SeaQuest E906

UNIVERSITY of VIRGINIA

Deep Neural Network-Based Reconstruction to extract unpolarized Drell-Yan Angular Dependence from SeaQuest E906 Data

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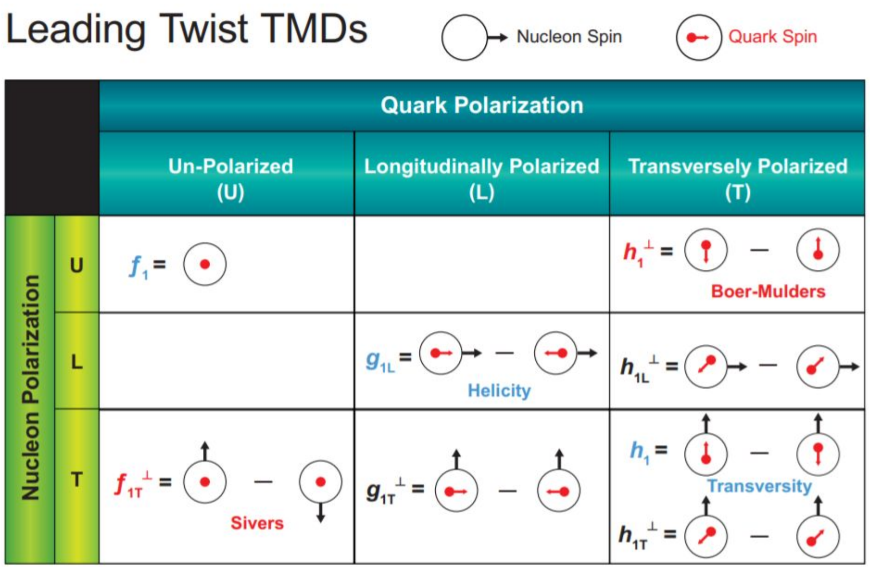
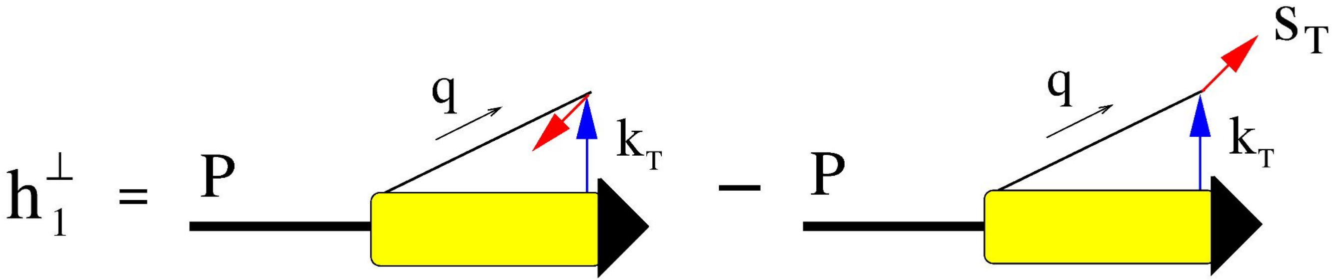
SOLID POLARIZED TARGET GROUP at the UNIVERSITY of VIRGINIA

The Boer Mulders Function

- Describes the net polarization of the partons inside an unpolarized nucleon.
- When the nucleon is moving in a direction, the partons can be preferentially polarized in a certain direction.
- If this function is nonzero, then it reflects the presence of a handedness inside the nucleon.

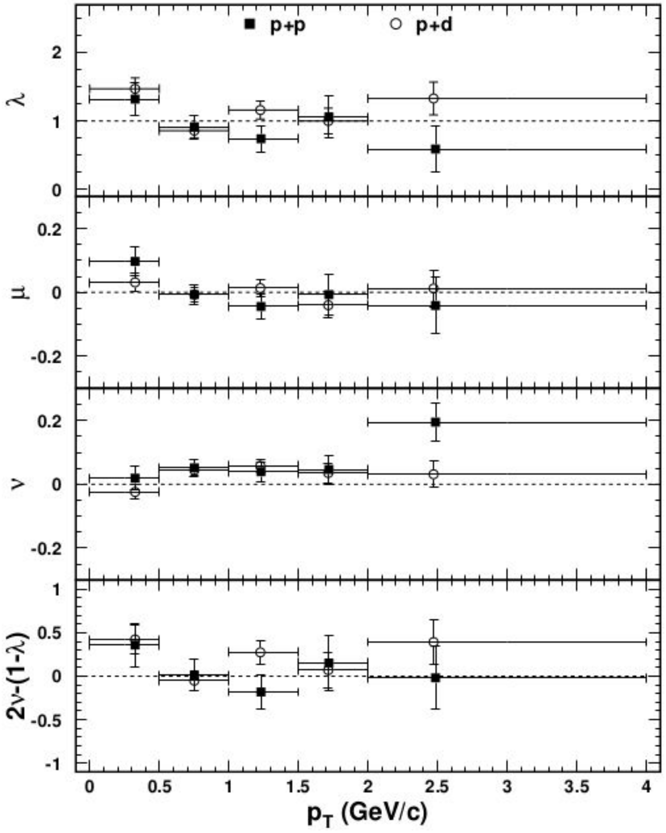




Drell-Yan Angular Dependence

- A non-zero Boer-Mulders asymmetry can give rise to a *cos(2ϕ)* dependence in unpolarized DY in the Collins-Soper frame.
- If there is an azimuthal dependence, either μ or ν are non-zero.
- Other experiments have measured these values, but at different energy.

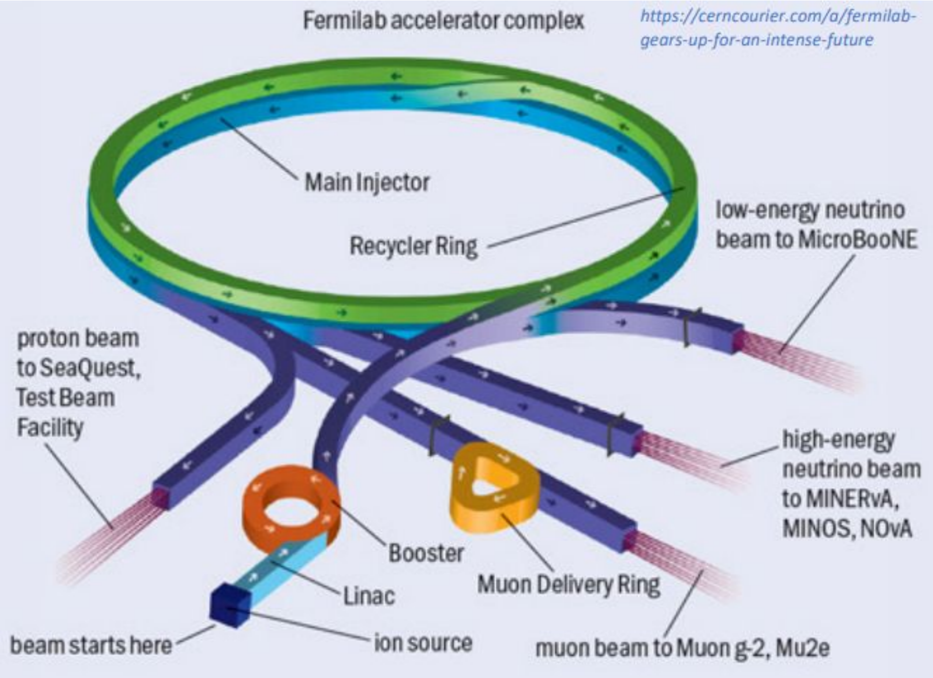
$$\frac{d\sigma}{d\Omega} \propto 1+\lambda\cos^2\theta+\mu\sin 2\theta\cos\phi+\frac{1}{2}\nu\sin^2\theta\cos 2\phi$$



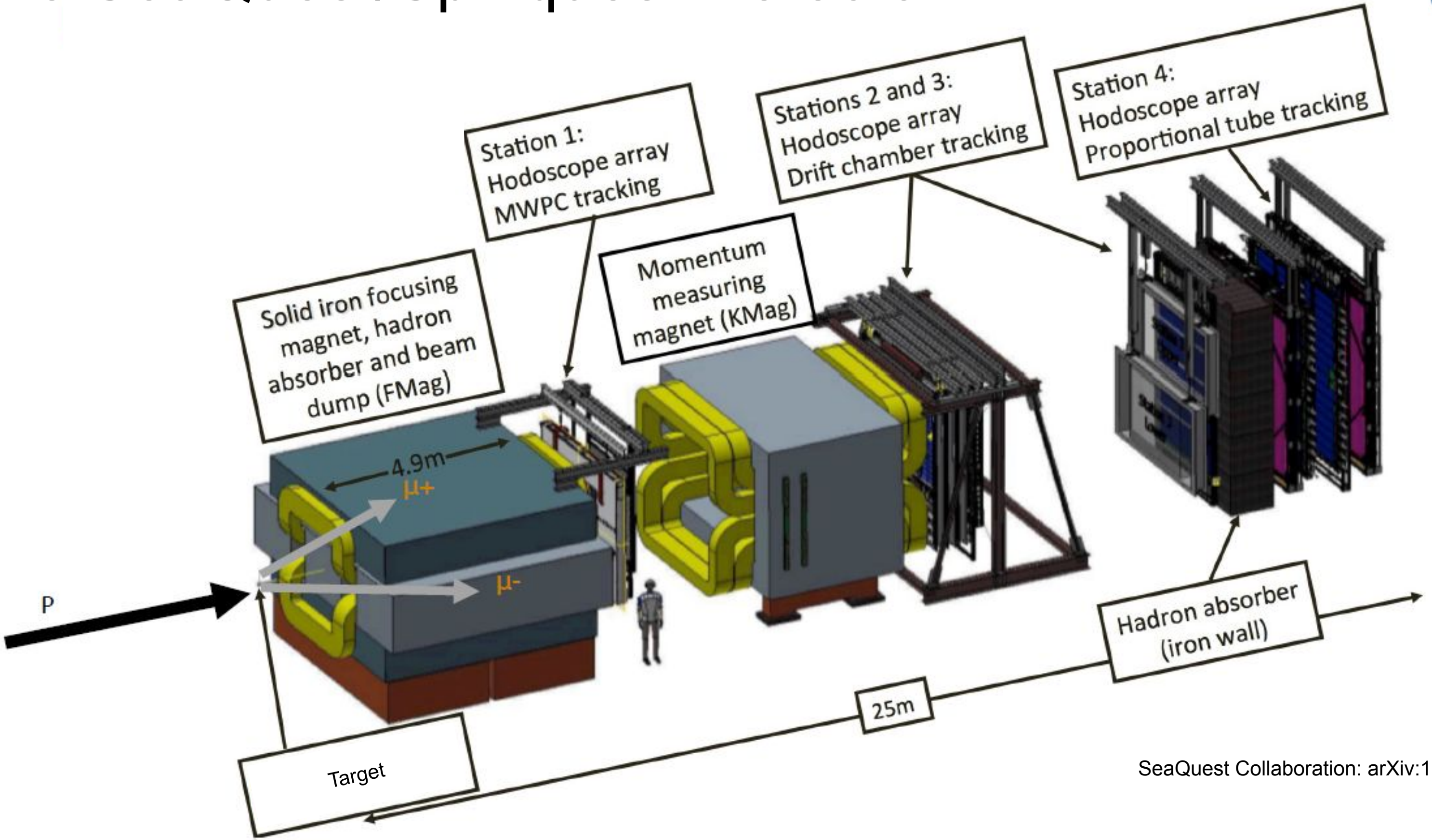
Parameters λ, μ, ν and 2ν − (1 − λ) vs. p T in the Collins-Soper frame. From E866 NuSea at Fermilab.
Ref: L. Y. Zhu et al. arXiv:0811.4589 [nucl-ex]

The SeaQuest Experiment

- Fermilab experiment that collected data from 2014-2017
- Designed to probe the sea quark structure of the nucleon.
- Fixed hydrogen, deuterium, carbon, iron, and tungsten targets.
- Used the 120 GeV main injector beam at Fermilab.
- Designed to measure Drell-Yan process with target anti-quarks and beam quarks.
- Covered target x range from [0.1,0.55].

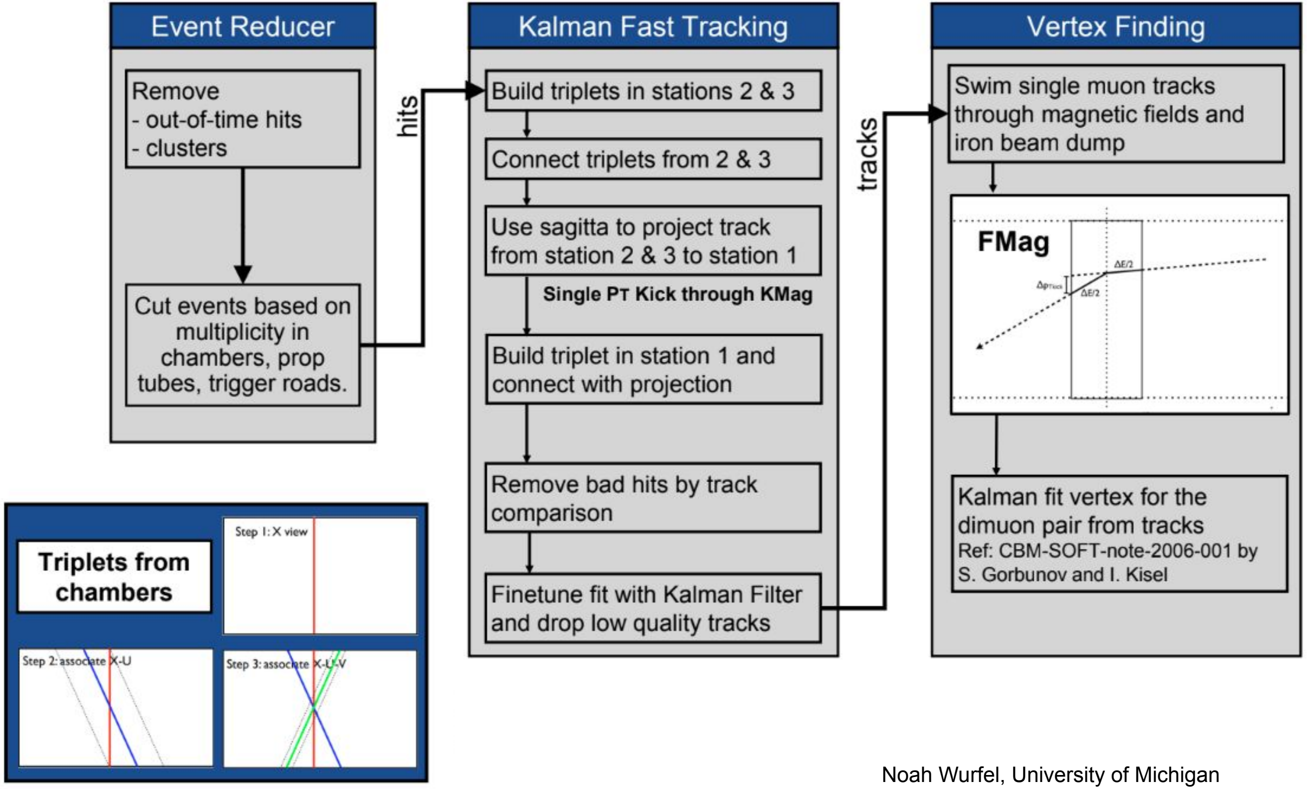


The SeaQuest/Spinquest Detector



SeaQuest Collaboration: arXiv:1706.09990 [physics.ins-det]

Kalman Filter Based Reconstruction (KTracker)



Noah Wurfel, University of Michigan

Neural-Network-Based Reconstruction (QTracker)

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Raw Data

Event data is represented as a 2-d (54x201) image that can be fed into image processing networks.

Event Classification CNN

A modified version of AlexNet is used to classify events into non-reconstructable, single-muon, or dimuon events.

Track Finder CNN

A modified and expanded version of LeNet is used to identify the element ID for each detector associated with a muon hit. The predicted track are then matched to real hits timing information.

Kinematic Reconstruction DNN

Using the particle track, a deep-neural-network calculates the particle three-momenta for each detected muons.

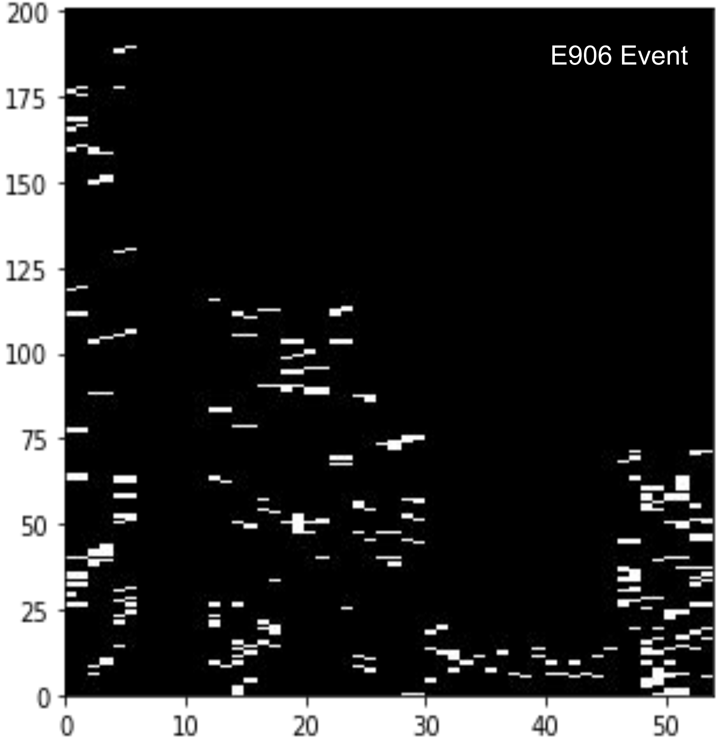
Vertex Finding DNN

Using the Kinematics and the particle track, a DNN calculates the position at which the detected muons were created.

After filtering by vertex location, track finding and reconstruction can be done iteratively to increase precision.

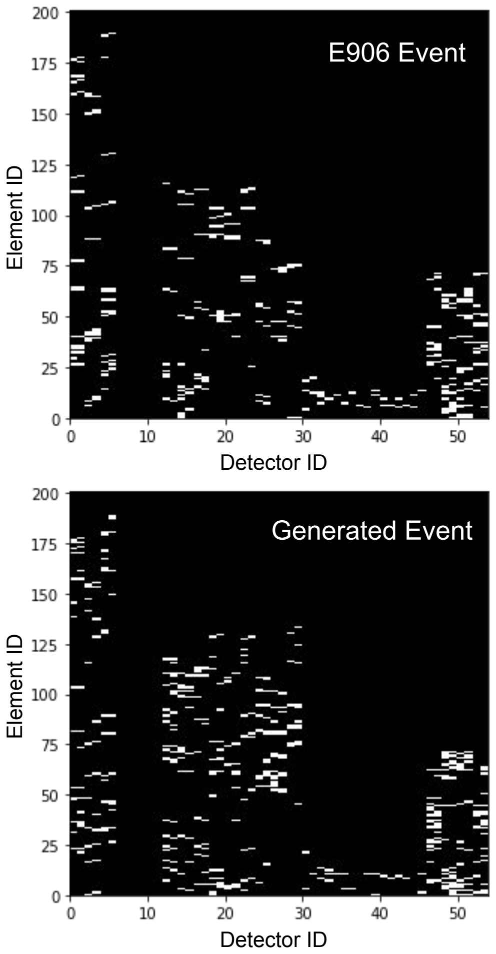
Raw Data

- Visual representation of a triggered event – a hit matrix
- Most hits come from muons, but very few come from Drell-Yan muons from the target.
  - Good hits: hits that are part of a fully reconstructable muon track
  - Noisy hits: hits from tracks that are too fragmented to reconstruct.
- Of triggered events, very few have a reconstructable full track of a dimuon.



Training Data Generation

- Using Pythia and GEANT, generate a large number of examples of dimuons passing through the detector array.
- Place the Monte Carlo generated detector hits on a 54x201 array that corresponds to each detector and their corresponding elements.
  - For each hit, decide whether or not to include a hit based on detector sensitivity.
- Add additional random and correlated hits to the array to mimic real data.
  - Random electronic noise hits
  - Muon partial track hits



Comparison to Kalman Filter Reconstruction

	KTracker		**QTracker**	
	Precision	Accuracy	Precision	Accuracy
Dimuon Identification	92%	9% (Recall)	99%	54% (Recall)
p_x	0.42 GeV/c	0.16 GeV/c	0.22 GeV/c	-0.05 GeV/c
p_y	0.36 GeV/c	0.20 GeV/c	0.32 GeV/c	-0.03 GeV/c
p_z	4.1 GeV/c	-1.42 GeV/c	5.05 GeV/c	0.27 GeV/c
p_T	0.43 GeV/c	-0.18 GeV/c	0.36 GeV/c	0.05 GeV/c
x_1	0.04	0.03	0.06	0.005
x_2	0.04	-0.01	0.02	0.004
M	0.62 GeV/c^2	0.02 GeV/c^2	0.32 GeV/c^2	-0.06 GeV/c^2
θ	0.17 radians	0.02 radians	0.10 radians	-0.02 radians
ϕ	0.63 radians	-0.03 radians	0.41 radians	0.01 radians
Time (10,000 Dimuons)	23.5 hours		52 seconds	

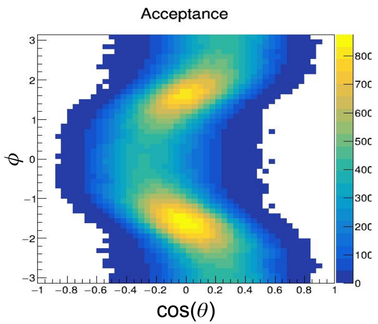
University of Virginia

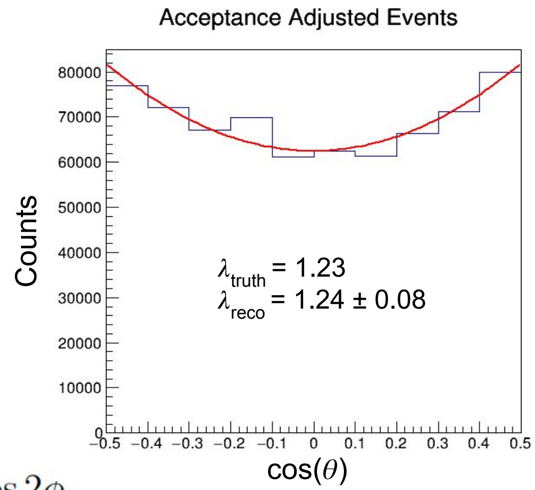
Summary of QTracker Advantages

- Higher statistics
  - Approximately 6x as many reconstructed dimuons compared to geometric reconstruction.
  - Data also cleaner – fewer non-dimuon events are identified as dimuons.
- Faster reconstruction
  - GPU reconstructs in less than 1/1000th the time of single CPU core.
- More precise reconstruction of kinematic variables
  - QTracker has closer agreement with Monte Carlo truth values for most variables, critically including θ and ϕ.

Asymmetry Fitting: Chi-Square Fit Method

- Events are binned into 2-d histogram of *cos(θ)* and ϕ.
- Those histograms are then adjusted using the bin-by-bin acceptance of the detector and reconstruction algorithm.
- The acceptance-adjusted histograms are then fit using a chi-square method to the differential cross-section to find values of λ, μ, and ν.

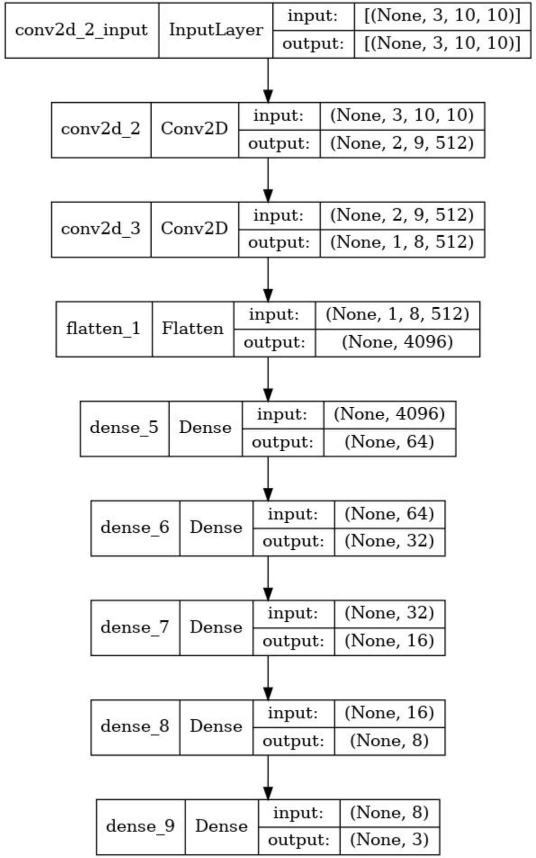




$$\frac{d\sigma}{d\Omega} \propto 1+\lambda\cos^2\theta+\mu\sin 2\theta\cos\phi+\frac{1}{2}\nu\sin^2\theta\cos 2\phi$$

Asymmetry Fitting: Neural Network Method

- Like with chi-squared method, events are binned into 2-d histograms and given acceptance corrections.
- Those 2-d histograms are then fed into Convolutional Neural Networks that calculate λ, μ, and ν.

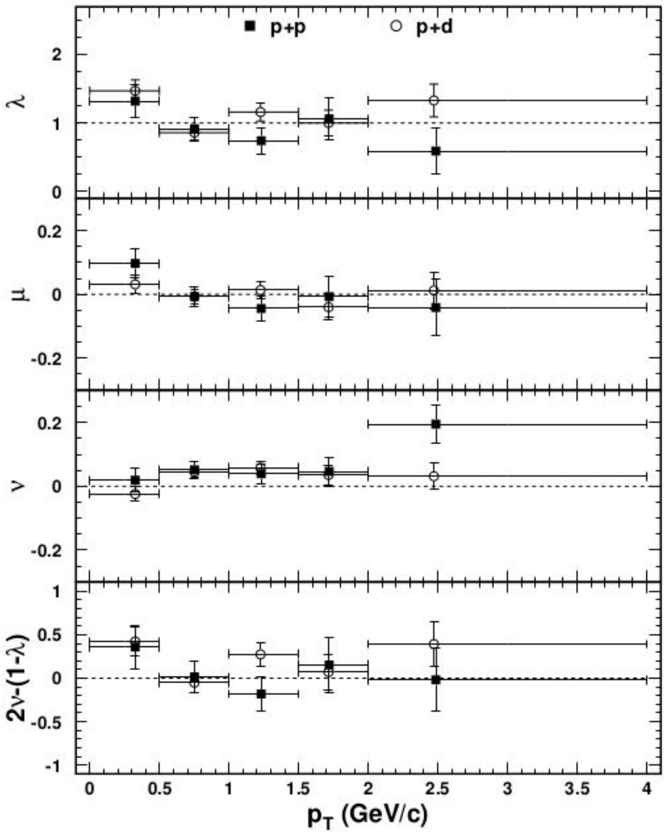


Inputs three 10x10 histograms :
cos(θ) vs ϕ,
cos(θ) vs cos(ϕ),
cos(θ) vs cos(2ϕ)

Outputs:
λ, μ, and ν.

Testing the two methods

1. Randomly select λ, μ, and ν from the ranges [0.5,1.5], [-0.4,0.4], [-0.4,0.4], respectively.
2. Generate 10,000 Drell-Yan events with the selected angular dependence via von Neumann Rejection.
3. Reconstruct the kinematics of the Drell-Yan events using QTracker.
4. Save the reconstructed kinematics.
5. Perform the fitting method and compare to the true values of λ, μ, and ν.



Parameters λ, μ, ν and 2ν − (1 − λ) vs. p T in the Collins-Soper frame. From E866 NuSea at Fermilab. Ref: L. Y. Zhu et al. arXiv:0811.4589 [nucl-ex]

Performance of the Two Methods

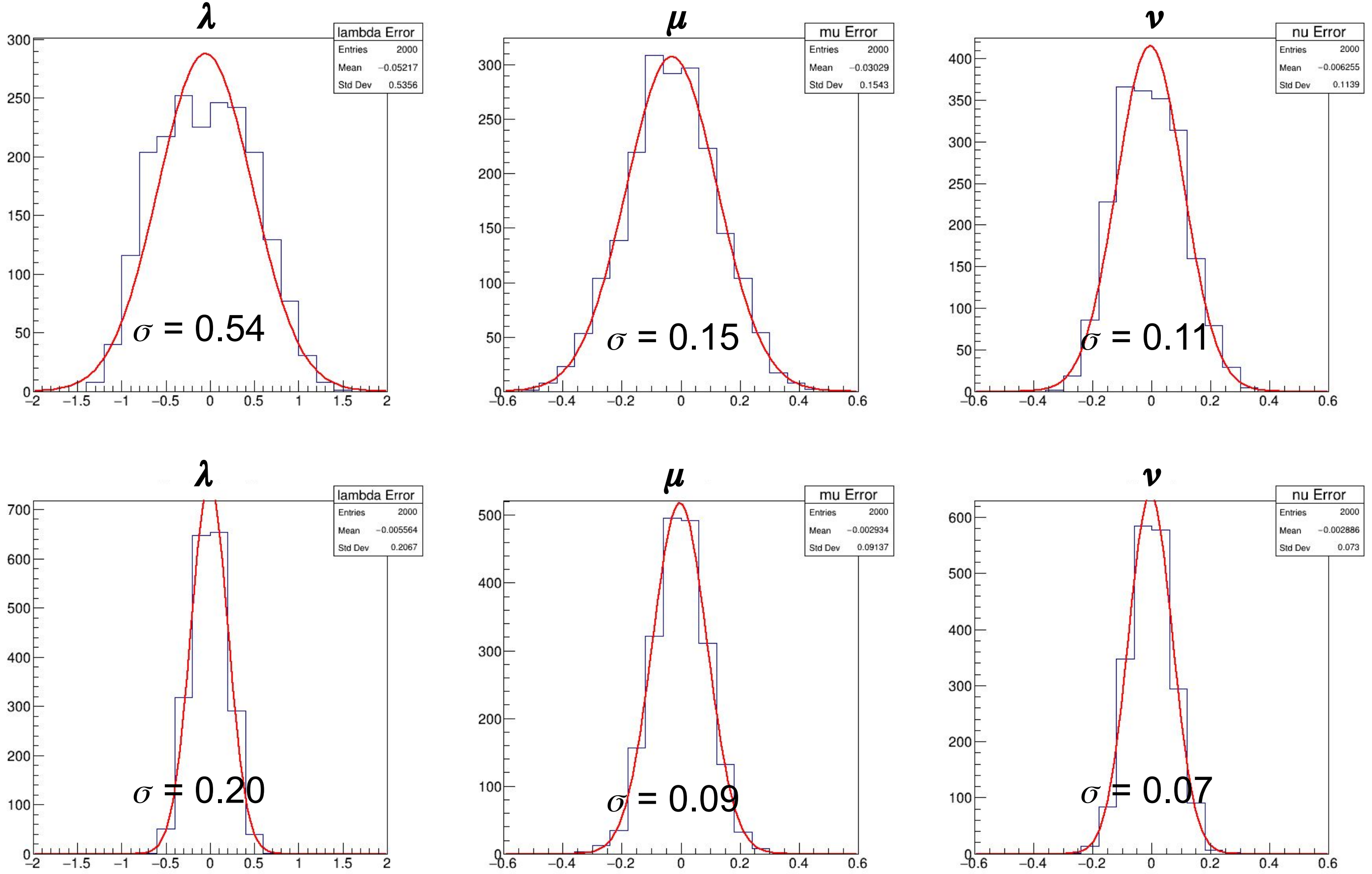
	Truth	Chi-Square Method	CNN Method
λ	0.85	1.0 ± 0.2	0.87 ± 0.10
μ	-0.05	-0.08 ± 0.04	-0.06 ± 0.02
ν	0.10	0.08 ± 0.04	0.09 ± 0.02
λ	1.24	0.8 ± 0.3	1.15 ± 0.08
μ	0.23	0.15 ± 0.06	0.21 ± 0.05
ν	-0.12	-0.10 ± 0.04	-0.11 ± 0.03
λ	0.98	0.7 ± 0.2	0.95 ± 0.09
μ	0.01	-0.04 ± 0.07	0.03 ± 0.04
ν	0.01	0.04 ± 0.02	0.0 ± 0.02

Errors for Chi-Square method are uncertainties from fits, for CNN method, errors are empirical from similar kinematics.

Performance of the Two Methods (Empirical)

Chi-Square

Neural Network



Summary and Outlook

- QTracker method shows promise for fast performance, high statistics, and low error reconstruction of physics variables.
- QTracker, along with neural-network based extraction able to calculate the angular dependence variables of Drell-Yan data with high precision.
- Higher statistics will allow us to be able to optimize the binning of kinematic variables (x_1, x_2, x_F, M, p_T) for which we can measure asymmetry variables, enabling a better global extraction of the Boer-Mulders function.
- Work is ongoing on systematic studies and analysis of real data.