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Community-preserving Graph Convolutions for Structural and Functional Joint Embedding of Brain Networks

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***Abstract*—We propose a framework of Siamese community-preserving graph convolutional network (SCP-GCN) to learn the structural and functional joint embedding of brain networks. Specifically, we use graph convolutions to learn the structural and functional joint embedding, where the graph structure is defined with structural connectivity and node features are from the functional connectivity. Moreover, we propose to preserve the community structure of brain networks in the graph convolutions by considering the intra-community and inter-community properties in the learning process. Furthermore, we use Siamese architecture which models the pair-wise similarity learning to guide the learning process. To evaluate the proposed approach, we conduct extensive experiments on two real brain network datasets. The experimental results demonstrate the superior performance of the proposed approach in structural and functional joint embedding for neurological disorder analysis, indicating its promising value for clinical applications.**

***Index Terms*—Graph Neural Networks, Community-preserving Graph Convolutions, Siamese Network, Brain Network Analysis**

I. Introduction

In recent years, advances in neuroimaging technology have given rise to various modalities of brain imaging data, which provide us with multiple perspectives for investigating the inner organization and activity of human brains. For example, functional magnetic resonance imaging (fMRI) can be used to study the functional activation patterns of human brain based on the cerebral blood flow and the BOLD response [1], [2], while techniques like diffusion tensor imaging (DTI) can be used for examining the tractography of the white matter fiber pathways and thus for exploring the structural connectivity in the brain. Meanwhile, brain networks derived from these brain imaging data have been widely studied for neurological disorder analysis[3], [4]. Structural brain networks derived from DTI brain data and functional brain networks derived from fMRI brain data are the primary networks of interest.

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Most existing works in brain network analysis focus on either the analysis of structural connectivity or on functional connectivity [5], [6], [7]. However, both the anatomical characteristics captured by structural connectivity and the physiological properties that form the basis of functional connectivity are important to understand the integrated organization and brain activity, and thus it would be of considerable benefit if both structural and functional networks could be considered jointly [8]. Although some recent works have used multi-view embedding methods to learn representations from both structural and functional networks for neurological disorder analysis [9], [10], [11], the representations derived from each view in these methods are enforced to reach consensus, making distinct intrinsic properties of individual network being ignored. Therefore, it is desirable to find a way to jointly learn from structural and functional brain networks while considering their intrinsic properties.

In this paper, we propose to use graph convolutional network (GCN) for learning the embedding of brain network by jointly using the structural brain network and the functional brain network. Generally, GCN takes two inputs: a representative description of the graph structure in matrix form (e.g. adjacency matrix) and a feature vector for every node in the graph. The convolutions are then performed based on the neighborhood structure indicated by the given graph structure [12], [13]. Although GCN has been shown to be effective for network representation learning [14], there are some challenges that we need to address when using it to learn the structural and functional joint embedding of brain network embedding for neurological disorder analysis, as listed below:

- **Joint embedding of DTI and fMRI**: The structural connectivity in DTI reflects the anatomical pathways of white matter tracts connecting different regions, whereas the functional connectivity in fMRI encodes the correlation between the activity of brain regions. How to apply GCN on the DTI brain network and the fMRI network jointly, so that the resulted embedding could encode the inherent

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properties of both structural connectivity and functional connectivity, is a key problem.

- **Community-structure preserving**: Modular/community structure, as one of the key properties of brain networks, has been shown as an important factor in neurological disorder analysis [8], [15]. It is crucial to preserve the community structure while learning the embedding of brain network. However, existing GCN methods do not consider the community structure. How to make the graph convolutions be able to preserve the community structure for brain network analysis is a challenging problem.
- **Limited sample quantity**: Training a deep learning model requires a large amount of training data, but neurological disorder analysis often suffers from data scarcity problem. How to address this problem is another key issue when using GCN for embedding learning.
- **Neurological Disorder Analysis**: How to leverage the brain network joint embedding learned by the community-preserving graph convolutions to facilitate neurological disorder analysis is also a critical problem.

To address these challenges, we propose a framework of Siamese community-preserving GCNs for learning the structural and functional joint embedding of brain networks. Our contributions can be summarized as follows:

- We propose to use graph convolutions for learning the joint embedding of fMRI functional brain network and DTI structural brain network, where DTI network defines the graph structure and fMRI network is used as node features in the convolutions. By considering the structural and functional networks jointly in this way, both the inherent structural information and the functional patterns can be captured and leveraged in the learning process.
- We propose to incorporate the community-preserving property into GCNs to preserve the intrinsic modular/community structure of human brain networks while learning their structural and functional joint embedding. Specifically, we propose a community-preserving loss to facilitate the community-preserving graph convolutions. Both the intra-community property and inter-community property are considered when formulating the community-preserving loss.
- We use the Siamese architecture [16] and exploit pairwise similarity learning of brain networks to guide the learning process, which could help alleviate the data scarcity problem.
- We apply the proposed framework on two real brain network datasets (i.e., Bipolar and HIV [10]) to learn the structural and functional joint embedding for the detection of these two disorders. The experimental results demonstrate the superior performance of the proposed approach in structural and functional joint analysis for clinical investigation and application.

II. Preliminaries

Notations. Vectors are denoted by boldface lowercase letters, and matrices are denoted by boldface capital letters. An element of a vector $\mathbf{x}$ is denoted by x_i, and an element of a matrix $\mathbf{X}$ is denoted by $\mathbf{X}_{ij}$. For any vector $\mathbf{x} \in \mathbb{R}^n$, $Diag(\mathbf{x}) \in \mathbb{R}^{n\times n}$ is the diagonal matrix whose diagonal elements are x_i. $\mathbf{I}_n$ denotes an identity matrix with size n. We denote an undirected graph as $G = (V, E, \mathbf{A})$, where V is the set of nodes, $E \subset V \times V$ is the set of edges, and $\mathbf{A} \in \mathbb{R}^{n\times n}$ is the weighted adjacency matrix, where the entry $\mathbf{A}_{ij}$ denotes the pairwise affinity between node i and node j of graph G.

Before formally defining our problem, we first introduce the concept of "brain network" and "module" in brain networks. A brain network is a weighted undirected graph $G = (V, E, \mathbf{A})$, where each node v_i in V denotes a specific brain region of interest (ROI) and the edge connecting v_i and v_j represents the connection between region v_i and region v_j, whereas the element $\mathbf{A}_{ij}$ in $\mathbf{A}$ denotes the weight of their connection. In functional brain network derived from fMRI, the edges indicate the functional correlations between two brain regions, while in structural brain network derived from DTI, the edges indicate the neural fiber connections between different regions. A module (or community) in brain networks is a subset of nodes that are densely connected to each other while having sparse connections to the nodes in other modules [8].

Problem Definition. Assume we are given a set of brain network instances $D = \{G_1, G_2, \cdots, G_N\}$, and each instance G_i incorporates a structural brain network $G_i^{(s)} = (V^{(s)}, E^{(s)}, \mathbf{A}^{(s)})$, and a functional brain network $G_i^{(f)} = (V^{(f)}, E^{(f)}, \mathbf{A}^{(f)})$, where $V^{(s)}$ and $V^{(f)}$ contain the same number of nodes representing the same set of brain regions, $|V^{(s)}| = |V^{(f)}| = n$, $E^{(s)}$ is the set of edges in $G_i^{(s)}$ and $E^{(f)}$ is the set of edges in $G_i^{(f)}$, $\mathbf{A}^{(s)} \in \mathbb{R}^{n\times n}$ is the adjacency matrix of $G_i^{(s)}$, and $\mathbf{A}^{(f)} \in \mathbb{R}^{n\times n}$ is the weighted adjacency matrix of $G_i^{(f)}$, where each element represents the functional correlation between two brain regions. We aim to obtain a network embedding $\mathbf{Z} \in \mathbb{R}^{n\times d}$ for each G_i by jointly learning from $G_i^{(s)}$ and $G_i^{(f)}$, where d represents the dimension of each node embedding. The joint embedding should not only capture both the inherent structural information and functional characteristics of the brain network, but should also preserve the underlying community/modular structure of the brain network.

III. Framework

In this paper, we propose a Siamese community-preserving graph convolutional network (SCP-GCN) framework for structural and functional joint embedding of brain networks. An overview of the framework is shown in Fig. 1.

A. Graph Convolutions for Structural and Functional Joint Embedding

We propose to use graph convolutions to learn the structural and functional joint embedding of brain networks. In the graph convolutions, the graph structure is defined by the structural connectivity and the node features come from functional connectivity. By considering the structural and functional

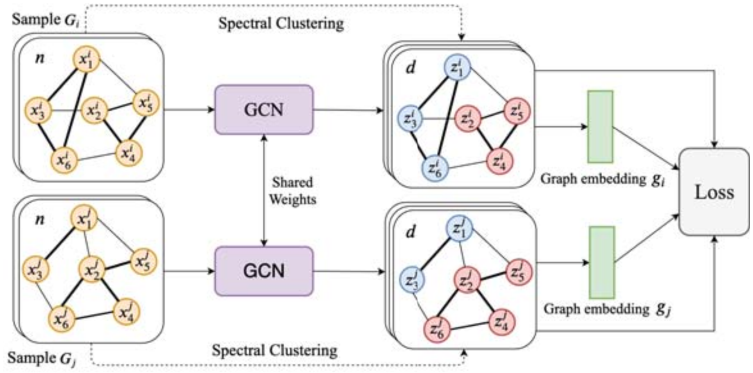

Fig. 1. An overview of the proposed SCP-GCN framework. Each of the two input samples is a graph whose nodes represent brain regions and the connections (*i.e.,* edges) between these brain regions are defined by the DTI brain network. An n-dimensional feature vector $\mathbf{x}_w^i$ is assigned on each node w of sample G_i, which is the adjacent vector of the corresponding node in the fMRI functional network. The Siamese GCN takes a pair of samples $< G_i, G_j >$ as input, and learns a d-dimensional node embedding $\mathbf{z}_w^i$ for each node of G_i and $\mathbf{z}_w^j$ for each node of G_j, which are then concatenated into a graph embedding $\mathbf{g}_i$ and $\mathbf{g}_j$, respectively. Spectral clustering is employed on the DTI brain network to get the communities of nodes (shown by different node colors in the figure). The graph embeddings, node embeddings, and community information are used to compute the loss function elaborated in section III.

networks jointly in this way, both the inherent structural information and the functional patterns can be captured during the learning process.

Given a brain network instance G from D, with structural brain network $G^{(s)} = (V^{(s)}, E^{(s)}, \mathbf{A}^{(s)})$ and a functional brain network $G^{(f)} = (V^{(f)}, E^{(f)}, \mathbf{A}^{(f)})$, we set $\mathbf{A} = \mathbf{A}^{(s)}$ as the adjacency matrix for the graph. Then the normalized graph Laplacian can be defined as $\mathbf{L} = \mathbf{I}_n - \mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}}$, where $\mathbf{I}_n$ is an identity matrix and $\mathbf{D} \in \mathbb{R}^{n\times n}$ is the diagonal degree matrix of the graph with leading entries $\mathbf{D}_{ii} = \sum_j \mathbf{A}_{ij}$.

Consider a n-dimensional signal $\mathbf{x} : V \to \mathbb{R}^n$ defined on graph G, which can be regarded as an one-dimensional feature vector, with $x_i \in \mathbb{R}$ assigned to the i^{th} node. According to [17], the convolution operation in the Fourier domain can be defined as the multiplication of the signal $\mathbf{x}$ with a filter $g_{\boldsymbol{\theta}}$ parameterized by $\boldsymbol{\theta} \in \mathbb{R}^n$:

$$g_{\boldsymbol{\theta}} * \mathbf{x} = \mathbf{U} g_{\boldsymbol{\theta}}(\boldsymbol{\Lambda})\mathbf{U}^T\mathbf{x} \tag{1}$$

where $\mathbf{U} = [u_0, \ldots, u_{n-1}] \in \mathbb{R}^{n\times n}$ is the eigenvector matrix of the normalized graph Laplacian $\mathbf{L}$, *i.e.,* $\mathbf{L} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^T$, where $\boldsymbol{\Lambda} = Diag([\lambda_0, \ldots, \lambda_{n-1}]) \in \mathbb{R}^{n\times n}$ is the diagonal matrix of its eigenvalues, and $g_{\boldsymbol{\theta}}(\boldsymbol{\Lambda}) = Diag([g_{\boldsymbol{\theta}}(\lambda_0), \ldots, g_{\boldsymbol{\theta}}(\lambda_{n-1})])$.

Based on [18] and [19], we can derive it into the following equation [20]:

$$g_\theta * \mathbf{x} \approx (\mathbf{I}_n + \mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}})\mathbf{x} \tag{2}$$

Then we apply the renormalization trick introduced in [19]: $\mathbf{I}_n + \mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}} \to \hat{\mathbf{D}}^{-\frac{1}{2}}\hat{\mathbf{A}}\hat{\mathbf{D}}^{-\frac{1}{2}}$, with $\hat{\mathbf{A}} = \mathbf{A} + \mathbf{I}_n$ and $\hat{\mathbf{D}}_{ii} = \sum_j \hat{\mathbf{A}}_{ij}$, and we generalize the definition to a signal $\mathbf{X} \in \mathbb{R}^{n\times p}$ with p input channels [19]. Specifically, in our structural and functional joint embedding scenario, since the functional brain network is derived from the fMRI signals, which capture the brain activity features of each brain region, we propose to use the functional correlation matrix $\mathbf{A}^{(f)}$ as the input signal matrix, *i.e.,* $\mathbf{X} = \mathbf{A}^{(f)}$ with the number of input channels $p = n$.

In this paper, we consider a multi-layer graph convolutional network with the convolutions defined above and the layer-wise propagation rule proposed in [19]. Assume the activation of the l-th layer is represented as $\mathbf{H}^{(l)} \in \mathbb{R}^{n\times d}$ and the layer-specific trainable weight matrix for the l-th layer is denoted by $\boldsymbol{\Theta}^{(l)}$, according to the propagation rule, we have:

$$\mathbf{H}^{(l+1)} = \sigma(\tilde{\mathbf{D}}^{-\frac{1}{2}}\tilde{\mathbf{A}}\tilde{\mathbf{D}}^{-\frac{1}{2}}\mathbf{H}^{(l)}\boldsymbol{\Theta}^{(l)}) \tag{3}$$

where $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I}_n$ is the weight matrix of the undirected graph with added self-connections, and $\sigma(\cdot)$ denotes the activation function. $\mathbf{H}^{(0)} = \mathbf{A}^{(f)} = \mathbf{X}$ is the input feature matrix.

In the problem setting, we take the node features in functional brain network as the input features of the graph, and set $\mathbf{H}^{(0)} = \mathbf{A}^{(f)} \in \mathbb{R}^{n\times n}$, which is the weighted adjacent matrix of functional brain network. That is to say, for the i^{th} node $V_i^{(s)} \in V^{(s)}$, we assign $\mathbf{a}_i^{(f)} \in \mathbb{R}^n$, the i^{th} row of $\mathbf{A}^{(f)}$, as the feature vector of that node. The output $\mathbf{Z} = \mathbf{H}^{(l)}$ of the last layer will be the final node embedding of the brain network, where the i^{th} row of $\mathbf{Z}$ represent the embedding vector for the i^{th} node. For the further calculation of the distance between graphs for similarity learning in Siamese network, we concatenate all the rows of $\mathbf{Z}$ into a vector $\mathbf{g}$ as the graph embedding for G.

B. Siamese Graph Convolutional Network

Siamese network is first proposed in [21] to solve signature verification as an image matching problem. The Siamese network takes a pair of inputs, and output the similarity between the inputs. [16] introduces this architecture into one-shot learning problem setting in which correct predictions must be given only based on a single training sample of each new class, demonstrating the superior learning ability enabled by Siamese network, even with a small sample size.

In this paper, we use the Siamese architecture and exploit the pair-wise similarity learning of brain networks to guide the learning process, and also to help address the data scarcity problem caused by the limited sample size.

Contrastive loss function [16] is used to train Siamese network:

$$L_S = \frac{y}{2}\|\mathbf{g}_i - \mathbf{g}_j\|_2^2 + (1-y)\frac{1}{2}\{max(0, m - \|\mathbf{g}_i - \mathbf{g}_j\|_2)\}^2 \quad (4)$$

where $\mathbf{g}_i$ and $\mathbf{g}_j$ are the graph embeddings of instance i and j computed from the GCN, m is a margin value which is greater than 0. $y = 1$ if two input sample are from the same class and $y = 0$ if they are from the different classes. The loss function minimizes the Euclidean distance between two input vectors when two samples are from the same class, and maximizes it when they belong to different classes.

C. Siamese Community-preserving GCN Framework

In order to preserve the community structure in brain networks, we propose to incorporate the community-preserving property into the Siamese GCN model. We integrate the community-preserving property and the pair-wise similarity learning strategy into a unified framework and call it Siamese Community-Preserving GCN (SCP-GCN).

The goal of community preserving is that if two nodes are from the same community in the original graph, the Euclidean distance between the learned node embeddings should be small, otherwise they should have a large distance in their node embedding space. As shown in Fig. 1, we employ spectral clustering [22] to detect the communities from the original structural network. Spectral clustering, which detect communities of nodes in a graph based on the eigenvalues (spectrum) of Laplacian matrix built from the graph, has been shown to be an effective way to obtain the community/modular structure in brain networks [23], [24]. Therefore, we employ the spectral clustering algorithm [25] on $G^{(s)}$ to capture the community structure of the structural brain network in the original space, and we aim to preserve this community structure in the learning process of Siamese GCN.

Each community c detected in the network $G^{(s)}$ is represented as a set S_c, which contains the indexes of nodes belonging to community c. We compute a community center embedding $\hat{\mathbf{z}}_c = \frac{1}{|S_c|}\sum_{i \in S_c} \mathbf{z}_i$ for each community c, where $\mathbf{z}_i$ is the embedding of the i^{th} node, i.e., the i^{th} row in the graph embedding $\mathbf{Z}$.

The community-preserving objective consists of two components: 1) minimizing the intra-community loss, i.e. the distance between community center $\hat{\mathbf{z}}_c$ and node embeddings belonging to community, and 2) maximizing the inter-community loss, i.e., the distance between the centers of different communities. By combining these two parts, we have the following function as community-preserving loss:

$$L_{CP} = \alpha(\sum_c \frac{1}{|S_c|}\sum_{i \in S_c} \|\mathbf{z}_i - \hat{\mathbf{z}}_c\|_2^2) - \beta \sum_{c,c'} \|\hat{\mathbf{z}}_c - \hat{\mathbf{z}}_{c'}\|_2^2 \quad (5)$$

where the first part computes the Euclidean distance between node embedding $\mathbf{z}_i$ and its community center $\hat{\mathbf{z}}_c$. The second part computes the distance between community center $\hat{\mathbf{z}}_c$ and $\hat{\mathbf{z}}_{c'}$. α and β are weights of intra/inter-community loss.

Now we have the overall loss function for our SCP-GCN framework, which can be written as

$$L = \sum_{i,j} L_S + \sum_i^N L_{CP} \quad (6)$$

By combining the contrastive loss with community-preserving loss in this way, we can leverage the community structure in the learning process of GCN in Siamese network. The community structure in the original brain network could be preserved in the embedding space when we minimize the loss in Equation (6). After the training process, we can use either branch of the twin GCN networks in SCP-GCN for computing a structural and functional joint graph embedding for a given brain network, and the output graph embedding will not only contain group-contrasting features but also preserve the community structure of the structural brain network, both of which are important for further neurological disorder analysis.

IV. Experiments

In order to evaluate the proposed framework for structural and functional joint embedding of brain networks, we compare our approach with the state-of-the-art methods in this field on two real-world brain datasets for neurological analysis.

A. Datasets and Preprocessing

- *Human Immunodeficiency Virus Infection (HIV)*: This dataset is collected from the Chicago Early HIV Infection Study at Northwestern University[26]. This clinical study involves 77 subjects (56 early HIV patients and 21 seronegative controls). This dataset contains both the fMRI and DTI images for each subject, from which we can construct the fMRI and DTI brain networks.
- *Bipolar*: This dataset consists of the fMRI and DTI image data of 52 bipolar I subjects who are in euthymia and 45 healthy controls with matched age and gender [27].

The detailed description of the datasets and preprocessing can be found in [20].

B. Baselines and Metrics

- **DeepWalk**[28] is a method for learning node embedding in graphs. It uses local information obtained from random walks on graphs to learn latent node representations. In our experiments, we run DeepWalk on DTI and fMRI networks separately to get the node embedding of each network. Graph embedding is obtained by concatenating the node embeddings of the two networks.
- **node2vec** [29] learns node embedding by extending DeepWalk with more complicated random walk or search method. In our experiment, we follow the same experiment setup as DeepWalk.
- **SDBN** [7] is a CNN based deep learning method. Since this method can only deal with single-view brain network, we apply it on fMRI brain network and DTI brain network respectively and report the best performance from the two cases.
- **MVGE-HD** [9] is a multi-view graph embedding method for jointly learning multi-view embedding and hubs from brain networks. In the evaluation, we treat fMRI brain

TABLE I
CLASSIFICATION ACCURACY (MEAN ± STD).

Methods	*Bipolar*	*HIV*
DeepWalk	0.520 ± 0.034	0.575 ± 0.041
node2vec	0.555 ± 0.031	0.625 ± 0.029
SDBN	0.648 ± 0.010	0.665 ± 0.010
MVGE-HD	0.656 ± 0.012	0.681 ± 0.015
GCN	0.547 ± 0.038	0.618 ± 0.049
CP-GCN	0.562 ± 0.039	0.648 ± 0.061
S-GCN	0.649 ± 0.033	0.701 ± 0.090
SCP-GCN	**0.677 ± 0.033**	**0.768 ± 0.110**

TABLE II
CLASSIFICATION F1 SCORE (MEAN ± STD).

Methods	*Bipolar*	*HIV*
DeepWalk	0.589 ± 0.024	0.634 ± 0.021
node2vec	0.614 ± 0.029	0.640 ± 0.015
SDBN	0.637 ± 0.010	0.667 ± 0.010
MVGE-HD	0.661 ± 0.010	0.705 ± 0.011
GCN	0.612 ± 0.029	0.713 ± 0.039
CP-GCN	0.617 ± 0.036	0.766 ± 0.055
S-GCN	0.744 ± 0.029	0.787 ± 0.010
SCP-GCN	**0.750 ± 0.033**	**0.840 ± 0.010**

network and DTI brain networks as two views and apply the MVGE-HD to get the embedding of all the instances.

- **GCN** is the graph convolutional network approach presented in [19]. We apply it on the fMRI and DTI brain networks by using DTI structural connectivity as graph structure and using fMRI functional connectivity as node features during the graph convolutions to learn the structural and functional joint embedding.
- **CP-GCN** is the graph convolutional network approach with the community-preserving property, i.e., the proposed SCP-GCN without Siamese architecture.
- **S-GCN** is the Siamese graph convolutional network introduced in III-B, i.e., the proposed SCP-GCN without community-preserving property.
- **SCP-GCN** is the full framework proposed in this paper.

To evaluate the quality of the learned brain network embedding for neurological disorder analysis, we feed the learned brain network representation to a sigmoid classifier for neurological disorder detection. We use accuracy and F1 score as the evaluation metrics. For all the GCNs in the compared methods, we use 2 convolutional layers followed with one fully connected layer, with 256 features for the first convolutional layer and 128 features for the second convolutional layer. We use binary cross entropy loss [30] for the baseline GCN method, and we use the ADAM optimizer [31] as the optimization algorithm. We run each experiment for 100 times and report the average performance in Table I and Table II. More details about the experimental setup can be found in [20].

C. Evaluation Results

As we can see from Table I and Table II, the embedding obtained by the proposed SCP-GCN results in the best performance on both datasets in terms of classification accuracy and F1 score. Among the eight methods, we observe that DeepWalk and node2vec achieve lower accuracy and F1 score compared to the other six methods which are all deep learning models. This indicates that the deep neural networks could better capture the complicated graph features from brain networks for the classification task compared to these two traditional network embedding methods. In addition, SDBN, MVGE-HD, CP-GCN and SCP-GCN are the ones that consider community structure of brain networks during the representation learning. By comparing CP-GCN with GCN and SCP-GCN with S-GCN, we find that adding the community-preserving property helps improve the learning performance of GCN and S-GCN, indicating the importance of community structure in brain network analysis. By comparing S-GCN with GCN and SCP-GCN with CP-GCN, we can see that the pair-wise similarity learning enabled by Siamese network leads to a better learning performance, which shows the pair-wise similarity learning component can guide the representation learning towards a better network embedding for group-contrasting analysis. It can also help reduce the possible over-fitting problem due to the small sample size of brain network data. Based on these observations, we find that the community structure preserving, structural and functional information integration as well as the Siamese similarity learning are three key factors that facilitate the learning ability of the proposed SCP-GCN approach, resulting in a superior performance of SCP-GCN in neurological disorder detection. More evaluation details, case studies and parameter analysis are provided in [20].

V. RELATED WORKS

Brain network analysis has been an emerging research area, as it yields new insights concerning the understanding of brain function and many neurological disorders [32]. Existing works in brain networks mainly focus on discovering brain network from spatio-temporal voxel-level data or mining from brain networks for neurological analysis [33], [23], [34], [10], [7], [35]. For example, in [34], an unsupervised matrix tri-factorization method is developed to simultaneously discover nodes and edges of the underlying brain networks in fMRI data. In [10], the functional network and structural network of each subject are stacked together into a tensor and a tensor factorization based multi-view embedding method is applied to learn a consensus embedding from the two networks for clustering analysis. Recently, [36], [37] introduce GCN based similarity learning for brain network analysis. However, they focus on learning a similarity metric on fMRI brain networks, whereas our goal is to jointly learn graph embedding from both DTI and fMRI networks for neurological disorder detection.

In recent years, Graph convolutional network (GCN) has been widely investigated to facilitate graph mining [13], [19], [38], [39]. In the application of semi-supervised classification for nodes, [19] presents a simple and effective way to learn node embeddings through a re-normalization trick to simplify and speed up computations of previous GCNs. LanczosNet [38] leverages the Lanczos algorithm to construct a low rank approximation of the graph Laplacian, which provides an efficient way to gather multi-scale information for graph convolution. Our community-preserving GCN provides a new perspective for many applications that involves community structure in the learning on graphs.

VI. Conclusions

Heterogeneous sources of brain data provide a valuable opportunity for a more comprehensive understanding of connectivity and function of the human brain. In this paper, we push forward the analysis of human brain by combining structural connectivity network (e.g., DTI) and functional signals (e.g., fMRI) in a uniform framework, in which the task of accurately classifying brain disease is achieved by incorporating the community-preserving property into graph convolutional networks while learning their structural and functional joint embedding. A pair-wise similarity learning strategy is devised into this unified framework called Siamese Community-Preserving GCN (SCP-GCN). The superiority of our framework is demonstrated by empirical results on two real brain network datasets (i.e., Bipolar and HIV) against state-of-the-art approaches.

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