

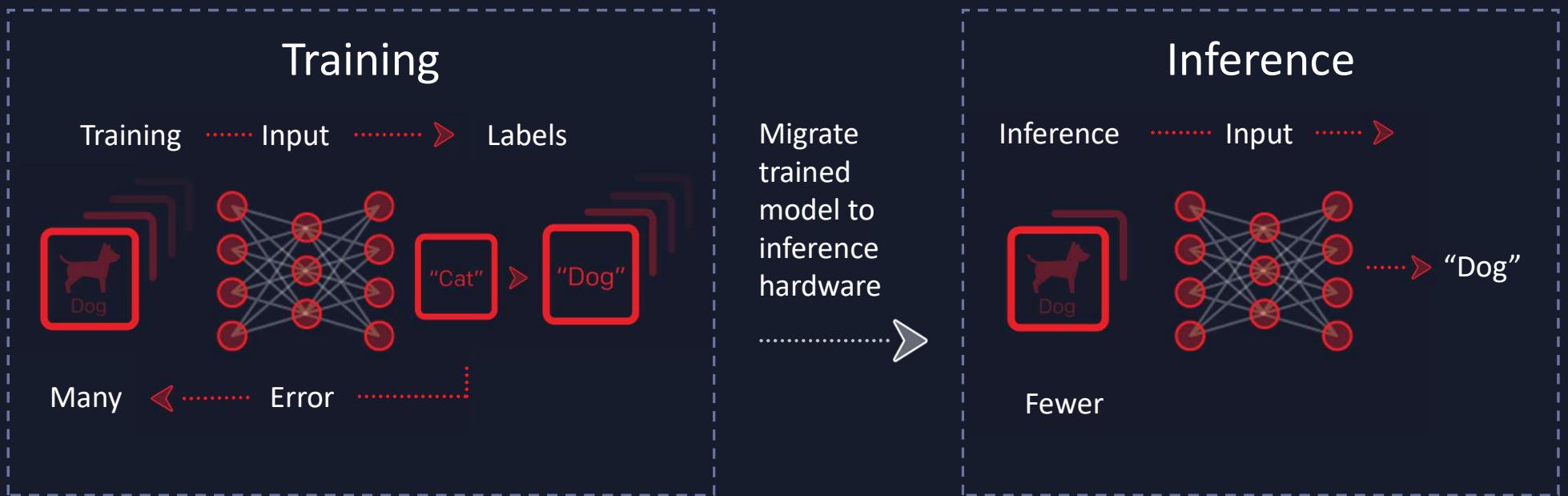


AI Acceleration

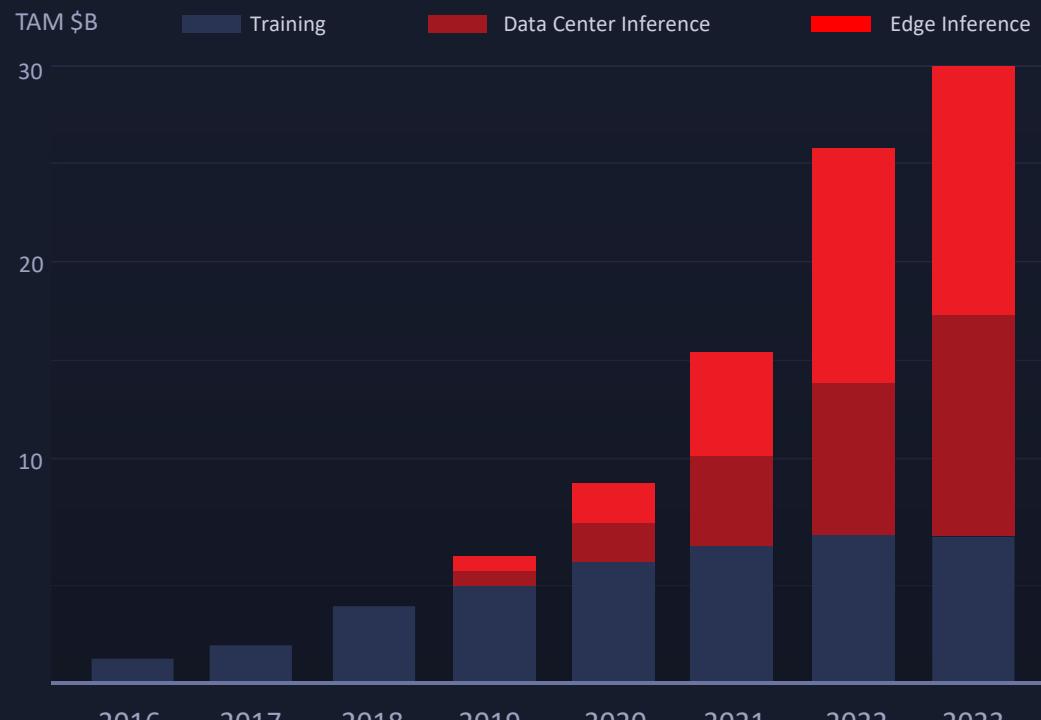
Andy Luo



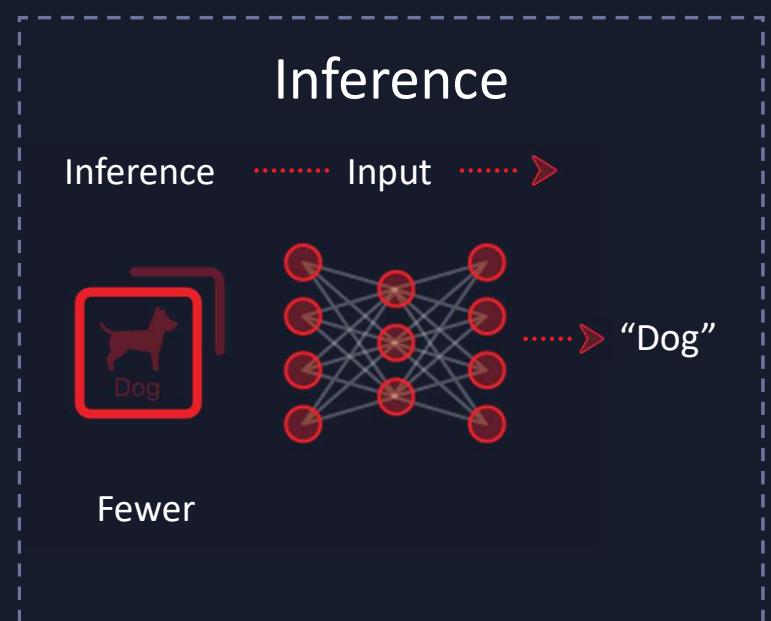
➤ Training vs. Inference



► Inference Projected Growth



Barclays Research, Company Reports May 2018



➤ Inference Challenges



The rate of AI innovation



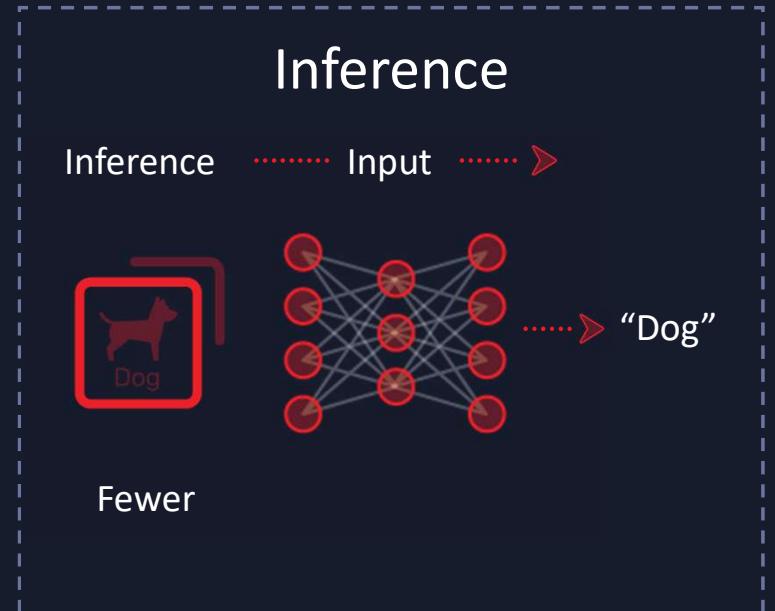
Performance at low latency



Low power consumption



Whole app acceleration



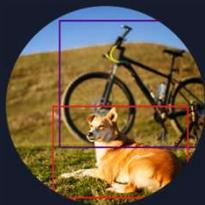
➤ The Rate of AI Model Innovation

APPLICATIONS

Classification



Object Detection



Segmentation



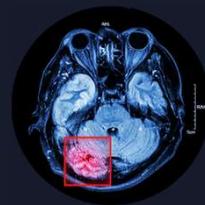
Speech Recognition



Recommendation Engine



Anomaly Detection



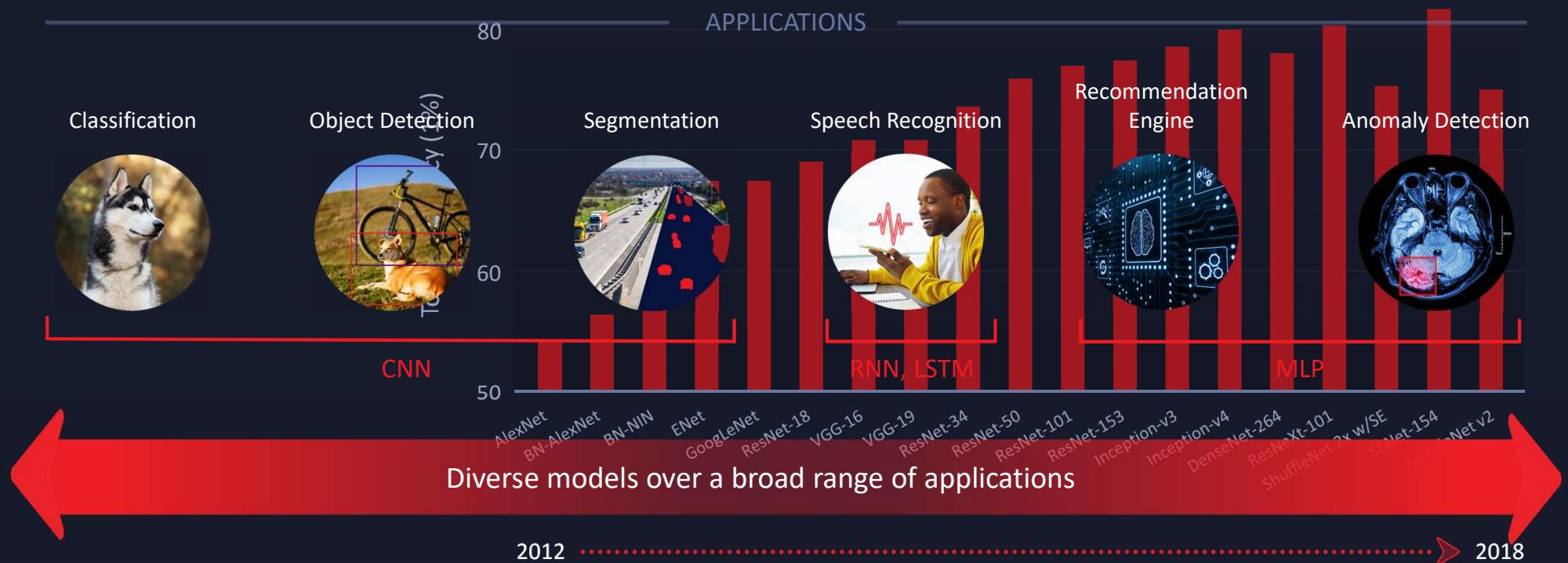
CNN

RNN, LSTM

MLP

Diverse models over a broad range of applications

➤ The Rate of AI Model Innovation: Classification



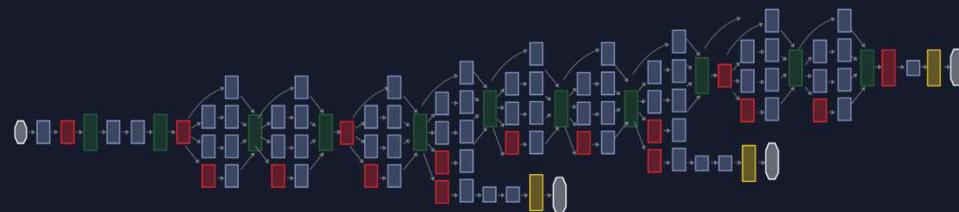
Source:
<https://arxiv.org/pdf/1605.07678.pdf> <https://arxiv.org/pdf/1608.06993.pdf>
<https://arxiv.org/pdf/1709.01507.pdf> <https://arxiv.org/pdf/1611.05431.pdf>

► Network Complexity is Growing

AlexNet



GoogLeNet



DenseNet





The Rate of AI Innovation



Inference is Moving to Lower Precision

RELATIVE ENERGY COST

Operation:	Energy (pJ)
8b Add	0.03
16b Add	0.05
32b Add	0.1
16b FP Add	0.4
32b FP Add	0.9

Source: Bill Dally (Stanford), Cadence Embedded Neural Network Summit, February 1, 2017

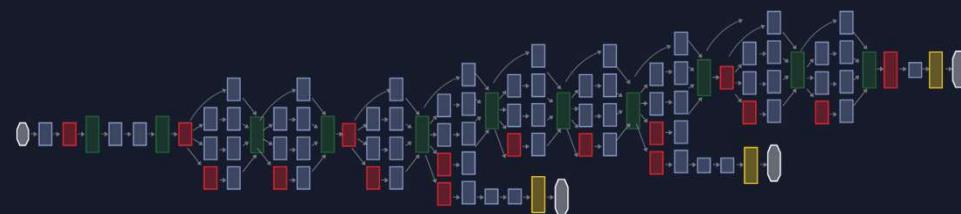


➤ Rate of Innovation Outpaces Silicon Cycles

AlexNet



GoogLeNet



DenseNet



Silicon lifecycle





➤ Only Adaptable Hardware Addresses Inference Challenges

Custom data flow



Custom memory hierarchy



Custom precision



Domain Specific Architectures
(DSAs)
on Adaptable Platforms



The Rate of AI Innovation

➤ DeePhi Joins Xilinx

Custom data flow



Custom memory hierarchy



Custom precision



DEEPhi Now Part of **XILINX.**



Pruning



Quantization



Patented Compression Technology

- Reduces DL accelerator footprint
- Increases performance per watt

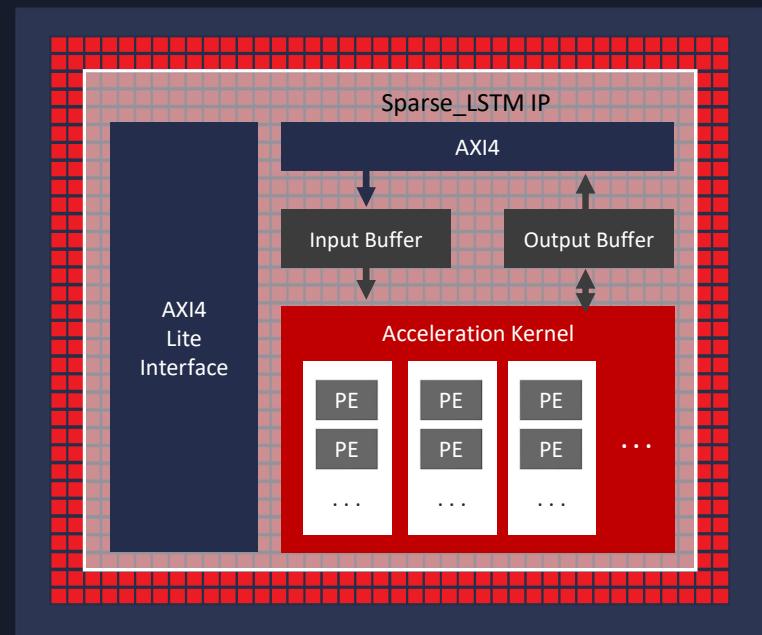


➤ Example: DeePhi LSTM

Custom data flow
LSTM for speech recognition

Custom memory hierarchy
Sparse matrix implementation in memory

Custom precision
12 bit weights, 16 bit activations



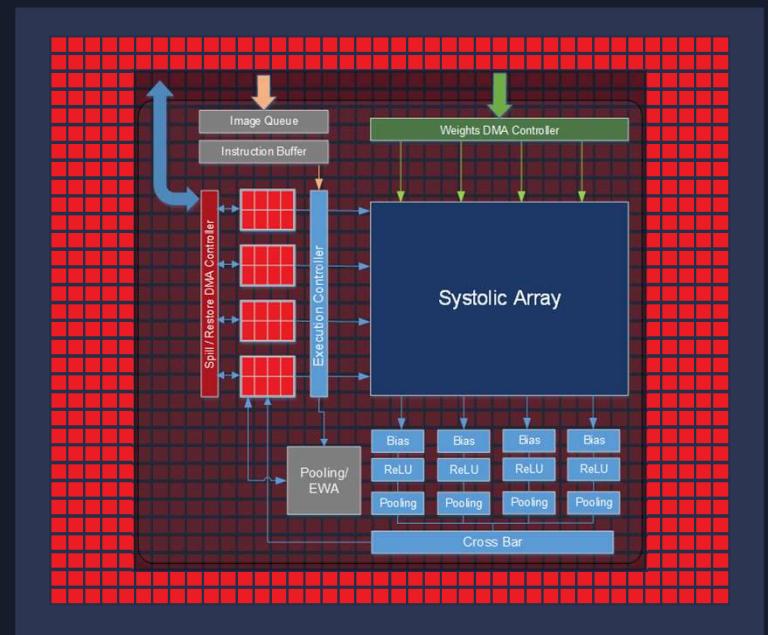


➤ Example: xDNN

Custom data flow
Optimized for latest CNN

Custom memory hierarchy
Optimized on-chip memory

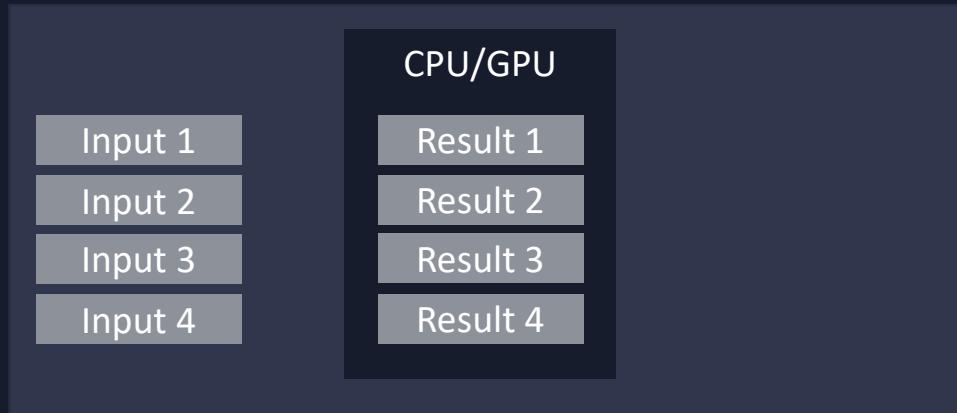
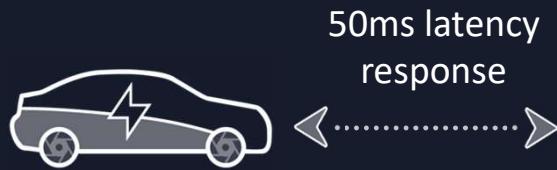
Custom precision
Int8



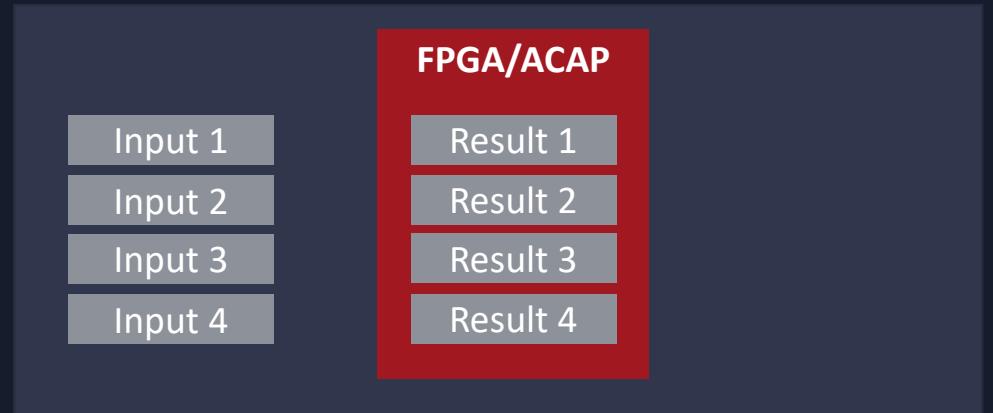


Performance at Low Latency

➤ Low Latency is Critical for Inference



High throughput **OR** low latency

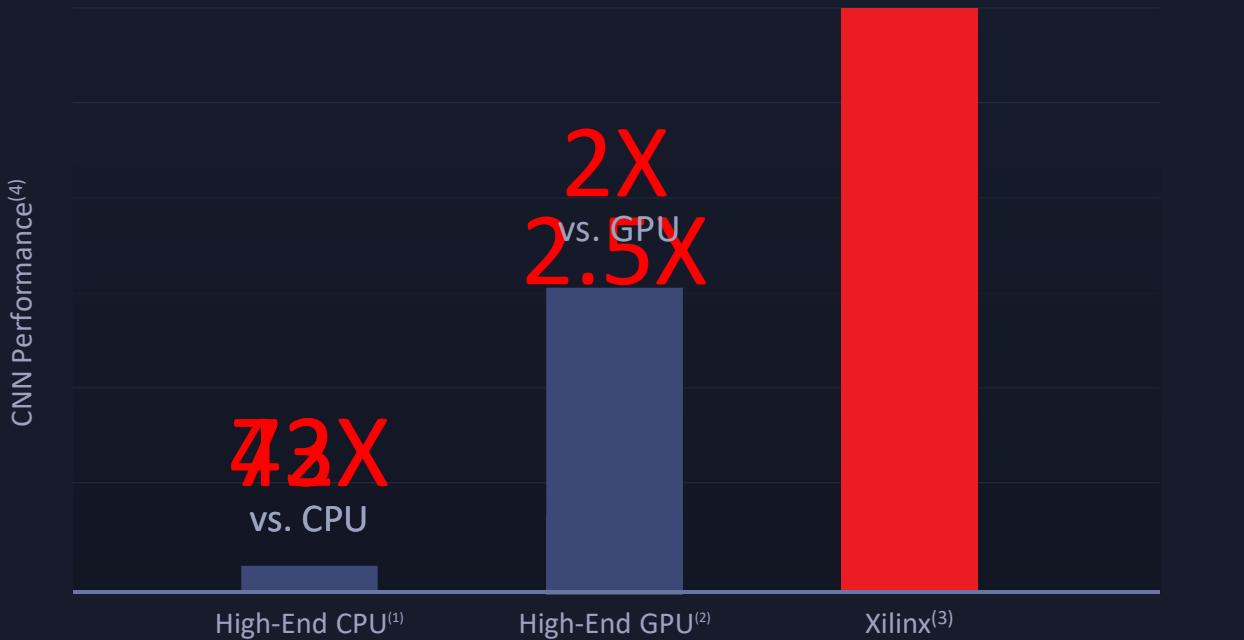


High throughput **AND** low latency



➤ Low Latency: Xilinx's Unique Advantage

Latency Insensitive Inference



(1) Measured on EC2 Xeon Platinum 8124 Skylake, c5.18xlarge AWS instance, Intel Caffe: <https://github.com/intel/caffe>

(2) V100 numbers taken from Nvidia Technical Overview, "Deep Learning Platform, Giant Leaps in Performance and Efficiency for AI Services"

(3) Versal Core Series

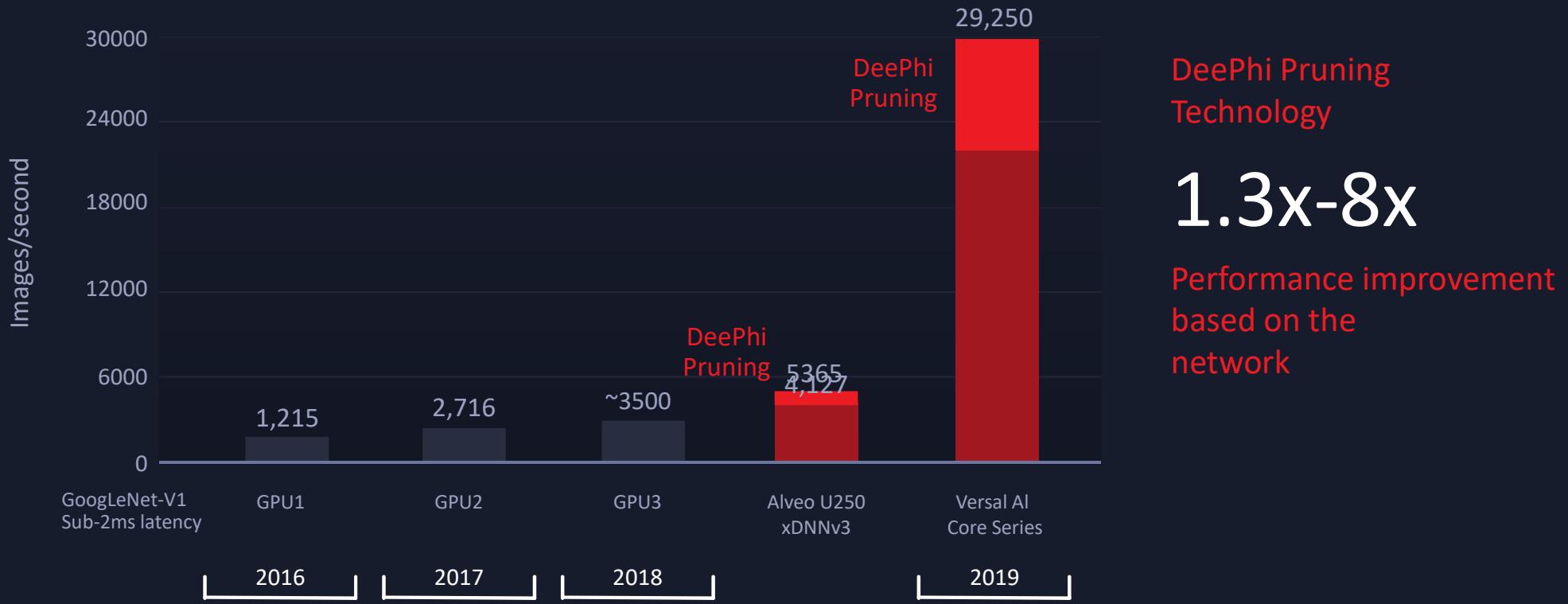
(4) GoogLeNet V1 throughput (lImg/sec)

AI Inference Acceleration

Leveraging AI Engines

Majority of Adaptable & Scalar Engines available for Whole App Acceleration

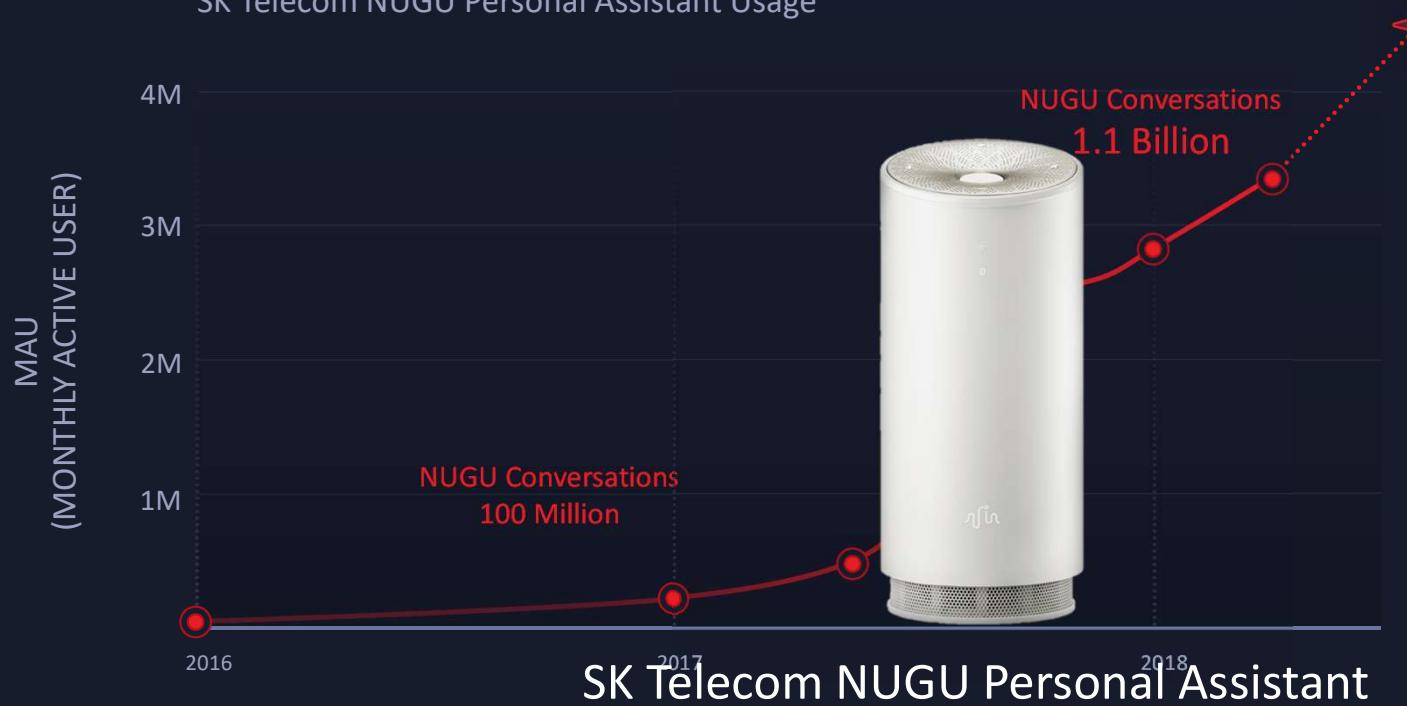
➤ Low-Latency CNN Inference Performance



Sources: Alveo - Published (INT8); Versal - Projected (INT8), 65% PL reserved for whole application; GPU 1 - P4 Published (INT8); GPU 2 - V100 Published (FP16/FP32); GPU 3 - T4 Projected

➤ Power Is Critical for Inference Applications

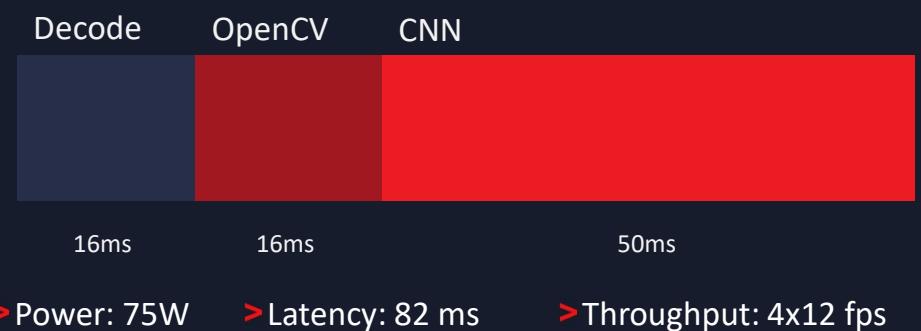
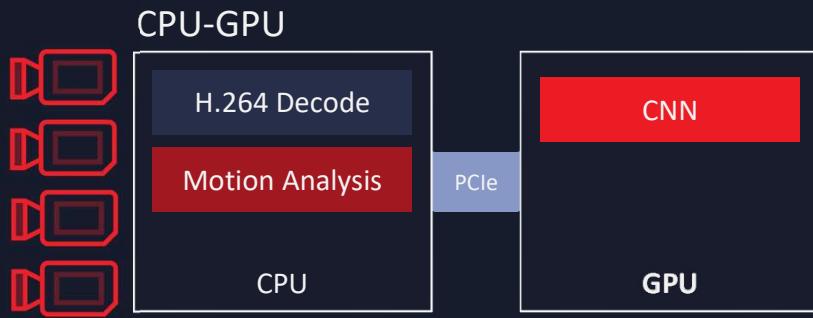
Cloud Inference
SK Telecom NUGU Personal Assistant Usage



16x
Perf/watt
vs. GPU



➤ Whole Application Acceleration: Smart City / Security



➤ Whole Application Acceleration: Online Video Streaming



1
Aup2603



Video transcoding + AI analytics



48 ZU7EV

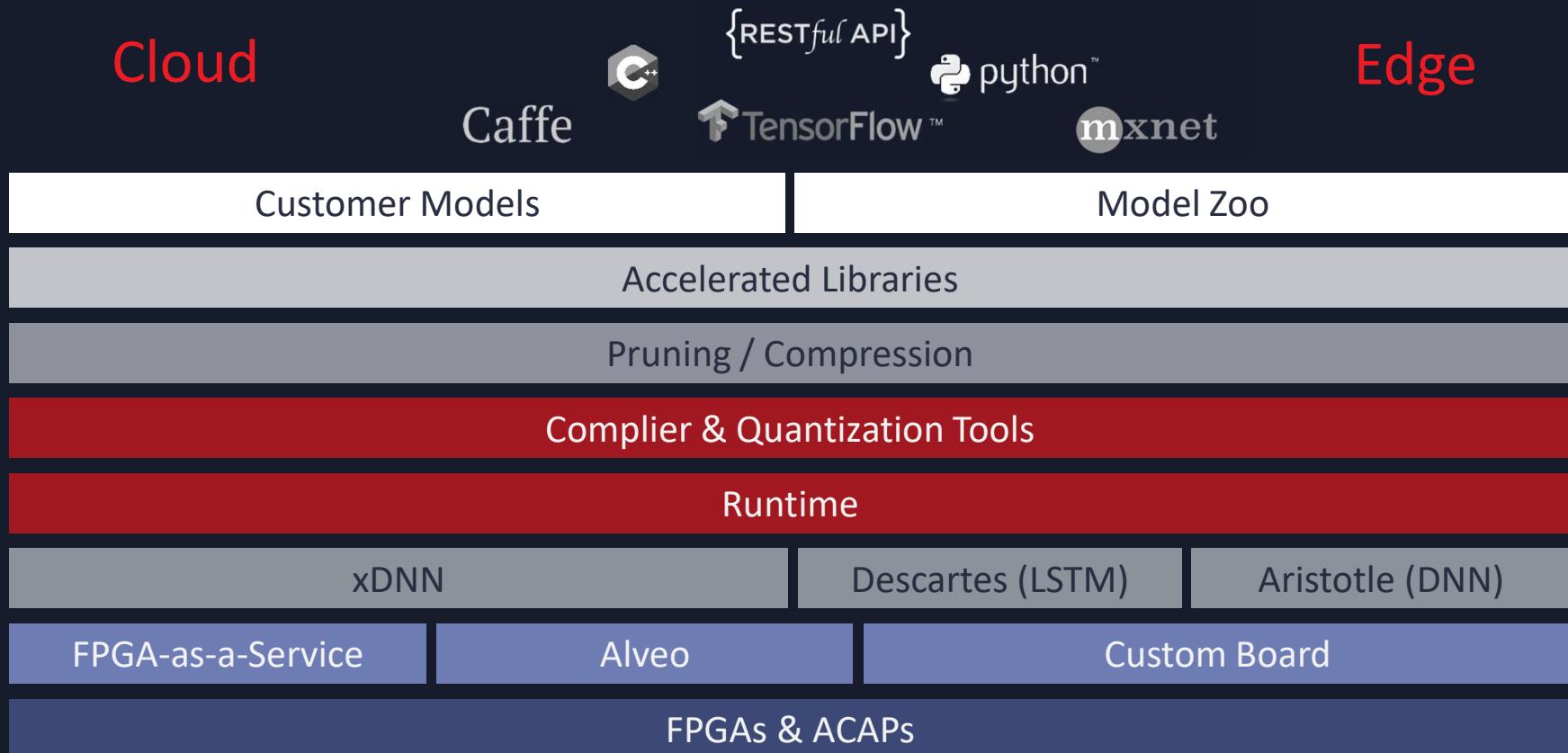
Energy 10x

Performance 3.3x

30
E5 Servers



➤ Enabling the Development Community



IN SUMMARY

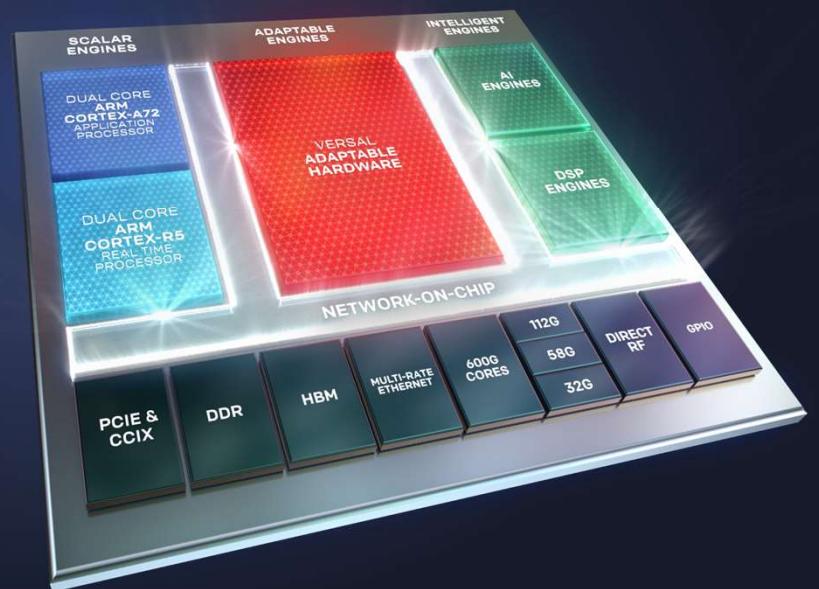
Only Xilinx Adaptable Devices Can:

Match the speed of AI innovation

Give the best performance
at low latency

Give the best power results

Accelerate the whole application





Xilinx

► Building
the Adaptable,
Intelligent World