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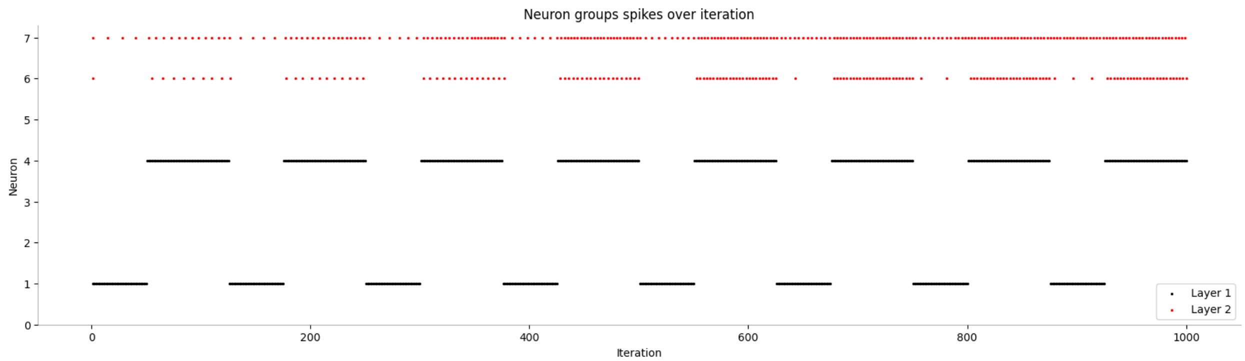
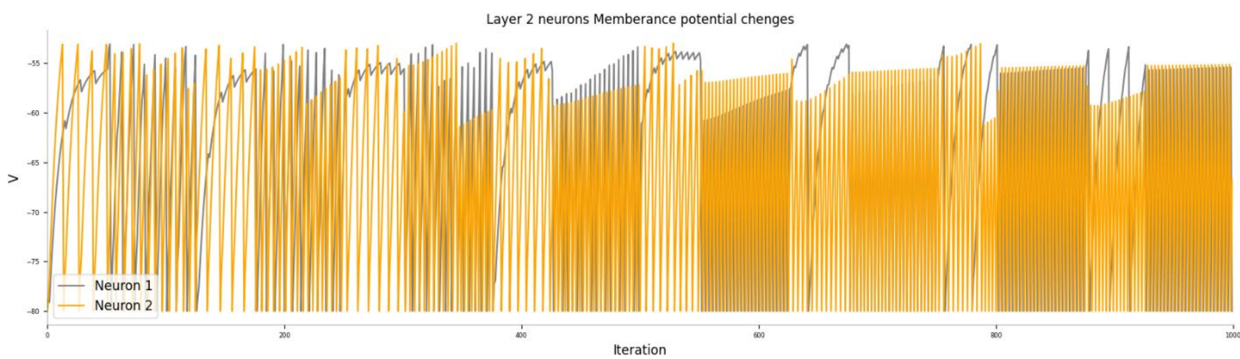
Analysis of neurons structures and their impact on learning in Spiking neurons networks.

Network design: to investigate the impact of neuron structure on learning, we designed a Spiking Neural Network with an input layer consisting of 6 neurons and an output layer comprising 2 neurons. Each input neurons was fully connected to each output neuron. The Spiking-Timing-Dependent Plasticity (STDP) rule was employed for learning weights, facilitating synaptic adjustments based on the timing of spikes from pre- and post- synaptic neurons.

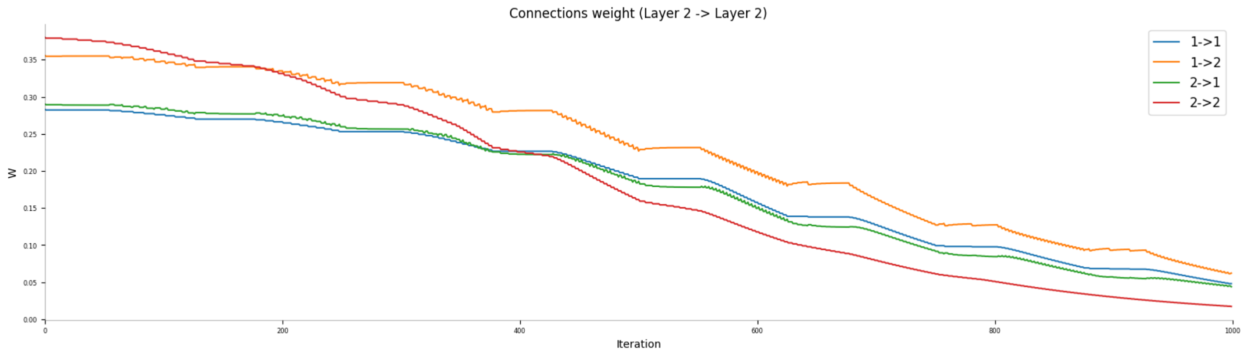
a. **Lateral Inhibition:**
   Lateral inhibition was introduced to the network to enhance pattern differentiation. The network was trained with two distinct patterns, [0,1,0,0,0,0,0] and [0,0,0,0,1,0], to observe the effect on learning.



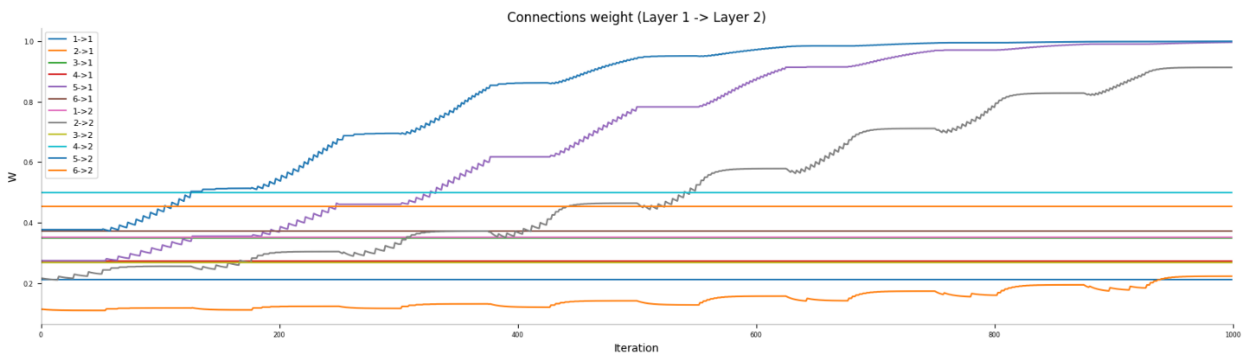
1: This plot illustrates the spike activity of neuron groups over multiple iterations. The black points represent the neurons in the input layer, while the red points indicate the neurons in the output layer.



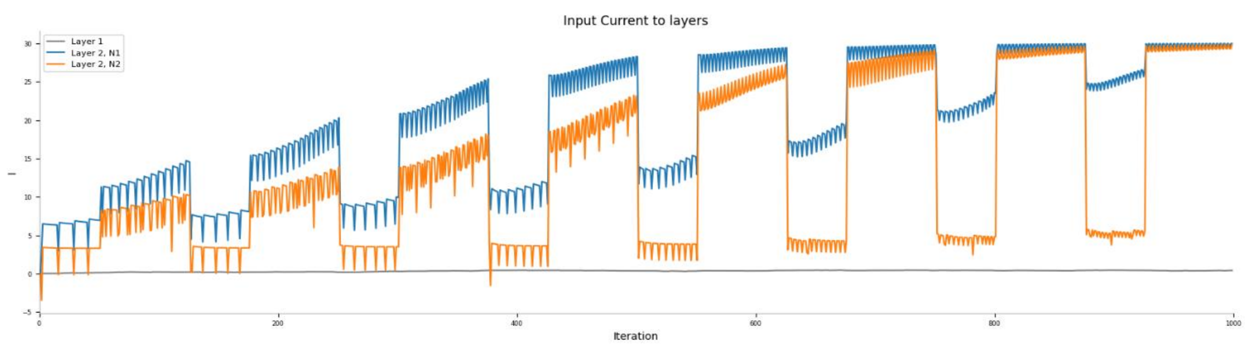
2: This figure illustrates the membrane potential changes of neurons in the second layer of the Spiking Neural Network (SNN) across multiple iterations. Each points represents the membrane potential trajectory of an individual neuron over time.



5: This figure illustrates the evolution of connection weights between neurons within the second layer of the Spiking Neural Network (SNN) across multiple iterations.



4: This figure illustrates the evolution of connection weights between neurons in the first (input) layer and the second layer of the Spiking Neural Network (SNN) across multiple iterations.

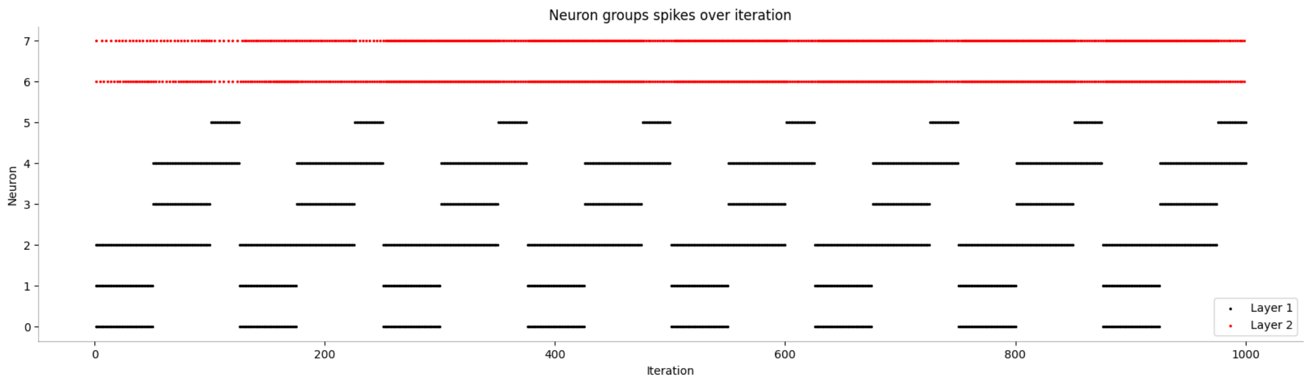


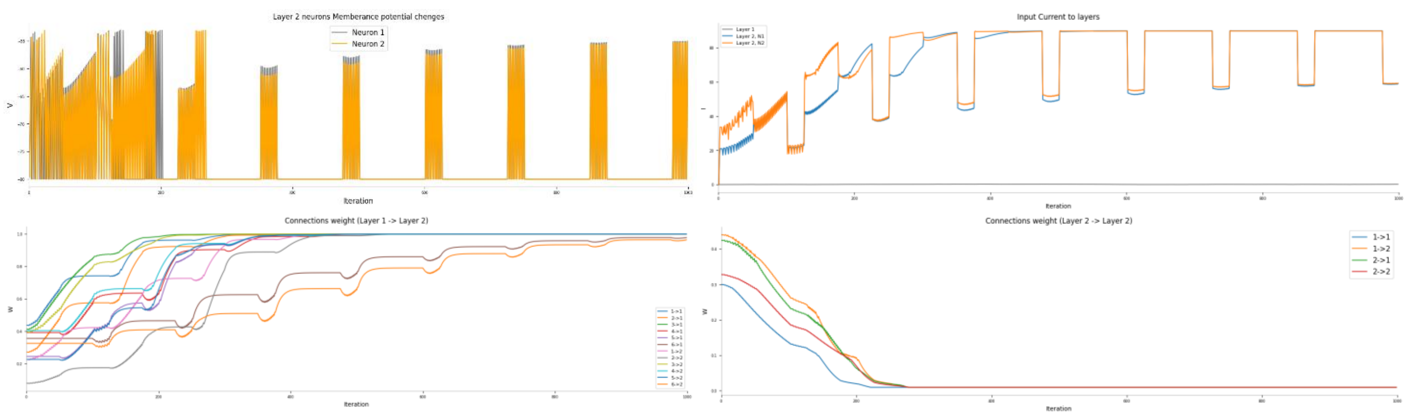
3: This figure displays the input current to neurons in both the first (input) layer and the second layer of the Spiking Neural Network (SNN). It is important to note that the input currents to all neurons in the input layer are identical.

These plots illustrate the effect of adding lateral inhibition on the sensitivity of neurons in the second layer of the Spiking Neural Network (SNN) to different input patterns over time. Specifically, neuron one in the second layer exhibits heightened sensitivity to the input patterns compared to the other neurons. The response of neuron one to each input pattern becomes more pronounced after a certain period, demonstrating a consistent reaction to the input patterns.

The other neurons in the second layer also show sensitivity to the input patterns, but to a lesser extent than neuron one. Over time, the responses of these neurons to the input patterns also stabilize, indicating that they are capable of recognizing the input patterns, albeit with lower sensitivity.

Plots highlight the role of lateral inhibition in enhancing the selectivity and response consistency of the neurons in the second layer. It shows that after the addition of lateral inhibition, neuron one becomes a reliable indicator of the presented input patterns, always reacting consistently after a certain amount of time.



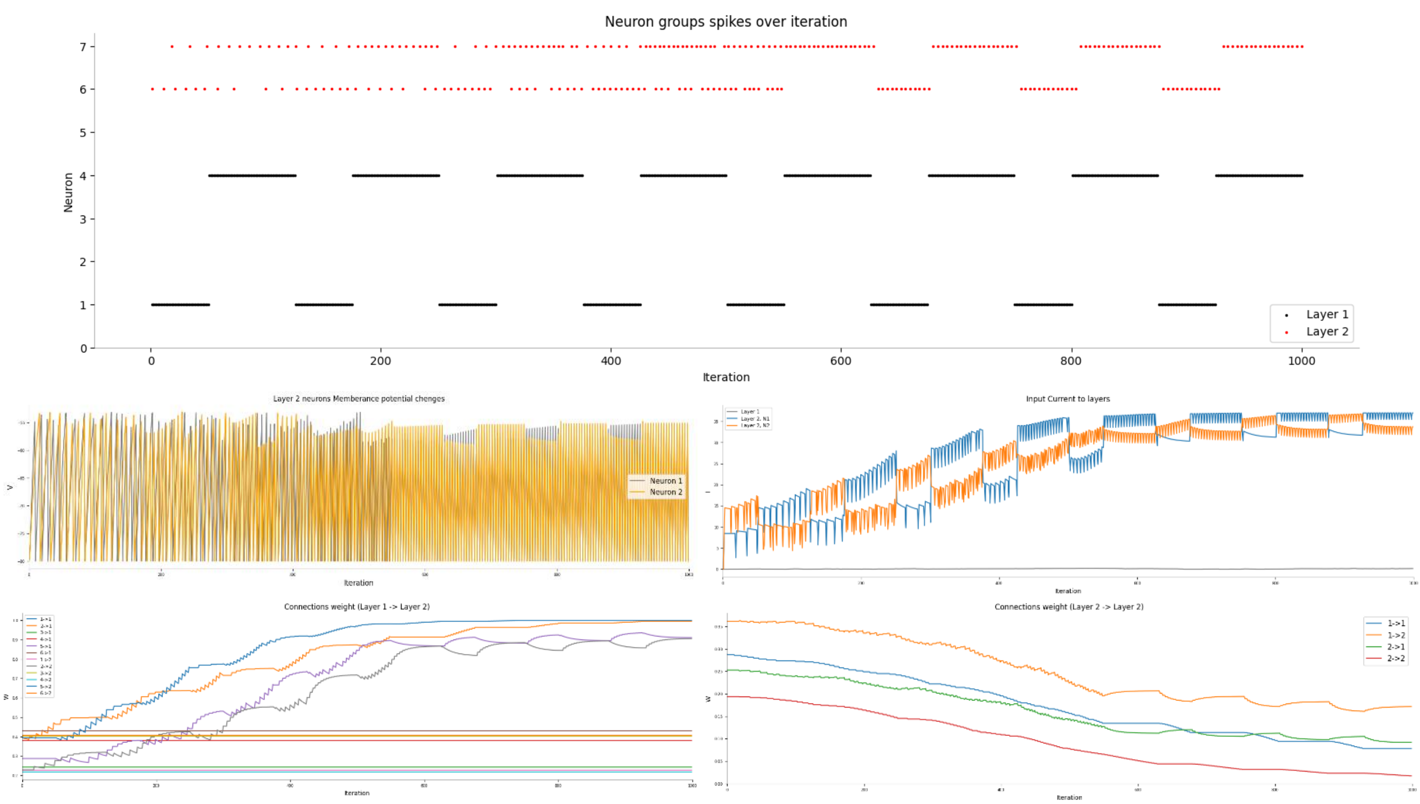


This plot illustrates the response of neurons in the second layer of the Spiking Neural Network (SNN) to new input patterns {[1,1,1,0,0,0], [0,0,1,1,1,0], [0,0,0,0,1,1]} after the addition of lateral inhibition. The results show that both neurons in the second layer exhibit high sensitivity to all input patterns but fail to differentiate between them effectively, resulting in continuous spiking activity.

The plot indicates that the connection weights between the input and second layer neurons converge to a value of one after several iterations. This uniformity in weights suggests that the learning process is malfunctioning, as the network cannot distinguish between the different input patterns.

The consistent spiking of both neurons in response to all patterns highlights the inability of the current network structure, with lateral inhibition, to correctly process and differentiate these intersecting input patterns. This behavior demonstrates that the structure and learning rule implemented cannot support proper pattern recognition for the given set of inputs.

b. **K Winners Take All (KWTA):** In the next phase, a KWTA mechanism was implemented in the second layer. This structure allows only a subset of neurons (the "winners") to remain active, promoting competition among neurons. The network was then trained with different patterns, similar to the previous step, to evaluate the influence of the KWTA structure on learning efficiency.
The network was trained with two distinct patterns, [0,1,0,0,0,0,0] and [0,0,0,0,1,0], to observe the effect on learning.



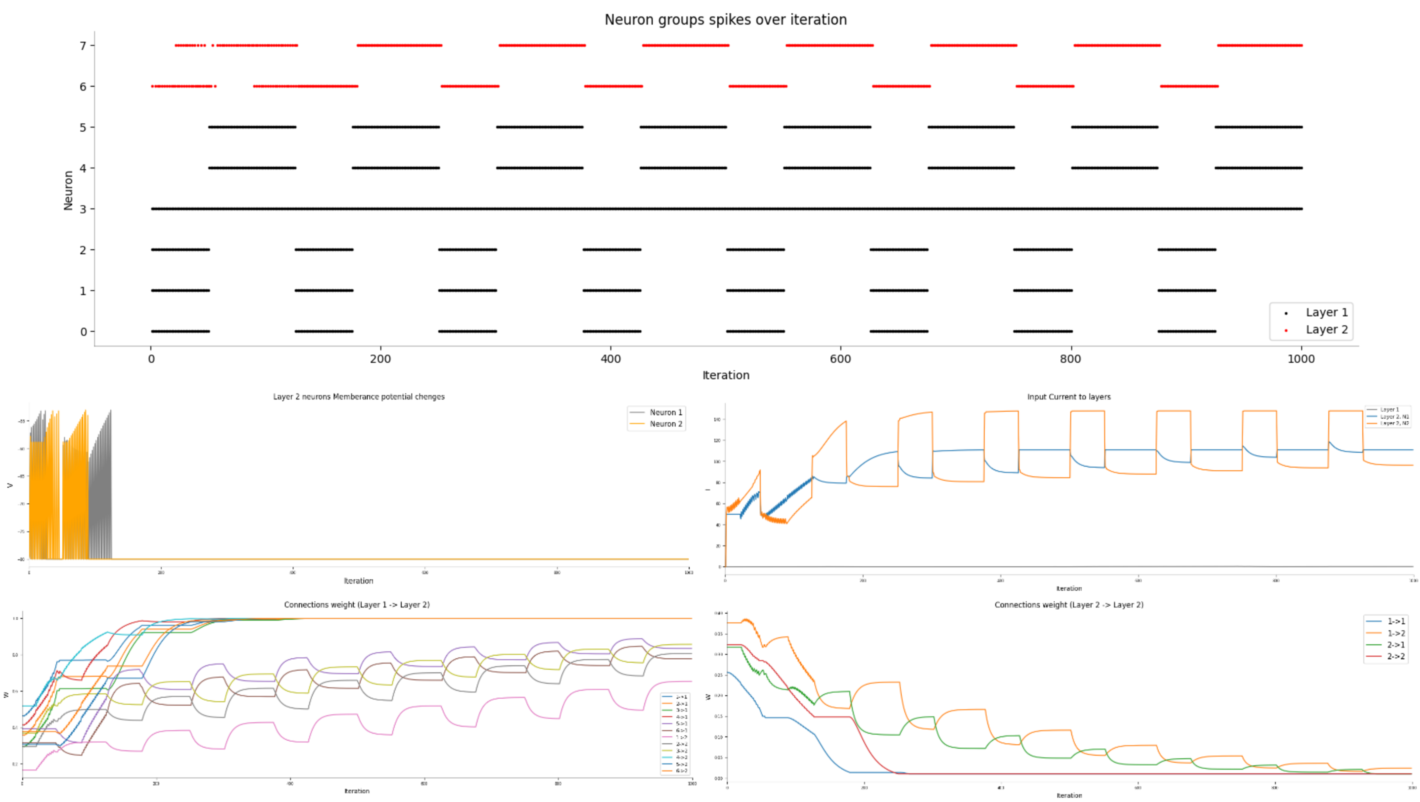
This plot illustrates the impact of implementing K Winners Take All (KWTA) with K = 1 in the second layer of the Spiking Neural Network (SNN) on the sensitivity of neurons to learning patterns {[0,1,0,0,0,0], [0,0,0,0,1,0]}.

The results demonstrate a significant improvement in the network's ability to recognize and classify the input patterns. After many iterations, neuron one in the second layer consistently responds to the first pattern, while neuron two reliably reacts to the second pattern. This clear separation of response indicates that the network has effectively learned to differentiate between the two input patterns.

Furthermore, the implementation of KWTA with K = 1 helps prevent overfitting by ensuring that only the most active neuron in the second layer responds to each input pattern. This boosts the overall performance of the network in pattern recognition and classification tasks.

The plot underscores the importance of incorporating mechanisms such as KWTA to enhance the learning and generalization capabilities of SNNs, ultimately improving their effectiveness in real-world applications.

The network was trained with two distinct patterns, [1,1,1,1,0,0,0] and [0,0,1,1,1,1], to observe the effect on learning.



This plot illustrates the training of the Spiking Neural Network (SNN) with two new input patterns {[1,1,1,1,0,0] and [0,0,0,1,1,1]} after the implementation of K Winners Take All (KWTA) in the second layer.

The results demonstrate that the learning process is significantly accelerated compared to previous experiments. The network quickly recognizes and distinguishes between the two input patterns, converging to stable connection weights in a short period.

The rapid convergence of connection weights indicates that the addition of KWTA effectively separates the intersecting patterns and facilitates faster learning. By promoting competition among neurons and ensuring that only the most active neuron responds to each pattern, KWTA enhances the network's ability to discriminate between different inputs and accelerates the learning process.

These findings highlight the effectiveness of KWTA in improving pattern recognition and learning speed in Spiking Neural Networks, making it a valuable mechanism for real-world applications where fast and accurate learning is crucial.

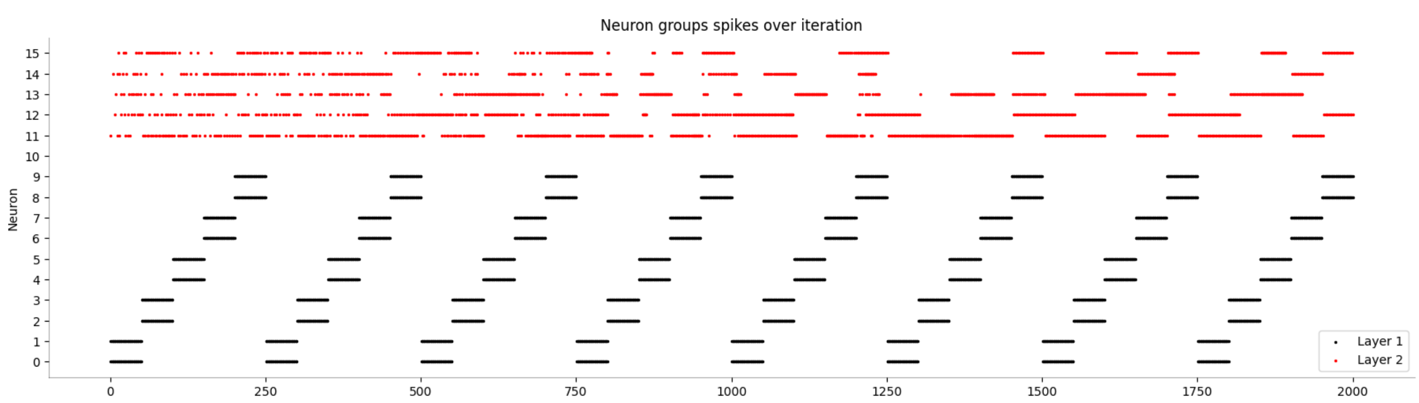
c. **Homeostasis:** To further understand the role of homeostasis in neural learning, the output layer was expanded to 5 neurons, and a homeostatic mechanism was incorporated. The network was trained with 5 distinct input patterns, and the results were recorded to analyze the impact on learning and network stability.

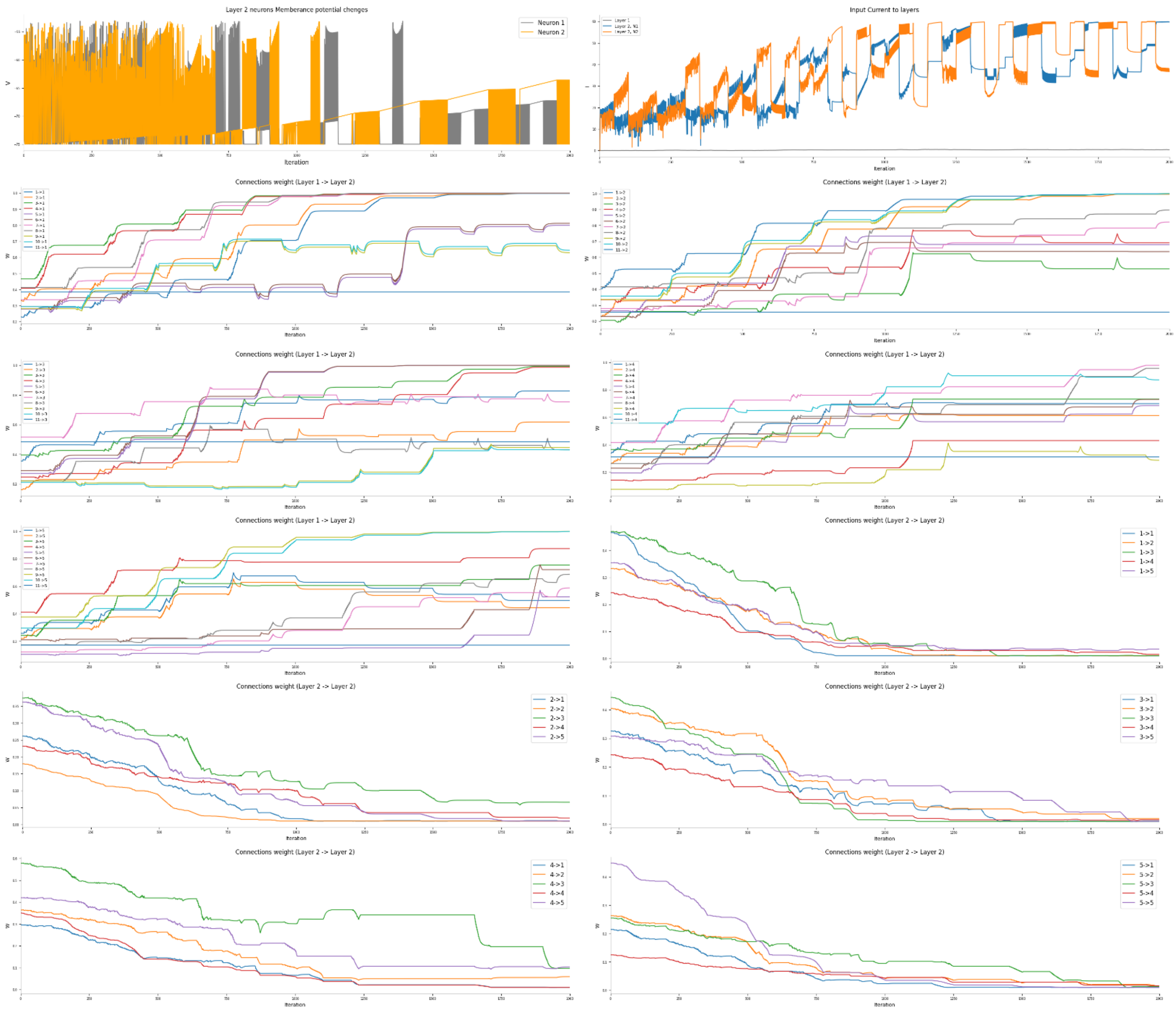
The network was then trained with five distinct input patterns:

- [1,1,0,0,0,0,0,0,0,0,0]
- [0,0,1,1,0,0,0,0,0,0,0]
- [0,0,0,0,1,1,0,0,0,0,0]
- [0,0,0,0,0,0,1,1,0,0,0]
- [0,0,0,0,0,0,0,0,1,1,0]

The network was trained over many iterations using the input patterns. Homeostasis mechanisms were integrated into the network to prevent neurons from becoming either too excited or too inhibited, ensuring balanced activity levels across the network.

The result is as below:





- **Learning and Pattern Recognition:** After several iterations, the neurons in the network successfully learned to recognize and respond to the five distinct input patterns. The connection weights converged appropriately, indicating effective learning.
- **Learning Speed:** The speed of learning was observed to be satisfactory, with the network quickly adapting to the input patterns and stabilizing the connection weights.
- **Network Dynamics:** The overall dynamics of the network improved, with a clear distinction between different patterns and reduced overfitting. The homeostasis mechanism contributed significantly to this improvement by maintaining balanced activity levels, preventing any neuron from dominating or being suppressed excessively.

- **Pattern Recognition:** The network demonstrated a high accuracy in recognizing and distinguishing the input patterns, showcasing its enhanced pattern recognition capabilities.
- **Overfitting Reduction:** The introduction of homeostasis helped in reducing overfitting, ensuring that the network did not memorize the training patterns but rather generalized from them effectively.

In the next part, the network was trained using two different strategies: one with three input patterns and another with six input patterns. The objective was to evaluate the network's learning behavior and performance under varying complexities of input data.

Three Pattern Strategy:

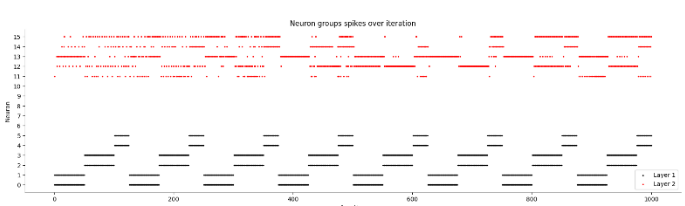
- 1.,1.,0.,0.,0.,0.,0.,0.,0.,0.,0.
- 0.,0.,1.,1.,0.,0.,0.,0.,0.,0.,0.
- 0.,0.,0.,0.,1.,1.,0.,0.,0.,0.,0.

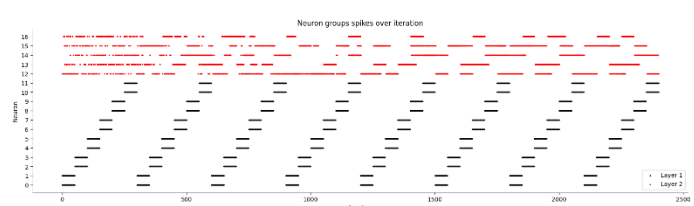
Six Pattern Strategy:

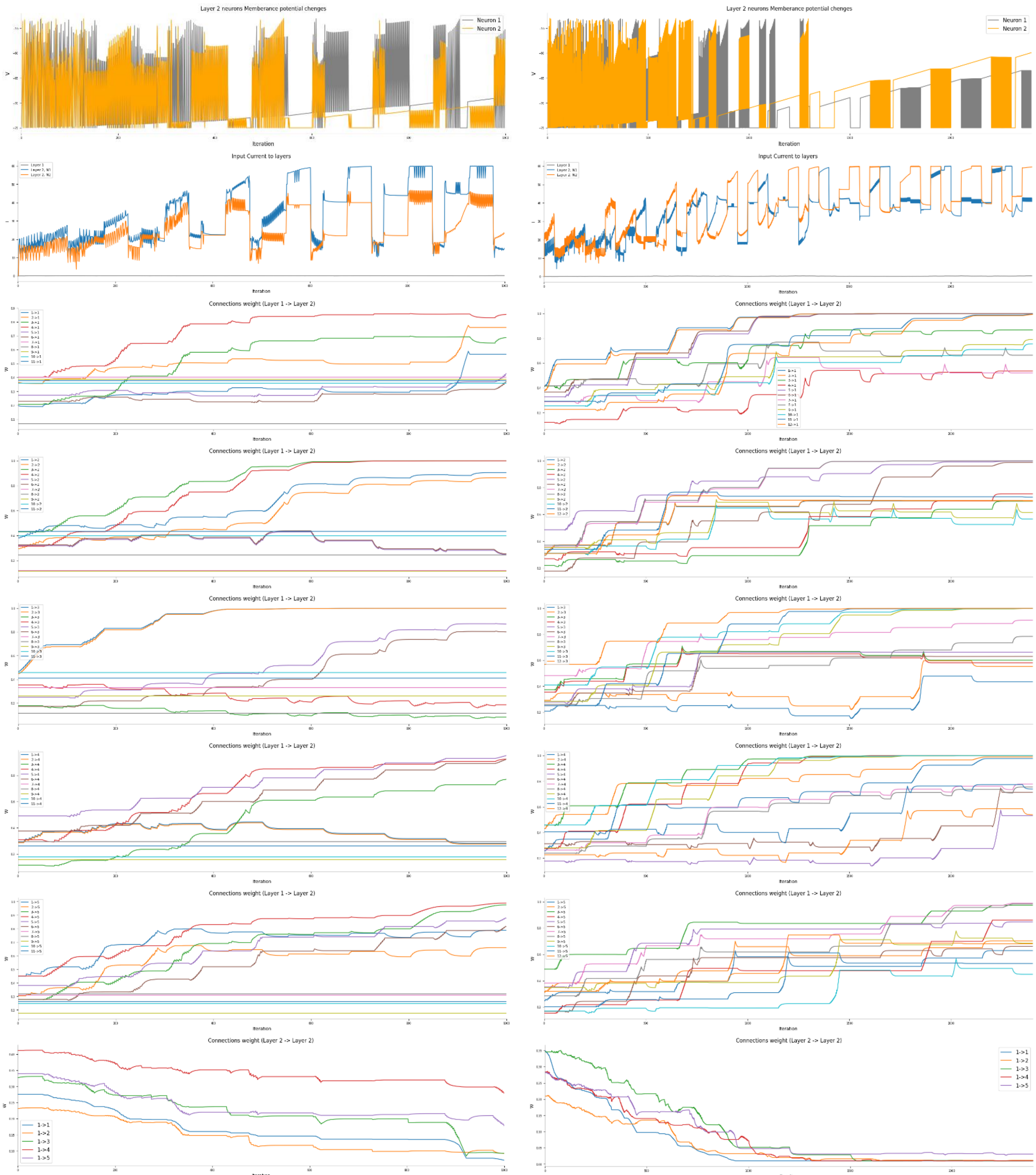
- 1.,1.,0.,0.,0.,0.,0.,0.,0.,0.,0.
- 0.,0.,1.,1.,0.,0.,0.,0.,0.,0.,0.
- 0.,0.,0.,0.,1.,1.,0.,0.,0.,0.,0.
- 0.,0.,0.,0.,0.,0.,1.,1.,0.,0.,0.
- 0.,0.,0.,0.,0.,0.,0.,0.,1.,1.,0.,0.
- 0.,0.,0.,0.,0.,0.,0.,0.,0.,0.,1.,1.

The network, with an input layer of 11 neurons and an output layer of 5 neurons, was trained using the two strategies over many iterations. The goal was to observe how the network learns and adapts to different numbers of input patterns. The connection weights and spike times of the neurons were monitored throughout the training process.

The result is as below:






Layer 2 neurons Memberance potential chenges
Neuron 1
Neuron 2
Iteration
Input Current to layers
Layer 1
Layer 2, N1
Layer 2, N2
Iteration
Connections weight (Layer 1 -> Layer 2)
Iteration
Connections weight (Layer 2 -> Layer 2)
1->1
1->2
1->3
1->4
1->5
Iteration

Conflict and Pattern Memory:

- Neurons exhibited conflicting spike times as they tried to learn and remember the patterns. The adjustments in spike times were reflected in the updating of their connection weights, shaping the learning process to encode the input patterns effectively.

Comparison of Learning Difficulty:

- Learning the three-pattern input set proved to be more challenging than learning the six-pattern input set. This counterintuitive result suggests that the network found it easier to distribute and encode the more diverse set of input patterns provided by the six-pattern strategy.

Weight Convergence:

- In both strategies, the connection weights converged in a manner that indicated successful learning of the input patterns. The neurons adjusted their weights to form distinct responses to each pattern, showcasing the network's ability to differentiate between them.

Certainly! Here's a detailed description for the last part of your report:

Effect of Different Parameters on Network Learning

In the final phase of the project, we explored the impact of various parameters on the learning performance and behavior of the Spiking Neural Network (SNN). Specifically, we examined the effects of parameters in Voltage-Based Homeostasis, K Winners Take All (KWTA), and Lateral Dendritic Input mechanisms.

1. **Voltage-Based Homeostasis:**
    - **Target Voltage (target_voltage):** Adjusting the target voltage altered the baseline excitability of the neurons. A higher target voltage increased neuron activity, leading to faster initial learning but potentially causing instability if set too high. Lower target voltages reduced neuron activity, making the network more stable but slowing down the learning process.
    - **Maximum (max_ta) and Minimum (min_ta) Thresholds:** Expanding the range between max_ta and min_ta allowed for greater flexibility in neuron activity, which helped in accommodating a wider range of input patterns. Narrowing this range made the neurons more selective, improving precision but increasing the risk of underfitting.
    - **Learning Rate (eta_ip):** Higher values of eta_ip accelerated the adaptation of neurons to the target voltage, speeding up learning but increasing the risk of oscillatory behavior. Lower values led to more gradual adaptation, providing stability but slowing the learning process.
2. **K Winners Take All (KWTA):**
    - **K (Number of Winners):** Increasing the value of k allowed more neurons to be active simultaneously, which improved the network's ability to handle more complex patterns by distributing the learning across more neurons. However, it also increased the likelihood of overfitting. Keeping k at 1 (the default) ensured that only the most strongly activated neuron responded, which was beneficial for clear pattern separation but could limit the network's capacity to recognize complex patterns.
3. **Lateral Dendritic Input:**
    - **Current Coefficient (current_coef):** Higher values of current_coef amplified the influence of lateral dendritic inputs, enhancing the network's ability to suppress irrelevant neuron activity. This increased pattern recognition accuracy but could also lead to excessive inhibition if set too high. Lower values reduced this effect, making the network more sensitive but potentially less precise.
    - **Inhibitory Setting (inhibitory):** Keeping the lateral input inhibitory (True) helped in maintaining balanced neuron activity and preventing runaway excitation. Changing this to excitatory would make the network more responsive but risked instability and loss of pattern differentiation.