

High Area/Energy Efficiency RRAM CNN Accelerator with Pattern-Pruning-Based Weight Mapping Scheme

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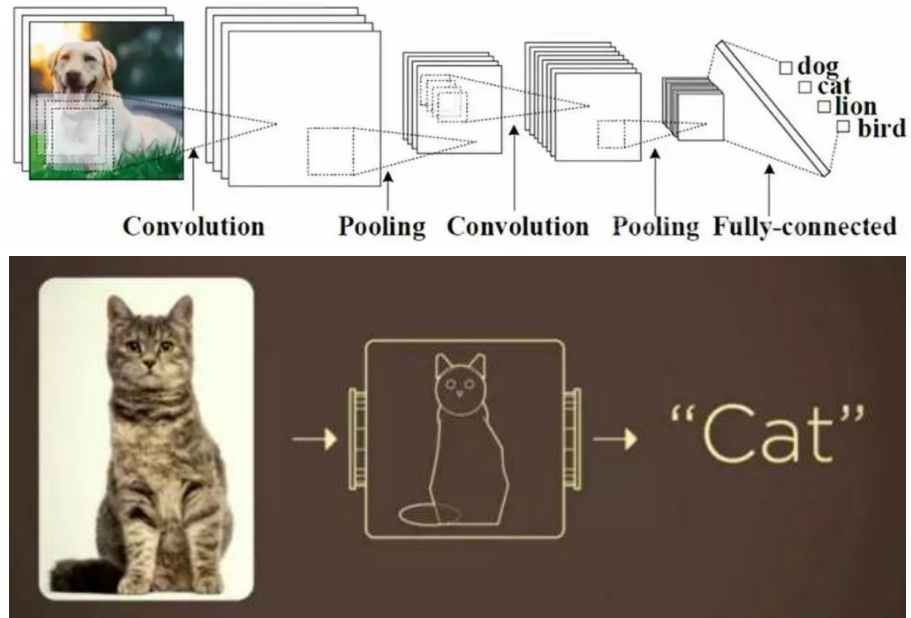
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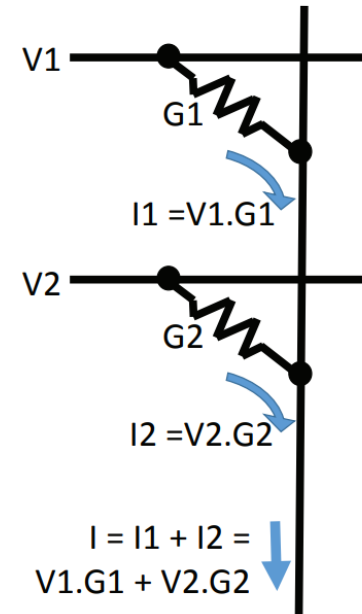
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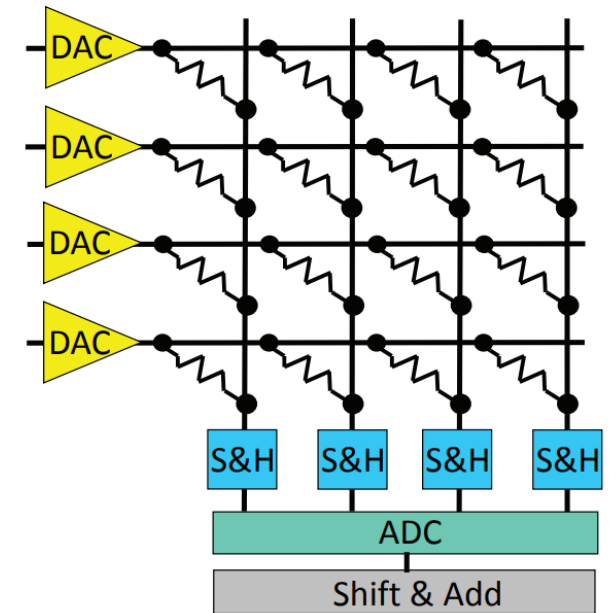
Introduction



Widely used convolutional neural networks (CNN)



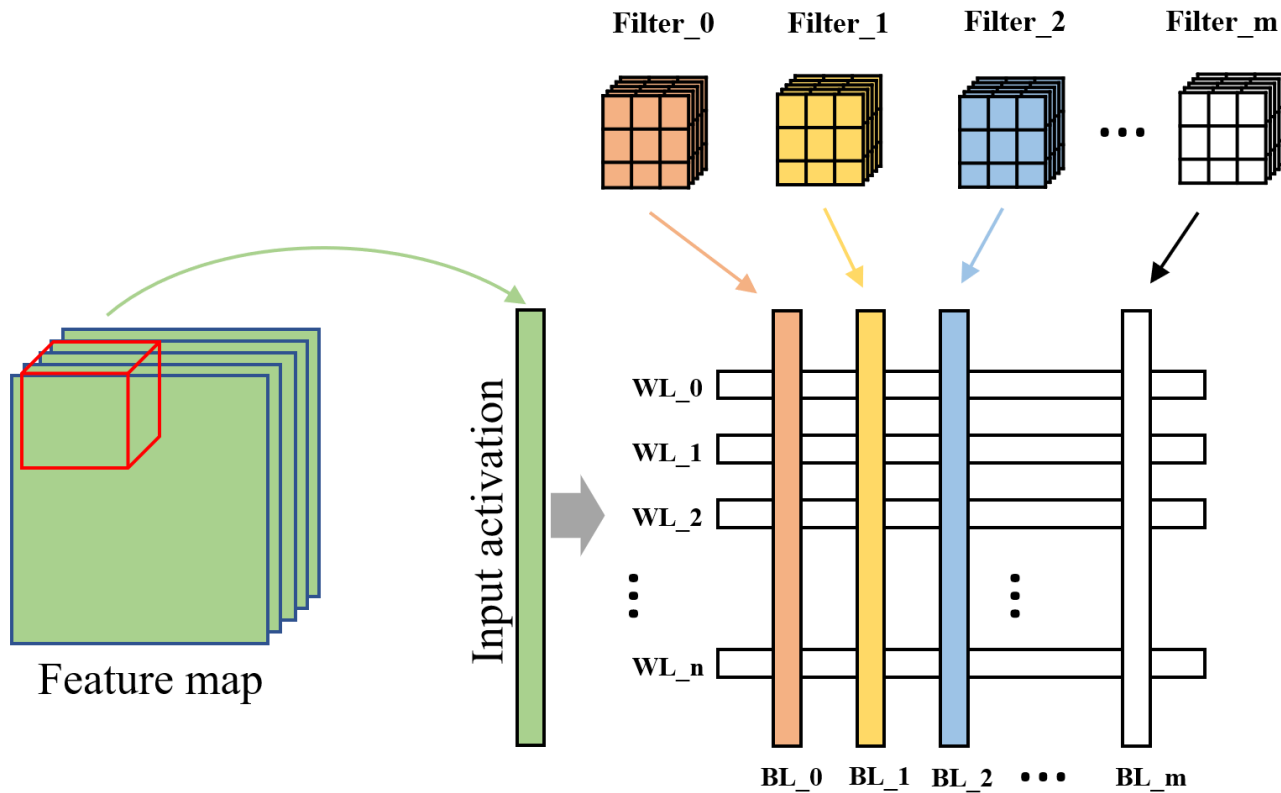
(a) Multiply-Accumulate operation



(b) Vector-Matrix Multiplier

RRAM array for data storage and computing, figure from[1].
(a) Using a bitline to perform an analog sum of products operation.
(b) A RRAM crossbar used as a vector-matrix multiplier.

Background and motivation



A straightforward weight mapping scheme for CNN in RRAM array

Weight mapping:

Every filter is mapped to one column

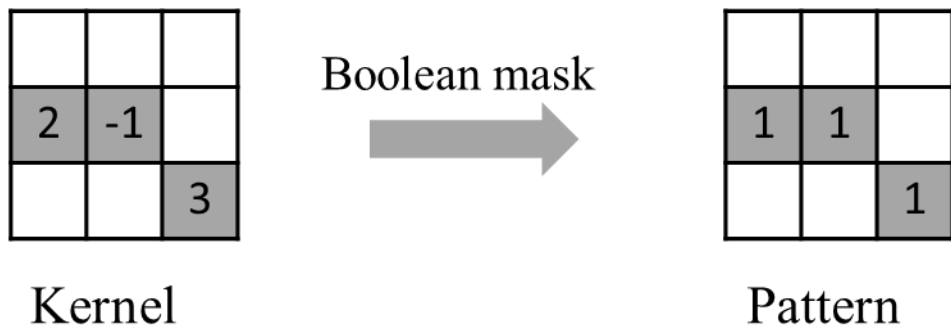
Executing:

Unroll the activation to vectors and fed into each row.

Disadvantages:

Hard to exploit the sparsity of the neural network
Overidealized. Activate a whole array will cause severe accumulate error.

Background and motivation



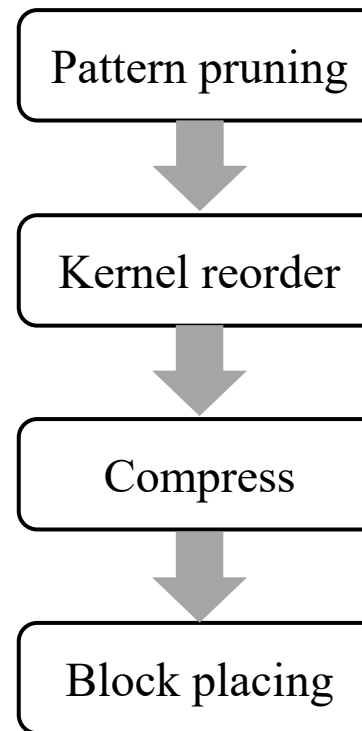
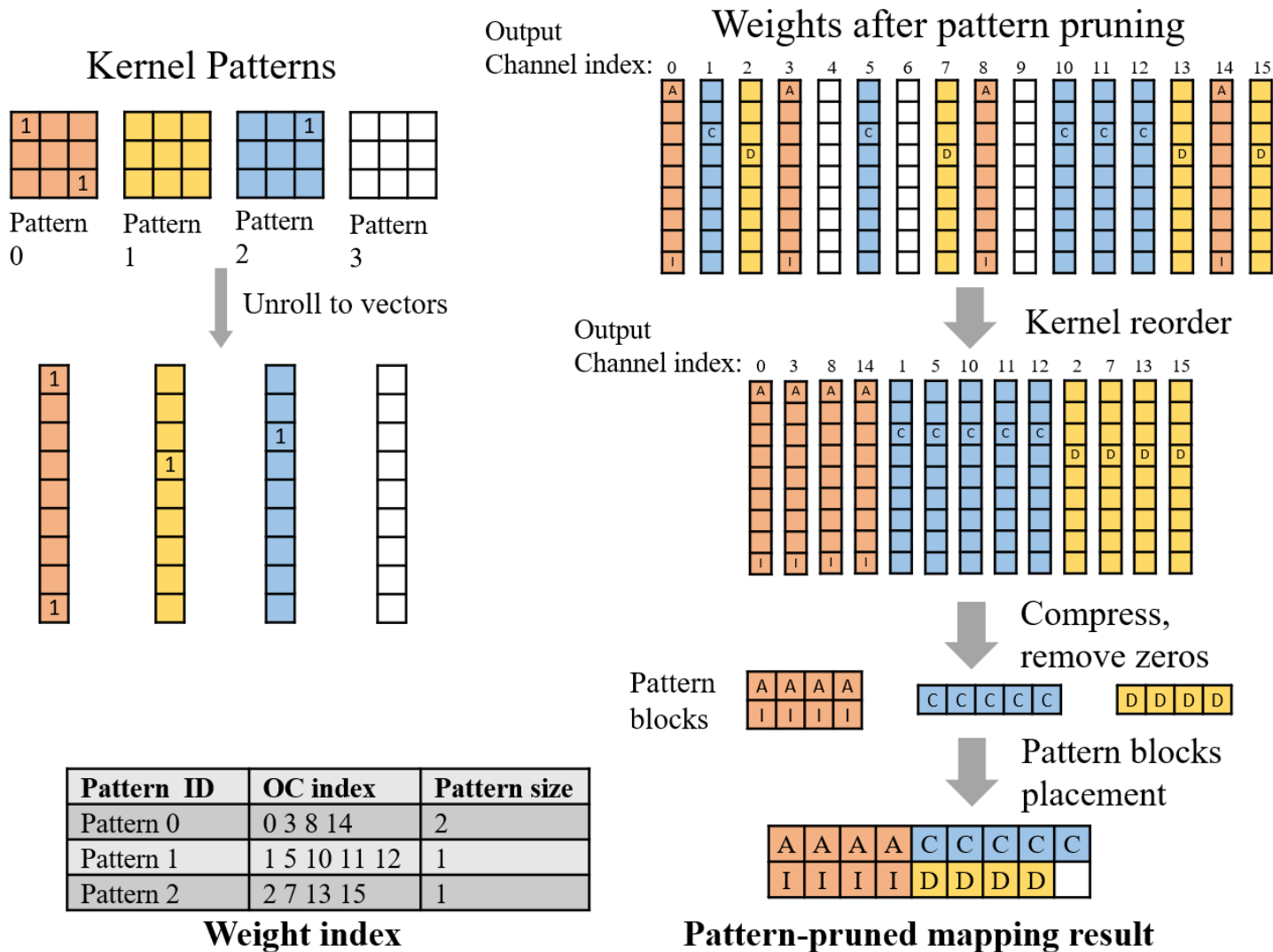
Max pattern number: $2^{3 \times 3} = 512$

Pattern pruning: new opportunity for exploiting weight sparsity on RRAM-based CNN accelerator.

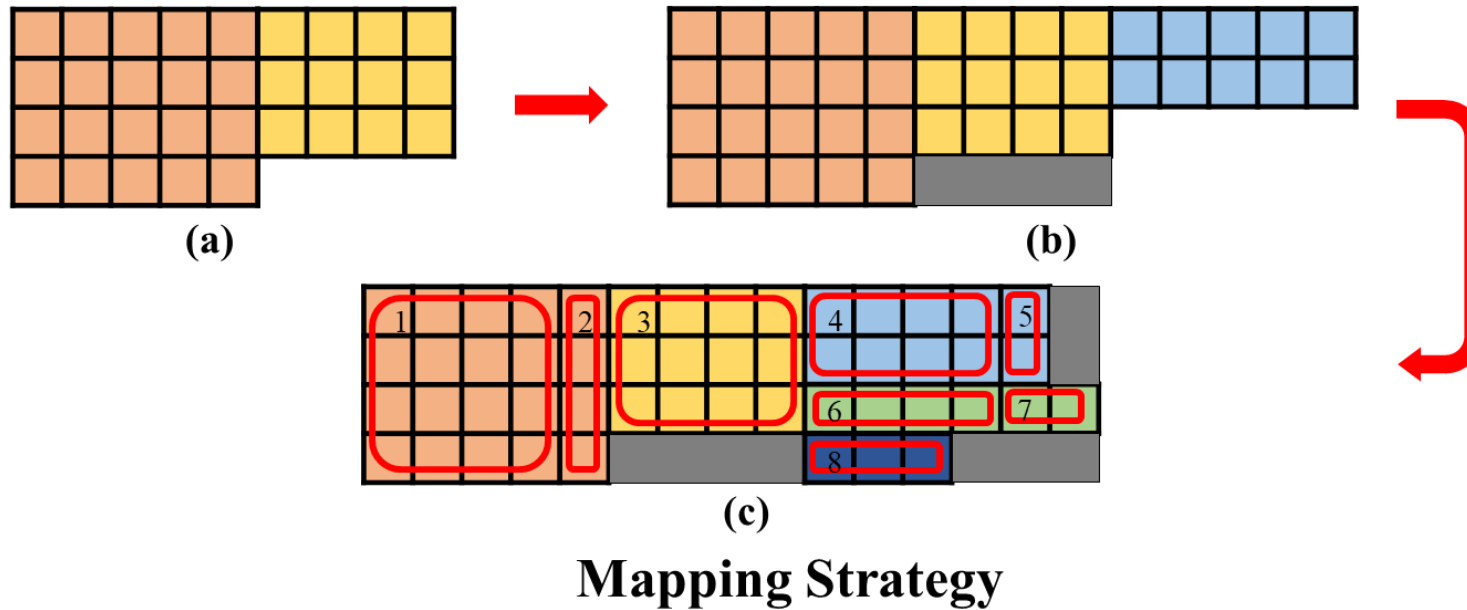
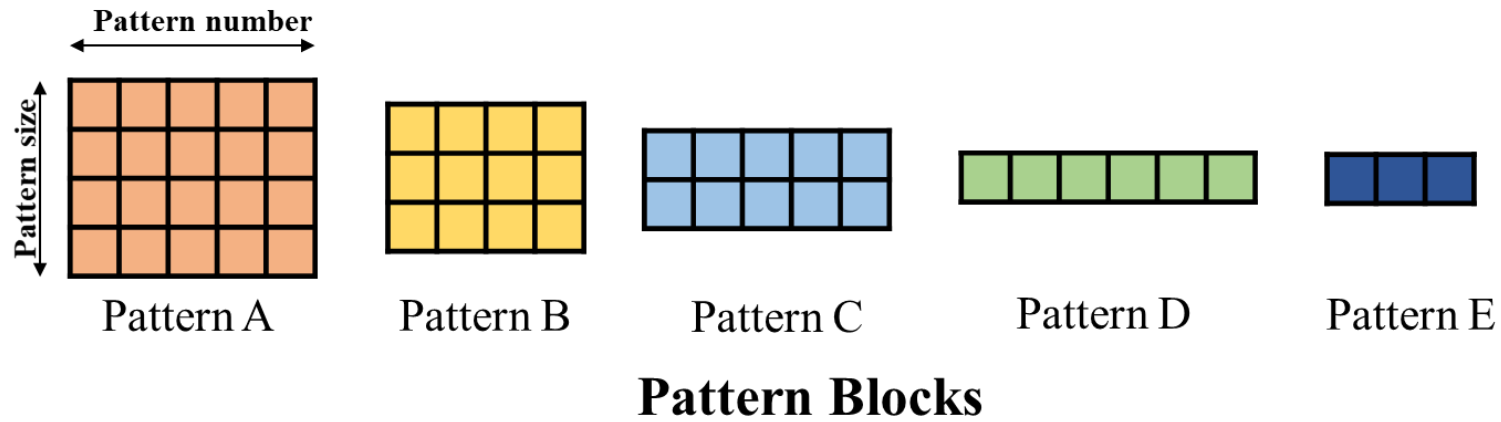
A intermediate type between non-structured pruning and structured pruning.

High accuracy & high sparsity,
with high regularity level

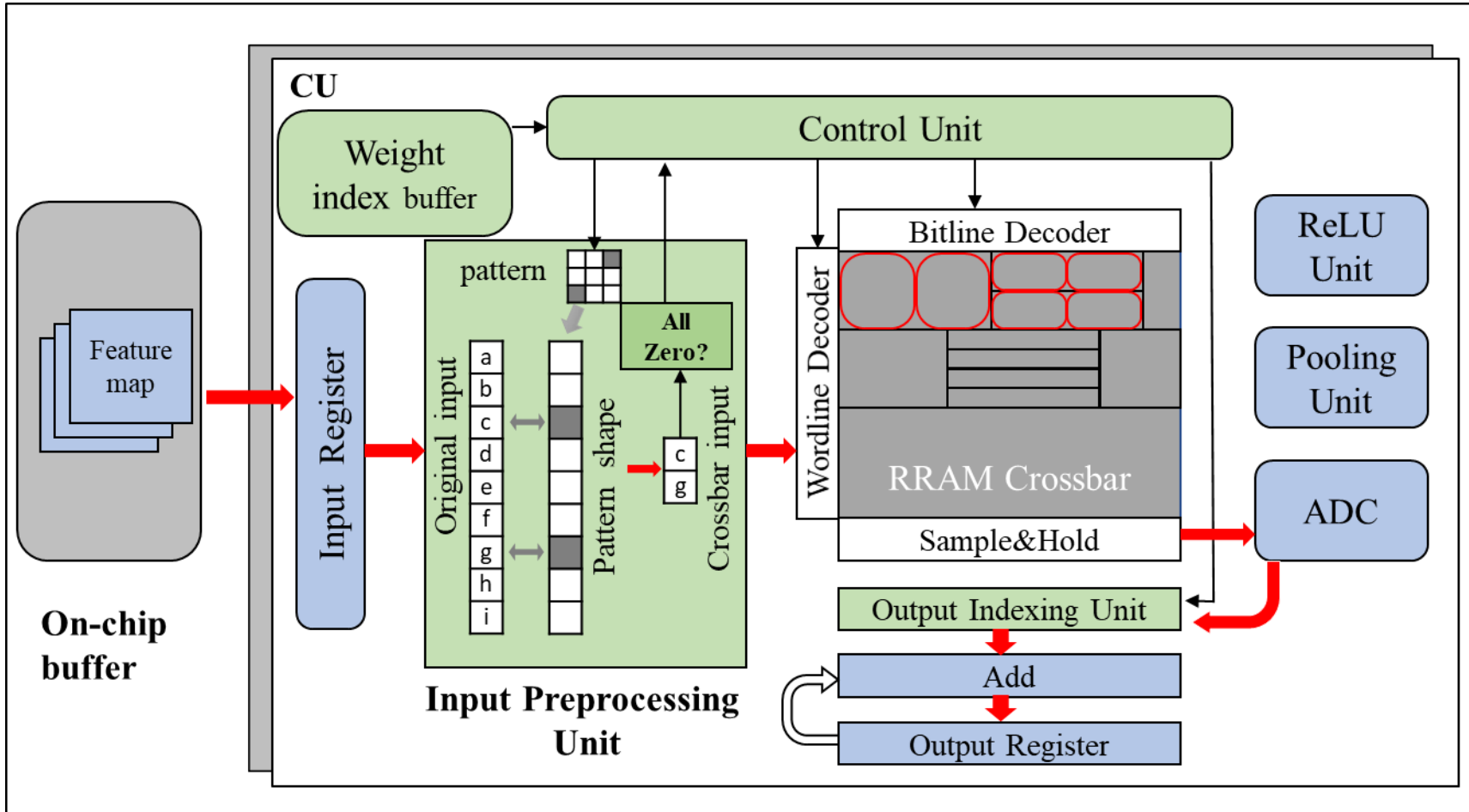
Mapping scheme



Pattern block placement



Architecture design



Input preprocessing unit:
Compress input, skip all-zero

Output indexing unit:
Reorder the outputs and store them into right address

Evaluation and results

Components	Parameters	Spec	energy
ADC	Precision	8 bits	1.67 pJ/op
	Frequency	1.2 GSps	
DAC	Precision	4 bits	0.0182 pJ/op
	Frequency	18 MSps	
RRAM Array	OU size	9×8	4.8 pJ/OU/op
	bits per cell	4	
	size	512×512	

Evaluation setup

Hardware Parameter for energy consuming: table on the left.

Simulator: behavior level, built in python.

Network: VGG16 trained on CIFAR-10, CIFAR-100 and ImageNet.

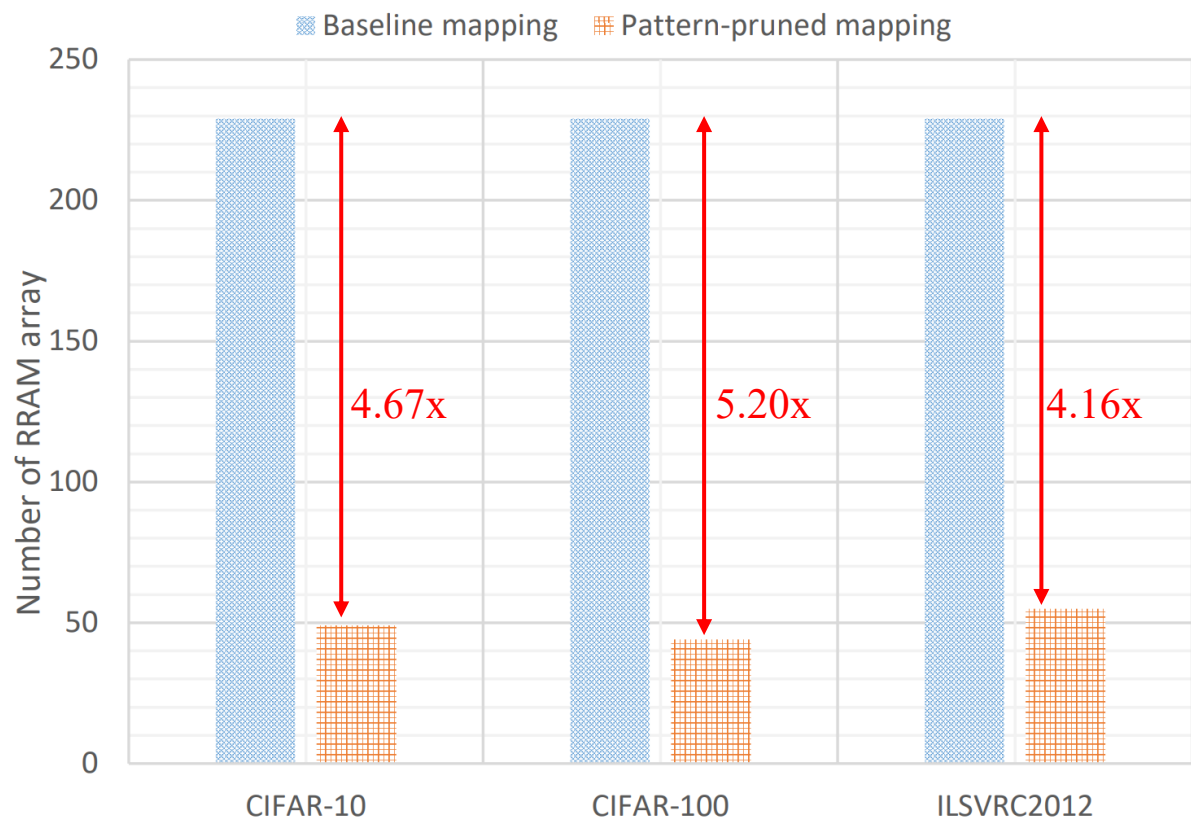
Baseline: a straightforward weight mapping scheme.

Dataset	Sparsity	Pattern Numbers in Each Conv layer	Total	top-1	top-5
CIFAR-10	86.03%(+4.08%)	[2, 2, 2, 6, 8, 8, 8, 6, 5, 4, 6, 6, 8]	71	92.63%(-0.09%)	/
CIFAR-100	85.23%(+3.28%)	[2, 2, 2, 2, 2, 8, 8, 8, 5, 6, 7, 6, 8]	66	72.73%(+0.01%)	92.23%(+0.79%)
ImageNet	82.48%(-0.90%)	[2, 2, 2, 2, 2, 9, 12, 12, 9, 10, 6, 4, 4]	76	71.15%(-0.75%)	89.98%(-0.51%)

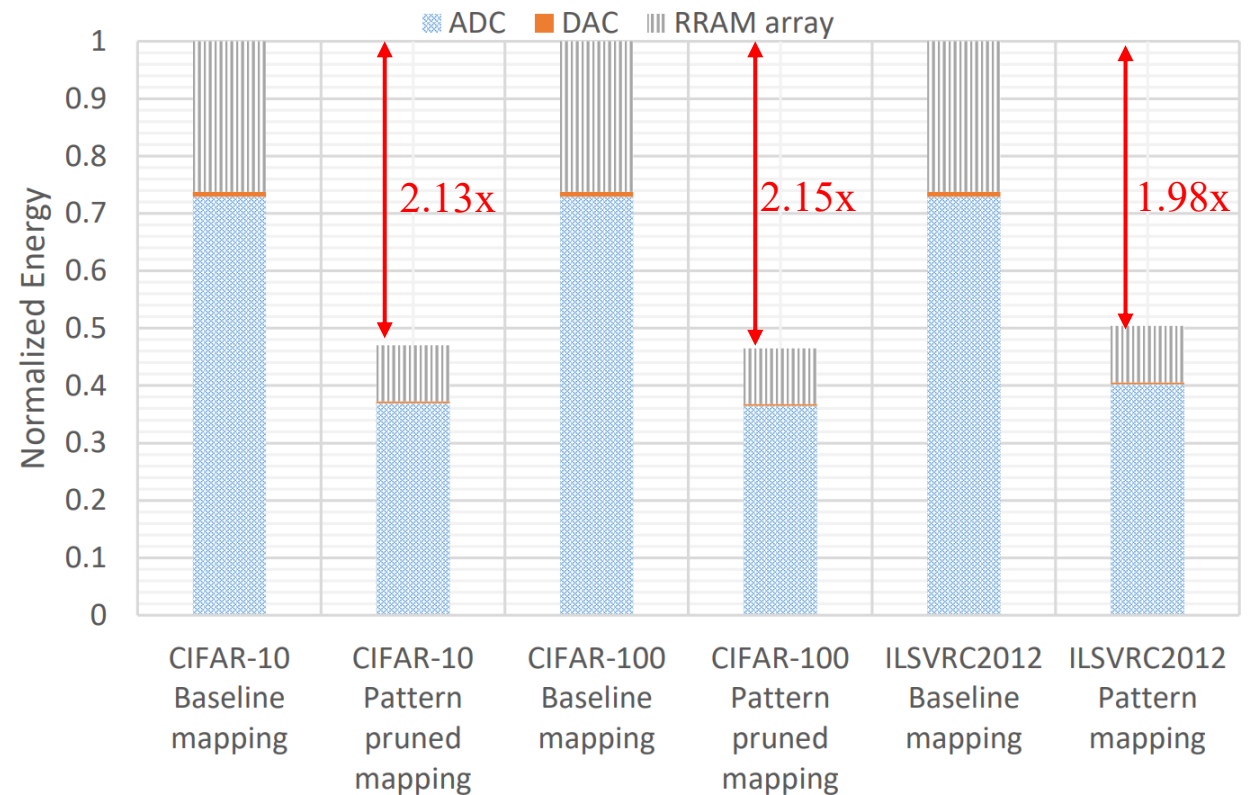
Pattern pruning results

Evaluation and results

RRAM area



Normalized energy



Experiment results summary

- **Area efficiency:** 4.67x/5.20x/4.16x for networks trained on CIFAR-10, CIFAR-100, and ImageNet, respectively. This means that we save 78.5%/80.8%/76.0% RRAM array comparing to the baseline.
- **Energy efficiency:** 2.13x/2.15x/1.98x on CIFAR-10, CIFAR-100, and ImageNet, respectively (only RRAM, ADCs and DACs in energy evaluation).
- **Performance Speedup:** 1.35x/1.15x/1/17x on CIFAR-10, CIFAR-100, and ImageNet, respectively. The speedup is achieved mainly by the deleted all-zero patterns which are neither stored in RRAM nor computed.

Conclusion

- A novel area-efficiency weight mapping scheme based on pattern pruning
 - High area efficiency

- An RRAM-based sparse CNN accelerator architecture
 - High energy efficiency

Thank you!

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