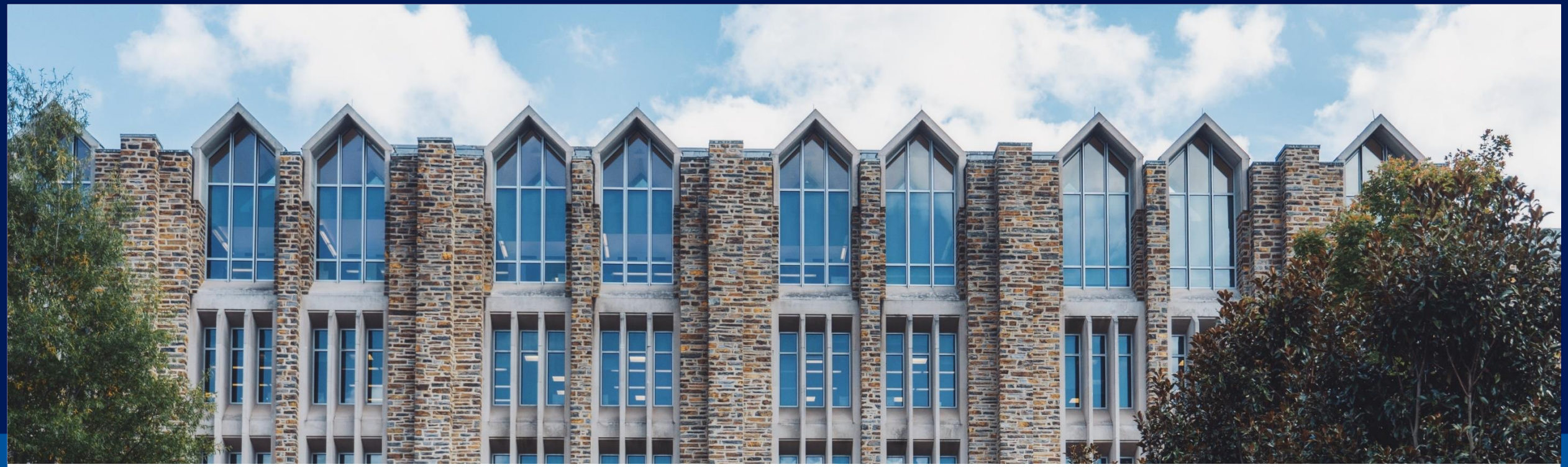

Prosperity: Accelerating Spiking Neural Networks via Product Sparsity

Chiyue Wei, Cong Guo, Feng Cheng, Shiyu Li, Hao “Frank” Yang, Hai “Helen” Li, Yiran Chen

Duke

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Duke University

Yiran Chen
Duke University

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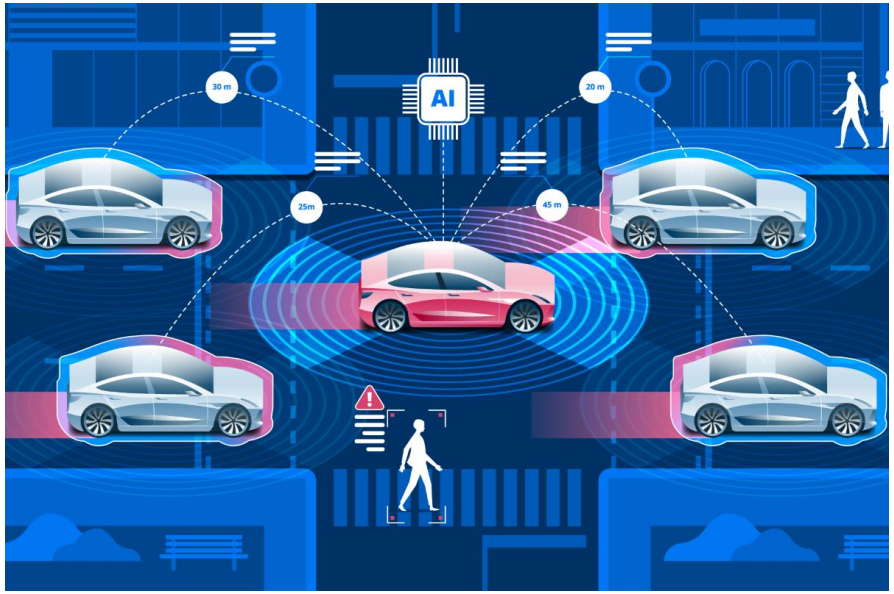
Spiking Neural Networks (SNNs)

- Brain-inspired Neural Networks
- Low energy consumption
- Resource-constrained scenario



Autonomous Driving

Augmented Reality

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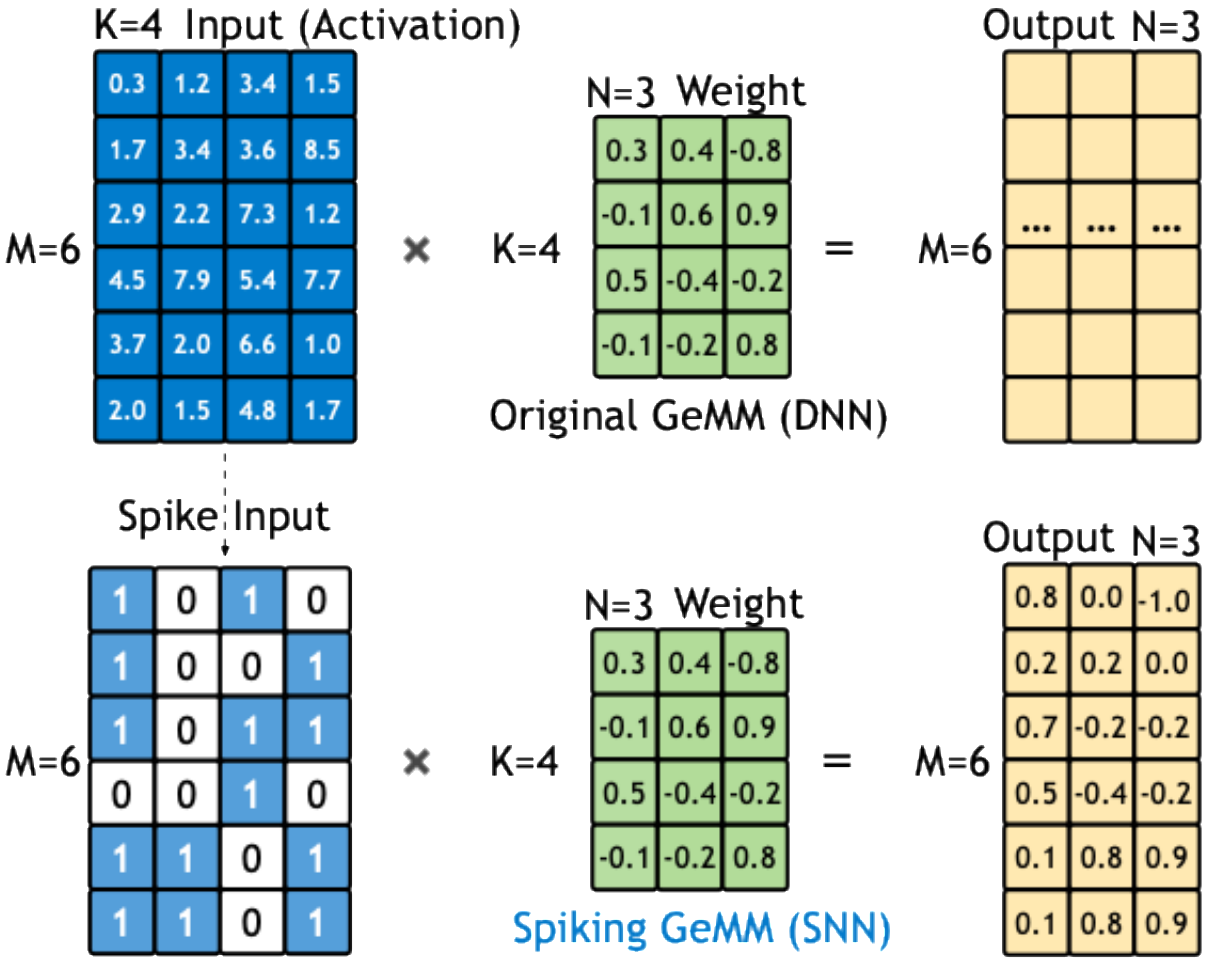
Image credit: https://www.smartcitiesworld.net/opinions/driving-autonomous-vehicles-forward-with-intelligent-infrastructure
https://gazeintelligence.com/eye-tracking-solutions

Computation in SNNs

- Similar to DNN computation
- Difference: Binary Spike Input
  - Inherent sparsity: **BitSparsity**

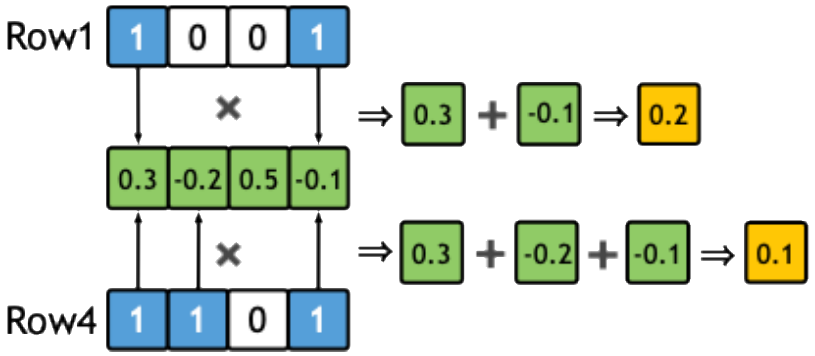


Is BitSparsity Enough?

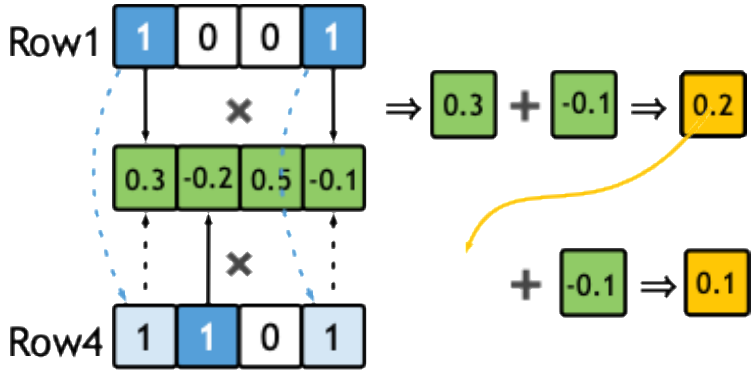
- BitSparsity: Does not fully harness the potential sparsity in SNNs

- New sparsity opportunities: **Product Sparsity** (**ProSparsity**)

BitSparsity in Inner Product
2 Ops + **3** Ops = **5** Ops



ProSparsity in Inner Product
2 Ops + **1** Ops = **3** Ops



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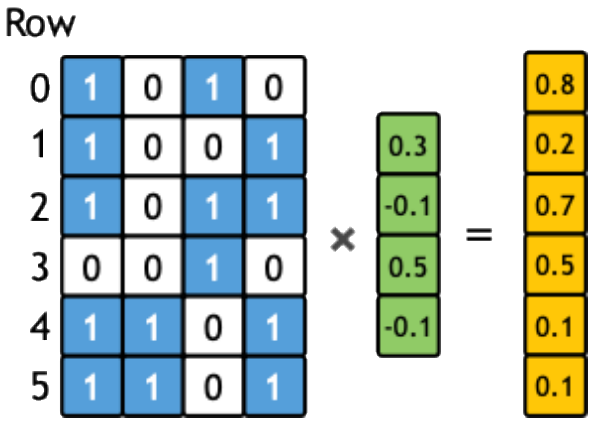
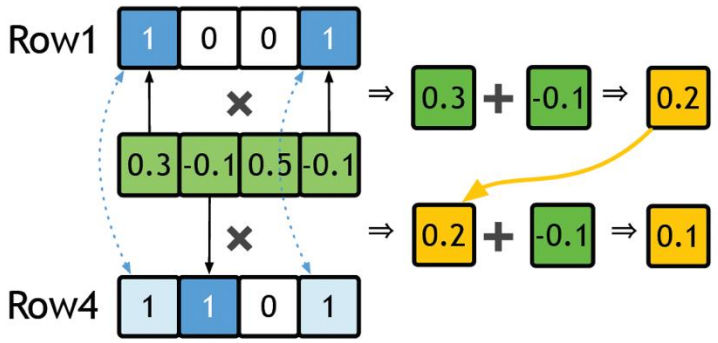
Product Sparsity (ProSparsity)

- Leverage the similarities between binary rows to skip operations
- Two types of **spatial** relationship between rows



Spiking GeMM



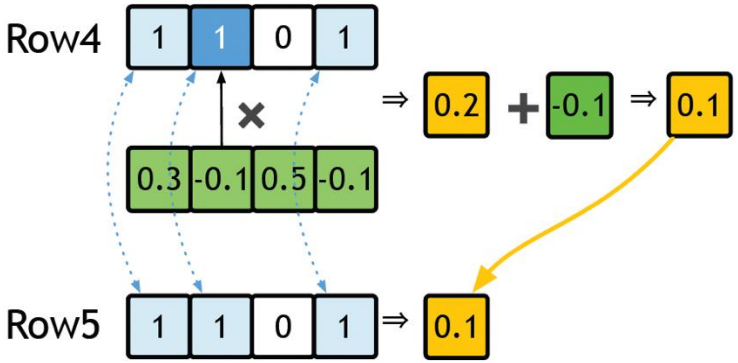
Partial Match (PM)

$S_1 \subset S_4$,

$S_1 = \{0, 3\}, S_4 = \{0, 1, 3\}$

Row4 reuses result of Row1

Save 2 OPs



Exact Match (EM)

$S_4 = S_5$,

$S_1 = \{0, 1, 3\}, S_4 = \{0, 1, 3\}$

Row5 reuses result of Row4

Save 3 OPs

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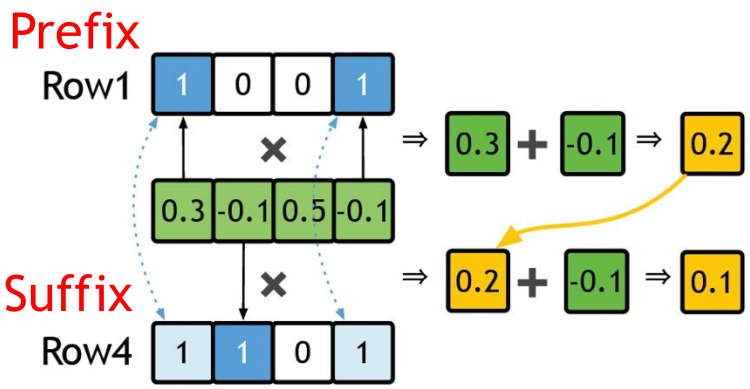
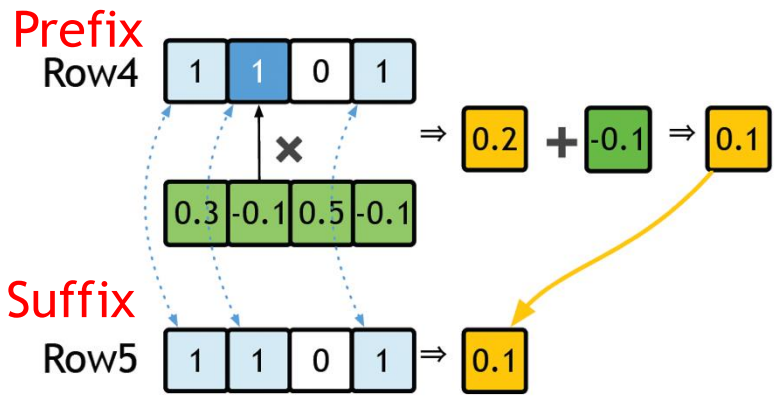
Temporal order in ProSparsity

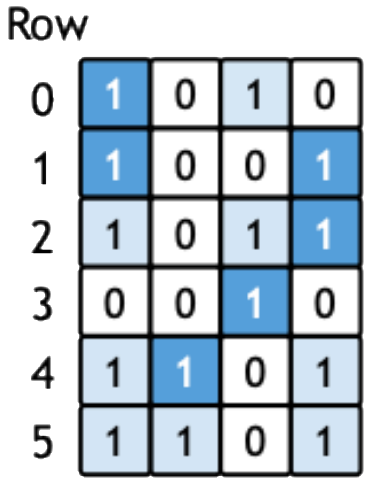
- Define **temporal relationship** within spatial relationships
- Specific **temporal order** has to be followed in execution



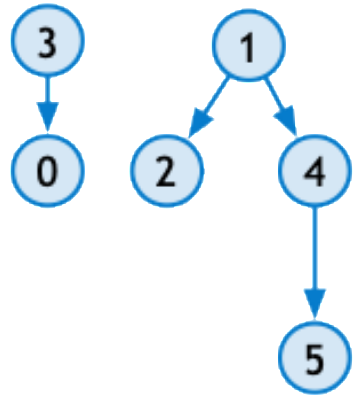
Partial Match (PM)



Exact Match (EM)



Spike Matrix



ProSparsity Forest

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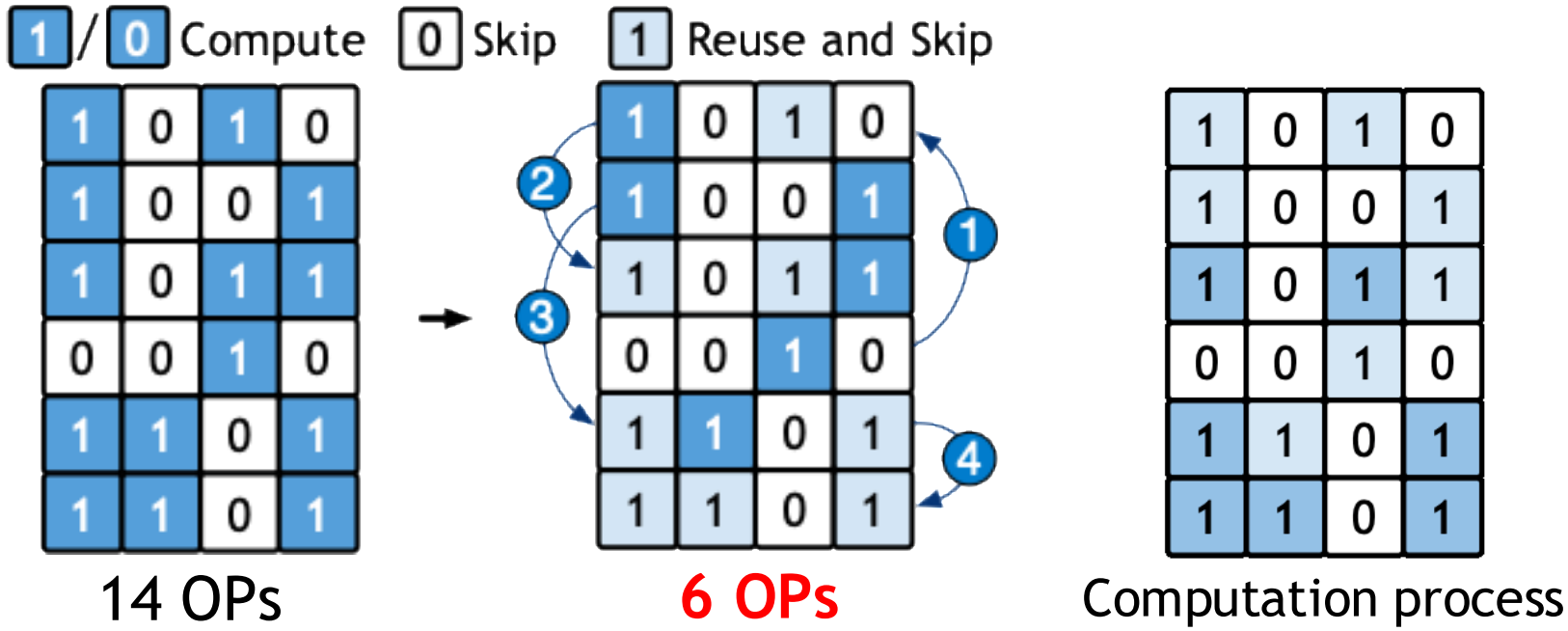
Effect of ProSparsity

- Reduce Ops significantly



- Num Ops reduced by **3.6x** on Spiking ResNet-18

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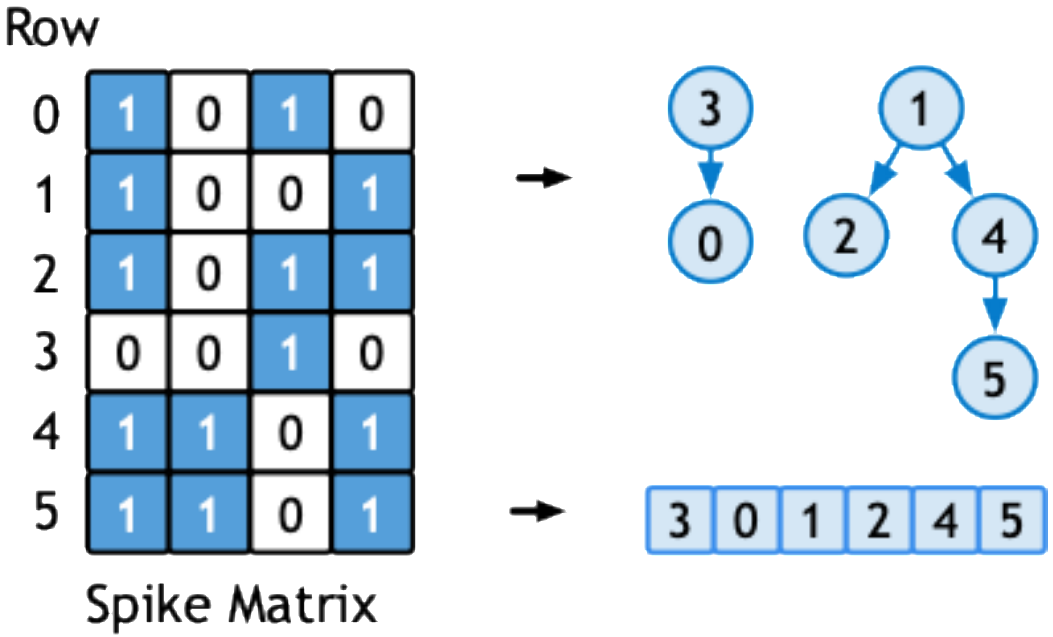
Challenges in ProSparsity

- Spike activation is **dynamic**
- Generate ProSparsity **on the fly**



Detect spatial and temporal relationships

Generate temporal order

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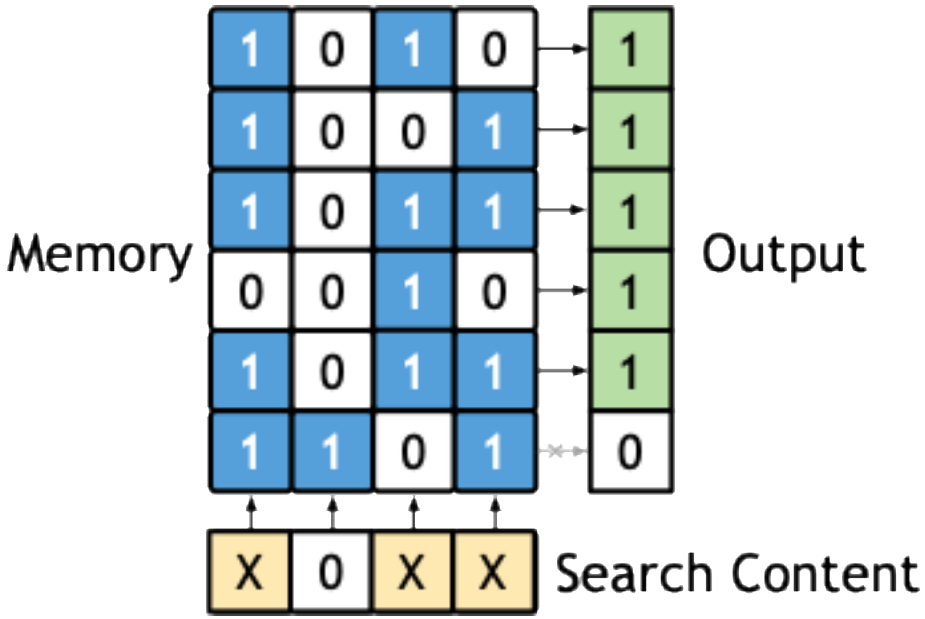
Solution to Challenges

- Efficiently generates ProSparsity on the fly

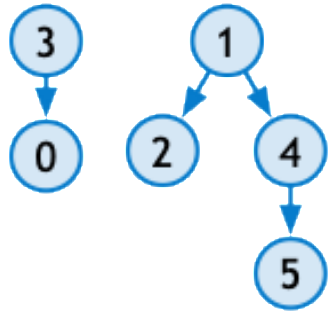
Fast Relationship Detection

TCAM

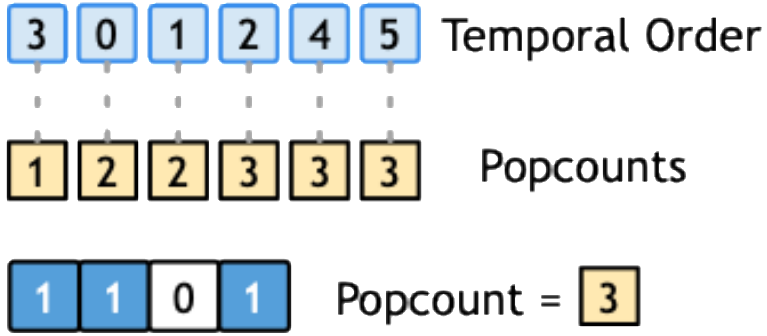


Efficient Temporal Order Generation

Popcounts (number of ones) as temporal order



ProSparsity Forsest



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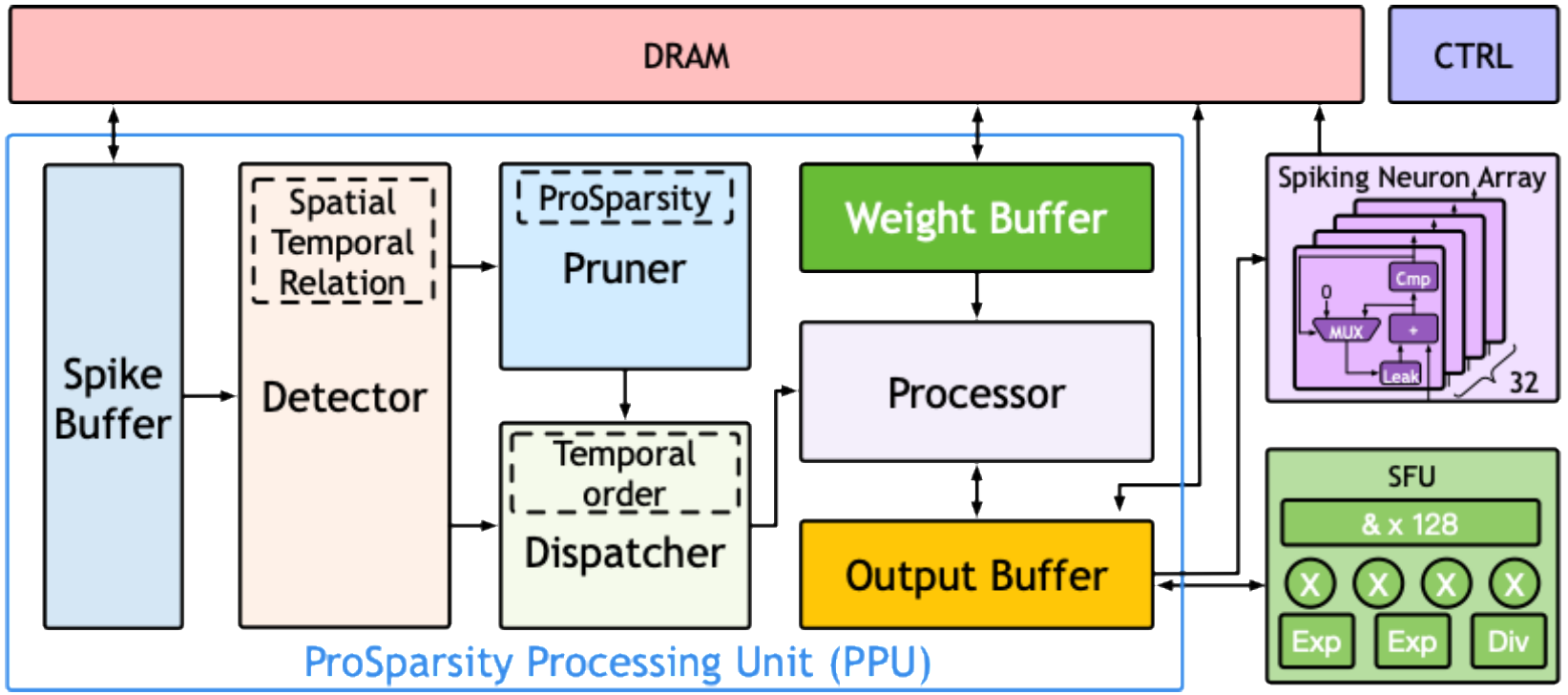
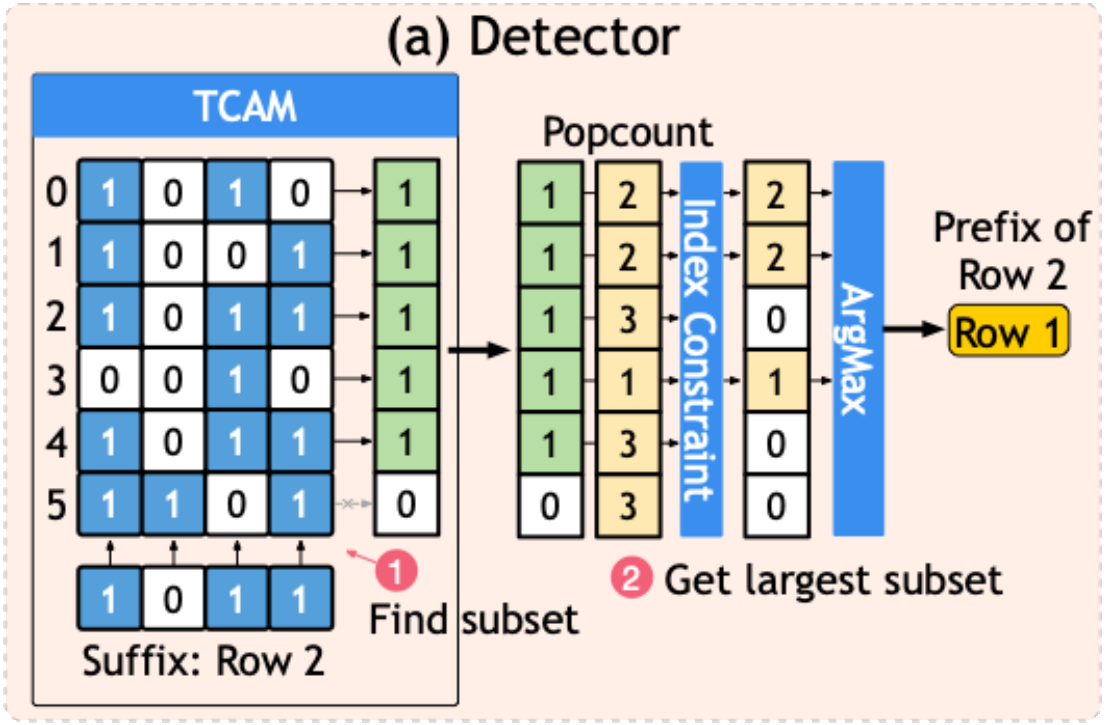
Architecture Overview

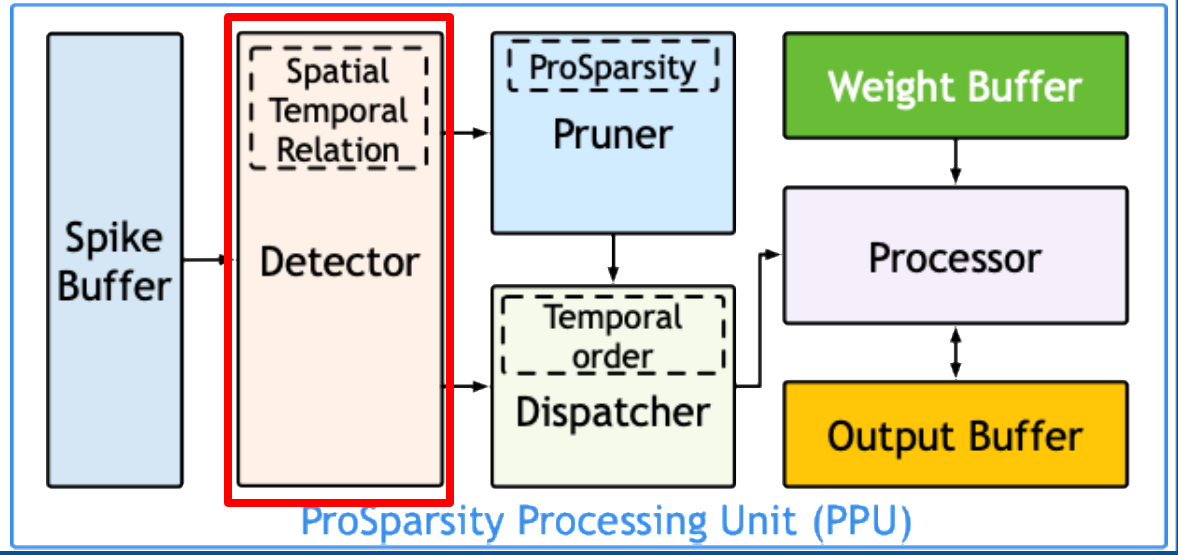
- An architecture generate and utilize ProSparsity
- The main component: ProSparsity Processing Unit (PPU)



Detector

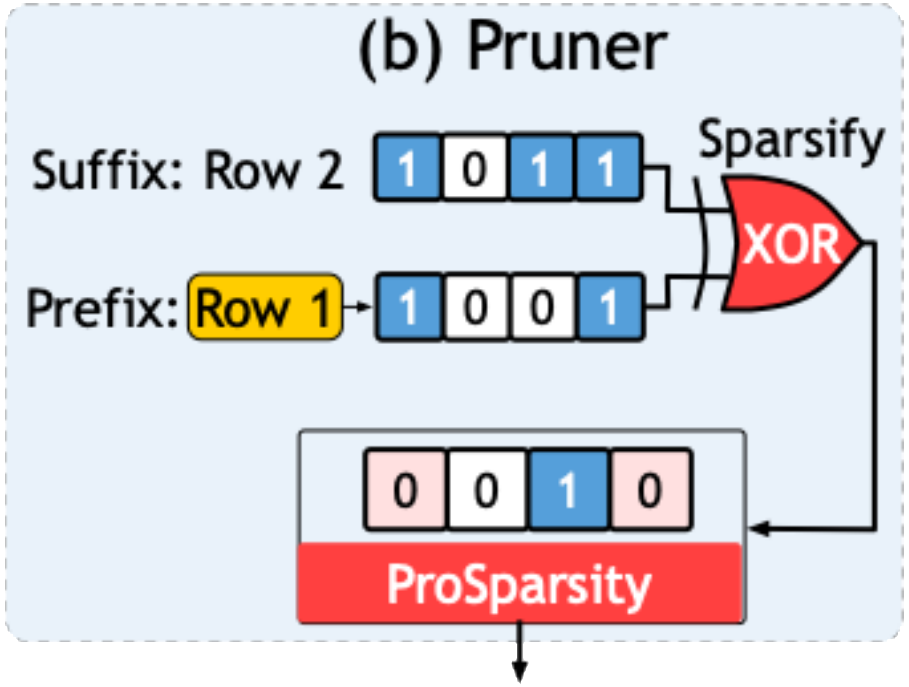
- Detect a prefix for a suffix
  - 1. Find subset of a suffix row
  - 2. Get the largest subset
  - 3. The largest subset as prefix

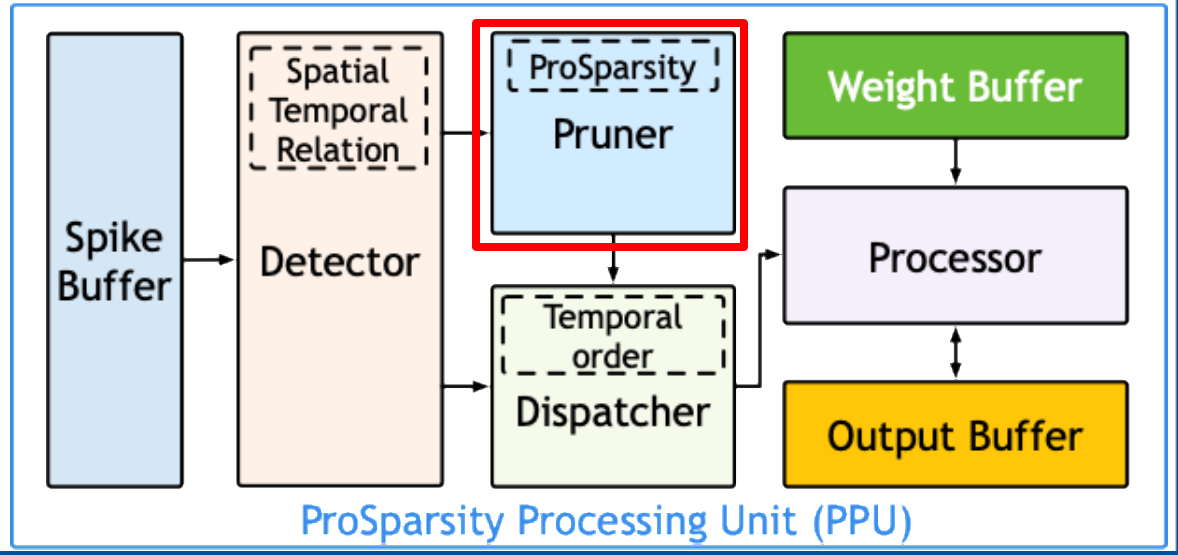




Pruner

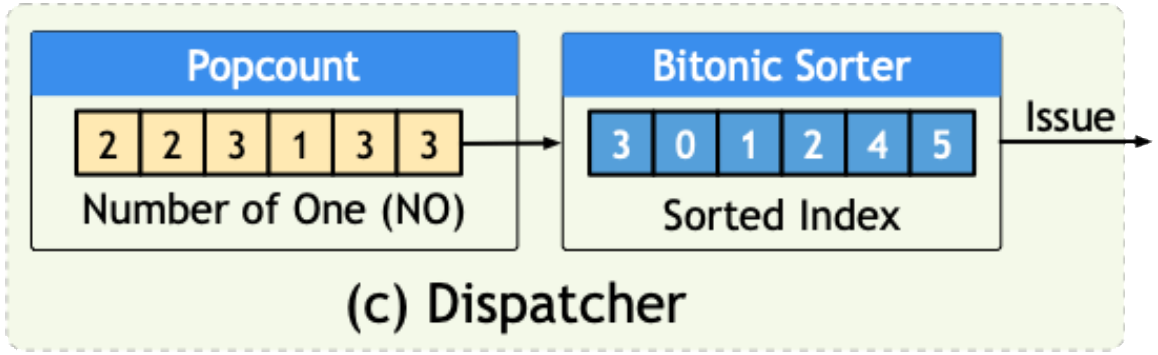
- Generate ProSparsity
  - 1. Get suffix and prefix row
  - 2. Perform bit-wise **XOR**
  - 3. Get ProSparsity for suffix

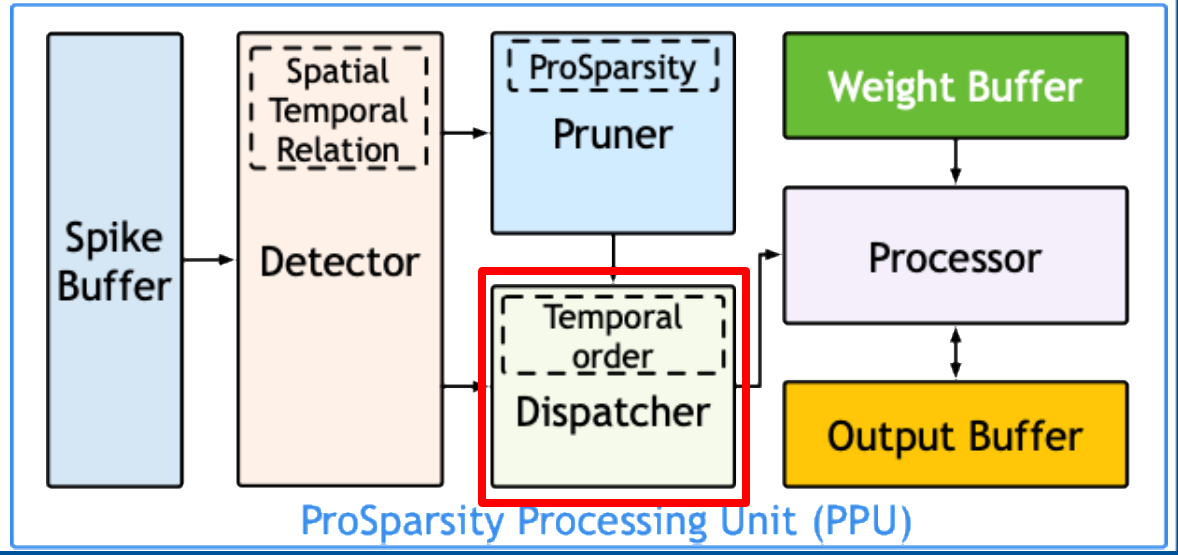




Dispatcher

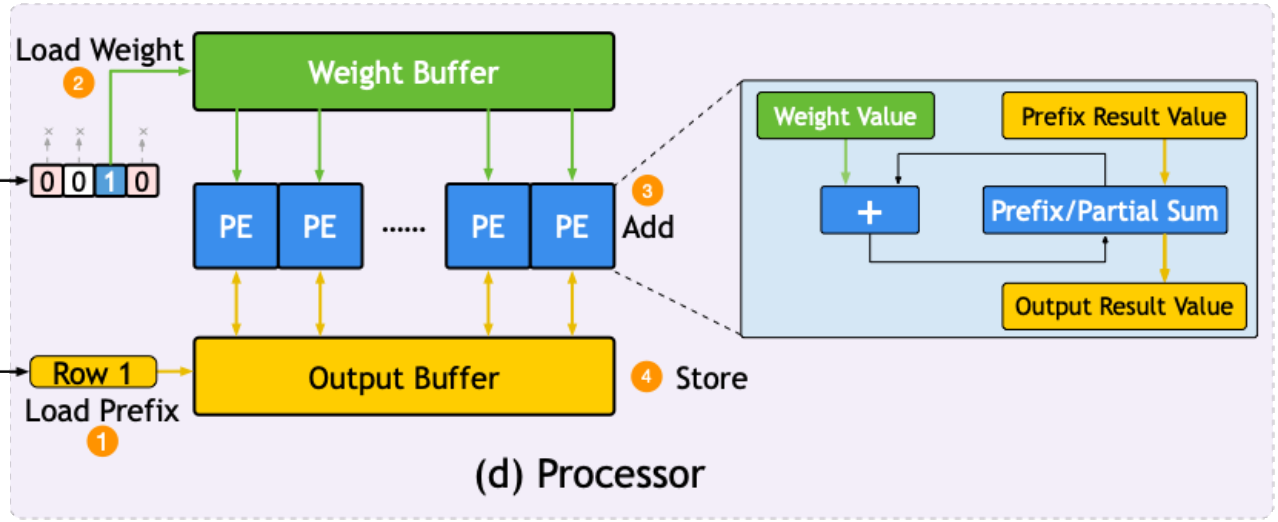
- Generate Temporal Order
  - 1. Get Popcount for each row
  - 2. Sort according to popcount
  - 3. Issue to Processor in sorted order

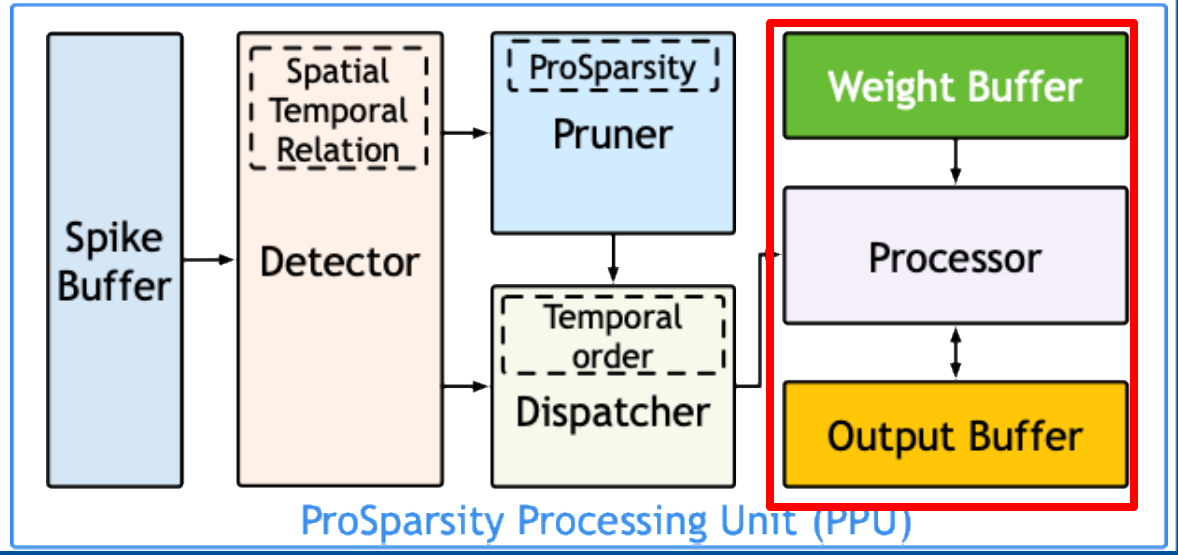




Processor

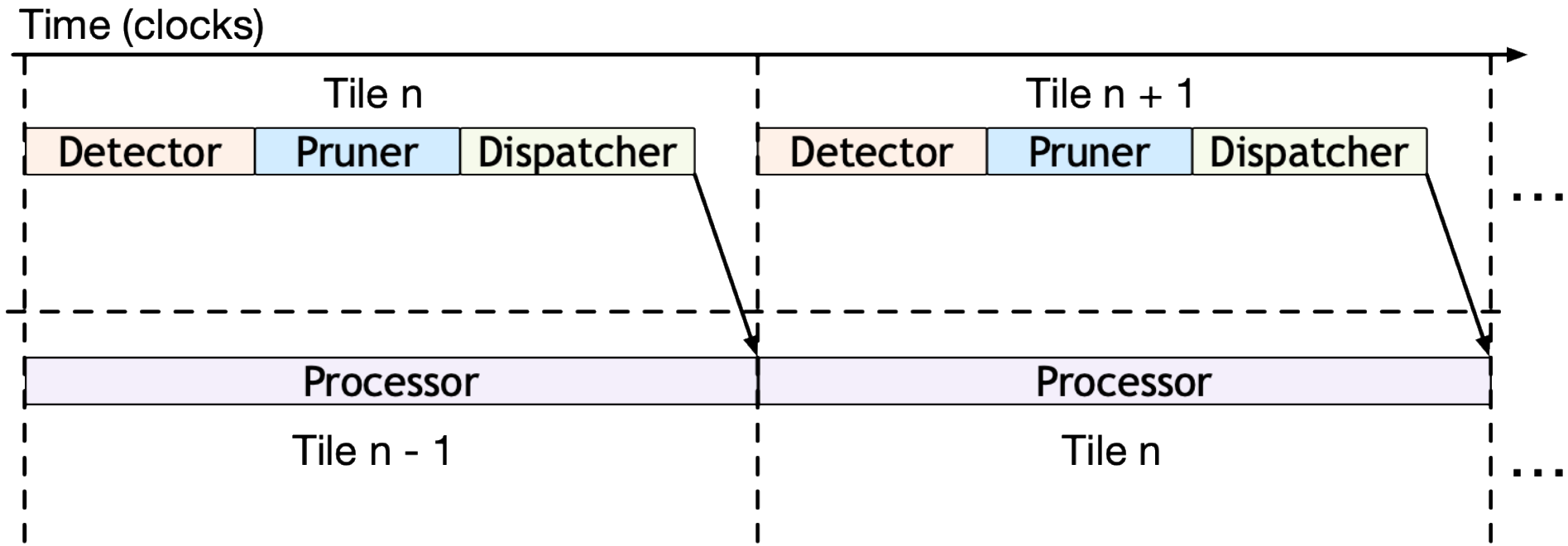
- Perform matrix computation
  - 1. Get prefix result value
  - 2. Load weight according to ProSparsity
  - 3. Accumulate weight
  - 4. Store output value





Pipeline Scheduling

- Tile-wise pipeline to maximize Processor utilization



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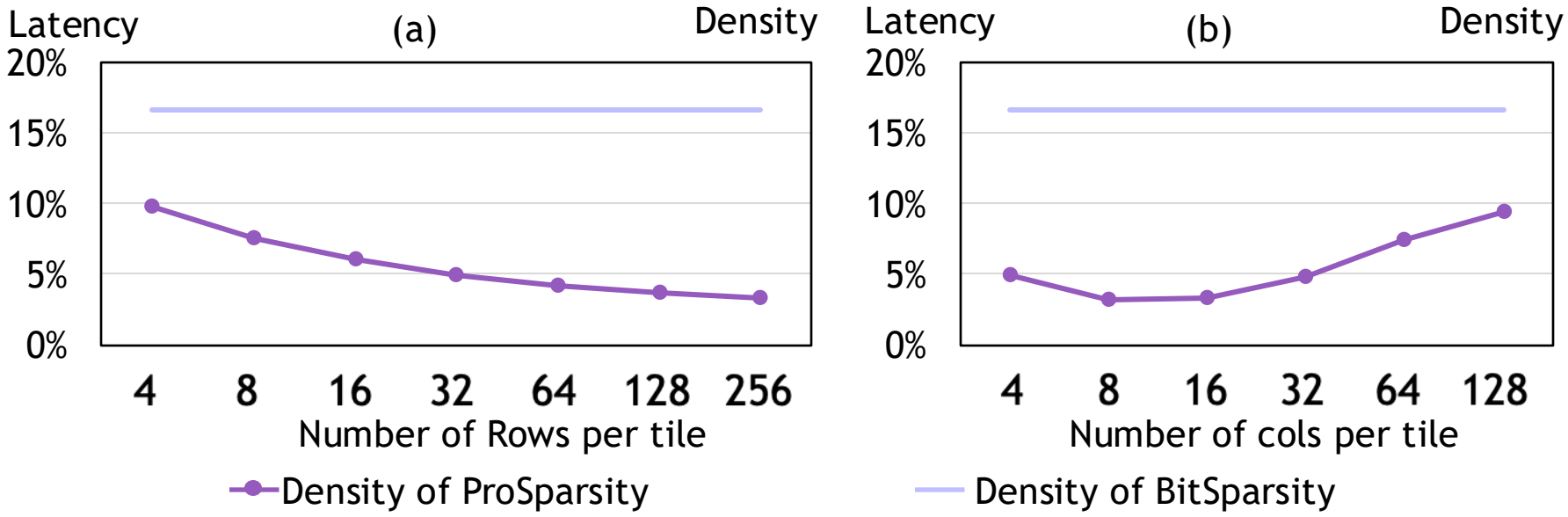
Tiling Exploration

- More rows per tile make ProSparsity better, but higher overhead
- Number of cols needs to be selected carefully



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Evaluation Baseline and Tools

Methods	Type	Sparsity
Eyeriss	DNN accelerator	Dense
A100	GPU	Dense
PTB (HPCA'22)	SNN accelerator	BitSparsity
SATO (DAC'22)	SNN accelerator	BitSparsity
MINT (ASP-DAC'24)	SNN accelerator	BitSparsity
Stellar (HPCA'24)	SNN accelerator	BitSparsity
Prosperity (Ours)	SNN accelerator	**ProSparsity**

Tools	
Synopsys Design Compiler	Logic synthesis
CACTI	Buffer simulation
DRAMsim3	DRAM simulation

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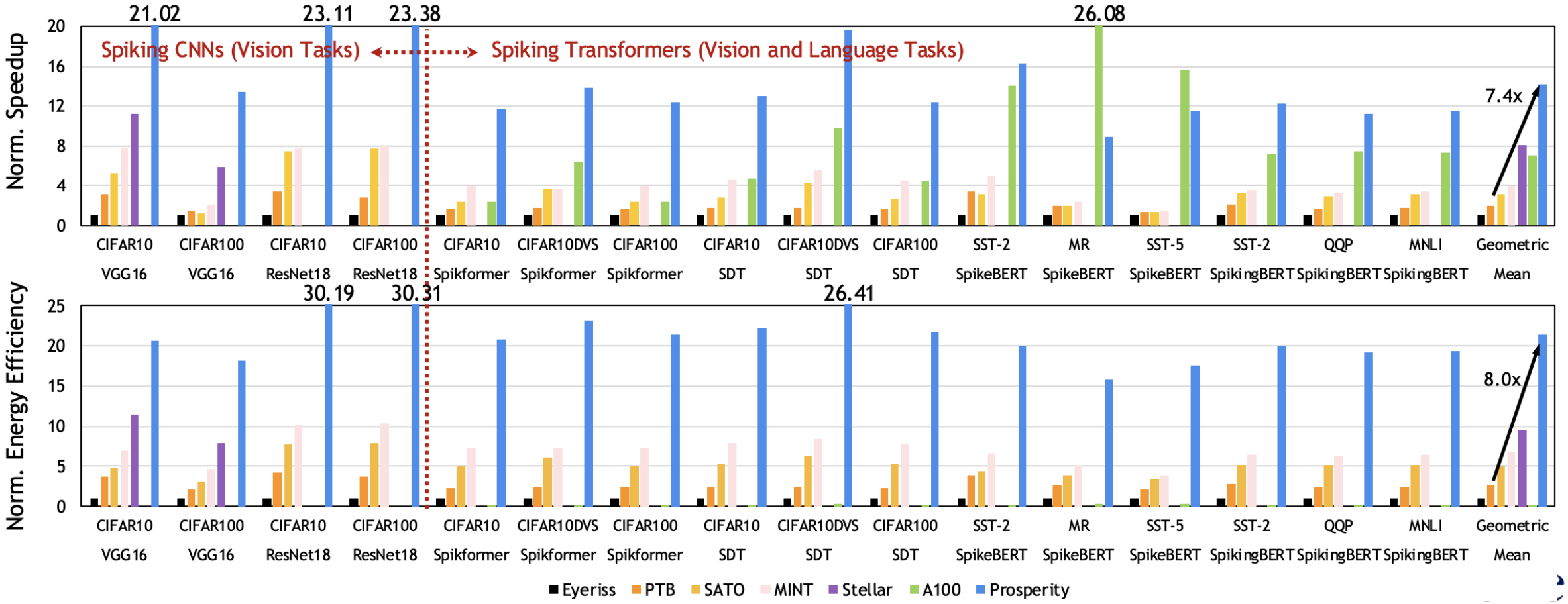
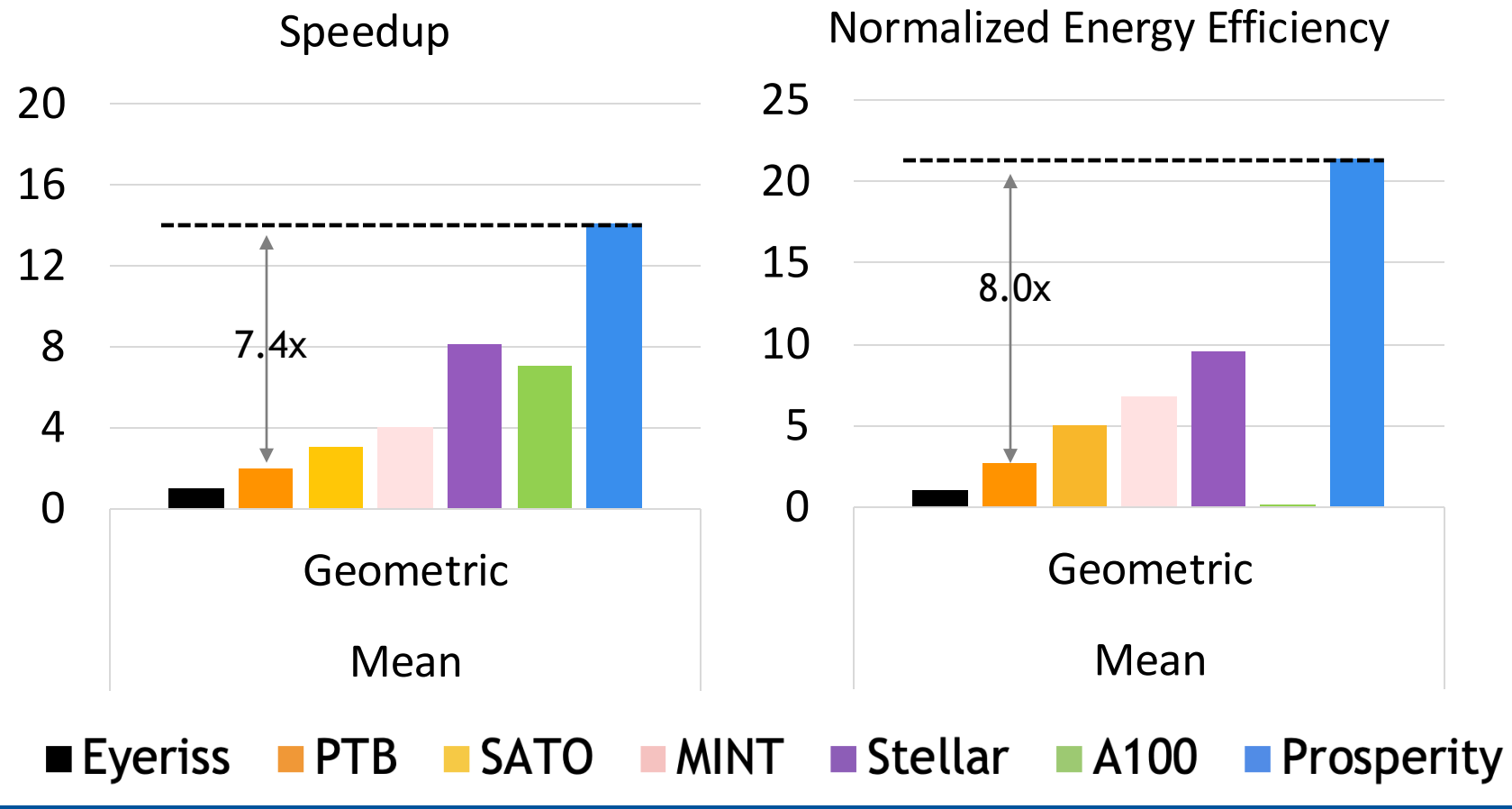
Performance and Energy

- Compared with baselines (DNN accelerator, GPU, SNN accelerators) on various SNN models and datasets



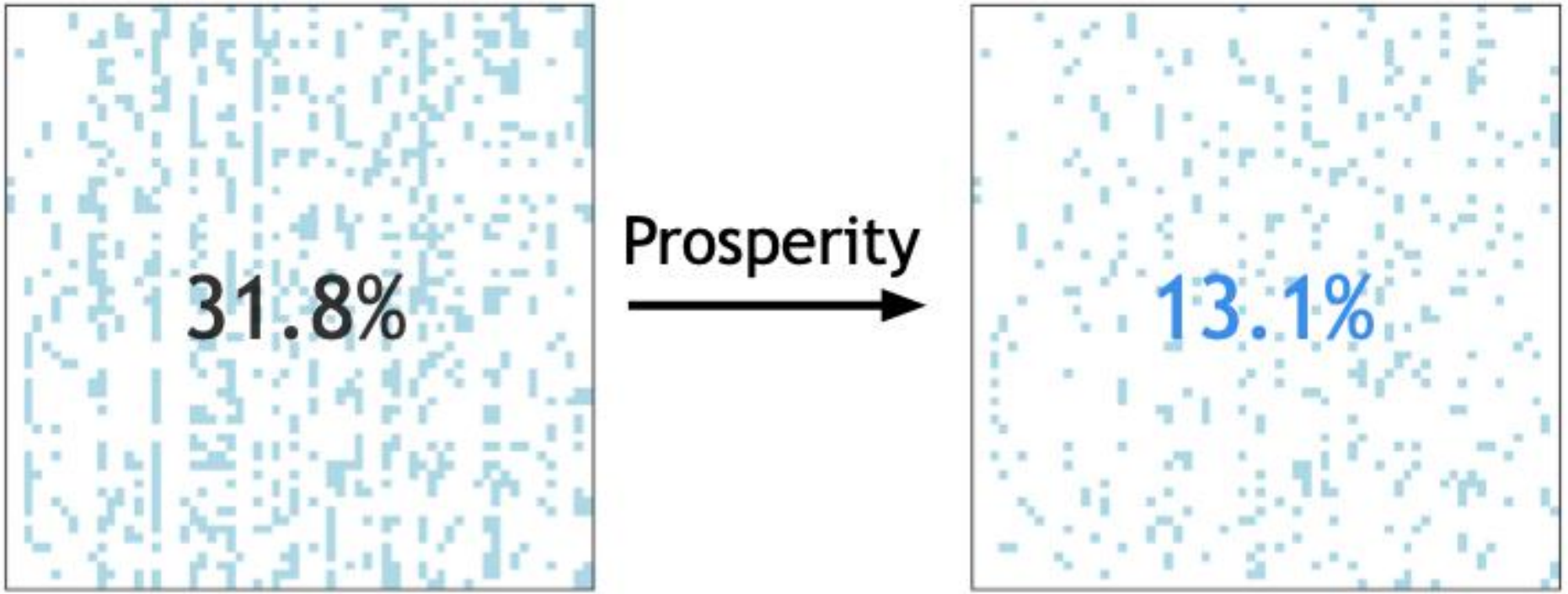
Performance and Energy

- Outperform GPU and all accelerators, 7.4x speedup and 8.0x energy efficiency over PTB (HPCA'22)



Demonstrating ProSparsity

- ProSparsity on a spiking transformer model



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Takeaways

- **ProSparsity**: A sparsity paradigm for SNN that leverage similarities between rows to remove the redundant computations.

- Our proposed architecture: **Prosperity**, addresses the challenges in ProSparsity and achieve significant speedup over state-of-the-art accelerators

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Thanks & QA

Welcome to use our open-source code at

https://github.com/dubcyfor3/Prosperity

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