



Phi: Leveraging Pattern-based Hierarchical Sparsity for High-Efficiency Spiking Neural Networks

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Duke

*Both author contributed equally to this work

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I Background & Motivation

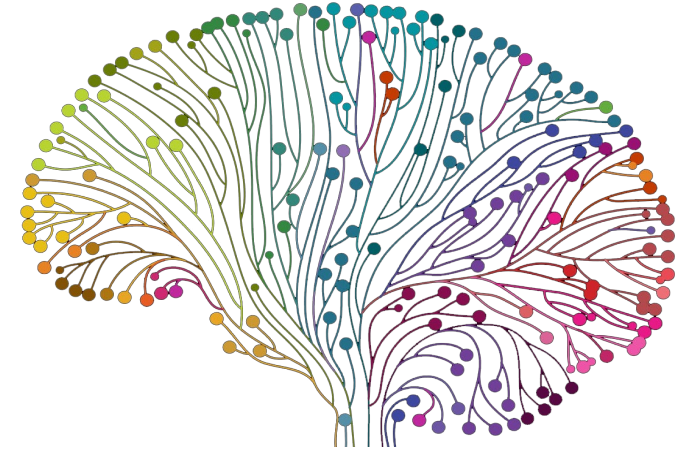
I Pattern-based Hierarchical Sparsity

I Phi Architecture Design

I Evaluation & Discussion

Spiking Neural Networks (SNNs)

- Biologically inspired neural networks
- Various applications
- Higher energy efficiency



Robotics



Brain-computer Interface

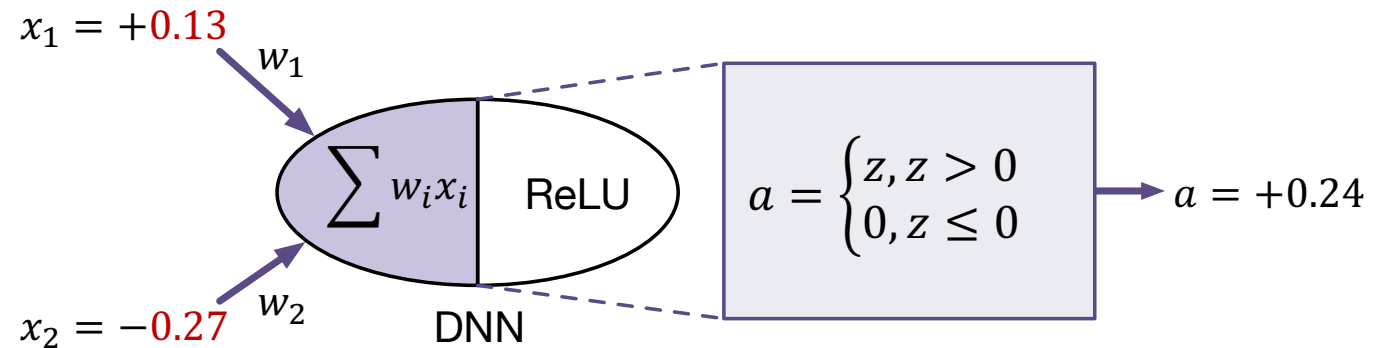


Autonomous Driving

Comparison Between SNNs and DNNs

Similarity:

- Main Operand: Matrix multiplication

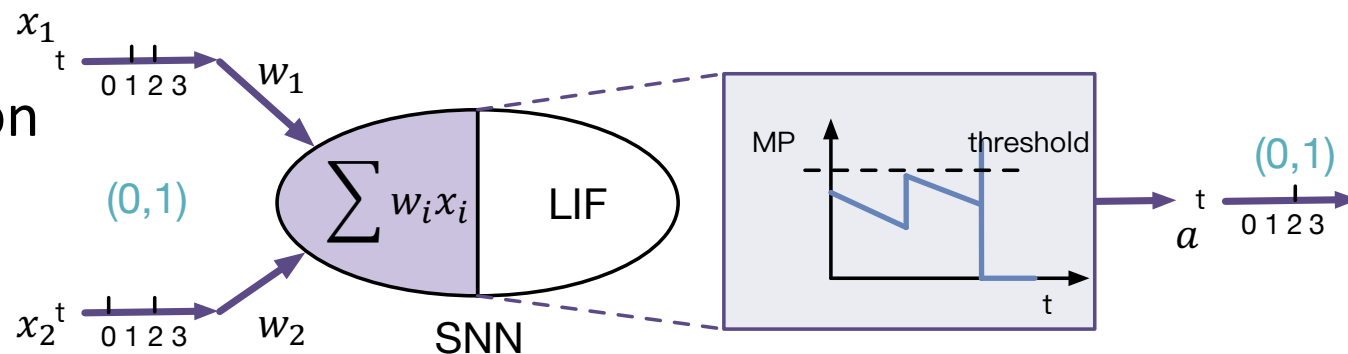


Dense

0.1	0.2	0.5	0.5
0.2	0.8	0.4	0.2
0.3	0.2	0.3	0.4
0.2	0.5	0.4	0.9

Difference:

- Single-bit spike activation
- Inherent Bit Sparsity



Bit Sparsity

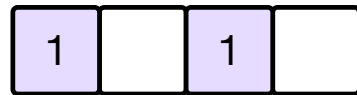
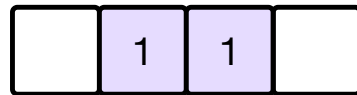
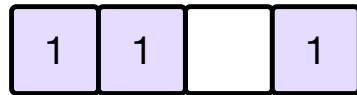
1	1		1
1	1		
1	1	1	
			1

Distribution of Activations

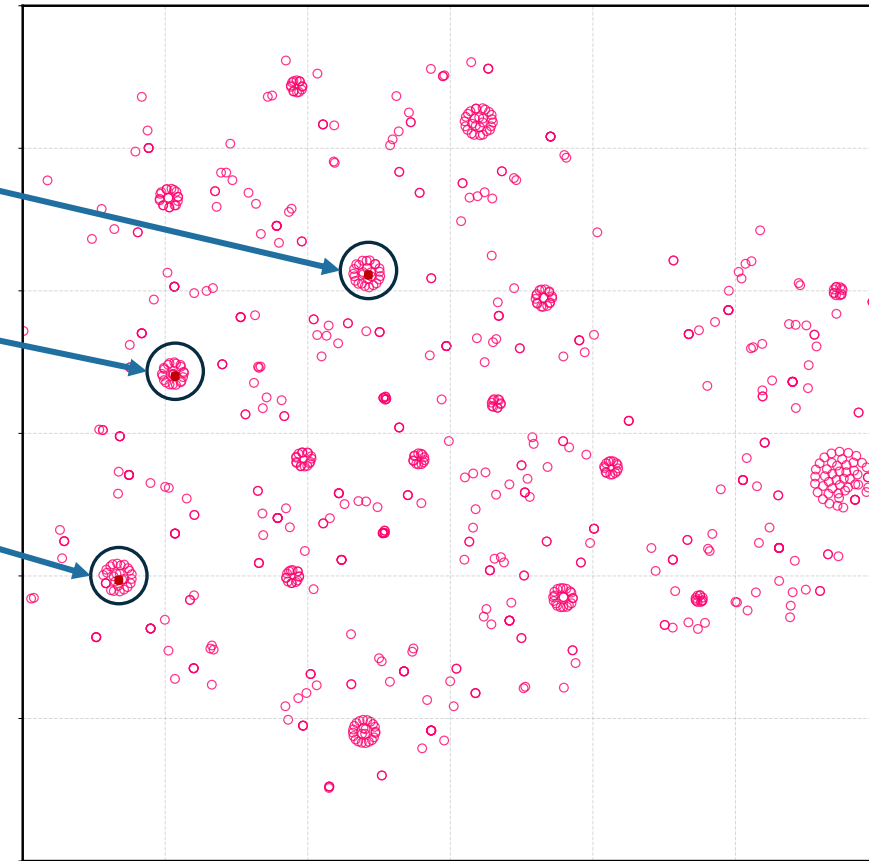
Regularities in SNNs activations

SNN (0,1) Activation

- Patterns



- Can we take advantage of these patterns?



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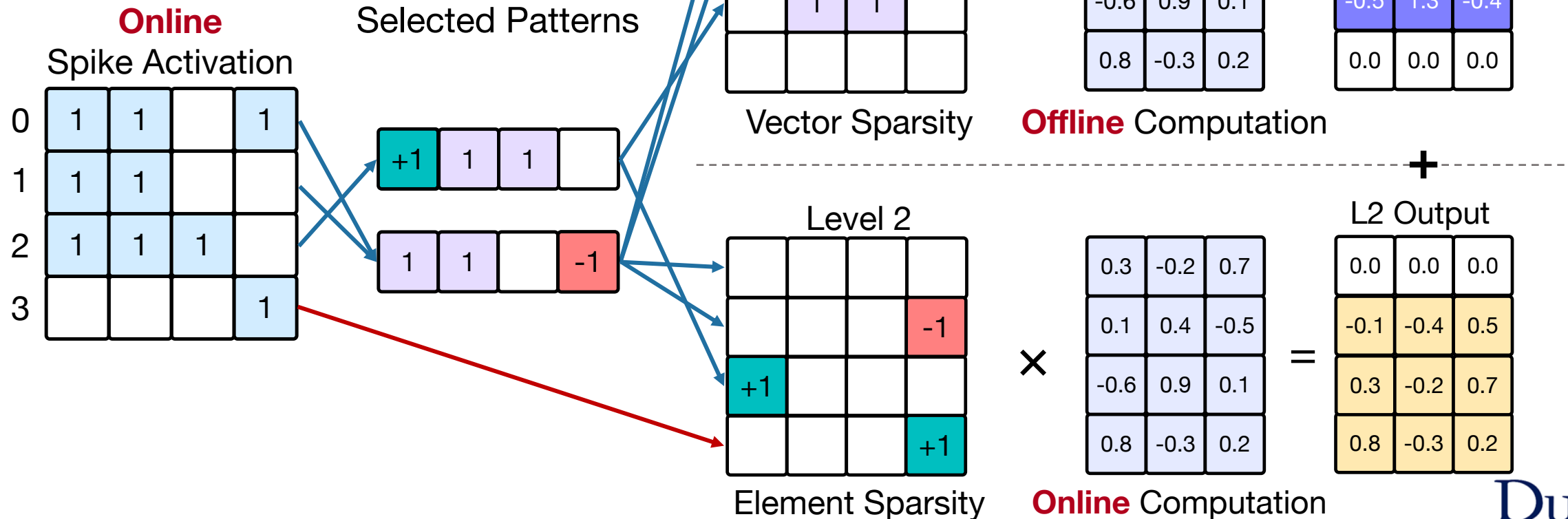
I Evaluation & Discussion

Pattern-based Hierarchical (Phi) Sparsity

Utilize pre-defined patterns to skip operations

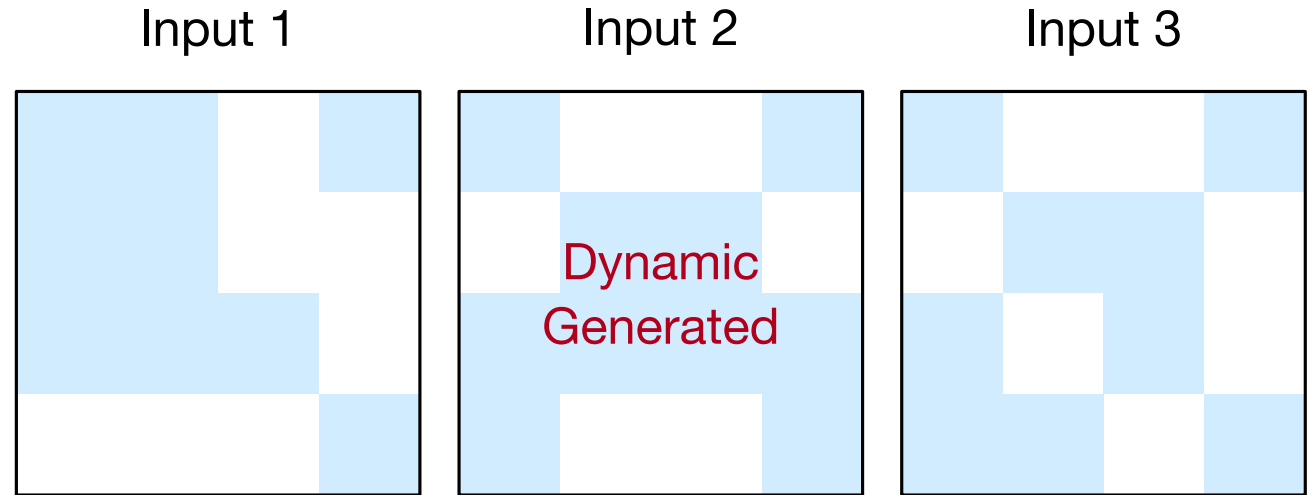
L1: Vector Sparsity

L2: Element Sparsity

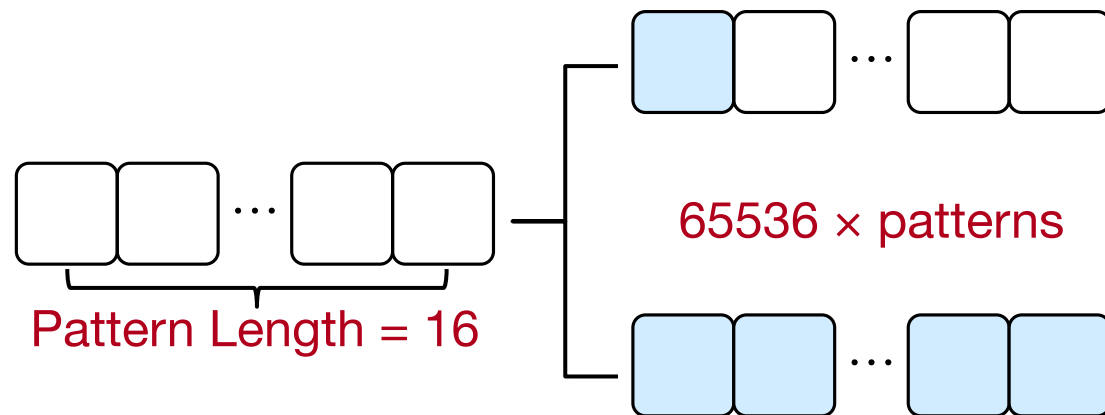


Challenges: Algorithm

Uncertainty of activations



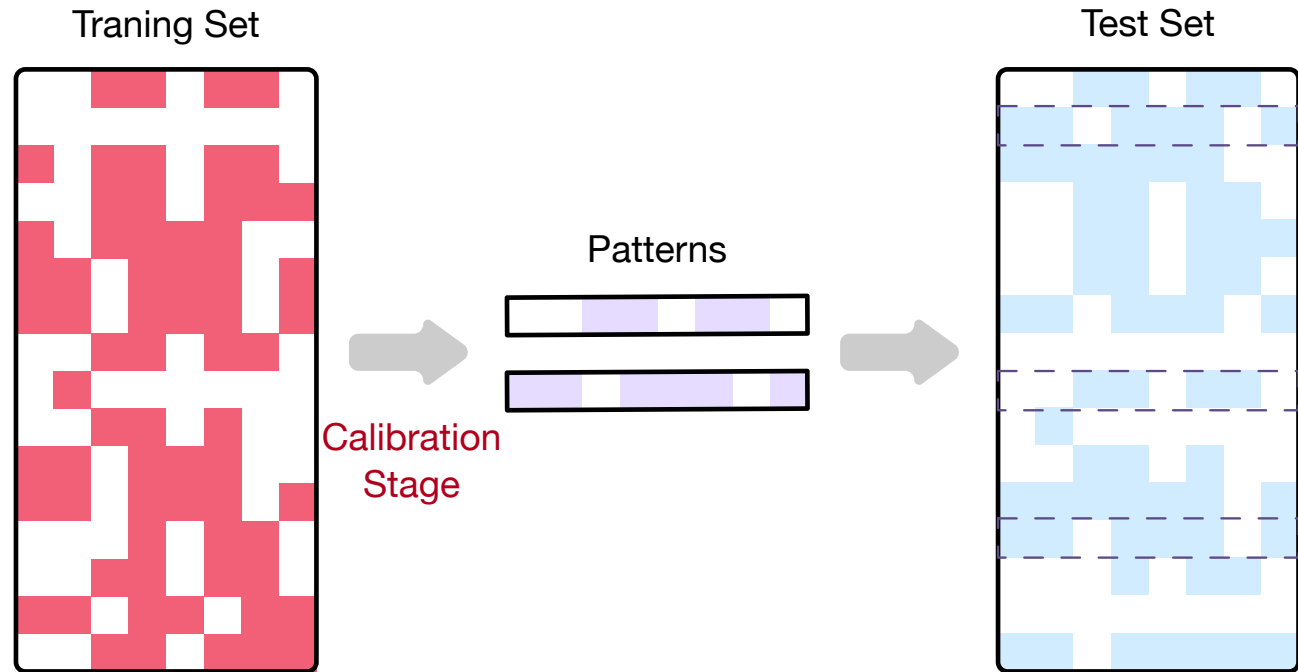
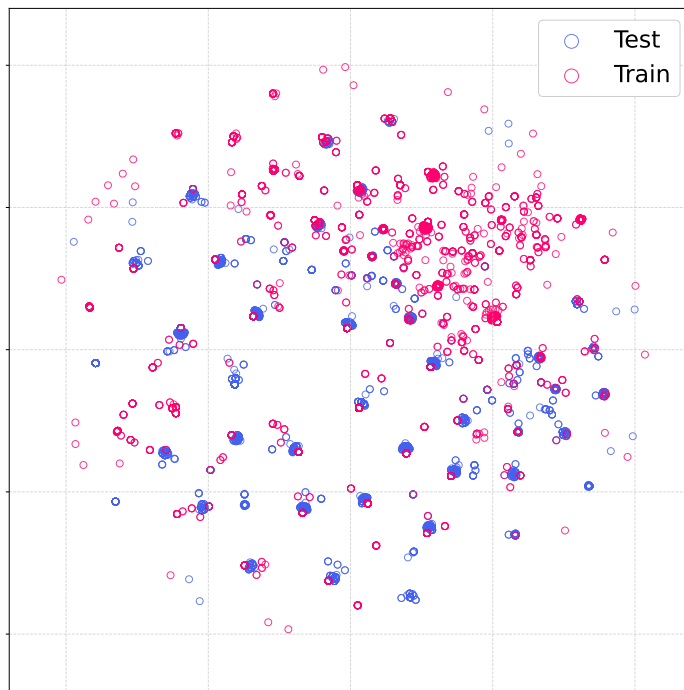
Complexity of patterns



How to select patterns?

Phi Sparsity Calibration Set

- Similarity between training set and test set
 - Use a calibration set to identify patterns

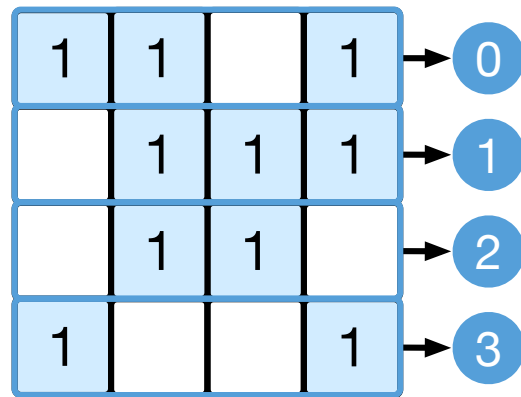


Phi Sparsity Generation Stage

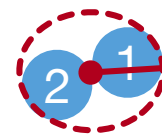
D K-means-based clustering algorithm

- Filter out all zero and one-hot rows
- Use Hamming distance

Offline Calibration
Spike Activation

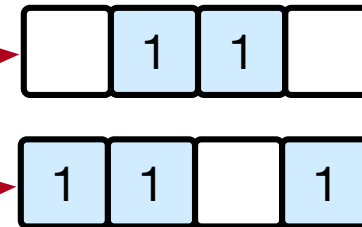


1. Node conversion



2. K-Means

K-Means Centroids
(Patterns)



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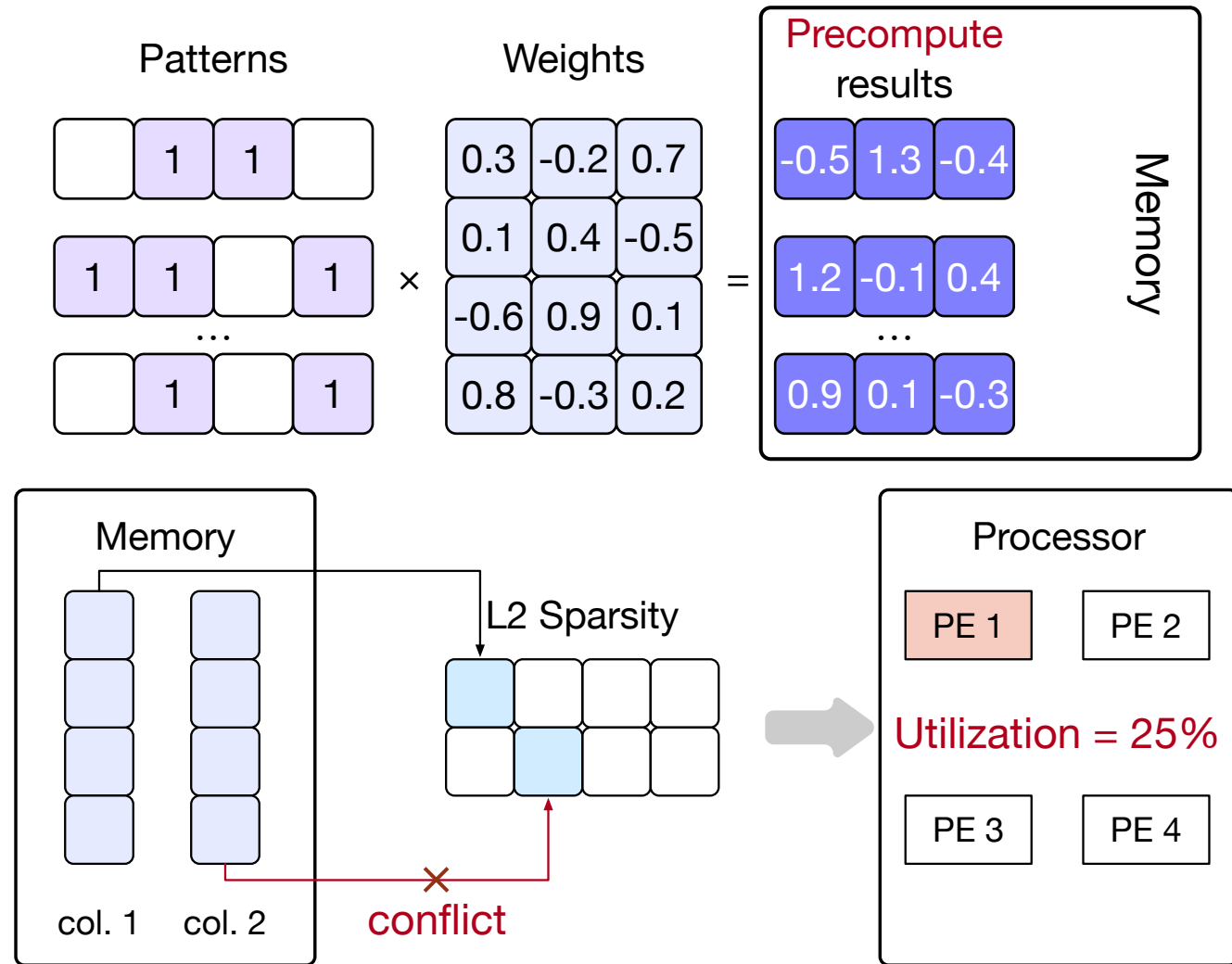
Challenges: Hardware

Memory Overhead

- 9x memory access

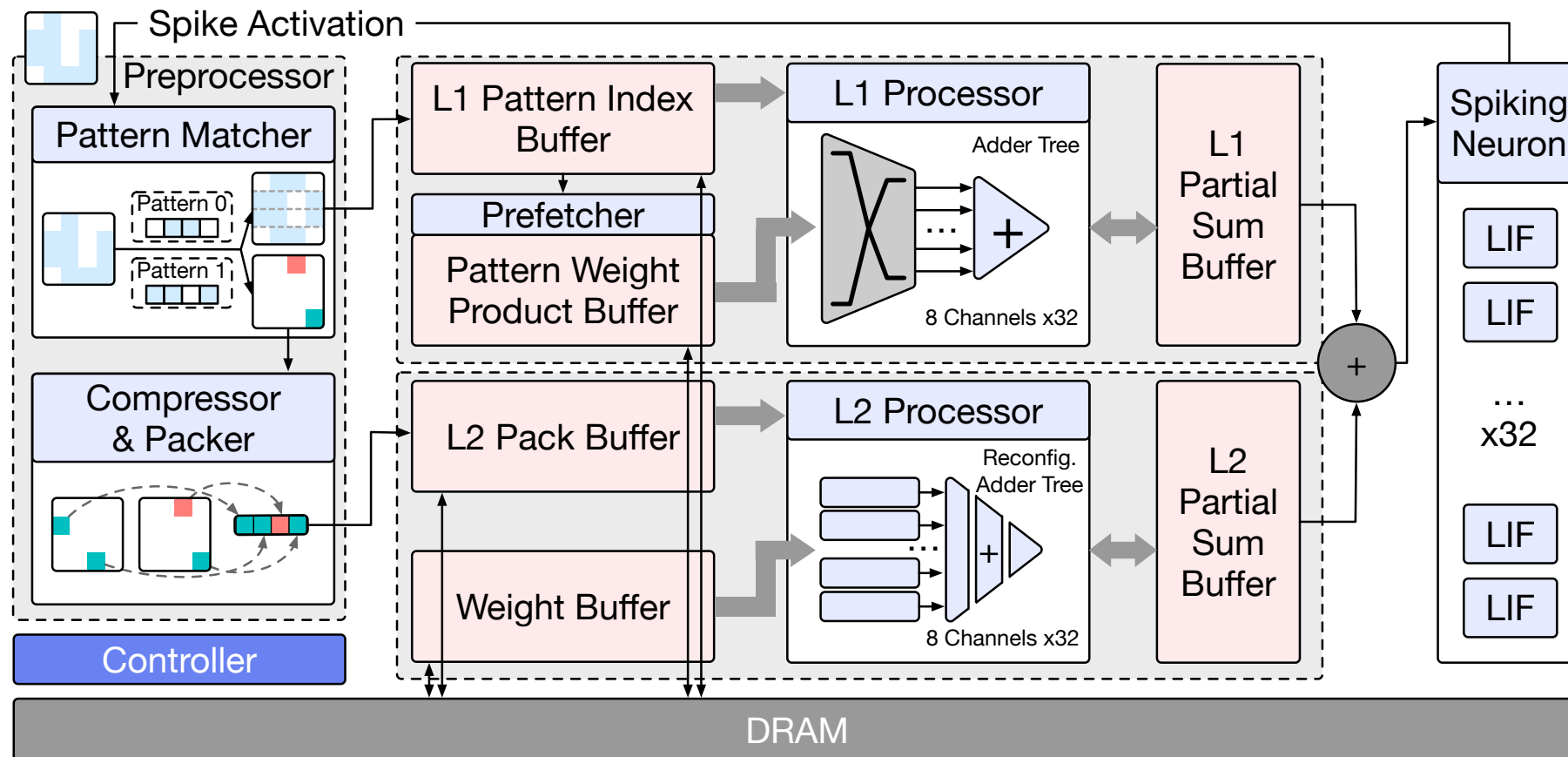
Sparsity Processing

- Data read/write **conflicts**
- Low hardware **utilization**



Architecture Overview

- An architecture generates and processes two levels of Phi sparsity
- Main components: Preprocessor, L1 processor, L2 processor

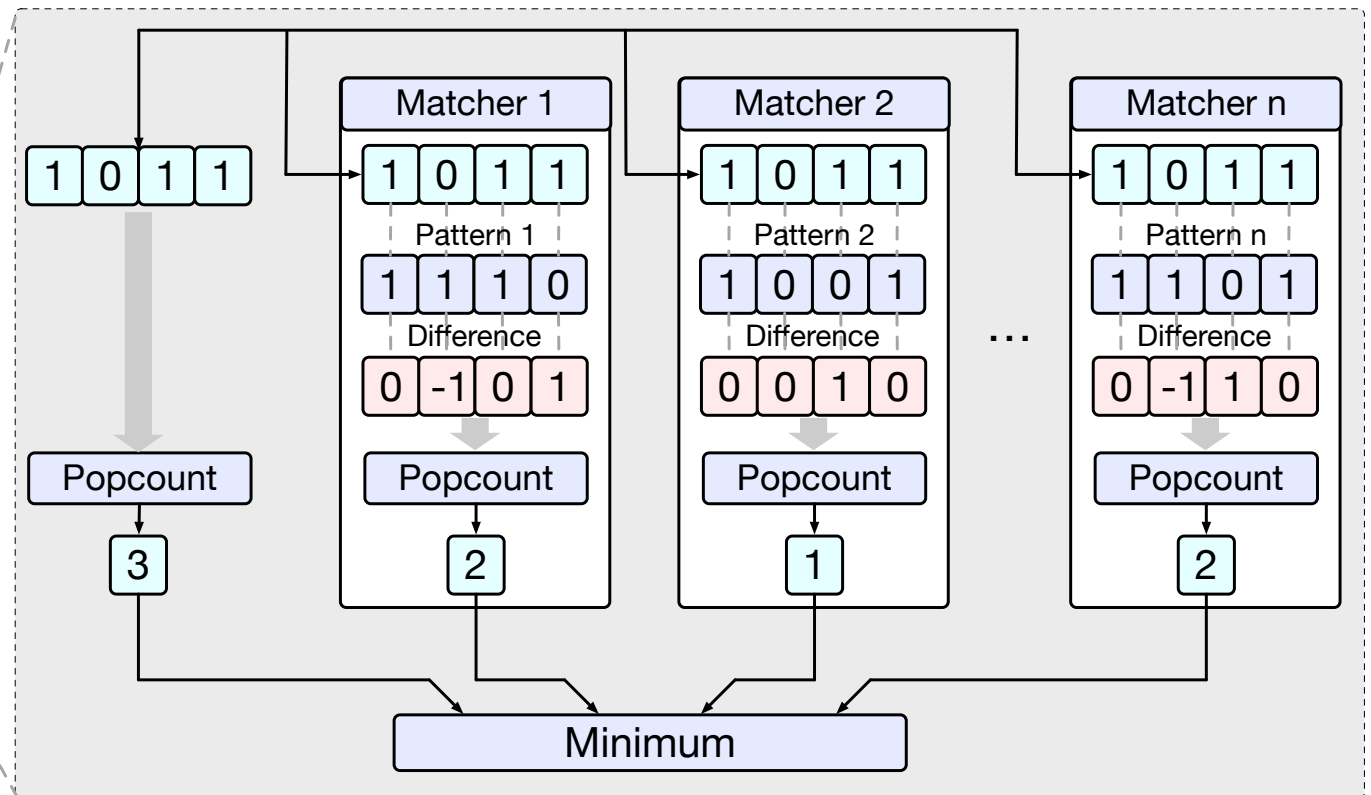
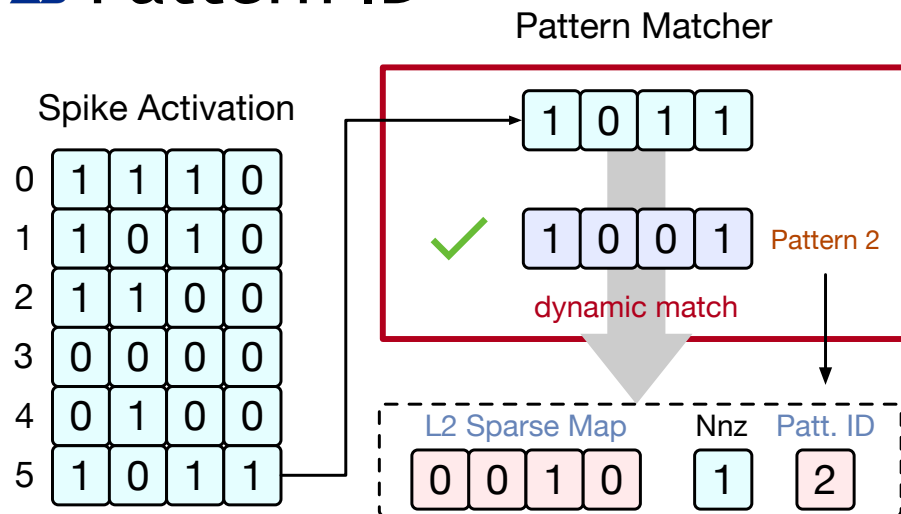


Pattern Matcher

Dynamic matching pattern

Get L2 sparse map

Pattern ID



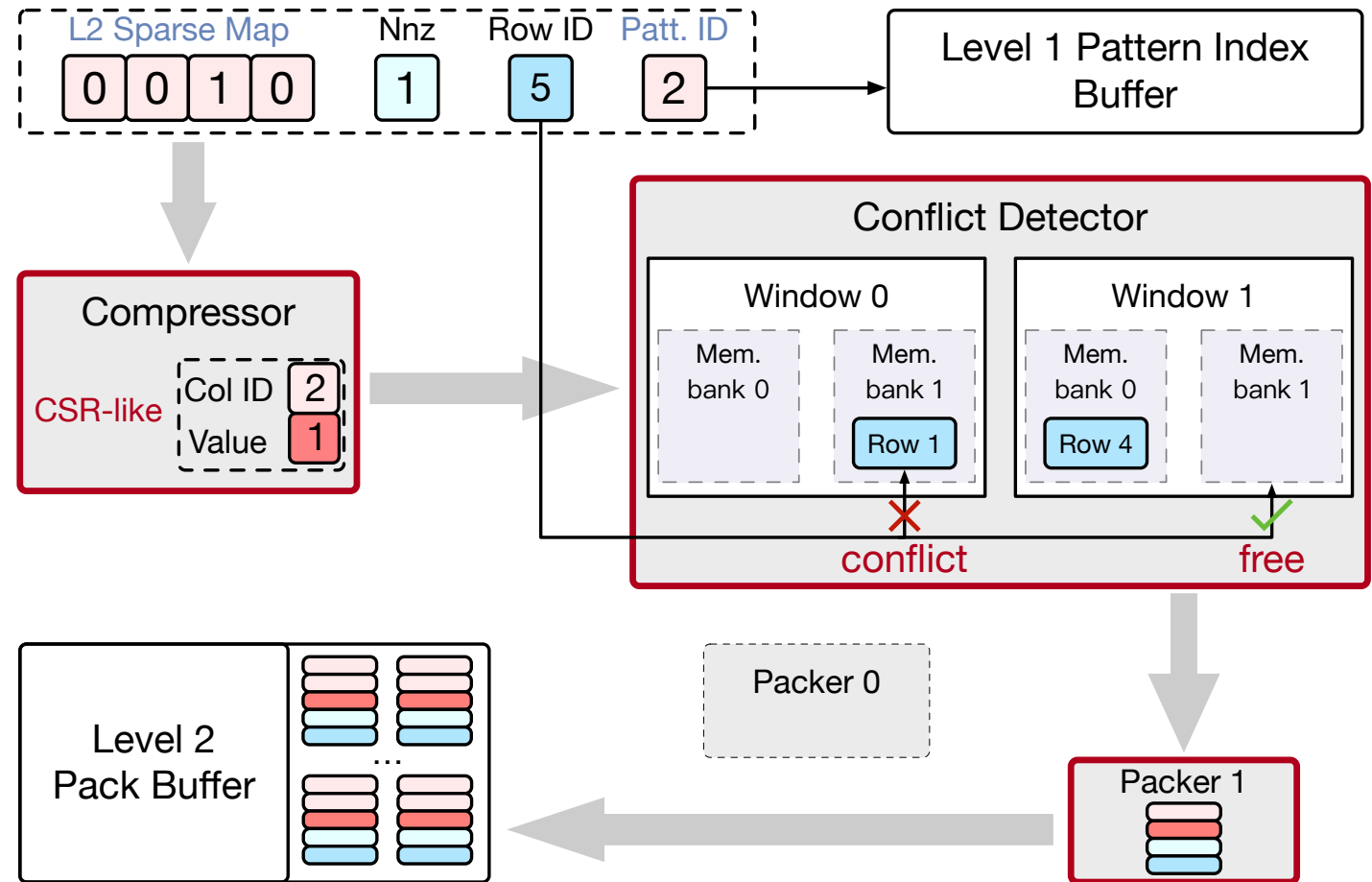
Compressor & Packer

CSR-like format

- Reduce memory access

Multi window packing

- Conflict free



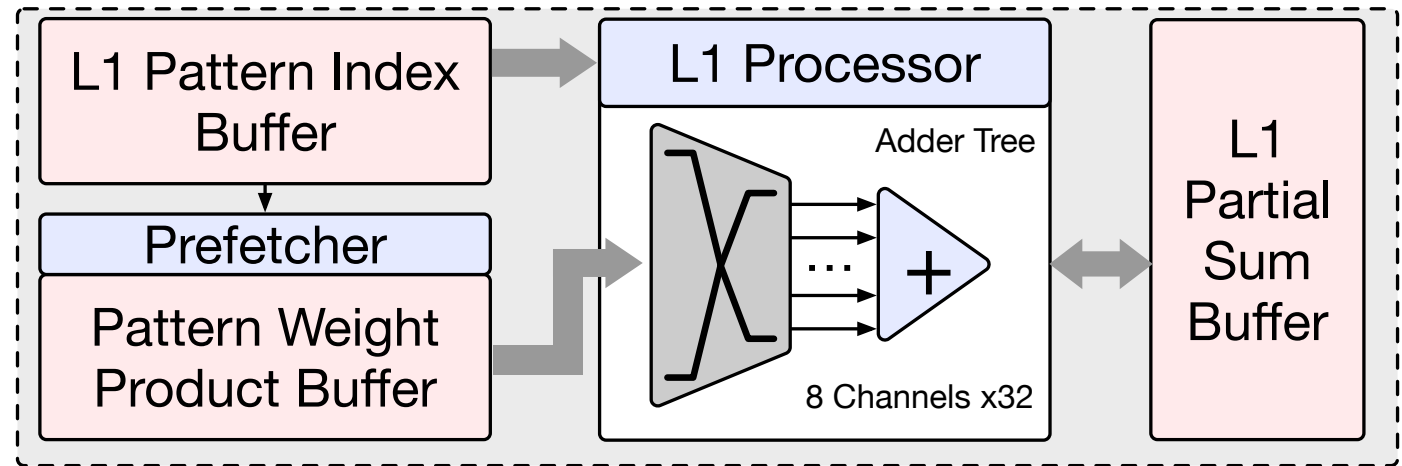
Computation: structured sparsity

■ Prefetcher

- Only read the necessary PWP
- Reduce memory traffic

■ L1 Processor

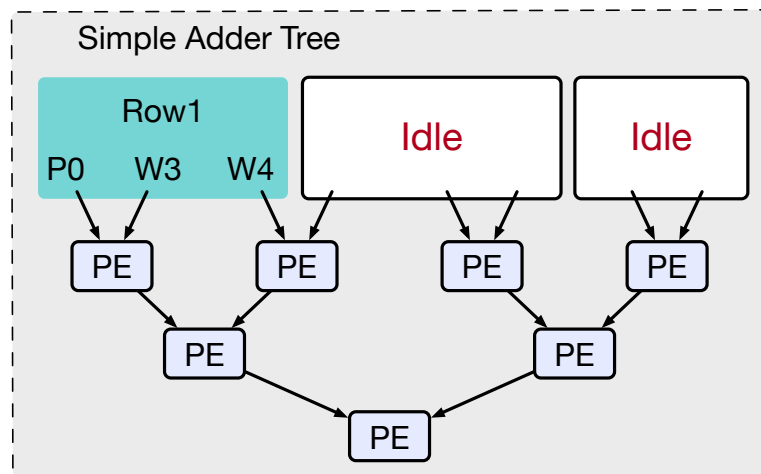
- 16:8 structured sparsity
- 8 channels adder tree



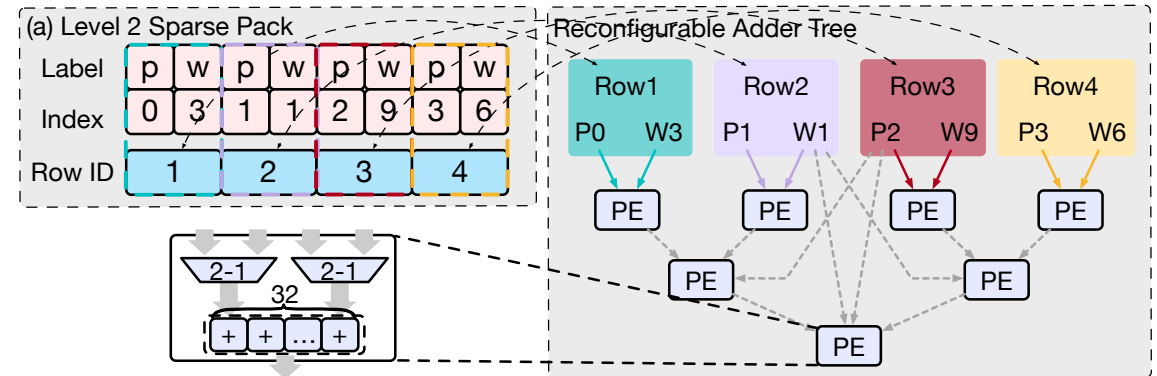
Computation: unstructured sparsity

Reconfigurable Adder Tree

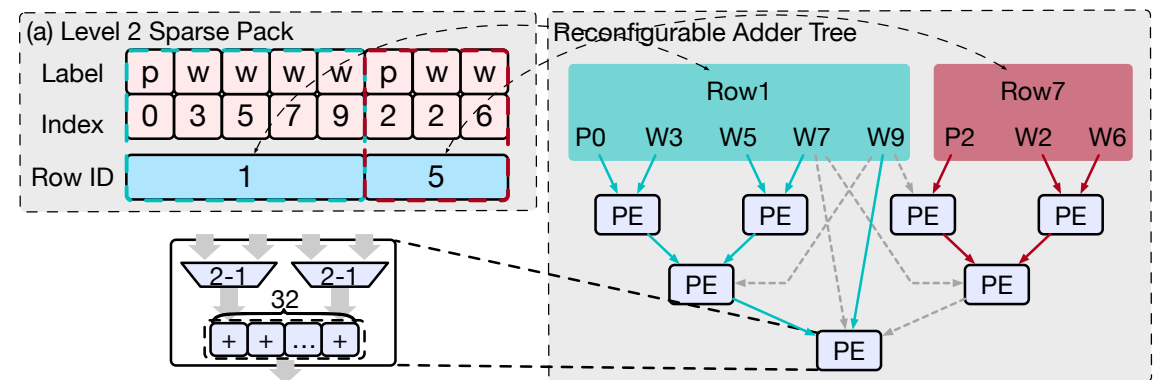
- High utilization
- Minimal overhead



Simple adder tree
Utilization = 37.5%



Input packed in 2-2-2-2



Input packed in 5-3

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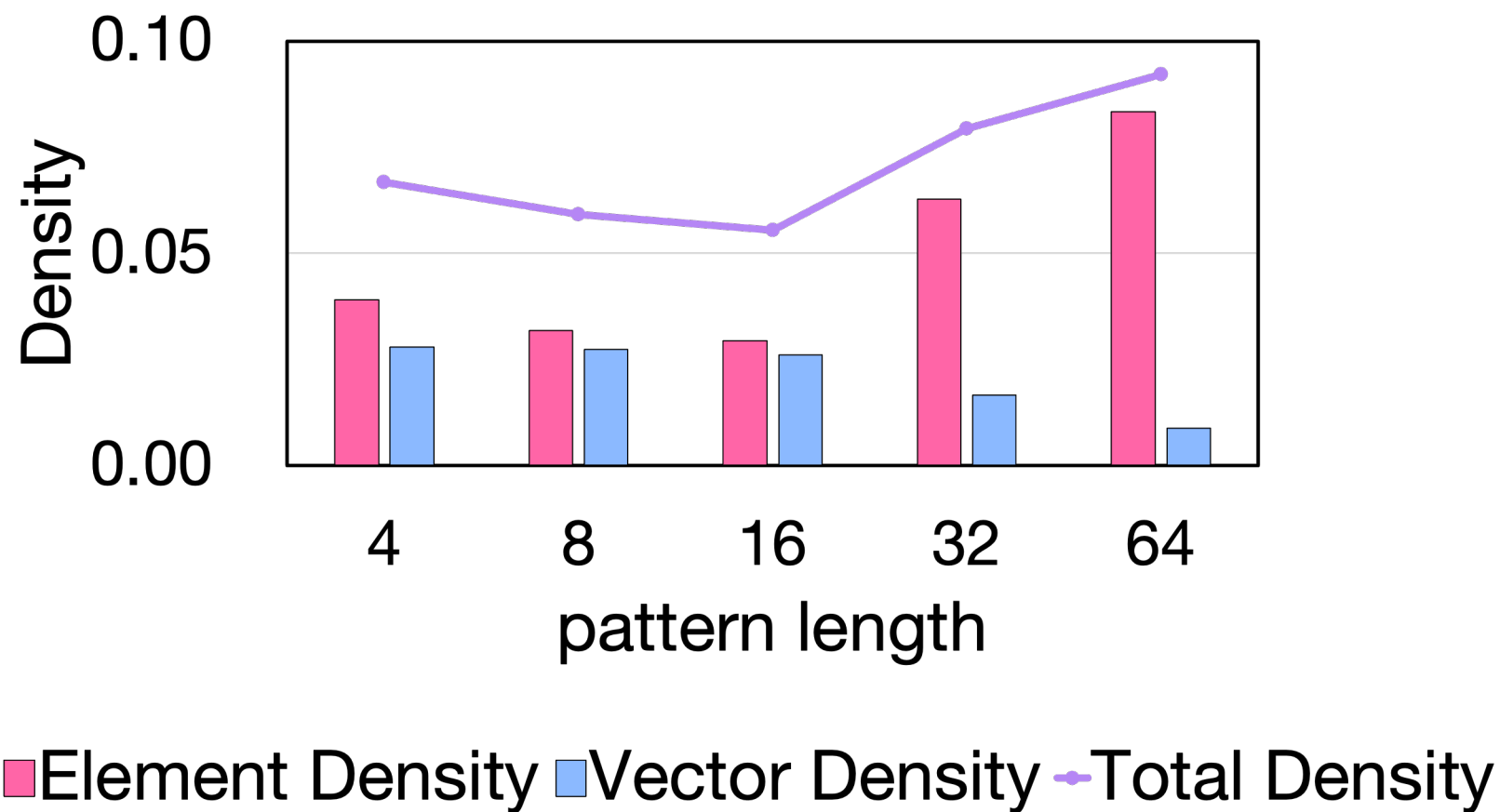
Design Space Exploration

■ Pattern length

■ Balance L1 & L2
density

■ Minimize total
density

■ $L = 16$



(a) Density with the **pattern length**.

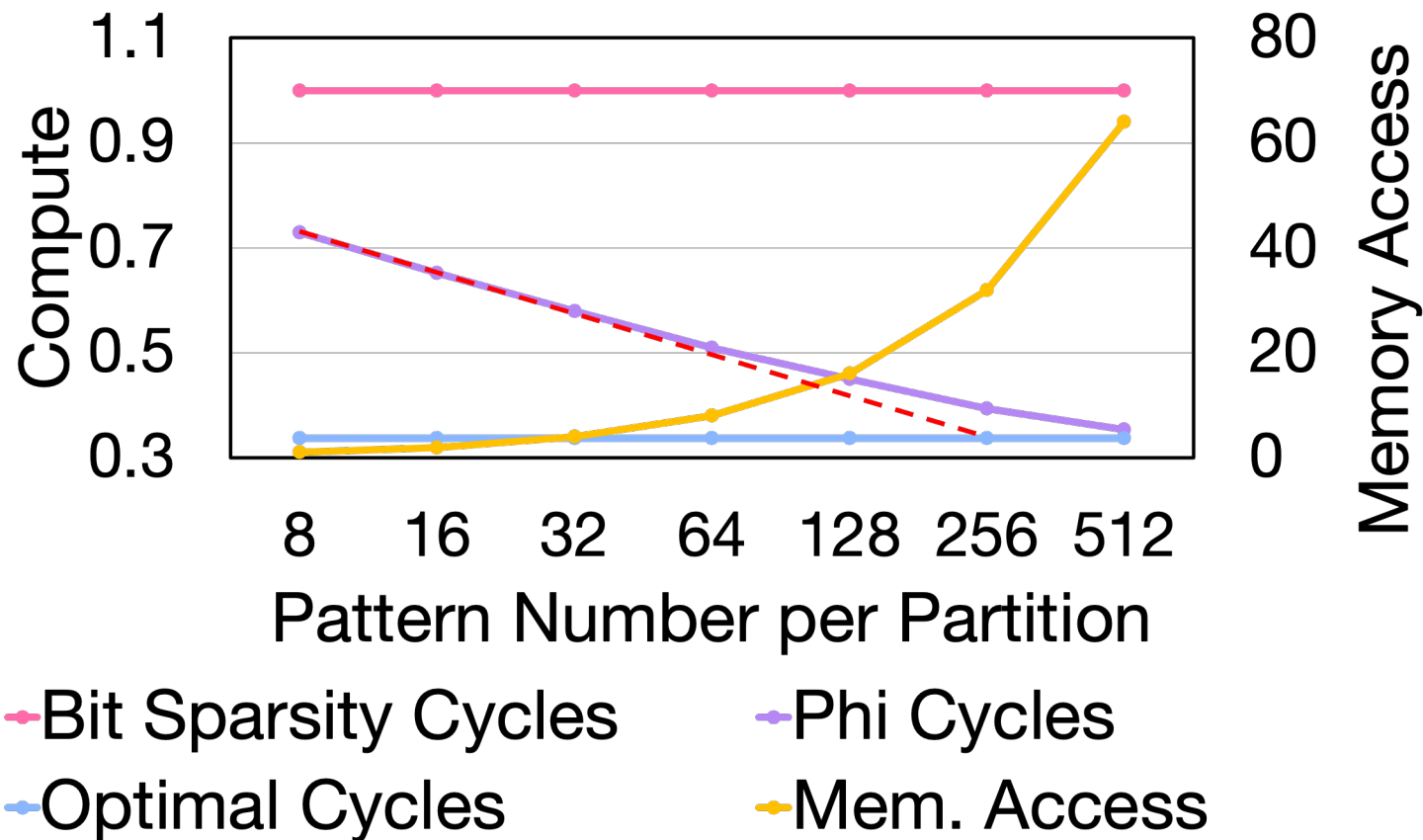
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Design Space Exploration

■ Pattern number

■ Balance computation cycles and memory overhead

■ #patterns = 128



(b) Compute cycles with # patterns.

Evaluation Setup

Baselines

Sparsity

Spiking Eyeriss (ISCA'20)

Dense

SpinalFlow (ISCA'20)

Bit Sparsity

PTB (HPCA'22)

Bit Sparsity

SATO (DAC'22)

Bit Sparsity

Stellar (HPCA'24)

Bit Sparsity

Phi (Ours)

Phi Sparsity

Tools

Synopsys Design
Compiler

Logic synthesis

CACTI

Buffer simulation

DRAMsim3

DRAM simulation

Type

Models

Data set

Spiking
CNN

VGG16

ResNet18

Spikformer

SDT

Spiking
Transform
er

SpikingBERT

SpikeBERT

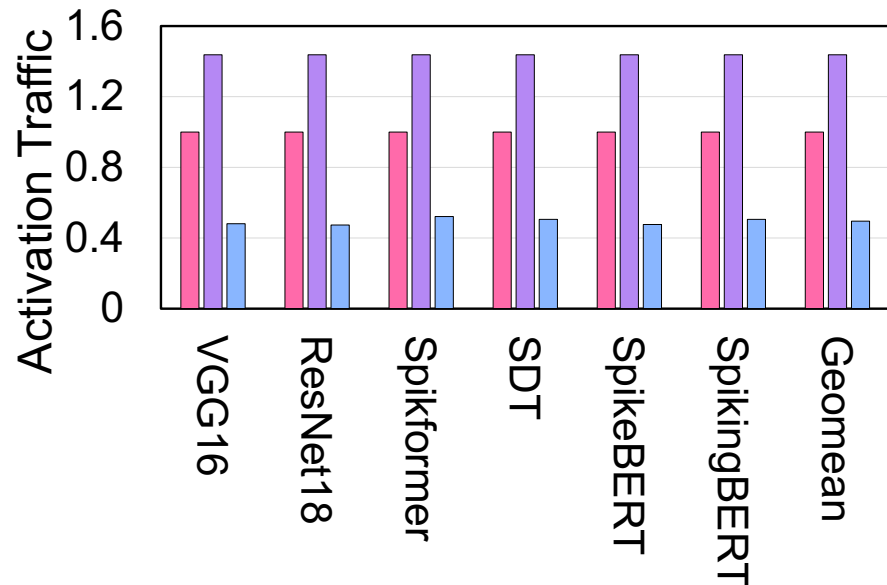
Cifar10, Cifar100,
Cifar10dvs

SST-2, SST-5, MNLI

Memory Traffic Reduction



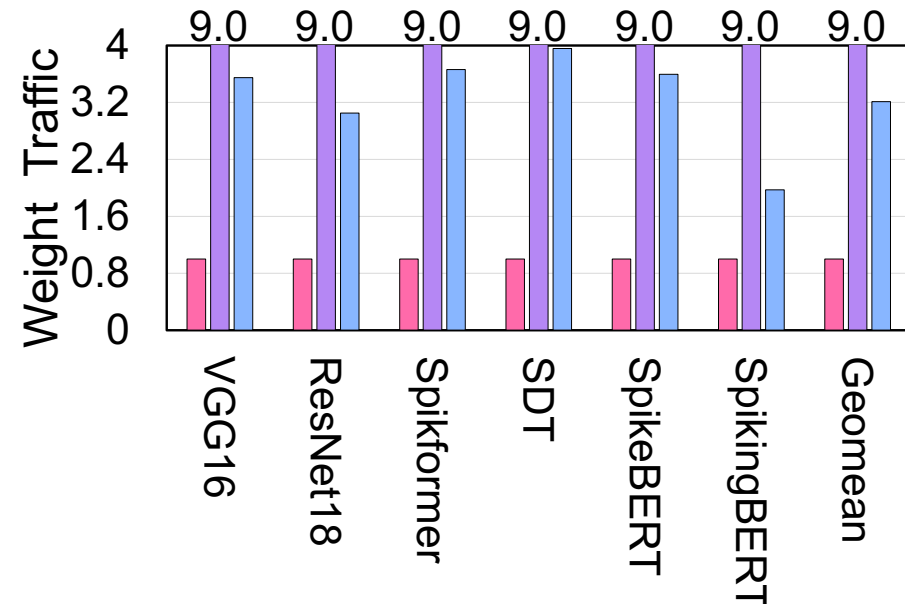
Compact data structure



- Norm. Dense Memory Traffic
- Norm. Phi (w/o Compress) Memory Traffic
- Norm. Phi (w Compress) Memory Traffic

**(a) Activation memory traffic
(normalized by dense).**

Pattern prefetcher

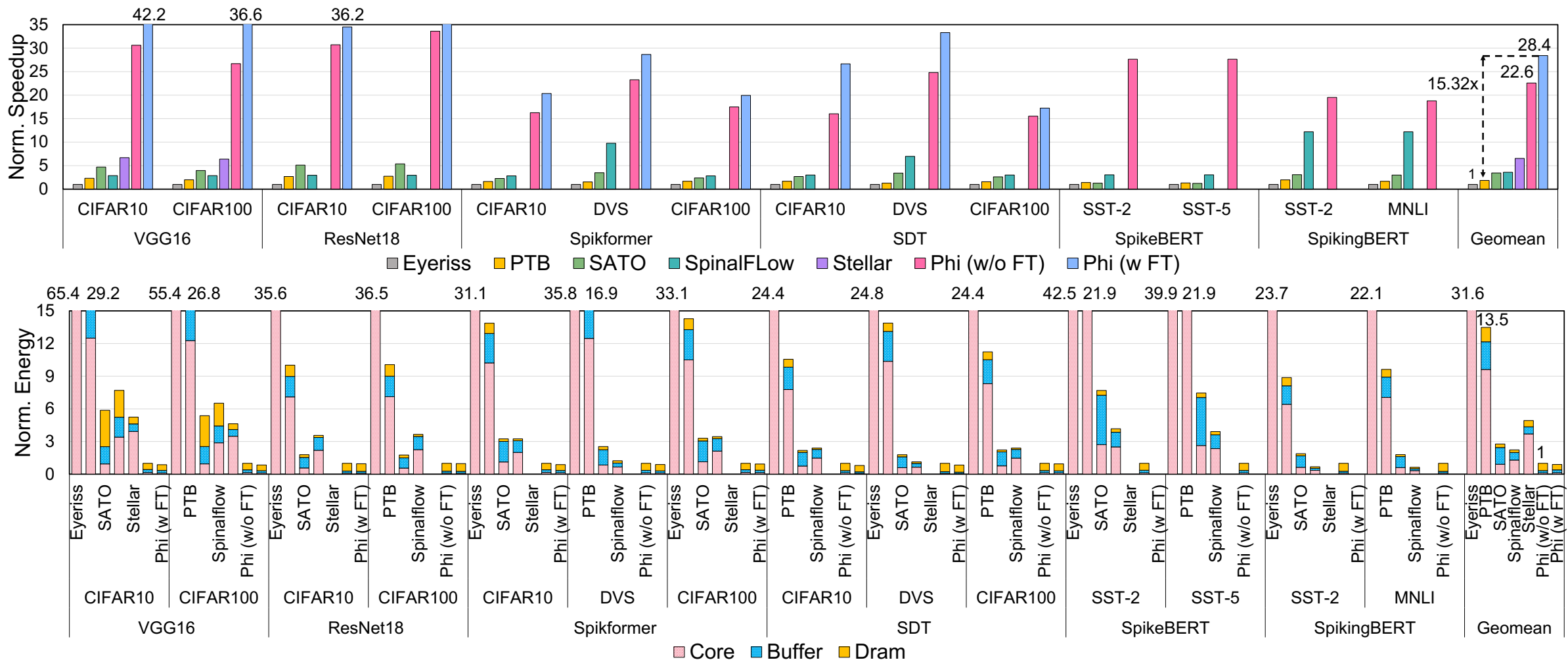


- Norm. Dense Memory Traffic
- Norm. Phi (w/o Prefetch) Memory Traffic
- Nor. Phi (w Prefetch) Memory Traffic

**(b) Weight memory traffic
(normalized by dense).**

Speedup and Energy

3.45x speedup, 4.93x energy efficiency compared to Stellar



Conclusion

- **Phi Sparsity**: A novel hierarchical sparsity framework for SNNs that leverages structural patterns in SNN activations to generate two levels of sparsity.
- Our proposed algorithm: addresses key challenges through k-means-based pattern selection and pattern-aware fine-tuning.
- Our proposed architecture: **Phi**, generates and processes both levels of sparsity on the fly, achieves performance improvements compared to existing state-of-the-art accelerators.

Thanks & QA
