

David W. Miller

Enrico Fermi Institute



January 15, 2019





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Outline

7 Challenges of the Energy and Luminosity Frontier

2 ATLAS Phase I & II Hadronic Trigger Systems

3 Machine learning using FPGAs and MPSoCs



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The overwhelming hadronic environment of the LHC HL-LHC: $\mathcal{L}_{inst} = 10^{35} cm^{-2} s^{-1} = 0.1 \text{ pb}^{-1} s^{-1} = 30 \text{ kHz of dijet events}$



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Hadronic final states: major part of LHC physics program



Physics may be compromised due to trigger & data proc. limitations
Even if we *can* trigger, offline data management may be a bottle-neck

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Go GLOBAL: global feature extraction trigger (gFEX) for ATLAS Run 3



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Goal

analyze event-level features for characteristics of moderate $p_{\rm T}$ $(\sim 100$'s of GeV) signatures of new and key physics processes

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Strategy

input entire calorimeter **onto a** single trigger board

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analyze event-level features for characteristics of moderate $p_{\rm T}$ (~100's of GeV) signatures of new and key physics processes

Strategy

input entire calorimeter **onto a** single trigger board

Tactics

- coarse towers (0.2×0.2)
- state-of-the-art FPGAs
- MPSoC for control, additional processing

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gFEX Performance for Run 3

- Signal: e.g. boosted tops
- Compare to Run 2 triggers



gFEX can efficiently identify jet structure at 300 GeV!

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The gFEX trigger design



• Implement new algorithms using state-of-the-art FPGAs + SoCs

Image-like event format is well-suited for computer vision & ML

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gFEX Design: Virtex 7 & Zynq UltraScale+



2.3 Tb/s of calorimeter data received by gFEX

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gFEX already recorded Stable Beams data in Run 2!

• gFEX recorded data Stable Beams data on Oct 16, 2018!

- Calorimeter back-end system is a prototype for the Phase I/II upgrade (Run 3 & 4)
- This is a major milestone, but there is certainly more to come





Run 3 ideas for Run 4 reality: Global Event Processor



Receives trigger object information from all systems (jets, electrons, muons, timing, and possibly tracks). Makes global trigger decision about the event.

Built from a *common module* with both a **Zynq and two processor FPGAs**.

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Run 3 ideas for Run 4 reality: Hardware Track Triggers



Regional tracking at 1 MHz and global tracking at 100 kHz accomplished with associative memory **ASICs** (AMTP) with tracking in **FPGAs** (SSTP)

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Machine Learning for Future Triggers Systems

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4 Summary and conclusions

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Convolutional neural networks (CNN) for jet identification



Komiske, Metodiev, Schwartz (arXiv:1612.01551)

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Convolutional neural networks (CNN) for jet identification



Effectively the same CNN from Komiske, *et al.* can be used for top-tagging, using either high-level observables or jet images.



Komiske, Metodiev, Schwartz (arXiv:1612.01551)

Moore, Nordström, Varma, Fairbairn (arXiv:1807.04769)

(CNNs here use 4 layers, 64 filters in the conv. layers, and 128 node dense layer.)

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There is a significant benefit to modern MPSoC devices:

- Execute high-level applications on CPU/RPU
- Perform low/fixed latency operations on FPGA
- Offload simple vector/matrix operations to GPU

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Prune

Finetune

Pruning

(Less number of param)



15/19

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Dense Neural Network

(FP32)

Proof-of-principle with the gFEX Zynq: ResNet-50

Implement ResNet-50 neural network for image classification on our Zynq UltraScale+ MPSoC for gFEX

- \rightarrow Dramatically larger network!
- \rightarrow Thousands of filters
- $\rightarrow \ \sim 10 \text{ billion operations}!!$
- \rightarrow merely a Proof-of-principle



Work conducted by Emily Smith (grad student), in collaboration with Giordon Stark (UC Santa Cruz) and two UChicago undergraduates Jack Huang, Ben Warren.

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Proof-of-principle with the gFEX Zynq: ResNet-50



In ResNet50 CONV layers ... DPU CONV Execution time: 13607us DPU CONV Performance: 566.62GOPS n ResNet50 FC lavers ... DPU FC Execution time: 236us DPU FC Performance: 16,9492GOPS op[0] prob = 0.993050 name = English setter prob = 0.001493 name = clumber, clumber spaniel op[2] prob = 0.001493 name = Brittany spaniel [3] prob = 0.001163 name = English springer, English springer spaniel op[4] prob = 0.000705 name = Great Pyrenees bad image : 2ILSVRC2012 test 00068213.JPEG un ResNet50 CONV layers ... DPU CONV Execution time: 13595us DPU CONV Performance: 567.12GOPS In ResNet50 FC lavers ... DPU FC Execution time: 236us DPU FC Performance: 16.9492GOPS op[0] prob = 0.915599 name = rock beauty, Holocanthus tricolor [1] prob = 0.075157 name = king penguin, Aptenodytes patagonica prob = 0.001768 name = anemone fish op[3] prob = 0.000835 name = fiddler crab op[4] prob = 0.000650 name = toucan bad image : 2ILSVRC2012 test 00042675.JPEG un ResNet50 CONV layers ... DPU CONV Execution time: 13586us DPU CONV Performance: 567,496GOPS un ResNet50 FC layers ... DPU FC Execution time: 235us DPU FC Performance: 17.0213GOPS [0] prob = 0.977076 name = jaguar, panther, Panthera onca, Felis onca prob = 0.017896 name = leopard, Panthera pardus prob = 0.000891 name = tiger, Panthera tigris prob = 0.000540 name = cheetah, chetah, Acinonyx jubatus op[4] prob = 0.000540 name = tiger cat



Image processing at the level of $\mathcal{O}(ms)$, expected to decrease to $\mathcal{O}(\mu s)$ for jet network and 30×30 "images" (i.e. gFEX events).

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Summary

- Major challenge to measurements and searches in hadronic final states at the future LHC will be triggering and data management
- Run 3 trigger systems (gFEX) have **unique and novel capabilities** as part of both baseline design and **ML on MPSoC & FPGAs**
 - Co-processor applications using FPGA+CPU+GPU would be very interesting!
- Clear **opportunities for the Phase II trigger system** in terms of hadronic final state physics, tracking, and more for the trigger system currently planned
 - There is much to be explored in Hardware-based Track Triggers for HLT!
- Strong involvement with scalable systems, hardware accelerators, and even data management plans for the "offline" world may be essential to realize gains further in physics potential

Outline



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Appendix



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gFEX prototypes and production boards



- **Prototype** (1×**VU9P** + 1×**ZU19**) used for integration and commissioning at CERN since Q1 2018.
- Final board (3×VU9P + 1×ZU19) delivered to CERN on 25 June, 2018, 5 years from proposal to delivery!
- Installation \sim now, ready for Run 3



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gFEX Multi-Processor System-on-Chip: Zynq Ultrascale+



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gFEX Virtex 7 Ultrascale+ Processor FPGAs



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gFEX Multi-Processor System-on-Chip: Zynq Ultrascale+



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gFEX Multi-Processor System-on-Chip: Zynq Ultrascale+

Zynq® UltraScale+™ MPSoCs: EG Block Diagram



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Zynq Ultrascale+ Processors



64 bit ARM quad-core processor



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Processor and Zynq FPGA comparison for gFEX boards

	Processor FPGA			Zynq	
gFEX version	v1	v2/v3	v3/v4	v1/v2	v3/v4
FPGA type	VX690T	VU160	VU9P	Z7045	ZU19
Logic Cells (M)	0.7	2.0	2.6	0.4	1.1
CLB (M)	0.9	1.9	2.4	0.3	1.0
Total RAM (Mb)	52.9	115.2	345.9	17.6	70.6
DSP slices (K)	3.6	1.6	6.8	0.4	2.0

Global Event Processor Information



Zynq MPSoC also available on future Phase II trigger system.

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Industrial neural networks and ResNet-50

From Canziani, Culurciello, Paszke "An Analysis of Deep Neural Network Models for Practical Applications" (arXiv:1605.07678)



"operations count represent a good estimation of inference time."

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