Machine Learning Applications For EIC

Thomas Britton, **David Lawrence**, Yulia Furletova, Dmitry Romanov, Chris Tennant

Jefferson Lab

July 25, 2019

EIC User's Group Meeting

Paris, France

Jefferson Lab

U.S. DEPARTMENT OF ENERGY | Office of Science

JSA

Why ML Now?

1. Advances in Deep Learning Tools
   Industry has driven the technology for many, many applications
   (perhaps you've heard of some?)

2. Era of heterogeneous HPC and HTC
   Some current and most next generation HPC resources will have combinations of CPU + GPU + TPU + FPGA + ???

"ML separates algorithm development from the specialized hardware it will run on"

- David Lawrence July 25, 2019

Accelerator Performance

(based on work by Chris Tennant, Tom Powers, Yves Roblin, Anna Solopova)

Continuous Electron Beam Accelerator Facility (CEBAF)

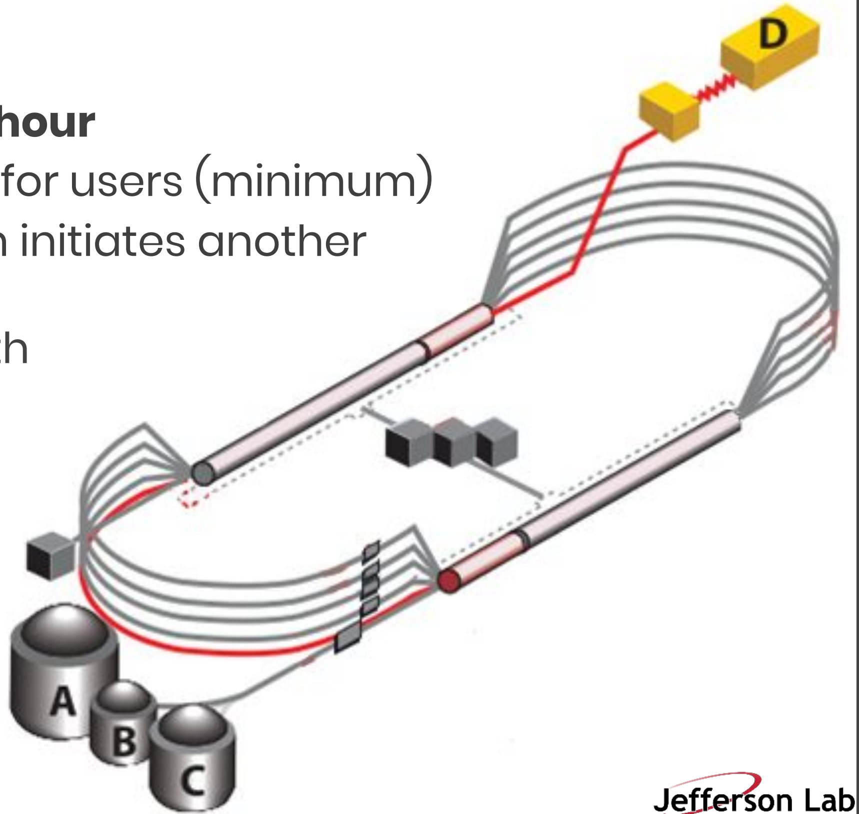
- CEBAF is a CW recirculating linac utilizing 418 SRF cavities to accelerate electrons up to 12 GeV through 5-passes

- **cavity faults occur multiple (7-12) times per hour**
- **each trip represents 90 seconds of lost data** for users (minimum)
- cavities are strongly coupled so one trip often initiates another

- 88 cavities (11 cryomodules) are designed with a digital low-level RF system (C100)

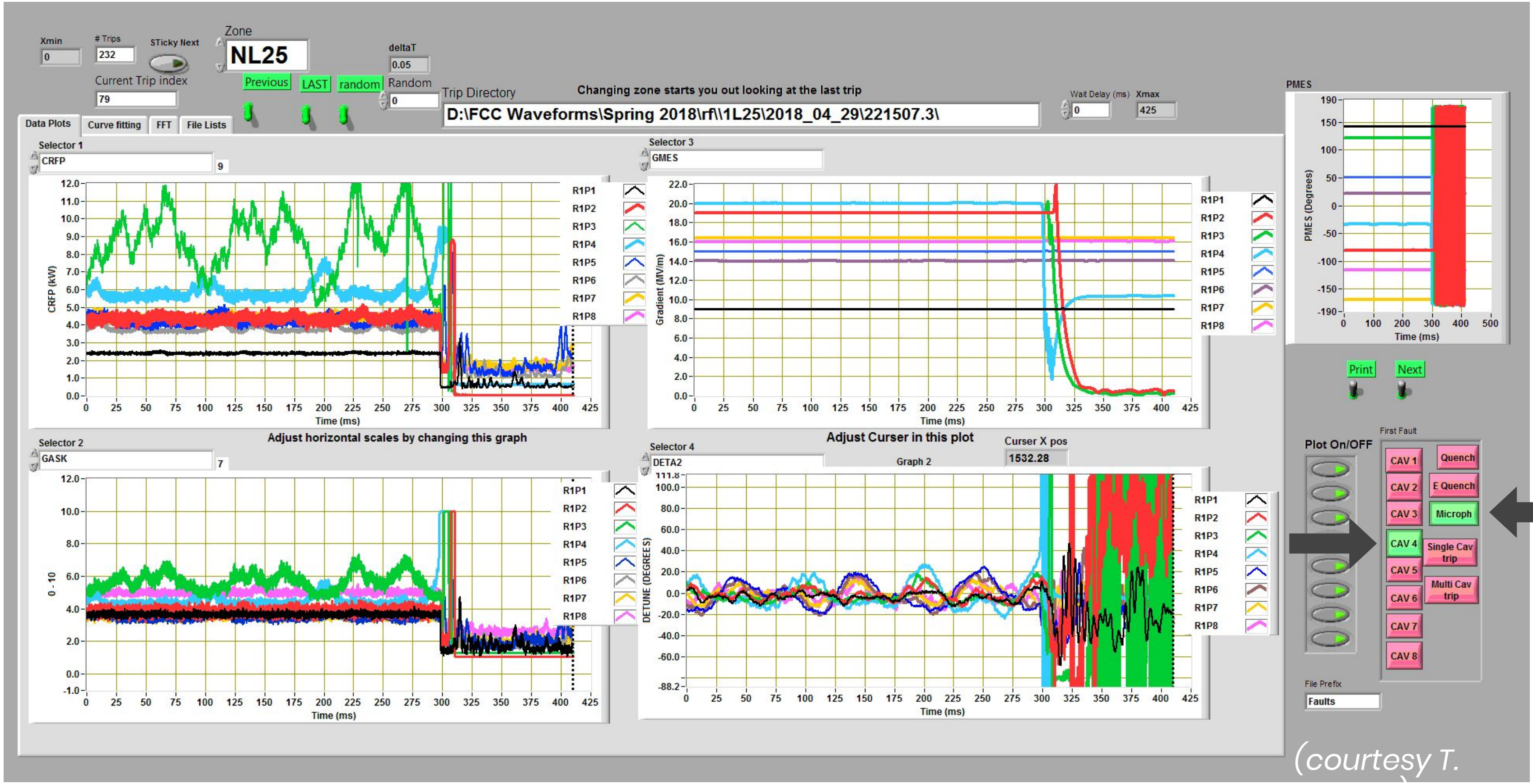
- the system has been configured so a **cavity fault triggers waveform recordings** of 17 RF signals for each of the 8 cavities within the cryomodule (***136 waveforms***)

- the data allows subject matter experts to classify the type of cavity fault



Jefferson Lab

Waveform Data



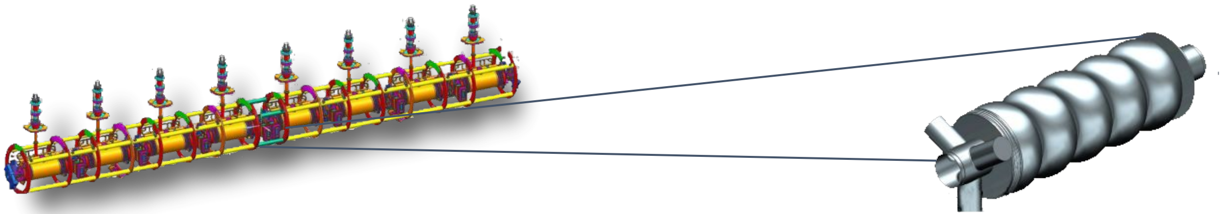
(courtesy T.

17 signals/cavity × 8 cavities = 136 traces

Jefferson Lab

Defining the Problem

- accurate information about which cavity in the string is responsible allows operators to retain gradient in other cavities



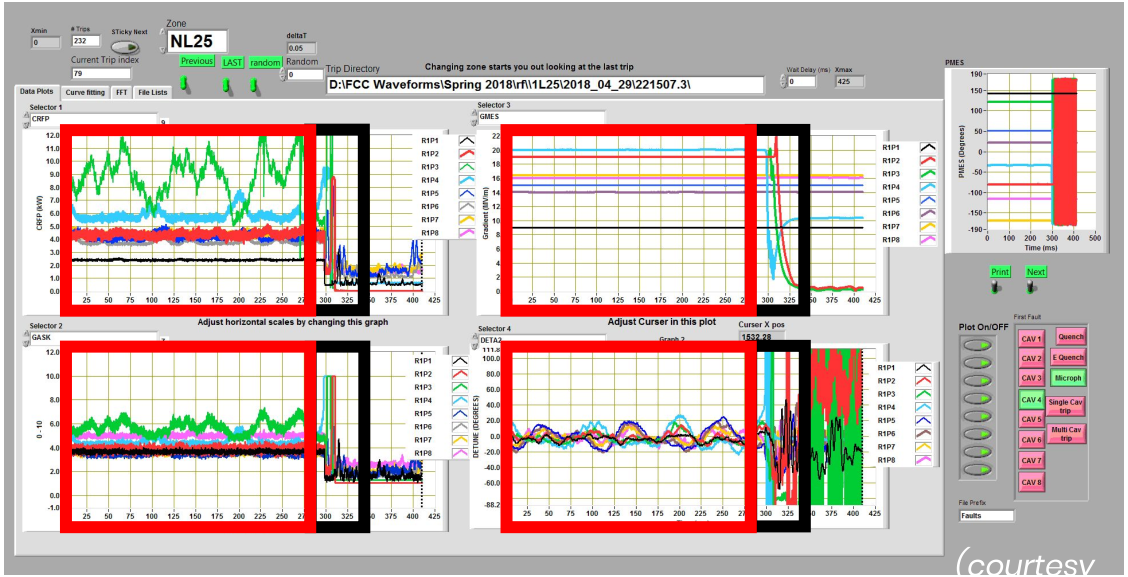
- have data with 500+ *labeled* examples
  - ✔ **{microphonics, quench, electronic quench, single cavity, multi-cavity, controls trip}**

train a model to correctly classify the type of RF fault given waveform data

$\underbrace{\text{train a model}}_{\text{(shallow) machine learning}}$ to $\underbrace{\text{correctly classify the type of RF fault}}_{\text{multi-class classification}}$ $\underbrace{\text{given waveform data}}_{\text{time-series data}}$

Next Steps

- can we anticipate trips before they occur?

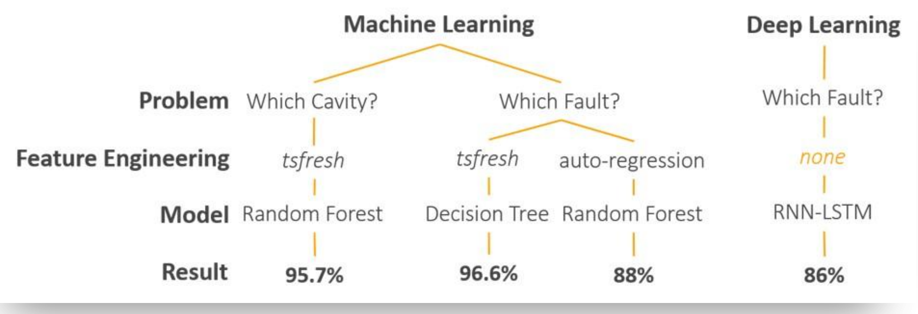


(courtesy

- this problem is **not**:
  - ✔ time-series forecasting
  - ✔ an anomaly detection system

Machine Learning for Accelerator Modeling and Control

In the last 6 months we have made significant progress applying machine learning to the problem of classifying C100 cavity faults. Though still in the early stages, the work has been presented at workshops/conferences, has spawned LDRD proposals, has been the catalyst for forming several collaborations and sparked interest in the wider accelerator community (including DOE).



- Workshop/Conference Talks
  - ✔ "SRF Cavity Fault Classification Using Machine Learning at CEBAF"*
    2019 International Particle Accelerator Conference, Melbourne, Australia (2019)
  - ✔ "Recent Results of SRF Cavity Fault Classification Using Machine Learning at Jefferson Laboratory"
    2nd ICFA Workshop on Machine Learning for Particle Accelerators", PSI, Switzerland (2019)
- FY2020 LDRD Proposals
  - ✔ "Applying Knowledge Discovery in Databases to Archived CEBAF Data" *C. Tennant (PI)*
  - ✔ "Machine Learning Based Cavity Fault Classification and Prediction" *A. Solopova (PI)*
- Collaborations
  - Old Dominion University (K. Iftekharuddin)
  - SLAC (through their LDRD, informal conversations)

* generated significant interest from DOE representative in audience

Data Quality Monitoring

(based on work by Thomas Britton)

Jefferson Lab

U.S. DEPARTMENT OF ENERGY | Office of Science

JSA

A better way?

- Data Quality Monitoring (DQM) of experimental data tends to rely on people continuously scanning plots

- This is labor intensive, limited in frequency and does not hold the attention of shift takers
(nor is it the best use of their time!)

LHC is already beginning

Towards automation of data quality system for CERN CMS experiment

Maxim Borisyak, Fedor Ratnikov, Denis Derkach, Andrey Ustyuzhanin

(Submitted on 25 Sep 2017)

CHEP IOP Publishing
IOP Conf. Series: Journal of Physics: Conf. Series **898** (2017) 092027 doi:10.1088/1742-6596/898/9/092027

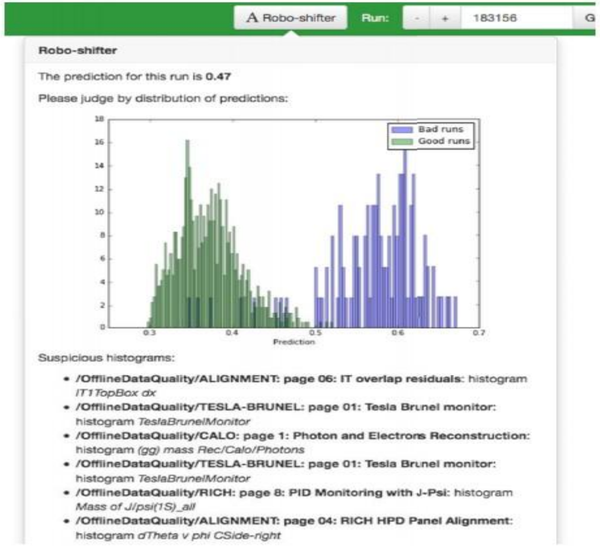
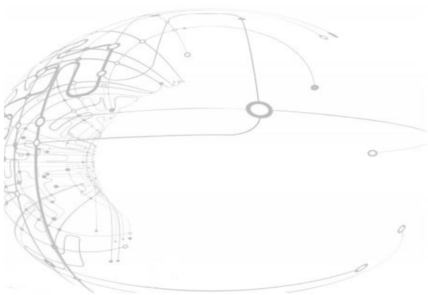
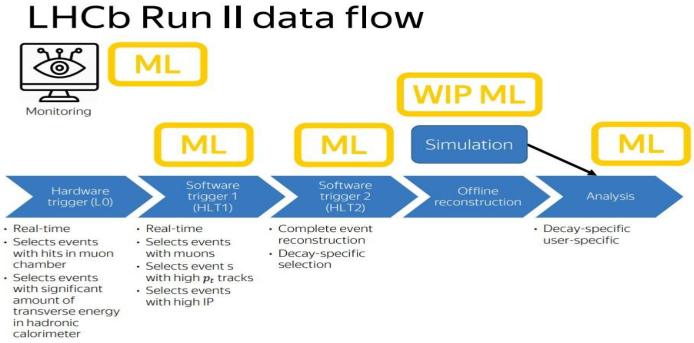


Figure 3. Robo-shifter interface

CERN openlab Summer Student Report 2016





[Real-time physics, alignment, and reconstruction in the LHCb trigger] 3

Data Quality Monitoring at CMS with Machine Learning

July-August 2016

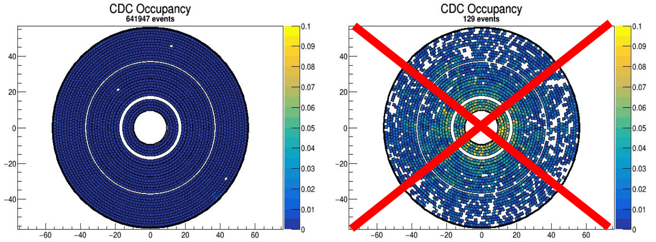
Author:
Aytaj Aghabayli

Supervisors:
Jean-Roch Vlimant
Maurizio Pierini

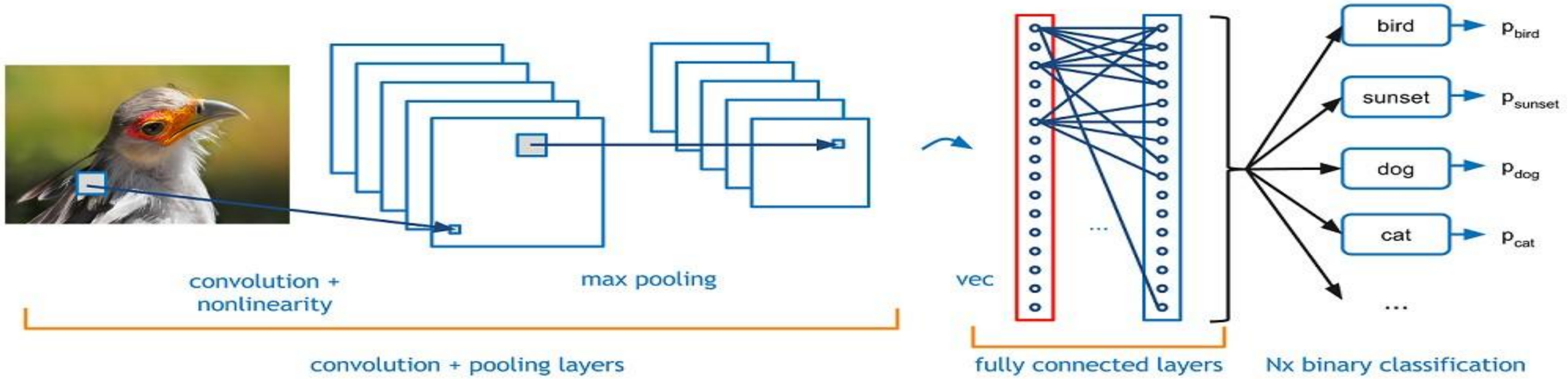
CERN openlab Summer Student Report 2016

Preliminary work at JLab

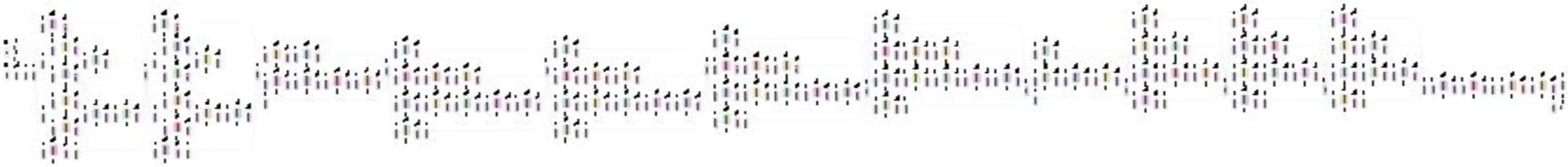
- My own: achieved **~96%** accuracy.
  - Needed to use a more sophisticated network
- Introducing **inceptionV3**
  - Think of it like a network trying various convolutions and figuring out which is best



GlueX Central Drift Chamber



BCAL Results (Thomas labeling)



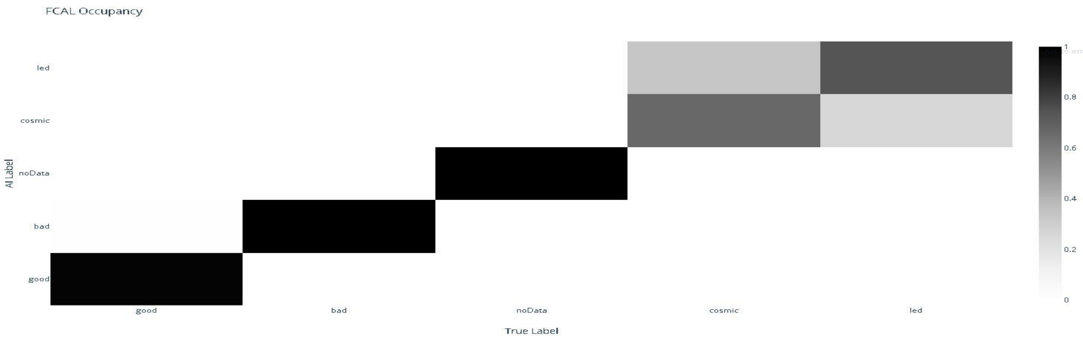
- "Good" accuracy of **99.4%**
  - False positive rate of **1.8%**
- "NoData" accuracy of **100.0%**
  - No false positives/negatives
- "Bad" accuracy of **93.3%**

FCAL Results (Collin's labeling)

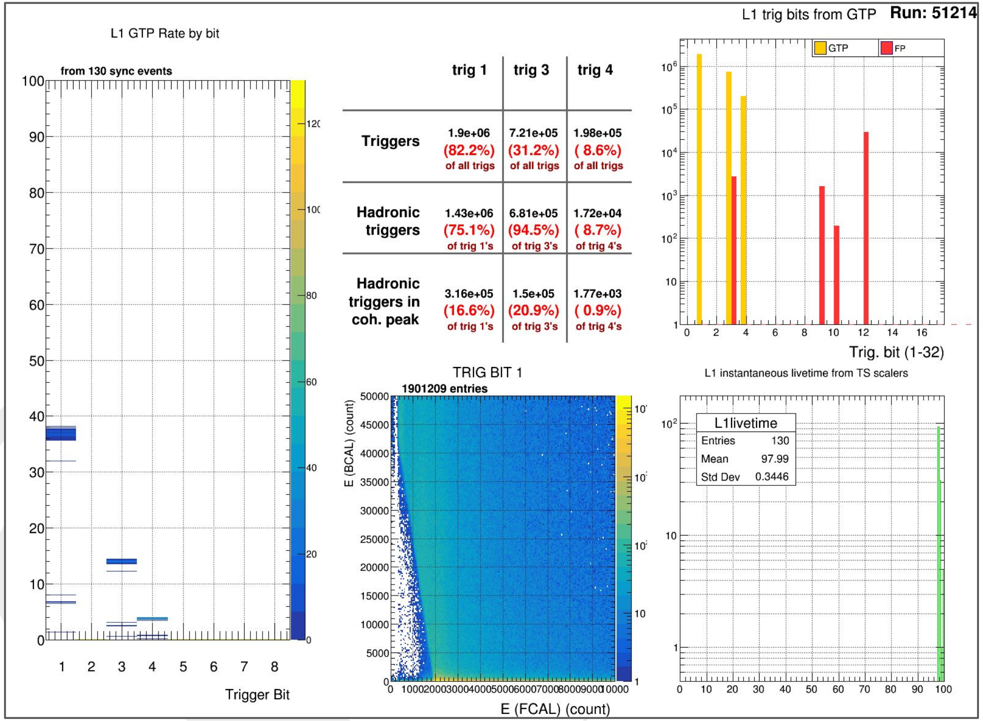
- "Good" accuracy of **98.8%**
  - False positive rate of **0%**

- "NoData" accuracy of **100.0%**
  - No false positives/negatives

- "Bad" accuracy of **100.0%**
  - False positive rate **0.5%**



Leveraging Visual Classification Techniques



Monitoring system pages are already designed to give shift workers a visual of the data quality

Recent boon in image classification fits well with this task

Biggest challenge is "labeling" the training set.

Need system for shift workers to continuously contribute to training

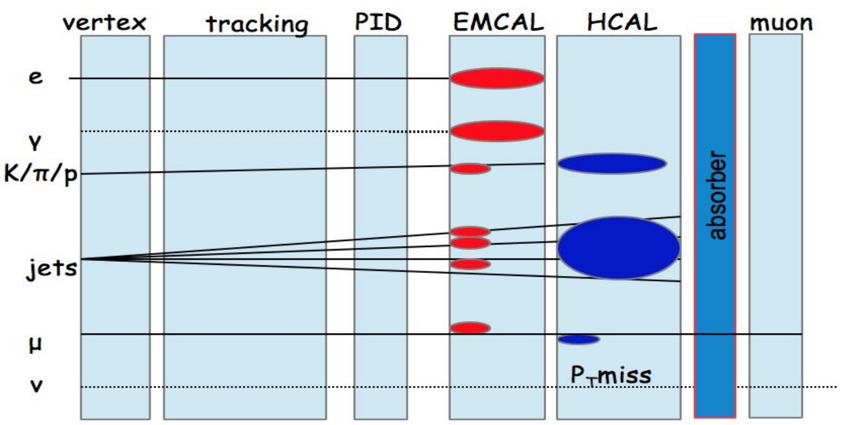
Particle Identification

(based on work by Yulia Furletova, Dmitry Romanov)

Particle identification

Limited number of "stable" final state particles:

- Scattered and secondary electrons
- Gammas
- Individual hadrons ($\pi^{\pm}$, $K^{\pm}$,p)
- Jet/Jets
- Muons (absorber and muon chamber)
- Neutrinos (missing PT in EM+HCAL)
- Neutral hadrons (n,K^0_L) (HCAL)



Looking at topology

- Electrons: EMCAL cluster + track pointing to cluster
- Gammas (γ): EMCAL cluster, no track pointing to cluster
- Neutrinos (ν): missing P_T
- Muons: track, min. energy in EMCAL, min. energy in HCAL, track in muon det.

Other Methods for PID (mass difference):

-dE/dx: (p<1GeV)

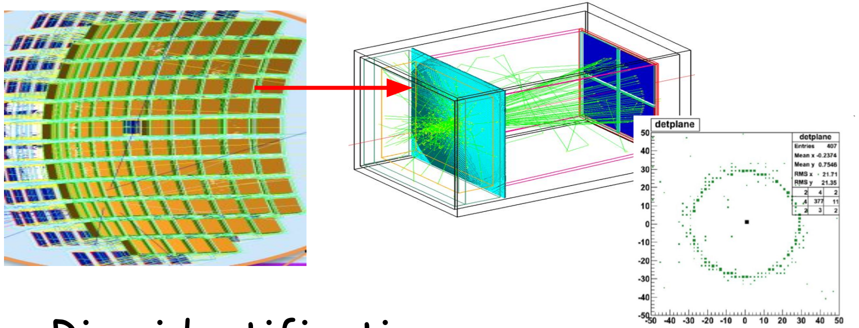
-Time-of-Flight: (p<3-6GeV)

-Cherenkov radiation: p < 5 (50) GeV)

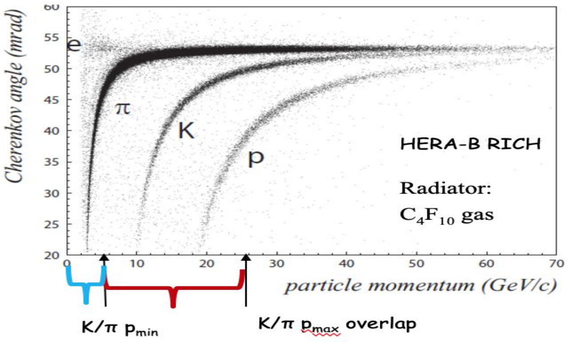
-Transition radiation: (e/h separation) 1 < p < 100GeV

ML for Cherenkov, TOF, tracking detectors

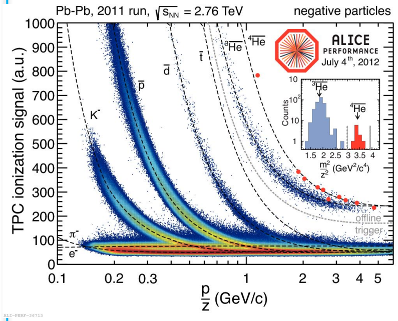
Example, Modular RICH for EIC

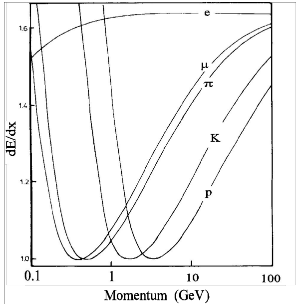


- Ring identification
  Capsule (pixelated) ML algorithms
- Particle IDs
  Multivariate classification



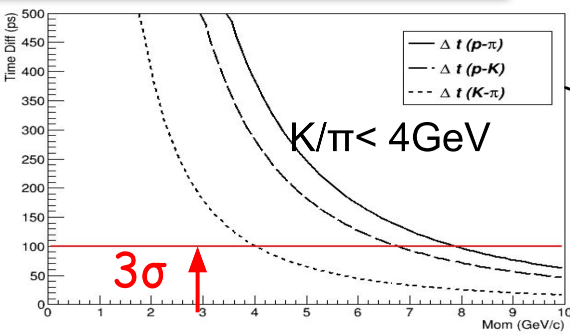
dE/dx in tracking detectors





TOF

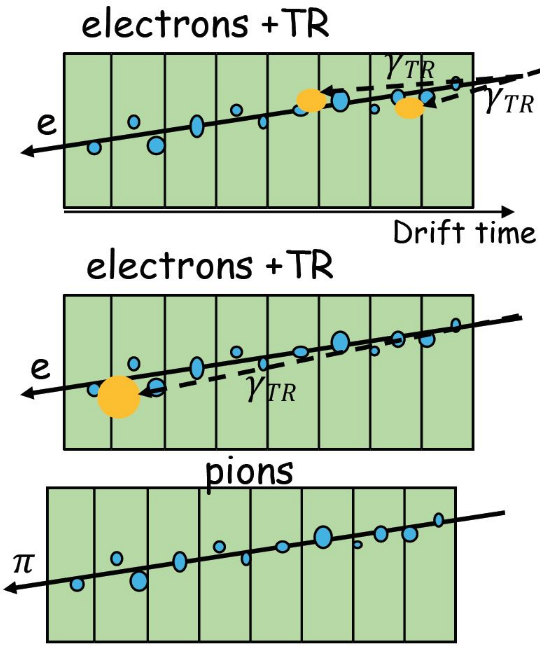
EIC TOF Ion-side 435 cm

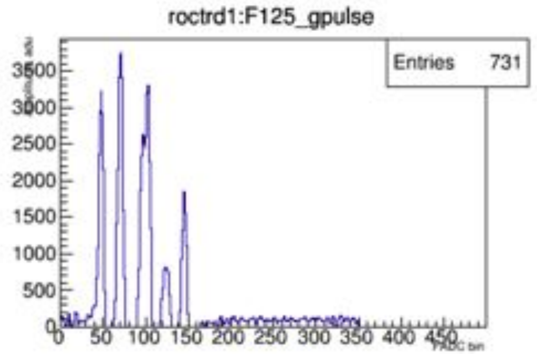


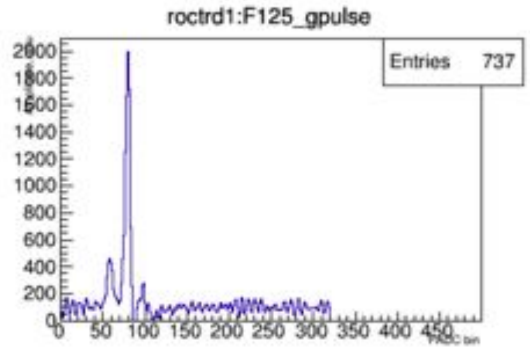
Mickey Chiu

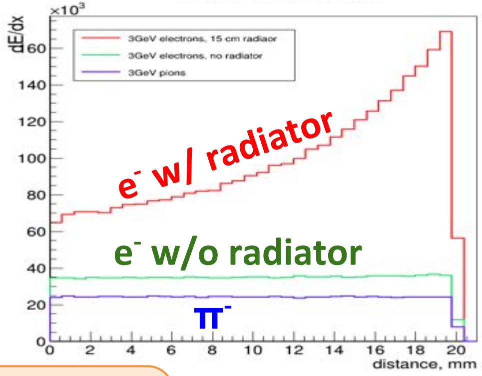
Yulia Furletova

Electron and pion identification (TR photons)









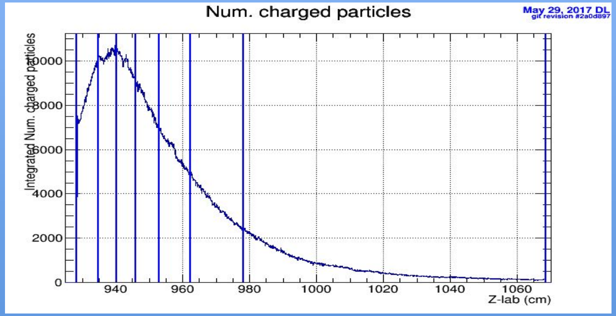
- Electrons (dE/dx + TR photons)
  - <u>Soft TR-photons:</u>
    - absorbs near entrance window, therefore have large drift time
  - <u>Hard TR-photons:</u>
    - penetrate deeper leading to flat drift time distribution
- Pions: dE/dx only

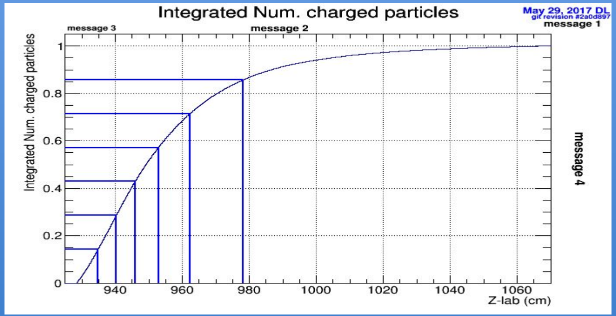
Separation/ Identification of TR-clusters and dE/dx clusters

Uniformity of Iron Absorber Thickness

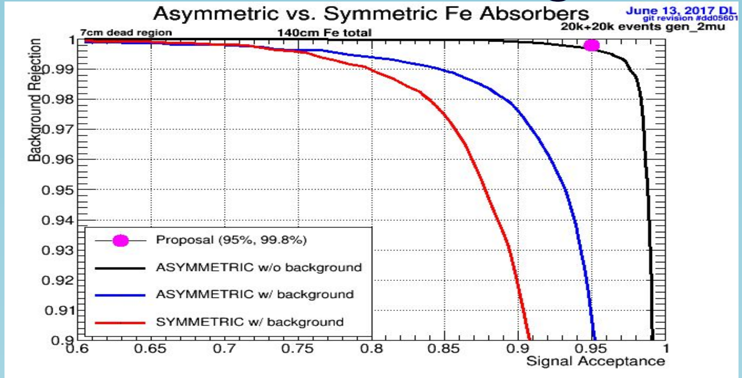
• Human Derived Concept

- Integrate number of particles as function of depth in Iron for $\pi^{\pm}$ showers
- Split Iron so sections contain equal number of particles



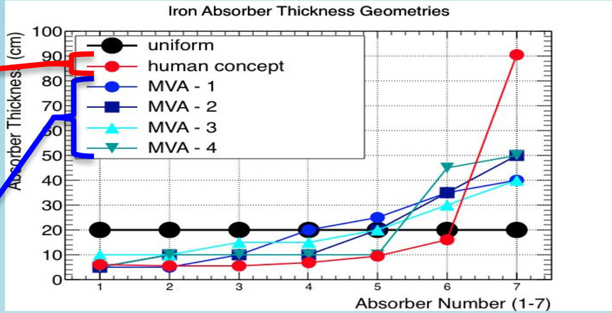


• Machine Learning



(human)

Top 4 MVA results of 741 geometries tested



Software Trigger *(streaming readout)*

(based on work by a lot of folks …)

ML Already implemented for Trigger* or Studied for many Experiments

BELLE II[1], LHCb[2], PANDA[3], ATLAS[4]

[1]doi:10.1051/epjconf/201715000009

[2]ACAT2019
https://indico.cern.ch/event/708041/contributions/3309523/attachments/1810605/2956864/ConorFitzpatrick_ACAT2019.pdf

[3]GlueX-PANDA Workshop 2019
https://www.jlab.org/indico/event/306/session/5/contribution/10/material/slides/0.pdf

[4]Workshop on GPU CC-IN2P3
https://indico.in2p3.fr/event/18772/contributions/70486/attachments/52899/68602/GPU-Workshop-ATLAS-04042019.pdf

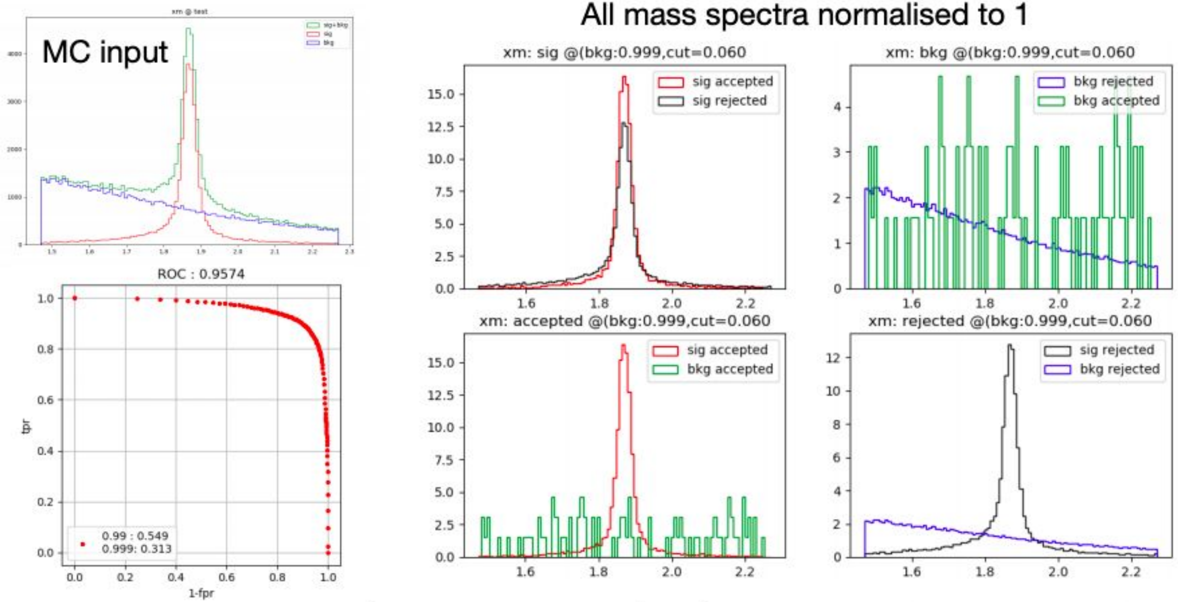
Obligatory image of brain mixed with digital circuitry-like line all in blue hues

**Trigger = any event filter applied to reduce data volume prior to long term storage*

Shown at GlueX-PANDA Workshop May 2019 Washington, DC

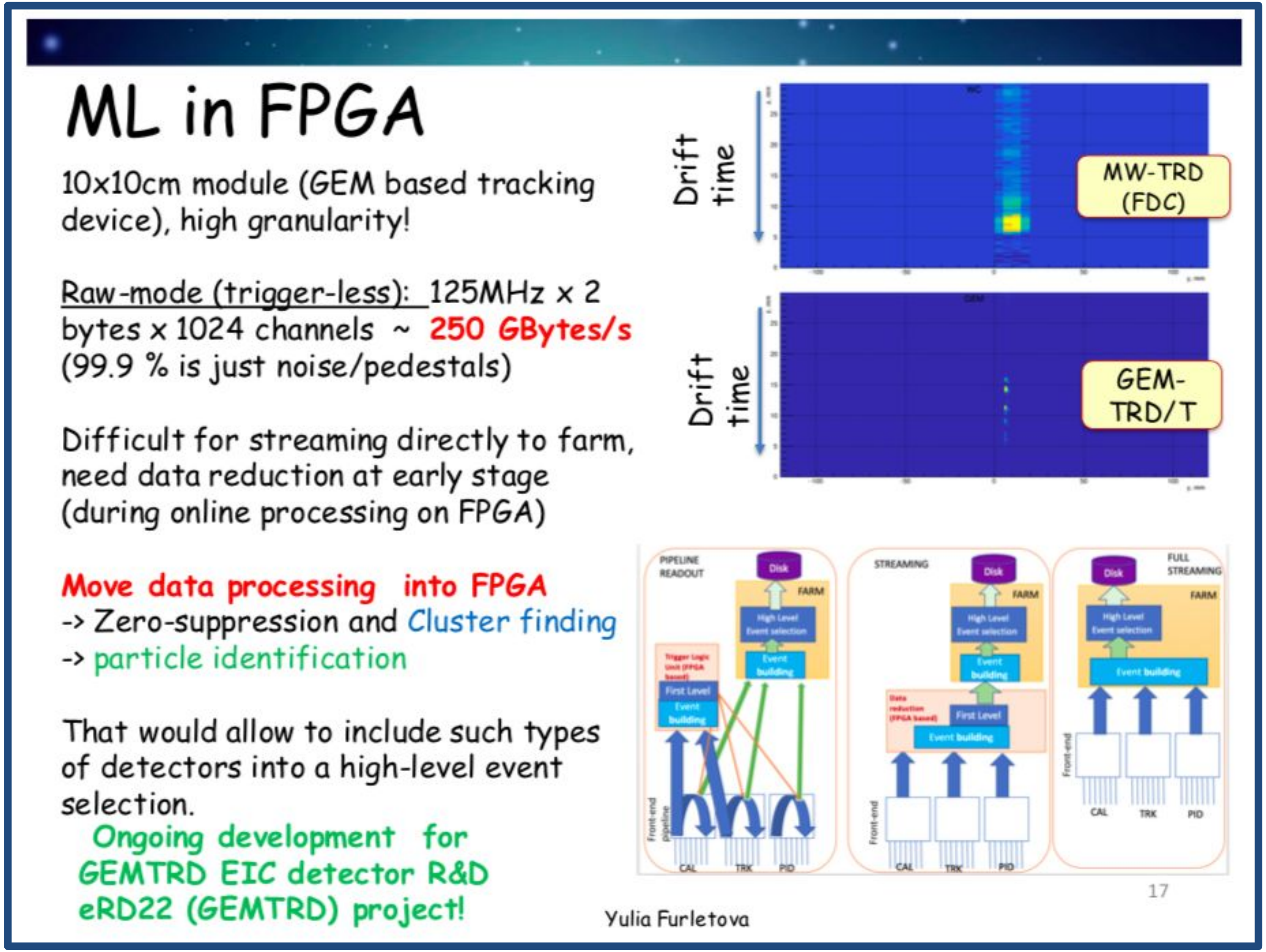
Software Trigger on GPU

FullSim - Artificial Neural Network - training on GTX1080Ti



Reaction: $p\bar{p} \rightarrow D^+D^- \rightarrow K^-\pi^+\pi^+\ D^-(incl.) \qquad (\&\ cc.)$

34



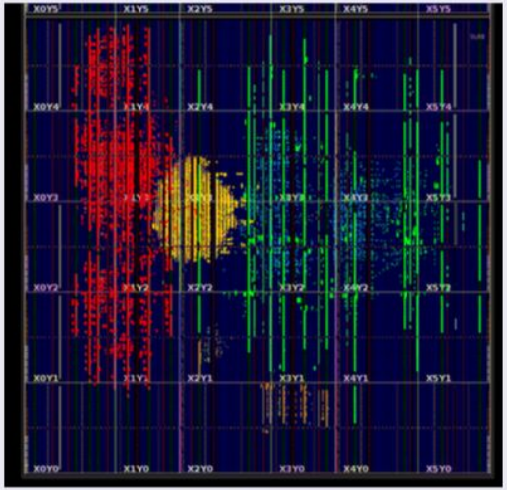
Transition Radiation Detector(TRD)

Data reduction implemented on FPGA

Shown at JLab ML Workshop Mar 2019 Newport News, Virginia

Example Network Results: Utilization

- Utilization dominated by 2D Convs (apart from BRAM from dense layers)
- $N_{\text{DSP}} \approx N_{\text{MAC}} \cdot \frac{f_{\text{D}}}{f_{\text{P}}}$
- LUT, FF util. $\lesssim \frac{1}{6}$ of available per DSP used
- Acceptable BRAM util. by dense layers



(example network on device:
$\sim$ 13k MACs, 400 MHz
21k LUTs ($<$ 2%),
35k FFs ($<$ 2%),
1310 DSPs ($\sim$ 19%),
166 BRAMs ($\sim$ 8%)

From Conclusions Slide

- Networks consisting of Dense, 2D Conv/Pooling Layers implementable
- Keras network → VHDL files for inclusion into FPGA design (via Python script)

Shown at ACAT19 Workshop Mar 2019 Saas Fee, Switzerland

Summary

- There are many more places that our software is likely to benefit from ML

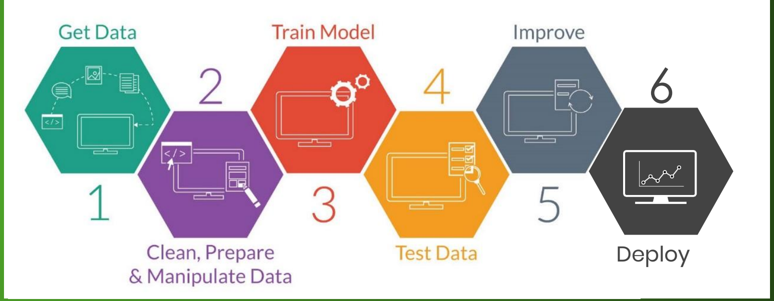
- Some of our next generation scientists will become experts in model development just as previous generations became experts in algorithm development

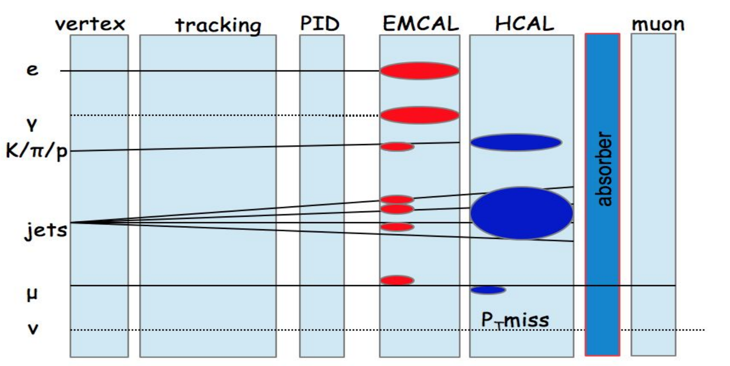
- **Accelerator Performance**
- **Software Trigger** (streaming readout)
- **Data Quality Monitoring**
- **Reconstruction**
- Simulation
- Analysis

Backups

ML Applications for EIC

Accelerator cavity fault prediction and identification

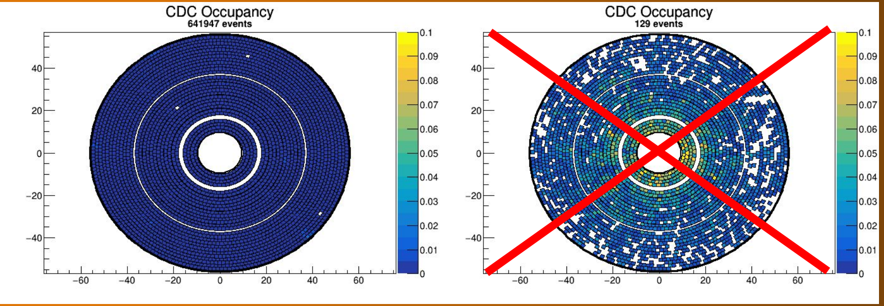




Particle Type Identification in experimental data

ML Applications for EIC

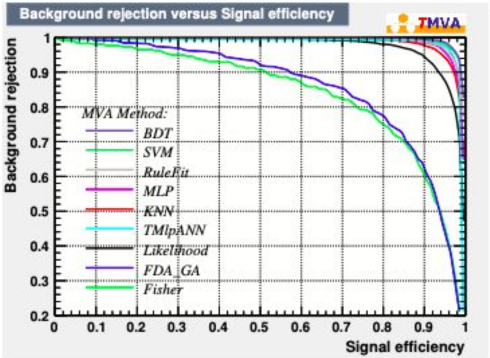
Automated Experimental Data Quality Monitoring



Software trigger in Streaming DAQ

Shown at GlueX-PANDA Workshop May 2019 Washington, DC

Software Trigger - TMVA

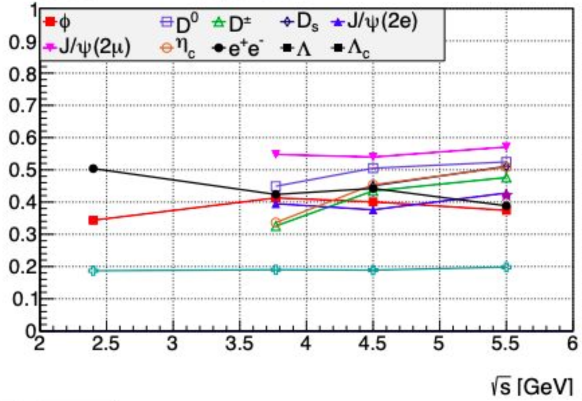


- First studies with many algorithms
- Dependence on offered observables

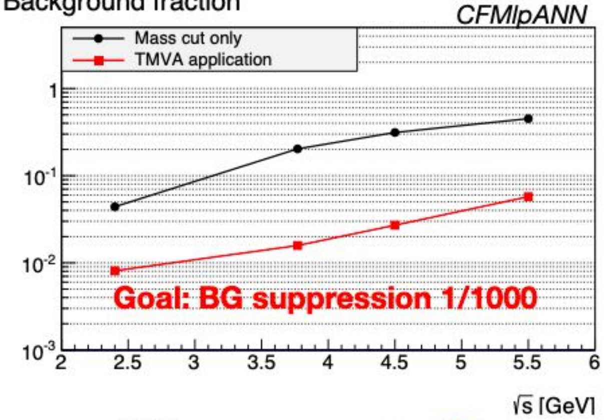
  —> output performance

  —> calculation speed

Efficiency - TMVA application



Background fraction



2014

32