Detecting Clusters with Sensory Neurons

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Introduction

- The typical neuron consists of highly branched extensions called axons and dendrites. The axons sends signals out to other neurons, while the dendrites receive incoming signals. These signals are transferred using neurotransmitters and take place at the synapse. It has been proven that the connections between neurons can be strengthened or weakened due to outside influences. This idea is called neural plasticity[1].
- There are several mathematical models that can simulate the underlying mechanism of neuron signaling. The basis for many of this is Hebb rule, where it is proposed that when neuron A repeatedly participates in firing neuron B, the strength of the action of A onto B increases [2]. This led to the idea that changes in synaptic strengths in a neural network is a function of the pre-and post-neural activities [3].
- It has also been proven that sensory neurons become selective after a period of training, meaning that they will responds strongly to certain stimuli and weaker to others. In this experiment, data points were treated as stimuli and a model sensory neuron was built to detect clusters in data sets.

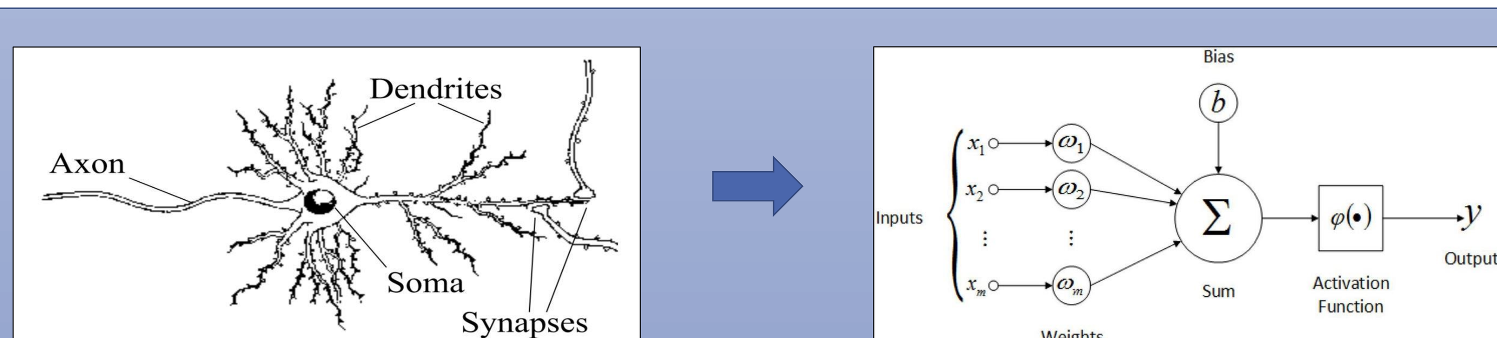


Figure 1: Anatomy of a neuron and the linear model for a neuron

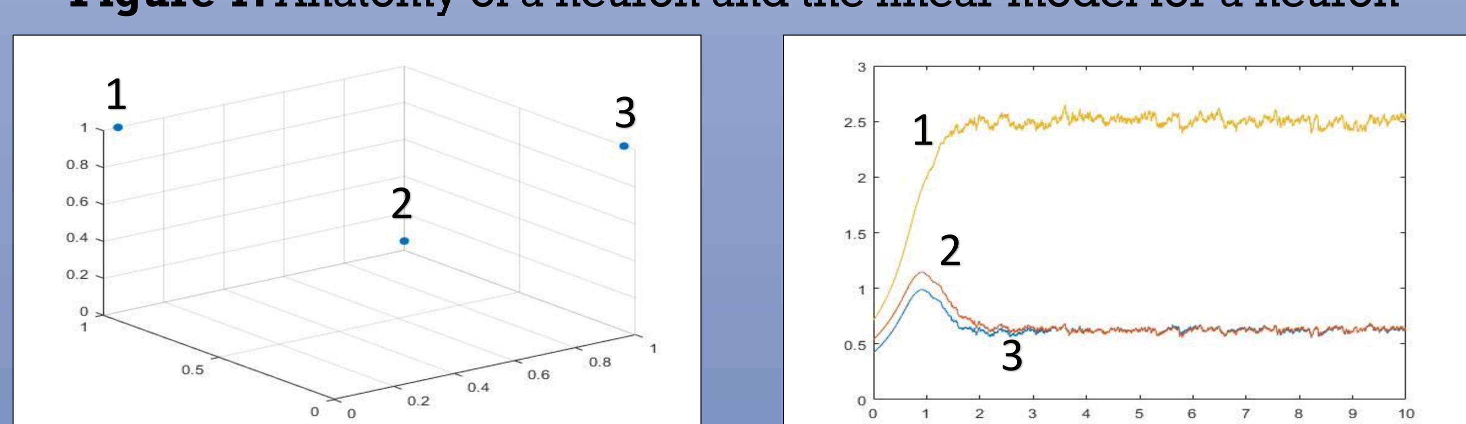


Figure 2: Synaptic responses of a sensory neuron on 3 arbitrary points, demonstrating selectivity

Methods

- Oja's rule is a variant of Hebb's rule which implements a decay term added to the synaptic weights. This results in spatial competition between inputs, which leads to neuronal selectivity. The differential form of Oja's rule equations are described below.

$$y = wx$$
$$\boldsymbol{w} = yx - y^2 w$$

- To simulate, the equations are also discretized to

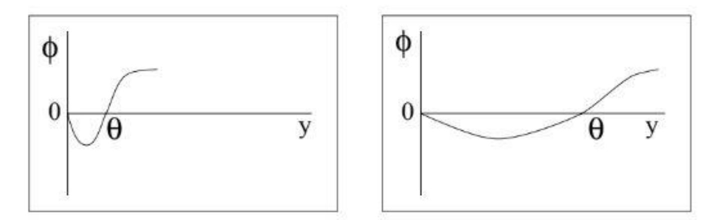
$$y_n = w_n x_n$$
$$w_{n+1} = w_n + \eta \Delta T (yx - y^2 w)$$

where η is the learning rate and ΔT is time in between iterations.

Methods Cont.

- BCM theory was introduced in [4] and presents a stabilized version of Hebb's rule by incorporating a function of postsynaptic activity Φ (y), which has a super-linear modification threshold θ.
- While there are many forms of the Φ function, the one used in this study follows the differential form of the BCM rule, resulting in

$$y = wx$$
$$\boldsymbol{w} = \eta y (y - \theta) x$$
$$\boldsymbol{\theta} = \boldsymbol{E}_{\tau}[y^2]$$



- To simulate the learning rule, the equations are discretized to

$$y_n = w_n x_n$$
$$w_{n+1} = w_n + \eta y (y - \theta_{n+1}) x_n$$
$$\theta_{n+1} = \theta_n + \frac{1}{\tau}(y^2 - \theta_n)$$

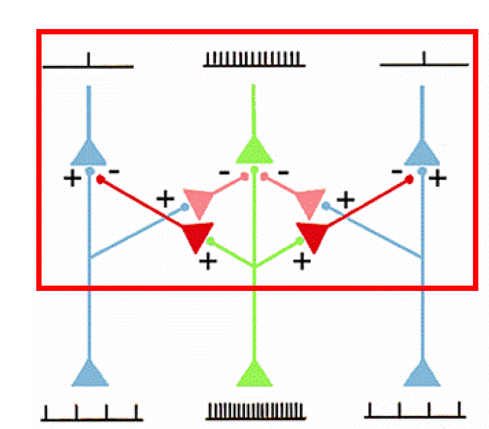
where η is the learning rate and τ is the threshold averaging constant.

- So far, both models described above deal with a single neuron, which can be trained with a dataset, and then clustered by removing stimuli with the highest synaptic responses.
- However, in the case of lateral inhibition, multiple neurons compete with one another with the expectation that after training, each neuron will become selective to a unique cluster.
- BCM based lateral inhibition uses the discretized matrix form,

$$\begin{bmatrix} y_a \\ y_b \\ y_c \end{bmatrix} = \begin{bmatrix} 1 & \gamma & \gamma \\ \gamma & 1 & \gamma \\ \gamma & \gamma & 1 \end{bmatrix}^{-1} \begin{bmatrix} S_a \\ S_b \\ S_c \end{bmatrix}$$

$$\begin{bmatrix} W_a \\ W_b \\ W_c \end{bmatrix}^{i+1} = \begin{bmatrix} W_a \\ W_b \\ W_c \end{bmatrix}^{i} + dt \cdot \eta \cdot diag\left(\begin{bmatrix} y_a \\ y_b \\ y_c \end{bmatrix} .\cdot \left\{ \begin{bmatrix} y_a \\ y_b \\ y_c \end{bmatrix} \begin{bmatrix} \theta_a \\ \theta_b \\ \theta_c \end{bmatrix} \right\} \right) \begin{bmatrix} x_i \\ x_i \\ x_i \end{bmatrix}$$

$$\begin{bmatrix} \theta_a \\ \theta_b \\ \theta_c \end{bmatrix}^{i+1} = \begin{bmatrix} \theta_a \\ \theta_b \\ \theta_c \end{bmatrix}^{i} + (1/\tau_\theta)\left(\begin{bmatrix} y_a \\ y_b \\ y_c \end{bmatrix}^2 - \begin{bmatrix} \theta_a \\ \theta_b \\ \theta_c \end{bmatrix} \right)$$



Conclusions

- Overall, the experiment was a success, as we were able to apply sensory neurons to create a cluster detection algorithm.
- It was proven that over many iterations, a sensory neuron will become more receptive to a very specific kind of signal and less receptive to others.
- Because of this selective nature of sensory neurons, data sets containing very distinct class types were more effectively clustered using the BCM and Oja's learning rules.
- When the lateral inhibition network was implemented, cluster detection accuracy improved across all the data sets, as the effects of selectivity were further exemplified.

Acknowledgements

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Results

- All results were obtained through MATLAB.

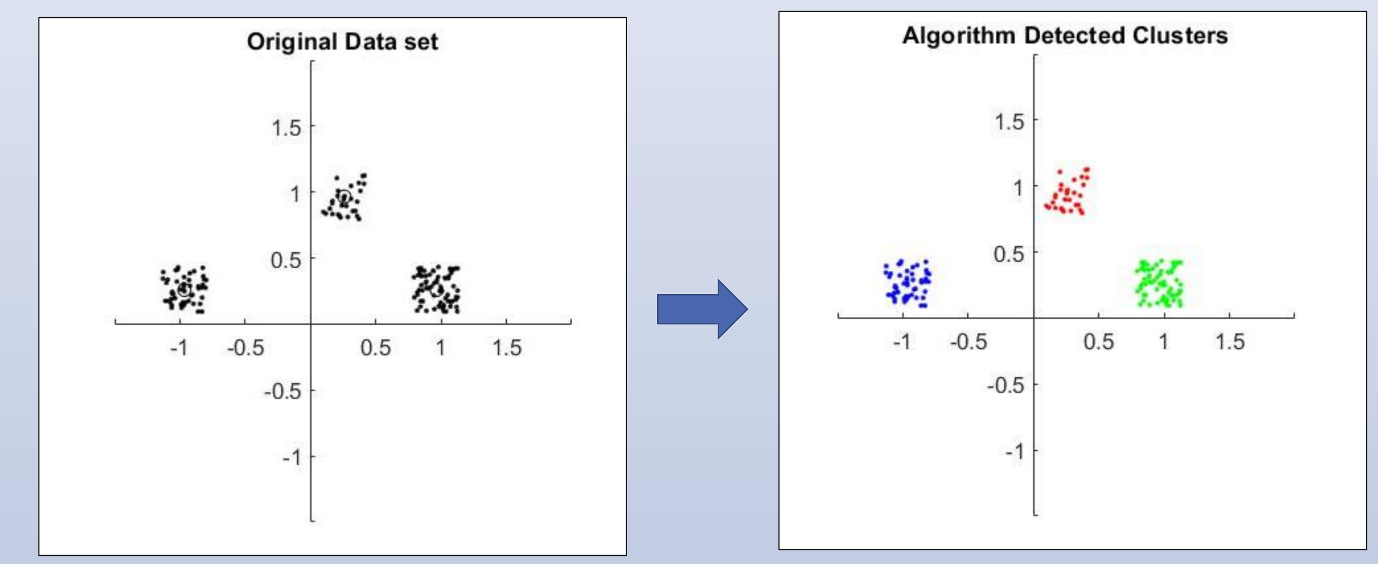

Figure 3: BCM neuron cluster detection on 2D data set

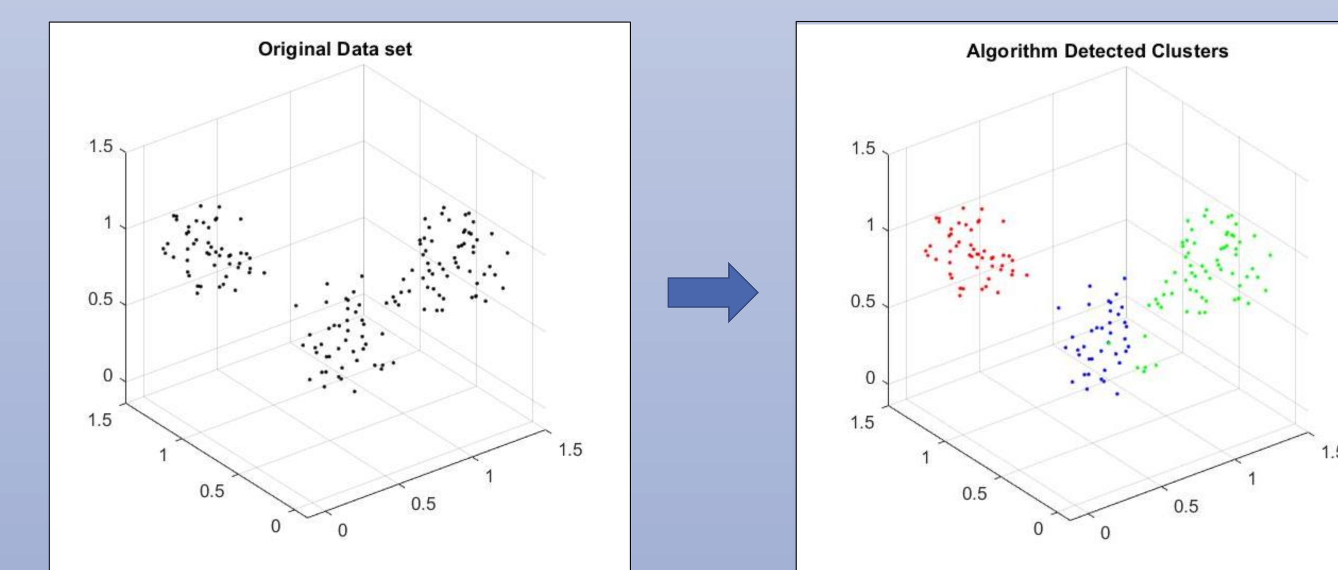

Figure 4: Oja neuron cluster detection on a 3D data set

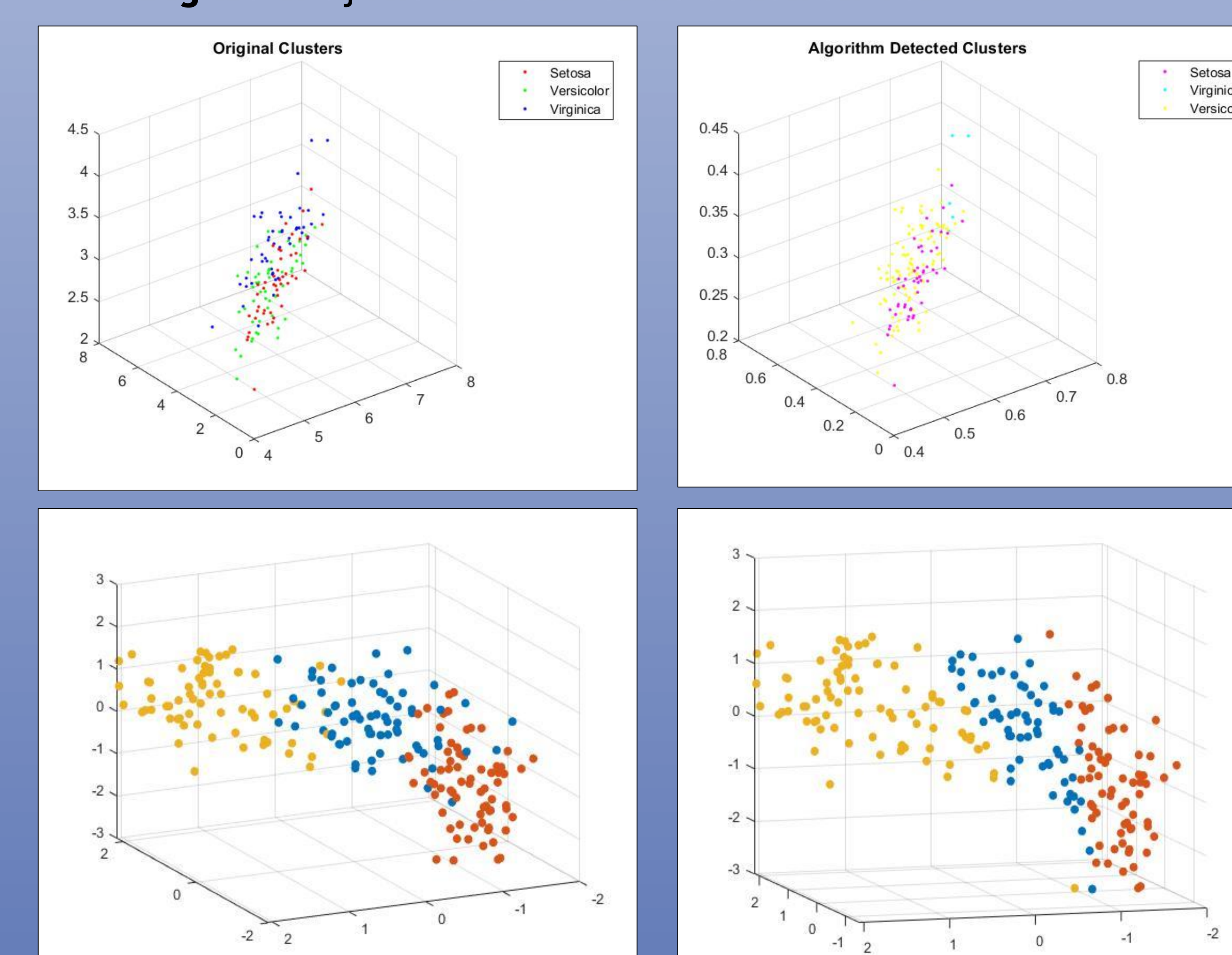

Figure 5: Single BCM neuron (Top) vs. three neuron lateral inhibition network (Bottom) cluster detection on Iris data set

References

[1] Jane B. Reece Berkeley, Lisa A. Urry Michael L. Cain, Steven A. Wasserman, Peter V. Minorsky, Robert B. Jackson Campbell Biology 10th Edition. Pearson Education, Glenview, Illinois, 2014.
[2] Donald Hebb The organization of behavior. New York: Wiley; 1949.
[3] Emergent Dynamical Properties of the BCM Learning Rule https://www.ncbi.nlm.nih.gov/ Lawrence Udeigwe, Paul W. Munro, G. Bard Ermentrout
[4] Bienenstock, Elie L., Leon N. Cooper, and Paul W. Munro. "Theory for the development of neuron selectivity: orientation specificity and binocular interaction in visual cortex." Journal of Neuroscience 2.1 (1982): 32-48.