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Institut de Neurosciences des Systèmes

Human Brain Project

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Inferring the seizure propagation patterns using a data-driven model of a threshold network

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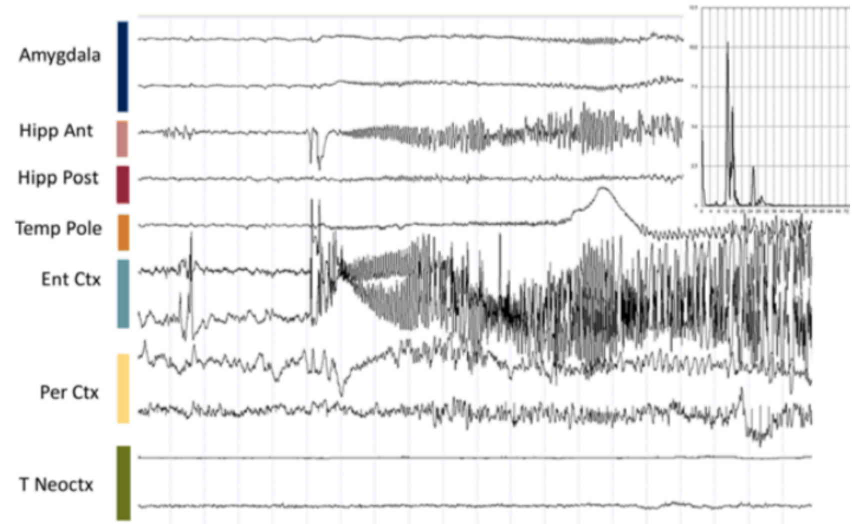
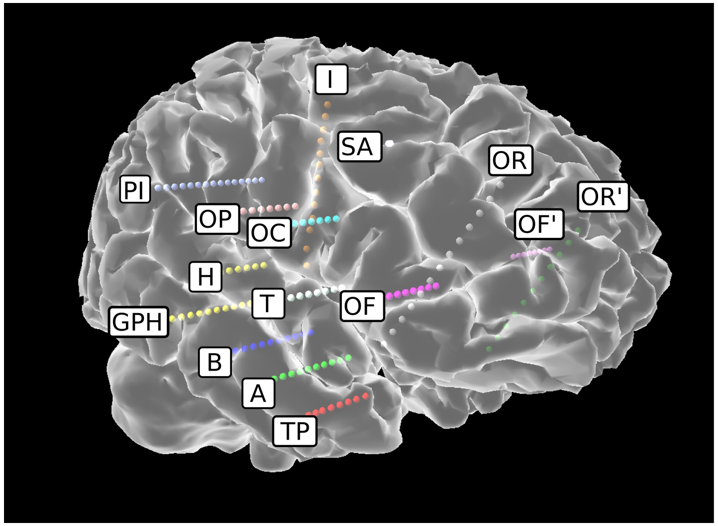
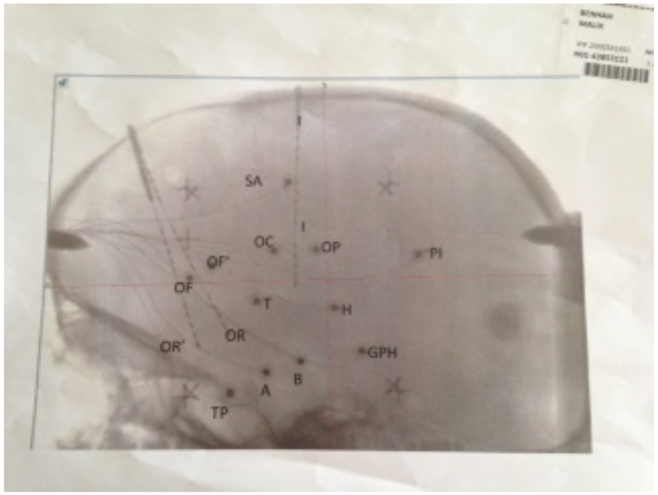
Threshold Networks, 22 - 24 July, Nottingham

Epilepsy

- During focal epileptic seizures, abnormal electrical activity spreads through the brain network.
- Intracranial electroencephalography is used to observe the activity.
- Whole network cannot be observed (subsampling problem).





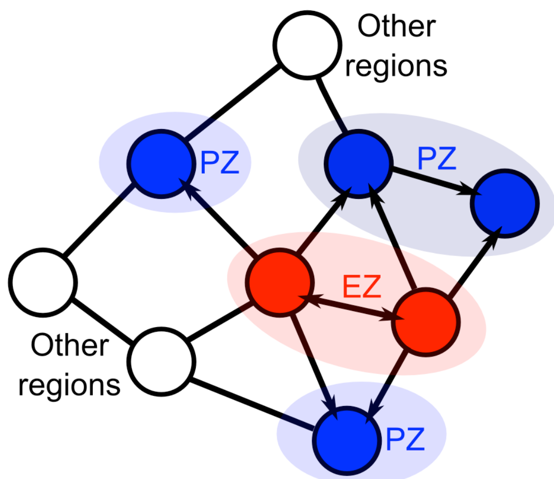


Bartolomei et al. Brain (2017)

Epileptogenic zone

- "The site of the beginning of the epileptic seizures and of their primary organization." (Talairach, Bancaud 1965)

- "The area of cortex that is necessary and sufficient for initiating seizures and whose removal is necessary for complete abolition of seizures." (Luders 1993)

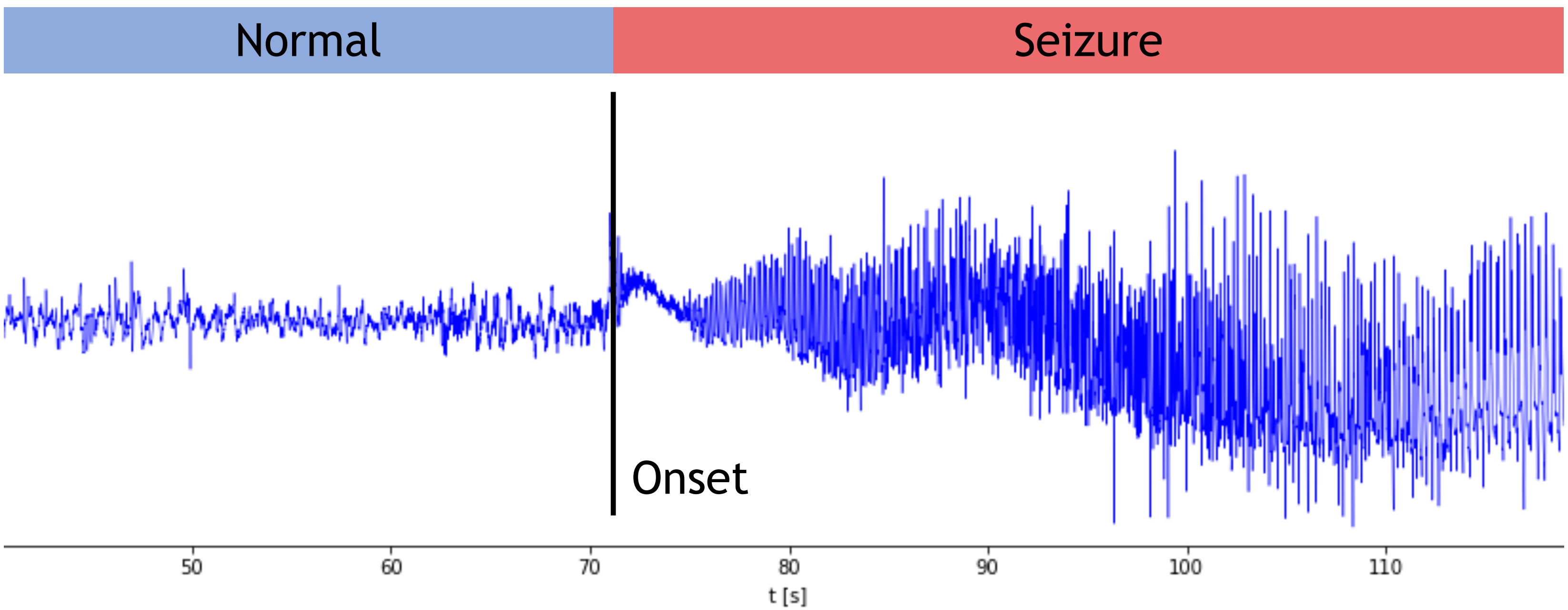


EZ: Epileptogenic zone
PZ: Propagation zone

Jirsa et al, NeuroImage (2016)

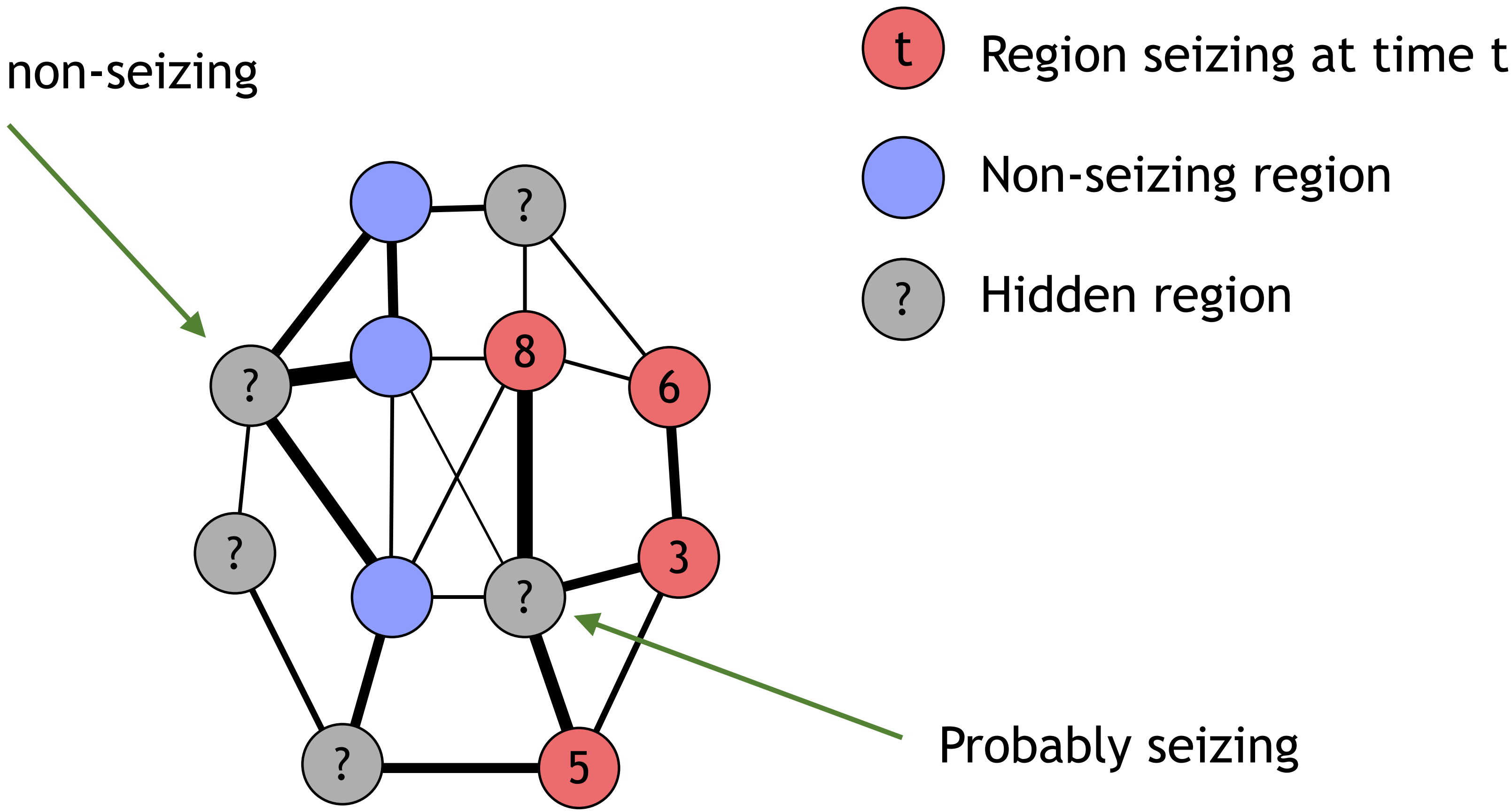
- Surgery success rate around 60 - 70%.

Normal and seizure activity



Conceptual view

Probably non-seizing

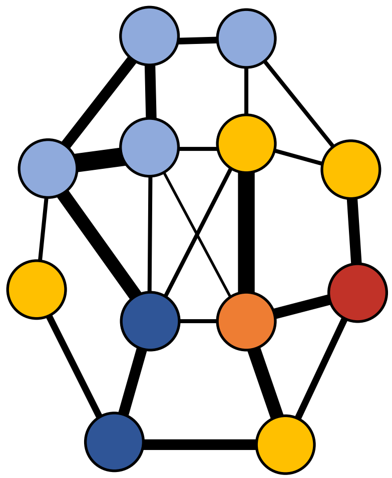


Probably seizing

Goal: To infer what happens in the hidden regions.

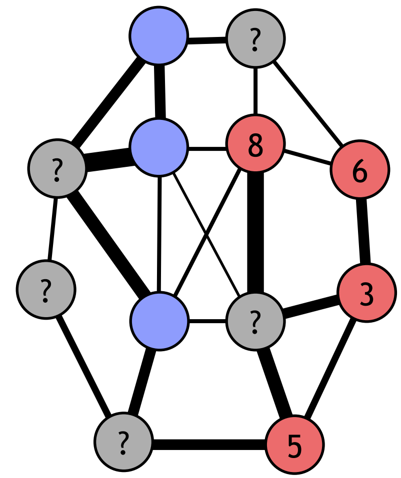
Conceptual view

Structure (known)
+ excitabilities (unknown)



Propagation
dynamics
(unknown)
→

Onset times (partially known)



- Data: structural and functional data from tens of subjects
- Assumption: Propagation dynamics is shared among subjects

Threshold model of seizure propagation

$$\dot{z}_i = f_{\boldsymbol{q}}\left(c_i,\ \sum_{j=1}^{n} w_{ij} H(z_j - 1)\right), \quad z_i(0) = 0$$

Network effects

Region excitability

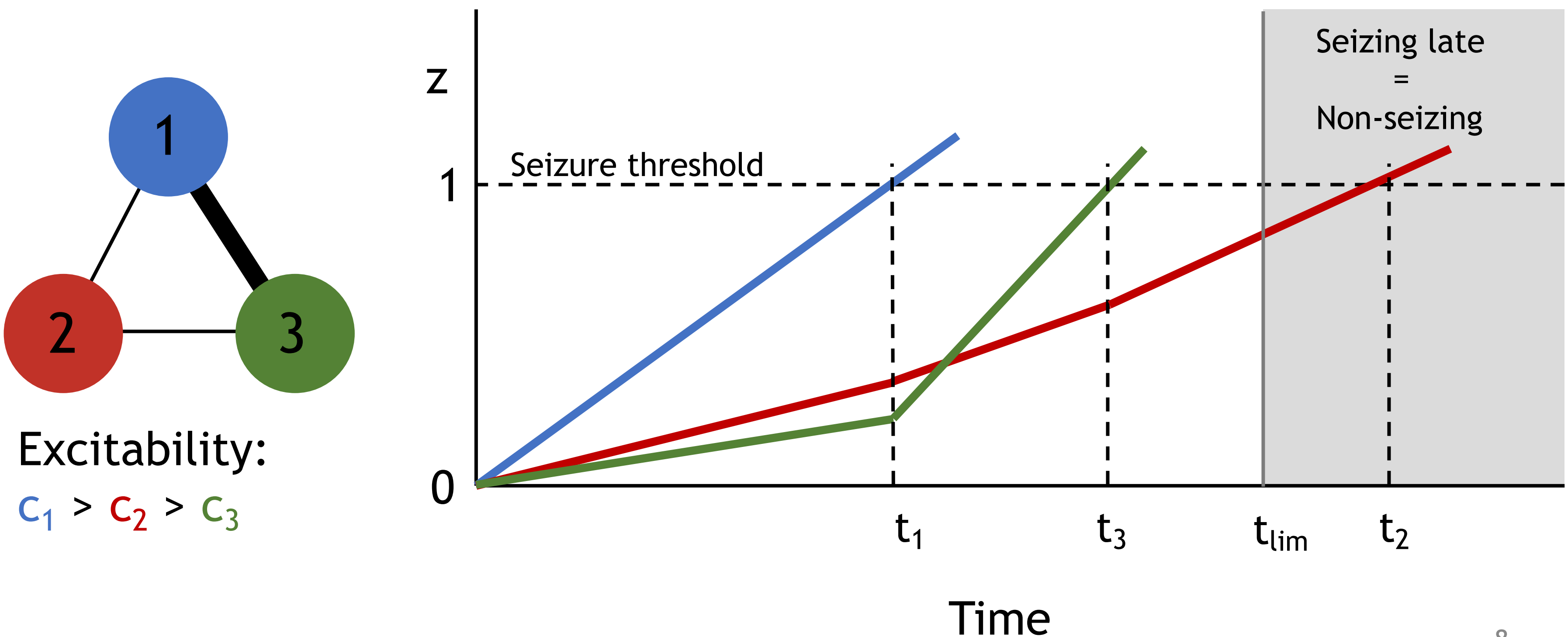
”Bucket”

Function $f_{\boldsymbol{q}}$:

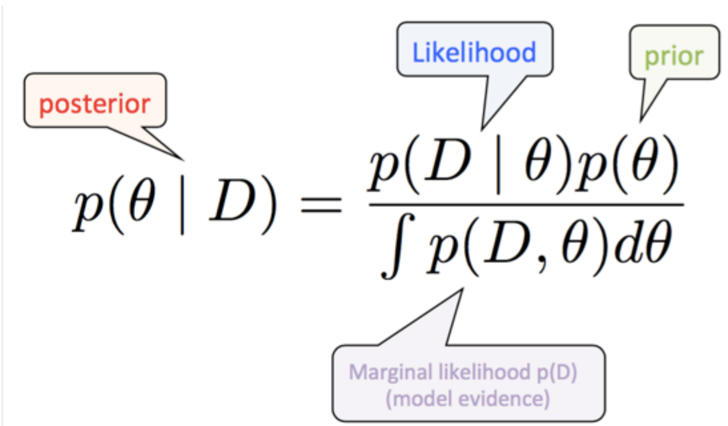
- Positive
- Increasing in the first variable
- Parameterized by vector $\boldsymbol{q}$

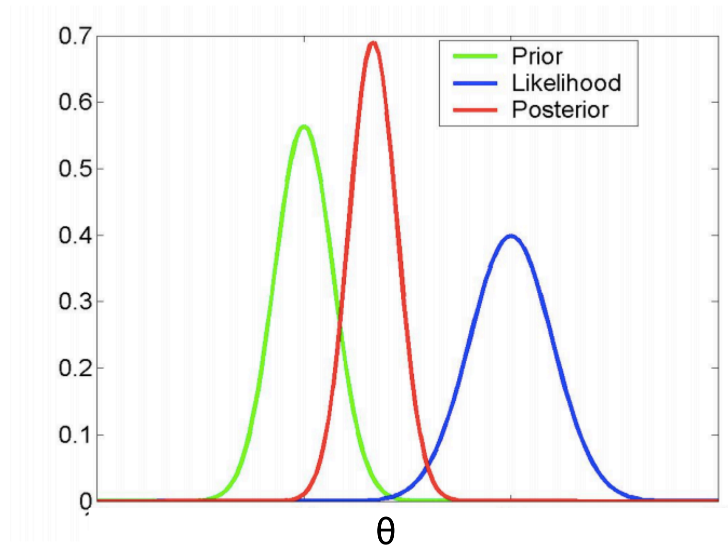
Threshold model of seizure propagation

$$\dot{z}_i = f_{\boldsymbol{q}}\left(c_i,\ \sum_{j=1}^{n} w_{ij} H(z_j - 1)\right), \quad z_i(0) = 0$$



Bayesian inference





Thomas Nichols: Bayesian inference

D … observed data
θ … unknown parameters

Hierarchical model

Parameters

Hyperparameters (4) — $\boldsymbol{q}$ — Non-informative prior

Seizure-specific excitabilities ($n_{seizures}$ x $n_{regions}$) — $\boldsymbol{c_1}$ $\boldsymbol{c_2}$ $\boldsymbol{c_3}$ ... — N(0, 1)

PRIOR

Connectome matrices — $\boldsymbol{W_1}$ $\boldsymbol{W_2}$ $\boldsymbol{W_3}$ ...

Dynamical model

$$\dot{z}_i = f_{\boldsymbol{q}}\left(c_i, \sum_{j=1}^{n} w_{ij} H(z_j - 1)\right)$$

Observations

- Seizing/non-seizing regions
- Onset times

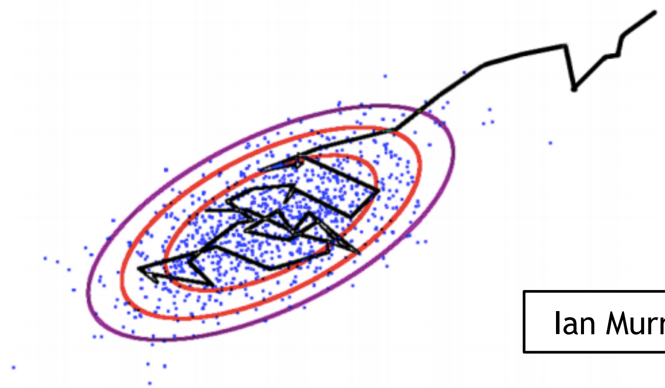
$\boldsymbol{obs_1}$ $\boldsymbol{obs_2}$ $\boldsymbol{obs_3}$ ...

LIKELIHOOD

Sampling from the posterior

Markov Chain Monte Carlo (MCMC):

Build a Markov chain whose steps approximate the posterior distribution.



Ian Murray: Advanced MCMC methods (2006)

Metropolis-Hastings:

- Random walk + acceptance probability

Hamiltonian Monte Carlo (HMC):

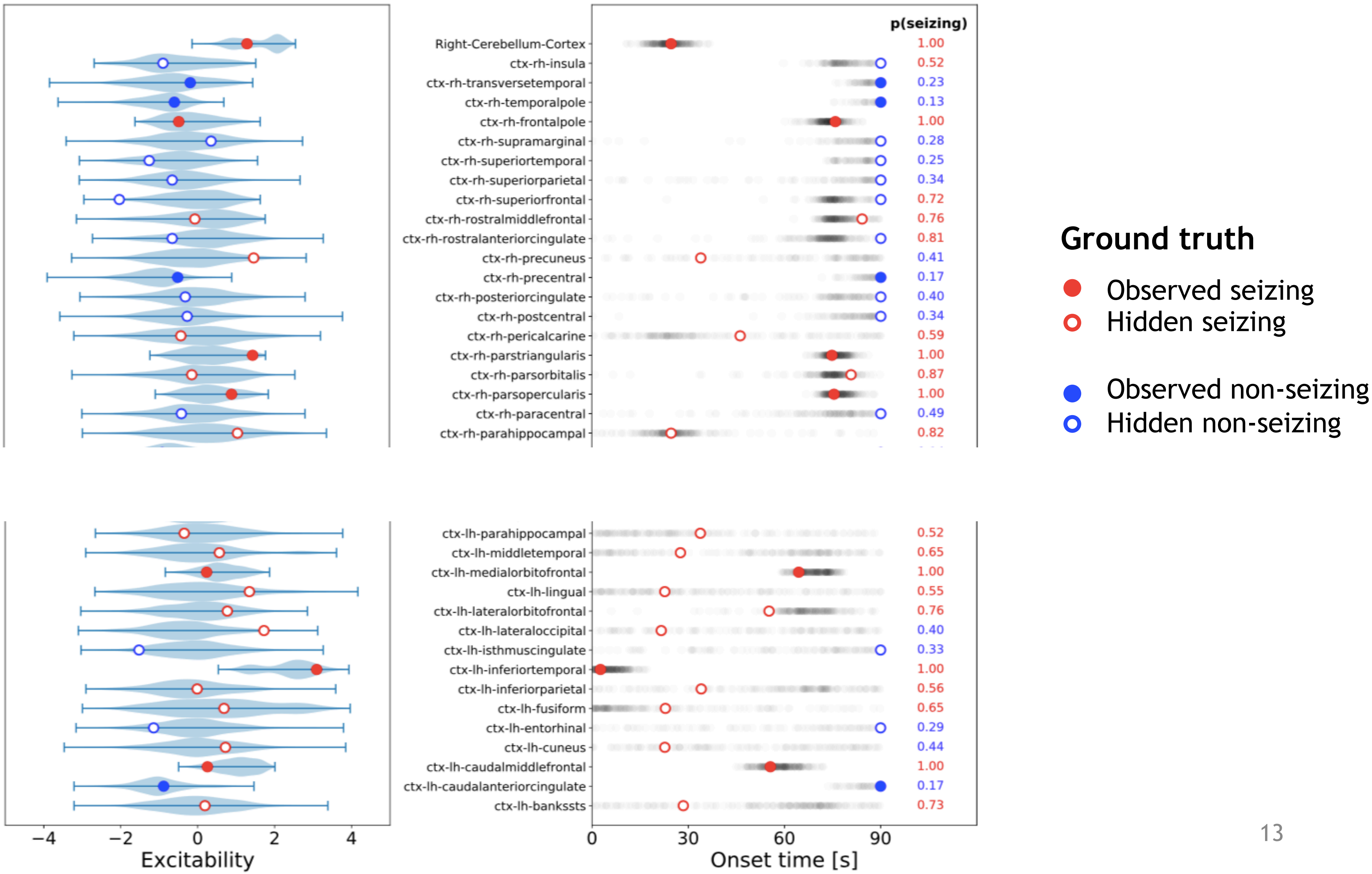
- MCMC method using the potential and kinetic energy to explore the posterior distribution.
- More efficient for complicated geometries in high dimensional spaces

Validation with synthetic data

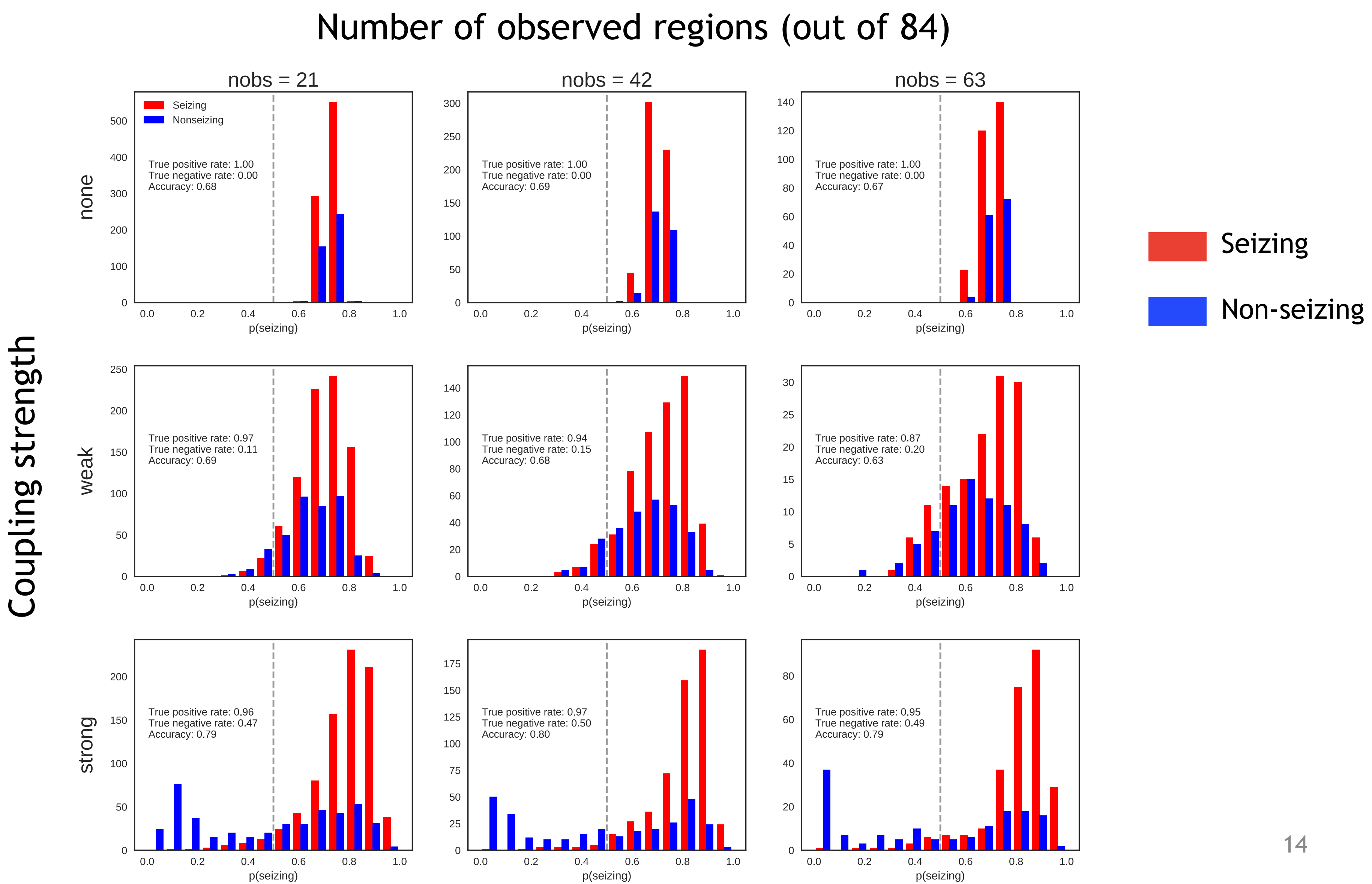
- Realistic brain networks with 84 regions (Desikan-Killiany atlas)
- No, weak, strong coupling
- 21, 42, 63 observed regions out of 84
- Each combination: two batches with 10 seizures each
- Excitabilities drawn randomly from standard normal distribution
- Random selection of observed nodes

Example

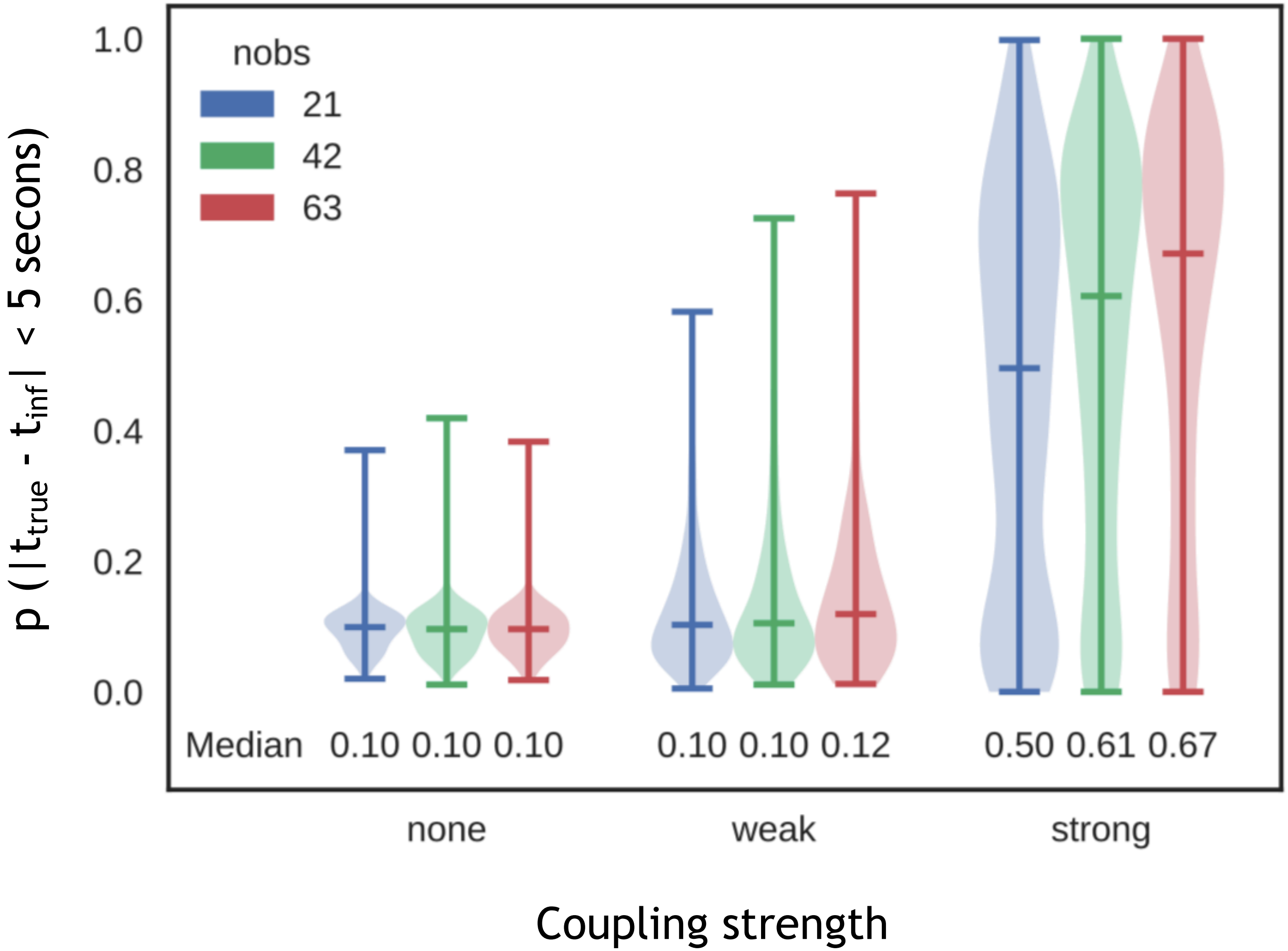
Strong coupling, 84 regions, 21 observed, 10 seizures in a batch



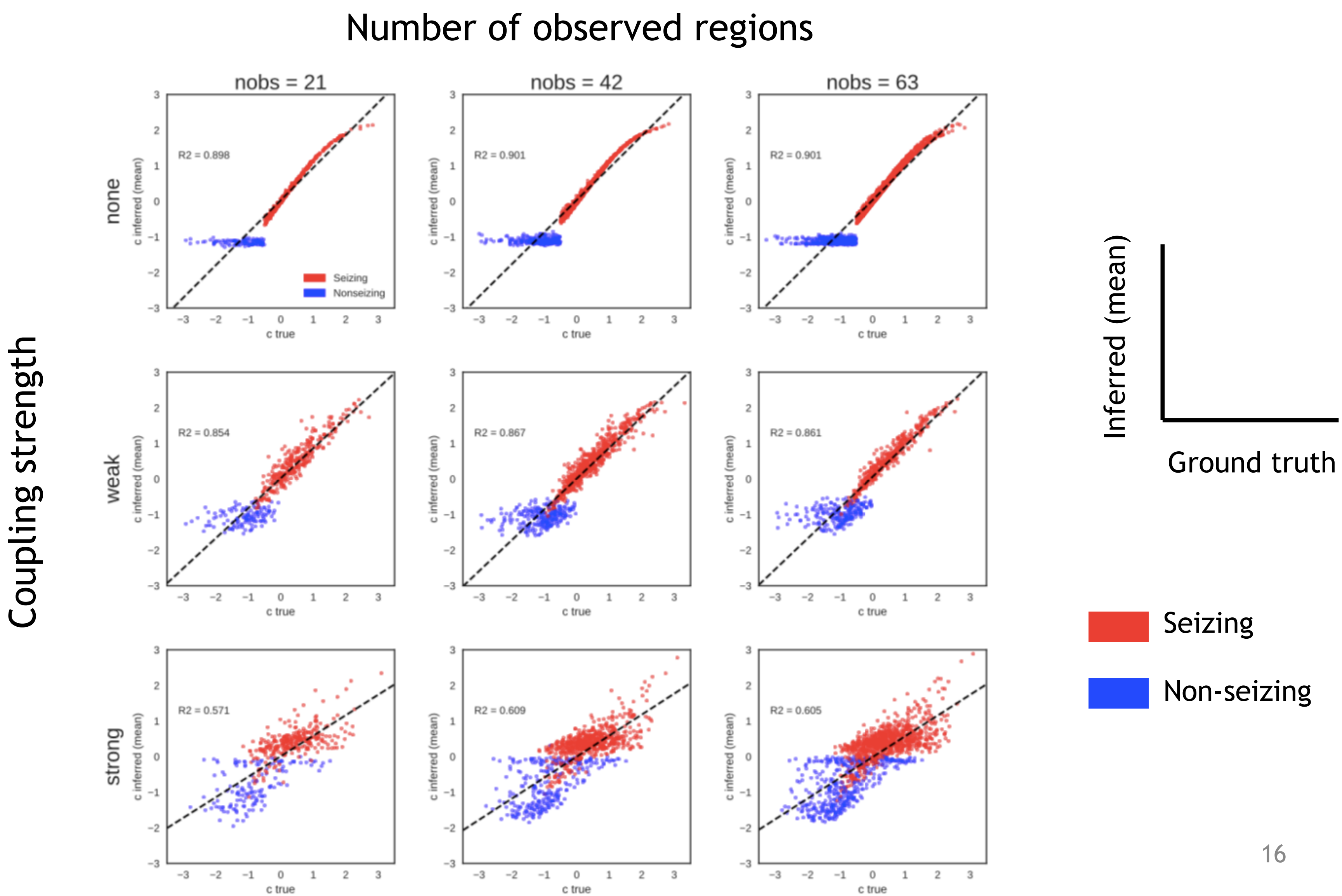
Can we determine if a hidden region is seizing?



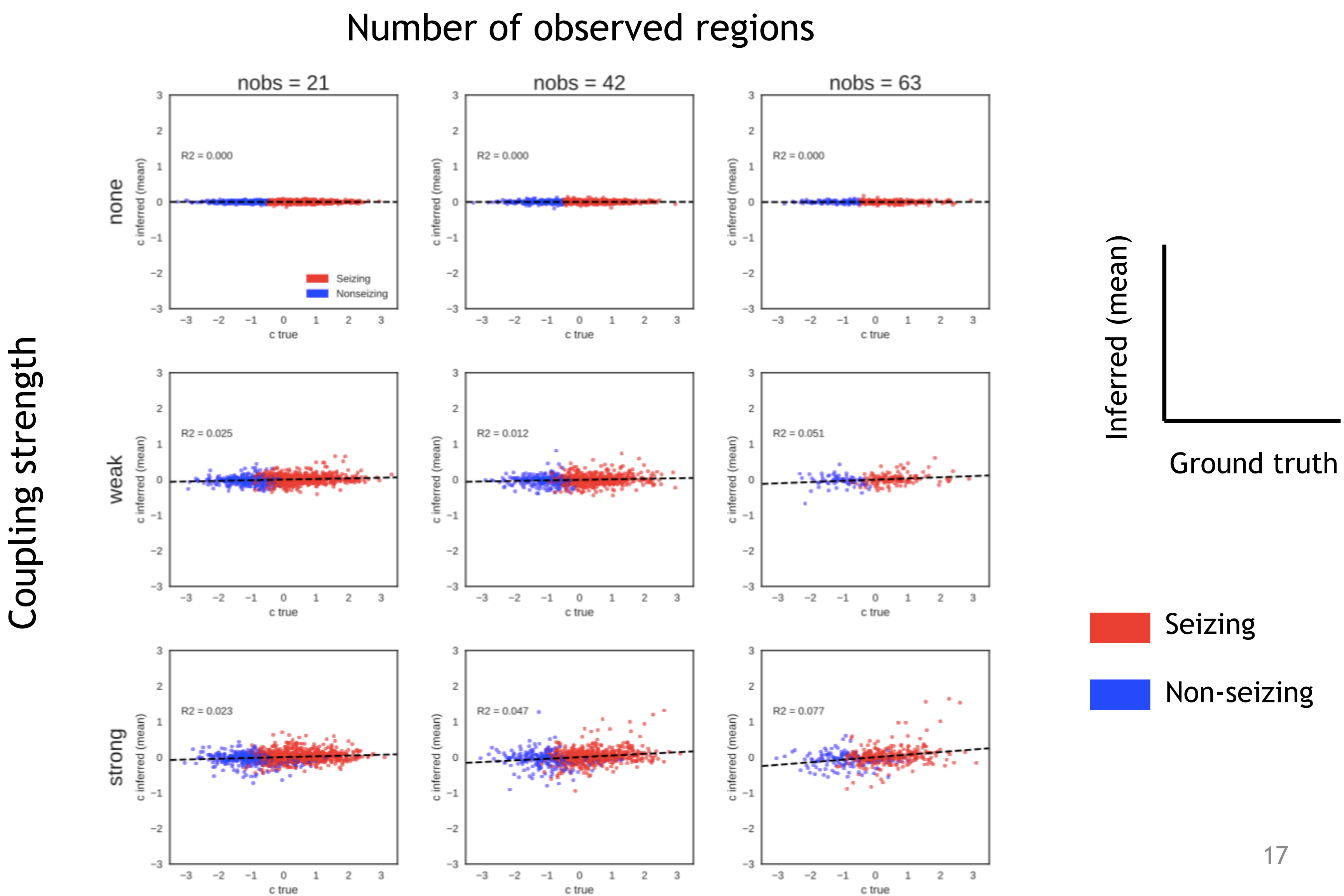
Can we determine when a hidden region starts to seize?



Can we infer the excitabilities?
Observed regions



Can we infer the excitabilities?
Hidden regions



Summary

- Simple model with minimal assumptions:
  - Binary healthy/seizure state
  - Seizure propagates along the network
  - Seizing nodes destabilize neighbours
  - Recruitment influenced by the internal excitability
- Only few constants to set:
  - Temporal scale of interest
  - Wide priors on the hyperparameters
- Simple model allows for full brain network inference for batch of subjects.
- With strong enough coupling effects, onset times in the hidden network can be in part inferred.

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