

Acceleration of a CMS DNN based Algorithm

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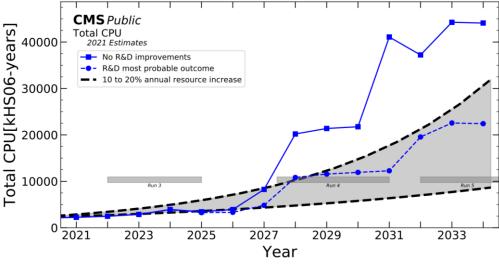
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Acceleration of a CMS DNN based Algorithm

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Motivation

- Data rate set to increase with High-Luminosity LHC upgrade
- Current approach not scalable to meet requirements of additional processing due to increased luminosity



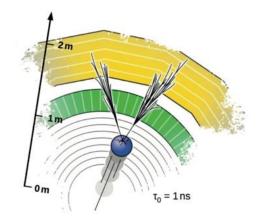
https://twiki.cern.ch/twiki/bin/view/CMSPublic/CMSOfflineComputingResults

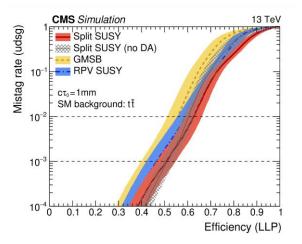
Contributions

- Novel parallel architecture for Long-Lived Particle (LLP) jet tagging
 - compute: both space and time
 - accelerated processing: reduce cost of storage for post-processing
- Explore an FPGA architecture using a highly computationally intensive algorithm which could benefit from acceleration

Long-Lived Particle Tagger

- CMS Collaboration, A deep neural network to search for new long-lived particles decaying to jets, Mach. Learn.: Sci. Technol. 1 (2020) 035012 (<u>arXiv:1912.12238</u>)
- Many models of new physics predict existence of exotic long-lived particles
- Lifetime frontier yet to be fully explored at the LHC
- Deep Neural Network trained on Monte Carlo to classify jets into Standard Model (light, b/c-quark gluon) and exotic long-lived particles
- Trained for lifetimes ct \in [10 µm,10 m] with lifetime as a parameter 1mm benchmark \rightarrow

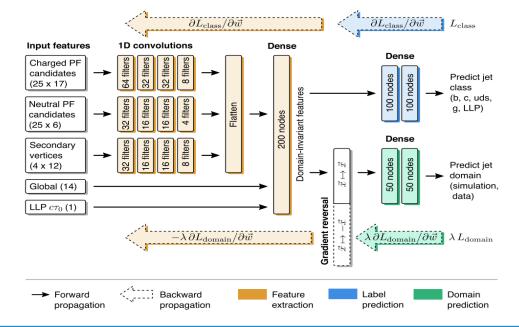




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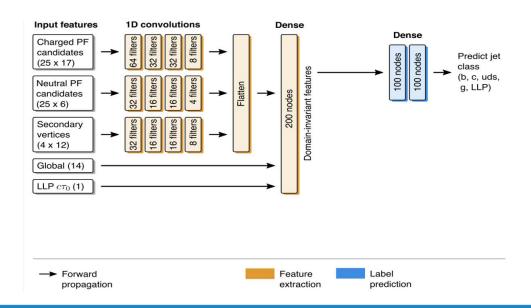
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LLP Jet Tagging Algorithm



- Multiclass classification
- Jet class trained on 638 input features per labelled jet
 - Charged and neutral particles, properties of secondary vertices and global jet variables ...
- Unsupervised domain adaptation via backpropagation
 - Trained on data and Monte Carlo in control region
- Architecture progressively compresses
 and extracts most discriminating features
- Resample jet p_T and η to have same distribution for all classes – discrimination only via correlations with other features

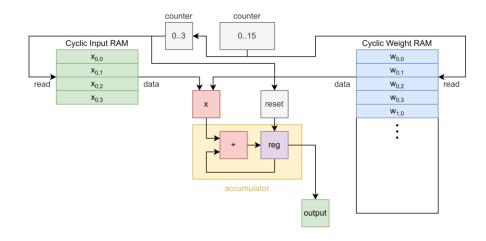
LLP Jet Tagging Algorithm



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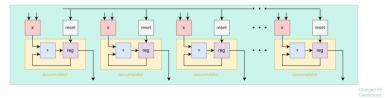
Serialised Cyclic RAM Multiply Accumulate

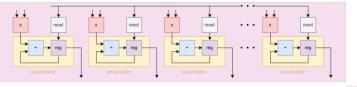
- Cyclic RAM block: RAM with read address connected to a counter
- Resource utilisation is heavily reduced as opposed to conventional convolution method
- Resource saving can be invested in instance duplication to increase throughput.



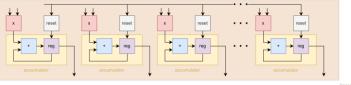
Instance Duplication Across Channels

- MAC units can be duplicated across the dimension common throughout the convolution layers
- MAC units can be duplicated across input channels
- Compute in space by taking advantage of computationally independent data streams





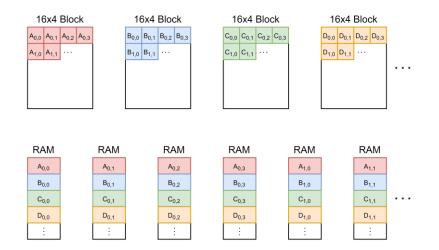




Vertices

Elementwise Matrix Indexing for RAM Storage

- Matrices usually stored contiguously in memory
- Alternative storage mode: elements in same position in matrices stored in same RAM element
- Faster and simplified read mechanism compared to traditional storage mode



Dataflow and Maxeler

- Dataflow computing involves channelling data between bespoke compute units (kernels)
- Benefit of faster development as opposed to use of Verilog/VHDL and exposure to the rich ecosystem that Java provides
- MaxCompiler (Java based HLS tool) chosen for simplified pipelining and latency control
- Communication between host CPU and FPGA over PCIe interface

Results – Test Setup

- Hardware implementations running on a Xilinx VU9P @ 100MHz
- Resource utilisation comprised of usage of:
 - Look Up Tables (LUT)
 - Flip Flops (FF)
 - Digital Signal Processors (DSP)
 - Block Random Access Memory (BRAM)
- Resource utilisation: $\frac{1}{4} \left(\frac{Used \ LUT}{Total \ LUT} + \frac{Used \ FF}{Total \ FF} + \frac{Used \ DSP}{Total \ DSP} + \frac{Used \ BRAM}{Total \ BRAM} \right) \times 100\%$

Results – Serialised Cyclic RAM Multiply Accumulate

			Single	Column
Hardware	Fully	Partial	MAC	MAC
Design	Unrolled	Unroll	Unit	Units
f (MHz)	100	100	350	250
Latency (ns)	80.00	210.00	140.00	24.00
LUT (%)	26.86	13.24	1.08	17.31
FF (%)	21.61	16.88	1.07	19.22
DSP (%)	29.94	1.86	0.06	0.94
BRAM (%)	8.24	3.11	2.36	2.98
RU (%)	21.66	8. 77	1.14	10.11

Results – Elementwise Matrix Indexing for RAM Storage

Hardware	Single	Double	Elementwise
Design	Buffer	Buffer	RAM Storage
f (MHz)	100	100	100
Latency (ns)	100.00	80.00	20.00
LUT (%)	1.65	3.38	0.71
FF (%)	6.43	13.22	2.90
DSP (%)	0.00	0.00	0.00
BRAM (%)	9.28	18.56	8.12
RU (%)	4.34	8. 77	1.14

Comparisons to Prior Implementations

- C++ implementation ran on Intel Xeon Gold 6154 CPU @ 3.00 GHz
- Took 780ns to convolve two 16x4 input matrices
- Fastest FPGA implementation offers ~32.5x latency reduction
- FPGAs offer a viable route to online processing, especially after HL-LHC upgrade