

Award Ceremony

2021 Challenge

Lightning-Fast Modulation Classification with

Hardware-Efficient Neural Networks

Part of



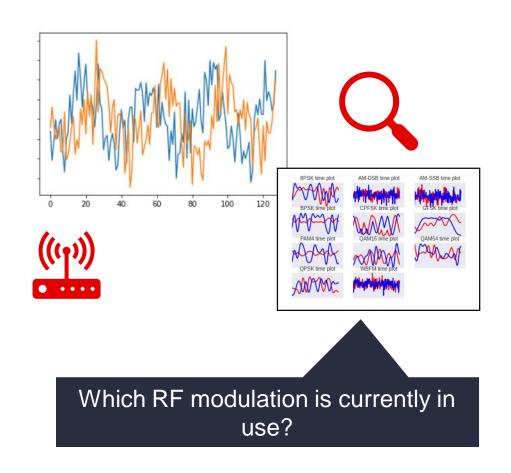


Agenda

- Introduction & Statistics
- Awards ceremony with Xilinx CTO Ivo Bolsens
- ▶ Lightning talks from top submissions
- RadioML on FPGAs



Modulation Classification: what's in my RF spectrum?

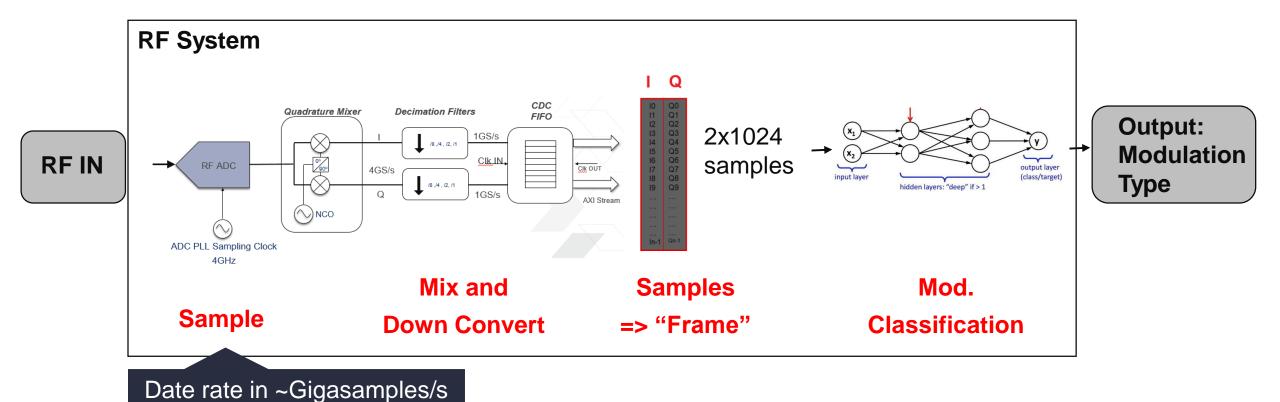


- Rapidly label + understand RF spectrum
- Key enabler for...
 - spectrum interference monitoring
 - radio fault detection
 - dynamic spectrum access
 - numerous regulatory and defense applications
- DNNs promising for modulation classification
 - Especially for short-time observations

[O'Shea et al., Over the Air Deep Learning Based Radio Signal Classification, IEEE JSTSP'17]



Challenges: Inference Throughput



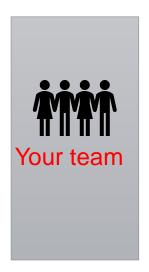
Sample-rate inference throughput is a challenge



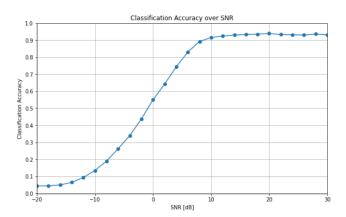
Goal: Enabling many future DNN-based RF applications with extreme throughput and ultra-low latency



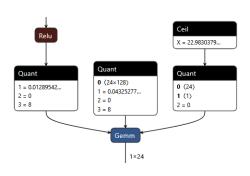
The Challenge



Train a DNN on **RadioML 2018.01A**



Achieve at least 56.000% average accuracy over full SNR range



Minimize inference cost



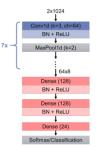
Brevitas

O PyTorch





Sandbox environment for quantization-aware training



Provide training script for baseline model



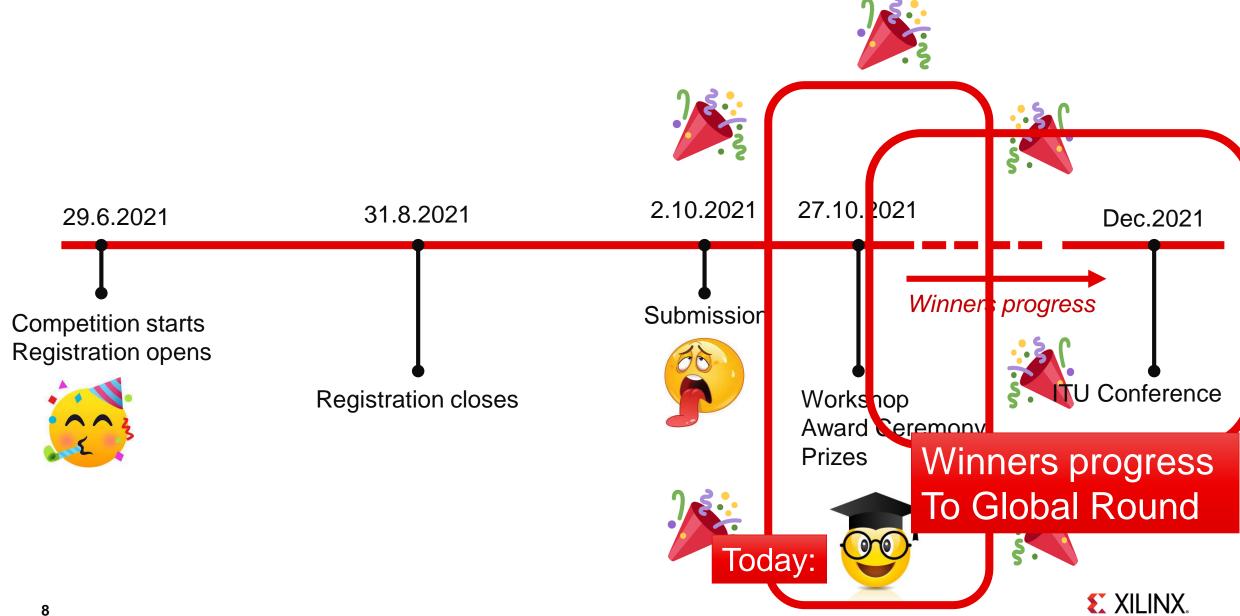




Support, evaluate and rank the **submissions** on basis of inference cost



Timeline

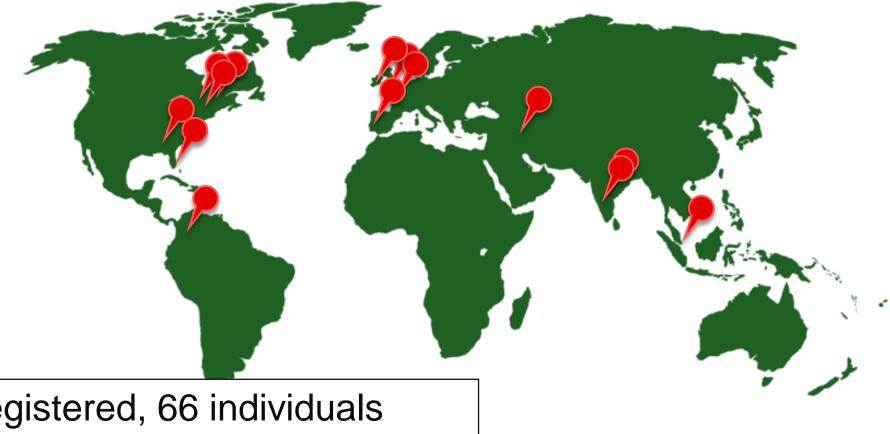


Statistics



Statistics and Geography of Participants

- North America
- South America
- Europe
- Middle East
- South-East Asia

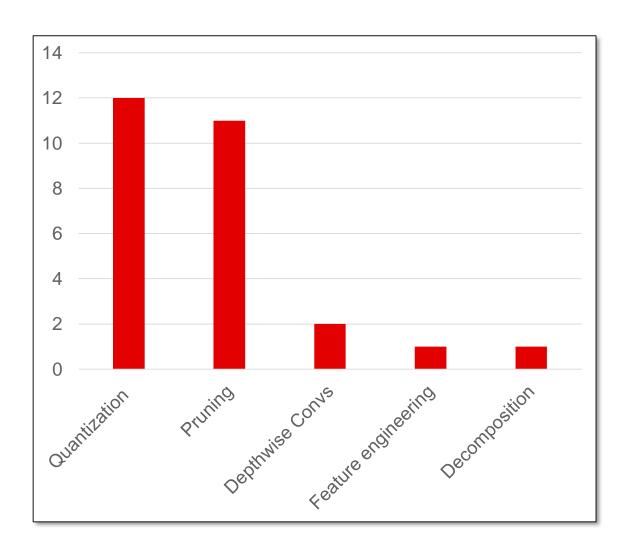


41 teams registered, 66 individuals 13 teams with 32 participants submitted



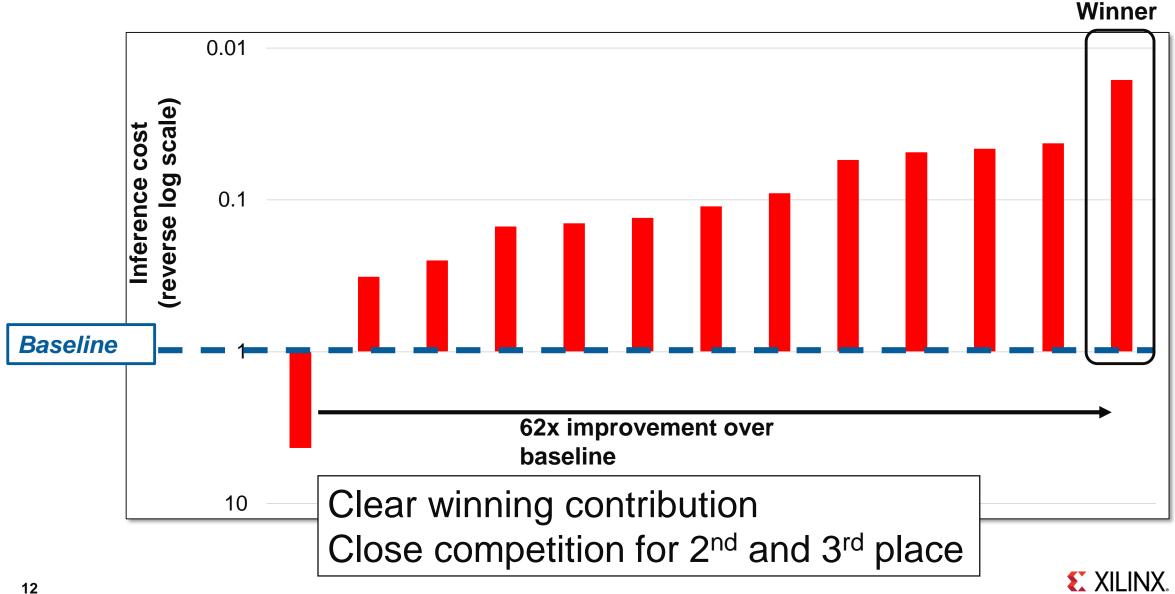
Techniques Adopted

- Most teams adopted variations of the baseline topology with a mixture of quantization and pruning
- Some teams switched to more efficient MobileNet-like topologies
- The winning team is a mixture of the above techniques





Results Across Teams





Results









Third Place: Aaronica

- ▶ Inference cost score 0.046007
 - 22x better than baseline!
- **▶** Team members
 - Mohammad Chegini
 - Pouya Shiri





Second place: The A(MC) Team

- ▶ Inference cost score 0.042467
 - 24x better than baseline!

- ▶ Team members:
 - Jakob Krzyston
 - Rajib Bhattacharjea
 - Andrew Stark





First place: BacalhauNET



- ▶ Inference cost score 0.016211
 - 62x better than baseline!

- ▶ Team members:
 - José Rosa
 - Guilherme Carvalho
 - Daniel Granhão
 - Tiago Gonçalves





Full Ranking

https://bit.ly/brevitas-radioml-challenge-21-results

-	Rank	Team Name	Inference cost	Accuracy		
Y	1	BacalhauNET	0.016211	0.56241		
Y	2	The A(MC) Team	0.042467	0.562543		
	3	Aaronica	0.046007	0.561585		
	4	Red Gecko	0.048649	0.5604		
	5	Wolf	0.054512	0.560464		
	6	LightNeting (iSmart)	0.090334	0.566972		
	7	Imperial_IPC	0.1106	0.564		
	8	ANTENNAE	0.131579	0.566405		
	9	TCD	0.143013	0.563407		
	10	TeamX	0.149641	0.563247		
	11	sing-rb	0.250492	0.563508		
	12	Team Velocity	0.321127	0.5607		
	13	FAU-CA-AI	4.307883	0.5719		



Team Presentations



Team Presentations

- Imperial_IPC
- 2. Aaronica
- 3. The A(MC) Team
- 4. BacalhauNet

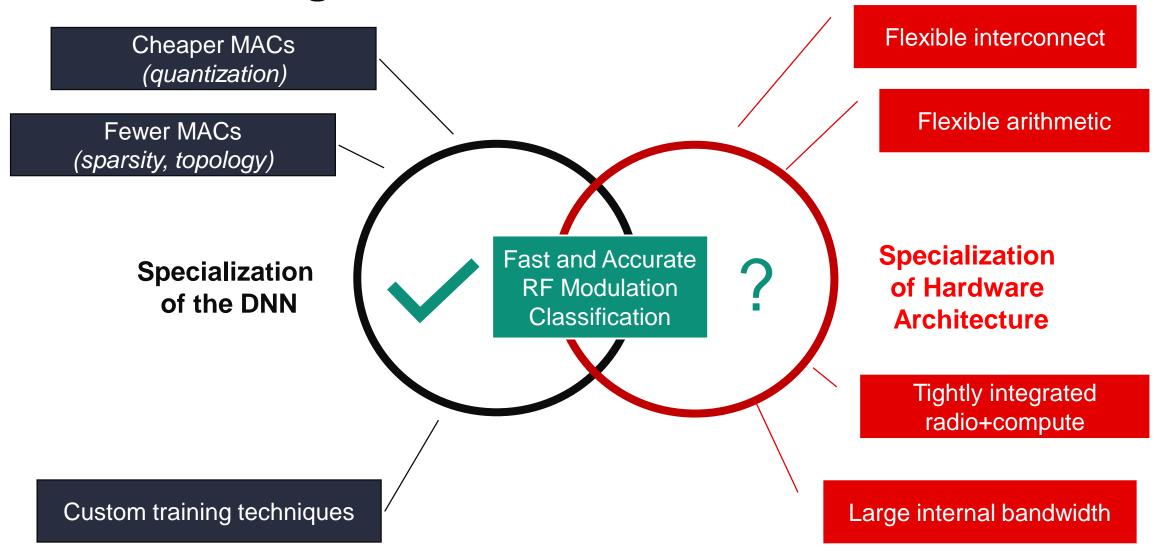


FINN for RadioML on FPGAs

Yaman Umuroglu, Xilinx Research Labs Felix Jentzsch, Paderborn University



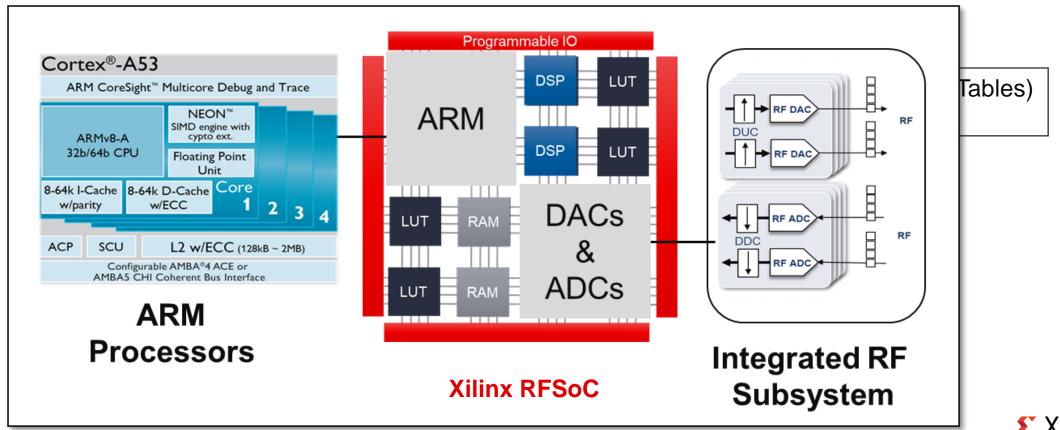
Where do we go from here?





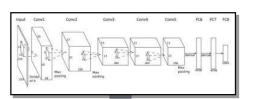
A Refresher on FPGAs and Xilinx RFSoC Customizable, Programmable Hardware Architectures

Customizes IO interfaces, compute architectures, memory subsystems to meet the specific application requirements



Customized DNN to FPGA Solution Stack





Brevitas / QKeras*
Training with
algorithmic optimizations

Train highly efficient, customized DNNs

ONNX Intermediate Representation

INN compiler
Specializations of hardware architecture

- Hardware optimizations
- Generates dedicated FPGA accelerator

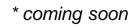
Deployment

Integrate accelerator into system and deploy











Harnessing FPGA Specialization with FINN

 FPGAs can scale DNN performance through extreme specialization

FINN

Reduced precision quantized arithmetic



- Arbitrary bitwidth
- Mix & match bitwidths between layers

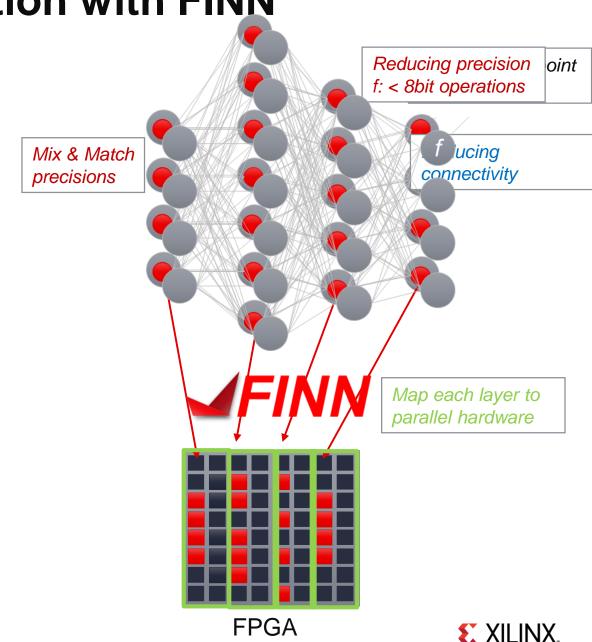
Precision	MAC cost (LUTs)		
1-bit	~1.1		
2-bit	~4.4		
4-bit	~17.6		
8-bit	~70.4		



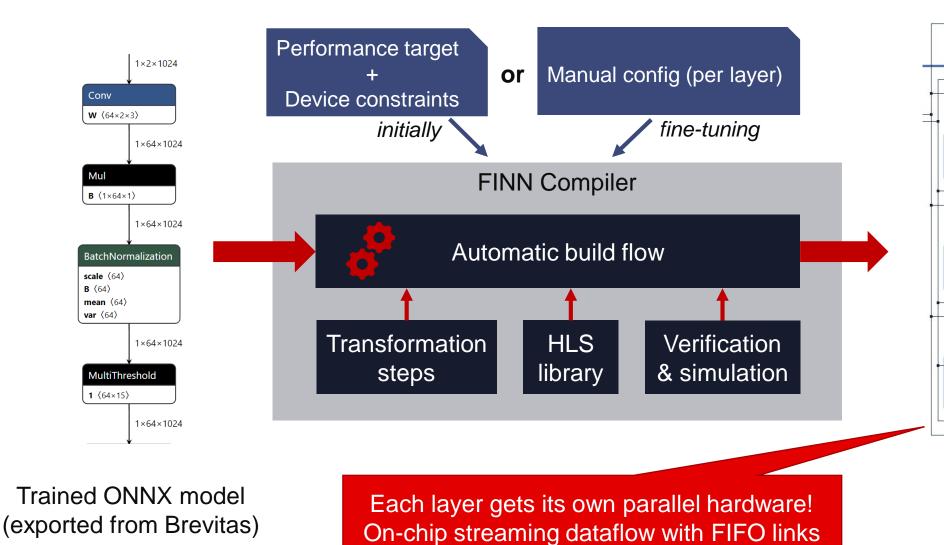
Fine-grained sparsity



Layer-parallel dataflow implementation



✓ FINN compiler flow: at a glance



Vivado IPI design
+ PYNQ deployment

ConvolutionInputGenerator1D 0

Convolutioninputgenerator1d 0 (Pre-Production

StreamingDataWidthConverter Batch 1

Streamingdatawidthconverter_batch_1 (Pre-Produc

StreamingFIFO 4

StreamingFIFO 4

StreamingFCLayer_Batch_0

out_V_V +

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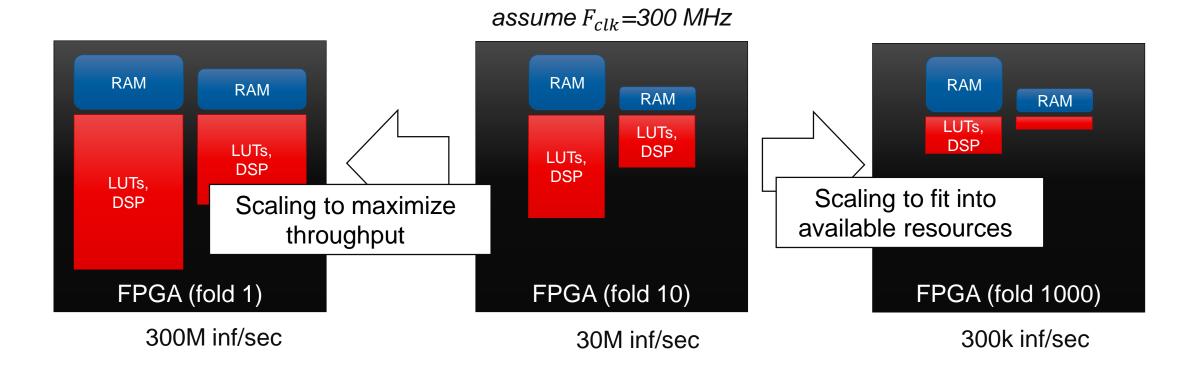
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o ap rst n



Dataflow Hardware Generation with the FINN Compiler: Scaling to Meet Performance & Resource Requirements



- 1. Scale performance & resources to meet the application requirements
- 2. If resources allow, we can completely unfold to create a circuit that inferences at clock speed (not practical for RadioML-sized circuits)

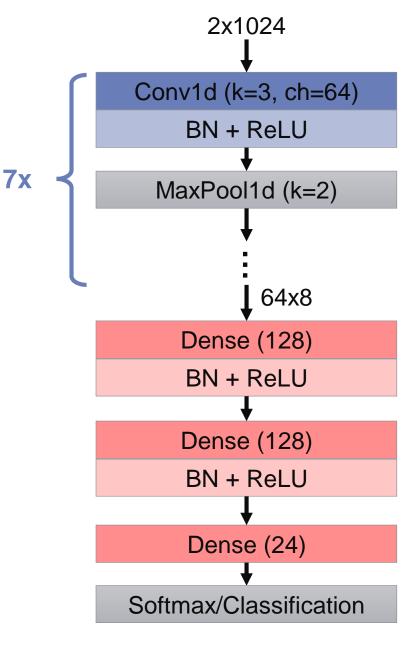


First FINN RadioML Prototypes

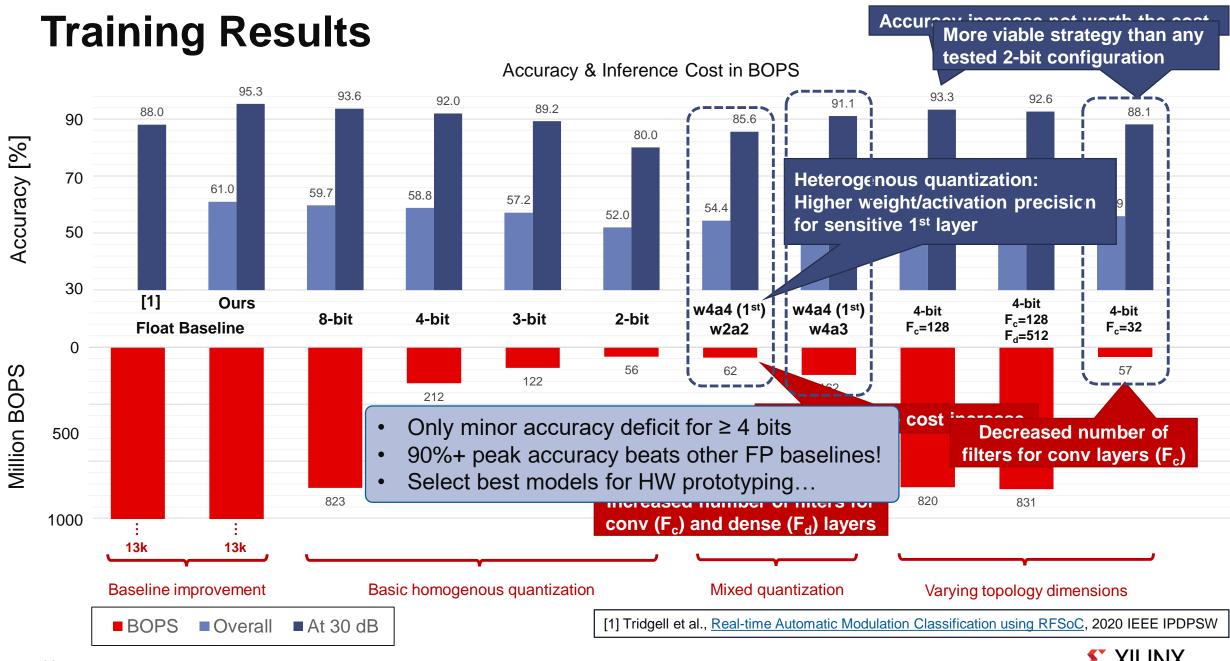


Initial Topology for our Experiments

- ▶ 1-dimensional convolutional neural net (VGG10)
 - Proposed by dataset creators along 2018 dataset
 - Proven performance against traditional classification techniques
 - Simple starting point without residual connections
- Baseline topology for competition
- Brevitas training setup
 - 8-bit input quantization to fixed range
 - ~98% percentile across whole dataset at high SNR
 - Using all available training data (whole SNR range)
 - Focus on overall accuracy
 - If only high SNR accuracy is of interest: Train on high SNR for ~1-2% gain









Current FINN Hardware Prototypes

▶ Working prototypes on ZCU111 @ 200 MHz:

	Α	В	C
Topology	VGG10	VGG10	VGG10, F _c =32
Quantization	w4a4+w4a3	w4a4+w2a2	w4a4 Same parallelism
Accuracy overall	58.5%	54.4%	55.9 ► same performance
Accuracy @ 30 dB	91.1%	85.6%	88.1
Throughput [samples/s]	190M	190M	190M
Latency [us]	16	16	16
LUT (util.)	196k (46%)	105k (25%)	82k (19%)
BRAM18 (util.)	358 (17%)	176 (8%)	116 (5%)
			Not limited by
Inference at ~ 1	sample/cycle!		resource constraints (scale-up WIP)



Your Submissions vs. our Prototype

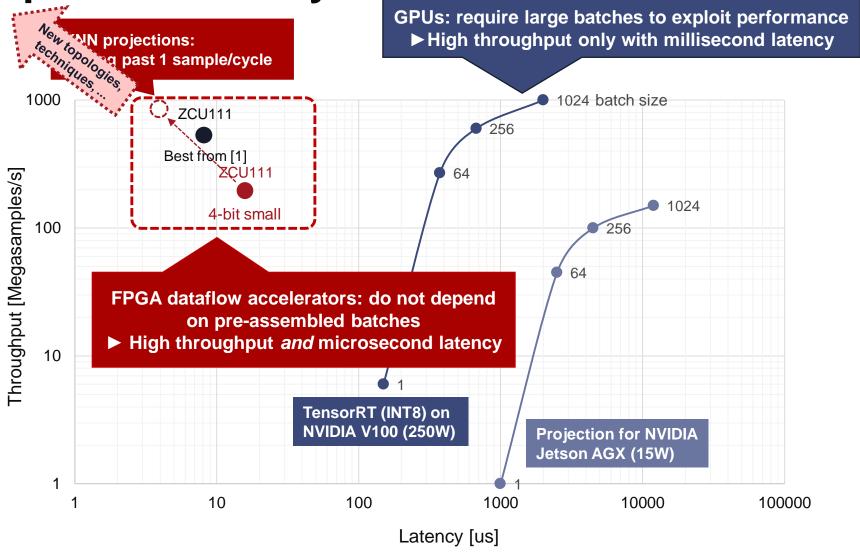
Unstructured pruning is challenging to exploit

	Team	W Bits	BOPS	Sparsity	Cost Score		BRAM	LUT
	Prototype A (4/3-bit)	536k	162M	~10%	0.316		358	196k
	Prototype B (4/2-bit)	137k	53M	~40%	0.088		176	105k
	Prototype C (4-bit, Fc=32)	237k	50M	~10%	0.126	,	116	82k
reach ~56%	3. Aaronica	53k	40M	~30%	0.046			
overall accuracy	2. The A(MC) Team	68k	24M	~90%	0.042			
	1. BacalhauNET	11k	19M	~80%	0.016		•	

Winning submissions look very promising



Throughput vs. Latency



[1] Tridgell et al., Real-time Automatic Modulation Classification using RFSoC, 2020 IEEE IPDPSW



Conclusion & Future Work



Conclusion

- ▶ DL in communications demands extreme throughput & latency
 - Your submissions show how much smaller the models could be
- Specialized DNNs + streaming dataflow showcase what's possible with FPGAs
 - High-throughput, low-latency, streaming inference without batching
 - Brevitas + FINN well-suited for exploration & implementation
- ▶ Initial FINN prototypes for RF modulation classification
 - Already achieving near 200M samples/sec at <20 us latency, with 90%+ accuracy
 - Soon available as part of finn-examples GitHub repository



Future Work

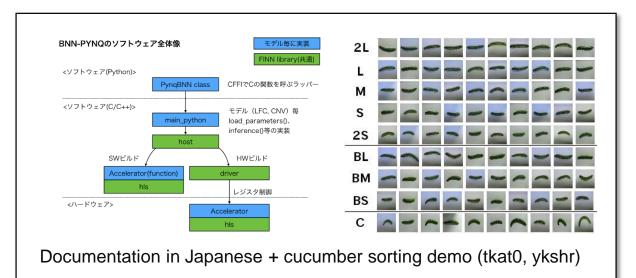
- ▶ Further FINN improvements geared towards 1D/time-series networks
- Explore advanced topologies, leveraging recent work on ResNets in FINN
- ▶ Enable you to get your models running on FPGAs

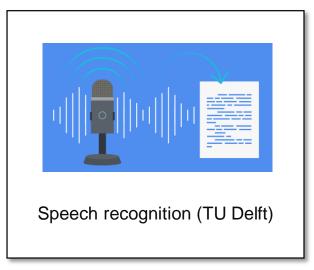


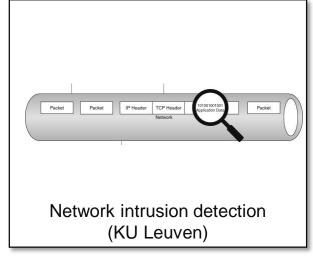
Join the growing FINN community!

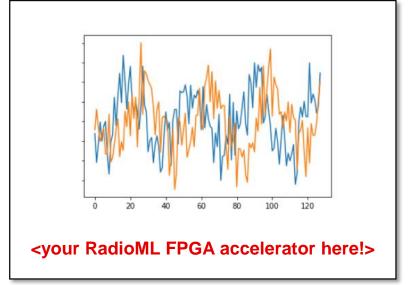
https://github.com/Xilinx/finn/discussions https://gitter.im/xilinx-finn/community















Thank You

Please fill out the feedback form, it only takes a minute: https://bit.ly/brevitas-radioml-challenge-21-feedback

