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File Classification Based on Spiking Neural Networks

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"The global data sphere will grow from 33 zettabytes in 2018 to 175 zettabytes in 2025. Almost 30 percent of the world's data will have to be processed in real time." [8]

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Introduction

Challenges posed by data:

- Data storage
- Data management
- Data analytics

Task: Efficient data classification system

Data

- Files of various types
- Described with metadata (set of key-value pairs)

Model

- Artificial neural networks (ANNs) require high-precision arithmetic and are in general energy inefficient
- Spiking neural networks (SNNs) are biologically inspired
- SNNs rely on sequences of spikes (ones and zeros) to propagate information [6][7]
- SNNs are well suited to process sparse and asynchronous data

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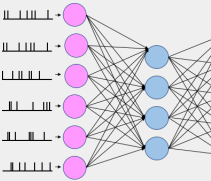
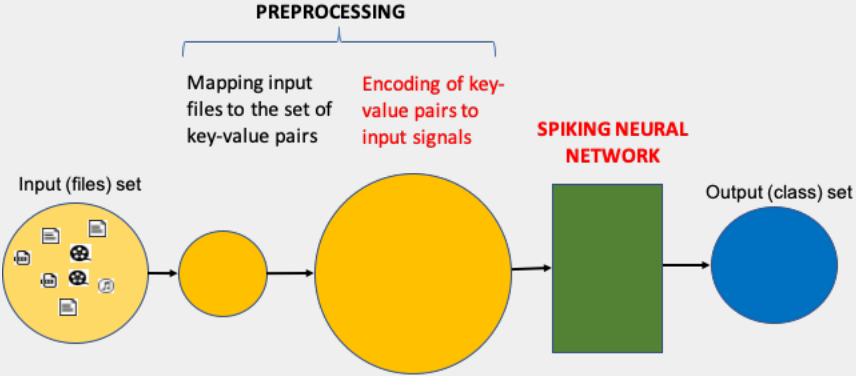


System Architecture


PREPROCESSING
Mapping input files to the set of key-value pairs
Encoding of key-value pairs to input signals
SPIKING NEURAL NETWORK
Input (files) set
Output (class) set

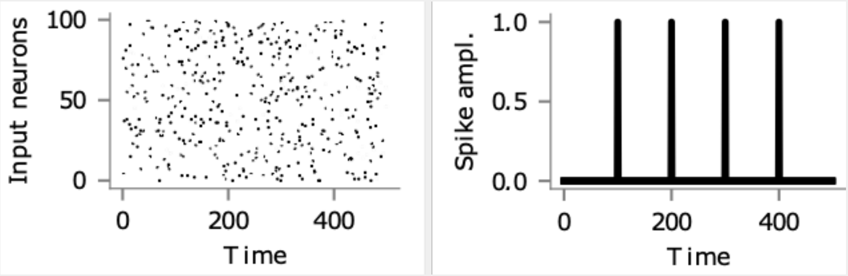


Figure: Input spike pattern (left). Zooming on spiking of one input neuron (right).

At the output of the SNN we generate output spike patterns, and we want to induce spikes at precise spike instants (target spike pattern)

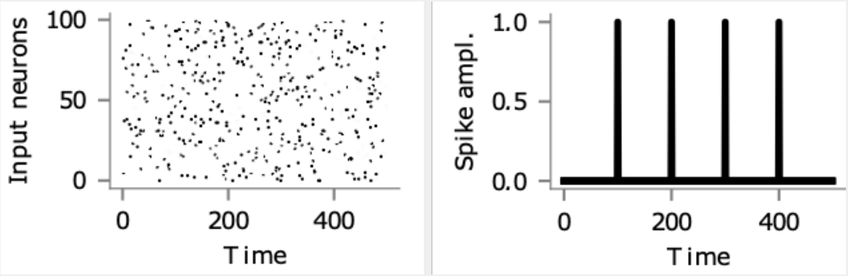


Figure: Input spike pattern (left). Zooming on spiking of one input neuron (right).

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Correlative Time Encoding (CTE)

CTE: Translate *similarities* among the input files into the *correlations* of input spike patterns

- each key *k* is associated with a set of input neurons of SNN
- neurons associated with key *k* generate spikes at pseudo-random time instants, depending on the value the key assumes for the given input file
- neurons are fixed for a given key *k* and pseudo-random spike patterns are fixed for a given key-value pair

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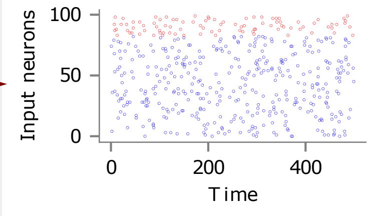

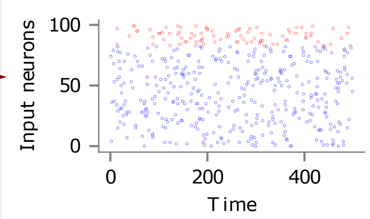

Spiking Neural Network - Learning

Devising an effective training algorithm is one of the biggest challenges that SNNs pose

Spiking Neural Network - Learning

STDP [10]

spike-timing-dependent plasticity

- Local learning rule
- Believed to underlie learning in the brain
- Weights reflect tight temporal correlations between the spikes of pre- and postsynaptic neuron

BPTT probabilistic [5]

backpropagation through time

- Two layers
- Probabilistic neuron model, maximize log-likelihood to induce spiking at target spike patterns
- Weight updates using derivatives
- Requires approximations

BPTT deterministic [13]

backpropagation through time

- Arbitrary number of layers
- Training using ANN frameworks
- Minimizes weighted cross entropy loss

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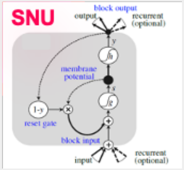

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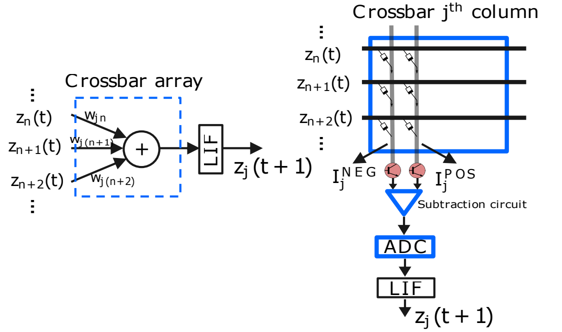
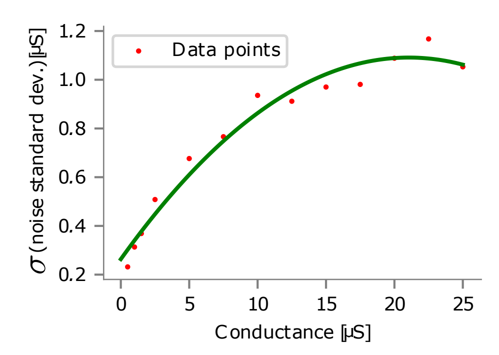


Memristive devices [12][4] when organized in a crossbar array can be used to realize the neuronal connectivity in different layers of the SNNs [9][3]



Phase change memory (PCM) [2] devices are easy to program and have low-power consumption [1][11], however, they exibit non negligible conductance variations

Simulation Results

Table: Simulation Results for Different Data Sets.

Model	Adult Income	Nursery School	Car Evaluation	Connect Four
Log. Reg.	85.2%	93%	86.3%	75.6%
SVM (RBF)	85.3%	98.8%	92.2%	77.7%
STDP unsupervised rate encoded	77.5%	67.2%	50.5%	64.9%
STDP unsupervised	77.8%	70.3%	59.6%	65.8%
STDP supervised	75.6%	73.7%	70.2%	65.8%
Probab. BackProp. one layer	72.9%	73.9%	65.5%	59.8%
Probab. BackProp. two layers	79.2%	88.4%	87.7%	64.5%
Determ. BackProp. two layers	85.4%	99.6%	96.7%	74.4%
Determ. BackProp. five layers	85.7%	99.3%	97%	73.6%

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Table: Inference Results with Hardware Simulator.

Model	Adult Income	Nursery School	Car Eval.	Connect Four
Software	85.4%	99.6%	96.7%	74.4%
HW (st. dev. = σ)	85.1%	99.4%	97%	73.5%
HW (st. dev. = 5 * σ)	81.6%	93.8%	93.2%	69.6%
HW (st. dev. = 10 * σ)	70.6%	73.1%	80.9%	44.4%

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Conclusion

SNN-based system for energy-efficient file classification

Novel CTE scheme to encode input files using pseudo-random spike patterns

The hardware implementation of the system using memristive arrays does not significantly affect performance

Real time classification of asynchronously injested files appears to be a promising application for SNNs, especially if implemented efficiently using memristive hardware

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