Evaluating Online Learning in Memristive Neuromorphic Circuits

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Overview

- Architecture
- NIDA
- Memristors
- Online-Learning
- STDP
- Verification
- Experiments and Results

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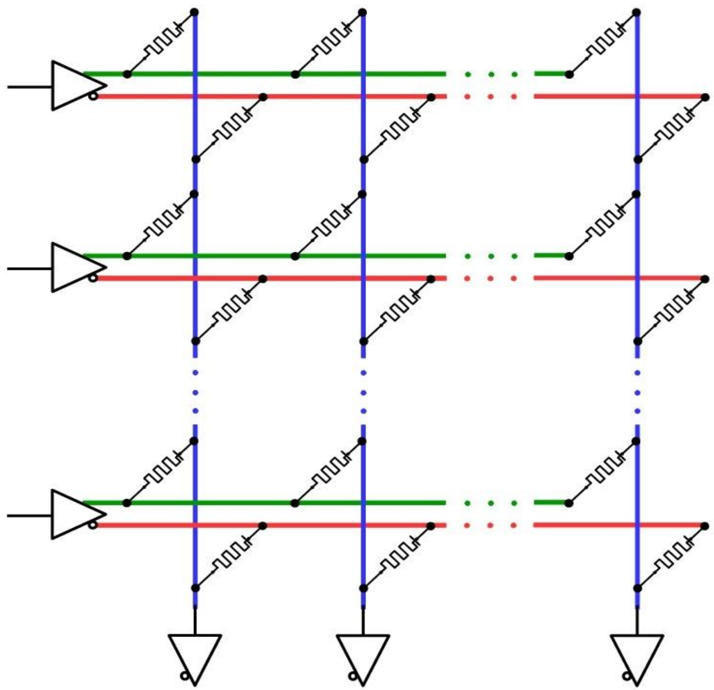
Our Neuromorphic Architecture

- Reconfigurable Neuromorphic Fabric
- Programmable Neuromorphic Cores
- Act as a Coprocessor
- Scalable
- Simulators for Different Granularity



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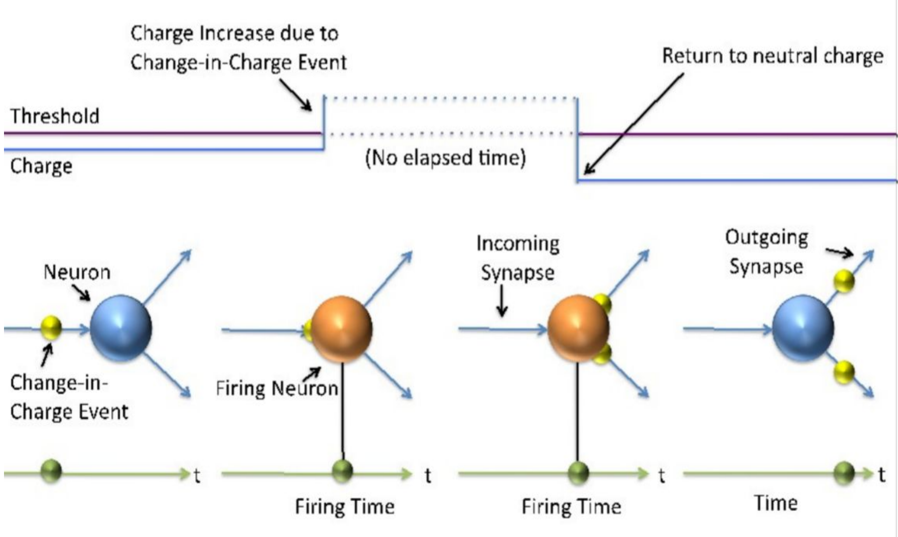
NIDA Model

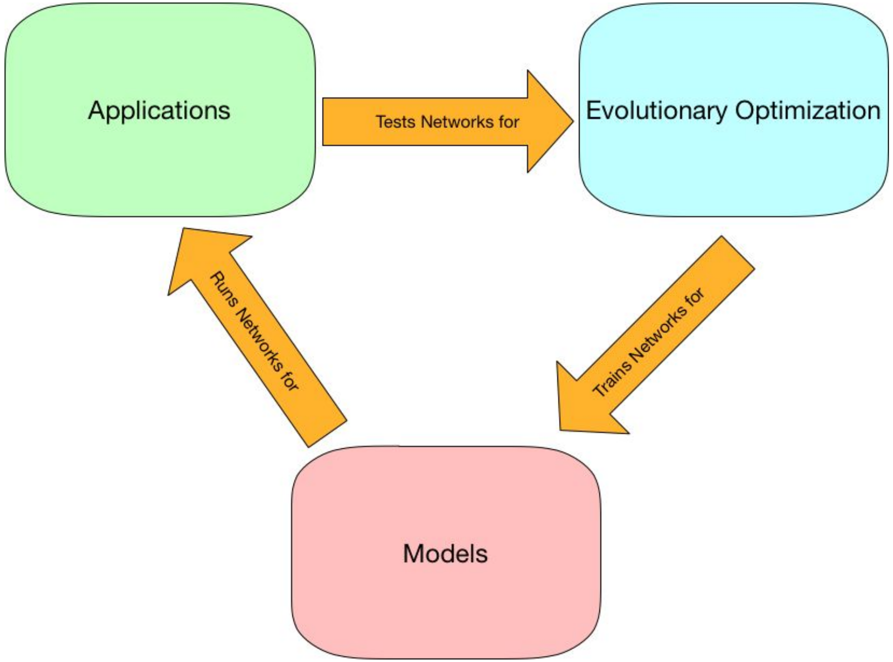
- Spiking Architecture with Neurons and Synapses
- Embedded in 3-Dimensional Space
- Synaptic Delays Depend on Distance
- Optimization in Delay Space
- Proven Model



Ref.: C. D. Schuman, “Neuroscience-inspired dynamic architectures,”2015.

Training with NIDA

- Established Tools
- No Fixed Network Topology
- Networks Typically Recurrent
- Well-suited for Spatio-Temporal Applications
- Optimize to the Application
- Effective Comparison of Models



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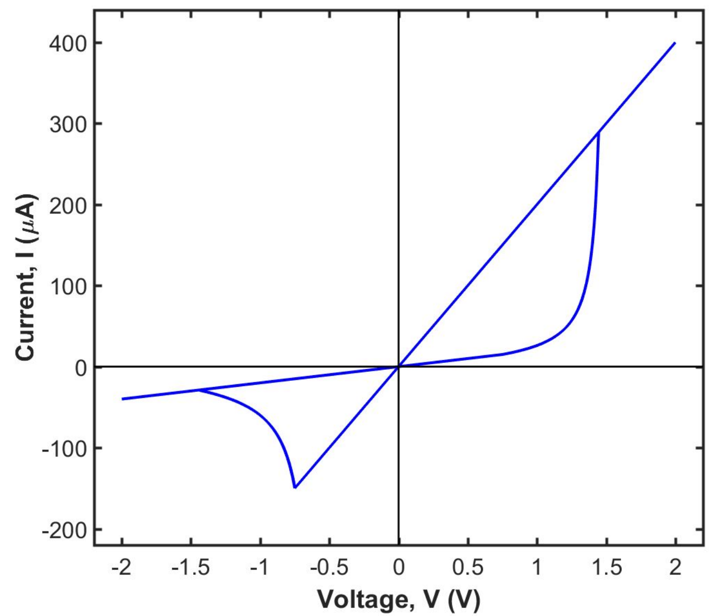
Memristors as Synapses

- Non-volatile Memory Resistor
- Memristance Depends on Previous Voltages
- Memristance Acts as Synaptic Weight
- Programmable Weights
- Area and Energy Efficient



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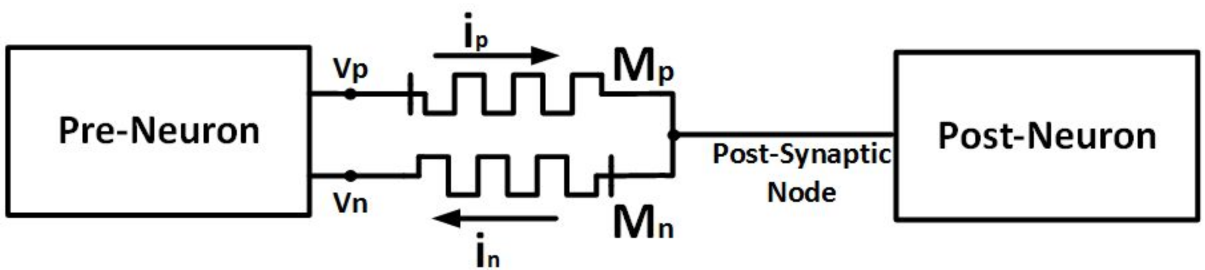
Twin Memristor

- Two Memristors for Each Synapse
- Allows Positive and Negative Weights
- Synapse Converts Spikes into Current
- Currents are Summed in the Post-Synaptic Neuron



Building on the NIDA Model

NIDA

- Asynchronous Events
- Continuous Delays
- Arbitrary Synaptic Weights
- No Restriction on Connections

Memristive NIDA

- Synchronous Clock
- Discrete Delays
- Low Granularity Synaptic Weight Initialization
- Connection Limited to Adjacent Cores

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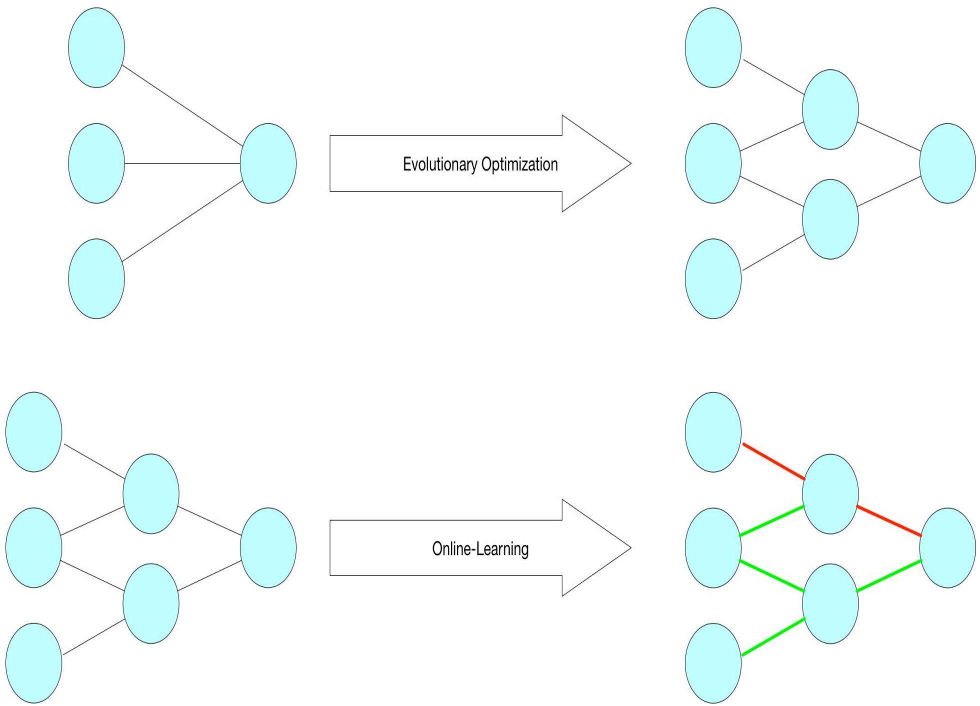
Online Learning

- Motivation:
    - Limited Programming Resolution
    - Improves Generalization
    - Process Variation
- Unsupervised
- Potentiation/Depression



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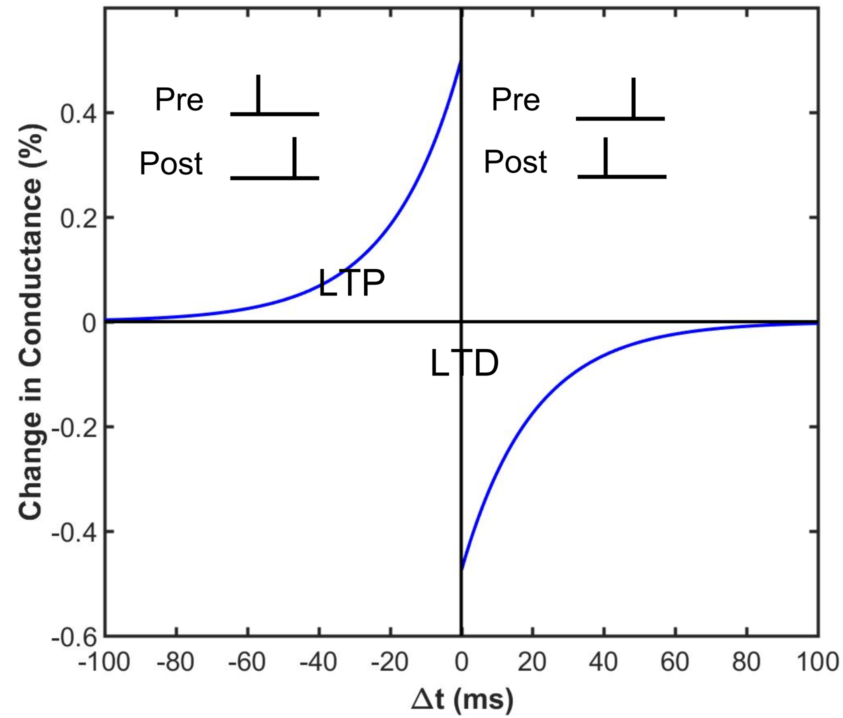
Spike-Timing-Dependent Plasticity

- Biologically Inspired
- Potentiation and Depression of Synaptic Weights
- Change in Weight Relation to Δt
- Synapses Closest to Fire Events Updated Most



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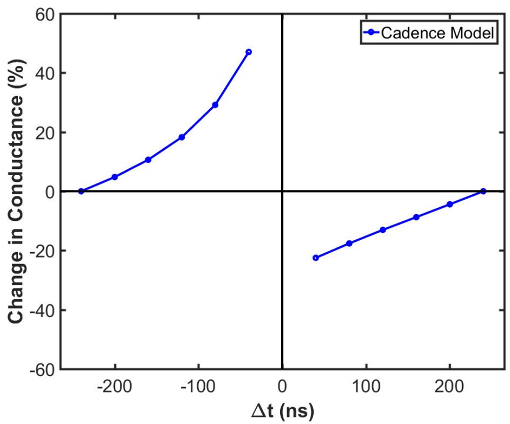
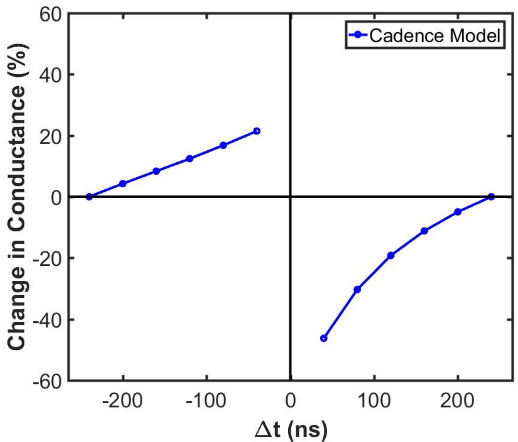
STDP in Memristive Model

- Programmable Cycle Window
- Discretized
- Express Δt in Cycles
- Approximately Exponential
- Enabled During Training
- Avoid Divergence



STDP of positive weight



STDP of negative weight

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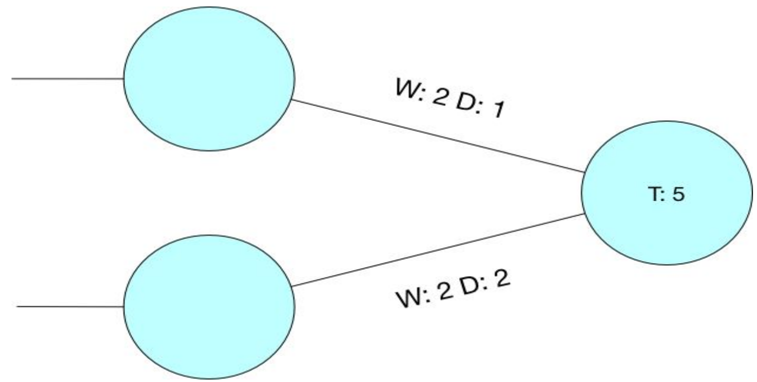
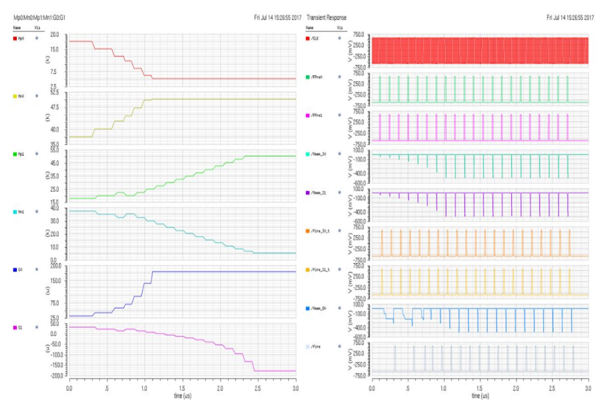
Verifying the Model

- Simulations at Circuit and Network Level
- Simple Network for Testing
- Compare Neuron Fires and Synaptic Weights
- Fires Match on Cycle





Identical To

```
CYCLE 2
0.000000 0.000000  2 Fired
0.000000 6.000000  0 NOTFired
1.000000 0.000000  2 Fired
CYCLE 3
0.000000 0.000000  0 NOTFired
0.000000 6.000000  2 NOTFired
1.000000 0.000000  0 NOTFired
CYCLE 4
0.000000 0.000000  0 NOTFired
0.000000 6.000000  2 Fired
1.000000 0.000000  0 NOTFired
CYCLE 5
0.000000 0.000000  0 NOTFired
0.000000 6.000000  0 NOTFired
1.000000 0.000000  0 NOTFired
```

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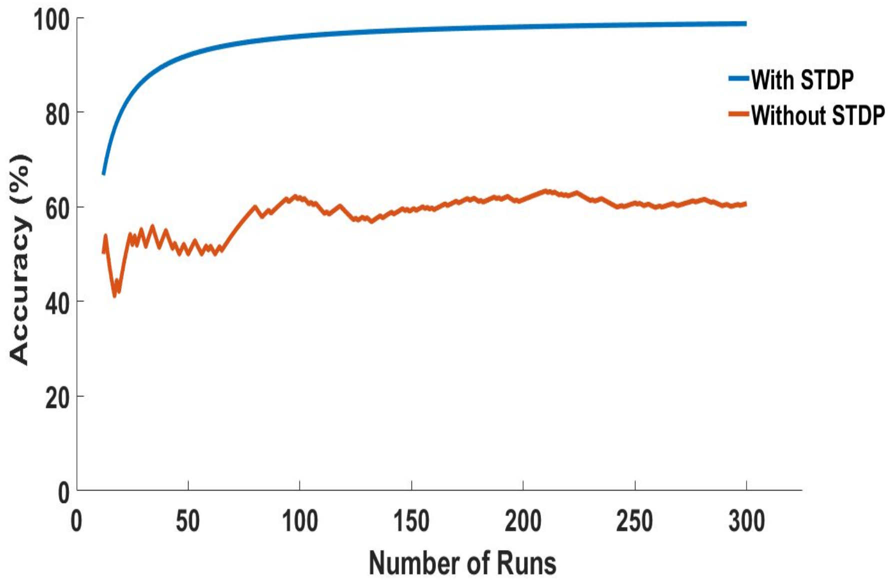
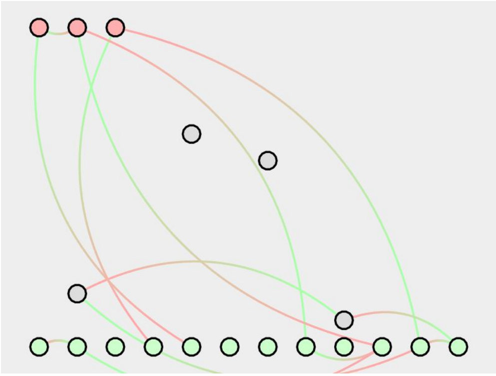
STDP for XOR

- Network Accuracy Only 60% Without STDP
- Limited Programming Resolution
- Enables More Synaptic Weights
- Online-Learning Reinforces Behavior



Classification

- 3 Datasets
  - Iris
  - Pima Indians Diabetes
  - Wisconsin Breast Cancer
- Train with STDP On and Off
- Accuracy Measured on Test Set
- Generalization



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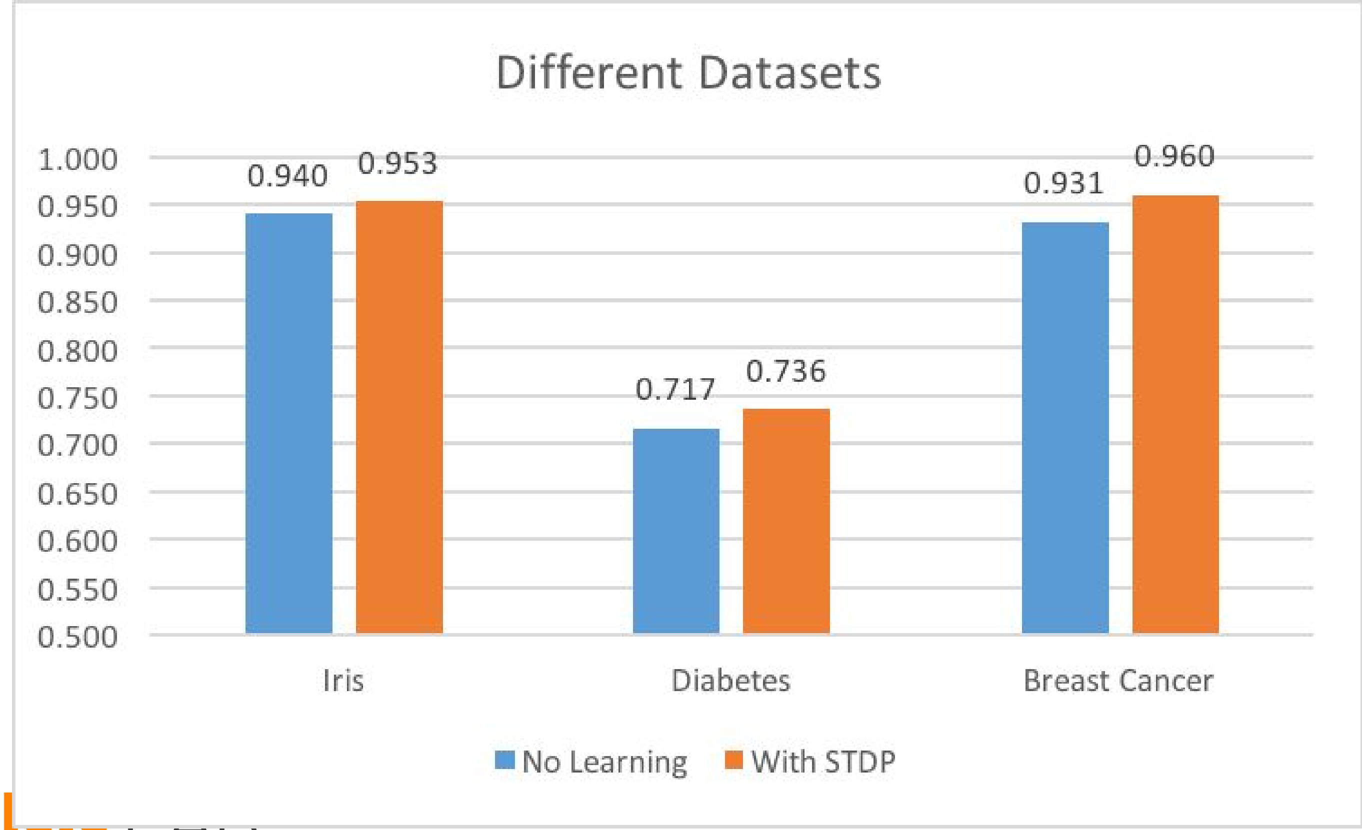
Generalization



Different Resolutions

Programmable Weights	Improvement by STDP
3	2.370%
7	1.778%
21	1.333%

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Conclusions

- There is a need for simulators at the circuit level as well as at the application level
- A synchronous memristive NIDA is a viable neuromorphic architecture
- Online-Learning provides a small increase in generalization for classification applications in our model
- Online-Learning can provide increased granularity in synaptic weights for memristive neuromorphic systems

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Future Work

- Test the impact of online-learning on more difficult applications
- Measure the impact of the choice of memristor on online-learning at the application level
- Understand how process and cycle to cycle variation affect online-learning
- Investigate structural differences, if any, in networks with and without learning
- Compare the design trade-offs of different STDP cycle windows at a circuit and application level

Acknowledgments

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Questions?