

# Personalized modeling of brain responses to noninvasive stimulation

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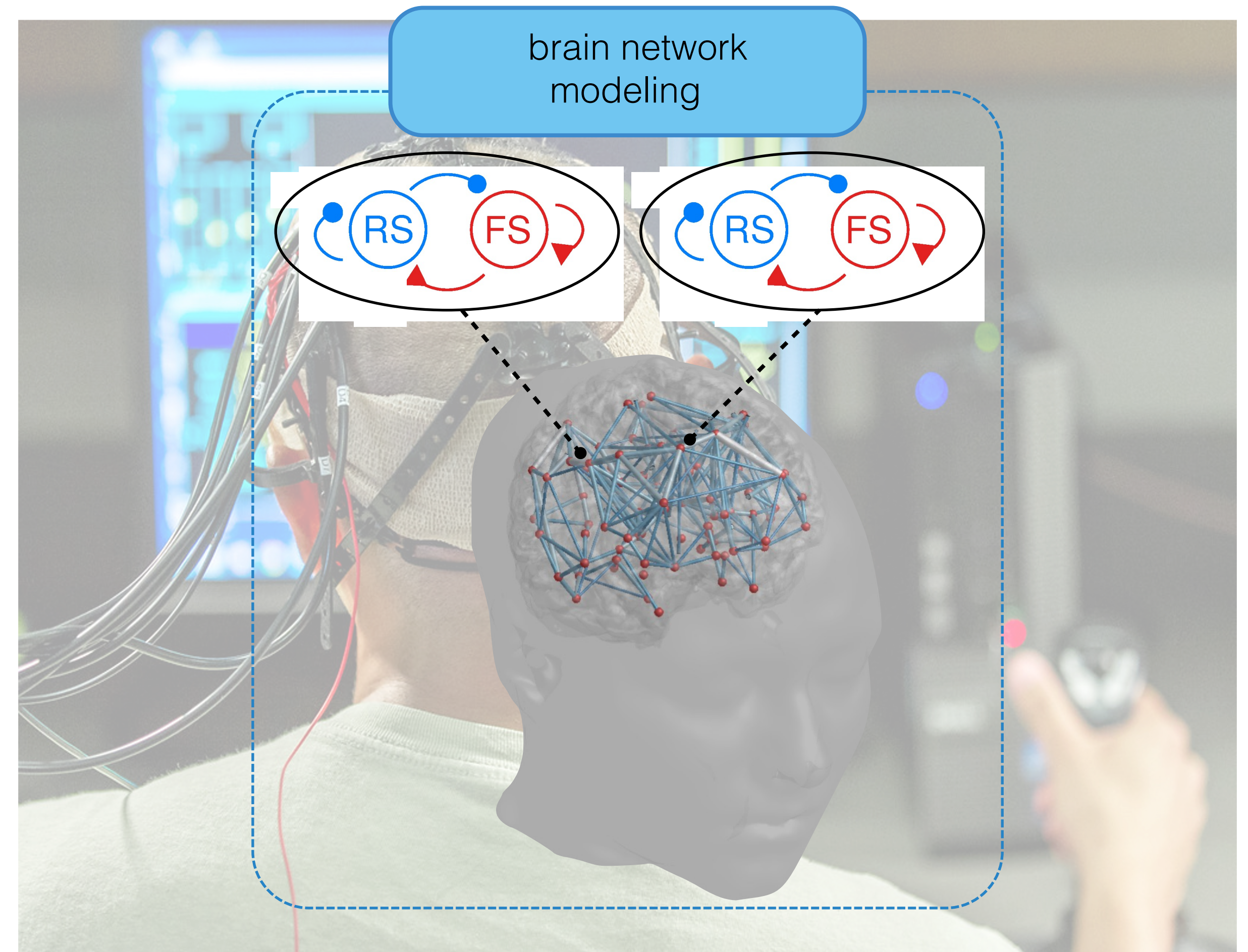
<sup>3</sup>Ecole Polytechnique Fédérale de Lausanne (EPFL), Geneva and Sion, Switzerland

<sup>4</sup>Clinical Neuroscience, University Medical School of Geneva, Geneva, Switzerland

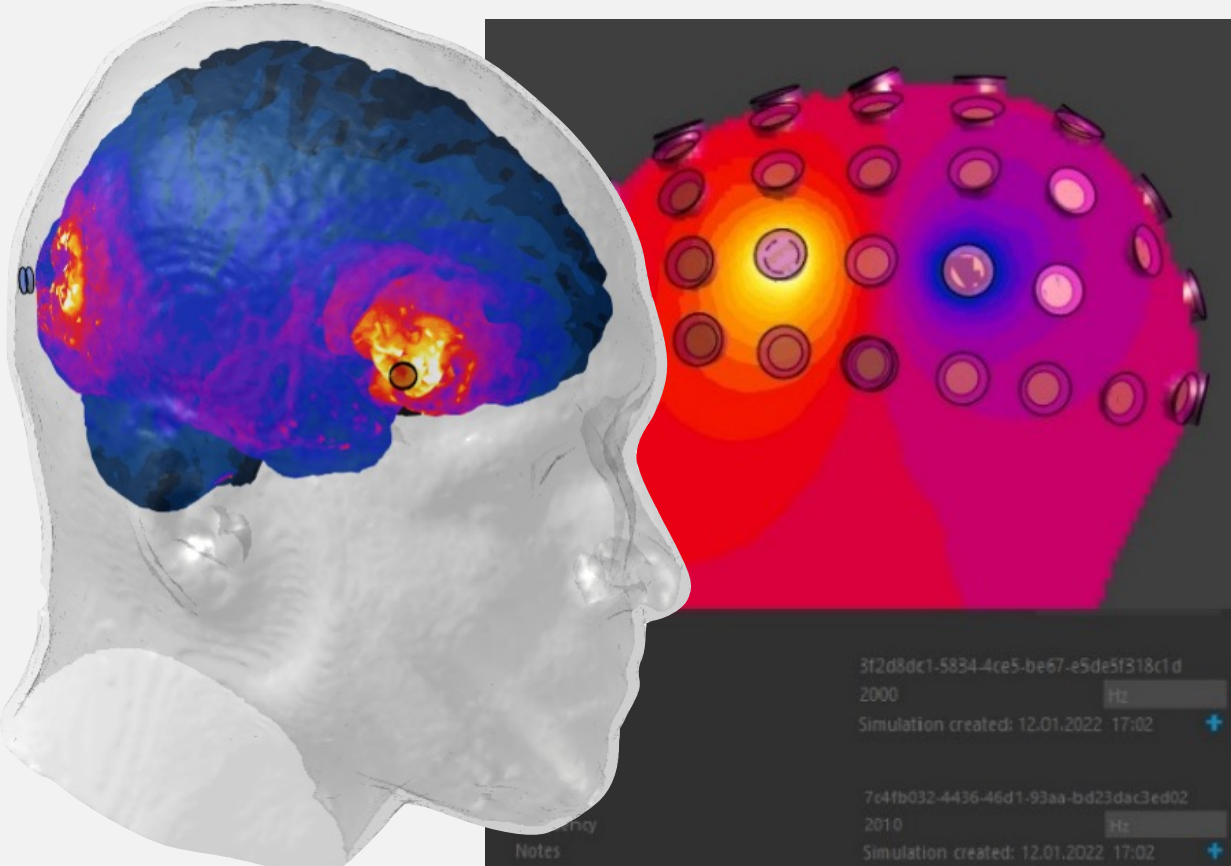


# Motivation

- Neurological/psychiatric disorders: epilepsy, **stroke**, **spinal cord injury**, Parkinson's/Alzheimer's disease, depression...
- Electromagnetic (EM) brain stimulation provides a powerful therapeutic approach for brain disorders
- But a one-size-fits-all does not capture significant variation in anatomy & physiology → **personalization required**

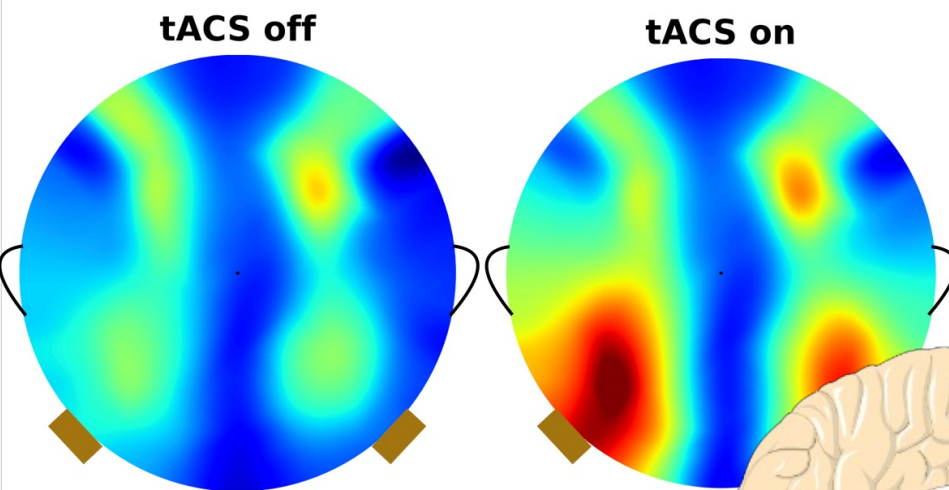


# From Targeted Exposure to Optimized Functional Responses



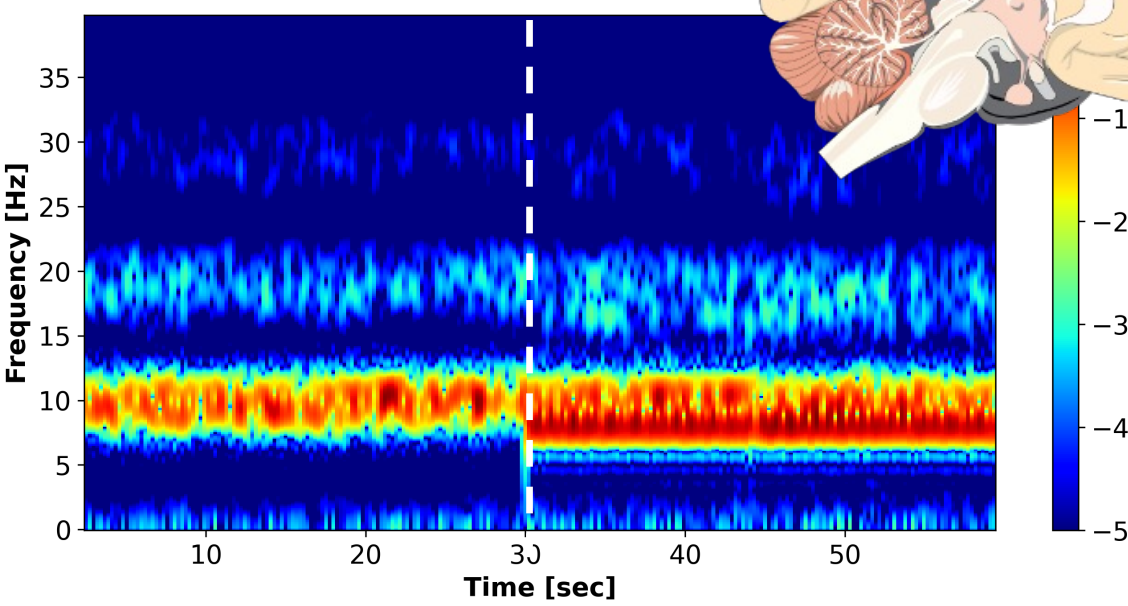
■ EM exposures are computed over the space of candidate stimulation configurations → targeted field distributions

■ coupled functional responses are simulated, then characterized using dimensionality reduction



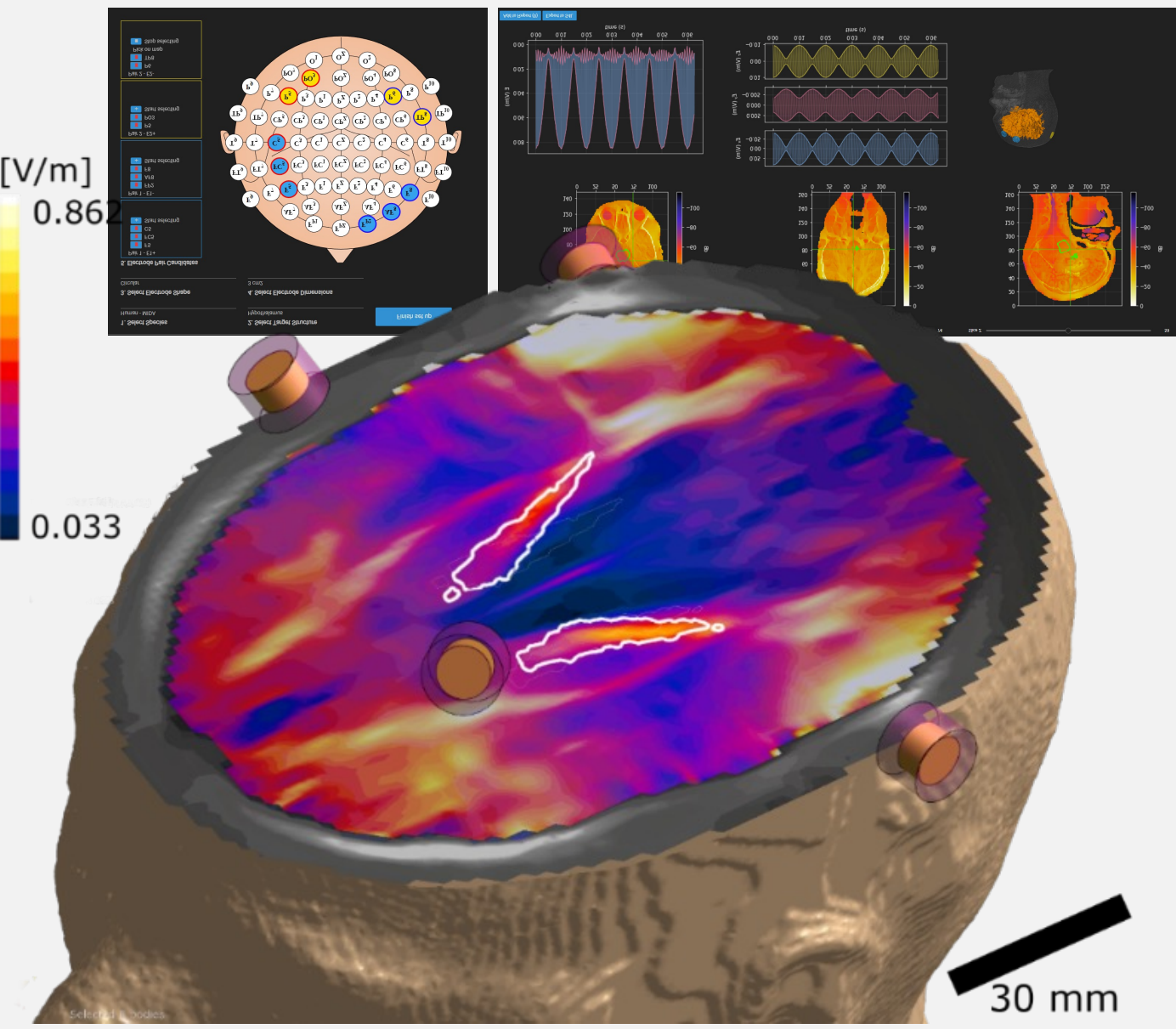
tACS off      tACS on

×10<sup>-3</sup>  
16  
14  
12  
10  
8  
6  
α band



Frequency [Hz]  
35  
30  
25  
20  
15  
10  
5  
0

Time [sec]  
10 20 30 40 50



■ targeted exposure – neural activity coupling permits optimization of functional responses

# Automated Model Generation

## ■ Segmantic pipeline

- AI & CV
- data augmentation, ensemble prediction (best of the best networks)

## ■ postprocessing

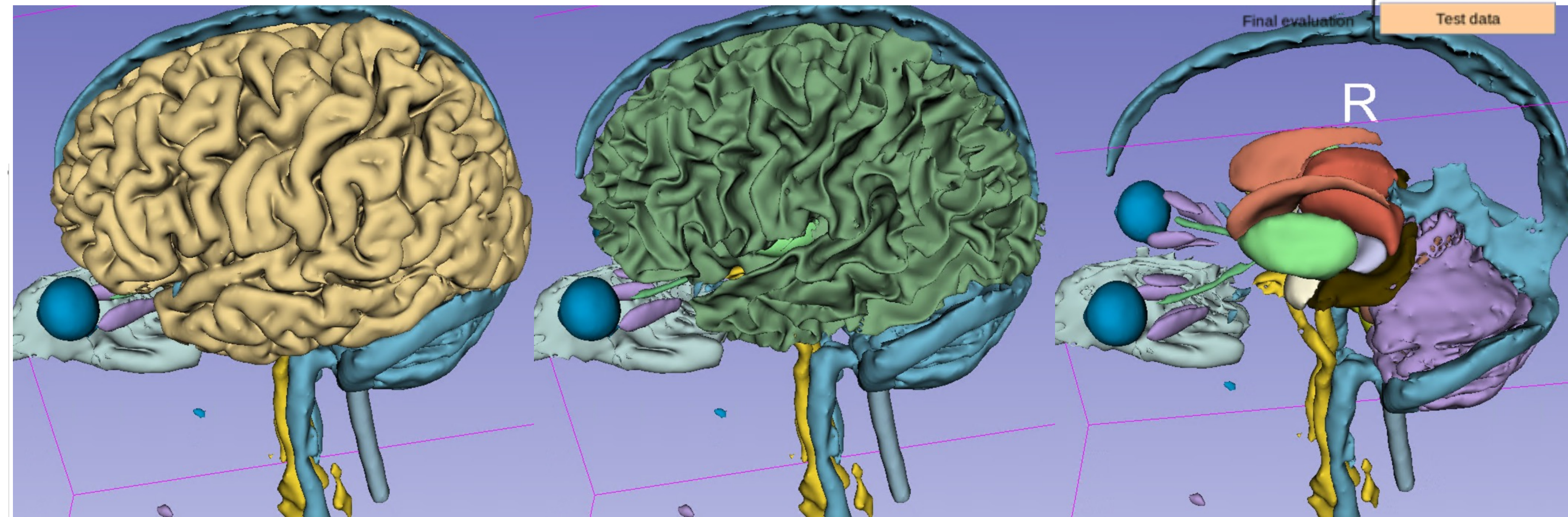
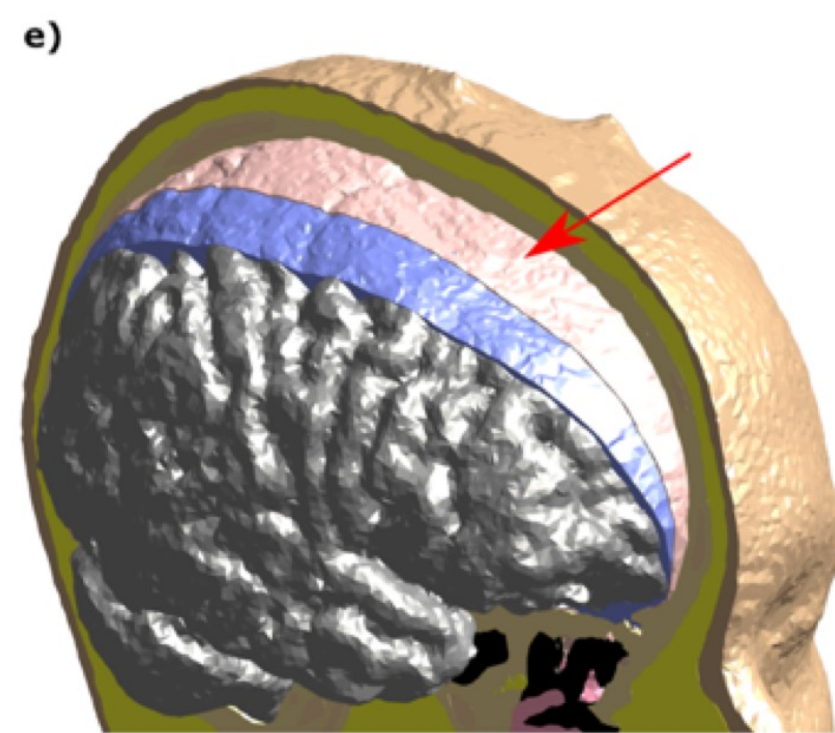
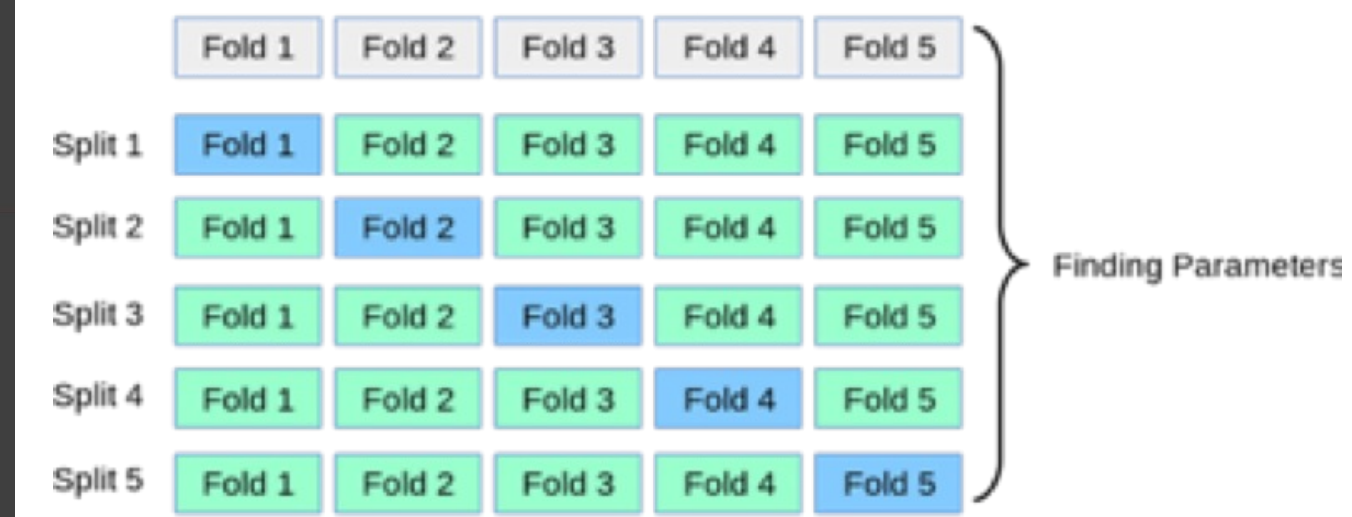
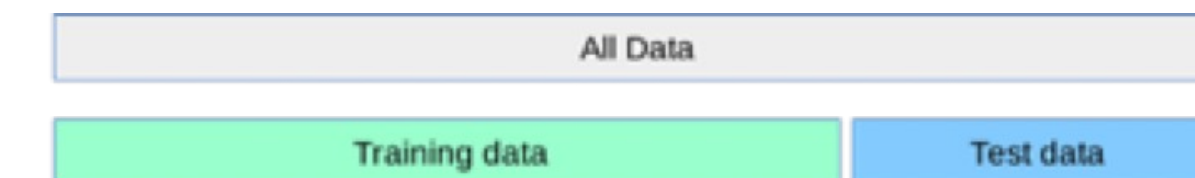
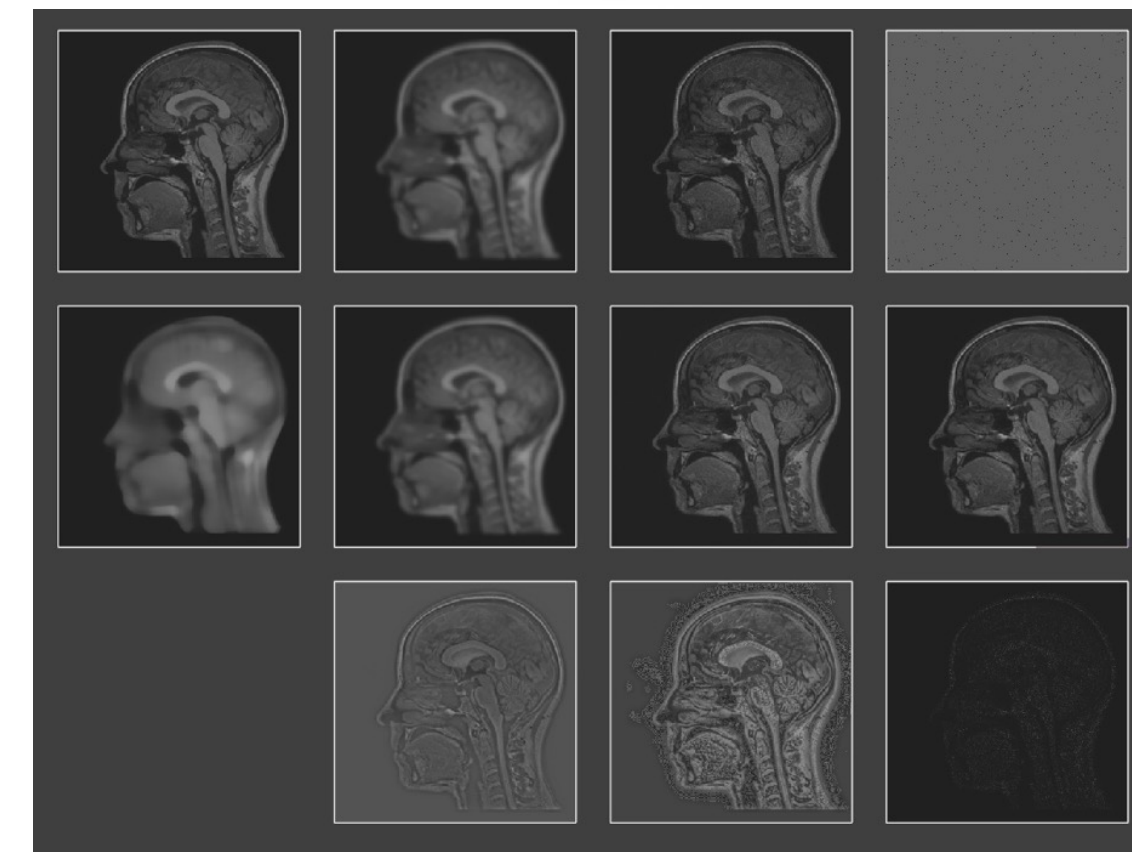
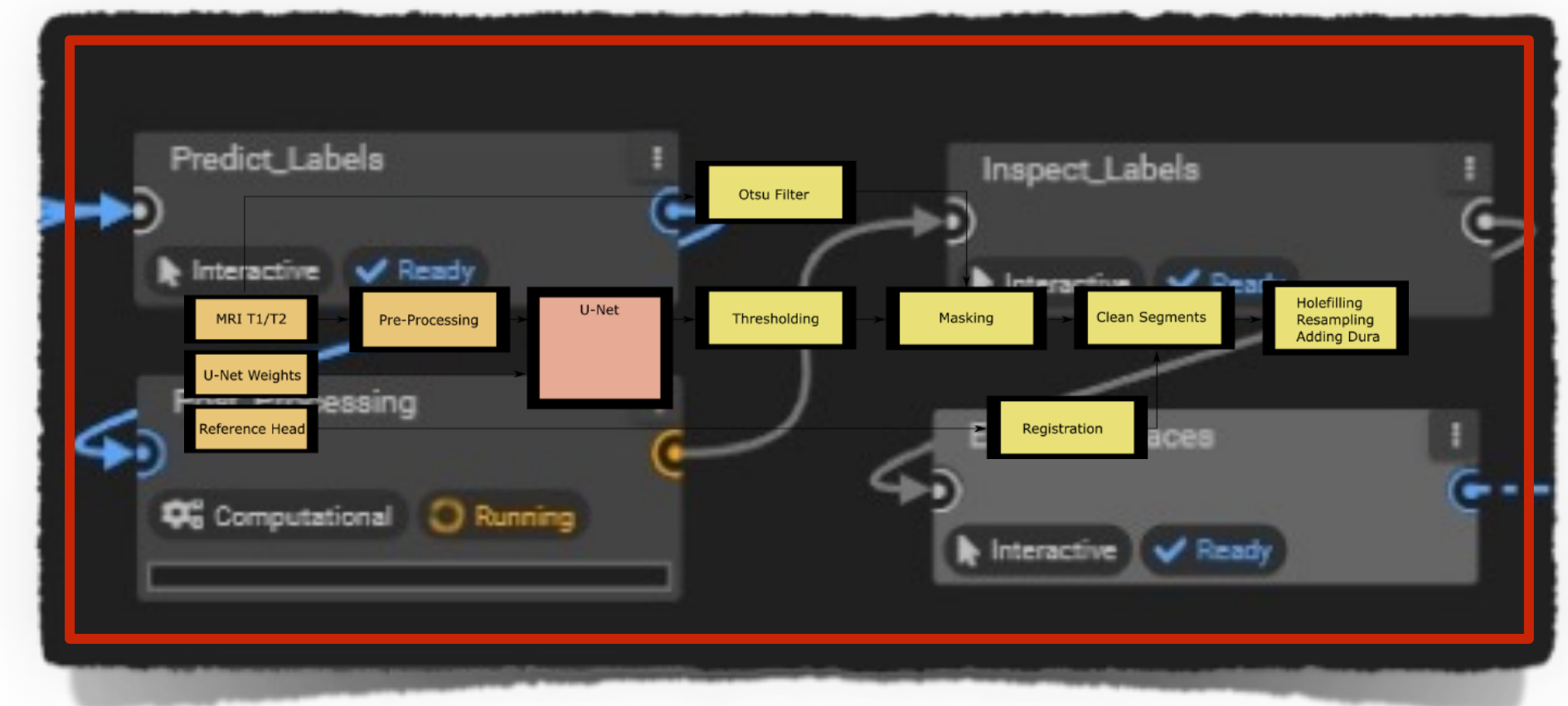
- further improves segmentation quality
- inserts additional tissue regions

## ■ brain parcellation

- hybrid AI-registration

## ■ superior segmentation quality and realism, in no time

- 40 tissues
- seconds to minutes vs. hours
- robust



# Automated Model Generation

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- AI & CV
- data augmentation, ensemble prediction (best of the best networks)

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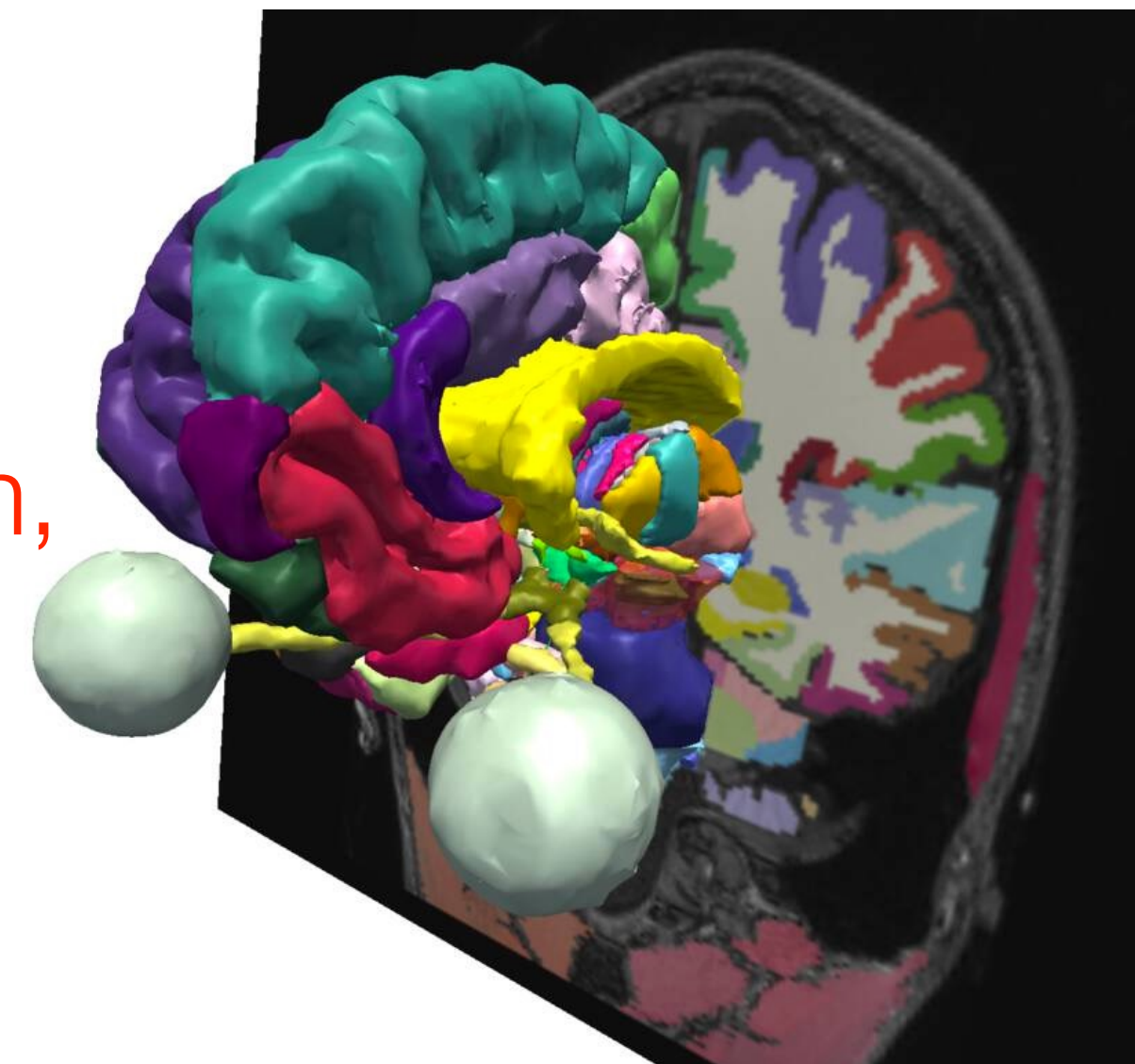
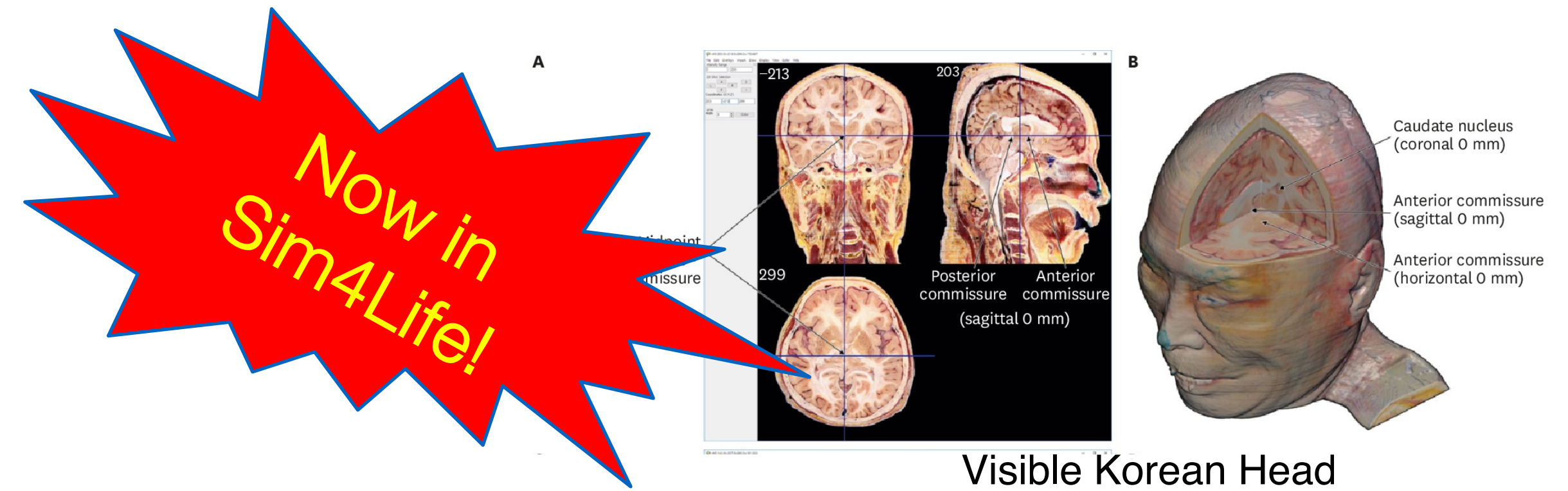
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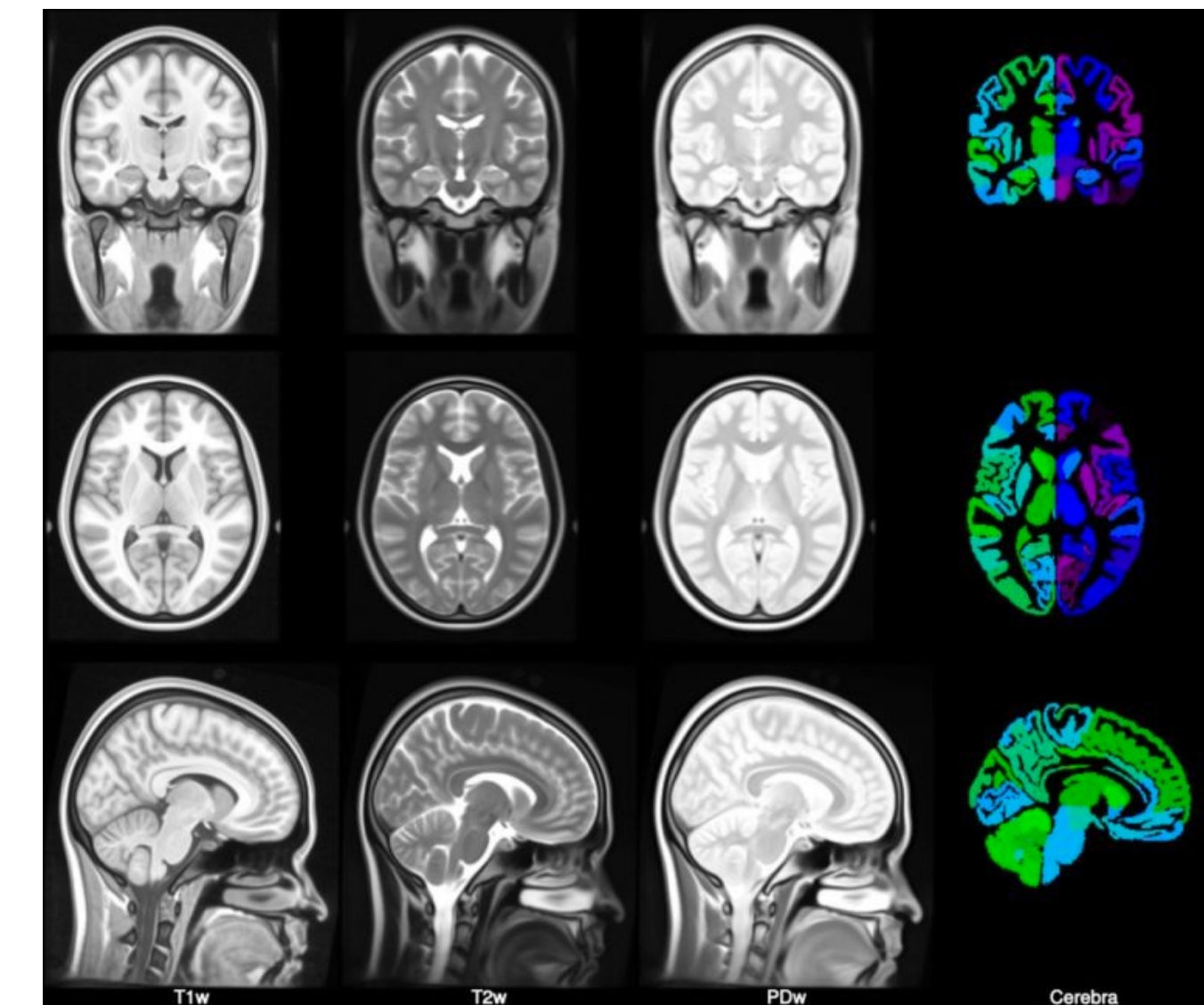
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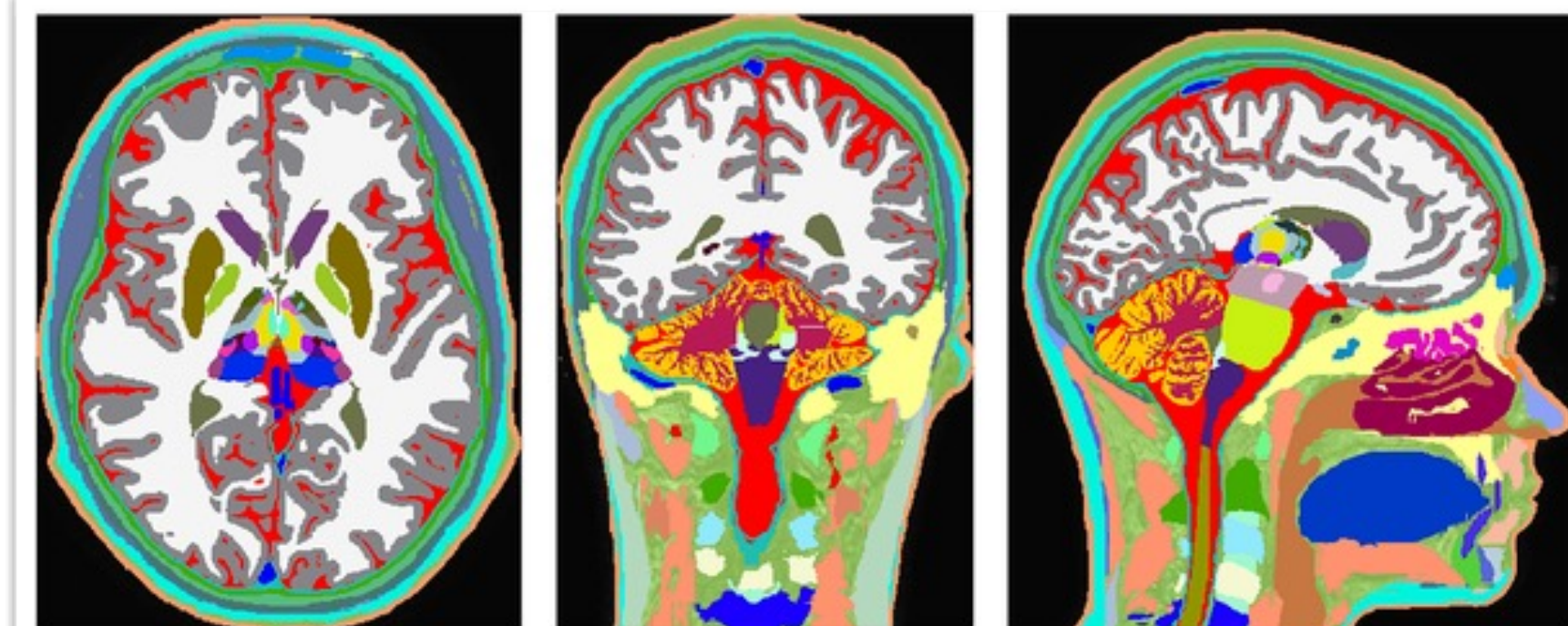


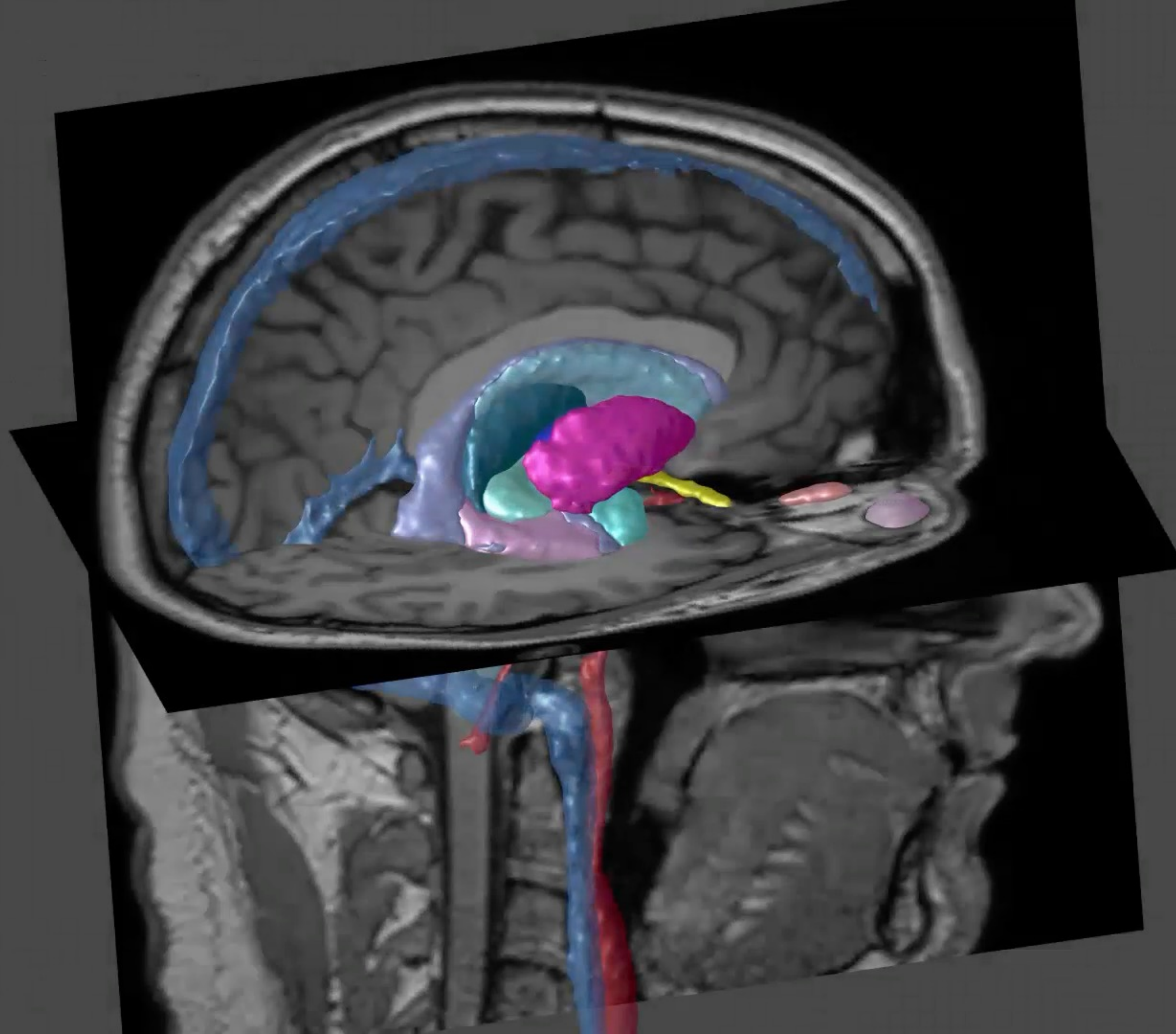
SP/NAC Brain Atlas



MIDA Head Model

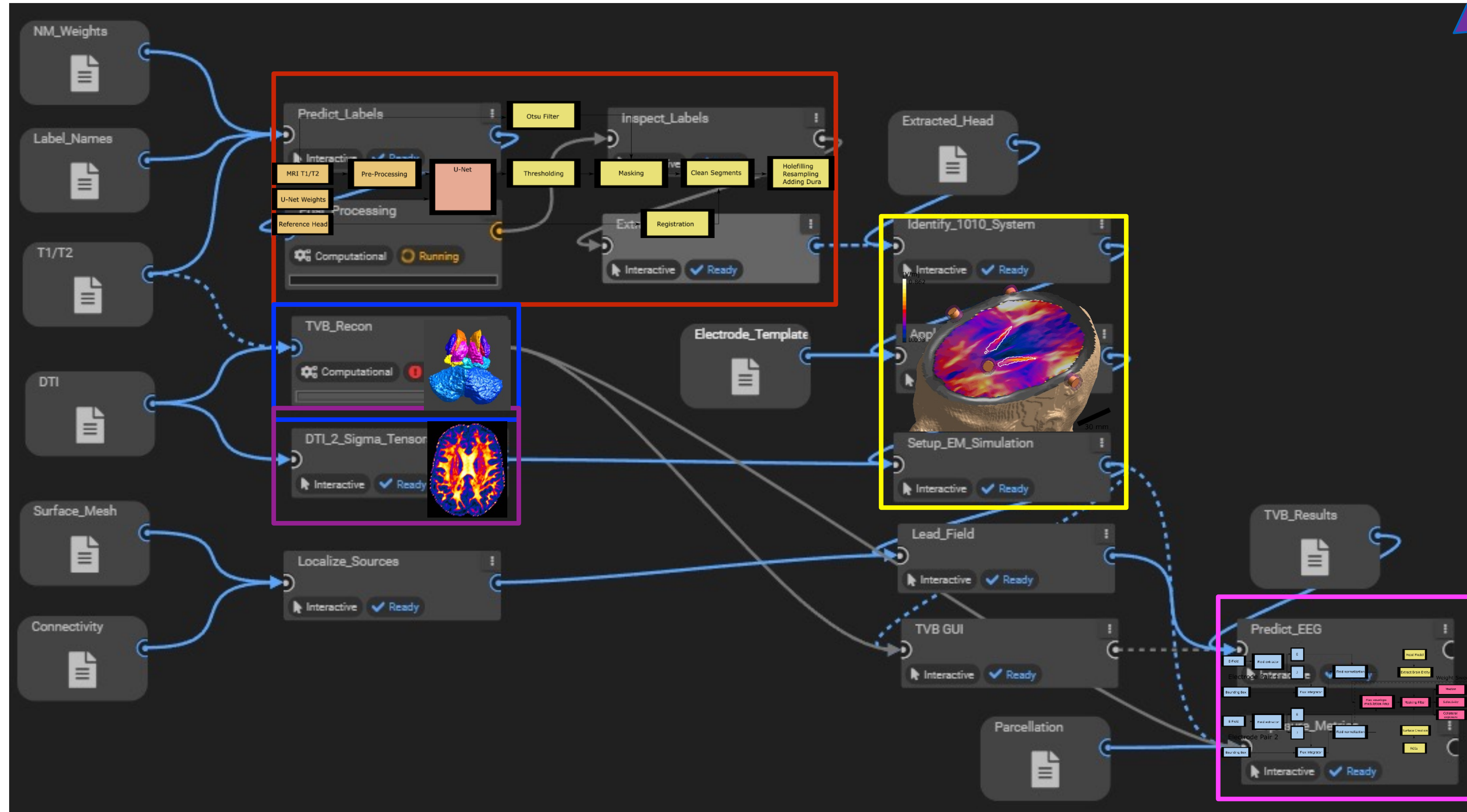
ICBM 152 (Cerebra)





# The Pipeline on o2S2PARC: Overview

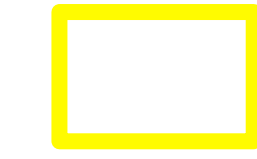
Coming to S4L Web!



Automated Model Generation



Personalized Conductivity Mapping



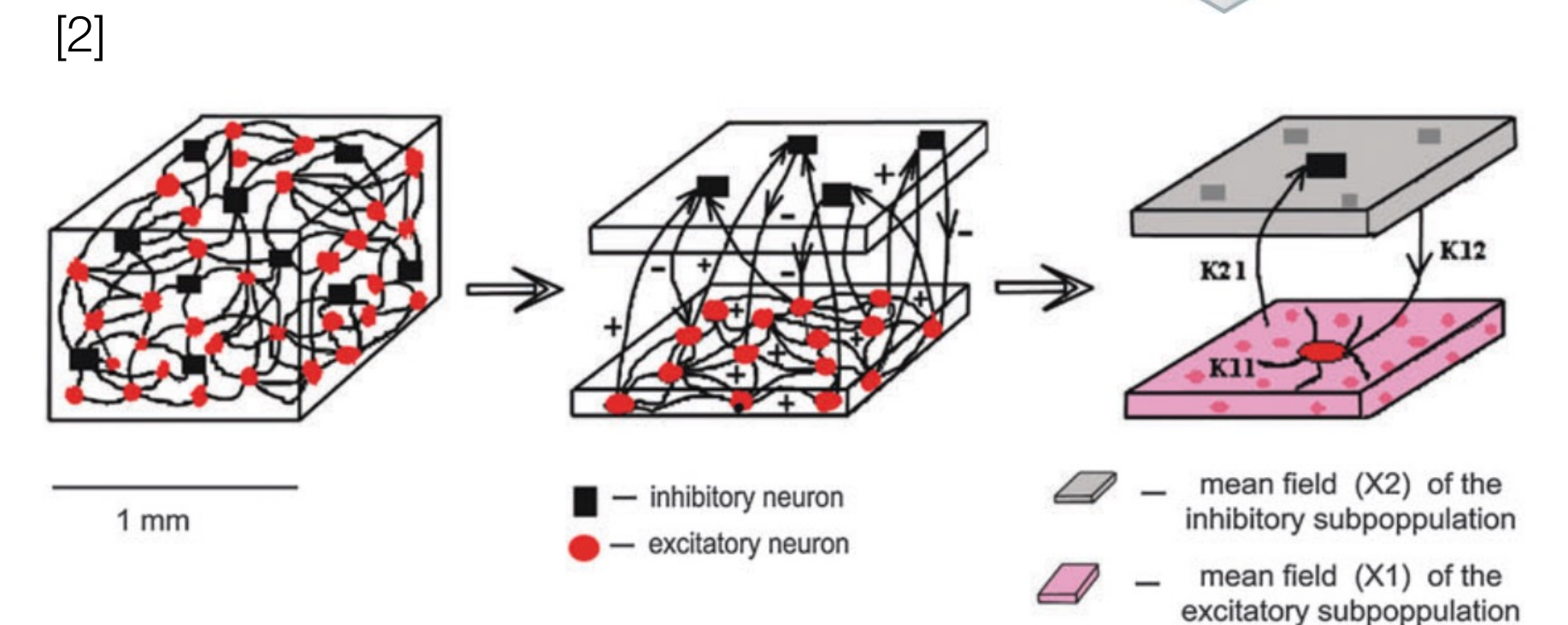
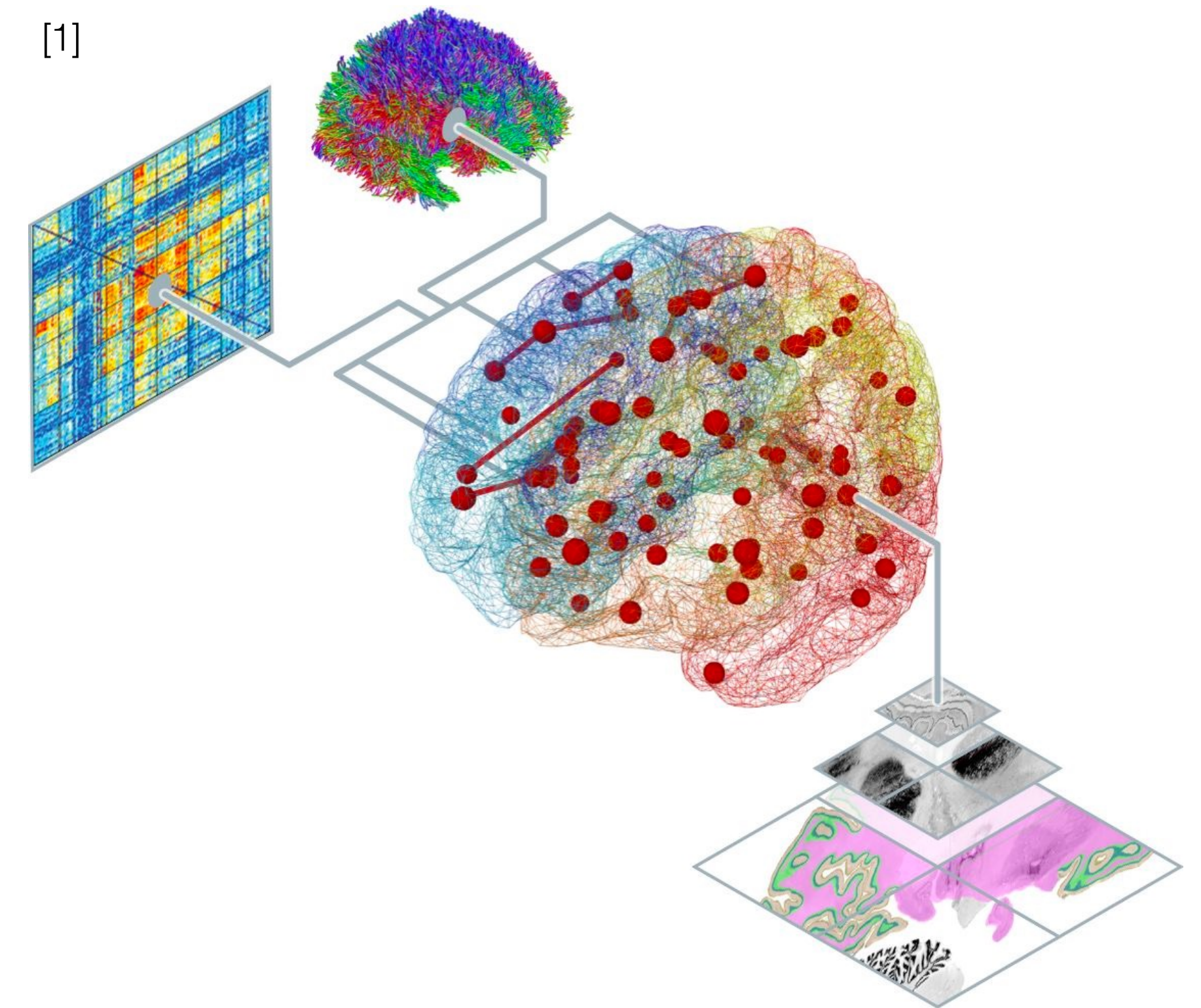
E-Field Exposure Simulation



Temporal Interference Evaluation

# Brain Network Responses to tES

- mean field models: low dimensional representation of the average activity of a neuronal population
  - neural mass models (NMM): one-dimensional nodes
  - neural field models: captures spatial dependence
- coupling NMM-based description of brain activity to EM stimulation input closes the loop between stimulus and response → advanced/personalized tES schemes; effect-driven
- gaps in the standard approach:
  - lead field matrix personalization
  - EM exposure coupling control paradigms

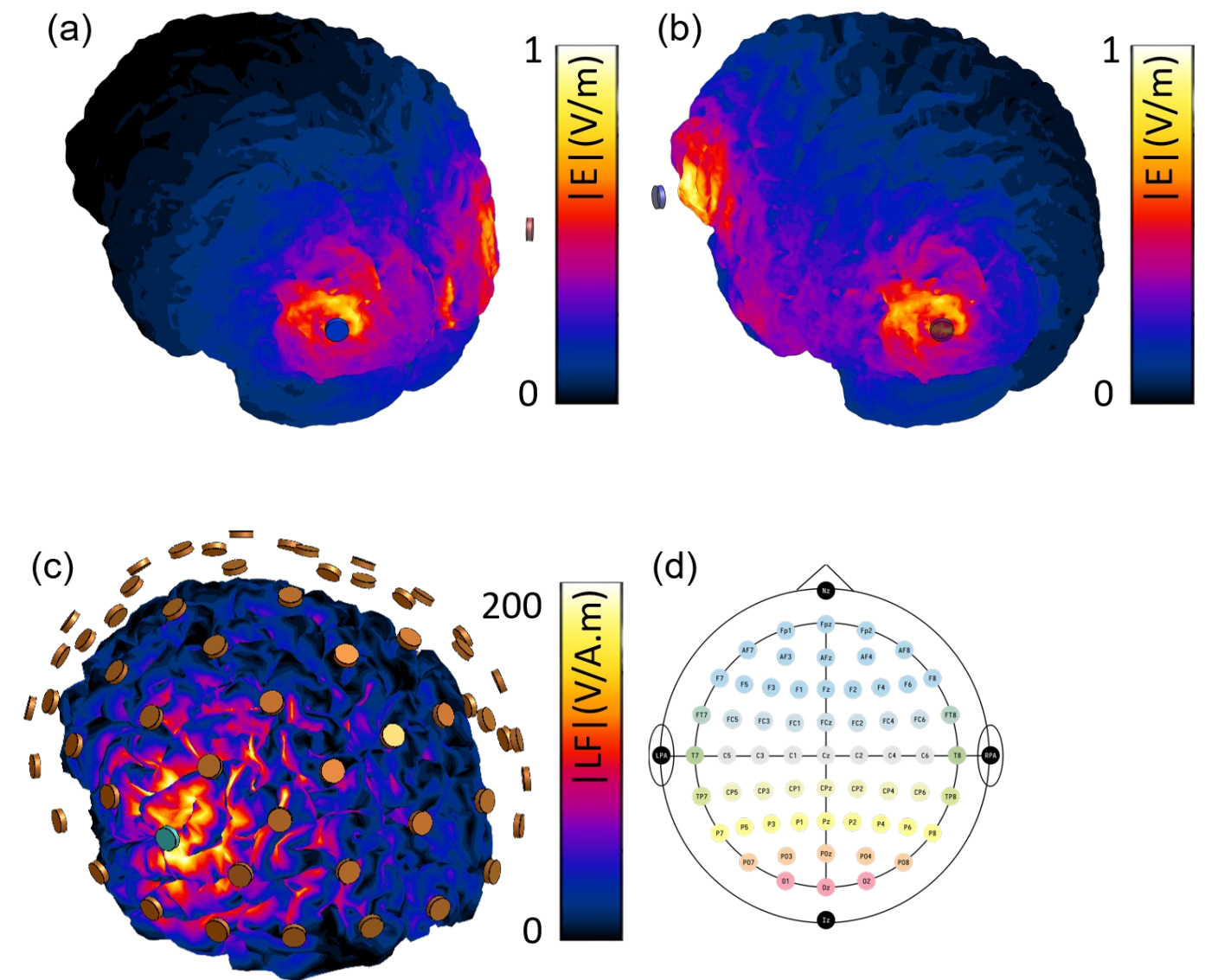
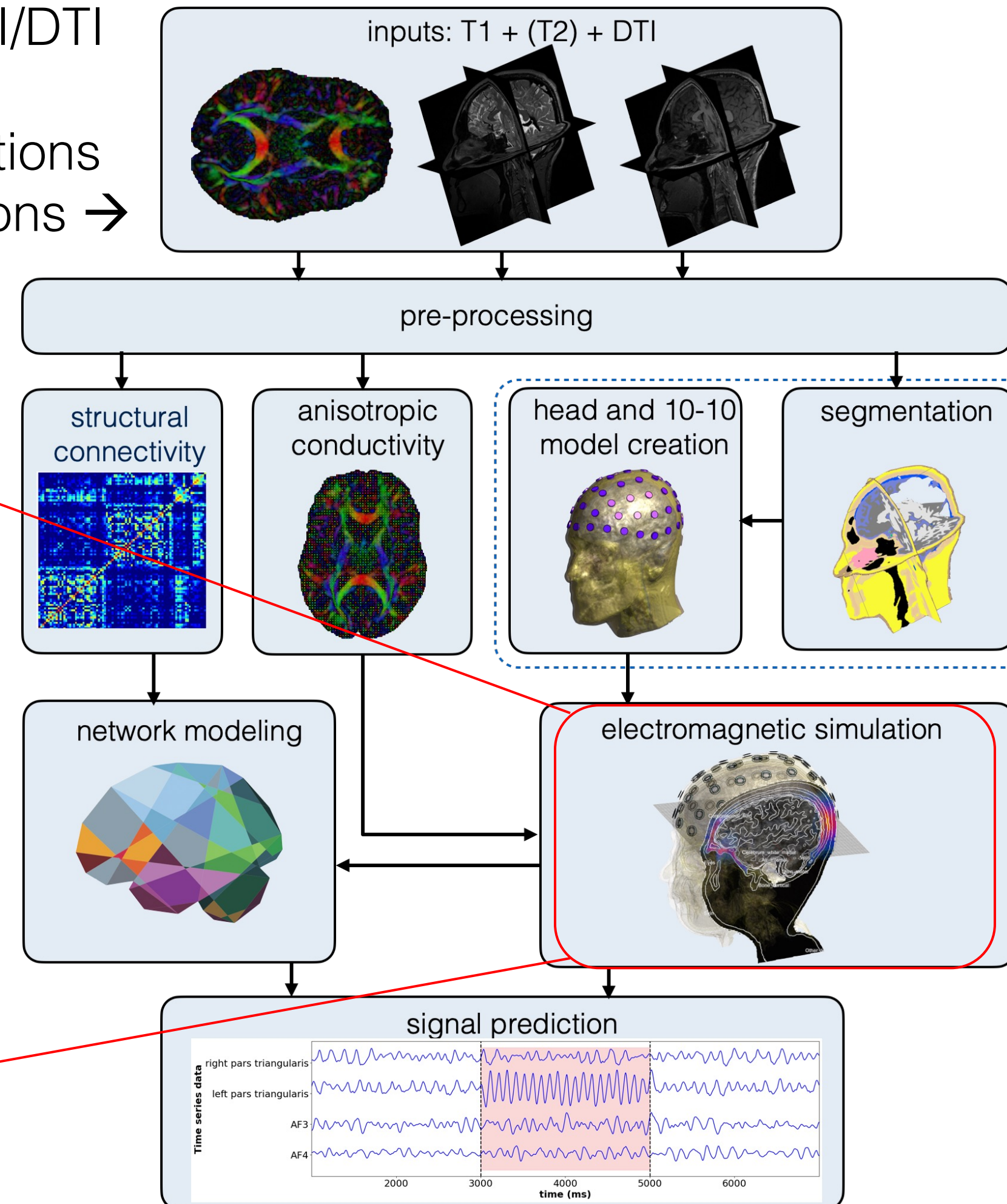
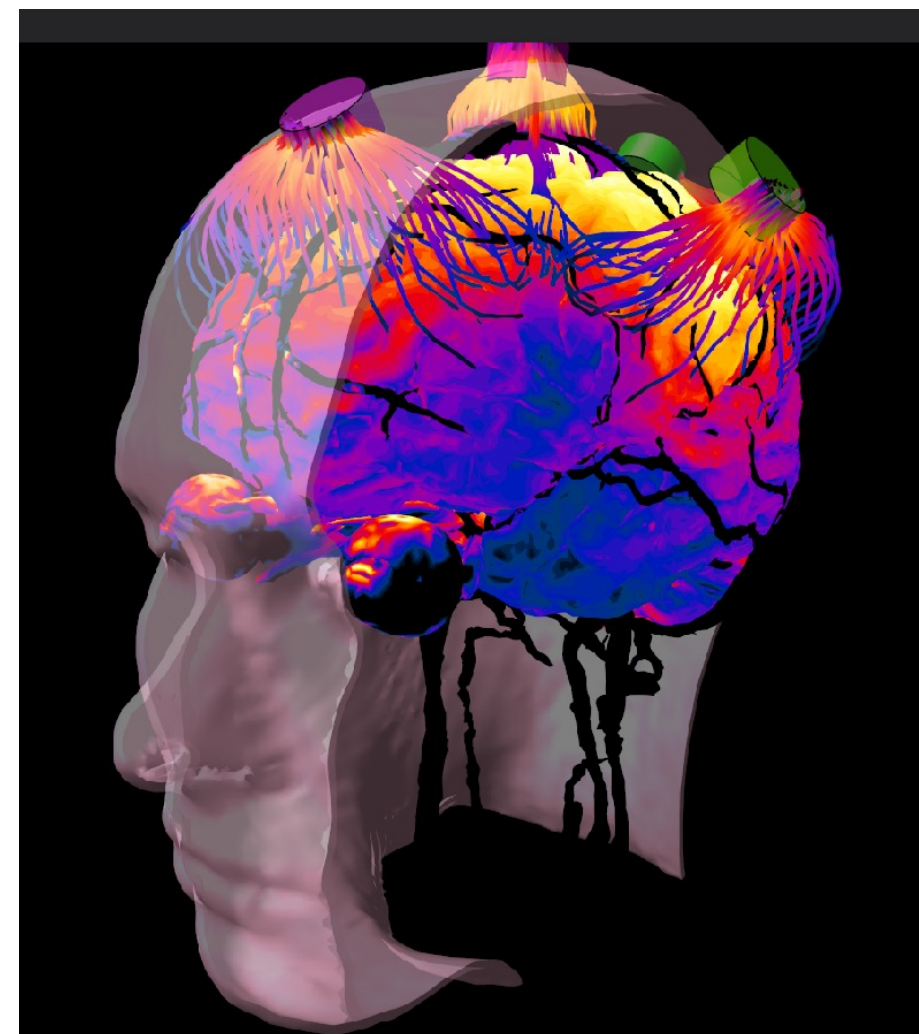


[1] [www.ebrains.eu](http://www.ebrains.eu)

[2] Stefanescu, Roxana A., and Viktor K. Jirsa. (2008)

# Brain Network Responses to tES

- brain modeling pipeline: MRI/DTI inputs → AI-based model reconstruction → EM simulations → coupled network simulations → *in silico* signal generation



(a-b) Cortical E-field distribution induced by transcranial alternating current stimulation applied via 10-10 EEG system. (c) Visualization of a lead field matrix row (corresponding to the FC5 electrode, colored in light blue). (d) 10-10 EEG system representation.

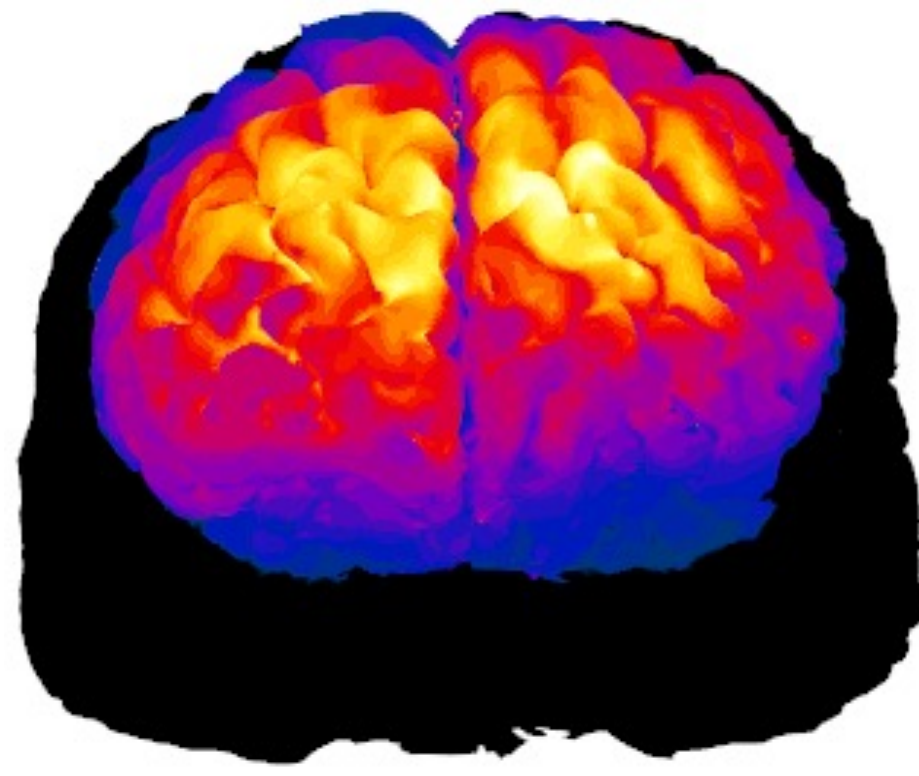
[1] [www.ebrains.eu](http://www.ebrains.eu)

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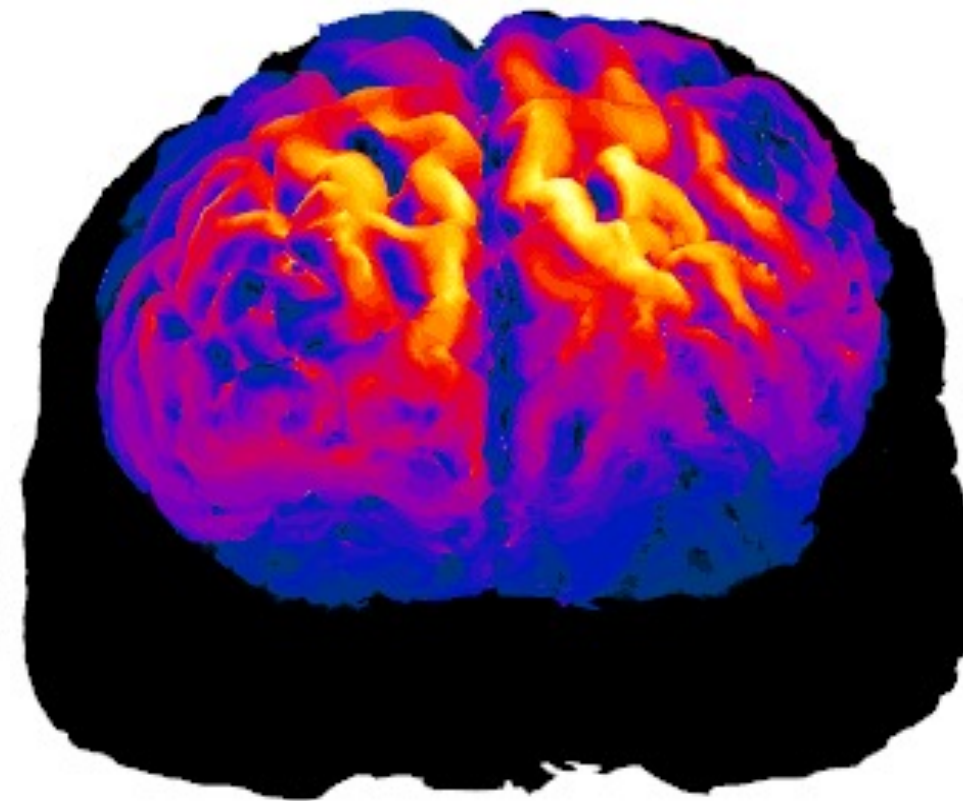
# EM Exposure Simulation

TES

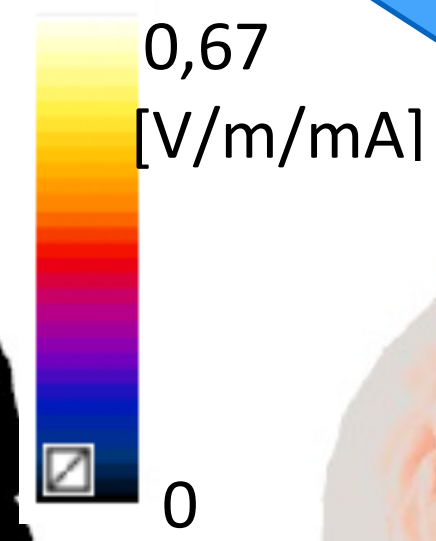
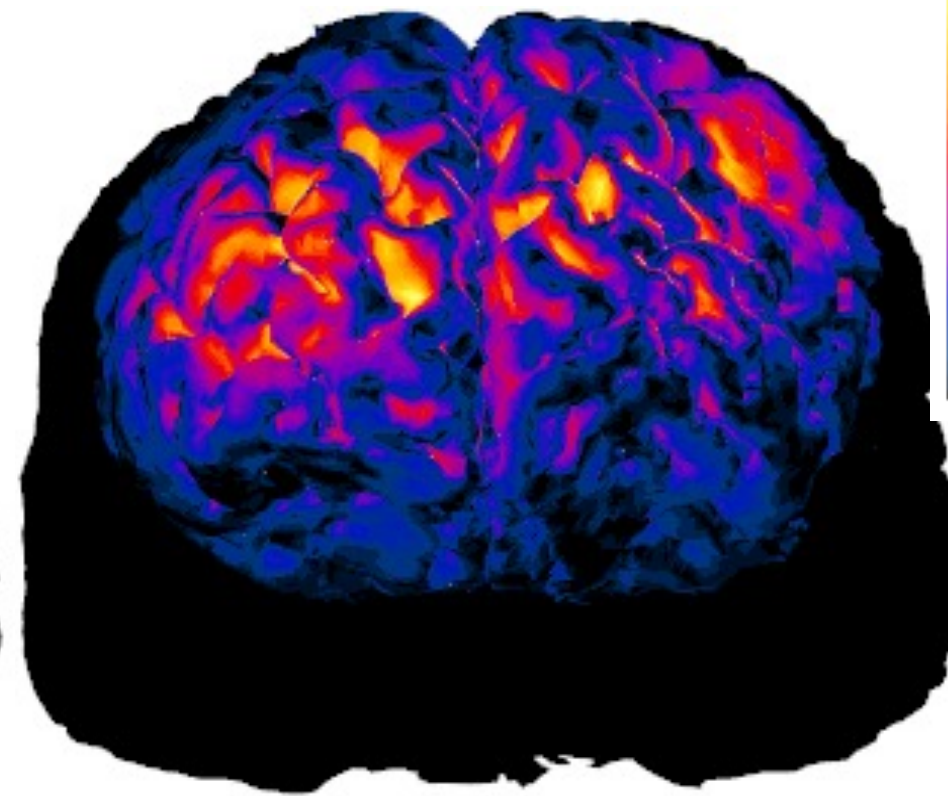
E\_total



E\_parallel



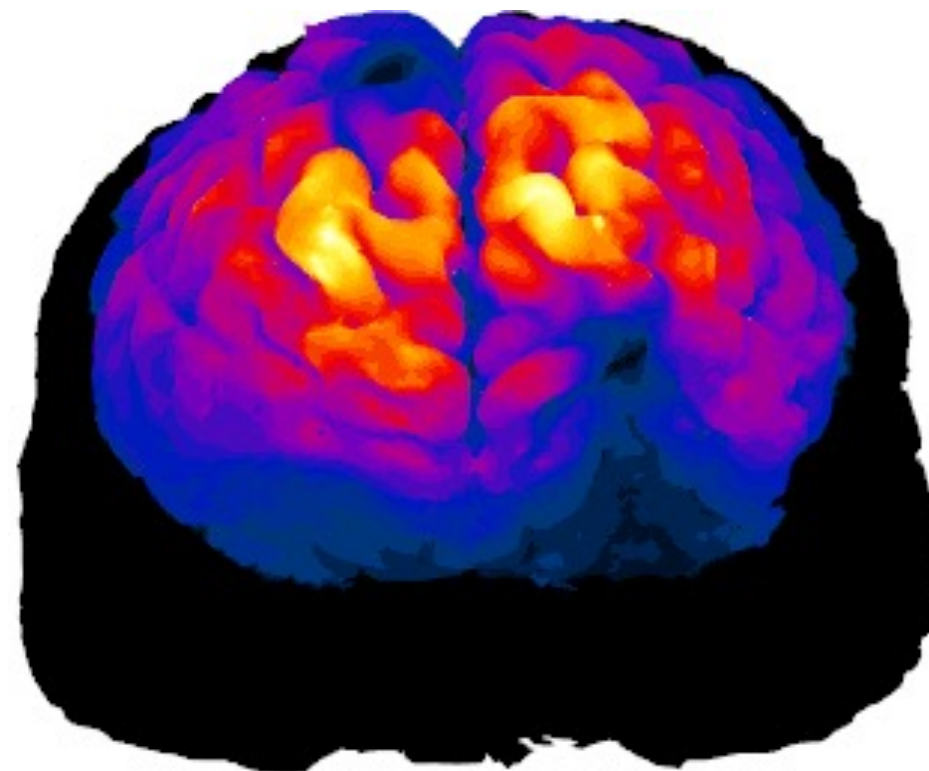
E\_normal



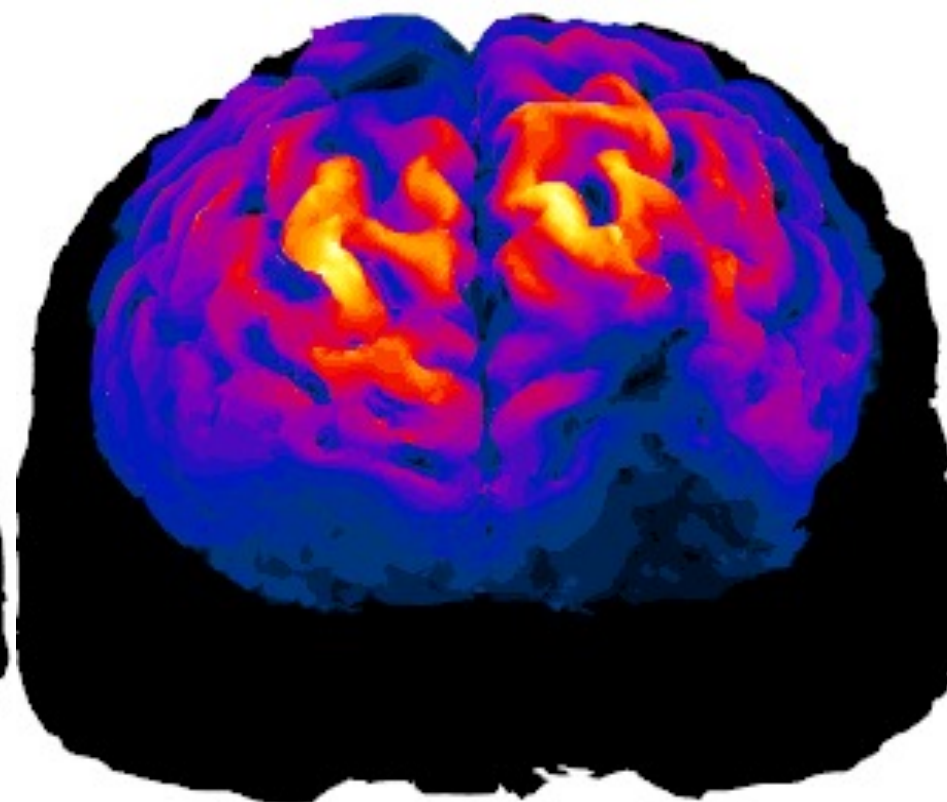
0,67

TMS

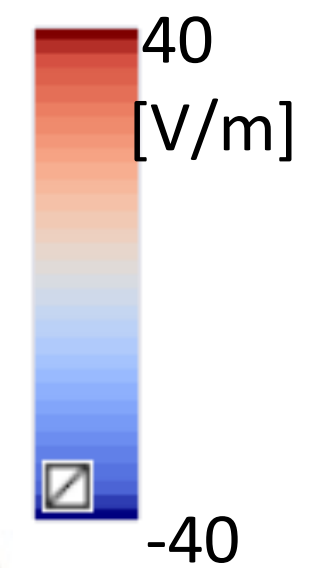
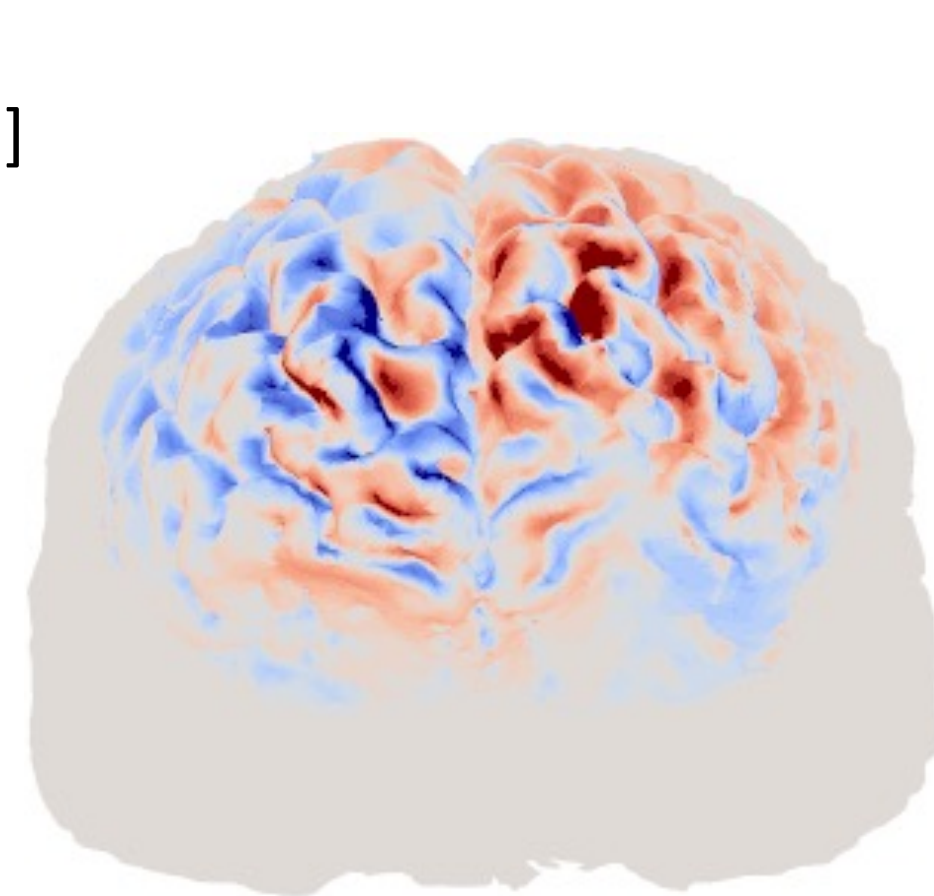
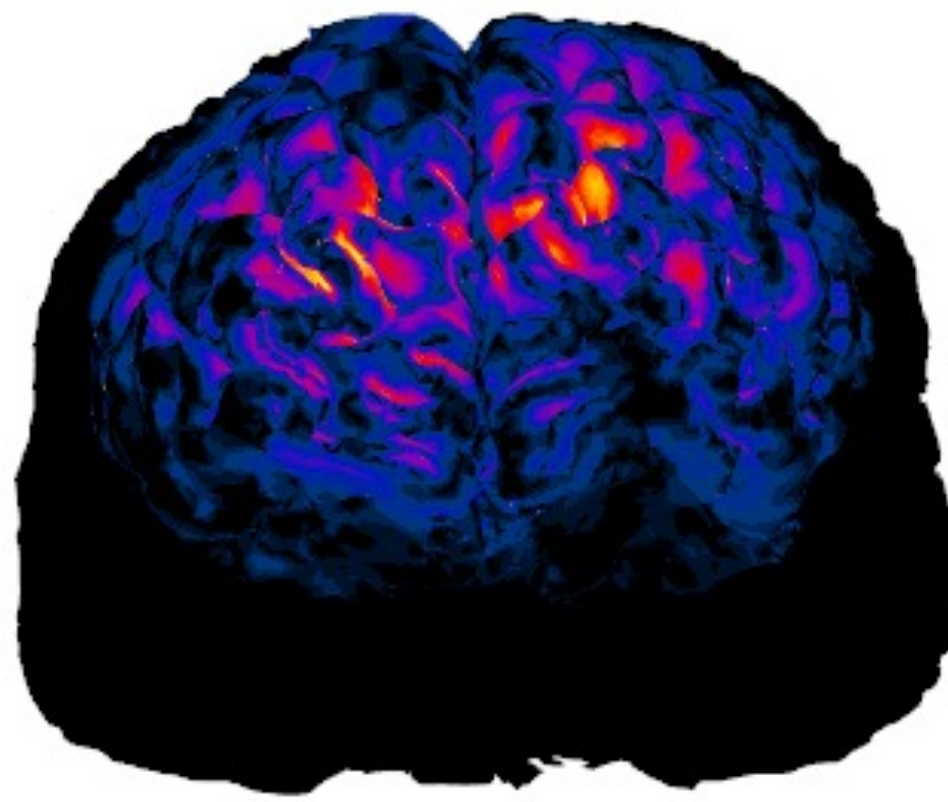
Etotal



Eparallel

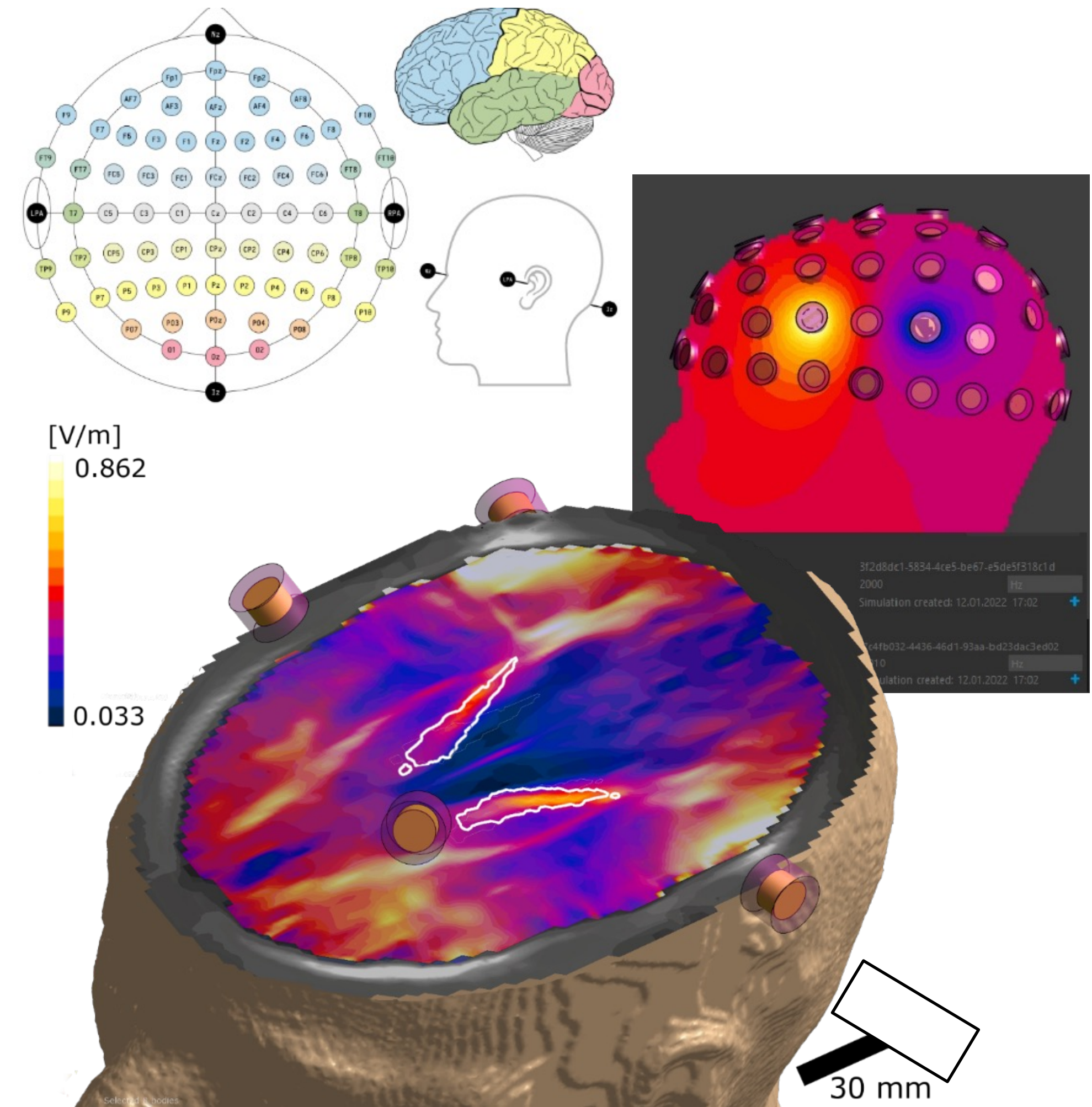
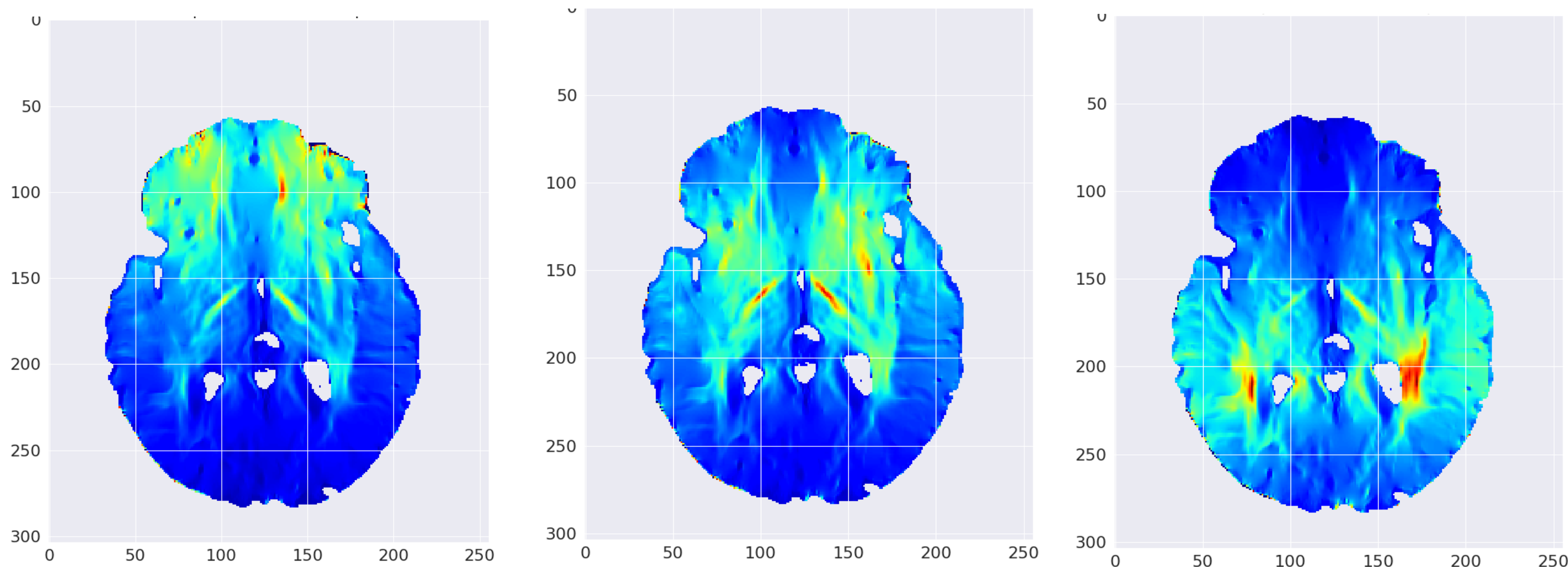


Enormal



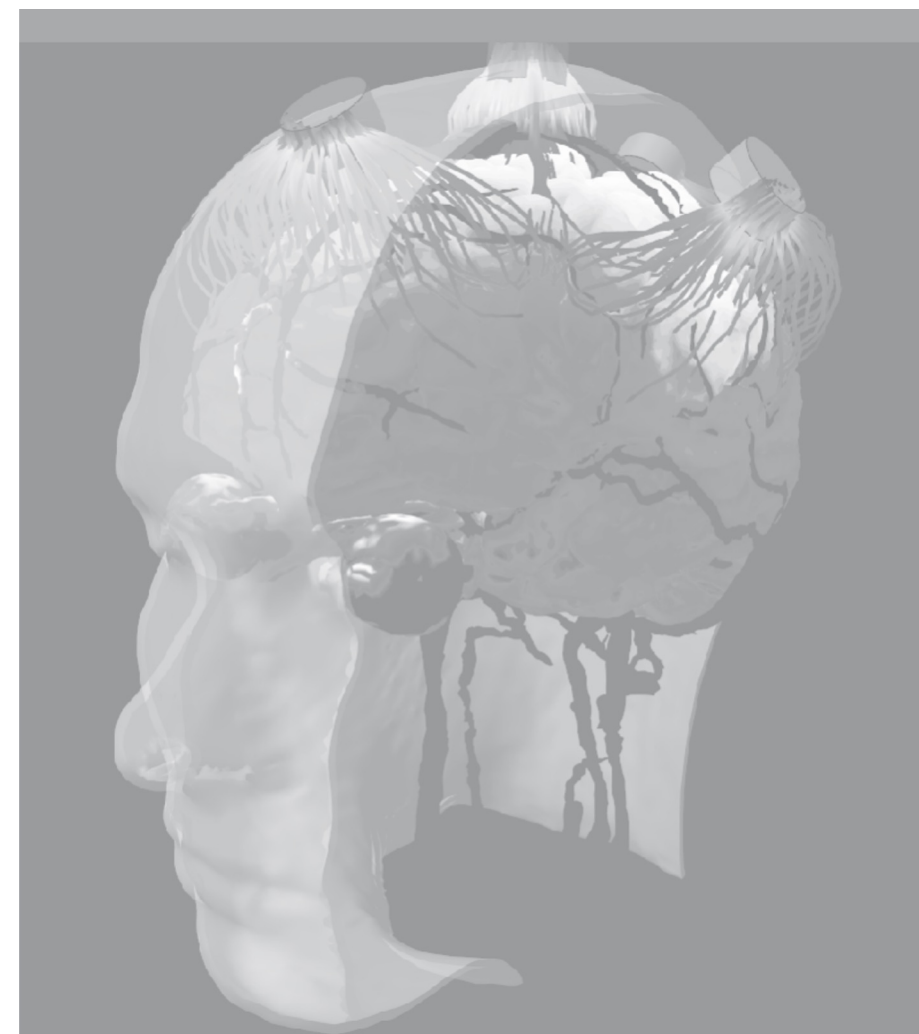
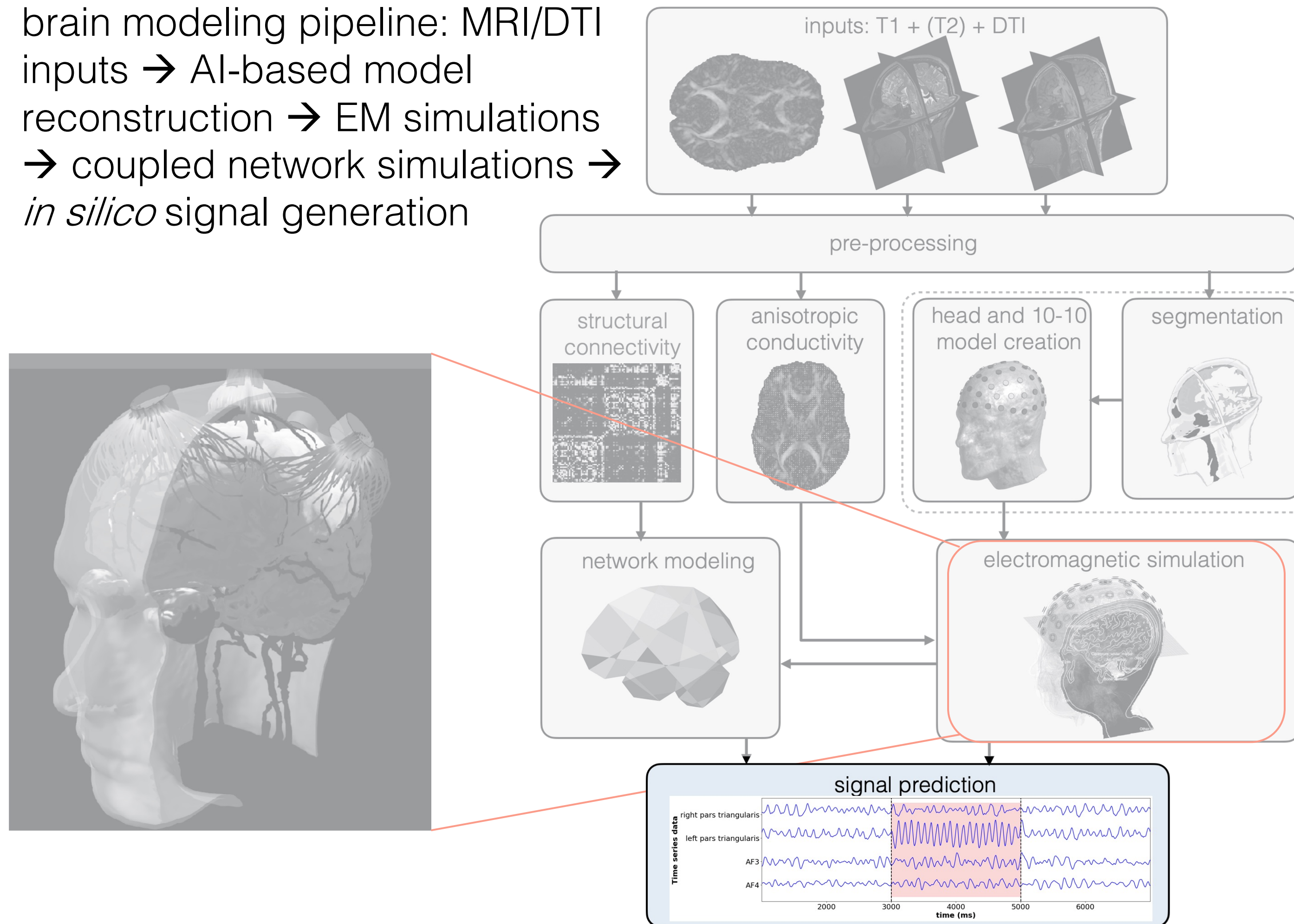
# Field Library Generation

- automatic simulation setup and generation of EM field library
- rapid generation of a large library of exposure configurations

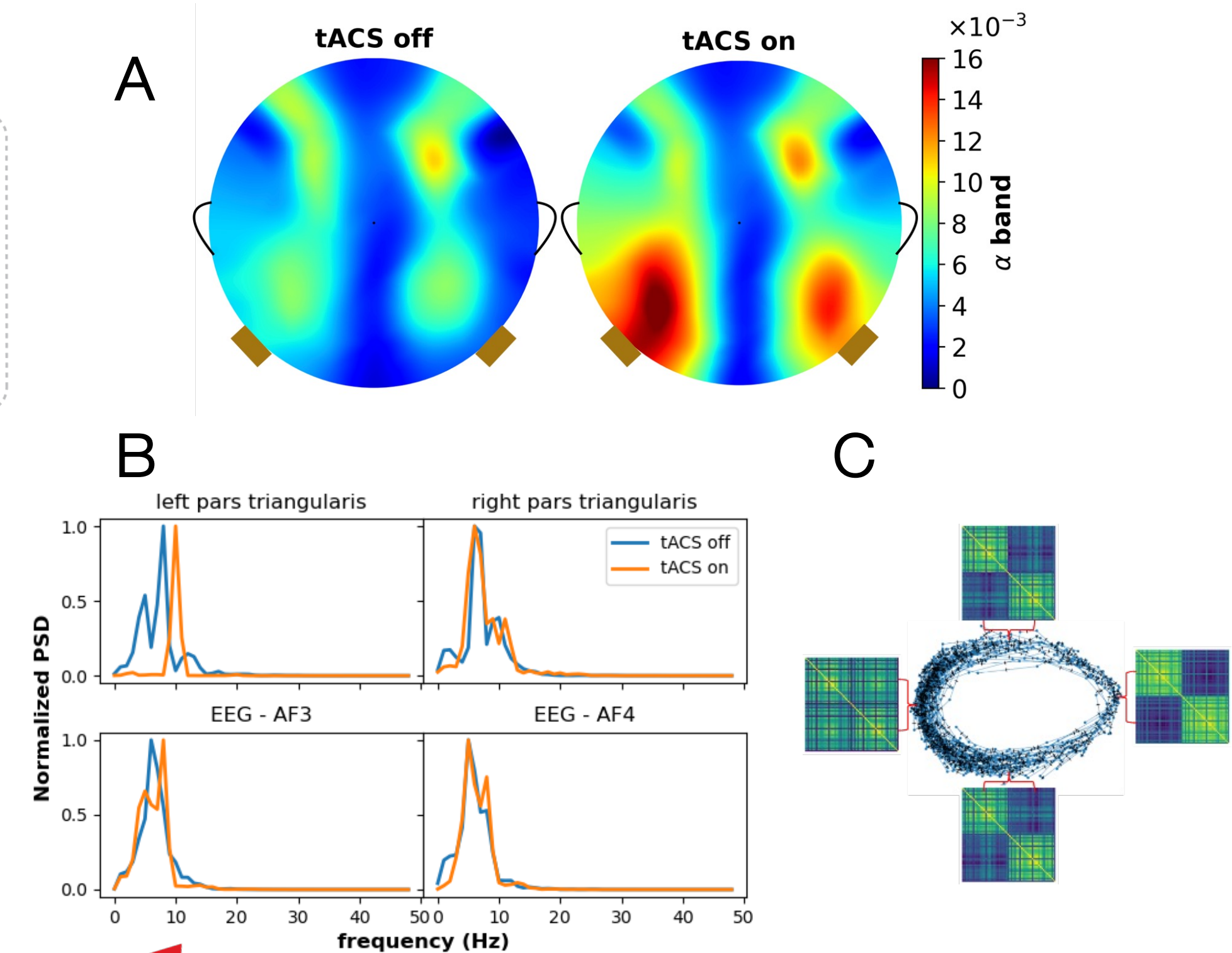


# Brain Network Responses to tES

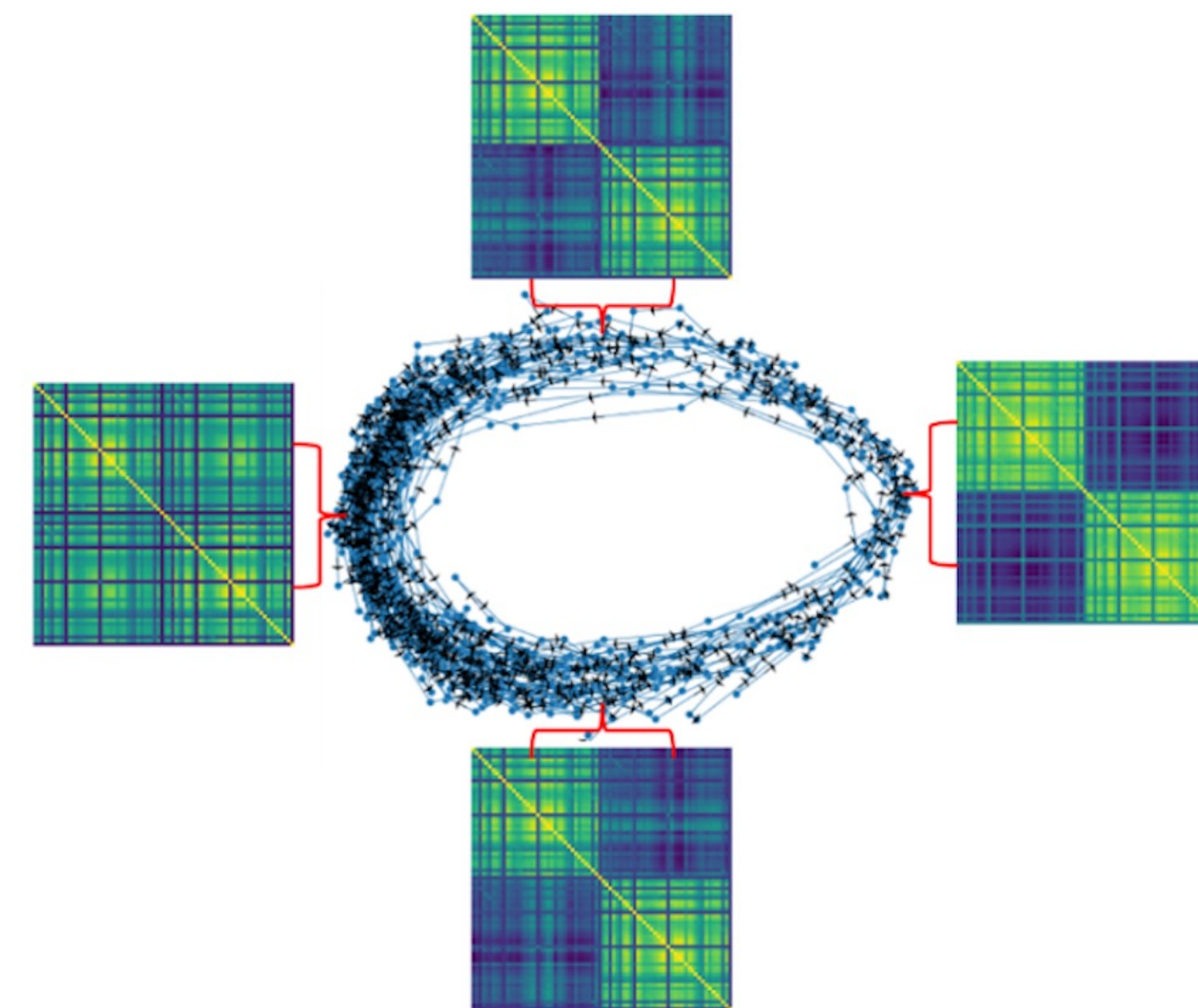
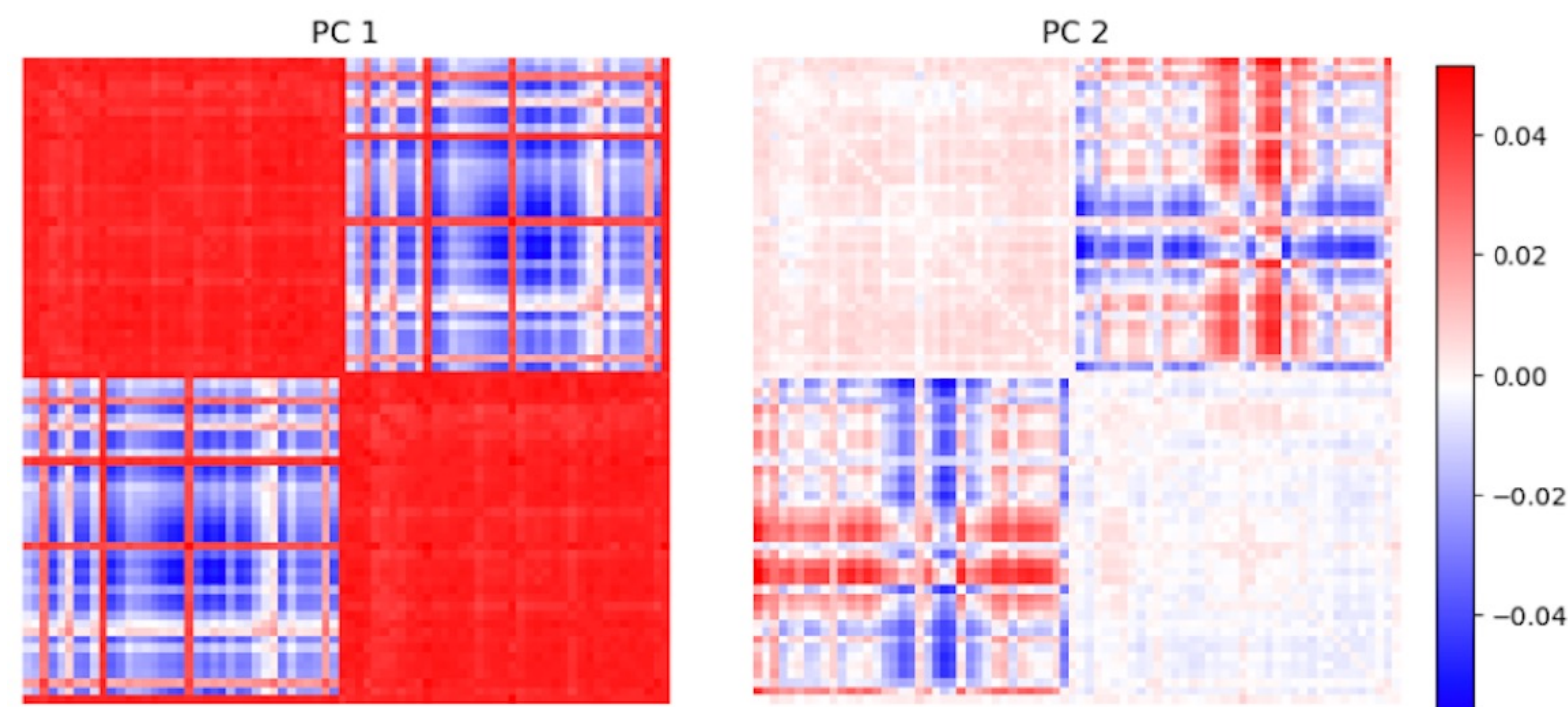
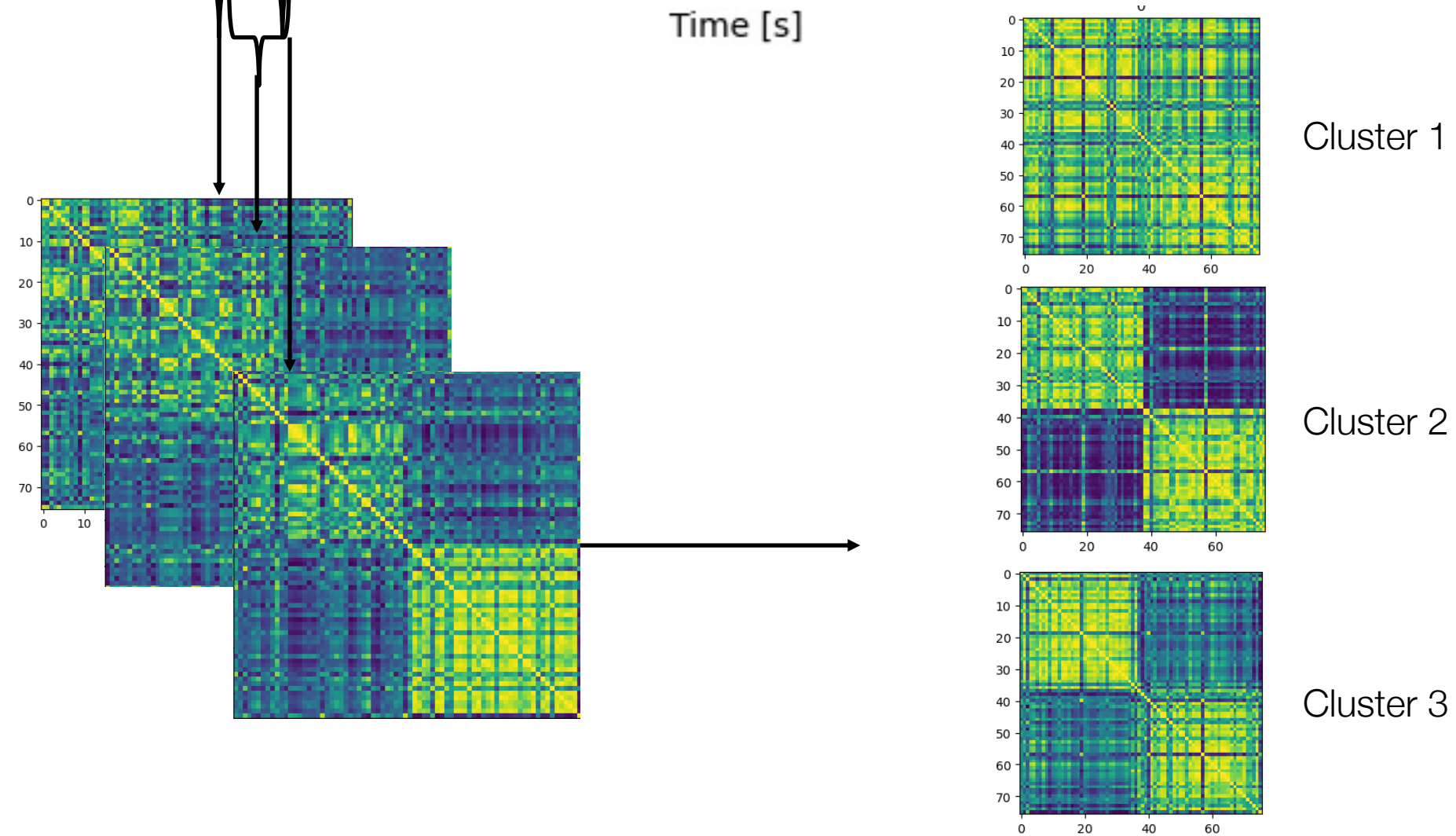
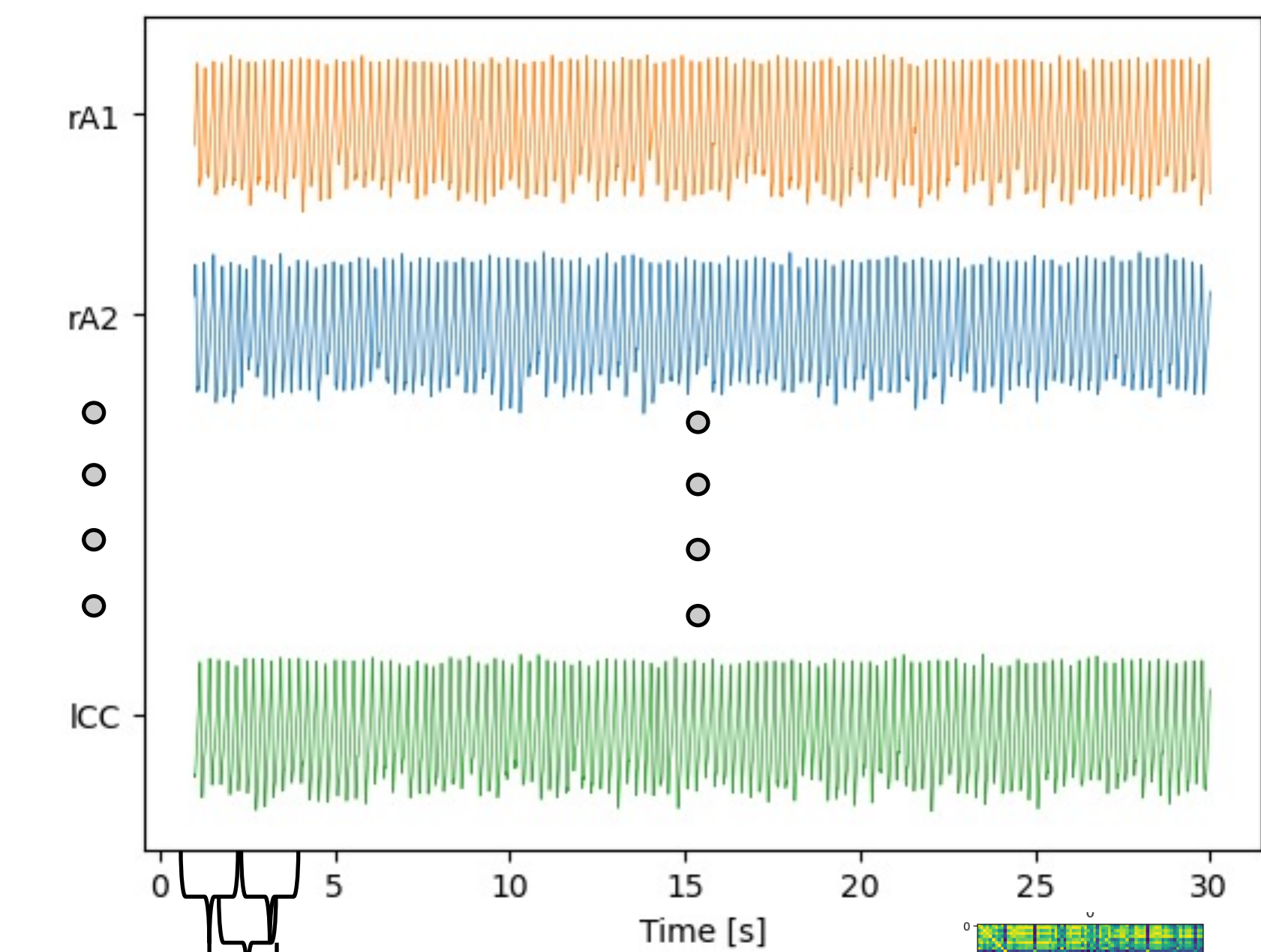
- brain modeling pipeline: MRI/DTI inputs → AI-based model reconstruction → EM simulations → coupled network simulations → *in silico* signal generation



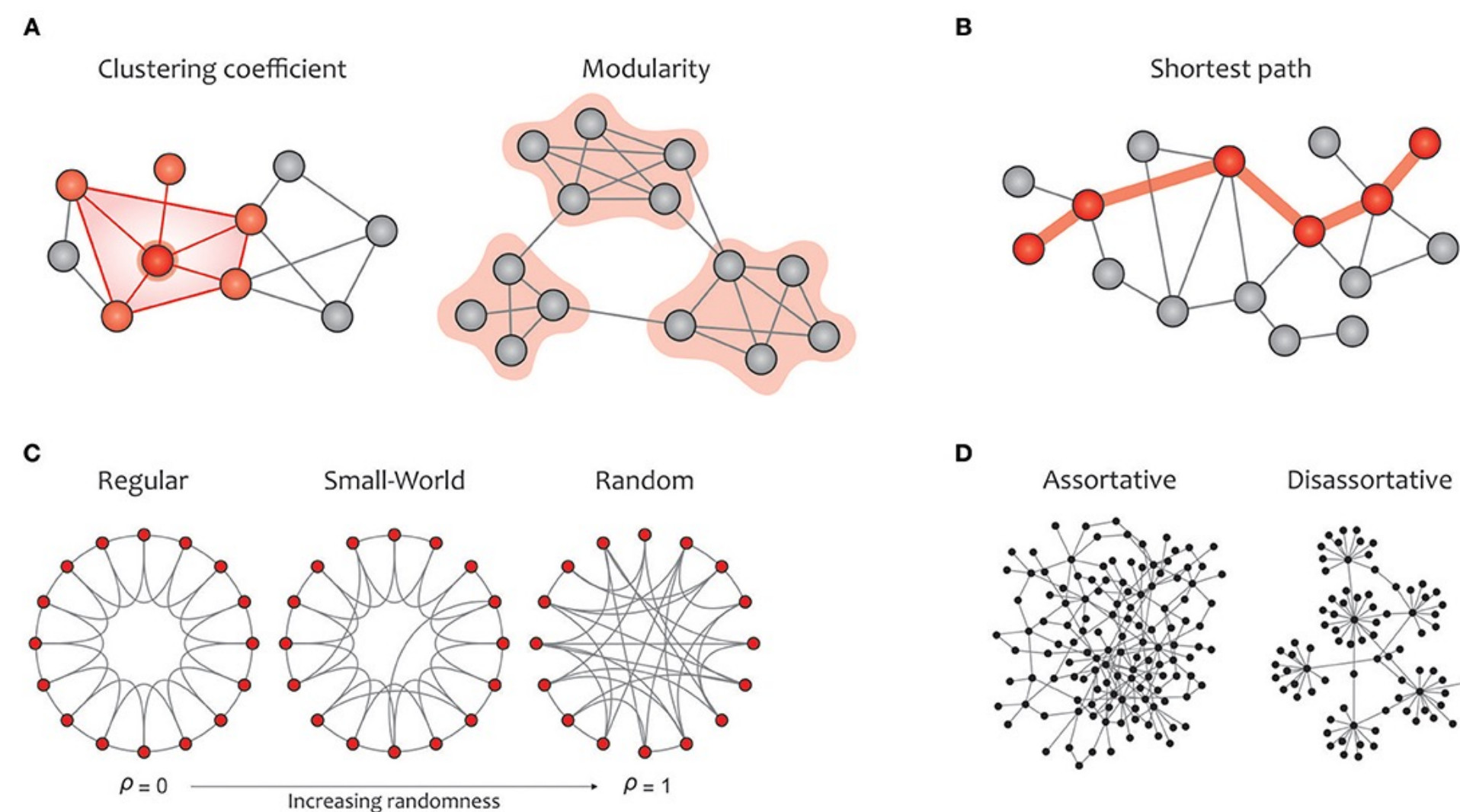
- network response: A) topographic EEG alpha band power map; B) normalized PSD for raw activity of two brain regions and two EEG channels; C) PCA of dynamic functional connectivity states



# Dynamical Functional Connectivity (DFC) Analysis

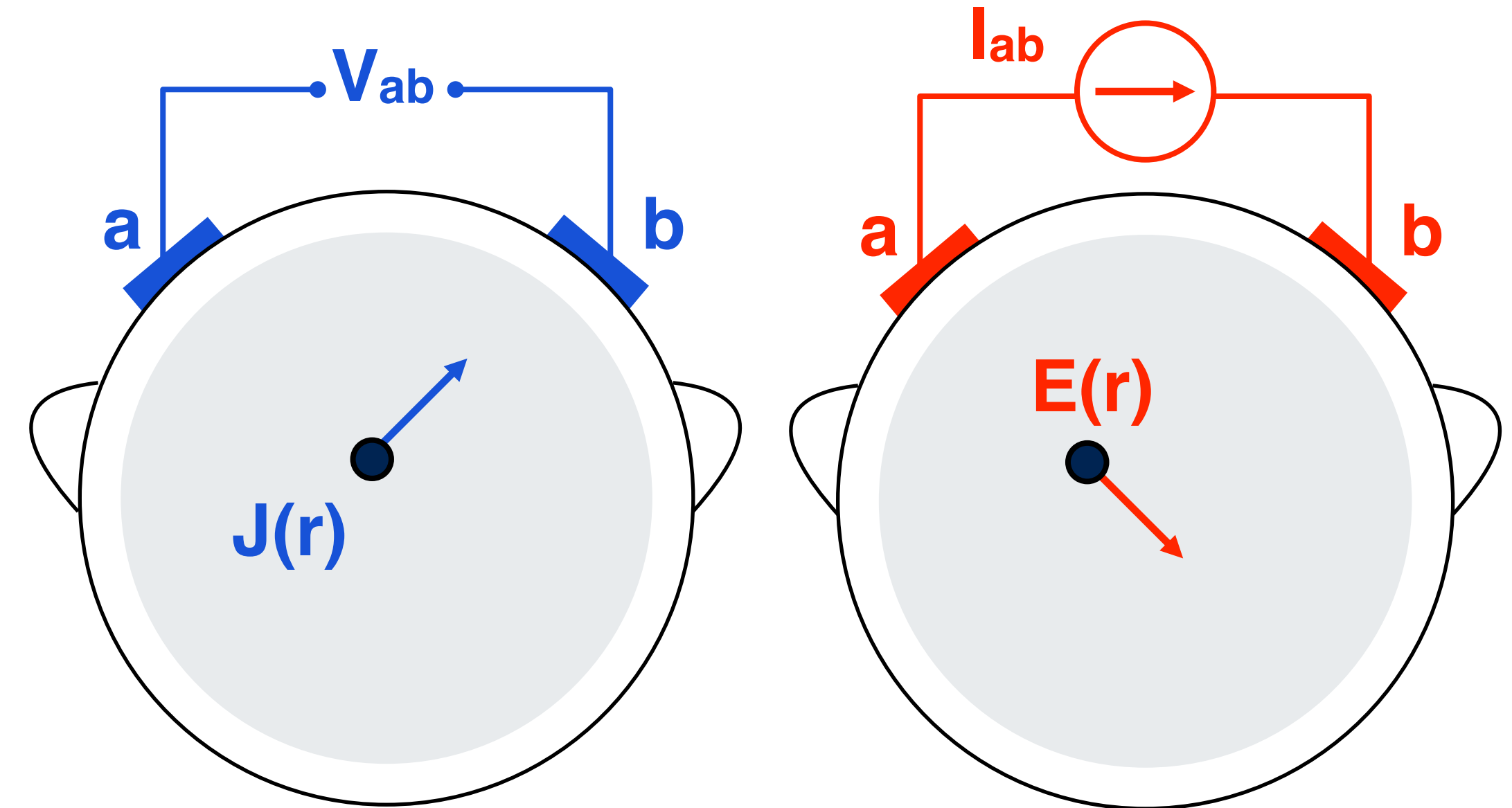


Typical global measures (Farahani, Karwowski, and Lighthall, "Application of Graph Theory for Identifying Connectivity Patterns in Human Brain Networks.")



# Personalized Lead Field Matrices

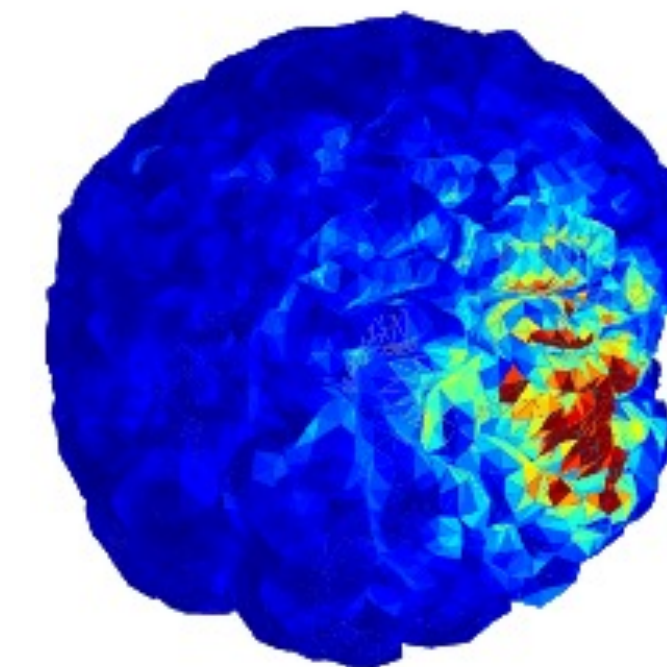
- personalized source-to-sensor mapping (lead field matrix,  $M$ )
- direct calculation is computationally intensive
  - simulate each dipole as a current source to compute induced voltage on “ $n$ ” EEG electrodes
- reciprocity-based approach**
  - apply current between EEG electrodes and compute electric field at sources just once
  - determine a basis ( $n-1$ ) of electrode E-fields
  - simulate desired non-invasive stimulation
  - sample E-field at ‘node’ locations to obtain  $E(r)$  → lead field matrix ( $n-1$  x #sources):  $M = -E(r)/I_{ab}$



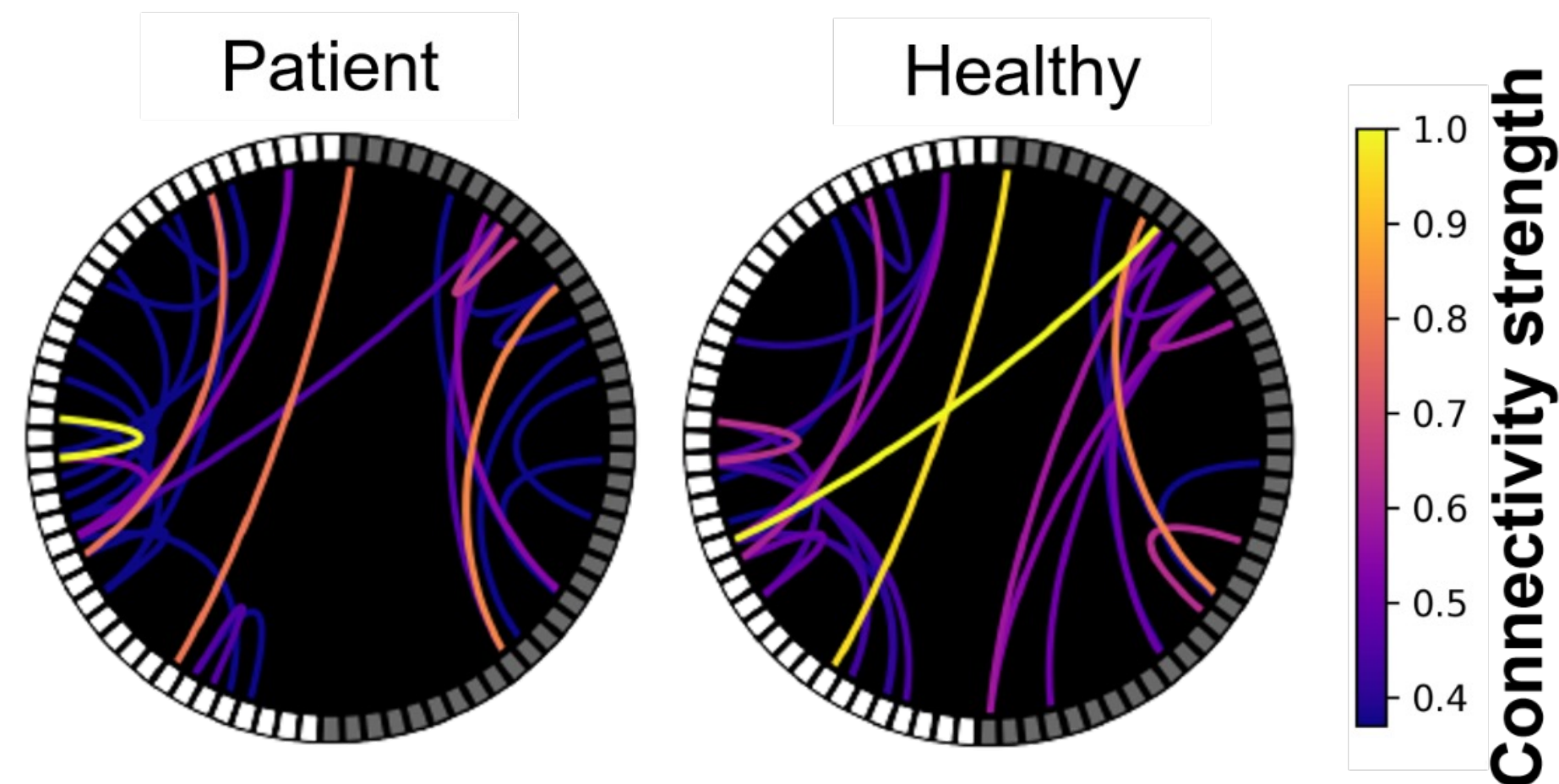
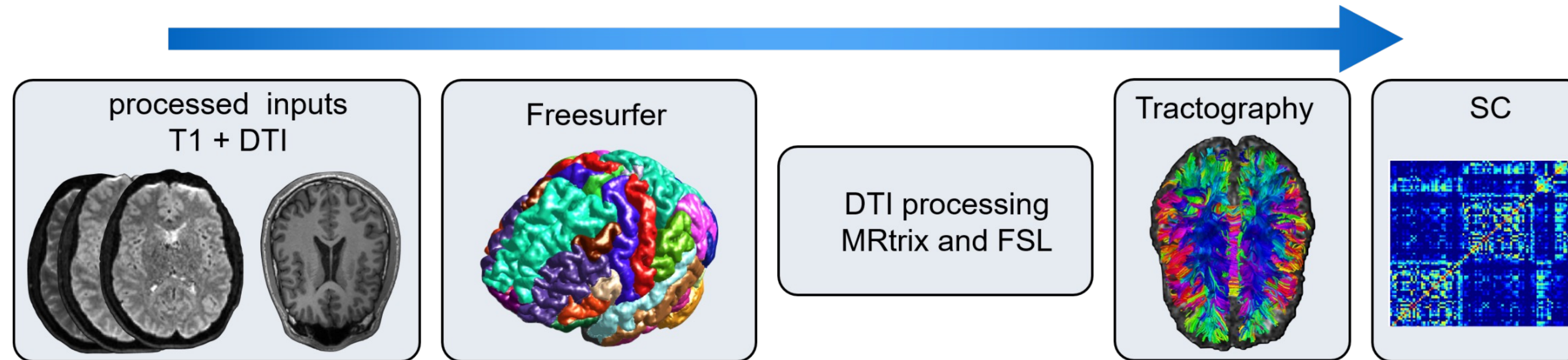
$$V_{ab} I_{ab} = -J(r)E(r)$$

**#simulation = #sources (~10k)**

**#simulation = #sensors (~100)**



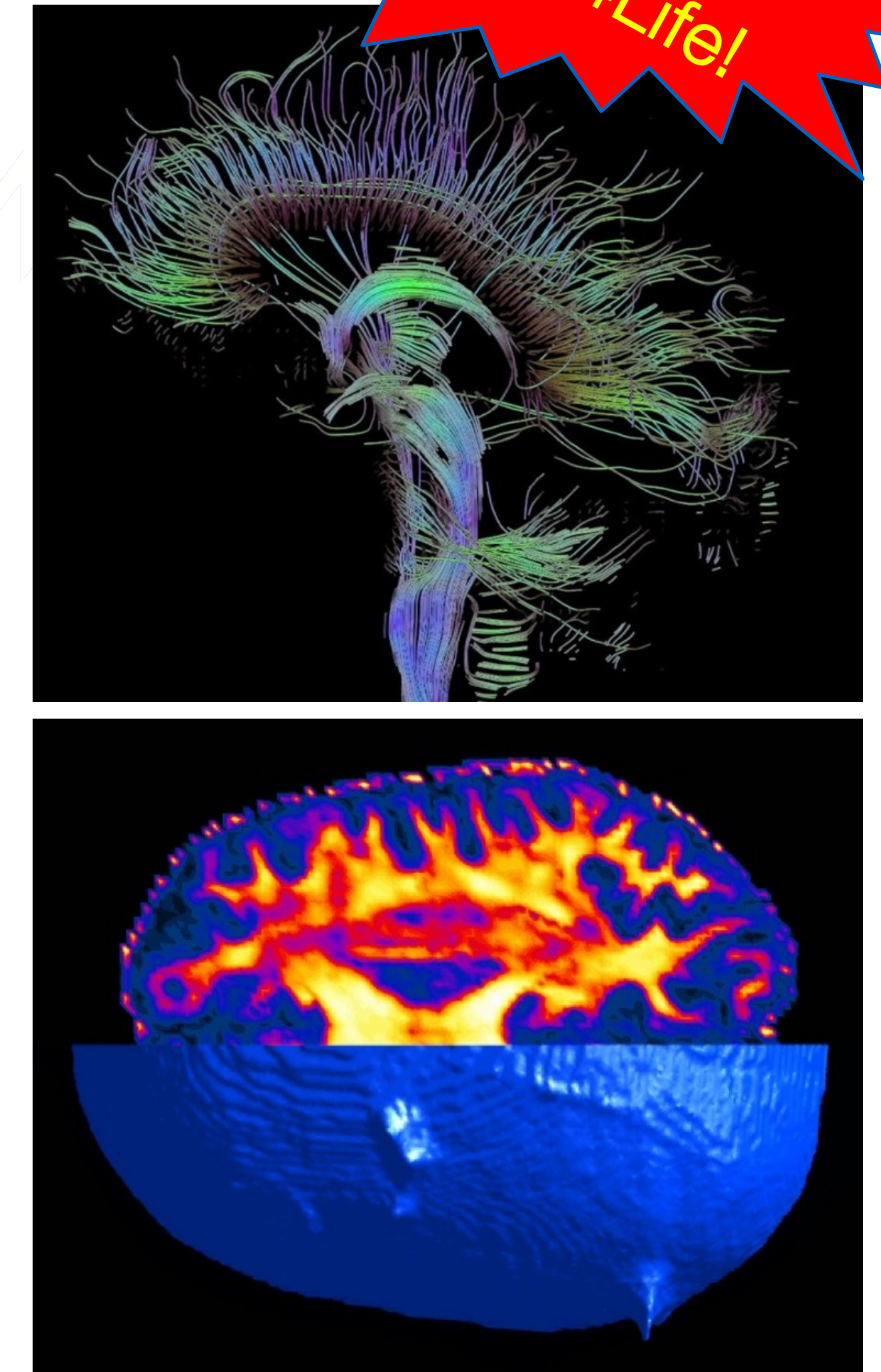
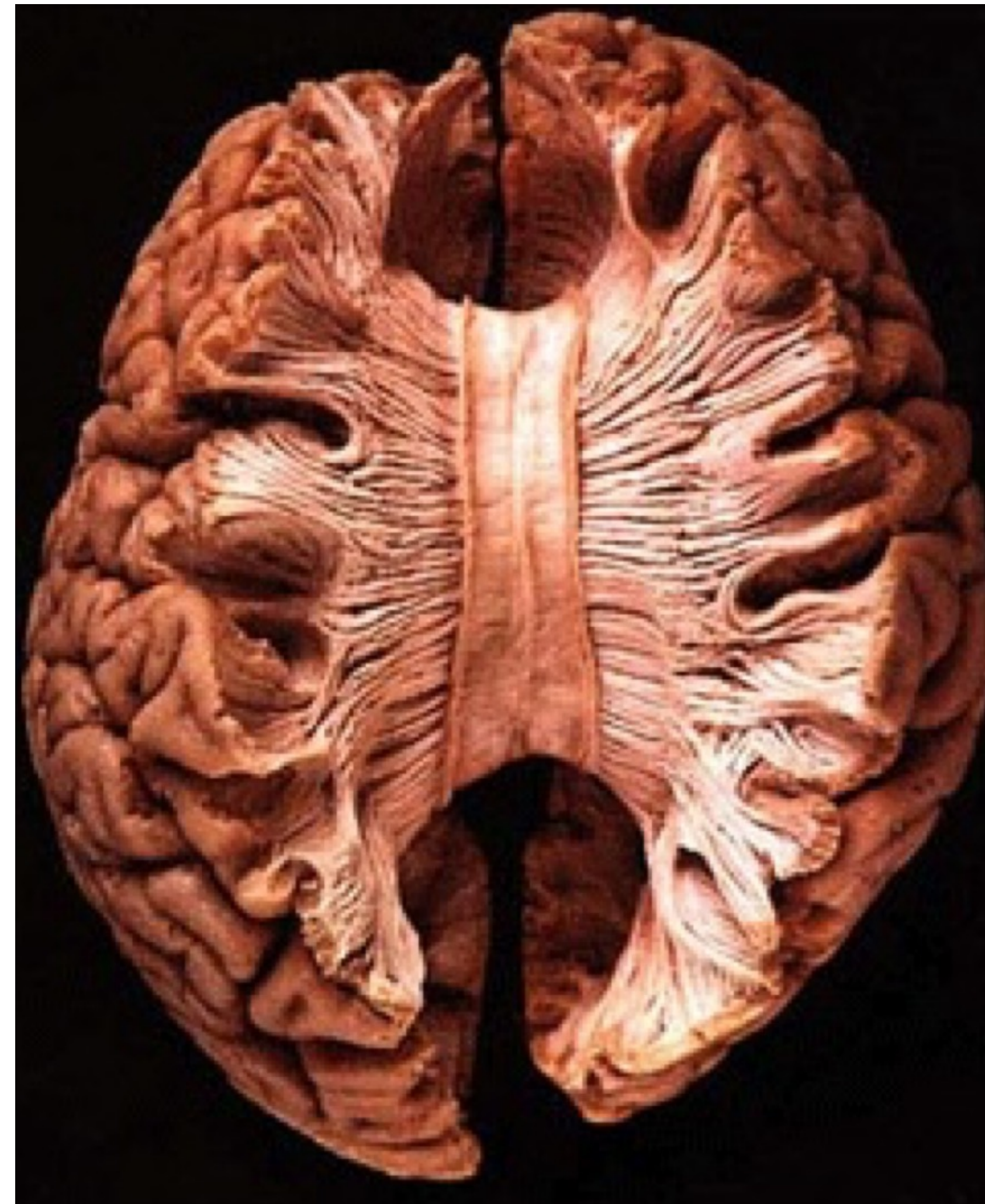
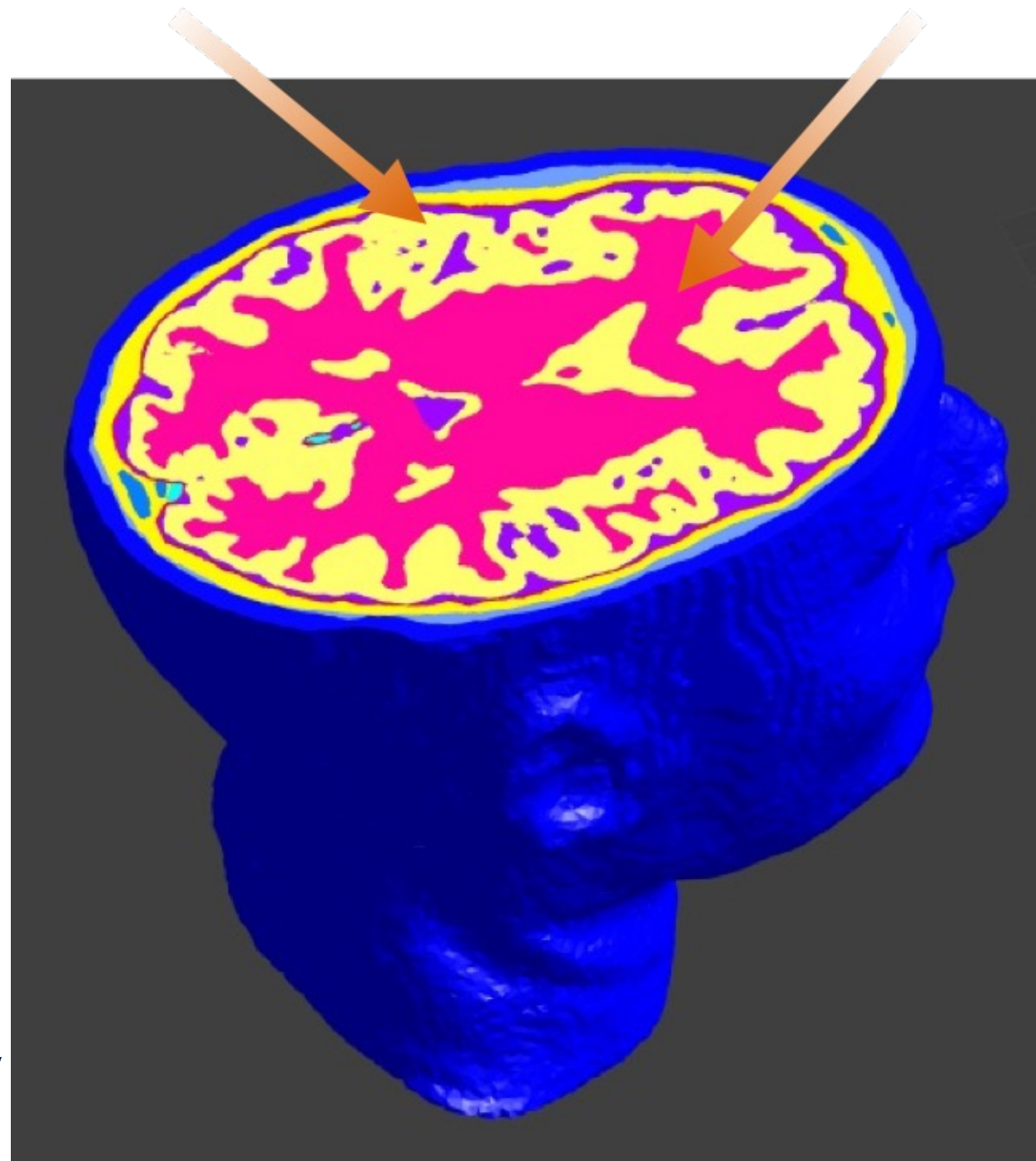
# Network Personalization



- Fiber tractography can be used to infer the connection strengths (SC) between nodes in a brain-wide NMM
- Left: SC for a stroke patient versus a healthy subject; each rectangle at the circle's perimeter represents a brain region. Note the missing connections in the stroke patient due to cortical lesions.

# DTI-based Conductivity Maps for White Matter

Now in  
Sim4Life!

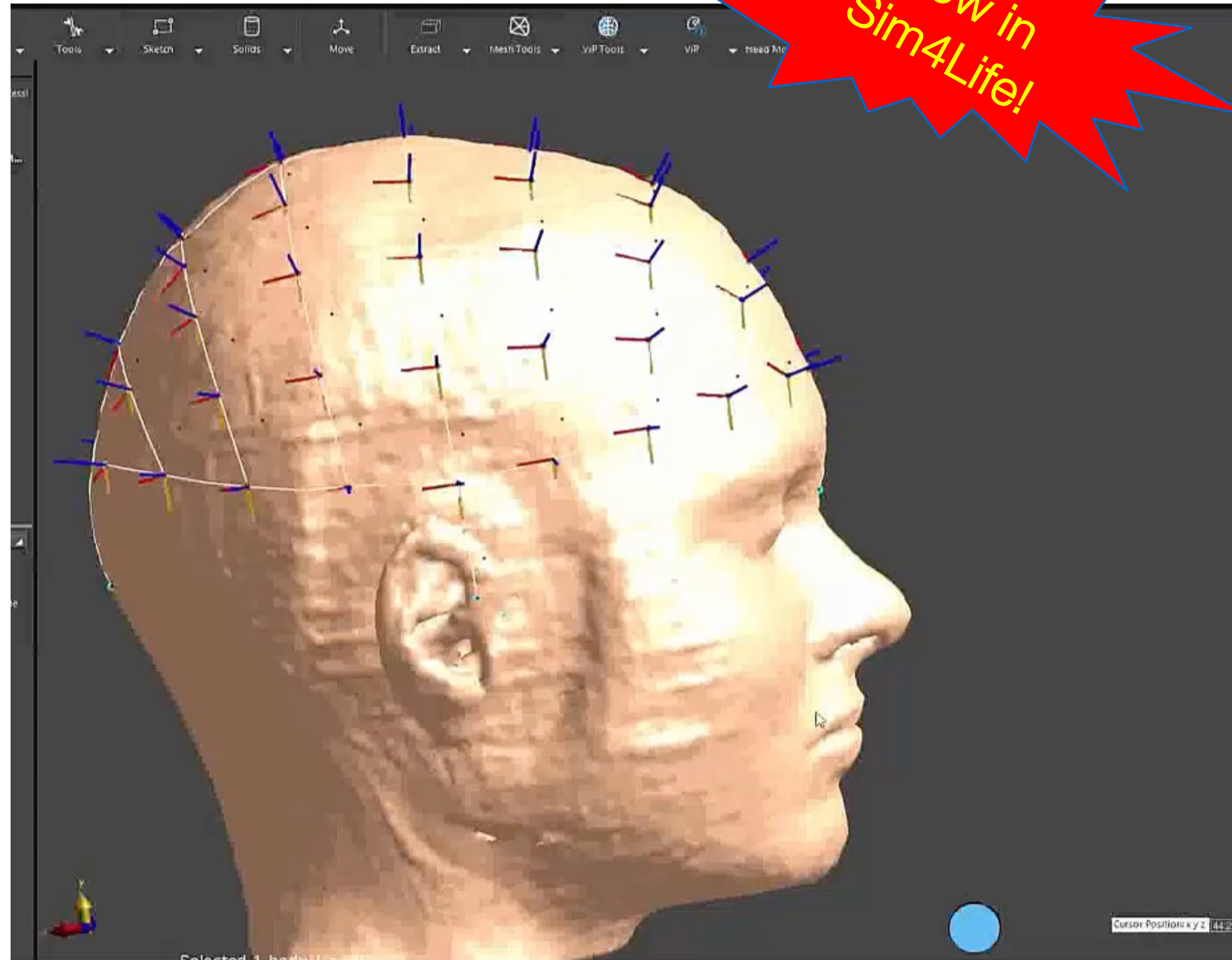
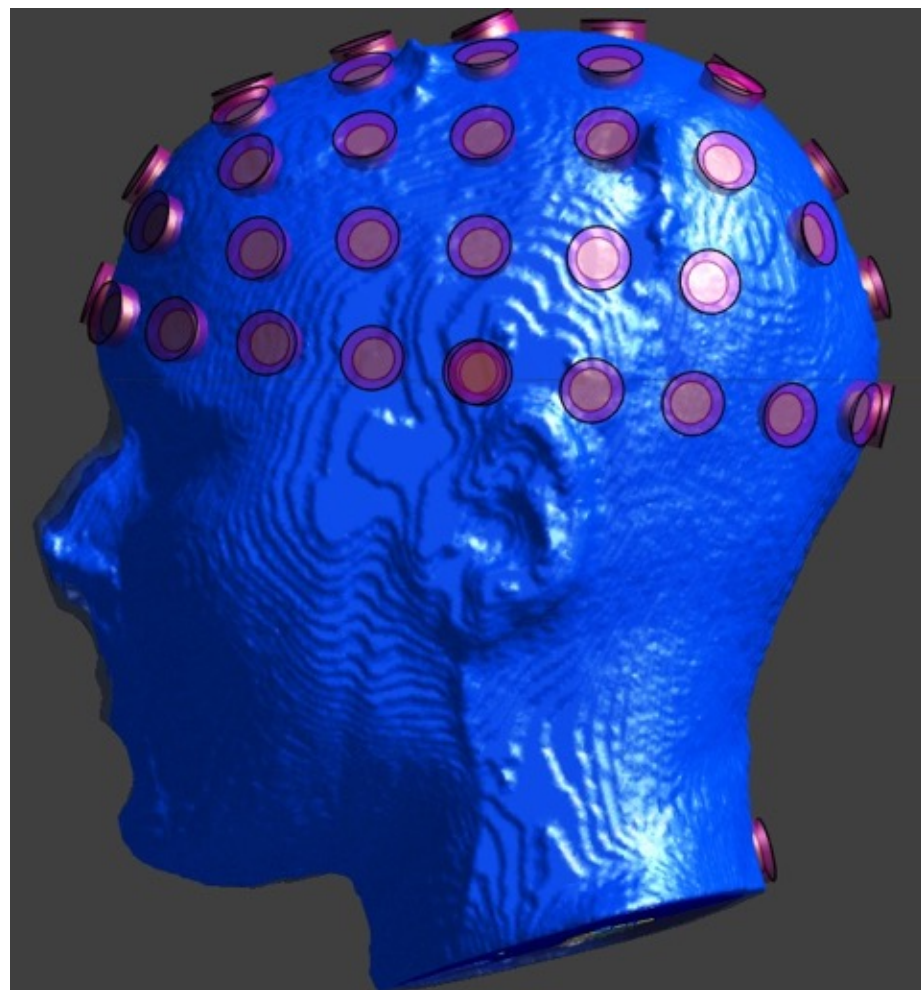


DTI → anisotropic conductivity map\*

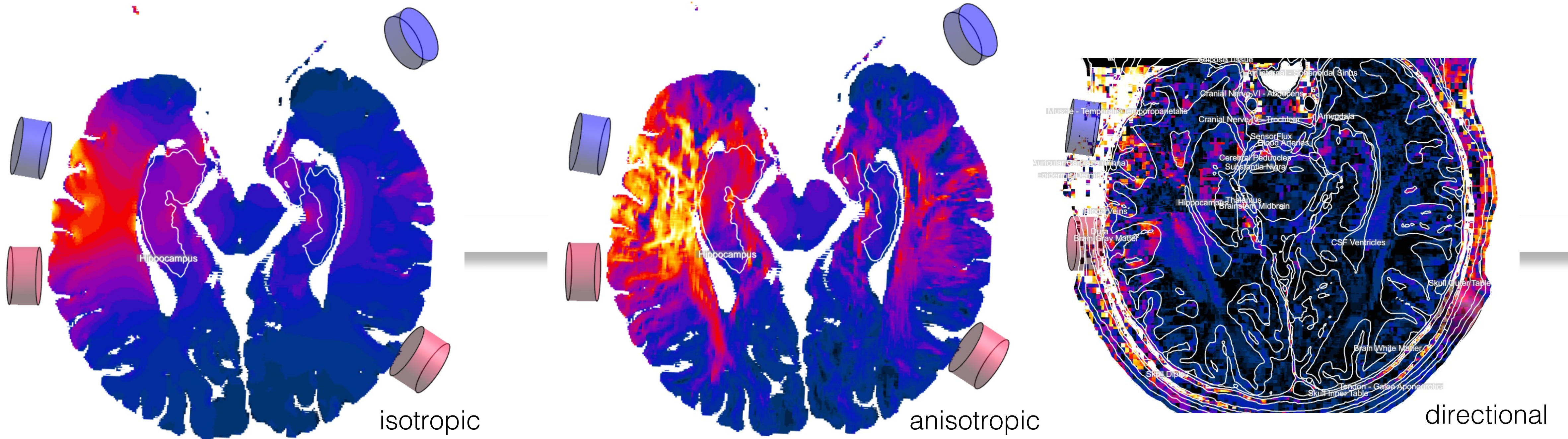
\* Tuch et al, "Conductivity mapping of biological tissue using diffusion MRI."

# Electrode Placement

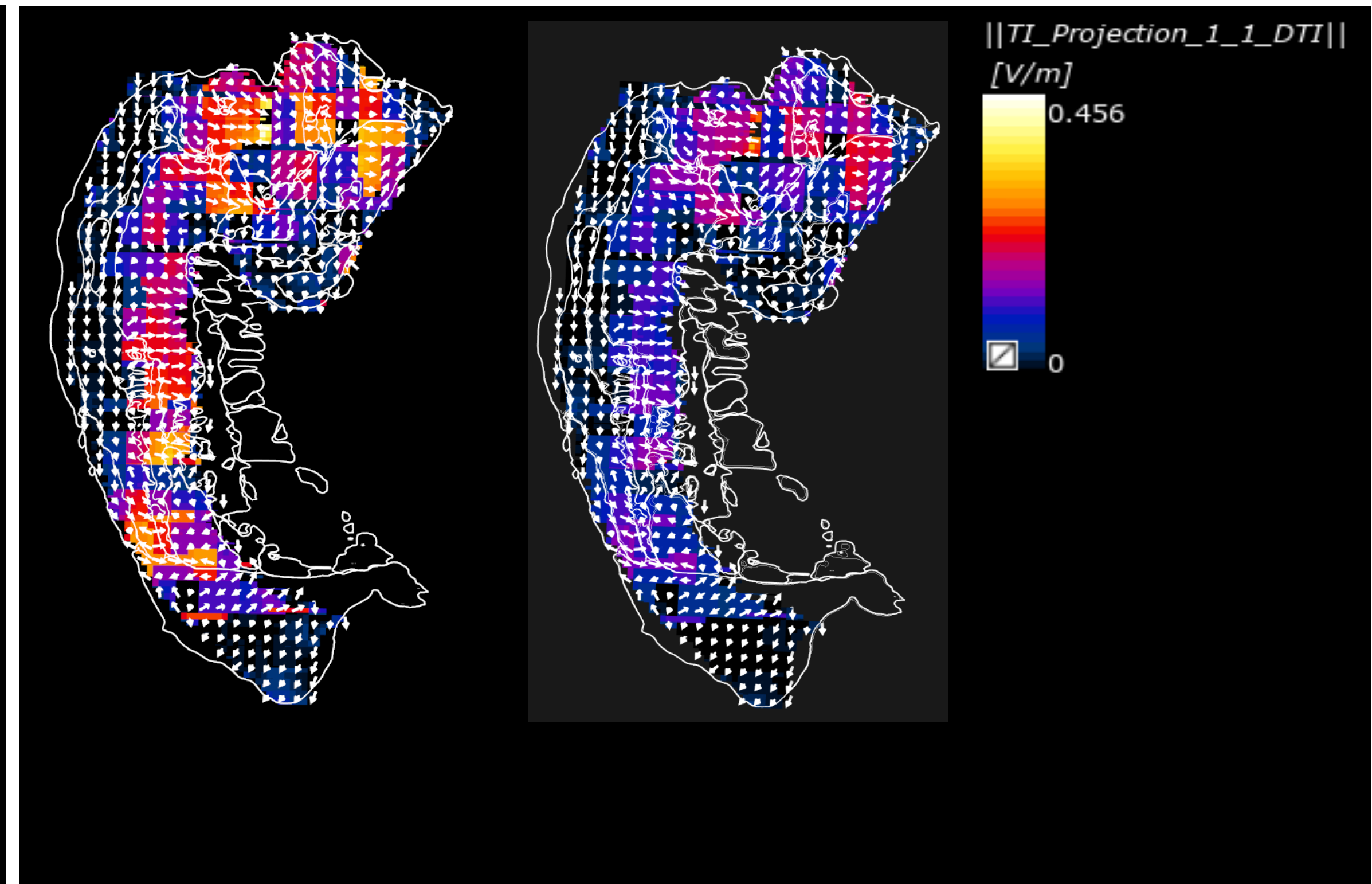
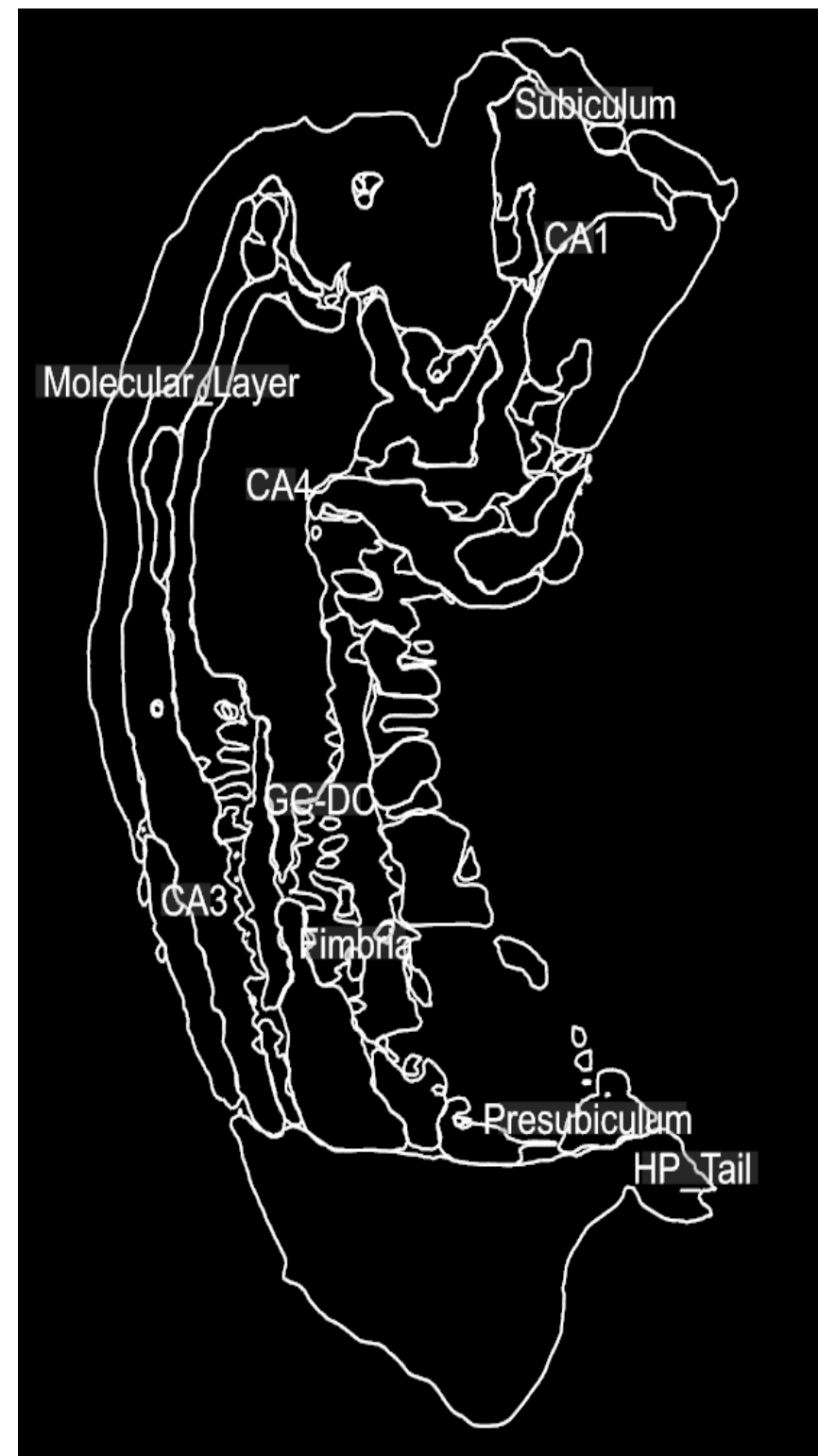
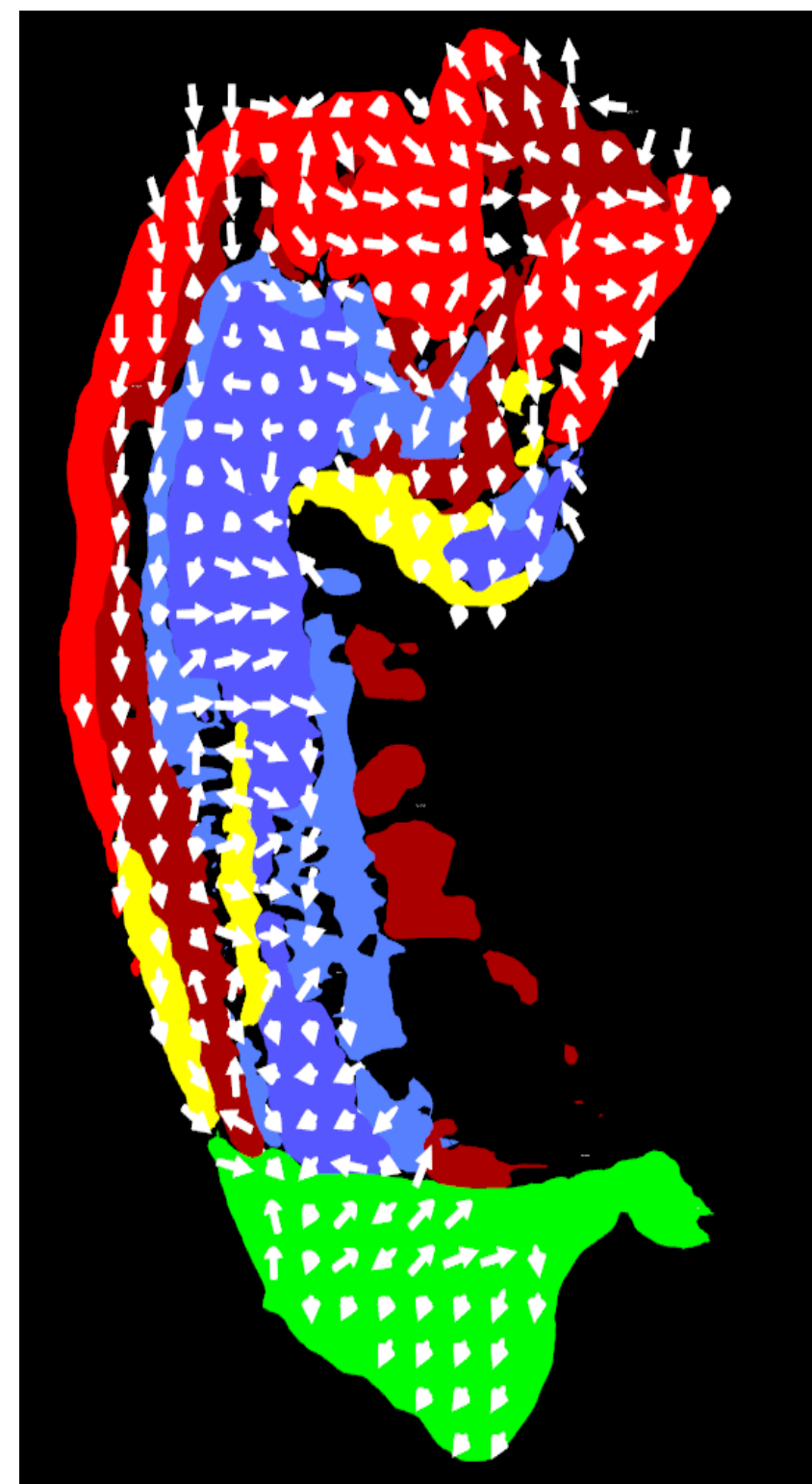
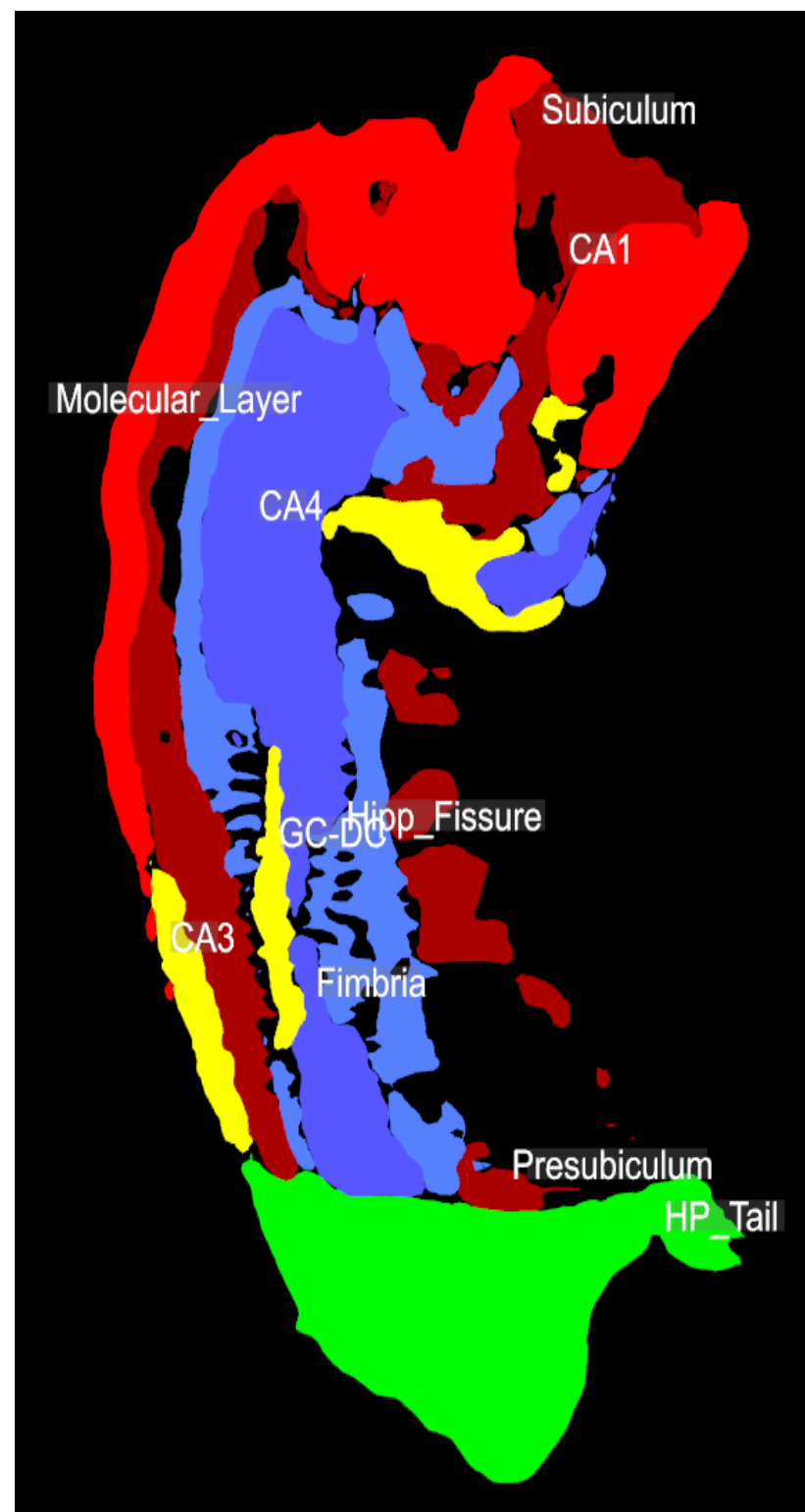
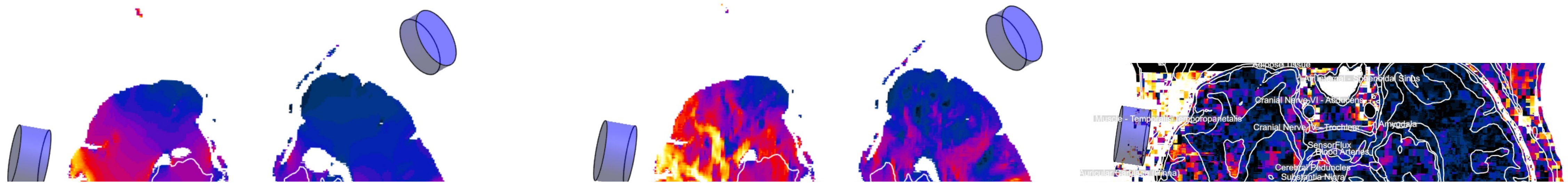
- AI identifies 4 fiducial points
  - nasion
  - inion
  - LPA
  - RPA
- automatic 10-10 system identification
- electrode placement



# Tissue Anisotropy



# Tissue Anisotropy



Labels

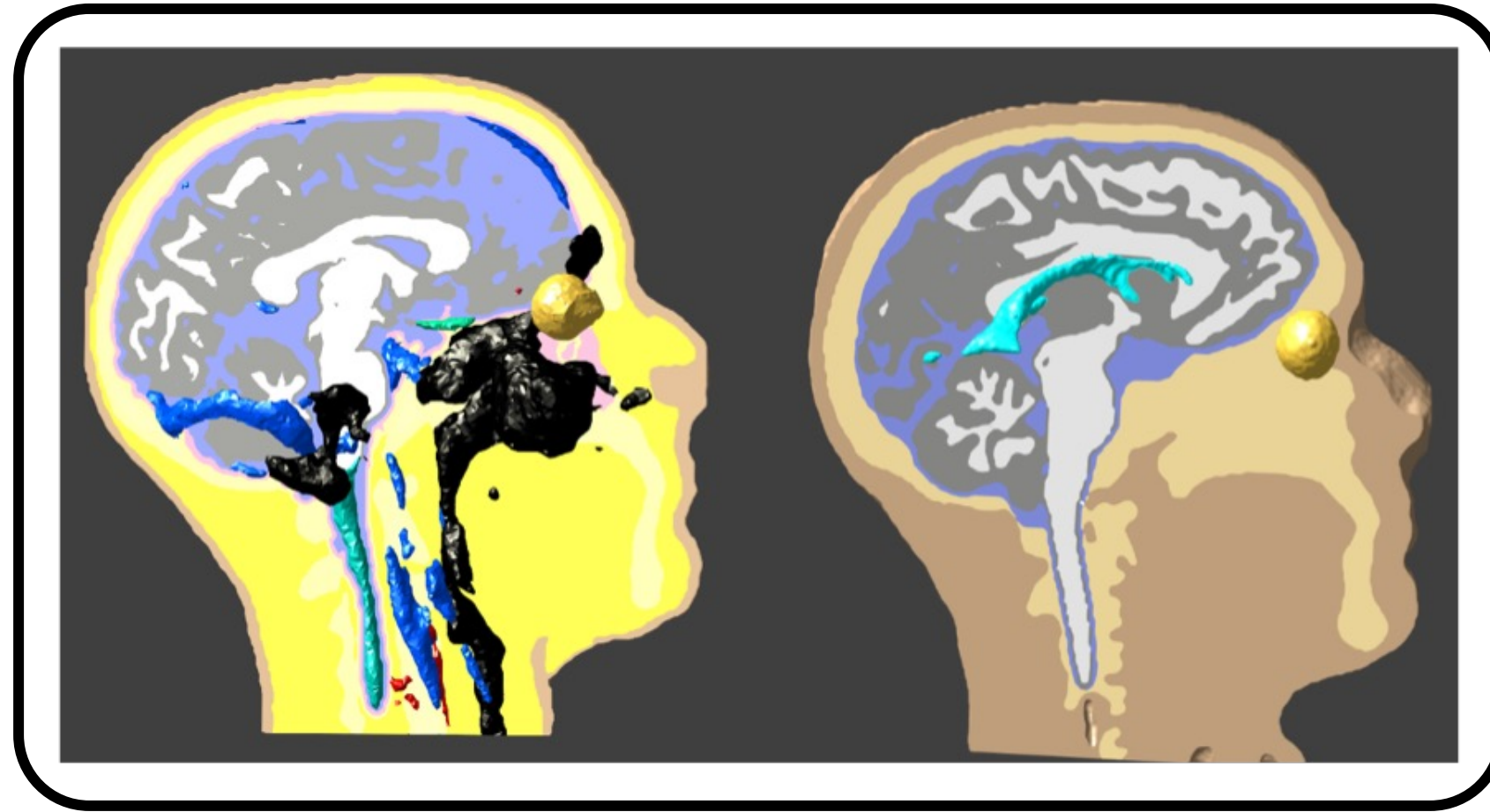
DTI Directions

Contours

TI Directional Projection

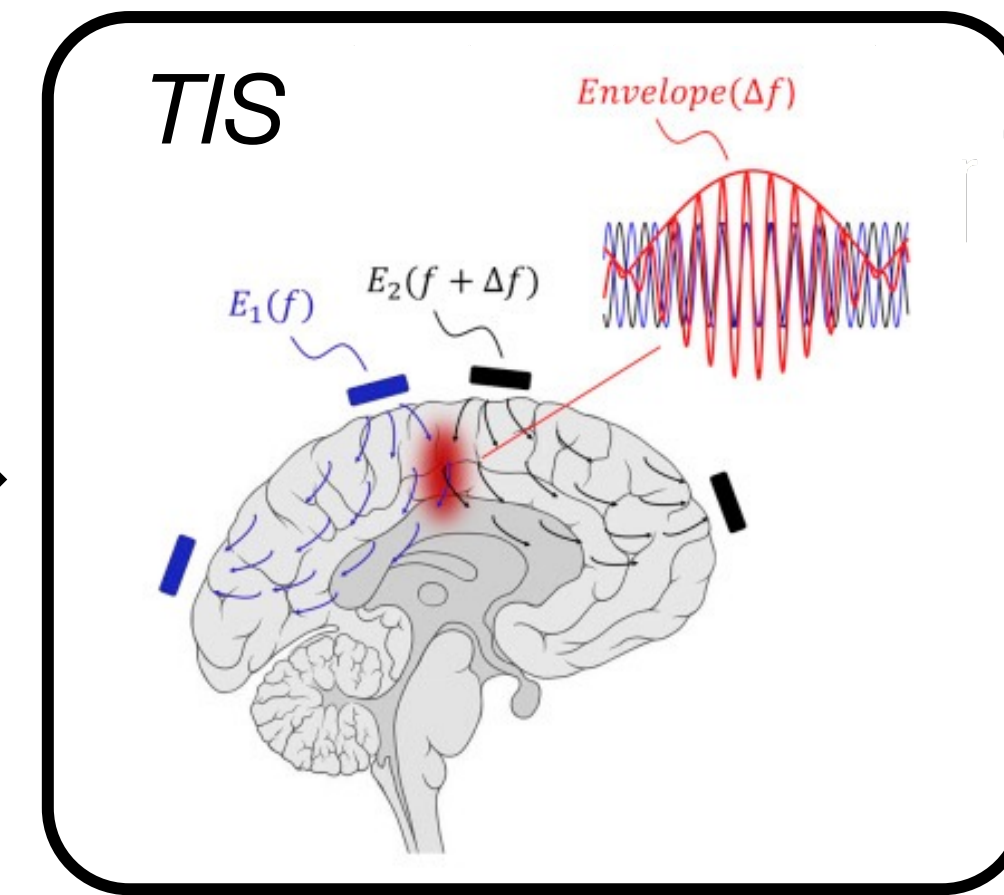
# Restoring Healthy Brain Patterns

personalized head & brain models

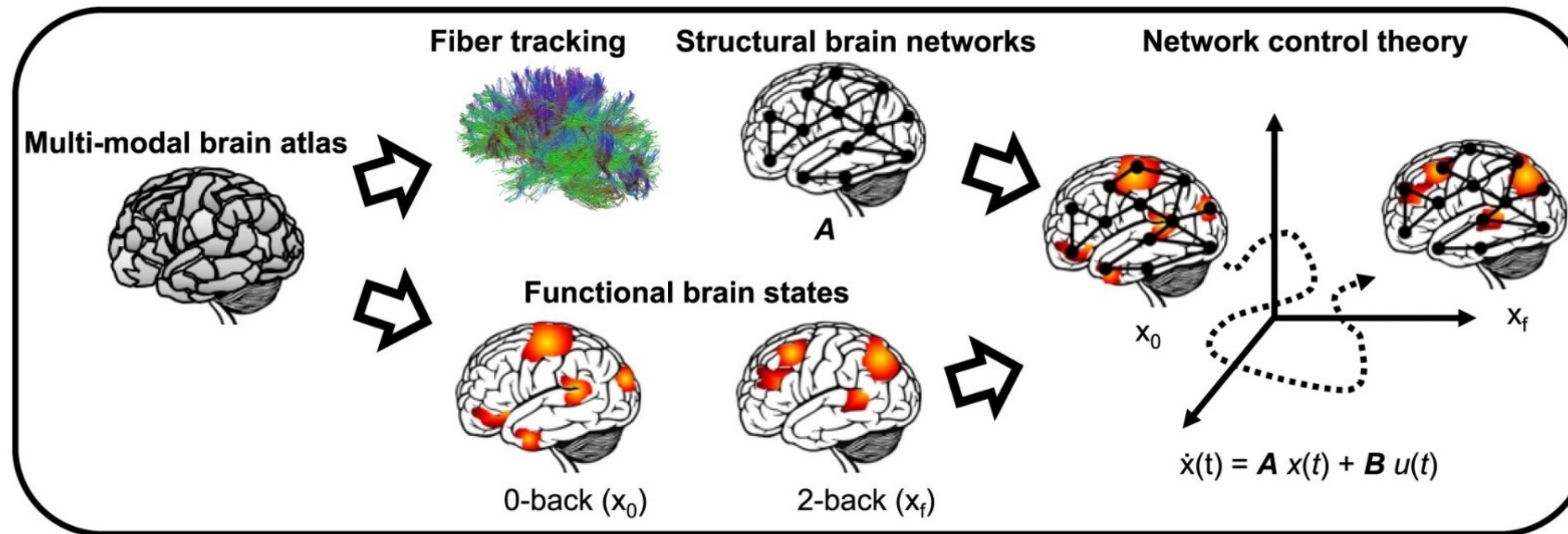


optimal non-invasive exposure

Grossman *et al.* (2017)

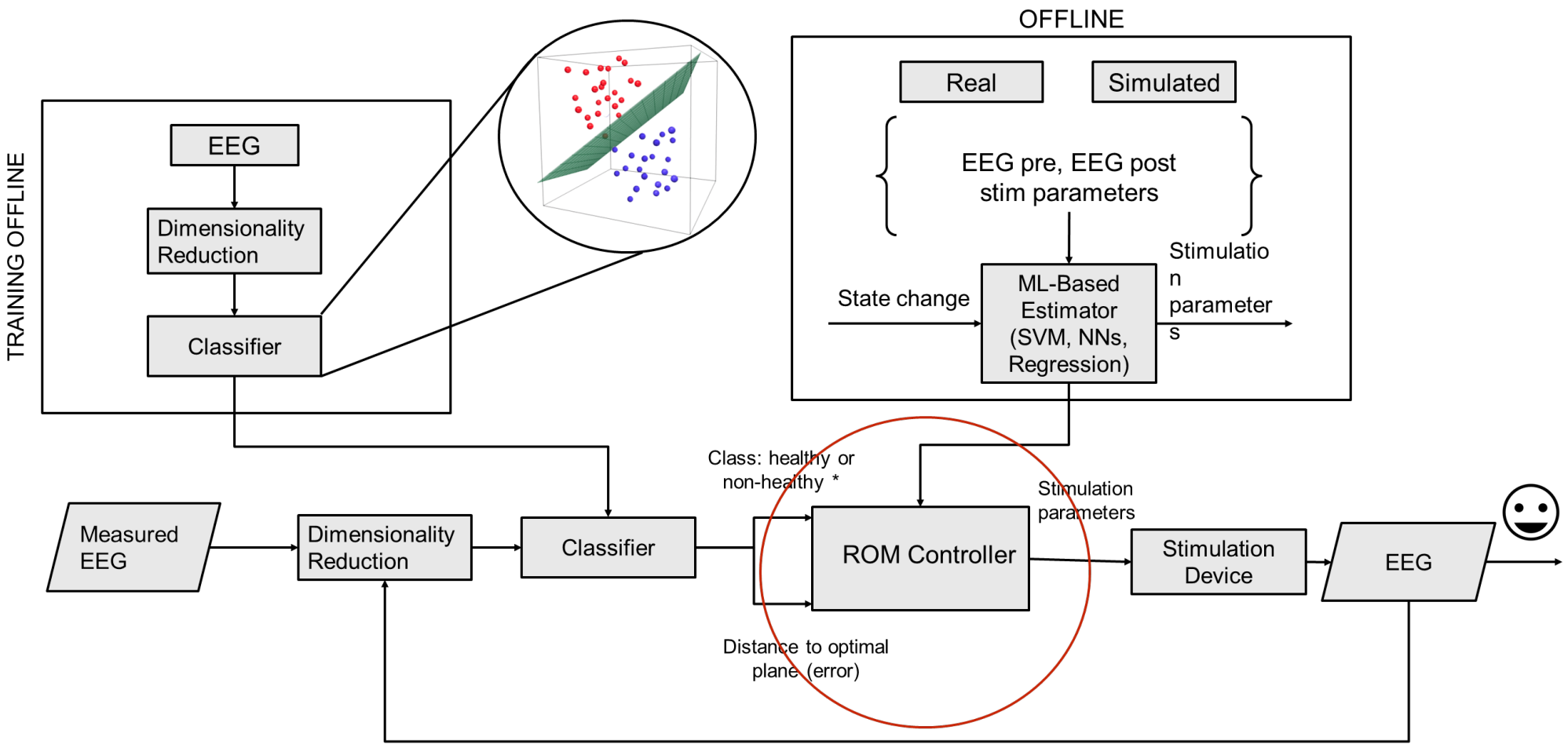


closed-loop network control



Braun *et al.* (2021)

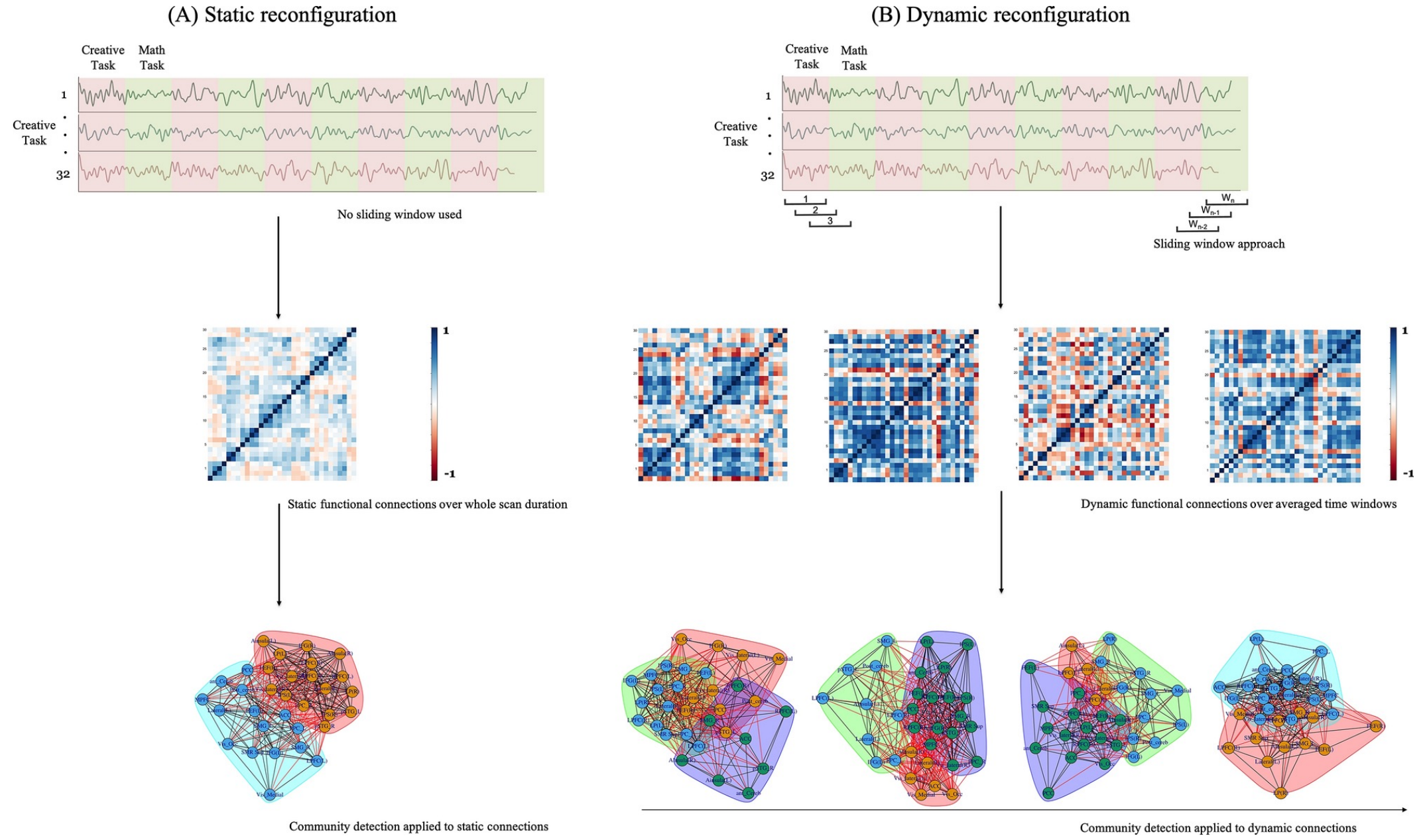
# State-Synchronized Control



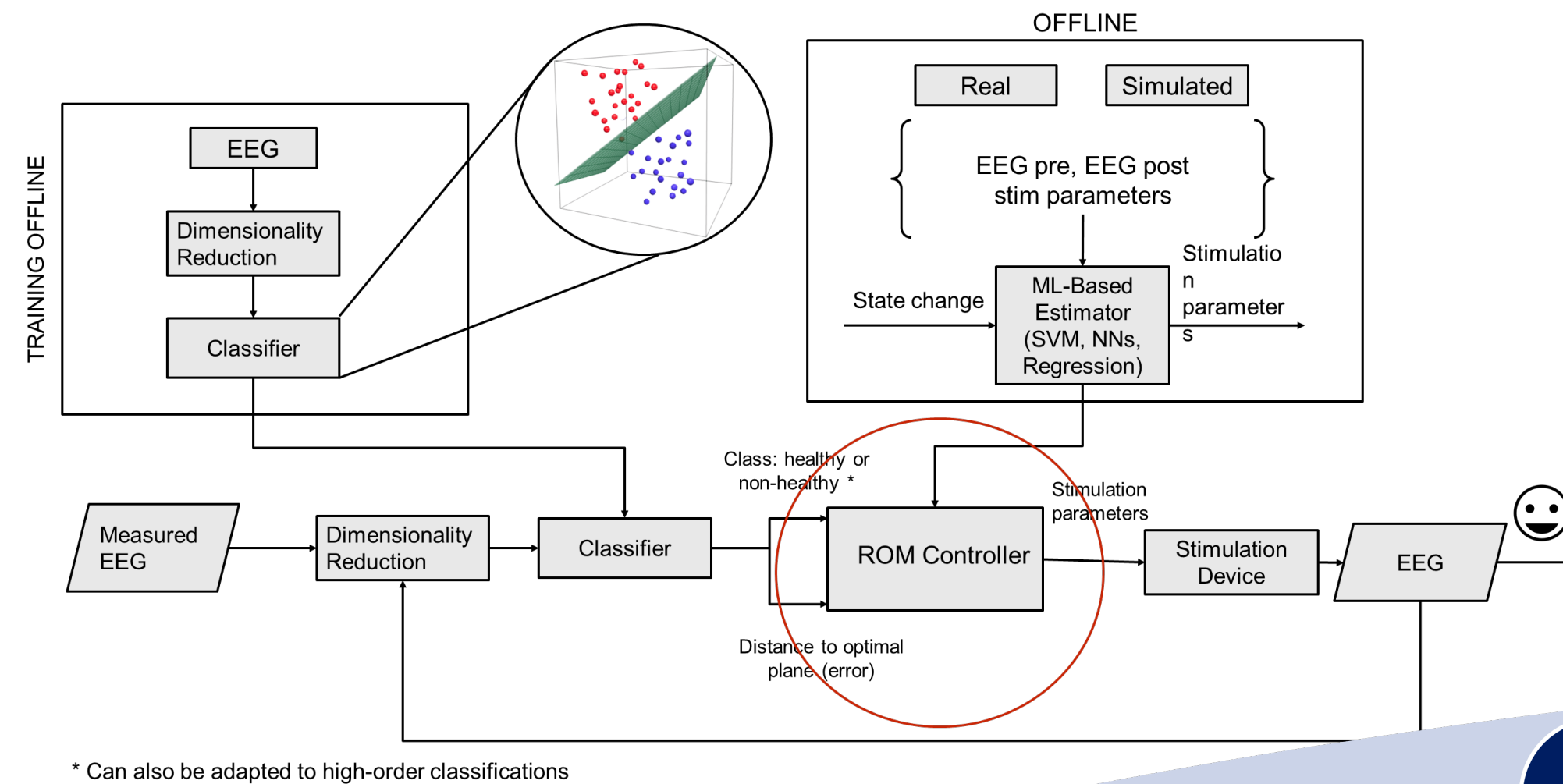
\* Can also be adapted to high-order classifications

High-level brain fluidity metrics (e.g., dynamic functional connectivity) can be used to quantify “healthy” activity patterns

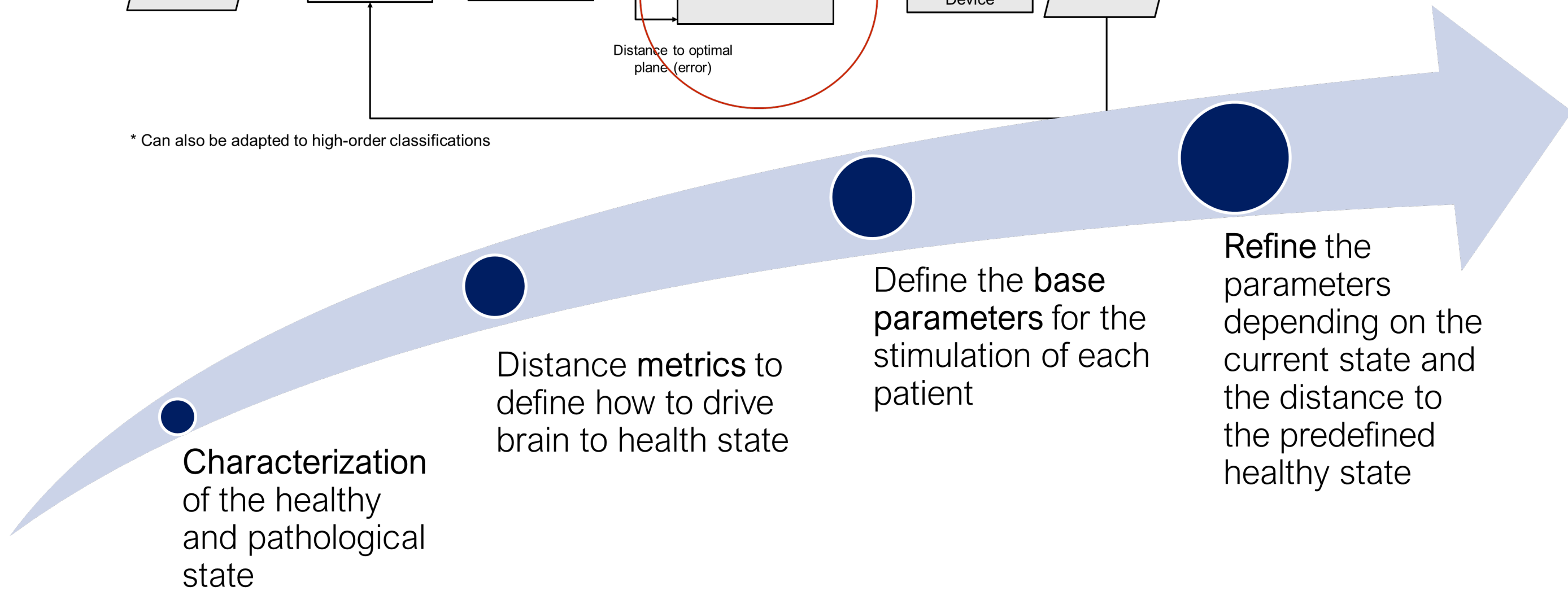
State-driven control architectures for closed-loop neurostimulator design



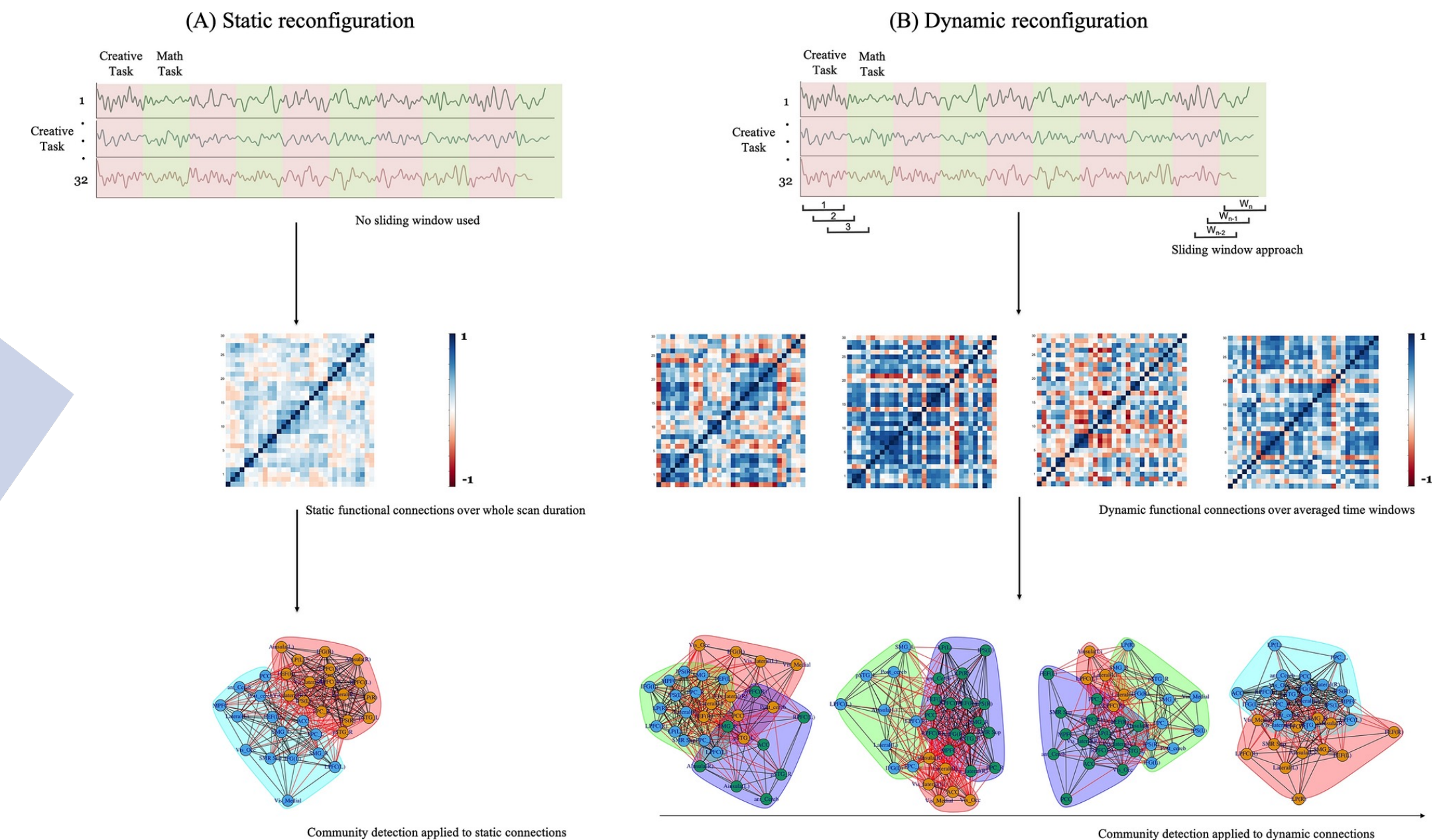
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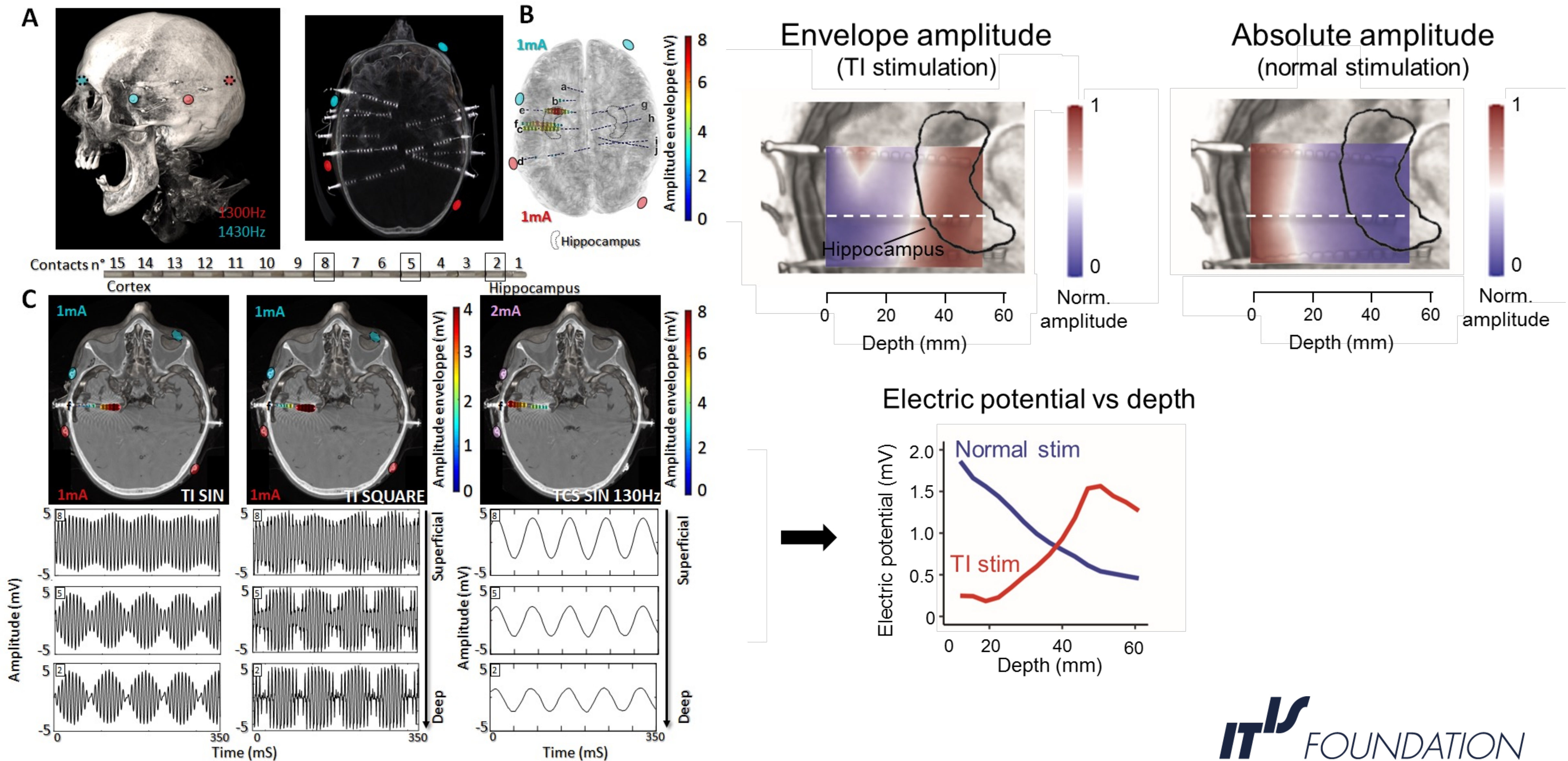
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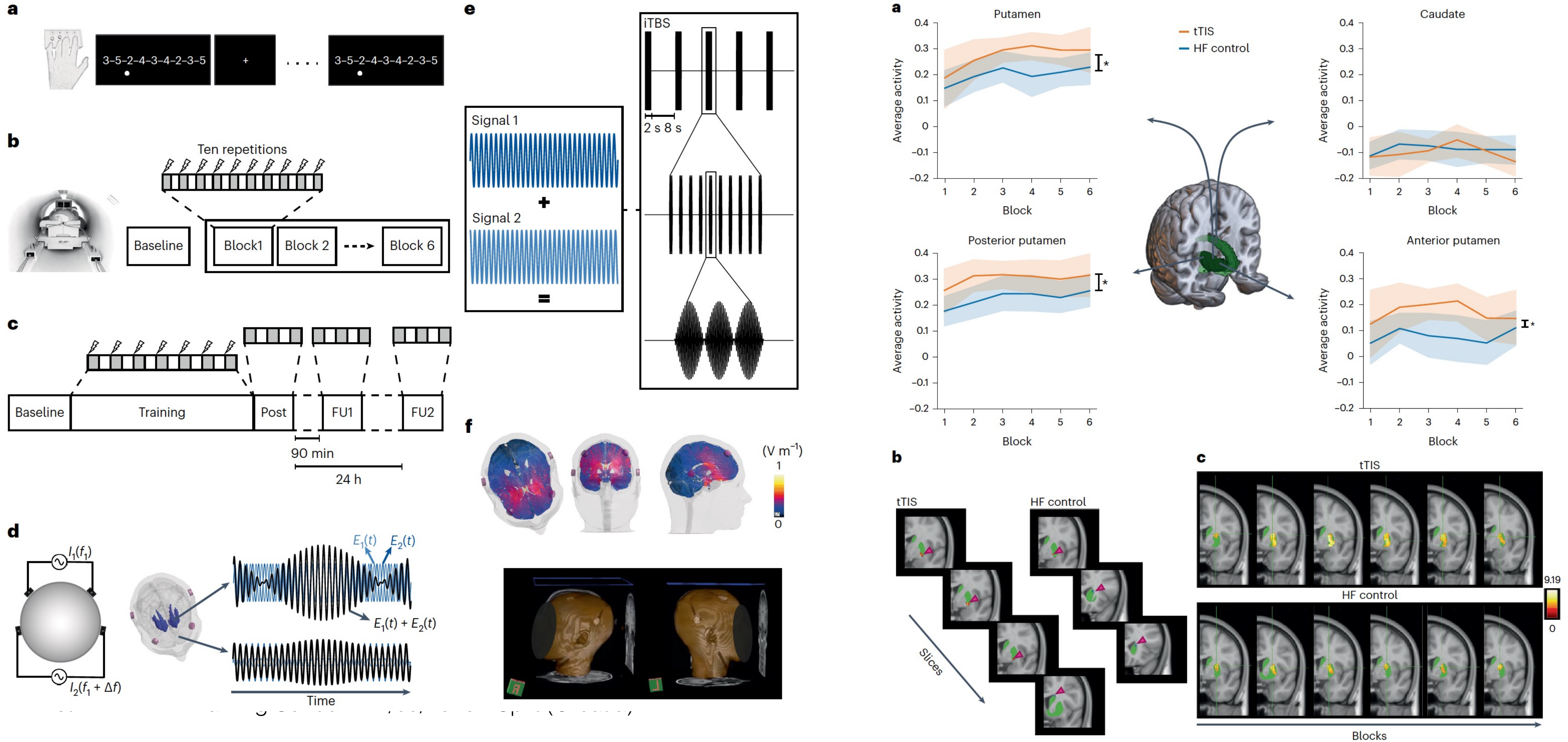
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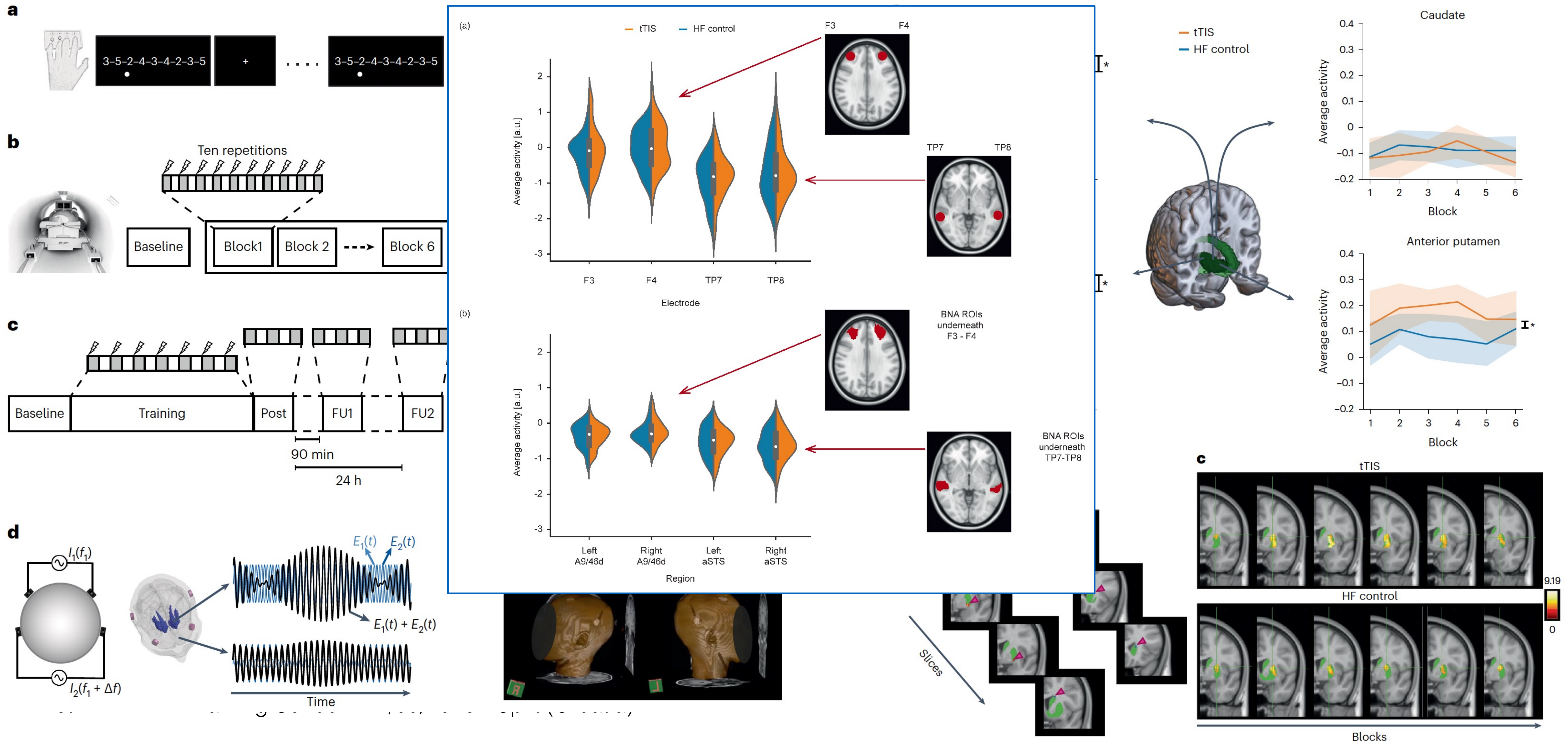
# Experimental Validation of Exposure Predictions



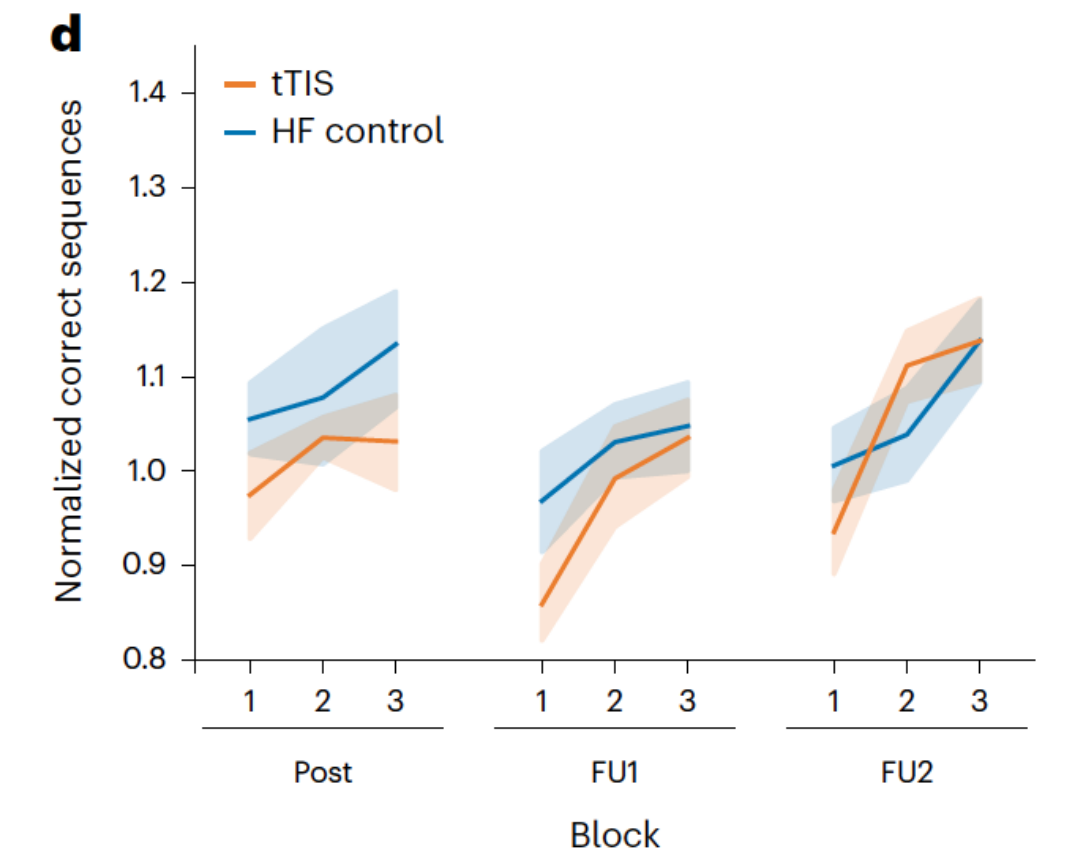
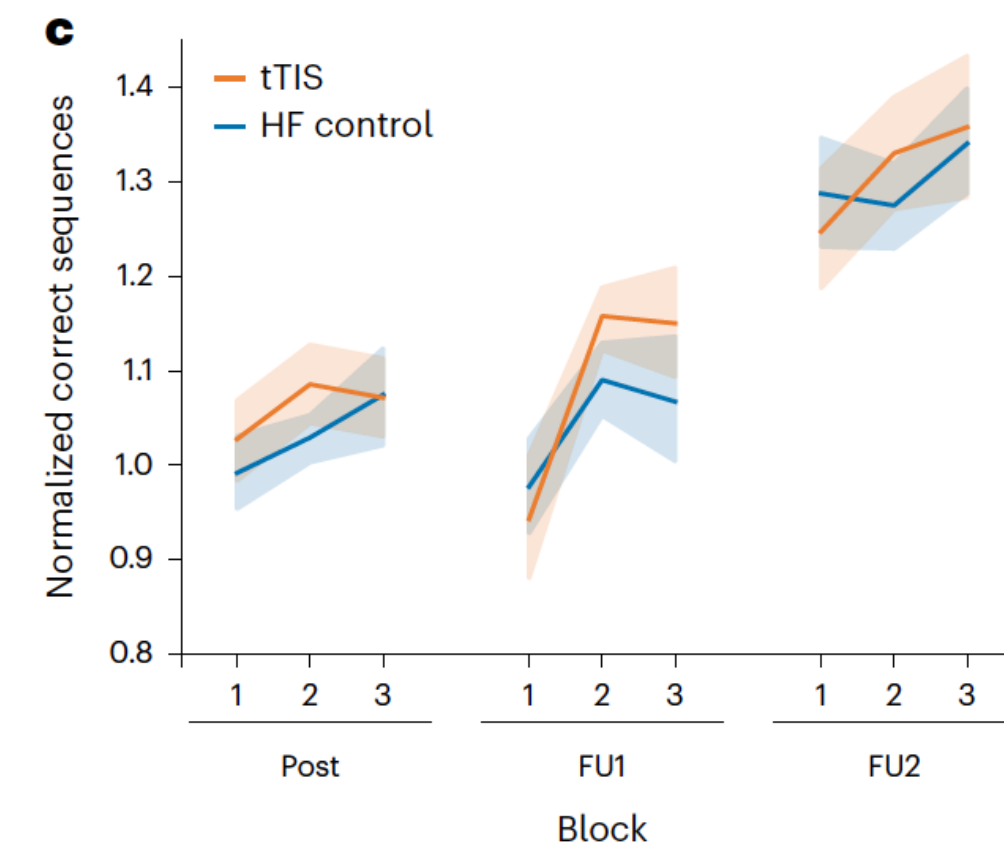
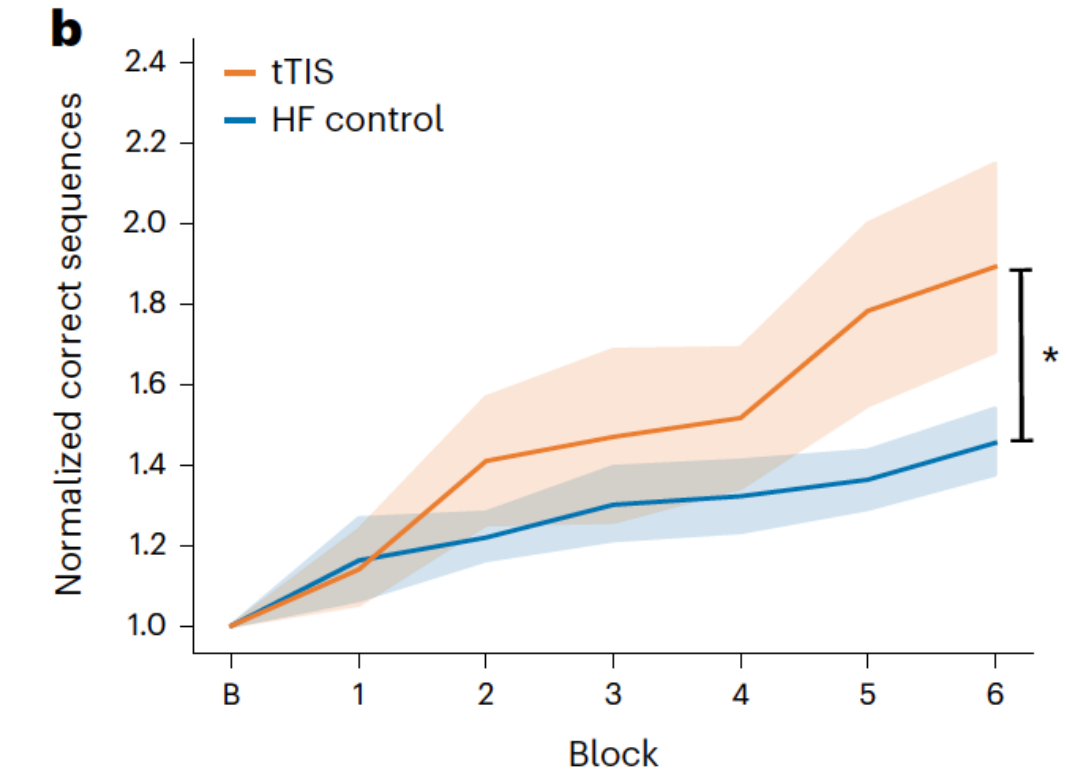
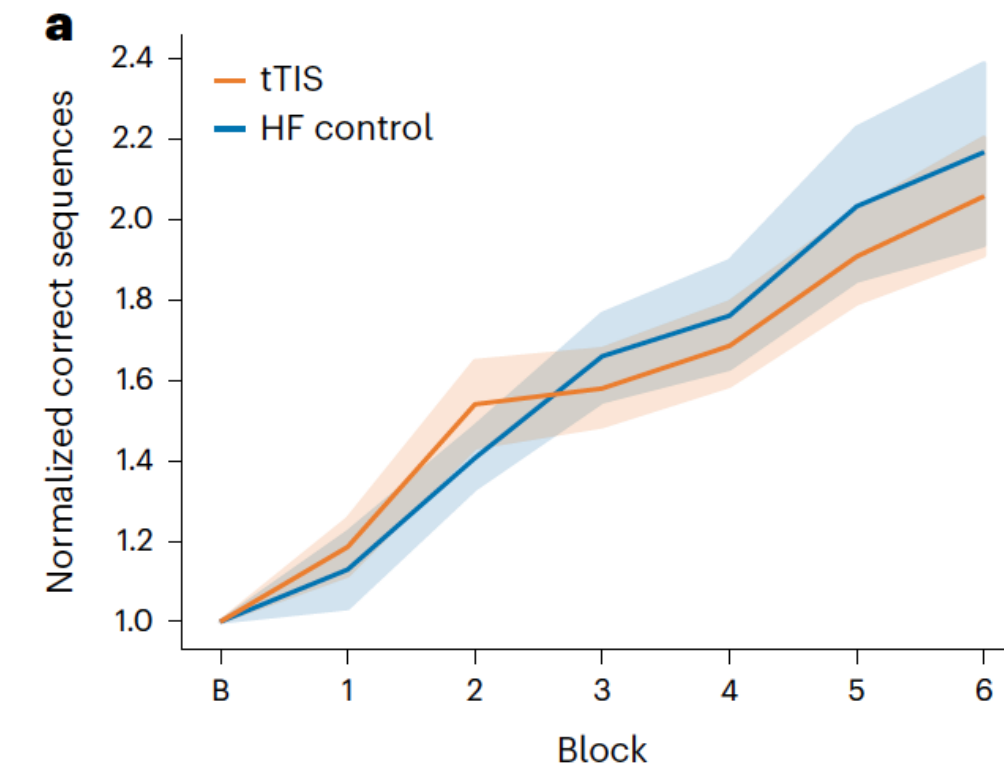
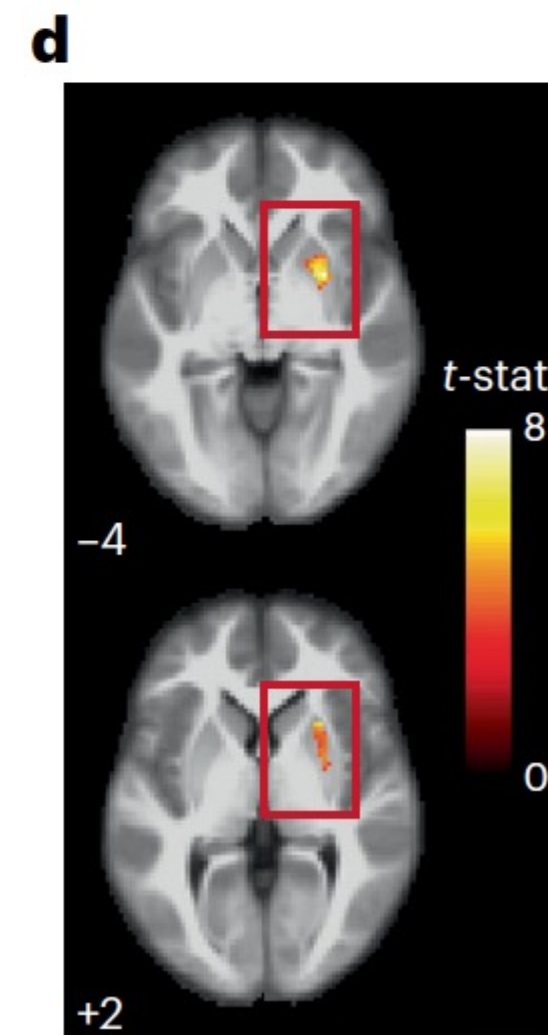
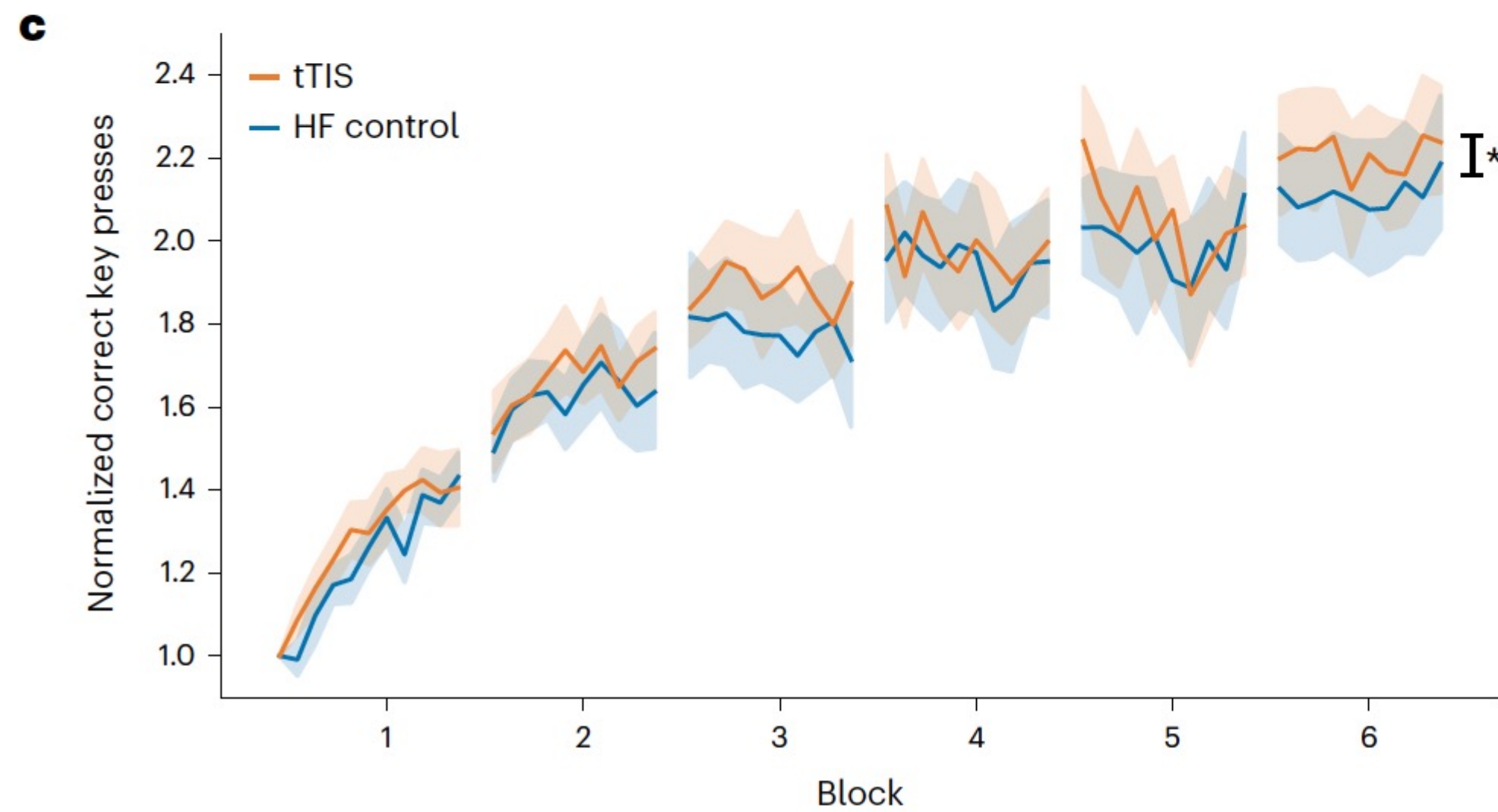
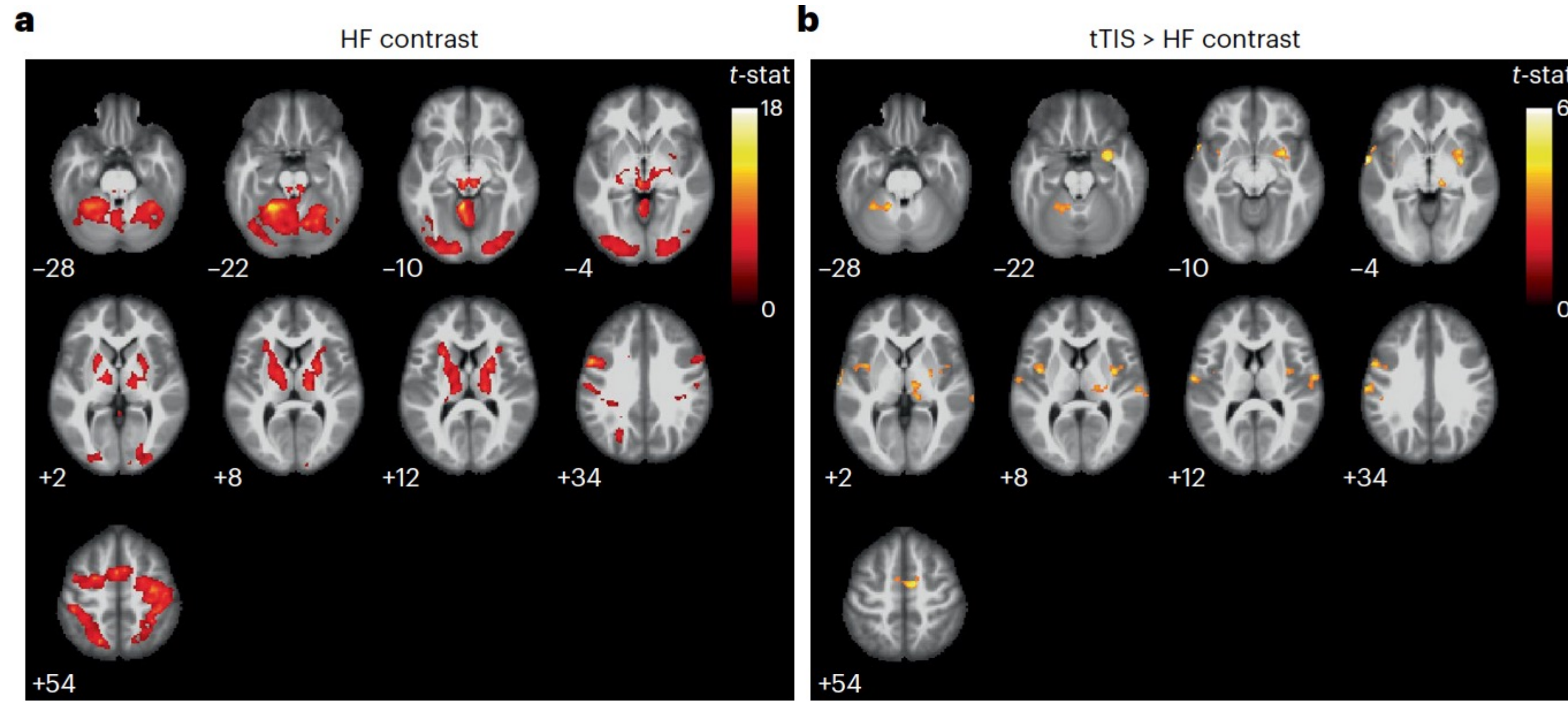
# Noninvasive theta-burst stimulation of the human striatum enhances striatal activity and motor skill learning



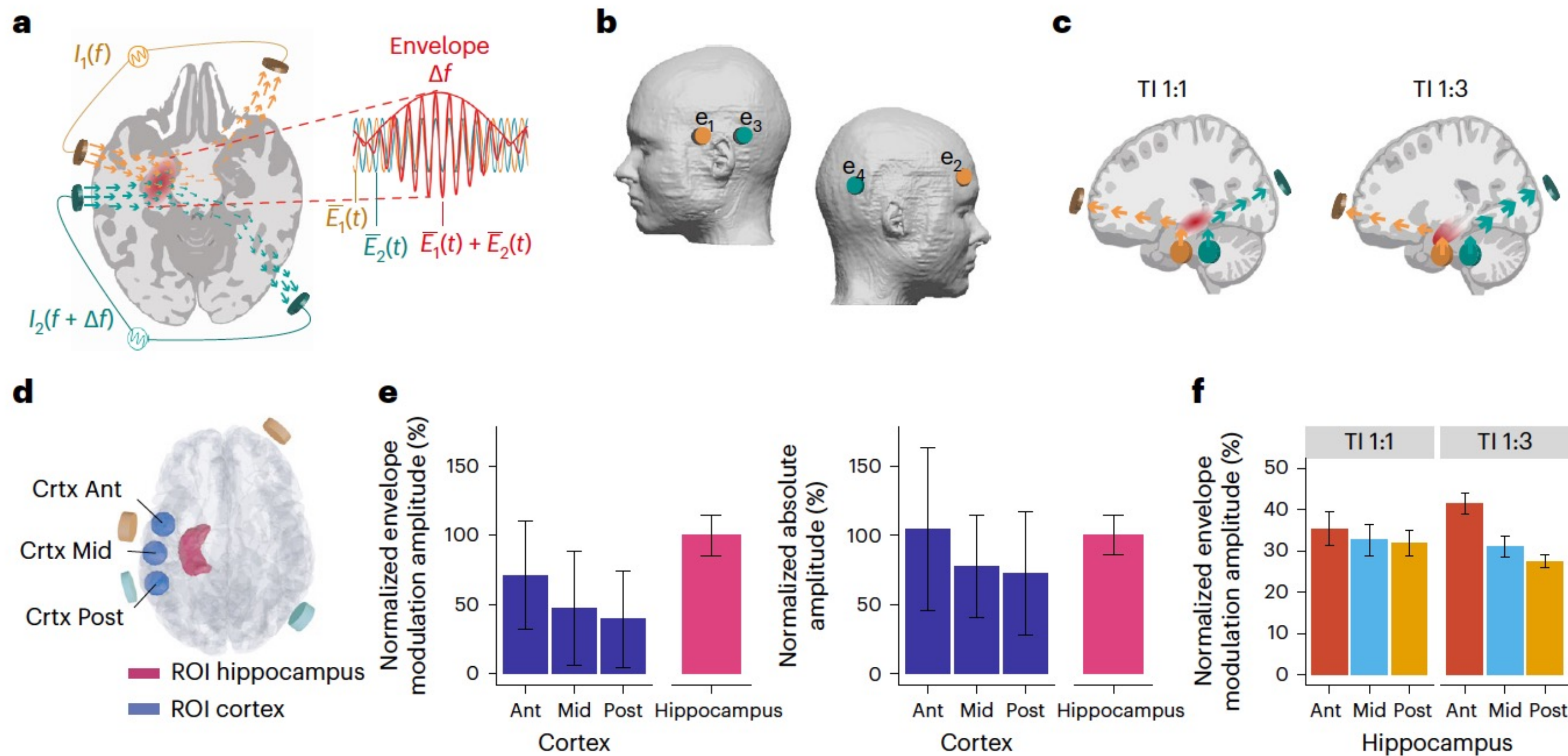
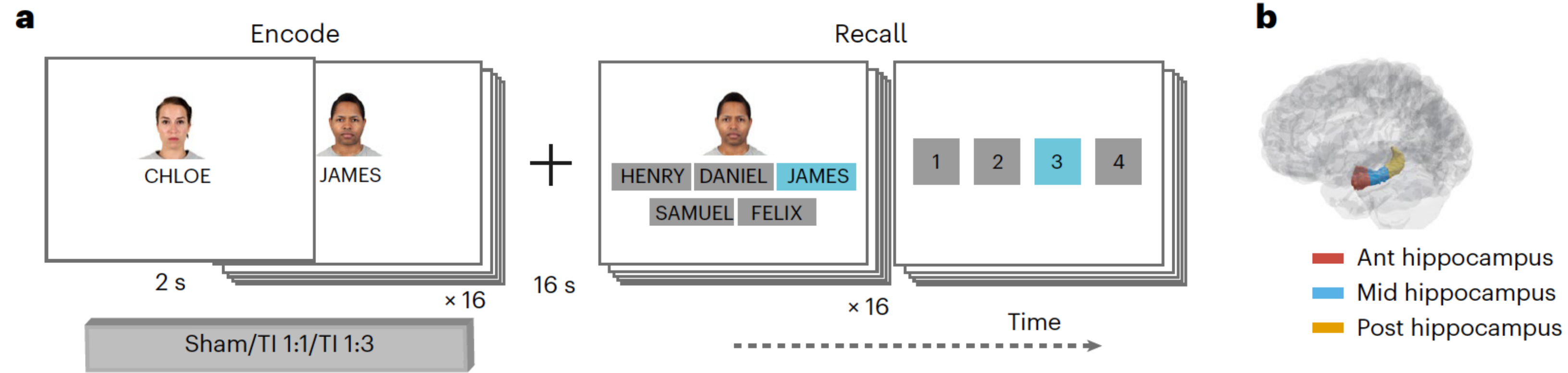
# Noninvasive theta-burst stimulation of the human striatum enhances striatal activity and motor skill learning



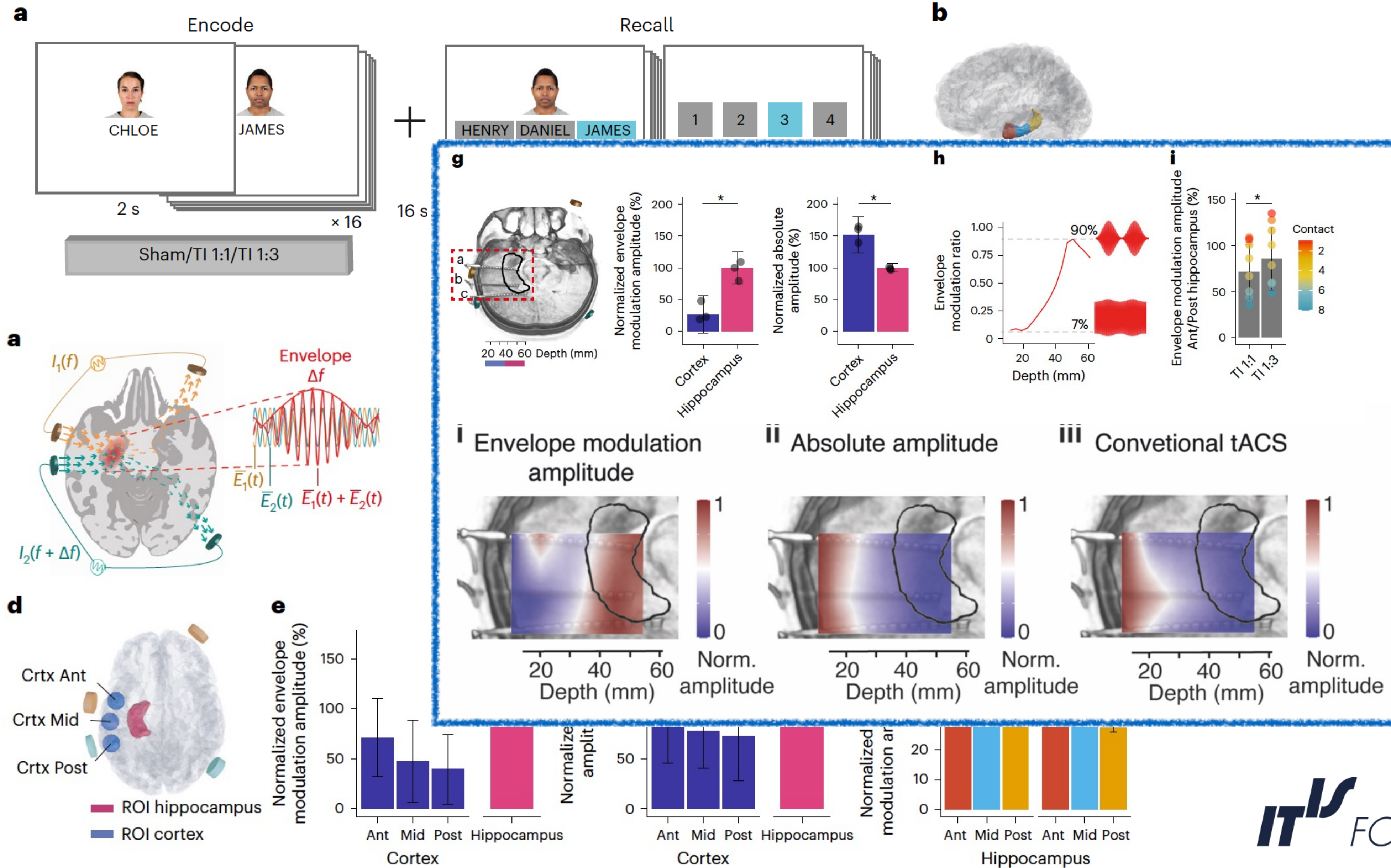
# Noninvasive theta-burst stimulation of the human striatum enhances striatal activity and motor skill learning



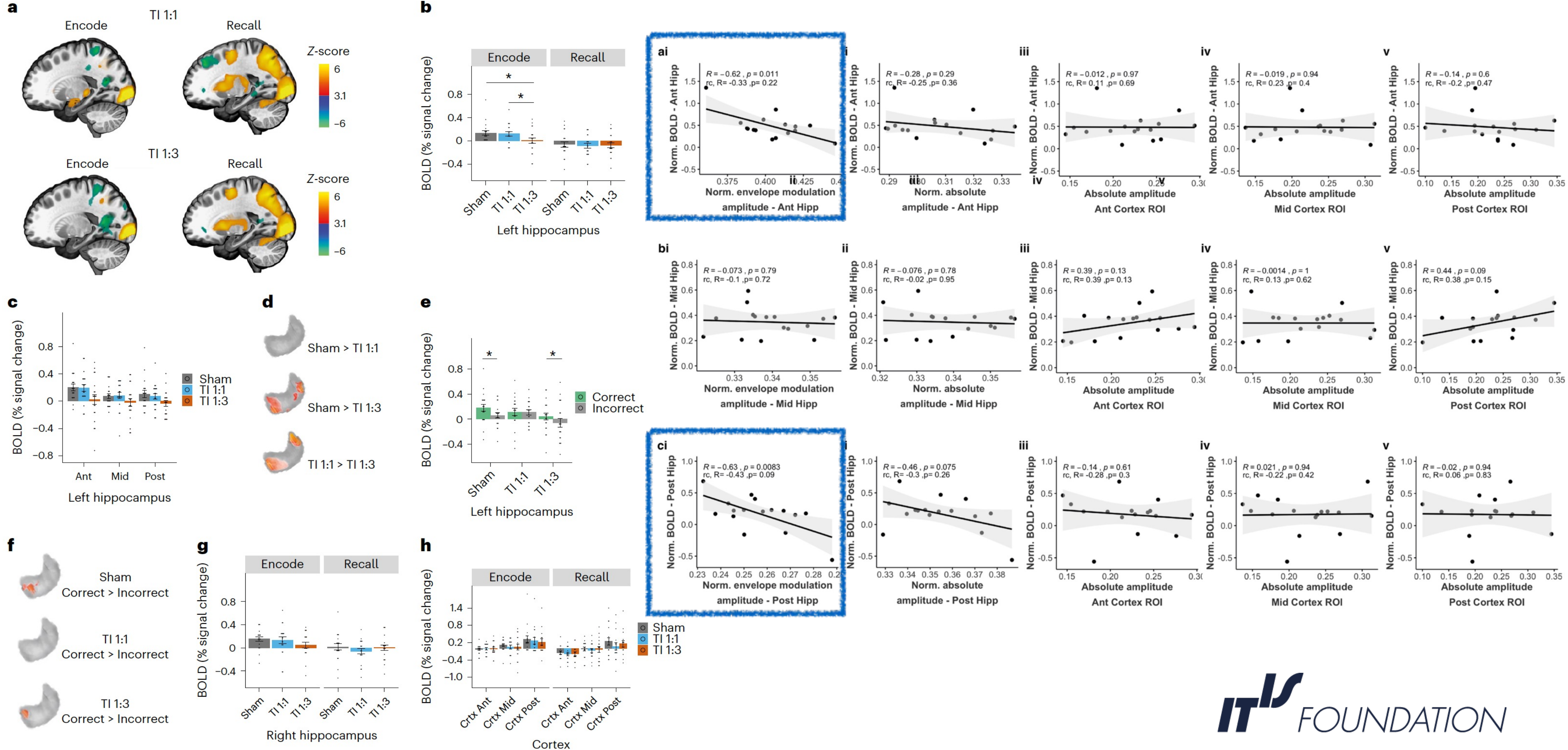
# Non-invasive temporal interference electrical stimulation of the human hippocampus



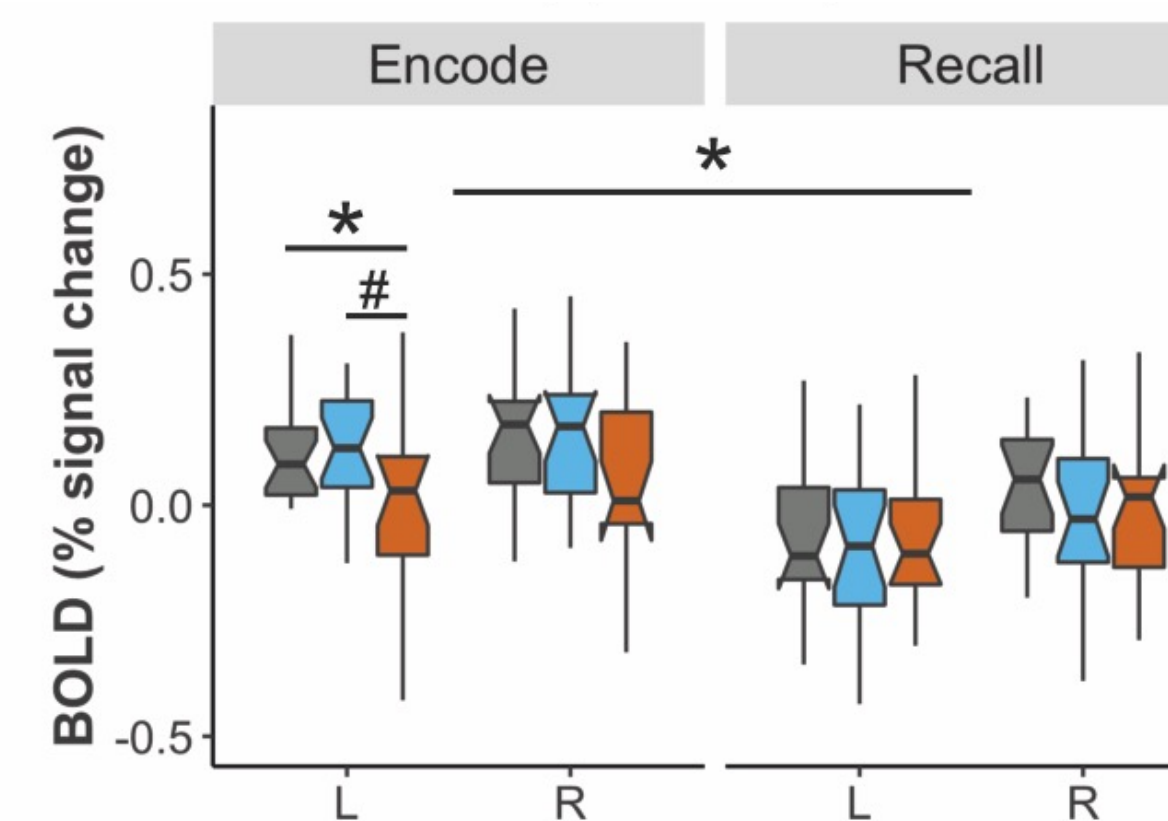
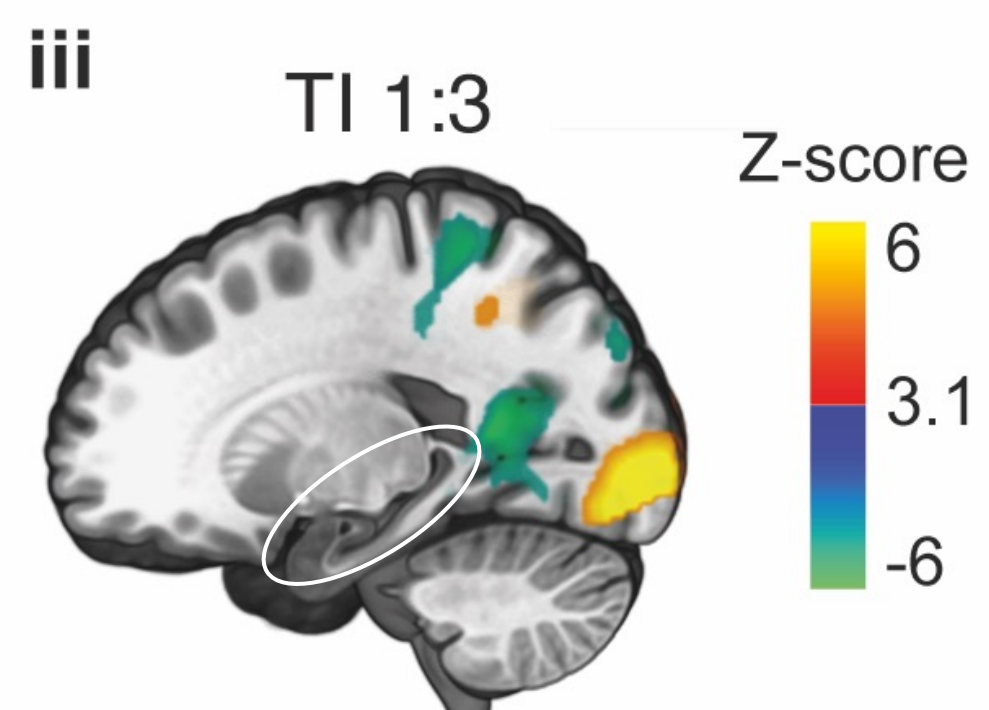
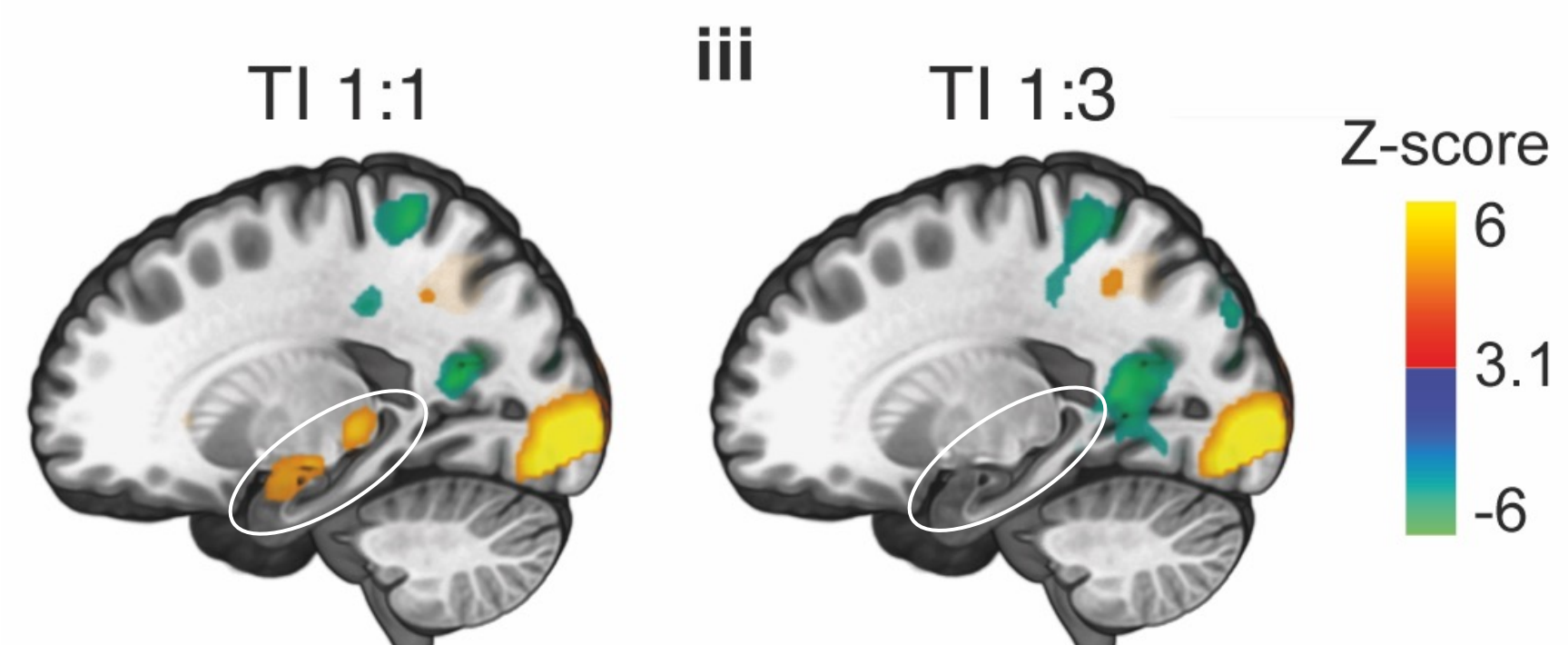
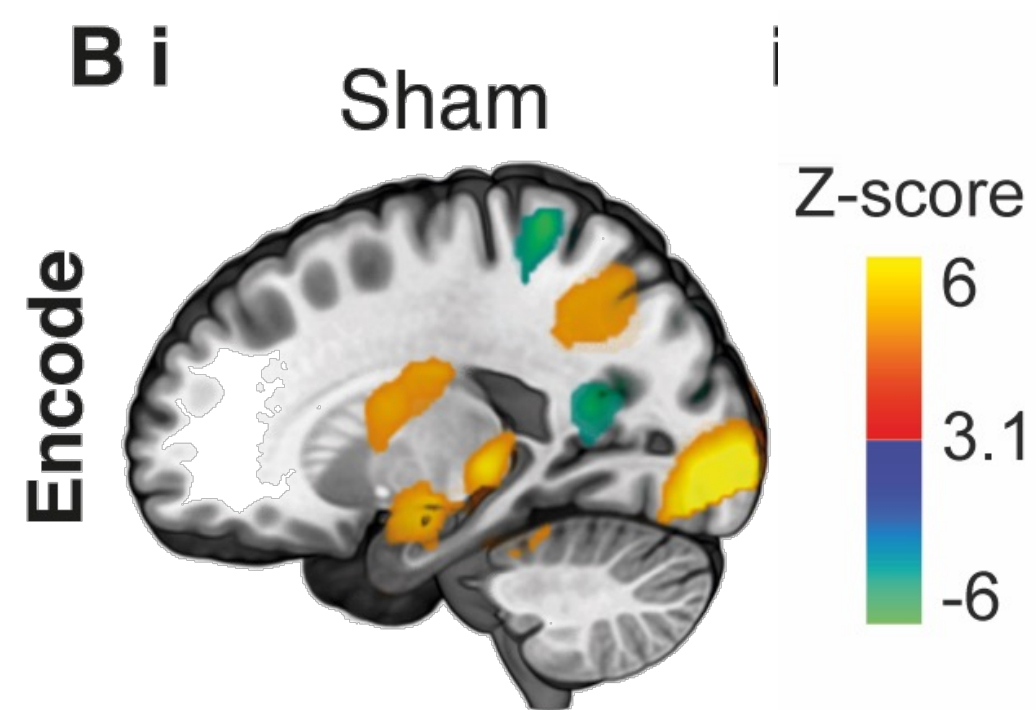
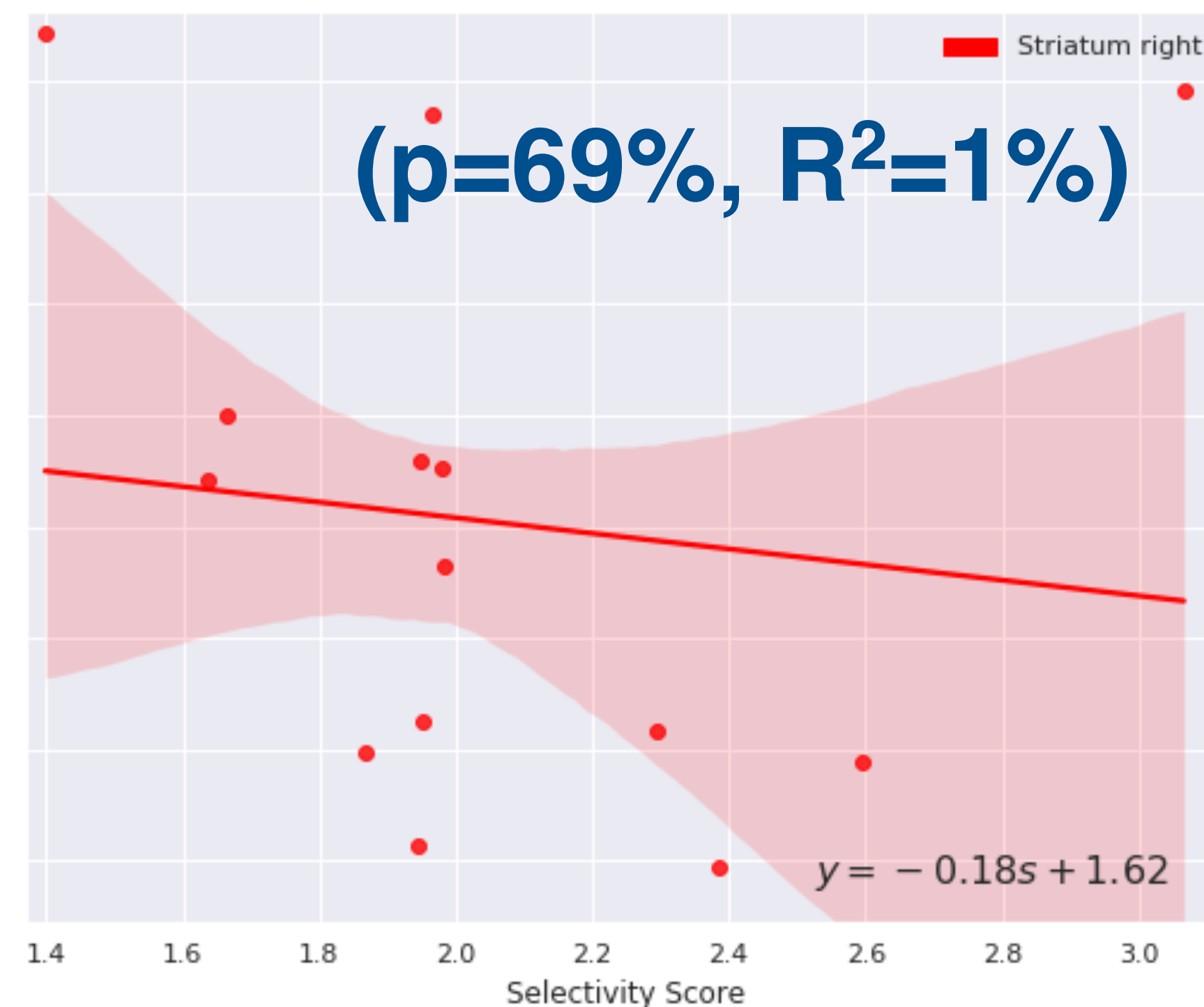
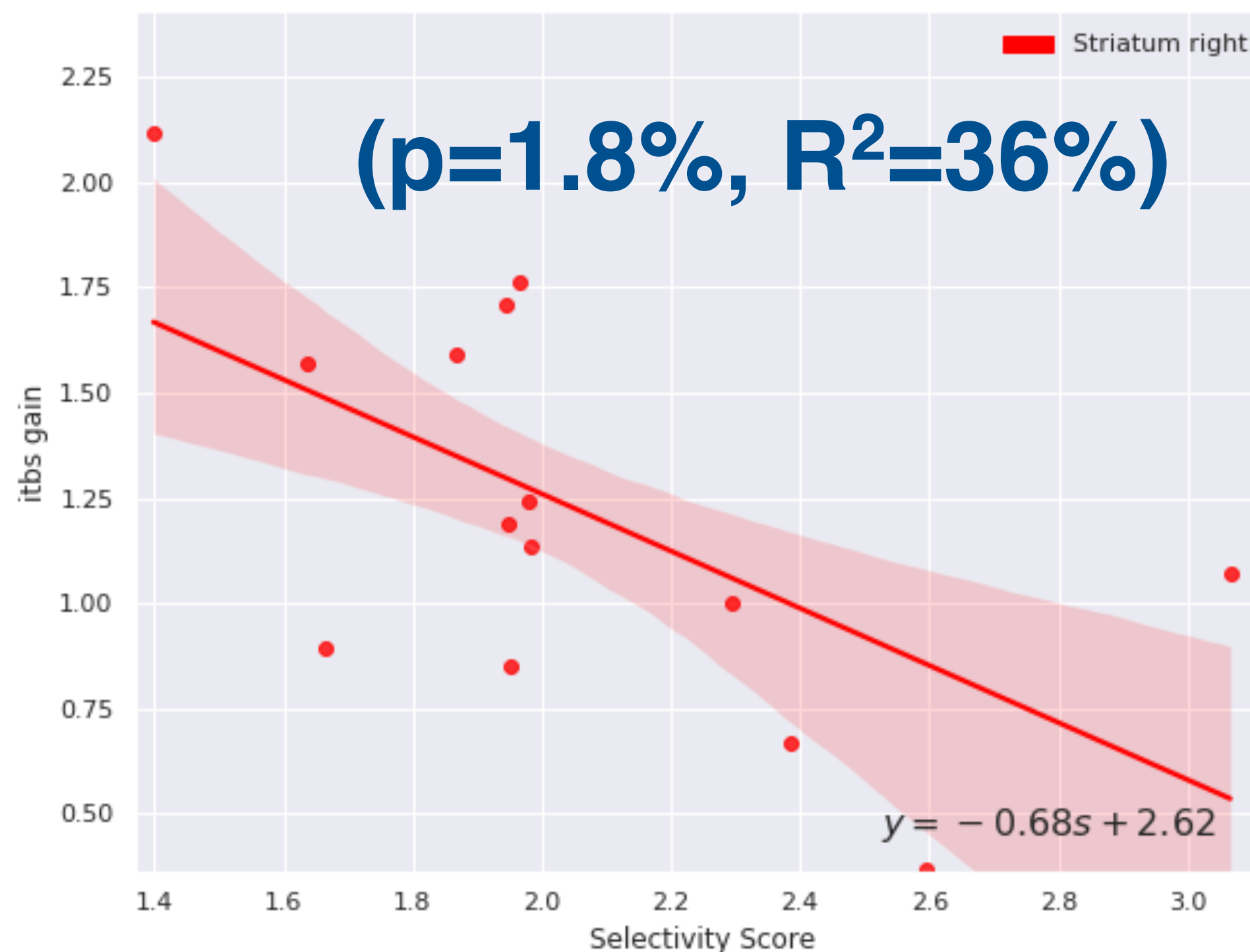
# Non-invasive temporal interference electrical stimulation of the human hippocampus



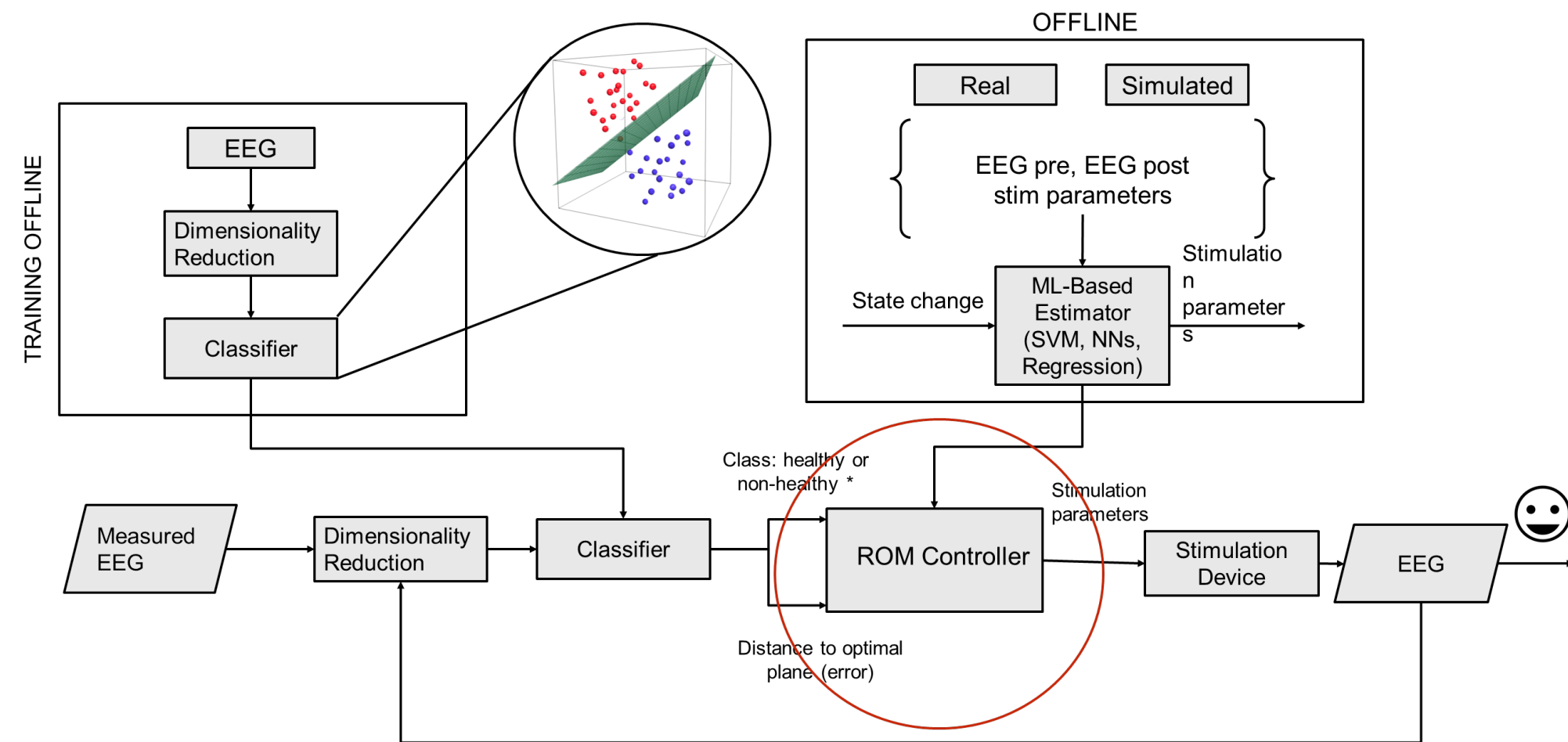
# Non-invasive temporal interference electrical stimulation of the human hippocampus



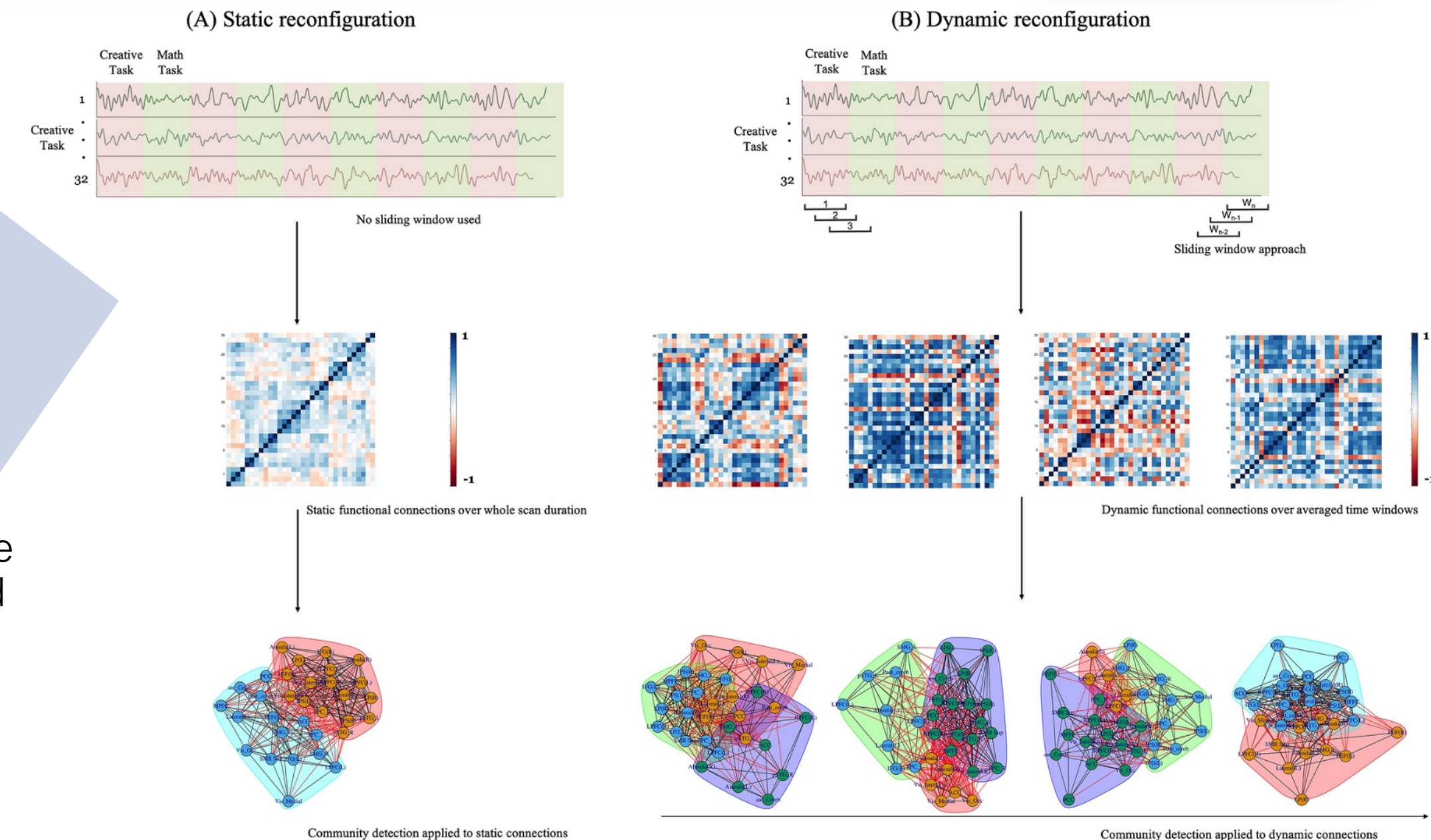
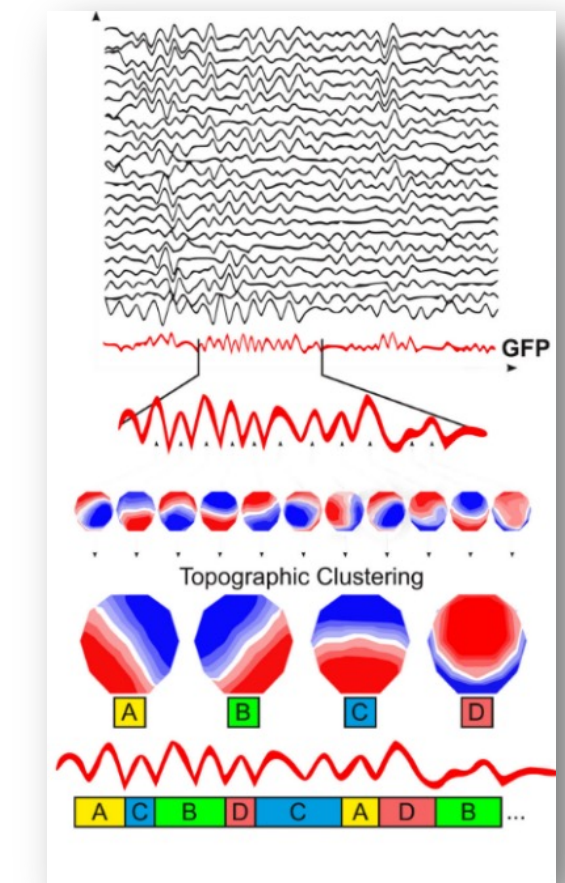
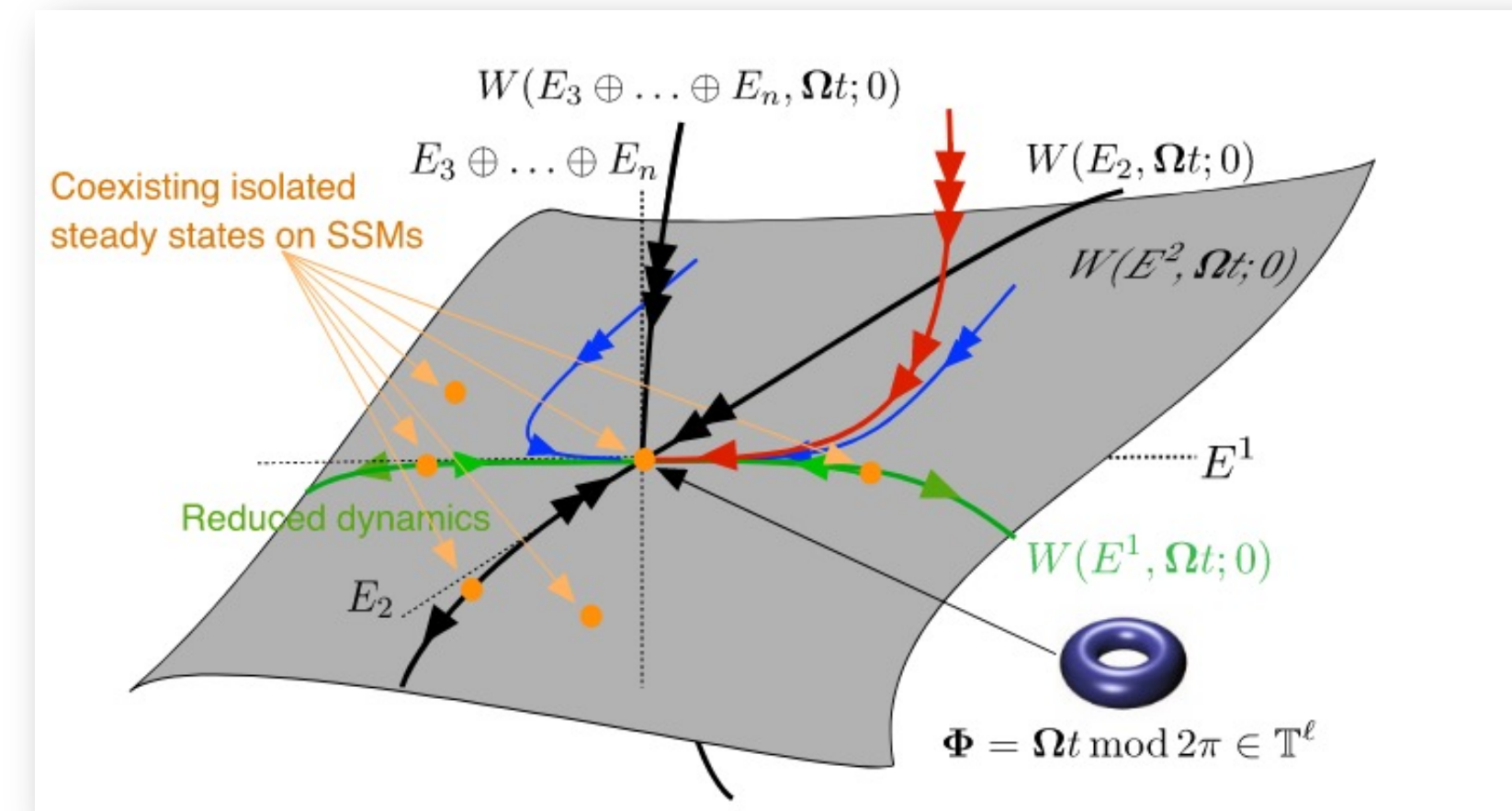
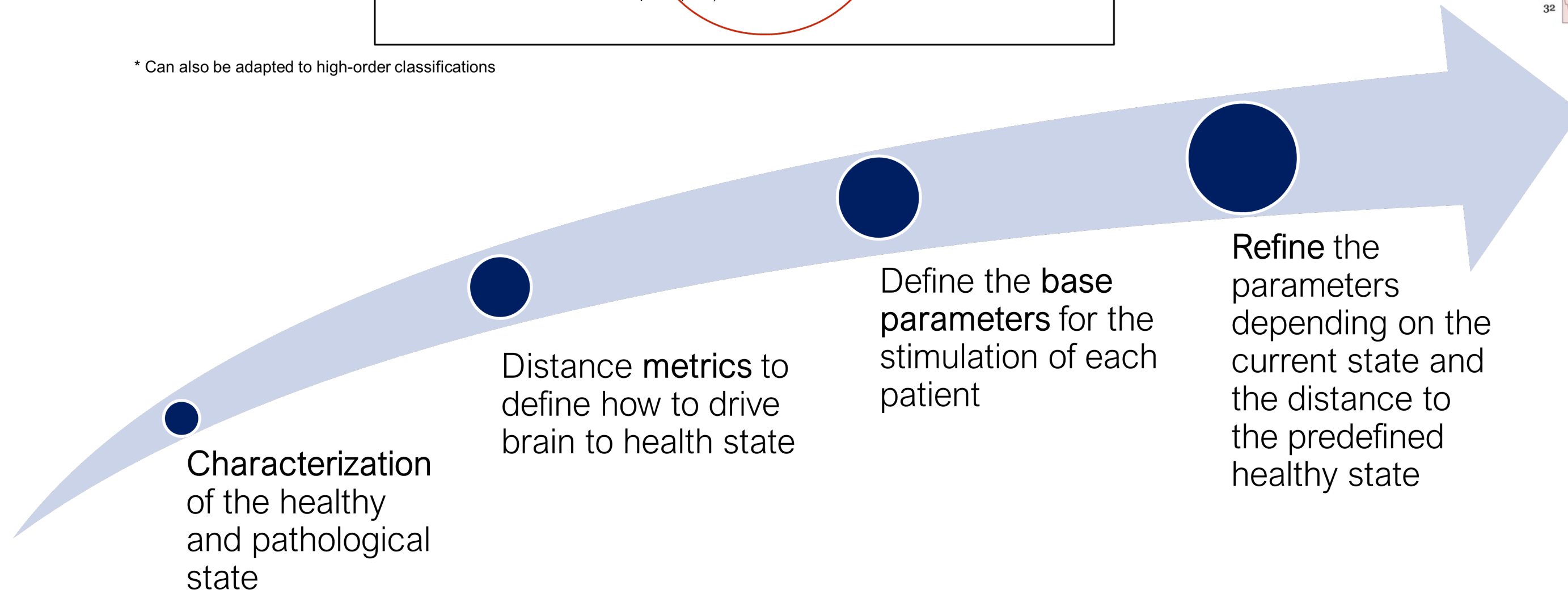
# Personalized Selectivity Modeling Predicts Learning Response



# Towards State-Driven Control



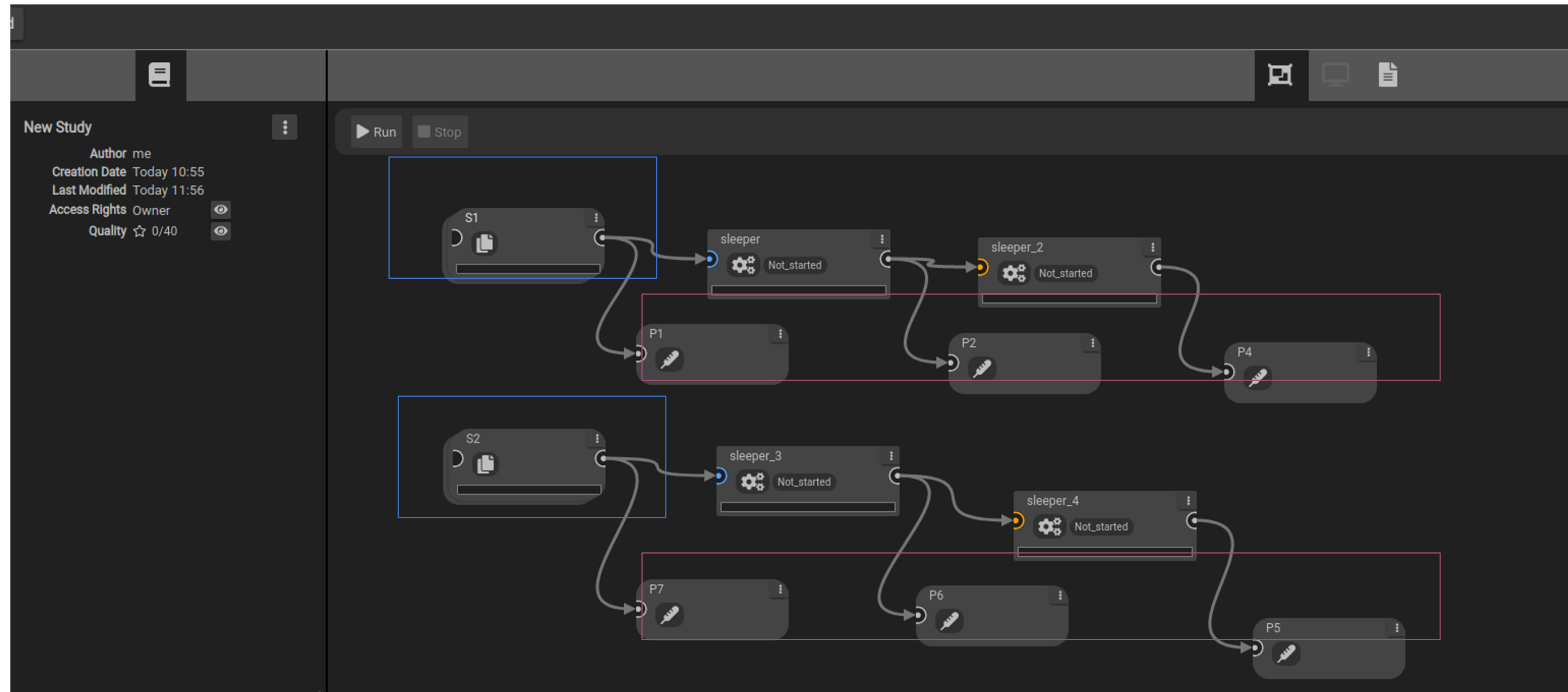
\* Can also be adapted to high-order classifications



# Parameterized Studies



1. Iterative
2. Computational
3. Probes



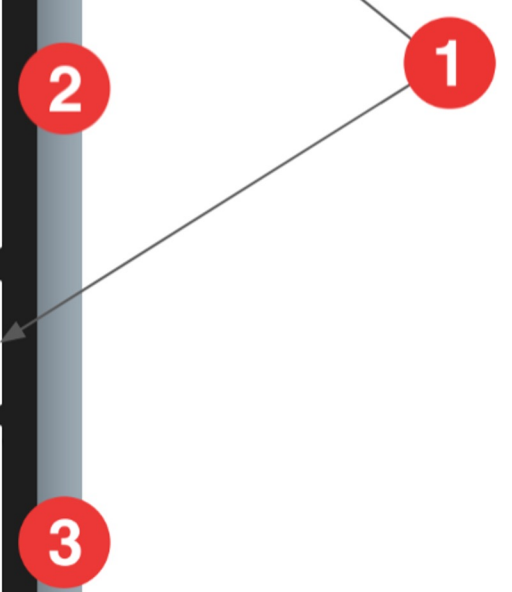
**Iterations**

Name	S1	S2	P1	P2	P4	P5	P6
New Study/0	0	0	0	6	3	4	8
New Study/1	0	1	0	8	1	1	3
New Study/2	0	2	0	3	7	2	6
New Study/3	1	0	1	4	5	5	3
New Study/4	1	1	1	8	2	1	2
New Study/5	1	2	1	8	8	2	6

1 of 6 rows  
Open Iteration

```

1 def sensitivity(func, paramrefs, paramdiff, diff_or_fact, lin_or_power):
2     sensitivities = []
3     linearities = []
4
5     refval=func(paramrefs)
6
7
8
9     if len(paramrefs)!=len(paramdiff):
10        return [refval,sensitivities,linearities]
11
12    linear_regressor = LinearRegression()
13
14    for i in range(len(paramrefs)):
15        paramtestplus=paramrefs.copy()
16        paramtestminus=paramrefs.copy()
17        if diff_or_fact:
18            paramtestplus[i]+=paramdiff[i]
19        else:
20            paramtestplus[i]*=paramdiff[i]
21        if diff_or_fact:
22            paramtestminus[i]-=paramdiff[i]
23        else:
24            paramtestminus[i]/=paramdiff[i] #check that not zero
25
26        testvalplus=func(paramtestplus)
27
28        testvalminus=func(paramtestminus)
29
30
31
32        x=np.array([paramrefs[i],paramtestplus[i],paramtestminus[i]]).reshape((-1, 1))
33        y=np.array([refval, testvalplus, testvalminus])
34        if not lin_or_power:
35            x=np.log(x/x[1]) #must be larger than zero
36            y=np.log(y/y[1])
37        model = linear_regressor.fit(x,y)
38        sensitivities.append(model.coef_[0])
39        linearities.append(model.score(x,y))
40
41    return [refval,sensitivities,linearities]
42
    
```



**Slideshow**

Edit Slideshow App Mode

**Snapshots**

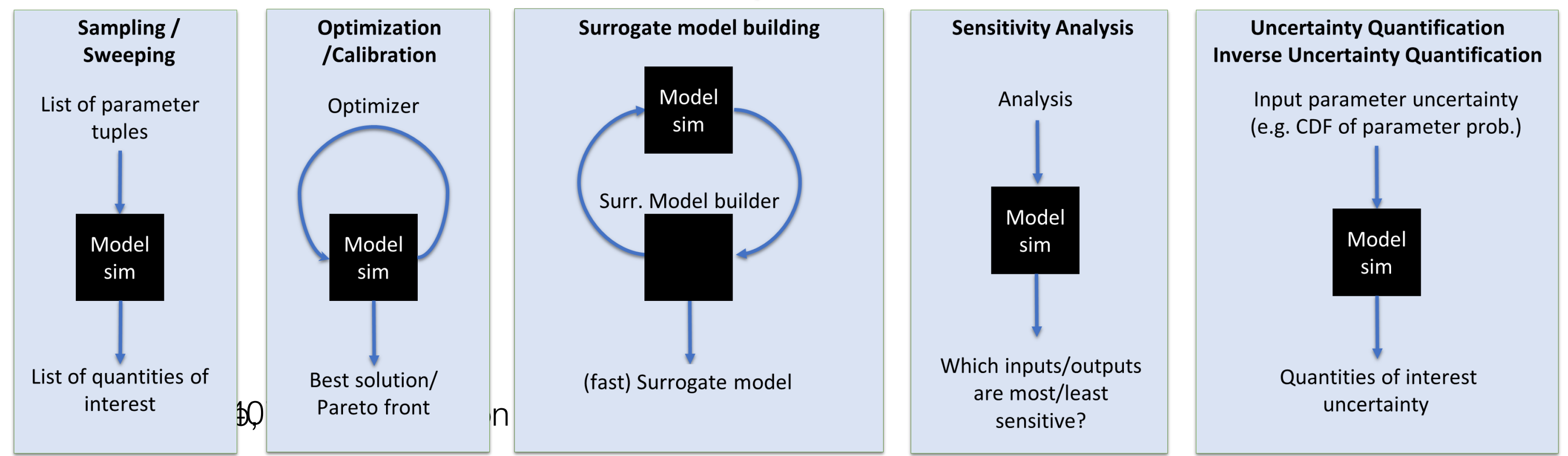
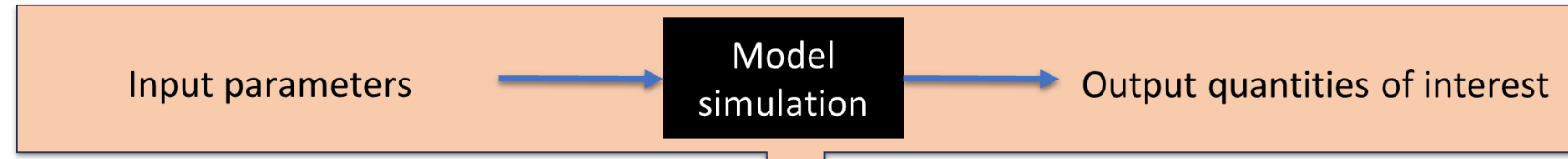
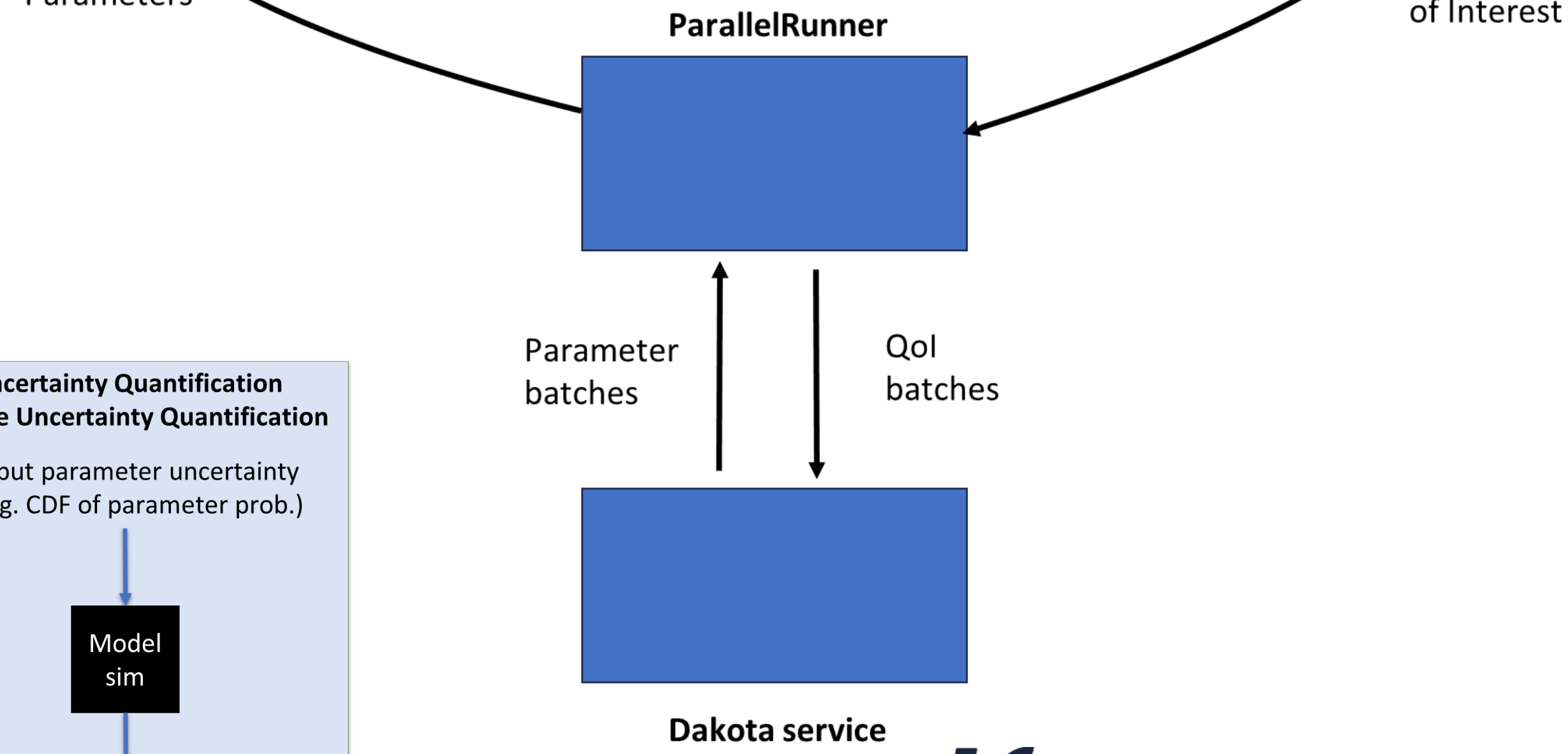
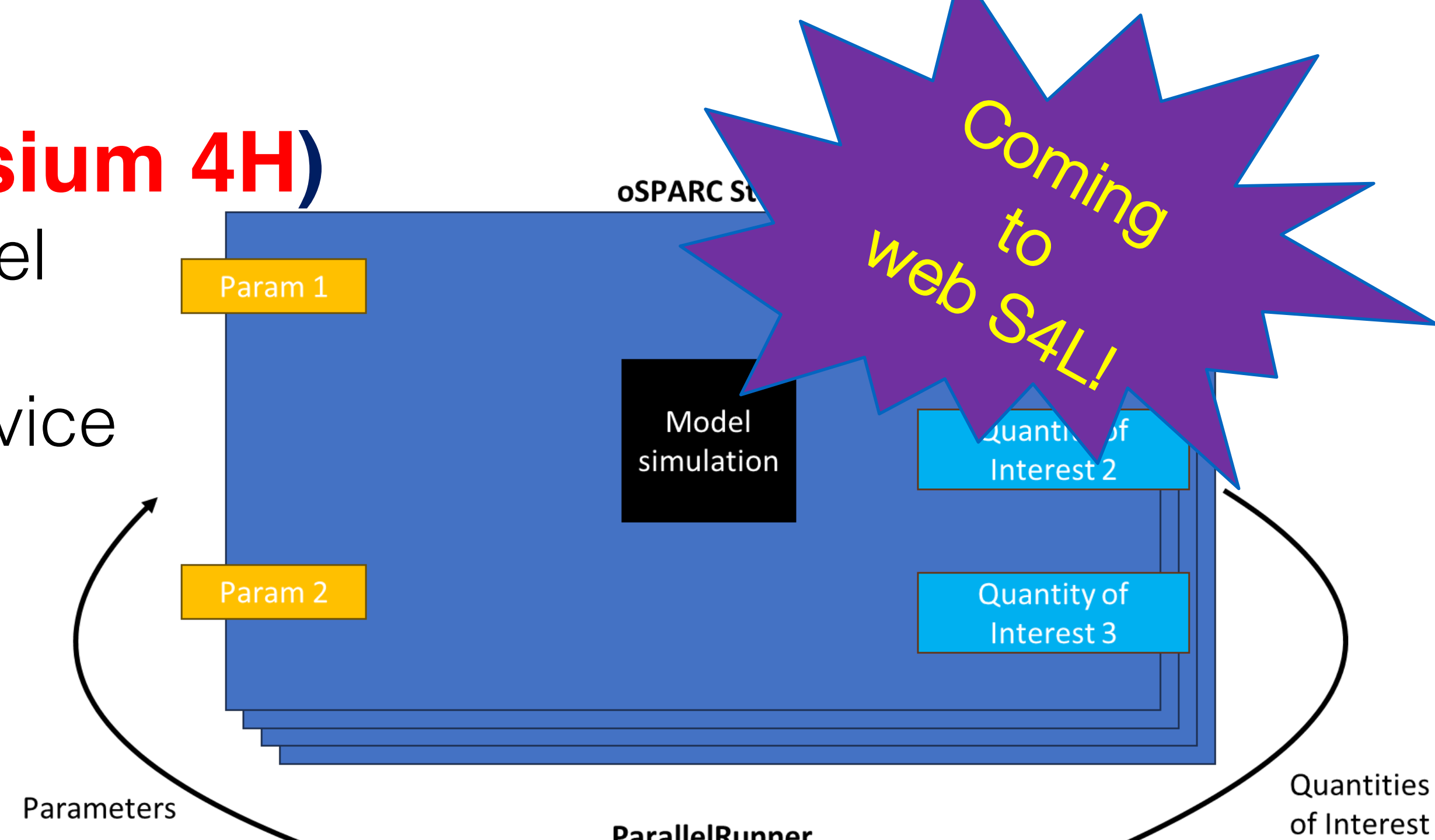
New Show Snapshots

**Iterations**

Create Iterations Show Iterations

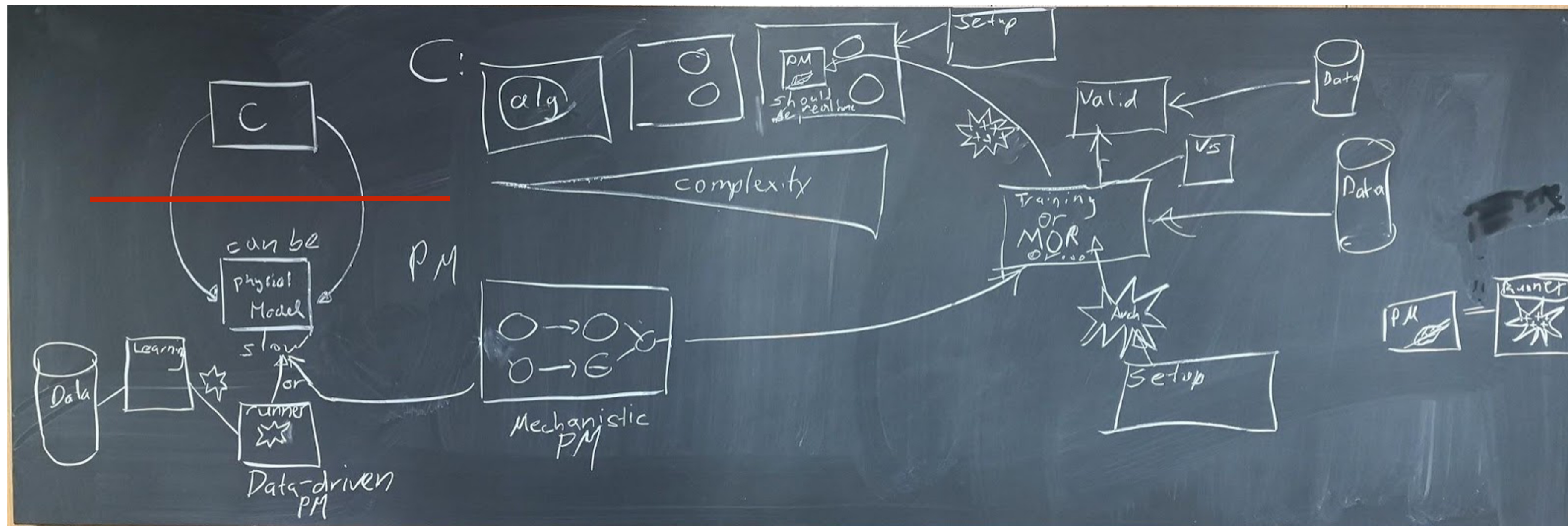
# Meta-Modeling Framework (Symposium 4H)

- parametrized pipelines evaluated in parallel
- cloud-inherent scalability
- Dakota (Sandia National Laboratories) service
  - optimization
  - uncertainty analysis
  - design of experiments
  - risk & failure analysis
  - sensitivity analysis
  - parameter estimation
  - surrogate modeling



# In Development: Control Framework

- **modular, mutually agnostic** combination of (predefined) **control strategies** and simulations of the controlled physiology
- minimal but sufficient **coupling and control API**
  - can be voluntarily satisfied by o2S2PARC
  - service that satisfy this API can automatically be used as
    - \* part of coupled multi-physics/physiology modeling
    - \* for closed-loop control simulations
- SuMo / MOR to establish light-weight, internal models for **intelligent (i.e., model-based) control**



# Conclusions

- Sim4Life is the platform for the modeling of neuromodulation and neural sensing
  - leading EM, FUS, NEURO (across scales), T... simulators capable of handling complex anatomical environments
  - the most realistic anatomical population (incl. pre-functionalization)
  - image-based, personalized modeling and treatment planning
  - and much more
- browser-based and cloud-hosted web version of Sim4Life
  - collaborate and publish, access scalable resources on demand, GUI- and API-based usage supported
  - released soon: integrate with powerful 3rd party services and applications (e.g., for computational neurosciences), build advanced pipelines, publish guided applications (e.g., for treatment planning)
- continuously expanding, innovative functionality
  - new: rapid stimulation predictors, leading AI for head model creation (incl. 10-10 system placement & brain atlas registration)
  - coming soon: powerful meta-modeling framework (SuMo-based), model-predictive control framework