

# DNNWEAVER: From High-Level Deep Network Models to FPGA Acceleration

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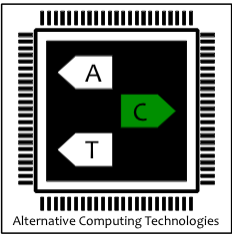
Emmanuel Amaro

Hadi Esmaeilzadeh

Alternative Computing Technologies (**ACT**) Lab  
Georgia Institute of Technology

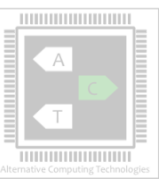
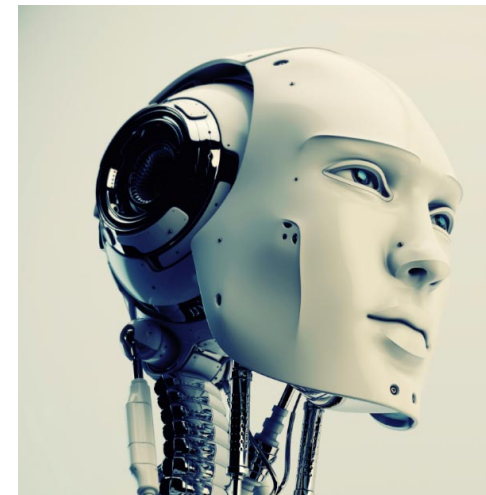
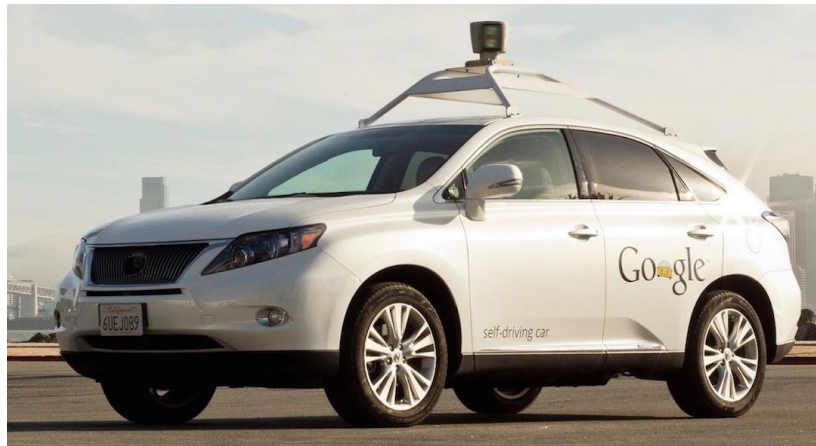
†Intel Corporation

MICRO'16

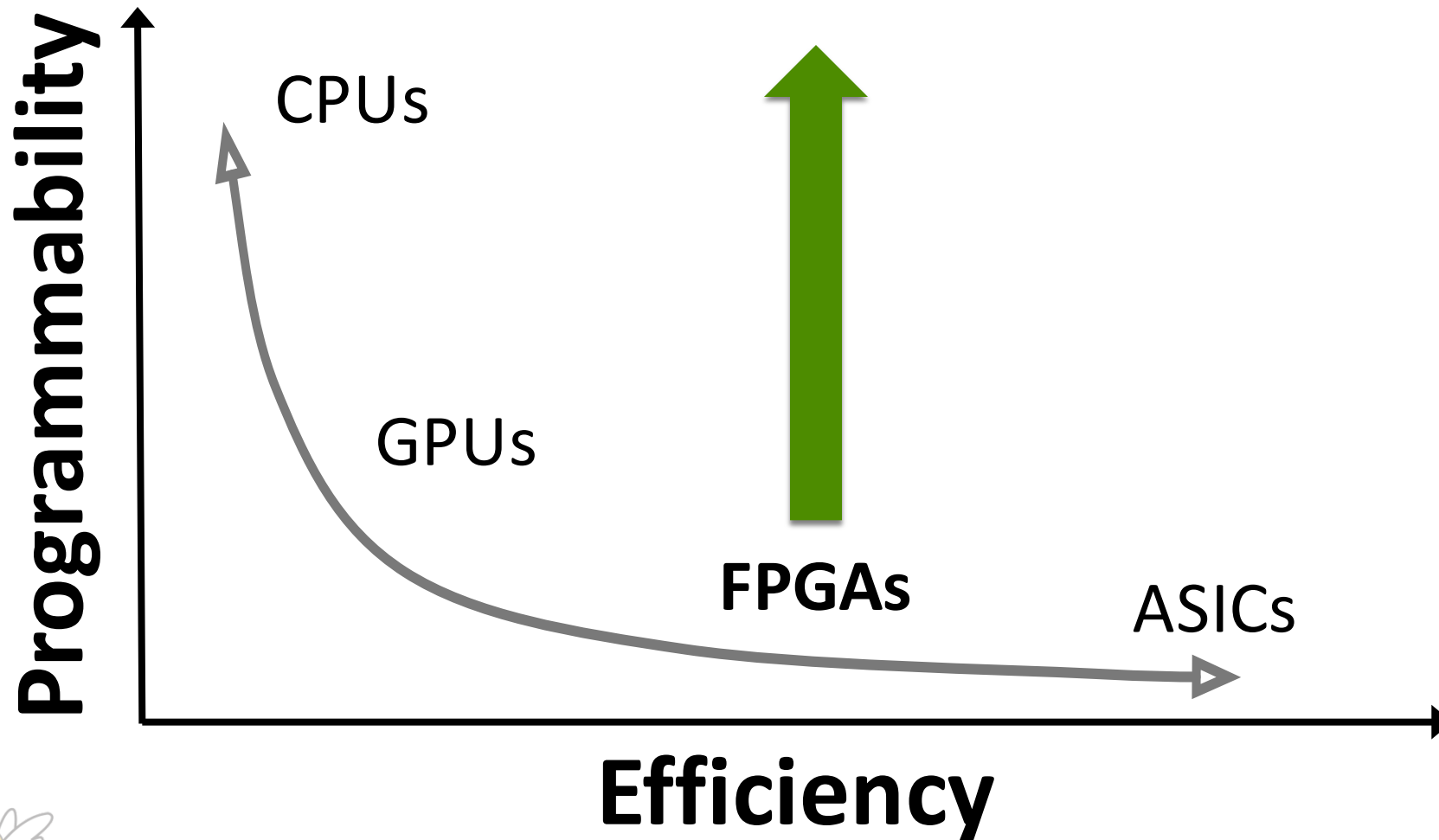




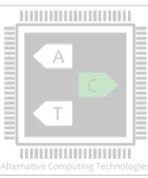
# Deep Neural Networks: A Move Towards Artificial Intelligence



# Programmability is a First-Order Concern



*Different applications require different DNNs!*

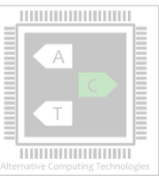


# FPGAs are Hard to Program!

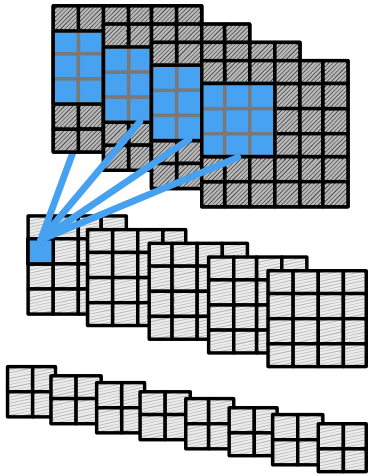
Over 10,000 lines of code for DNN hardware templates in 14 months!

**DNNs are Big, on-chip FPGA storage is small!**

AlexNet is 119 MBytes whereas Arria 10 has 5 MB!



# Bridging the Semantic Gap



**Translator**

**Design  
Planner**

**Design  
Weaver**

**Integrator**

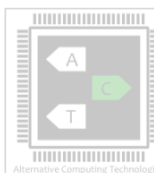
High-level  
Model  
Specification

Macro  
Dataflow  
Graph

Execution  
Schedule

Accelerator  
Configuration

Accelerator  
Core



# 1. Translator

## High-Level DNN model – Caffe\*

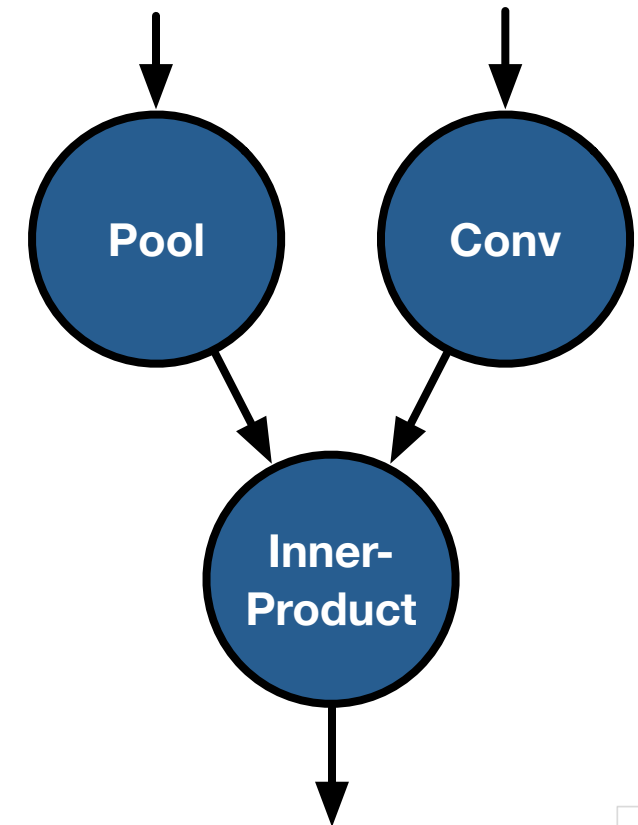
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  name: Pool,
  type: POOLING,
  params{...}}

  layer{
  name: Conv,
  type: CONVOLUTION,
  params{...}}

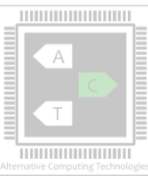
    layer{
  name: Inner-Product,
  type: INNER_PRODUCT,
  params{...}}
```



## DNNWEAVER ISA

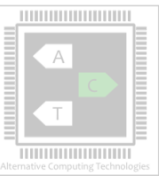
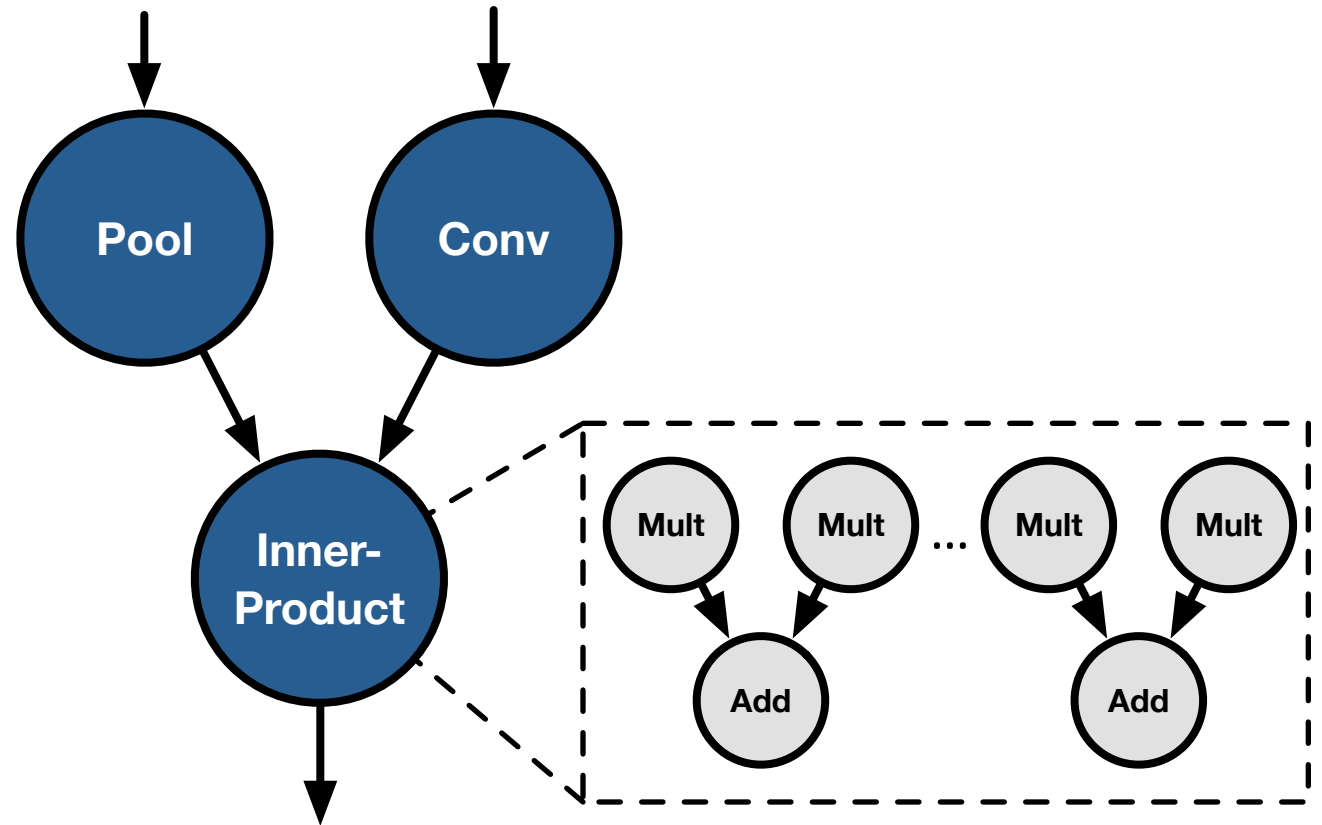


\*Caffe: Convolutional Architecture for Fast Feature Embedding. arXiv:1408.5093



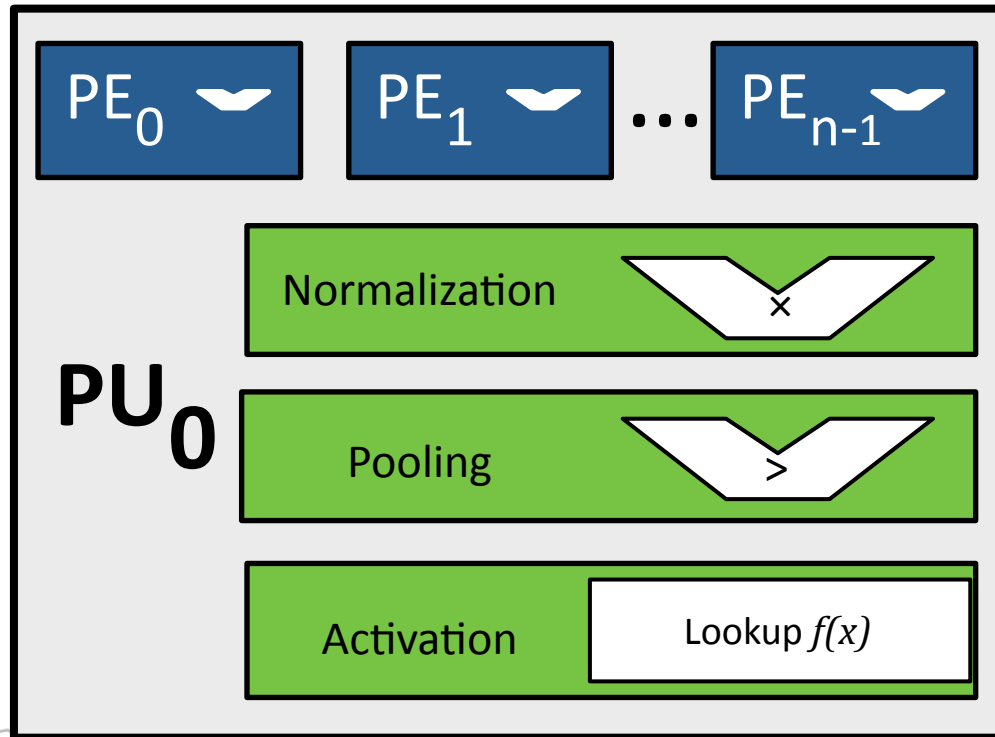
# ISA: Abstracting DNNs

Abstract DNNs as a **macro-dataflow graph**

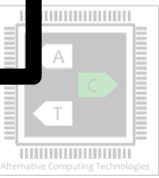
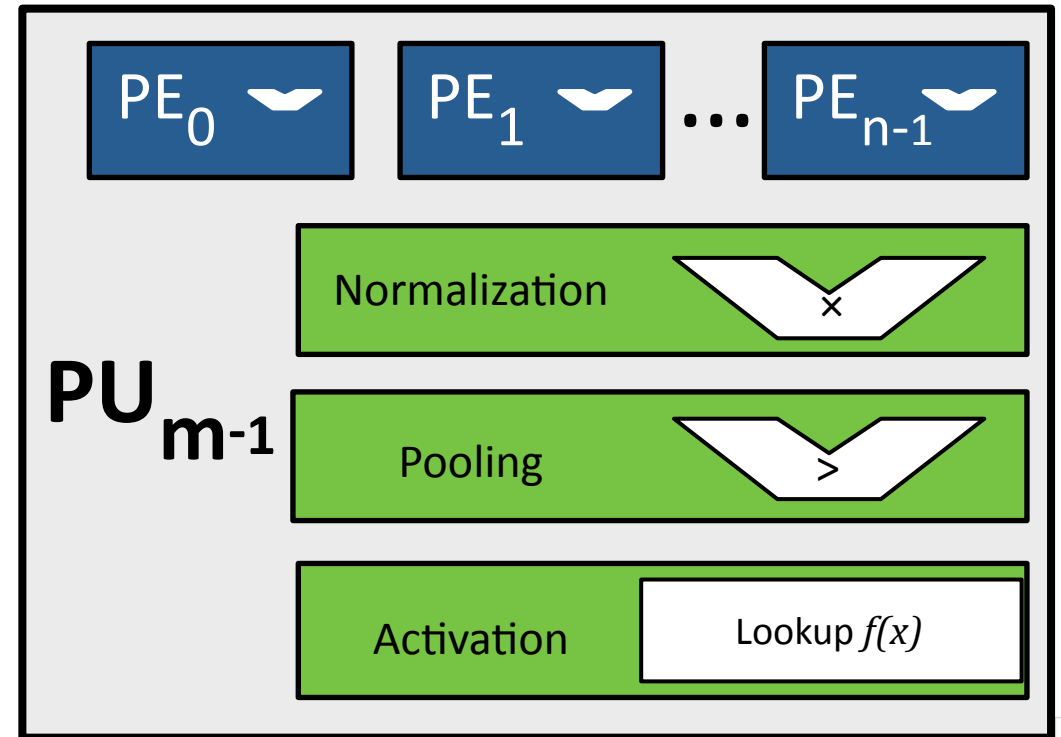


# Template Architecture

## Accelerator Core



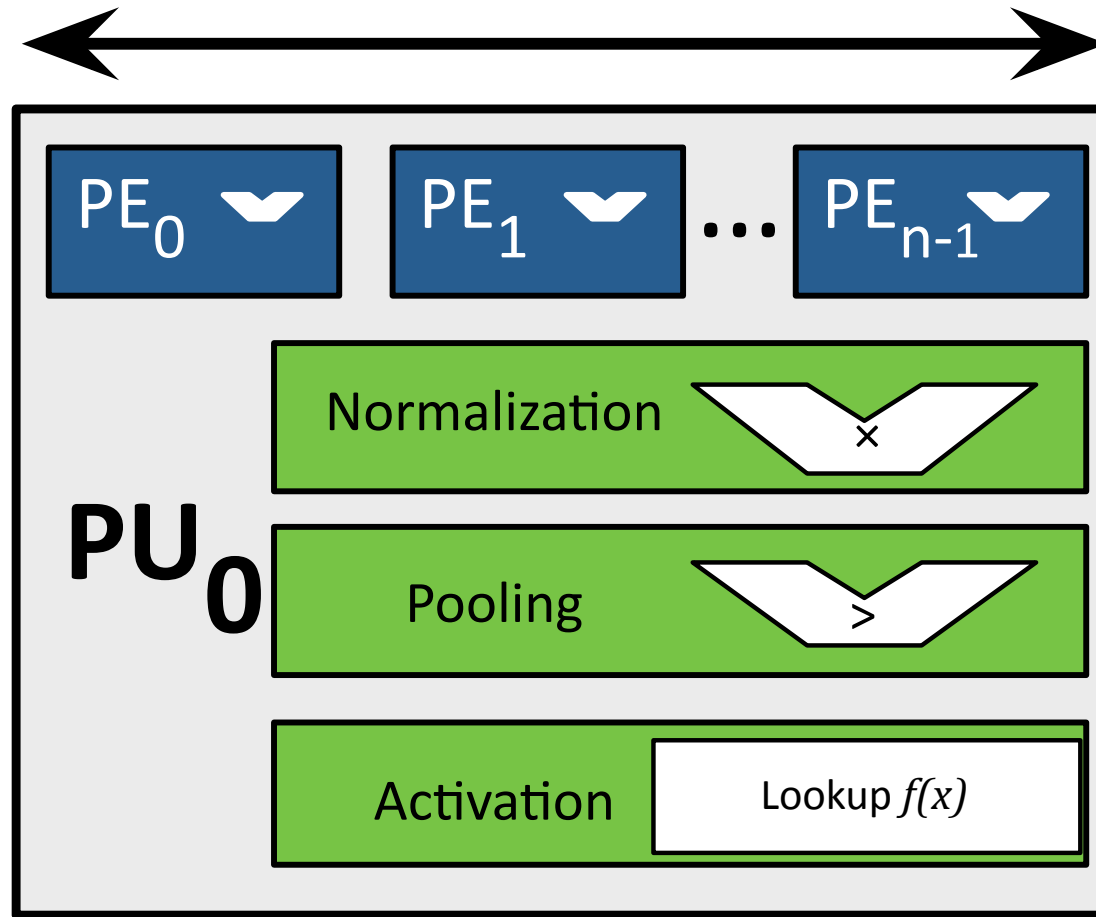
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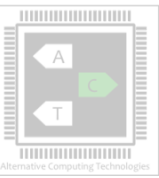


# Processing Unit

Flexible #PEs

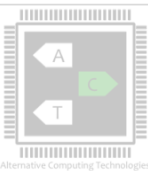
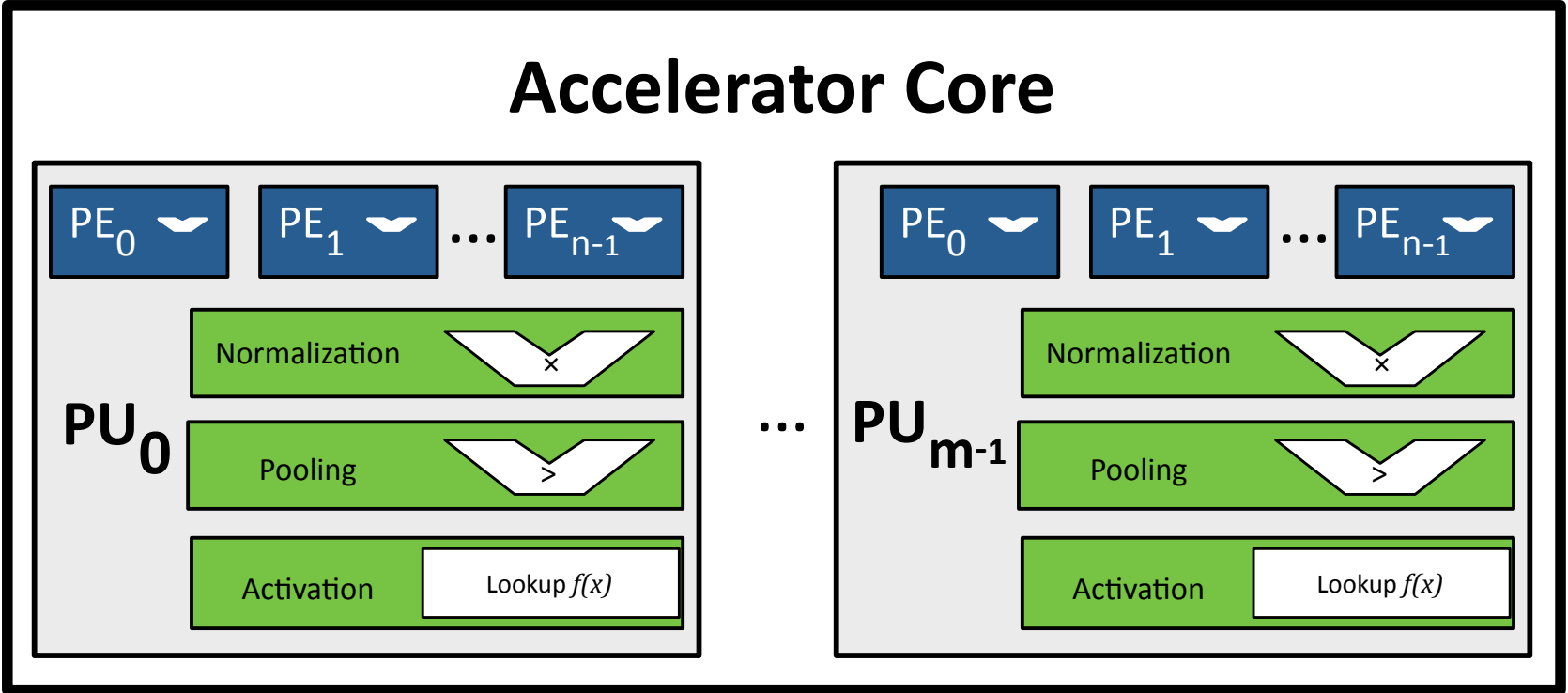
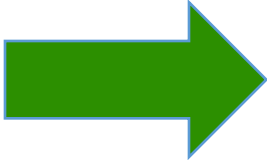
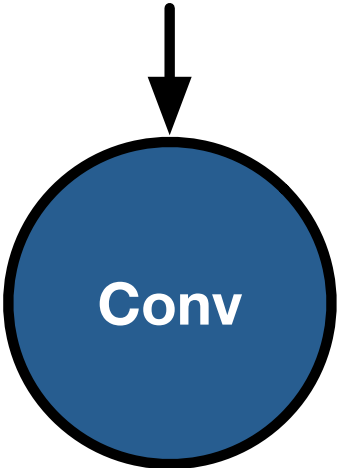


Exchangeable  
Components

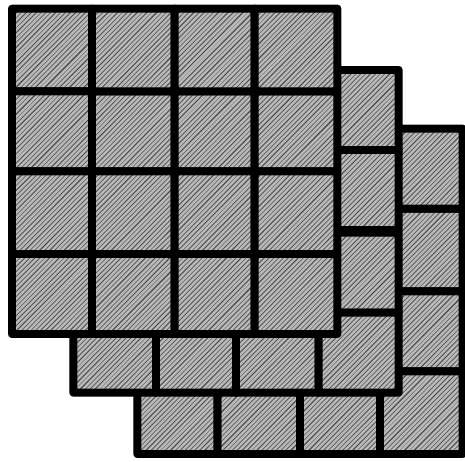
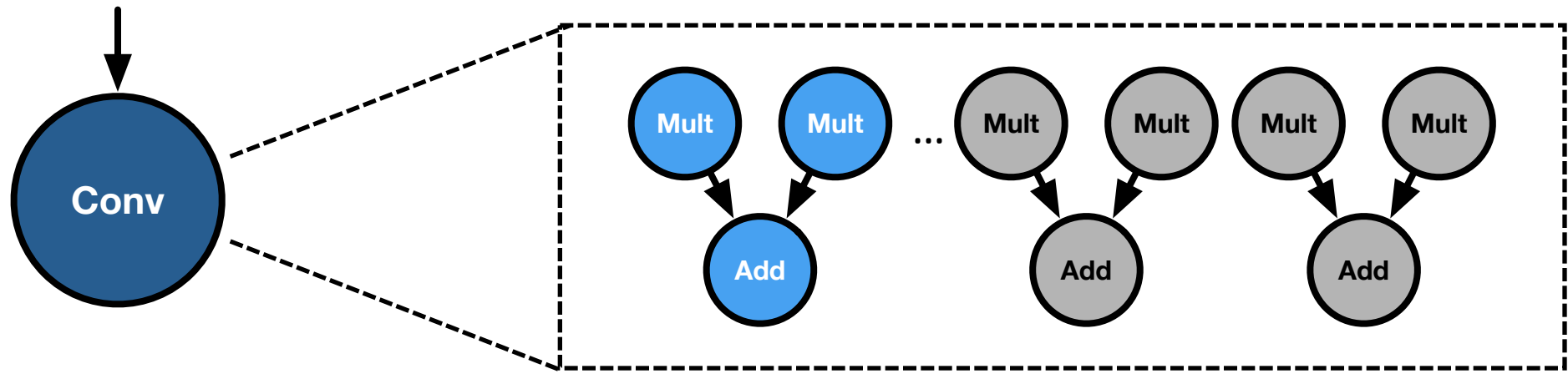


# Executing the Macro Dataflow Graph

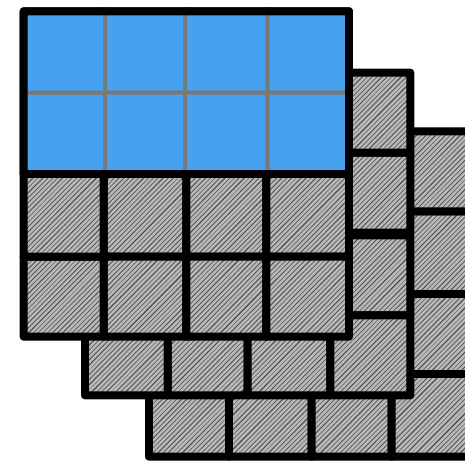
## Template Architecture



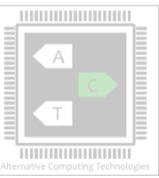
# Slicing the Dataflow Graph



**Convolution Node  
Output**

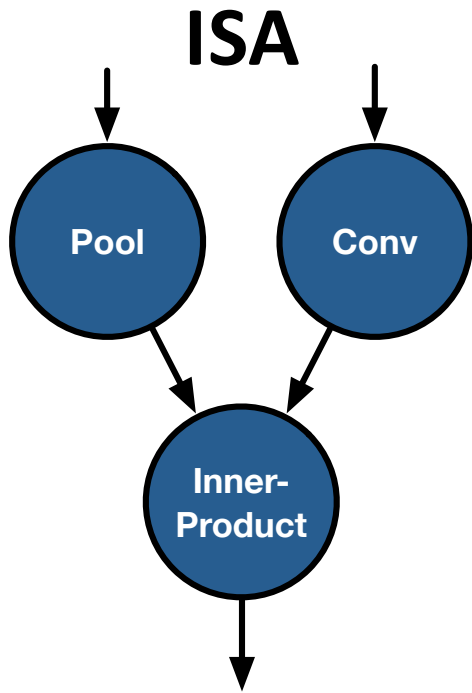


**Sliced Output**



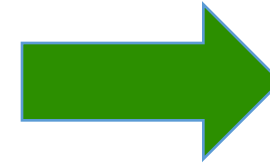
# 2. Design Planner

## Macro-Dataflow

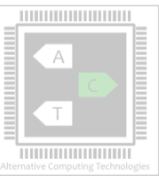


## FPGA Specification

# of DSPs  
# of BRAMs  
BRAM capacity  
# LUTs



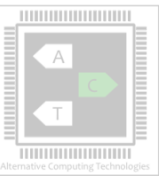
Co-optimize  
Hardware and  
Execution  
Schedule



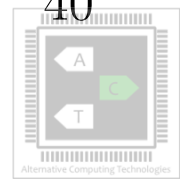
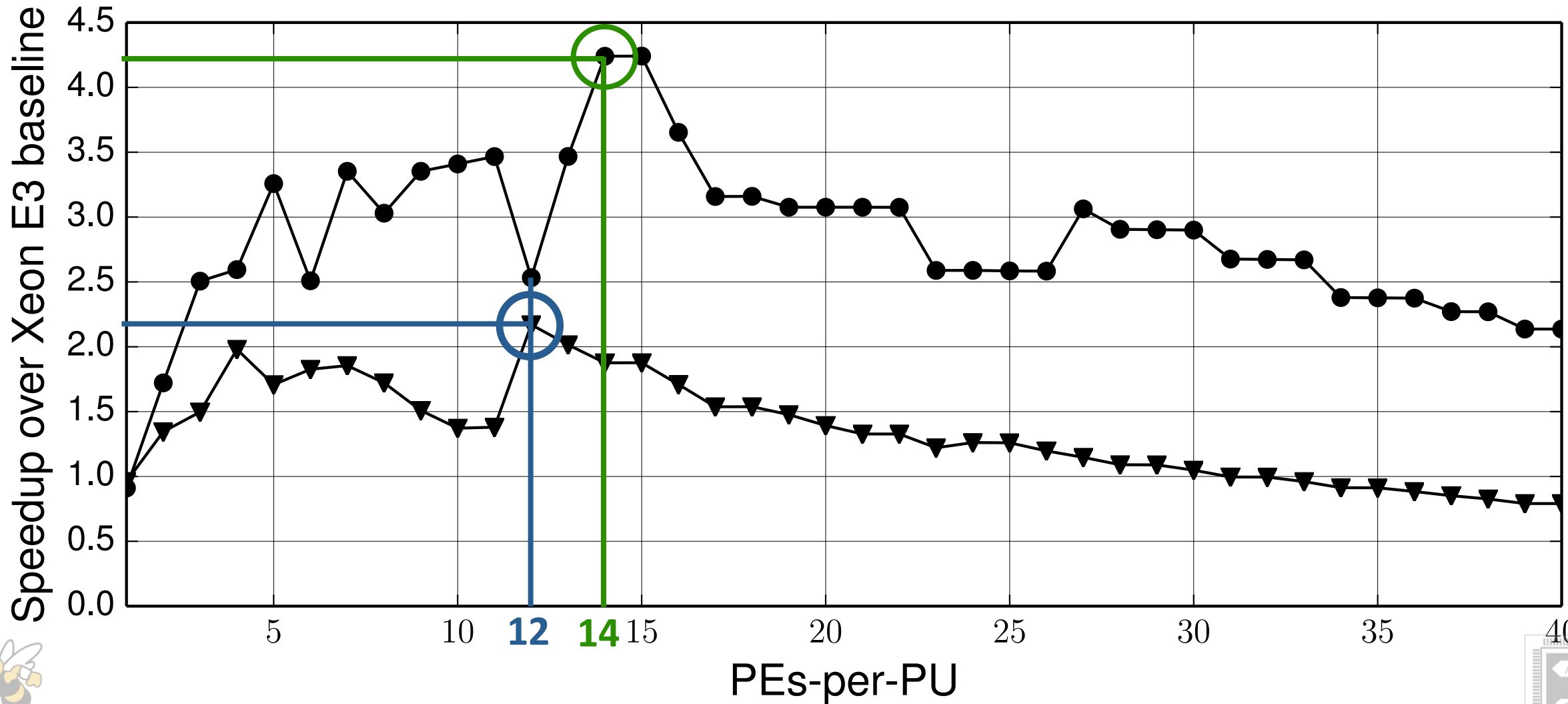
# Using FPGA's Programmability

Significant variations between different DNN models: # layers, Model Size, Operations, etc.

**Specialize for each DNN model!**



# Co-optimization



# 3. Design Weaver

Design Planner



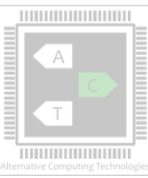
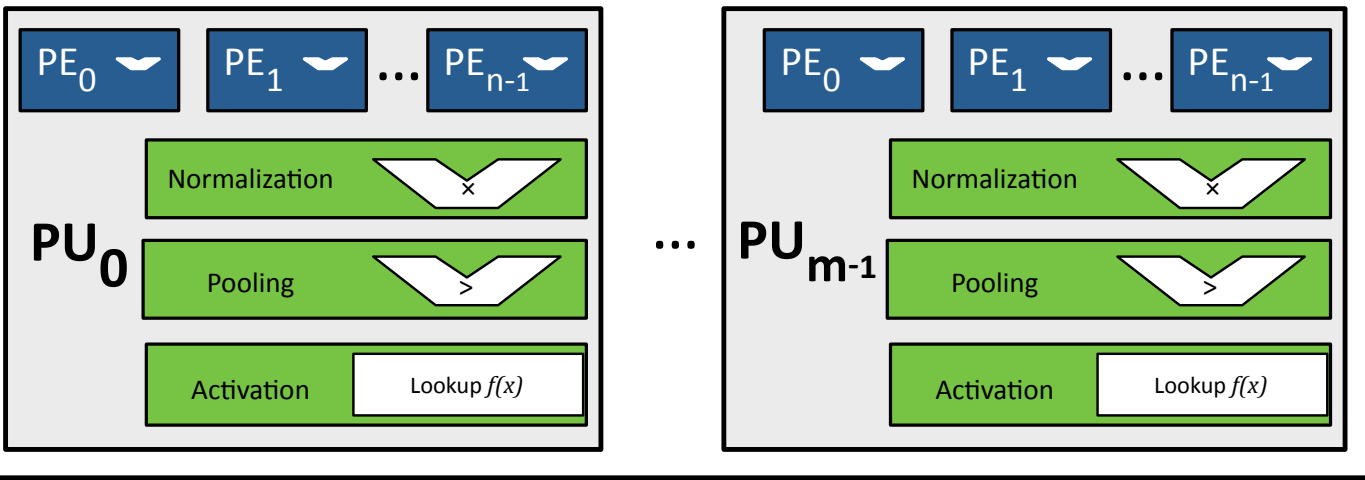
Accelerator Configuration

Verilog

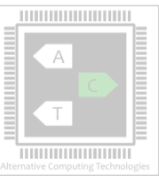
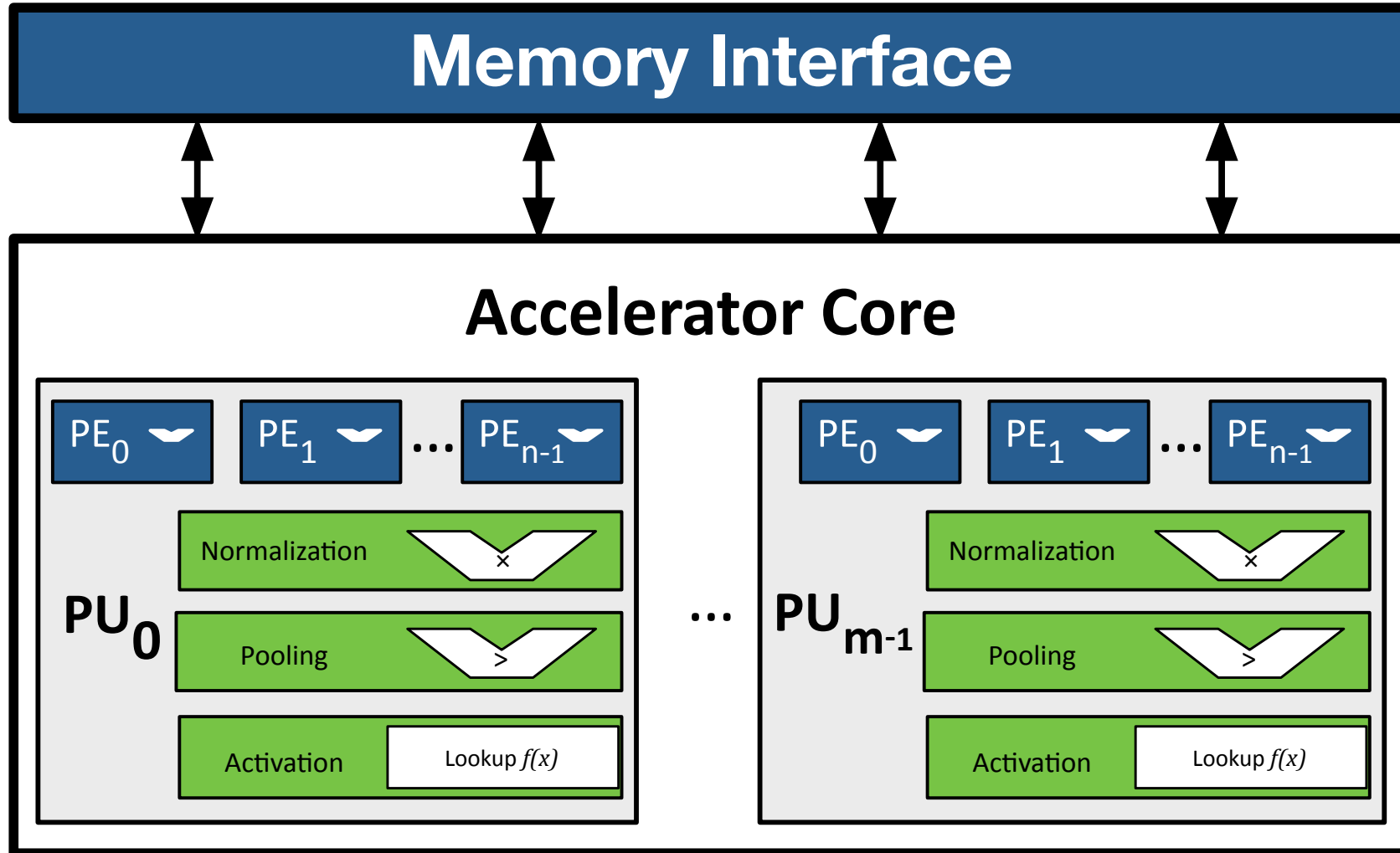
Execution Schedule

Decode

Accelerator Core



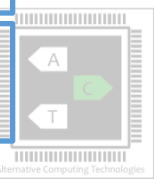
# 4. Integrator





# Benchmark DNNs

Name	# Layers	Model Size(MB)	# Operations (Mops)	Lines of Code
VGG-16	36	324.0 MB	16362 MOps	347
OverFeat	16	278.0 MB	2798 MOps	196
VGG-CNN-S	19	196.0 MB	2666 MOps	200
AlexNet	20	119.0 MB	1147 MOps	278
Djinn	13	48.4 MB	25 MOps	105
NiN	28	14.5 MB	1106 MOps	516
LeNet	7	0.8 MB	2 MOps	128
CIFAR-10Full	12	0.2 MB	12 MOps	156



# Platforms Tested

High  
Performance

Low Power

**FPGA**

Altera Arria 10

Altera Stratix V

Xilinx ZC702

**CPU**

Intel Xeon E3

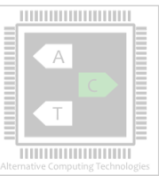
ARM Cortex 15

**GPU**

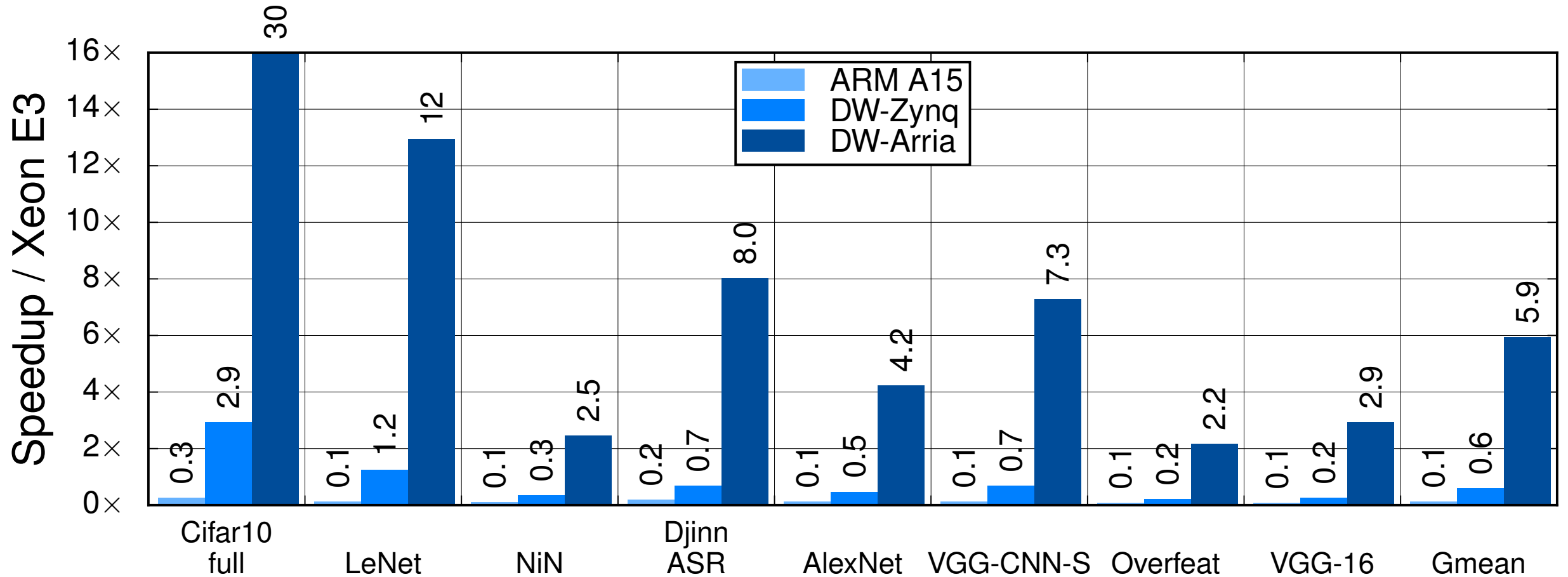
Tesla K40

GTX 650 Ti

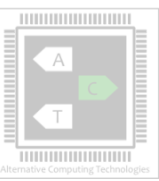
Tegra K1



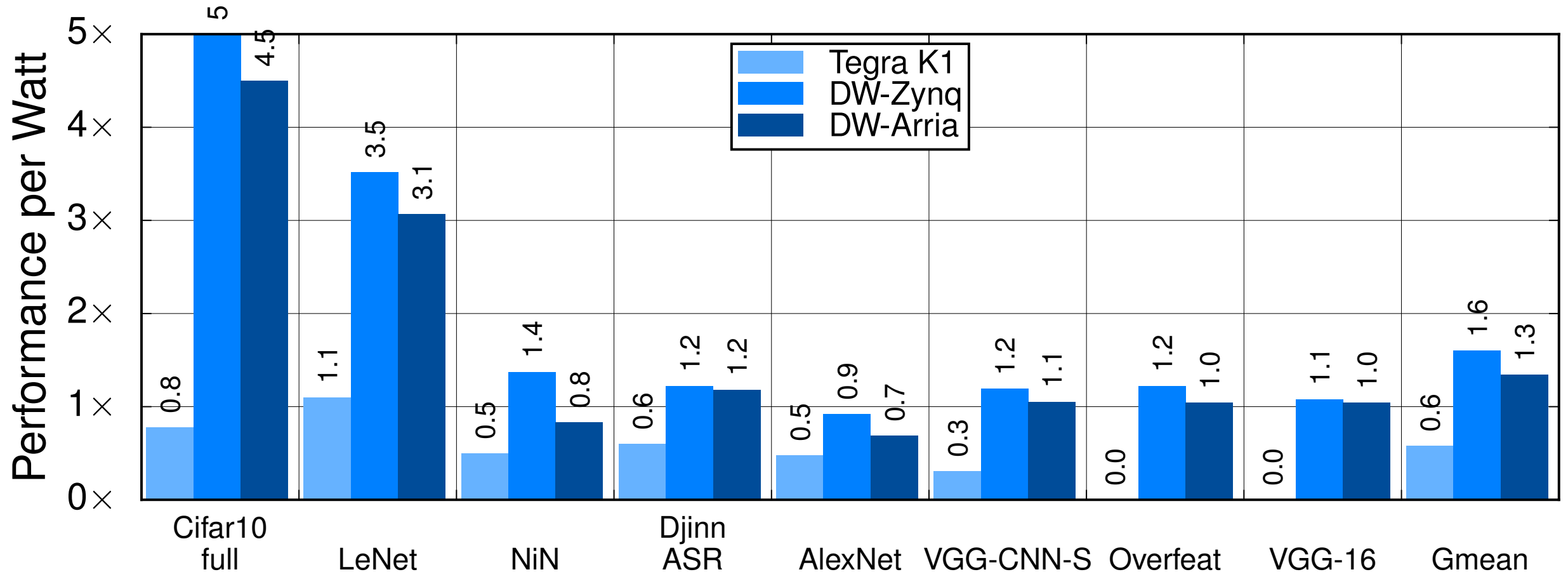
# Performance vs CPUs



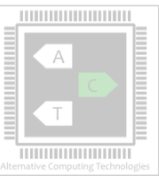
Compared to Xeon, Arria10 is **5.9x** faster, and Zynq is **0.6x** faster.



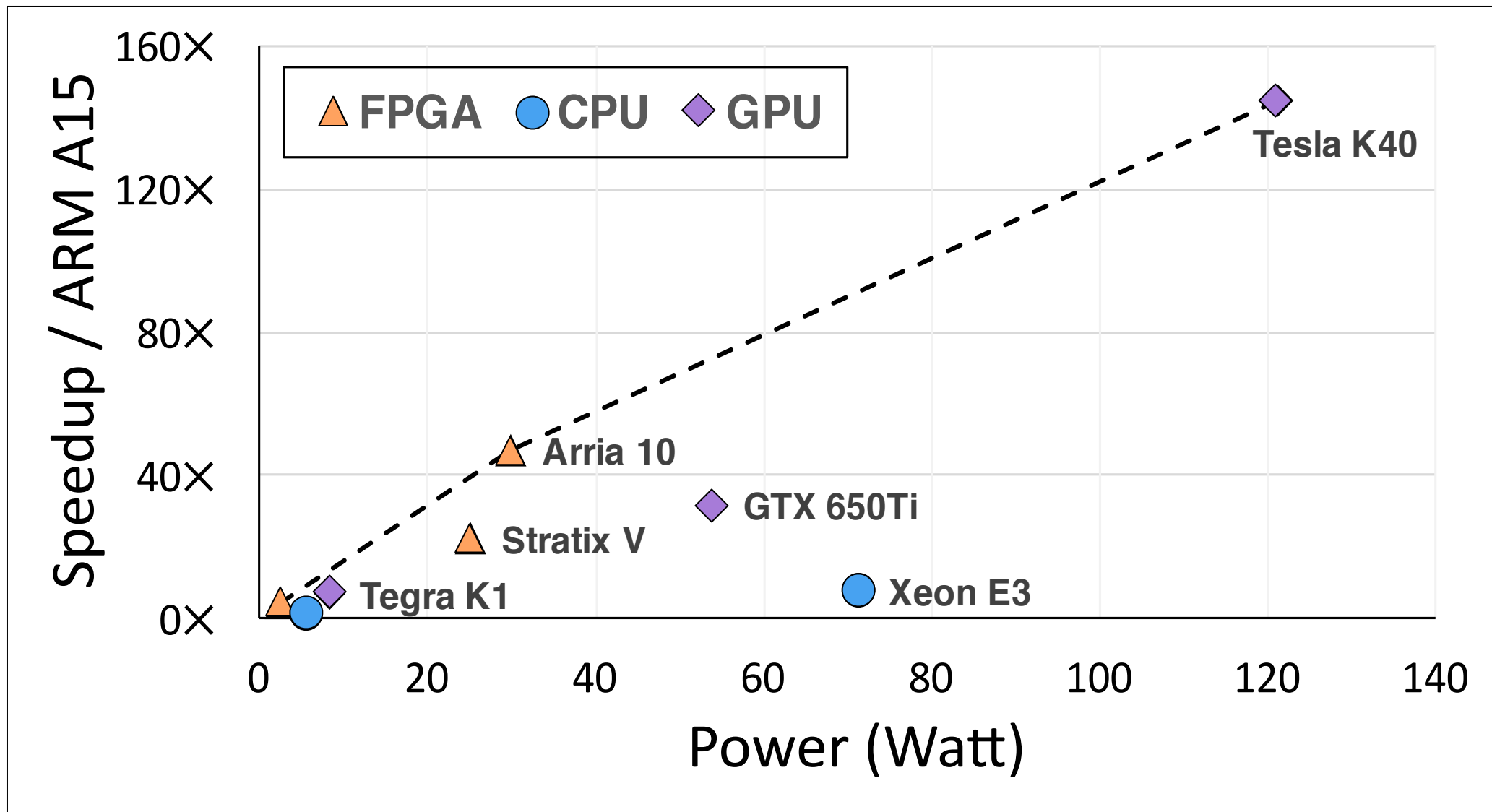
# Performance-per-Watt vs GPUs



Compared to TeslaK40, Zynq is **1.6x**, and Arria10 is **1.3x** more power efficient.



# Performance vs Power

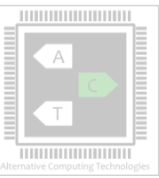


# Conclusion

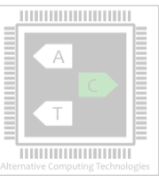
FPGAs are a promising option for low-mid power range

However, there is a semantic gap between the high-level DNN models and FPGA acceleration

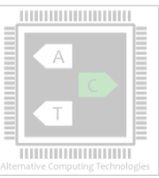
**DNNWEAVER is an initial step in making FPGAs more accessible to DNN programmers**



# Questions?

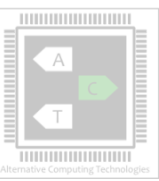
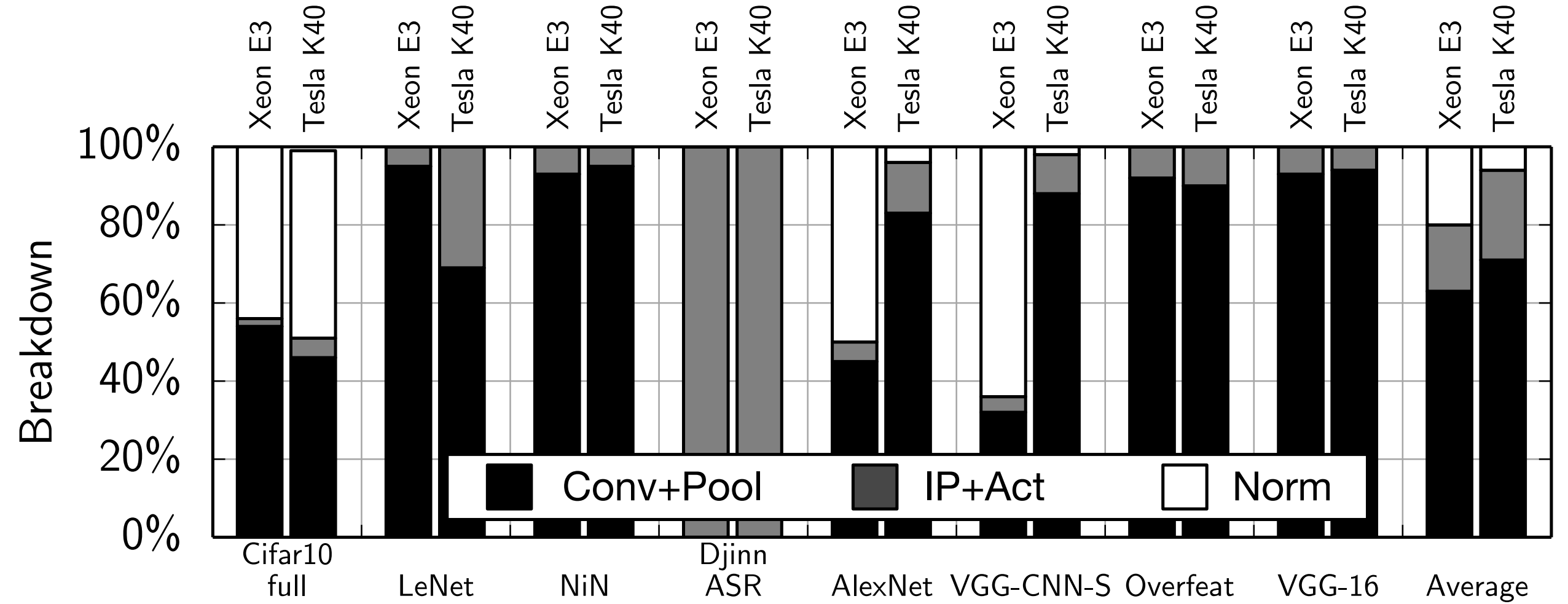


# Backup Slides

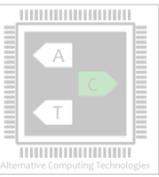
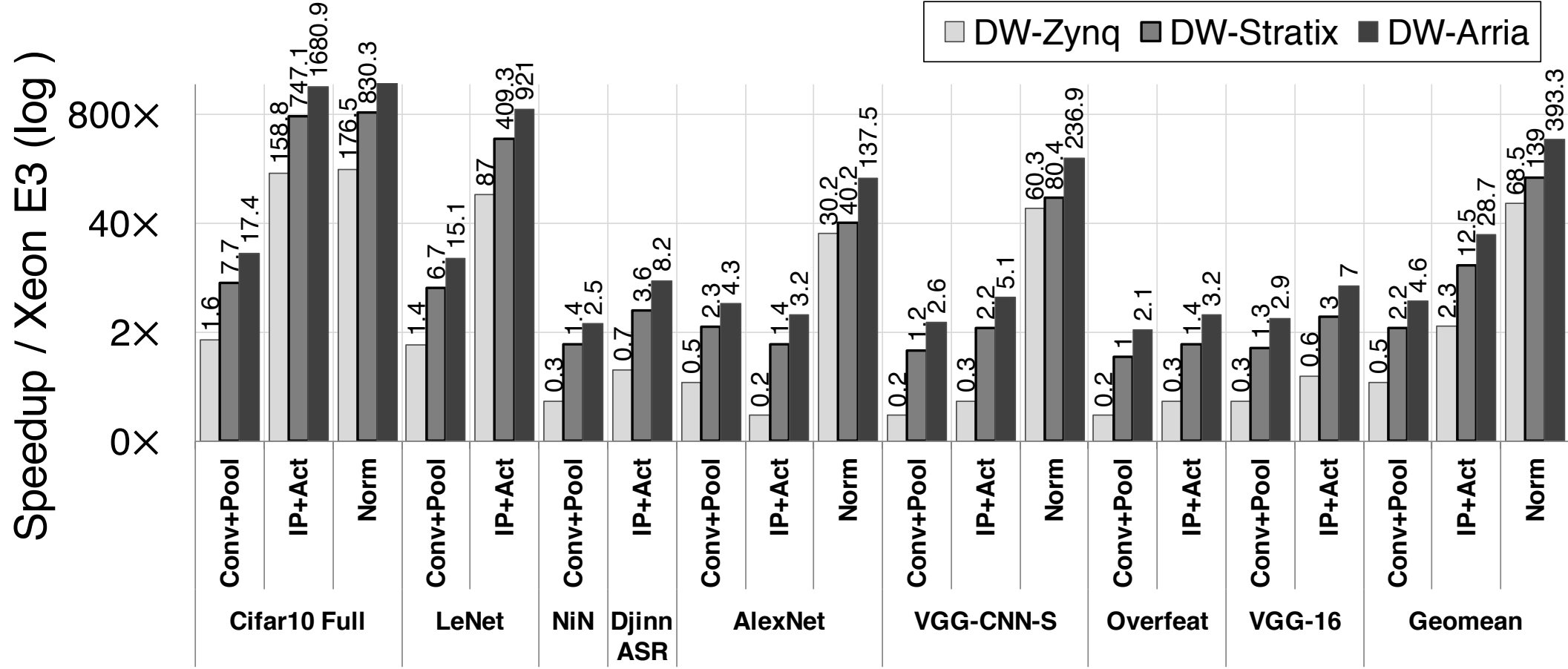




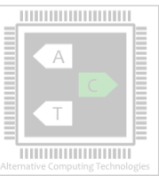
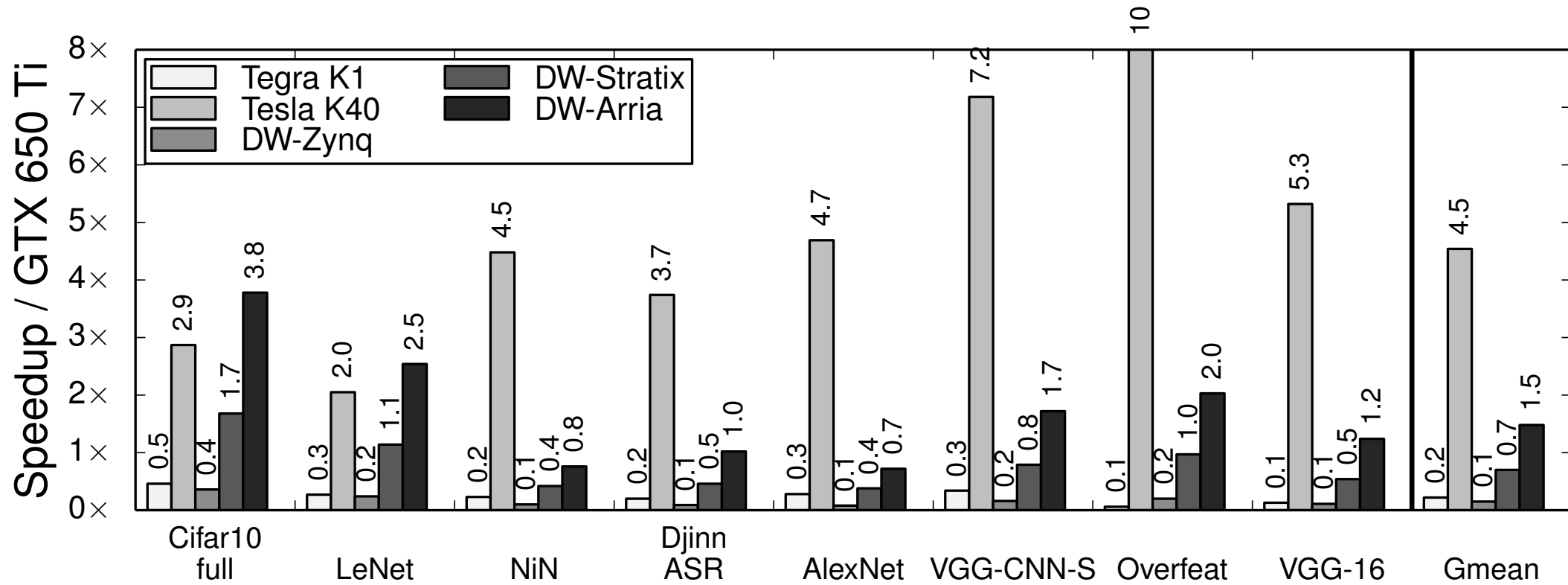
# Runtime Breakdown



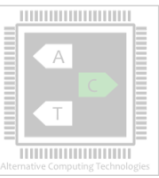
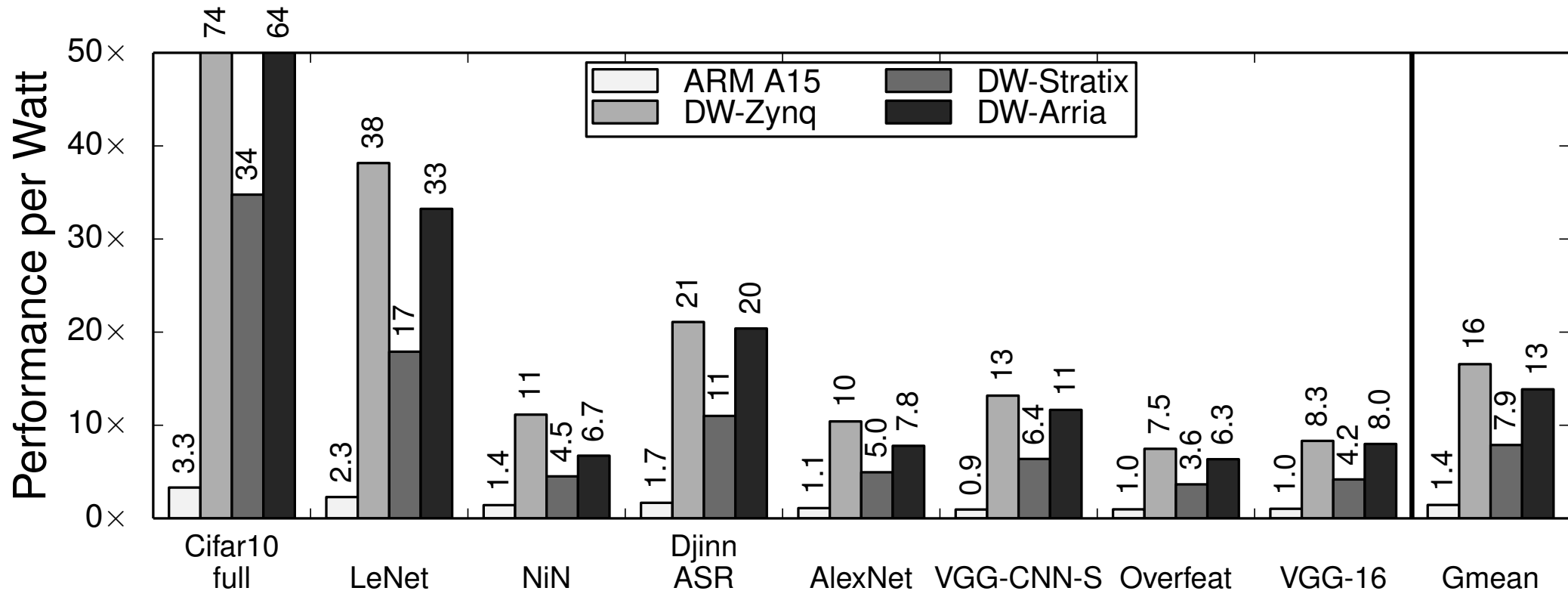
# Per Layer Speedup CPU



# Performance vs GPU

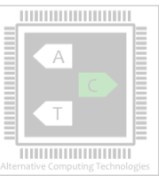


# Performance-per-Watt vs CPU

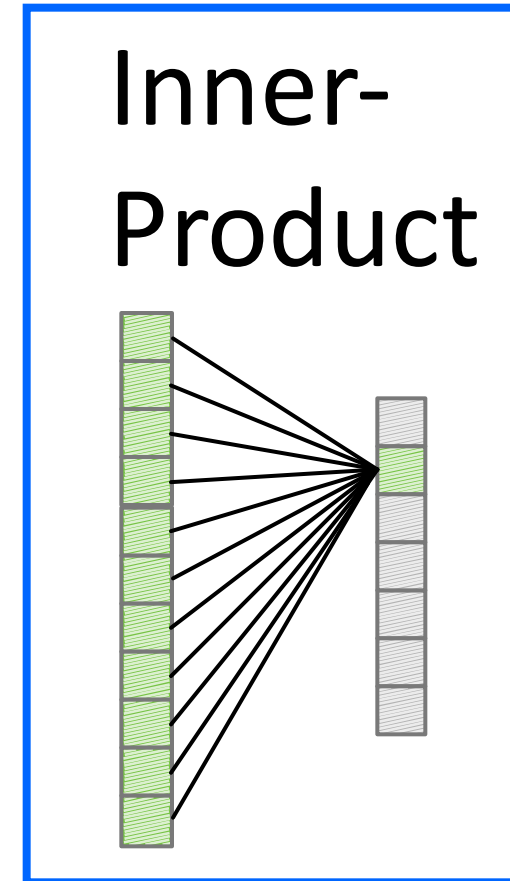
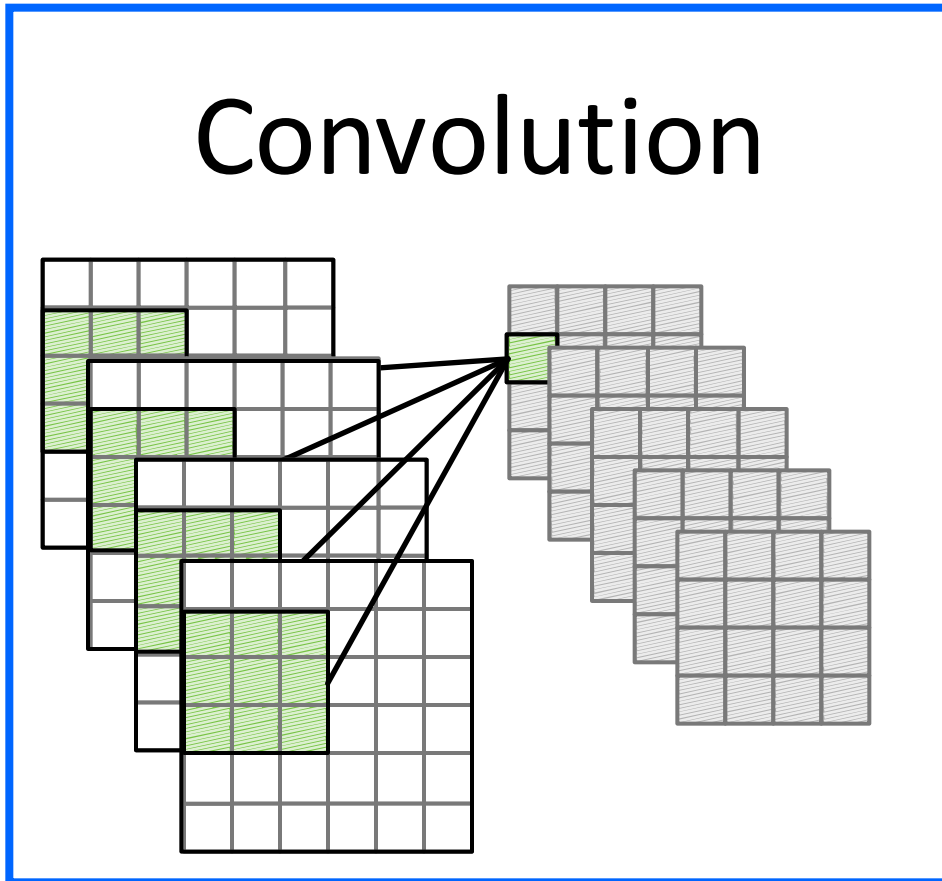


# Platforms Tested

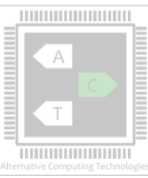
<b>Altera Arria 10</b> TDP:35W \$4495	<b>Altera Stratix V</b> TDP:25W \$6999	<b>Xilinx Zynq ZC702</b> TDP: 2W \$129
<b>Intel Xeon E3-1276 V3</b> TDP: 84W \$339	<b>ARM Cortex 15</b> TDP: 5W \$191	
<b>Tegra K1 GPU</b> TDP: 10 W \$191	<b>GTX 650 Ti</b> TDP: 110 \$150	<b>Tesla K40</b> TDP: 235 W \$5499



# Deep Neural Networks (DNNs)

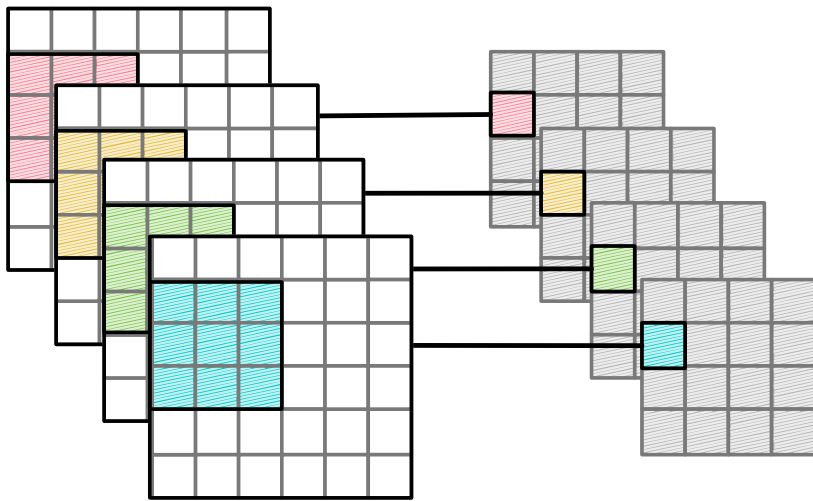


**Convolution and Inner-Product are the Learnable Layers**

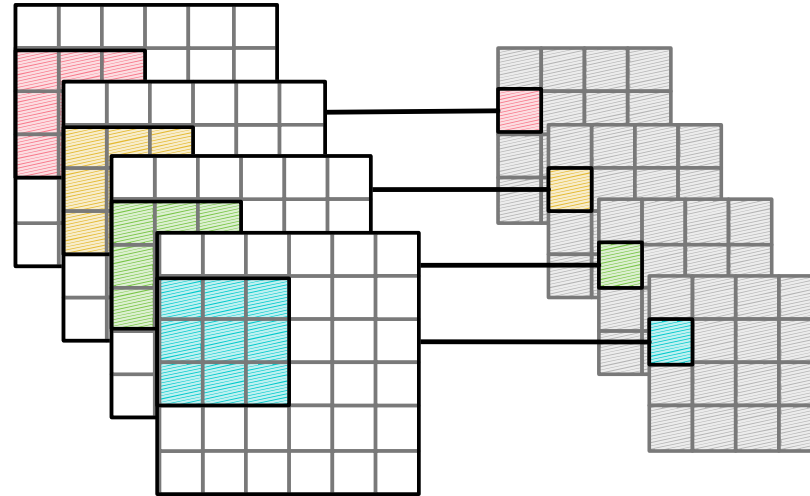


# Deep Neural Networks (DNNs)

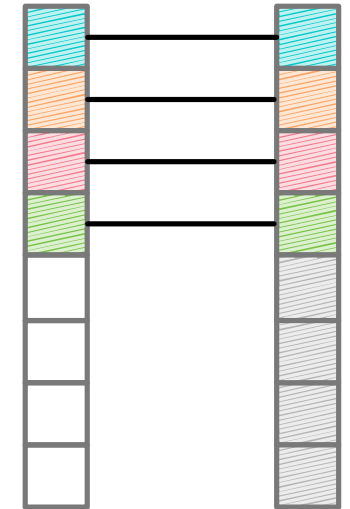
Pooling



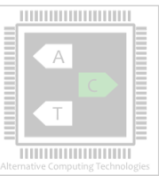
Normalization



Activation

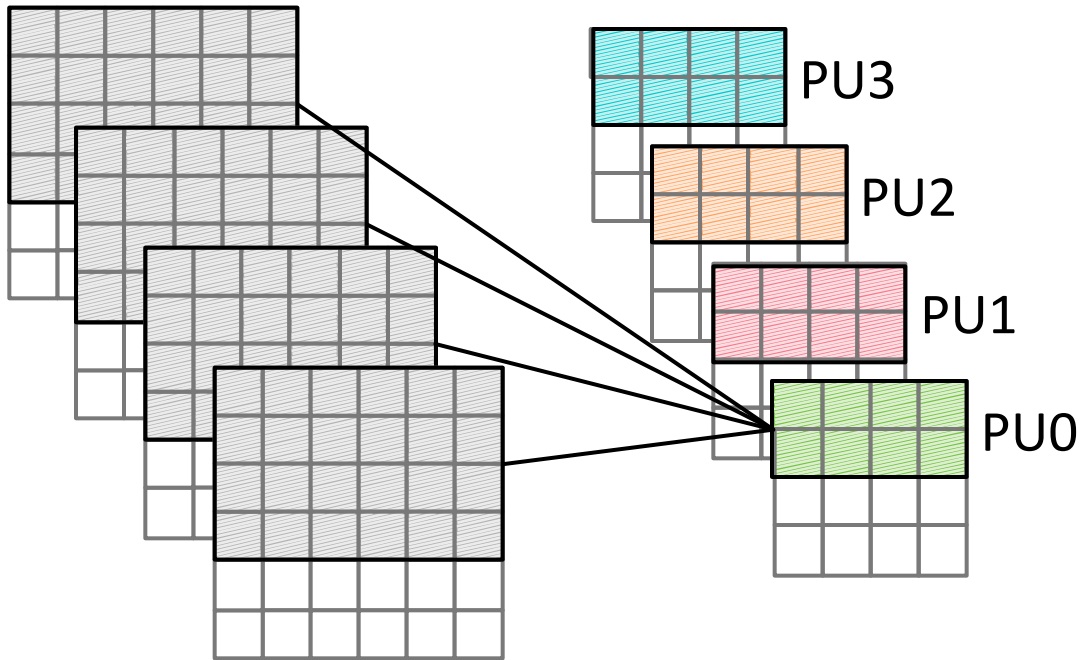


**DNNWEAVER supports all these five layers.**

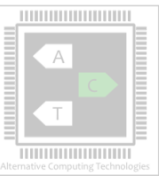
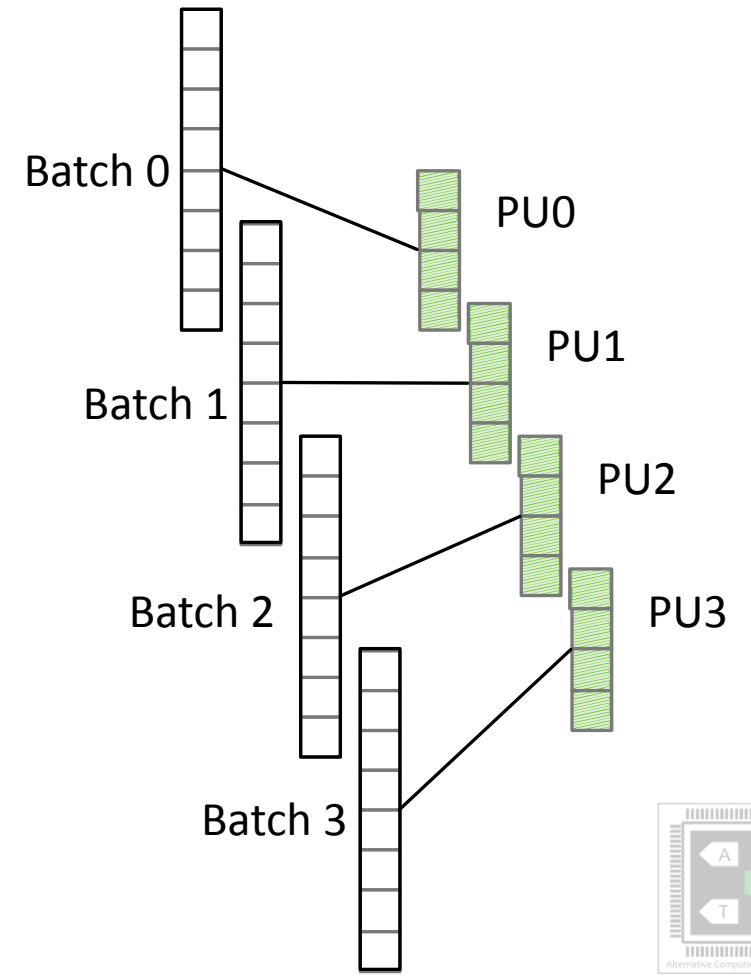


# Scheduling Operations on Hardware

## Convolution

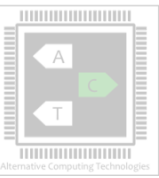


## Inner-product

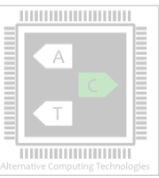




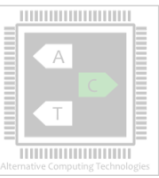
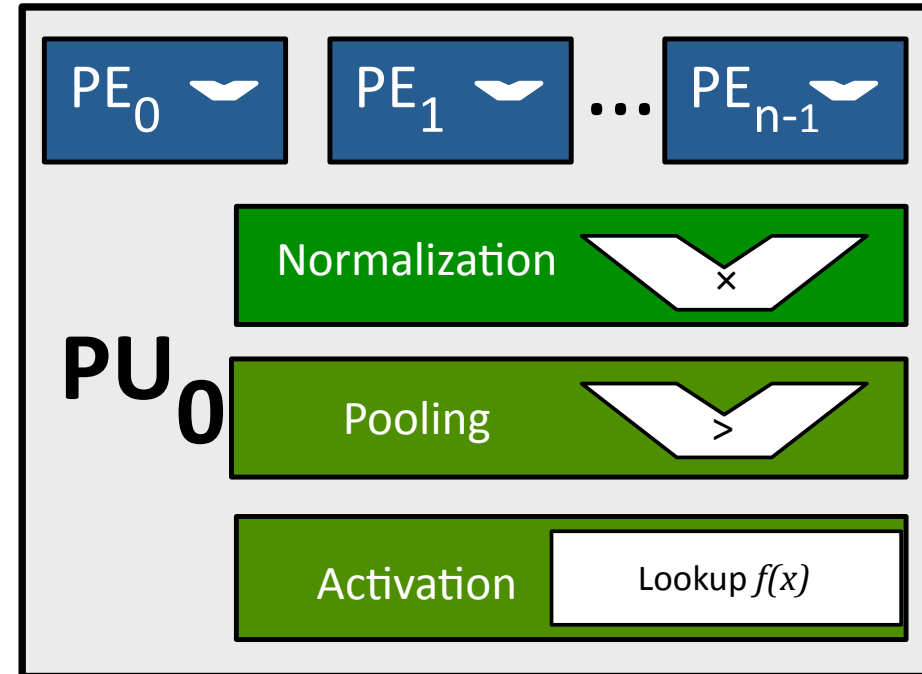
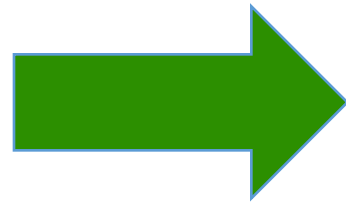
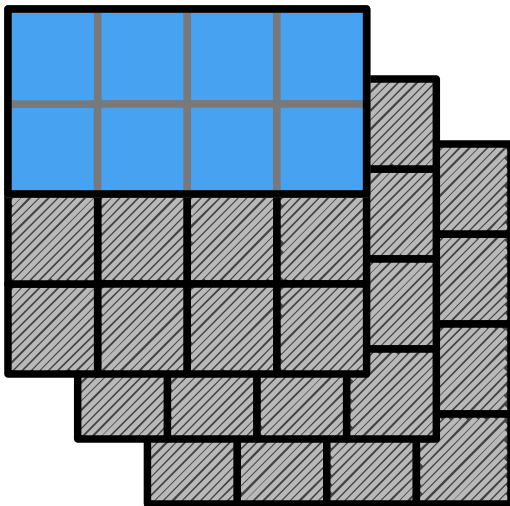
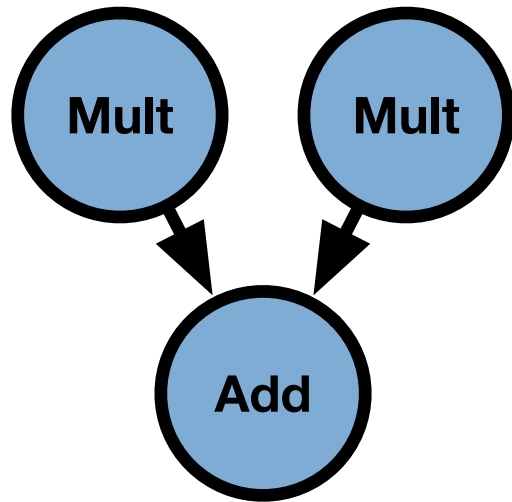
# Performance vs GPU



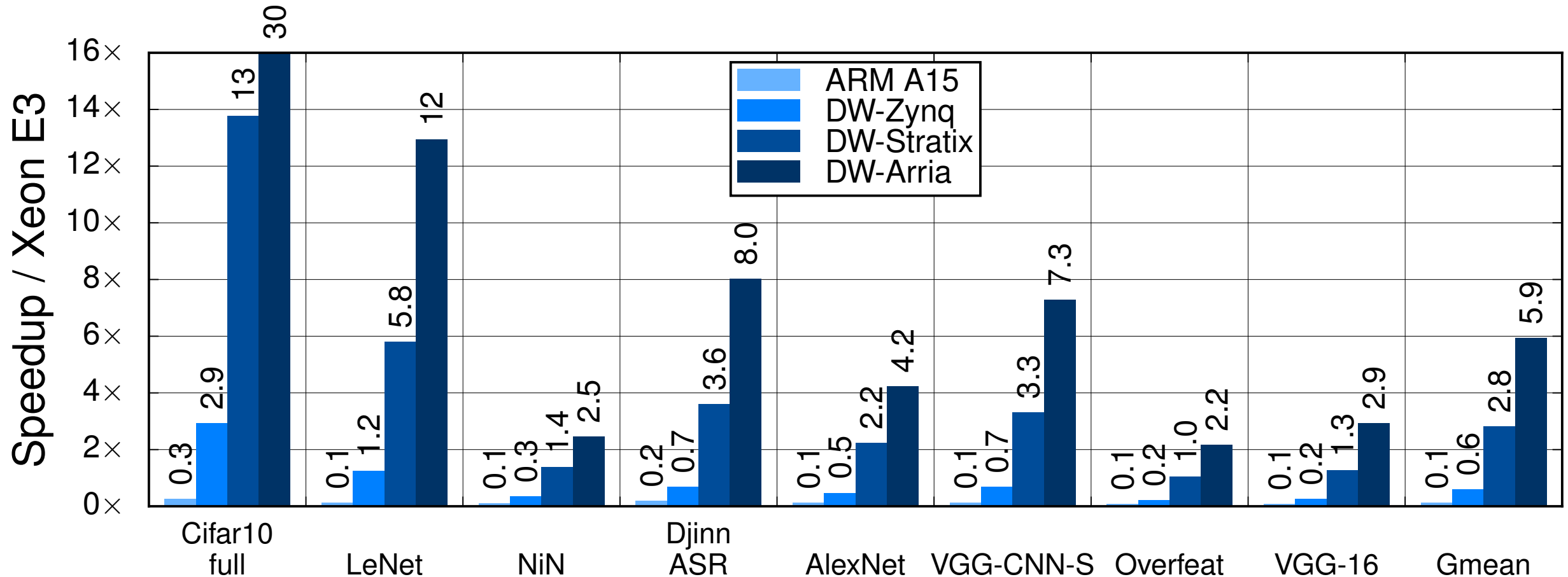
# Performance-per-Watt vs CPU



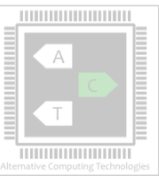
# Executing the Slice



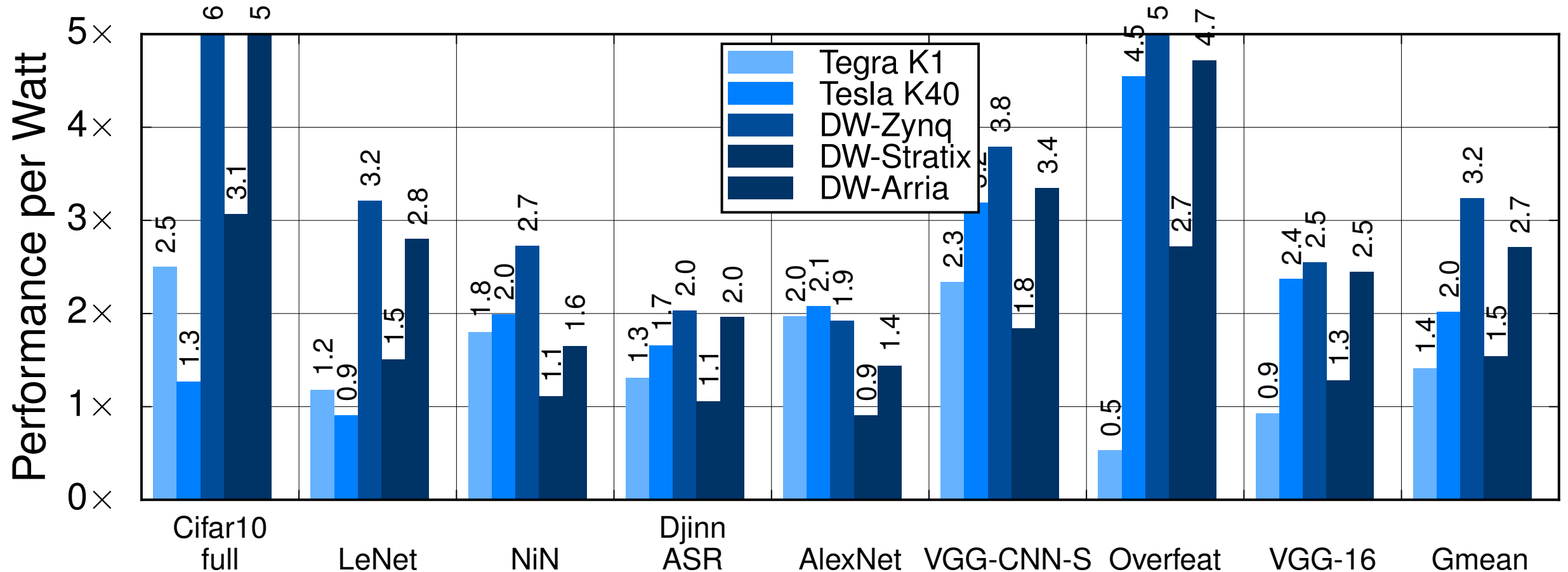
# Performance vs CPUs



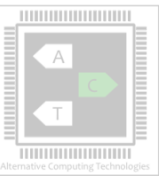
Compared to Xeon, Arria10 is **5.9x** faster,  
Stratix V is **2.8x** faster, and Zynq is **0.6x** faster.



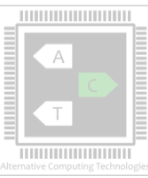
# Performance-per-Watt vs GPUs



Compared to GTX650, Zynq is **3.2x**, Stratix V is **1.5x**, and Arria10 is **2.7x** more power efficient.



# Co-optimize Hardware and Execution Schedule



# Processing Engine

