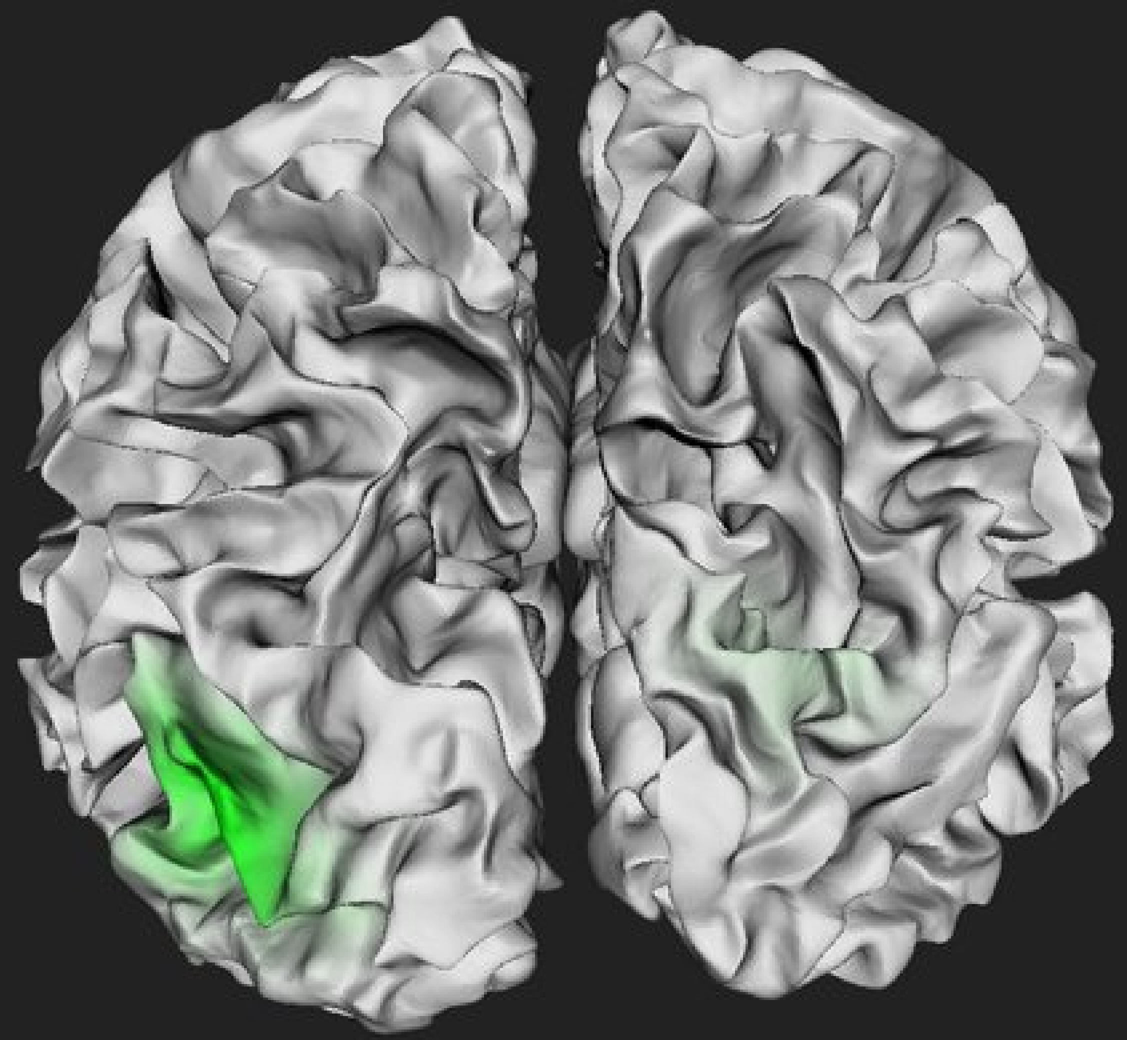
What are all the paths from A to B?

No directionality

No notion of 'in use'

Functional data : Traffic camera





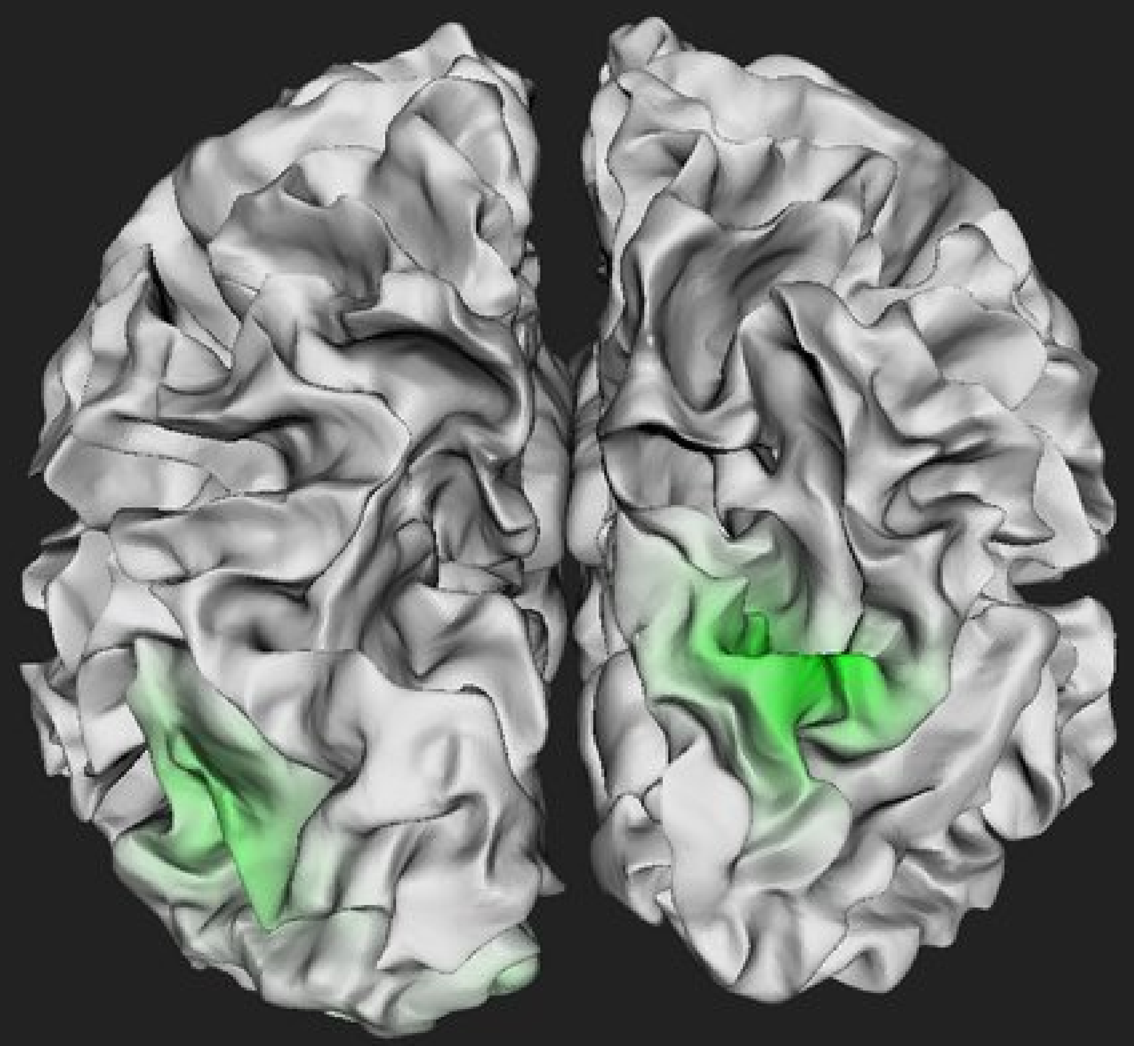
8:00 - Home, 8:22 - Gas station, 8:47 - Work

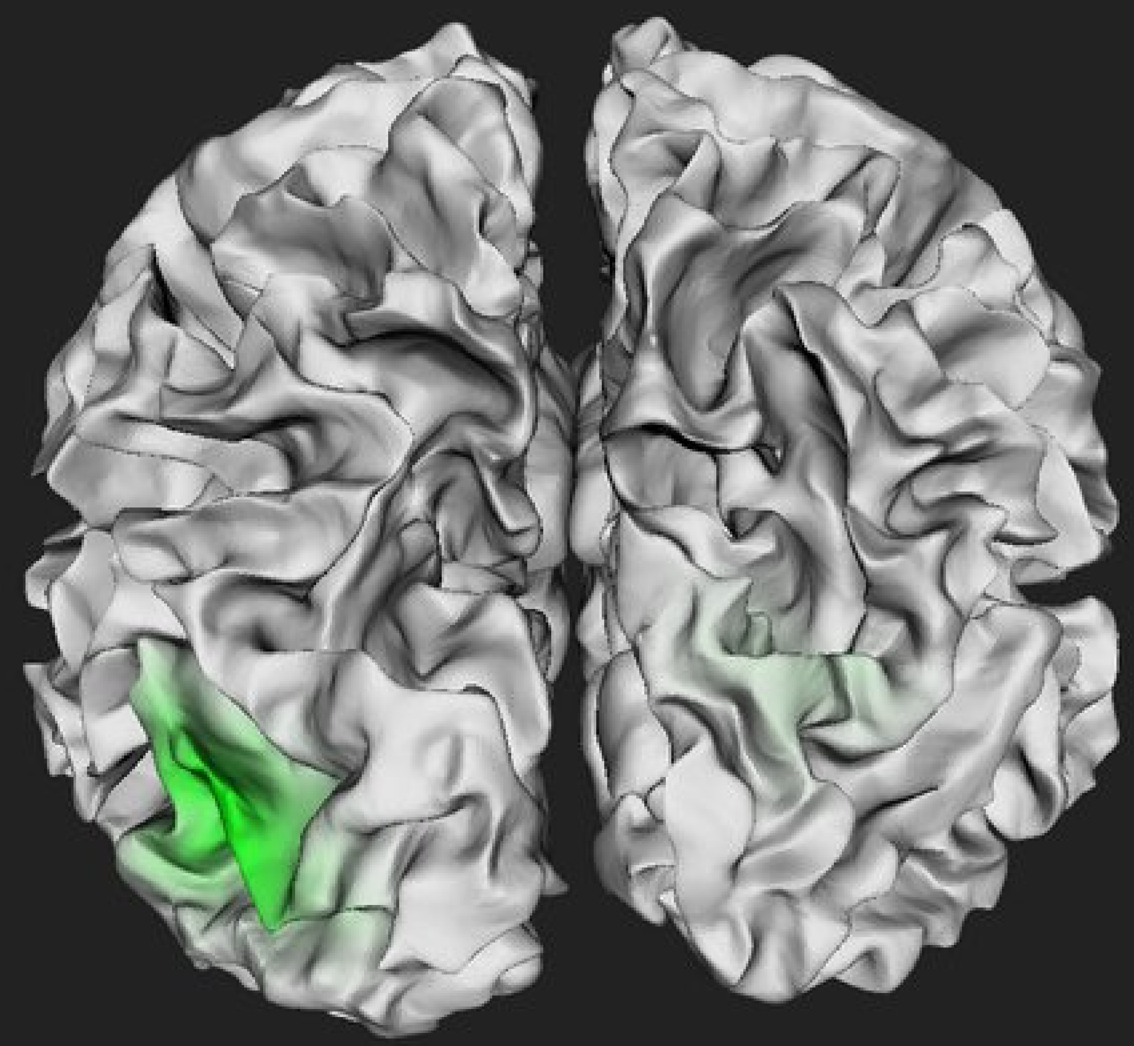
Enough information to recover the route taken?

Only if the the sampling rate is fast enough!

Tractography + functional data

Information travels at 6 m/s





Delay: 20 ms

Connection 1: 120mm

Connection 2: 240mm

Tractography + functional data

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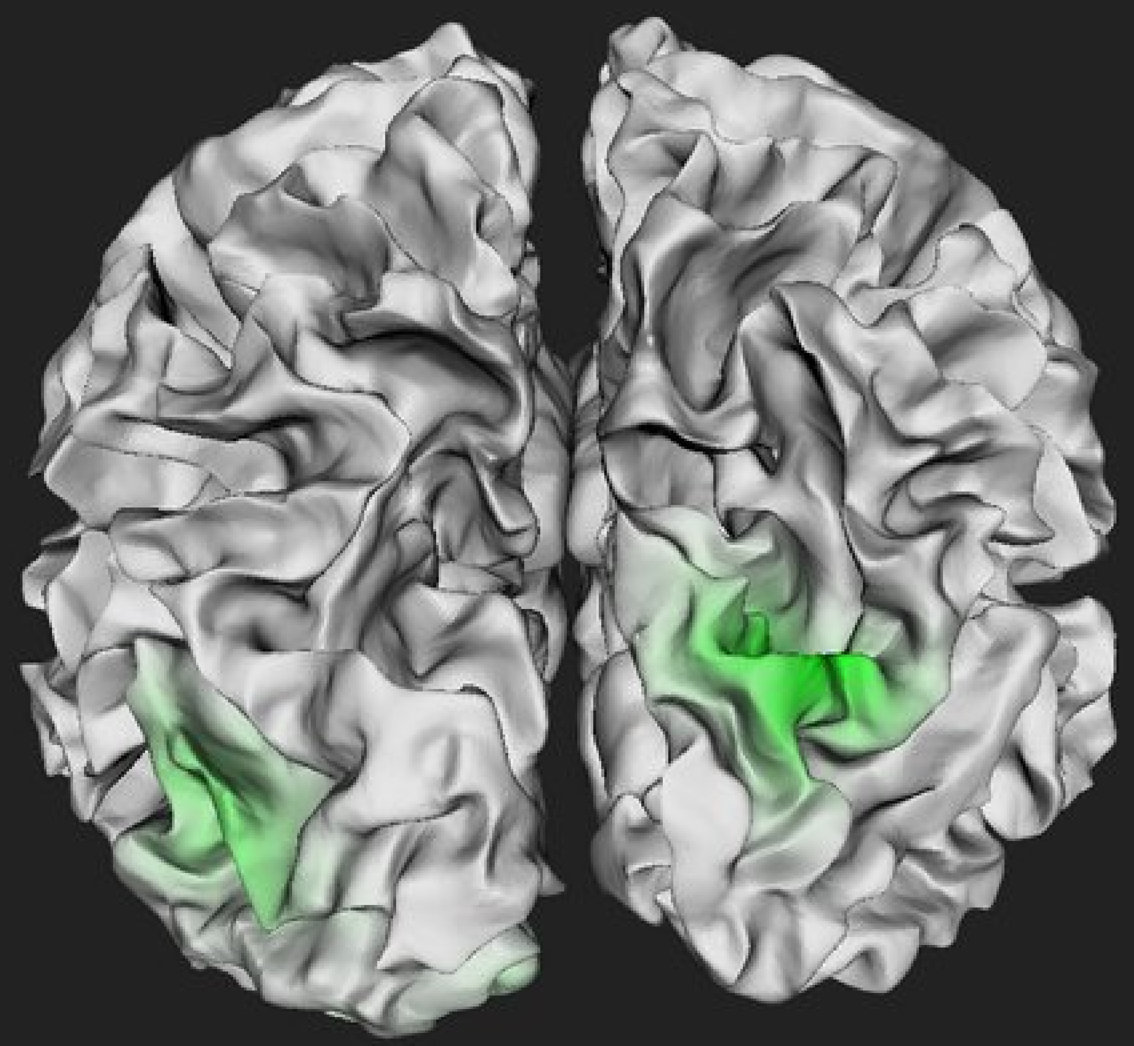

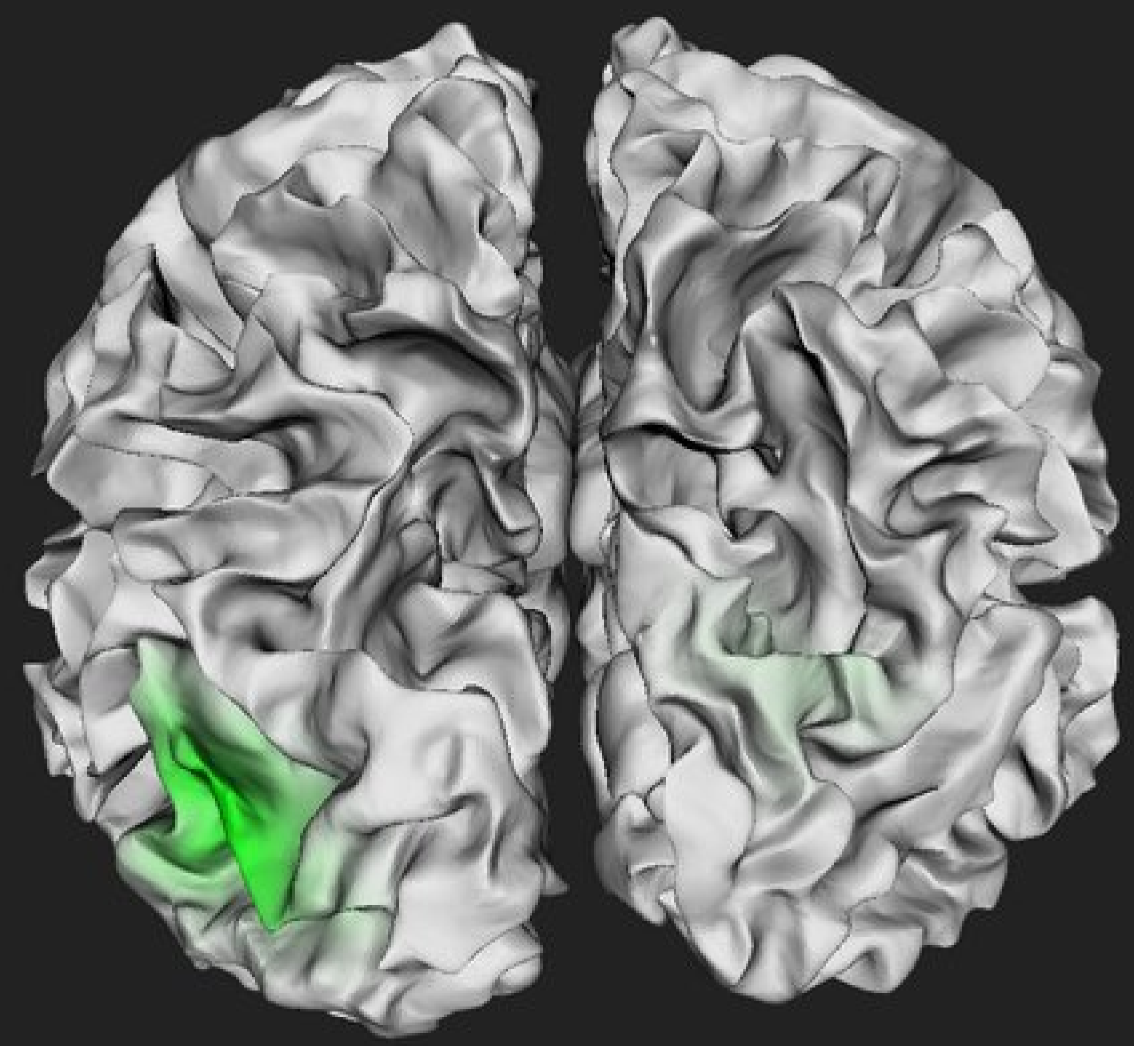

Delay: 40 ms

Connection 1: 120mm

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Tractography + functional data

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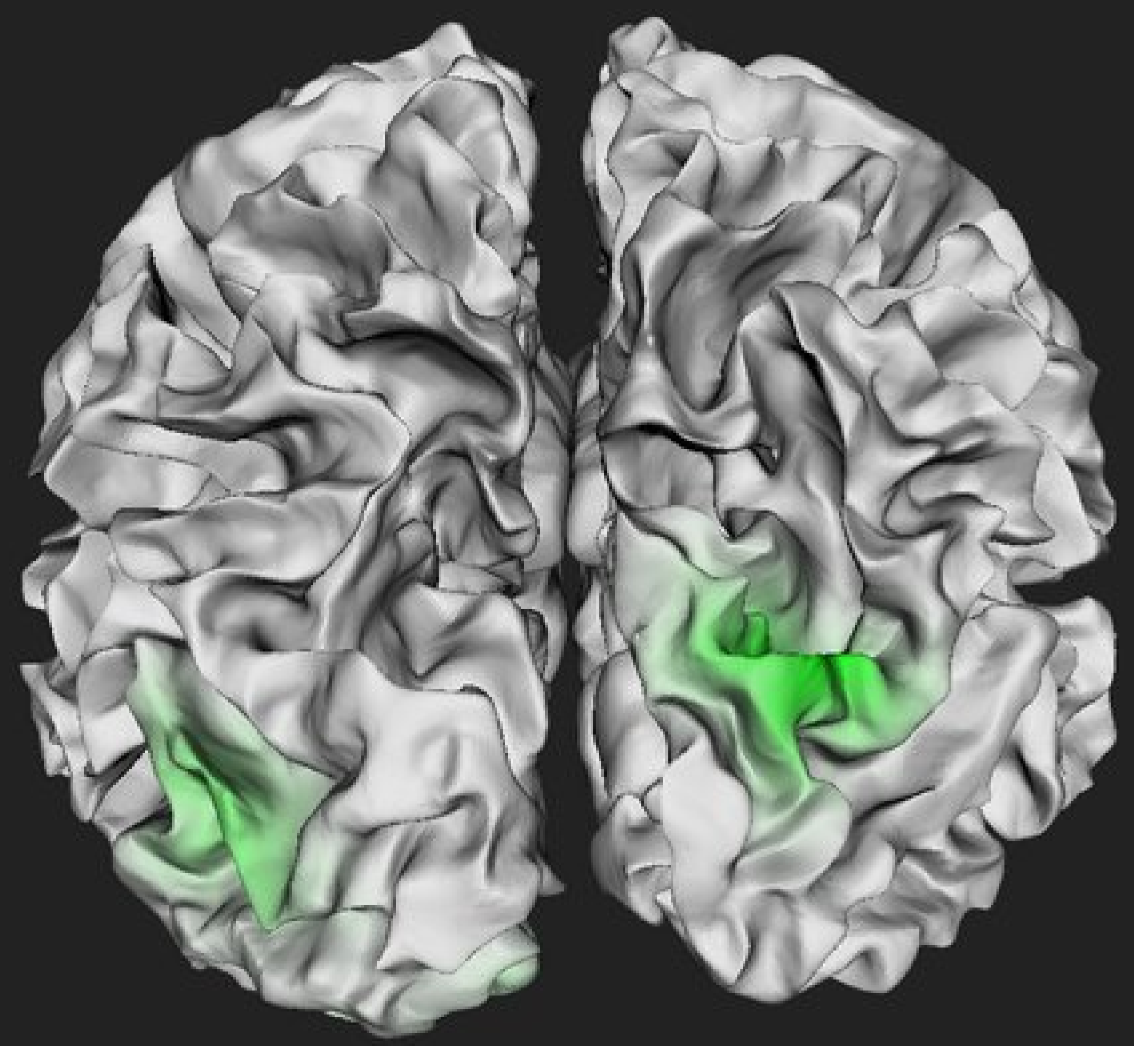
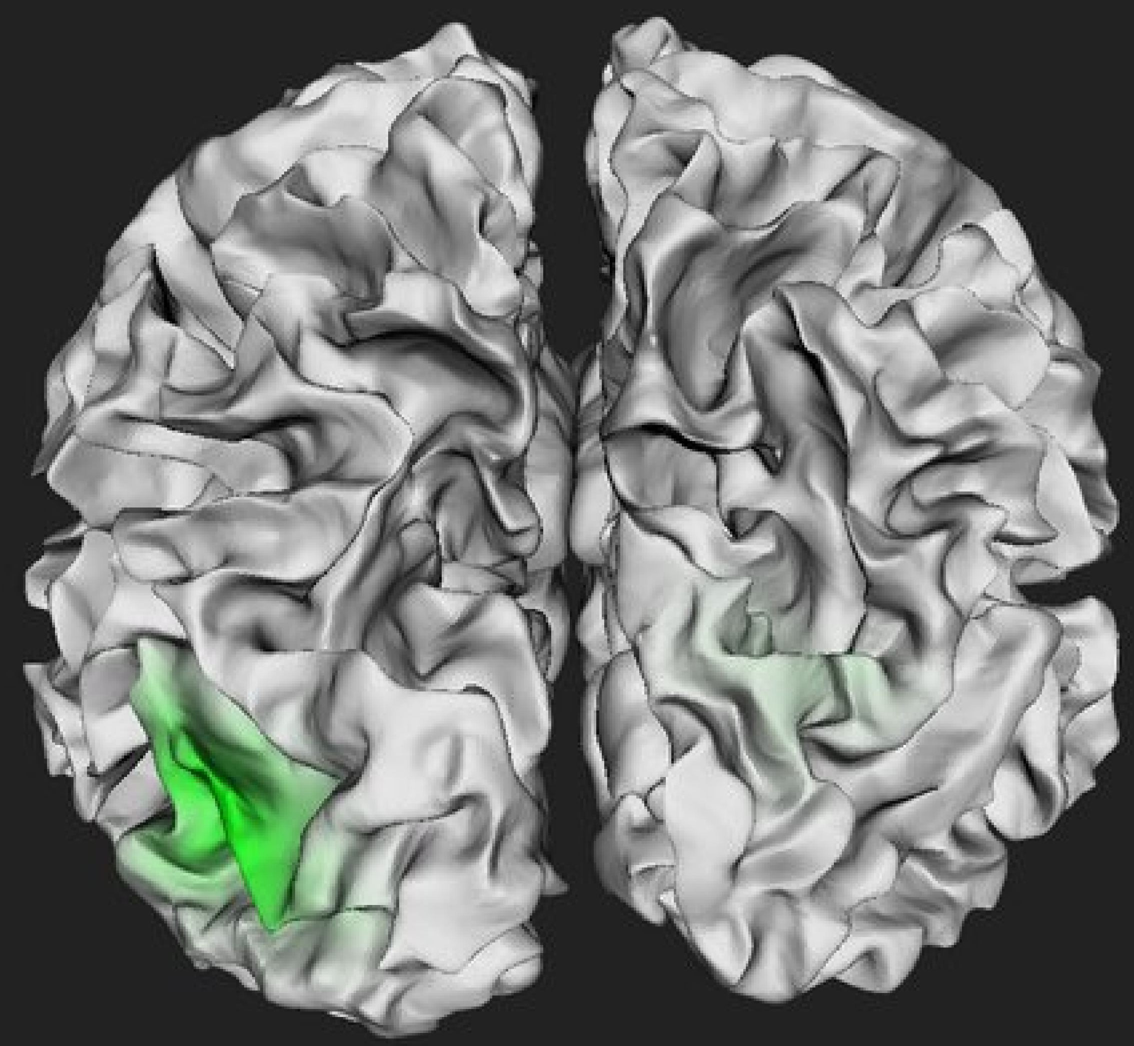


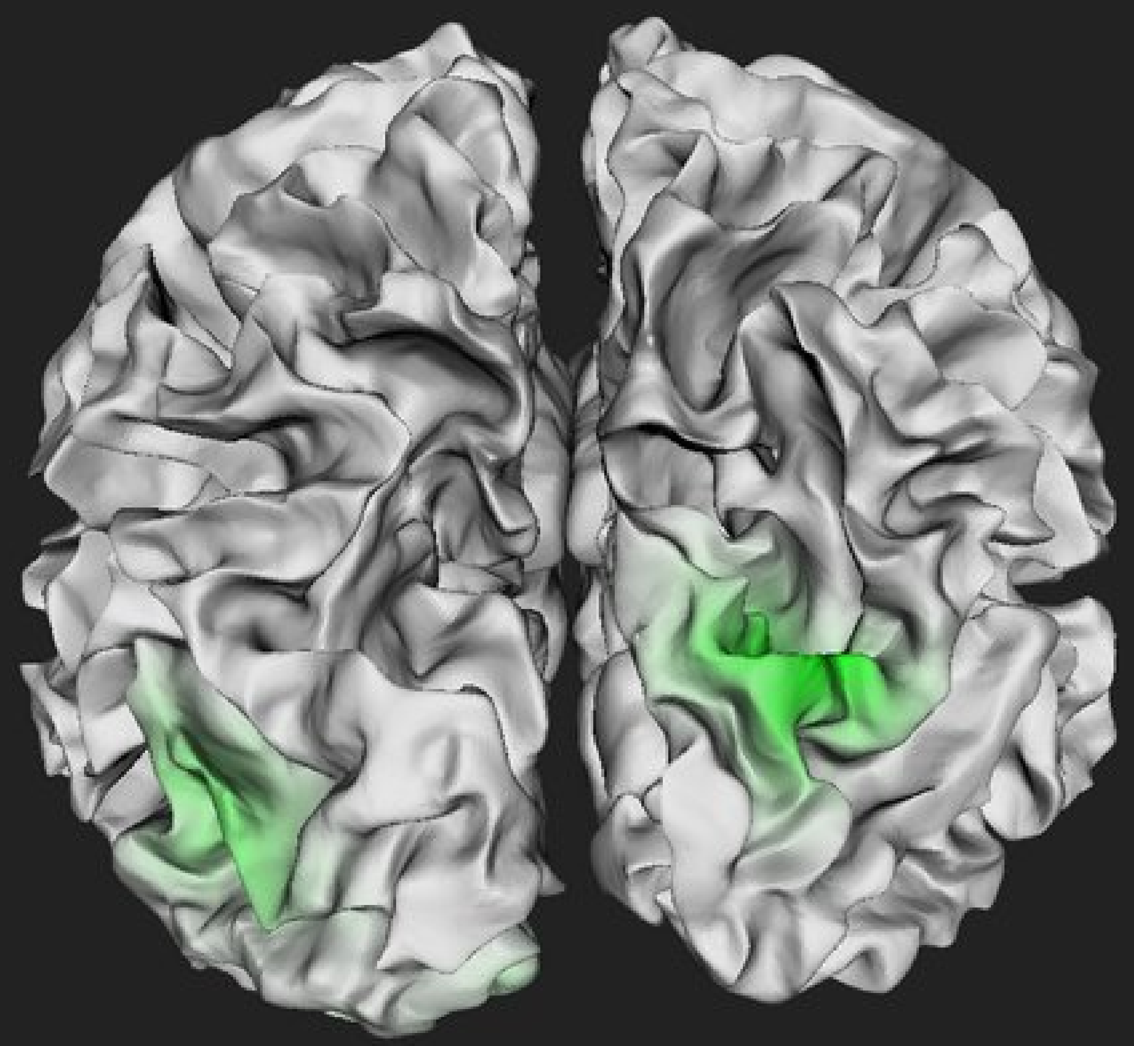


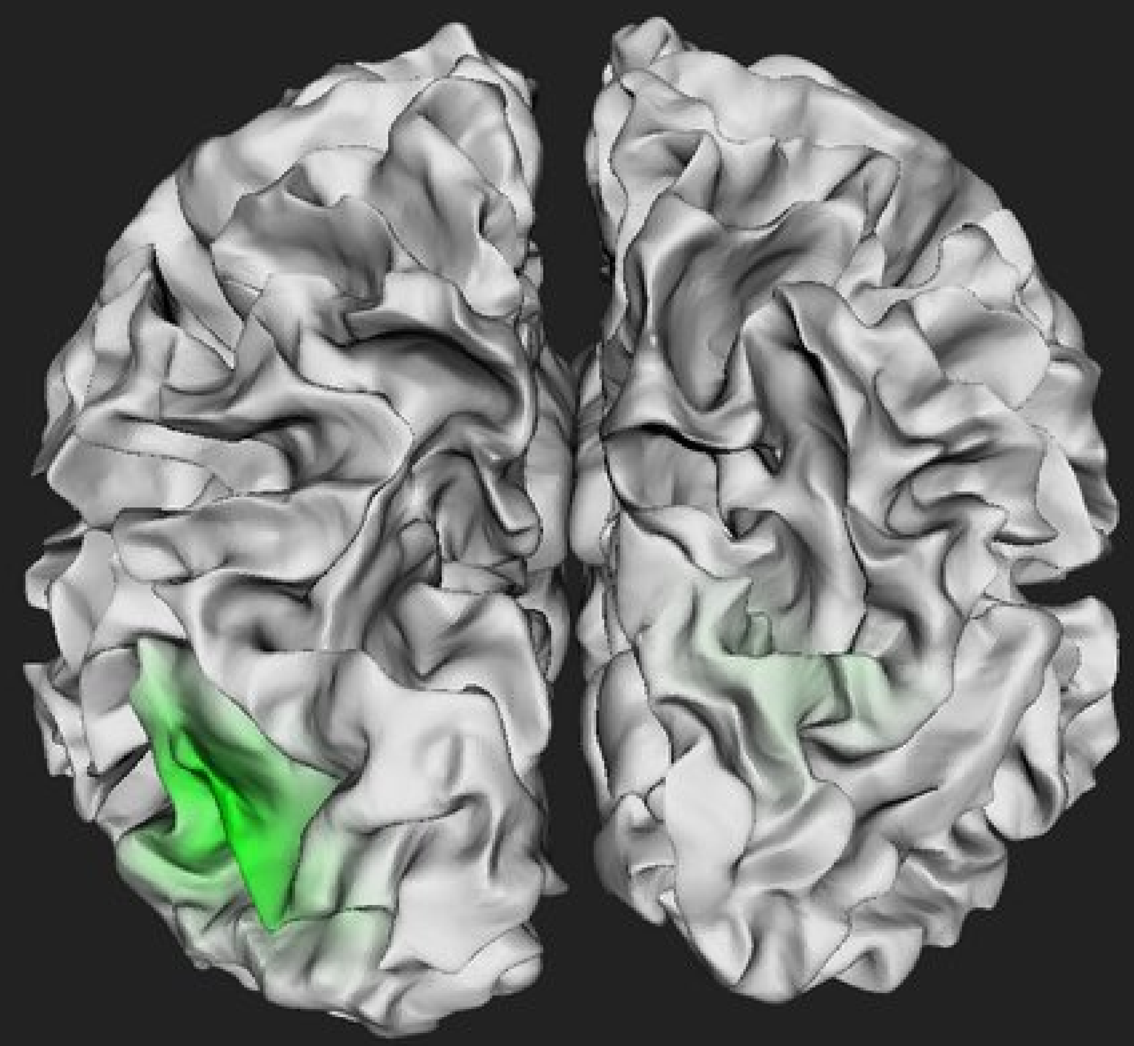
Delay: 40 ms

Connection 2: 240mm

Tractography + functional data

Information travels at 6 m/s





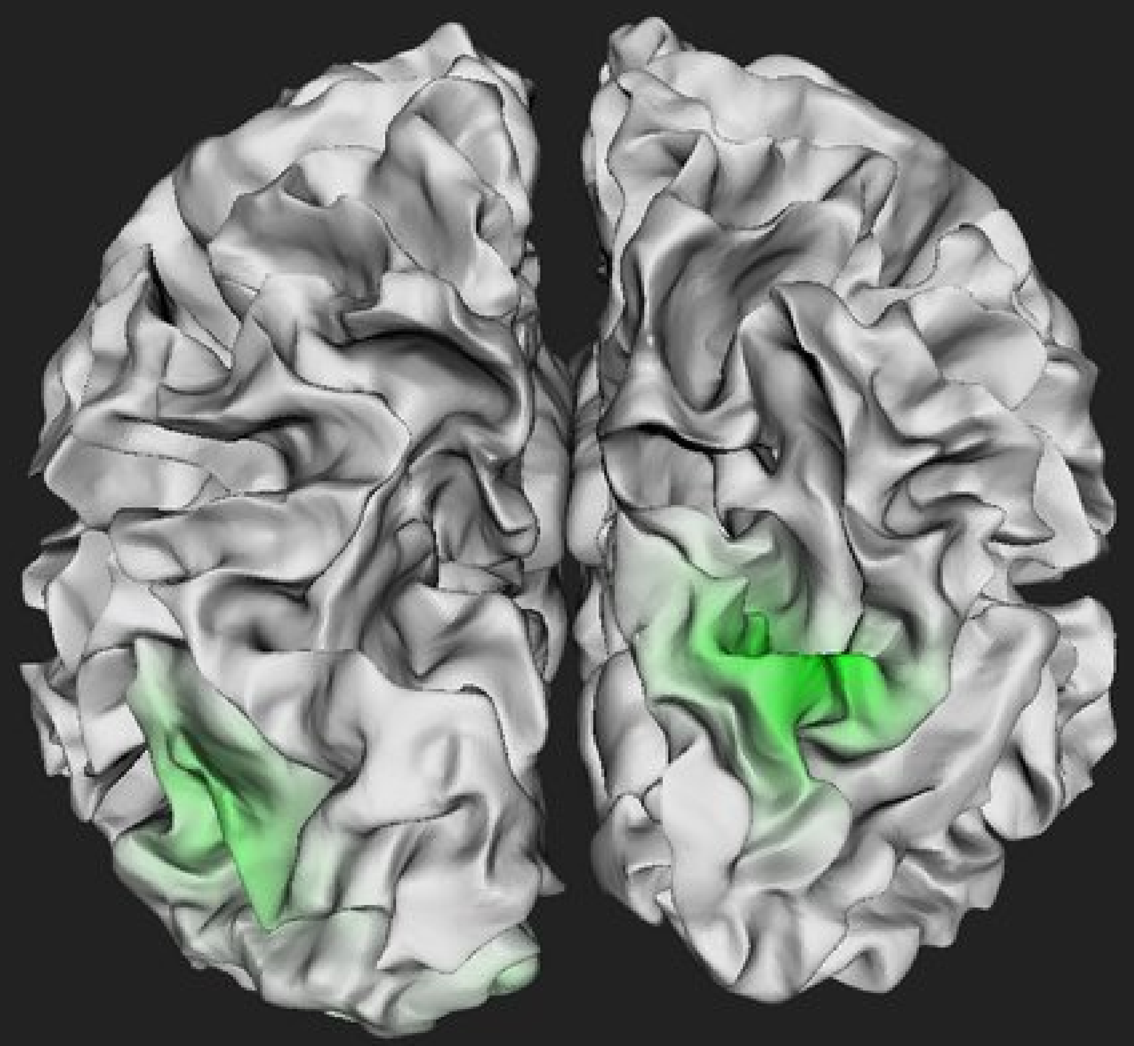
Delay: 30 ms

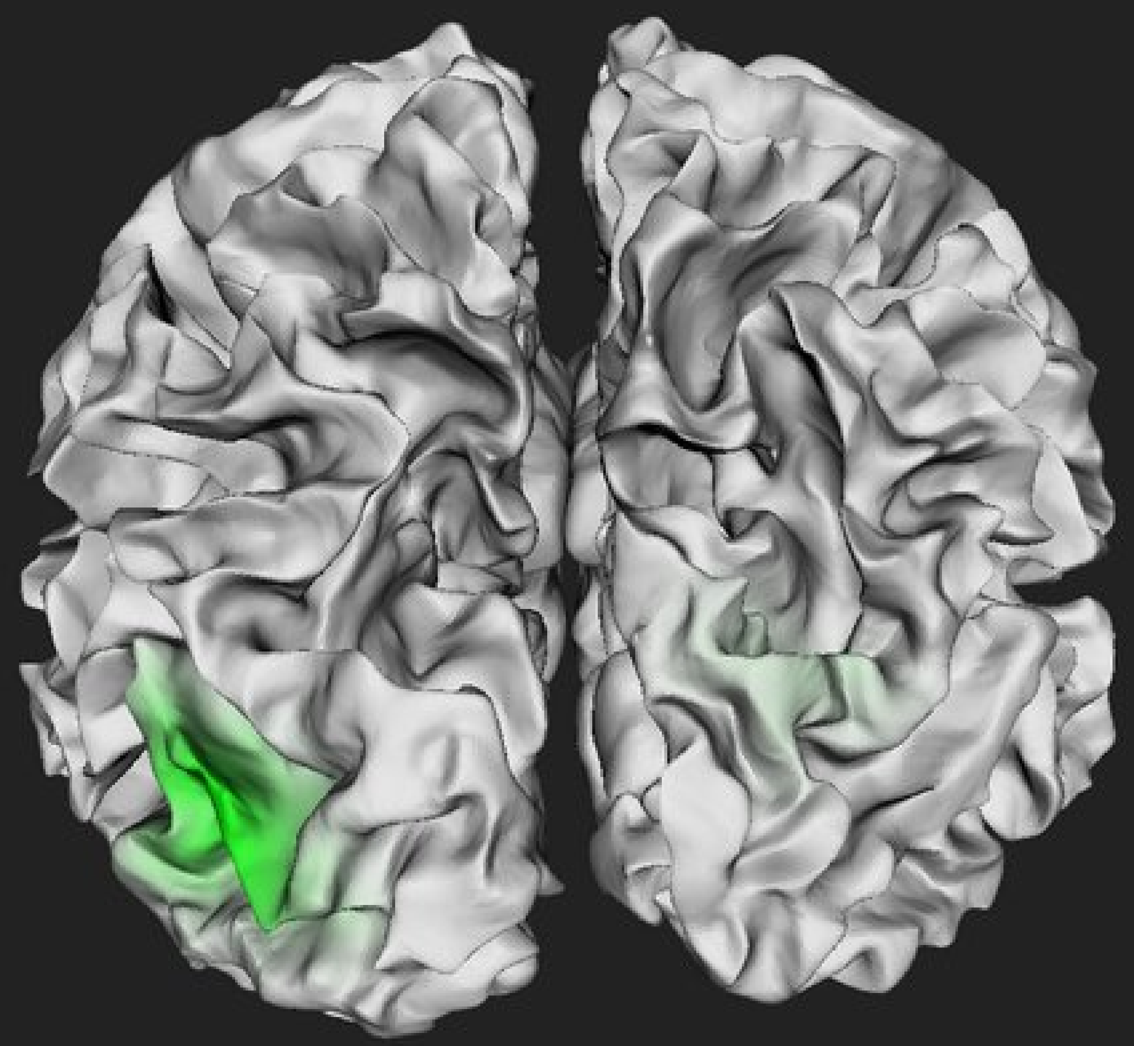
Connection 1: 120mm

Connection 2: 240mm

Tractography + functional data

Information travels at 6 m/s





Delay: 30 ms

MEEG INVERSE PROBLEM

Sources to measurements (forward model)

$$m_t = Gx_t$$

Measurements to sources (inverse problem)

$$x_t = G^{-1}m_t$$

$$X = G^{-1}M$$

Vectorized problem

$$x = \bar{G}^{-1}m$$

DIFFUSION MRI AND MEEG

Autoregressive models

$$x_t = \sum_{p=1}^{P} A_p x_{t-p}$$

[Maksymenko et al. 2017, Belaoucha et al. 2017, Fukushima et al. 2014]

Connectivity Informed Maximum Entropy on the Mean

$$D_{KL}(p(x)) - \lambda(m - G\int xp(x)dx) - \lambda_0(1 - \int dp(x))$$

[Deslauriers-Gauthier et al. MICCAI 2017, Gallardo et al. 2017]

CIMEM

Connectivity Informed Maximum Entropy on the Mean

[Deslauriers-Gauthier et al. MICCAI 2017, Amblard et al. 2004]

$$\underset{p(x),\lambda,\lambda_0}{\text{minimize}}\ \mathcal{L}(p(x),\lambda,\lambda_0)$$

where

$$\mathcal{L}(p(x),\lambda,\lambda_0) = D_{KL}(p(x)) - \lambda(m - G\int xp(x)dx) - \lambda_0(1 - \int dp(x))$$

with

$$D_{KL}(p(x)) = \int_{-\infty}^{\infty} p(x)\ln\frac{p(x)}{\mu(x)}dx$$

[Amblard et al. 2004, Jaynes 1957]

$$\underset{p(x),\lambda,\lambda_0}{\text{minimize}}\ \mathcal{L}(p(x),\lambda,\lambda_0)$$

is completely determined by

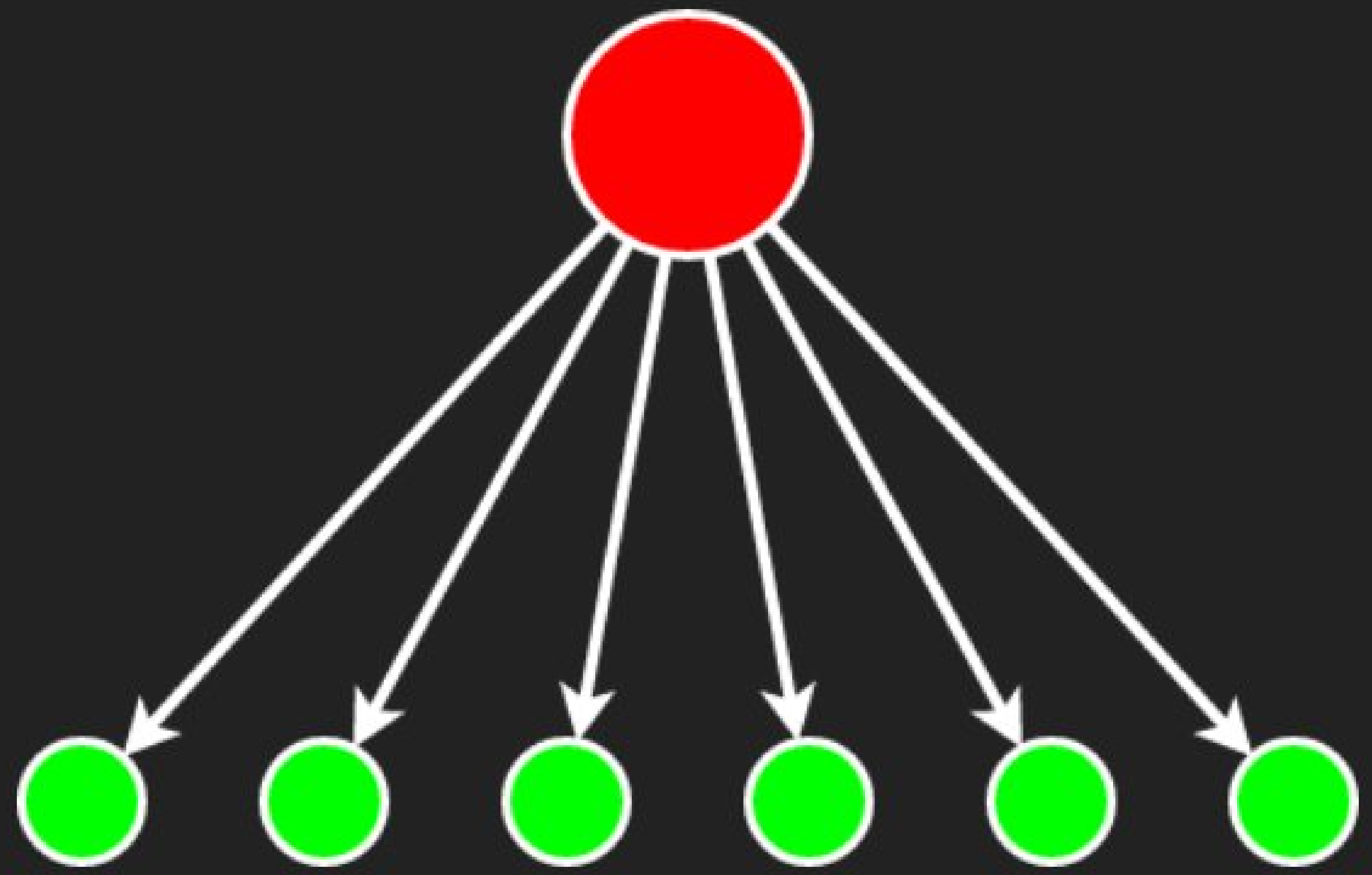
$$\lambda^* = \underset{\lambda}{\text{argmin}}\ \ \ln Z(\lambda) - (\lambda^T m - \lambda^T \Sigma_\epsilon^2 \lambda)$$

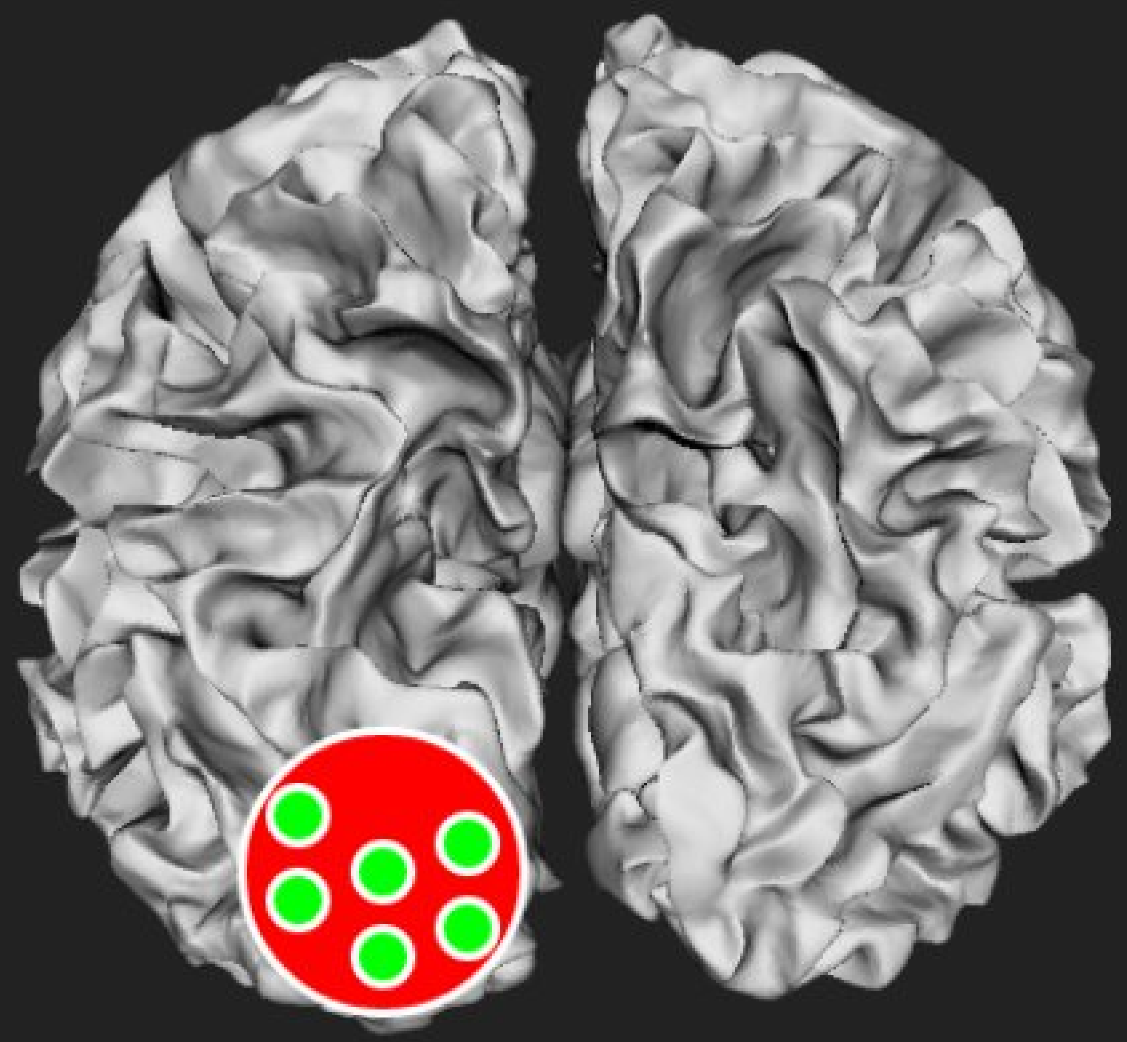
where

$$Z(\lambda) = \int \exp(\lambda^T G x) d\mu(x)$$

$d\mu(x)$ encodes all of our prior knowledge

Sources are grouped into N_S clusters with a state S_k

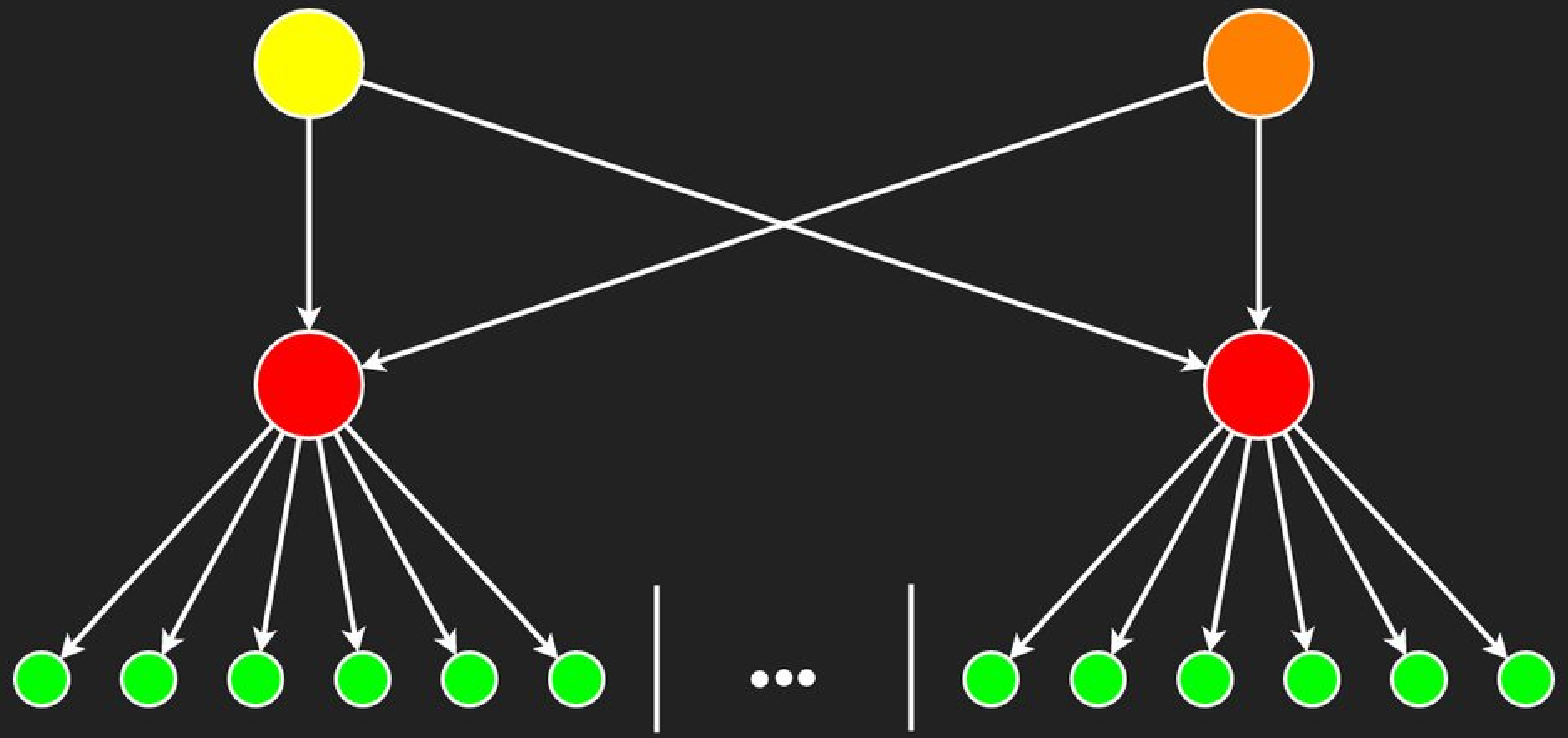


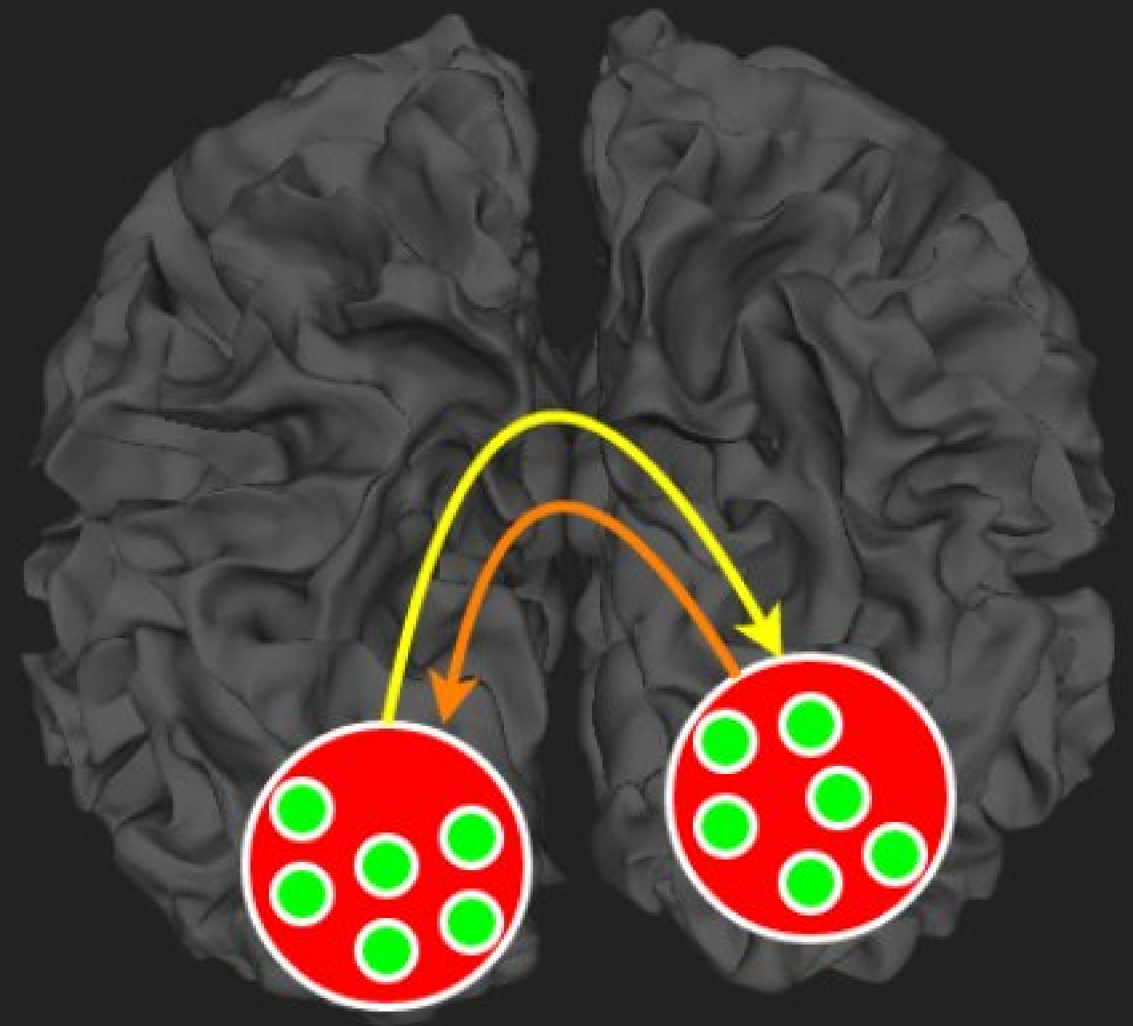


The intensities of the source x_k depend on the state S_k

$$d\mu(x, S) = \pi(S) \prod_{k=1}^{K} d\mu(x_k | S_k)$$

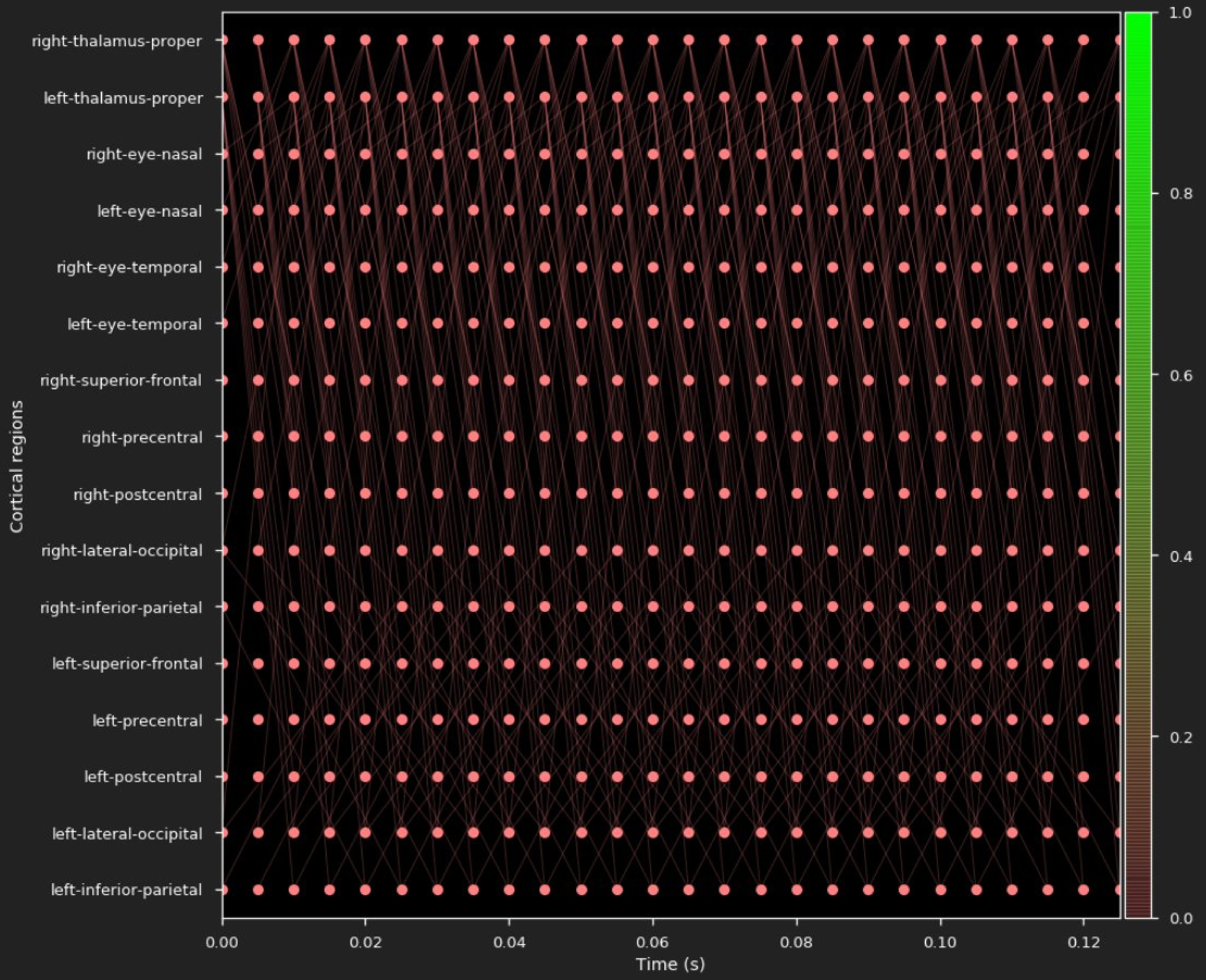
Pairs of clusters are connected by N_C connections with a state C_i





$$d\mu(x, S, C) = \prod_{i=1}^{N_C} \varphi(C_i) \prod_{k=1}^{N_S} \pi(S_k | C_{\gamma(k)}) d\mu(x_k | S_k)$$

Complete model



$d\mu(x, S, C)$ is a Bayesian network

$$d\mu(x) = \sum_{\{C\}} \prod_{i=1}^{N_C} \varphi(C_i) \sum_{\{S\}} \prod_{k=1}^{N_S} \pi(S_k | C_{\gamma(k)}) d\mu(x_k | S_k)$$

We can now solve

$$\lambda^* = \underset{\lambda}{\operatorname{argmin}} \; \ln Z(\lambda) - (\lambda^T m - \lambda^T \Sigma_\epsilon^2 \lambda)$$

where

$$Z(\lambda) = \int \exp{(\lambda^T G x)} d\mu(x)$$

$$Z(\lambda) = \int \exp\left(\lambda^T G x\right) d\mu(x) = \sum_{\{C\}} \prod_{i=1}^{N_C} \varphi(C_i) \prod_{k=1}^{N_S} Z_k(\lambda)$$

with

$$Z_k(\lambda) = \sum_{\{S\}} \pi(S_k | C_{\gamma(k)}) \int \exp\left(\lambda^T G_k x_k\right) d\mu(x_k | S_k)$$

$Z(\lambda)$ is marginalization over the whole network ... what if we leave out C_i?

$$Z^*(C_i) = \frac{1}{Z(\lambda^*)} \sum_{\{C\} \setminus C_i} \prod_{i=1}^{N_C} \varphi(C_i) \prod_{k=1}^{K} Z_k(\lambda^*)$$

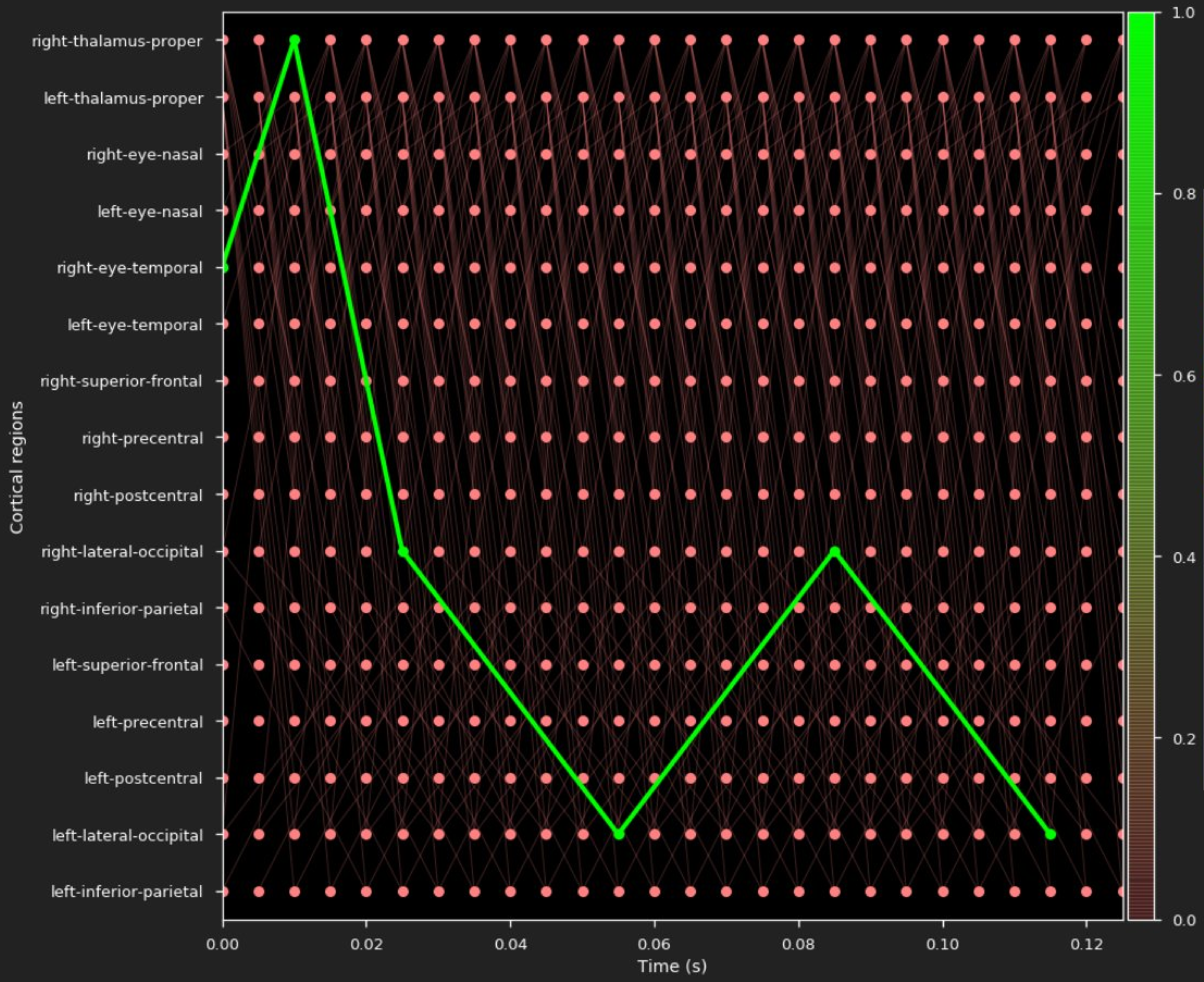
$Z^*(C_i = c_n)$ is the *posterior* probability that the i^{th} connection is in a state c_n

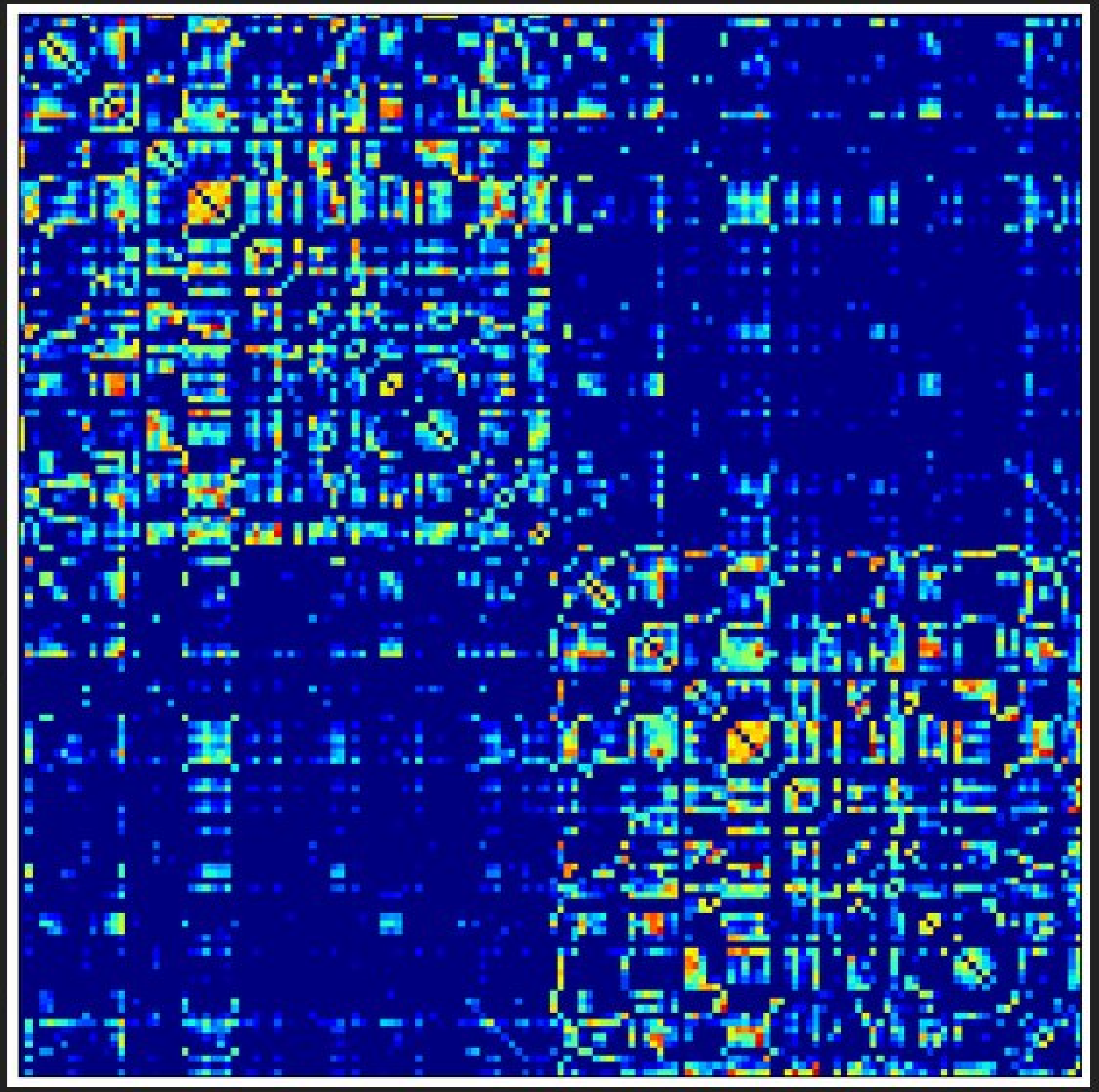
CIMEM IN 4 STEPS

Given M/EEG data, clusters, and connections:

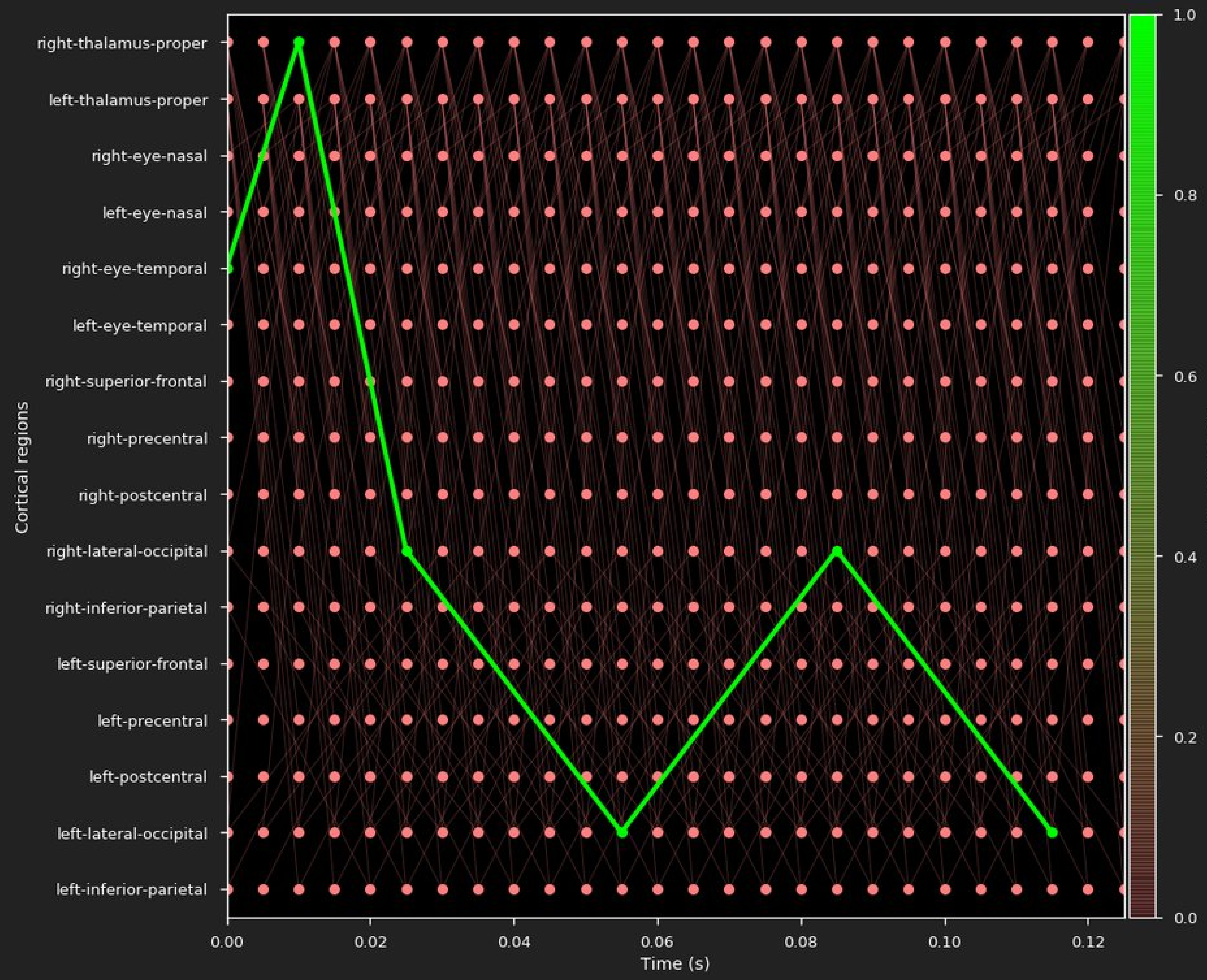
- Build your Bayesian network $d\mu(x, S, C)$
- Fit your data to find λ^*
- Compute posterior probabilities $Z^*(C_i)$ and source intensities x
- Look at your results!

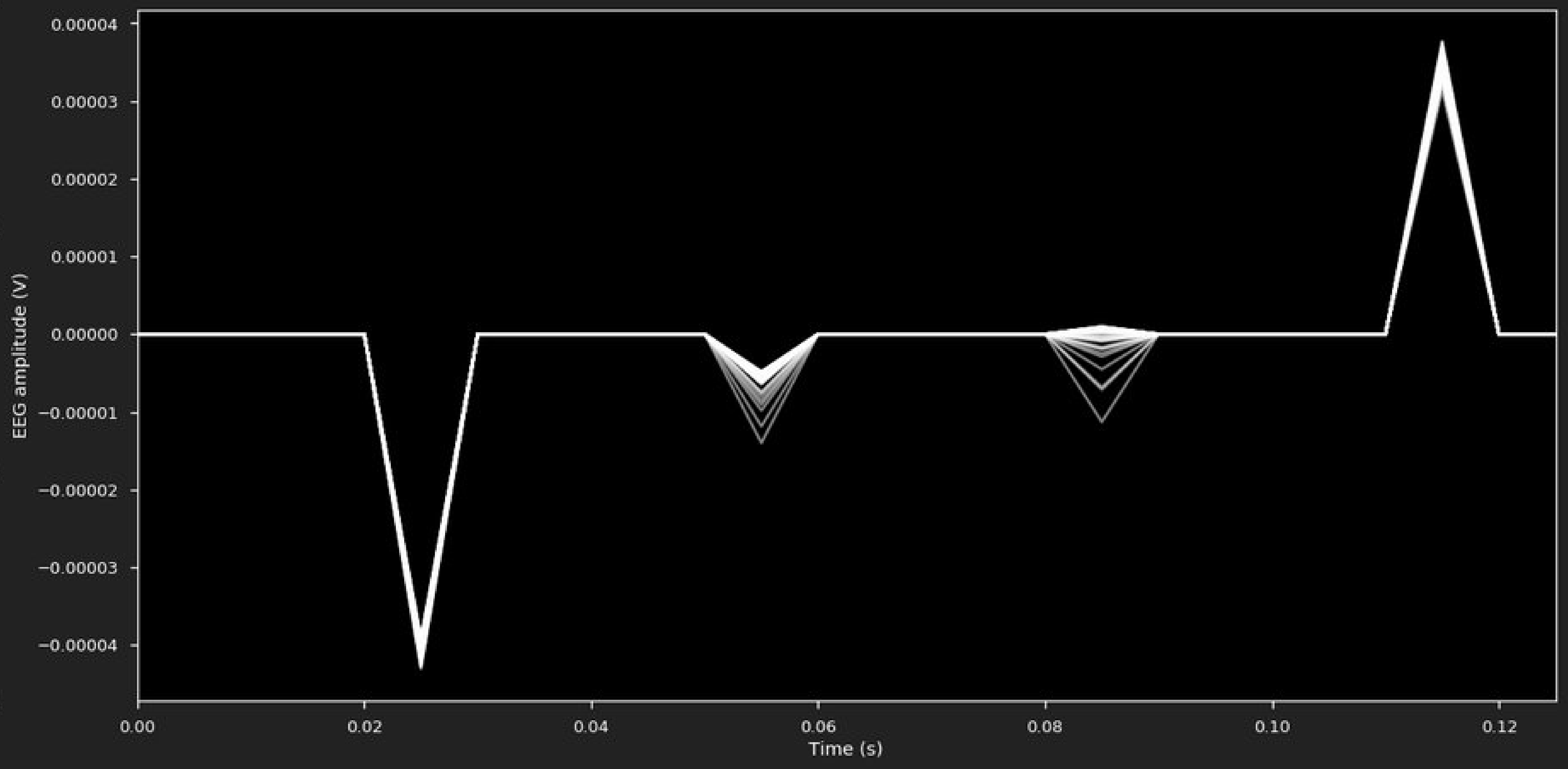
Information flow diagram (dynamic connectome?)



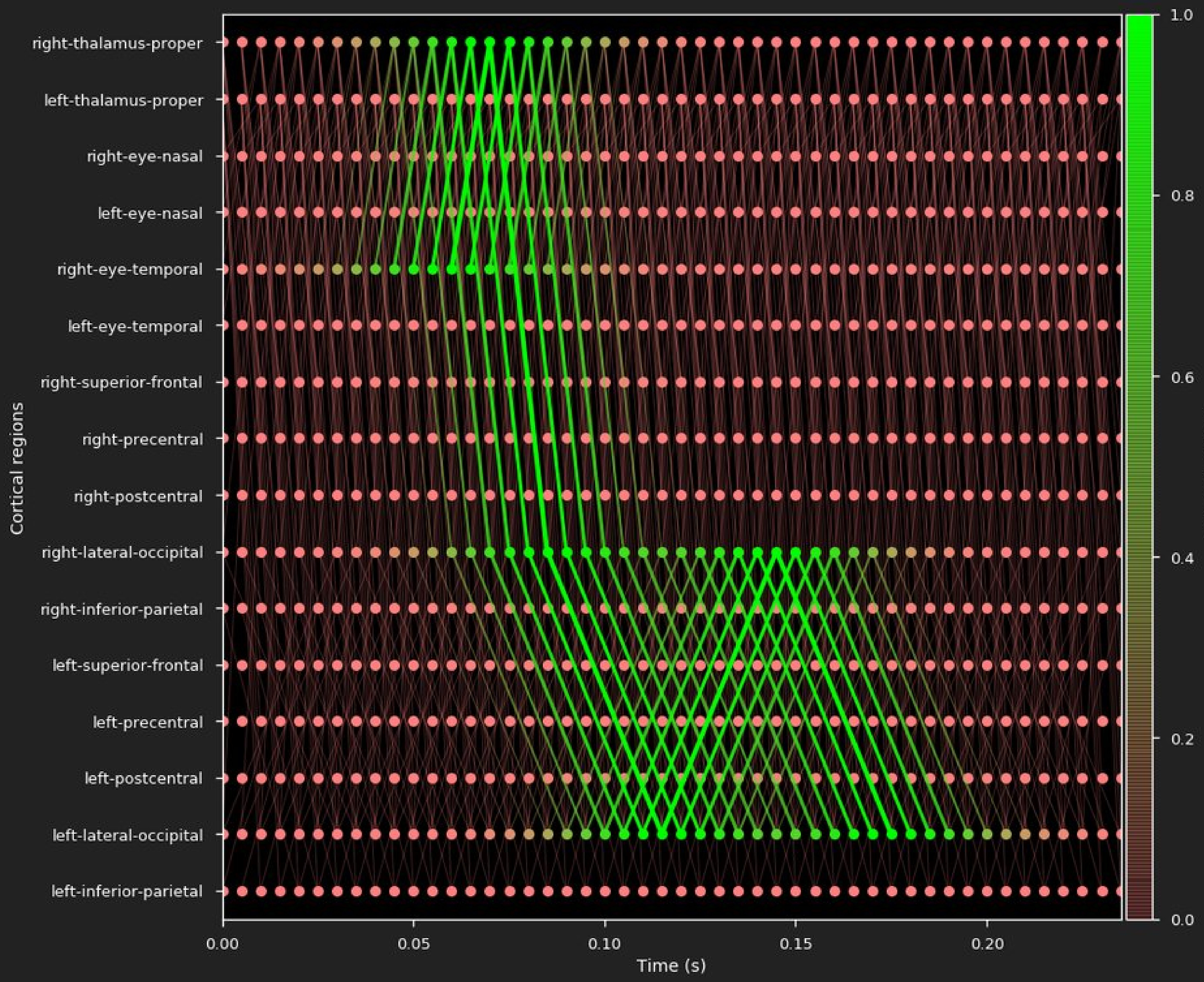


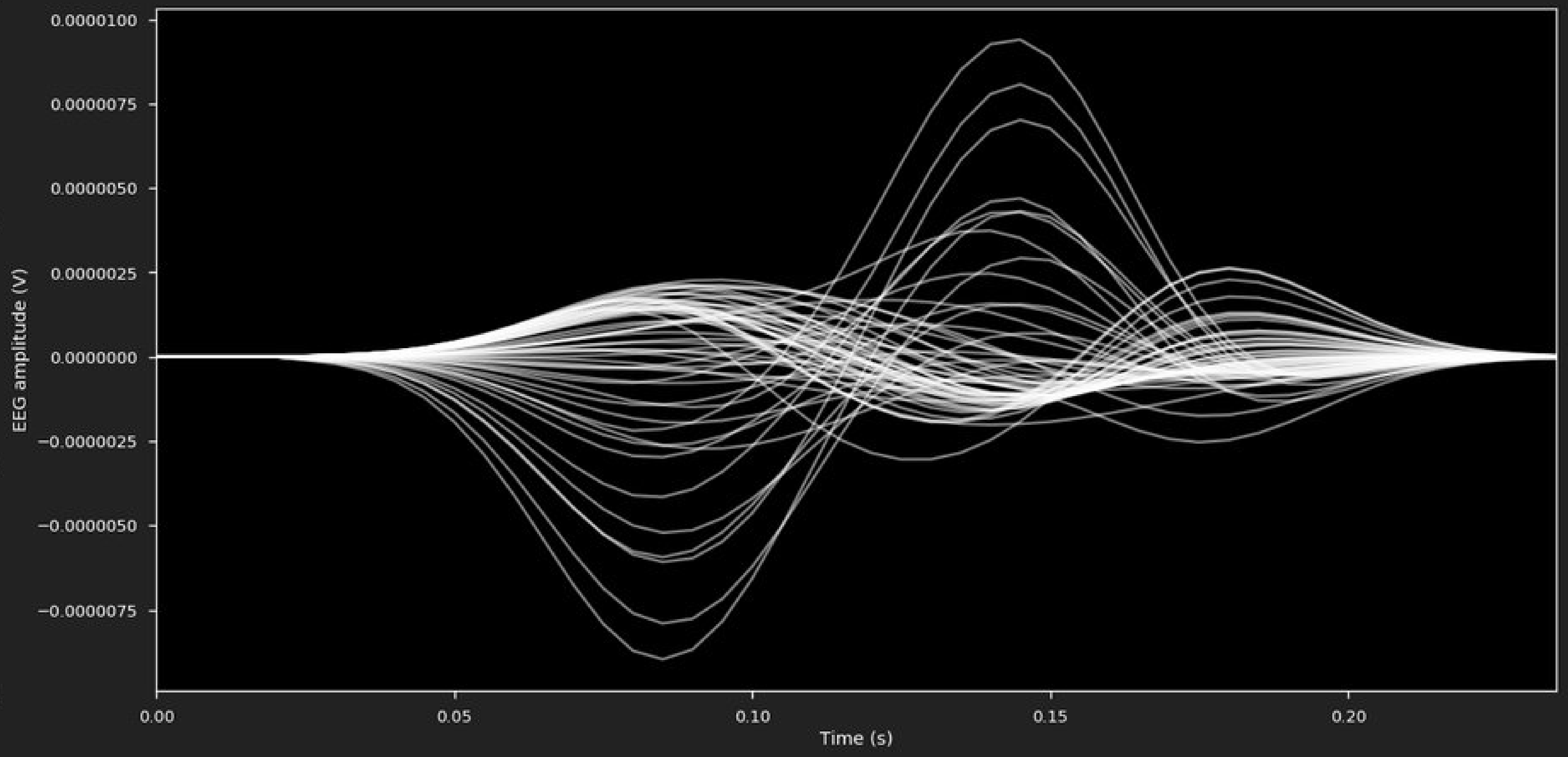
Information flow diagram





Information flow diagram





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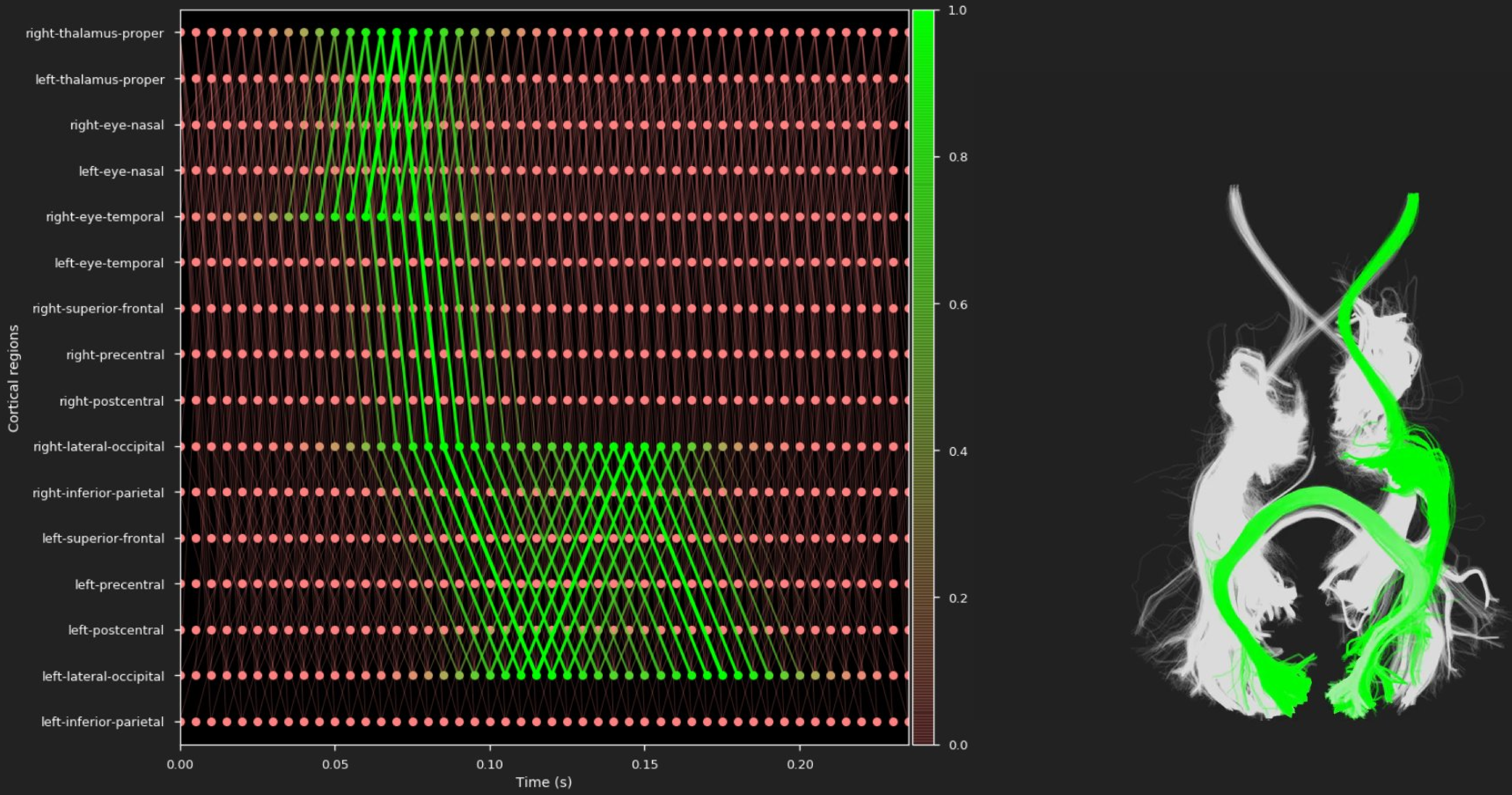


PIPELINE OVERVIEW

Use your favorite tool to:

- Acquire dMRI and (task) M/EEG data
- Compute a tractogram (DIPY, SCIL)
- Extract the cortical, scalp, and skull surfaces (FreeSurfer)
- Register your sensors, surfaces, and streamlines (?)
- Compute your forward operator (OpenMEEG, MNE)
- Generate cortical clusters (logpar, FreeSurfer)
- Generate white matter connections (DIPY)
- Preprocess your M/EEG data (Brainstorm, MNE)
- Compute information flow and source intensities (CIMEM)

Result on subject 109123 of the HCP

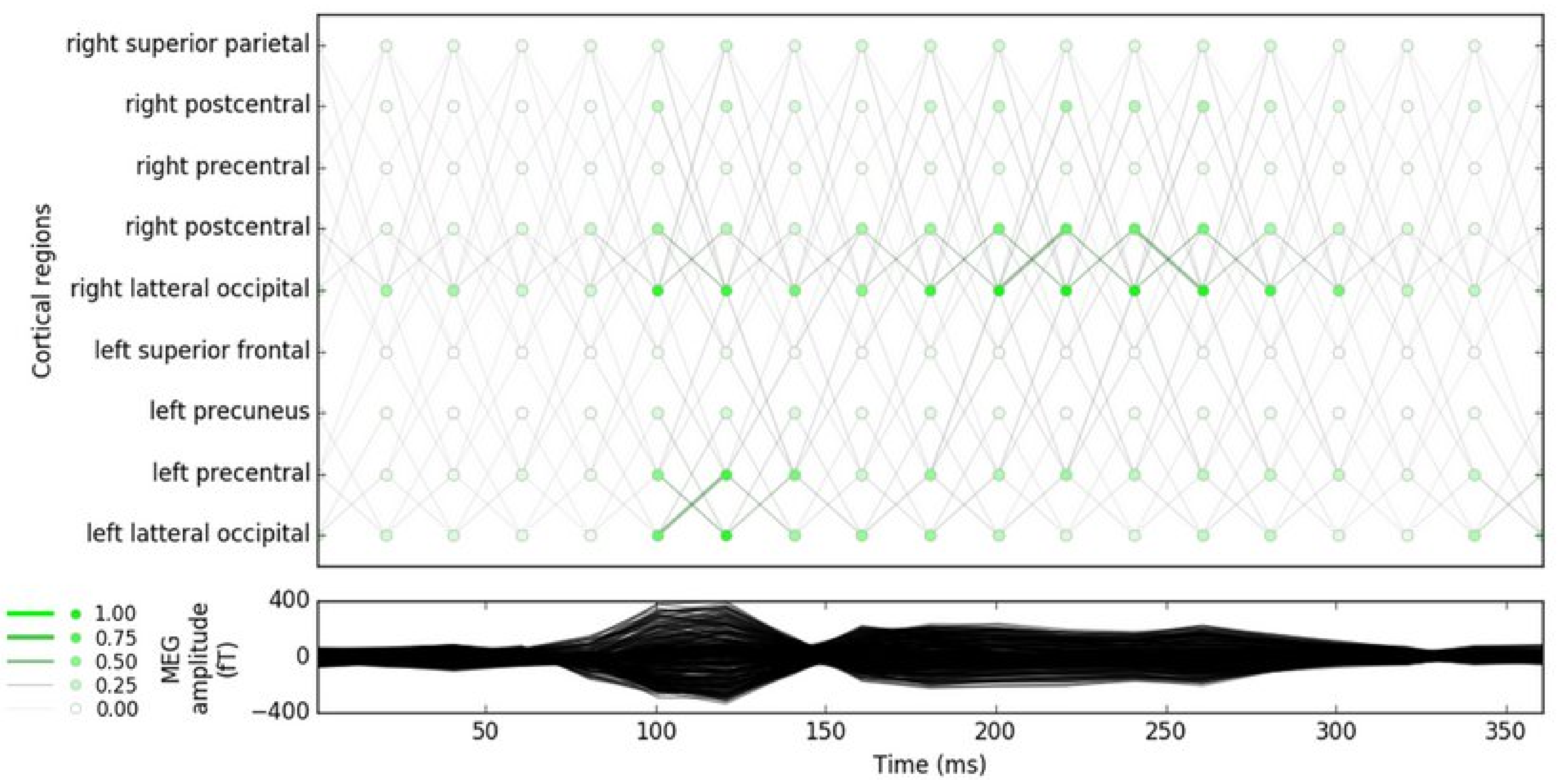


Figure 1. Information flow during the left hand movement task and corresponding MEG measurements. The cortical parcellation is connectivity driven, however cortical regions are identified using the overlapping Desikan-Killiany atlas for clarity.

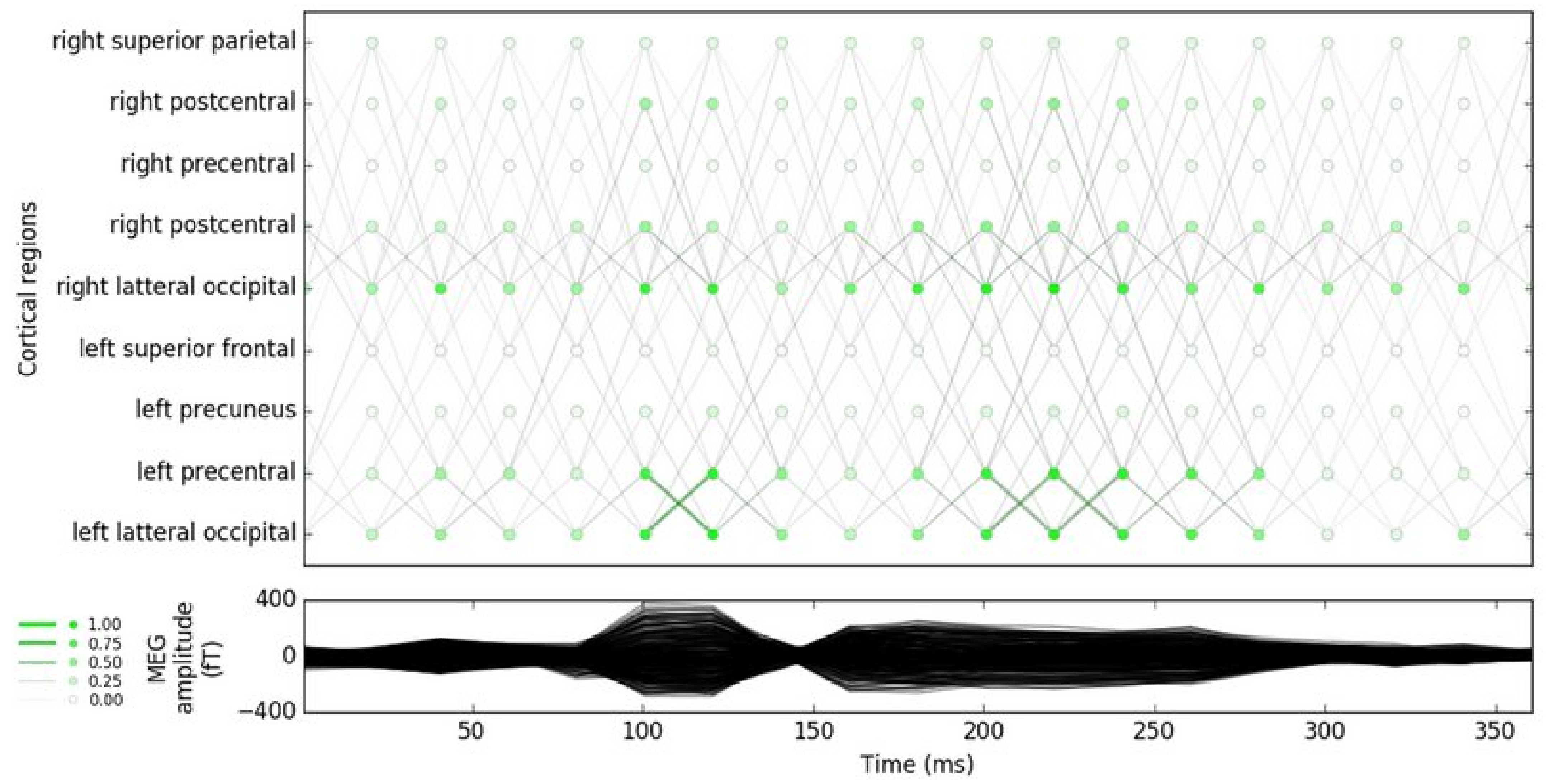
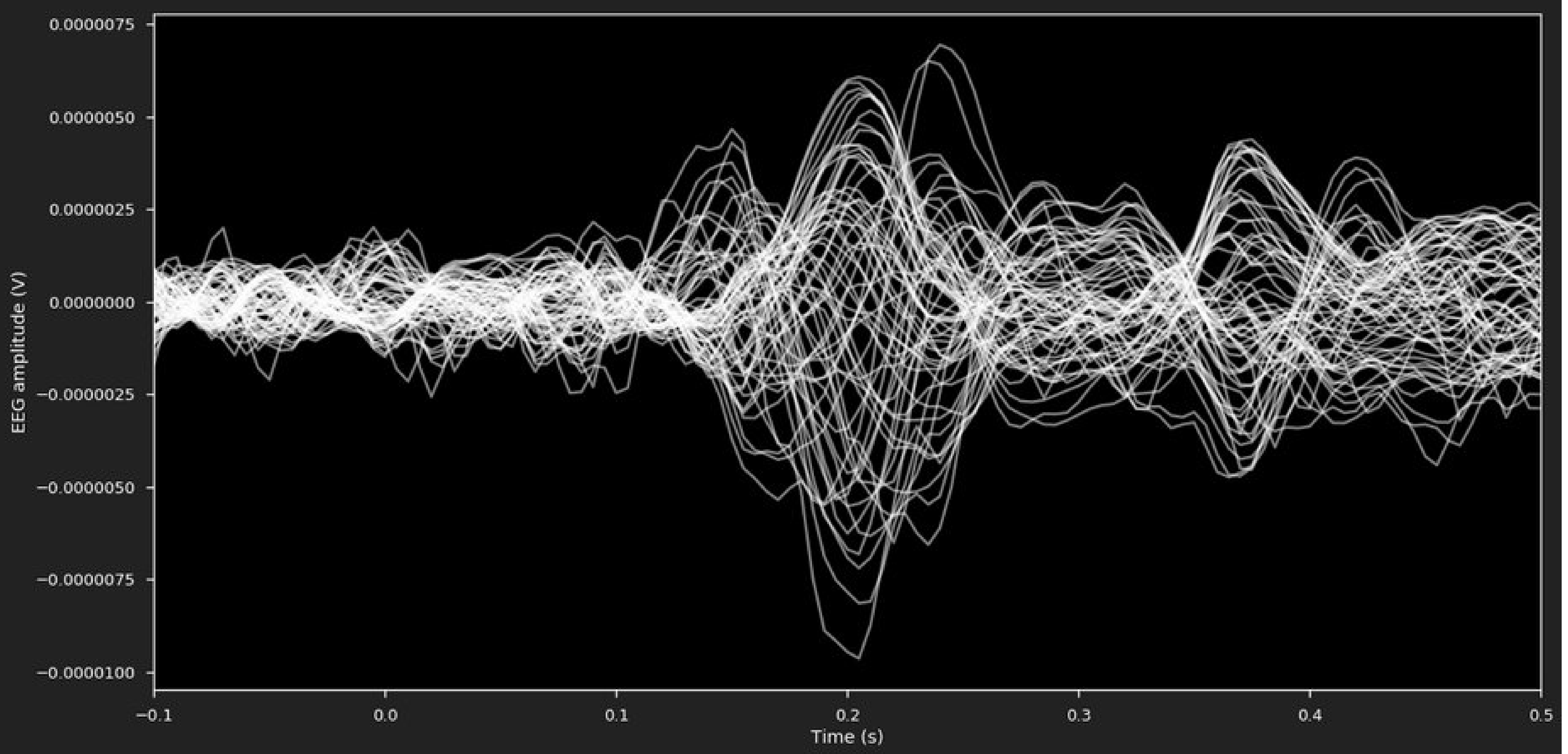
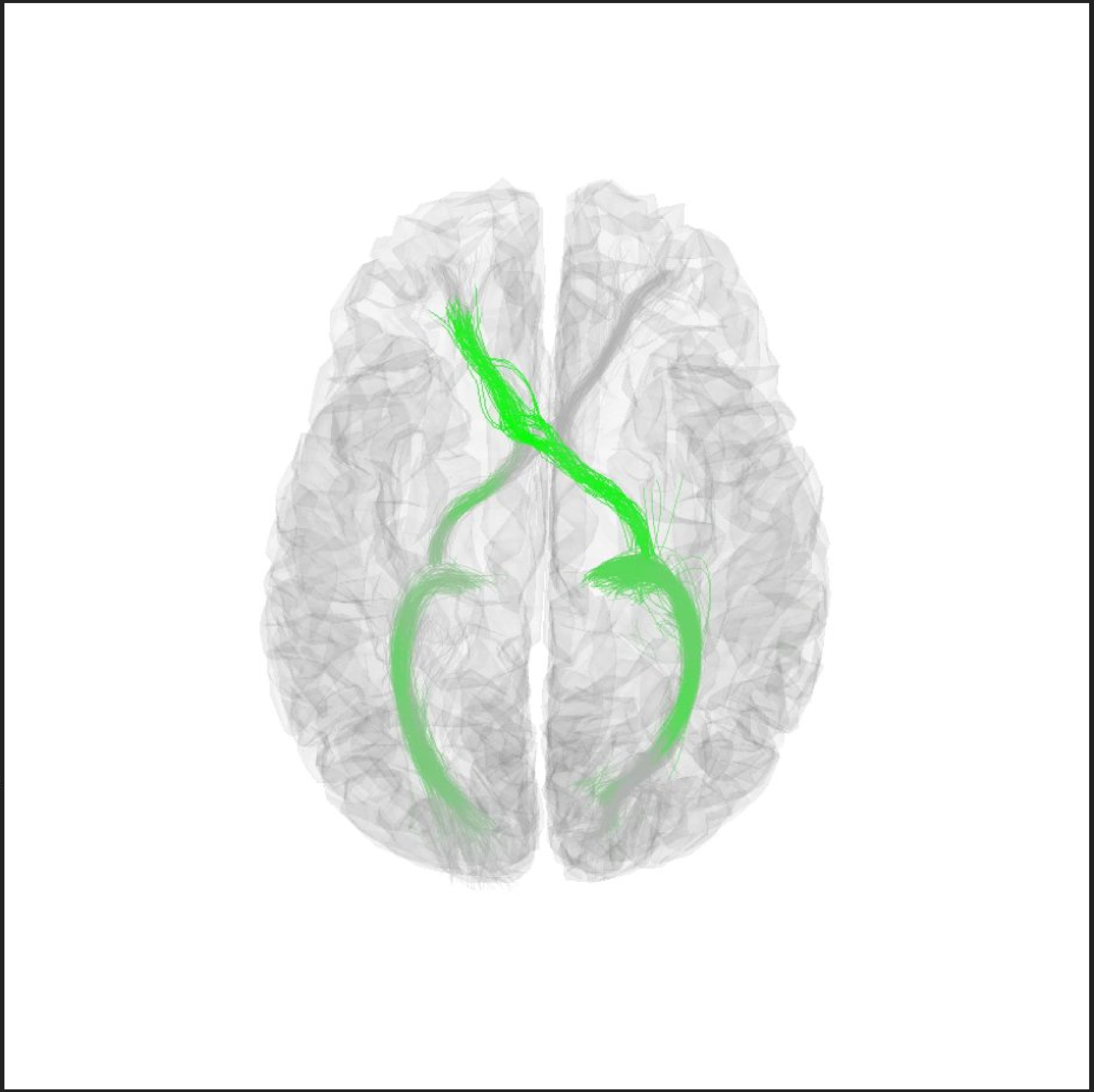


Figure 2: Information flow during the right hand movement task and corresponding MEG measurements. The cortical parcellation is connectivity driven, however cortical regions are identified using the overlapping Desikan-Killiany atlas for clarity.

[Gallardo et al. OHBM 2017]

Results obtained on lateralized visual stimuli





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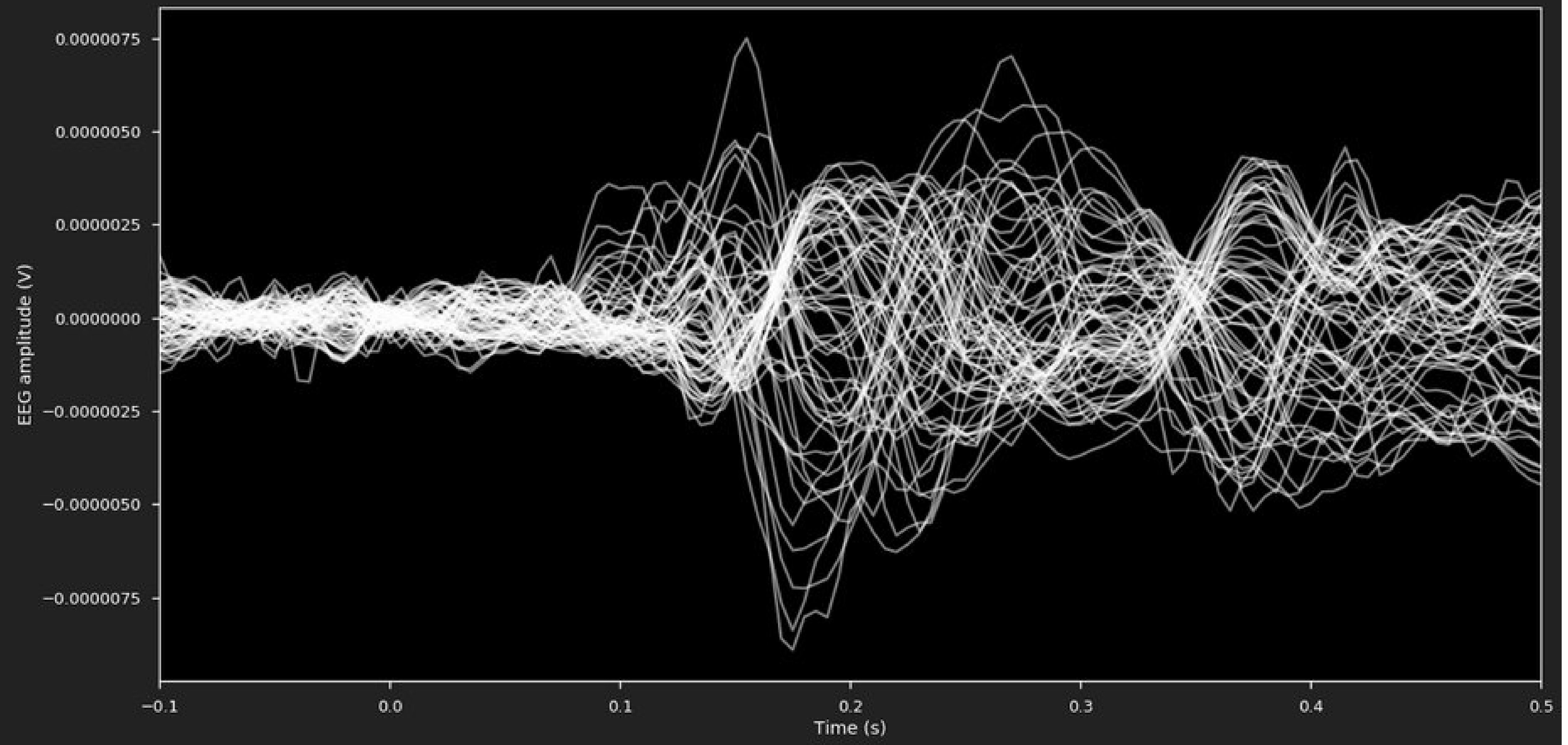

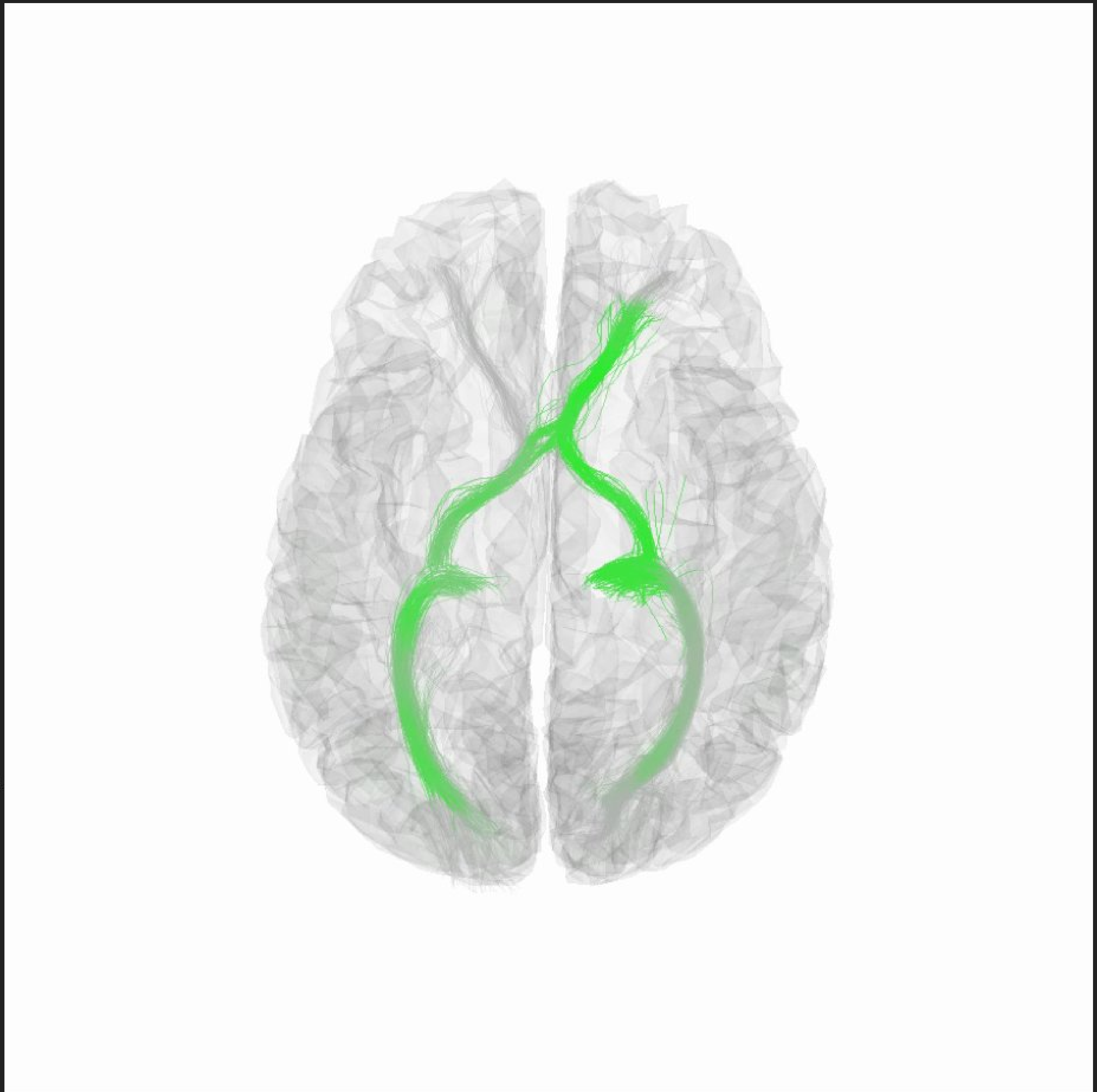

TAKE HOME MESSAGE

dMRI and M/EEG provides information invisible to dMRI or M/EEG

THANKS YOU!

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Guillermo Gallardo, Jean-Marc Lina, Kevin Whittingstall

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