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

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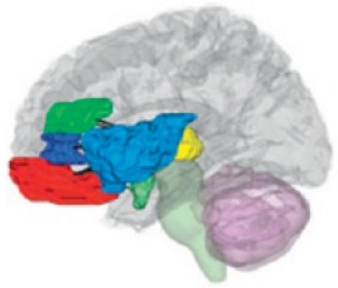
Background

- Brain networks represent complex structures of human brain connectivities.
  - Effective for understanding biological mechanisms of brain functions and helpful for mental health analysis.

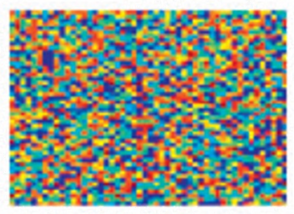


- Joint utilizing multiple modalities of brain networks often leads to consistent improvement.
  - Different modalities of brain networks (e.g., structural and functional) provide complementary information to each other.

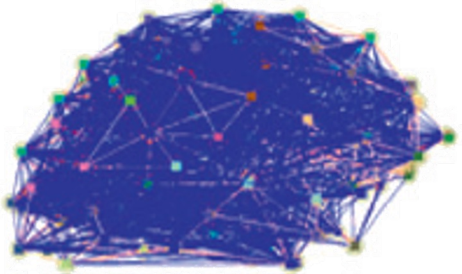
Challenges

- Different modalities encode different biomedical semantics of brain regions ⇒ learn effective embeddings in multiview setting.

- Most brain networks are organized in a form of weighted adjacency matrix describing connections among brain regions without initial node features ⇒ design informative node attributes and leverage edge weights for GNNs to learn.

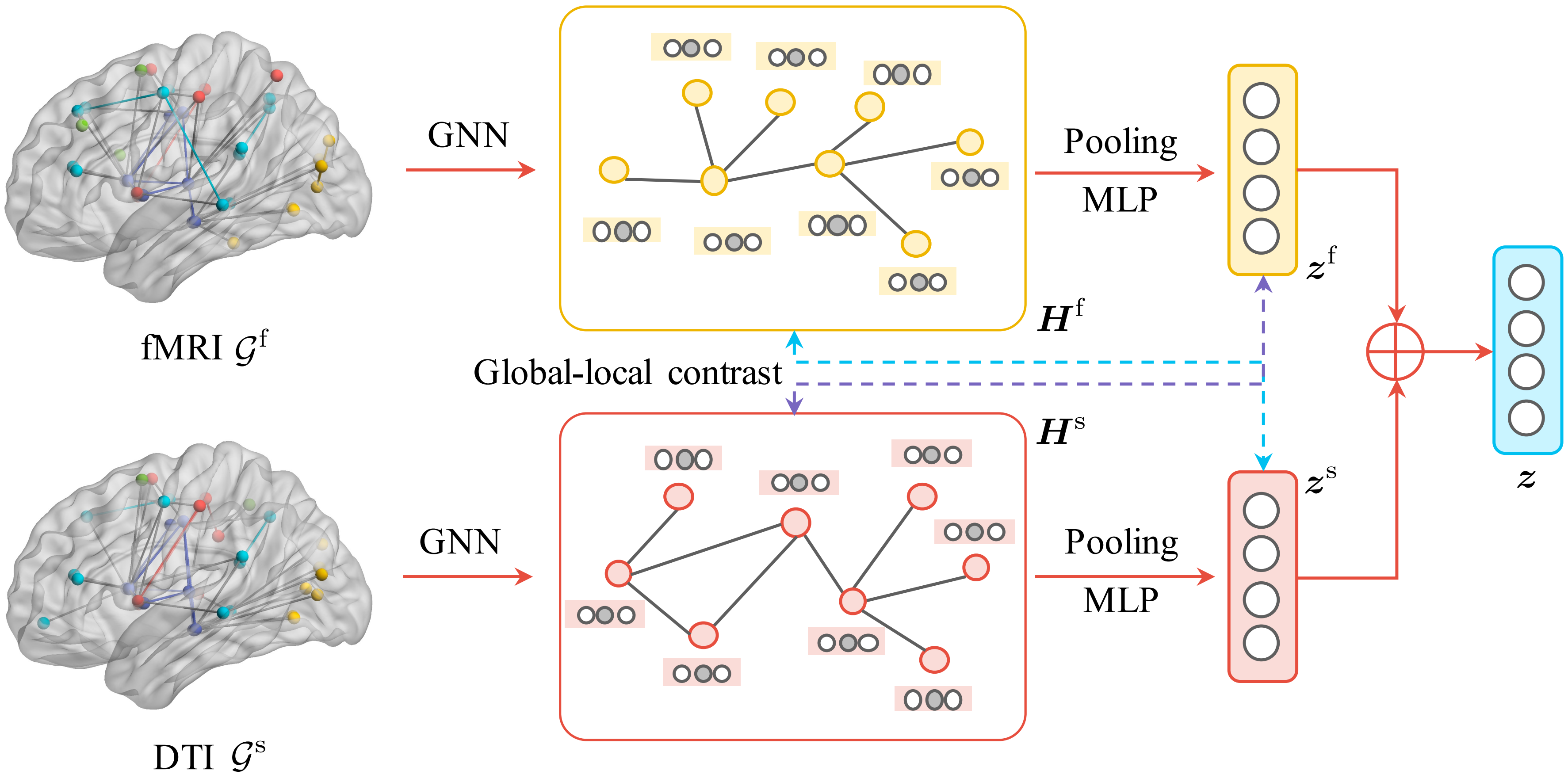


Connectivity matrix



Brain networks

The Proposed Framework



The Proposed Framework

- Multimodal fusion
  - Treat brain networks under different modalities as multiple views.
  - Resort to contrastive learning for adaptively embedding structural and functional brain networks.
- Contrastive learning
  - The contrastive objective distinguishes node representations of one view with graph representations of the other:

$$\mathcal{J}_{\mathrm{con}} = \frac{1}{2S} \sum_{\mathcal{G}_i \in \mathcal{M}} \left[\frac{1}{N} \sum_{v_j \in \mathcal{V}} \left(I(\boldsymbol{h}_j^{\mathrm{f}}; \boldsymbol{z}_i^{\mathrm{s}}) + I(\boldsymbol{h}_j^{\mathrm{s}}; \boldsymbol{z}_i^{\mathrm{f}}) \right) \right].$$

$$I(\boldsymbol{h}_i; \boldsymbol{z}_i) = -\,\mathrm{sp}(-d(\boldsymbol{h}_i, \boldsymbol{z}_i)) - \frac{1}{N-1} \sum_{v_j \in \mathcal{V} \setminus \{v_i\}} \mathrm{sp}(d(\boldsymbol{h}_i, \boldsymbol{z}_j)),$$

The Proposed Framework

- Message-passing-based graph neural networks
  - Derive statistical node attributes from original multimodal data.
  - Leverage a general message passing GNN model to embed edge weights into learned node representations.

The Proposed Framework

- Message-passing-based graph neural networks
  - Node features: Local Degree Profiles (LDP)

$$\boldsymbol{x}_n = \left[\deg(n)\,;\, \min(\mathcal{D}_n)\,;\, \max(\mathcal{D}_n)\,;\, \mathrm{mean}(\mathcal{D}_n)\,;\, \mathrm{std}(\mathcal{D}_n)\right].$$

  - Message vectors composed of node features and edge connectivities:

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

  - Message aggregation among neighborhoods:

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

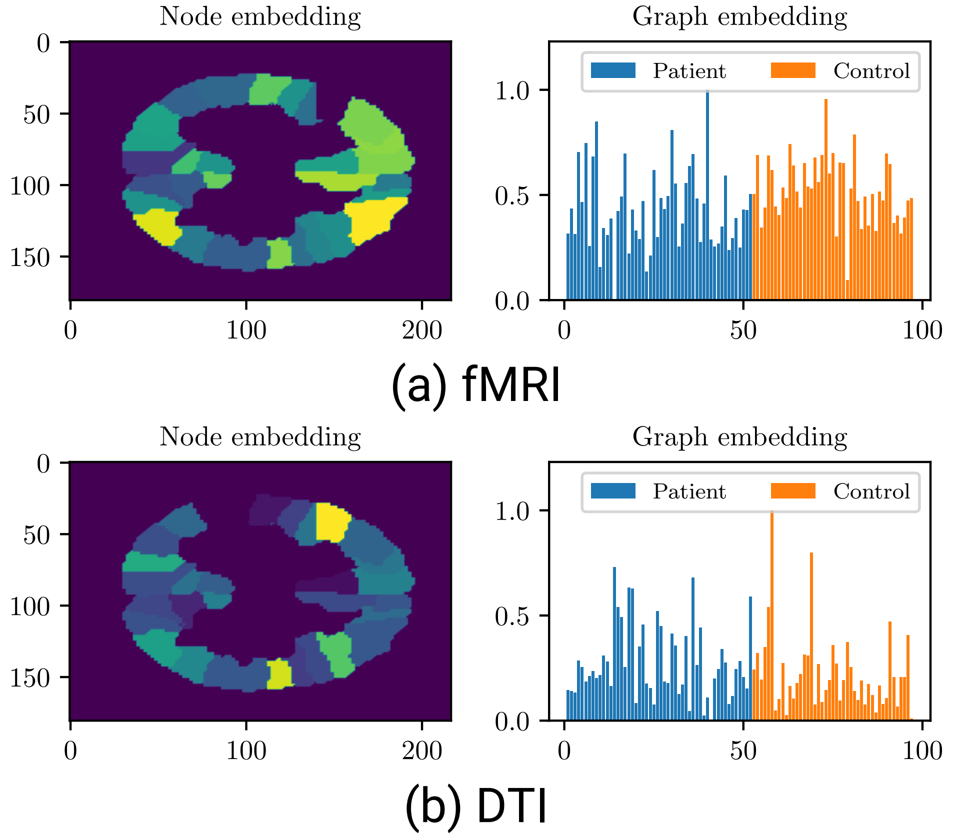
  - Readout with residual connections:

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

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



Visualization of learned embeddings

Concluding Remarks

- We have proposed a novel BrainNN framework that jointly embeds multimodal brain networks with GNNs for mental illness diagnosis.
- Extensive experiments on two real-world datasets demonstrate the effectiveness of our proposed method.
- Transfer learning and pre-training techniques may help alleviate the data scarcity problem in health care domain in the future.


THANKS