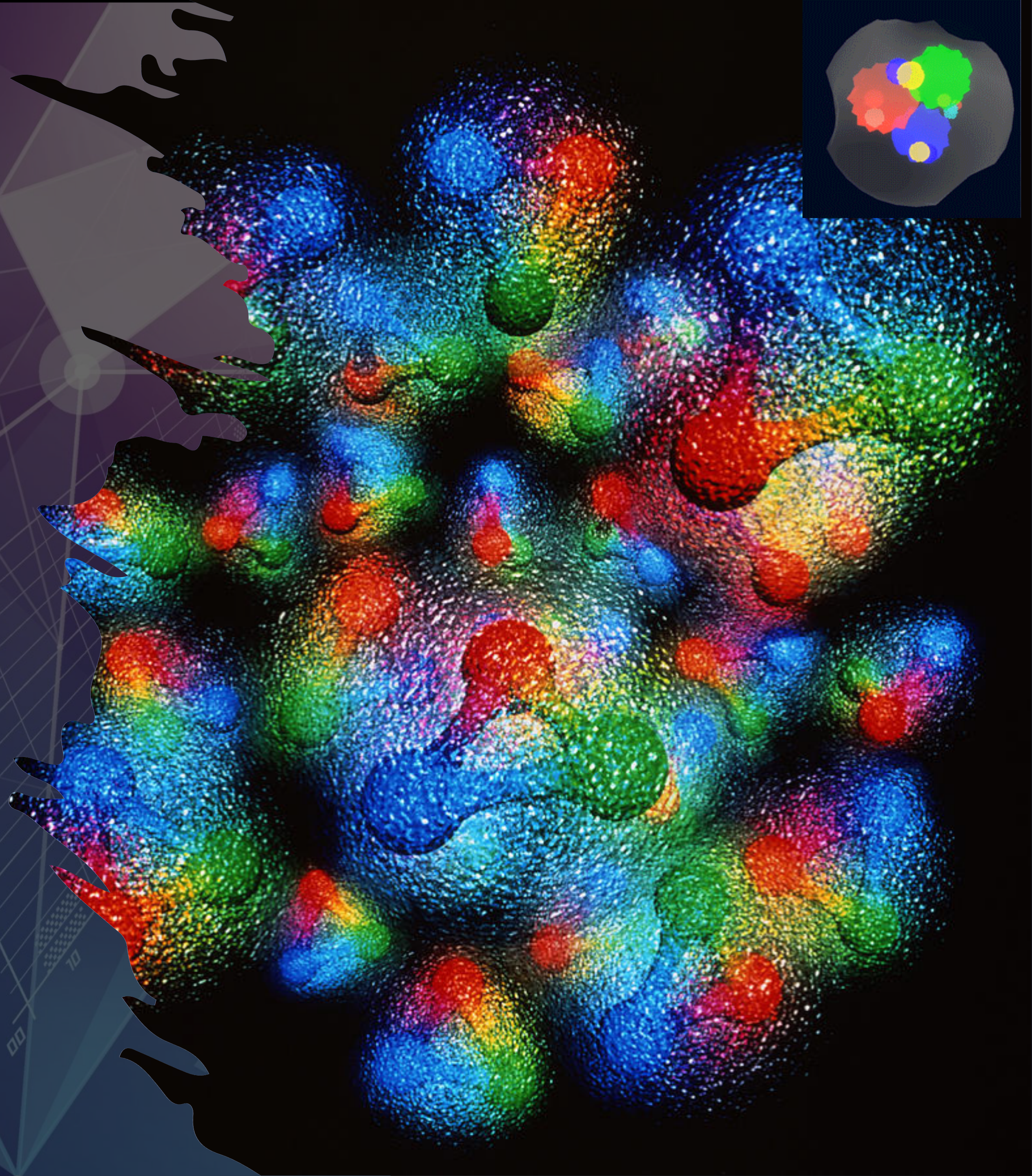
ML for QCD analysis: 3D imaging

Simonetta Liuti



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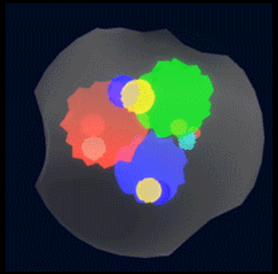
DVES Global Analysis@UVA



DVCS formalism

- 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

ML

- J. Grigsby, B. Kriesten, J. Hoskins, S. Liuti, P. Alonzi and M. Burkardt, Phys. Rev. D104 (2021)
- Manal Almaeen, Jake Grigsby, Joshua Hoskins, Brandon Kriesten, Yaohang Li, Huey-Wen Lin and S. L

  ``Benchmarks for a Global Extraction of Information from Deeply Virtual Exclusive Scattering,''

  [arXiv:2207.10766 [hep-ph]].

GPD Parametrization for global analysis

- B. Kriesten, P. Velie, E. Yeats, F. Yepez-Lopez and S. Liuti,

Phys. Rev D 105 (2022), arXiv:2101.01826

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Charge for this talk and workshop discussion

Address current ML applications in QCD theory while navigating the current *"Strategic moment to discuss how to fully take advantage of the new opportunities offered by AI/ML to advance research, design, and operation of EIC."*

Cristiano Fanelli (AI4EIC workshop 2021)

- ML is key for discovery

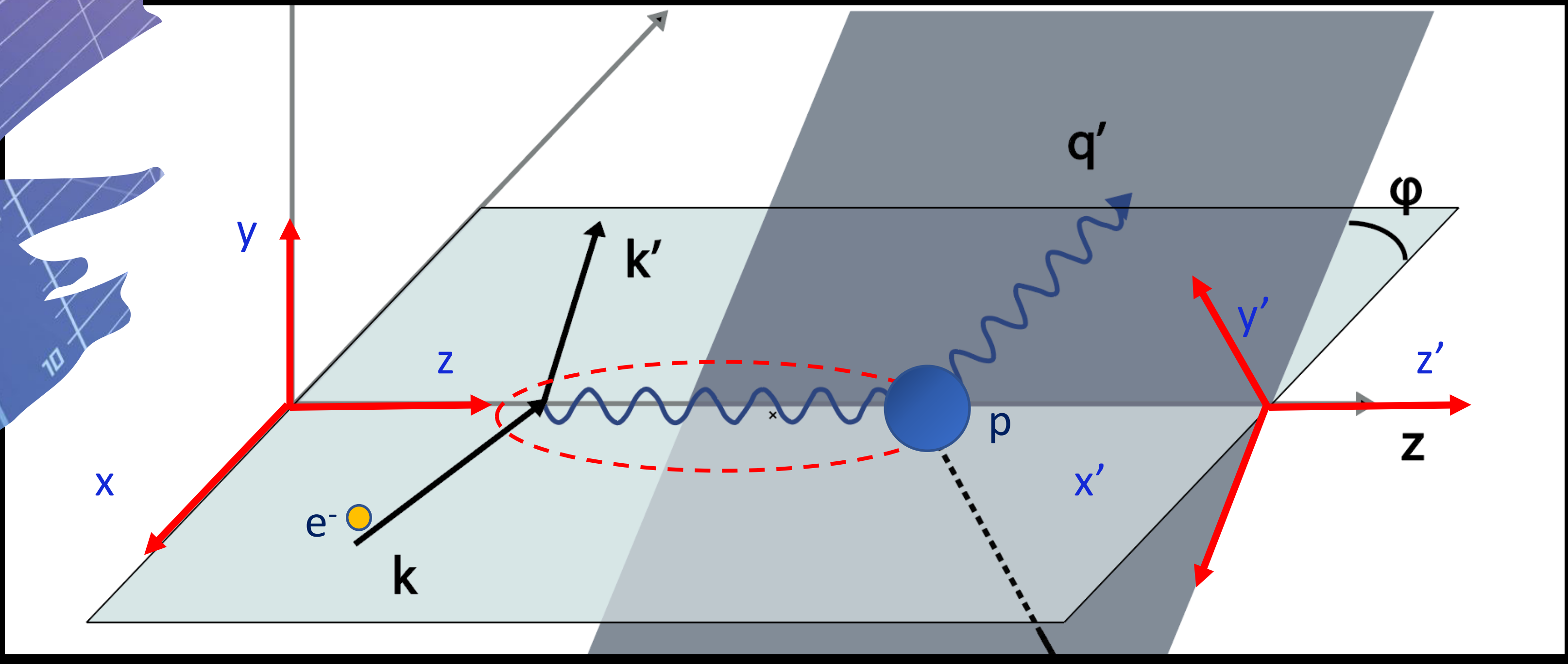
- Using statistical methods, ML algorithms uniquely allow us to obtain key insights from the data, through classifications and predictions.

- These insights are conducive to:
  1. abstracting physics concepts
  2. identifying the most relevant physics questions
  3. identifying the data which are needed to answer them.

- ML applications are currently impacting two main directions in QCD theory

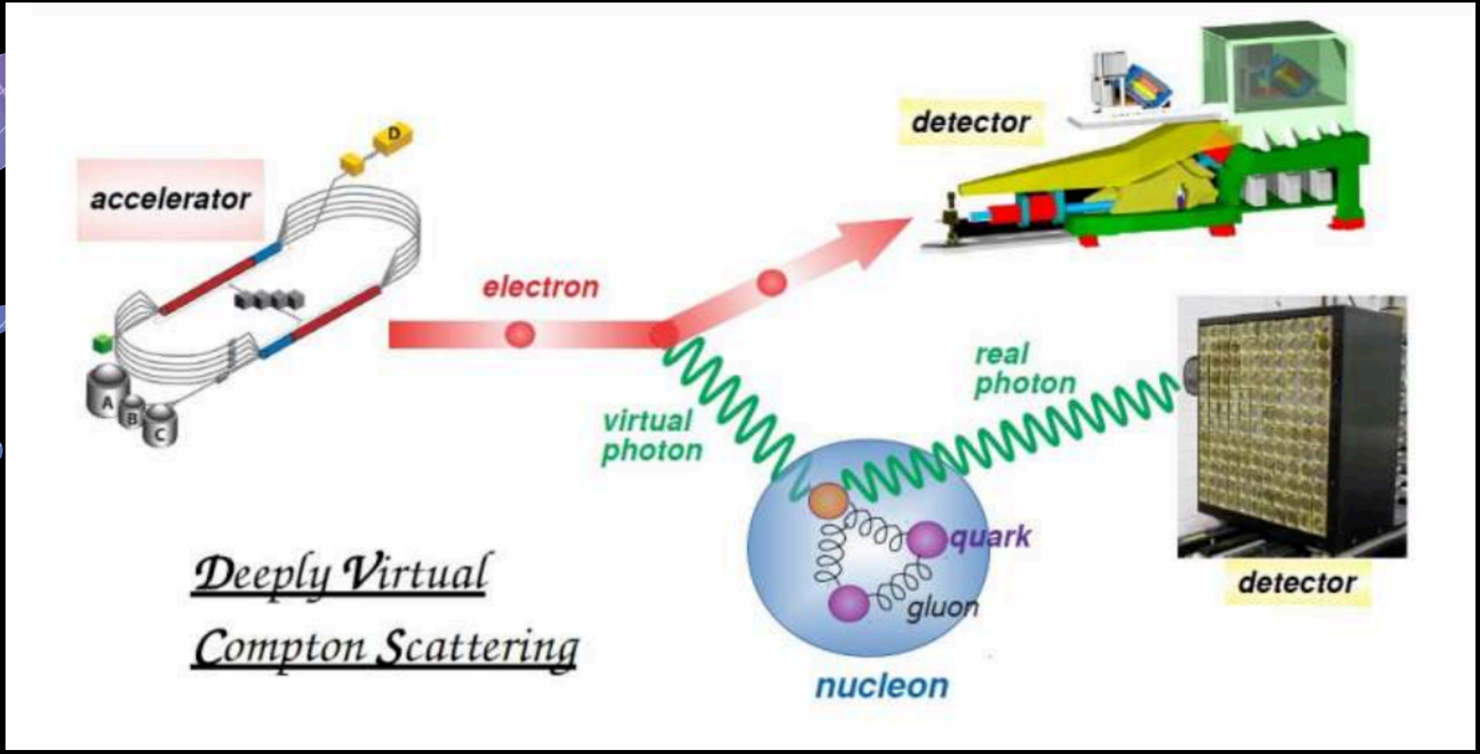
- ab initio calculations (lattice QCD+EFT+many body calculations)
- phenomenology
- phenomenology + lattice QCD (H.-W. Lin)

A working example : global fitting of deeply virtual exclusive scattering data



A working example : global fitting of deeply virtual exclusive scattering data

I. Fadelli , Phys.org (2020)



Quark/gluon physics observables we hope to extract from DVES

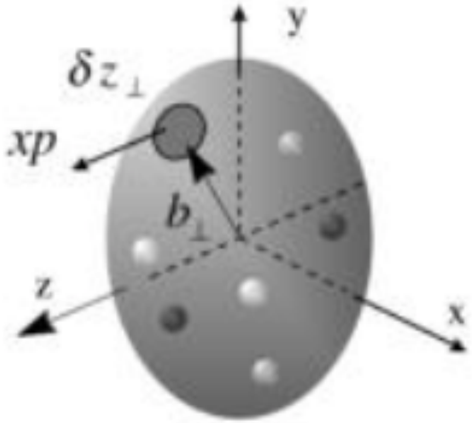
Angular momentum

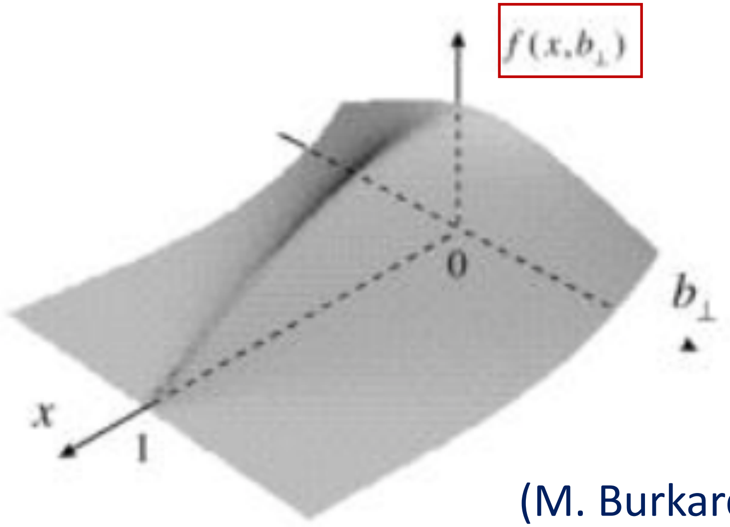
$$\frac{1}{2}\int_{-1}^{1} dx\,x\,[H_q(x,0,0)+E_q(x,0,0)] = J_q$$

(X. Ji, 1997)

These distributions are not directly observable!

3D Structure





(M. Burkardt, 2000)

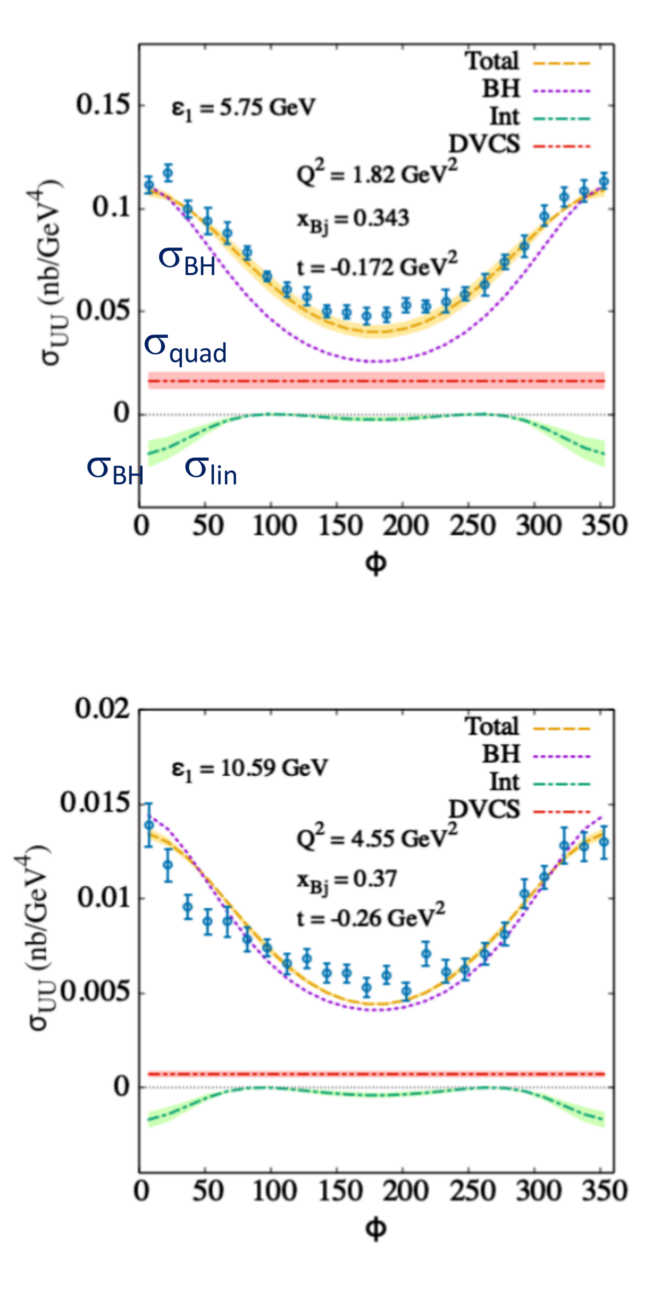
The challenge for QCD phenomenology

Is the information on $J_{q,g}(t)$ in DVES data?

What information is in the data?

Cross section

$$\frac{d^4\sigma}{d\phi\, dx dt\, dQ^2} = \sigma_{BH} + \sigma_{lin}(d\phi, dx, dt, dQ^2; \mathcal{F}_1, ..., \mathcal{F}_8) + \sigma_{quad}(d\phi, dx, dt, dQ^2; \mathcal{F}_1^2, ..., \mathcal{F}_8^2)$$



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Our approach

1. Precursor: can ML model the cross section?
   J. Grigsby, B. Kriesten *et al.* Phys. Rev. D104 (2021)

2. Introduce ML models with architectures that reflect physics constraints from the theory : i) less modeling error; ii) reduced demand
   on data points; iii) faster training; iv) improved generalization.

Precursor: can ML model the cross section?

J. Grigsby, B. Kriesten *et al.* Phys. Rev. D104 (2021)

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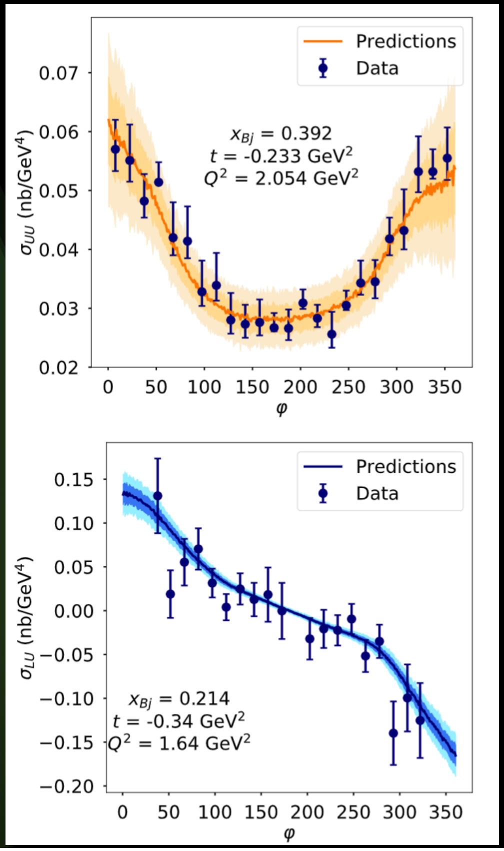
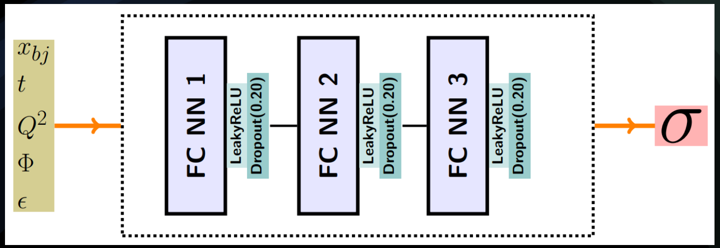


Comparison with baseline models

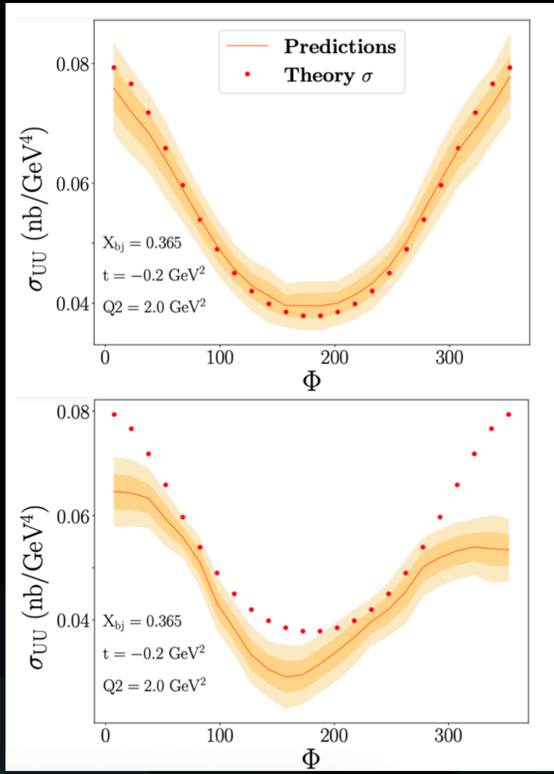
	UU				LU			
	Standard		Harmonic Features		Standard		Harmonic Features	
Method	Median % Error	Accuracy (%)	Median % Error	Accuracy (%)	Median % Error	Accuracy (%)	Median % Error	Accuracy (%)
Linear	238.87	2.10	343.68	1.0	293.03	19.68	333.23	22.34
SVR	45.73	19.14	37.57	27.13	68.09	57.71	72.97	57.98
Theory	13.39	49.50	N/A	N/A	62.46	62.67	N/A	N/A
FemtoNet	**9.99**	**61.97**	N/A	N/A	**56.06**	**63.03**	N/A	N/A

Physics informed ML models

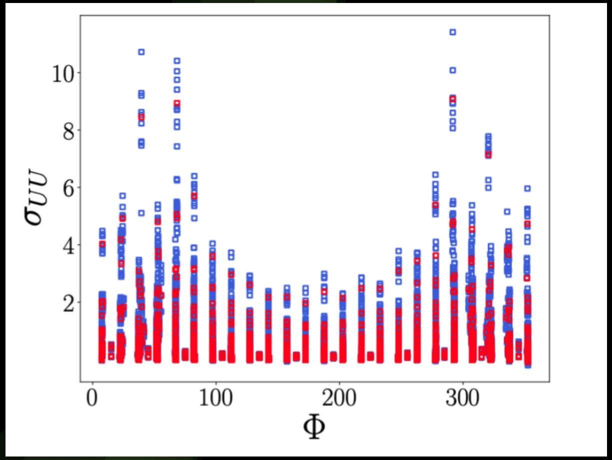
M. Almaeen et al. [arXiv:2207.10766 [hep-ph]].



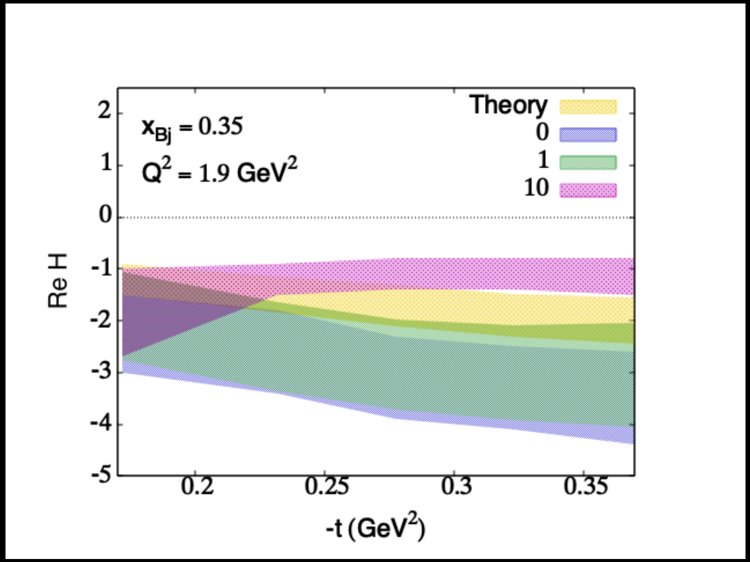
Including symmetries from theory



Data augmentation from physical x-sec error

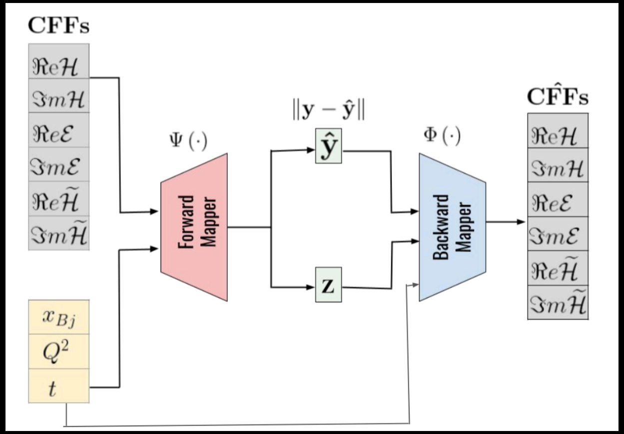


Observables extraction



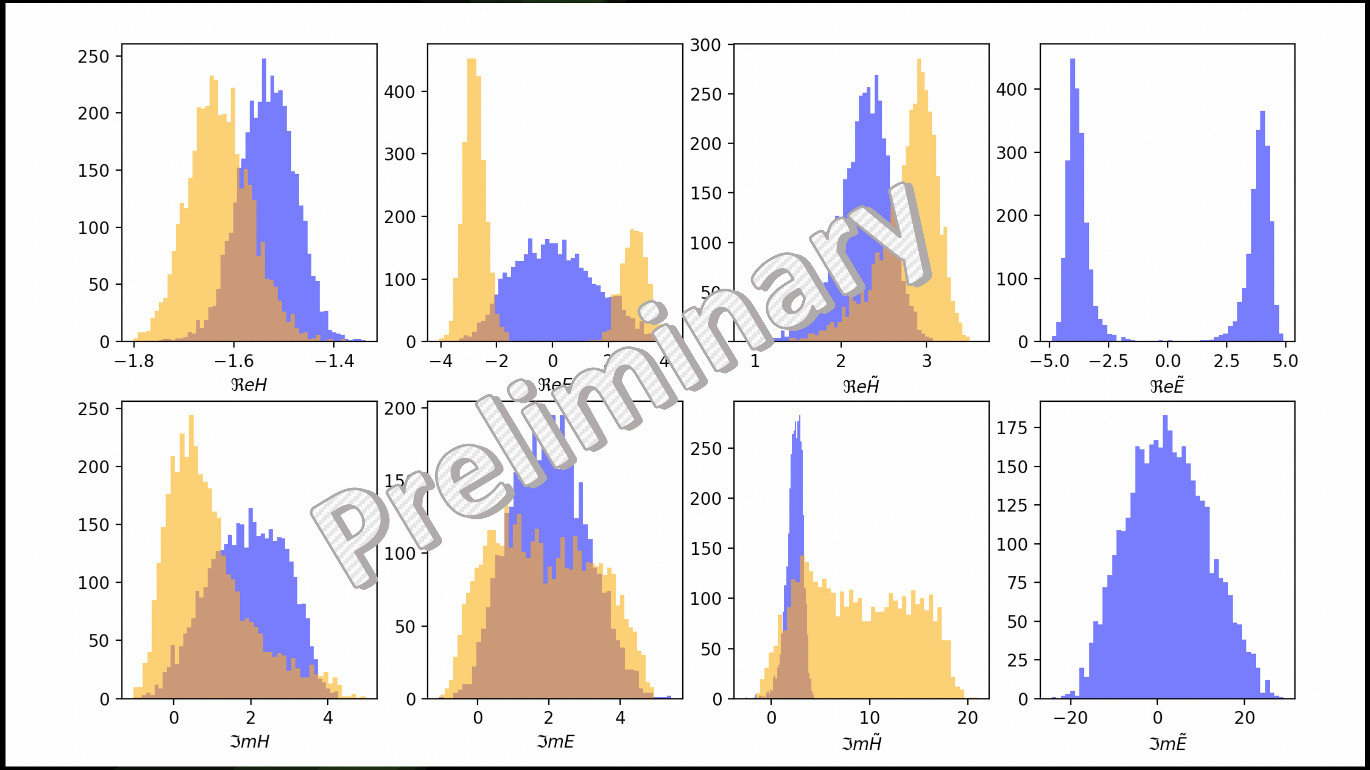
Future

1. VAIM
2. Including Lattice QCD constraints
3. Reinforcement Learning
4. Uncertainty Quantification

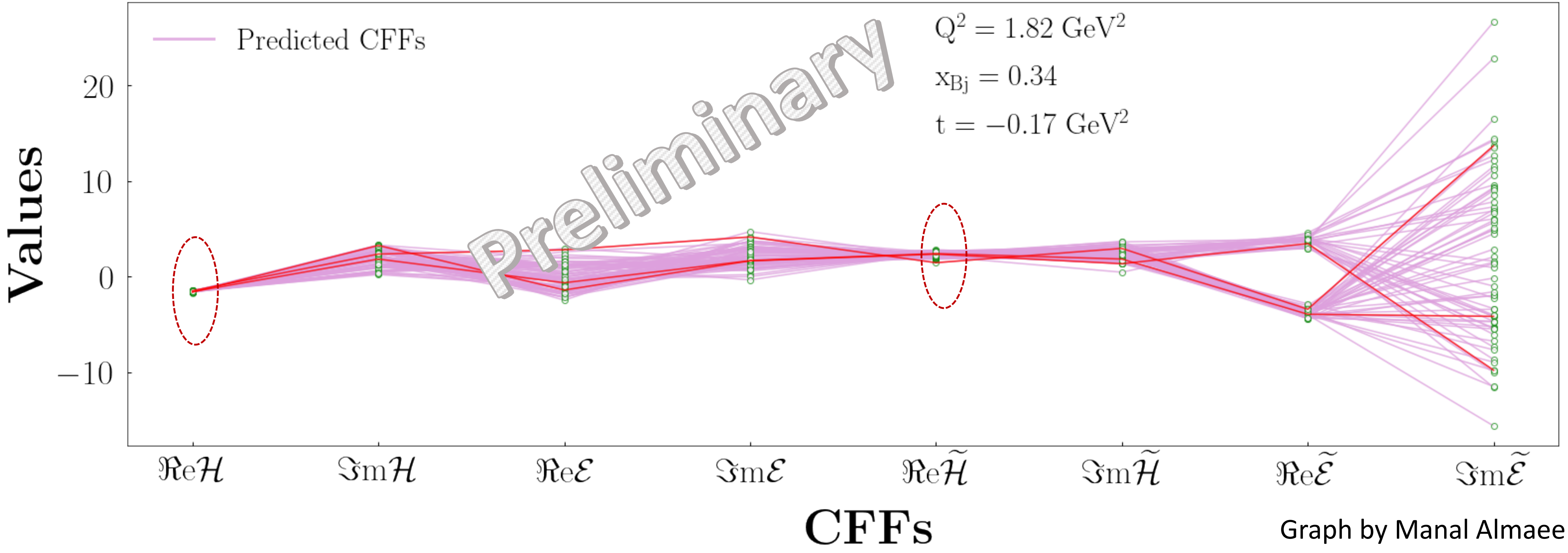


M. Almaeen

First quantitative extraction of observables (CFFs)



Going beyond standard fitting procedures: Variational Autoenconder example



Graph by Manal Almaeen

- M. Almaeen, J. Grigsby, J. Hoskins, B. Kriesten, Y. Li, H. W. Lin and S. Liuti, *in preparation*

Our team: interdisciplinary workforce

- Phenomenology/Theory: B. Kriesten, SL
- CS: Y. Li, M. Almaeen, J. Hoskins, (J. Grigsby)
- Lattice QCD: H.W. Lin
- Experiment: N. Kalantarian

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AI/ML for QCD Phenomenology

- **Information**: by extending VAIM/RL/similar methods to all observables, including J_q , we will be able to test what type of information can be found in the data.

- **Data augmentation:** VAIM/similar methods can be used for data augmentation. New field of Data-Sparse environments

- **Uncertainty quantitifcation**: distinguishing epistemic from aleatoric origin of uncertainty. ML methods can uniquely address this question differently from standard regression where epistemic uncertainty is given by an unquantifiable dependence on the functional form.

For the EIC community: A rigorous benchmarking process

EIC analyses should be based on rigorous benchmarking that allows for quantitative comparison of different approaches.

In our DVES example:

- Physics Benchmarks
  - number and type of CFFs
  - Q^2 dependence of the cross section and observables: kinematic terms, PQCD evolution (LO, NLO, NNLO), and dynamical beyond LO terms (higher twists)

- Machine Learning Benchmarks
- ML architectures hyperparameters (number of layers, size of hidden nodes, activation functions, drop-out rates, loss functions, gradient descent methods)
- Features specific to data-centric analysis (feature selection and transformation, data augmentation, data synthetics, and data cleansing)
- Uncertainty Quantification
  - Inherent statistical fluctuations in physics (statistic)
  - Errors inherent from measurement system (systematic)
  - Errors in ML models
  - Errors in the training procedure

Proposal of future workforce organization based on **synergy/two ways process**

ML enhances and allows physics discovery ⟷ Problems posed by physicists tare of interest to ML

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<u>Examples:</u>

- Dealing with small amounts of data/sparse data
- Question of how we interpret information
- Is adding more data always good? Breaking or going beyond the paradigms of the “standard model of statistics”.

Lets organize it!

https://peaceproject.com/