NEURAL DATA SCIENCE (NERDS) LAB

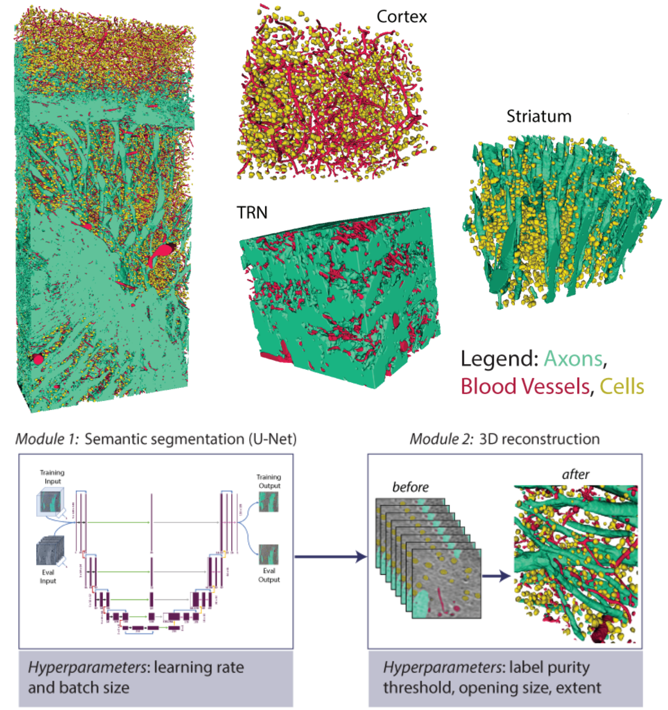
Georgia Tech

The **Neural Data Science (NerDS) Lab** focuses on the development of computational approaches for processing and understanding large scale neural datasets. Their research spans a range of areas in modern-day neuroscience such as computational neuroanatomy, connectomics, neurodegenerative disease modeling, diagnosis of traumatic brain injury, and population-level analyses of single unit data. Areas of interest on this front include dimensionality reduction, low-rank signal models, representation learning and optimization. The NerDS lab also supports the ideals of open science and is therefore invested in the interpretability of black-box systems, standardization and development of scalable data science workflows to accelerate neuroscience research.

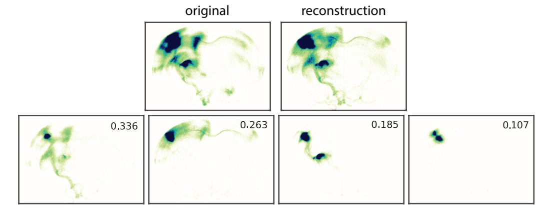
Left: Henry, Erik, Joe, Max and Aish hanging out at GT's local watering hole. Center: Aish, Eva and Joe at the Marine Biological Laboratory with one of Shinya Inoue's microscopes. Right: A bunch of the NerDS on a hike outside of Atlanta.

https://dyerlab.gatech.edu | http://github.com/nerdslab | evadyer@gatech.edu

Modeling brain architecture and organization across many spatial scales



Semantic segmentation (top) and black-box hyperparameter optimization (bottom) for multi-scale brain mapping



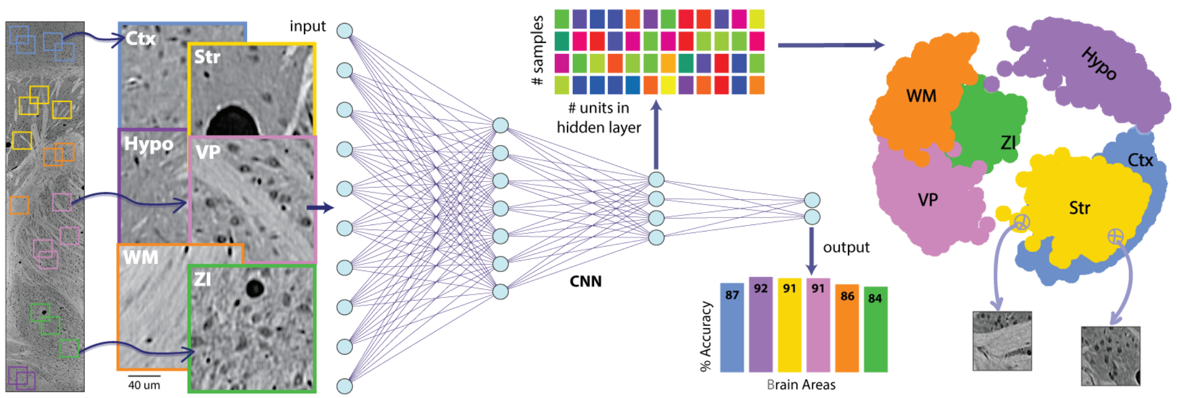
cell type-specific connectivity patterns learned from the Allen Mouse Connectivity Atlas

The lab is actively developing unsupervised learning and computer vision methods for modeling neural architecture and connectivity. Some recent projects have developed methods for: mapping and discovery of brain areas, finding layers in cortical and retinal tissues, and decomposing spatial maps of whole-brain connectivity. We are also developing global optimization approaches for system optimization across multi-stage pipelines to accelerate learning and inference on large neuroanatomy datasets.

Interactive atlas: http://bossdb.org/prasad2020

Related publications: Dyer et al., Quantifying mesoscale neuroanatomy using x-ray microtomography, eNeuro, 2017; Prasad et al., A three-dimensional thalamocortical dataset for characterizing brain heterogeneity.

Low-dimensional models and representation learning



Data often exhibit low-dimensional structure and can be thought of as being generated by far fewer latent factors than their ambient dimension. A core focus of the lab's work is in learning and leveraging low-dimensional structure in large-scale ensembles of data. We develop manifold learning and geometric signal processing methods to discover and interpret low-dimensional structure in data, and apply these methods to both datasets arising in anatomy (above) as well as physiology (see the panel to the right).

Related publications: Balwani and Dyer, Modeling variability in brain architecture with deep feature learning, Asilomar, 2019
Dyer et al., Greedy feature selection for subspace clustering, JMLR, 2014

Comparing latent distributions across time, space, and behavior

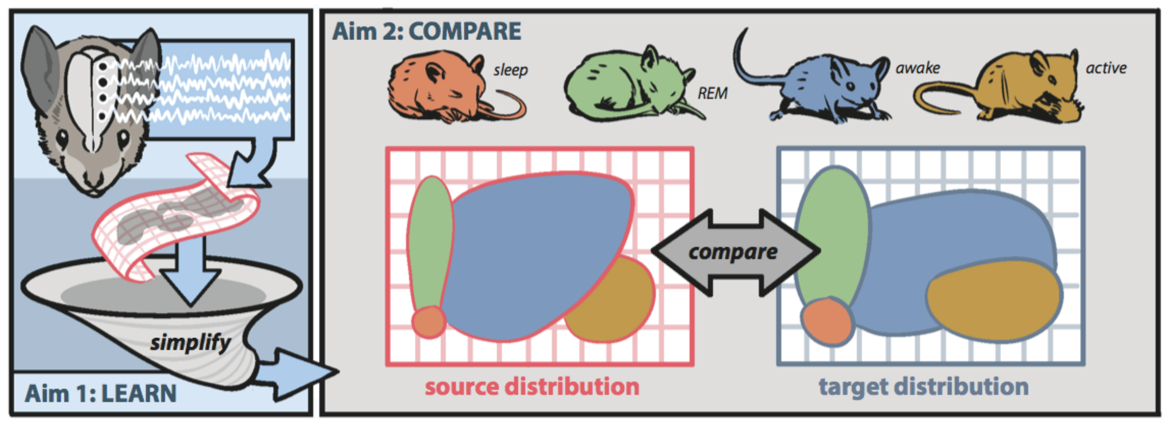


illustration: benjamin dewey, concept: eva dyer, ben bewey

In many settings, it is necessary to compare high-dimensional datasets. In this line of research in the lab, we tackle comparative analyses through the use of distribution alignment and optimal transport. With alignment methods, it is possible to solve a wide range domain adaptation and transfer learning problems.

Related publications: Dyer, et al., A cryptography-based approach for movement decoding, Nature BME, 2017; Lee, et al., Hierarchical optimal transport for multimodal distribution alignment, NeurIPS, 2019.

Code and additional info: http://nerdslab.github.io/neuralign