

Energy-Efficient Continual Learning Systems

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Continual Learning/Lifelong Learning

- Rapid adaptation to new conditions without forgetting previous knowledge
- Continuous improvement in performance while executing previously learnt tasks and novel tasks





MODEL LIFETIME

Current State of **AI Compute Hardware**

A paradigm shift is needed in compute architectures to sustain the growing AI compute demands



OpenAl Five (DOTA 2 video game)

- Training equivalent ~ 45,000 years
- Operations ~ 770 PFLOP/s-days

Dactyl (Deep RL)

- 2.8GWh of electricity
- 100 years of training



- AI compute is doubling ~3.5 months
- Compute cost decreasing by 1 order ~4-12 years
- Training cost of top models ~\$10M

D. Patterson et al., "The Carbon Footprint of Machine Learning Training Will Plateau, Then Shrink," in Computer, vol. 55, no. 7, pp. 18-28, July 2022

Current State of **AI Compute Hardware**





A. Reuther, et al., "Survey of Machine Learning Accelerators," 2020 IEEE HPEC

Shih-Chii Liu, "Edge AI with Neuromorphic Spiking Sensors"

Blouw, Peter, et al. "Benchmarking keyword spotting efficiency on neuromorphic hardware." NICE. 2019.

Example Plasticity Mechanism for Lifelong Learning

Metaplasticity: Protects previous knowledge encoded in important synapses to reduce catastrophic forgetting





- Metaplasticity can be based on
 - Activity
 - Weight Change
 - Temporal Correlation
 - STDP
- Plasticity of previously active neurons is reduced to prevent them from being overwritten.
- Plasticity of inactive neurons is increased to allow them to respond to multiple stimuli.

 $Plasticity = \exp(-abs(m * w))$

N. Soures, P. Helfer, A. Daram, T. Pandit, and D. Kudithipudi, "TACOS: Task agnostic continual learning in spiking neural networks," ICML Workshop on theory and foundations in Continual Learning, 2021. N. Soures and D. Kudithipudi. "Exploring the Plasticity-Stability Trade-Off in Spiking Neural Networks," in CCN, 2022.

Example Accelerator with Metaplasticity





Architecture of the digital accelerator

- Systolic array processing elements(PEs) for parallel processing and efficient data movement
- Each PE incorporates bi-linear metaplasticity function to enable lifelong learning, reducing the computational overhead
- Model parameters represented with 8-bit dual fixed-point to reduce quantization error and memory footprint

V. Karia, F. T. Zohora, N. Soures, and D. Kudithipudi, "SCOLAR: A spiking digital accelerator with dual fixed point for continual learning." 2022 IEEE ISCAS



Options for hardware friendly bi-linear metaplasticity functions



Accelerator Performance





SECOND FIRST CLASS CLASS





FIRST

CLASS

SECOND

CLASS

Realtime training at 30 images/sec



1.573W power consumption on Xilinx **ZYNQ FPGA**



2MB on-chip SRAM memory



Near SOTA accuracy on Split **MNIST** dataset with dual fixed-point representation

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- Neural Plasticity
- Dynamic Algorithms

NEURALLY INSPIRED ALGORITHMS



- Spiking Neural Networks
- Rate Based Neural Networks

NEUROMORPHIC SYSTEMS



- Memristors
- Digital & Mixed Signal Design

ENERGY EFFICIENT ML



- Model Compression
- Low Precision formats
- Circuit & Architecture Optimization

EMERGING TECHNOLOGIES



- 3D
- FeFETs

Acknowledgements















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Thank You

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