

## **Tools** (e.g. for streaming DAQ, fast ML, automation/self running DAQ,...)

Mia Liu, Nhan Tran, Fermilab + input from many in Fast ML and broader community! DOE Basic Research Needs Study (Community meeting for TDAQ) December 3rd, 2019







## The dream TDAQ

- Powerful intelligent algorithms
  - Sophisticated algorithms
  - Training/updating on the fly
- Autonomous, self-calibrating
  - Safe with minimal down-time
- Analyze everything, no data loss
  - Modular, multiple processing layers



## **Generic system**

Detector, Accelerator



TDAQ-1 (reconstruct)



TDAQ-N (reconstruct)







## Specific systems



























Computing challenges: Need to investigate in how to integrate heterogeneous computing platforms



# **On-detector sophisticated algorithms**

[https://arxiv.org/abs/1804.06913], [fastmachinelearning.org/hls4ml]

### ML in the hardware trigger

- All FPGA design
  - Flexible: many algorithm kernels for processing different architectures
- Application and adoption growing across the LHC and beyond!
- Growing interest with many on-going developments
  - CNNs, Graphs, RNNs, auto-encoders, binary/ternary
  - Alternate HLS (Intel, Mentor, Cadence)
  - Co-processors, multi-FPGA
  - Intelligent ASICs
- See Phil's talk





> 5000 parameter fully connected network in 100 ns





## hls4....nl...4asic?

### Hardware acceleration with an emphasis on co-design and fast turnaround time

First project: Autoencoder with MNIST benchmark (28 x 28 x 8-bits @ 40 MHz)



Enable edge compute : e.g. data compression
Programmable and Reconfigurable: reprogrammable weights
Hardware – Software codesign: algorithm-driven architectural approach
Optimized Mixed signal / Analog techniques: Low power and low latency
for extreme environment (ionizing radiation, deep cryogenic)





Compressed data



Reconstructed data

- Efficient bandwidth usage
- Reduced power consumption (data transfer)

First tests of 1-layer design Latency: 9ns Power (FPGA, 28nm) ~ 2.5 W Power (ASIC, 65nm) ~ 40 mW

Area = 0.5mm x 0.5mm



## **Off detector: heterogeneous computing**



### **FLEXIBILITY**





### Advances in heterogeneous computing driven by machine learning

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- Opportunities for deploying accelerated heterogeneous **compute** for real-time analysis
- How best to integrate into a given TDAQ workflow
  - ML/not ML
  - Service or direct connect
  - GPU, FPGA, ASIC
- Proof-of-concept for ML with FPGAs as a service, https://arxiv.org/abs/1904.08986















# Autonomous, self-tuning accelerator Data **Real-Time** Detector reconstruction using ... ML algorithm

- Anomaly detection and weight updating
- Transient detection algorithms
- Reinforcement learning
- Neuromorphic algorithms (spiking)









## **Tools for dream**

### **Powerful intelligent algorithms**

- FPGAs designed for ML and vice versa
- Opportunities for heterogeneous hardware (e.g. Versal)
- Push up to the frontest end (ML in ASIC, reconfigurable weights)
- New types of algorithms beyond classification & regression
- Autonomous, self-calibrating
  - Automation for (a) when conditions have changed (b) what actions to take
  - Fast DAQ paths with deep buffers for monitoring individual channels, how to deal with different time scales?
  - Training and recalibration "offline-system" (GPU...) or small-scale in situ (ARM processor, in FPGA)

## Analyze everything, no data loss

- Modular, portable, multiple processing layers
- Data storage Affordable, new/different storage technologies for persistent (parked) datasets
- Streaming fast analysis accessible programming paradigms; SoC R&D





**Electronics hardware** and infrastructure

Systems designed for operations and control











