DVCS analysis using machine learning methods

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Mechanical properties of hadrons: Structure, dynamics, visualization

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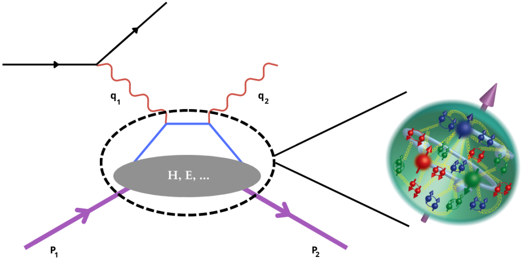
UCONN

Nucleon structure



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

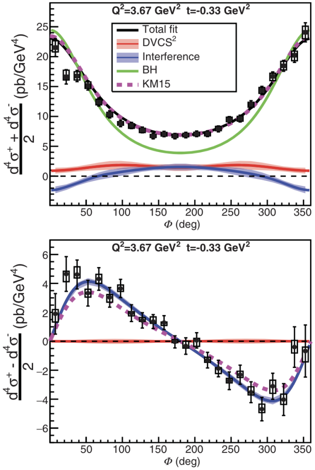
$$\downarrow$$

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

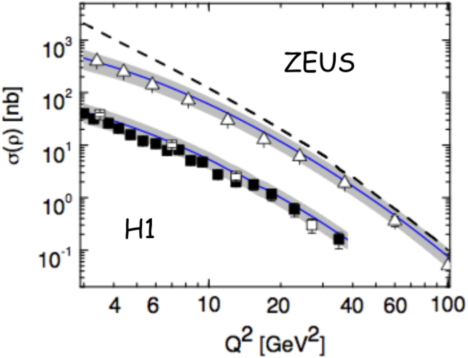
Inverse problem

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

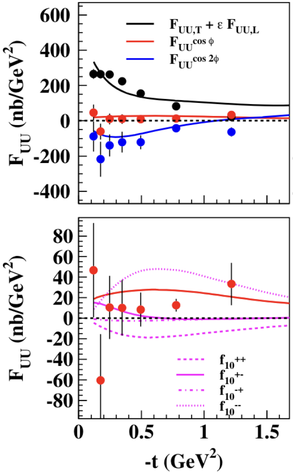
Popular GPD models



(a) Kumerički-Müller

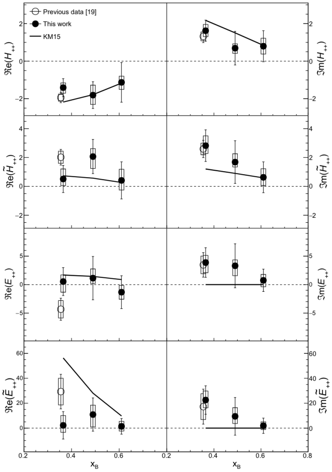


(b) Goloskokov-Kroll

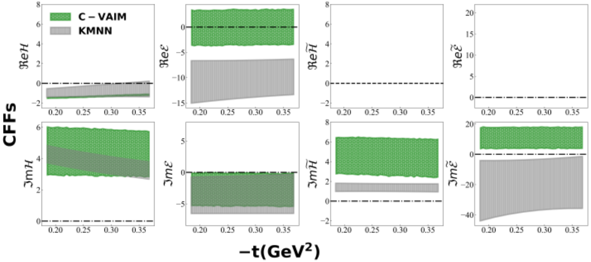


(c) Goldstein-Gonzalez-Liuti

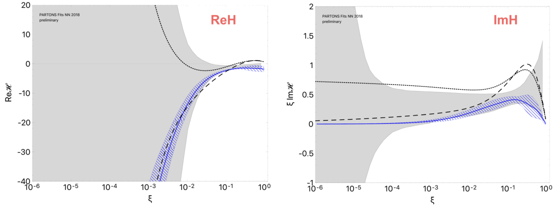
Recent CFF extraction



Hall A, PRL, 2022

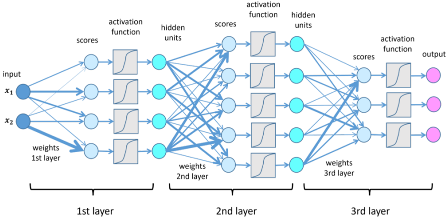


M. Almaeen et al, 2024, vs MČ et al, PRL, 2020

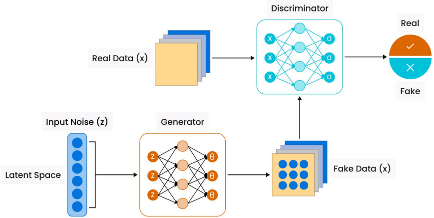


H. Moutarde et al, EPJ, 2019

Machine learning methods on the market

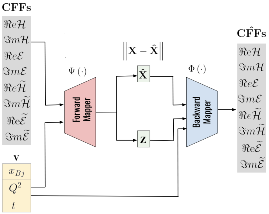


Deep neural networks

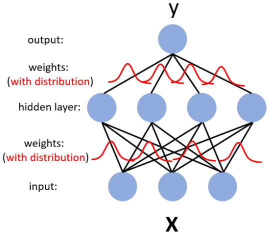


Generative adversarial network

Symbolic regression



and many more...



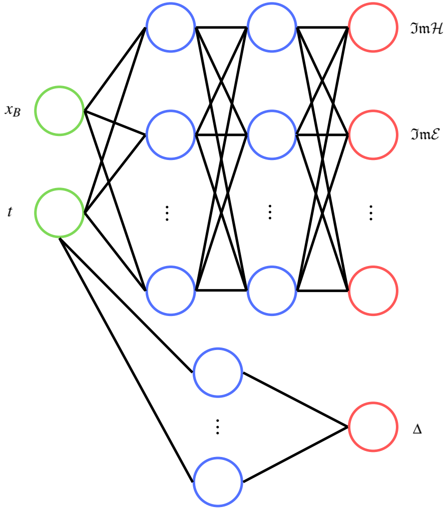
Variational autoencoder inverse mapper

Bayesian neural networks

Neural network architecture with dispersion relations

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

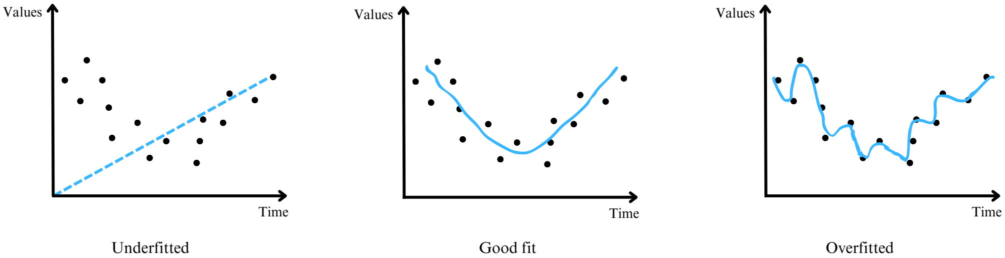
We only model 4+1 functions instead of 8.



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:

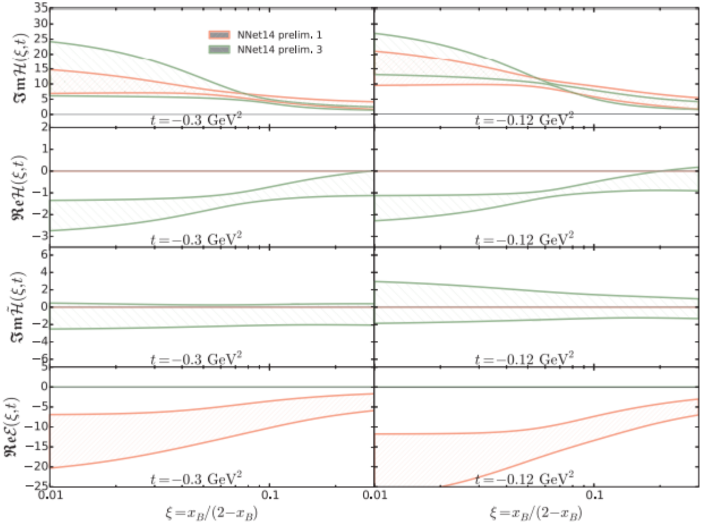
$$|f(x) - \hat{f}(x)| < \epsilon \quad \text{for all } x \in K.$$



Model independent (mostly) and MC propagation of uncertainties.

HERMES asymmetries

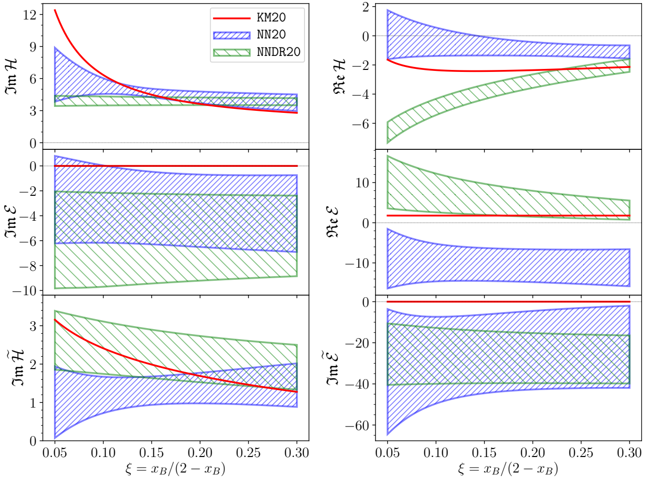
K. Kumerički, D. Müller, QCD Evol. 2014



JLab up to 6 GeV

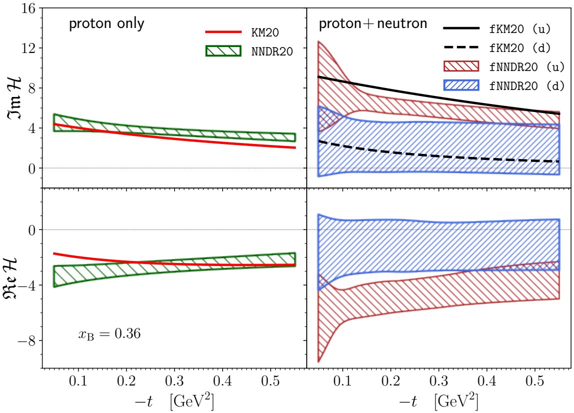
MČ, K. Kumerički, A. Schäfer, PRL 2020

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

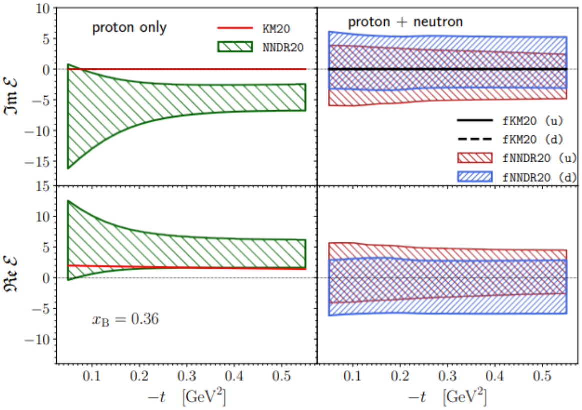


Flavor separation

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



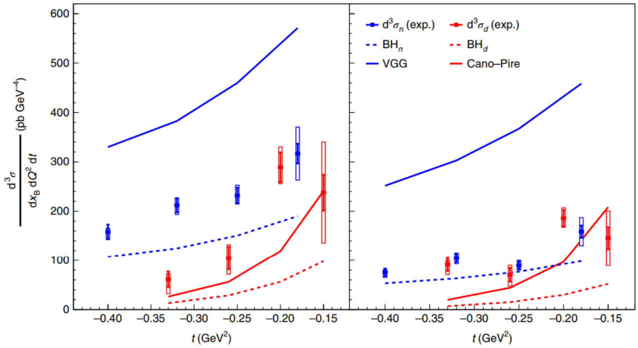
(a) $\mathcal{H}$ flavor separation

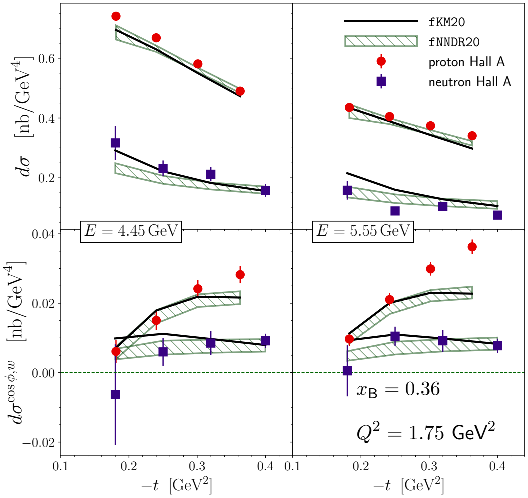


(b) $\mathcal{E}$ flavor separation

Data representation

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





JLab 12 GeV upgrade

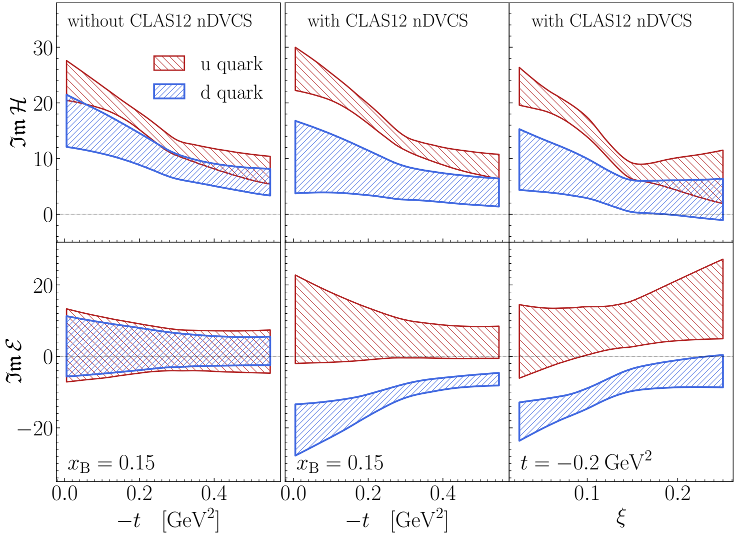
Fits from 2020 poorly represented the new BSA proton and neutron data. We performed new NN and NNDR fits on harmonics with new CLAS 2022 data (39 points with $-t < 0.5$ GeV^2) and previously available JLab data (257 points).

	2020	2023
fNN	1.5	1.25
fNNDR	1.5	$>$3

Table: χ^2/N_{pts}

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

New flavor separation

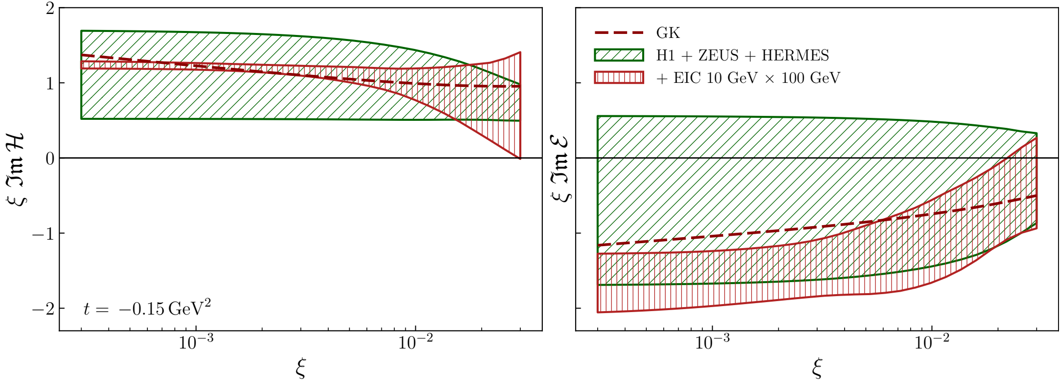


A. Hobart, S. Niccolai, MC, K. Kumerički et al, PRL, 2024

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

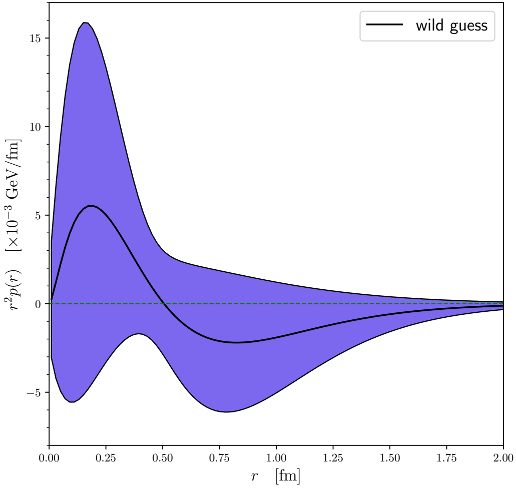
Simulated EIC data

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



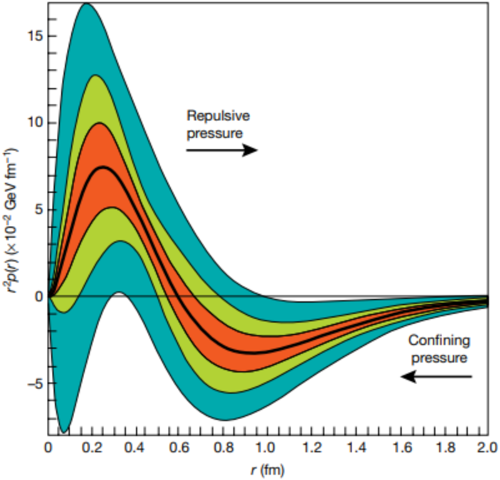
Pressure inside the proton

K. Kumerički, Nature, 2019



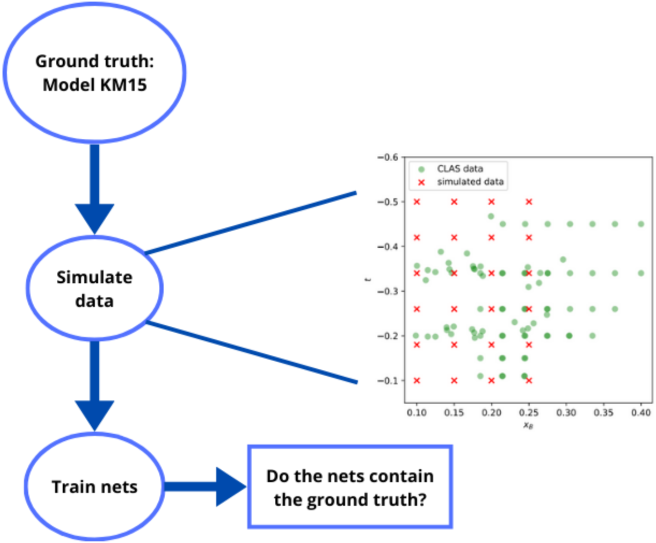
VS

V. D. Burkert et al, Nature, 2018



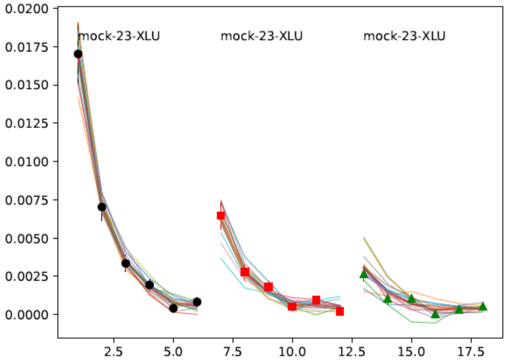
How reliable are these results?

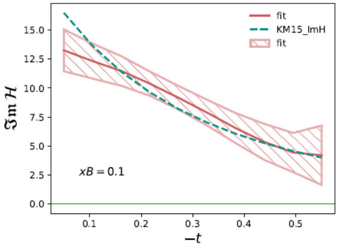
Testing our method with closure tests

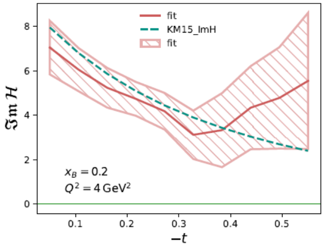


Which observables are required for CFF extraction?

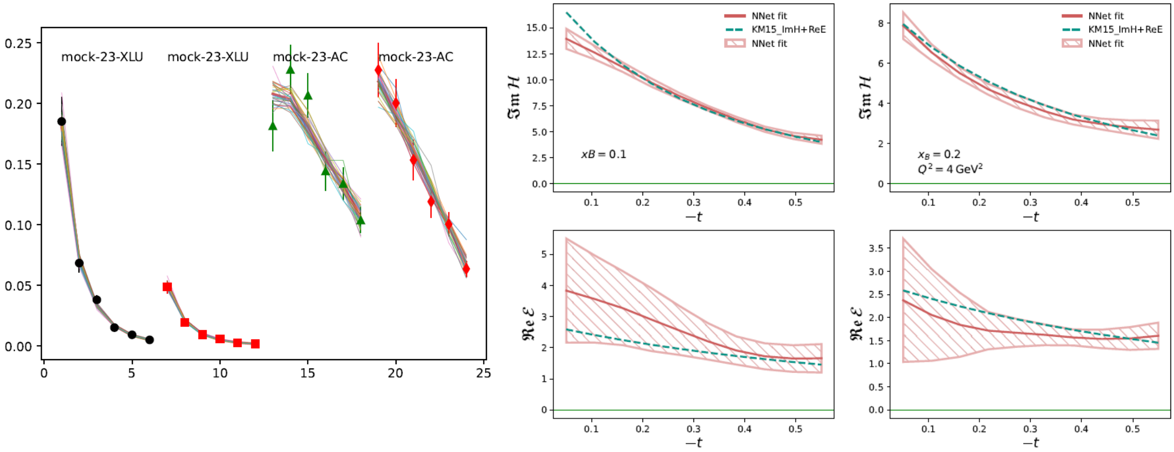
$\Im\mathfrak{m}\mathcal{H}(x_{\mathrm{B}}, t)$ from X_{LU}



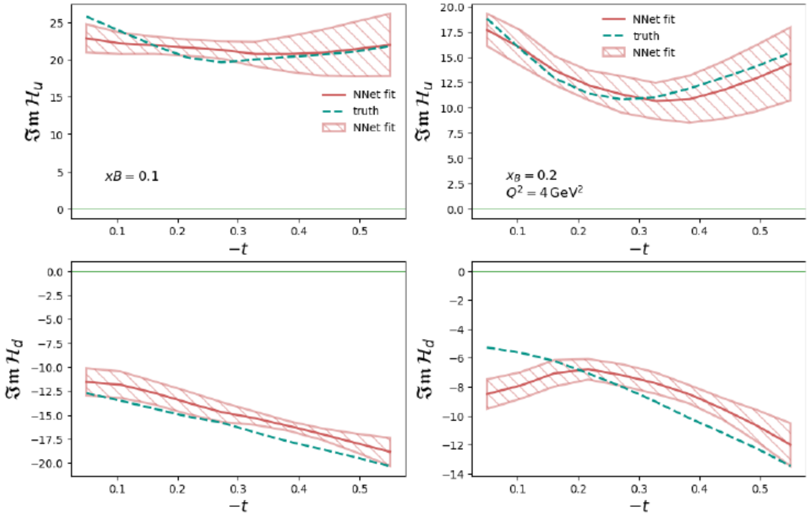




$\Im\mathfrak{m}\mathcal{H}(x_B, t)$ and $\Re\mathfrak{e}\mathcal{E}(x_B, t)$ from X_{LU} and A_C

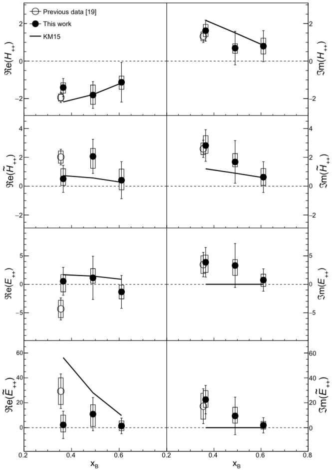


$\mathcal{H}$ flavor separation from X_{UU} and X_{LU}

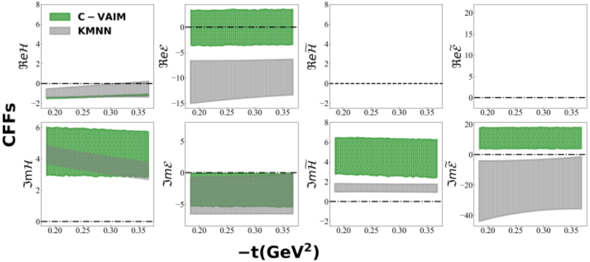


Ground truth is a single net from the JLab fNN model.

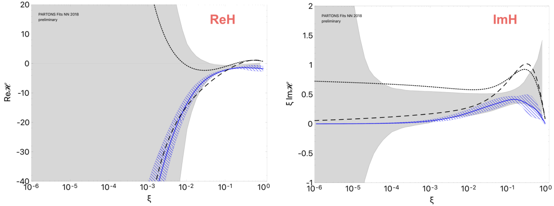
If the methods are sound, how do we reconcile these results?



Hall A, PRL, 2022

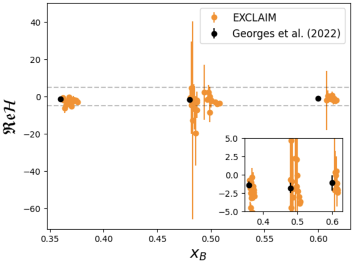


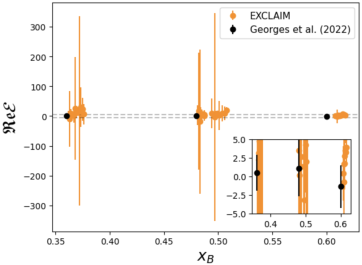
M. Almaeen et al, 2024, vs MČ et al, PRL, 2020

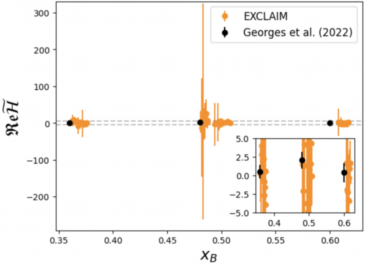


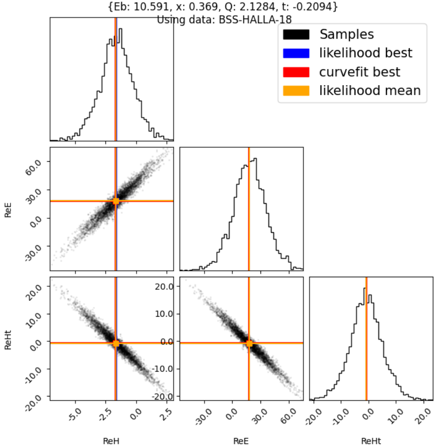
H. Moutarde et al, EPJ, 2019

What can we extract from data?









D. Q. Adams et al, 2024

Outtakes

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