

### **FPGA-based Machine Learning Inference for** CMS with the Micron Deep Learning Accelerator

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## CERN Openlab

## **MARCICON®**





### **Technology: Micron Deep Learning Accelerator**

- SB852 PCIe board, Xilinx VU9P, 2x QSFP
- > 64GB DDR4, PCIe x16 Gen3 to host
- deep learning inference offers ~Tera MAC/s

### 2x QSFP 25G



Firmware: Proprietary Inference Engine, scalable and programmable solution to



Xilinx VU9P FPGA



### **Technology: Micron Deep Learning Accelerator**









\*User friendly API; reports diagnostics of interest e.g latency, precision, bandwidth

No need to write VHDL to run most DL models on FPGA







### **Application: The CMS Detector at the LHC**

- > 2.4 billion collisions / second
- » In CMS ~ 100M sensors
- » Produce ~ 1.5 MB @ 40 MHz, ~500 Tb/s
- » Impossible to read out (or store) all data
- » Need fast 'trigger' to select *interesting* collisions for analysis
- » Two layered:
- \_evel 1: Fixed latency of 3.2 microseconds -> ASICs and FPGAs required - High Level Trigger: Flexible latency ~100 ms compute / event -> CPUs/GPUs





### Extension to CMS TDAQ: 40 MHz Scouting

- Acquire L1 trigger data at full bunch crossing rate
- > subset of detector information, limited resolution
- > Allows for analysis of certain topologies at full rate
- » semi real-time analysis and/or
- » storing of tiny event record

- Demonstrated for first time at end of 2018
- Current plans to scout objects from the Global Muon Trigger, Barrel Muon Trigger & Calorimeter Trigger at LHC Run 3





### CMS 40 MHz Scouting with SB-852





### **Extension to CMS TDAQ: 40 MHz Scouting**

- Firmware ported and developed for SB852
- Optical link interface implemented and tested













### Why ML for scouting?

- Trigger objects calibrated for best efficiency at threshold
- Not for best physics analysis
- But we have full offline reco & trigger objects for Zero Bias and Triggered events
- Can we use the offline objects as target to correct the parameters of the trigger level objects?
- > Use of classical neural networks to 'correct' L1 information e.g muon helix parameters
- > Inputs L1 objects e.g GMT muons: Target Offline fully reconstructed objects







### **GMT** with Neural Network

> Able to achieve ~2x improvement in track parameter resolution for some interesting areas of phase-space



- analysis in the L1 Scouting system. Produced with Zero Bias data.
- offline muon tracks for matched muons ( $\Delta R < 0.1$  at 2nd muon station).



Applied a neural network to the L1 muons to improve their accuracy for real-time

 $\Delta \eta$ ,  $\Delta \phi$ ,  $\Delta p_T$  is the difference between the prediction (or GMT) values, and the



### Fake muon pair classifier

- > Train a DNN with ZB data to predict fake muon pairs
- > Can use to improve purity of di-muon sample





input

Dense

units = 16

activation = relu

?×14



### GMT Scouting data from 2018 re-calibrated with NN



- GMT muons; Barrel-Barrel pairs **>>**
- Muon p<sub>T</sub> 0-15 GeV **>>**
- » NN re-calibrations & fake pair prediction applied
- Duplicate removal d $\phi$  < 0.1 rad
- Equivalent results obtained for **>>** endcap, overlap, and mixed TF pairs

 $\mu^+ \mu^-$  invariant mass [GeV]



### Scouting: Latency and precision

- Close to latency target:



Model w/ integer inputs, no batch norm

99%



Q

### Autoencoder for anomaly detection in L1 Trigger

- > Anomalous events -> may be new physics candidates
- Model/theory independent
- > Train on Standard Model 'QCD' background
- Inputs: fixed size arrays/images of up to 10 jets, 4 muons & 4 electrons & MET (each with 3 parameters)
- Test with simulated Beyond Standard Model events e.g new massive vector bosons, unusual Higgs decays
- Option to run in scouting system (no strict latency requirement)
- Developing both classical, convolution, and variational autoencoders and comparing all approaches

**Classical AE option** input\_1 ∕latMul N×1×1×56 **B** (3×16) shape <2> Add **B** (16) MatMul **B** (56×32) BatchNormalizatio **scale** (16) **B** (16) **B** (32) **mean** (16) **var** (16) scale (32) **B** (32) mean (32) var (32) ∕latMul **B** (16×32) ∕latMul **B** (32×16) **B** (32) **B** (16) BatchNormalizatio scale (32) **B** (32) BatchNormalizatio mean (32) scale (16) **var** (32) **B** (16) /latMul ∕latMul **B** (32×56) **B** (16×3) Add **B** (56) **B** (3) BatchNormalizatio scale (3) **B** (3) N×56 mean <3> var (3) dense\_









### Autoencoder for anomaly detection in L1 Trigger



Successfully ran on SB-852 - ironing out precision differences - latency ~625ns





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### Summary and next steps

- > Challenging year (for everybody), but progress made on all fronts
- > Run 3 delayed Q1 2022
- > Focus: testing and integrating aspects of the scouting system & associated to test system in situe
- Performance of deep-learning driven anomaly detection algorithm being evaluated for use at LHC Run 3
- > Thank you to the team at Micron for the great collaboration - looking forward to see what 2021 brings!





### hardware, firmware, software - use of monthly 'Global Runs' with cosmic muons













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