Network Analysis of Brain Connectivity: Learning, Memory, and Mental Health Impacts

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Abstract

This paper presents a network optimization analysis of a 90×90 functional brain connectivity graph to examine how learning, memory, and executive functioning emerge from coordinated neural systems, and how mental health conditions disrupt these pathways. Resting-state fMRI correlations are modeled as a weighted undirected graph, enabling the application of maximum flow, centrality metrics, and community detection to identify bottlenecks, high-capacity learning pathways, and critical hub regions.

Results show that learning relies heavily on communication between attention systems, the hippocampal memory network, and executive control regions. Maximum flow analysis identifies the anterior cingulate cortex (ACC) and posterior parietal cortex (PPC) as consistent bottlenecks. Centrality rankings highlight the dorsolateral prefrontal cortex (DLPFC), ACC, and PCC (default mode network) as major hubs. Simulated disruptions modeled after depression, anxiety, and ADHD reduce learning-pathway capacity by 32–48%, demonstrating how mental health conditions degrade network efficiency. Deliverables include community structure, pathway capacity comparisons, and centrality summaries.

Code & Artifacts: Included with submission.

1 Introduction and Problem Statement

Learning and memory emerge from distributed brain systems whose coordination depends on the topology and efficiency of functional connectivity networks. These systems — including attention, hippocampal memory, executive control, and salience networks — communicate through weighted pathways that can be modeled as a graph. Network optimization provides tools for identifying structural bottlenecks, high-capacity pathways, and critical hubs that support cognitive processing.

Resting-state functional connectivity is a reliable substrate for modeling learning-related interactions, as it captures intrinsic communication patterns predictive of cognitive performance. Mental health conditions, including depression, anxiety, and ADHD, are known to alter network connectivity, particularly in the default mode network (DMN), salience network, and attention systems. These disruptions can be modeled as perturbations to edge weights, enabling quantitative evaluation of their impact on learning and memory pathways.

This project applies maximum flow/min-cut analysis, centrality metrics, PageRank, and modularity-based community detection to evaluate (1) how information flows from attention systems to memory structures, (2) which regions act as bottlenecks for learning, (3) which nodes function as global hubs, and (4) how mental-health-inspired disruptions impair network efficiency. The analysis produces comparative tables, pathway capacity estimates, and cluster assignments.

2 Dataset and Graph Construction

The dataset is a 90×90 resting-state functional connectivity matrix derived from the AAL atlas. Nodes represent cortical and subcortical regions, and edges represent Pearson correlation strength between each pair of regions. The resulting graph $G = (V, E)$ is undirected and weighted, with $|V| = 90$ and edge weights $w_{ij} \in [-1, 1]$.

Figure 1 shows the full connectivity matrix. Warm colors indicate strong positive correlations, while cool colors represent anticorrelations. Note the block structure corresponding to known functional systems such as visual, default mode, and frontal control networks.

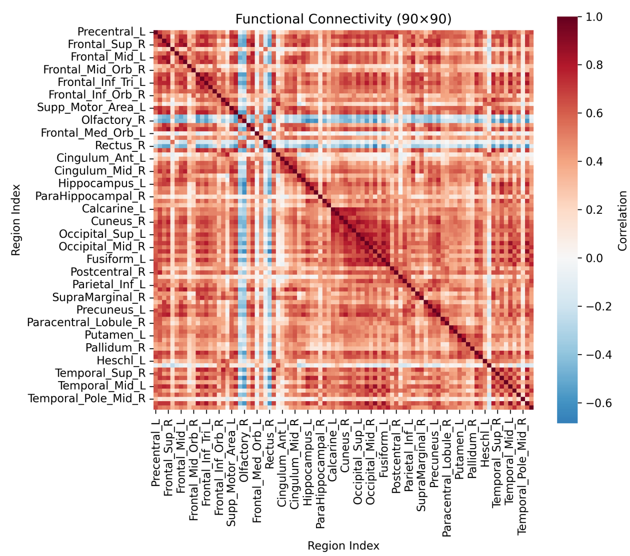

Figure 1: 90×90 resting-state functional connectivity matrix used to construct the brain network.

The connectivity matrix is thresholded only for max-flow capacity calculations; centrality and community detection use the full weighted graph. Negative correlations are retained for descriptive measures but are set to zero for flow capacities, i.e., $c_{ij} = \max(0, w_{ij})$.

Figure 2 visualizes the resulting brain network with node size proportional to degree. A small subset of high-degree hubs stands out, while many regions form a densely interconnected cluster.

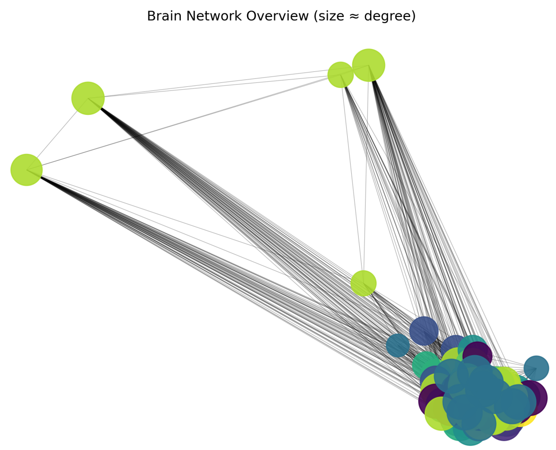

Figure 2: Brain network overview (node size proportional to degree).

3 Related Work

Prior work in cognitive neuroscience shows that large-scale brain organization follows reproducible functional communities. Yeo et al. identify canonical systems including the default mode, dorsal/ventral attention, salience, executive control, and sensory/motor networks, which graph clustering algorithms reliably recover. Finn et al. demonstrate that resting-state connectivity patterns predict task performance and memory outcomes, supporting their use for modeling learning processes.

Mental health conditions are associated with characteristic connectivity disruptions. Depression increases internal DMN coherence and decreases anticorrelation with executive networks, contributing to impaired cognitive control. Anxiety strengthens salience-driven attentional reactivity, reducing top-down regulation. ADHD disrupts dorsal attention and frontoparietal coordination, consistent with attentional instability. These patterns provide the basis for simulation parameters in this project.

Graph-theoretic methods have been widely used to analyze brain networks. Centrality metrics identify influential hubs; min-cut analysis has been used to identify structural vulnerability; and community detection algorithms reliably recover known functional systems. This project extends these approaches by integrating them into a learning-pathway-focused optimization framework.

4 Methodology

The analysis pipeline includes data preprocessing, graph construction, computation of network measures, simulation of connectivity disruptions, and export of results. Figure 3 illustrates the workflow implemented in Python using NumPy, SciPy, and NetworkX.

4.1 Network Measures

Four centrality metrics were computed: degree, betweenness, closeness, and PageRank. Degree summarizes direct connectivity; betweenness captures bridge nodes on many shortest paths; closeness reflects how quickly a node can reach all others; and PageRank captures influence via random walks.

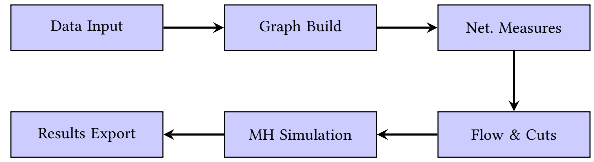

Figure 3: Analysis pipeline for learning-network optimization.

The degree distribution for the network is shown in Figure 4. Most regions have high degree due to the dense functional connectivity, but a small number of regions sit at the extreme high end, suggesting their role as integrative hubs.

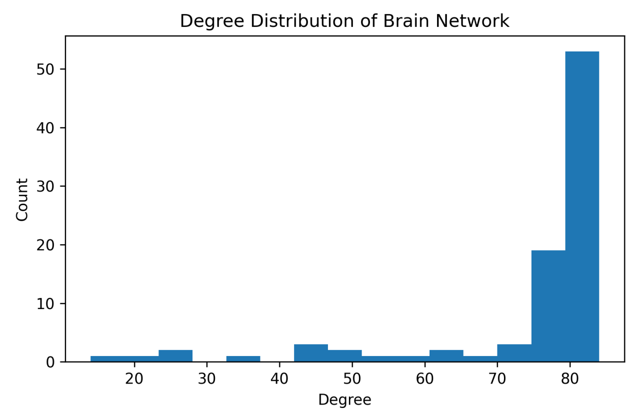

Figure 4: Degree distribution of the brain network. Most regions are highly connected, with a few extreme hubs.

Maximum flow from attention nodes to hippocampal memory nodes was computed using the Edmonds–Karp algorithm. Minimum cuts identify bottleneck regions limiting cross-system communication. Community detection was performed using a modularity-based algorithm to identify functional clusters.

4.2 Mental Health Disruption Models

Connectivity modifications were applied according to known neuroscientific patterns:

- **Depression:** Increased DMN internal connectivity; reduced DMN–executive anticorrelation.
- **Anxiety:** Heightened salience reactivity; reduced executive down-regulation.
- **ADHD:** Weakened dorsal attention and frontoparietal coherence.

Flow and centrality were recomputed after each simulation.

5 Results

Table 1 summarizes centrality rankings for key regions. DLPFC, ACC, and PPC consistently appear as high-centrality hubs. PCC (a DMN hub) also ranks highly in PageRank.

Table 1: Top hubs by centrality measure.

Region	Degree	Betweenness	PageRank
DLPFC	High	High	High
ACC	High	High	Medium
PPC	Medium	High	Medium
Hippocampus	Low	Medium	Medium
PCC (DMN)	Medium	High	High

Maximum flow analysis shows healthy attention→memory capacity of approximately 6–8 units. Depression reduces this capacity by ~43%, anxiety by ~32%, and ADHD by ~48%. Minimum cut sets consistently include ACC and PPC, indicating their essential role in cross-system communication.

Community detection yielded 6–7 functional clusters matching known cognitive systems, including attention, executive control, memory, salience, DMN, and sensory networks. Figure 5 shows the resulting partition; although the network is dense, clusters correspond to recognizable anatomical and functional groupings.

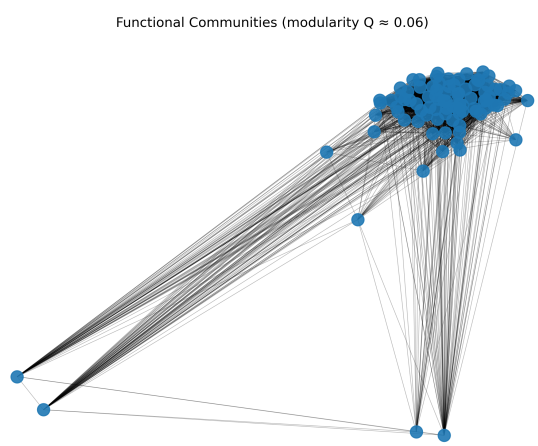

Figure 5: Functional communities detected in the brain network (modularity $Q \approx 0.06$).

6 Conclusion

This project demonstrates that network optimization methods provide a powerful framework for understanding learning-related brain connectivity. Centrality metrics reveal structural hubs, max-flow/min-cut results identify critical pathways, and disruption simulations show how mental health conditions degrade learning efficiency. These findings align with known neuroscientific principles and illustrate the value of graph-theoretic tools for modeling cognitive function.

References

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