Temporal Graph Representation Learning for Autism spectrum disorder Brain Networks

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2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) | 978-1-6654-0126-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/BIBM52615.2021.9669613

***Abstract*—Modeling spatio-temporal dynamics in functional brain networks is critical for underlying the functional mechanism of autism spectrum disorder (ASD). In our study, we propose an end-to-end framework called temporal graph representation learning for brain networks, which thoroughly captures spatio-temporal features in resting-state functional magnetic resonance imaging (rs-fMRI) data. Specifically, we first transform rs-fMRI time-series into temporal multi-graph using a sliding window technique. A temporal multi-graph clustering is then designed to eliminate the inconsistency of the temporal multi-graph series. Then, a graph structure aware LSTM (GSA-LSTM) is proposed to capture the spatio-temporal embedding for temporal graphs. The proposed GSA-LSTM can not only capture discriminative features for prediction but also impute the incomplete graphs for the temporal multi-graph series. Extensive experiments on autism brain imaging data exchange (ABIDE) dataset shows the effectiveness of our proposed framework. The results demonstrate that the proposed dynamic brain network embedding learning outperforms the state of-the-art brain network classification models. Furthermore, the obtained clustering results are consistent with the previous neuroimaging-derived evidence of biomarkers for autism spectrum disorder (ASD).**

***Index Terms*—Dynamic brain network, Autism spectrum disorder, Diagnosis, Resting-state fMRI, Spatio-temporal modeling**

I. Introduction

Autism is increasingly recognized as a common brain disorder with altered brain networks [1]. Neuroimaging studies have explored functional connectivity (FC) of ASD through resting-state functional MRI (fMRI) studies. Functional magnetic resonance imaging (fMRI) that measures the changes of blood oxygenation level-dependent (BOLD) signal in a noninvasive manner has become the most common tool to explore functional connectivity (FC) of Autism Spectrum Disorder (ASD) through resting-state fMRI(rs-fMRI) studies Compared with structural MRI, fMRI is able to measure the changes in hemodynamics caused by neuron activity at a series of time points for the whole brain. Most of works typically construct a brain network with FC to characterize the relationships between different brain regions during resting states and distinguish brain disorder patients from NC(Normal control), under an implicit assumption that FC of the human brain is stationary throughout the whole fMRI recording period [2]. It is important to extract an appropriate graph representation from the brain network for understanding the functional mechanisms of human brain and facilitating the brain network classification task. Traditional graph-based analyses have focused on the graph theoretical metrics for globally summarizing the functional connectivity for each node. Recent works have applied graph convolutional networks (GCN) [3] on the functional network to extract latent features from the graph [5], [6], [13]. However, the existing GCN methods applied to rs-fMRI often fail to consider both spatial and temporal characteristics of the brain network. They either neglect the functional dependency between different brain regions in a network or discard the information in the temporal dynamics of brain activity.

Dynamic functional connectivity analysis provides valuable information for understanding functional brain activity underlying different cognitive processes [7]–[9]. Compared with static brain network analysis, dynamic analysis is much more challenging since the network structure evolves over time. How to effectively model discriminative spatial-temporal features and preserve the graph structures is still a challenging problem. Another problem is that there always exist heterogeneity in the multi-site data [4], which compromises the coherence of information between different sites. The inconsistent FC distribution contains large number of noisy and irrelevant FC, which causes an overfitting issue of the model learning, whilst the inconsistent signal lengths result in the incomplete dynamic temporal graphs construction. The traditional spatio-temporal graphs learning methods fail to succeed in learning the complicated relationship because they assume the FC distribution is consistent among the subjects and the lengths of dynamic temporal graphs are equal.

To overcome those shortcomings, we formulate functional connectivity networks with spatio-temporal graphs. There exist a co-occurrence relationship between spatial and temporal domains. At first, we incorporate multi-graph clustering into GCN model to enhance the important connections and remove the irrelevant connections with a supervision scheme. The the coarsened brain network construction combined with clustering could generate more robust and biologically meaningful functional connectivity networks. To capture the spatial-temporal features, we propose a new graph structure aware LSTM(GSA-LSTM) architecture combining both GCN and L-STM to model the spatial and temporal correlations effectively in dynamic brain networks. It can deal with complex dynamic associations by capturing the spatio-temporal features in the temporal consistent coarsened brain neworks, and extract a rich spatio-temporal embedding. Moreover, with the co-occurrence relationship, we propose a unified framework that can (i) adaptively generate graph data rather than imputing the original signal through modeling the graph dynamic correlation and (ii) temporal brain network embedding learning with a multi-task learning scheme. Our model jointly learns temporal coarsened graph generation, graph imputation and graph representations for classification in an end-to-end fashion. Extensive experiments on the ABIDE dataset demonstrates that the dynamic functional connectivity analysis of our framework is capable of handling spatio-temporal data for capturing the dynamic functional connectivity and improve prediction performance.

II. METHOD

A. Overview

An illustration of the proposed temporal multi-graph embedding learning for brain network classification is shown in Fig. 1. We will introduce each component in detail.

B. Problem statement

Rs-fMRI time-series data can be seen as a multivariate time series, in which each ROI corresponds to a variable and has a corresponding time-series signal. More formally, Let $\mathcal{D} = \{G_1^{(j)}, G_2^{(j)}, ..., G_T^{(j)}\}_{j=1}^N$ denotes temporal multi-graphs of all subjects, where each sample is indicated as a sequence graphs, T is the number of rs-fMRI time-series segments, and N is the number of subjects. All networks share the same brain region set of vertices V where each vertex corresponds to a specific brain region. The $G_t^{(j)}$ defined at the t-th segment for the j-th subject can be represented by an adjacency matrix $A_t^{(j)} \in \mathbb{R}^{M \times M}$, where M is the number of the brain regions, reflecting the connectivity strength between the paired brain regions. Given the temporal multi-graphs of each subject $G^{(j)} = \{G_1, G_2, ..., G_T\}$ and its corresponding label of $y_j \in \{-1, 1\}$, our study aims at learning a mapping function $f : G^{(j)} \rightarrow y_j$.

C. Construction of Temporal Multi-graph in Brain Network

To better characterize the temporal variability of the functional connection associated with a set of given regions, we employ a sliding window approach to segment fMRI time-series data into T overlapping windows of constant size $\mathcal{L}$. Specifically, we set a window with a const size $\mathcal{L}$, and then roll it on the fMRI time-series data with a constant stride $\mathcal{S}$. We then obtain a sequence of T time-series segments. The strength of the functional connection of the brain network is often measured by the strength of the correlation between the BOLD time-series of each ROI. In this study, we adopt Pearson correlation coefficient (PCC) to calculate the correlation between ROIs. Each vertex v_i represents a brain region, and the corresponding time series is indicated as x_i. PCC between the time series x_i at the vertex v_i and x_j at the vertex v_j is given by

$$r_{ij} = \frac{cov(x_i, x_j)}{\sqrt{cov(x_i, x_i) * cov(x_j, x_j)}} \tag{1}$$

where $cov(x_i, x_j)$ represents the covariance of time series x_i and x_j.

We calculate the correlation between each pair of brain regions for each segment. Then, a series of dynamic graphs are generated.

D. Temporal multi-graph clustering

In the brain network, the dimension of functional connectivity could be relatively large and thus not very discriminant. The noisy connections that are most influenced by experimental noise need to be removed for further analysis. In this study, we develop a functional connectivity reduction strategy based on multi-graph clustering [10] to obtain the subgraphs as supernodes and remove the noisy connections for diagnosing of a disorder. Our objective is well-motivated by reducing the noisy correlation edges through a multi-graph clustering, a better brain network can be learned.

Multi-graph clustering aims to improve clustering accuracy by leveraging information from different domains, which has been shown to be extremely effective for achieving better clustering results than single graph based clustering algorithms. The unsupervised graph clustering is to approximate the given graph through a low-rank matrix factorization $\mathcal{A} \approx \mathcal{F}^T \mathcal{A}^s \mathcal{F}$, where $\mathcal{F}$ is an $M \times C$ indicator matrix, $\mathcal{A}^s$ is a $C \times C$ symmetric matrix and C ($C = 10$ in our work) indicates the number of the subgraphs (supernodes). Each item $\mathcal{F}_{ip}$ can be interpreted as the membership of the i-th brain region to the supernode S_p. Given multiple graphs, the underlying clustering $\mathcal{F}$ are shared among graphs. With multi-graph clustering, we can obtain a set of subgraphs as supernodes $S_1, S_2, ..., S_C$ and the weighted adjacency matrix of the supergraph: $\mathcal{A}^s = \mathcal{F}\mathcal{A}\mathcal{F}^T$. With the supernodes $S_1, S_2, ..., S_C$ and the weighted adjacency matrix $\mathcal{A}^s$, a coarsened graph is constructed.

Different from traditional clustering which groups the similar nodes together, the aim of multi-graph clustering is to hide the noisy connectivity by grouping them into a supernode, thus highlighting the indicative edges connecting the supernodes. In other words, the weight of functional connection connecting the node crossing different supernodes is enhanced whereas the nodes within supernodes and their connections are removed.

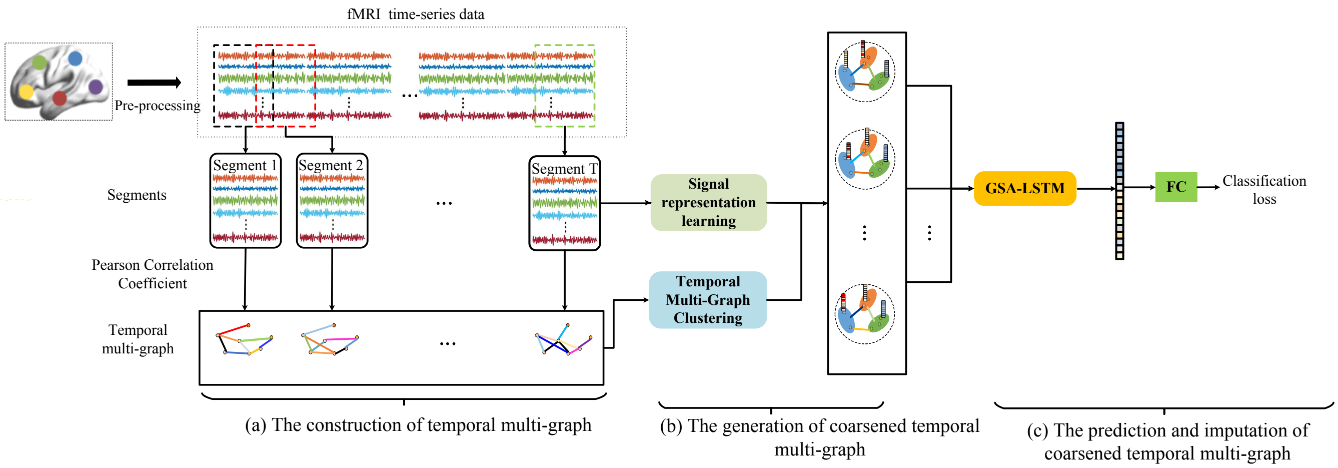

Fig. 1: The overall architecture of our proposed spatio-temporal dynamics modeling framework. (a): The construction of the temporal multi-graph contains two steps. The fMRI time-series data of each subject is first partitioned into a series of time-series segments. A graph (brain network) is constructed on each segment. Finally, we obtain the corresponding temporal multi-graph for each subject. (b): With the constructed temporal graph series, we propose a temporal multi-graph clustering to eliminate noisy edges in temporal multi-graphs and achieve a temporal coarsened graph series which are consistent for all the subjects by sharing the clustering parameter. (c): A GSA-LSTM is proposed to sufficiently model the spatio-temporal patterns of the temporal supergraph series.

Furthermore, based on the assumption that the adjacent graphs over the time series should have similar graph structure, we design a temporal smoothness to constrain the similar graph structure of adjacent graphs. We assume that the difference of the clustering between two successive graphs is relatively small. With this assumption, a temporal smoothness regularization for graph structures can be embedded to learn the cluster indicator matrix $\mathcal{F}$, which is formulated as $|\mathcal{F}_{t+1}-\mathcal{F}_t|$. Most learning approaches treat clustering and classification separately or sequentially. We incorporate the grouping multi-graph clustering into the GCN model to improve both clustering and classification performance in an end-to-end scheme.

E. Node embedding learning with signal representation learning

We first design a signal representation learning (SRL) block for learning the temporal features from the BOLD signal of each node as the corresponding node initial embedding via a stack of convolutional layers. Using each time-series segment of each node (brain region) as the input, the SRL block employs a series of convolutional components to learn local-to-global spatial properties from time-series data. The signal embedding obtained is indicates as $\hat{h}^s$. Finally, we aggregate the signal representation of all the nodes $\hat{h}^s$ within a supernode to generate a supernode embedding $\hat{h}^s$ as the initial embedding of the coarsened graphs.

F. Dual temporal graph LSTM

Exploring spatial and temporal features of the brain network modeling is vital for the disease diagnosis. However, while GCN is a very effective deep learning framework for exploring spatial domain information,it is not capable of capturing temporal characteristics. Due to the fully connected operator within LSTM, there is a limitation with regard to ignoring spatial correlation for the brain regions. To address this problem, we propose a block to incorporate the graph convolution into the LSTM to capture the spatio-temporal features for effectively modeling dynamic brain networks. The input of this block is the temporal coarsened multi-graph with node embedding. The GSA-LSTM has four gates: the input gate, the forget gate, the output gate and the imputing gate. The input gate, the forget gate and the output gate are the same as traditional LSTM. However, the operation of each gate is instead a stack of graph convolutional layers to capture the spatial features of the graph structures. The input of the GSA-LSTM cell has two parts: $\widetilde{H}_{t-1}$ and $\hat{G}_t$. $\hat{G}_t = \langle hatH^s_t, \mathcal{A}^s_t\rangle$, where $\hat{H}^s_t$ is a set of initial node features $\{\hat{h}^s_c\}_{c=1}^C$ and $\mathcal{A}^s_t$ is the adjacency matrix of t-th graph structure. Both H^s and $\mathcal{A}^s$ are obtained by the signal representation learning (SRL) block and the temporal multi-graph clustering. Inspired by DenseNet showing excellent performance in image recognition tasks, the hidden state obtained in (t-1)-th step is concatenated by all preceding layers to improve the information flow. The enhanced hidden state is indicated as $\widetilde{H}_{t-1} = [H_0, \ldots, H_{t-2}]$ Unlike traditional LSTM based on vectors, the input $\hat{G}_t$, hidden state $\widetilde{H}_t$, and cell memory C_t of GSA-LSTM are all graph-structures.

The updating process can be formulated as:

$$I_t = \sigma(W_{gi} * f_{gcn}(\hat{G}_t) + W_{hi} * f_{gcn}(\widetilde{H}_{t-1}) + b_i \qquad (2)$$

$$F_t = \sigma(W_{gf} * f_{gcn}(\hat{G}_t) + W_{hf} * f_{gcn}(\widetilde{H}_{t-1}) + b_f \qquad (3)$$

$$O_t = \sigma(W_{go} * f_{gcn}(\hat{G}_t) + W_{ho} * f_{gcn}(\widetilde{H}_{t-1}) + b_o \qquad (4)$$

$$P_t = \sigma(W_{gp} * f_{gcn}(\hat{G}_t) + W_{Po} * f_{gcn}(\widetilde{H}_{t-1}) + b_o \quad (5)$$

$$U_t = ReLU(W_{gc} * f_{gcn}(\hat{G}_t) + W_{hc} * f_{gcn}(\widetilde{H}_{t-1}) + b_c \quad (6)$$

$$C_t = Tanh(I_t * U_t + F_t * C_{t-p}) \quad (7)$$

$$H_t = O_t * Tanh(C_t),\ Z_t = P_t * Tanh(C_t) \quad (8)$$

where I_t, F_t, O_t and P_t are the input gate, the forget gate, the output gate and the imputing gate, P_t is the set of predicted node embedding vector in the imputed graph, $f_{gcn}(\cdot)$ represents a graph convolution operation. The graph convolution for l-th layer can be formulated as

$$\hat{H}_t^{g(l+1)} = ReLU(\mathcal{A}_t^s \hat{H}_t^{g(l)} W^{(l)}) \quad (9)$$

where $W^{(l)}$ is a trainable weight matrix of l-th layer, $\hat{H}_t^{g(l)}$ is the node embedding computed after l steps of the GCN and the node embeddings. Noting that $\hat{H}_t^{g(0)}$ is the initial embedding of $\hat{G}_t$ which is equal to $\hat{H}_t^s$ obtained by SRL.

In this work, we propose a multi-task learning framework for imputation with incomplete longitudinal data. Since the imputation and prediction on the temporal graphs depend on each other and are performed alternatively. It is believed that the temporal prediction is able to improve the imputation performance, and the appropriately imputed values help enhance the predictive performance. In the training stage, at a certain time point, the imputation module firstly predicts the node feature values of a current time point using the encoded latent representations from the previous time point in a our GSA-LSTM. If the graph is available in the current time, the loss is calculated with both the node level embedding and the graph embedding from the imputed graph and the real graph. Otherwise, the predicted graph is consider to replace the missing one as the current graph to fed into the GSA-LSTM model. It is worth noting that the loss function was only evaluated using available graphs. Moreover, the F of the imputed graph is not obtained by our imputation model, thus the structures of the imputed graphs are set as the nearest observed graph. Hence the imputed graph is represented as $\hat{Z}_t = \left\langle P_t, \mathcal{A}_{t-1}^s \right\rangle$ The max length of the temporal graph series is considered as a complete graph series, then the incomplete temporal graph series are required to be imputed. To cope with the imputation and prediction at the same time, a imputation gate is proposed and a multi-objective function for the proposed imputation-encoding prediction network is devised and optimized in an end-to-end manner.

To guide the imputation, we design a similarity measure to estimate the imputation loss from two levels: graph level and node level.With a simple readout layer, a global graph-level embedding is obtained. Both $\boldsymbol{z}_t \in \mathbb{R}^D$ and $\boldsymbol{g}_t \in \mathbb{R}^D$ indicate the graph embedding of the imputed graph $\hat{G}_t$ and real graph $\hat{G}_t$. Given the graph-level embeddings $\boldsymbol{z}_t$ and $\boldsymbol{g}_t$, we use Neural Tensor Networks (NTN) [20] to model the relation between two graph-level embeddings:

$$S_{graph}^t = -\sigma(\boldsymbol{z}_t W_m^{[1:K]} \boldsymbol{g}_t + V_m \begin{bmatrix} \boldsymbol{z}_t \\ \boldsymbol{g}_t \end{bmatrix} + b) \quad (10)$$

where $W_m^{[1:K]} \in \mathbb{R}^{D \times D \times K}$ is a learnable weight tensor, $V_m \in \mathbb{R}^{K \times 2D}$ is a learnable weight vector, K is a hyperparameter controlling the number of interaction (similarity) scores. The similarity loss from the graph level may result in the loss of the node feature distribution. To solve it, the imputation loss is estimated from the node level. Specifically, the imputed node vector of the imputed graph P_t and the real graph G_t at the t-th time step, respectively. Both p_t^i and g_t^i indicate the corresponding node embedding of the two graphs, the similarity measure loss is estimated as follows,

$$S_{node}^t = -\frac{1}{M} \sum_{i=1}^{M} \sigma((p_t^i)^T g_t^i) \quad (11)$$

G. Objective function

In this paper, we argue that these three tasks are relevant and present a joint clustering, imputation and prediction framework. With these objectives in mind, we integrate the cross entropy classification loss, the temporal multi-graph clustering loss and the imputation loss into our model with the following objective function:

$$L = L_{ce} + \lambda_1 L_{mlc} + \lambda_2 \sum_{j=1}^{N} \sum_{t=0}^{T_{imp}^j} (S_{graph}^{j,t} + S_{node}^{j,t}) \quad (12)$$

where T_{imp}^j indicates the amount of the missing graphs for the j-th subjects. Note that if the temporal graph series is completed, $T_{imp}^j = 0$.

The multi-graph clustering loss L_{mlc} is defined as:

$$L_{mlc} = |\mathcal{F}_{t+1} - \mathcal{F}_t| + L_{neg} + L_{orth} + L_{bal}, \quad (13)$$

where $L_{neg} = \sum_{i=0}^{N} \sum_{j=0}^{C} ReLU(-F_{i,j})$ is designed to avoid the negative value of $\mathcal{F}$, the orthogonal constraint $L_{orth} = \sum_{i,j=0 \wedge i \neq j}^{C} \left((F^T F)_{i,j}\right)^2$ to hinder the overlap between different clusters, the balance loss: $L_{bal} = Var(diag(F^T F))$ is proposed to balance the group sizes for a better interpretability.

III. Experiment

A. Datasets and Evaluation Protocols

1) Dataset: We evaluated our proposed model on the ABIDE database (Autism Brain Imaging Data Exchange database) [11]. ABIDE database collected 1112 subjects, including 539 individuals with ASD and 573 typical controls (ages 7-64 years, median 14.7 years across groups) from different 17 acquisition sites. We used data from the ABIDE preprocessed connectome project (PCP) data preprocessed by the Configurable Pipeline for the Analysis of Connectomes (CPAC). The detailed procession of PCP and CPAC can be found in [12]. After the preprocessing, we obtain 871 quality MRI images with phenotypic information, comprising 402 individuals with ASD and 464 normal controls acquired at 17 different sites.

2) Evaluation matrics: In our experiments, we chose four measure metrics: classification accuracy (ACC), the area under the receiver operating characteristic (ROC) curve (AUC), sensitivity (SEN), and specificity (SPE), to evaluate the performance of our proposed method. We employed a 10-fold cross-validation strategy to evaluate the performances.

B. Comparison with the State-of-the-art Methods

To validate the effectiveness of our proposed method on the binary classification on the fMRI time-series data, we compared our proposed method with several current state-of-the-art methods on ABIDE.

GroupINN [13] is an end-to-end interpretable neural network-based method jointly grouping the nodes and extracting graph features.

ASD DiagNet [14] is a joint learning method combining an autoencoder with a single layer perceptron (SLP) to improve quality of extracted features and optimized parameters for the classification model. In this method, we employ the same autoencoder structure as described in [14].

Eigen_Pooling GCN [15] is a joint learning method combining an end-to-end trainable graph pooling with server GCNs to produce hierarchical representations of graphs.

ST-GCN [5] is a joint learning method combining CNN with GCN to model the spatio-temporal dependency in fMRI data.

TCN-GCN [6] is a joint learning method combining CNNs with GCNs to model the spatio-temporal dependency in fMRI data. Different from Gadgil *et al.* [5], they replace CNNs with TCNs and combine with a GCN framework which learns node embedding and edge embedding alternately to produce representations of graphs.

The results of the comparisons in the binary classification tasks are reported in Table I. We can see that our methods can consistently and significantly outperform the previous brain network classification methods on the ABIDE dataset. Compared to existing methods, our proposed method jointly consider the potential relations of different regions of the brain in both spatial dimension and temporal dimension, which can provide more discriminative ability for the ASD diagnosis. These experimental results validate the superiority of our method. Specifically, existing methods that only incorporate spatial graph convolution (including GroupINN and Eigenpool GCN) often pay more attention to the spatial features from the data. They usually transform the fMRI time-series data into a brain network and perform a GCN network to extract spatial domain features, thereby potentially losing temporal information in the BOLD time series. We conclude that the analysis of dynamic brain networks is better than the analysis on the static brain network. For ASD-DiagNet, they flatten the correlation matrix and feed it into a fully connected network for representation learning and classification. It focuses on mining the global features from a brain network, unable to capture the graph and temporal structures within the brain network, essential in neuroscience research. Compared with

TABLE I: Performance comparison of various methods on ABIDE dataset. A student's t-test (with the significance level at 0.05) on the metric values is performed by our method and each competing method.

Method	ACC(%)	AUC (%)	SEN(%)	SPE(%)
ASD DiagNet [14]	66.6*	66.2*	57.3*	**75.2**
GroupINN [13]	63.4*	64.7*	62.4*	64.4*
BrainNetCNN [16]	65.1*	68.8*	63.6*	66.4*
Eigenpooling GCN [15]	58.6*	65.5*	59.6*	57.4*
BrainGNN [19]	67.1*	68.3	62.1*	67.9*
Population GCN [18]	63.5*	67.5*	62.1*	61.7*
ST-GCN [5]	64.5*	63.9*	61.8*	67.9*
TCN-GCN [8]	67.2*	67.8*	63.6*	69.1*
ours	**68.4**	**70.5**	**64.4**	69.8

the other spatio-temporal modeling methods (including TCN-GCN and ST-GCN), our proposed method achieved better performance. The main reason can fall into two aspects: 1) they ignore the inconsistency of brain networks between subjects, which makes learning a good representation a challenge; 2) they only consider the signal-level temporal dynamics ignoring the graph-level temporal dynamics.

C. Ablation Study

1) The effectiveness of each component: To demonstrate the effectiveness of our framework design, a careful ablation study was conducted. Specifically, the comparison was conducted between our method and the intermediate method or basic method with a single component or a combination of multiple components. The experimental results are reported in Table II. Our systematic study suggests the following trends:

1. GSA-LSTM-CS (our model) yielded the best performance with respect to all the metrics, demonstrating the advantage of our proposed components.

2. We compared GSA-LSTM(w/o imputation) with a simple combination of GCN and LSTM (named GCN-LSTM), where a series of temporal graph embeddings are obtained by GCN and then fed into the LSTM without preserving the graph structure. GCN-LSTM shows the worst performance among the algorithms for all metrics, even worse than GCN. The result indicates that the GCN-LSTM model does not appropriately capture the dynamic pattern in fMRI data, which loses discriminative and robust temporal information. The observation validates our motivation that incorporating graph convolution into LSTM with considering the dynamic graph structure variation is able to model the spatio-temporal dependency.

3. The result demonstrates that adding SRL for the node embedding learning allowed improving the capacity classification performance for the dynamic graph modeling. It also demonstrates that the BOLD signal and temporal graph structure are complementary. Adopting a dual temporal learning scheme for the brain network can take sufficiently advantage of the temporal information to improve classification performance.

4. By comparing GSA-LSTM-C and GSA-LSTM, it can be clearly observed that the temporal multi-graph clustering

TABLE II: Ablation study on ABIDE dataset.

Method	GCN	LSTM	Clustering	SRL	GSA-LSTM	Imputation	ACC(%)	AUC(%)	SEN(%)	SPE(%)
GCN	√						58.6	65.5	59.6	57.4
GCN-LSTM	√	√					58.4	58.8	59.1	57.1
GSA-LSTM w/o imputation					√		64.3	63.1	62.5	65.5
GSA-LSTM					√	√	65.1	63.7	63.3	66.9
GSA-LSTM-C w/o imputation			√		√		65.9	66.7	62.6	**69.8**
GSA-LSTM-C			√		√	√	67.2	68.8	64.1	68.0
GSA-LSTM-CS (**ours**)			√	√	√	√	**68.4**	**70.5**	**64.4**	**69.8**

improves the discrimination capability of modeling the spatio-temporal characteristic. Therefore, it is essential to design an unified framework for jointly eliminating the inconsistency in dynamic FCs.

5. GSA-LSTM, GSA-LSTM-C and GSA-LSTM-CS are all better than the ones w/o imputation, verifying jointly training of prediction and imputation is able to exploit the two complementary tasks for improve the classification performance.

IV. Conclusion

Recently, functional connectivity networks constructed from the functional magnetic resonance image (fMRI) hold great promise for understanding the functional mechanisms of the human brain distinguishing the patients with neurological disorders from Normal controls. Learning dynamic graph embeddings is aimed at modeling spatio-temporal dynamics in brain networks for improved classification performance. In order to achieve a better dynamic graph embedding from brain networks, we develop a temporal graph representation learning framework, which sufficiently exploit the spatio-temporal features in rs-fMRI data through temporal multi-graph clustering that removing noisy edges, BOLD signal feature learning and temporal graph learning and imputing for learning temporal characteristics in fMRI data. We conduct extensive experiments on the ABIDE dataset to verify the effectiveness of our model, which demonstrates its superior performance compared with state-of-the-art baselines.

Acknowledgment

This research was supported by the National Natural Science Foundation of China (No.62076059) and the Fundamental Research Funds for the Central Universities (No. N2016001).

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