Tracking Particles using AI in CLAS12

Track reconstruction and identification with AI

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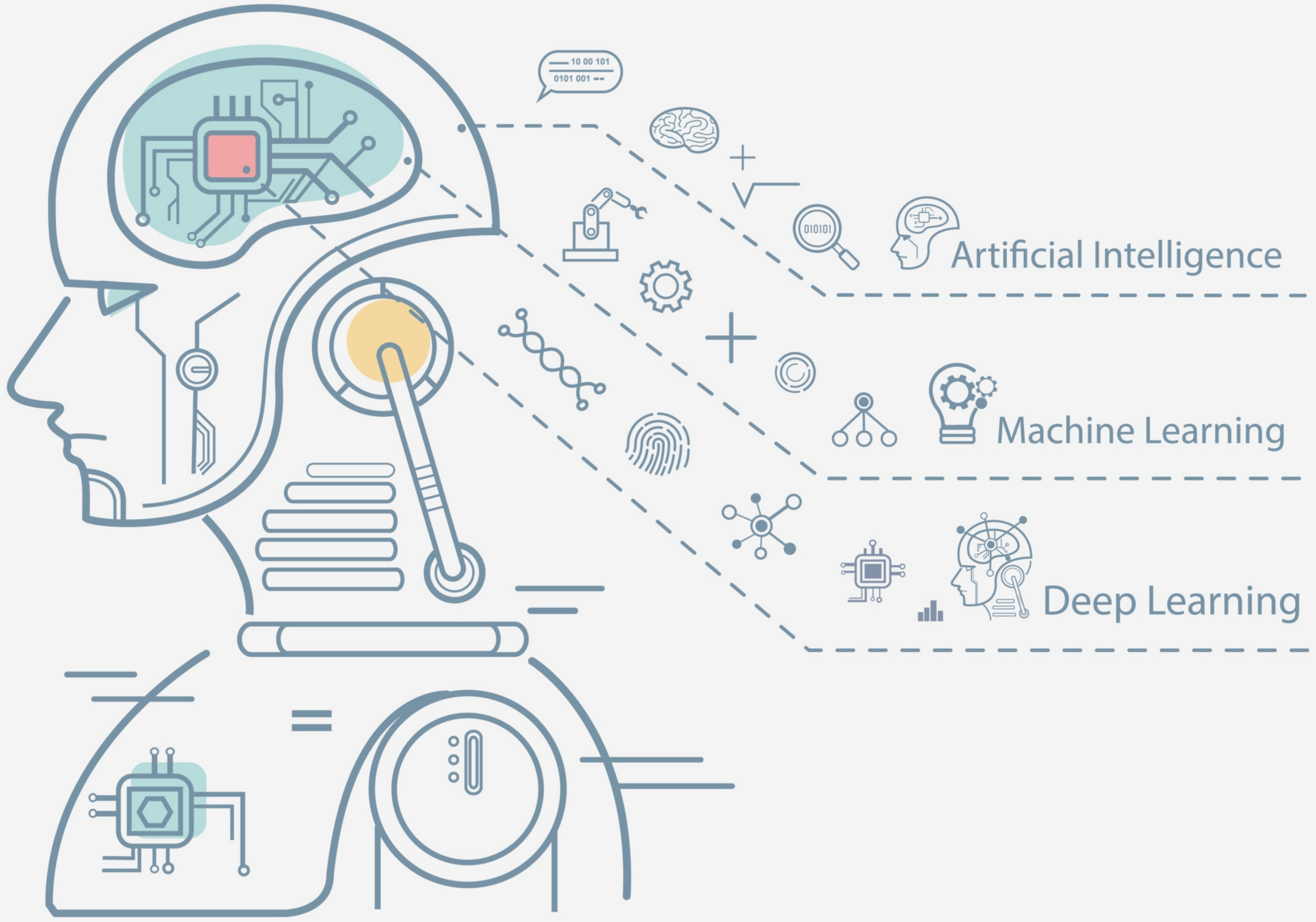
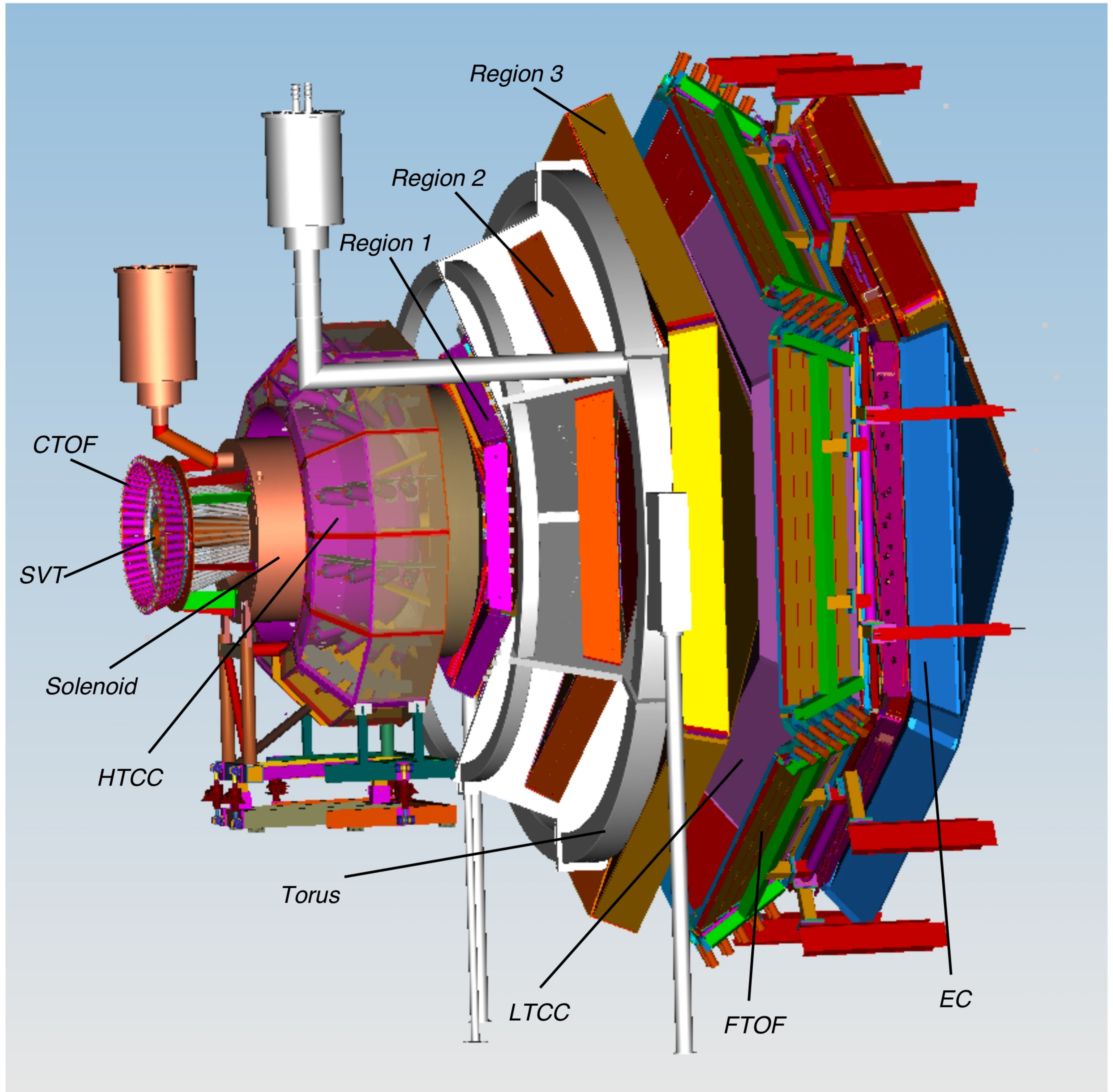
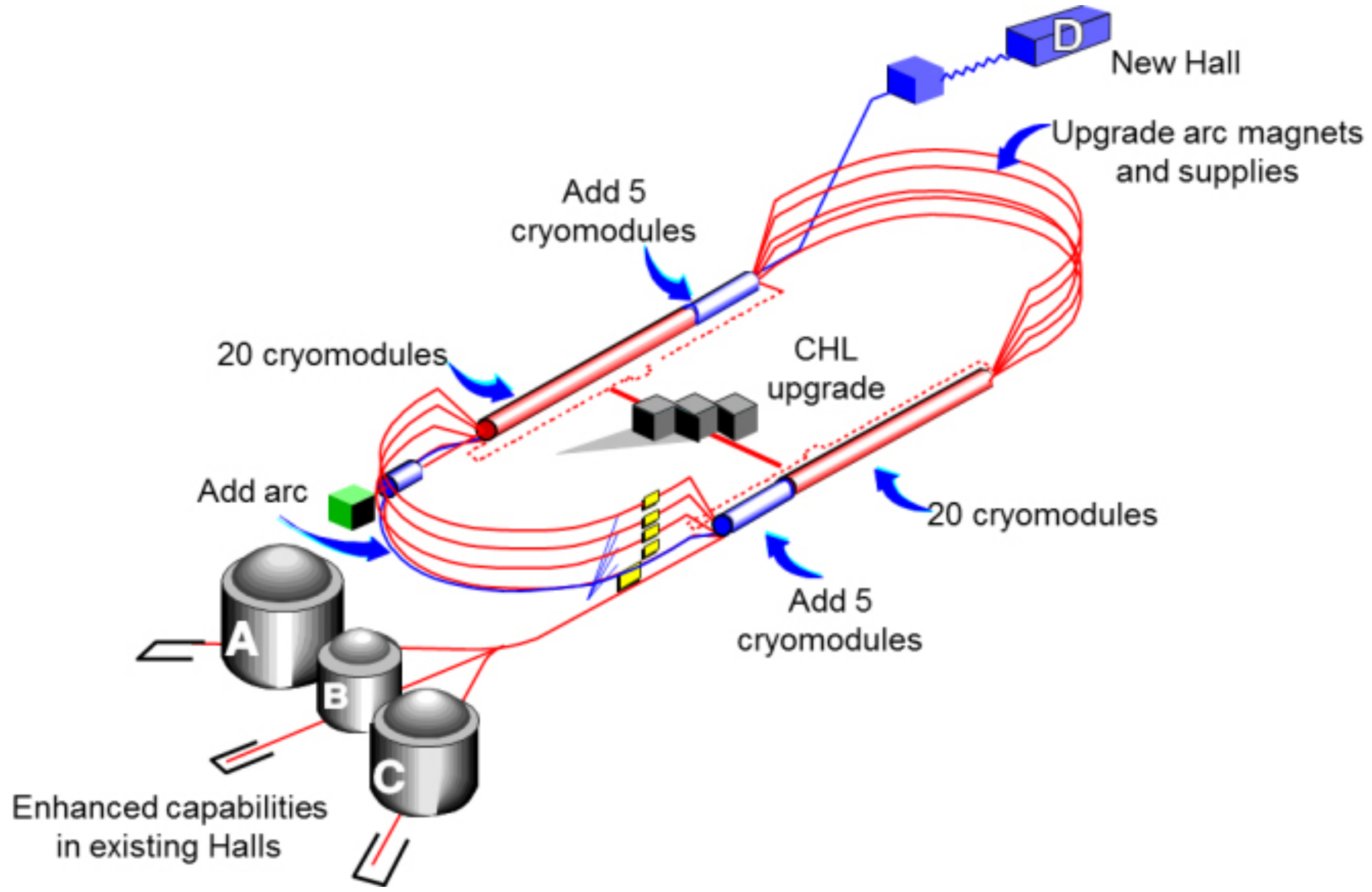


AI4EIC (September 8,2021)

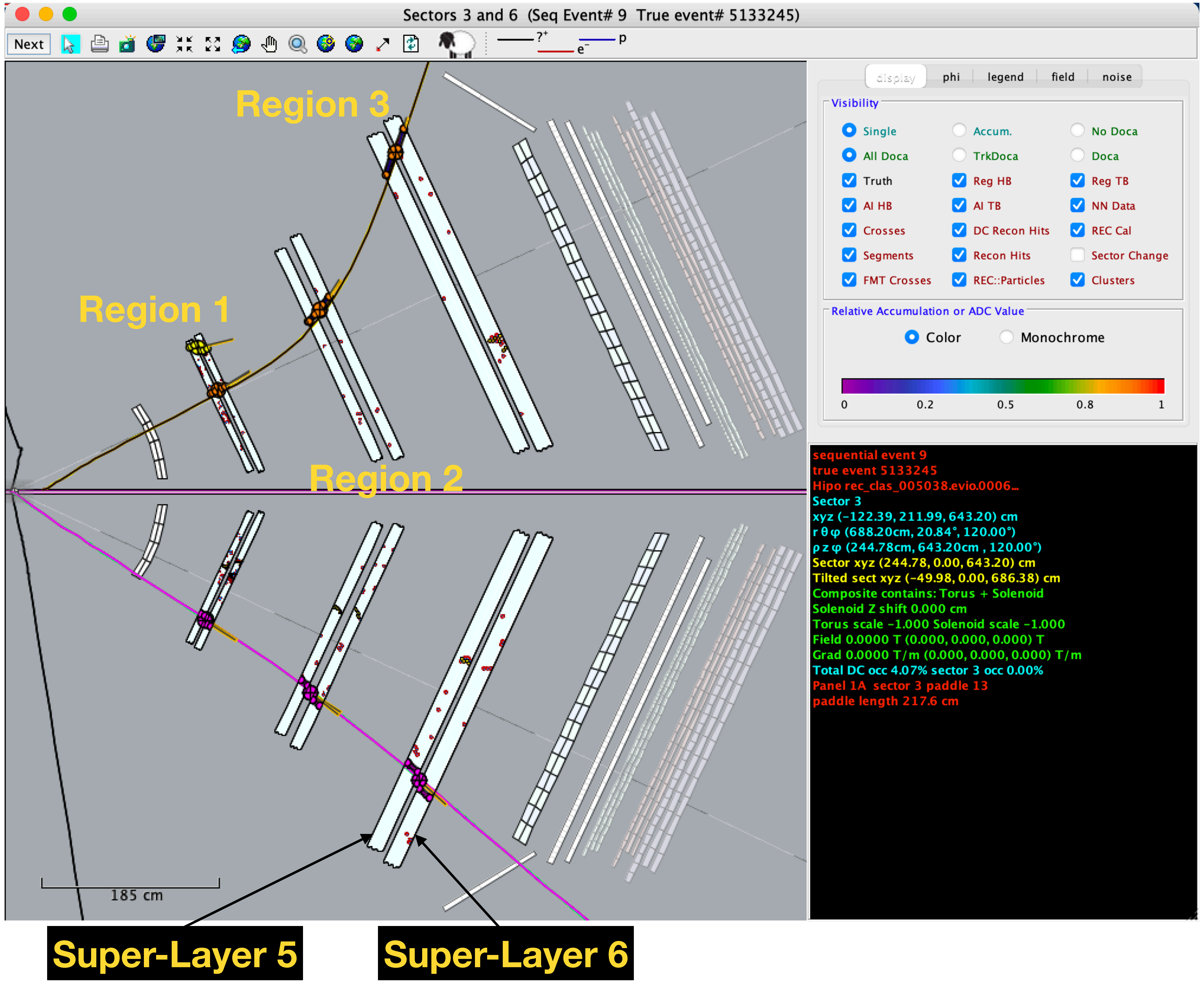
CLAS12 (Hall-B)





- Drift Chamber inside Toroidal field for forward tacks.
- Electromagnetic Calorimeter for electron identification and neutral particle detector.
- Time of Flight system for particle identification.
- High Threshold Cherenkov Detector for electron pion rejection.
- Silicon tracker for central detector charged particle tracking in Solenoidal Filed.
- Central Neutron Detector for neutron identification.

- DAQ data rate 12 kHz,
- Data rate 400 Mb/sec
- Up-to-Date collected ~1.2 Pb



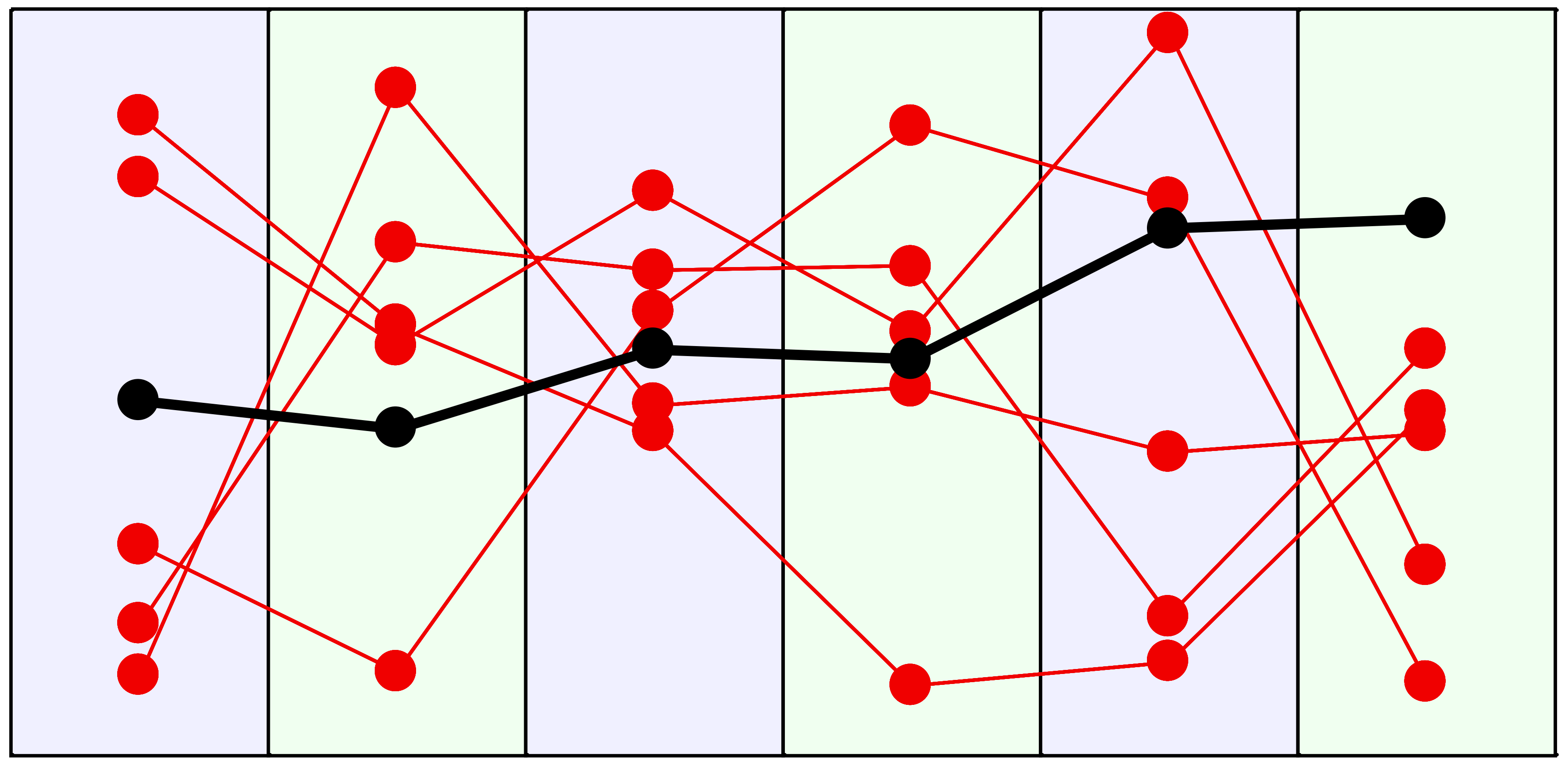
Charged Particle Tracking

- Charged particles are tracked using Drift Chambers inside toroidal magnetic field.
  - Each sector consists of 3 regions
  - Each region consists of two cambers (Super-Layer)
  - Super-Layer has 6 layers
  - Each Layer has 112 wires
- Each sector is matrix of 36x112 wires that charged particles passes
- Each super layer hits are clustered together
- Track candidate is format from 6 clusters (one from each super layer)

CLAS12 tracking

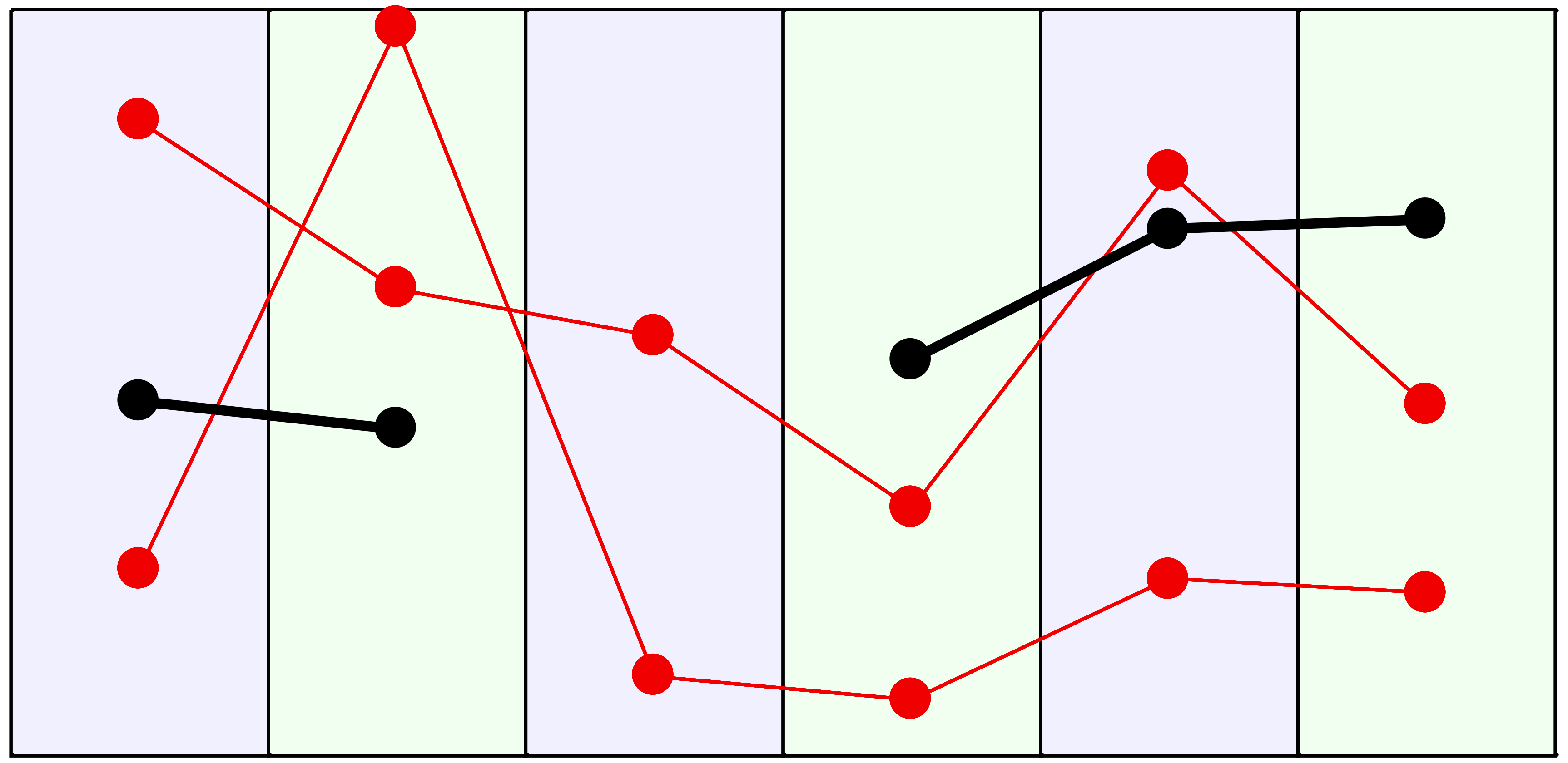
Six sectors shown

Problems we are trying to solve



Classification

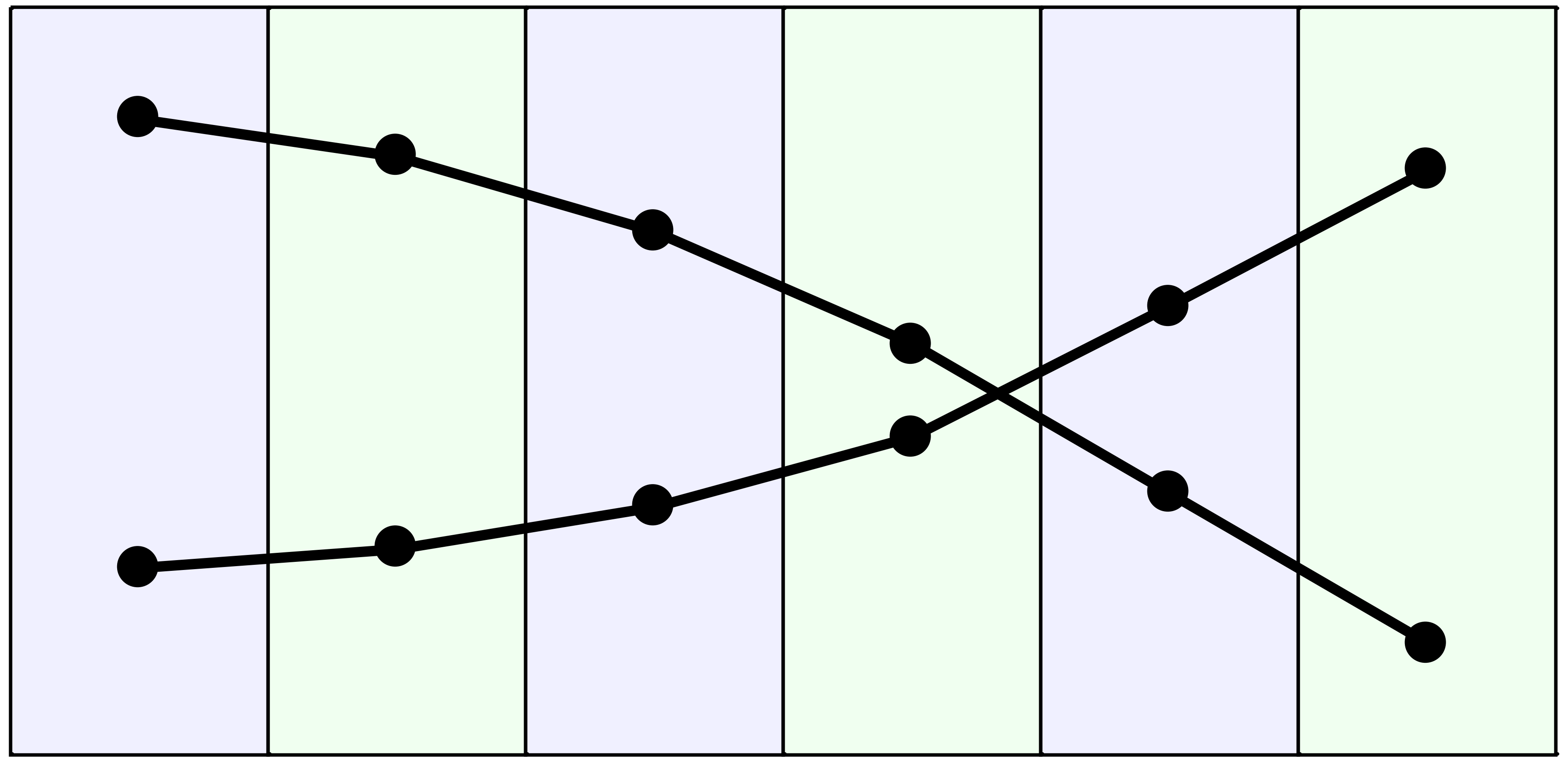
- Each event contains many combinations of clusters that can form a track.
- Teaching AI which combinations are good and which are bad will help the network to discern from given combinatorics which candidate has higher probability to be a good track.
- Possibly will speed up tracking code (80%-90% of total data processing time) by considering only AI suggested track candidates.



Fixing Inefficiencies

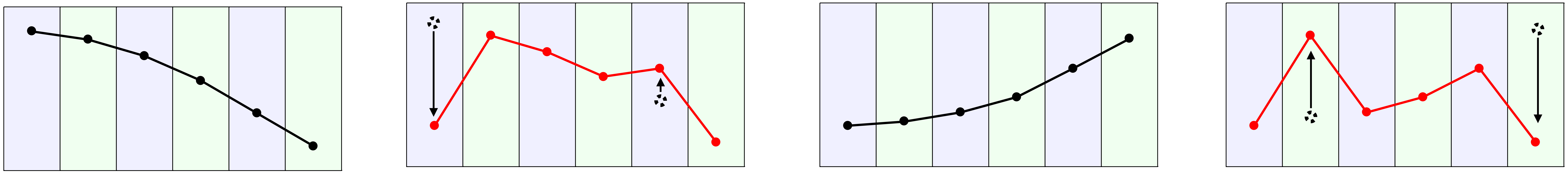
- Some regions of inefficiency in drift chambers can result in missing clusters in one of the super layers.
- Track classifier can recognize good tracks composed of 6 clusters.
- We need some methods to predict where missing cluster position will be.
- Then classifier can identify good track candidate.

Track Data

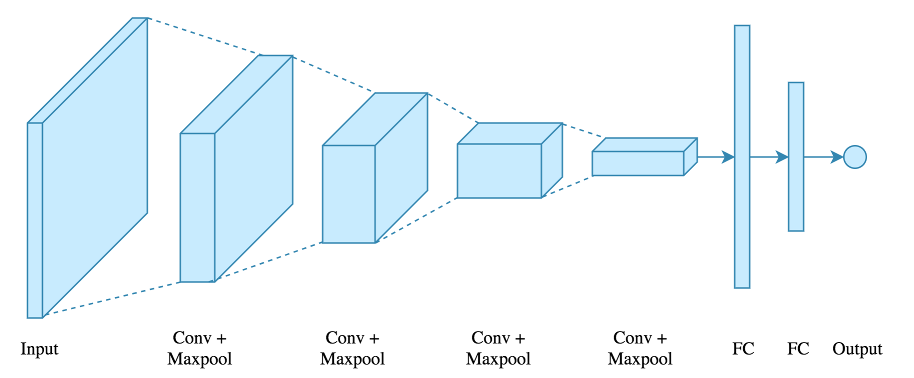


- Events with 2 tracks in one sector are chosen for training sample generation.
- 4 training track candidates are constructed:
  - 2 "**TRUE**" tracks that were reconstructed by tracking algorithm
  - 2 "**FALSE**" tracks by swapping 1 or 2 (decided by random number generator) clusters from adjacent track.

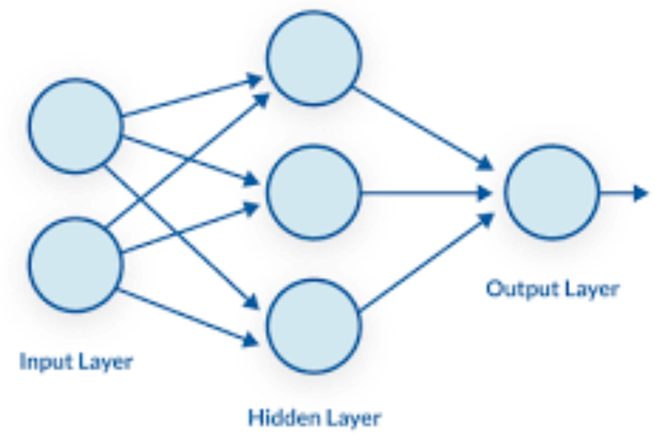
TRUE TRACK | FALSE TRACK | TRUE TRACK | FALSE TRACK



Convolutional Neural Network (**CNN**)

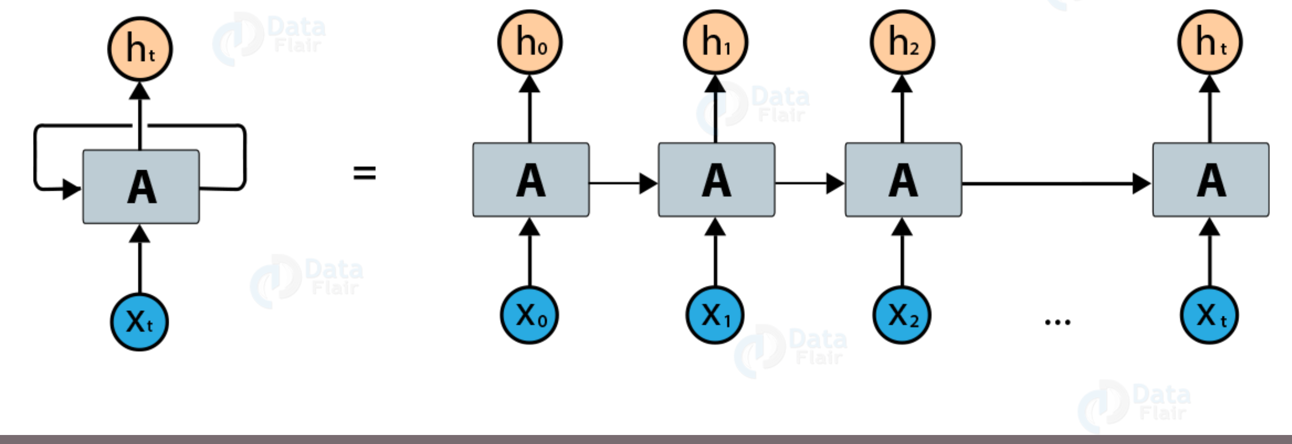


Multi-Layer Perceptron (**MLP**)



Extremely Randomized Trees (**ERT**)

Recurrent Neural Network (**RNN**)



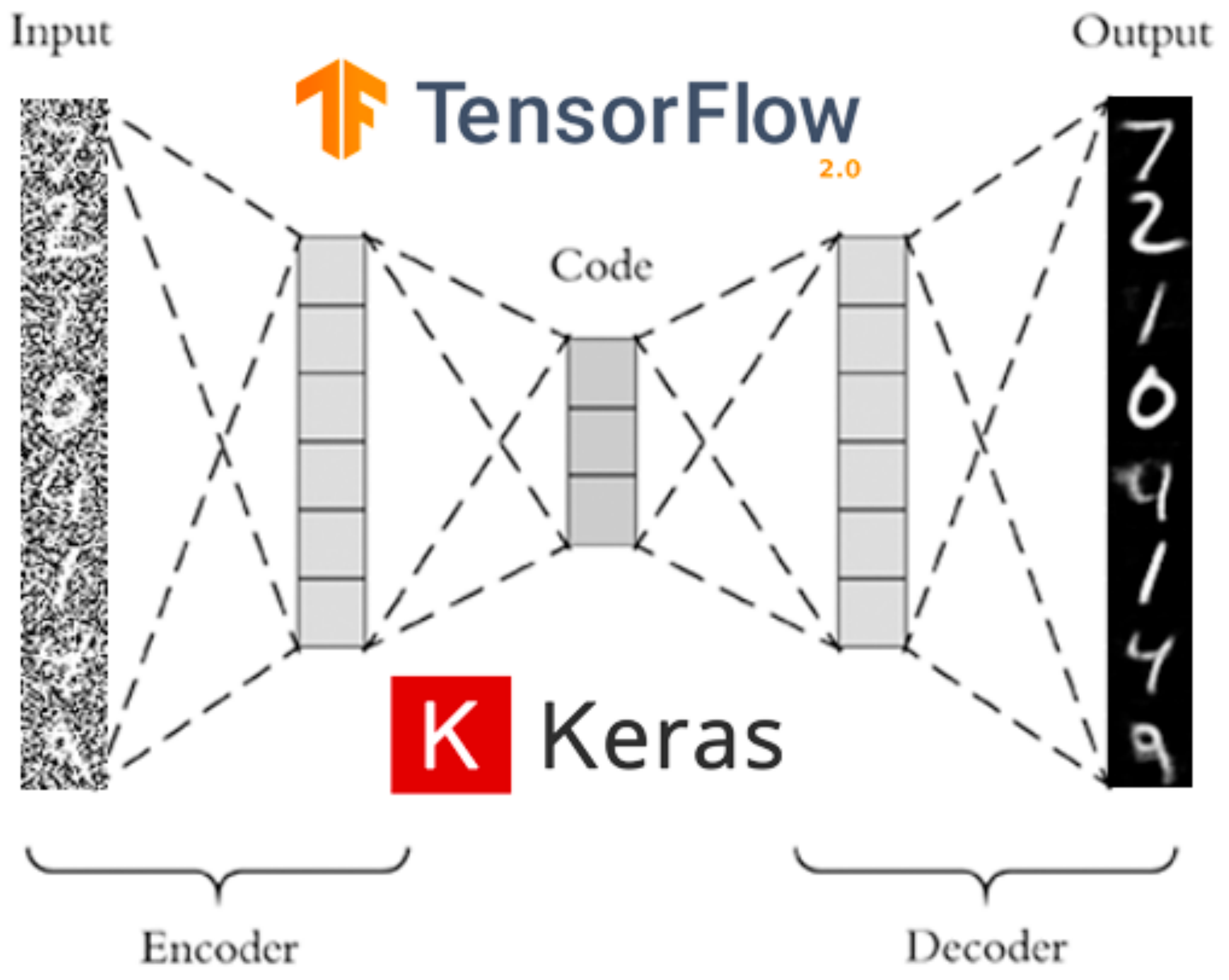
- Different Network types were evaluated for accuracy and speed.
- MLP is chosen to be the best fit, due to implementation simplicity, accuracy and inference speed.

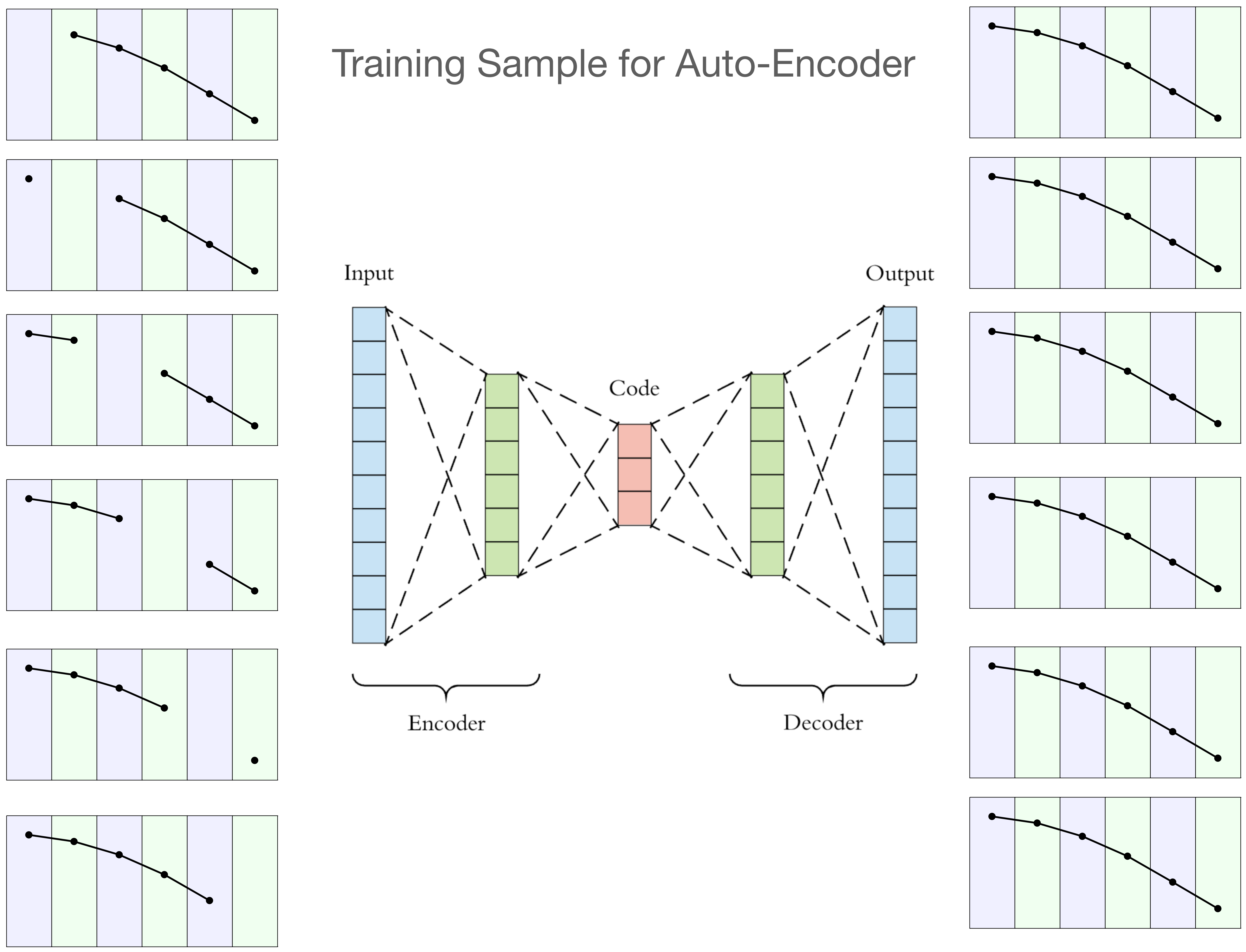
	Features	TP	FP	PA	TA	Time (ms)
ERT	6	100%	6.14%	100%	100%	0.36
MLP	**6**	**99.96%**	**10.77%**	**98.88%**	**99.65%**	**0.12**
CNN	36x112	96.11%	28.11%	94.26%	94.26%	1.2
RNN	36	88.40%	11.60%	-	-	-

TP - True Positive
FP - False Positive
TA - Training Accuracy
PA - Positive Accuracy : percentage of tracks where False Positive in an event has lower probability than True Positive

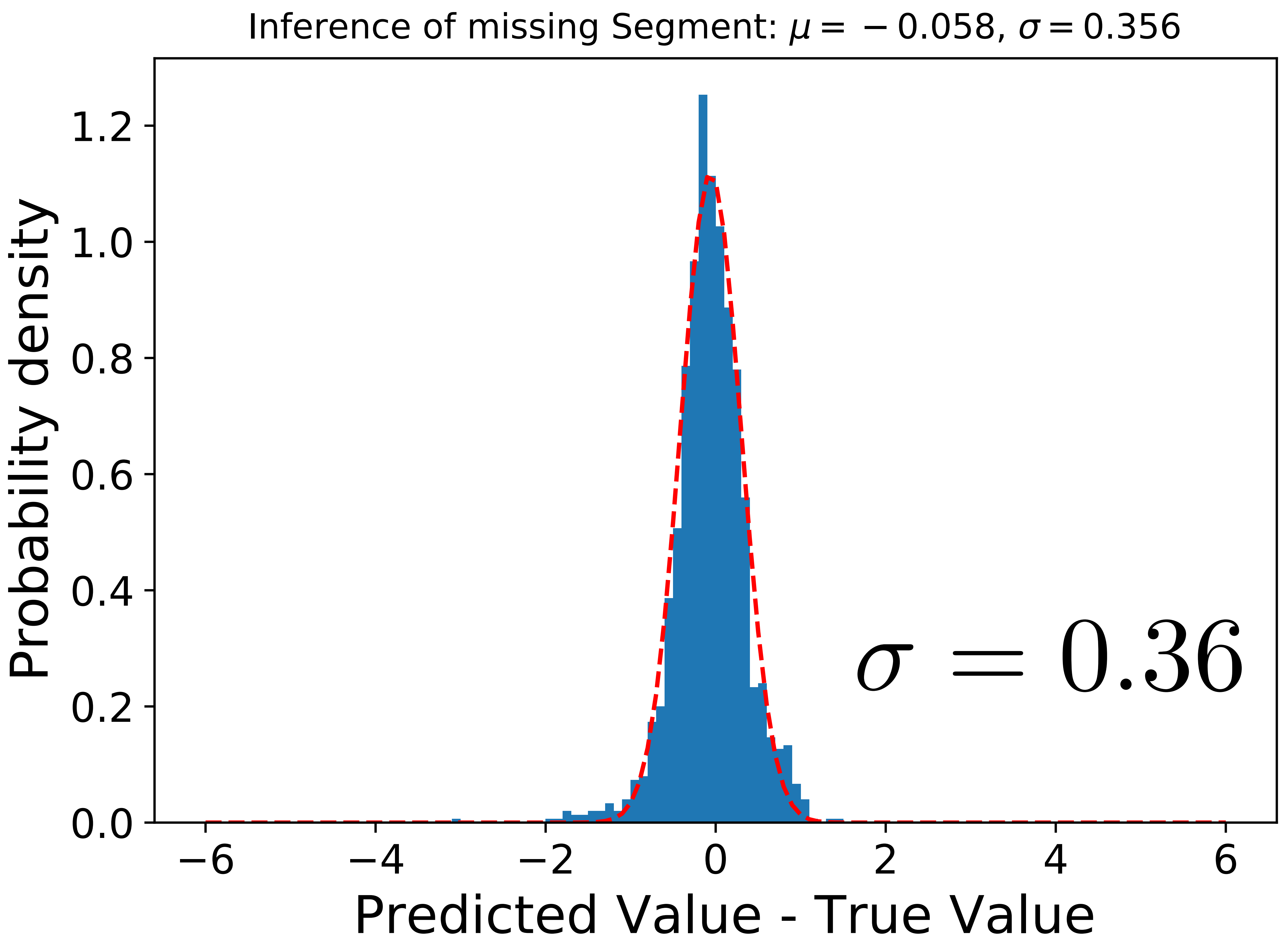
Fixing inefficiencies

- Auto-encoder is a type of neural network that can be used to learn a compressed representation of raw data.
- 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).**

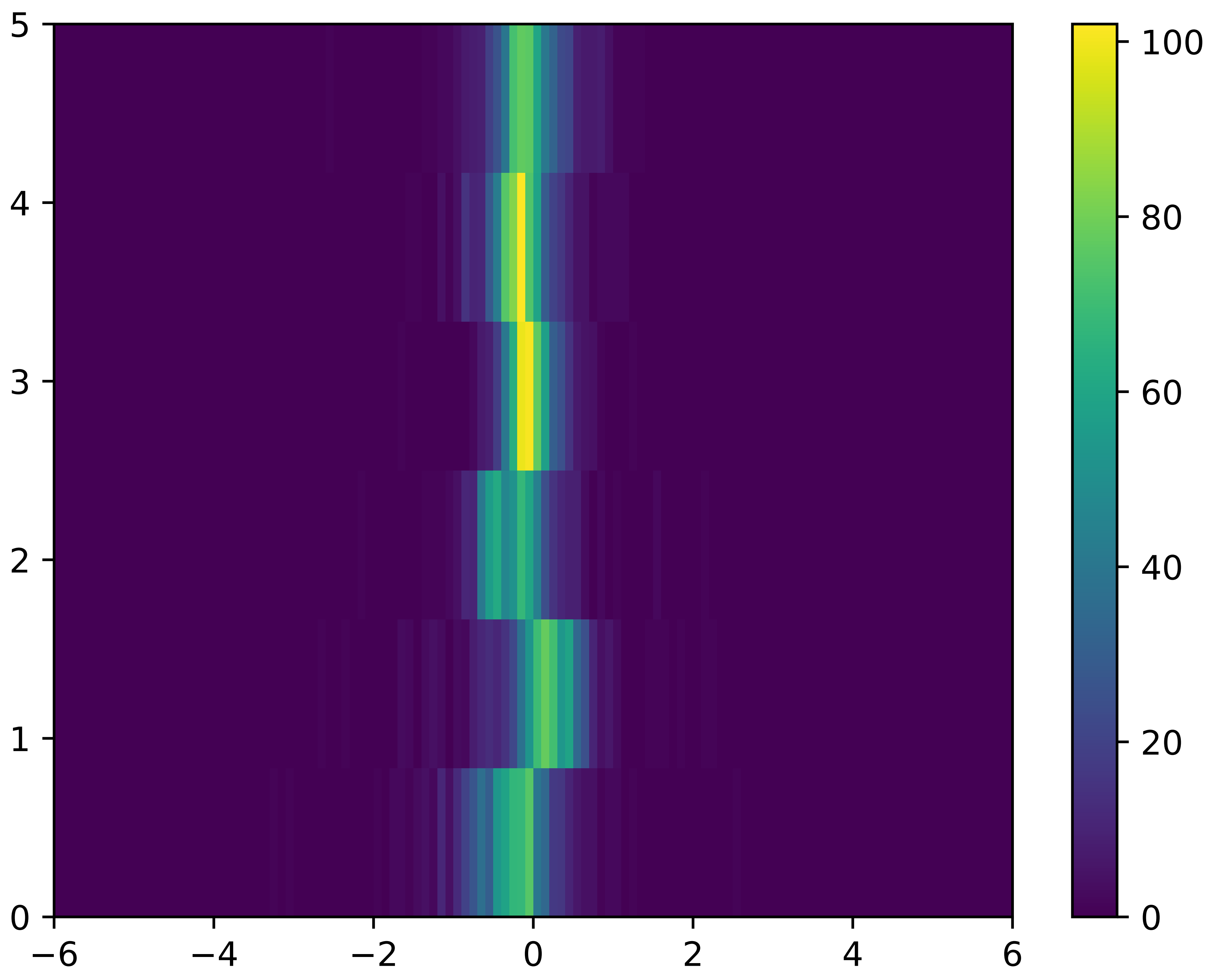




- Use Auto-Encoders to fix the missing cluster (provide a position)
- Good reconstructed tracks are used to generate training samples by removing one cluster from each super layer



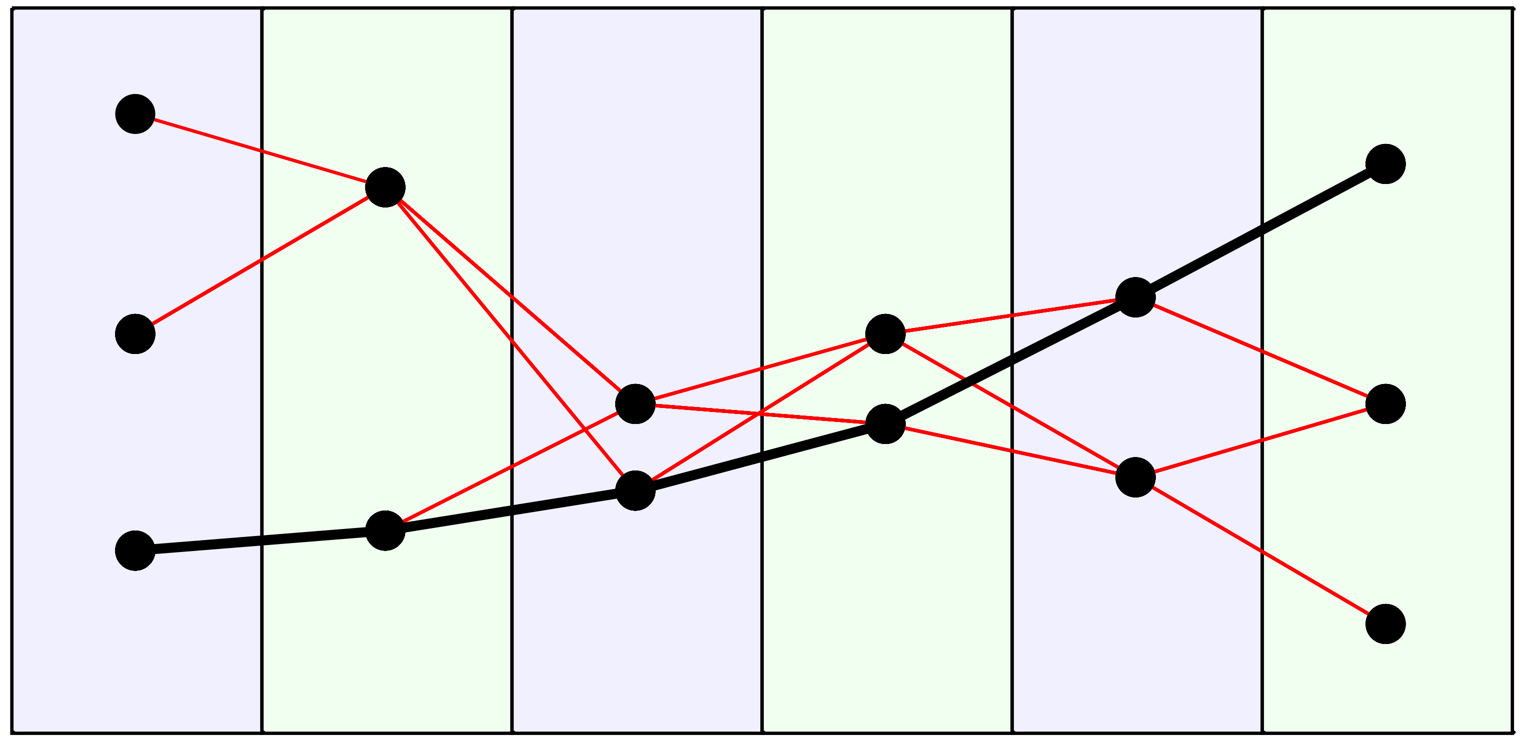
- Uncertainty in prediction for cluster position for good tracks is 0.36 wire out of 112



- Uncertainty in prediction for cluster position vs Super-layer with missing cluster

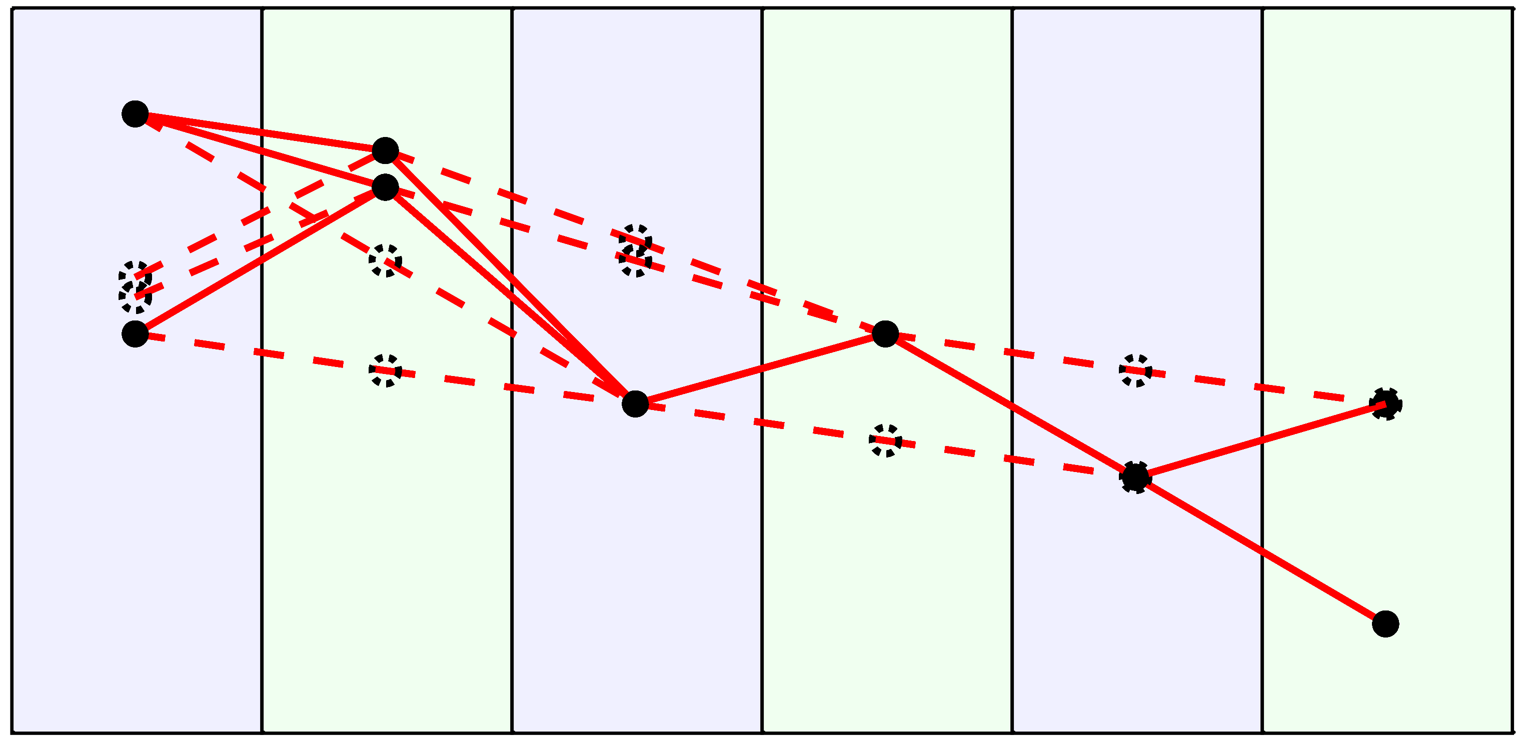
Identifying tracks using both networks

25 candidates

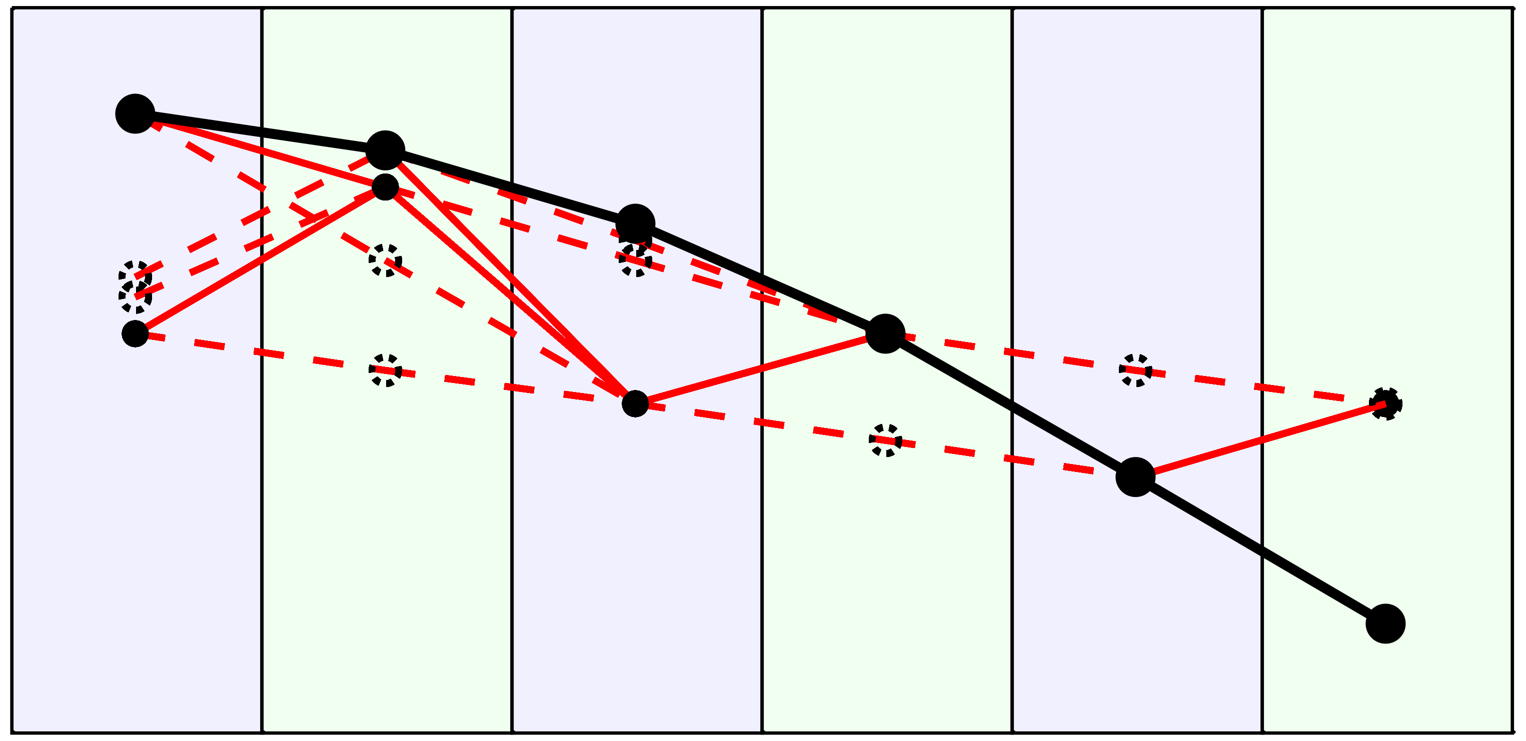


- Construct all combinations of 6 cluster tracks from hits (25 candidates in the example)
- Evaluate track candidate likelihood using classifier neural network
- Remove hits belonging to the track from list of hits.
- Add track candidate to the list of possible tracks (with it's probability provided by classifier)

29 candidates



- Construct combinations of 5 cluster track candidates (29 combinations in the example)
- Generate pseudo-hits in missing super-layers using Auto-Encoder neural network
- Turn them into 6 super-layer track candidates



- Evaluate 6 clusters track candidates (with pseudo-hit) using classifier neural network
- Add track candidate to the list of possible tracks with appropriate probability

Why Did we need the second Network (Auto-Encoder)

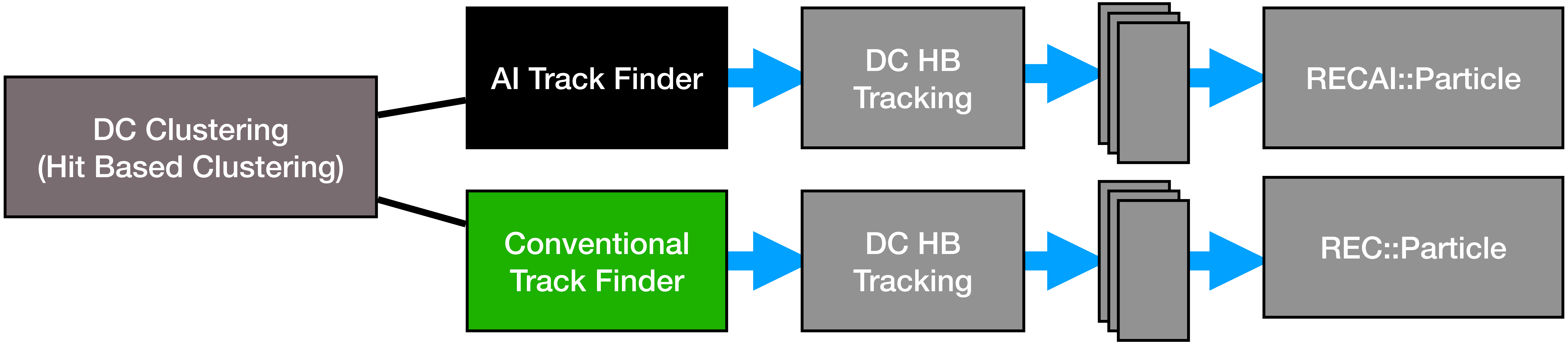
- Relative fraction of 5 super-layer tracks is about ~10% of total positively charge particles.
- The gain in number of 5 super-layer tracks is about x2.2 (120% increase)
- The gain in 6 super-layer track reconstruction with AI suggested track candidates is ~6%.
- Due to high gain in 5 super-layer track (where combinatorics is much larger for given number of segments) the total increase in tracks reconstructed is ~15.6%

Positive Charge	Conventional	Artificial Inteligence	Gain
6 CLUSTER	242,145	256,175	1.0579
5 CLUSTER	24,155	52,839	**2.1875**
TOTAL	267,339	309,058	**1.1561**

- Questions:
  - Are these real tracks ?
  - How does this translate into physics ?
  - Is this gain real ?

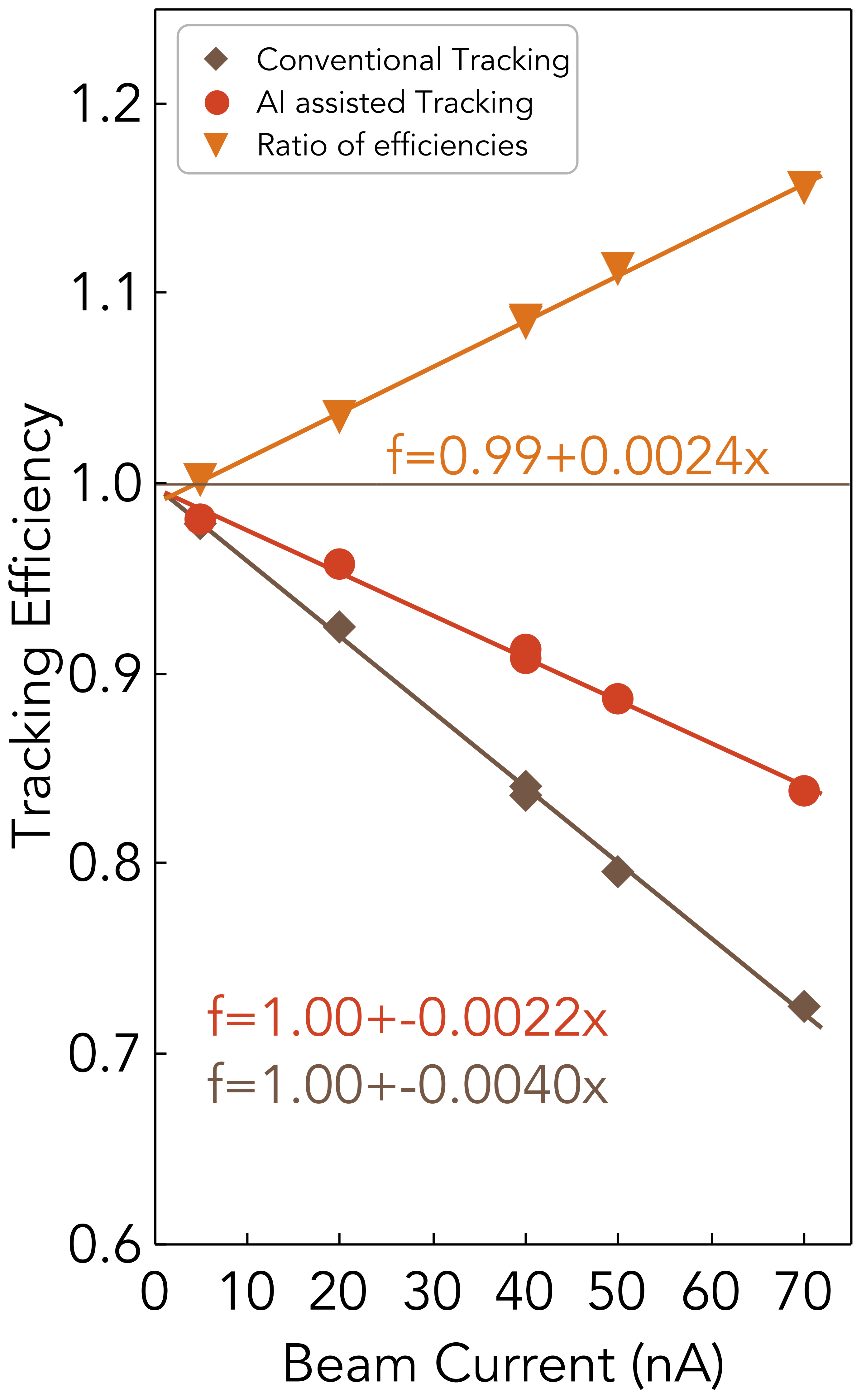
AI Tracking Reconstruction Tools

- AI track classification and segment recovery network was implemented as a CLARA service.
- Tracking code was modified to separate clustering from track finding



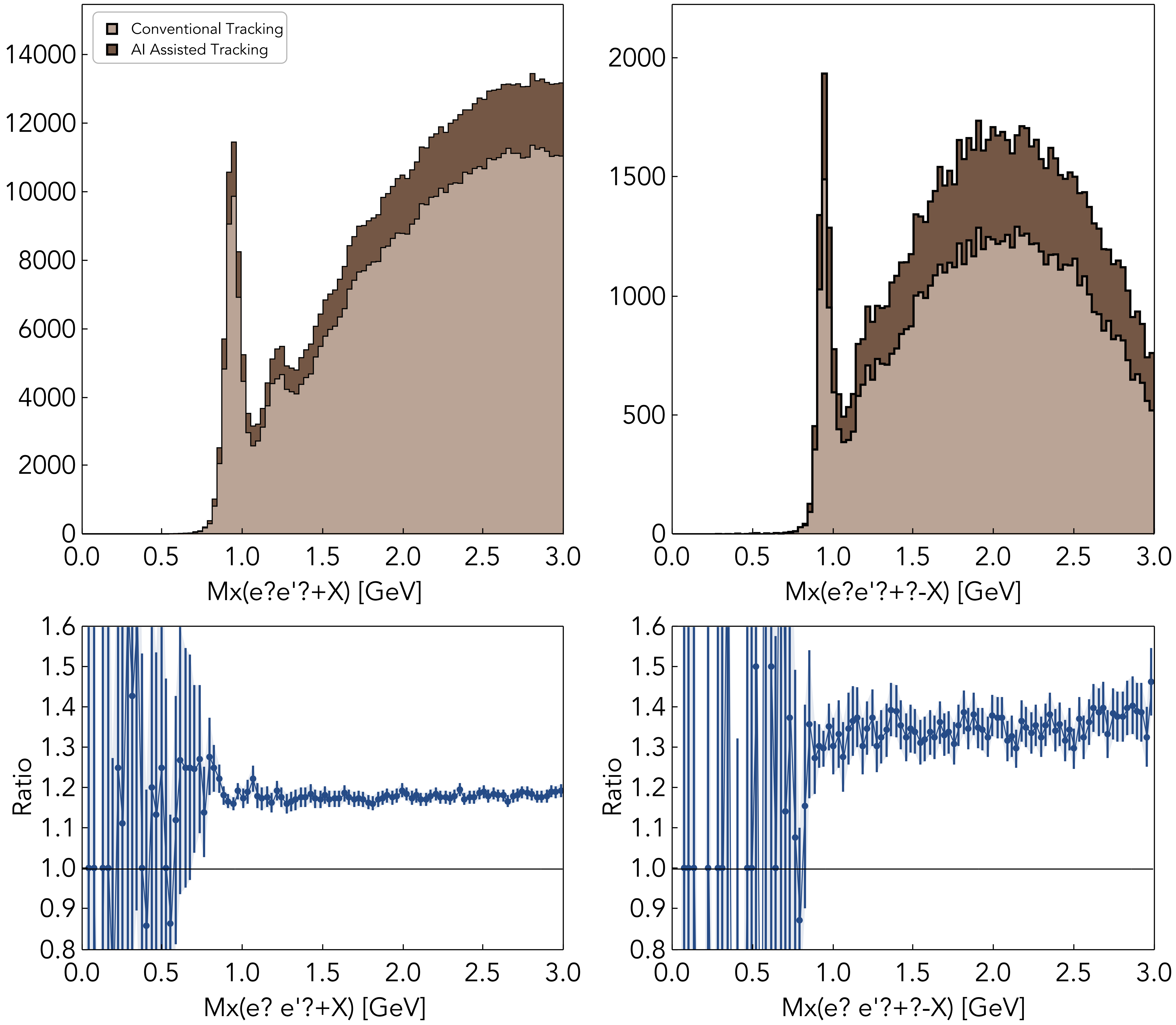
- Data analyzed in two parallel service compositions with separate output for Time Based Tracking
- The parallel branches produce separate particle banks
- Tracking code in the AI branch is 35% faster compared to conventional branch
- The full chain will be available soon for users to analyze and compare results from AI assisted tracking with conventional tracking.

Physics Impact



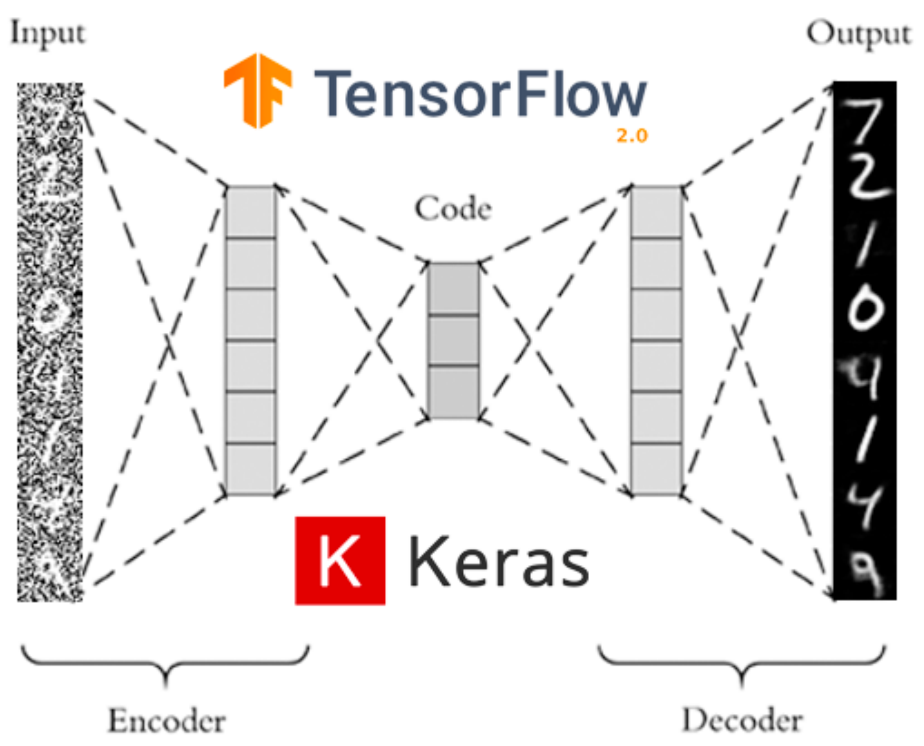
- Implementation of AI assistance in CLAS12 tracking lead to tracking speed improvement of ~35%.
- Particle reconstruction efficiency increased when using only AI suggested tracks.
- Study was performed to measure tracking efficiency as a function of experiment luminosity (beam current)
- Conventional tracking efficiency decreases by 0.40% per nA of beam current.
- AI assisted tracking efficiency drops by 0.22% per nA.
- Efficiency drop improved by factor of ~2x.

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

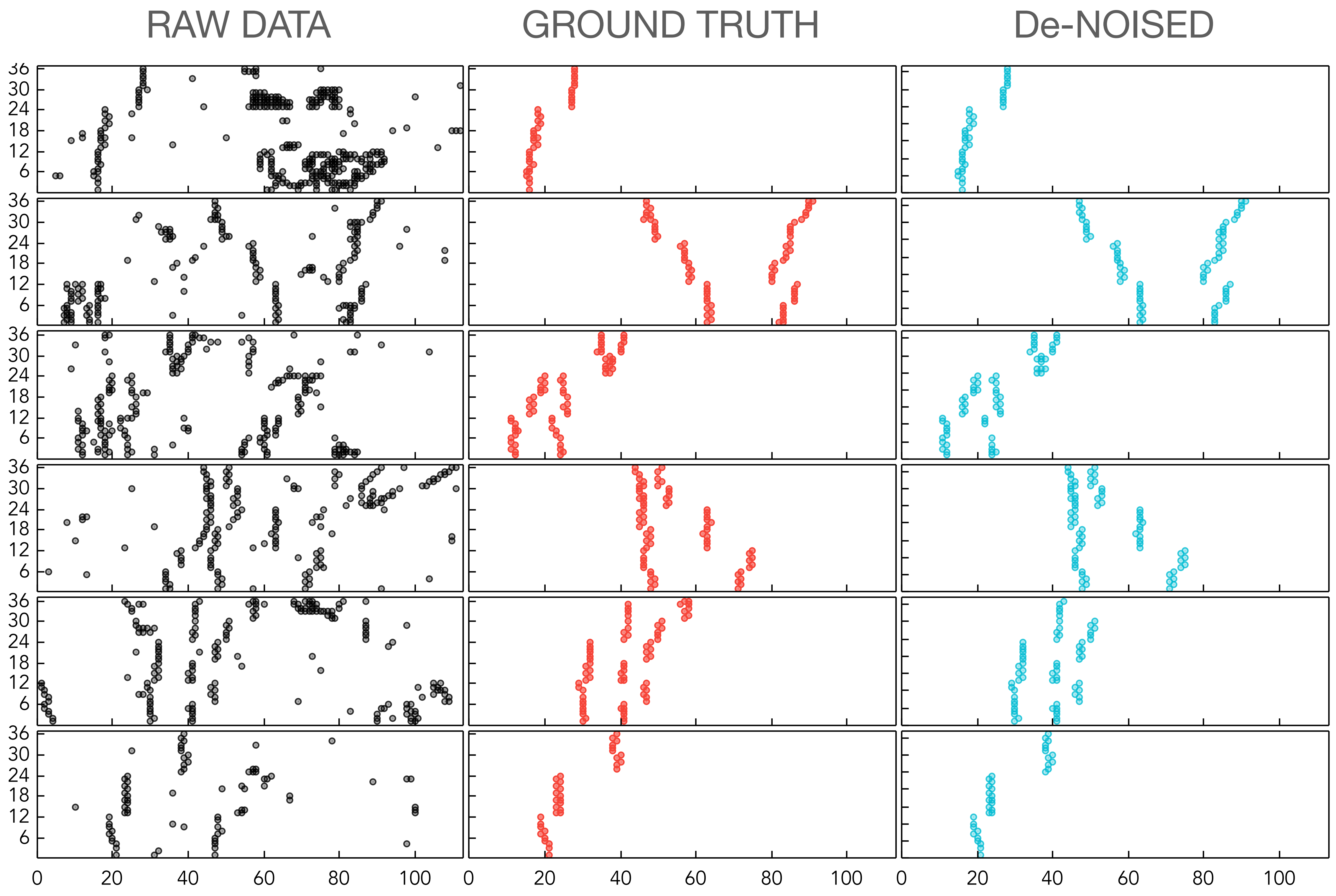


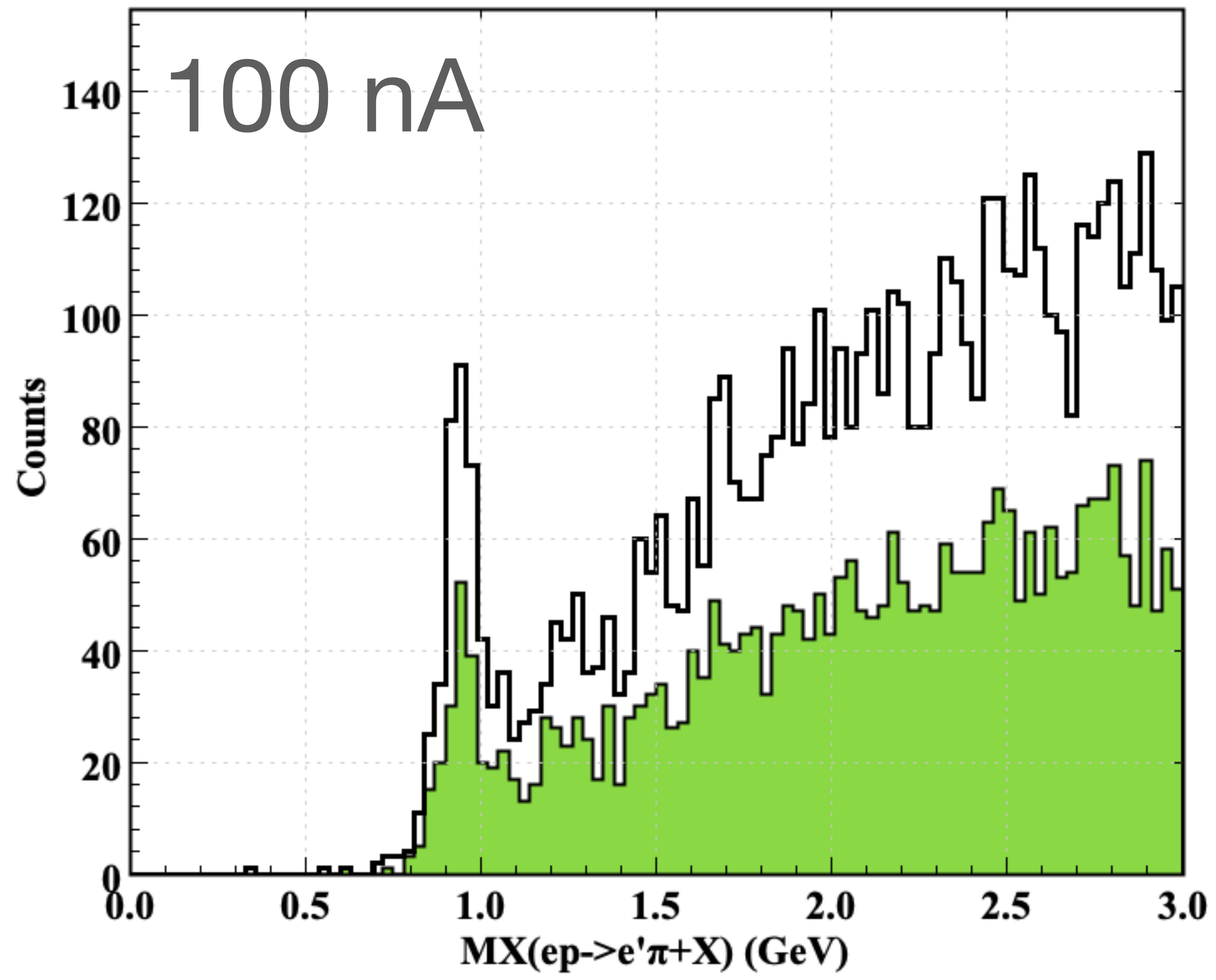
- CLAS12 tracking code reconstruction efficiency improved with introduction of AI into track candidate finding.
- The tracking code speed improved by ~35%
- What is the physics impact ?
- Tow particle final state (ep->e'pi+X) missing mass shows ~20% more event under proton peak. The gain is constant over the whole range of missing mass.
- Three particle final state (ep->e'pi+pi-X) missing mass shows ~35% increase in statistics of missing proton.

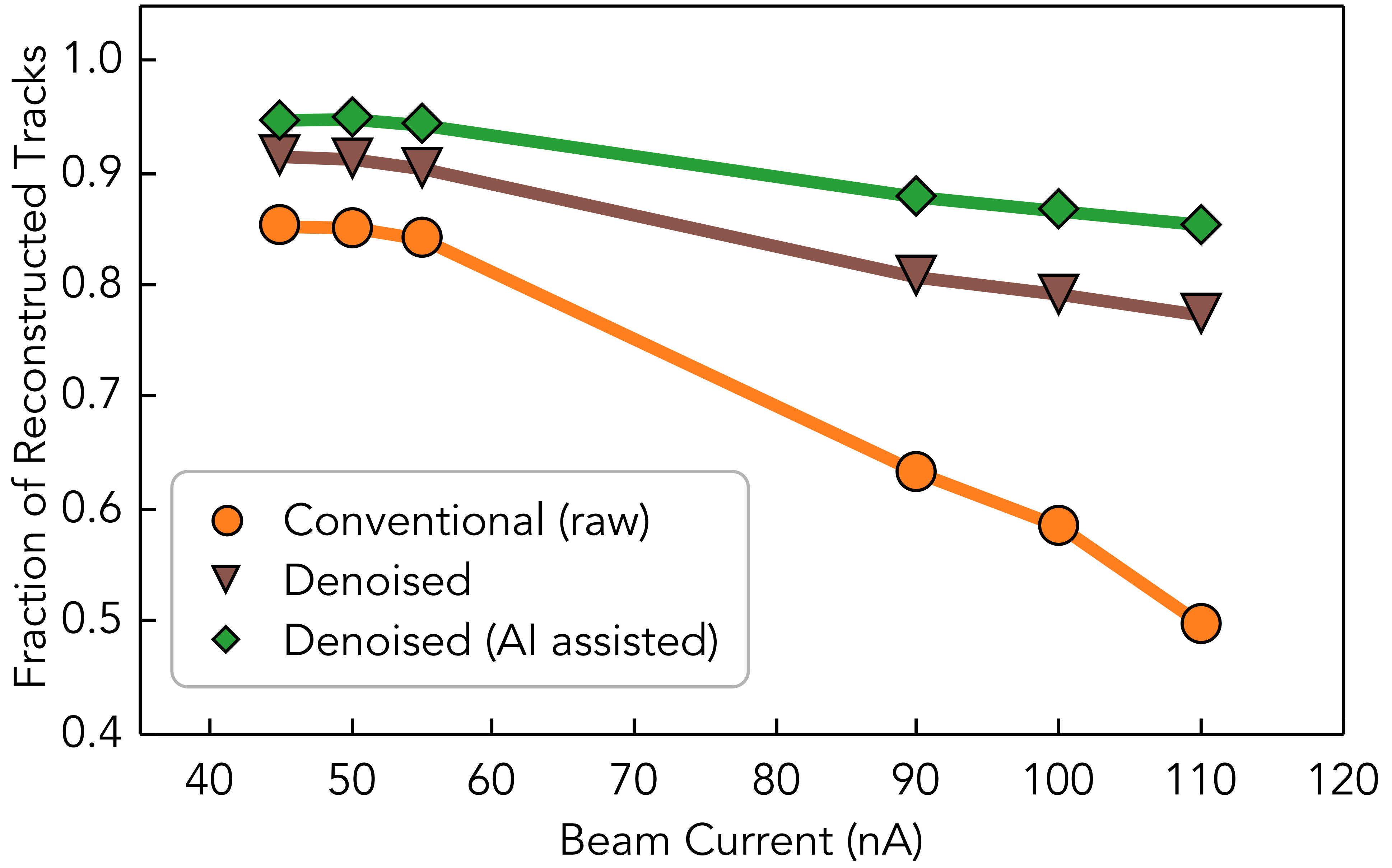
De-noising (CLAS12 Drift Chambers)



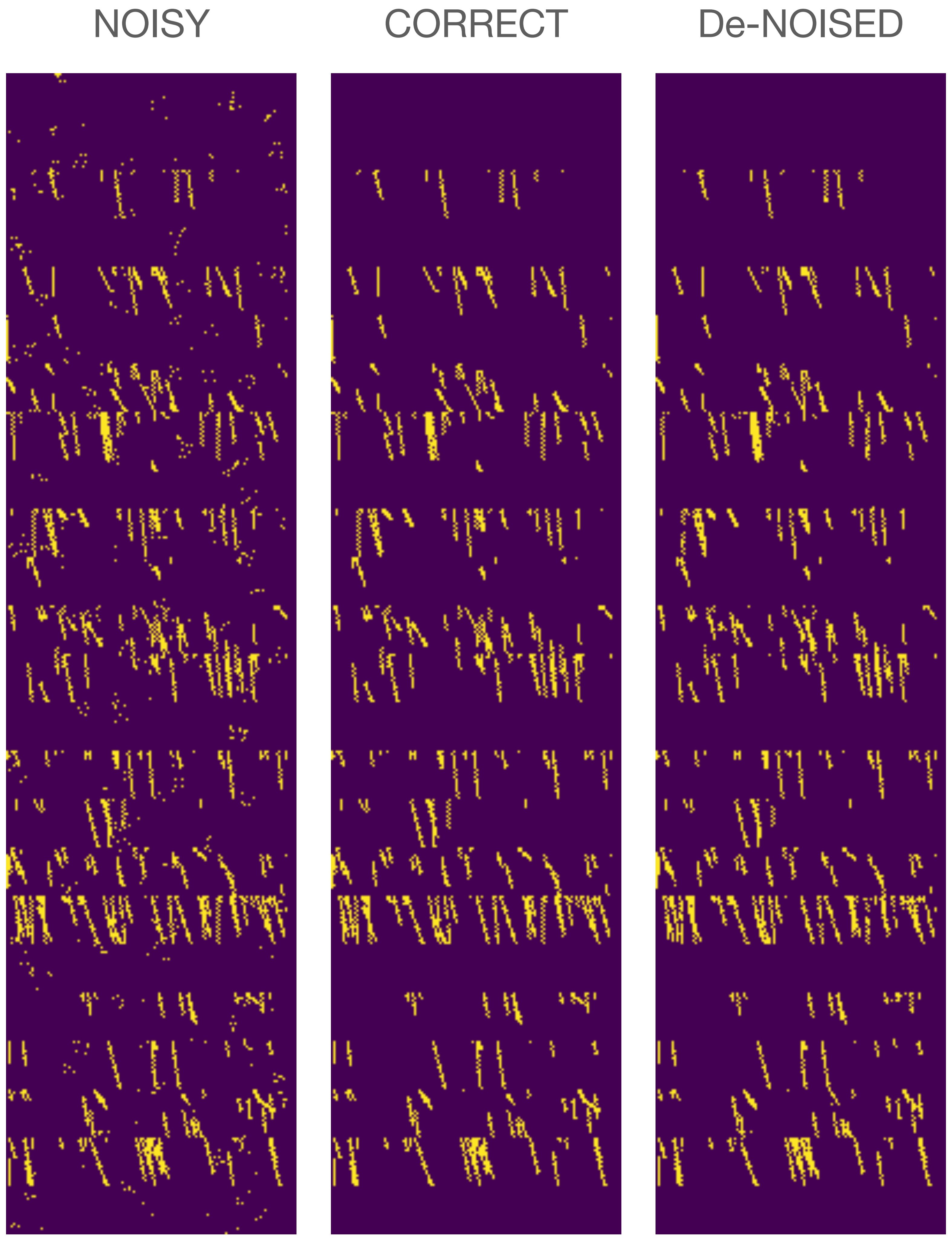
- Using Convolutional Auto-Encoders we can clean raw data sample to leave only hits that belong to a track.
- Network is trained on "good" reconstructed tracks from experimental data.



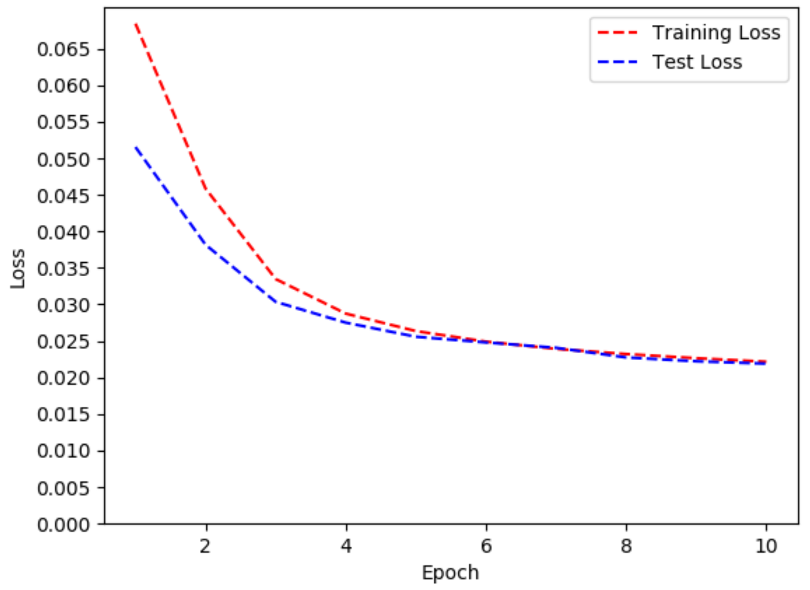


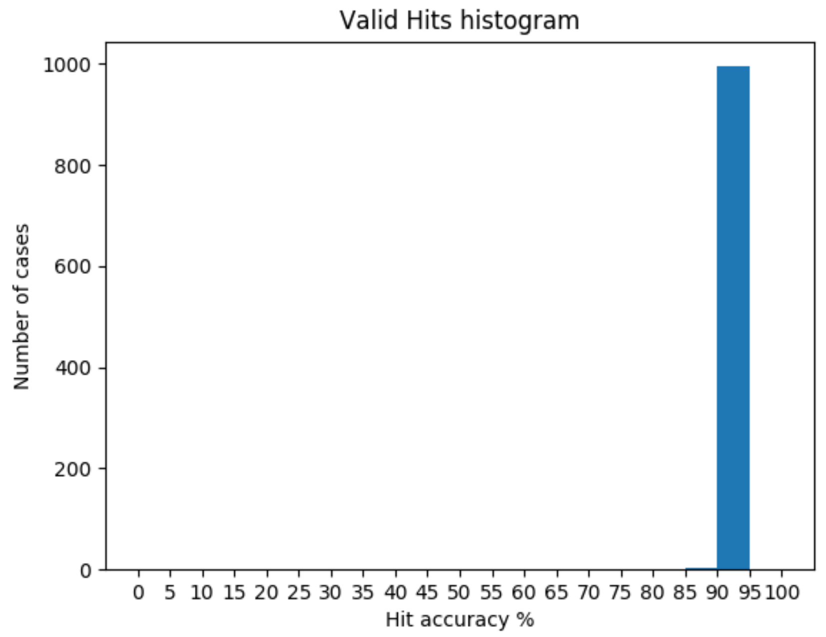


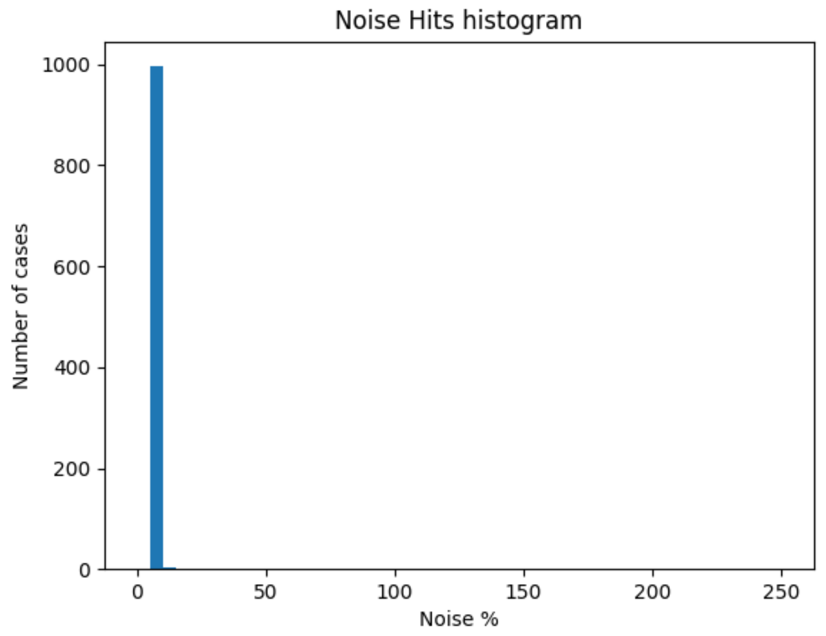
De-noising (mTPC)

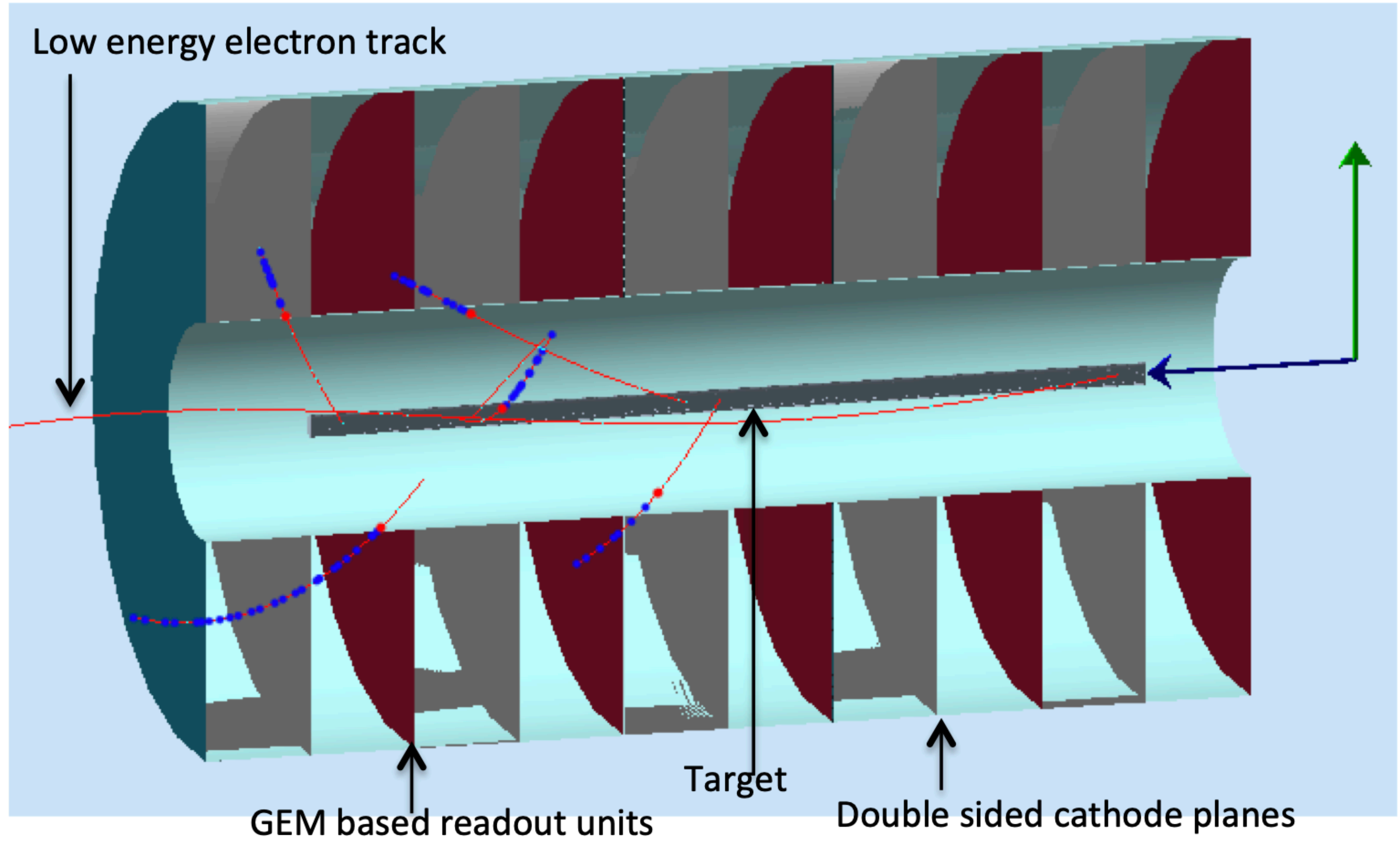


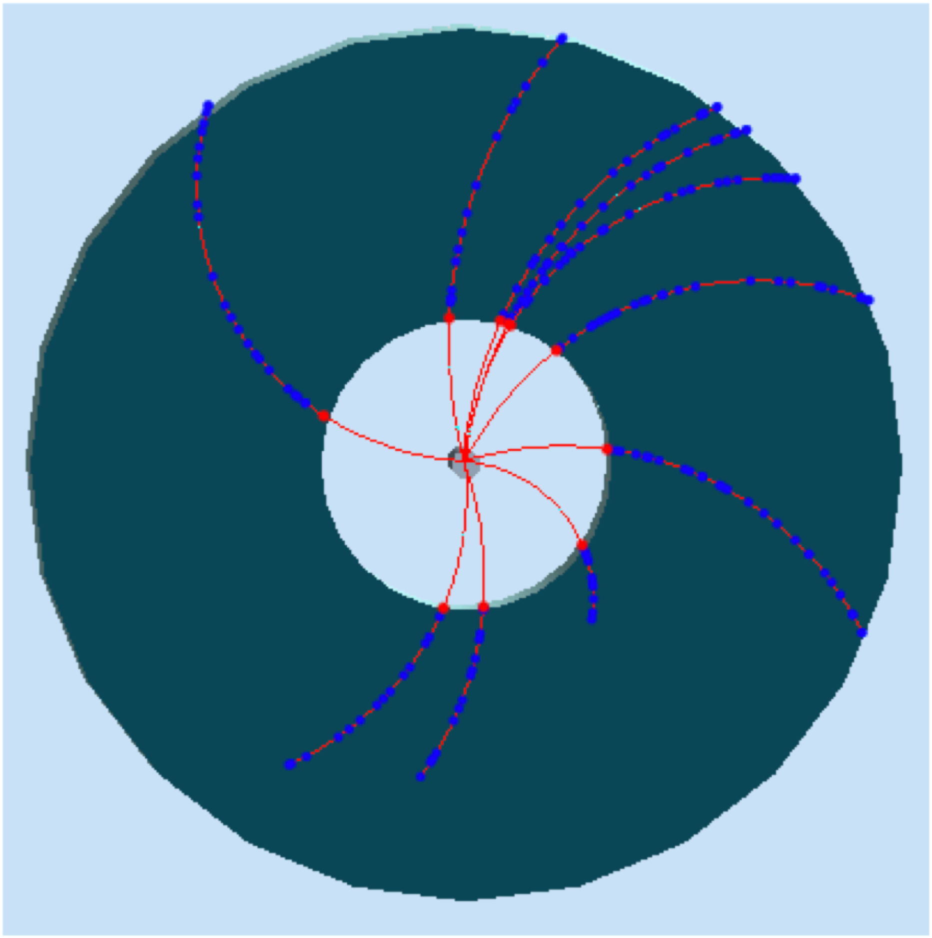
- Generated 250 tracks with background, trained on noisy image and ground truth
- Over 90% of original hits are reconstructed on the de-noised image
- Less than 5% of noise remains on the de-noised image
- Validation curve matching with training accuracy ensures no over-fitting

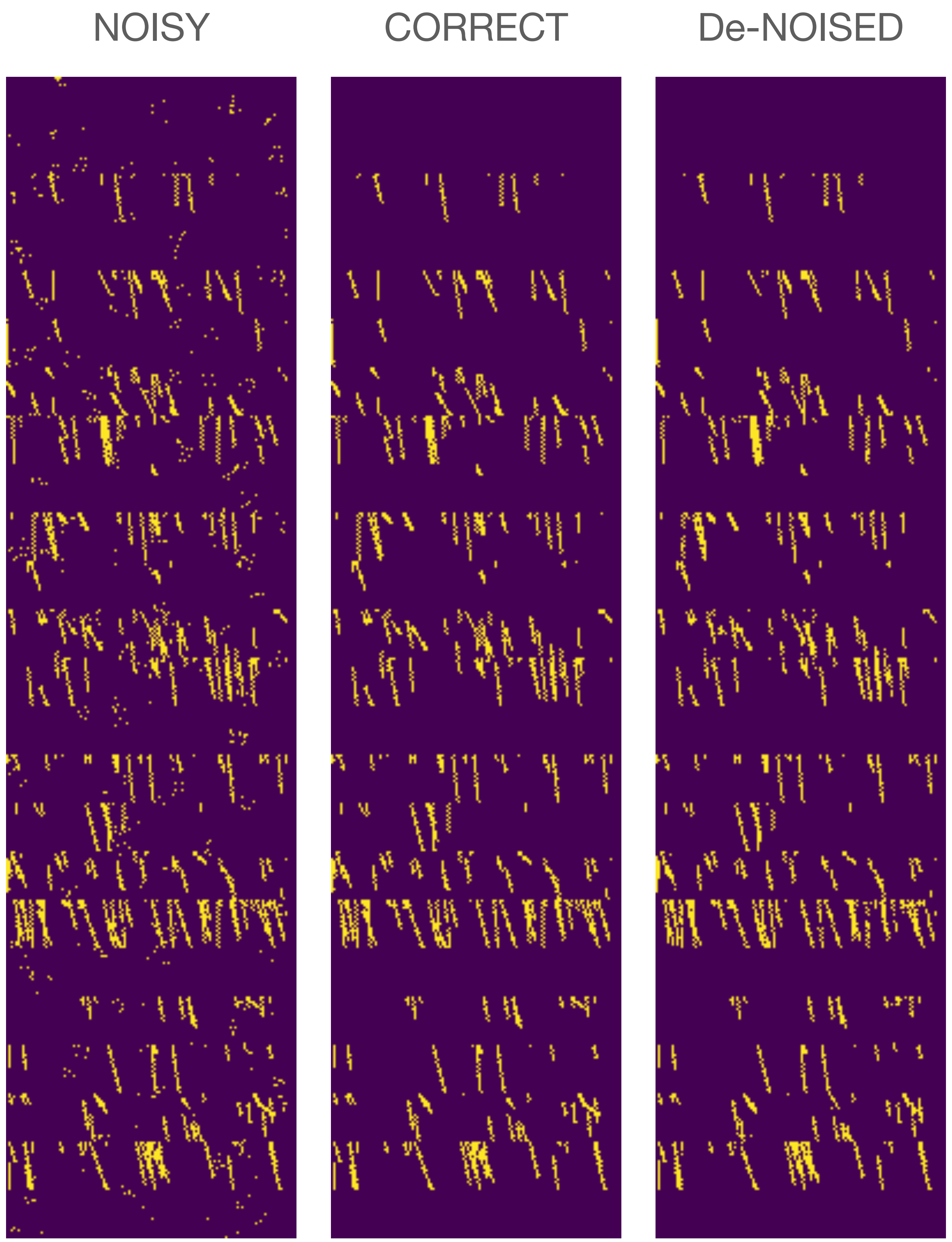






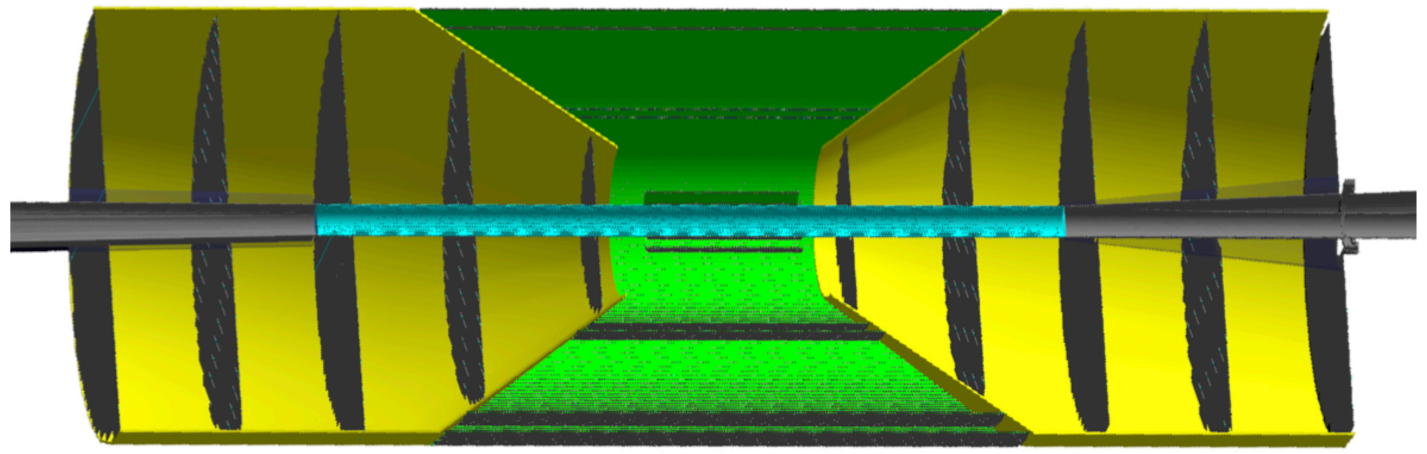


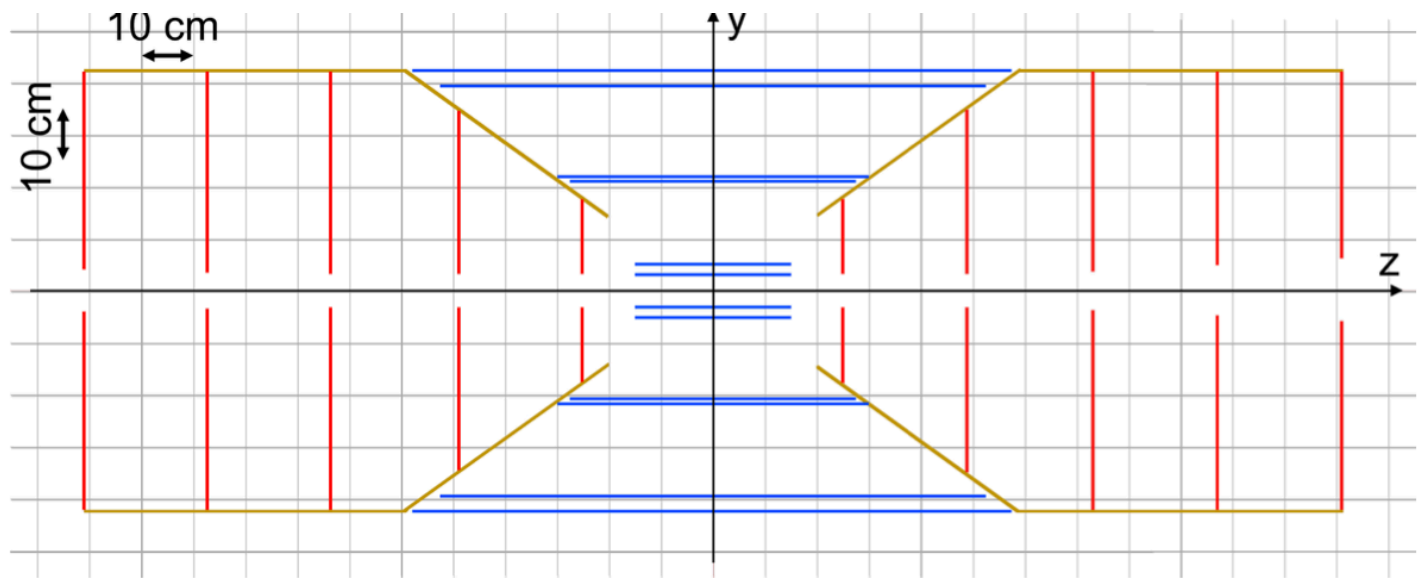




- Similar De-noising techniques can be used for EIC tracker to clean background hits
- With many interactions classification from combinatorics can help identify good tracks.
- Predicting missing hits (inefficiencies can also benefit tracking efficiency)

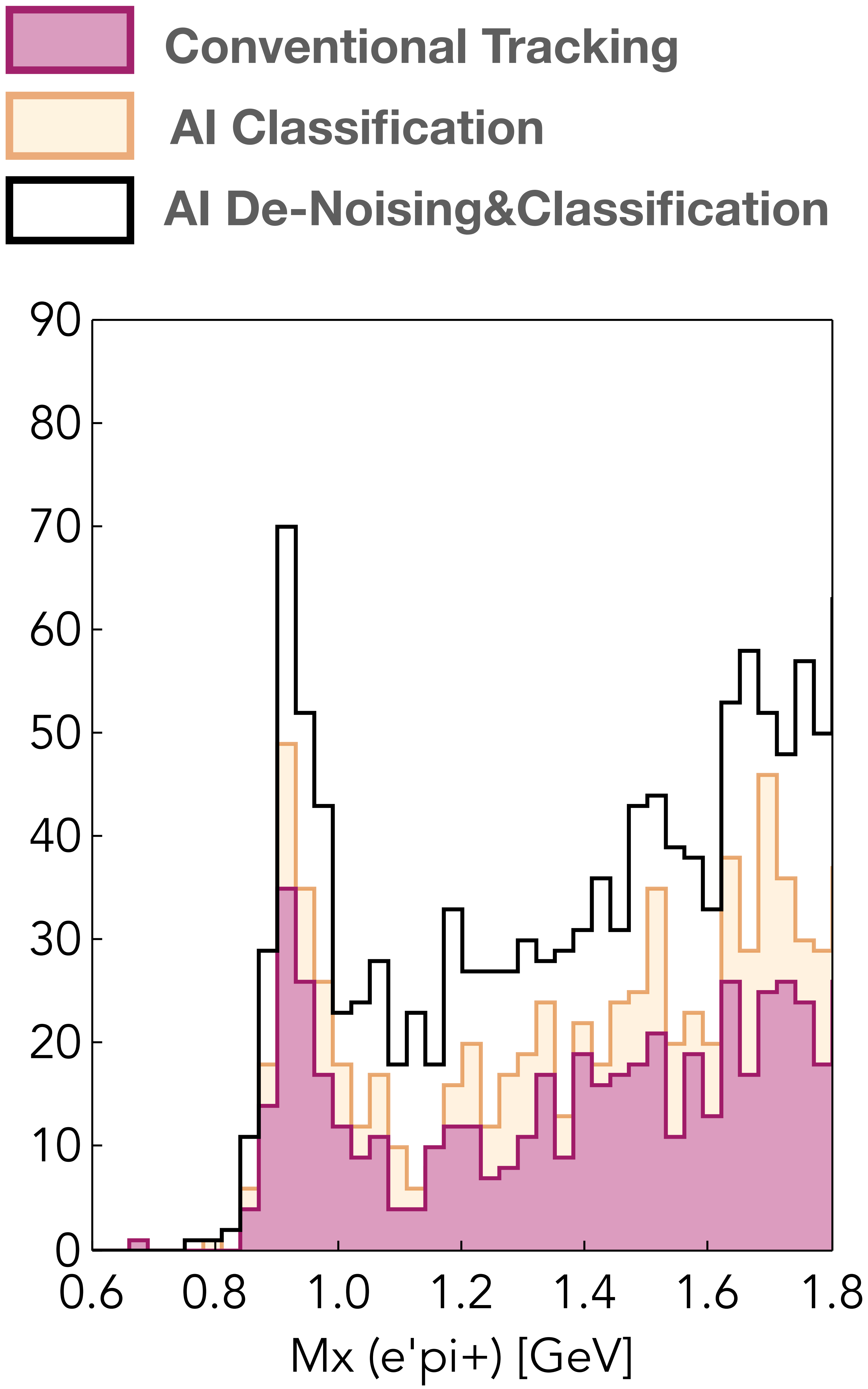
EIC Tracker



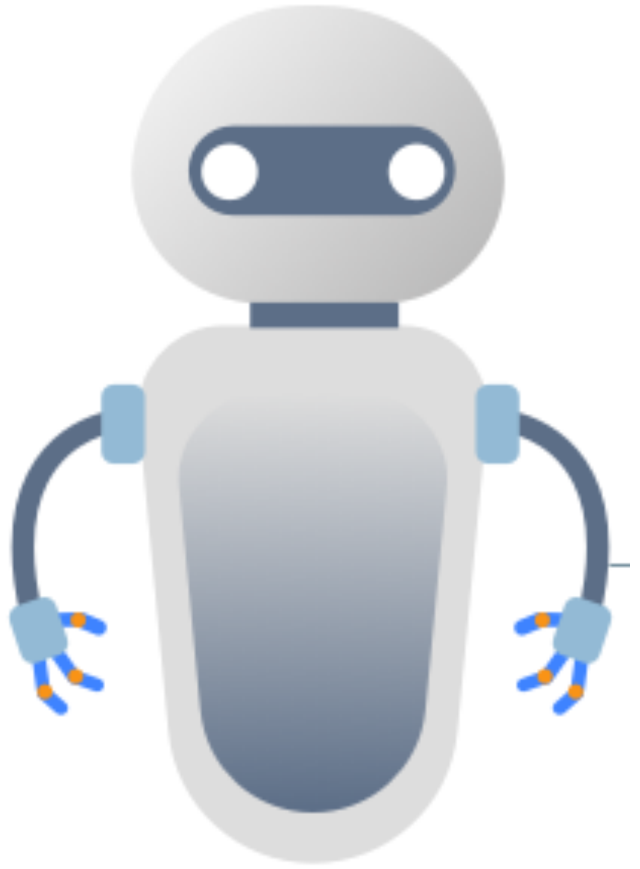


Conclusions

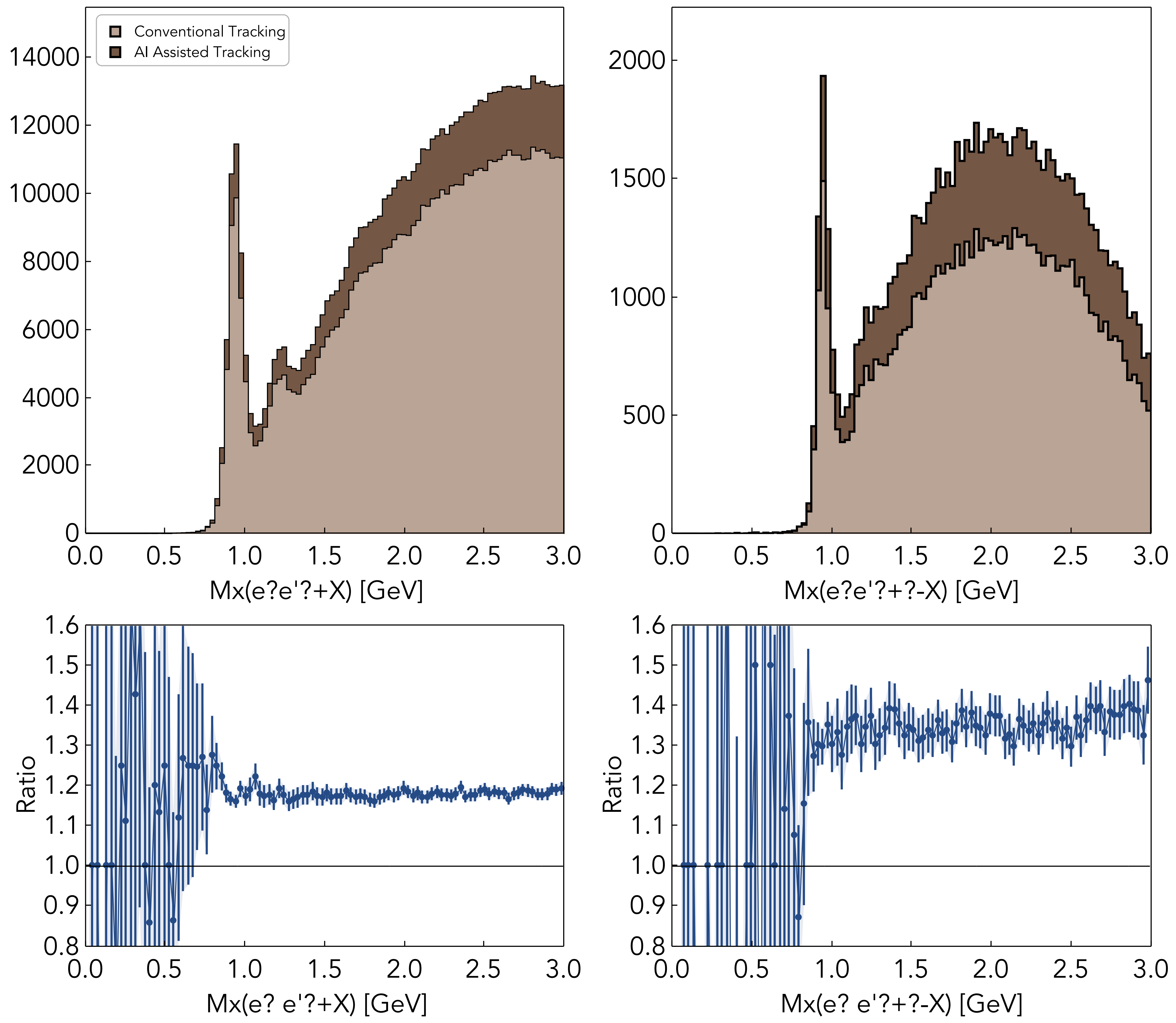
- AI assisted tracking:
  - Two types of Neural Networks are developed to assist tracking code:
    - Track candidate classifiers
    - Inefficiency recovery network based on Auto-Encoders
  - The implementation in standard reconstruction code lead to improvements:
    - Tracking code speedup of ~35%.
    - Particle track reconstruction efficiency improvement of ~15% for standard running conditions (40-50nA).
- Physics Impact
  - Improved efficiency for physics outcome for multi particle final sates
    - Improvement in statistics 20%-35% (for standard running conditions)
- Future work
  - Use the network we developed for other detectors mTPC (Bonus), Micro-Megas (other?)
  - Use for other Experiments GlueX, Solid, EIC ?



BACKUP SLIDES



50 nA AI assisted



50 nA AI assisted de-noised