

**Dec 10, 2019**

# **Trigger, DAQ and Machine Learning**

**CPAD 2019**

**Verena Martinez Outschoorn and Isobel Ojalvo**



# DAQ Concepts Edge ML

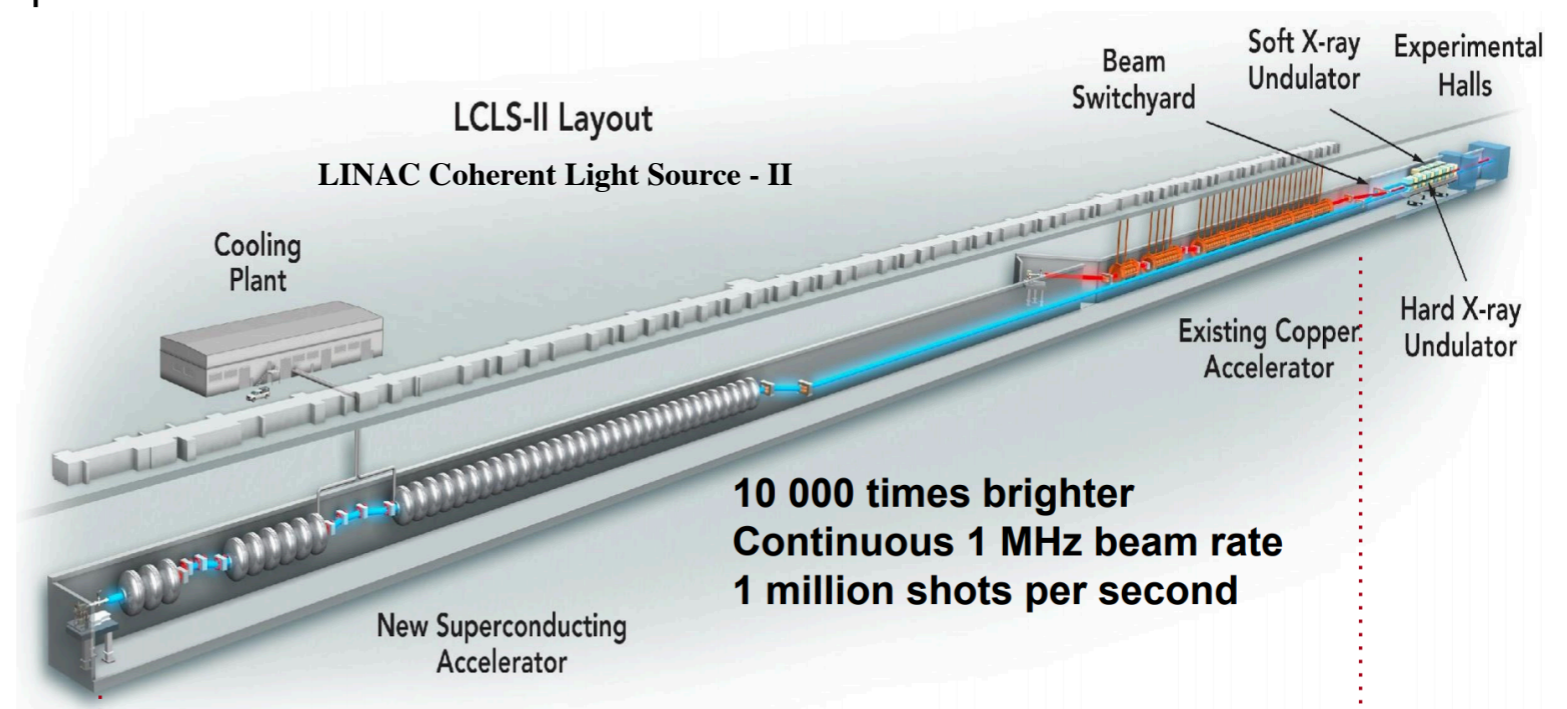
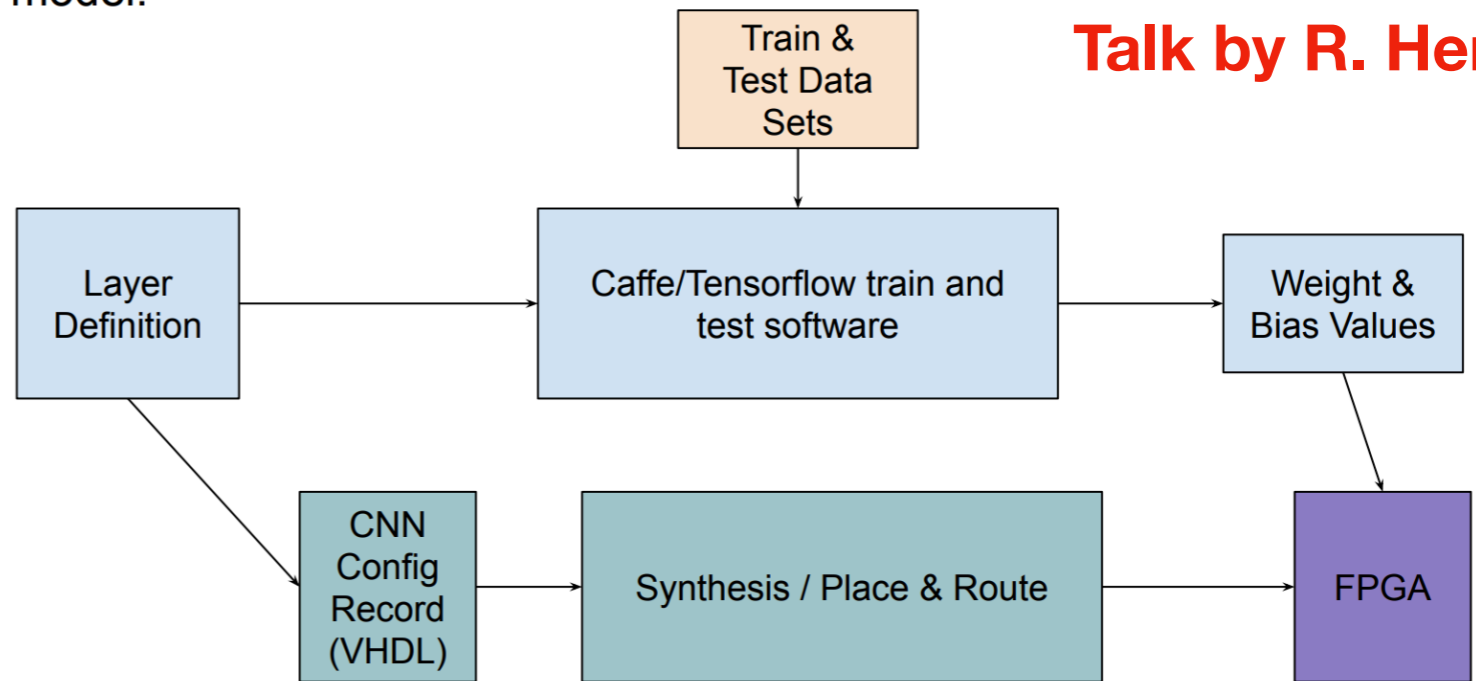
Talk by R. Herbst

Framework to provide a configurable VHDL based **inference engine**

- Layer Types supported: Convolution, Pool & Full

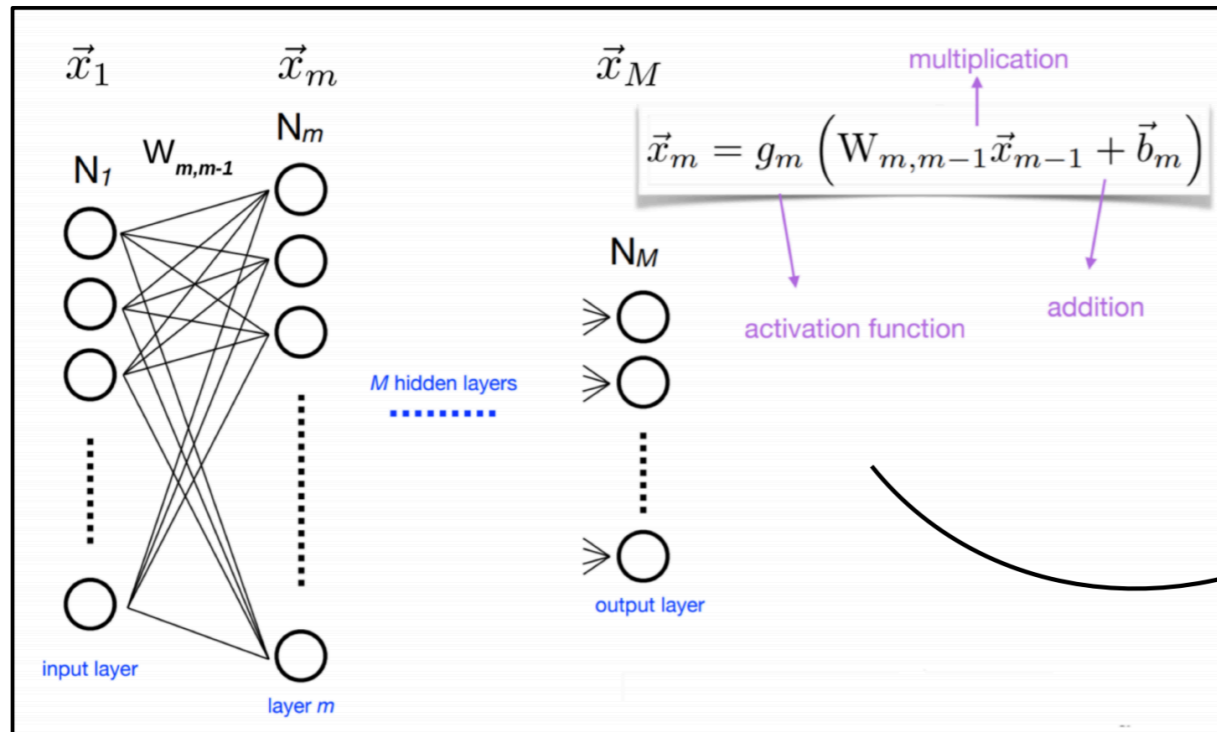
Developed as a proof of concept but applicable for many HEP experiments

developed for **Linac Coherent Light Source II**



# DAQ Concepts Edge ML

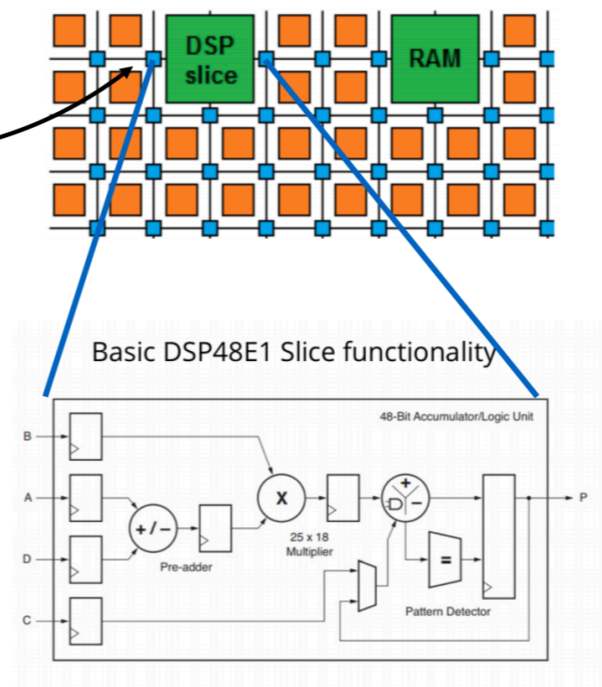
Typical NN operations:



Maps naturally into the functionality of DSP slices available in modern FPGAs

Device	# of DSPs
Kintex-7 325T	840
Virtex-7 690T	3600
Kintex UltraScale KU115	5500
Virtex UltraScale+ VU9P	6800

- ◆ DNN
  - Including support for large layers
- ◆ Binary and Ternary DNN
  - Low precision (1 or 2 bit) weights performance
  - Implemented in LUTs



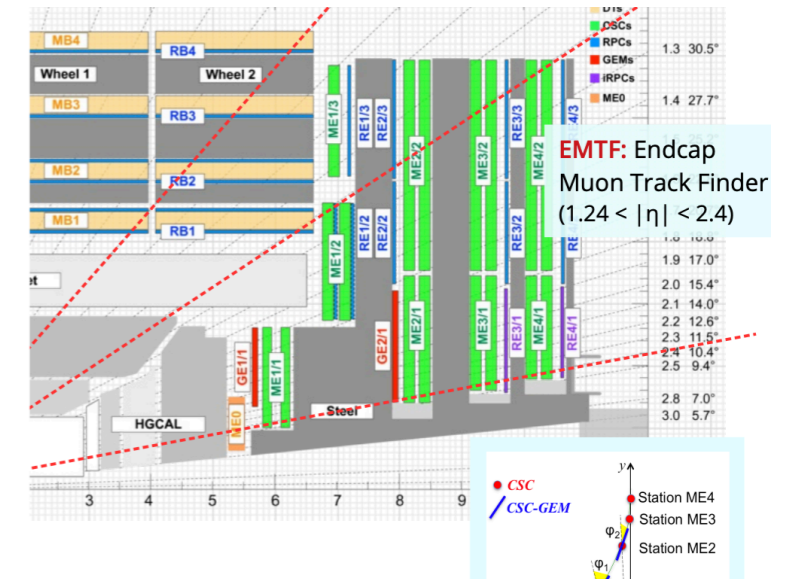
- ◆ Conv1D and Conv2D (small)
  - Large Convs and Binary/Ternary coming soon
- ◆ Other features
  - Batch normalization
  - Various activation functions
  - Tools for comparing C and RTL simulation results

Talk by S. Jindariani

# Machine Learning based algorithm for reconstructing prompt and displaced muons at Level-1 in CMS detector



Talk by J. F. Low

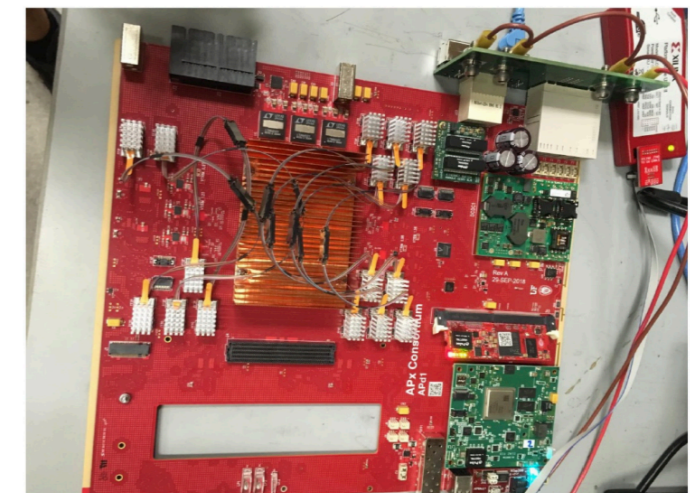


At CMS L1 muon transverse momentum assignment has used ML for inference since LHC Run-1

- Traditionally Used LUTs
- NN Inference also should be possible!
  - Trade off in FPGA resource usage

For **Phase-2** the **EMTF** algorithms will evolve to incorporate **new detectors**, **pile up**, **maintain efficiency**, also **incorporate displaced Muon ID**

APd board being developed



Looking into the Phase-2 APd board<sup>[3]</sup> with Virtex US+ VU9P FPGA, which has 3X more LUT & FF, and 2X more DSP.

NN should comfortably fit in the VU9P (DSP usage is 35%)

32 clk @ 333 MHz ≈ 100 ns latency

HLS estimates

```

===== Utilization Estimates =====
* Summary:
+-----+-----+-----+-----+-----+
| Name   | BRAM_18K | DSP48E | FF   | LUT   | URAM |
+-----+-----+-----+-----+-----+
| DSP    | -         | -       | -    | -     | -    |
| Expression | -       | -       | 0    | 6     | -    |
| FIFO   | -         | -       | -    | -     | -    |
| Instance | 39      | 2420   | 69109 | 90580 | -    |
| Memory | -         | -       | -    | -     | -    |
| Multiplexer | -       | -       | -    | 1404  | -    |
| Register | 0        | -       | 4280 | 32    | -    |
+-----+-----+-----+-----+-----+
| Total  | 39       | 2420   | 73389 | 92022 | 0    |
+-----+-----+-----+-----+-----+
| Available | 4320    | 6840   | 2364480 | 1182240 | 960 |
+-----+-----+-----+-----+-----+
| Utilization (%) | ~0     | 35     | 3     | 7     | 0    |
=====
  
```

Displaced EMTF++: NN performance

# Detect New Physics with Deep Learning

Talk by Z. Wu

## Example AE Model

- Train with simulated ZeroBias event at 200 pileup
- Use simulated Puppi Jet/MET/MHT inputs (18 inputs) with preprocessing
- Activation function: ReLU
- Loss function: **L1Loss**
- Training - validation ratio : 0.8
- Number of epochs: 100-200 epochs
- Number of layers: 8 layers
- Model is designed with simplicity for firmware implementation and resource/latency requirement

$$\ell(x, y) = L = \{l_1, \dots, l_N\}^T, \quad l_n = |x_n - y_n|$$

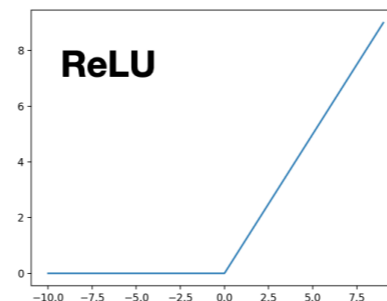
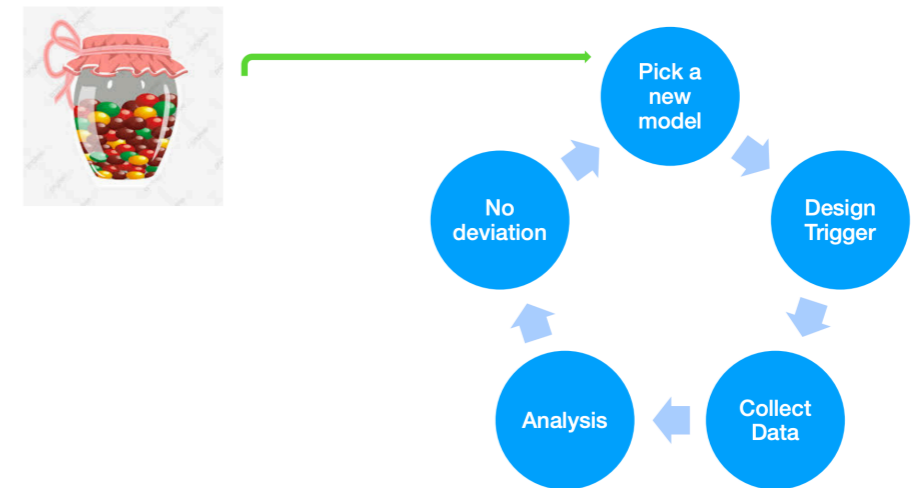


Illustration by Jeff Lewonczyk

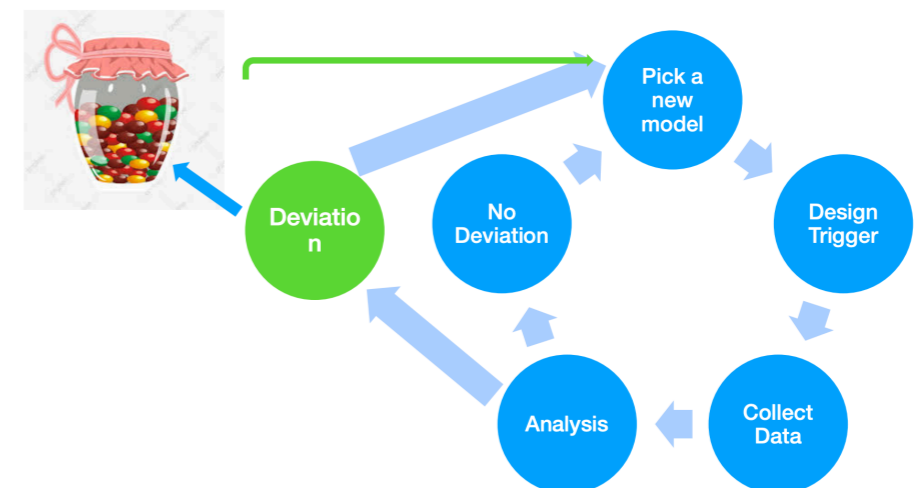
Not to claim a discovery!

But to give an idea of what Exotic Signals to integrate into our trigger menus

## Traditional Workflow of Searches

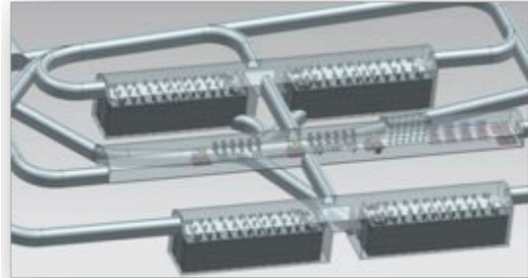
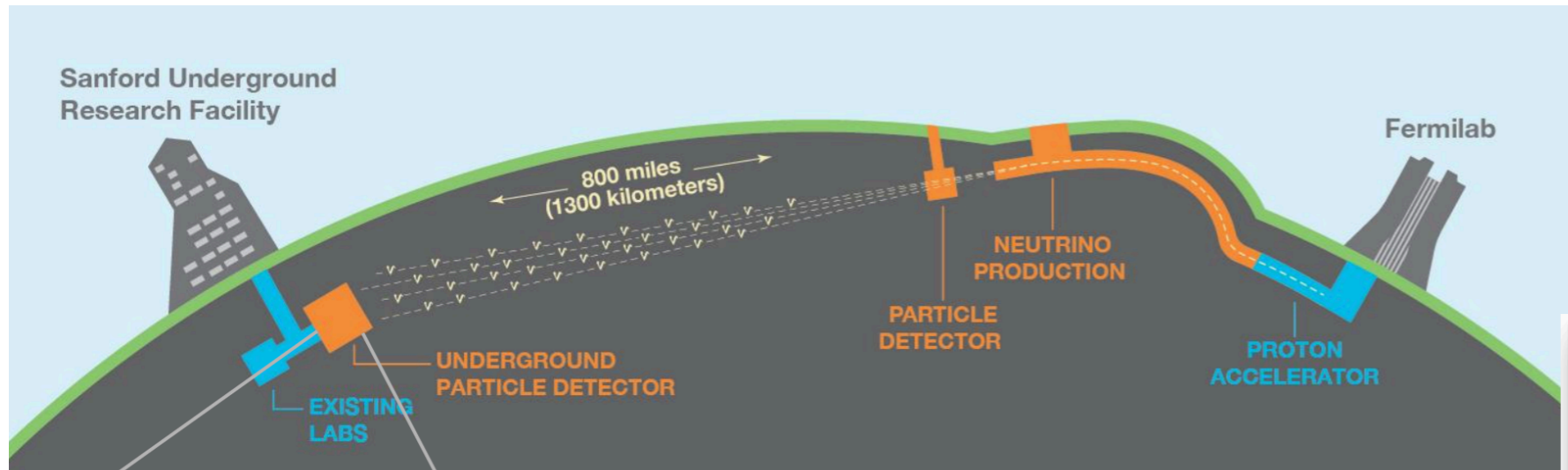


## Auto Encoder Workflow of Searches



# Machine Learning-based Trigger for DUNE

Talk by G. Ge

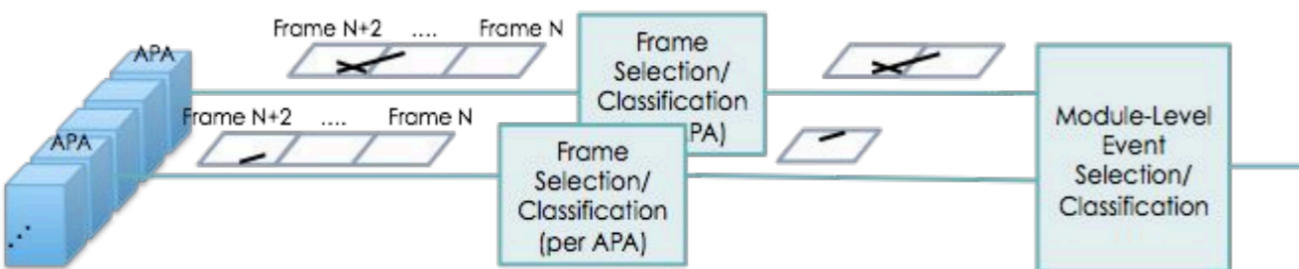
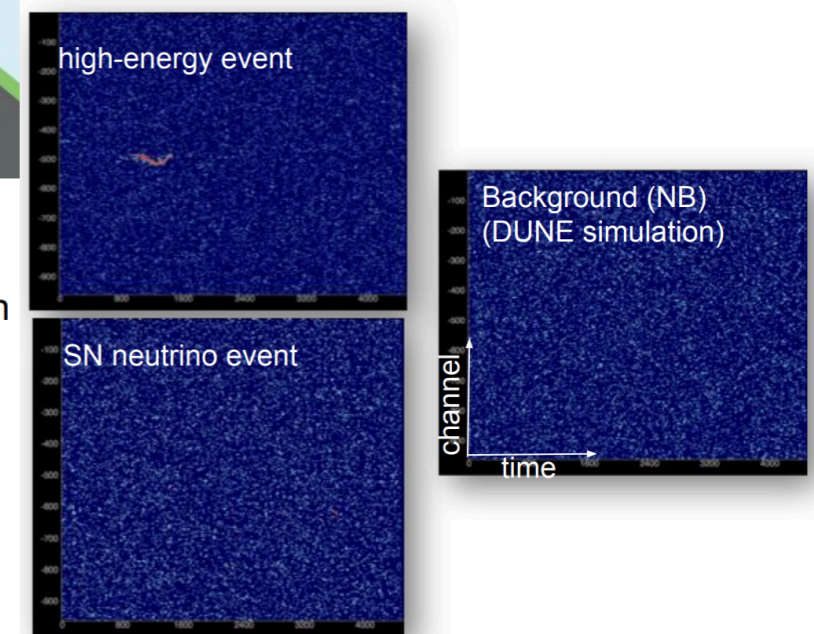


Far detector:

- 4 liquid argon time projection chamber (LArTPC) modules, each with 10kton fiducial mass
- underground (1.5km deep)

Physics goals of DUNE:

- CP violation in the lepton sector
- neutrino mass ordering
- search for rare events, e.g. proton decay, supernova burst neutrinos



**1. Low-level:**  
CNN-based  
APA-frame  
selection and  
reweighting

**2. Module-level:**  
APA-frame  
coincidence  
across module  
and  
over 10 seconds

Performance and power analysis of CNN<sub>s</sub>:

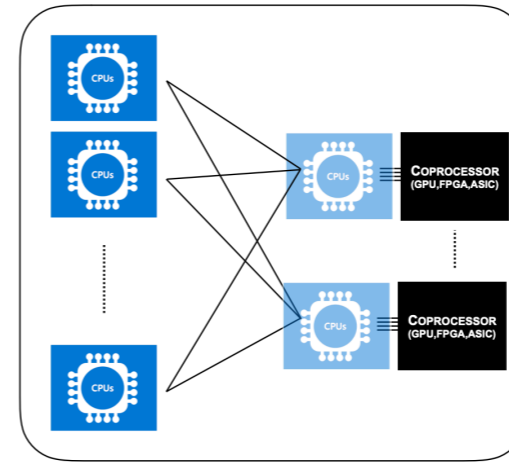
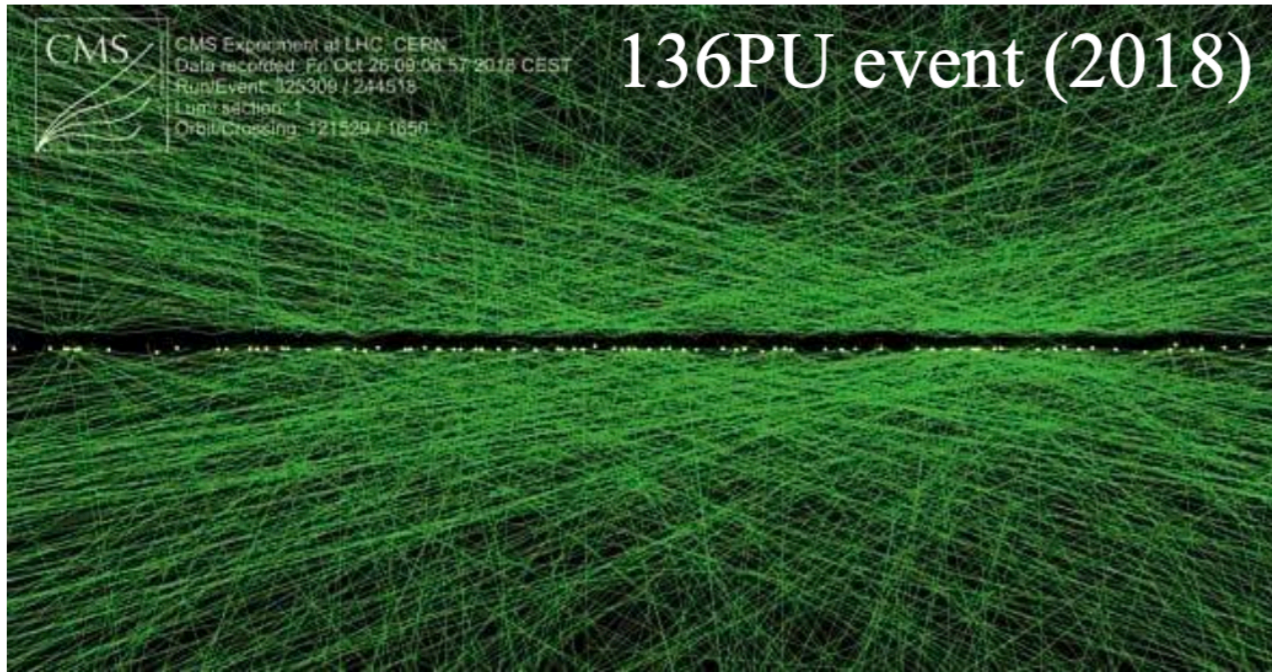
Platform	Model	Time (s)	Power (W)	Energy Efficiency (img/s/W)
ARM C-A53	CNN <sub>s</sub>	0.0855	2.871	4.074
FPGA	CNN <sub>s</sub>	0.0511	1.110	17.630

\*G. Karagiorgi, Y. Jwa, G. di Guglielmo, L. Carloni;  
DOI: 10.1109/NYSDS.2019.8909784

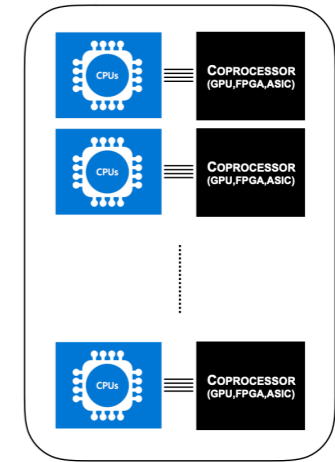
# Accelerated Machine Learning Inference as a Service

Talk by N. Tran

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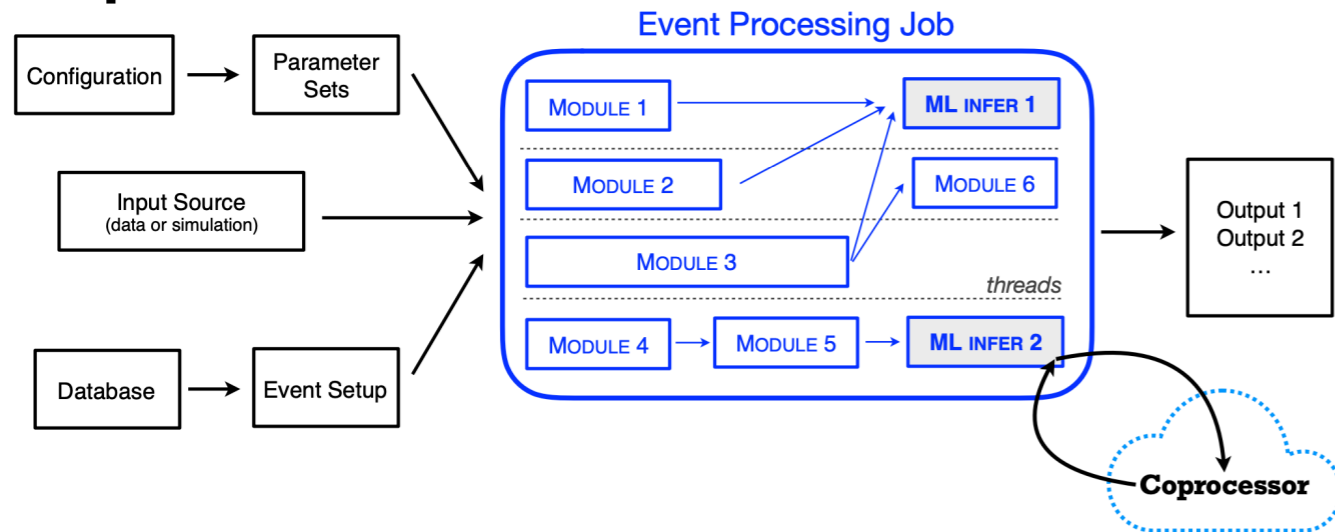


**Pros:**  
scalable algorithms  
scalable to the grid/cloud  
heterogeneity (mixed hardwares)



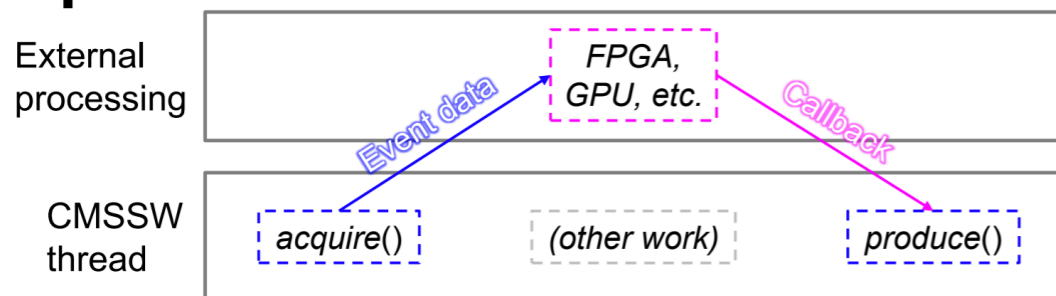
**Pros:**  
less system complexity  
no network latency

## co-processor aaS



	HCal Reco Network	Resnet-50 (Top tag) Network
CPU (single-thread)	67 inf/s	0.6 - 2 img/s (depends on CPU)
GPUaaS w/TensorRT	333 inf/s (batch 16000)	140 img/s (batch 1) 667 img/s (batch 32)
FPGA (batch 1)	500 inf/s (batch 1)	660 img/s (Brainwave, aaS)

## co-processor aaS



# SONIC

Services for **O**ptimized **N**etwork **I**nferece on **C**oprocessors



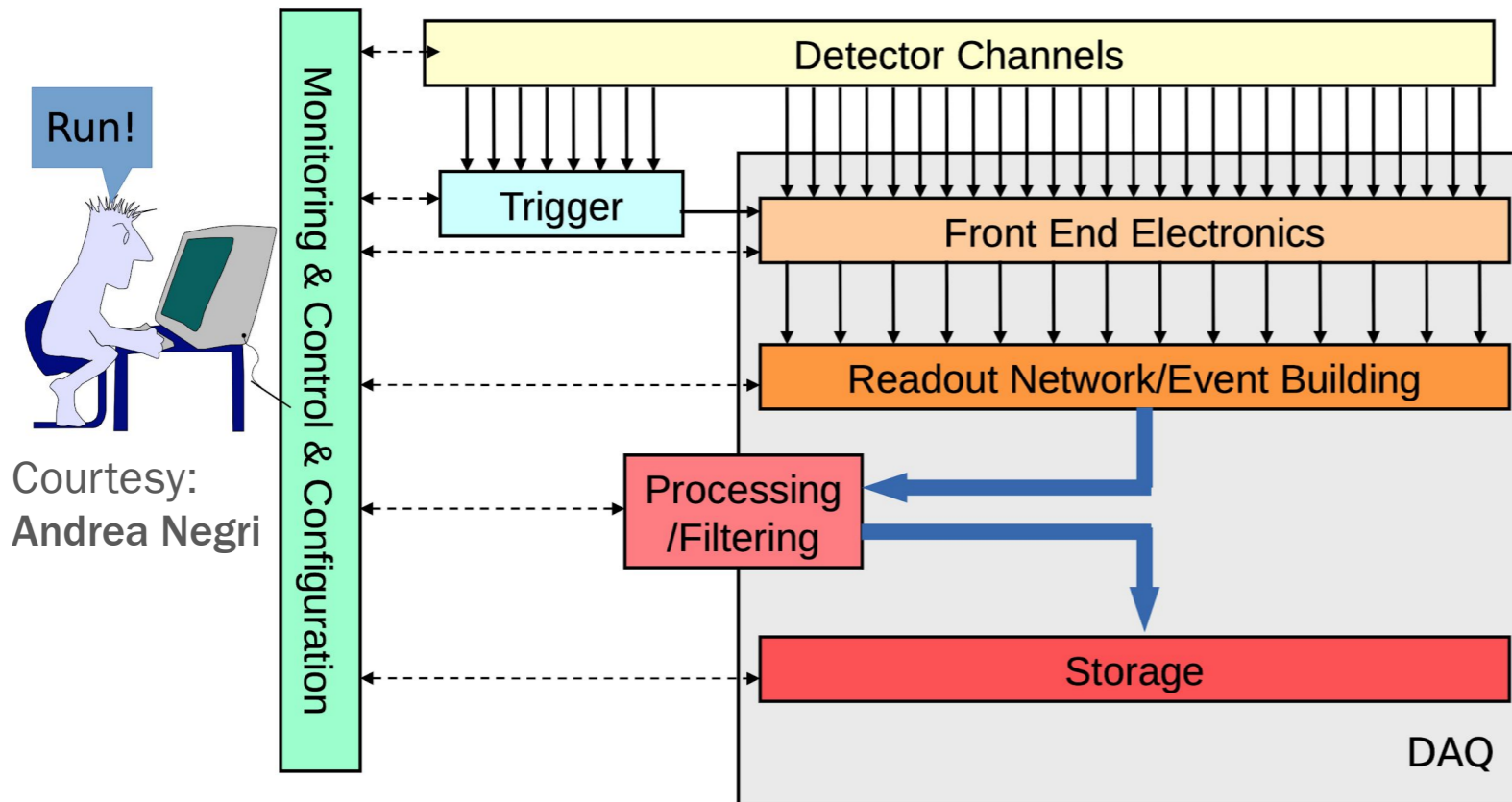
# Overview of Trigger & DAQ Systems

Talk by K. Chen

- Triggered readout
  - ATLAS
  - CMS
  - ALICE
- Streaming readout
  - LHCb (Run-3)
  - EIC (in R&D)
- Hybrid readout
  - sPHENIX
  - ProtoDUNE-SP
  - SBND
  - DUNE ← Intensity Frontier

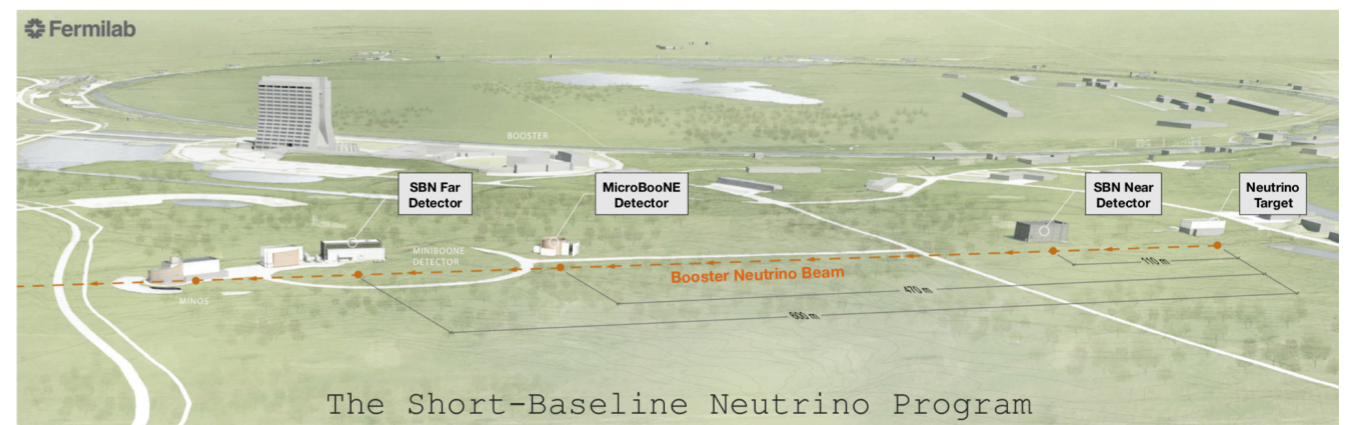
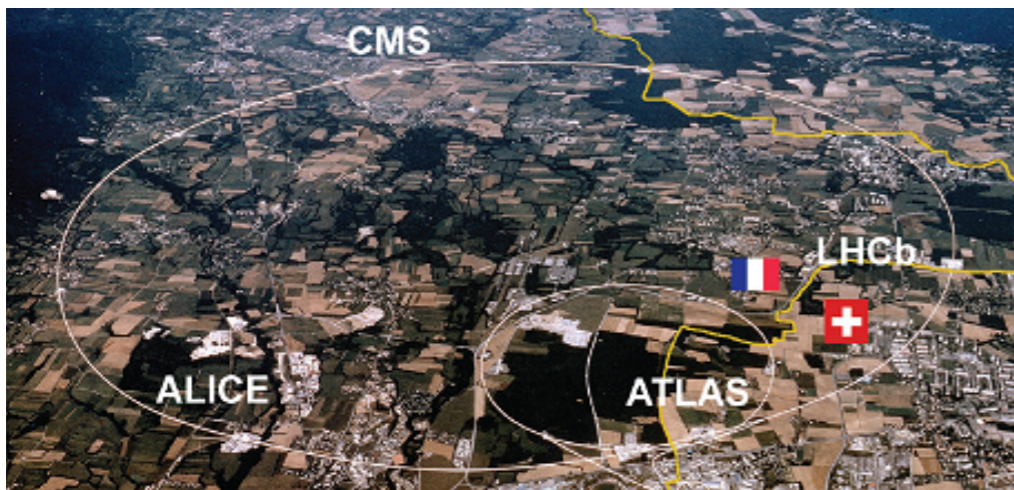
Energy Frontier

Intensity Frontier



Courtesy: Andrea Negri

Energy Frontier

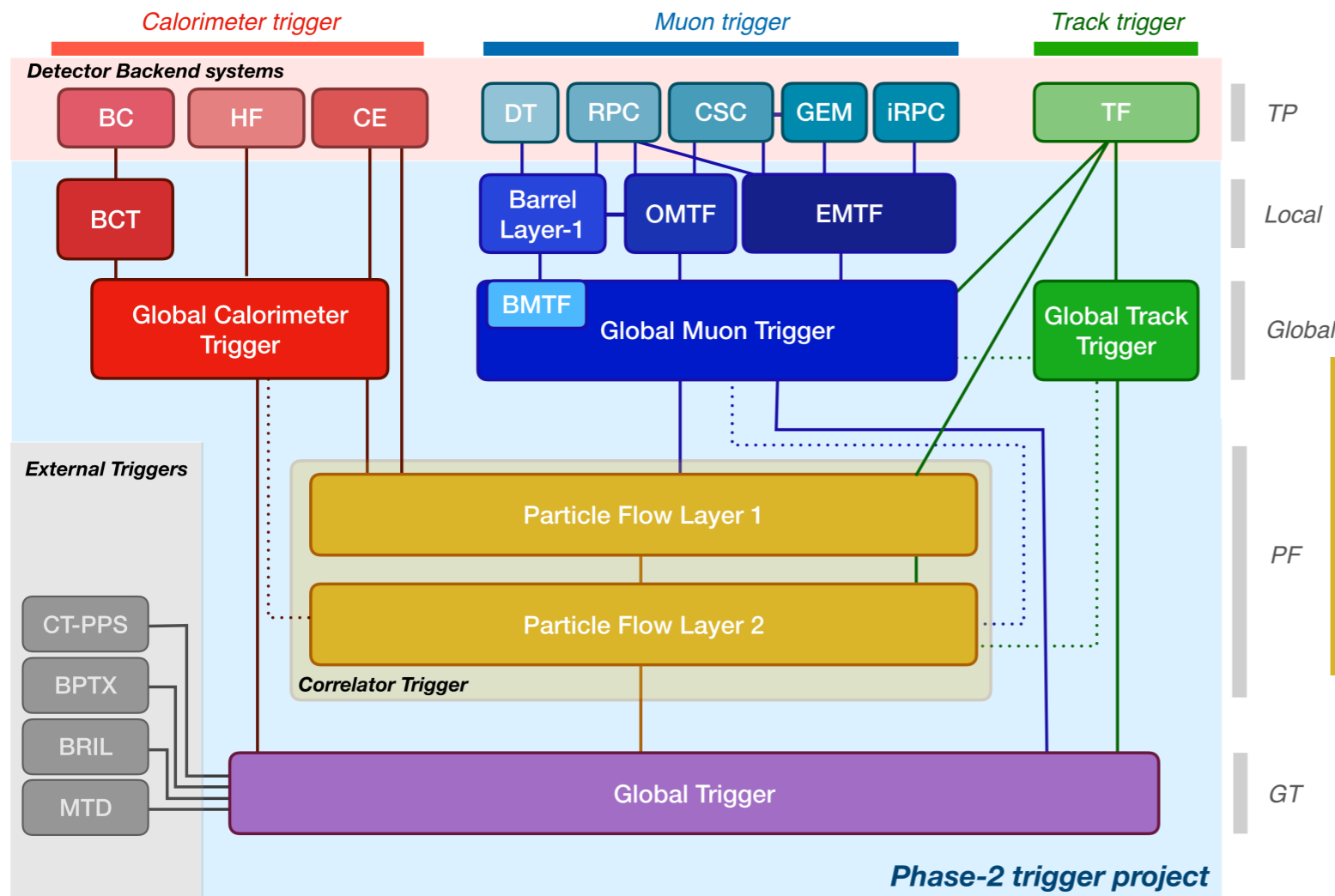




# Triggered Readout - CMS

Talk by C. Herwig

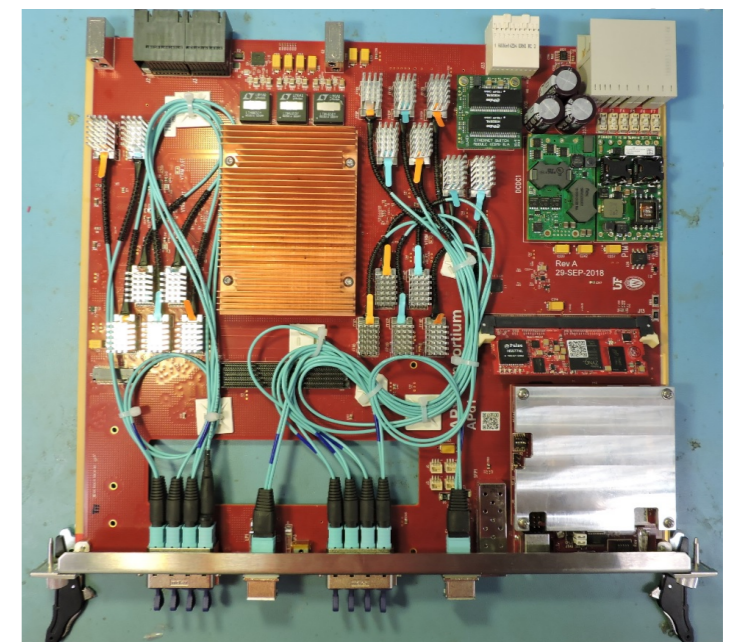
## Example of CMS Phase 2 Architecture (for HL-LHC)



Combine detailed **Calorimeter** & **Muon** Information with

track trigger at L1,  $p_T > 3-4$  GeV, Vertices

Implement offline-like algorithms  
 Layer 1 → run "particle-flow candidate" reconstruction & pileup  
 Layer 2 → run algorithms on candidates



Sophisticated algorithms to combine information from all sub detectors at 40MHz  
 Algorithms with latency of  $O(100\text{ns})$  implemented in FPGAs using ATCA hardware

**Similar strategy pursued by ATLAS**

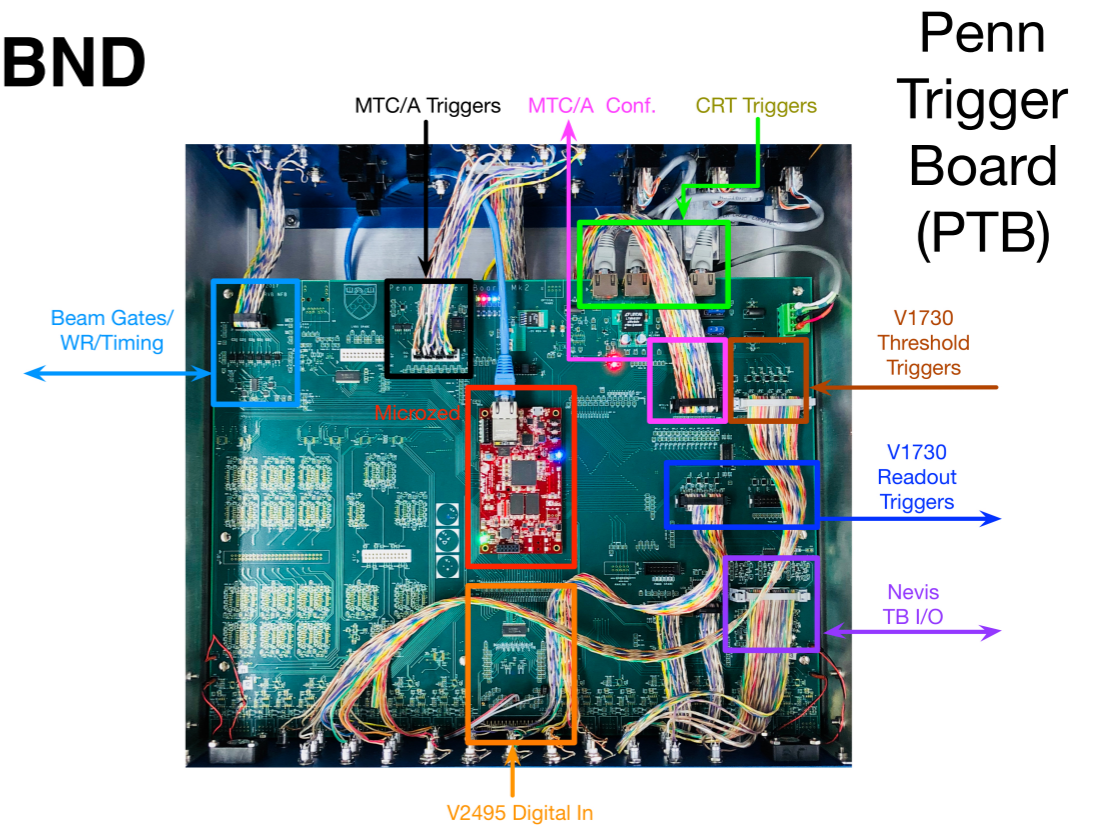
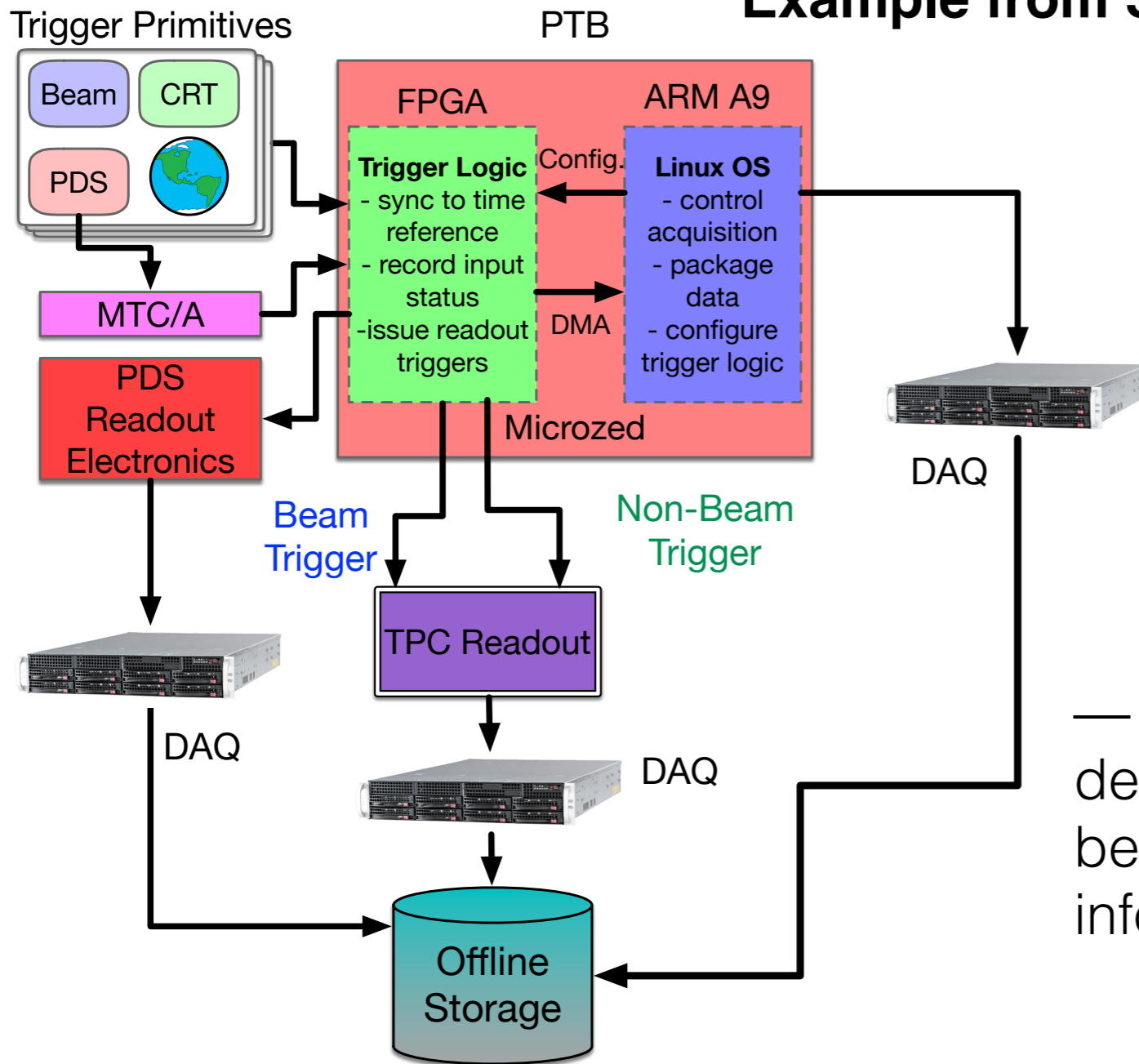
# Triggered Readout - SBND

Talk by D. Rivera

Trigger decision is critical for LArTPC due to slow drift and high granularity of detectors

— Data rates and storage increasingly become an issue

## Example from SBND



Penn Trigger Board (PTB)

— Hardware trigger implemented to decide whether or not the TPC should be read out based on combination of information from several key sources

# Real-Time Reconstruction - LHCb

Talk by D. Craik

Several interesting physics signals are high rate processes at LHCb

- improved sensitivity by accessing event information early on

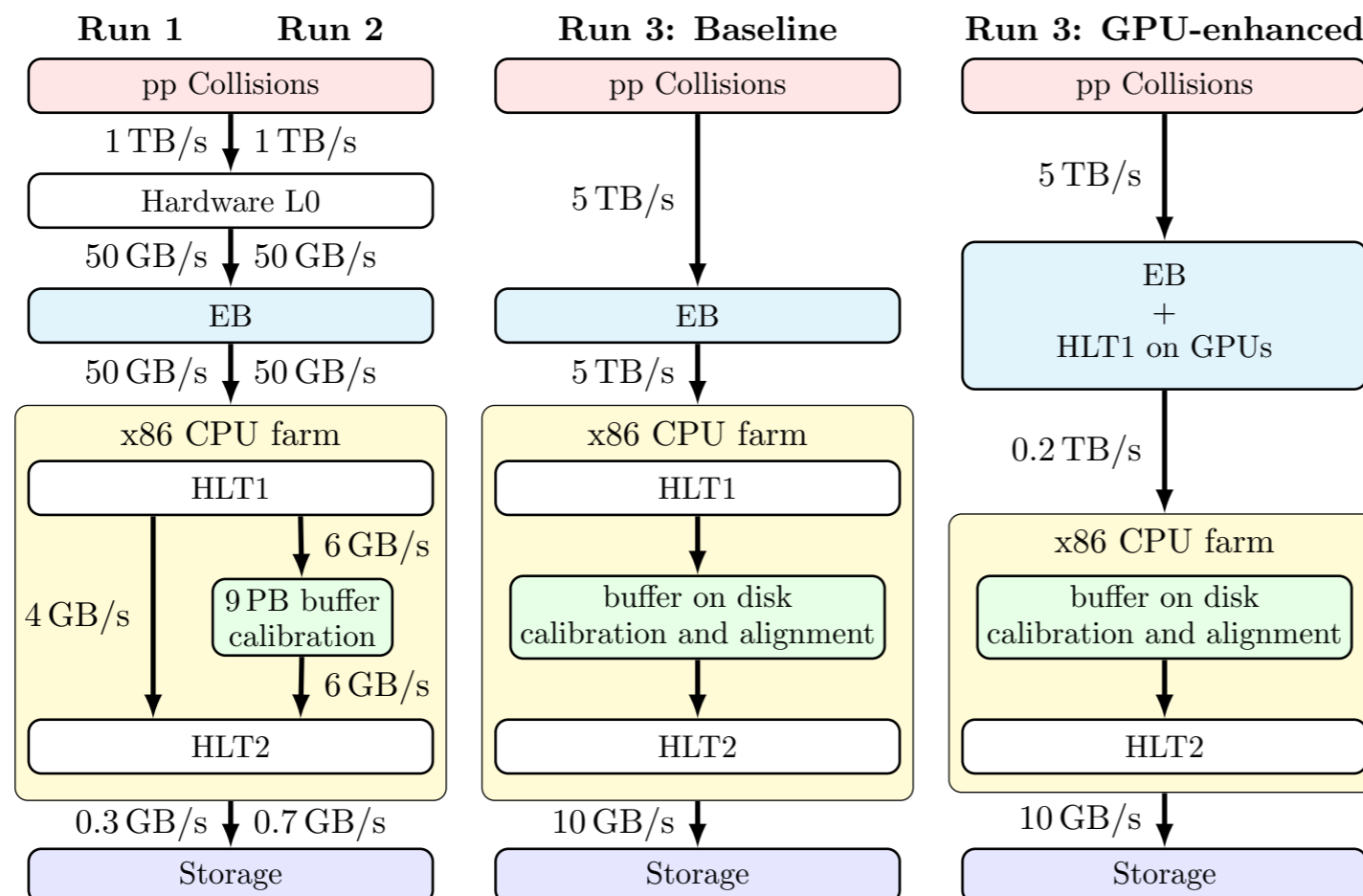
LHCb performs analysis in real time

- Data is buffered before final stage of trigger to derive calibrations & alignment

- Perform reconstruction at bunch-crossing rate with same quality as offline for most objects

- Full raw event is no longer stored, reduce load on offline reconstruction

**Already successfully used for several results & plans for extension for next run**

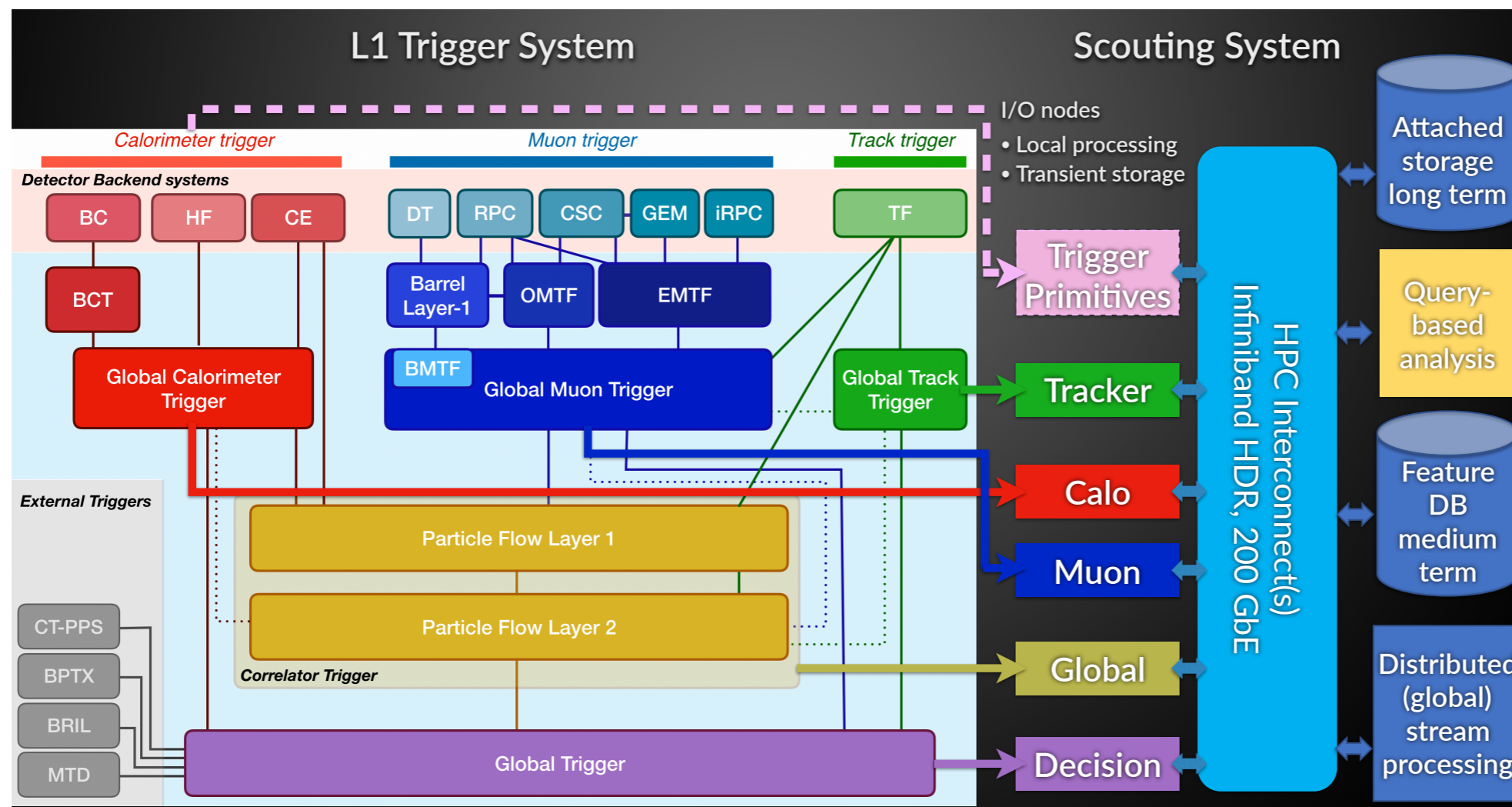


Several options explored e.g. use alternative processors (GPUs)

# Real-Time Analysis - CMS

Talk by R. Mommsen

CMS is planning a 40 MHz real-time analysis stream for HL-LHC  
— Interesting for physics and as diagnostic & monitoring tool



Gained experience in Run 2, plans for expansion in Run 3

Successful implementation requires R&D activities on several fronts

- HW inference engines
- Stream processing
- Distributed algorithms (MPI)
- NVRAM latency
- Searchable Feature DB
- Key-value store to assemble and buffer event fragments

# Continuous Readout - MicroBooNE

Talk by I. Ponce

MicroBooNE's Continuous Readout Stream targets seeks to observe supernova signal

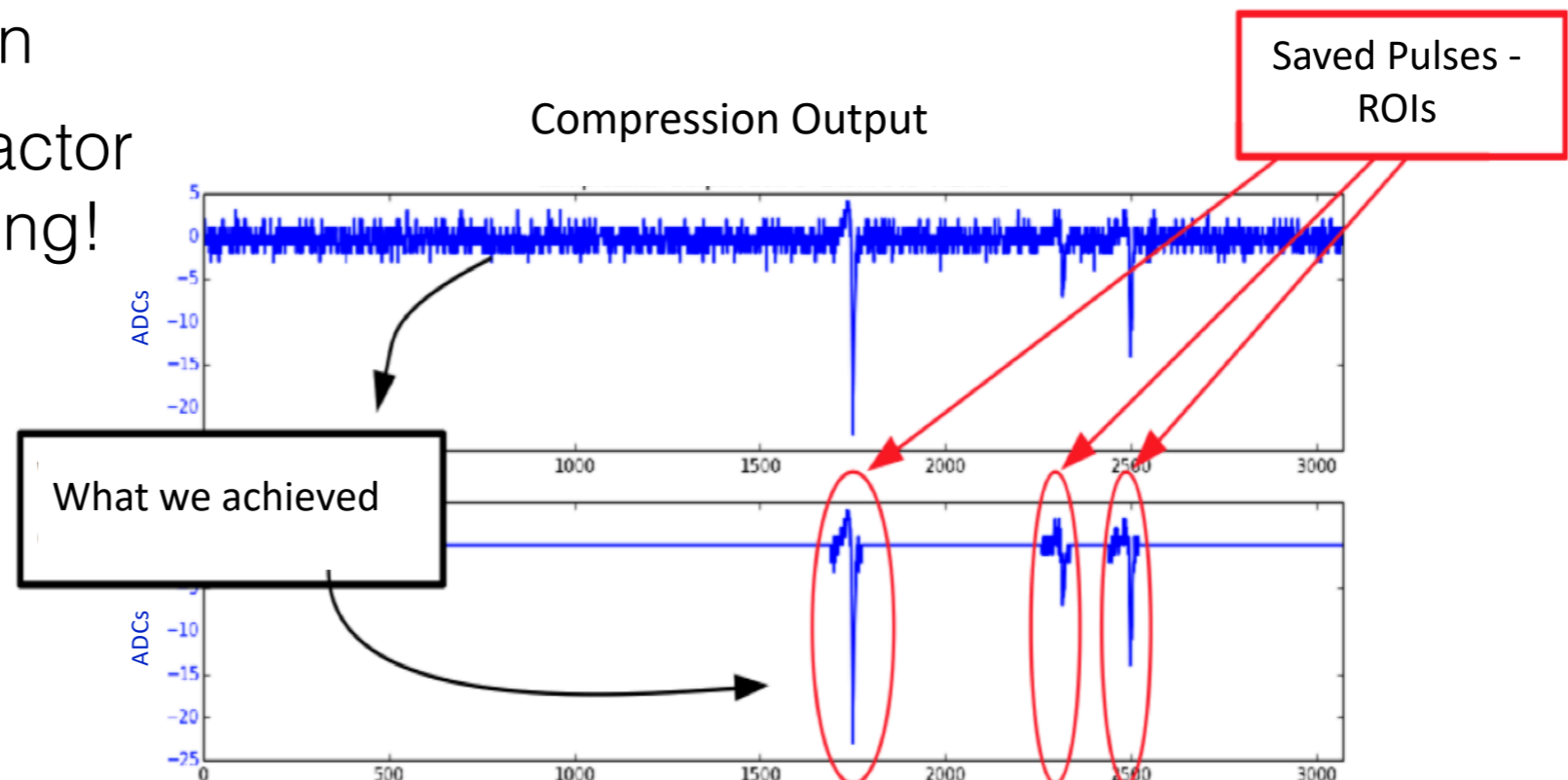
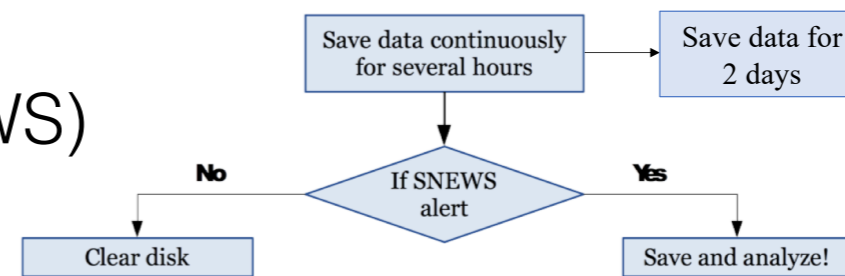
— Reads out data continuously and stores it until external trigger is issued

▶ Supernova Early Warning System (SNEWS)

— Requires data compression

▶ Achieved data reduction factor of 80 & successfully operating!

**Mechanisms for reducing the transmitted data volume is another key area of future R&D**



# Common Challenges and R&D

Talk by K. Chen

Experiments with large data rates over many links require R&D

*Data transmission: higher bandwidth, radiation hard, lower mass, lower power consumption*

Electrical links between front-end ASIC and high-speed transmitter

- For RD53, ATLAS: up to 6 m @ 1.28 Gbps;

High-speed fiber optical links:

- R&D towards 28G/56G

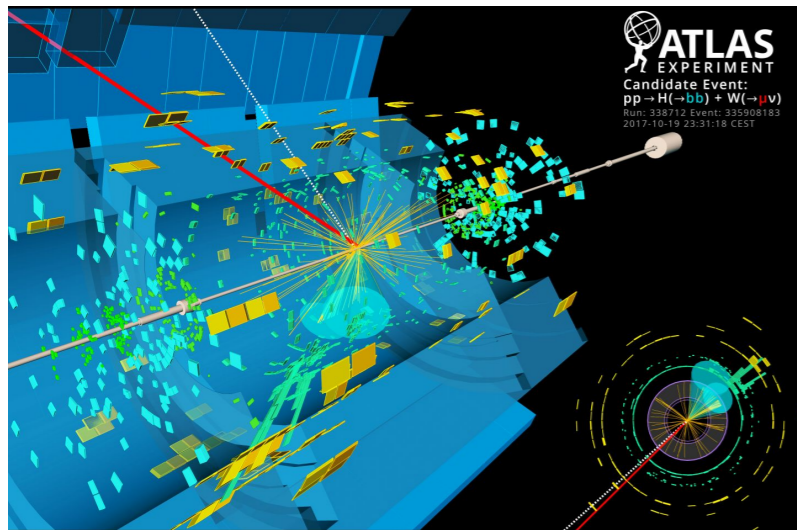
Wireless transmission:

- R&D by groups like WADAPT for tracking detector: 60G band and 240G carrier have been demonstrated.
- Data rate 1/10 carrier frequency (OOK, BPSK)

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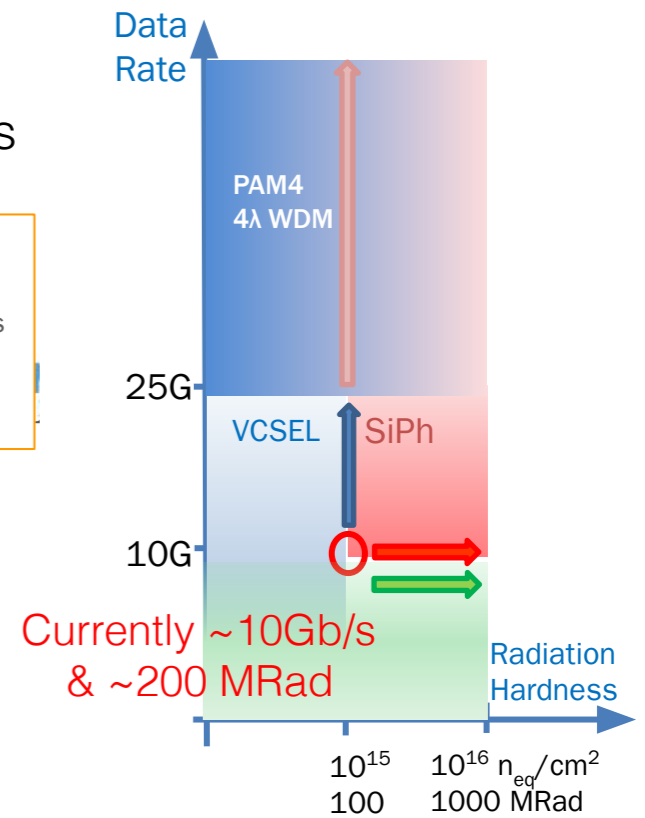
ATLAS raw data from detector: **1Pb/s**

**FCC-hh: ~10Pb/s**

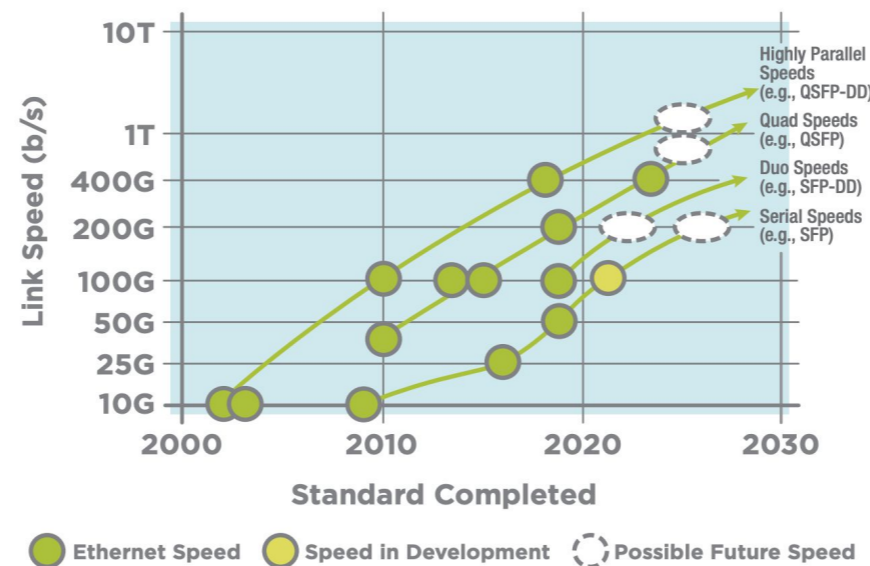
Crucial for future colliders!

Radiation hard high-speed serializer and optoelectronics

28Gbps NRZ / 56Gbps PAM4 Transmitter with 28nm CMOS  
Si-Photonics: integration of optoelectronic devices in a "Photonic Si chip", by using WDM: 40Gbps NRZ is possible. Mach-Zehnder Modulator is also insensitive to NIEL.



## TO TERABIT SPEEDS



Exploring high-bandwidth COTS solutions  
— Terabit Ethernet: 800 Gb/s and 1.6 Tb/s may become IEEE standard in 2025

A decorative header image showing particle tracks or data points on a dark background, with some tracks forming circular arcs.

# Exciting developments in Trigger DAQ and ML!

**Thank You!**