

Classification and Information Propagation in Biological Reservoir Computers

Noah Chongsiriwatana, Ian Whitehouse, Anna Emenheiser, Jeneh Perry, Sylvester Gates III, Lahiru Wijerathna, Behtash Babadi, Wolfgang Losert

University of Maryland, Physics

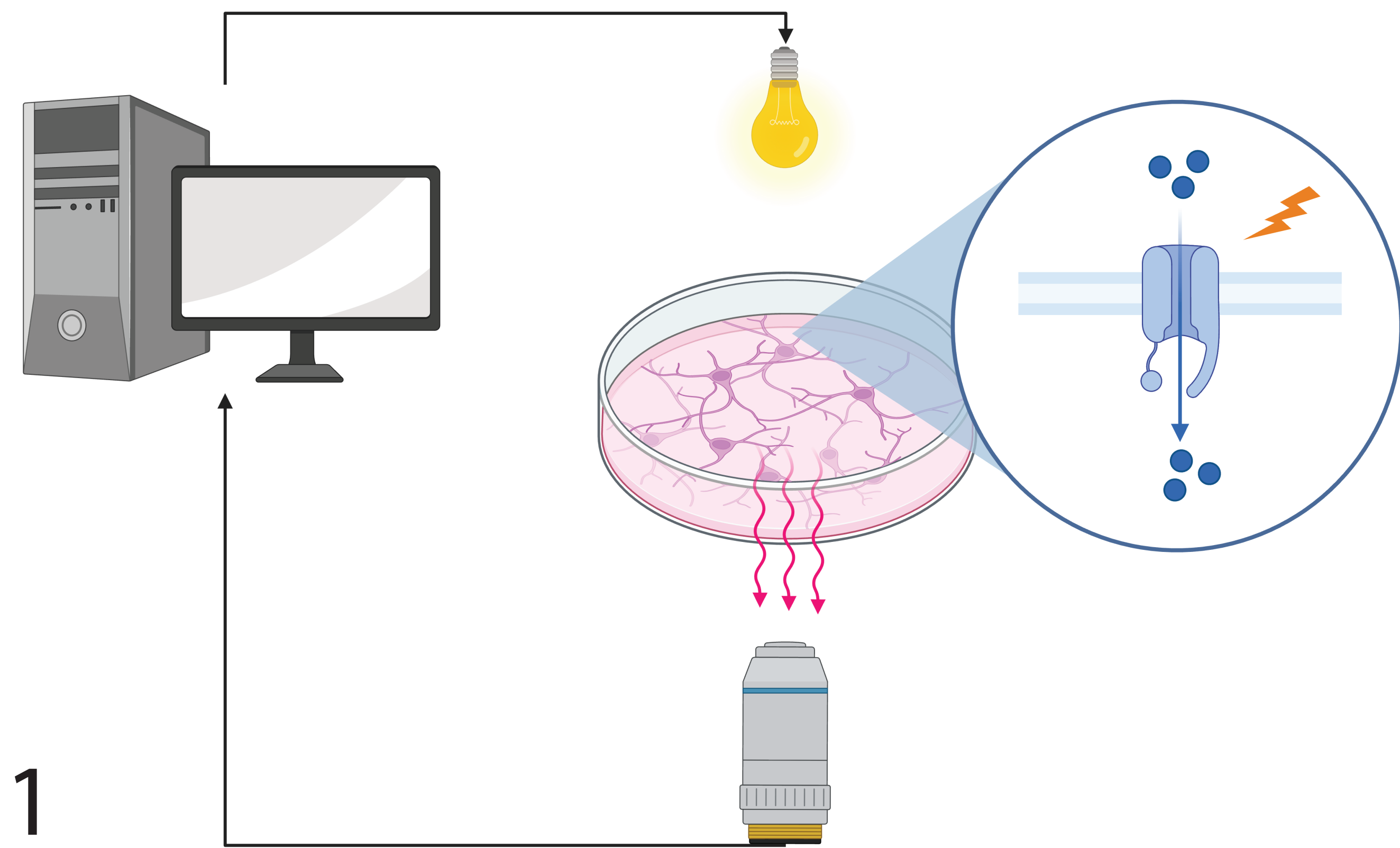


Computing Applications of Biological Neurons

On-chip learning has been a central theme of next generation hardware research. This allows for novel non-von Neumann learning approaches, which may prove to greatly reduce the energy cost and increase the capabilities of AI models. We argue that to continue discovering novel, neuromorphic learning algorithms, an increased understanding of the network-scale mechanics of living neural networks is required. To do this, we harness living neural networks directly as a computing element, implementing biological neural networks as an information processing device. We use the networks as a reservoir computer, applying it to two tasks: MNIST digit classification, and MNIST digit classification with induced STDP.

Optically Interfaced Biological Neural Networks

Our computing platform with biological neural networks is based on neural cells obtained from rat embryos via dissection. Cells were infected with a viral vector to artificially insert two genes into the cells, jGCaMP8s [1] and ChrimsonR-ST [2]. Then, these genes expressed fluorescent calcium indicator proteins and optically activated ion channels respectively, allowing action potentials to be triggered and measured during experiments. The process is shown in Figure 1.



Classification and Information Propagation

To measure how information flowed within the neural reservoir, the cells were shown the 0 and 1 MNIST digits [3]. After stimulating a central region with a given image, we measured the responses of neurons as seen in Figure 2 [4]. Two linear classifiers were then trained separately on both the stimulation region (tinted grey in Figure 3a) and the response region (tinted red in Figure 3a). Our experiments confirmed that information input via spatially patterned photostimulation was processed by the reservoir, then transmitted with low loss to the response region.

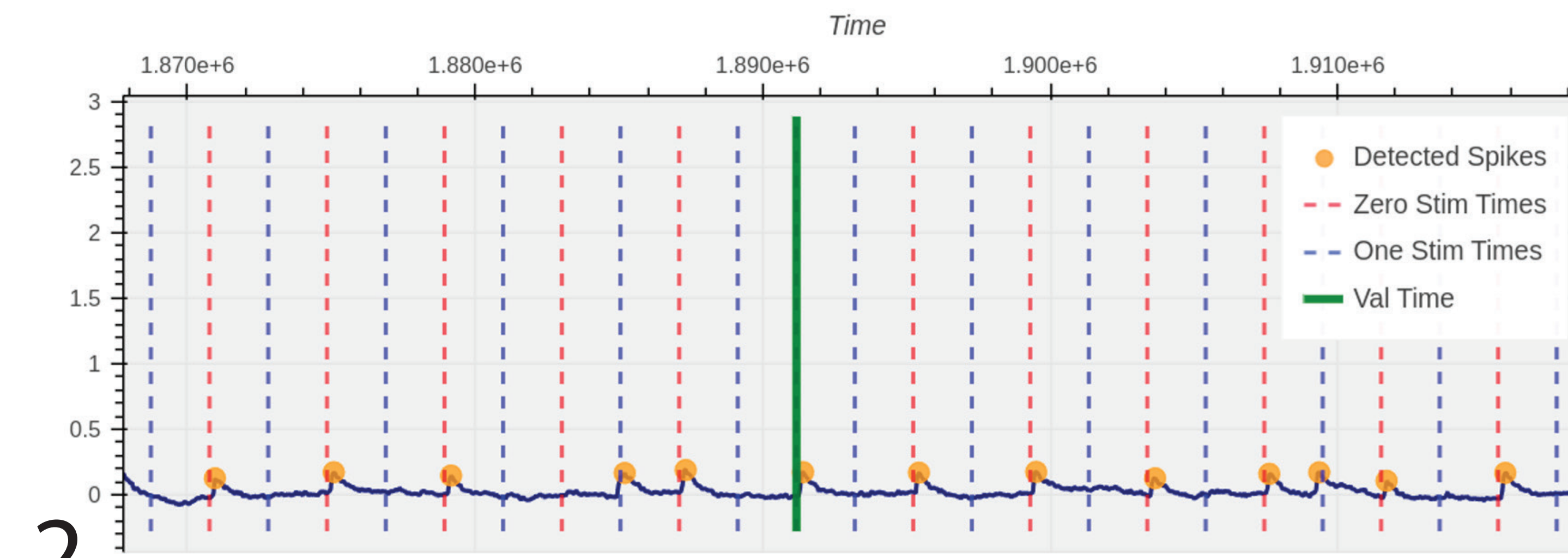
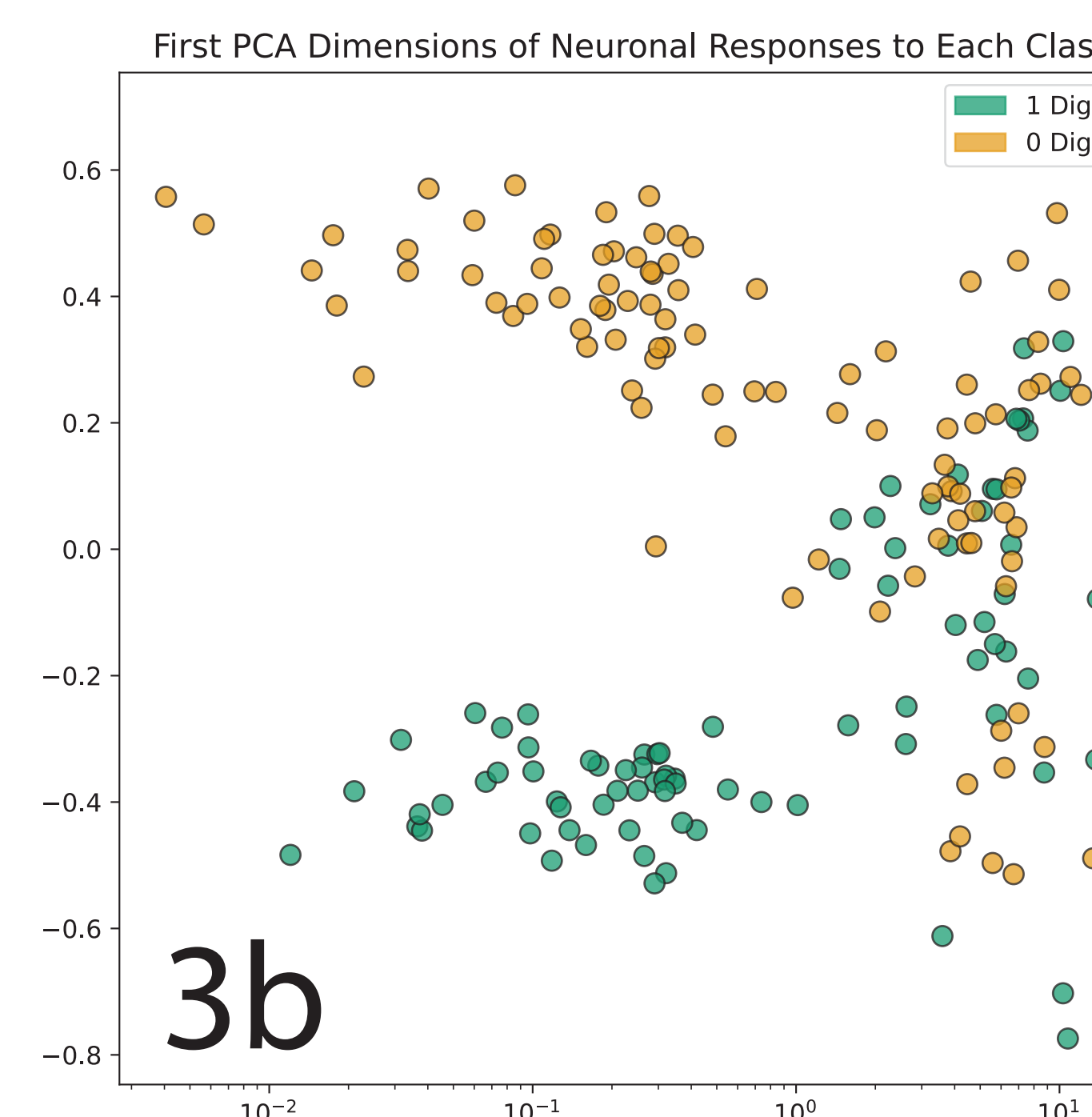


Figure 3b, based on the recording of these neurons, shows that the responses to the two classes are linearly separable. In addition, we see in Figure 3c that usable information does flow from the stimulated region to the unstimulated region since the linear decoder shows strong performance on the test set in both regions.



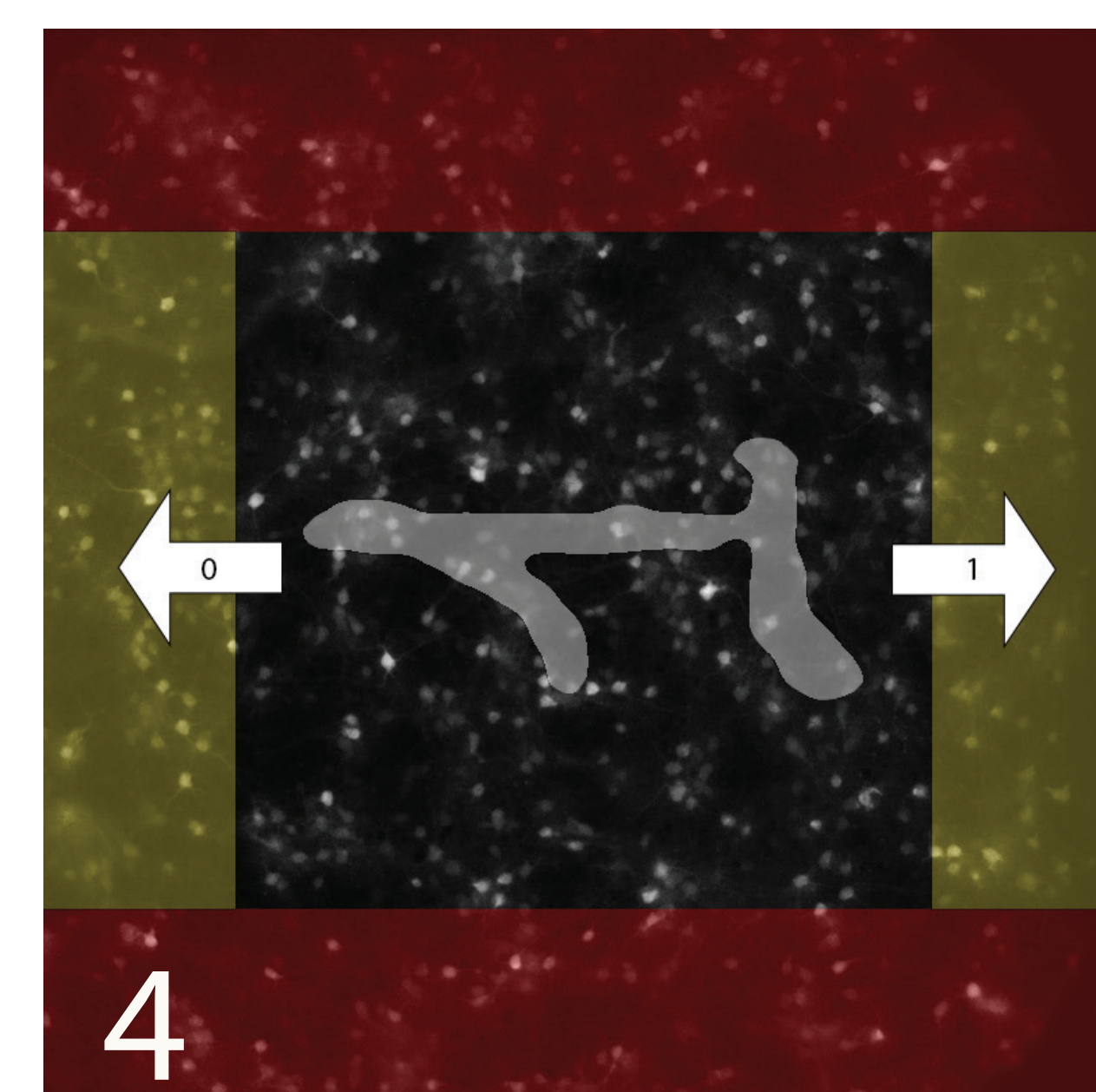
3c

Region	Precision	Recall	F1-Score
Stim.	0.95	0.95	0.95
Non-stim.	0.96	0.96	0.96

Classification with Spike Timing Dependent Plasticity

We additionally performed experiments to induce class-based spatial bias in neural responses. We modified our stimulation procedure to include one additional step, which

took advantage of the spike timing dependent plasticity (STDP) mechanism. Following the onset of stimulation with a digit image (tinted grey in Figure 4), a region to the left or right of the image (tinted yellow in Figure 4) was stimulated 15 ms later. This timing is within the window for STDP to occur [5]. After this training period, a validation period took place where digits were stimulated without direct stimulation of the response regions.

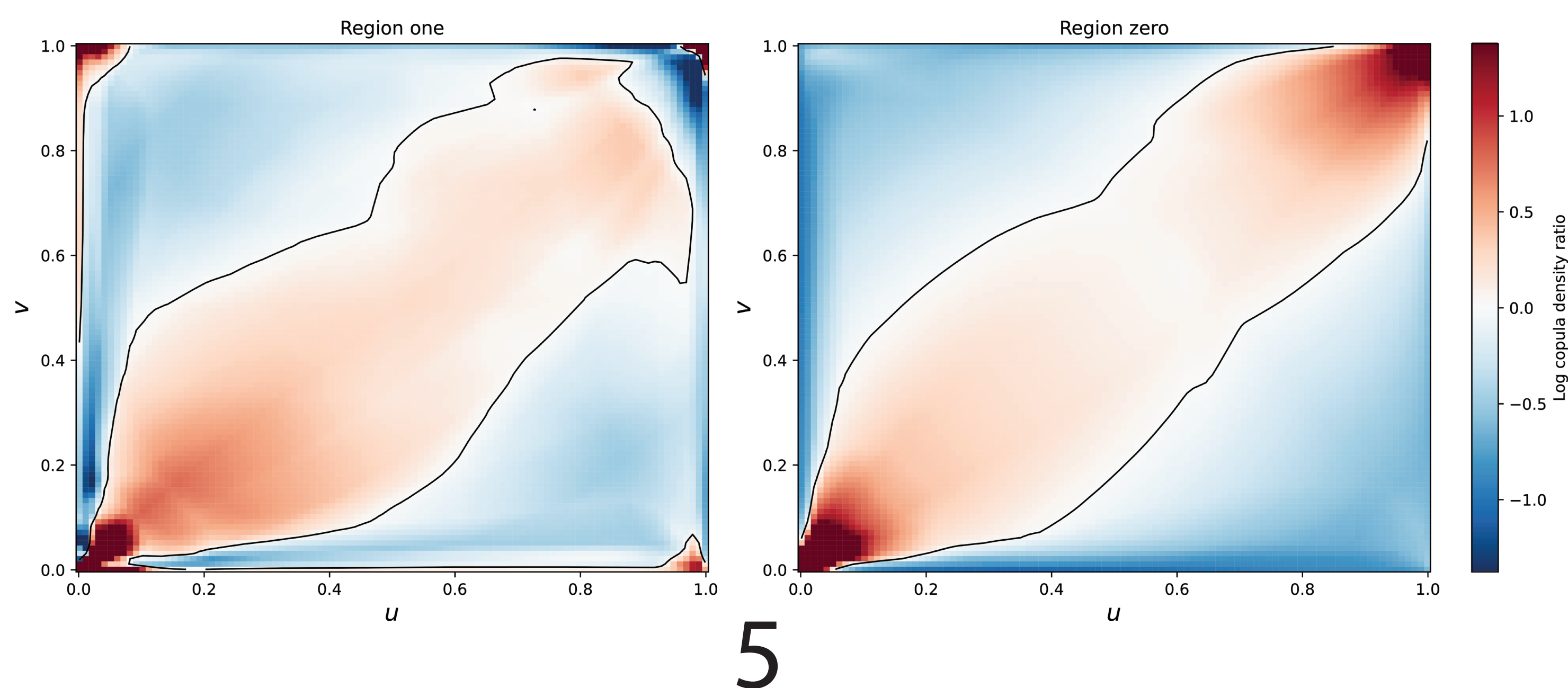


STDP Induced Selective Synchronization

To compare the preferred stimulus against the alternative stimulus within a given region during the validation phase, we consider the log copula density ratio.

$$\Delta_r(u, v) = \log c_{r,\text{pref}}(u, v) - \log c_{r,\text{alt}}(u, v) = \log \left(\frac{c_{r,\text{pref}}(u, v)}{c_{r,\text{alt}}(u, v)} \right)$$

Figure 5 illustrates the log copula density ratios for each region. High values indicate regions of copula space (red) where the preferred stimulus assigns greater dependence mass, while low values indicate stronger relative mass under the alternative stimulus (blue). In particular, elevated values near the diagonal indicate more synchronized responses under the preferred stimulus, whereas negative values away from this structure suggests deviation from this dependence structure under the alternative stimulus.



Conclusion

Biological neural networks demonstrate performance capabilities along with unique learning mechanisms. The MNIST classification task highlighted how neurons can process and transmit spatial information robustly. MNIST classification in conjunction with STDP activation induced selective synchronization. This implies that the group firing observed in induced STDP neural networks are spatiotemporal patterns which require group observations to detect.

References

1. Zhang Y. et al., Nature 615, 7954 (March 2023), 884–891
2. Klapoetke N. et al., Nature Methods 11, 3 (March 2014), 338–346
3. Lecun Y. et al., Proc. IEEE 86, 11 (1998), 2278–2324
4. Takuma Sumi T. et al., Proceedings of the National Academy of Sciences 120, 25 (2023), e2217008120
5. Caporale N. and Dan Y. 2008. Annual Review of Neuroscience 31, Volume 31, 2008 (July 2008), 25–46