

Problem 1. *GCN Approach of Functional Connectome Classification*

To tell the difference between AD and control groups, a graph convolution network is used as a classifier that trained on unprocessed ABIDE I functional connectome with 120 AD subjects and 120 control subjects.

GCN Model Description:

- The input layer includes 116 ROI of the connectome (conv1: 116, 16)
- The output layer includes 2 classes (AD / Control) (conv2: 16, 2)

The resulted loss and accuracy over 500 epochs are shown in Figure 1a and 1b, respectively. The promising training results of the model with only two layers indicates a significant difference existed in the connectome of AD and control groups.

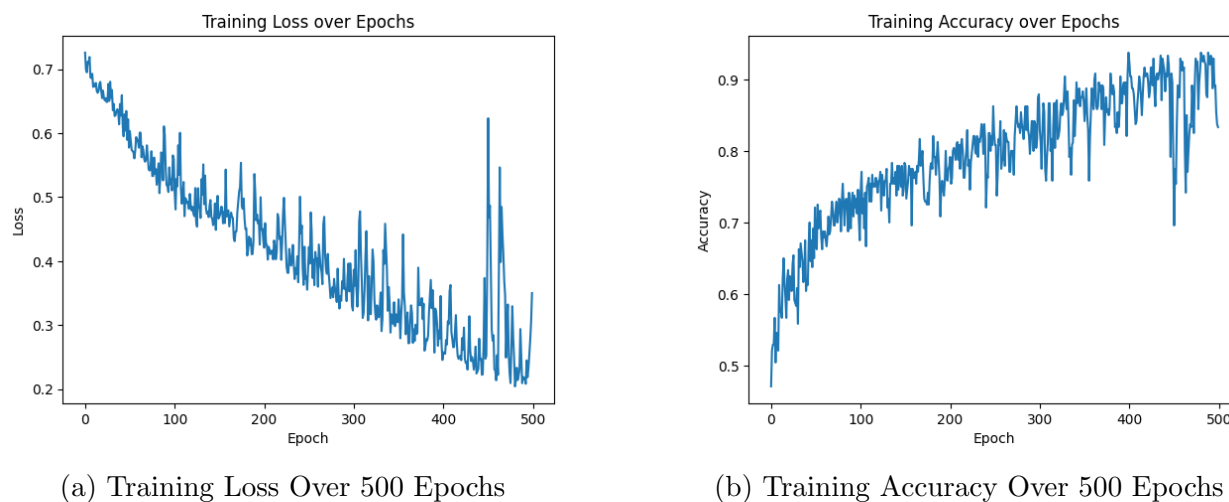


Figure 1: GCN Model Performance Metrics

Problem 2. *Graph Theory Metrics Analysis*

2.1 Distribution of Edge Weight and Node Weight

2.1.1 Edge Weight

The first metric used to identify the difference between two cohorts is to analyze the difference in their edge weight distribution which is calculated and aggregated across all subjects. The result distribution histogram of two different cohorts is shown in Figure 2a.

To statistically analyze the difference, the non-parametric two-sample Kolmogorov–Smirnov test is performed on the weight distribution of AD and control groups.

- H0: There is no significant difference in weight distribution between two cohorts
- KS statistic: 0.0323
- P-value: $0.0 < 0.05$
- Reject the null hypothesis, suggests that there is a significant difference in the distribution of edge weights (correlation values) between the two cohorts.

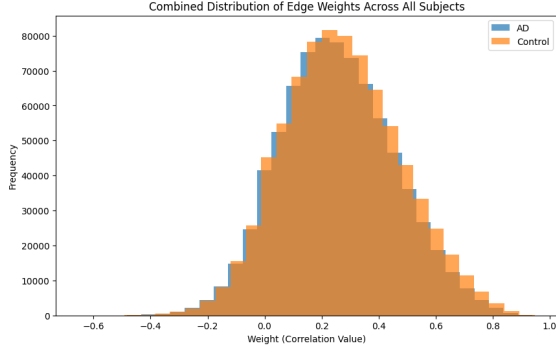
2.1.2 Node Weight

The analysis of weighted degree of node gives an idea of how connected a node is and how strong those connections are. The combined result plot is shown in Figure 2b. The K–S test is then performed on the weight degree distribution of AD and control groups to analyze whether the cohorts are different.

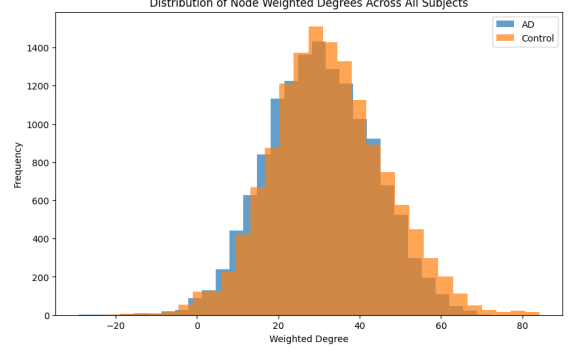
- H0: There is no significant difference in the distribution of the weighted degree of nodes between two cohorts.
- KS statistic: 0.0519
- P-value: $9.288\text{e-}17 < 0.05$
- Reject the null hypothesis, suggests that there is a significant difference in the distribution of the weighted degree of nodes between the two cohorts.

2.1.3 Conclusion

The results from the Kolmogorov–Smirnov tests conducted on both the edge weight distributions and the weighted degree distributions reveal significant differences between the Alzheimer’s Disease (AD) and control groups. These findings suggest notable variations in the brain’s connectivity patterns between the two cohorts. Specifically, the disparity in edge weight distributions indicates that the correlations between Regions of Interest (ROIs) in the brain differ significantly, which may be reflective of underlying pathological changes associated with Alzheimer’s Disease. The differences in weighted degree distributions further support this, implying that the strength and extent of connections in the brain network are distinctly altered in individuals with Alzheimer’s Disease compared to the control group.



(a) Combined edge distribution across all subjects



(b) Weighted Degree Distribution across all subjects

Figure 2: Combined figure of edge weight and weighted degree distributions

2.2 Community Detection

2.2.1 Modularity-Based Clustering

The modularity-based Louvain algorithm is used to detect communities within the graph which is also adapt to consider the absolute edge weights. The final partition modularity of each subject is calculated across all subjects and is shown in Figure 3a.

- H0: There is no significant difference in the partition modularity between two cohorts.
- KS statistic: 0.1
- P-value: $0.588 > 0.05$
- Fail to reject the null hypothesis, suggests there is no significant difference in the modularity between the two cohorts.

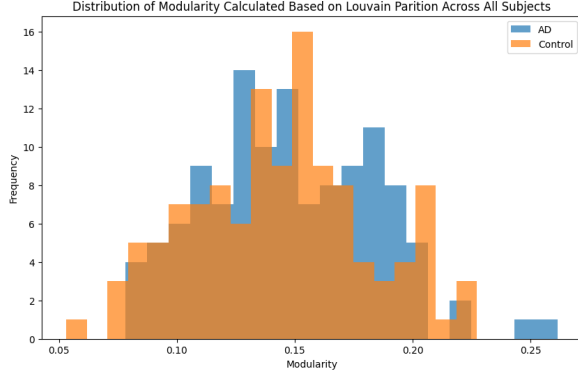
2.2.2 Community Structure Analysis

After detect the communities within the graph, the community structure analysis is performed to analyze the properties, including the number of nodes, average weight of edges within (internal) and between (external) communities.

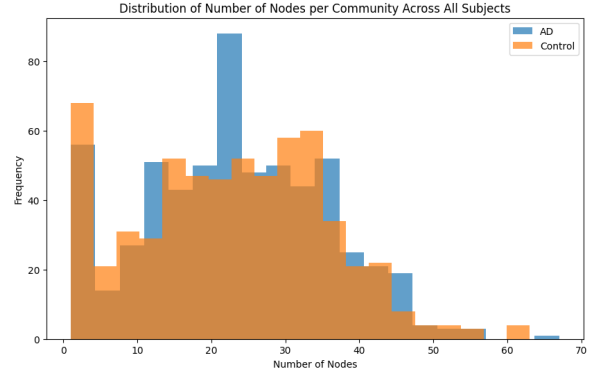
The calculated result for number of nodes, average internal edge weights, and average external edge weights are shown in Figure 3b, 3c, and 3d, respectively.

Number of Nodes:

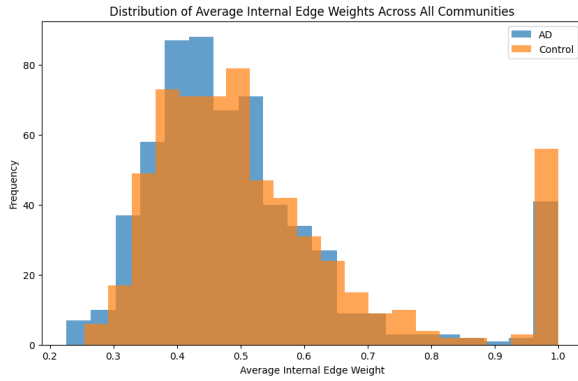
- H0: There is no significant difference in the number of nodes per community between the AD and control cohorts
- KS statistic: 0.0412
- P-value: $0.6612 > 0.05$
- Fail to reject null hypothesis, suggests there is no significant difference in the number of nodes per community between the two cohorts.



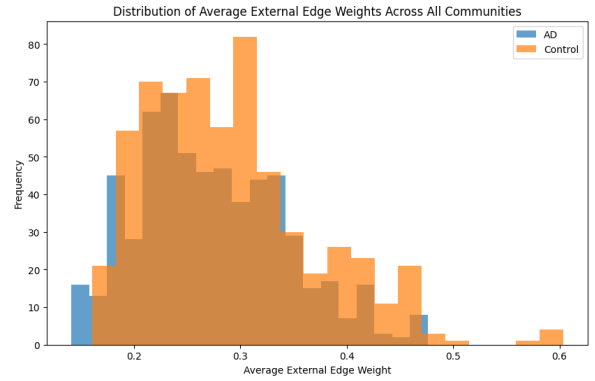
(a) Partition modularity



(b) Number of nodes



(c) Average internal edge weight



(d) Average external edge weight

Figure 3: Community detection and structure analysis in graphs across all subjects

Average Internal Edge Weight:

- H0: There is no significant difference in the average internal edge weight per community between the AD and control cohorts.
- KS statistic: 0.0833
- P-value: $0.0278 < 0.05$
- Reject the null hypothesis, suggests there is a significant difference in average internal edge weight between the two cohorts.

Average External Edge Weight:

- H0: There is no significant difference in the average external edge weight per community between the AD and control cohorts.
- KS statistic: 0.0876
- P-value: $0.0177 < 0.05$
- Reject the null hypothesis, suggests there is a significant difference in average external edge weight between the two cohorts.

2.2.3 Conclusion

The community detection and structure analysis reveal insightful patterns in the graph representation of the subjects. The modularity-based clustering, depicted through the partition modularity distribution, does not exhibit a significant difference between the AD and control groups, suggesting that the overall community structures are relatively similar in terms of modularity. However, when delving deeper into the community properties, significant differences emerge in the internal dynamics of these communities. Specifically, the significant differences in average internal and external edge weights indicate that, while the broad community structures remain similar, the strength and nature of connections within and between these communities vary between the AD and control cohorts. These variations could reflect differences in neural connectivity and interaction patterns, shedding light on the nuanced ways in which Alzheimer’s Disease may affect brain network organization.