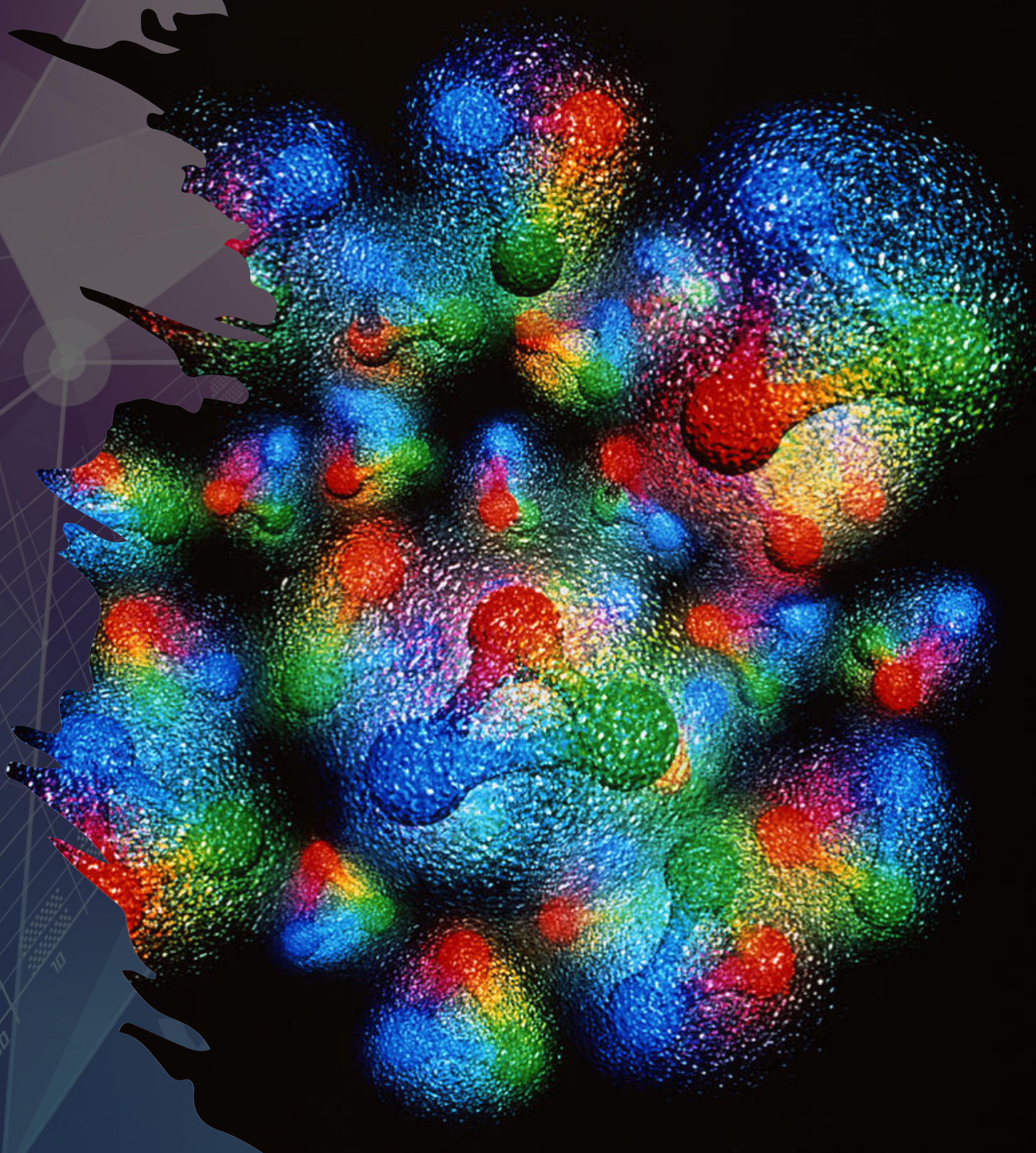
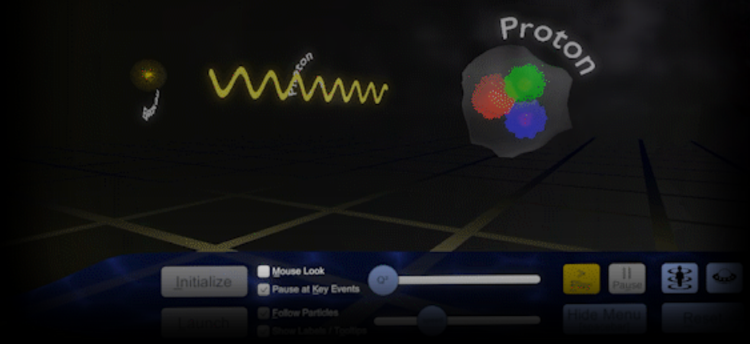
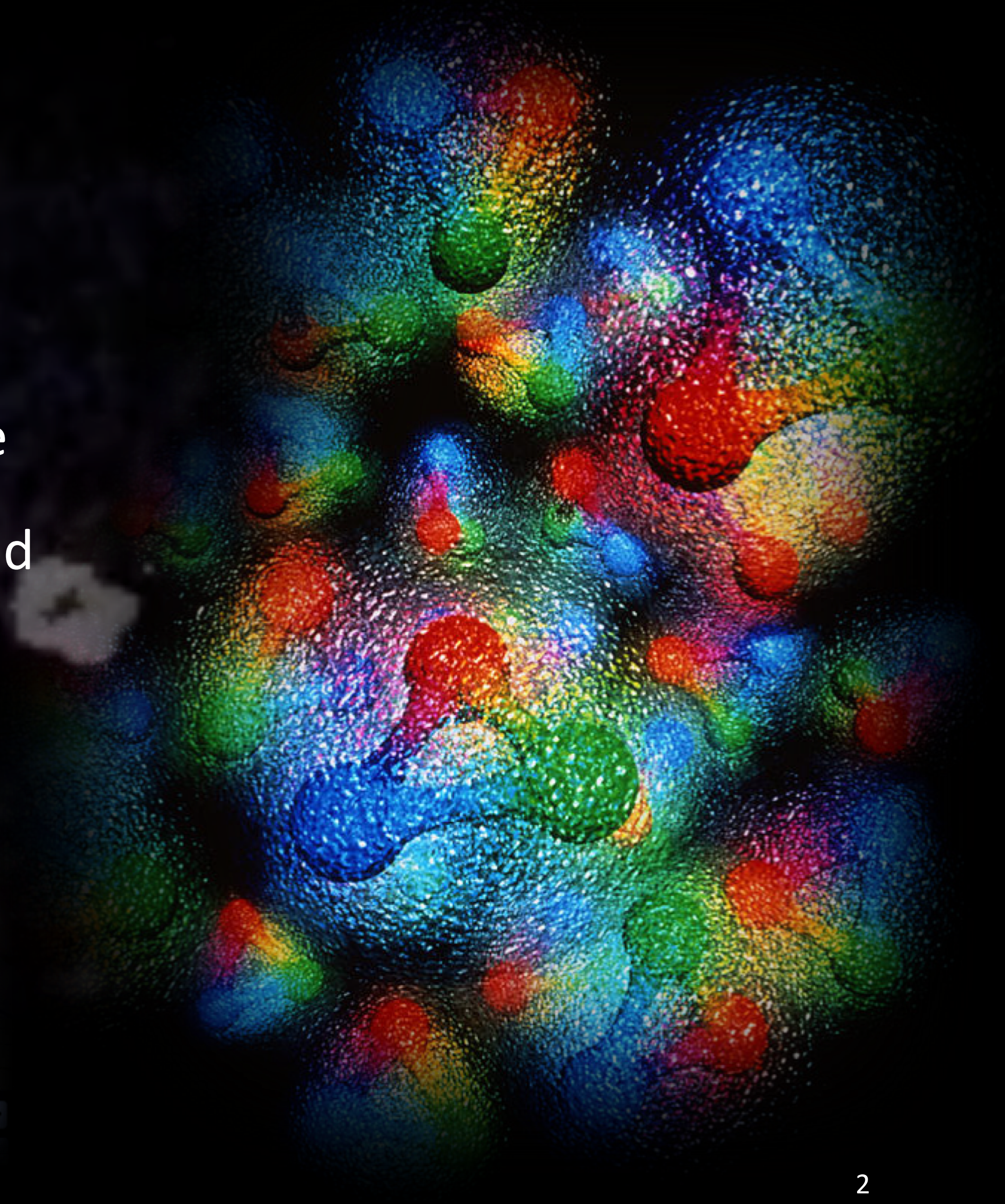
AI for Nuclear Physics: Highlights from the EXCLAIM project



Simonetta Liuti

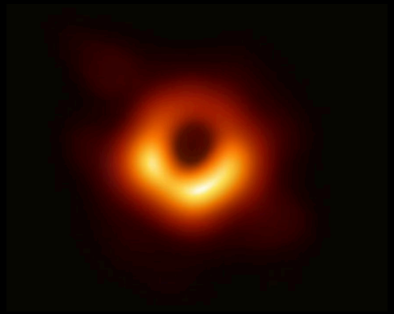
Recent advances in nuclear theory, QCD phenomenology and experiments at the future EIC will allow us to both penetrate and visualize the deep structure of visible matter, answering questions that we could not even afford asking before



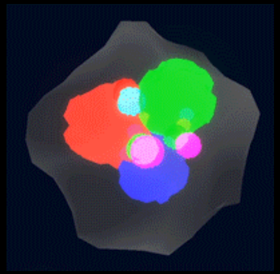


The importance of imaging

M87*

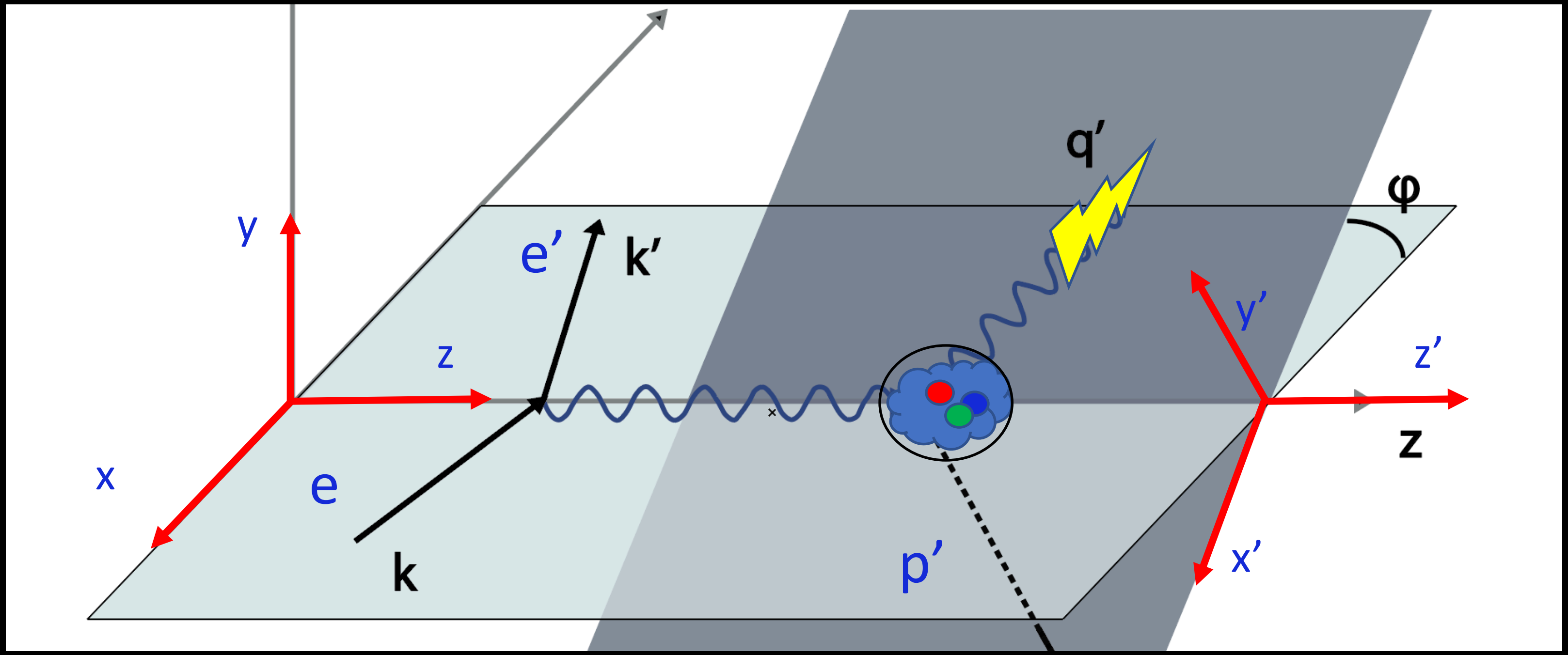


The Event Horizon Telescope (EHT) imaged and object 55 M light-years away= 5 x 10^{23} m

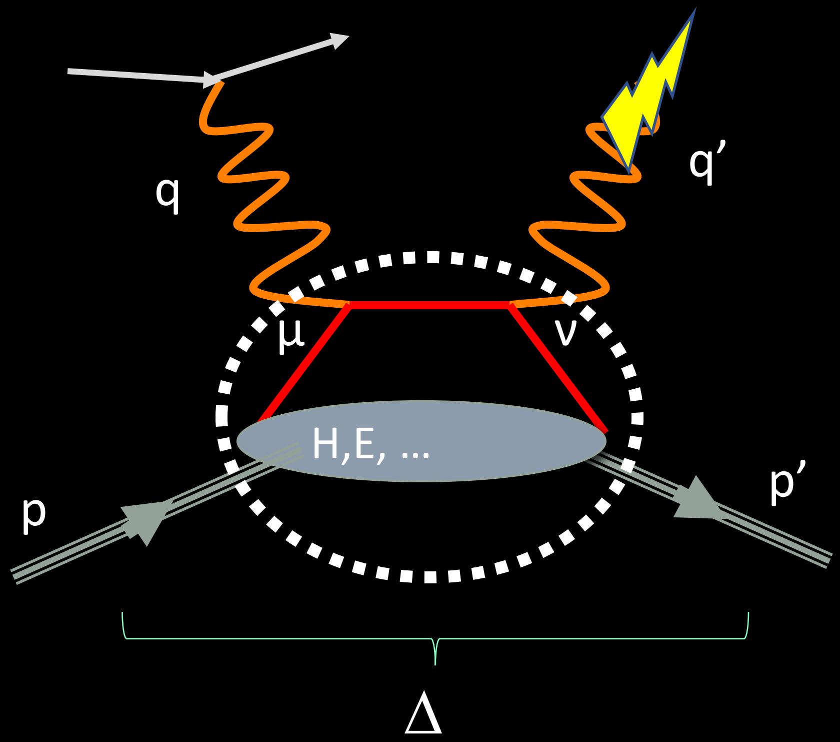


… but … what does it really take to have an image of the proton and can we really observe its spatial structure (10^{-15} m) ?

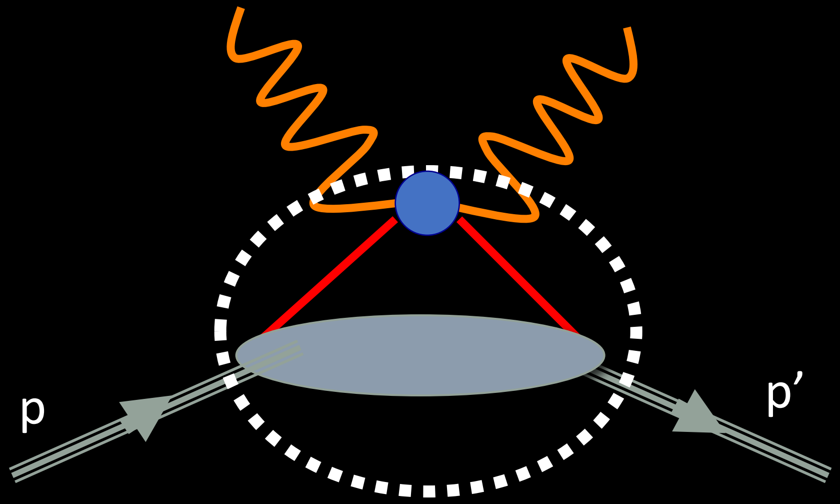
Deeply virtual exclusive scattering experiments allow us to access the internal spatial structure of the nucleon



QCD matrix element



Local Operator



Generalized Parton Distribution ➡ GPD Moments → (EMT) Form Factors

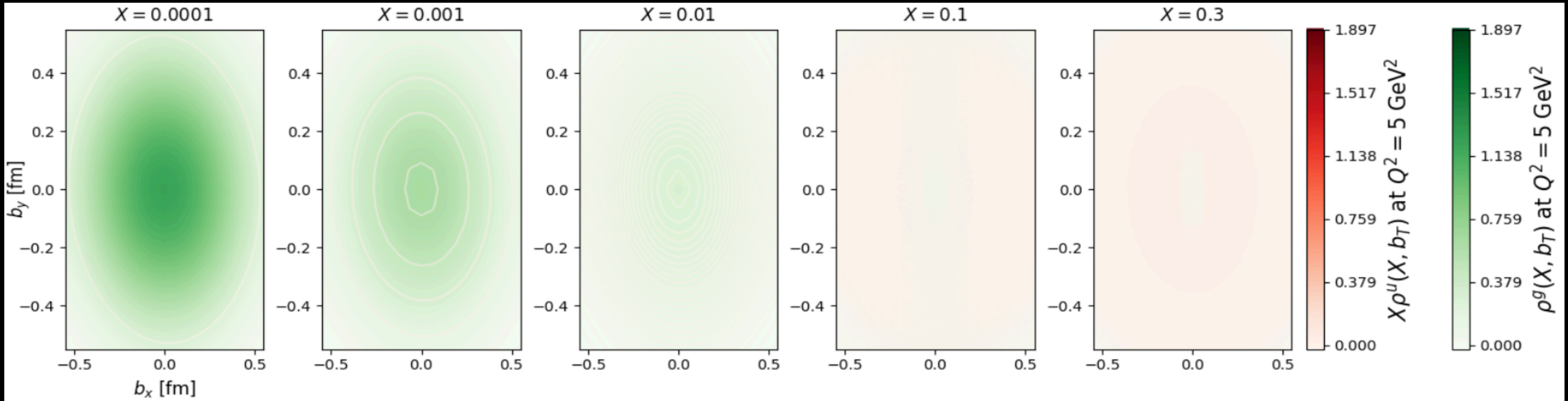
➡ Additional information from measurement of final state particles, q', p' (Δ)

3D Coordinate Space Representation

Observables from DVES matrix elements can be Fourier transformed from momentum space into coordinate space, providing insight into the spatial distributions of quarks and gluons inside the proton, besides matter and charge distributions.

$$\underbrace{\boxed{\mathcal{H}^q(X,0,b_T)}}_{\text{Wigner phase space distribution}} = \int \frac{d^2\Delta_T}{(2\pi)^2} \underbrace{\boxed{H^q(X,0,\Delta_T)}}_{\text{GPD}} e^{-i\Delta_T \cdot b_T}$$

Z. Panjsheeri



UVA gluon GPD parametrization (from lattice QCD and experiment)

B. Kriesten. P. Velie, E. Yeats, F. Y. Lopez, & S. Liuti, *Phys.Rev.D* 105 (2022) 5, 056022

We can also study two body densities and parton overlaps, beyond **one-body densities**

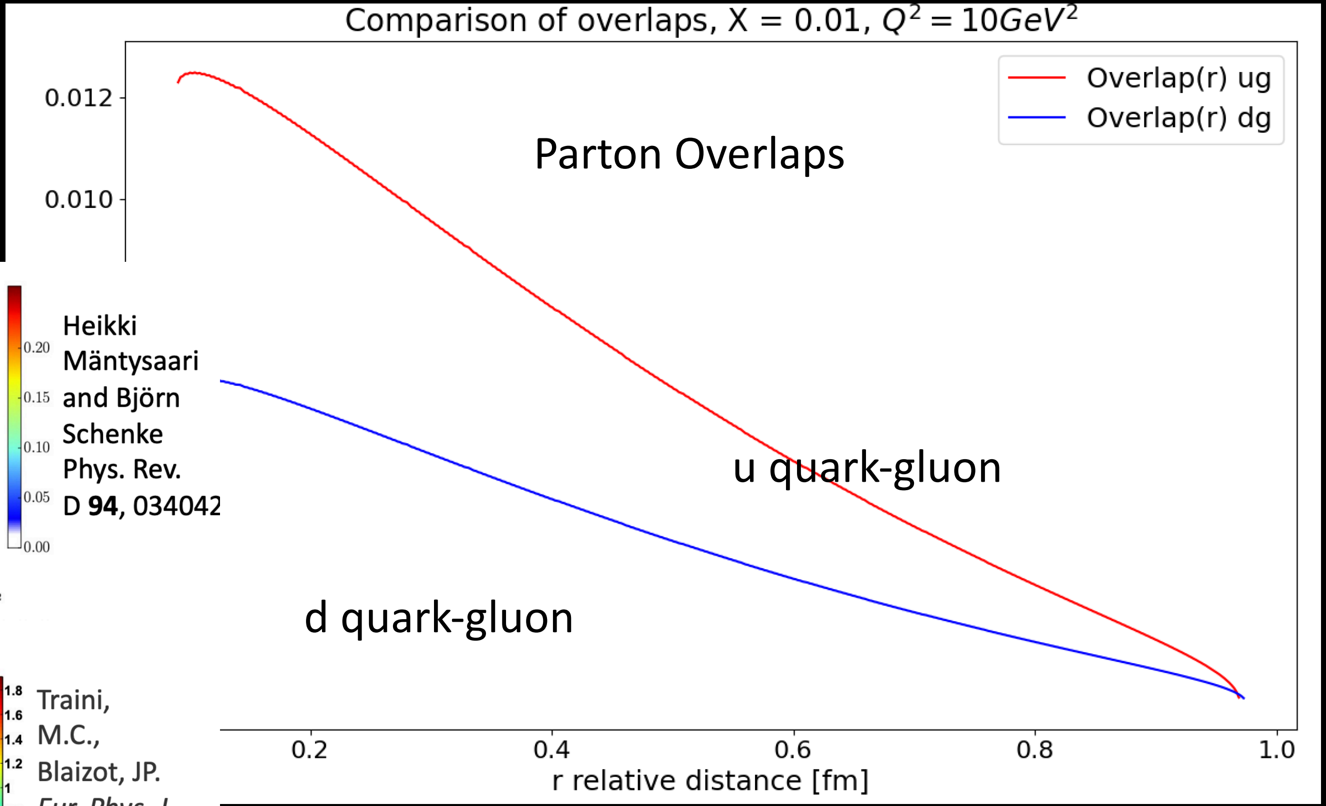
Z. Panjsheeri, J. Bautista, SL, soon on arXiv

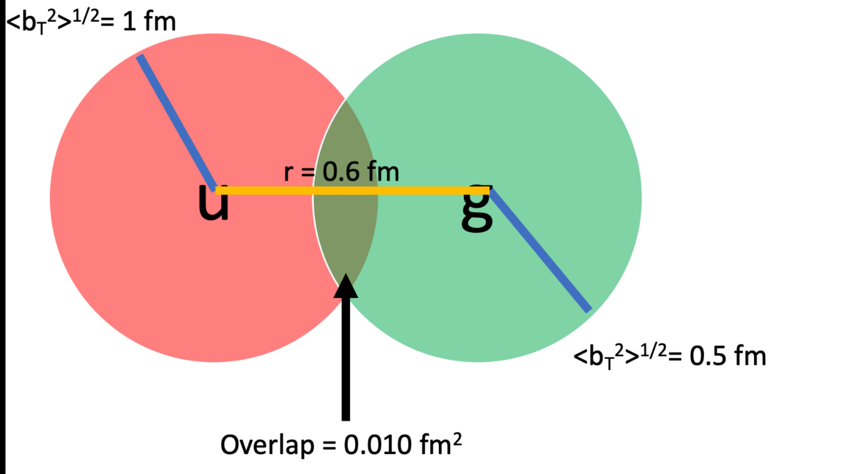
Two parton correlation function

$$
W^{\Gamma}_{\Lambda,\Lambda'} = \int \frac{dy^- d\mathbf{y}_T}{(2\pi)^3} \int \frac{dz_1^-}{2\pi} \frac{d\mathbf{z}_{1T}}{(2\pi)^2} \frac{dz_2^- d\mathbf{z}_{2,T}}{(2\pi)^2}
\times e^{i\Delta_2 y}\, e^{i(k_1+\Delta/2)z_1}\, e^{i(k_2 z_2)} \sum_{\mathcal{X}} \langle p', \Lambda' | \overline{\psi}_+ (0)\, \overline{\psi}_+ (y + z_1/2 + z_2/2) | \mathcal{X} \rangle \langle \mathcal{X} | \psi_+ (z_1)\, \psi_+ (y + z_1/2 - z_2/2) | p, \Lambda \rangle
$$

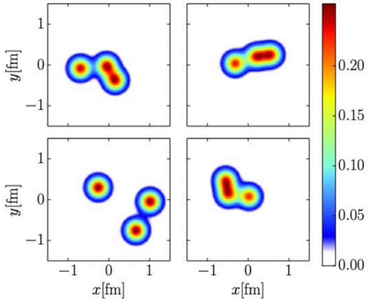
Two body density

$$
\rho_2^{qq}(X_1, X_2, \mathbf{b}_1, \mathbf{b}_2) = \frac{1}{2}\left[\rho(\mathbf{b}_1)\rho(\mathbf{b}_2) - \frac{1}{2}\rho(\mathbf{b}_1, \mathbf{b}_2)\right]
$$



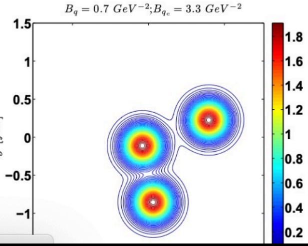


X = 0.01, Q^2 = 10 GeV^2



(a) $B_{qc} = 3.3\ \mathrm{GeV}^{-2}$, $B_q = 0.7\ \mathrm{GeV}^{-2}$

Heikki Mäntysaari and Björn Schenke Phys. Rev. D **94**, 034042



Traini, M.C., Blaizot, JP. *Eur. Phys. J. C* **79**, 327 (2019)

Z. Panjsheeri, J. Bautista, SL, soon on arXiv

Z. Panjsheeri, SPIN 2023

To reconstruct the spatial structure of the proton/nucleus from deeply virtual exclusive measurements we need a “new paradigm”that makes use in an optimal way of the powerful computational tools from ML

Machine learning and AI are upon us, in everyday life: commercial products recommendations, facial recognition, financial apps, email spam filtering, predictive text, mobile voice …

ML finds solutions to problems using statistics and finding patterns in large possibly chaotic data, becoming more and more sophisticated with the application of Natural Language Processing or LLM

ML seems to be ideal for physics analyses

ML tools have been applied to physics analyses in an automated, **seamless transition from what is commercially/industrially available**.

However…

- The problem we are dealing with in physics is to extract information from data: **interpretability**

- The goal of ML is to obtain statistical model that has **predictivity** from the data

- Both sides define an **inverse problem**: more cross talking is needed between CS experts and physicists to explore all the synergies, the common aspects, focusing on **why** any given method works

- An immense potential: through ML we will be able to see the emergence of **new physics relations/laws**

The EXCLAIM collaboration

https://exclaimcollab.github.io/web.github.io/#/

CoPIs: Marie Boer, Gia-Wei Chern , Michael Engelhardt, Gary Goldstein, Yaohang Li, Huey-Wen Lin, SL, Matt Sievert, Dennis Sivers
Postdocs: Douglas Adams, Marija Cuic, Saraswati Pandey, Emanuel Ortiz, Kemal Tegzin

OUR PROGRAM

EXCLAIM is developing ***physics aware*** networks by using ***theory constraints*** in ***deep learning*** models (not PINN)

1. ML is not treated as a set of “black boxes” whose working is not fully controllable

2. Utilize concepts in *information theory and quantum information theory* to interpret the working of ML algorithms necessary to extract information from data

3. At the same time, use ML methods as a testing ground for the working of quantum information theory in a large class of deeply virtual scattering processes

September 2023/May 2024

Statistics

Cross section information

Compton form factors extraction

1st inverse problem

2nd inverse problem

More theoretical questions

- Factorization

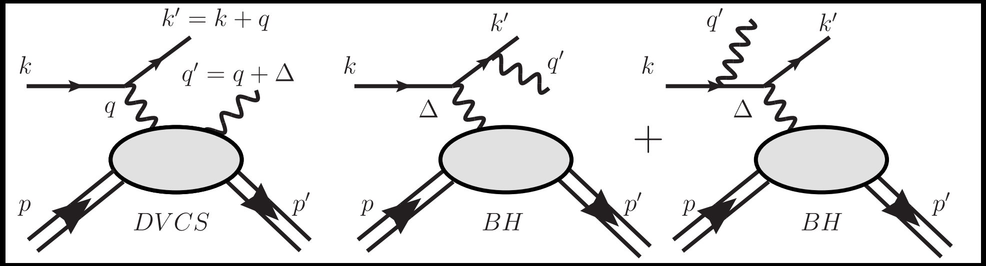
- Information on:

> GPDs/QCD matrix elements

> Angular momentum

> Spatial d.o.f.

1st Inverse Problem: extracting Compton form factors from cross section



$$\frac{d^4\sigma}{dx_{Bj}dQ^2dtd\phi} = \sigma_{BH} + \sigma_{DVCS} + \sigma_{\mathcal{I}}$$

At leading twist: 4 different Compton Form Factors because of the 4 possible different helicity configurations

$$\sigma^{unp}_{DVCS} = \frac{\Gamma}{Q^2(1-\epsilon)} \Big\{ (1-\xi^2)\Big[(\Re e\mathcal{H})^2 + (\Im m\mathcal{H})^2 + (\Re e\widetilde{\mathcal{H}})^2 + (\Im m\widetilde{\mathcal{H}})^2 \Big] +$$

$$\frac{t_o - t}{2M^2}\Big[(\Re e\mathcal{E})^2 + (\Im m\mathcal{E})^2 + \xi^2(\Re e\widetilde{\mathcal{E}})^2 + \xi^2(\Im m\widetilde{\mathcal{E}})^2 \Big] -$$

$$2\xi^2 \left(\Re e\mathcal{H}\,\Re e\mathcal{E} + \Im m\mathcal{H}\Im m\mathcal{E} + \Re e\widetilde{\mathcal{H}}\,\Re e\widetilde{\mathcal{E}} + \Im m\widetilde{\mathcal{H}}\Im m\widetilde{\mathcal{E}} \right) \Big\}$$

spin non-flip

spin flip

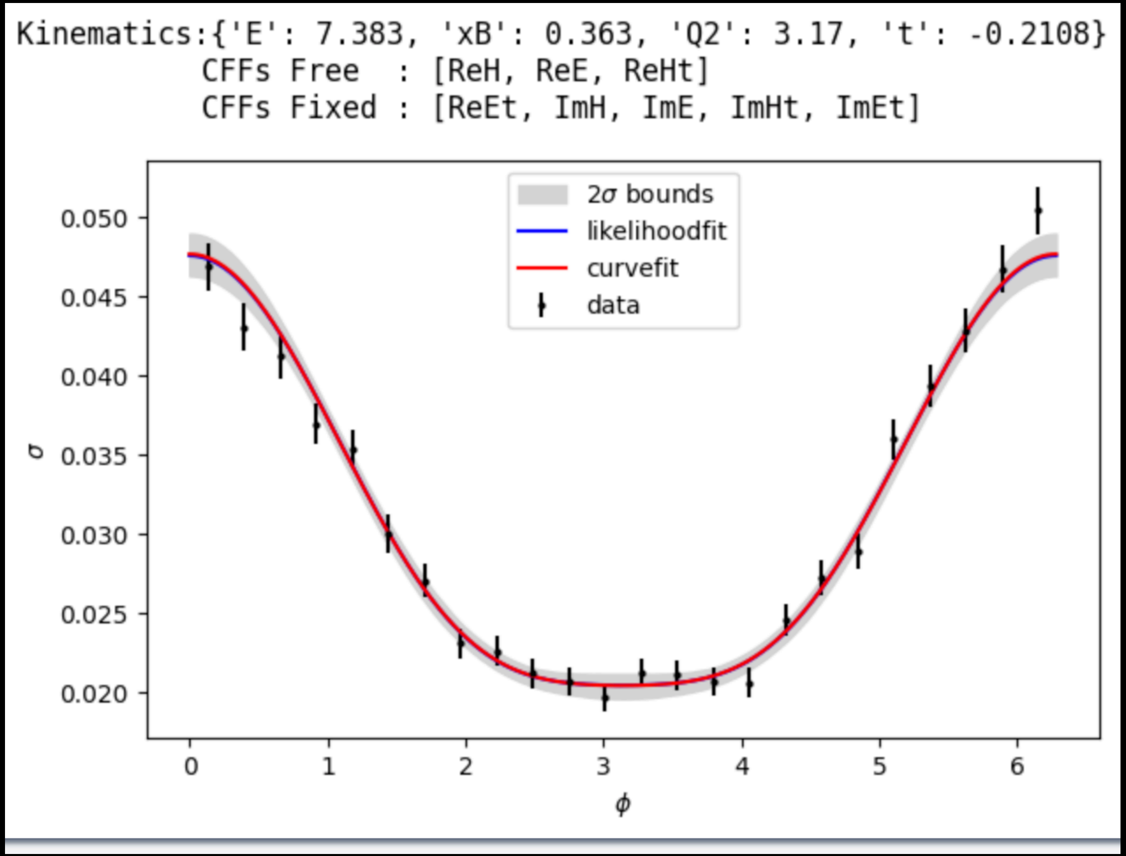
mixed

$$\sigma^{unp}_{\mathcal{I}} = \frac{\Gamma}{Q^2(1-\epsilon)} \Big\{ A^{\mathcal{I}}_{UU}\,(F_1\Re e\mathcal{H} + \tau F_2 \Re e\mathcal{E}) + B^{\mathcal{I}}_{UU}(F_1+F_2)(\Re e\mathcal{H} + \Re e\mathcal{E}) + C^{\mathcal{I}}_{UU}(F_1+F_2)\Re e\widetilde{H} \Big\}$$

Azimuthal angle ϕ dependent coefficients

- B. Kriesten et al, *Phys.Rev. D* 101 (2020)
- B. Kriesten and S. Liuti, *Phys.Rev. D105 (2022),* arXiv 2004.08890
- B. Kriesten and S. Liuti, Phys. Lett. B829 (2022), arXiv:2011.04484

DVCS Cross section



F. Georges, Hall A, PRL 128 (2022)

A multiprong approach

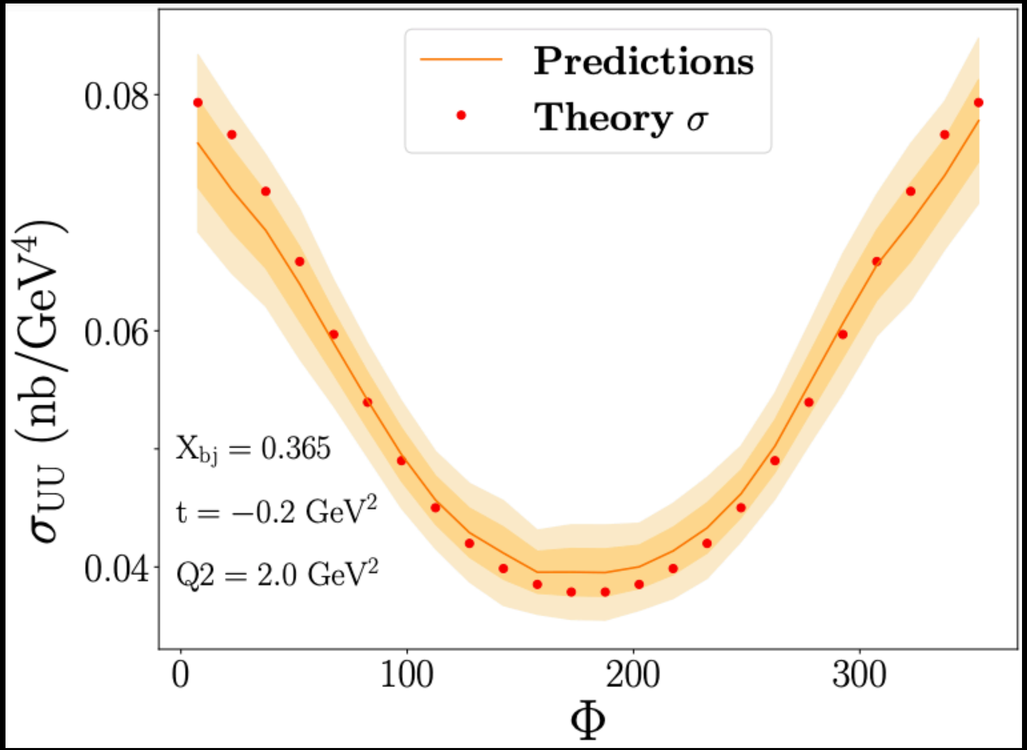
1) Standard NN
2) Variational Autoencoder Inverse Mapper
3) Likelihood analysis/MCMC
4) Comparison of likelihood analysis and VAIM

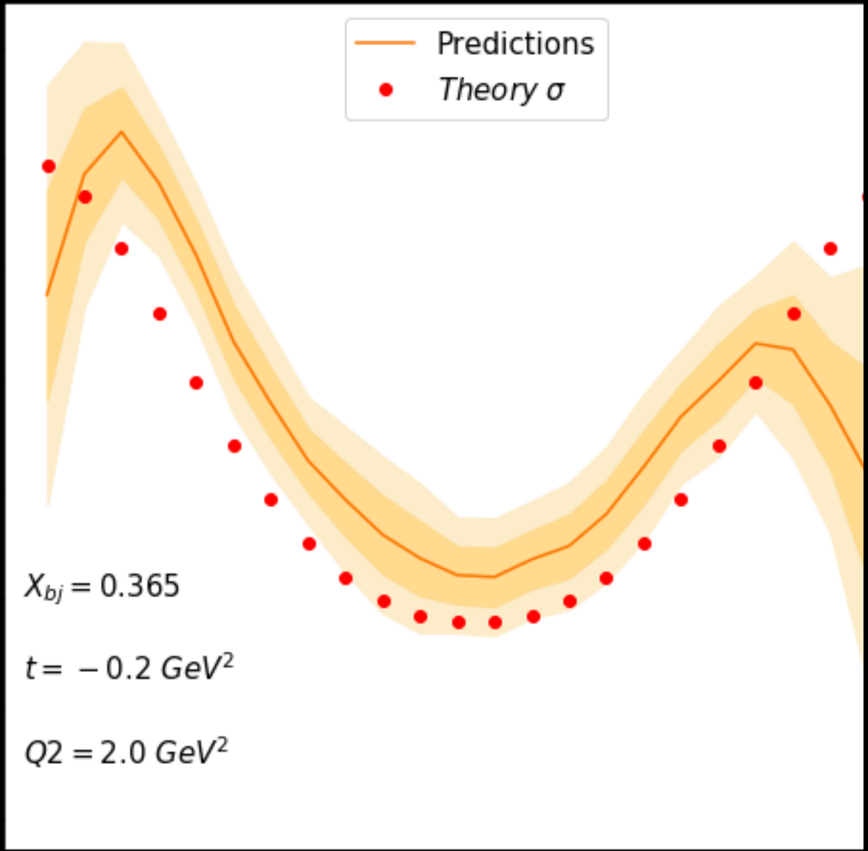
All these methods have the goals of:

1) Performing a sound and robust statistical analysis
2) Going beyond simple regression by understanding the underlying correlations of the system

(1) "Physics Aware NNs" : When physics is injected at any point in the analysis

Effect of Parity





M. Almaeen et al. arXiv 2207.10766

(2)

- **A variational autoencoder inverse mapper solution to Compton form factor extraction from deeply virtual exclusive reactions** arXiv: 2405.05826

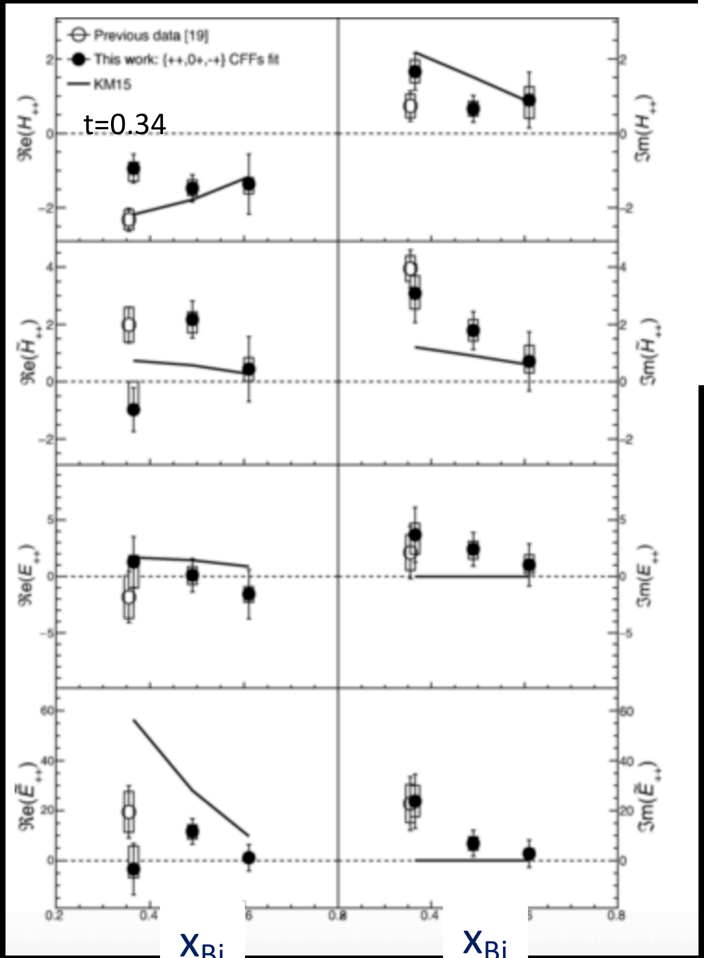
Experiment

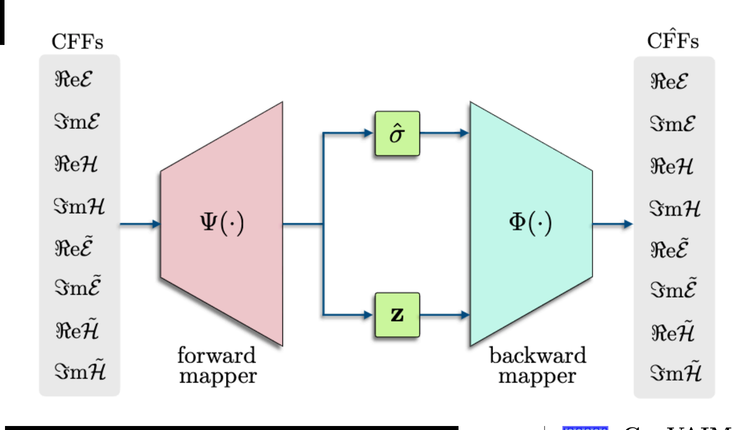
H

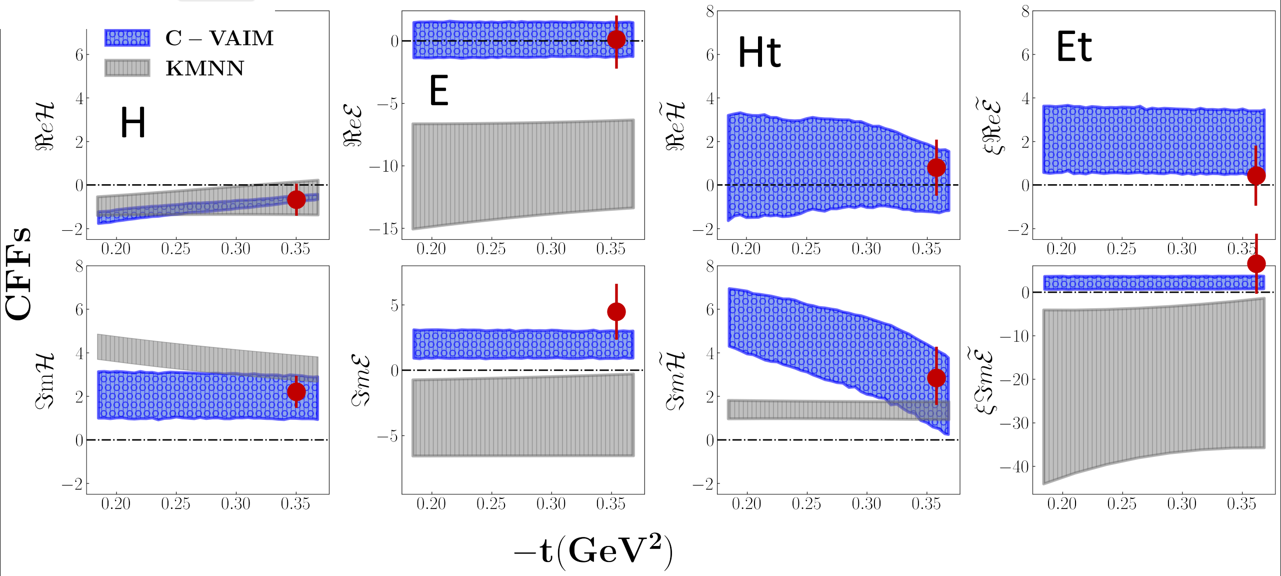
Ht

E

Et



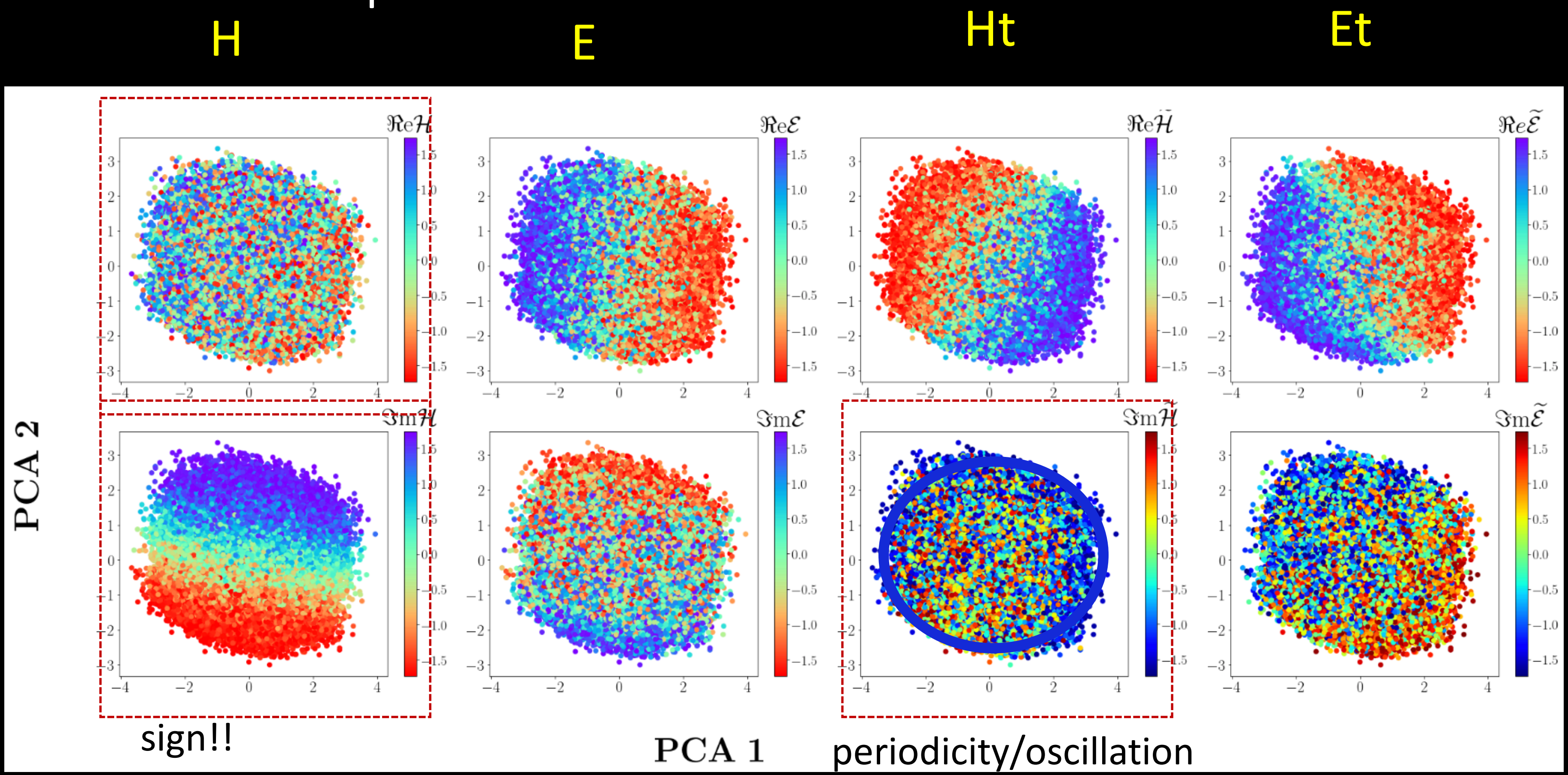




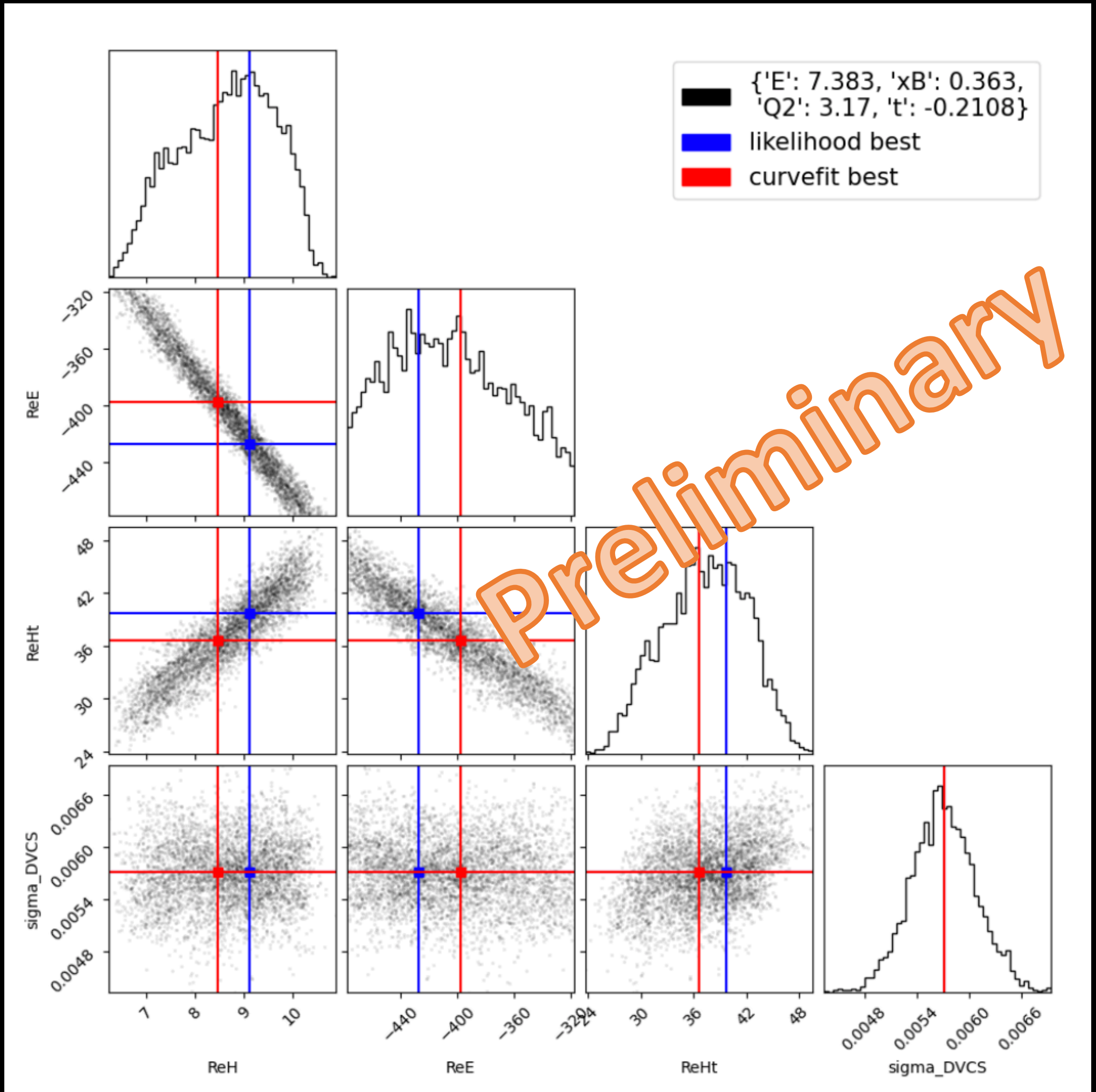
Hall A, https://arxiv.org/pdf/2201.03714.pdf

- KMNN, Cuic, Kumericki, Schaefer, https://arxiv.org/abs/2007.00029

CFFs Analysis of Latent Space



"A likelihood analysis of the DVCS cross section model vs. Jlab data"



Only three CFFs are non degenerate!

CFFs cannot be extracted from unp DVCS x-sec

Outliers analysis (not shown) improves results

Predict where to place future measurements

Douglas Adams

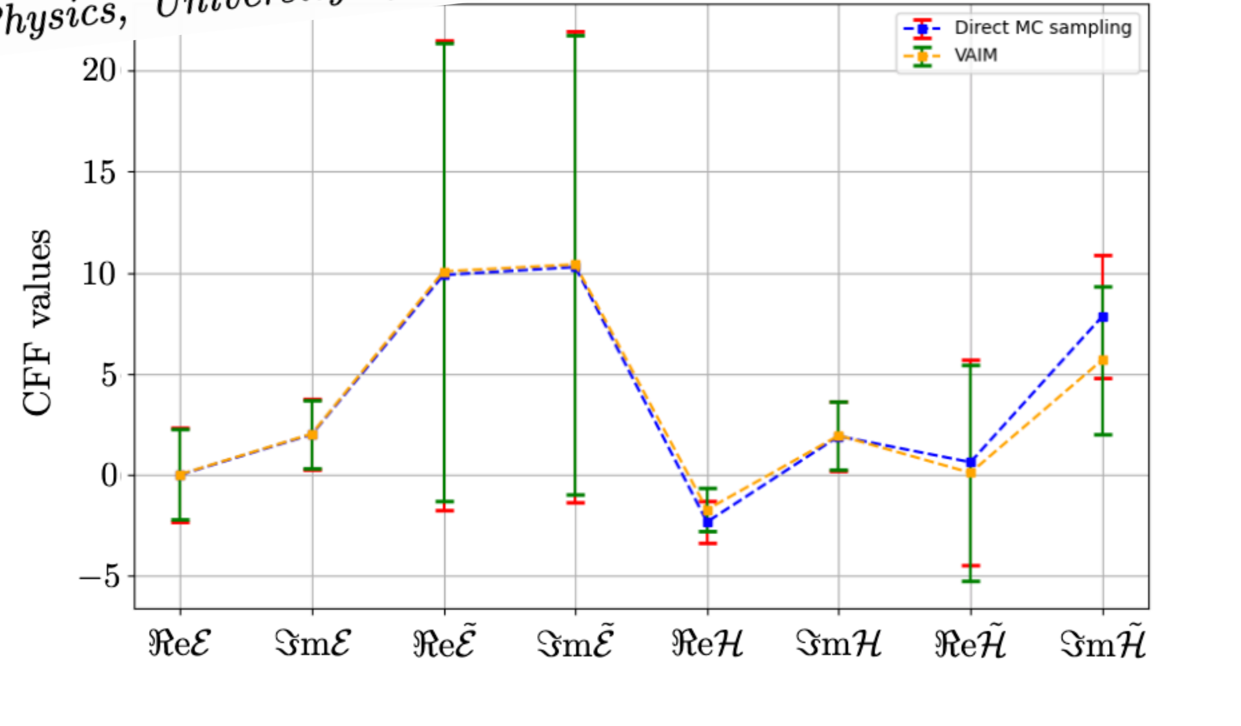
Comparison of MC sampling and VAIM

Variational autoencoder inverse mapper for extraction of Compton form factors: Benchmarks and conditional learning

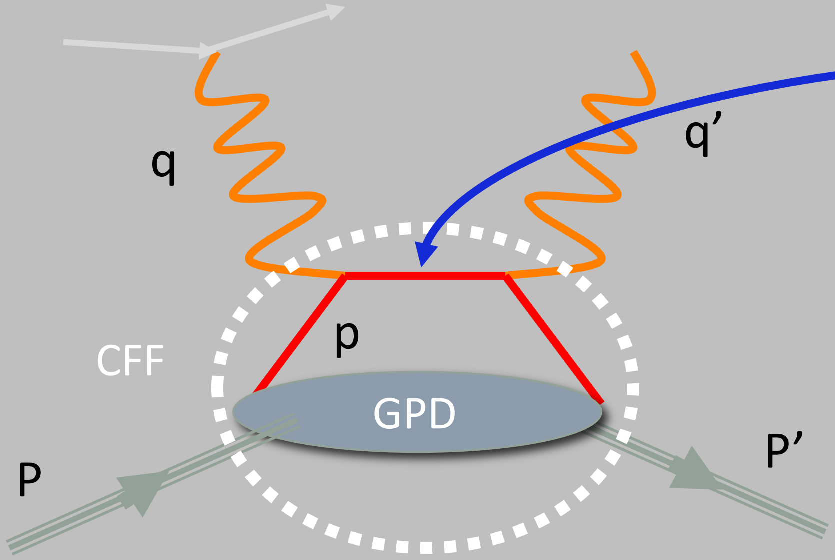
Fayaz Hossen,[1] Joshua Bautista,[2] Douglas Adams,[2] Yaohang Li,[1,*] Gia-Wei Chern,[2,†] and Simonetta Liuti[2,‡]

[1] *Department of Computer Science, Old Dominion University, Norfolk, VA 23529, USA.*

[2] *Department of Physics, University of Virginia, Charlottesville, VA 22904, USA.*



2^{nd} Inverse Problem: Extracting QCD matrix elements/GPDs (?) from CFFs



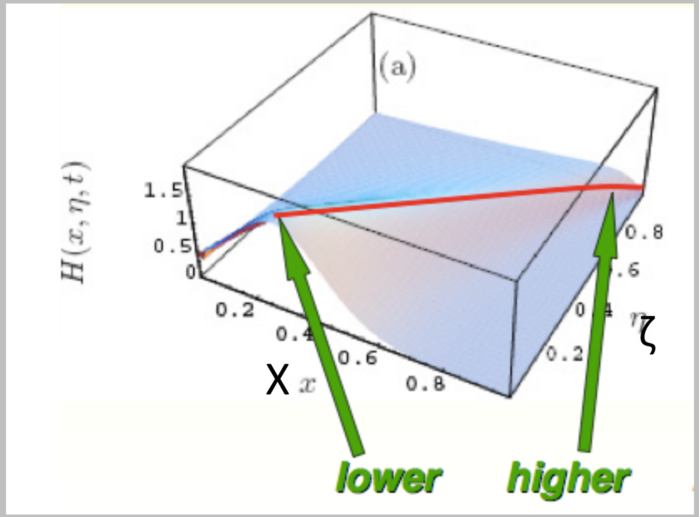
$$\frac{1}{(p+q)^2 - m^2 + i\varepsilon} = PV\frac{1}{(p+q)^2 - m^2} - i\pi\delta((p+q)^2 - m^2)$$

$$\rightarrow \frac{1}{-Q^2 + 2(pq) + i\varepsilon} \rightarrow \frac{1}{-Q^2/2(Pq) + (pq)/(Pq)} = \frac{1}{-\zeta + X}$$

CFF in QCD

$$\mathcal{F}_q = \boxed{P.V.\int_{-1+\zeta} dX\, F_q(X,\zeta,t)\left[\frac{1}{\zeta - X} - \frac{1}{X}\right]} + i\,\boxed{\pi e_q^2 F_q(\zeta,\zeta,t)}$$

GPD **GPD**

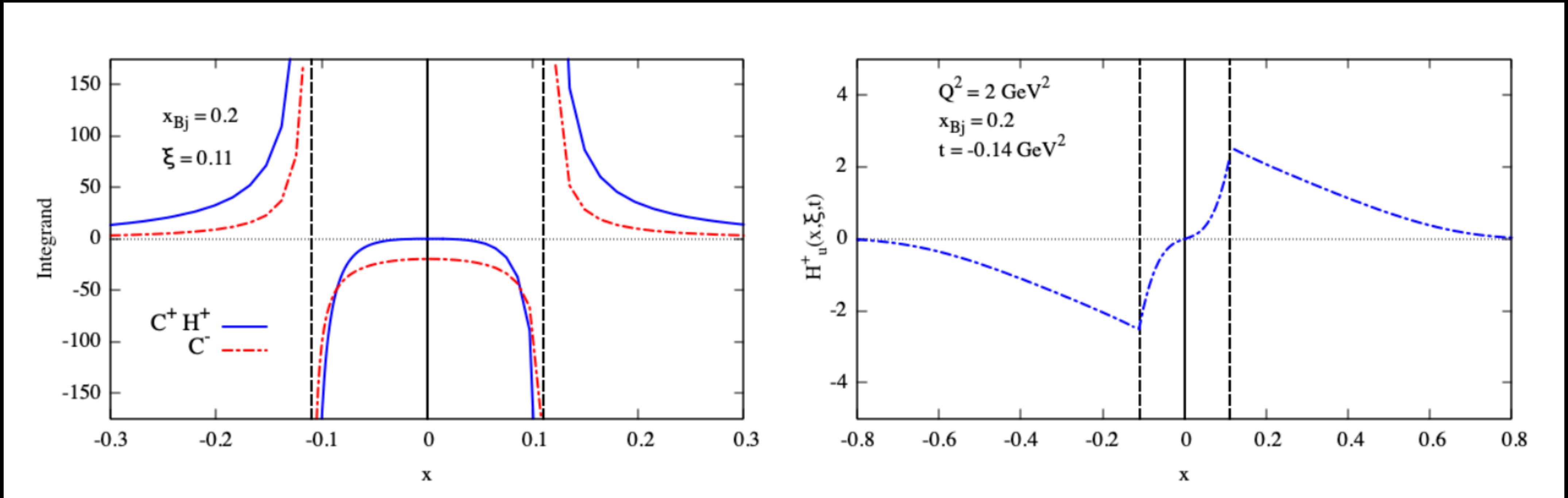


KM model

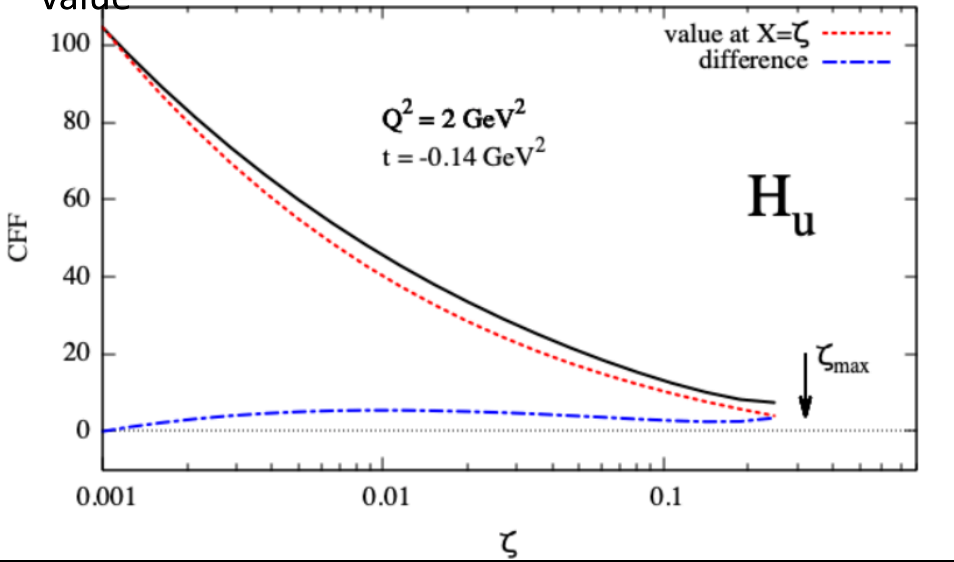
Finally, what types of GPDs are we extracting?

Kernels in convolution

GPD "+"-distribution



Taylor expansion of GPD around x=ζ vs. true value



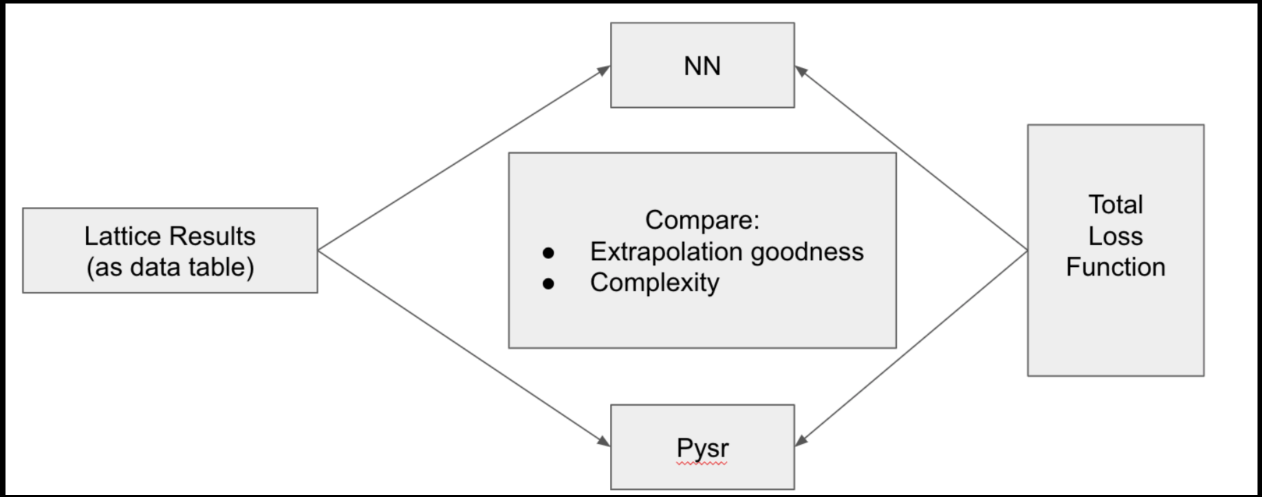
- ✓ It is not going to be possible to extract GPDs from the observables of simple DVES processes
- ✓ We will need multiparticle final states
- ✓ … and Lattice results

We are devising a multiprong approach

- Bernstein polynomials reconstruction
- Symbolic regression
- Symbolic regression and Ioffe time reconstruction

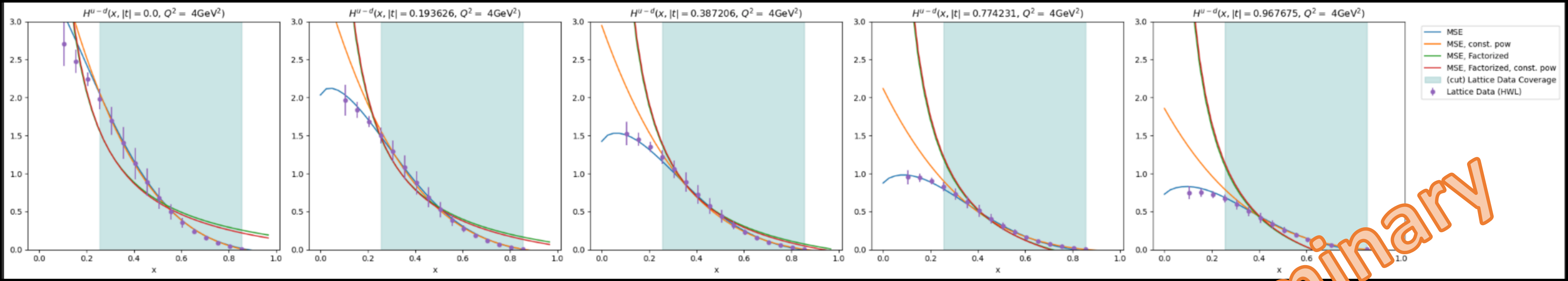
What is symbolic regression?

SR searches over the space of all possible mathematical expressions for the one that best predicts the output variable taking as input a set of base functions e.g. addition, trigonometric functions, and exponentials



Douglas Adams (UVA), Andrew Dotson (NMSU), Anusha Singireddy (ODU), Zaki Panjsheeri (UVA)

A. Dotson



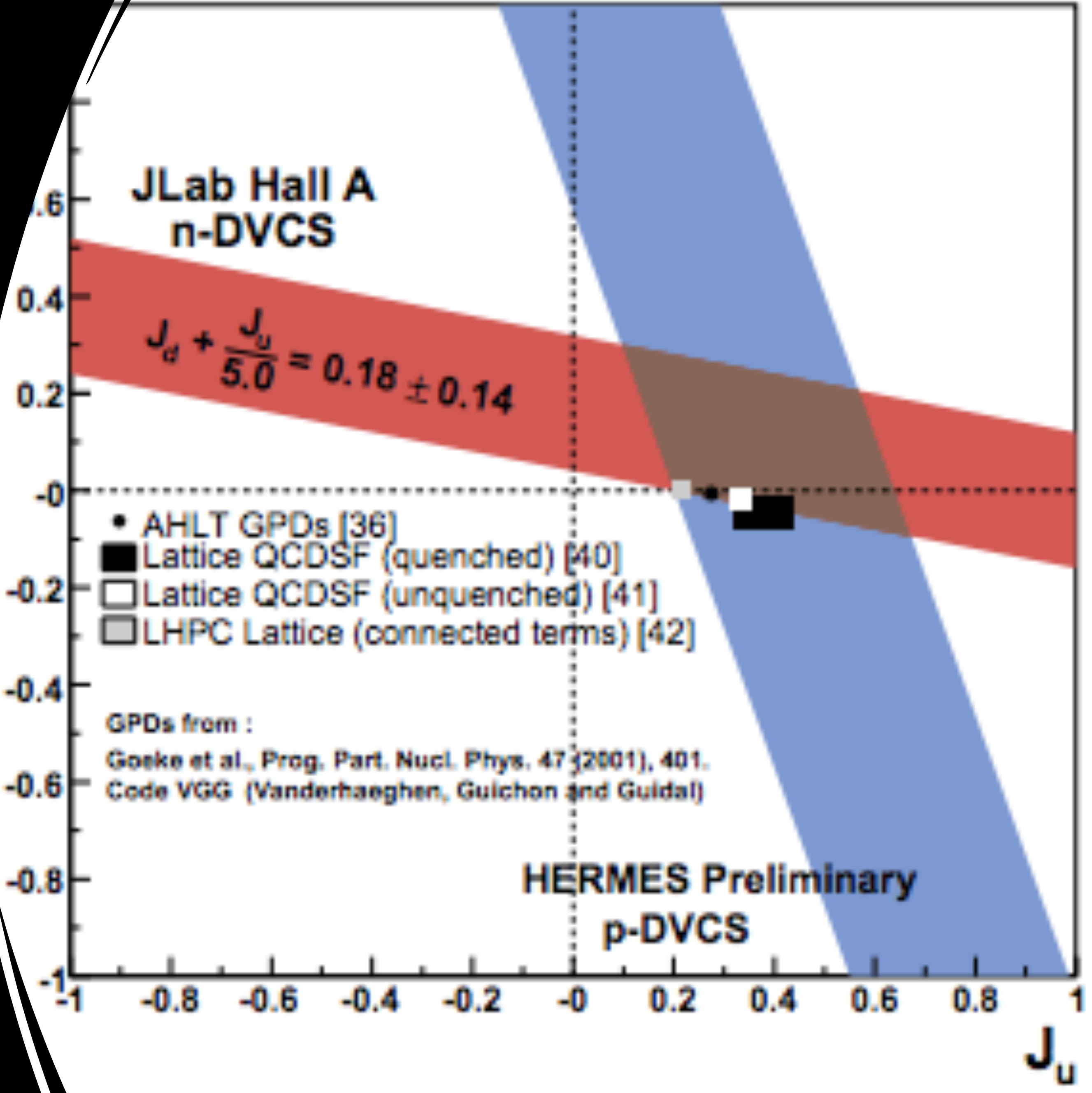
Preliminary

Example of prediction (MSE constant power)

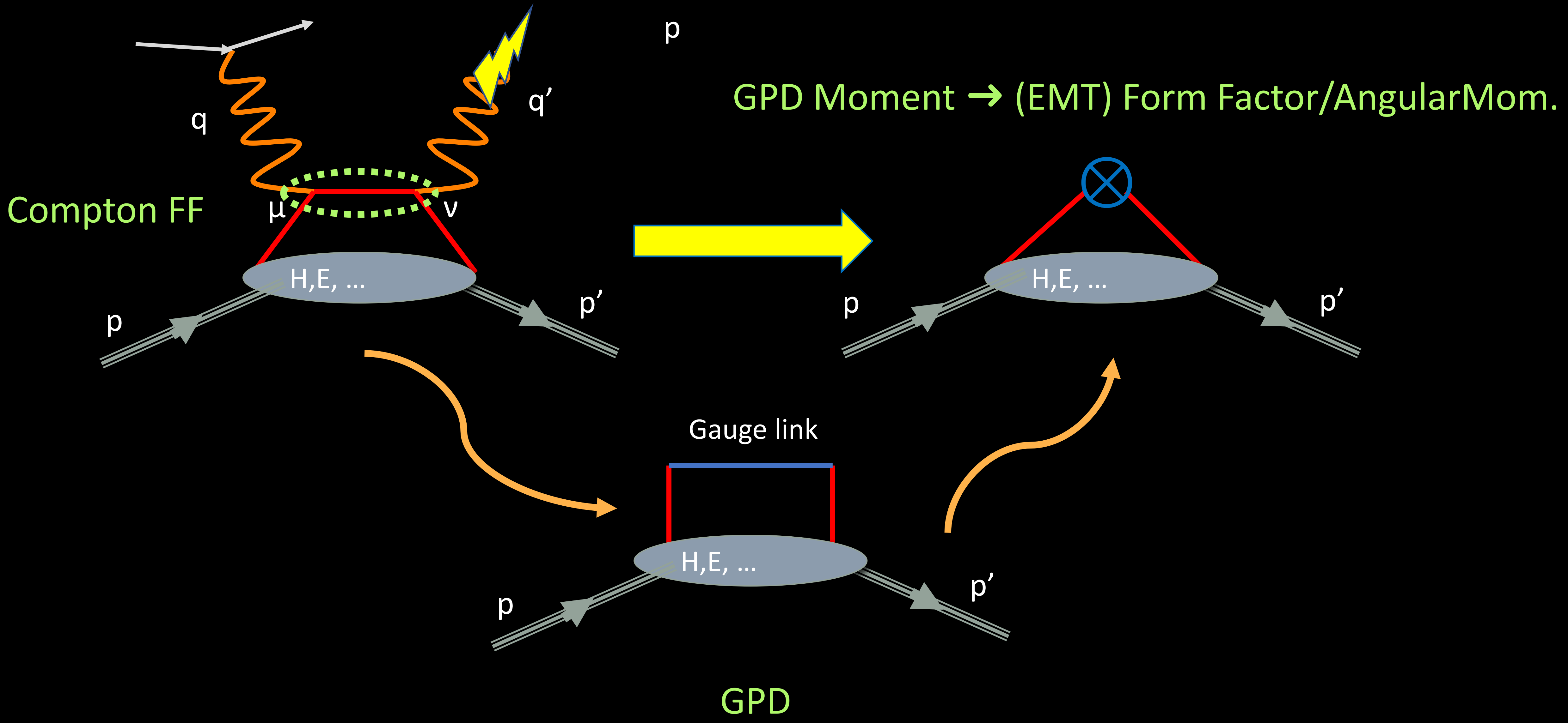
A factorized in x and t form!

$$\frac{1.07 \cdot \left(2.78\,(1-0.766x)^{3.83} - 0.0437\right)}{-t+0.603}$$

- Finally: do we need to calculate GPDs to extract OAM?



End to End Analysis



What I did not talk about:

- treatment of Uncertainty Quantification
- Epistemic and aleatoric uncertainty through BNN
- Moreover, the learning methods using ML allow us to obtain "more" from the analysis
- "More" >>>>> access to latent space

Conclusions

1. A successful reconstruction of the **spatial structure of the proton** (and all of its mechanical properties) relies on our ability to understand the **cross section** for **all the various DVES processes**

2. This implies solving **multiple inverse problems**

3. The first step is to extract the **observables**: the Compton Form Factors from data and ab initio QCD calculations

4. From CFFs to GPDs

5. Obtaining spatial images from data on GPDs will also be at reach using AI/ML to extend the momentum transfer reach for an accurate Fourier transformation

6. This problem is at the heart of the EIC program and solutions are at reach using **appropriate statistics techniques**
7. various AI/ML techniques: a very prominent one we used is the VAIM. More techniques: SR, BNN, …more ideas