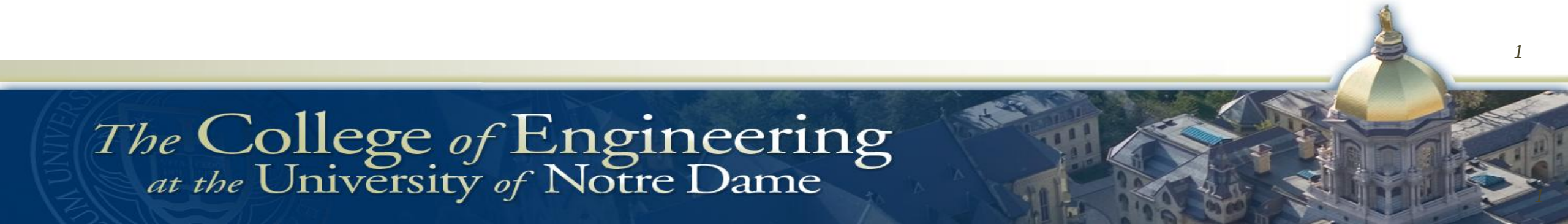
Hardware/Software Co-Exploration of Neural Architecture

—— Published and Ongoing Works

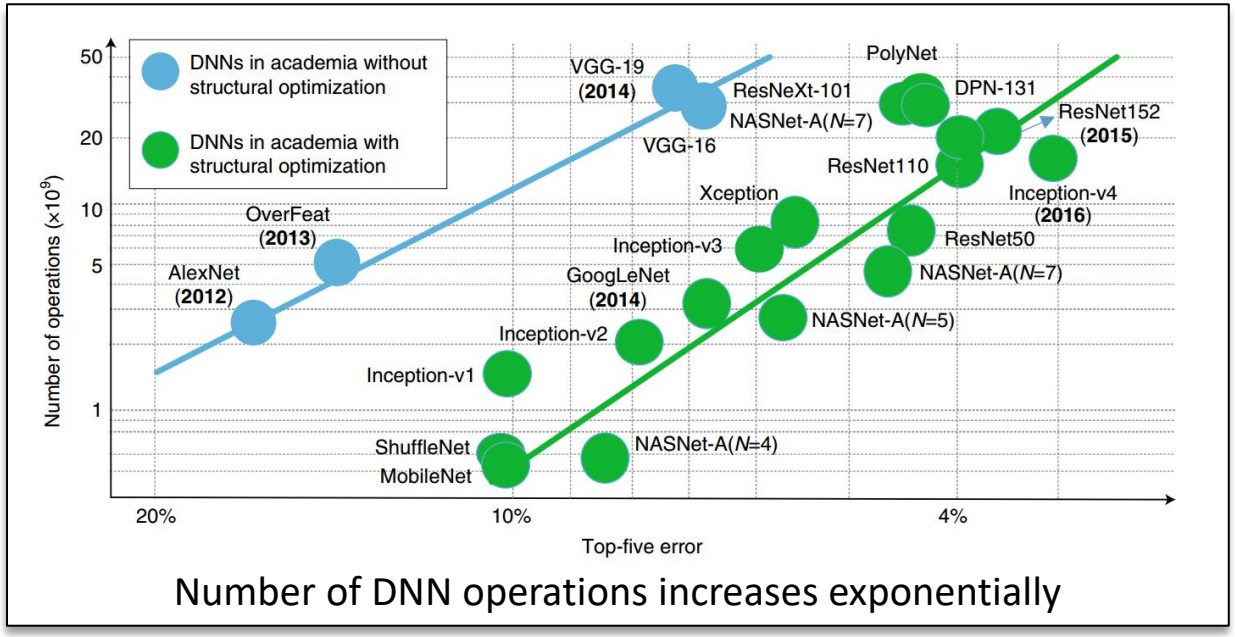
Weiwen Jiang
wjiang2@nd.edu

Outline

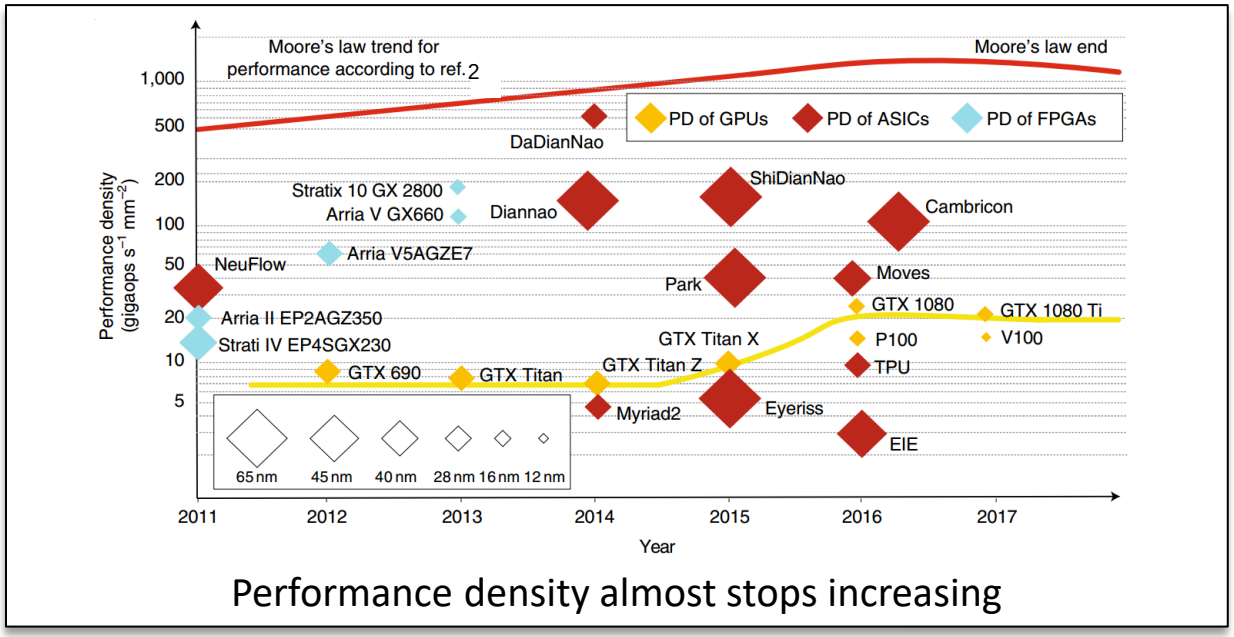
- **Introduction**
- Co-Exploration of Neural Architecture and FPGA Implementation
  - DAC'19 (Best Paper Nomination)
- Other Research Directions
- Conclusion



Computation Gap



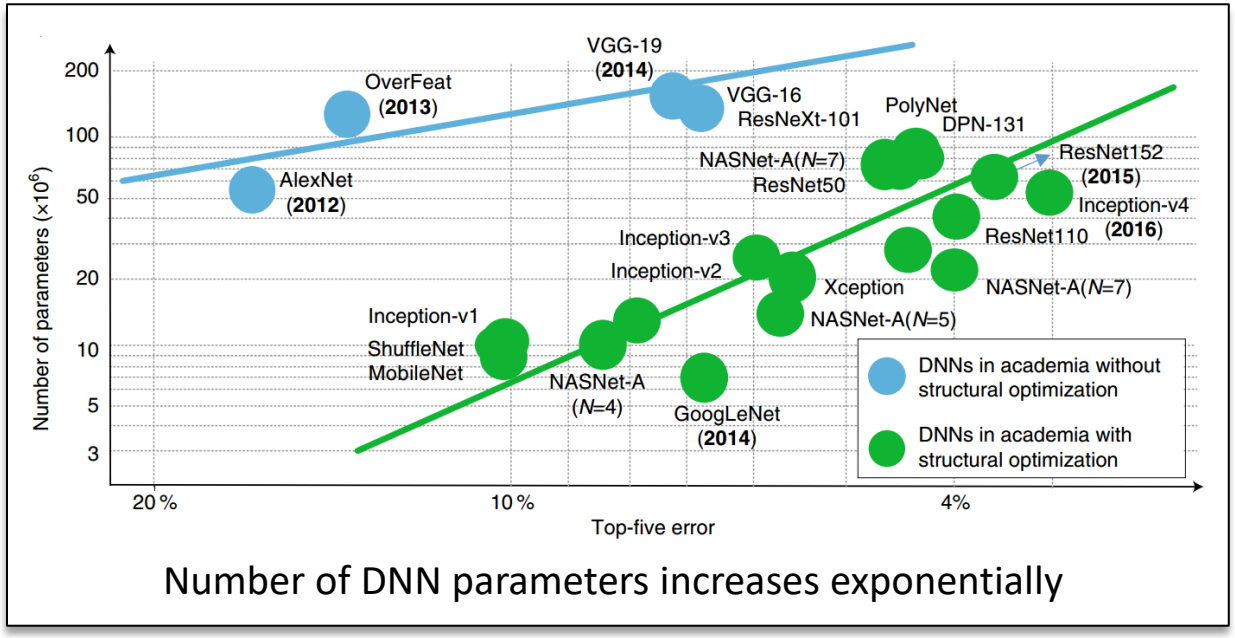
Number of DNN operations increases exponentially



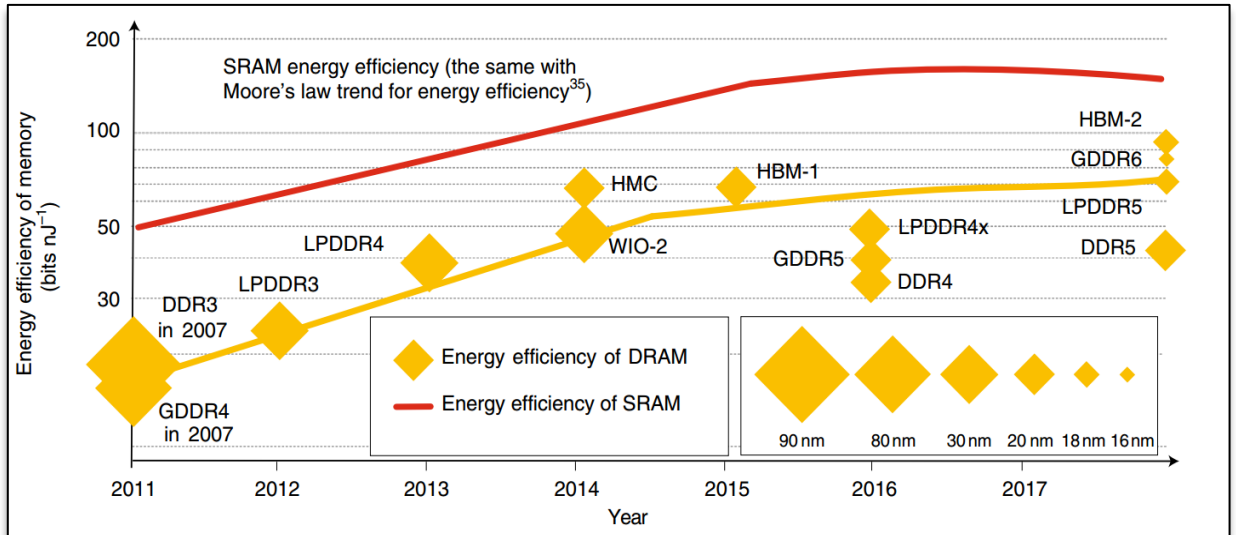
Performance density almost stops increasing

[ref.1] Xu, Xiaowei, et al. "Scaling for edge inference of deep neural networks." Nature Electronics 1.4 (2018): 216.
[ref.2] Sutter, H. The free lunch is over: A fundamental turn toward concurrency in software. Dr Dobb's J. 30, 202–210.

Storage Gap



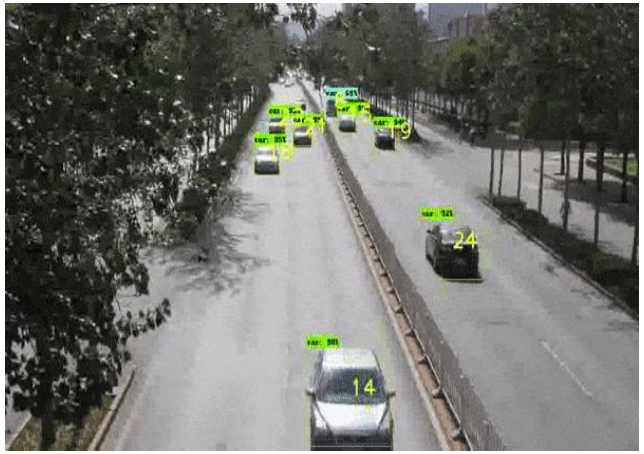
Number of DNN parameters increases exponentially



Energy efficiency of memory almost stops increasing

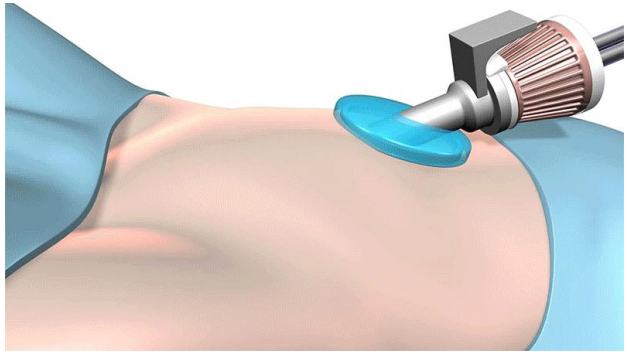
[ref.1] Xu, Xiaowei, et al. "Scaling for edge inference of deep neural networks." Nature Electronics 1.4 (2018): 216.
[ref.2] Sutter, H. The free lunch is over: A fundamental turn toward concurrency in software. Dr Dobb's J. 30, 202–210.

Real-Time Requirement



Traffic Surveillance

Self-Driving Vehicle



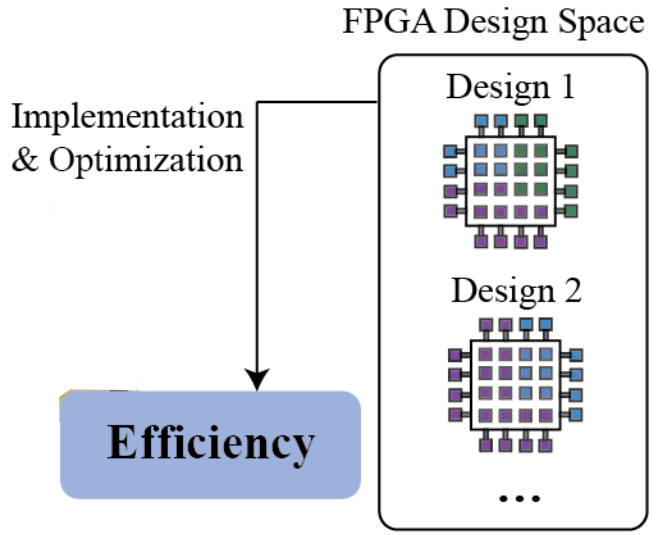
Robots in Surgery

Increasing Demands on Real-Time Machine Learning Applications

[ref.1] Google's Waymo
[ref.2] da Vinci Surgical Robot at St. Francis Health Center - Robotic Gizmos

Efforts on Both Software and Hardware Sides are Demanded

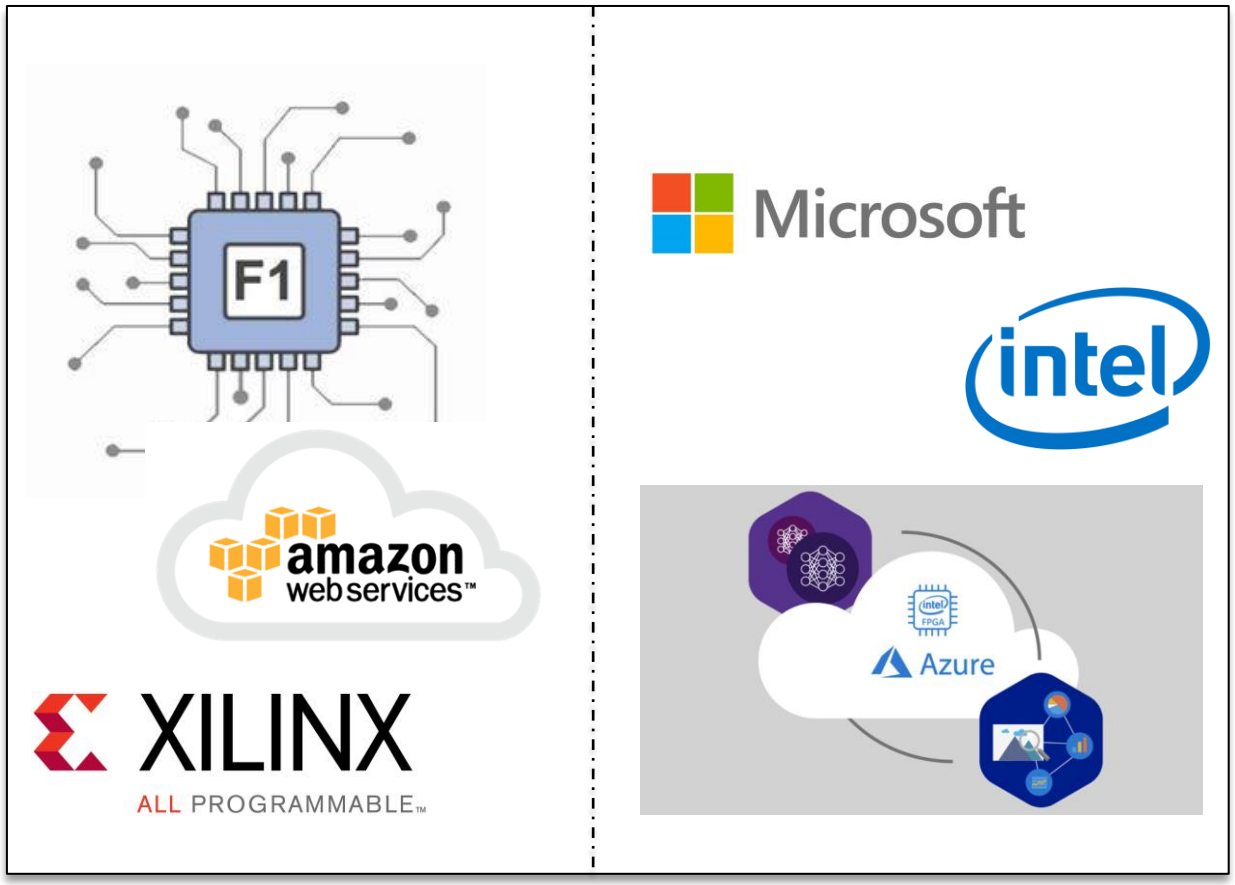
—— Hardware Implementation and Optimization



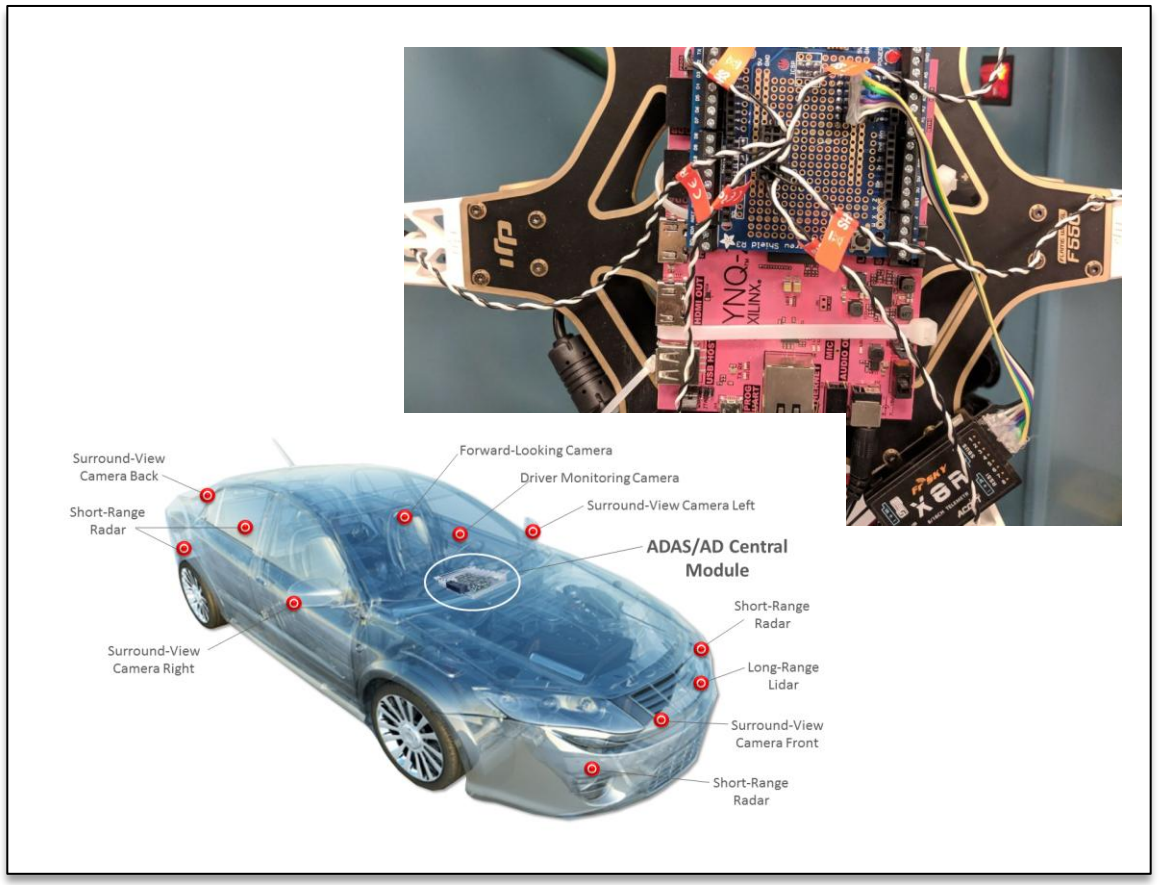
Neural Architecture Implementation on Hardware

FPGAs in DNN Applications

FPGA in Cloud Computing



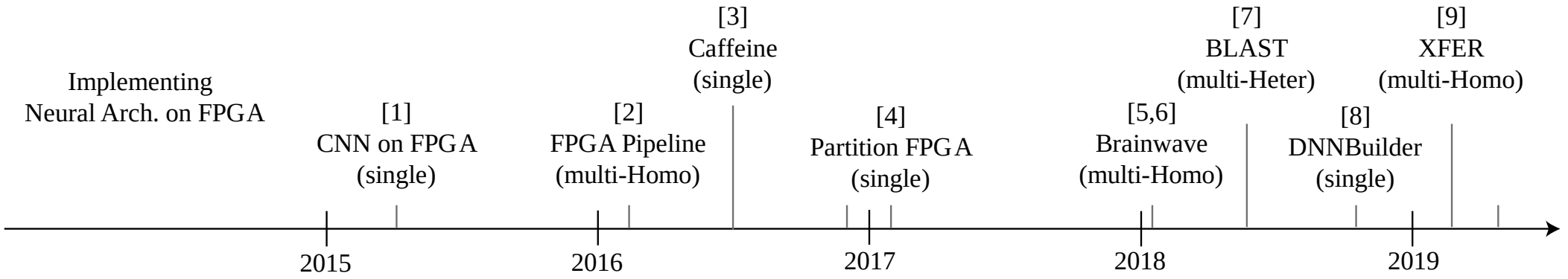
FPGA in Edge Computing



[ref] Where Do FPGAs Stand in Auto IC Race? https://www.eetimes.com/document.asp?doc_id=1333419#

[ref] PYNQ on UAV http://brennancain.com/pynqcopter-an-open-source-fpga-overlay-for-uavs/

Implementing Fixed NNs on FPGAs



[1] Chen Zhang, et al. Optimizing fpga-based accelerator design for deep convolutional neural networks. In FPGA, 2015.

[2] Chen Zhang, et al. Energy-efficient cnn implementation on a deeply pipelined fpga cluster. In ISLPED, 2016.

[3] Chen Zhang, et al. Caffeine: Towards uniformed representation and acceleration for deep convolutional neural networks. ICCAD, 2016.

[4] Yongming Shen, et al. Maximizing cnn accelerator efficiency through resource partitioning. In ISCA, 2017.

[5] Eric Chung, et al. Serving dnns in real time at datacenter scale with project brainwave. IEEE Micro, 2018.

[6] Jeremy Fowers, et al. A configurable cloud-scale dnn processor for real-time ai. In ISCA, 2018.

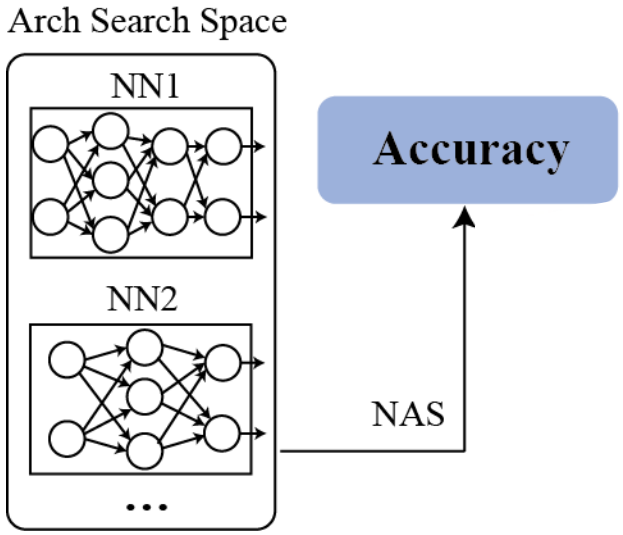
[7] Weiwen Jiang, et al. Heterogeneous fpga-based cost-optimal design for timing-constrained cnns. CASES – TCAD, 2018.

[8] Xiaofan Zhang, et al. Dnnbuilder: an automated tool for building high-performance dnn hardware accelerators for fpgas. In ICCAD, 2018.

[9] Weiwen Jiang, et al. Xfer: A novel design to achieve super-linear performance on multiple fpgas for real-time ai. In FPGA 2019.

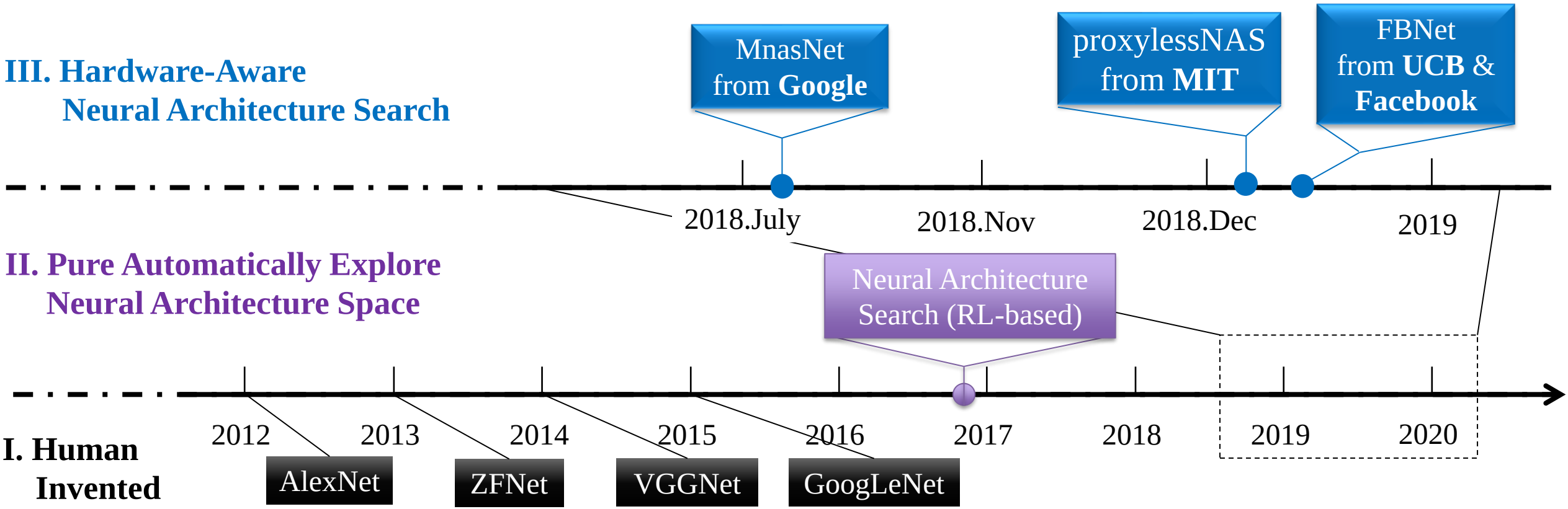
Efforts on Both Software and Hardware Sides are Demanded

—— Neural Architecture Design

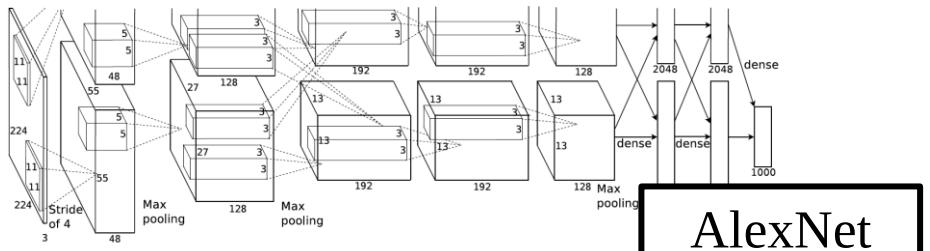


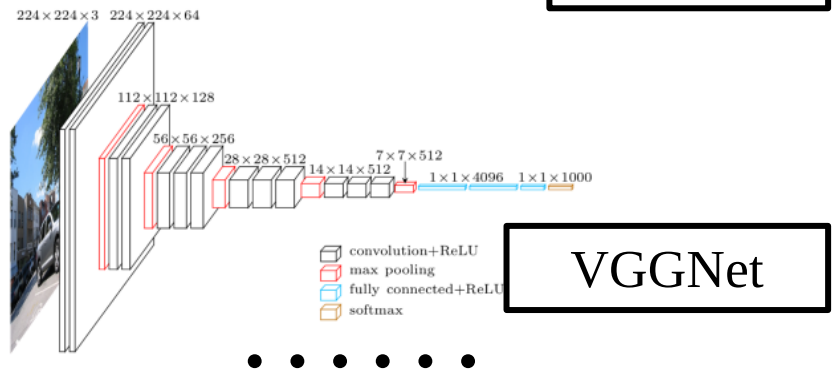
Neural Architecture Search

Evolution of Exploring Deep Neural Architectures

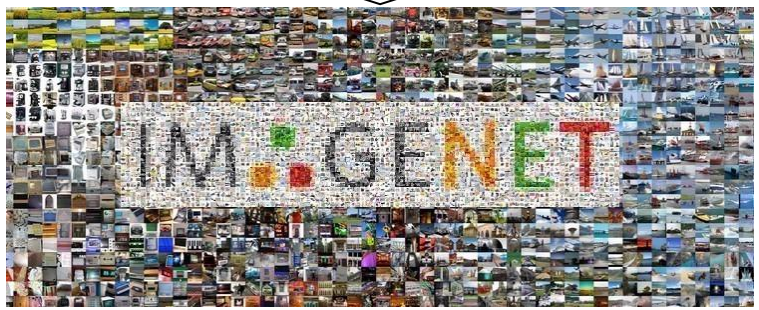


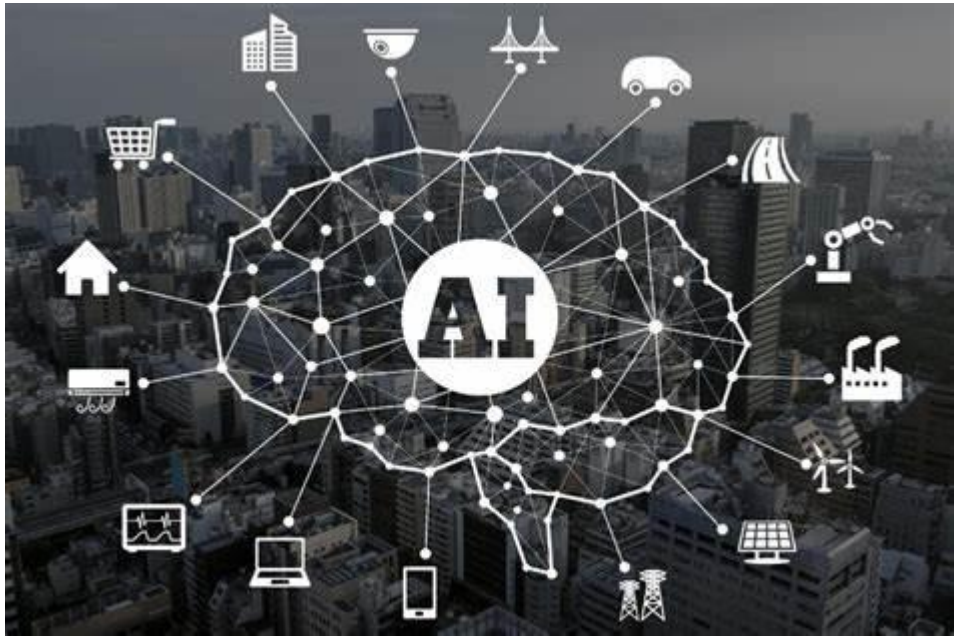
Phase I: Human Invented





Design arch. for dedicated application



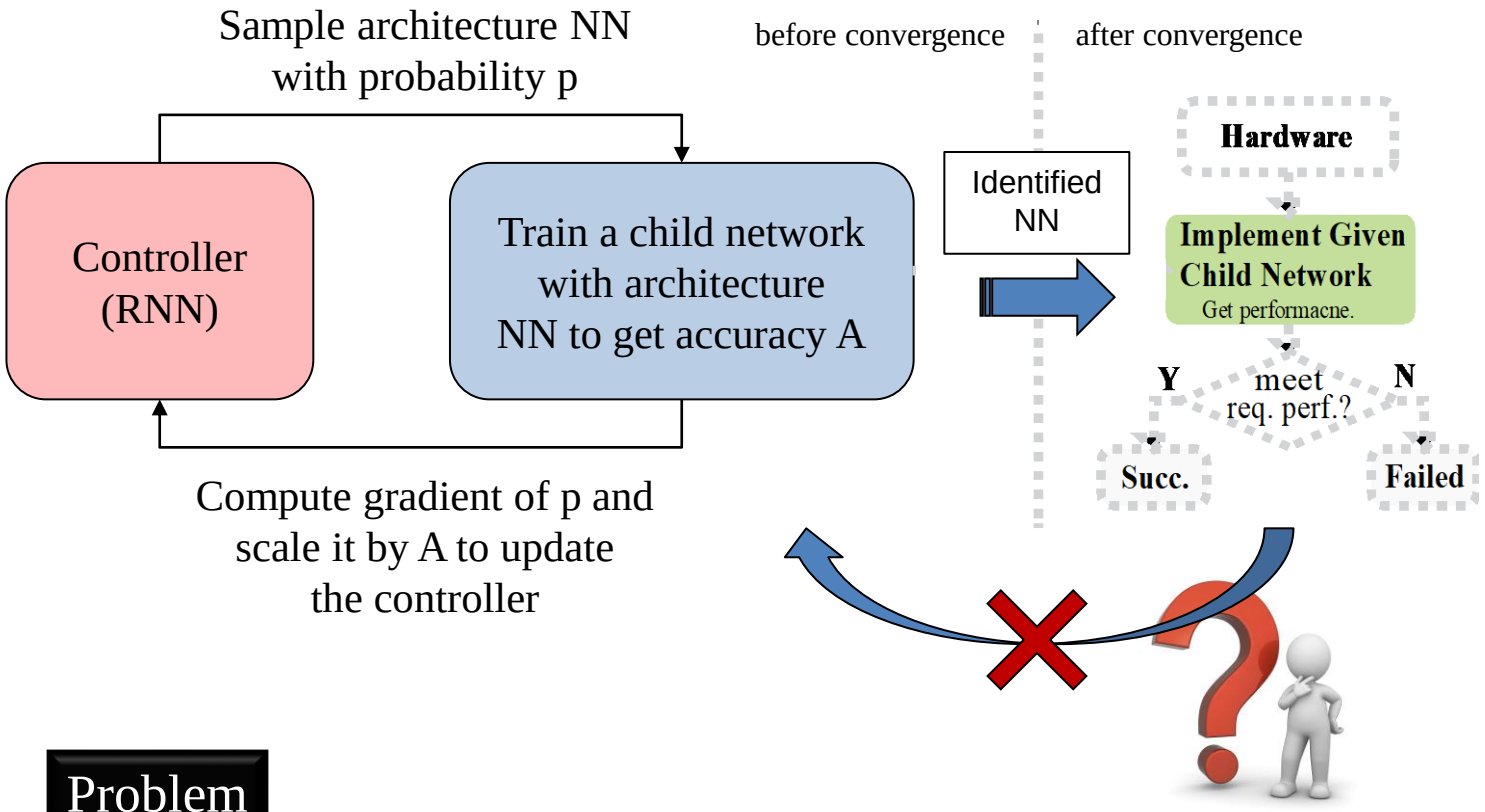


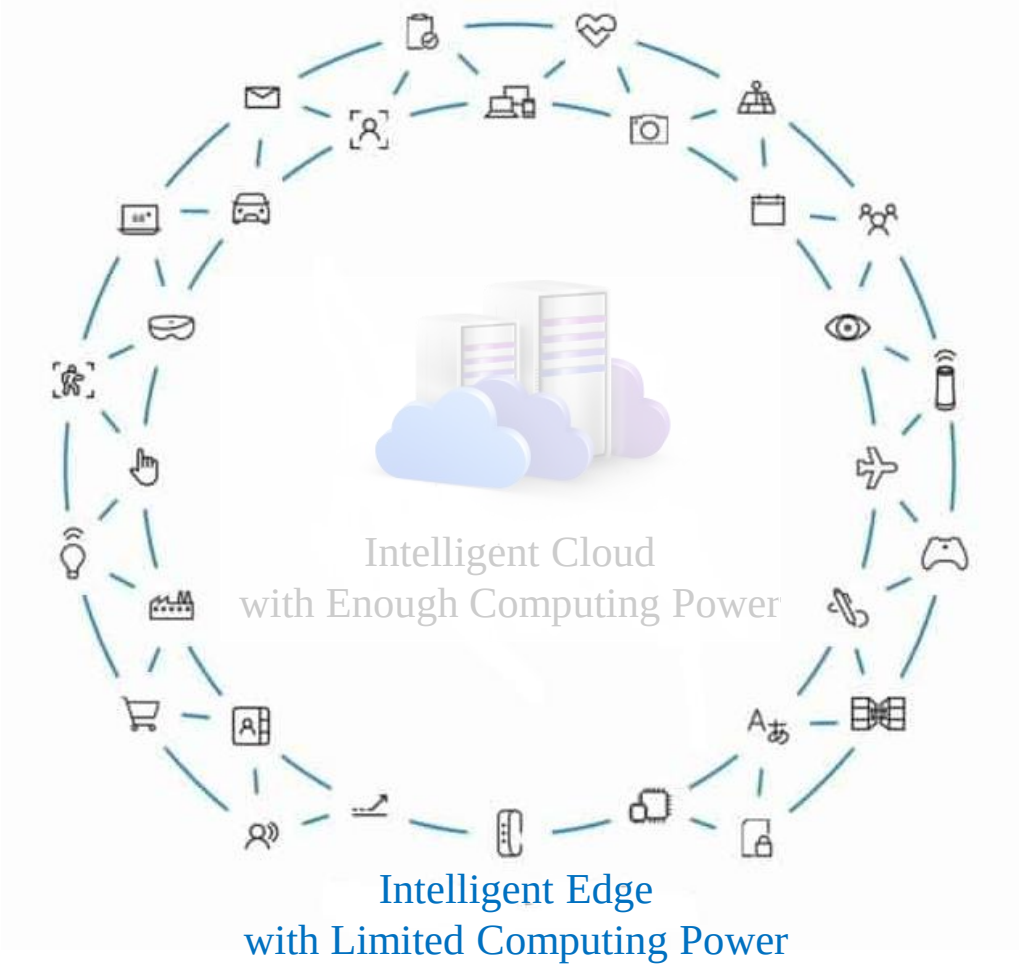
Era of AI Democratization

Problem

- **Domain knowledge and excessive labor**
- **It is impossible to manually design specific arch. for dedicated application in the era of AI democratization**

Phase II: Neural Architecture Search (NAS)



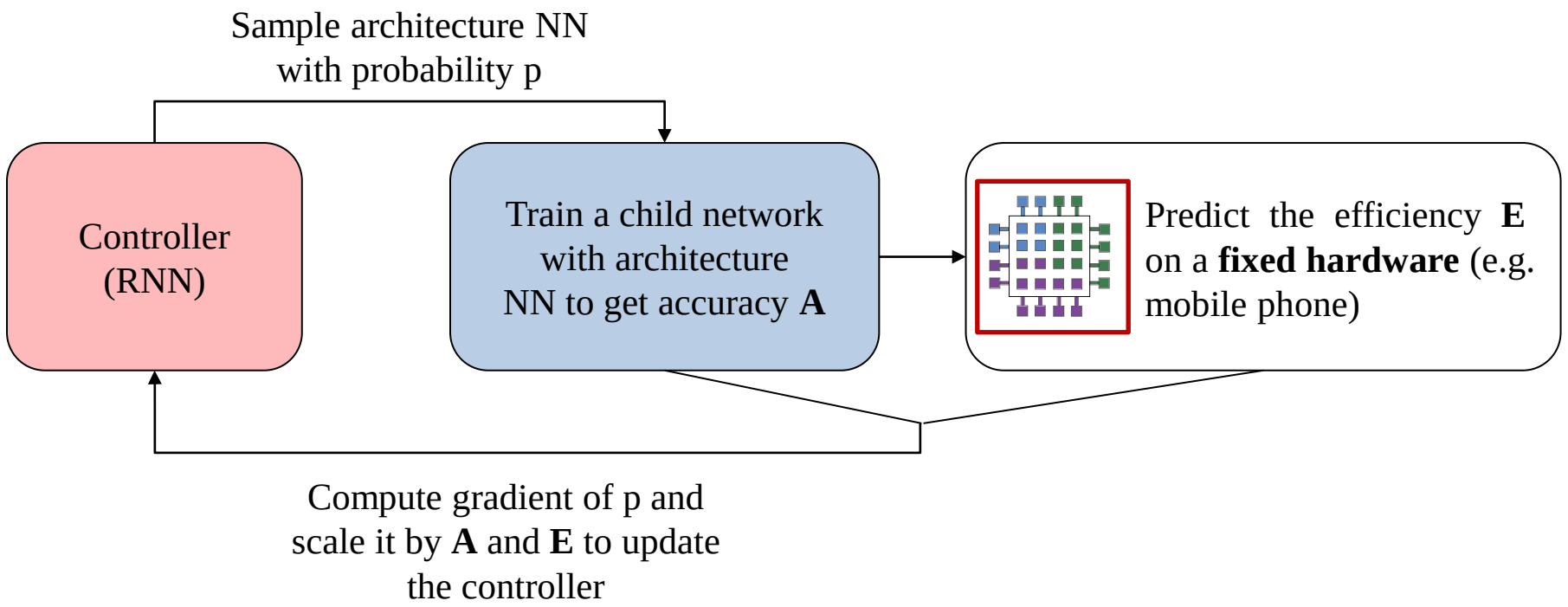


Problem

- **No constraint on hardware resource consumed**

REF: Zoph, Barret, and Quoc V. Le. "Neural architecture search with reinforcement learning." *ICLR 2017*

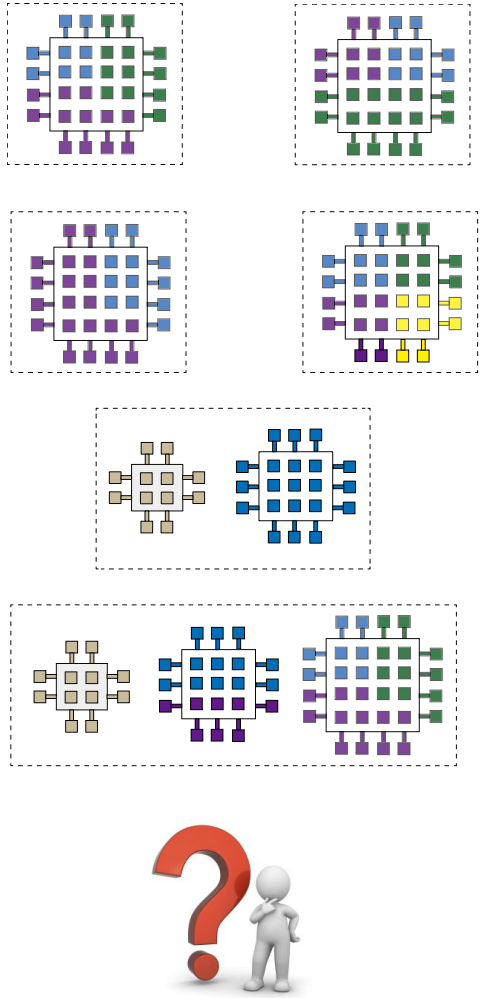
Phase III. Hardware-Aware NAS



Problem

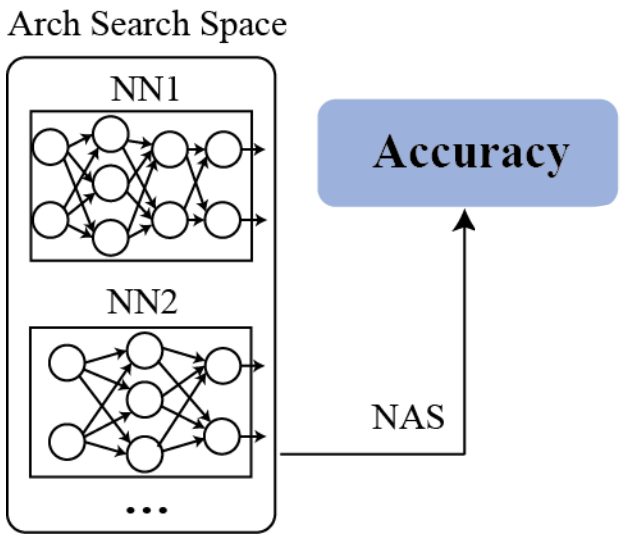
- **It works for particular fixed hardware, but not suitable for programmable hardware**

Different Hardware Designs

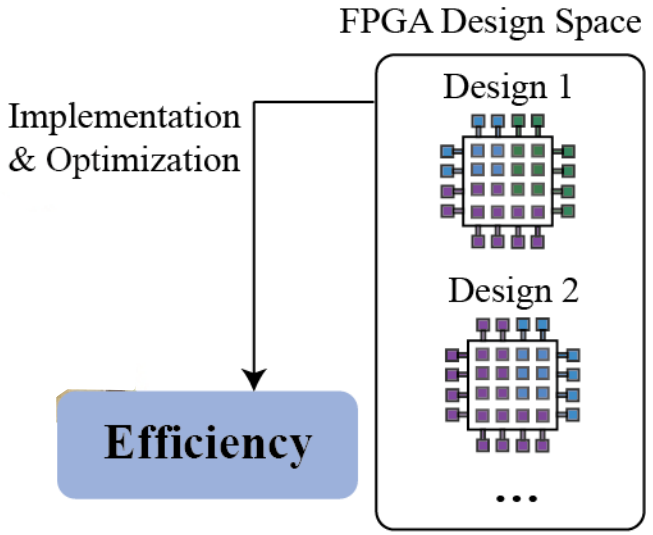


REF: Mingxing Tan, et al. "MnasNet: Platform-Aware Neural Architecture Search for Mobile." arXiv 2018

A Missing Link between Two Design Spaces

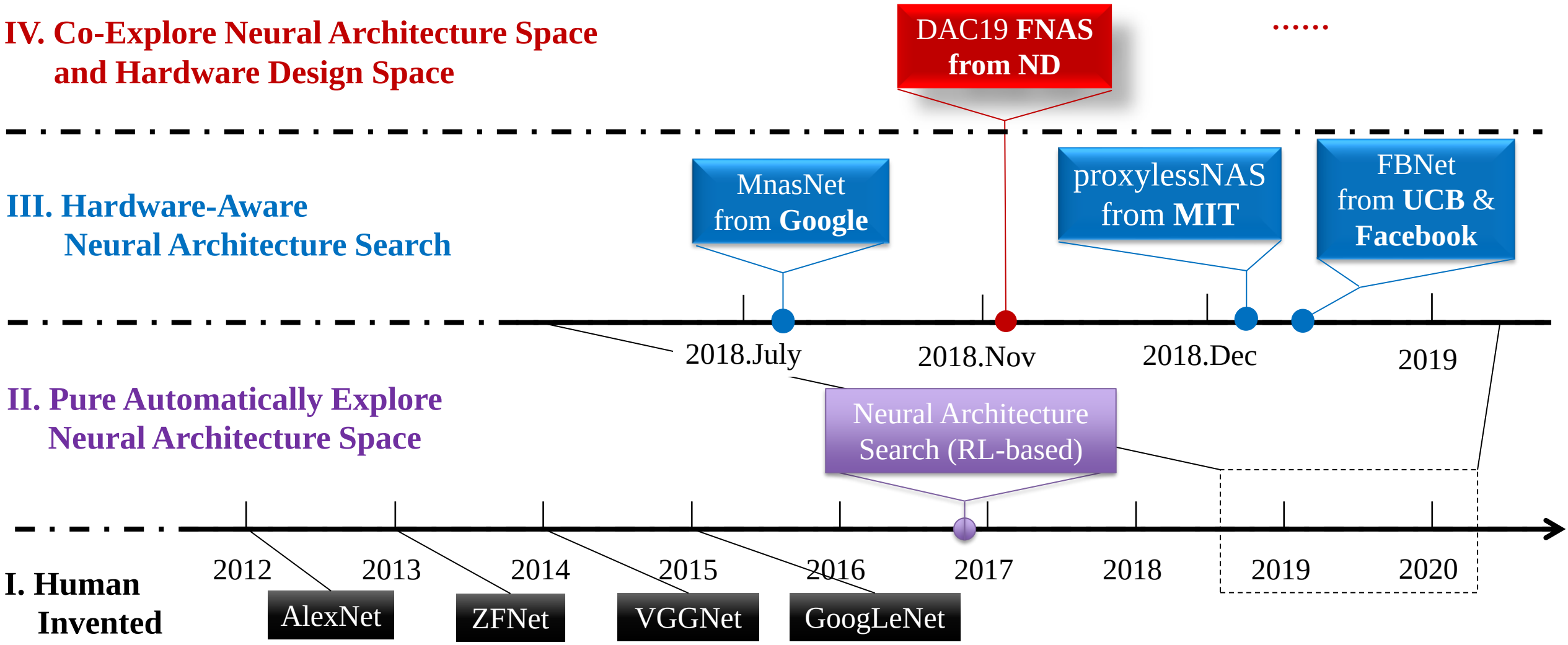


Neural Architecture Search



Neural Architecture Implementation on Hardware

Evolution of Exploring Deep Neural Architectures



Outline

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- **Co-Exploration of Neural Architecture and FPGA Implementation**

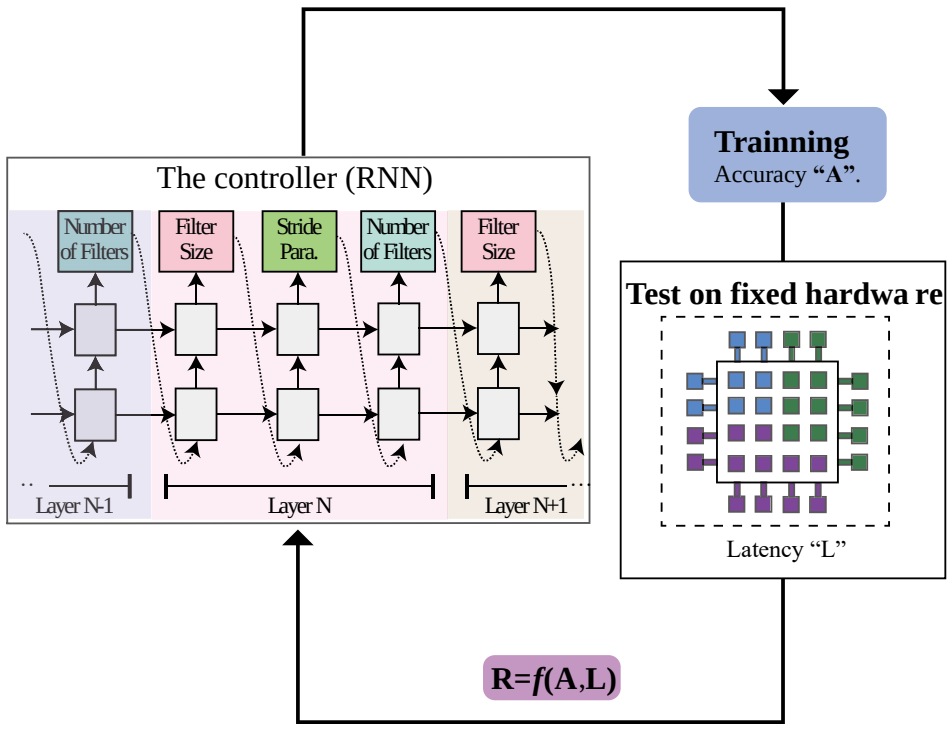
  - DAC 2019 (Best Paper Nomination)

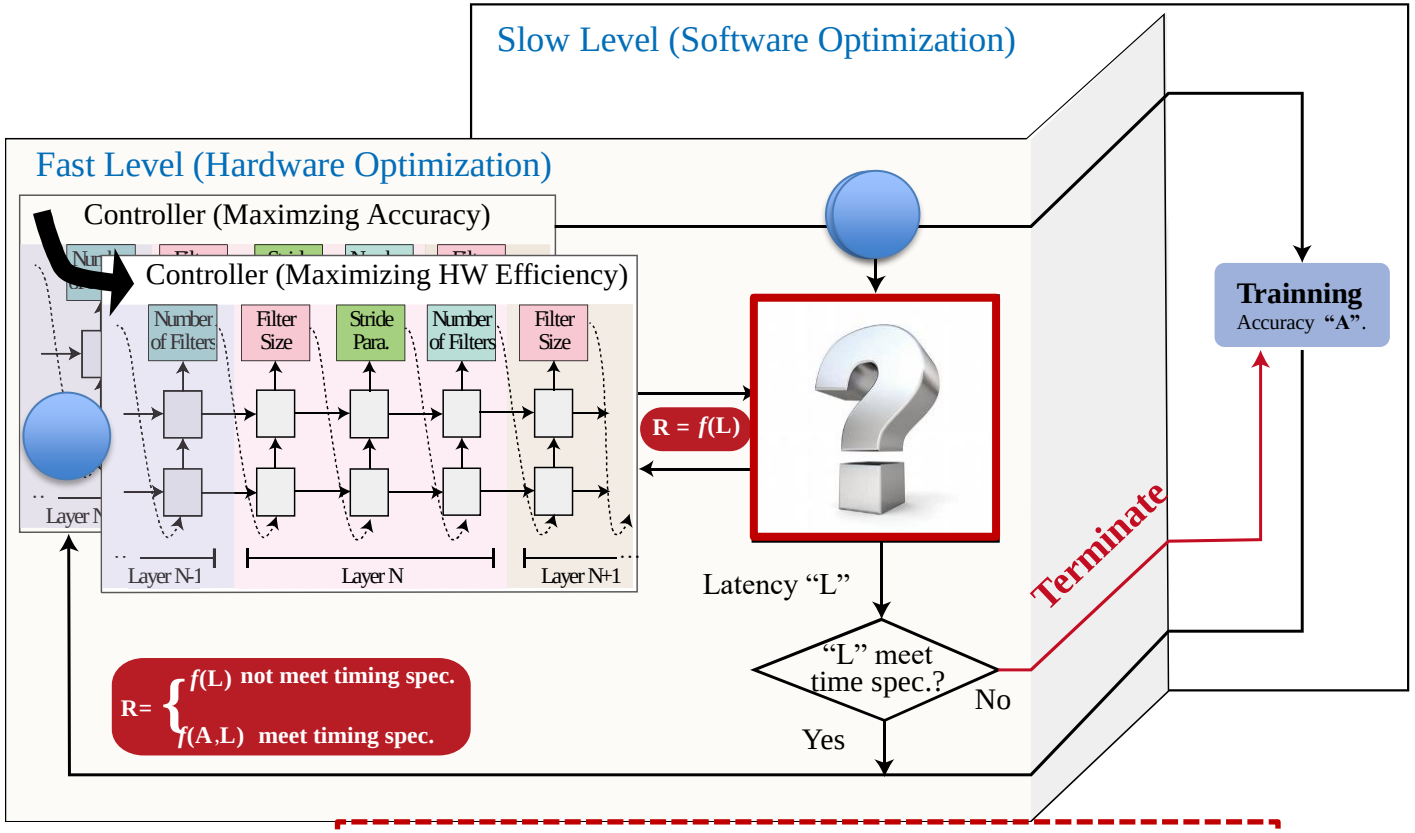
- Other Research Directions
- Conclusion

15

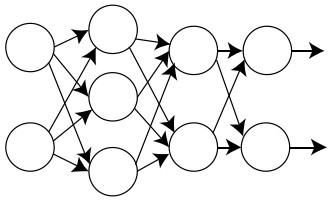
FNAS Framework

HW-Aware NAS vs. FPGA-Implementation Aware NAS（FNAS）



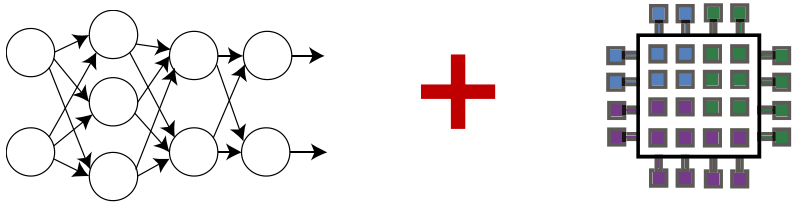


Output: A neural architecture



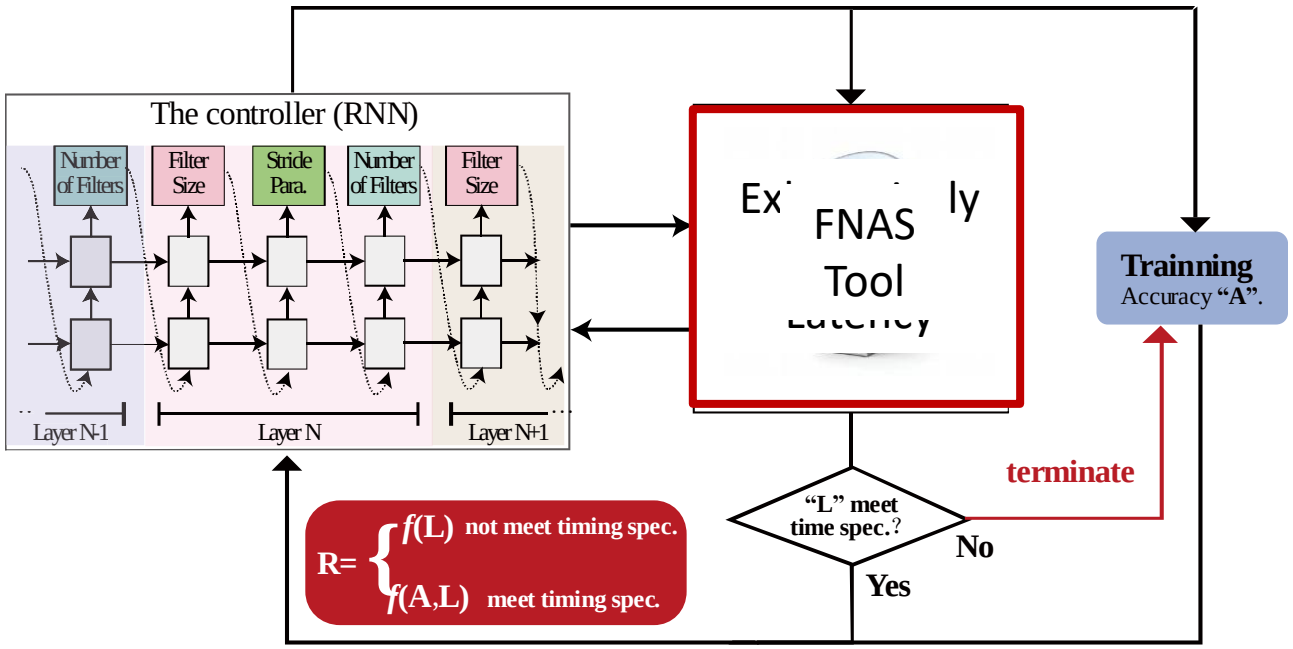
HW-Aware NAS

Output: A pair of neural architecture and hardware design



FNAS

Solutions & Challenges



Our Solution: FNAS tools to response to challenges

FNAS-Design "Design on Program Logic" C1	**FNAS-GG** "Tile-based Task Graph Generator" C2
FNAS-Sched "Scheduler on Processing System" C2	**FNAS-Analyzer** Estimate Performance " L" C3

Naïve Solution: HW-Aware + Exhaustively Evaluate Lat.

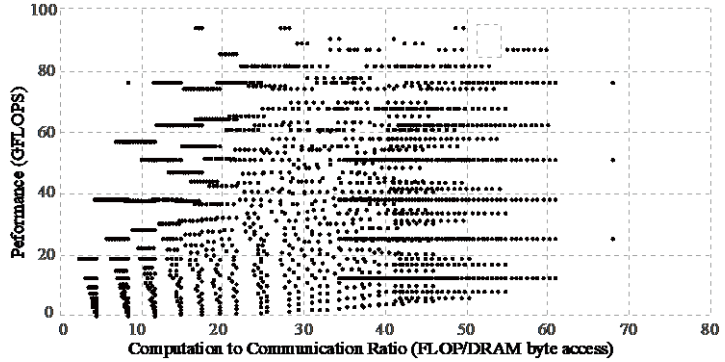


Fig1. Possible designs for Layer 5 of AlexNet on ZCU102

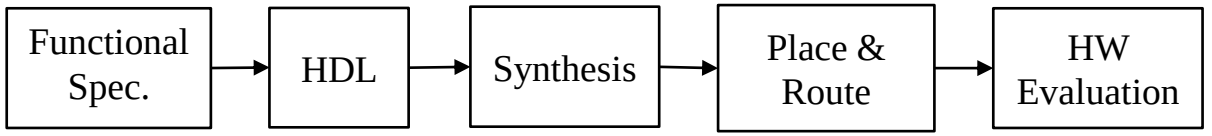


Fig2. Procedure of performance evaluation

Challenges:

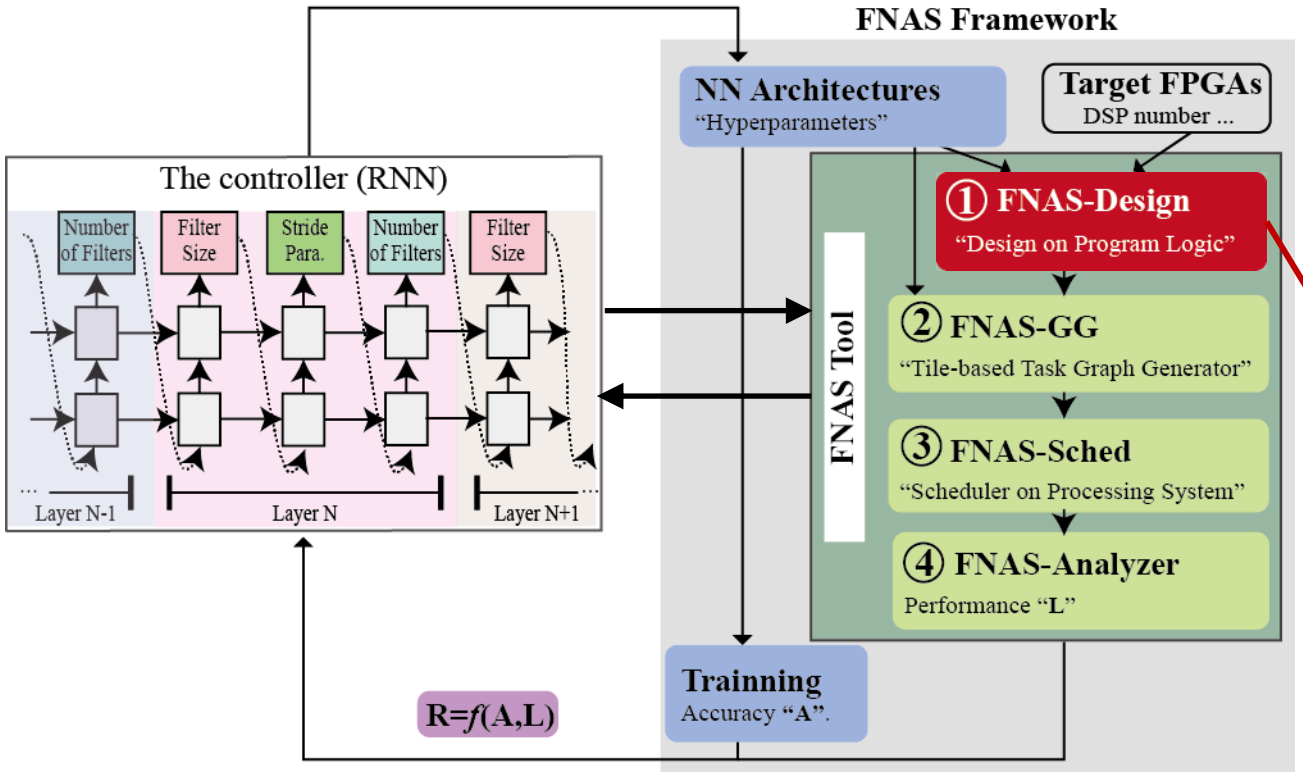
C1: Huge design space!

C2: Multi-FPGA design!

C3: Time-consuming evaluation!

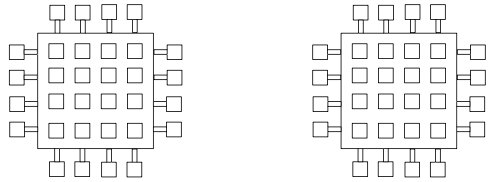
Infeasible

FNAS: Design Optimization (on-chip design)



Given:

1. FPGAs with attributes including LUTs, DSPs, BRAM, etc.



2. A neural architecture with determined hyperparameters

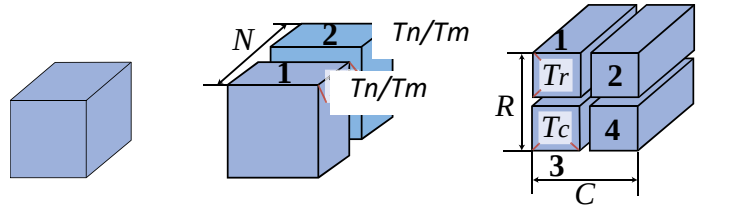
On-chip accelerator design:

Determine:

1. On-chip buffer allocation; 2. Accelerator size for computing

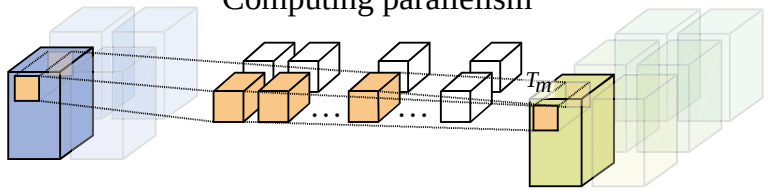
(note: both are determined by tiling parameters, Tm, Tn, Tr, Tc)

One layer:



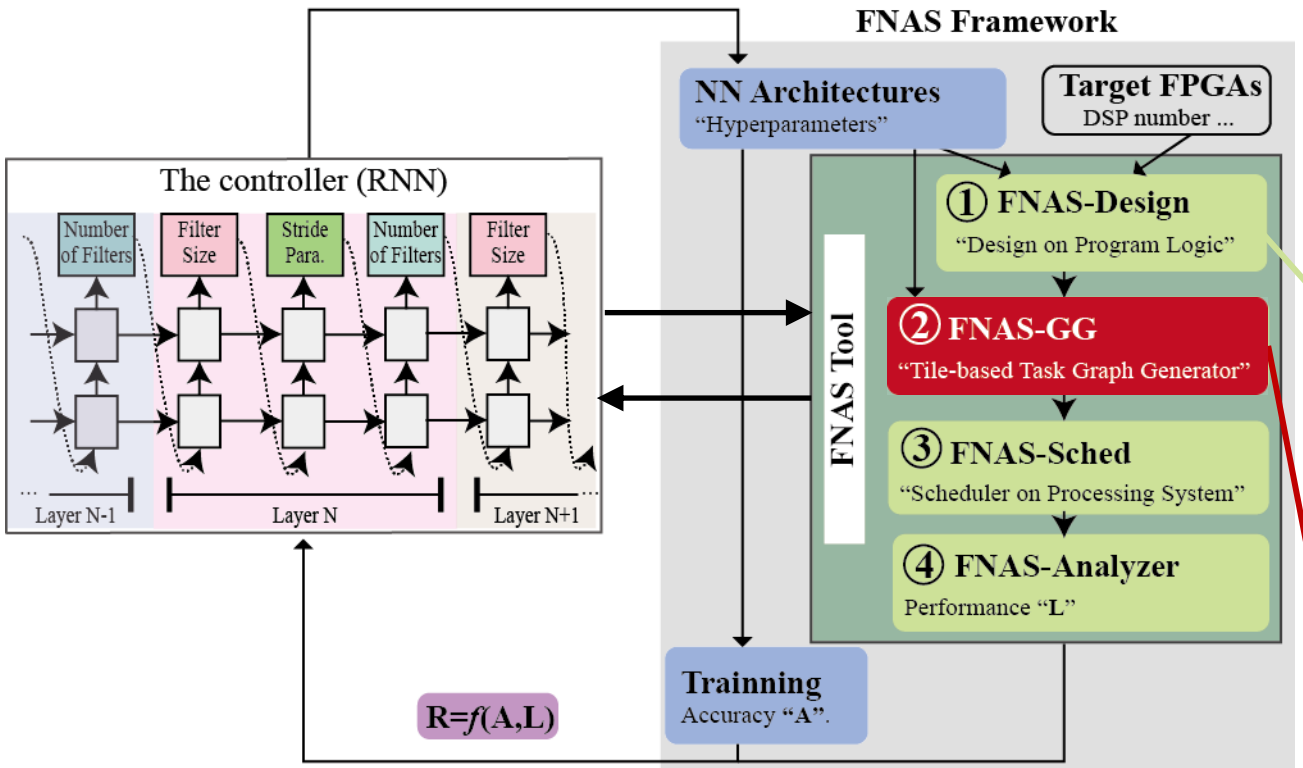
Computing parallelism

Multiple layers:



REF: Chen Zhang et al. 2015. Optimizing fpga-based accelerator design for deep convolutional neural networks. In Proc. of FPGA.

FNAS: Graph Generator



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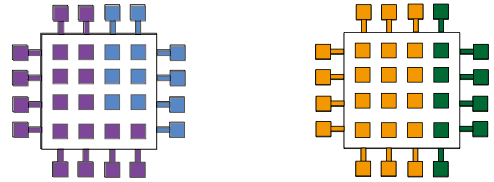

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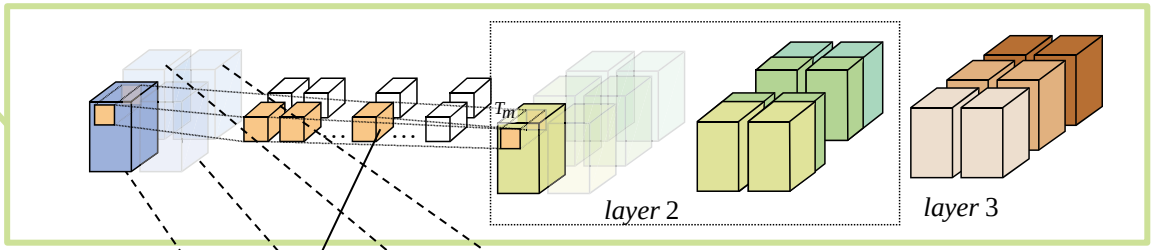
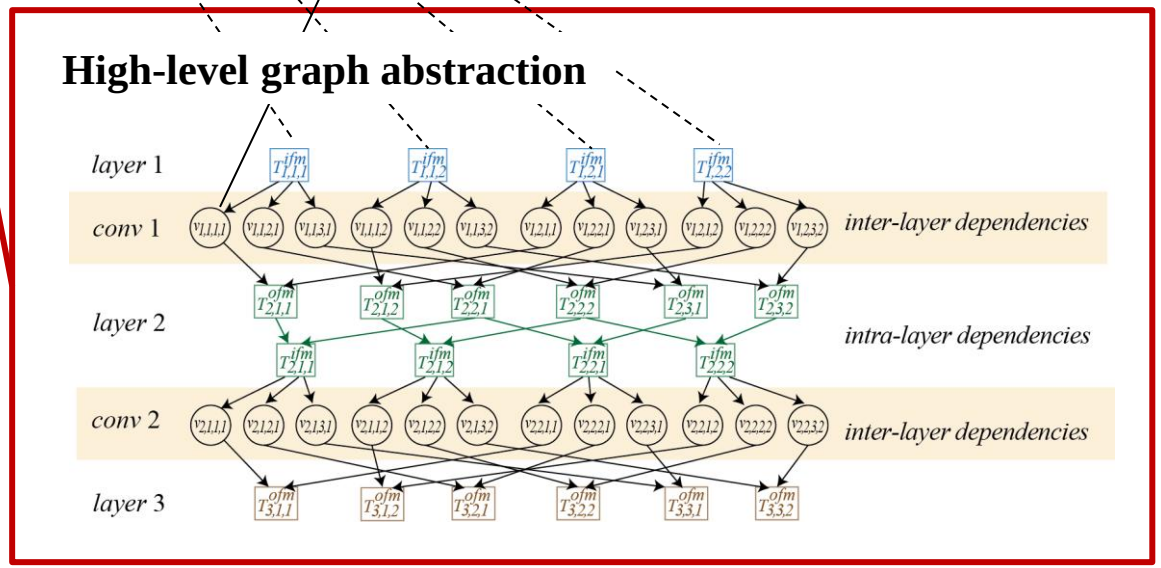
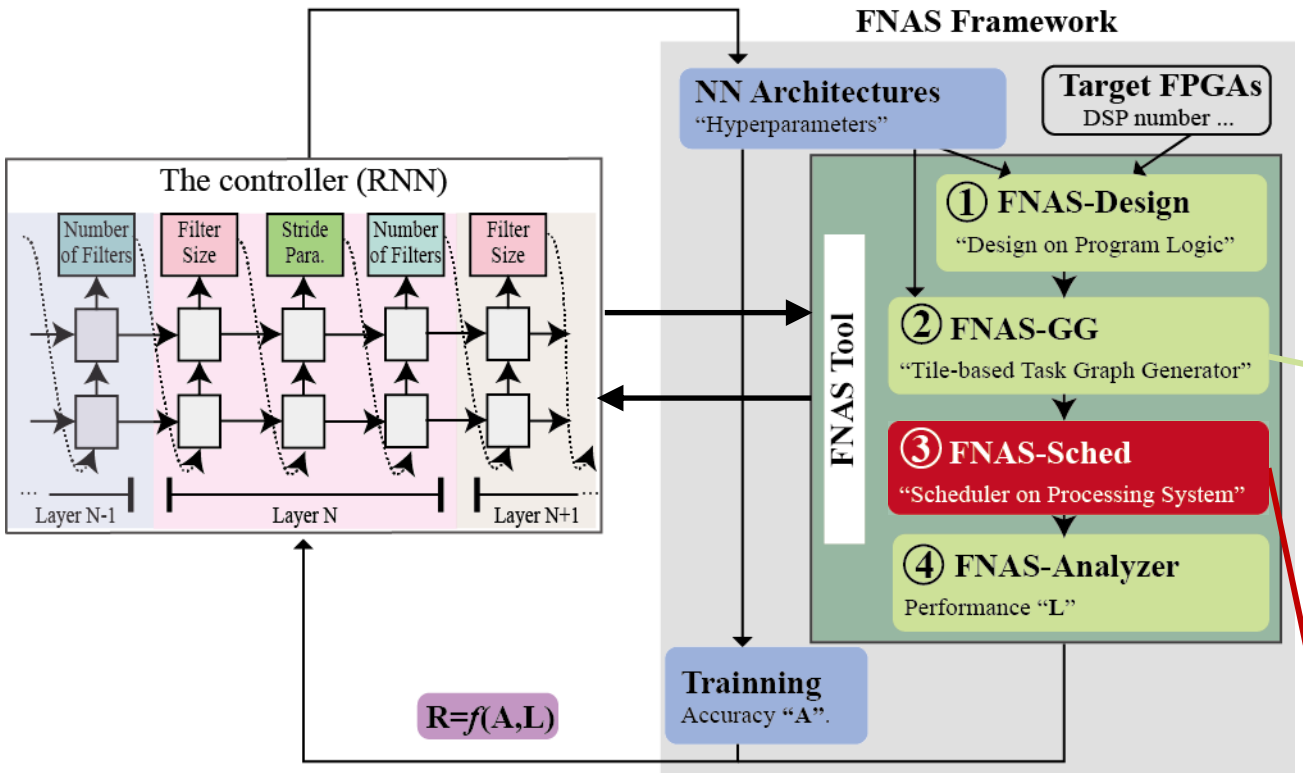
2. A neural architecture with determined hyperparameters





FNAS: Schedule (off-chip design)



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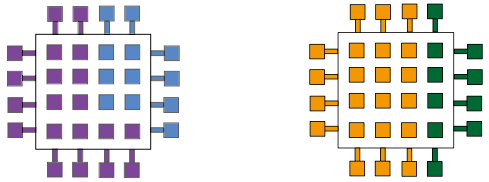

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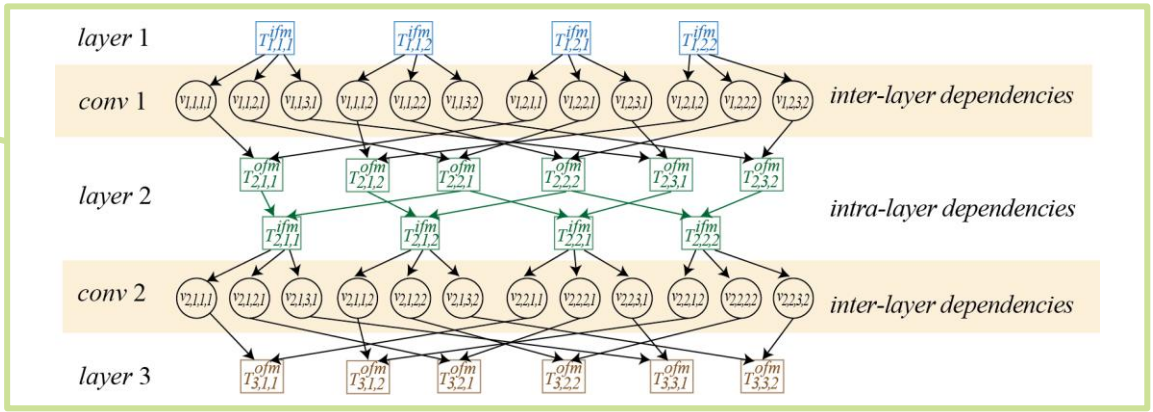
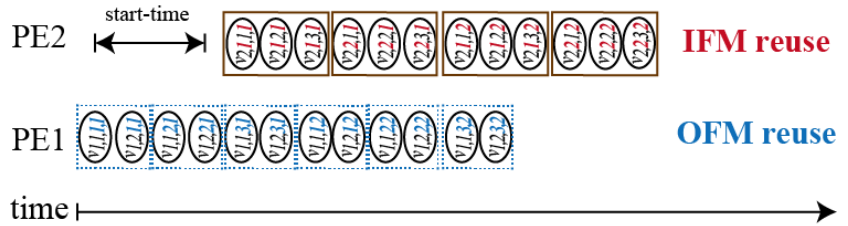
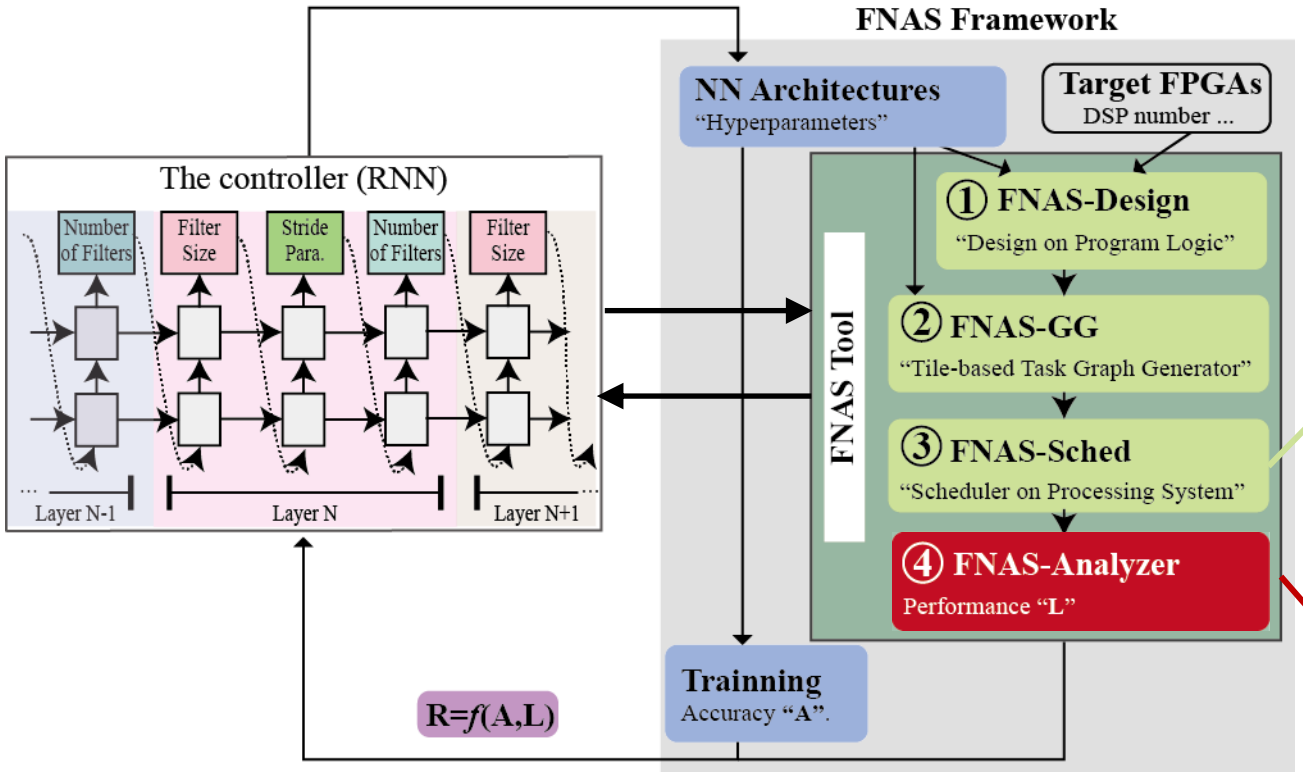


Schedule of tasks in graph on multiple FPGAs

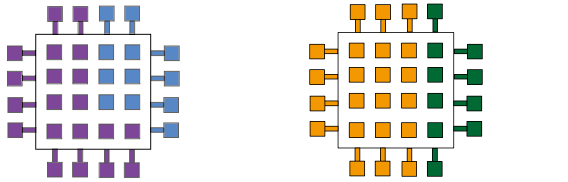


FNAS: Analyzer

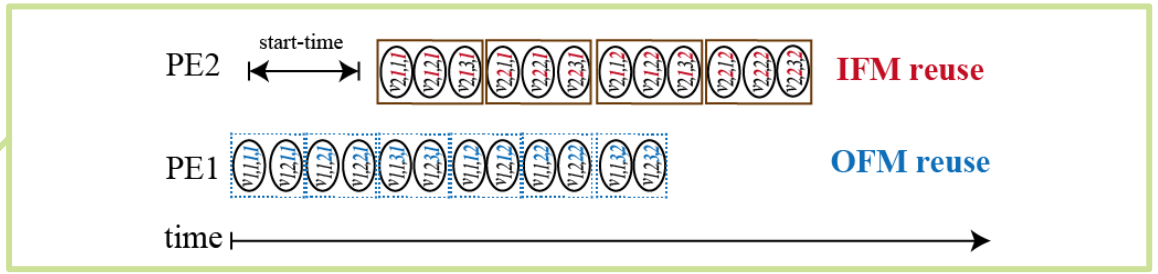


Given：

1. FPGAs with attributes including LUTs, DSPs, BRAM, etc.



2. A neural architecture with determined hyperparameters



Latency = pipeline start time + processing time

Output：

1. A tailored FPGA Design
2. The system latency

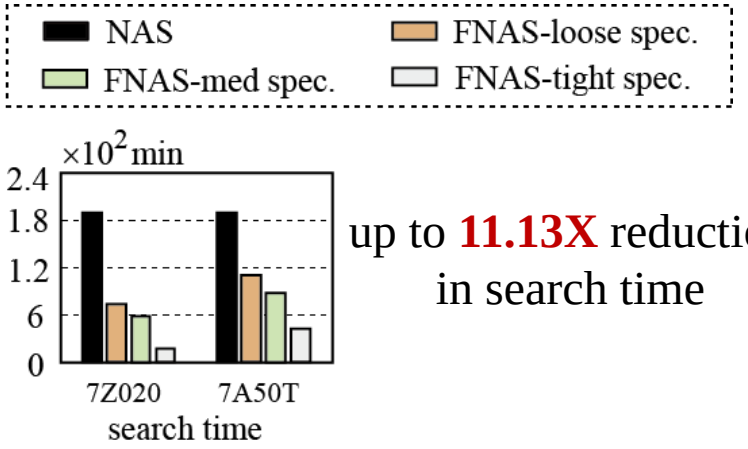
Experimental Results

Experimental Setting

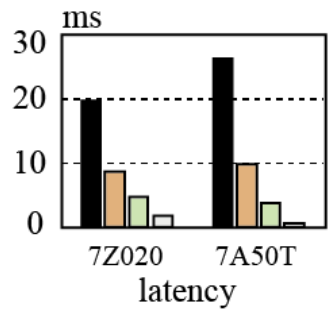
FPGAs		Xilinx 7A50T		Xilinx 7Z020
Datasets	 MNIST		 CIFAR-10	 ImageNet
NAS Search Space	Layer Num.	up to 5	up to 10	up to 15
	Filter Size	[5, 7, 14]	[1, 3, 5, 7]	[1, 3, 5, 7]
	Filter Num.	[9, 18, 36]	[24, 36, 48, 64]	[16, 32, 64, 128]
HW Search Space	Channel Tiling Para. (Tm,Tn); Row Tiling Para. (Tr); Col Tiling Para. (Tc); Schedule			
Timing Spec. (ms)		[2, 5, 10, 20]	[1.5, 2, 2.5, 10]	[2.5, 5, 7.5, 10]

Experimental Results

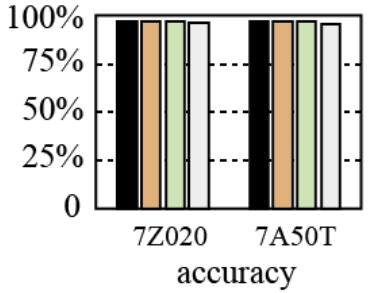
Different Hardware (CIFAR-10)



up to **11.13X** reduction in search time

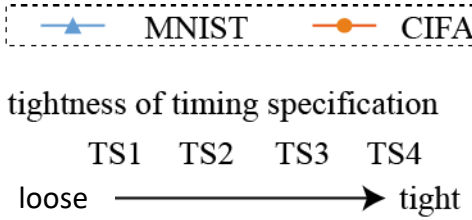


up to **7.81X** reduction in inference latency

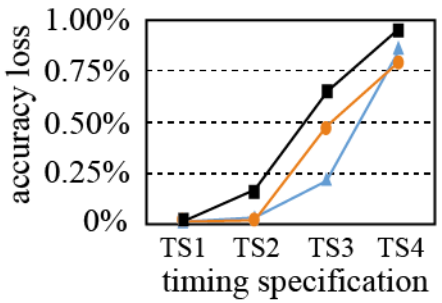


below **0.9%** loss in accuracy

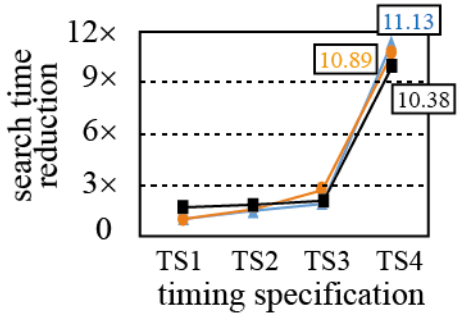
Different Datasets (7Z020)



Baseline: NAS

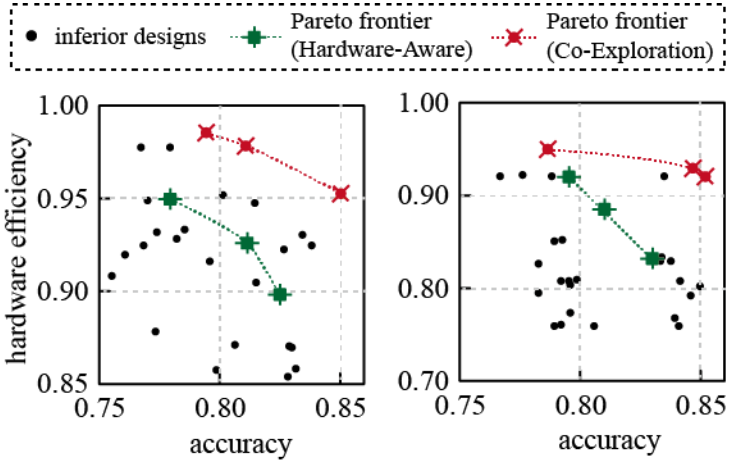


below **1%** loss in accuracy



up to **10X** reduction in inference latency

Compare to HW-Aware NAS (CIFAR-10 + 7Z020)



FNAS can significantly **push forward** the Pareto frontiers between **accuracy and efficiency** tradeoff

Experimental Results: Superior to Existing Approaches

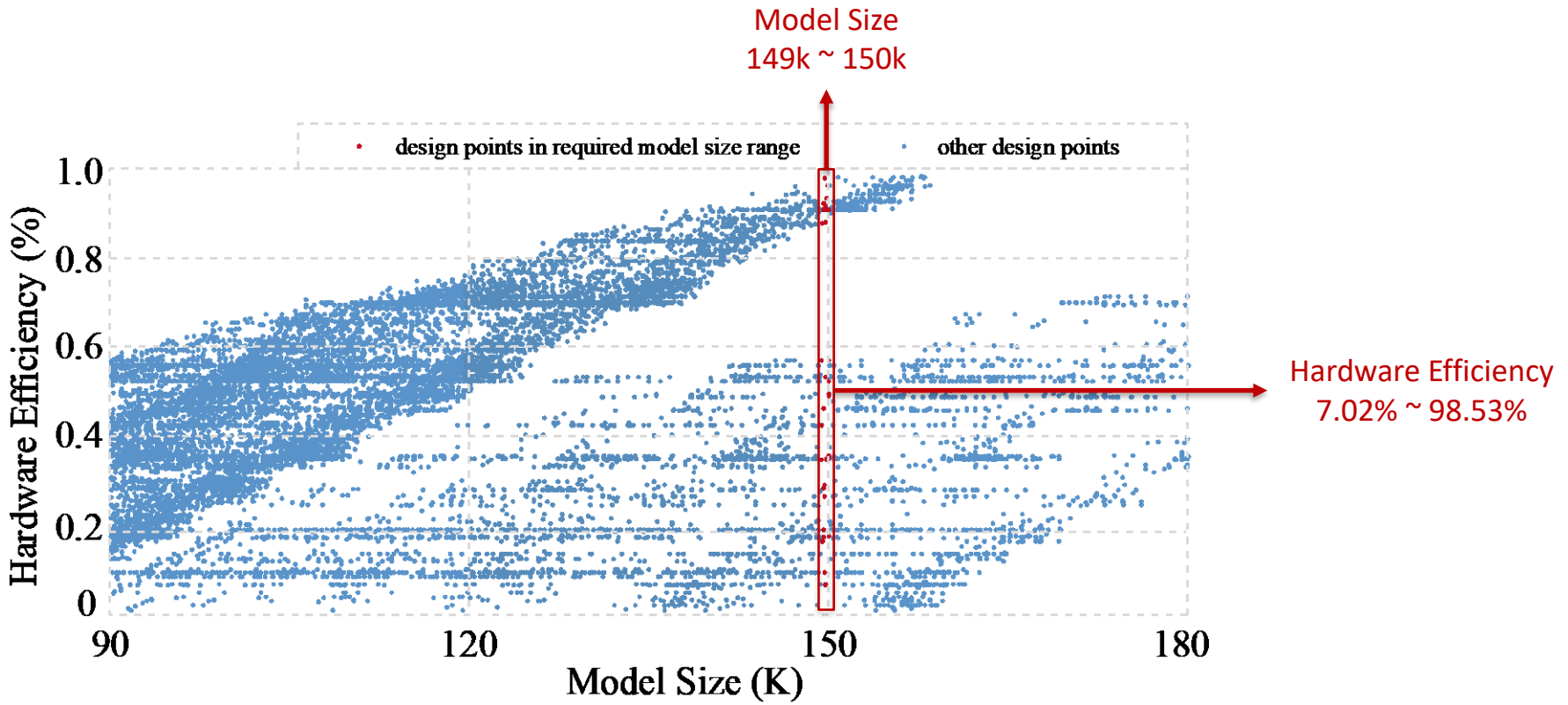
Optimizing Hardware Efficiency

Comparison the proposed Co-Exploration with Hardware-Aware NAS and Heuristic Sequential Optimization

Dataset	Models	Depth	Parameters	Accuracy (Top1)	Accuracy (Top5)	Pipeline Eff.	FPS	Energy Eff. GOPS/W
CIFAR-10	Hardware-Aware NAS	13	0.53M	84.53%	-	73.27%	16.2	0.84
	Sequential Optimization	13	0.53M	84.53%	-	92.20%	29.7	1.36
	Co-Exploration (OptHW)	10	0.29M	80.18%	-	99.69%	35.5	2.55
	Co-Exploration (OptSW)	14	0.61M	85.19%	-	92.15%	35.5	1.91
ImageNet	Hardware-Aware NAS	15	0.44M	68.40%	89.84%	81.07%	6.8	0.34
	Sequential Optimization	15	0.44M	68.40%	89.84%	86.75%	10.4	0.46
	Co-Exploration (OptHW)	17	0.54M	68.00%	89.60%	96.15%	12.1	1.01
	Co-Exploration (OptSW)	15	0.48M	70.24%	90.53%	93.89%	10.5	0.74

Optimizing Network Accuracy

Experimental Results: Importance of Co-Exploration



In the design space:

Models with similar model sizes may have distinct hardware efficiency

=> **Cannot restrict model size** to guarantee **hardware efficiency**

Outline

- Introduction
- Co-Exploration of Neural Architecture and FPGA Implementation

  - DAC 2019 (Best Paper Nomination)

- **Other Research Directions**
- Conclusion

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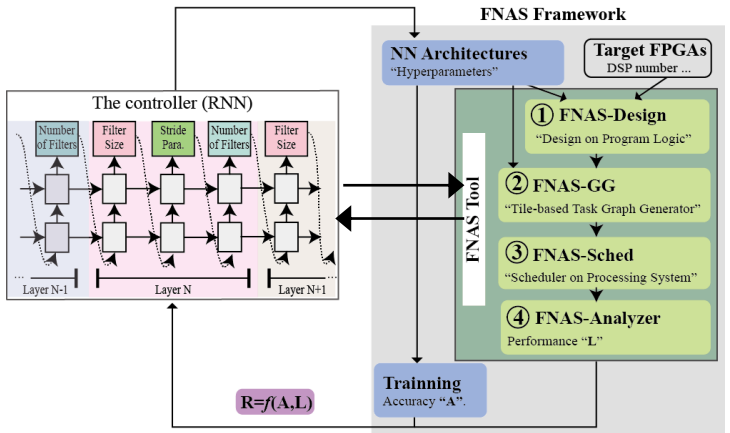
Our Work on Co-Exploring Neural Architecture and Hardware

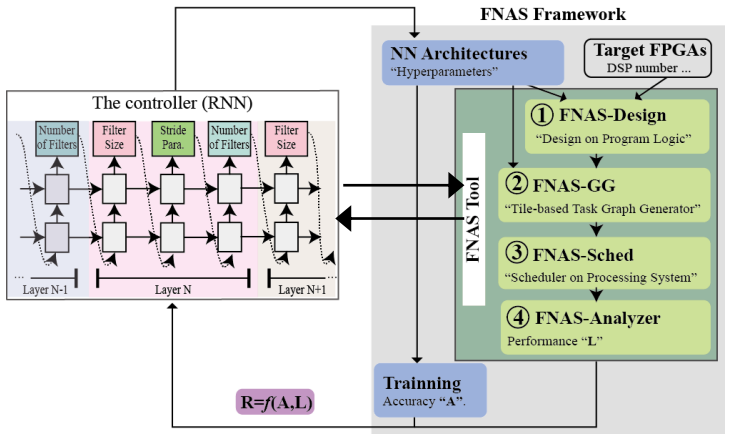
FPGA Implementation-Aware NAS (FNAS)



DAC'19 Best Paper Nomination

Our Work on Co-Exploring Neural Architecture and Hardware

FPGA Implementation-Aware NAS (FNAS)

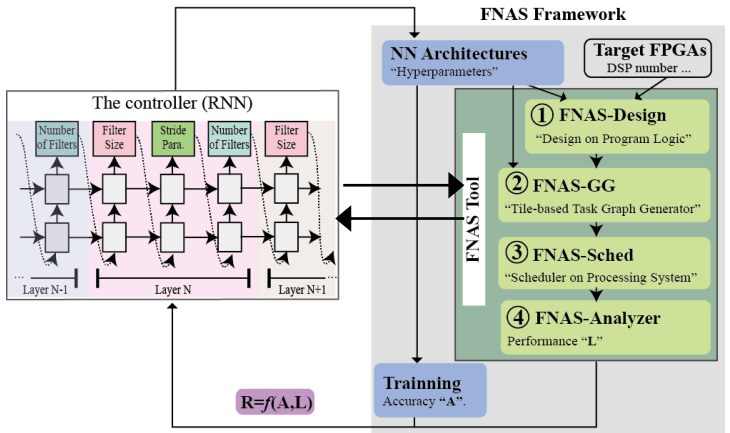


DAC'19 Best Paper Nomination

- **Scalability** in Cloud Computing (multiple-FPGAs, NoCs, etc.)
- **Limited Resource** in Edge Computing (quantization, etc.)
- **Novel Computing Architectures** (in-memory Computing, NVM, etc.)
- ……

Design Neural Networks on Scalable Architecture

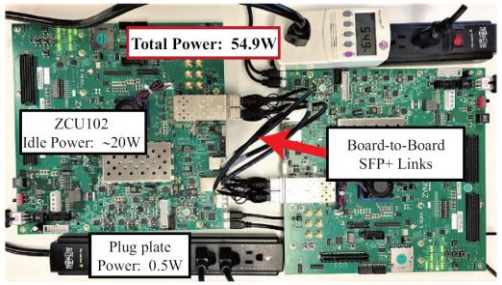
FPGA Implementation-Aware NAS (FNAS)



DAC'19 Best Paper Nomination

Scalability in Cloud Computing (multiple-FPGAs, NoCs, etc.)

Super-Linear Speedup across Multiple FPGAs (XFER)

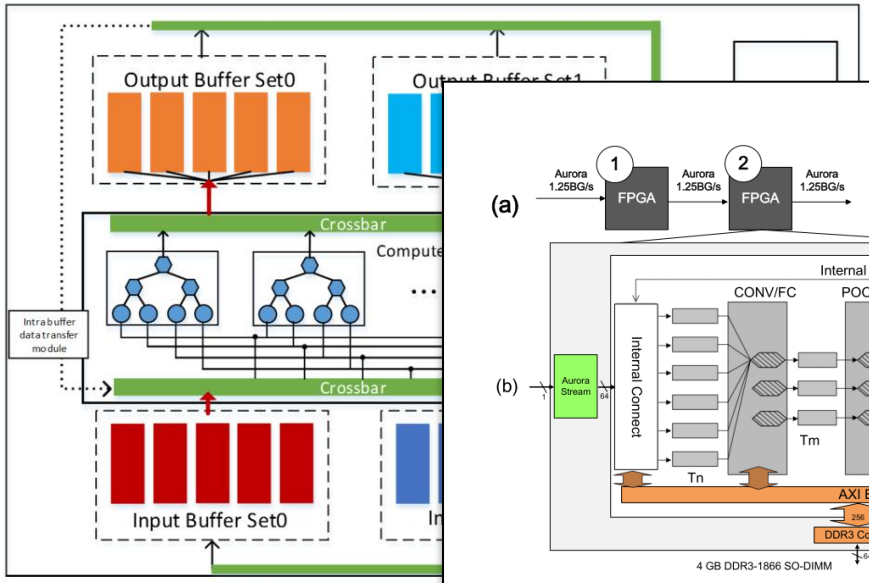


CODES+ISSS'19

Best Paper Nomination

Existing Implementations

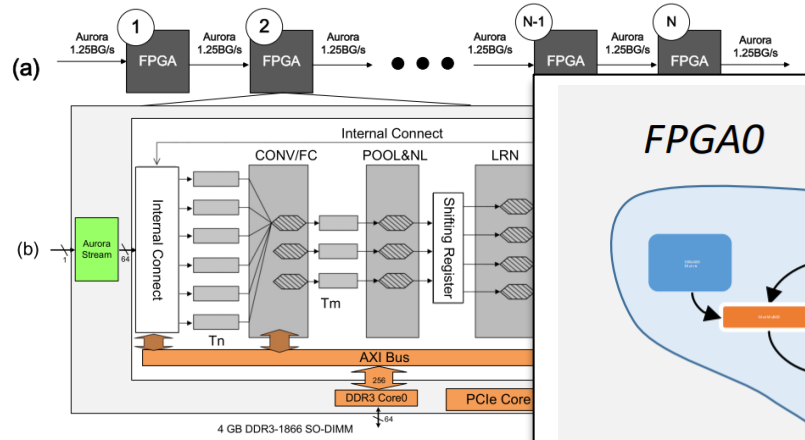
Single-FPGA



Limited Resource

[Ref] C. Zhang et al. Optim
neural networks. In Proc. o

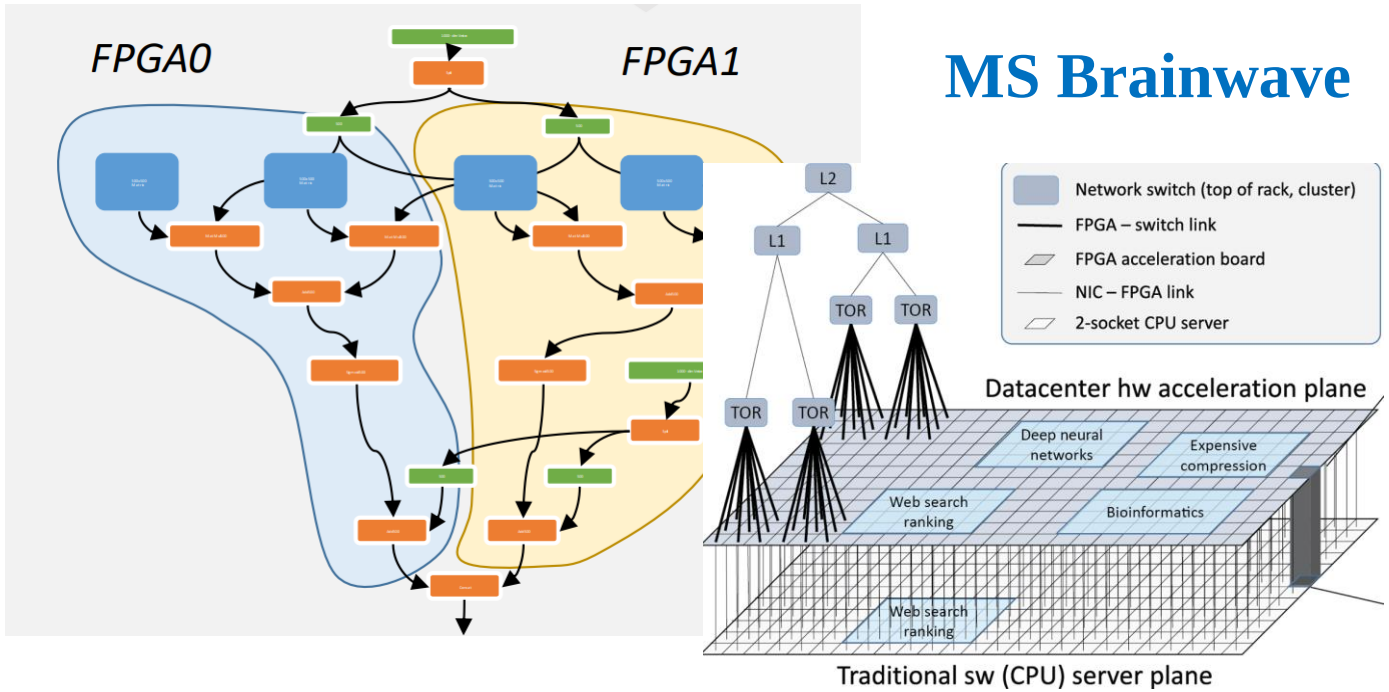
Pipelined FPGAs



Pipeline → High

[Ref] C. Zhang et al. Energy-effici
cluster. In Proc. of ISLPED, pages

MS Brainwave

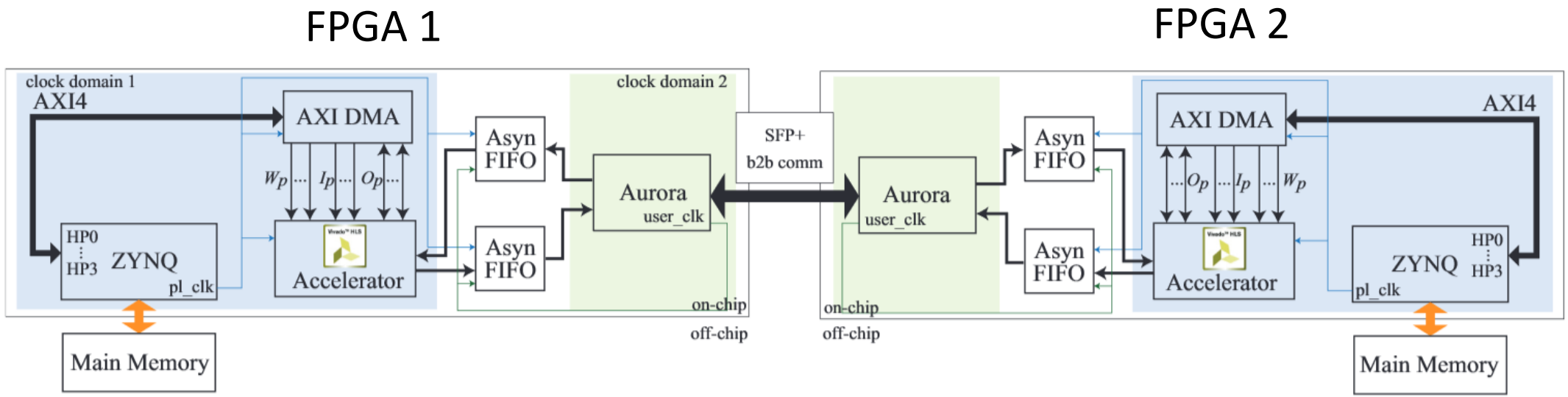


Lock weights to multiple FPGAs → Specific for RNN

Not applicable for sharing weights (e.g. CNN)

[Ref] Eric Chung, et al. Serving DNNs in Real Time at Datacenter Scale with Project Brainwave, In IEEE Micro, 2018

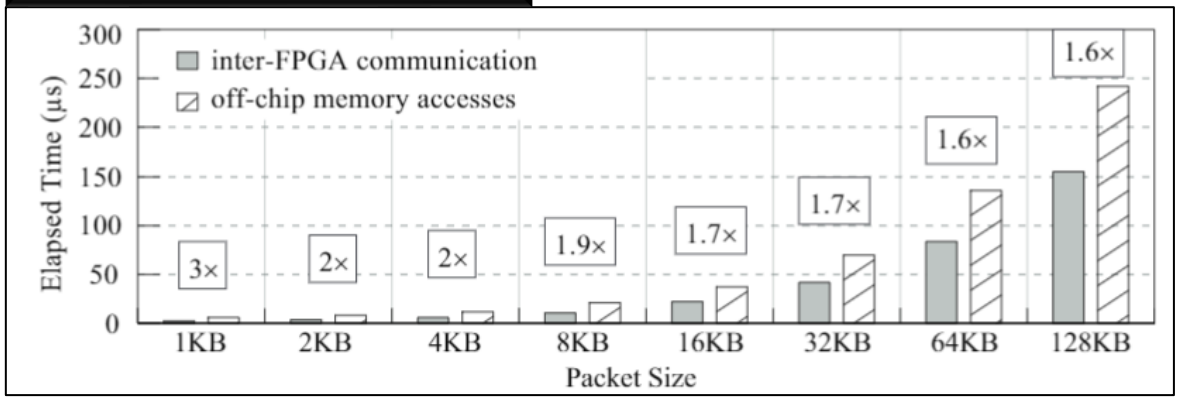
XFER: Architecture and Motivation



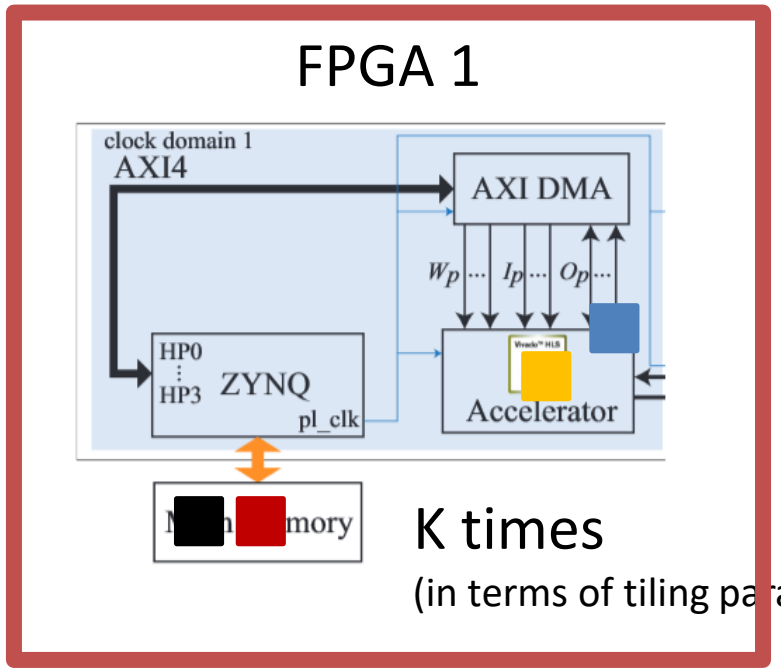
Feature

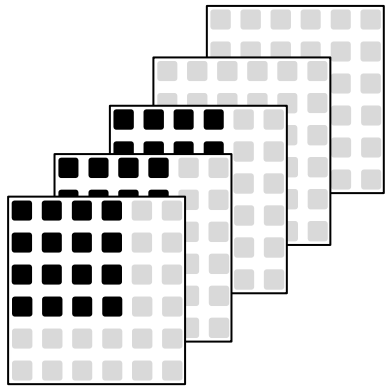
- Different **clock domains** for computation (**low**) and communication (**high**)
- Communication **not go through Off-Chip Memory**, but **directly switch between on-chip buffers**

Results & Motivations

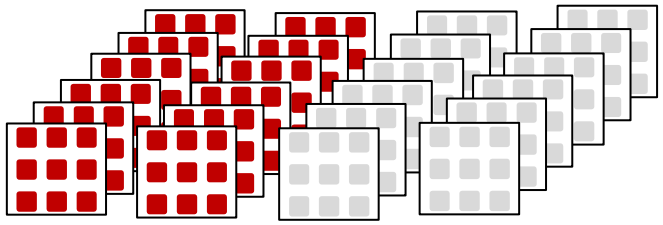


Performance on Single FPGA bounded by Limited Resource

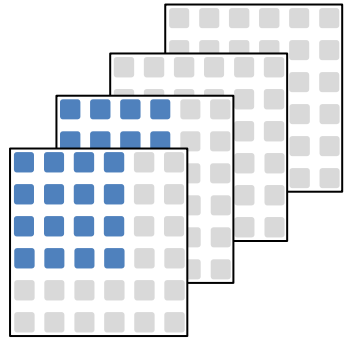




IFM



Weights

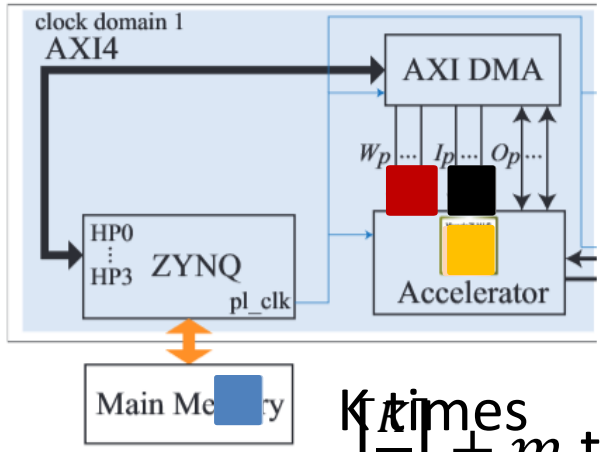


OFM

NN	Operation	Cycles	Note
AlexNet Layer 5	Comm_IFM	2,612	Performance Dominated by **Comm_Weights** **Latency is 5,658**
	Comm_Weights	**5,658**	
	Comm_OFM	368	
	Computation	3,326	

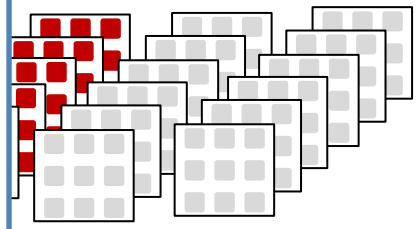
Double Computation Resource cannot Double Performance

FPGA 1

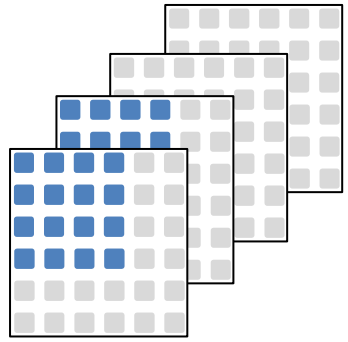


Observation:

1. Loading IFM, OFM, Computation are conducted **independently** on two FPGAs
2. Performance is still dominated by **loading weights**, and weights are **duplicated** on two FPGAs



Weights



OFM

IFM

K times

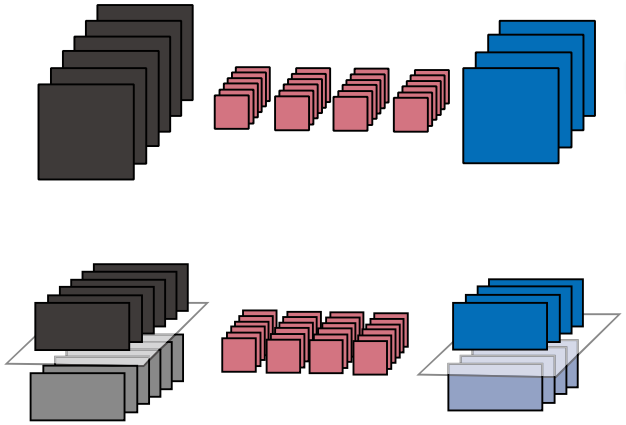
$\left\lfloor \frac{K}{2} \right\rfloor + m$ times

(in terms of tiling parameters)

(K is in terms of tiling parameters)

(m is in terms of stride and padding)

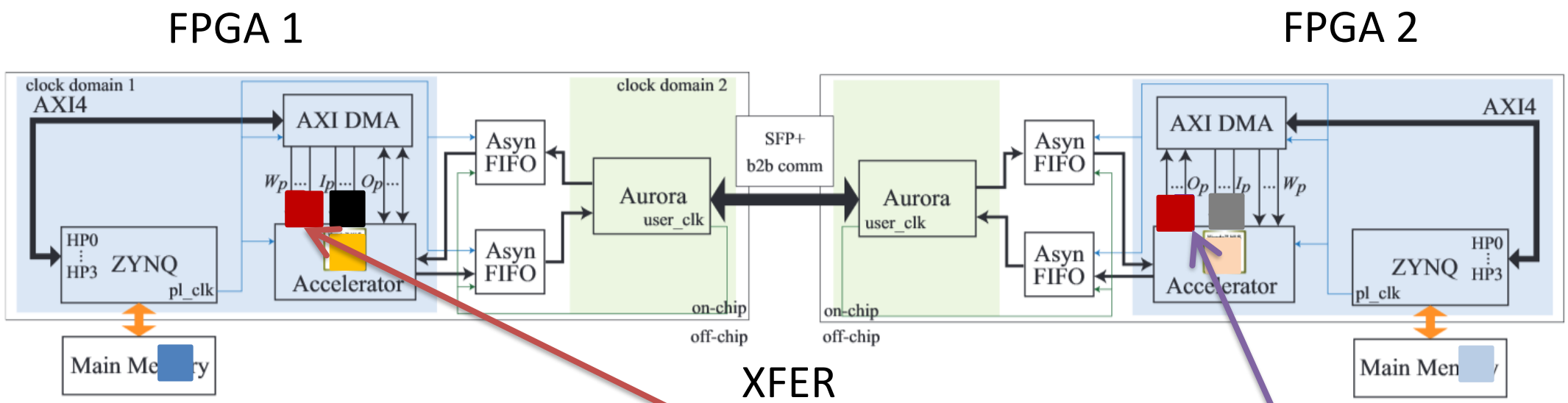
NN	Operation	Single	w/o XFER	Note
AlexNet Layer 5	Comm_IFM	2,612	1,412	**1.91X Speedup**
	Comm_Weights	**5,658**	**2,953**	
	Comm_OFM	368	234	
	Computation	3,326	1,782	



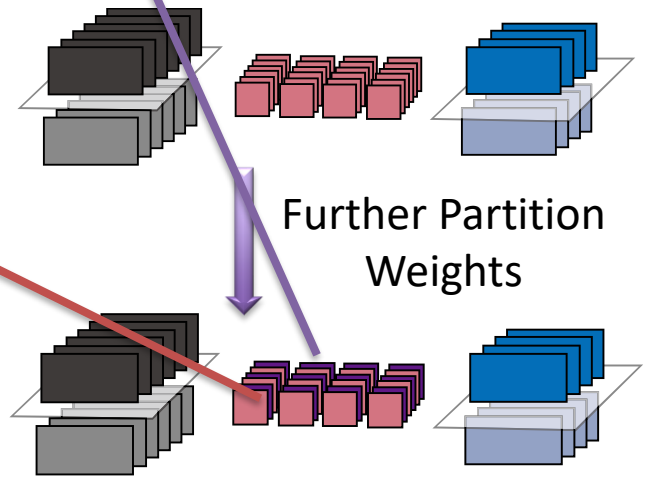
Partition for Parallel

XFER: Achieve Super-Linear Speedup by Transferring Accesses

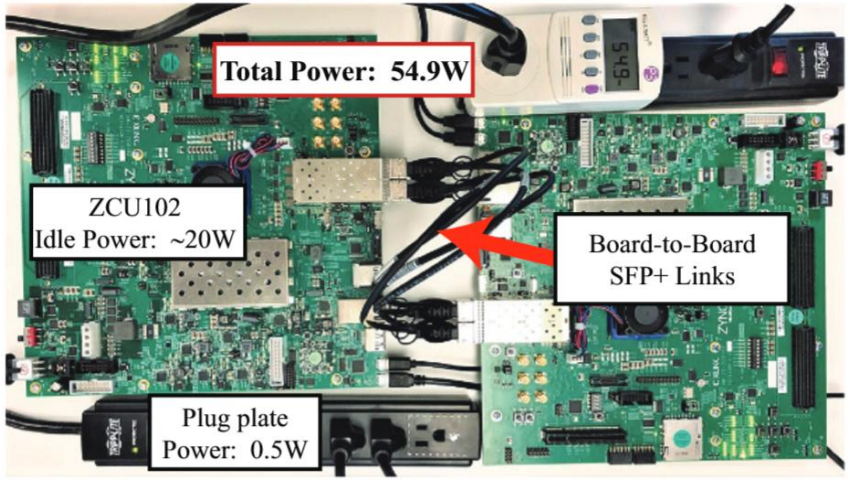
—— from Off-Chip Memory to Inter-FPGA Links



NN	Operation	Single	w/o XFER	w/ XFER	Note
AlexNet Layer 5	Comm_IFM	2,612	1,412	1,412	Bottleneck Moves to Comp. 3.18X Speedup
	Comm_Weights	**5,658**	**2,953**	1,695	
	Comm_OFM	368	234	234	
	Computation	3,326	1,782	**1,782**	



Experimental Results



Testbed:
Xilinx ZUC102 FPGAs connected by SFP+ Links

Comparison results of **XFER** with comparisons to **GPUs** and the **existing FPGA designs**

Design	mGPU		GPU		*FPGA15*		*ISCA17*		*ISLPED16*		**XFER**			
Precision	32bits float		32bits float		32bits float		32bits float		16bits fixed		32bits float		16bits fixed	
Device	Jetson TX2		Titan X		VX485T		VX485T		4×VX690t		2×ZCU102		2×ZCU102	
Freq (MHz)	1300MHz		1139MHz		100MHz		100MHz		150MHz		100MHz		200MHz	
Power (Watt)	16.00		162.00		18.61		-		126.00		52.40		54.40	
DSP Uti.	-		-		80%		80%		-		90.79%		55.87%	
BRAM Uti.	-		-		49.71%		43.25%		-		72.92%		92.43%	
Overall Perf.	Lat. *ms*	Thr. *GOPS*	Lat. *ms*	Thr. *GOPS*	Lat. *ms*	Thr. *GOPS*	Lat. *ms*	Thr. *GOPS*	Lat. *ms*	Thr. *GOPS*	Lat. *ms*	Thr. *GOPS*	Lat. *ms*	Thr. *GOPS*
	11.1 - 13.2	110.75	5.1 - 6.4	235.55	21.62	69.09	60.13	85.47	30.6	128.8	10.13	149.54	**2.27**	**679.04**
E.-E. (GOPS/W)	6.88		1.45		3.71		-		1.02		2.85		**12.48**	

Lowest Latency among all competitors

Experimental Results

Comparison results of **XFER** with SOTA single FPGA design

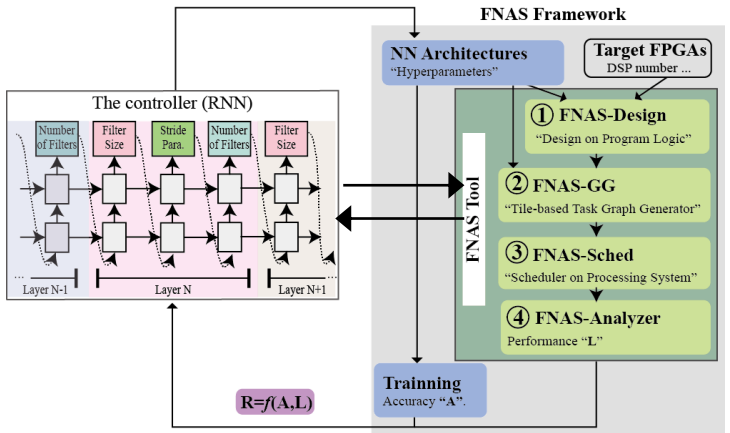
Design	32bits float				16bits fixed			
	FPGA15		**Super-LIP**		*FPGA15*		**Super-LIP**	
$\langle T_m, T_n \rangle$	⟨64, 7⟩		⟨64, 7⟩		⟨64, 24⟩		⟨128, 10⟩	
Power (W)	25.70 (1 FPGA)		**52.40 (2 FPGAs)**		26.00 (1 FPGA)		**54.40 (2 FPGAs)**	
Perf.	Lat. ms	Thr. GOPS	**Lat. ms**	**Thr. GOPS**	Lat. ms	Thr. GOPS	**Lat. ms**	**Thr. GOPS**
conv1	7.36	28.6	**3.66**	**57.6**	3.74	56.5	**0.94**	**224.5**
conv2	5.20	86.1	**2.55**	**175.5**	1.48	302.6	**0.48**	**933.1**
conv3	4.50	66.4	**1.73**	**172.7**	1.20	249.6	**0.33**	**906.2**
conv4	3.41	65.7	**1.31**	**171.0**	0.89	252.6	**0.35**	**640.8**
conv5	2.28	66.0	**0.88**	**170.9**	0.59	251.7	**0.17**	**879.5**
overall	22.75	66.6	**10.13**	**149.5**	7.90	195.1	**2.27**	**679.0**
Perf. Impr.	1.00×		**2.25×**		1.00×		**3.48×**	
E.-E. (GOPS/W)	2.59		**2.85**		7.51		**12.48**	
E.-E. Impr.	-		**9.21%**		-		**39.86%**	

Achieve Super-Linear Speedup

for both 32-bits and 16-bits implementations

Design Neural Networks on Scalable Architecture

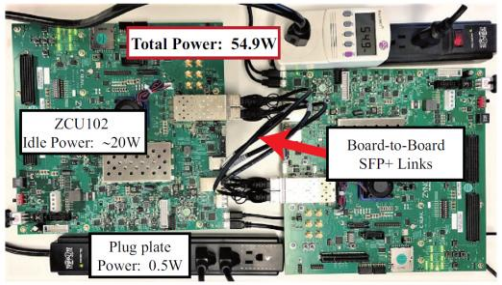
FPGA Implementation-Aware NAS (FNAS)



DAC'19 Best Paper Nomination

Scalability in Cloud Computing (multiple-FPGAs, NoCs, etc.)

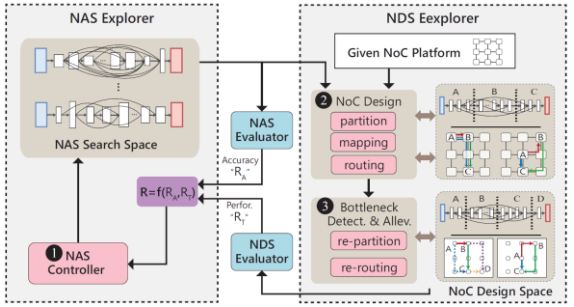
Super-Linear Speedup across Multiple FPGAs (XFER)



CODES+ISSS'19

Best Paper Nomination

Co-Explore Network-on-Chip Design and Neural Architectures (NANDS)

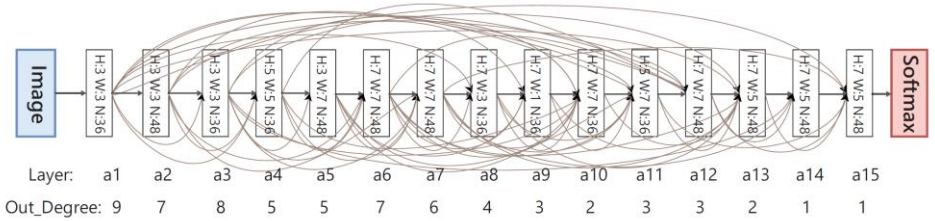


ASP-DAC'20

Best Paper Nomination

NANDS: Co-Explore NoC Design and Neural Architectures

Why NoC? Complicated Structure from NAS

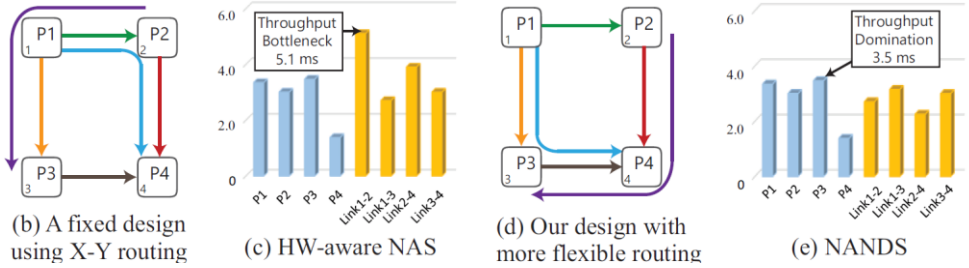


(a) The neural network architecture found by NAS

Operation Time \ Platforms	Single Processing Element	4 Processing Elements	
		Bus Interconnection	2-D Mesh NoC
Computation (ms)	12.4	3.4	3.4
Data transmission (ms)	—	14.7	6.2

(b) The timing performance of network implementations on different platforms

Fixed design (X-Y routing) leads lower performance



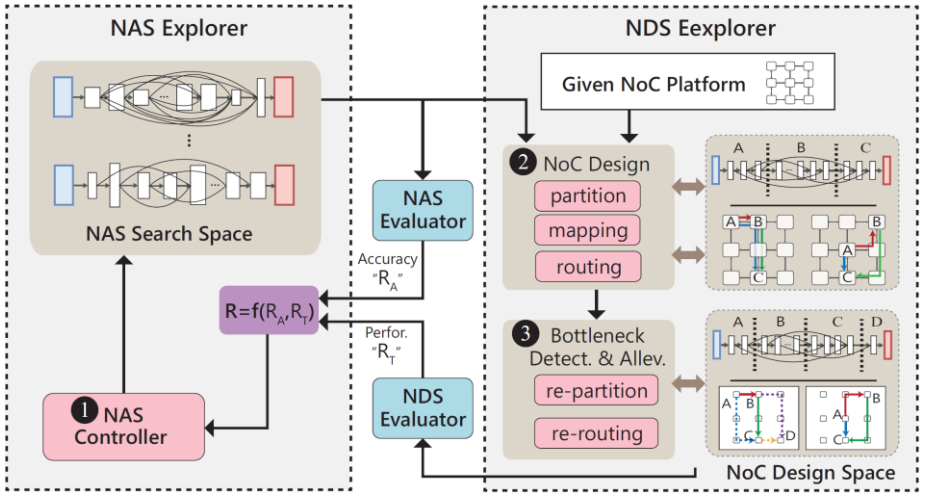
(b) A fixed design using X-Y routing

(c) HW-aware NAS

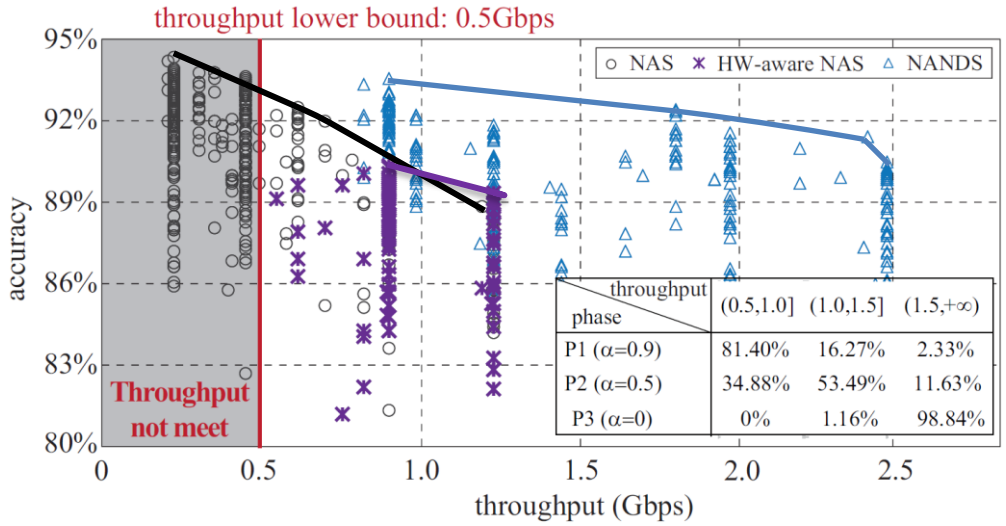
(d) Our design with more flexible routing

(e) NANDS

Co-Exploration Framework



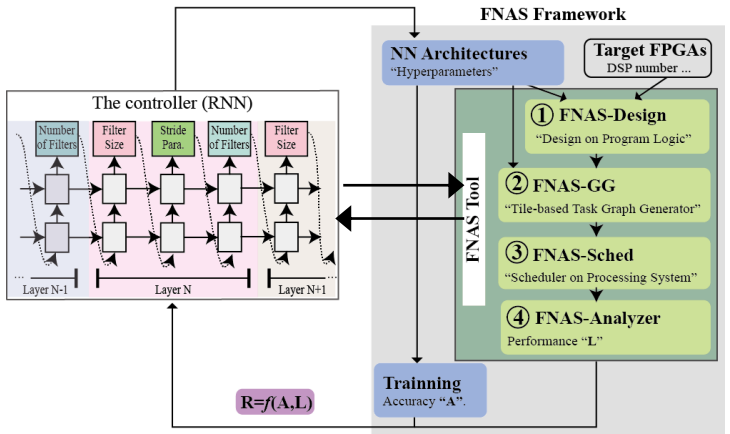
Results



phase \ throughput	(0.5,1.0]	(1.0,1.5]	(1.5,+∞)
P1 (α=0.9)	81.40%	16.27%	2.33%
P2 (α=0.5)	34.88%	53.49%	11.63%
P3 (α=0)	0%	1.16%	98.84%

Design Neural Networks for Resource-Limited Device

FPGA Implementation-Aware NAS (FNAS)

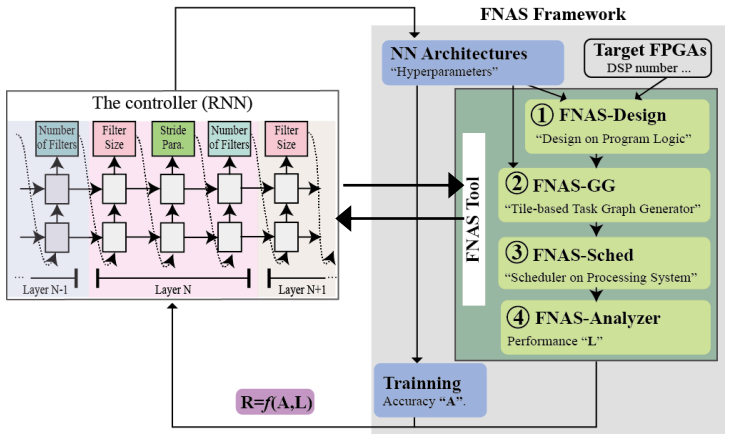


DAC'19 Best Paper Nomination

- **Scalability** in Cloud Computing (multiple-FPGAs, NoCs, etc.)
- **Limited Resource** in Edge Computing (quantization, etc.)
- **Novel Computing Architectures** (in-memory Computing, NVM, etc.)
- ……

Design Neural Networks for Resource-Limited Device

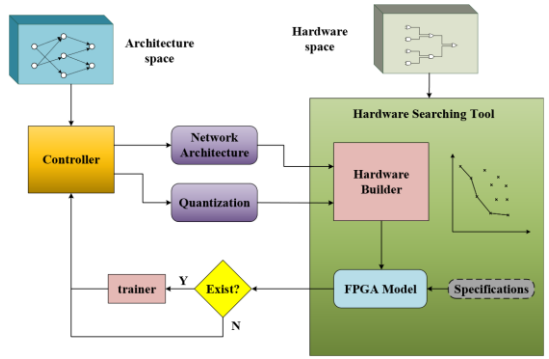
FPGA Implementation-Aware NAS (FNAS)



DAC'19 Best Paper Nomination

Limited Resource in Edge Computing (quantization, etc.)

Co-Explore Quantization and Neural Architectures (QuanNAS)



ICCAD'19

QuanNAS: Co-Explore Quantization and Neural Architectures

Search Space

Parameter	Symbol	Value
# filters	N	(24, 36, 48, 64)
filter height	Fh	(1, 3, 5, 7)
filter width	Fw	(1, 3, 5, 7)
stride height	Sh	(1, 2, 3)
stride width	Sw	(1, 2, 3)
pooling size	Ps	(1, 2)
activation integer bits	Ai	(0, 1, 2, 3)
activation fractional bits	Af	(0, 1, 2, 3, 4, 5, 6)
weight integer bits	Wi	(0, 1, 2, 3)
weight fractional bits	Wf	(0, 1, 2, 3, 4, 5, 6)

Besides filter size and shape, **we co-explore bit width of weights and activation data, for FPGAs and ASICs.**

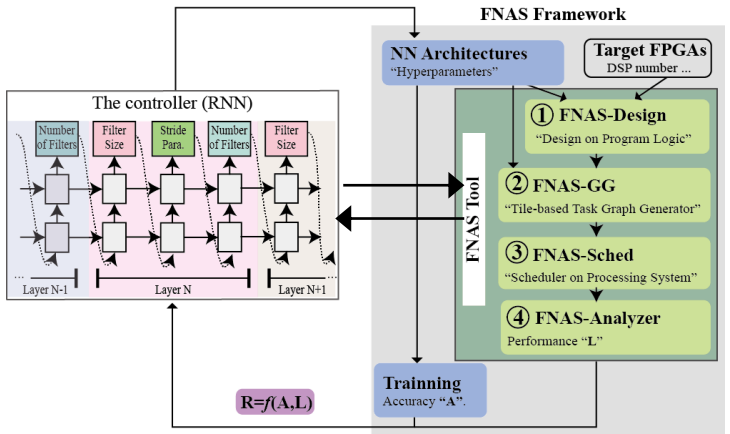
Results

Design	rL	rT	Acc w/o Quan	Acc w/ Quan	#LUTs	FPS	para size (kbits)
A_1-d_1	100,000	500	87.76%	80.23%	99,871	556	1,867
A_1-d_2	100,000	1000	87.76%	25.79%	99,848	1157	1,189
B_1-d_1	100,000	500	89.71%	87.64%	96,904	512	3,463
B_1-d_2	100,000	1000	89.71%	64.35%	98,752	1020	2,784
B_1-d_3	300,000	2000	89.71%	50.93%	285,441	2083	2,835
D	30,000	1000	83.65%	82.98%	29,904	1293	457
E	100,000	1000	86.99%	82.76%	94,496	1042	1,923
F	300,000	2000	87.03%	84.92%	299,860	2089	1,217

- A,B are first explored by NAS, then to be quantized. In this way, the **accuracy loss** by quantization is huge.
- D,E,F are explored by our Co-Exploration framework, which output **better accuracy** for quantized network with **smaller parameter size**

Design Neural Networks for Novel Computing Architectures

FPGA Implementation-Aware NAS (FNAS)



DAC'19 Best Paper Nomination

- **Scalability** in Cloud Computing (multiple-FPGAs, NoCs, etc.)
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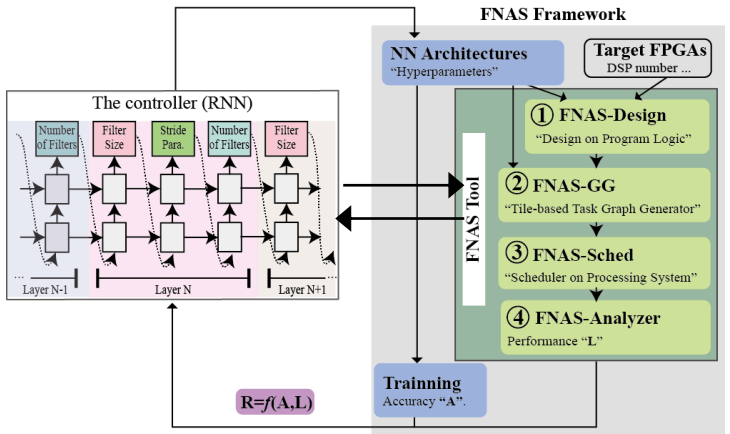
Design Neural Networks for Novel Computing Architectures

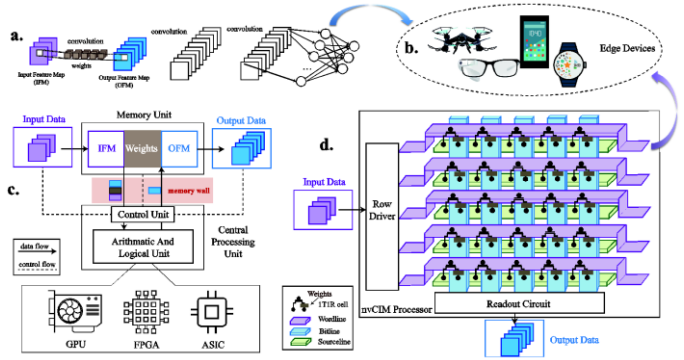
FPGA Implementation-Aware NAS (FNAS)



DAC'19 Best Paper Nomination

Novel Computing Architectures (in-memory Computing, NVM, etc.)

Integrating Memristors and CMOS for Better AI



Nature Electronics'19

Co-Explore Neural Architectures and Devices

Submitted to TC

Outline

- Introduction
- Co-Explore Neural Architecture and FPGA Implementation

  - DAC 2019 (Best Paper Nomination)

- Research Directions
- **Conclusion**

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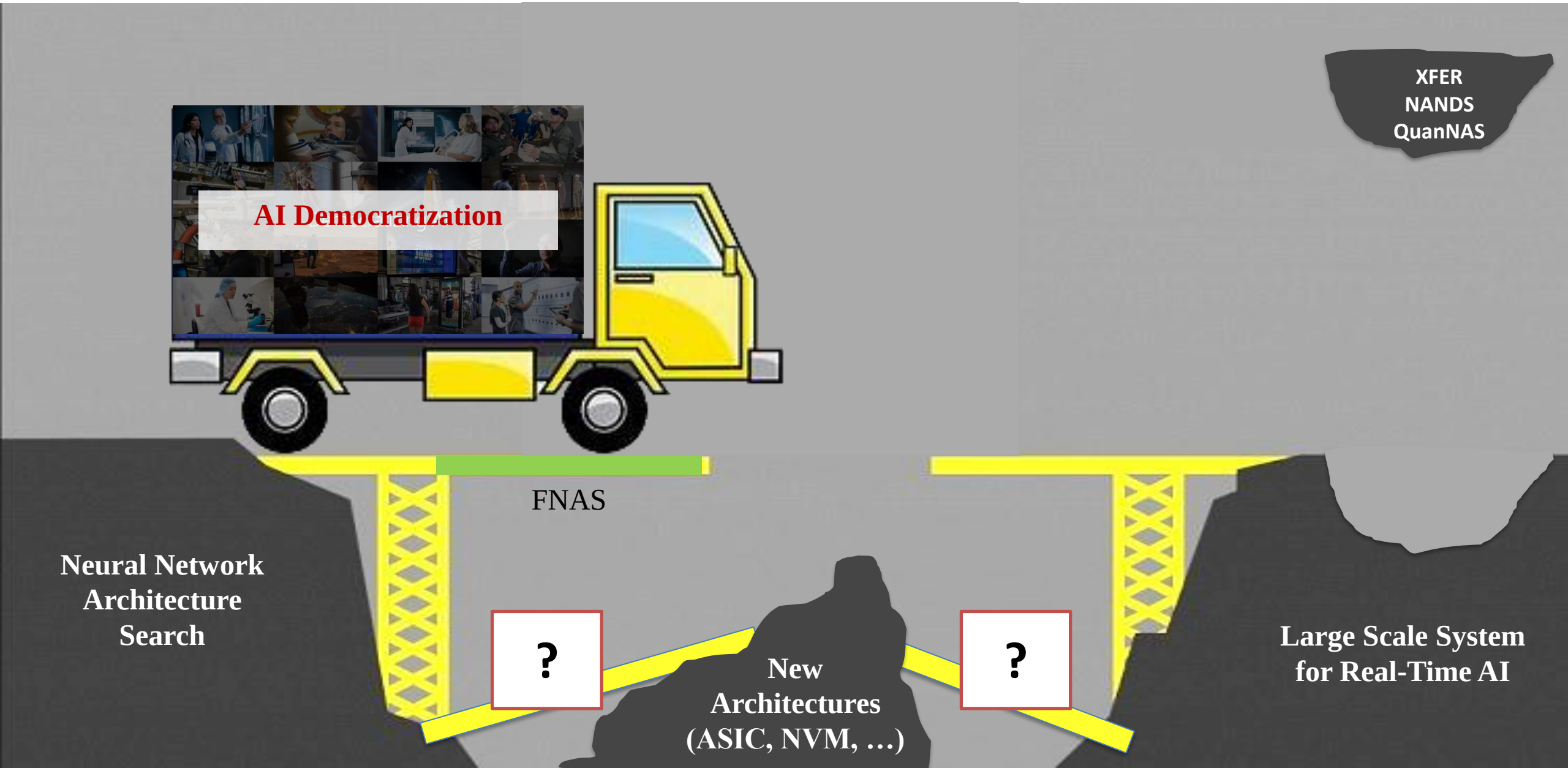
Conclusion and Future Work



Reference

[1] Weiwen Jiang, Xinyi Zhang, Edwin H.-M. Sha, Qingfeng Zhuge, Lei Yang, Yiyu Shi and Jingtong Hu, "Accuracy vs. Efficiency: Achieving Both through FPGA-Implementation Aware Neural Architecture Search," in Proc. of **DAC 2019**. **(Nominated for Best Paper Award)**

[2] Weiwen Jiang, Edwin Sha, Xinyi Zhang, Lei Yang, Qingfeng Zhuge, Yiyu Shi and Jingtong Hu, "Achieving Super-Linear Speedup across Multi-FPGA for Real-Time DNN Inference," **CODES+ISSS 2019** and **ACM TECS** **(Nominated for Best Paper Award)**

[3] Lei Yang, Weiwen Jiang, Weichen Liu, Edwin Sha, Yiyu Shi and Jingtong Hu, "Co-Exploring Neural Architecture and Network-on-Chip Design for Real-Time Artificial Intelligence," **ASP-DAC 2020** **(Nominated for Best Paper Award)**

[4] Qing Lu, Weiwen Jiang, Xiaowei Xu, Yiyu Shi and Jingtong Hu, "On Neural Architecture Search for Resource-Constrained Hardware Platforms," in Proc. of **ICCAD 2019** (Invited Paper)

[5] Weiwen Jiang, Bike Xie, Chun-Chen Liu and Yiyu Shi, "Integrating Memristors and CMOS for Better AI," **Nature Electronics**, September 2019

Thank You!