Class-Aware Hidden Markov Model for functional connectivity estimation and classification

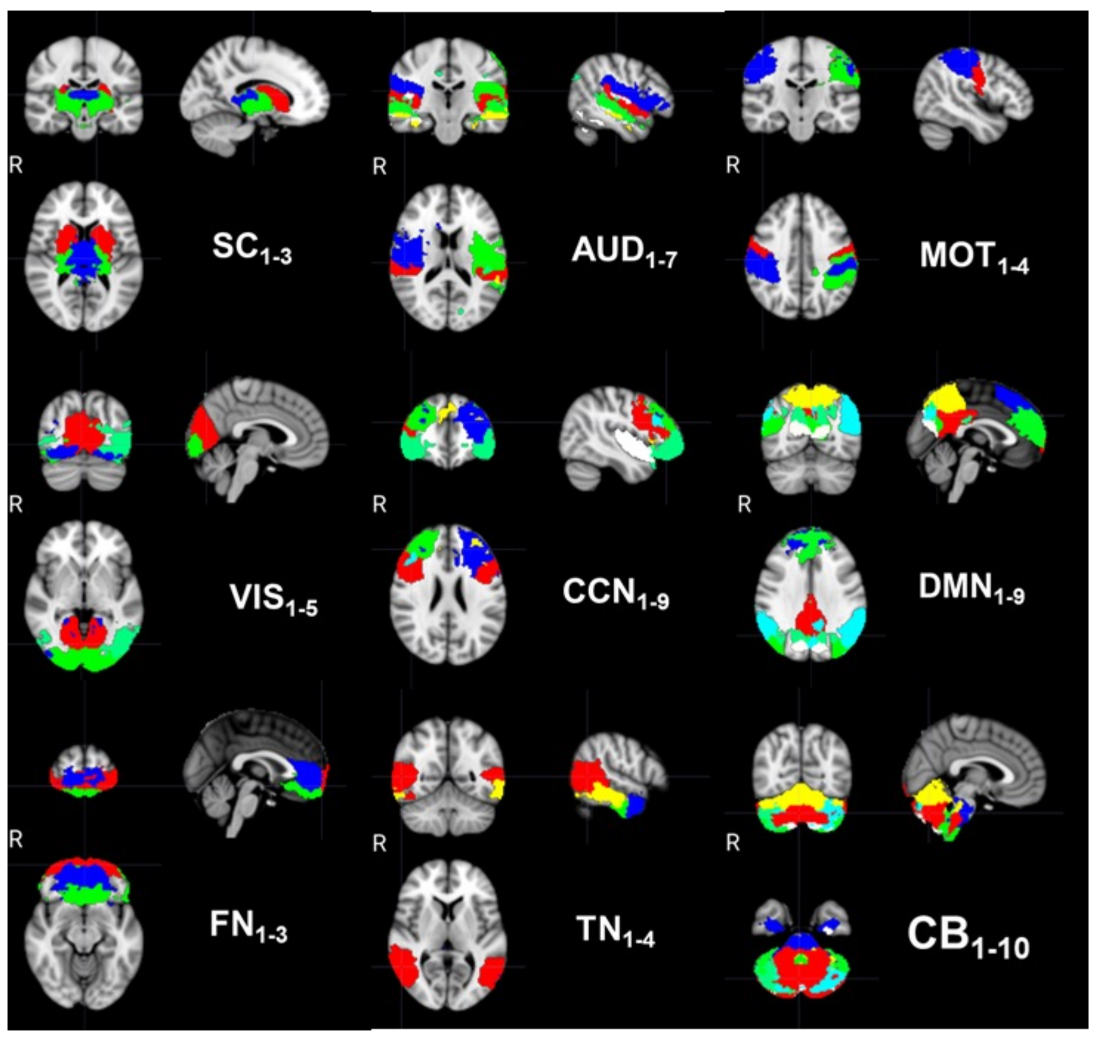
Chendi Han[1], Pavithran Pattiam Giriprakash[1], Rajesh Nandy[2], and Dietmar Cordes[2*]
[1]Cleveland Clinic Lou Ruvo Center for Brain Health, Las Vegas, NV 89106
[2]University of North Texas Health Science Center, Fort Worth, TX 76107
*cordesd@ccf.org

Introduction

Several approaches have been adopted to characterize the temporal dynamics of resting-state fMRI connectivity. Compared to sliding window methods [1-2], Hidden Markov Models (HMM) are suitable for rapid state transitions, with the covariance matrix directly measuring brain connectivity [3-4]. In this paper, we propose a framework to classify fMRI data based on HMM. Compared with the two-step approach, feature extraction and subsequent classification based on selected features [5-8]. Our proposed method directly uses the joint probability to compute the posterior probability, which is more efficient and maintains interpretability [9-10]. We evaluate the classification accuracy using real fMRI datasets.

Dataset

- **ADNI [11]** 292 subjects: 74 Cognitively Normal (CN), 119 Mild Cognitive Impairment (MCI), and 99 Alzheimer's Disease (AD)
- **Preprocessing**
  (1) Slice-timing correction and rigid-body realignment
  (2) Co-registration
  (3) Spatial normalization to MNI152
  (4) Detrending
- **Independent component analysis (ICA)**



54 ICA components [12]:

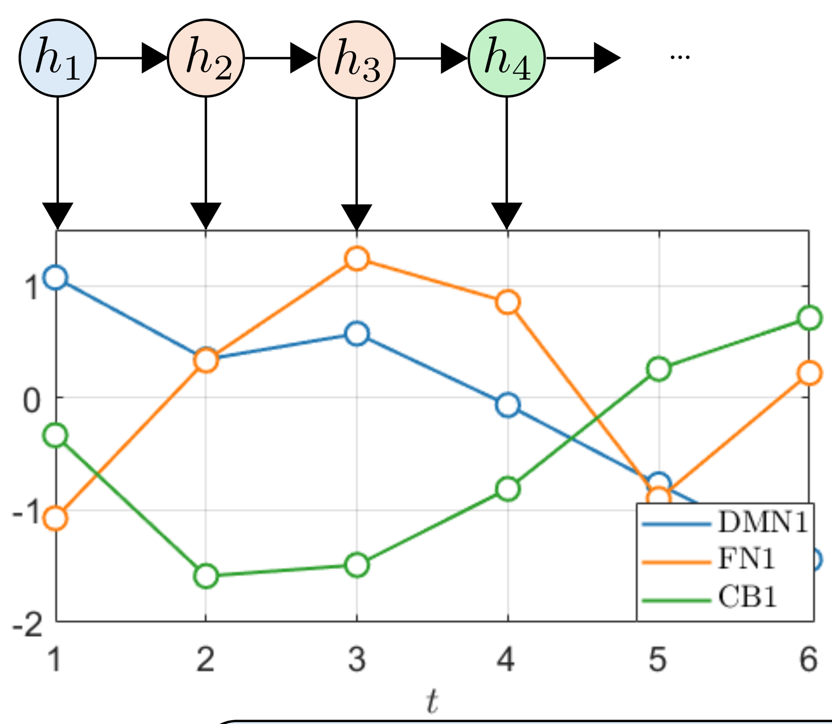
3 subcortical (SC)
7 auditory (AUD)
4 motor (MOT)
5 visual (VIS)
9 cognitive control (CCN)
9 default mode (DMN)
3 frontoparietal (FN)
4 temporal (TN)
10 cerebellar (CB)

Data size: $X \in \mathfrak{R}^{N \times T \times p}$

$N = 292$: Number of subjects
$T = 135$: Number of time points
$p = 54$: Number of ICA components

Each time series (per subject/ICA component) is normalized to have mean 0 and variance 1.

Hidden Markov Model (HMM)



Observation: $x_t \in \mathfrak{R}^{1 \times 54}$

Hidden states: h

Transition probability:

$$p(h_t|h_{t-1}) = A_{h_{t-1}h_t}$$

Emission probability:

$$p(x_t|h_t) = \mathcal{N}\left[\mu(h_t), \Sigma(h_t)\right]$$

Joint probability:

$$\psi = \max_{A,\mu,\Sigma} \sum_t \sum_{\mathcal{H}} p(h_t|h_{t-1}) p(x_t|h_t)$$

HMM for multiclass
- Different classes (NC/MCI/AD) have the same number of hidden states.
- Different classes have different transition/emission probability.
- Each class is evaluated using a different EM algorithm with the same initial condition.

Evaluation

- **Training phase**
  Normal subjects ⇒ HMM1
  MCI subjects ⇒ HMM2
  AD subjects ⇒ HMM3
- **Testing phase**

Testing subjects ⇒

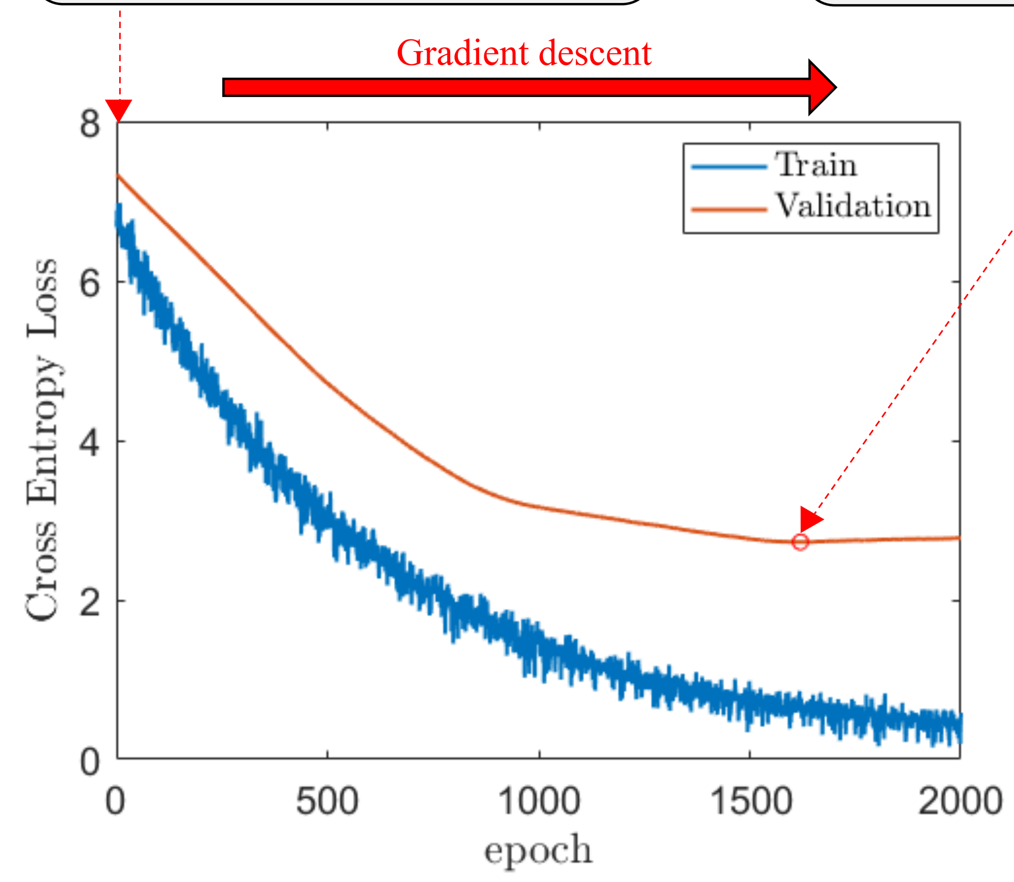
$$\psi^{(NC)} = \sum_t \sum_{\mathcal{H}} p^{(NC)}(h_t|h_{t-1}) p^{(NC)}(x_t|h_t)$$
$$\psi^{(MCI)} = \sum_t \sum_{\mathcal{H}} p^{(MCI)}(h_t|h_{t-1}) p^{(MCI)}(x_t|h_t)$$
$$\psi^{(AD)} = \sum_t \sum_{\mathcal{H}} p^{(AD)}(h_t|h_{t-1}) p^{(AD)}(x_t|h_t)$$

$$\Rightarrow \quad p(c|X) = \frac{\psi^{(c)}(X)}{\sum_i \psi^{(i)}(X)}$$

Discriminative training

Assumption
- The joint probability measures the total probability of an unknown time series belonging to a certain class.
- The EM algorithm maximizes the joint probability for each class but does not guarantee good class separation.
- Additional discriminative training can improve classification accuracy.

Supervised generative model: class-aware HMM ⇒ **Supervised discriminative model:** Hidden conditional random field [9]



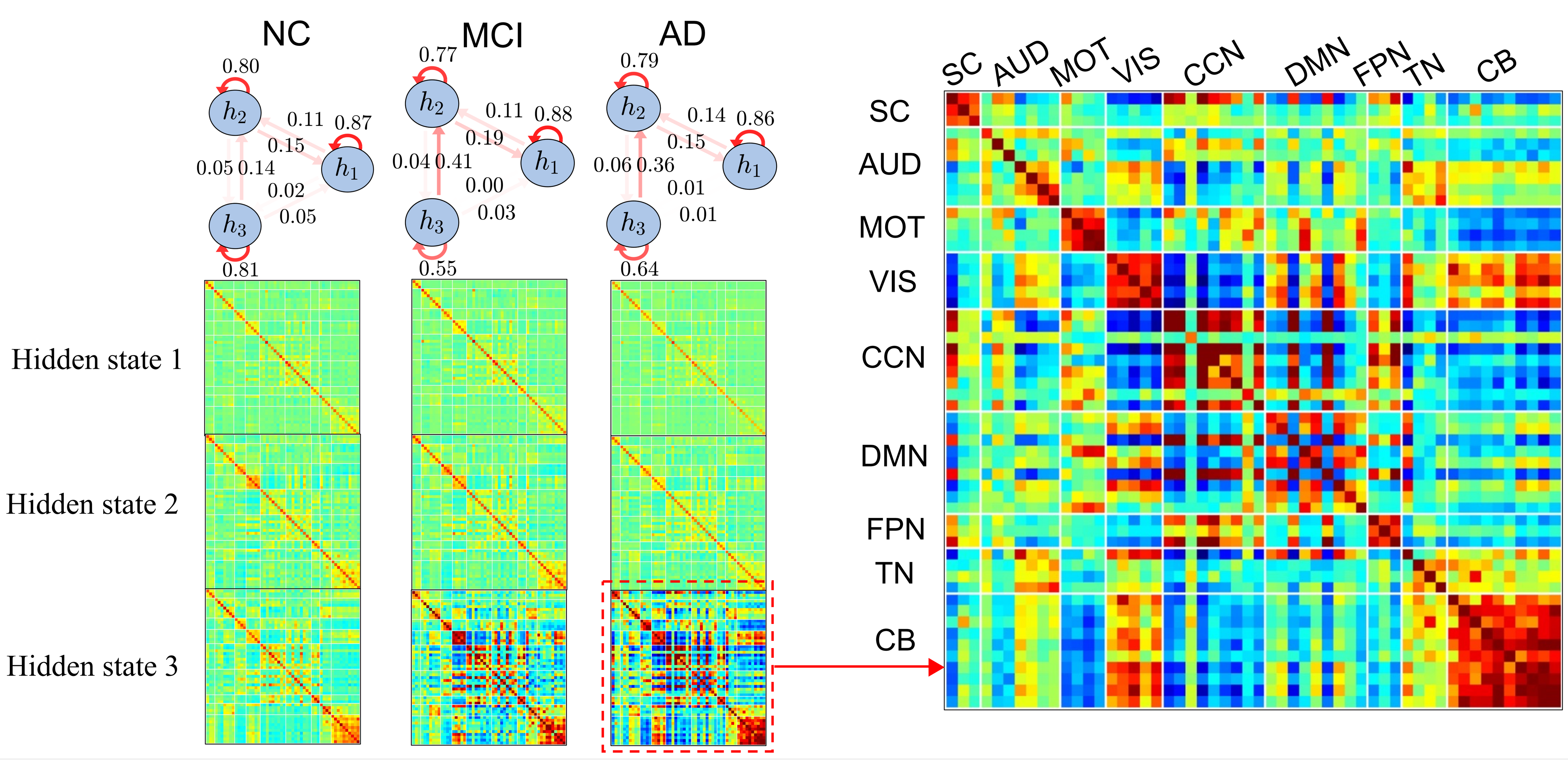
Pytorch parameters
Learning rate: 10^{-5}
Optimizer: Adam
Steps: 2000
Loss: Cross entropy

Classification accuracy

- **Data separation**
  (1) 70% Train, 20% Eval and 10% Test
  (2) Up sampling for CN and AD group
  (3) Repeat 100 times for statistical average
- **Two/Three class classification accuracy**

	NC/MCI	MCI/AD	NC/AD	NC/MCI/AD
Supervised generative model	73.12%	75.62%	82.50%	**65.69%**
Supervised discriminative model	78.12%	80.42%	90.44%	**72.36%**

Expectation-maximization algorithm



Acknowledge

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