# Separation of GPD flavors using neural networks and DVCS on neutron

**Krešimir Kumerički**

University of Zagreb, Croatia

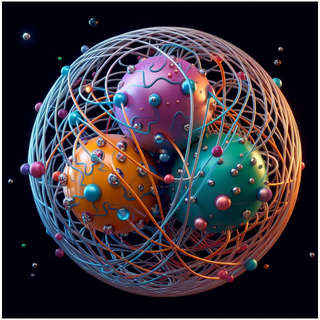
**Towards improved hadron tomography with hard exclusive reactions**

5-9 August, 2024, ECT*, Trento

HrZZ Croatian Science Foundation

EUROPSKI STRUKTURNI I INVESTICIJSKI FONDOVI

STRONG 2020



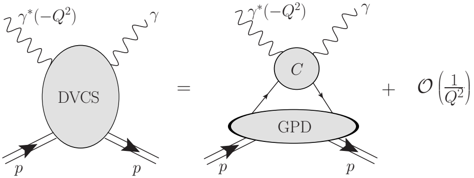
# DVCS ⟶ CFFs ⟶ GPDs

- At leading order DVCS cross-section depends on four complex

**Compton form factors (CFFs)**

$$\mathcal{H}(\xi, t, Q^2), \quad \mathcal{E}(\xi, t, Q^2), \quad \widetilde{\mathcal{H}}(\xi, t, Q^2), \quad \widetilde{\mathcal{E}}(\xi, t, Q^2)$$

- [Collins et al. '98]




- CFFs are convolution:

$$^{a}\mathcal{H}(\xi, t, Q^2) = \int \mathrm{d}x \; C^a(x, \xi, \frac{Q^2}{Q_0^2}) \; H^a(x, \eta = \xi, t, Q_0^2)$$

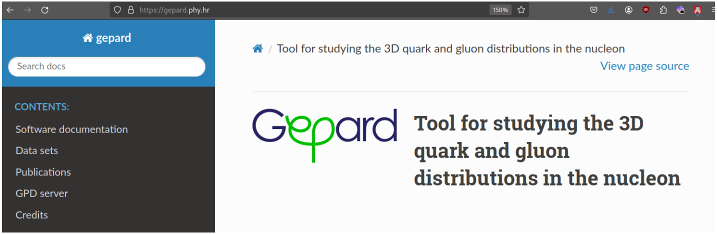
$a{=}q,G$

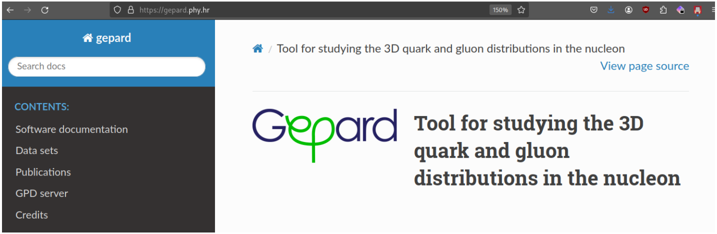
- $H^a(x, \eta, t, Q_0^2)$ — Generalized parton distribution (GPD)

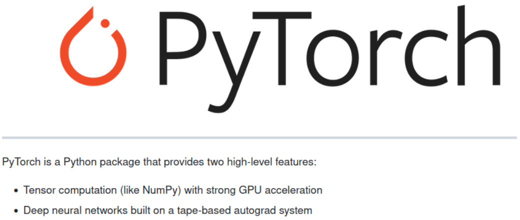
[Müller '92, et al. '94, Ji, Radyushkin '96]

# Two approaches to global fits

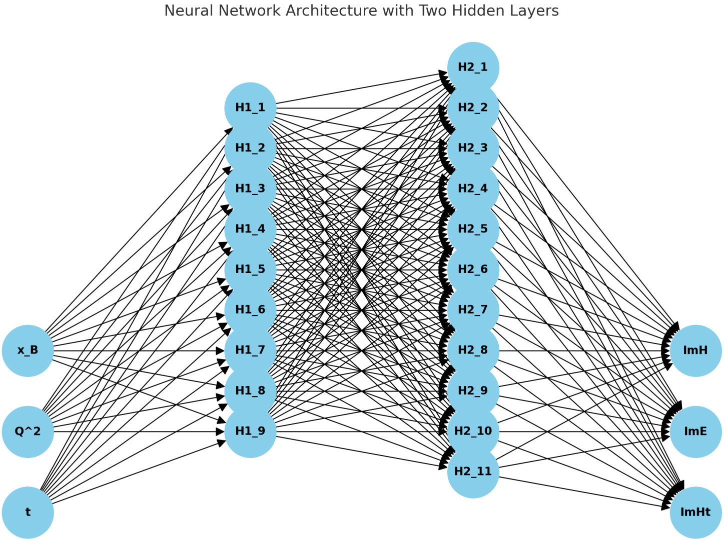
1. Fitting QCD/Regge-inspired physical GPD models
   - perturbative QCD at NLO (NNLO in the future [Braun et al.])
   - true tomography possible
   - DVCS + DVMP + ... [Čuić, Duplančić, K.K., Passek-K. '23]
2. Fitting CFFs parametrized by neural networks
   - unbiased
   - realistic uncertainties (good for impact studies)


https://gepard.phy.hr
gepard
Search docs
CONTENTS:
Software documentation
Data sets
Publications
GPD server
Credits
Tool for studying the 3D quark and gluon distributions in the nucleon
View page source
Gepard
Tool for studying the 3D quark and gluon distributions in the nucleon


https://gepard.phy.hr
150%
gepard
Search docs
CONTENTS:
Software documentation
Data sets
Publications
GPD server
Credits
Tool for studying the 3D quark and gluon distributions in the nucleon
View page source
Gepard
Tool for studying the 3D quark and gluon distributions in the nucleon


PyTorch
PyTorch is a Python package that provides two high-level features:
• Tensor computation (like NumPy) with strong GPU acceleration
• Deep neural networks built on a tape-based autograd system

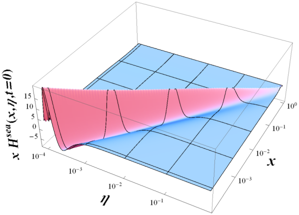
# Typical neural networks architecture



# How deep is your net?

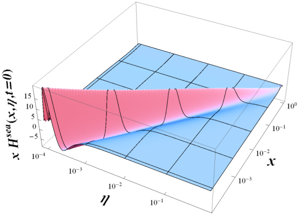
# How deep is your net?

- When considering various fancy neural net architectures, keep in mind that we are after this:



# How deep is your net?

- When considering various fancy neural net architectures, keep in mind that we are after this:




- . . . and not after this:

# Closure tests

# Testing the extraction procedure

- To each observable many GPDs/CFFs contribute. Can we tell them apart?
- Is the extraction procedure guaranteed to converge to actual underlying physical hadron structure functions?

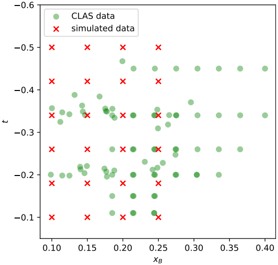
# Testing the extraction procedure

- To each observable many GPDs/CFFs contribute. Can we tell them apart?
- Is the extraction procedure guaranteed to converge to actual underlying physical hadron structure functions?
- Closure [NNPDF] a.k.a. feasibility [PARTONS] test:
  1. Take the known GPD/CFF model - “ground truth”
  2. Generate simulated (mock) data by calculating observables in a certain kinematic range (possibly correspoding to the real measurements of interest)
  3. Apply your fitting/extraction procedure to simulated data
  4. Check that the result is consistent with ground truth

# How we tested

- As a ground truth we used KM15 model [K.K. and Müller '15]
- Kinematical points are equidistant, but roughly overlap CLAS12 kinematics

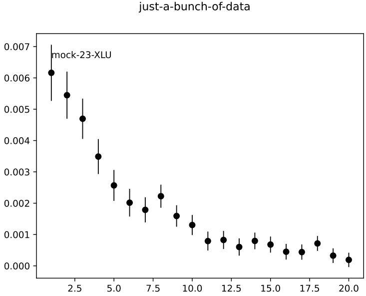
(For speed, $\phi = \pi/4$)




- DVCS observables are a subset of:
  1. helicity dependent and independent cross-sections ($X_{\rm LU}$, $X_{\rm UU}$)
  2. beam spin asymmetry ($A_{\rm LU}$) - not an independent observable
  3. beam charge asymmetry ($A_{\rm C}$)
  4. transversal target spin asymmetry ($A_{\rm UT,DVCS}$)

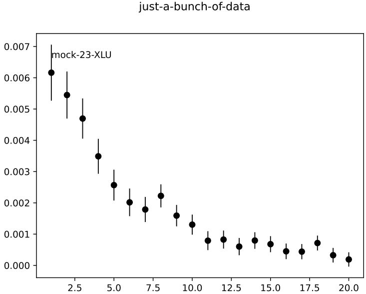
# (Almost) toy example (1/2)

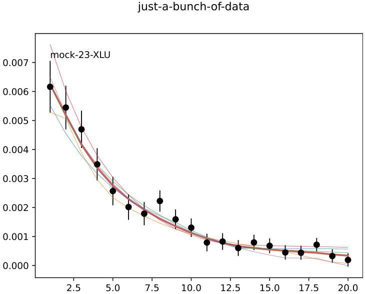
- Only $\mathfrak{Im}\,\mathcal{H}(t)$ (fixed $x_B = 0.2$), only $X_{\rm LU}$.



# (Almost) toy example (1/2)

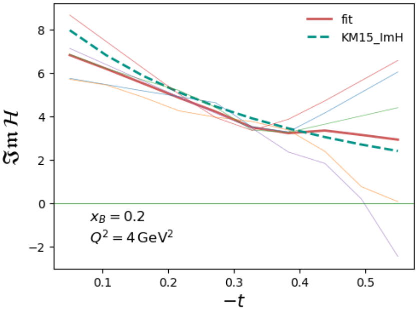
- Only $\mathfrak{Im}\,\mathcal{H}(t)$ (fixed $x_B = 0.2$), only $X_{\rm LU}$.



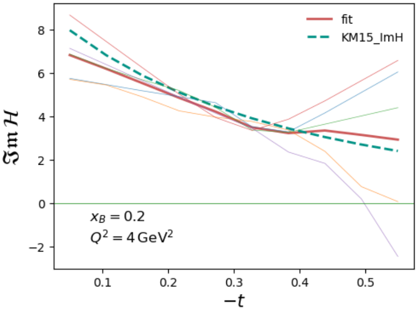



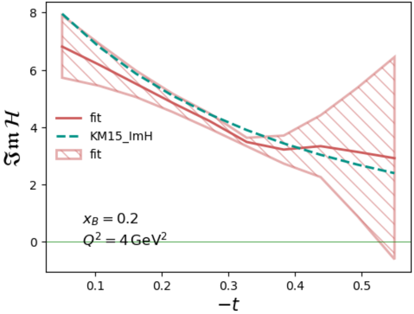

(Unless explicitly specified, x-axis just counts data points, and corresponds to $t$.)

# (Almost) toy example (2/2)



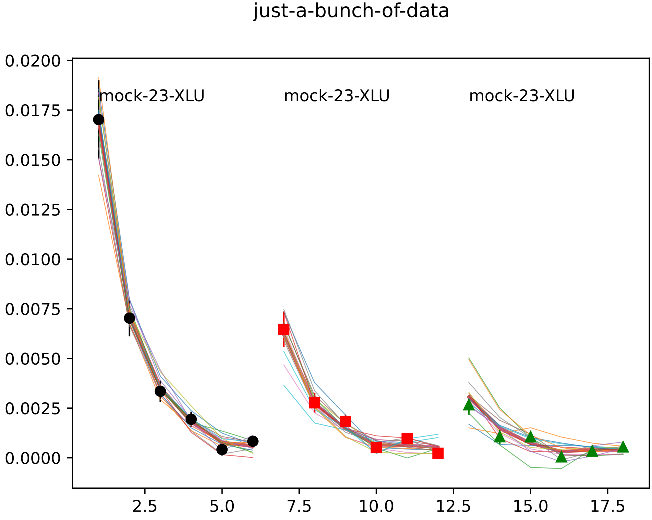
# (Almost) toy example (2/2)



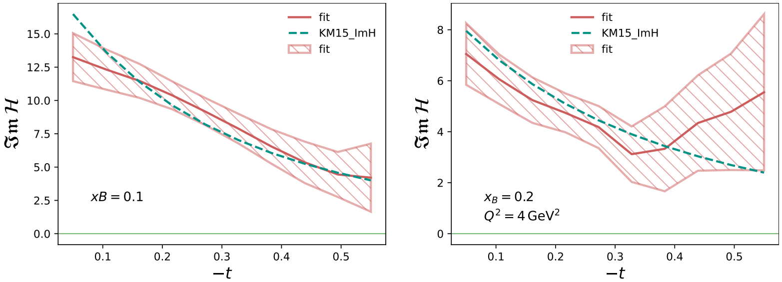



# Example 2: $\mathfrak{Im}\,\mathcal{H}$ $t$ and $x_B$ dependence (1/2)

- $\mathfrak{Im}\,\mathcal{H}(x_B, t)$, still only $X_{\mathrm{LU}}$.



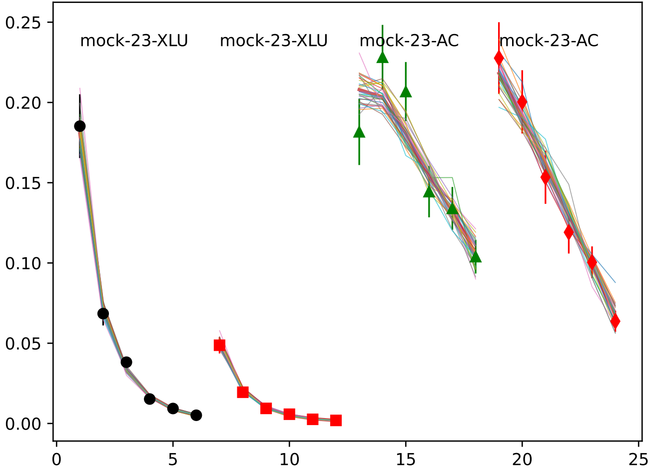
# Example 2: $\Im\mathfrak{m}\,\mathcal{H}$ $t$ and $x_B$ dependence (2/2)



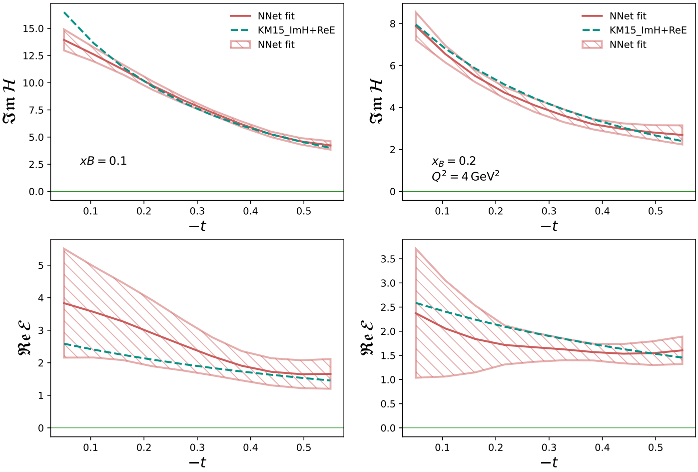
# Example 3: $\mathfrak{Im}\,\mathcal{H}$ and $\mathfrak{Re}\,\mathcal{E}$ (1/3)

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

just-a-bunch-of-data

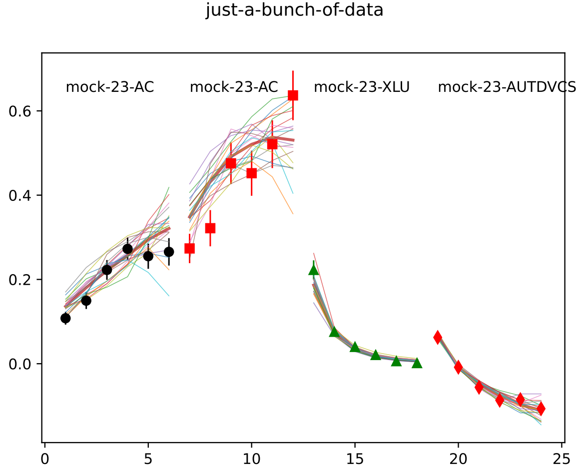


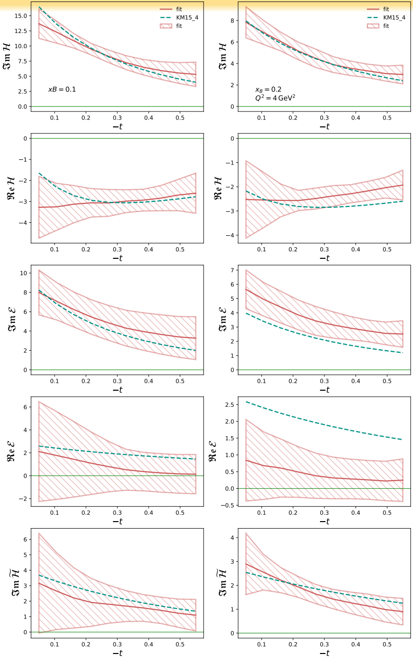
# Example 3: $\mathfrak{Im}\,\mathcal{H}$ and $\mathfrak{Re}\,\mathcal{E}$ (2/3)



# Example 4: Five CFFs (1/3)

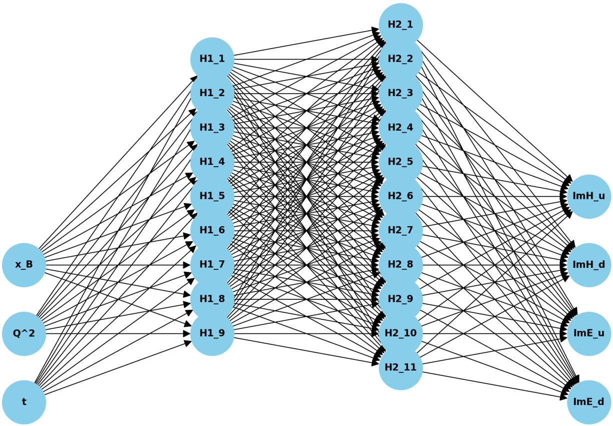
- $\mathfrak{Im}\,\mathcal{H}$, $\mathfrak{Re}\,\mathcal{H}$, $\mathfrak{Im}\,\mathcal{E}$, $\mathfrak{Re}\,\mathcal{E}$, and $\mathfrak{Im}\,\widetilde{\mathcal{H}}$, from $X_{\rm UU}$, $X_{\rm LU}$, $X_{\rm UL}$, $A_{\rm C}$, and $A_{UT,DVCS}$




fit
KM15_4
fit
$xB = 0.1$
$x_B = 0.2$
$Q^2 = 4\,\mathrm{GeV}^2$
$\Im\mathfrak{m}\,\mathcal{H}$
$\Re\mathfrak{e}\,\mathcal{H}$
$\Im\mathfrak{m}\,\mathcal{E}$
$\Re\mathfrak{e}\,\mathcal{E}$
$\Im\mathfrak{m}\,\widetilde{\mathcal{H}}$
$-t$

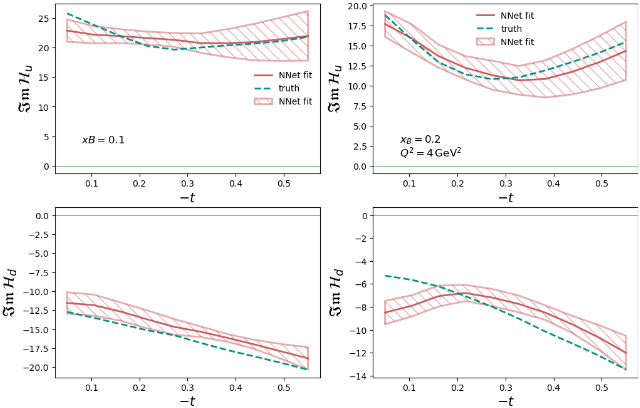
# "Flavored" neural net

Neural Network Architecture with Two Hidden Layers and Four Output Nodes

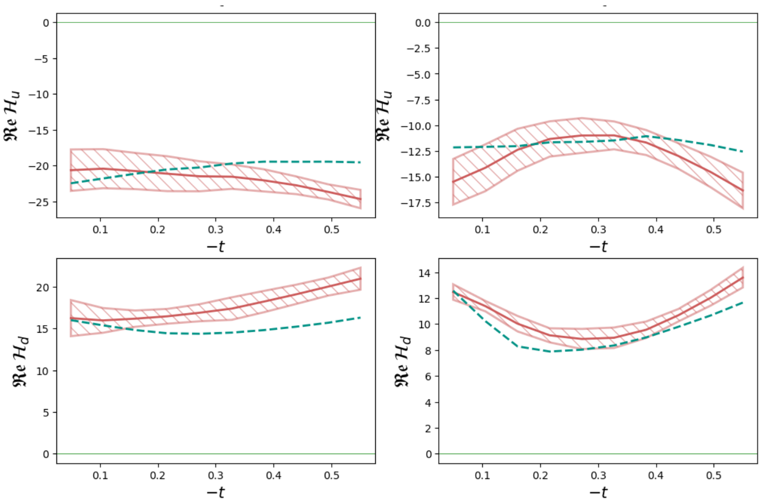


# Example 5: $\mathcal{H}$ flavor separation (1/2)

- $\mathfrak{Im}\,\mathcal{H}_u$, $\mathfrak{Im}\,\mathcal{H}_d$, $\mathfrak{Re}\,\mathcal{H}_u$, $\mathfrak{Re}\,\mathcal{H}_d$, from $X_{\rm UU}$ and $X_{\rm LU}$ on proton and neutron
- Ground truth is a random smooth single neural net trained on subset of JLab proton and neutron data



# Example 5: $\mathcal{H}$ flavor separation (2/2)



# Application: $\mathfrak{Im}\,\mathcal{E}$

# Accessing $\mathfrak{Im}\,\mathcal{E}$ in DVCS

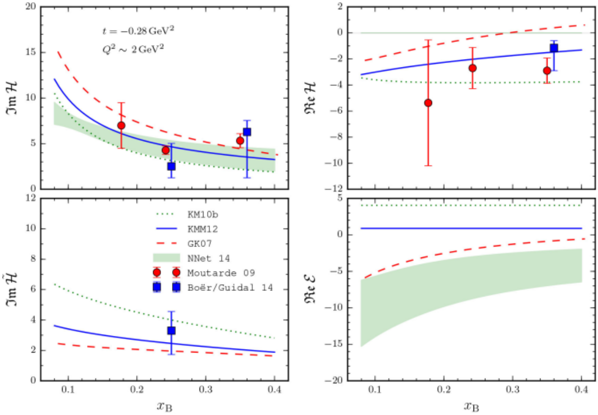
- Good observable is DVCS beam spin asymmetry:

$$A_{\rm LU} \propto \sin\phi \left[ F_1\,\mathfrak{Im}\,\mathcal{H} - \frac{t}{4M_p^2} F_2\,\mathfrak{Im}\,\mathcal{E} + \frac{x_{\rm B}}{2-x_{\rm B}}(F_1+F_2)\,\mathfrak{Im}\,\widetilde{\mathcal{H}} \right]$$

- Two strategies:
  1. measure $A_{\rm LU}$ very precisely over wide kinematic range
  2. measure $A_{\rm LU}$ on neutron where $F_2 > F_1$

# Status (2016)

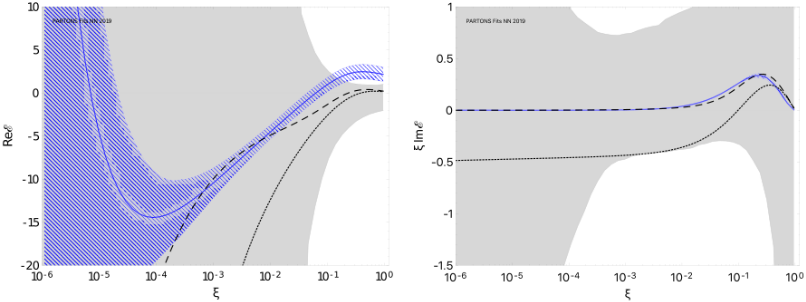
- [K.K., S. Liuti, H. Moutarde, '16] (review)




- $\mathfrak{Im}\,\mathcal{E}$ does not make an appearance

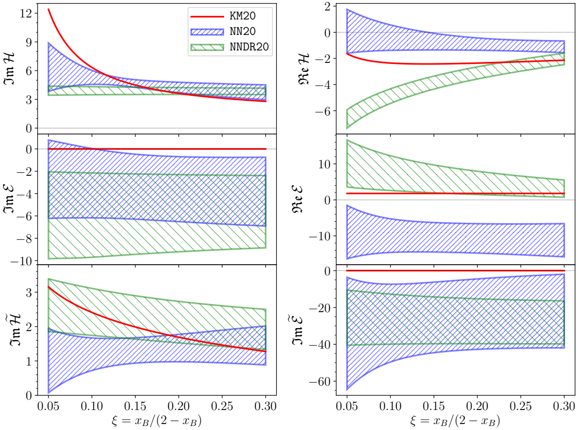
# PARTONS (2019) world global NNet fit

- [H. Moutarde, P. Sznajder, J. Wagner, '19]

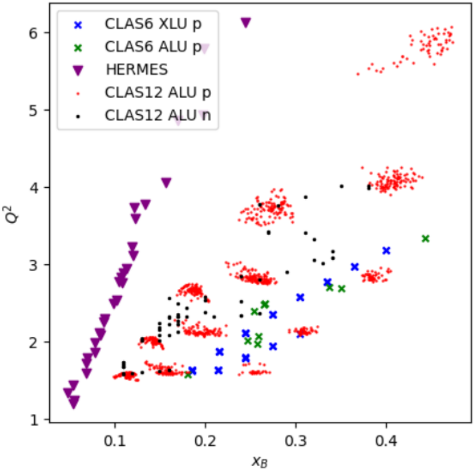


# 6/8 CFFs extraction (2020) from JLab 6 GeV data

- [M. Čuić, K.K., A. Schäfer, '20]

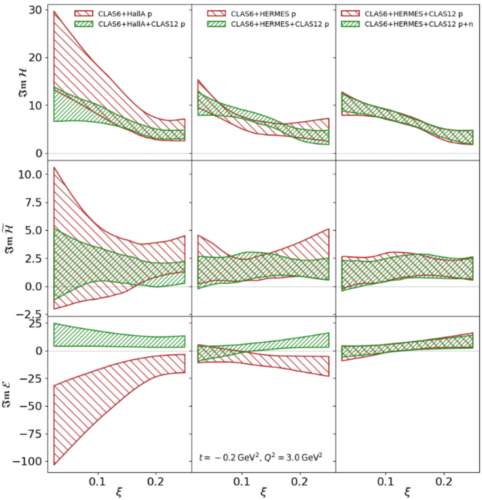


# Adding CLAS12 data (1/4)



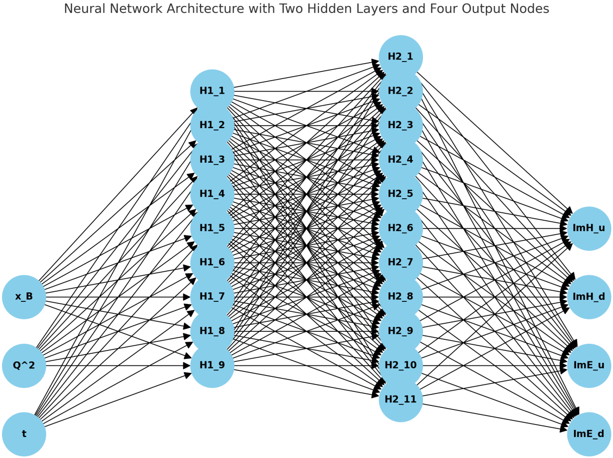

- $A_{\rm LU}$ proton: [G. Christiaens et al. (CLAS), PRL 130 (2023) 211902]
- $A_{\rm LU}$ neutron: [A. Hobart et al. (CLAS), arXiv:2406.15539]

# Adding CLAS12 data (2/4)

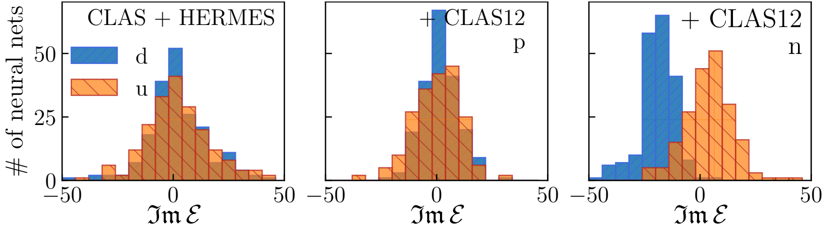



- proton DVCS is enough for total $\mathfrak{Im}\,\mathcal{E} = \mathfrak{Im}\left(4\mathcal{E}_u + \mathcal{E}_d\right)/9$

# Flavored neural net

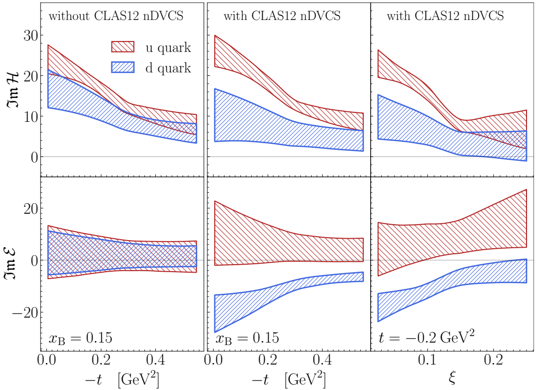


# Adding CLAS12 data (3/4)




- isospin symmetry: $\mathfrak{Im}\,\mathcal{E}_u^{\rm neutron} = \mathfrak{Im}\,\mathcal{E}_d$ (and vice versa)
- neutron DVCS enables separation of $\mathfrak{Im}\,\mathcal{E}_u$ and $\mathfrak{Im}\,\mathcal{E}_d$

# Adding CLAS12 data (4/4)




- [A. Hobart et al. (CLAS), arXiv:2406.15539]

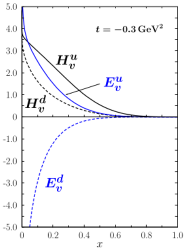
# $\Im\mathfrak{m}\,\mathcal{E}$ from electromagnetic form factors vs. DVCS

DVCS ($C$-even):

$$\Im\mathfrak{m}\,\mathcal{E}_q(\xi,t) = \pi\, e_q^2 \Big( E_q(\xi,\xi,t) - E_q(-\xi,\xi,t) \Big) \qquad \text{(at LO)}$$

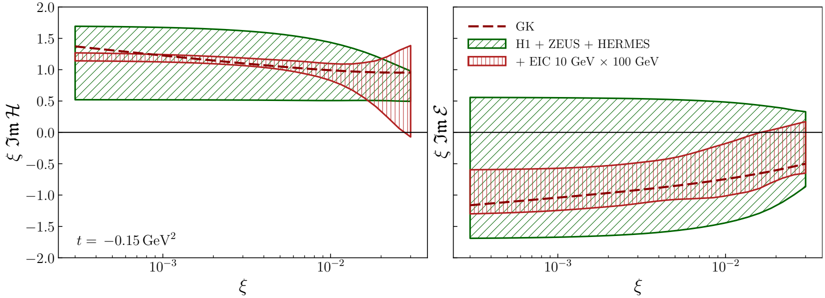
EFFs ($C$-odd):

$$\int_{-1}^{1} dx\, E_q(x,\xi,t) = F_2^q(t)\,; \qquad F_2^q(0) = \kappa_q = \begin{cases} 1.67 & \text{u quark} \\ -2.03 & \text{d quark} \end{cases}$$




[Diehl and Kroll '13]
(Radyushkin model fit)

# Instead of summary: look into the future (EIC)




- Only $A_{\mathrm{LU}}$, only on proton
- [E. Aschenauer et al., really soon now on arXiv] (see talk by A. Jentsch)

# Thank you!