Computing a Generalized Logical Network from Neural Codes

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***Short Abstract* — Based on Across-Neural-Pattern theory, we planned to model the encoding and decoding processes that occur during neural activity. By preprocessing our data set into multiple resolutions based on window size and utilizing the sliding window approach to generate their values, we are learning to create a Generalize Logical Network. Our plan is to create two GLN networks; one for the encoding process and the other for the decoding process. Each network will consist of several resolution nodes and 4 stimulus nodes.**

***Keywords* — Generalize Logical Network, neural coding, and generative modeling**

I. Purpose

OVERALL, there are two theories proposed for understanding neural activity: Label Line theory and Across-Neuron-Pattern theory. Label Line theory suggests that a neuron, or a group of neurons, signal a specific stimulus. The Across-Neuron-Pattern theory argues that information of a stimulus is carried as a pattern from one neuron to the other. Based upon the Across-Neuron-Pattern, we've designed a Generalized Logical Network, or GLN, to model the encoding and decoding process of neural activity.

II. Data

Data was gathered by surgically inserting a tungsten probe roughly 200 micrometers from the NTS cell of 18 male Sprague-Dawley rats. [1] All subjects were exposed to 4 stimuli: 0.1M NaCl, 0.5M Sucrose, 0.01M Quinine HCl, and 0.01M HCl. Testing followed a strict procedure when introducing a stimulus: 10 second baseline period with no stimulus present, 5 second exposure to the stimulus, 5 second waiting period, and a 20 second distilled water rinse. Repeated stimulus exposure continued for as long as the cell was well isolated. Data was formulated into spike trains measured in milliseconds.

III. Methods

Our approach uses multi-resolutions to generate different nodes for our network. Resolutions are defined by the size of the window, or time period. When a window size is defined and applied to a spike train, we obtain the number of spikes that have occurred within the window, and then utilize the sliding windows approach to gather remaining values. For each value, we divide by a ratio, which causes the value to resist small changes; thus allowing uncertainty.

After completing this preprocessing method, we'll have a list of values for all resolution nodes at different times. Our network will contain several resolution nodes and 4 binary, stimulus nodes. A stimulus node is considered active, or assigned a value of 1, if the preprocessed spike train was exposed to the stimulus. For encoding, we'll infer parents for the highest resolution node; this node will be considered the spike node. For decoding, we'll infer parents for all stimulus nodes.

To begin the inference process, we'll generate states to create trajectories. A state is the set of value gathered from all nodes in the network at a certain time. As time increments, the set of states form a trajectory. Using the trajectories, we'll infer a GLN network and simulate our results back into trajectory for evaluation.

IV. Evaluation

The evaluation process for encoding will determine how well our results fair compared to spike trains characterized as having random spikes, no spikes, and all spikes. For each spike train previously mentioned, this process analyzes differences using the observed spike trains as a comparison. Once completed, we can determine whether our inference methods are producing adequate results by reviewing all 4 comparisons.

The evaluation process for decoding utilizes Receiver Operating Characteristic curves, or ROC curves. An ROC curves is produced for each stimulus. The threshold is compared to the number of times the specified stimulus was inferred "active" divided by the total number of states in the inferred trajectory.

V. Conclusion

Our results for encoding suggest looking for parents of resolution nodes found to be linked to the spike node. For decoding, relationships existed with lower resolution nodes. As we progress, we plan on using our initial results to construct a foundation for our future work.

References

[1] Di Lorenzo, P. M. and J. D. Victor: Taste response variability and temporal coding in the nucleus of the solitary tract of the rat. *Journal of Neurophysiology* 2003, 90: 1418-1431.

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