

SpikeHard

Efficiency-Driven Neuromorphic Hardware for Heterogeneous Systems-on-Chip

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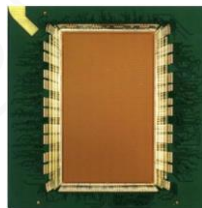
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Introduction

- **Neuromorphic Computing** mimics biological brains.
- Human brain only consumes as much energy as a light bulb.
- Promising approach to energy-efficient embedded AI.

- We expect future **embedded neuromorphic apps** to depend on non-neuromorphic computations.
 - Sensory input pre-processing, e.g.:
 - Fast Fourier Transform (FFT) [4].
 - 2D Convolution (CONV2D) [5].

Popular Proprietary Neuromorphic Chips



TrueNorth [1]



Loihi 2 [2]



Akida [3]

**Heterogeneous
Many-Accelerator
Systems-on-Chip (SoCs)**

[1] Akopyan et al. TrueNorth: Design and tool flow of a 65 mW 1 Million neuron programmable neurosynaptic chip. *IEEE TCAD* 34, 10 (2015), 1537–1557.

[2] Intel. <https://download.intel.com/newsroom/2021/new-technologies/neuromorphic-computing-loihi-2-brief.pdf>

[3] BrainChip. https://brainchip.com/wp-content/uploads/2023/03/BrainChip_second_generation_Platform_Brief.pdf

[4] Arsalan et al. 2022. RadarSNN: A resource efficient gesture sensing system based on mm-Wave radar. *T-MTT* 70, 4 (2022), 2451–2461.

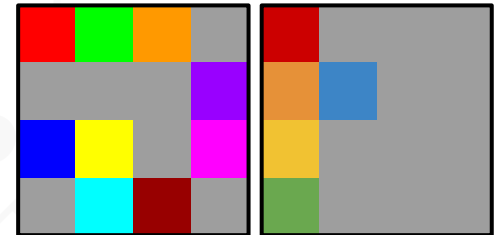
[5] Chandarana et al. 2021. An adaptive sampling and edge detection approach for encoding static images for spiking neural networks. *In Proc. of IGSC*. 1–8.

Open-Source Alternatives

- **RANC: Reconfigurable Architecture for Neuromorphic Computing** [6]
 - Highly configurable at design time → great for testing new architectural optimizations.
 - Similar architecture to TrueNorth and Loihi → good algorithmic compatibility.
 - Deployable on FPGA → fast prototyping.
- **SpikeHard (our work)** is based on RANC.

Limitations of RANC that SpikeHard Solves

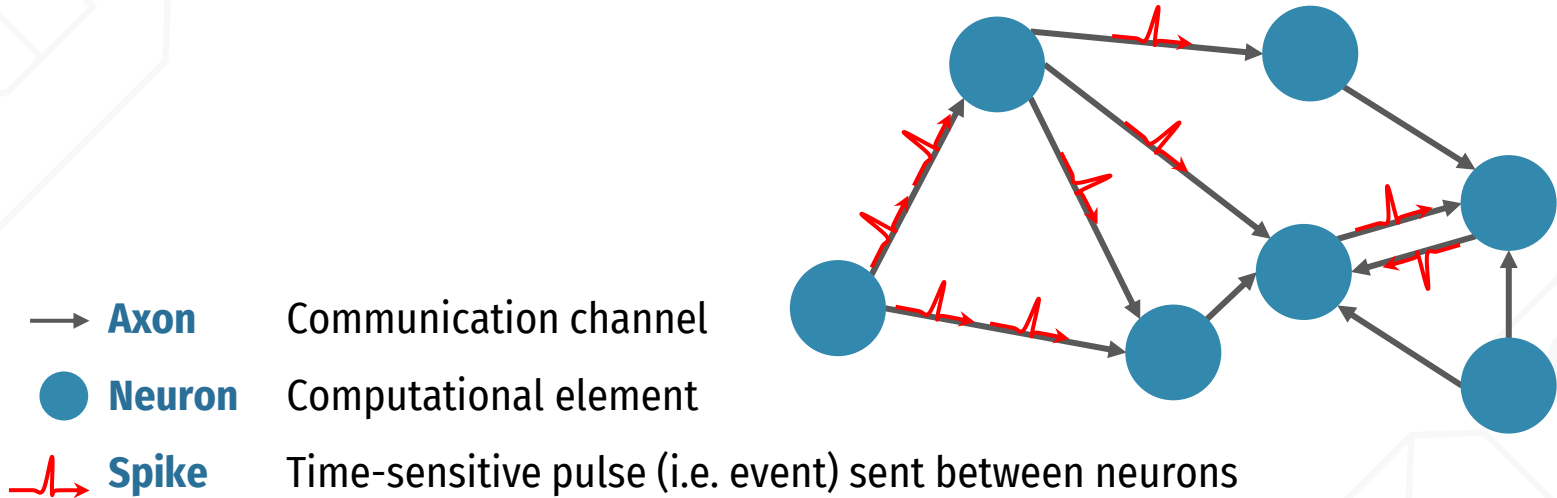
- **Lacks a standard interface:**
 - New interface required for integration in a heterogeneous many-accelerator SoC.
- **Not runtime-programmable:**
 - Model specified at design time → immutable at run time.
- **Model generation** tool includes **mapping model to hardware**. But,
 - Suboptimal resource utilization.
 - Performance, energy efficiency, and resource usage vary based on hardware architecture.
 - Hence, we created a new tool that:
 - Minimizes resource usage for a given architecture.
 - Enables architectural design-space exploration (DSE).



Grey → unused resource
Colored → used resource

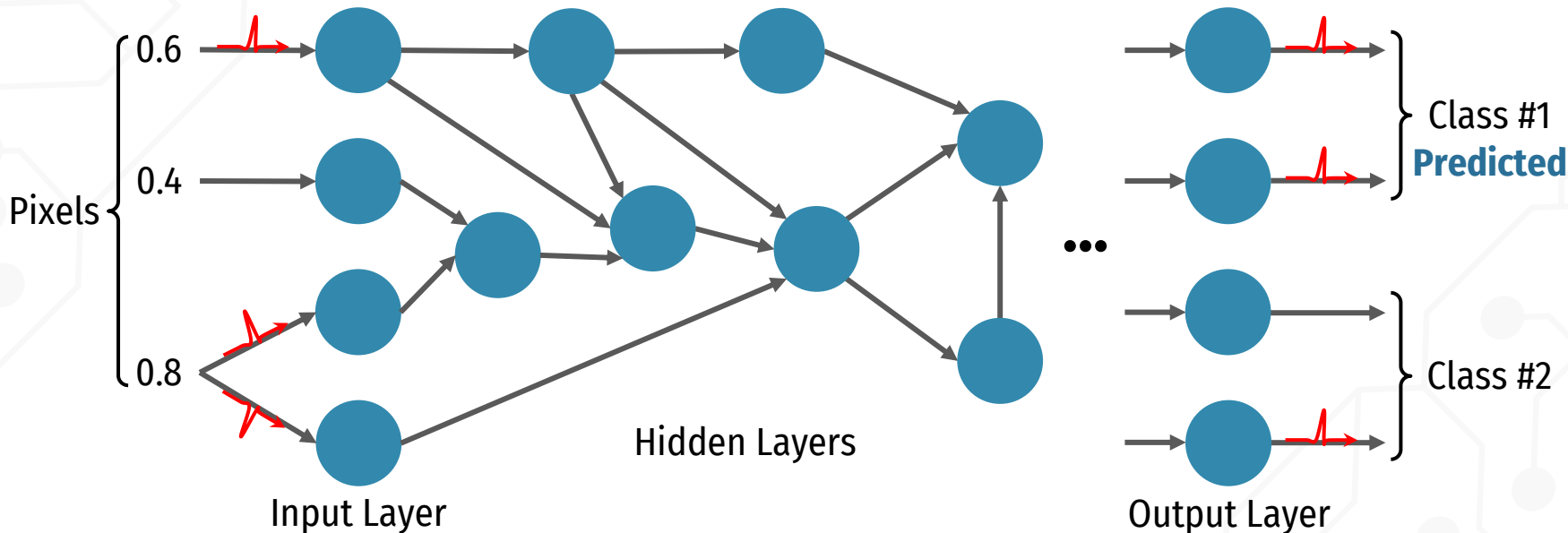
Spiking Neural Network (SNN)

Learning model used in neuromorphic computing is the **Spiking Neural Network (SNN)**.



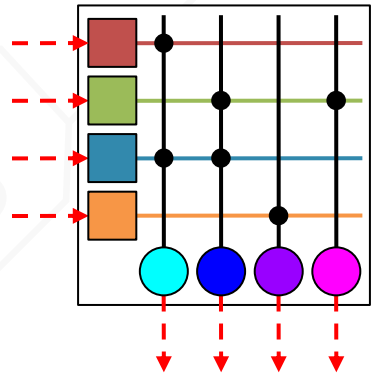
Example SNN – MNIST Image Classification [7]

- For each greyscale pixel $\in [0, 1]$, if rounded = 1, then spike generated for that pixel.
- Multiple neurons can receive spikes from same pixel.
- Each class assigned a set of neurons. Predicted class is the one with the most output spikes.



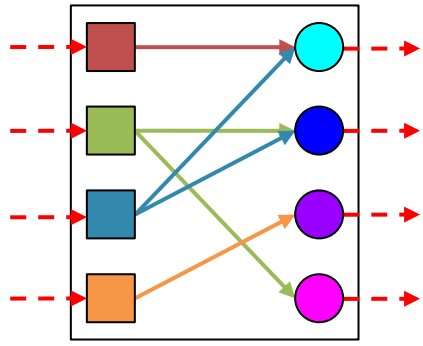
Hardware Implementation

- **Axon** Communication channel
- **Neuron** Computational element
- - -> **Spike** Time-sensitive event



Axon-Neuron Crossbar

=



Graph Representation

Neuromorphic Processor Architecture

- Multiple interconnected cores.
- Each core implements a crossbar.

Spike Timing

- Spike is received at a particular **tick**.
- **Tick Period**: Time elapsed between ticks.
 - Mainly depends on core architecture.
 - Minimize to maximize performance.

Model Restructuring

Model is already mapped to a hardware architecture (e.g. model generated by RANC).

Goal

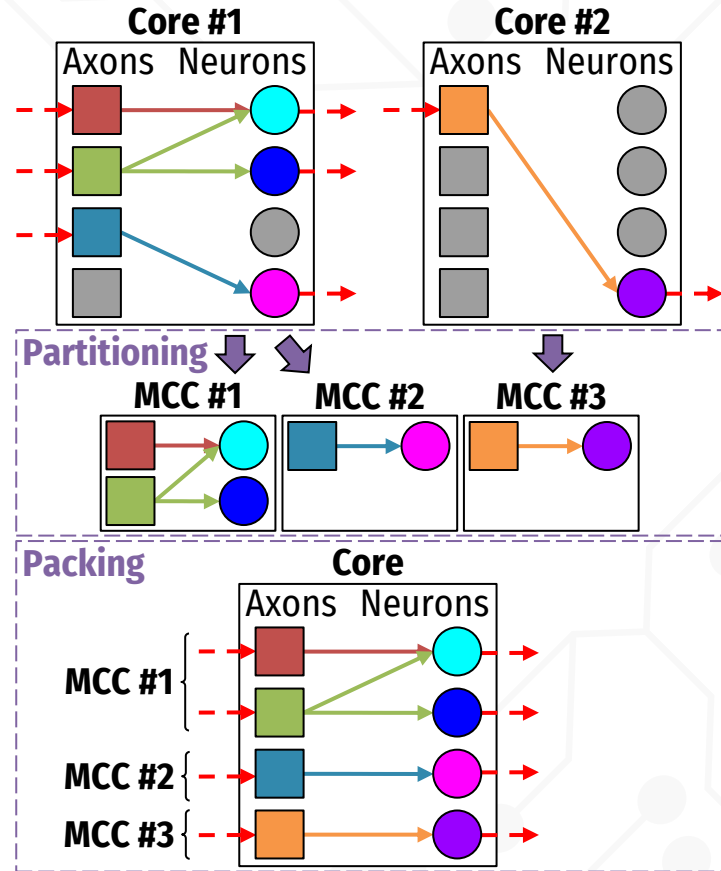
Use minimum number of cores.

Minimal Connected Components (MCCs)

Smallest disjoint subsets of connected neurons and axons in a core.

Integer Linear Program (ILP)

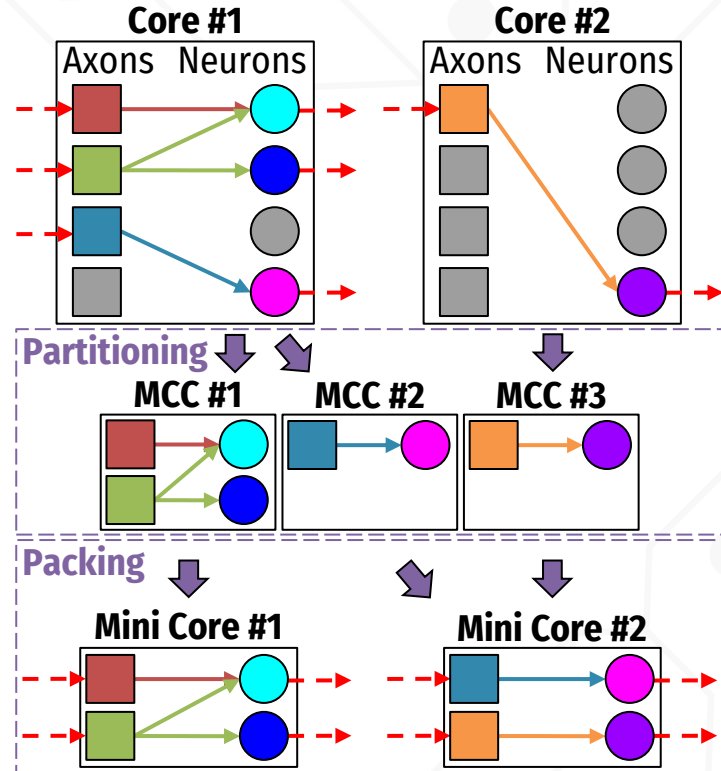
Problem similar to **bin packing**. Objective and constraints can be described as an ILP. Use standard ILP solver to find optimal solution.



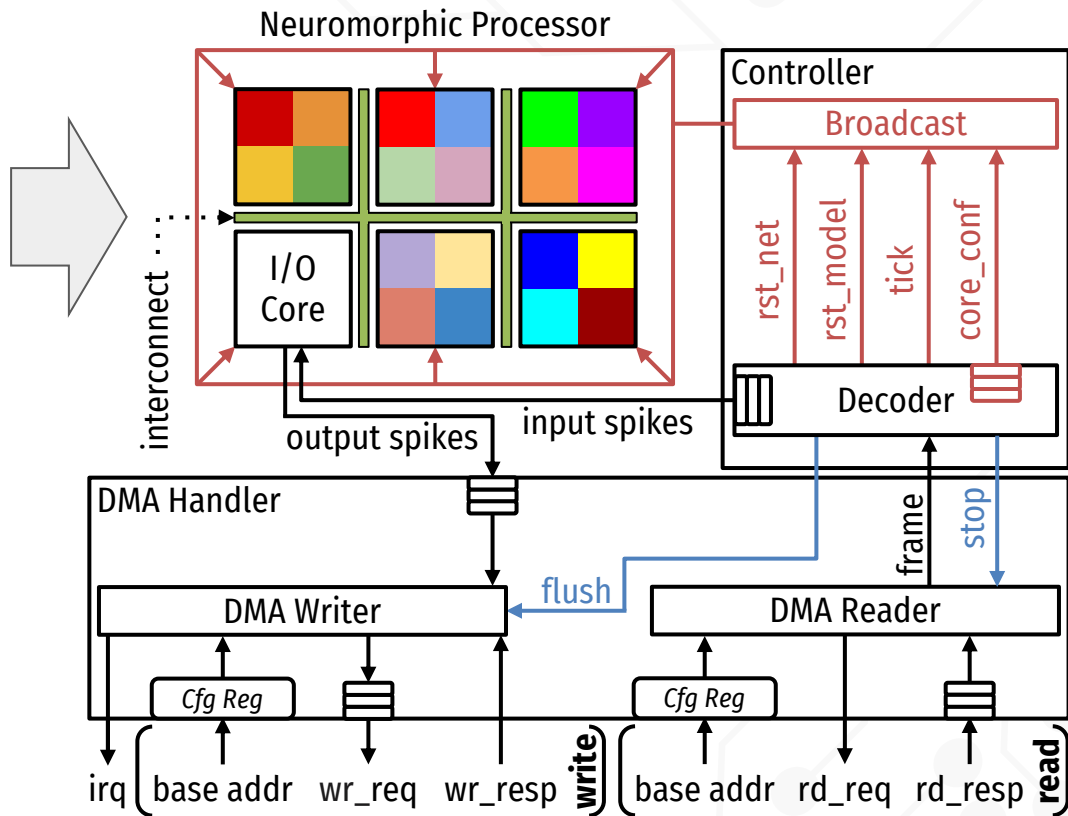
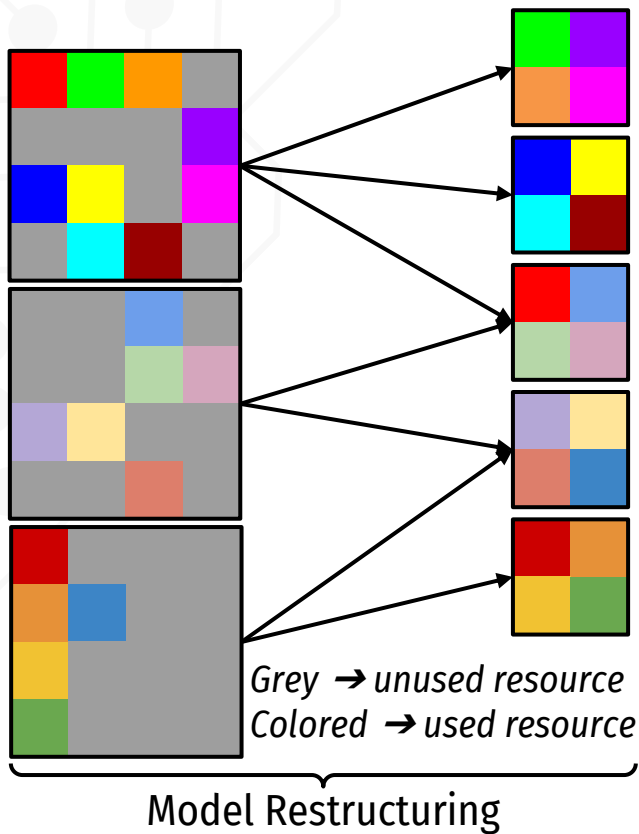
Model Restructuring

Additional Goal

Optimally remap to a different hardware architecture (e.g. smaller cores).

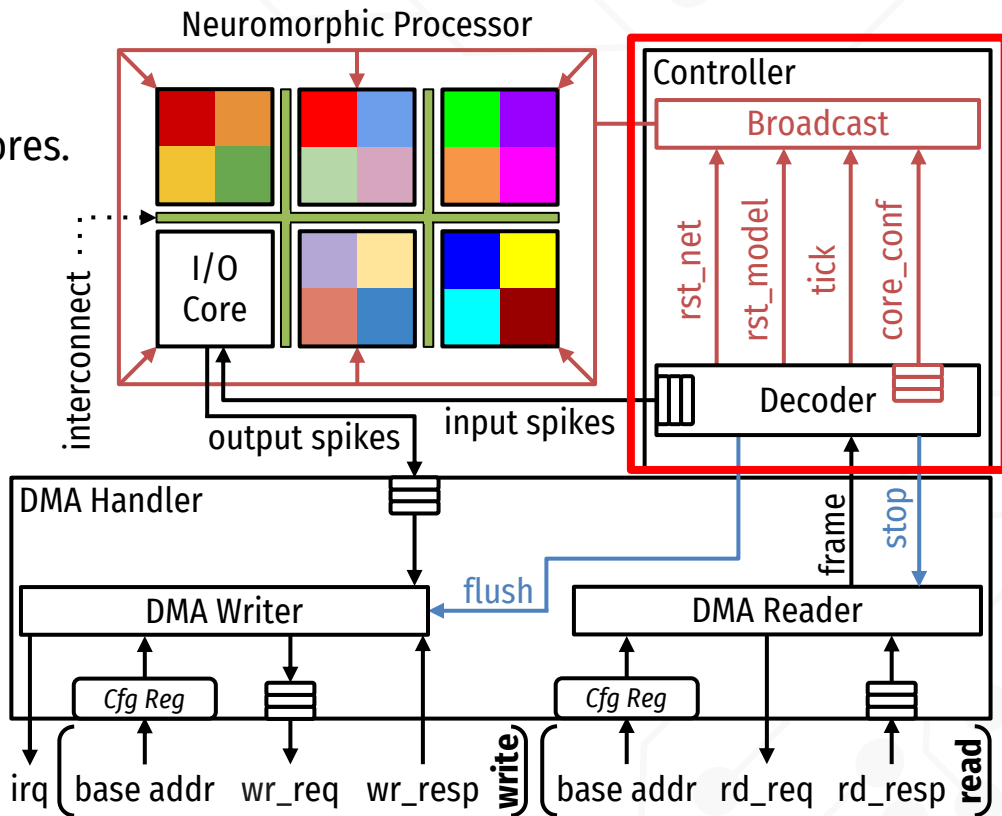


SpikeHard Accelerator

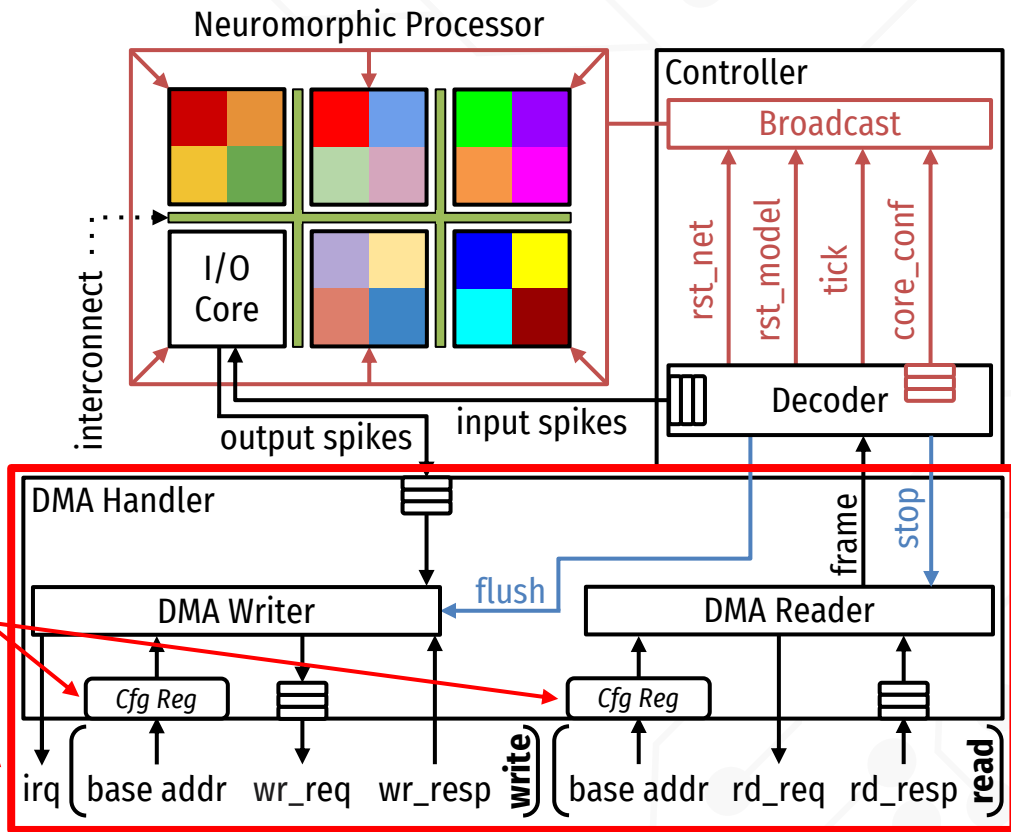


SpikeHard Accelerator

- Controller decodes input data.
- Commands are broadcasted to all cores.



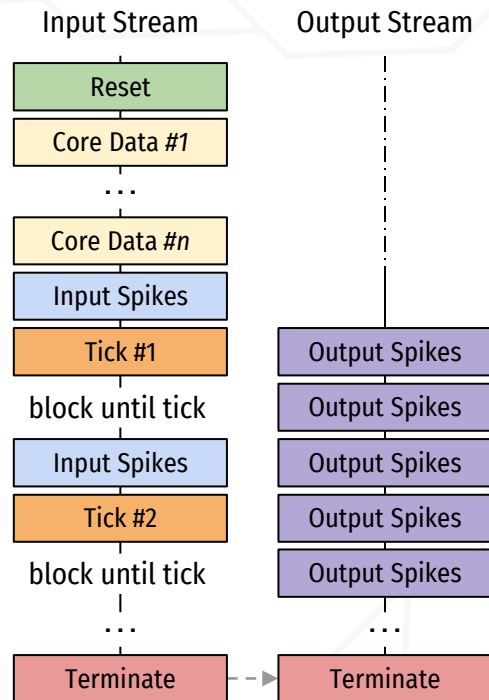
SpikeHard Accelerator



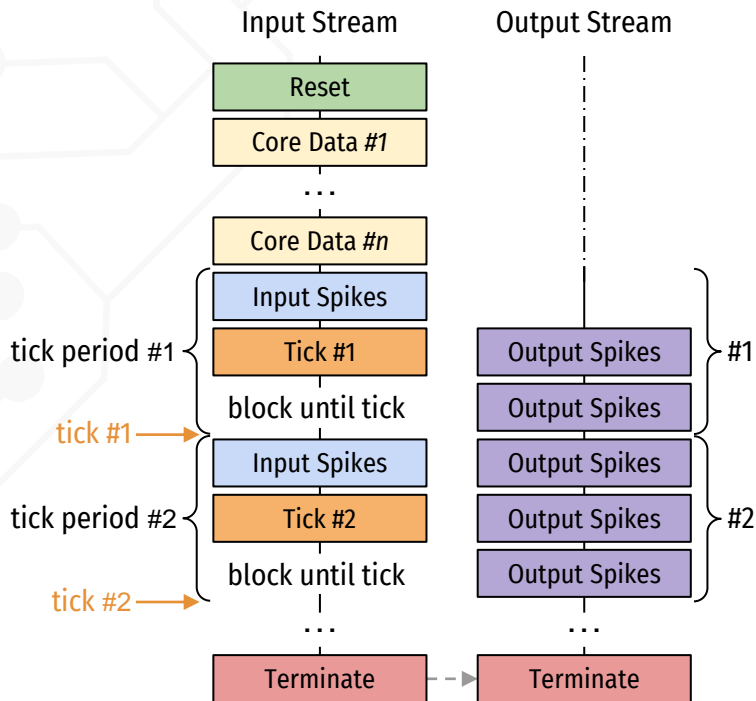
- Main memory accessed via DMA.
- Base addresses provided at the start.
- irq asserted at the end to notify CPU.

Accelerator Interface

- **Input Stream of Frames**
 - Input spikes (e.g. input image to classify).
 - Commands (e.g. for model loading).
- **Output Stream of Frames**
 - Output spikes (e.g. predicted image class).
- **Frame**
 - 128-bit header:
 - 3 bits encode frame type.
 - Remaining bits frame-type specific.
 - Optional payload adjacent to header.



Accelerator Interface



Frame Type	Description
Reset	Reset dynamic state (<code>rst_net</code>) or unload model (<code>rst_model</code>).
Core Data	Configure model parameters for a given core (<code>core_conf</code>).
Input Spikes	Send spikes to specific axons (e.g. input image to classify).
Output Spikes	Output spikes for a given tick (e.g. predicted image class).
Tick	Proceed to next algorithmic time step (<code>tick</code>).
Terminate	End-of-File token.

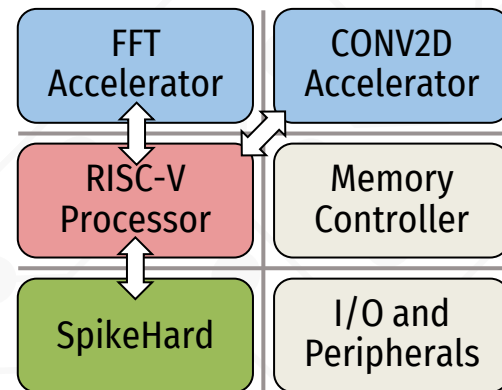
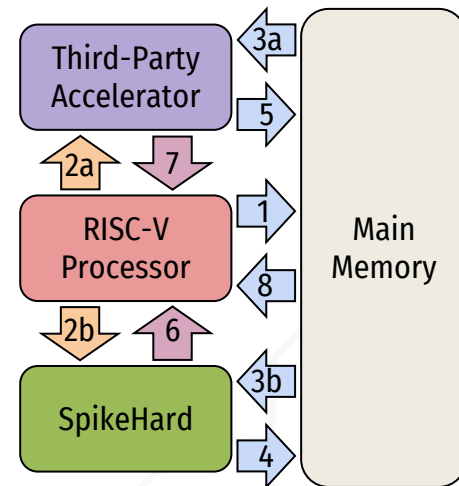
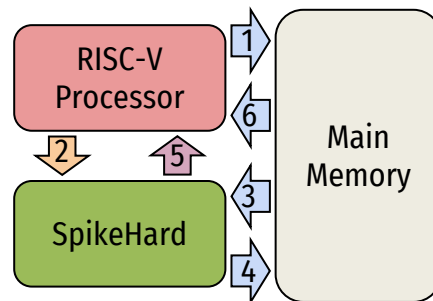
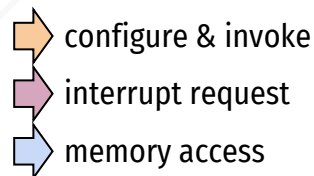
SoC Integration



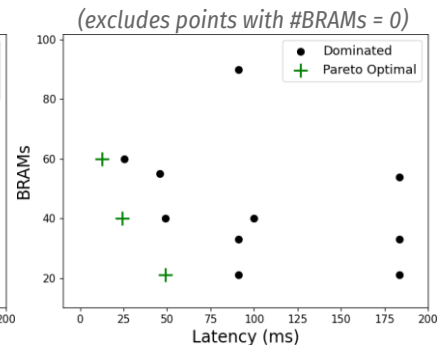
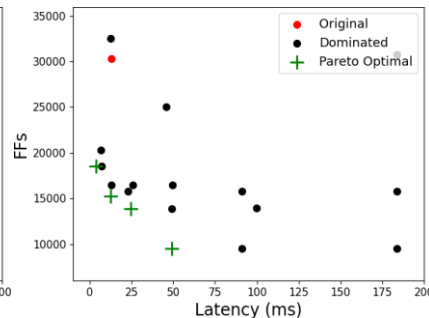
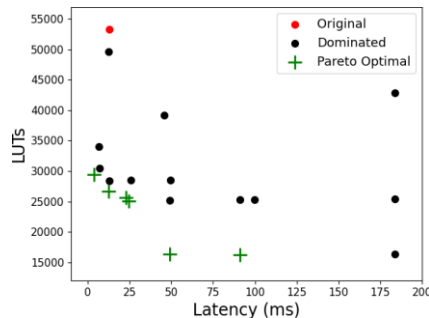
We used **ESP** [8], an open-source SoC design platform.

SpikeHard was integrated as part of a standalone SoC containing:

- **Third-party accelerators:** FFT and CONV2D.
- **General-purpose 64-bit RISC-V CVA6 processor:**
 - Orchestrates accelerator execution.
 - Runs Linux from which app invokes the accelerators.
 - We tested parallel execution of SpikeHard, FFT, and CONV2D.
 - SpikeHard no longer a performance bottleneck after DSE.



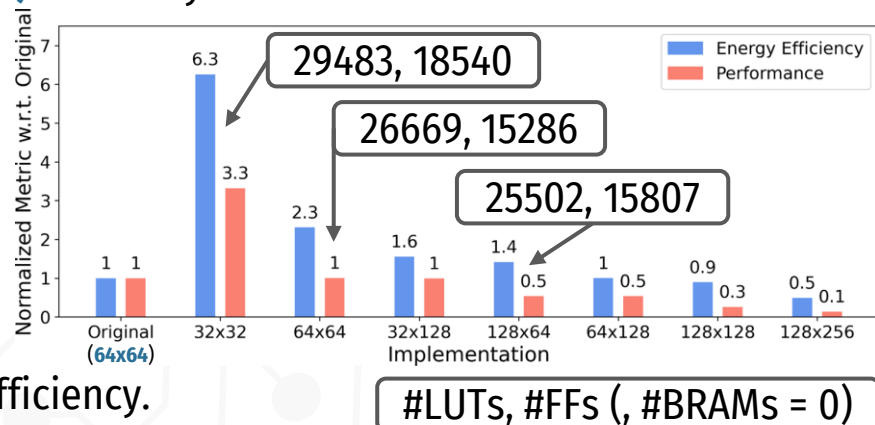
Evaluation



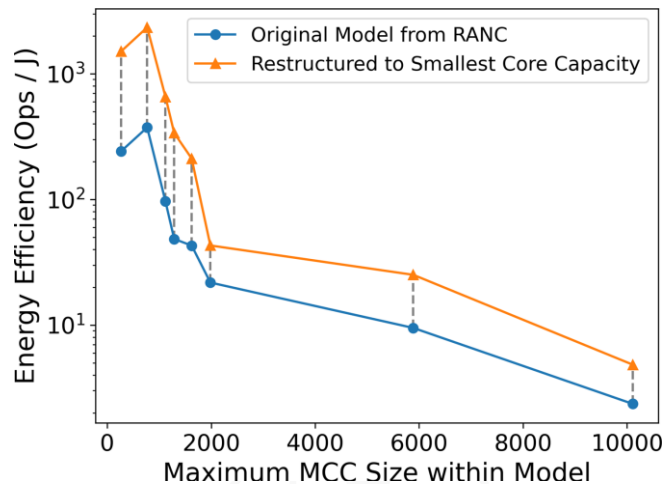
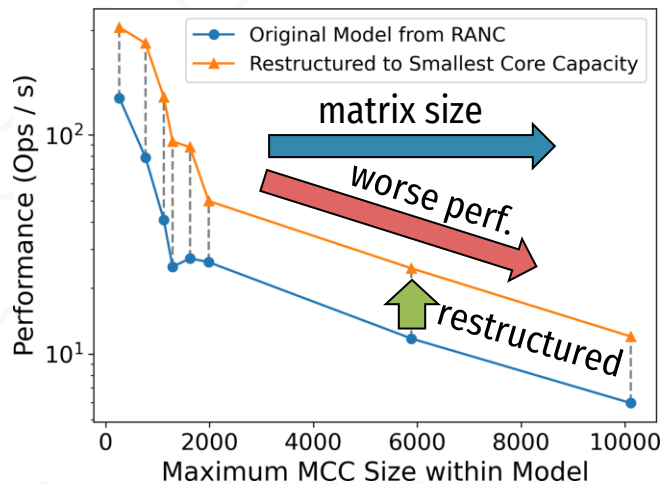
- Deployed SoCs on the **Xilinx VCU128 FPGA** with 75 MHz clock frequency.
- Model estimates **Vector-Matrix Multiplication (VMM)** for a 6 by 6 matrix.

- **Original mapping from RANC:** 64x64.
- **AxN:** each core has **A** axons and **N** neurons.
- Varied **A** & **N** via model restructuring.
- Tested: $\forall A, N \in \{32, 64, 128, 256, 512\}$.

- Larger cores \rightarrow better resource usage.
- Smaller cores \rightarrow better performance and energy-efficiency.
- Restructuring to smallest core capacity (32x32) improved:
 - Performance by **3.3x (89x)**
 - Energy efficiency by **6.3x (170x)**
 } w.r.t. original with(out) tuned tick period.



Larger VMMs



- Restructuring to smallest core capacity improved:
 - Performance by **1.90 – 3.73x**.
 - Energy efficiency by **1.97 – 6.96x**.
- Larger matrix → larger and more numerous MCCs (bigger model).
- Larger MCCs → worse performance and energy-efficiency.

Conclusion

- We developed SpikeHard, a neuromorphic hardware accelerator that is:
 - Programmable at runtime.
 - Easy to integrate into a heterogeneous many-accelerator SoC.
 - Suitable for embedded apps with both neuromorphic and non-neuromorphic kernels.
- We devised an optimization algorithm (model restructuring) that:
 - Minimizes resource utilization for a particular neuromorphic architecture.
 - Enables a model to be optimally remapped to different architectures.
- We performed broad DSE on FPGA:
 - Significant improvements in performance and energy-efficiency over baseline.
- We have released the contributions of this work in the public domain:
 - <https://github.com/sld-columbia/spikehard>

Thank You!