Clustering Goal-Directed Animal Behavior

Stanley Park, Alex Kumar

December 16, 2022

1 Introduction

The basal ganglia (BG) is an inner region of the brain known to regulate movement. To study the mechanism of the BG, we must be able to conduct experiments on complex movements, such as reaching behavior [1]. However, most studies in neuroscience today are confined to simple experiments, such as mice pressing levers for water [1]. This is primarily due to limitations in technology. Not only is tracking the movement of the mouse difficult, but segmenting the movement of the mouse into meaningful behaviors is challenging. The latter is critical to studying the mouse's behavior along with neural data. For instance, with the clustered time points, we can investigate how the neural activity of the BG facilitates the transition from drinking to aiming. Therefore, we investigated the effectiveness of the Louvain algorithm in clustering time-series reaching movement of a mouse into meaningful behaviors [3].

2 State of the Art

2.1 B-SOiD's HDBSCAN

The current state-of-the-art program used in neuroscience for behavior identification and segmentation is B-SOiD. There are many steps in the B-SOiD program, but the one we took special interest in was the clustering step. It uses Hierarchical Density-Based Spatial Clustering of Applica- tions with Noise (HDBSCAN) to cluster the data. HDBSCAN uses mutual reachability (MR) distance. This takes the max of distance to point a's kth NN, distance to point b's kth NN, and distance between a and b. Then, it constructs the minimum spanning tree using MR distance. Using the minimum spanning tree, it creates a clustering hierarchy, merging clusters based on the sliding threshold of MR distance. After setting a minimum cluster size value, a flattened cluster persistence graph is generated from the hierarchical clustering tree. HDBSCAN then chooses clusters with the largest area, the idea being that the most persistent clusters have the largest area. [2]

[1] Reaching behavior consists of the mouse aiming, reaching, retracting, and drinking

2.2 Issues

However, there are a few issues with the HDBSCAN output. First is the issue of choosing the value for hyperparameter minimum cluster size. This parameter influences how many clusters are output and is very sensitive. Either the number of clusters either is too few and doesn't allow for meaningful interpretation, or it outputs too many clusters, segmenting the larger behaviors we want for interpretation into its sub-behaviors. The second problem stems from the first. It is crucial to get the timing of the transitions between behaviors exactly right, as the transitions between different behaviors are going to analyze the basal ganglia when synced with the neural activity data. When the number of clusters is too few or too great, it doesn't allow for the behaviors to be synced in an interpretable way.

3 Methods

As we want to improve upon B-SOiD to achieve better, more interpretable clustering, we framed our problem as a community detection problem. As we have too many sub-behavior clusters and as we want larger interpretable behavior clusters, we can identify communities of sub-behaviors and collapse them into the interpretable behaviors! To do this, we used the Louvain community detection algorithm.

3.1 Louvain Algorithm

The Louvain algorithm maximizes over modularity, which is given by the equation:

$$H = \frac{1}{2m}\sum_{c}(e_c - \gamma\frac{K_c^2}{2m})$$

Intuitively, this maximizes the difference between the actual density of community c, or e_c, and the expected density of community c, or $\frac{K_c^2}{2m}$. Gamma, or γ, is a hyperparameter that we can adjust which adjusts our expectation of density, raising or lowering the threshold for moving a node to a new community. Therefore, adjusting γ will result in adjusting the number of communities we get at the end of the algorithm. [3] As we intuitively want four main behaviors - aiming, reaching, retracting, drinking - we added the constraint to only consider graphs with four nodes. As we observe these four main behaviors happening in a strict sequential order, we intuitively want the end graph to have a strong cycle of length four.

3.2 Resolution: γ

We iteratively adjusted the resolution, γ, of the Louvain algorithm over the range (0,2] with a step size of 0.01. At each iteration, we evaluated the quality of the clustering in two ways.

First, we identified any cycles in the clusters formed by the Louvain algorithm. We then measured the strength of each cycle using the following equation:

$$\textbf{Cyclic Strength}(\gamma) = \max_j(\sum_{E_i \in C_j} E_i) \tag{1}$$

For each γ, C_j represents the set of all edges in cycle j, and E_i represents the edge weight for edge i in C_j. We consider the cyclic strength of γ to be equal to the cycle with the maximum sum. This method is intuitively sound as the target sequences of behavior, which should form a cycle in the graph, should have the greatest transition probabilities, and therefore the greatest sum of the edge weights.

Second, we supervised the clustering using video tracking to evaluate the performance of the cluster generated by γ.

4 Results

4.1 Optimizing resolution

We found that the γ value corresponding to a graph with greater cyclic strength resulted in better clustering. We assessed this using raster plots, plotting the clusters against time over multiple reaching events.

4.2 Clustering using Louvain Algorithm Using Optimized Resolution

We were able to cluster the eleven nodes produced by B-SOiD into four clusters, each representing meaningful, interpretable behavior over time. We interpreted the four clusters to represent aiming, reaching, retrieving, and drinking. We evaluated the performance of the clusters based on the kinematics of the mouse's body parts (hand, nose, and mouth) over time, as well as observation using supervised video tracking.

5 Conclusion

We successfully clustered time-series events of reaching motion into four meaningful behaviors using the Louvain algorithm on top of B-SOiD's HDBSCAN clustering. We optimized γ of the Louvain algorithm by using cyclic strength values. We noted that sometimes the segmentation of aiming and drinking is less clear, with inappropriate overlaps. We also noted that sometimes the clusters have a few miliseconds of delay from the actual onset of the behavior, determined by kinematic values. Such are limitations we look to address in the future.

Professor Xiaobai Sun informed us of another method to optimize γ, parametizing γ as $\tan\theta$ By iteratively checking $0 < \theta < 90$ at small increments (eg 10), we are able to identify the optimal range of the γ. We plan to try this method to optimize γ next. We will also attempt to add kinematic values to the vertices of the graph to allow for even more effective clustering of the animal behavior.

References

[1] Claire E Geddes, Hao Li, and Xin Jin. "Optogenetic editing reveals the hierarchical organization of learned action sequences". In: *Cell* 174.1 (2018), pp. 32–43.

[2] Leland McInnes, John Healy, and Steve Astels. "hdbscan: Hierarchical density based clustering". In: *The Journal of Open Source Software* 2.11 (Mar. 2017). DOI: `10.21105/joss.00205`. URL: `https://doi.org/10.21105%5C%2Fjoss.00205`.

[3] Vincent A Traag, Ludo Waltman, and Nees Jan Van Eck. "From Louvain to Leiden: guaranteeing well-connected communities". In: *Scientific reports* 9.1 (2019), pp. 1–12.