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OPTIMISED EVENT-DRIVEN SNN ARCHITECTURES

tinyML Asia 2023

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Collaborators

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The problem of learning at edge

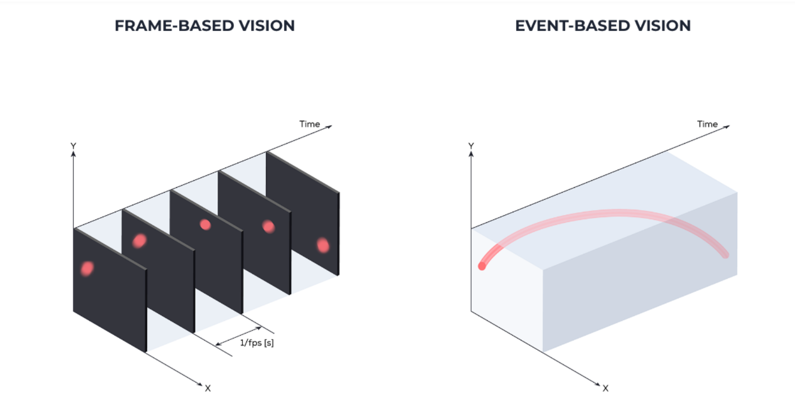
- Error-Backpropagation is computationally expensive -> High Power
- Requires a symmetric backward pathway to pass full precision values
- Backpropagation requires precise and synchronous orchestration of gradient calculation and weight updates. It leads to a ‘locking effect’ when implemented in hardware
- The von-Neumann bottleneck. We need co-located memory and compute in hardware
- Possible for small networks, but not scalable
- The result: Most solutions are only inference at edge rather than learning at edge

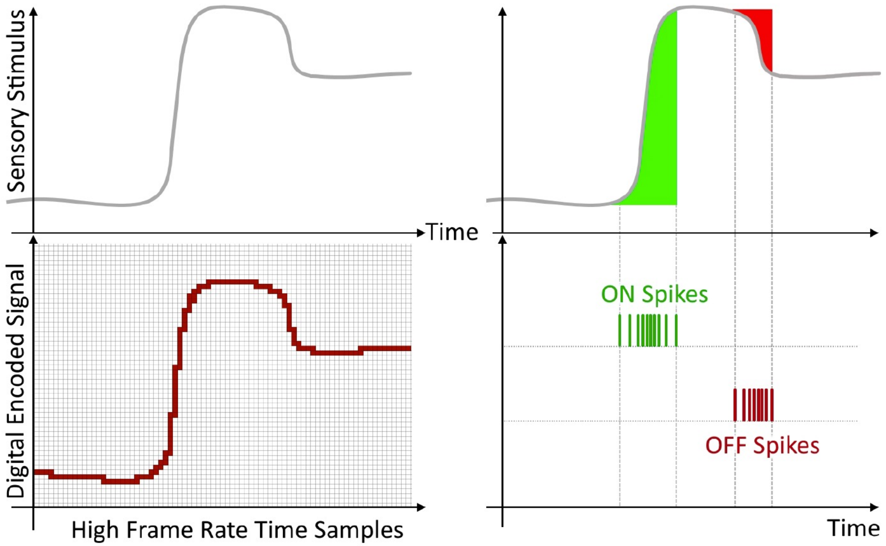
Lessons from nature

- Communication sparsity
- Computation sparsity
- Massive parallelism
- Local Independence

Communication Sparsity

- Information coding in spikes
- Spike only when necessary
- Neuromorphic sensors have proved to be energy efficient solutions for sampling data with high temporal precision yet generating sparse data rates
- Timing is key





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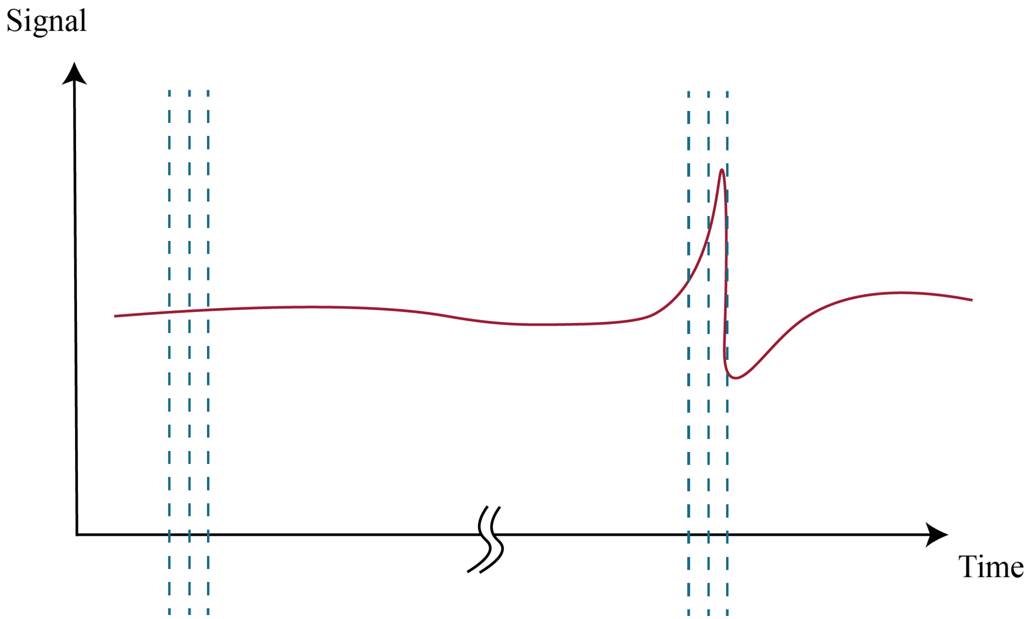
Computation Sparsity

- Asynchronous computing at the arrival of spikes
- Long periods of boredom with sudden bursts of activity!
- Sensors like event-based cameras solve it at the sensing end. Need similar capabilities at the processing end of things.
- Compute only when necessary



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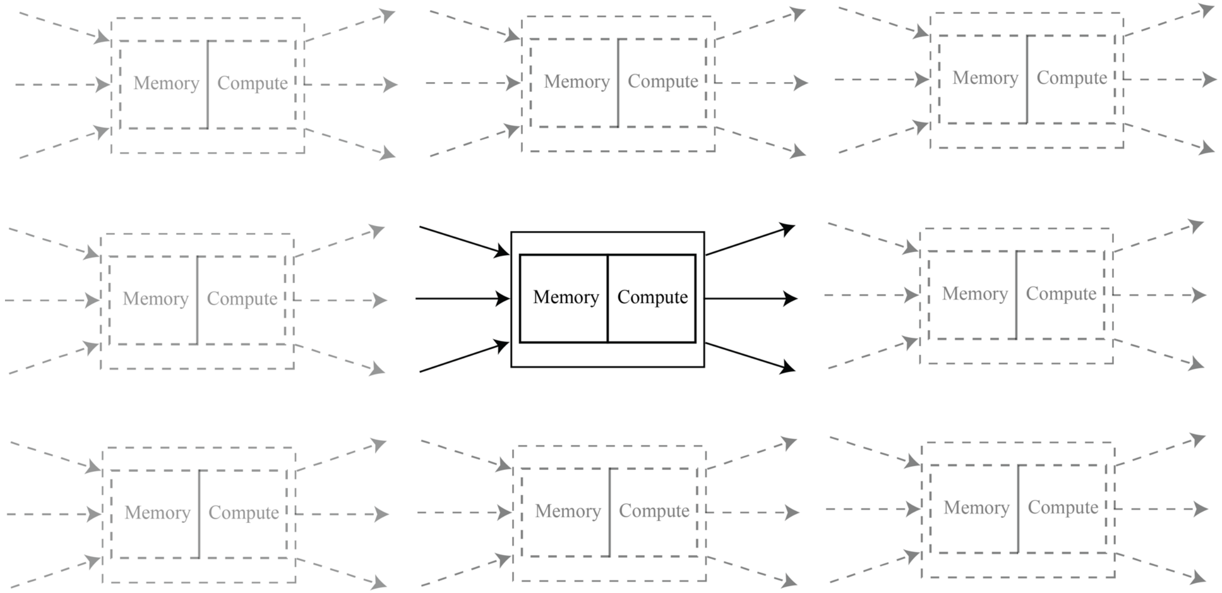
Local Independence and Parallelism

- Local learning vs Global learning
- Scalable network architectures that can be decomposed into entities that can operate independently
- The smaller the better
- The similar the better
- Fault tolerant and extensible



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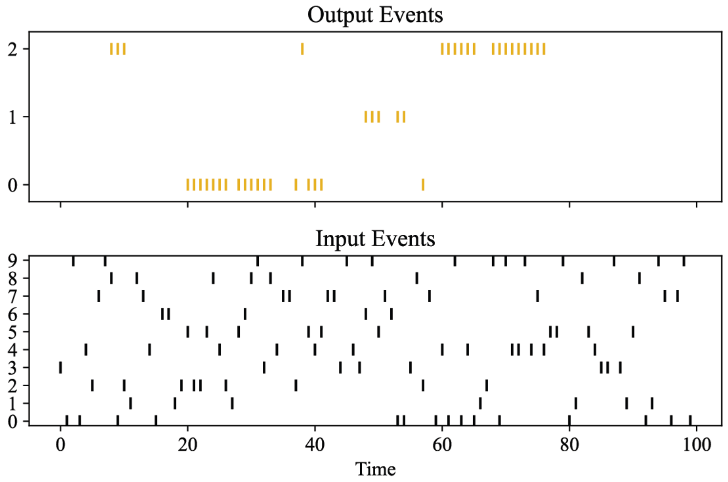
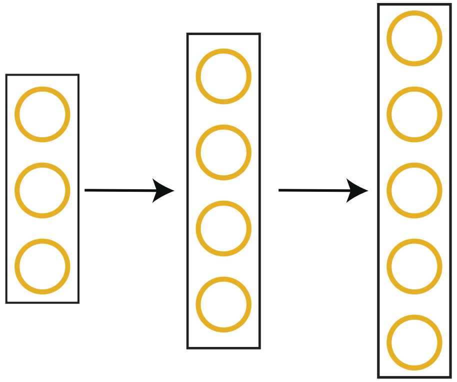
Event-driven Neural Architectures

Event-driven



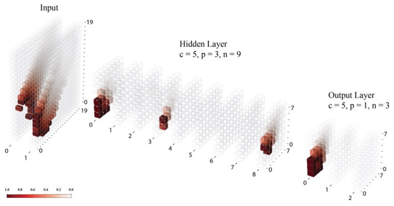
Asynchronous

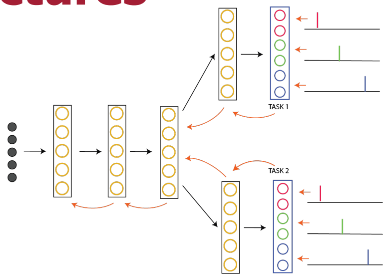
Neural

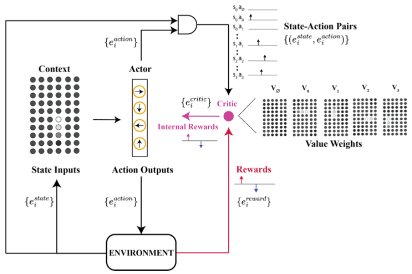


Distributed and Scalable

Architectures

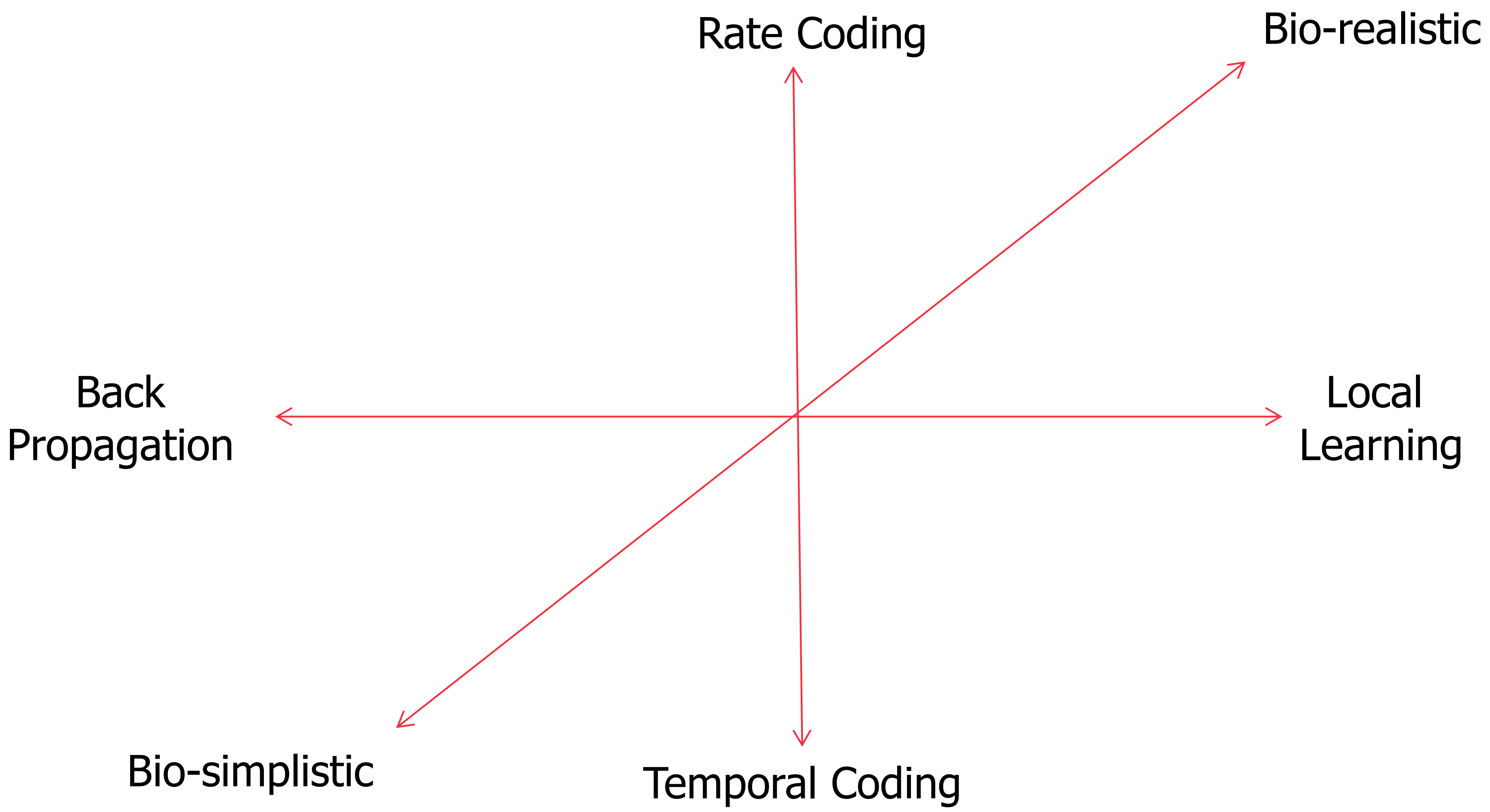






Compositional and Inductive Priors

The SNN Zoo


Rate Coding
Bio-realistic
Back Propagation
Local Learning
Bio-simplistic
Temporal Coding

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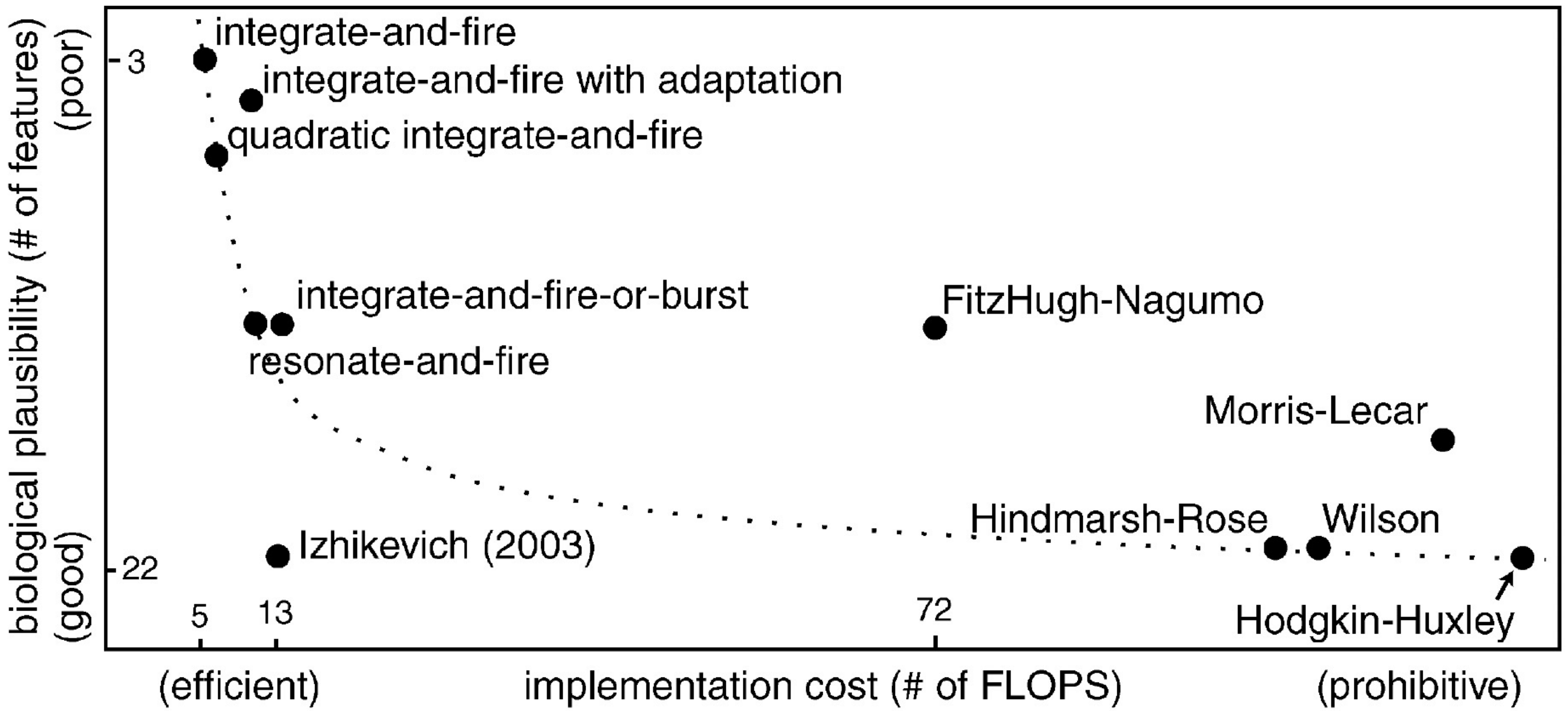
Abstraction of Spiking Neural Networks



Izhikevich, E. M. (2004). Which model to use for cortical spiking neurons? IEEE transactions on neural networks, 15(5).

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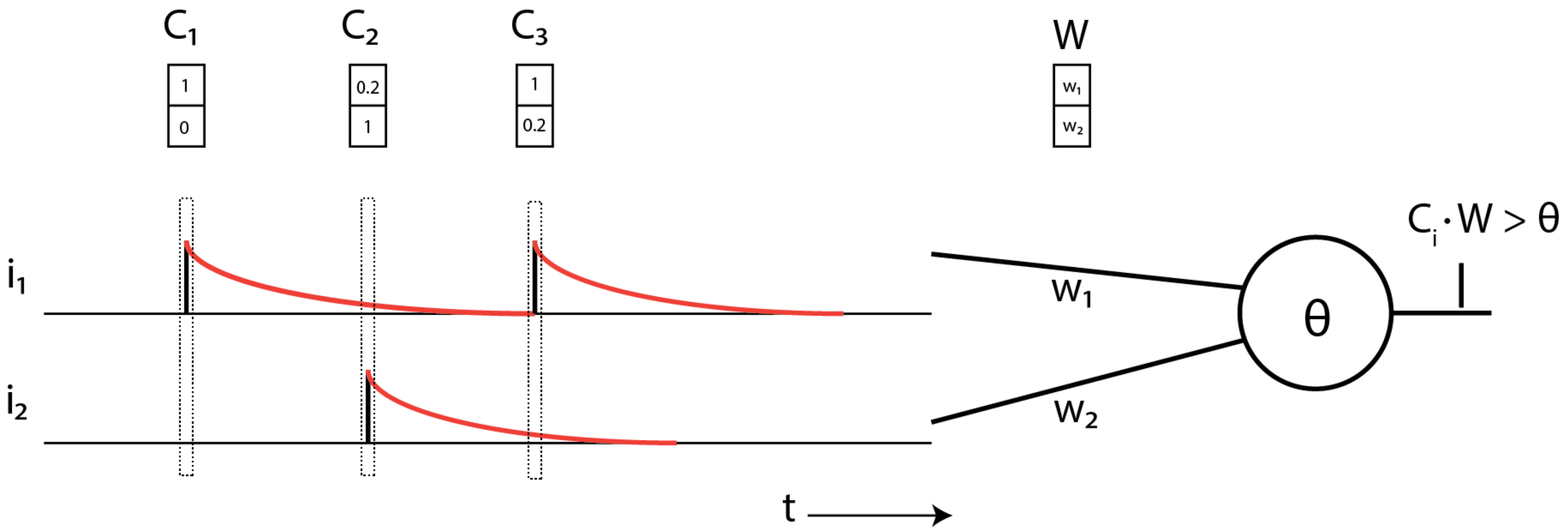
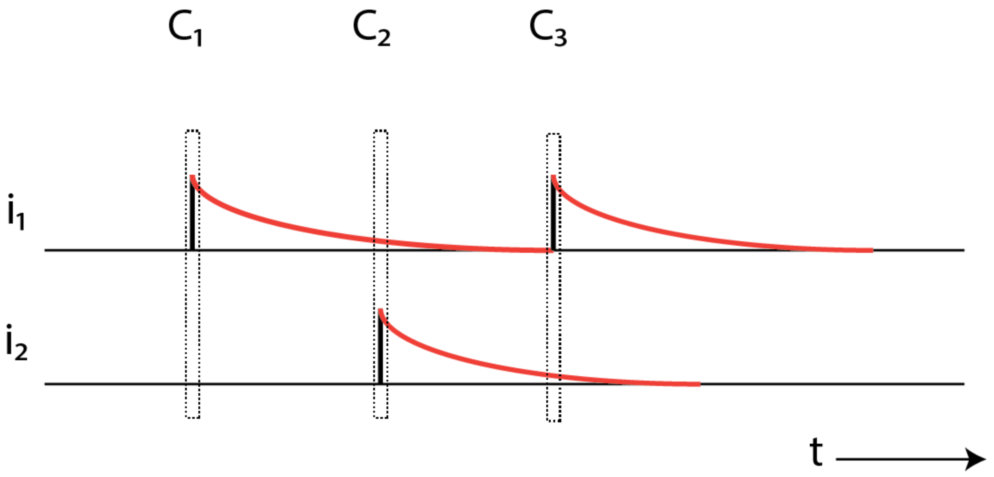
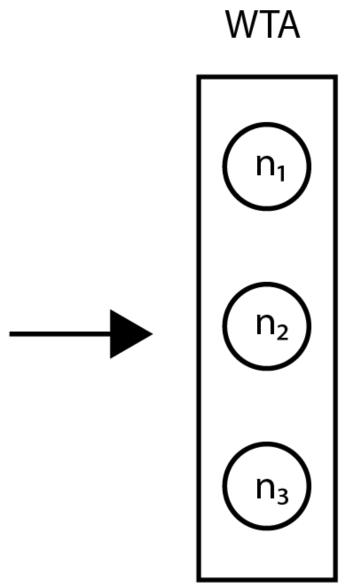
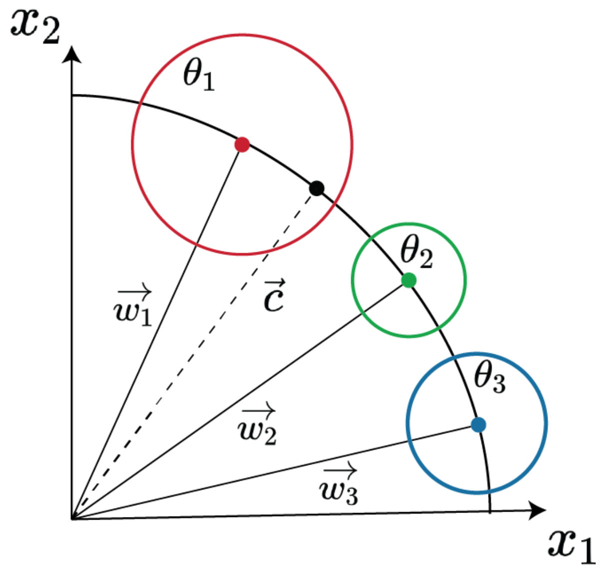
Timesurfaces and dot products for abstraction of spiking neurons

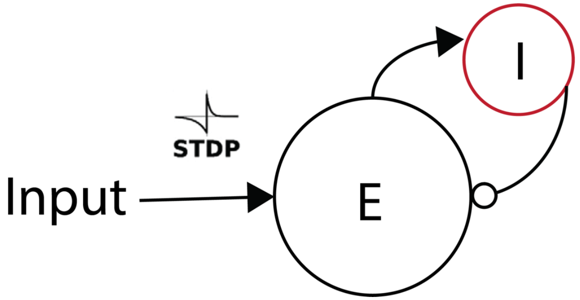


Winner-Takes-All and Selection Thresholds









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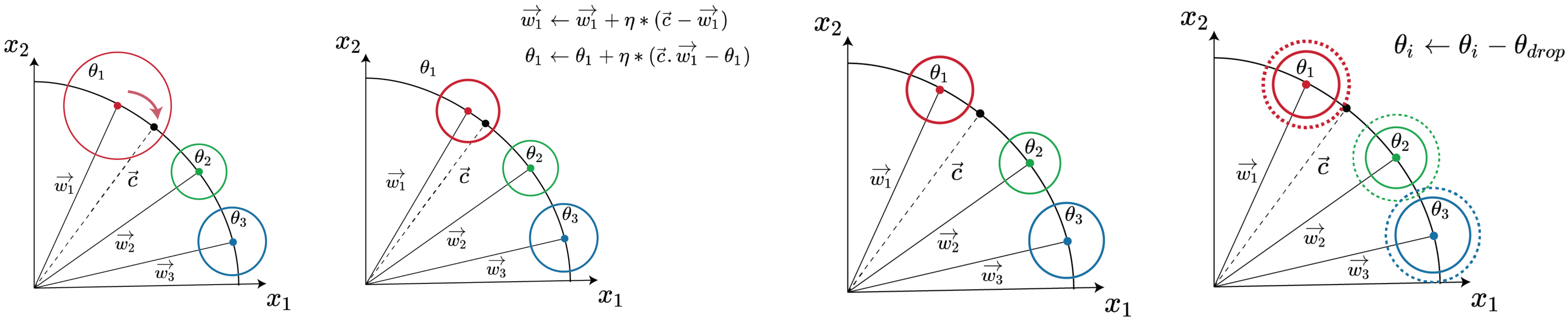
Unsupervised feature extraction using selection thresholds



Afshar, Saeed, et al. (2020) "Event-based feature extraction using adaptive selection thresholds." Sensors

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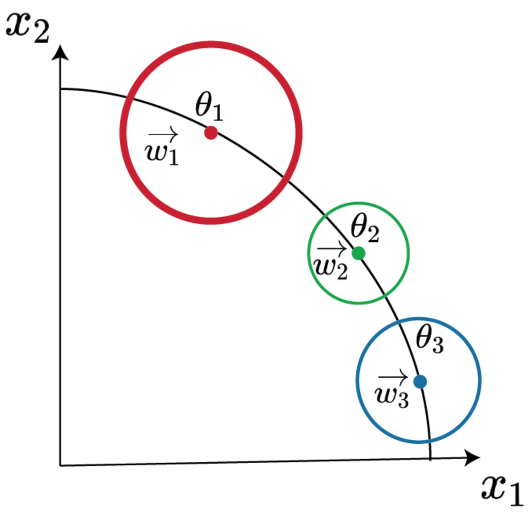
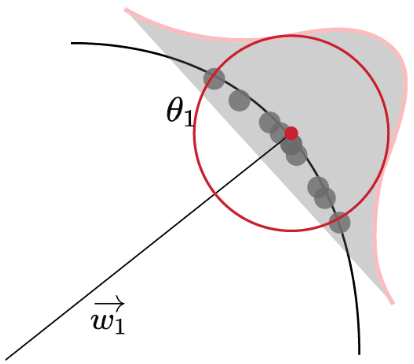
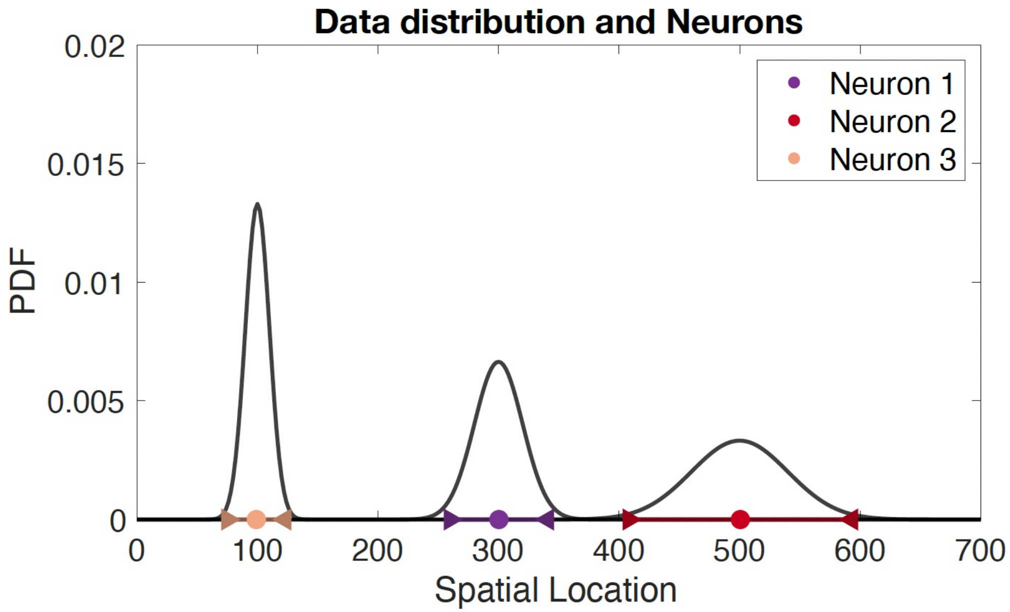
Role of weights and thresholds





$$\vec{w_1} \leftarrow \vec{w_1} + \eta * (\vec{c} - \vec{w_1})$$
$$\theta_1 \leftarrow \theta_1 + \eta * (\vec{c}.\vec{w_1} - \theta_1)$$



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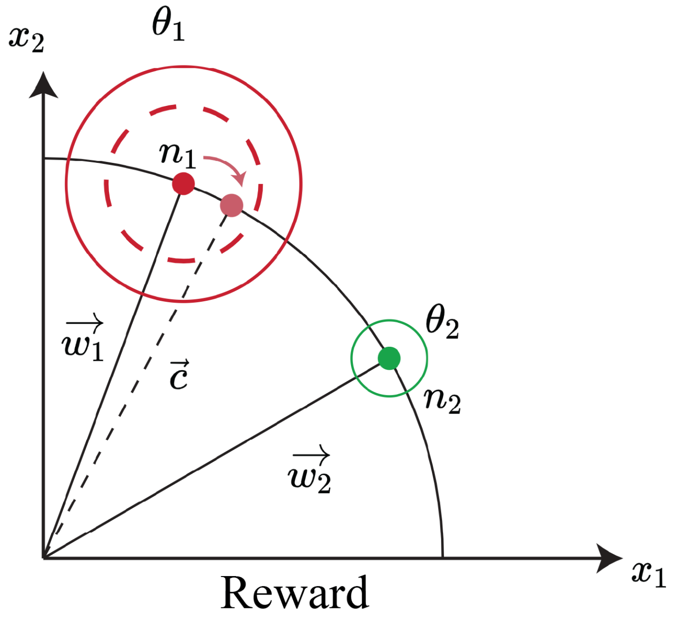
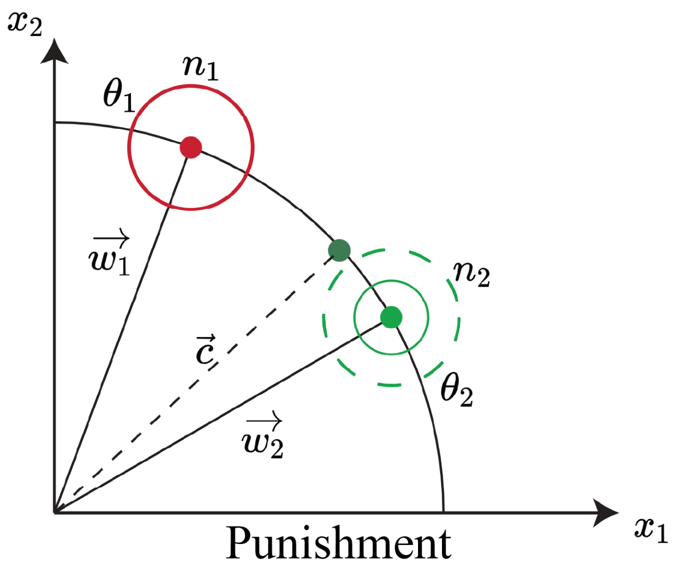
Supervised learning

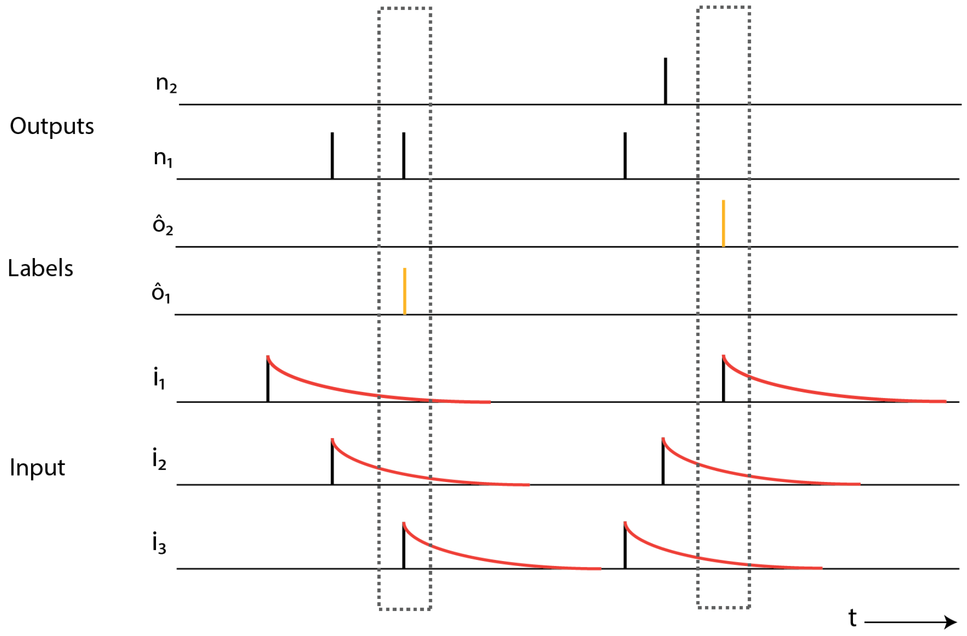
$$\overrightarrow{w_1} \leftarrow \overrightarrow{w_1} + \eta * (\vec{c} - \overrightarrow{w_1})$$

$$\theta_1 \leftarrow \theta_1 + \eta * (\vec{c}.\overrightarrow{w_1} - \theta_1)$$



$$\theta_2 \leftarrow \theta_2 - \theta_{drop}$$





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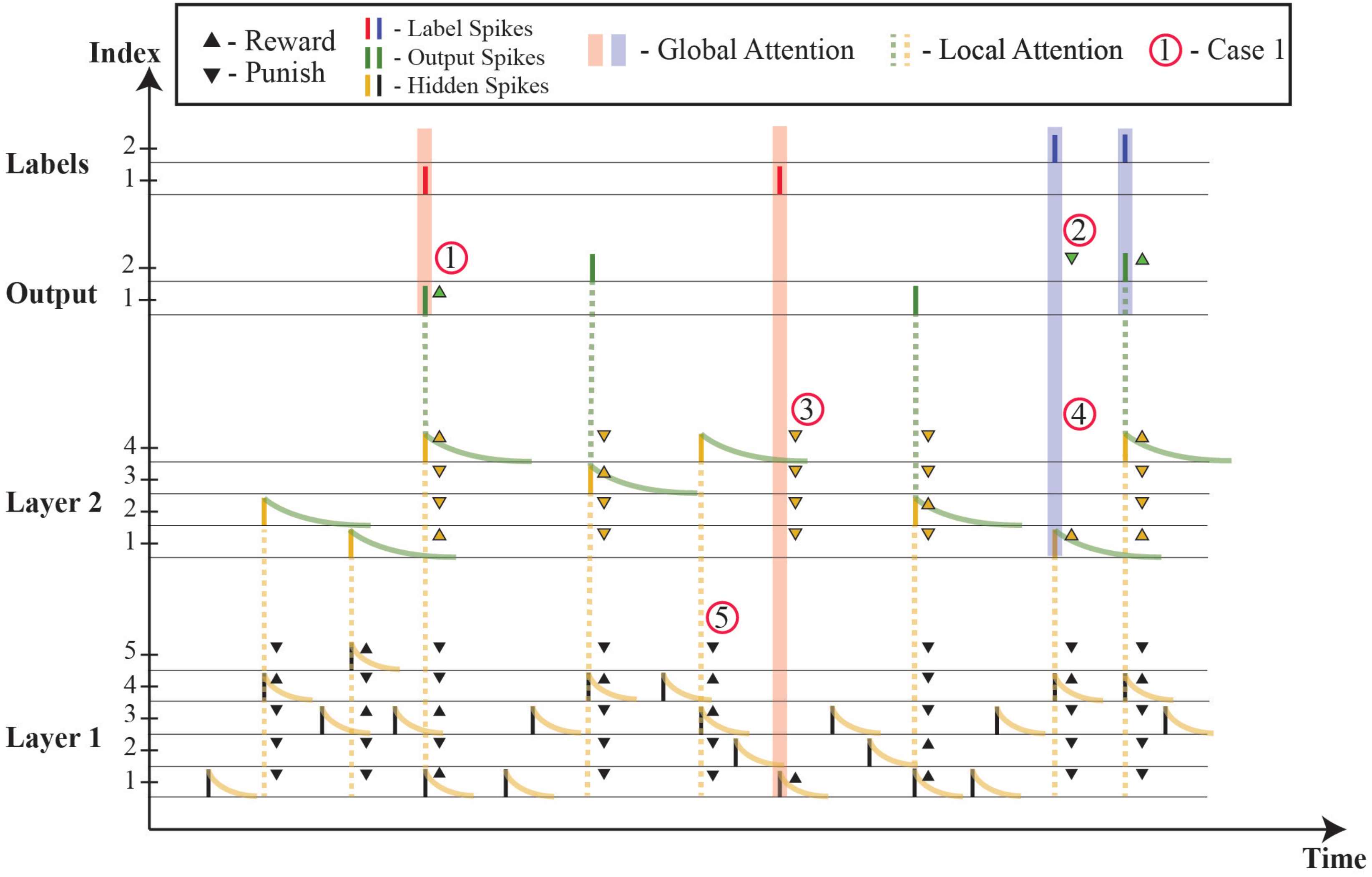
Spike-Timing-Dependent Threshold Adaptation



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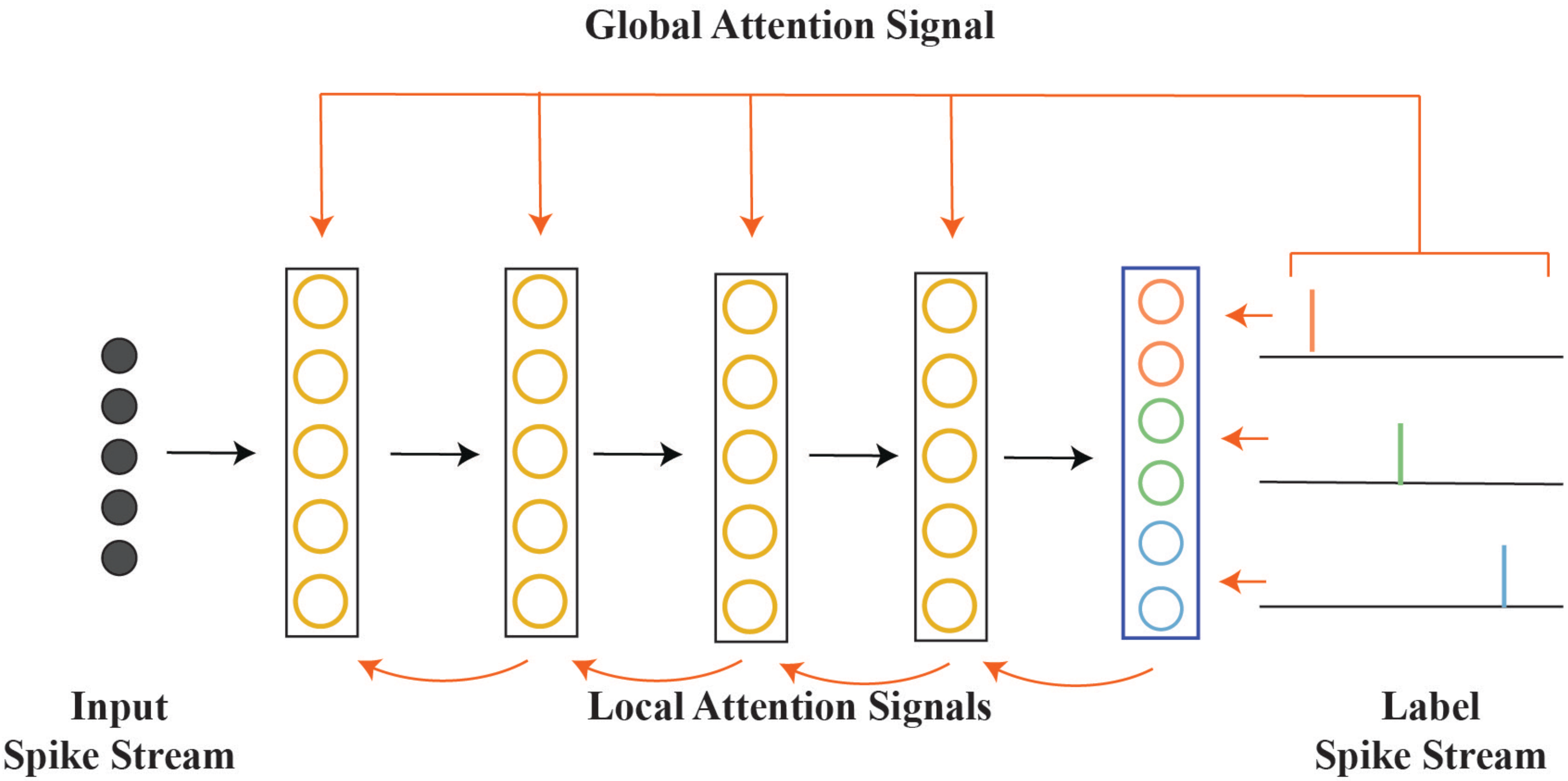
Optimised Deep Event-driven SNN Architecture (ODESA)



Bethi, Y., Xu, Y., Cohen, G., Van Schaik, A. and Afshar, S., 2022. An optimized deep spiking neural network architecture without gradients. IEEE Access, 10

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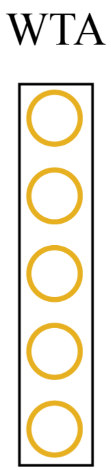
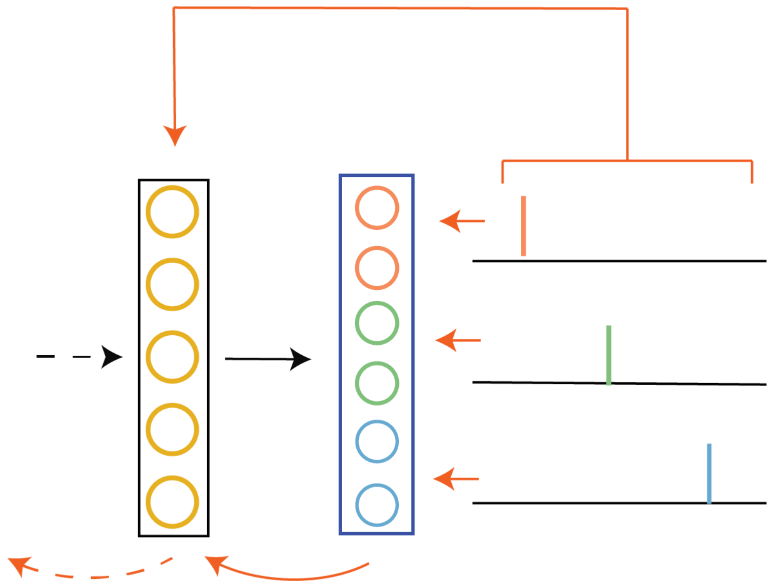
Local Competition and Global Cooperation



Local competition via Winner-Takes-All



Global cooperation through binary attention signals

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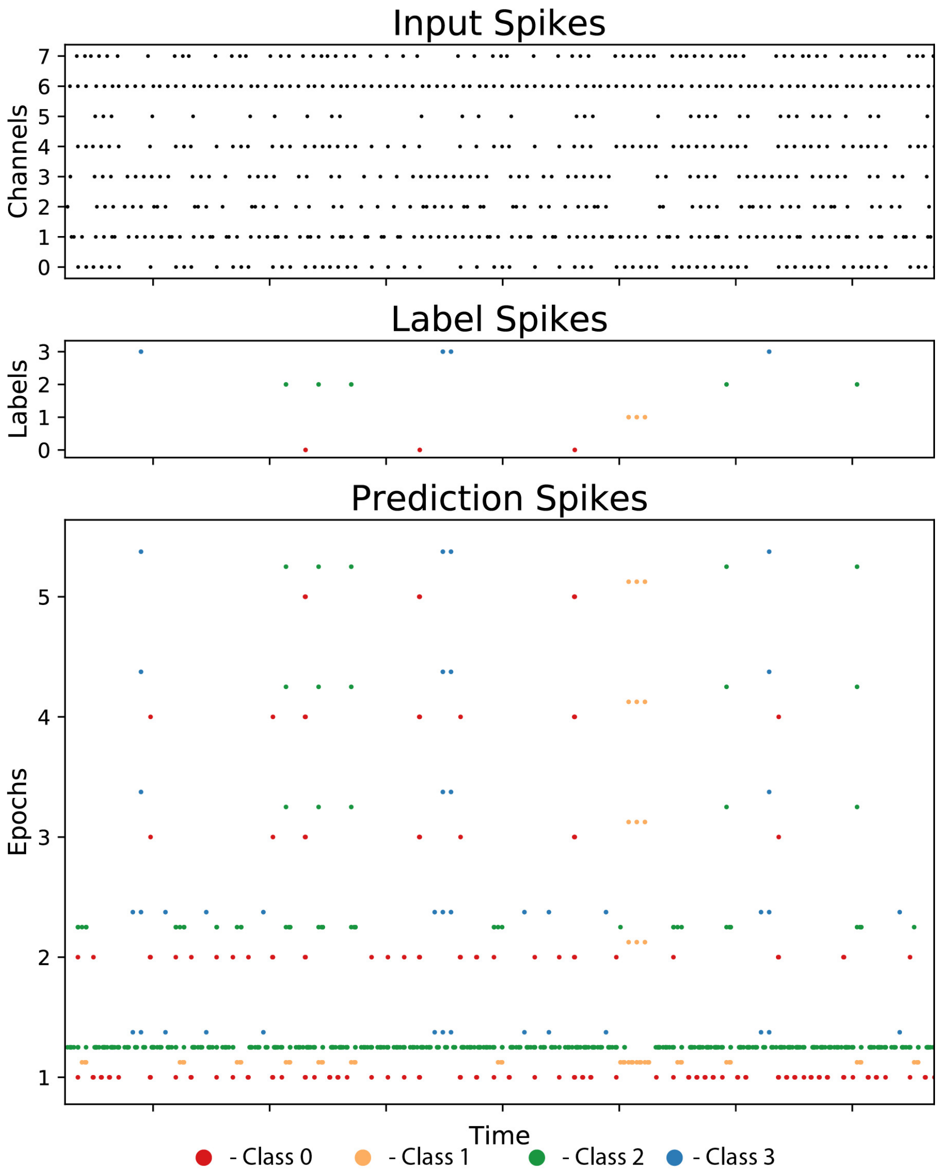
ODESA results



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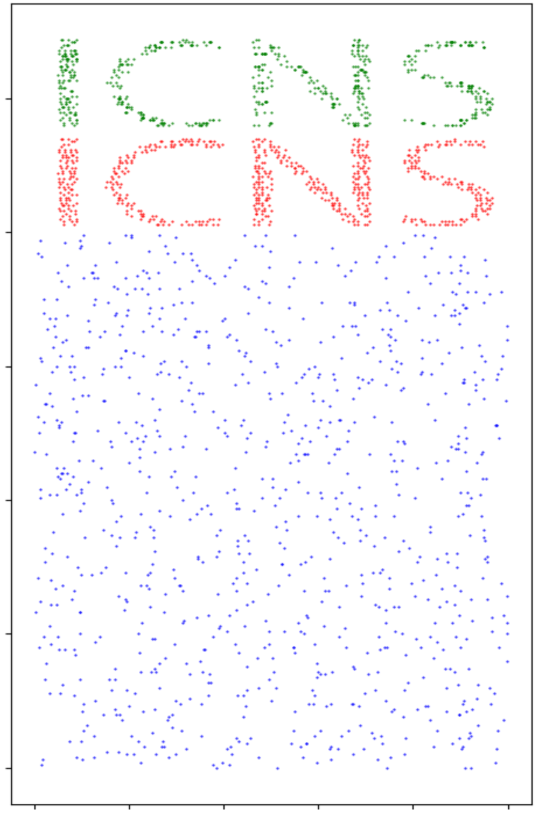
ODESA Results



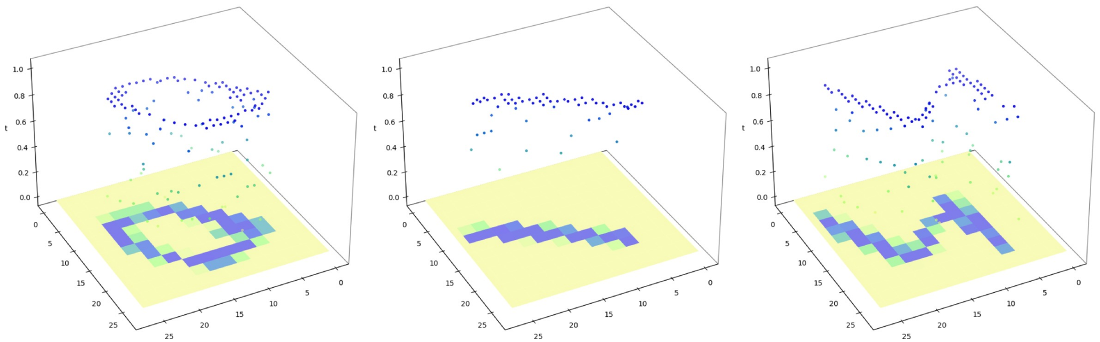
Predicted Spikes

Target Spikes

Input Spikes

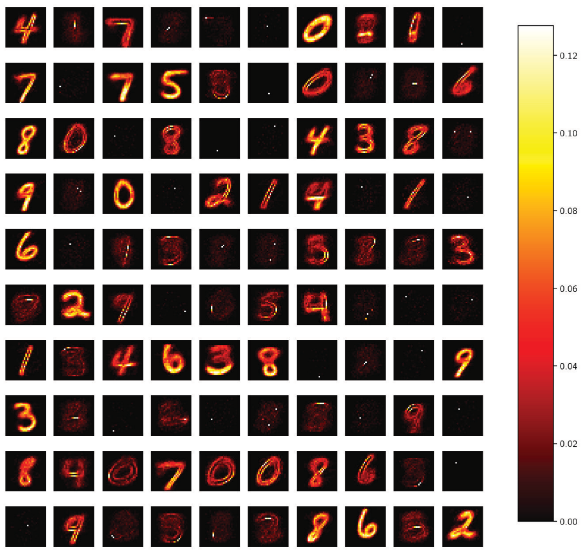
Oxford Spike Pattern
0.67 IOU per input spike

ODESA Results

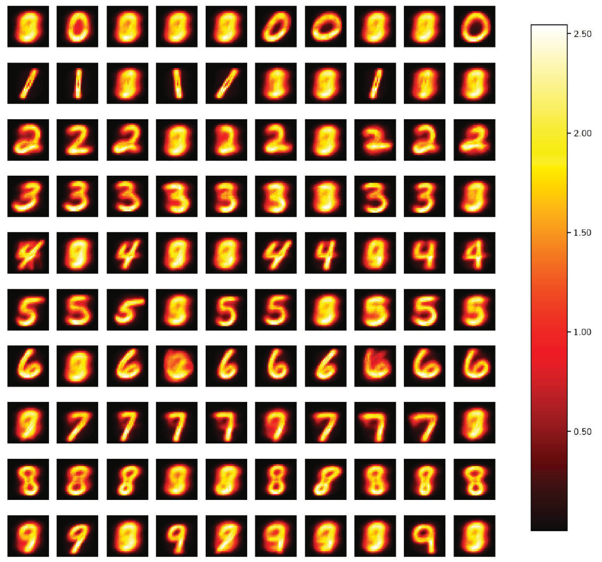


Method	Pre-Processing	Test Accuracy
Two Layer with Exponential STDP + *a posteriori* neuron selection [63]	Rate Coding	95.00%
Spiking RBM + Contrastive Divergence, Linear Classifier [64]	Thresholding + Rate coding	89.00%
Spiking RBM + Contrastive Divergence [65]	Thresholding + Spike Coding	91.90%
Dendritic neurons + Morphology Learning [66]	Rate Coding	90.30%
Multi-layer hierarchical network + STDP with Calcium variable [67]	Orientation Detection + Spike Coding	91.60%
Spiking CNN + Tempotron Rule [68]	Scaling, Orientation, Thresholding + Spike Coding	91.30%
Three Layer SNN + STDP-Backpropagation [69]	Rate Coding	97.20%
Deep SNN + Backpropagation [70]	Rate Coding	98.60 %
Two Layer SNN + SGD [71]	Latency based Spike Encoding	96.92%
ODESA (Our method)	Latency based Spike Encoding	93.24%

100 Random neurons out of W_H



$W_O \times W_H$



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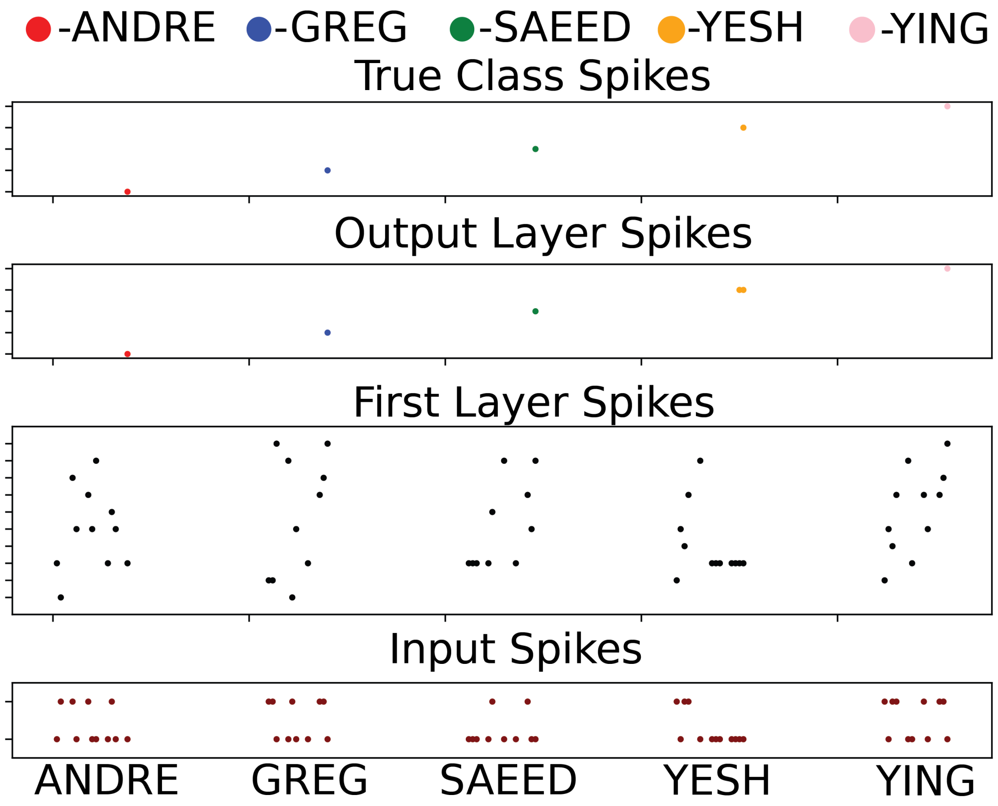
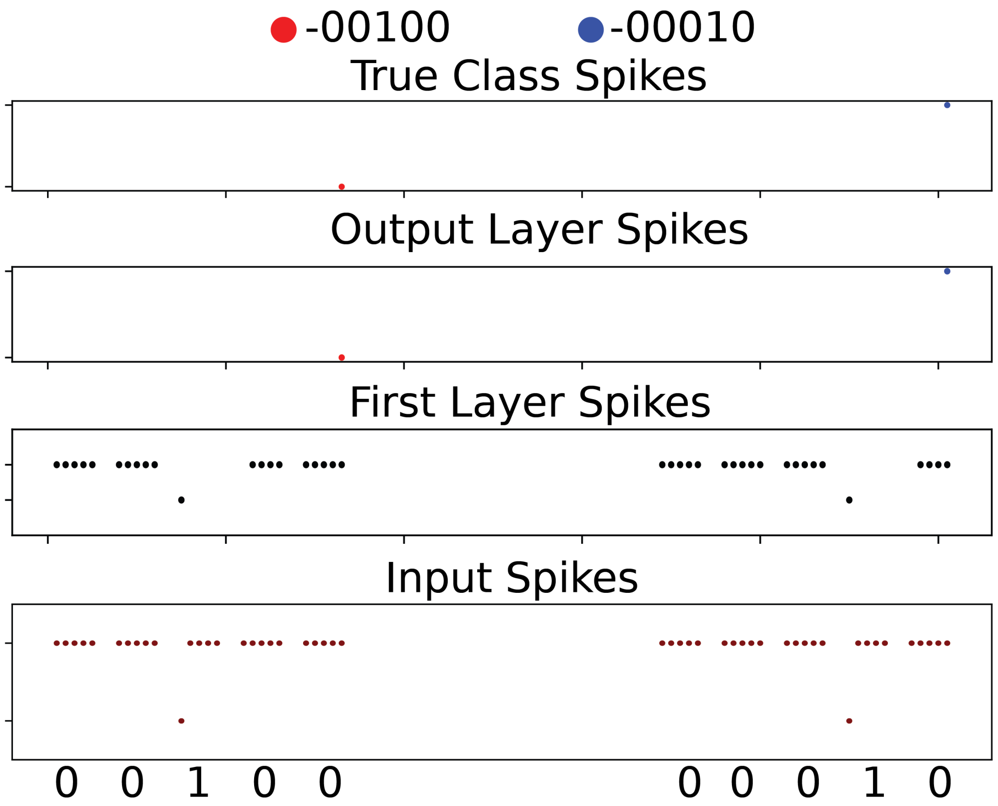
ODESA Results





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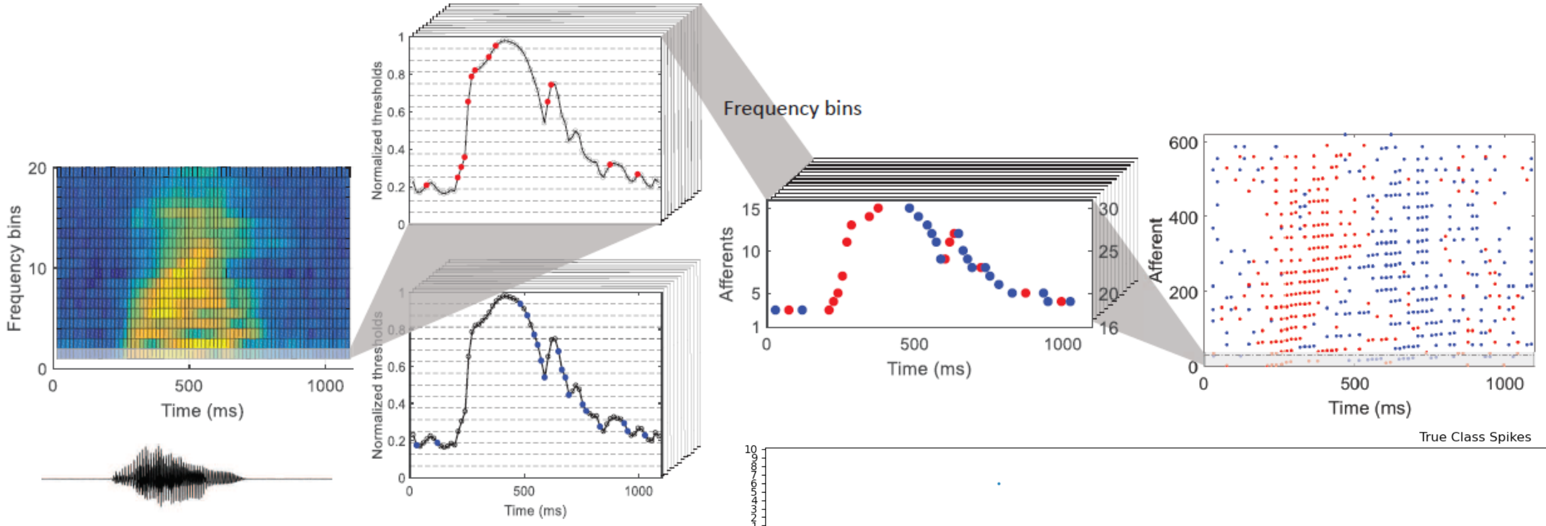
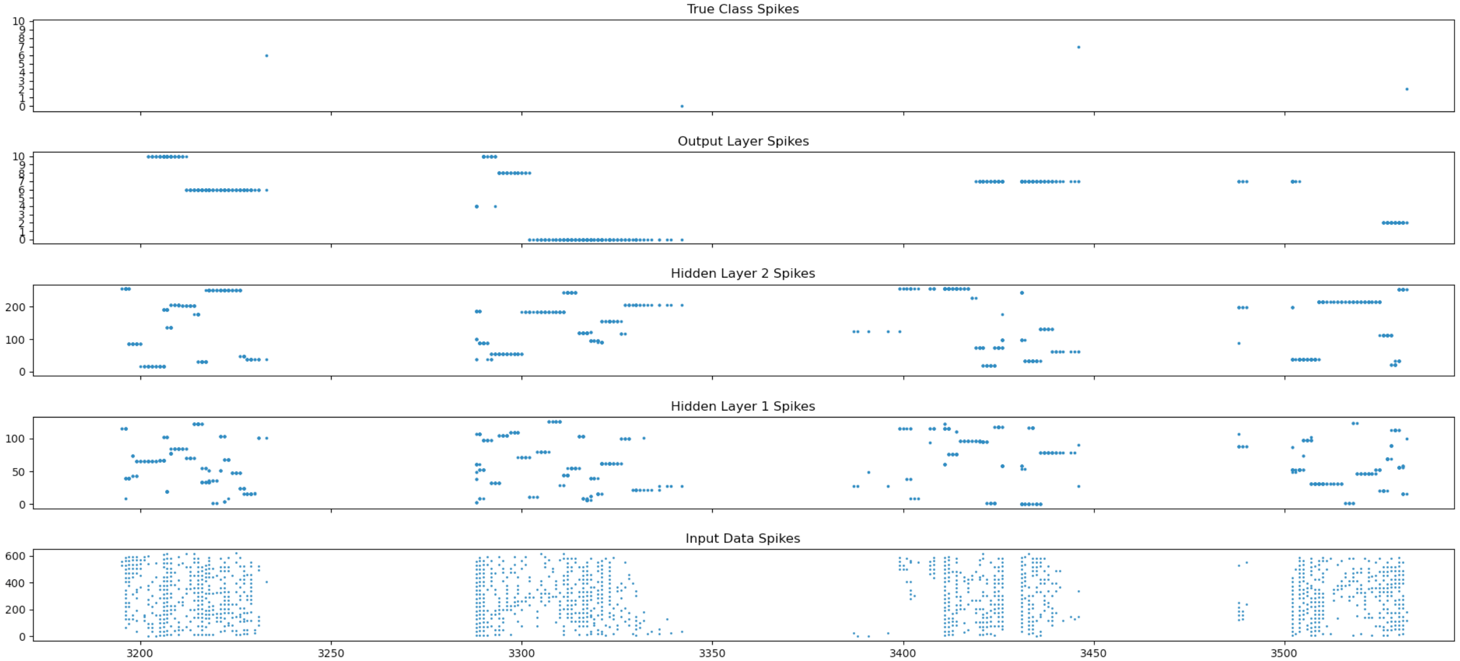
ODESA Results





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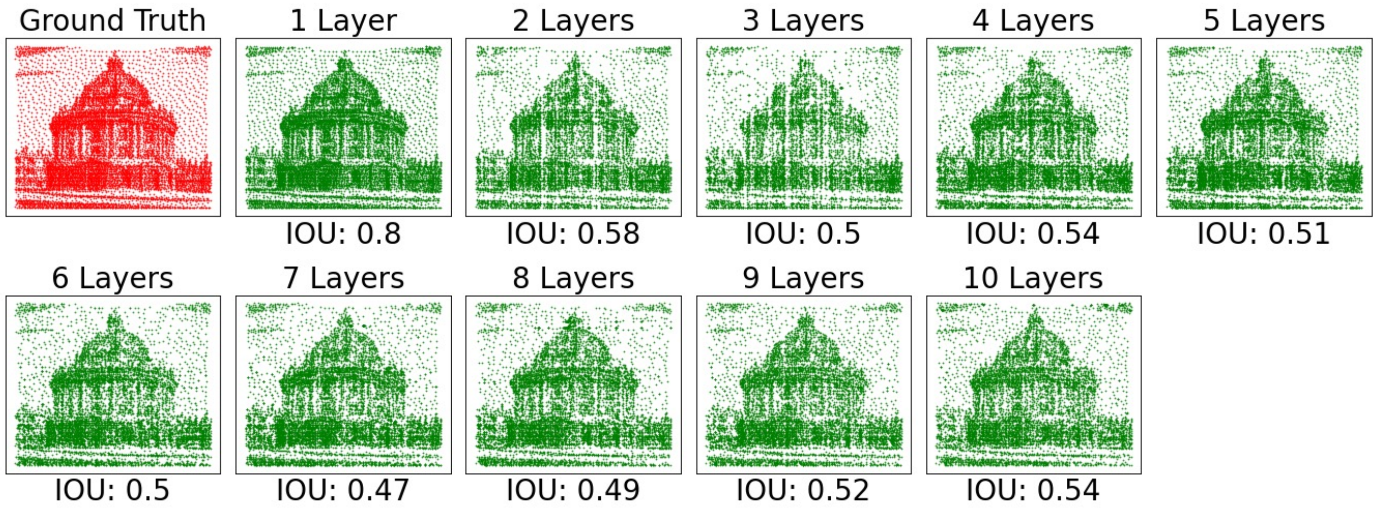
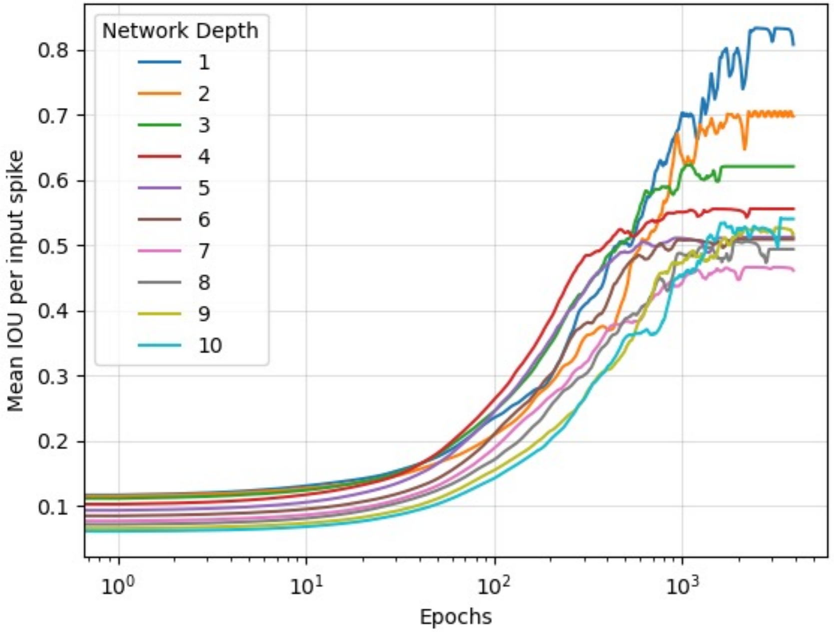
How deep is deep?





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Advantages of ODESA

- Online continuous learning
- Learning hierarchical spatio-temporal features simultaneously at different time scales
- An end-to-end spiking architecture
- Event-driven and computationally efficient
- Gradient-free learning. An alternative to Error Backpropagation, and gradient descent
- Sparse activity due to hard WTA
- Modular and extensible

```
from ODESA.FullyConnected import FullyConnected as HiddenLayer
from ODESA.Classifier import Classifier as OutputLayer
from ODESA.FCModel import FCModel as Model

# Instantiate the hidden layers
input_layer = HiddenLayer(input_layer_context_rows,
                          input_layer_context_cols,
                          input_layer_n_neurons,
                          input_layer_eta,
                          input_layer_threshold_open,
                          input_layer_tau,
                          input_layer_trace_tau,
                          input_layer_thresh_eta,
                          cumulative_ts=True)

# Instantiate the output layer
output_layer = OutputLayer(output_layer_context_rows,
                           output_layer_context_cols,
                           output_layer_n_neurons_per_class,
                           output_layer_n_classes,
                           output_layer_eta,
                           output_layer_tau,
                           output_layer_threshold_open,
                           thresh_eta = output_layer_thresh_eta,
                           cumulative_ts=True)

# Initalize a Feast Model to have all the layers.
model = Model()
# Add hidden layers. Copy the statement to add more layers to the network.
model.add_hidden_layer(input_layer)
# Finally add the output layer. Every model has to have an output layer.
model.add_output_layer(output_layer)


# Each labelled event can be passed to the model using the forward function. If the event has no lal
# 'label' should be equal to '-1'.
hidden_layer_winners, output_layer_winner, output_class = model.forward((x,y,ts,1),label)
```

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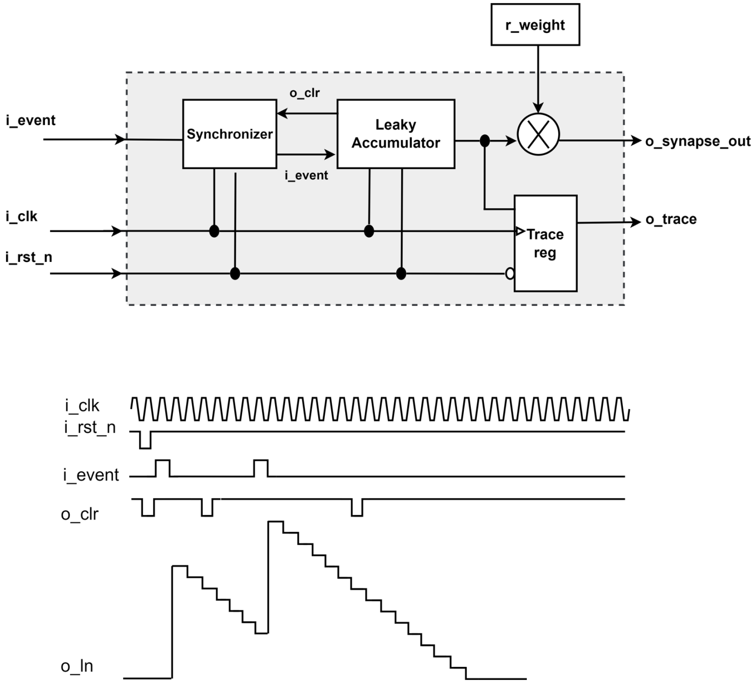
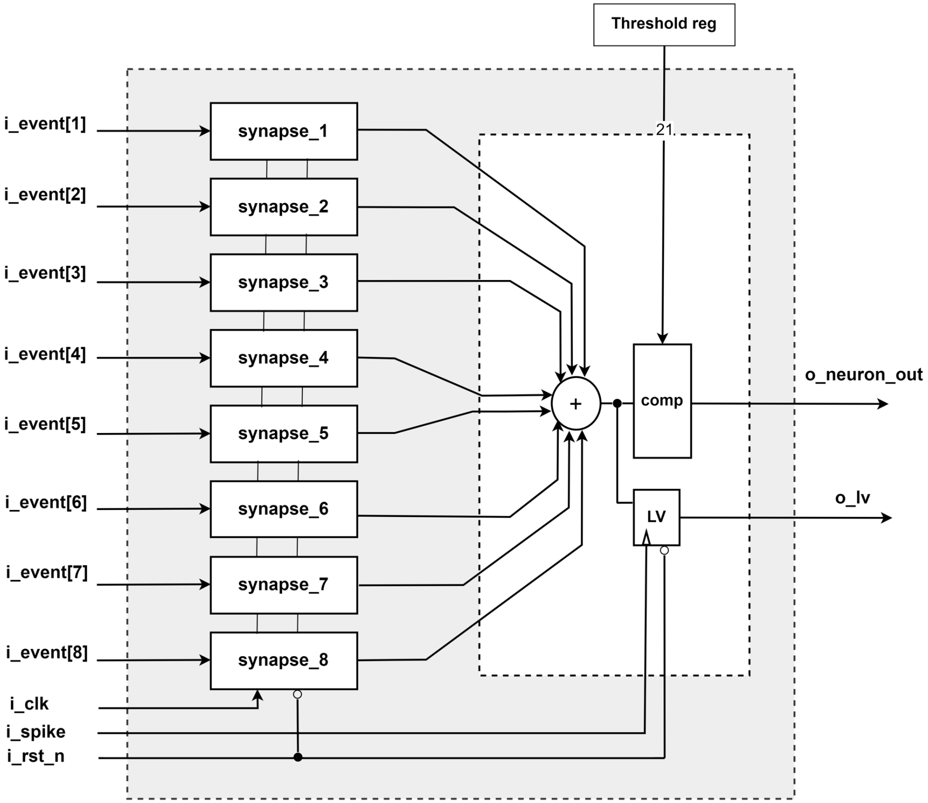
A digital implementation of ODESA



Synapse Design



Neuron Design

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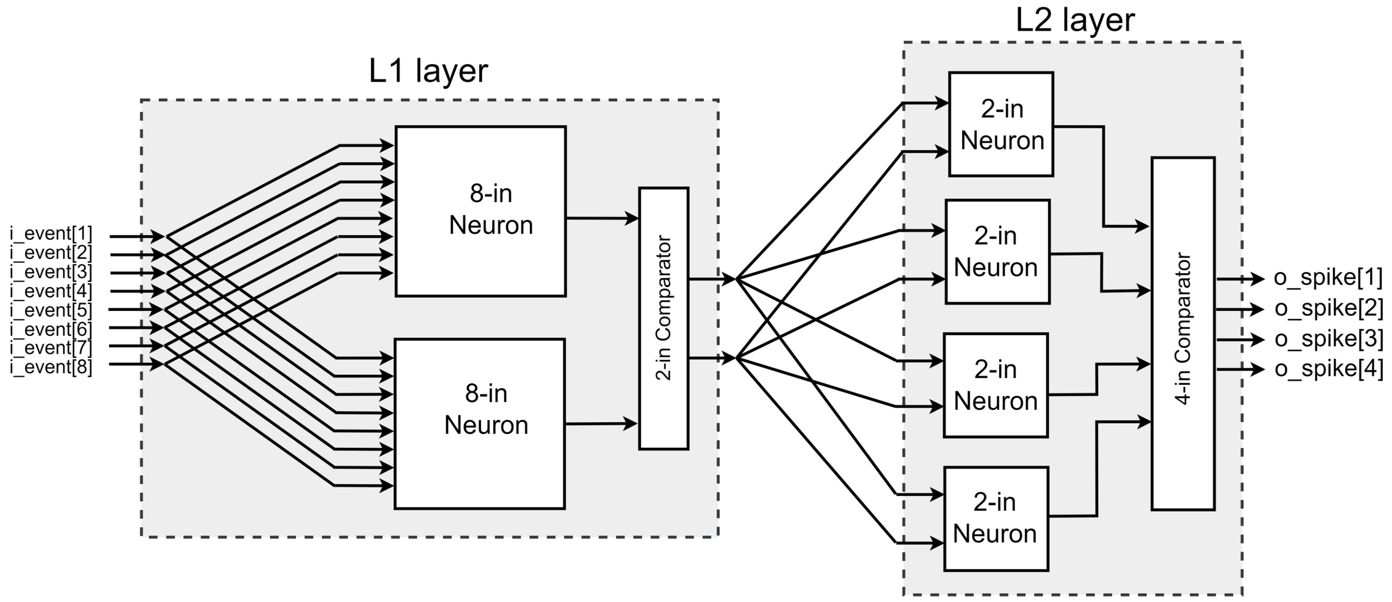
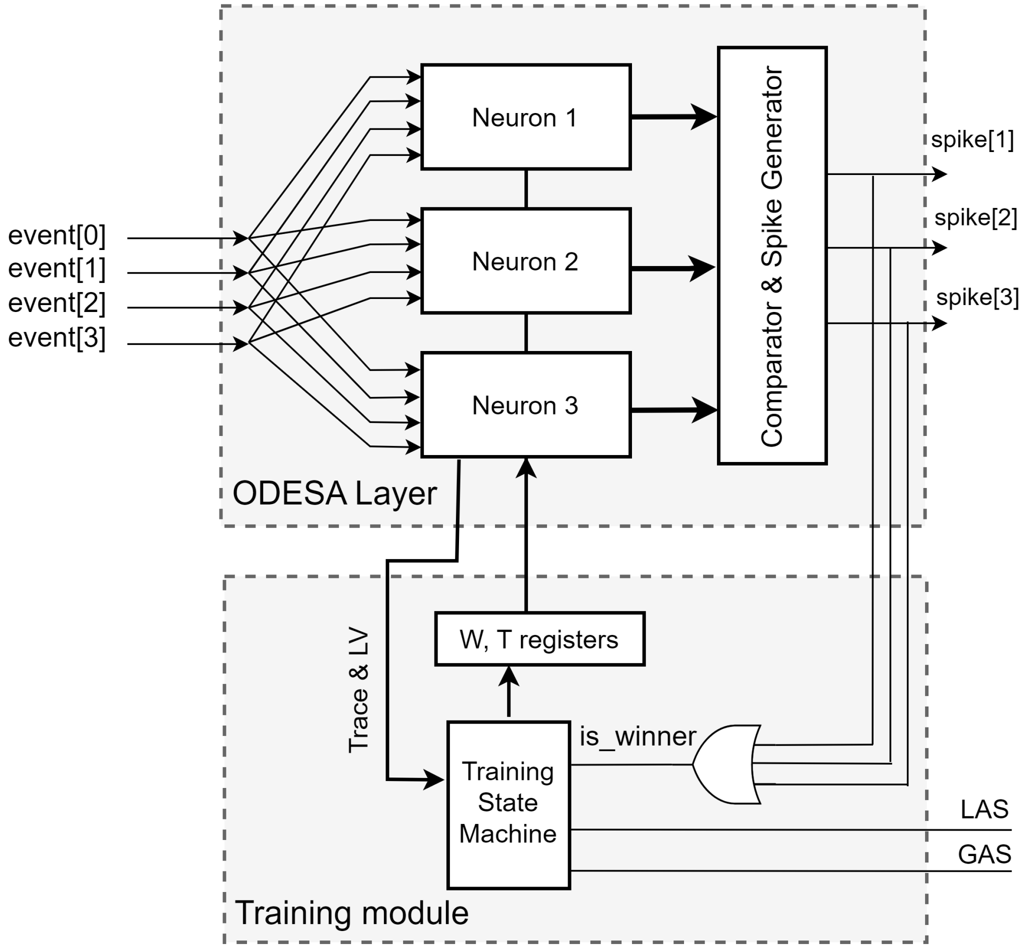
A digital implementation of ODESA



Layer Design



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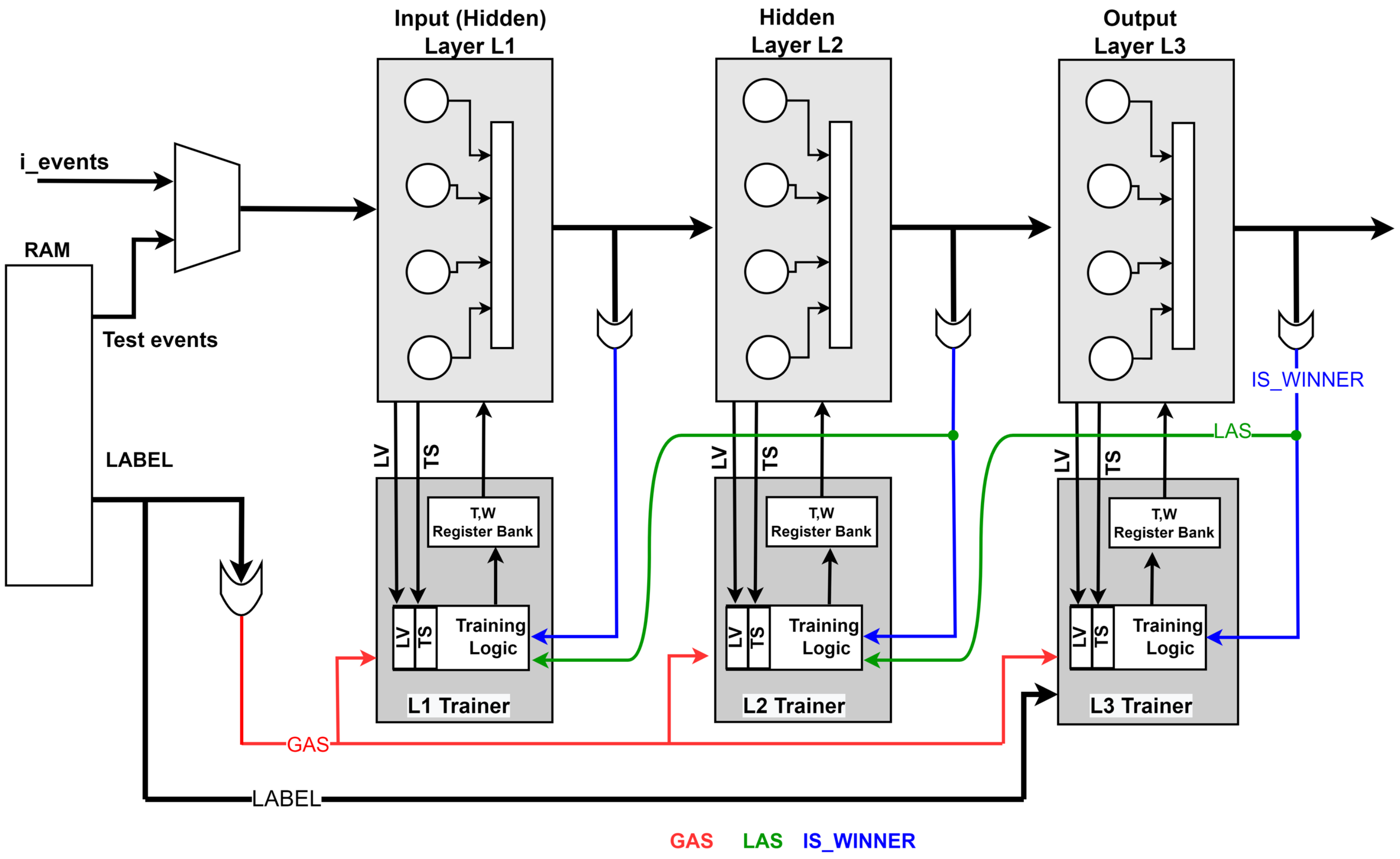
A digital implementation of ODESA



Mehrabi, Ali, et al. (2023) "An Optimized Multi-layer Spiking Neural Network implementation in FPGA Without Multipliers." Procedia Computer Science

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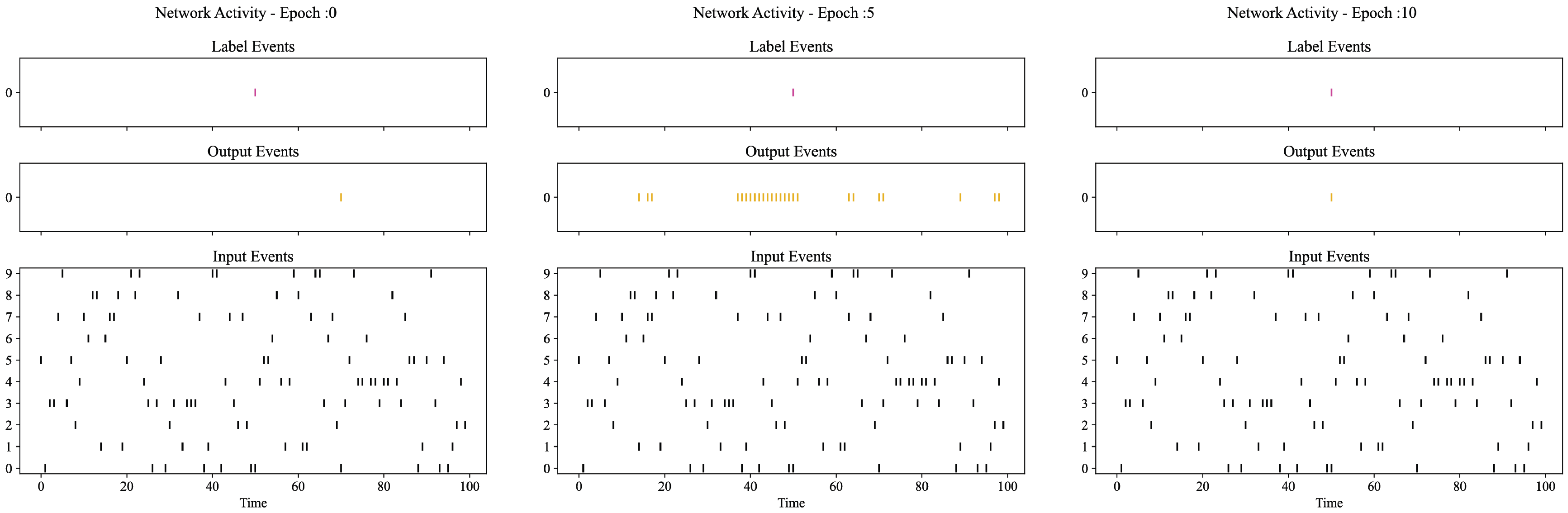
Conclusion



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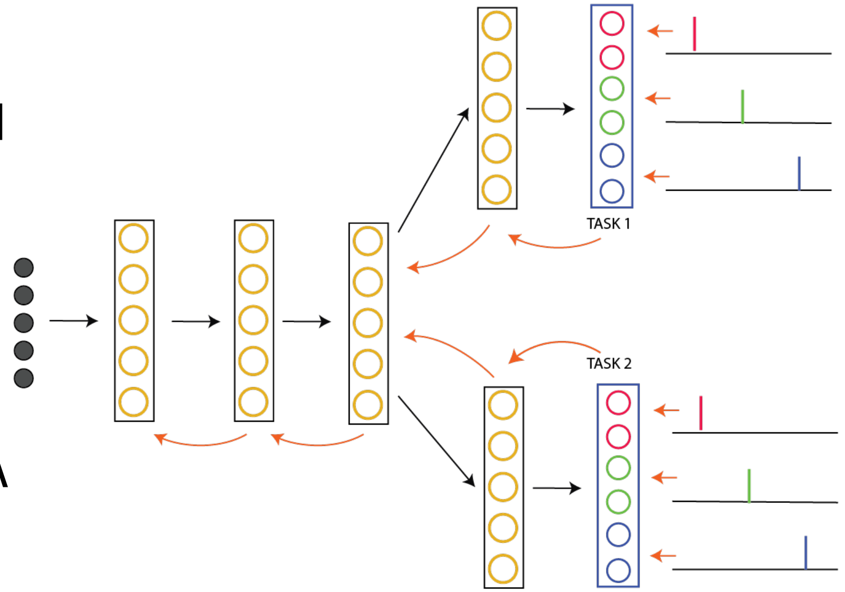
Conclusion

- Spike-timing-dependent threshold adaptation is the underlying principle for all the ODESA architectures
- The operation and memory of each individual computational component of ODESA networks are independent of each other, and thus enable scalability unlike ANNs
- The entirety of computation in all the layers and components of ODESA architectures is event-driven and thus asynchronous.
- The entirety of communication between each component in ODESA architectures including the feedback signals is binary event-based
- The solutions offer blueprints for future neuromorphic hardware design



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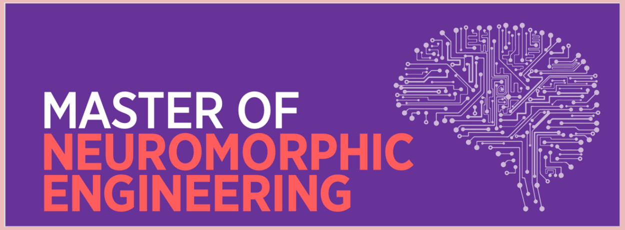
Thank You!

Check out: https://www.westernsydney.edu.au/icns/masters_program



Email: Y.Bethi@westernsydney.edu.au

Additional Slides

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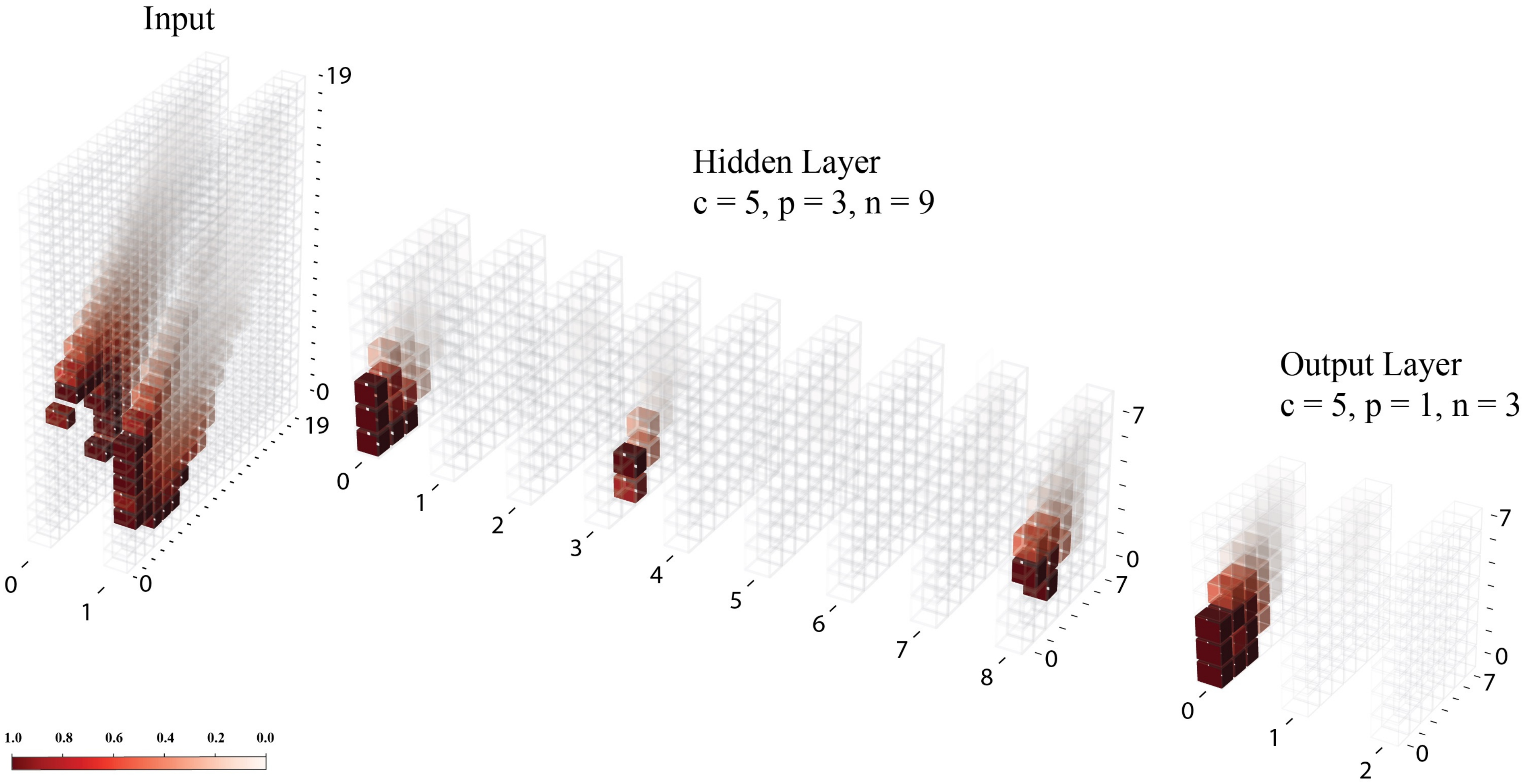
Convolutional ODESA



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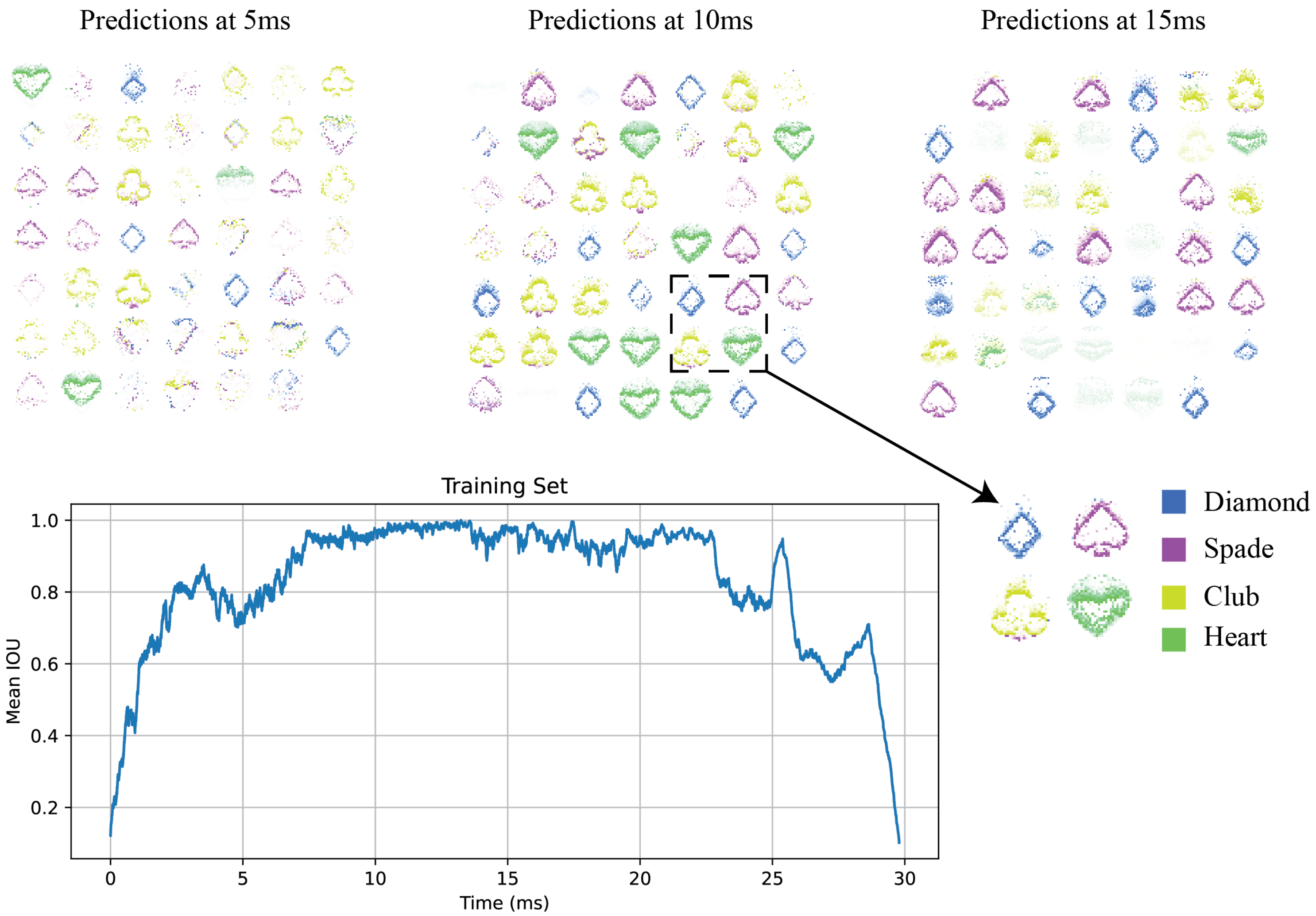
Conv Results



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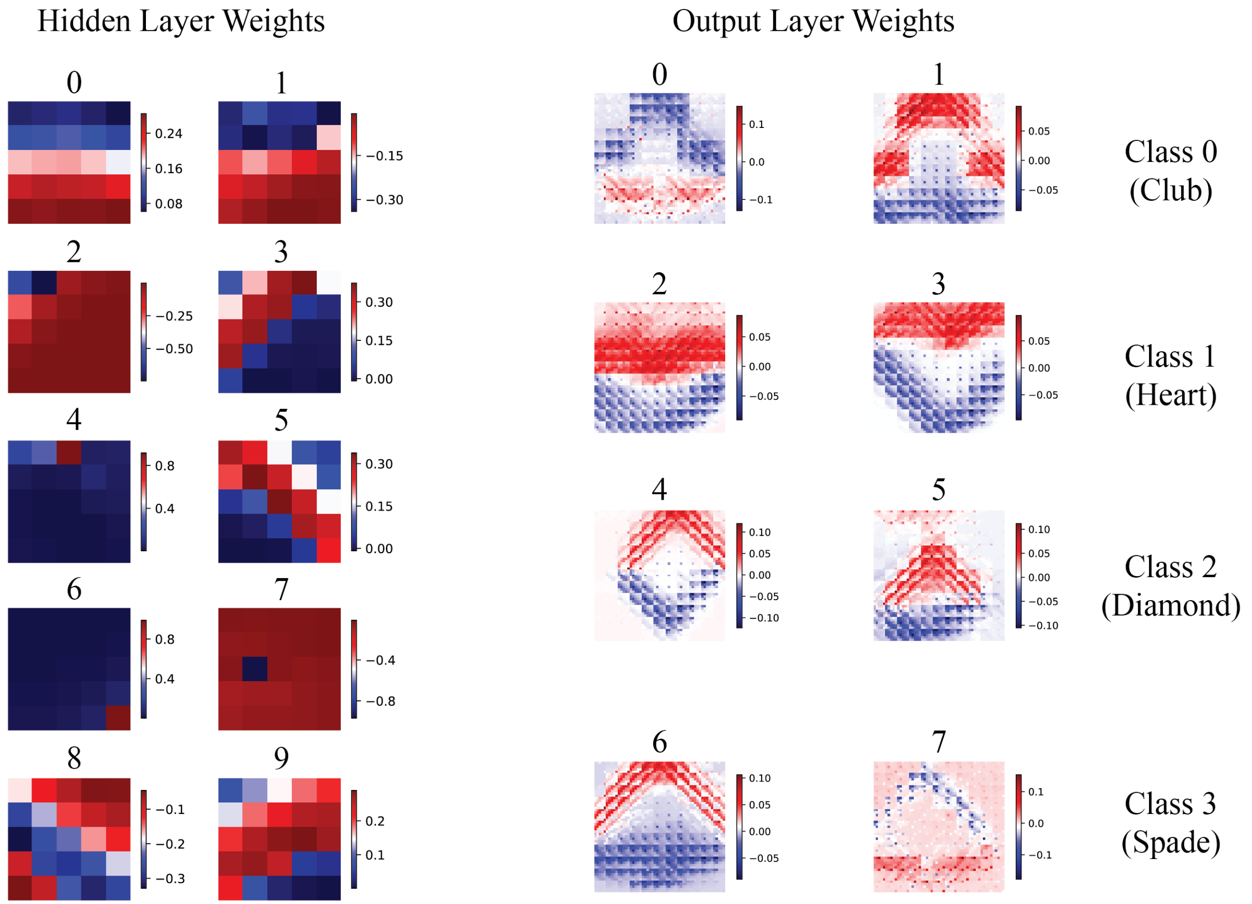
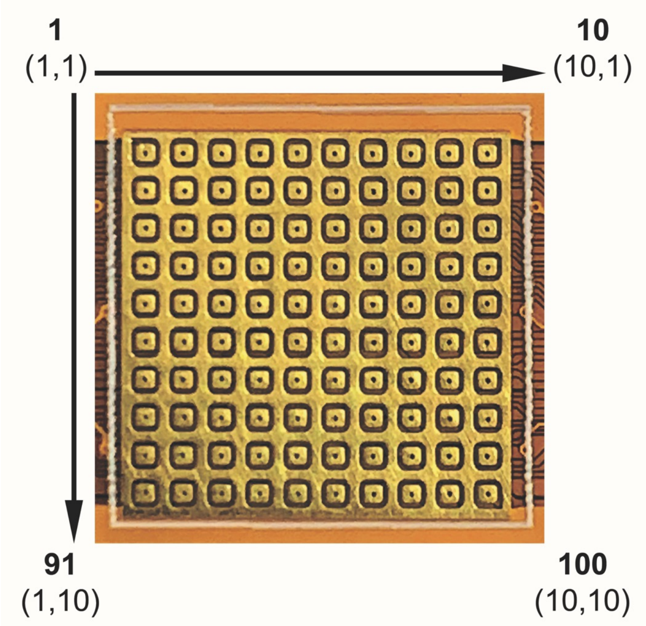
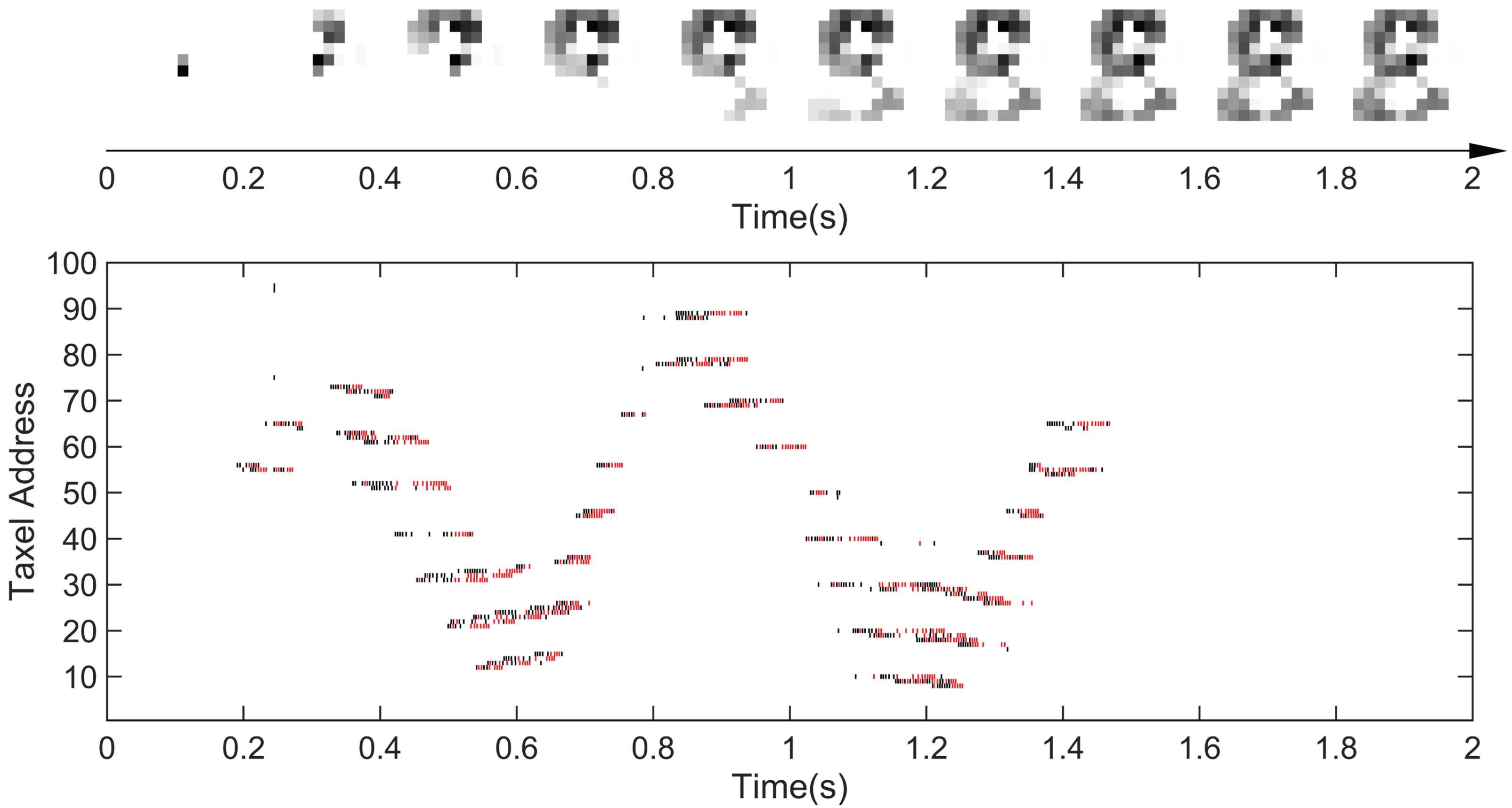
Conv Results



Tactile MNIST





Figures from: *See, H.H., Lim, B., Li, S., Yao, H., Cheng, W., Soh, H. and Tee, B.C., 2020. ST-MNIST--The Spiking Tactile MNIST Neuromorphic Dataset. arXiv preprint arXiv:2005.04319.*

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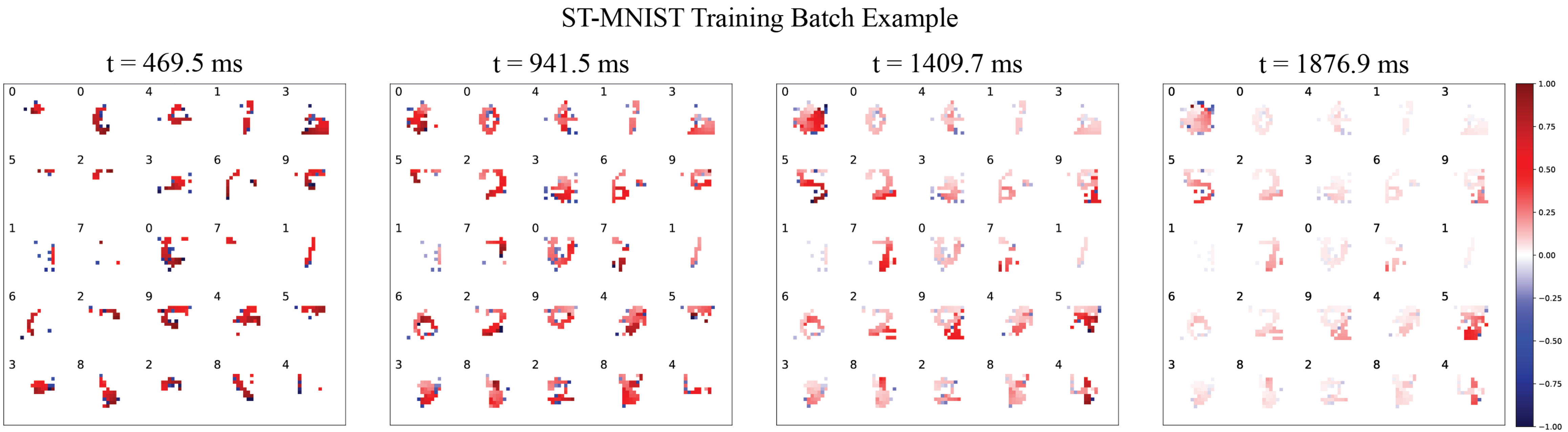
Tactile MNIST



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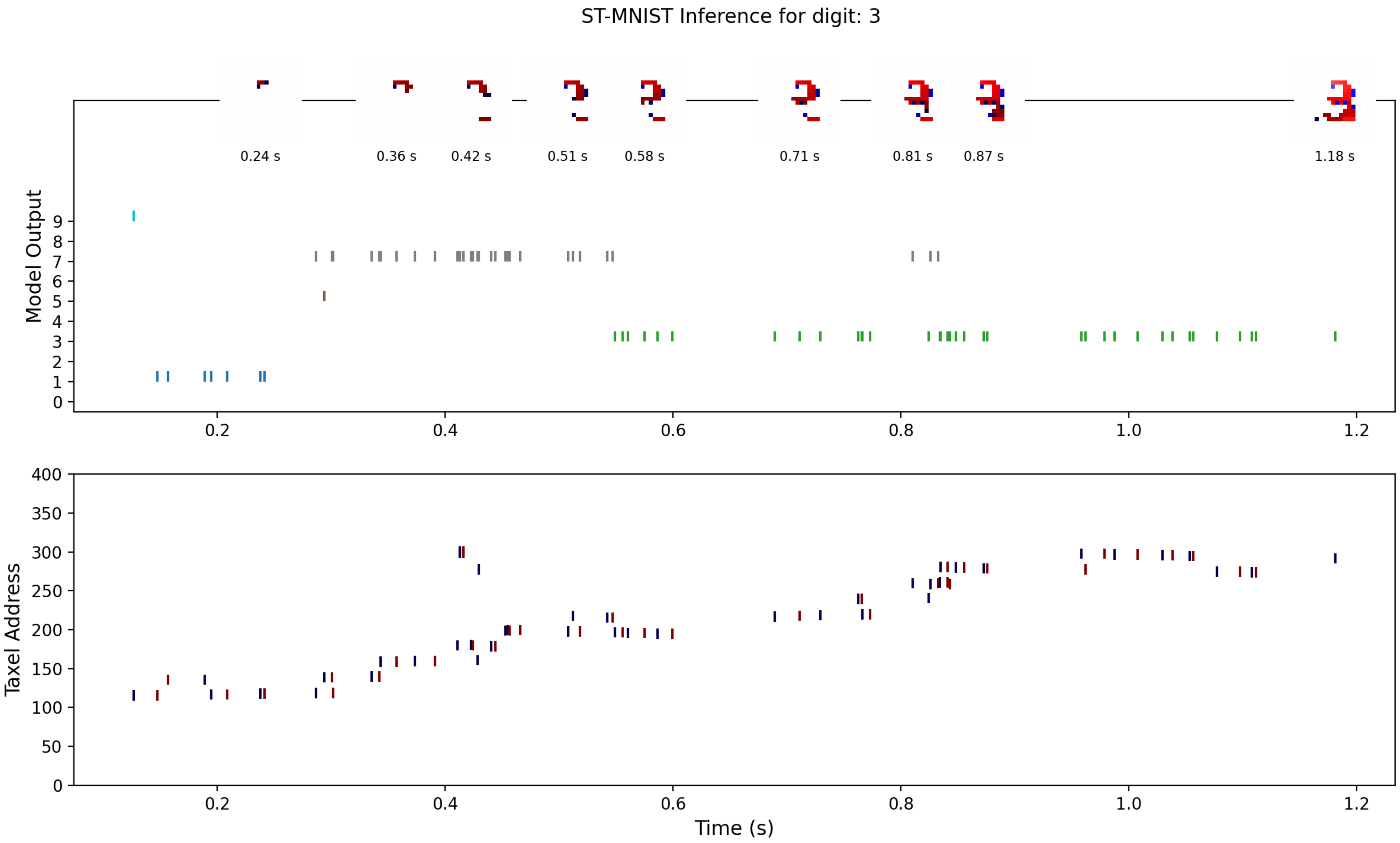
Conv Results



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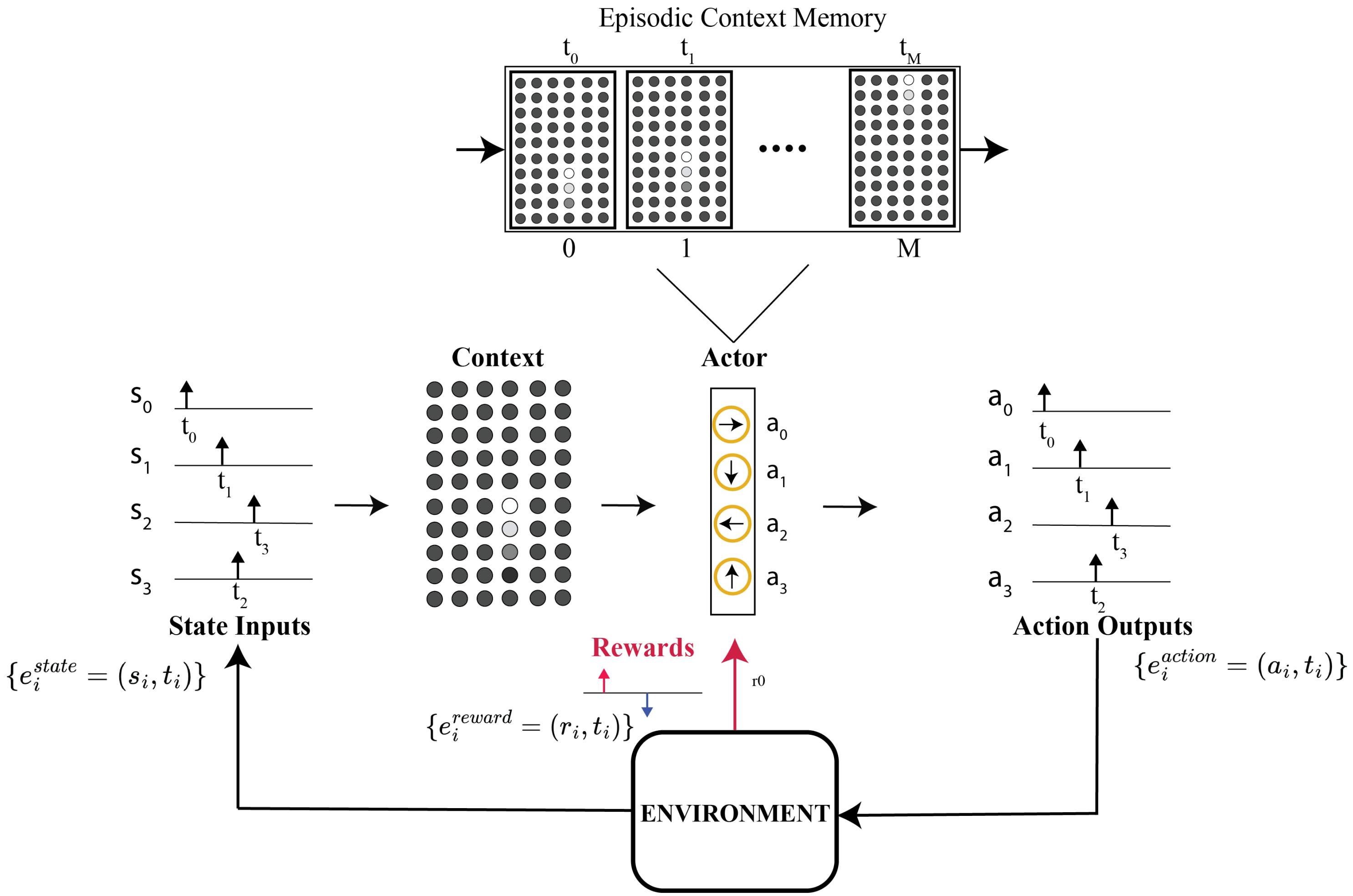
Actor layer with Episodic Context Memory



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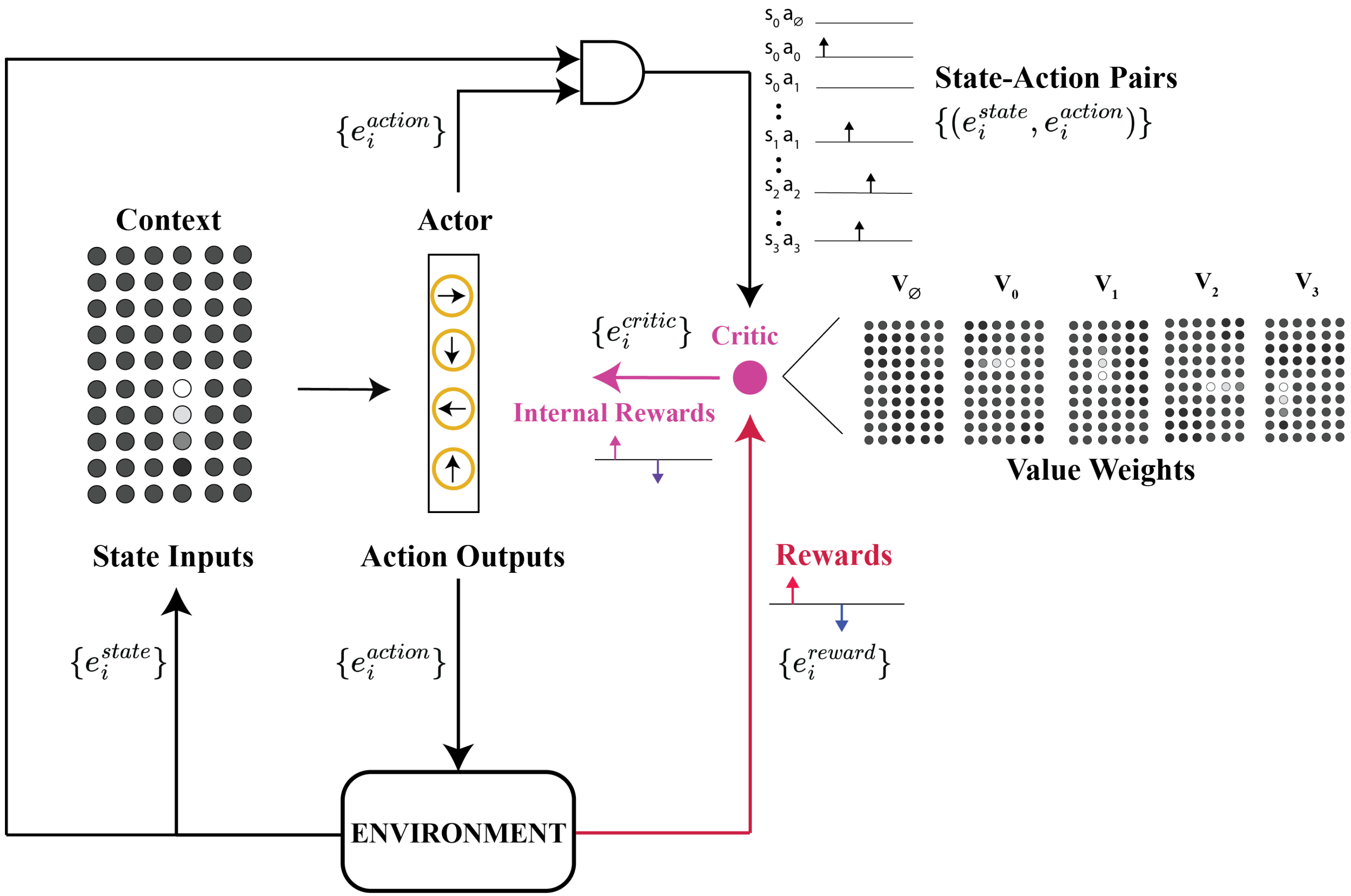
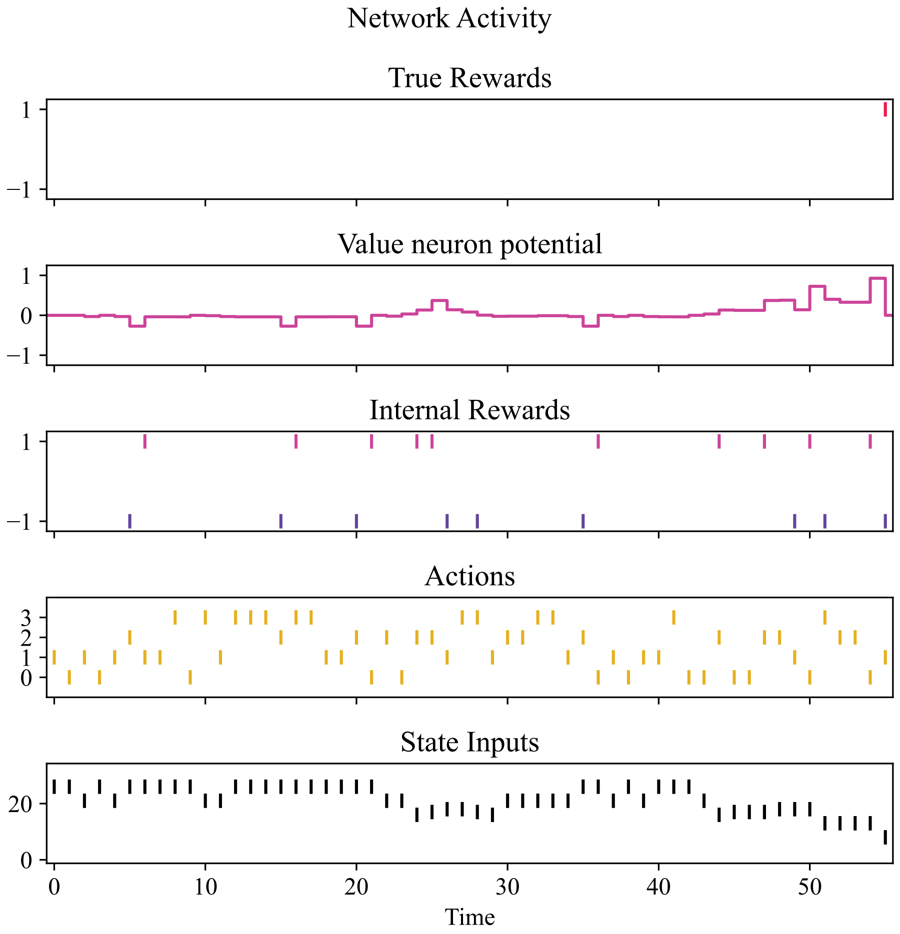
Actor Critic Architecture





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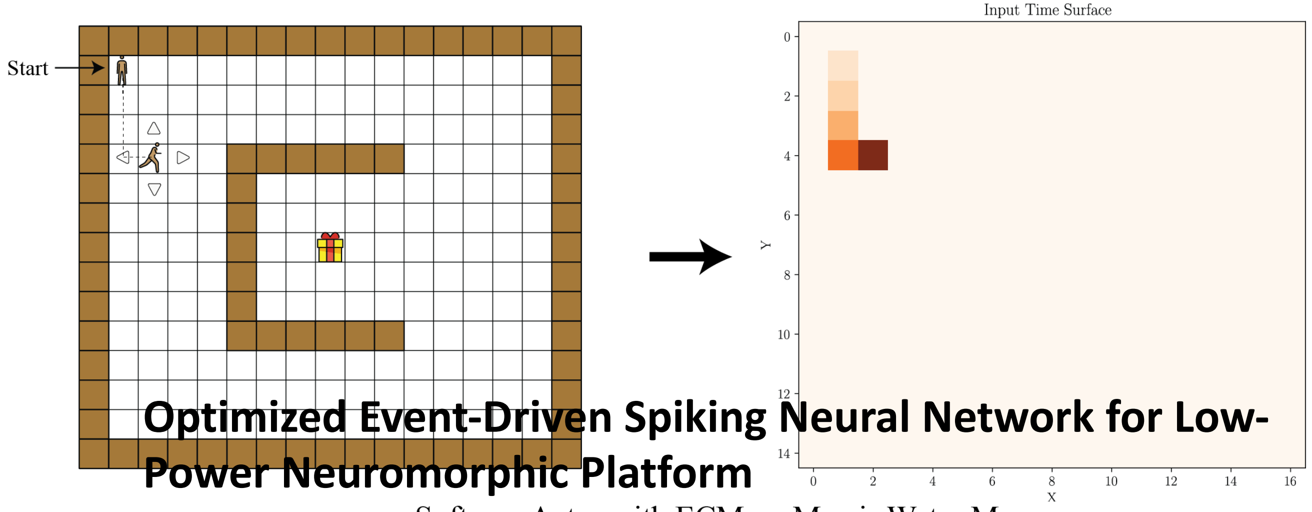
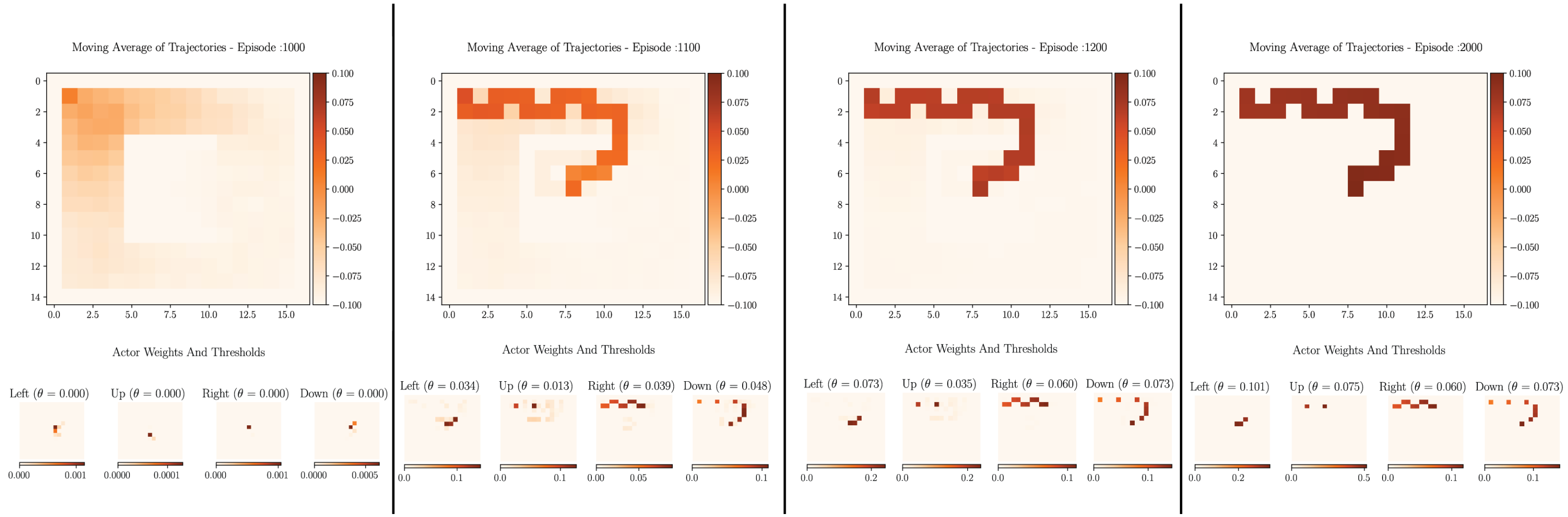
Grid Worlds



Optimized Event-Driven Spiking Neural Network for Low-Power Neuromorphic Platform

Softmax Actor with ECM on Morris Water Maze



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