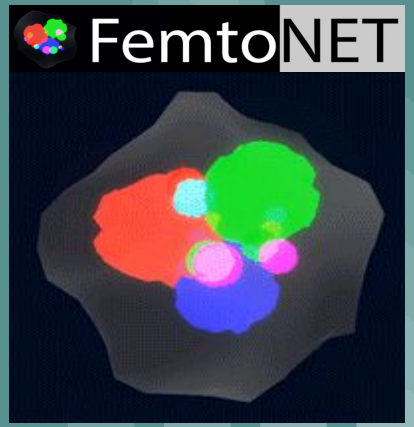
Reconstructing Lost Information in Deeply Virtual Exclusive Processes

B. Kriesten

CENTER *for* NUCLEAR FEMTOGRAPHY

Jefferson Lab Cake Seminar

November 9, 2022



FemtoNet

Phenomenology

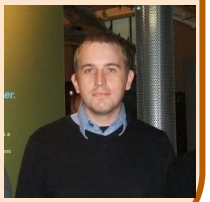
Simonetta Liuti
Univ. of Va.

Brandon Kriesten
CNF

Machine Learning

Yaohang Li
ODU

Joshua Hoskins
Univ. of Va.



Students

Jake Grigsby
Univ. of Va.

Manal Almaeen
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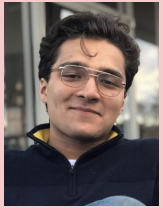
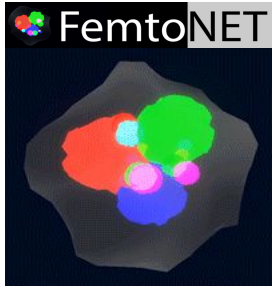
Zaki Panjsheeri
Univ. of Va.



Joshua Bautista
Univ. of Va.

Lattice QCD

Huey-Wen Lin
MSU



FemtoNet Analysis Framework

FemtoNET Software

https://femtonet.phys.virginia.edu/ (under construction)

REPOSITORY

FemtoViz

A visualization web app to easily plot and compare calculated GPDs from a model calculation.

FemtoEvolve

A framework for perturbative QCD evolution of generalized parton distributions.

FemtoNN

A code release for neural network framework for femtography and extracting information.

FemtoNet Publications

Machine Learning

- Deep Learning Analysis of Deeply Virtual Exclusive Photoproduction **PRD 104 (2021)**
- Benchmarks for a Global Extraction of Information from Deeply Virtual Exclusive Scattering Experiments **arXiv:2207.10766**
- VAIM - CFF: A variational autoencoder inverse mapper solution to Compton form factor extraction from deeply virtual exclusive reactions **(in progress)**
- Deep learning partonic angular momentum through VAIM **(in progress)**

Phenomenology

- Extraction of generalized parton distribution observables from deeply virtual electron proton scattering experiments **PRD 101 (2020)**
- Theory of deeply virtual Compton scattering off the unpolarized proton **PRD 105 (2022)**
- Novel Rosenbluth extraction framework for Compton form factors from deeply virtual exclusive experiments **PLB 829 (2022)**
- Parametrization of quark and gluon generalized parton distributions in a dynamical framework **PRD 105 (2022)**
- Deeply virtual Compton scattering from fixed target to collider settings **(in progress)**

Some open questions

- What are the physical properties that we can define in the context of QCD? (mass, radii, OAM) but also **moving beyond static properties** to understanding multi-parton correlations in the nucleon.
  - Going beyond the interaction of a single particle, what information are we learning?
- Do we understand the behavior of certain physical properties. Such as r_g and r_q ?
  - What can we learn about the color forces keeping the proton at a certain radius? What can we learn about **color confinement**?
- What are the limits of standard analysis techniques? Can we quantify exactly how much information we can extract from data?
  - Many analyses have been done in the past extracting CFFs, what does it say that we are all different? What does it mean that some of the results we are the same?
  - Can we reframe the analysis of deeply virtual exclusive reactions as a reconstruction of lost information?

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  - Many analyses have been done in the past extracting CFFs, what does it say that we are all different? What does it mean that some of the results we are the same?
  - **Can we reframe the analysis of deeply virtual exclusive reactions as a reconstruction of lost information? The answer is yes!**

Outline

- Physics Motivation
- Femtography
- DNN Framework
- DVCS Cross Section Data
- CFF Extraction
- Outlooks/Conclusions

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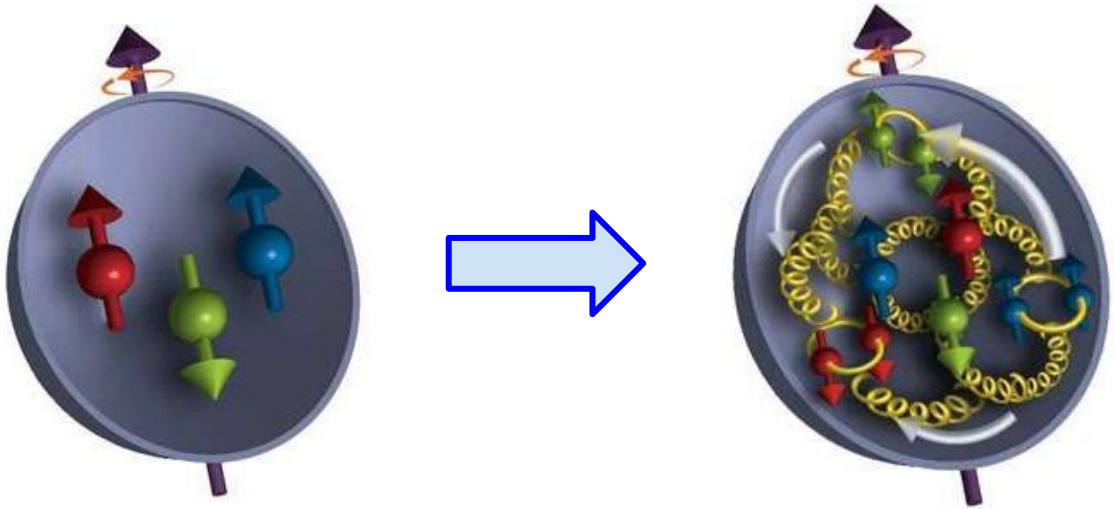
Emergent Phenomena of QCD: Spin and Mass



The naive parton model cannot explain the dynamical origin of hadronic properties.

Orbital motion of the quarks and gluons could be the answer. Emergent properties of QCD.

Fundamental Properties of the Nucleon and the QCD EMT

$$T^{\mu\nu}_{QCD} = \frac{1}{4}\,\overline{\psi}\gamma^{(\mu}D^{\nu)}\psi + Tr\left\{F^{\mu\alpha}F^{\nu}_{\alpha} - \frac{1}{2}g^{\mu\nu}F^{2}\right\}$$

$$\begin{bmatrix} T^{00} & T^{01} & T^{02} & T^{03} \\ T^{10} & T^{11} & T^{12} & T^{13} \\ T^{20} & T^{21} & T^{22} & T^{23} \\ T^{30} & T^{31} & T^{32} & T^{33} \end{bmatrix}$$

Energy Density

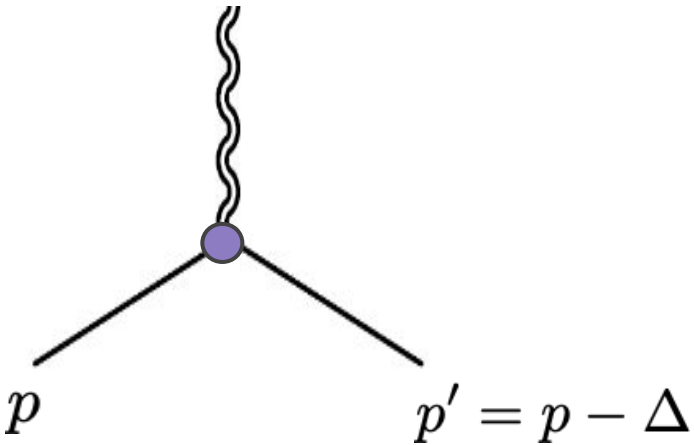
Momentum Density

Pressure Distribution

Shear Forces

Energy Momentum Tensor Form Factors

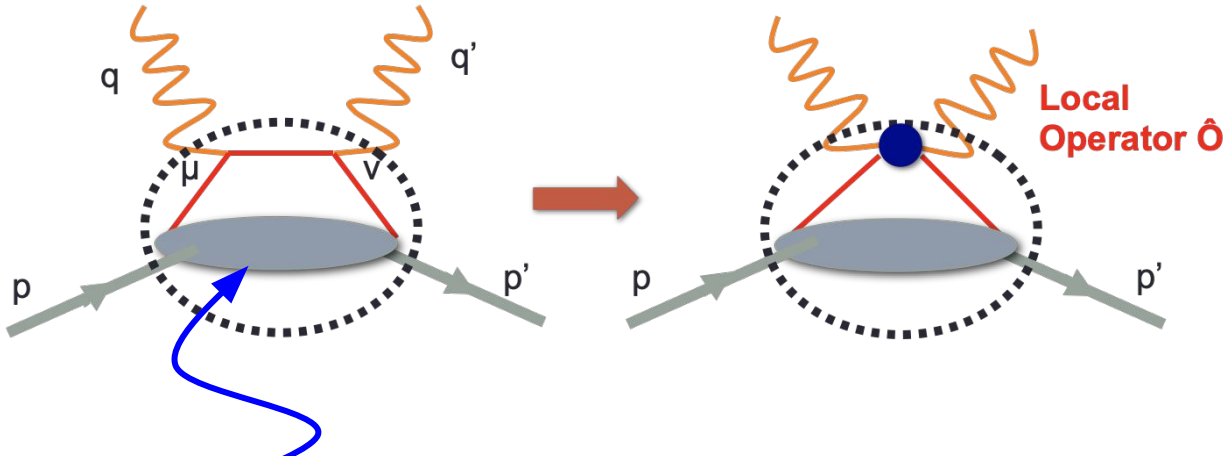
$$\langle P'|T^{\mu\nu}_{q,g}|P\rangle = \overline{U}(P')[A_{q,g}(\Delta^2)\gamma^{(\mu}\overline{P}^{\nu)} + B_{q,g}(\Delta^2)\overline{P}^{(\mu}i\sigma^{\nu)\alpha}\Delta_\alpha/2M$$
$$+C_{q,g}(\Delta^2)(\Delta^\mu\Delta^\nu - g^{\mu\nu}\Delta^2)/M + \overline{C}_{q,g}(\Delta^2)g^{\mu\nu}M]U(P)$$



X. Ji **PRL. 78 (1997)**

The matrix elements of the energy momentum tensor can be parameterized by **form factors** describing elastic scattering of a graviton off a proton.

Connection between Local Operators and GPDs



$$\int dx x H(x,\xi,t) = A(t) + \xi^2 C(t)$$

$$\int dx x E(x,\xi,t) = B(t) - \xi^2 C(t)$$

X. Ji, W. Melnitchouk, X. Song **PRD 56 (1997)**
X. Ji, **PRD. 55 (1997)**

Image credit: **Simonetta Liuti**

GPDs and Angular Momentum

$$J^q = \int dx x [H^q(x,0,0) + E^q(x,0,0)]$$

$$J^i_{q,g} = \frac{1}{2}\epsilon^{ijk} \int d^3x M^{0jk}$$

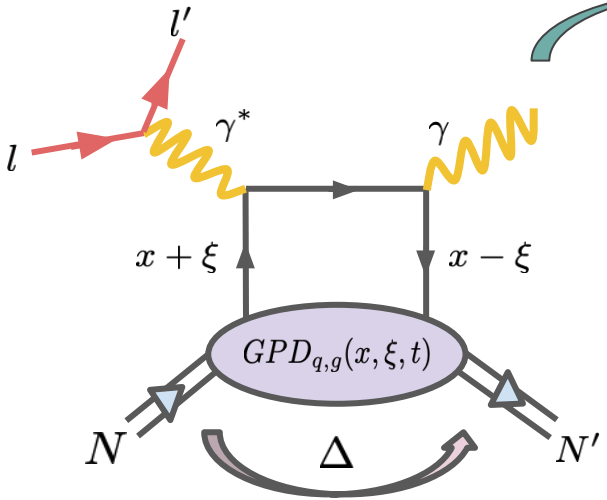
$$J^i_{q,g} = \frac{1}{2}\epsilon^{ijk} \int d^3x (T^{0k}_{q,g} x^j - T^{0j}_{q,g} x^k)$$

$$J^z_{q,g} = \frac{1}{2}[A_{q,g}(0) + B_{q,g}(0)]$$

X. Ji **PRL. 78 (1997)**

Going back to open questions

How do we go from experiment to properties of hadrons?



Even more critical: How much information on hadron structure can be disentangled from experimental measurements? … Femtography

Outline

- Physics Motivation
- **Femtography**
- DNN Framework
- DVCS Cross Section Data
- CFF Extraction
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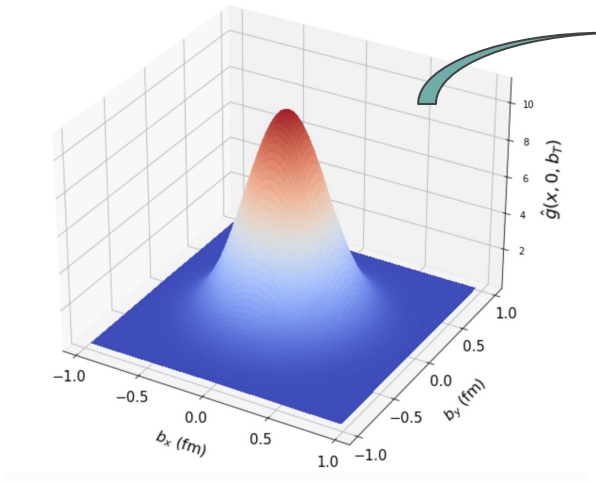
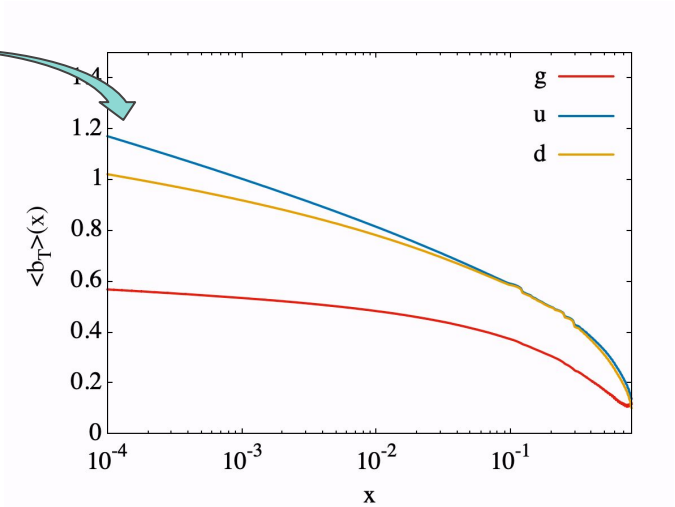
What is Femtography? Our current picture …

One body densities



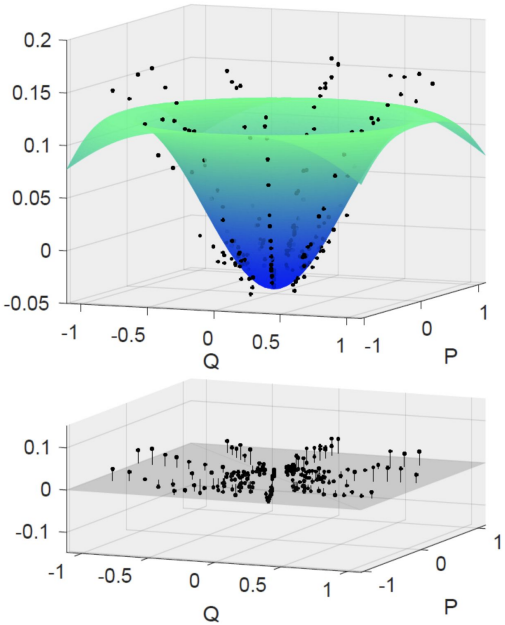
Properties



Femtography - a **data driven** framework that connects **experimental observables** to the **<u>dynamics</u>** of *quarks* and *gluons* through QM phase space distributions.

Z. Panjsheeri, J. Bautista, BK, S.Liuti **(in progress)**
B. Kriesten, P. Velie, E. Yeats, F.Y. Lopez, S. Liuti **PRD 105 (2022)**

Phase space distributions in quantum mechanics



Phase space → Wigner Distributions: are **not new** to quantum mechanical systems.

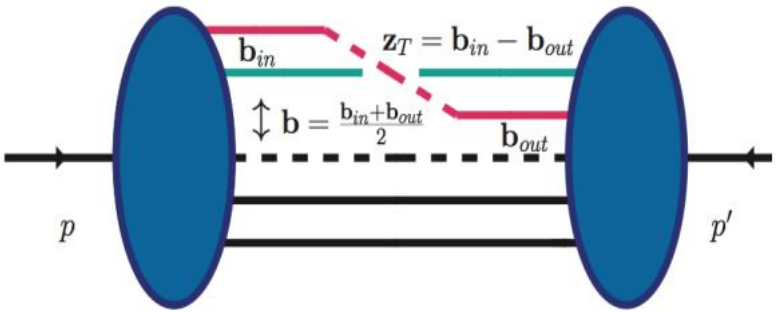
Quasi-probability distributions since they, by definition, violate the Heisenberg uncertainty principle.

$$\Delta x \Delta p \geq \frac{\hbar}{2}$$

R. Nehra, A. Win, M. Eaton, R. Shahrokhshahi, N. Sridhar, T. Gerrits, A. Lita, S. W. Nam, O. Pfister **Optica. 6 (2019)**
R. Nehra, M. Eaton, C. Gonzalez-Arciniegas, M. S. Kim, T. Gerrits, A. Lita, S. W. Nam, O. Pfister **PRR 2 (2020)**

Generalized parton distributions

$$F^{[\Gamma]}_{\Lambda,\Lambda'}(x,\xi,t) = \frac{1}{2}\int \frac{dz^-}{2\pi} e^{ixP^+z^-} \langle p',\Lambda'|\overline{\psi}\Big(-\frac{z}{2}\Big)\Gamma\mathcal{W}\Big(-\frac{z}{2},\frac{z}{2}|n\Big)\psi\Big(\frac{z}{2}\Big)|p,\Lambda\rangle\Big|_{z^+=z_T=0}$$



b_T Relative average transverse position from the center of momentum of the system ⟷ Δ_T

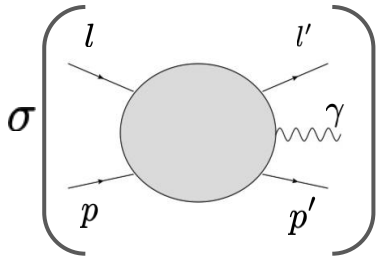
k_T Relative average transverse momentum (integrated) ⟷ z_T

Image credit: A. Rajan, M. Engelhardt, S. Liuti **PRD 98 (2018)**

X. Ji **PRL. 78 (1997)**
A. Radyushkin **PRD. 56 (1997)**

D. Muller, et. al. **(1994)**
M. Diehl **Phys.Rep. (2003)**

How do we measure GPDs?



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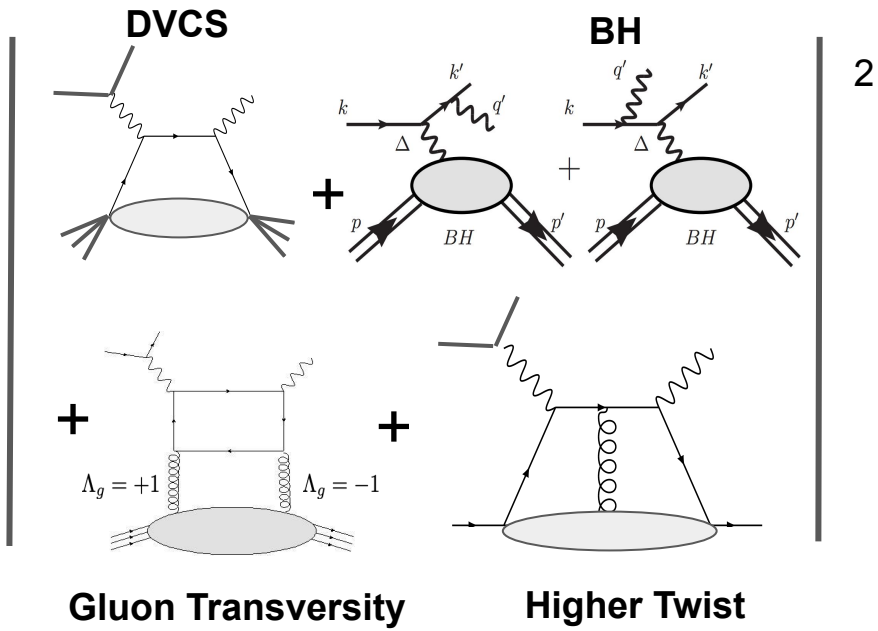

DVCS is known to probe **generalized parton distributions** and is accompanied by various background processes.

X. Ji, **PRD. 55 (1997)**

B.Kriesten, S.Liuti, et. al. **PRD. 101 (2020)**

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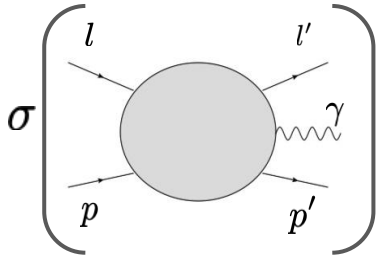

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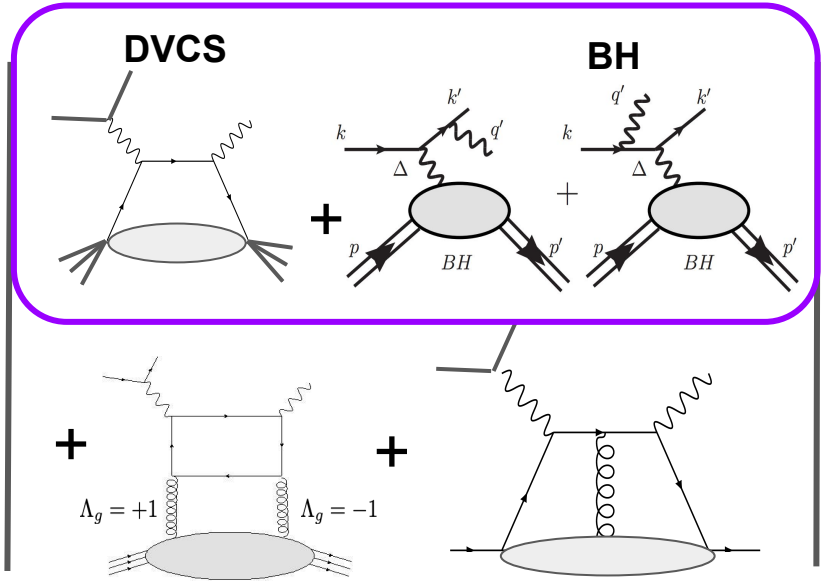

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X. Ji, **PRD. 55 (1997)**

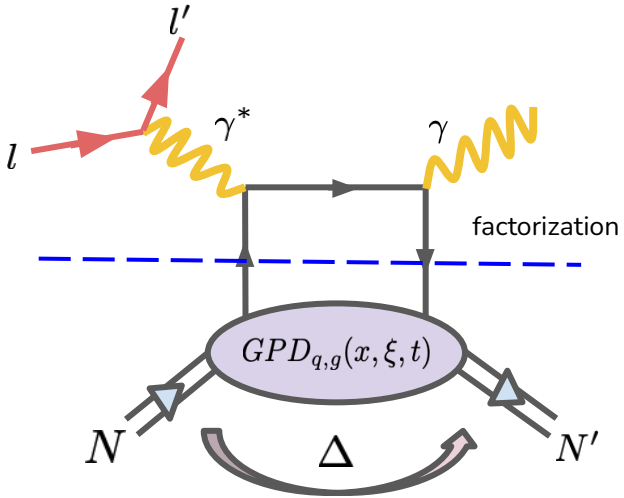
B.Kriesten, S.Liuti, et. al. **PRD. 101 (2020)**

Important, but reserved for a future seminar …

CFFs and GPDs from Experiment

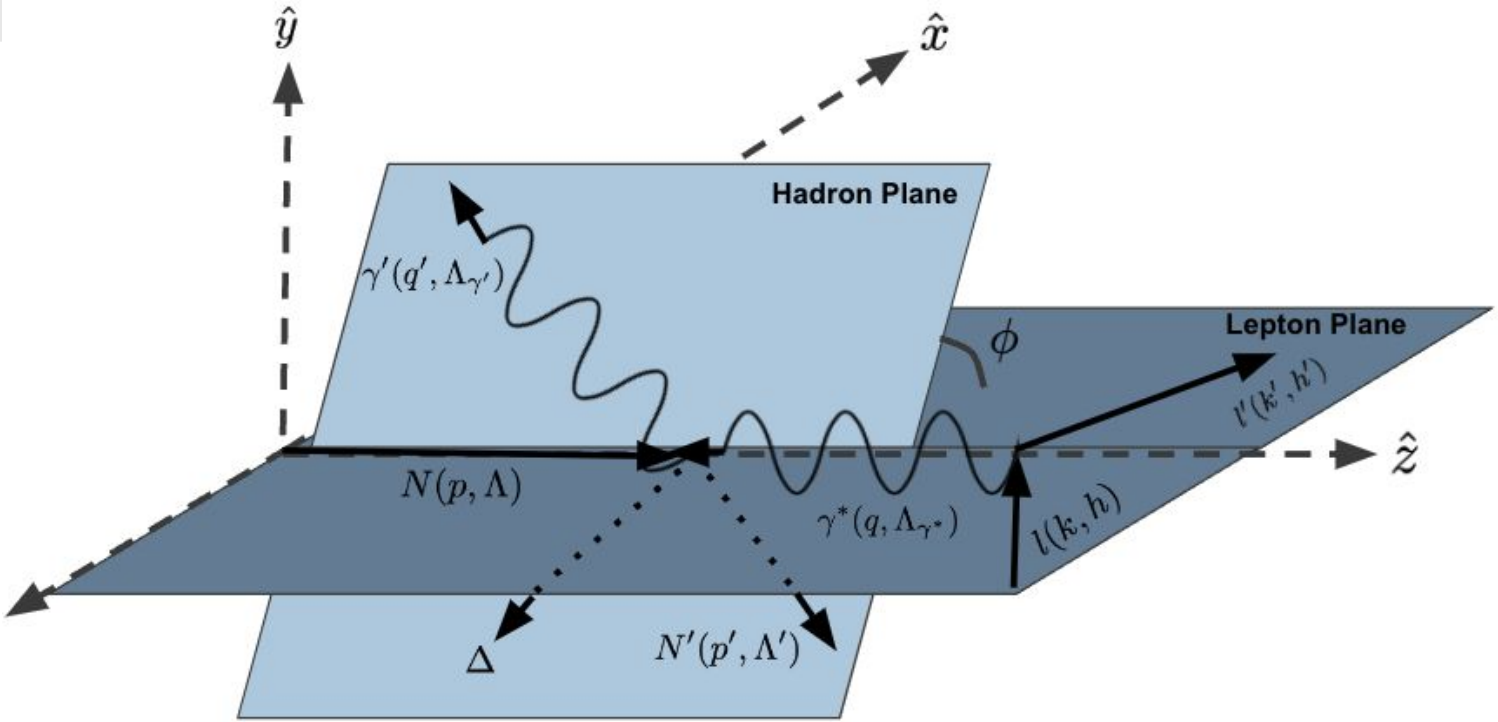
It is an immediate goal to extract the quark and gluon GPDs from data.

GPDs come convoluted with Wilson coefficient functions (Compton Form Factors) meaning we only have experimental access to integrals (ReCFF) or specific points in x (ImCFF) of these distributions.



$$\mathcal{H}^q(\xi,t) = e_q^2\, P.V. \int_{-1}^{+1} dx \left[\frac{1}{\xi - x} - \frac{1}{\xi + x}\right] H^q(x,\xi,t) + i\pi e_q^2 H^+(\xi,\xi,t)$$

DVCS Scattering Planes



DVCS Cross Section

$$\varepsilon_\mu^{\Lambda_\gamma^*}(hadron) = e^{-i\Lambda_\gamma^*\phi}\,\varepsilon_\mu^{\Lambda_\gamma^*}(lepton)$$

$$\begin{aligned}
\frac{d^5\sigma_{DVCS}}{dx_{Bj}dQ^2d|t|d\phi d\phi_S} &= \Gamma\left|T_{DVCS}\right|^2 \\
&= \frac{\Gamma}{Q^2(1-\epsilon)}\Big\{F_{UU,T} + \epsilon F_{UU,L} + \epsilon\cos 2\phi F_{UU}^{\cos 2\phi} + \sqrt{\epsilon(\epsilon+1)}\cos\phi F_{UU}^{\cos\phi} \\
&+ (2h)\sqrt{2\epsilon(1-\epsilon)}\sin\phi F_{LU}^{\sin\phi} \\
&+ (2\Lambda)\Big[\sqrt{\epsilon(\epsilon+1)}\sin\phi F_{UL}^{\sin\phi} + \epsilon\sin 2\phi F_{UL}^{\sin 2\phi} \\
&+ (2h)\left(\sqrt{1-\epsilon^2}F_{LL} + 2\sqrt{\epsilon(1-\epsilon)}\cos\phi F_{LL}^{\cos\phi}\right)\Big] \\
&+ (2\Lambda_T)\Big[\sin(\phi-\phi_S)\left(F_{UT,T}^{\sin(\phi-\phi_S)} + \epsilon F_{UT,L}^{\sin(\phi-\phi_S)}\right) \\
&\quad + \epsilon\sin(\phi+\phi_S)F_{UT}^{\sin(\phi+\phi_S)} + \epsilon\sin(3\phi-\phi_S)F_{UT}^{\sin(3\phi-\phi_S)} \\
&\quad + \sqrt{2\epsilon(1+\epsilon)}\left(\sin\phi_S F_{UT}^{\sin\phi_S} + \sin(2\phi-\phi_S)F_{UT}^{\sin(2\phi-\phi_S)}\right)\Big] \\
&\quad + (2h)(2\Lambda_T)\Big[\sqrt{1-\epsilon^2}\cos(\phi-\phi_S)F_{LT}^{\cos(\phi-\phi_S)} + \sqrt{2\epsilon(1-\epsilon)}\cos\phi_S F_{LT}^{\cos\phi_S} \\
&\quad + \sqrt{2\epsilon(1-\epsilon)}\cos(2\phi-\phi_S)F_{LT}^{\cos(2\phi-\phi_S)}\Big]\Big\}
\end{aligned}$$

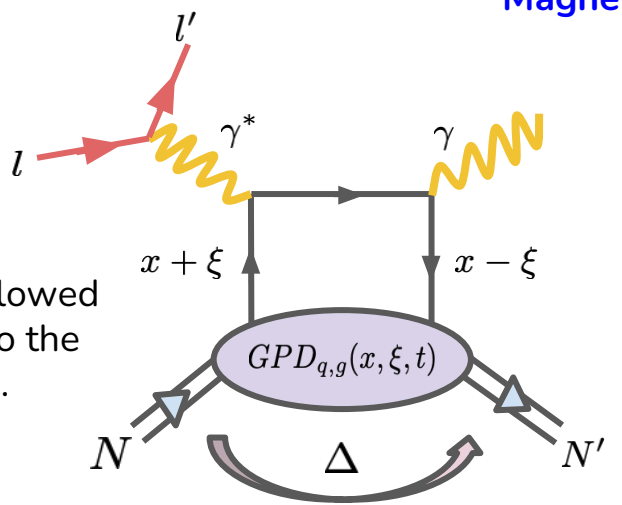
Interference and CFFs

$$\mathcal{I} = e_l \frac{\Gamma}{Q^2 \mid t \mid} \left\{ A^{\mathcal{I}}_{UU} \Re e(F_1 \mathcal{H} + \tau F_2 \mathcal{E}) + B^{\mathcal{I}}_{UU} G_M \Re e(\mathcal{H} + \mathcal{E}) + C^{\mathcal{I}}_{UU} G_M \Re e \widetilde{\mathcal{H}} + \frac{\sqrt{t_0 - t}}{Q} F^{\mathcal{I},tw3}_{UU} . \right\}$$

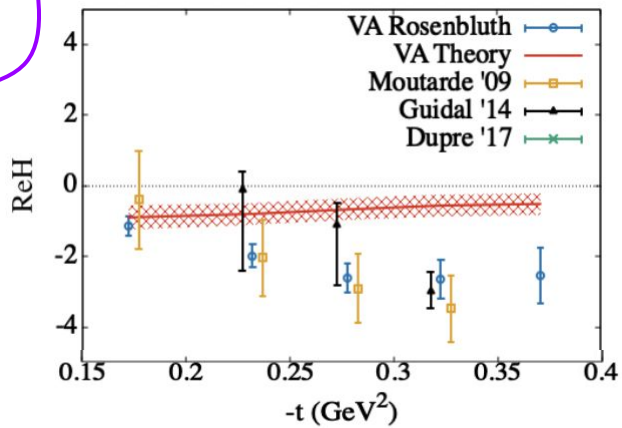
$$\mid T_{BH} \mid^2 = \frac{1}{t^2(1-\epsilon_{BH})} B_{BH} \left[F_T + \epsilon_{BH} F_L \right]$$

Magnetic Electric

Similar structure appear as in the Bethe-Heitler process, suggests **Rosenbluth separation** similar as in e-p scattering.

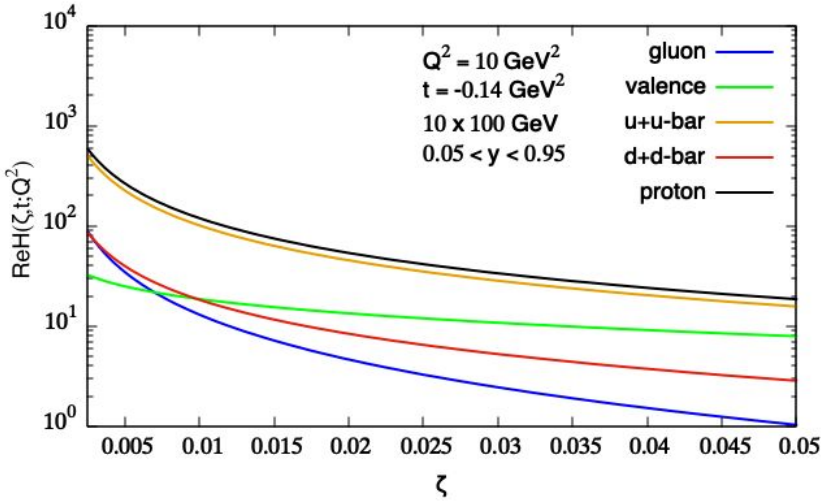


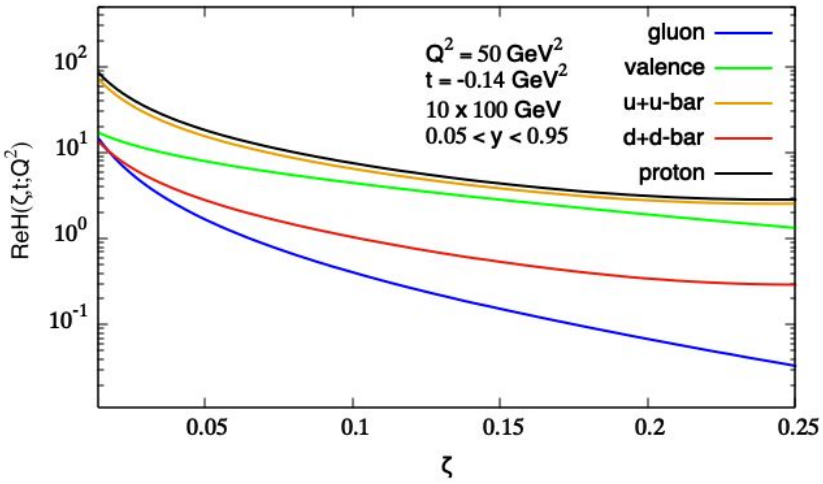
Axial vector contribution allowed by parity due to the second photon.



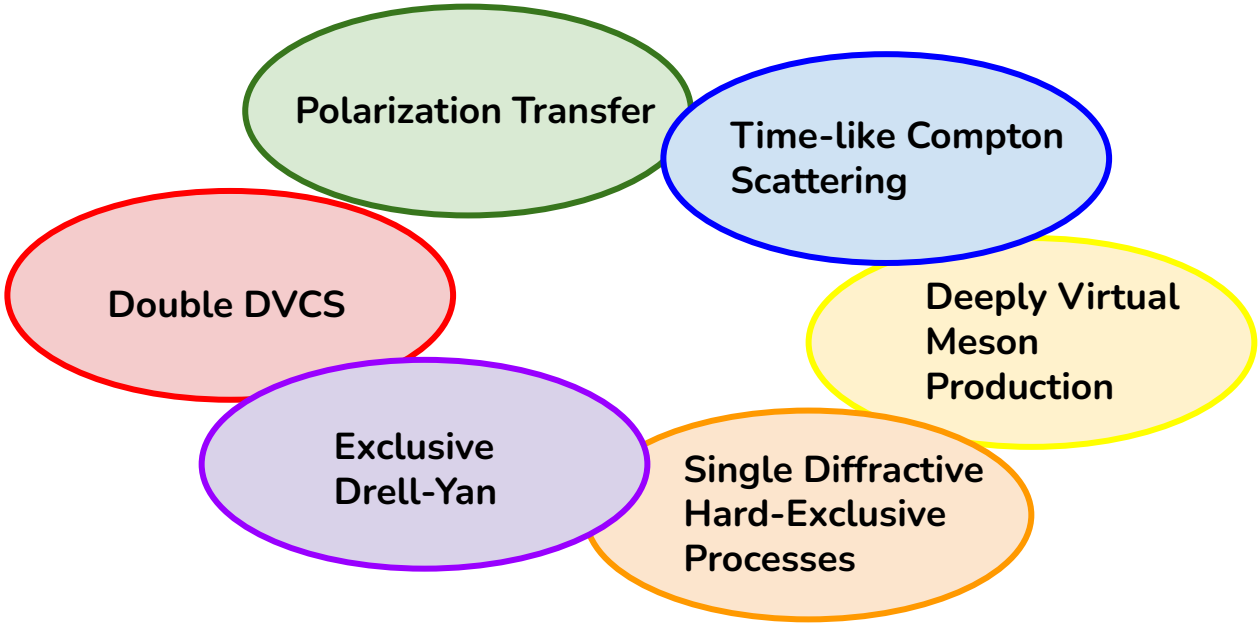
CFFs at an EIC … what are we measuring?

Role of gluons and quark sea …





A Plethora of Observables



Many new avenues for experimental observables, development of formalism in a clear and concise manner with studies of impact on hadronic properties is crucial. A framework to connect these observables in a multi-channel global analysis.

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- DVCS Cross Section Data
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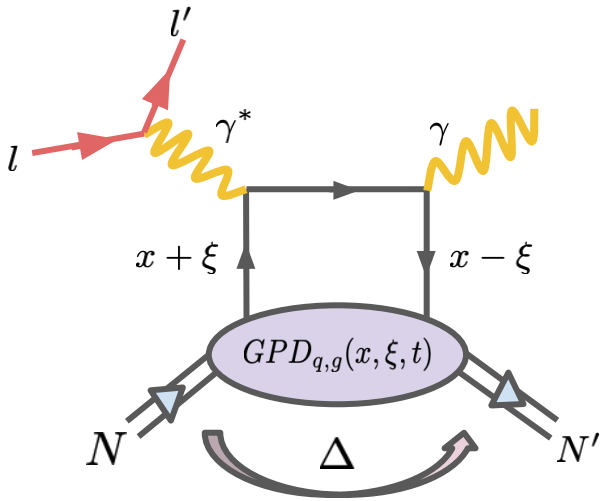
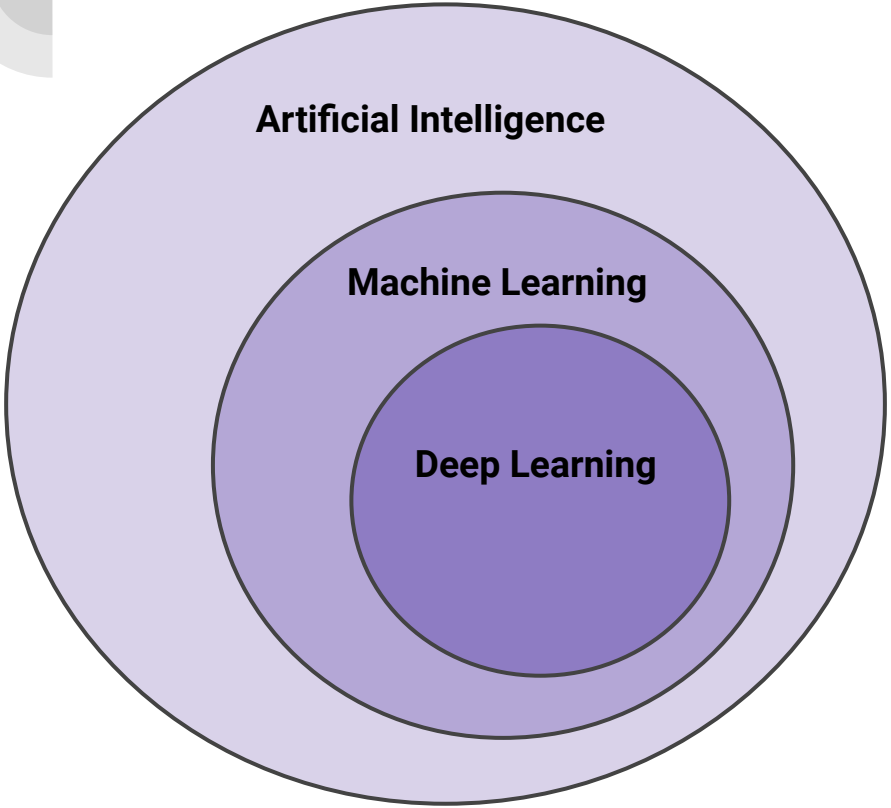
A statement …



Machine Learning methods are an ideal framework for extracting **essential information** from deep-exclusive scattering experiments to **reconstruct the quantum mechanical phase space distributions** of the quarks and gluons inside of the nucleon**.**

Deep Learning Models



Machine learning (ML) is a subset of a larger category of Artificial Intelligence. ML methods utilize **statistical techniques** to train “machines” to improve and learn how to perform tasks given a large set of experiences.

Deep Learning utilizes a **multi-layered neural network** to teach itself how to perform tasks given a set of input data.

Physics Constrained Deep Learning Models

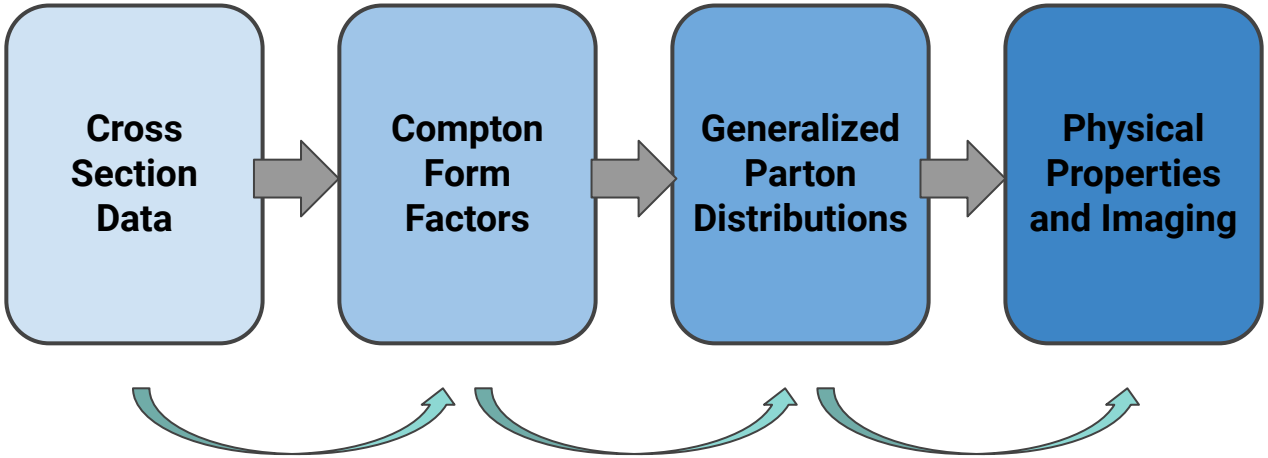
DNN models can spend a lot of computational resources to learn physical laws from data. To reduce computation time and improve network performance/generalization, we can incorporate those laws into the architecture of the network so that certain physical properties are inherently satisfied in the network's predictions.

Physics Constraints

- Cross section structure built into the loss function
- Experimental error bars
- Lorentz invariance - polynomiality property
- Positivity constraints
- Forward limit constraints of GPDs
- Dispersion relations with threshold effects
- Evolution constraints

Information Abstraction

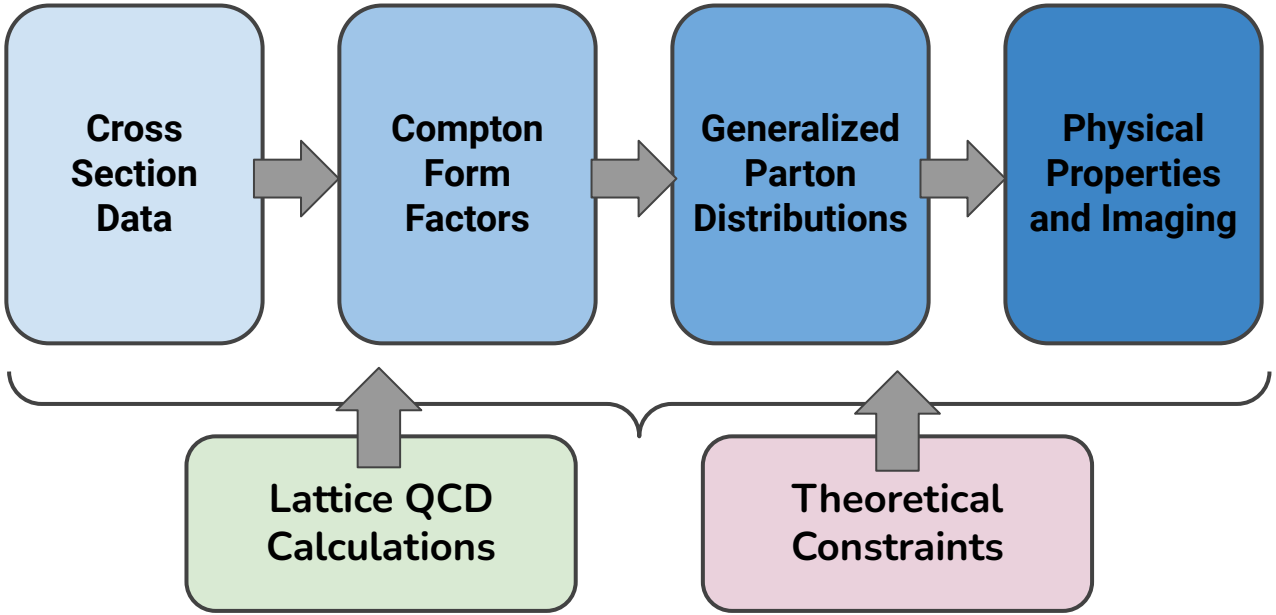
There are many levels of abstraction going from what we get from experiment and the properties of what we are interested in looking at.



Can we capture all information contained in going from one step of the analysis to the next? What are we missing, what is abstracted away?

Machine Learning as a Femtography Framework

Application of **ML techniques** can help us study this question, but first we need to **establish a common language** between the two fields and **create a framework for synergistic studies**.



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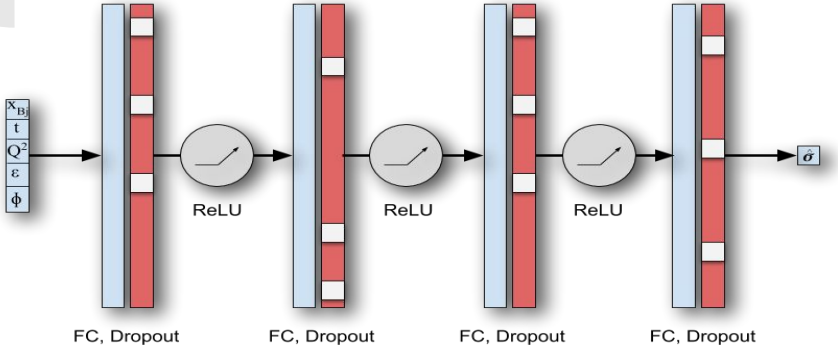
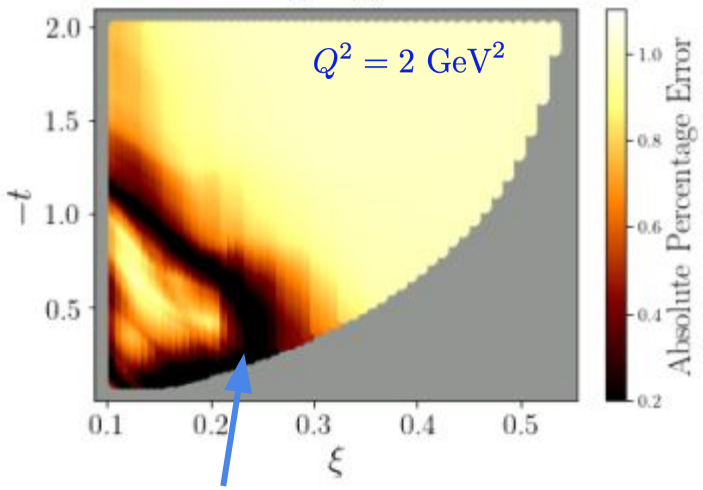
Deep Learning DVCS Data





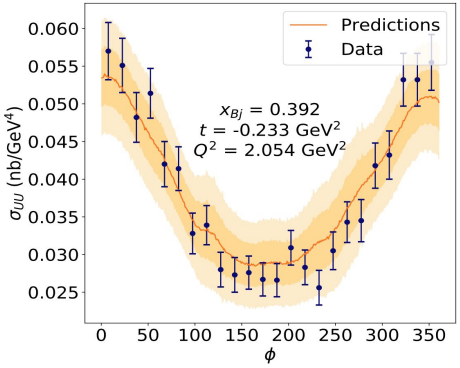
Why do we need a deep neural network?

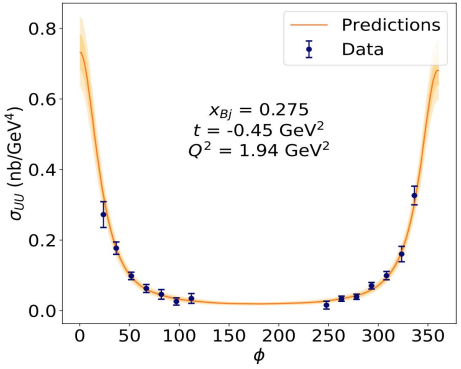
- DNN provide **efficient** and **accurate** predictions of the cross section while squeezing as much information from data as possible.

J. Grigsby, BK, S. Liuti, et. al. **PRD 104 (2021)**
M. Almaeen, J. Grigsby, J. Hoskins, BK, Y. Li, H-W. Lin, S. Liuti **arXiv:2207.10766**

Deep Learning Benchmarks

	UU				LU			
	Standard		Feature Engineering		Standard		Feature Engineering	
Method	Median Error (%)	Accuracy (%)	Median Error (%)	Accuracy (%)	Median Error (%)	Accuracy (%)	Median Error (%)	Accuracy (%)
Linear	238.87	1.61	347.77	0.53	239.37	22.44	289.60	24.02
SVR	57.70	15.86	58.92	13.17	94.92	43.70	68.55	59.06
Random Forest	32.90	24.73	32.27	26.88	62.87	59.45	**63.65**	59.06
KNN	19.84	37.63	**20.93**	34.41	**62.36**	60.24	68.09	56.69
DNN	**19.11**	**61.3**	21.56	**60.5**	145.86	**62.0**	150.62	**65.8**



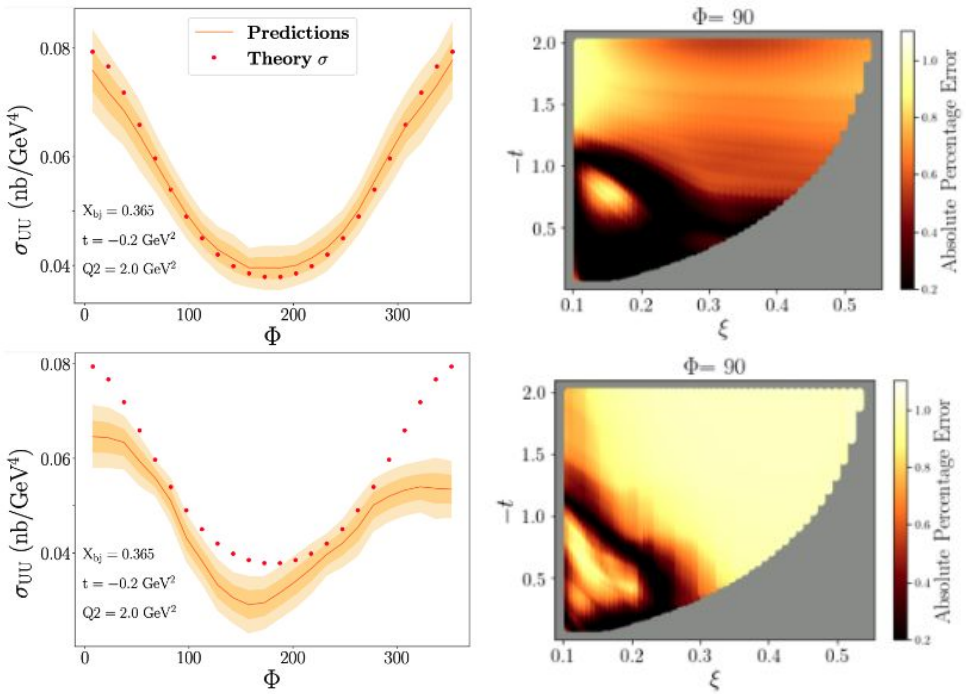


J. Grigsby, BK, S. Liuti, et. al. **PRD 104 (2021)**
M. Almaeen, J. Grigsby, J. Hoskins, BK, Y. Li, H-W. Lin, S. Liuti **arXiv:2207.10766**

Physics constrained cross section predictions

Simple physics constraints such as symmetry properties of the unpolarized cross section in the loss function lead to increased generalization of the DNN predictions.

$$\|f(x_{Bj}, t, Q^2, \phi, \epsilon) - f(x_{Bj}, t, Q^2, -\phi, \epsilon)\|$$

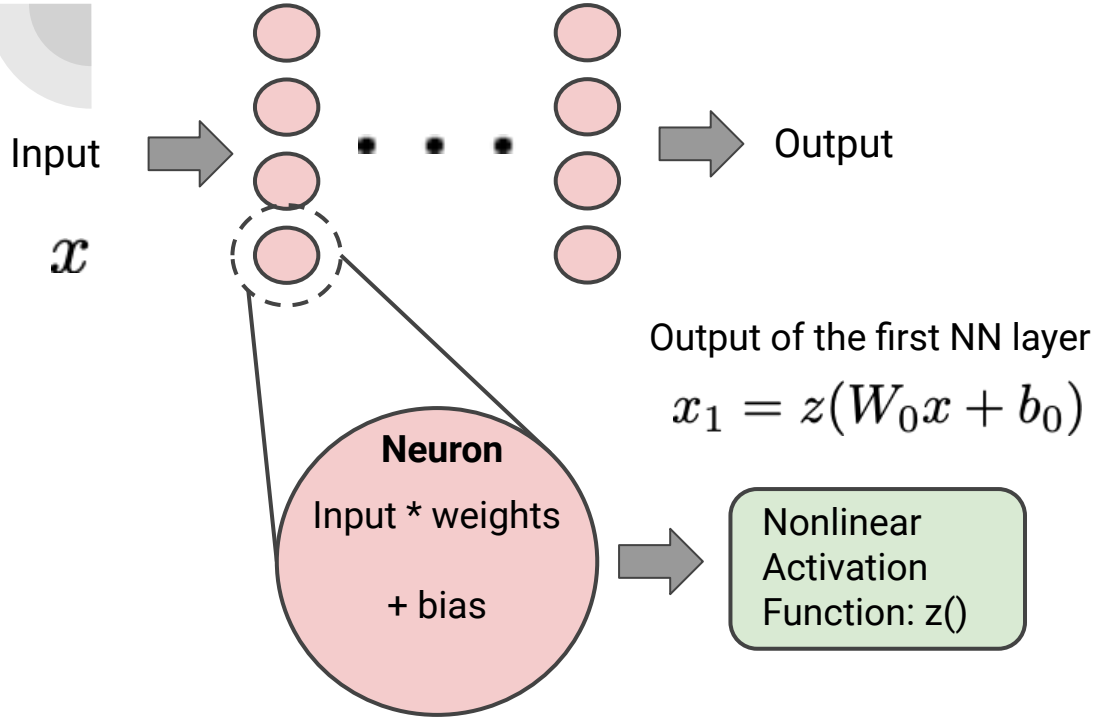


J. Grigsby, BK, S. Liuti, et. al. **PRD 104 (2021)**
M. Almaeen, J. Grigsby, J. Hoskins, BK, Y. Li, H-W. Lin, S. Liuti **arXiv:2207.10766**

Outline

- Physics Motivation
- Femtography
- DNN Framework
- DVCS Cross Section Data
- **CFF Extraction**
- Outlooks/Conclusions

Fitting Cross Sections with Supervised Deep Learning Networks



$$f_\theta(\mathbf{x}) = \mathbf{W}_k(z(\mathbf{W}_{k-1}(\ldots(z(\mathbf{W}_0\mathbf{x} + \mathbf{b}_0))) + \mathbf{b}_{k-1})) + \mathbf{b}_k$$

Weights: optimized during the training process. Quantify the importance of each input in the training process.

Biases: allows for generalization to the network by allowing 0 inputs to produce inputs into the next layer.

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Physics Information in the Loss Function

Standard Loss Function

$$\mathcal{L}_{\theta_t} = \frac{1}{2}(y - f_{\theta_t}(x))^2$$

$$\theta_{t+1} = \theta_t - \alpha \nabla_{\theta_t} \frac{1}{B} \sum_{i=0}^{B} \mathcal{L}_{\theta_t}(x^{(i)}, y^{(i)})$$

Modified Loss Function

$$\mathcal{L}^{CFF}_{\theta,\phi} = \frac{1}{2}(\sigma - f_\phi(g_\theta(x)))^2$$

$$\theta_{t+1} = \theta_t - \lambda \nabla_{\theta_t} \frac{1}{B} \sum_{i=0}^{B} \mathcal{L}^{CFF}_{\theta_t,\phi}(\mathbf{x}^{(i)}, \sigma^{(i)})$$

A standard loss function measures the distance between the DNN model's predicted values and the training data.

When predicting CFFs the loss function has to be modified since the predicted NN value is a derived quantity from the data. This is indicated by the functional composition where f() is the cross section function.

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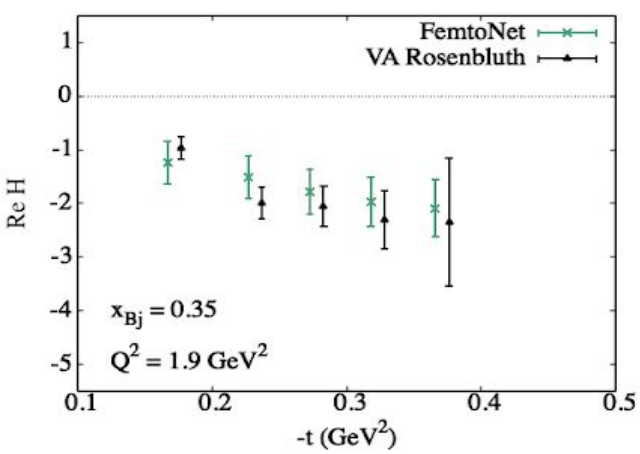
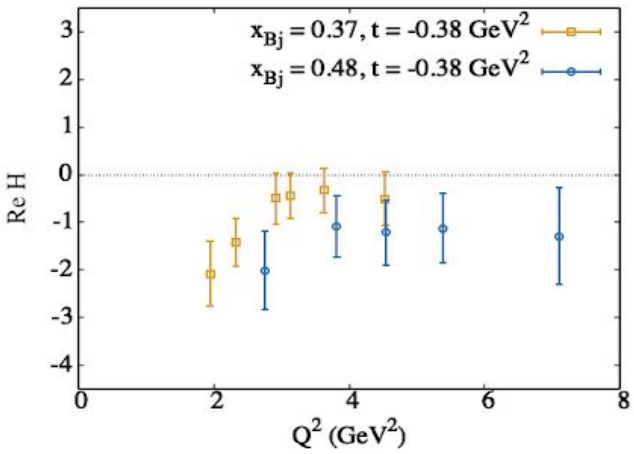
Extraction of Compton Form Factors

What can we extract from current Jefferson Lab data and what are the associated errors?





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Reframing the Extraction of Compton Form Factors

Standard

8 CFFs / 8 polarization configurations.

All observables have to match at the exact kinematics, with controllable uncertainties and systematics from each experiment.

Amazing statistics needed

FemtoNet

Extraction of 8 CFFs from a single polarization observable treated as an "inverse problem" of extracting 8 unknowns from a single equation.

Quantification of **information that is possible to extract** from certain experiments.

Informed high impact measurements.

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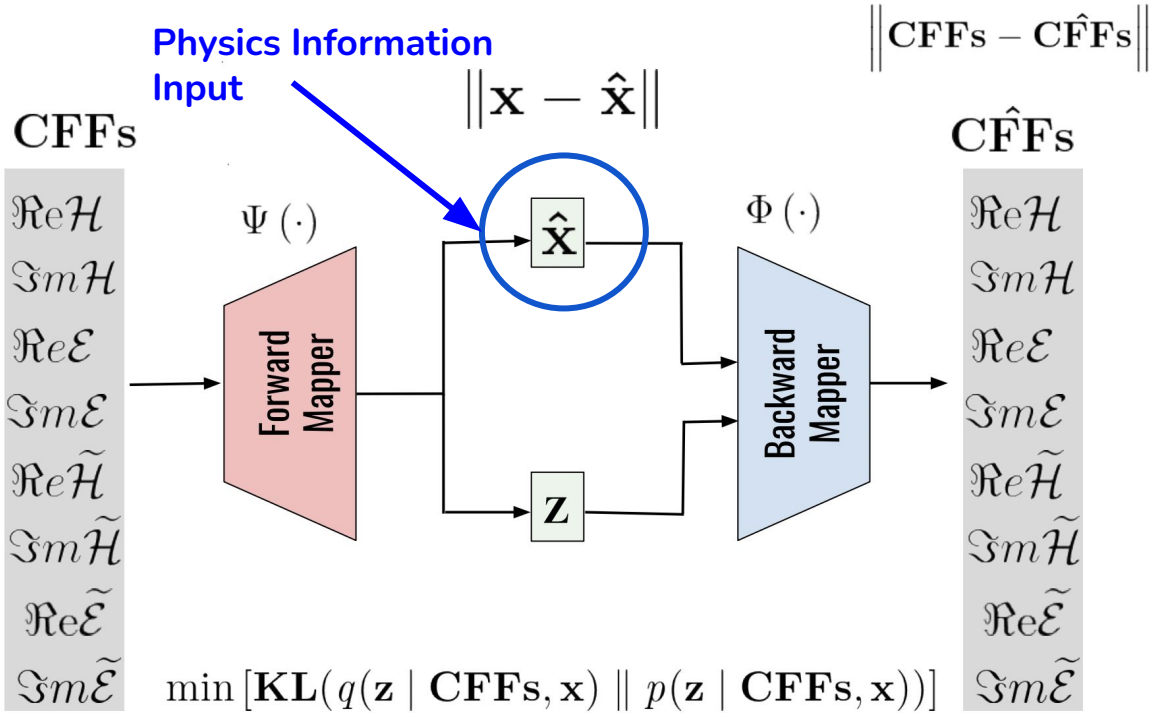
VAIM-CFF Framework



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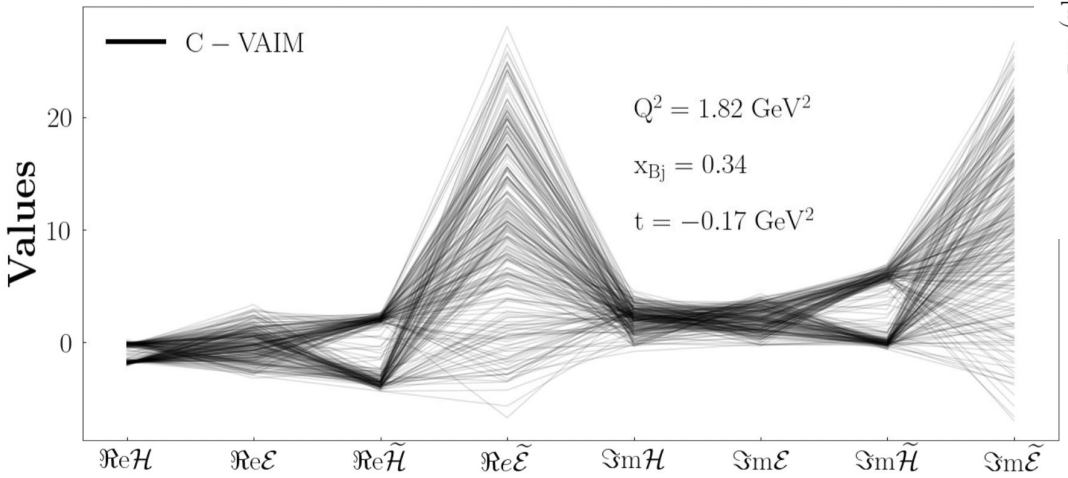
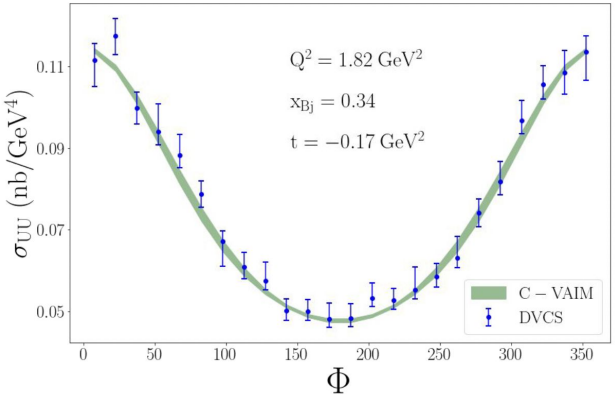
VAIM-CFF Results





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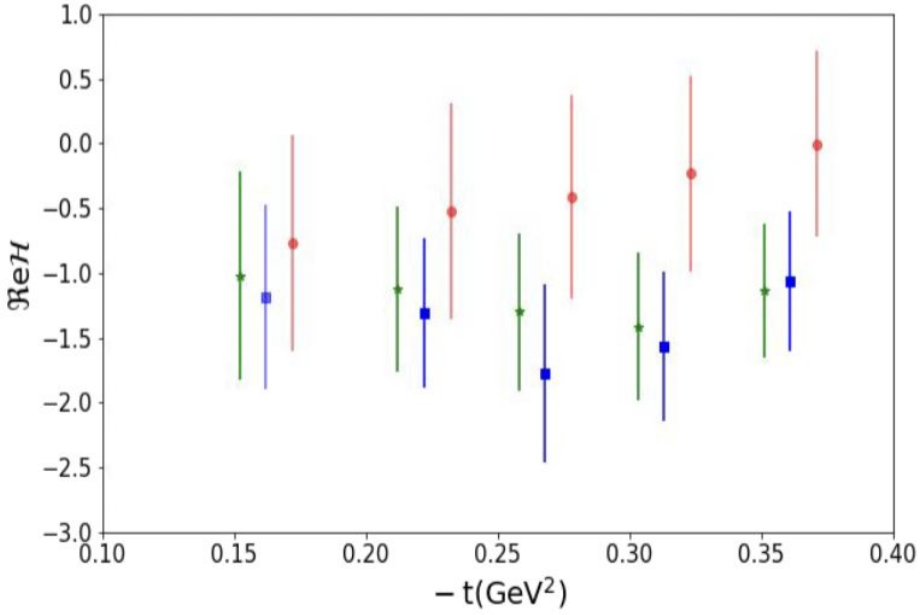
Conditional VAIM and kinematic trends



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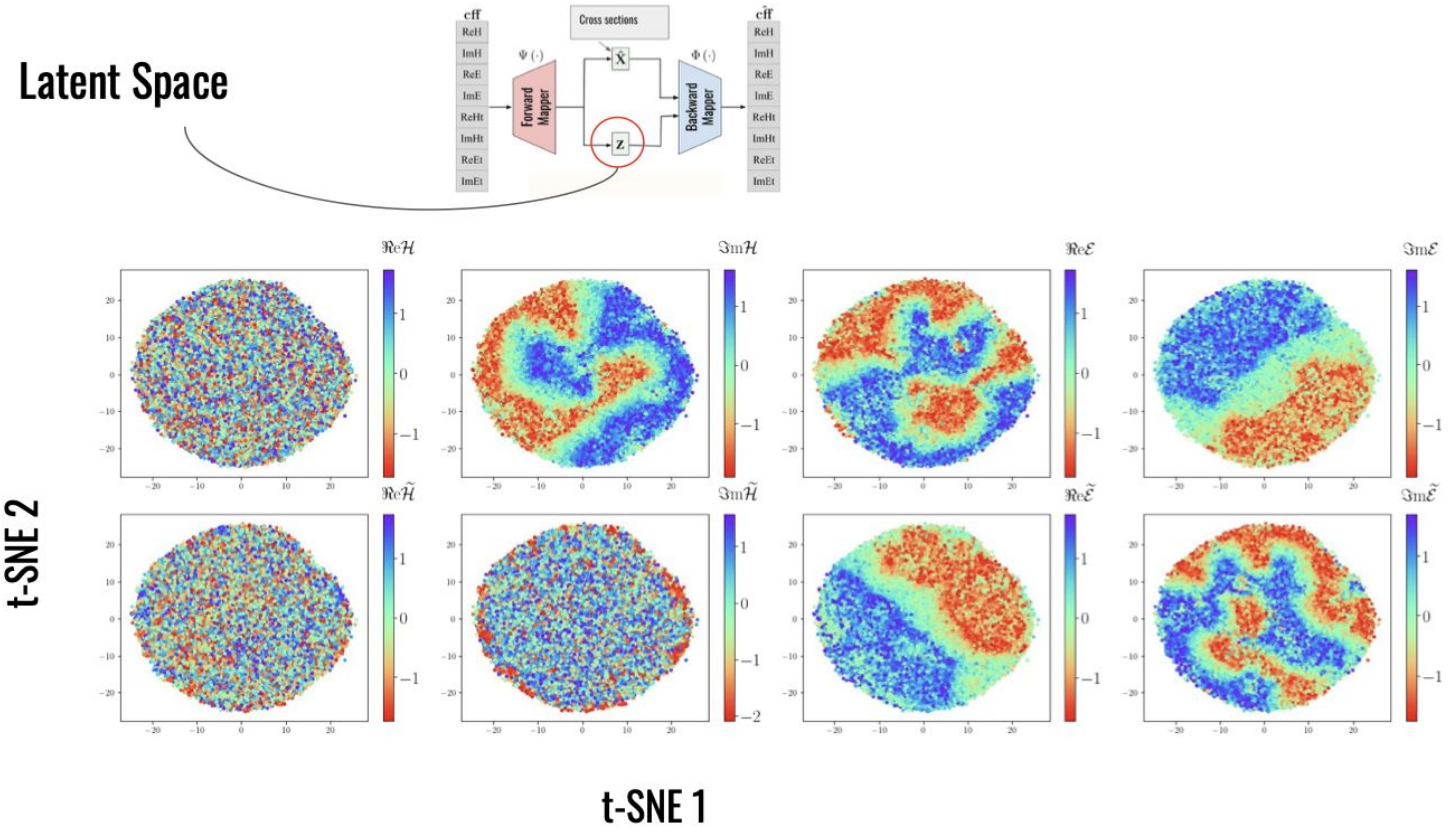
Reconstructing lost information



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Uncertainty Quantification and DVCS Error Analysis

Uncertainty arises in many places when using ML algorithms, it is critical to make sure we understand how much we can trust the algorithms predictions. Four factors vital for understanding uncertainty are:

1. Statistical uncertainty from experimental measurements
2. Systematic uncertainties from physics measurements

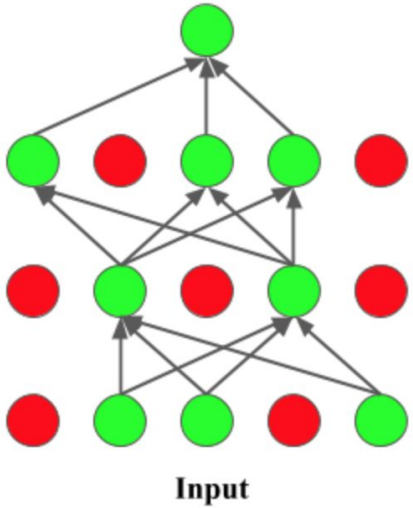
Irreducible

3. Error in the ML model and its architecture
4. Errors in training procedures

Reducible

We have to make sure we are properly propagating irreducible errors through our DNN architectures and that we understand the size of our network errors. We do this through a method called **random targets**.

Estimation of Network Uncertainty

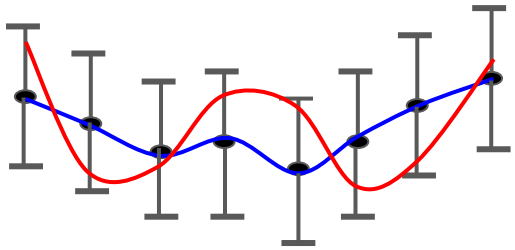


- Same input to the neural network produces several outputs since different “dropout masks” are used (different neuron connections are severed) with each forward pass.
- One can take the variance of the output and treat it as the statistical uncertainty of the network.
- This is just one piece of uncertainty that enters into DNNs.

Y. Gal et. al. **arXiv:1506.02142**

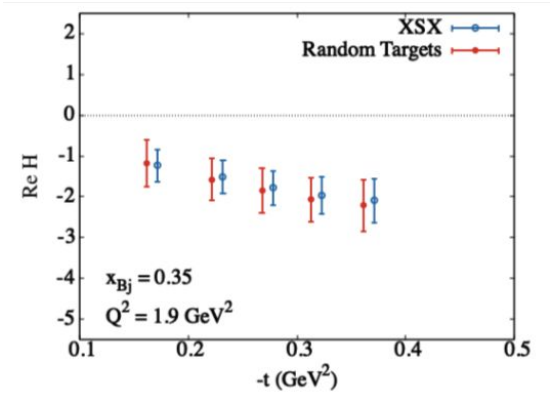
Random Targets Method

Quantify uncertainty by predicting on **random targets** that are Gaussian distributed where the central value of the observable is the center of the Gaussian distribution and the standard error is the width of the experimental error.



Dropout approximates a large ensemble of number of different networks.

The **random targets** resample the dataset within the error bars before they train each member of the ensemble of networks.



M. Almaeen, J. Grigsby, J. Hoskins, BK, Y. Li, H-W. Lin, S. Liuti **arXiv:2207.10766**
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Outlooks for Femtography and ML

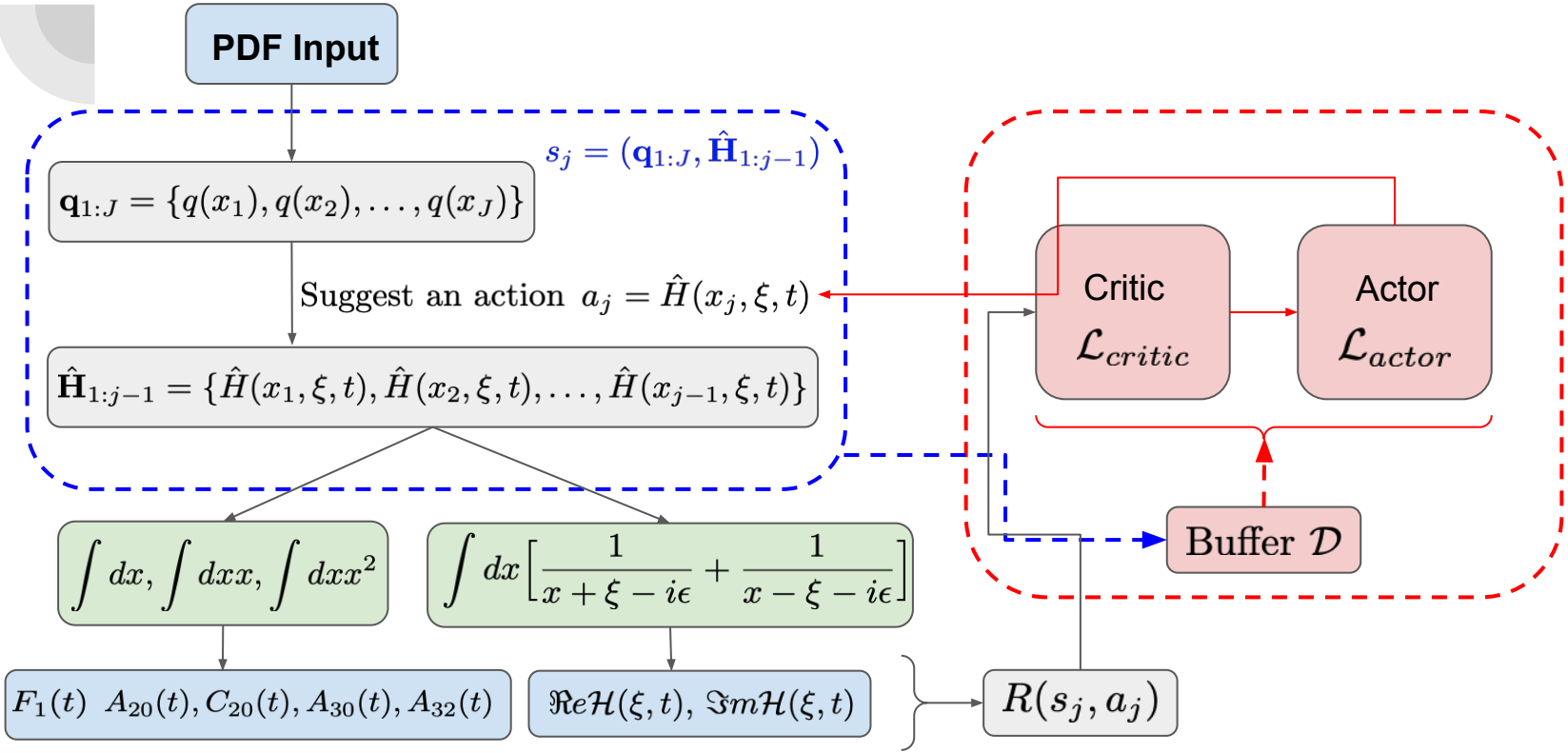
It has become extraordinarily apparent that it is impossible to extract the full x-dependence of GPDs from only DVCS data alone.

- Lattice QCD calculation of moments
- Experimental measurements of elastic form factors
- GPD properties (polynomiality, positivity, symmetries, forward limits)
- DVES data from multi-channel global analysis

This complicated reconstruction of the information from all the information we have on GPDs requires **new and innovative ML techniques**.

Ex. semi-supervised learning algorithms, generative algorithms, etc.

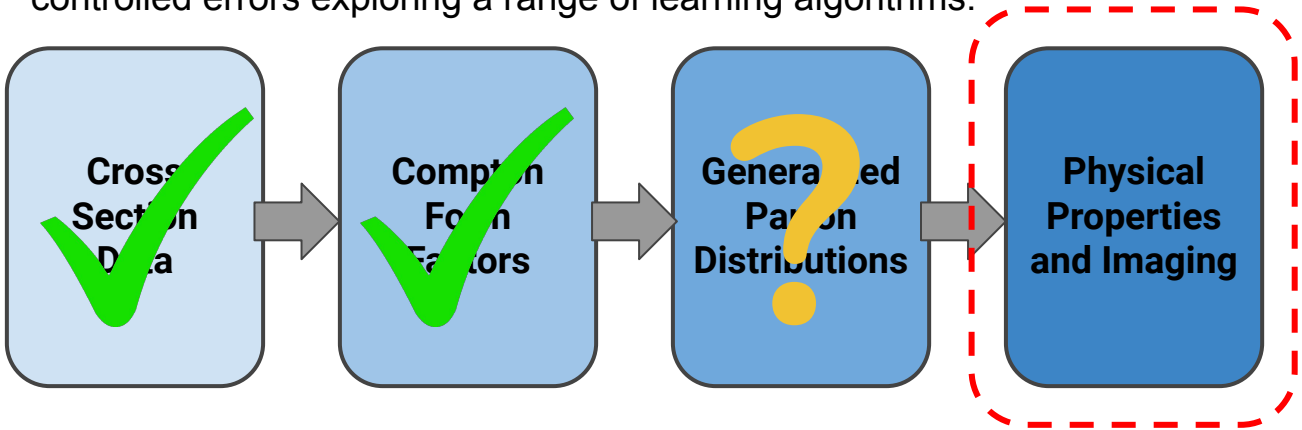
New ideas from NLP and Reinforcement Learning



Conclusions

- The extraction of GPDs requires using a variety of exclusive processes to place constraints on the quark and gluon distributions.

- There exist many steps in going from data to physical properties of the nucleon. All of these steps can be controlled through a DNN framework with controlled errors exploring a range of learning algorithms.



- Uncertainty quantification is a requirement for propagating error through DNNs and understanding the generalization of errors beyond the training data sets.

Thank you!