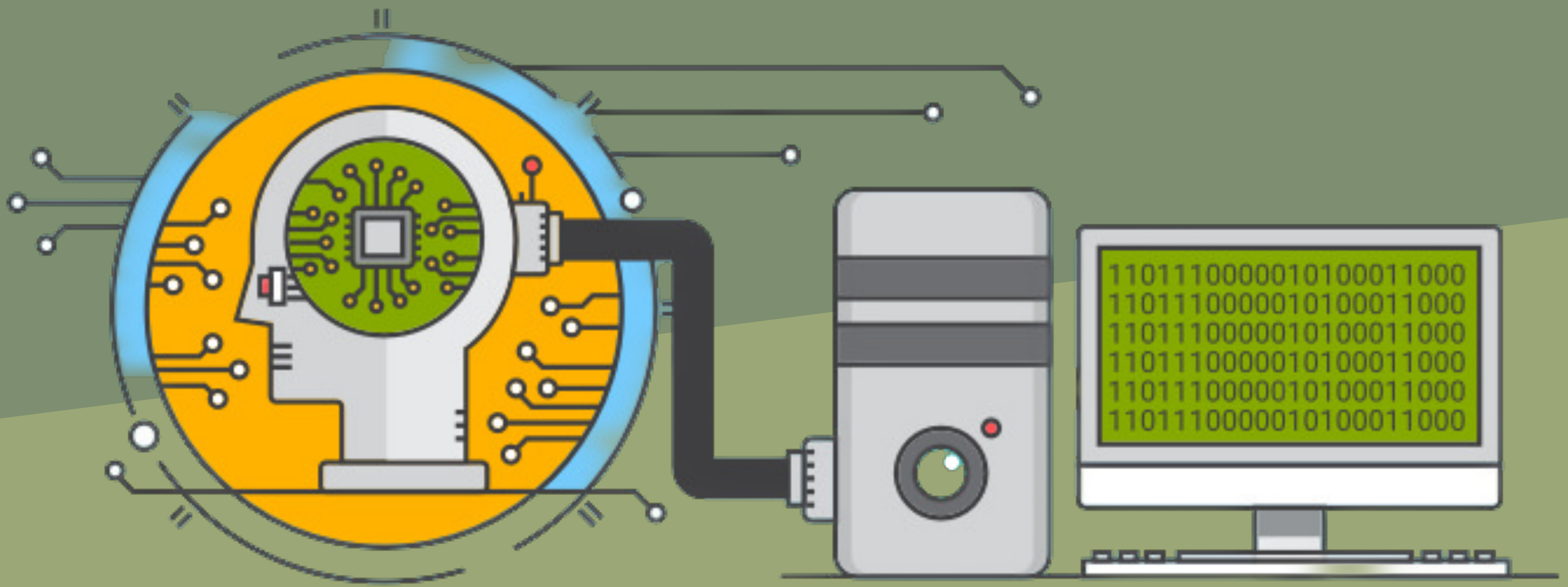
Artificial Intelligence in CLAS12

Artificial Intelligence/Machine Learning for Physics Applications

G.Gavalian (Jefferson Lab)



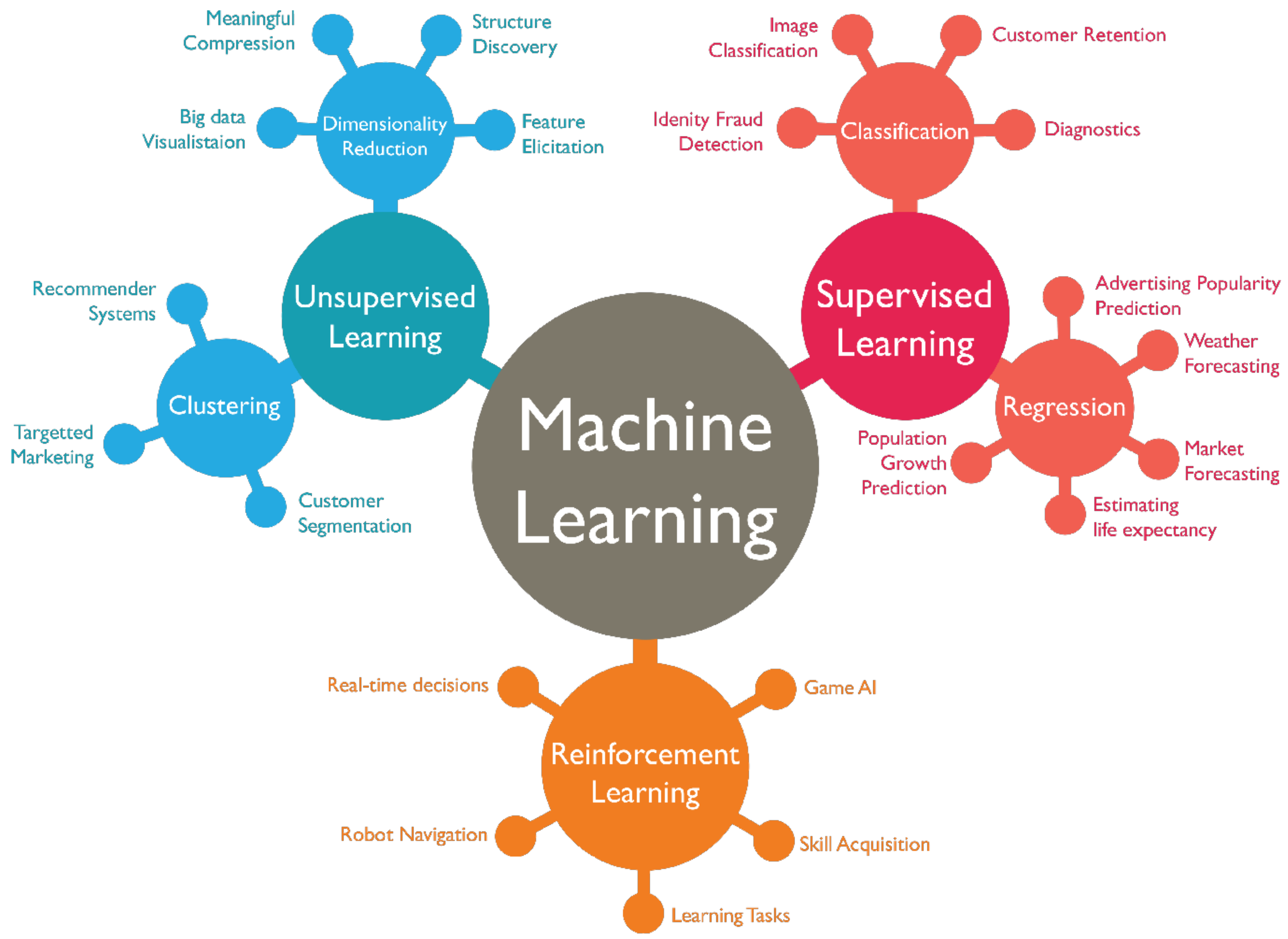
Richard Tyson (University of Glasgow)

Angelos Angelopoulos (CRTC)
Polykarpos Thomadakis (CRTC),
Nikos Chrisochoides (CRTC)
Department of Computer Science,
Old Dominion University, Norfolk, VA, 23529

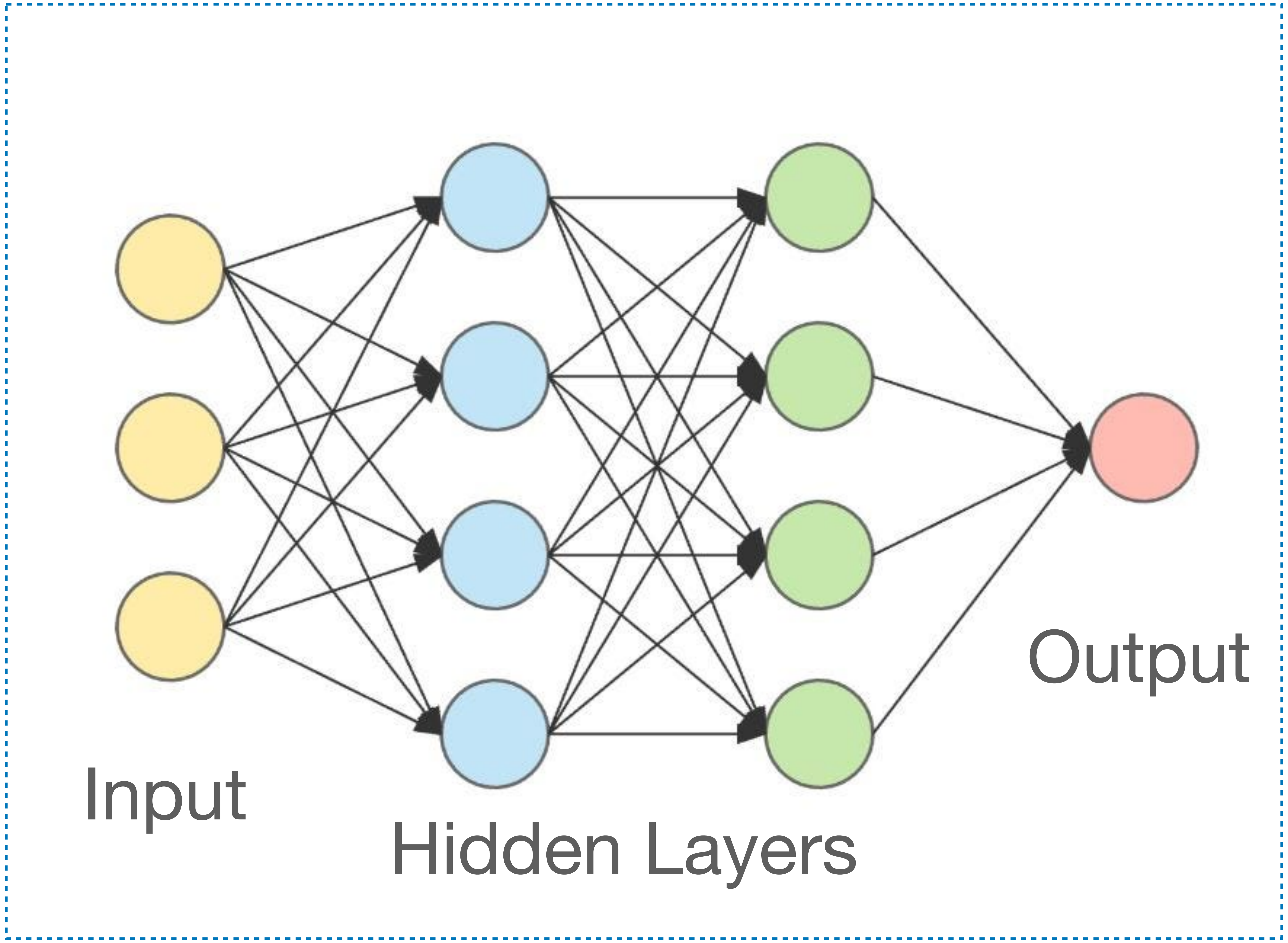
(JULO) Newport News (June 28,2023)

Outlook

- Outline:
    - The world of Machine Learning
    - Track identification in Drift Chambers
    - Drift Chamber Data De-Noising
    - Impact on the experiment outcome
    - Level-3 Trigger (impact on High Luminosity Running)
    - RICH (Ring Cherenkov) Particle Identification

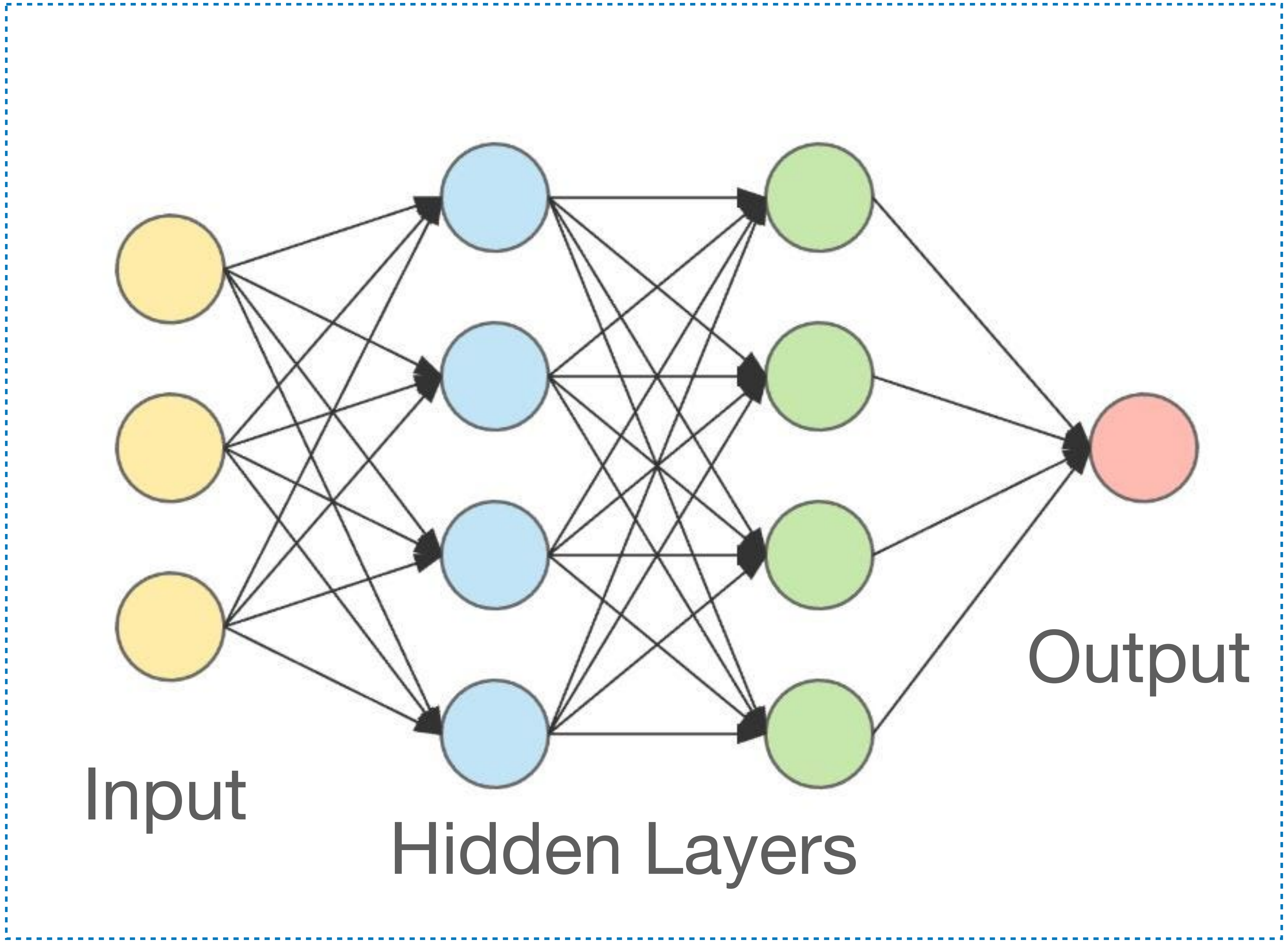


- Machine Learning (ML) is part of artificial intelligence.
- Machine learning is a field of inquiry devoted to understanding and building methods that 'learn', that is methods that leverage data to improve performance on some set of tasks.
- Machine learning algorithms build a model based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so.

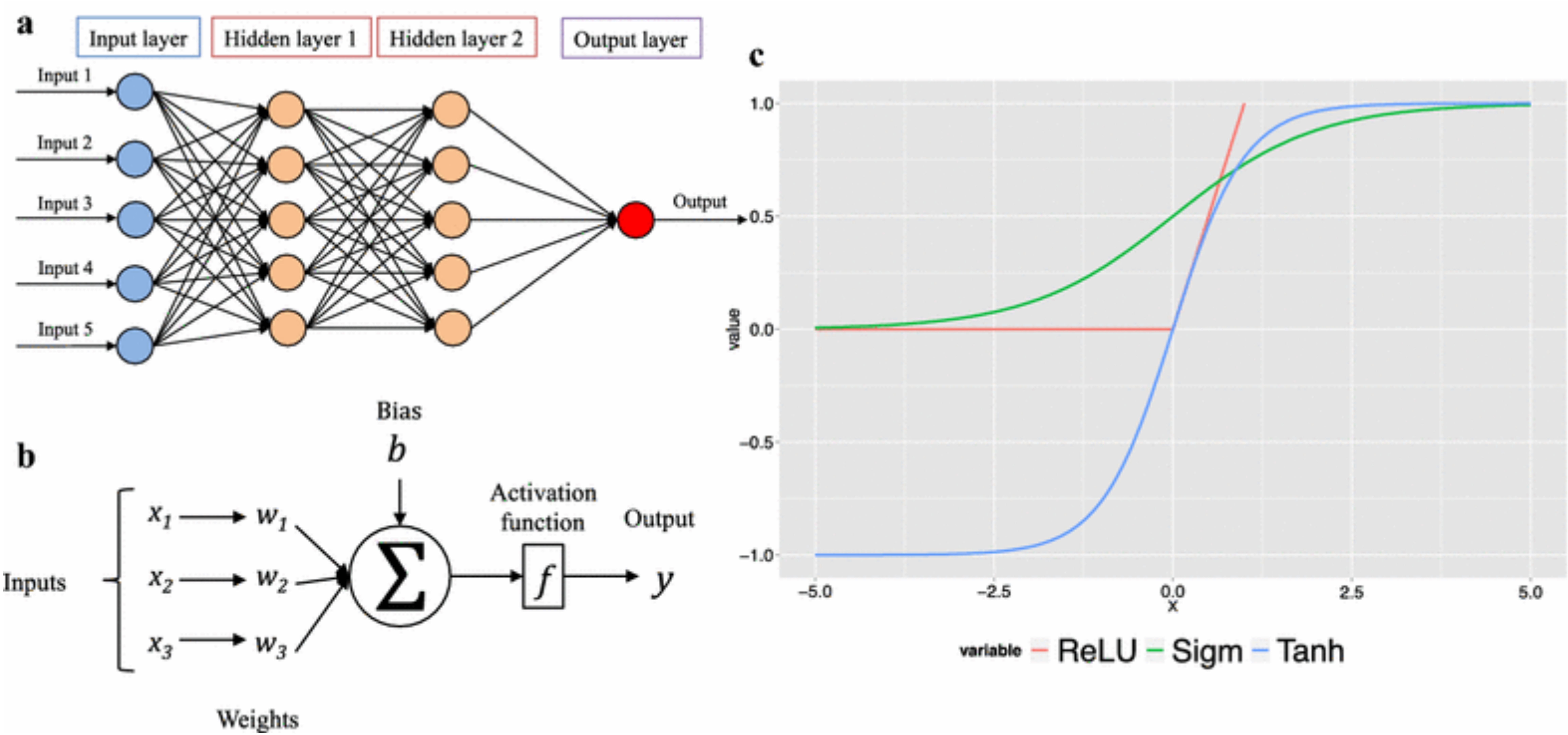


“Iron”

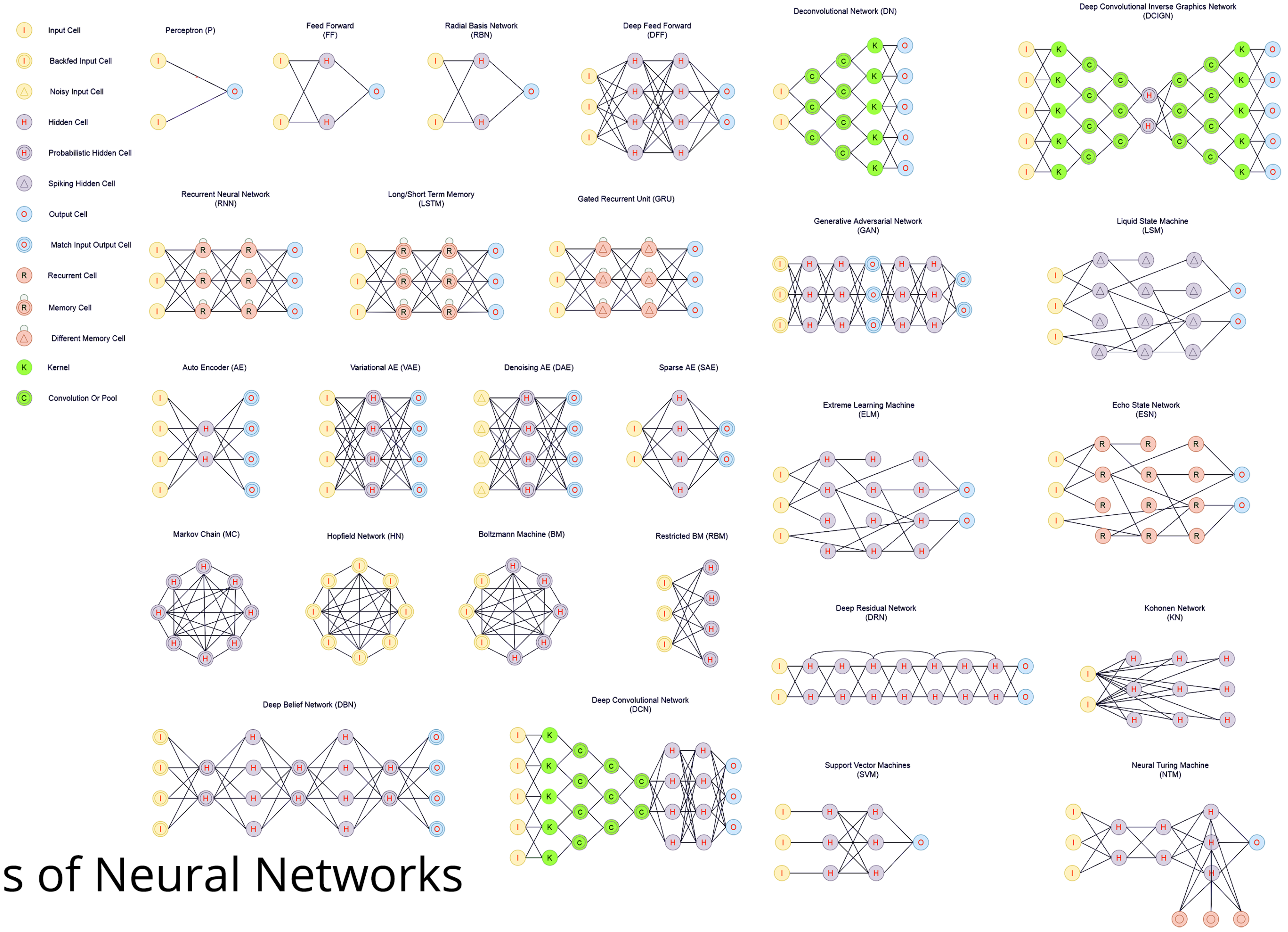
Outlook



"Iron"

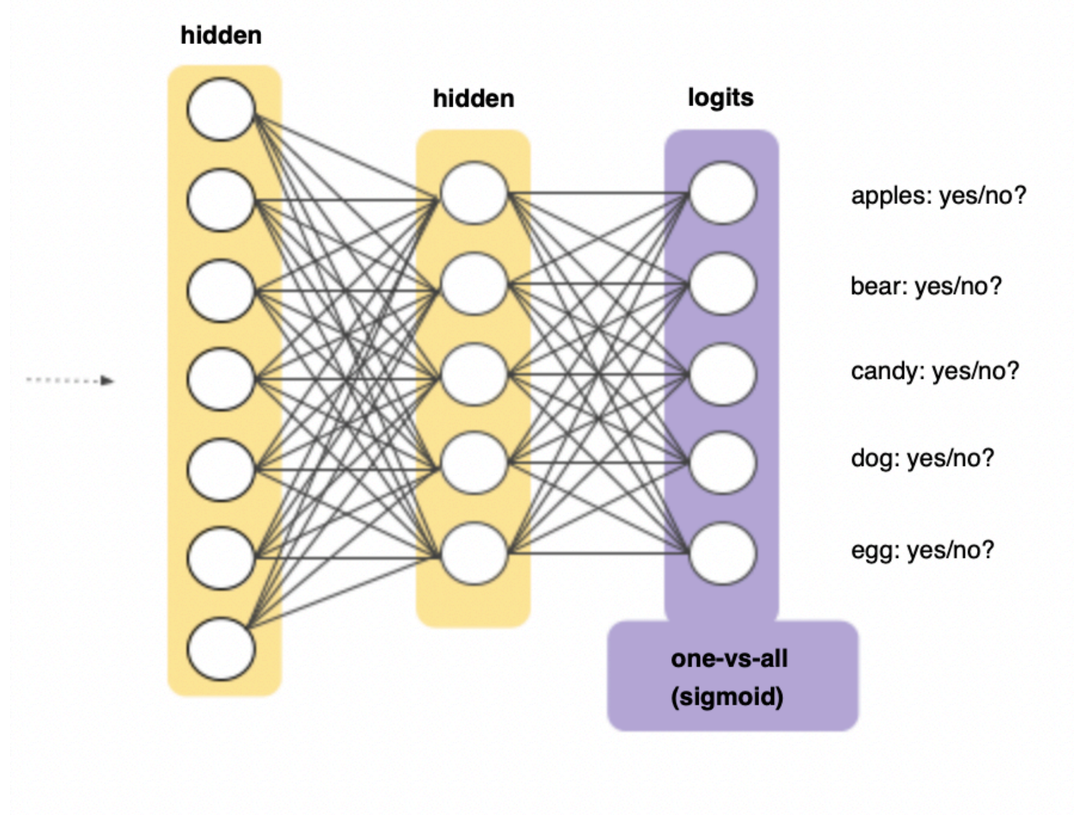

a
Input layer
Hidden layer 1
Hidden layer 2
Output layer
Input 1
Input 2
Input 3
Input 4
Input 5
Output
b
Bias
b
Inputs
x1
x2
x3
w1
w2
w3
Weights
Σ
Activation function
f
Output
y
c
1.0
0.5
0.0
−0.5
−1.0
value
−5.0
−2.5
0.0
2.5
5.0
x
variable
ReLU
Sigm
Tanh

Artificial Intelligence/Machine Learning



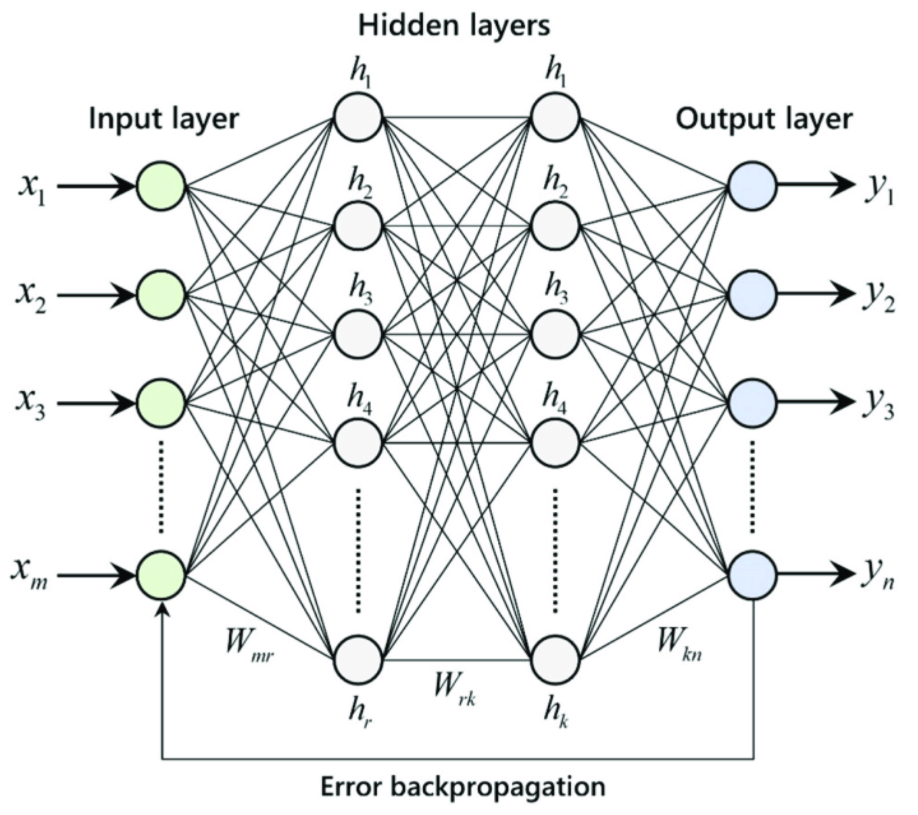
Main Types of Neural Networks

Classifier Neural Network



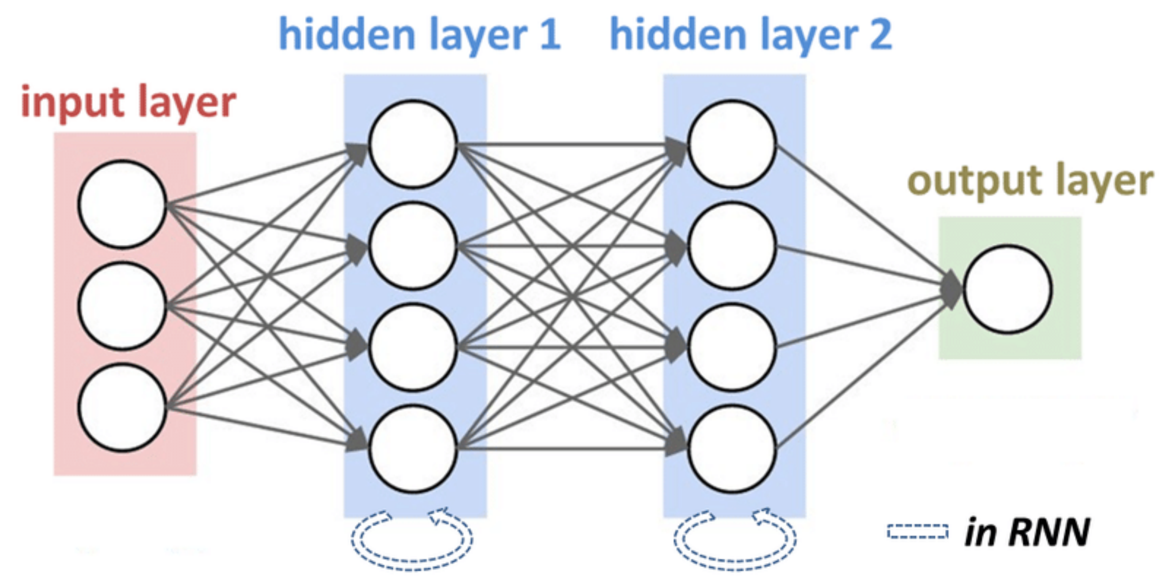
- Based on the input (image/vector) decide what type (or class) of data it is.
- Used to identify dogs/cats in the image
- Identify what king of particle it is based on the signals from detector components

Regression Neural Network



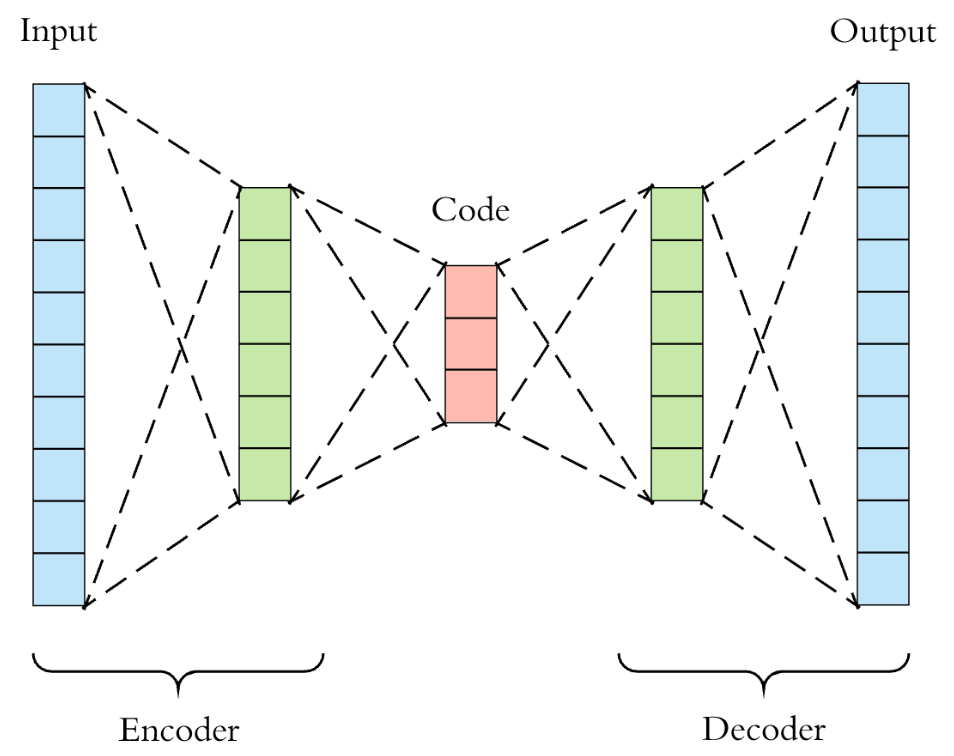
- For the given input (image/vector) calculate some values characteristic of the input
- Calculate the amplitude of a peak given points of the histogram
- Predict the speed of the object from series of measurements

Recurrent Neural Network



- For the given series predict the next value.
- Predict the next word in the sentence.
- Predict the next point for a given trajectory

Auto-Encoder Neural Network

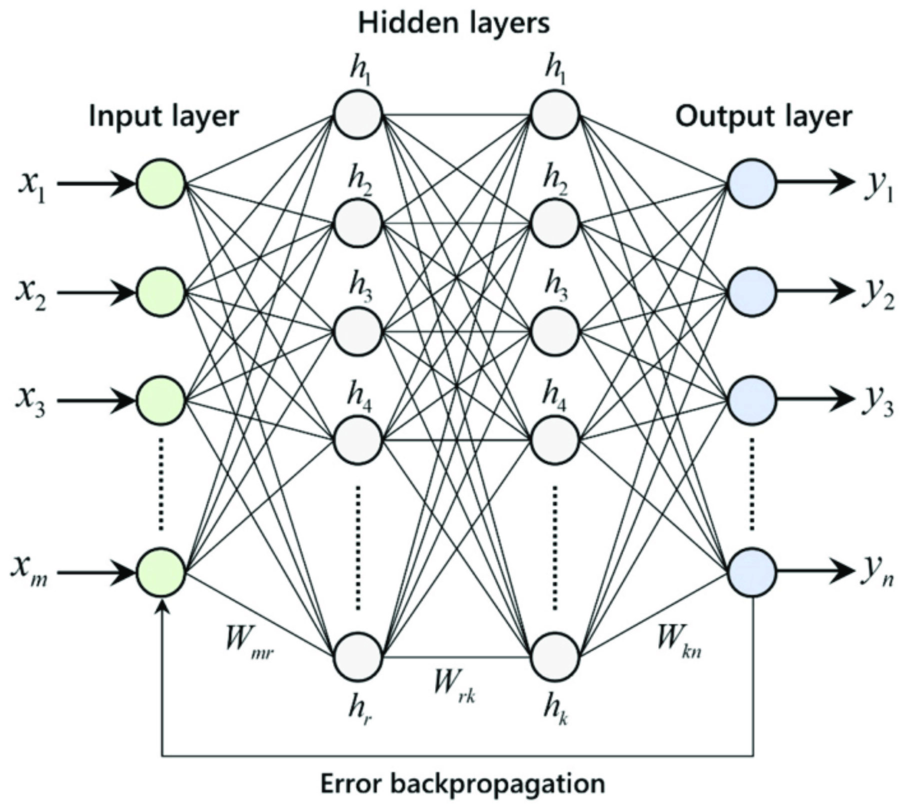


- Modify the input data to correct for some deficiencies
- Used for de-noising images
- Predicting missing information in the input

Classifier Neural Network

- Based on the input (image/vector) decide what type (or class) of data it is.
- Used to identify dogs/cats in the image
- Identify what king of particle it is based on the signals from detector components

Regression Neural Network



- For the given input (image/vector) calculate some values characteristic of the input
- Calculate the amplitude of a peak given points of the histogram
- Predict the speed of the object from series of measurements

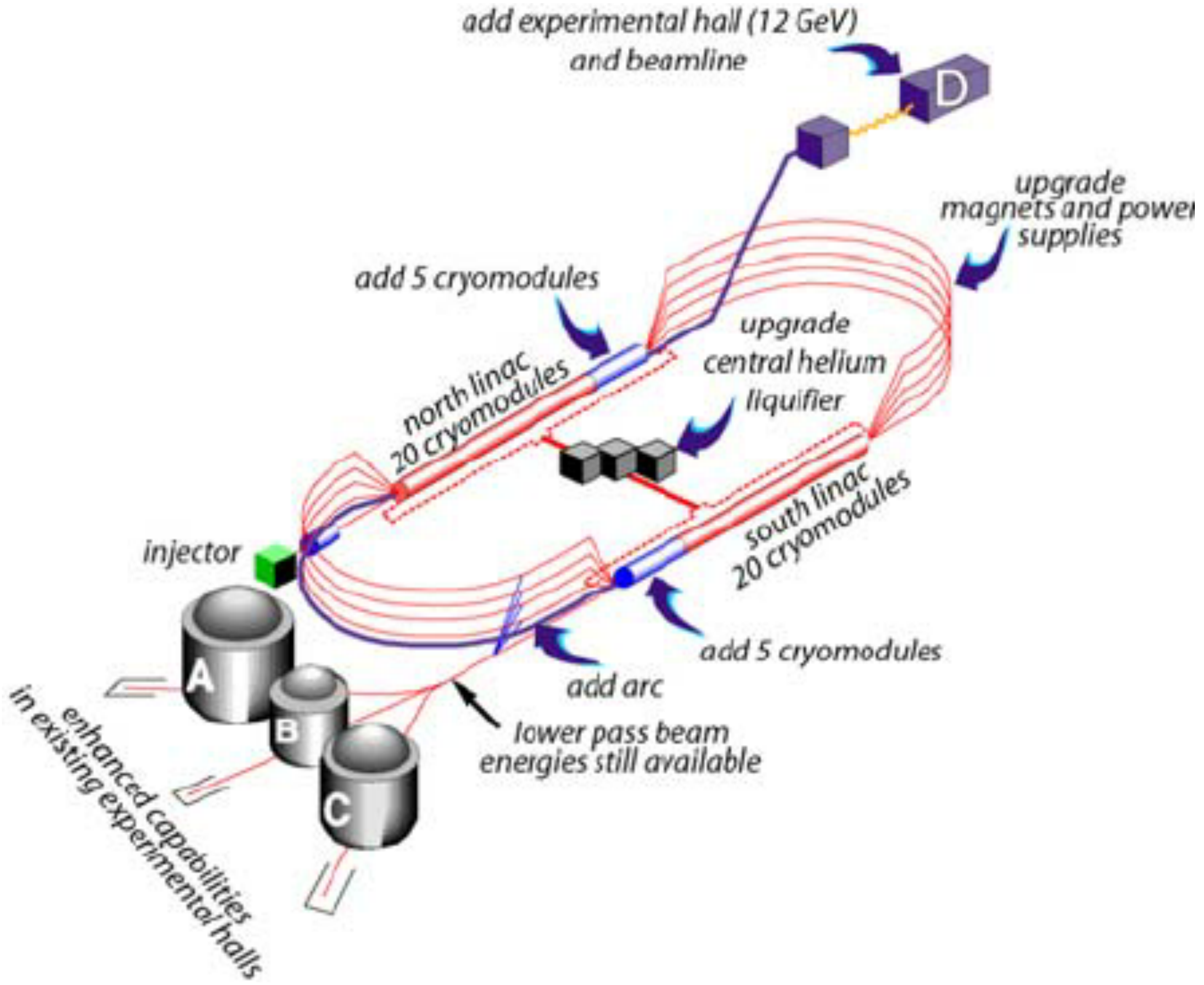
Recurrent Neural Network

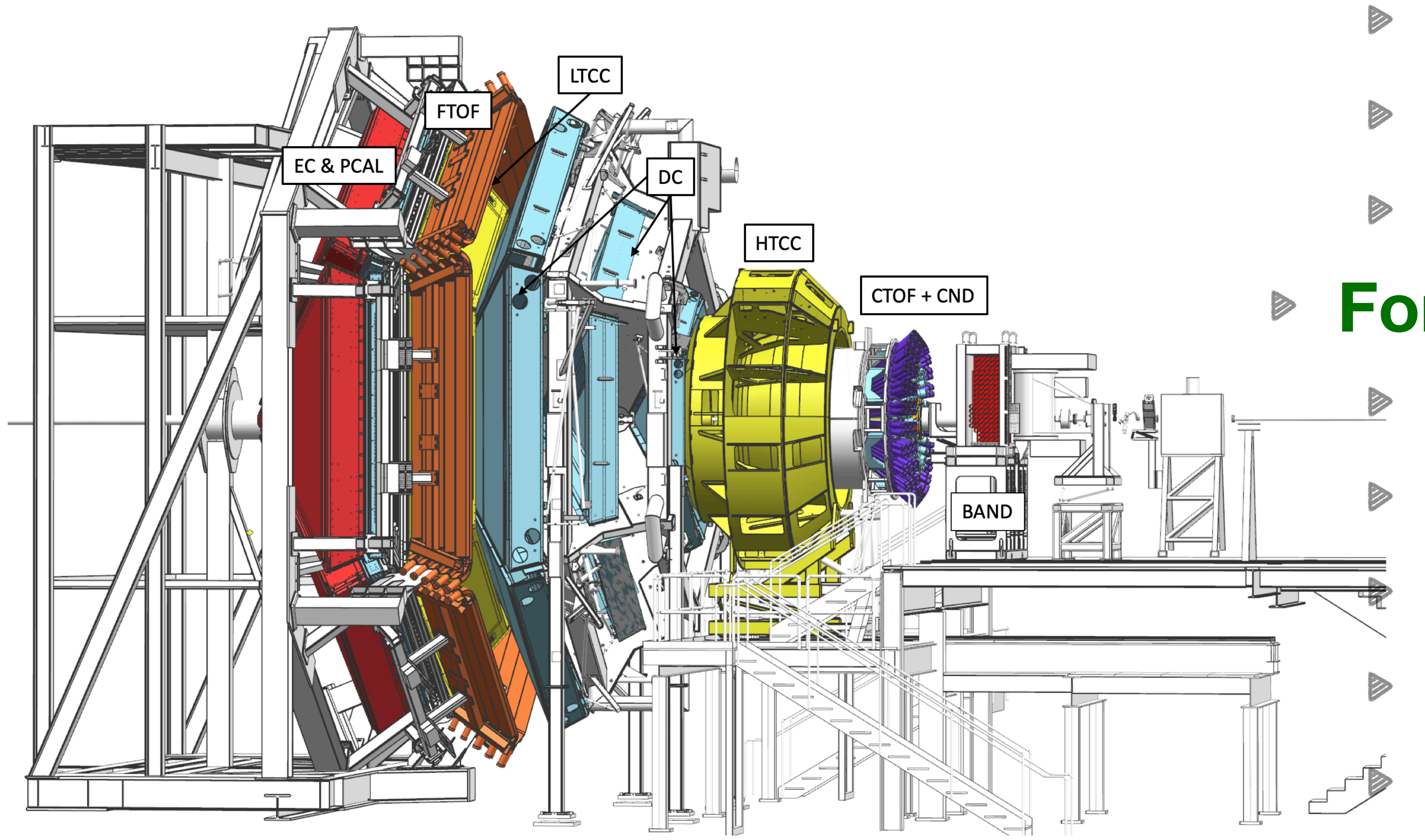
- If one collects all world data and feeds it to Regression Neural Network the answer should come out 42.

- For the given series predict the next value.
- Predict the next word in the sentence.
- Predict the next point for a given trajectory

Auto-Encoder Neural Network

- Modify the input data to correct for some deficiencies
- Used for de-noising images
- Predicting missing information in the input

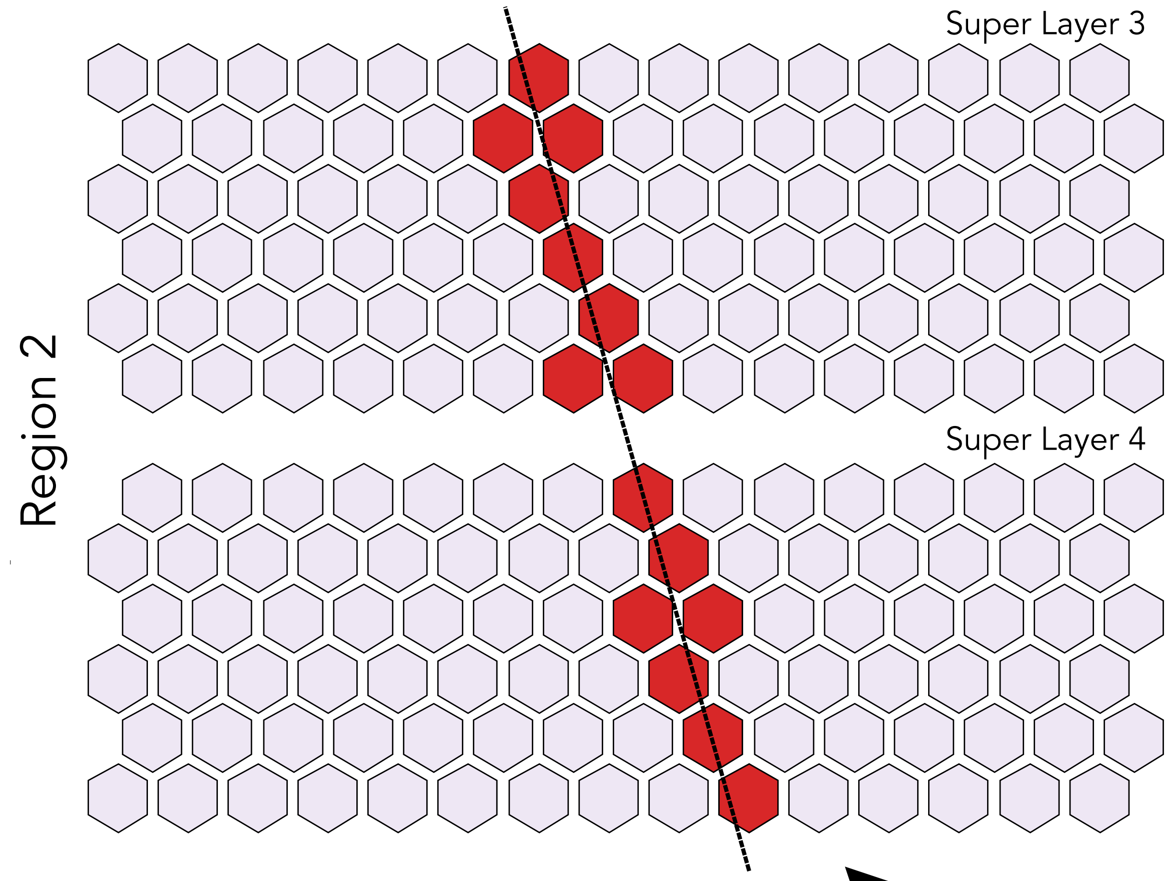




- CEBAF
  - 12 GeV electron beam distributed to 4 experimental hall
  - Each experimental hall contains a detector system for specific experiments

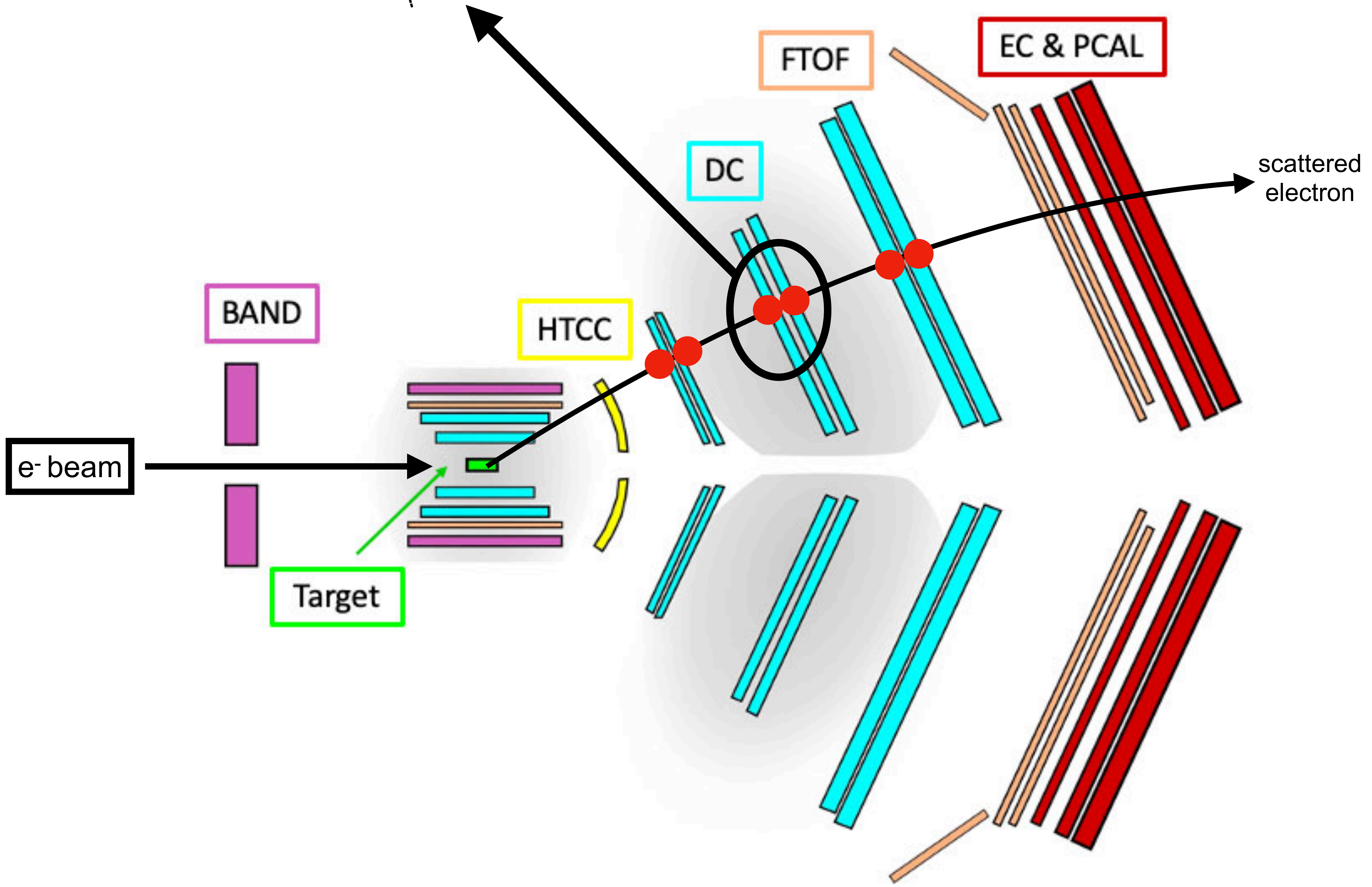
- **Hall-B:**
  - CEBAF Large Acceptance Spectrometer (CLAS12) Located in Hall-B
  - **Central Detector:**
    - Silicon Tracker
    - Time-Of-Flight
    - Neutron Detector
  - **Forward Detector:**
    - Drift Chambers
    - Time of Flight
    - High Threshold Cherenkov Counter
    - Ring Imaging Cherenkov Counter
    - Electromagnetic Calorimeter

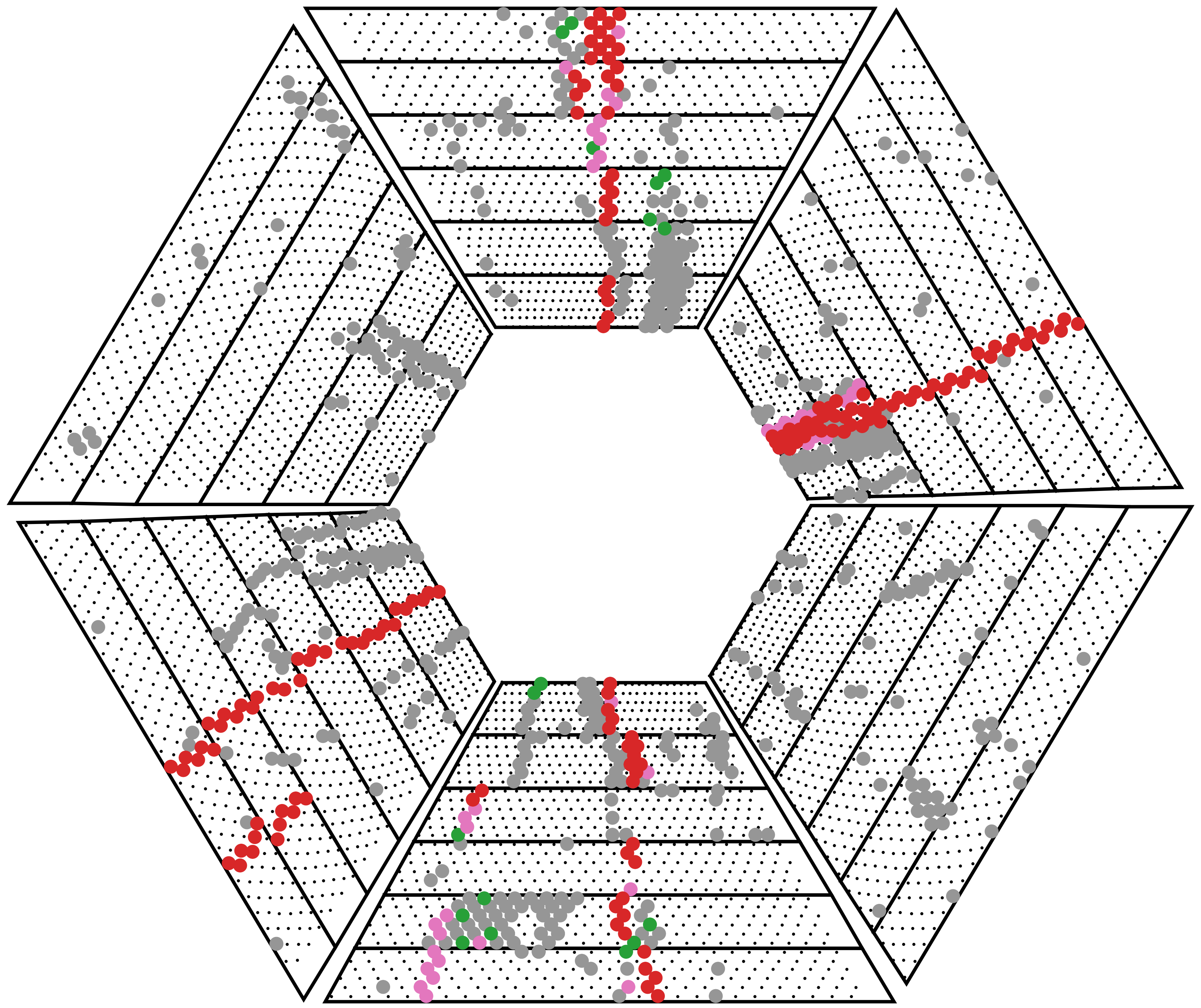
CLAS12 Detector



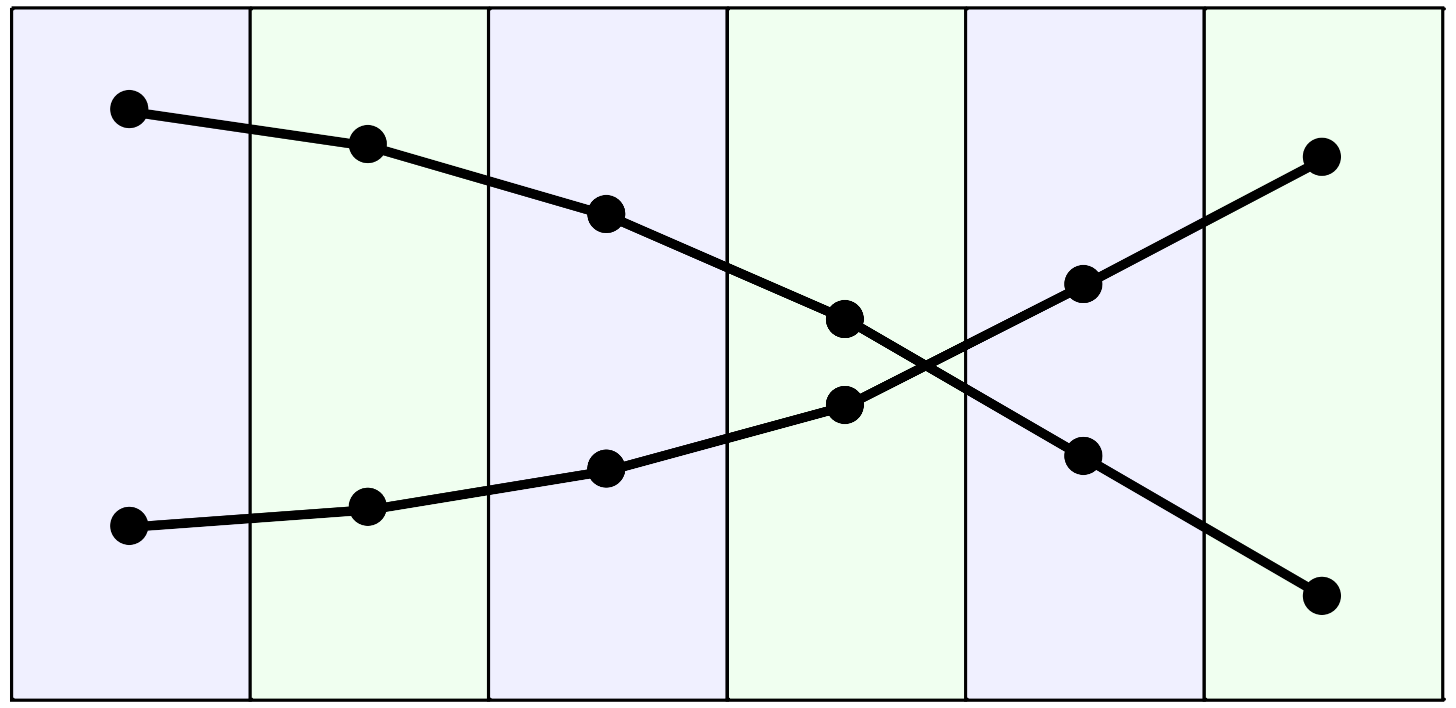
- 2 super layers in each region
- 6 wire planes in each super layer with 6-degree tilt relative to each other, (112 wires in each plane)
- Clusters in each super layer are considered part of the track trajectory

- Charged particle tracking is computationally extensive (about 80% of data processing time)
- The multi-particle final states produce numerous clusters in each sector which have to be analyzed to find the right combinations of clusters that form a track
- Identifying correct cluster combinations can speed up the tracking process and improve efficiency



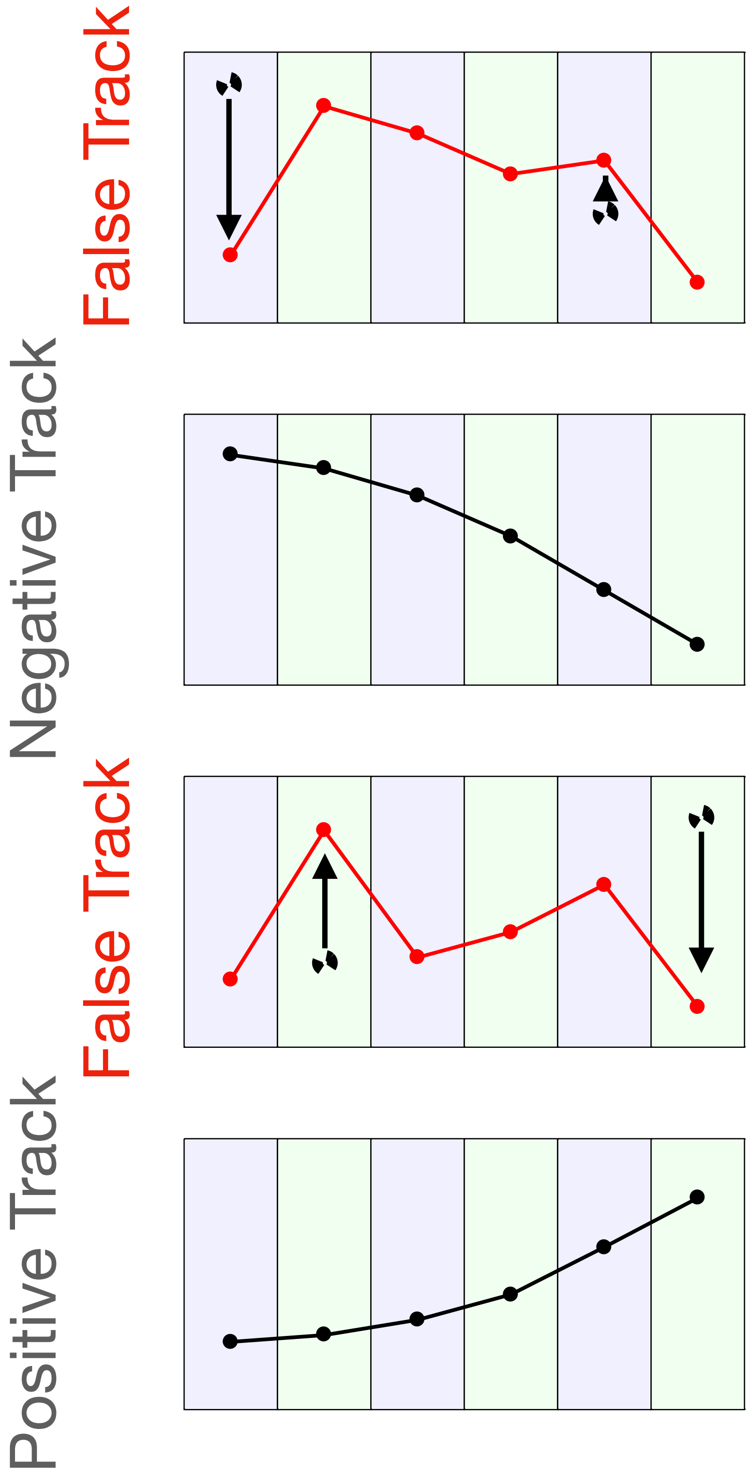


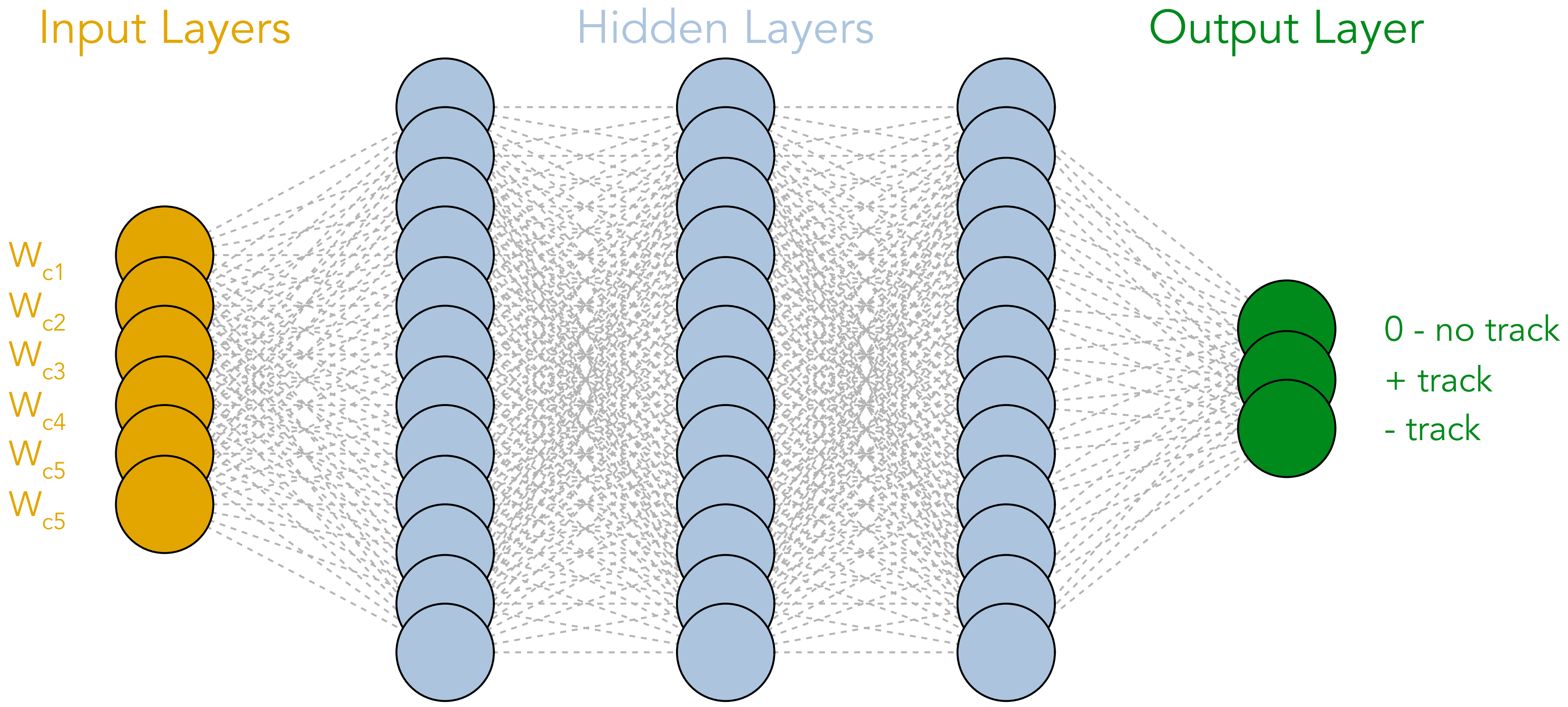
Physics Results



- True tracks are identified by conventional algorithms from real data.
- One negative and one positive track (different curvature due to magnetic field)
- False tracks are constructed by interchanging randomly one or two clusters with the clusters from the other track in the event
- Training sample balancing is done by choosing equal tracks for each momentum and angular bin.

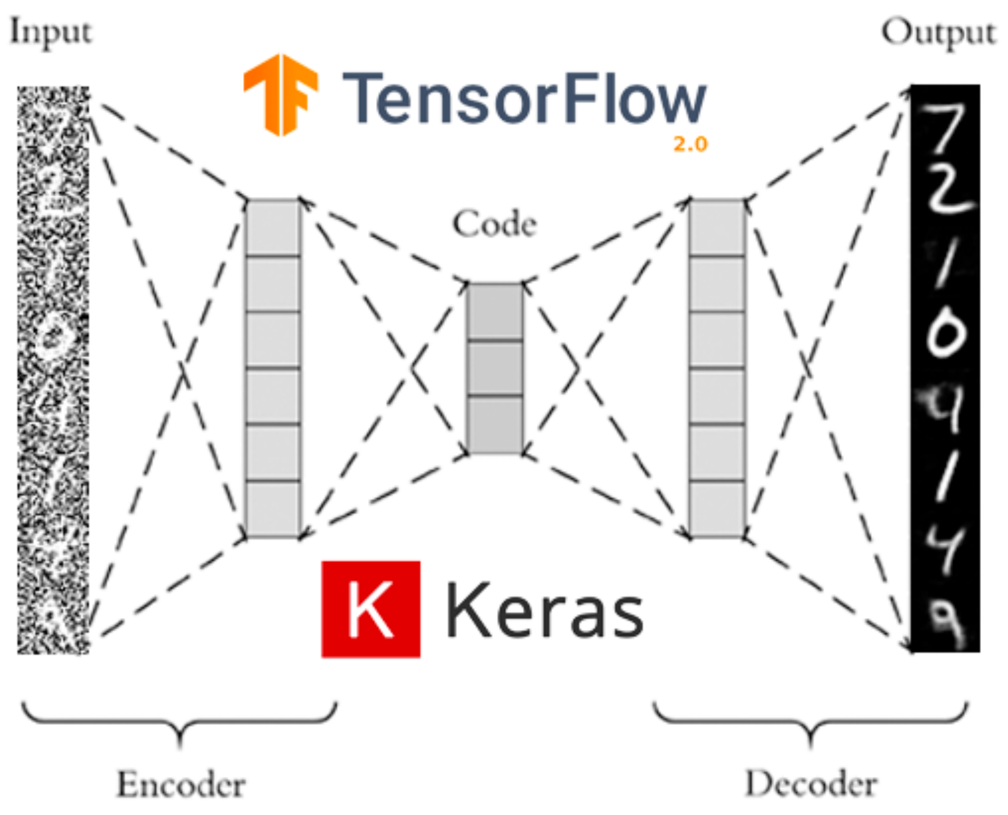
- The average wire position in each super layer is used as an input to Multi-Layer Perceptron (MLP)
- The network is trained on 6 inputs and produces three outputs:
  - False track
  - Negative Track
  - Positive Track



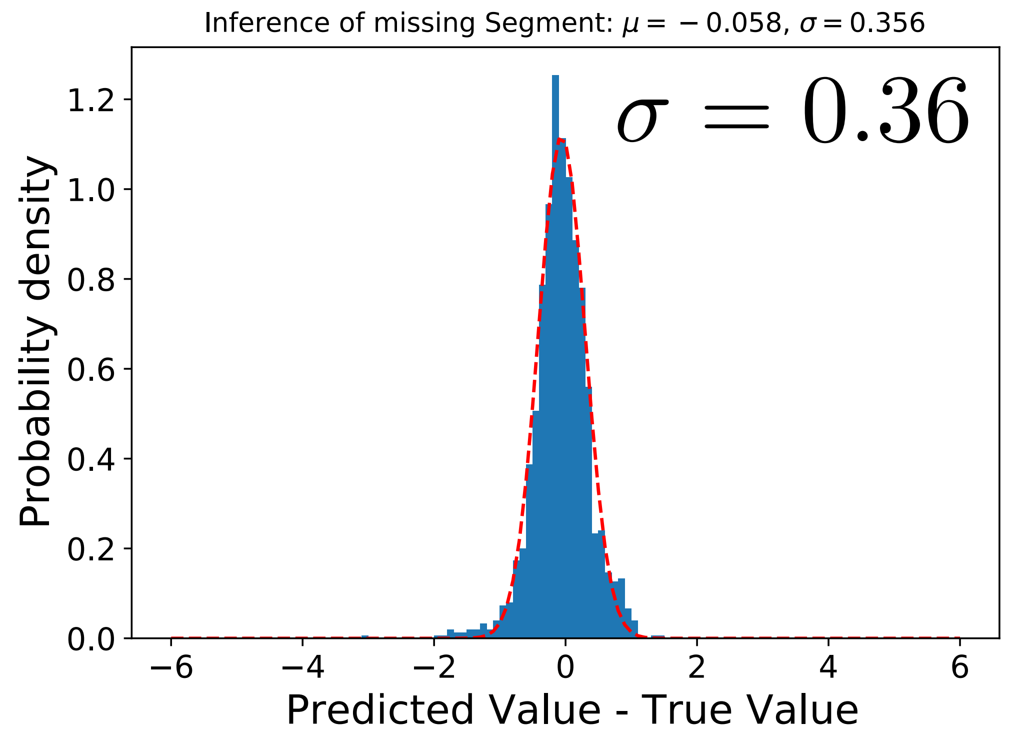


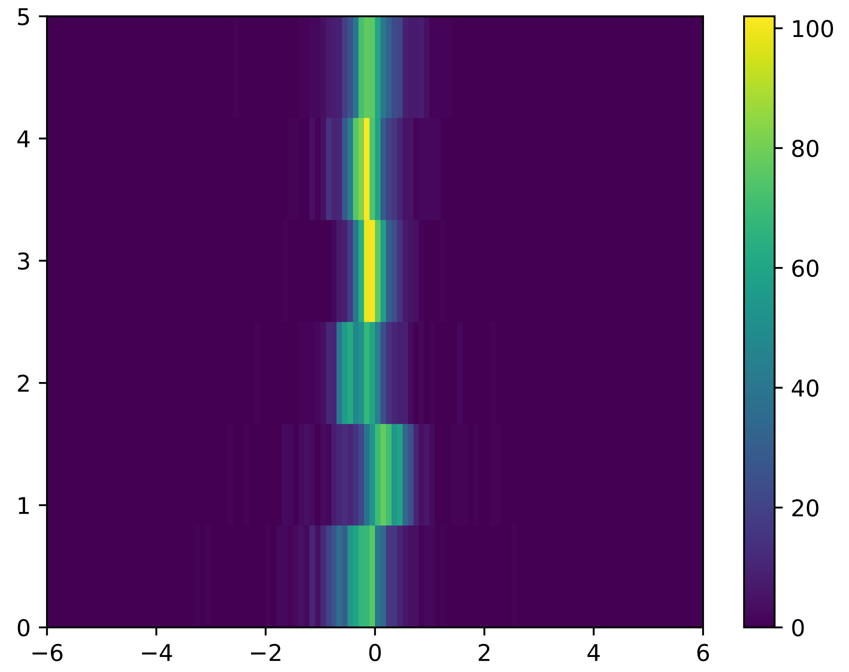
Corruption Auto-Encoder

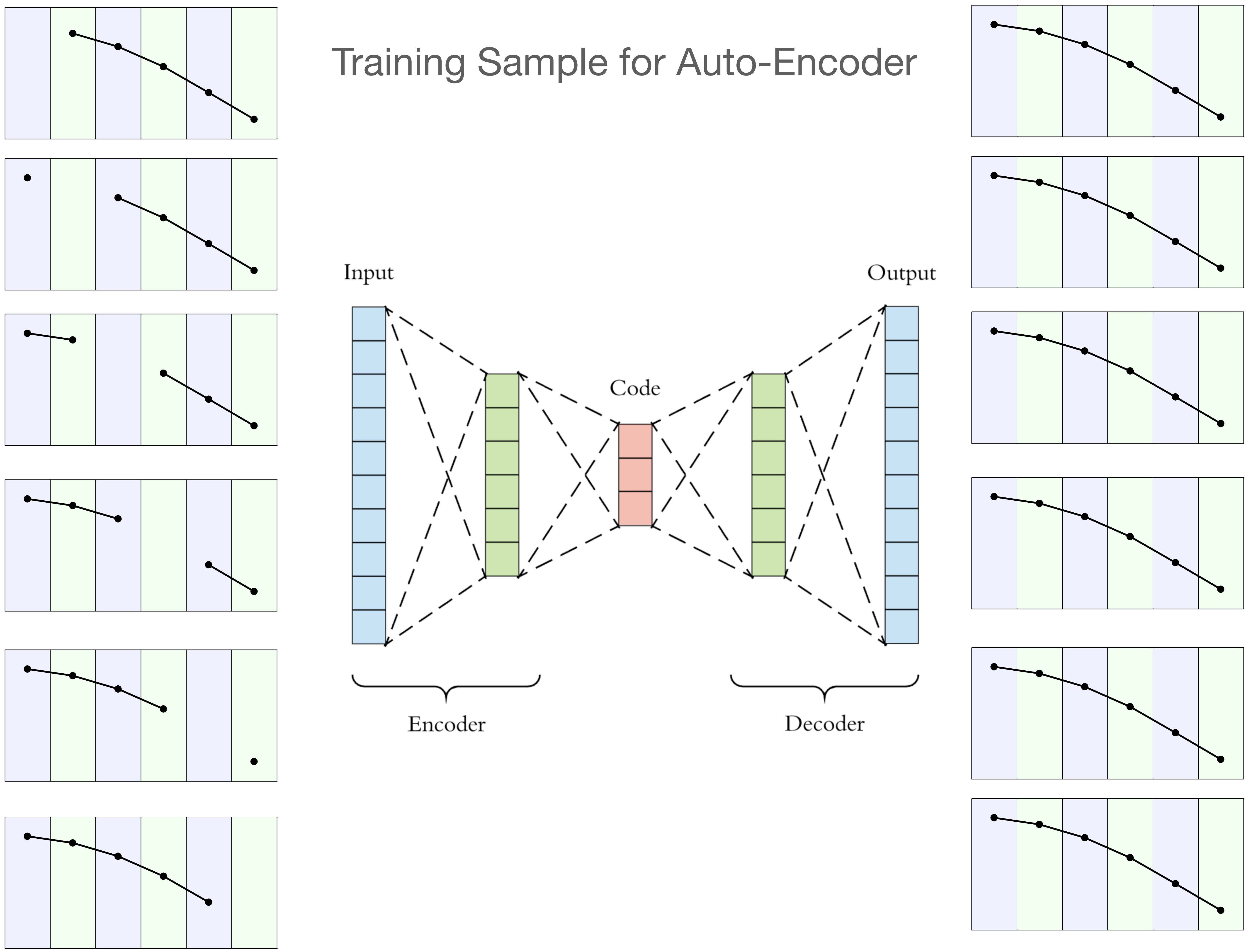
- An auto-encoder is composed of an encoder and a decoder sub-models. The encoder compresses the input and the decoder attempts to recreate the input from the compressed version provided by the encoder.
- **Typically used for de-noising, but can be used for fixing glitches (our case).**



- The network Predicts the missing cluster position with a precision of 0.36 Wire

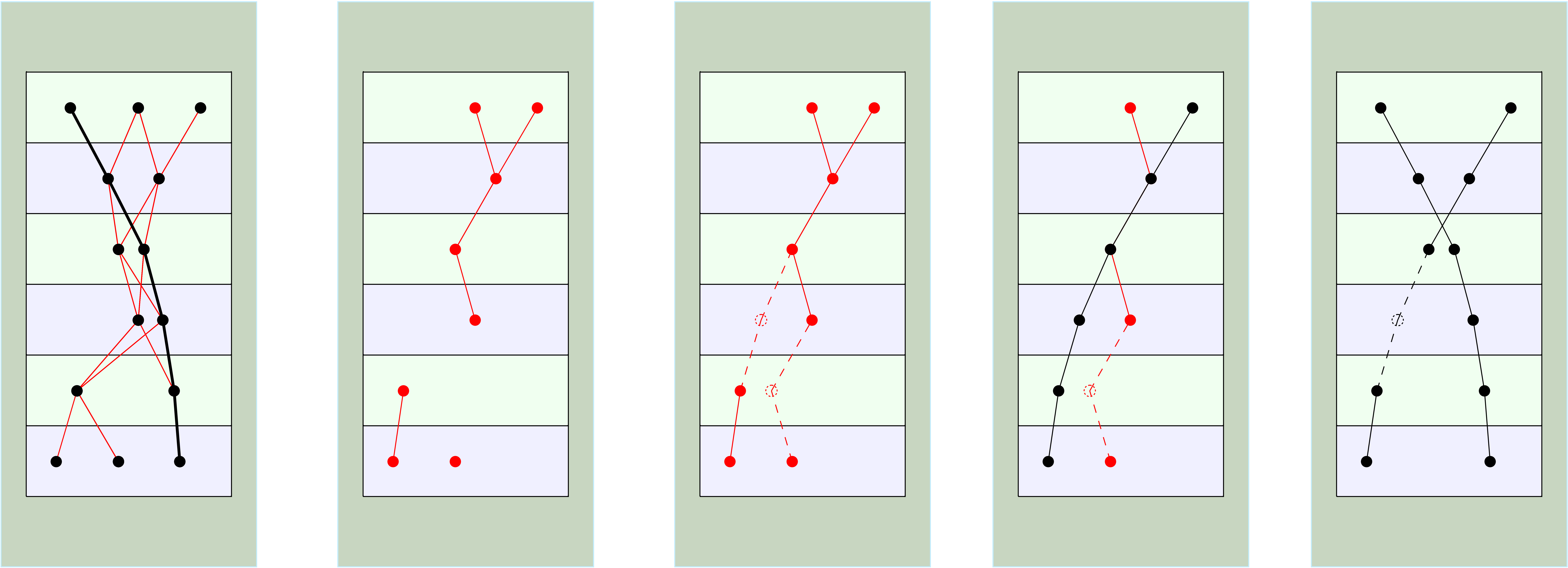






- Use Auto-Encoders to fix the missing cluster (provide a position)
- Good reconstructed tracks are used to generate training samples by removing one cluster from each super layer

Putting things together



Classifier picks the correct track from 6 super-layer combinations

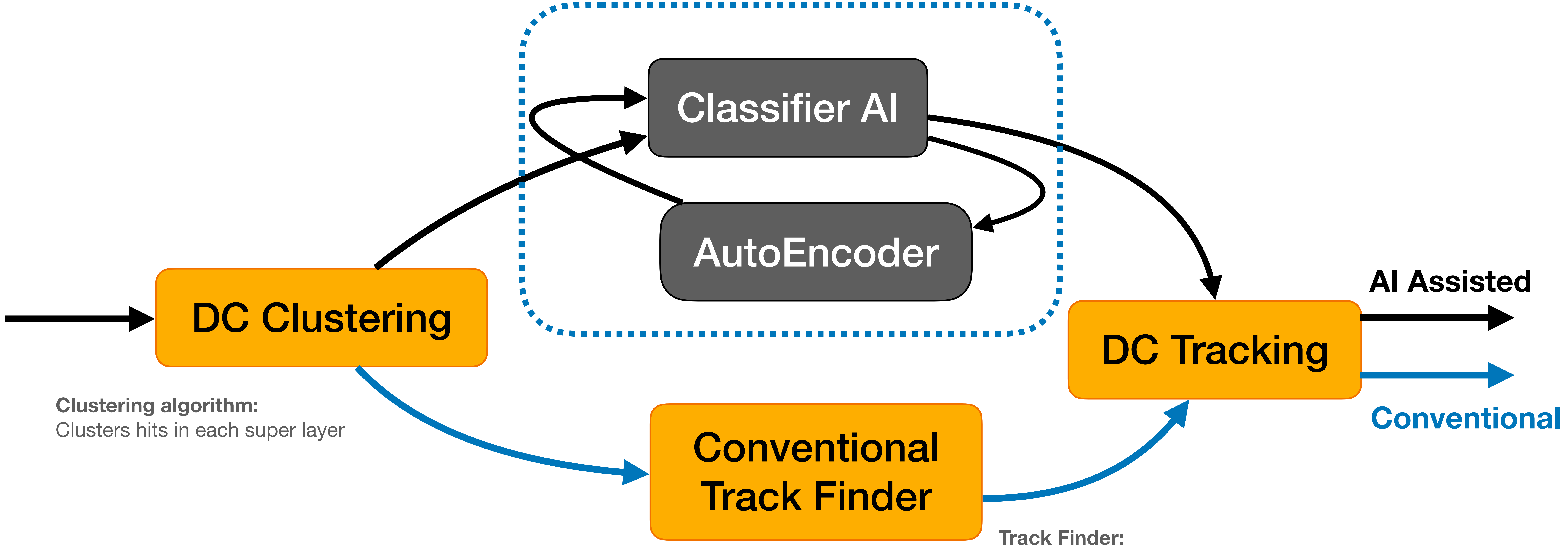
Remove all clusters belonging to identified track

Construct pseudo-clusters for all 5 super layer combinations using Corruption Auto-Encoder

Identify tracks using 6 super layer candidates with pseudo-clusters

Voila!

- CLAS12 Reconstruction Software is based on Service Oriented Architecture (SOA)
- Allows running parallel services for each algorithm producing common output.

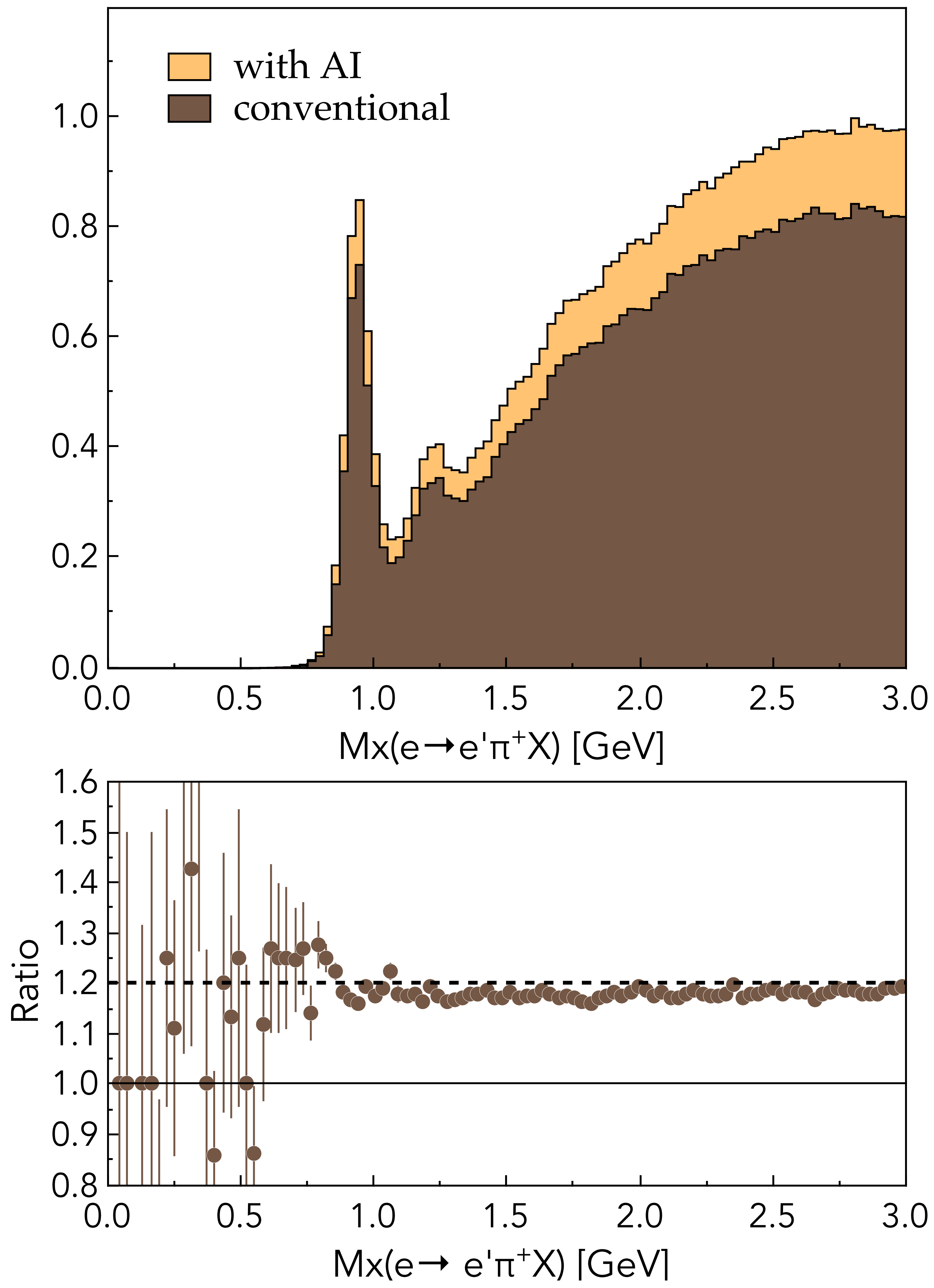


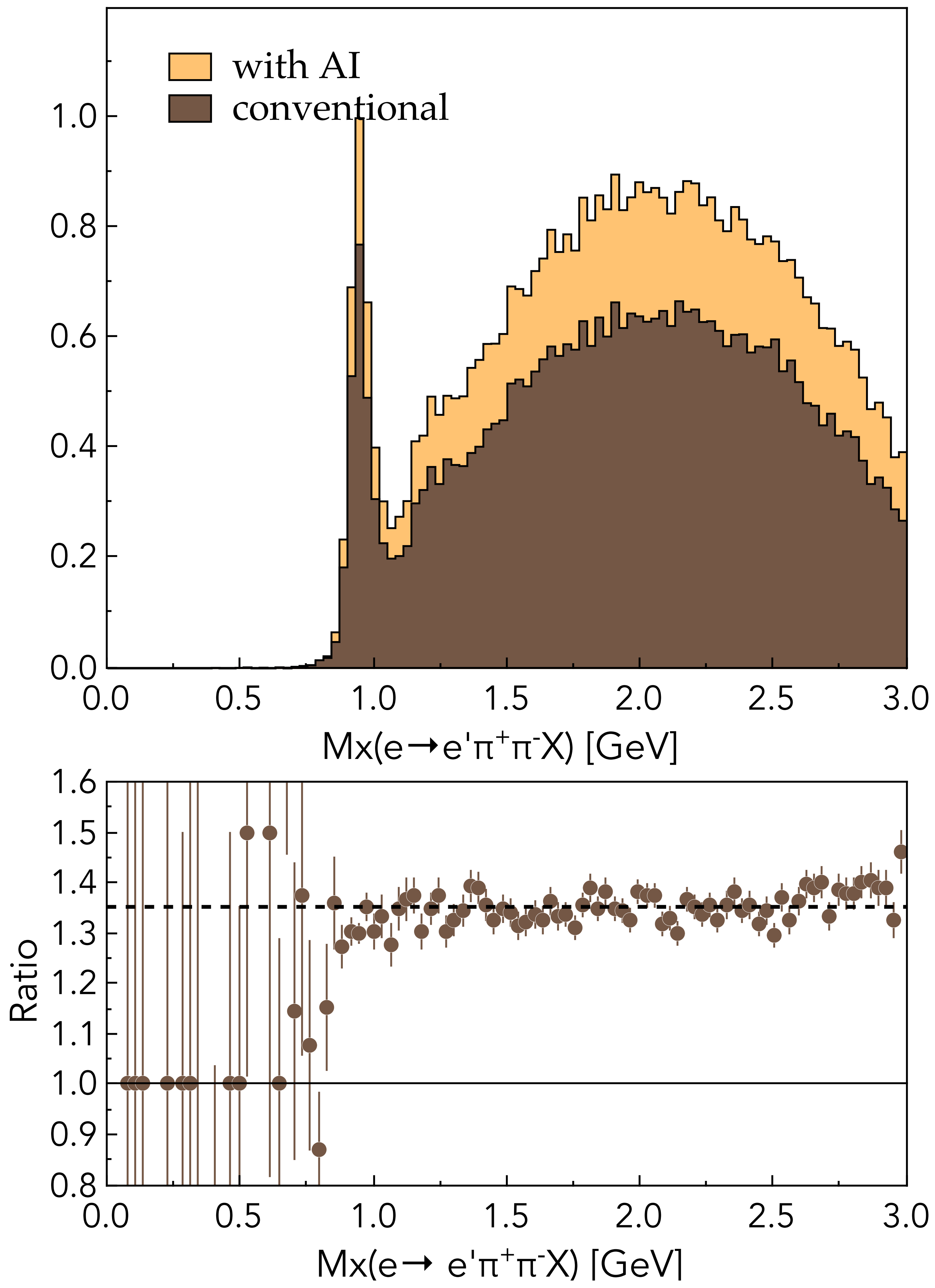
Clustering algorithm:
Clusters hits in each super layer

Track Finder:
Considers all combinations of 6 and 5 super layer track candidates Fits them and accepts/rejects them based on chi2.

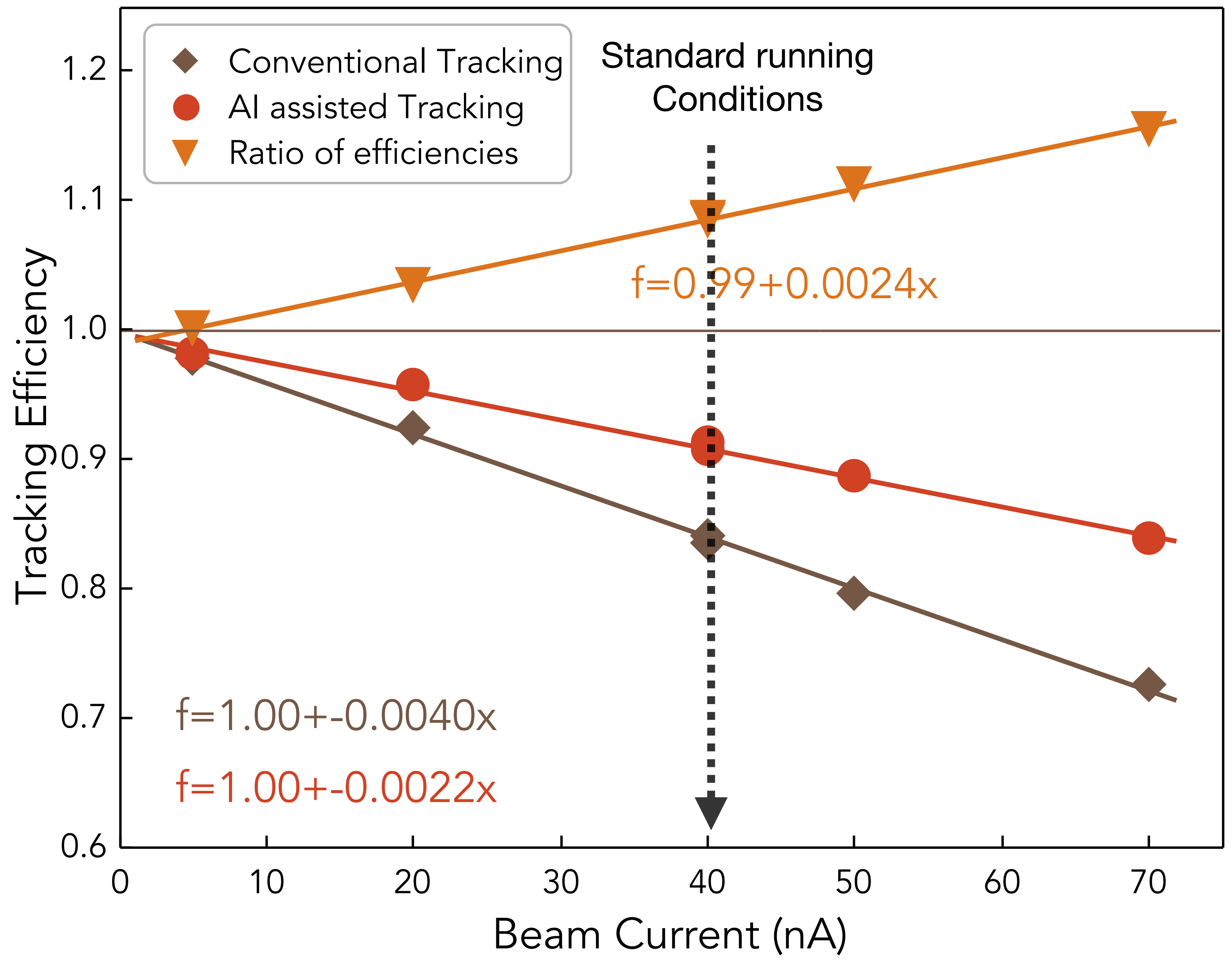
AI-assisted track candidate classification and Inefficiency Reduction Auto-Encoder

$ep \rightarrow e'\pi^+(X)$ $ep \rightarrow e'\pi^+\pi^-(X)$





- Single particle efficiency increases by ~10%.
- The impact on physics for a multi-particle final state is dramatic (20% for the two-particle final state and ~35% for the three-particle final state)
- The tracking code speedup is ~30%.

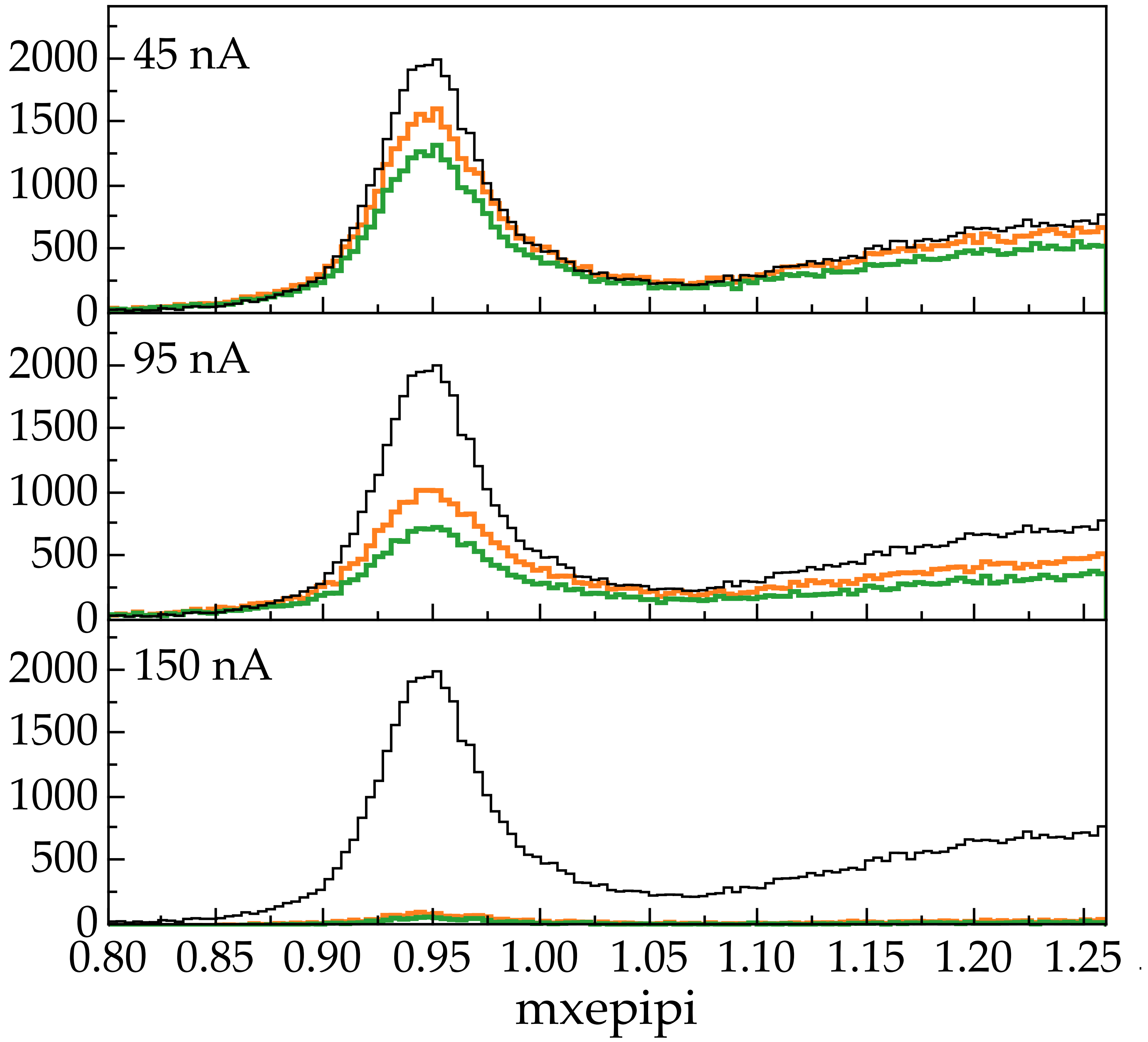


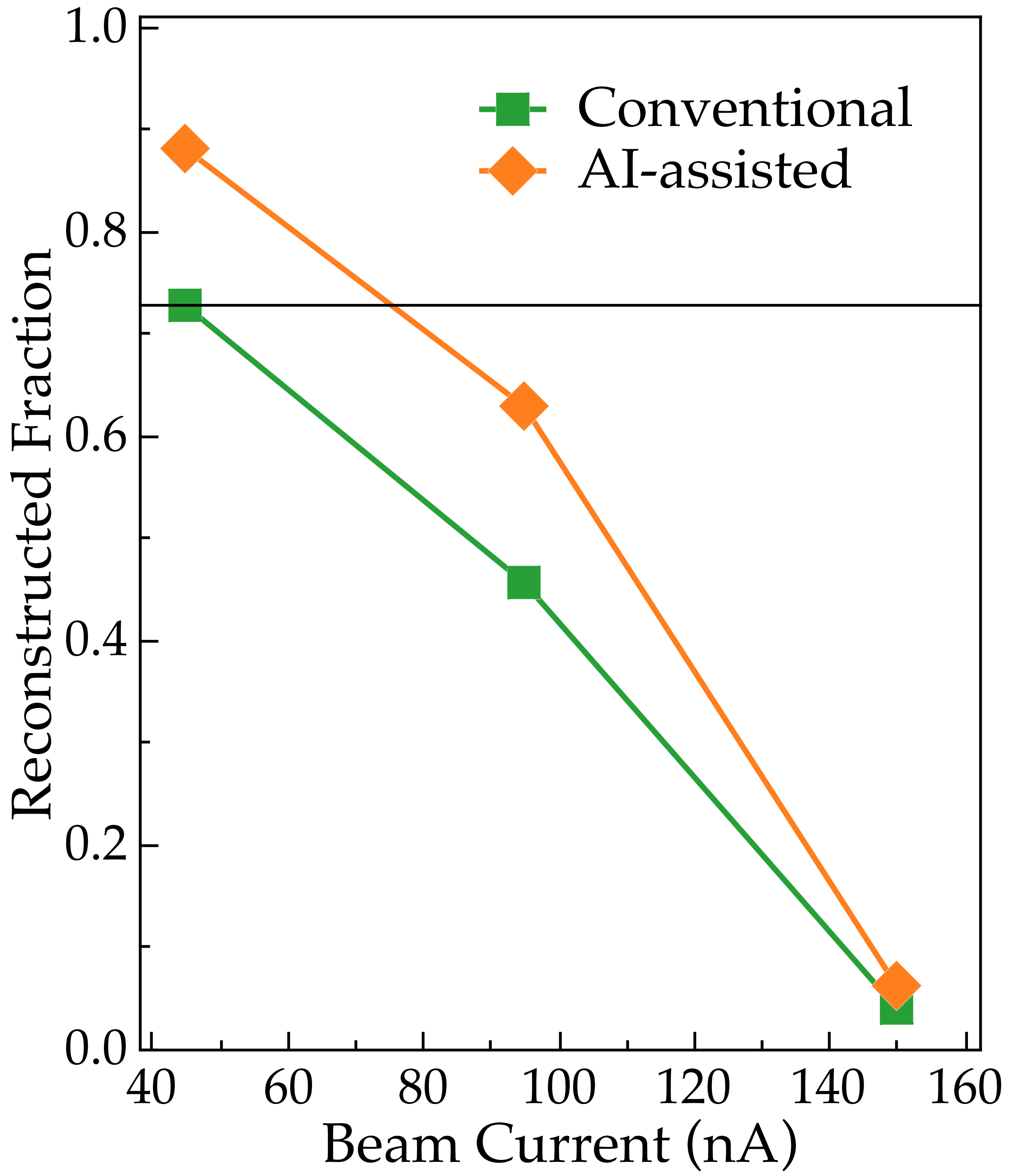
Up to ~35% gain in physics
Just using Classifiers

Moving to higher Luminosities

De-Noising

Performance of track identification for higher luminosity





- Pythia simulated physics reaction:

$$ep \to e'\pi^+\pi^- p$$

- Data for each luminosity (beam current) is created by standard background merging software.
- For each luminosity the yield of missing protons is calculated in:

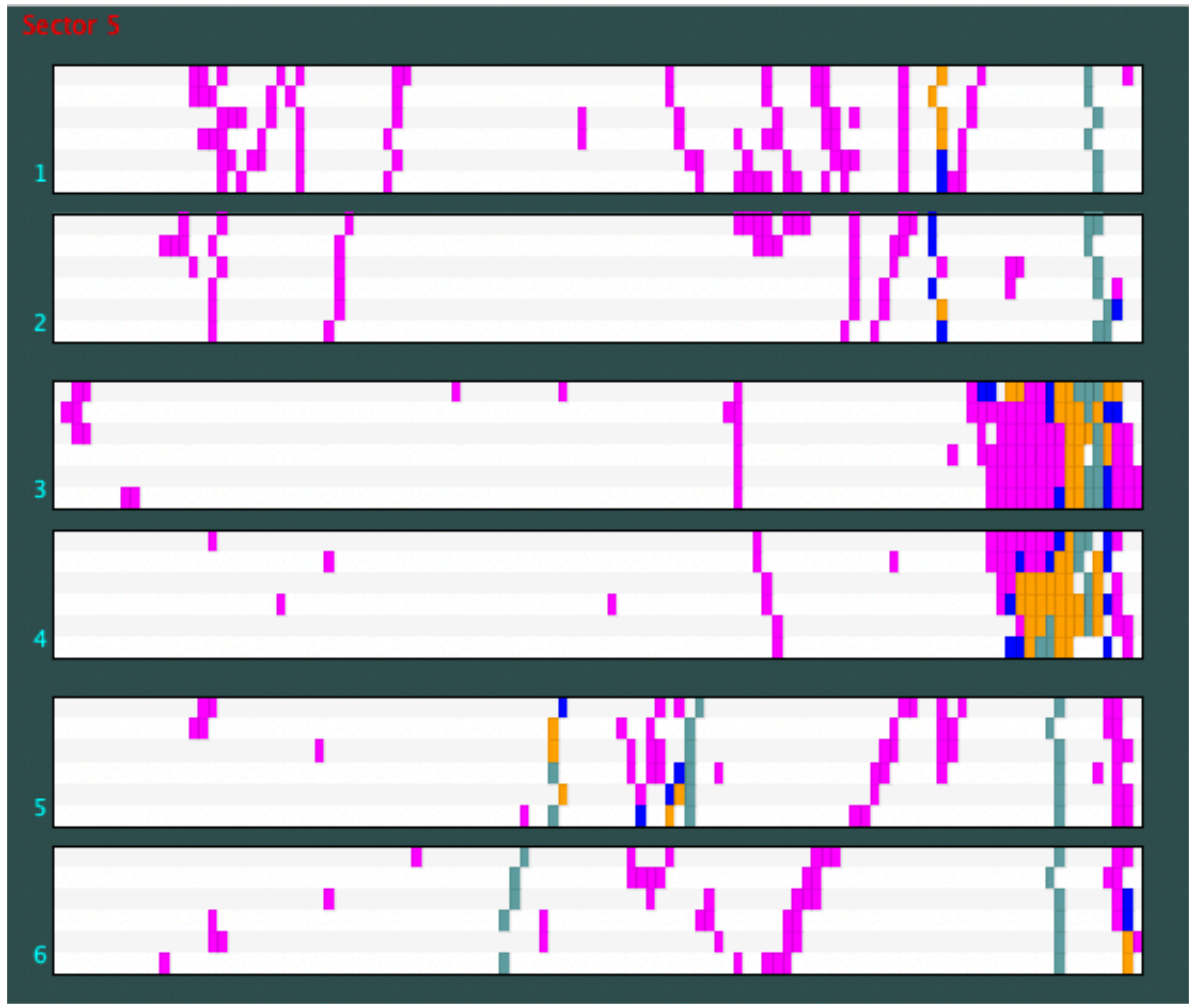
$$ep \to e'\pi^+\pi^- X$$

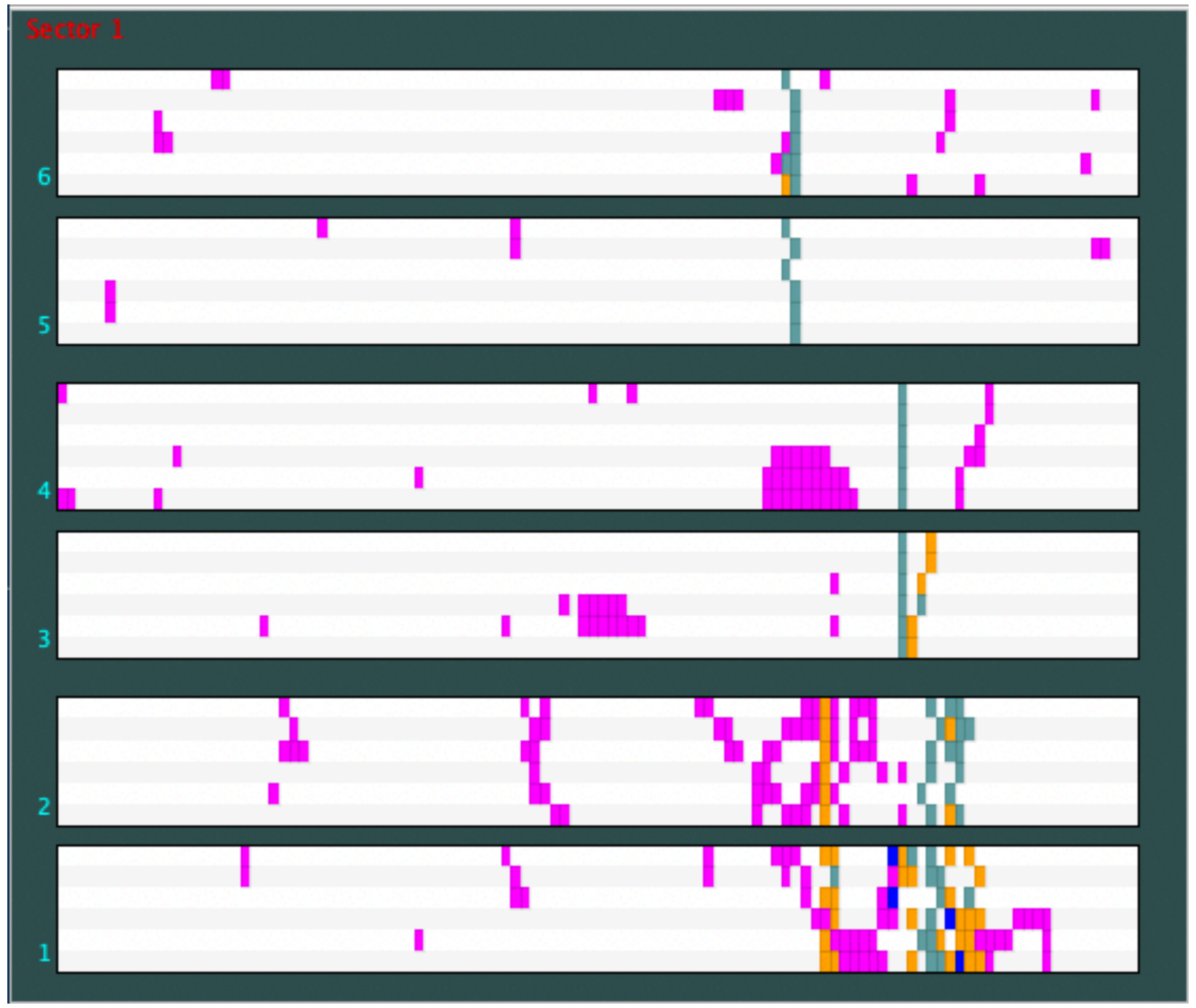
- With increased luminosity the efficiency of reconstructed three particle final state drops sharply
- Even with the power of AI-assisted tracking (capable of resolving the combinatorics) the efficiency drop follows the same trend.

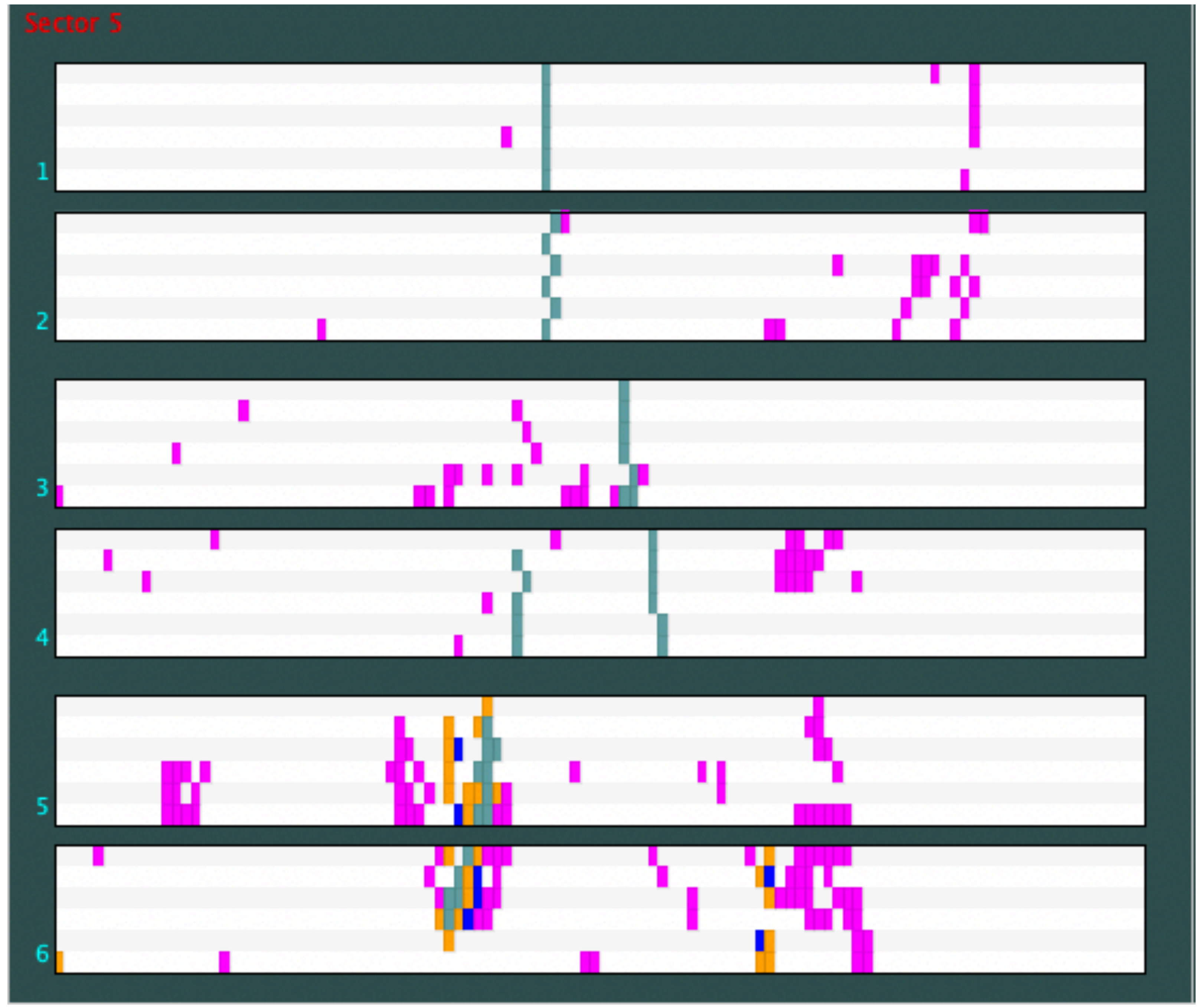
De-Noising

- In high luminosities the noise level increases and forming clusters (or segments in each chamber becomes challenging)
- This results in loss of clusters and AI-assited tracking can no longer help with combinatorics resolution

CLAS12 Event Display Examples (Drift Chambers)

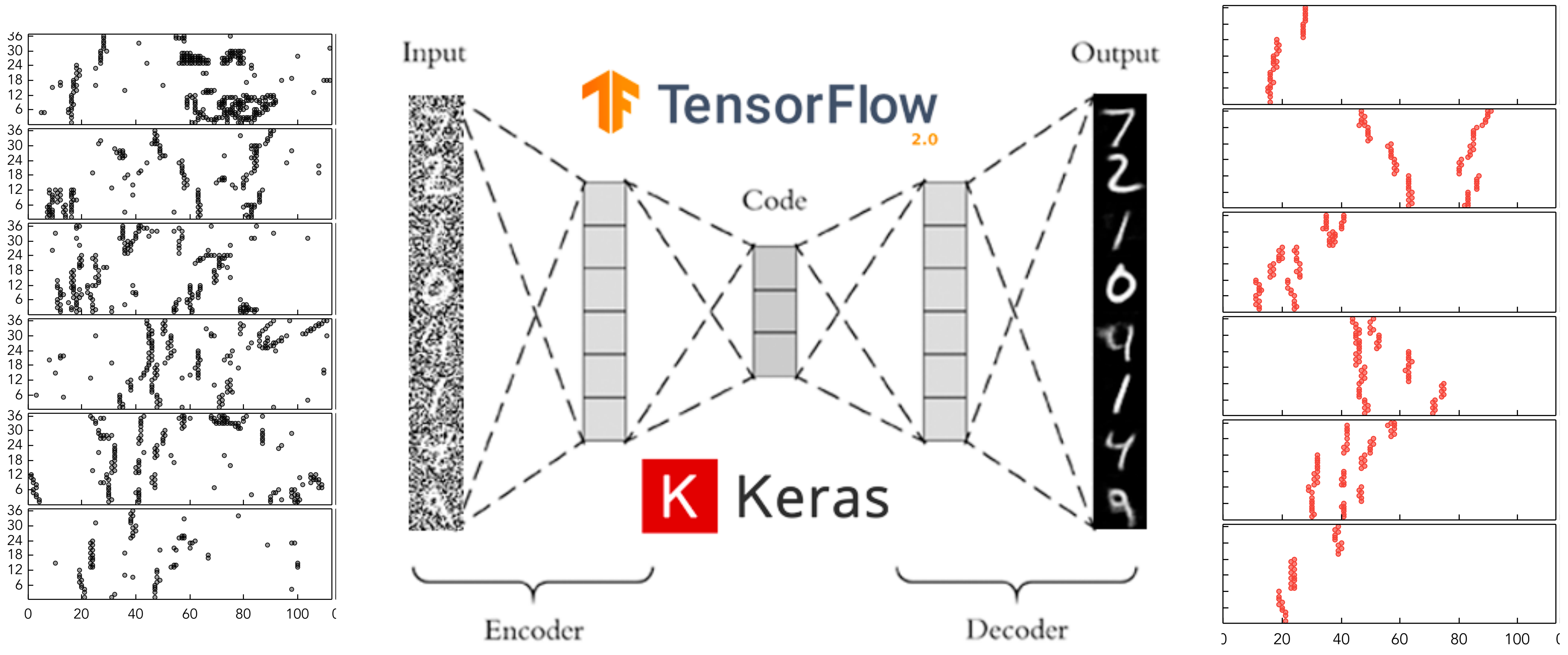


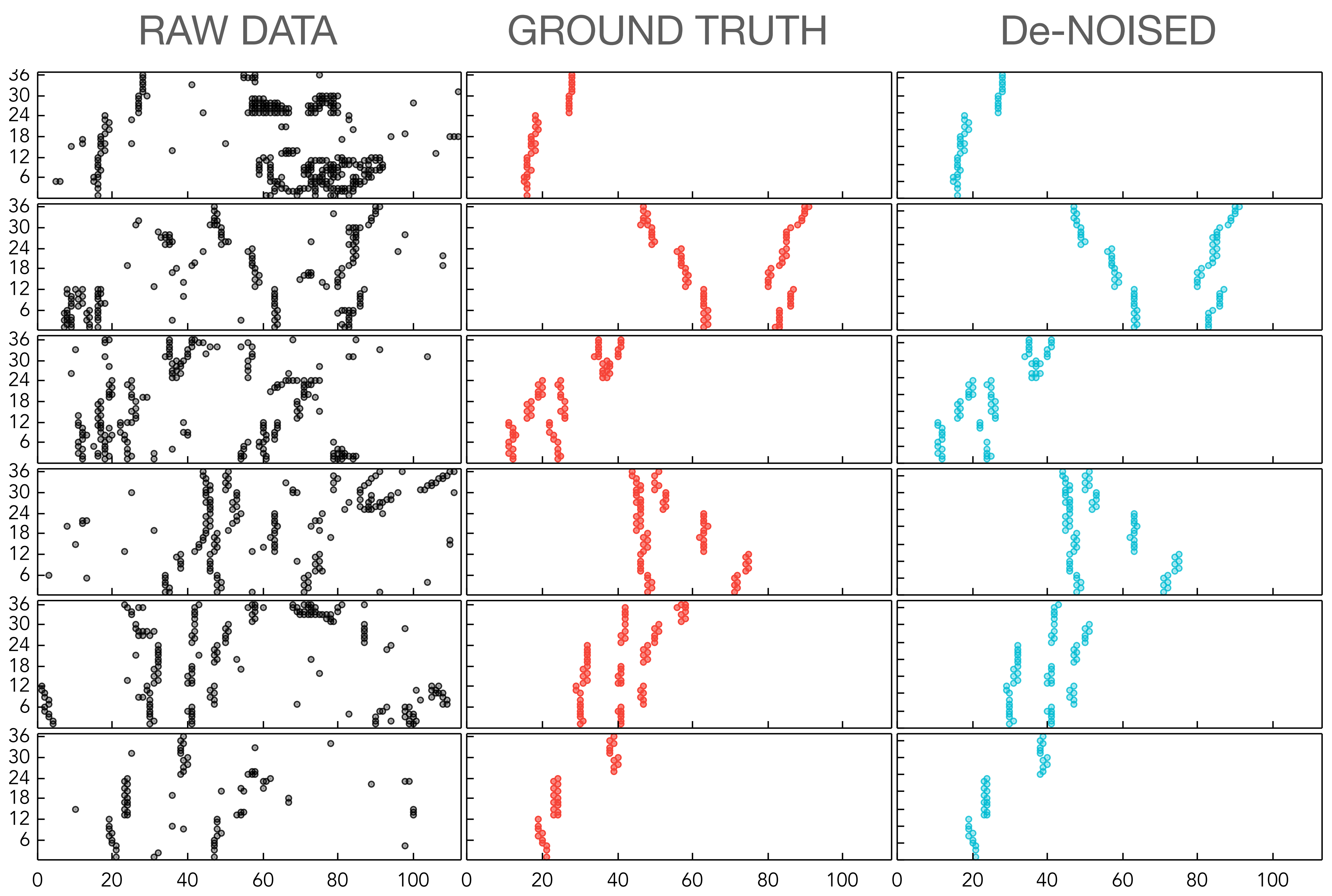




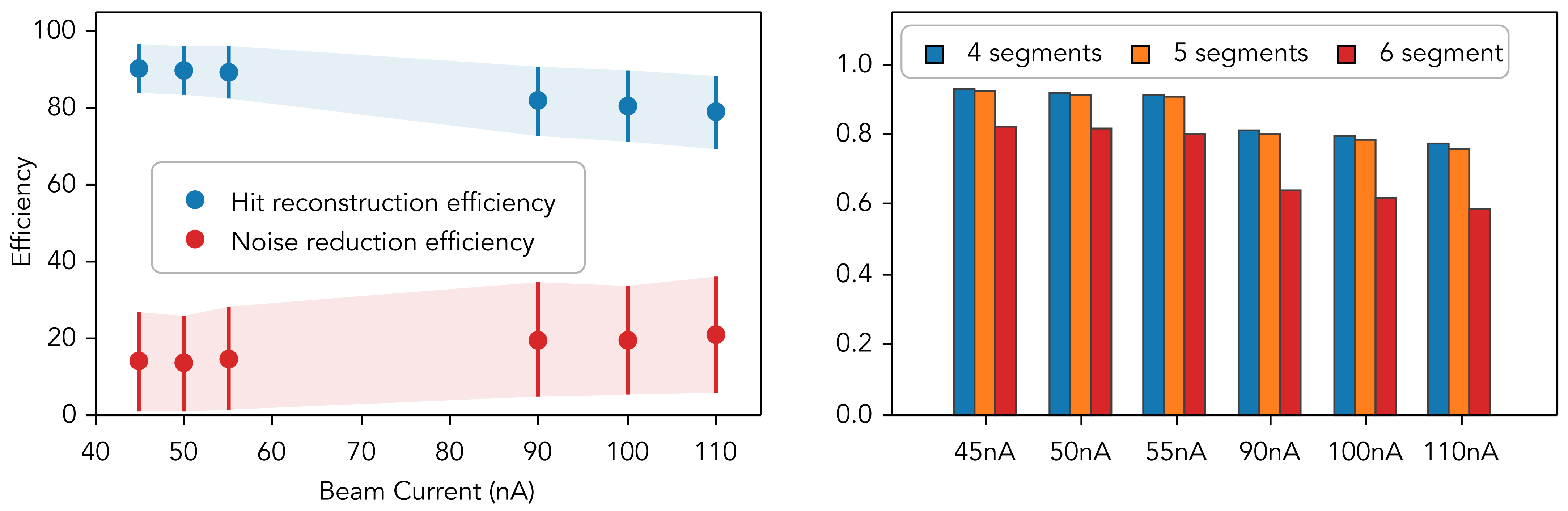
De-Noising

- Convolutional Auto-Encoder is used to de-noise raw data from drift chambers.
- The network is trained on reconstructed data with track hits isolated from raw DC hits.
- The network is able to isolate hits that potentially belong to a valid track through drift chambers



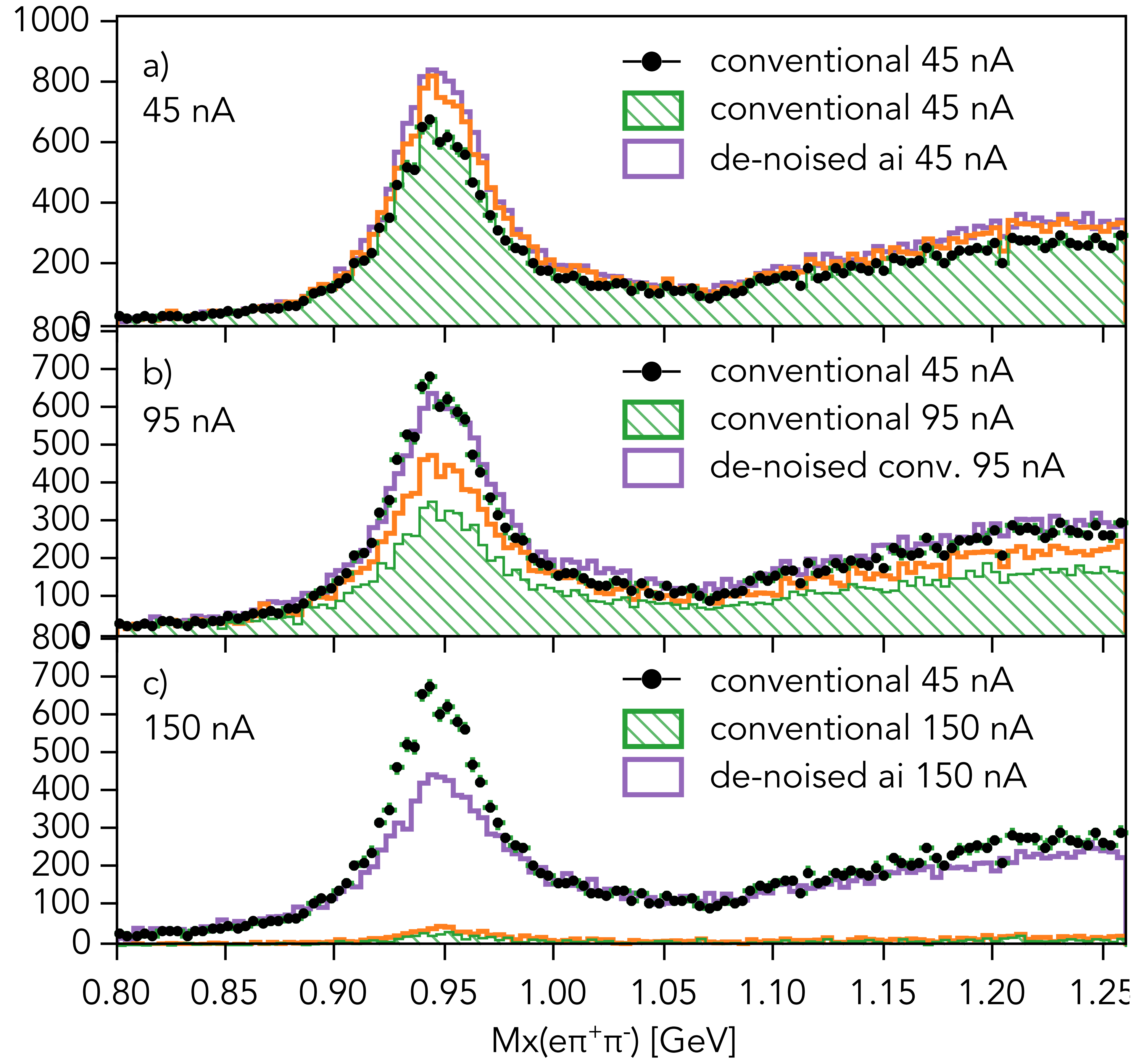


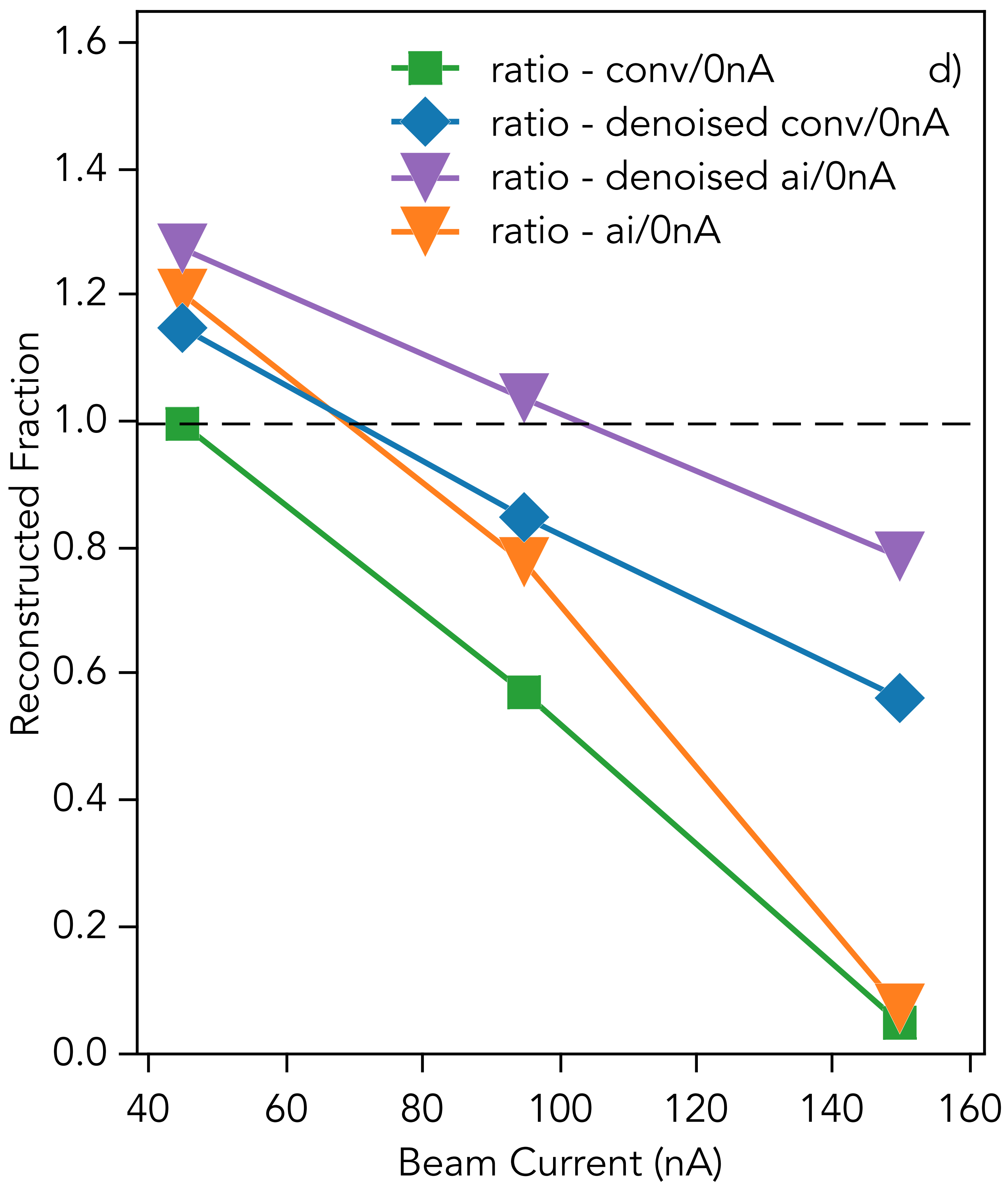
Network Performance Summary



De-Noising Results (simulation)

- The reconstruction is run on simulated data with a merging background for different incident beam currents (luminosity)
- The simulated three-particle final state is analyzed to measure yield for de-noised data and for conventional

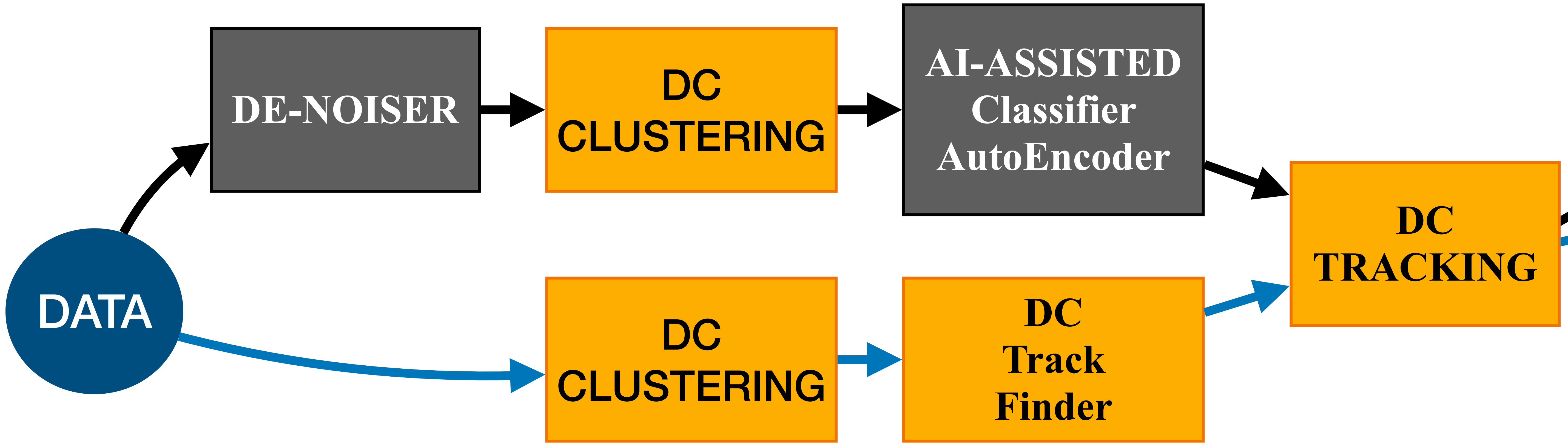


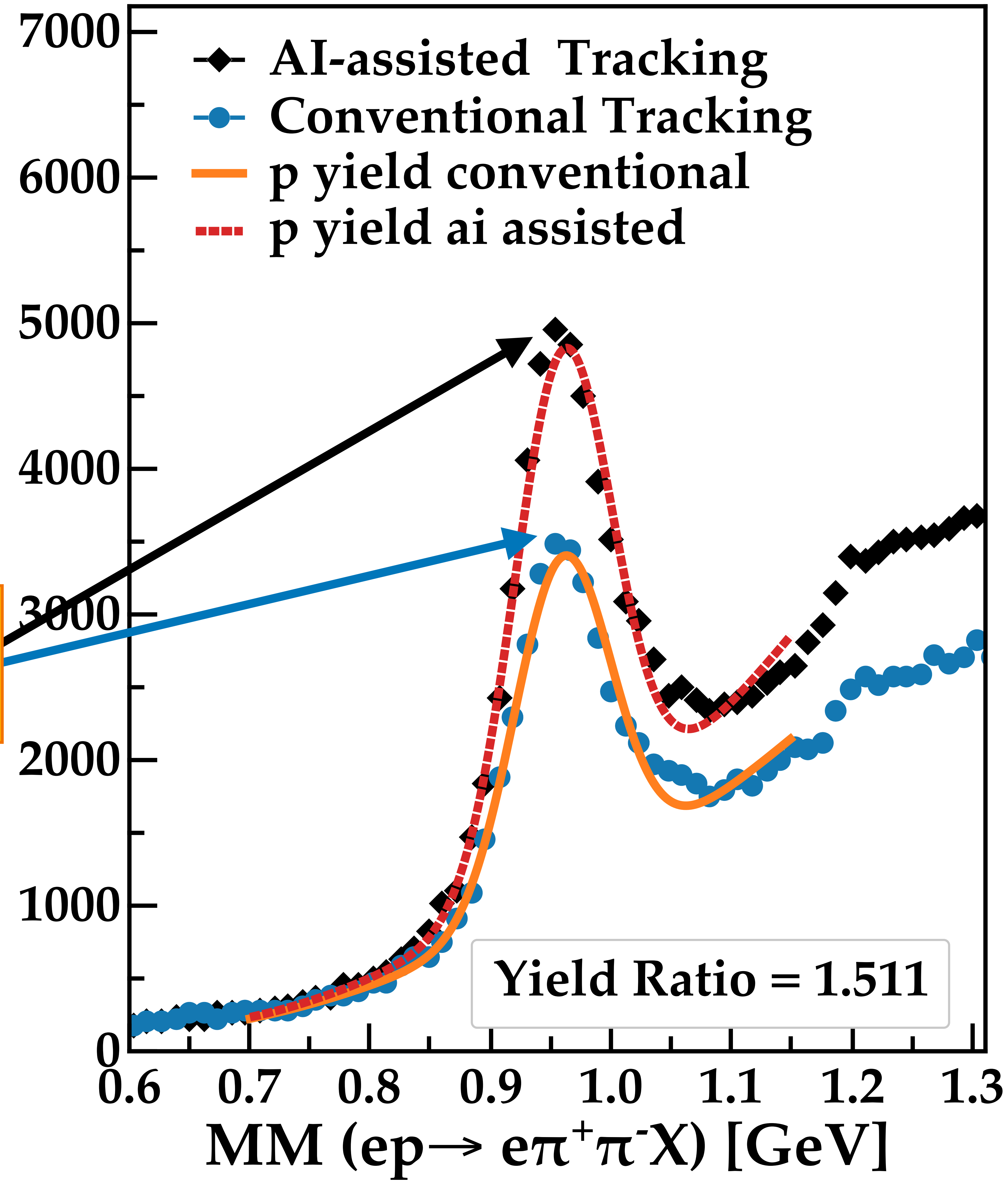


- At standard running luminosity, the de-noising slightly increases the yield compared to AI-assisted tracking.
- With increased luminosity, the de-noising helps to increase the yield significantly compared to conventional and AI-assisted tracking.
- Simulation underestimates the gain in yield significantly. In data the gain is much larger.

Current Workflow

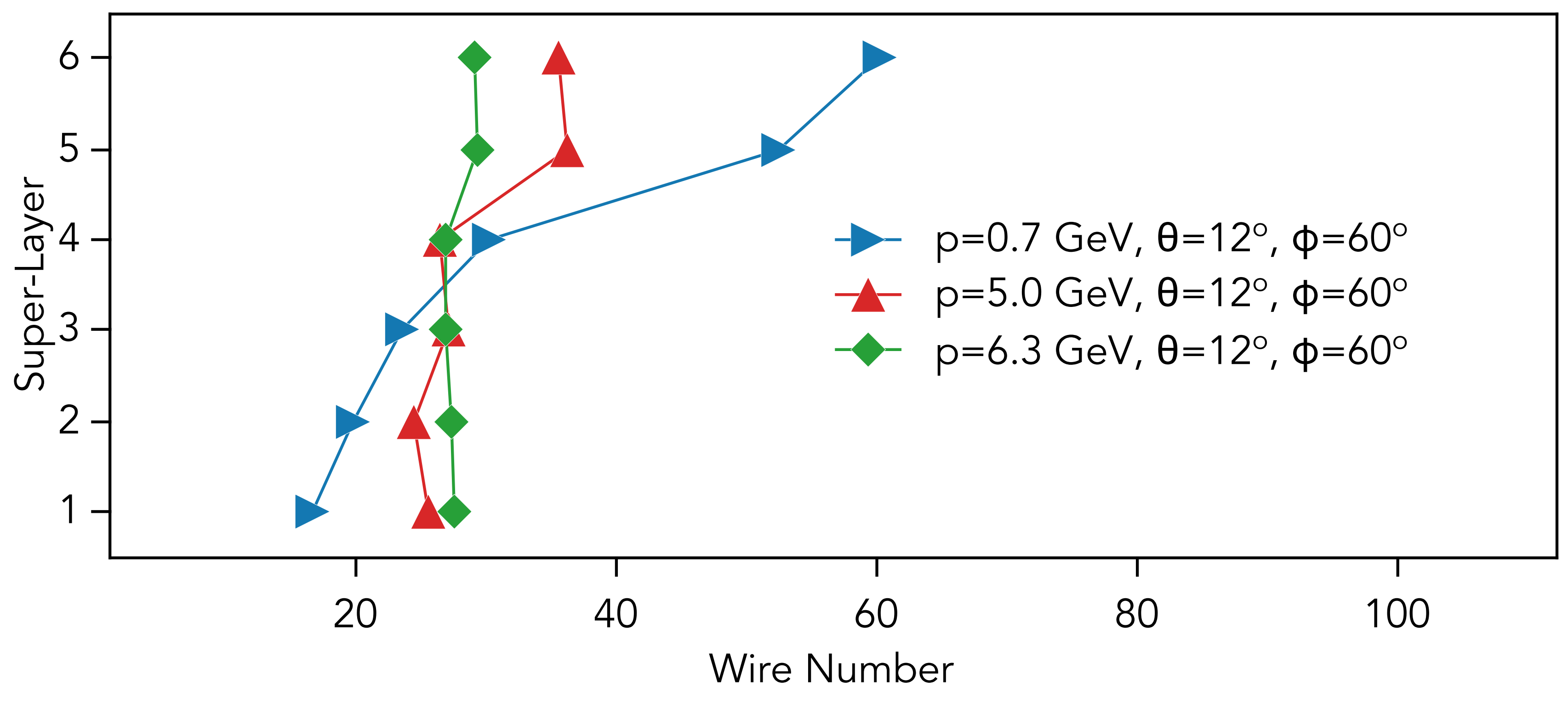
- CLAS12 Reconstruction software is based on SOA (CLARA) approach, where each detector reconstruction runs as a separate service
- The data reconstruction workflow now included de-nosier running prior to standard clustering and AI-Assisted tracking running prior to DC track finding.
- Drift Chambers code runs tracks suggested by AI-assisted tracking through Kaman-filter for final track parameter calculations.

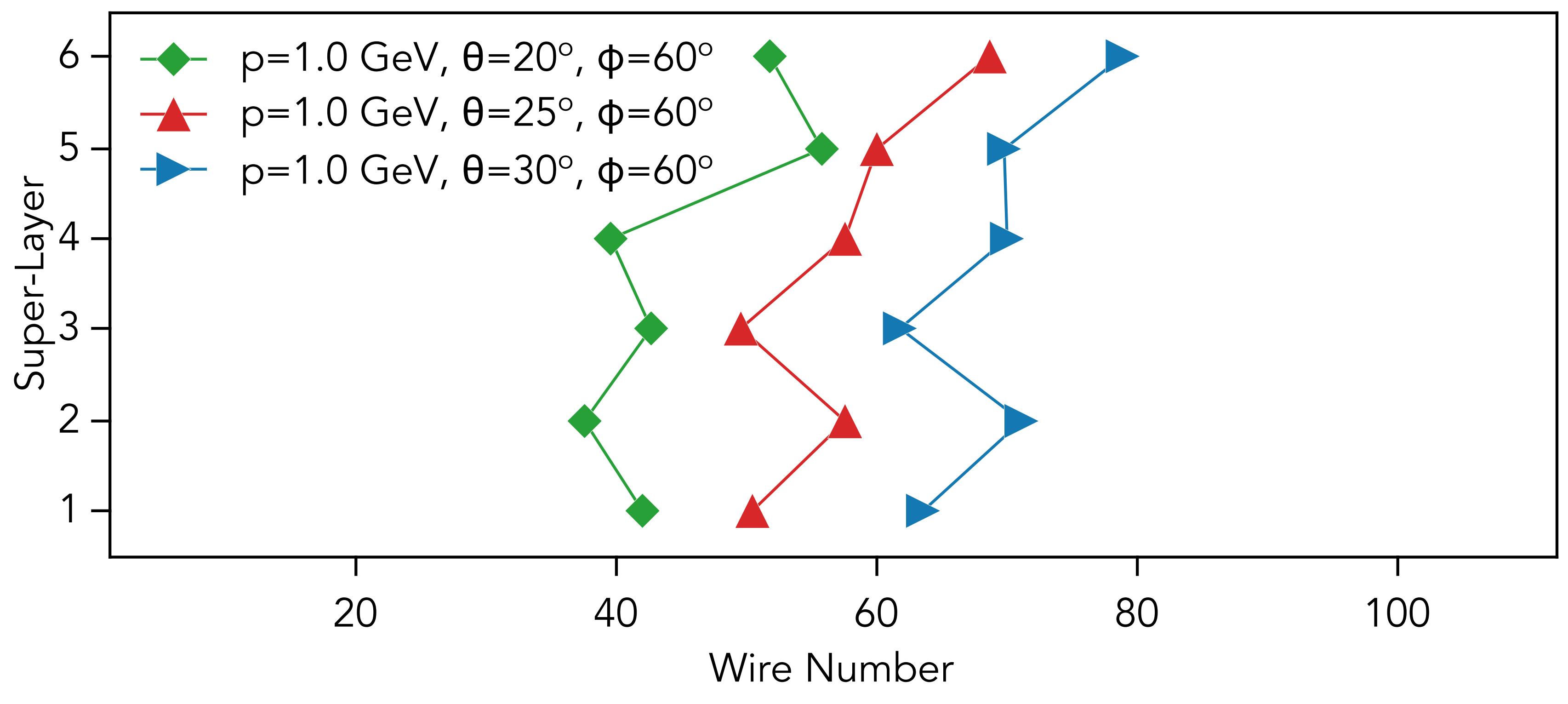


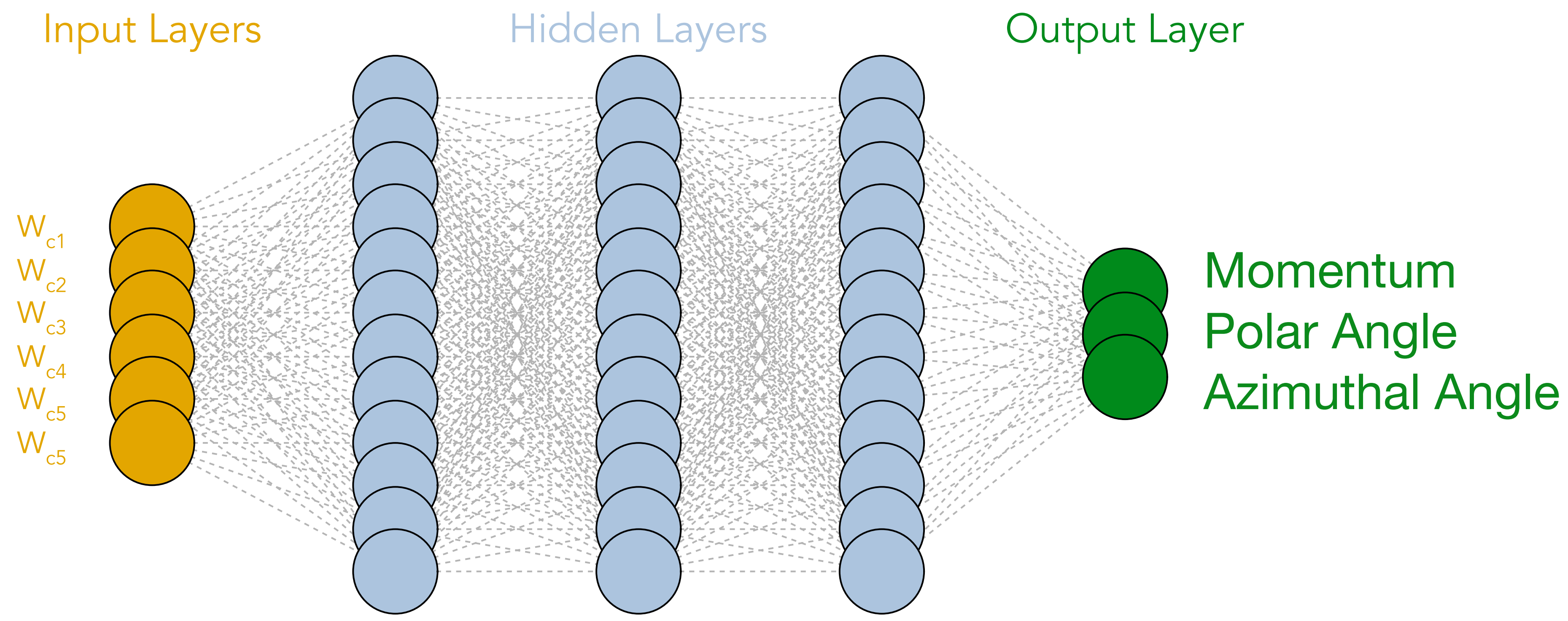


- Running at standard conditions (45 nA beam current) the AI increased the yield of missing protons by 51%.
- The improvement in yield is reaction and kinematics dependent, and for some event topologies reaches even 83% (J/psi with 3 particles detected final state).

Track Parameter Reconstruction

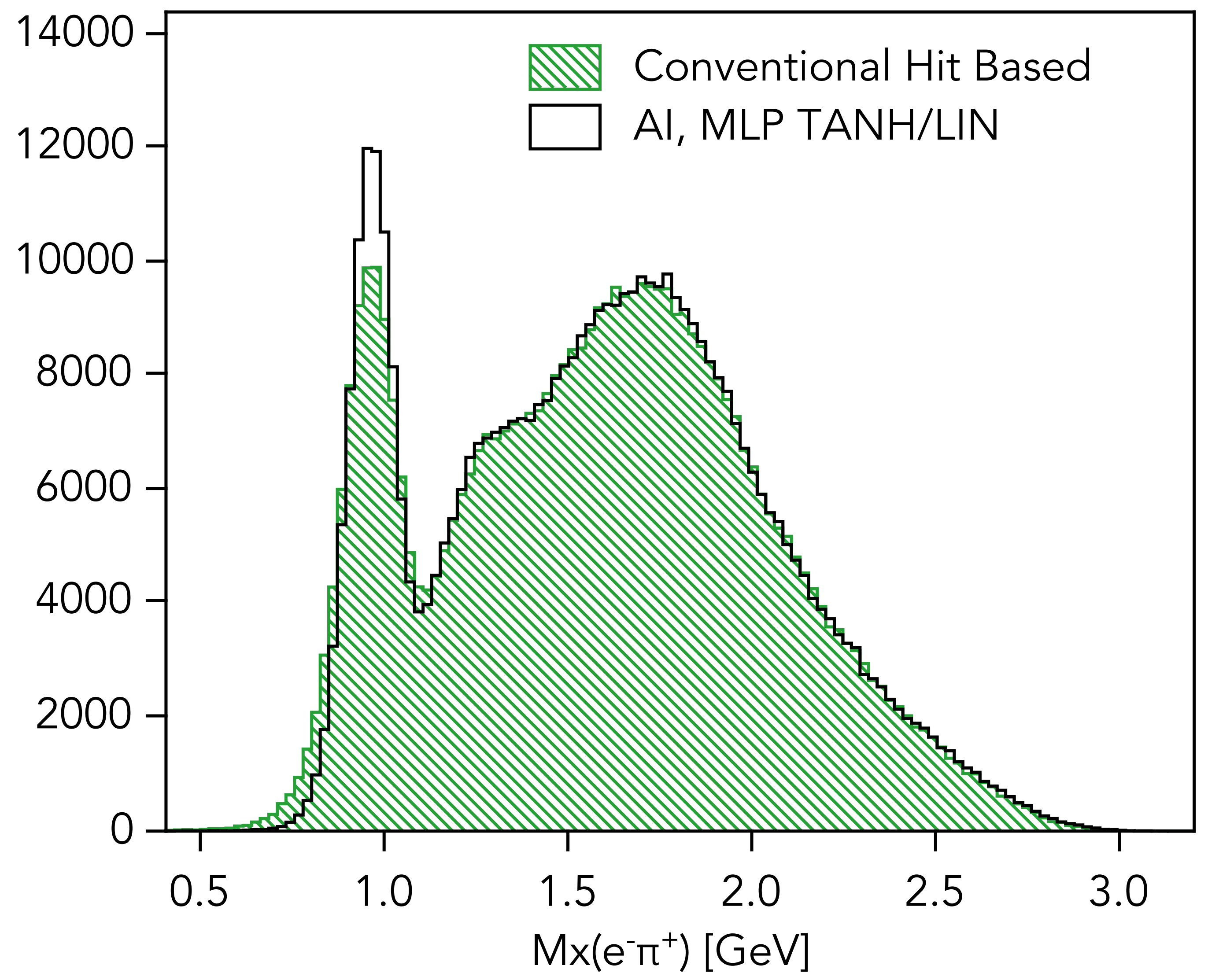






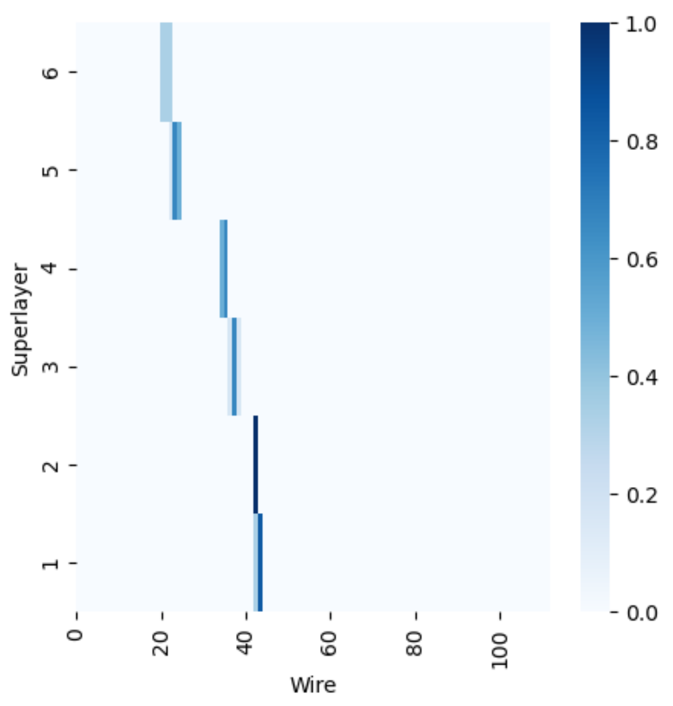
- Charge Track Parameter Inference
  - Reconstruct momentum and angles of particles based on the cluster positions of the tracks
  - Particles have distinct trajectories through drift chambers depending on their momentum, polar and azimuthal angle.
  - Design an MLP network and investigate different combinations of activation functions to derive the best network for this problem.

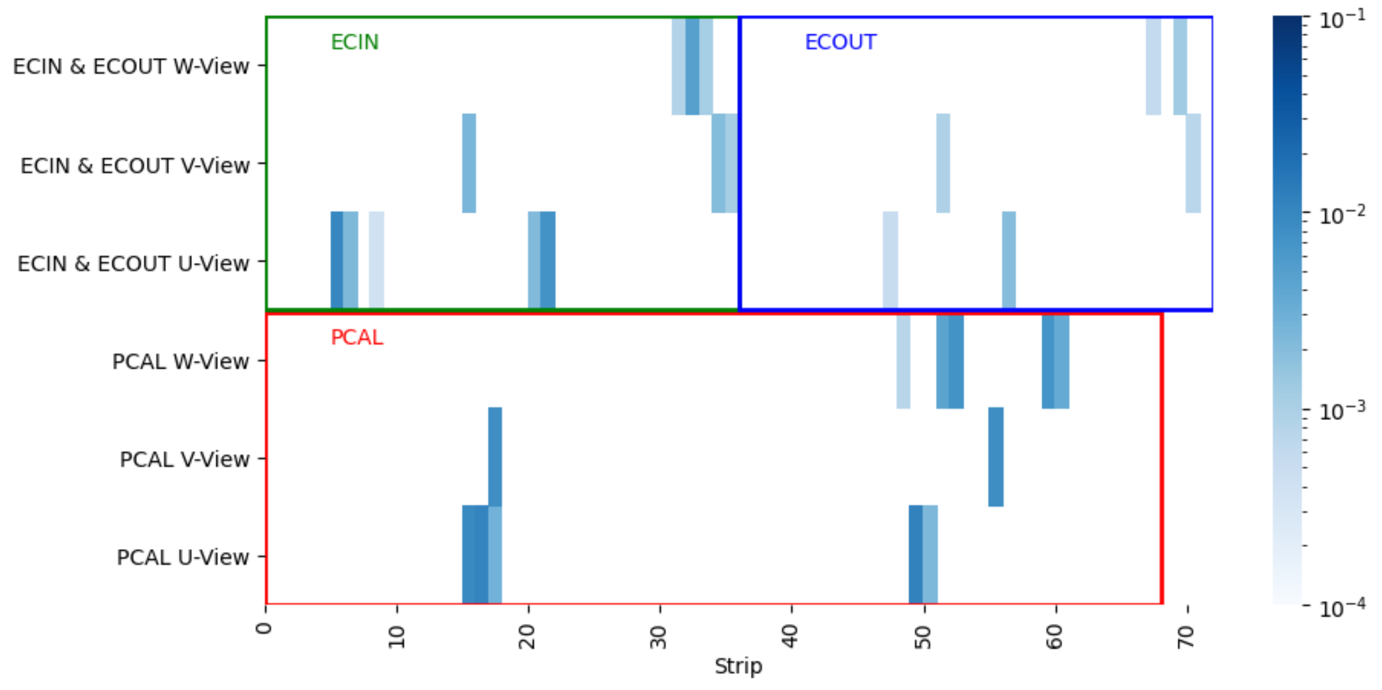
$$ep \to e^- n\pi^+$$

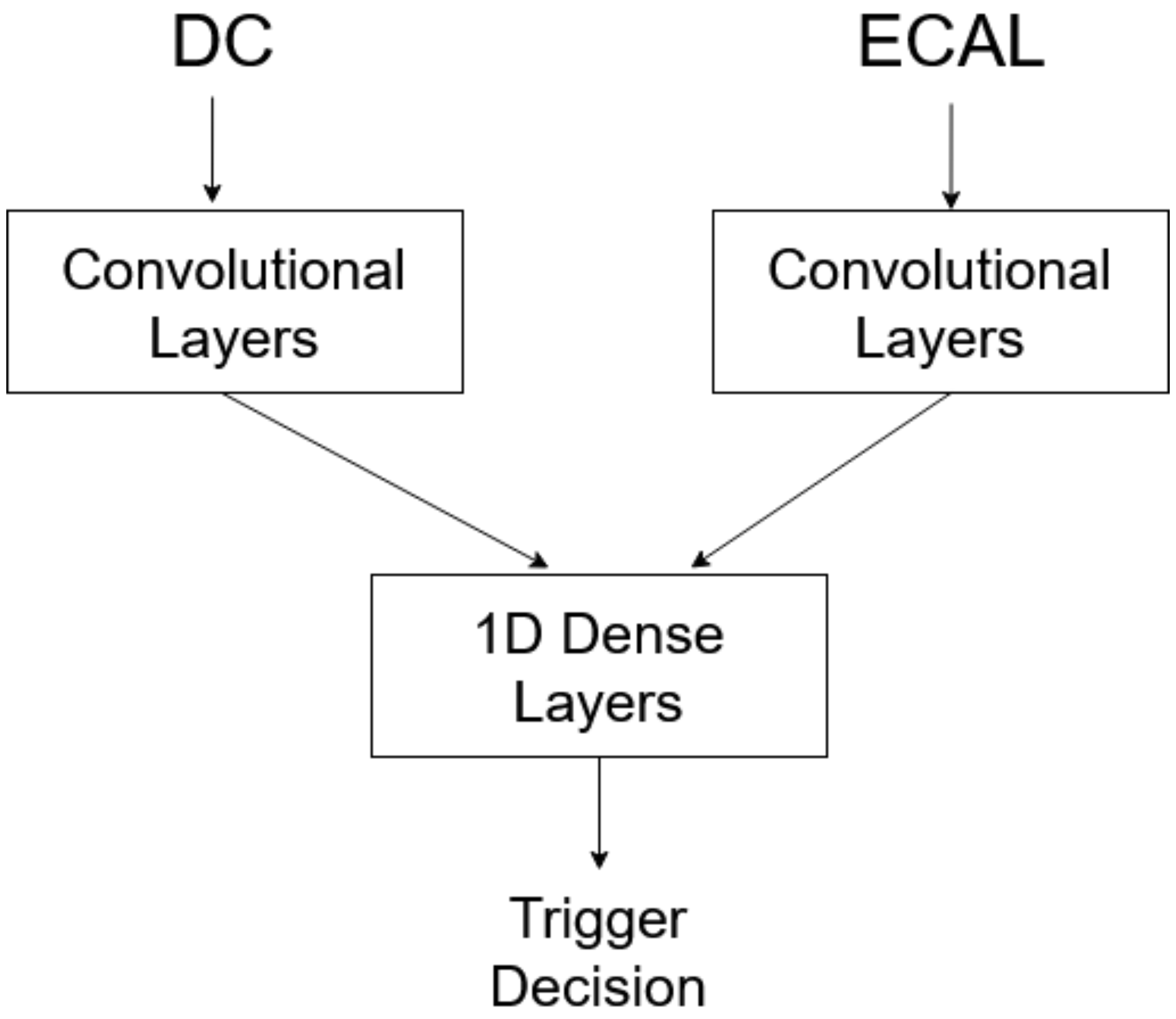


- Missing mass of two particles calculated using particle momenta from Hit-Based Tracking compared to missing mass calculated from AI particle parameter inference.
- Hit Based Tracking works ~250 ms per event
- AI reconstructs particle parameters <0.5 ms per event

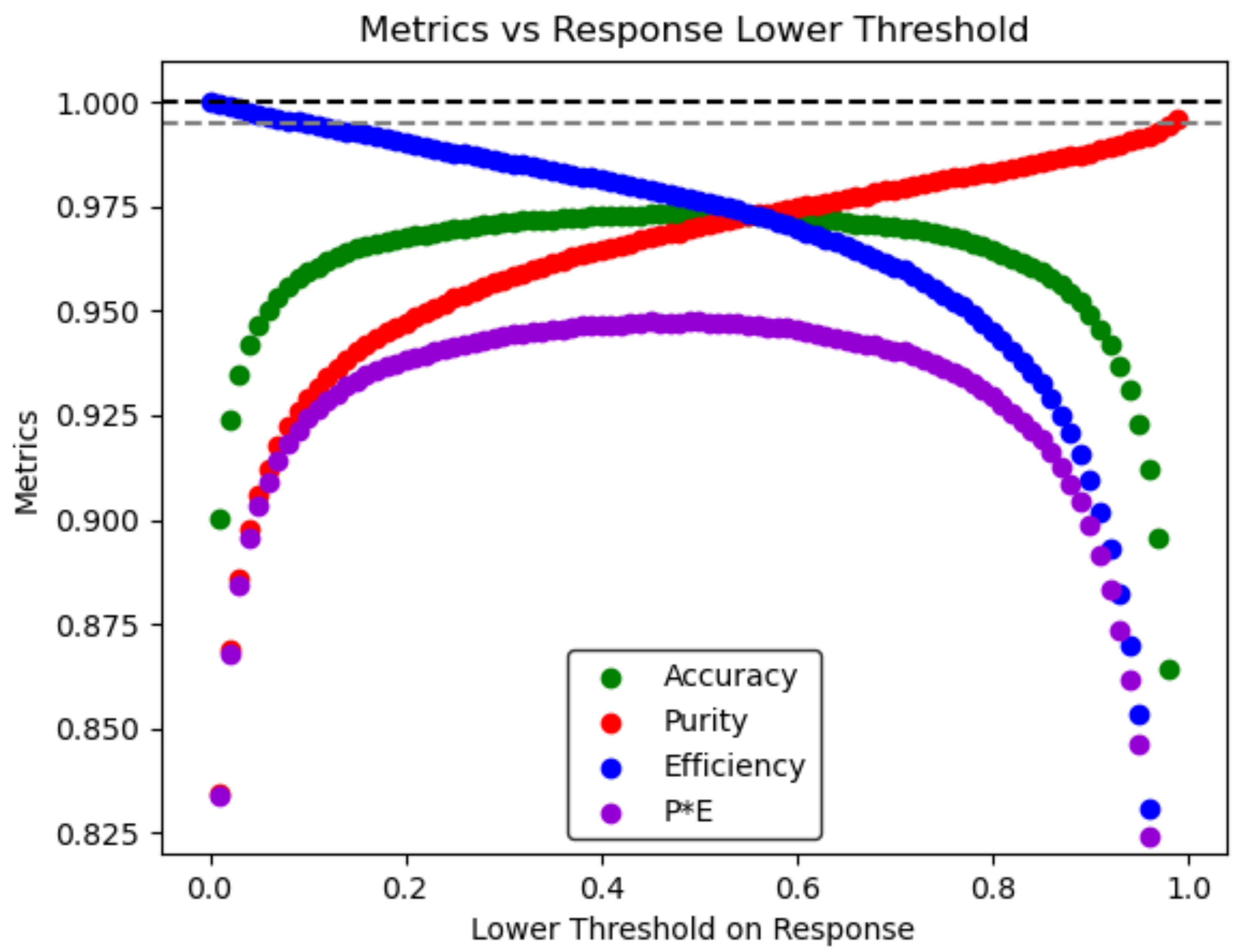
Data Collection Efficiency (Level-3 trigger)





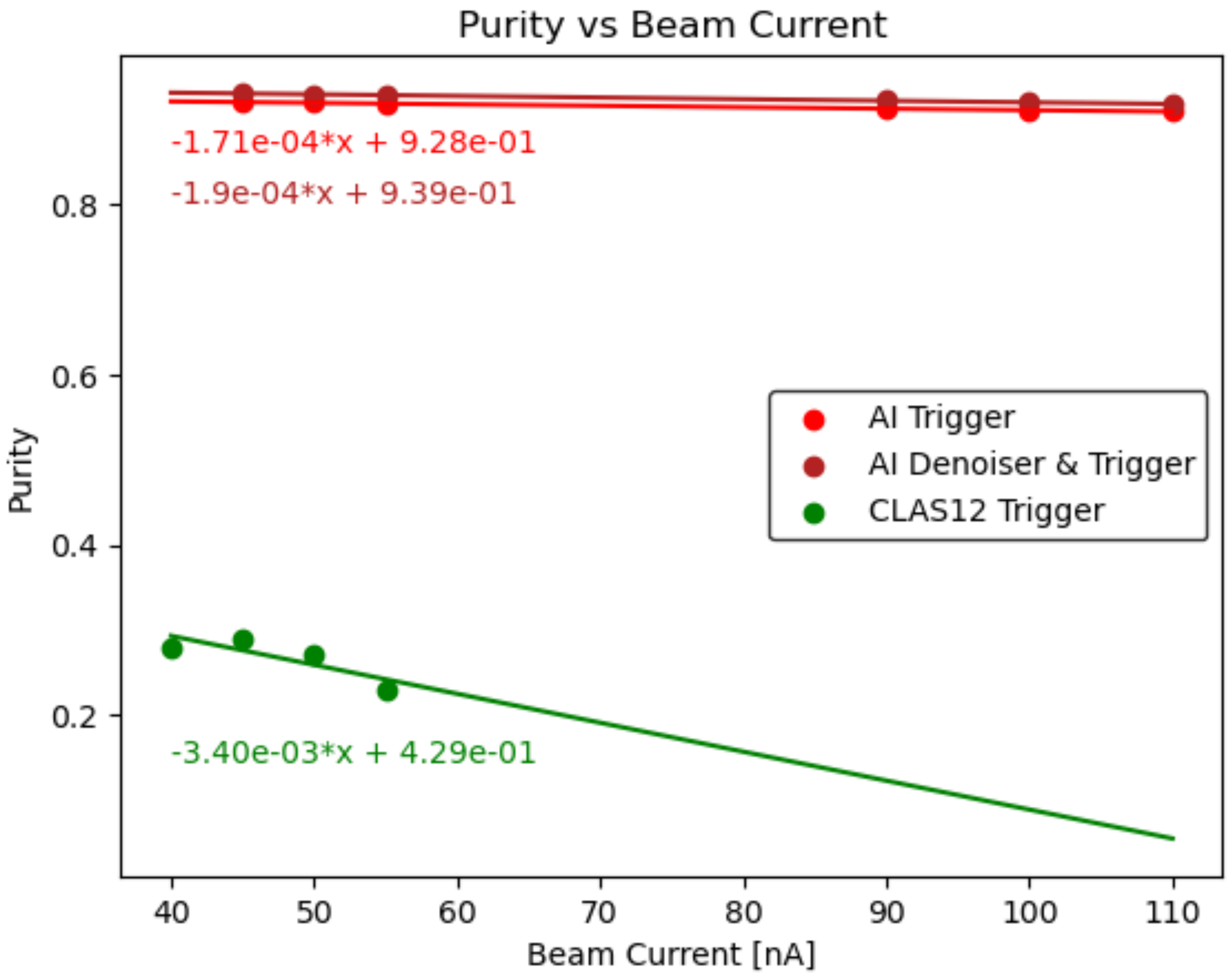


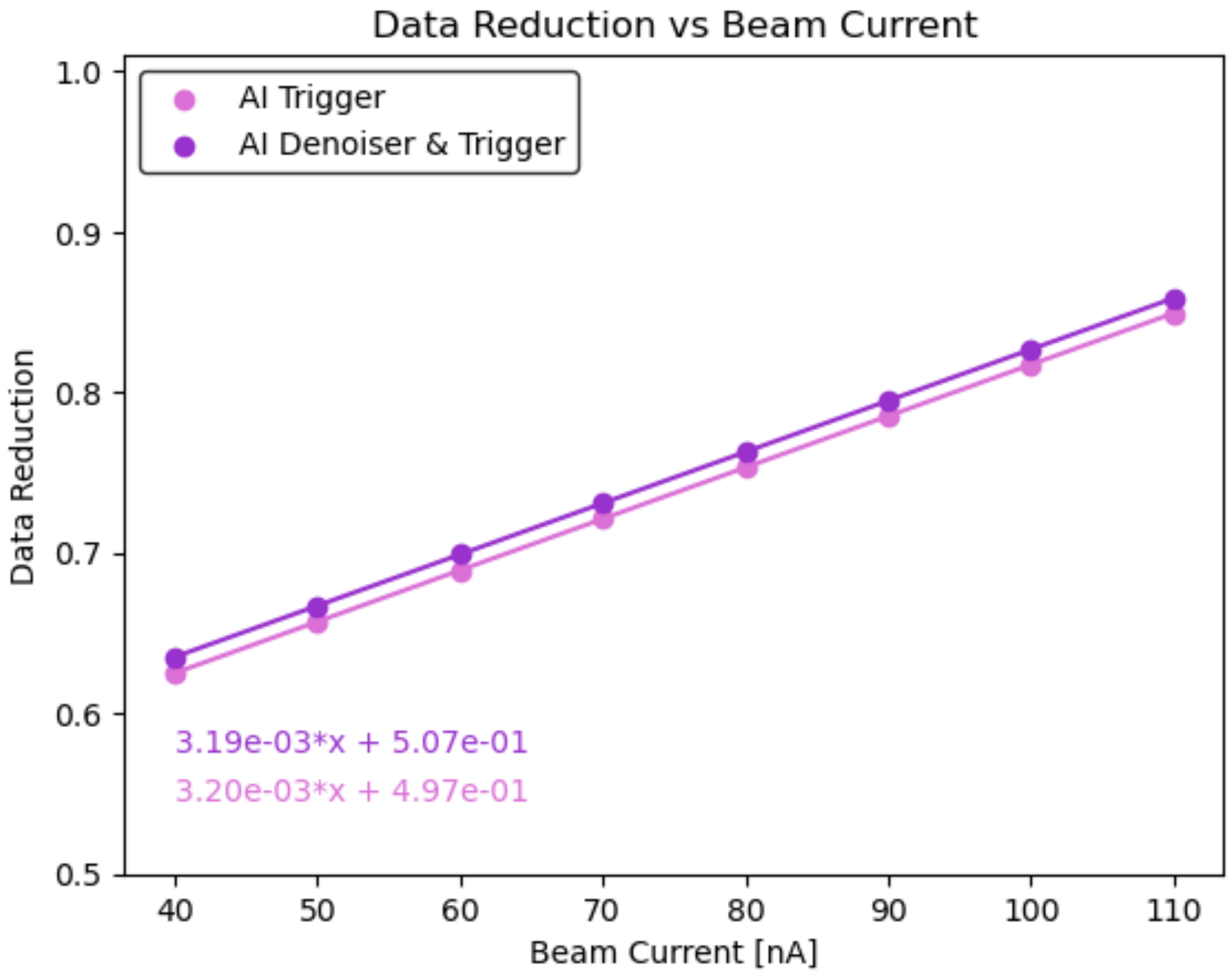
Threshold	Purity	Efficiency	Accuracy
0.0012	0.841	0.9999	0.906
0.03	0.930	0.999	0.962
0.47	0.977	0.99	0.983



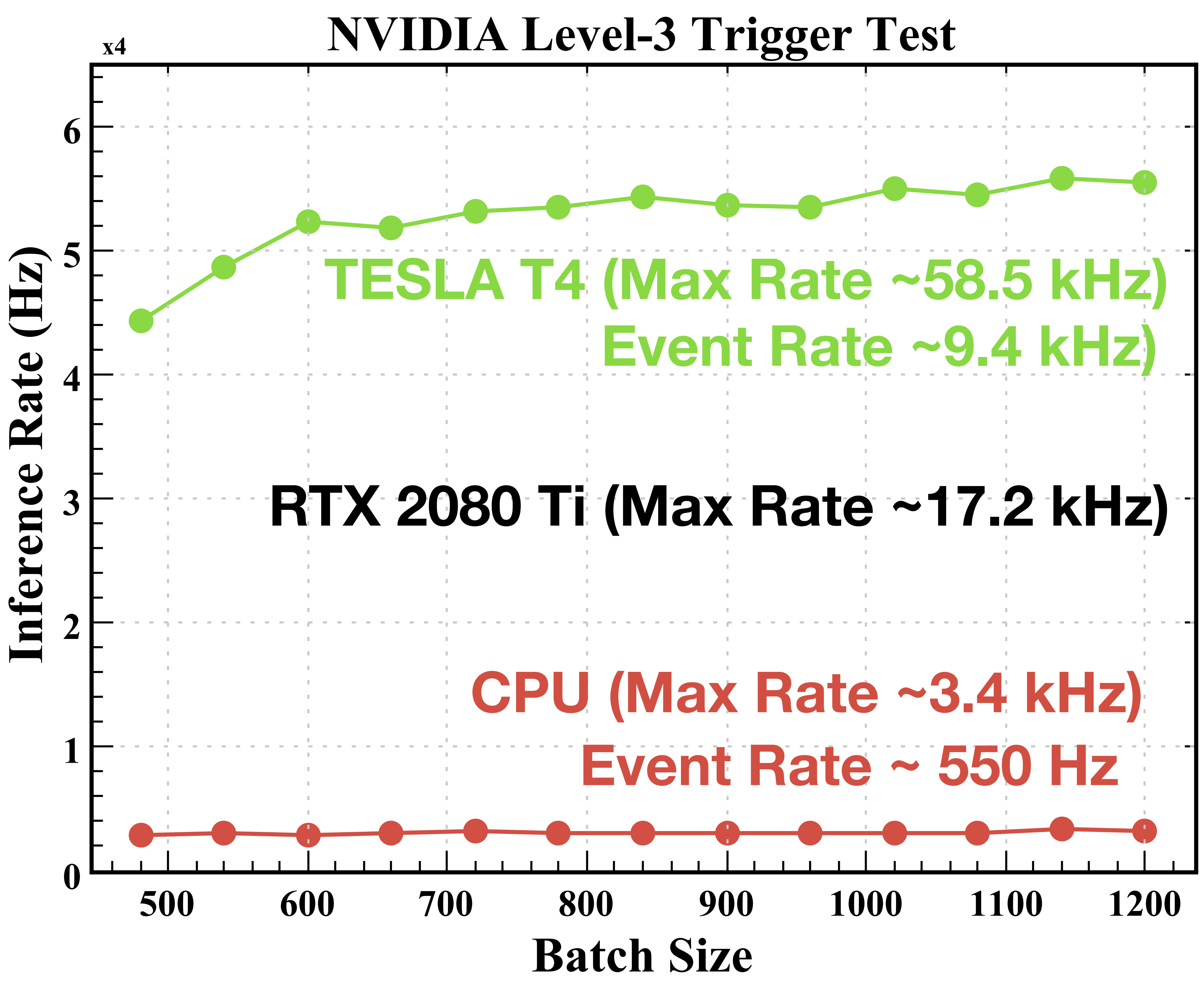
- Level-3 Trigger
  - A Convolutional Neural Network with a Computation graph is used to identify electrons.
  - The DC image is analyzed separately from the EC image, then combined to make a decision.
  - The ECIN, ECOUT, and PCAL are combined into one image 6x72
  - The current implementation does not use information from High-Threshold Cherenkov Detector

Level-3 Trigger Performance compared to conventional Trigger





- Neural Network was developed for Level-3 trigger studies. (Richard Tyson, University of Glasgow)
- The Software was tested on clonfarm11 node with two NVIDIA Tesla T4 GPUs (2 available, tested only on 1), over 3 times faster than RTX 2080 Ti
- Results are reported as inference per second (inference is per one sector)
- The real data rate is inference divided by 6
- Results are reported for 1 CPU core and 1 GPU unit

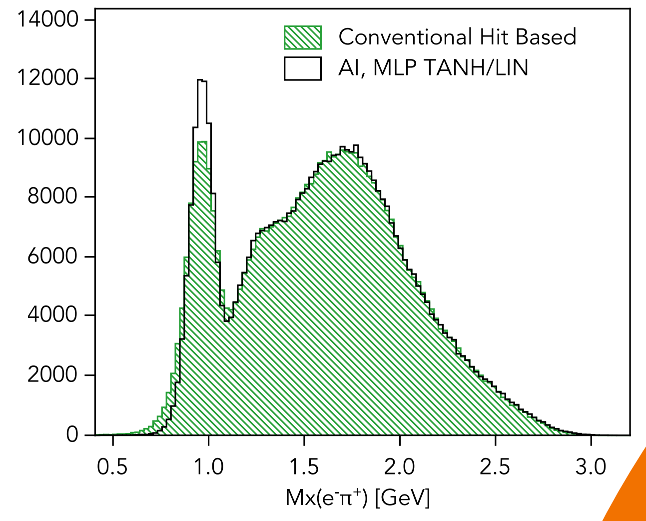


- Online multi-threaded data decoder into HIPO is implemented (C++)
- Currently contains only DC and ECAL decoding
- The ET-RING is set up to convert EVIO events into HIPO data frames (100 events per frame) and store HiPO frames in secondary ET-RING
- The Level-3 trigger will be tested during the next run
- With HiPO ET-RING we can now implement online data reconstruction (AI track reconstruction will be easy to add)
- Online data calibration is also possible

Threshold	Purity	Efficiency	Accuracy
0.0012	0.841	0.9999	0.906
0.03	0.930	0.999	0.962
0.47	0.977	0.99	0.983

Future of CLAS12-AI (ALL components exist, moving towards online)

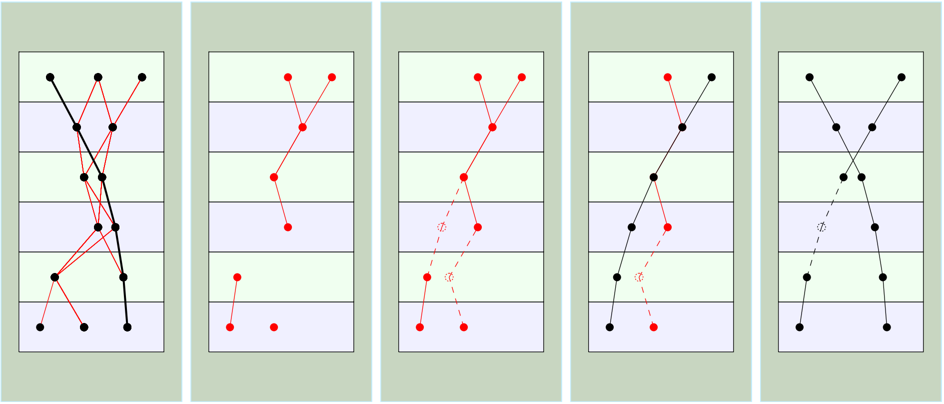
Physics Reconstruction (AI)



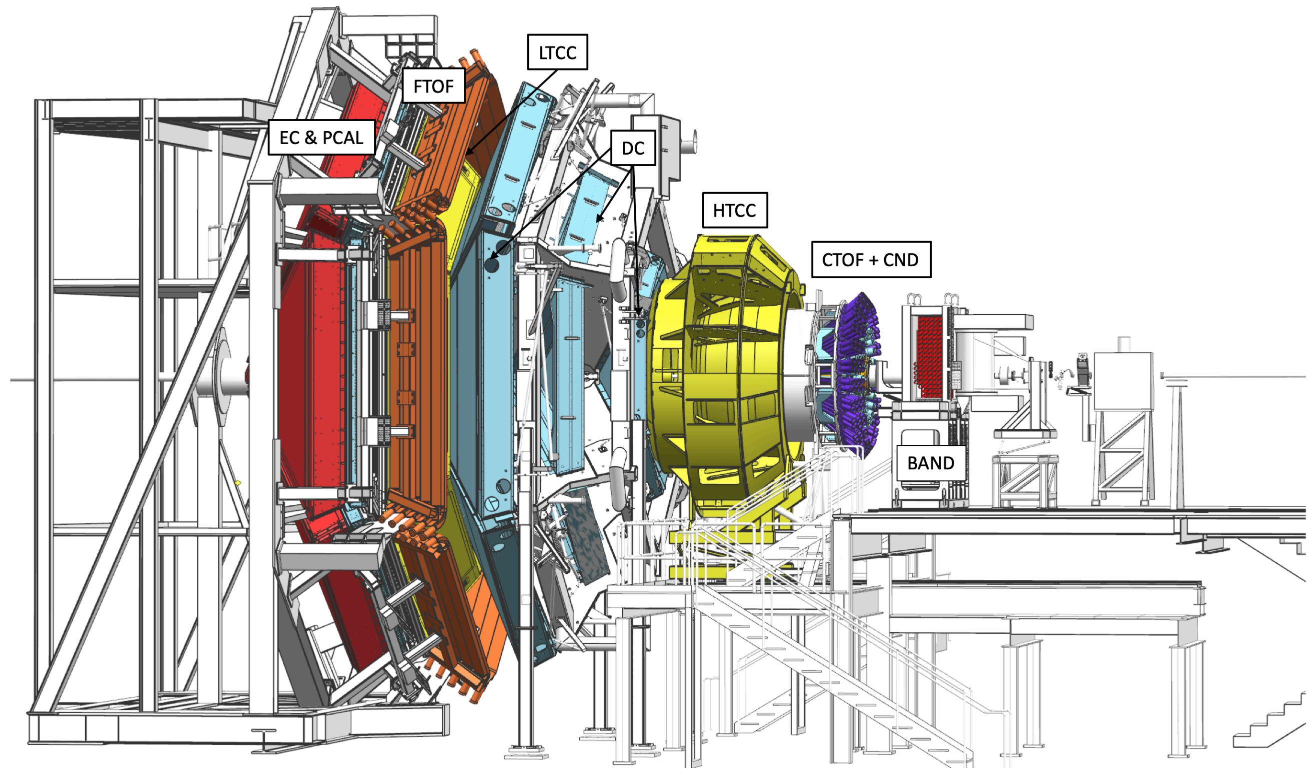
Data Persistence

Saving experimental data
Already containing tracks
And physics topologies
Identified by AI

Track Classification (AI)



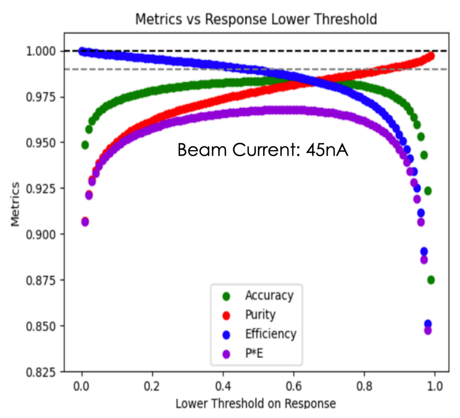
Classifying track candidates from
Reconstructed clusters
In real-time

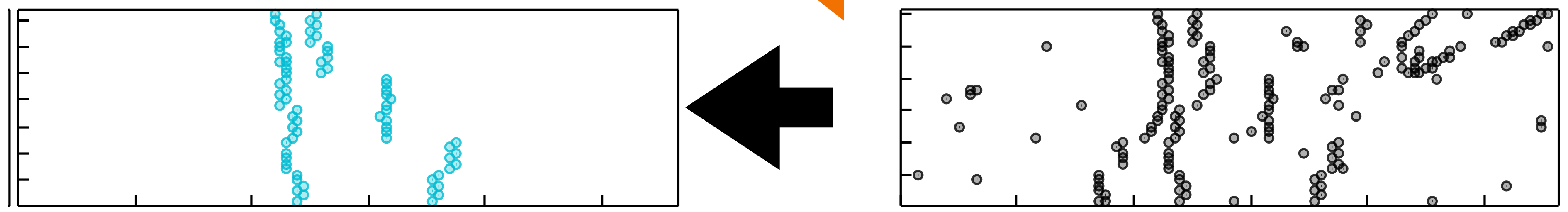


Data Acquisition

Level-3 Trigger (AI)

Threshold	Purity	Efficiency	Accuracy
0.0012	0.841	0.9999	0.906
0.03	0.930	0.999	0.962
0.47	0.977	0.99	0.983



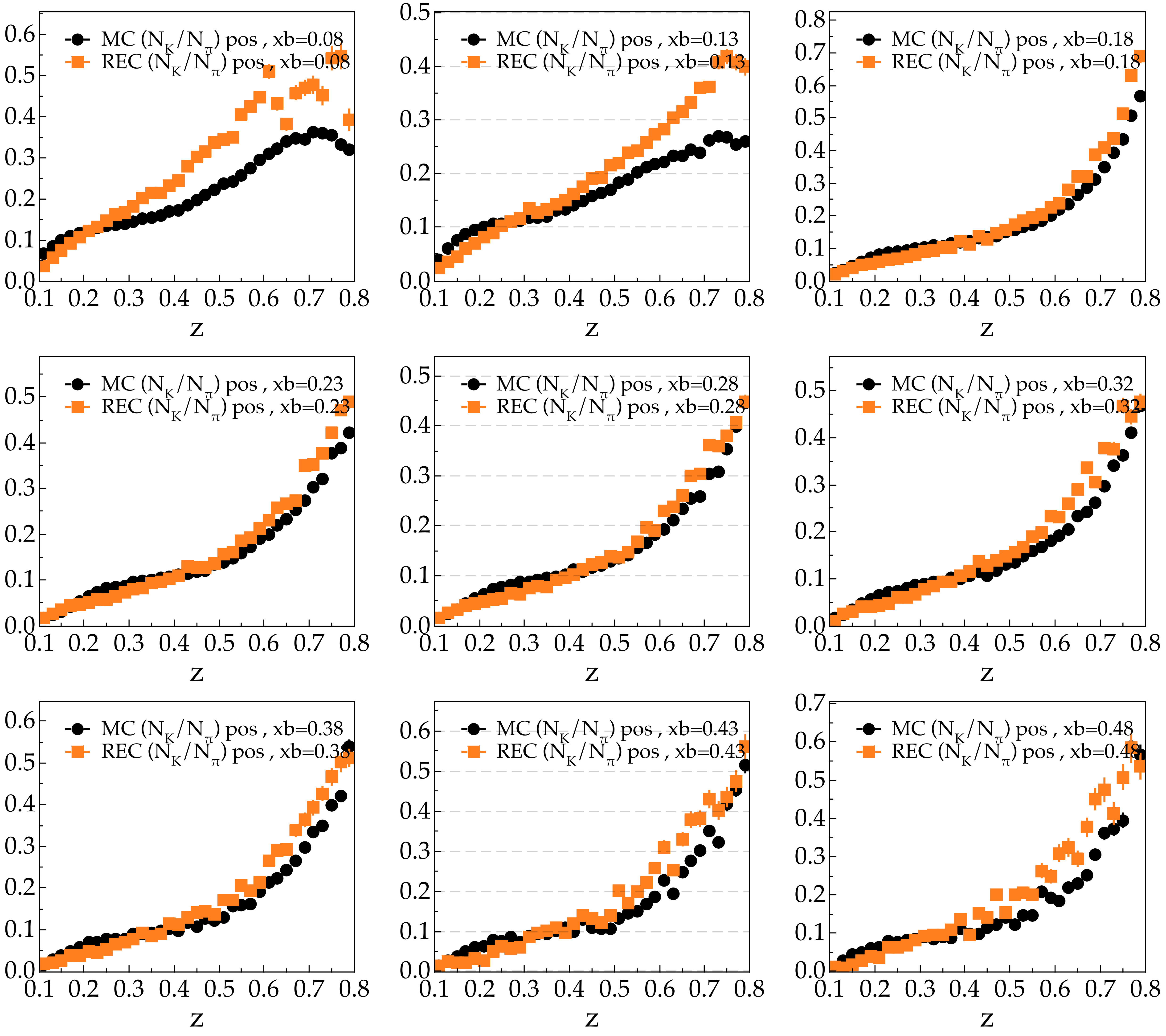


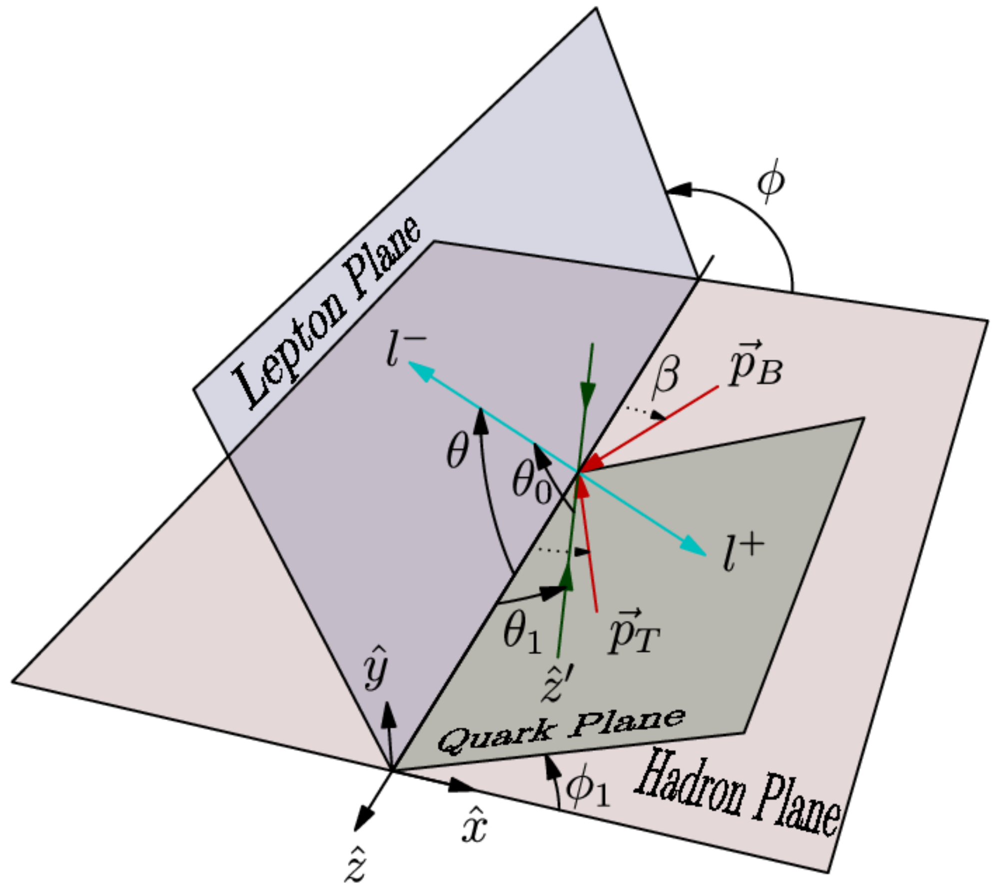
Removing Noise signals
From tracking detectors

Data De-Noising (AI)

Particle Identification

Physics Analysis/Particle Identification





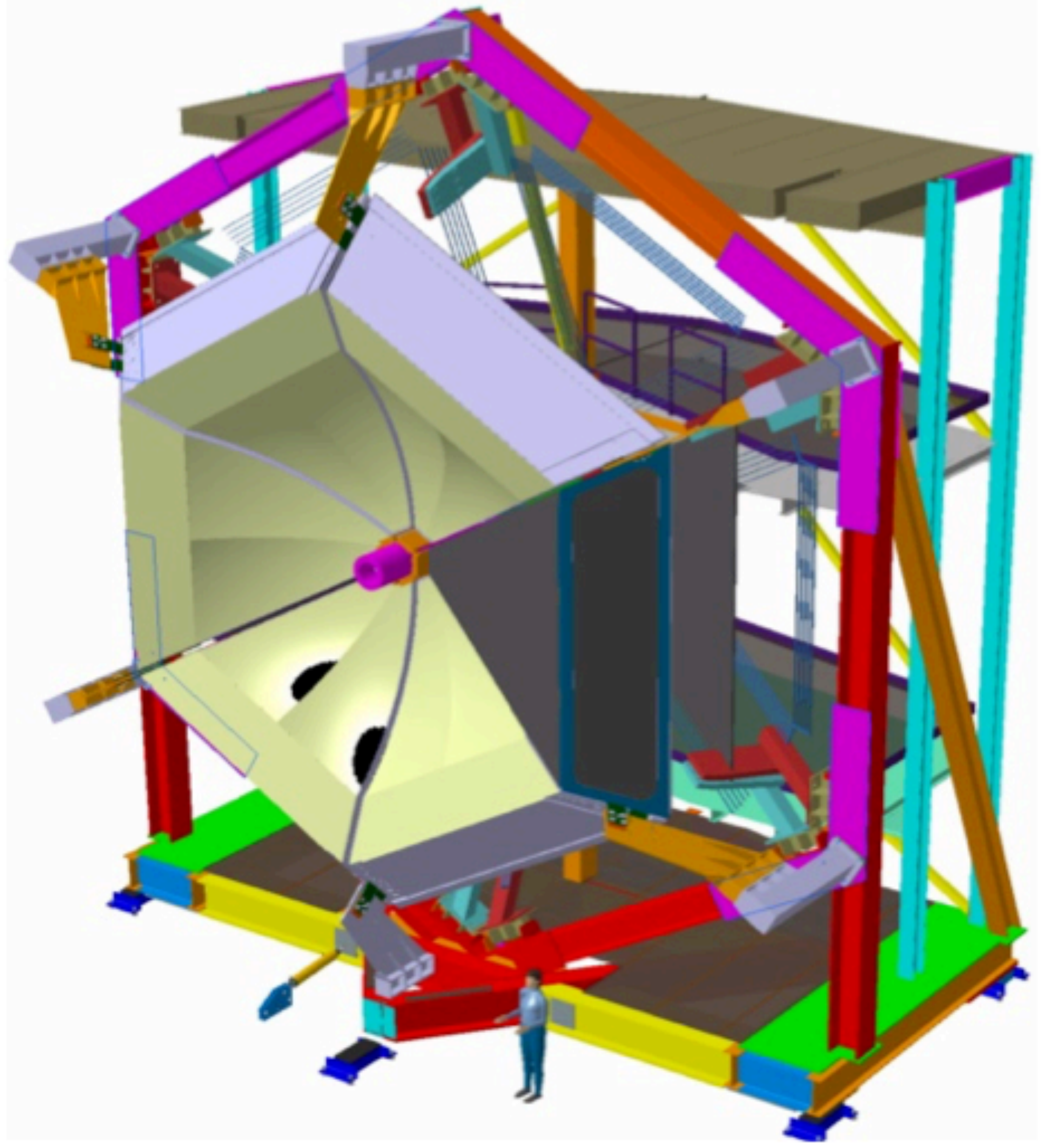
	U	L	T
Quarks	γ^+	$\gamma^+\gamma^5$	$i\sigma^{i+}\gamma^5$
U	$\boldsymbol{f_1}$		$h_1^\perp$
L		$\boldsymbol{g_1}$	$h_{1L}^\perp$
T	$f_{1T}^\perp$	g_{1T}	$\boldsymbol{h_1}$, $h_{1T}^\perp$
LL	$\boldsymbol{f_{1LL}}$		$h_{1LL}^\perp$
LT	f_{1LT}	g_{1LT}	h_{1LT}, $h_{1LT}^\perp$
TT	f_{1TT}	g_{1TT}	h_{1TT}, $h_{1TT}^\perp$

- Traditional (time-of-flight) can effectively separate pi/K up to 3.5 GeV
- For full measurement of hadron multiplicities as a function of z and Pt need to separate hadrons at higher momenta to measure:
  - Hadron multiplicities
  - Single Spin Asymmetries (SSA)
  - Double Spin Asymmetries
- Measure fragmentation functions:

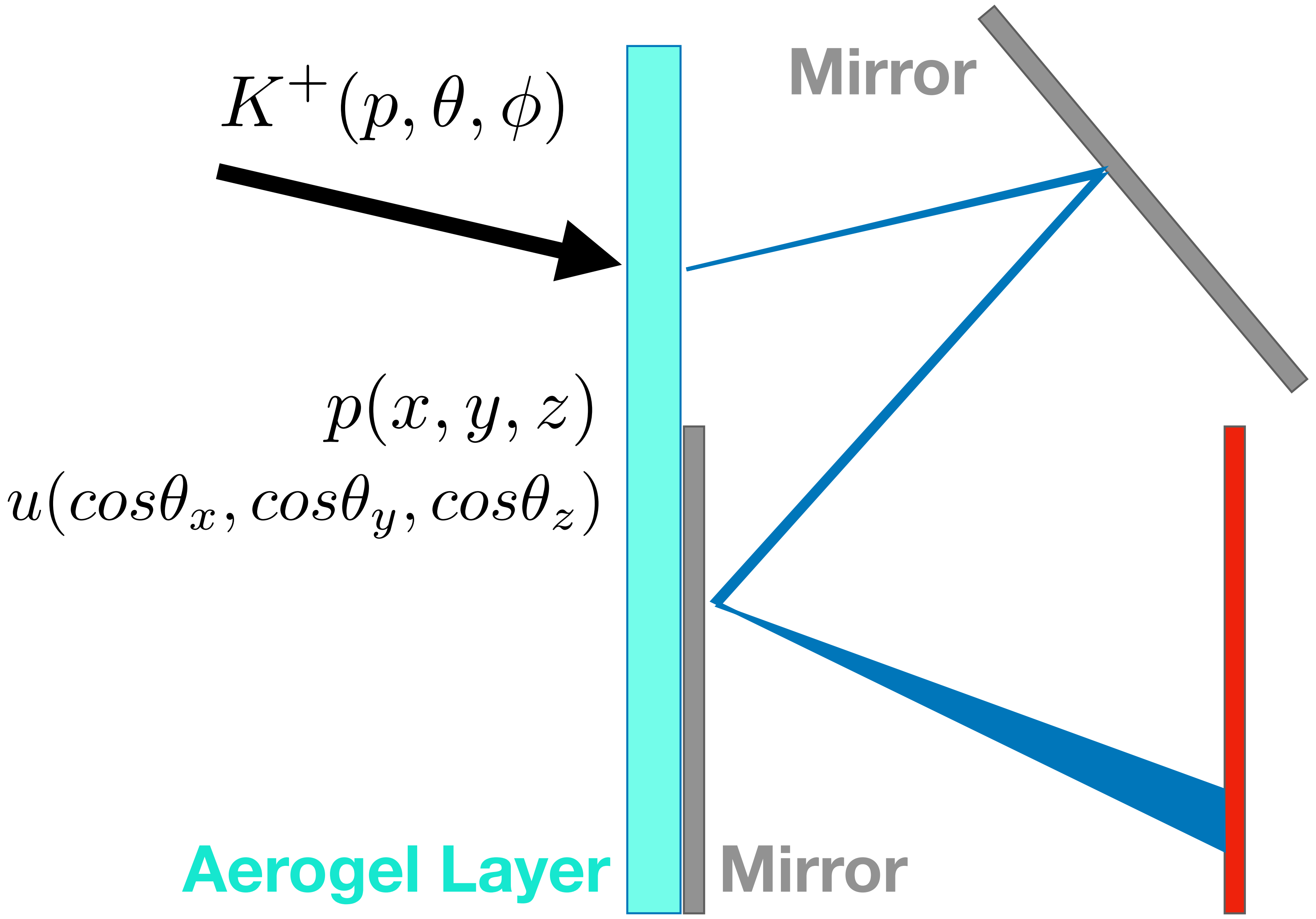
$$D^{q\to K}(z, P_T), D^{q\to\pi}(z, P_T)$$

CLAS12 – RICH

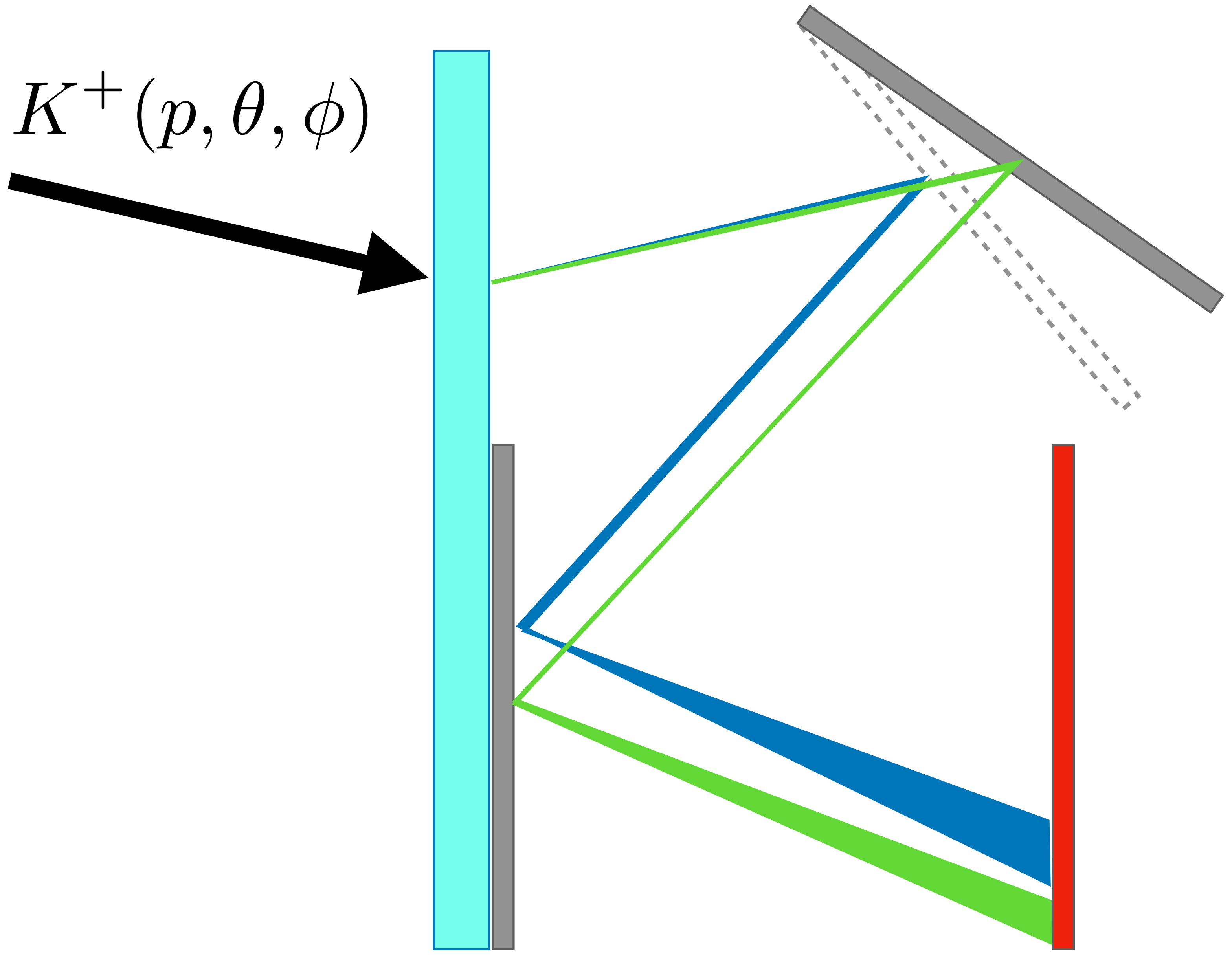
- The Ring Imaging Cherenkov detector (RICH) is designed to improve CLAS12 particle identification in the momentum range 3-8 GeV/c and will replace one sector of the existing LTCC detector.
- The RICH design incorporates aerogel radiators, visible light photon detectors, and a focusing mirror system, which will be used to reduce the detection area instrumented by photon detectors to ~1 m^2 . Multi-anode photomultiplier tubes (MA-PMTs) provide the required spatial resolution and match the aerogel Cherenkov light spectrum (visible and near-ultraviolet region).
- For forward scattered particles ($\theta < 13^o$) with momenta 3 - 8 GeV/c, a proximity imaging method with thin (2 cm) aerogel and direct Cherenkov light detection will be used.
- For larger incident particle angles of $13^o < \theta < 25^o$ and momenta of 3 - 6 GeV/c, the Cherenkov light will be produced by a thicker aerogel (6 cm), focused by a spherical mirror, undergo two further passes through the thin radiator material and a reflection from planar mirrors before detection.



- RICH Ideal Geometry
  - If the ideal geometry and position of mirrors are known the ray-tracing can help recover the Cherenkov angle
  - Calculating the Cherenkov angle for each of the hits on the photomultiplier plane allows to identify the particles.



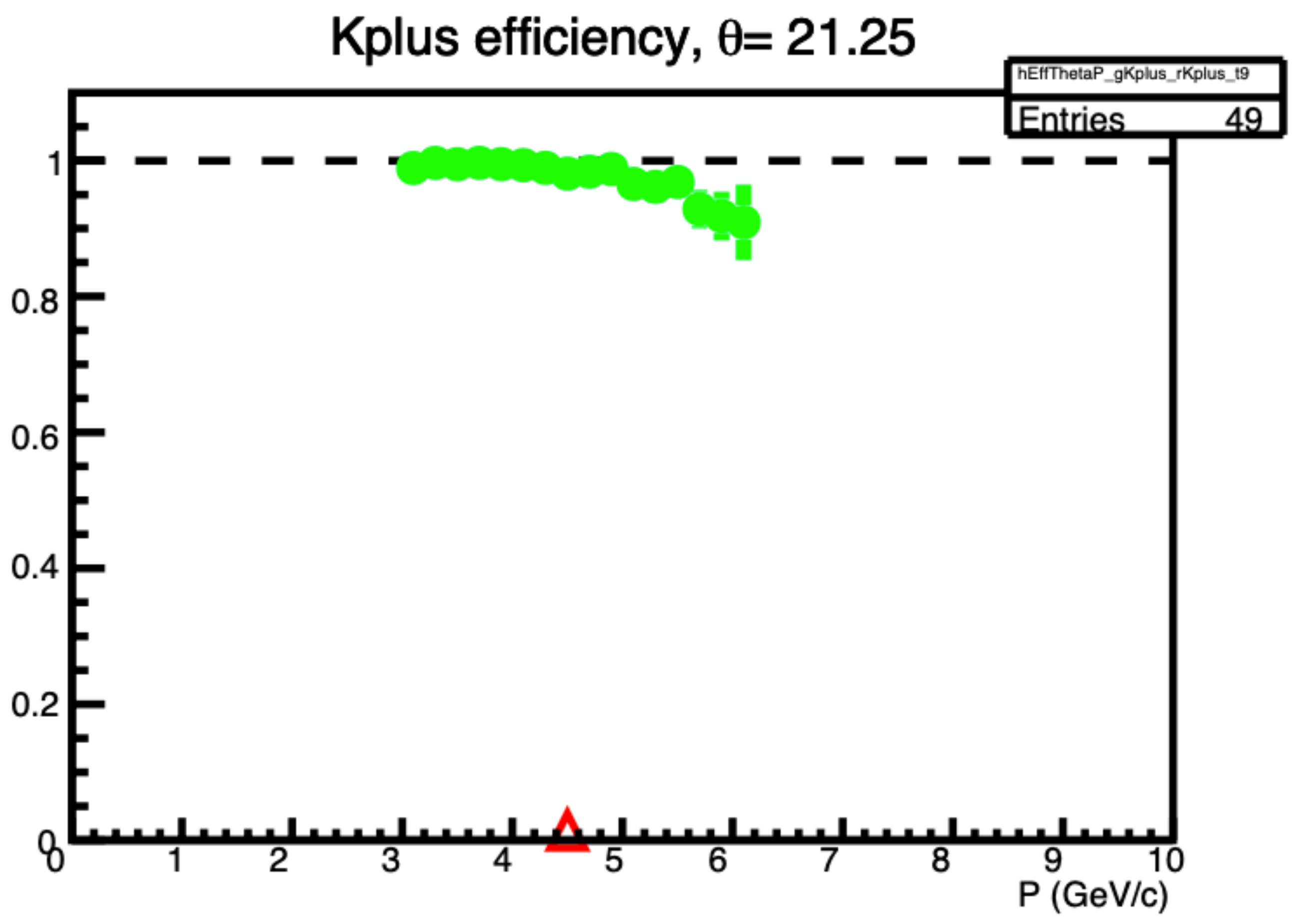
- RICH Real World Geometry
  - Ray tracing will predict an inaccurate position for the hit on the detector plane
  - This affects the efficiency of particle identification

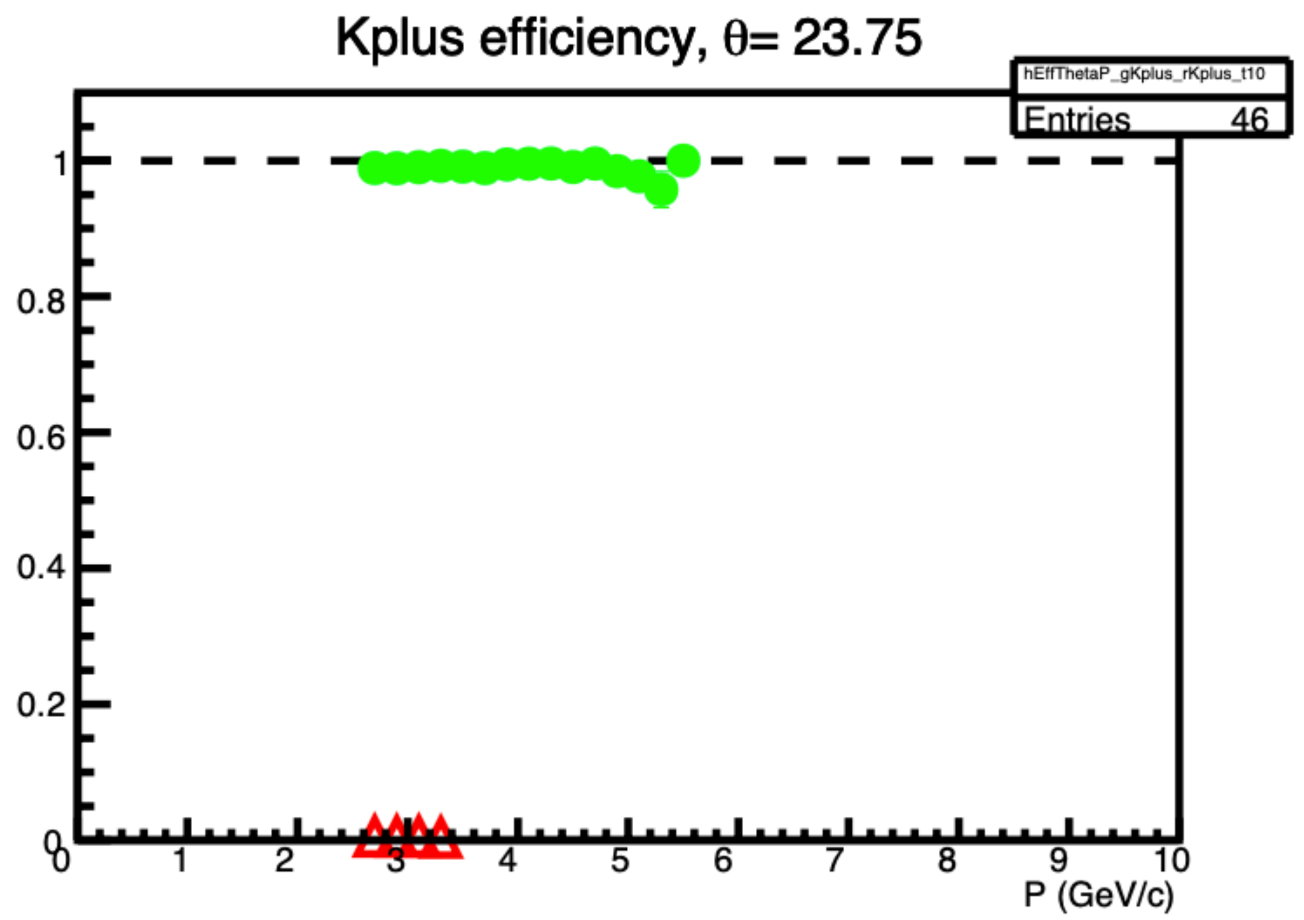


- Neural Networks can be trained on Real-World data which includes miss-alignments
- It can learn the Cherenkov ring patterns for incident particles, given interaction point and direction at crossing the aerogel layer

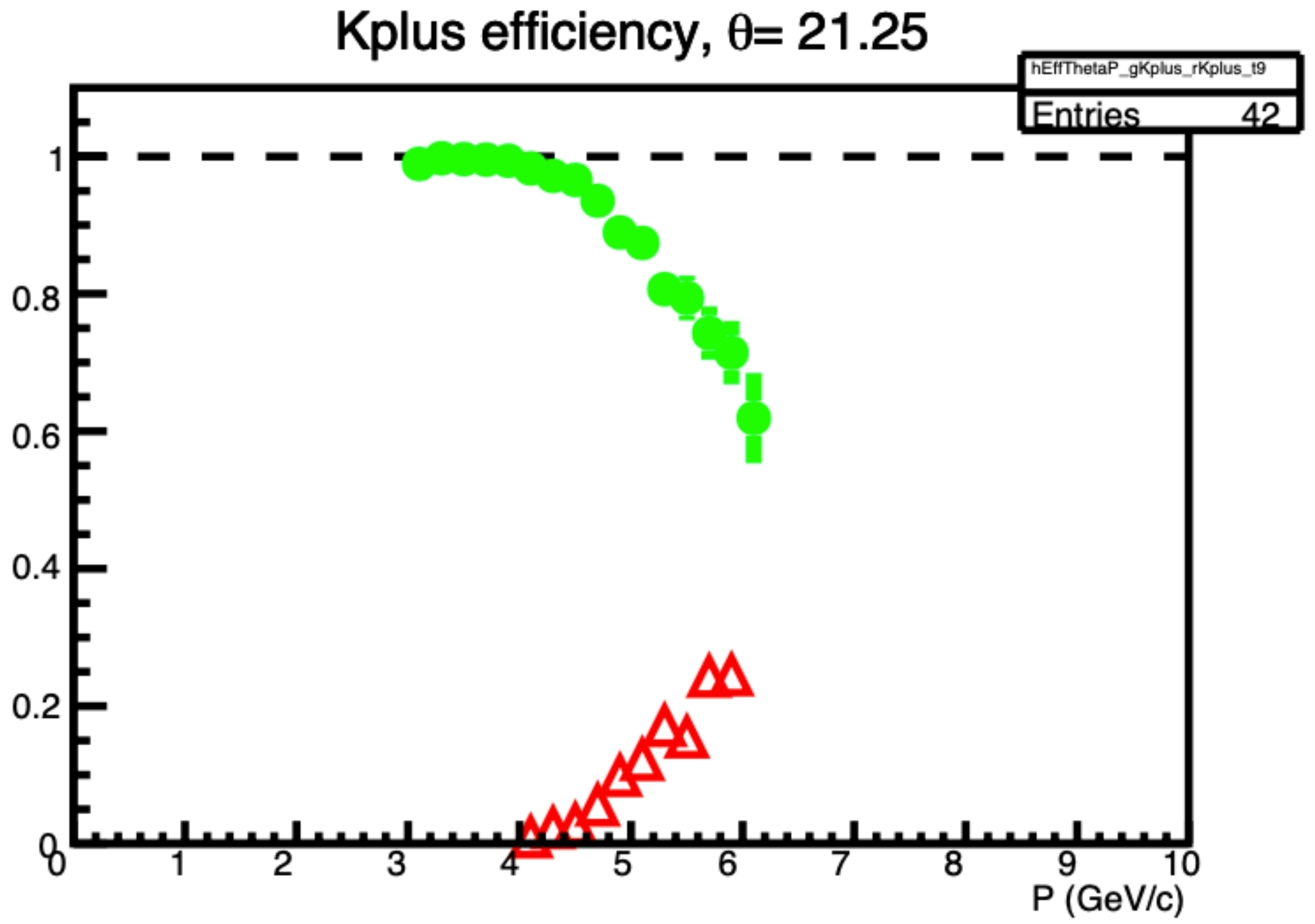
Rich Detector (preliminary)

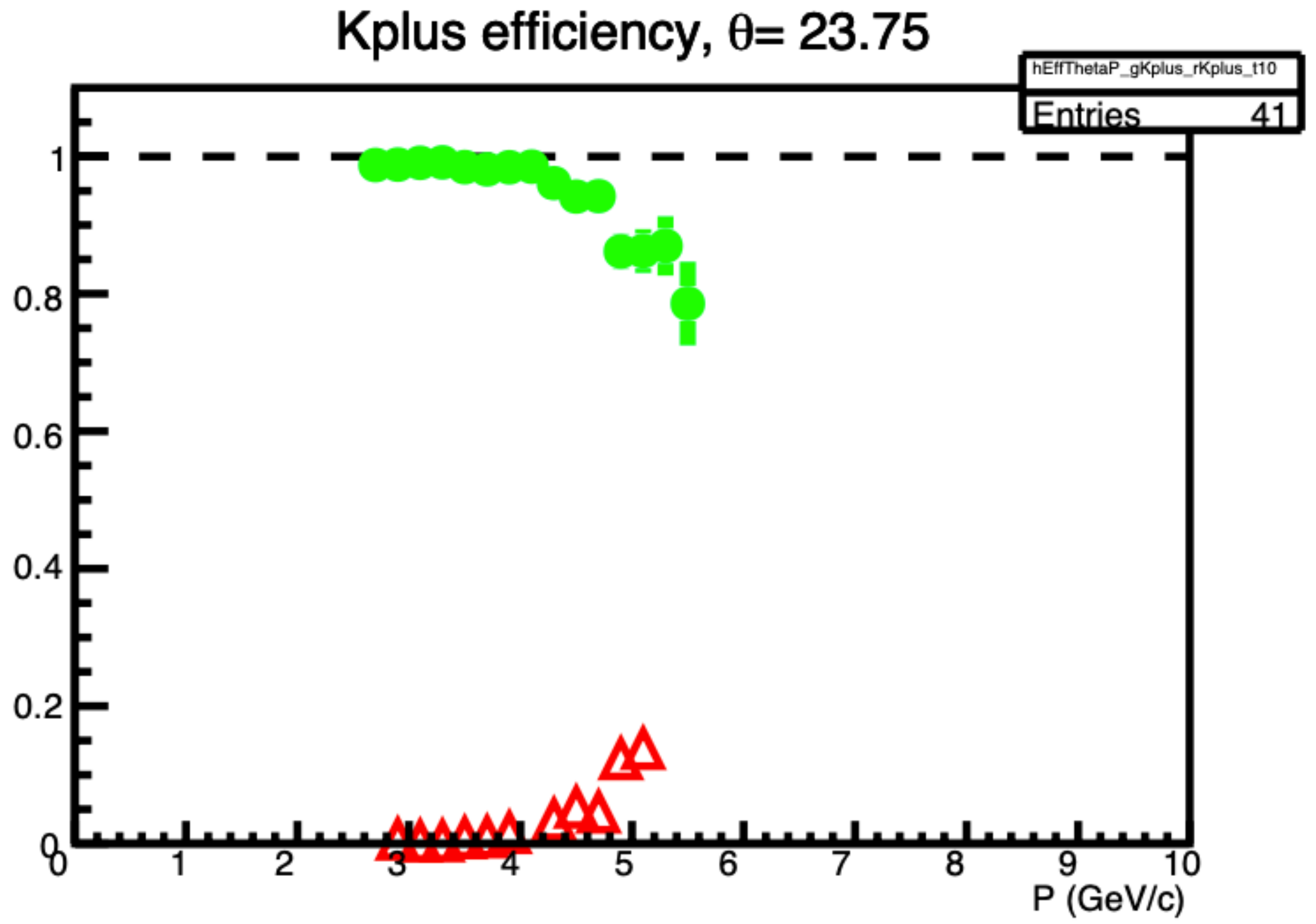
Kaon Identification Efficiency (IDEAL GEOMETRY)

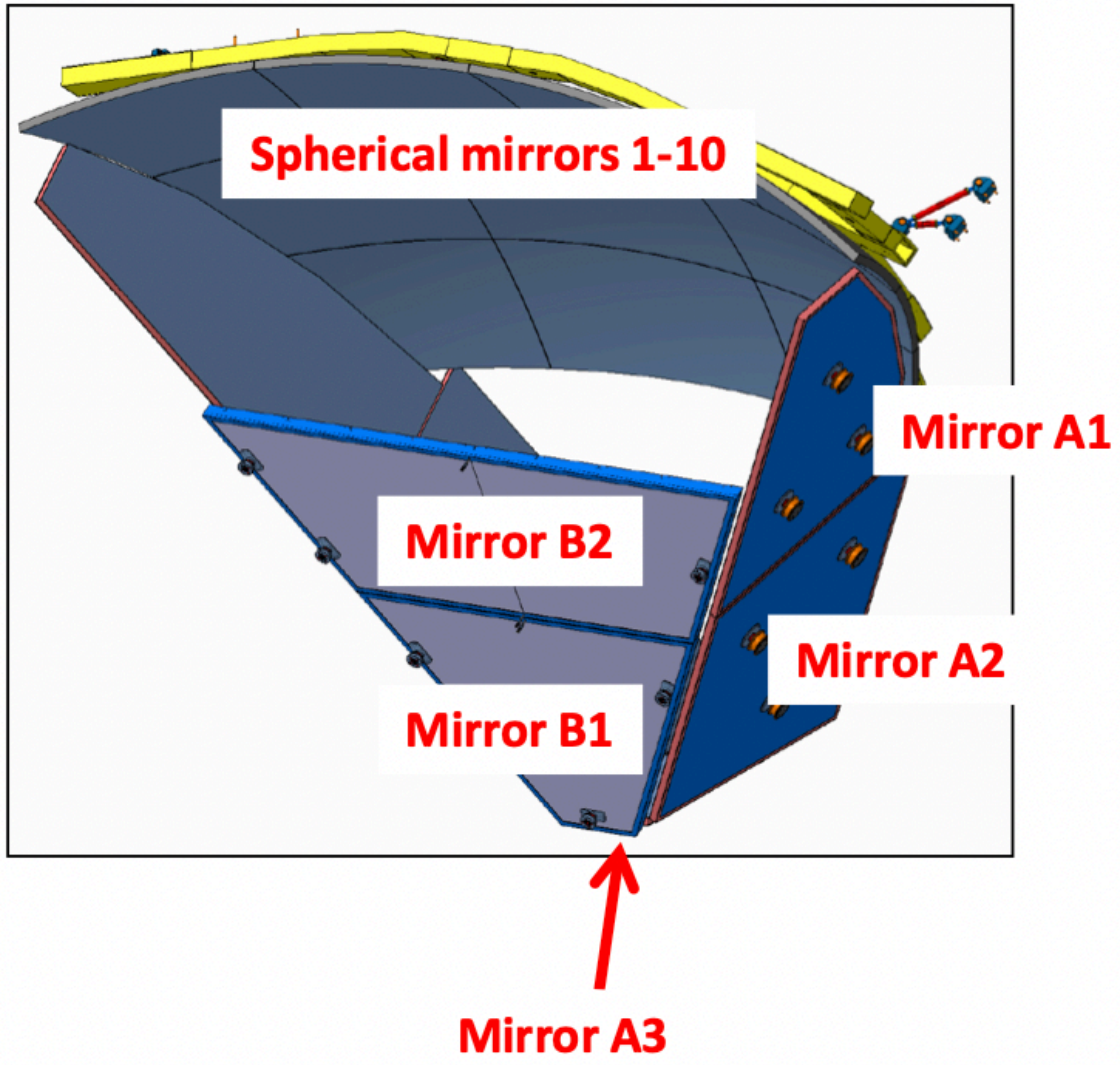




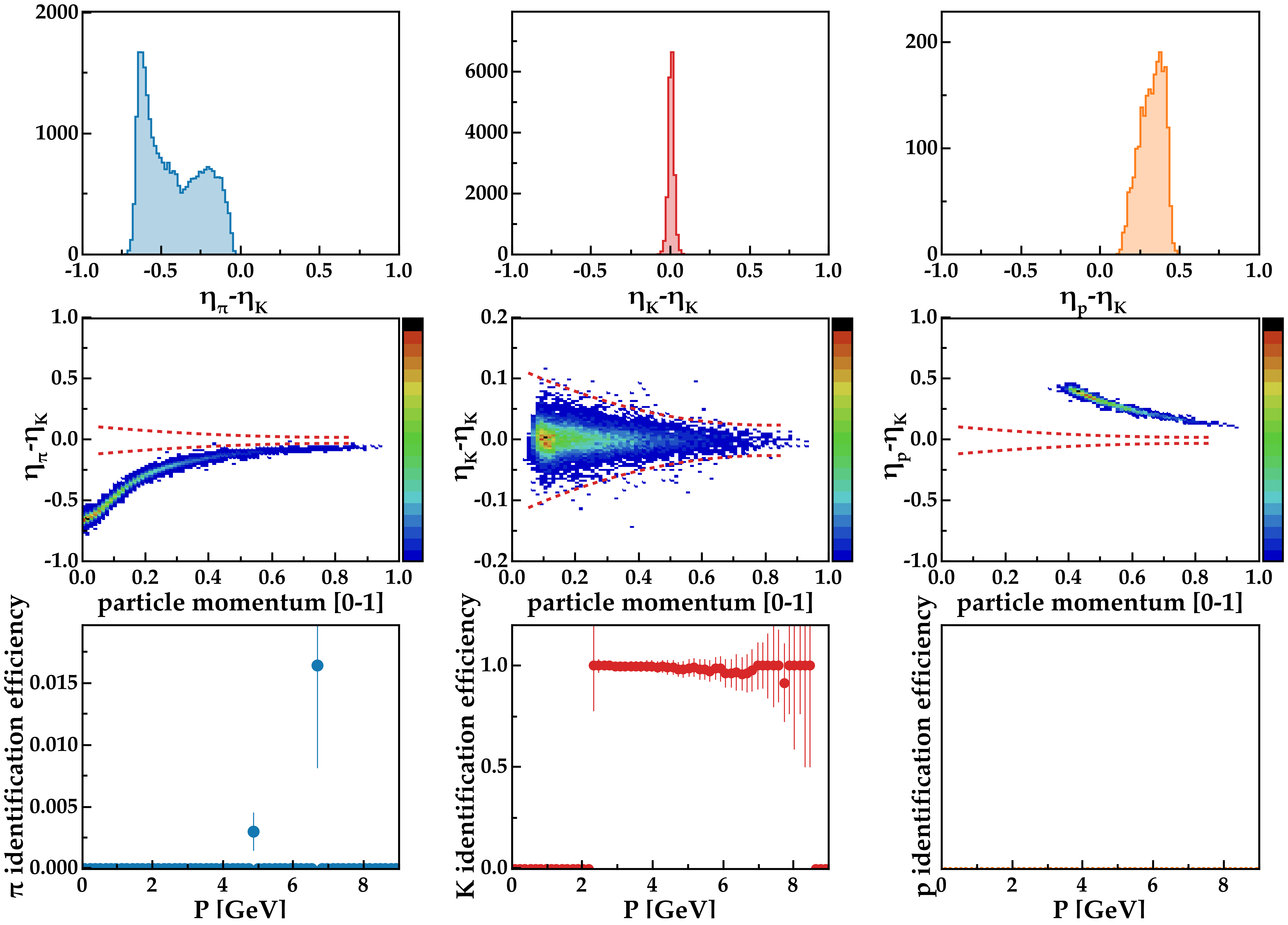
Kaon Identification Efficiency (MIS-ALLIGNED GEOMETRY)







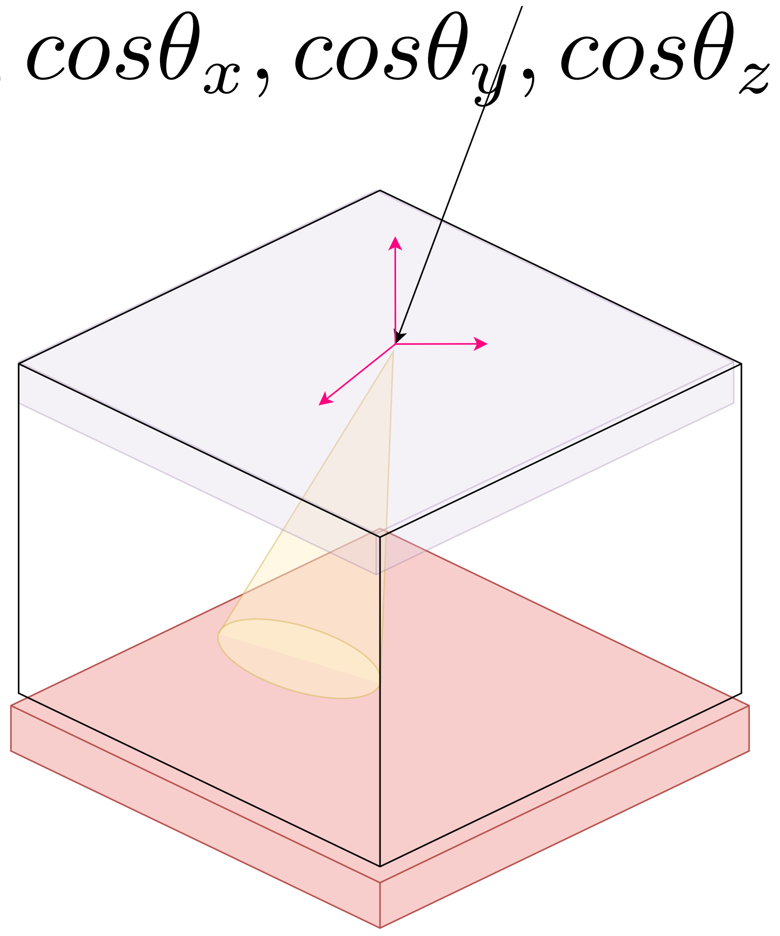
Rich Detector (particle identification)



- Neural Network predicts Cherenkov angle for incoming particles based on the hits on the RICH photo-multipliers
- Kaon efficiency is uniform across the momentum range
- The Network is trained on misaligned data
- Kaon efficiency is calculated from misaligned data
- The detector will not need to be aligned when trained on experimental data.

Input:

$X[P, X, Y, cos\theta_x, cos\theta_y, cos\theta_z, X_h, Yh]$



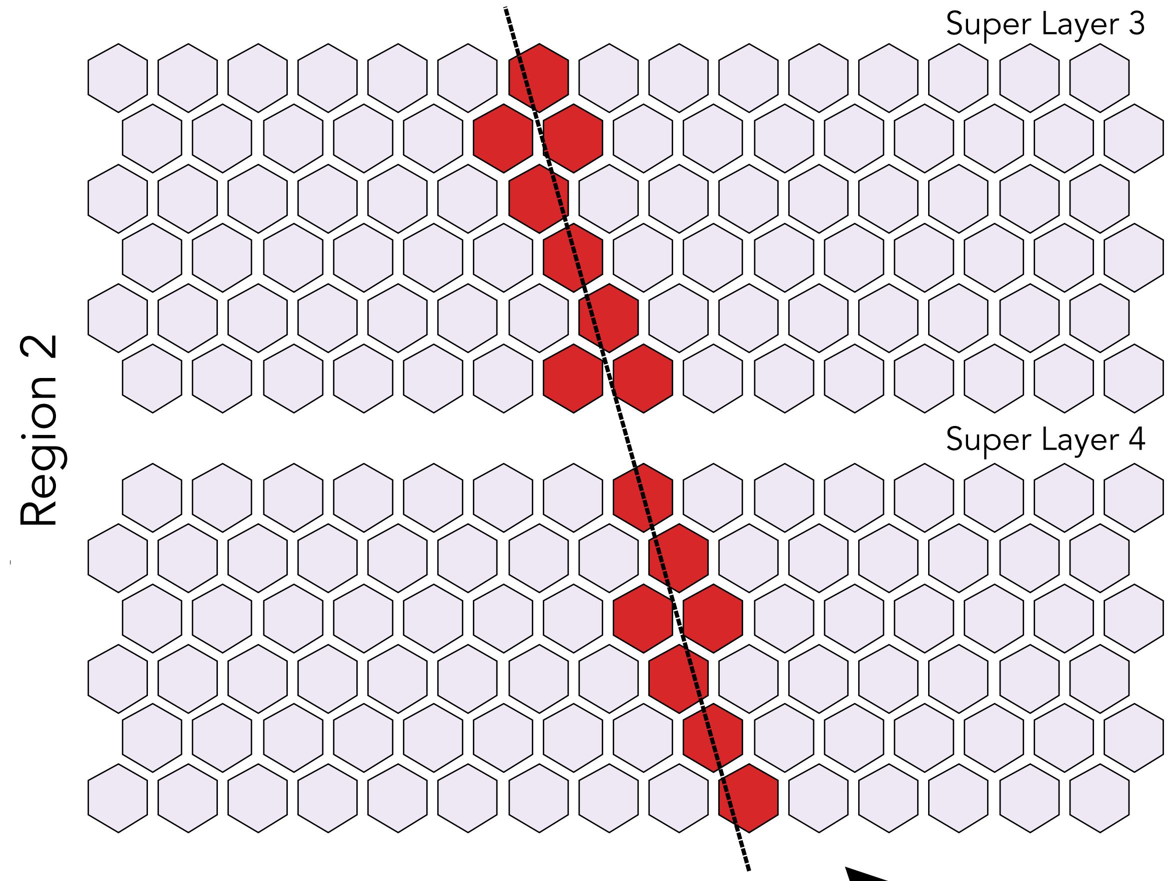
Output: η

Summary

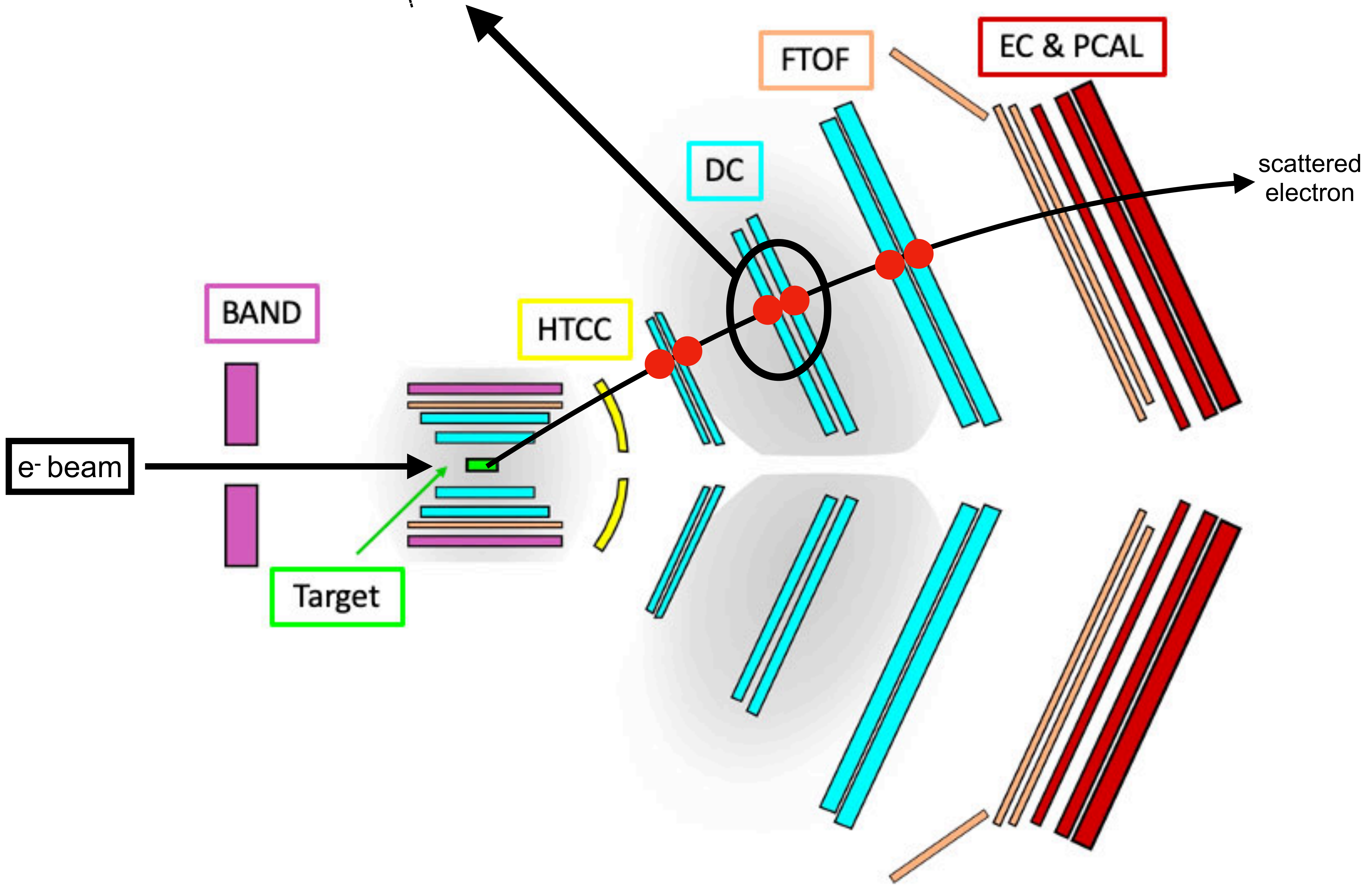
- CLAS12 uses three neural networks for track reconstruction in forward drift chambers:
  - De-Nonoiser: Convolutional Auto Encoder Network
  - Corruption Recovery Network: Multi-Layer Perceptron AutoEncoder
  - Track Classifier: Multi-Layer Perceptron Neural Network
- The combined effect of three neural networks resulted in increase of single particle efficiency ~15%-18%.
- The resulting increase in statistics for physics observables is ~50%-80%
- Implementation of AI track identification also resulted in tracking code speedup of ~35%.
- The use of neural networks in track reconstruction paves the way for high-luminosity running where conventional methods can not be used.
- Future: working on neural networks for other detectors

Backup Slides

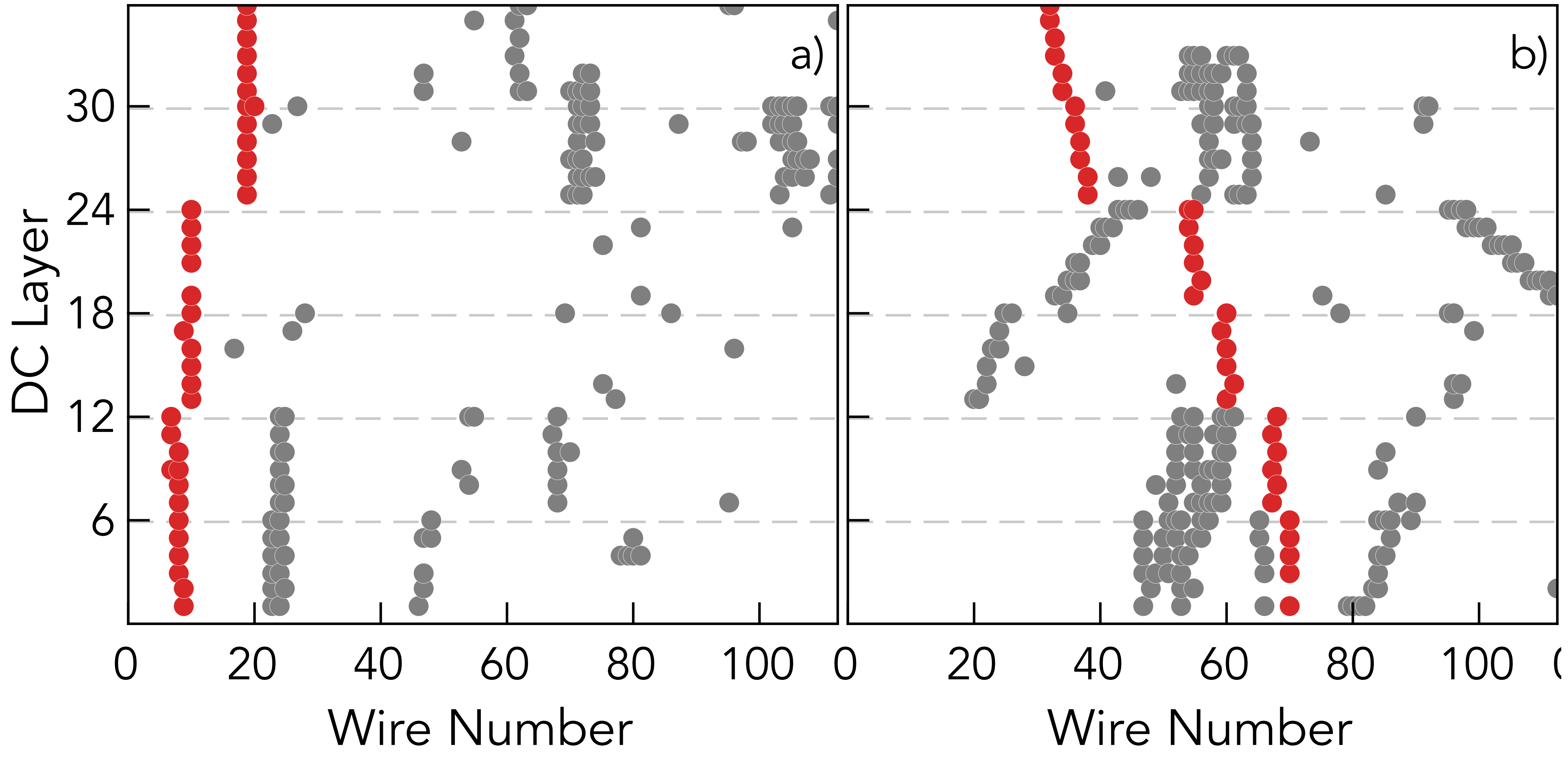
CLAS12 Detector



- 2 super layers in each region
- 6 wire planes in each super layer with 6-degree tilt relative to each other, (112 wires in each plane)
- Clusters in each super layer are considered part of the track trajectory

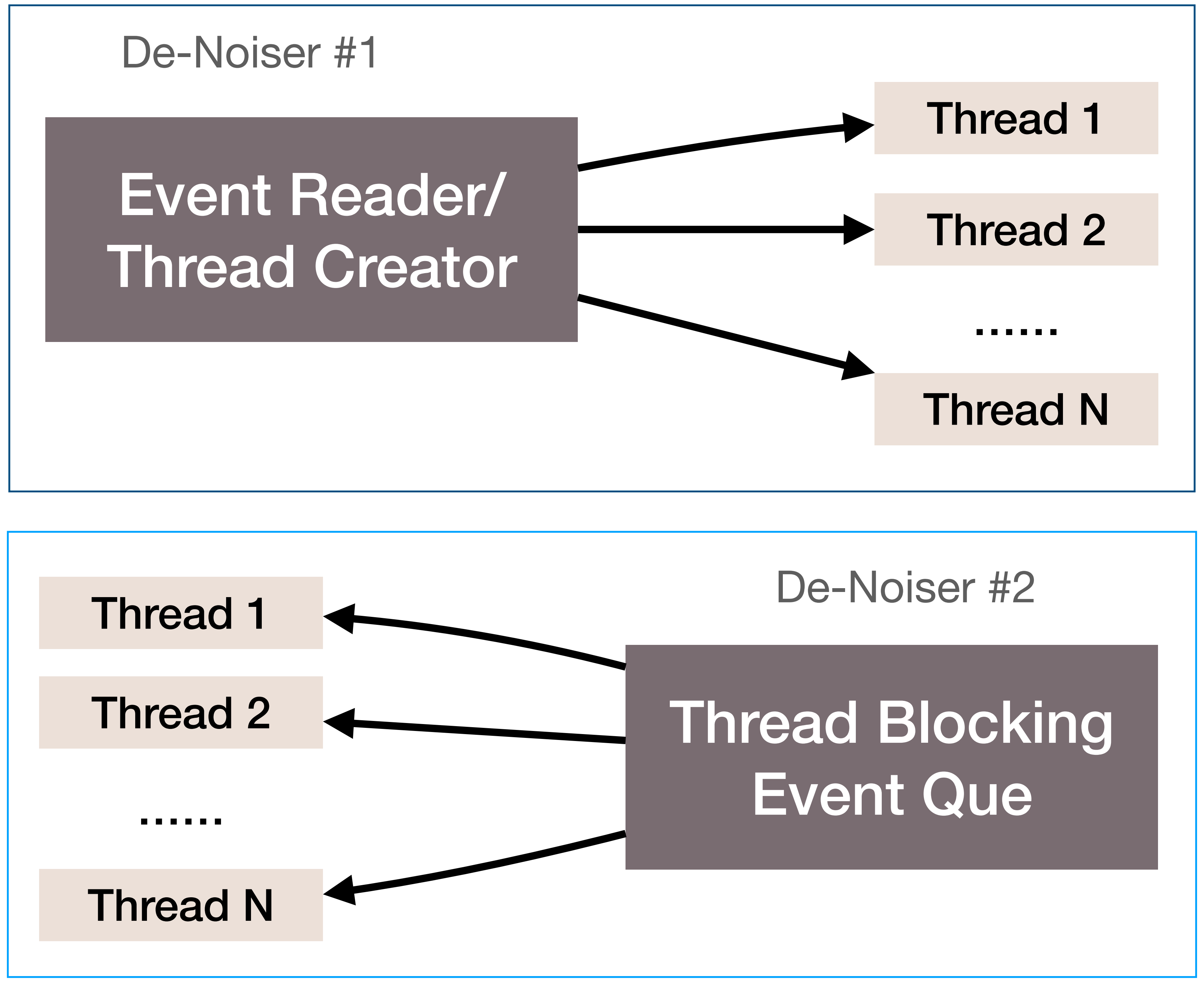


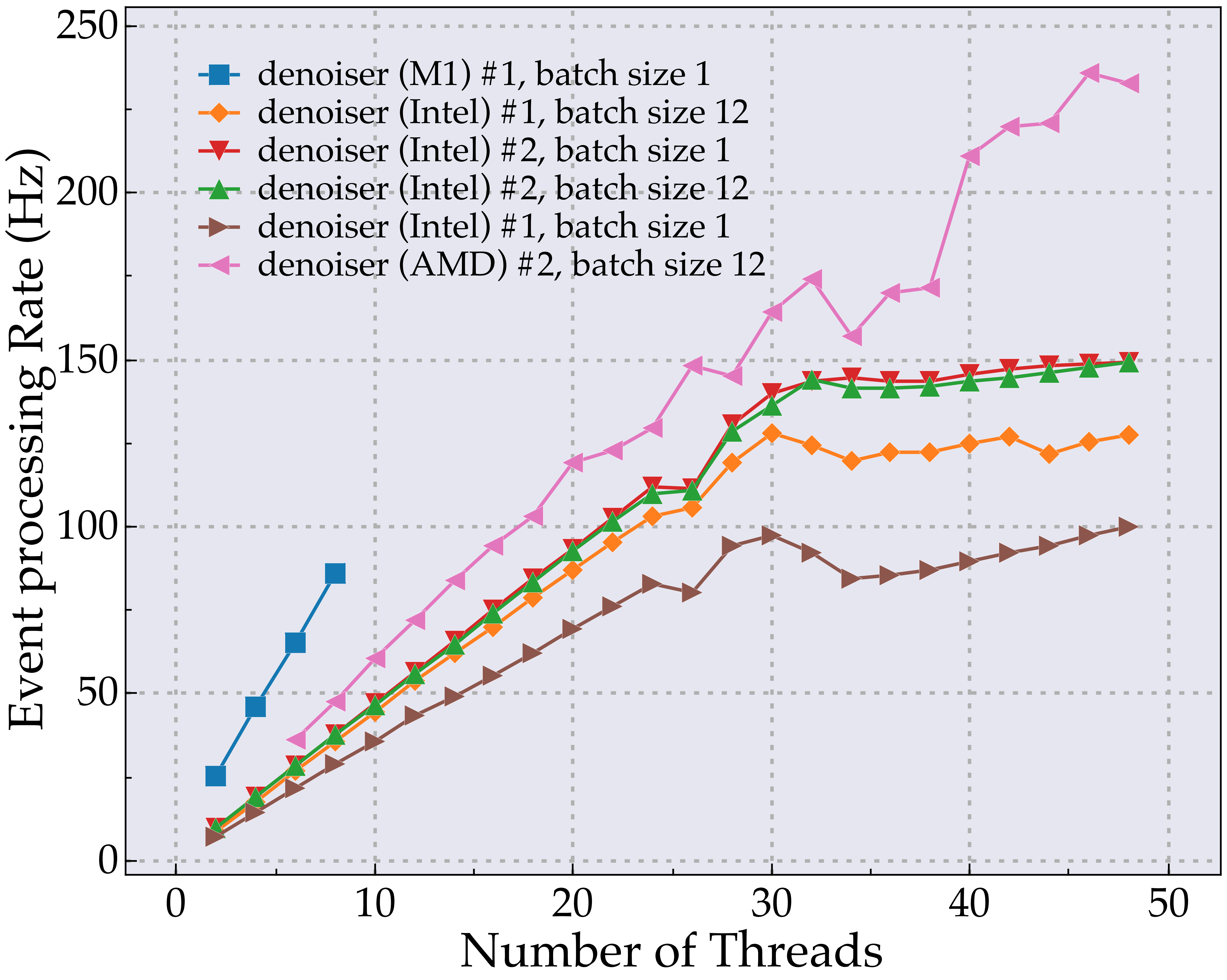
- Charged particle tracking is computationally extensive (about 80% of data processing time)
- The multi-particle final states produce numerous clusters in each sector which have to be analyzed to find the right combinations of clusters that form a track
- Identifying correct cluster combinations can speed up the tracking process and improve efficiency



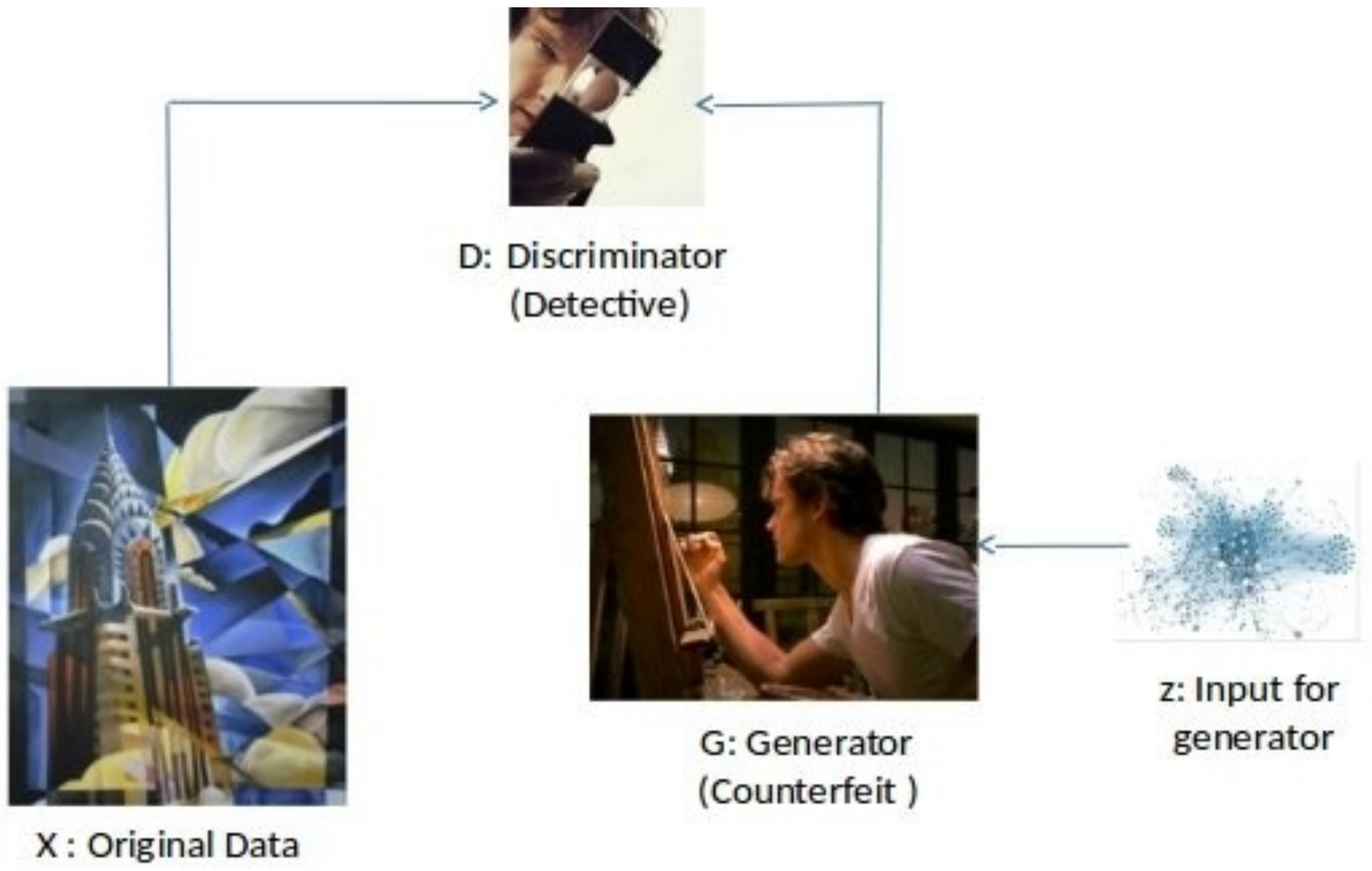
De-nosing Performance Multi-Threaded

- **C++:** Keras model inference in C++ code implemented for CLAS12 de-noiser.
- **Multi-Threading**: Multi-threading implemented to process data files (using std::thread)





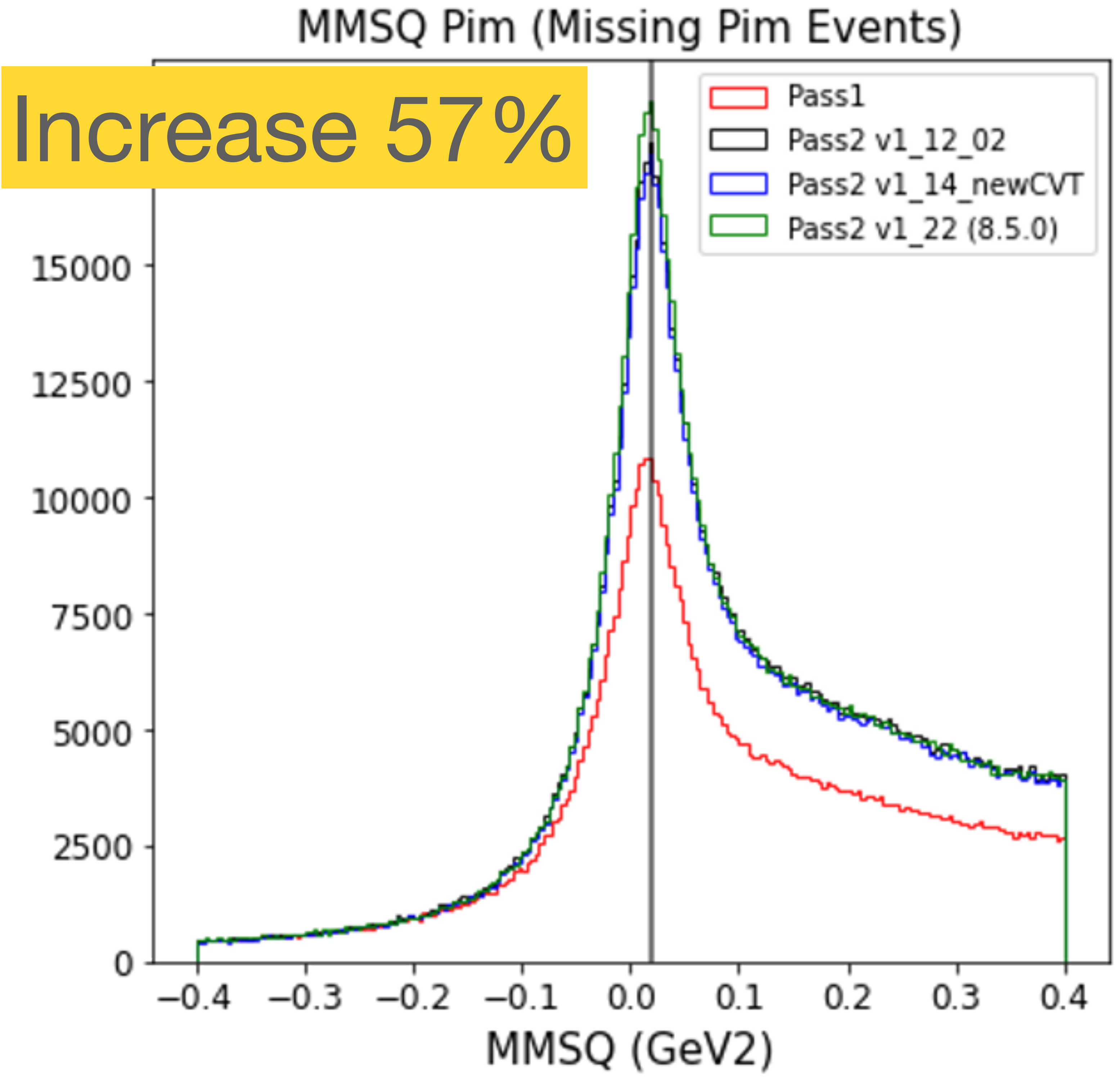
- Image Generation:
  - AI tools to generate images based on the description
  - Ability to generate images with the style of a certain painter



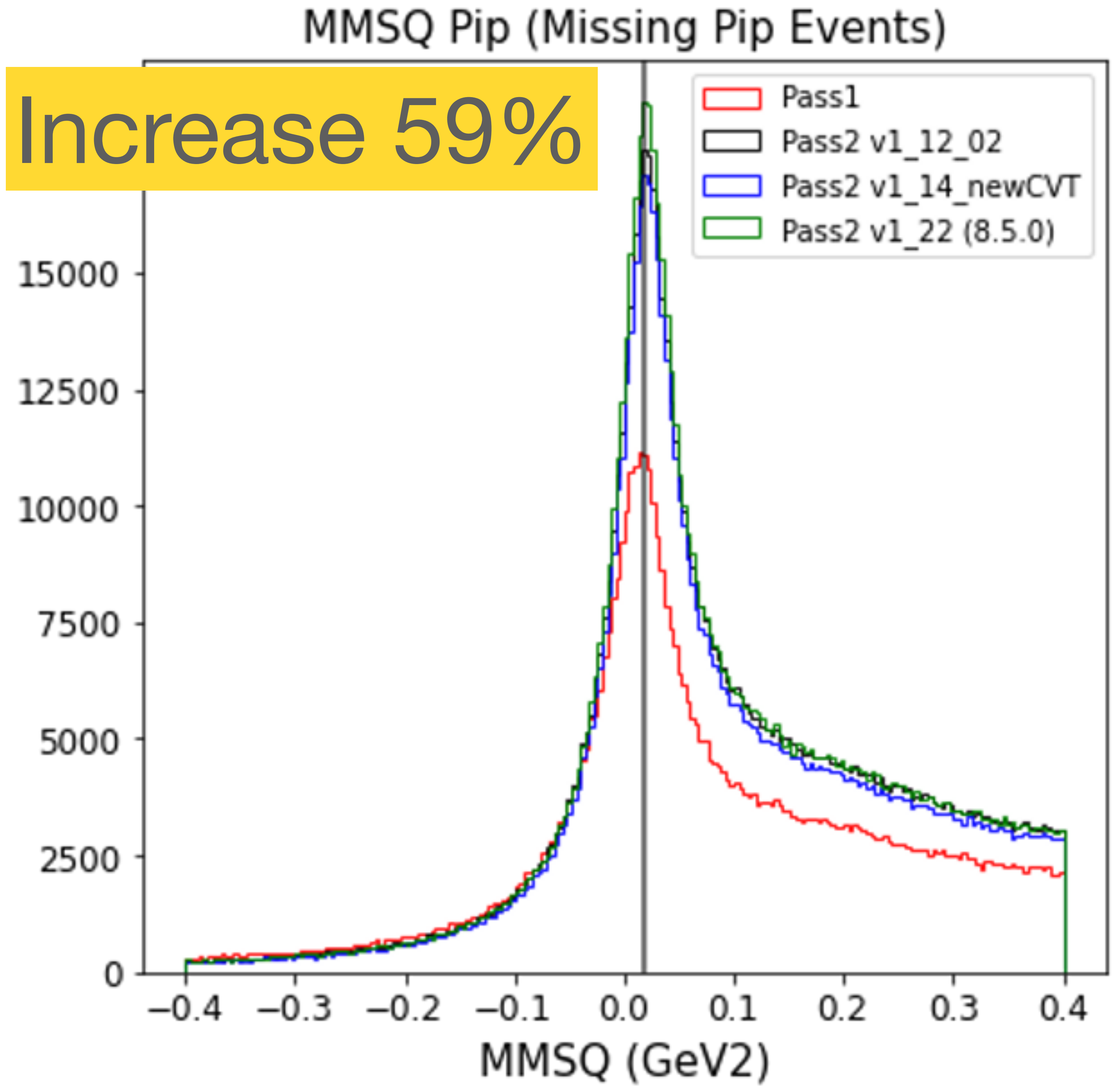
De-Noising Results (data)

RUN GROUP-A Pass2 Validation Cooking
Includes De-Nosing and AI-assisted Tracking

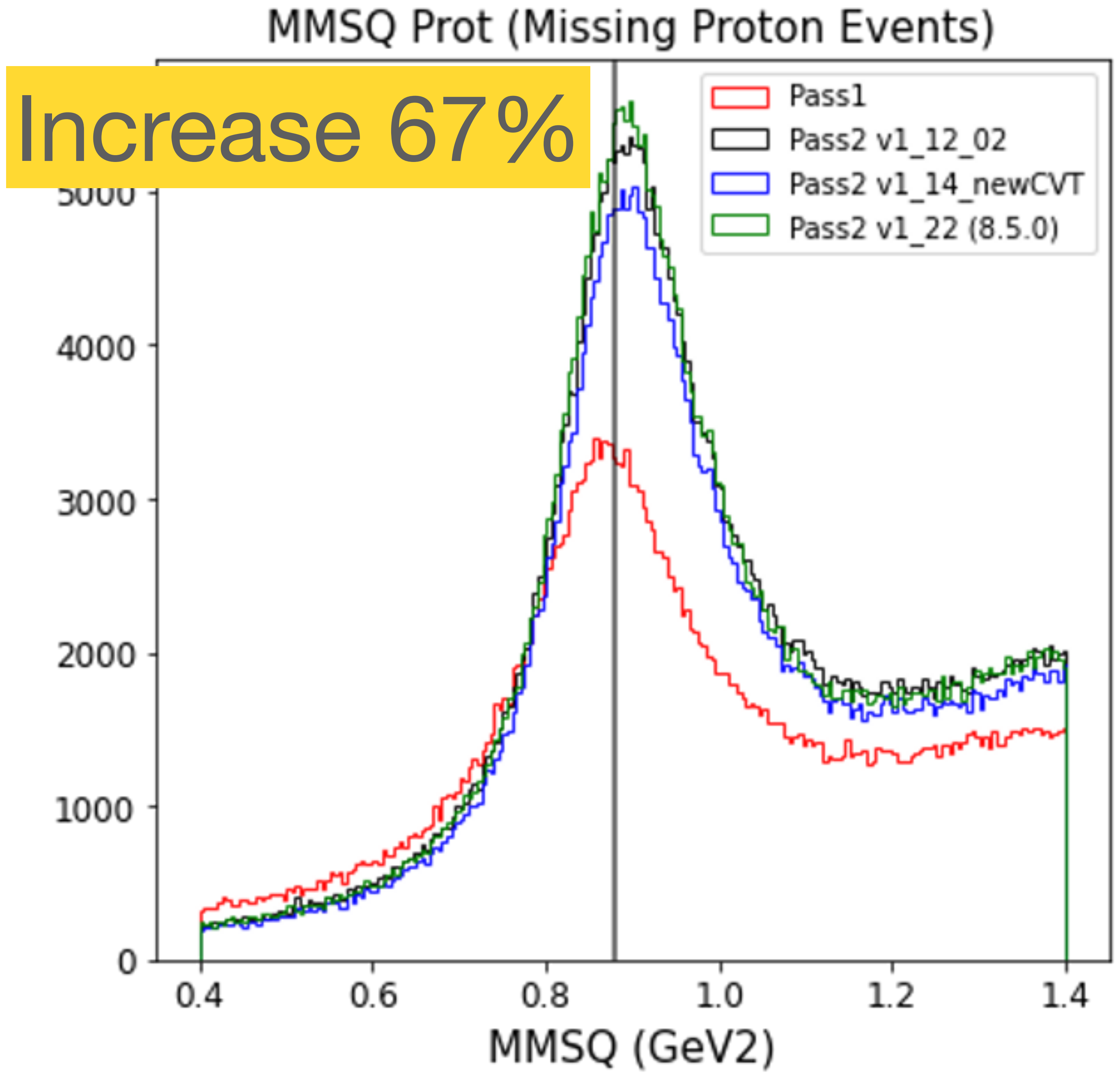
$$ep \rightarrow e'p\pi^-(X)$$



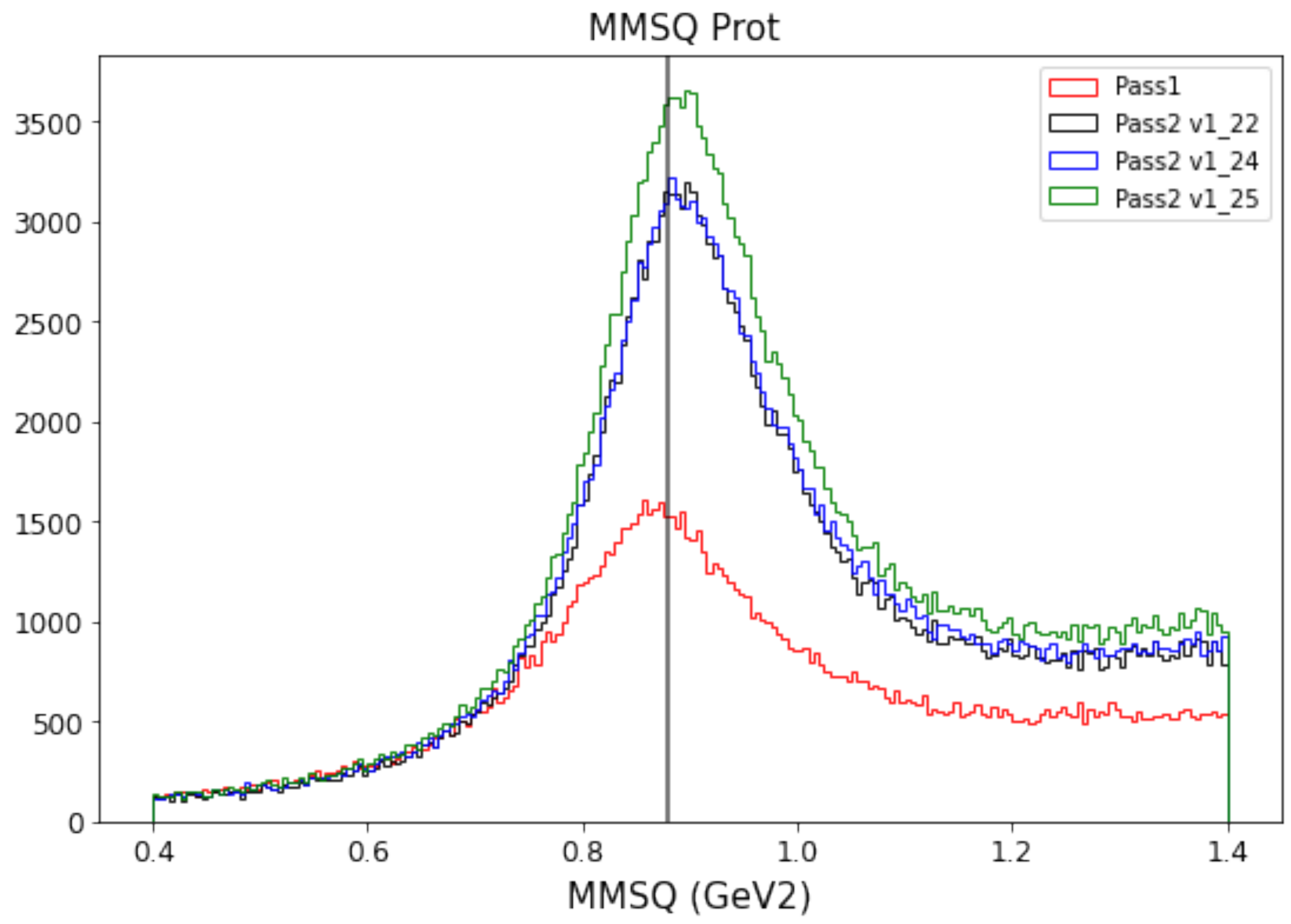
$$ep \rightarrow e'p\pi^+(X)$$

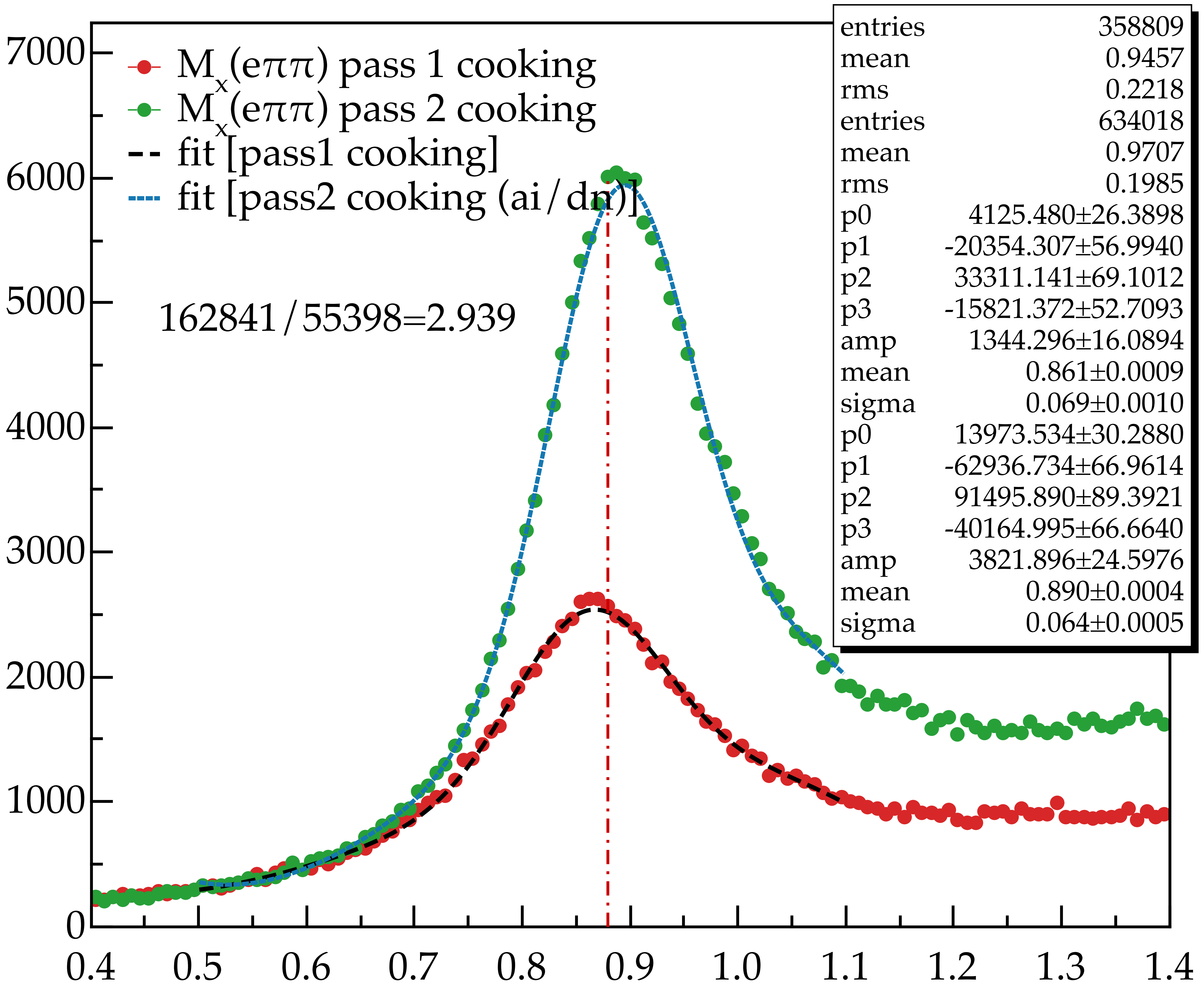


$$ep \rightarrow e'\pi^+\pi^-(X)$$



De-nosing Performance With Central Detector





pass1 = 129894
pass2 v1_22/pass1 = 1.618
pass2 v1_24/pass1 = 1.662
pass2 v1_25/pass1 = 1.866

De-nosing Performance Multi-Threaded