Computational statistics for whole brain CLARITY analysis using the Open Connectome Project

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Challenge

- Statistically differentiate between three classes of mouse brains

Figure 1: Source: Author

Background

The CLARITY brain clearing technique is a method for studying neurological diseases by observing structure [5].

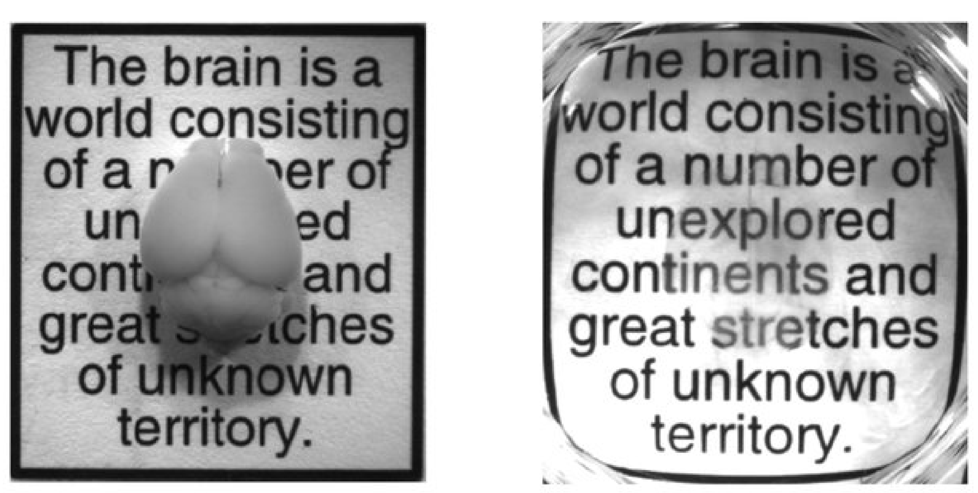

Figure 2: Effect of 'brain clearing' technique on a mouse brain. Source: New York Times

After the clearing process, each volume is imaged using light sheet microscopy.

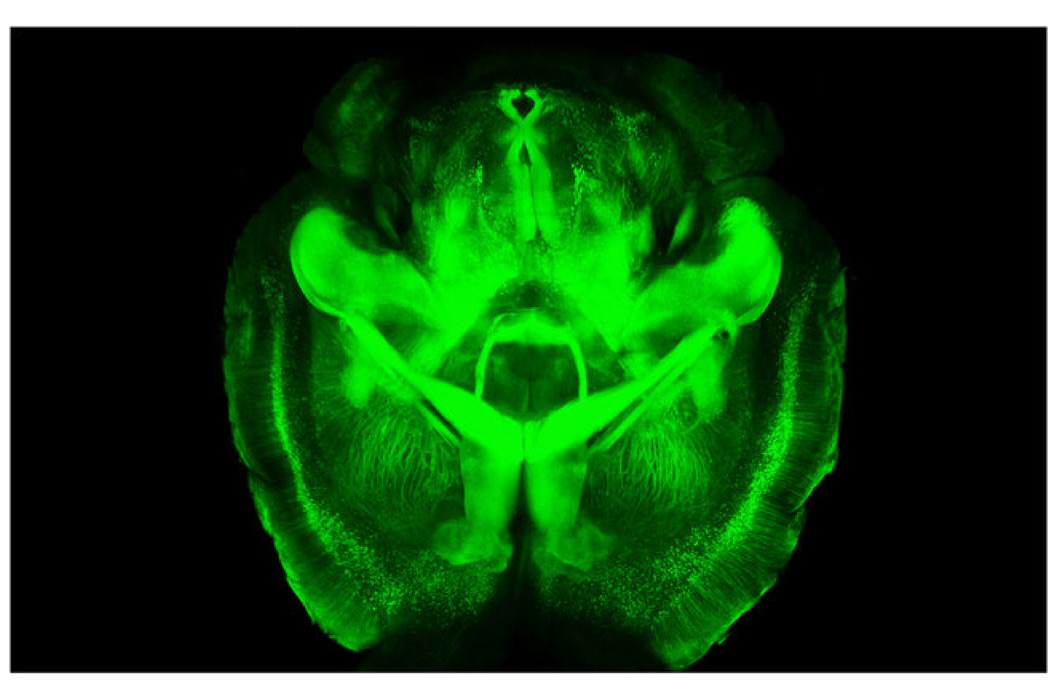

Figure 3: Mouse brain imaged with light sheet microscopy. Source: New York Times

Methods

- **Ingest data into the Open Connectome Project (OCP)**

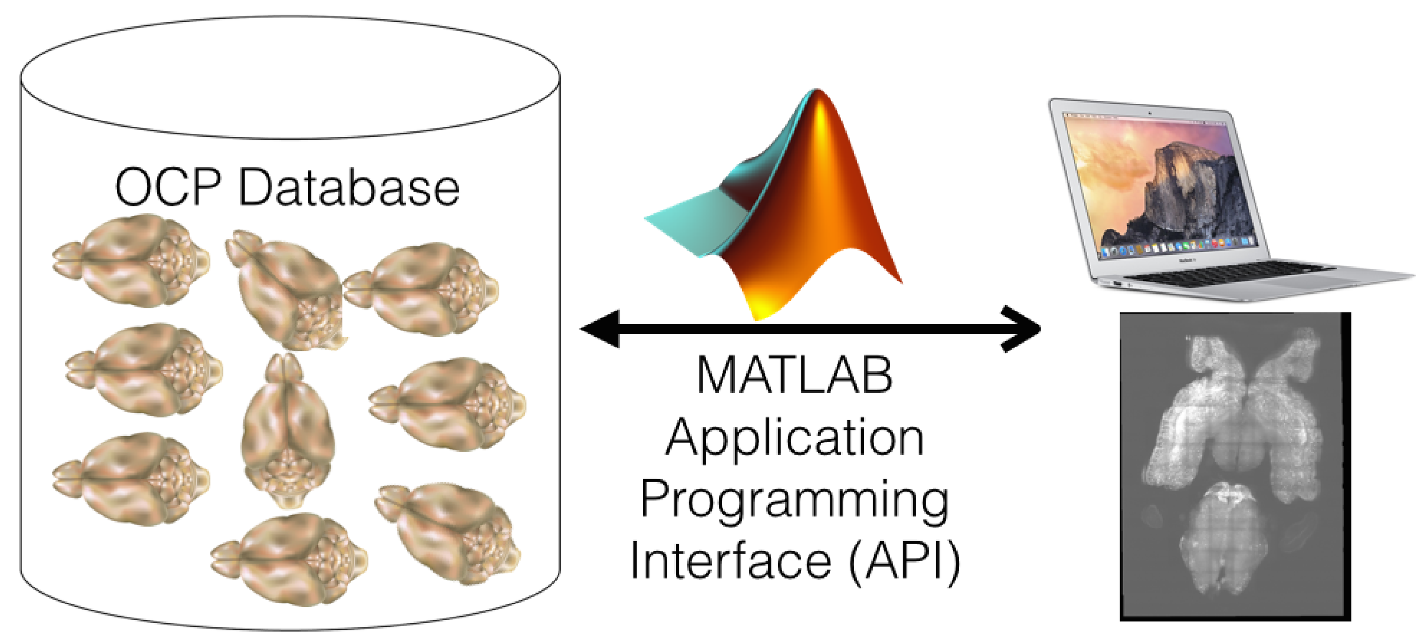

Figure 4: How OCP was used in this analysis. Source: Author

The data was hosted on servers at John Hopkins University. Using the MATLAB API, we queried data as needed for the analysis [1].

- **Register and Align to the Allen Mouse Brain Atlas**
  Each CLARITY volumes was aligned to the Allen Mouse Brain Atlas using non-linear transformations [4].

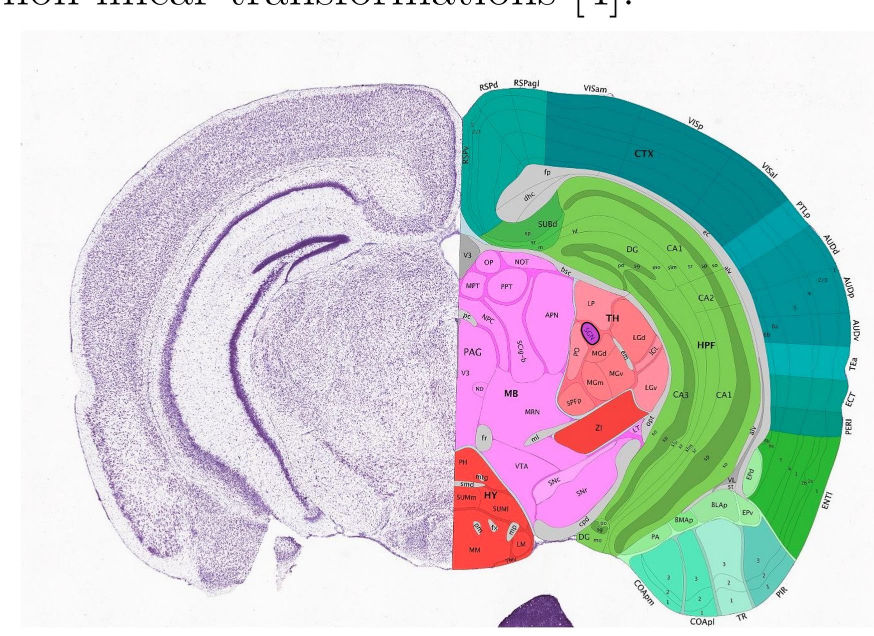

Figure 5: Coronal slice of the mouse brain atlas, indicative of the average atlas slice. Source: Allen Institute for Brain Science

- **Compute Haralick Features for each Region of Interest (ROI)**

  For each CLARITY Volume
  - Normalize volume (subtract mean, divide by standard deviation)
  - Extract ROI
  - Calculate 3D Co-Occurrence Matrix and Haralick Features [3]
  - Vectorize ROI and calculate mean, standard deviation

  Cluster and evaluate the features using the Adjusted Rand Index (ARI).

Results

- Demonstrated statistical differences between the various classes
- Small number of features (1-3) are sufficient for accurate classification

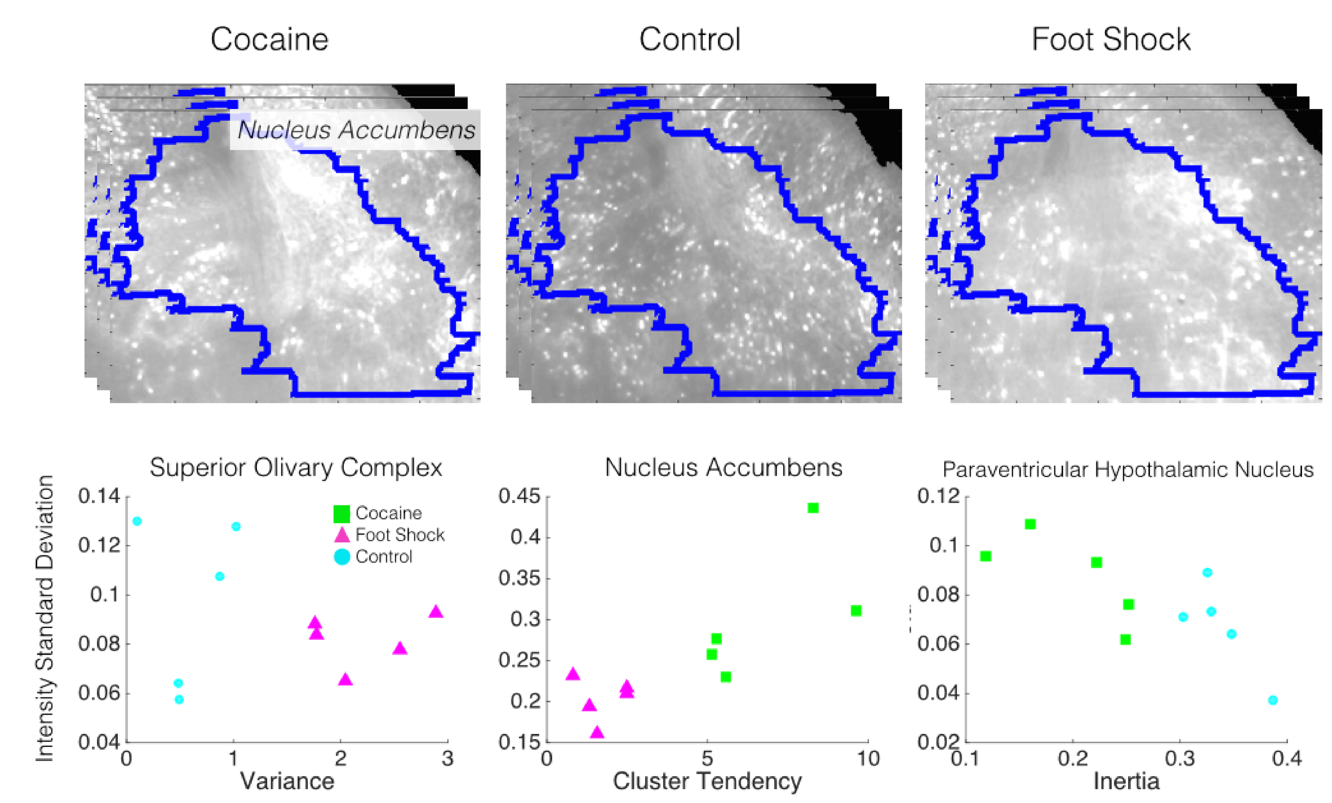

Figure 6: First row: Nucleus Accumbens under the 3 conditions. Second row: three pairwise comparison plots demonstrating accurate class separation. Source: Author

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- NIMH
- DARPA NeuroFAST

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