EXCITATORY AND INHIBITORY NEURONS EXHIBIT DISTINCT ROLES FOR TASK LEARNING, TEMPORAL SCALING, AND WORKING MEMORY IN RECURRENT SPIKING NEURAL NETWORK MODELS OF NEOCORTEX

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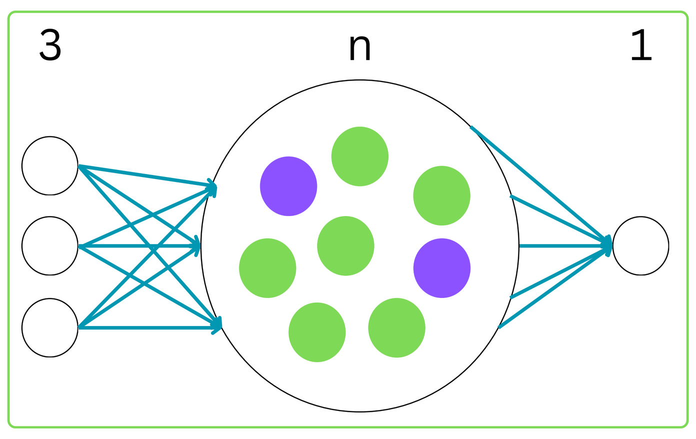
1. Introduction

Recurrent Spiking Neural Networks(RSNNs) are machine learning algorithms that use spiking neurons to learn tasks. They are biologically realistic models of neocortex due to their recurrent and spiking nature, and they hold potential for illuminating cortical dynamics and computations. The brain contains various of excitatory (pyramidal cells) and Inhibitory (PValb, SST, 5Htr3a) neuron types. Each neuron takes on unique responsibilities like inhibition, disinhibition, excitation, amplification, temporal scaling etc. The specific roles of distinct inhibitory neuron subclasses in RSNN models for learning temporal tasks remain unexplored. To address this, we developed a framework to analyze the roles of distinct interneuron types in temporal task learning.

2. Network



3. Biological Realism

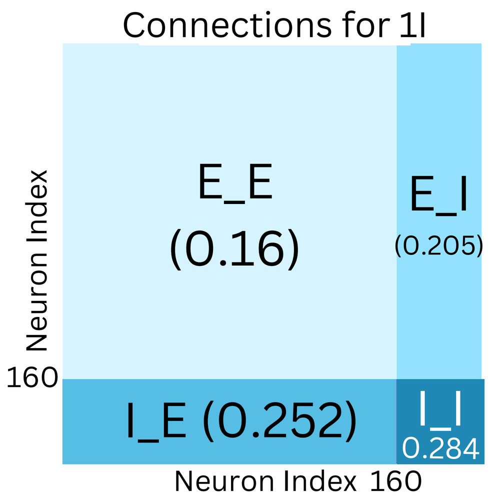
- 3 Interneuron Subclasses:

E	PValb	SST	5Htr3a
β = 0.85	β = 0.7	β = 0.3	β = 0.6

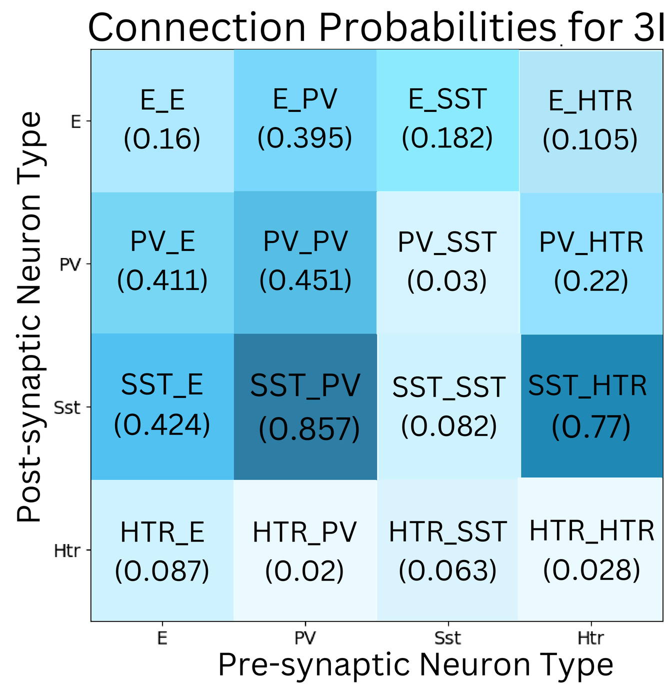
$$V_{t+1} = \begin{cases} \beta \cdot V_t + I_{t+1}, & \text{if } V_t < V_{\text{thresh}} \\ V_{\text{reset}}, & \text{if } V_t \geq V_{\text{thresh}} \end{cases}$$

- E:I = 4:1
- Sparse Connectivity
- 5 ms refractory period

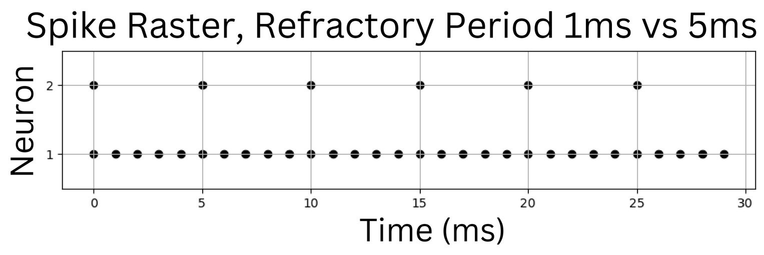
Connections for 1I



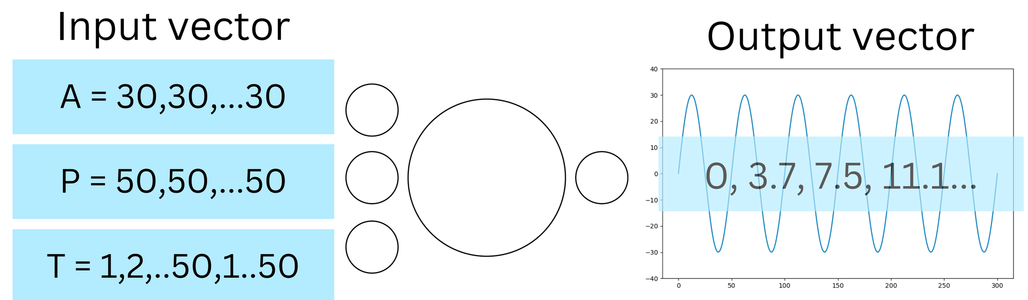
Connection Probabilities for 3I



Spike Raster, Refractory Period 1ms vs 5ms



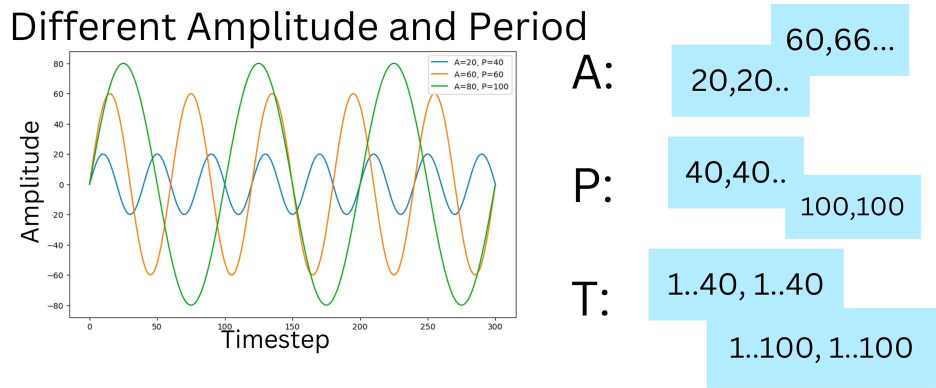
4. Sine Wave Task Structures



Variations:

a.Changing Period & Amplitude

Different Amplitude and Period



b. Amplitude and Period provided for the first 10 ms

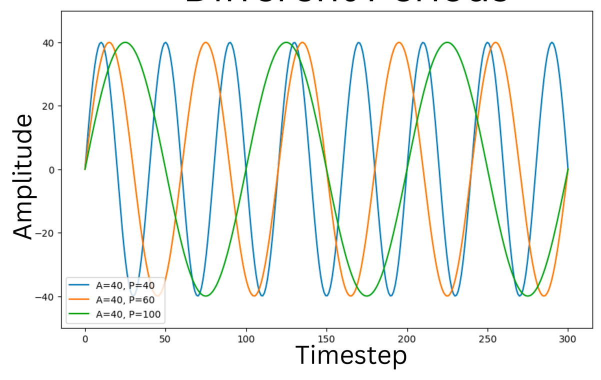
30,30, 30, ... 0,0

50, 50, 50, ... 0,0

1,2,50,1,...50

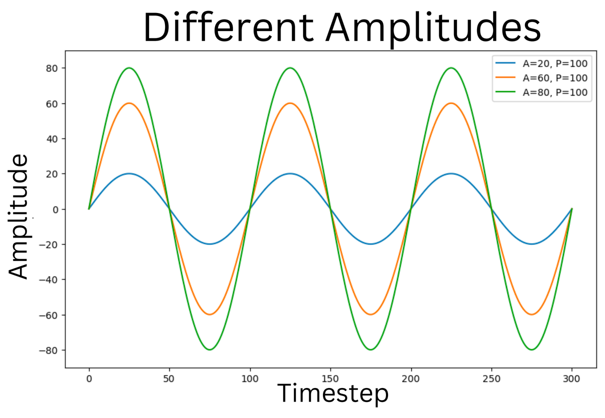
c. Changing period, constant amplitude

Different Periods



d. Changing amplitude, constant period

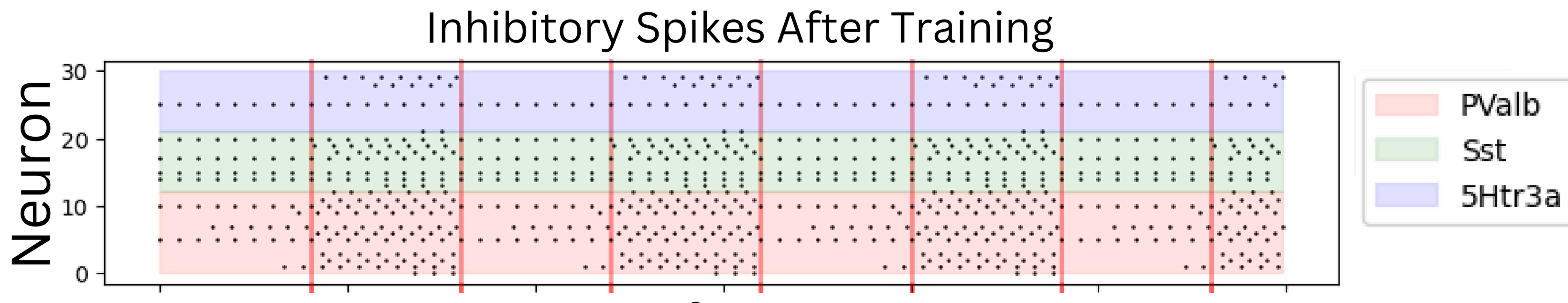
Different Amplitudes



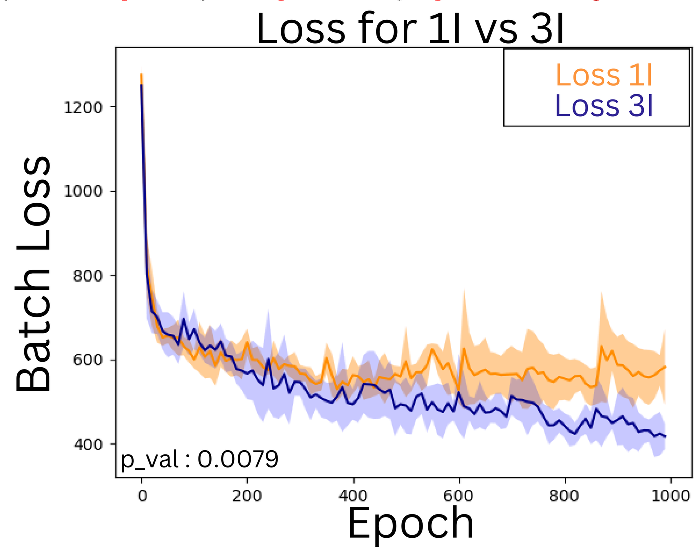
5. Roles of I and E Neurons

a. Interneuron subclasses create varied timescales, improving temporal task performance.

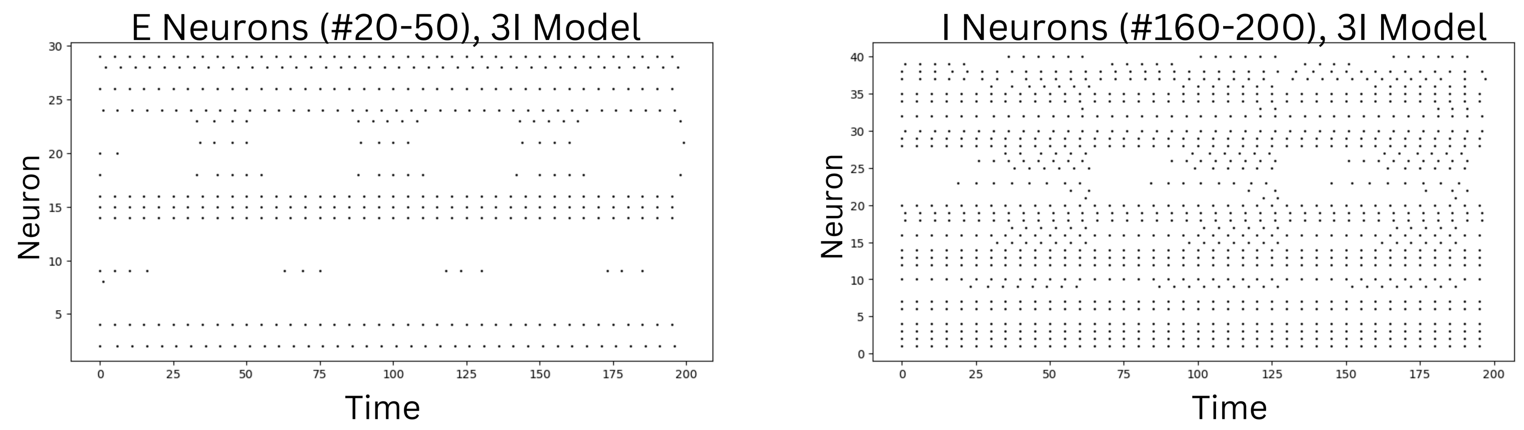
Inhibitory Spikes After Training



Loss for 1I vs 3I

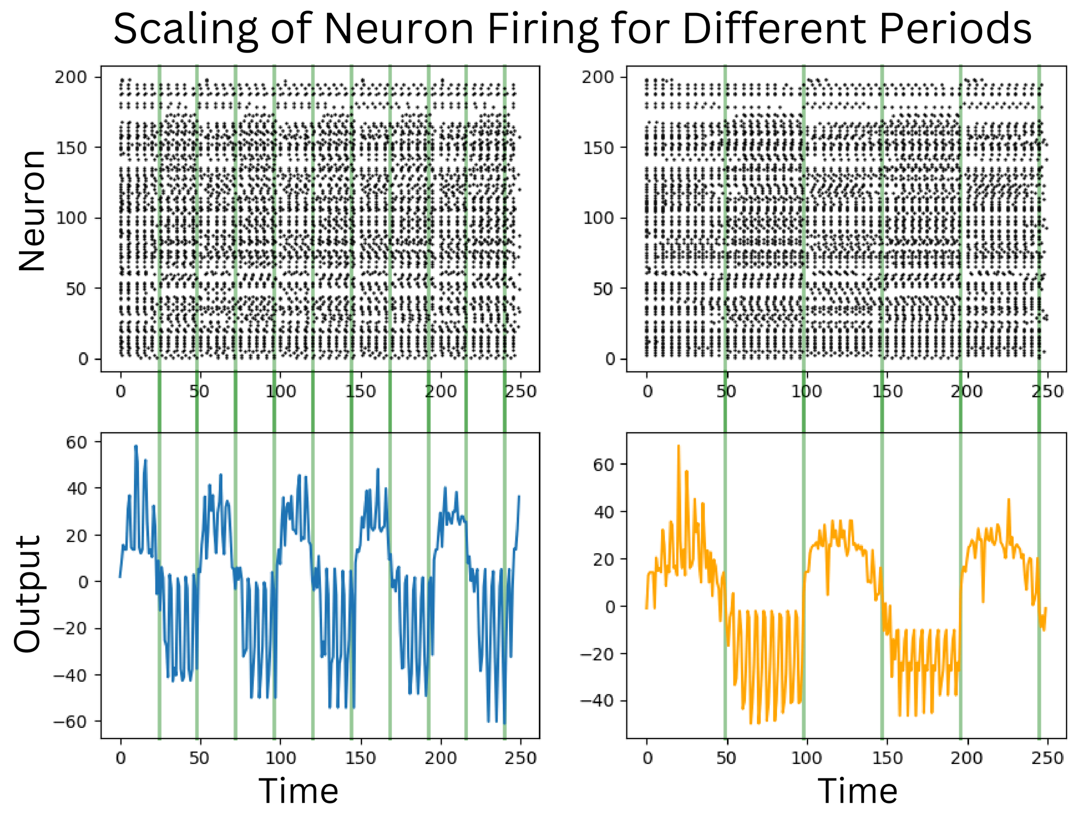


b. E and I neurons become phase-tuned.

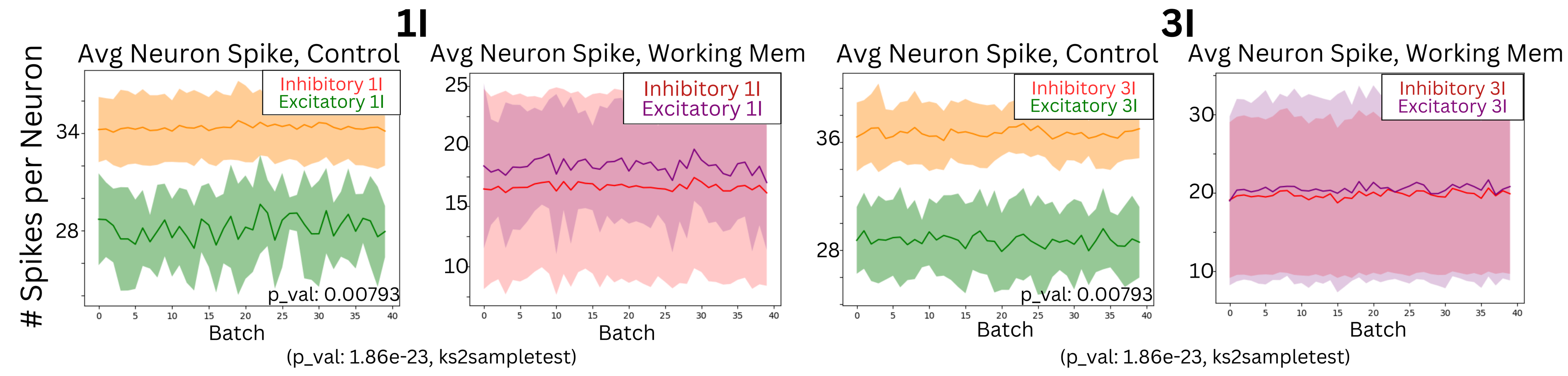


c. E and I neurons exhibit temporal scaling.

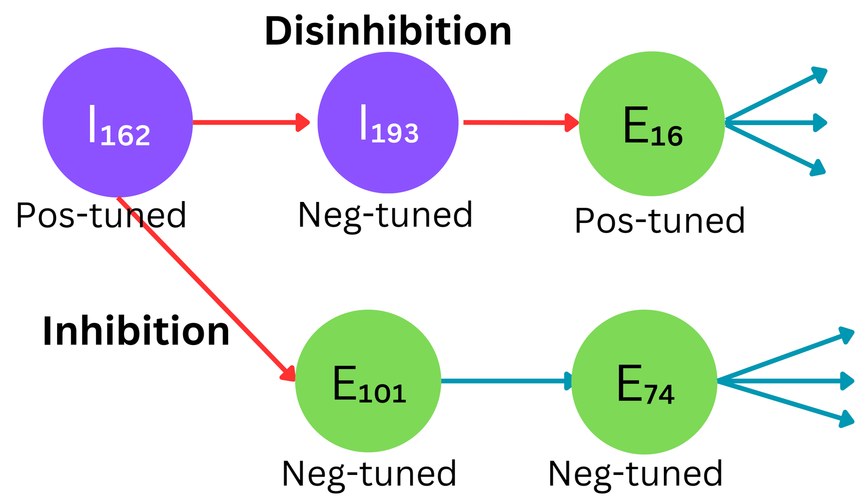
Scaling of Neuron Firing for Different Periods



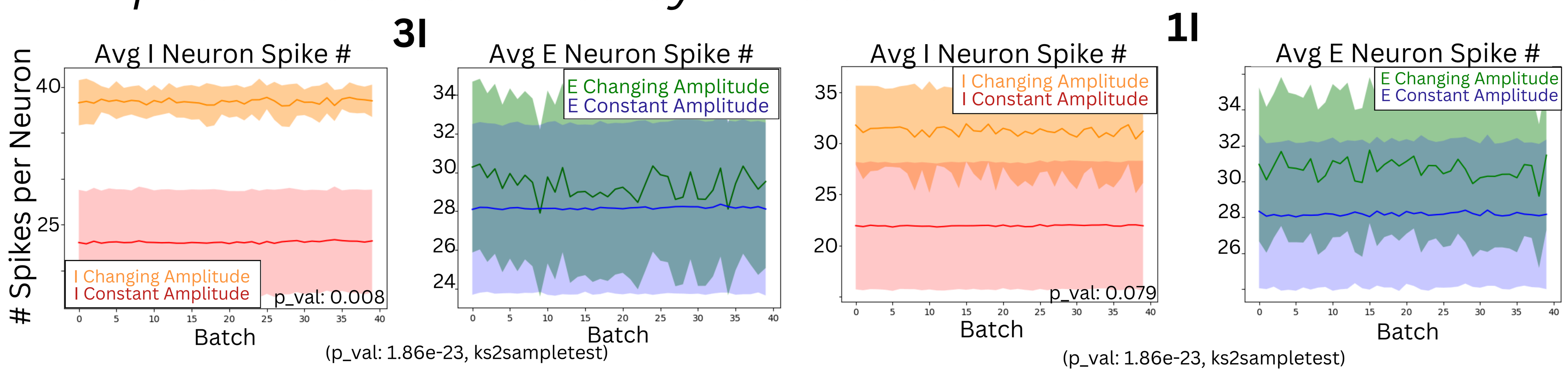
d. Working memory requires a higher ratio of E to I neuron activation for self-sustained activity.



e. I neurons drive phase transitions.



f. Amplitude is determined by inhibition.



6. Conclusion

1. Distinct interneuron sub-classes create varied timescales, contributing to overall improved task performance.
2. E and I neurons temporally scale their firing.
3. Some E and I neurons tune themselves to distinct phases/states.
4. E activity increases to self sustain network dynamics.
5. I neurons drive phase changes.
6. I activity changes to accomodate for changing amplitude.

References

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Funding Acknowledgement: We thank the Pomona College SURP Program, the Richter Memorial Fund, and the Pomona Technology Fund for making this experience possible.

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