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

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Statement

- We declare that there is no conflict of interest.
- The data used in this paper comes from Alzheimer's Disease Neuroimaging initiative (ADNI)*. All the data are publicly accessible, and patients' information is protected.
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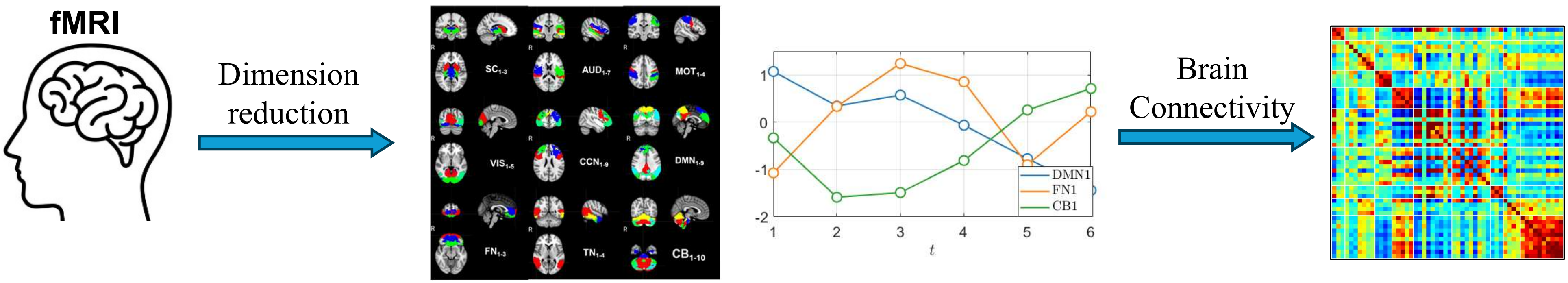
*Data used in preparation of this article were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). As such, the investigators within the ADNI contributed to the design and implementation of ADNI and/or provided data but did not participate in analysis or writing of this report. A complete listing of ADNI investigators can be found at: http://adni.loni.usc.edu/wp-content/uploads/how_to_apply/ADNI_Acknowledgement_List.pdf

Background



	Dynamic	Fast state transition	Classification
Correlation based [1]	No	No	No
Sliding Window (SW)	Yes [2]	No	Additional classifier [3]
Hidden Markov Model (HMM) [4]	Yes	Yes	No
Ours	**Yes**	**Yes**	**Yes**

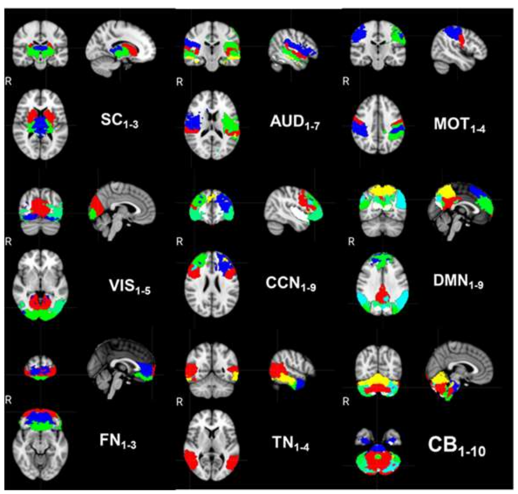
[1] Biswal, B., et al., Magnetic resonance in medicine, 1995
[2] Allen, E.A., et al., Cerebral cortex, 2004
[3] Ji, J., et al., IEEE Journal of Biomedical and Health Informatics, 2021
[4] Zhang, G., et al., IEEE transactions on medical imaging, 2019

Step 1: Dimensionality reduction

- ADNI dataset

	Number of subjects (AV45>1.1)
Normal Control (NC)	74
Mild Cognitive Impairment (MCI)	119
Alzheimer's (AD)	99
Total	292

- Independent component analysis [5] 54 Components corresponding to 9 different regions



Subcortical (SC)
Auditory (AUD)
Motor (MOT)
Visual (VIS)
Cognitive control (CCN)
Default mode (DMN)
Frontal (FN)
Temporal (TN)
Cerebellar (CB)

$X \in \Re^{N \times T \times p}$

$N = 292$ Number of subjects

$T = 135$ Number of time points

$p = 54$ Number of ICA componenets

[5] McKeown, M.J., et al., Human brain mapping, 1998

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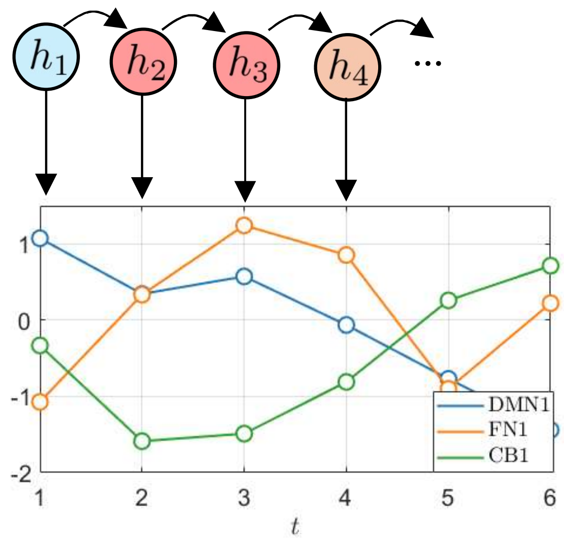
Step 2: Hidden Markov Model



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 multiple class

Normal subjects → HMM1

MCI subjects → HMM2

AD subjects → HMM3

- Testing

Testing subjects →

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

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

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

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Step 3: Supervised learning

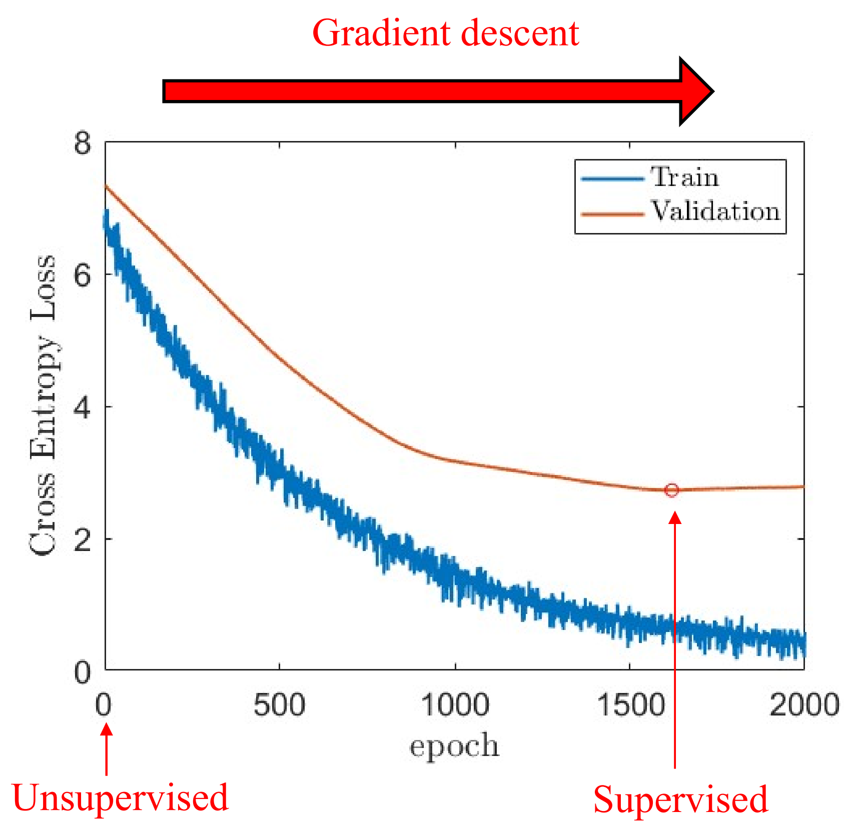
- Hidden conditional random fields [6]

Normalized probability: $p(c|X) = \dfrac{\psi^{(c)}(X)}{\sum_i \psi^{(i)}(X)}$

Learning rate: 10^{-5}

Optimizer: Adam

Train/Validate/Test= 7/2/1



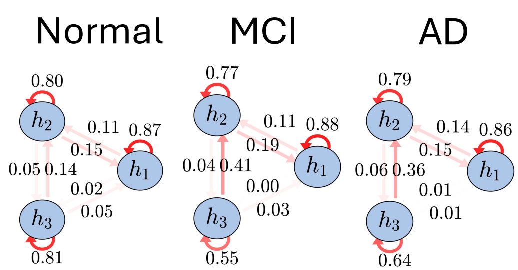
[6] Quattoni, A., et al., IEEE Transactions on Pattern Analysis and Machine Intelligence, 2007

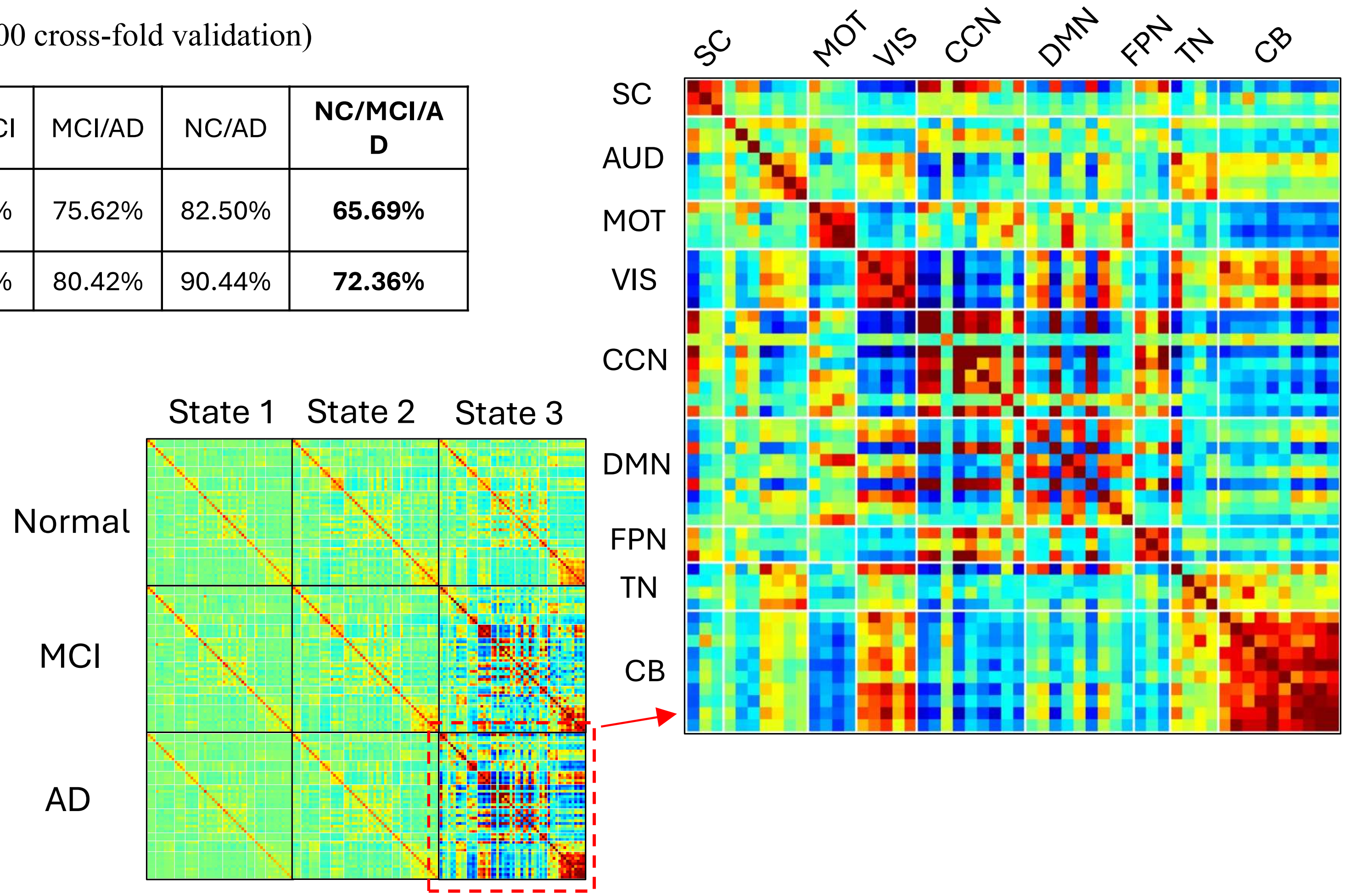
Results

- **Classification accuracy** (100 cross-fold validation)

	NC/MCI	MCI/AD	NC/AD	**NC/MCI/AD**
Unsupervised [Zhang, G., et al. 2019]	73.12%	75.62%	82.50%	**65.69%**
Supervised (Ours)	78.12%	80.42%	90.44%	**72.36%**

- **Functional connectivity**





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Summary

Previously Sliding Window Methods

- Require fixed window size
- Not adaptive to fast transitions
- Need separate classifier

Previous HMM-based Methods

- Unsupervised; trained separately for each class
- Ignored inter-class information → lower accuracy

Our results

- Supervised HMM framework → improved prediction accuracy
- Joint connectivity estimation and classification → Faster, cleaner, and adaptive to rapid state changes

Thanks for your attention !