Neuronal classification from network connectivity

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Abstract:

The mammalian brain is a large network of neurons (~10^8 in rodents, up to 10^11 in humans), sparsely interconnected by synapses (~10^4 per neuron). Most synapses are directional contacts between extensive tree-like structures, namely the axon of the sending (output) neuron and the dendrite of the receiving (input) neuron. The ongoing assembly of complete maps of such circuits ("connectomes") is crucial to understanding the brain structure-function relationship. Yet analyzing and interpreting the forthcoming connectomic data remains an unsolved challenge, particularly in light of the huge number of neural connections expected in a single brain map. Although the exact connectivity pattern of each neuron is unique, the common working assumption posits the existence of distinct "neuronal classes," where neurons in the same class share similar connectivity patterns compared to neurons in different classes. Nonetheless, a rigorous definition of a neuronal class is still lacking, and even the order of magnitude of the number of neuronal classes is a source of wide disagreement.

Here we introduce a probabilistic model that formalizes the concept of neuronal class based on network connectivity. Given a complete list of all neurons and their connections in a network, we present a technique to estimate the number of neuronal classes, and an assignment of each neuron to a class. We model the connectome using a random dot product model. The connection probability is determined by the dot product of latent vectors associated with the pre- and post-synaptic neurons. We fit the model using sparse singular value decomposition, and cluster the latent vectors into groups, which define the proposed neuronal classes. Using neurobiologically realistic surrogate data, we demonstrate that this approach is robust and computationally tractable. This model provides both a practical and theoretical foundation to bridge neuronal- and system-level neuroanatomy.