Artificial Intelligence in CLAS12

Artificial Intelligence/Machine Learning for Physics Applications

G.Gavalian (Jefferson Lab)



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Outlook

Machine Learning in CLAS12

Charged Particle Tracking

- Track identification in Drift Chambers
- Drift Chamber Data De-Noising
- Track Parameter reconstruction with Machine Learning
- Level-3 Trigger
 - Data reduction with online electron identification with AI
- RICH Cherenkov Particle Identification
 - Particle Identification



Outlook

ChatGPTgets real



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Can you write a code to fill a histogram with gaussian distribution and fit it for GROOT?

Will insisted



Outlook

ChatGPT

Can you write a code to fill a histogram with gaussian distribution and fit it with GROOT?



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chatGPT_fit2.java
                                                                                                      П
 🗙 Welcome
                    reactionFit.jshell
                                    E data_pvalue.txt J chatGPT_fit2.java 1 X
       Users > gavalian > Work > Software > project-10.5 > jaw-2.3 > 🤳 chatGPT_fit2.java > 😫 GaussianFill > 🛇 main(String[])
              import java.util.Random;
          5
go .
         7
              public class GaussianFill {
              Run | Debug
⇒
æ
             public static void main(String[] args) {
         9 // Define the histogram range and number of bins
             double xMin = -5.0;
         10
             double xMax = 5.0;
         11
             int nBins = 100;
         12
         13 // Create the histogram
         14 H1F hist = new H1F("hist", nBins, xMin, xMax);
            // Create the Gaussian distribution parameters
         15
         16 double mean = 0.0;
         17
              double sigma = 1.0;
             // Fill the histogram with random data from the Gaussian distribution
         18
             Random rand = new Random();
         19
             for (int i=0; i<10000; i++) {</pre>
         20
                 double x = rand.nextDouble()*(xMax - xMin) + xMin;
        21
         22
                 double val = rand.nextGaussian()*sigma + mean;
         23
                 hist.fill(rand.nextGaussian());
         24
         25
             F1D func = new F1D("func", "[amp]*gaus(x,[mean],[sigma])", xMin, xMax);
         26
             func.setParameter(0, 500.0);
         27
             func.setParameter(1, 0.0);
         28
              func.setParameter(2, 1.0);
         29
         30
         31
             hist.fit(func);
         32
             // Create the canvas and draw the histogram
         33
              Canvas canvas = new TCanvas("canvas", 800, 600);
         34
              canvas.draw(hist);
         35
              canvas.draw(func, "same");
         36
         37
         38
         39
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```



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> ~						



Jefferson Lab





- ▷ CEBAF
- ► CLAS12

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12 GeV electron beam distributed to 4 experimental hall

Each experimental hall contains a detector system for specific experiments

CEBAF Large Acceptance Spectrometer (CLAS12) Located in Hall-B











CLAS12 Detector



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- Charged particle tracking is computationally extensive (about 80% of data processing time)
- The multi-particle final states produce numerous clusters in each sector which have to be analyzed to find the right combinations of clusters that form a track
- Identifying correct cluster combinations can speed up the tracking process and improve efficiency

scattered electron









Physics Results



- magnetic field)

- The average wire position in each super layer is used as an input to Multi-Layer Perceptron (MLP)
- The network is trained on 6 inputs and produces three outputs:
 - False track
 - Negative Track
 - Positive Track



True tracks are identified by conventional algorithms from real data. One negative and one positive track (different curvature due to

False tracks are constructed by interchanging randomly one or two clusters with the clusters from the other track in the event







Corruption Auto-Encoder

- ▶ 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 Wire

















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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









Putting things together





Classifier picks the correct track from 6 super-layer combinations

Remove all clusters belonging to identified track

clusters for all 5 super layer **Corruption Auto-**Encoder

Construct pseudocombinations using





Identify tracks using 6 super layer candidates with pseudoclusters



Voila!



Physics Results



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Al-assisted track candidate classification and Inefficiency Reduction Auto-Encoder

- Particle efficiency increases with luminosity by ~10%.
- The impact on physics for a multi-particle final state is dramatic (20% for the twoparticle final state and ~35% for the threeparticle final state)
- The tracking code speedup is $\sim 30\%$.







Results

~35% gain in physics

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Did we stop here?



De-Noising

Performance for higher luminosity



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De-Noising

CLAS12 Event Display (Drift Chambers)



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De-Noising

- data from drift chambers.
- track hits isolated from raw DC hits.
- belong to a valid track through drift chambers



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Beam Current (nA)





De-Noising Results (simulation)

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- (luminosity)



The reconstruction is run on simulated data with a merging background for different incident beam currents

The simulated three-particle final state is analyzed to measure yield for de-noised data and for conventional

- At standard running luminosity, the de-noising slightly increases the yield compared to AI-assisted tracking.
- With increased luminosity, the de-noising helps to increase the yield significantly compared to conventional and AI-assisted tracking.
- Simulation underestimates the gain in yield significantly.









De-Noising Results (data)

RUN GROUP-A Pass2 Validation Cooking Includes De-Nosing and AI-assisted Tracking



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De-Noising Results (data)

Generic figure downloaded from Internet



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With De-Noising and Al-assisted tracking the extracted number of J/psi increased by 83%





Track Parameter Reconstruction



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Charge Track Parameter Inference

Reconstruct momentum and angles of particles based on the cluster positions of the tracks

Particles have distinct trajectories through drift chambers depending on their momentum, polar and azimuthal angle.

Design an MLP network and investigate different combinations of activation functions to derive the best network for this problem.

$$ep \rightarrow e^{-}n\pi^{+}$$

$$\square Conventional Hit Based AI, MLP TANH/LIN$$

$$0.5 1.0 1.5 2.0 2.5 3.0$$

1.0

1.5

Mx(e⁻π⁺) [GeV]

- Missing mass of two particles calculated using particle momenta from Hit-Based Tracking compared to missing mass calculated from AI particle parameter inference.
- Hit Based Tracking works ~250 ms per event
- Al reconstructs particle parameters <0.5 ms per event

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Results

Leve-3

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Trigger



Level-3 Trigger



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Richard Tyson (Glasgow)



Level-3 Trigger

- A Convolutional Neural Network with a Computation graph is used to identify electrons.
- The DC image is analyzed separately from the EC image, then combined to make a decision.
- ▶ The ECIN, ECOUT, and PCAL are combined into one image 6x72
- The current implementation does not use information from High-Threshold Cherenkov Detector

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







Level-3 Trigger

Level-3 Trigger Performance compared to conventional Trigger



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Level-3 Trigger

- Neural Network was developed for Level-3 trigger studies. (Richard Tyson, University of Glasgow)
- The Software was tested on clonfarm11 node with two NVIDIA Tesla T4 GPUs (2 available, tested only on 1), over 3 times faster than RTX 2080 Ti
- Results are reported as inference per second (inference is per one sector)
- The real data rate is inference divided by 6
- Results are reported for 1 CPU core and 1 GPU unit

- Online multi-threaded data decoder into HIPO is implemented (C++)
- Currently contains only DC and ECAL decoding
- The ET-RING is set up to convert EVIO events into HIPO data frames (100 events per frame) and store HiPO frames in secondary ET-RING
- The Level-3 trigger will be tested during the next run
- With HiPO ET-RING we can now implement online data reconstruction (AI track reconstruction will be easy to add)
- Online data calibration is also possible

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Future of CLAS12-AI

Level-3 Trigger (AI)

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



Physics Reconstruction (AI)



Track Classification (AI)



Classifying track candidates from **Reconstructed clusters** In real-time





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Data Persistence

Saving experimental data Already containing tracks And physics topologies Identified by AI



Removing Noise signals From tracking detectors

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CLAS12 – RICH

- The Ring Imaging Cherenkov detector (RICH) is designed to improve CLAS12 particle identification in the momentum range 3-8 GeV/c and will replace one sector of the existing LTCC detector.
- The RICH design incorporates aerogel radiators, visible light photon detectors, and a focusing mirror system, which will be used to reduce the detection area instrumented by photon detectors to ~1 m². Multi-anode photomultiplier tubes (MA-PMTs) provide the required spatial resolution and match the aerogel Cherenkov light spectrum (visible and near-ultraviolet region).
- For forward scattered particles ($\theta < 13^{\circ}$) with momenta 3 8 GeV/c, a proximity imaging method with thin (2 cm) aerogel and direct Cherenkov light detection will be used.
- For larger incident particle angles of $13^{\circ} < \theta < 25^{\circ}$ and momenta of 3 - 6 GeV/c, the Cherenkov light will be produced by a thicker aerogel (6 cm), focused by a spherical mirror, undergo two further passes through the thin radiator material and a reflection from planar mirrors before detection.

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RICH Ideal Geometry

- If the ideal geometry and position of mirrors are known the raytracing can help recover the Cherenkov angle
- Calculating the Cherenkov angle for each of the hits on the photomultiplier plane allows to identify the particles.



- Neural Networks can be trained on Real-World data which includes miss-alignments
- the aerogel layer

- RICH Real World Geometry
 - Ray tracing will predict an inaccurate position for the hit on the detector plane
 - This affects the efficiency of particle identification



It can learn the Cherenkov ring patterns for incident particles, given interaction point and direction at crossing









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- Neural Network predicts Cherenkov angle for incoming particles based on the hits on the RICH photo-multipliers
- Kaon efficiency is uniform across the momentum range
- The Network is trained on misaligned data
- Kaon efficiency is calculated from misaligned data
- When trained on experimental data, the detector will not need to be aligned.







Summary

Charged Particle Tracking

- Fully implemented AI-assisted tracking in the data processing workflow
- Drift Chamber de-noising is implemented as a pre-processing stand-alone software
- Pass-2 cooking is going to use both AI (de-noising and assistance), and there is a significant increase in the efficiency of reconstruction (57%-83% physics outcome)
- The particle parameter inference network is fully implemented and will be used online to provide track information and help to monitor tracking detectors.

Level-3 Trigger

- Level-3 AI is implemented and tested on cooked data
- Work is ongoing to convert EVIO to HIPO online to be able to use the Level-3 trigger with data acquisition
- This will lead to significant data reduction and a decrease in data processing times

RICH Cherenkov Particle Identification

- The first developments in RICH particle identification with AI achieved good results
- Maybe we can avoid traitorous alignment if the AI can be trained on real detector data

Hall-B is the first to use AI/ML in the data processing and analysis at the LAB

More AI projects coming soon

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Machine Learning in CLAS12

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Backup Slides



De-nosing Performance Multi-Threaded



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De-nosing Performance Multi-Threaded



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pass1 = 129894
pass2 v1_22/pass1 = 1.618
pass2 v1_24/pass1 = 1.662
pass2 v1_25/pass1 = 1.866





Kaon Identification Efficiency (MIS-ALLIGNED GEOMETRY)



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- Alignment is important for traditional reconstruction
- Reconstruction is done using ideal geometry for mirrors
- Simulation in one case is done using ideal geometry
- In the second case, the simulation is done using miss-aligned mirrors
- Efficiency drops significantly when the geometry is not known well.

