JOHNS HOPKINS UNIVERSITY

Statistical Connectomics - Homework 3

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1 MODELING $\mathscr{Z}$

Prompt: For the Bock et al. (2011) Connectomics paper, propose a model for z , where z accounts for the directional selectivity of the neurons in the sample space.

Solution:

(1) Defining the sample space

First, let's define the other components of Ξ , the sample space. It includes all the neurons in the volume being studied. We have to account for the connectivity of the neurons($\mathscr{X}$, all the possible undirected graphs that can be constructed with the given number of neurons), their type ($\mathscr{Y}$, whether they are excitatory or inhibitory) and their responsiveness to stimuli ($\mathscr{Z}$, directional selectivity).

$$\Xi_n = \mathscr{X} \times \mathscr{Y} \times \mathscr{Z}$$

$$\Xi_n = (0,1)^{n\times n} \times \{0,1\}^n \times \mathscr{Z}$$

(2) Defining $\mathscr{Z}$

V1 neurons represent directional selectivity, which ranges from 0 to π. However, the orientations they encode can't be etirely continuous because that would necesitate an infinate number of neurons. So we need to chop up this continuum. Cool. There are many ways to do this. If we want to be super exhaustive, we can make $\mathscr{Z} = [180]^n$, because that's a good estimation of the maximum cognitive sensitivity for the orientation of line segments. But if we are to assume the population coding hypothesis for orientation selectivity, then we can get away with many fewer. A good estimation would be $\mathcal{Z} = [18]^n$, because many neurons are broadly tuned to a maximum output for around 10 degrees. This could even be too many, as the same thing can be accomplished with fewer groups of orientation selectivity (although a higher sensitivity to the firing rate is required, but that's another story), e.g. Bock et al. (2011) used 8. However, to be the most biologically accurate, which might be a good thing when modeling the brain, we propose using the 18 group model:

$$\mathcal{Z} = [18]^n$$

2 Structure of $\vec{\rho}$ and $\vec{\beta}$

In other SBMs, we've made $\vec{\rho} \in \Delta_k$ and $\vec{\beta} \in (0,1)^{k\times k}$. This comes from the most basic definition of SBM, where a scalar quantity (k, number of blocks) and two data structures are used to define the model. One of the data structures, $\vec{\beta}$, is a matrix that gives the probability that two vertices of different type are connected. The second data structure, $\vec{\rho}$, gives the group index of each node, so it 'tags' each node.

3 Special Notes

Modeling $\mathcal{Z}$ using stochastic block model (SBM) approach may not be the best approach in this instance. In a SBM, each node (neuron) is assigned to one of many k blocks based on the nodes to which they are connected and the connectivity pattern between the nodes. This is not the case of the neurons in the optical cortex, since they are not clustered based on their orientation preference. They simply take the input stimuli, fire based on their preference and send their signal to the closest interneuron in the second cortical layer. Some of them connect to each other, but not based on directional selectivity, so applying a SBM would group neurons in K blocks that may not be biologically accurate.