Joint Embedding of Structural and Functional Brain Networks with Graph Neural Networks for Mental Illness Diagnosis

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TL;DR

- We study the applicability of Graph Neural Networks (GNNs) on multiview brain networks in the absence of node and edge features.
- We propose a novel multiview contrastive learning framework for brain network analysis, which adaptively extracts information from both structural and functional modalities of brain networked data.
- Comprehensive experiments on two real-world brain disease classification datasets demonstrate the effectiveness of our proposed method.

Motivation

Mental Illness Diagnosis

- Highly prevalent and impactful for people's physical health
- Brain networks which characterize complex structures of human brain connectivities could be helpful in mental health analysis [1]

Brain Network Analysis

- Different modalities encode different biomedical semantics of brain regions [2]
  - Structural aspects: Diffusion Tensor Imaging (DTI)
  - Functional aspects: functional Magnetic Resonance Imaging (fMRI)
- The fusion of multiple modalities could lead to consistent improvements for brain analysis [3–5]

Graph Neural Networks for Multiview Brain Network Analysis

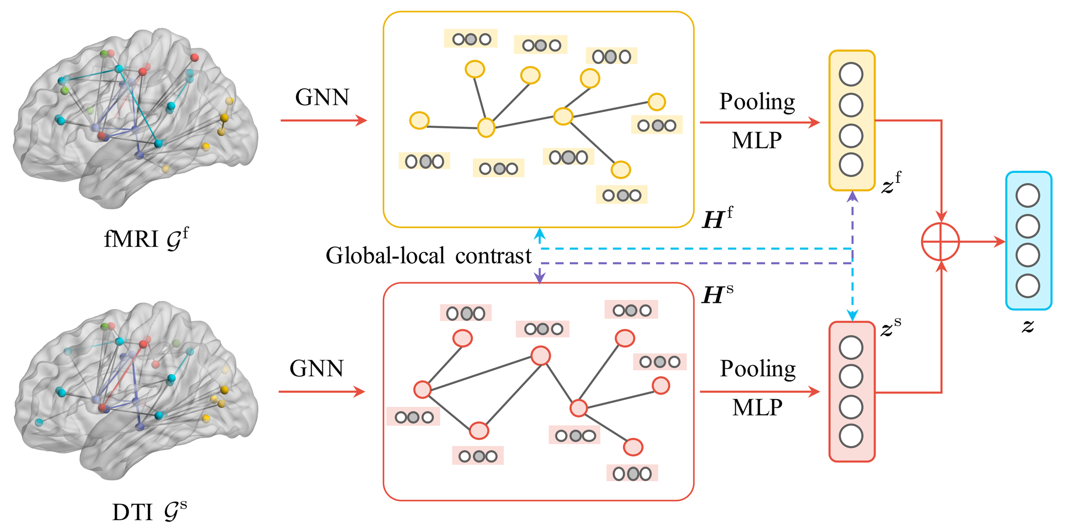
- Most brain networks are organized in a form of weighted adjacency matrix describing connections among brain regions, where GNNs can be applied for analyzing brain networks usually of high nonlinearity [5].

Challenges:

- How to learn effective node embeddings in such a multiview setting with GNNs remains rarely explored.
- Brain networks do not have initial node features. How to design informative node attributes and utilize edge weights for GNNs to learn is left unsolved.

Our Proposed Approach

BrainNN jointly embeds multimodal brain networks with message passing GNNs:



Multimodal Fusion

- Treat the brain networks under different modalities as multiple views of the brain and resort to contrastive learning for jointly embedding structural and functional brain networks.
- Contrastive learning distinguishes node representations of one view with graph representations of the other and vice versa [6, 7].

Message Passing GNNs for Brain Networks

Derive statistical node attributes from original data and leverage a message passing GNN to properly embed edge weights into learned node representations.

- Node features: we compute local degree profiles (LDP) [8] for each modality.
- Message passing GNN for handling edge weights:
- Message vectors composed of node features and edge connectivities:

$$\boldsymbol{m}_{ij}^{(l)} = t_\Theta\left(\left[\boldsymbol{h}_i^{(l)}; \boldsymbol{h}_j^{(l)}; w_{ij}\right]\right). \tag{1}$$

- Message aggregation among neighborhoods:

$$\boldsymbol{h}_i^{(l)} = \sigma\left(\sum_{j\in\mathcal{N}_i\cup\{i\}} \boldsymbol{m}_{ij}^{(l-1)}\right). \tag{2}$$

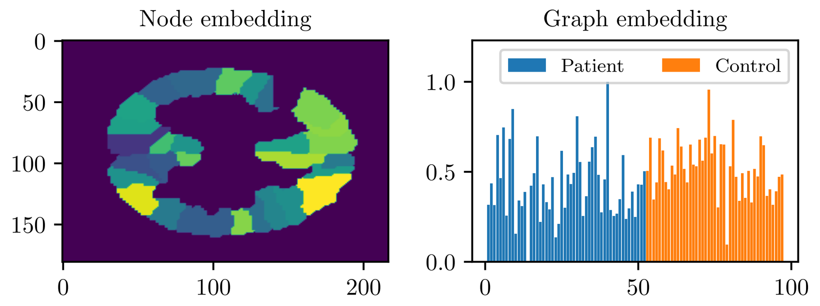
- Readout with residual connections:

$$\boldsymbol{z}' = \sum_{i\in\mathcal{V}} \boldsymbol{h}_i^{(k)}, \qquad \boldsymbol{z} = t_\Phi(\boldsymbol{z}') + \boldsymbol{z}'. \tag{3}$$

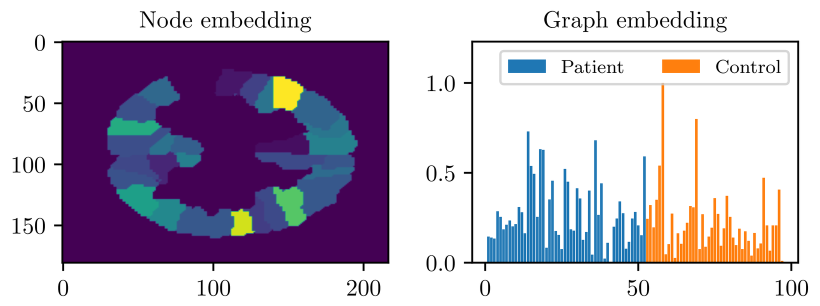
Experiments

Method	HIV		BP	
	Accuracy	AUC	Accuracy	AUC
M2E	50.61	51.53	57.78	53.63
MIC	55.63	56.61	51.21	50.12
MPCA	67.24	66.92	56.92	56.86
MK-SVM	65.71	68.89	60.12	56.78
3D-CNN	74.31	73.53	63.33	61.62
GAT	68.58	67.31	61.31	59.93
GCN	70.16	69.94	64.44	64.24
DiffPool	71.42	71.08	62.22	62.54
MVGCN	74.29	73.75	62.22	62.64
V-GCN	70.00	75.83	67.14	61.17
CONCAT	66.36	72.39	67.27	61.13
BrainNN	**77.14**	**79.79**	**73.64**	**67.54**

Overall performance and ablation studies



(a) fMRI



(b) DTI

Visualization of embedded features

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