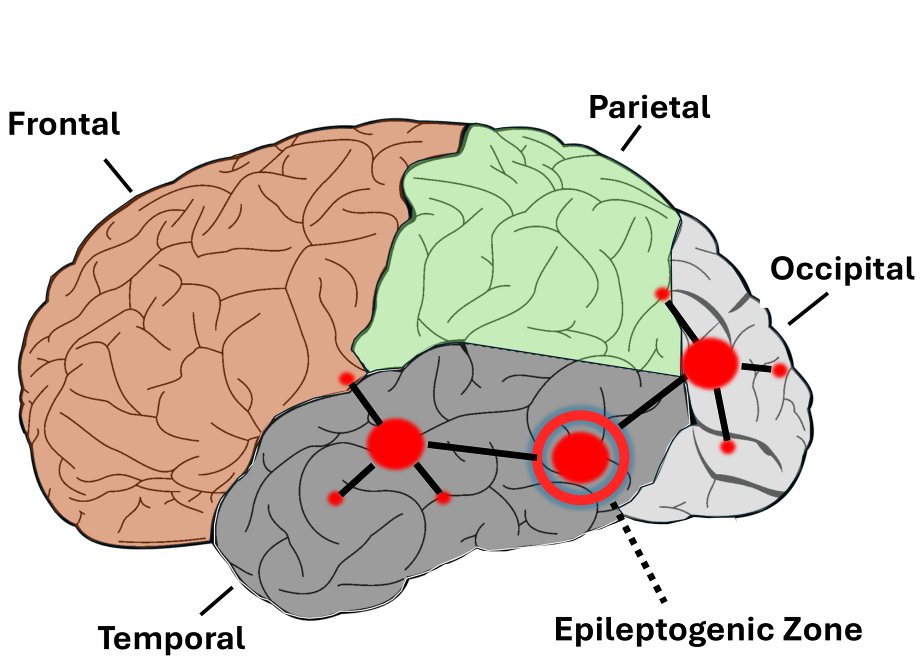
Inferring Seizure Propagation Networks via Mathematical Modelling of EEG Data

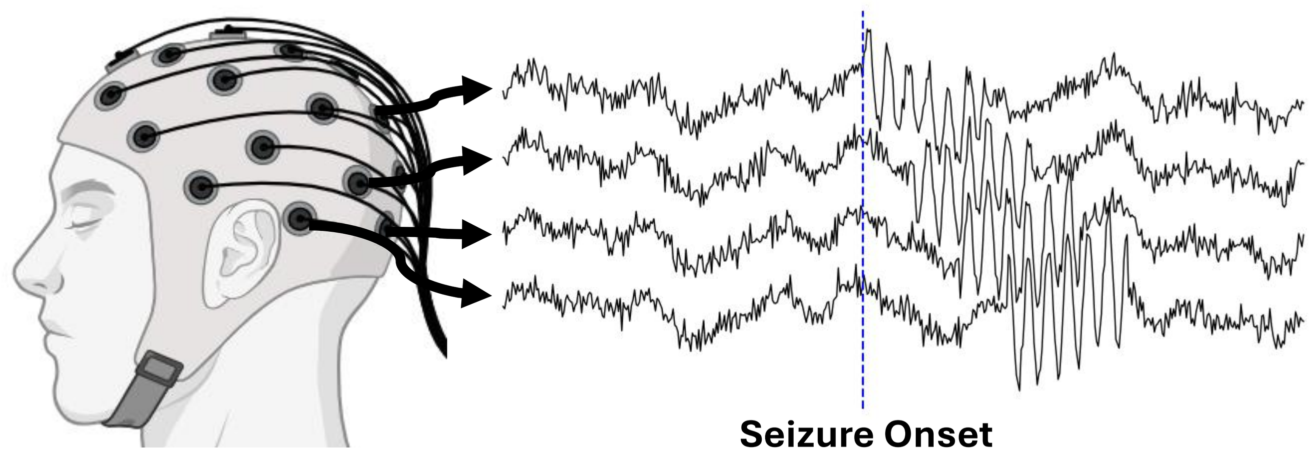
Carson McKee* Maria Kalli

Department of Mathematics, King's College London, London WC2R 2LS, United Kingdom

Background and Motivation

- Epileptic seizures often start in a localised area of the brain (epileptogenic zone or EZ).
- Sometimes the seizure propagates to other areas according to the brain's network structure.
- If we can infer this propagation network, then:
  - Doctors can surgically remove the EZ.
  - Specialised devices can administer shocks to abort the seizure.



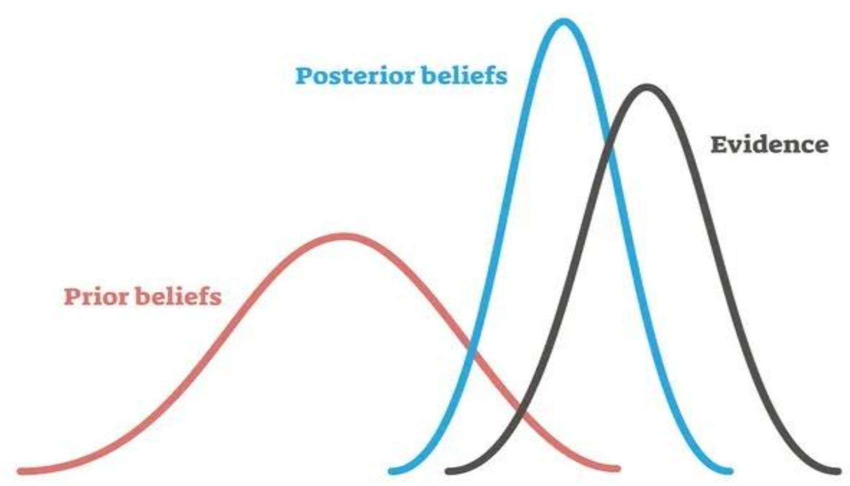


- EEGs record the brain's electrical activity over time using electrodes placed on the scalp.
- Seizures results in the EEG signals behaving abnormally.

Goals

- Develop a model which can:
  - Infer the onset time of a seizure.
  - Automatically infer the propagation network.
  - From the network, infer the EZ.
  - Provide uncertainty quantification on these inferences.
  - Allow experts to incorporate their existing knowledge.

Bayesian Inference



$$\underbrace{f(\vartheta|Y)}_{\text{Posterior}} \propto \underbrace{f(Y|\vartheta)}_{\text{Likelihood}}\underbrace{f(\vartheta)}_{\text{Prior}}$$

- A change-point (CP) is an unknown time at which a signal (e.g. an EEG) changes its behaviour (potentially indicating a seizure).
- A (directed) network is defined by a collection of nodes and edges.

Y = EEG Data (signal from each sensor)

ϑ = CP locations + network edges

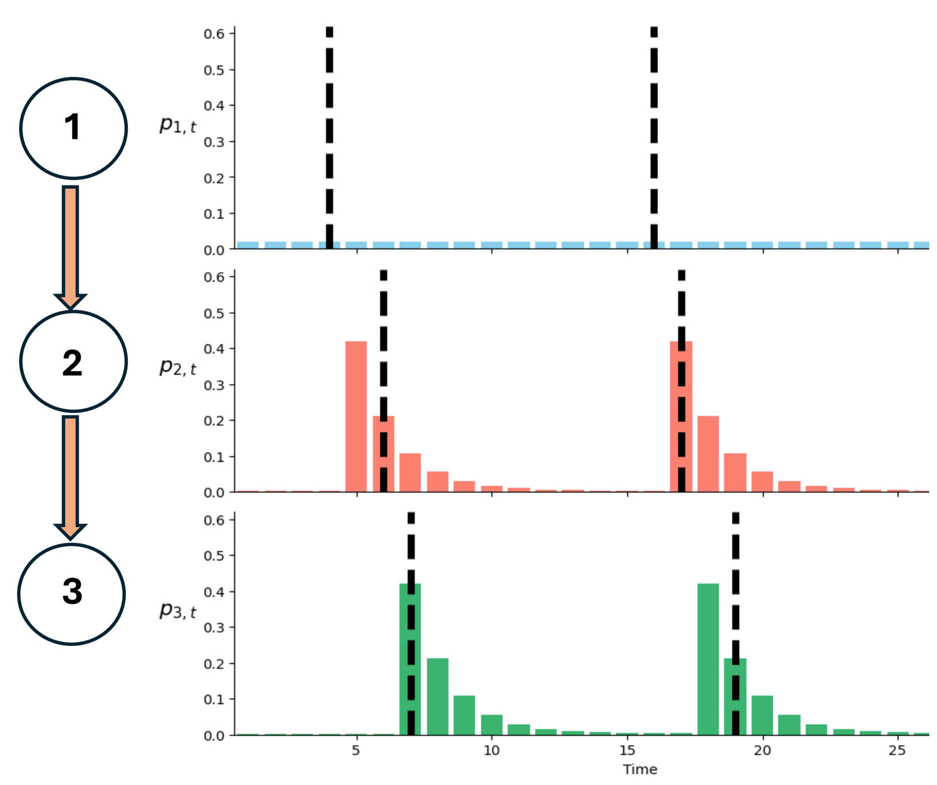
We must specify a prior distribution for ϑ, then compute $f(\vartheta|Y)$.

Hierarchical Model Structure

- If a seizure propagates, we often see delays between CPs in different EEG signals.
- If two signals/sensors i and j are linked by an edge $i \to j$, then a CP in i should increase the likelihood of a CP in j shortly after.
- This mimics the propagation we wish to model.
- Bayesian inference allows us to build one large model from a hierarchy of sub-models.

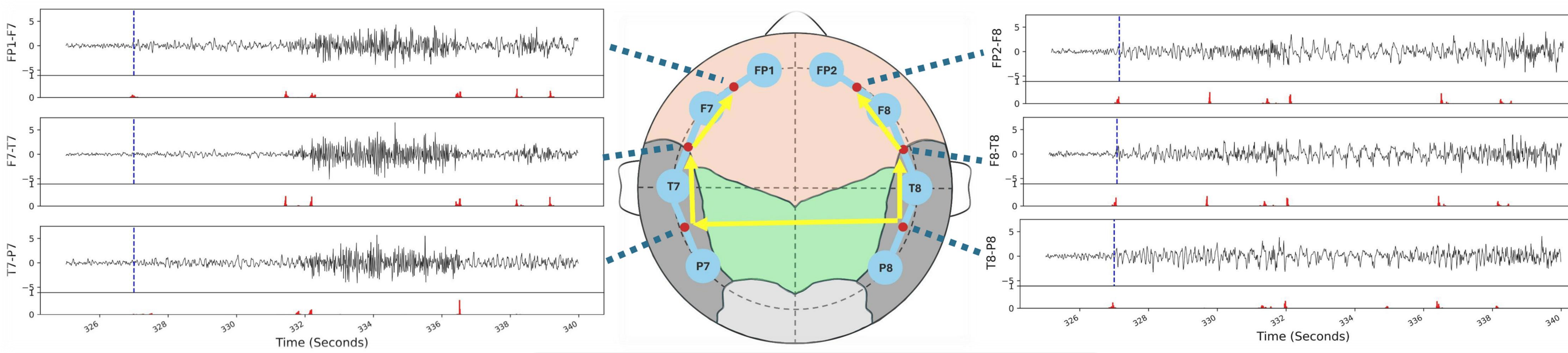
Y	**Observed EEG**
ϑ	**Change-Points**
	Network

- We build our prior for ϑ in two parts:
  1. A prior distribution on the network's edges
     $Pr(A_{i,j} = 1) = p_{i,j}, \quad p_{i,j} \in [0,1]$
     where $A_{i,j} = 1$ represents an edge $i \to j$.
     $p_{i,j}$ controls our prior beliefs on the network.
  2. Then, conditional on the network:
     $Pr(\text{CP at time t in signal } j) \propto$
     $\sum_{j:A_{i,j}=1} g(\text{dist. to previous CP in signal } i)$
     where the function $g()$ controls the delays between CPs in connected series.



- Obtaining the posterior is often very difficult and requires numerical approximation. We develop novel Particle Markov Chain Monte Carlo algorithms.

Boston Children's Hospital (CHB) Dataset



- Data was collected from a paediatric epilepsy patient at CHB.
- Neurologists manually inspected the data and estimate the seizure began at 327s in the right temporal lobe.
- Temporal Lobe Epilepsy is one of the most common forms of focal epilepsy in children.

Posterior Analysis

- The model's maximum posterior probability network (yellow arrows) suggests the seizure started in the right temporal lobe before spreading to the left and frontal lobes.
- The model places high probability (red bars) on the true seizure onset time (dashed blue line).
- This aligns with the neurologist's assessment.

References

Guttag, J. (2010). CHB-MIT Scalp EEG Database (version 1.0.0), PhysioNet.

McKee, C. & Kalli, M. (2025) Network Modelling of Asynchronous Change-Points in Multivariate Time Series, arXiv:2506.15801.

*carson.mckee@kcl.ac.uk