Machine Learning Approaches to Hard Exclusive Processes

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Synergies between the EIC and the LHC

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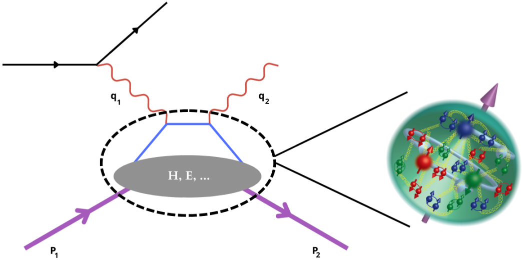
Nucleon structure



$$d\sigma \propto 4\,(1-x_{\rm B})\left(|\mathcal{H}|^2 + |\widetilde{\mathcal{H}}|^2\right) - \cdots$$

$$\downarrow$$

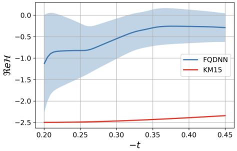
$$\mathcal{H}^A\left(\xi, \Delta^2, Q^2\right) = \int_{-1}^{1} \frac{dx}{2\xi} \underbrace{{}^{A}T\left(x, \xi \middle| \alpha_{\rm s}\left(\mu_{\rm R}\right), \frac{Q^2}{\mu_{\rm F}^2}\right)}_{\text{hard scale}} \underbrace{H^A\left(x, \eta, \Delta^2, \mu_{\rm F}^2\right)}_{\text{soft scale}}$$

Inverse problem

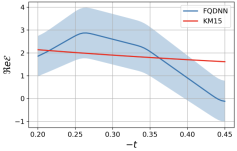
observables $\rightarrow$ CFFs $\rightarrow$ GPDs $\Rightarrow$ ill-posed problem!

Some recent CFF extractions

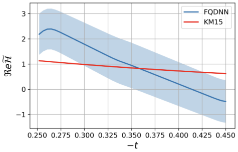
B. B. Le, D. Keller, arXiv:2504.15458, 2025



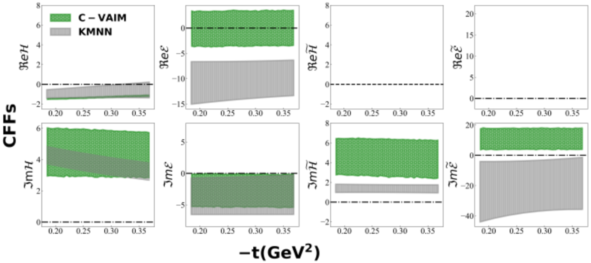
(a) $\Re e\mathcal{H}$ vs $-t$ with $x_B = 0.365$



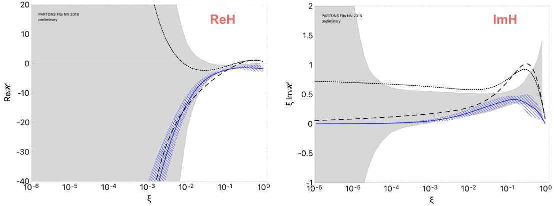
(b) $\Re e\mathcal{E}$ vs $-t$ with $x_B = 0.275$



(c) $\Re e\widetilde{\mathcal{H}}$ vs $-t$ with $x_B = 0.305$

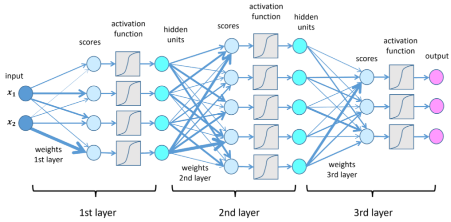


M. Almaeen et al, 2024, vs MČ et al, PRL, 2020

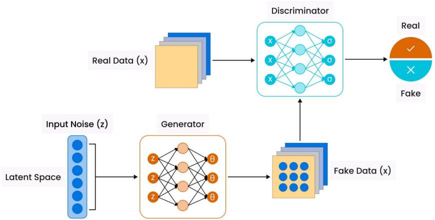


H. Moutarde et al, EPJ, 2019

Some machine learning methods on the market

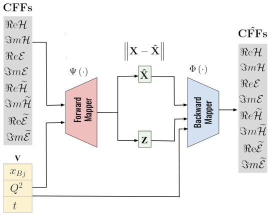


Deep neural networks



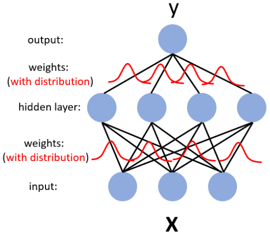
Generative adversarial network

Symbolic regression



Variational autoencoder inverse mapper

and many more...



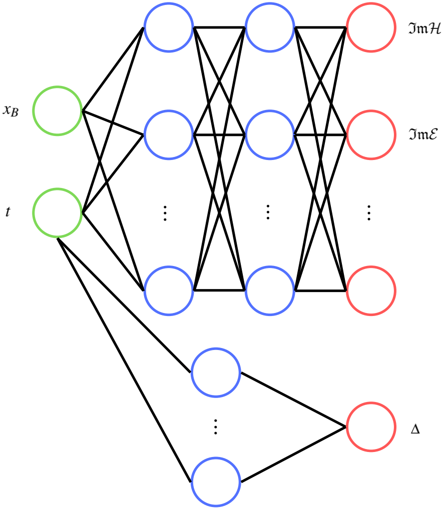
Bayesian neural networks

Neural network architecture with dispersion relations

$$\mathfrak{Re}\mathcal{H}(\xi,t) = \Delta(t) + \frac{1}{\pi}\,\text{P.V.}\int_0^1 \mathrm{d}x \left(\frac{1}{\xi - x} - \frac{1}{\xi + x}\right)\mathfrak{Im}\mathcal{H}(x,t)$$

We only model 4+1 functions instead of 8.

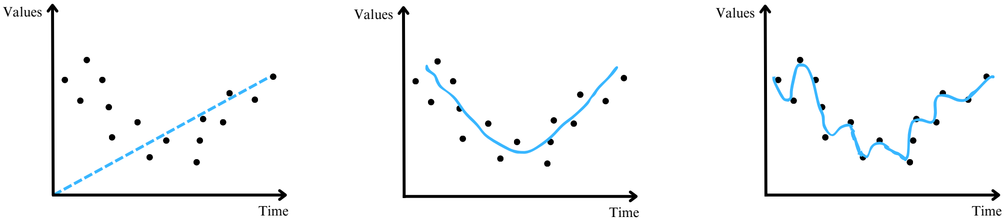
Loss function is reduced through gradient descent.



Universal approximation theorem

Let $C(K)$ be the space of continuous functions on a compact set $K \subseteq \mathbb{R}^n$. For any continuous function $f \in C(K)$ and for any $\varepsilon > 0$, there exists a feedforward neural network $\hat{f}$ with a single hidden layer such that:

$$|f(x) - \hat{f}(x)| < \epsilon \quad \text{for all } x \in K.$$



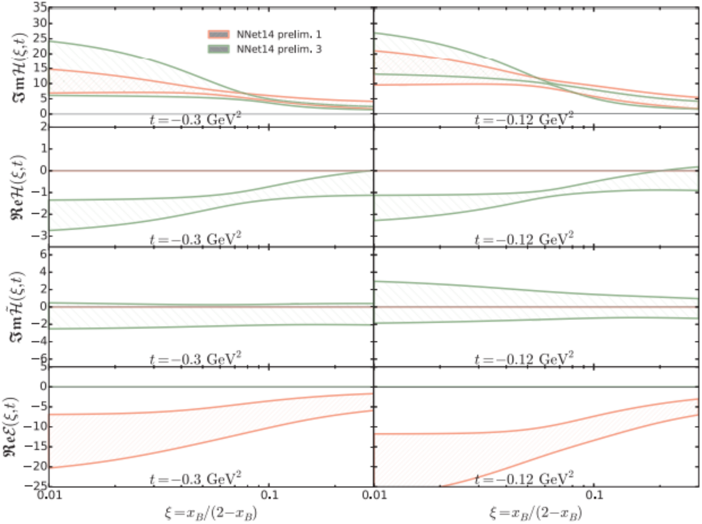
Underfitted Good fit Overfitted

Model independent (mostly) and MC propagation of uncertainties.

HERMES asymmetries

K. Kumerički, D. Müller, QCD Evol. 2014

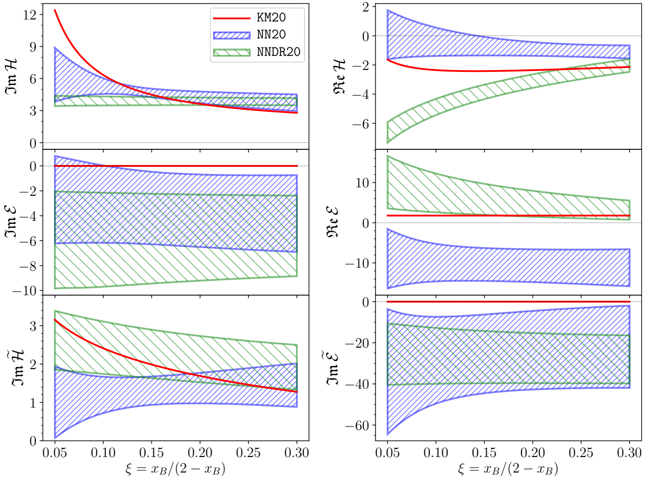
A good middle ground between global and local fits!



JLab up to 6 GeV

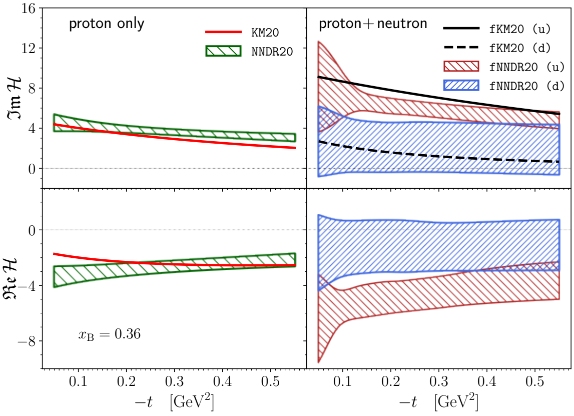
MČ, K. Kumerički, A. Schäfer, PRL 2020

Observable	n_{pts}	KM20	NN20	NNDR20	fKM20	fNNDR20
# CFFs + Δs		3+1	6	4+1	5+2	8+2
Total (harmonics)	277	1.3	1.6	1.7	1.7	1.8
CLAS A_{LU}	162	0.9	1.0	1.1	1.2	1.3
CLAS A_{UL}	160	1.5	1.7	1.8	1.8	2.0
CLAS A_{LL}	166	1.3	3.9	0.8	1.1	1.6
CLAS $d\sigma$	1014	1.1	1.0	1.2	1.2	1.1
CLAS $\Delta\sigma$	1012	0.9	0.9	1.0	0.9	1.1
Hall A $d\sigma$	240	1.2	1.9	1.7	0.9	1.3
Hall A $\Delta\sigma$	358	0.7	0.8	0.8	0.7	0.7
Hall A $d\sigma$	450	1.5	1.6	1.7	1.9	2.0
Hall A $\Delta\sigma$	360	1.6	2.2	2.2	1.9	1.7
Hall A $d\sigma_n$	96				1.2	0.9
Total (ϕ-space)	4018	1.1	1.3	1.3	1.2	1.3

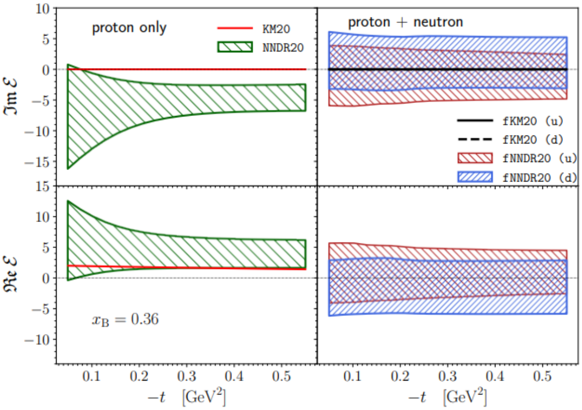


Flavor separation with neutron DVCS

We separately model $\mathcal{F}^u$ and $\mathcal{F}^d$.



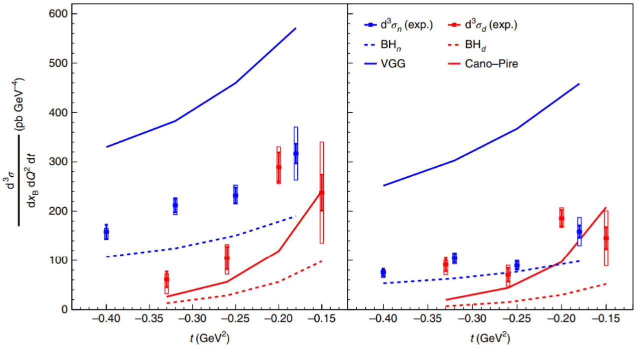
(a) $\mathcal{H}$ flavor separation

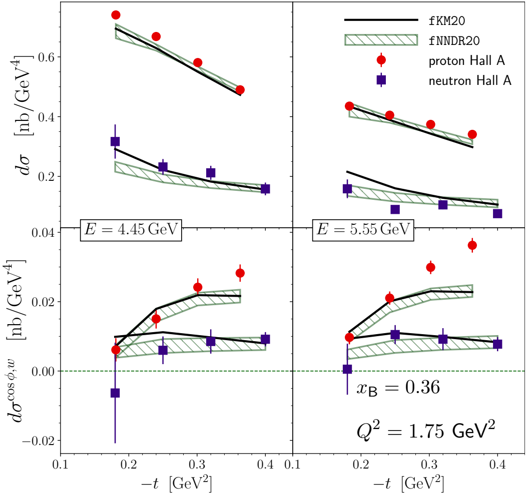


(b) $\mathcal{E}$ flavor separation

Data representation

Benali et al. '20, DVCS off a deuterium target





JLab 12 GeV upgrade

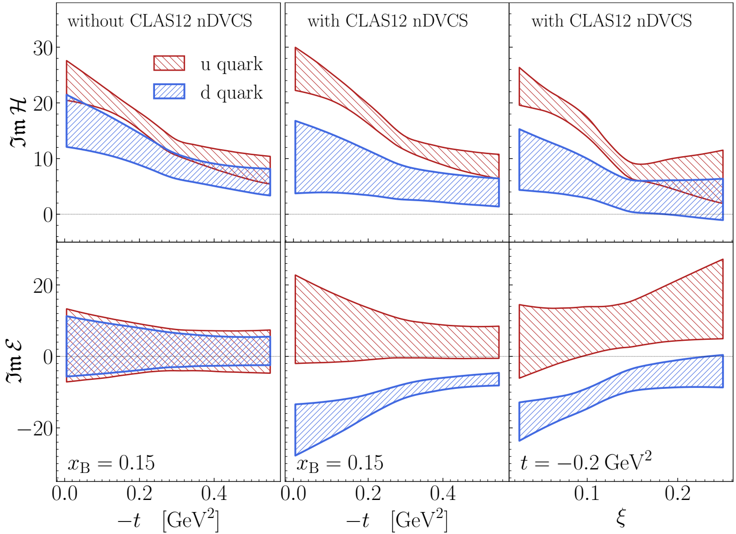
Fits from 2020 poorly represented the new BSA proton and neutron data. We performed new NN and NNDR fits on harmonics with new CLAS 2022 data (39 points with $-t < 0.5$ GeV^2) and previously available JLab data (257 points).

$$A_{\mathsf{LU}} = \frac{d\sigma^{\uparrow} - d\sigma^{\downarrow}}{d\sigma^{\uparrow} + d\sigma^{\downarrow}} \propto \mathfrak{Im}\left\{F_1\mathcal{H} + \xi\left(F_1 + F_2\right)\widetilde{\mathcal{H}} - \frac{\Delta^2}{4M^2}F_2\mathcal{E}\right\}\sin(\phi)$$

	2020	2023
fNN	1.5	1.25
fNNDR	1.5	$>$3

Table: χ^2/N_{pts}

New flavor separation

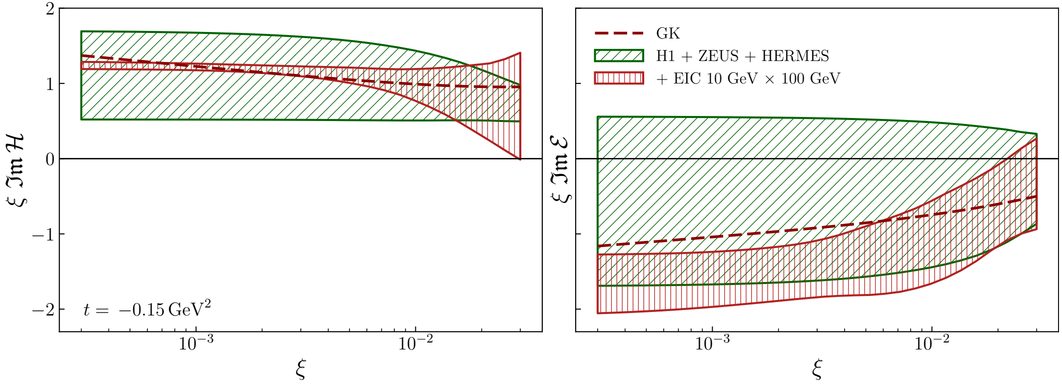


A. Hobart, S. Niccolai, MČ, K. Kumerički et al, PRL, 2024

We refitted only imaginary CFFs to A_{LU}, A_{UL}, X_{LU} and X_{UU}. Flavor separation of $\mathfrak{Re}\mathcal{H}$ is lost.

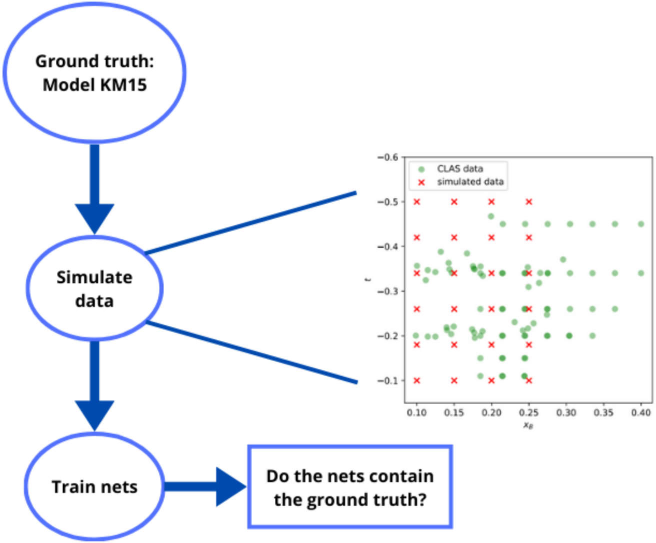
Simulated EIC data

E. C. Aschenauer et al, PRD, 2025, extraction from simulated beam-spin asymmetry



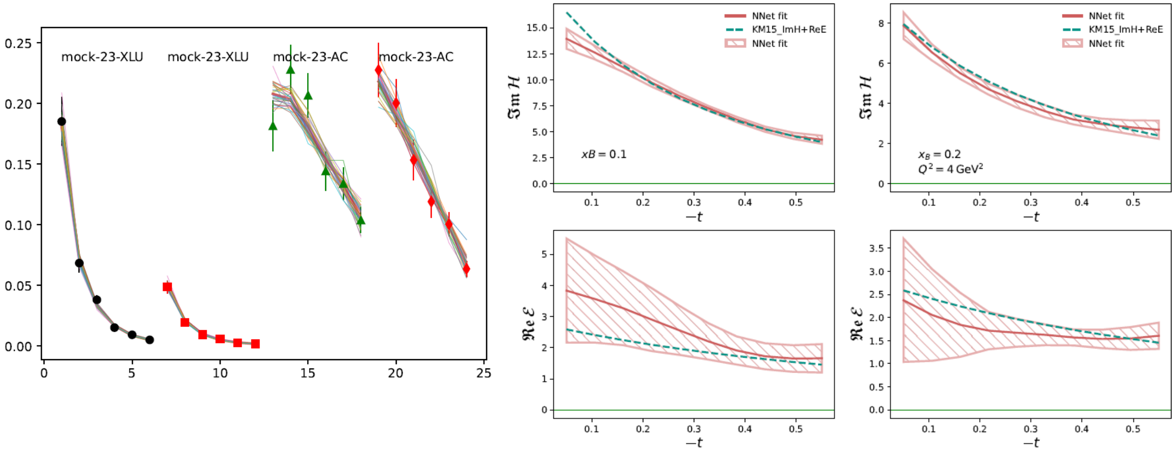
How reliable are these results?

Testing our method with closure tests

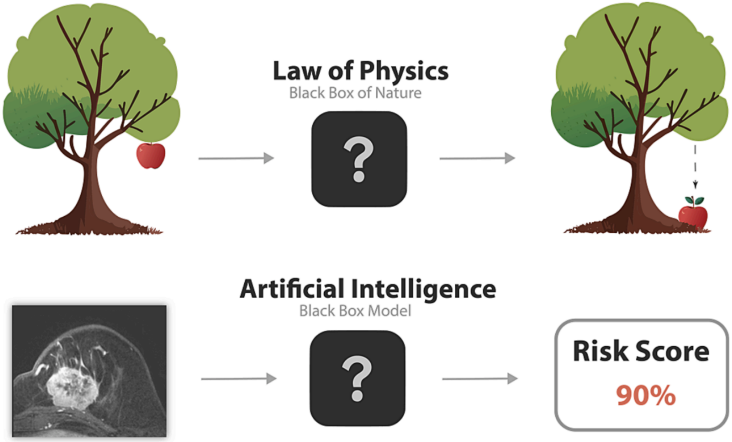


Which observables are required for CFF extraction?

$\mathfrak{Im}\mathcal{H}(x_{\mathrm{B}}, t)$ and $\mathfrak{Re}\mathcal{E}(x_{\mathrm{B}}, t)$ from X_{LU} and A_{C}



Are neural networks black boxes? Why do they do what they do?



Can we criticize the model? Can we interpret its inner workings? How? Why? Can we build it with interpretability in mind?

L. Sharkey et al, arXiv:2501.16496, 2025

M. T. Ribeiro et al, proceeding, 2016

All of physics is a black box!

Figure: E. Marcus, J. Teuwen, Eur. J. Rad, 2024

Outtakes

- Is the data too noisy for reliable extraction?
- Do we understand systematic uncertainties and experimental methods well enough for precise extraction?
- Can we benchmark?
- Are more sophisticated ML methods really necessary?
- Can we get reliable results in kinematic gaps?