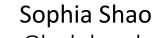
## Next-Generation Deep-Learning Accelerators: From Hardware to System

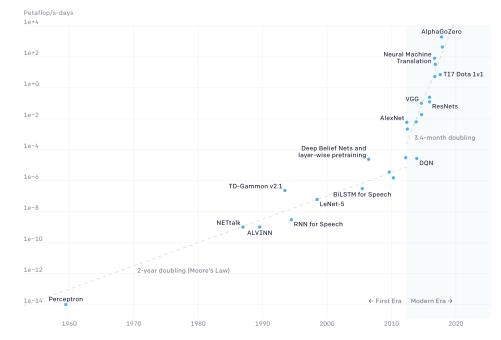


ysshao@berkeley.edu Electrical Engineering and Computer Sciences

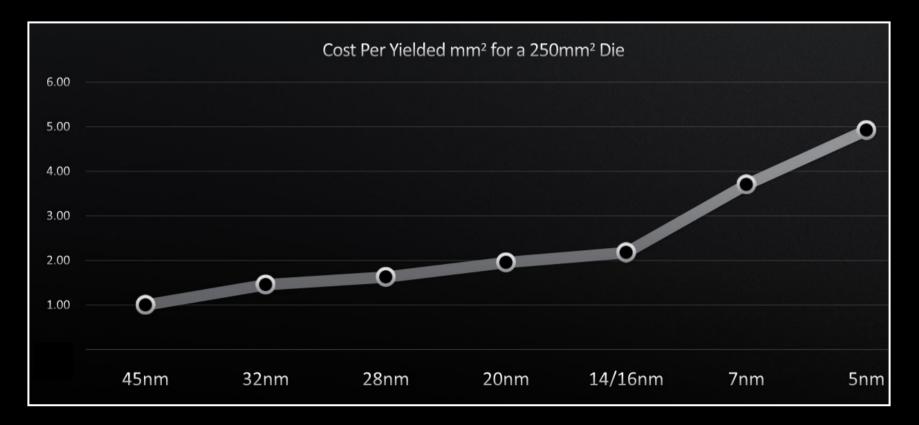


## Growing Demand in Computing

#### Two Distinct Eras of Compute Usage in Training AI Systems



OpenAl



## **Slowing Supply in Computing**

AMD, HotChips, 2019





## Domain-Specific Accelerators

Growing Demand in Computing



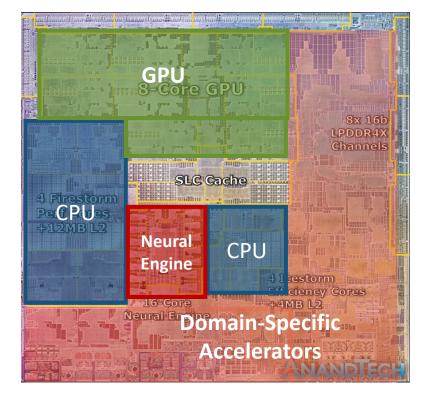
Slowing Supply in Computing

## **Domain-Specific Accelerators**

 Customized hardware designed for a domain of applications.



Apple M1 Chip 2020



#### **Full-Stack Optimization for DL Accelerators**

Design of Accelerators  Simba [MICRO'19 Best Paper Award, CACM RH, VLSI'20, JSSC'20 Best Paper Award]

Integration of Accelerators

- Chipyard [IEEE Micro'20]
- Gemmini [DAC'21, Best Paper Award]

# Scheduling of Accelerators

#### **Full-Stack Optimization for DL Accelerators**

Design of • S Accelerators

 Simba [MICRO'19 Best Paper Award, CACM RH, VLSI'20, JSSC'20 Best Paper Award]

Integration of Accelerators

# Chipyard [IEEE Micro'20] Gemmini [DAC'21, Best Paper Award]

Scheduling of Accelerators

## **Scalable Inference Accelerators**

#### Motivation

• Need for fast and efficient inference accelerators from mobile to datacenter.

#### Challenge

• High design cost of building unique hardware for each design target.

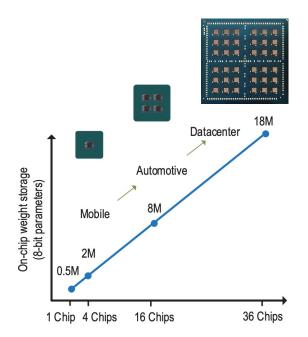
#### Opportunities

- Deep learning inference is intrinsically scalable with abundant parallelism.
- Recent advances in package-level integration for multi-chip-module-based designs.

## The Multi-Chip-Module Approach

#### • Advantages:

- Build systems larger than reticle limit
- Smaller chips are cheaper to design
- Smaller chips have higher yield
- Faster time-to-market
- Challenges:
- Area, energy, and latency for chip-tochip communication



#### Simba: Scaling Inference with MCM-based Architecture

#### Best Paper Award at MICRO'2019, CACM Research Highlights

#### Simba Testchip:

•

- Package and chiplet architecture Processing element design Baseline uniform tiling across chiplets and PEs Simba Characterization: Comparison with GPUs NoP bandwidth sensitivity NoP latency sensitivity Simba NoP-Aware Tiling:
- Non-uniform work partitioning
- Communication-aware data placement
- Cross-layer pipelining

Output

Output

#### Simba: Scalable MCM-Based Architecture

47.5 mm

#### Package and chiplet spec

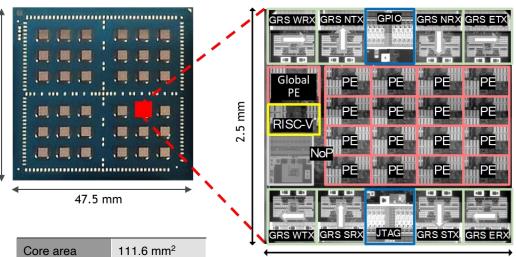
6mm<sup>2</sup> chiplet in TSMC 16nm 36 chiplets/package

#### Chip-to-chip interconnect

Ground-Referenced Signaling

#### **Efficient compute tiles**

128 TOPS 0.11 pJ/Op 8-bit integer datapath



2.4mm

0.52-1.1 V

0.48-1.8 GHz 624KB/chip

23MB/package

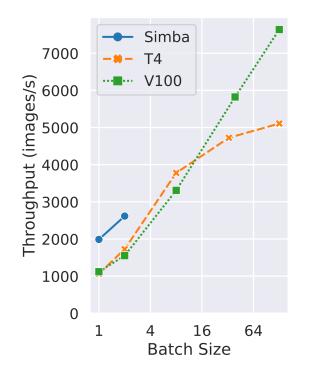
Voltage

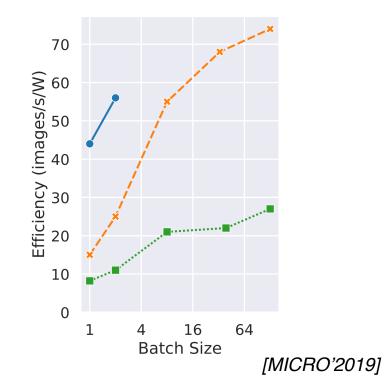
SRAM

Frequency

#### **Simba Characterization**

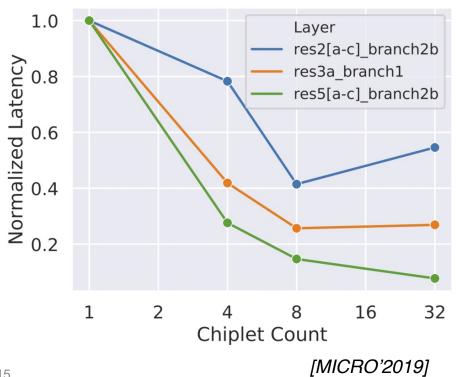
• Comparison with GPUs running ResNet-50





## Simba Characterization

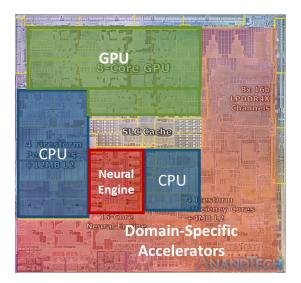
- Layer Sensitivity
- Running three ResNet-50 layers across different number of chiplets.
- Increasing the number of active chiplets does not always translate to performance gains.
- The cost of communication hinders the <sup>2</sup> ability to exploit parallelism.



#### **Full-Stack Optimization for DL Accelerators**



#### Accelerators don't exist in isolation.

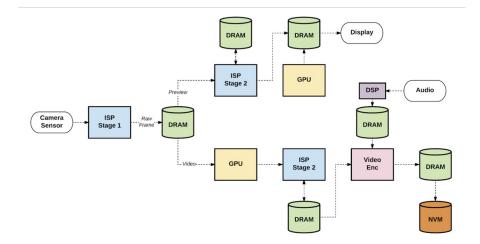




http://vlsiarch.eecs.harvard.edu/research/accelerators/die-photoanalysis/

## Mobile SoC Usecase

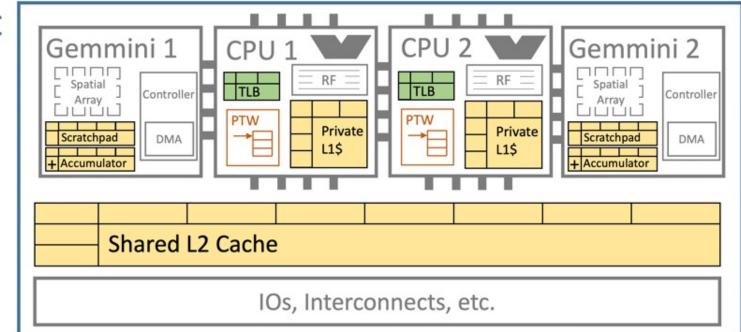
- Mainstream architecture has long focused on general-purpose CPUs and GPUs.
- In an SoC, multiple IP blocks are active at the same time and communicate frequently with each other.
- Example:
  - Recording a 4K video
  - Camera -> ISP
    - "Preview stream" for display
    - "Video stream" for storage
  - DRAM for data sharing



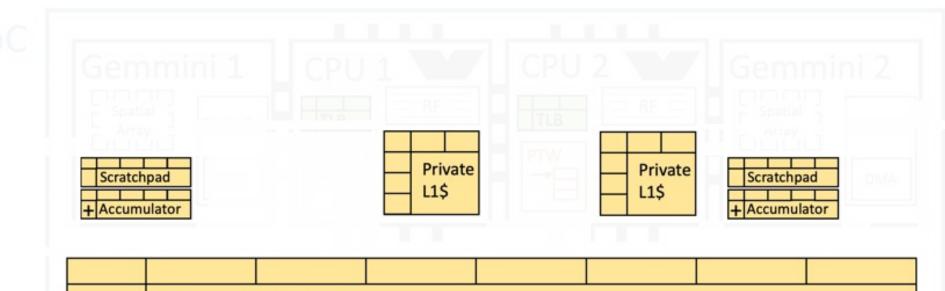
Two Billion Devices and Counting: An Industry Perspective on the State of Mobile Computer Architecture, IEEE Micro'2018

## **Full-System Visibility for DL Accelerators**





#### **Full-System Visibility: Memory Hierarchy**

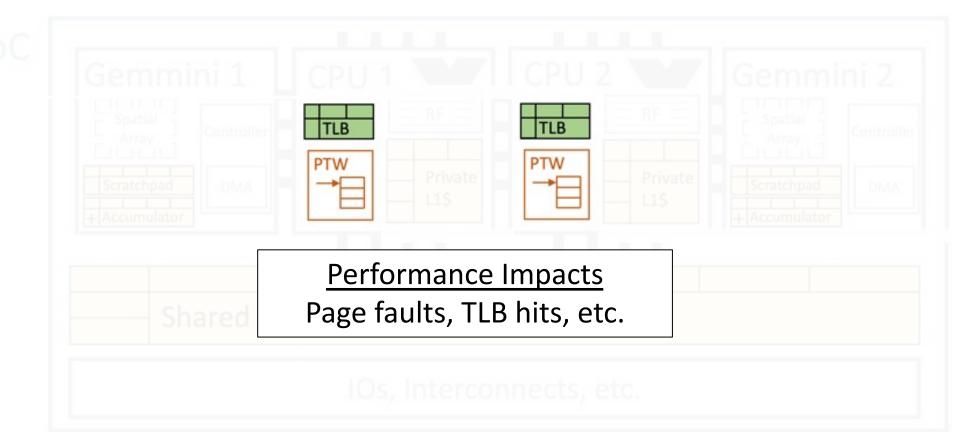


#### Shared L2 Cache

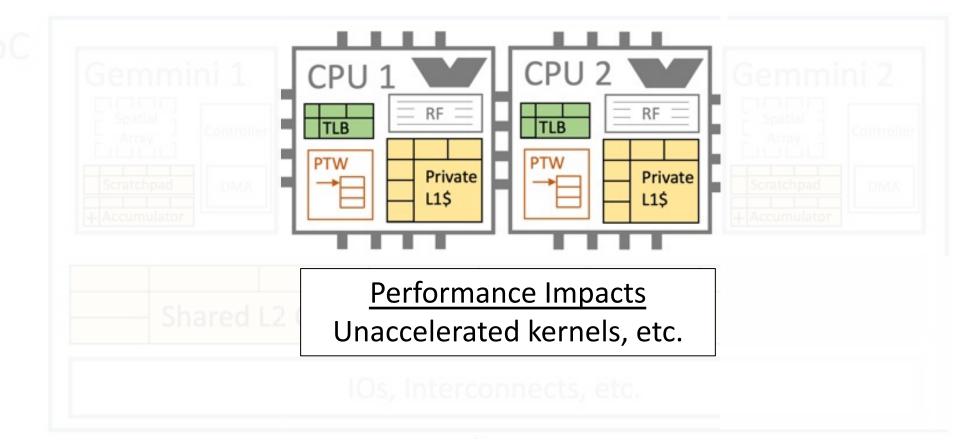
Performance Impacts

Resource contention, cache coherence, etc.

#### **Full-System Visibility: Virtual Addresses**

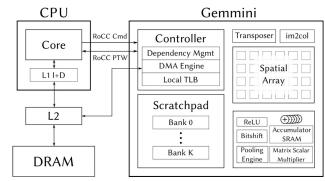


#### **Full-System Visibility: Host CPUs**



#### **Gemmini: Full-System Co-Design of Hardware Accelerators**

- Full-stack
  - Includes OS
  - End-to-end workloads
  - "Multi-level" API
- Full-SoC
  - Host CPUs
  - Shared memory hierarchies
  - Virtual address translation

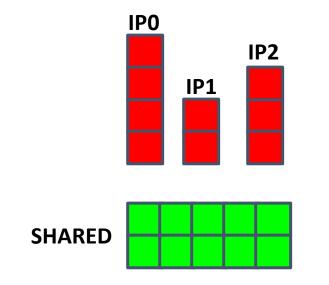


	Property	NVDLA	VTA	PolySA	DNNBuilder	MAGNet	DNNWeaver	MAERI	Gemmini
Hardware Architecture Template	Multiple Datatypes Multiple Dataflows Spatial Array Direct convolution	Int/Float ★ vector	Int X vector X	Int ✓ systolic ✗	Int ✓ systolic	Int ✓ vector	Int vector	Int ✓ vector	Int/Float vector/systolic
Programming Support	Software Ecosystem	Custom Compiler	TVM	Xilinx SDAccel	Caffe	С	Caffe	Custom Mapper	ONNX/C
	Hardware-Supported Virtual Memory	×	×	×	×	×	×	×	1
System Support	Full SoC OS Support	×	×	× ×	× ×	X X	× ×	× ×	<i>\</i> <i>\</i>

https://github.com/ucb-bar/gemmini

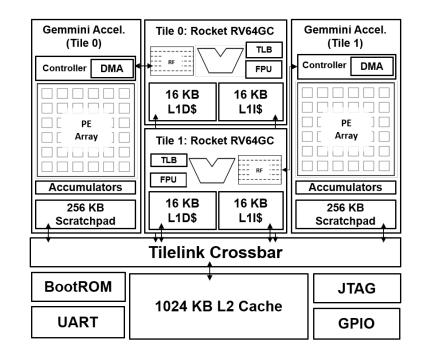
[DAC'2021 Best Paper Award]

## Gemmini Case Study: Allocating on-chip SRAM



#### Where to allocated SRAM?

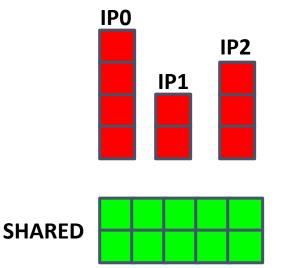
- Private within each IP
- Shared



https://github.com/ucb-bar/gemmini

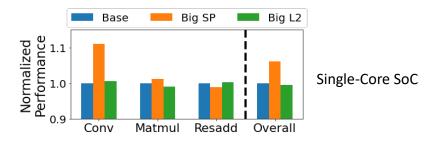
[DAC'2021 Best Paper Award]

## Gemmini Case Study: Allocating on-chip SRAM



- Where to allocated SRAM?
  - Private within each IP
  - Shared

• Application dependent.



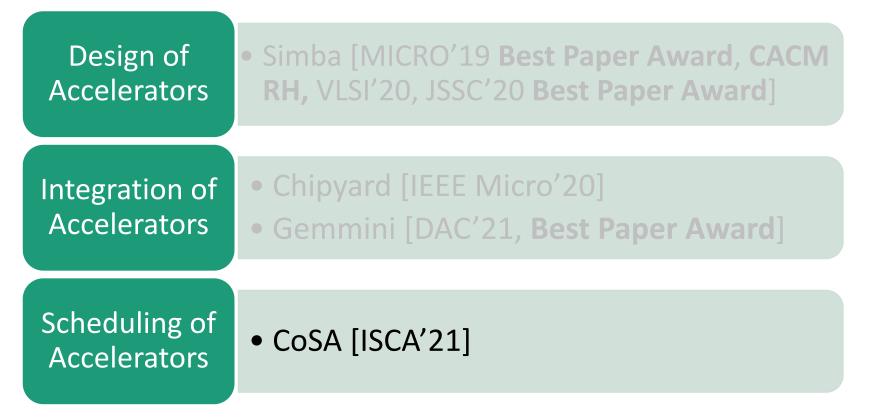
SoC configuration dependent.



https://github.com/ucb-bar/gemmini

[DAC'2021 Best Paper Award]

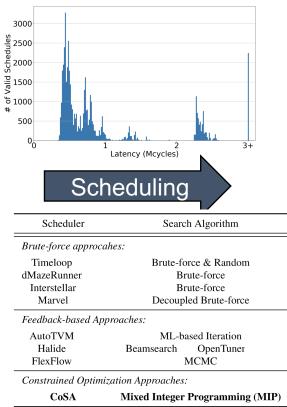
#### **Full-Stack Optimization for DL Accelerators**



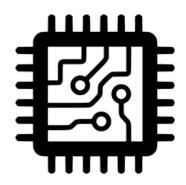
## Large Space of Mapping Algorithms to ML Hardware

#### Algorithm

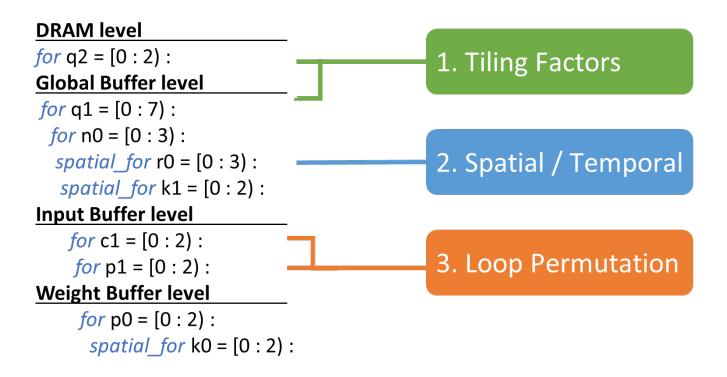


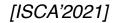


#### Hardware



## Navigating the Mapping Space



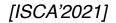


#### **CoSA: Constrained-Optimization for Spatial Architecture**

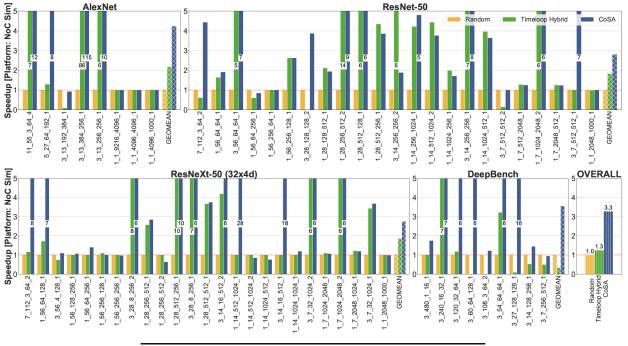
**ML** Operator

Inputs Weights Outputs Weight Buffer DRAM C イ S + apits (F - 1) x Stride + R S Buffer ¥ Input Ø **Global Buffer** σţ Ρ C R **Processing Element** Reduction R Router R, S: weight width and height P, Q: output width and height Schedule C: input channel size Accumulation K: output channel size Buffer N: batch size MULT Adder CoSA Variables Constraints **Objectives** 

**Spatial Accelerator** 



#### Results



	CoSA	Random $(5 \times)$	Timeloop Hybrid
Avg. Runtime / Layer	4.2s	4.6s	379.9s
Avg. Samples / Layer	1	20K	67M
Avg. Evaluations / Layer	1	5	16K

#### Acknowledgement









Jenny Huang

Seah Kim

- Collaborators from UC Berkeley and NVIDIA!
- Sponsored by DARPA, a Facebook Research Award, a Google Research Award, and ADEPT/SLICE industry sponsors!

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