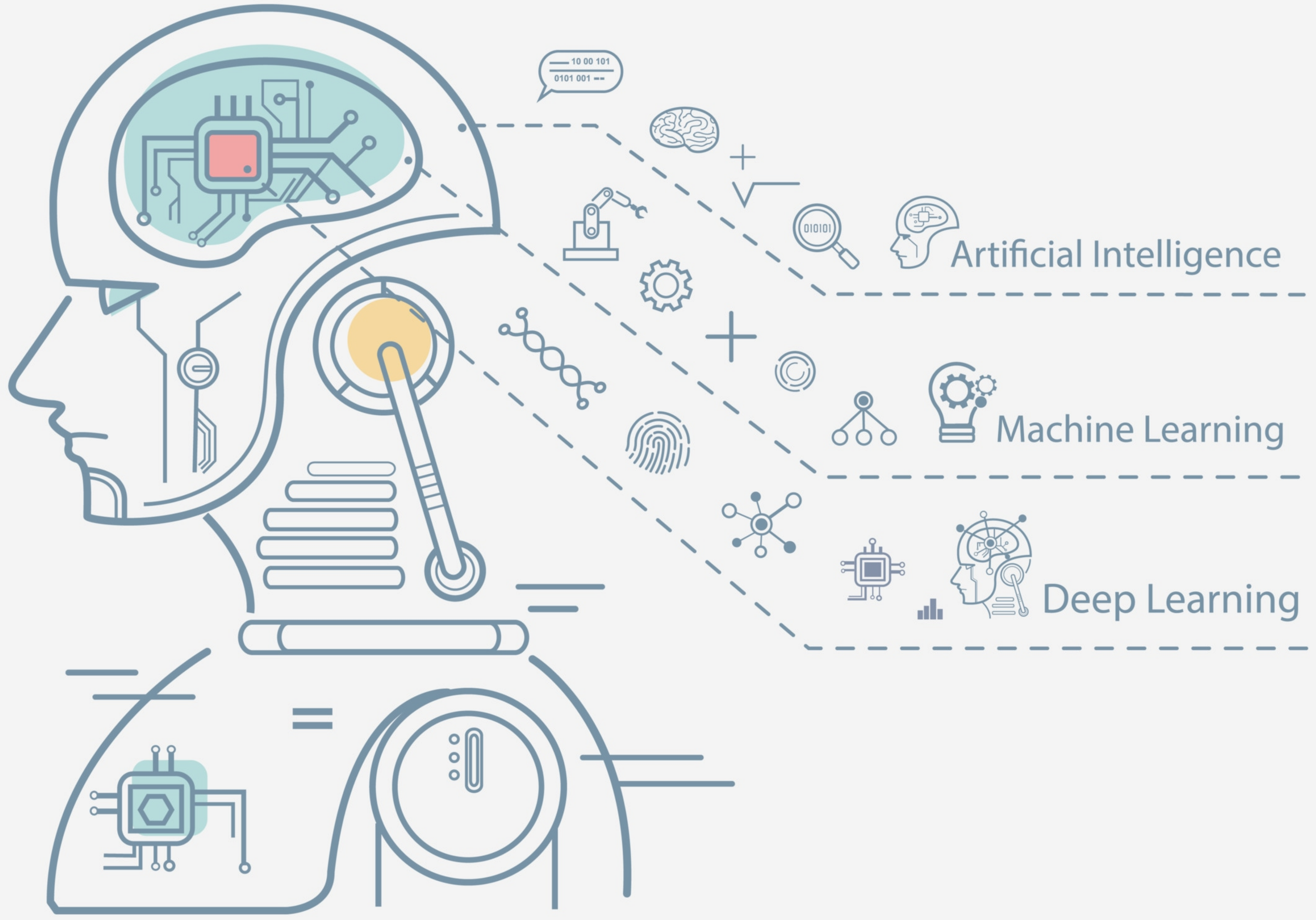
Tracking Particles using AI in CLAS12

Track reconstruction and identification with AI

G.Gavalian (Jefferson Lab)



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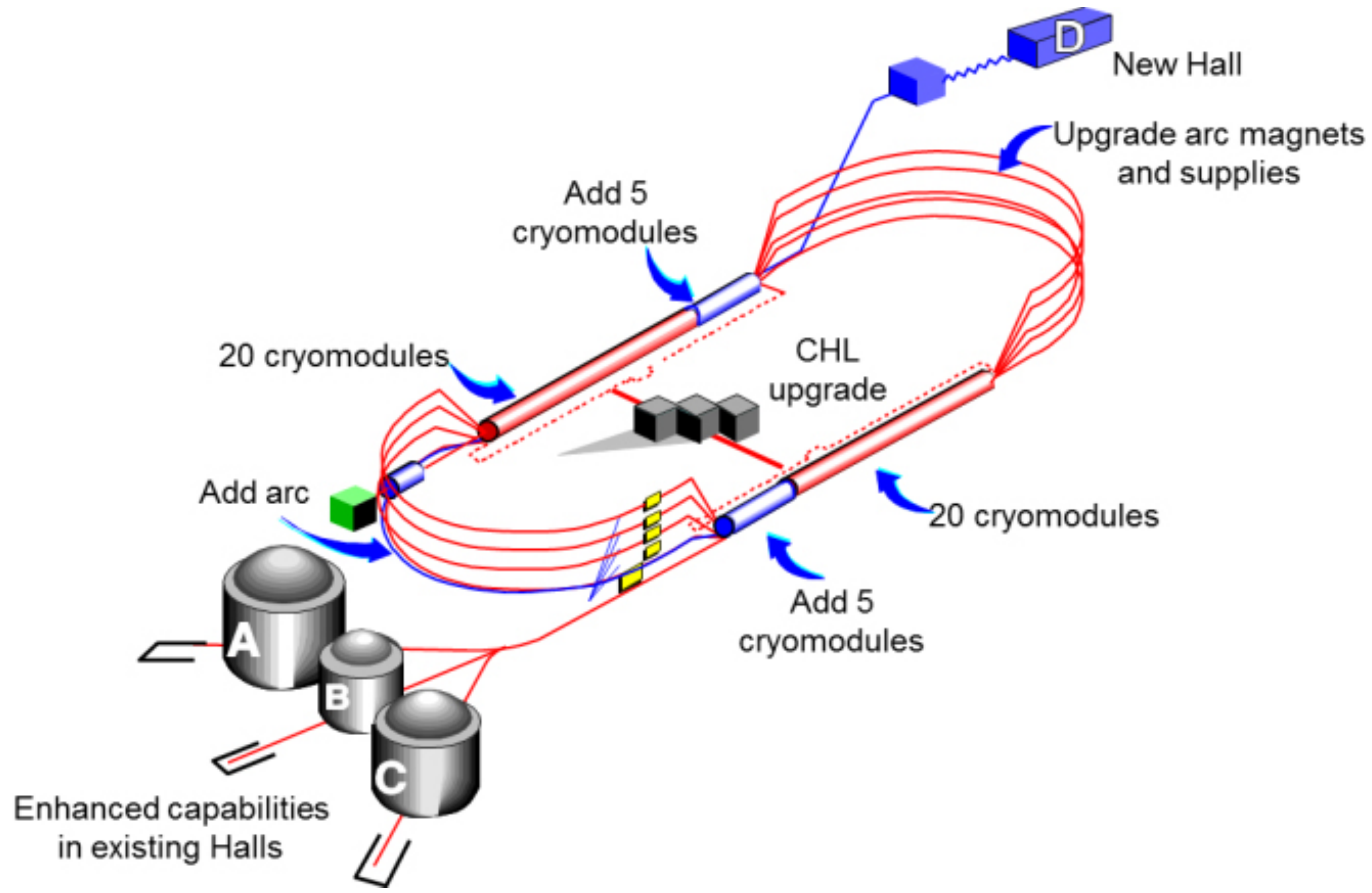
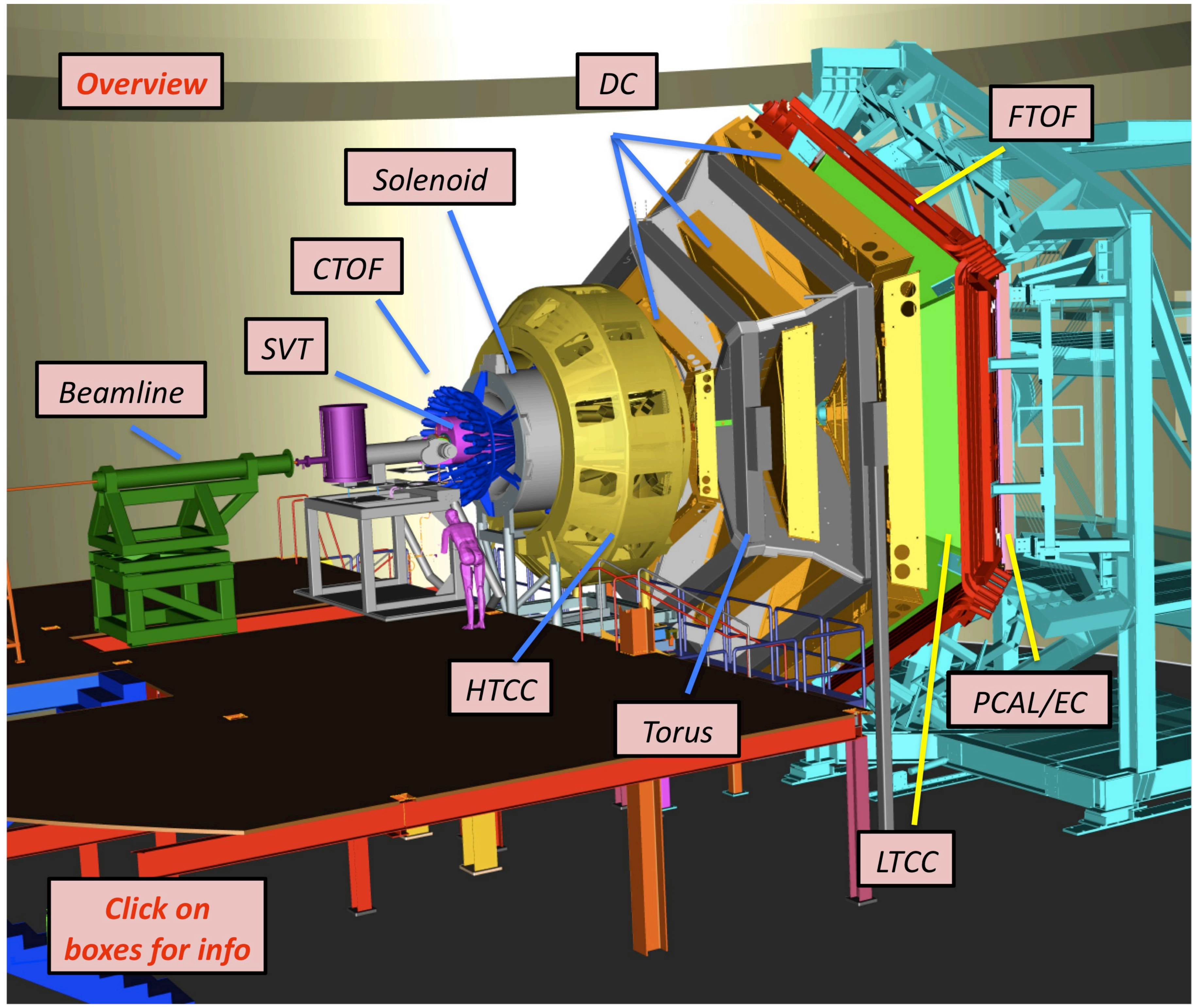
CLAS12 Detector

CLAS12 Tracking with Artificial Intelligence



Experimental Hall-B (CLAS12)

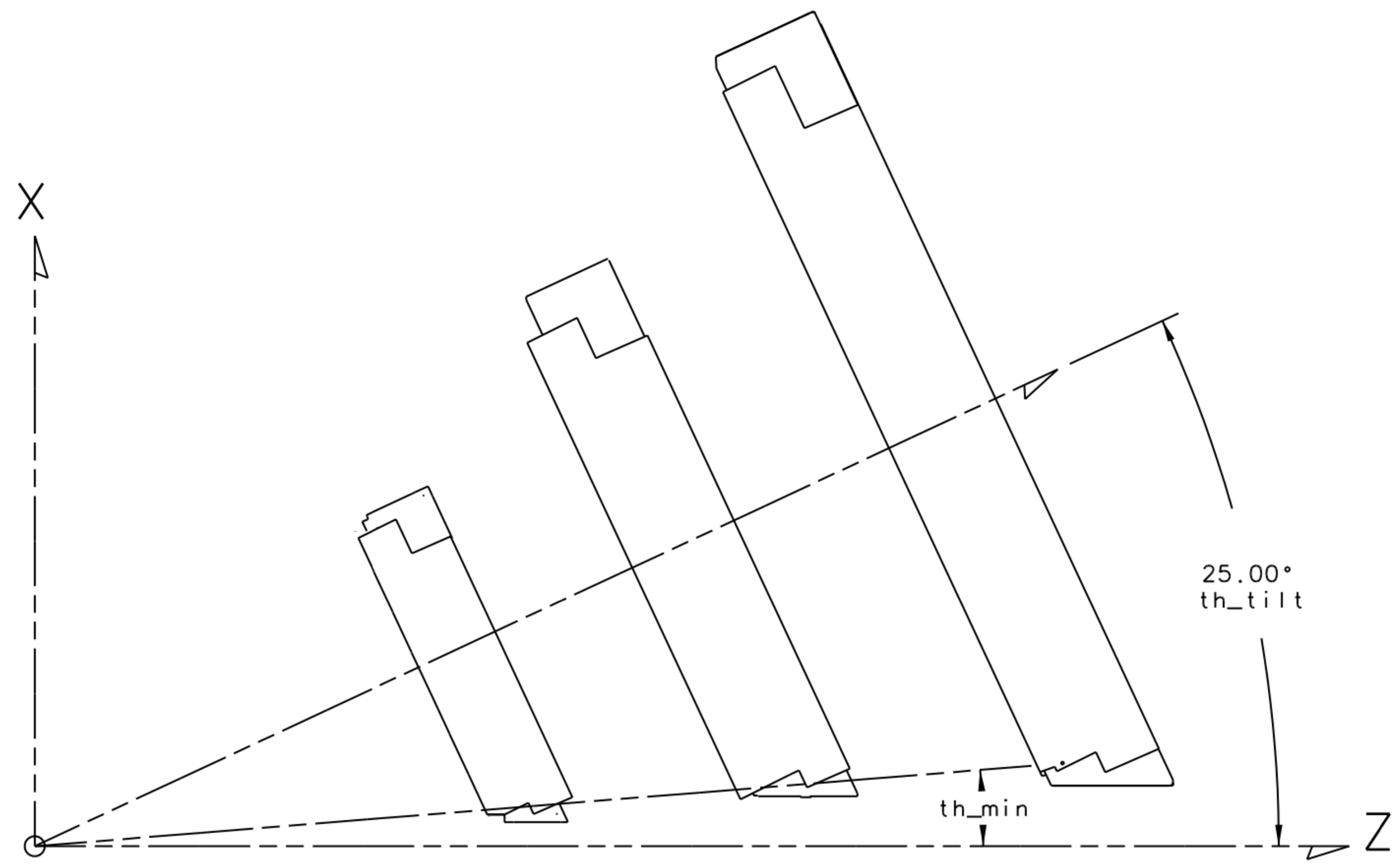


- Jefferson Lab accelerator recently upgraded to 12 GeV
- With addition of new experimental Hall (D)
- Provides beam for 4 experimental Halls

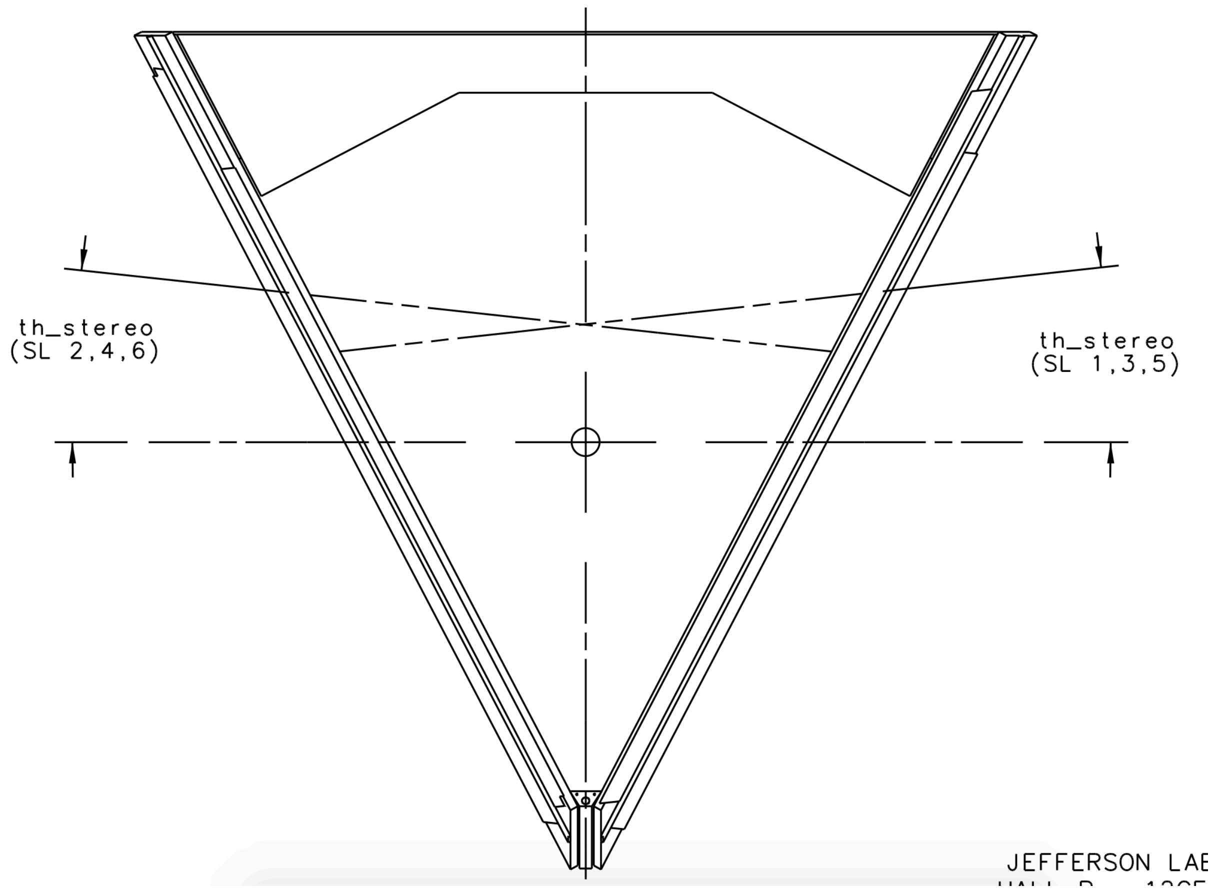
- 4 π detector consisting of 6 sectors
- Forward Drift Chambers are inside toroidal magnetic field

CLAS12 Drift Chambers

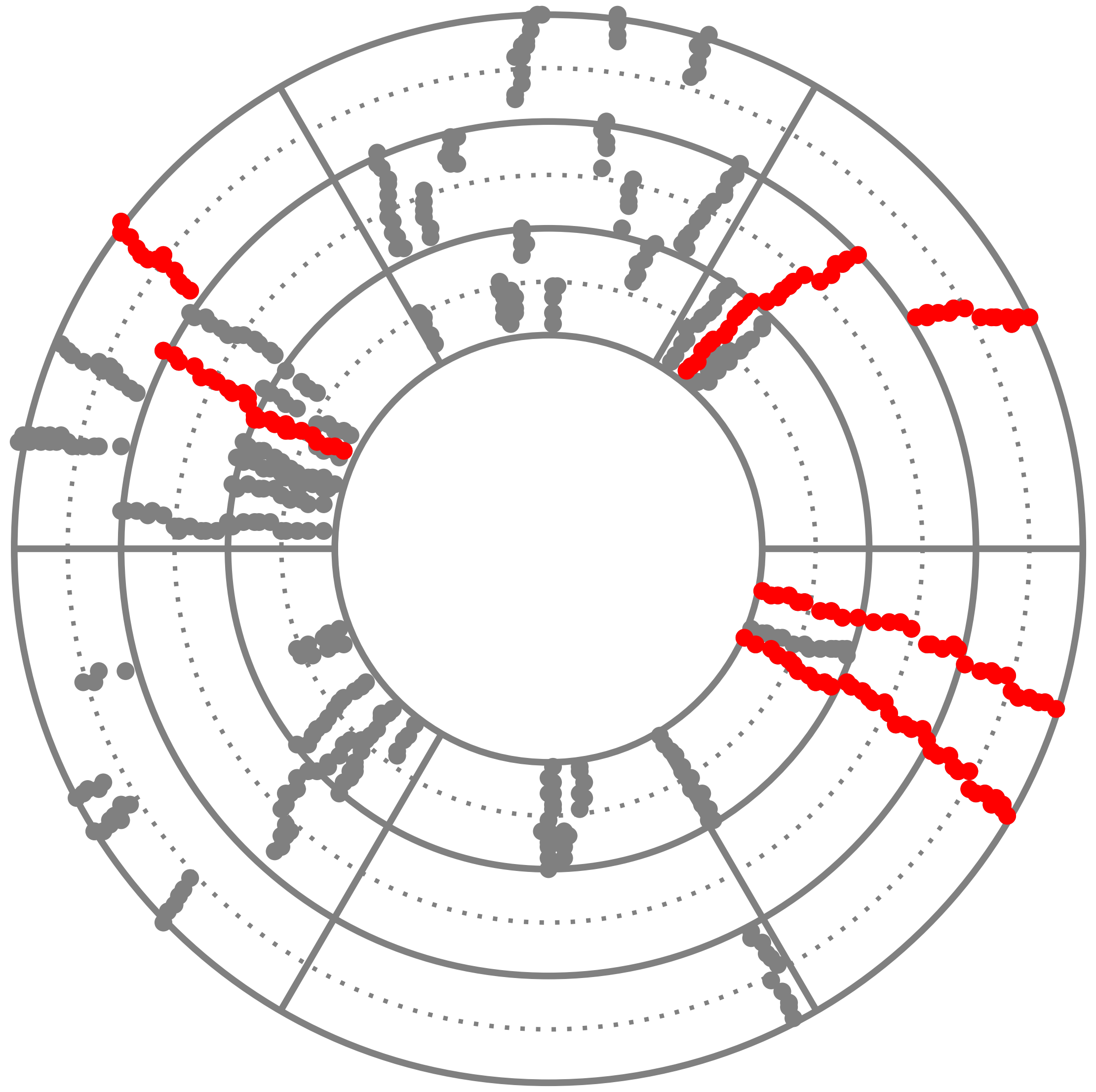
CLAS12 Tracking with Artificial Intelligence



- Drift Chambers consist of three regions (inside the magnetic field)
- Each region consists of two chambers (super-layers), each with 6 layer of wires
- Each layer in super-layers contains 112 wires.
- the wire planes in each super-layers in the region are tilted by 6 degrees relative to each other to detect position of interaction of particle in the cell.



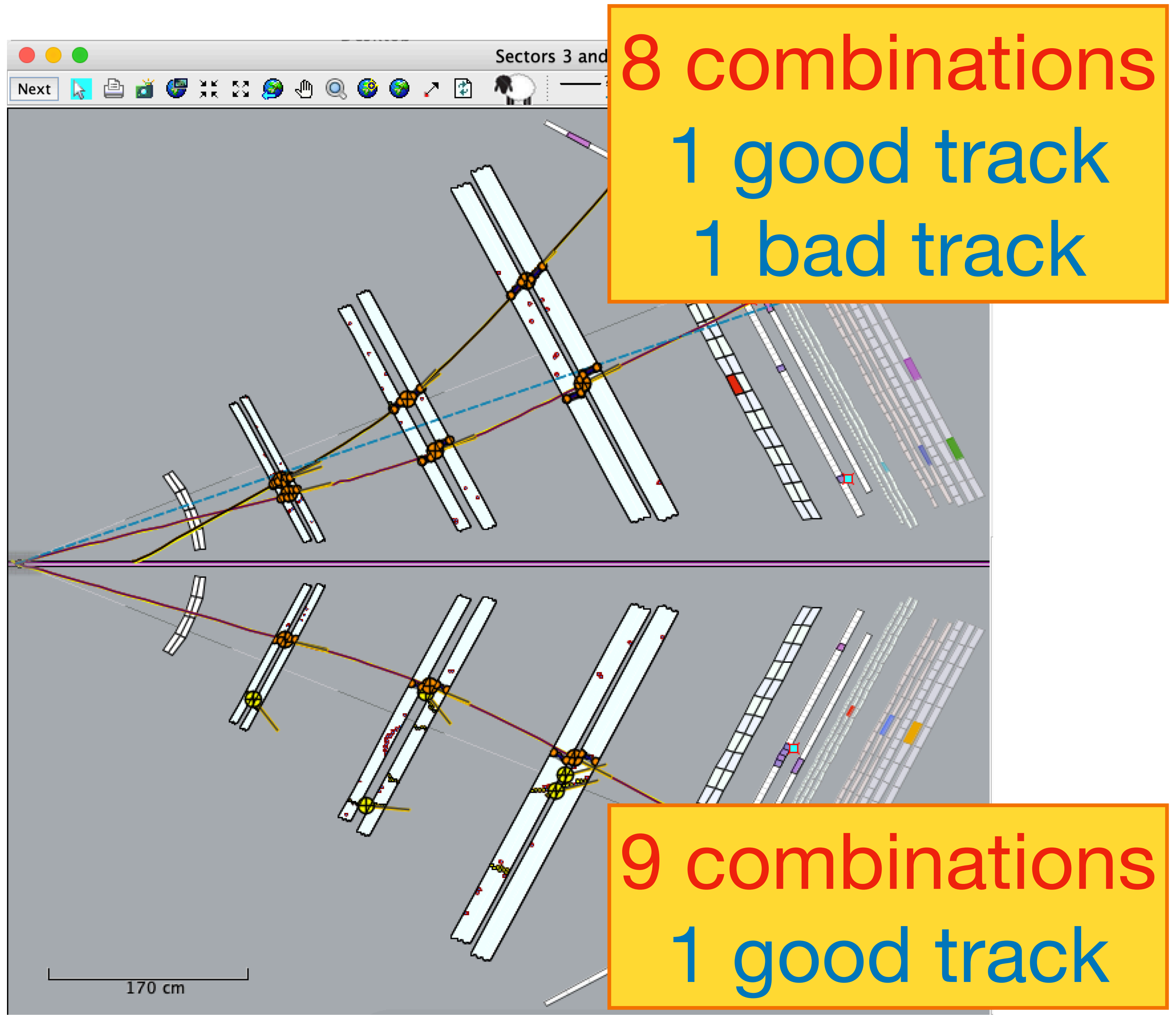
- Particle passing through drift chambers leaves signal in each layer
- There are background hits in the chambers that have to be considered by tracking algorithm.
- All combinations of segments in each super-layer have to be considered by tracking algorithm and fitted by Kalman filter to determine if it's a valid track.



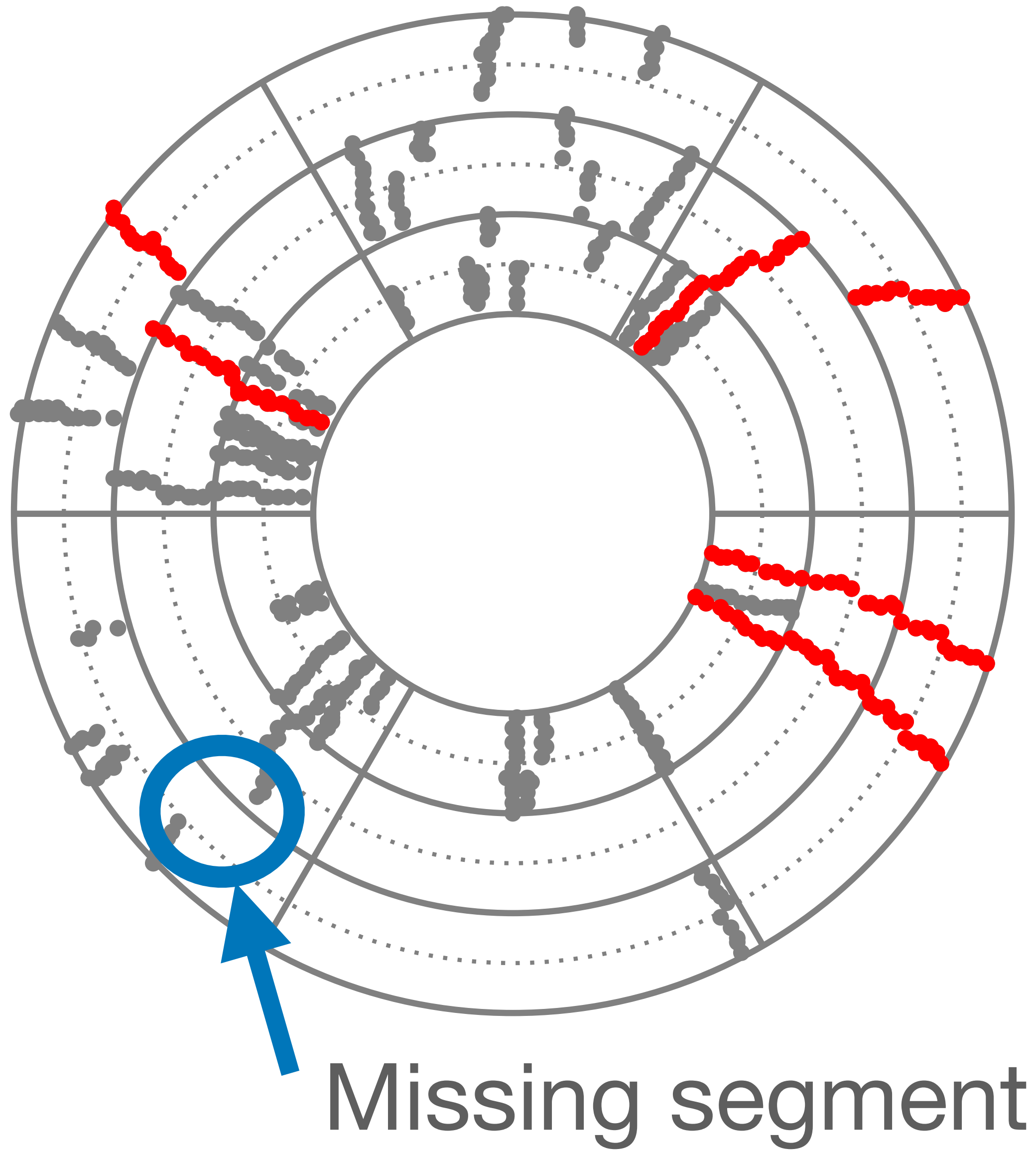
Tracking Challenges
CLAS12 Tracking with Artificial Intelligence

Combinatorics

- Tracking is computationally intensive (~94% reconstruction time)
- It relies on fitting tracks with Kalman-Filter
- Reduction of track candidates to fit can lead to significant speed up of the code.
- 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.



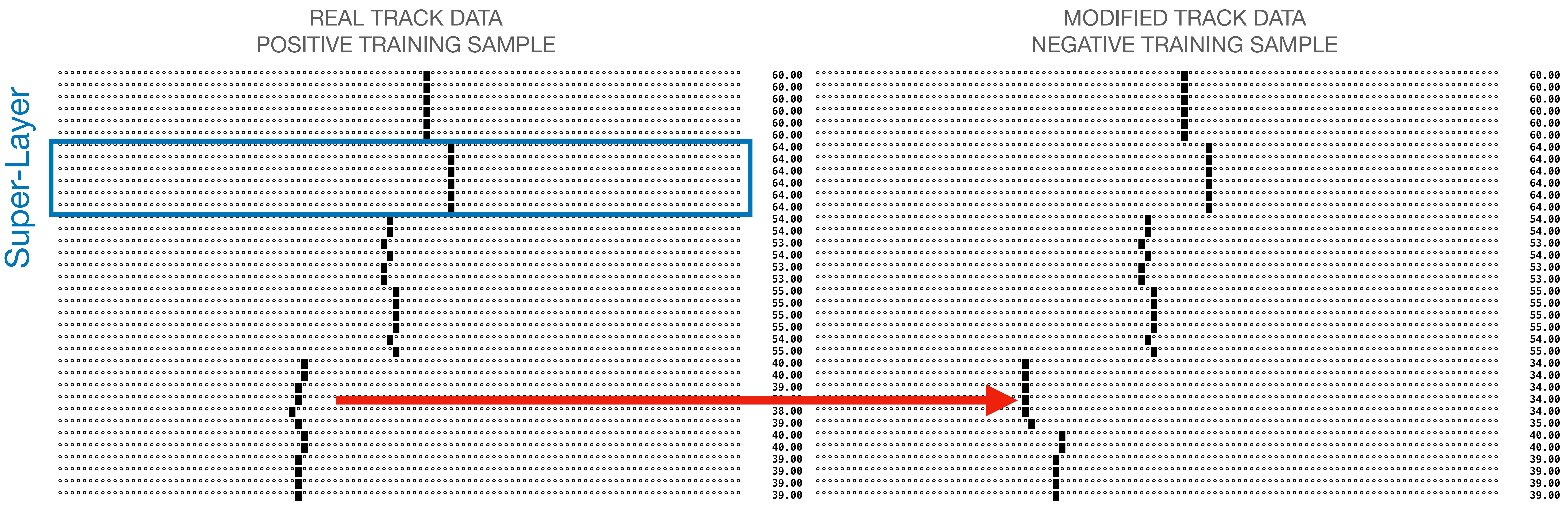
Missing Segments



- Inefficiencies and dead channels in drift chambers can leas 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.

Training Data

CLAS12 Tracking with Artificial Intelligence

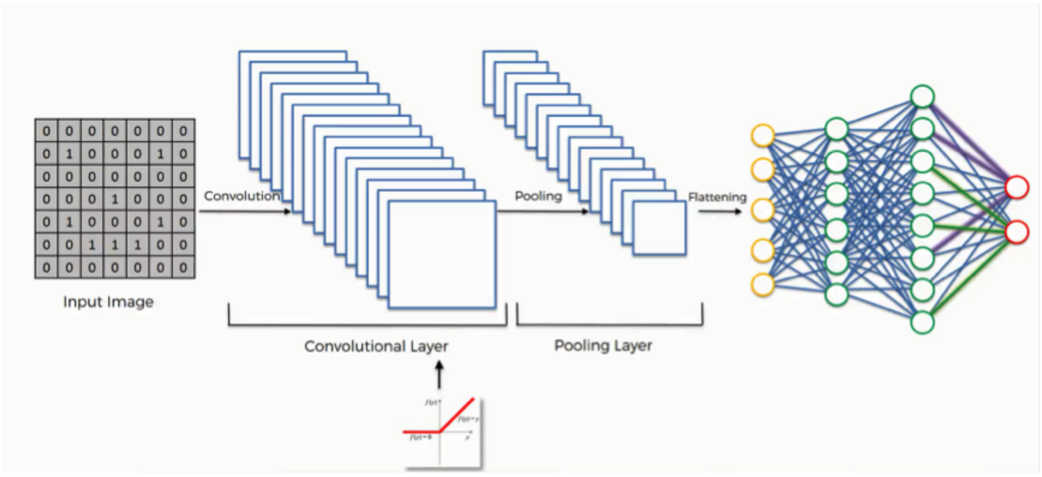


- Training sample is composed of real track data for positive sample and a modified track data where one of the segments is replaced with random segment in the drift chamber from the same event
- The segment is chosen to be closest to the track, since we found that network learns best when negative sample 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)

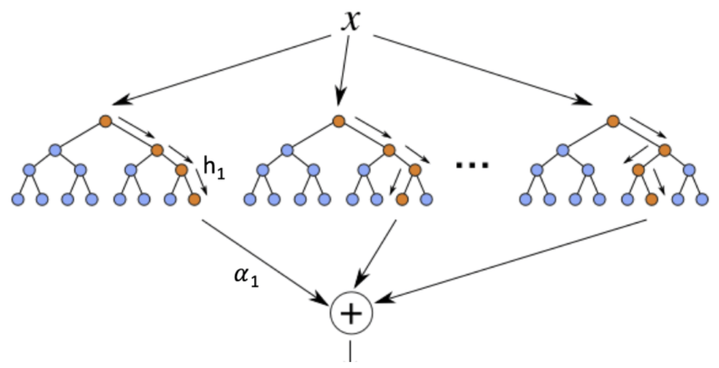
Training Data

CLAS12 Tracking with Artificial Intelligence

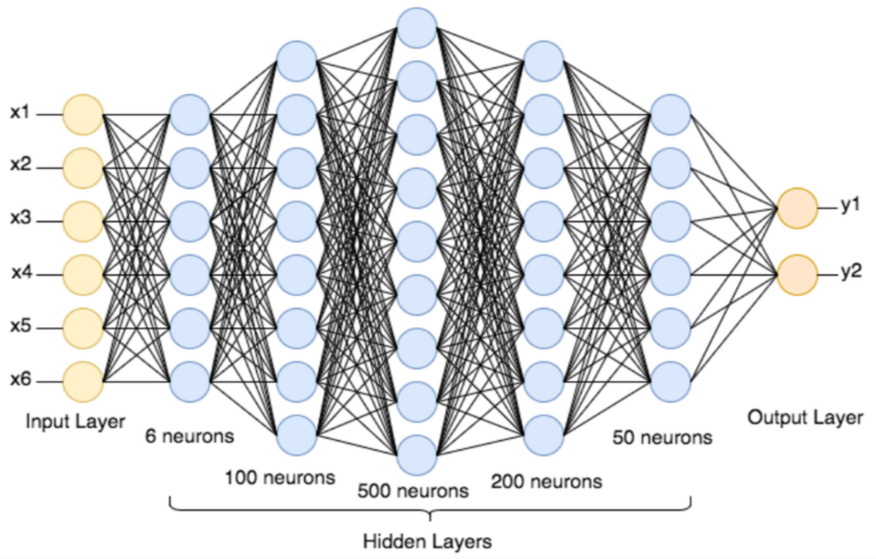
CNN



ERT

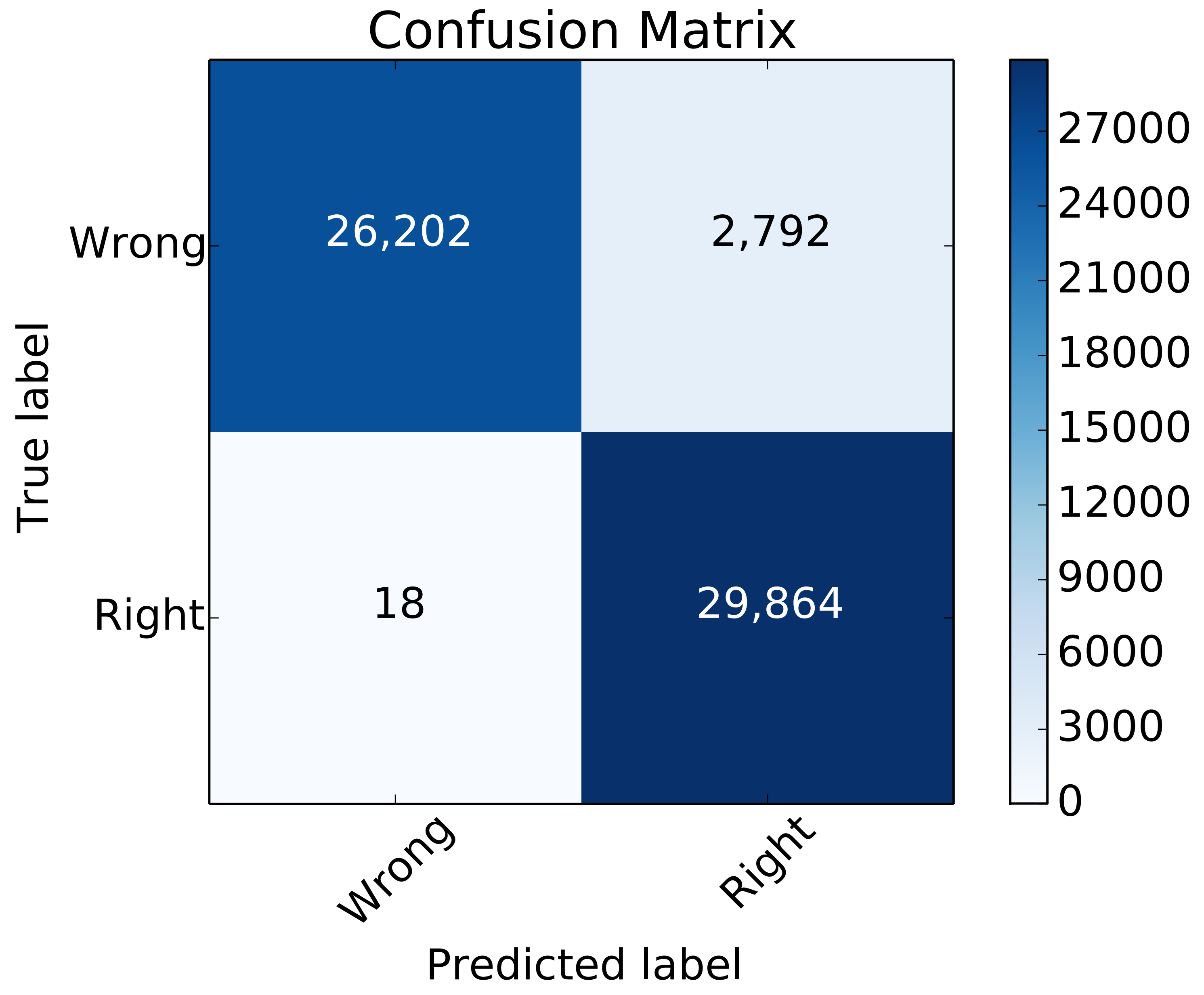


MLP



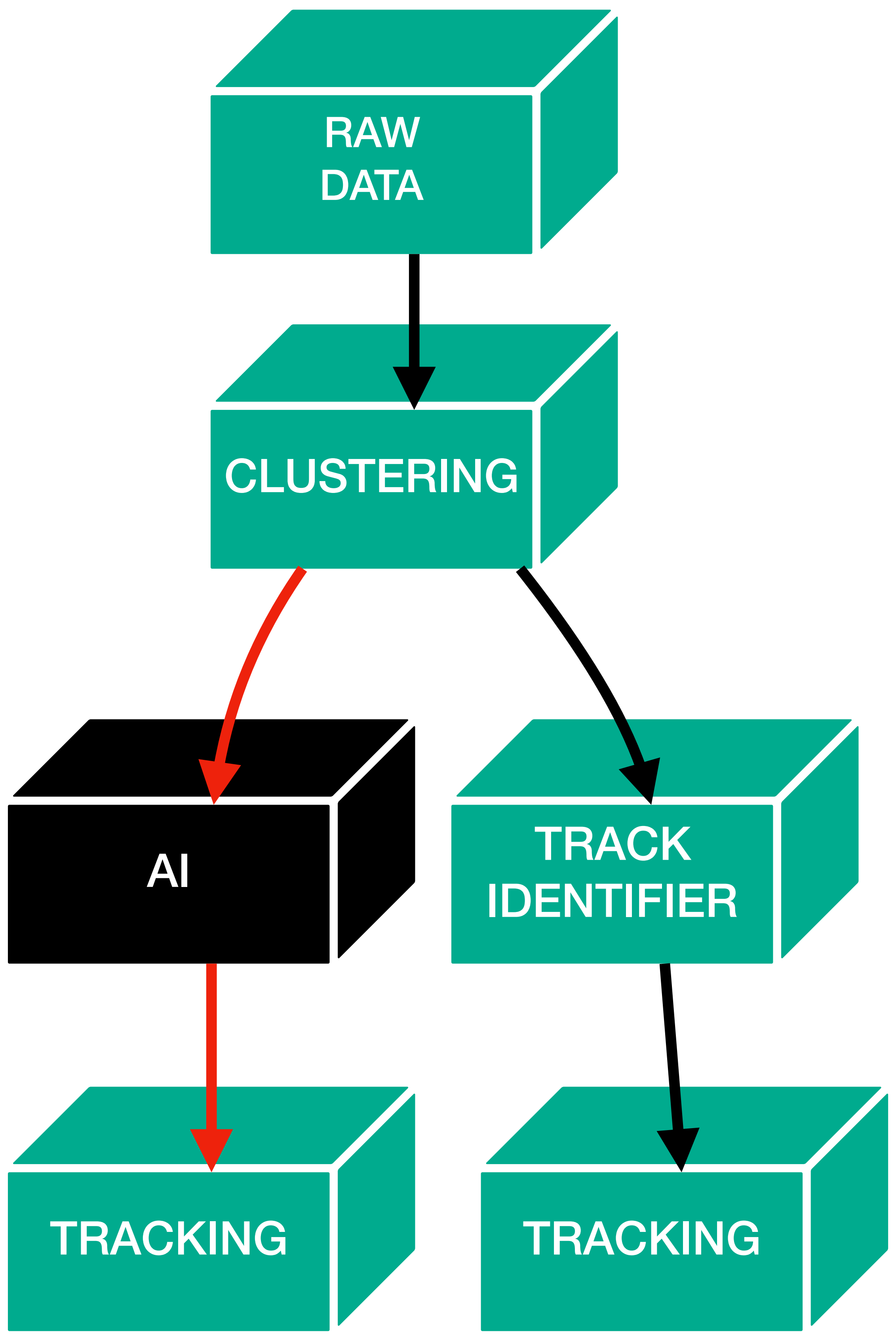
- Conventional metrics does not reflect true performance of the network.
- Training accuracy also reflects false positives, which are not crucial for our case as long as true positive is given higher probability of being a good candidate.
- New metrics was introduced to measure network performance on event-by-event basis (not track by track)
- Ah is the percentage of the "true" tracks in the event identified by network as good candidates with higher probability than other candidates in the same event.
- If two candidates have sharing segments the one with higher probability is taken.

Model Type	*A1* Metric	*Ac* Metric	*Ah* Metric	*Af* Metric	Training Accuracy	Time to Train	Time to Predict / sample
MLP	96.5%	20.2%	98.7%	1.3%	94.7%	252 *sec*	4 *µs*
ERT	93.3%	19.9%	91.9%	6.6%	99.9%	1.7 *sec*	5 *µs*
CNN	96.4%	30.1%	89.4%	3.5%	93.4%	457 *sec*	1.2 *ms*

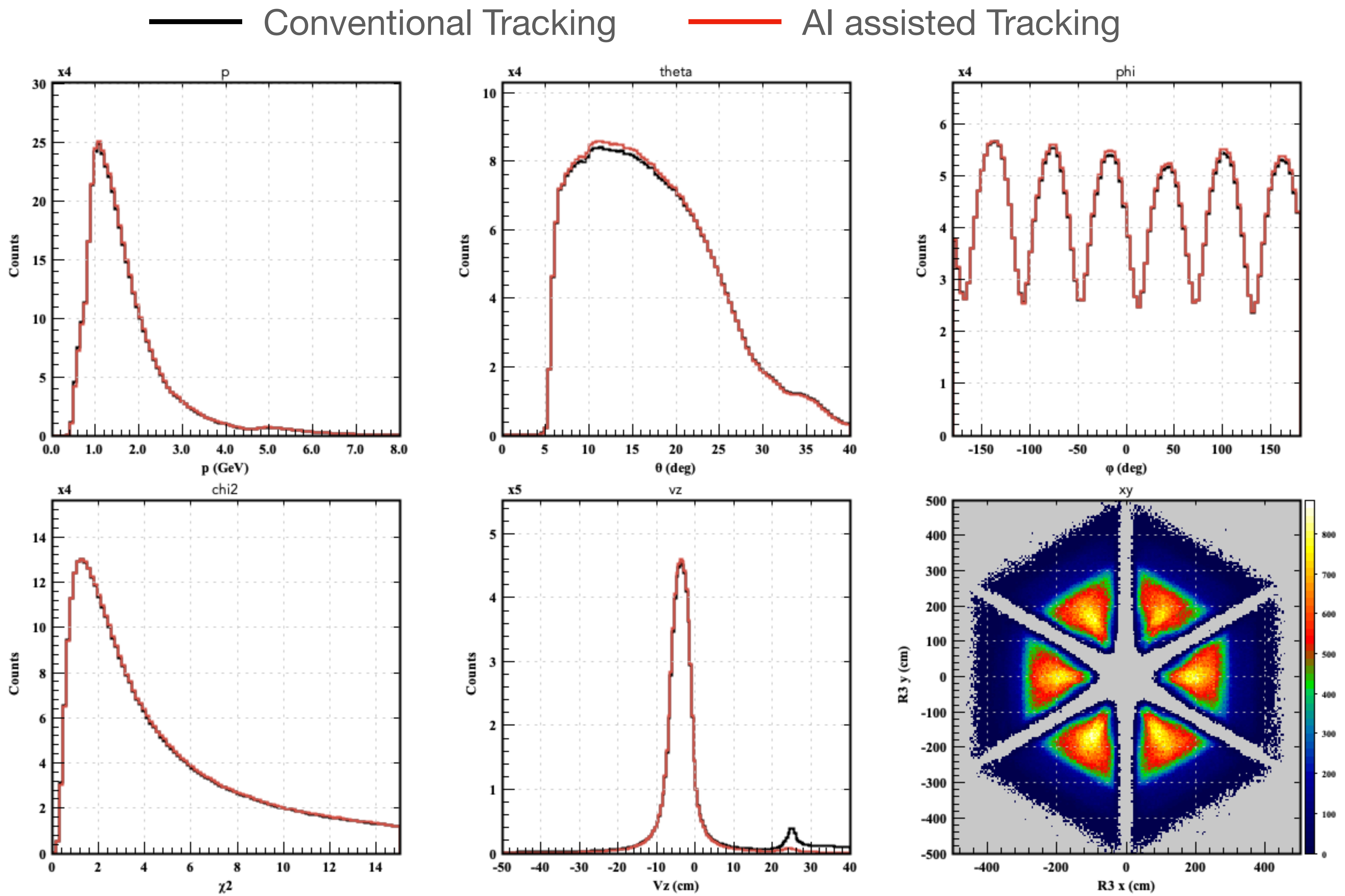


Results (Comparison of conventional and AI tracking)

CLAS12 Tracking with Artificial Intelligence

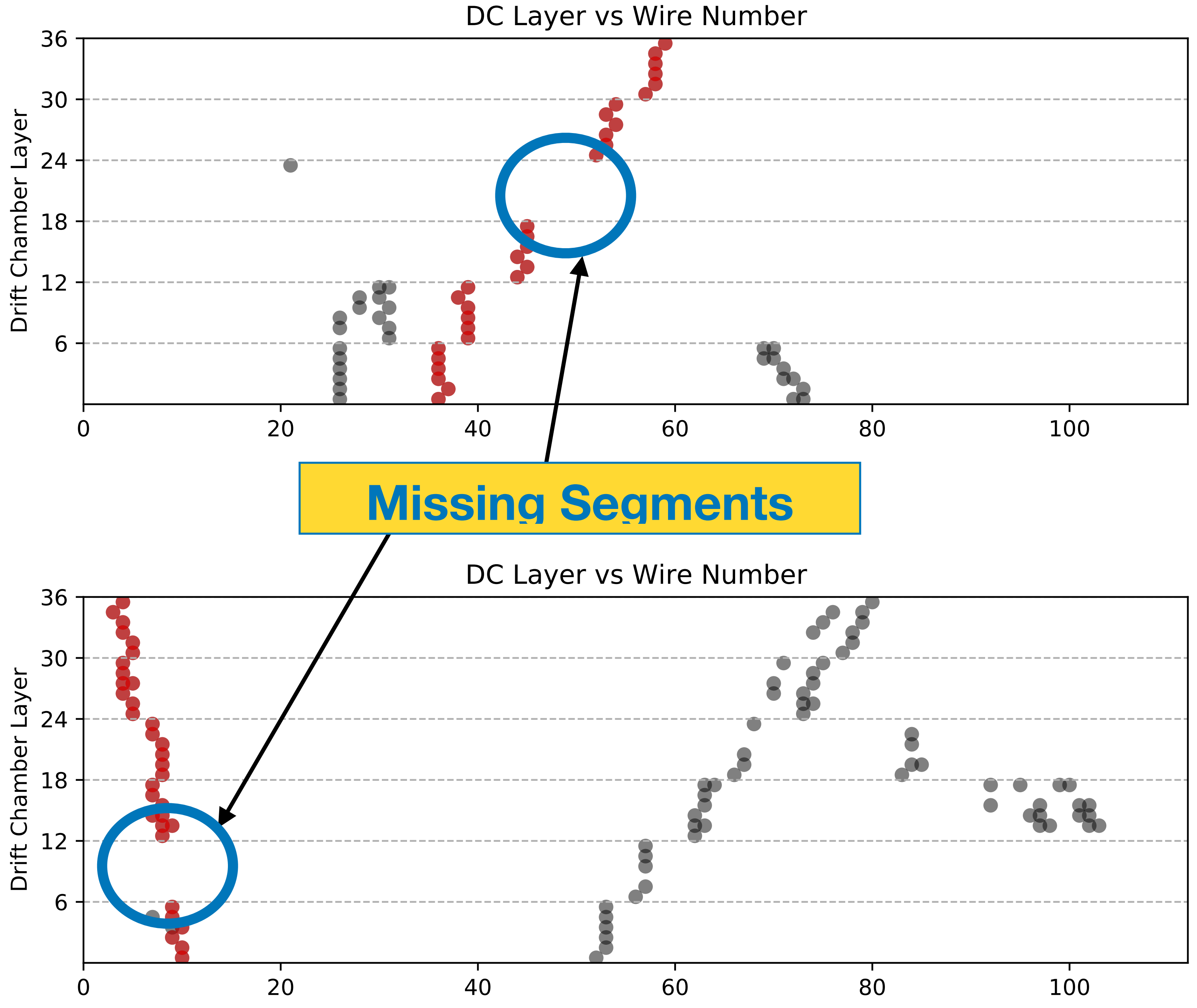


x4 Speed up

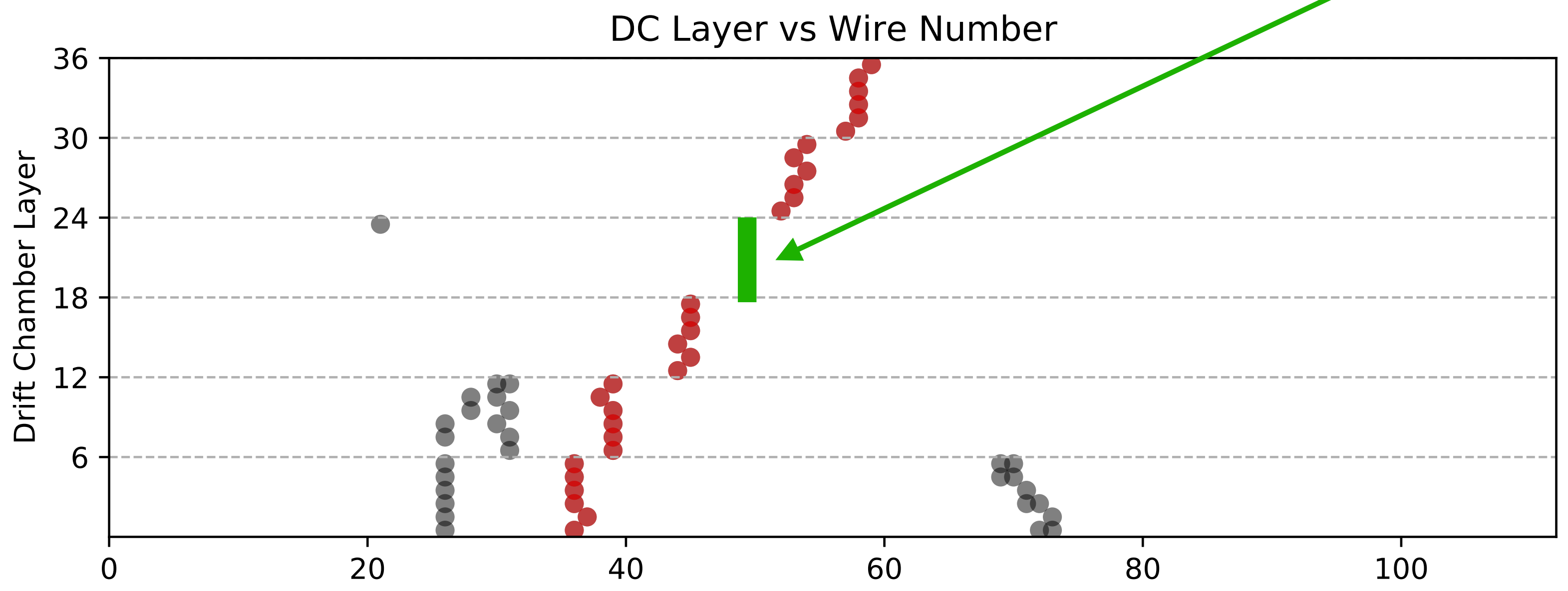


AI Tracking

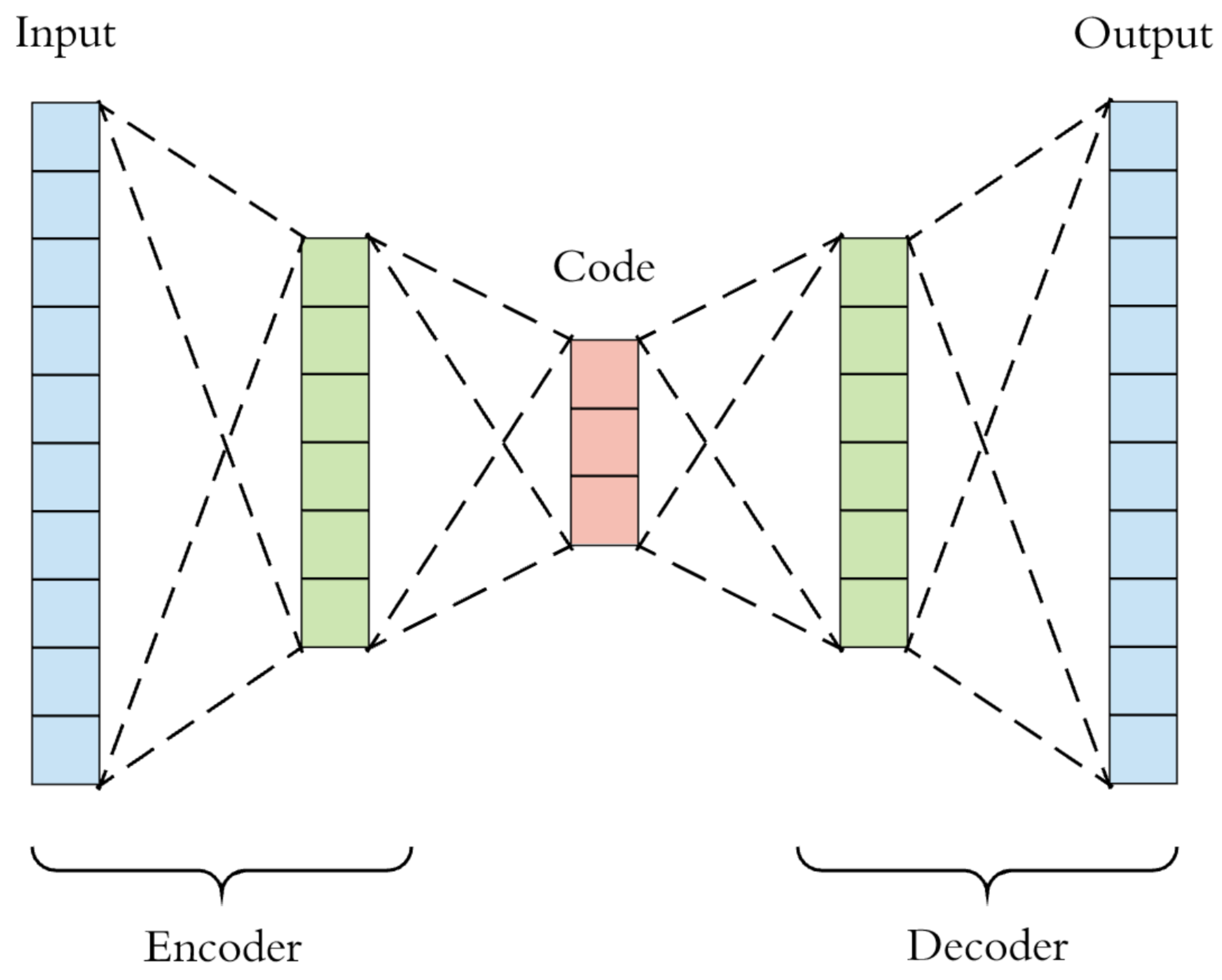
CLAS12 Tracking with Artificial Intelligence



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



- **Auto-encoders:**
  - An **auto-encoder** is a type of artificial neural network used to learn efficient data codings in an unsupervised manner. The aim of an **auto-encoder** is to learn a representation (encoding) for a set of data, typically for dimensionality reduction, by training the network to ignore signal “noise”
  - The input and output of encoder is vector of the same size. And it learns the output vector even if there is a corruption in the input.



- **What we want Network to do:**
  - Given combinations of 5 segment data network should predict the position of 6th segment
  - The 6 segment track candidate can be validated with track classifier.

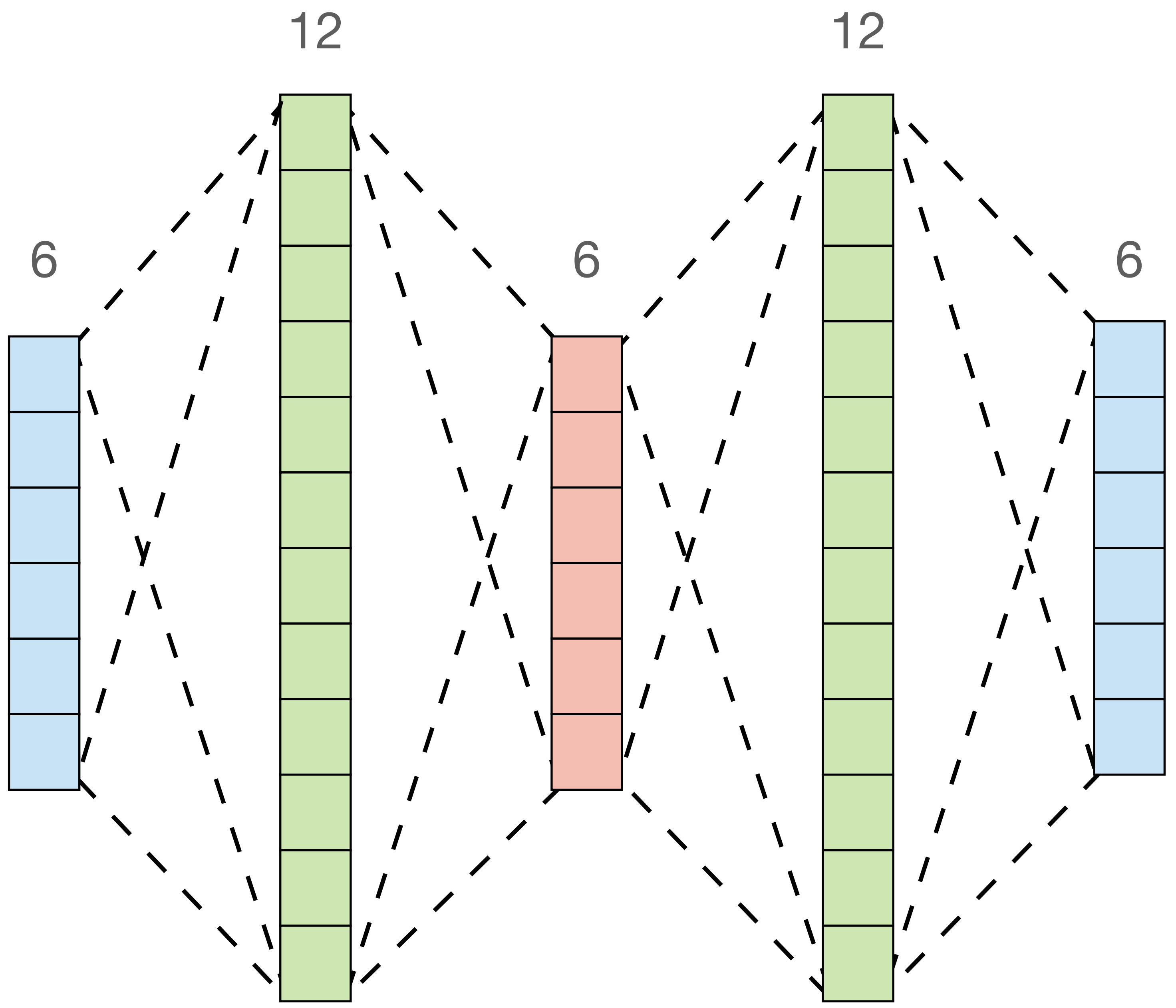
AI Tracking

CLAS12 Tracking with Artificial Intelligence

Introduction of Corruption into data set

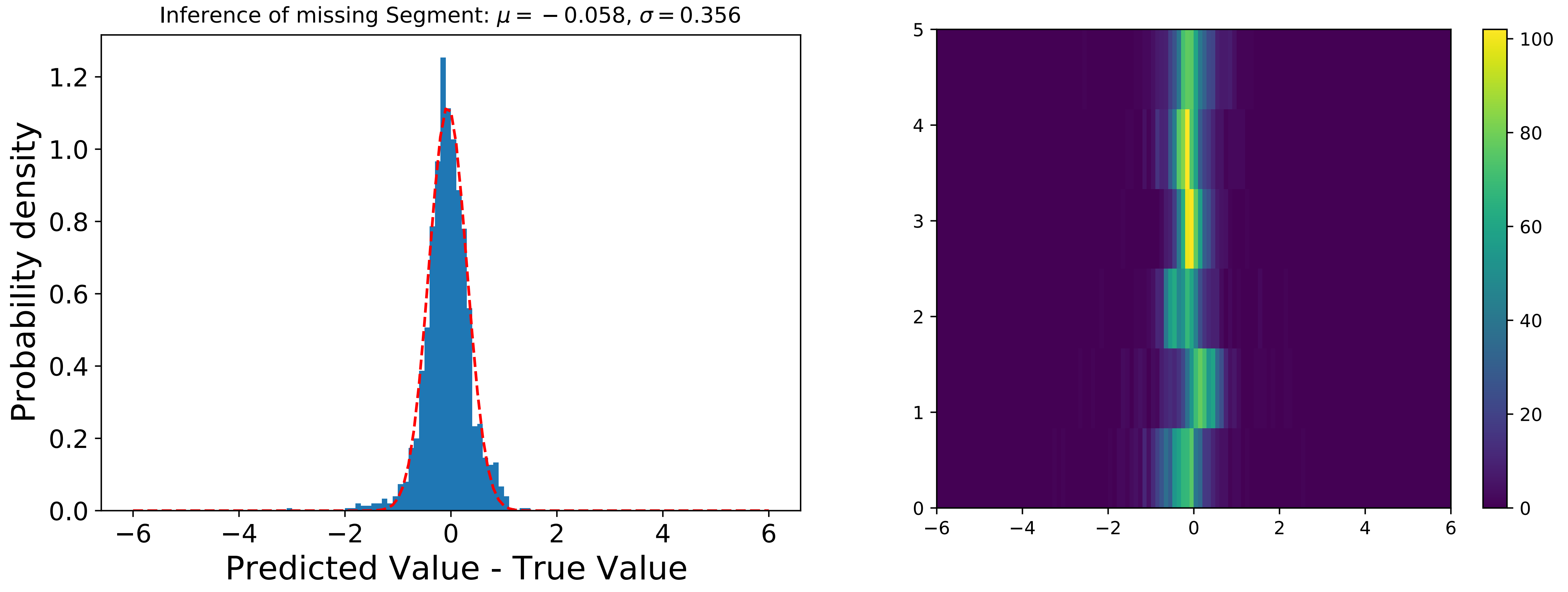
$$(x_1,x_2,x_3,x_4,x_5,x_6)\begin{cases} X(\underline{0.0,}\,x_2,x_3,x_4,x_5,x_6)\rightarrow & Y(x_1,x_2,x_3,x_4,x_5,x_6) \\ X(x_1,\underline{0.0,}\,x_3,x_4,x_5,x_6)\rightarrow & Y(x_1,x_2,x_3,x_4,x_5,x_6) \\ X(x_1,x_2,\underline{0.0,}\,x_4,x_5,x_6)\rightarrow & Y(x_1,x_2,x_3,x_4,x_5,x_6) \\ X(x_1,x_2,x_3,\underline{0.0,}\,x_5,x_6)\rightarrow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

Auto-Encoder Architecture



- Starting from fully reconstructed tracks (with 6 segments), we introduced corruption into training data set.
- xi represents the average wire position in the segment.
- The network was trained with corrupted data as input and original data as output
- The network was tested on 6 segment data by corrupting one of the segments and having network to reconstruct missing segment information.
- The average position of segment was reconstructed with accuracy of 0.36 wires.

AI Inference Results



Summary

CLAS12 Tracking with Artificial Intelligence

- Neural Network track candidate classification was developed and implemented into CLAS12 reconstruction code.
- Provides 99.7% track identification accuracy and results in x4 code speed up.
- Neural Network based on Auto-Encoders successfully corrects for inefficiencies in Drift chambers (recovers 99.8% of the tracks with missing segments)
- Track Classification using AI:
  - https://arxiv.org/abs/2008.12860
- Auto-Encoders for track reconstruction:
  - https://arxiv.org/abs/2009.05144
- There are ongoing work on denoting Neural Networks for Drift chambers using auto-encoders and LSTM for track segment reconstruction, soon to be published
- CLAS12 reconstruction is in JAVA, present work was done using DL4J libraries:
  - https://deeplearning4j.org

BACKUP SLIDES