

Spiking Neuron Implementations of Several Fundamental Machine Learning Algorithms



PRESENTED BY

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Can neural inspired computational elements deliver on this potential???

³ Universal Function Approximation



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4 Neural Module

- Block of P neurons
- Neurons n_i use discretized LIF
- Each neuron has a spiking threshold ⊖ x_i and leakage rate (not shown in figure) ¹≤
- Inputs to neurons are linear
 combinations of external input plus a
 bias signal
- Each neuron generates a temporal coded output ρ_i(t) which defines the latency of the spike signal



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5 Fundamental Algorithms Using Temporal Coding



6 SpikeMin

Finding the min where $P \ge N$



SpikeMax



Finding the min where P < N





Average runtimes for 10000 simulations of the spikemax neural spiking algorithm

7 Spiking Sort



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- Spiking Similarity
 - In many cases, machine learning algorithms are based upon a distance computation to infer relationships to other data points
 - After the initial presentation of input values which are scaled and integrated then a nominal input is passed to all neurons driving them to fire
 - This firing latency is inversely proportional to similarity between the input and the neural response encoding



9 Nearest Neighbor

k-Nearest Neighbor (k-NN)

- Non-parametric method for classification
- Determines class membership as the class of the majority of the k nearest data points

<u>k-NN Algorithm</u>:

Given query point *q* Calculate distances from unknown point *q* to all data Find k nearest neighbors Vote on labels of k nearest neighbors



10 Spiking Nearest Neighbor (s-NN)

- Each neuron correspond to a data point
- Perform spiking similarity & identifying the first k spikes
- The k-winner layer determines when the k nearest neighbors have been found and then primes the max layer
- As a supervised problem, the classes attributed to the data are known & increment neurons corresponding to the individual classes



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- 11 Adaptive Resonance Theory (ART)
 - Originally developed by Carpenter and Grossberg
 - An online learning family of algorithms
 - "Resonance" drives learning
 - Inputs are compared against stored templates
 - If a sufficiently similar representation exists
 - Update winning template
 - Otherwise a new category needs to be learned



12

- Implemented by first performing spiking similarity to determine the closest matching template
- The vigilance similarity comparison constraint may be directly incorporated by only allowing a temporal response within ρ time steps
- If a sufficient match is found weights of the winning neuron are updated accordingly
- Otherwise a new uncommitted neuron is added with weights set to the present input



13 FUGU



¹⁴ FUGU: PIV Cross-Correlation Example

- Particle Image Velocimetry (PIV) is a well studied method for using particles to determine the local velocity flow in many applications throughout science and engineering
- Cross-Correlation finds agreement in signals
 - Computed as a sliding scalar product
 - $(f \star g)(n) = \Sigma_m f(n)g(m+n) \neq$
- Mapped to the SNL STPU & IBM TrueNorth Neuromorphic architectures



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Severa et al., ICRC2016

15 **Conclusion**

- There are some bold & exciting claims surrounding neuromorphic computing
- Presented spiking neural circuit implementations of several fundamental computer science & machine learning algorithms
 - Working on neuromorphic implementation as well as computational complexity analysis
 - Broad applicability and various benefits
- Just scratching the surface of NICE potential looking forward to the amazing algorithms & architectures over next few days!





Neuromorphic Hardware in Practice and Use

Description of the workshop

Abstract – This workshop is designed to explore the current advances, challenges and best practices for working with and implementing
algorithms on neuromorphic hardware. Despite growing availability of prominent biologically inspired architectures and corresponding interest,
practical guidelines and results are scattered and disparate. This leads to wasted repeated effort and poor exposure of state-of-the-art results. We
collect cutting edge results from a variety of application spaces providing both an up-to-date, in-depth discussion for domain experts as well as an
accessible starting point for newcomers.

Goals & Objectives

- This workshop strives to bring together algorithm and architecture researchers and help facilitate how challenges each face can be overcome for mutual benefit. In particular, by focusing on neuromorphic hardware practice and use, an emphasis on understanding the strengths and weaknesses of these emerging approaches can help to identify and convey the significance of research developments. This overarching goal is intended to be addressed by the following workshop objectives:
 - Explore implemented or otherwise real-world usage of neuromorphic hardware platforms
 - Help develop 'best practices' for developing neuromorphic-ready algorithms and software
 - Bridge the gap between hardware design and theoretical algorithms
 - Begin to establish formal benchmarks to understand the significance and impact of neuromorphic architectures

http://neuroscience.sandia.gov/research/wcci2018.html

Call: https://easychair.org/cfp/nipu2018