Neuromorphic Computing: Where Hardware Meets AI

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My Background

• Ph.D. in Computer Science from the University of Tennessee
  – National Science Foundation Graduate Research Fellowship to study evolutionary algorithms and spiking neural networks

• Joined ORNL in 2015 as a Liane Russell Early Career fellow
  – Project: Programming and Usability of Neuromorphic Computing

• 55+ publications in spiking neural networks and neuromorphic computing, 6 patents
  – A Survey of Neuromorphic Computing and Neural Networks in Hardware

• Joint faculty with the Department of Electrical Engineering & Computer Science at the University of Tennessee

• Co-founder of the TENNLab

• Department of Energy Early Career Award in 2019
Why should you care about hardware?
Looming End of Moore’s Law
(And the end of Dennard scaling)

Artificial Intelligence and Machine Learning

Rise of the Internet of Things
Neural Hardware and Neuromorphic Computing

Neural Hardware

Accelerates traditional neural network and deep learning computation

- Google TPU
- Intel Movidius Neural Compute Stick

- Well-suited to existing algorithms
- Fast computation or low power
- Currently deployed in cloud or mobile devices
## Neural Hardware and Neuromorphic Computing

### Neural Hardware

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### Neuromorphic Computing

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<th>Implements spiking recurrent neural network computation and can be suitable for neuroscience simulation</th>
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<td>• Intel Loihi</td>
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<td>• IBM TrueNorth</td>
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<td>• Significant promise for future algorithmic development</td>
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What is Neuromorphic Computing?

**Von Neumann Architecture**

- Sequential processing
- Separated memory and computation
- Power intensive
- Programmed
- High precision
What is Neuromorphic Computing?

Von Neumann Architecture

- Sequential processing
- Separated memory and computation
- Power intensive
- Programmed
- High precision

Neuromorphic Architecture

- Massive parallelization
- Collocated memory and computation
- Very low power
- Training or learning
- Low precision
How do you program a neuromorphic computer?
How do you program a neuromorphic computer?

Spiking Neural Network!
Traditional Artificial Neural Networks

Input Layer  Hidden Layer  Hidden Layer  Output Layer
Traditional Artificial Neural Networks
Traditional Artificial Neural Networks

\[ f(W^{(1)}x) = u \]
Traditional Artificial Neural Networks

\[ f(W^{(2)} u) = v \]
Traditional Artificial Neural Networks
Spiking Neural Networks

- Time component on synapses
- More complex network structures
- Temporal input
- Temporal output
Spiking Neural Networks
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Spiking Neural Networks
How do you build (or train) a spiking neural network to solve a particular problem?

How many neurons?

How many synapses?

What should the delays on each synapse be?

What should the weights on each synapse be?

What should the threshold or activation value be for each neuron?
How do you build a spiking neural network for a particular neuromorphic implementation?

- Different neuromorphic implementations have different:
  - Neuron models (how the neuron functions, how many parameters)
  - Synapse models (how the synapse functions, how many parameters)
  - Levels of connectivity
  - Devices and materials, which may radically change how the networks can function
Example Neuromorphic Implementations

**DANNA2**
- Fully digital implementation
- Two versions:
  - DANNA2-dense is programmable
  - DANNA2-sparse is application-specific


**mrDANNA**
- Mixed analog-digital implementation
- Synapses implemented with twin memristors
- Programmable


**SOEN**
- Optoelectronic
- Neurons implemented using superconducting optoelectronics
- Delays are on neurons, not synapses

How do you build a spiking neural network for a neuromorphic system for a particular problem?

Not only do we have to come up with the right spiking neural network structure, that spiking neural network also has to work within the hardware constraints: architecture, device, AND materials.
Evolutionary Optimization for Neuromorphic Systems (EONS)

Random Initialization → Evaluate and Rank → Ordered Population

Evaluate and Rank → Select

Best → Parents → Reproduce

Worst → Child Population
Why Evolutionary Optimization?

- Applicable to a wide variety of tasks
- Applicable to different architectures and devices
- Operates within the characteristics and constraints of the architecture/device
- Can learn topology and parameters (not just synaptic weights)
- Can interact with software simulations or directly with hardware
- Parallelizable/scalable on HPC
Applications of Neuromorphic Computing

- Scientific discovery
- Co-processor
- Large-scale data analytics
- Cyber security
- Autonomous vehicles
- Robotics
- Internet of things
- Smart sensors
Danna2 Sparse Neuromorphic Device Plays Asteroids

The right outputs are "don't fire" and "fire". Ties are broken to not fire.
Data from MINERvA (Main Injector Experiment for ν-A)

- Neutrino scattering experiment at Fermi National Accelerator Laboratory
- The detector is exposed to the NuMI (Neutrinos at the Main Injector) neutrino beam
- Millions of simulated neutrino-nucleus scattering events were created
- Classification task is to classify the horizontal region where the interaction originated

Two Data Inputs Types (Three Views)

Deep Learning: Energy values as interpreted as pixels

Spiking: Time when energy deposition goes over a very low threshold
Spiking Neural Networks
Best Results: Single View

Convolutional Neural Network Result: ~80.42%

- 90 neurons, 86 synapses
- Estimated energy for a single classification for mrDANNA implementation: 1.66 μJ

Spiking Neural Network Result: ~80.63%

Example Application: Autonomous Robot Navigation

- **Task:** Navigate and explore an unfamiliar environment while avoiding obstacles

- **Challenges:**
  - No explicit instructions on how to operate
  - No prior knowledge about the environment
  - Limited input resolution (LIDAR sensors)
  - Process all inputs and make control decisions on-board the robot (no communication to/from the robot to another computer system)
  - Train only in simulation
Application: Robotics Control Results

Student Application: Parker Mitchell and Grant Bruer (Spring 2017)
Application: Robotics Control Results

Student Application: Parker Mitchell and Grant Bruer (Spring 2017)
Summary

• The future of AI is likely to include custom hardware like neural hardware and neuromorphic computing

• Neuromorphic computing systems are non-trivial to program

• We’ve developed a spiking neural network training methodology based on evolutionary optimization that has been applied to multiple implementations and many applications

• Now is the time to get involved!
Interested in Learning More about Neuromorphic?

“A Survey of Neuromorphic Computing and Neural Networks in Hardware”
https://arxiv.org/abs/1705.06963
Work supported by:
Department of Energy
Air Force Research Lab

neuromorphic.eecs.utk.edu
Thank you!

Questions?

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Twitter: @cdschuman
Non-Traditional Input Encoding Schemes for Spiking Neuromorphic Systems

- IJCNN 2019
- In collaboration with Jim Plank, Grant Bruer, and Jeremy Anatharaj from UT
Key Challenge: Input Encoding

Spiking neural networks require spikes over time as input.
Key Challenge: Input Encoding

Numerical Input Data

| 0.7 | 0.4 | -0.3 |

How do you convert numerical data into spikes?
Common Approaches

Rate Coding

Temporal Coding
Common Approaches

Key Issue:
Limited input resolution for real-time processing applications
Proposed Input Encoding Schemes

• Motivation: Develop encoding schemes that:
  – Can be applied to a wide variety of input data types
  – Can represent single input values over a very short period of time so that they can be applied to real-time classification or control tasks

• Encoding schemes:
  – Binning
  – Spike-count
  – Charge-injection
  – Complex encoding schemes
    • Combining binning, spike-count, and charge-injection encoding to form more complex calculations

Assumption: For a given input k, we assume that all possible input values fall in the range $m_k$ to $M_k$
The encoding scheme chosen has an impact on application performance.
Key Observations

The encoding scheme chosen has an impact on application performance.
Key Observations

The appropriate encoding scheme depends primarily on the application, rather than the implementation.
Multi-Objective Optimization for Size and Resilience of Spiking Neural Networks

- IEEE Ubiquitous Computing,
- In collaboration with Mihaela Dimovska (University of Minnesota), Travis Johnston, Parker Mitchell, and Tom Potok
Size Optimization: Pruning Post-Training

- Strategy: Prune internal neurons with low spiking frequency

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<td>75.09</td>
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<td>32.61</td>
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<td>438.18</td>
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<td>292.2</td>
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<td>Average number of internal neurons</td>
<td>2.43</td>
<td>4.97</td>
<td>35.24</td>
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<tr>
<td>Average number of synapses</td>
<td>21.53</td>
<td>62.52</td>
<td>35.24</td>
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<td>Average performance</td>
<td>288.7</td>
<td>0.778</td>
<td>208.3</td>
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Size Optimization: Multi-Objective for Size

- Strategy: Adjust the training fitness function to include minimizing size as an objective

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<td>5.08</td>
<td>0.56</td>
<td>1.3</td>
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<td>23.41</td>
<td>122.9</td>
<td>147.17</td>
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<td>297.5</td>
<td>0.788</td>
<td>235.22</td>
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Multi-Objective Optimization for Resiliency

Network $N$, score = 300 sec.  
Network $N_1$, score = 280 sec.  
Network $N_2$, score = 290 sec.

$$F(N) = 0.5 \cdot 300 \cdot (1 - \frac{5}{13} \cdot 0.001) + 0.5 \cdot \left(\frac{280+290}{2}\right) \approx 292.44$$

Weighting factor  
Score  
Size multiplier  
Weighting factor  
Average of scores of perturbed networks
Multi-Objective Optimization for Resiliency

In training
- Perturbation: a sampled synapse has 8th bit flipped.
- 5 variations: each synapse has its 8th bit flipped with probability 0.1

Experiment
- Generate 20 size and size-and-resiliency optimized SNNs
- 500 random synapse (8th bit flip) perturbations per network
Island Model for Parallel Evolutionary Optimization of Spiking Neuromorphic Computing

- GECCO 2019
- In collaboration with Jim Plank (UT), Robert Patton, and Tom Potok
Scalable Island Model

Legend
- Network
- Communication via MPI or socket
- Communication via pipe
Scalable Island Model

- Islands with communication saw **consistently better** results in the same amount of time on the same computational resources as islands without communication.
- More resources generally lead to better results faster (with the right hyperparameters).
Scalable Island Model: Hyperparameters Matter
Scalable Island Model: Hyperparameters Matter