CFFs Fits using AI

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Towards Improved Hadron Femtography with Hard Exclusive Reactions Workshop
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Outline

- Introduction
- DVCS Channel
- Scope of Works
- Particle Swarm Optimization
- Neural-Net Architecture
- Preliminary Results
- Outlook

Introduction

Generalized Parton Distributions (GPDs) provide correlated information of the **transverse position** and the **longitudinal momentum** distributions of partons.

$$GPDs\,(\underbrace{x,\ \xi},\ t\ =\ \Lambda^2)$$

2 longitudinal momentum fractions

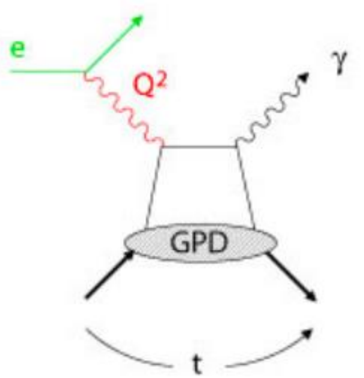
squared momentum transfer to the proton

$$t \to \Delta_T \xrightarrow{Fourier\ transform} \mathbf{b}\ (transverse\ position)$$

At leading twist there are 8 GPDs:

Chiral even GPDs

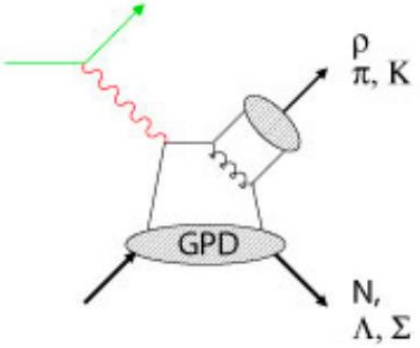
H, E, $\widetilde{H}$ and $\widetilde{E}$



Appear in DVCS

Chiral Odd GPDs

H_T, E_T, $\widetilde{H}_T$ and $\widetilde{E}_T$



Appear in exclusive meson production

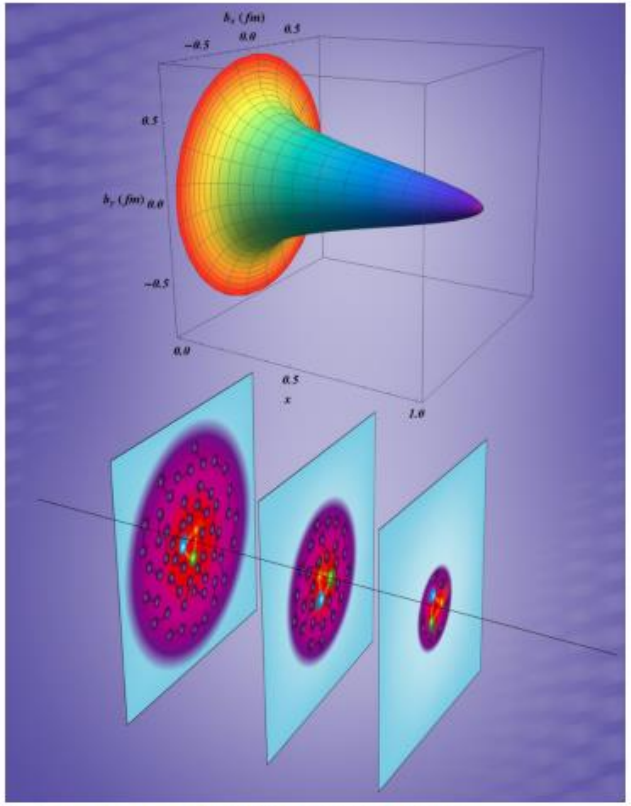
For a more detail about GPDs please see the talks on Theory Session Monday 09.00 :

- General Theory Exclusive Reaction
- GPDs from exclusive production
- Transition GPDs at EIC

Introduction

Generalized Parton Distributions (GPDs) provide key access to important nucleon properties:

- Nucleon Tomography:

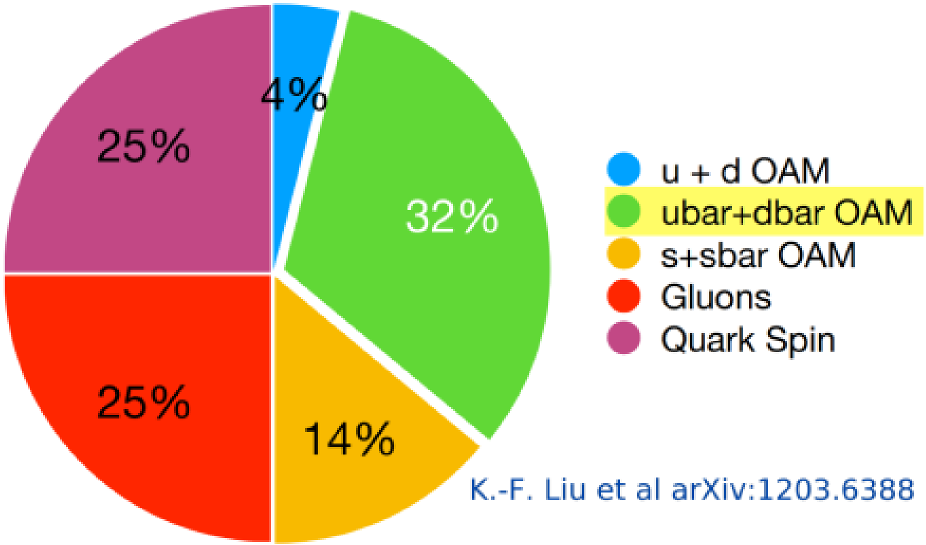


R. Dupre et al arXiv:1704.07330

- Angular momentum of the partons

Ji's angular momentum sum rule

$$\int_{-1}^{+1} dx \, \{H^q(x,\xi,0) + E^q(x,\xi,0)\} = A(0) + B(0) = 2J^q$$



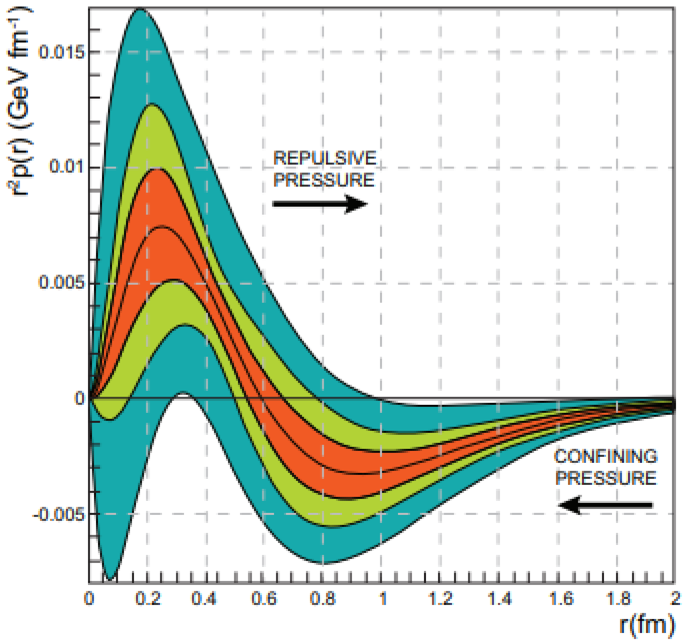
K.-F. Liu et al arXiv:1203.6388

Proton spin contributions from Lattice QCD

Introduction

Generalized Parton Distributions (GPDs) provide key access to important nucleon properties:

- Mechanical properties of the nucleons (pressure, force, …)



Pressure distributions inside proton

🟦 without JLab 6 GeV data

🟩 with JLab 6 GeV data

🟧 with JLab 12 GeV data (projected)

V. D. Burkert[1]*, L. Elouadrhiri[1] & F. X. Girod[1]

Mass and force/pressure distributions

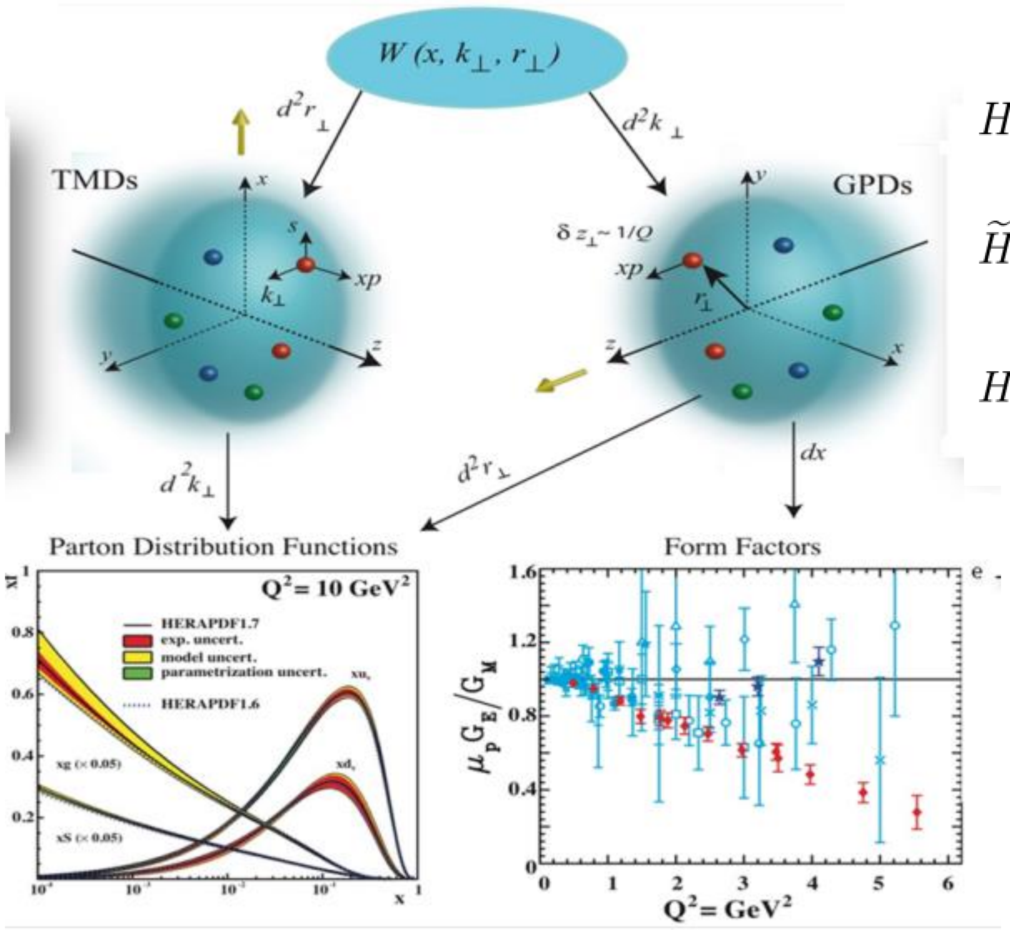
$$M_2^q(t)+\frac{4}{5}d_1(t)\xi^2=\frac{1}{2}\int_{-1}^{1}\mathrm{d}x\,xH^q(x,\xi,t)$$

$$d_1(t)\propto\int\frac{j_0(r\sqrt{-t})}{2t}p(r)\mathrm{d}^3r$$

Introduction

Generalized Parton Distributions (GPDs) provide key access to important nucleon properties:

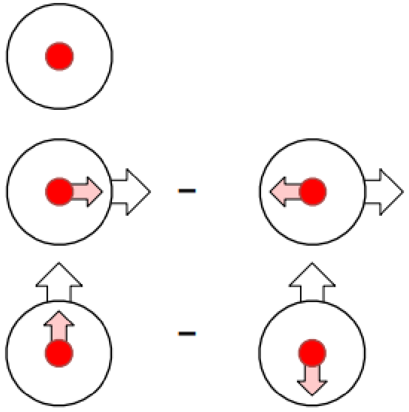
- Access to PDFs and Elastic Forms Factors



$$H^q(x,0,0) \equiv q(x)$$

$$\widetilde{H}^q(x,0,0) \equiv \Delta q(x)$$

$$H_T^q(x,0,0) \equiv h_1(x)$$

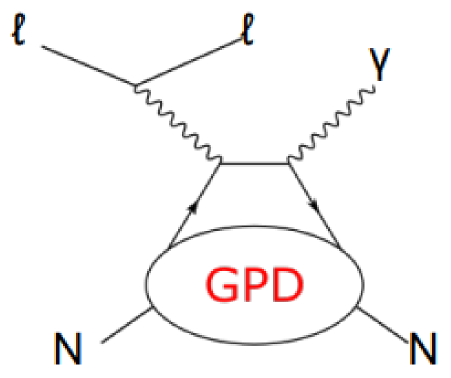


$$\int_{-1}^{1} dx\, H^q(x,\xi,t) \equiv F_1^q(t) \qquad \int_{-1}^{1} dx\, E^q(x,\xi,t) \equiv F_2^q(t)$$

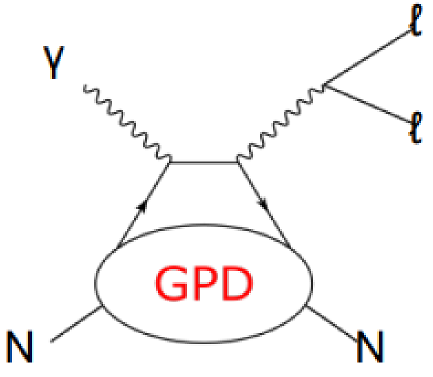
$$\int_{-1}^{1} dx\, \widetilde{H}^q(x,\xi,t) \equiv g_A^q(t) \qquad \int_{-1}^{1} dx\, \widetilde{E}^q(x,\xi,t) \equiv g_P^q(t)$$

Introduction

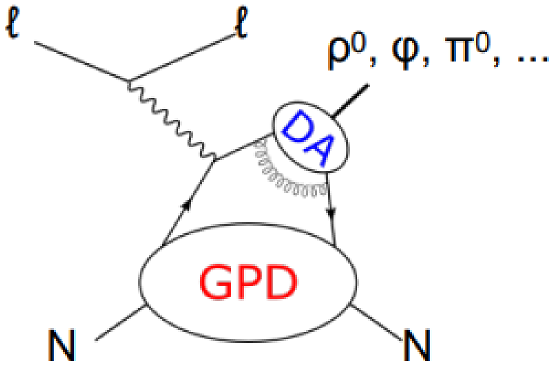
GPDs are accessible from various production channels:



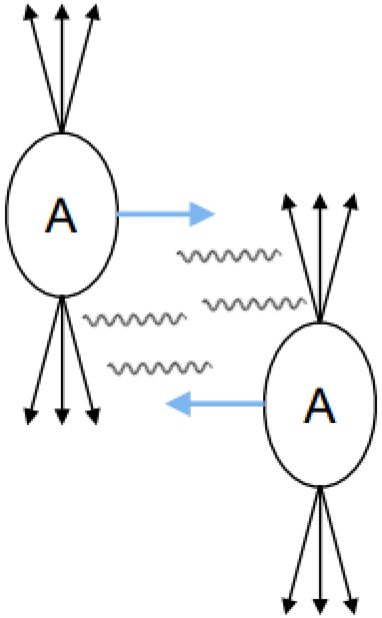
DVCS
Deeply Virtual Compton Scattering



TCS
Timelike Compton Scattering



HEMP
Hard Exclusive Meson Production



UPC
Ultra Peripheral Collisions

This talk is about DVCS
Session: Compton like: Fits, DVCS and beyond (Monday 09.00)

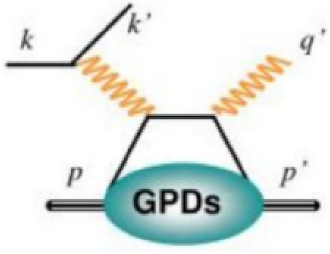
Session: Compton like TCS
Monday 14.00

Session: HEMP
Tuesday

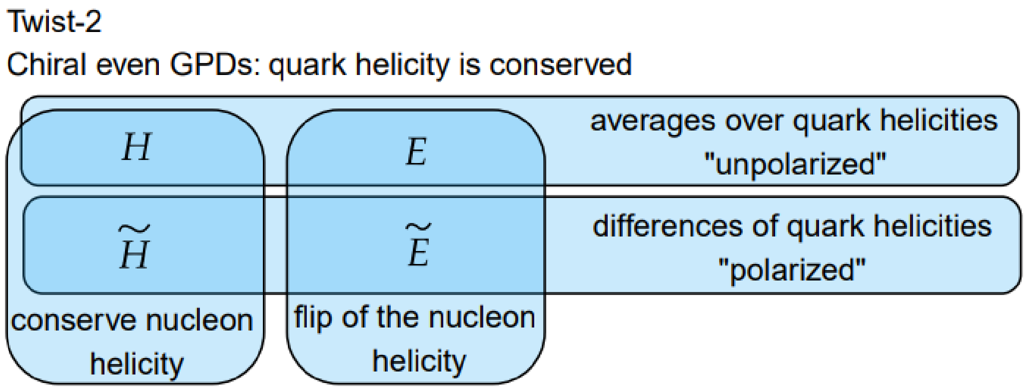
Session: HEMP
Tuesday

DVCS channel

4 chiral even GPDs can be accessed via DVCS



$ep \longrightarrow e^{'}p^{'}\gamma$



Twist-2

Chiral even GPDs: quark helicity is conserved

	conserve nucleon helicity	flip of the nucleon helicity
averages over quark helicities "unpolarized"	H	E
differences of quark helicities "polarized"	$\widetilde{H}$	$\widetilde{E}$

GPDs are related to Compton-Form Factors (CFFs) via convolution

$$\mathcal{H}\left(x_B,\, t,\, Q^2\right) = \int_{-1}^{1} dx \left[\frac{1}{\xi - x - i\epsilon} - \frac{1}{\xi + x - i\epsilon}\right] H\left(x,\, \xi,\, t,\, Q^2\right)$$

CFFs extractions (access directly via cross section or asymmetry measurements) is a good way to obtain GPDs

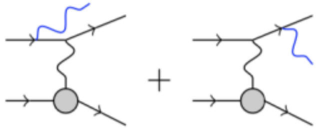
- Past: PDFs from FFs extractions
- Present: GPDs from CFFs extractions

DVCS channel

Cross sections = DVCS + Bethe-Heitler (BH)

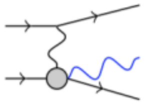
$$\sigma \propto |\mathscr{A}|^2 = |\mathscr{A}_{BH} + \mathscr{A}_{DVCS}|^2 = |\mathscr{A}_{BH}|^2 + |\mathscr{A}_{DVCS}|^2 + \mathscr{I}$$

Bethe-Heitler process

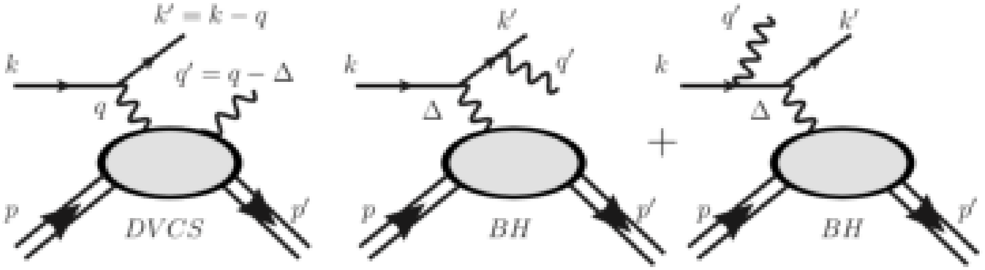


calculable within QED

DVCS



parametrised by CFFs



$$\underbrace{\frac{d^5\sigma}{dx_{Bj}\,dQ^2\,d|t|\,d\phi\,d\phi_S} = \frac{\alpha^3 x_B y^2}{16\pi^2 Q^4\sqrt{1+\epsilon^2}}\frac{1}{e^6}\left[|\mathcal{T}^{BH}|^2 + |\mathcal{T}^{DVCS}|^2 + \mathcal{I}\right]}_{f(k,Q^2,x_B,t,\phi)}$$

k	Energy of the incoming electron.
Q^2	Electron squared momentum transfer: $-(k-k')^2$
t	Squared momentum transfer to the proton: $(p'-p)^2$
x_B	Bjorken variable: $x_B = \frac{Q^2}{2(pq)}$ Momentum fraction of the quark or gluon on which the photon scatters.

DVCS Cross sections formulas:

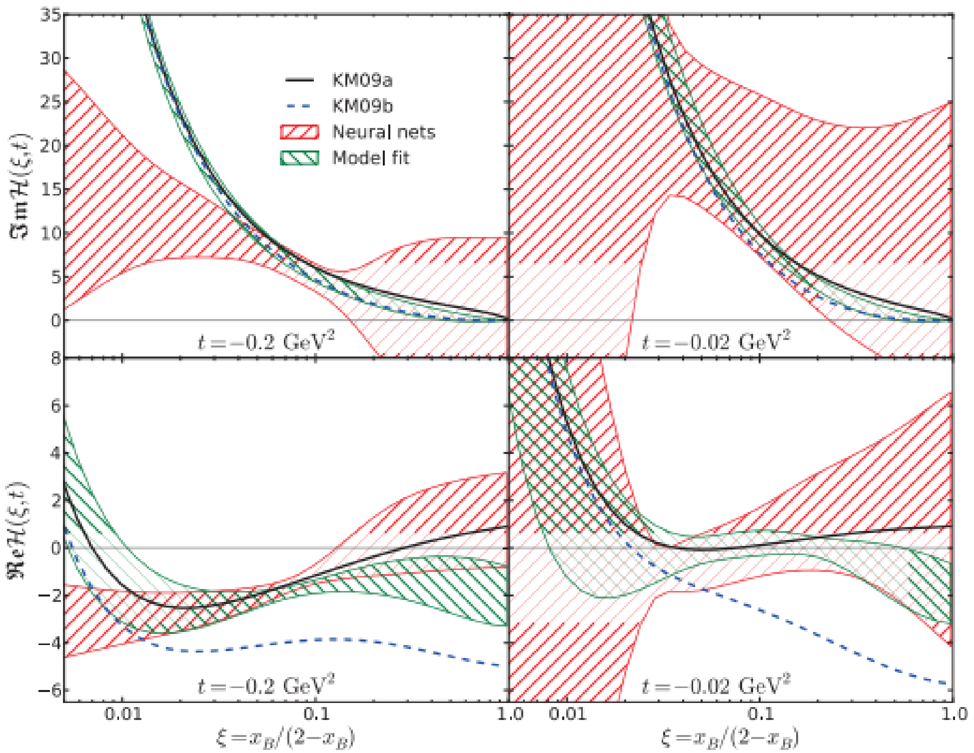
- Ji (1996)
- BKM (Belitsky, Muller, Kirchner): BKM02, BKM10
- BMJ (Belitsky, Muller, Ji, 2012)
- BMMP (Braun, Manashov, Muller, Pirnay, 2014)
- VA (B. Kriesten et all,): VA 19, VA 21
- Yuxun Guo et all, 2021

CFFs Model:

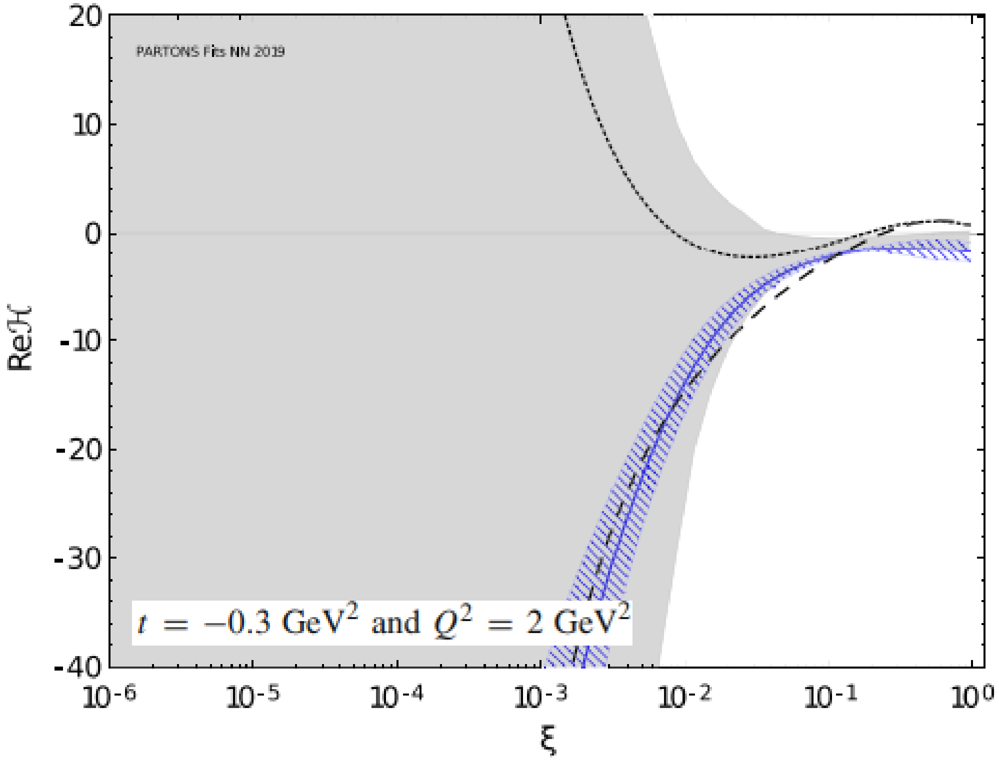
- VGG (Vanderhaeghen, Guichon, Guidal, 1999)
- GK (Goleskokov, Kroll, 2005)
- KM (Kumericki, Muller): KM09, KM10, KM15
- KMM12 (Kumericki, Muller, Murray, 2012)
- VA-reggeized spectator (B. Kriesten, S. Liuti, 2021)

DVCS channel

Neural-Net based CFFs extraction



Kumericki et all, 2011: First proof of concept



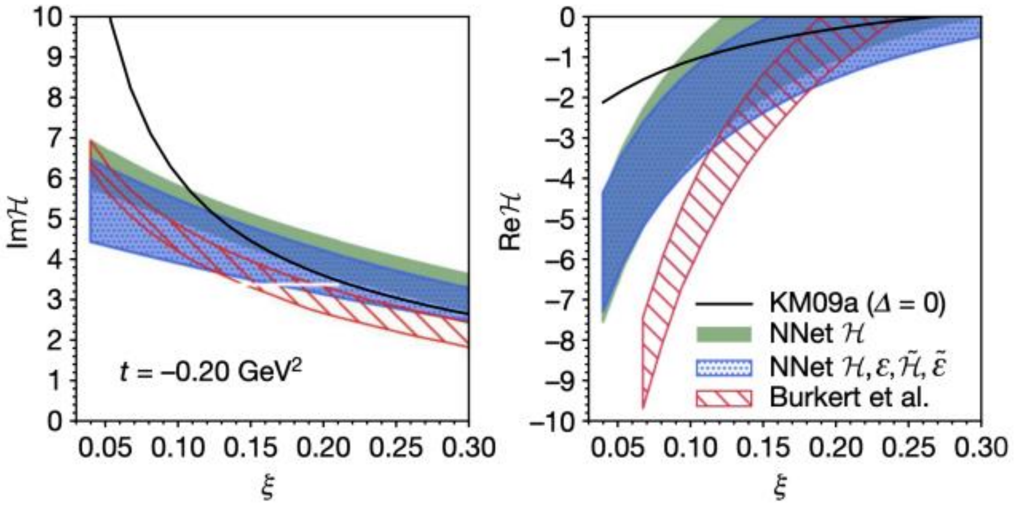
First global fit utilizing Neural net (2624 points)

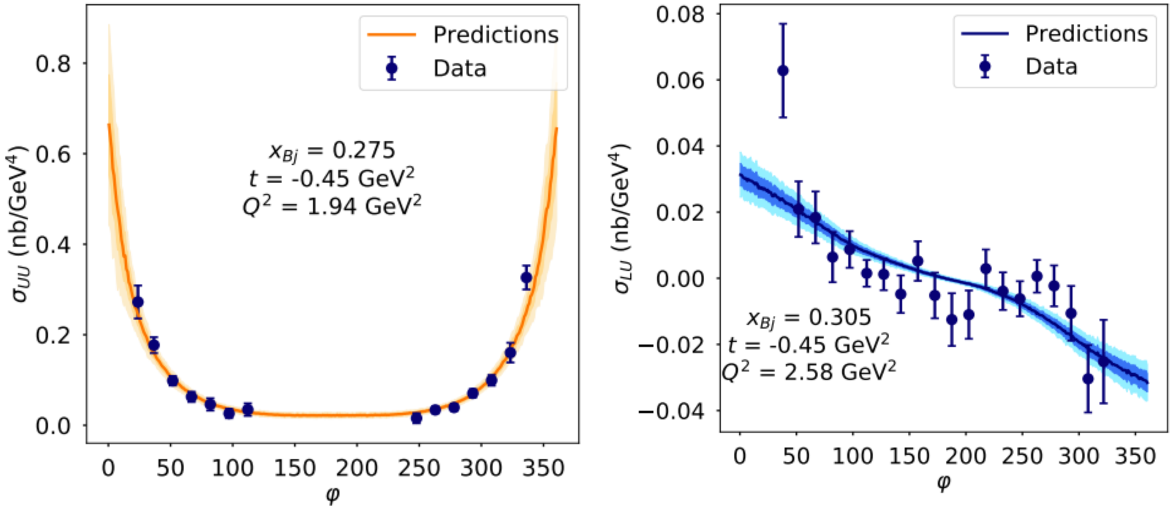
H. Moutarde, PS, J. Wagner, Eur. Phys. J. C79 (2019) no. 7 614

DVCS channel

Neural-Net based CFFs extraction

K. Kumerički, Nature 570 (2019) no.7759, E1





Global fit and prediction for the cross sections and asymmetry using NN (J. Grigsby et all, 2020)

Scope of Works

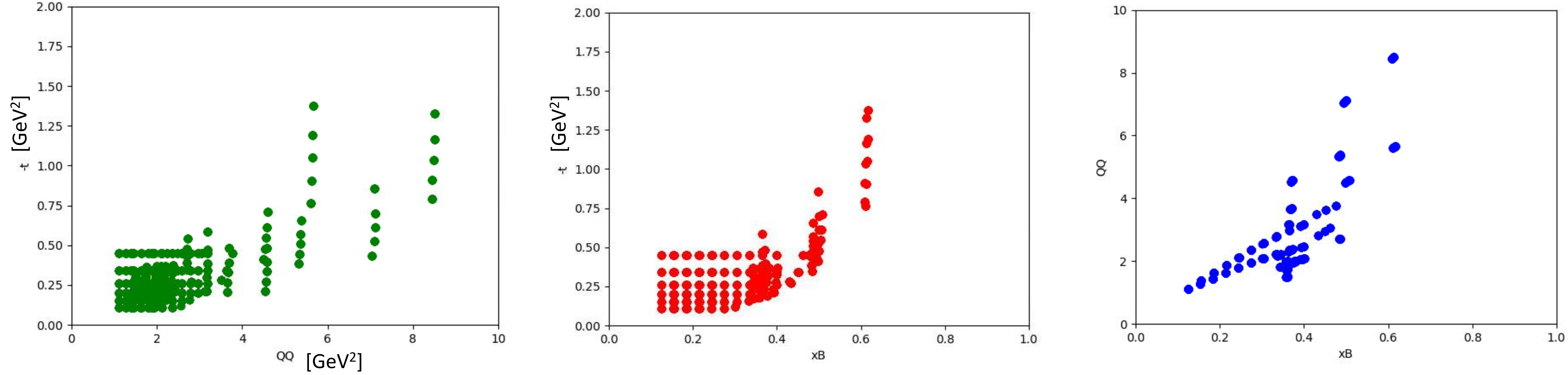
DVCS Data on Cross sections and Asymmetries:

- No φ-dependence: HERMES, COMPASS, ZEUS, A1
- High statistics with φ-dependence: JLAB Hall A, CLAS (Hall B)

Data used in this work: All φ-dependence cross-sections

- JLAB Hall A experiment: E00-110 (2015), E07-007 (2017), E12-06-114 (2022)
- JLAB Hall B experiment: e1-DVCS1 (2015)

A total of 195 kinematic sets (3882 data points) are used in this analysis



Scope of Works

We us BKM10 Formulism at leading twist

$$\frac{d^5\sigma}{dx_{Bj}\,dQ^2\,d|t|\,d\phi\,d\phi_S} = \frac{\alpha^3 x_B y^2}{16\pi^2 Q^4\sqrt{1+\epsilon^2}}\frac{1}{e^6}\Big[\underbrace{|\mathcal{T}^{BH}|^2}_{\substack{\text{Exact (QED)}\\ \text{FFs: } F_1,\, F_2}} + \underbrace{|\mathcal{T}^{DVCS}|^2}_{\phi\text{-indep}} + \underbrace{\mathcal{I}}_{\text{3 CFFs}}\Big]$$

$$\mathcal{I}^{BMK} = \frac{e^6}{x_B y^3 t \mathcal{P}_1(\phi)\mathcal{P}_2(\phi)}\Big[A_{UU}^{BKM}\Big(F_1\Re e\mathcal{H} - \frac{t}{4M^2}F_2\Re e\mathcal{E}\Big) + B_{UU}^{BKM}G_M\big(\Re e\mathcal{H} + \Re e\mathcal{E}\big) + C_{UU}^{BKM}G_M\Re e\widetilde{\mathcal{H}}\Big]$$

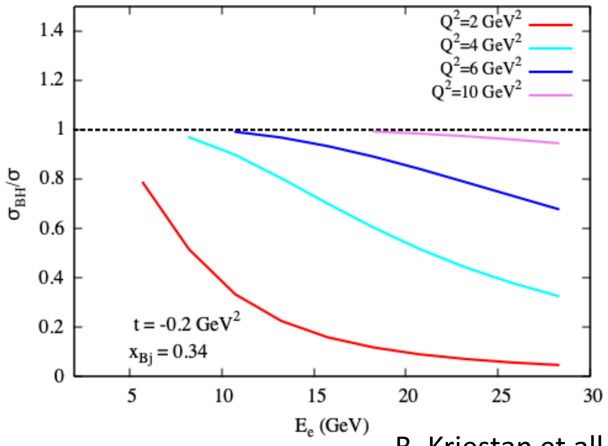
$$|\mathcal{T}_{DVCS}|^2 = \frac{e^6}{y^2Q^2}\Big\{2(2-2y-y^2)\Big\}\underbrace{C_{unp}^{DVCS}(\mathcal{F},\mathcal{F}^*)}_{\text{8 CFFs}}$$

4 fit parameters:

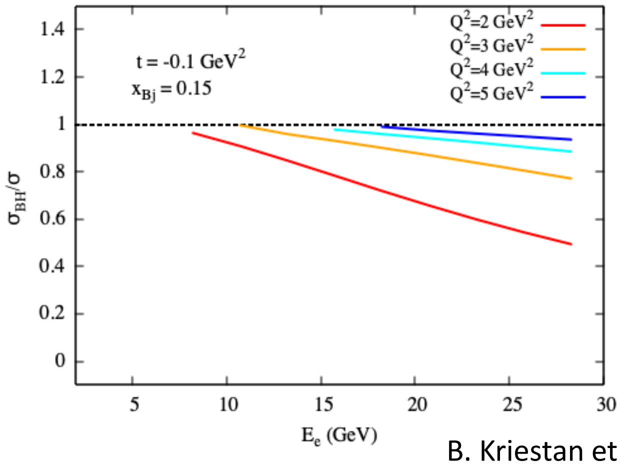
$\Re e\mathcal{H}$, $\Re e\mathcal{E}$, $\Re e\widetilde{\mathcal{H}}$,
pure DVCS

Scope of Works

Challenge: Huge BH background



B. Kriestan et all



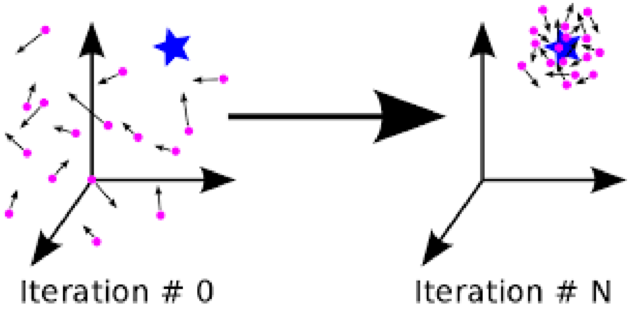
B. Kriestan et all

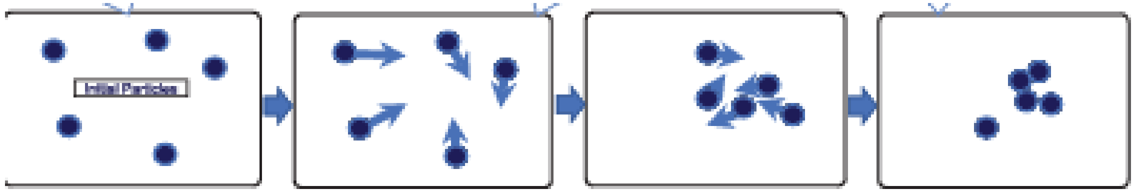
Approach:

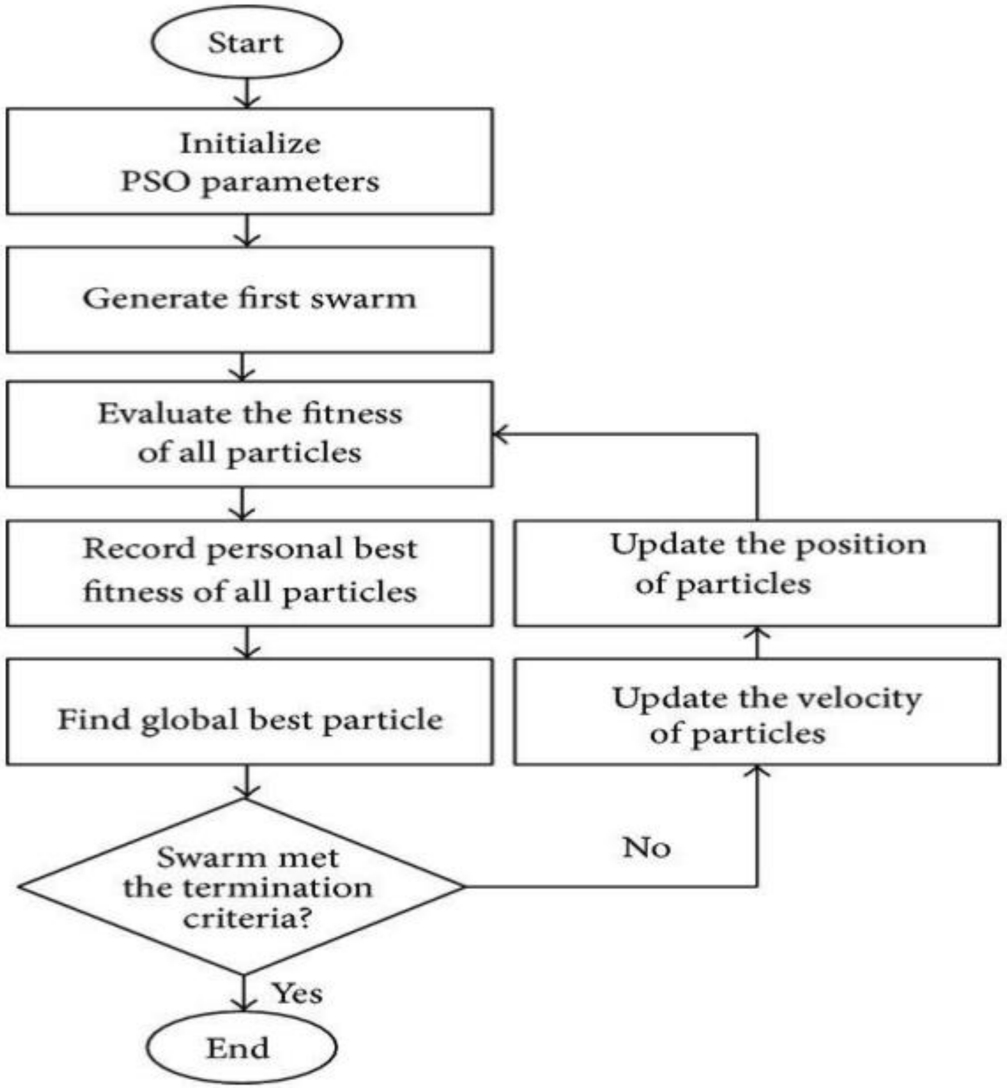
- Local fit to obtain CFFs for each kinematic sets using Root-Minuit & Particle Swarm Optimization (PSO)
- Global Fit using Neural Network
- Test the methods to the pseudo data generated using KM15 model and smeared according to the experimental uncertainty
- The pseudo data are generated with mimicking real data kinematics (195 sets) and uncertainties

Particle Swarm Optimization (PSO)

- Inspired from the nature social behavior and dynamic movements with communications of insects, birds and fish
- Uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution
- Each particle in search space adjusts its “flying” according to its own flying experience as well as the flying experience of other particles
- Each particle has three parameters position (velocity, and previous best position). Particle with best fitness value is called as global best position






Start

Initialize PSO parameters

Generate first swarm

Evaluate the fitness of all particles

Record personal best fitness of all particles

Find global best particle

Swarm met the termination criteria?

No

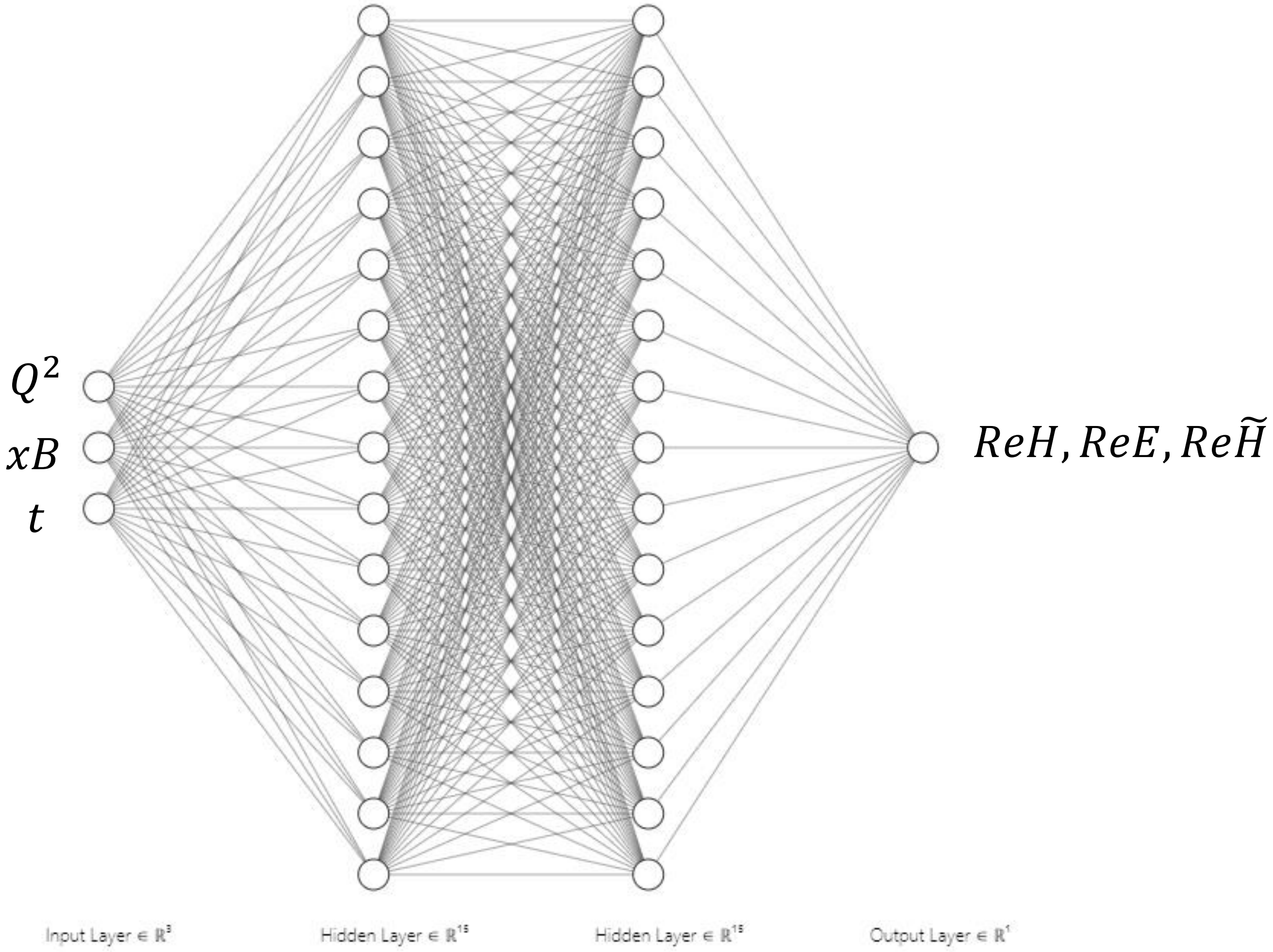
Update the velocity of particles

Update the position of particles

Yes

End

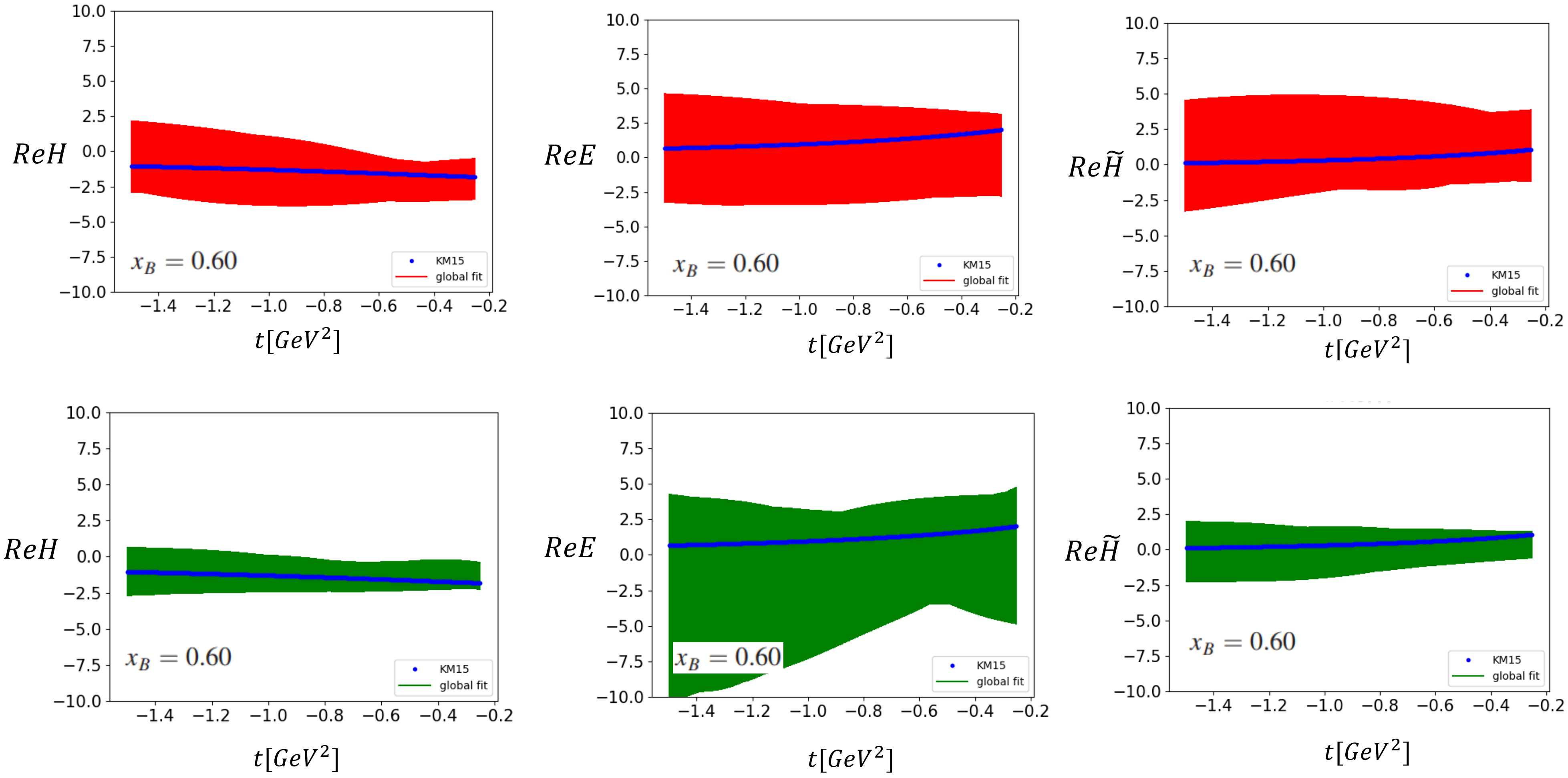
Neural Net Architecture



NN architecture & features:

- Each CFFs are global-fitted separately
- 3 input neurons, 1 output neuron
- 2 x 15 hidden layers
- Set splitting (training & validation)
- Multi-Step decay learning rate
- $tanh$ activation function
- Adam optimizer
- Input normalization
- Early stopping on Validation set
- Replicas by smearing the CFFs according to the uncertainty from local fit
- 1000 Replicas
- MSE loss function

Preliminary Results: Pseudo data

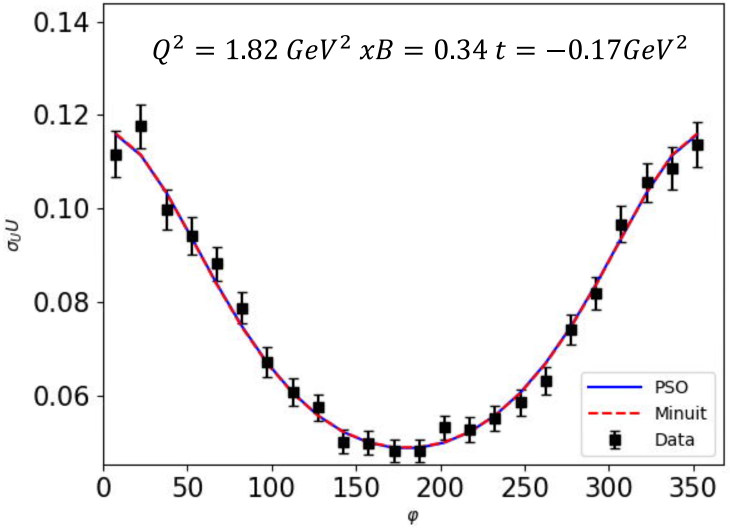


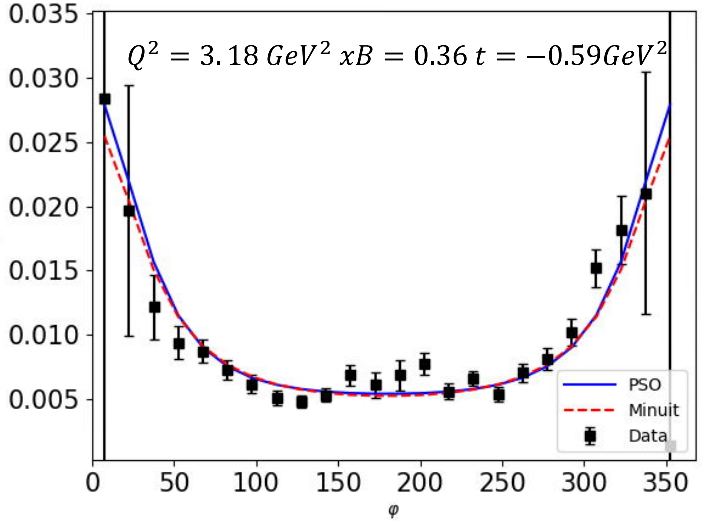
PSO

Minuit

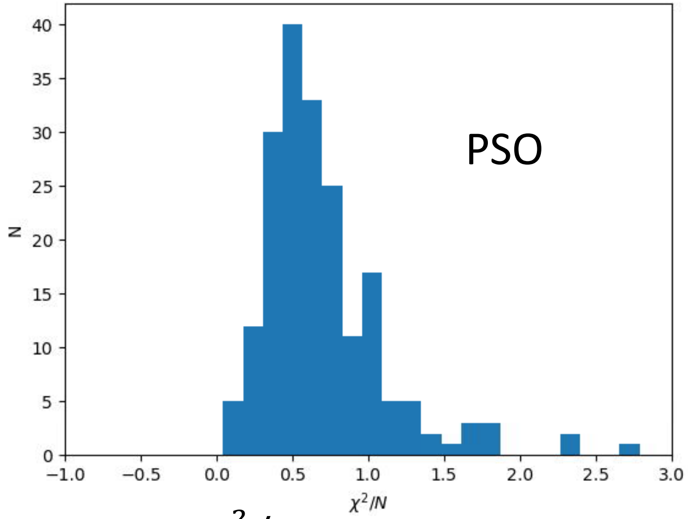
Note: Band represents all values from 1000 replicas

Preliminary Results: Local Fit on Experimental Data

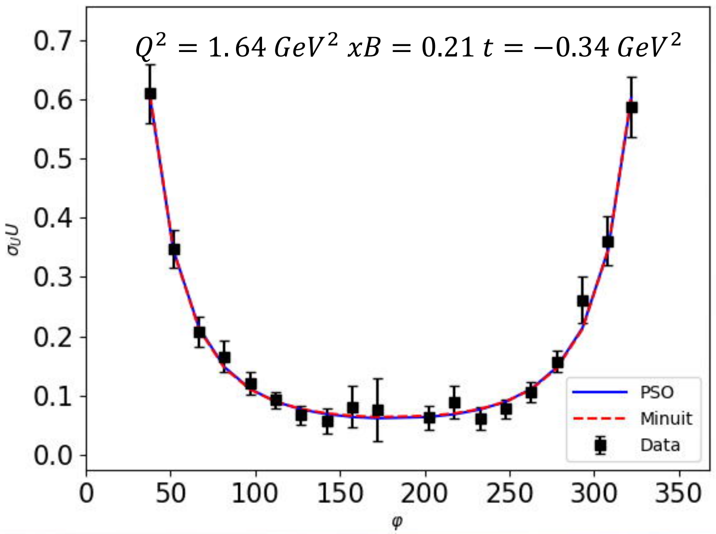


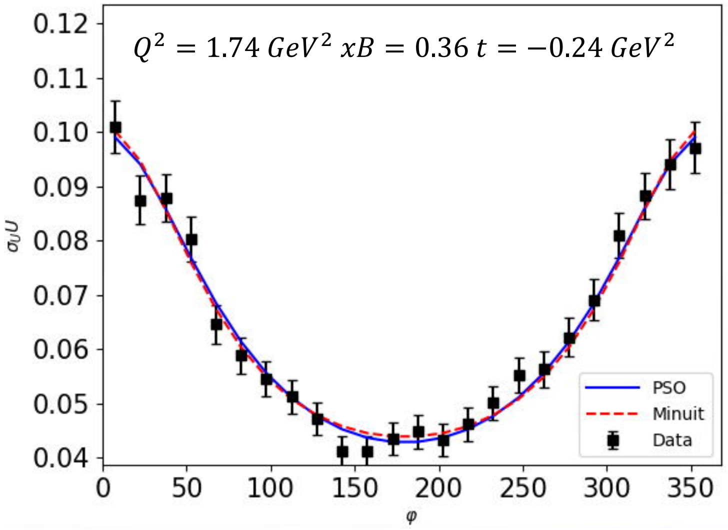


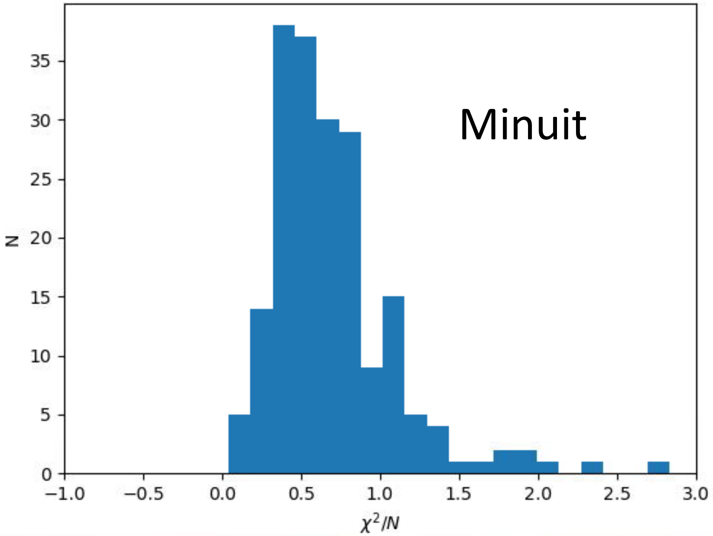
PSO $\chi^2/_{Ntotal} = 0.73902$



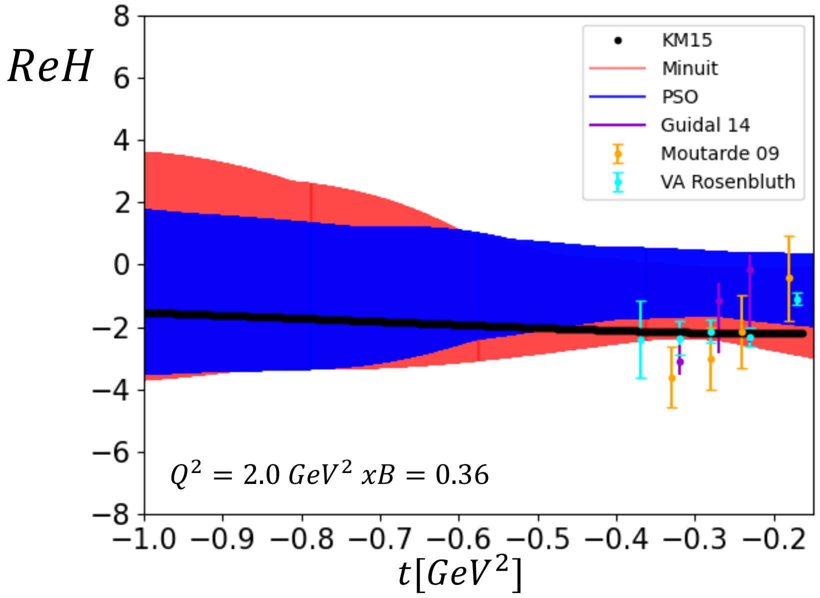
Minuit $\chi^2/_{Ntotal} = 0.73996$

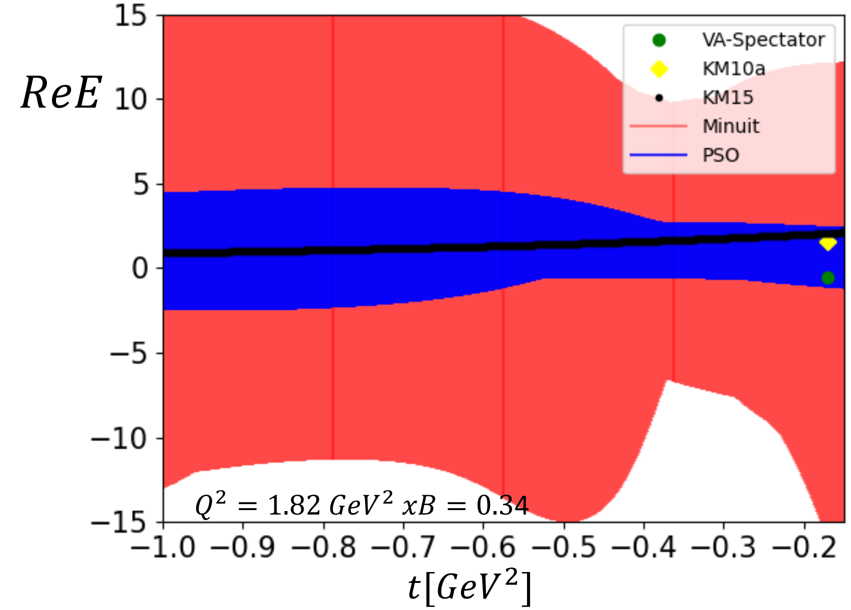


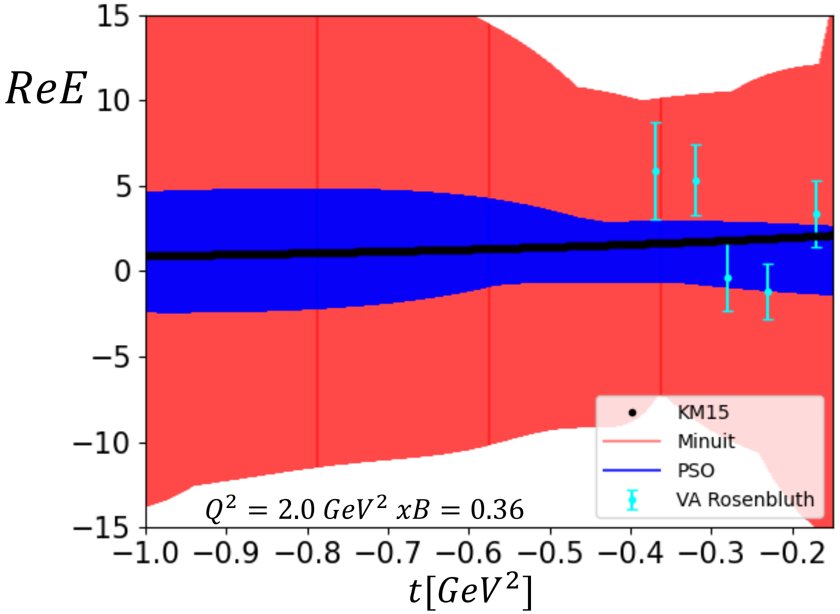


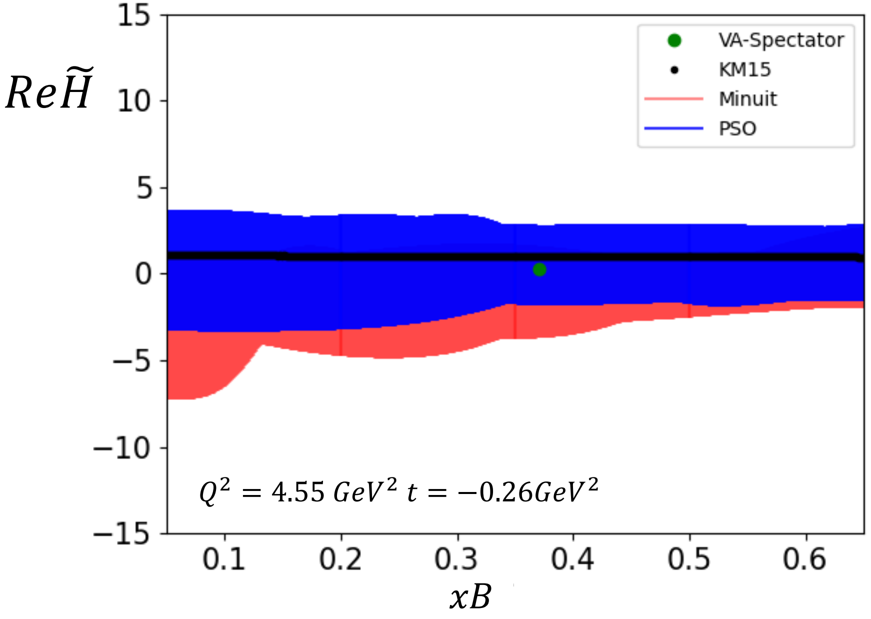


Preliminary Results: Global Fit on Data







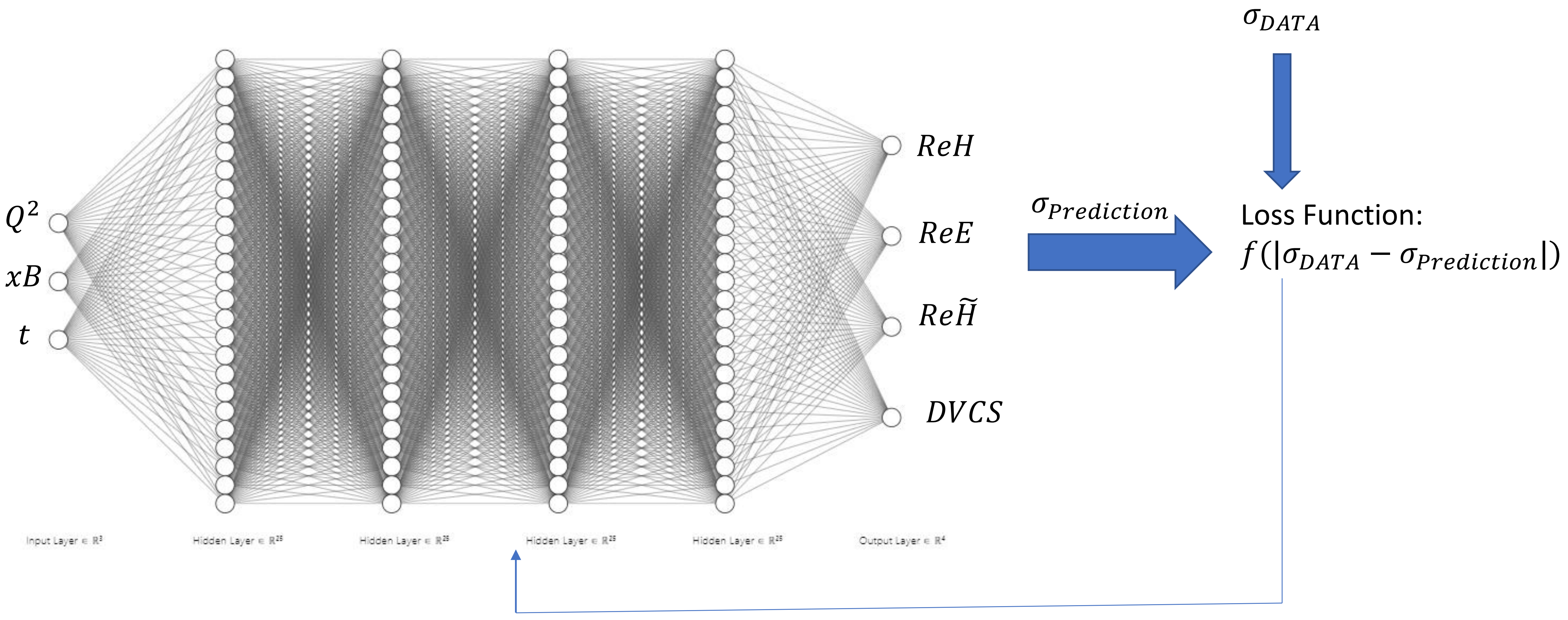


Note:

- Band represents all values from 1000 replicas
- Data points for comparison were extracted from B.Kriesten et all

Outlook

- Deep Neural Net for local & global fit (different architecture)

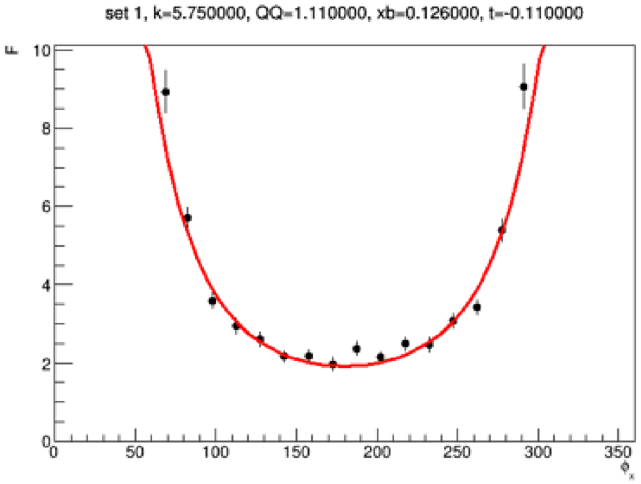


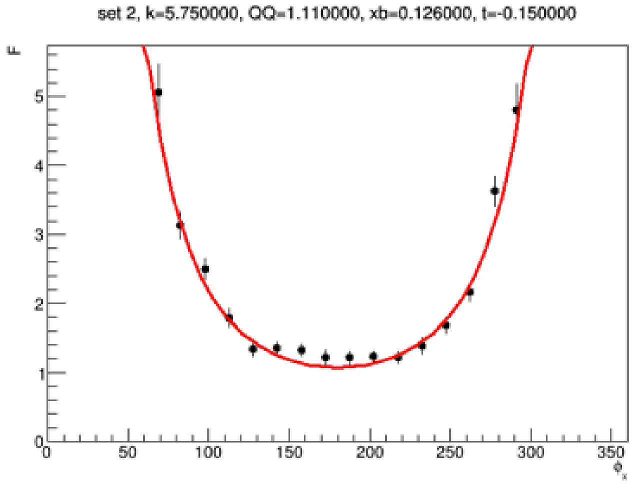
Loss Function:
$f(|\sigma_{DATA} - \sigma_{Prediction}|)$

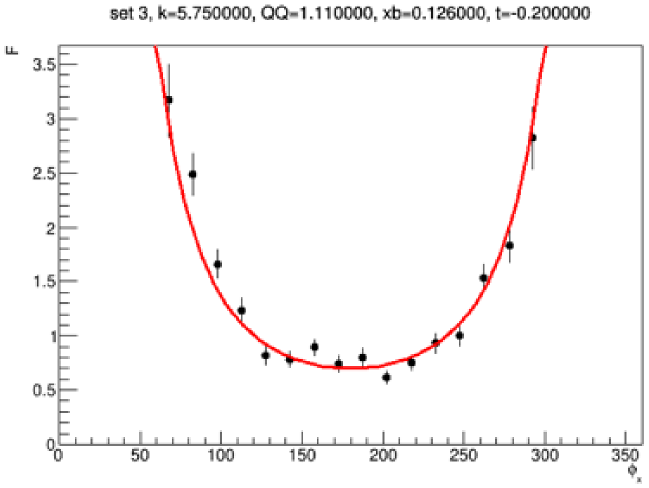
Back propagation

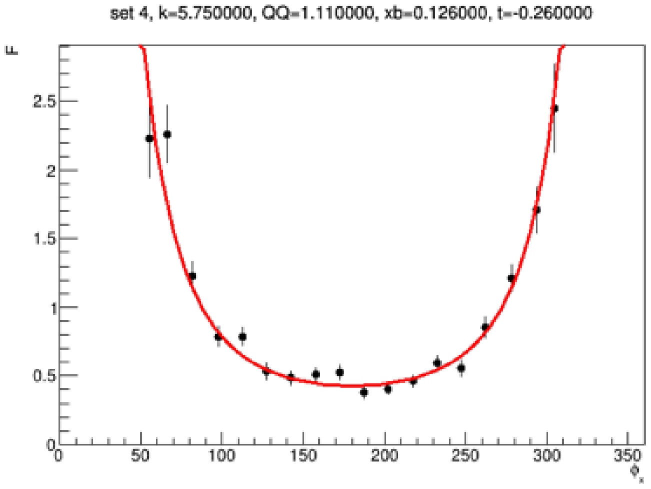
Outlook

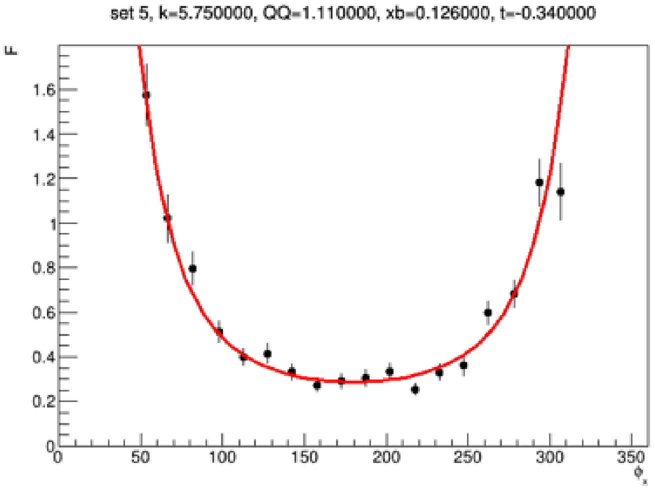
- Deep Neural Net for local & global fit (different architecture): preliminary results

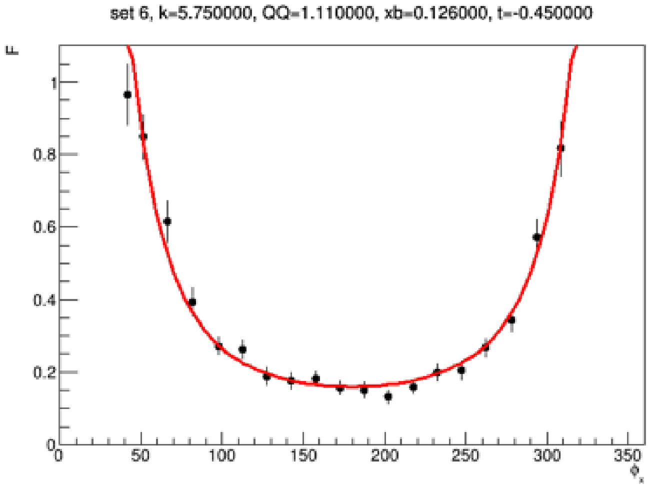

set 1, k=5.750000, QQ=1.110000, xb=0.126000, t=-0.110000


set 2, k=5.750000, QQ=1.110000, xb=0.126000, t=-0.150000


set 3, k=5.750000, QQ=1.110000, xb=0.126000, t=-0.200000


set 4, k=5.750000, QQ=1.110000, xb=0.126000, t=-0.260000

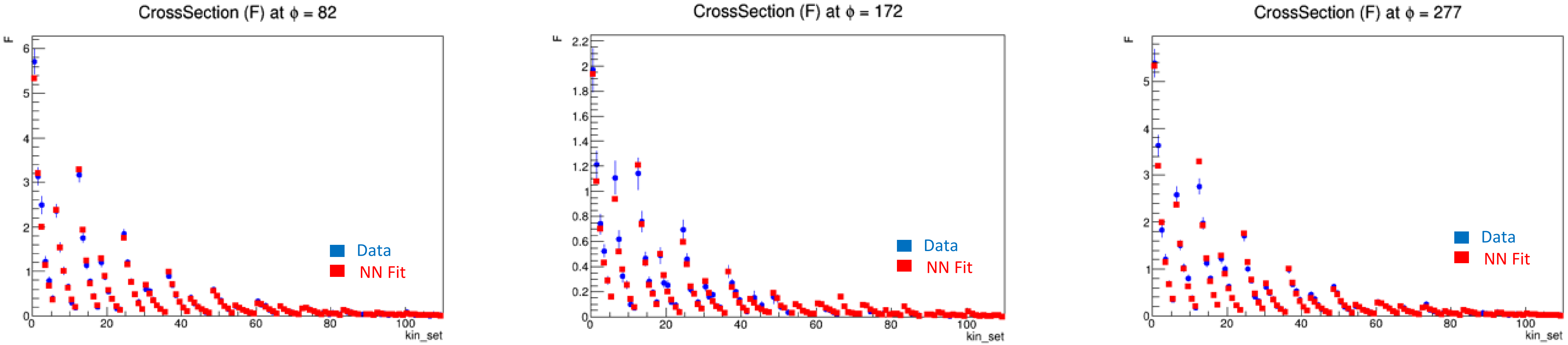

set 5, k=5.750000, QQ=1.110000, xb=0.126000, t=-0.340000


set 6, k=5.750000, QQ=1.110000, xb=0.126000, t=-0.450000

Outlook

- Deep Neural Net for local & global fit (different architecture): preliminary results

The comparison of predicted cross sections (F) and real data from CLAS e1-DVCS (110 kinematic sets)



- Include more data (asymmetry) from JLAB and other experiments
- Higher twist
- Systematics study by generating pseudo data from various models &formulism and study the differences between fitted and truth values

SPINQUEST (E1039) EXPERIMENT AT FERMILAB

$$\frac{d^2\sigma}{dx_1 dx_2} = \frac{4\pi\alpha^2}{9x_1x_2}\frac{1}{s} \times \sum_i e_i^2[q_{ti}(x_t)\bar{q}_{bi}(x_b) + \bar{q}_{ti}(x_t)q_{bi}(x_b)]$$

Fermilab E866/NuSea

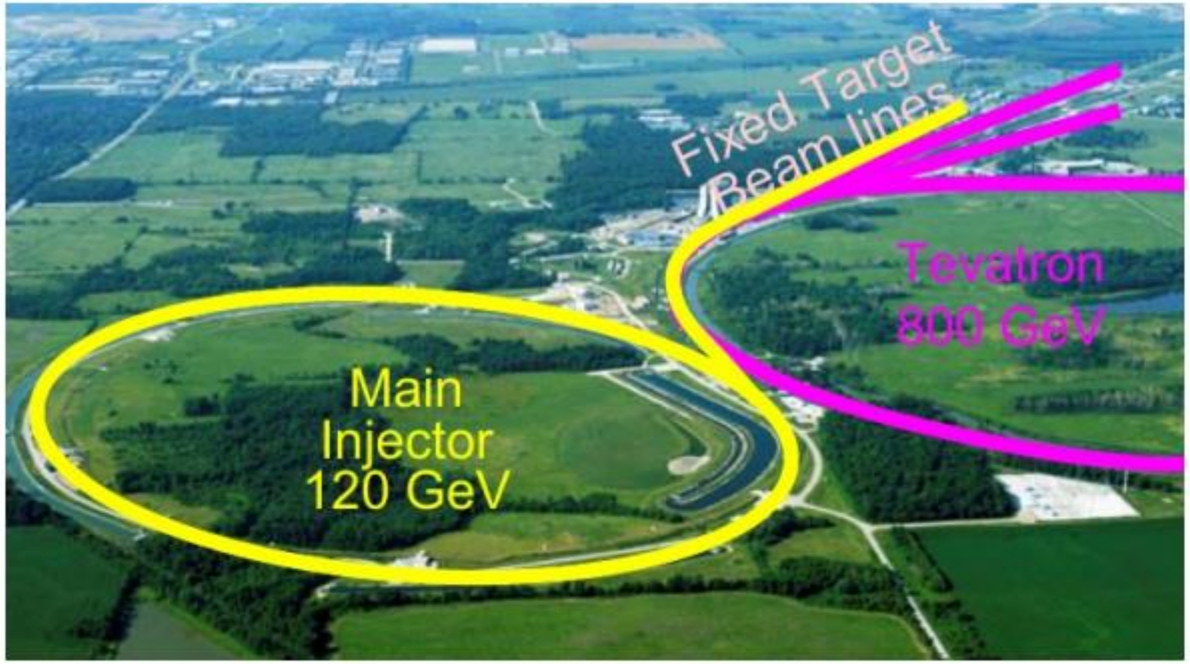
Data in 1996-1997
^{1}H, ^{2}H and nuclear targets
800 GeV proton beam

Fermilab E906/E1039

Data in > 2010
^{1}H, ^{2}H and nuclear targets
120 GeV proton beam

Therefore, the SpinQuest/E1039 experiment will get,

- Cross-Section scales as ~7 times compare to that with 800 GeV beam
- Luminosity is ~7 times compare to that with 800 GeV beam
- ~49 x Statistics with 800 GeV beam

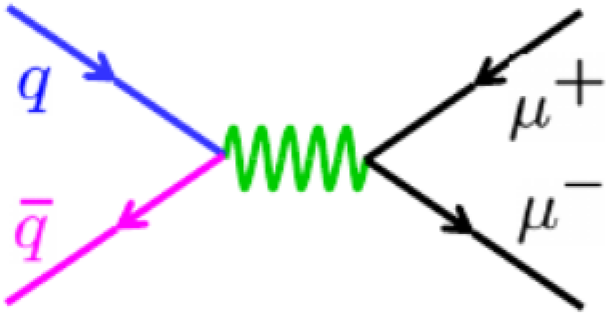


SPINQUEST (E1039) EXPERIMENT AT FERMILAB

➢ Measurement of 'sea' quark Sivers function

beam: valence quarks at high x

target: sea quarks at low/intermediate x



Sea-quarks dominance

$$\frac{d^2\sigma}{dx_b dx_t} = \frac{4\pi\alpha^2}{x_b x_t s} \sum_{q\in\{u,d,s,\dots\}} \boxed{e_q^2}\left[\bar{q}_t(x_t)q_b(x_b) + \cancel{q_t(x_t)\bar{q}_b(x_b)}\right]$$

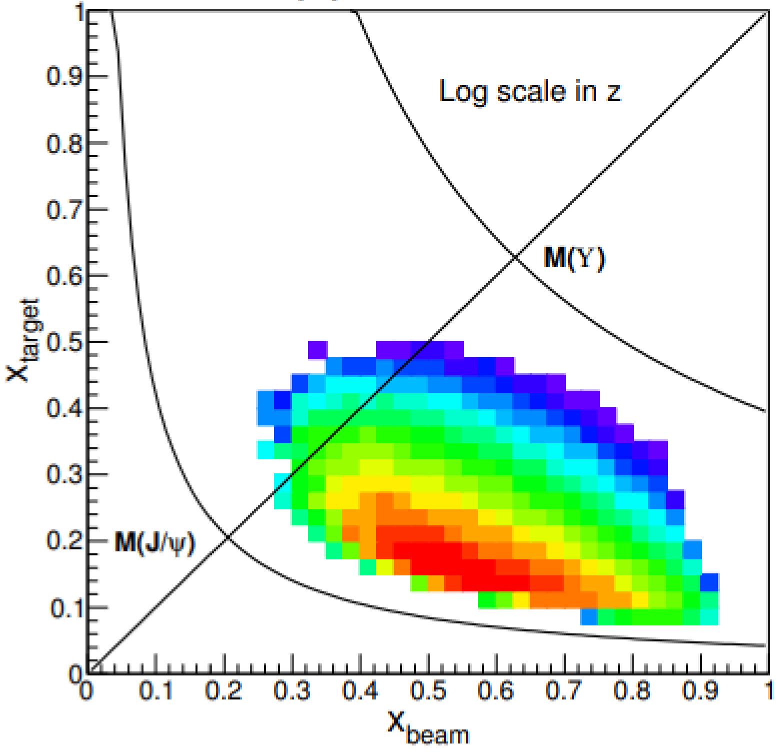
u-quark dominance

$(2/3)^2$ vs. $(1/3)^2$

Acceptance is optimized for sea-quarks

(Fixed Target, Hadron Beam)

From E1039 proposal

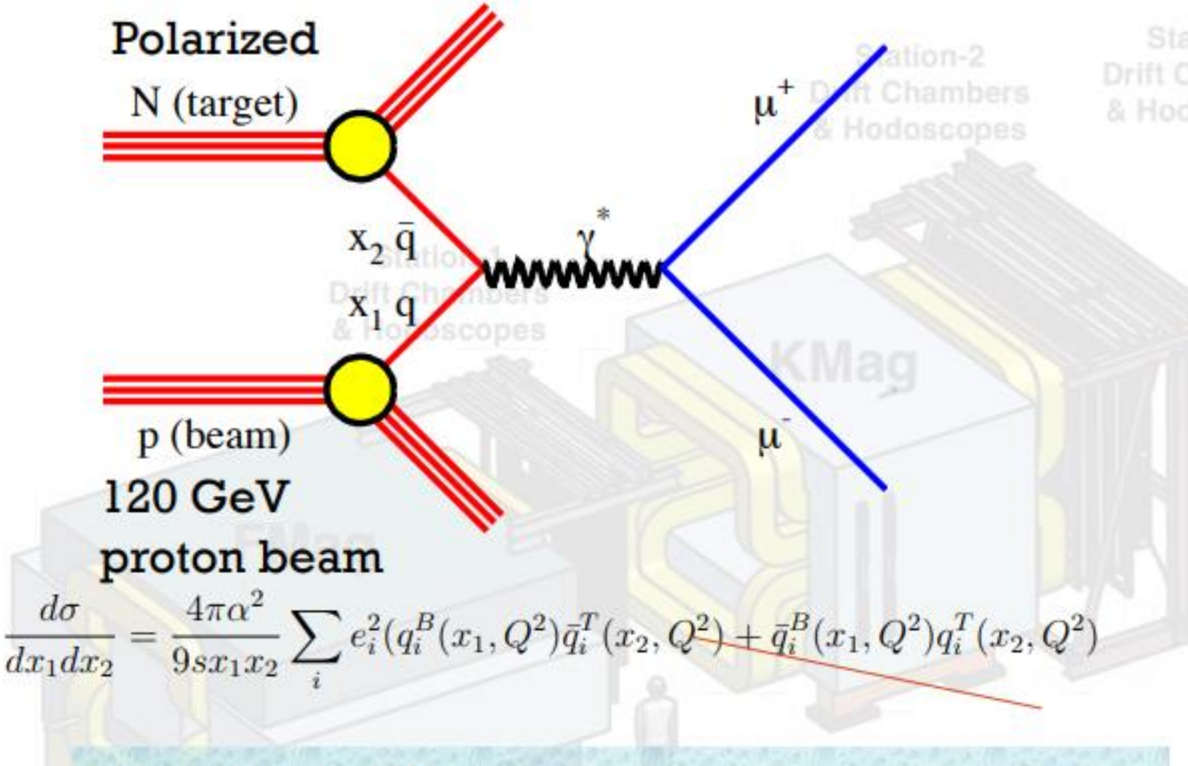


SPINQUEST (E1039) EXPERIMENT AT FERMILAB

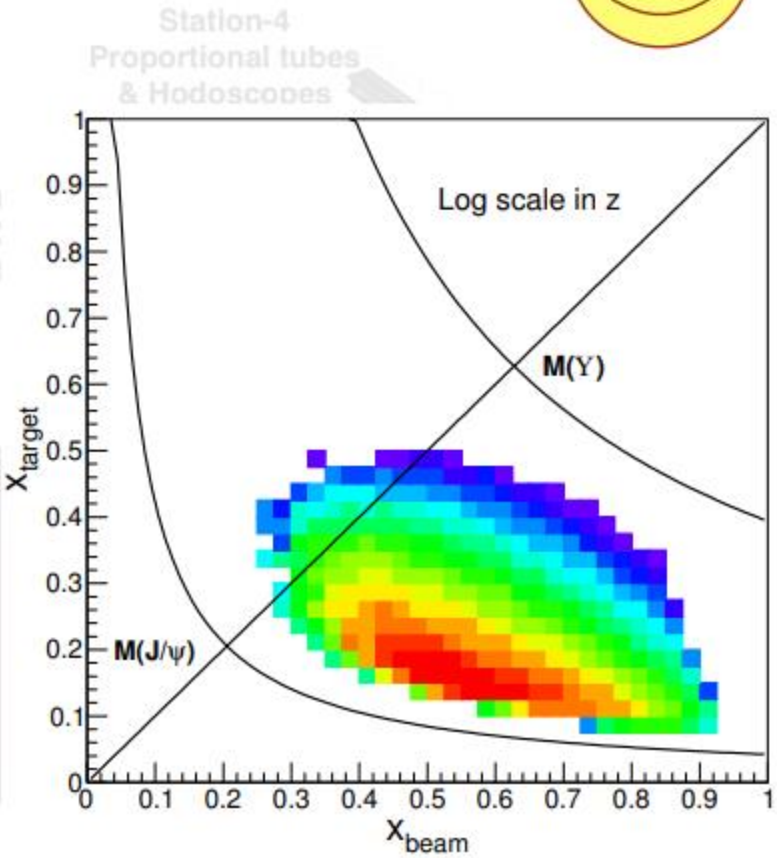
- ➢ Measurement of ‘sea’ quark Sivers function

Stay Tuned!

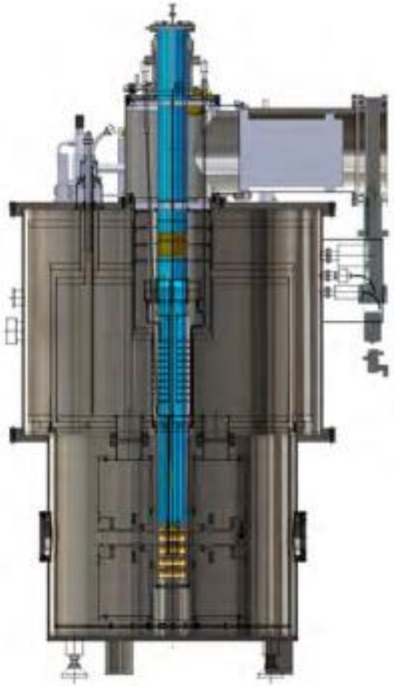
$pp^{\uparrow}(d^{\uparrow}) \rightarrow \mu^+\mu^- X,\ 4 < M_{\mu\mu} < 9\ GeV$



$$\frac{d\sigma}{dx_1dx_2} = \frac{4\pi\alpha^2}{9sx_1x_2}\sum_i e_i^2(q_i^B(x_1,Q^2)\bar{q}_i^T(x_2,Q^2)+\bar{q}_i^B(x_1,Q^2)q_i^T(x_2,Q^2)$$



The plan is to run with Highest instantaneous proton beam intensity on a polarized target ever!



LANL-UVA
Polarized Target

https://spinquest.fnal.gov/
http://twist.phys.virginia.edu/E1039/

Please Join The Effort

Dustin Keller (dustin@virginia.edu)[Spokesperson]
Kun Liu ([Spokesperson])

Thank You

UNIVERSITY of VIRGINIA

UVA - Spin
PHYSICS GROUP

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