# Learning to Predict with Network of Spiking Neurons

Biswadeep Chakraborty, Saibal Mukhopadhyay

GREEN LAB

Georgia Institute of Technology

Gigascale Reliable Energy Efficient Nanosystems LAB

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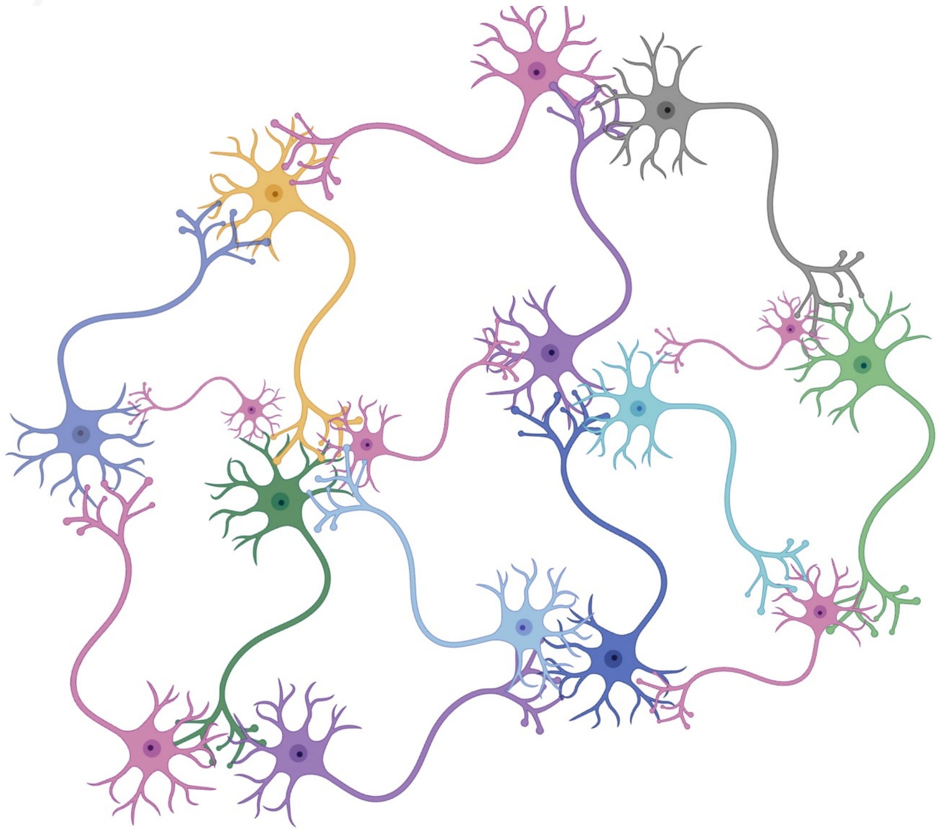
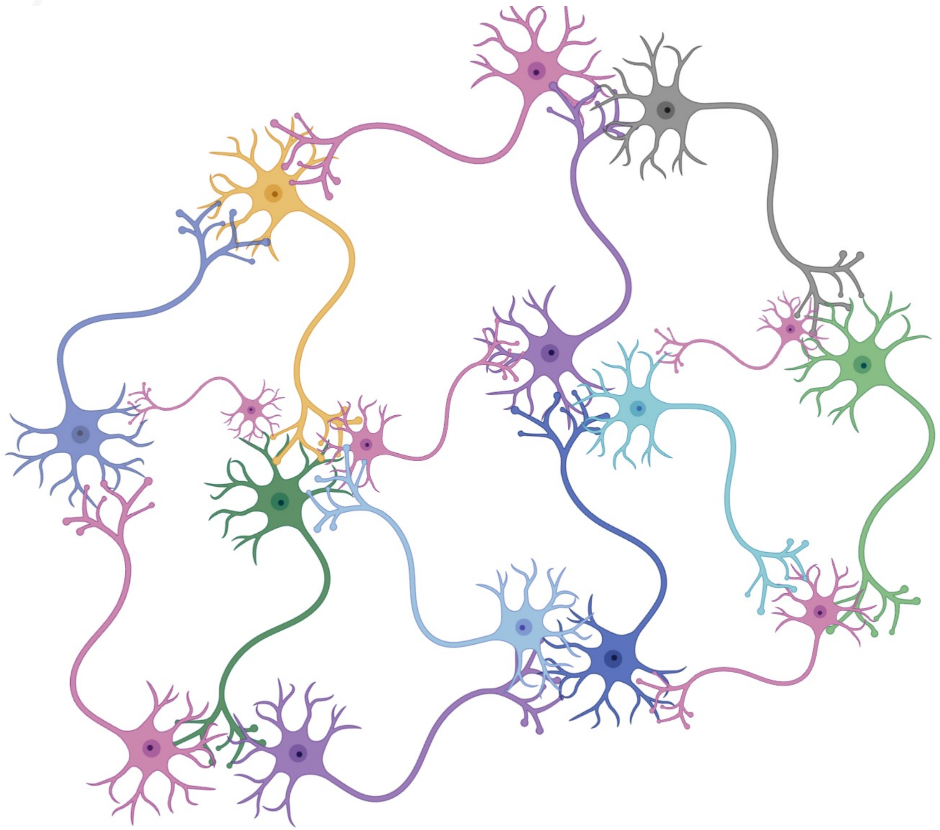
# Overview



Brain-Inspired Learning using Spiking Neural Networks

- ❖ Impact of Heterogeneity
- ❖ Continuous Unsupervised Learning

# Overview

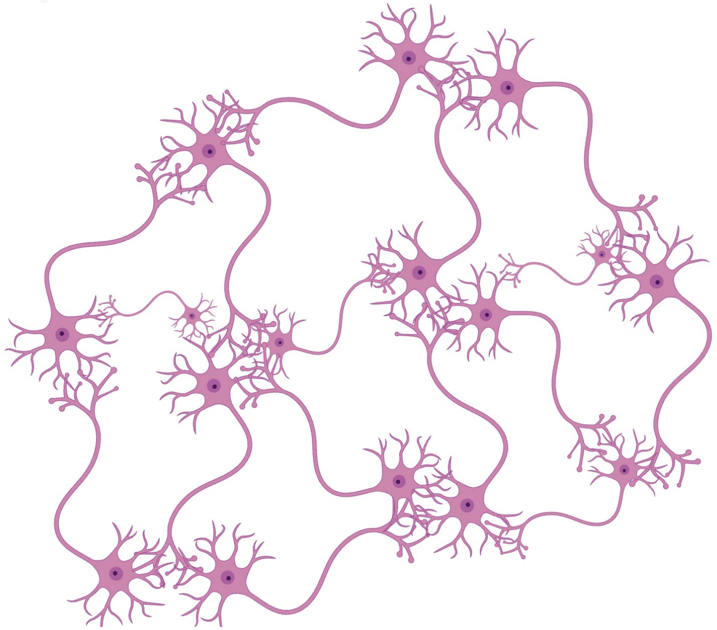


## Brain-Inspired Learning using Spiking Neural Networks

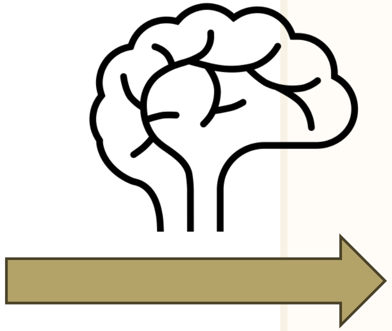
- ❖ Impact of Heterogeneity
- ❖ Continuous Unsupervised Learning

# Brain-Inspired Heterogeneous SNNs

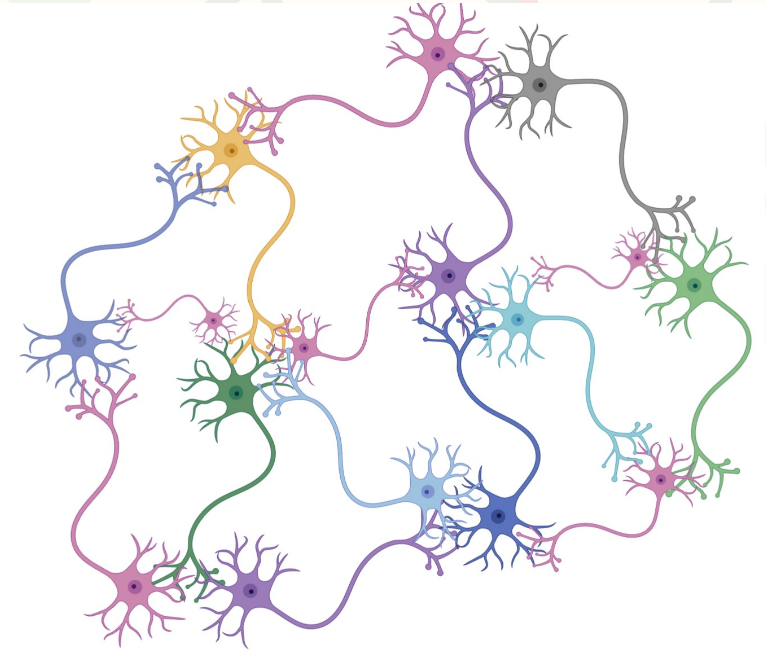




Homogeneous Neurons and Learning Rules



Brain-Inspired



Heterogeneous Neurons and Learning Rules

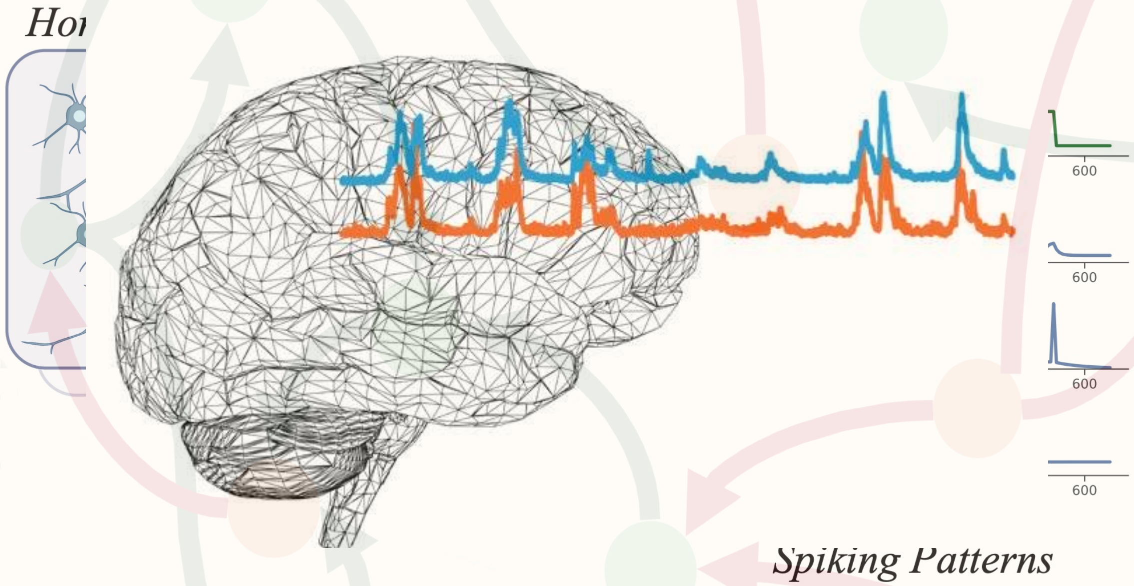
# Role of Heterogeneity

1. Increased Computational Power

2. Learning and Adaptation

3. Robustness to Perturbations

4. Emergent Phenomena

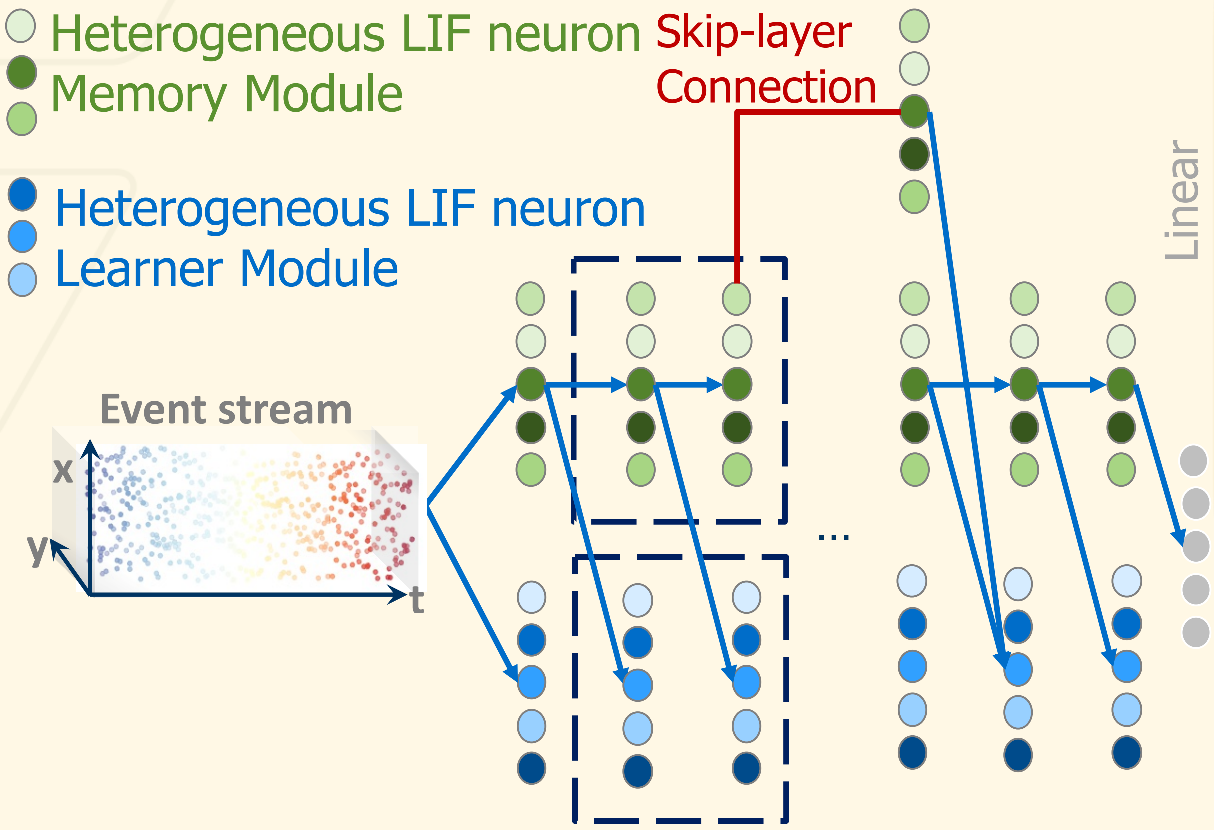




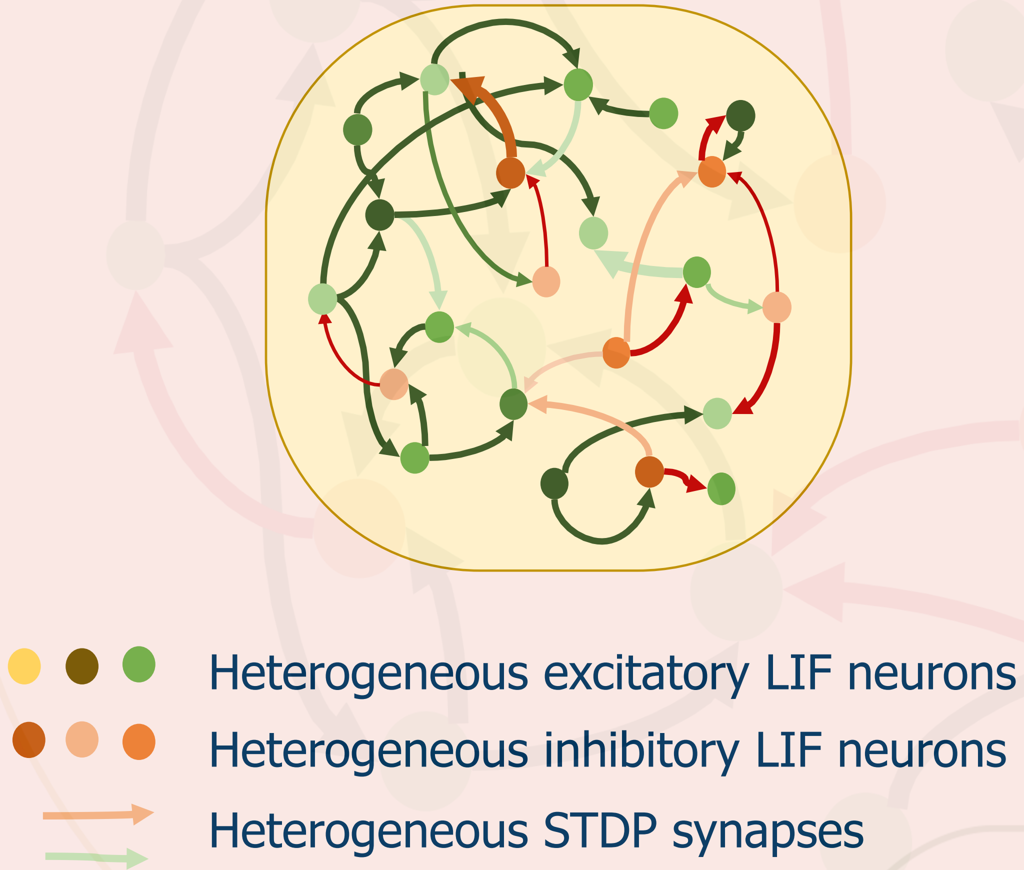

Ref: https://www.the-scientist.com/infographics/infographic-understanding-our-diverse-brain-30678
Figure credit: Shen, G., Zhao, D., Dong, Y., Li, Y. and Zeng, Y., 2023. Dive into the Power of Neuronal Heterogeneity. *arXiv preprint arXiv:2305.11484*.

# Heterogeneous Spiking Neural Network

## Heterogeneous Feedforward SNN




## Heterogeneous Recurrent SNNs

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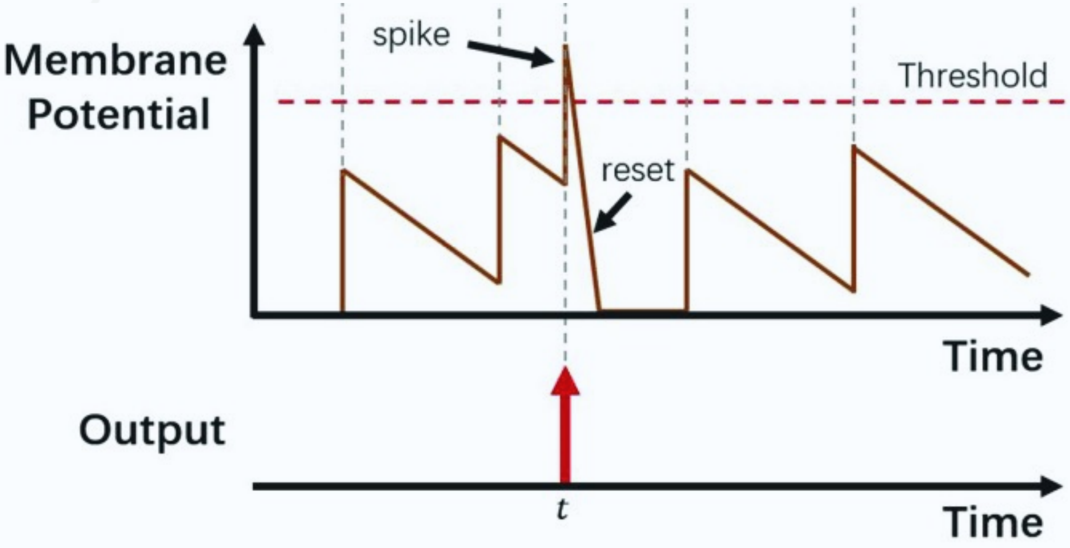
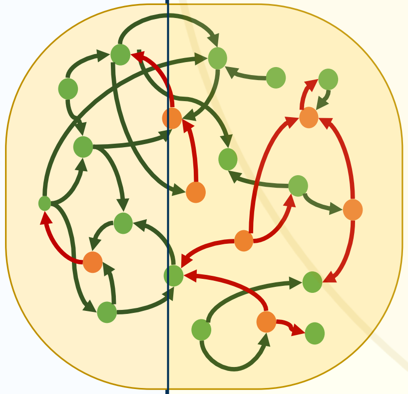
# Model

## Leaky Integrate and Fire (LIF) Neurons

$$\tau_m \frac{dv_i(t)}{dt} = -(v_i(t) - v_{rest}) + I_i(t)$$

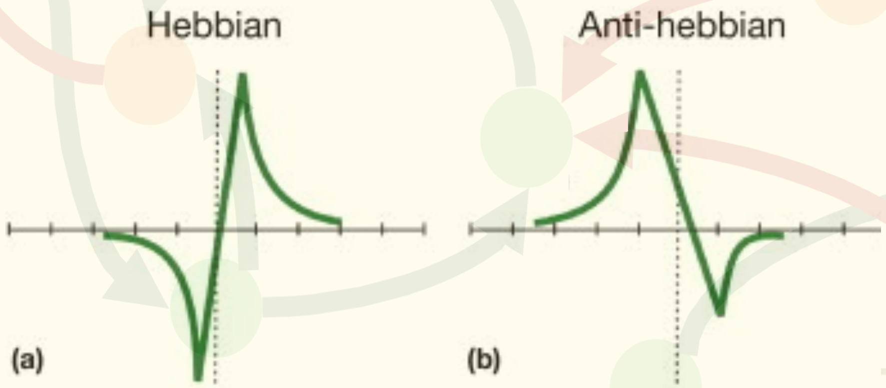


## Spike Timing Dependent Plasticity (STDP)

$$\Delta w(\Delta t) = \begin{cases} A_+(w)e^{-\frac{|\Delta t|}{\tau_+}} \; if \; \Delta t \geq 0 \\ -A_-(w)e^{-\frac{|\Delta t|}{\tau_-}} \; if \; \Delta t < 0 \end{cases}$$

$$s.t. A_+(w) = \eta_+(w_{max} - w),$$
$$A_-(w) = \eta_-(w - w_{min}))$$



# Heterogeneous SNN for Prediction

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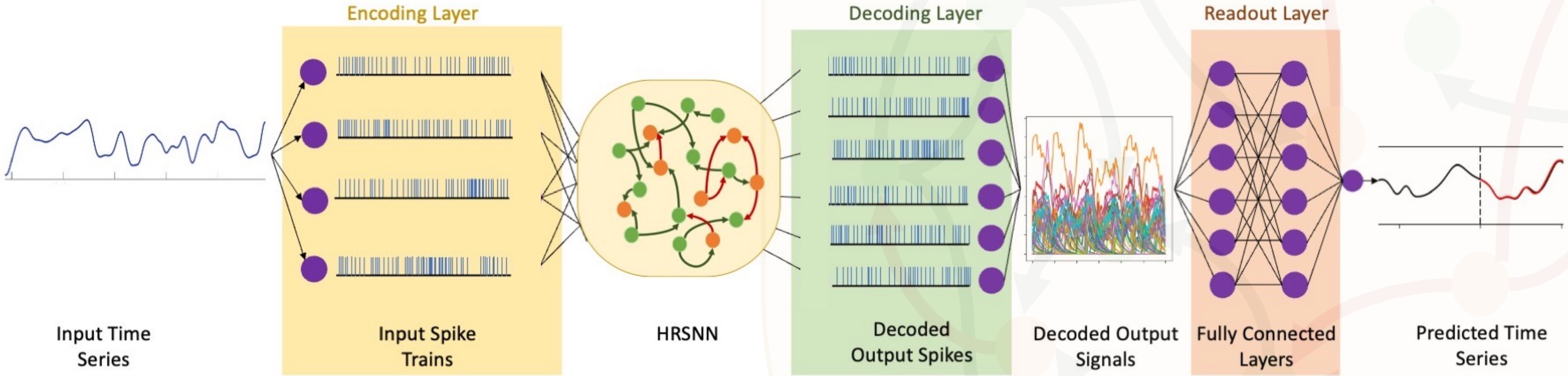
# Flowchart – HRSNN for Prediction

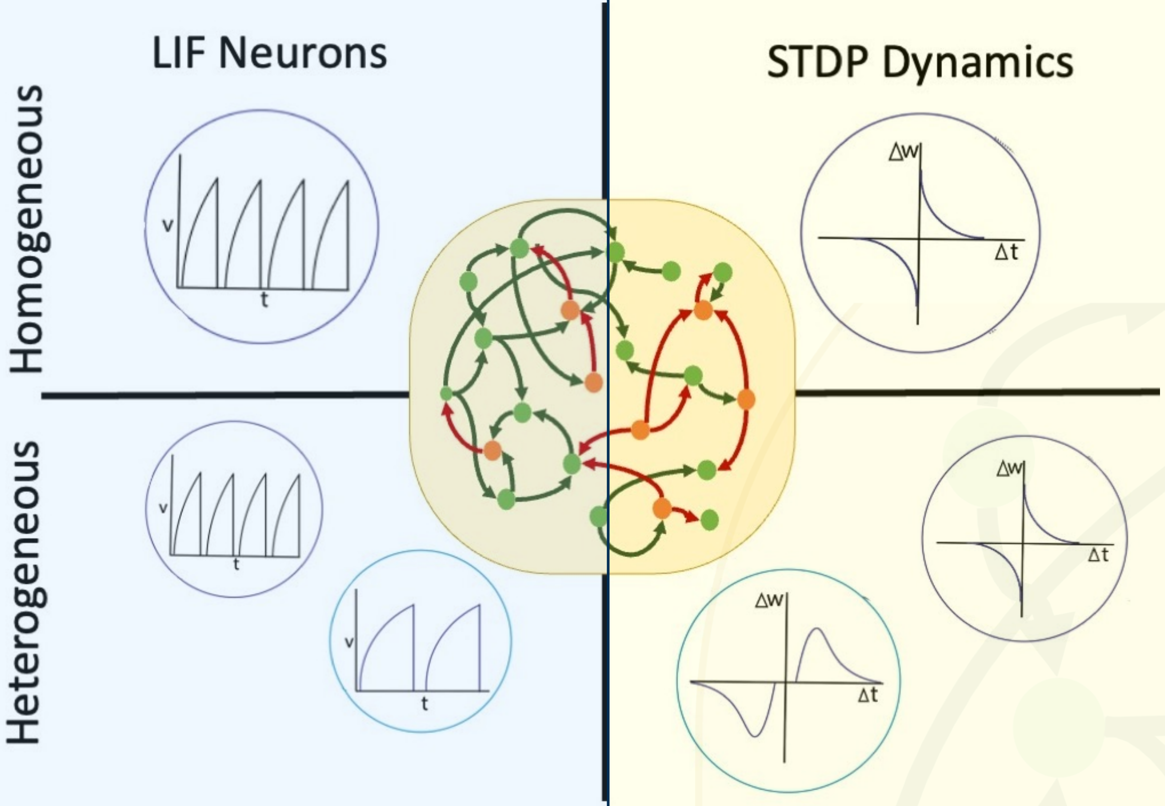


# Heterogeneity

**Heterogeneity in LIF dynamics:**

*What is it?*
Diversity of neuronal dynamics

Key Analytical Results:
- Heterogeneity in neuronal dynamics improves memory capacity, leading to better performance




**Heterogeneity in STDP dynamics:**

*What is it?*
Diversity of synaptic dynamics

Key Analytical Results:
- Heterogeneity in synaptic dynamics reduce spiking activity but preserve memory capacity

# Heterogeneity in LIF dynamics

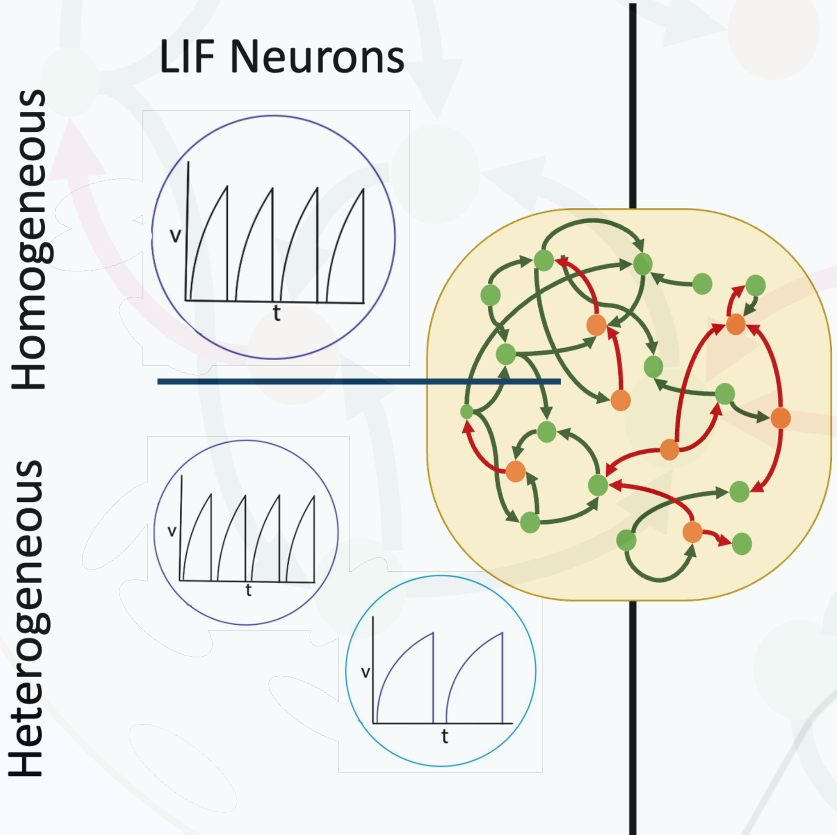
**Heterogeneity in LIF dynamics:**

LIF Neuron: $$\tau_m \frac{dv_i(t)}{dt} = -(v_i(t) - v_{rest}) + I_i(t)$$

Heterogeneity in LIF parameters

*What is it?*

Diversity of neuronal dynamics




*Pros:*

Improves Memory capacity (learn more distinct input patterns)

⇨ Improved classification and prediction performance

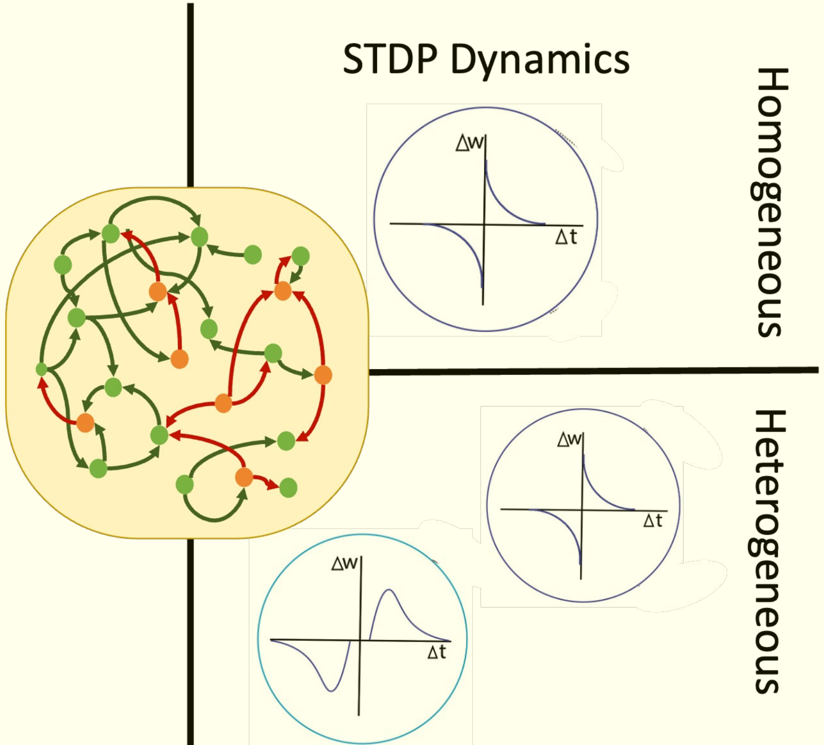
*Cons:*

Overfitting

# Heterogeneity in STDP Dynamics

$$\Delta w(\Delta t) = \begin{cases} A_+(w)e^{-\frac{|\Delta t|}{\tau_+}} \; if \; \Delta t \geq 0 \\ -A_-(w)e^{-\frac{|\Delta t|}{\tau_-}} \; if \; \Delta t < 0 \end{cases}$$

$$s.t. A_+(w) = \eta_+(w_{max} - w), \qquad A_-(w) = \eta_-(w - w_{min}))$$




**Heterogeneity in STDP dynamics:**

*What is it?*

Diversity of synaptic dynamics

*Pros:*

Helps to regularize the model
Reduce spike count

*Cons:*

Does not improve Memory Capacity
- Performance remains constant

# Prediction Results

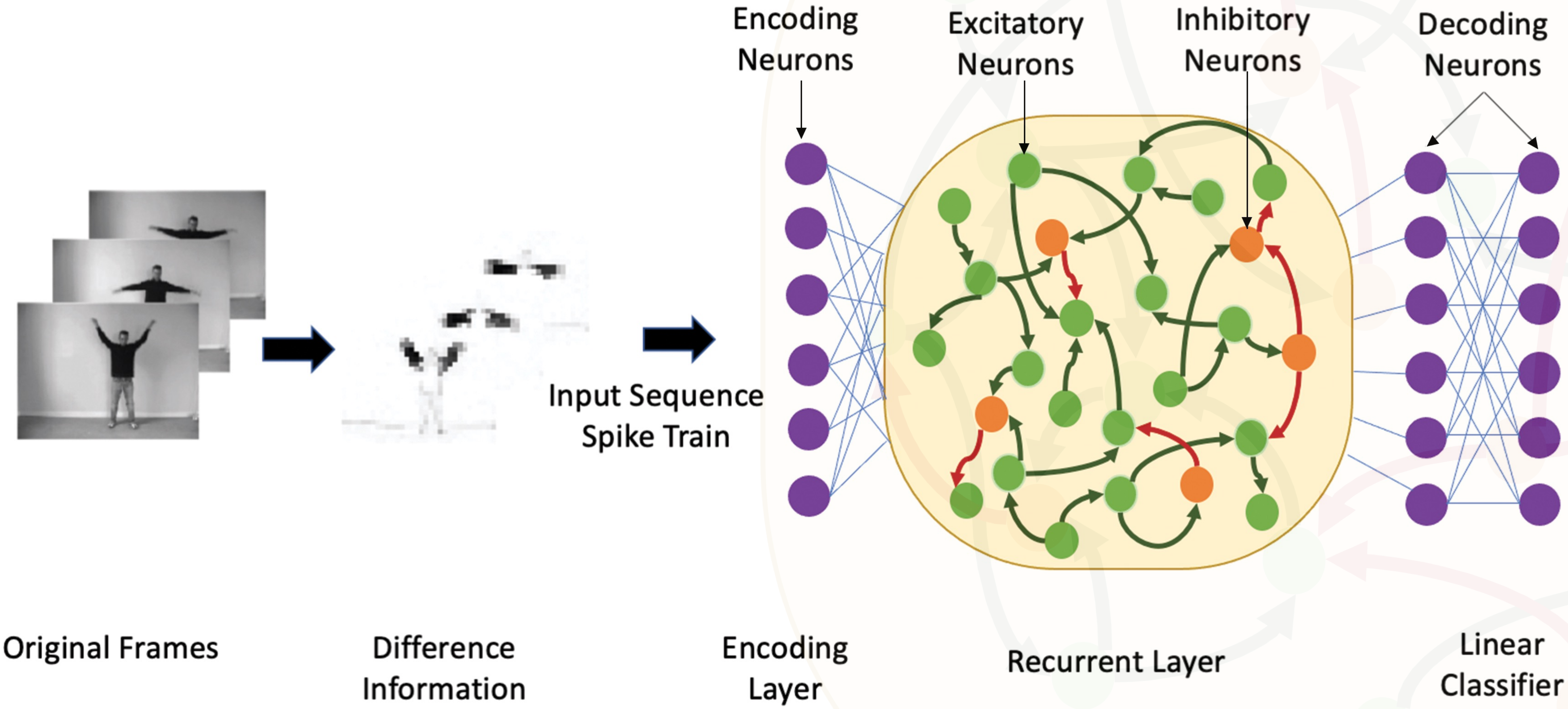
| | Method | Heterogeneous LIF | Heterogeneous STDP | Lorenz System (Prediction) | | |
|---|---|---|---|---|---|---|
| | | | | NRMSE | Norm. Avg. Firing Rate | Efficiency (1/NRMSE*Avg. Firing Rate) ($\times 10^{-3}$) |
| **RSNN with BP** | MRSNN-BP | ❌ | - | 0.182 | 0.857 | 1.16 |
| | HRSNN-BP | ✅ | - | 0.178 | 1.233 | 1.09 |
| **Unsupervised RSNN** | MRSNN | ❌ | ❌ | 0.395 | -0.768 | 0.787 |
| | HRSNN-HLIF | ✅ | ❌ | 0.203 | -0.143 | 1.302 |
| | HRSNN-HSTDP | ❌ | ✅ | 0.372 | -1.102 | 0.932 |
| | HRSNN | ✅ | ✅ | 0.195 | -1.018 | 1.725 |



**Summary:** HRSNN with heterogeneity in both STDP and LIF parameters shows the best performance

# Heterogeneous SNN for Classification

# Action Recognition

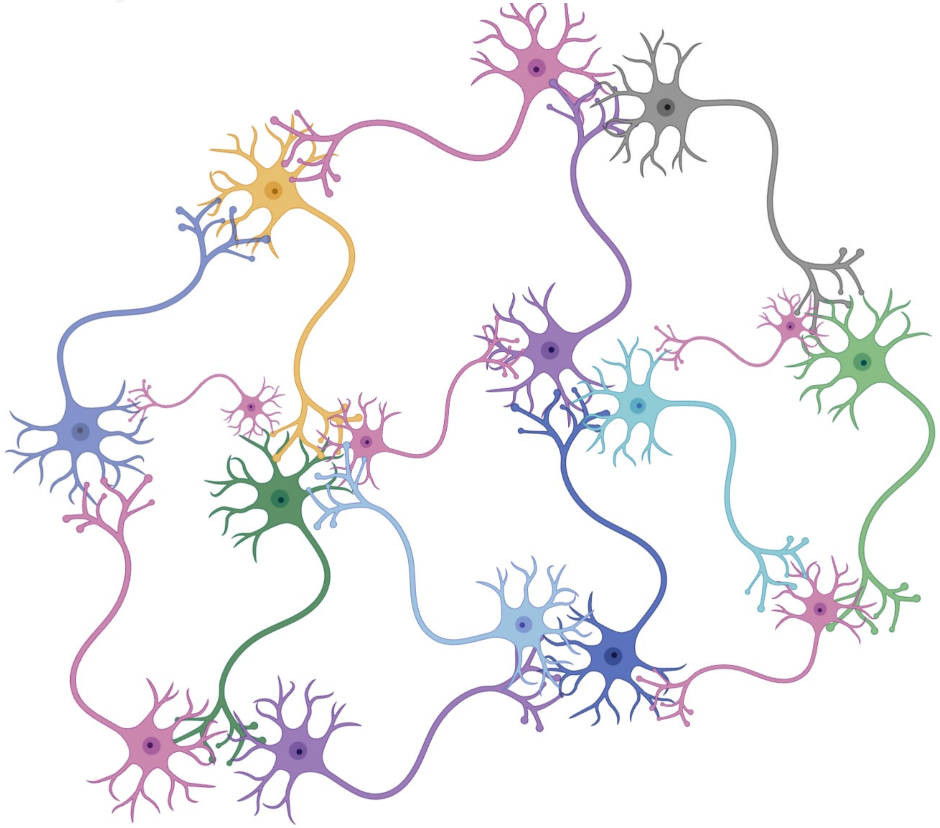


# Spatio-Temporal Classification Results

| | Model | DVS128 Accuracy |
|---|---|---|
| DNN | RG-CNN [5] | 97.2 |
| Homogeneous Supervised SNN | Liu et al. [4] | 92.7 |
| | DECOLLE | 97.5 |
| | She et al [3] | 95.0 (feedforward) |
| | Chakraborty et al. [2] | 97.1 (recurrent) |
| Heterogeneous Supervised SNN | Perez et al. [6] | 82.9 |
| | She et al [1] | 98.0 (feedforward) |
| | Chakraborty et al. [2] | 98.1 (recurrent) |
| Homogeneous Unsupervised SNN | CMA-ES [7] | 89.3 |
| | She et al [3] | 91.3 (feedforward) |
| | Chakraborty et al. [2] | 90.3 (recurrent) |
| Heterogeneous Unsupervised SNN | She et al [1] | 96.6 (feedforward) |
| | Chakraborty et al. [2] | 96.5 (recurrent) |

Dataset: DVS-Gesture 128

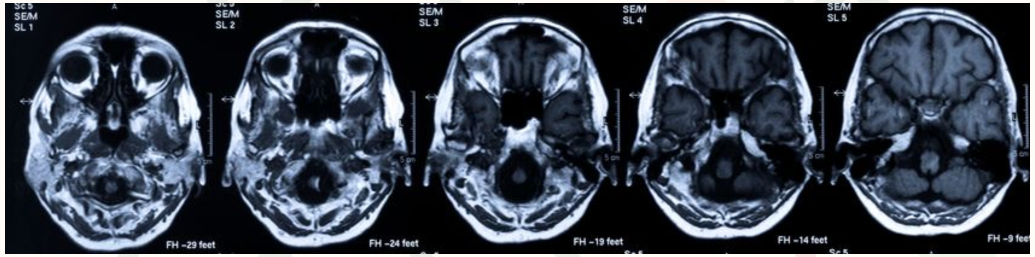
# Overview

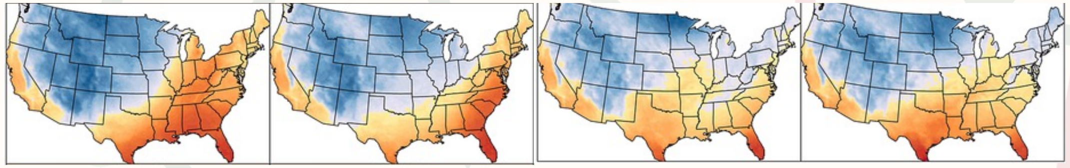


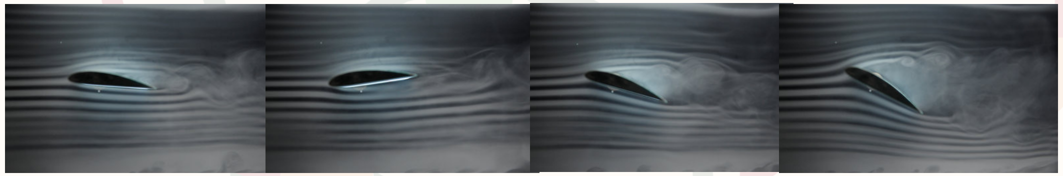
- Brain-Inspired Learning using Spiking Neural Networks
- Impact of Heterogeneity in
  - Recurrent Neural Networks
  - Feedforward Neural Networks
- Continuous Unsupervised Learning

# Overview

- **Real-world systems are not static and keep evolving with time**
  - Need for an evolving learning system.







- **Online learning methods**
  - Predictions made by extracting the underlying dynamics from the observed time series
  - Critical for real-time learning and prediction of time-varying environments for ML models running at the edge

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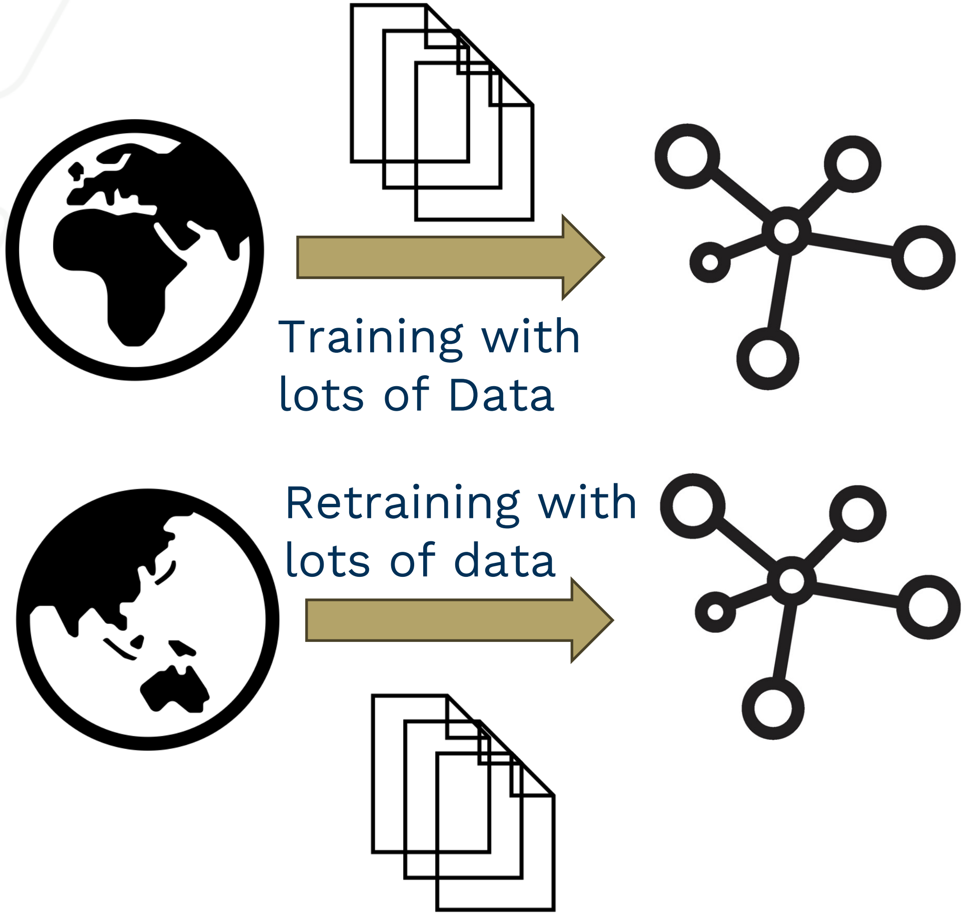
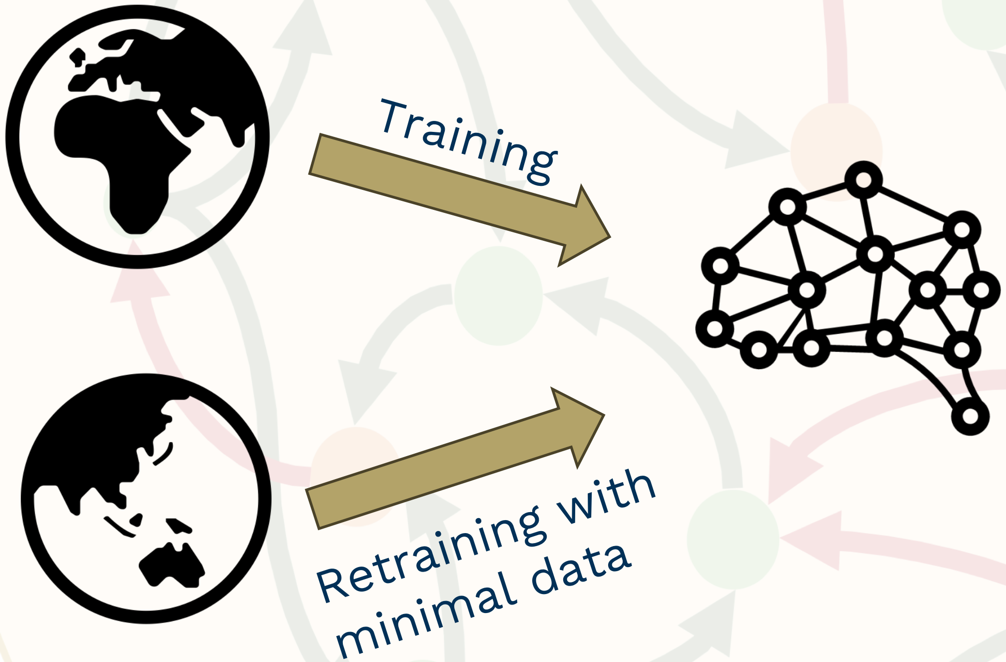
# Motivation

- Static Supervised Learning




- Continuous Unsupervised Learning



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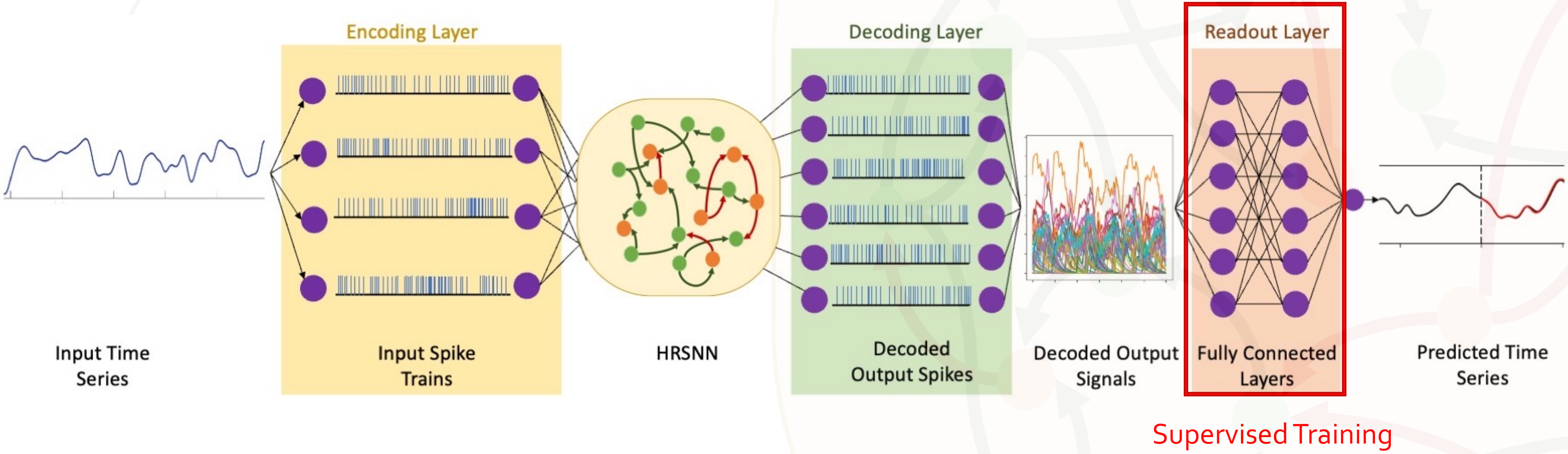
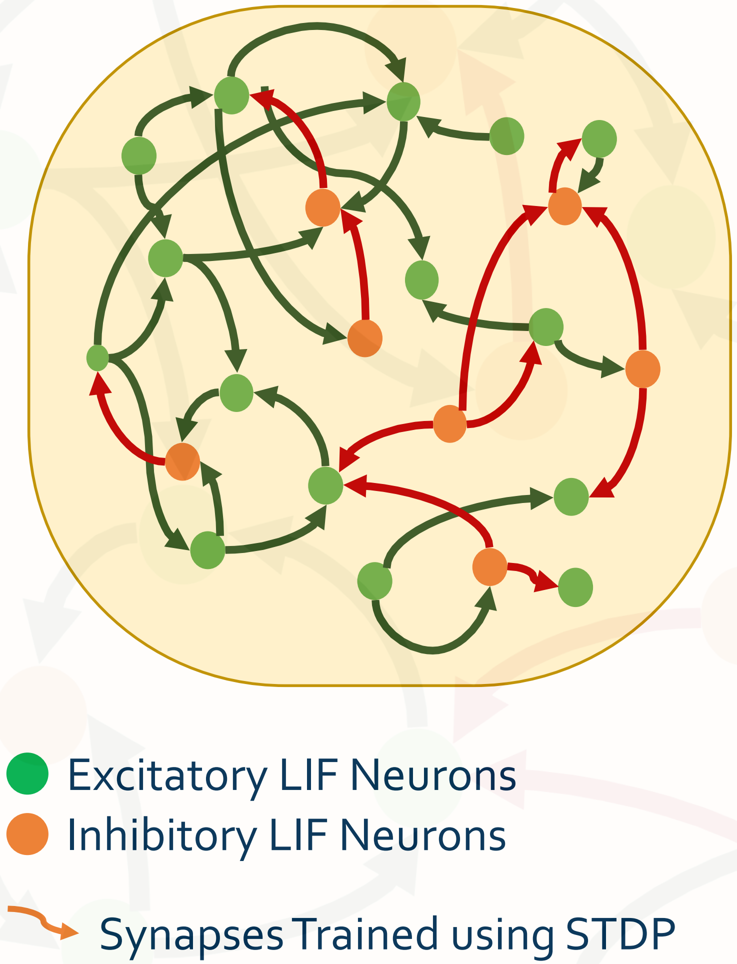
# Problem Statement



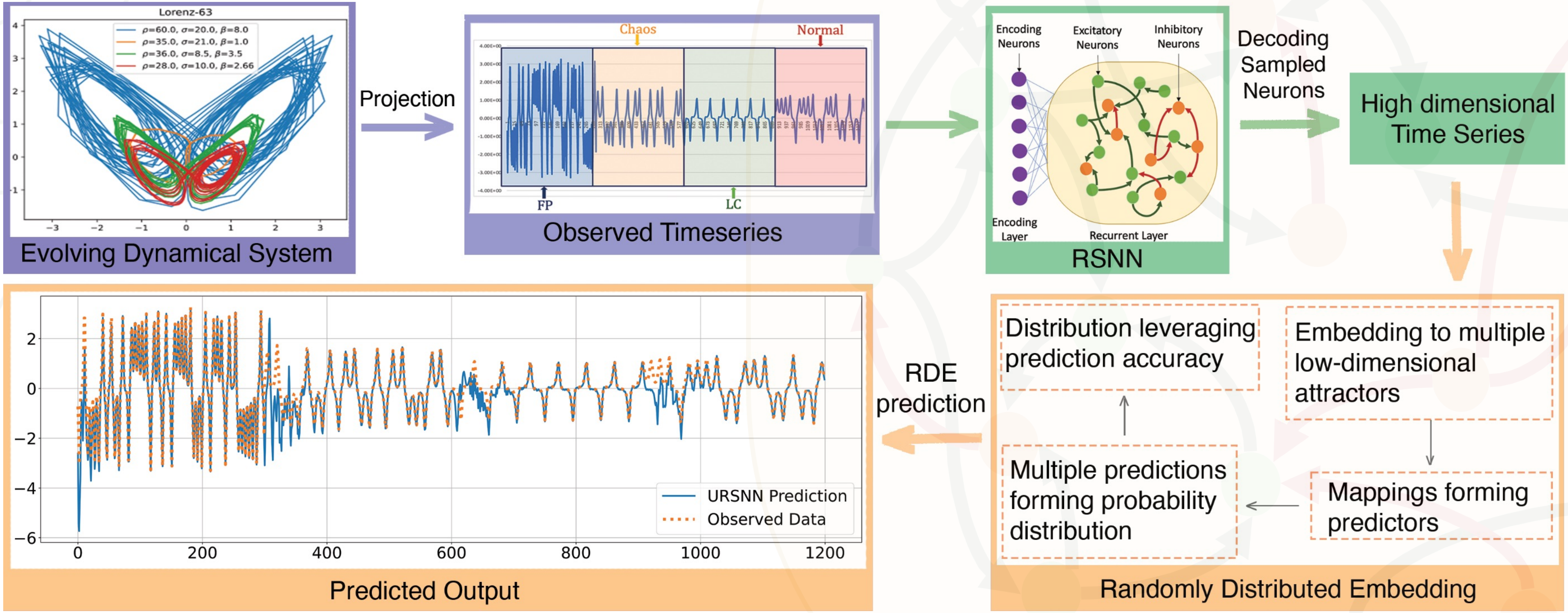
# Continuous Learning and Online Adaptation

- Completely unsupervised prediction of the time series
  - quick and robust in adapting to new unseen dynamics.
- Recurrent spiking neural networks
  - continually learn from streaming incoming data using brain-inspired plasticity rules.

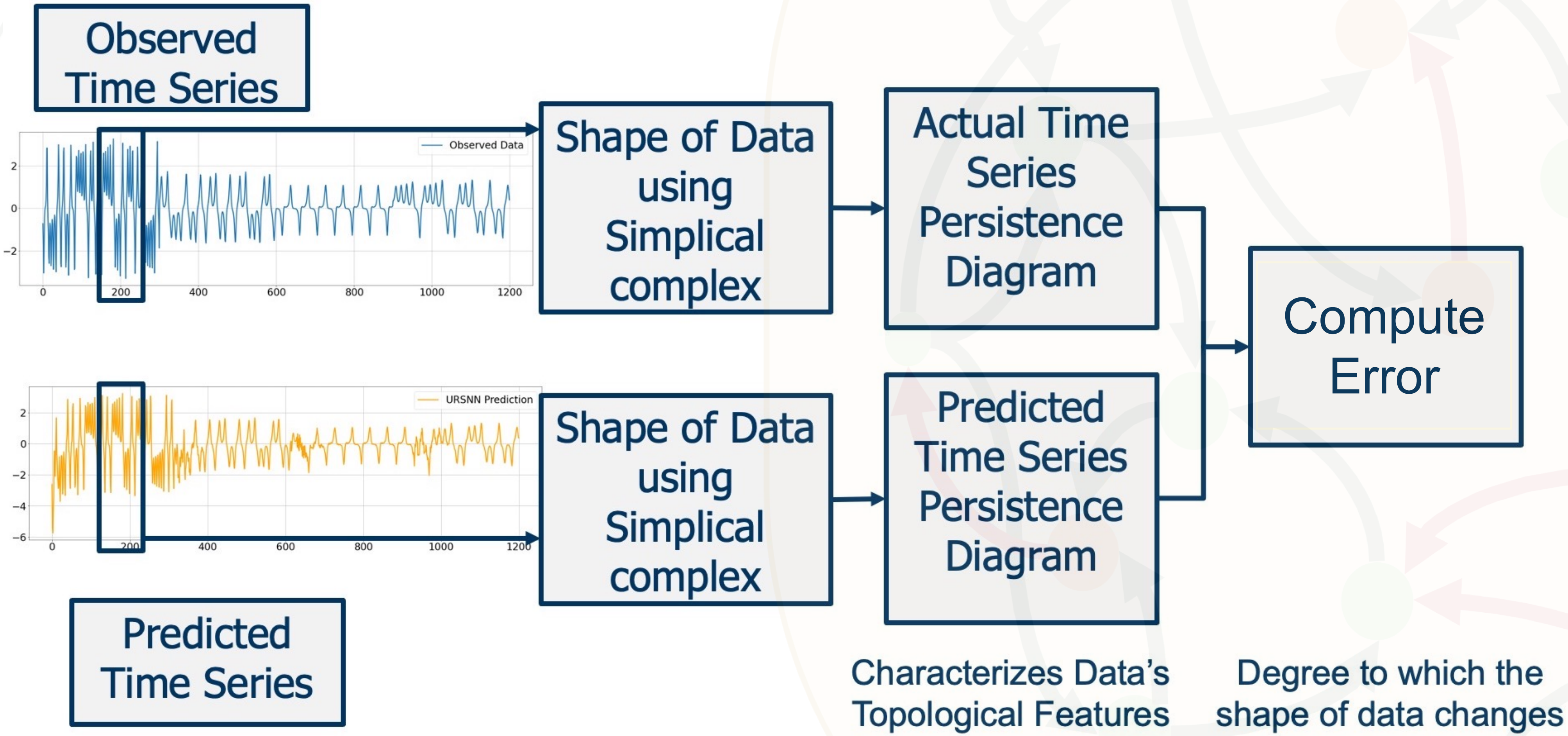
- The model continually learns representations of the underlying dynamical systems from which the data is generated.



# Flowchart for Unsupervised Prediction

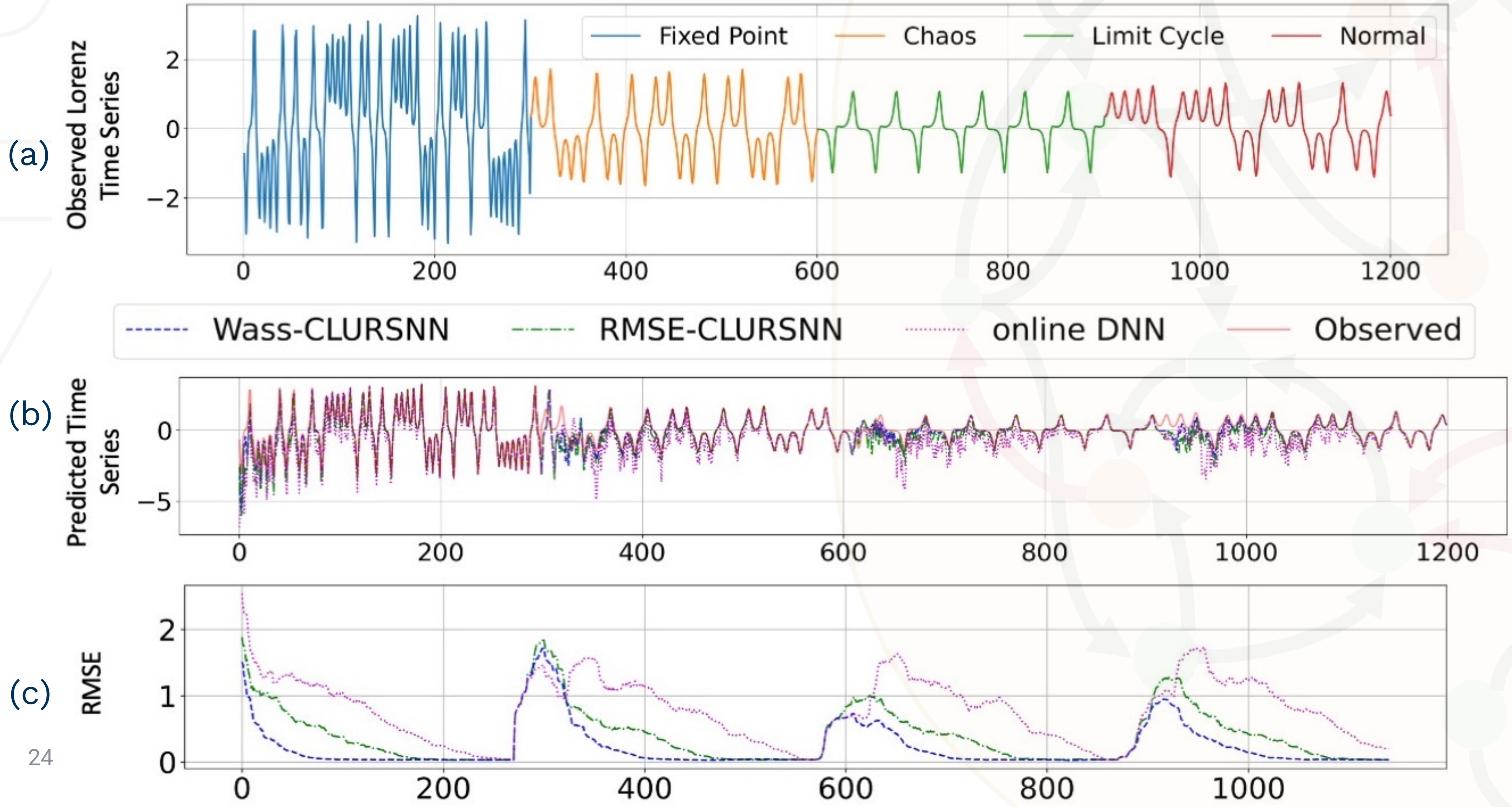


# Wass-CLURSNN




Block Diagram showing the error computation between the persistence homologies of the observed and the predicted time series

# Prediction Results



# Summary

- Heterogeneity in Neuronal and Synaptic Dynamics help us engineer more efficient neural network models which better resemble the workings of the brain

- Heterogeneity in parameters helps to learn richer representation space

- Bio-inspired learning methods like STDP continually synchronizes with the underlying dynamical system it is trained on

# Acknowledgements

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