

The background of the slide features a dark blue space-like background with numerous small white stars. Three large, semi-transparent spheres are overlaid on the scene. The largest sphere on the left contains a complex network of particle tracks in red, blue, and green, with bright spots indicating interaction points. Two smaller spheres on the right and top-right also show similar track patterns. The title text is centered over the largest sphere.

# Machine Learning for particle identification

Yulia Furletova (JLAB)

# Outline

- Introduction or global strategy for next generation of particle experiments
- Application of Machine Learning algorithms for particle identification
- Current implementation of ML algorithms for transition radiation detectors/trackers (as example)
- Conclusions

# Third millennium accelerator/detector technologies for "Femto-world"

**High luminosity accelerator facilities**  
(need for precision measurements and rear physics)



**High granularity detectors**  
(high rate and precision measurements)



=> New requirements for **data processing** => especially for **online data processing**

FPGA based

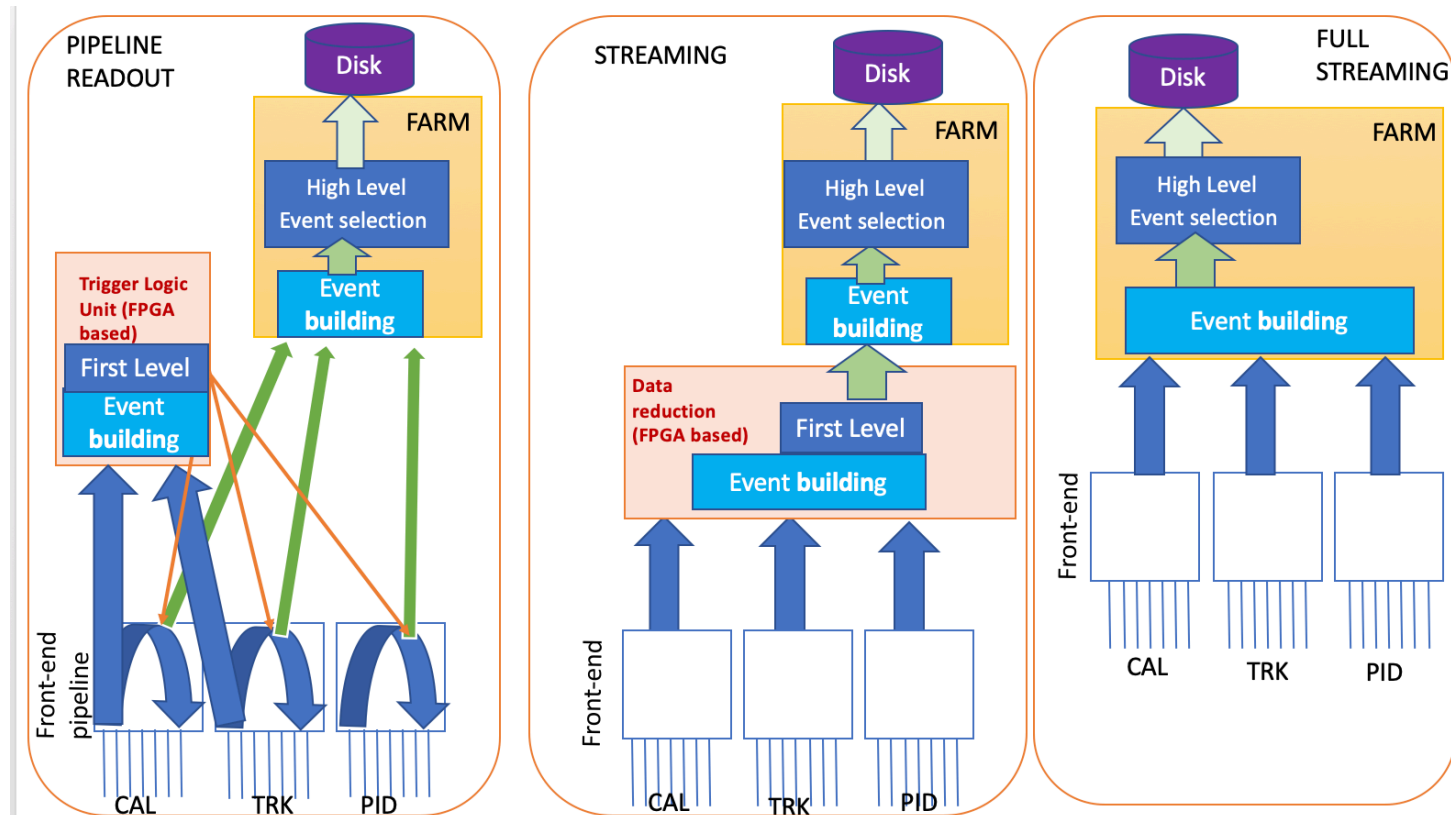


Computer Farm based

# Online reconstruction of physics quantities

Readout system capable to handle high rate environments would allow to run at higher luminosity.

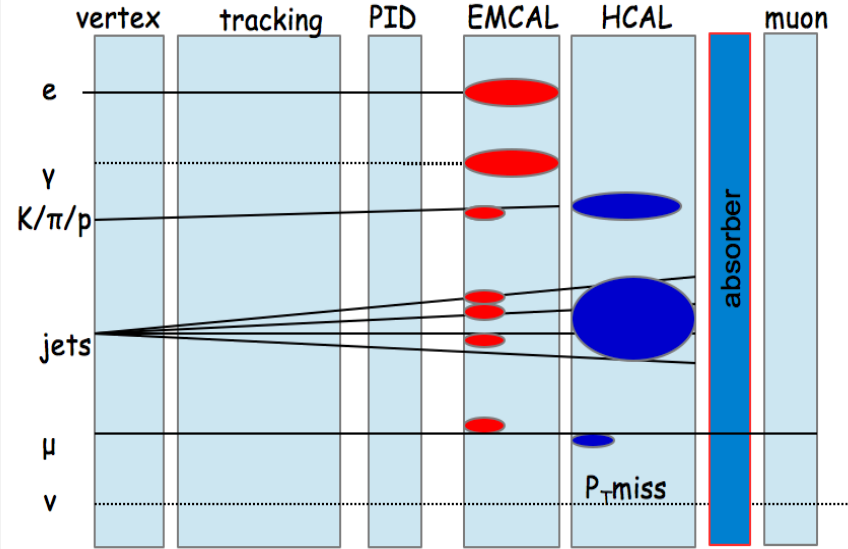
=> Having a possibility to reconstruct physics properties (p, E, vtx, pid) would allow to perform physics event selections ( or online data reduction) more efficiently (before storage).



# 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  $P_T$  in EM+HCAL)
- Neutral hadrons ( $n, K^0_L$ ) (HCAL)



## Looking at topology

- Electrons: EMCAL cluster + track pointing to cluster
- Gammas ( $\gamma$ ): EMCAL cluster, no track pointing to cluster
- Neutrinos ( $\nu$ ): 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: ( $p < 1\text{GeV}$ )
- Time-of-Flight: ( $p < 3-6\text{GeV}$ )
- Cherenkov radiation:  $p < 5 (50)\text{ GeV}$
- Transition radiation: (e/h separation)  $1 < p < 100\text{GeV}$

# Machine Learning tools

## Multivariate classification:

- **JETNET** ( Fortran based Artificial Neural Network)
- **ROOT-based Toolkit** for Multivariate Data Analysis (TMVA)

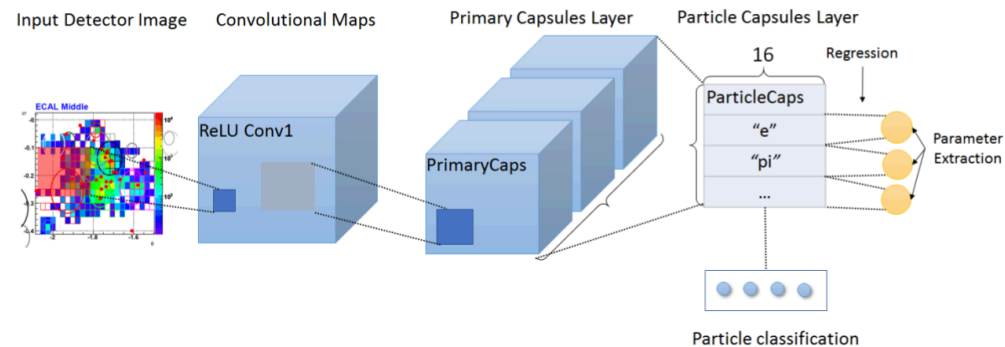
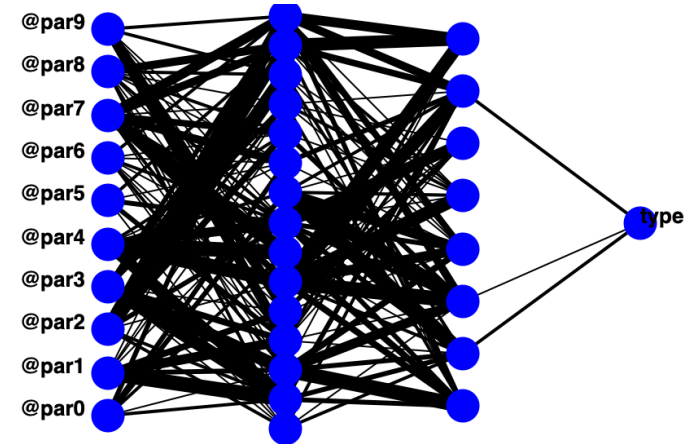
<https://root.cern.ch/tmva:>

- > Deep networks (DN)
- > Multilayer perception (MP)
- > Boosted decision trees

## Capsule Networks (pixelated)

(first introduced by Geoffrey Hinton in 2017): joint proposal of ODU and Jefferson Lab to study application of capsule networks

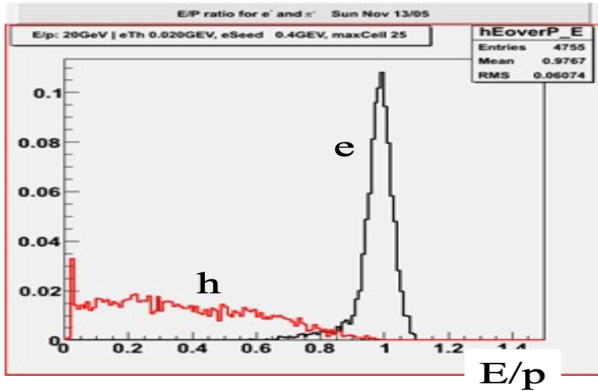
(Khan M. Iftakharuddin (ODU), D.Romanov (JLAB))



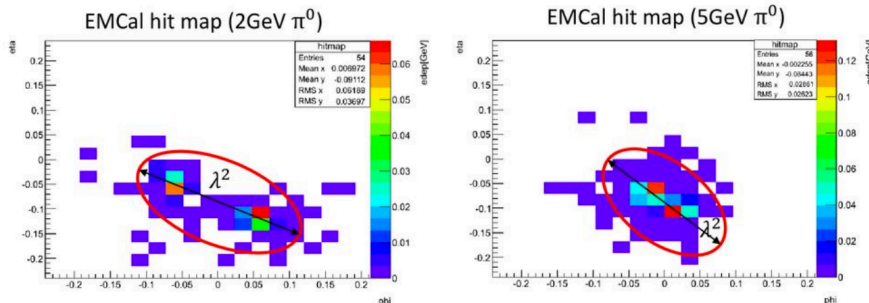
# ML for PID with Calorimeter

- EMCAL Calorimeter:
  - electron/hadron identification (shower profile, E/p)

Multivariate classification



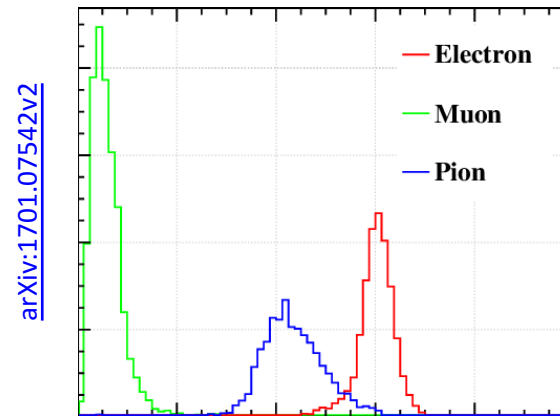
- gamma vs  $\pi^0 \rightarrow \gamma\gamma$  (cluster profile)
- Capsule (pixelated) ML algorithms



Pictures: Phenix collab.

- Hadronic Calorimeter :
    - electron/hadron identification (shower profile, EMCAL/HCAL)
    - Muons (EMCAL/HCAL)
- Multivariate classification

Fractal dimension using both ECAL and HCAL for  $e^-$ ,  $\mu^-$  and  $\pi^+$  at 40 GeV



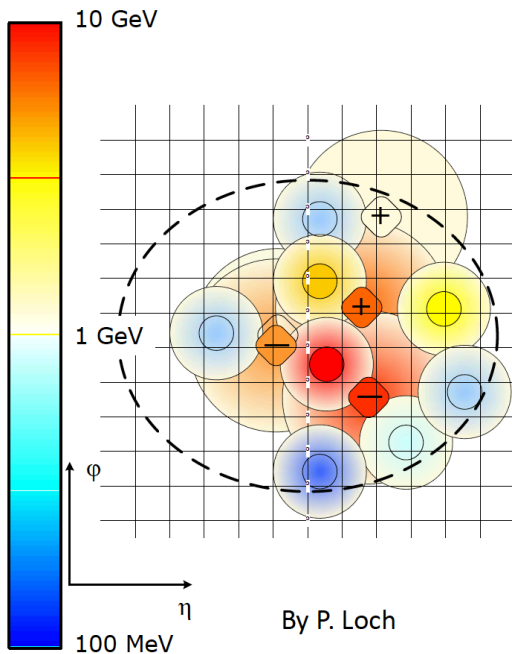
[arXiv:1701.07542v2](https://arxiv.org/abs/1701.07542v2)

- Jets
- Capsule (pixelated) ML algorithms

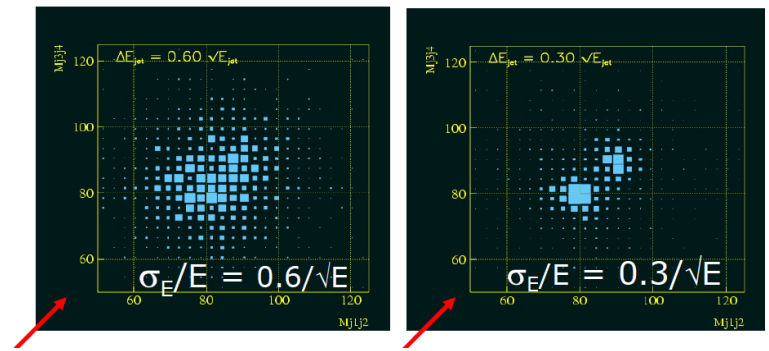
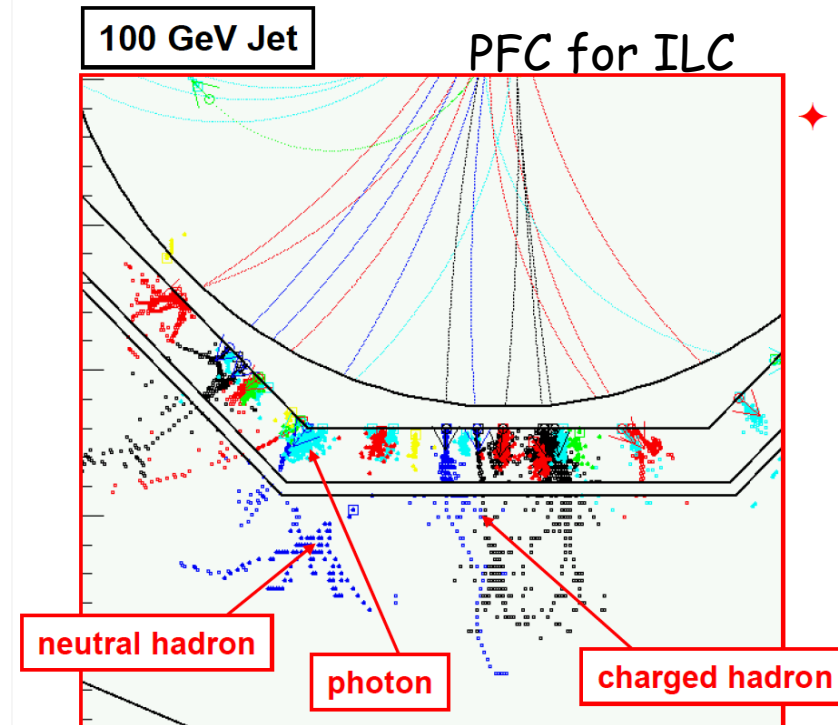
# ML for Jets

## Capsule (pixelated) ML algorithms

- Jet-finding algorithms (shape of jet cone)
- Overlapping jets
- Sub-structure of jets



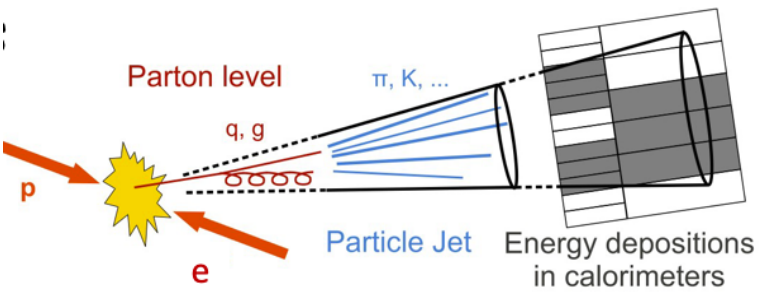
## Particle-flow calorimeter





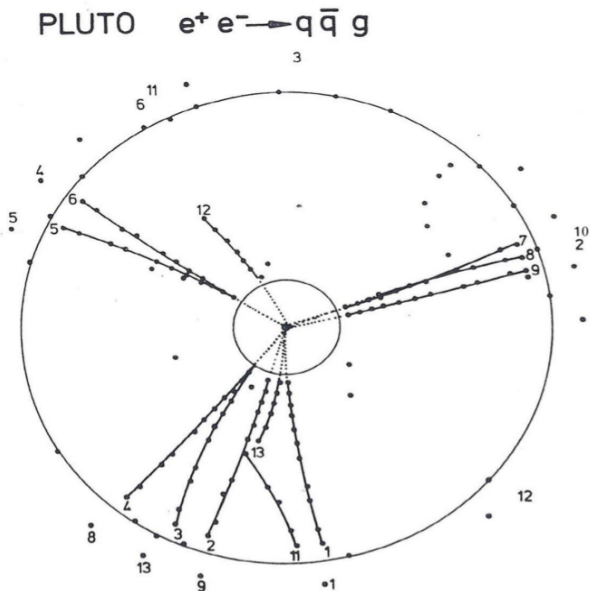
# JET identification at parton level

## Multivariate classification



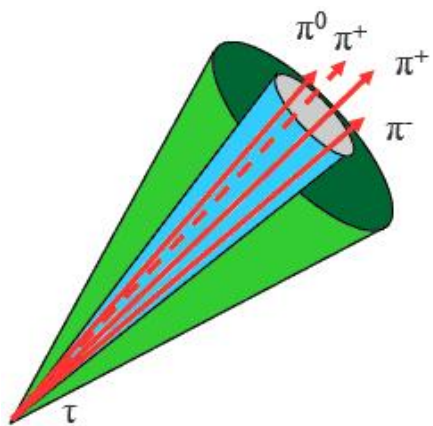
Use such properties as number of particles in jet, particle id, energy, shape, displaced vertex, etc..

## light-quark vs gluon-jet



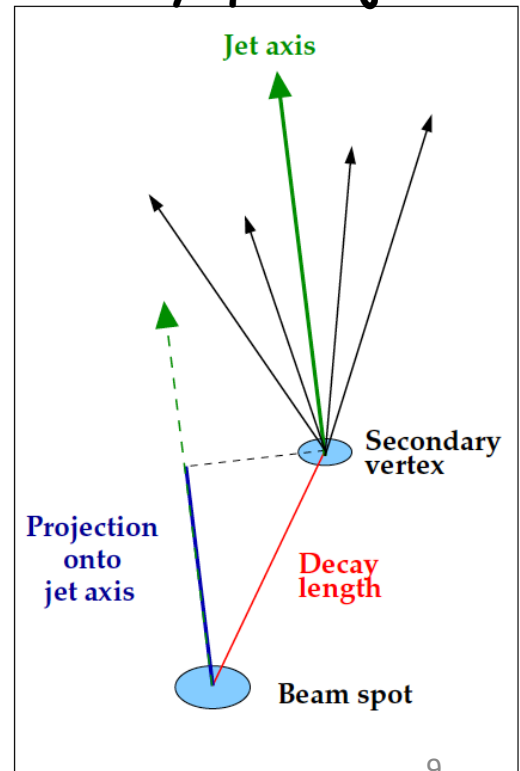
DORIS e+e- storage ring (DESY)

## Tau-Jets



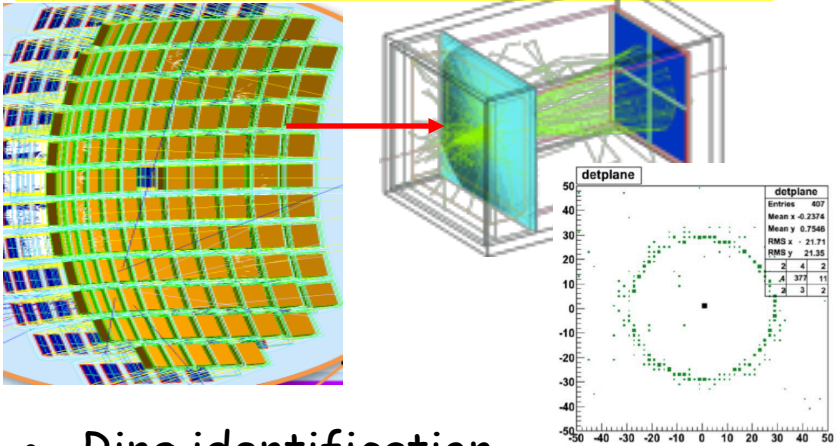
Yulia Furletova

## Heavy quark jets

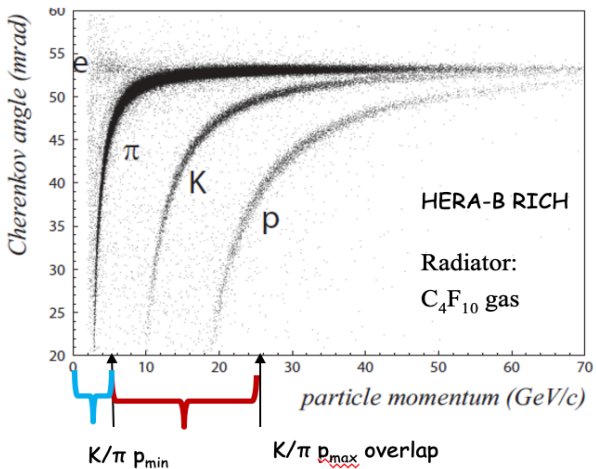


# ML for Cherenkov, TOF, tracking detectors

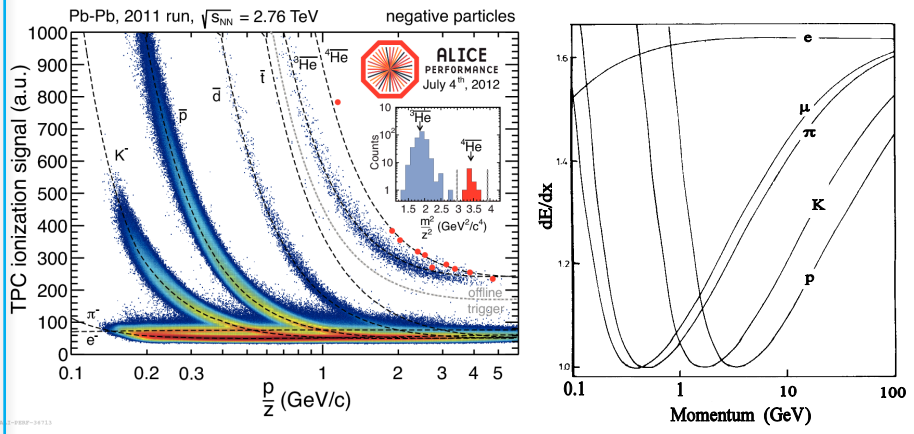
## Example, Modular RICH for EIC



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

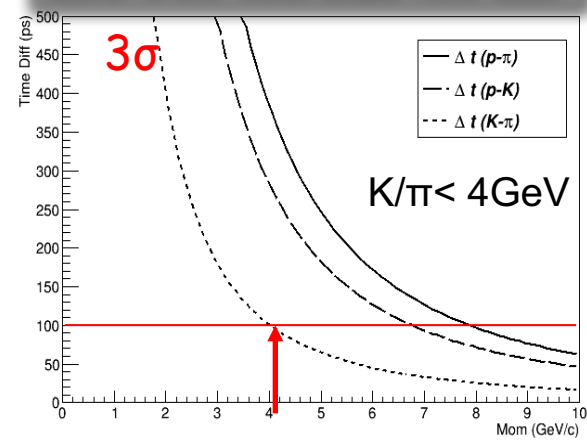


## dE/dx in tracking detectors



## TOF

### EIC TOF Ion-side 435 cm



Mickey Chiu

# ML for Transition radiation detector

(ongoing EIC detector R&D eRD22 project)

- Jefferson Lab:
  - ✓ Howard Fenker
  - ✓ Yulia Furletova
  - ✓ Sergey Furletov
  - ✓ Lubomir Pentchev
  - ✓ Beni Zihlmann
  - ✓ Chris Stanislav
  - ✓ Fernando Barbosa
  - ✓ Cody Dickover
- University of Virginia
  - ✓ Kondo Gnanvo
  - ✓ Nilanga K. Liyanage
- Temple University
  - ✓ Matt Posik
  - ✓ Bernd Surov

# ML for Transition radiation detector

(ongoing EIC detector R&D eRD22 project)

Transition radiation is produced by a charged particles when they cross the interface of two media of different dielectric constants

Use TRD for electron identification, electron/hadron separation (for particle  $\gamma > 1000$ )

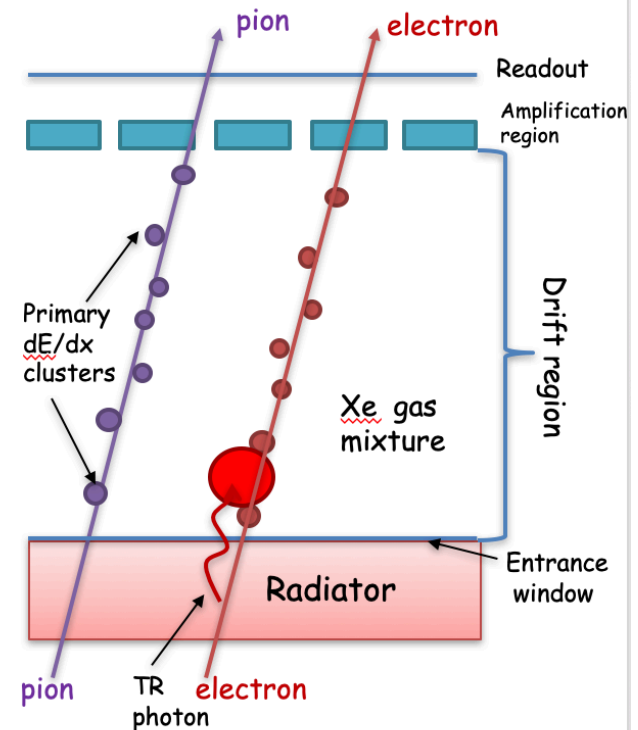
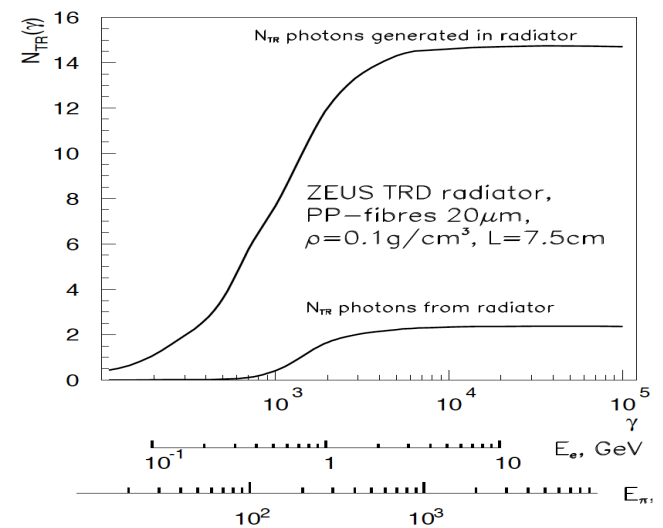
TR in X-ray region is extremely forward peaked within an angle of  $1/\gamma$

Energy of TR photons are in X-ray region (2 - 40 keV)

Total TR Energy ETR is proportional to the  $\gamma$  factor of the charged particle

TRD combined with GEM tracker: high granularity (high rate capabilities).

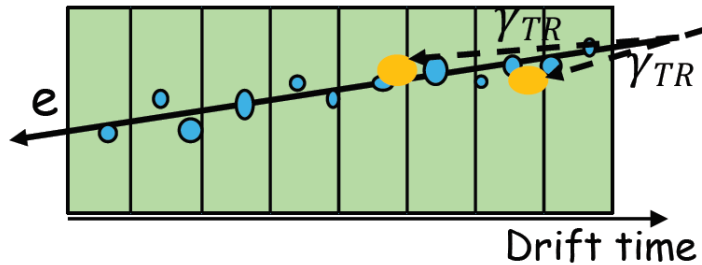
Overlapping clusters TR and dE/dx measurements



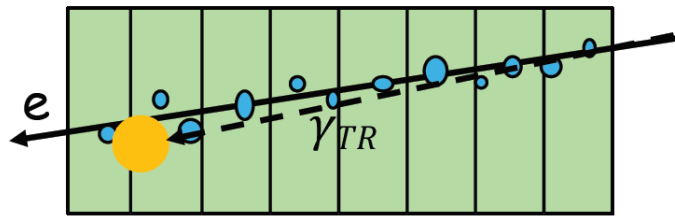
# Electron and pion identification (TR photons)

Electrons ( $dE/dx + TR$  photons)

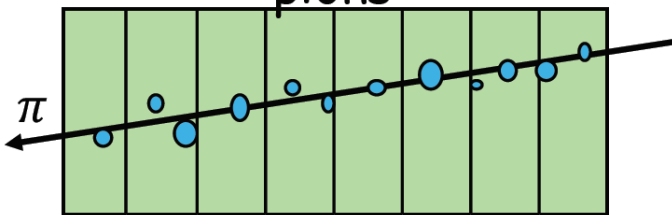
electrons + TR



electrons + TR



pions



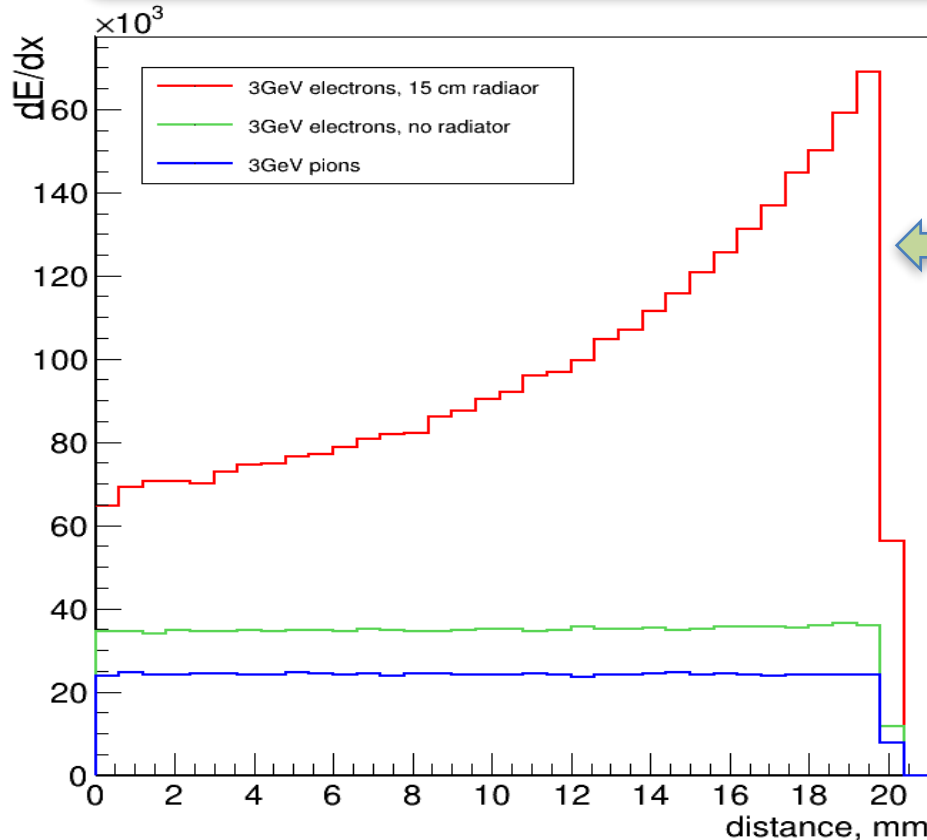
Separation/ Identification  
of TR-clusters and  $dE/dx$   
clusters

- Soft TR-photons:
  - absorbs near entrance window, therefore have large drift time
  - sensitive to dead volumes, like Xe-gap, cathode material.
  - Increase of radiator thickness does not lead to increase of number of soft-photons (radiator self-absorption)
- Hard TR-photons:
  - Depending on energy of TR-photons, could escape detection (depends on detection length)
  - Increase of radiator leads to increase of hard TR-spectra.

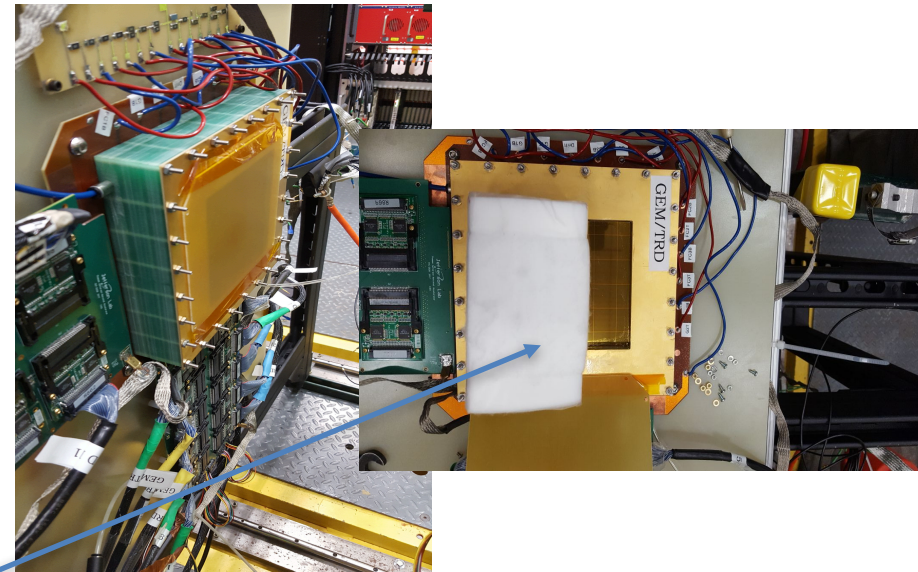
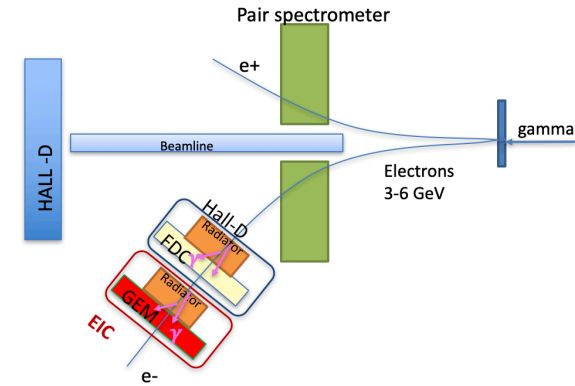
➤ Pions:  $dE/dx$  only

# GEANT4: electron and pion comparison

Energy deposition ( $dE/dx + TR$ ) vs drift distance



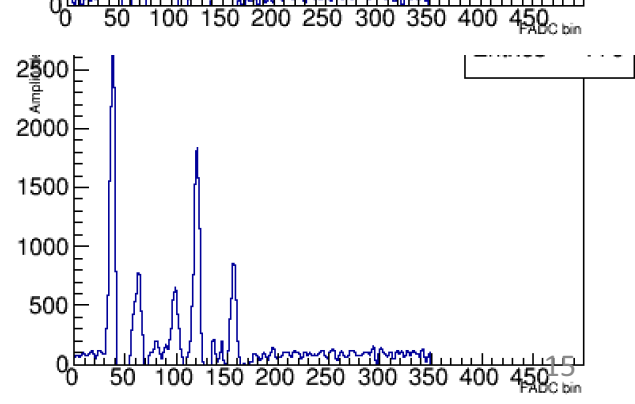
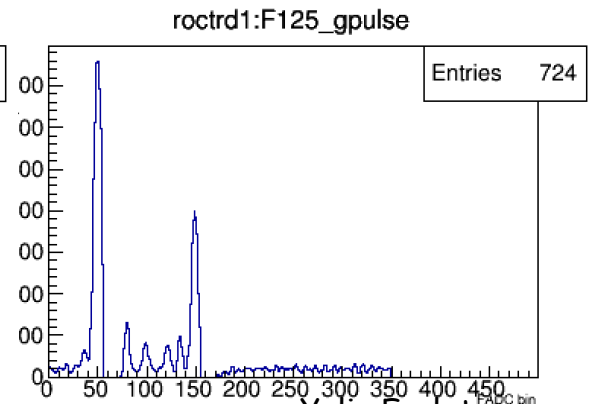
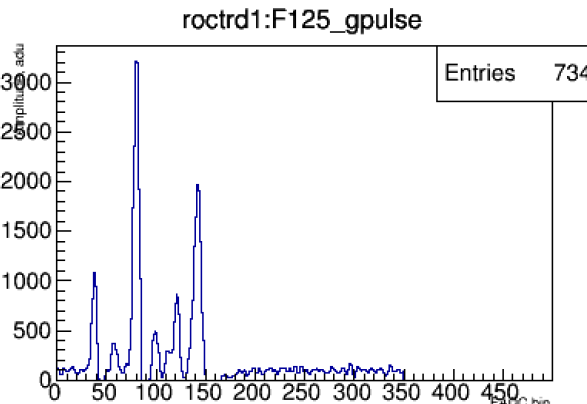
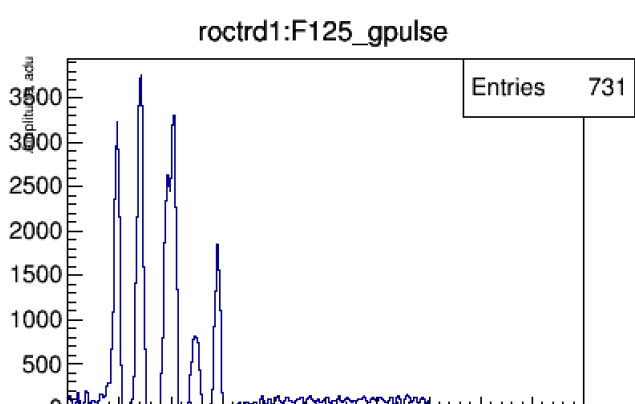
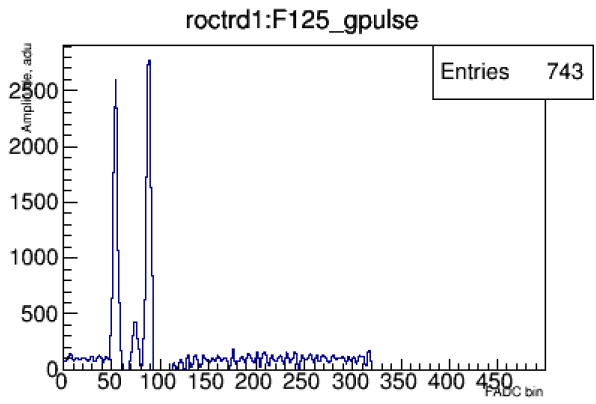
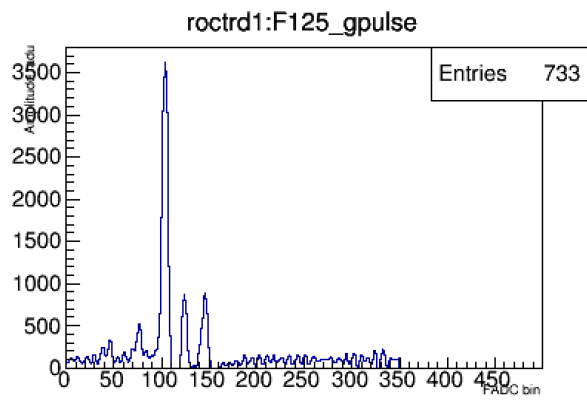
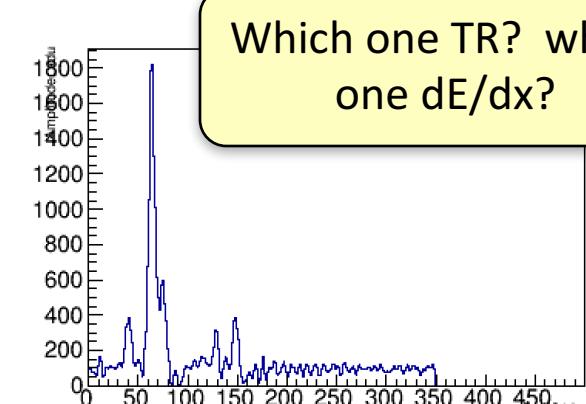
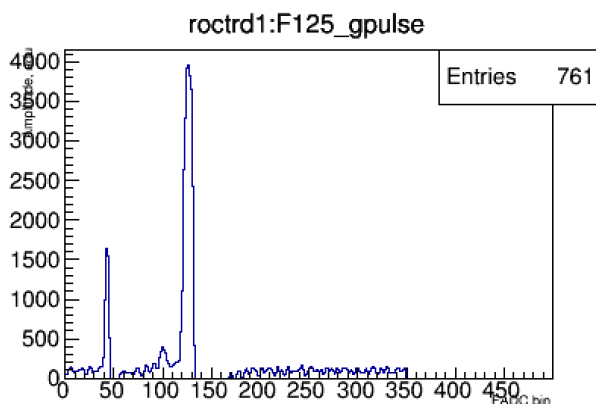
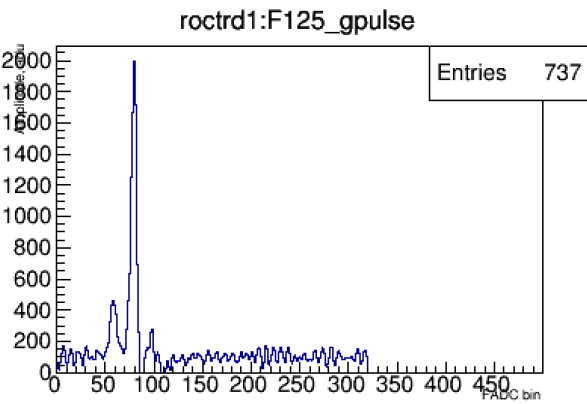
$e, \pi \sim 3$  GeV



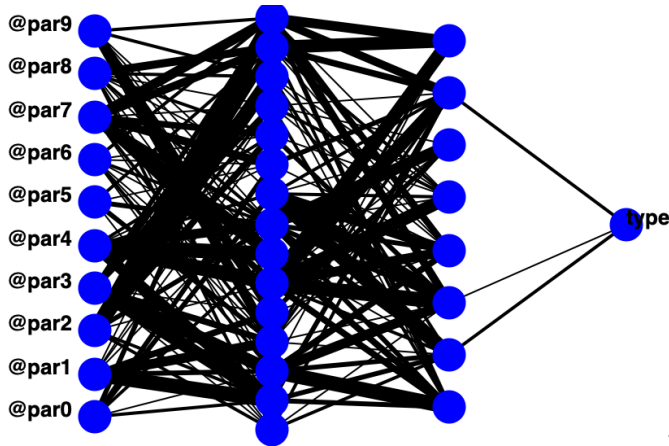
- 3-6 GeV electrons in Hall-D from pair spectrometer
- covered  $\frac{1}{2}$  of the sensitive area with radiator (to mimic pion beam)

# Signals from GEM TRD using FlashADC125

Which one TR? which one dE/dx?

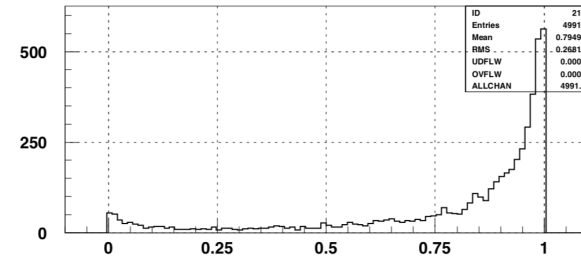
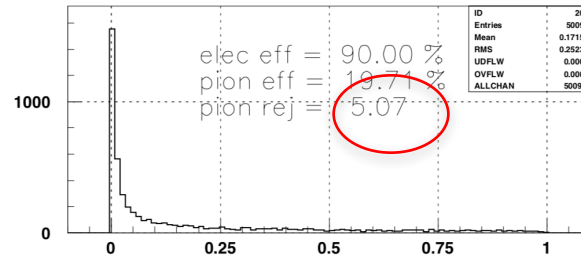


# Machine learning technique



Used different methods/programs (**JETNET**, **Root based-TMVA**, etc) for cross-check. Ca. 23 input variables ( $\langle E \rangle$  per slice along drift distance, timing, etc)

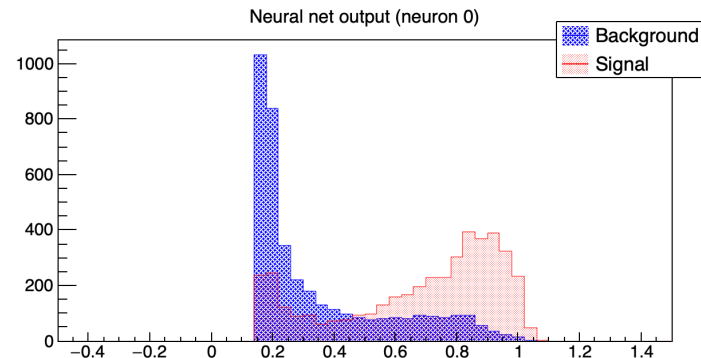
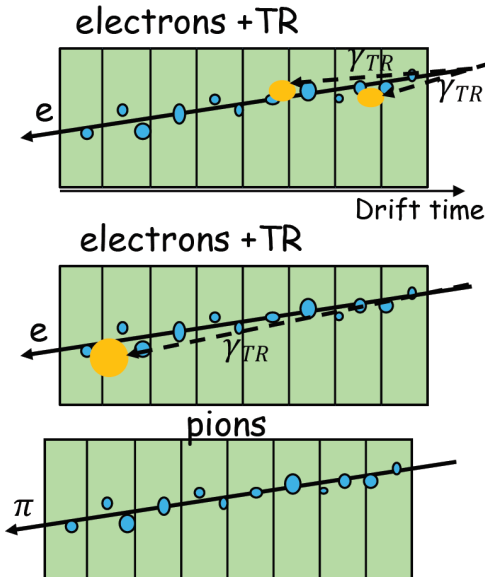
Neural network output for  $e/\pi$  identification



OUT 0 teach

OUT 1 teach

Multilayer perceptron output for a single module (DATA sample)





# ML in FPGA

10x10cm module (GEM based tracking device), high granularity!

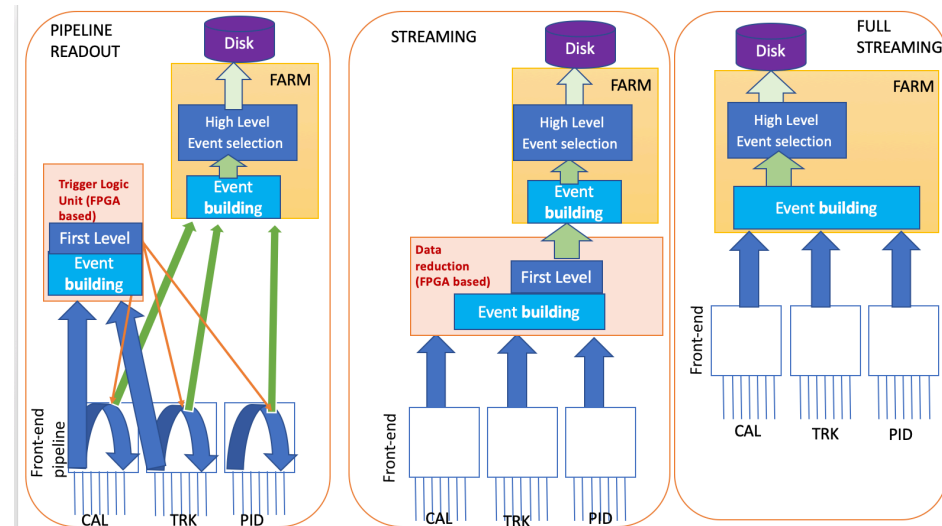
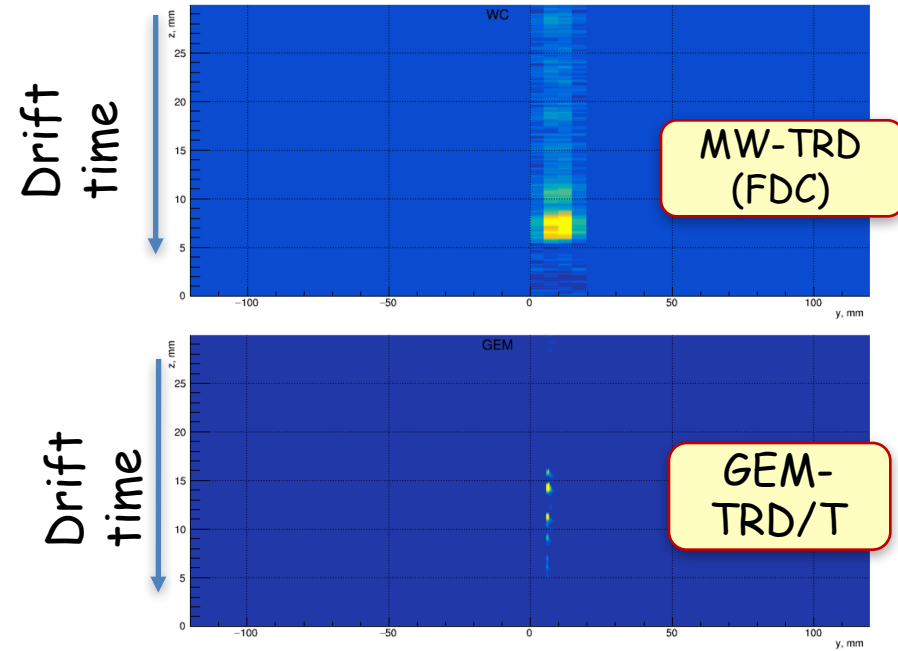
Raw-mode (trigger-less): 125MHz x 2 bytes x 1024 channels ~ **250 GBytes/s** (99.9 % is just noise/pedestals)

Difficult for streaming directly to farm, need data reduction at early stage (during online processing on FPGA)

**Move data processing into FPGA**  
-> Zero-suppression and **Cluster finding**  
-> **particle identification**

That would allow to include such types of detectors into a high-level event selection.

**Ongoing development for GEMTRD EIC detector R&D eRD22 (GEMTRD) project!**



# Summary

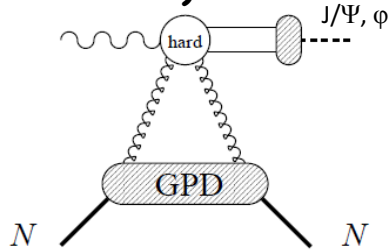
- **Particle identification** is very important for EIC physics. That's directly related to a physics event selection efficiency and precision measurements at the femto-scale level.
- With high luminosity and high data rate environment we should have a **FAST decision (data reduction)** along data transfer => **ML in FPGA are naturally suited for that type of applications** ( online data reduction or high level physics event selection/trigger)
- Offline (**on farm** ) ML particle identification algorithms could be used for **GLOBAL Particle identification** ( combined information from different sub-detectors CAL, TOF, Cherenkov, dE/dx, TRD, etc), after individual sub-detectors FPGA ML decisions.

Thank you!

Backup

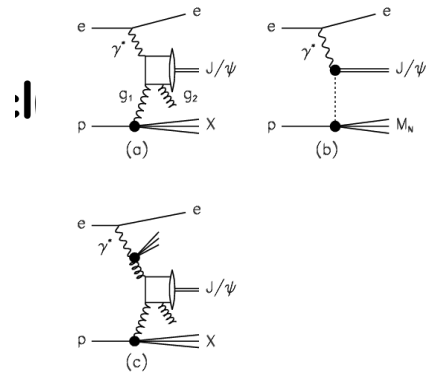
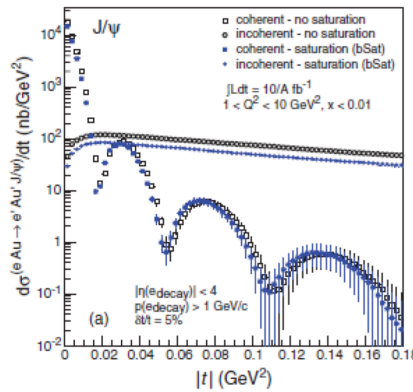
# Electron identification (e/hadron separation)

## ➤ GPD and Coherent Exclusive Diffraction (saturation)

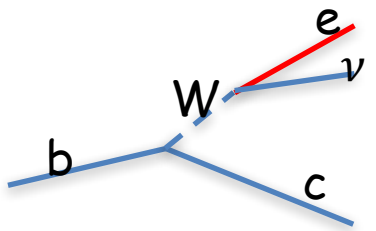


$$\text{Br}(J/\psi \rightarrow e+e^-) \sim 6\%$$

$$\text{Br}(J/\psi \rightarrow \mu+\mu^-) \sim 6\%$$

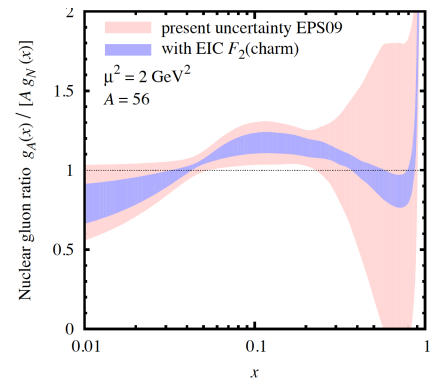
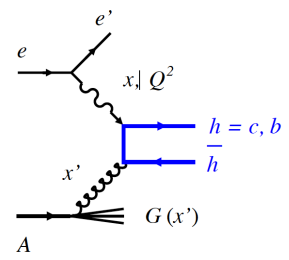


## ➤ Heavy quark tagging

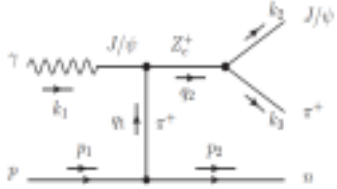


$$\text{Br}(D^\pm \rightarrow e+X) \sim 16\%$$

$$\text{Br}(B^\pm \rightarrow e+\nu+X_c) \sim 10\%$$

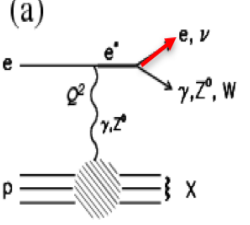


## ➤ Exotic spectroscopy (pentaquarks, tetraquarks, XYZ)

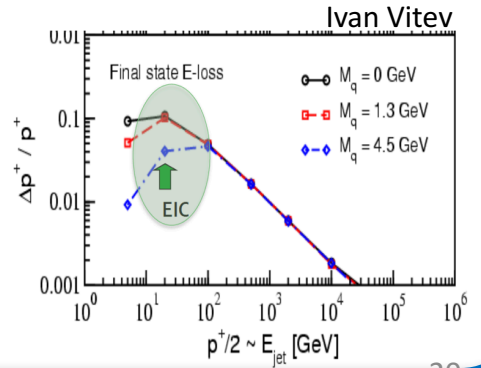
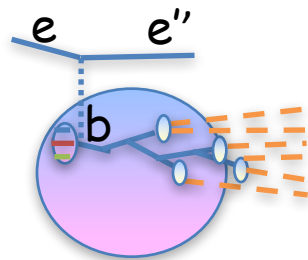
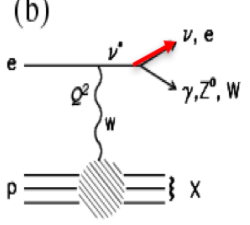


## ➤ Other BSM physics

$$ep \rightarrow e^* \rightarrow e\gamma X$$



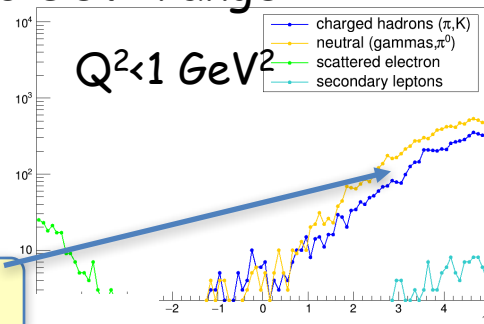
$$ep \rightarrow \nu^* \rightarrow \nu\gamma X$$



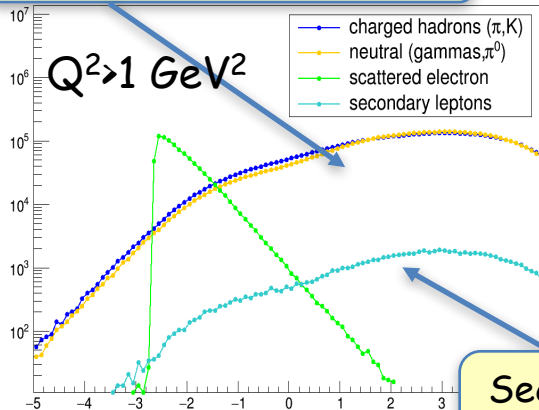
# Electron/hadron separation

- The main detector for e/hadron separation is a **Calorimeter**. Also  $dE/dx$  in tracking detectors, as well as Cherenkov detectors could be used in the limited momentum range.
- TRD offers high e/h rejection for electrons in 1-100 GeV range

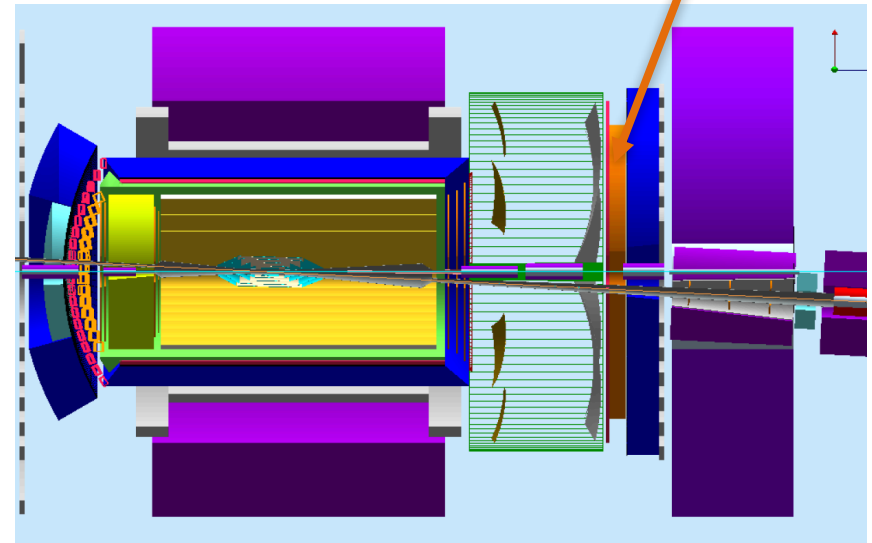
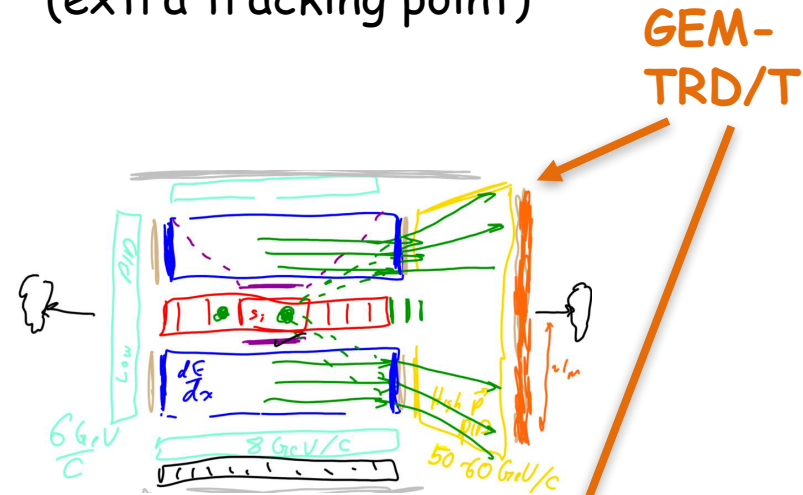
- Hadron end-cap
- between dRICH and EMCAL (extra tracking point)



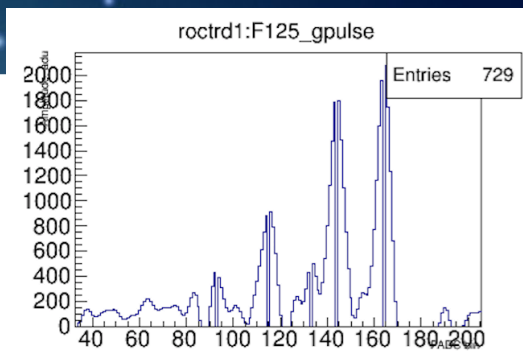
High hadron background



Secondary electrons,  $p_T > 100 \text{ MeV}$



# Electronics:



	MHz	ns/bin	Peaking time	Range	Channels/channel cost	ADC bits	Shaper
FlashADC125	125	8	30ns	1 $\mu$ s or stream	\$50/channel	14bit	-Undershooting -No baseline restorer
APV25	40	25	50ns	625ns	128 chan/chip		Analog output (no digitalization)
DREAM (CLAS12)	40	25	50ns		64chan/chip		Analog output (no digitalization)
VMM3 (ATLAS)	4	250	25-200ns		64chan/chip	10bit	L0 or continuous
SAMPA (ALICE)	10-20	100-50	160ns	Stream 3.2Gbit/s	32chan/chip 30\$/chip 1\$/channel	10bit	500ns- return to baseline Baseline restorer, DSP (zero-suppression, thr)