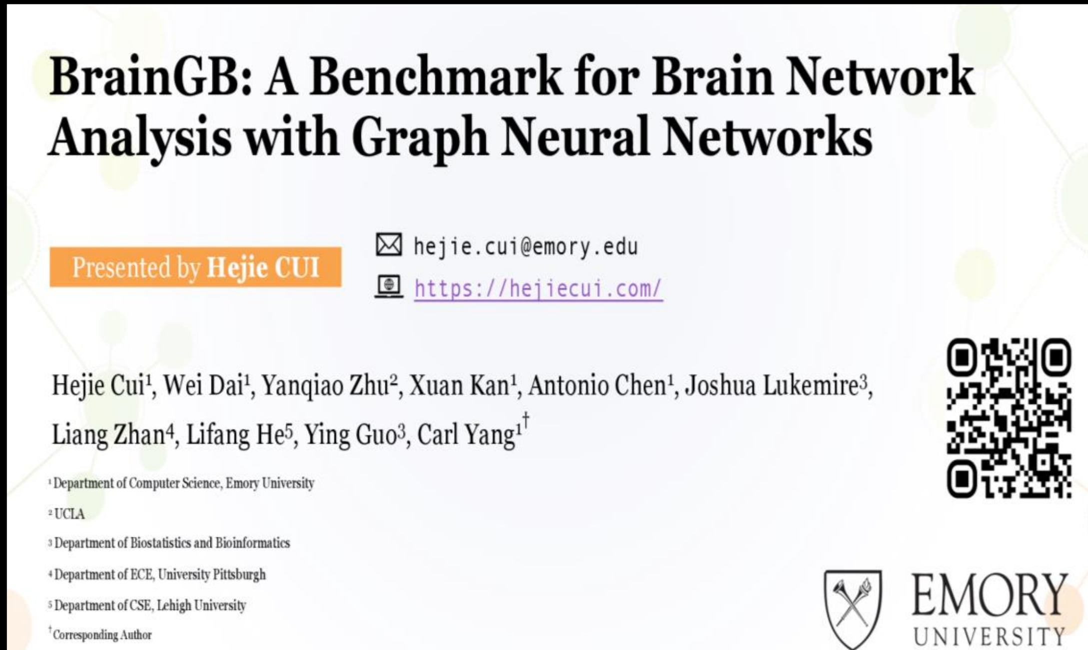

BrainGB: A Benchmark for Brain Network Analysis with Graph Neural Networks

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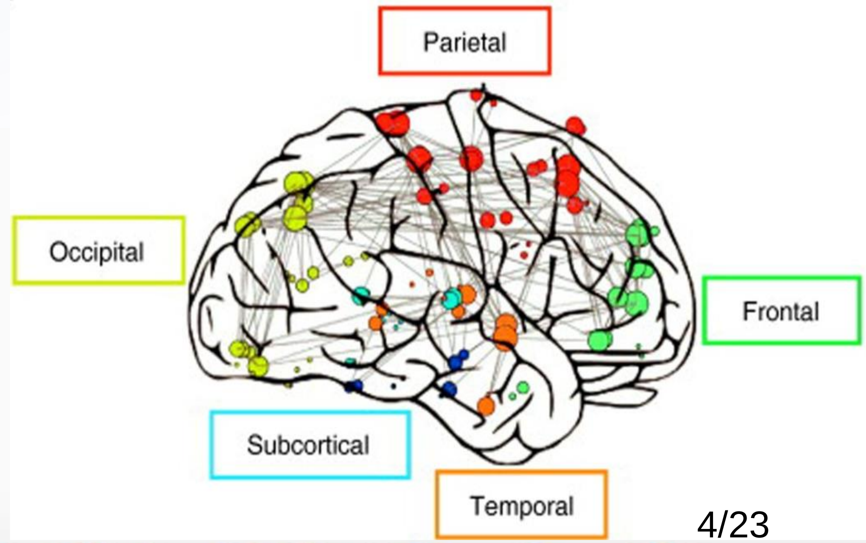
مقدمات

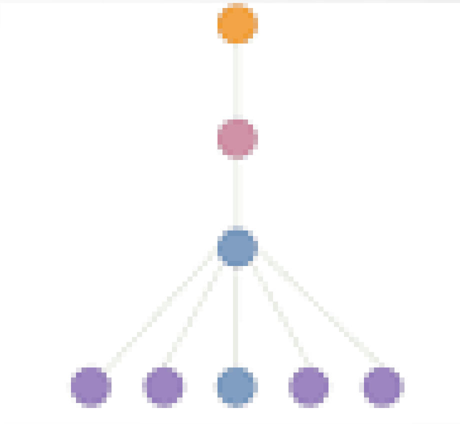
- مغز، مرکز سیستم نوروبیولوژیک
- ساختار بسیار پیچیده‌ی مغز
- کاربرد مطالعات مغزی (مدلسازی شبکه عصبی، تراپی مشکلات روانی، هوش مصنوعی و ...)
- تعامل مدارات عصبی و زیرسیستم‌ها در توسعه‌ی علوم عصبی و همچنین تحلیل بیماری‌ها بسیار موثر است.
- برای نشان دادن تعاملات بین نواحی مختلف مغز می‌توان از نظریه‌ی گراف الهام گرفت.
- ویژگی نا اقلیدسی تصاویر مغز و بدون نظم و قاعده بودن
- Benchmark: مجموعه‌ای از استانداردهاست که می‌تواند معیاری برای اندازه‌گیری و سنجش عملکرد باشد.
- Pipeline: در واقع BrainGB ساختار مغز را با استفاده از pipelineها به صورت خلاصه مدلسازی می‌کند.

مفاهیم کلی گراف

- Input: a brain network dataset of N subjects $D = \{G_n, y_n\}_{n=1}^{N}$
  - $G_n = \{V_n, E_n\}$: brain network of subject n
  - y_n: prediction label (e.g., neural diseases)
- Properties:
  - In D, $\forall n, V_n = V = \{v_i\}_{i=1}^{M}$
  - $W_n \in \mathbb{R}^{M \times M}$ describes the connection strengths between ROIs: real-valued and noisy
- Output: a prediction $\hat{y}_n$ for each subject n
  - can be further analyzed for biomarkers



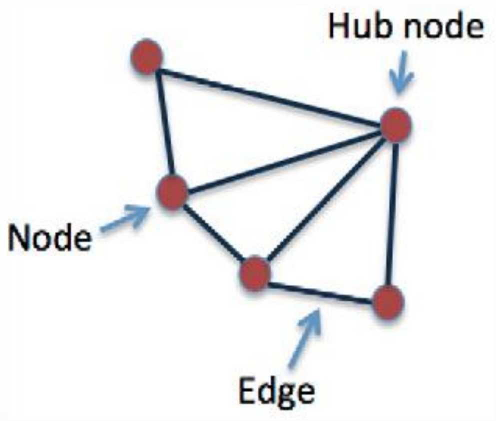
خواص سیستم‌های پیچیده گراف



سلسله مراتب

مرکزیت

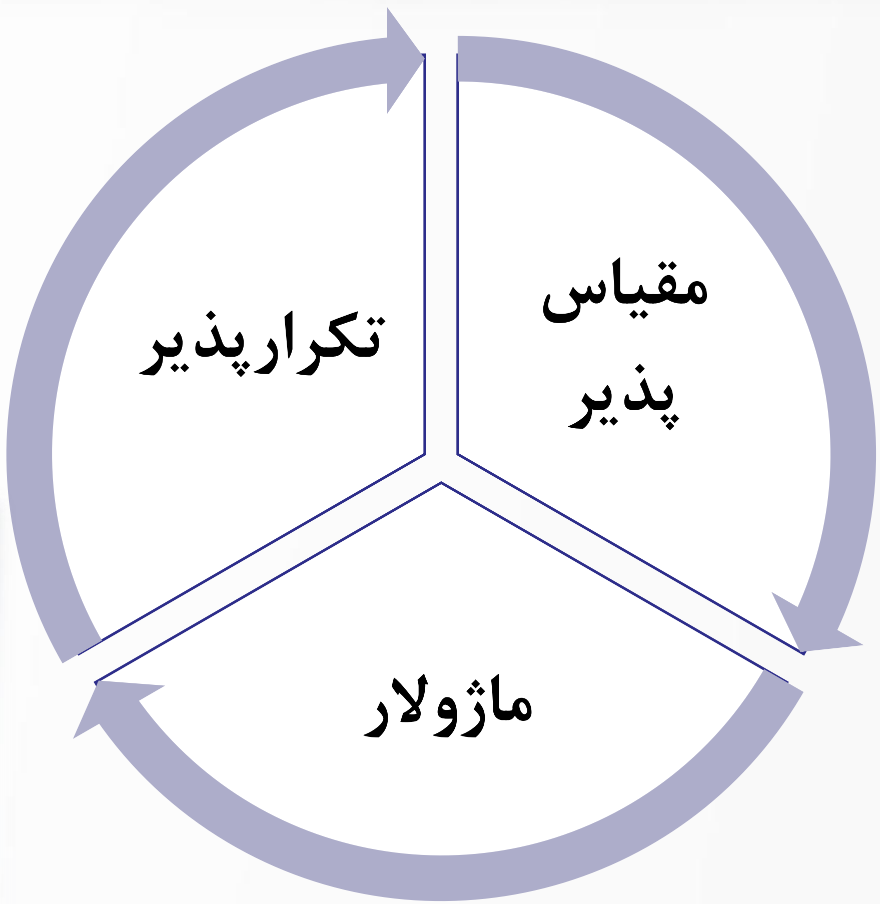
توزیع شبکه hub



مطالعات گذشته

- مدلهای کم عمق گراف
- تجزیه tensor

ویژگی benchmark طراحی شده



ساختار مقاله

Overview

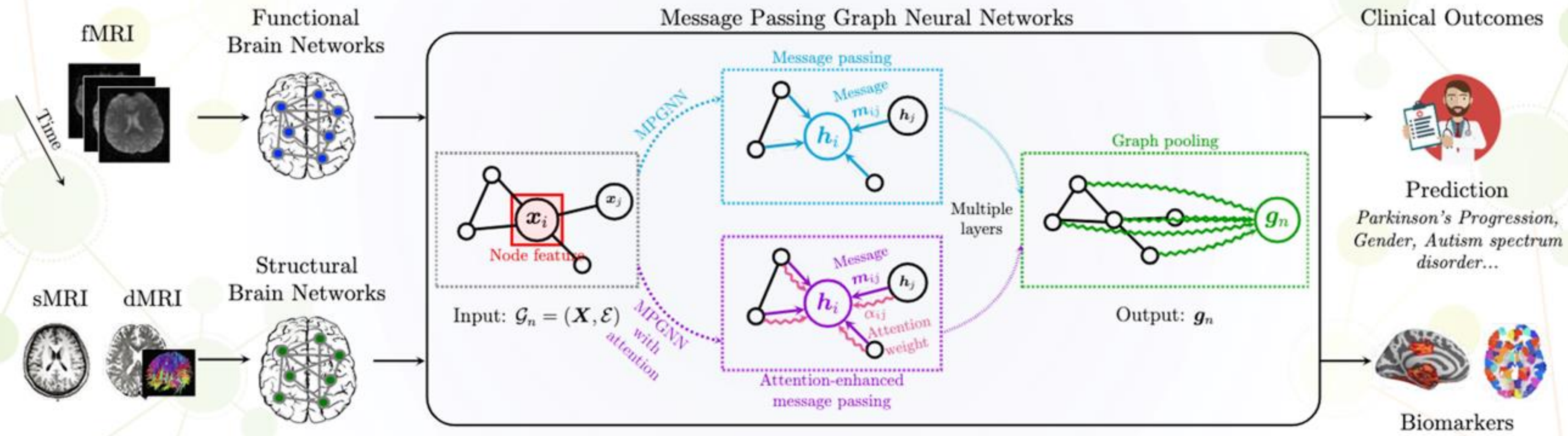


Fig. 1. Overview of BrainGB framework for brain network analysis with graph neural networks.

- Various medical imaging techniques: MRI, EEG, PET, etc.
- Magnetic-Resonance Imaging (MRI) are the most widely used for brain analysis research.
  - Function MRI (fMRI)

    → functional brain networks

    describe correlations between time series signals of brain regions
  - Diffusion Tensor Imaging (DTI)

    → structural brain networks

    describe the physical connectivity between gray matter regions

نمایش تمایز بین بافتها

قدرت تفکیک مکانی بالا

حساسیت بالا در تشخیص

چالشهای مربوط به دیتای MRI

- عدم استفاده از داده‌ی خام
- پیش‌پردازش و حذف نویز
- وجود ابزارهای مختلف جهت پیش پردازش و بالا بودن مدت زمان اجرا
- عدم کارایی ابزارهای موجود برای انجام تمامی پیش پردازش ها در داده‌های **dMRI**
- مراحل مختلف پیش پردازش در **modality** های مختلف

پیش پردازش fMRI

Functional Brain Network Construction

Functional MRI Data Preprocessing	SPM 12	AFNI	FSL	Free Surfer	CONN	fMRI Prep	ANTs	Nilearn
Brain Extraction Remove voxels not necessary for analysis such as bone, dura, air, etc., leaving just the brain	✓	✓	✓	✓		✓	✓	✓
Slice-Timing Correction Adjust for the fact that each slice in the volume is taken at a different time, not all at once	✓	✓	✓	✓	✓	✓		
Motion Correction/Realignment Correct movement made during scanning by aligning all the functional images with one reference	✓	✓	✓	✓	✓	✓	✓	
Co-registration Align participant's functional images with the anatomical structural images for localization	✓	✓	✓	✓	✓	✓	✓	
Normalization Wrap the data across subjects to a template/atlas standardized space	✓	✓	✓	✓	✓	✓		
Smoothing Perform weighted averages of individual voxels with neighboring voxels	✓	✓	✓	✓	✓		✓	✓

Functional Brain Network Construction

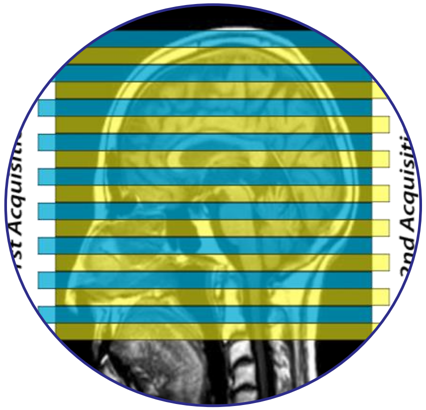
Brain Region Parcellation	→	Construct Network
Segment each subject into the ROI defined by the given atlas		Calculate pairwise correlations between ROIs as edges

Recommended Software: **CONN, GraphVar, Brain Connectivity Toolbox**

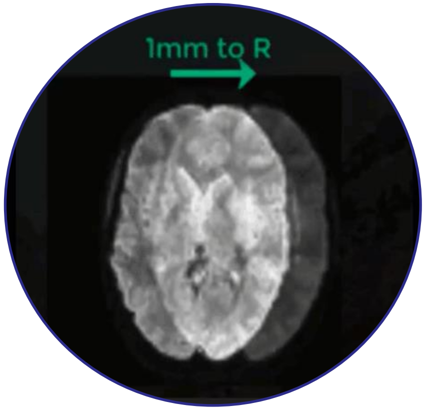
Fig. 2: The framework of fMRI data preprocessing and functional brain network construction procedures, with recommended tools for each step shown on the right. The more commonly-used tools for the functional modality are placed at the front.

پیش پردازش fMRI

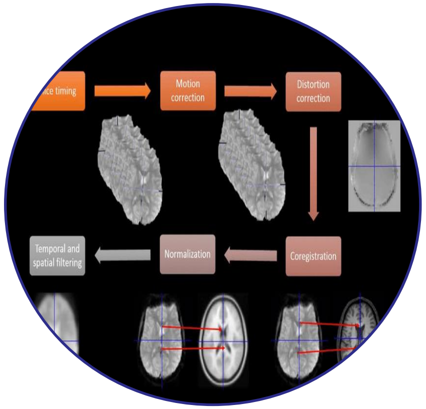
Brain extraction



Slice timing correction



Motion correction



Coregistration and normalization

پیش پردازش dMRI

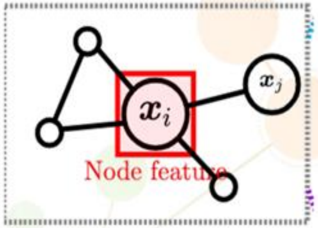
Structural Brain Network Construction

Diffusion MRI Data Preprocessing	FSL	AFNI	Free Surfer	Track Vis	3D Slider	Tortoise	MRtrix3	DSI Studio
Eddy-current and Head Motion Correction Align all raw images to the b0 image to correct for head motion and eddy current distortions	✓	✓	✓		✓	✓	✓	✓
EPI Induced Susceptibility Artifacts Correction Correct the spatially nonlinear distortions caused by B_0 inhomogeneities in Echo-planar imaging	✓	✓	✓		✓	✓	✓	
Brain Extraction Remove voxels not necessary for analysis such as bone, dura, air, etc., leaving just the brain	✓	✓	✓		✓		✓	✓
Reconstruct Local Diffusion Pattern Fit a diffusion tensor model at each voxel on preprocessed and eddy current corrected data	✓	✓	✓	✓	✓	✓	✓	✓
Tractography Reconstruct brain connectivity graphs using brain tractography algorithms like FACT	✓	✓		✓	✓		✓	✓
Brain Region Parcellation Parcellate ROIs from T1-weighted structural MRI	✓	✓				✓	✓	✓

Structural Brain Network Construction	
Construct Network Compute the network based on the generated label and the reconstructed whole brain tractography	Recommended Software: **FSL, Metric, DSI Studio**

Fig. 3: The framework of dMRI data preprocessing and structural brain network construction procedures, with recommended tools for each step shown on the right. The more commonly-used tools for the structural modality are placed at the front.

M1: Node Feature Construction



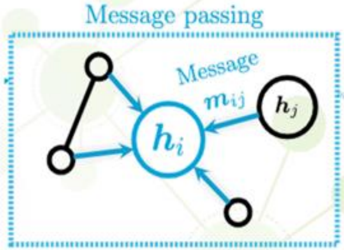
Input: $\mathcal{G}_n = (\boldsymbol{X}, \mathcal{E})$

- **Identity**: unique one-hot feature for each node
- **Eigen**: eigen decomposition performed on the weighted matrix, then the top *k* eigenvectors are used to generate a *k* dimensional feature vector for each node.
- **Degree**: degree value as a one-dimensional vector
- **Degree profile**:

$$\boldsymbol{x}_i = [\deg(v_i) \parallel \min(\mathcal{D}_i) \parallel \max(\mathcal{D}_i) \parallel \mathrm{mean}(\mathcal{D}_i) \parallel \mathrm{std}(\mathcal{D}_i)],$$

- **Connection profile**: the corresponding row for each node in the edge weight matrix

M2: Message Passing Mechanisms



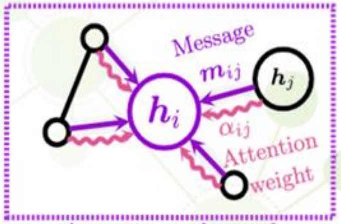
Message passing

$$\boldsymbol{m}_i^l = \sum_{j \in \mathcal{N}_i} \boldsymbol{m}_{ij} = \sum_{j \in \mathcal{N}_i} M_l\left(\boldsymbol{h}_i^l, \boldsymbol{h}_j^l, w_{ij}\right),$$

$$\boldsymbol{h}_i^{l+1} = U_l\left(\boldsymbol{h}_i^l, \boldsymbol{m}_i^l\right),$$

- **Edge weighted**: $$\boldsymbol{m}_{ij} = \boldsymbol{h}_j \cdot w_{ij}.$$
- **Bin concat**: $$\boldsymbol{m}_{ij} = \mathrm{MLP}(\boldsymbol{h}_j \parallel \boldsymbol{b}_t).$$
- **Edge weight concat**: $$\boldsymbol{w}_{ij} = \Vert_1^d\, w_{ij} = w_{ij} \parallel w_{ij} \parallel \ldots \parallel w_{ij},$$ $$\boldsymbol{m}_{ij} = \mathrm{MLP}(\boldsymbol{h}_j \parallel \boldsymbol{w}_{ij}).$$
- **Node edge concat**: $$\boldsymbol{m}_{ij} = \mathrm{MLP}(\boldsymbol{h}_i \parallel \boldsymbol{h}_j \parallel w_{ij}).$$
- **Node concat**: $$\boldsymbol{m}_{ij} = \mathrm{MLP}(\boldsymbol{h}_i \parallel \boldsymbol{h}_j).$$

M3: Attention-enhanced Message Passing

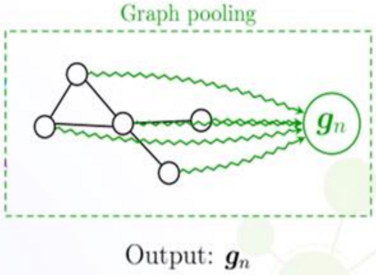


Attention-enhanced message passing

- **Attention weighted**: $\boldsymbol{m}_{ij} = \boldsymbol{h}_j \cdot \alpha_{ij}.$

$$\alpha_{ij} = \frac{\exp\left(\sigma\left(\boldsymbol{a}^\top \left[\boldsymbol{\Theta}\boldsymbol{x}_i \parallel \boldsymbol{\Theta}\boldsymbol{x}_j\right]\right)\right)}{\sum_{k\in\mathcal{N}(i)\cup\{i\}} \exp\left(\sigma\left(\boldsymbol{a}^\top \left[\boldsymbol{\Theta}\boldsymbol{x}_i \parallel \boldsymbol{\Theta}\boldsymbol{x}_k\right]\right)\right)},$$

- **Edge weighted w/ attn**: $\boldsymbol{m}_{ij} = \boldsymbol{h}_j \cdot \alpha_{ij} \cdot w_{ij}.$
- **Attention edge sum**: $\boldsymbol{m}_{ij} = \boldsymbol{h}_j \cdot (\alpha_{ij} + w_{ij}).$
- **Node edge concat w/attn**: $\boldsymbol{m}_{ij} = \mathrm{MLP}(\boldsymbol{h}_i \parallel (\boldsymbol{h}_j \cdot \alpha_{ij}) \parallel w_{ij}).$
- **Node concat w/attn**: $\boldsymbol{m}_{ij} = \mathrm{MLP}(\boldsymbol{h}_i \parallel (\boldsymbol{h}_j \cdot \alpha_{ij})).$



M4: Pooling Strategies

In the second stage of GNNs, a feature vector for the whole graph is computed using the pooling strategy *R*,

$$\boldsymbol{g}_n = R\left(\{\boldsymbol{h}_i \mid v_i \in \mathcal{G}_n\}\right).$$

- Mean pooling:

$$\boldsymbol{g}_n = \frac{1}{M}\sum_{k=1}^{N_n} \boldsymbol{h}_k.$$

- Sum pooling:

$$\boldsymbol{g}_n = \sum_{k=1}^{M} \boldsymbol{h}_k.$$

- Concat pooling:

$$\boldsymbol{g}_n = \|_{k=1}^{M}\, \boldsymbol{h}_i = \boldsymbol{h}_1 \parallel \boldsymbol{h}_2 \parallel \ \ldots \ \parallel \boldsymbol{h}_k.$$

نتایج

Modular Performance Report

Tab.2. Performance report (%) of different message passing GNNs in the four-modular design space with other two representative baselines on four datasets.

Module	Method	HIV			PNC			PPMI			ABCD		
		Accuracy	F1	AUC	Accuracy	F1	AUC	Accuracy	F1	AUC	Accuracy	F1	AUC
Node Features	*Identity*	50.00±0.00	33.33±0.00	46.73±10.57	57.34±0.17	36.44±0.17	52.58±4.80	79.25±0.24	44.21±0.08	59.65±6.80	49.97±0.13	33.32±0.06	50.00±0.20
	Eigen	65.71±2.86	65.45±2.69	65.31±2.89	51.40±3.92	48.63±5.42	50.18±7.57	74.09±2.77	47.36±4.26	49.21±1.58	50.79±0.82	50.79±0.83	51.18±1.16
	Degree	44.29±5.35	35.50±6.10	42.04±4.00	63.89±2.27	59.69±3.85	70.25±4.38	79.52±2.31	49.40±5.17	59.73±4.31	63.46±1.29	63.45±1.28	68.16±1.41
	Degree profile	50.00±0.00	33.33±0.00	50.00±0.00	51.40±7.21	33.80±3.21	50.00±0.00	77.02±1.97	49.45±3.51	58.65±2.44	49.92±0.11	33.30±0.05	50.00±0.00
	Connection profile	65.71±13.85	64.11±13.99	**75.10±16.95**	69.83±4.15	66.20±4.74	**76.69±5.04**	77.99±2.78	52.96±4.52	**65.77±4.09**	82.42±1.93	82.30±2.08	**91.33±0.77**
Message Passing	*Edge weighted*	50.00±0.00	33.33±0.00	49.80±4.20	64.87±5.44	59.70±7.04	69.98±4.19	79.25±0.24	44.21±0.08	62.26±2.80	74.47±1.17	74.36±1.23	82.37±1.46
	Bin concat	50.00±0.00	33.33±0.00	49.39±9.25	54.74±5.88	36.42±3.97	61.68±3.91	79.25±0.24	44.21±0.08	52.67±7.16	53.72±4.97	43.26±12.43	61.86±5.79
	Edge weight concat	51.43±2.86	44.36±6.88	48.16±10.13	63.68±3.31	60.27±5.97	67.34±3.02	79.25±0.24	44.21±0.08	59.72±4.65	64.59±1.30	64.30±1.43	70.63±1.02
	Node edge concat	65.71±13.85	64.11±13.99	75.10±16.95	69.83±4.15	66.20±4.74	76.69±5.04	77.99±2.78	52.96±4.52	65.77±4.09	82.42±1.93	82.30±2.08	91.33±0.77
	Node concat	70.00±15.91	68.83±17.57	**77.96±8.20**	70.63±2.35	67.12±1.81	**78.32±1.42**	78.41±1.62	54.46±3.08	**68.34±1.89**	80.50±2.27	80.10±2.47	**91.36±0.92**
Message Passing w/ Attention	*Attention weighted*	50.00±0.00	33.33±0.00	49.80±8.52	65.09±2.21	60.74±4.89	69.79±4.24	79.25±0.24	44.21±0.08	63.24±3.77	77.74±0.97	77.70±1.01	85.10±1.10
	Edge weighted w/ attn	50.00±0.00	33.33±0.00	42.04±15.63	62.90±1.22	61.14±0.57	69.74±2.37	79.25±0.24	44.21±0.08	54.92±4.80	78.04±1.96	77.81±2.33	86.86±0.63
	Attention edge sum	51.43±7.00	49.13±5.65	54.49±15.67	61.51±2.86	55.36±4.76	69.38±3.50	79.11±0.40	44.17±0.12	60.47±6.26	75.71±1.52	75.59±1.68	83.78±0.82
	Node edge concat w/ attn	72.86±11.43	72.52±11.72	78.37±10.85	67.66±5.07	64.69±5.36	74.52±1.20	77.30±1.52	50.96±4.20	63.93±4.89	83.10±0.47	83.03±0.52	**91.85±0.29**
	Node concat w/ attn	71.43±9.04	70.47±9.26	**82.04±11.21**	68.85±6.42	64.29±10.15	**75.36±5.09**	78.41±1.43	49.98±1.87	**68.14±5.01**	83.19±0.93	83.12±0.96	91.55±0.59
Pooling Strategies	*Mean pooling*	47.14±15.39	41.71±17.36	58.78±18.63	66.86±2.33	61.39±4.88	74.20±3.39	79.25±0.24	44.21±0.08	59.64±5.47	81.13±0.35	81.06±0.34	88.49±1.12
	Sum pooling	57.14±9.04	52.23±12.65	57.96±11.15	60.13±2.87	53.96±7.61	66.11±4.22	79.39±0.52	47.68±3.12	61.29±2.11	77.48±3.75	76.96±4.58	87.90±0.65
	Concat pooling	65.71±13.85	64.11±13.99	**75.10±16.95**	69.83±4.15	66.20±4.74	**76.69±5.04**	77.99±2.78	52.96±4.52	**65.77±4.09**	82.42±1.93	82.30±2.08	**91.33±0.77**
Other Baselines	BrainNetCNN	60.21±17.16	60.12±13.56	70.93±4.01	71.93±4.90	69.94±5.42	78.50±3.28	77.24±2.09	50.24±3.09	58.76±8.95	85.1±0.92	85.7±0.83	93.5±0.34
	BrainGNN	62.98±11.15	60.45±8.96	68.03±9.16	70.62±4.85	68.93±4.01	77.53±3.23	79.17±1.22	44.19±3.11	45.26±3.65	OOM	OOM	OOM

نتایج

- **Node features**: the connection profile captures the whole picture of structural information in the brain network and preserves rich information on pairwise connections used to perform brain parcellation.
- **Message passing**: node concat reinforces self-representation of the central node during each step of message passing.
- **Attention-enhanced message passing**: the attention mechanism utilizes learnable attention weights in addition to the fixed edge weights in the aggregation and update process of GNNs.
- **Pooling strategies**: in concat pooling, the final node representations of all the brain regions are kept in the graph-level representation for classifiers.

محدودیت‌ها

- **Graph structure mysteriousness**: for brain networks, what kinds of graph structures (e.g., communities, subgraphs) are effective beyond the pairwise connections are still unknown.

- **Limited Datasets**: the small size of neuroimaging datasets may limit the effectiveness and generalization ability of complex deep learning models.

پیشنهادات برای آینده

- **Neurology-driven GNN designs**: to design the GNN architectures based on neurological understanding of predictive brain signals, especially disease-specific ones.

- **Pre-training and transfer learning of GNNs**: to design techniques that can train complex GNN models across studies and cohorts. Besides, information sharing across different diseases could lead to a better understanding of cross-disorder commonalities.

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THANK YOU!