DBGSL: Dynamic Brain Graph Structure Learning

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MIDL Nashville 2023

Overview

- GNNs applied to fMRI data assume brain graphs are static over time and the graph adjacency matrix is known prior to model training.
- We propose Dynamic Brain Graph Structure Learning (DBGSL), a method for learning the optimal time-varying dependency structure of fMRI data induced by a downstream prediction task.

Problem formulation

- Let $\mathbf{X}_{1:T'} = (\mathbf{x}_1, \dots, \mathbf{x}_{T'}) \in \mathbb{R}^{V\times T'}$ denote BOLD signal from V brain regions measured over T' timepoints and $y \in [0, \dots C-1]$ a class label.
- Let the unknown BOLD dependency structure be represented by a dynamic brain graph $G_{1:T} = (\mathbf{A}_{1:T}, \mathbf{F}_{1:T})$ consisting of a dynamic adjacency matrix $\mathbf{A}_{1:T} \in \mathbb{R}_{\geq 0}^{V\times V\times T}$ and a dynamic node feature matrix $\mathbf{F}_{1:T} \in \mathbb{R}^{V\times B\times T}$ over $T \leq T'$ snapshots.
- With DBGSL we aim to predict class labels $\hat{y}$ given input $\mathbf{X}_{1:T'}$ using an intermediary learnt dynamic brain graph $F_\theta(\mathbf{X}_{1:T'}) = F_{\theta_C}(F_{\theta_G}(\mathbf{X}_{1:T'})) = F_{\theta_C}(G_{1:T}) = \hat{y}$ where $F_{\theta_G}(\cdot)$ is a dynamic graph learner and $F_{\theta_C}(\cdot)$ is a dynamic graph classifier.

Dynamic graph learner F_{θ_G}

- Region-wise BOLD signals $\mathbf{X}_{1:T'}$ extracted for fMRI data are first split into windows

$$f_{\theta_W}(\mathbf{X}_{1:T'}) = \tilde{\mathbf{X}}_{1:T} = (\tilde{\mathbf{X}}_1, \dots \tilde{\mathbf{X}}_T), \quad \tilde{\mathbf{X}}_t = \mathbf{X}_{tS:tS+P}, \quad t = 1, \dots, T$$

  where P and S are hyperparameters specifying window length and stride, respectively, and T is the number of windows.
- Windowed BOLD signals $\tilde{\mathbf{X}}_{1:T}$ are next input to a 2D CNN to extract K_E-dimensional brain region embeddings $f_{\theta_E}(\tilde{\mathbf{X}}_{1:T}) = \mathbf{H}^G_{1:T} \in \mathbb{R}^{K_E\times V\times T}$
- Each window embedding $\mathbf{H}^G_t$ is used to learn the dependency structure between brain regions using scaled dot-product self-attention

$$\mathbf{A}_t = f_{\theta_S}(\mathbf{H}^G_t) = \text{Sigmoid}\left(\frac{\mathbf{Q}_t\mathbf{K}_t^\top}{\sqrt{K_S}}\right), \quad \mathbf{Q}_t = \mathbf{H}^G_t\mathbf{W}, \quad \mathbf{K}_t = \mathbf{H}^G_t\mathbf{W}$$

  where $\mathbf{Q}_t, \mathbf{K}_t \in \mathbb{R}^{V\times K_S}$ are query and key matrices, respectively, and $\mathbf{W} \in \mathbb{R}^{K_E\times K_S}$.
- To sparsify the learnt adjacency matrices, we propose a soft threshold operator

$$f_{\theta_P}(a_{i,j,t}) = \text{ReLU}(a_{i,j,t} - \text{Sigmoid}(\theta_P))$$

  where $\text{Sigmoid}(\theta_P) \in (0, 1)$ ia a learnable edge weight threshold and $a_{i,j,t} \in \mathbf{A}_{1:T}$.
- Dynamic node features $\mathbf{F}_{1:T}$ are created using the correlation matrix at each snapshot

$$\mathbf{F}_t = \tilde{\mathbf{D}}_t^{-1}\mathbf{\Sigma}_t\tilde{\mathbf{D}}_t^{-1}, \quad \tilde{\mathbf{D}}_t = \sqrt{\text{diag}(\mathbf{\Sigma}_t)}, \quad \mathbf{\Sigma}_t = \frac{1}{P-1}\tilde{\mathbf{X}}_t^\top(\mathbf{I}_P - \frac{1}{P}\mathbf{1}_P\mathbf{1}_P^\top)\tilde{\mathbf{X}}_t$$

  where $\mathbf{I}_P$ and $\mathbf{1}_P$ is a $P\times P$ identity matrix and $1\times P$ matrix of all ones, respectively.

Dynamic graph classifier F_{θ_C}

- We use a L_C-layered recurrent GNN to learn a K_C-dimensional brain graph representation

$$\mathbf{H}^C_{1:T} = \boldsymbol{\phi}(||_{l=1}^{L_C}\mathbf{H}^{(l)}_{1:T}) \in \mathbb{R}^{K_C L_C\times T}$$

  where $\boldsymbol{\phi} = \frac{1}{V}\mathbf{1}_{1\times V}$ is an average pooling matrix.
- Define a temporal attention score matrix to emphasize snapshots with the most important brain graph embeddings

$$\boldsymbol{\alpha} = \text{Sigmoid}(\text{ReLU}(\boldsymbol{\psi}\mathbf{H}^C_{1:T}\mathbf{W}_2)\mathbf{W}_3) \in (0,1)^{1\times T}$$

  where $\mathbf{W}_2 \in \mathbb{R}^{T\times\tau T}$, $\mathbf{W}_3 \in \mathbb{R}^{\tau T\times T}$ encode temporal dependencies via a bottleneck controlled by the hyperparameter $\tau \in (0, 1]$ and $\boldsymbol{\psi} = \frac{1}{K_C L_C}\mathbf{1}_{1\times K_C L_C}$.
- The final graph-level representation $\mathbf{h}_\mathcal{G} \in \mathbf{R}^{L_C K_C}$ is obtained using the temporal attention score matrix to take the weighted sum over snapshots

$$\mathbf{h}_\mathcal{G} = (\boldsymbol{\alpha} \odot \mathbf{H}^C_{1:T})\boldsymbol{\xi}^\top$$

  where $\xi = \mathbf{1}_{1\times T}$. The representation is then passed through a linear layer mapping onto class probabilities $p(y|\mathbf{X}_{1:T'}) = \text{Softmax}(\mathbf{h}_\mathcal{G}\mathbf{W}_4)$ where $\mathbf{W}_4 \in \mathbb{R}^{L_C L_K\times C}$.

Loss

- DBGSL is trained by minimizing cross-entropy loss $\mathcal{L}_{\text{CE}}(y, \hat{y})$ as well as a collection of prior constraints on the learnt graphs

$$\mathcal{L}(y, \{\hat{y}, G_{1:T}\}) = \mathcal{L}_{\text{CE}}(y, \hat{y}) + \lambda_{\text{FS}}\mathcal{L}_{\text{FS}}(\mathbf{F}_{1:T}, \mathbf{A}_{1:T}) + \lambda_{\text{TS}}\mathcal{L}_{\text{TS}}(\mathbf{A}_{1:T}) + \lambda_{\text{SP}}\mathcal{L}_{\text{SP}}(\mathbf{A}_{1:T})$$

  where $\lambda_{\text{FS}}, \lambda_{\text{TS}}, \lambda_{\text{SP}} \geq 0$ are hyperparameters weighting regularization contributions.
- Node feature smoothness (FS) and adjacency matrix temporal smoothness (TS) and sparsity regularization (SP) terms are defined

$$\mathcal{L}_{\text{FS}}(\mathbf{A}_{1:T}, \mathbf{F}_{1:T}) = \frac{1}{V^2}\sum_{t=1}^{T}\text{Tr}(\mathbf{F}_t^\top\hat{\mathbf{L}}_t\mathbf{F}_t), \quad \mathcal{L}_{\text{TS}}(\mathbf{A}_{1:T}) = \sum_{t=1}^{T-1}||\mathbf{A}_t - \mathbf{A}_{t+1}||_1$$

$$\mathcal{L}_{\text{SP}}(\mathbf{A}_{1:T}) = \sum_{t=1}^{T}||\mathbf{A}_t||_1$$

  where $\hat{\mathbf{L}}_t$ is the (symmetric) normalized Laplacian matrix.

Experiments

- We evaluate the performance of DBGSL on the task of biological sex classification.
- Resting-state (HCP-Rest) as well as emotional task (HCP-Task) fMRI data is used the Human Connectome Project (HCP).
- All brain images are parcellated into $V = 243$ mean region-wise BOLD signals using the Brainnetome atlas and transformed into a z-scores to remove amplitude effects.
- For baselines we include kernel ridge regression (KRR) [2], support vector machine (SVM), multilayer perception (MLP), bidirectional LSTM (BLSTM) [3] , BrainnetCNN (BNCNN) [5] , spatio-temporal GNN (STGCN) [1], STAGIN [6], FBNetGen (FBNG) [4] and Deep fMRI (DFMRI) [7].

Results

Table: Biological sex classification on HCP-Rest and HCP-Task. Results are mean plus/minus standard deviation across 5 runs. First and second-best results are red and purple, respectively. Statistically significant difference from DBGSL marked *.

Model	HCP-Rest		HCP-Task	
	ACC (%, ↑)	AUROC (↑)	ACC (%, ↑)	AUROC (↑)
KRR	83.50 ± 1.94 *	0.9187 ± 0.0025 *	81.37 ± 2.17 *	0.9031 ± 0.0185 *
SVM	82.70 ± 2.68 *	0.9170 ± 0.0089 *	83.16 ± 1.91 *	0.9097 ± 0.0184 *
MLP	81.47 ± 3.29 *	0.9091 ± 0.0281 *	81.10 ± 3.44 *	0.8837 ± 0.0250 *
BLSTM	81.50 ± 1.26 *	0.9058 ± 0.0081 *	77.24 ± 4.05 *	0.8526 ± 0.0188 *
BNCNN	76.83 ± 7.46 *	0.6156 ± 0.0837 *	70.66 ± 8.23 *	0.5945 ± 0.0499 *
STGCN	62.63 ± 4.50 *	0.6991 ± 0.0264 *	54.87 ± 3.37 *	0.5629 ± 0.0355 *
DFMRI	82.65 ± 3.40 *	0.8941 ± 0.0342 *	81.34 ± 2.19 *	0.8024 ± 0.0317 *
FBNG	81.57 ± 2.90 *	0.8967 ± 0.0170 *	77.16 ± 3.90 *	0.8548 ± 0.0320 *
STAGIN	83.13 ± 2.11 *	0.8597 ± 0.0467 *	81.88 ± 2.73 *	0.8088 ± 0.0404 *
DBGSL	92.32 ± 2.22	0.9623 ± 0.0433	89.54 ± 3.48	0.9496 ± 0.0423

- DBGSL outperforms all baselines across both datasets by statistically significant margins.
- We attribute this to the brain graph being learnt rather than fixed as well as incorporating temporal dynamics.

Interpretability

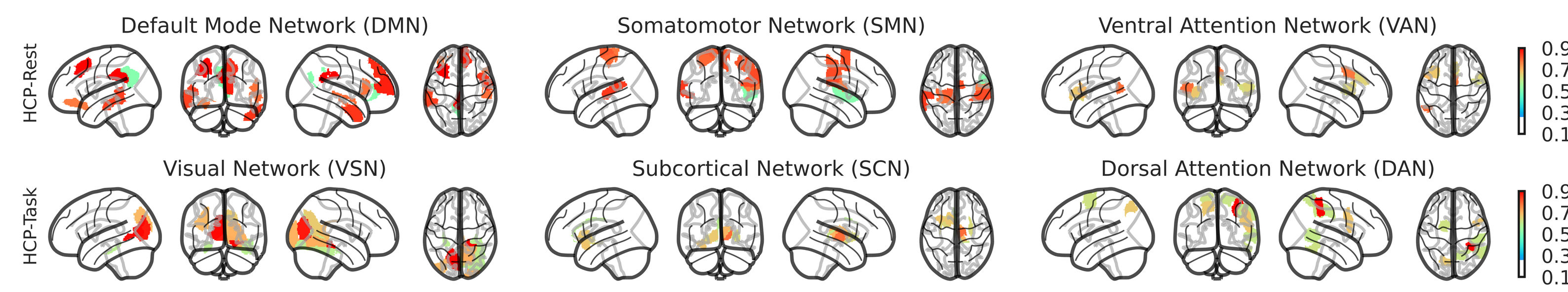

Figure: Sex-discriminative brain region scores for HCP-Rest (top) and HCP-Task (bottom). Score vectors are created using temporally weighted node degree $\mathbf{z} = \frac{1}{T}\sum_{t=1}^{T}(\sum_{j=1}^{V}\mathbf{A}_{j,t})\alpha_t \in \mathbb{R}^V$.

- HCP-Rest brain regions fall in the dorsal anterior cingulate cortex, middle frontal gyrus, and posterior superior temporal cortex within the default mode network (DMN).
- HCP-Task brain regions fall in the parahippocampal gyrus, medial occipital cortex, and superior parietal lobule within the posterior visual network (VSN).

Conclusion

- DBGSL is an end-to-end trainable model capable of learning optimal time-varying dependency structure from fMRI data in the form of a dynamic brain graph.
- Learnt dynamic graph adjacency matrices reveal prediction-related brain regions that align with existing neuroscience literature.

References

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