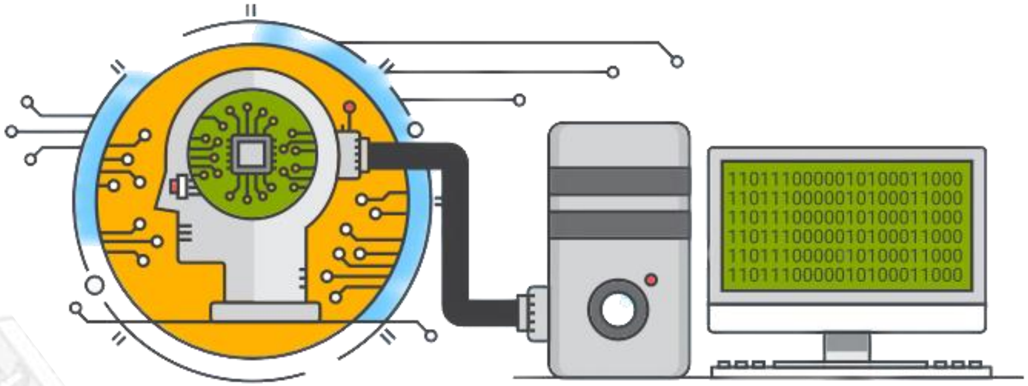
IWHSS-CPHI-2024, Yerevan, 30 September - 4 October 2024



Artificial Intelligence in CLAS12

Raffaella De Vita (Jefferson Lab)
for the CLAS Collaboration

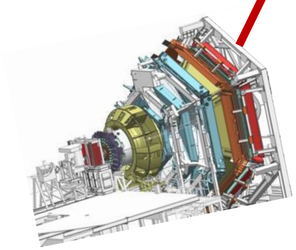
Introduction & Outline

- In recent years, the use of AI/ML tools in our field has grown progressively, with applications in
  - Simulations
  - Detector design
  - Accelerator operation
  - Detector monitoring and operation
  - Event reconstruction
  - Data analysis
  - Data preservation
  - …

- The CLAS12 experiment at Jefferson Lab has been leveraging AI/ML techniques to enhance its performance, from online data-taking, to offline reconstruction and data analysis. In this talk:
  - Charged particle tracking in high-background conditions to increase detection efficiency and allow high-luminosity operation
  - Fast online event reconstruction for highly selective software trigger
  - Real-time detector monitoring and fault identification
  - Signal-background separation in physics analysis

- A few notes:
  - I am not an AI expert…
  - Results based on the work of many within the CLAS Collaboration and Jlab staff
  - Thanks to G. Gavalian for all the presentation material

Jefferson Lab @ 12 GeV



- Accelerator Upgrade completed in September 2017
  - CW electron beam
  - E_{max} = 12 GeV, I_{max} = 90 mA, Pol_{max} ~ 90%
- Physics Operation
  - 4 halls running simultaneously since January 2018

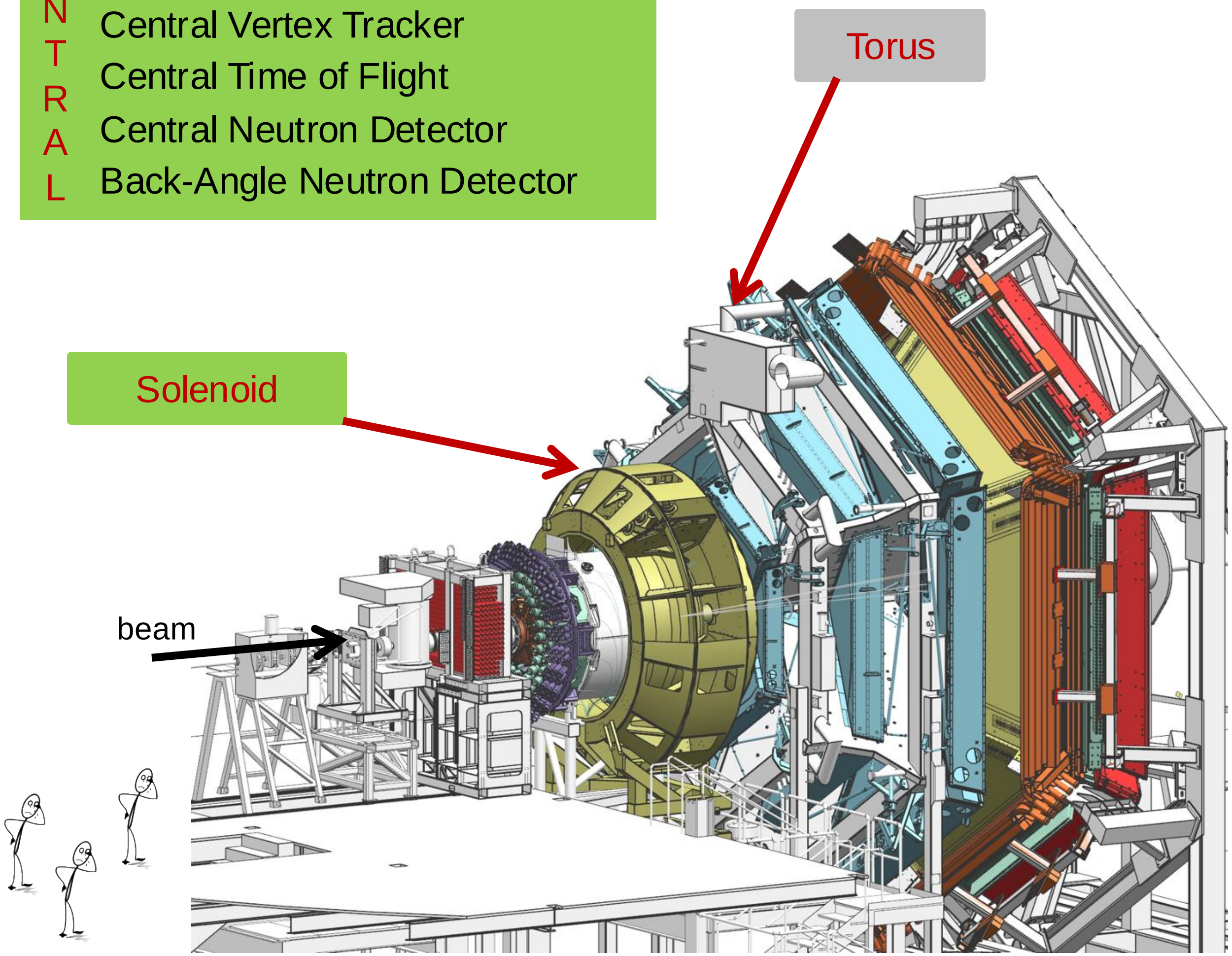
CLAS12

C E N T R A L

- Beamline
- Target
- Central Vertex Tracker
- Central Time of Flight
- Central Neutron Detector
- Back-Angle Neutron Detector

F O R W A R D

- High Threshold Cherenkov
- Forward Tagger
- Drift Chambers
- Low Threshold Cherenkov
- Ring Imaging Cherenkov
- Forward Time of Flight
- EM Calorimeter

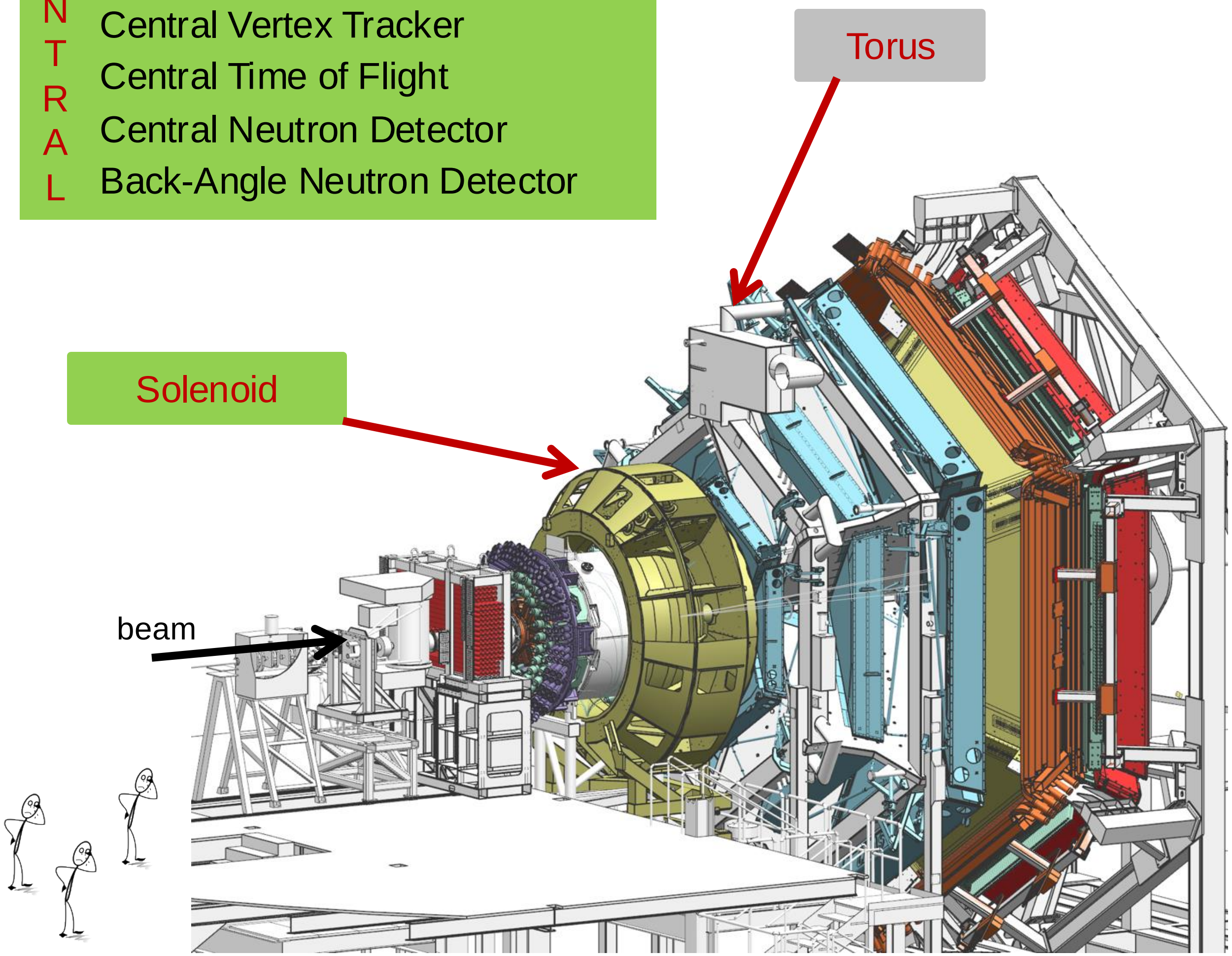


	Forward	Central
Angular coverage	5º – 35º	35º – 135º
Momentum resolution	dp/p < 1%	dp/p < 5%
θ resolution	1 mrad	5 – 10 mrad
ϕ resolution	1 mrad/sinθ	5 mrad/sinθ

CLAS12

C	Beamline
E	Target
N	Central Vertex Tracker
T	Central Time of Flight
R	Central Neutron Detector
A	Back-Angle Neutron Detector
L	

F	High Threshold Cherenkov
O	Forward Tagger
R	Drift Chambers
W	Low Threshold Cherenkov
A	Ring Imaging Cherenkov
R	Forward Time of Flight
D	EM Calorimeter



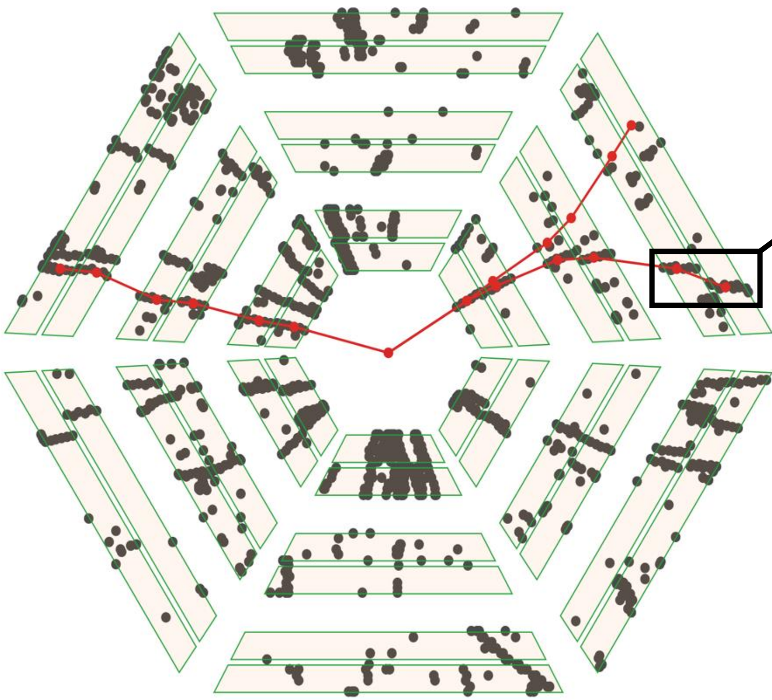
- Readout channels >100000
- Luminosity $10^{35} cm^{-2} s^{-1}$ limited by detector occupancy due to beam-related background
- Trigger rate up to 25 kHz (>> rates of reactions of interest)
- Data rate ~500 MB/s
- Data size ~1 PB/y
- Large acceptance for both charged and neutral particles

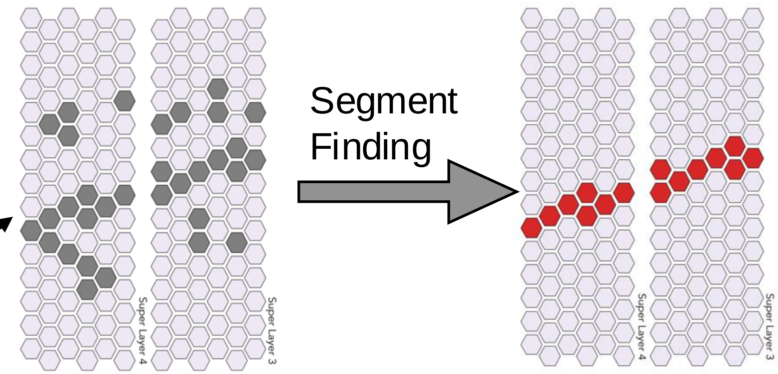
→ **Ideal for studying multiparticle final states with small cross-sections**

Forward-detector tracking

Drift chambers:

- 6 sectors with 3 regions in each sector
- 12 wire planes in each region grouped in 2 superlayers with 6-degree stereo angle
- 112 wires per plane, hexagonal cells





(Conventional) Tracking:

- Find segments in each superlayer
- Combine segments into track candidates
- Identify the correct combinations among the candidates
- Fit the candidates to determine the particle 3-momentum (Kalman-Filter)

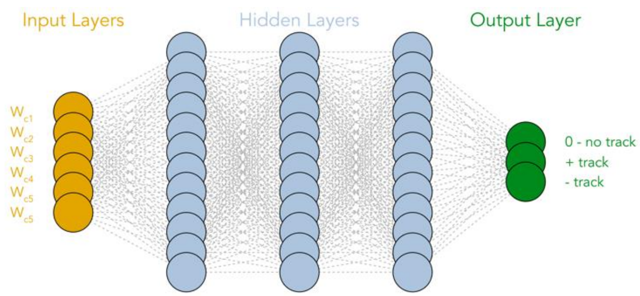
Challenges:

- Separated true hits from background in segment finding
- Limit the number of track candidates that are fitted
- Maximize the efficiency and reduce the processing time

AI/ML in track finding

First inefficiency that was addressed is in "track finding", i.e. linking segments into tracks

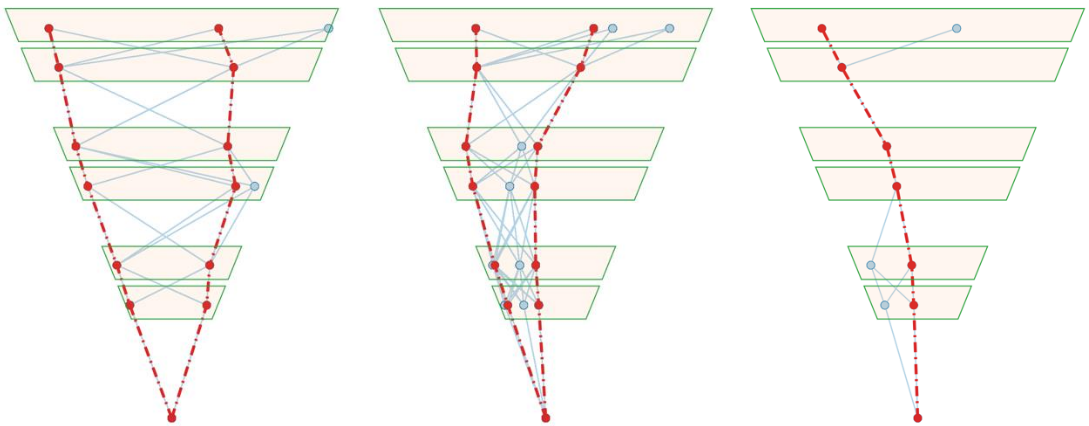
- In conventional tracking, done building and fitting all combinations with minimal cuts
- Slow and inaccurate when only wire positions are used



- Input: W [1..6] - average wire position of the segment
- Output: [false track, positive track, negative track]

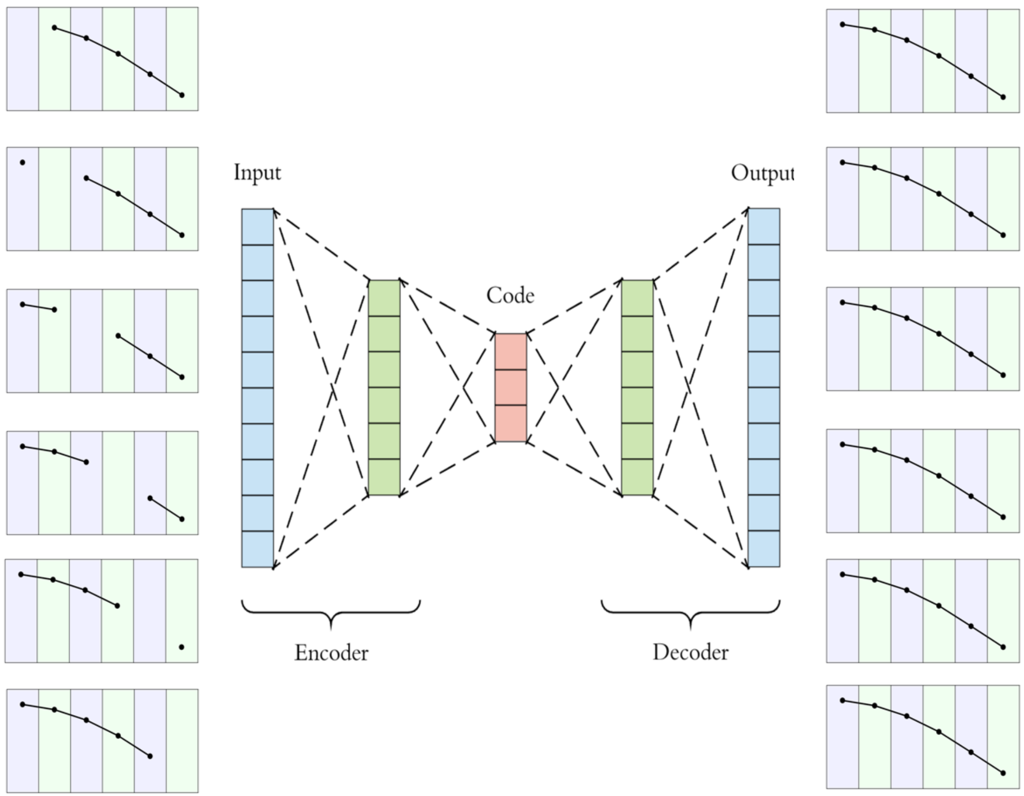
With AI, a neural network is used to recognize segments' combinations of real tracks:

- The track classifier assigns a probability of the track candidate to be a positive, a negative, or a false track.
- The network is trained on reconstructed data where the right combinations are determined with the conventional algorithm
- False combinations of segments are generated by interchanging clusters from different tracks



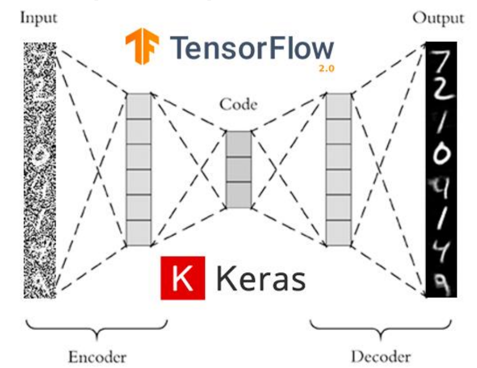
AI/ML in track finding

- Allow for a **missing superlayer segment** to improve tracking efficiency
- Use **Corruption Auto-Encoders** to find the position of the missing segment

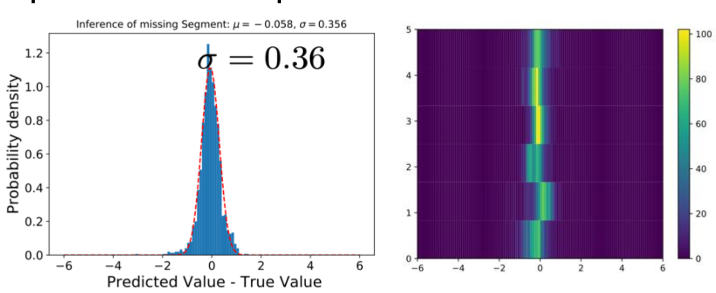


Good, 6-superlayers, reconstructed tracks are used to generate training samples by removing one of the segments

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 wires

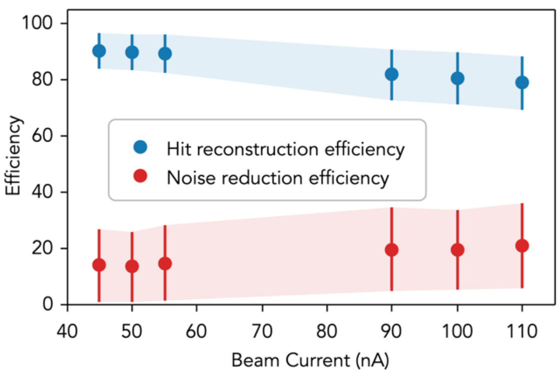


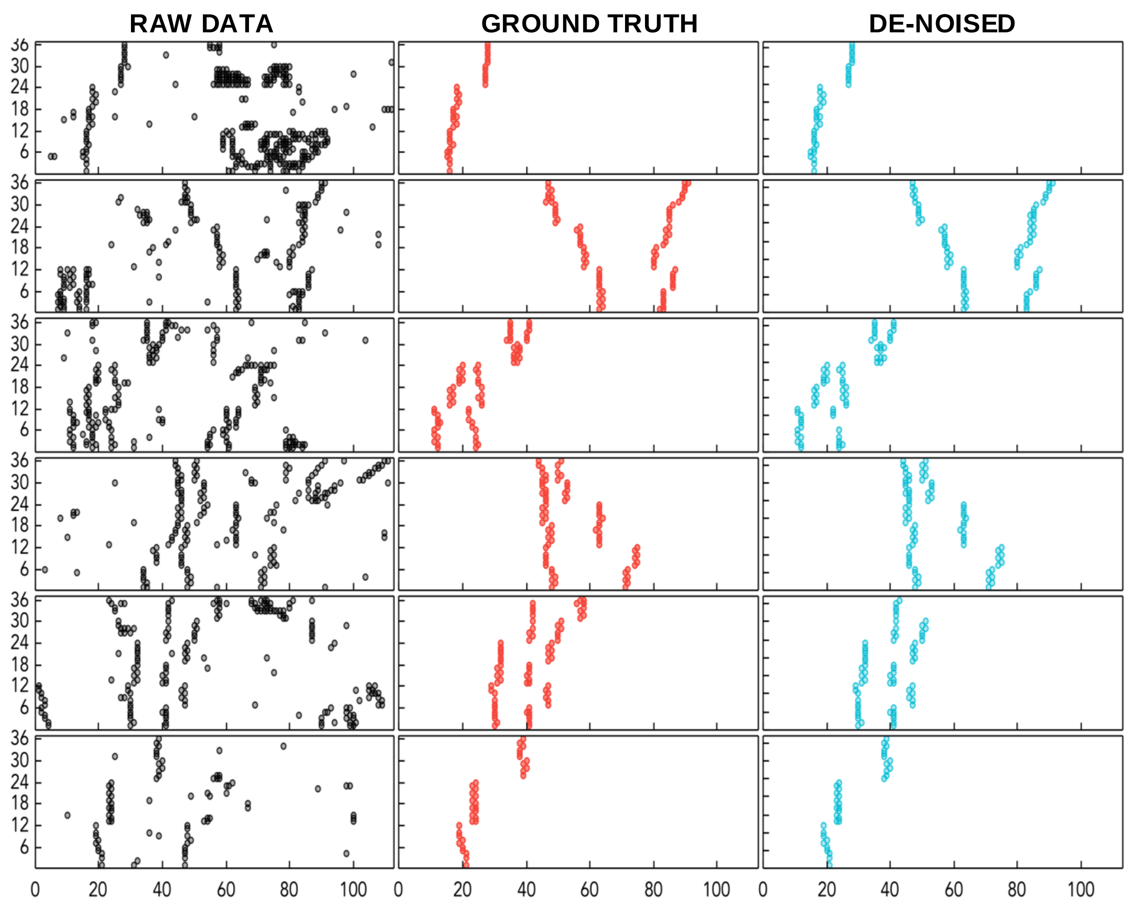
“De-noising”

A Convolutional Auto-Encoder is also used to **de-noise** drift chamber raw data

- The network is trained on reconstructed data, separating hits-on-track among raw hits
- The resulting model can isolate hits that potentially belong to valid tracks from the background
- Large background reduction at the expense of some hit loss

Network Performance





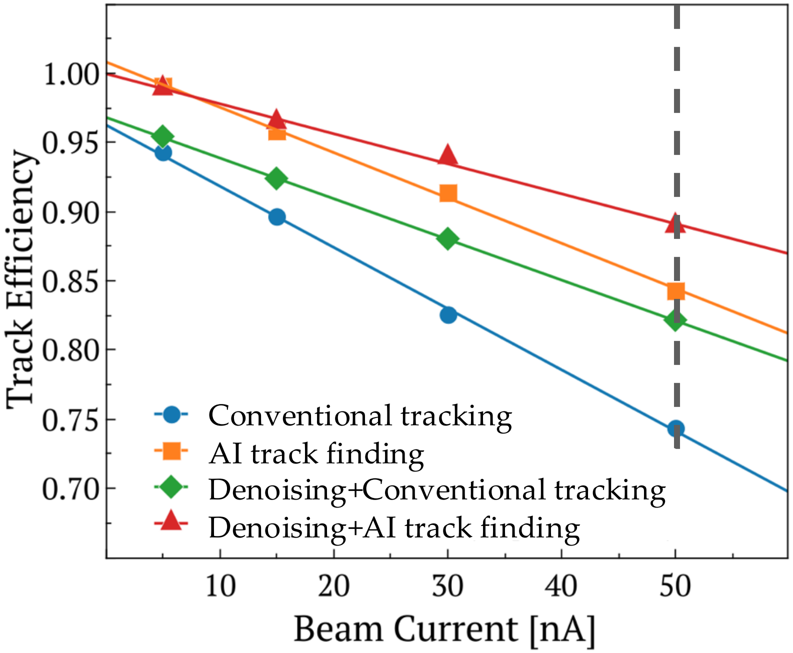
Performance and impact on physics

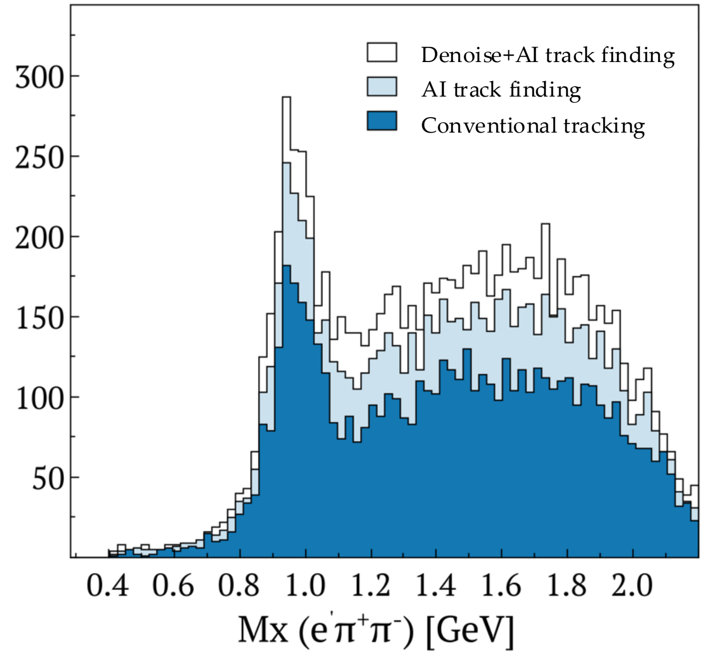
Performance of AI-based vs. conventional tracking algorithms studied in detail:

- Event-by-event comparison of reconstructed tracks to determine the relative efficiency and gain
- Dependence of luminosity of track multiplicities to estimate absolute efficiency
- Processing time

~18% gain per track
>50% gain per event, in 3-tracks final states
>30% reduction in overall processing time

Typical current on LH2 target
($\mathcal{L}$~0.7 x $10^{35}cm^{-2}s^{-1}$)

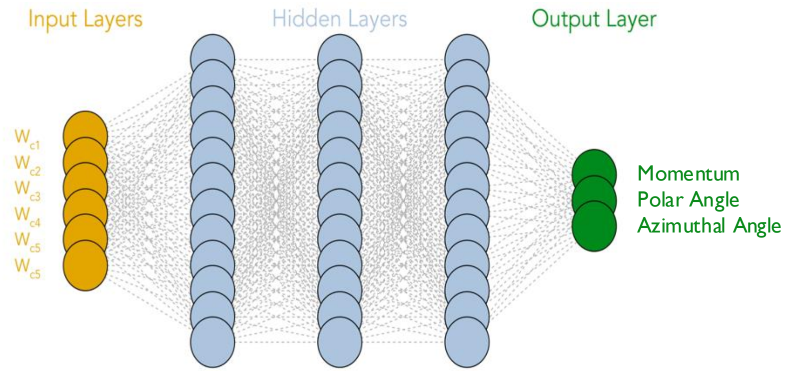




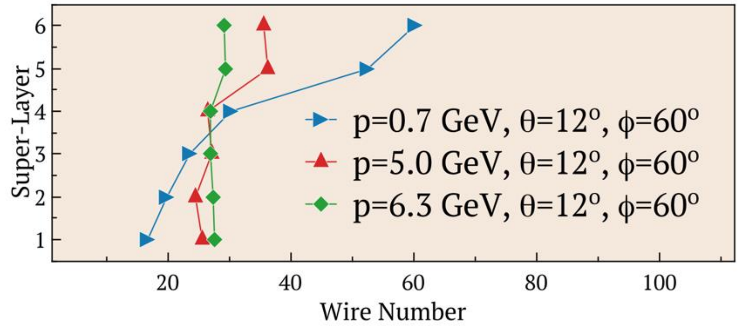
New developments: InstaRec

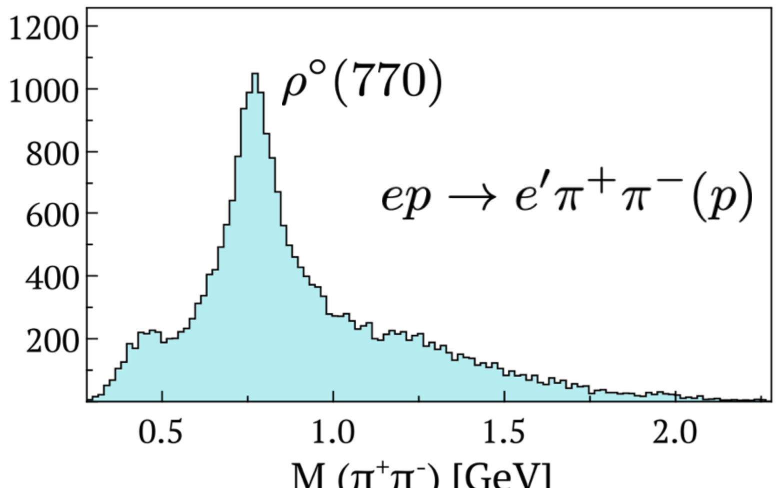
Move towards full event reconstruction:

- **Predict track 3-momentum**
- Link tracks to hits/clusters in Cherenkov detectors, ToF, and calorimeters to determine particle ID



Input: W [1..6] - average wire position of the segment
Output: track momentum and angles





- Reconstruction rates of tens of kHz on a single CPU
  - Comparable to current triggered DAQ rate
- Possibility for:
  - Extensive online data quality monitoring
  - Real-time event filtering for high-rate triggerless DAQ
  - Event tagging for fast data processing/analysis
  - …

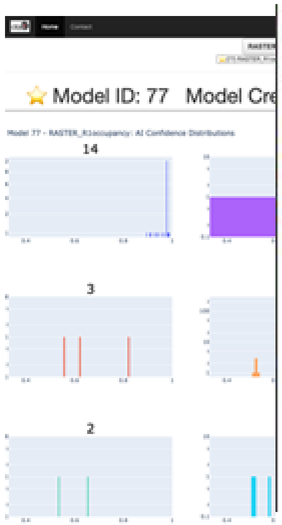
AI/ML for data monitoring

HYDRA

Front-End components

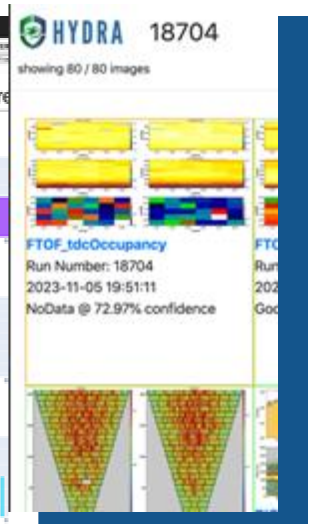
Data Labeler

Efficiently label hundreds (thousands) of images



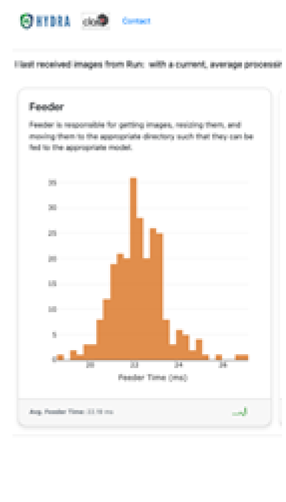
Library

Contains enhanced confusion matrix, thresholds, active model designations



Run

See predictions in real time



Status

Monitor heartbeats for back end processes and image processing time

Grafana

Dashboard displays all predictions over time

Log

Display concerning plots sorted by detector from previous day

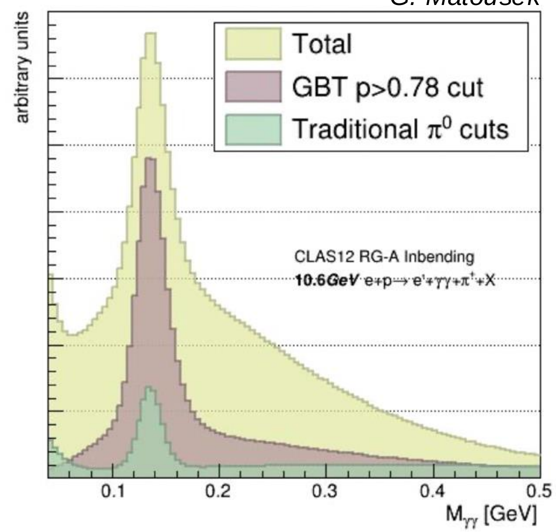
Extensible framework for real-time data quality monitoring using computer vision
Initially developed for Hall D/Gluex, then adopted by Hall B/CLAS12, now deployed in the 4 Halls

Supported by JLab EPSCI group

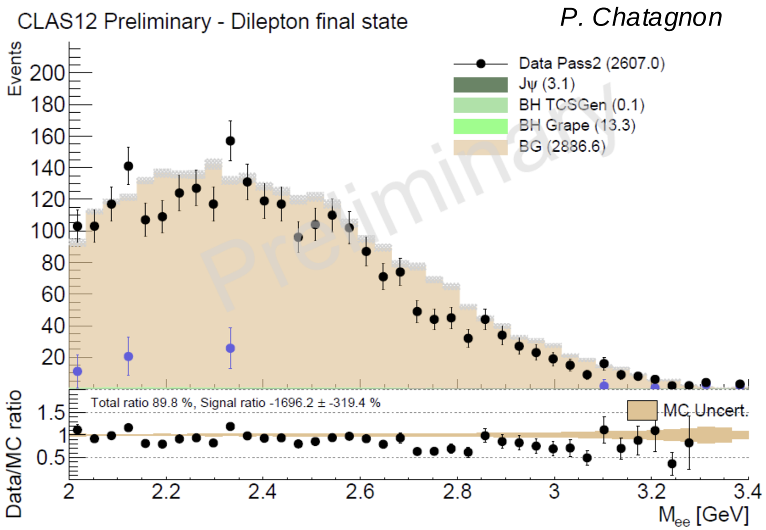
AI/ML in data analysis

- Increasing use of AI/ML to solve complex, multiparametric problems in physics analysis
- Some examples:
  - Modeling Dilepton Background using Boosted Decision Trees
  - Lepton Identification using TMVA Methods
  - Gradient Boosted Decision Trees for photon classification
  - Neutron identification in the central detector
  - …
- AI group established within the collaboration to share tools, know-how, …

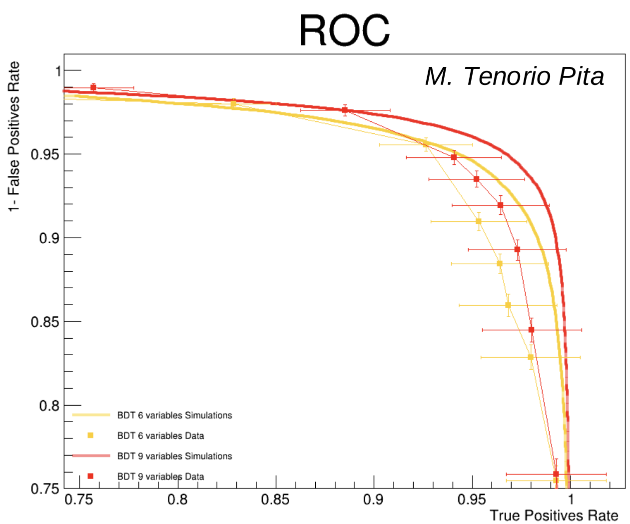
G. Matousek



P. Chatagnon



M. Tenorio Pita



Summary

- AI/ML tools are used in CLAS12 to support data taking, reconstruction, and analysis
- Large impact on experiment performance
- Further development in progress, aiming at real-time event reconstruction for event selection and data reduction in future high-luminosity runs
- Progressively increasing use of AI/ML techniques in data analysis to solve complex, multiparametric problems