



AI/ML HIGH PERFORMANCE COMPUTING WITH FPGAS

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Diverse Applications for FPGAs



Advanced,
multi-function
accelerators



Flexibility for highly-
differentiated
products



H/W re-programmability
for evolving market
requirements & changing
standards

EDGE/EMBEDDED

NEC NeoFace Facial
Recognition Accelerator

NETWORK

Rakuten Cloud-Native
Mobile Network

DATA CENTER



Microsoft

Microsoft AI Acceleration at
Cloud Scale for Azure and Bing

Industry Has Reached an Inflection Point



“...It may prove to be more economical to build large systems out of smaller functions, which are separately packaged and interconnected.”

Gordon E. Moore

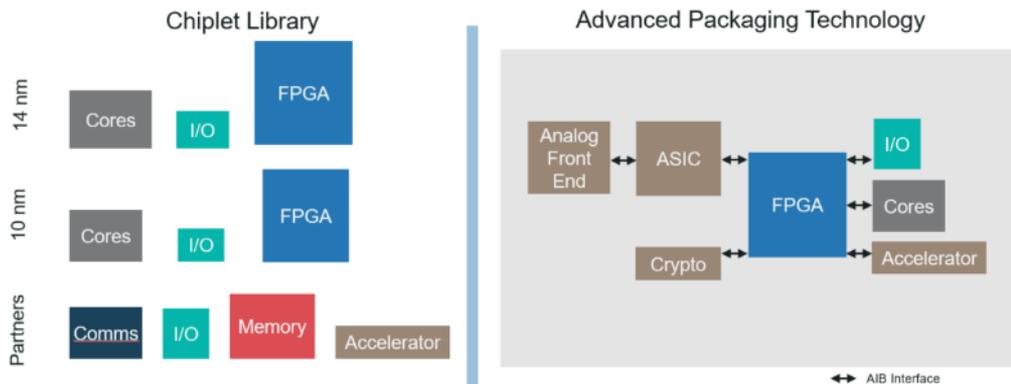
Industry Has Reached an Inflection Point



Rapidly Emerging Workloads Demands Flexibility and Interoperability

Breakthrough Packaging Technologies Approach On-Die Capabilities

Heterogeneous Integration – Innovation Through Chiplet Ecosystem!



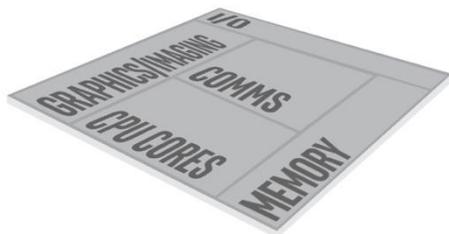
HETEROGENEOUS INTEGRATION

2D and 3D Packaging Drive New Design Flexibility

The combination of advanced 2D and 3D packaging technologies allows Intel to flexibly combine smaller chipllets of IP to meet the demands of a huge range of applications, power envelopes, and form factors. Intel® embedded multi-die interconnect bridge (EMIB) and Foveros are advanced 2D and 3D packaging technologies, delivering high performance at low cost.

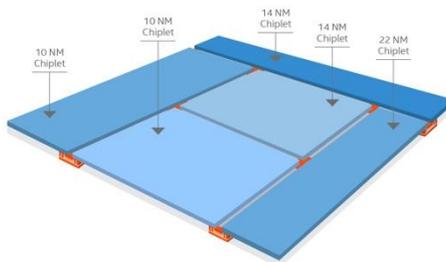
MONOLITHIC

Integrate functions on a single die for high performance on a single silicon technology



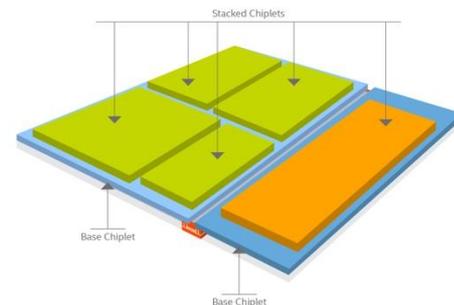
2D INTEGRATION

Combine IPs built with separate processes into a single package with Intel EMIB, helping improve yield, cost, time-to-market, and total capability



3D INTEGRATION

All the benefits of 2D integration plus a new level of density thanks to Foveros, allowing for a radical re-architecture of systems-on-chips



Any-to-Any Heterogenous 3D Packaging

EMBEDDED MULTI-DIE INTERCONNECT BRIDGE

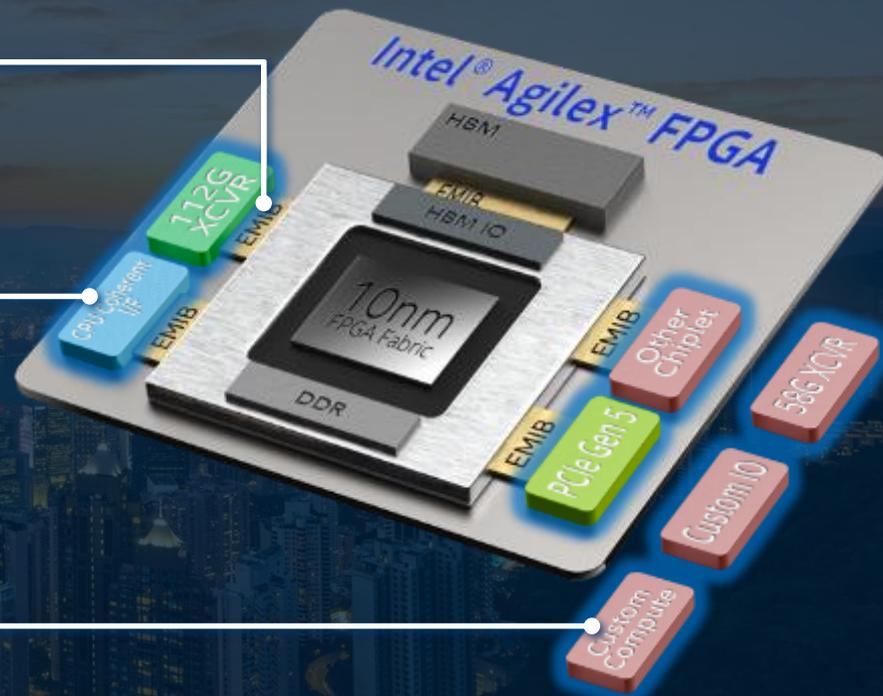
No compromise die-to-die packaging interconnect with high performance, low cost, and high density

CHIPLET

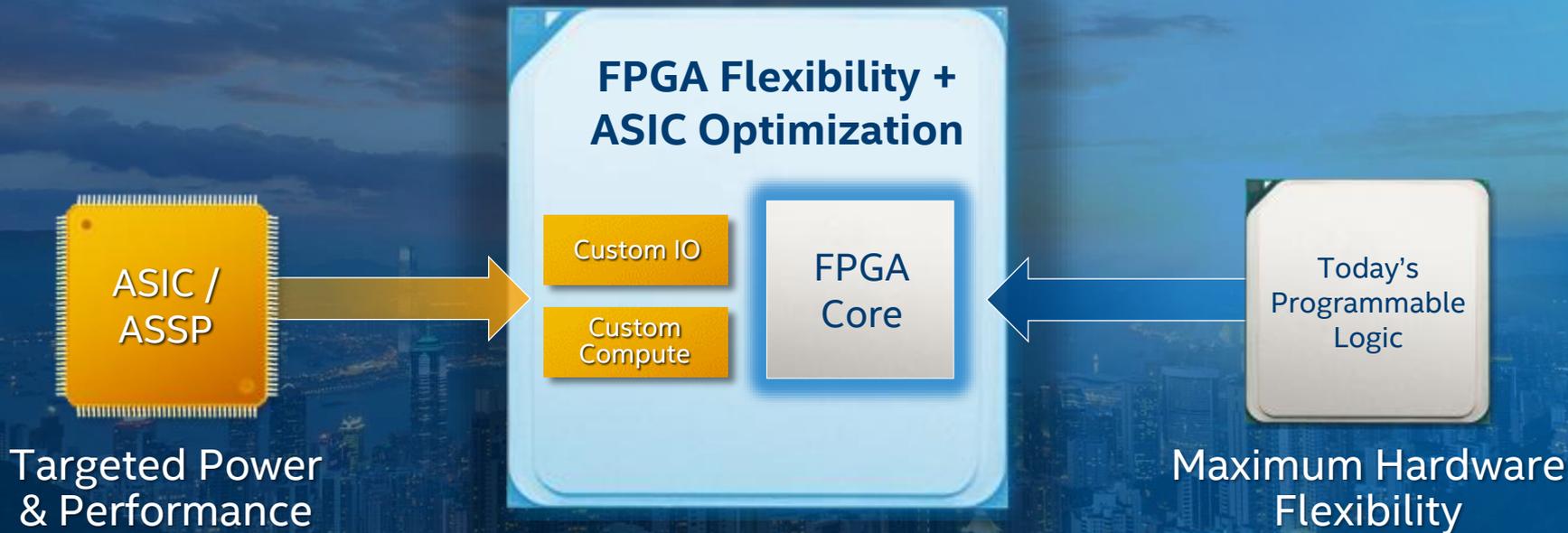
Library of chiplets including transceivers, custom I/O & custom compute tiles

Intel® eASIC™

Ultimate customization with integrated Intel® eASIC™ chiplet



Delivering Best of Both Worlds



Agile and Flexible Artificial Intelligence

UP TO
40 TFLOPS
DSP PERFORMANCE

Configurable DSP

- FP32
- BFLOAT16
- FP16
- INT8

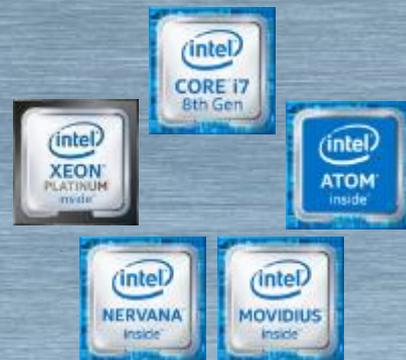


Flexibility for evolving AI workloads and integrating AI with other functions

Supports low-precision INT7 through INT2 configurations for high performance

Only FPGA supporting hardened
BFLOAT16 & FP16

Complementary to:



oneAPI

Optimized Applications, Middleware, Frameworks

FPGA Summary

Fine-grained general-purpose spatial arch.
(bit-level, cycle-level, dataflow-level programmable)

Sea of Programmable Logic and Routing

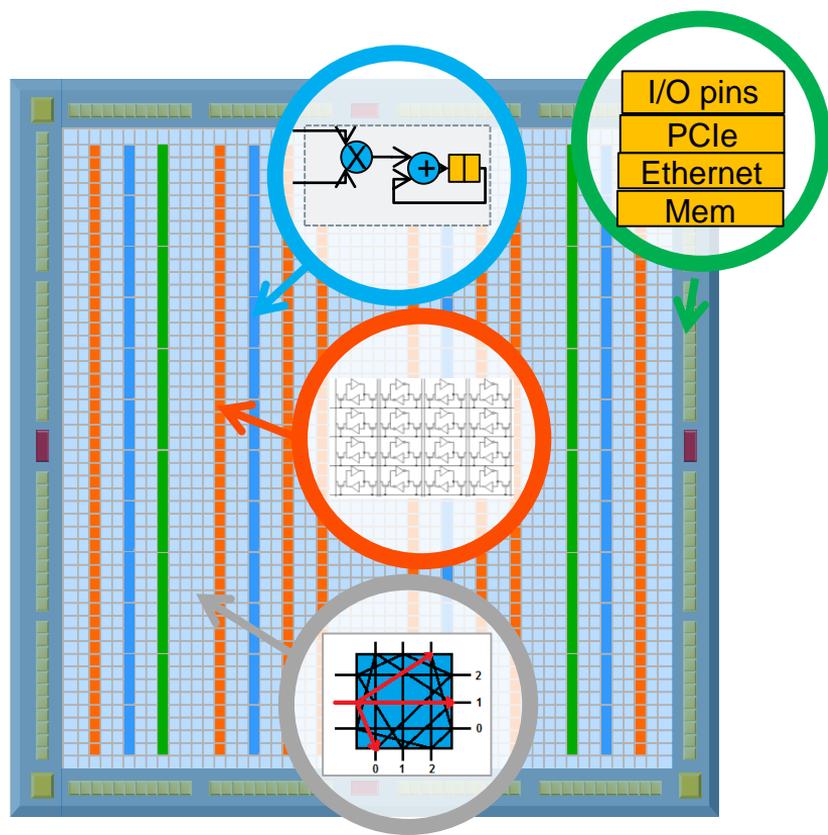
1000s of hard compute units ("DSP")
(e.g., ~10 TFLOP/s FP32 in Stratix 10 2800)

1000s of Hard Scratchpads ("M20Ks")
(e.g., ~30MBs total size, ~10s TB/s in Stratix 10 2800)

Many I/Os options

"Bare-metal" RTL "program"

Great for near-data latency-sensitive fine-grained apps



Commercial DNN Platforms Continue to Evolve

Few years ago

DNNs on general purpose platforms

CPU



GPGPU



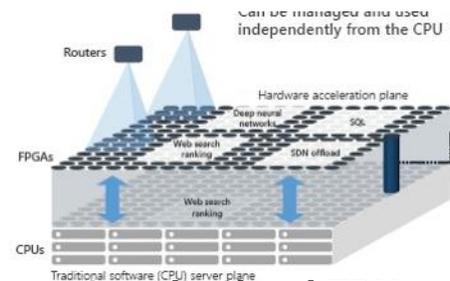
Some Examples Now

Customized DNNs platforms are available (i.e., HW accelerators in cloud/embedded/IoT)

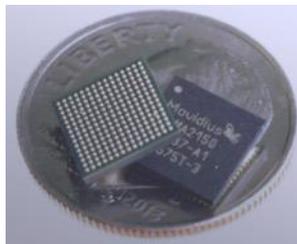
Nvidia Volta
GPU+TensorCore



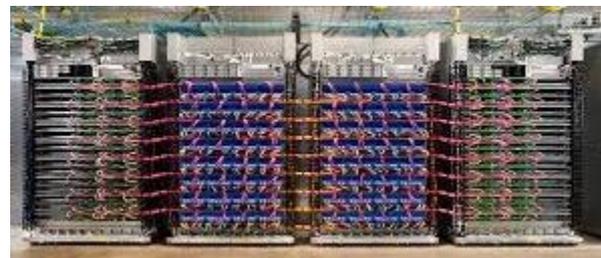
Microsoft Brainwave
(AI cloud using Intel FPGAs)



Intel Movidius



Google Cloud TPU



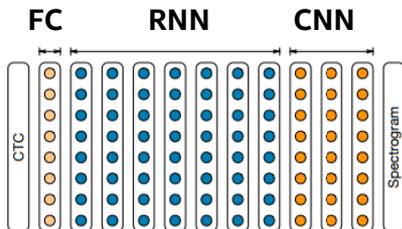
Source: E. Nurvithadi, et.al. Intel Labs

DNN Trends Going Forward

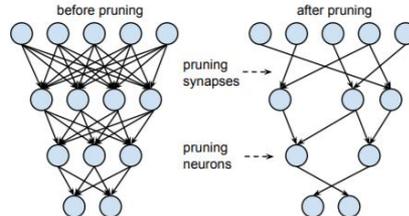
Mix of precisions (just a few examples below)



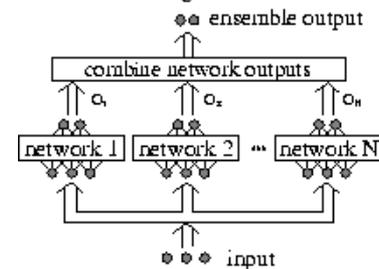
Mix of NN layer types (e.g., DeepSpeech2)



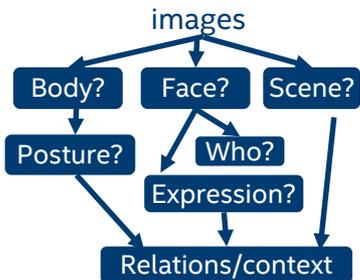
Mix of sparse layers (e.g., NIPS'15)



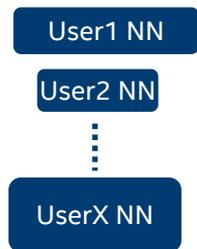
Ensemble of NNs



Mix of uses (e.g., context analyses)

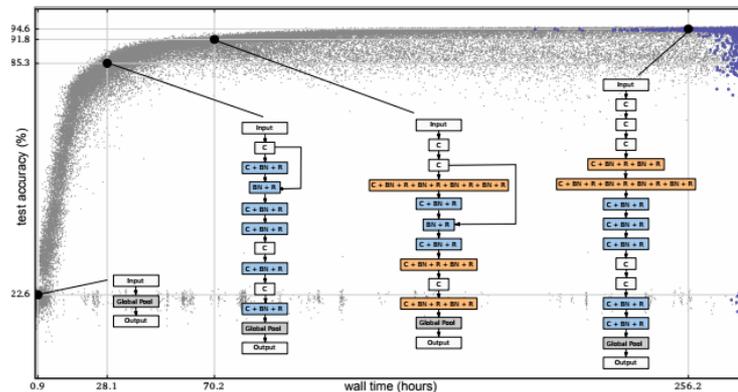


Multi Tenants



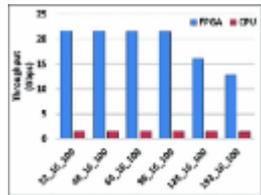
Needs programmability + customizability

AutoML: Computer-generated custom NNs (e.g., available in Google Cloud)



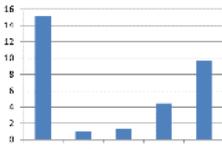
FPGAs Are Excellent Accelerators for Latency-Sensitive Irregular Computations

“Source: USC” (2016) Network Security [1]



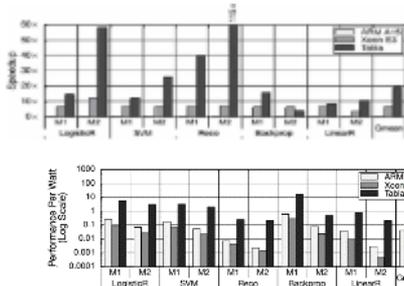
10X gain †

“Source: UCLA” (2011) Navigation [2]



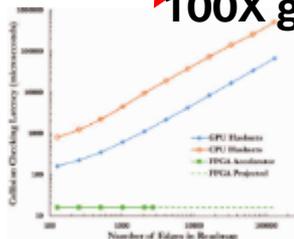
10X gain †

“Source: Georgia Tech.” (2016) Statistical Machine Learning [3]



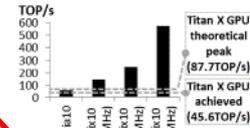
5X gain †
100X gain †

“Source: Duke Univ.” (2016) Collision Checking [4]

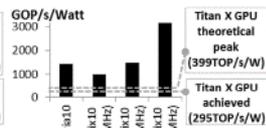


100X gain †

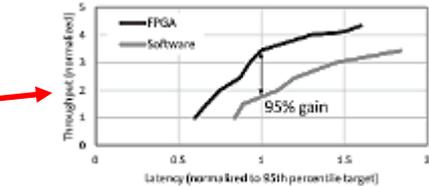
8X gain †



10X gain †

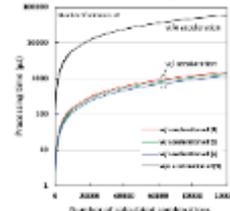


“Source: Intel” (2017) Binary/Ternary Deep Neural Network scoring [6]



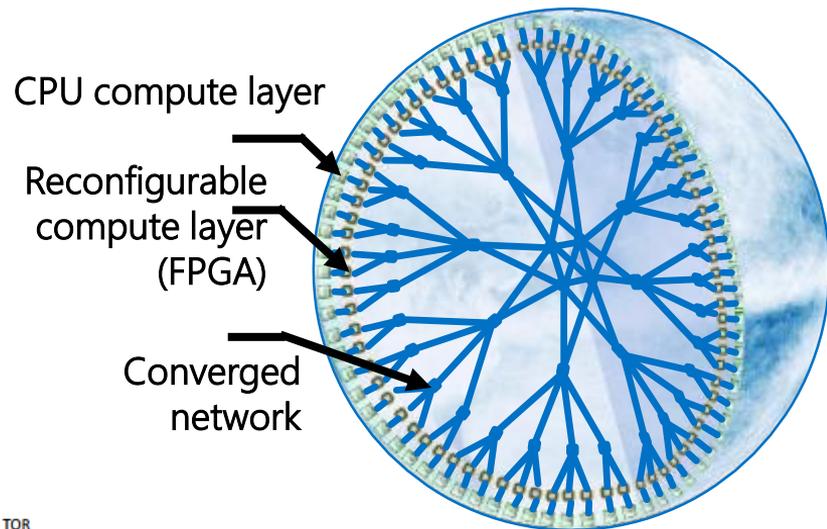
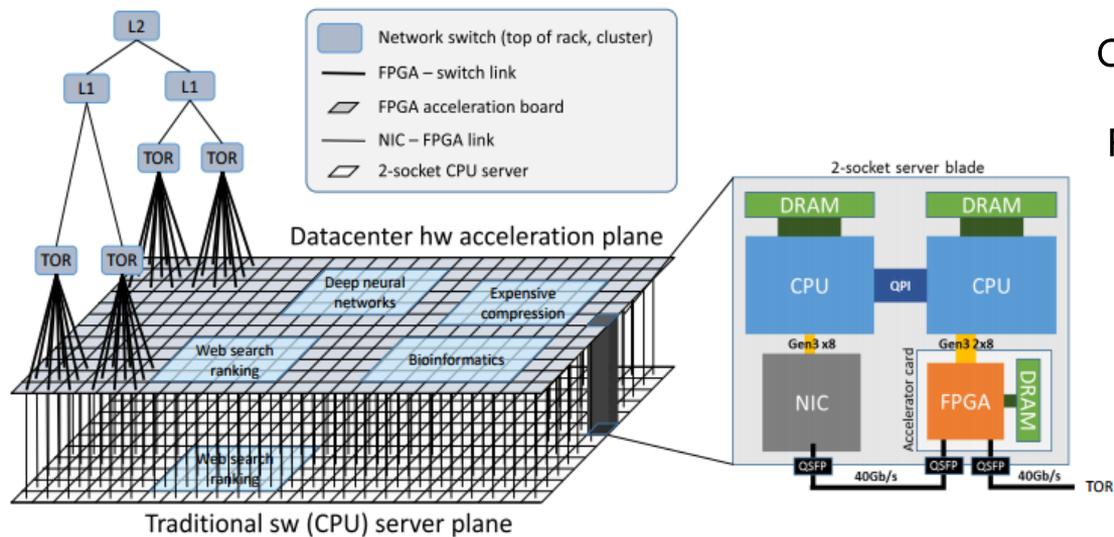
“Source: Microsoft” (2014) Bing Search [7]

100X gain †



“Source: NTT” (2017) Radio Resource Scheduling [5]

FPGAs Are Scalable



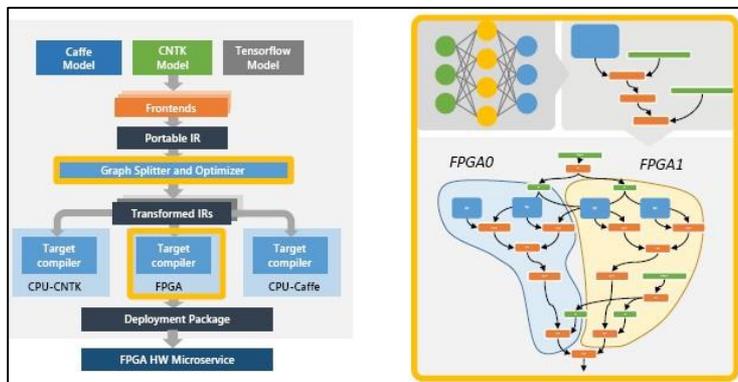
Figures from: Microsoft* Configurable Cloud talk/paper

E.g. MSFT reconfigurable cloud: “planet scale” apps on many networked FPGAs

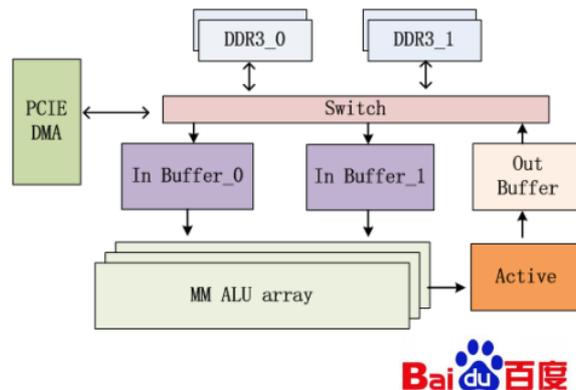
Others are also integrating FPGAs in their cloud (e.g., Amazon, Baidu)

FPGAs already used for Deep Learning Today

E.g., MSFT BrainWave (2017)



E.g., Baidu's SDA for DNNs (2015)



ISFPGA'18 Panel on DL: value of FPGA's flexibility

- MSFT: 1 week to add a new op in BrainWave
- MSFT: an intern repurposed BrainWave for another workload in 12 weeks
- FB Research: FPGAs for irregular DLs (e.g., FFTs)

Implications to Computing + Opportunities for FPGAs

- Too much data → process near data, minimize movement
 - *FPGAs already in key places where data flows (network, storage, sensors)*
- Myriad AI algorithm variations → programmability + customizability
 - *FPGAs spatial fabric are highly configurable + general purpose programmable*
- Interactive, real-time AI services → latency optimized architecture
 - *FPGAs are known for their deterministic and latency-optimized characteristics*
- Larger data and AI models → need scalable solution
 - *FPGAs are tightly coupled with transceivers to facilitate multi-node connections*

Tremendous opportunities in combined AI requirements and FPGA capabilities

Case Study of programming RNNs on NPU Overlay

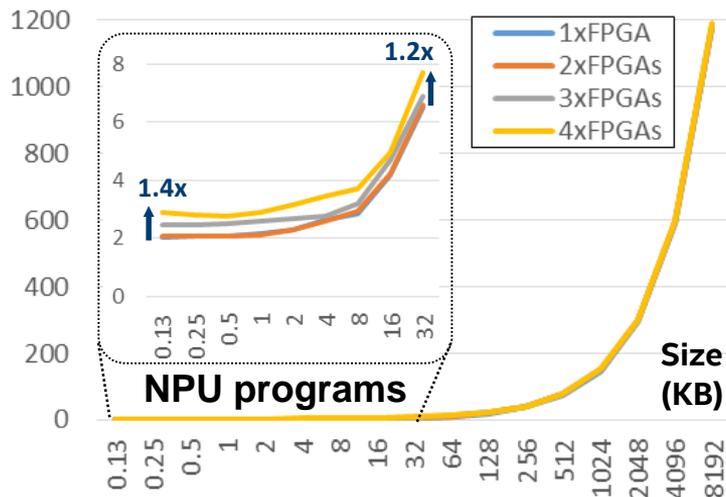
How fast can we program our overlay?

How fast can we write + optimize programs?

Ver	Description	Inst Count	Est. Engr. Hours	RAM Footprint
V1	Baseline functionality	20	4 hrs	Base
V2	Loop unroll, SW pipeline	20	1 hr	1x V1
V3	Efficient graph mapping	19	1 hr	1.1x V2

Can optimize RNN programs within ~hours
Compile time in seconds

PCIe CPU-FPGAs load time(us)



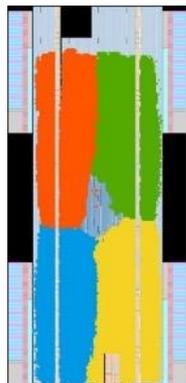
Typical programming time <8us,
even when targeting multiple FPGAs

Does it perform well?

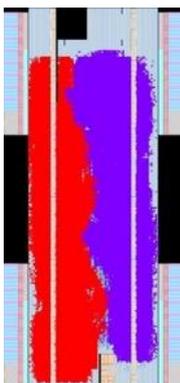
Ran various RNNs,
GRUs, LSTMs from
Deep Bench (batch1)

2 bitstreams, tuned to Stratix 10 2800

NPU	ALMs	M20Ks	DSPs	Freq. (MHz)	Peak TOPS
INT8 4T-120D-40L	567,98 2 (61%)	9,018 (77%)	4,880 (85%)	275	10.6
FP32 2T-64D-32L	286,02 4 (31%)	4,441 (38%)	4,768 (83%)	200	2.5



(a) 4-tile INT8



(b) 2-tile FP32

Our S10 FPGA NPU has 6x lower peak FP32 TOP/s than a large Titan V GPU

However, S10 performs better by 3x (FP32) & 10x (INT8) on average

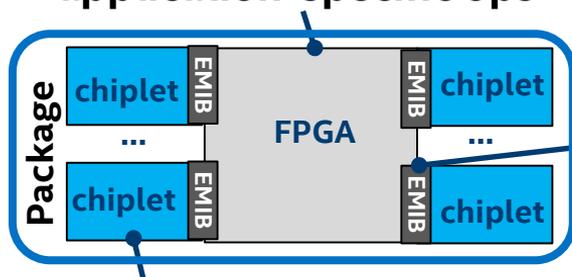
Why? GPU underutilize its available TOP/s, even with latest cuDNN with persistent AI support

Workload	Platform	Latency (ms)	Speedup
RNN h=1152 t=256	FP32 GPU	1	-
	FP32 FPGA	0.742	1.3
	INT8 FPGA	0.210	4.8
	INT8 TensorRAM	0.109	9.2
RNN h=1792 t=256	FP32 GPU	1.38	-
	FP32 FPGA	1.749	0.8
	INT8 FPGA	0.433	3.2
	INT8 TensorRAM	0.141	9.8
LSTM h=256 t=150	FP32 GPU	0.44	-
	FP32 FPGA	0.164	2.7
	INT8 FPGA	0.110	4.0
	INT8 TensorRAM	0.082	5.4
LSTM h=512 t=25	FP32 GPU	0.15	-
	FP32 FPGA	0.079	1.9
	INT8 FPGA	0.027	5.6
	INT8 TensorRAM	0.021	7.1
LSTM h=1024 t=25	FP32 GPU	0.44	-
	FP32 FPGA	0.254	1.7
	INT8 FPGA	0.064	6.9
	INT8 TensorRAM	0.036	12.2
LSTM h=1536 t=50	FP32 GPU	5.7	-
	FP32 FPGA	1.062	5.4
	INT8 FPGA	0.246	23.2
	INT8 TensorRAM	0.102	55.9
GRU h=512 t=1	FP32 GPU	0.085	-
	FP32 FPGA	0.003	28.3
	INT8 FPGA	0.00145	58.6
	INT8 TensorRAM	0.00098	86.7
GRU h=1024 t=1500	FP32 GPU	12.5	-
	FP32 FPGA	11.774	1.1
	INT8 FPGA	3.139	4.0
	INT8 TensorRAM	1.828	6.8
GRU h=1536 t=375	FP32 GPU	29.94	-
	FP32 FPGA	6.063	4.9
	INT8 FPGA	1.454	20.6
	INT8 TensorRAM	0.633	47.3

Enhancing FPGAs with Chiplets for AI [FPL'18][FCCM'19]

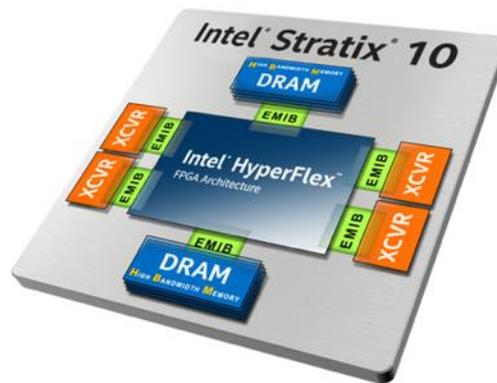
Stratix10 FPGAs already System-in-Package: use 2.5D EMIBs to offer xcvr and memory chiplets next to FPGA

FPGA: flexibility for custom application-specific ops



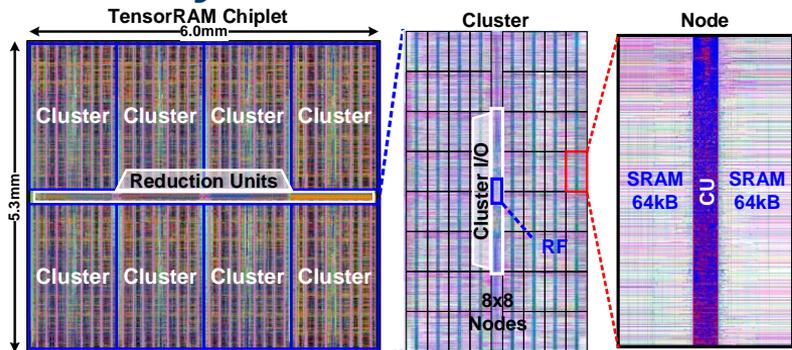
Intel's 2.5D EMIB for integration

Chiplets: efficiency for domain-shared ops



[FPL'18] E. Nurvitadhi, J. Cook, A. Mishra, D. Marr, et. al., "In-Package Domain-Specific ASICs for Intel® Stratix® 10 FPGAs: A Case Study of Accelerating Deep Learning Using TensorTile ASIC," FPL 2018.
[FCCM'19] E. Nurvitadhi, D. Kwon, A. Jafari, A. Boutros, et. al., "Why Compete When You Can Work Together: FPGA-ASIC Integration for Persistent RNNs," FCCM 2019.

Very Scalable: Can Mix & Match FPGAs + Tiles

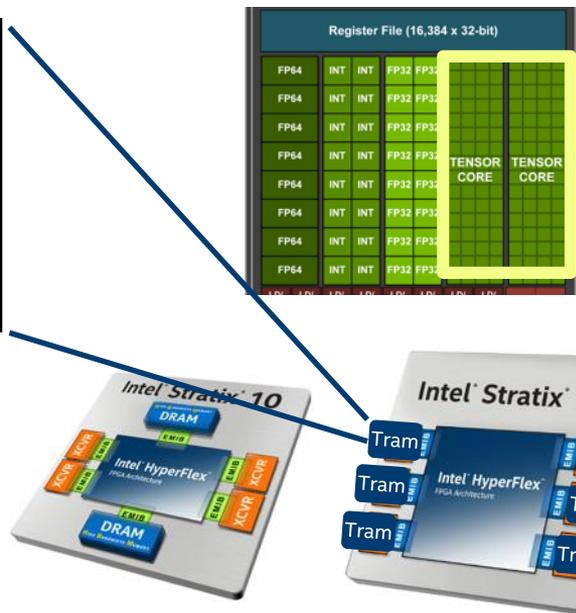


TensorRAM 32 mm² 10nm layout [IL/CRL]

Est. 64 TOPs (INT8) in a T-ram



Small



Volta: GPU + Tensor Cores

125 TOPs (FP16)
26 MB on-chip RAMs



3.1x and 15.8x better peak TOPs and RAMs

S10 2800 + 6x data-intensive chiplets on 10nm

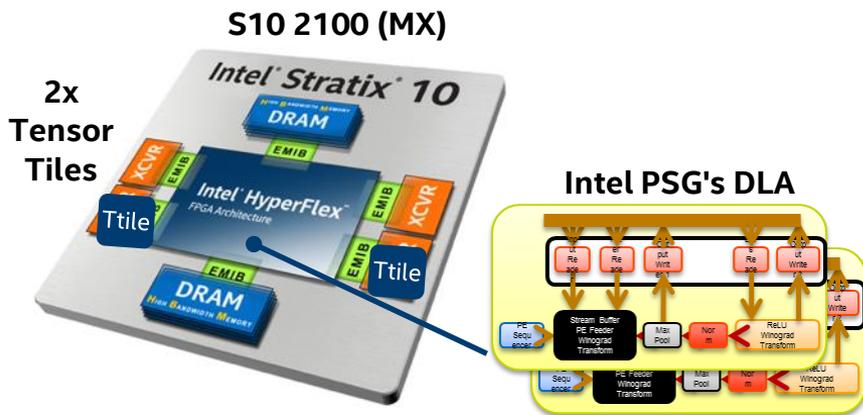
Est. 393 TOPs (INT8)
412MB on-chip RAMs

Large

Can also build multiple variants of chiplets. Example of data-intensive 10nm chiplet "TensorRAM" for persistent AI shown here.

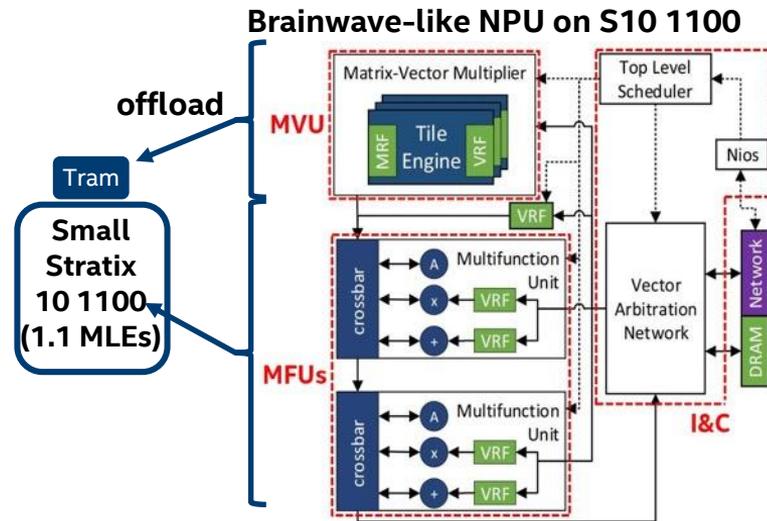
Case Studies

(1) AlexNet (FP16) Inference, low batch



The 2x tiles improved performance and performance/Watt by 4x and 3.3x vs. FPGA only for CNN workload

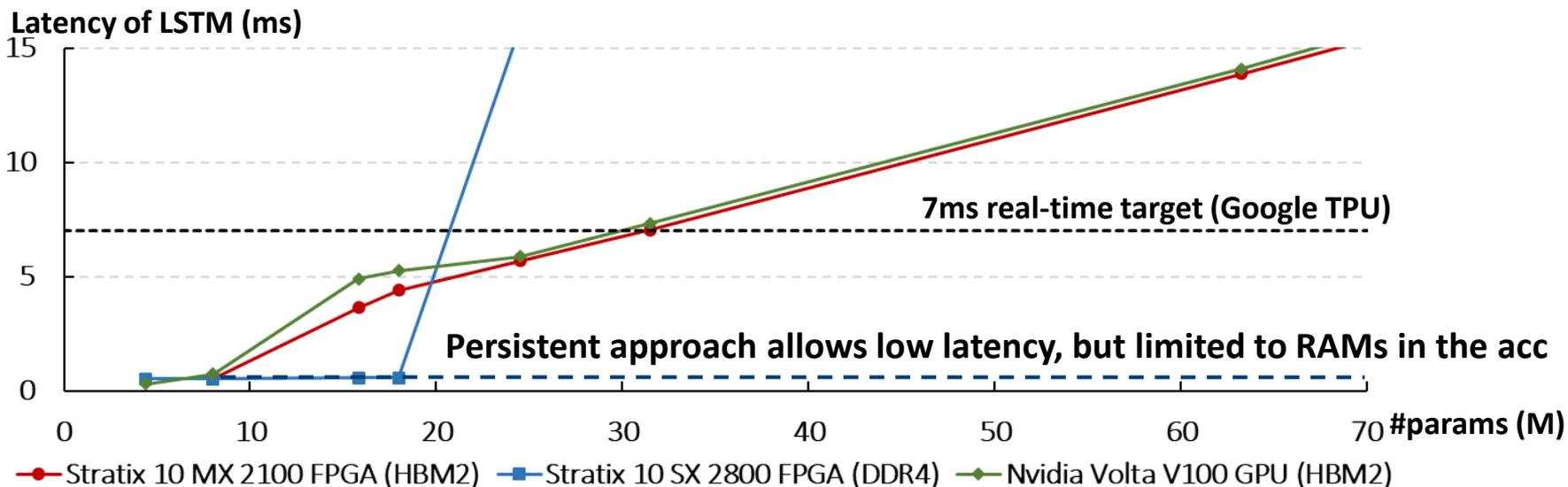
(2) Persistent RNN/GRU/LSTM (INT8)



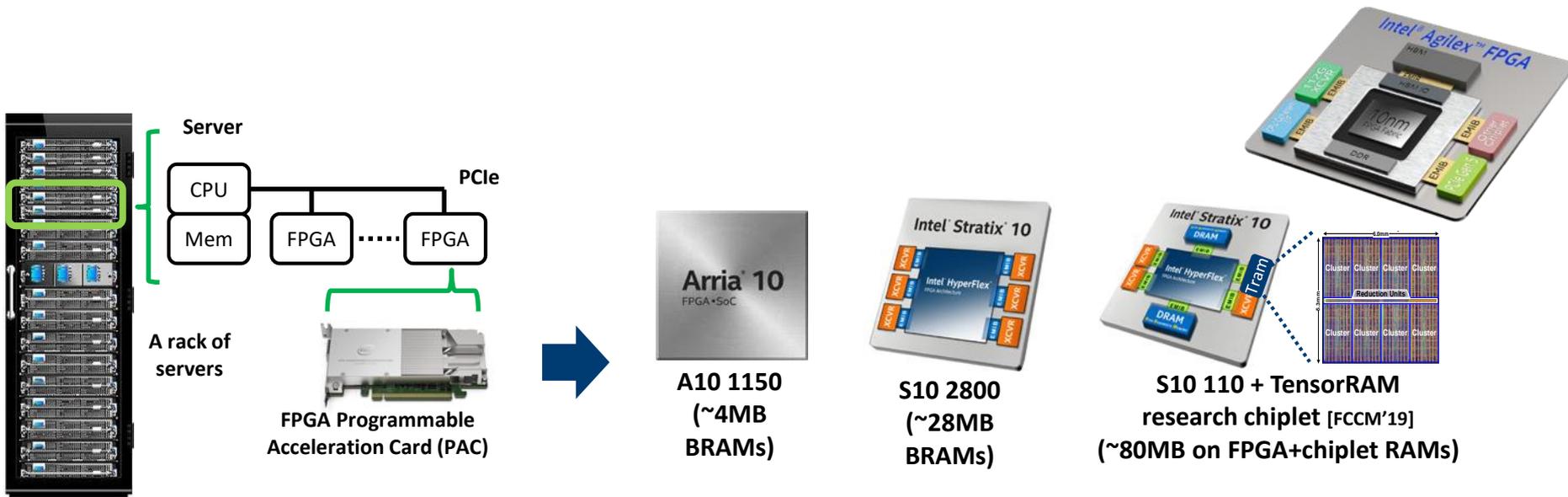
A small S10 1100 with 1 T-RAM (INT8) offers 16x better latency than GPU (FP32) and 34x energy efficiency across RNN, GRU, LSTM workloads

How to keep low latency inference as AI models gets bigger?

- AI models gets better and **larger**
 - E.g., NMT use ~200M parameters, BERT use ~300M
- Single accelerator solution does not scale well



Persistent Model Across Multiple FPGAs in a Server



Dell Server R740
(Xeon CPU + multiple FPGA PCIe PACs)

Multiple generations of FPGA,
with 1x to 8x FPGAs in a server

The FPGA for the Data-Centric World

PROCESS DATA

2ND
GENERATION INTEL[®]
HYPERFLEX™ FPGA
ARCHITECTURE

UP TO
40%
HIGHER
PERFORMANCE¹

UP TO
40%
LOWER
POWER¹

UP TO
40 TFLOPS
DSP PERFORMANCE²

STORE DATA

DDR5 &
HBM

INTEL[®] OPTANE™ DC
PERSISTENT MEMORY SUPPORT

MOVE DATA



INTEL[®] XEON[®] PROCESSOR COHERENT
CONNECTIVITY (CXL*) & PCIe* GEN5

112G

TRANSCEIVER
DATA RATES



¹ compared to Intel[®] Stratix[®] 10 FPGAs

² with FP16 configuration

³ Based on current estimates, see backup slide for details
CXL = Compute Express Link

Intel® Agilex™ FPGAs for the Data-Centric World

Intel® Agilex™ FPGAs enable transformative applications in edge computing, embedded, networking (5G/NFV), and data centers

Any-to-Any integration enables Intel to offer FPGAs with application-specific optimization and customization, delivering new levels of flexibility and agility

First FPGAs leveraging Intel's unmatched innovation:
10 nm process, 3D packaging, Intel Xeon® Scalable Processor cache coherency via CXL*, 112G transceivers, PCI Express* (PCIe*) Gen5, OneAPI, Intel eASIC™ devices, Intel Optane™ DC persistent memory support



