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### Hardware-Software Codesign of Weight Reshaping and Systolic Array Multiplexing for Efficient CNNs

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#### Background: Systolic Array



# Challenges for Systolic Array

- Sparse matrix multiplication is inefficient in systolic array
- Disadvantages of systolic array
  - Not good at exploiting irregular parallelism
  - Relatively special purpose → need software, programmer support to be a general purpose model



https://safari.ethz.ch/architecture/fall2020/lib/exe/fetch.php?media=onur-comparch-fall2020-lecture27-systolicarrays-afterlecture.ptx

H. T. Kung, B. McDanel, and S. Q. Zhang, "Packing Sparse Convolutional Neural Networks for Efficient Systolic Array Implementations: Column Combining Under Joint Optimization," in Proceedings of the Twenty-Fourth International Conference on Architectural Support for Programming Languages and Operating Systems, 2019, pp. 821–834.

### Previous work: Weight Pruning for Systolic Array

1	6	1	1	1	1	1	1
2	1	1	2	1	1	1	1
1	3	1	2	4	3	1	3
6	1	1	2	4	1	2	2
1	1	2	1	2	1	1	1
4	3	2	4	5	2	1	1
1	1	5	2	1	2	3	1
1	1	1	2	3	1	1	4

**Unstructured Pruning** 



	6	1	1				
2	1	1	2				
	3	1	2	4	3		3
6	1	1	2	4	1	2	2
1	1	2	1	2	1		
4	3	2	4	5	2		
		5	2	1	2	3	
		1	2	3			4
		0	0	0			

Block-wise Pruning (DAC '19)

#### Pros:

- Less computation
- No input modification

#### Cons:

Low compression ratio

					+						
	6		1		1						
2			2	1							
	3		2	4	3		3				
6			2	4		2	2				
		2		2	1						
4	3	2	4	5	2						
		5	2		2	3					
			2	3			4				

#### Column Combining (ASPLOS '19) Pros:

- Less computation
- Relative high accuracy (or low compression ratio)

#### Cons:

- Hard to find optimal group
- Rearrange input before computation
- MUX for each PE

B. Asgari et al., "LODESTAR: Creating Locally-Dense CNNs for Efficient Inference on Systolic Arrays," in Proceedings of the 56th Annual Design Automation Conference 2019, 2019, pp. 233:1-233:2.

H. T. Kung, B. McDanel, and S. Q. Zhang, "Packing Sparse Convolutional Neural Networks for Efficient Systolic Array Implementations: Column Combining Under Joint Optimization," in Proceedings of the Twenty-Fourth International Conference on Architectural Support Array Implementations: Column Combining Languages and Operating Systems, 2019, pp. 821–834.

# Solution

To **fully** utilize the systolic array with **high compression ratio of CNN models**, we propose a **hardware-software codesign framework**.

The framework outputs a **flexible** systolic array structure that sustains a balance between **latency** and **hardware cost** by:

- s Row swapping for compact storing of weight matrix
- $s\$  Block selection to cover the dense cluster of weights
- н Systolic array multiplexing
- н Genetic searching for flexible structure



# Unstructured Pruning and Row Swapping

- Unstructured pruning<sup>[1]</sup> is chosen to achieve a high compression ratio
- Row swapping is applied for compact weight matrix
  - Only rows with non-zero weights should be indexed when each column has weights
  - A small number of columns should be indexed only when some columns are empty



### **Block Selection**

- After row swapping, weights are reorganized into a dense cluster
- To find the optimal block set to cover the **weight cluster** seamlessly, we enumerate all the possible block sets according to the hardware constraint





Unstructured Pruning

**Row Swapping** 

				2				
				2	4			
				2	4			
	2	6	2	4	2	3		3
	6	3	2	2	5	2	2	2
	4	3	5	2	3	2	3	4

2 2 4

2 6 2 4 2

			2				
			2	4			
			2	4			
2	6	2	4	2	3		3
6	3	2	2	5	2	2	2
4	3	5	2	3	2	3	2

				2				
				2	4			
				2	4			
	2	6	2	4	2	3		3
	6	3	2	2	5	2	2	2
-								

				0				
				0				
				2				
				2	4			
	0	0	0	2	4	0	0	0
_	0 2	0 6	0 2	2	4	0 3	0	0 3
	0 2 6	0 6 3	0 2 2	2 4 2	4 2 5	0 3 2	0 0 2	0 3 2

				0				
				0				
				0				
				0				
				2				
	0	0	0	2	4	0	0	0
	0	0	0	2	4	0	0	0
	2	6	2	4	2	3	0	3
	6	3	2	2	5	2	2	2
	4	3	5	2	3	2	3	4

# Microarchitecture of Systolic Array

- To support the concurrent computations of various blocks with the corresponding inputs on systolic arrays, multiplexers are inserted into the arrays.
- To support the row swapping, a controller and selection modules are required to schedule the multiplication results.



# Computation of Modified Systolic Array

- 1. Decode row indices of weights by the **controller**
- 2. Load weights
- 3. Load inputs
- 4. Multiply weights and inputs
- 5. Transmit products to selection modules
- 6. Controller sends signal to selection modules
- 7. Selection modules handle received products
  - If weight are in the different row of the weight matrix, stores products respectively
  - If weights are in the same row of the weight matrix, add products and store the addition results



# Genetic Algorithm for Multiplexer Assignment

- The locations of multiplexers for **different CNN models** vary significantly
- A genetic algorithm is deployed to select where the multiplexers should be inserted considering both latency and hardware cost

Algorithm 1: Genetic algorithm

START

- 1 Generate the initial population
- 2 Compute fitness: *E* REPEAT
- 3 Tournament selection
- 4 Crossover
- 5 Polynomial Mutation
- 6 Compute fitness:  $E = C_l * L + C_a * A + C_w * W$

UNTIL stopping criteria are satisfied

Mutation equation:  $x_i^{\{1,t+1\}} = x_i^{\{1,t\}} + \beta_i$  $\beta_i = \begin{cases} (2u_i)^{\frac{1}{\eta_u+1}} - 1, & u_i < 0.5\\ 1 - [2(1-u_i)]^{\frac{1}{\eta_u+1}}, & u_i \ge 0.5 \end{cases}$ 

#### **Experimental Results**

#### TABLE I EXPERIMENTAL RESULTS COMPARED WITH THE UNSTRUCTURED PRUNING METHOD

Dataset	Compression Ratio (%)		Accura	acy (%)	Late	Latency #Multiplexers		
CIFAR-100	Baseline	Proposed	Baseline	Proposed	Baseline	Proposed	Proposed	#Mult./#PEs (%)
VGG-16	94.67	93.66	71.32	72.07	1	0.324	128	3.13
VGG-19	94.76	94.04	70.81	71.5	1	0.398	128	3.13
PreResNet-110	92.89	67.37	65.2	73.59	1	0.681	64	1.56
DenseNet-BC-40	90.99	75.11	67.27	71.95	1	0.291	192	4.69
DenseNet-BC-100	93.41	75.48	73.87	76.56	1	0.269	192	4.69





After genetic searching

### Conclusion

A hardware-software codesign framework is proposed to exploit systolic arrays for the computations of various CNNs efficiently

By row swapping, block selection, systolic array multiplexing and genetic searching for multiplexer assignment, a flexible systolic array structure is developed with accordingly pruned CNN models

The experimental results show that the latency can be reduced significantly with low hardware cost and high inference accuracy



✤ All the questions and comments are welcomed