Multiple GraphHeat Networks for Structural to Functional Brain Mapping

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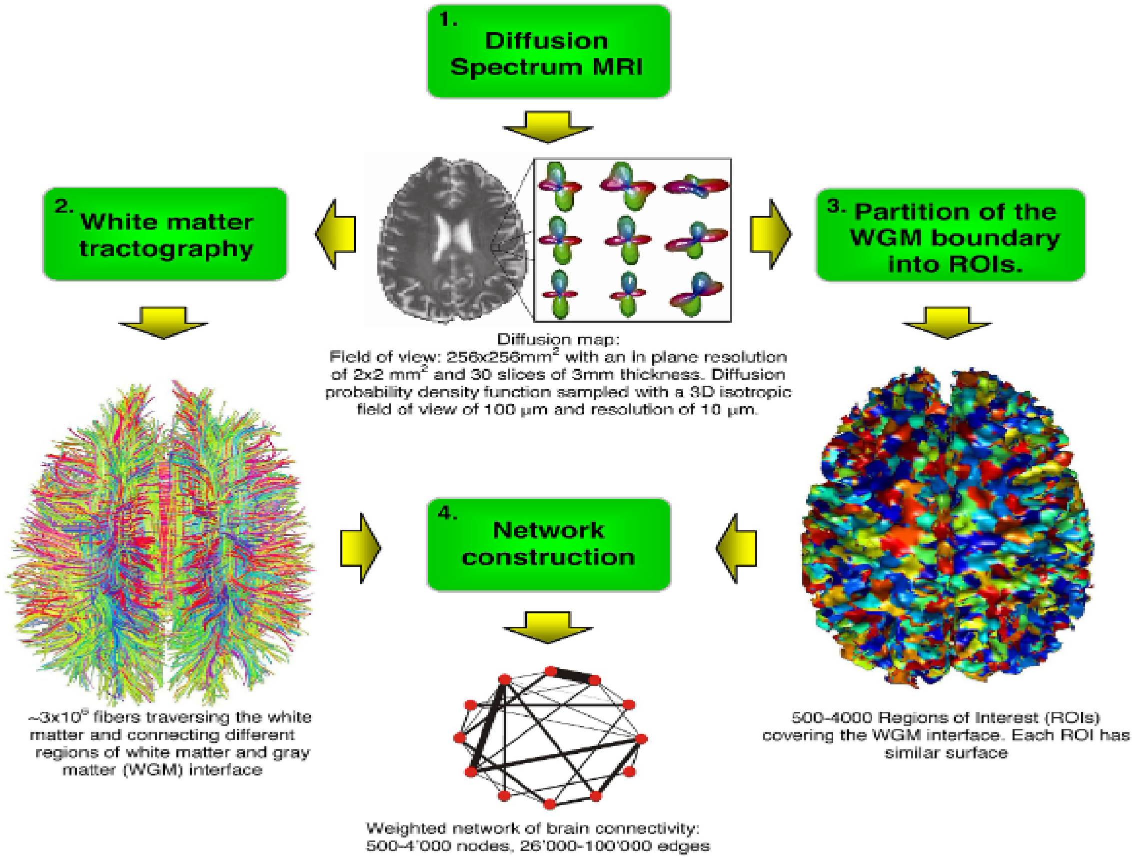
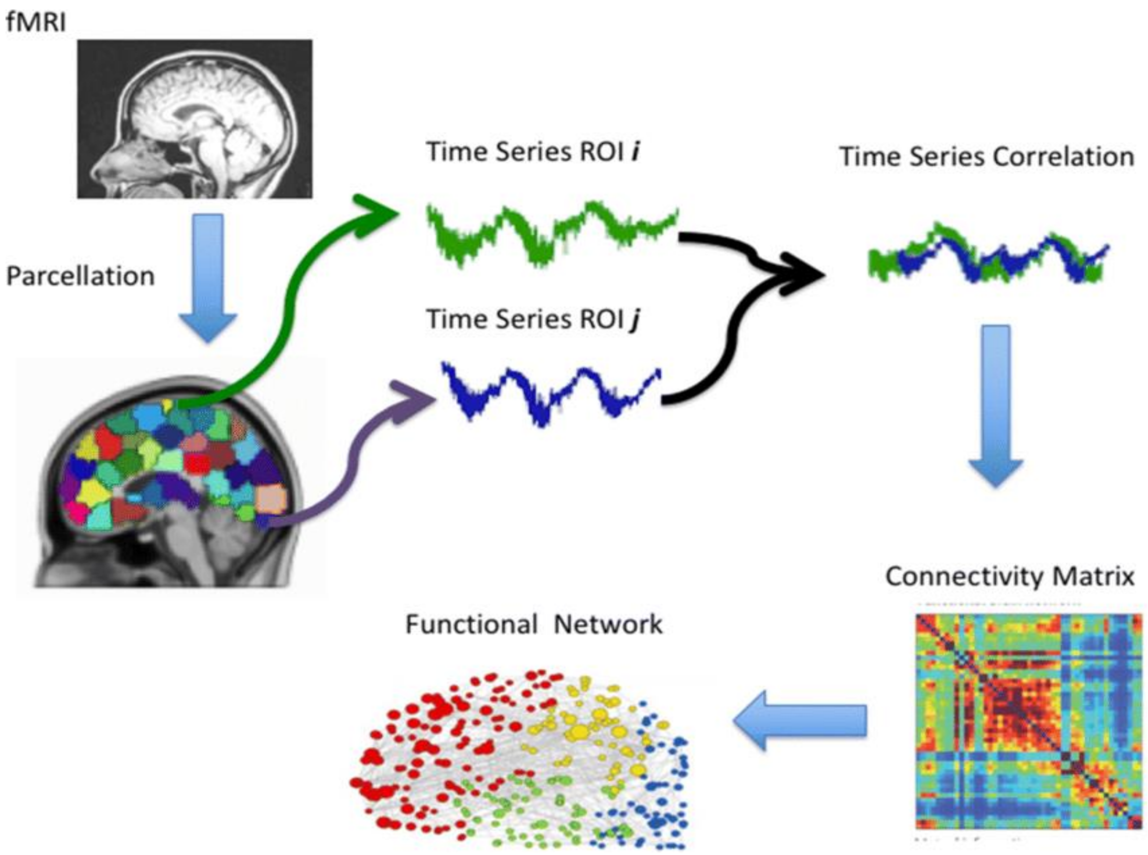
Introduction

- The human brain’s structural topology is estimated from **diffusion tensor images (DTI)** to derive the **structural connectivity (SC)** matrix that summarizes the **fiber connectivity density among the brain regions**.
- **Functional connectivity (FC)** among these regions is estimated by computing the **correlation coefficient (usually Pearson)** of the respective time-varying resting-state functional magnetic resonance imaging (rsfMRI) signals.

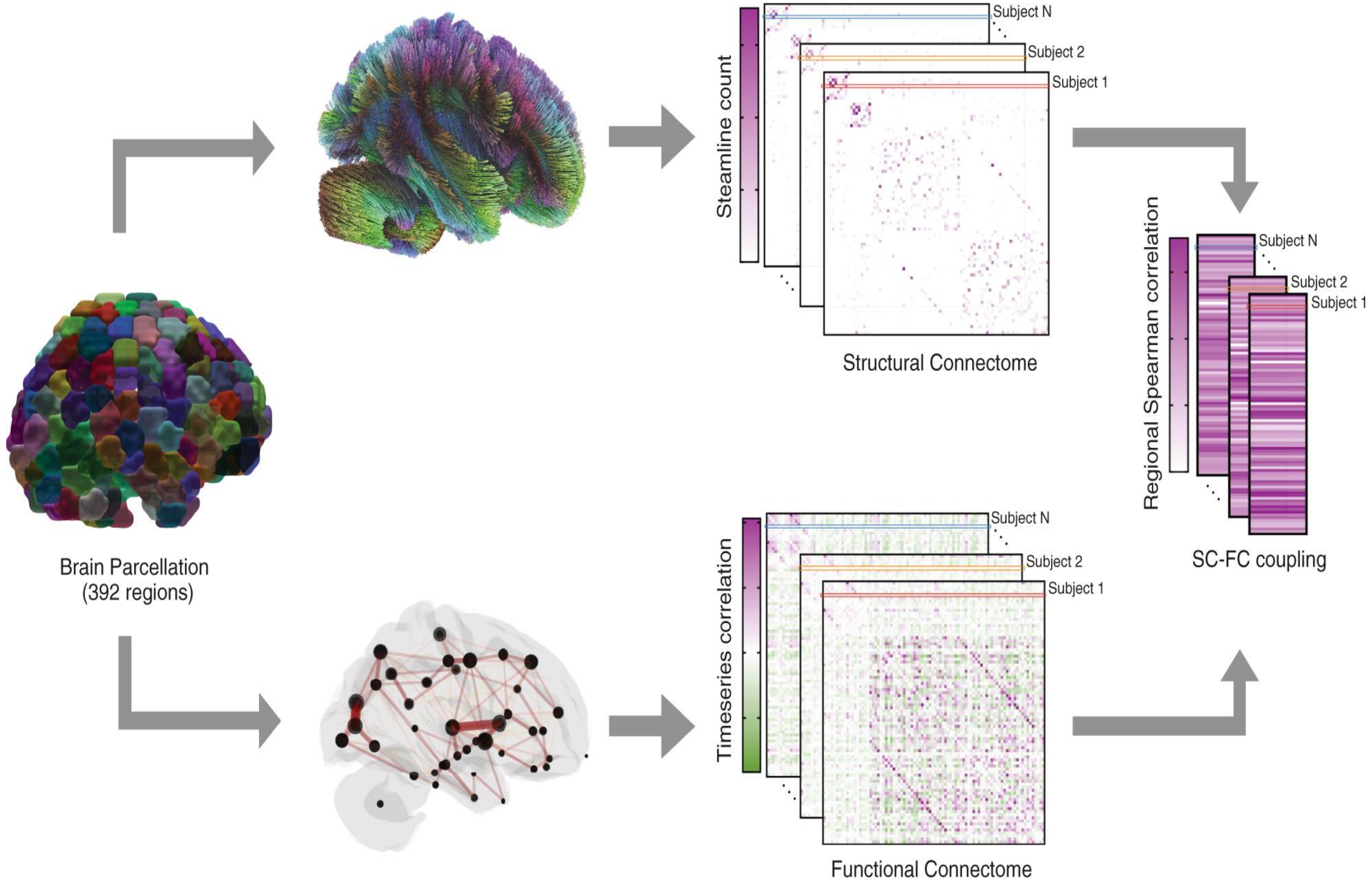




Hagmann et al. 2007, Milano et al. 2019

Why SC-FC mapping is important?

- We can identify the biomarkers that underlie any deviation from the expected FC based on the SC in various diseases such as Autism Spectrum Disorder (ASD), Dementia, etc,.
- Helpful to characterize the functional recovery patterns resulting from therapy comparing the FC observed with the predicted FC based on healthy structural topology.



Synder et al. 2018

Three popular SC-FC mapping methods

- Whole Brain Modeling of SC-FC
- Graph-theoretic Modeling using Linear Models
- Deep Learning Models for SC-FC Mapping

Whole Brain Modeling of SC-FC

Predicting human resting-state functional connectivity from structural connectivity

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In the cerebral cortex, the activit
are continuously fluctuating. Whe
using functional MRI (fMRI), is te
ulations, those populations are sa
Functional connectivity has prev
with structural (anatomical) conn
level. In the present study we inv
tational modeling, whether syste
networks—including their spatia
across time—can be accounted fo
anatomical network. We measur

Resting-State Functional Connectivity Emerges from Structurally and Dynamically Shaped Slow Linear Fluctuations

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Brain fluctuations at rest are not random but are structured in spatial patterns of correlated activity across different brain areas. The question of how resting-state functional connectivity (FC) emerges from the brain's anatomical connections has motivated several experimental and computational studies to understand structure–function relationships. However, the mechanistic origin of resting state is obscured by large-scale models' complexity, and a close structure–function relation is still an open problem. Thus, a realistic but simple enough description of relevant brain dynamics is needed. Here, we derived a dynamic mean field model that consistently summarizes the realistic dynamics of a detailed spiking and conductance-based synaptic large-scale network, in which connectivity is

Honey et al. 2009, Deco et al. 2013

Graph-theoretic Modeling using Linear Models

Network diffusion accurately models the relationship between structural and functional brain connectivity networks

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Abstract

The relationship between anatomi
connectivity is of immense import
required complex simulations whi
coupling between regions as deriv
these non-linear simulations, they
from anatomic connectivities. Littl
properly designed linear model ap
capturing the brain's long-range s
between anatomic and functional
based on graph diffusion, whereby
We test our model using subjects
network diffusion model applied t
structures derived from their fMRI
the proposed approach is that it ca
connectivity. And since it is linear
data. The success of our model co
implies that their long-range corre
mechanistic processes enacted on

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Multiple Kernel Learning Model for Relating Structural and Functional Connectivity in the Brain

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A challenging problem in cognitive neuroscience is to relate the structural connectivity (SC) to the functional connectivity (FC) to better understand how large-scale network dynamics underlying human cognition emerges from the relatively fixed SC architecture. Recent modeling attempts point to the

Abdelnour et al. 2016, Surampudi et al. 2018

Deep Learning Models for SC-FC Mapping

MAPPING BRAIN STRUCTURAL CONNECTIVITIES TO FUNCTIONAL NETWORKS VIA GRAPH ENCODER-DECODER WITH INTERPRETABLE LATENT EMBEDDINGS

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ABSTRACT

In this paper, the relationship between functional and structura networks is investigated by training a graph encoder-decod tem to learn the mapping from brain structural connectivit to functional connectivity (FC). Our work leverages a grap volutional network (GCN) model in the encoder which int both nodal attributes and the network topology information erate new graph representations in lower dimensions. Usin SC graphs as inputs, the novel GCN-based encoder-decod tem manages to account for both direct and indirect interacti tween brain regions to reconstruct the empirical FC networ

Structure-Function Mapping via Graph Neural Networks

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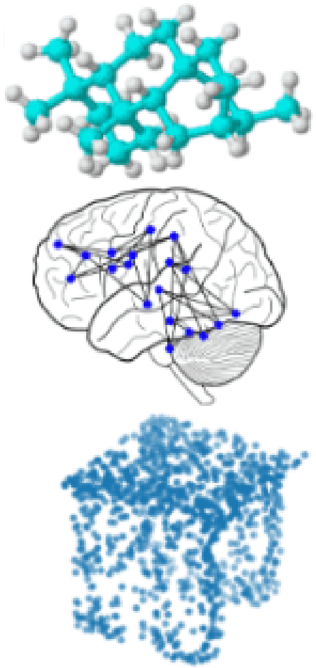
Abstract. Understanding the mapping between structural and functional brain connectivity is essential for understanding how cognitive processes emerge from their morphological substrates. Many studies have investigated the problem from an eigendecomposition viewpoint, however, few have taken a deep learning viewpoint, even less studies have been engaged within the framework of graph neural networks (GNNs). As deep learning has produced significant results in several fields, there has been an increasing interest in applying neural networks to graph problems. In this paper, we investigate the structural connectivity and functional connectivity mapping within a deep learning GNNs based framework,

Li et al. 2019, Ji et al. 2021

Why Graph Convolutional Networks (GCNs)?

- Graphs are a super general representation of data with intrinsic structure.
- We can represent brain graphs from functional medical imaging, social networks, point clouds, and even molecules and proteins.



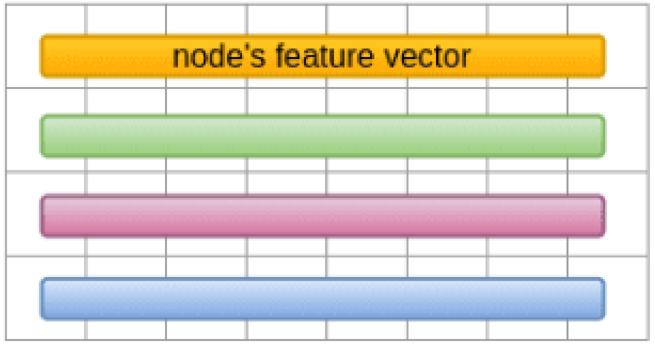
Structure = Adjacency matrix

$$A \in R^{N \times N}$$

1	0	1	0
0	1	0	0
1	0	1	1
0	0	1	1

Graph Signal (feature matrix)

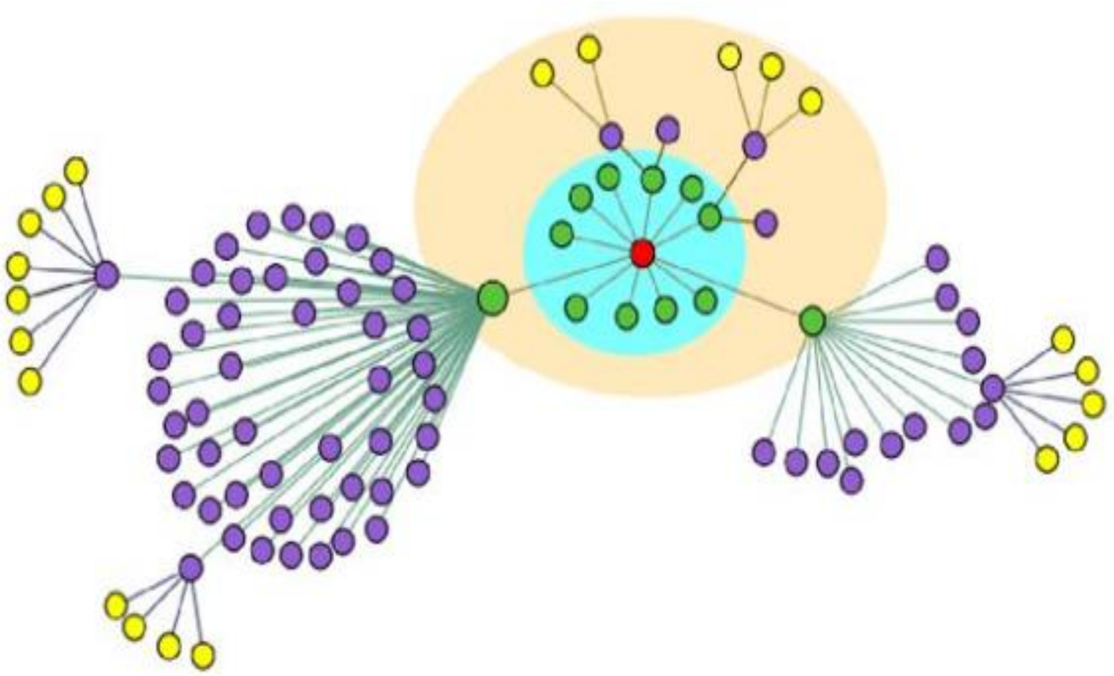
$$X \in R^{N \times F}$$

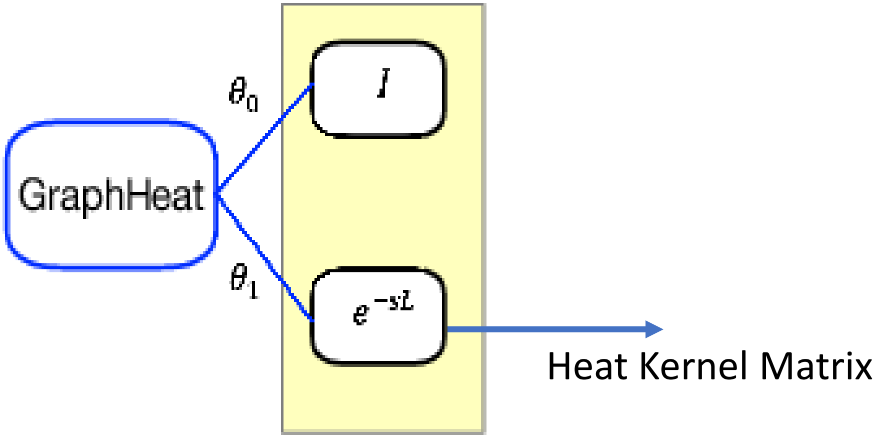


Kipf et al. 2016

GraphHeat Networks

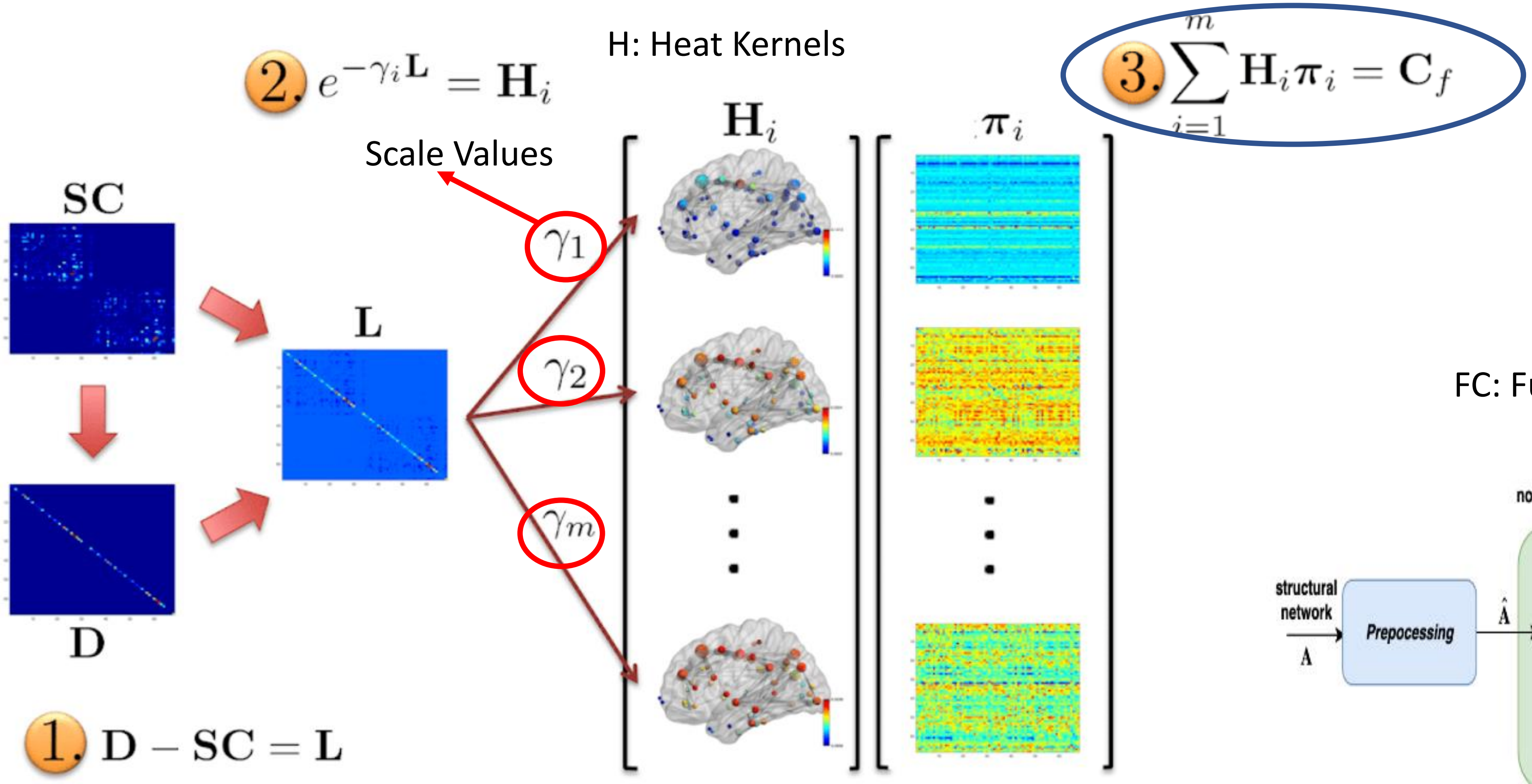
- GCNs determine neighborhood according to the hops away from center node, i.e., in an order-style
  - Nodes in different colors
- GraphHeat determines neighborhood according to the similarity function by heat diffusion over graph
  - Nodes in different circles



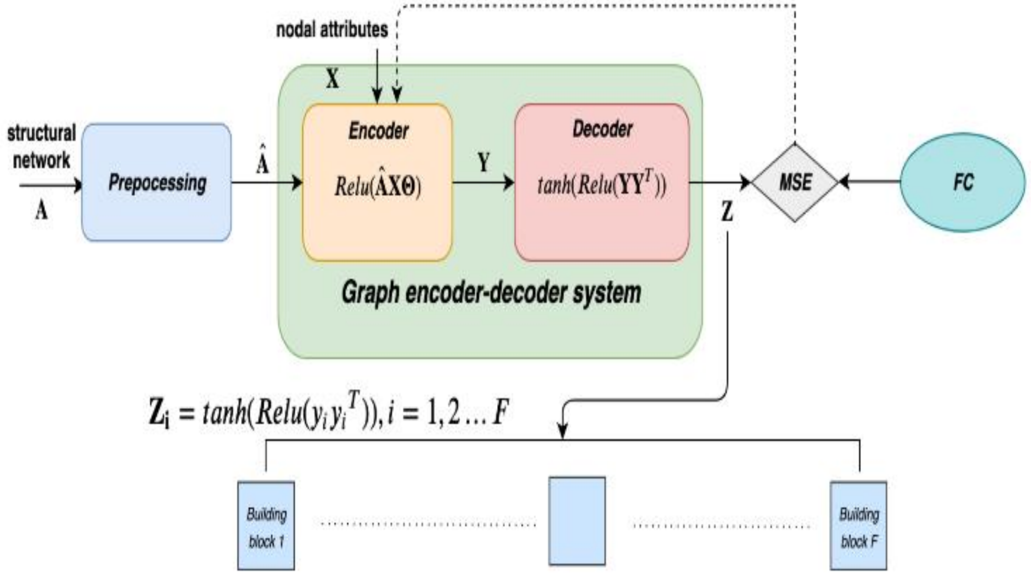


Motivation

Lasso Regression



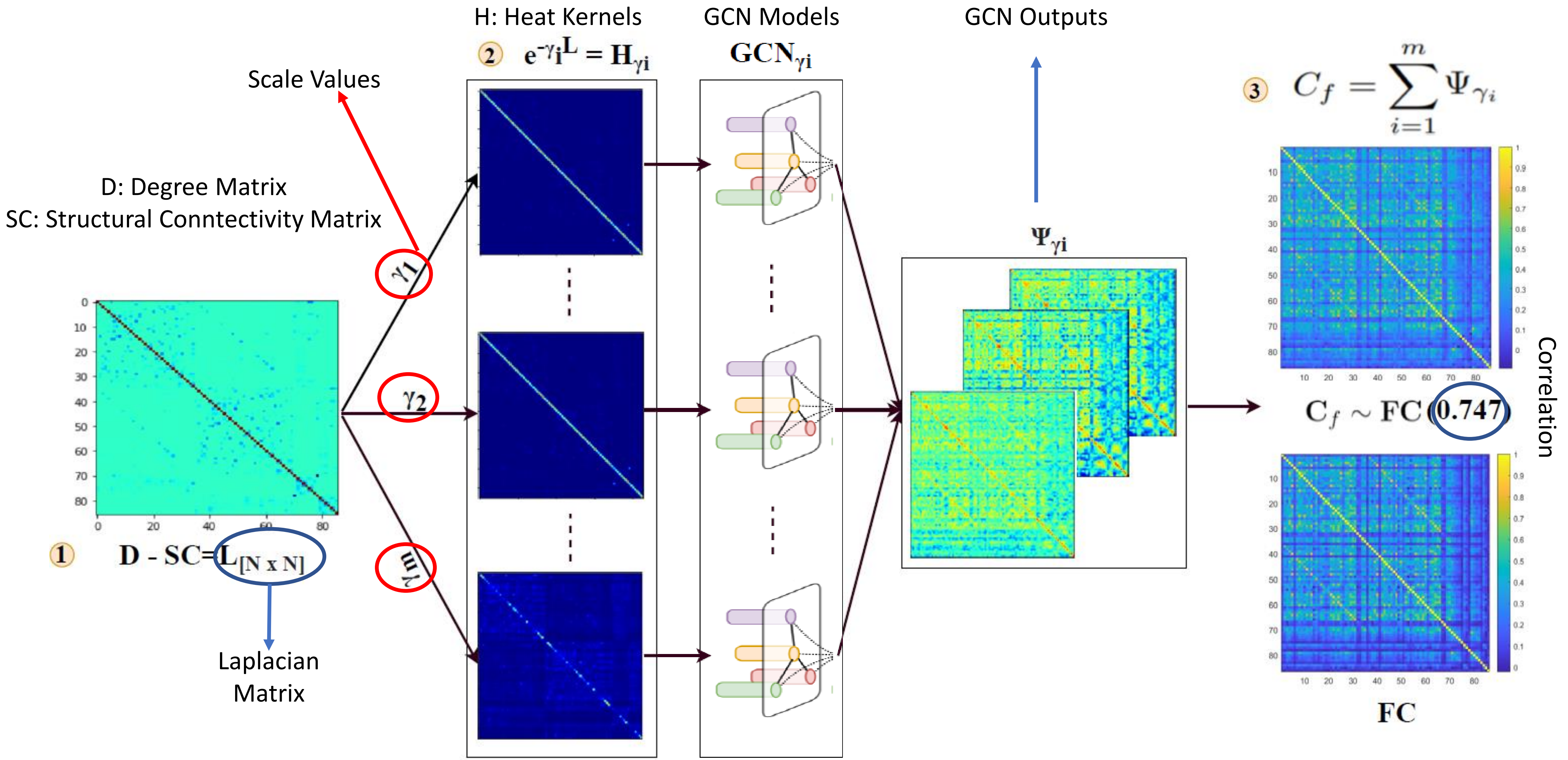
A: Structual Matrix
FC: Functional Conntectivity Matrix
Z: Predicted FC



D: Degree Matrix
SC: Structural Conntectivity Matrix
L: Laplacian Matrix

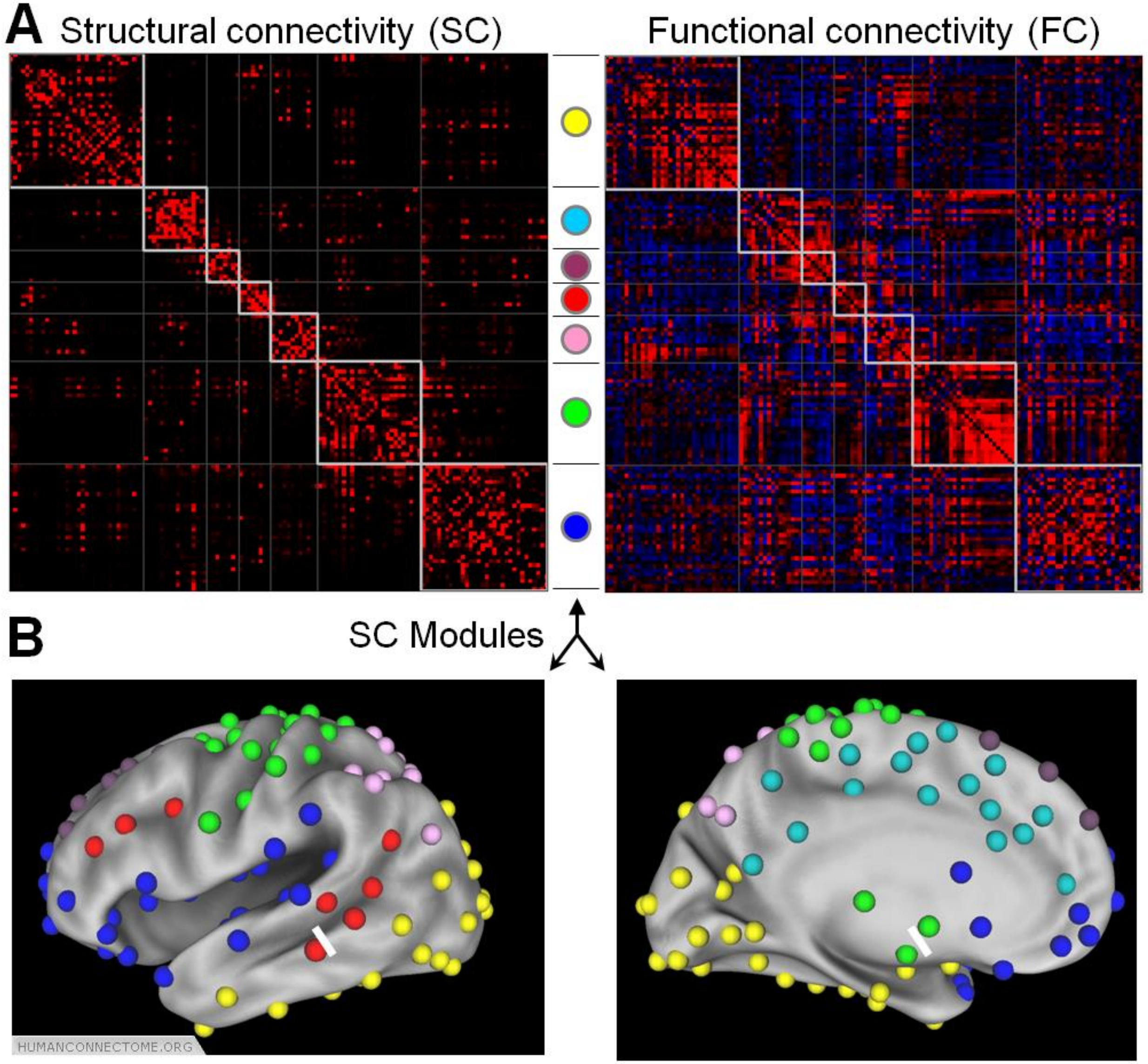
Surampudi et al. 2018, Li et al. 2019

M-GHN Architecture



HCP Dataset

- 100 subjects of SC – FC paris from the HCP repository.
- Participants underwent resting-state functional imaging (no task condition) with their eyes closed.
- The blood oxygen level dependent (BOLD) time-series signal available for each participant has 1200 time points aggregated across 86 regions of interest (ROIs) as per the AAL brain atlas.



Bullmore et al. 2009, Dosenbach et al. 2008

Experimental Setup

- Three experimental settings
  - Randomly sampled 50 subjects (45 – training, 5 – validation), and remaining subjects used for testing.
  - Leave-one-out-crossvalidation
  - 5-fold crossvalidation

Comparison of M-GHN with previous methods

- The Pearson correlation between the ground-truth FC and predicted FC of test subjects.

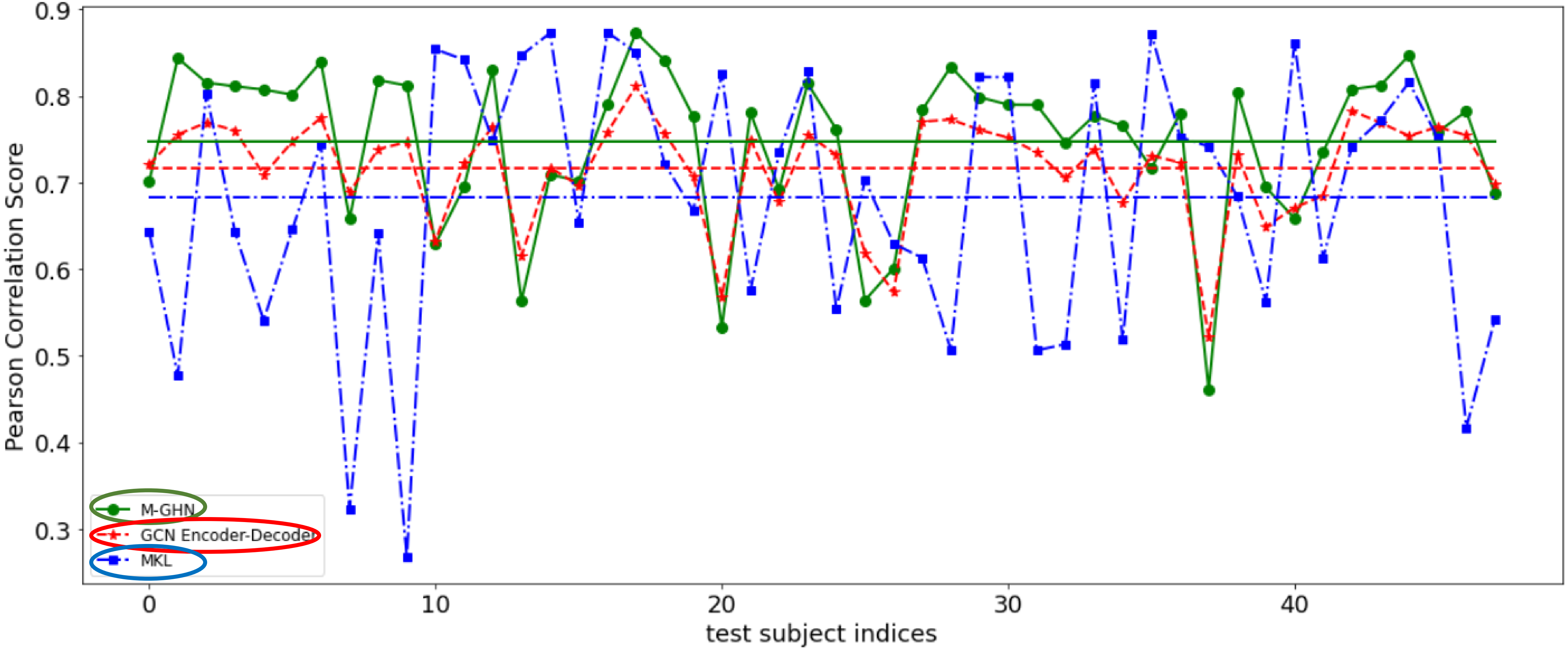
Add noise to input SCs during training while correct SCs in testing

Model	Correlation
Perturbation of Input SC (Training)	0.353
MKL	0.691
GCN Encoder Decoder	0.732
Autoencoder	0.561
Macroscale SC-FC	0.501
GTN	0.715
Random M-GHN	0.572
M-GHN	**0.747**

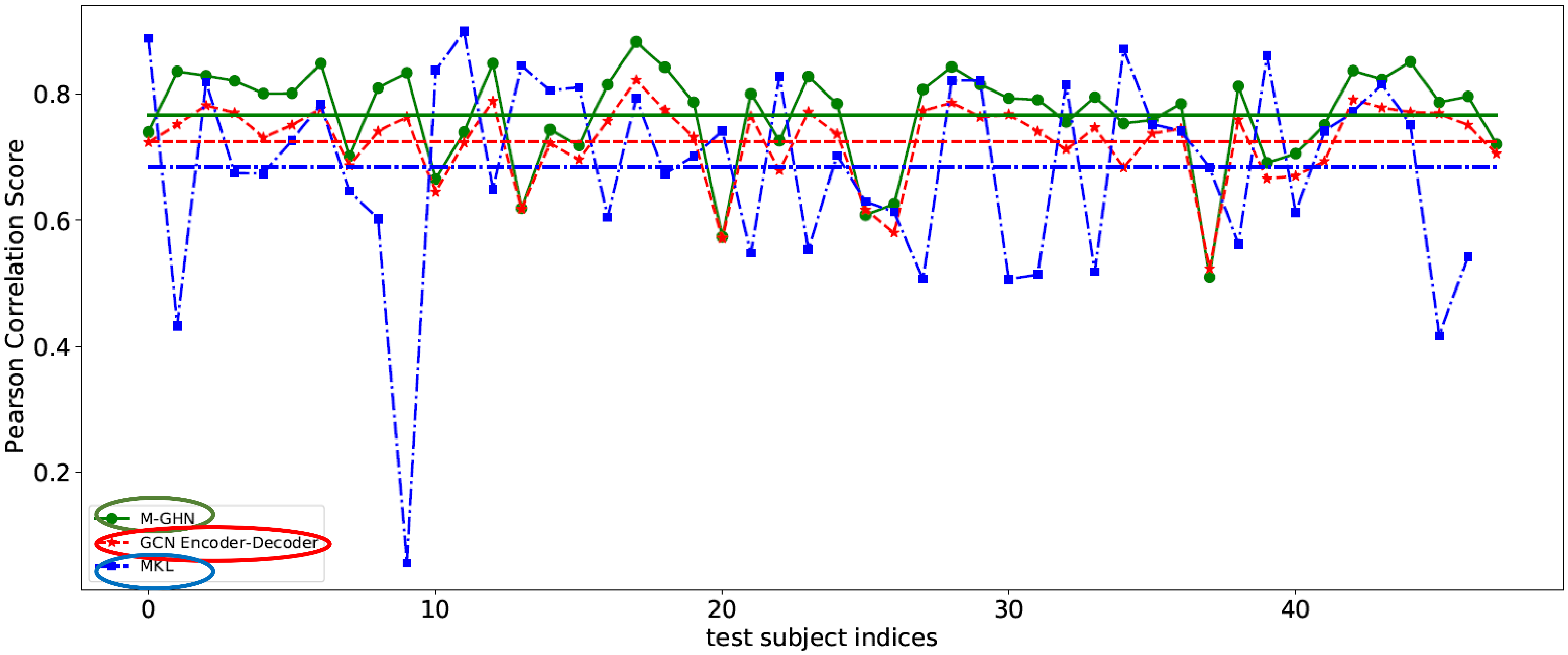
Multi-layer perceptron as encoder-decoder model.

GNNs (GCN + GTN)

Results: Randomly sampled experiment



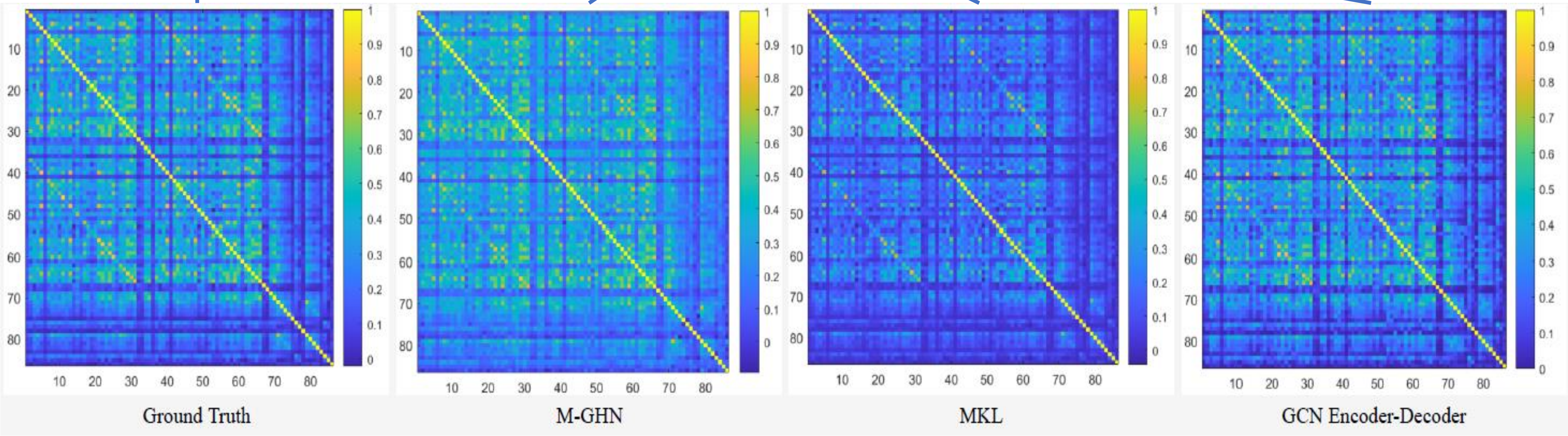
Results: LOOCV



Qualitative Analysis: Functional Connectivity matrices (FCs).

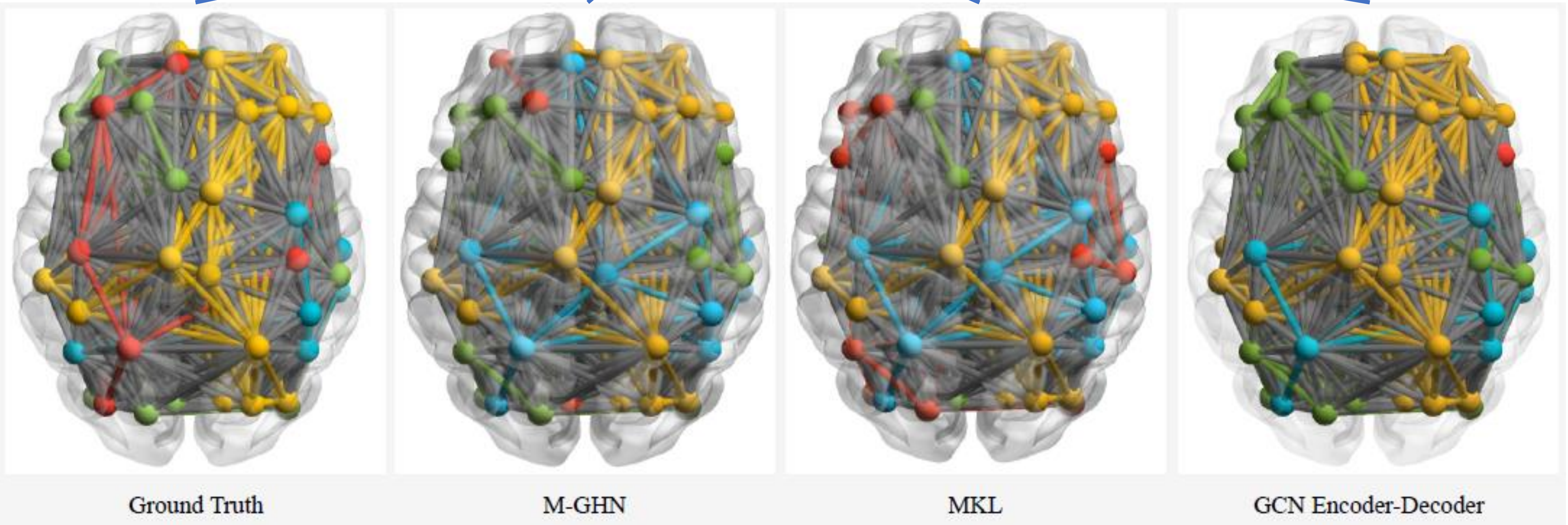
mean of the test FCs

mean of the predicted FCs of each model



Qualitative Analysis: Functional Connectivity Networks.

Each color indicates the nodes in that particular community



Discussion

- We adopt the representation of the graph signal in terms of graph heat kernel.
- The proposed M-GHN method is grounded in the theory of the reaction-diffusion process in the cognitive domain.
- Proposed M-GHN model displays superior performance as compared to baseline models such as GCN Encoder-Decoder, MKL model, and previous state-of-the-art methods.
- The M-GHN model is easily scalable to any brain parcellation (for example, Gordon Atlas with 333×333, Glasser Atlas with 360×360 parcellations).
- Also, the MGHN model requires learning of 51,772 parameters (7 scales: 7x7396) that is comparatively lower than learning 118,336 parameters in the MKL framework (16 scales: 16x7396).
- Further, the proposed framework is inherently scalable to more diffusion scales, more hidden layers in the GHNs, and can potentially be used for transfer learning on other datasets.