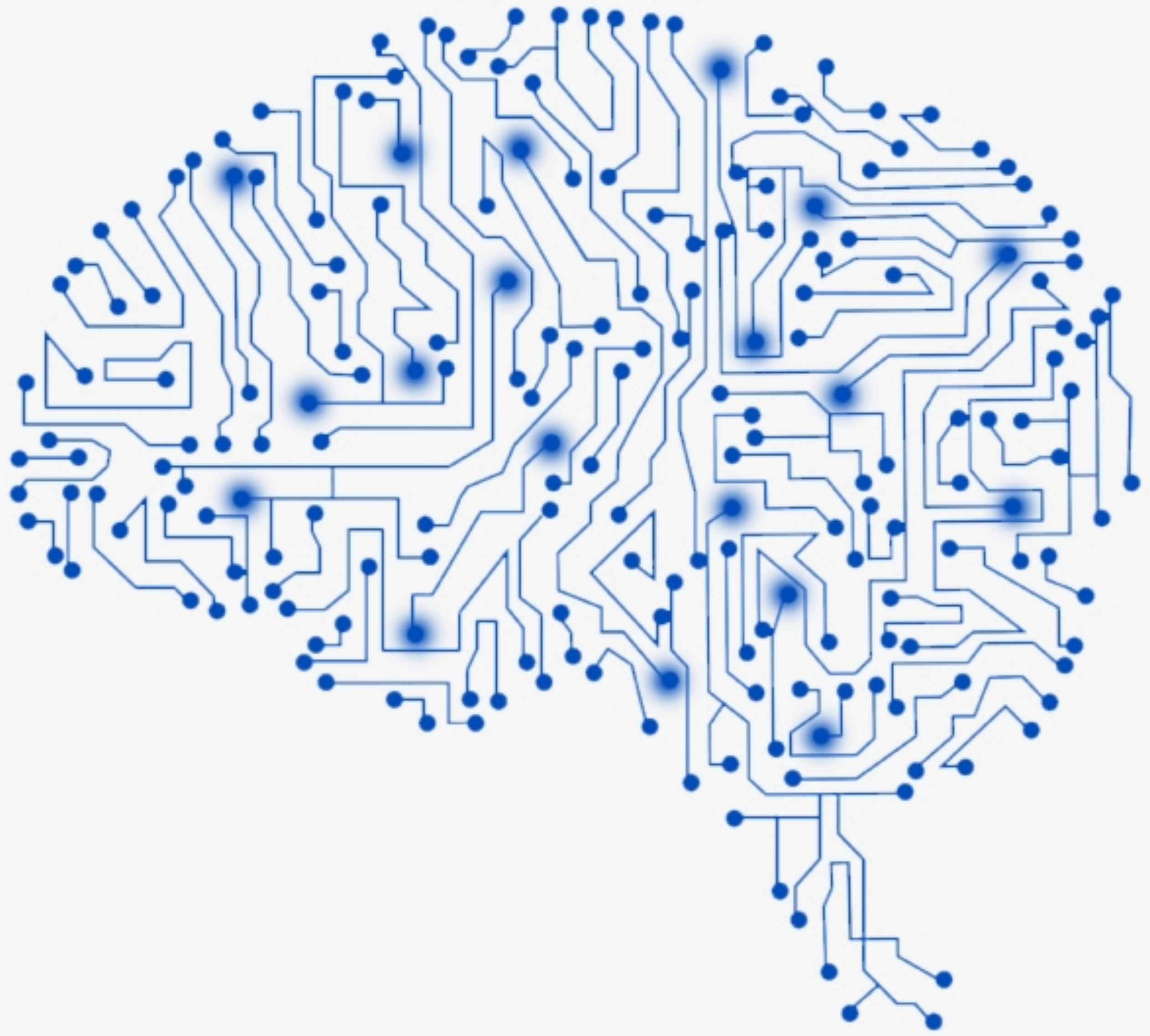
Artificial Intelligence in CLAS12

Artificial Intelligence/Machine Learning for Physics Applications

G.Gavalian (Jefferson Lab)



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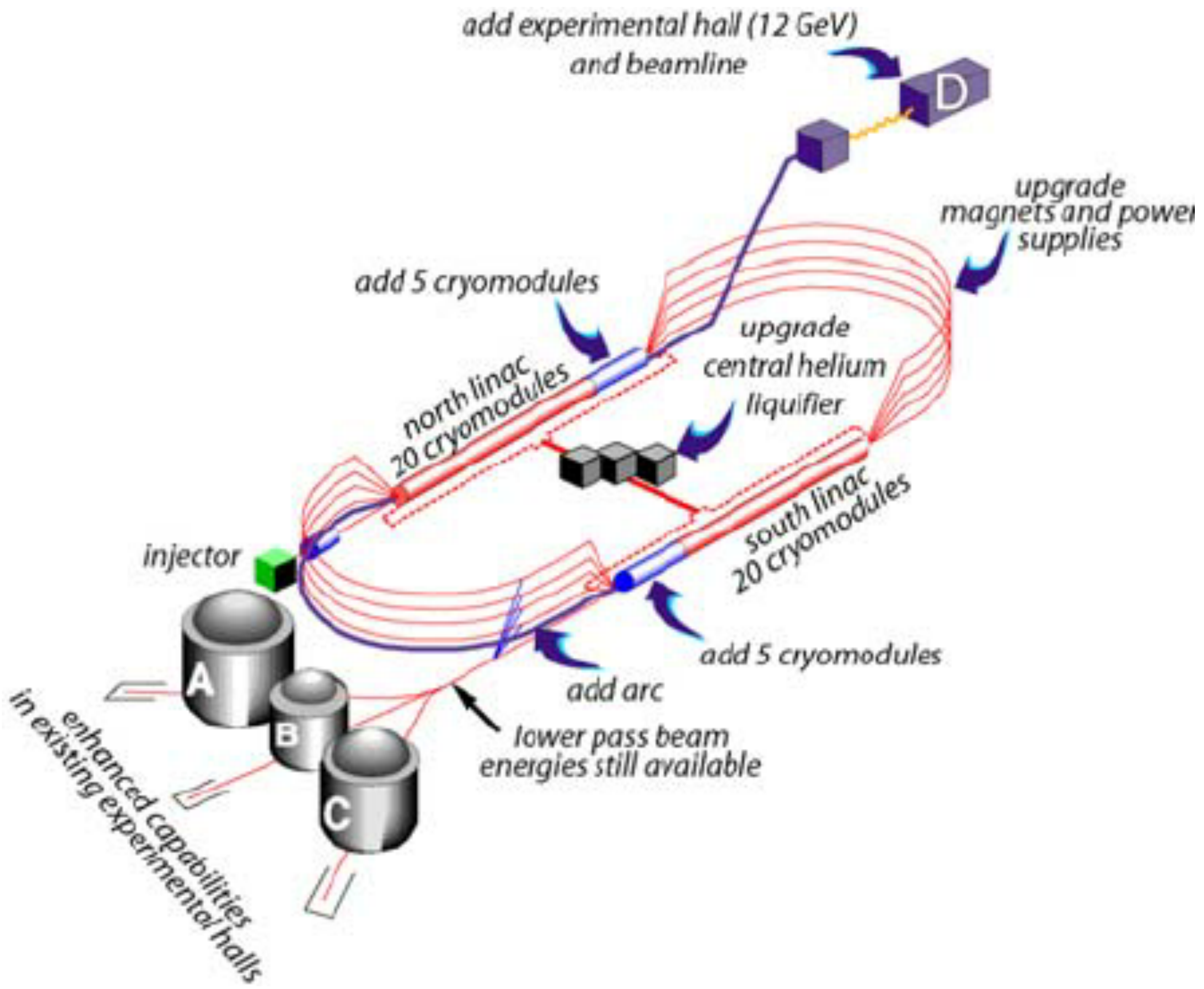
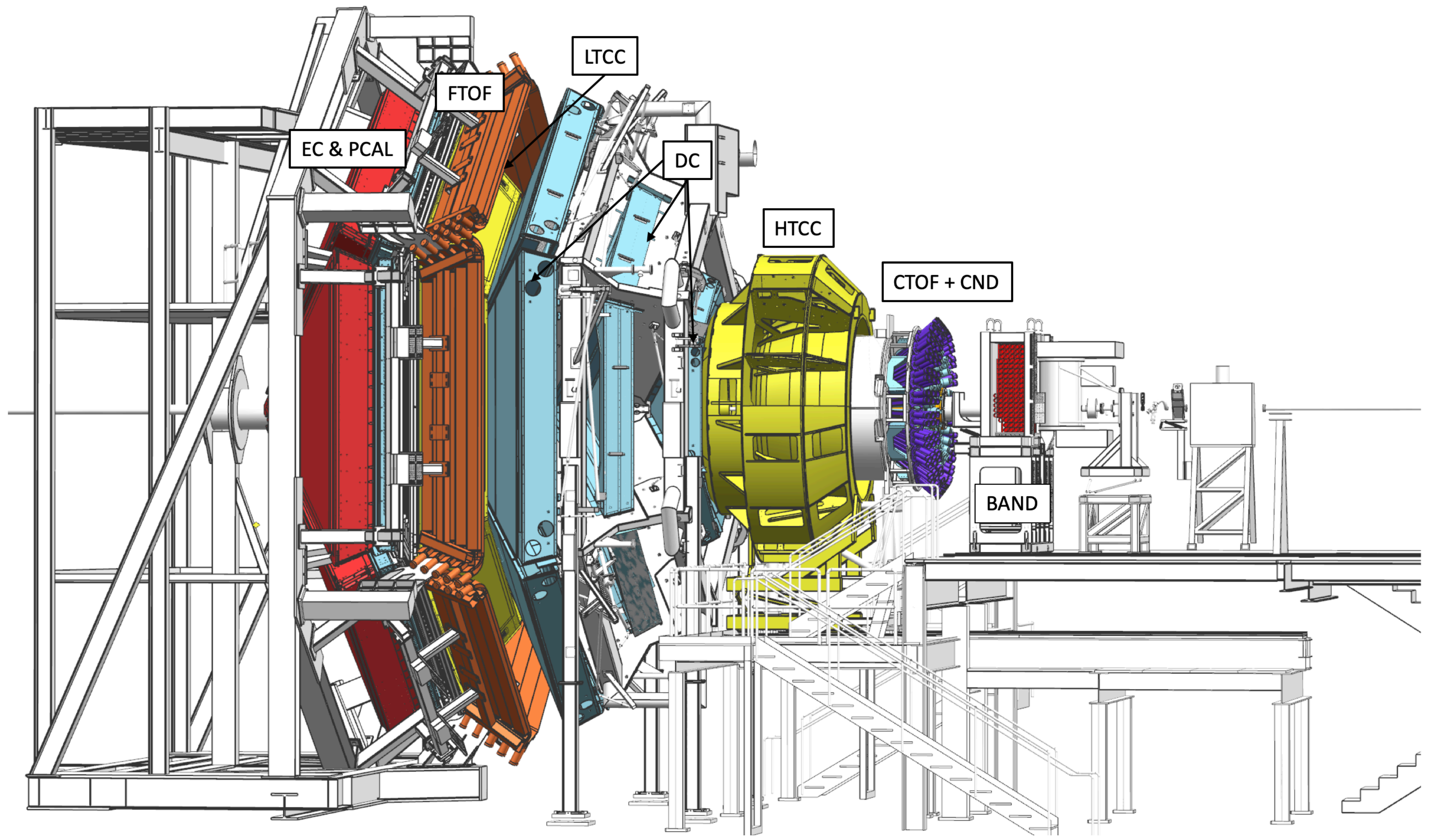
Norfolk (May 9,2023)

- Charged Particle Tracking:
  - Track identification in Drift Chambers
  - Drift Chamber Data De-Noising
  - Impact on the experiment outcome

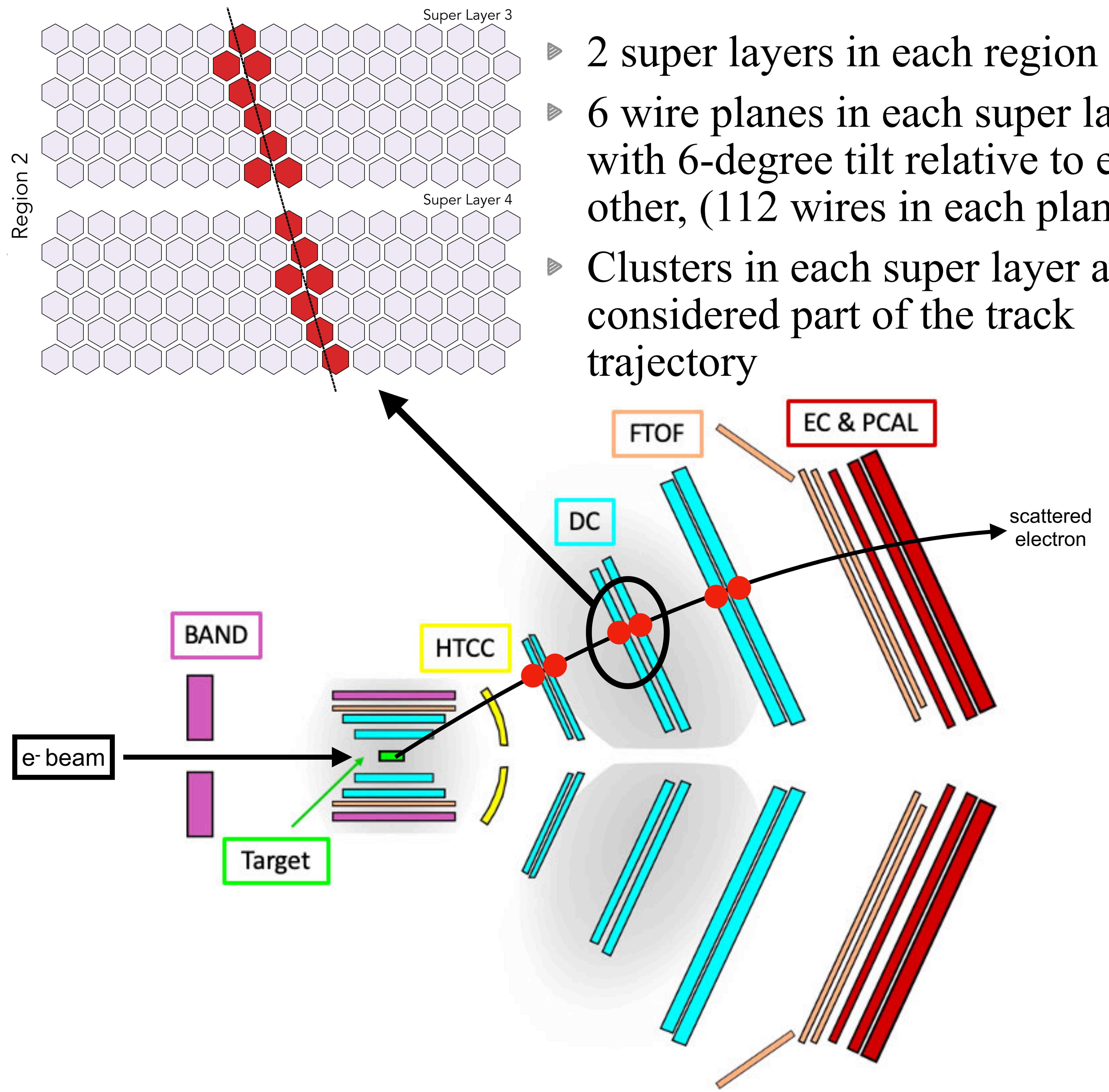




- CEBAF
  - 12 GeV electron beam distributed to 4 experimental hall
  - Each experimental hall contains a detector system for specific experiments

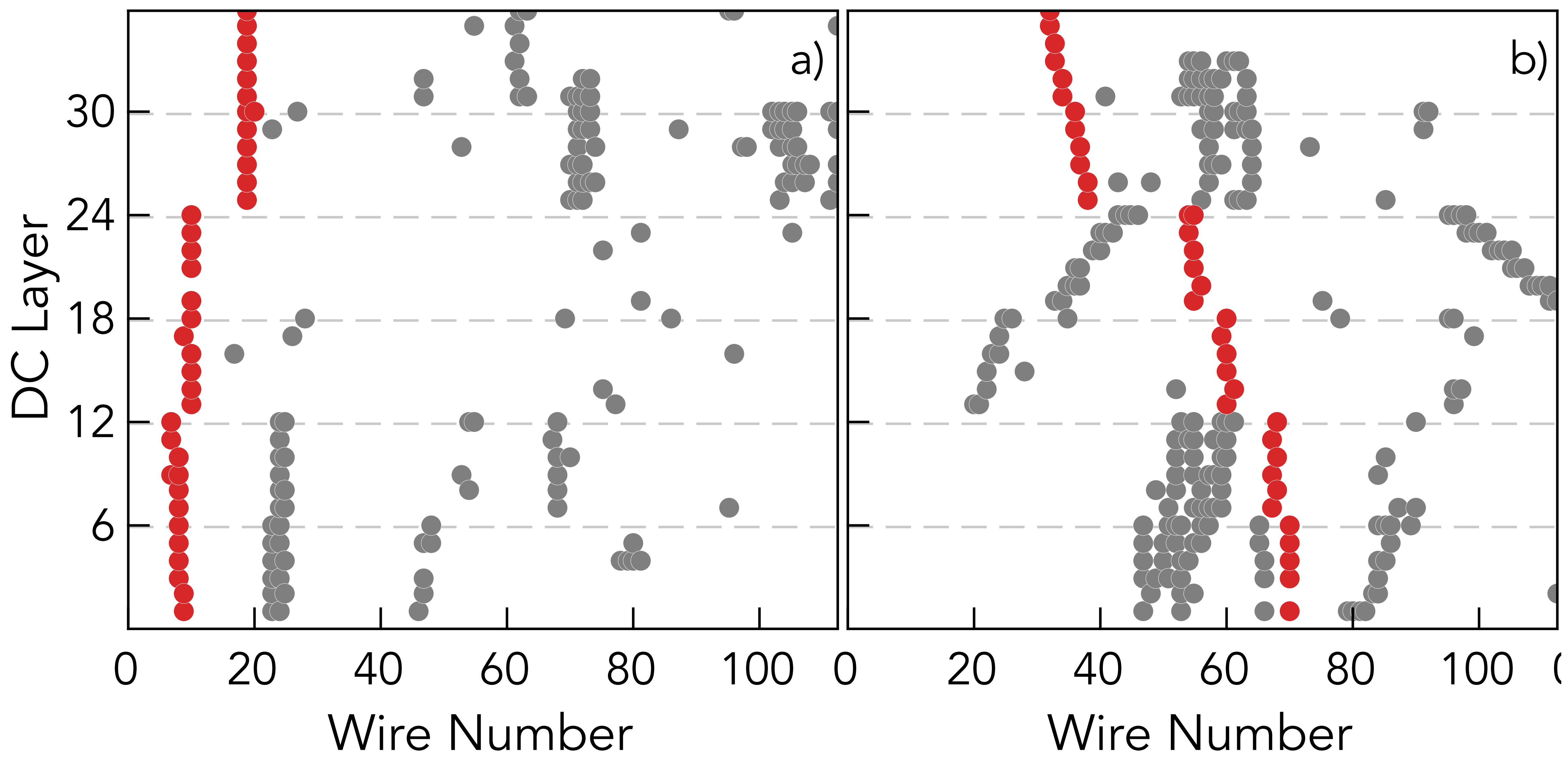
- CLAS12
  - CEBAF Large Acceptance Spectrometer (CLAS12) Located in Hall-B

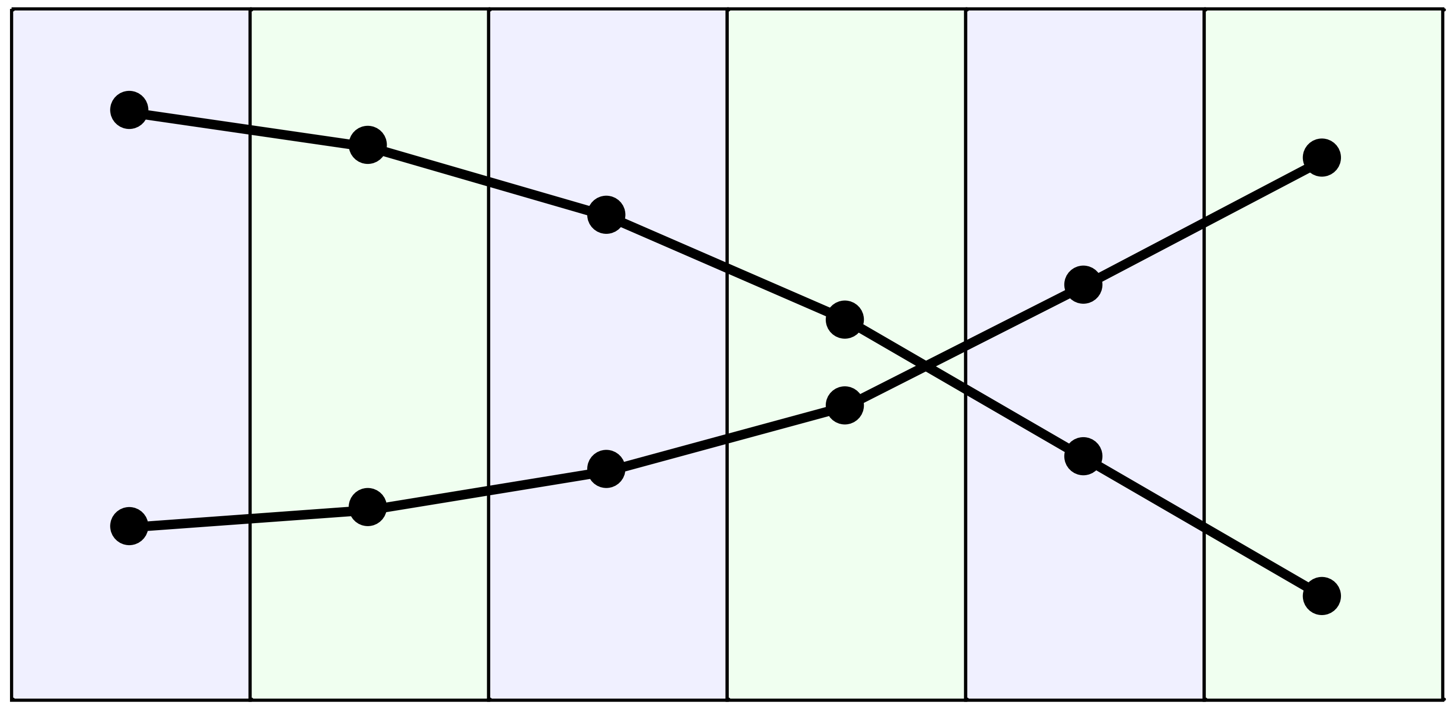
CLAS12 Detector



- 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

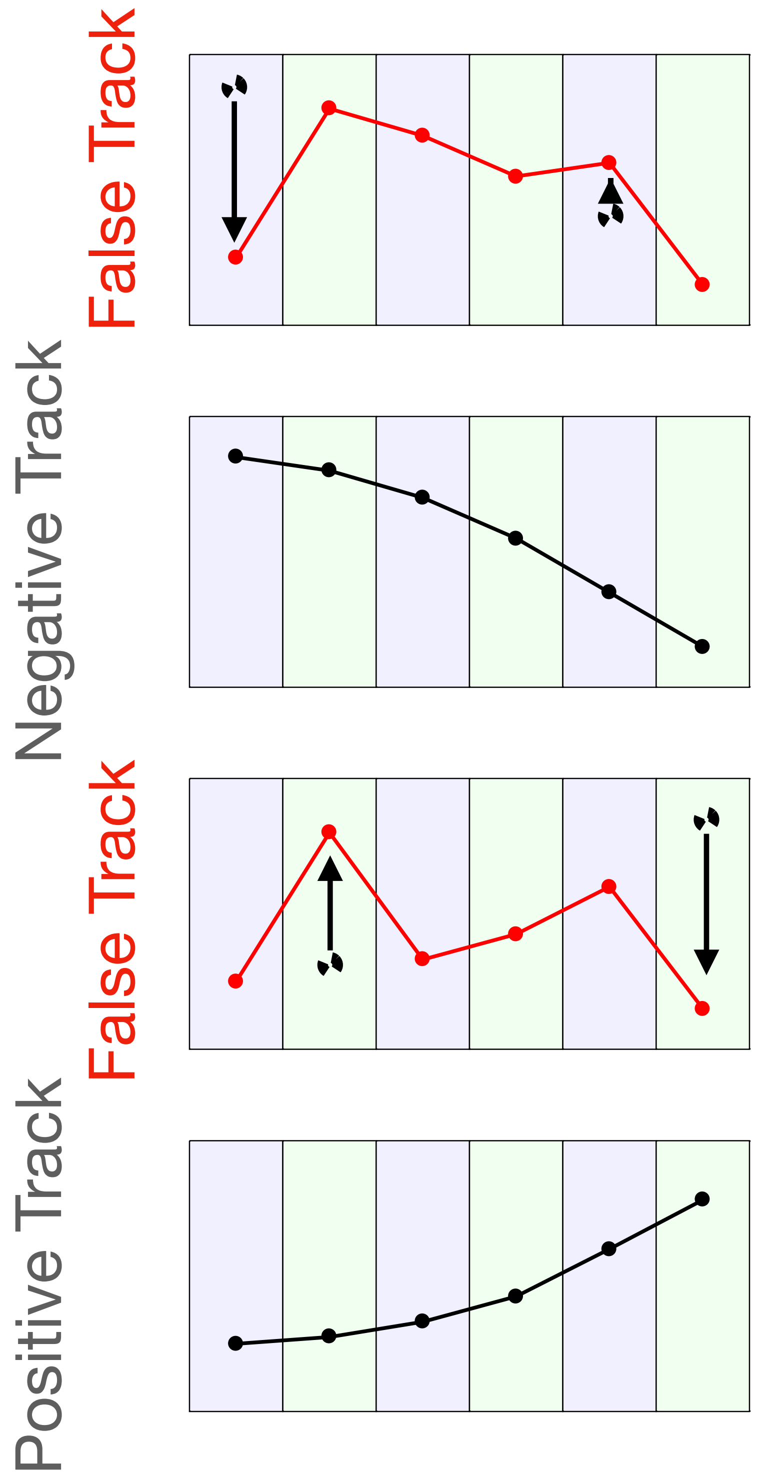
- Charged particle tracking is computationally extensive (about 80% of data processing time)
- The multi-particle final states produce numerous clusters in each sector which have to be analyzed to find the right combinations of clusters that form a track
- Identifying correct cluster combinations can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

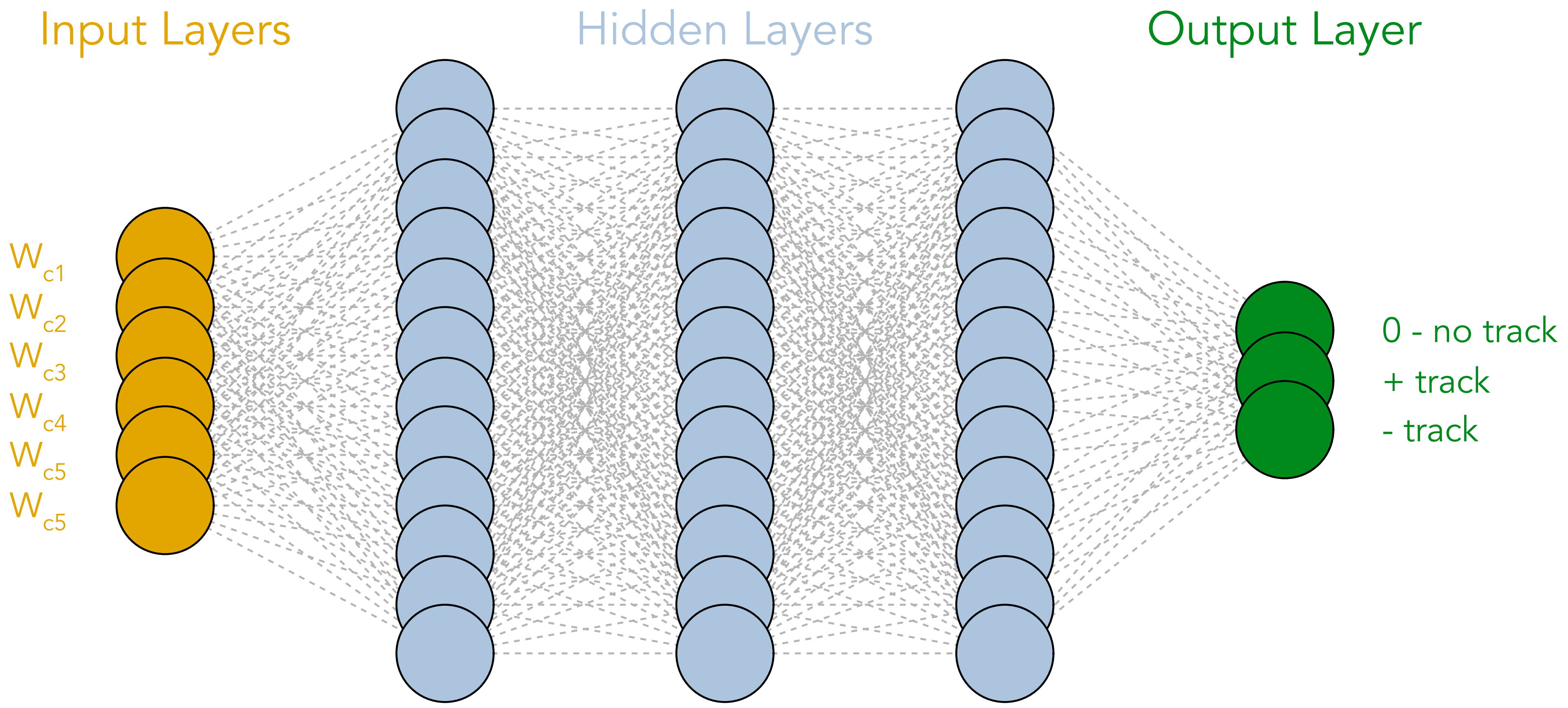




- True tracks are identified by conventional algorithms from real data.
- One negative and one positive track (different curvature due to magnetic field)
- False tracks are constructed by interchanging randomly one or two clusters with the clusters from the other track in the event

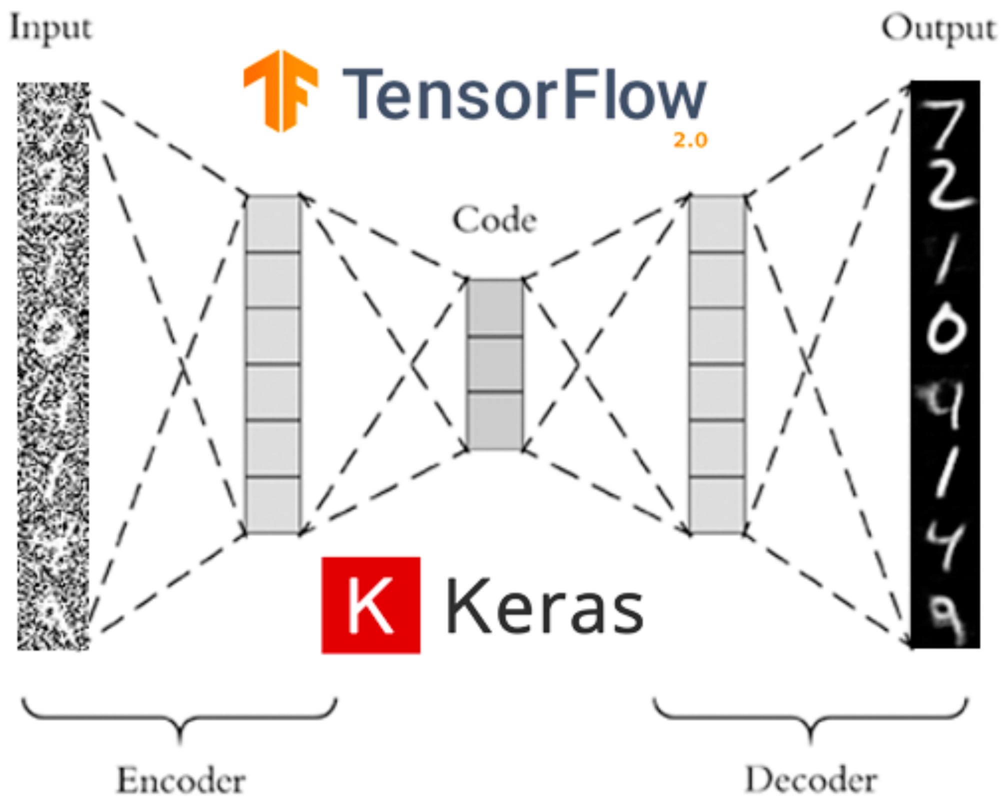
- The average wire position in each super layer is used as an input to Multi-Layer Perceptron (MLP)
- The network is trained on 6 inputs and produces three outputs:
  - False track
  - Negative Track
  - Positive Track



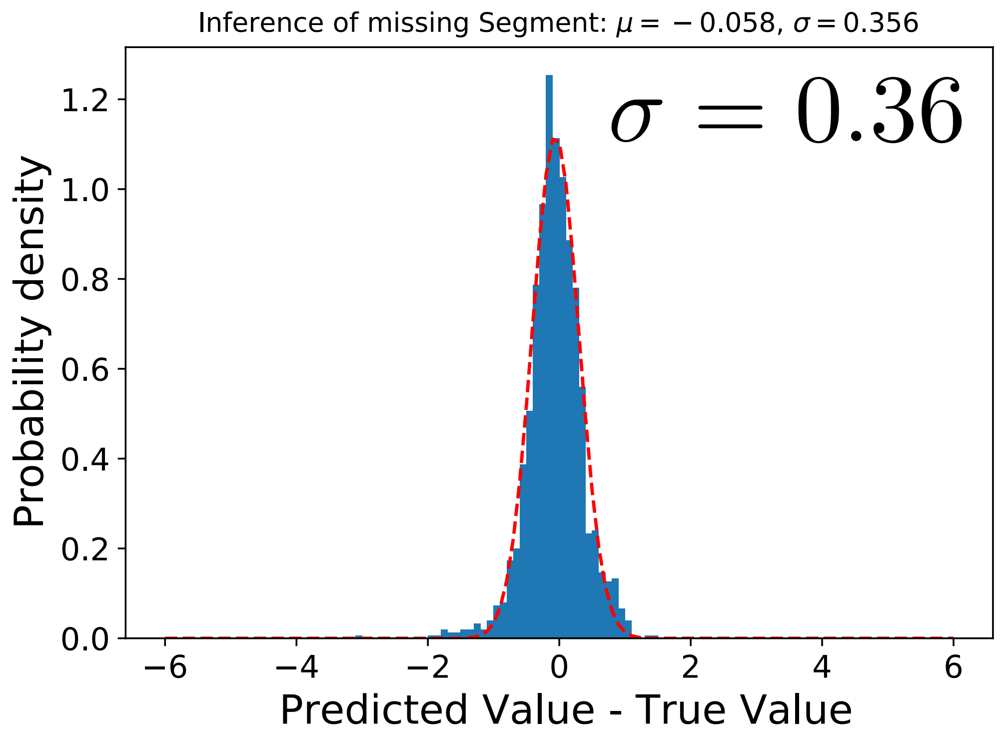


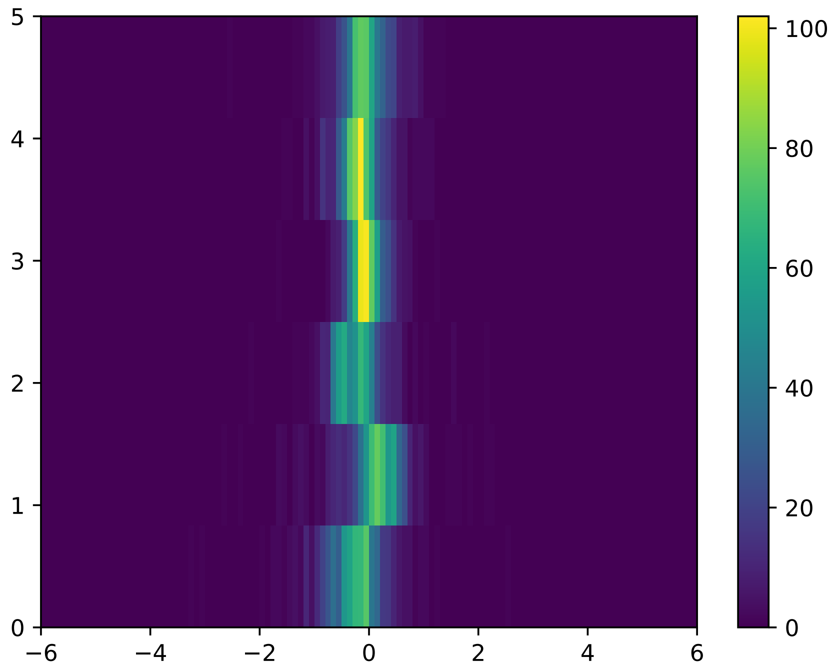
Corruption Auto-Encoder

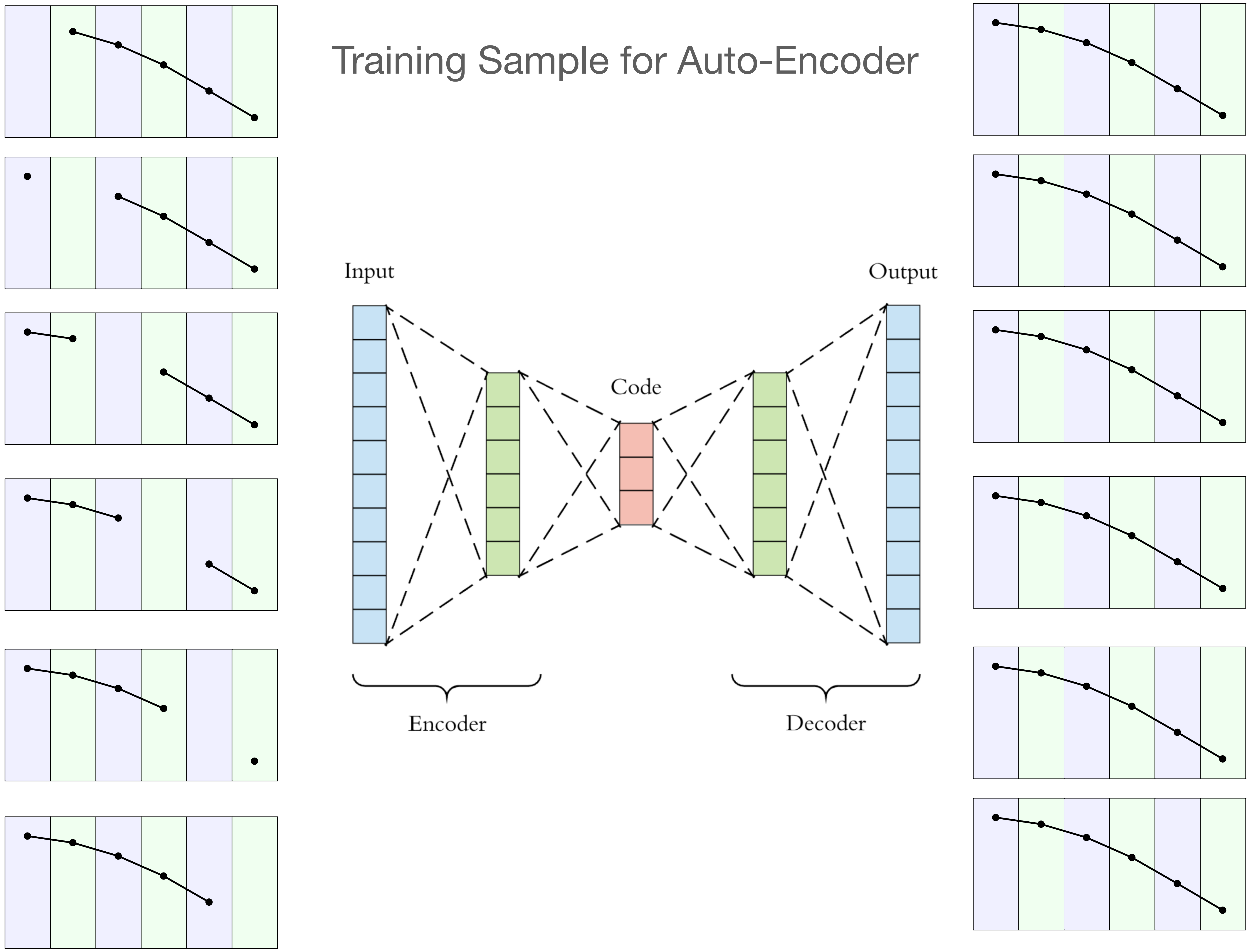
- An auto-encoder is composed of an encoder and a decoder sub-models. The encoder compresses the input and the decoder attempts to recreate the input from the compressed version provided by the encoder.
- **Typically used for de-noising, but can be used for fixing glitches (our case).**



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

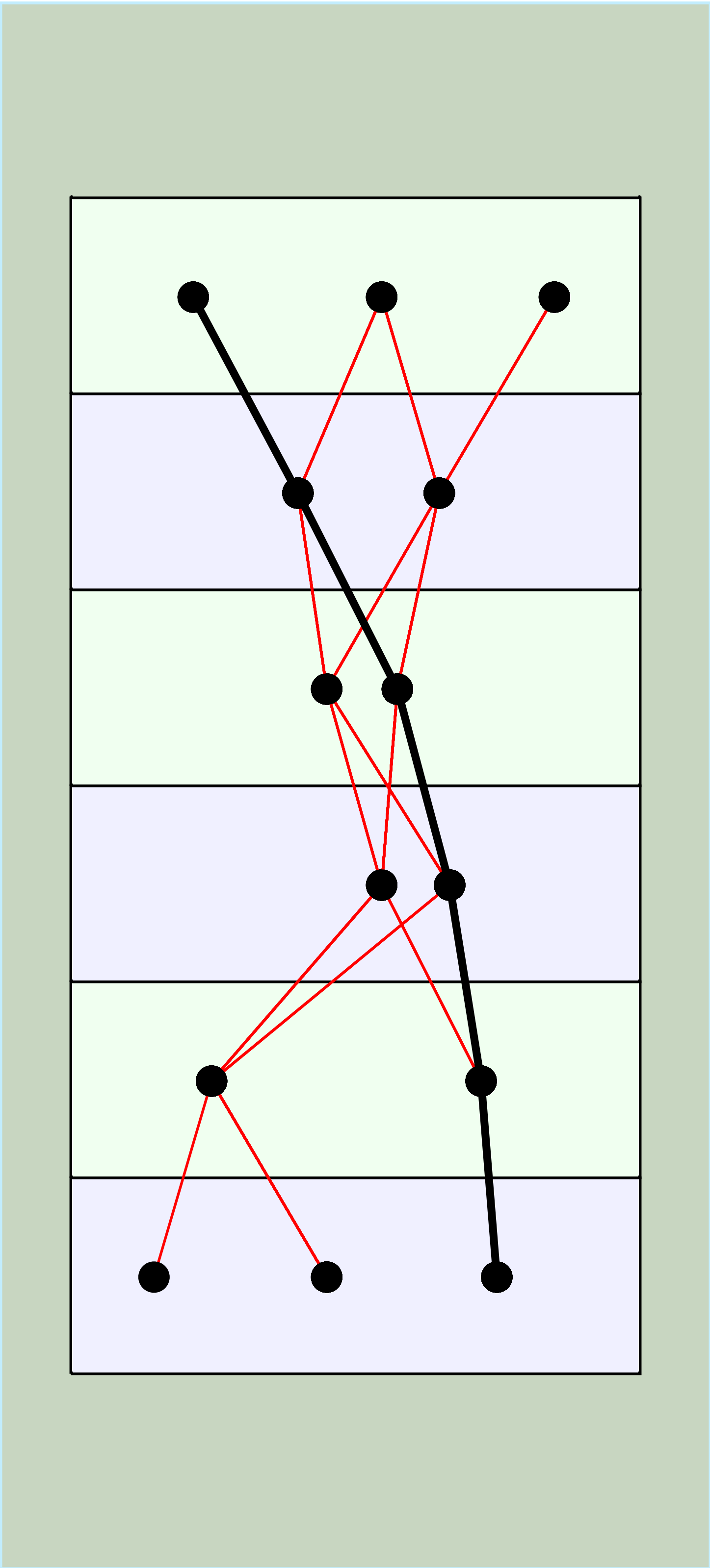




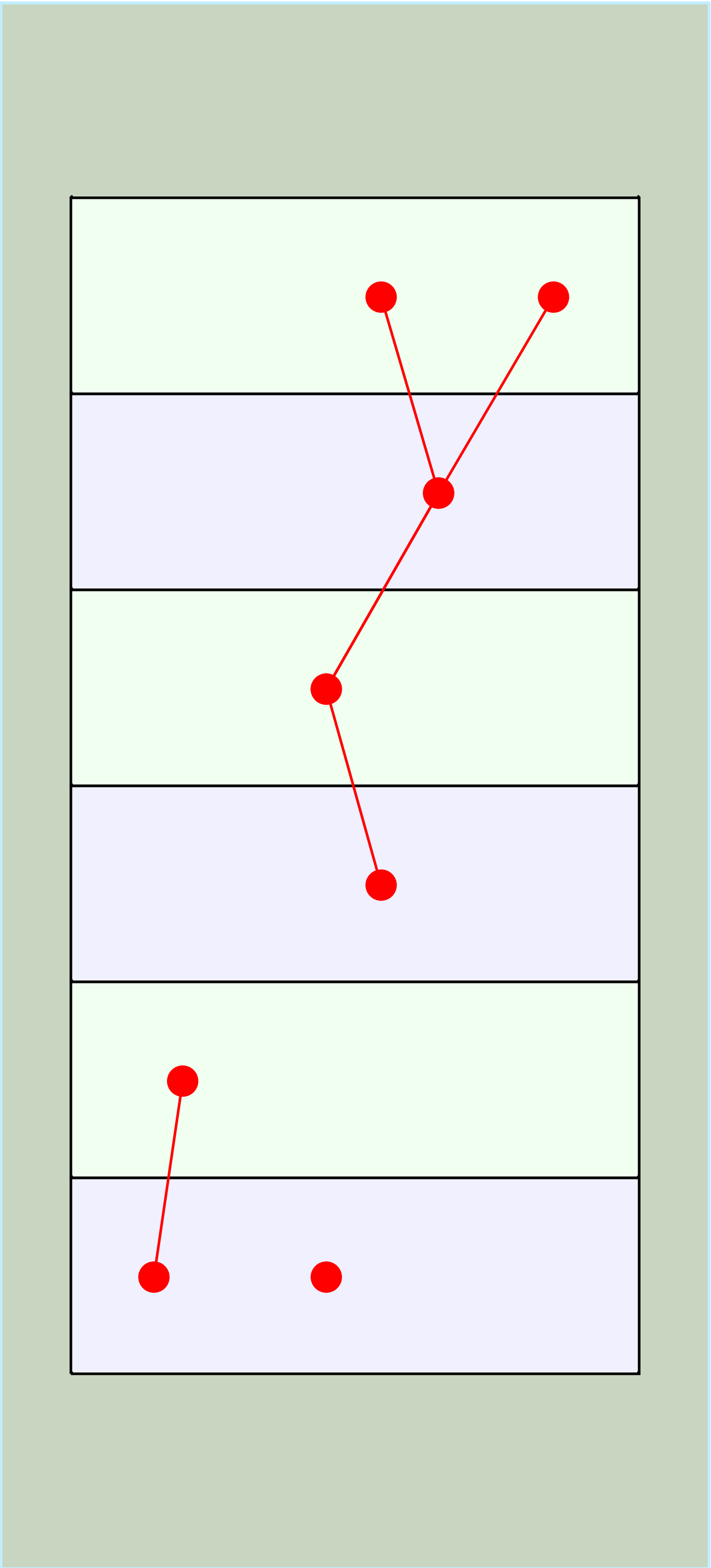


- Use Auto-Encoders to fix the missing cluster (provide a position)
- Good reconstructed tracks are used to generate training samples by removing one cluster from each super layer

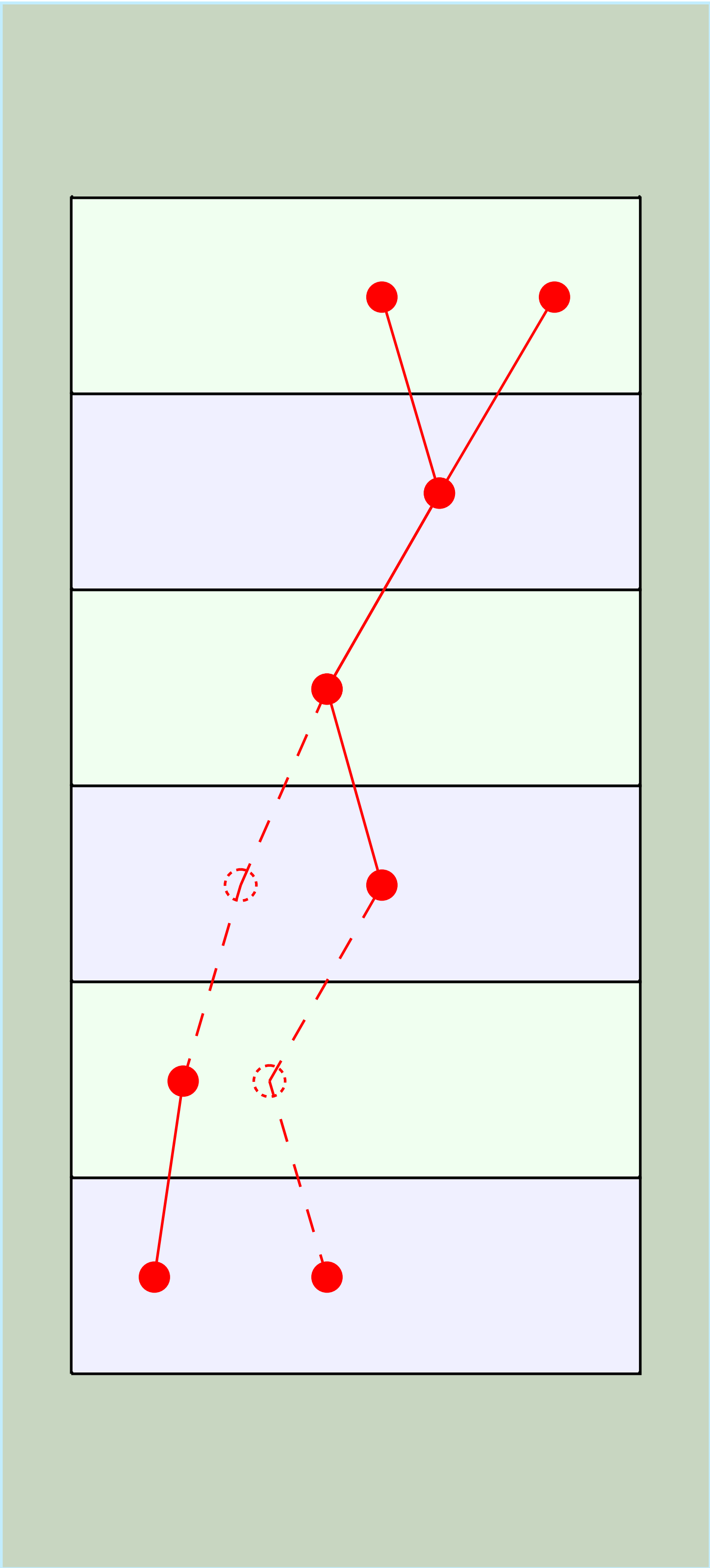
Putting things together



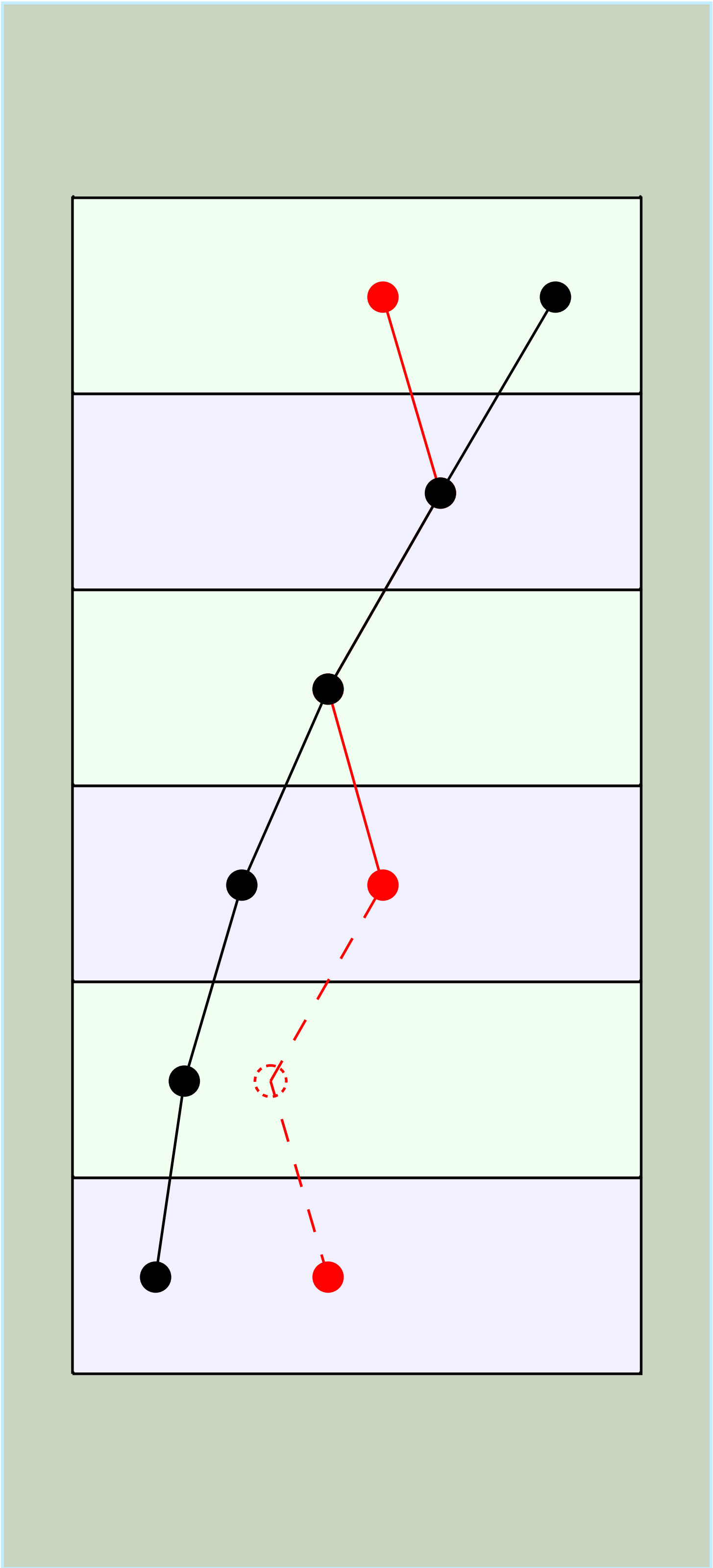
Classifier picks the correct track from 6 super-layer combinations



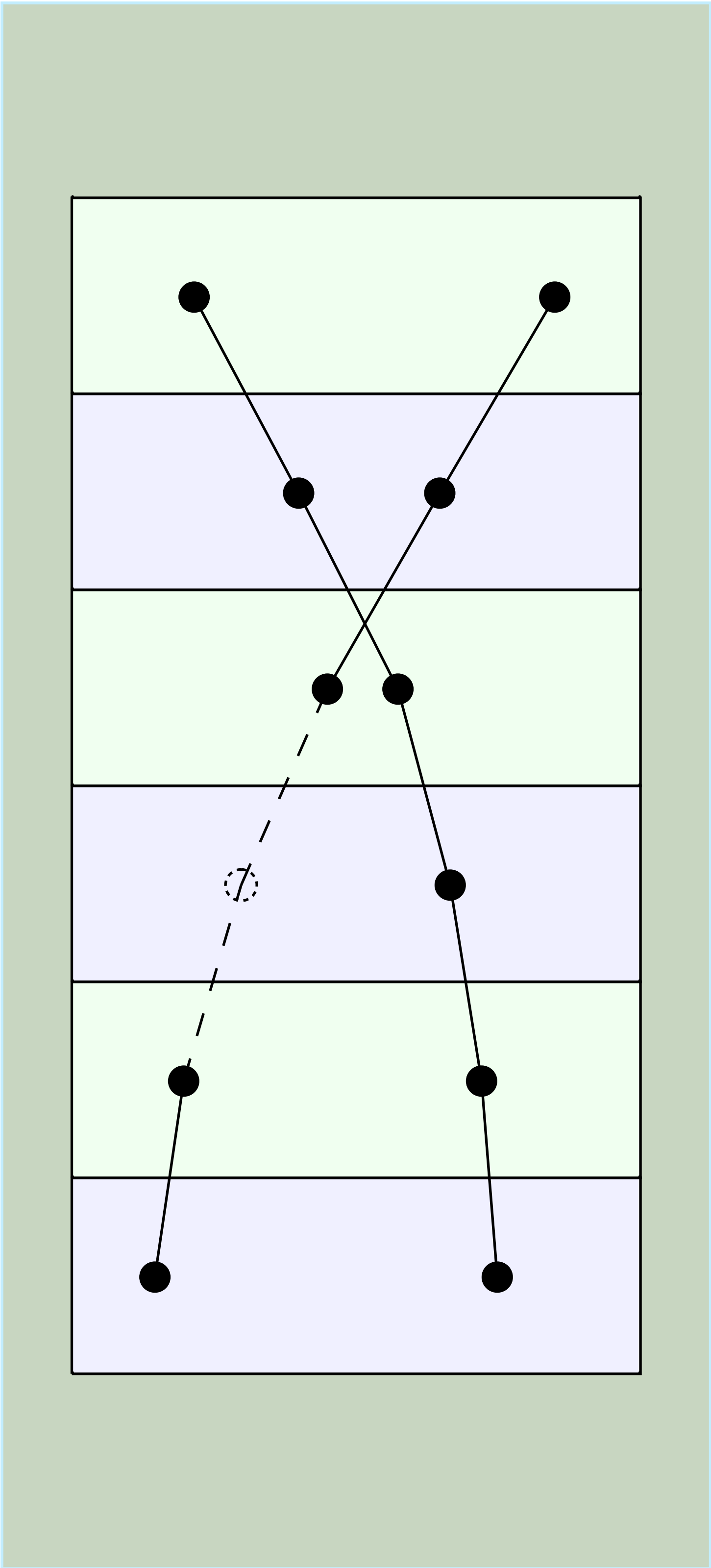
Remove all clusters belonging to identified track



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



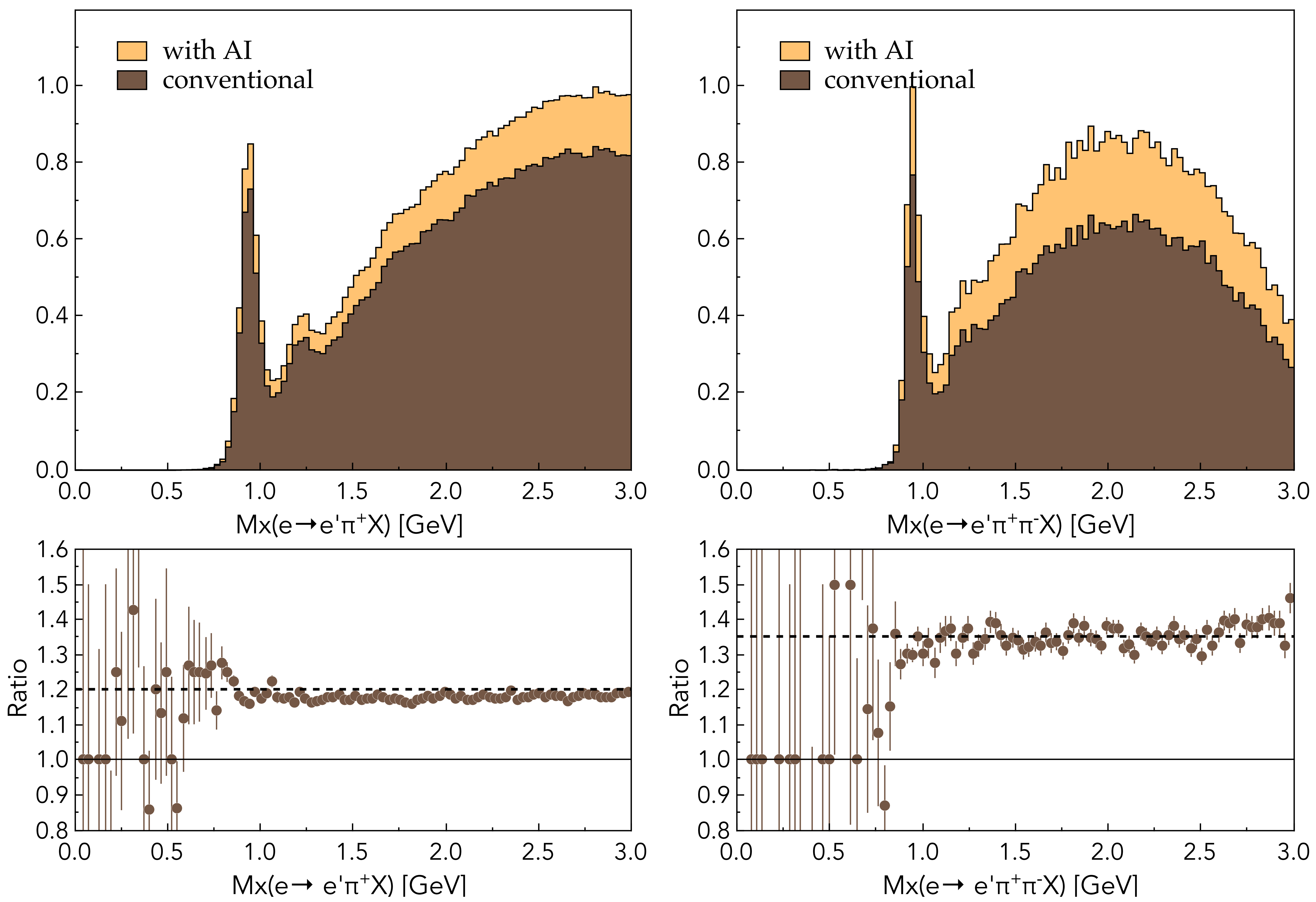
Identify tracks using 6 super layer candidates with pseudo-clusters



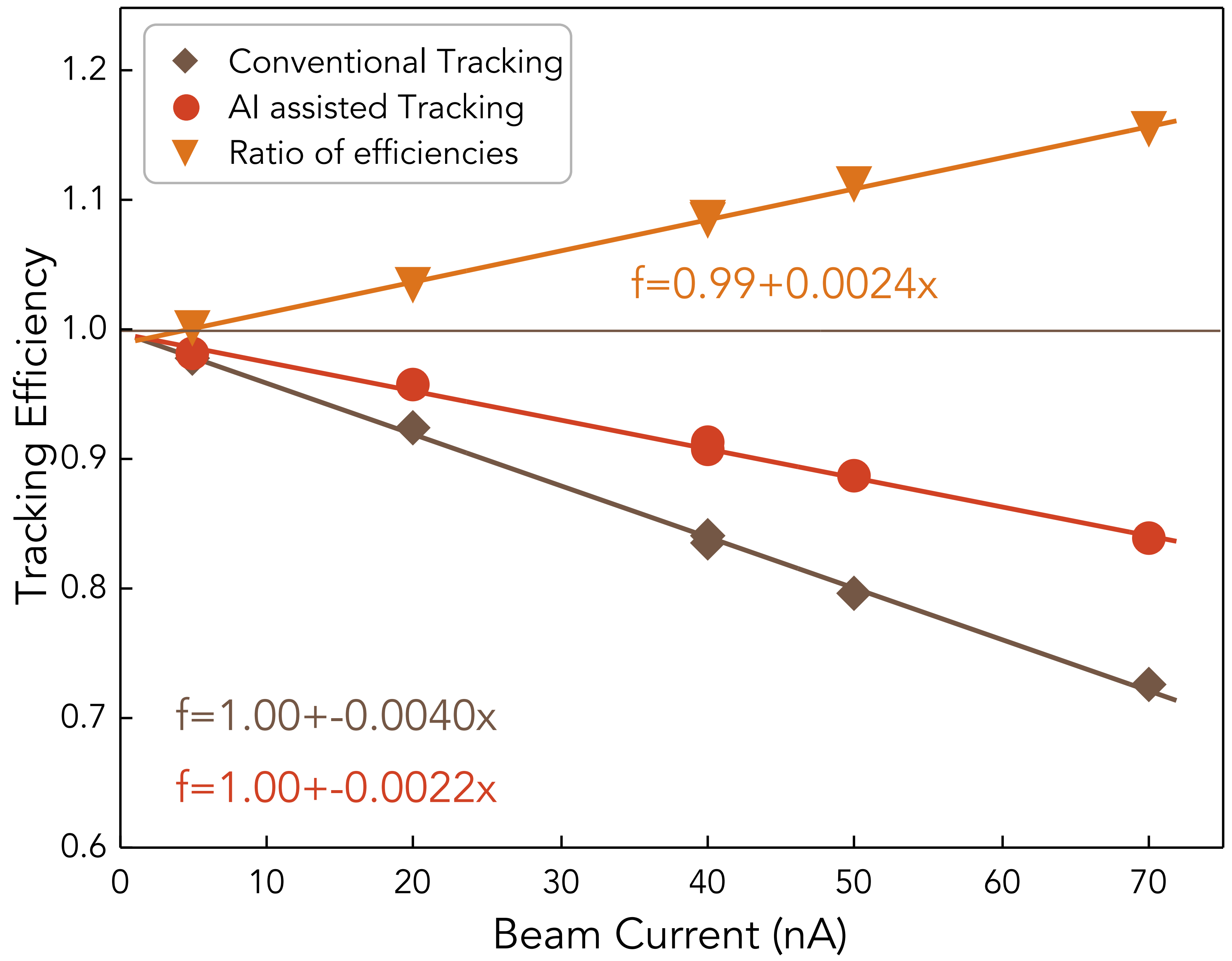
Voila!

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

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



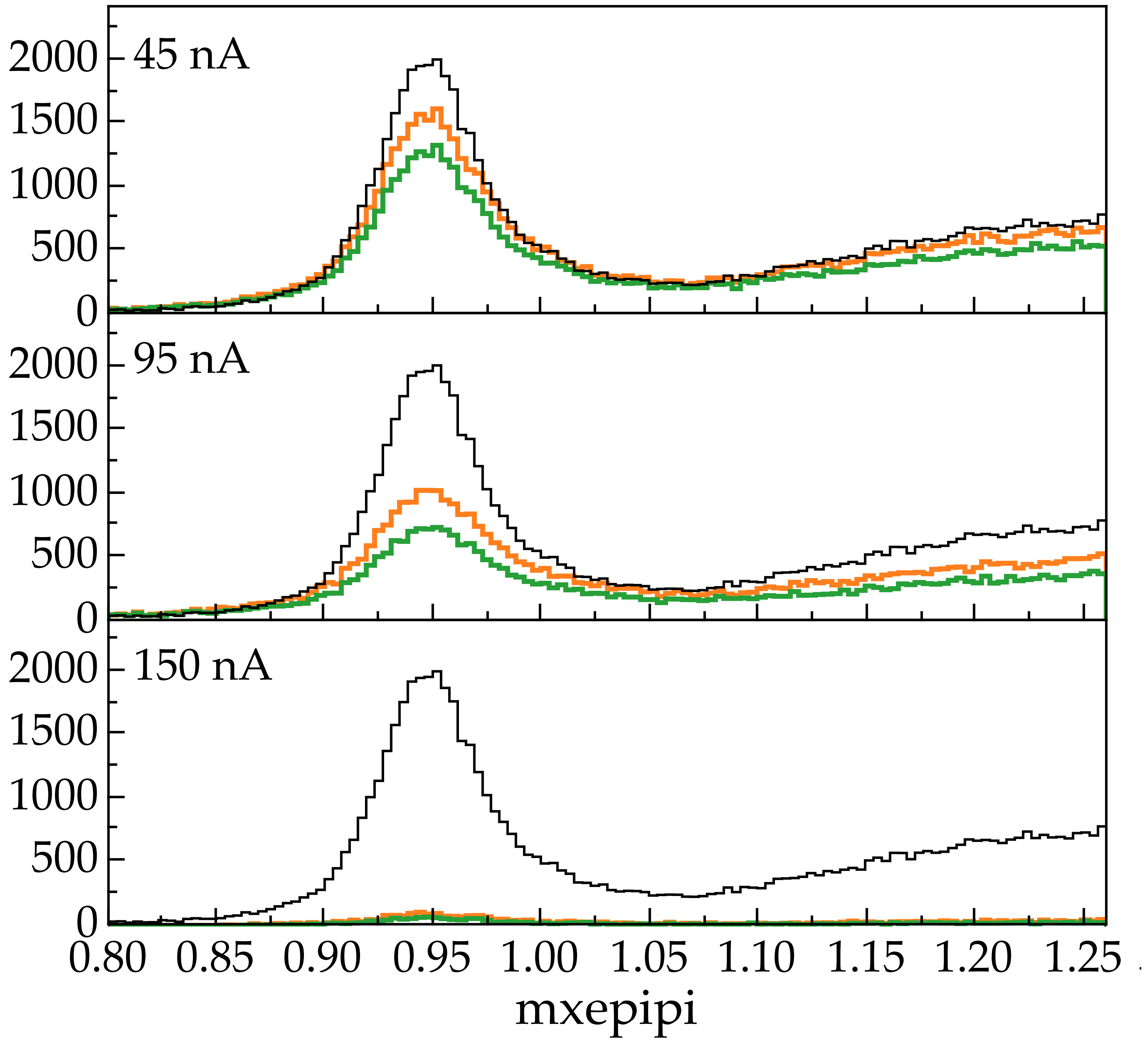
- Single particle efficiency increases by ~10%.
- The impact on physics for a multi-particle final state is dramatic (20% for the two-particle final state and ~35% for the three-particle final state)
- The tracking code speedup is ~30%.

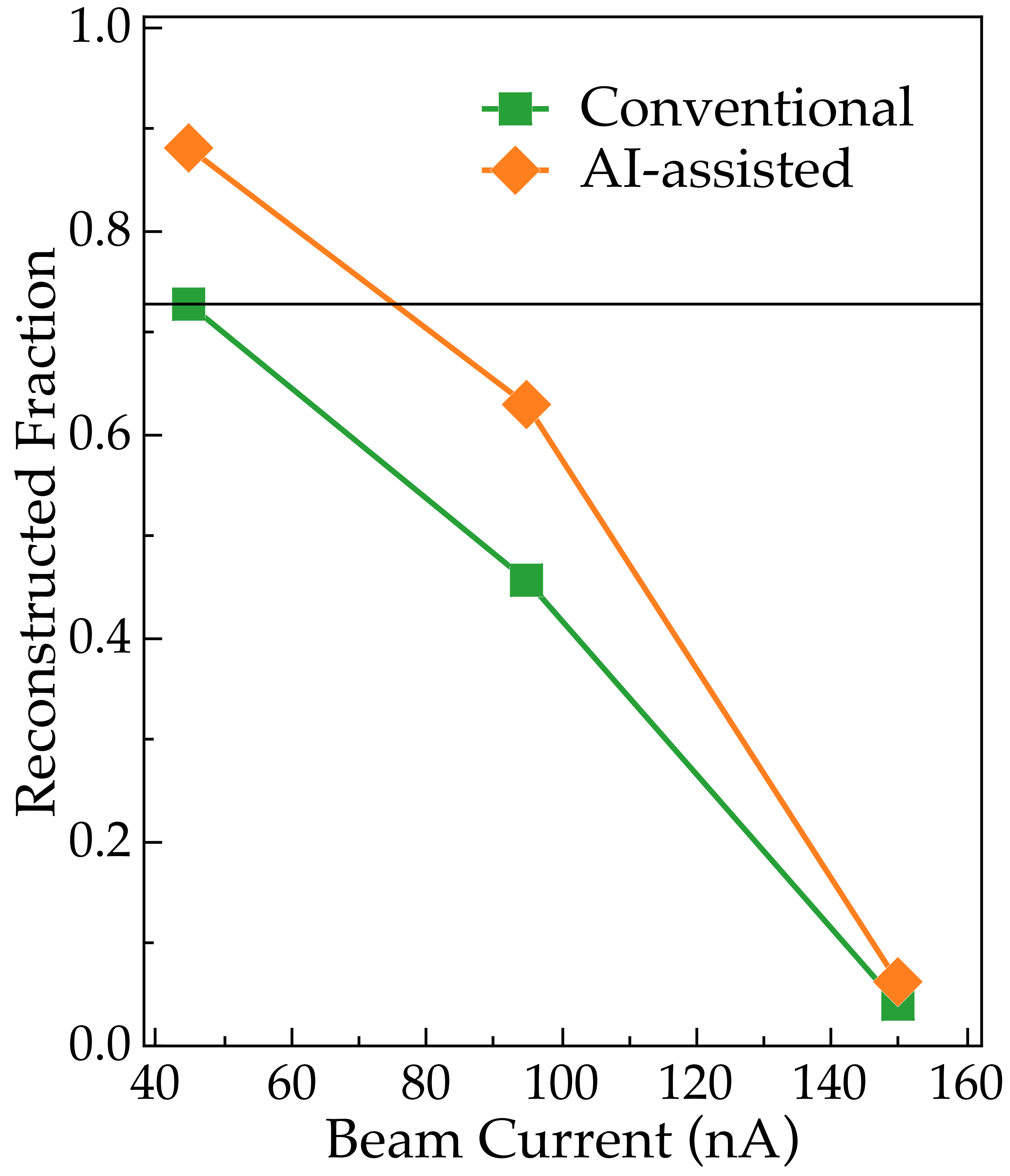


~35% gain in physics

Moving to higher Luminosities

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:

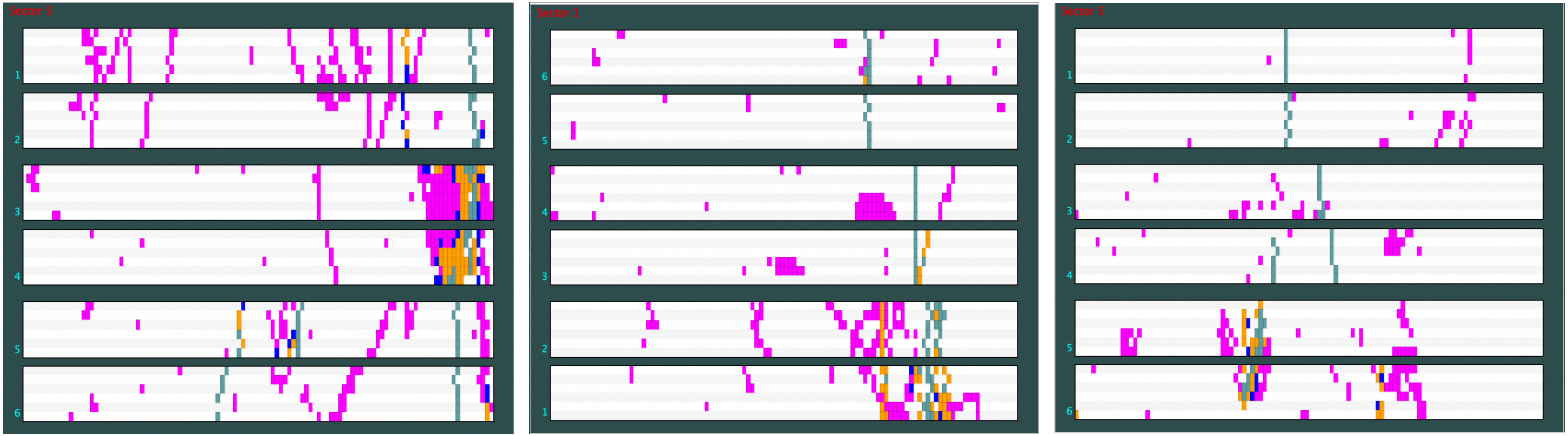
$$ep \to e'\pi^+\pi^- X$$

- 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

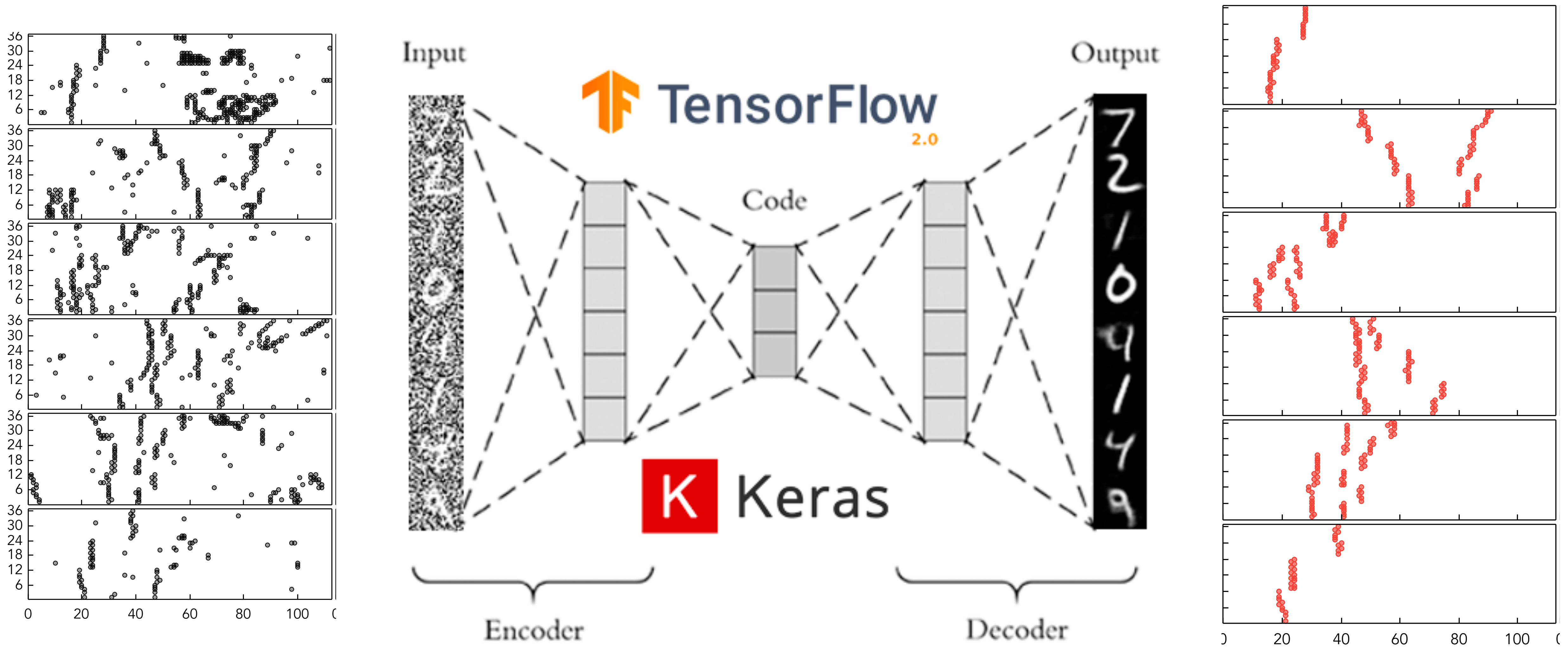
- In high luminosities the noise level increases and forming clusters (or segments in each chamber becomes challenging)
- This results in loss of clusters and AI-assited tracking can no longer help with combinatorics resolution

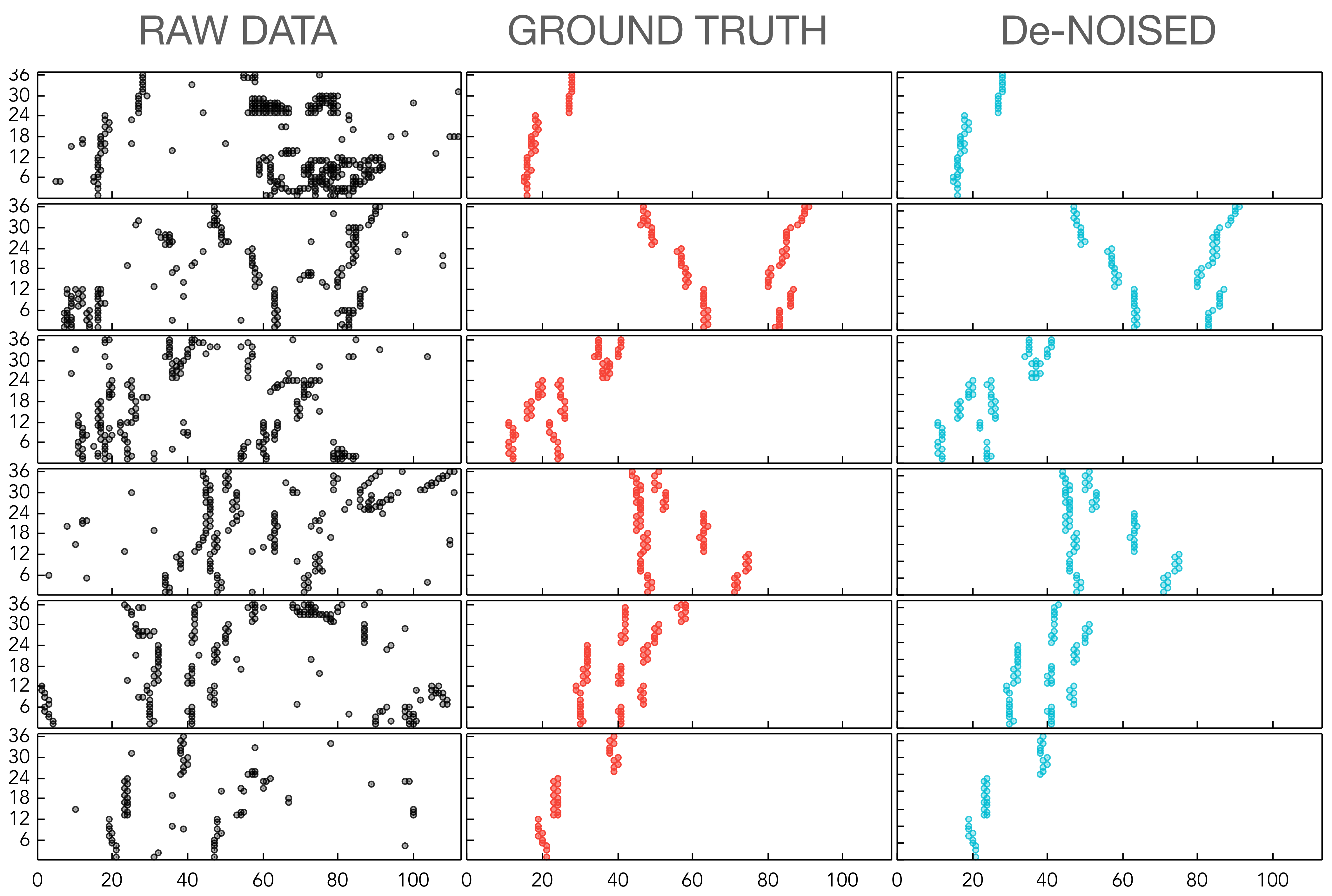
CLAS12 Event Display Examples (Drift Chambers)



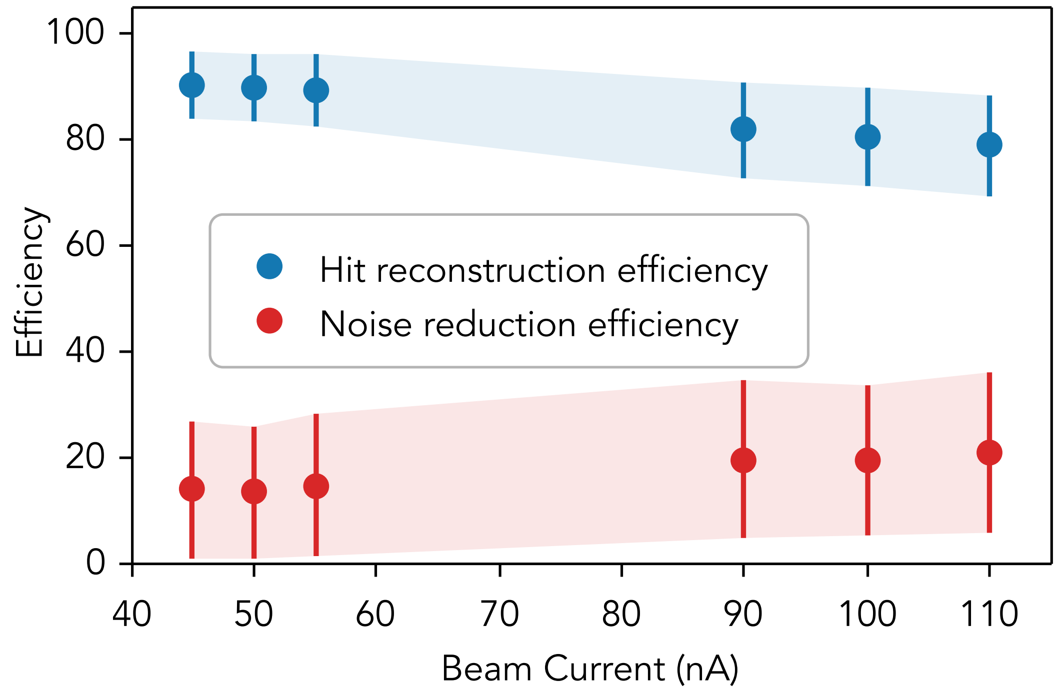
De-Noising

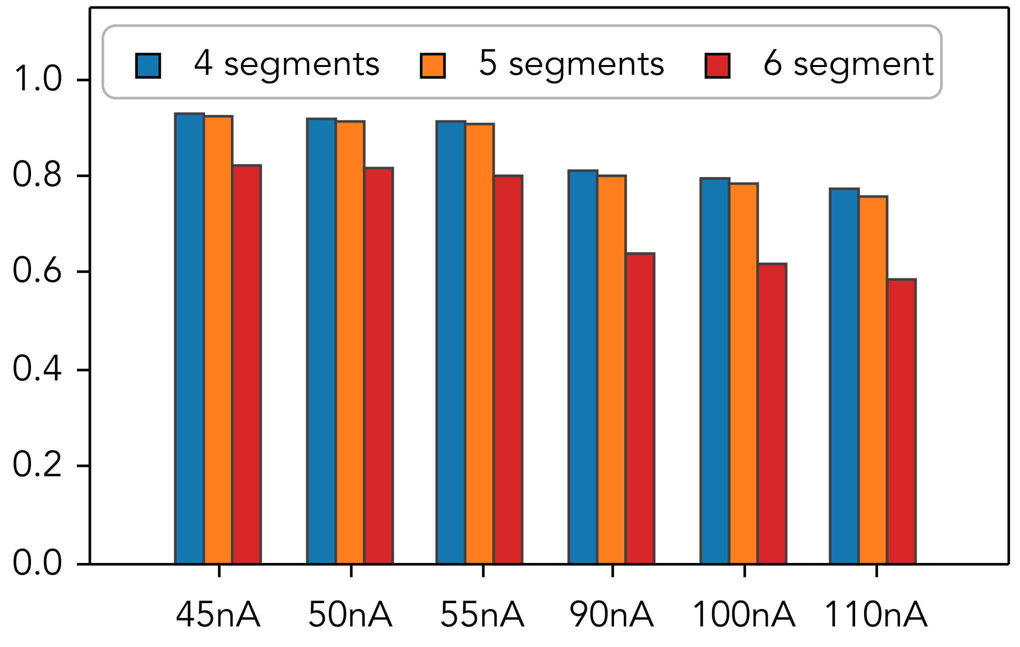
- Convolutional Auto-Encoder is used to de-noise raw data from drift chambers.
- The network is trained on reconstructed data with track hits isolated from raw DC hits.
- The network is able to isolate hits that potentially belong to a valid track through drift chambers





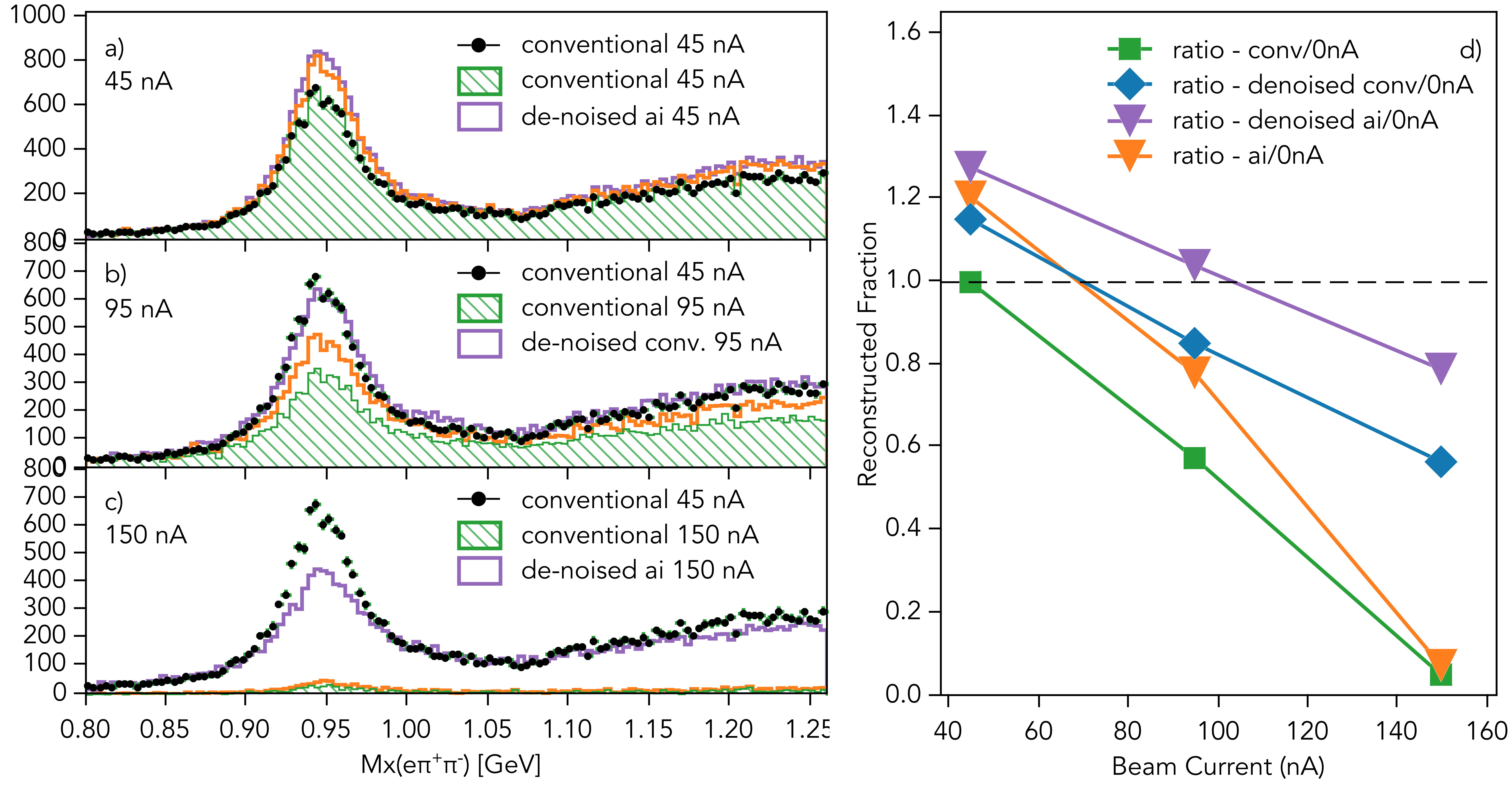
Network Performance Summary





De-Noising Results (simulation)

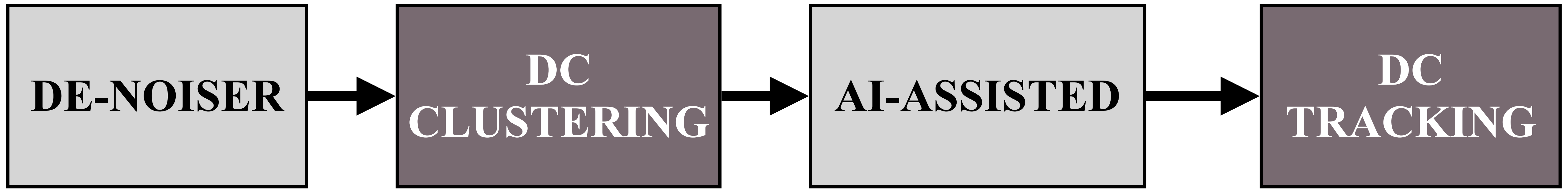
- The reconstruction is run on simulated data with a merging background for different incident beam currents (luminosity)
- The simulated three-particle final state is analyzed to measure yield for de-noised data and for conventional



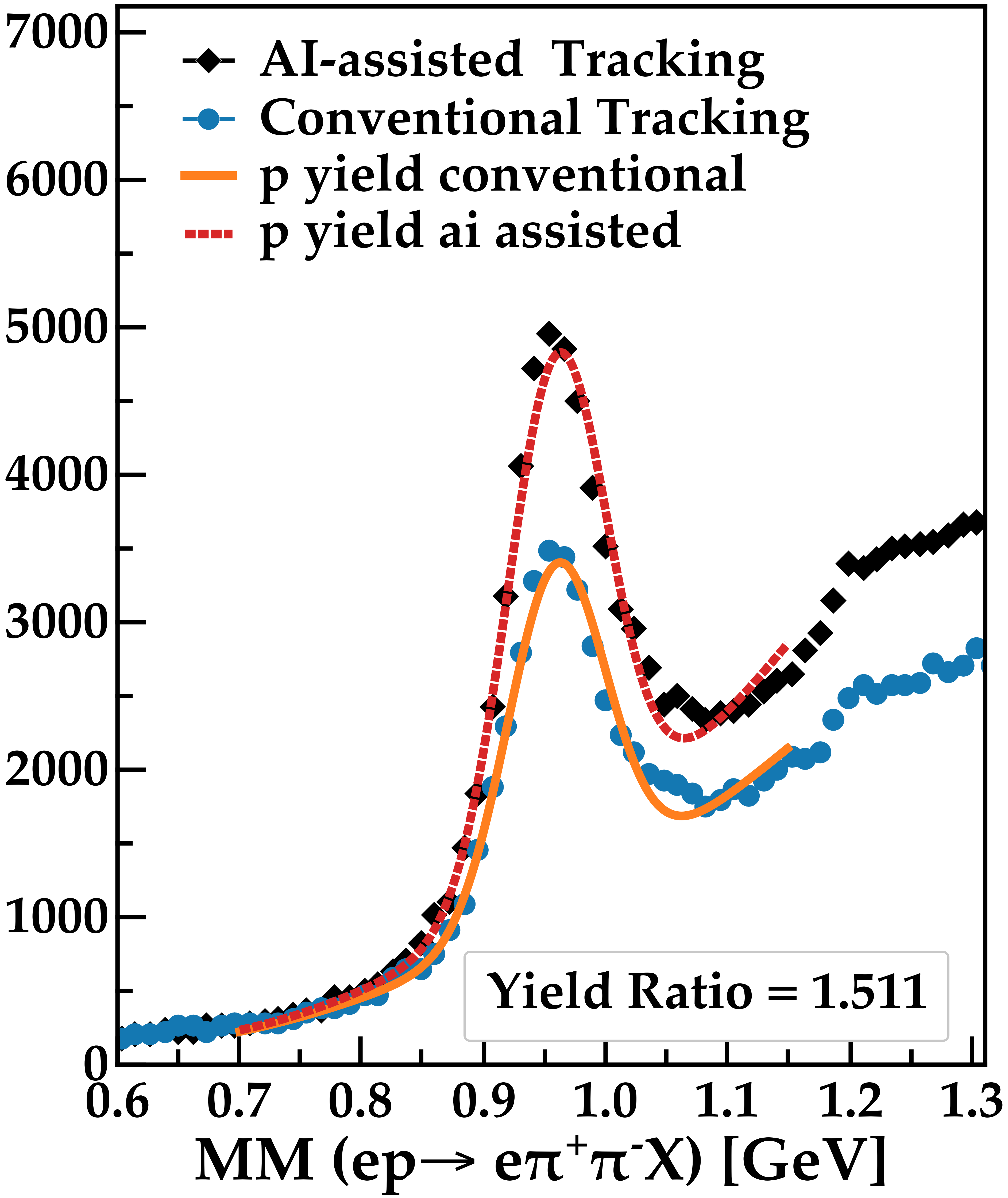
- At standard running luminosity, the de-noising slightly increases the yield compared to AI-assisted tracking.
- With increased luminosity, the de-noising helps to increase the yield significantly compared to conventional and AI-assisted tracking.
- Simulation underestimates the gain in yield significantly.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



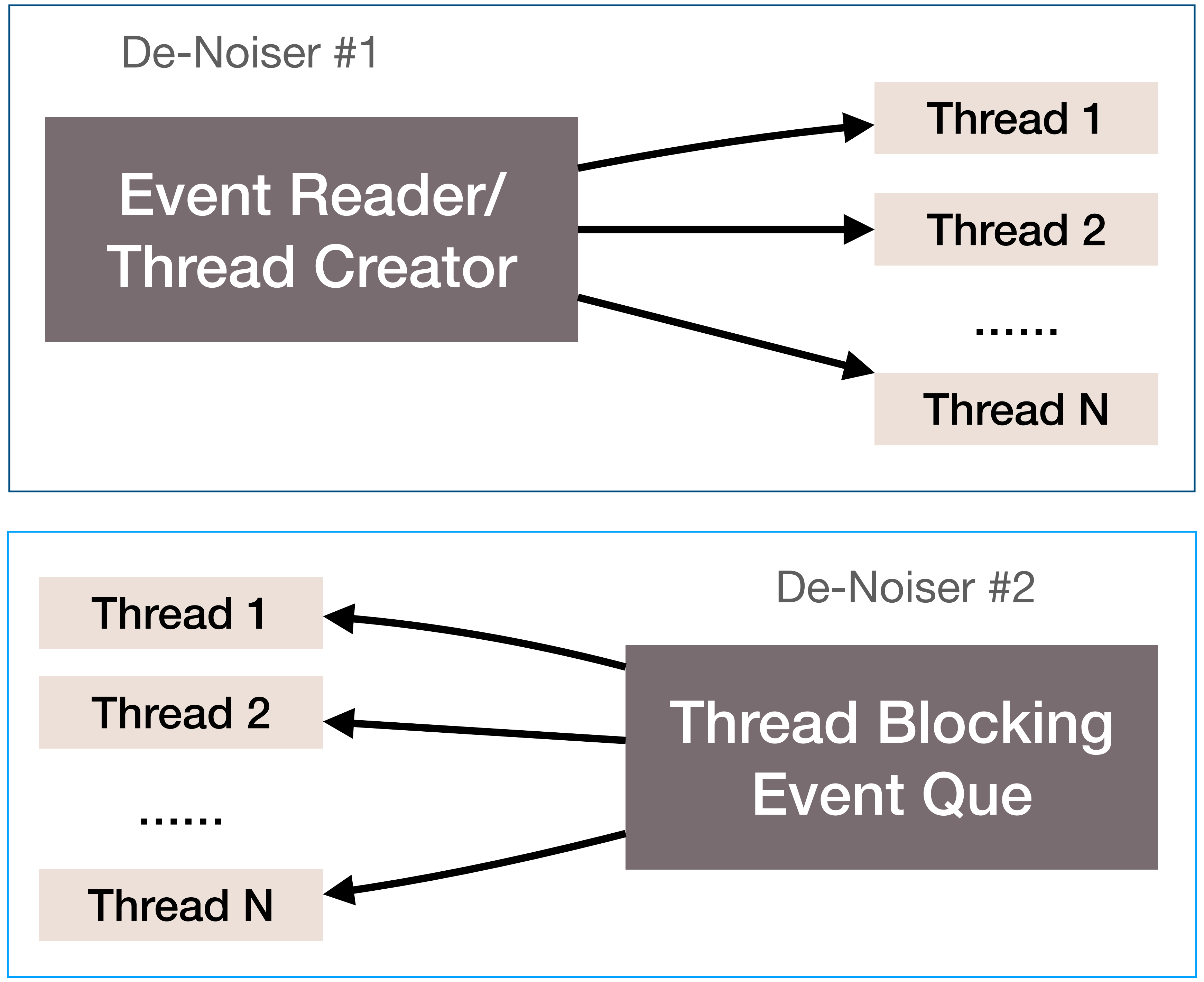
Summary

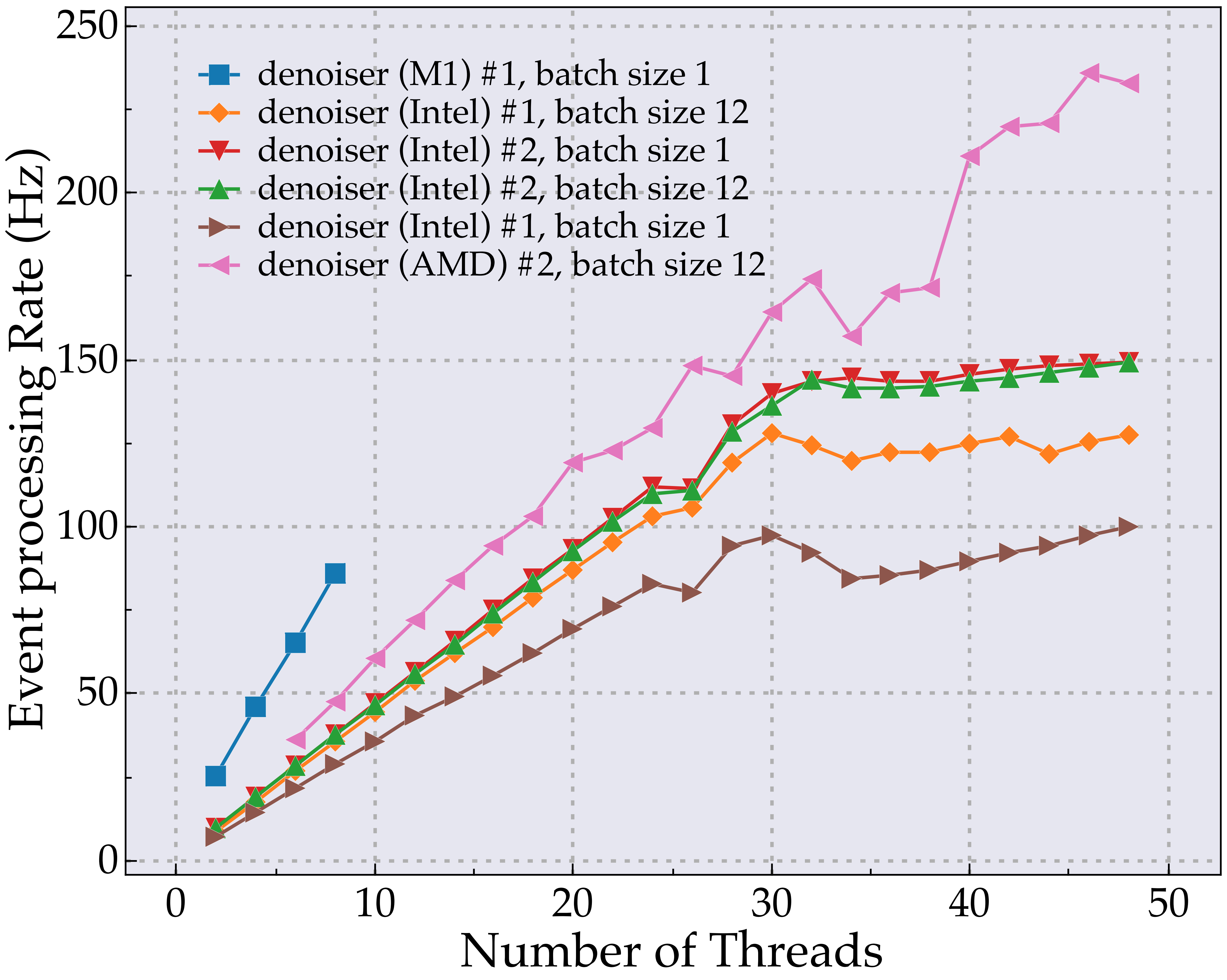
- CLAS12 uses three neural networks for track reconstruction in forward drift chambers:
  - De-Nonoiser: Convolutional Auto Encoder Network
  - Corruption Recovery Network: Multi-Layer Perceptron AutoEncoder
  - Track Classifier: Multi-Layer Perceptron Neural Network
- The combined effect of three neural 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 pave the way for high luminosity running where conventional methods can not be used.
- Future: working on neural networks for other detectors

Backup Slides

De-nosing Performance Multi-Threaded

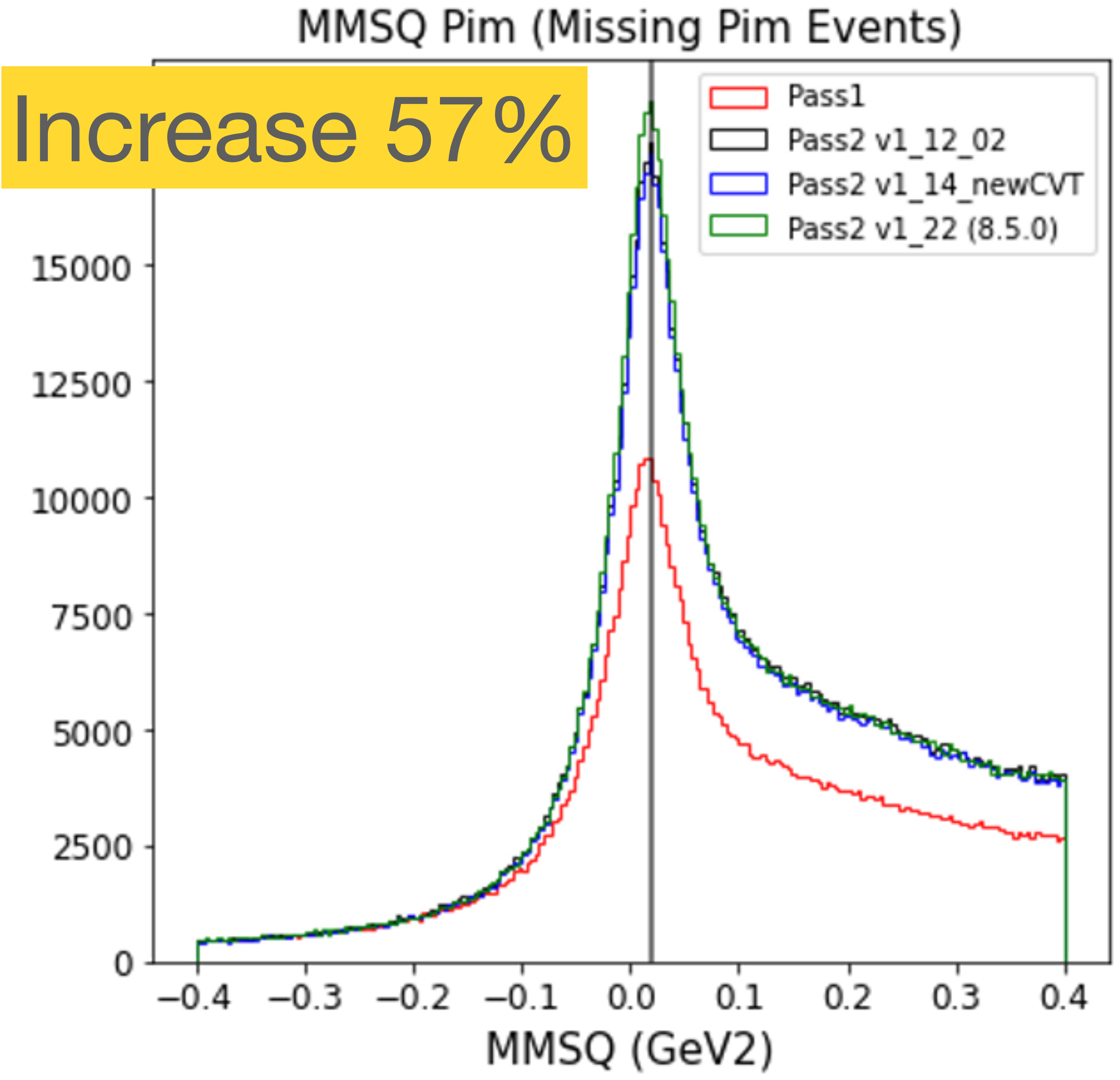
- **C++:** Keras model inference in C++ code implemented for CLAS12 de-noiser.
- **Multi-Threading**: Multi-threading implemented to process data files (using std::thread)



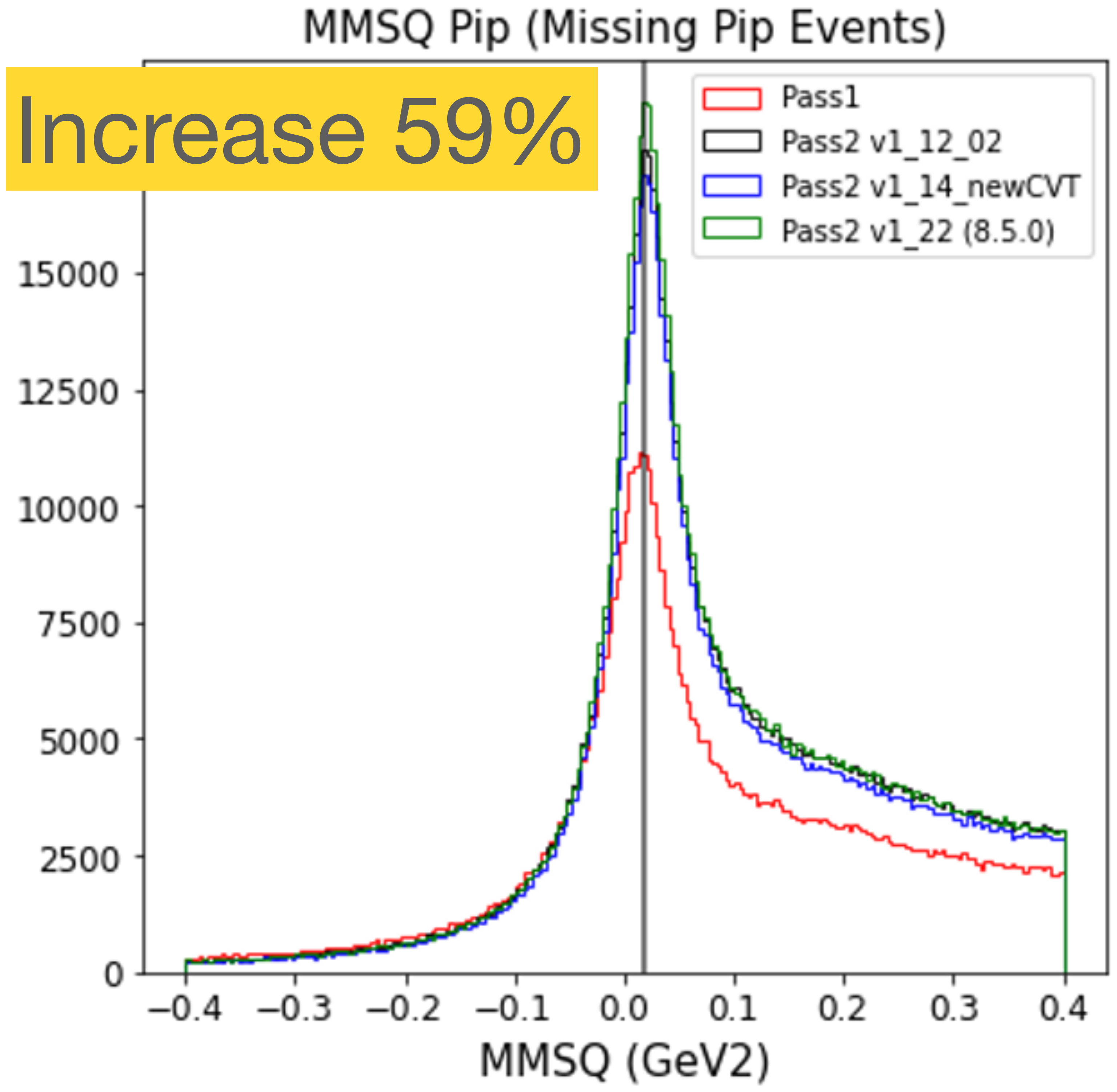


RUN GROUP-A Pass2 Validation Cooking
Includes De-Nosing and AI-assisted Tracking

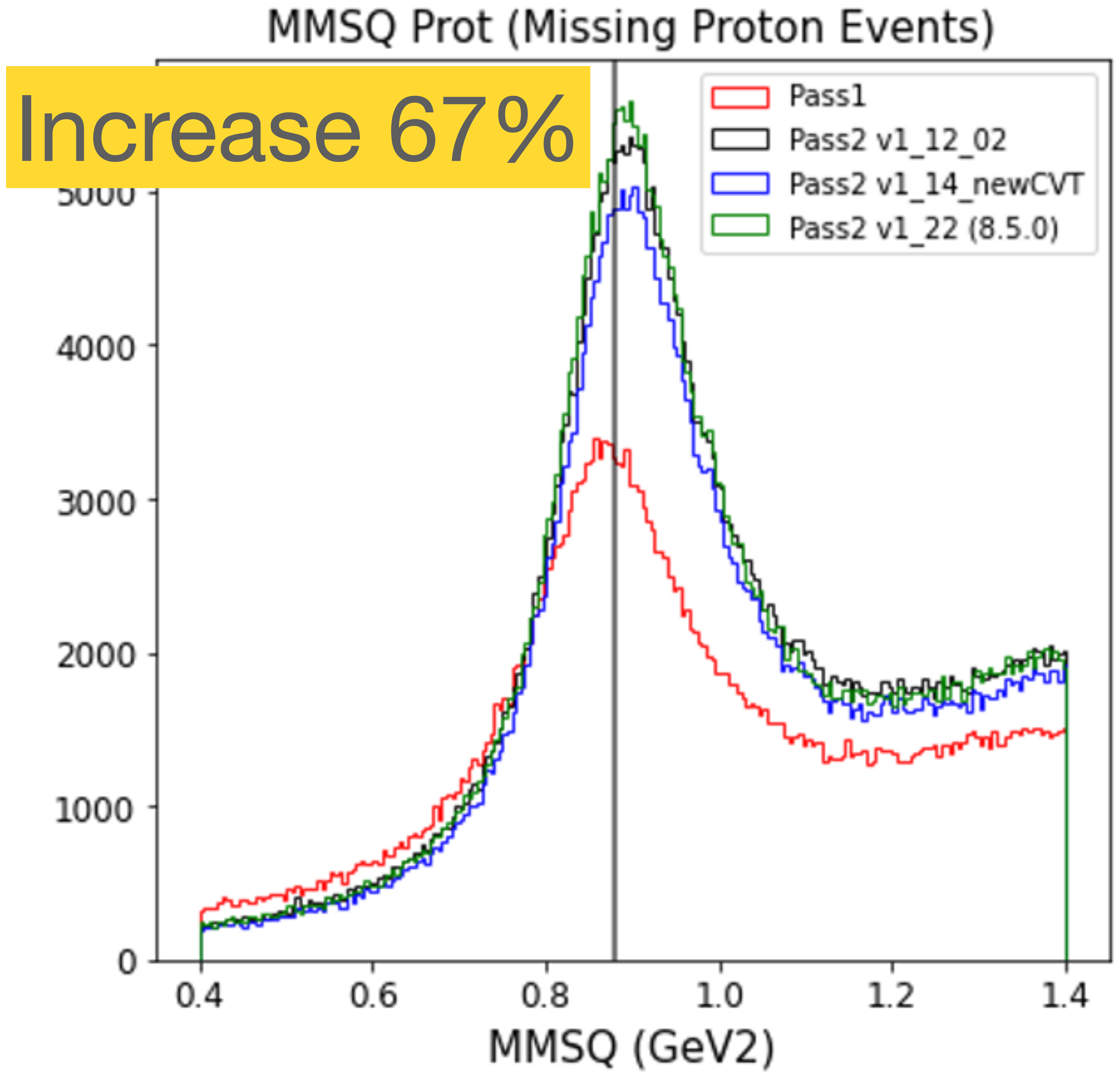
$$ep \to e' p \pi^- (X)$$



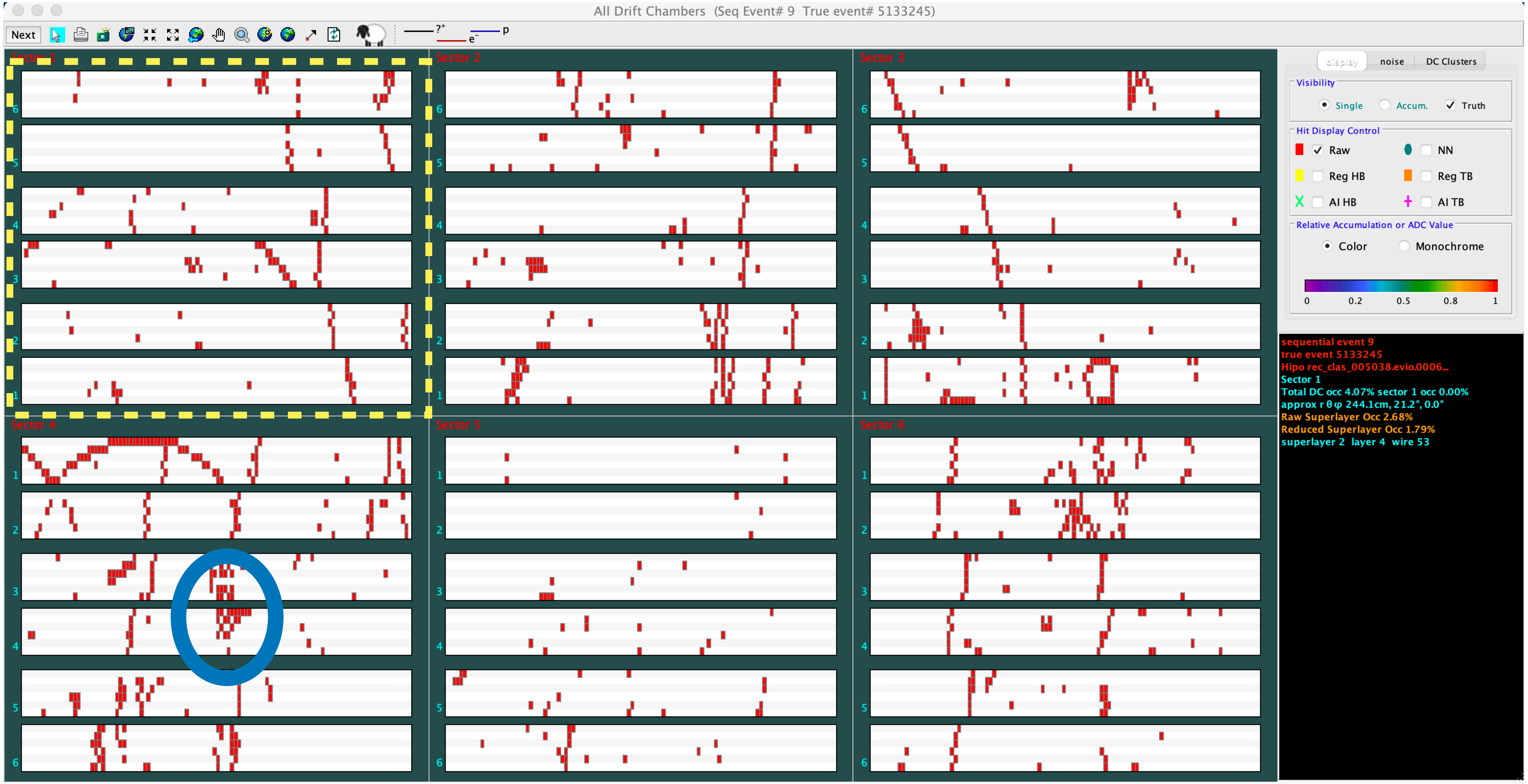
$$ep \to e' p \pi^+ (X)$$



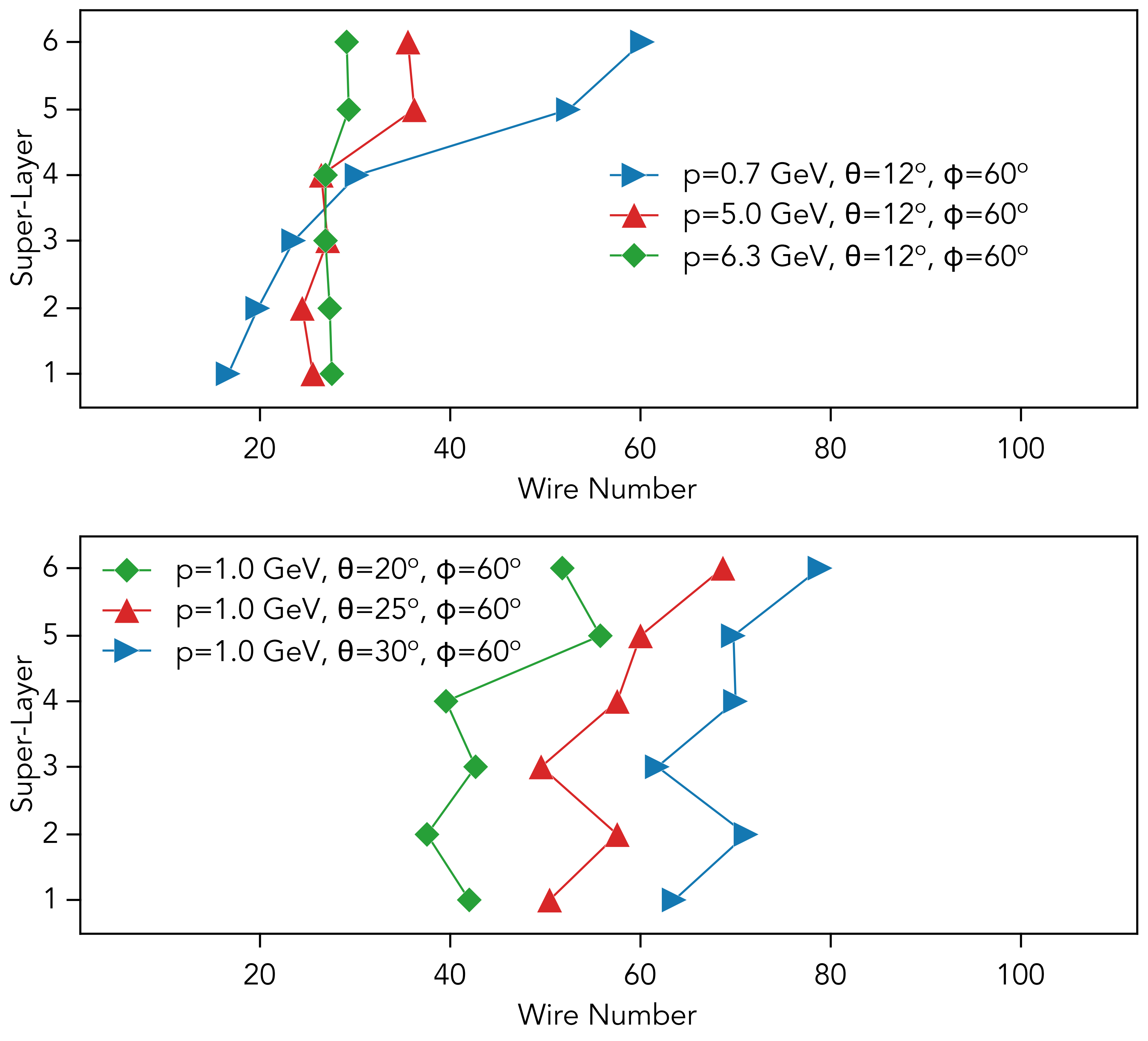
$$ep \to e' \pi^+ \pi^- (X)$$

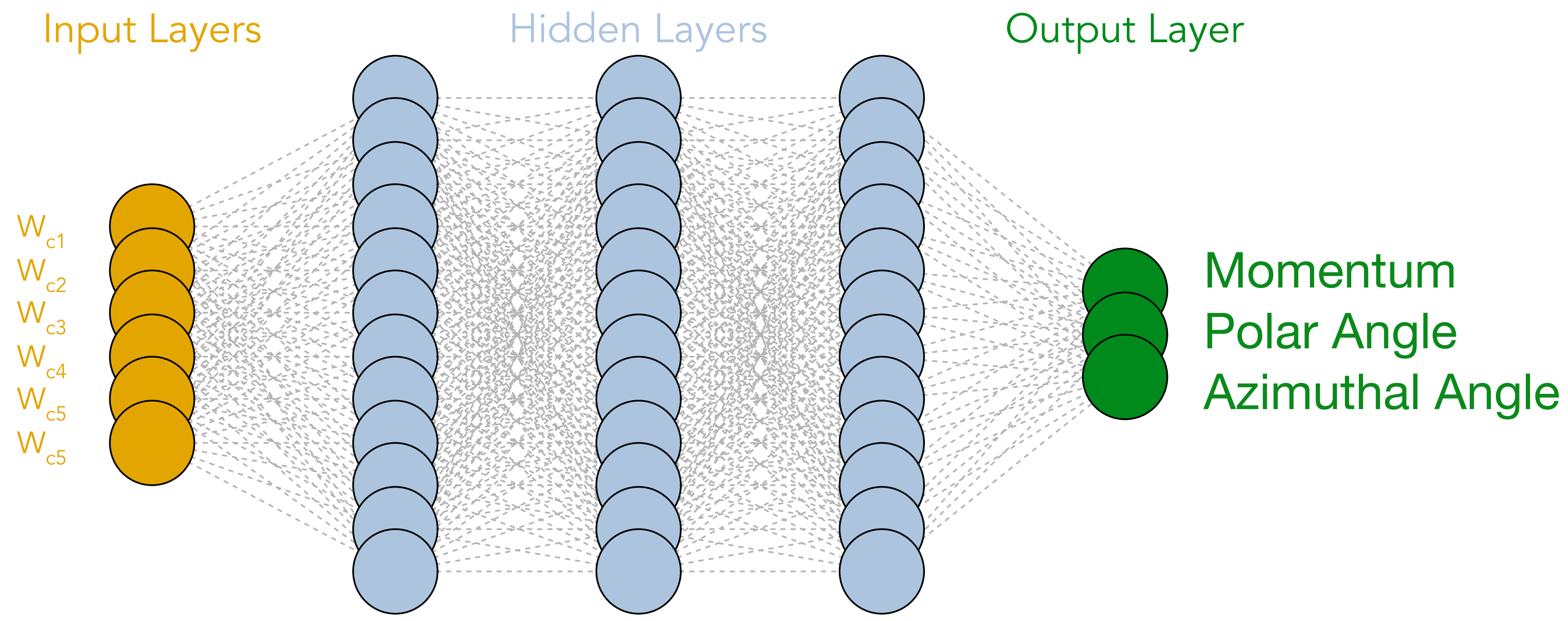


CLAS12 Event Display (Drift Chambers)



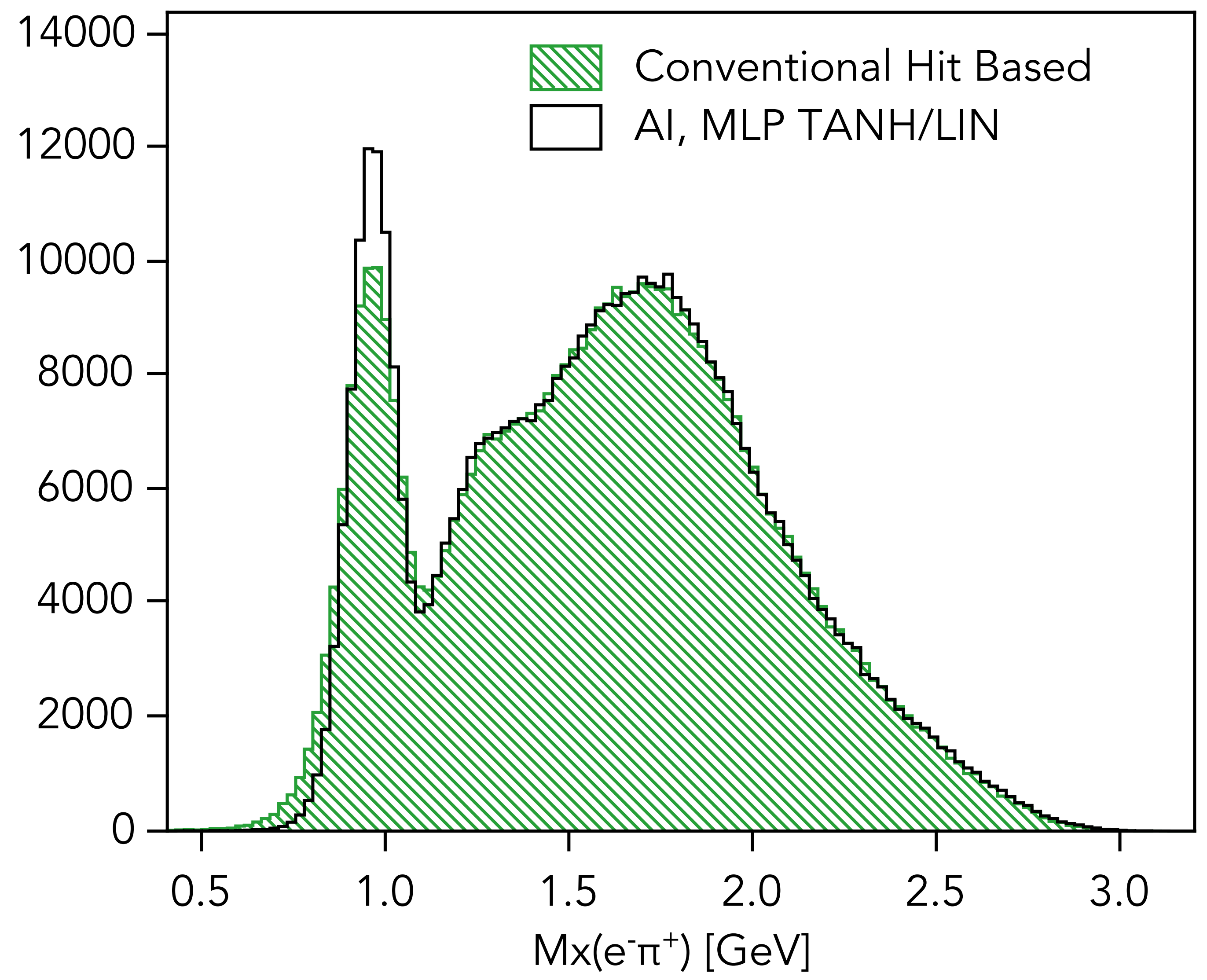
Track Parameter Reconstruction





- 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.

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

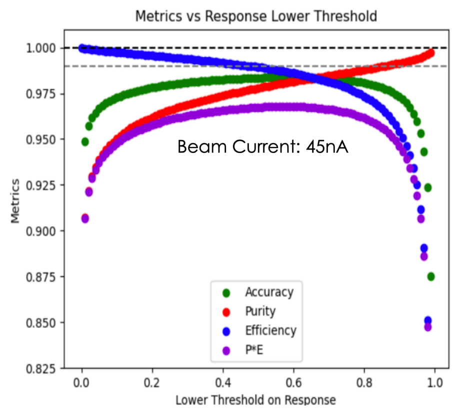


- Missing mass of two particles calculated using particle momenta from Hit-Based Tracking compared to missing mass calculated from AI particle parameter inference.
- Hit Based Tracking works ~250 ms per event
- AI reconstructs particle parameters <0.5 ms per event

Future of CLAS12-AI

Level-3 Trigger (AI)

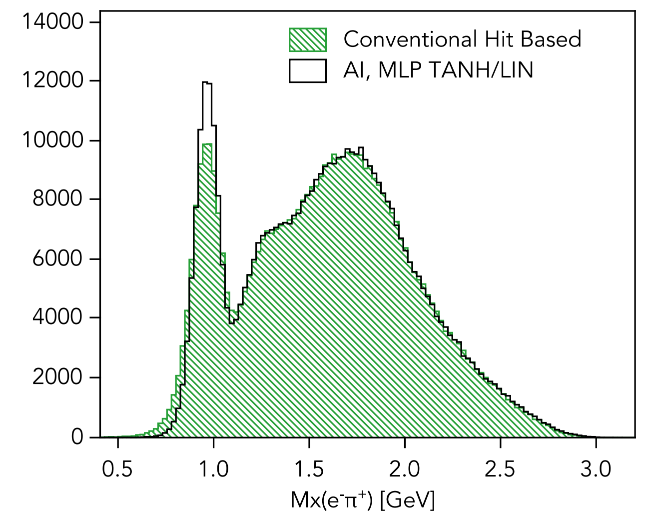
Threshold	Purity	Efficiency	Accuracy
0.0012	0.841	0.9999	0.906
0.03	0.930	0.999	0.962
0.47	0.977	0.99	0.983

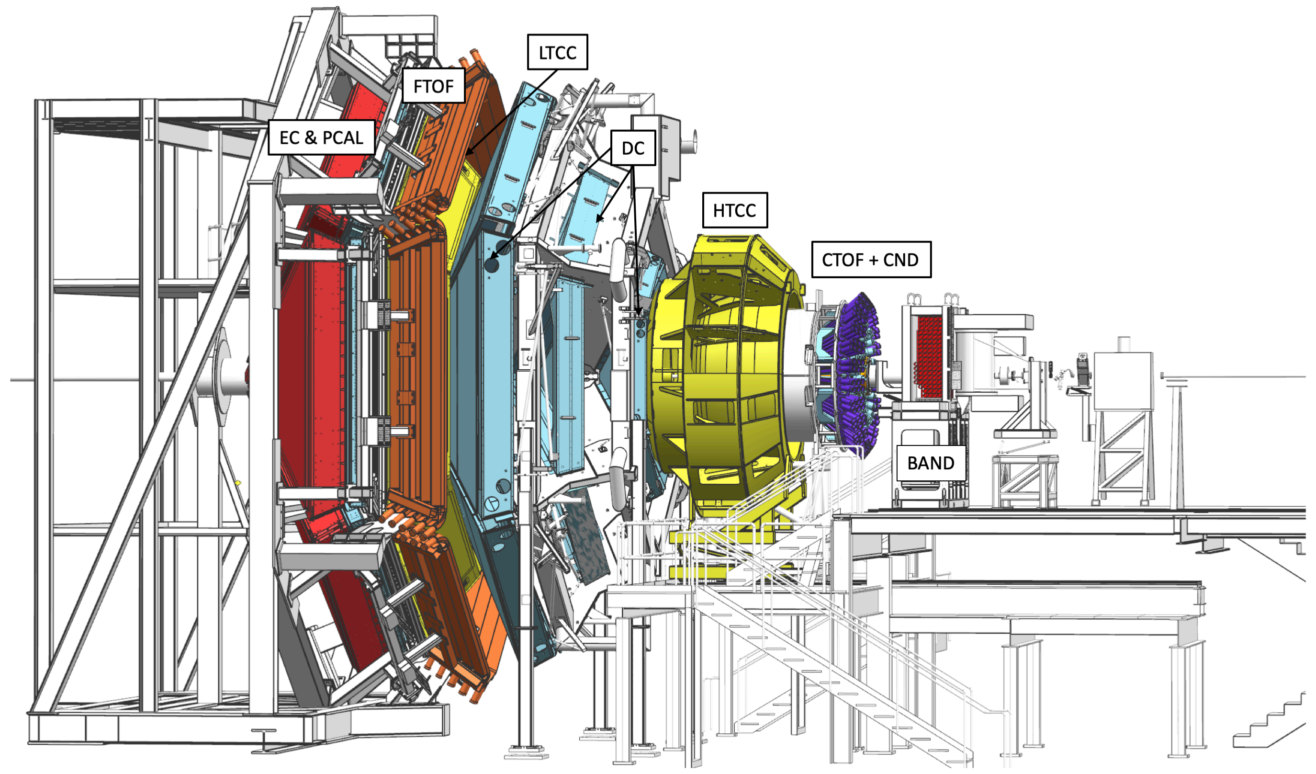


Data Persistence

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

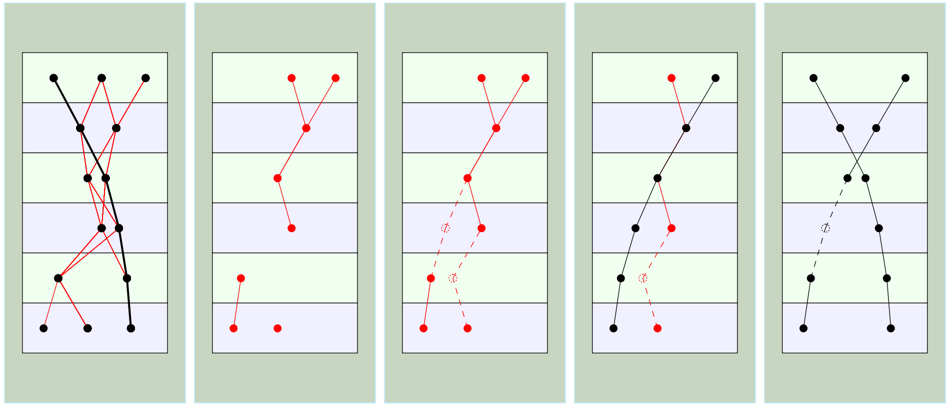
Physics Reconstruction (AI)



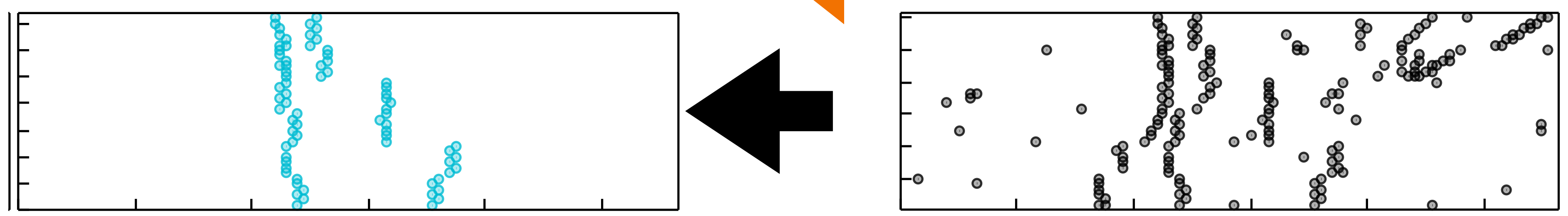


Data Acquisition

Track Classification (AI)



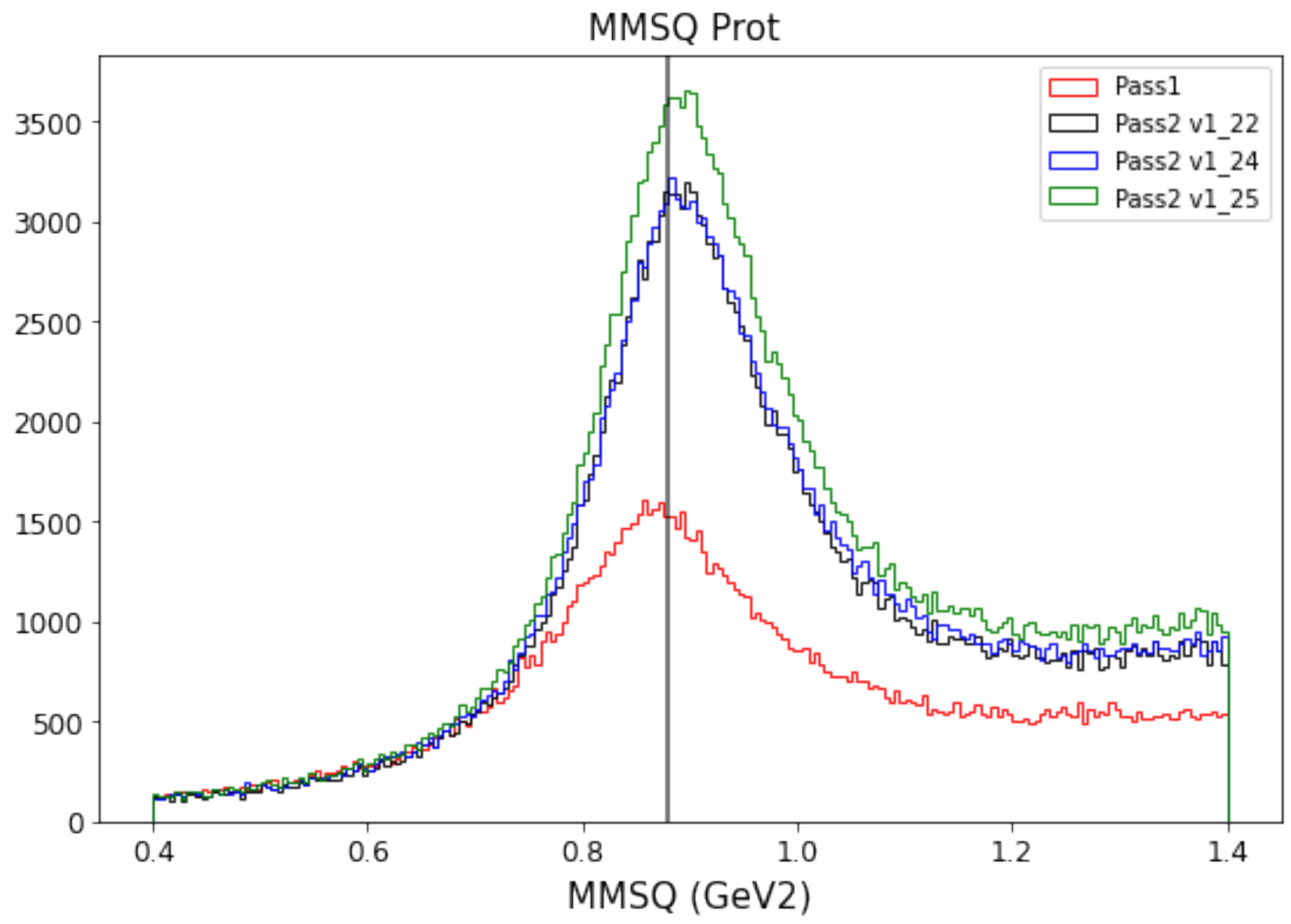
Classifying track candidates from
Reconstructed clusters
In real-time



Removing Noise signals
From tracking detectors

Data De-Noising (AI)

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