TMDPDFs extractions employing AI

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Based on : https://doi.org/10.1103/PhysRevD.108.054007





This work is supported by DOE contract DE-FG02-96ER40950

Outline

- Motivation
- A brief introduction to TMDs
- Sivers asymmetry from SIDIS
- DNN Approach for $SU(3)_{flavor}$
- DNN Method Testing
- DNN Fits & Results for Sivers function
- Summary and Outlook

Motivation

- TMDs: so far, model-dependent extractions \rightarrow assumptions, limitations and biases
- Information from data: Has the full potential of the data been taken into account?

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- TMDs: so far, model-dependent extractions \rightarrow assumptions, limitations and biases
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Introducing this <u>'novel' method</u> with Deep Neural Network (DNN) First time in TMD extractions

- Capacity to handle complex patterns, relationships in data with multi-D dependence.
- Data-driven
- Minimally biased \rightarrow un-biased
- Uncertainty propagation (from data) using bootstrap method by generating 'replicas' (Statistical & Systematic uncertainties from the experimental data are combined in quadrature)
- Recursive improvements to the DNN
- Systematic component can be quantified by a dedicated analysis

Intended to be Exploratory & Instructional

TMD PDFs

$$\Phi(x, k_T; S) = \int \frac{d\xi^- d\xi_T}{(2\pi)^3} e^{ik.\xi} \langle P, S | \bar{\psi}(0) \mathcal{U}_{[0,\xi]} \psi(\xi) | P, S \rangle|_{\xi^+ = 0}$$

At leading-twist, the Quark correlator can be decomposed into 8 components (6 T - even and 2 T -odd terms)









$$\mathbf{DIS} \quad \frac{d^5 \sigma^{lp \to lhX}}{dx dQ^2 dz d^2 p_\perp} = \sum_q e_q^2 \int d^2 \mathbf{k}_\perp \, \left(\frac{2\pi\alpha^2}{x^2 s^2} \frac{\hat{s}^2 + \hat{u}^2}{Q^4}\right) \\ \times \hat{f}_{q/p^\uparrow}(x, k_\perp) D_{h/q}(z, p_\perp) + \mathcal{O}(k_\perp/Q) \, ,$$

$$\hat{f}_{q/p^{\uparrow}}(x,k_{\perp}) = f_{q/p}(x,k_{\perp}) + \frac{1}{2} \Delta^{N} f_{q/p^{\uparrow}}(x,k_{\perp}) \vec{S}_{T} \cdot (\hat{p} \times \hat{k}_{\perp})$$
$$\Delta^{N} f_{q/p^{\uparrow}}(x,k_{\perp}) = 2\mathcal{N}_{q}(x)h(k_{\perp})f_{q/p}(x,k_{\perp})$$
$$\vec{p}_{A}$$

DNN Approach

$$A_{UT}^{\sin(\phi_h - \phi_S)}(x, z, p_{hT}) = \mathcal{A}_0(z, p_{hT}, m_1) \left(\frac{\sum_q \mathcal{N}_q(x) e_q^2 f_q(x) D_{h/q}(z)}{\sum_q e_q^2 f_q(x) D_{h/q}(z)} \right)$$



Experimental-data Manuta

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$$\mathcal{N}_q(x) = N_q x^{\alpha_q} (1-x)^{\beta_q} \frac{(\alpha_q + \beta_q)^{(\alpha_q + \beta_q)}}{\alpha_q^{\alpha_q} \beta_q^{\beta_q}}$$

generating function







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- We trained two separate models for "proton" and "neutron" (deuteron)
- ➢ To take full advantage of the information provided by the model testing in the previous slide, the steps from method testing with pseudo-data are performed again separately for proton and deuteron SIDIS data.

DNN Method testing

- Dashed lines represent the generating function in each iteration.
- A comparison:
 Improving the *generating function* Fine-tuning the hyperparameters
- Solid-lines and the band represent the mean and 68% CL with 1000 replicas of the DNN model.





Proton DNN Fit Results

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- All data points are well-described by the proton-DNN model. \geq
- No kinematic cuts were implemented. \geq

DNN Method: With Real data (Quality of the extraction)



The qualitative improvement of the extracted Sivers functions for u (blue), d (red), and s (green) quarks at x = 0.1 and $Q^2=2.4$ GeV² using the optimized proton-DNN model at the Second Iteration (solid-lines with dark-colored error bands with 68% CL), compared to the First Iteration (dashed-lines with light-colored error bands with 68% CL)

Sivers functions from the "Proton" DNN Model



Sivers 1st moments from the "Proton" Model



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3D Tomography from the "Proton" DNN Model

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$$\rho_{p\uparrow}^{a}(x,k_{x},k_{y};Q^{2}) = f_{1}^{a}(x,k_{\perp}^{2};Q^{2}) - \frac{k_{x}}{m_{p}}f_{1T}^{\perp a}(x,k_{\perp}^{2};Q^{2})$$



Projections from the "Proton" DNN Model



Projections of the of HERMES 2020 data for 3D kinematic bins, using the proton-DNN model including 68% C.L. error bands (in red) in comparison with the actual data points (in blue).

DNN Method: Results from the "Deuteron" Model

- ➤ Trained on COMPASS 2009 SIDIS data with Deuteron target.
- > Did not imposed iso-spin symmetric conditions, or data cuts.



 $f_{1T,u\leftarrow d}^{\perp} = f_{1T,d\leftarrow d}^{\perp} = \frac{f_{1T,u\leftarrow p}^{\perp} + f_{1T,d\leftarrow p}^{\perp}}{2}$

Deuteron DNN Fit Results

- No kinematic cuts are applied
 - Deuteron-DNN model can describe data reasonably well
- No iso-spin symmetry conditions are applied





DNN Model Projections: DY

 $\mathcal{B}_0(q_T,m_1)$ -

 q_T

Based on Anselmino et al. (2017) $A_N^{\sin(\phi_\gamma - \phi_S)}(x_F, M, q_T) = \mathcal{B}_0(q_T, m_1) \frac{\sum_q \frac{e_q^2}{x_1 + x_2} \mathcal{N}_q(x_1) f_{q/A}(x_1) f_{\bar{q}/B}(x_2)}{\sum_q \frac{e_q^2}{x_1 + x_2} f_{q/A}(x_1) f_{\bar{q}/B}(x_2)}$ Di-lepton Plane $\mathcal{B}_0(q_T, m_1) = \frac{q_T \sqrt{2e}}{m_1} \frac{Y_1(q_T, k_S, k_{\perp 2})}{Y_2(q_T, k_{\perp 1}, k_{\perp 2})}$ ϕ_S A Polarized Had $Y_1(q_T, k_S, k_{\perp 2}) = \left(\frac{\langle k_S^2 \rangle^2}{\langle k_T^2 \rangle + \langle k_T^2 \rangle \rangle^2}\right) \times \exp\left(\frac{-q_T^2}{\langle k_S^2 \rangle + \langle k_{\perp 2}^2 \rangle}\right)$ \vec{p}_B $Y_2(q_T, k_{\perp 1}, k_{\perp 2}) = \left(\frac{1}{\langle k_{\perp 1}^2 \rangle + \langle k_{\perp 2}^2 \rangle}\right) \times \exp\left(\frac{-q_T^2}{\langle k_{\perp 1}^2 \rangle + \langle k_{\perp 2}^2 \rangle}\right)$ \hat{x} $\frac{1}{\langle k_S^2 \rangle} = \frac{1}{m_1^2} + \frac{1}{\langle k_{\perp \perp}^2 \rangle}$ $\begin{array}{c} x_{1} \longrightarrow \mathcal{N}_{q} \longrightarrow \frac{e_{q}^{2}}{x_{1} + x_{2}} \mathcal{N}_{q}(x_{1,2}) f_{q/A}(x_{1}) f_{\bar{q}/B}(x_{2}) \\ x_{2} \longrightarrow \text{PDFs} \longrightarrow \frac{e_{q}^{2}}{x_{1} + x_{2}} f_{q/A}(x_{1}) f_{\bar{q}/B}(x_{2}) \end{array}$ $\langle k_{\perp 1}^2 \rangle = \langle k_{\perp 2}^2 \rangle = \langle k_{\perp}^2 \rangle = 0.25 \text{ GeV}^2$ $\Delta^{N} f_{q/p^{\uparrow}}(x,k_{\perp})\big|_{\text{SIDIS}} = -\Delta^{N} f_{q/p^{\uparrow}}(x,k_{\perp})\big|_{\text{DV}}$ Q_M $A_N^{
m DY}$ 25

DNN (Proton) Model Projections: DY





DNN Model Projections: DY

DNN Model Projections: DY

In Comparison with COMPASS 2024 Final



DNN Model Projections: DY @ SpinQuest



- SpinQuest (E1039) experiment at Fermilab is aiming to extract the Sivers function for the light-sea quarks.
- Unpolarized 120 GeV proton beam with polarized proton and deuteron targets (separately).
- Proton-DNN model predictions (Red)
 Deuteron-DNN model predictions
 (Orange)

Systematic Studies: data cuts

So far, the applicability of TMD factorization was ensured by applying cuts to SIDIS data based on various criteria in the literature.

$$egin{aligned} W^{\mu
u} &= \sum_f |\mathcal{H}_f(Q^2,\mu)|^{\mu
u} \ & imes \int d^2 k_\perp d^2 p_\perp \delta^{(2)}(z_h k_\perp + p_\perp - p_{hT}) \ & imes F_{f/N^\uparrow}(x,z_h k_\perp,S;\mu,\zeta_F) D_{h/f}(z_h,p_\perp;\mu,\zeta_D) \ & imes Y(p_{hT},Q^2), \end{aligned}$$

Examples:

1. Bury et al JHEP 05 (2021) 151 Q > 2 GeV

 $\delta = p_{hT}/zQ \le 0.3$

2. Echevarria et al JHEP 01 (2021) 126

 $q_T/Q < 0.75$

3. JAM2020

$$Q^2 > 1.63 \text{ GeV}^2$$
, $0.2 < z < 0.6$, $0.2 < p_{hT} < 0.9 \text{ GeV}$



FIG. 17. Solid lines with light band represent the u (in blue), d (in red) Sivers functions using the cut $Q^2 > 1 \text{ GeV}^2$. These resulting DNN models made from the cuts from all tests are also shown.

Systematic Studies: data cuts

$$egin{aligned} W^{\mu
u} &= \sum_f |\mathcal{H}_f(Q^2,\mu)|^{\mu
u} \ & imes \int d^2k_\perp d^2p_\perp \delta^{(2)}(z_hk_\perp+p_\perp-p_{hT}) \ & imes F_{f/N^\uparrow}(x,z_hk_\perp,S;\mu,\zeta_F) D_{h/f}(z_h,p_\perp;\mu,\zeta_D) \end{aligned}$$





$$\Delta^N f_{q/p^{\uparrow}}(x,k_{\perp}) = 2\mathcal{N}_q(x)h(k_{\perp})f_{q/p}(x,k_{\perp})$$



FIG. 19. Using two different $h(k_{\perp})$. Solid line with dark band represents the Sivers functions with $h(k_{\perp}) = \sqrt{2e} \frac{k_{\perp}}{m_1} e^{-k_{\perp}^2/m_1^2}$, whereas the dashed line with light band represents the Sivers functions with $h(k_{\perp}) = \frac{2k_{\perp}m_1}{m_1^2 + k_{\perp}^2}$.



- It is clear that the DNN is capable of incorporating both types of h(k) without affecting the Sivers functions in the final model as well as the asymmetries (with deviation less than 1%).
- This is because DNN demonstrates that it maps to the h(k) such that the Sivers function is nearly unchanged.

Systematic Studies : TMD Evolution

The solution of the TMD evolution equations

$$\mu^2 \frac{dF(x,b;\mu,\zeta)}{d\mu^2} = \frac{\gamma_F(\mu,\zeta)}{2} F(x,b;\mu,\zeta)$$
$$\zeta \frac{F(x,b;\mu,\zeta)}{d\zeta} = -\mathcal{D}(b,\mu)F(x,b;\mu,\zeta),$$

$$F(x,b;\mu,\zeta) = \left(\frac{\zeta}{\zeta_{\mu}(b)}\right)^{-\mathcal{D}(b,\mu)} F(x,b)$$

 $\mu \sim Q, \qquad \zeta_F \zeta_D \sim Q^4, \qquad \mu^2 = \zeta^2 = Q^2$



FIG. 21. The Sivers asymmetry evolution in Q^2 compared to the result from [6]. The red-colored solid line and the band represent the mean and standard deviation of the $A_{UT}^{\sin(\phi_h - \phi_S)}$ from 1000 replica models of the proton DNN at x = 0.12, z = 0.32, $p_{hT} = 0.14$ GeV.

Summary & Outlook

- We proposed a method for performing global fits to extract TMDs employing DNNs (first-ever application of DNNs in extracting TMDs).
- Extracting Sivers function was performed as an example of this method based on utilizing DNNs and the use of generating function to ensure the accuracy and precision.
- > We have successfully tested our method with pseudo-data, also a dedicated systematic study.
- \succ We chose Deep Neural Net (DNN) method to incorporate all x-dependent features of $\mathcal{N}_q(x)$.
- > We have already made a step-forward to consider incorporating TMD-evolution (needs more work)
- ➤ We performed global fit with experimental data: Separately on polarized SIDIS with Proton target and Deuteron target and obtained reasonably well description and extracted the Sivers functions for all light quark flavors in SU(3).
- We projected SIDIS and DY Sivers asymmetries: for already completed experiments (as a validation check: COMPASS) and upcoming experiments (such as SpinQuest). "Recursively Improving the DNN
- Currently working on Unpolarized TMDPDF extraction...

"Recursively Improving the DNN with multi-dimensional kinematic phase-space, and simultaneous information incorporation from experimental data (Nature)"

Next:

Applying the "DNN method" to extract other TMDs such as Transversity, Boer-Mulders function, as well as Spin-1 TMDs.



LANL-UVA Polarized Target <u>https://spinquest.fnal.gov/</u> http://twist.phys.virginia.edu/E1039/

Dustin Keller (<u>dustin@virginia.edu</u>)[Spokesperson] Kun Liu (<u>liuk@lanl.gov</u>)[Spokesperson]) Highest beam intensity on a polarized target ever!

See Liliet's talk



This work is supported by DOE contract DE-FG02-96ER40950

Backup Slídes

Backup Train loss (90% of data: First Iteration) Validation loss (10% of data: Second Iteration) Train Loss (100% of data: First Iteration) Train Loss (100% of data: Second Iteration)

800

600

0.0035

0.0030

0.0025

0.0020

0.0015

0.0010

0.0005

200

400

Number of Epochs

Loss

1000

TABLE III. The summary of the optimized sets of hyperparameters: The indications in the table are C_0^i and C_0^f for results from the pseudodata from the generating function, C_p^i , and C_p^f for results from SIDIS data from experiments associated with the polarized-proton target, and C_d^i and C_d^f for results from SIDIS data from experiments associated with the polarized-deuterium target, where *i* and *f* indicate the *First Iteration* and *Second Iteration* respectively. The initial learning rate is also listed (×10⁻⁴) as is the final training loss (×10⁻³). The accuracy and precision in each case are the maxima over the phase space.

Hyperparameter	\mathcal{C}_0^i	\mathcal{C}_0^f	${\cal C}^i_p$	\mathcal{C}_p^f	\mathcal{C}_d^i	\mathcal{C}^f_d
Hidden layers	5	7	5	7	5	8
Nodes/layer	256	256	550	550	256	256
Learning rate	1	0.125	5	1	10	1
Batch size	200	256	300	300	100	20
Number of epochs	1000	1000	300	300	200	200
Training loss	0.6	0.05	1.5	1	2	1
ε_{μ}^{\max}	95.67	99.27	55.21	94.04	56.80	93.02
$e_{\bar{\mu}}^{\max}$	42.62	98.09	52.57	96.70	34.83	91.40
e_d^{\max}	80.46	98.89	55.69	93.13	52.44	89.27
$e_{\bar{J}}^{\max}$	74.59	97.08	55.37	95.04	46.60	92.58
e_s^{\max}	45.53	79.27	49.54	90.64	36.34	93.41
$e_{\bar{s}}^{\max}$	59.27	91.13	33.89	82.51	65.57	91.45
σ_u^{\max}	3	0.1	5	2	2	0.4
$\sigma_{\bar{u}}^{\max}$	2	0.2	6	2	8	2
σ_d^{\max}	10	1	20	6	2	1
$\sigma_{\bar{d}}^{\max}$	7	4	20	8	7	1
σ_s^{\max}	2	0.2	4	1	6	2
$\sigma_{\overline{s}}^{\max}$	1	0.1	4	2	6	3