Utilizing Deep Neural Networks for the Extraction of Drell-Yan Angular Coefficients in pp Collisions with a 120 GeV Beam Energy

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APS-DNP-2023, November 29, 2023

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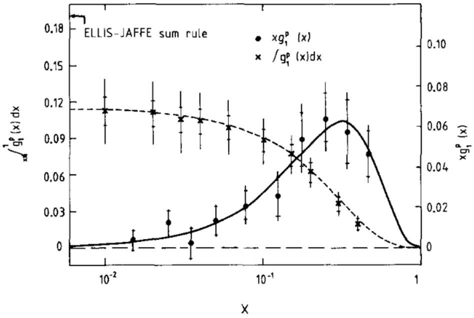
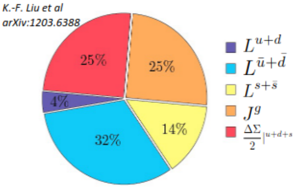
Internal Structure of the Proton & Transverse Momentum Distributions

J. Ashman et al. , DOI:10.1016/0370-2693(88)91523-7





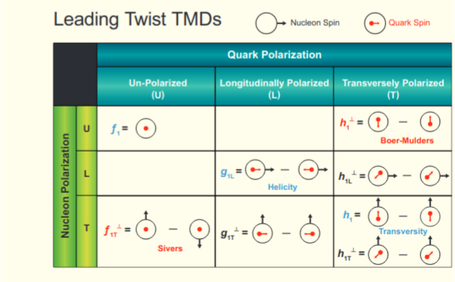
$\Delta\Sigma_q \approx 25\%$

$2\ L_q \approx 50\%$ (4% (valence)+46% (sea))

$2\ J_g \approx 25\%$

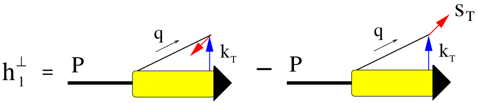
- Proton is a spin $\frac{1}{2}$ fermion.
- Total spin of the proton $\rightarrow$ internal structure of proton.

A. Accardi et al, arXiv:1212.1701



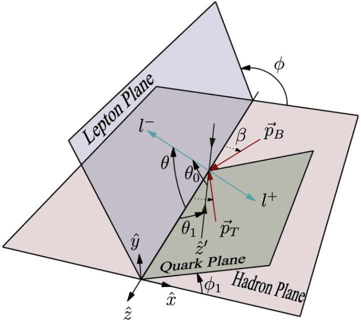
- TMDs : distributions of the hadron's quark or gluon momenta that are perpendicular to the momentum transfer between the beam and the hadron.

Boer-Mulders Function & Drell-Yan Process

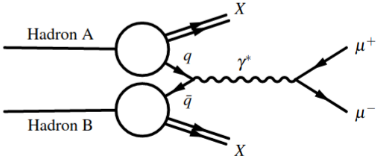


$$\frac{d\sigma}{d\Omega} \propto 1+\lambda\cos^2\theta+\mu\sin 2\theta\cos\phi+\frac{1}{2}\nu\sin^2\theta\cos 2\phi$$

J. C. Peng et al., arXiv:1808.04398



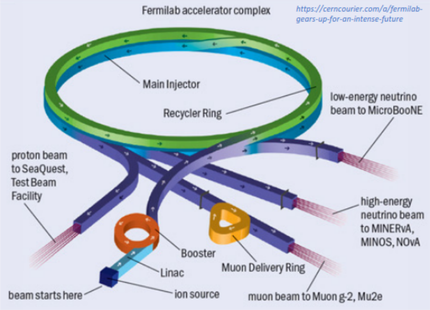
- BMF : Describes the net polarization of quarks inside an unpolarized proton.
- $h_1^{\perp}$ $\rightarrow$ quark distribution that quantifies a particular spin-orbit correlation.

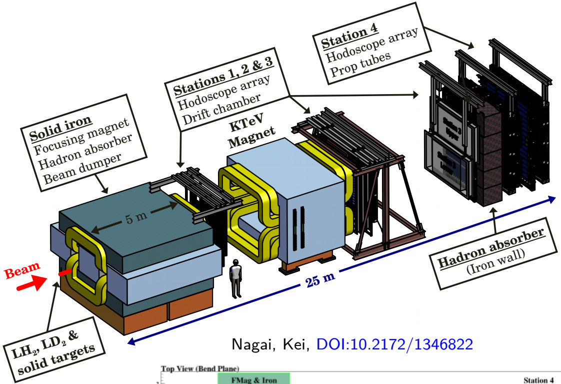


- Collins-Soper frame: rest frame of di-muons $\rightarrow$ using the beam proton direction to construct the azimuthal and polar angles.
- Extraction of the ν parameter $\rightarrow$ BM function.

FermiLab SeaQuest/E906 Experiment

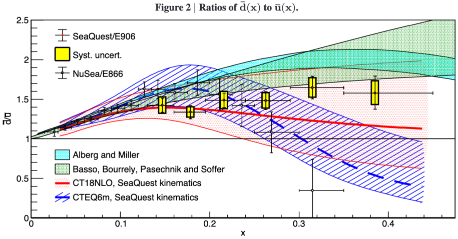
C. A. Aidala et al., arXiv:1706.09990

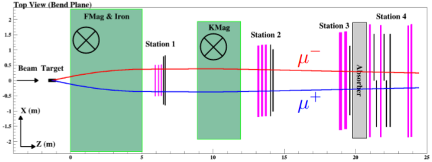




J. Dove et al., arXiv:2103.04024

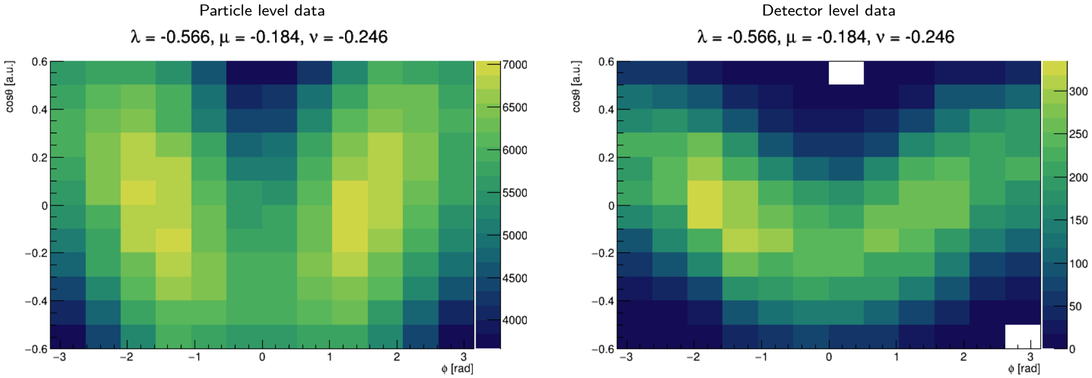
Nagai, Kei, DOI:10.2172/1346822





- Fixed target experiment at FermiLab.
- Use 120 GeV beam energy from main injector.

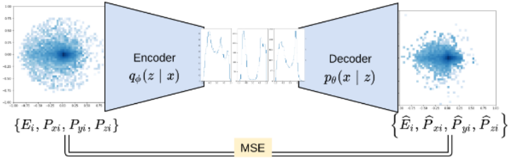
Unfolding Detector Level Data



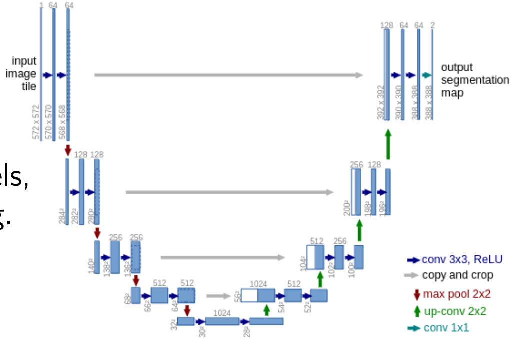
- Detector level data need to be corrected for acceptance, reconstruction inefficiencies, detector smearing, etc.
- Unfolding $\rightarrow f : X_{\text{detector}} \rightarrow X_{\text{particle}}$
- Deep neural networks excel at approximating complex non-linear functions, making them ideal for mapping between detector level and particle level.

Autoencoders and U-Nets

Taoli Cheng et al., arXiv:2007.01850



Olaf Ronneberger et al., arXiv:1505.04597

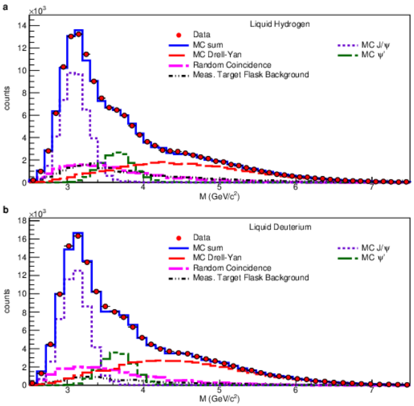


- Autoencoders(AE) are generative models, which are also used for image denoising.
- AEs encode input data to latent dimension (z) and then decoder try to reconstruct input data.
- U-Nets are U-shaped AEs that made a major breakthrough in image segmentation.
- We use U-Nets to reconstruct particle-level data using detector-level data as inputs.

Data Creation

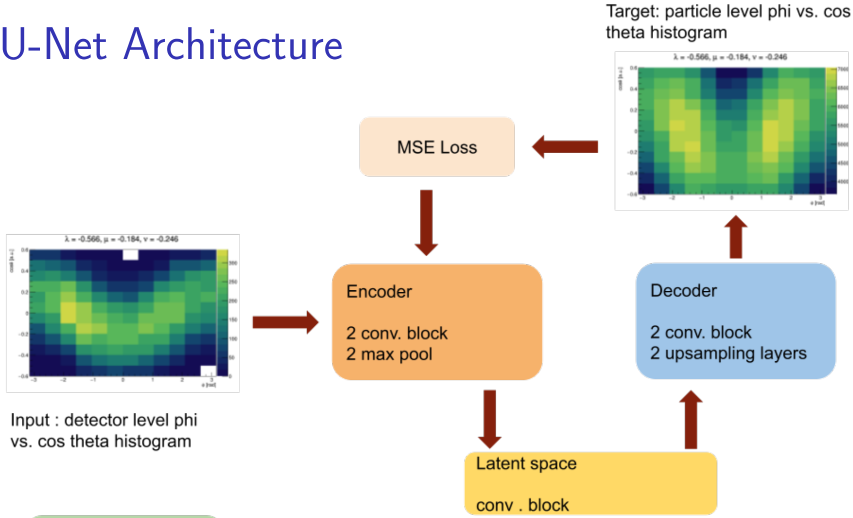
- Monte-Carlo data was generated using "PYTHIA" generator and events were passed trough E906 detector simulation using "GEANT4".
- λ, μ and ν values were sampled uniformly in the ranges [-1, 1], [-0.5, 0.5] and [-0.5, 0.5] respectively.
- DY angular coefficients were injected to the histograms by weighting the events using;

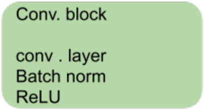
J. Dove et al., arXiv:2103.04024



$$w = \frac{1 + \lambda \cos^2\theta + \mu \sin 2\theta \cos\phi + \frac{1}{2}\nu \sin^2\theta \cos 2\phi}{1 + \cos^2\theta}$$

U-Net Architecture

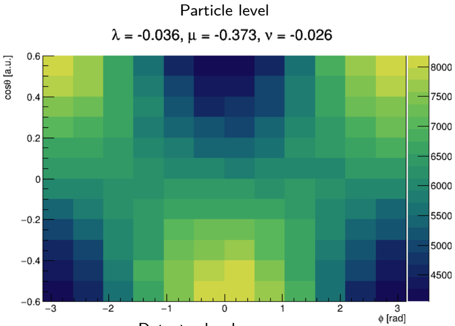


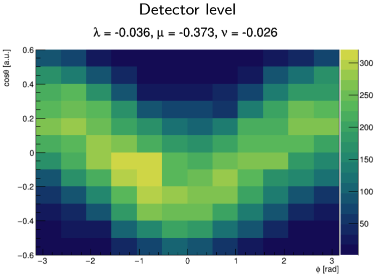


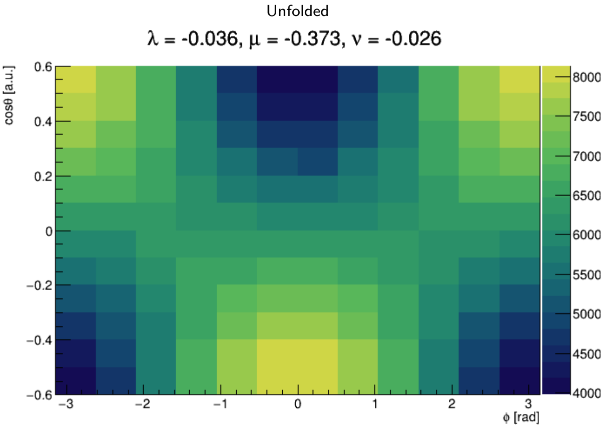
- Supervised learning

Model was trained in Fermilab Elastic Analysis Facility (EAF) using Nvidia A100 GPU.

Few Unfolded Histograms



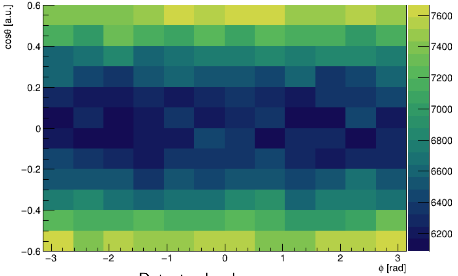




Few Unfolded Histograms

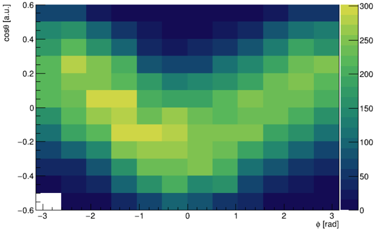
Particle level

$\lambda = 0.722,\ \mu = 0.003,\ \nu = 0.018$



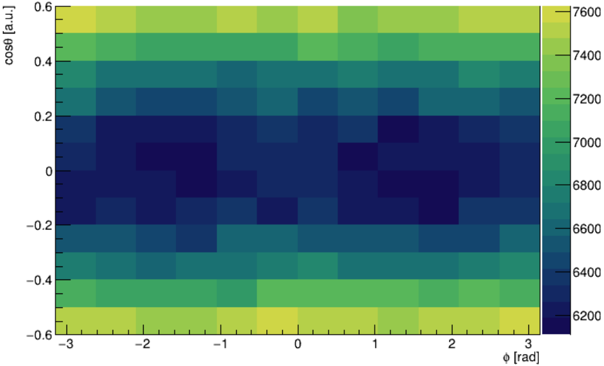
Detector level

$\lambda = 0.722,\ \mu = 0.003,\ \nu = 0.018$

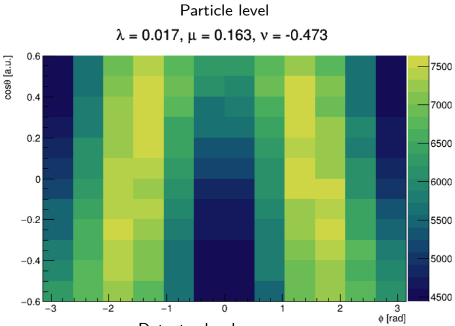


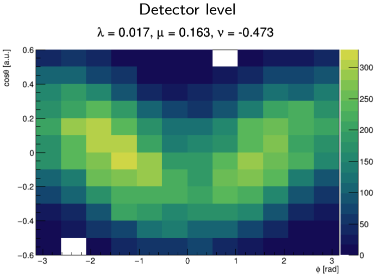
Unfolded

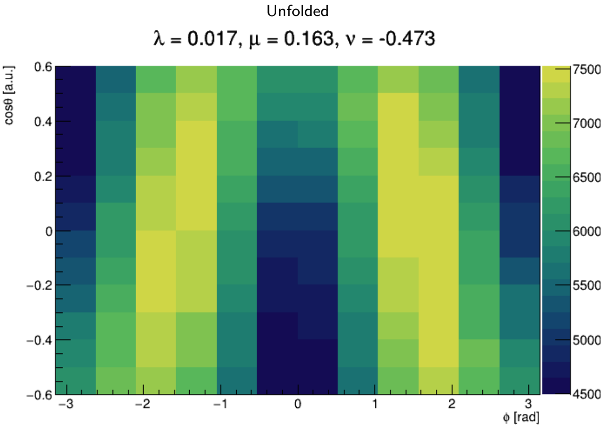
$\lambda = 0.722,\ \mu = 0.003,\ \nu = 0.018$



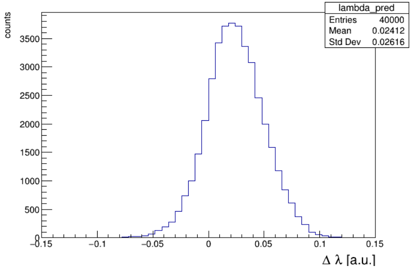
Few Unfolded Histograms

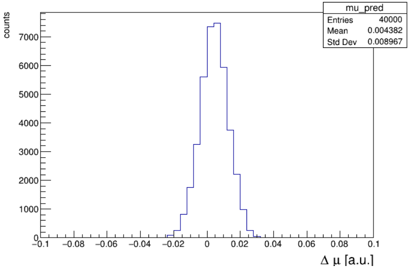


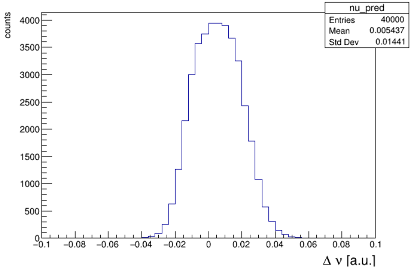




Resolution of the Unfolded Fit Results







- Unfolded ϕ-$\cos\theta$ histograms are fitted using;

$$f(\phi, \cos\theta) = A(1 + \lambda\cos^2\theta + \mu\sin 2\theta\cos\phi + \frac{1}{2}\nu\sin^2\theta\cos 2\phi)$$

- X axis; Δ = Injected $-$ Unfolded

Comparison of Few Unfolded Fit Results

	Particle level	Unfolded
λ	-0.584 $\pm$ 0.008	-0.579 $\pm$ 0.007
μ	-0.178 $\pm$ 0.002	-0.177 $\pm$ 0.002
ν	-0.238 $\pm$ 0.003	-0.241 $\pm$ 0.003
λ	-0.037 $\pm$ 0.009	-0.035 $\pm$ 0.009
μ	-0.367 $\pm$ 0.002	-0.370 $\pm$ 0.002
ν	-0.021 $\pm$ 0.003	-0.033 $\pm$ 0.003
λ	0.701 $\pm$ 0.011	0.689 $\pm$ 0.011
μ	0.006 $\pm$ 0.002	-0.004 $\pm$ 0.002
ν	0.0156 $\pm$ 0.003	0.019 $\pm$ 0.003

Summary

- The spin of the proton is an intrinsic property that can be used to understand the internal structure of the proton.
- A non-zero $\cos 2\phi$ asymmetry in the Drell-Yan process will provide information about the transverse motion of the quarks inside the proton.
- U-Nets can be utilized as a method to unfold detector-level data to particle-level data. This approach is applicable in high-dimensional feature spaces.
- We plan to use this method to extract the Drell-Yan angular coefficients from the FermiLab E906/SeaQuest data with higher precision.
- We plan to correct any discrepancies between experimental data and Monte Carlo (MC) simulations by reweighting.
- We plan to use the "Bootstrapping" method to enhance the precision of the prediction.
- Acknowledgment: This work was funded by the DOE Office of Science, Medium-Energy Nuclear Physics Program.