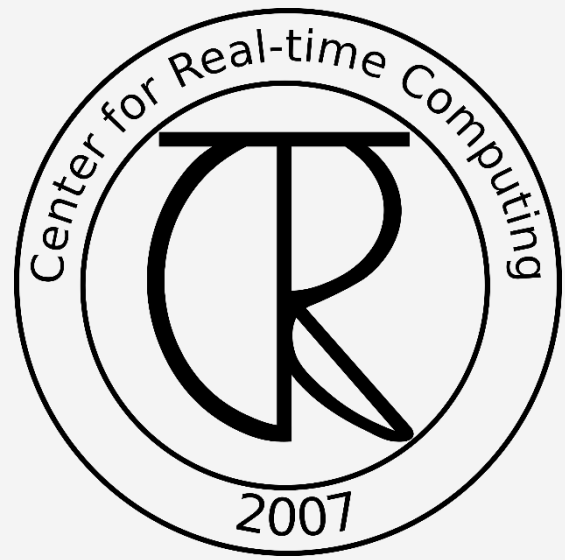


# Tracking Particles using AI in CLAS12

Track reconstruction and identification with AI

G.Gavalian (Jefferson Lab)



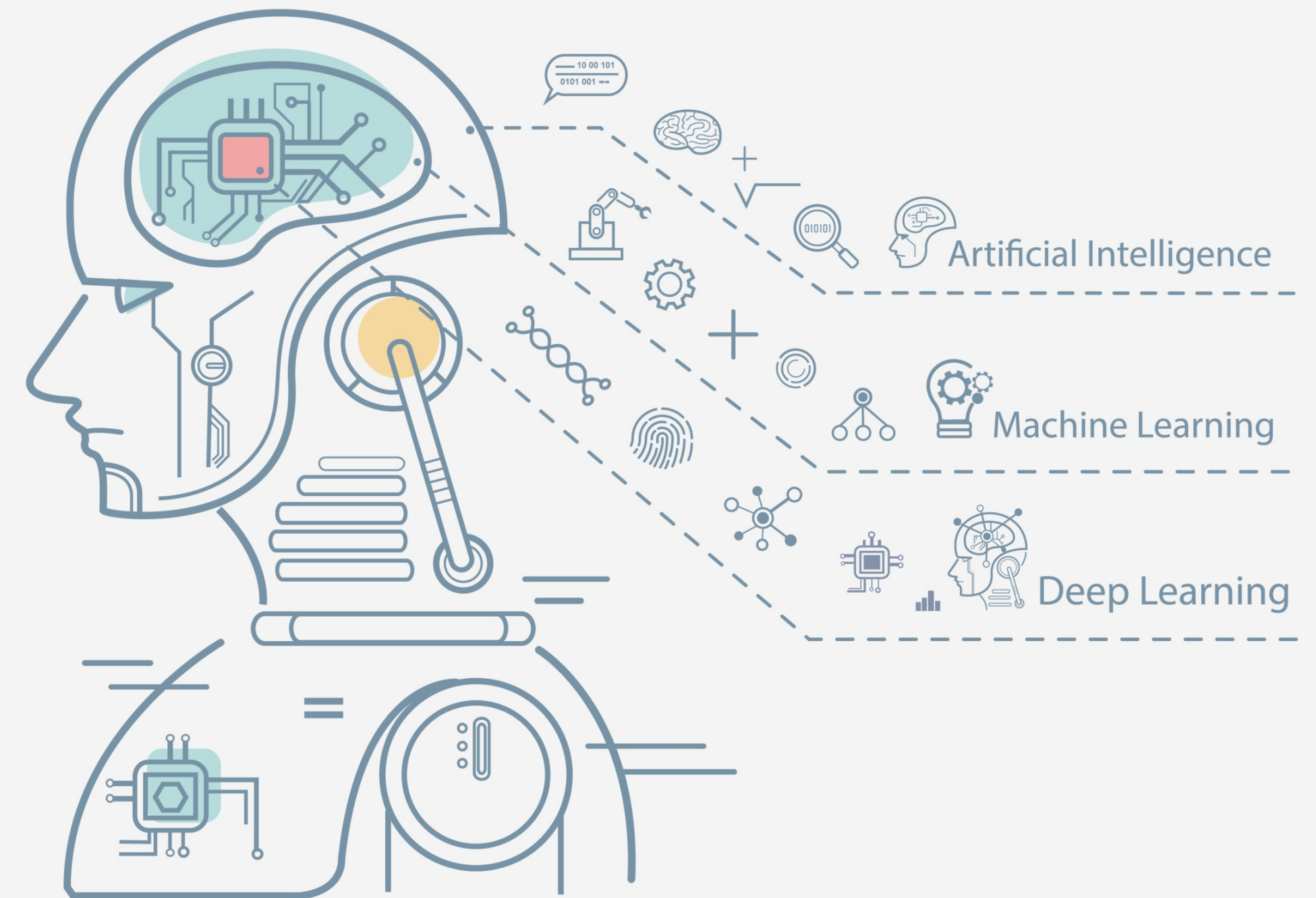
**Angelos Angelopoulos (CRTC)**

**Polykarpos Thomadakis (CRTC),**

**Nikos Chrisochoides (CRTC)**

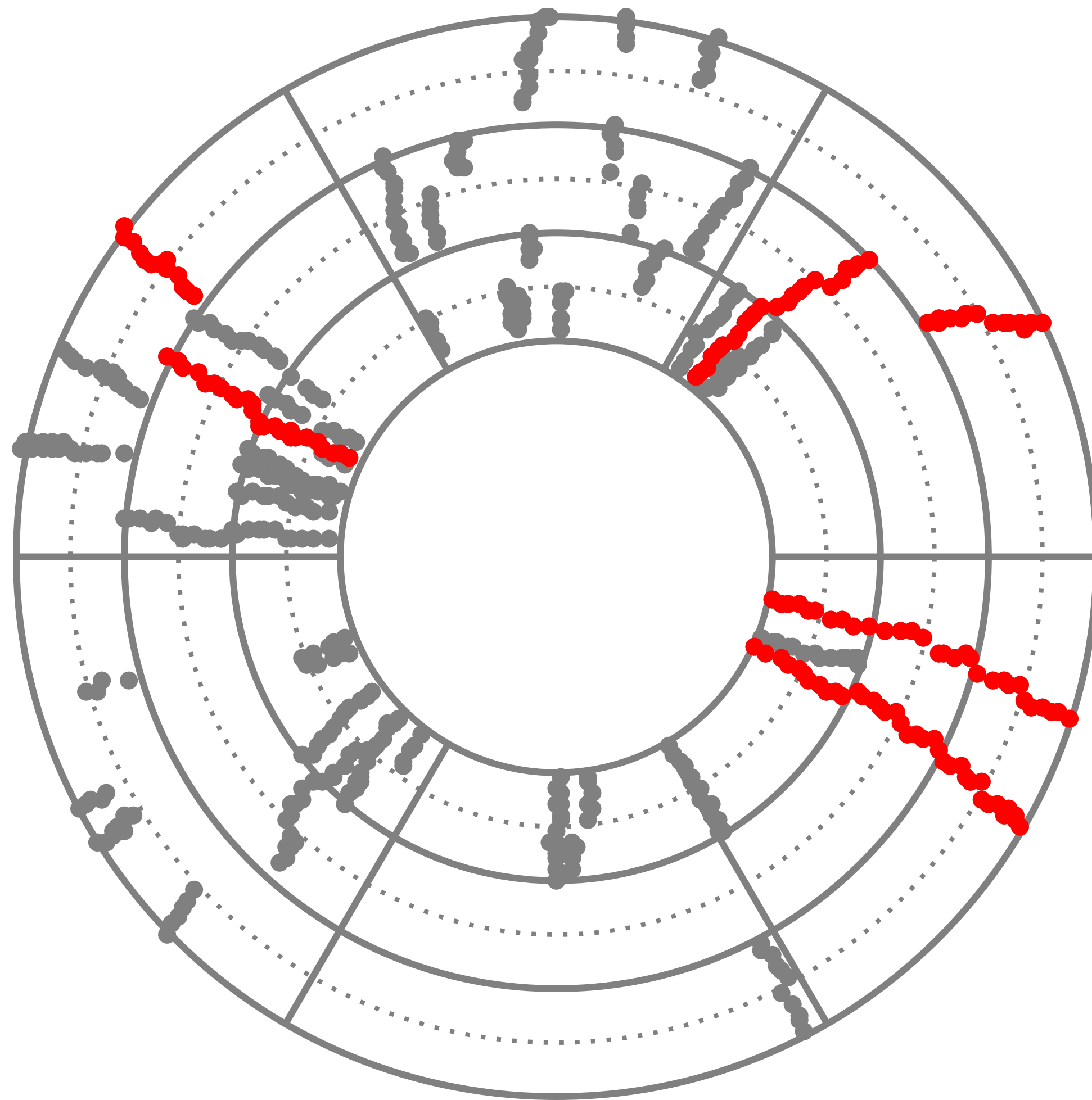
*Department of Computer Science,*

*Old Dominion University, Norfolk, VA, 23529*



# Tracking Challenges

## CLAS12 Tracking with Artificial Intelligence



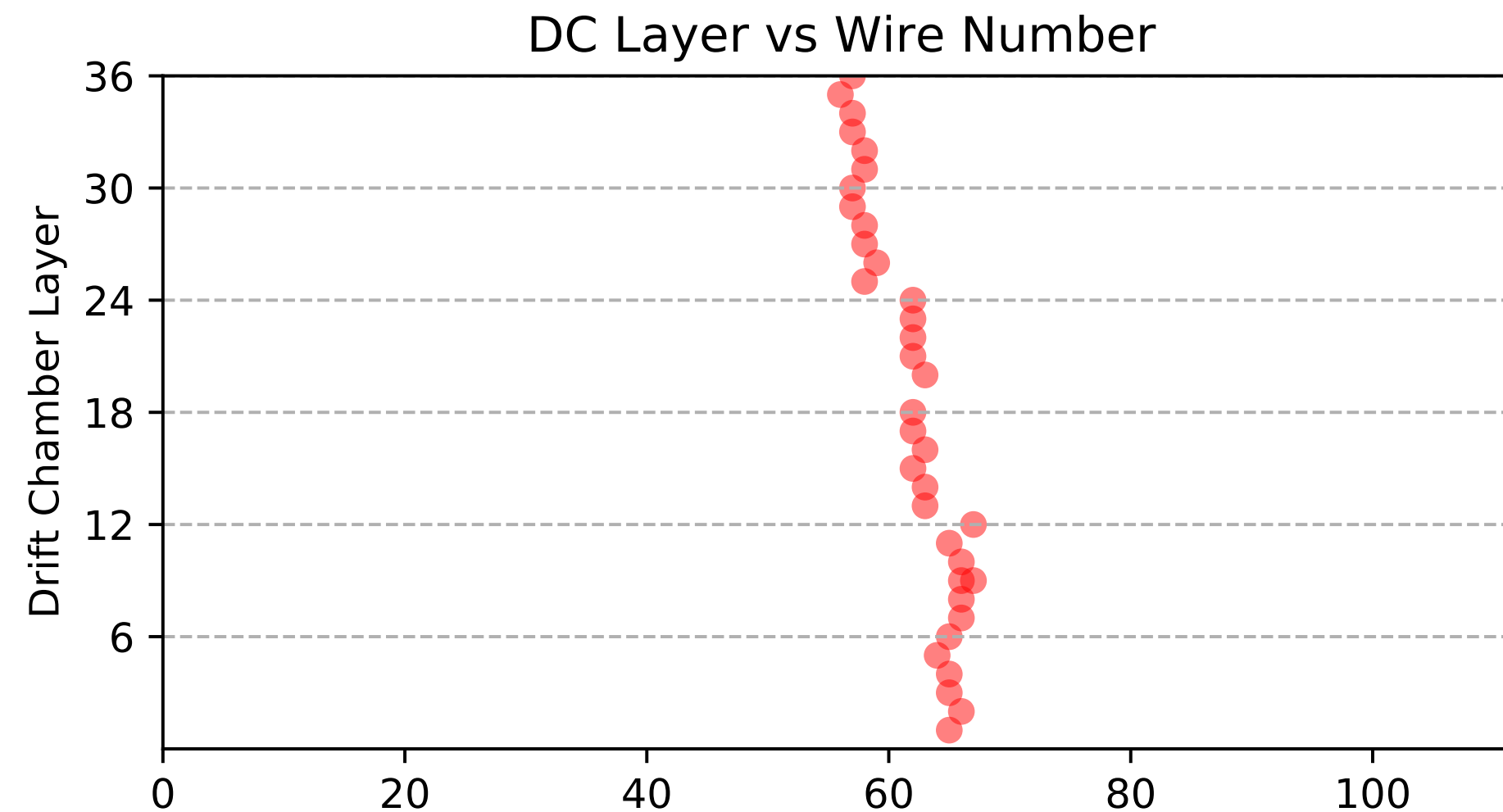
- ▶ Tracking is the most computationally intensive part of reconstruction process.
- ▶ High combinatorics with increased background
- ▶ Many combinations have to be considered to determine best track candidate
- ▶ Missing segments (inefficiencies) contribute to missing tracks

## Artificial Intelligence

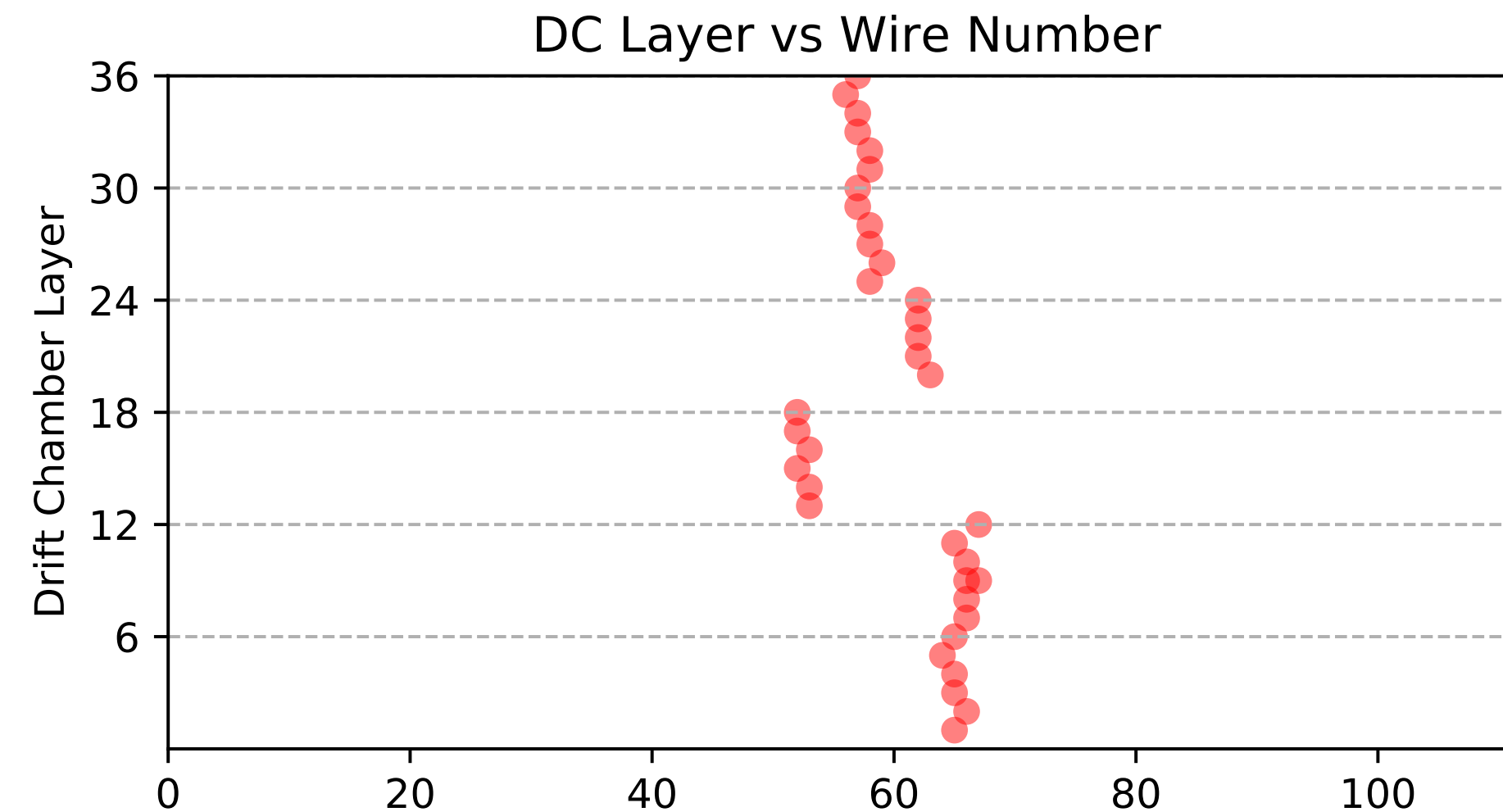
- ▶ Can help with identifying right combinations of segments to form a track
- ▶ Reduce processing time by only fitting suggested candidates
- ▶ Find best 5 segment combinations of tracks by predicting inefficiencies

# AI Track (6 Super-Layer)

## CLAS12 Tracking with Artificial Intelligence



**GOOD TRACK**

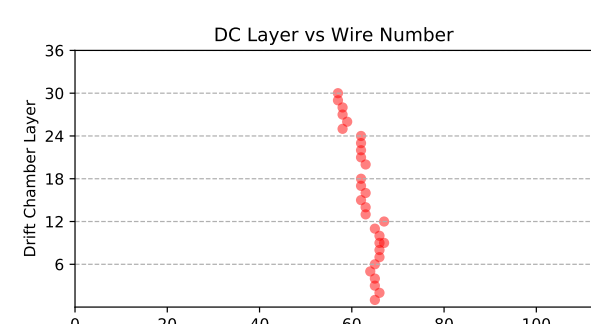
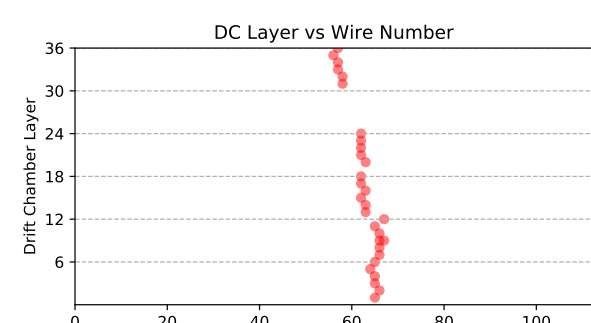
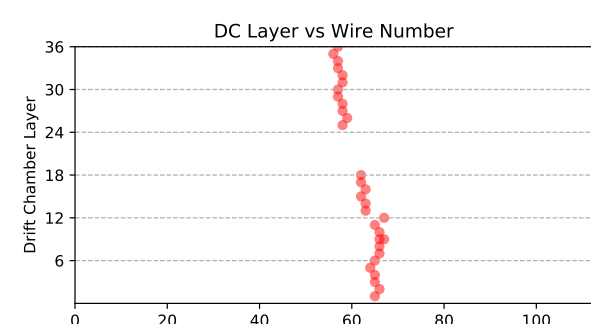
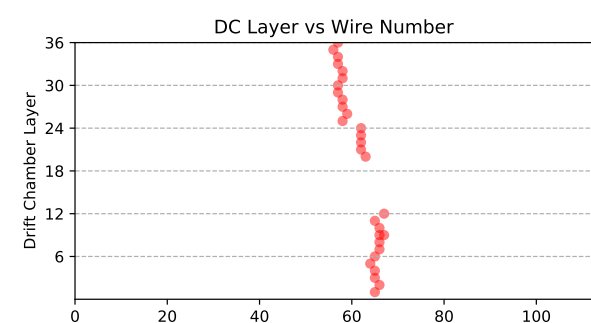
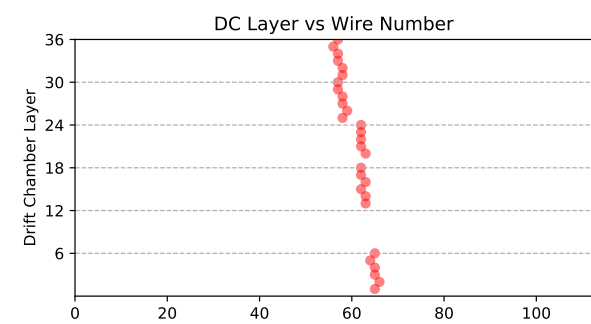
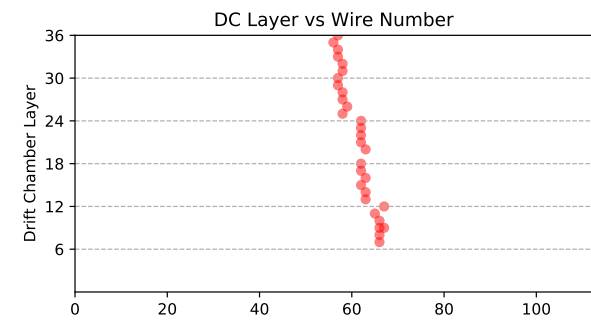


**BAD TRACK**

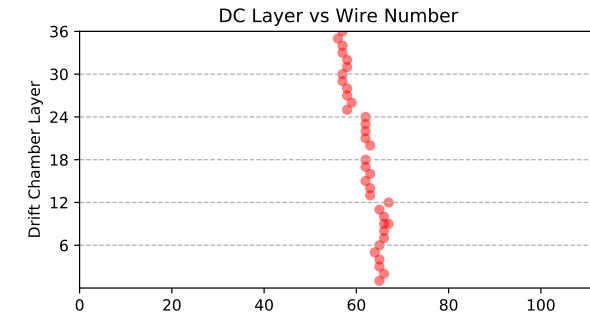
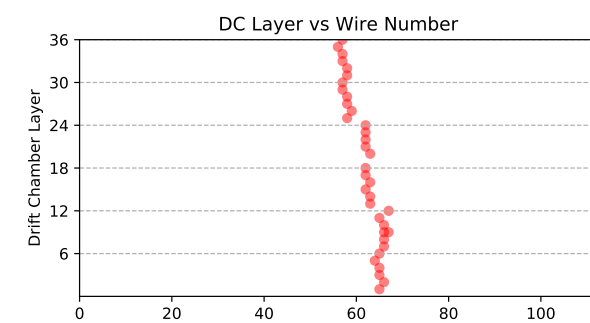
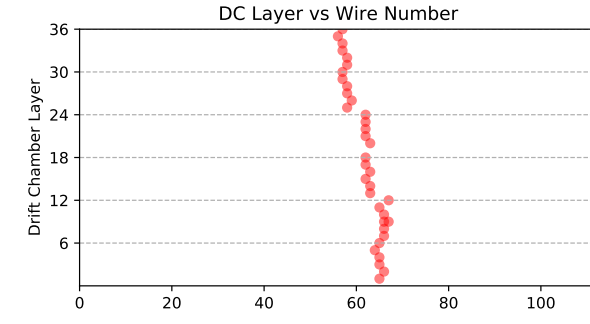
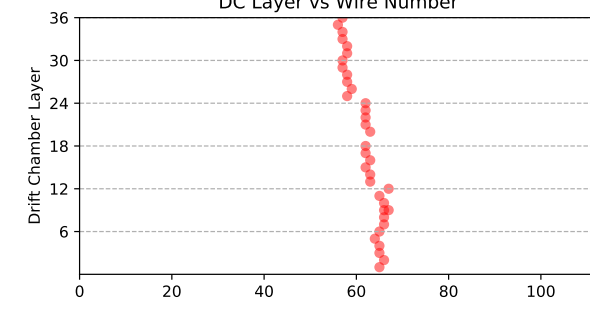
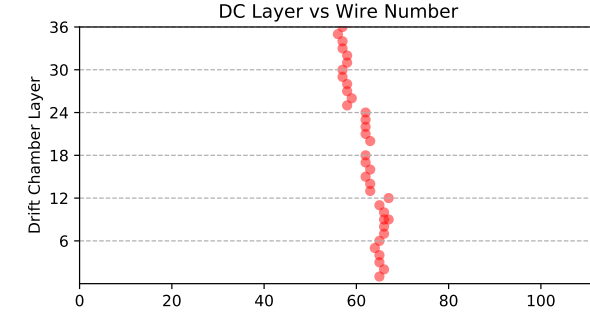
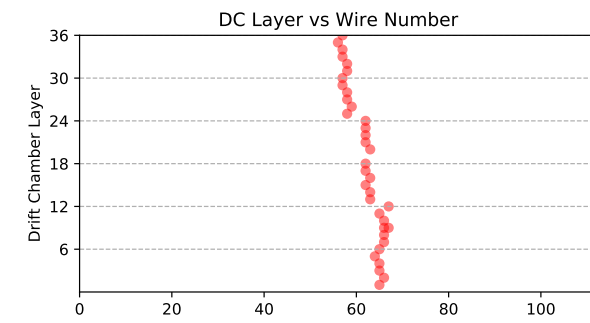
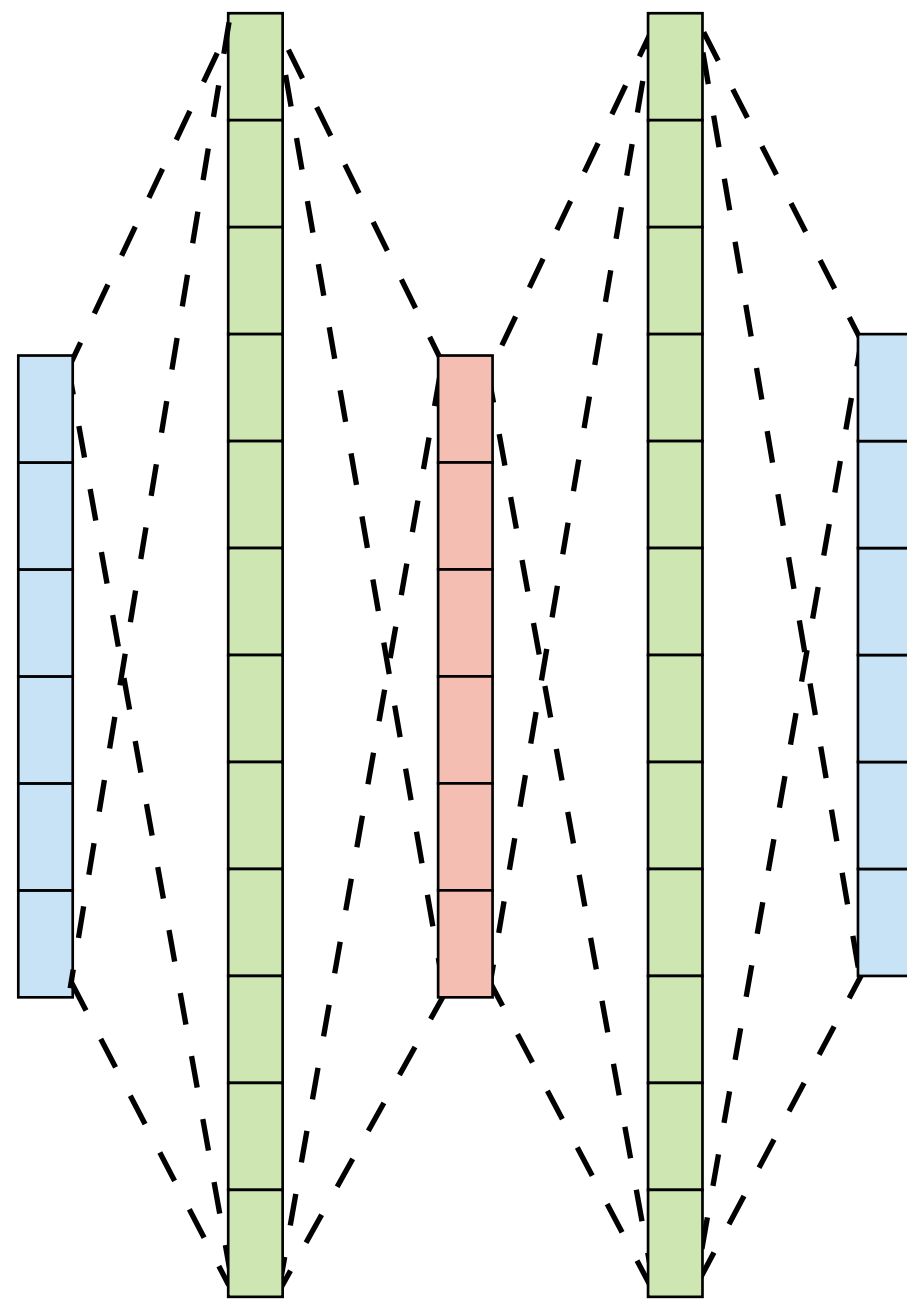
- ▶ Training sample is composed of real track data for positive sample and a modified track data where one of the segments is replaced with random segment in the drift chamber from the same event
- ▶ The segment is chosen to be closest to the track, since we found that network learns best when negative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

## CLAS12 Tracking with Artificial Intelligence

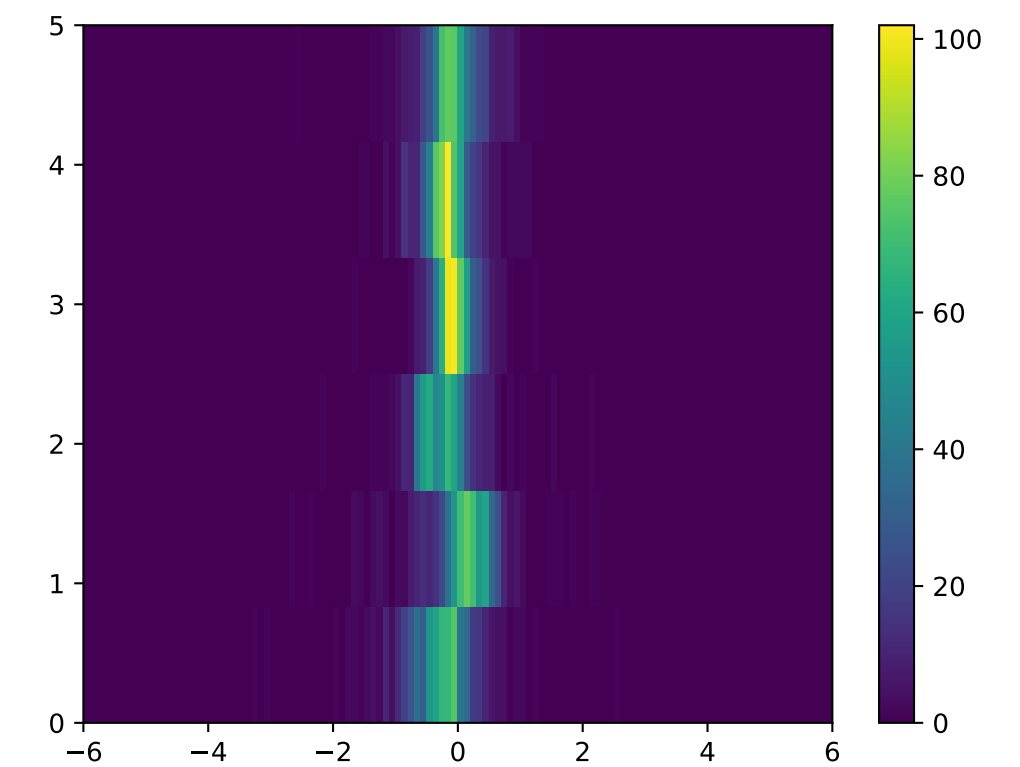
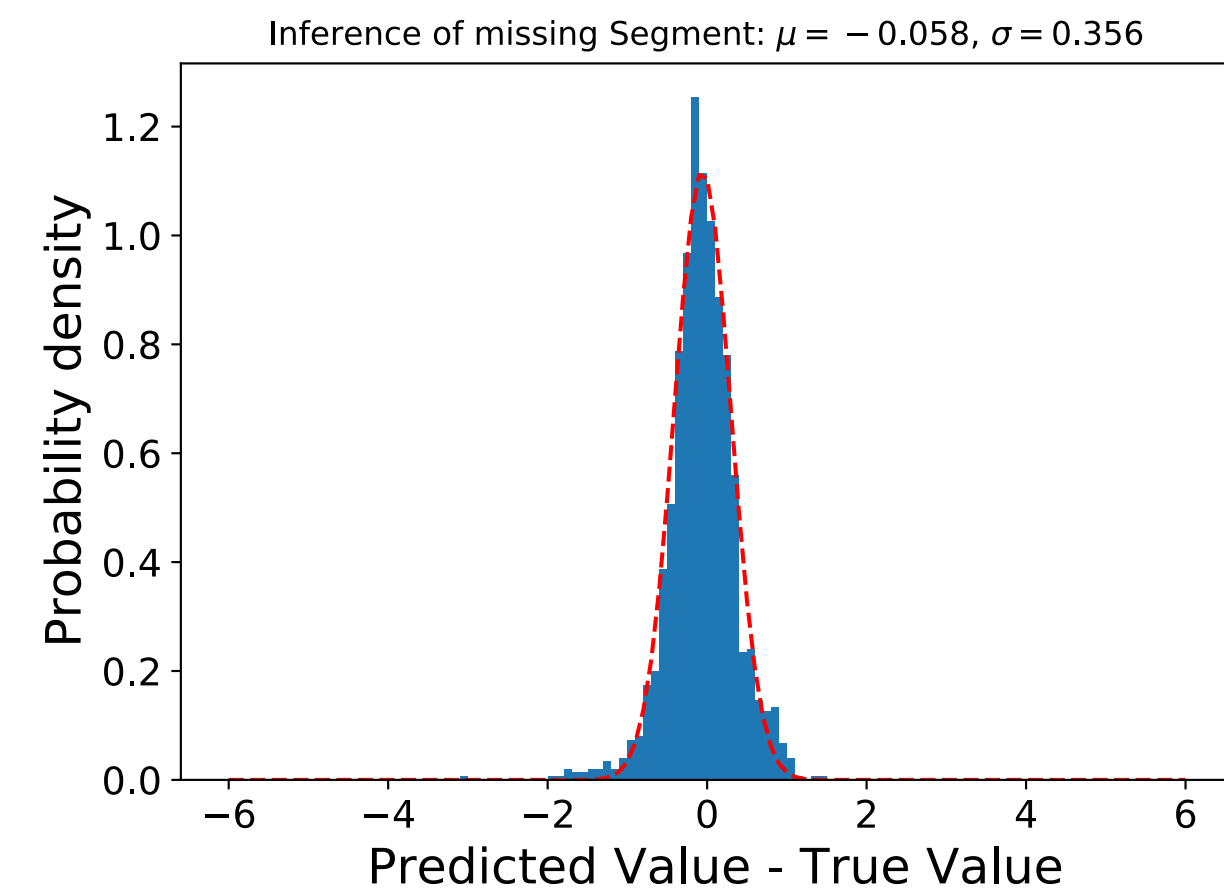


Auto-Encoder



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

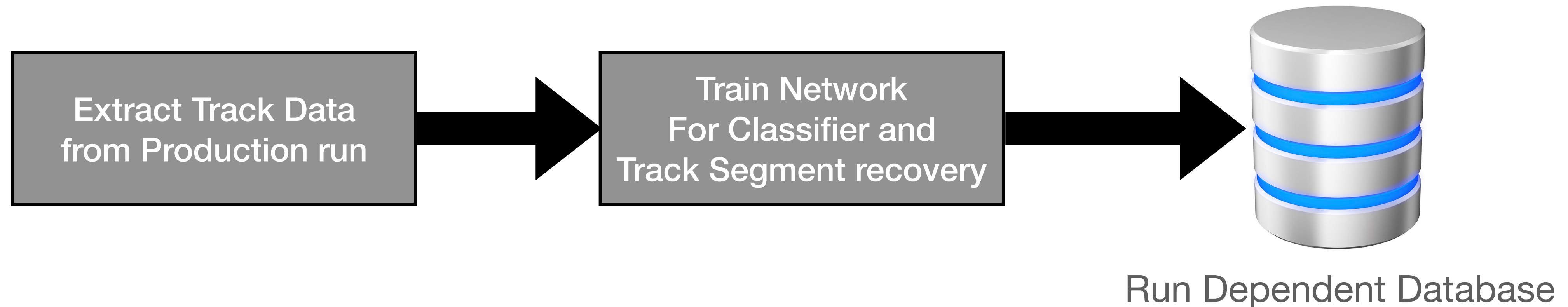
- ▶ Each Fully reconstructed track is corrupted for each super-layer and set as input for auto-encoder
- ▶ The output is fully reconstructed track.
- ▶ Neural Network learns how to fix the corruption
- ▶ Test sample is reconstructed with accuracy of  $\sim 0.36$  wires.



# AI Tracking Reconstruction Tools

## Tools

- ▶ User productivity tools for extracting training data samples from production run and training the network are implemented and documented:
  - ▶ [https://clasweb.jlab.org/wiki/index.php/CLAS12\\_AI\\_tools](https://clasweb.jlab.org/wiki/index.php/CLAS12_AI_tools)
- ▶ More tools are being developed for visualizing the training results and initial validation of training

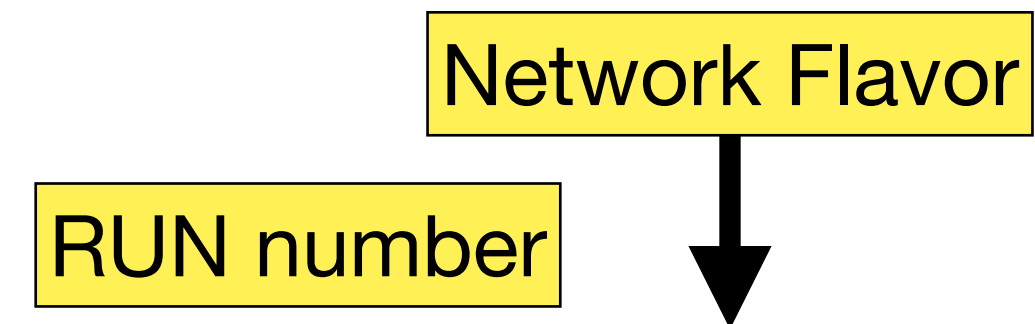


- ▶ Data for training is taken from cooked files with reconstructed time based tracks
- ▶ Command line tools used for training the classifier network and segment recovery network
- ▶ The resulting neural networks are stored in Run Dependent Database (custom developed for ML)
- ▶ The tracking AI finds appropriate entry in the database depending on RUN number that is being processed

# AI Tracking Reconstruction Tools

## Tools

- ▶ One Database to hold Neural network parameters
- ▶ Shipped with COATJAVA distribution as one file
- ▶ Database has run number and "flavor" assigned to each Neural Network file for flexibility. (Default flavor will be used if none specified)
- ▶ Flavor and run number can be overridden from YAML file.
- ▶ Run# selection similar to CCDB.
- ▶ Auto-lock prevents overwriting existing neural network by accident. (User manually has to remove an entry to create a new one with training tools)



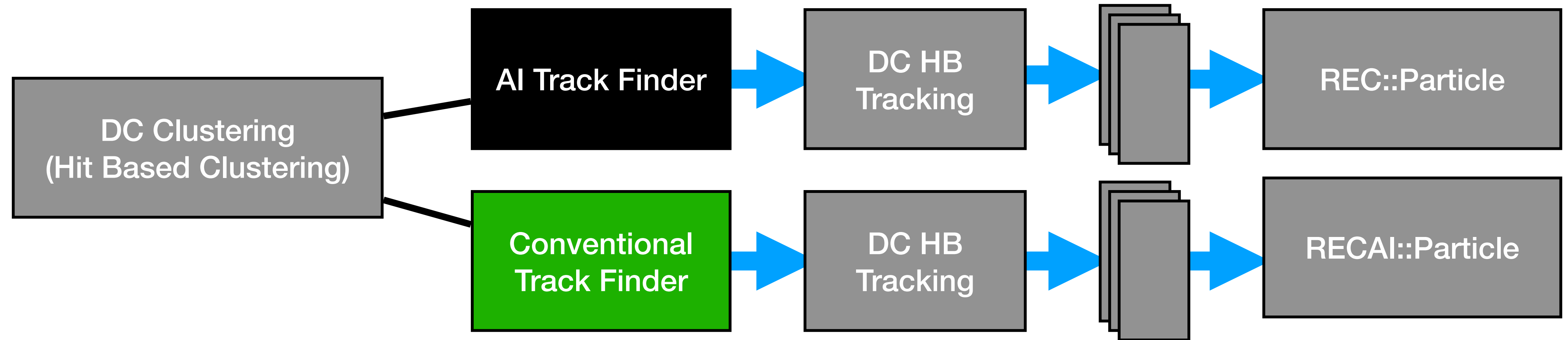
Run#	flavor	network file
5038	default	trackClassifier.network
5038	default	trackFixer.network
5038	default	trackParametersNegative.network
5038	default	trackParametersPositive.network
5089	orchid	trackClassifier.network
5089	orchid	trackFixer.network
5089	orchid	trackParametersNegative.network
5089	orchid	trackParametersPositive.network
5610	default	trackClassifier.network
5610	default	trackFixer.network
5610	default	trackParametersNegative.network
5610	default	trackParametersPositive.network
6230	default	trackClassifier.network
6230	default	trackFixer.network
6230	default	trackParametersNegative.network
6230	default	trackParametersPositive.network

- ▶ Interactive tools for listing the content of the database, remove entries and add entries
- ▶ Tools for running validation on cooked run for given run number and "flavor"

# AI Tracking Reconstruction Tools

## 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 **34%** 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.

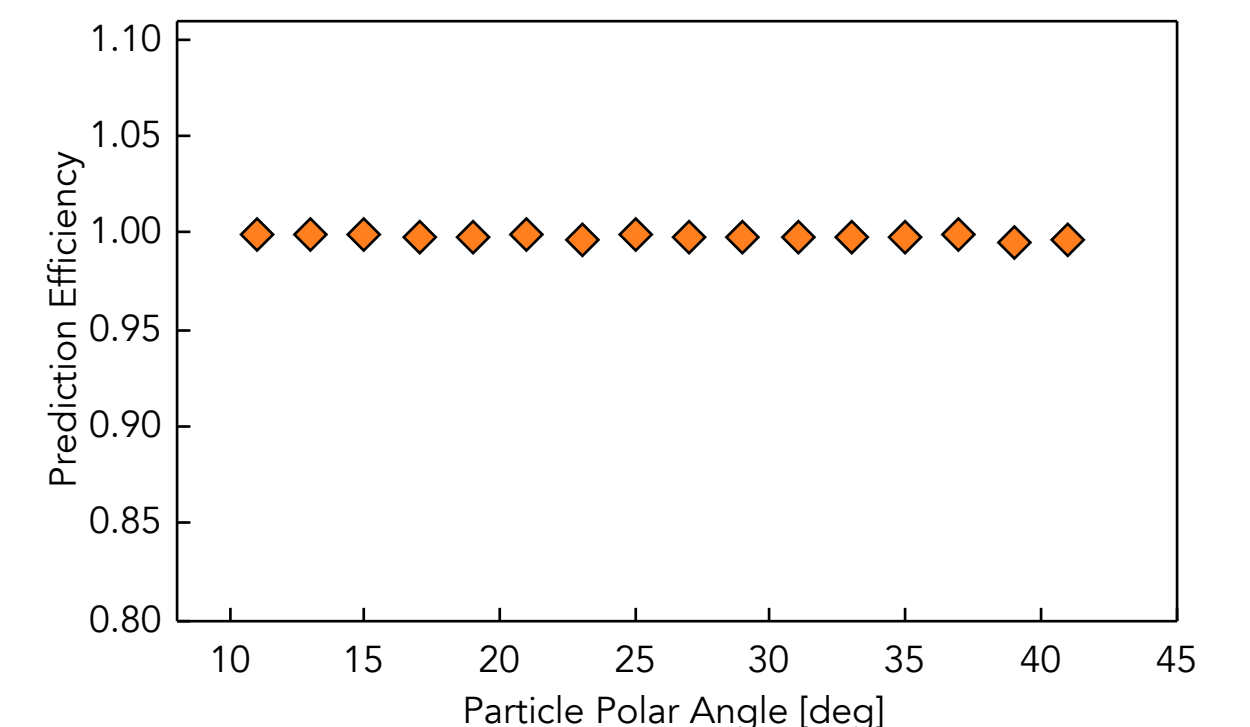
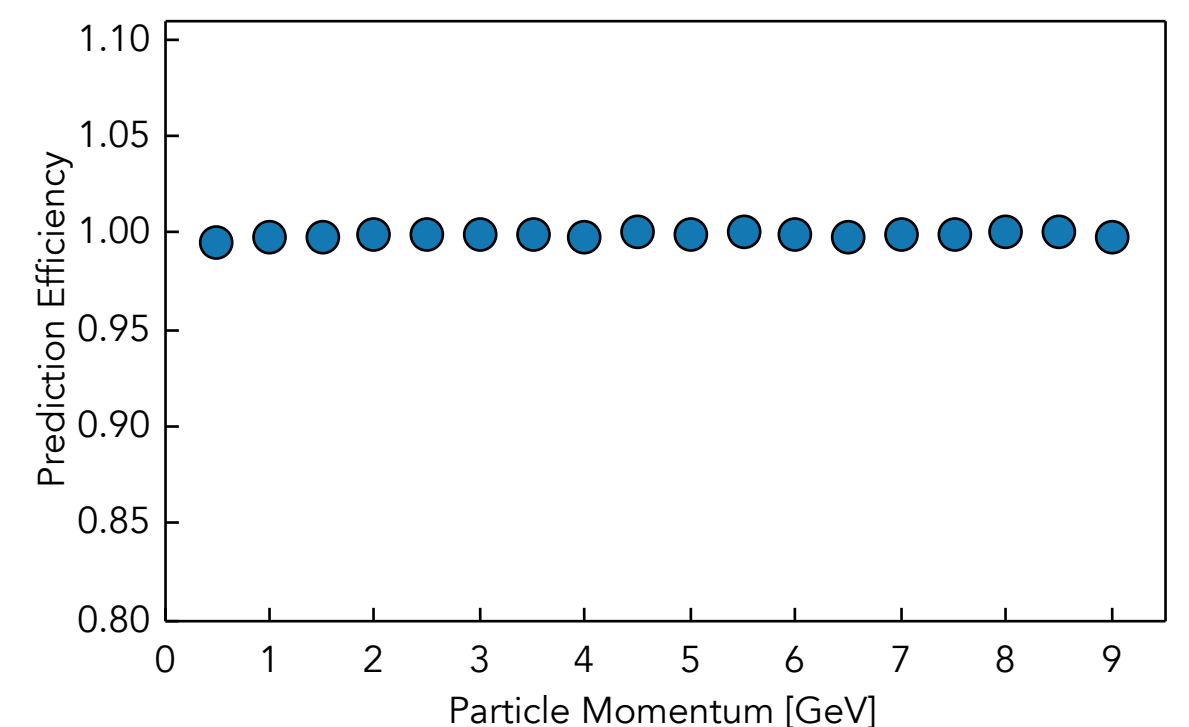
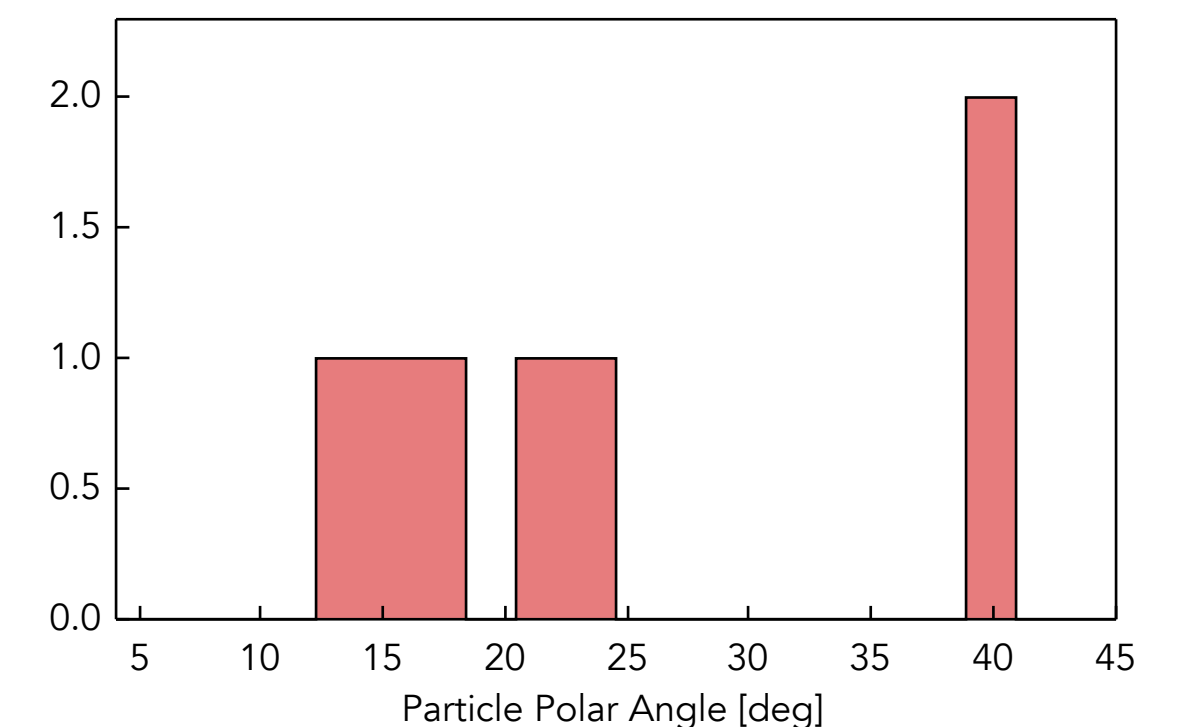
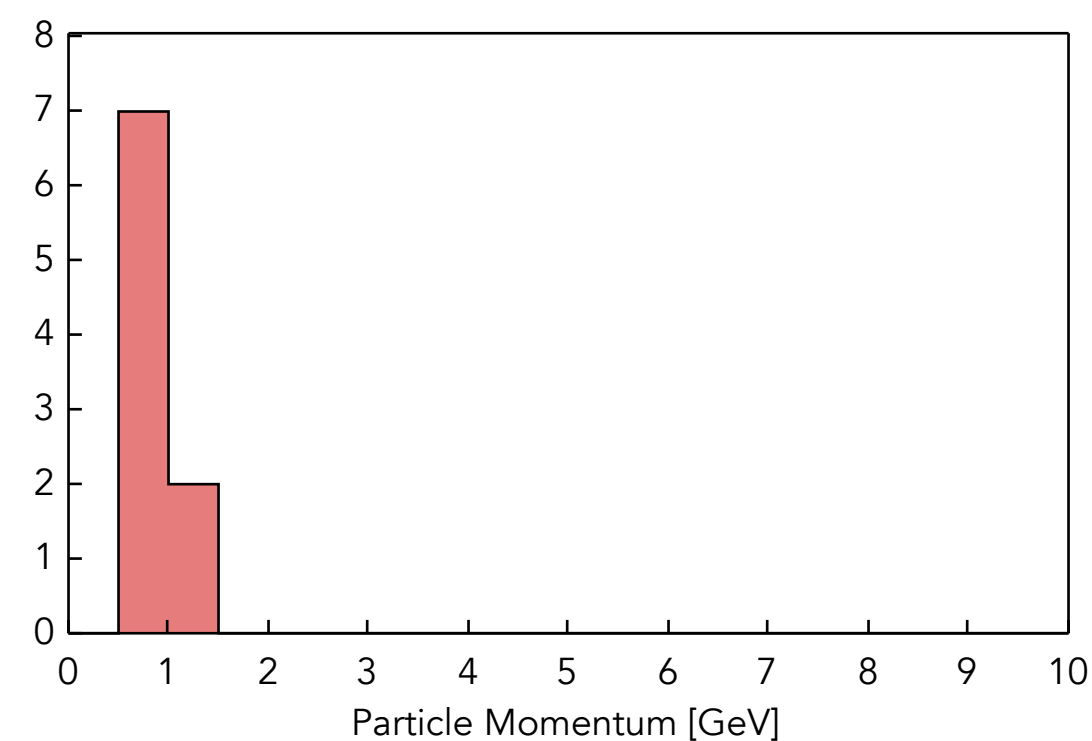
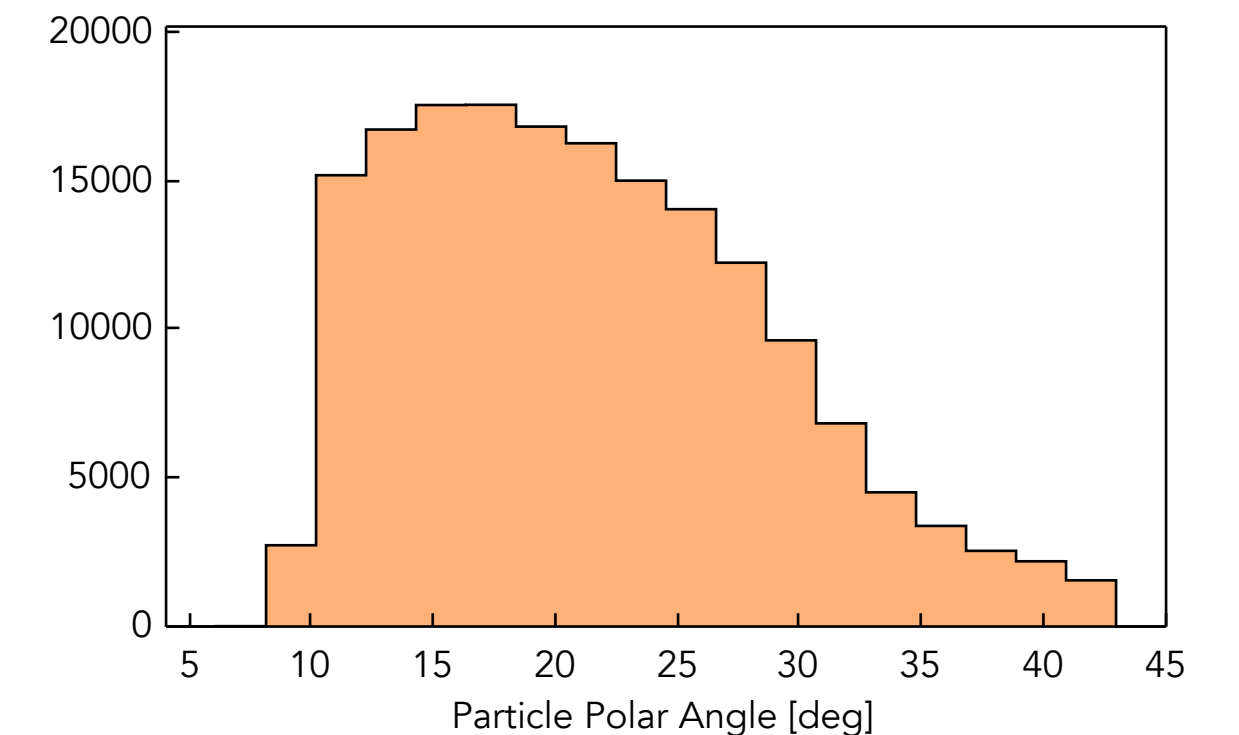
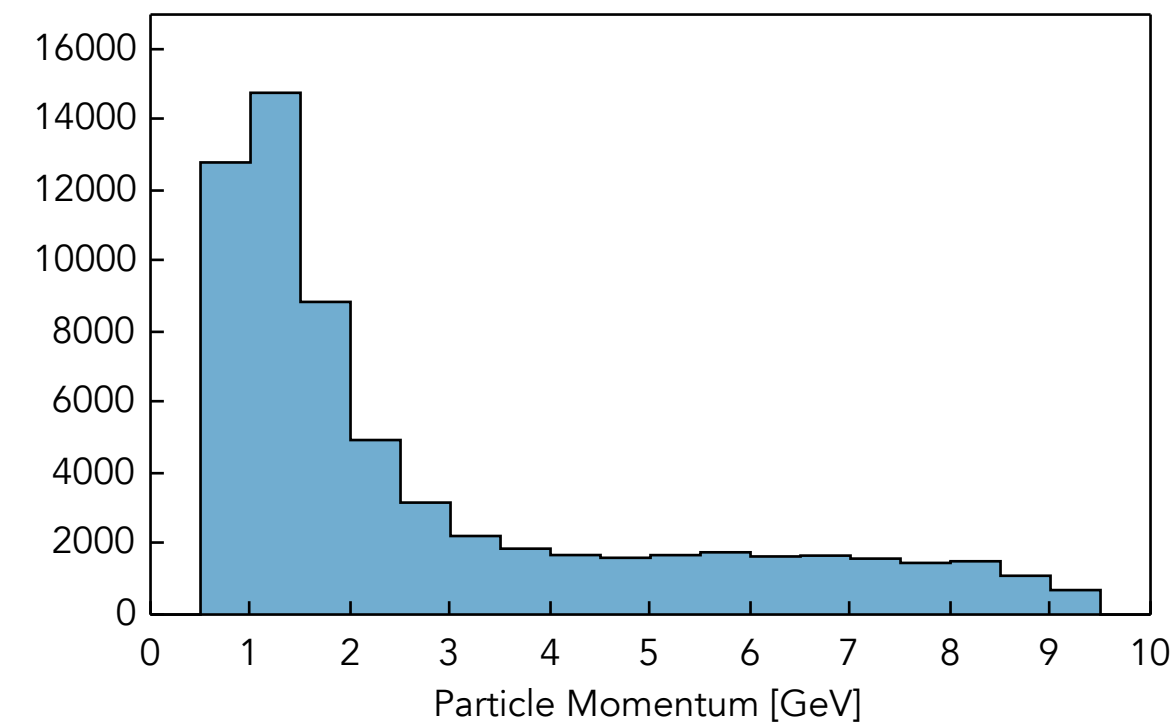
# AI Tracking (Project History)

## Track Reconstruction

- ▶ Initially the project aimed to identify all track candidates without any loss
- ▶ Provide tracking with track candidates so tracking code does not have to spend time on ghost tracks or non-converging tracks
- ▶ Improve reconstruction time by considering only valid track candidates.

## Lesson Learned:

Be careful what you wish for, you may just get more.



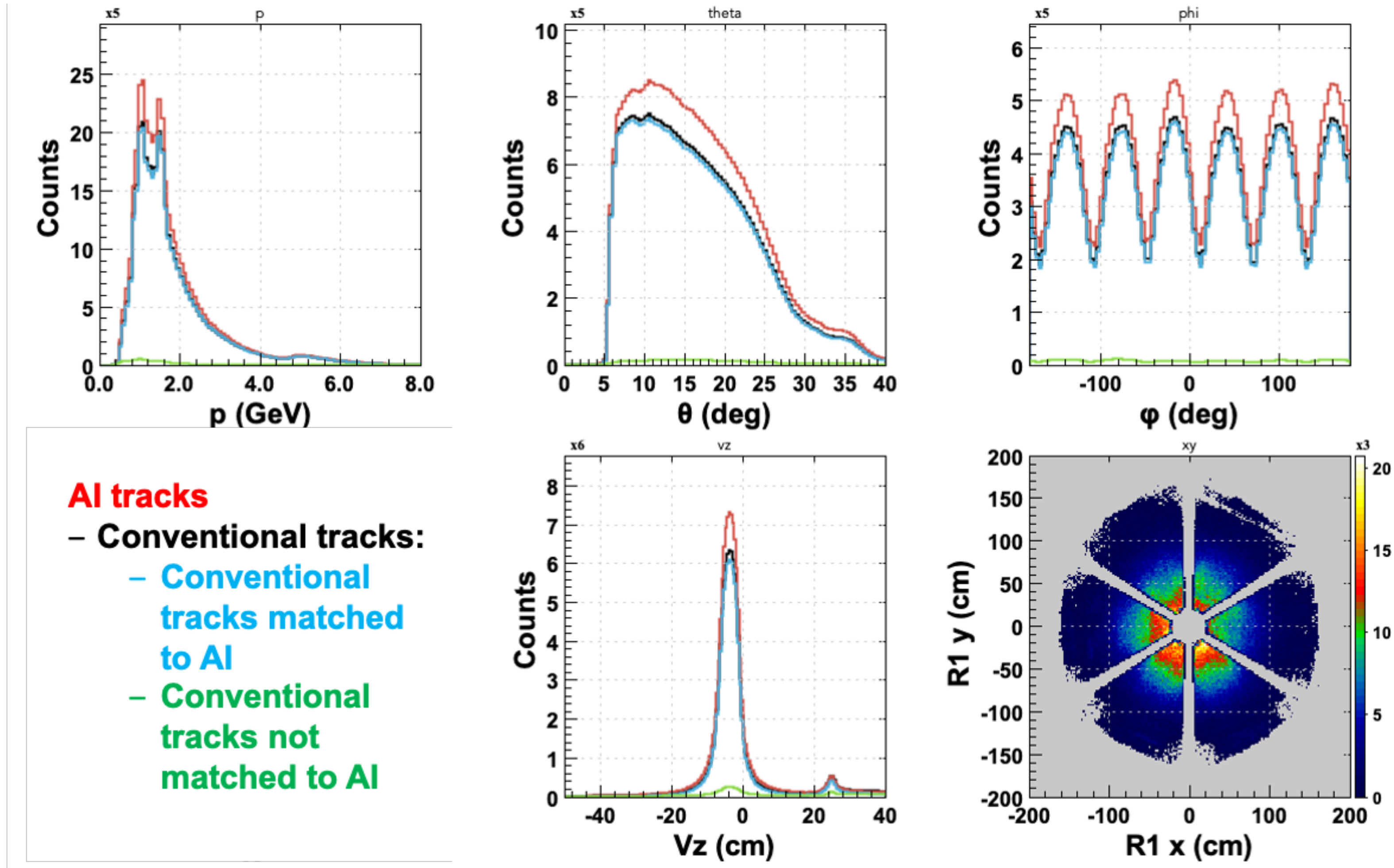


# AI Validation (all systematic Studies done by R. DeVita)

## CLAS12 Tracking with Artificial Intelligence

Track selection:

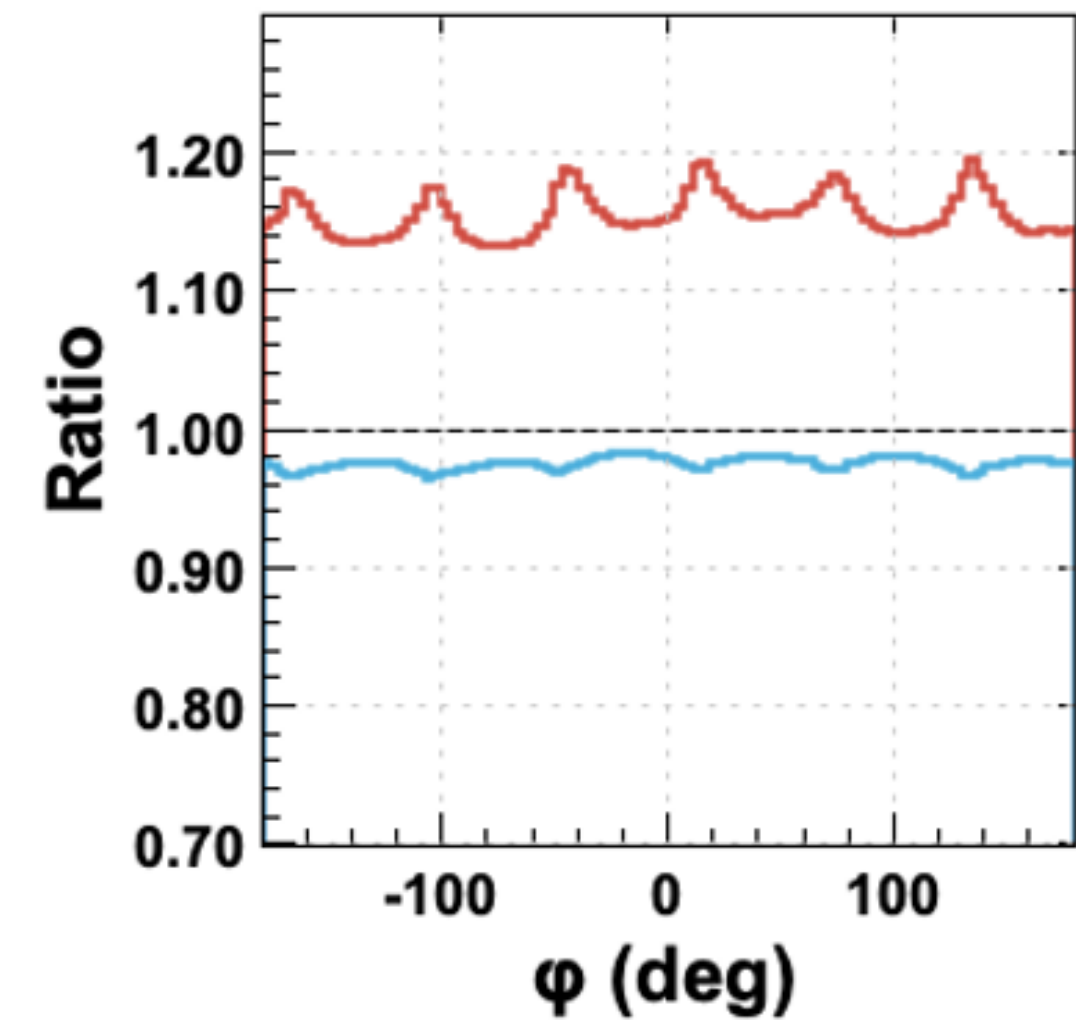
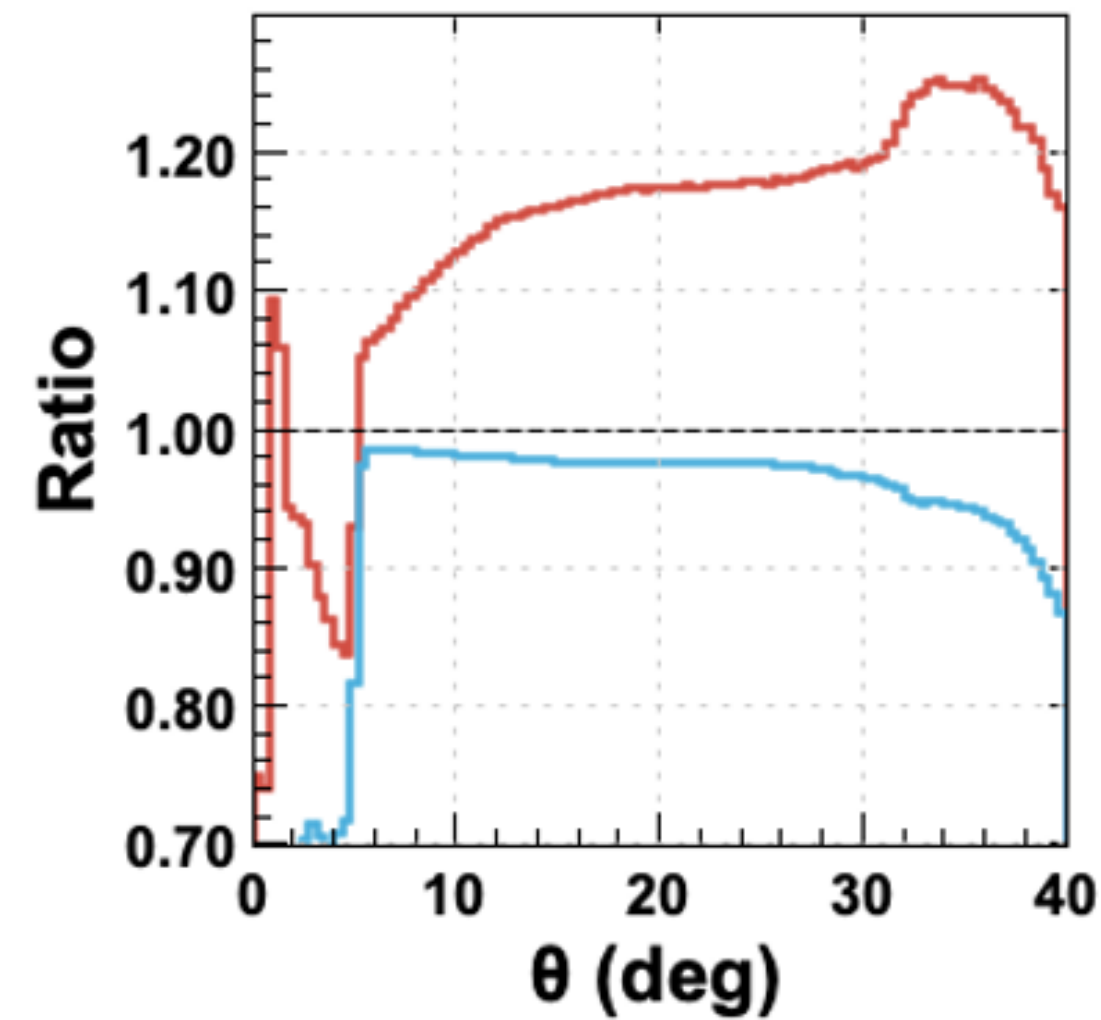
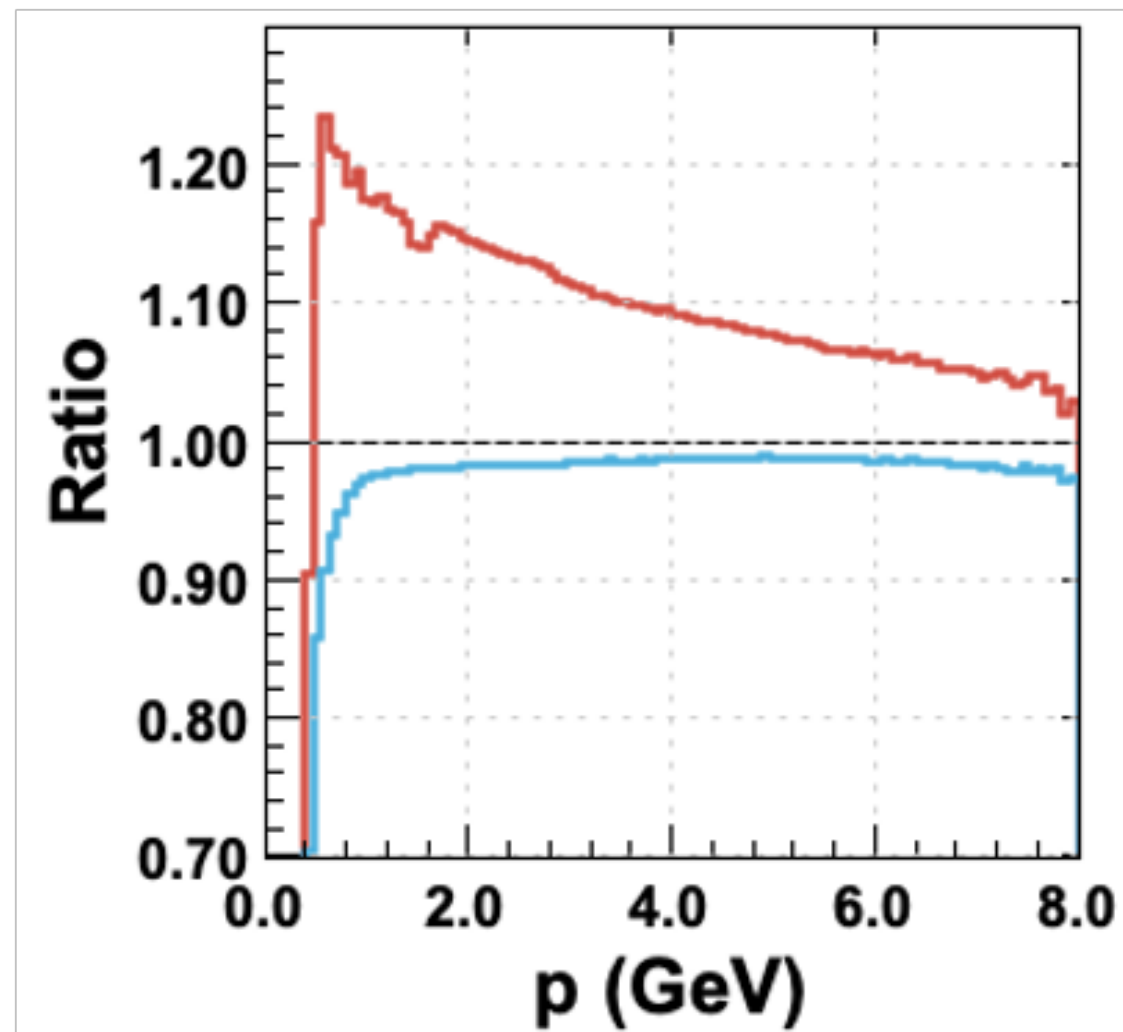
- $|v_z+5|<10$  on all plots except for the  $v_z$  distribution -  $\chi^2/NDF<10$  -  $|\chi^2_{pid}|<5$ -RG-A fiducial cuts



# AI Validation

## CLAS12 Tracking with Artificial Intelligence

- Relative Gain , - Relative Efficiency

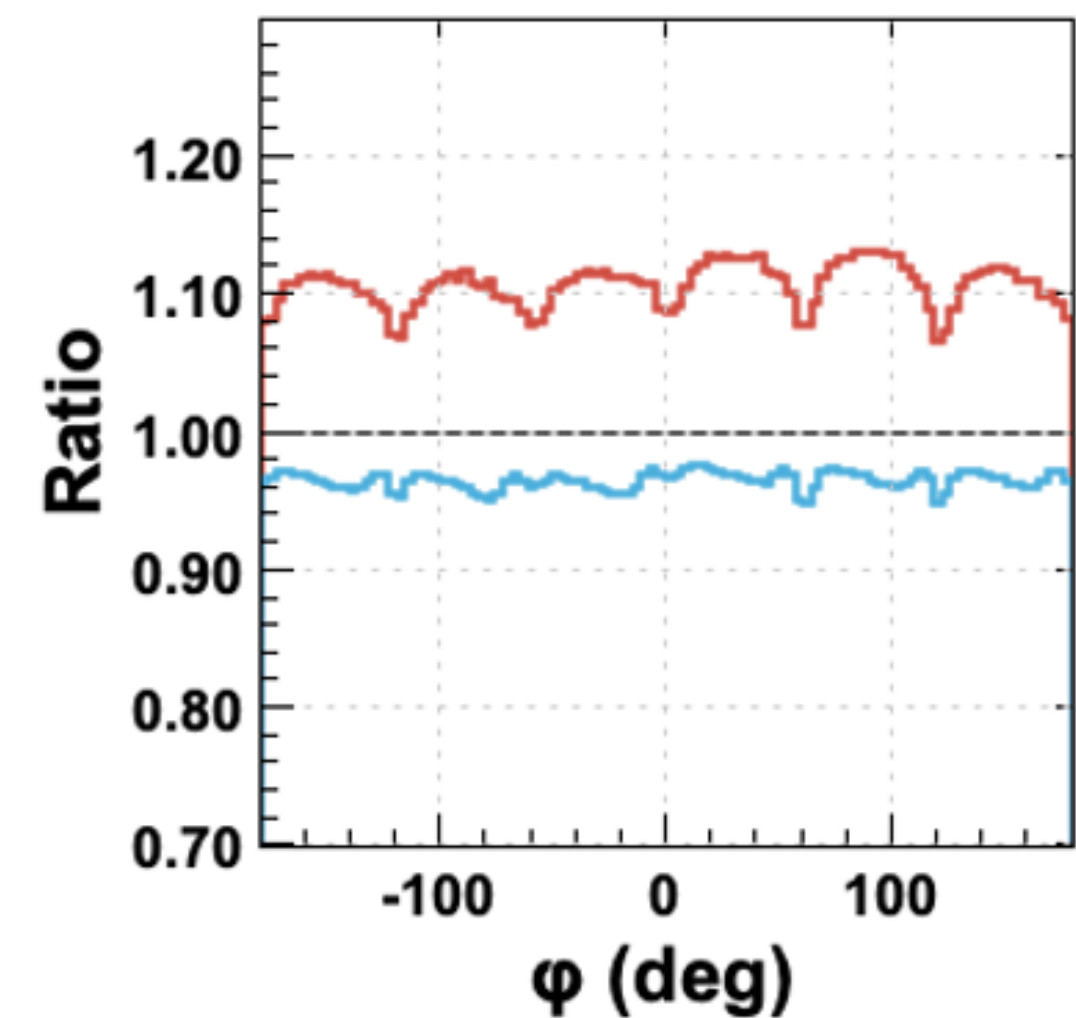
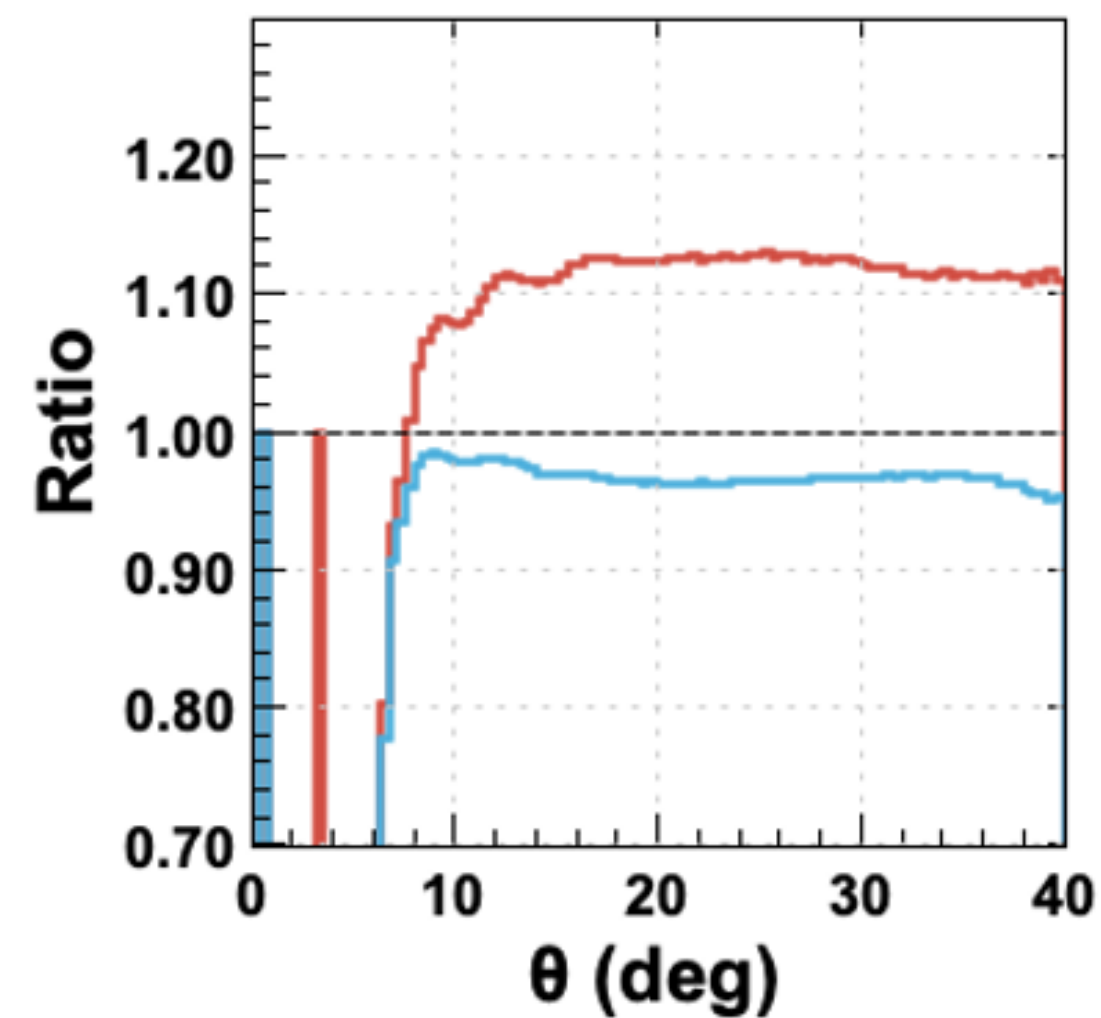
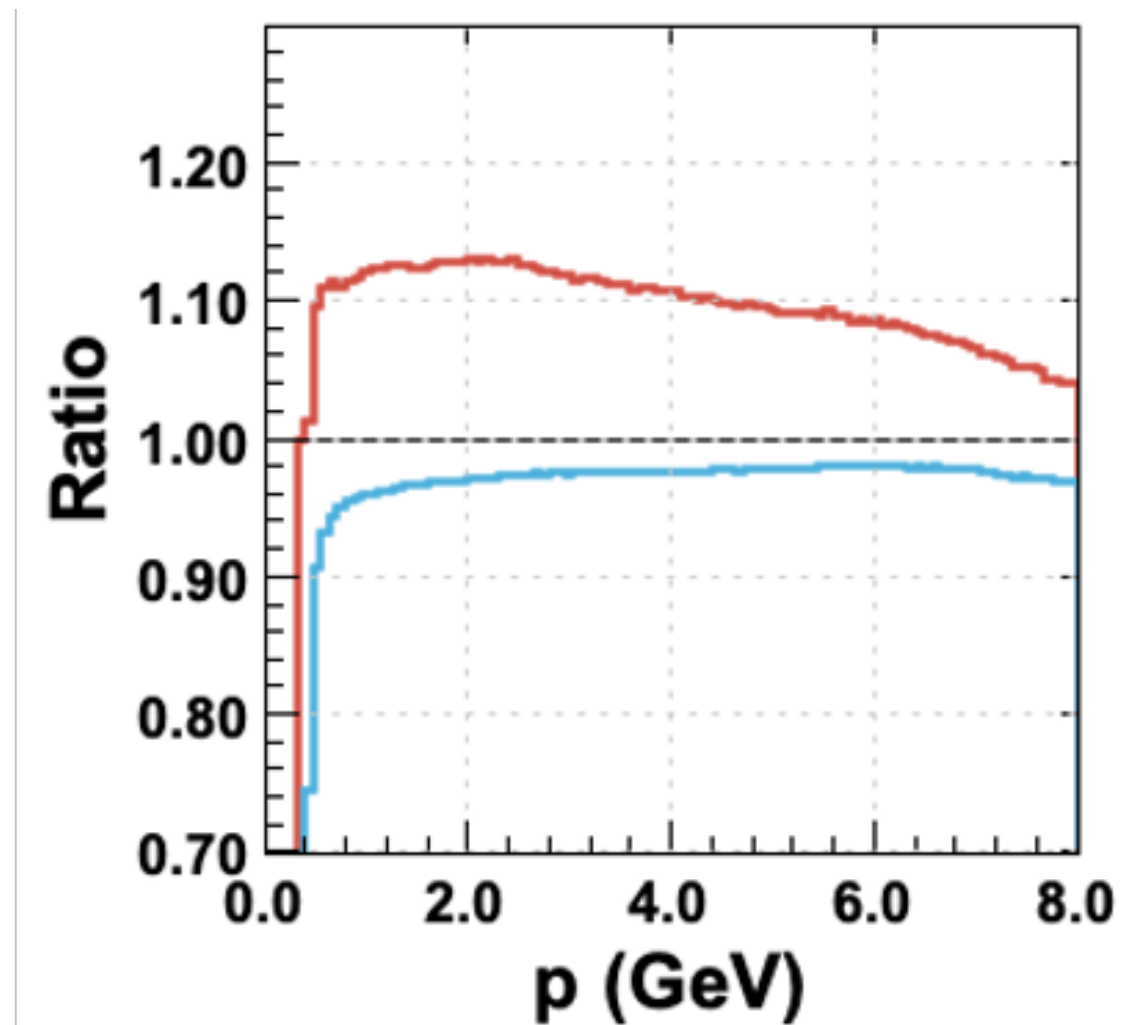


Positive

Average ~1.152

Average ~0.976

(>0.99 with 4 SL match)



Negative

Average ~1.103

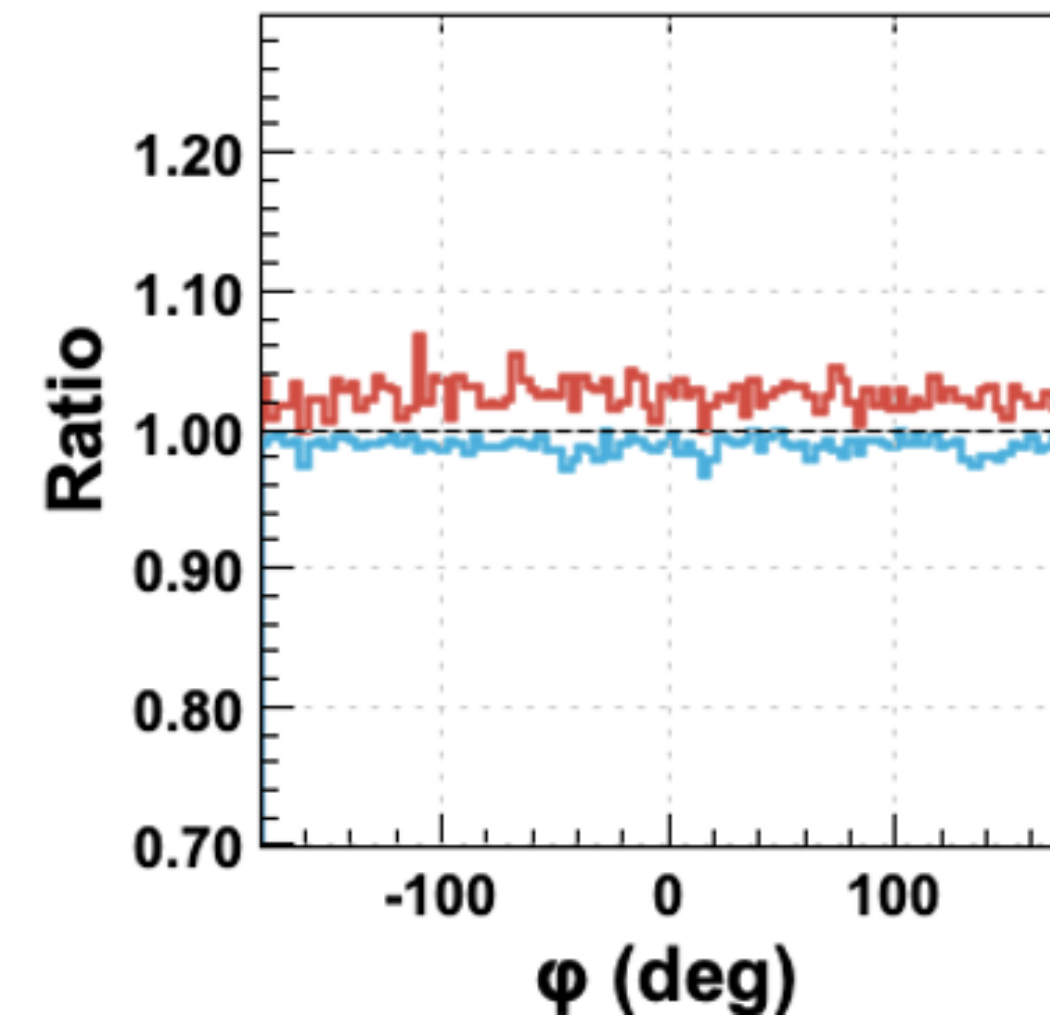
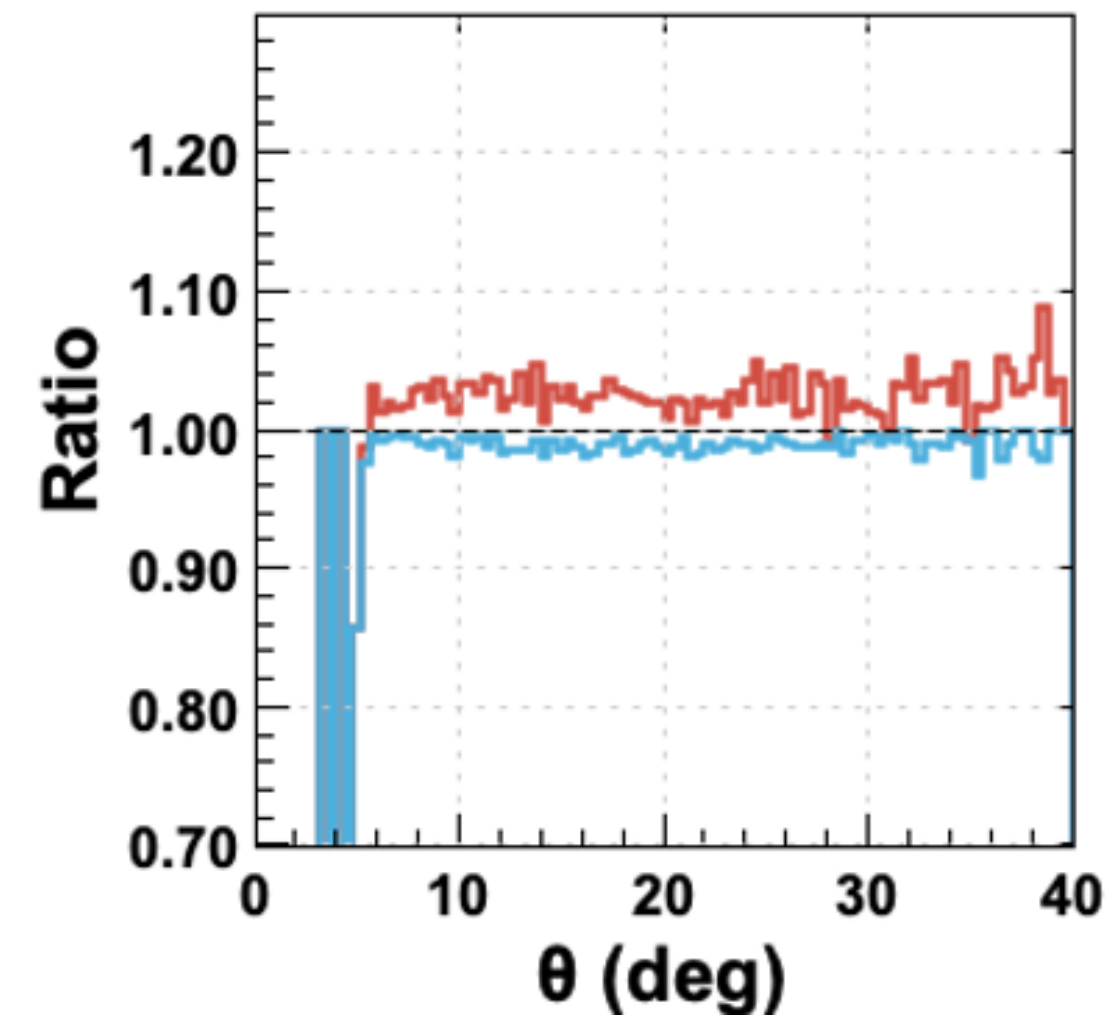
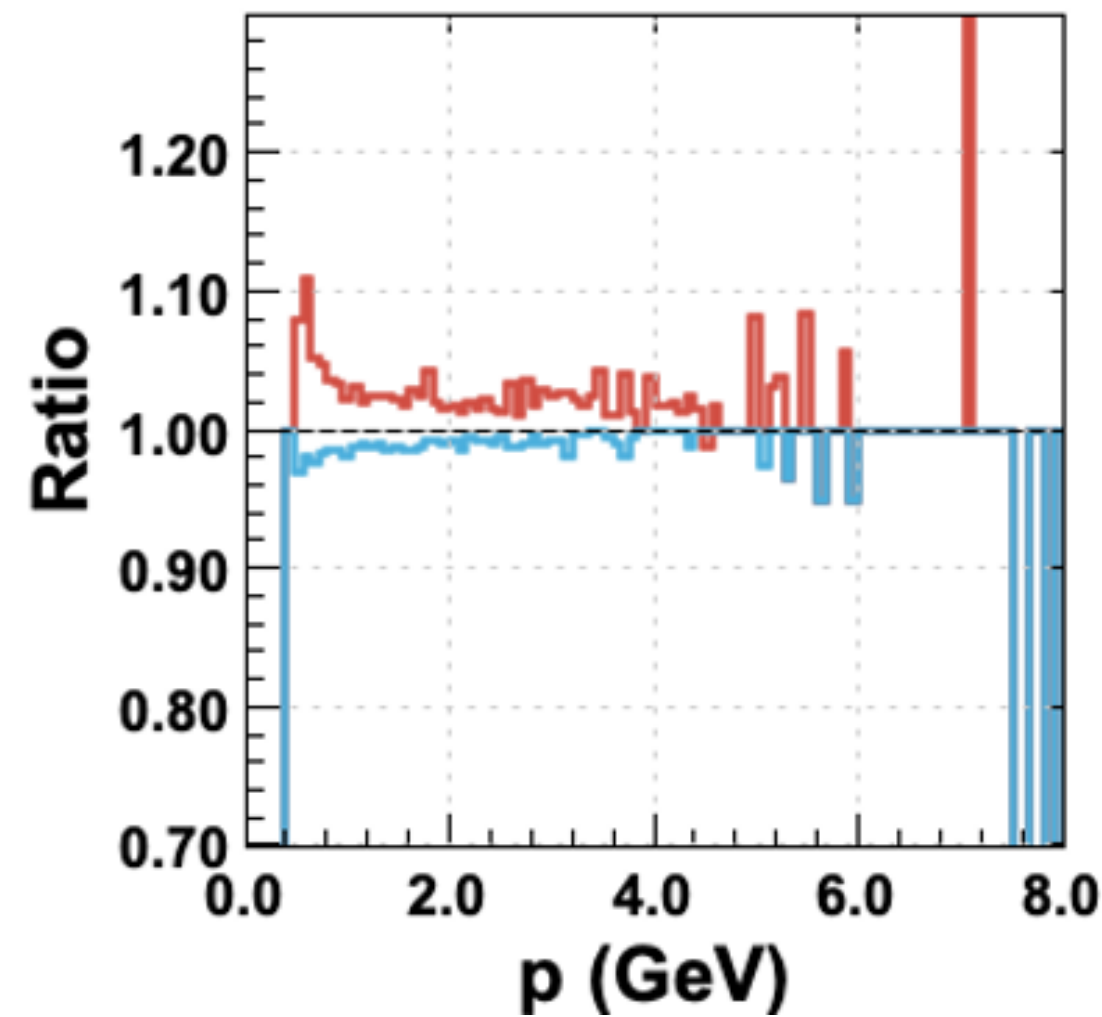
Average ~0.965

(>0.98 with 4 SL match)

# AI Validation (MC)

## CLAS12 Tracking with Artificial Intelligence

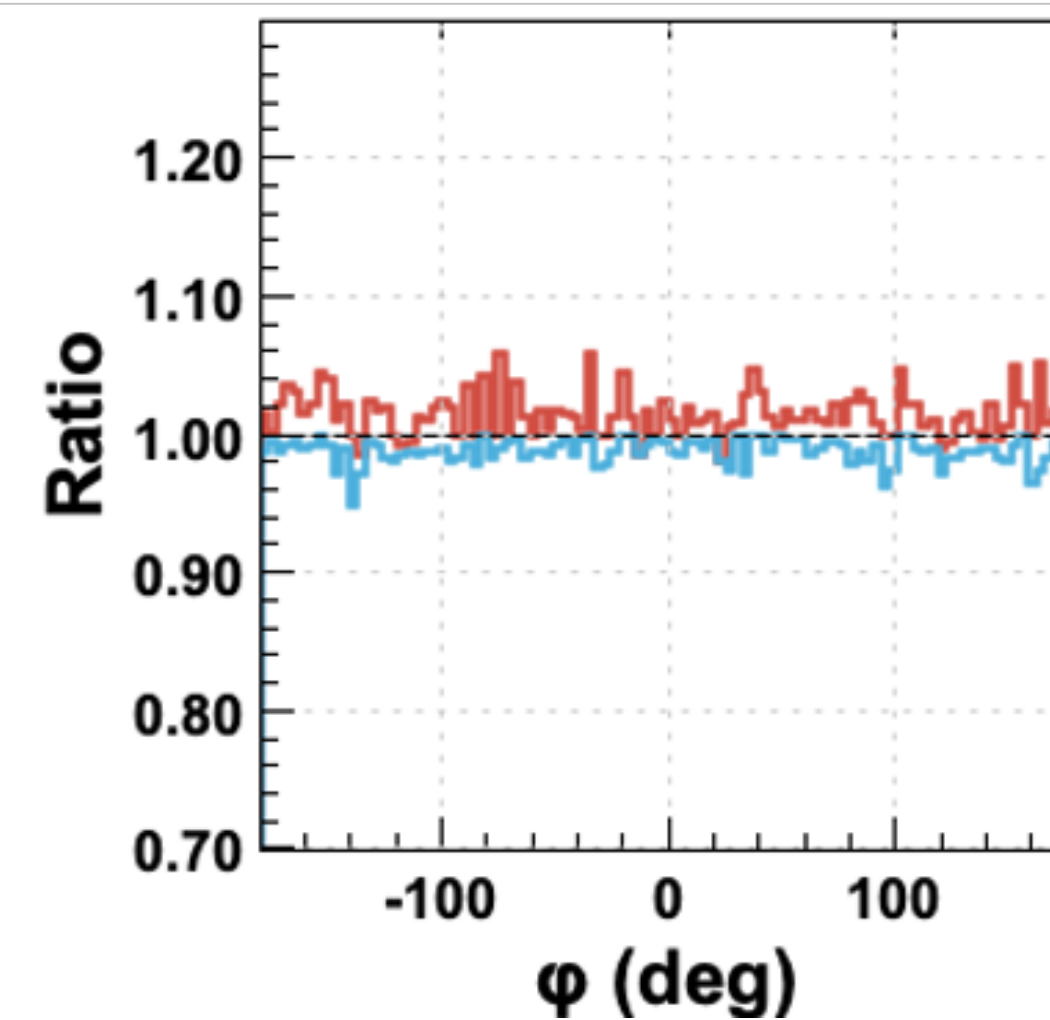
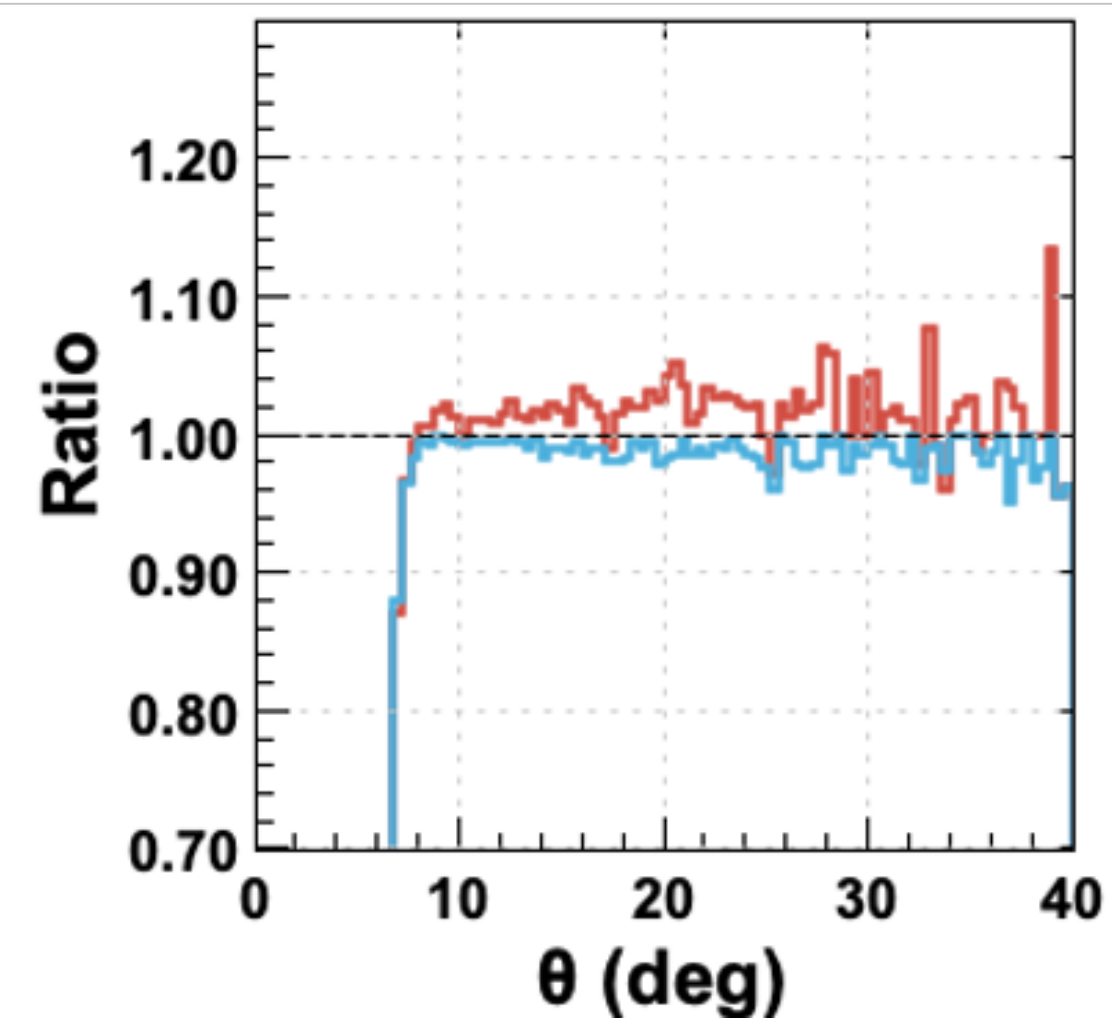
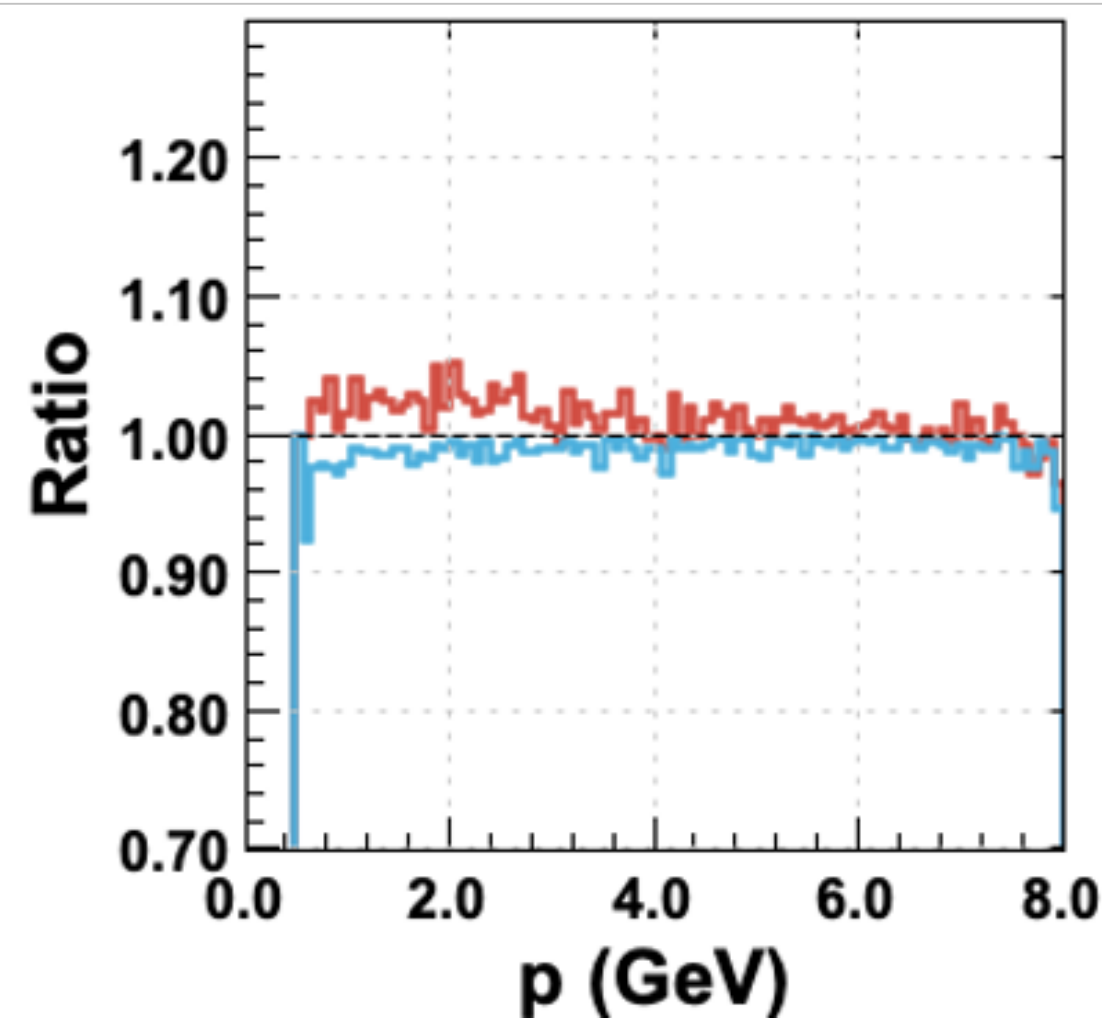
- Relative Gain , - Relative Efficiency



Positive

Average  $\sim 1.024$

Average  $\sim 0.988$



Negative

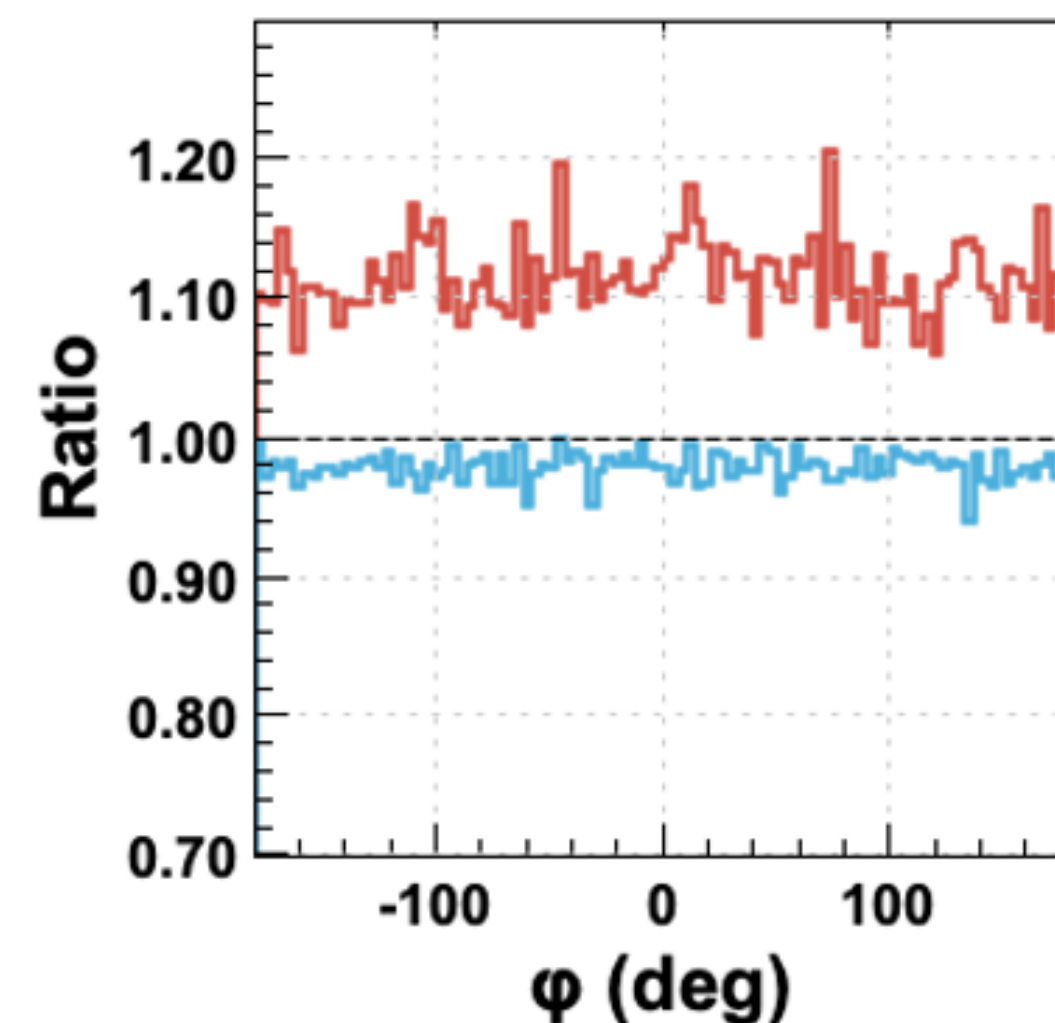
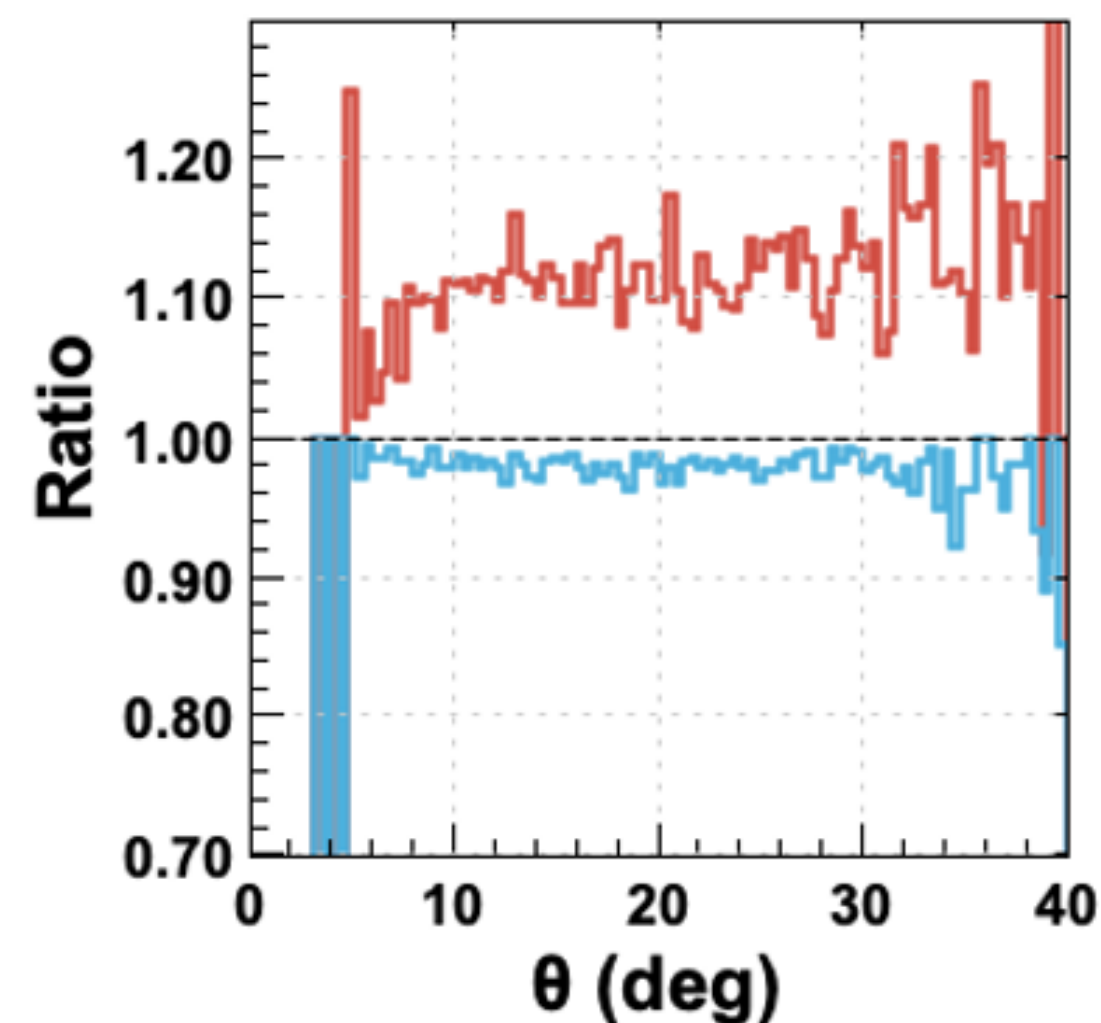
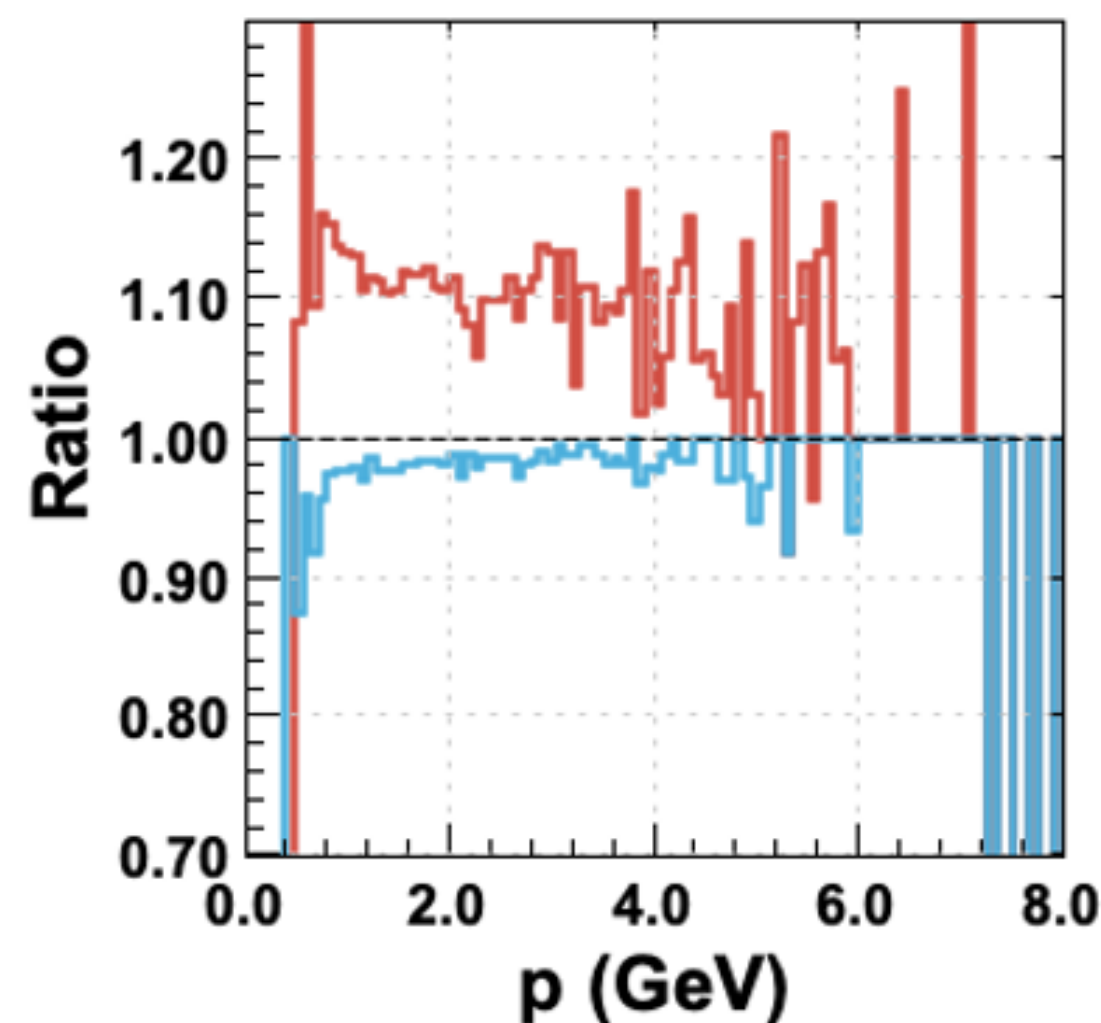
Average  $\sim 1.012$

Average  $\sim 0.988$

# AI Validation (MC) + 45 nA background

CLAS12 Tracking with Artificial Intelligence

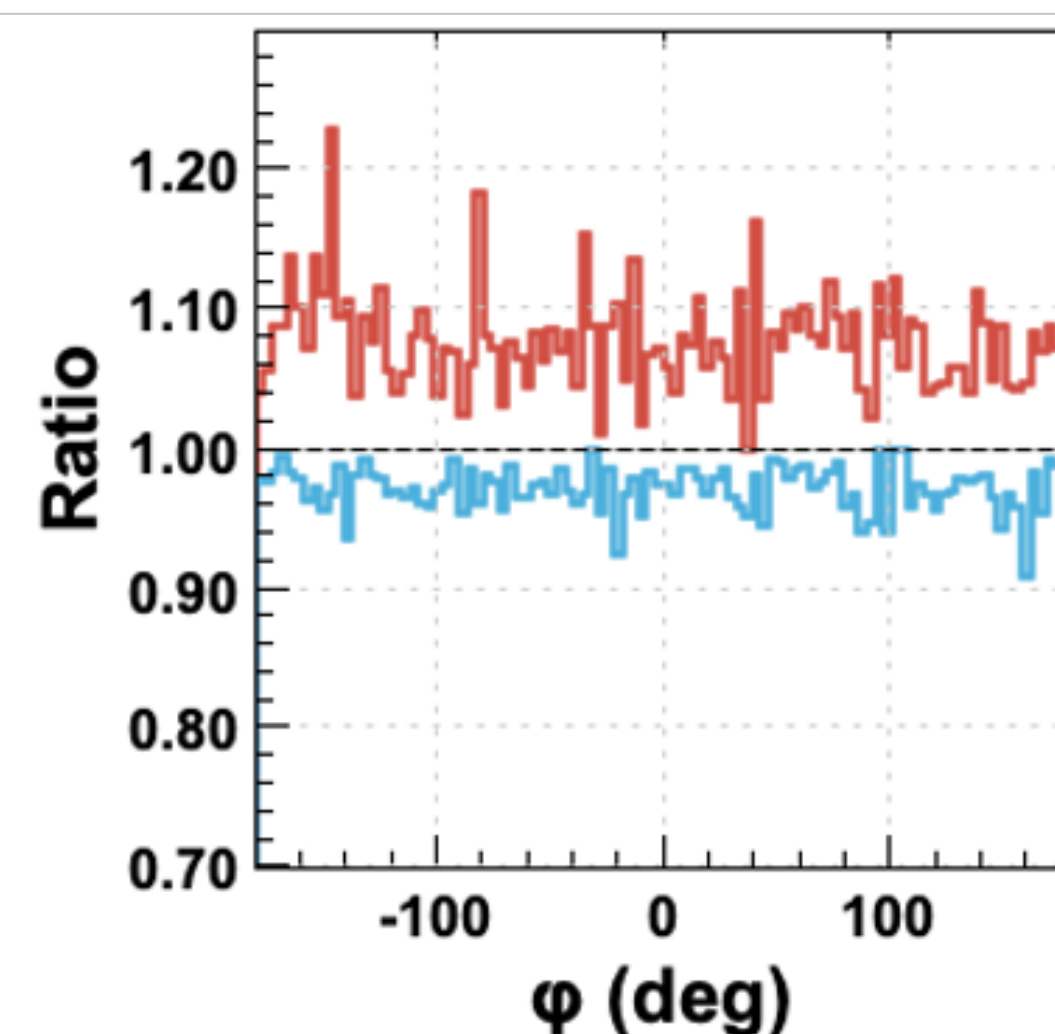
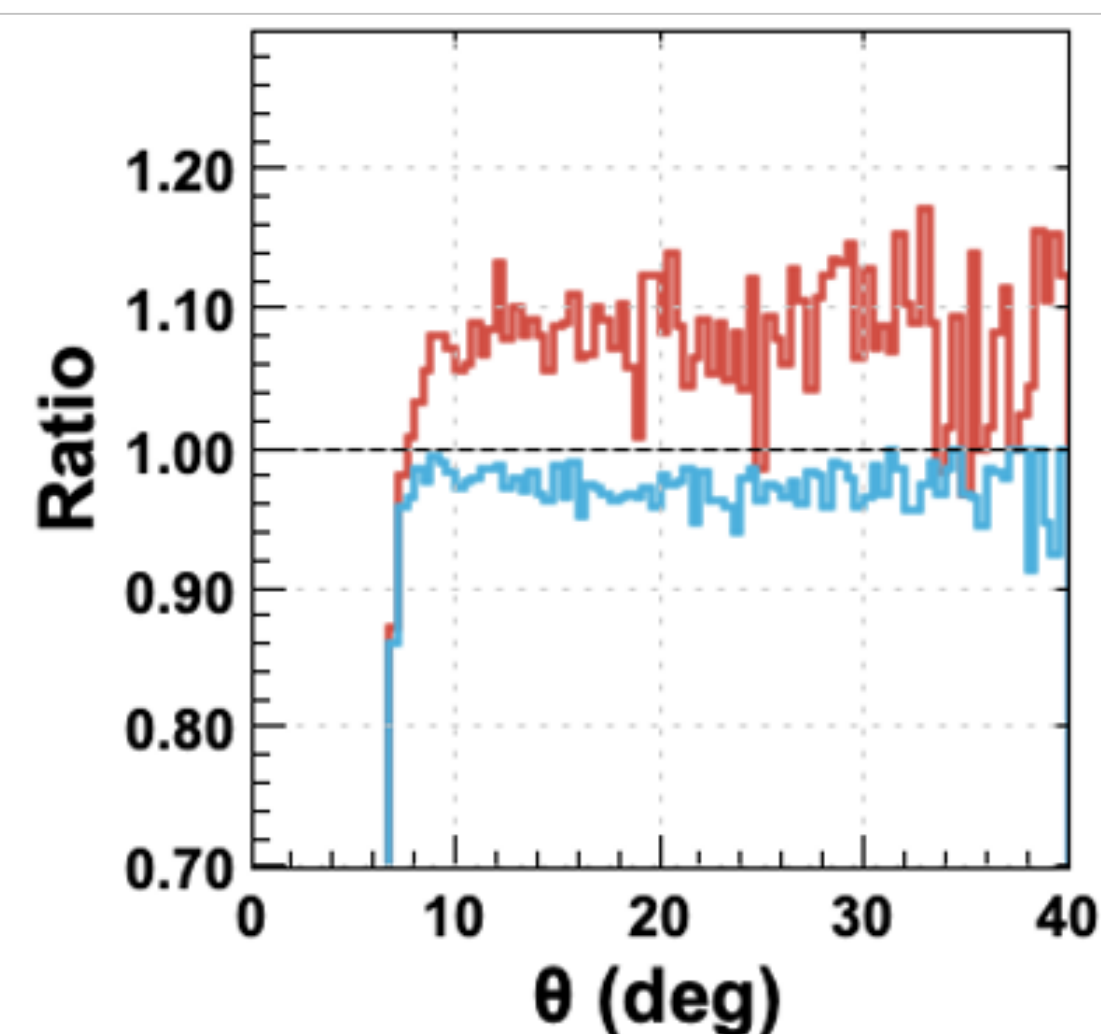
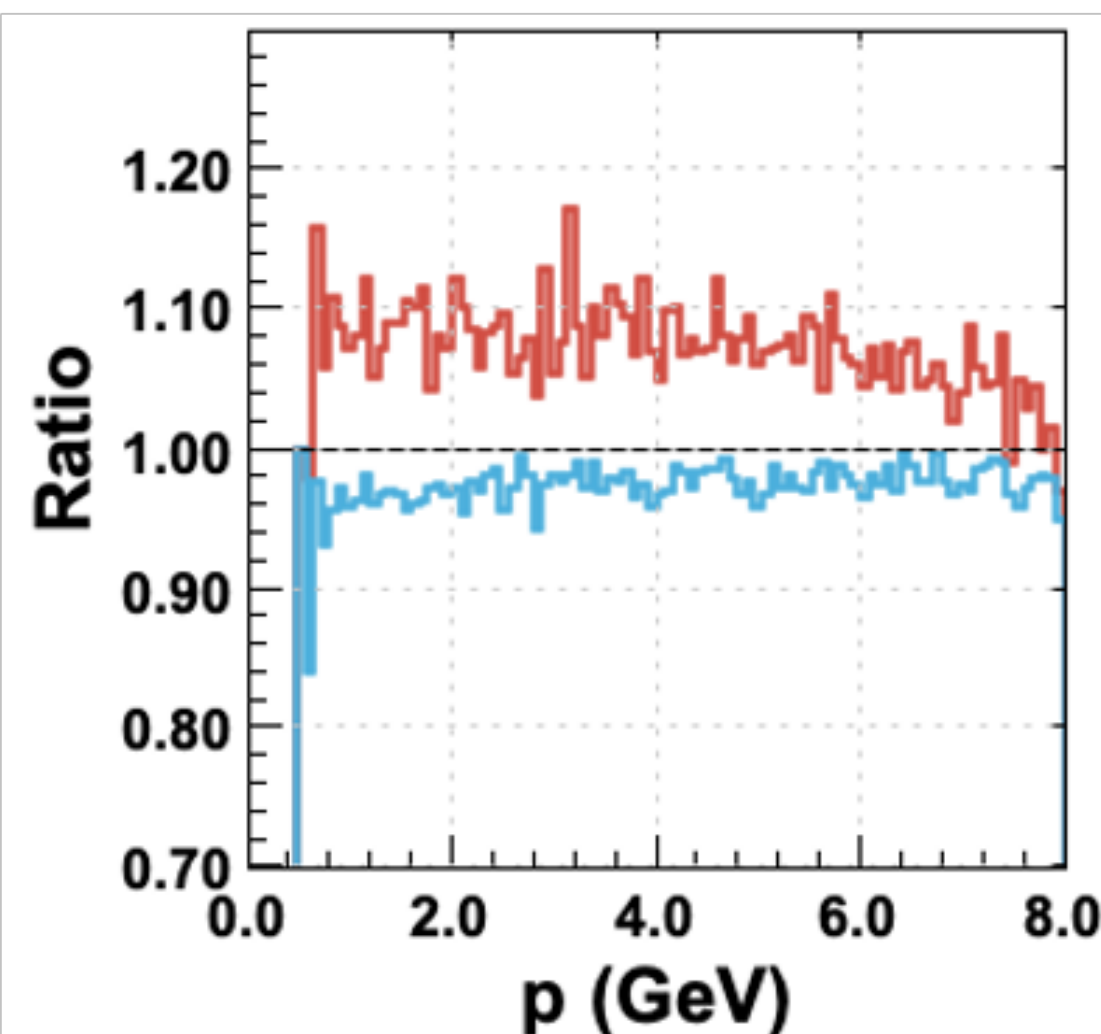
- Relative Gain , - Relative Efficiency



Positive

Average ~1.111

Average ~0.979



Negative

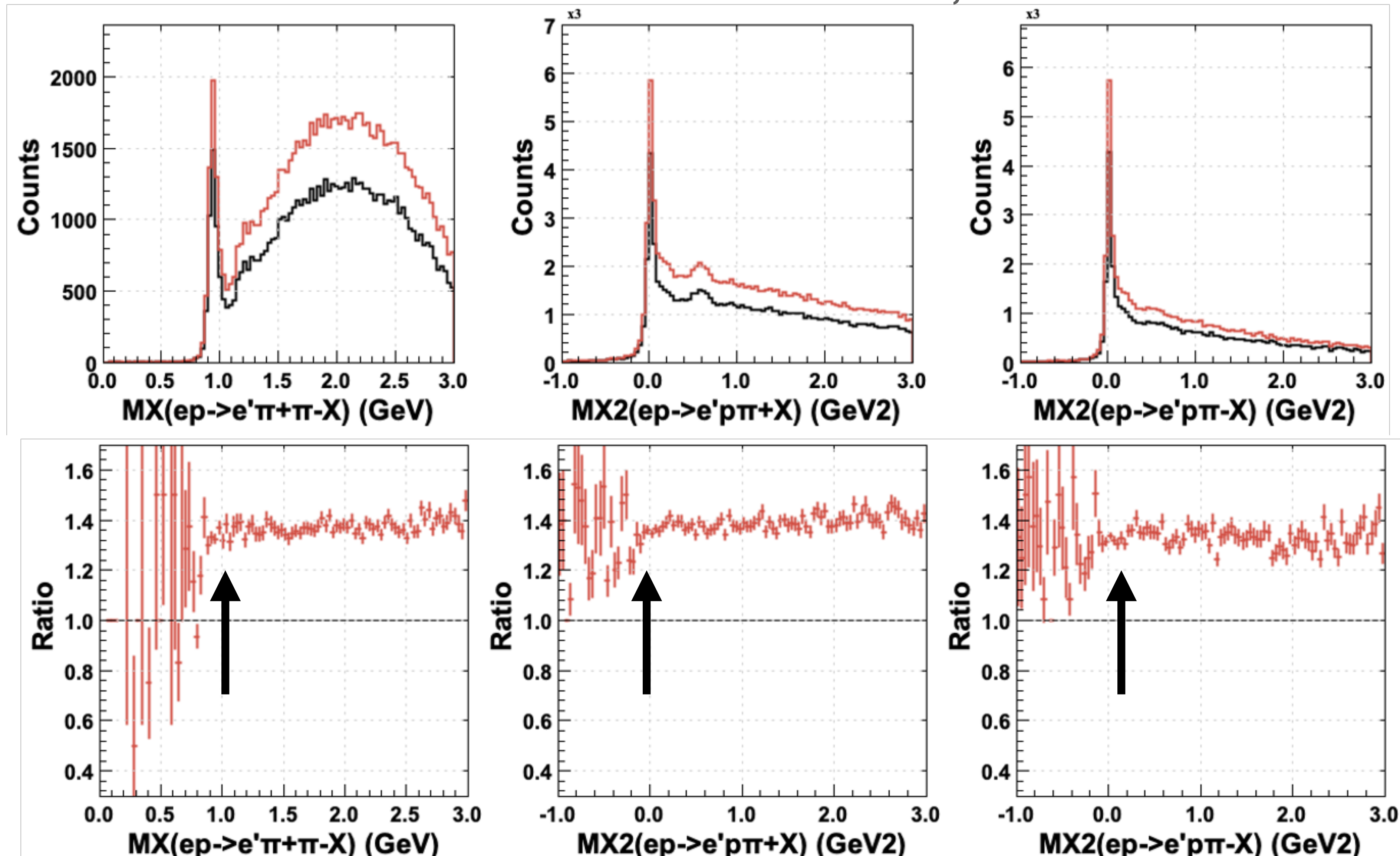
Average ~1.072

Average ~0.973

# AI Validation Physics impact

CLAS12 Tracking with Artificial Intelligence

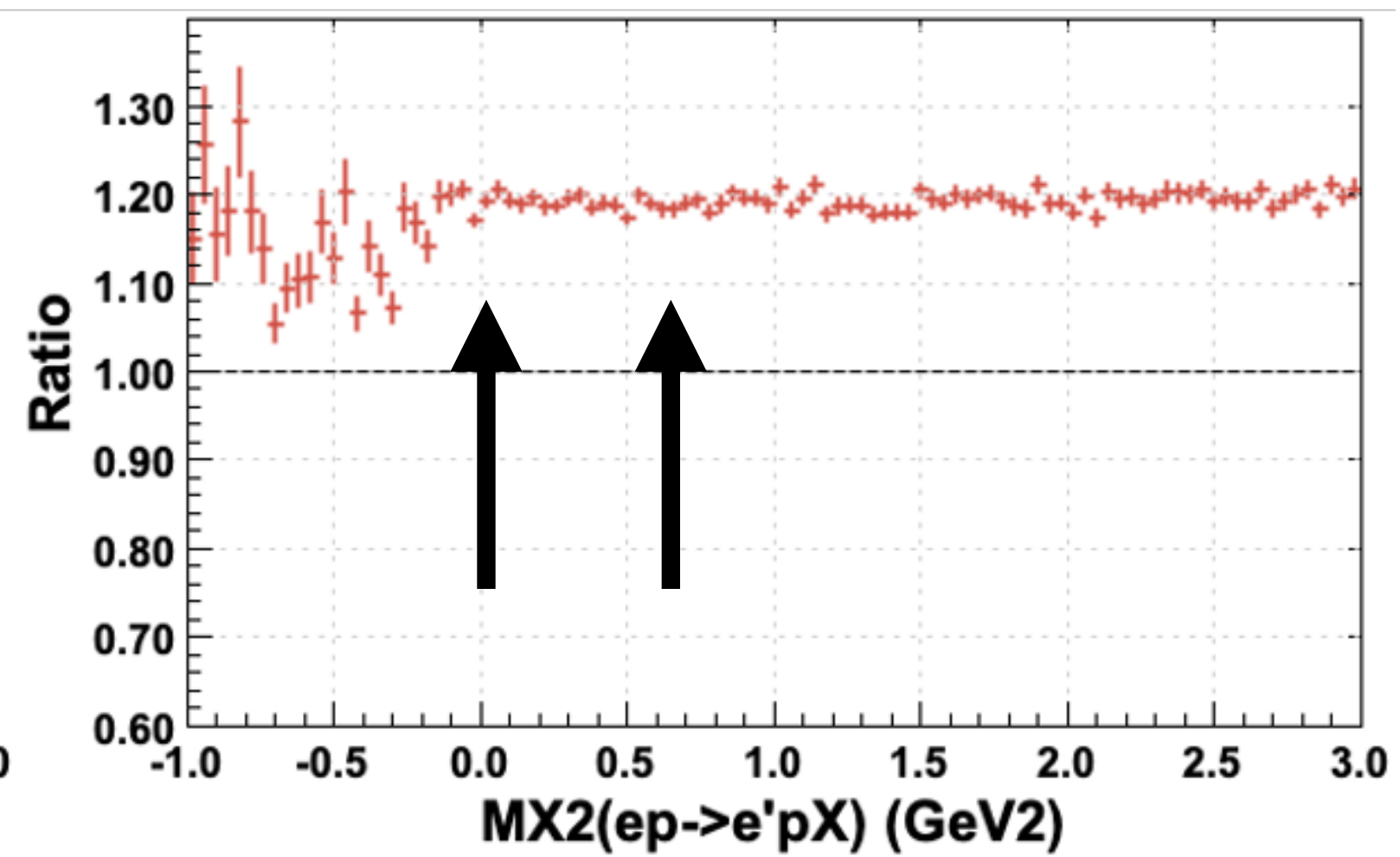
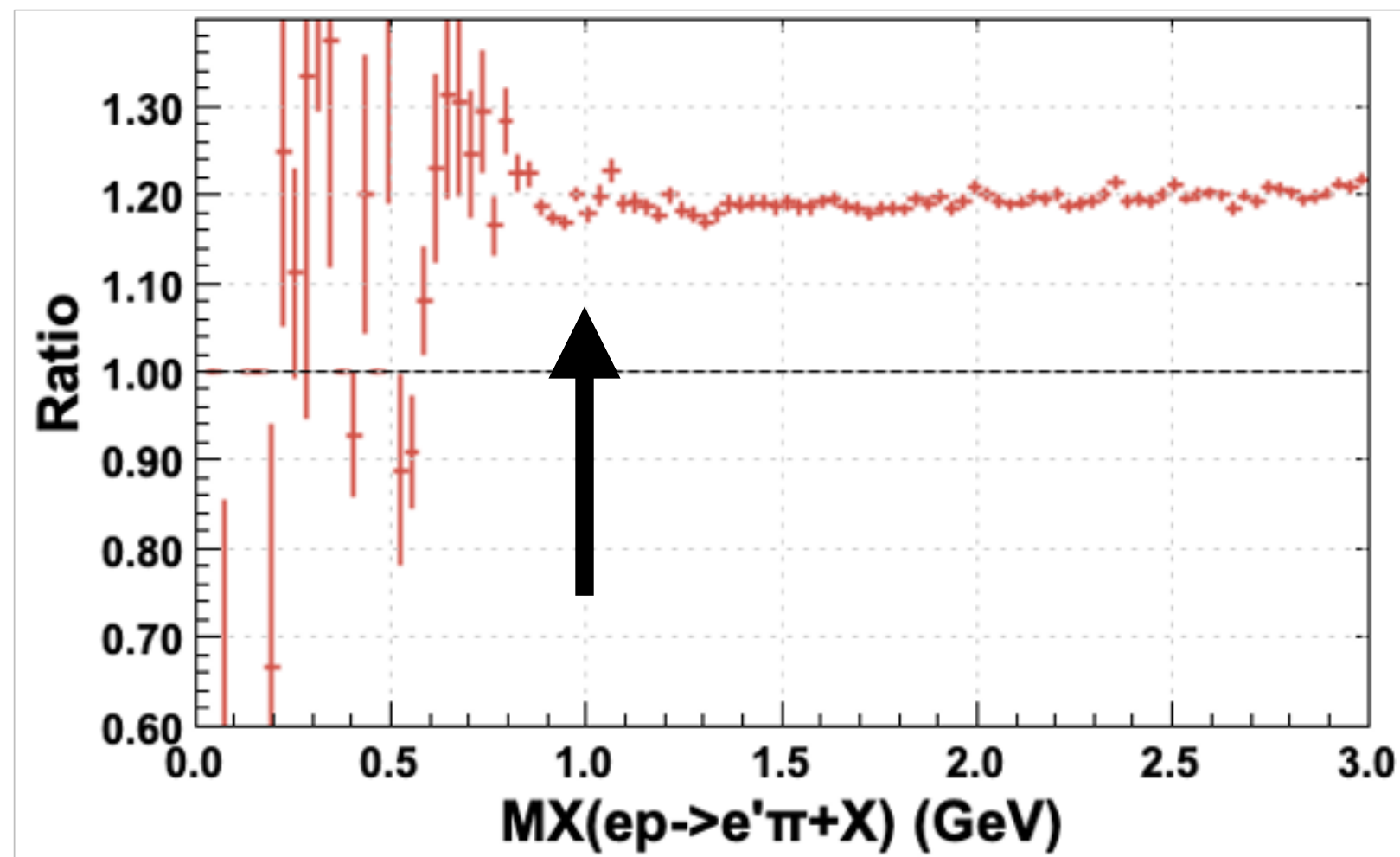
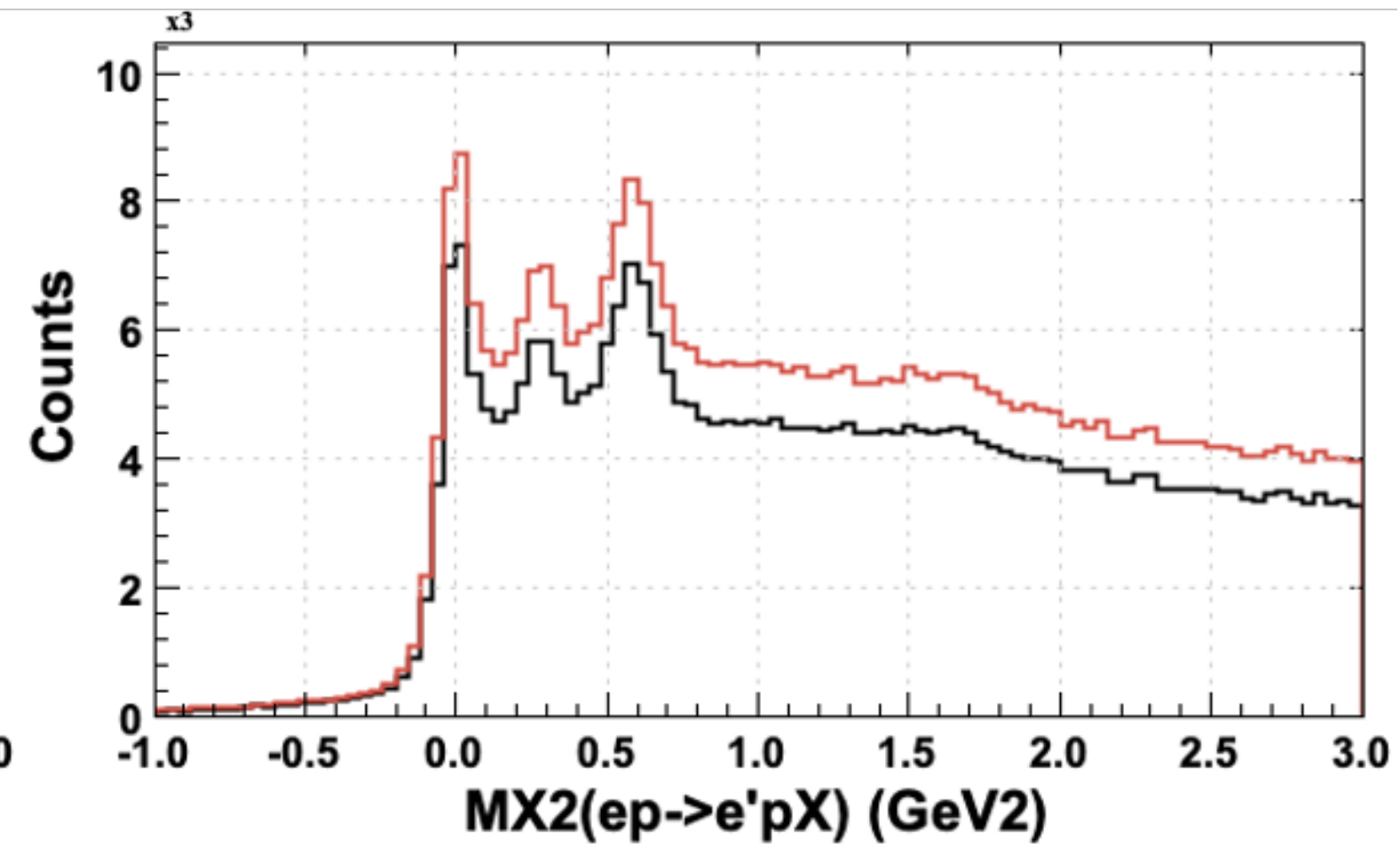
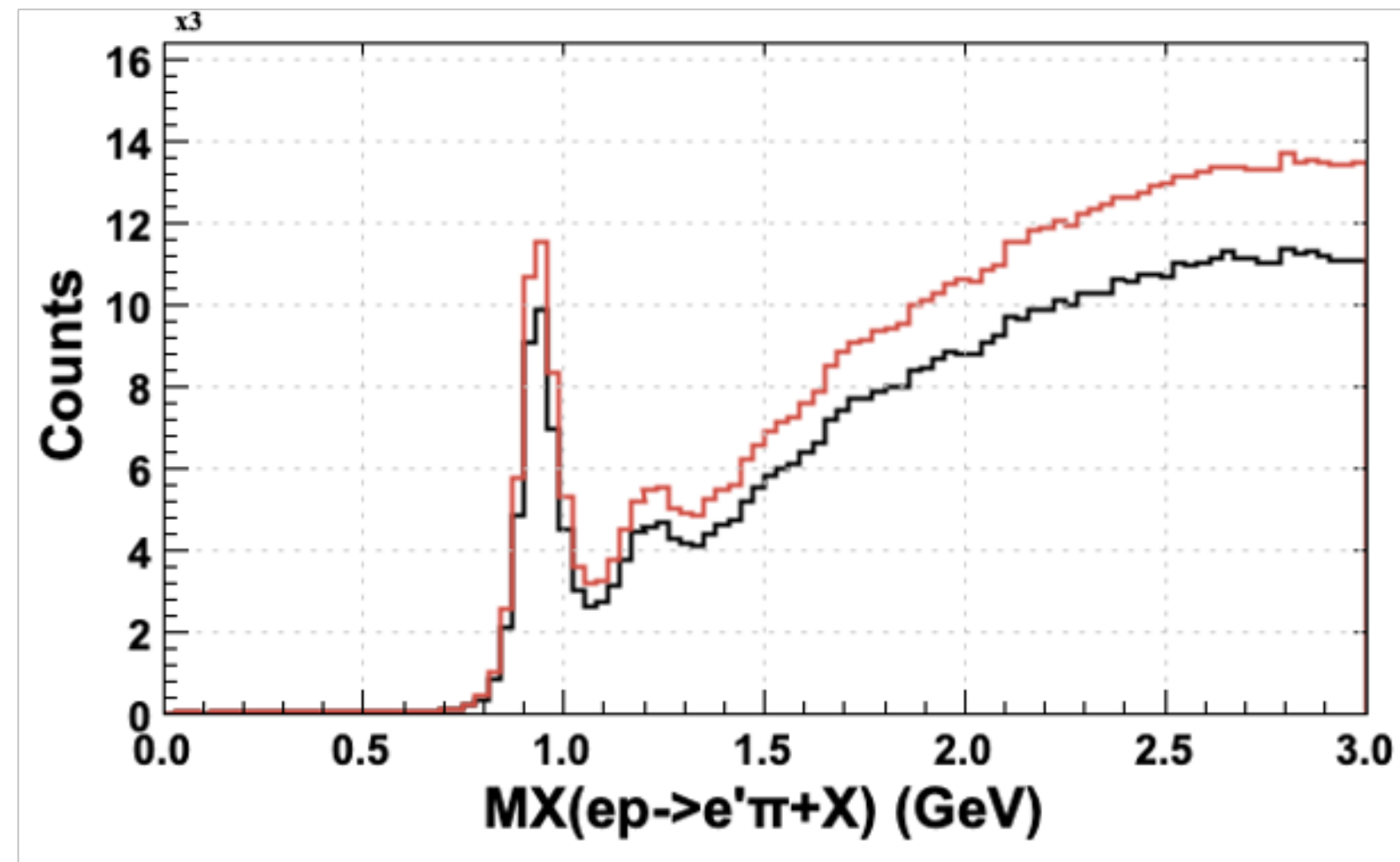
- AI tracks , - Conventional Tracks



# AI Validation Physics impact

## CLAS12 Tracking with Artificial Intelligence

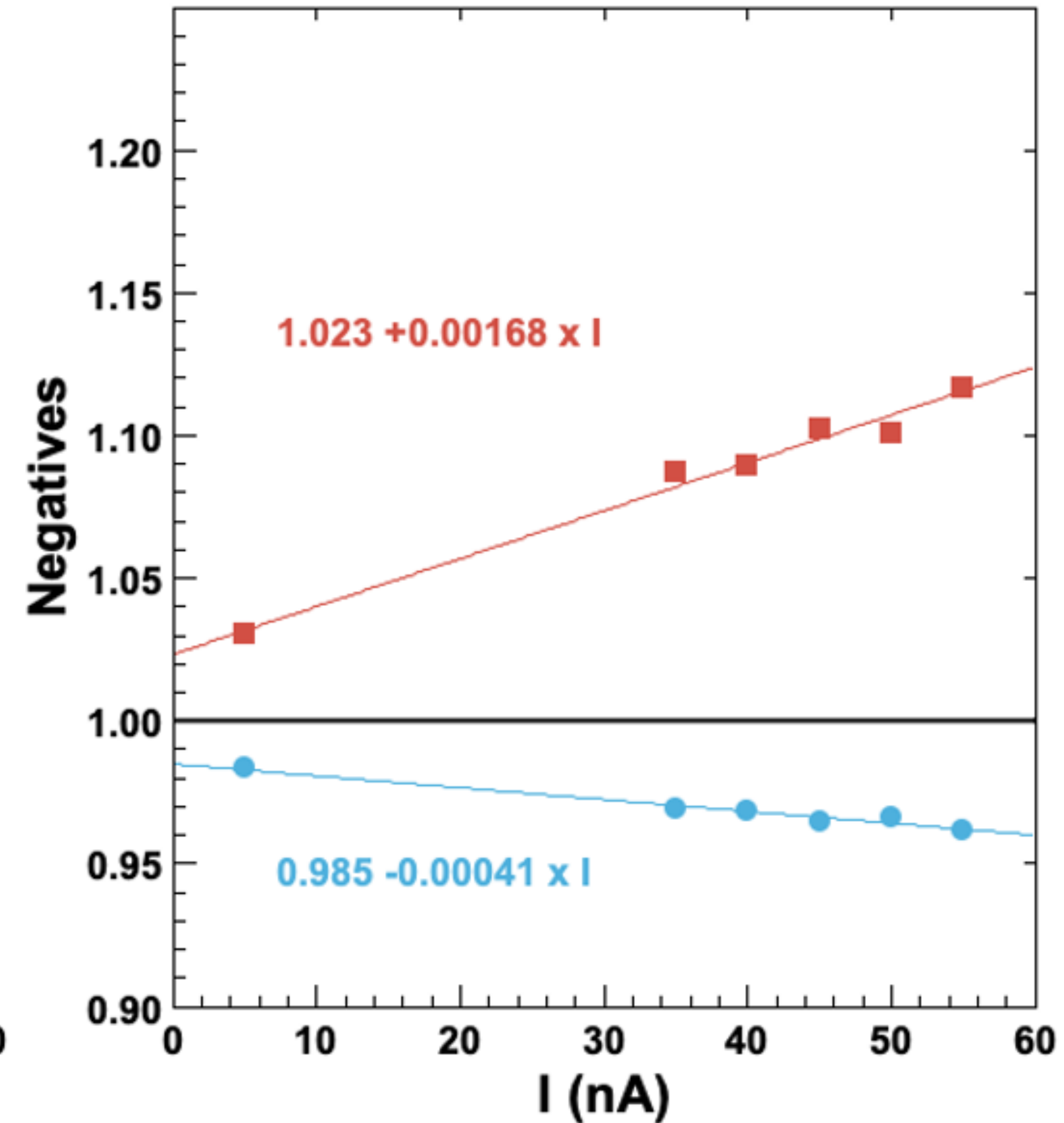
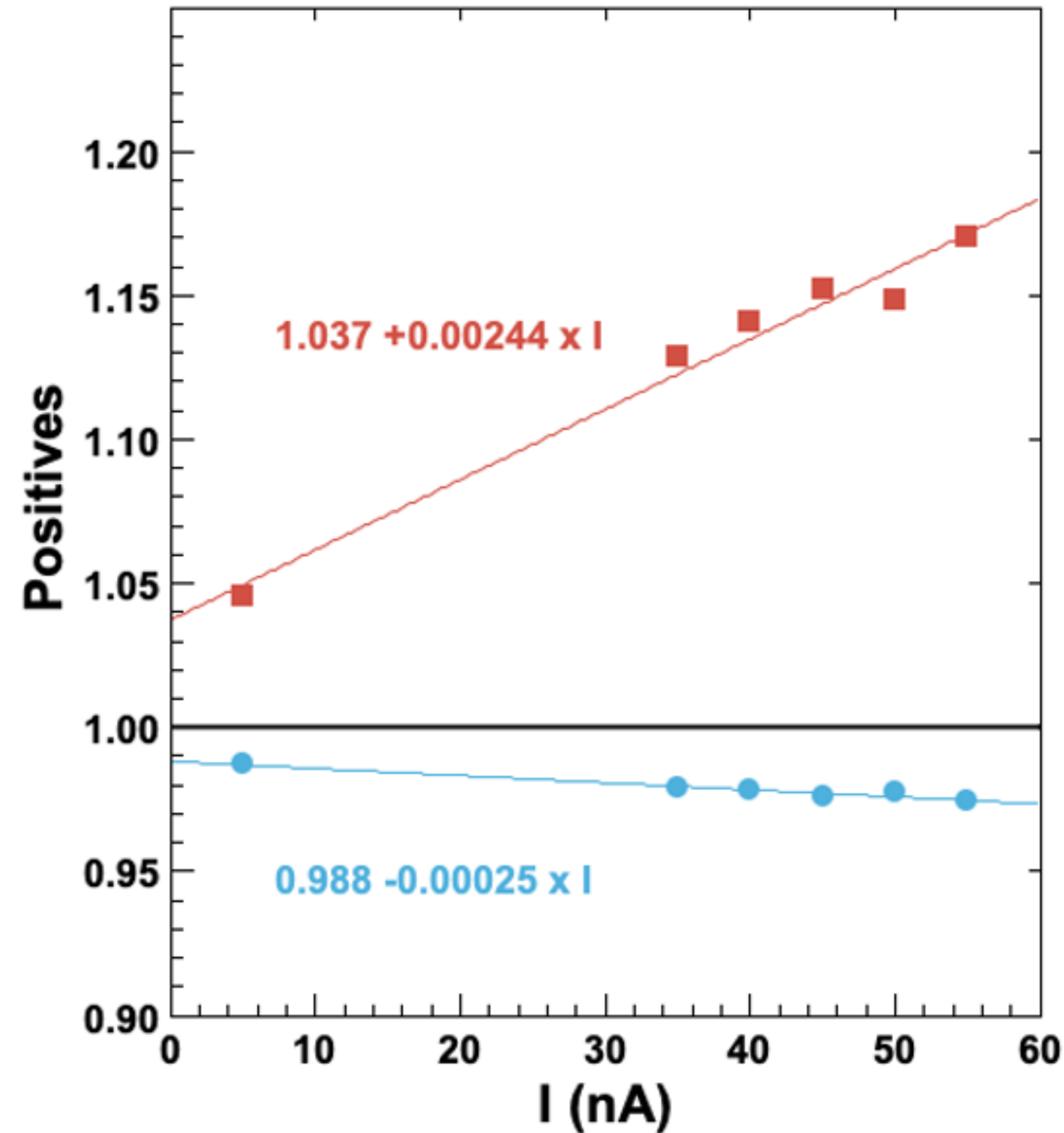
- AI tracks , - Conventional Tracks



# AI Validation Luminosity scan

## CLAS12 Tracking with Artificial Intelligence

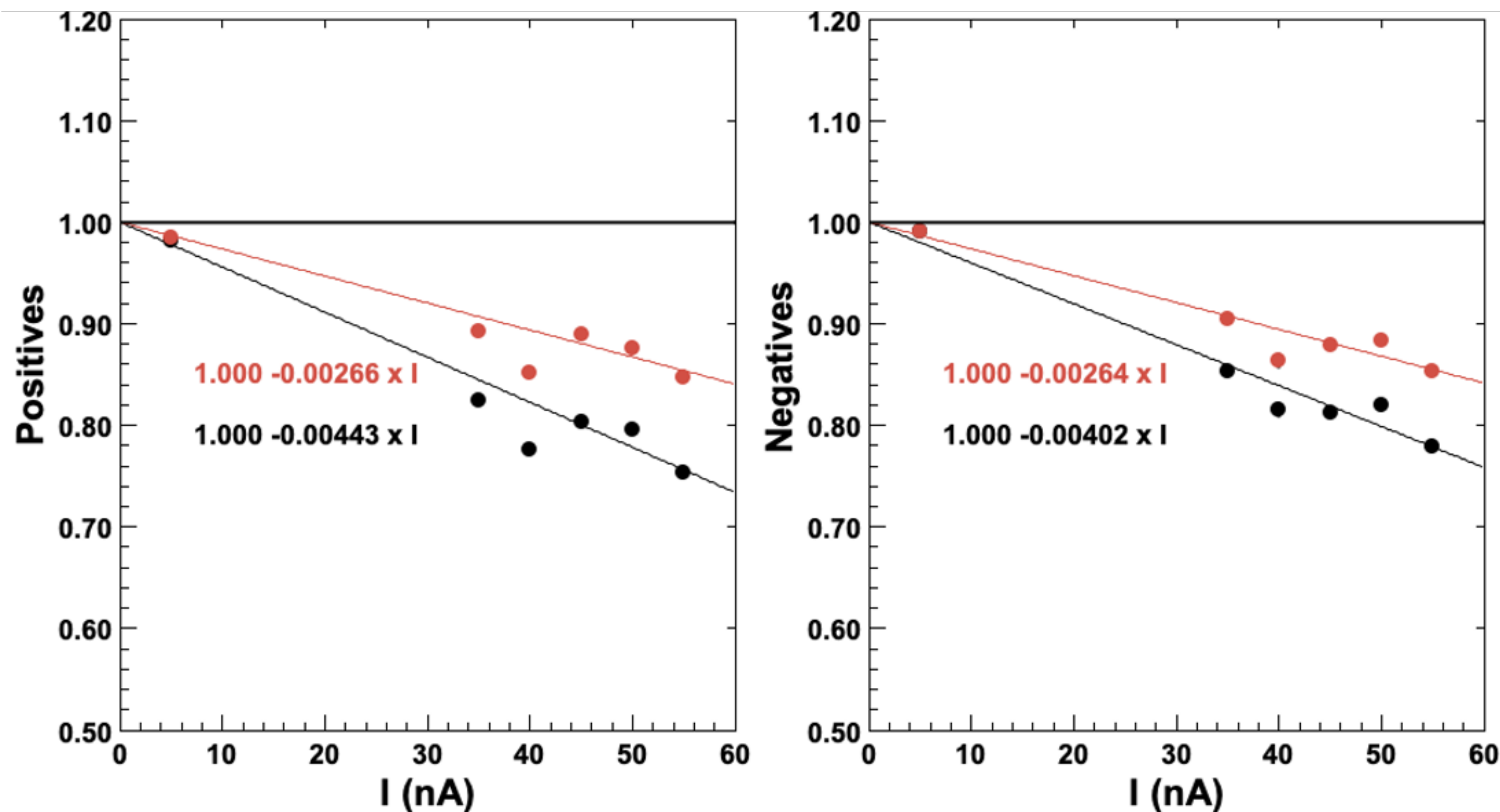
- Relative Gain , - Relative Efficiency



# AI Validation Physics impact

## CLAS12 Tracking with Artificial Intelligence

- **Absolute reconstruction efficiency** from ratio of  $eh^\pm/e$  as a function of beam current from RG-A inbending luminosity scan
- Runs: 5418 (5 nA), 5334 (35 nA), 5335 (40 nA), 5038 (45 nA), 5342 (50 nA), 5407 (55 na)

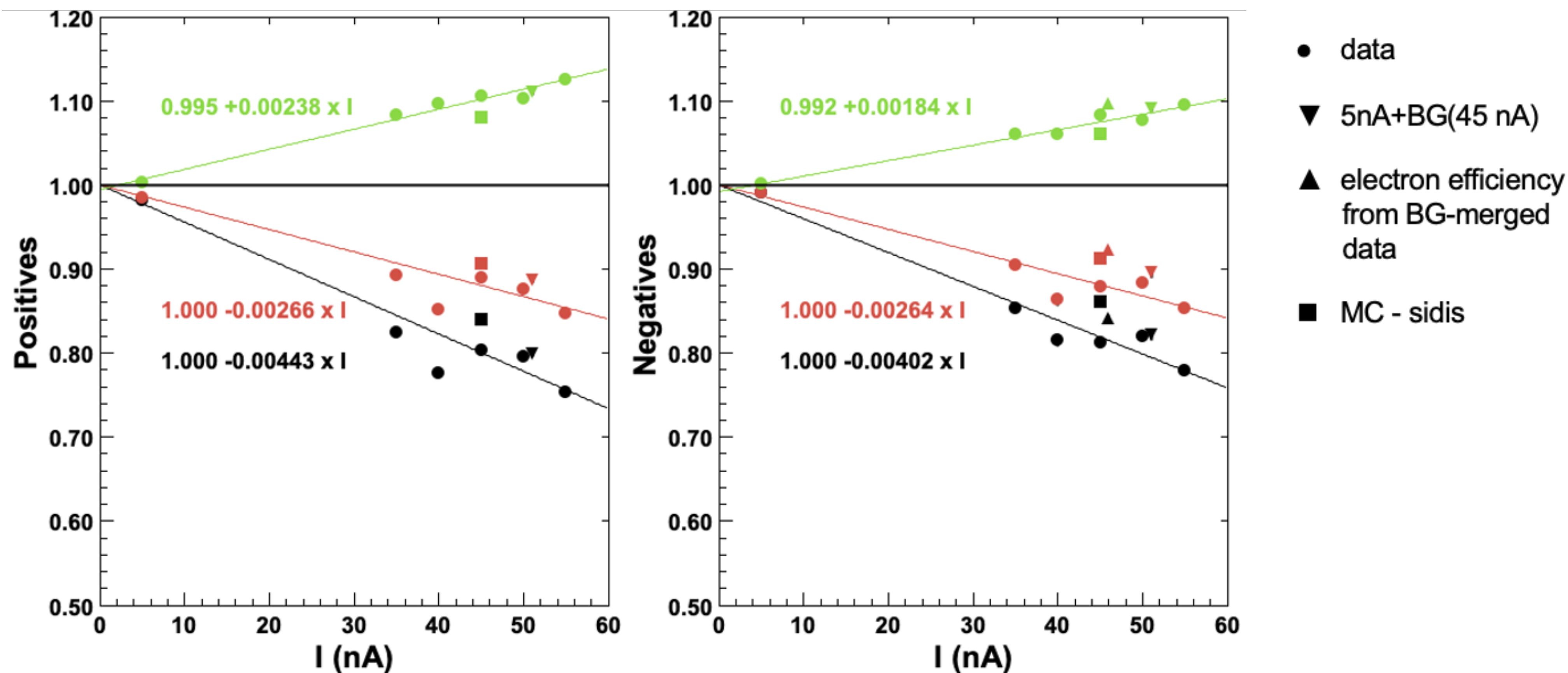




# AI Validation Physics impact

## CLAS12 Tracking with Artificial Intelligence

- **Absolute reconstruction efficiency** from ratio of  $eh^\pm/e$  as a function of beam current from RG-A inbending luminosity scan
- Runs: 5418 (5 nA), 5334 (35 nA), 5335 (40 nA), 5038 (45 nA), 5342 (50 nA), 5407 (55 nA)



# AI Tracking Reconstruction

## Process

- ▶ The AI track identification software was integrated with the standard reconstruction software.
- ▶ Tools are implemented for automated training and deploying trained network, documentation on CLAS12 wiki.
- ▶ Archiving software was developed for keeping run dependent (and flavor dependent) networks in organized form and can be used through YAML configuration.
  
- ▶ Studies with data indicate:
  - ▶ Efficiency (??) is above 98%.
  - ▶ Gain in number of tracks is sizable and is luminosity dependent and significant
  - ▶ The “goodness” of the gained tracks is confirmed by physics analysis
- ▶ Luminosity Scan analysis
  - ▶ Analysis of RG-A Fall 18 scan indicates a relative increase of 6% for negatives and 10% for positives in production conditions (45nA)
  - ▶ Analysis of low luminosity data (5nA) merged with background produces consistent results
- ▶ MC Analysis
  - ▶ Results from MC confirm AI provides higher tracking efficiency (consistent with data)
- ▶ The future with AI is here. (Also, the **reconstruction is 34% faster with AI track finding**)
- ▶ The AI reconstructed files will be distributed to analyzers soon to assess physics outcome improvements.

# BACKUP SLIDES