Application of Machine Learning to π_0 photoproduction from CLAS/g9a

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Overview

1. Motivation
2. Target Selection
3. Hydrogen Contamination on Carbon Target
4. Next Steps

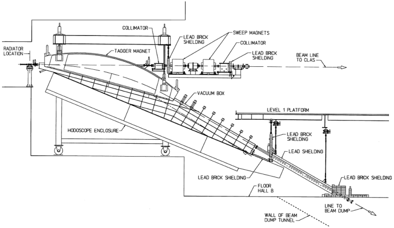
CLAS g9a/FROST Experiment

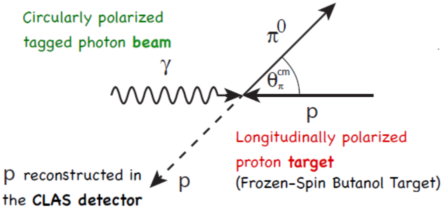
- Polarization Observables → Helicty Amplitudes → Resonances (PWA)
- Polarizable: Incoming photons, target & recoiling nucleons

	UP_T and UP_R	UP_T and P_R	P_T and UP_R	P_T and P_R
UP_B	$\frac{d\sigma}{d\Omega}$	P	T	$T_{x'}, T_{z'}, L_{x'}, L_{z'}$
LP_B	$-\Sigma$	$O_{x'}, (-T), O_{z'}$	$H, (-P), -G$	
CP_B		$-C_{x'}, -C_{z'}$	$F, -E$	

UP, P, LP, CP, B, T, R denote unpolarized, polarized, linearly polarized, circularly polarized, beam, target, and recoil, respectively.

- g9a/FROST - Circularly polarized photons with $E_\gamma \approx 0.4 - 2.4$ GeV and longitudinally polarized proton target:





Helicity Asymmetry E

- Double polarization observable E is the helicity asymmetry of the cross section:

$$E = \frac{\sigma_{3/2} - \sigma_{1/2}}{\sigma_{3/2} + \sigma_{1/2}} \qquad \text{for } \frac{3}{2} \;\&\; \frac{1}{2} \text{ are total helicty states}$$

- $\frac{d\sigma}{d\Omega}$ of polarized beam & polarized target for E (theo. & exp.):

$$\left(\frac{d\sigma}{d\Omega}\right)_{\frac{1}{2},\frac{3}{2}} = \frac{d\sigma_0}{d\Omega}(1 \mp (P_z P_\lambda)_{\frac{1}{2},\frac{3}{2}} E) \qquad \left(\frac{d\sigma}{d\Omega}\right)_{\frac{1}{2},\frac{3}{2}} = \frac{N_{\frac{1}{2},\frac{3}{2}}}{A \cdot F \cdot \rho \cdot \Delta x_i}$$

- E is measured via:

$$\boxed{E = \left[\frac{1}{D_f}\right]\left[\frac{1}{P_z P_\lambda}\right]\left[\frac{N_{\frac{3}{2}} - N_{\frac{1}{2}}}{N_{\frac{3}{2}} + N_{\frac{1}{2}}}\right]}$$

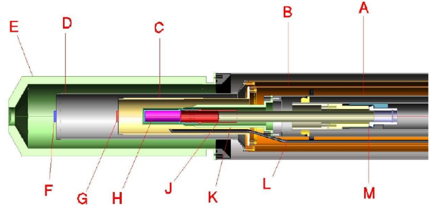
$D_f =$ dilution factor

$P_z =$ Polarization of target in $\hat{z}$

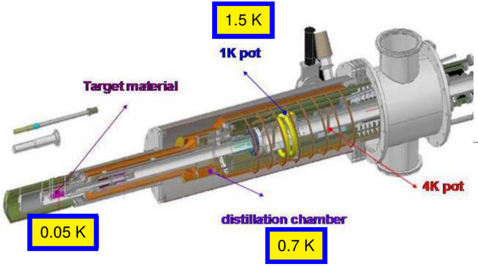
$P_\lambda =$ Polarization of beam

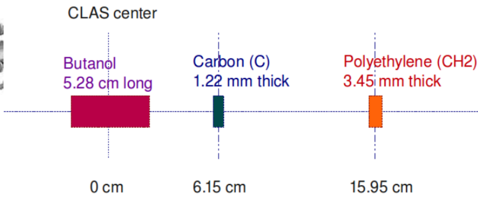
$N_{\frac{3}{2},\frac{1}{2}} = \#$ of events

g9a/FROST Target setup



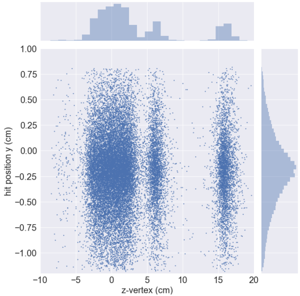
Side view of FROST target with beam entering from the right. (A) Primary head exchanger, (B) 1 K heat shield, (C) Holding coil, (D) 20 K heat shild,(E) Outer vacuum can , (F) Polyethylene target,(G) Carbon target,(H) Butanol target ,(J) Target insert, (K) Mixing chamber, (L) Microwave waveguide, and (M) Kapton cold seal.



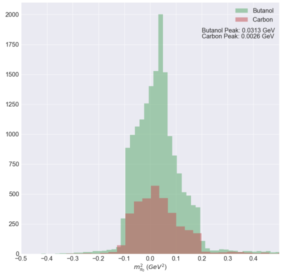


ML Objectives: Target Selection & Ice on Carbon

- Target Selection
  - Events with z-vertex $\in [2, 5]$cm, uncertain whether γ hit Butanol or Carbon

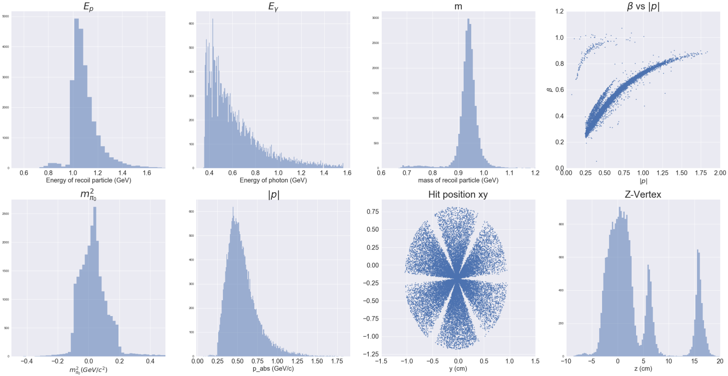


- Ice on Carbon
  - Carbon events (bound-nucleon) expected to have broader $m^2_{\pi_0}$ peak due to Fermi motion.
  - Sharp peak (free-nucleon) observed in the Carbon target region. Carbon events are scaled by $\sim$10.



Banks Used

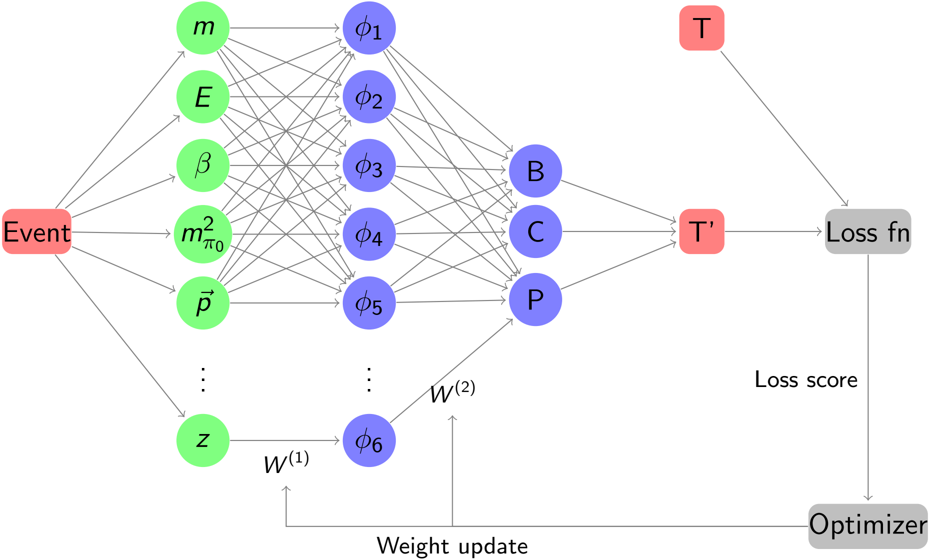
- GPID - pid, E, $\vec{p}$, β_c, β_m, m, and E_γ
- MVRT - vertex positions
- Only single tracked events with protons
- Removed events outside of target cup ($r = 7.5mm$) - He-Bath outside
- Removed events with $E_\gamma \approx 0$
- No Energy loss correction yet
- No fiducial cuts yet



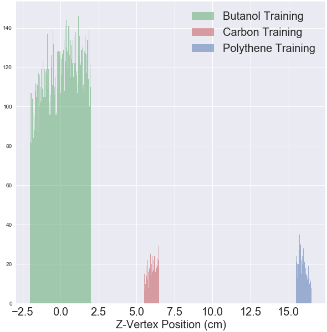
Neural Network Model Setup

- Two fully-connected (dense) neural layers
  1. Dense layer with 15 nodes - 15 parameters:
     - E, β, β_{diff}, β_m E_γ, m, $m^2_{\pi_0}$, pid,$|p|$, p_x, p_y, p_z, x, y, and z.
     - Too many parameters + insufficient train data $\rightarrow$ Too specific training $\rightarrow$ Overfitting (fail)
  2. Dense layer with 3 nodes - one for each target
     - For each event, this layer returns an array of 3 probability scores (butanol, carbon, or polythene) that sum to 1
- Optimizer used: AdamOptimizer
- Loss function used - Sparse categorical cross entropy:
  - $H_{y'}(y) = -\sum_i y'_i \log(y_i)$,where y_i is the predicted target and y'_i is the true target
- Python and Tensorflow

Neural Network Training Flowchart

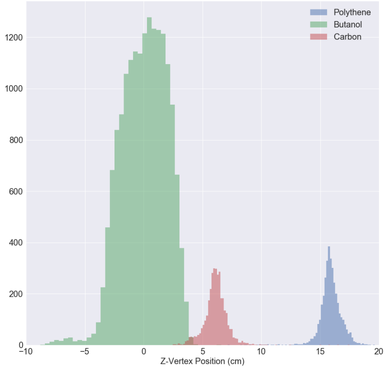


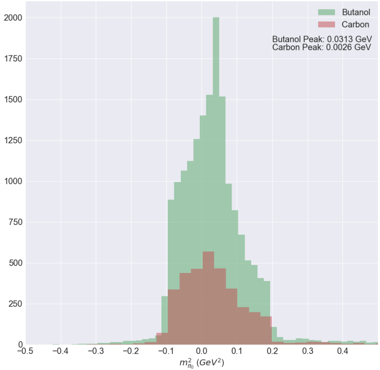
Training Data Selection



- Events with z-vertex position in close proximity of physical target region
  - Butanol $\in$ [-2, 2]cm
  - Carbon $\in$ [5.5, 6.5]cm
  - Polythene $\in$ [15.5, 16.5]cm

Result on Target Selection





- Classified Carbon events from Butanol in z-vertex $\in [2.5, 4.5]$cm
- Some Carbon events in Polythene regions & Polythene events in Butanol region.
- Tail of Butanol events in Carbon region are missing. Under review [S. Fegan].

Evidence of Hydrogen Contamination on Carbon

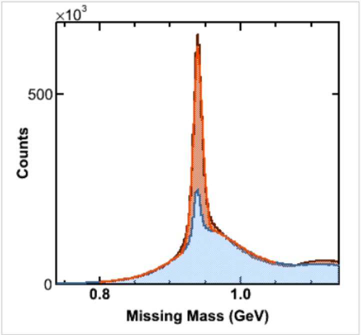


Figure 2: Missing-mass distribution for the π+n channel from FROST g9a data. W = 1.25 - 1.50 GeV, integrated over all angles. Events in the red histogram are from the butanol target and events in the blue histogram are from the 12C target with z-vertex larger 5.0 cm and smaller than 7.5 cm. The blue histogram is scaled by 5.26. The FROST distribution from the 12C target region show a **narrow peak** at the mass of then neutron.

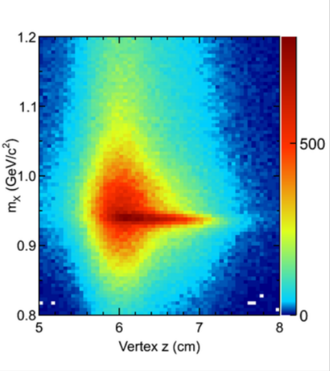
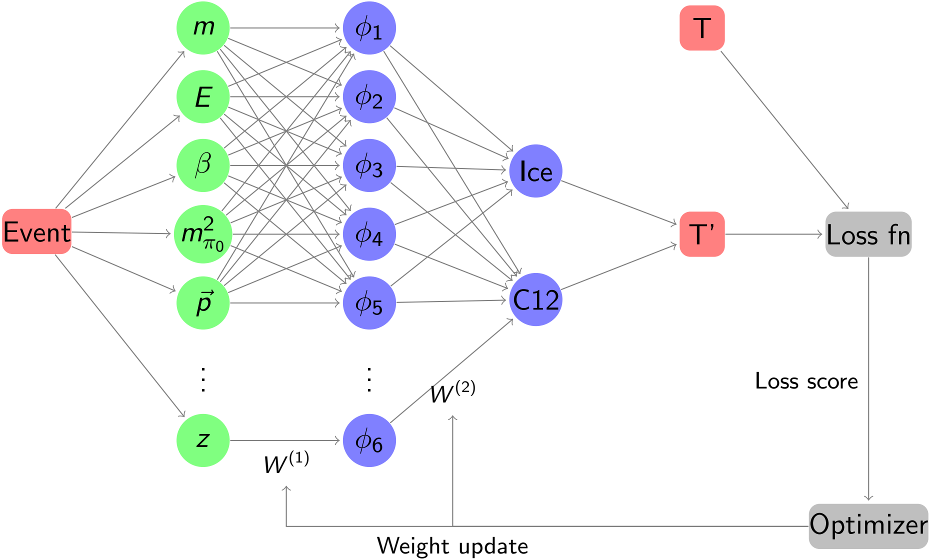


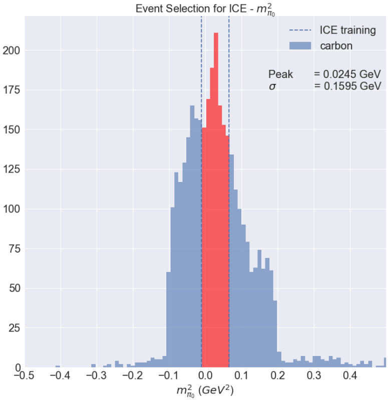
Figure 3: Missing-mass distribution as a function of the MVRT z vertex of the π+. The shape of the missing-mass distribution strongly changes with z. Event selection: $p_\pi > 0.2$ GeV/c and $\theta_\pi > 20^\circ$.

- Sharp peak at downstream end of Carbon foil → ice built up while cooling the target
- Ice formed on the right side of Carbon target: Z-vertex ∈ [6, 7]cm
- Plots from [Steffen Strauch]'s Analysis page of FROST Wikipage

Neural Network Training Flowchart for ice vs Carbon

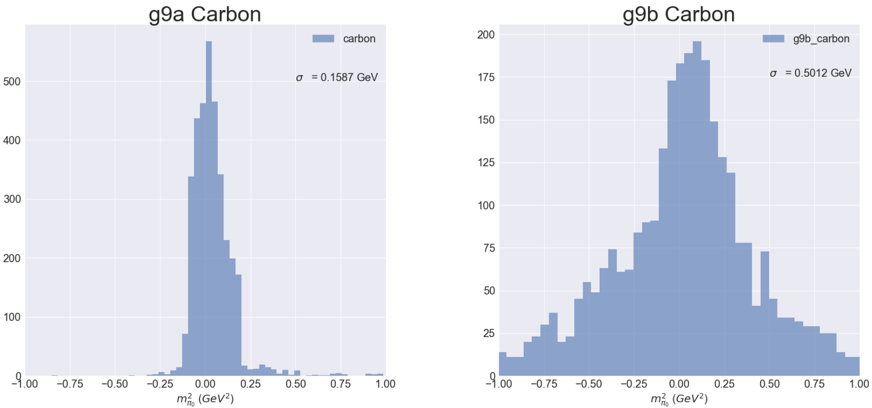


Training Data for ice



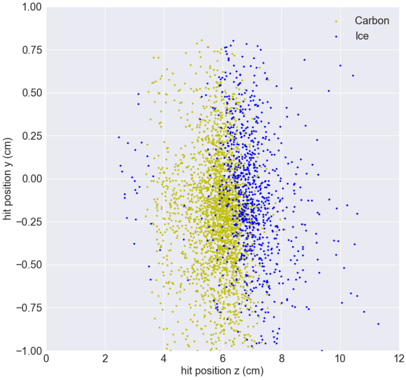
- Tight cut on the $m^2_{\pi_0}$ peak on g9a-Carbon data (or MC sim) as ice events [F. Klein].
  - Bound-nucleon (fermi p) $\rightarrow$ broader distribution $\rightarrow$ Sharper peaks from free-nucleon (ice) Broad background from bound-nucleon (carbon)

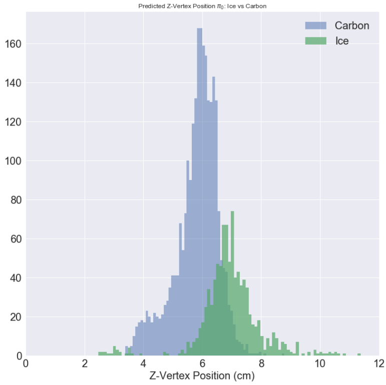
Training Data for Carbon from g9b



- g9b-carbon $m^2_{\pi_0}$ peak broader than g9a/Carbon $\rightarrow$ No ice on g9b
- During g9b, Carbon target was moved further in downstream.
- Shifted Z-vertex of g9b-Carbon events to use as training events for g9a [F. Klein].

Result on Hydrogen Contamination of Carbon Target





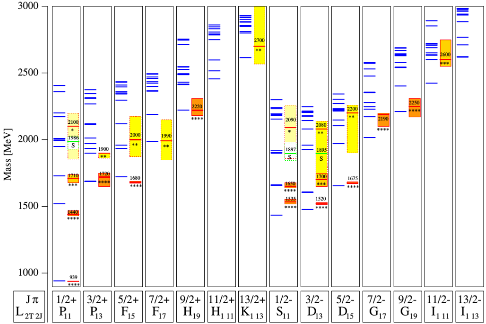
- Classified ice events from Carbon target in z-vertex $\in$ [6, 8]cm
- It is likely that ice was formed in 20 K heat shield in between Carbon and Polythene targets.

Next Steps

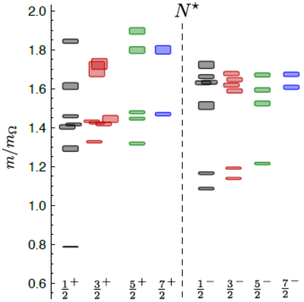
- Apparently, classification on target selection and extraction of ice events were successful. However, it is still a blackbox...
  - Need to understand underlying logic of the model (Tensorboard).
  - Find ways to implement physics (relativistic kinematics, branching ratios, forbidden angles, etc) into optimizer or loss function.
- Nuclear physics experiments data cannot have 100% confident true values for training
  - Try Unsupervised Learning techniques: Clustering
  - Find ways to measure efficiency and accuracy of predictions
- Need more data to avoid overfitting problem.
- Computational cost is too high for small fraction of the total data.
- Energy loss reconstruction via ML regression.

Backup Slides

Backup: Constituent Quark Models & LQCD Predictions of Non-Strange Baryon Resonances



Constituent Quark Model

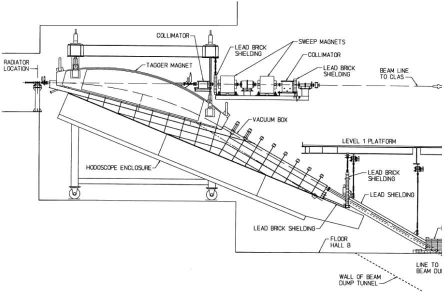


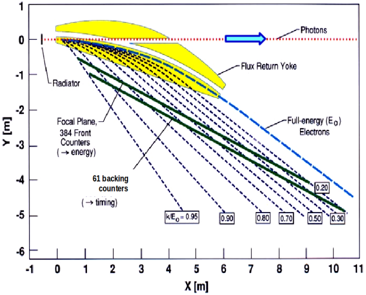
Lattice QCD

- Constituent Quark Models predicted states: 64 N^* & 22 Δ^*
- Experimentally confirmed state: 26 N^* & 22 Δ^*

Backup: Hall B Photon Tagger

- Bremsstrahlung radiation due to slowing of electrons by EM field of radiator (gold foil or thinyo diamond)
- Determine incoming photon energy of $\vec{\gamma}\vec{p} \to \pi^0 p$ by $E_\gamma = E_0 - E_e$
- g9a/FROST - circularly polarized photons with $E_\gamma \approx 0.4 \sim 2.4\ GeV$
- Tagger was built by the GWU, CUA, & ASU nuclear physics group





Backup: Circularly Polarized Photon Beam

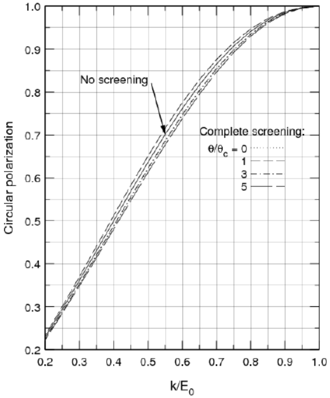
Linearly Polarized Electron Beam $\xrightarrow{\textit{Bremsstrahlung}}$ Circularly Polarized Photon Beam

- Polarization transfer:

$$P(\gamma) = P(e)\frac{4x - x^2}{4 - 4x + 3x^2}$$

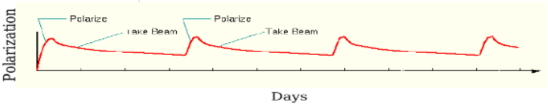
$$x = \frac{k}{E_0} = \frac{\text{photon energy}}{\text{incident electron energy}}$$

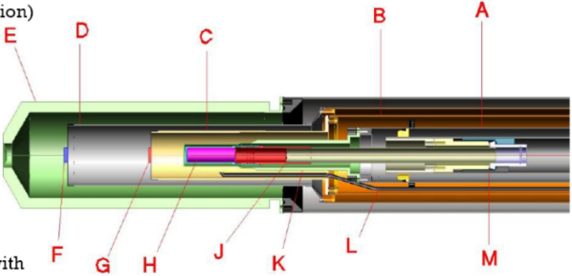
H. Olsen and L.C. Maximon, Phys. Rev. 114, 887 (1959)



Backup: Frozen Spin Target

The FroST target and its components:
A: Primary heat exchanger
B: 1 K heat shield
C: Holding coil
D: 20 K heat shield
E: Outer vacuum can (Rohacell extension)
F: CH2 target
G: Carbon target
H: Butanol target
J: Target insert
K: Mixing chamber
L: Microwave waveguide
M: Kapton coldseal

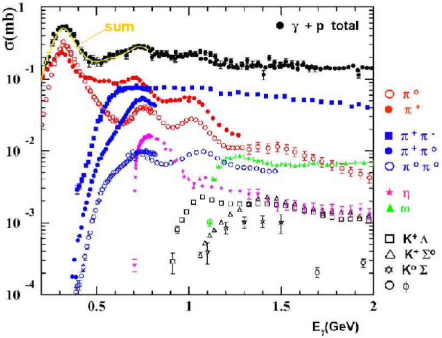




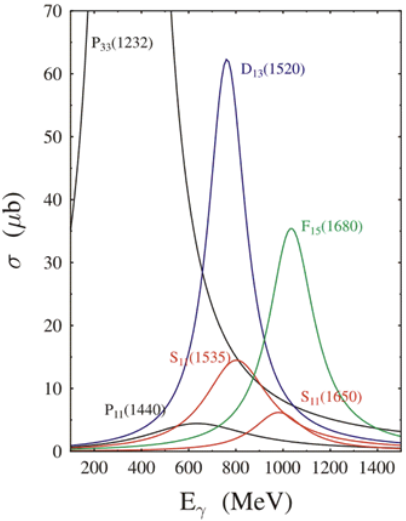
Performance Specs:
Base Temp: 28 mK w/o beam, 30 mK with
Cooling Power: 800 μW @ 50 mK, 10 mW @ 100 mK, and 60 mW @ 300 mK
Polarization: +82%, -90%
1/e Relaxation Time: 2800 hours (+Pol), 1600 hours (-Pol)
Roughly 1% polarization loss per day.

C. Keith et al. Nucl Instrum Meth A 684, 27 (2012)

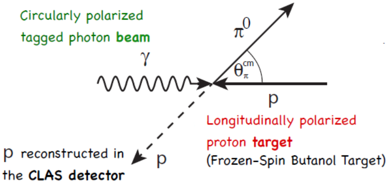
Backup: CLAS g9a/FROST Data



- Select only $\vec{\gamma}\vec{p} \rightarrow \pi^0 p$ events
- $\vec{\gamma}\vec{p} \rightarrow \pi^0 p$ resonance channels
- Appropriate enegy bins - include all resonances ($\lesssim$ 1500 MeV)



π^0 photoproduction



- From *T Matrix* to *Helicity Amplitudes* of $\vec{\gamma}\vec{p} \to \pi^0 p$:

$$\langle \mathbf{q}\ m_{s'} |\, T\, | \mathbf{k}\ m_s\ \lambda \rangle = \boxed{\langle m_{s'} |\, \mathbf{J}\, | m_s \rangle} \cdot \epsilon_\lambda(\mathbf{k}) \quad \Rightarrow \quad H_i(\theta) \equiv \langle \lambda_2 |\, \mathbf{J}\, | \lambda_1 \rangle$$

- 4 Complex Helicity Amplitudes:

$$H_1(\theta) = \left\langle +\frac{3}{2} \middle| \mathbf{J} \middle| +\frac{1}{2} \right\rangle \qquad H_2(\theta) = \left\langle +\frac{1}{2} \middle| \mathbf{J} \middle| +\frac{1}{2} \right\rangle$$

$$H_3(\theta) = \left\langle +\frac{3}{2} \middle| \mathbf{J} \middle| -\frac{1}{2} \right\rangle \qquad H_4(\theta) = \left\langle +\frac{1}{2} \middle| \mathbf{J} \middle| -\frac{1}{2} \right\rangle$$

Backup: Complete Experiment - 8 Polarization Observables

- Polarizable: incoming photons, target & recoiling nucleons
- 8 well chosen observables at fixed E_γ & angle $\rightarrow$ 4 helicity amplitudes

	UP_T and UP_R	UP_T and P_R	P_T and UP_R	P_T and P_R
UP_B	$\frac{d\sigma}{d\Omega}$	P	T	$T_{x'}, T_{z'}, L_{x'}, L_{z'}$
LP_B	$-\Sigma$	$O_{x'}, (-T), O_{z'}$	$H, (-P), -G$	
CP_B		$-C_{x'}, -C_{z'}$	$F, -E$	

UP, P, LP, CP, B, T, R denote unpolarized, polarized, linearly polarized, circularly polarized, beam, target, and recoil, respectively.

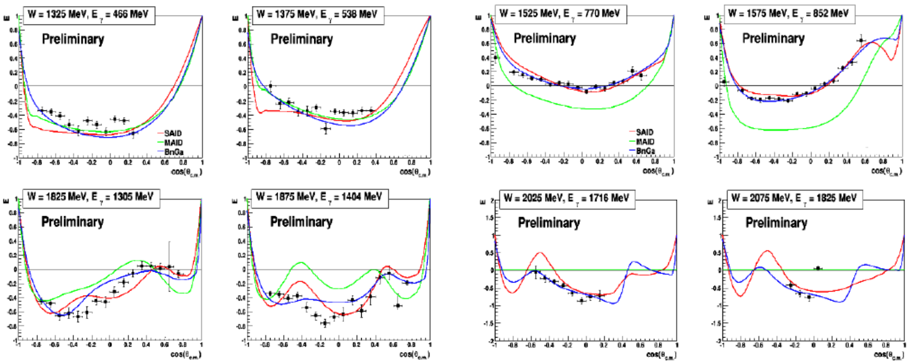
- Helicity asymmetry E related to other observables via Fierz identities:

$$E^2 + F^2 + G^2 + H^2 = 1 + P^2 - \Sigma^2 - T^2$$

$$FG - EH = P - \Sigma T$$

$$\vdots$$

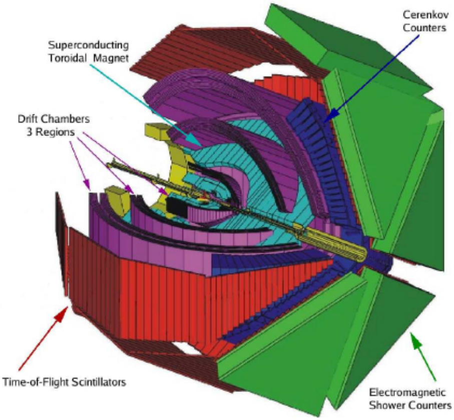
Comparison with PWA (SAID, MAID, BnGa) predictions

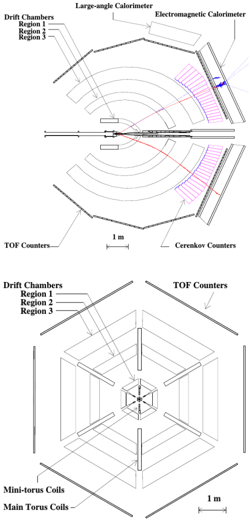


Sample of Helicity Asymmetry E versus CM angle, θ_{cm} in ranges of $E_\gamma = 466 - 1825\ MeV$ and $W = 1325 - 2075\ MeV$. The red, green, and black lines correspond to results from **SAID**, **MAID**, & **BnGa** respectively.

- Measured asymmetry E will be compared to PWA predictions
- Measured asymmetry E into SAID data base → new pole positions
- **SAID**, **MAID** & **BnGa** models agree at lower energies & deviate at higher energies

CEBAF Large Acceptance Spectrometer





Overtraining Limits

- Overtraining:

Excess training with only specific training data

$\downarrow$

Classification succeeds on training data, but fails on actual data

- Must determine adequate classifying variables & size of training data
- Rule of thumb for Decision Tree algorithm:

$$L_D(h) \quad \leq \quad L_S(h) + \sqrt{\frac{(n+1)\log_2(d+3) + \log(2/\delta)}{2m}}$$

$L_D(h)$ = Error of classification on actual data set
h = Error of classification on a training data set
δ = Confidence level of randomly selected training data points
n = Number of nodes

$L_S(h)$ = Error of classification on a training data set
d = Number of variables
m = Size of training data sets
• n & d inversely proportional to L_s