



ReRAM for Implementing Neural Network Synapses

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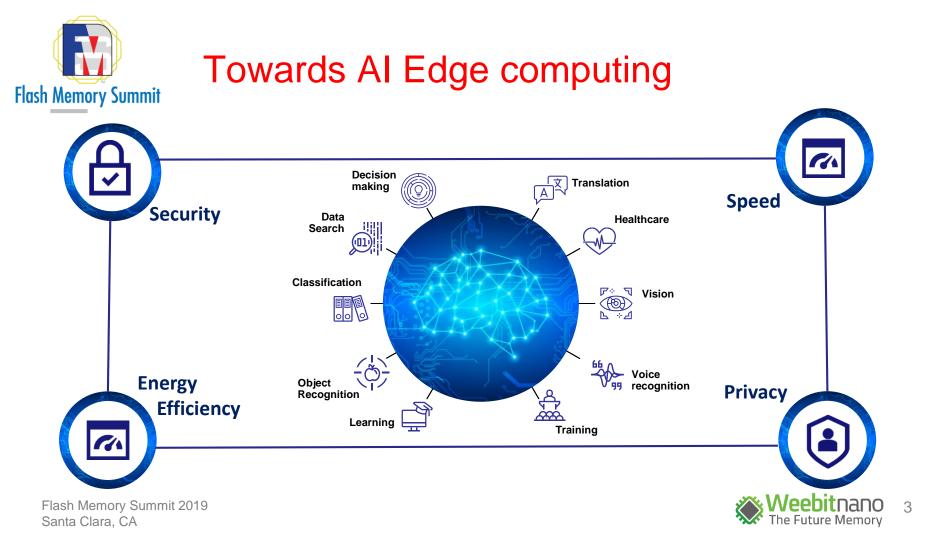


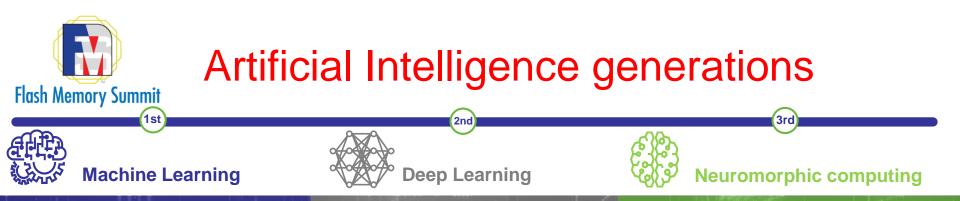


Introduction

- Towards AI Edge computing
- Accelerating Al
- Neuromorphic computing using ReRAM
- Weebit-Leti SPIRIT SNN demonstration
- Conclusions







Algorithms identify patterns in data, and use them to make predictions

Learning through mathematical models Linear regression Decision Trees

Not brain-inspired

Uses Artificial Neural Networks for learning

Networks with topology inspired by the human brain but not related implementation

Partially brain-inspired

Fully biologically-inspired computing

Implements spiking behavior similar to the human brain

Best exploited with neuromorphic hardware





Artificial Neural Networks

Partially brain-inspired networks, using neurons and synapses for computation

- Inputs are weighted through synapses and then summed (MAC)
- Weights are uploaded externally in DRAM chips
- Synchronous operation

Moving data between GPU and external memory cost 200x than staying inside the chip

Tremendous power consumption mainly due to data movement between computing cores and memory

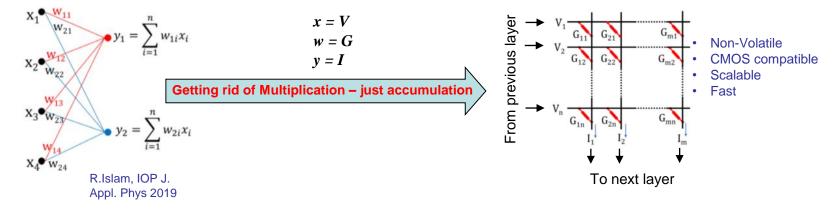
Neurons Synapses Multiply and accumulate (MAC) Activation function Output Transfer function





Accelerating AI with ReRAM

ReRAM for MAC operation naturally achievable using Ohm's and Kirchhoff laws



Co-location of memory / computing \rightarrow boosts performance and reduces consumption

Still not optimal: this is not how the really brain works



Why is our brain Flash Memory Summit SO special?



Massively parallel



Three-dimensionally organized and extremely compact



Extremely Power efficient



Combines storage and computation



Fault and variation tolerant



Self-learning and adaptive to changing environments

Flash Memory Summit 2019 Santa Clara, CA



Biological brain – towards efficient computing architecture





Why neuromorphic computing



Conventional computing:

- Already facing scaling challenge (Moore's law)
- Excessive power consumption 4-6 orders of magnitude than the brain
- Physical separation between CPU and memory – Von Neuman bottleneck



Neuromorphic computing:

- Mimic neuro-bio architecture of nervous system
- Highly energy efficient Asynchronous eventdriven algorithms
- Localization of the memory and processing units synapse and neurons

To fully exploit brain like capabilities new architectures are needed

VS

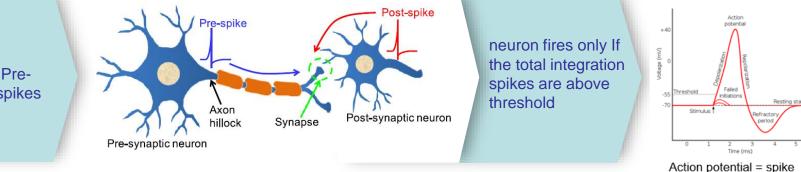




Neurons communicate through spikes – discrete events, robust to noise

^{10¹¹ Neurons} 10¹⁵ Synapses Massively parallel, highly energy efficient





Biological brain – the most efficient computing architecture



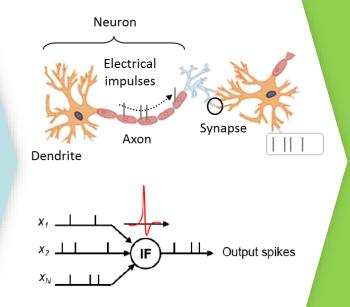


Getting closer to the brain - SNN

Spiking Neural Networks (SNNs)

Fully brain-inspired, use integrate & fire (IF) spiking neurons connected by analog synapses

- Each neuron integrates the incoming spikes, weighted through the synapses
- The neurons spike when the membrane potential threshold is exceeded



Spiking implementation allows for significant power reduction

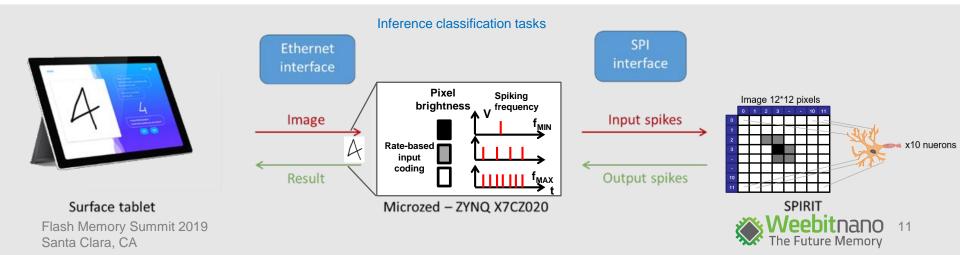
ReRAM will allow to integrate dense non-volatile synapses for huge connectivity





Weebit-Leti SPIRIT demonstration

1st co-integration of analog spiking neurons and ReRAM based synapses for inference task

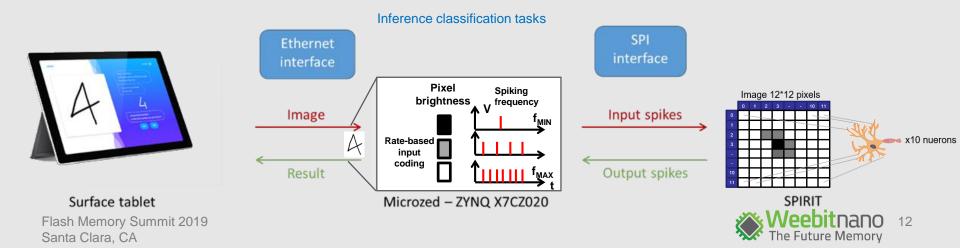




Weebit-Leti SPIRIT demonstration

SNN combining analog neurons and Weebit SiOx ReRAM synapses for MNIST digits recognition

- Fully connected each neuron is connected to the entire image through ReRAM synapses
- Greyscale converted to input spikes frequencies
- Integrate & Fire (IF) analog neurons integrate the incoming spikes and fire
- Neuron with highest firing rate becomes the winner







- Weebit Leti demonstrates 1st ever analog spiking neurons and ReRAM based synapses
- Neuromorphic computing will enable efficient AI-dedicated hardware
- ReRAMs can be used to implement:
 - Analog accelerators for common deep learning neural networks
 - Brain-inspired spiking neural networks with resistive elements and analog neurons





