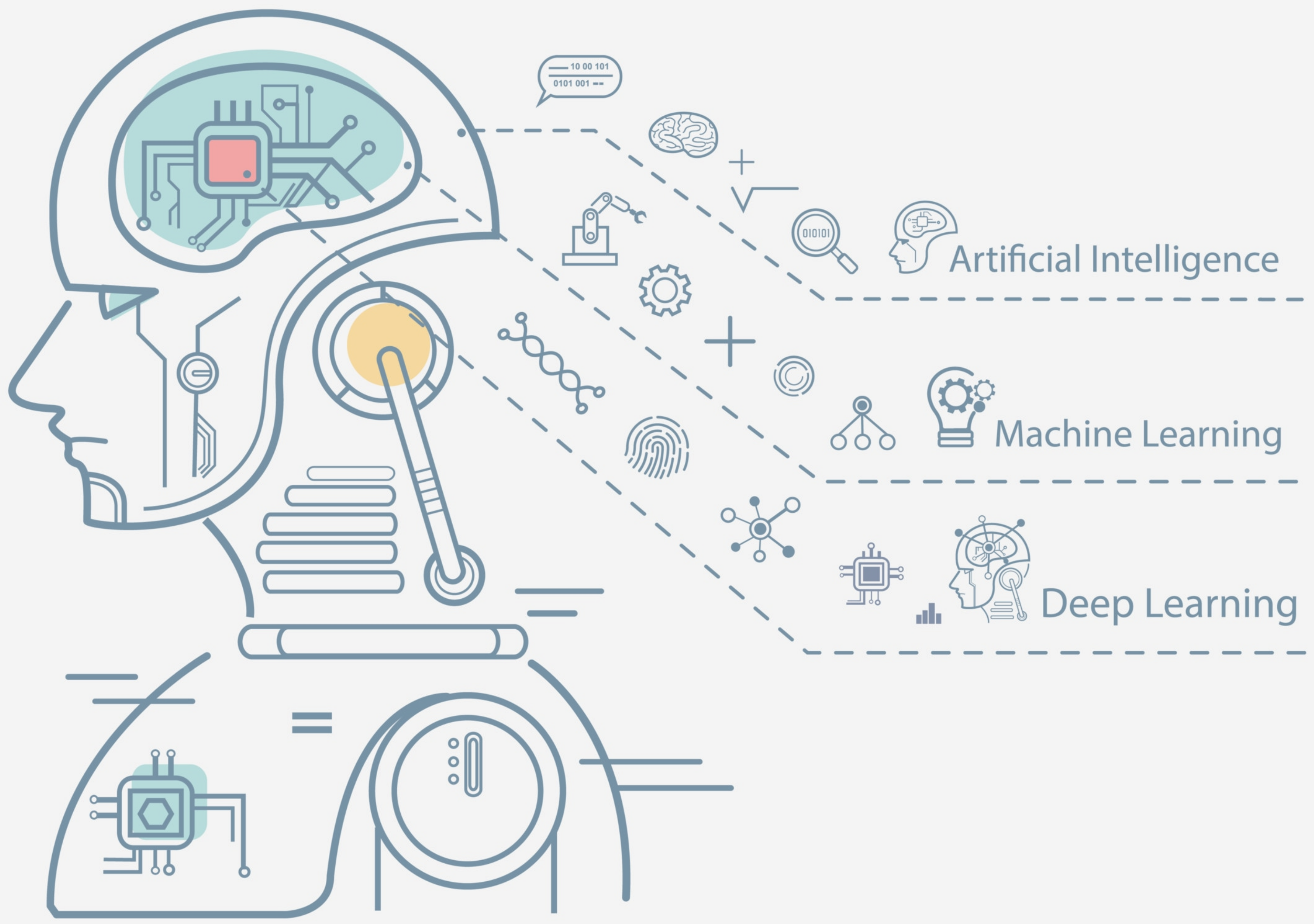
Tracking Particles using AI in CLAS12

Track reconstruction and identification with AI

G.Gavalian (Jefferson Lab)

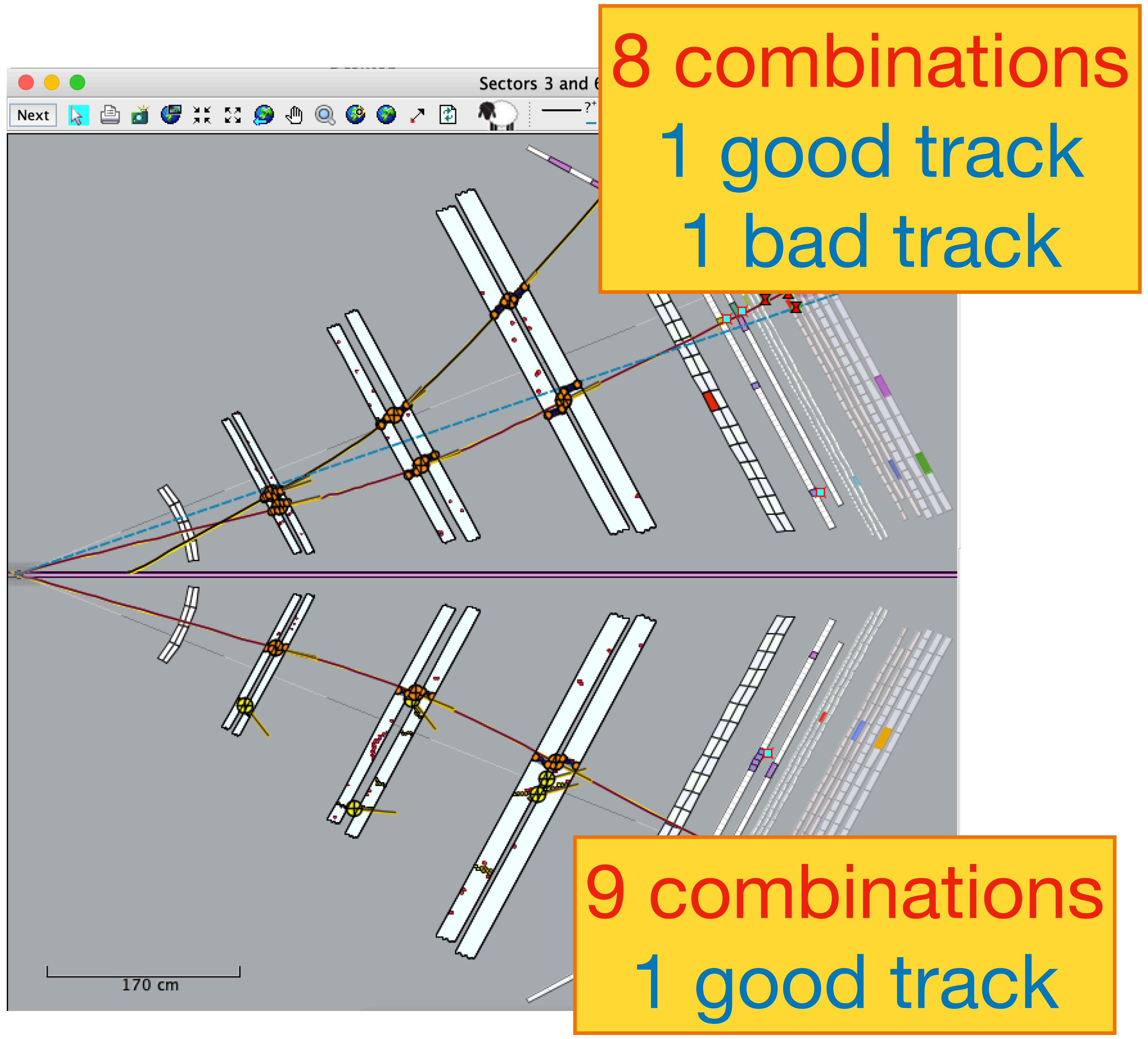
Angelos Angelopoulos (CRTC)
Polykarpos Thomadakis (CRTC),
Nikos Chrisochoides (CRTC)
Department of Computer Science,
Old Dominion University, Norfolk, VA, 23529



CLAS12 Collaboration Meeting (03/05/2021)

Tracking Challenges

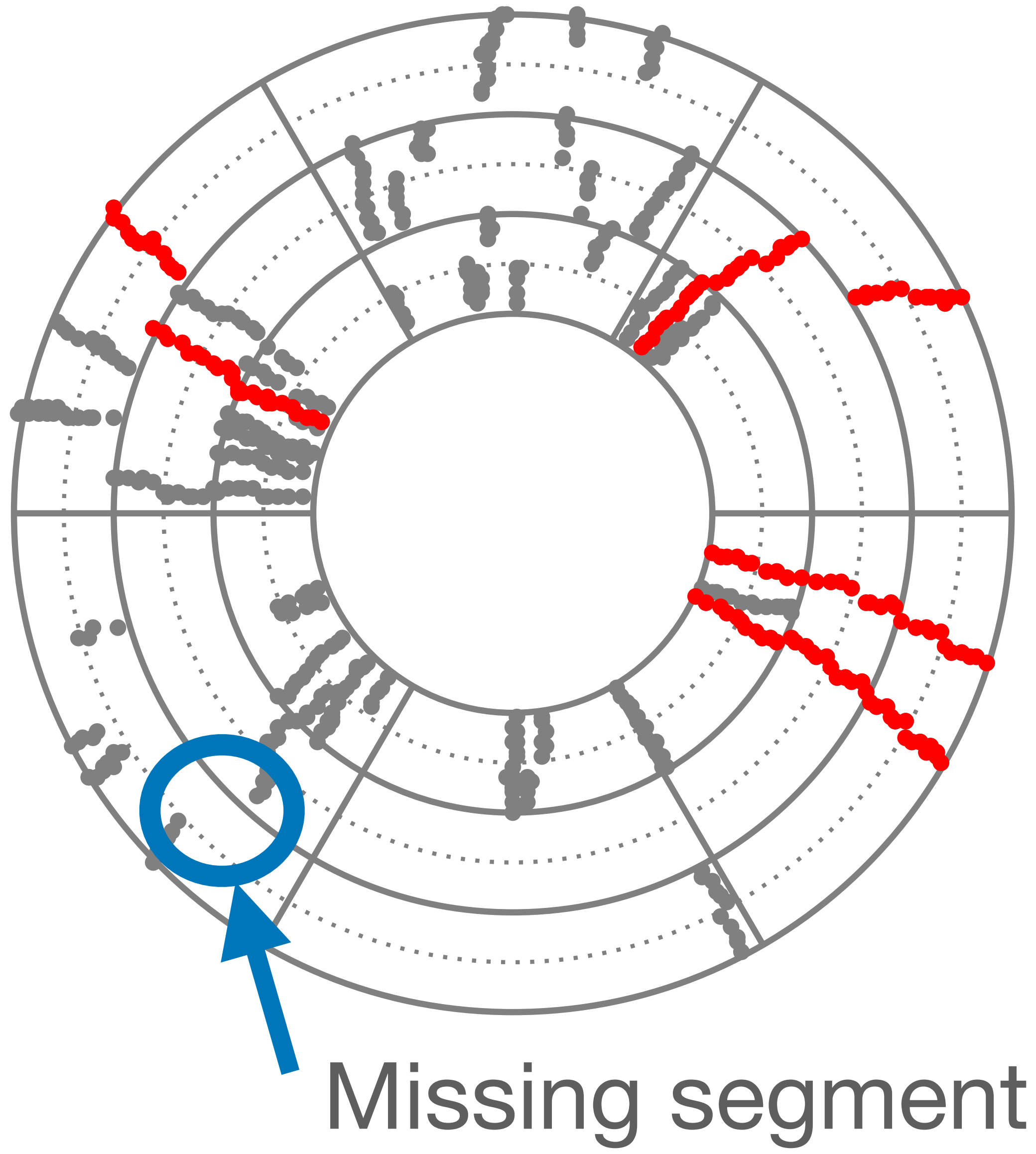
CLAS12 Tracking with Artificial Intelligence



Combinatorics

- Tracking is computationally intensive (takes a really long time)
- It relies on fitting tracks with Kalman-Filter
- Reduction of track candidates to fit can lead to speed up of the code (in theory).
- **DC tracking with clusters:**
  - Many combinations of clusters to form a track.
  - Many end up not as valid track, though time is spend on fitting them.
  - Even after fitting, some tracks are not traced to the target and have to be discarded.

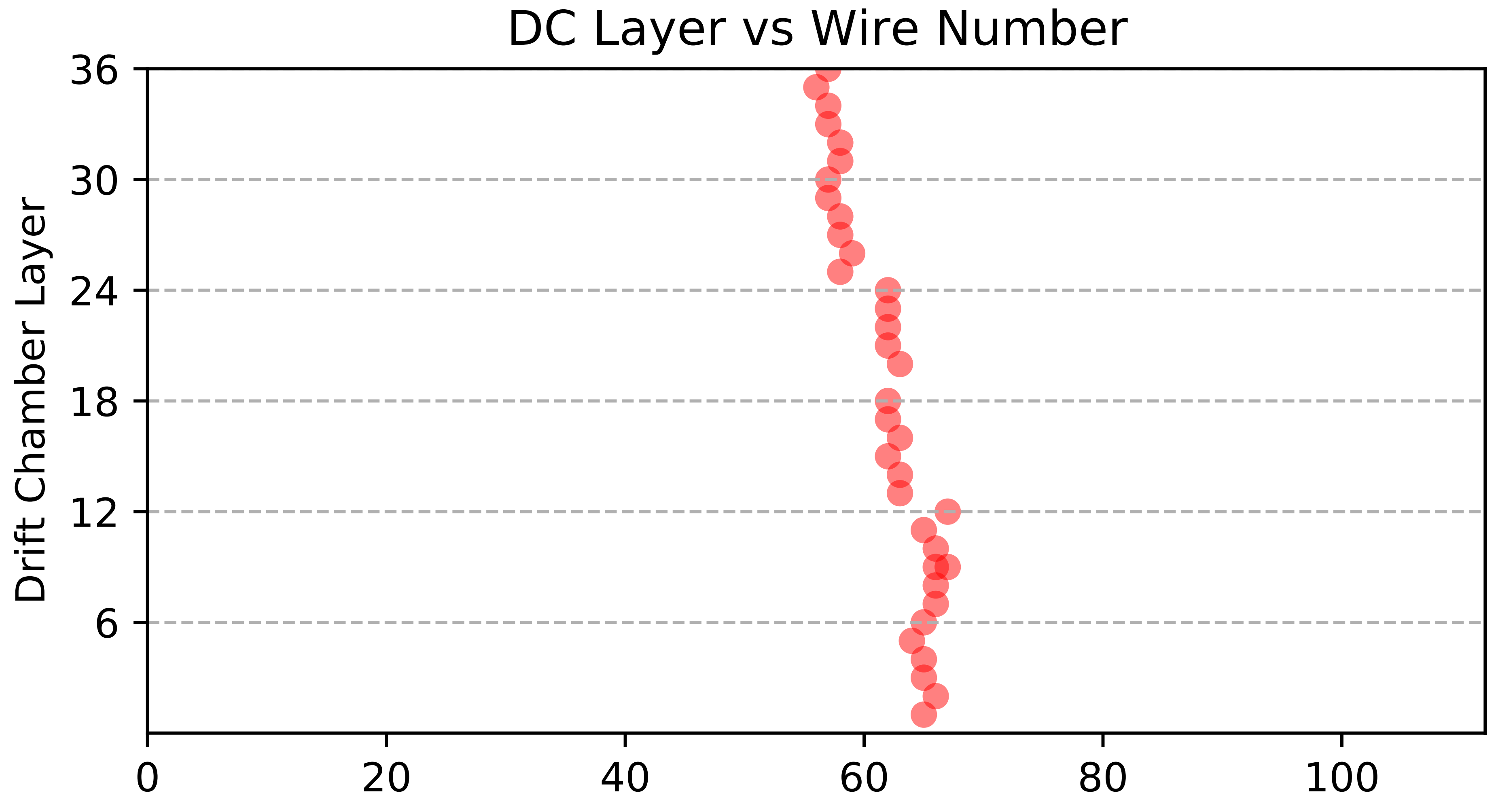
Missing Segments



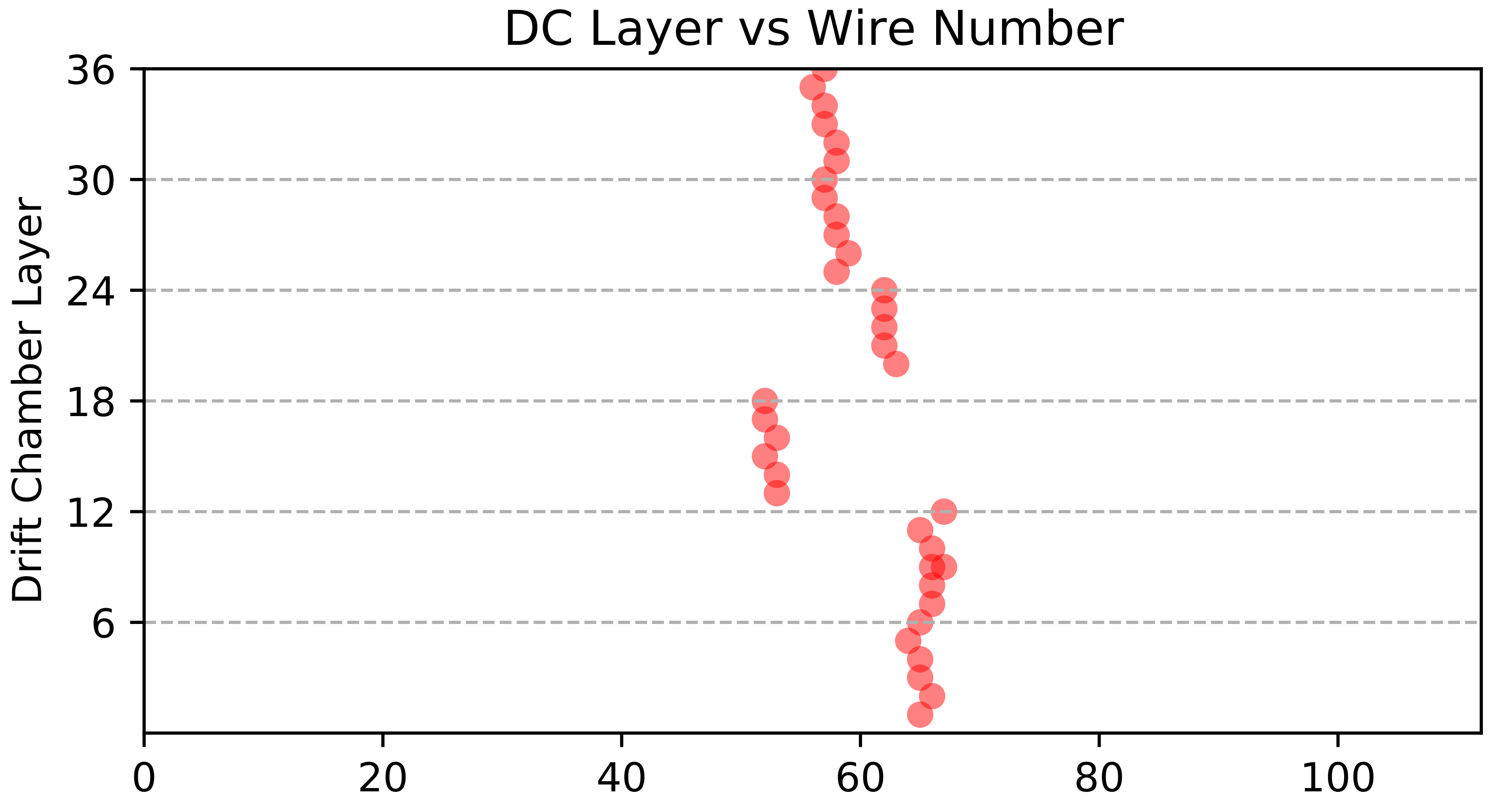
- Inefficiencies and dead channels in drift chambers can lead to lost tracks
- Traditional tracking algorithm also considers 5 segment combinations and recovers tracks
- If track candidate detection is replaced with AI, a method has to be developed to address the missing segment issue.

AI Track (6 Super-Layer)

CLAS12 Tracking with Artificial Intelligence



GOOD TRACK



BAD TRACK

- Training sample is composed of real track data for positive sample and a modified track data where one of the segments is replaced with random segment in the drift chamber from the same event
- The segment is chosen to be closest to the track, since we found that network learns best when negative sample is very close to positive sample.
- For CNN an image with dimensions 36x112 was used, for ERT and MLP 6 features were used which are average wire position of the segment in each super-layer.
- (more details on how to chose training sample is in the published work, see Summary)

AI Track (6 Super-Layer)

CLAS12 Tracking with Artificial Intelligence

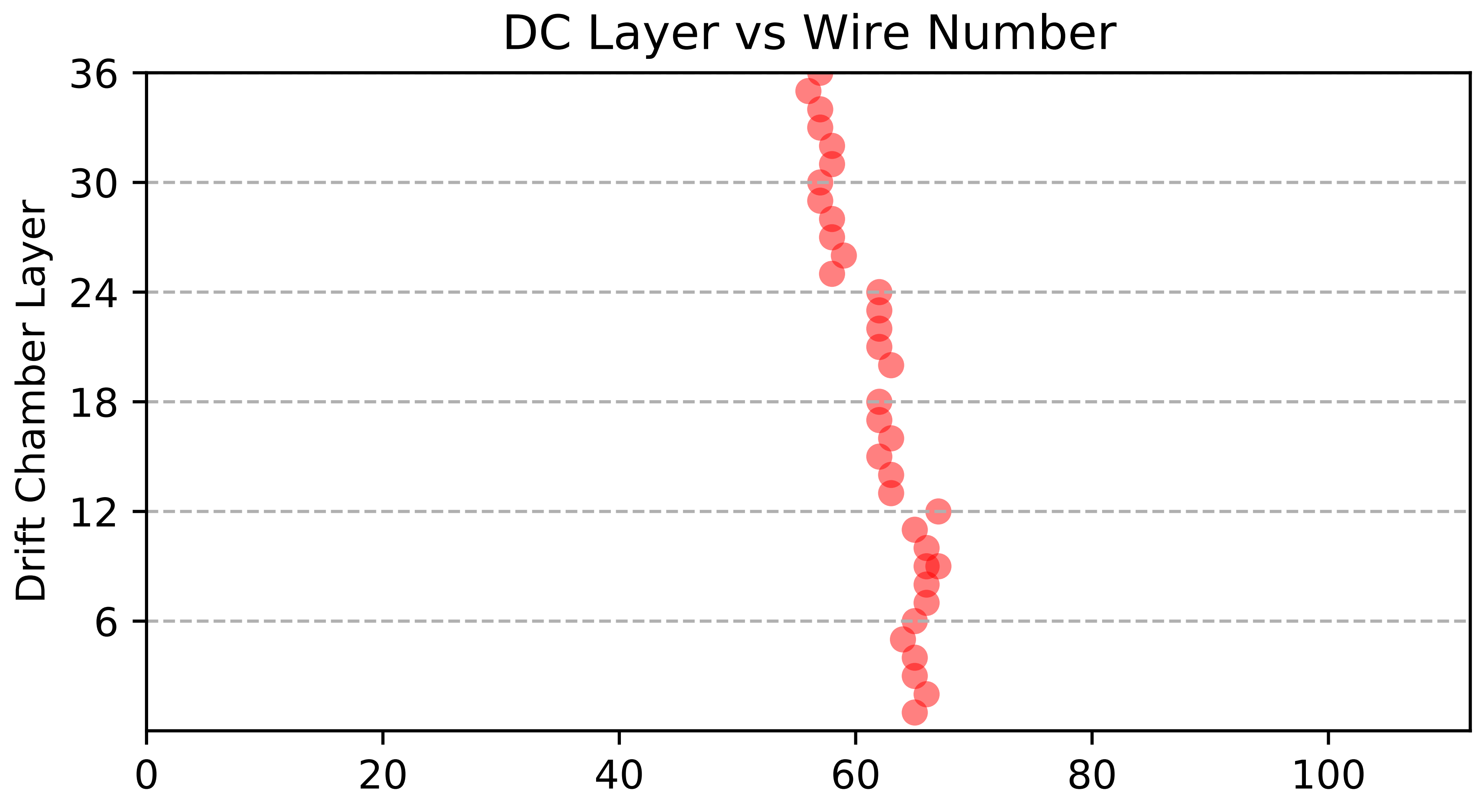
CONFUSION MATRIX

	none	no	neg	pos
none	0	0	0	0
no	0	19786	153	61
neg	0	19	9981	0
pos	0	26	0	9974

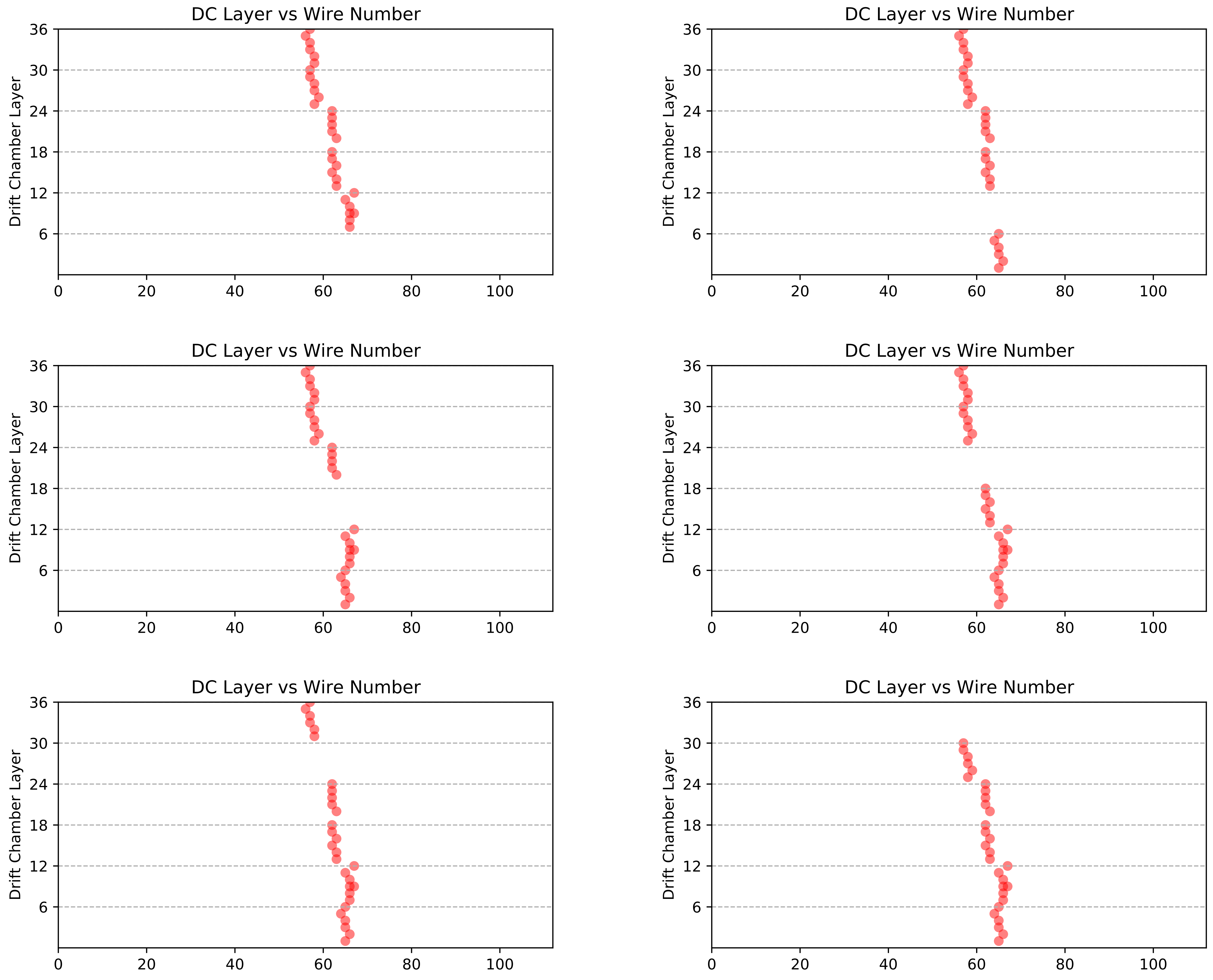
- false tracks identified as positive or negative track (false positives)
- negative tracks that were not identified as a good track (out of 10,000)
- positive tracks that were not identified as a good track (out of 10,000)

AI Track (5 Super-Layer)

CLAS12 Tracking with Artificial Intelligence

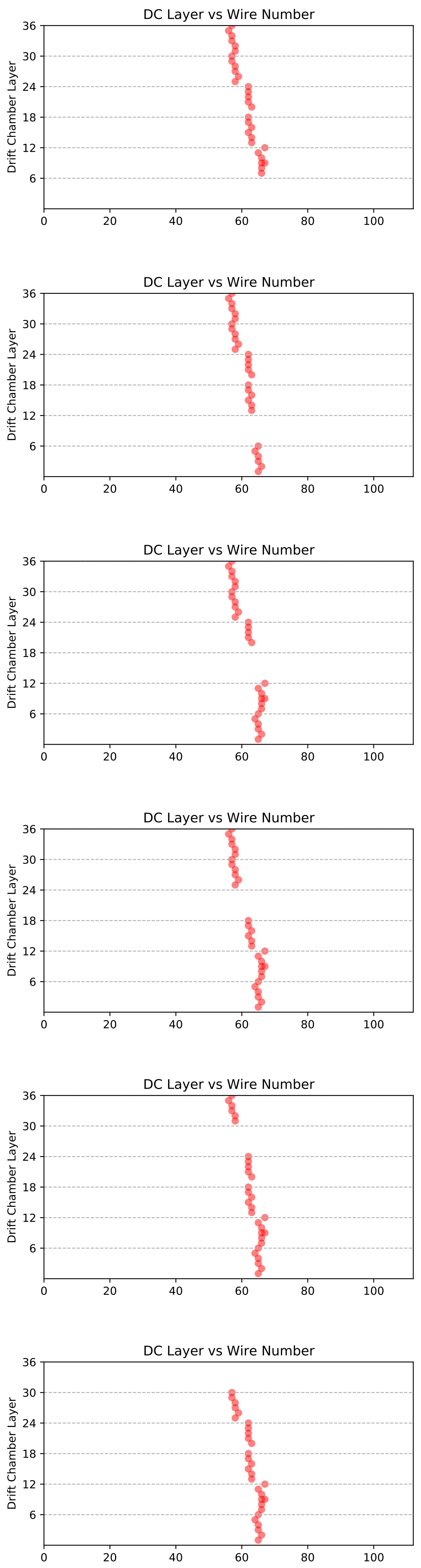


- Start with reconstructed track from Time Based Tracking
- Consider all combinations of missing super-layers
- Construct Auto-Encoder that takes as input a corrupt track and TRUE track as output.

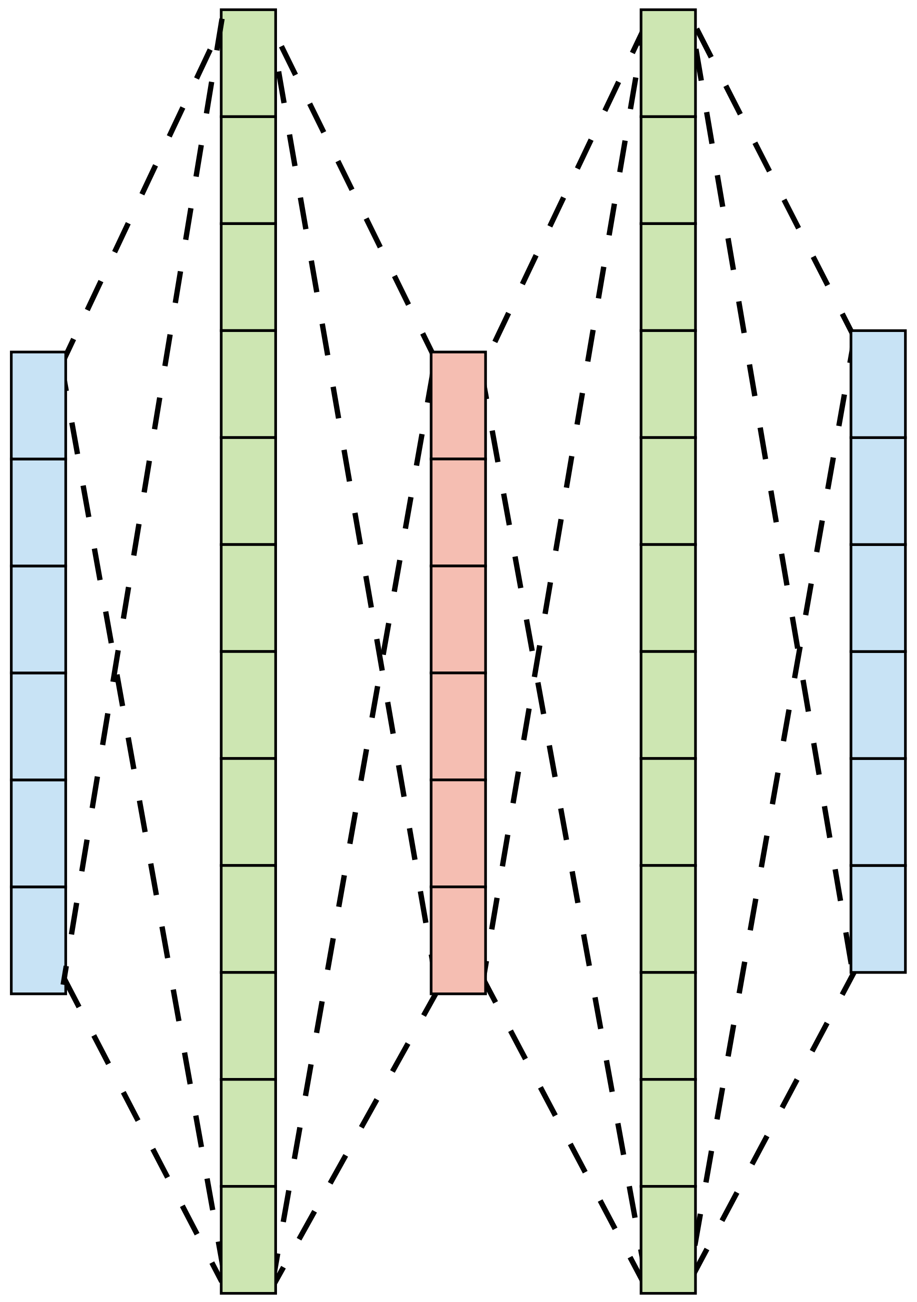


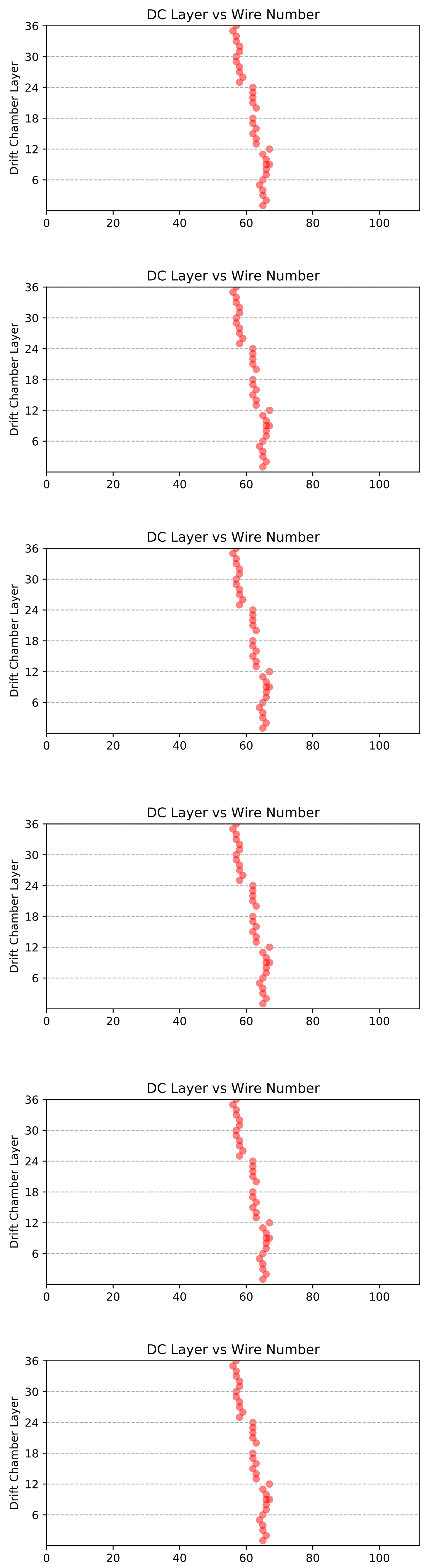
AI Tracking

CLAS12 Tracking with Artificial Intelligence



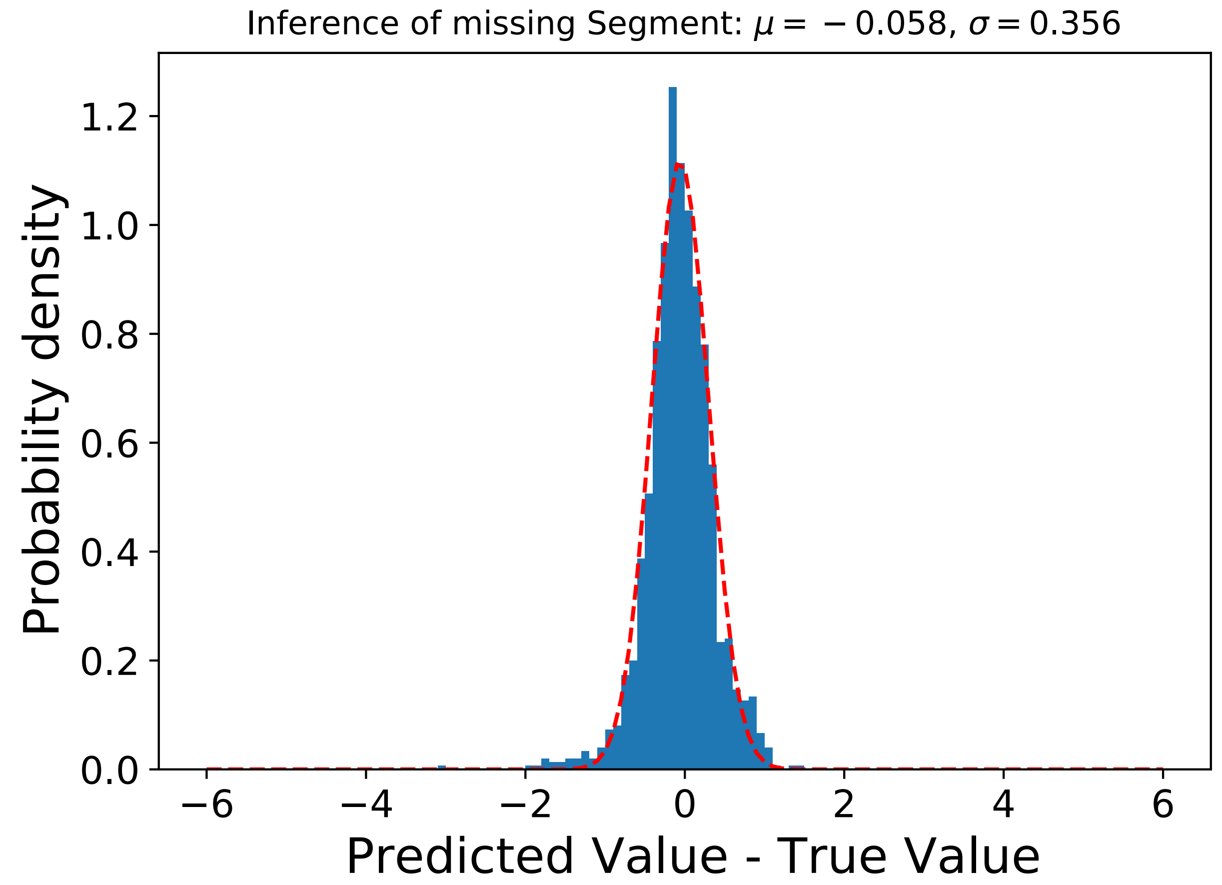
Auto-Encoder

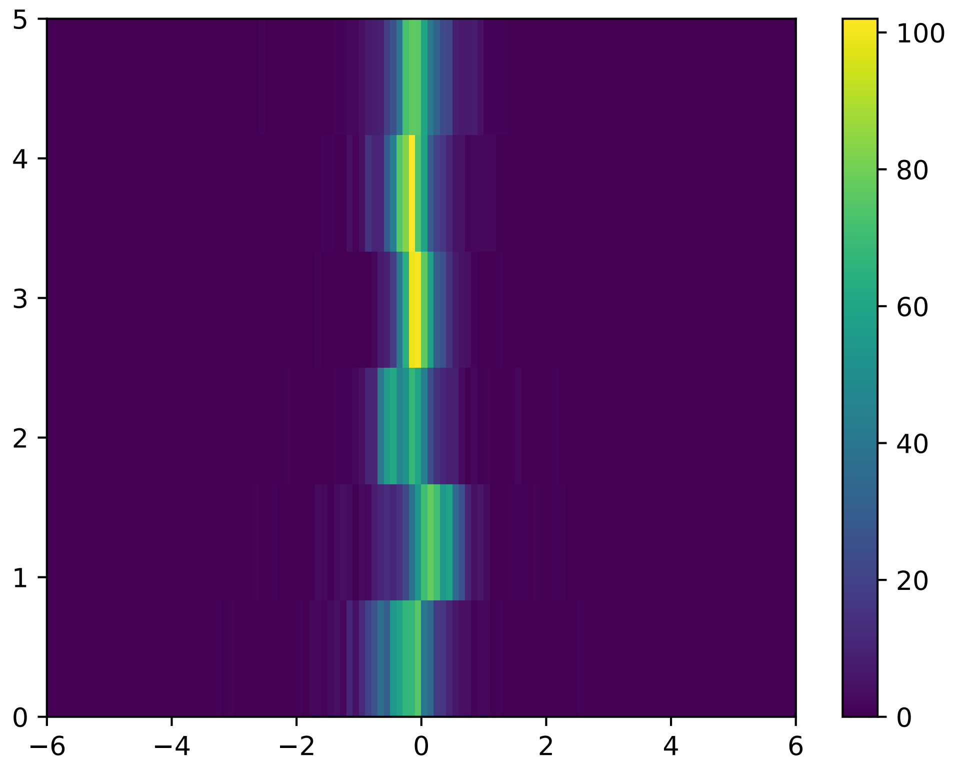




$$
(x_1,x_2,x_3,x_4,x_5,x_6)\begin{cases}
X(0.0,x_2,x_3,x_4,x_5,x_6)\rightarrow & Y(x_1,x_2,x_3,x_4,x_5,x_6)\\
X(x_1,0.0,x_3,x_4,x_5,x_6)\rightarrow & Y(x_1,x_2,x_3,x_4,x_5,x_6)\\
X(x_1,x_2,0.0,x_4,x_5,x_6)\rightarrow & Y(x_1,x_2,x_3,x_4,x_5,x_6)\\
X(x_1,x_2,x_3,0.0,x_5,x_6)\rightarrow & Y(x_1,x_2,x_3,x_4,x_5,x_6)\\
X(x_1,x_2,x_3,x_4,0.0,x_6)\rightarrow & Y(x_1,x_2,x_3,x_4,x_5,x_6)\\
X(x_1,x_2,x_3,x_4,x_5,0.0)\rightarrow & Y(x_1,x_2,x_3,x_4,x_5,x_6)
\end{cases} \tag{7}
$$

- Each Fully reconstructed track is corrupted for each super-layer and set as input for auto-encoder
- The output is fully reconstructed track.
- Neural Network learns how to fix the corruption
- Test sample is reconstructed with accuracy of ~0.36 wires.



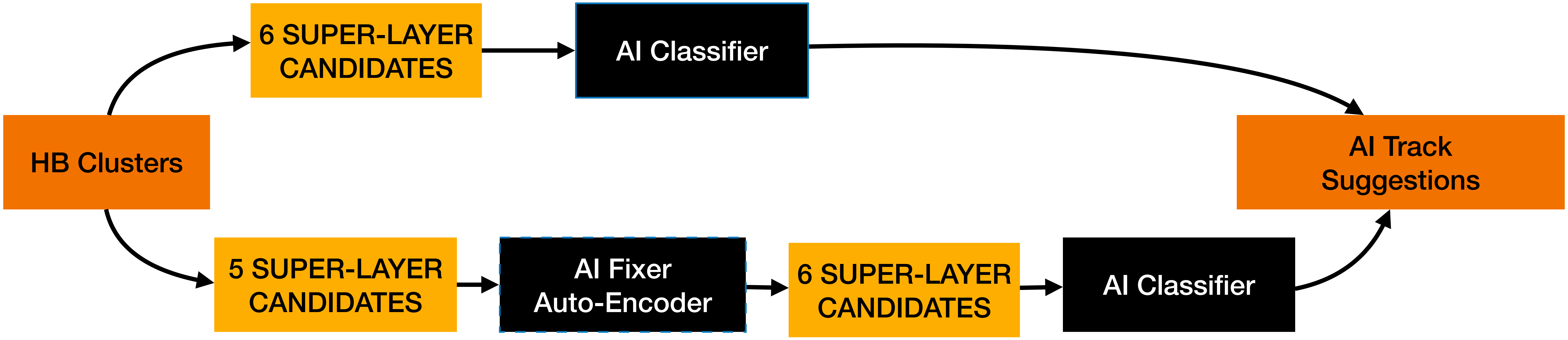


AI Tracking Reconstruction
Process

- After initial development of methods and procedures how to classify events and how to fix missing segments a software needs to be implemented as CLARA service
- Challenges:
  - CLAS12 software is Java based, one needs to find Java machine learning libraries
  - Light weight libraries are preferred due to portability of the code (you may not agree)
  - Solutions we found are not thread safe, can not be used in multi-threaded SOA
  - A lot of supplementary code has to be developed to construct cluster combinations, analyze evaluated tracks based on classifier probability and eliminate overlapping segments, re-analyze to determine possible 5-cluster combinations.
- There is long path from working prototype (ODU/CRTC students Polykarpos Thomadakis and Angelos Angelopoulos) to production ready code that can be validated and used by users to extract training sample, train network and use in reconstruction.
- A minimal neural network evaluator was developed to use for AI inference without any massive external libraries (with help from CNU, Will Phelps and Andru Quiroga)
- After software is implemented there is (was) a lot of back and forth with conventional tracking code developer (Veronique) to test and verify the information flow from AI suggested tracks to conventional algorithms
- There was a lot of work done cooking and running validation code to produce the AI vs Conventional comparison plots (Raffaella)
- IN SHORT: This is a big group effort, and it takes time to converge and produce production ready code.

AI (putting all together)

CLAS12 Tracking with Artificial Intelligence

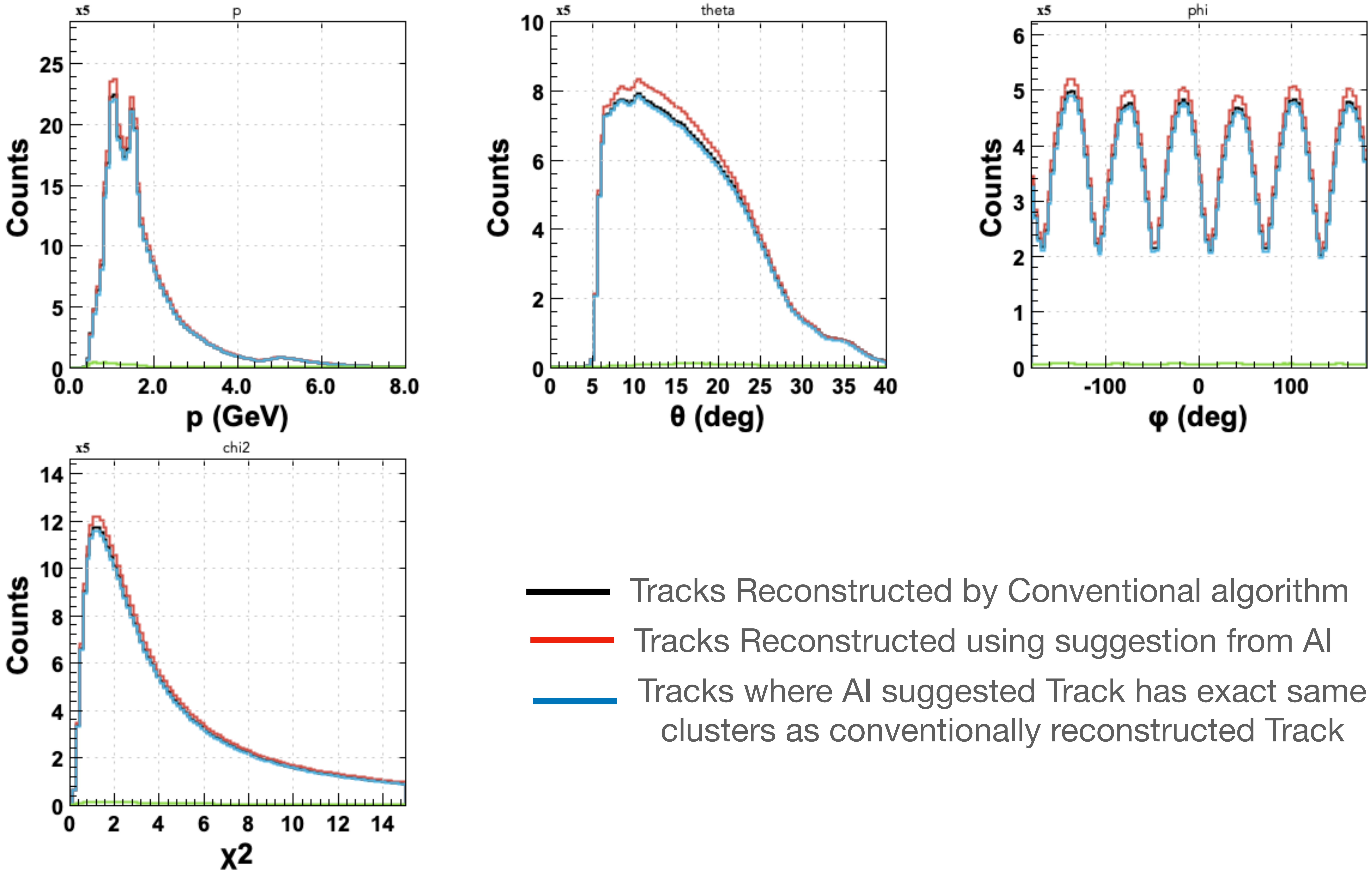


AI Fixer Auto-Encoder — Takes 5 Super-Layer Track candidates and generates a pseudo hit in missing layer

AI Classifier — Takes 6 Super-Layer Track candidates and generates probability for the candidate to be a good track.

AI Tracking Reconstruction

From all angles



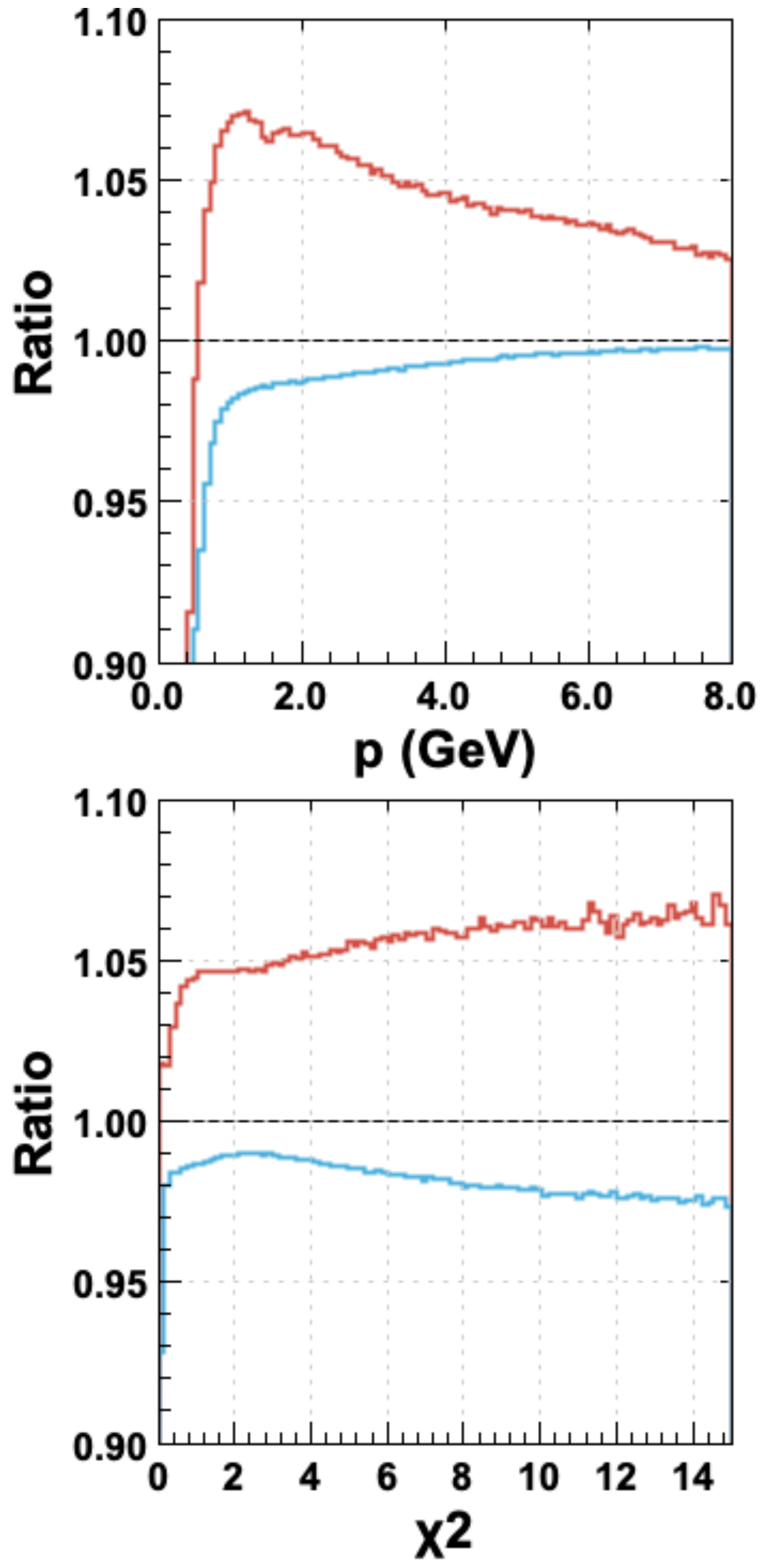
Tracks Reconstructed by Conventional algorithm

Tracks Reconstructed using suggestion from AI

Tracks where AI suggested Track has exact same clusters as conventionally reconstructed Track

AI Tracking Reconstruction

Track Reconstruction improvement

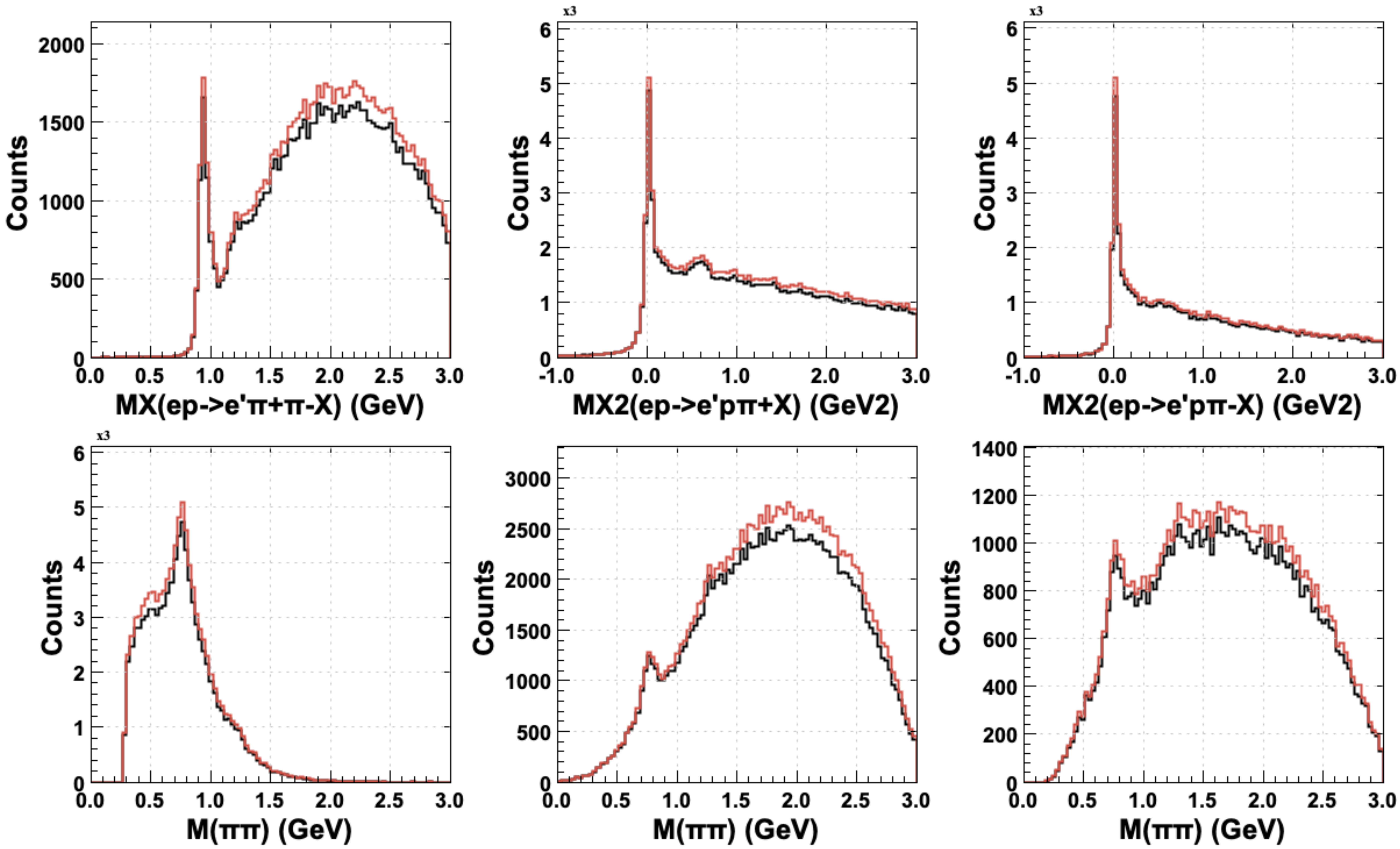


Ratio of tracks reconstructed using AI suggestion to total number of tracks reconstructed by conventional tracking

Ratio of conventional tracks that matched with AI to the total number of tracks

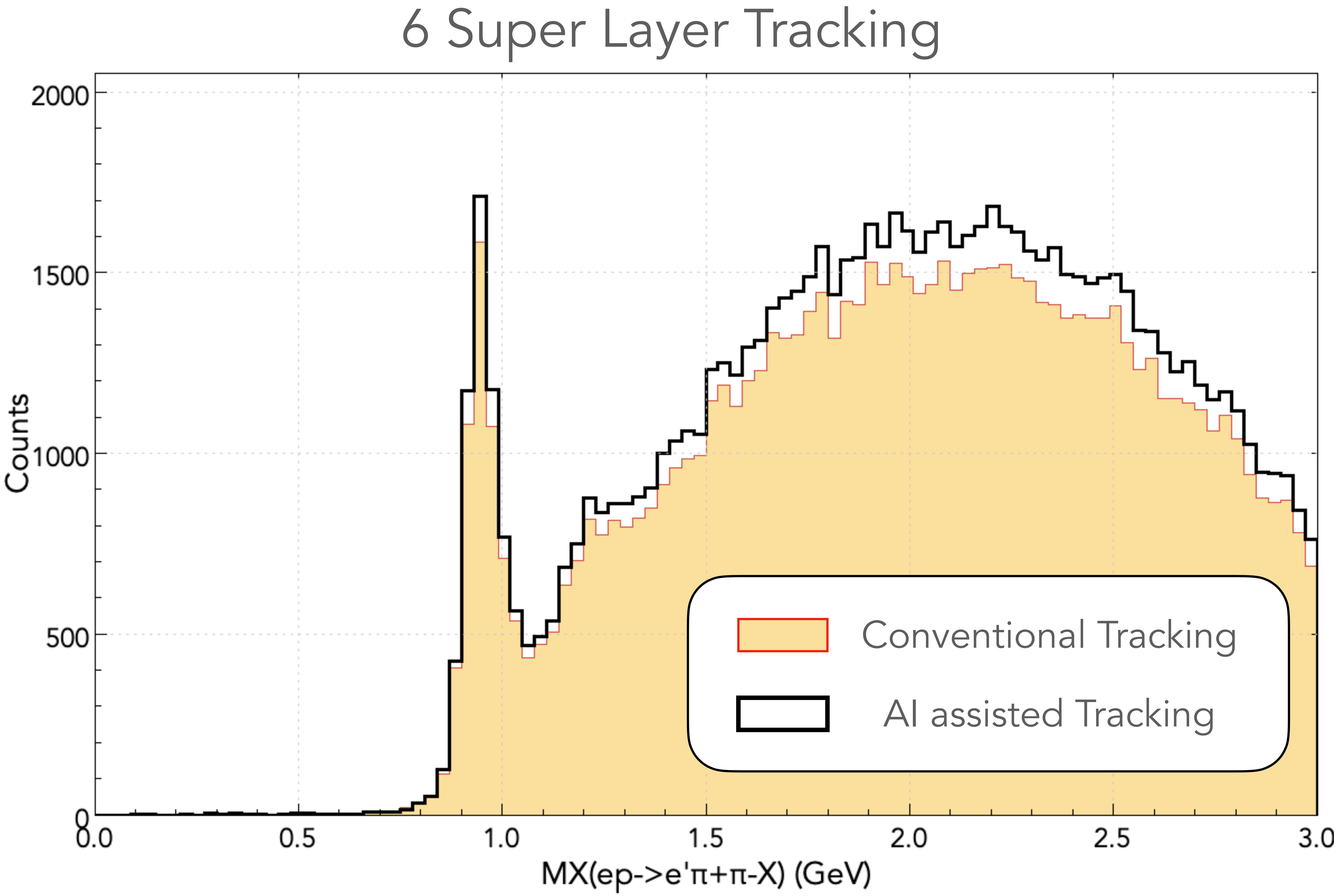
AI Tracking Reconstruction

Physics Impact



AI Tracking Reconstruction

Physics Impact

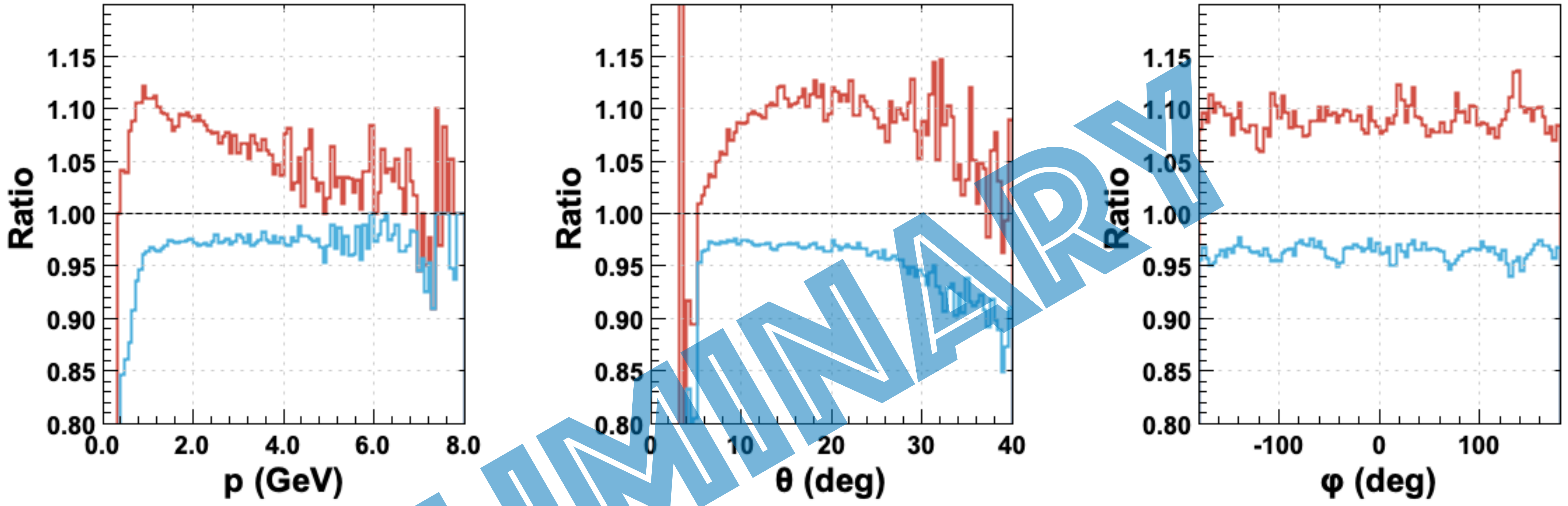


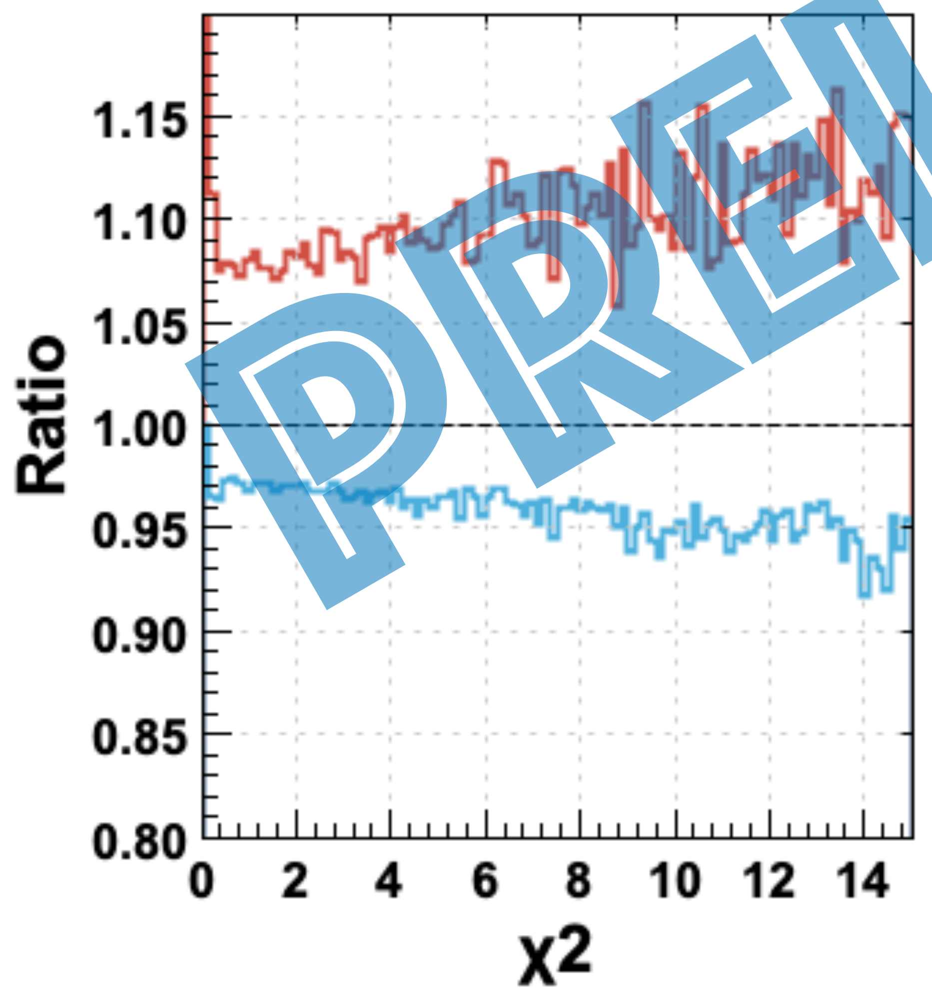
With AI we are not loosing events

AI Tracking Reconstruction (5 super layer)

5 super layer tracking

Results for 5 & 6 Super layer Combined





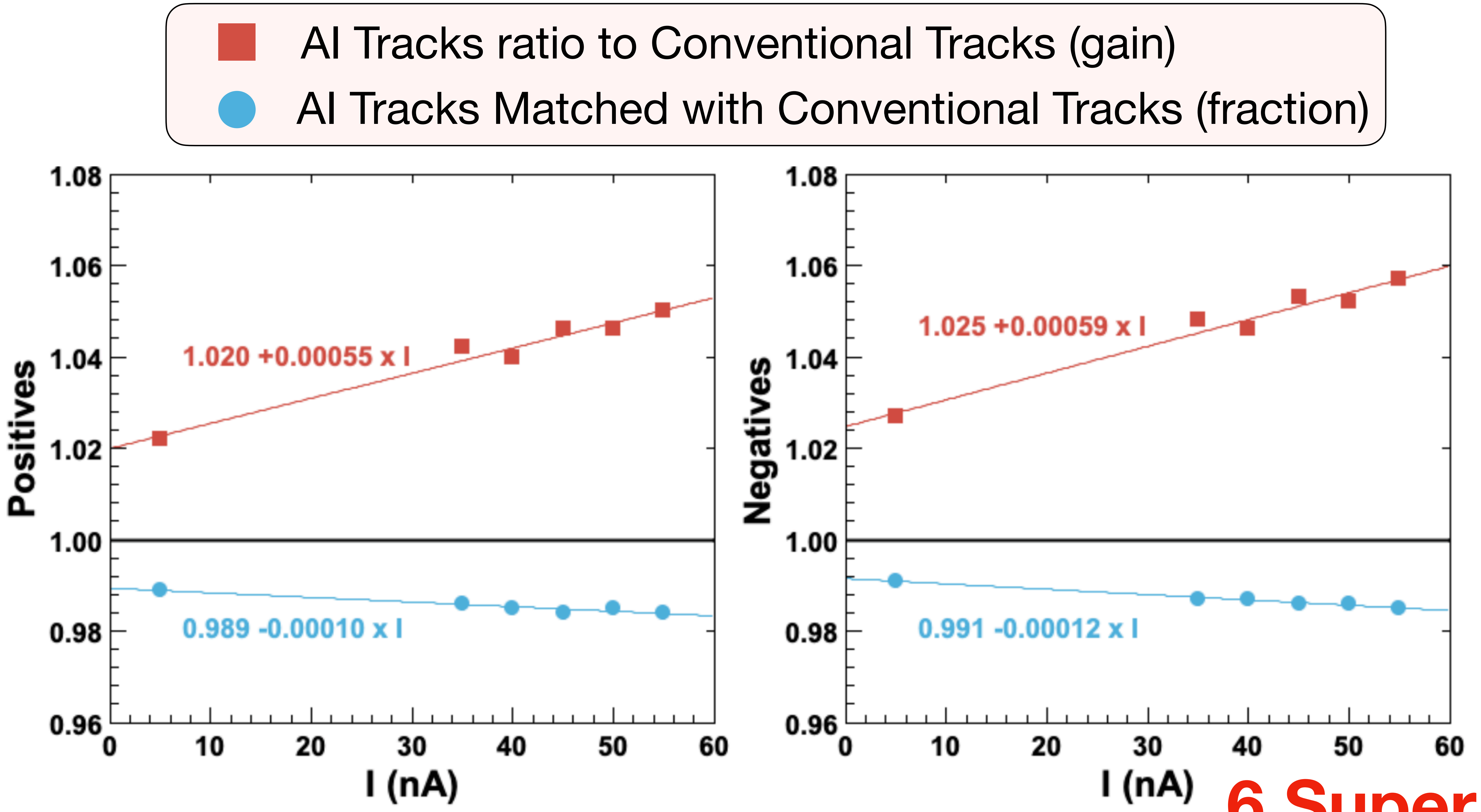
Ratio of tracks reconstructed using AI suggestion to total number of tracks reconstructed by conventional tracking

Ratio of conventional tracks that matched with AI to the total number of tracks

AI Tracking Reconstruction

Luminosity Scan

- Luminosity Scan was performed with 6 super layer tracking only. The gains over traditional tracking are those from slide #9 only. This slide is only to show that there is a positive trend with increased current.
- The gain Level may change once 5-super layer is added, the trend will probably be the same.



6 Super Layer ONLY

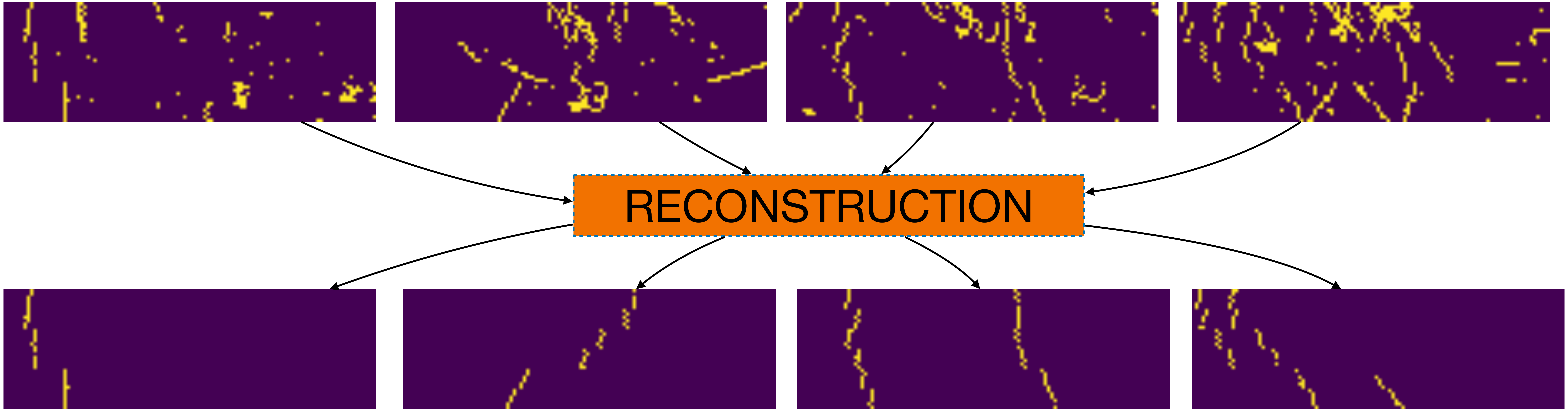
AI Tracking De-Noising

CLAS12 Tracking with Artificial Intelligence

De-Noising

AI Tracking De-Noising

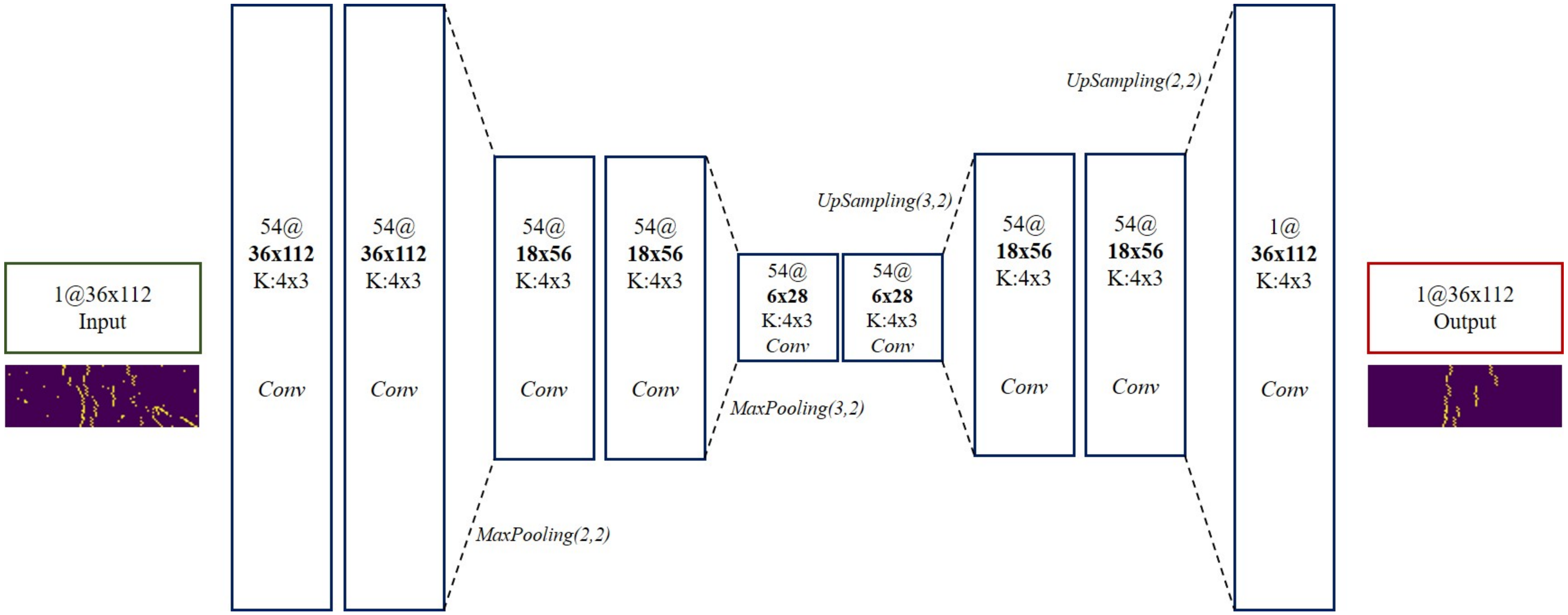
Luminosity Scan



- Reconstruction removes hits that seem to be noise, and clusters hits in each super layer.
- The track combinations are formed from clusters, and tracks are fitted
- With De-noising we hope to clean the hits leaving only hits that potentially will belong to a track.
- **Use cases:**
  - This can be used online with Level-3 trigger application (see later talk)
  - Reconstruction can use to clean up the sample in high luminosity to enable clustering in high occupancy regions.

AI Tracking De-Noising

Auto Encoders



- We use Convolutional Auto Encoders to teach network to remove hits that are not associated with tracks
- As input all hits from drift chamber is given to the network
- The output is only hits that belong to reconstructed tracks (number of tracks vary 1,2 or 3)
- Different Architectures were tried to determine the best performance combination.

AI Tracking De-Noising

Network Architectures

Model	Architecture
0	C48(4x6) ; MP(2,2) ; C48(4,6) ; MP(2,2) ; C48(4,6) ; US(2,2) ; C1(4x6)
0a	C48(5x4) ; MP(2,2) ; 2*C48(4x3) ; MP(3,2) ; 2*C48(4,3) ; US(3,2) ; 2*C48(5x4) ; US(2,2) ; C1(5x4)
0b	2*C54(4x3) ; MP(2,2) ; 2*C54(4x3) ; MP(3,2) ; 2*C54(4x3) ; US(3,2) ; 2*C54(4,3) ; US(2,2) ; C1(4x3)
0c	C48(5x4) ; AP(2,2) ; C48(4x3) ; AP(3,2) ; C48(4,3) ; US(3,2) ; C48(5x4) ; US(2,2) ; C1(5x4)
0d	2*C54(4x3) ; MP(2,2) ; 2*C54(4x3) ; MP(3,2) ; 2*C54(4x3) ; US(3,2) ; 2*C54(4,3) ; US(2,2) ; 2*C54(4x3) ; C1(4x3)
0e	2*C128(4x3) ; MP(4,2) ; 2*C128(4x3) ; US(3,2) ; 2*C128(4x3) ; C1(4x3)
0f	2*C28(4x3) ; MP(2,2) ; 2*C28(3x3) ; MP(3,2) ; 2*C28(3x3) ; US(3,2) ; 2*C28(3x3) ; US(2,2) ; 2*C28(4x3) ; C1(4x3)
1	C64(k:6x6,s:6x1) ; C64(k:2x2,s:2x1) ; DC64(k:2x3,s:2x1) ; DC1(k:6x6,s:6x1)
2	C64(k:3x3,s:3x1) ; C64(k:2x2,s:2x1) ; MP(1,2) ; C64(k:2x2) ; US(1,2) ; DC64(k:2x2,s:2x1) ; DC1(k:3x3,s:3x1)

C?? - Convolutional Layer with ?? kernels

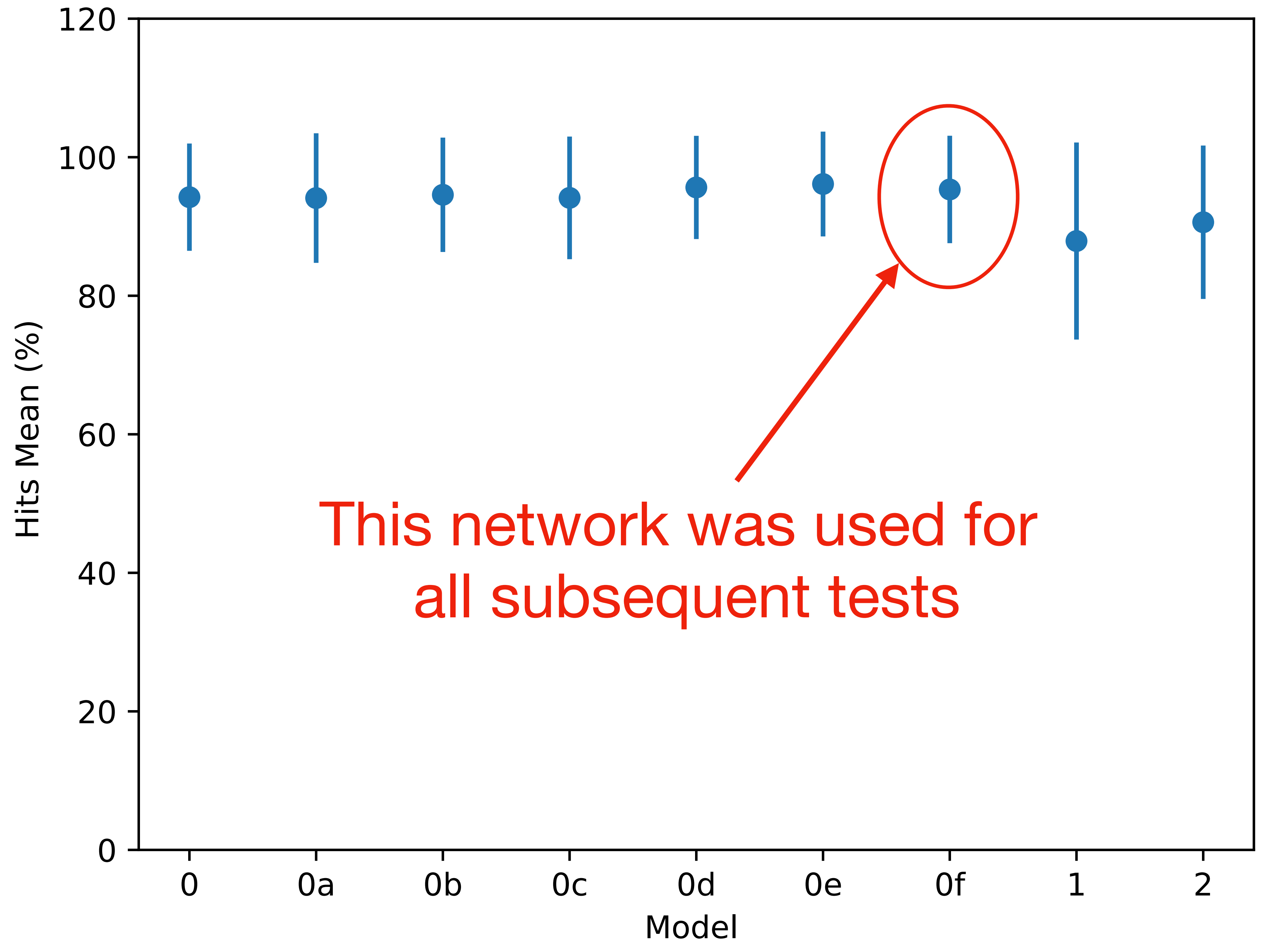
(2x2) - Convolutional Kernel size

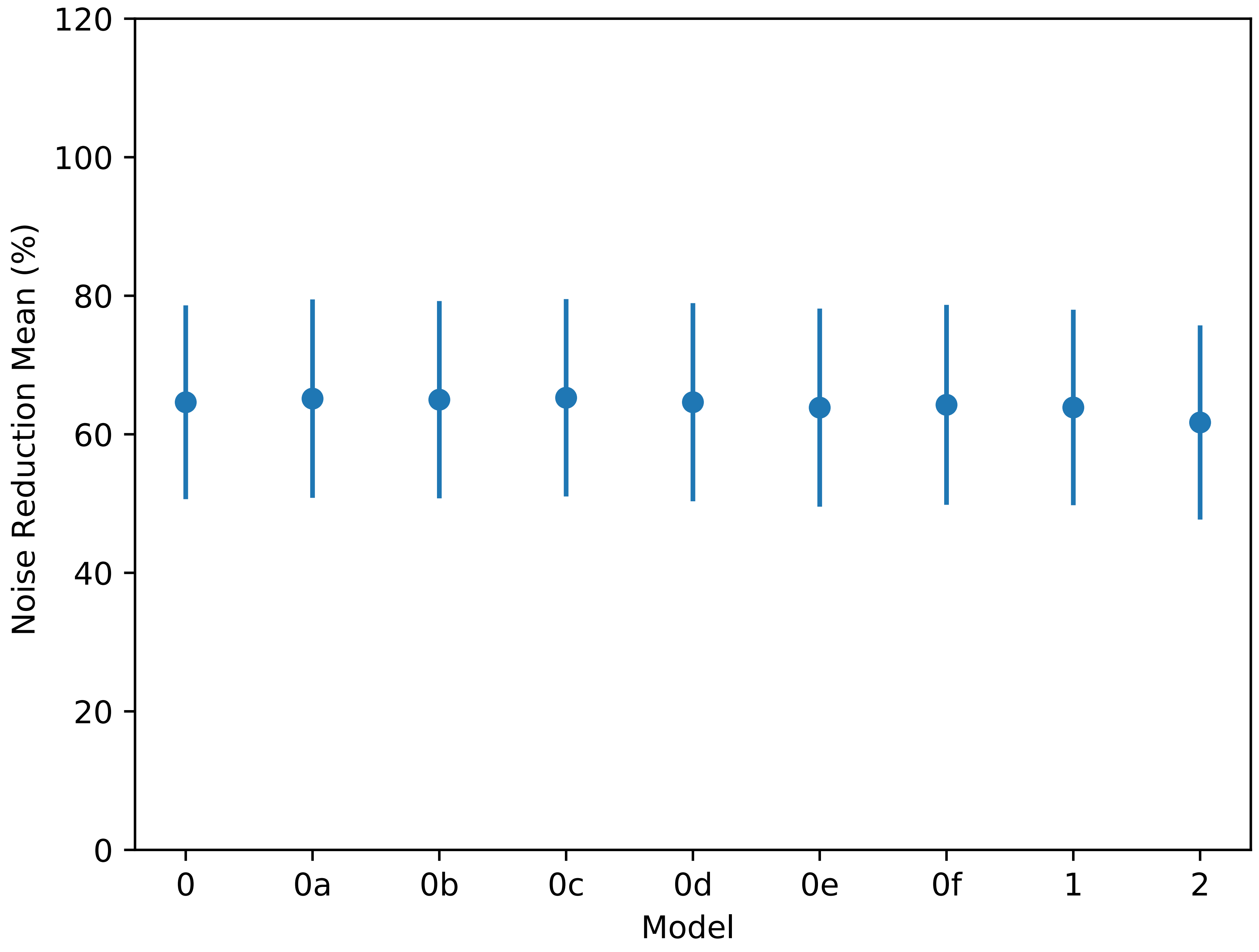
US - Up-Sampling Layer

MP - Max Pooling Layer

AI Tracking De-Noising
Network Architectures

- All Network configurations perform similar in reconstructing >90% of track hits in average
- The noise reduction is defined as fraction of hits reduced from initial sample, all models remove 60-70% of the original hits, while keeping >90% (in average) hits from tracks.



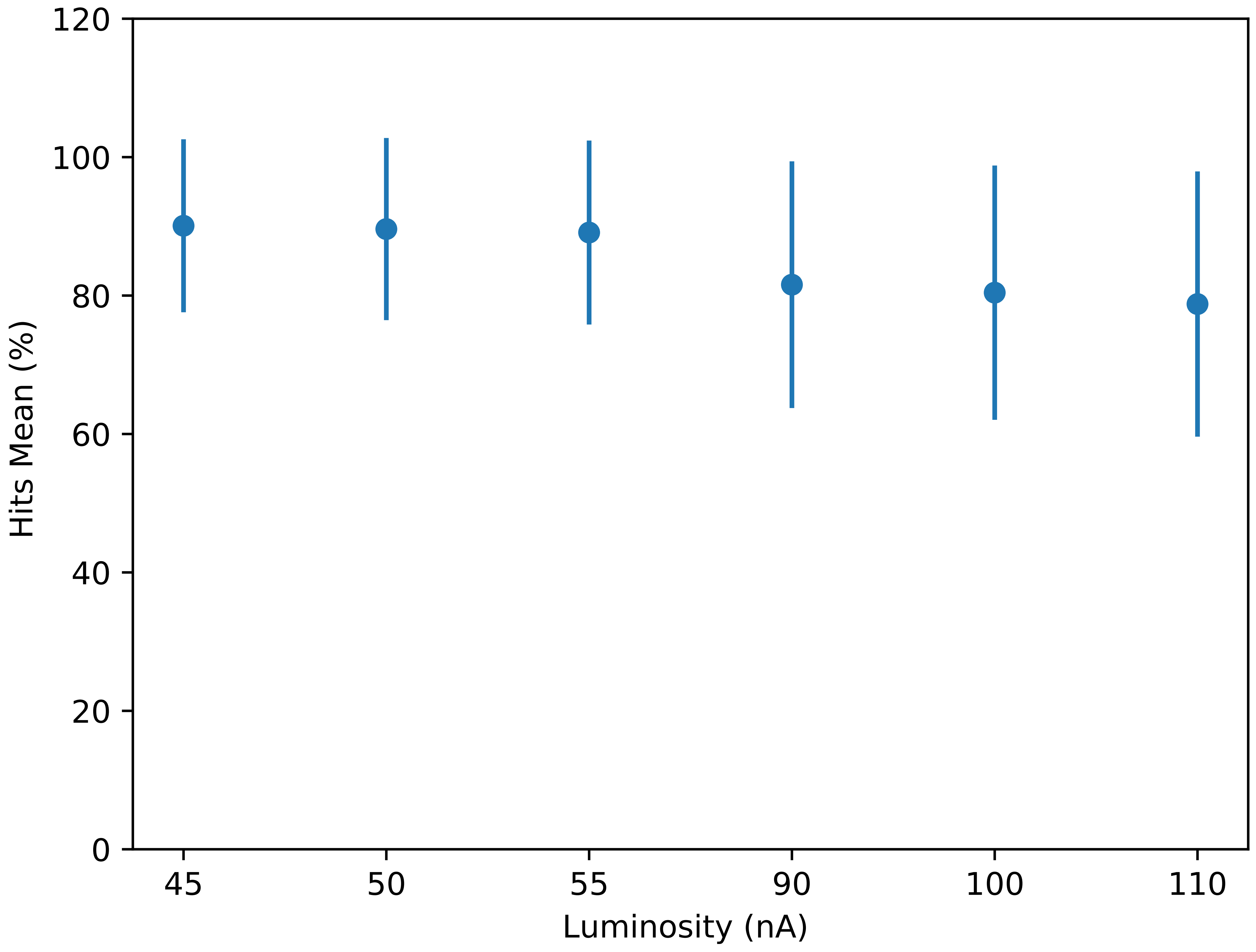


AI Tracking De-Noising

Network Architectures

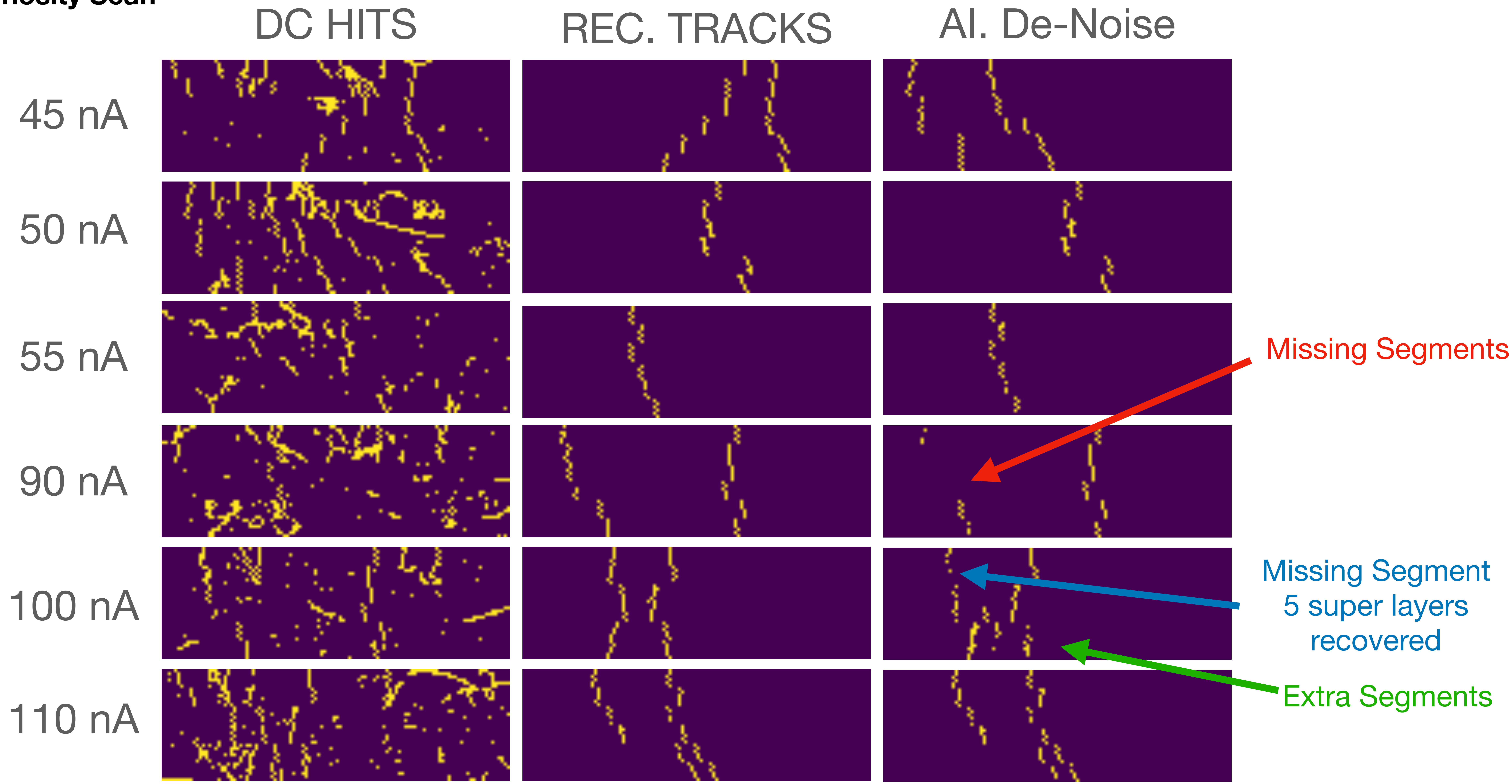
- Next we decided to test how network performed in more noisy environment.
- We used CLAS12 background merging software to produce higher luminosity data.

- We isolated hits that belong to a track (1 or 2) and saved the hits in DC::tdc bank.
- we used background files from 45, 50 and 55 nA to merge with original file to produce noisy samples.
- To produce 90, 100 and 110 nA we merged then with background files twice (we made sure that we prepared two different background files)
- The results of track hits reconstruction as function of beam current is shown on the figure



AI Tracking De-Noising

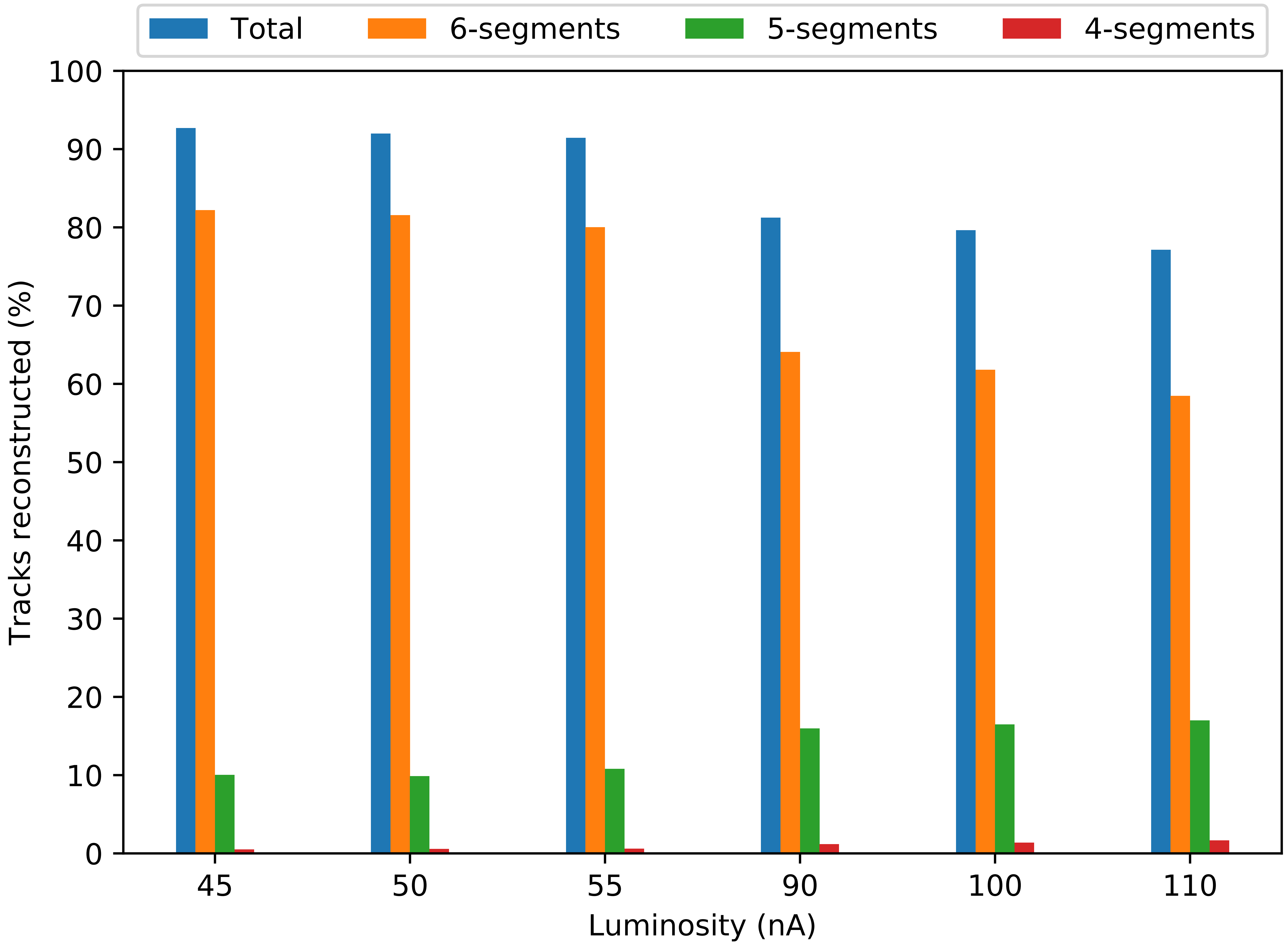
Luminosity Scan



AI Tracking De-Noising

CLAS12 Tracking with Artificial Intelligence

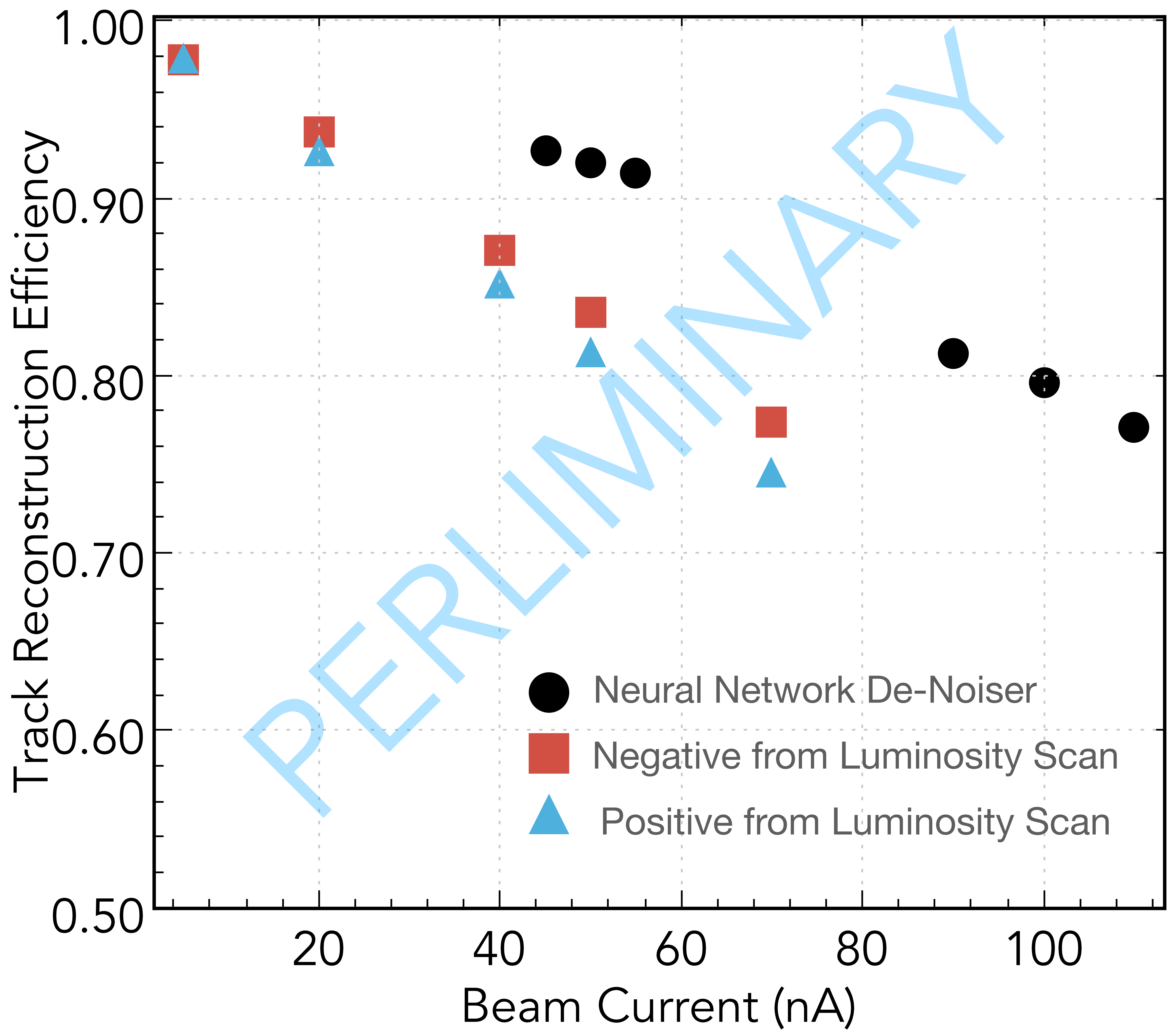
- Track hits reconstruction efficiency is ~90% in average, with +/- 10%
- How is this related to track reconstruction accuracy
- Three scenarios are considered:
  - clusters of the track in all six super layers are reconstructed
  - clusters of the track are reconstructed in 5 super layers
  - clusters of the track in super layers 3,4,5 and 6 are reconstructed
- The cluster is considered reconstructed if half of the hits in given super layer are reconstructed.



AI Tracking De-Noising

CLAS12 Tracking with Artificial Intelligence

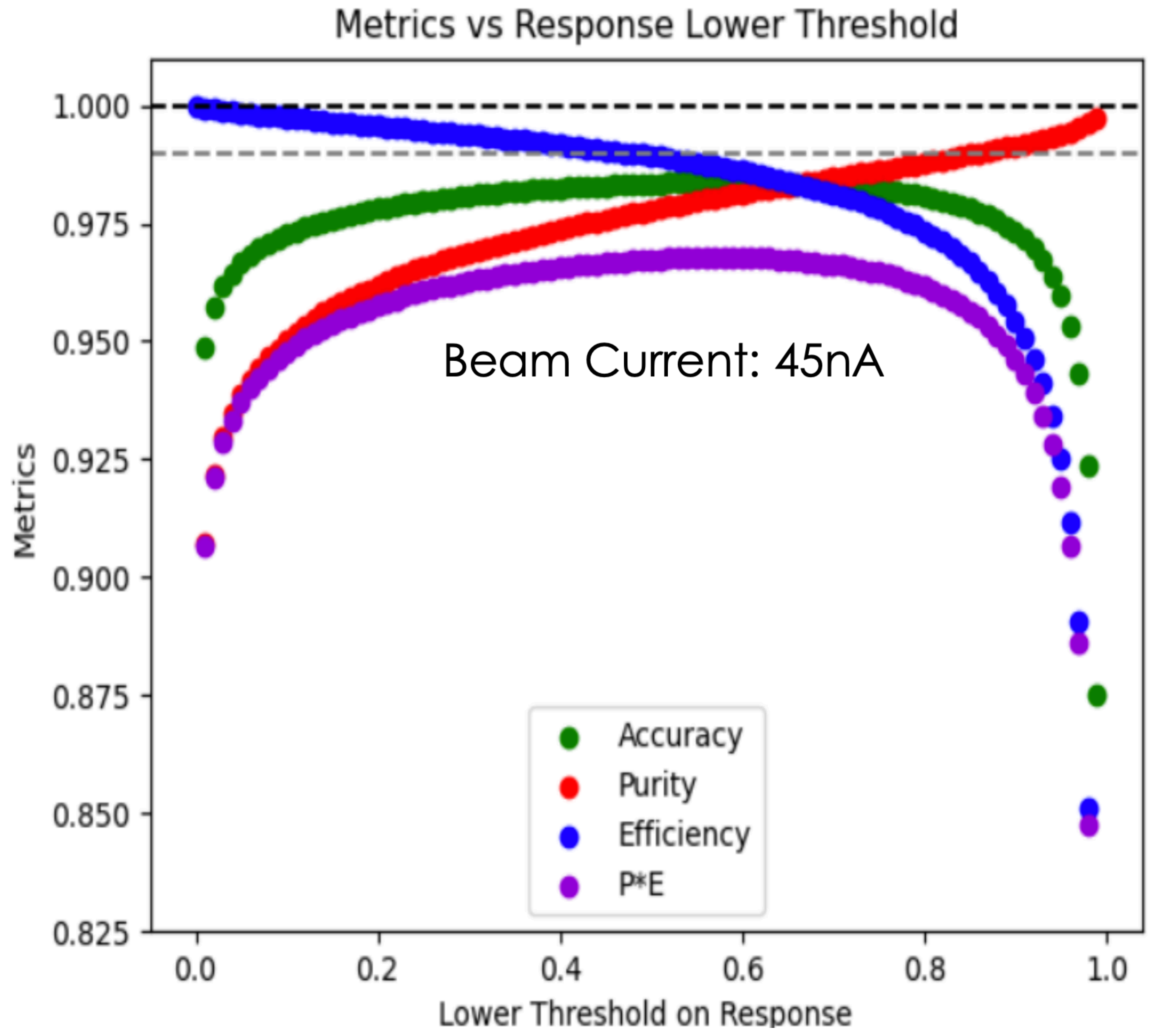
- Why is this significant ?
  - The studies of efficiency of track reconstruction as function of beam current lead to efficiency decrease of 0.35% per nA (both for positive and negative)
  - De-Noising results show efficiency reduction of 0.23% per nA.
  - The de-noising technique can be implemented as aid to traditional clustering algorithm, which can lead to increased efficiency at high luminosities.
  - We can investigate effect of de-noised on other tracking detectors.



Level-3 Trigger (Deep Learning)

CLAS12 Level-3 Trigger with Artificial Intelligence

- Neural Network was developed for Level-3 trigger studies. (Richard Tyson, University of Glasgow)
- The Network is able to predict electron trigger just from hits in drift chambers and hits in Calorimeters
- No tracking or Calorimeter clustering and hit reconstruction necessary.
- The efficiency that can be achieved with Neural Networks >99.5% with purity 93%-97%.
- Can lead to data reduction of 60-70% depending on run luminosity.
- Neural Network currently can work on GPU with the rate of 14 KHz, the tested GPU is not top of the line, so there is room for improvement.



Processor	Prediction Rate inference/s	Prediction Rate event/s
CPU	17 kHz	$3*10^3$ events/s
GPU	84 kHz	$14*10^3$ events/s

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

All details in Richard's talk.

Summary

CLAS12 Tracking with Artificial Intelligence

- Machine Learning driven track identification software was developed and is successfully deployed as a CLARA service.
- Tracking done based on Artificial Intelligence suggestions is faster and more efficient.
- There are several ongoing Machine Learning projects that will be implemented as part of either reconstruction chain or online analysis and monitoring.
  - Auto-Encoder based decoder for hit cleanup in Drift Chambers
  - Recurrent Neural Network (RNN/LSTM) based 4 segment track identification
  - Level-3 Trigger Artificial Intelligence engine
- Published Work:
  - Track Classification using AI:
    - https://arxiv.org/abs/2008.12860
  - Auto-Encoders for track reconstruction:
    - https://arxiv.org/abs/2009.05144
- In the pipeline to be published:
  - Convolutional Neural Network Auto-Encoders for Drift Chamber De-noising (next month)
  - Track Trajectory prediction in CLAS12 using LSTM (April)
  - Deep Learning Level-3 Trigger for CLAS12 (March/April)
- 2 more projects are in proof of concept stage and will be presented if/when successful (I have hope).

Final thoughts

CLAS12 Tracking with Artificial Intelligence

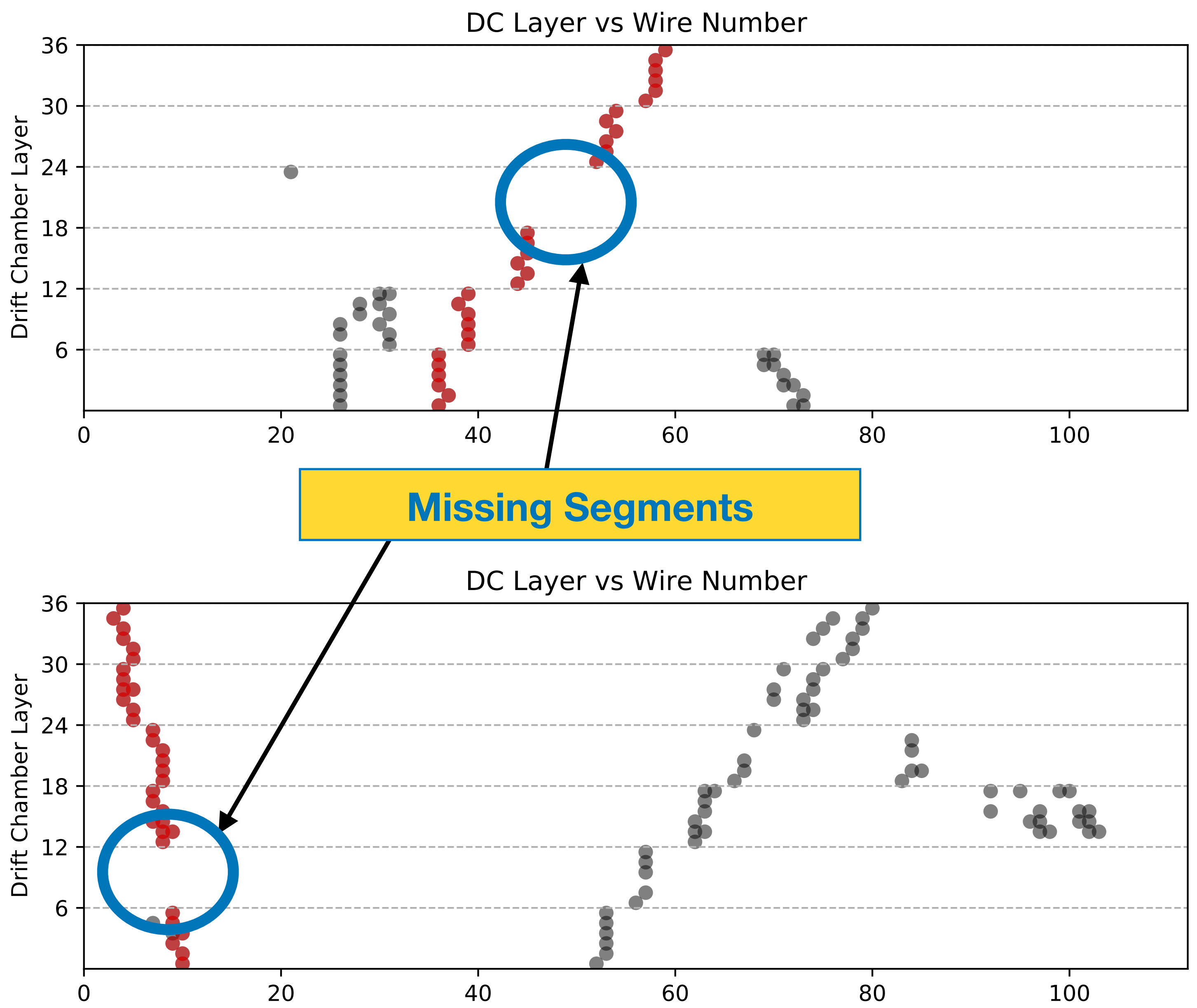
- There are several ongoing Machine Learning projects that will be implemented as part of either reconstruction chain or online analysis and monitoring.
  - Auto-Encoder based decoder for hit cleanup in Drift Chambers
  - Recurrent Neural Network (RNN/LSTM) based 4 segment track identification
  - Level-3 Trigger Artificial Intelligence engine
- Published Work:
  - Track Classification using AI:
    - https://arxiv.org/abs/2008.12860
  - Auto-Encoders for track reconstruction:
    - https://arxiv.org/abs/2009.05144
- In the pipeline to be published:
  - Convolutional Neural Network Auto-Encoders for Drift Chamber De-noising (next month)
  - Track Trajectory prediction in CLAS12 using LSTM (April)
  - Deep Learning Level-3 Trigger for CLAS12 (March)

- All this work is being done on 3 year old MacBook Air (1.4 GHz). It's progressing very slow.
- If I had a decent computer (if any collaborating university is willing to sponsor) I could work a lot more efficient (and may be you can get more tracks.)

BACKUP SLIDES

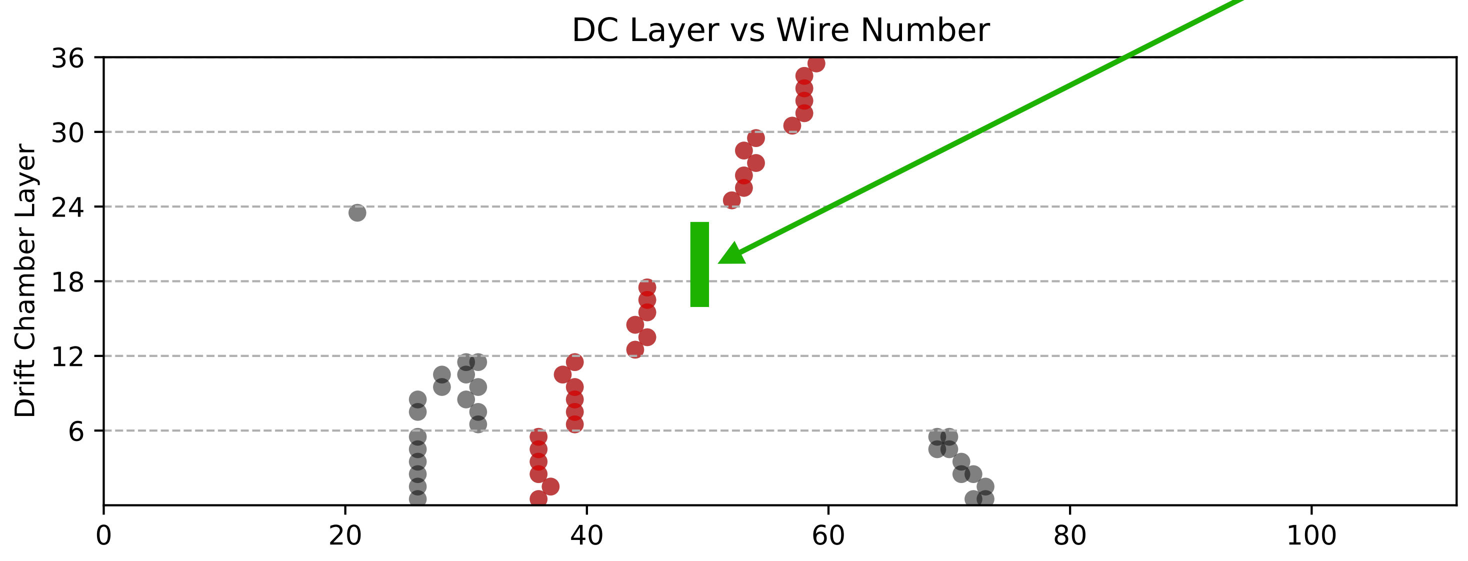
AI Tracking (Missing Segments)

CLAS12 Tracking with Artificial Intelligence

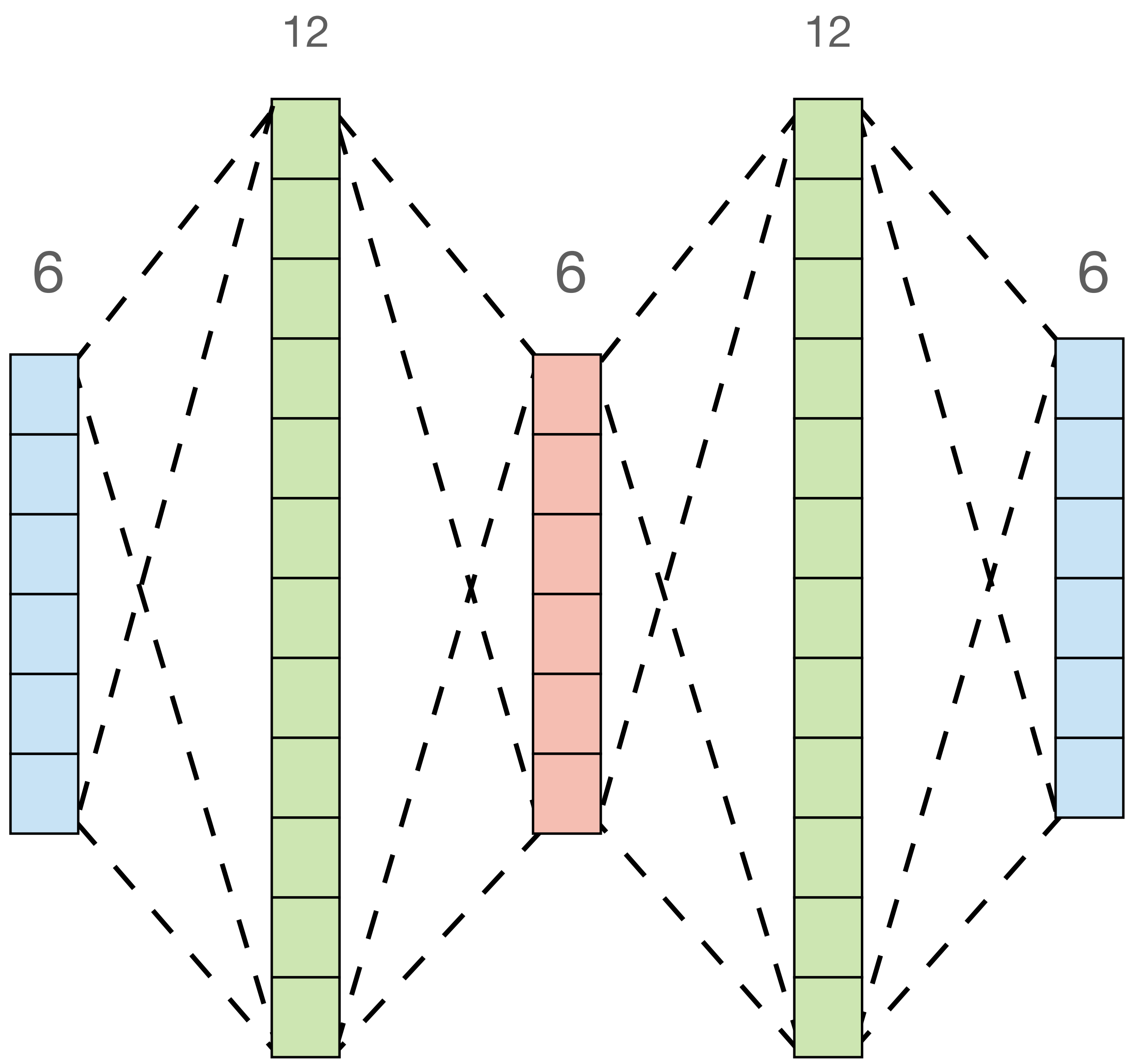


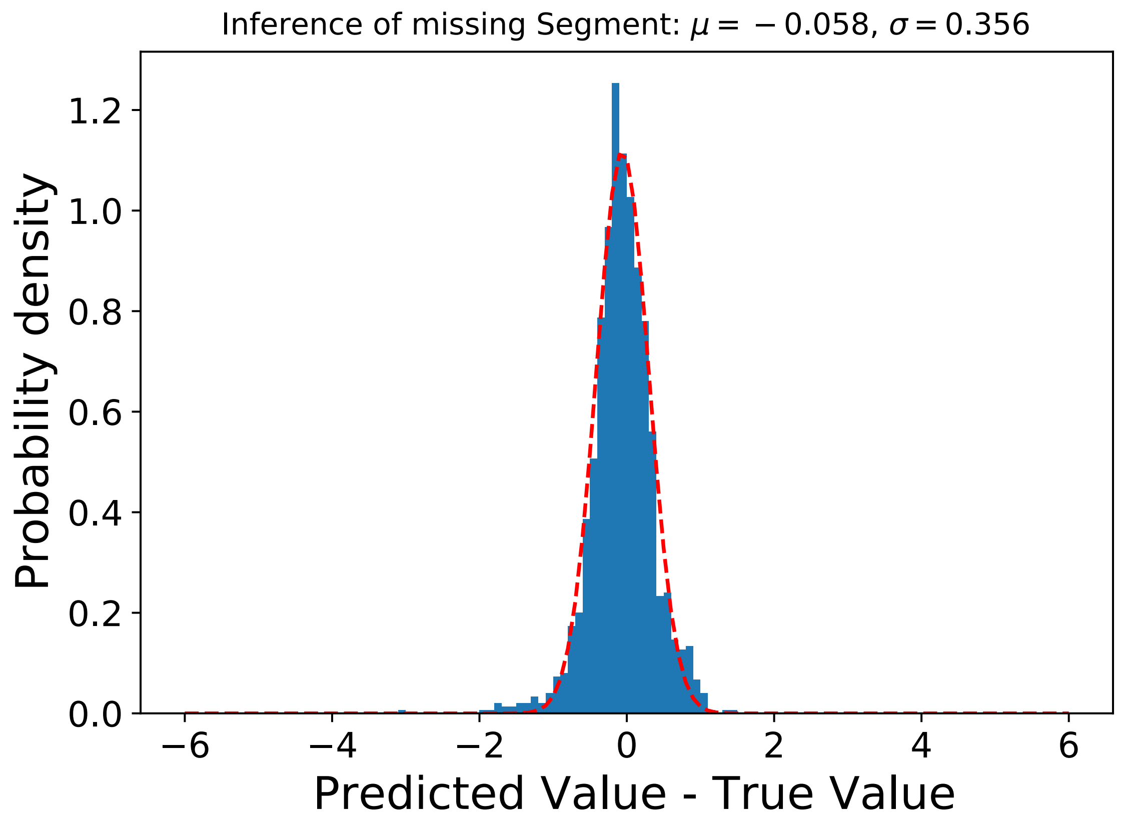
Network reconstructs the missing segment in the trajectory

$$X(x_1, x_2, x_3, 0, x_5, x_6) => Y(x_1, x_2, x_3, x_4, x_5, x_6)$$



- **Auto-encoders:**
  - Using auto-encoders to fix the corruption in track trajectory due to missing segments.
  - Training is performed on fully reconstructed tracks by removing one of the segments.





- **Neural Network results**
  - The missing segment is identified wit accuracy of ~0.36 wires.
  - No dependency on missing layer