

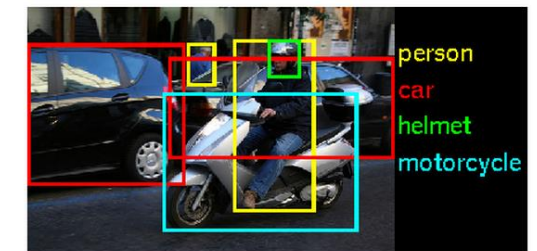
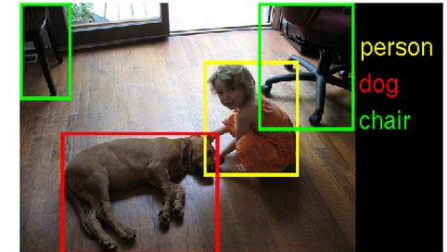
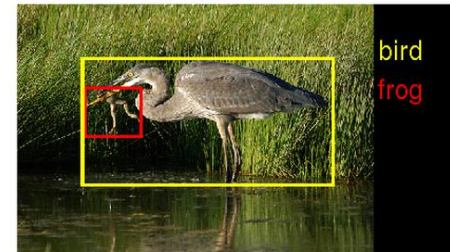
Toward Accelerating Deep Learning at Scale Using Specialized Hardware in the Datacenter

Kalin Ovtcharov, Olatunji Ruwase, Joo-Young Kim,
Jeremy Fowers, Karin Strauss, Eric S. Chung

Acknowledgments: Doug Burger and the Catapult Team, Trishul Chilimbi and the Digital Cortex Team, Altera Corporation

The Rise of Deep Learning

- Significant advances in
 - Computer vision
 - Speech recognition
 - Natural language processing
 - Recommendation systems
 - Intelligent agents
 - Etc.
- Examples
 - Convolutional Neural Networks (CNNs)
 - Deep Belief Networks (DBNs)
 - Recurrent Neural Networks (RNNs)
 - ... ?



Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification

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Abstract

Rectified activation units (rectifiers) are essential for state-of-the-art neural networks. In this work, we study rectifier neural networks for image classification from two aspects. First, we propose a Parametric Rectified Linear Unit (PReLU) that generalizes the traditional rectified unit. PReLU improves model fitting with nearly zero extra computational cost and little overfitting risk. Second, we de-

and the use of smaller strides [33, 24, 2, 25]), new non-linear activations [21, 20, 34, 19, 27, 9], and sophisticated layer designs [29, 11]. On the other hand, better generalization is achieved by effective regularization techniques [12, 26, 9, 31], aggressive data augmentation [16, 13, 25, 29], and large-scale data [4, 22].

Among these advances, the rectifier neuron [21, 8, 20, 34], e.g., Rectified Linear Unit (ReLU), is one of several keys to the recent success of deep networks [16]. It expe-

This Talk:
Are FPGAs a Promising Target in the
Datacenter for Deep Learning¹?

¹Case study: CNN-based Image Classification (inference)

Cloud Specialization Tradeoffs



CPU-Based Servers

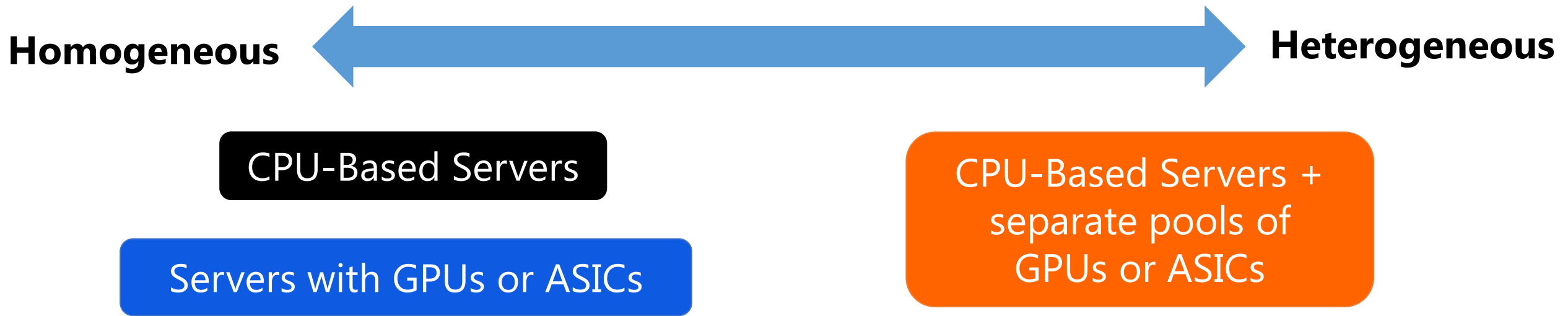
- + Excellent maintainability in datacenter
- + Maximum flexibility for all workloads
- Performance of CNNs/DNNs vastly slower than specialized HW

Cloud Specialization Tradeoffs



- + CNNs/DNNs that utilize GPUs or ASICs benefit significantly
- CNNs/DNNs cannot scale beyond limited pools
- Heterogeneity challenging for maintainability

Cloud Specialization Tradeoffs



+ Homogeneous

- Increased cost and power per server (particularly GPUs)
- Not economical for all applications in the datacenter (GPUs and ASICs)

Cloud Specialization Tradeoffs



CPU-Based Servers

Servers with GPUs or ASICs

CPU-Based Servers +
separate pools of
GPUs or ASICs

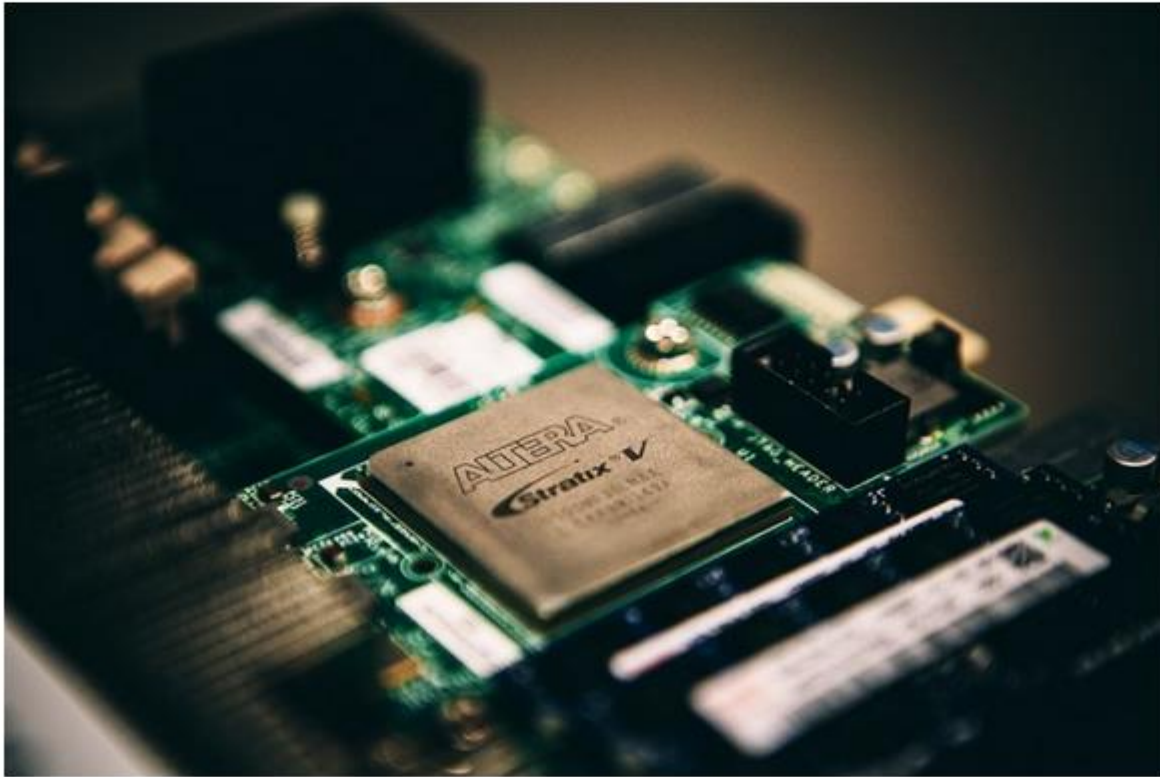
Servers with FPGAs

???

- + Homogeneous
- + Low overhead in power and cost per server
- + Flexibility benefits many workloads?
- Lower peak performance than GPUs or ASICs on some workloads

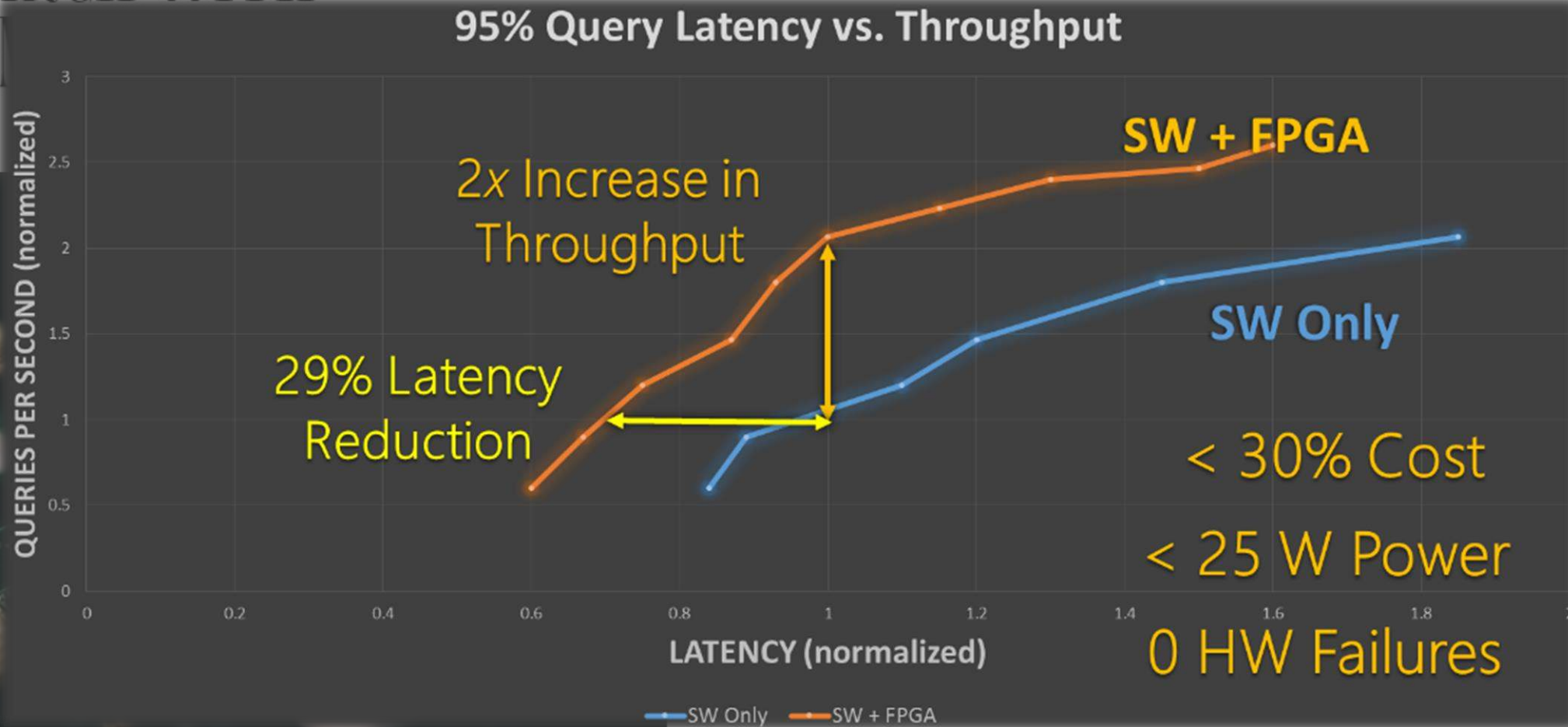
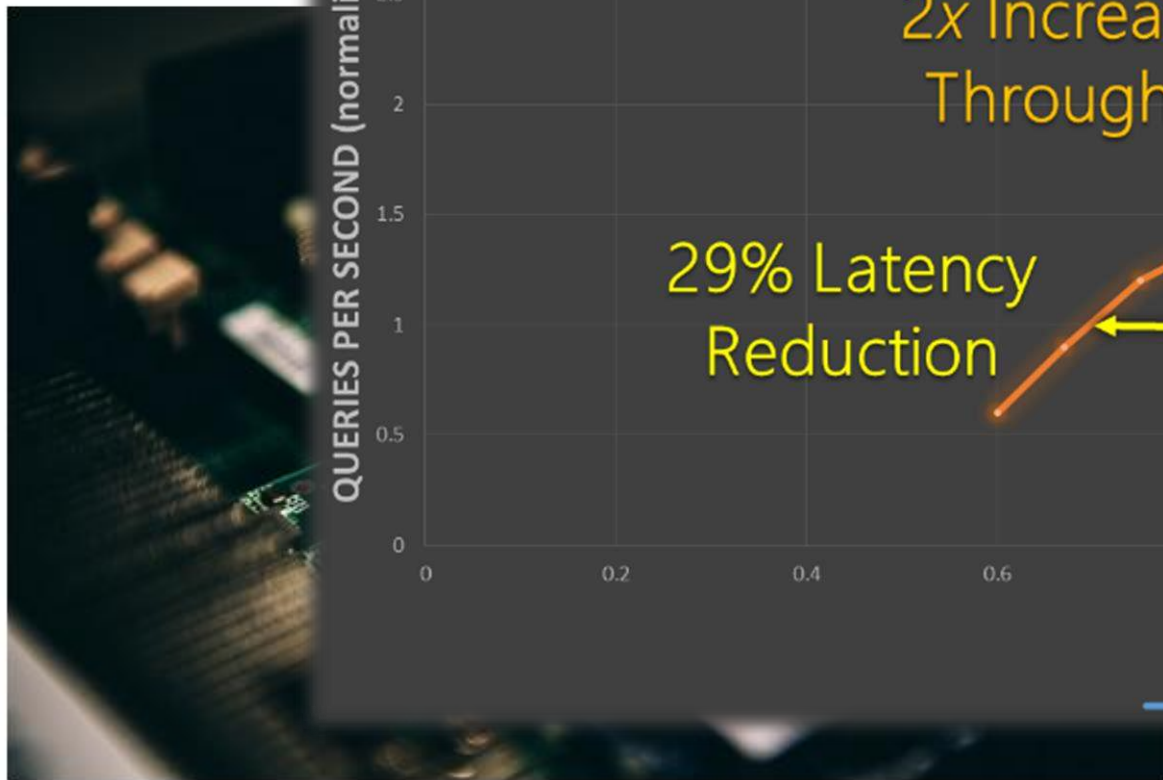
→ Overtake through scale?

MICROSOFT SUPERCHARGES BING SEARCH WITH PROGRAMMABLE CHIPS



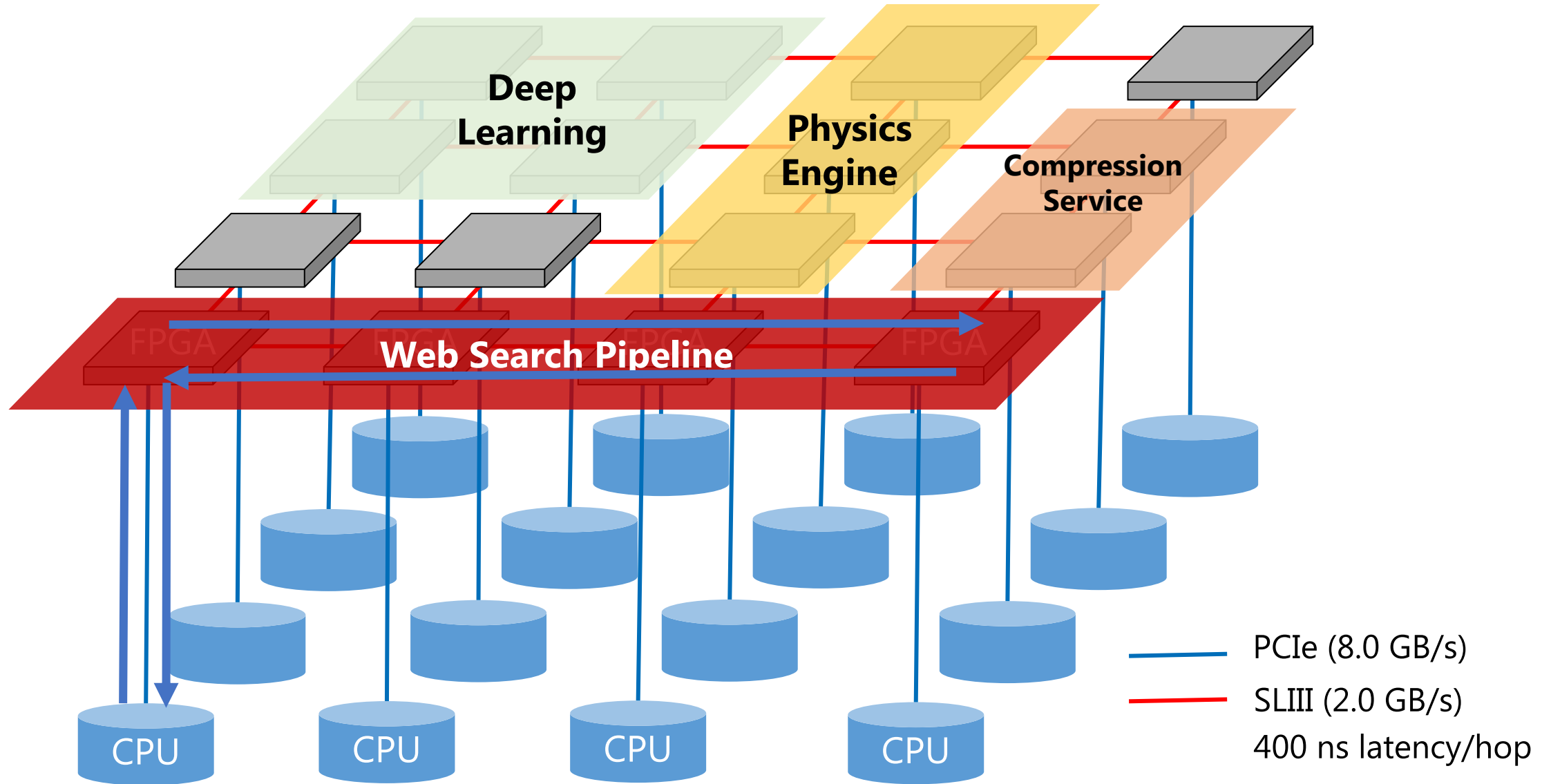
<http://www.wired.com/2014/06/microsoft-fpga/>

MICROSOFT SUPERCHARGES BING SEARCH WITH PROGRAM



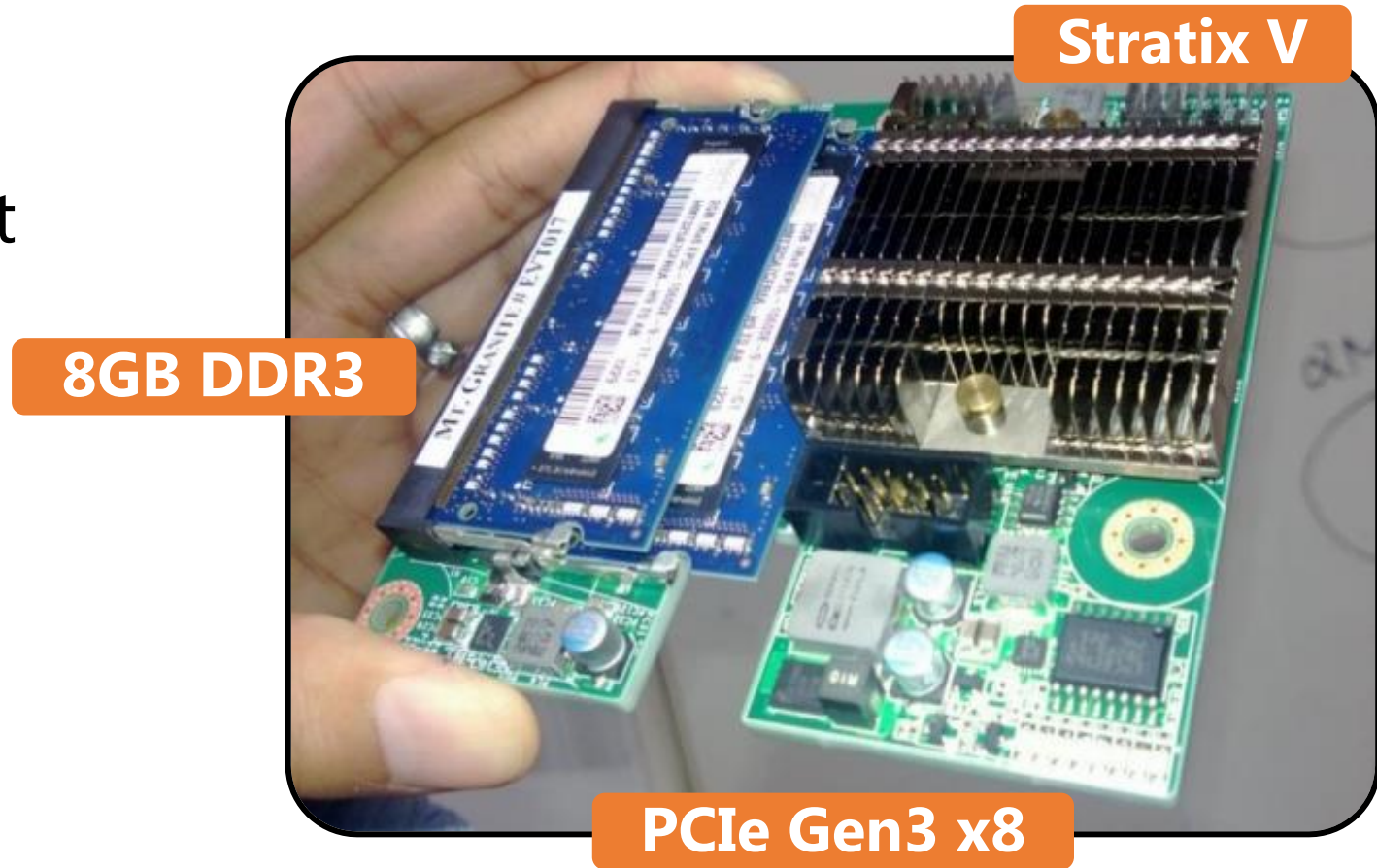
<http://www.wired.com/2014/06/microsoft-fpga/>

Catapult: An Elastic Reconfigurable Fabric for Datacenters



Catapult FPGA Accelerator Card

- Altera Stratix V D5
- 172,600 ALMs, 2,014 M20Ks, 1,590 DSPs
- PCIe Gen 3 x8
- 8GB DDR3-1333
- Powered by PCIe slot
- Torus Network



Microsoft Open Compute Server

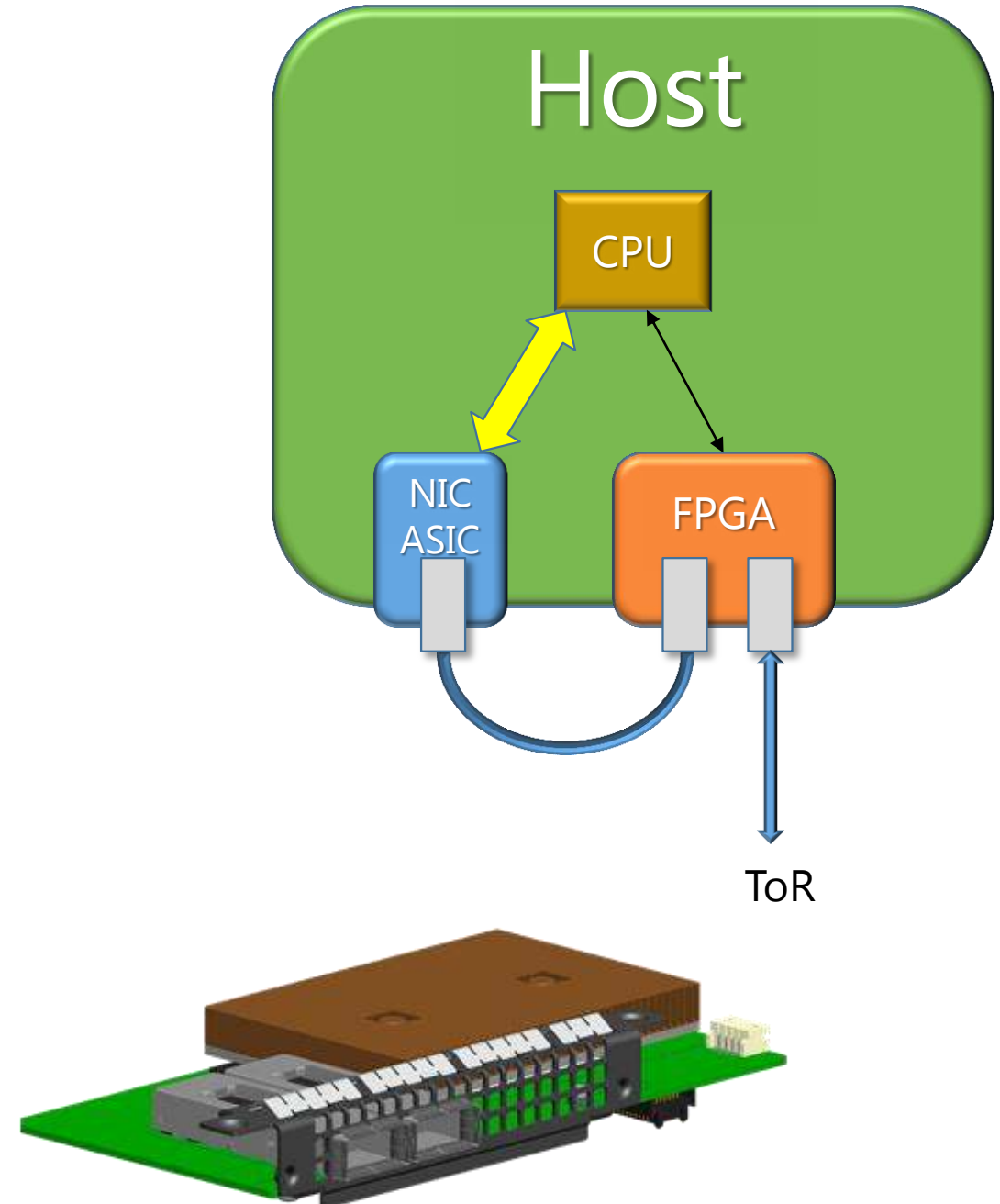


- Two 8-core Xeon 2.1 GHz CPUs
- 64 GB DRAM
- 4 HDDs @ 2 TB, 2 SSDs @ 512 GB
- 10 Gb Ethernet
- No cable attachments to server

Air flow
200 LFM
68 °C Inlet

Azure SmartNIC

- Use Catapult FPGAs for reconfigurable functions
 - Already used in Bing
 - Roll out Hardware as we do software
- Programmed using Generic Flow Tables (GFT)
 - Language for programming SDN to hardware
 - Uses connections and structured actions as primitives
- SmartNIC also does Crypto, QoS, storage acceleration, and more...

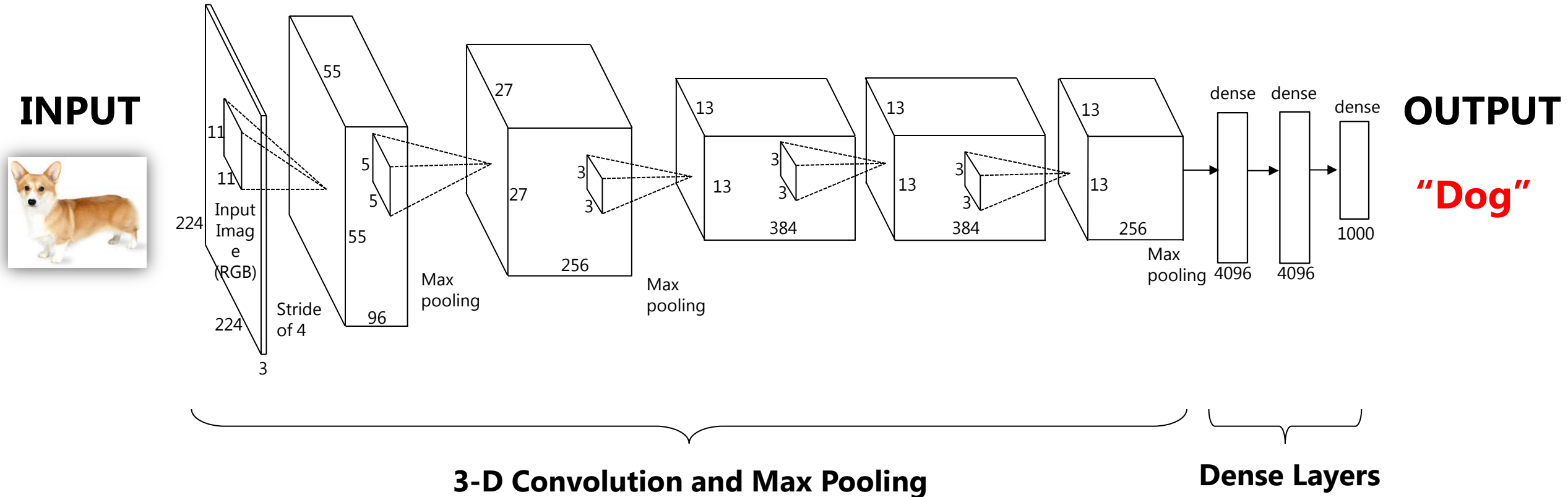


Harnessing Catapult for Deep CNNs

- Leverage abundant FPGA resources in the datacenter for scaling up evaluation and training¹ of deep CNNs
- Achieve order-of-magnitude performance gain relative to CPUs with low cost (<30%) and power (<10%) overheads
- Expose to practitioners as composable SW libraries

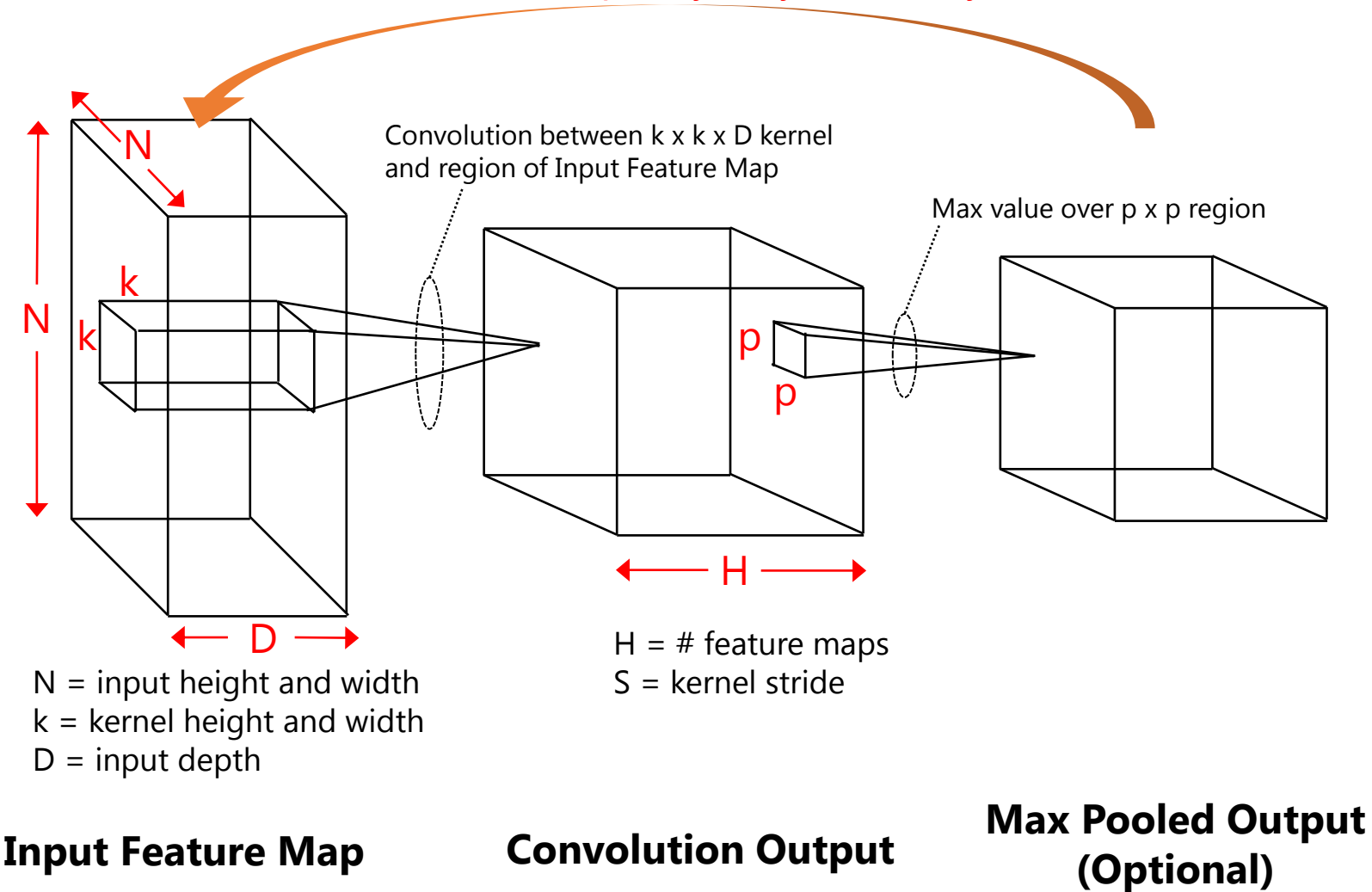
¹*Under development*

Deep Convolutional Neural Networks

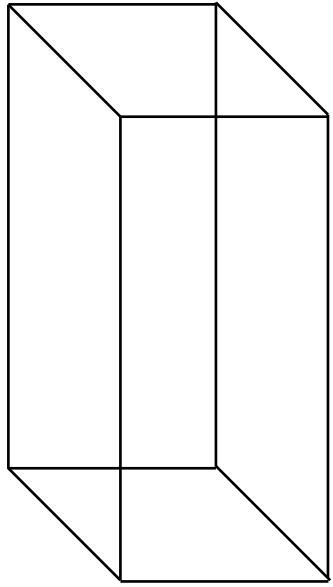


3-D Convolution and Max Pooling

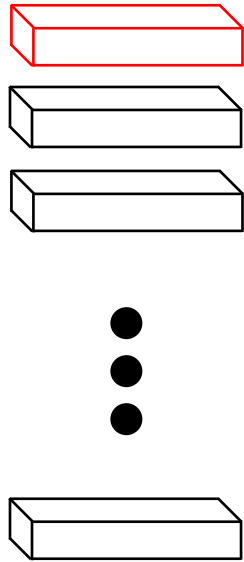
* N, k, H, and p may vary across layers



3-D Convolution



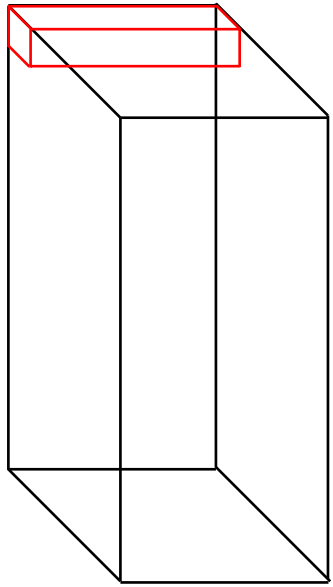
Input



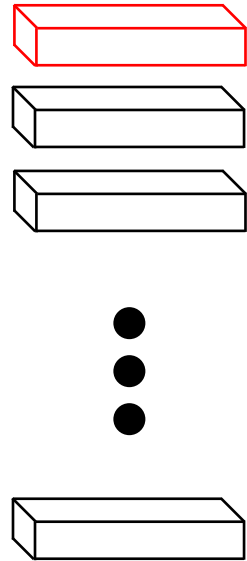
**Kernel
Weights**

Output

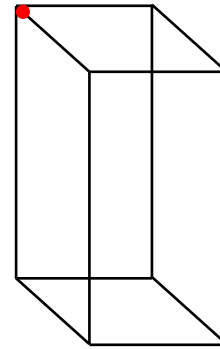
3-D Convolution



Input

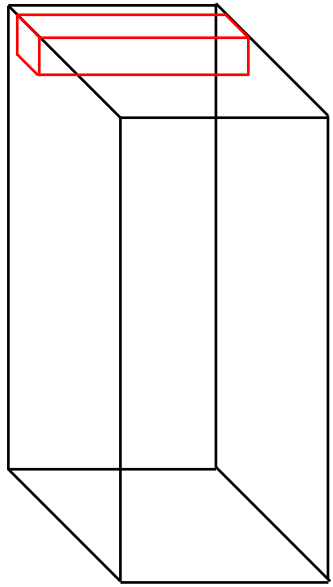


**Kernel
Weights**

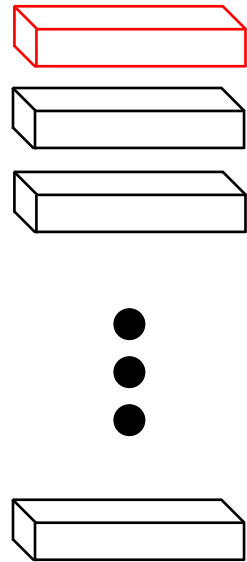


Output

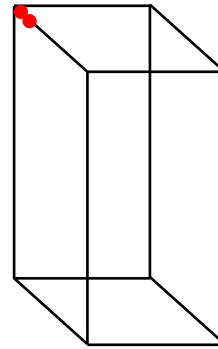
3-D Convolution



Input

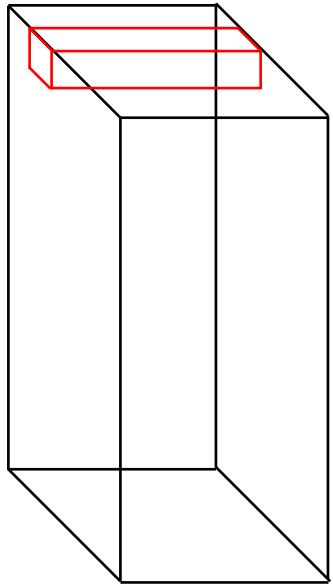


**Kernel
Weights**

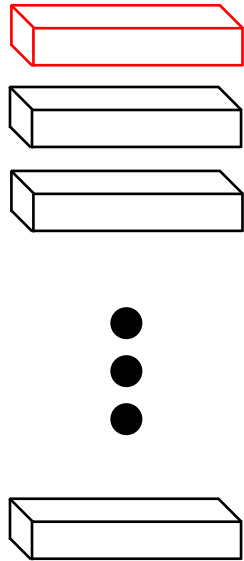


Output

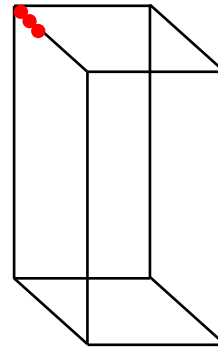
3-D Convolution



Input

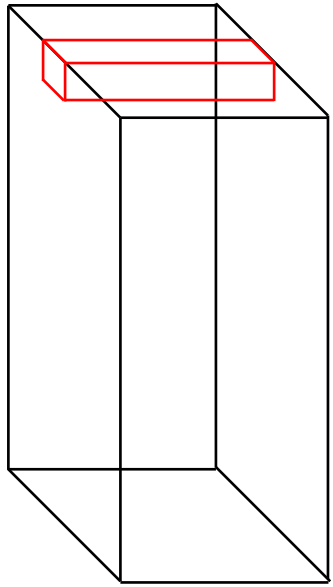


**Kernel
Weights**

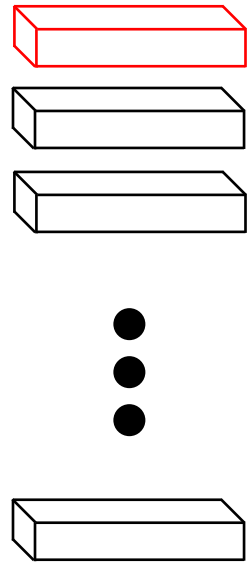


Output

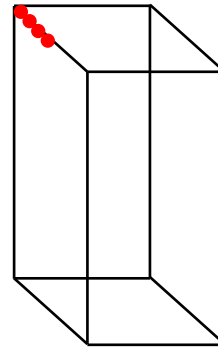
3-D Convolution



Input

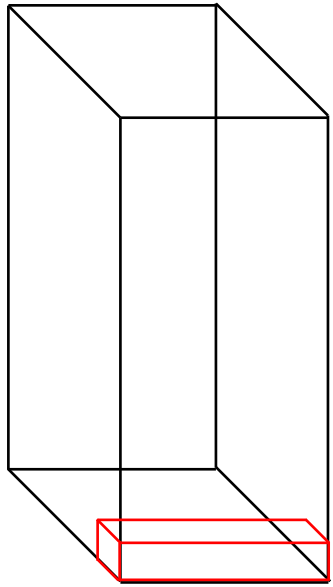


**Kernel
Weights**

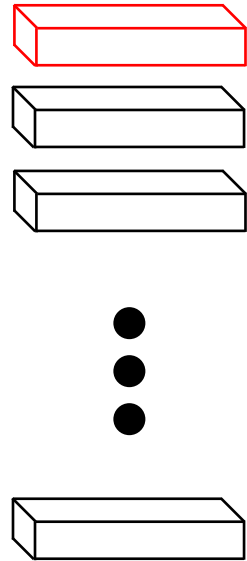


Output

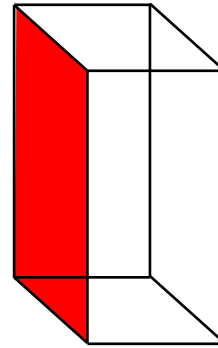
3-D Convolution



Input

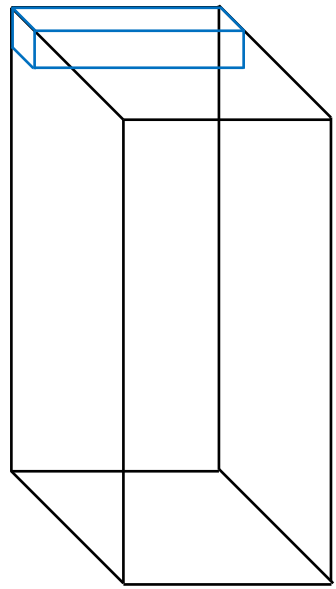


**Kernel
Weights**

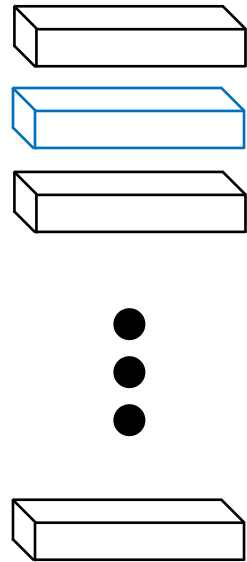


Output

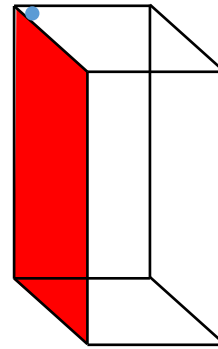
3-D Convolution



Input

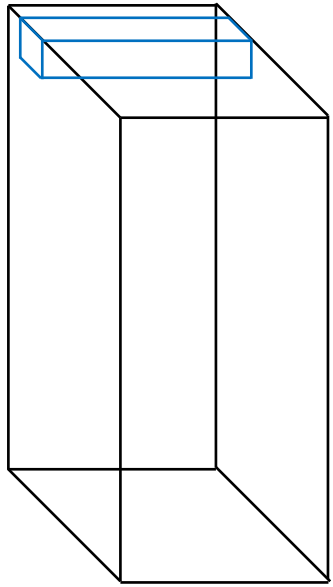


**Kernel
Weights**

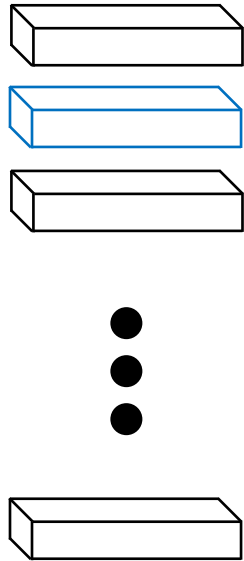


Output

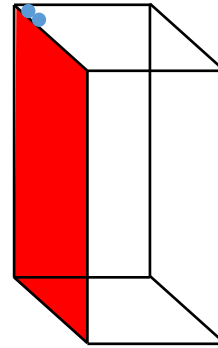
3-D Convolution



Input

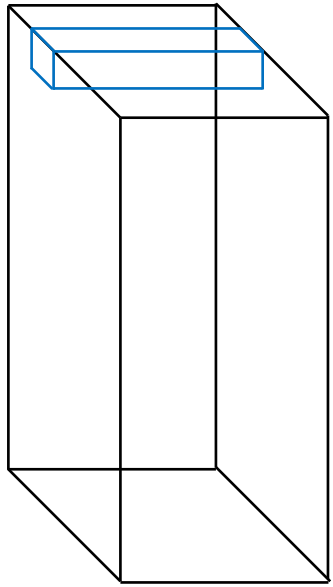


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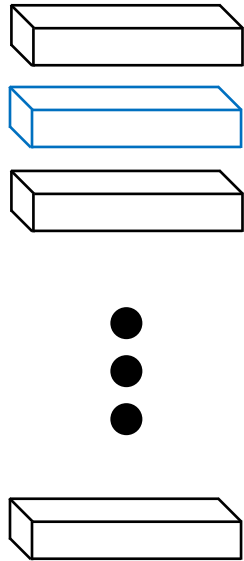


Output

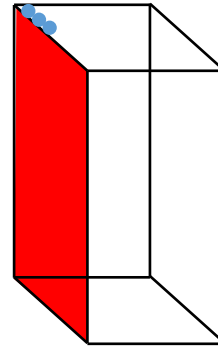
3-D Convolution



Input

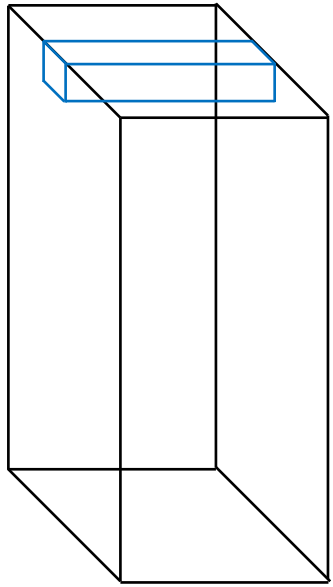


**Kernel
Weights**

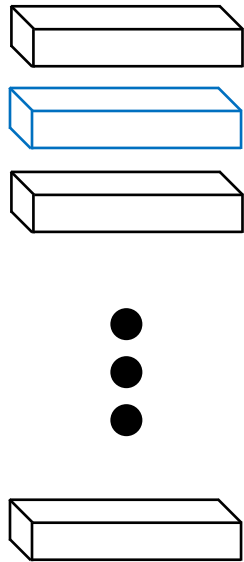


Output

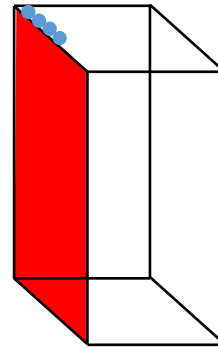
3-D Convolution



Input

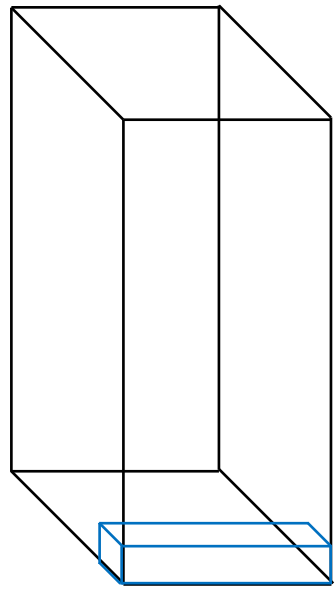


**Kernel
Weights**

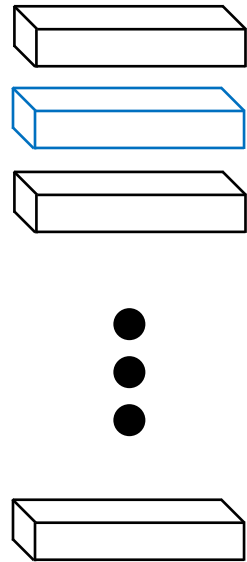


Output

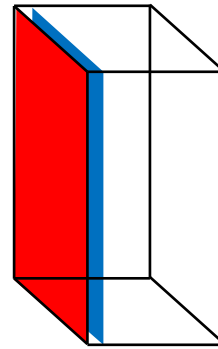
3-D Convolution



Input

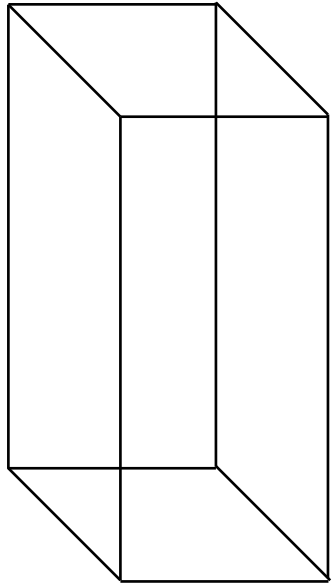


**Kernel
Weights**

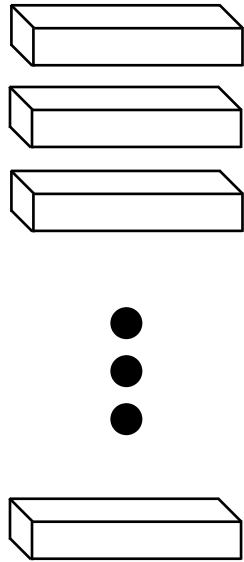


Output

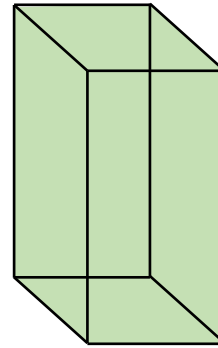
3-D Convolution



Input



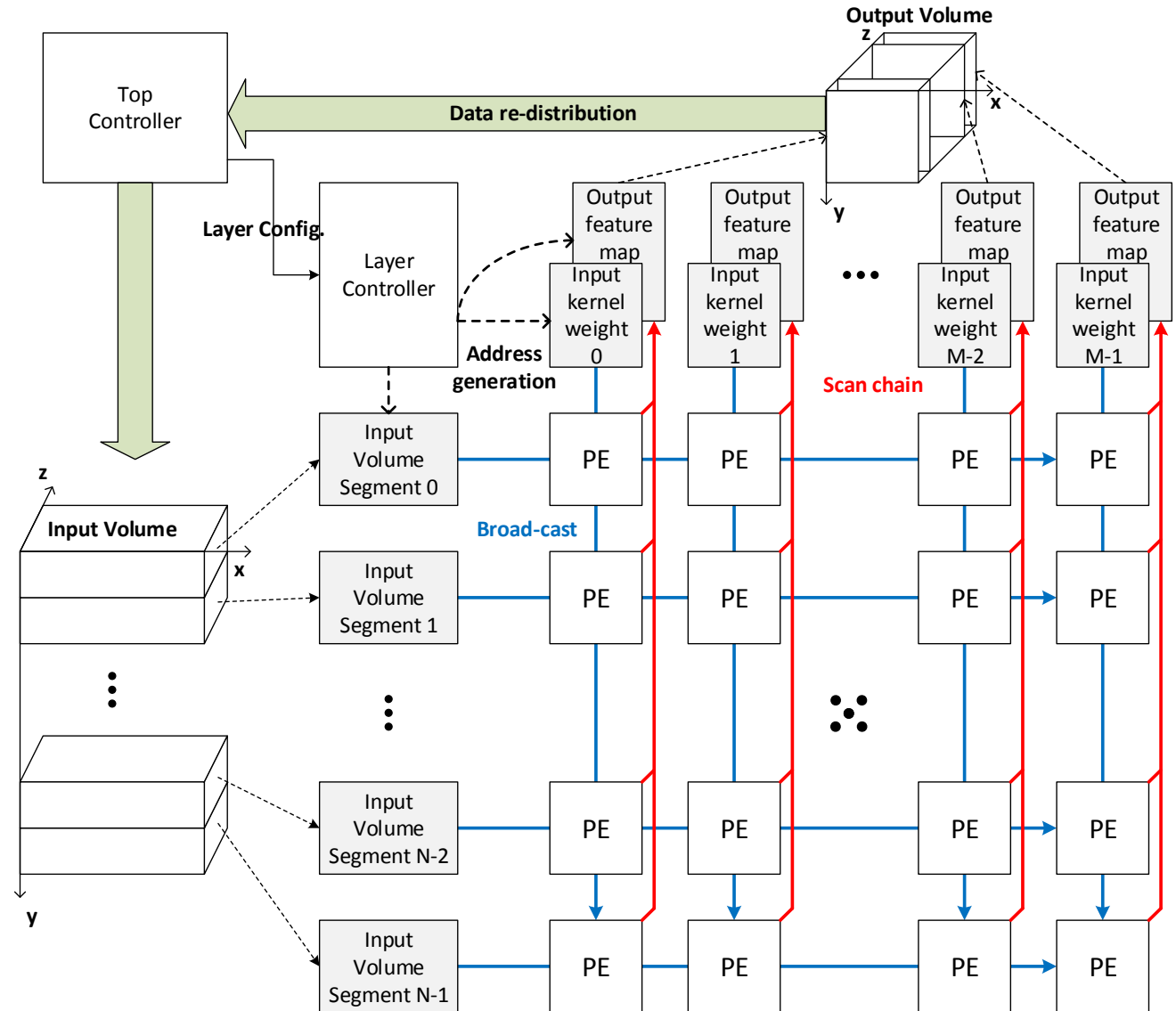
**Kernel
Weights**



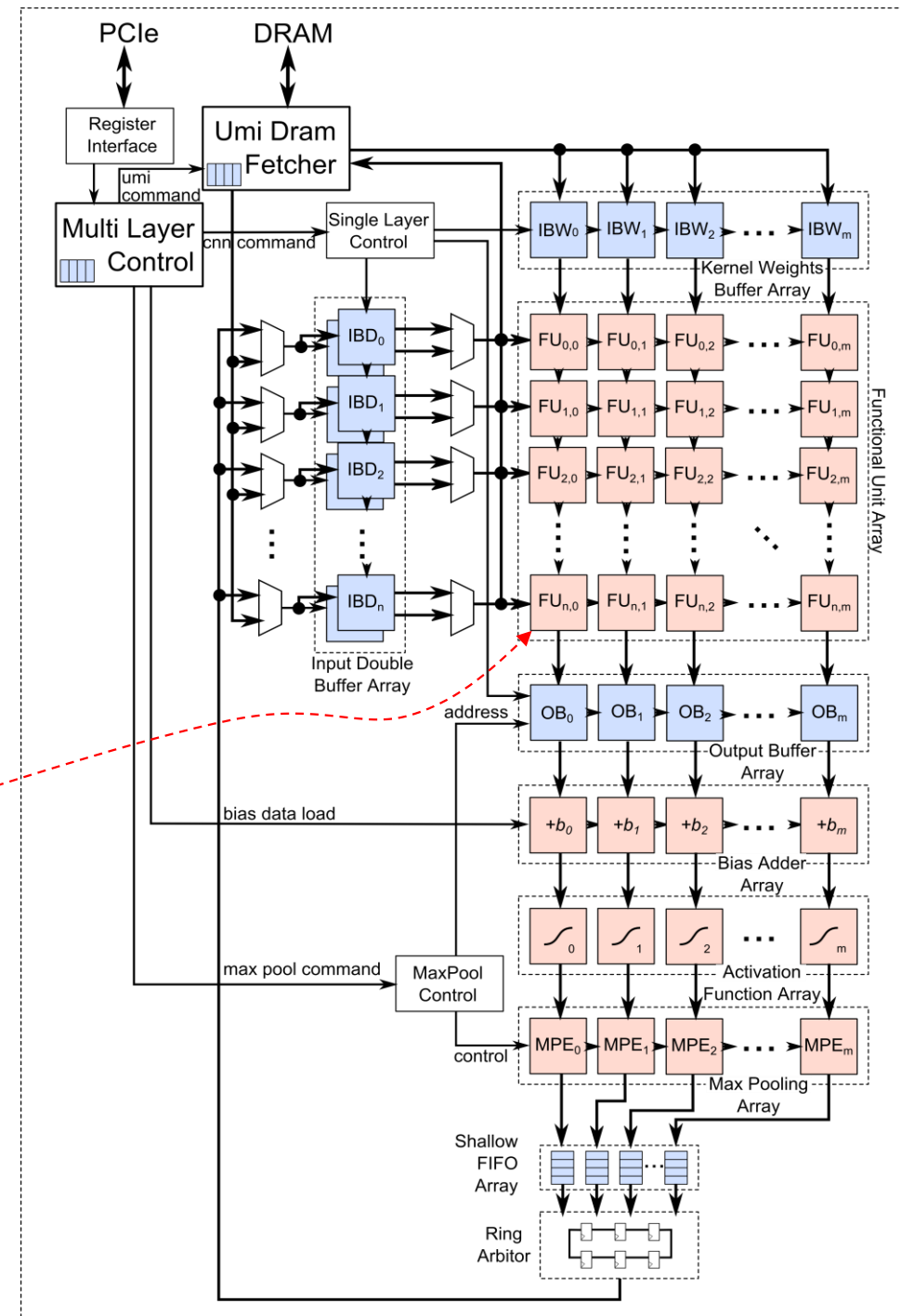
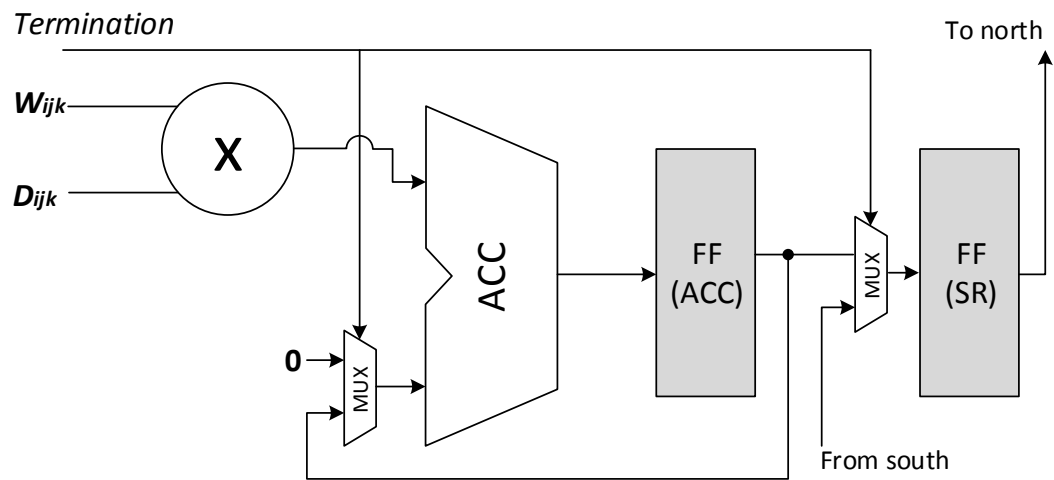
Output

CNN Accelerator Building Block

- Configurable
 - Numerical precision (static)
 - Number of layers
 - Layer dimensions
 - Stride and pooling
- Scalable
 - Can compose multiple engines together over Catapult network
- Efficient
 - Minimize memory bandwidth via data re-distribution NoC
 - On-chip per-row broadcast



Systemic Array Microarchitecture



DEMO

ImageNet-1K Classification Performance

Platform	Library/OS	ImageNet 1K Inference Throughput	Peak TFLOPs	Effective TFLOPs	Estimated Peak Power with Server	Estimated GOPs/J (assuming peak power)
16-core, 2-socket Xeon E5-2450, 2.1GHz	Caffe + Intel MKL Ubuntu 14.04.1*	53 images/s	0.27T	0.074T (27%)	~225W	~0.3
Arria 10 GX1150	Windows Server 2012	369 images/s ¹	1.366T	0.51T (38%)	~265W	~1.9

¹Dense layer time estimated

²<https://github.com/soumith/convnet-benchmarks>

ImageNet-1K Classification Performance

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Arria 10 GX1150	Windows Server 2012	369 images/s ¹	1.366T	0.51T (38%)	~265W	~1.9
NervanaSys-32 on NVIDIA Titan X	NervanaSys-32 on Ubuntu 14.0.4	4129 images/s ²	6.1T	5.75T (94%)	~475W	~12.1

Includes server power; however, CPUs available to other jobs in the datacenter

¹Dense layer time estimated

²<https://github.com/soumith/convnet-benchmarks>

ImageNet-1K Classification Performance

Platform	Library/OS	ImageNet 1K Inference Throughput	Peak TFLOPs	Effective TFLOPs	Estimated Peak Power for CNN Computation	Estimated GOPs/J (assuming peak power)
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Arria 10 GX1150	Windows Server 2012	369 images/s ¹	1.366T	0.51T (38%)	~40W	~12.8
NervanaSys-32 on NVIDIA Titan X	NervanaSys-32 on Ubuntu 14.0.4	4129 images/s ²	6.1T	5.75T (94%)	~250W	~23.0

Under-utilized FPGA vs. highly tuned GPU-friendly workload

¹Dense layer time estimated

²<https://github.com/soumith/convnet-benchmarks>

Projected Improvements with Tuning

Platform	Library/OS	ImageNet 1K Inference Throughput	Peak TFLOPs	Effective TFLOPs	Estimated Peak Power for CNN Computation	Estimated GOPs/J (assuming peak power)
16-core, 2-socket Xeon E5-2450, 2.1GHz	Caffe + Intel MKL Ubuntu 14.04.1*	53 images/s	0.27T	0.074T (27%)	~225W	~0.3
Arria 10 GX1150	Windows Server 2012	369 images/s ¹ ~880 images/s	1.366T	0.51T (38%) ~1.2T (89%)	~40W	20.6 ~30.6
NervanaSys-32 on NVIDIA Titan X	NervanaSys-32 on Ubuntu 14.0.4	4129 images/s ²	6.1T	5.75T (94%)	~250W	~23.0

*Projected Results Assuming
Floorplanning and Scaling Up PEs*

¹Dense layer time estimated

²<https://github.com/soumith/convnet-benchmarks>

Are FPGAs a Promising Target in the Datacenter for Deep Learning? **Yes.**

- Best-case FPGA design is $\sim 1/5$ th GPU throughput but can overtake at scale
- Although CNNs are ideal on GPUs, FPGAs with hardened FPUs can achieve GPU-like energy efficiency
- FPGA is 7X faster (~ 16 X within reach) than multicore CPUs while flexible enough for diverse cloud scenarios (Bing Ranking, Azure SmartNIC)

Related Work

- ASICs
 - [Holler'90], [Chen'14], [Cavigelli'15], etc.
- FPGAs
 - [LeCun'09], [Farabet'10], [Aysegul'13], [Baidu'14], [Gokhale'15], [Zhang'15], etc.
- GPUs, Appliances
 - Nervana, Nvidia DIGITS, Ersatz, etc.

Thank you!
erchung@microsoft.com