P04 report file

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Abstract

This report consists of an overview on the fourth project.

1 INTRODUCTION

As requested, a two-layer network has been implemented, utilizing the STDP rule along with KWTA and lateral inhibition for learning purposes.

2 ANALYSIS AND BEHAVIORS

2.1 Two Patterns

From now on, we assume that the output layers have parameters as Table1 and their connection scheme is full connectivity.
Patterns are spike trains which are activated for a time window, they are declared in such a way that only specific neurons become active. We simultaneously apply pattern 1 and pattern 2. Additionally, we introduce a third pattern consisting entirely of zeros between the application of the first and second patterns. This approach enhances our understanding of neural behaviors. At first, patterns has no neurons in common but eventually we increase their intersection.

Table 1: Output Neuron Group Parameters

Model	**Parameters**				
	$threshold$	R	u_{rest}	u_{reset}	τ
LIF (output)	-37	8	-60	-65	10

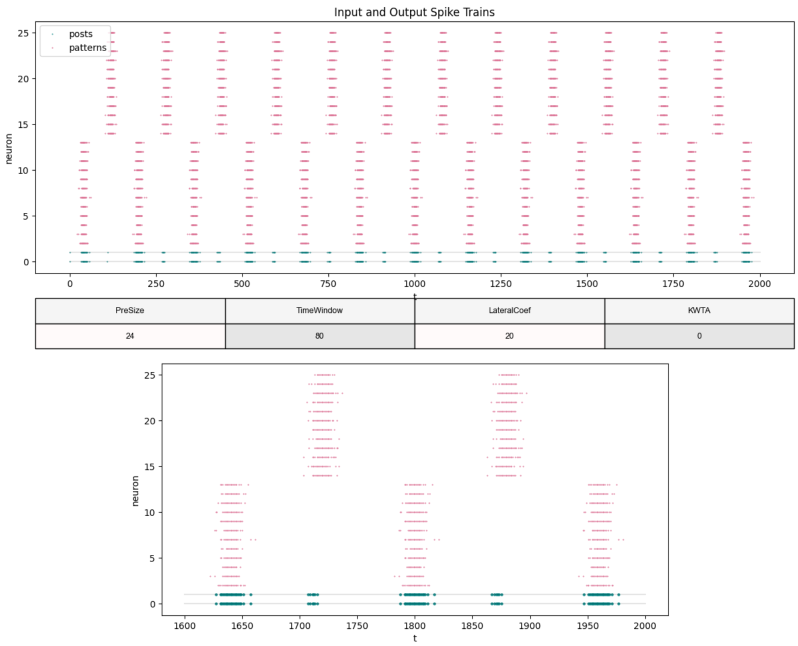
Table 2: Learning Parameters

Scheme	**Parameters**	
	A_p	A_m
STDP	0.07	0.05

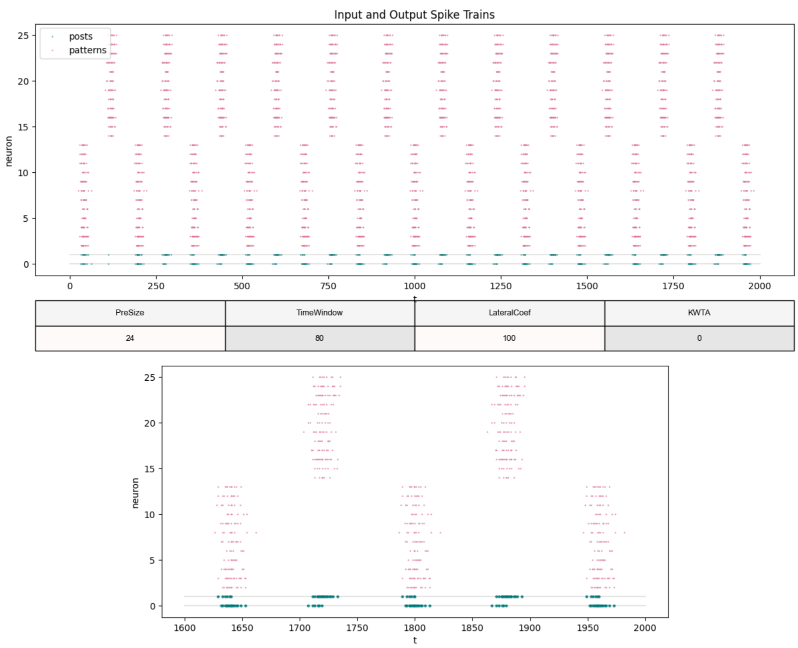
2.1.1 Lateral Inhibition

Lateral inhibition is a process where neurons that have spiked inhibit their neighboring neurons. When combined with KWTA, this behavior has observable effects. However, it's important to note that the likelihood of significant learning through lateral inhibition alone is not very high.

Figure 1: Lateral Inhibition, Patterns are different.

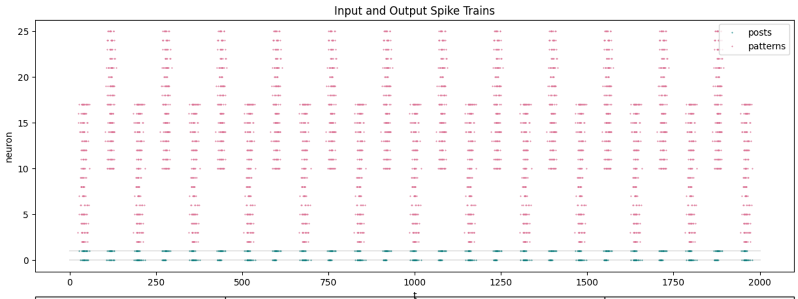


Both output neurons respond to both patterns.

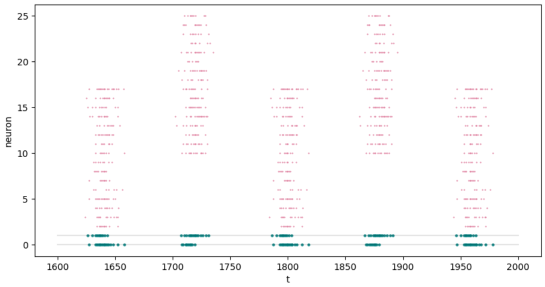


Each output neuron responds differently to each pattern.

Figure 2: Lateral Inhibition, Patterns have intersection.

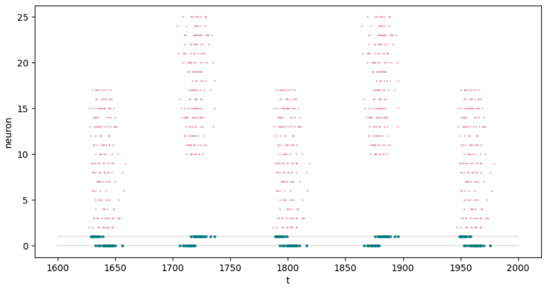


PreSize	TimeWindow	LateralCoef	KWTA
24	80	20	0



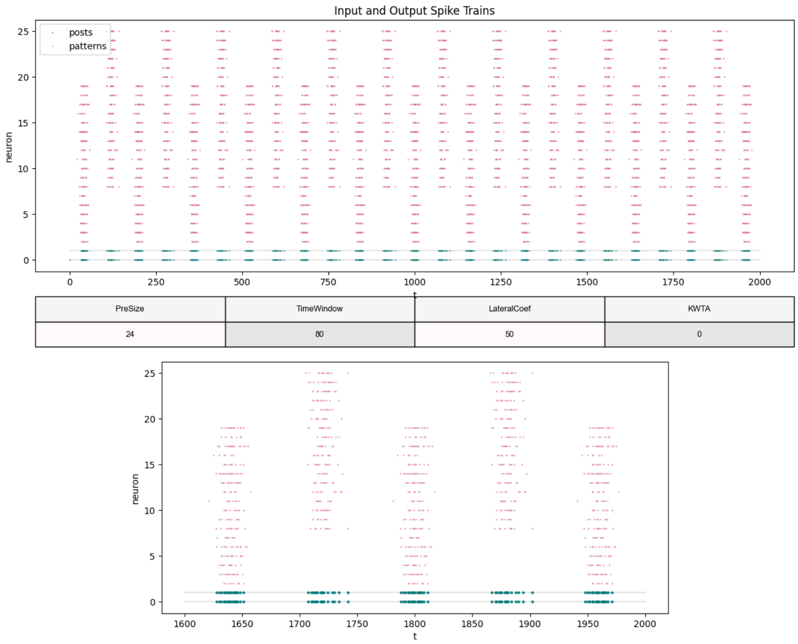
Both output neurons respond to both patterns almost same.

PreSize	TimeWindow	LateralCoef	KWTA
24	80	100	0

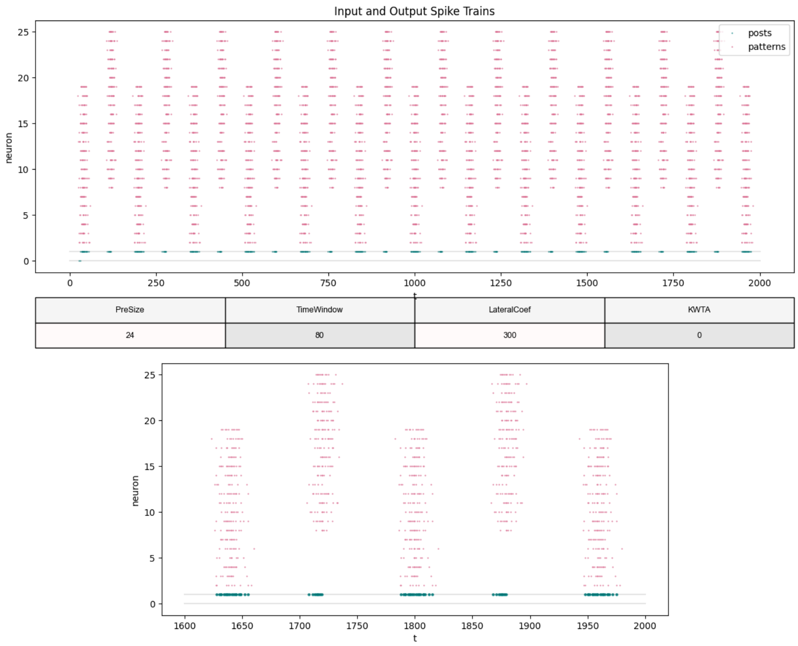


Each output neuron responds differently to each pattern.

Figure 3: Lateral Inhibition, Patterns have more intersection.



Both output neurons respond to both patterns same.



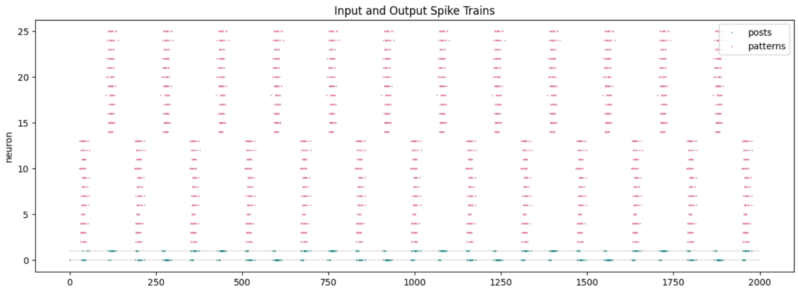
Increasing Lateral Inhibition results in having only one neuron responding.

In summary, Lateral Inhibition significantly influences neural behavior. However, when the intersection of patterns increases, learning diminishes, and neurons become sensitive to both patterns simultaneously.

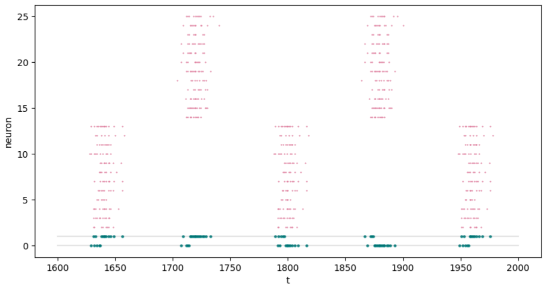
2.1.2 KWTA

KWTA is a neural network mechanism that promotes sparsity in neural activation. In KWTA, only the top K most active neurons are allowed to fire, while the rest remain suppressed. This selective activation helps enhance feature representation. The impact of incorporating KWTA will be evident in the plotted results.

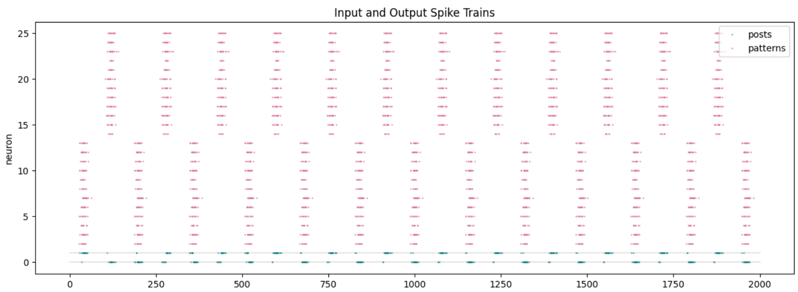
Figure 4: KWTA, Patterns are different.



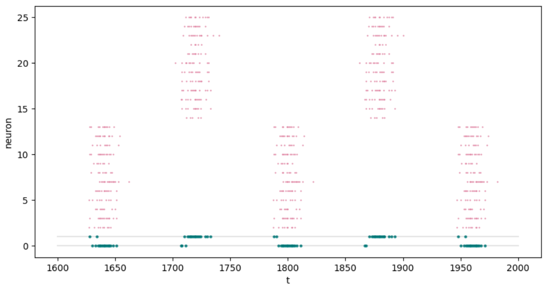
PreSize	TimeWindow	LateralCoef	KWTA
24	80	1	1



Both output neurons respond to both patterns due to the small Lateral Inhibition coefficient.

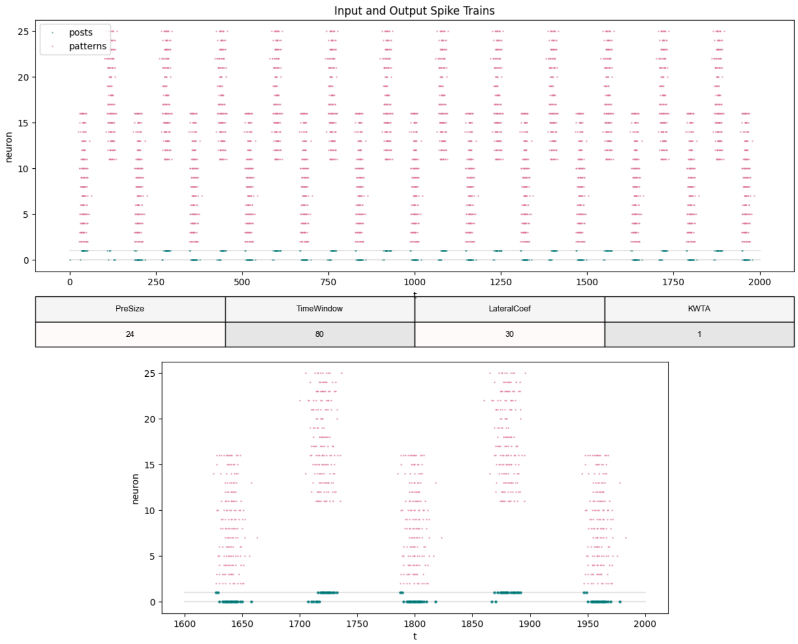


PreSize	TimeWindow	LateralCoef	KWTA
24	80	100	1



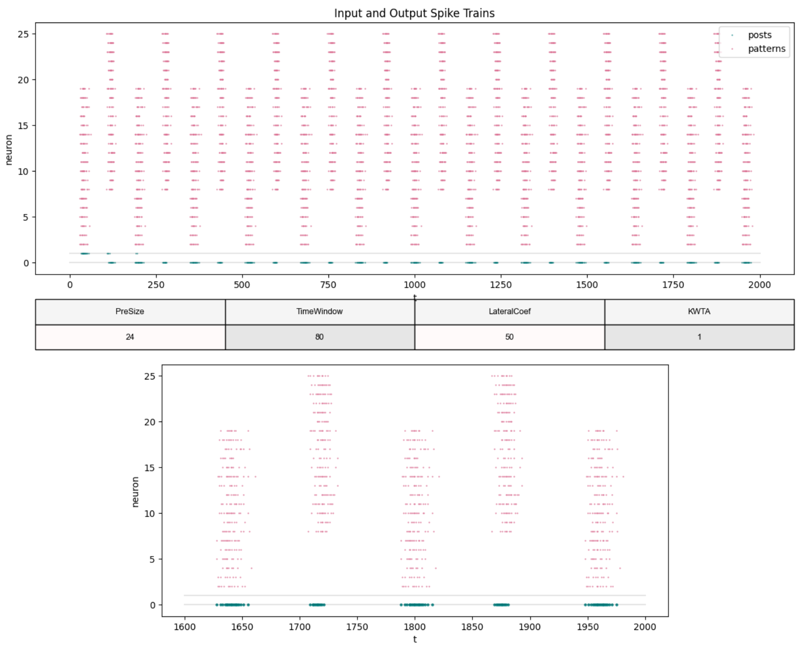
Each output neuron responds differently to each pattern.

Figure 5: KWTA, Patterns have intersection.



Despite the intersection, each output neuron responds uniquely to each pattern.

Figure 6: KWTA, Patterns have more intersection.



Due to the similarity of patterns and nearly identical neuron responses, KWTA consistently selects one neuron to fire each time.

In summary, the combined effects of KWTA and Lateral Inhibition significantly impact neural behavior. When used together, they lead to distinct responses from neurons for each pattern, resulting in optimal performance.

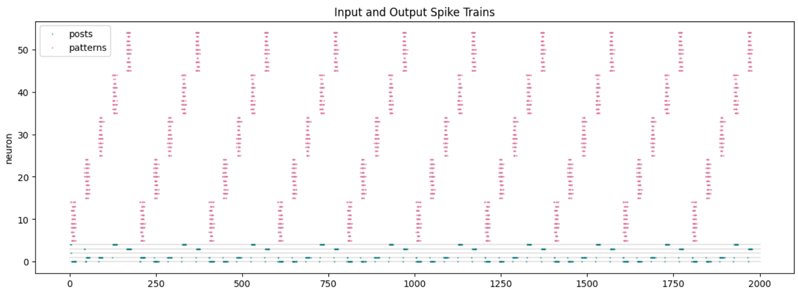
2.2 Five Patterns

Patterns are spike trains which are activated for a time window, they are declared in such a way that only specific neurons become active. We simultaneously apply all 5 patterns. At first, patterns has no neurons in common but eventually we increase their intersection.

2.2.1 Without Homeostasis

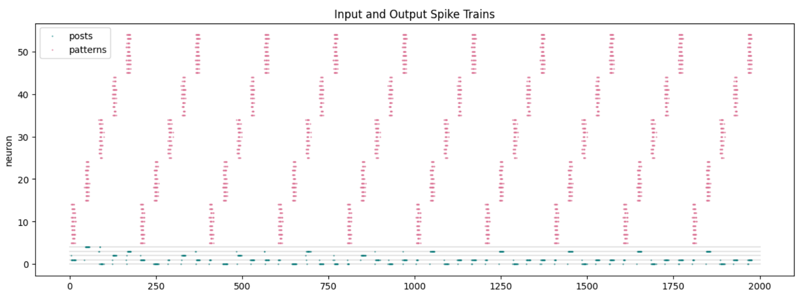
We can see that without homeostasis each neuron may learn more than one pattern.

Figure 7: Lateral Inhibition and KWTA, Patterns are different.

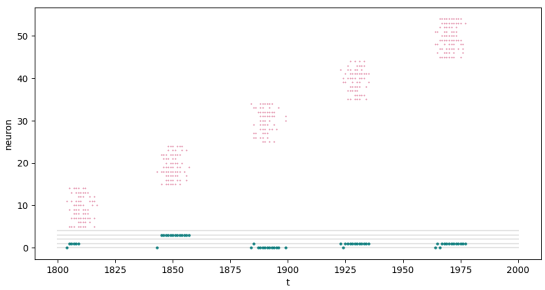


PreSize	TimeWindow	LateralCoef	KWTA	Homeostasis
50	20	50	1	OFF

Some output neurons respond to more than one pattern.



PreSize	TimeWindow	LateralCoef	KWTA	Homeostasis
50	20	100	1	OFF



Increasing Lateral Inhibition results in more distinguished responses. But still we have some neurons not responding.

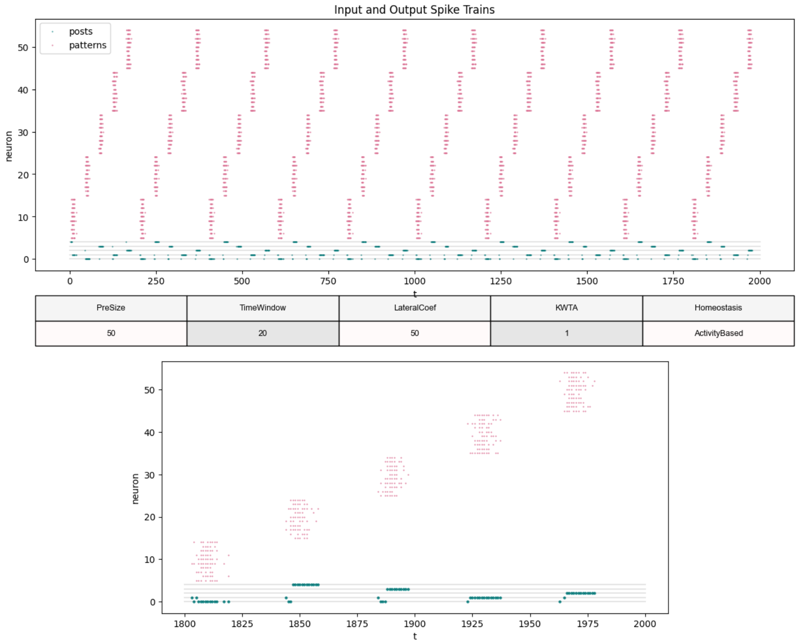
2.2.2 With ActivityBased Homeostasis

Now we apply activity based homeostasis with parameters as below.

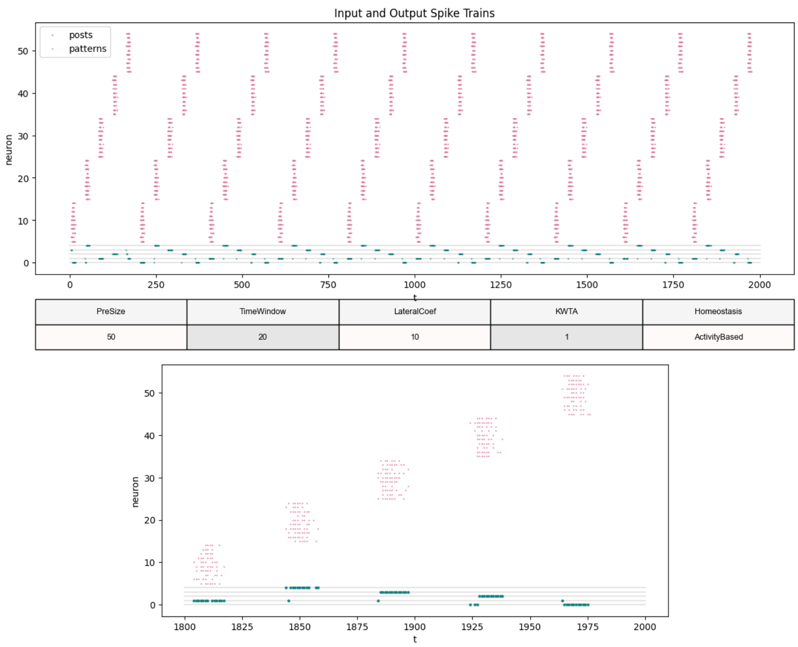
Table 3: Homeostasis Parameters

Model	Parameters			
	Window size	*Act. rate*	*Updating rate*	*Decay rate*
Act Based	200	10	1	0.85

Figure 8: Lateral Inhibition, KWTA and Homeostasis, Patterns are different.



Due to homeostasis, each output neuron responds exclusively to a single pattern. The limited spiking (10 times) within the applied time interval reinforces this selectivity.



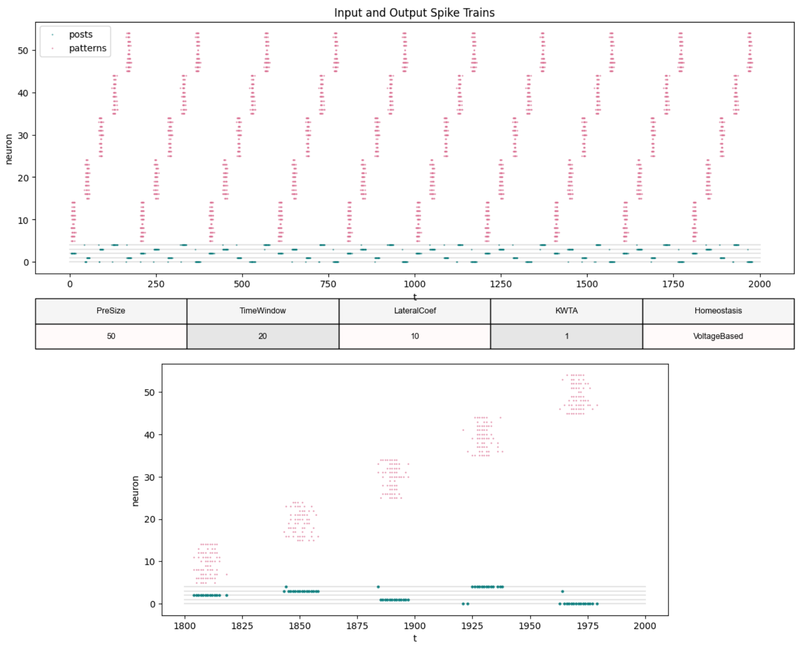
2.2.3 With VoltageBased Homeostasis

Now we apply Voltage based homeostasis with parameters as below.

Table 4: Homeostasis Parameters

Model	Parameters			
	Target vol.	*Max T*	*Min T*	*ETA IP*
Vol Based	-37	-37	-60	0.001

Figure 9: Lateral Inhibition, KWTA and Homeostasis, Patterns are different.



Due to homeostasis, each output neuron responds exclusively to a single pattern.

2.2.4 Comparing Voltage and Activity Based Homeostasis

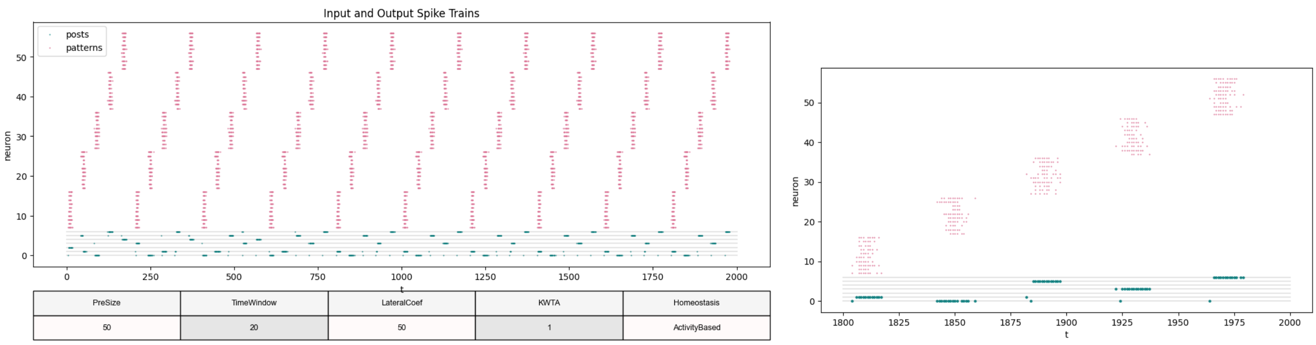
Feature	**ActivityBaseHomeostasis**	**VoltageBaseHomeostasis**
Basis for Homeostasis	Number of spikes (activity rate)	Membrane potential (voltage rate)
Main Parameter of Interest	`activity_rate`, `window_size`, `updating_rate`	`target_voltage`, `max_ta`, `min_ta`, `eta_ip`
Reward/Penalty Mechanism	Firing rewards and non-firing penalties	Excess voltage adjustments
Frequency of Adjustments	After every `window_size` iterations	Continuously during each forward pass
Updating Mechanism	Adjusts neuron thresholds based on activity	Adjusts neuron voltages based on deviations
Implementation Complexity	Moderately complex with window-based updates	Simpler with continuous voltage adjustments

Table 5: Comparison of Activity-Based and Voltage-Based Homeostasis Implementations

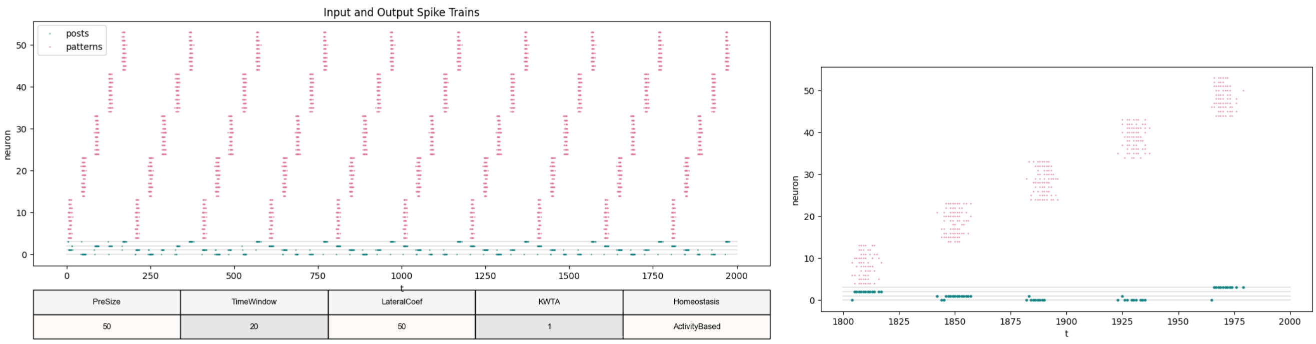
`ActivityBaseHomeostasis` is more focused on achieving a target spike rate over a defined time window, which can be useful in scenarios where temporal patterns of spikes are critical. `VoltageBaseHomeostasis` directly regulates the membrane potential of neurons, making it more suitable for maintaining stable voltage levels, potentially preventing excitotoxicity or inactivity due to extreme voltage levels.

2.2.5 Having More / Less Number of Neurons than Patterns

Figure 10: Lateral Inhibition, KWTA and Homeostasis, Patterns are different.



5 Patterns and 7 Neurons.



5 Patterns and 4 Neurons. second neuron responds to two different patterns each time.

When these mechanisms are combined in a network with fewer input patterns than output neurons, several key behaviors can be expected:
Homeostasis will adjust the thresholds to maintain a consistent level of neuron activation, despite the sparse input. KWTA ensures that only the most responsive neurons fire, promoting competition among neurons.Lateral inhibition increases the contrast between active and inactive neurons, enhancing the network's ability to discriminate between different input patterns, even if they are few. Some neurons may remain consistently inactive if they do not receive sufficient input or are not competitive enough to win in the KWTA mechanism, leading to underutilization of the network's capacity.
And in summary, when the number of input patterns exceeds the number of output neurons, the network will become highly competitive and efficient in its use of neurons. Homeostasis will ensure stability, KWTA will enforce selectivity and efficiency, and lateral inhibition will enhance contrast and discrimination. These mechanisms together will allow the network to robustly represent a diverse set of input patterns, but care must be taken to manage the increased complexity and potential for overfitting.