

Multimodal Cohort Hypergraph Architecture to Understand Adolescent Psychiatric Development

Keywords: Multimodal Imaging, Mental Health Data Science, Graph Fusion

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Problem Description

Background

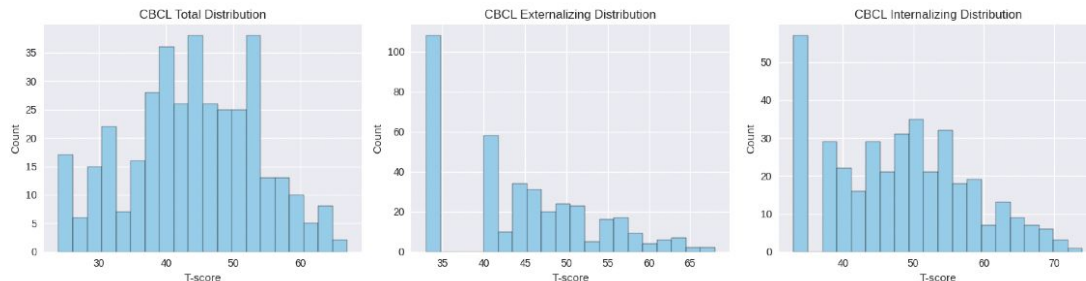
- ▶ Adolescence is a period of rapid neurodevelopment when psychiatric symptoms often emerge.
- ▶ Resting-state fMRI functional connectivity (FC), structural connectivity (SC), and morphometric (T1) features capture complementary aspects of brain organization.
- ▶ Cognitive testing provides a higher level look into brain organization

Child Behavior Checklist Scores

- ▶ Total Problems - A global index of behavioral and emotional dysregulation.
- ▶ Externalizing Problems - Measures outwardly directed dysregulation (Rule Breaking/Fighting)
- ▶ Internalizing Problems - Reflects inwardly directed distress (Depression/Anxiety)

Problem Statement

- ▶ Design a machine learning system capable of learning relationships between brain imaging features and cognitive scores
- ▶ Provide interpretable attributions to specific brain regions tied to behavioral targets.



Study Population (Dataset)

Dataset

Human Connectome Project – Development (HCP-D)

- ▶ Multimodal MRI data (resting-state fMRI, diffusion MRI, and T1-weighted structural scans) were obtained from the HCP–Development cohort, which captures brain development from childhood through young adulthood.
- ▶ Functional connectivity (FC), structural connectivity (SC), and morphometric features were preprocessed using the standardized HCP minimal preprocessing pipelines.
- ▶ Target behavior scores were derived from the **Child Behavior Checklist (CBCL)** scores, serving as continuous regression targets for subject-level prediction.

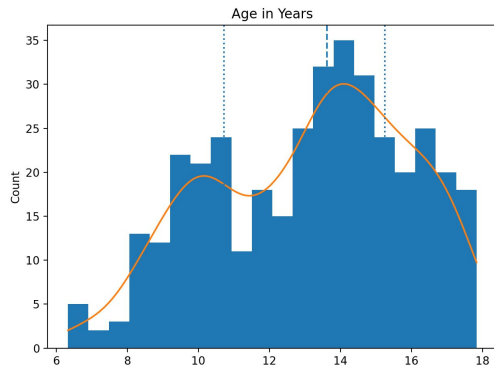
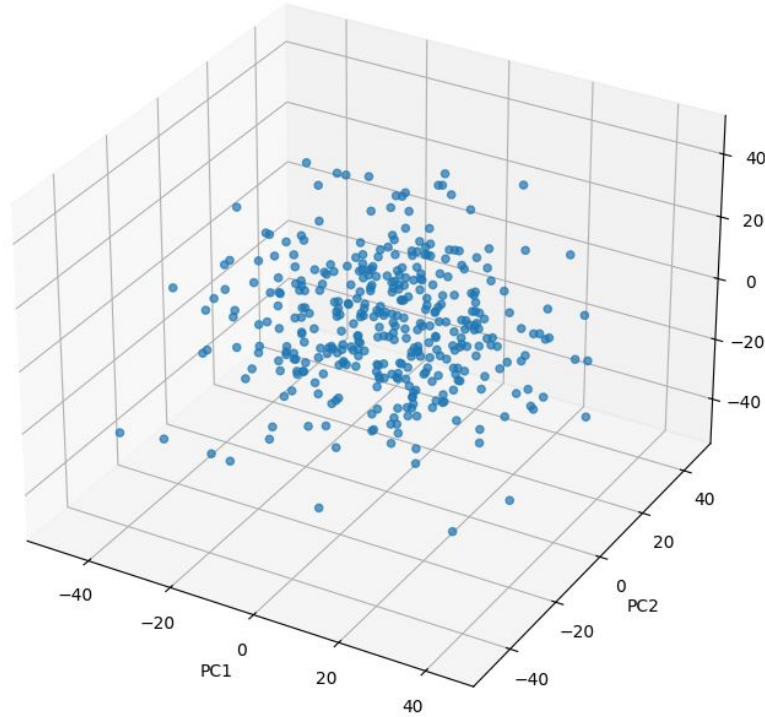


Table 1: Cohort after filtering (subjects with brain imaging, CBCL, and cognitive testing)

Characteristic	Count	%
Total subjects	376	
<i>Sex</i>		
Female	209	55.6
Male	167	44.4
<i>Race</i>		
White	255	67.8
Black or African American	27	7.2
More than one race	72	19.1
Asian	16	4.3
Other/Unknown	5	1.3
American Indian/Alaska Native	1	0.3

Cognitive Similarity Visualized

3D PCA of Cognitive Scores (Subjects)




Preprocessing

- ▶ We followed the HCP minimal preprocessing pipelines for sMRI, DTI and fMRI (Glasser et al., 2013).
- ▶ For sMRI, the structural images are corrected for gradient nonlinearity distortions, as well as intensity homogeneity correction. Following this, the images were registered and resampled to align with an averaged reference brain in the standard space.
- ▶ For fMRI, our preprocessing steps included iterative smoothing, frame censoring, motion correction, and motion parameter regression according to frame-wise displacement thresholds.
- ▶ DTI preprocessing is implemented in MRtrix utilizing denoising, distortion, and motion corrections, co-registration, tissue extraction, and streamline analysis to assist in the calculation of structural connectivity metrics within the same regions of interest (ROIs)

Models Used

Table 1: Benchmark comparison across models (Validation / Test MSE).

Method	
LASSO	
SVR	
KNN	
Kmeans	
No Hypergraph	
With Hypergraph	

Model Overview: Key Concepts

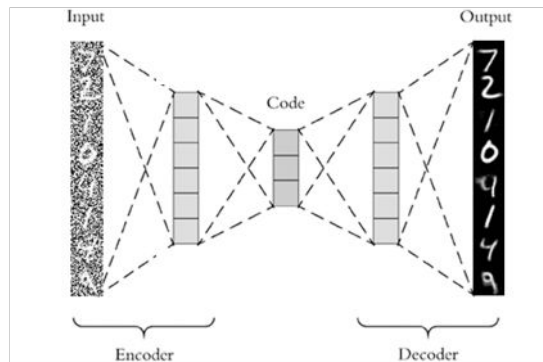


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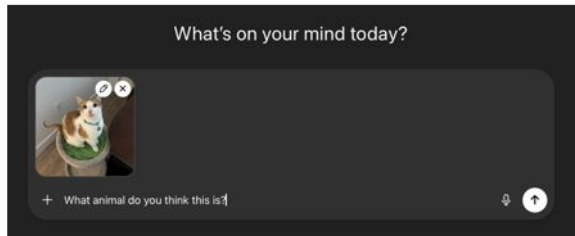
Graph Encoder

A graph encoder is a computational component that transforms a complex graph structure into a lower-dimensional embedding



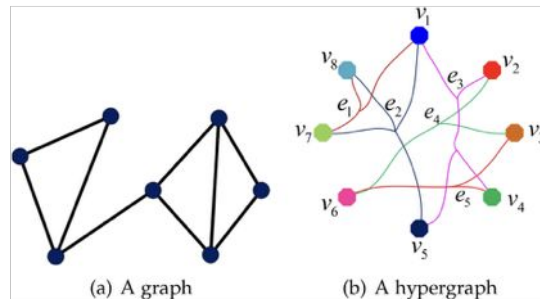
Cross Modal Attention

Way of quantifying how two different modalities influence each other

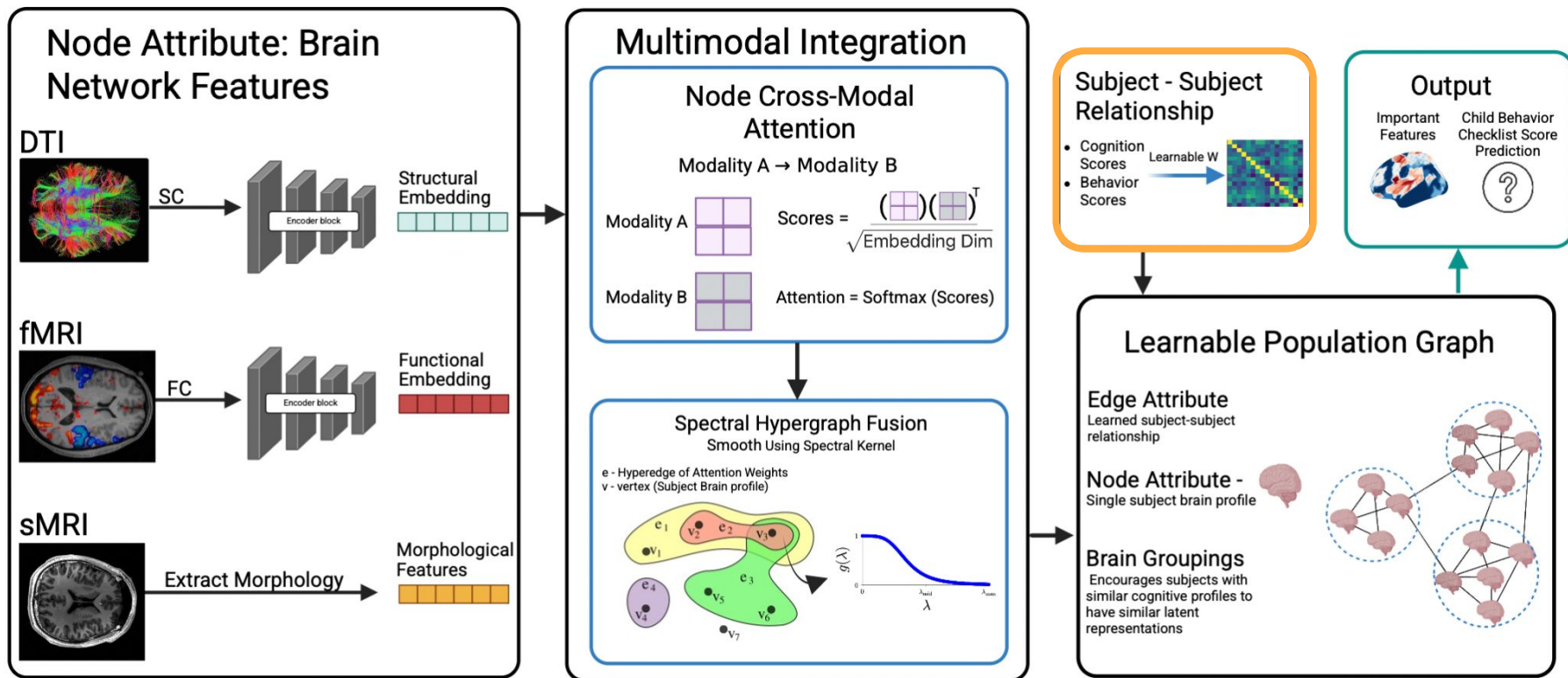


Hypergraph

A hypergraph is a generalization of a standard graph where hyperedges can connect any number of vertices (or nodes), rather than the two vertices of a traditional graph's edges. This allows for the direct modeling of multi-way relationships. (I.e. brain networks)



Model Overview



Cohort Cognitive Diffusion

1. Diffuse Cognitive Information across the the hypergraph, influencing subjects with similar cognitive testing scores to have similar latent representations
2. The diffusion effectively aligns neural embeddings (learned from spectral hypergraph fusion) with the behavioral features defined by cognitive testing, producing representations that co-vary with both neural and cognitive organization

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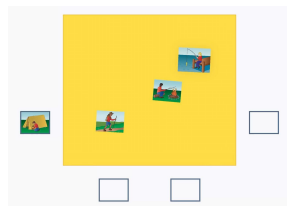


Incongruent



Congruent

<- Flanker



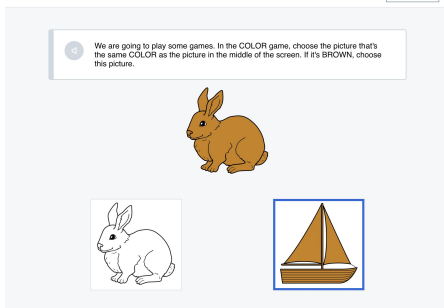
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Cognitive Similarity for Batch Size 16 Subjects

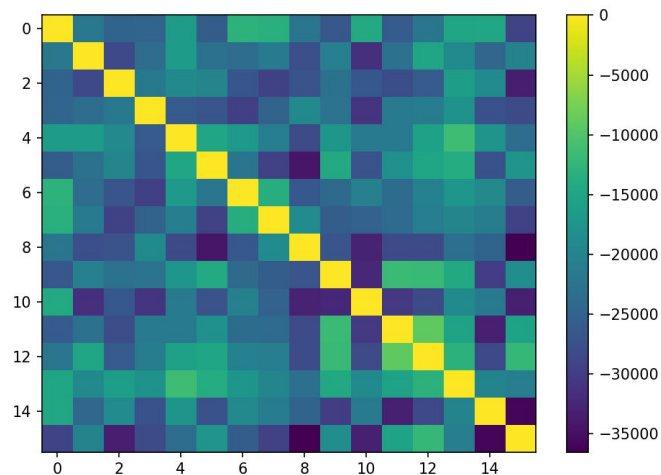


Table 1: Benchmark comparison across models (Validation / Test MSE).

Method	Val MSE	Test MSE
LASSO	146.54	139.51
SVR	83.60	98.36
KNN	86.08	105.77
Kmeans	67.50	97.96
No Hypergraph	75.64	740.40
With Hypergraph	67.99	91.25

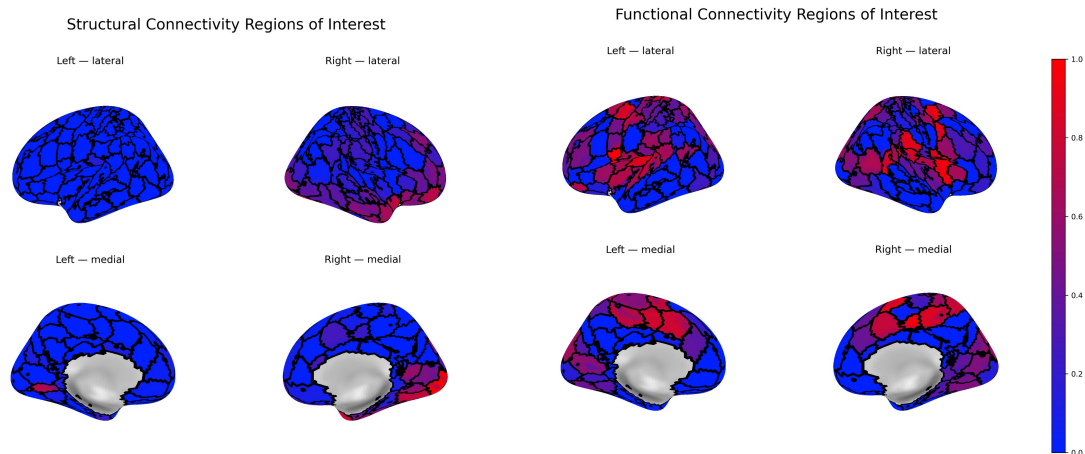
Interpretability for Individual Imaging Types

1. Functional Connectivity (FC):

- (a) Dominant networks: Salience/Ventral Attention \gg Somatomotor \gg Dorsal Attention
- (b) Key hubs: FrOperIns, Medial salience cortex, Pre/Post-central gyrus, Frontal Eye Fields
- (c) Interpretation: Behavioral variance in CBCL is driven by hyper-synchrony of salience and sensorimotor circuits, reflecting arousal, attention dysregulation, and externalizing behaviors
- (d) Laterality: Predominantly right-hemisphere, consistent with heightened emotional and attentional reactivity

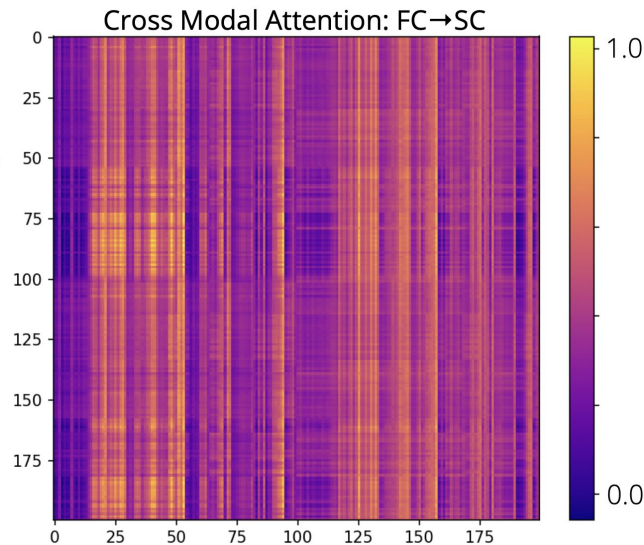
2. Structural Connectivity (SC):

- (a) Dominant networks: Visual \gg Salience/Ventral Attention \gg Limbic \gg Control \gg Default
- (b) Key hubs: Occipital (Vis_1–10), Temporal pole & OFC (Limbic), PFCI/PFCv (Control)
- (c) Interpretation: CBCL variance reflects stable anatomical coupling in sensory-emotional pathways—visual-limbic-salience tracts supporting perception–emotion integration
- (d) Laterality: Strong right-hemisphere bias emphasizing emotional–perceptual dominance



Interpretability for Cross Modal

The FC→SC attention map reveals structured “highways” through which functional synchronization is preferentially routed along stable anatomical tracts. These highways — most prominently in salience, motor, and visual systems — reflect how dynamic brain states (FC) are constrained and shaped by physical connectivity (SC) to produce behavior. In the CBCL context, this suggests that emotionally charged salience flow into motor and sensory pathways drives the behavioral variance captured by the model.



Conclusion/Discussion

- ▶ This study was conducted on a typical developing population, meaning that the effect of the models can only be so powerful
- ▶ More Cross-Site validation would be helpful
- ▶ More powerful machine learning models are needed to fully understand complex brain data
- ▶ The newly proposed method was able to improve on testing metrics and generate interpretable results aligned with neuroscientific principals