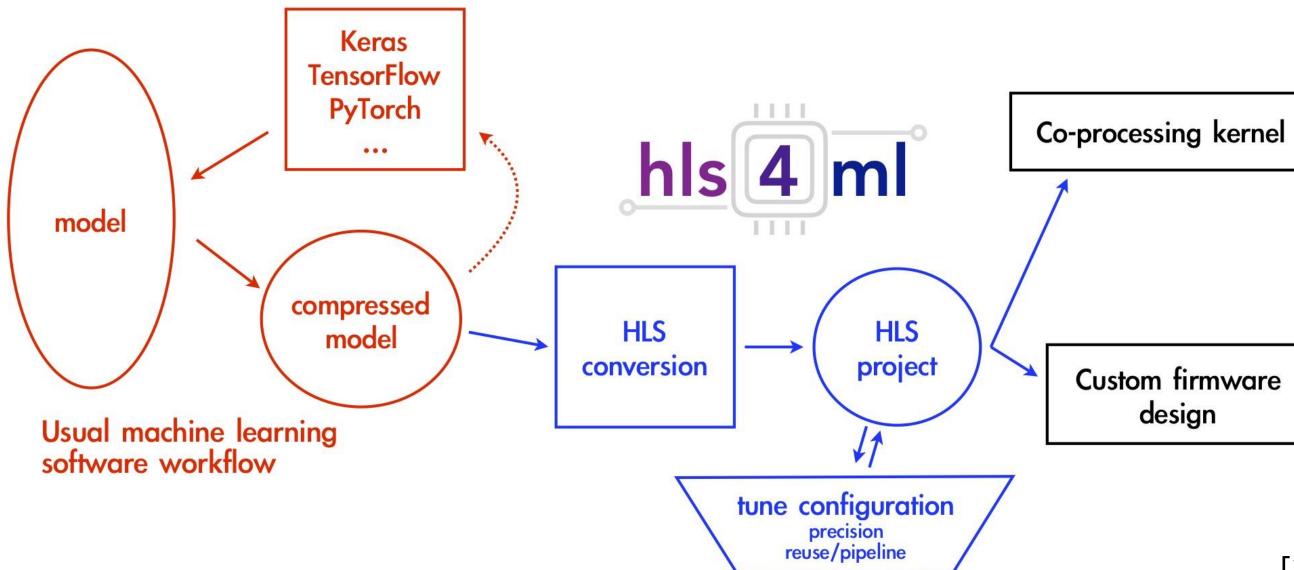
Benchmarking High Level Synthesis for Machine Learning Implementations versus Hand-optimized SystemVerilog

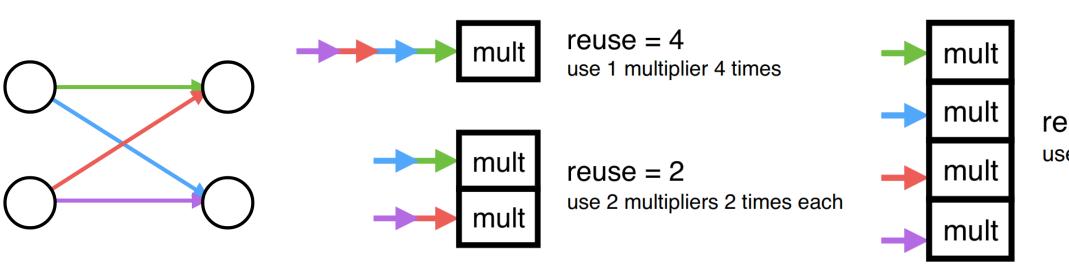
Waiz Khan, Caroline Johnson, Scott Hauck, Shih-Chieh Hsu, Geoff Jones

Introduction

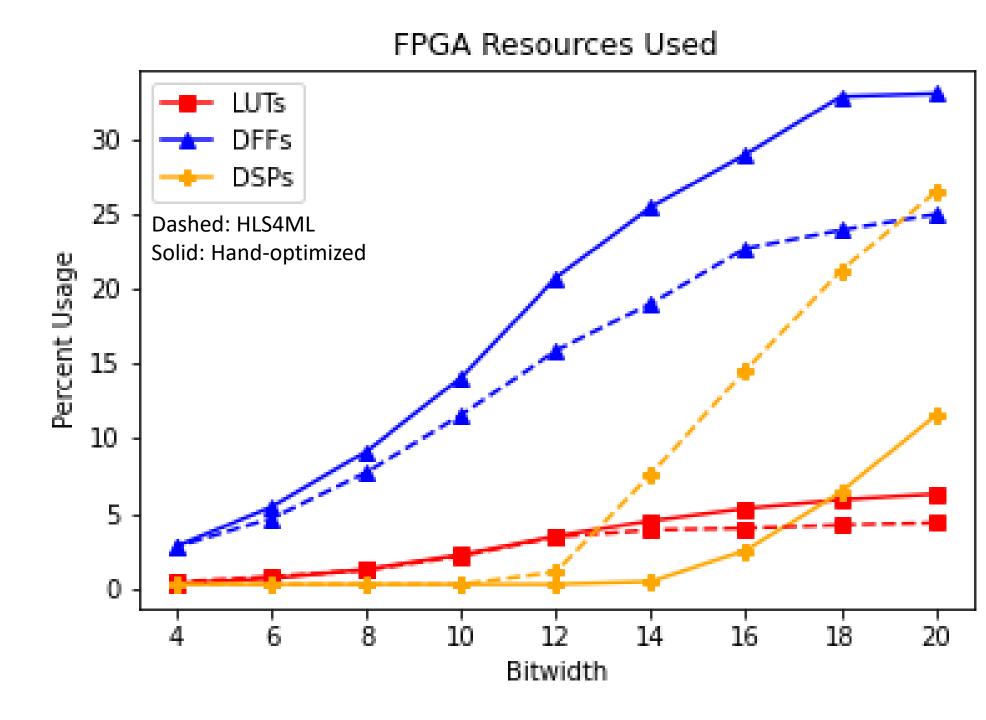
High Level Synthesis for Machine Learning (H enables rapid prototyping of Machine Learning into hardware designs.



Performance can be optimized by adjusting parameters such as Compression, Precision, and Resource Reuse factors.



Are HLS4ML's implementations efficient compared to lower-level implementations?



ILS4ML)
ng models

-	
214-11 VII	
Custom	firmuaro

Custom firmware design

[1]

reuse = 1use 4 multipliers 1 time each

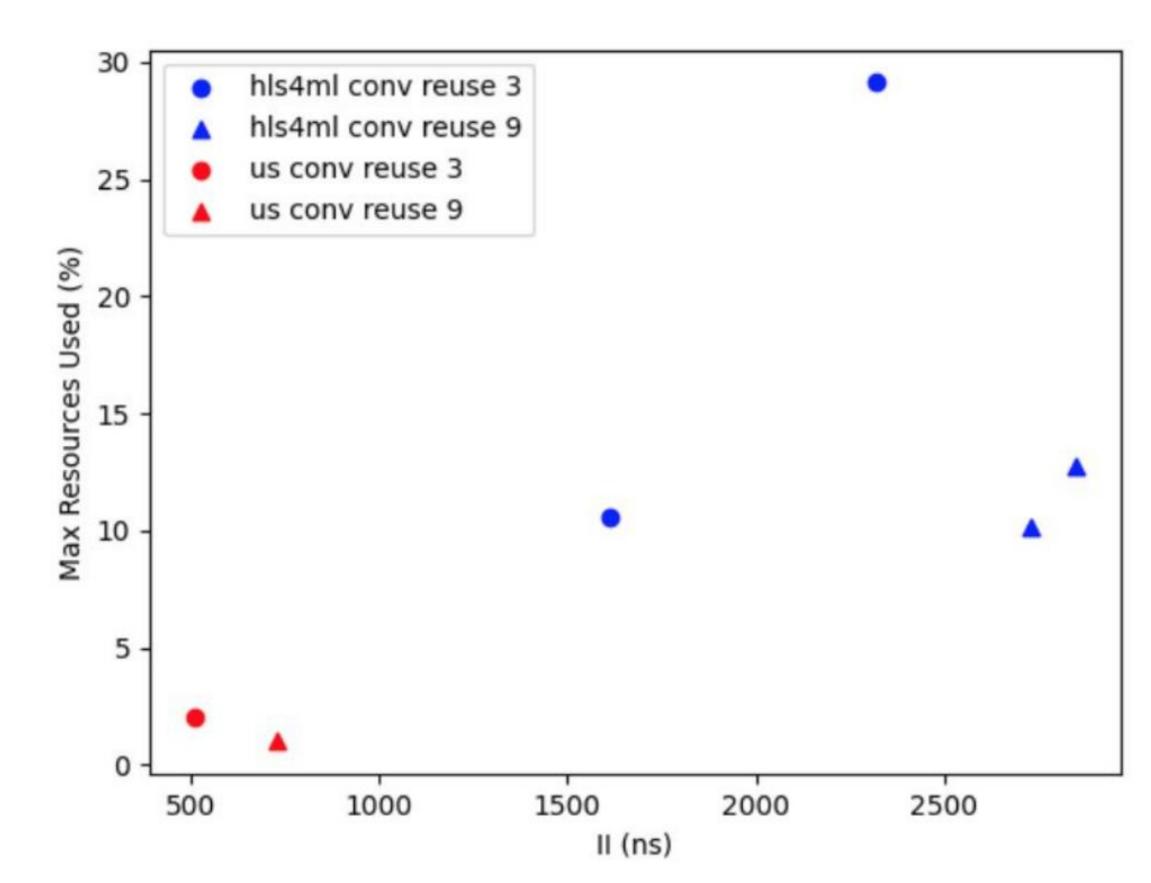
[1]

2D Conv Layer, Stride 2

Reuse Factor of 9:

PERFORMANCE	Min Period (ns)		Latency (Latenc	atency (ns) II		II (cycles)		ll (ns)	
HLS4ML - 256	6.2		592.5		3673.5		459.75		2850.45	
HLS4ML - 128	6.9		463.5		3198.15		395.25		2727.225	
Us	6.9		219		1511.1		105.75		729.675	
Model	RESOURCES	LU	Ts	Total L	UTs	DFFs		RAM		DSP
HLS4ML - 256	256		707		7073		11031		2	16
HLS4ML - 128	128				6502		8799		3.5	24
Us			231		2318		865		0.5	24
Available On Chip					693120		86640	14	470	3600
HLS4ML 256					1.02%	1:	2.73%	0.1	4%	0.44%
HLS4ML					0.94%	1	0.16%	0.2	4%	0.67%
Us					0.33%		1.00%	0.0	3%	0.67%

Percentage of Max Resource Utilization vs. Iteration Interval



Hand-implemented Conv2D Layer (stride of 2) with Reuse Factor of 9 achieves better performance than the HLS4ML implementations.

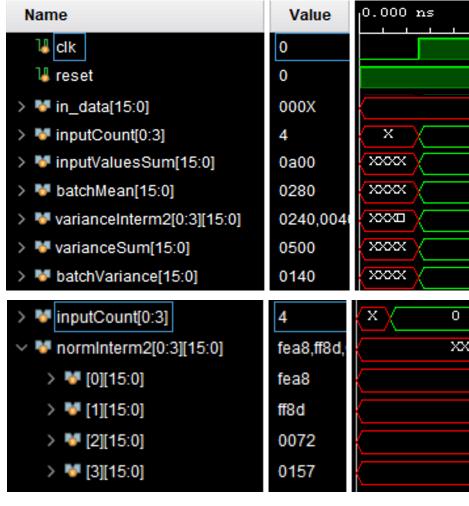
- 52.8% lower latency
- > 73.2% faster iteration interval
- 64.3% fewer total LUT's used
- 90.2% fewer DFFs used



Currently under development, small scale model functional

Batch Norm Layer algorithm:

Cycle	0	1	2	3	4	5	6	7	8	9	10	11	-
		Input	first bat	tch (4)				atch (4)			first bate	1.0000000000000000000000000000000000000	<u>.</u>
						Input se	econd ba	atch (4)	<u></u>	rocess	second b	batch (4)	
									•	Input	third bate	ch (4)	<u>.</u>



Conclusion

The possibility to improve CONV2D implementation in HLS4ML to be faster or efficient is demonstrated. The lower-level implementation required fewer resources to produce a model with lower latency.

Batch Normalization layer can be implemented efficiently in hardware but will require large LUTs to accelerate some parts of the computation.

Next Steps

> Implement an HLS4ML-inspired SystemVerilog implementation of Conv2D, stride 2 to improve performance

References



Batch size of 4, pipelined to three major stages, each taking four cycles

Values processed in the following order: (each step takes one cycle) Batch Mean, Batch Variance, Normalize value, Scale & Shift

Pipelined for efficiency to allow for parallel usage of resources

Small Scale Model Results: (values are in fixed point, 8 integer bits, 8 fraction bits)

1	200.000 ns		400.000	ns IIII		600.000 ns	₅ 		800.0
XXXXX	010	0 / 02	200	0300	04	•••		000X	
0		X	2	3	Χ		4		
	000	0		Χ		0a00			
	000	0		Χ		0280			
	0000,0000,0	0000,0000		0240,0040,0040,0240					
	000	0			X	0500			
	000	0			Χ		0140		
<u>1</u>	2 <u>3</u>	4 (fea8,ff8d,		(output	values	, converte	ed to de	ecimal)	
xxxxx		fea		-1.343					
>>>>>		ff8	39	-0.449					
XXXXX		007	72	0.494					
xxxx		01!	57	1.340					

> Implement a scaled-up batch norm layer, to compare with HLS4ML

