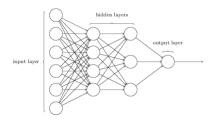
Accelerating AI in Datacenters Xilinx ML Suite

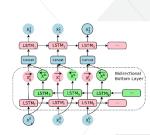
Kamran Khan Sr. Product Manager, Al and Machine Learning



Deep Learning Models – A broad spectrum







Multi-Layer Perceptron

- Classification
- Universal Function Approximator
- Autoencoder

Convolutional Neural Network

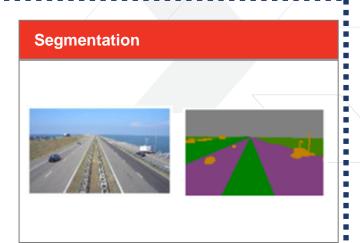
- Feature Extraction
- Object Detection
- Image Segmentation

Recurrent Neural Network

- Sequence and Temporal Data
- Speech to Text
- Language Translation

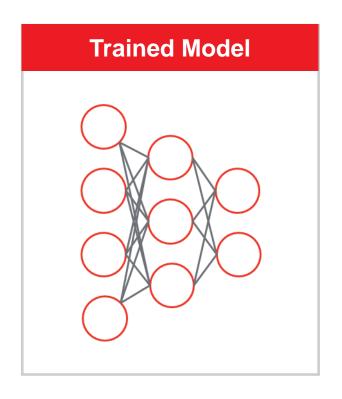


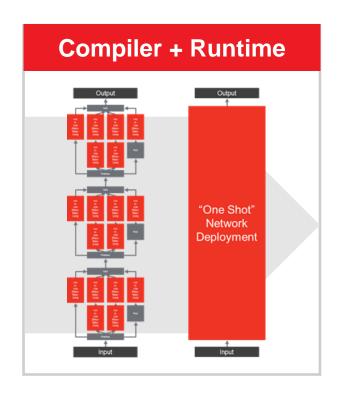


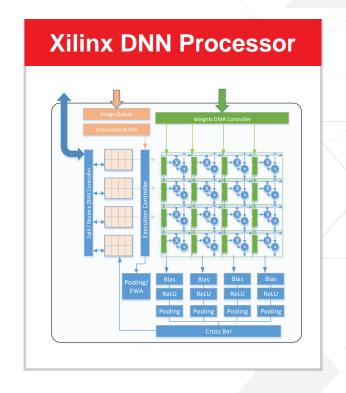




Xilinx ML Suite – DNN Processor + "Compiler, Quantizer, Runtime"







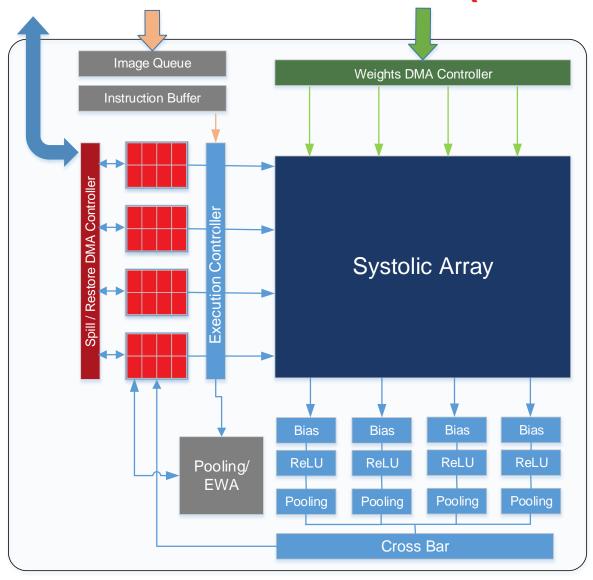
Low Latency, High Throughput – Batch 1

60-80% Efficiency

No FPGA Expertise Required



Xilinx DNN Processor (xDNN)



- > Configurable Overlay Processor
- DNN Specific Instruction Set Convolution, Max Pool etc.
- > Any Network, Any Image Size
- > High Frequency & High Compute Efficiency
- > Compile and run new networks



Rapid Feature and Performance Improvement

xDNN-v1 Q4CY17

- Array of Accumulator
- Int16 (Batch=1) and Int8 (Batch=2) support
- Instructions: Convolution, ReLU, Pool, Elementwise
- Flexible kernel size(square) and strides
- 500 MHz

xDNN-v2 Q2CY18

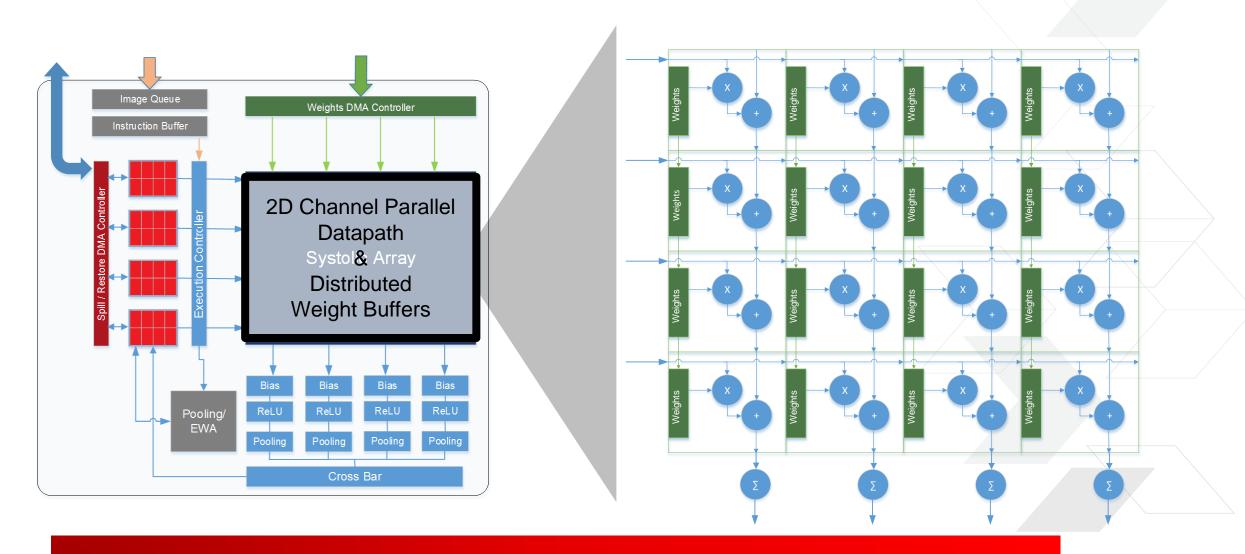
- All xDNN-v1 Features
- DDR Caching: Larger Image size
- New Instructions: Depth-wise Convolution, De-convolution, Up-sampling
- Rectangular Kernels
- 500 MHz

xDNN-v3 Q4CY18

- New Systolic Array Implementation: 2.2x lower latency
- Instruction Level Parallelism non-blocking data movement
- Batch=1 for Int8 lower latency
- Feature compatible with xDNN-v2
- 720+ MHz



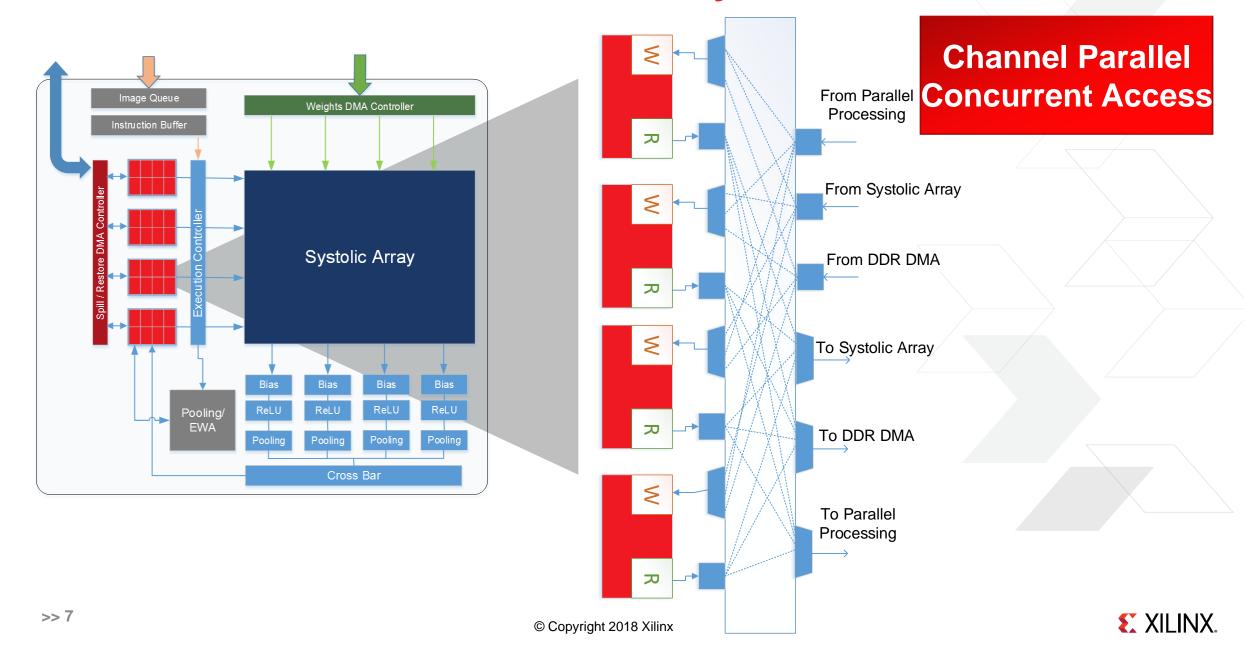
xDNN – Channel Parallel Systolic Array



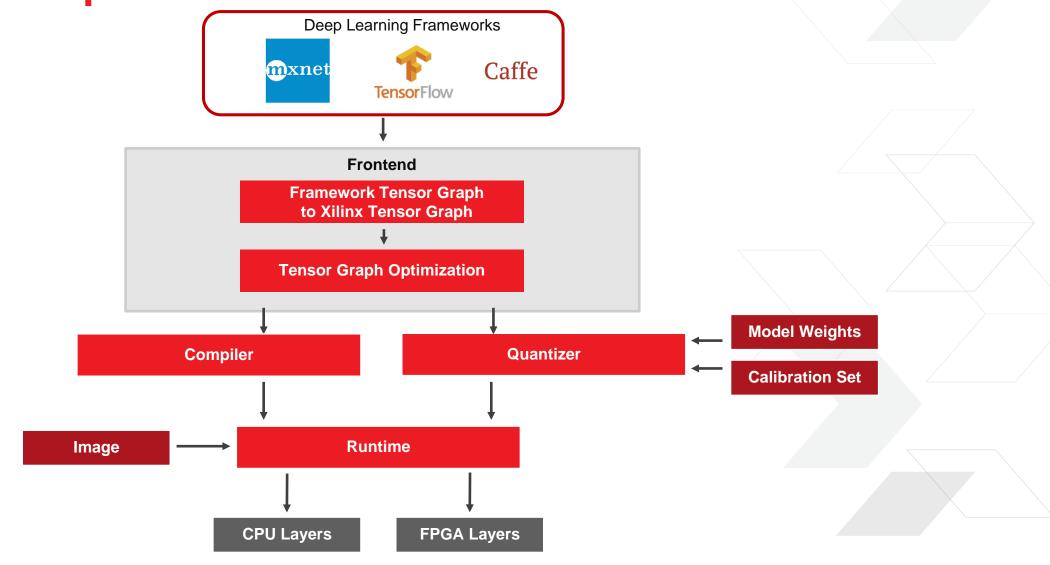
Micro-Architecture Optimized for underlying Ultrascale+ FPGA Fabric



xDNN Processor – Tensor Memory



xDNN Compiler + Runtime

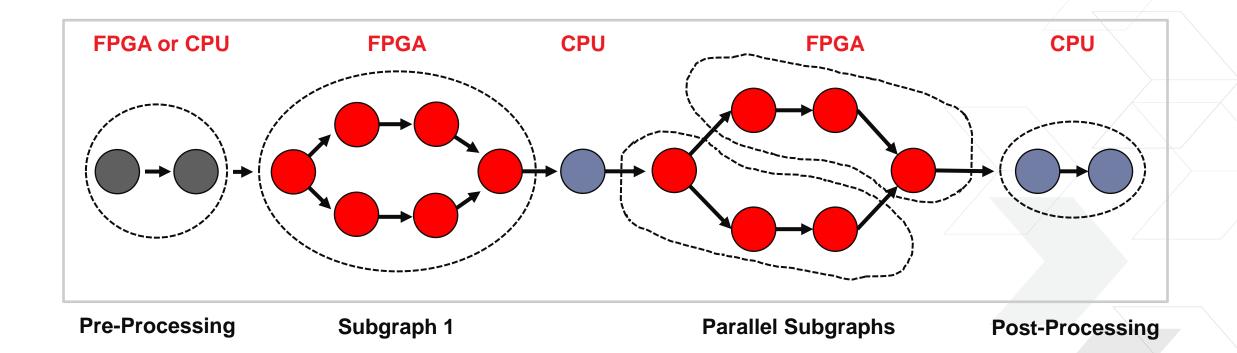


https://github.com/Xilinx/ml-suite



Graph Partitioning

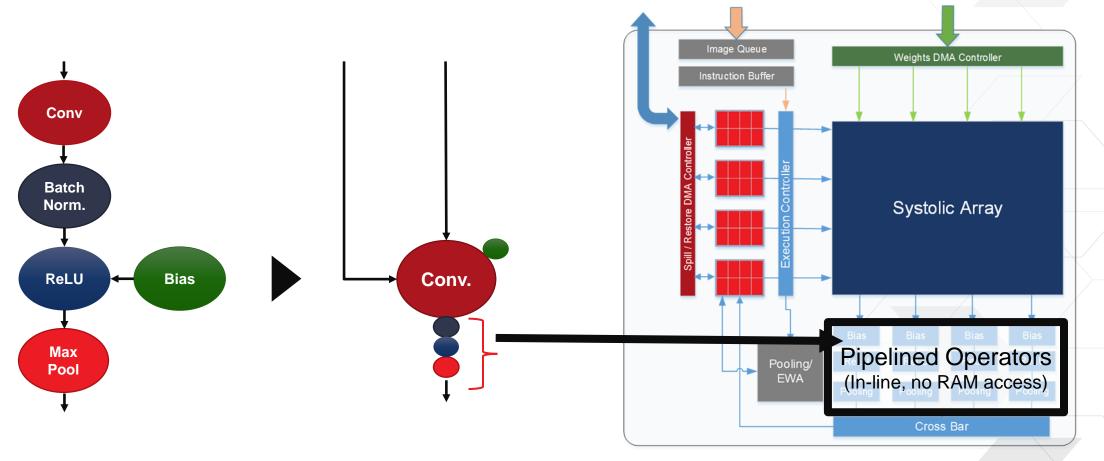
- > One time loading of sub-graph instructions
- Data Flow Execution



1 Core -> Multi-Core -> Multi-Chip



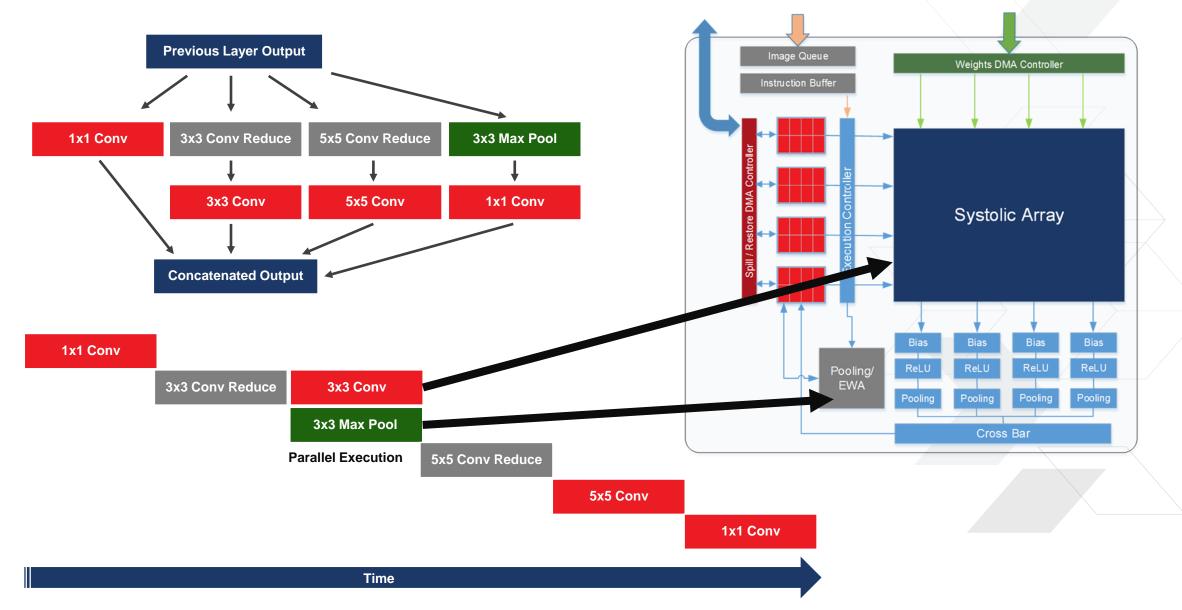
Fusing of Operations



- > Fuse operations as pipe-lined stages
- > Access activations only once

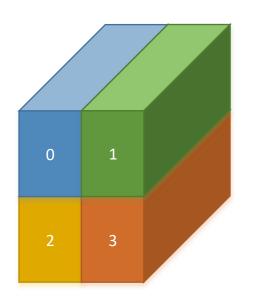


Instruction Level Parallelism



Automatic Intra Layer Tiling

- > Tile when Feature Map size exceeds on-chip memory
- > Work on full feature map depth



Any Feature Map Size





xfDNN Runtime Engine

- > ML specific engine built on top of SDx runtime
- > Lightweight and portable with no dependency on ML frameworks
- > Extensive C++/Python API with simplified use model
- > Asynchronous XDNN execution
- > Streaming/pipeline/Dataflow support for large imageset
- > Multiple CNN models running on single FPGA
- > Multiple FPGA support



Simple Usage

```
import xdnn, xdnn io
args = xdnn io.processCommandLine()
xdnn.createHandle(args['xclbin'], "kernelSxdnn 0", args['xlnxlib'])
(weightsBlob, fcWeight, fcBias) = xdnn io.loadWeights(args)
(fpgaInputs, batch sz) = xdnn io.prepareInput(args)
fpgaOutput = xdnn io.prepareOutput(args['fpgaoutsz'], batch sz)
xdnn.execute(args['netcfg'],
  weightsBlob, fpgaInputs, fpgaOutput,
  batch sz, args['quantizecfg'])
fcOut = xdnn.computeFC(fcWeight, fcBias, fpgaOutput)
softmaxOut = xdnn.computeSoftmax(fcOut)
xdnn_io.printClassification(softmaxOut, args);
xdnn.closeHandle()
```

```
Blocking
```

```
# exec_async() enqueues FPGA task and returns immediately
xdnn.exec_async(args['netcfg'],
  weightsBlob, fpgaInputs, fpgaOutput,
  batch_sz, args['quantizecfg'], args['PE'])

# get_result() blocks for FPGA result
xdnn.get_result(args['PE'])
```

```
numFPGAs = 8
args = xdnn_io.processCommandLine()
xdnn.createHandle(args['xclbin'], "kernelSxdnn_0", args['xlnxlib'], numFPGAs)
(weightsBlob, fcWeight, fcBias) = xdnn_io.loadWeights(args)
```

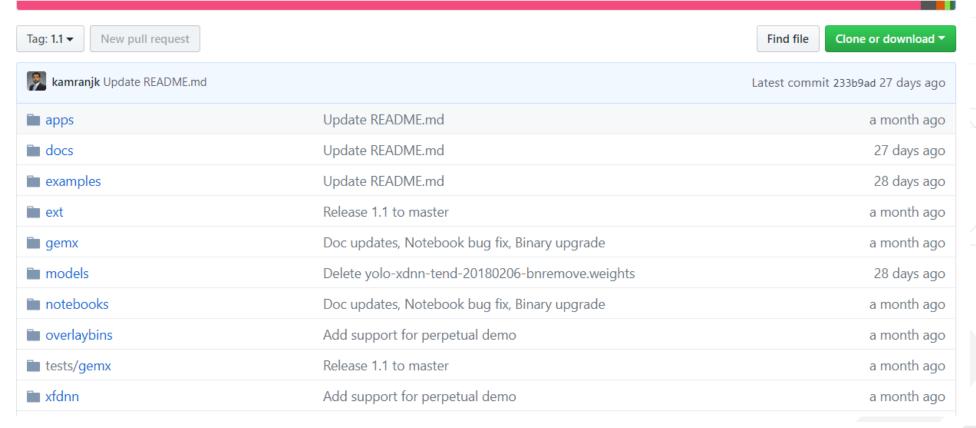






https://github.com/Xilinx/ml-suite

Xilinx ML Suite



Server Platforms
Intel x86, AMD Epyc,
Power9, ARM





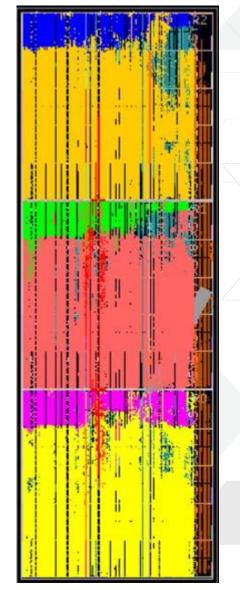
*Under Development



xDNN v3 Implementation on Alveo U200

- > 3 Large 96x16 PEs- 1 in each SLR 5.2 ML Shell
- > Kernels @ 720 MHz/360MHz

Resource	Count	Utilization
LUTs	658k	52%
DSPs	5661	80%
BRAM	1258	58%
URAM	864	92%

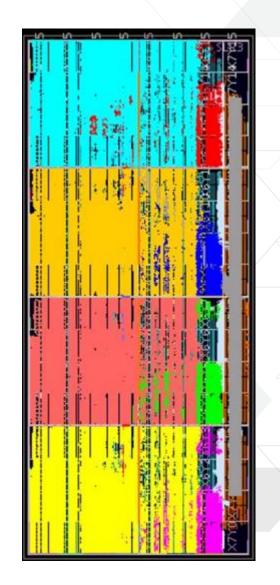




xDNN v3 Implementation on Alveo U250

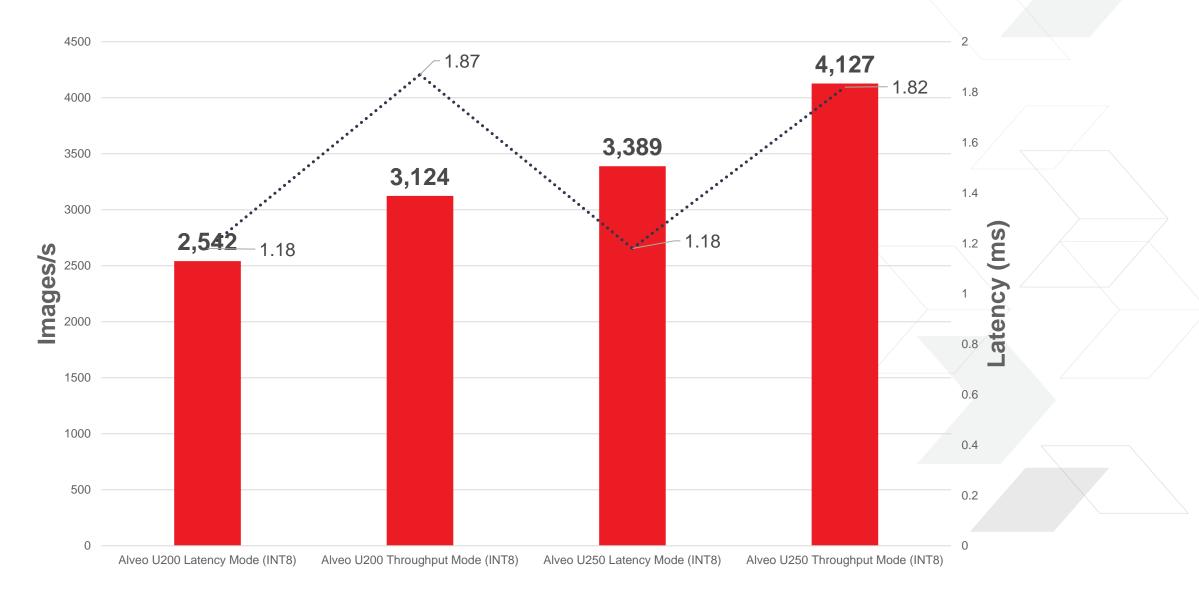
- > 4 Large 96x16 PEs- 1 in each SLR standard 5.2 Shell
- > Kernels at 700 MHz/350 MHz

Resource	Count	Utilization
LUTs	876k	51%
DSPs	7548	62%
BRAM	1632	61%
URAM	1152	90%



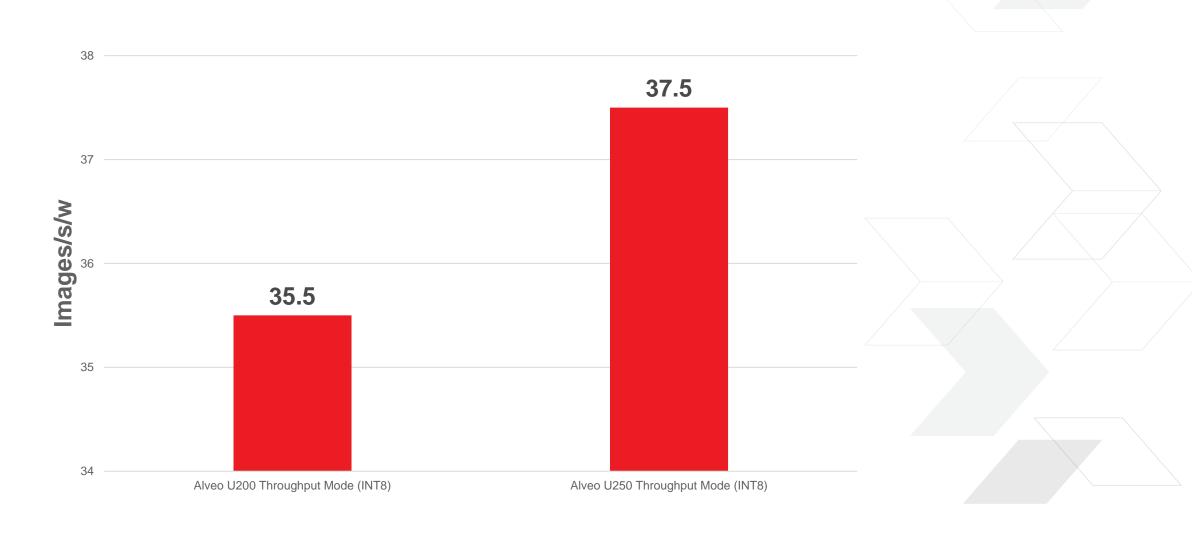


xDNN GoogLeNet v1 Performance – Image Size 224x224



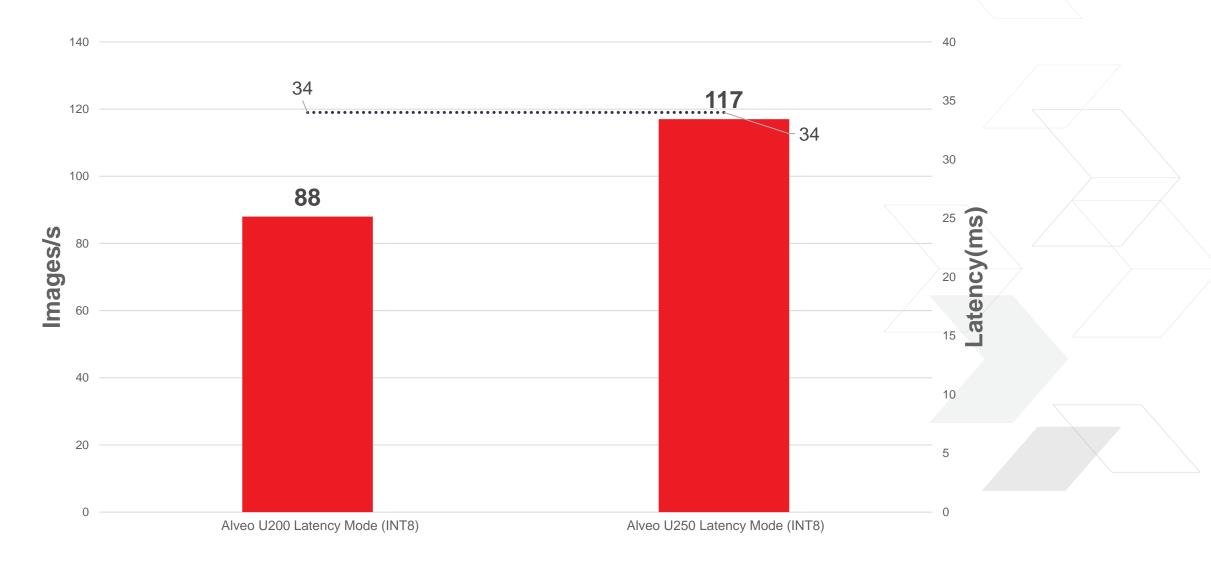


xDNN GoogLeNet v1 Energy Efficiency





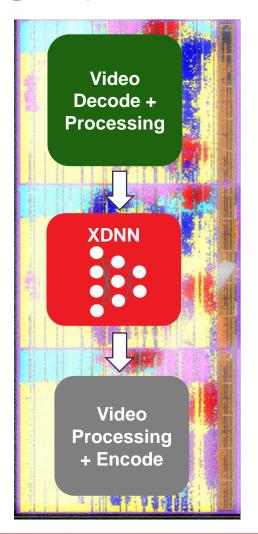
xDNN YOLO v2 Performance – Image Size 608x608

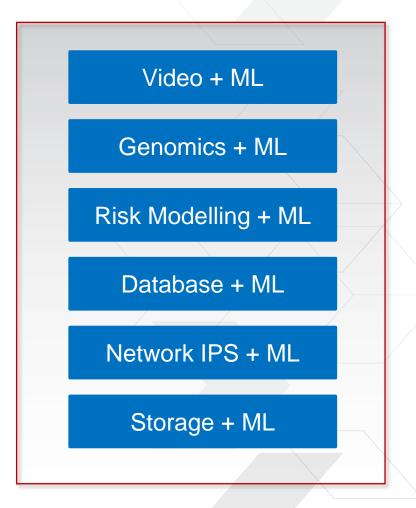


Custom Deep Learning Pipeline









Integrate Custom Applications with xDNN. Lower end-to-end latency



Additional Information

- Visit Alveo Demo Room
- > Refer to White Paper WP504
 - >> "Accelerating DNNs with Xilinx Alveo Accelerator Cards"
- > https://www.xilinx.com/applications/megatrends/machine-learning.html

White Paper: Alveo Data Center Accelerator Cards



Accelerating DNNs with Xilinx Alveo Accelerator Cards

The Xilinx xDNN processing engine, using Xilinx Alveo Data Center accelerator cards, is a high-performance energy-efficient DNN accelerator and outperforms many common CPU and GPU platforms today in raw performance and power efficiency for real-time inference workloads. The xDNN processing engine is delivered through the ML Suite available on many cloud environments, such as AWS EC2 or Nimbix NXS.

ABSTRACT

The Xilinx® Deep Neural Network (xDNN) engine provides high-performance, low-latency, energy-efficient DNN acceleration using Xilinx® Alveo™ Data Center accelerator cards. By keeping energy costs low and minimizing the number of specific accelerators needed in the implementation, total cost of ownership (TCO) can be significantly reduced.

Xilinx Alveo accelerator cards excel at high-performance, energy-efficient, flexible Machine Learning (ML) inference. The xDNN processing engine has been developed to generically execute Convolutional Neural Networks (CNNs) like ResNet50, GoogLeNet v1, Inception v4—even CNNs containing custom layers.

This white paper presents an overview of the xDNN hardware architecture and software stack, as well as benchmarking data that supports the claim of "Best in Class" energy-efficient inference.

Guidance to the reader is provided to enable re-creation of the results on the

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WP504 (v1.0) October 2, 2018

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Adaptable. Intelligent.



