# Exploring Predictor Communities Using Louvain Algorithm

## Introduction

This report outlines the steps taken to expand upon the initial results derived from the Boruta algorithm, which provided ranked predictors for each outcome. The primary goal of this subsequent analysis was to leverage the Louvain algorithm for community detection to identify clusters of outcomes and predictors, providing additional insights into their interrelationships.

## Methodology

### 1. Adjusting BinaryRank Threshold

A dynamic threshold was introduced to adjust the BinaryRank value, which determines the importance of predictors for each outcome. This allowed for interactive exploration of the most critical predictors based on varying thresholds.

### 2. Network Construction

A bipartite network was constructed using the predictors and outcomes. This network connects predictors to outcomes where their BinaryRank was deemed important. The network provided the basis for community detection.

### 3. Community Detection Using Louvain Algorithm

The Louvain algorithm, a modularity-based community detection method, was applied to the network to identify clusters of outcomes and predictors. Communities were defined as densely connected subgroups, reflecting shared relationships among predictors and outcomes.

### 4. Assigning Community Names

To enhance interpretability, communities were labeled based on the outcomes they included. For example, a community dominated by outcomes related to emotional states was labeled 'Emotional Outcomes.' Communities with no clear outcomes were excluded from further analysis.

### 5. Calculating an Importance Index

To summarize the influence of predictors within their respective communities, an 'Importance Index' was calculated for each predictor. The index was designed to assign higher positive values to predictors closer to the most influential rank, providing an intuitive measure of predictor importance.

### 6. Excluding Non-Informative Communities

Communities without meaningful outcomes (e.g., 'No Outcomes') were excluded from further analysis and visualization to maintain clarity and relevance in the results.

## Results

The results of the analysis revealed meaningful clusters of predictors and outcomes. These clusters offer clinicians a more structured approach to understanding predictor-outcome relationships and identifying key areas for intervention. Below, we outline the key findings and provide space for explanatory figures.

### Figure 1: Bipartite Network with Communities

Insert a visualization of the bipartite network showing Louvain communities here.

### Figure 2: Predictor Importance by Community

Insert the interactive dot plot or static visualization of predictor importance here.

### Figure 3: Community-Level Summaries

Insert a table or chart summarizing the most important predictors for each community here.

## Discussion

The incorporation of community detection into the analysis provided a richer perspective on predictor-outcome relationships. By identifying clusters, we were able to demonstrate patterns that go beyond individual predictor importance rankings, offering actionable insights for clinical decision-making. Additionally, the interactive exploration of thresholds allowed for dynamic refinement of the analysis.

## Conclusion

This expanded analysis highlights the utility of network-based approaches like the Louvain algorithm in uncovering meaningful structures within complex datasets. The insights derived from predictor communities complement the initial Boruta results and provide a valuable framework for clinical and research applications.